

**Evaluating Semantic Measures by Computing the
Coverage of a Condensed Text**

تقييم المقاييس الدلالية من خلال قياس تغطية النص المكثف

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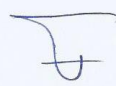


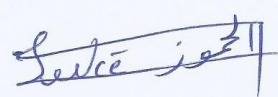
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بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

"وقل ربي زدني علماً"

Dedication

I would like to exploit this opportunity to dedicate this project to my father, mother, brothers and sisters, without whose invaluable support. I would not have been able to have achieved this in my lifetime.

May God bless them.

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LIST OF ABBRIVATIONS

CC	: Condensed Concepts.
DUC	: Document Understanding Conference.
HSO	: Hirst & St-Onge.
IC	: Information Content.
ICF	: Information Content Family.
KAON	: Karlsruhe Ontology.
LCH	: Leacock & chodorow.
LCS	: Least Common Subsumer.
MSE	: Mean Square Error.
NIST	: National Institute of Standards and Technology.
NLP	: Natural Language Processing.
OC	: Original Concepts.
PLF	: Path Length Family.
SM	: Semantic Measures.
SRF	: Semantic Relatedness Family
WS4J	: WordNet Similarity for Java.
WuP	: Wu and Palmer.

Evaluating Semantic Measures by Computing the Coverage of a Condensed Text

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Abstract

Automatic summarization systems that produce a condensed text are an essential topic in natural language processing (NLP). How to evaluate these systems is an issue for many researchers. There are several approaches to define the quality of a condensed text. This thesis used semantic measures to define the quality of a condensed text. Semantic measures compute the similarity and relatedness among concepts included in knowledge source. This thesis used semantic measures to find how much the condensed text cover the original text.

This thesis applied several experiments to find which semantic measure or measures best cover a condensed text. Well-known benched data sets have been collected with both original text and condensed text for those experiments. The main concepts for both the original and the condensed text have been extracted using ontological tools. Six semantic measures from three families (i.e. path, information contents and relatedness) have been applied to those extracted concepts; those measures are (WuP, LCH, Resnik, LIN, HSO and LESK). Above 10, 000 data items for 48 files for two data set groups have been used to find out and evaluate which semantic measure or measures are best to compute how much a condensed text covers its original. This thesis used mean square error to compute the

difference between the evaluation of the proposed semantic measures and the expert evaluation. The results showed that from six similarity measures, Resnik was the best measure that identified the quality of a condensed text where it gave minimum MSE (15.6%) from the expert evaluation with different acceptance rates. This thesis found that LCH has the minimum MSE (12%) in most cases if we assume that all condensed text have 100% coverage for the original text.

In the case of bad summaries i.e. where the expert stated that a condensed text has less than 40% coverage of the original text; in that case, this research recommended using LESK measure as it gave minimum MSE (3%). This thesis showed that the semantic measures can be used to identify not only the good coverage but also the bad coverage.

Keywords: Ontology, Concept, condensed text, extracted concepts, semantic similarity, semantic relatedness.

تقييم المقاييس الدلالية من خلال قياس تغطية النص المكثف

إعداد: زينب محمود بيرم

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المُلخص

نظم التلخيص التلقائي التي تنتج النص الملخص من اهم الموضوعات البحثية في معالجة اللغة و تقييم نوعية النصوص الملخصة. هناك عدة طرق لتحديد نوعية النصوص الملخصة، منها على سبيل المثال: أهمية الجملة بالنسبة للنص، عدد مرات استدعاء الجملة في النص الملخص. هذه الرسالة تستخدم المقاييس الدلالية لتحديد نوعية النص الملخص، وقياس مدى تشابه و تقارب المفاهيم المعرفية. تهدف هذه الرسالة الى معرفة مقدار تغطية النص الملخص للنص الاصلي باستخدام المقاييس الدلالية.

من خلال بحثنا، تم اجراء العديد من التجارب لايجاد اي مقياس/ مقاييس الدلالية المغطية للنص الاصلي بأفضل نسبة. تم جمع مجموعة من البيانات التي تحتوي على النصوص الاصلية و النصوص الملخصة. تم أستخراج المفاهيم الاساسية من كلا النصين الأصلي و الملخص. تم تطبيق ستة مقاييس دلالية من ثلاثه أنواع (المسار، محتوى المعلومات، القرابة) على هذه المفاهيم المستخرجة، حيث تم تطبيقها على 48 ملف من البيانات لمعرفة اي المقاييس الدلالية التي تعطي أفضل النتائج من حيث تغطية النص الملخص.

هذه الرسالة تستخدم متوسط مربع الخطأ لحساب الفرق بين تقييم المقاييس الدلالية وتقييم الخبراء. أظهرت النتائج ان من خلال استخدام ستة مقاييس دلالية، ان ريسنك (Resnik) كان افضل مقياس الذي يحدد نوعية النص الملخص بنسبة أقل خطأ (15.6%). كما اوجدت الدراسة ان مقياس ال سي اج (LCH) كان افضل مقياس لتحديد نوعية النص الملخص اذا افترضنا ان النص الملخص مغطى النص الاصلي بنسبة 100% وكانت نسبة الخطأ (12%). في حالة كان الملخص سي اي عند تقييم الخبير لتغطية النص الملخص وجد ان النص الملخص يغطي 40% من النص الاصلي. من خلال التجارب وجدنا ان مقياس ليسك (LESK) اعطانا نسبة خطأ (3%). من خلال البحث تبين ان المقاييس الدلالية يمكن استخدامها ايضا في معرفة الملخص السيء.

كلمات البحث: علم الوجود، المفاهيم، النص الملخص، المفاهيم المستخرجة، التشابه الدلالي، الارتباط الدلالي.

CHAPTER ONE

Introduction

1.1 Introduction

The importance of a text summarization system has been growing with the expansion of the quantity of online information. Condensing knowledge is the aim of many organizations. The data (original text) may be summarized in more than one concise form. The goal of automatic summarization is to take information source for a particular domain, and extract content from it while preserving the main information content of the original text and represent contents to the user in an abstract, condensed structure forming a text summary.

Automatic summarization research becomes an important topic in natural language processing (NLP), at the same time we need to discuss and clarify the issues on how to evaluate the text summarization systems. According to Steinberger and Jezek, the evaluation of summary quality is very hard and challenging task. There are several measures used to define the quality of a condensed text. Examples of these measures are sentence recall, sentence ranking and question answering. Different types of measures have been used to find which measure is the best measure (Steinberger and Jezek, 2009; House, et al., 2002).

1.1.1 Automatic Summarization and Evaluation

The main goal of automatic summarization is to take original text, extract the main content from it then presents the most important information to the user in condensed form. In general, summaries can be user focus (topic focus or query focus) which determine the contents as the users require or it could be generic which locate the main content covered by the original data.(Mani,2001a ;Mani, 2001b ; Alguliev & Aliguliyev, 2007).

Maintaining coherence in summary is important too, created a summary based on cutting & pasting the text can cause a problem on coherence among sentences. There are many ways to classify text summaries based on different criteria; Sparck-Jones classified summaries as below: (Sparck-Jones, 1999 as cited on Fukusima & Okumura 2001).

- Input factors: text length, genre, single vs. multiple documents.
- Purpose factors: who is the user, the purpose of summarization?
- Output factors: running text or headed text etc.

Evaluation text summarization is crucial. There are several challenges in evaluating summaries such as summaries are a result from (NLP), in some cases it is difficult to know what is the correct output. This is the same as machine translation output. Most machines generated summaries need an expert evaluation to judge the summary. Therefore, this may increase the expensive of evaluation. Normally, we can judge the relevance of the summaries by applying different methods which can be classified into two categories: intrinsic and extrinsic evaluating measures. (1) Intrinsic evaluation methods are based on analysis the summary or assess the coherence and informativeness of the summaries. (2) Extrinsic evaluation tests the summaries based on another task like reading comprehension, question answering. This research used intrinsic evaluation to define the coverage of a condensed text (Gupta, 2014).

Kayed et al. introduced a coverage measure to define the quality of description for specific domain knowledge where the higher coverage value indicates a better quality for description (Kayed, 2013).

1.1.2 Ontology and Semantic Measures

Jiang et al. defined the Ontology as “an abstract description system for knowledge composition in a certain domain”. Also, they added that ontology supplies a standardized vocabulary for representing entities in the domain. Ontologies can be classified in their purpose as: general purpose ontologies and domain specific ontologies. “Many researches are using WordNet¹ as ontology” (Jiang et al., 2013).

WordNet

WordNet is an online lexical which is created by the Cognitive Science Laboratory at Princeton University, it can be seen as an ontology. WordNet contains nouns, verbs, adjectives, and adverbs. It contains sets of synonymous word senses which are known as synsets. Version WordNet 2.0 contains 115,000 different synsets. These synsets contain 80,000 nouns, 13,500 are verbs, 18,500 are adjectives and 3700 are adverbs. Each synset may contain one or more synonymous word. Also, each synset has brief definition “gloss” to define the meaning of the synsets. WordNet also defines the relationships between each synset. A relation between each synset is known as the semantic relation, and the relation between the word senses is known as the lexical relation. The semantic relation is the relation between each two synsets such as (hypernym, hyponym, meronym, and holonym) relations (Michelizzi, 2005; Boon young & Mingkhwan 2015).

¹ <https://wordnet.princeton.edu/>

The relation hypernym/hyponym is known as is-a relationship. For example, an orange is a fruit. The relation meronym/holonym is known as part-of relationship. For example, a mouse is part of computer. The most common relation in WordNet is hypernym/hyponym (is-a) which is considered as 80% of the relations. In general, the hypernym/hyponym relation is considered about how two concepts are similar. The meronym/holonym relation is considered as how two concepts are related to each other (Meng et al., 2013).

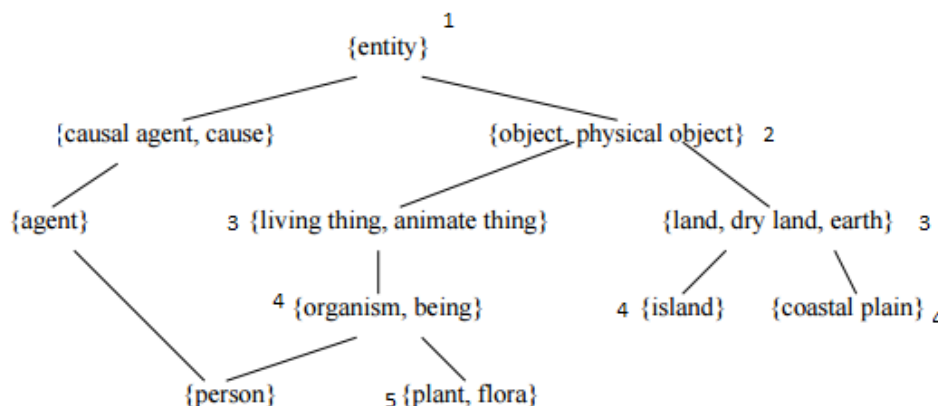


Figure 1.1: WordNet Hypernyms adapted from (Michelizzi, 2005)

To explain the relation clearly, Figure 1.1 shows a sample for WordNet hypernyms between nouns. For example, (land, dry land, earth) is the hypernym of (island) because an island is a land. Hyponym relation is the opposite of hypernym relation; this means that island is a hyponym of (land, dry land, earth). Figure 1.1 structure shows that the deeper concepts are the more specific and vice versa the upper concepts are more abstract. Thus, (plant, flora) is more specific than (living thing, animate thing). Therefore, the most abstract concept is entity which is considered as the root of the taxonomy (Meng et al., 2013).

Semantic Measures

Semantic measures can be classified into two groups: measures of semantic similarity and measures of semantic relatedness. Figure 1.2 shows the classification of semantic measures (Michelizzi, 2005). Each group contains a number of measures. We will use different measures from each type to find how much the condensed text covered the original text. Slimani, state that “semantic similarity and semantic relatedness are two related, but semantic similarity is more specific than relatedness and can be considered as a type of semantic relatedness. For example ‘student’ and ‘professor’ are related terms but not similar (Pederson, et al. 2004; Slimani, 2013).

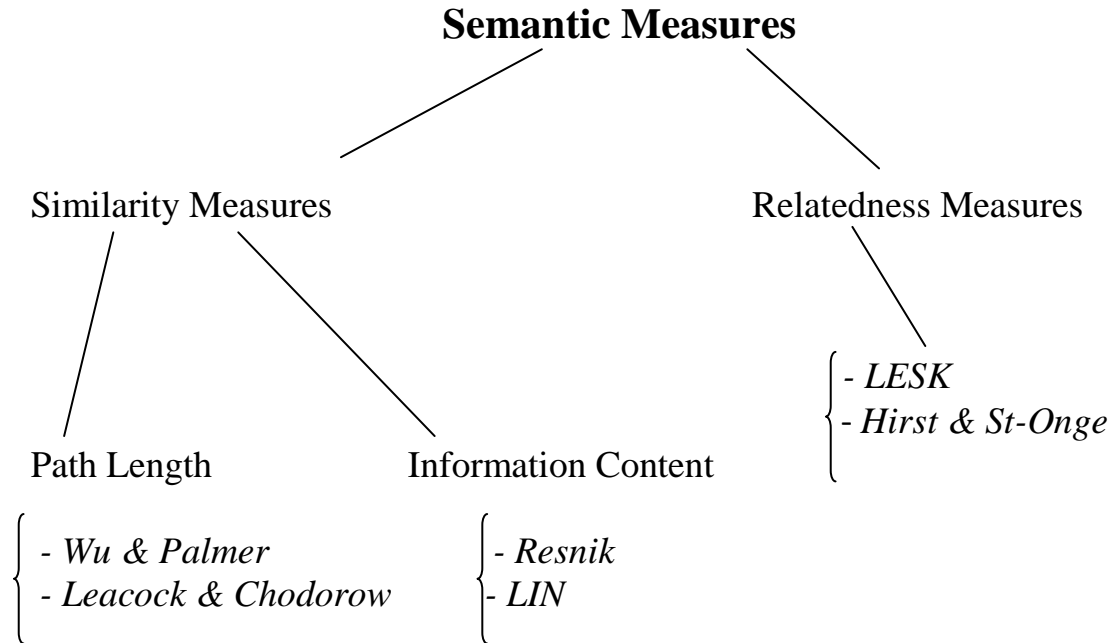


Figure 1.2: Taxonomy of Semantic Measures adapted from (Michelizzi, 2005)

Many ontological tools can be used to extract concepts from the text. For example: KAON², Swoogle³, and Portégé⁴. KAON is an ontology management infrastructure targeted for business applications. It includes a comprehensive tool suite allowing easy ontology creation, storage, retrieval and maintenance of ontologies.” Swoogle computes the rank of each semantic web documents and provides an online system to check the availability of ontologies in any domain. While Portégé is another tool that allows a user to construct domain ontology, customize data entry form, and enter data. This research uses KAON due to the availability, ease of use, and it has an efficient user interface”. This research used KAON to extract the main concepts from both the original text and the condensed (Kayed, et al. 2013).

1.2 Problem Statement

Automatic summarization is crucial and it is important for many domains. Knowledge summary (condensed text) is the aim of many knowledge extractors. There are several measures to define the quality of a condensed text such as sentence recall, sentence ranking and question answering. This research deploys the semantic measures to find the coverage between condensed text and original text. Semantic measures (similarity measures and relatedness measures) compute the similarity and relatedness between concepts included in knowledge source. This research assumes that the good condensed text is the text that has "good" coverage for the original text. This research used semantic measures to find how much the condensed text cover the original text. It also defines which measure or measures best compute the coverage for a text.

² <http://kaon2.semanticweb.org/>

³ <http://swoogle.umbc.edu/>

⁴ <http://protege.stanford.edu/>

1.3 Problem Statement Questions

- Which semantic measures can measure the coverage of a condensed text?
- How these semantic measures can be used to define the coverage for a condensed text?
- Which semantic measure is the best to evaluate a condensed text?

1.4 Limitations

This research collected data sets and used different semantic measures. This research limited its collected data to the following two datasets: The first dataset is a benchmark from NIST, which contains 34 original texts with its condensed text. The original text sizes vary from 4KB to 20KB with a condensed text size 1KB. The second dataset contains 14 original texts with its condensed text. The original text sizes vary from 3KB to 19KB while condensed text come with size 1KB. This research used KAON to extract the concepts from the original text and condensed text with default frequency (3). This research used six semantic measures (WuP, LCH, Resnik, LIN, HSO, and LESK).

1.5 Objectives

Evaluation the condensed text is an essential issue in summarization. This research aims to evaluate the condensed text. There are several measures have been used to compute the similarity or relatedness of concepts. This research deploys the semantic measures to evaluate the quality of condensed text. We used existing semantic measures to define the

quality of the condensed knowledge. The main aim is to give an efficient evaluation of all these measures and finds the best measure that can give the minimum error that define the coverage of the condensed text.

1.6 Motivation

There are many available tools for text summarization. Finding the best tool that can give the coverage among original text and condensed text is a challenge. In summarization as a fast development area, there is a need for finding a proper evaluation methodology. Many of research address summary evaluation by applying different evaluation methods to measure the quality of a condensed text. There is a lack of measurers that compute the quality of the condensed text. We need to find which measure from the semantic measures that best compute the coverage for an original text.

1.7 Contribution

Evaluating the text summarization is very important issue. This research finds how to evaluate the quality of the condensed text using semantic measures. This research contributes to defining the best semantic measures with minimal error that defines how much a condensed text covers its original text.

1.8 Organization of the Thesis

The thesis contains five chapters, references, and appendices. The following part explains a brief description for each chapter:

Chapter 2 presents a theoretical background and literature about the ontology, the importance of summarization and how important to evaluate the summaries. This chapter also contains an introduction about semantic measures.

Chapter 3 presents the proposed model steps. Its explain how to extract the concepts from condensed text and original text. Also describe the different types of semantic measure and how the concepts matching process are done using these measures.

Chapter 4 explains the experiments in details. Its present the matching process in details and how we define how much the condensed text cover its original text using semantic measures.

Chapter 5 present thesis discussion, conclusion and future work.

CHAPTER TWO

Literature Review & Related Works

Overview

This chapter presents a theoretical background and literature that relates to our study, we classified the literature into five parts: the first section is about automatic summarization and how important to evaluate the summaries. The second section discusses semantic measures and how it can be used in different domains to compute the relations between concepts and terms. The third section discusses the ontology and WordNet. The fourth part clarifies different types of semantic similarity and relatedness measures. Last section explain in brief summarization evaluation types.

2.1 Automatic Summarization Evaluation

In the following, we provide a brief idea about the automatic text summarization and why summary evaluation is important. It gives a background about methods used in evaluation, as each method has different measures. This research focus on semantic measures that can be classified into two parts: semantic similarity measures and semantic relatedness measures.

Jing, et al. used two methods to evaluate the automatic summarization systems which are: an evaluation of generated summaries against an ideal summary and evaluation of how well summaries help a person performs a task such as information retrieval. They carried two large experiments for both kinds. Their focus was on how different factors can be affected on the final evaluation results, for example, summary length. They found that summary length affects on both types. On the “ideal” summary based evaluation, accuracy decrease as summary length increase. While for the other type of evaluation they found that

summary length and accuracy on information retrieval task appeared to correlate randomly (Jing, et al. 1998).

Mani discussed different methods for evaluation automatic summarization systems. Hence, he lists several serious challenges in evaluation summaries such as automatic summarization is a machine producing output, in some cases the output may be correct but in others it's hard to arrive at notation of what the correct output is. He also classified the evaluation text summarization methods in two categories. The first method is the intrinsic evaluation, which is based judging the relevance of the condensed text by matching it with reference summary generated by a human. The second one is the extrinsic evaluation, which depends on completion of some task like reading comprehension. He also discussed some measures that to compare between different summaries such as sentence recall measure and sentence ranking measure (Mani, 2001a).

Gupta discussed how important the evaluation of text summary. The author states that we can judge any summary by the relevance of summary. This is done by applying extrinsic and intrinsic evaluation measures. The intrinsic evaluation techniques judge the summary relevance with human evaluation. Different factor discussed like maintaining coherence in summary, maintaining information in summary, calculating Recall and Precision, Ranking of lines, similarity of contents. Extrinsic evaluation techniques judge the quality of summary by performing some tasks on the summary like: game of questions and game of classification (Gupta, 2014).

2.2 Semantic Measures

This part discusses different types of semantic measures and the importance of semantics measures in many domains. Some of the researchers focuses on similarity measures while other focus on relatedness measures. Several studies use both measures to find which measure that gives the best result.

Pedersen, et al. discussed the semantic similarity and semantic relatedness on WordNet. Using similarity measures can tell how much two concepts or terms are alike. For example, the automobile might considered more like a boat than a tree. Similarity measures are restricted on pairs of nouns, verbs, adjectives, and adverbs. However, measures of relatedness can measures how pairs of concepts are related to each others. For example, murder and gun are related. Because of this, different measures of relatedness can be applied on wider area comparing it with similarity measures (Pedersen, et al. 2004).

Michelizzi classified the semantic measures into two main groups: measures of semantic similarity and measures of semantic relatedness. Semantic similarity measures work on noun-noun or verb-verb pairs using is-a hierarchies while semantic relatedness measures work on all open part of speech because there are not limited to is-a hierarchies. Semantic similarity measures can be classified in different families: the first one is path length similarity measures which are also known as the edge (or node) counting measures. These measures quantify similarity according to the length of the shortest path (example: Wu & Palmer). The second one is information content based measures; these measures compute

similarity as a function of the information content (IC) of the most specific common subsumer in the ontology (example: Resnik) (Michelizzi, 2005).

Buckley, et al. Proposed a new semantic similarity measure based on hybrid methods. They discussed the importance of semantic similarity measures in many fields. They focus on WordNet based semantic similarity measures which can be classified into three categories: first category is node-based methods which use information content(IC) to compute the amount of information contained in WordNet. Second category is edge-based methods which calculate the edge length between two concepts to find the shortest path between them. Third category is hybrid methods which use a combination of information from different resources to compute the similarity between concepts. The new semantic similarity used the internet as a corpus and the structure information from WordNet because they believe that the internet is the largest source and it can regularly be updated (Buckley, et al. 2011).

Slimani focuses on semantic similarity measures approaches. The author uses two widely used benchmarks. He classified the similarity measures into different methods. First method is structured - based measures which based on computing the path length between two concepts. Second method is information content measures based on information content to measure how two concepts are similar to each other. Information contents value depends on the frequency of concepts in a text. Third method is feature-based measures assume that each concept is defined by a set of concepts. Fourth method is hybrid measures combine between approaches such as information content based and path based measures. Several measures from each approach being compared to give an efficient evaluation of all

the measures. Although the author focus on semantic similarity measures but he also discuss ontologies used on semantic similarity and proposed several examples based on its purpose (general purpose ontologies or domain specific ontologies) (Slimani, 2013).

McInnes & Pedersen evaluated the measures if semantic similarity and relatedness in biomedical text. They measure how two concepts are similar or related to each other based on classification: similarity measures which are classified to path measures and information content measures and relatedness measures. The paper used MSH-WSD dataset which is provided from national library of medicine. Their focus was to evaluate the efficiency of these measures and find that the information content (IC) measures can give a higher accuracy than the other measures (McInnes & Pedersen, 2013).

Mittal & Jain studied the problem in query expansion, where most of the times user's query may contain unclear terms which add relevant and irrelevant terms to the query. They present a method to improve this problem by using semantic similarity and relatedness measures between the ambiguous terms. They apply different type of measures such as Leacock & Chodorow and Wu & Palmer similarity measures on noun only as most of the information is represented by nouns (Mittal & Jain, 2015).

Al-Khiaty & Ahmed reviewed the matching model as its an essential in many model management operations such as model evaluation and retrieval. The authors focus in software development models as for each software system there is a set of models that describes its structural, behavioral and functional perspectives. They identified the matching between models and finding the similarities and differences in each one, especially in UML diagrams (Unified Modeling Language) class diagram. They use

semantic similarity to compare concepts according to WordNet in class diagram where concepts here are (classes's names, operation's names, attributes' names, and the relation between classes). Semantic similarity used is based on semantic path-based measures. They used two measures supported by WordNet: path length and Wu & Palmer measures (Al-Khiaty & Ahmed, 2015)

2.3 Ontology

Ontology is an abstract description system for knowledge composition in a certain domain. It can give a description of concepts or terms in an effective way. Ontologies can be used in different domains; each domain has its own vocabularies, concepts or terms. Many researchers classified the ontologies based on their purpose.

Kayed et al. discussed the ontology importance in many domains. Ontology includes vocabularies of concepts and specification of their meaning. It also can improve understanding in how the concepts or terms are related to each others. They state that ontologies are used in many domains such as: artificial intelligence, software engineering, semantic web, biomedical informatics and library science. They focus on building ontology in software engineering domain. They developed new ontology in requirement engineering process using KAON's tool. This will enable developers to share a common concepts and terms and allow them to understand the domains in simple language (Kayed, et al. 2010).

Seddiqui. & Aono defined ontology base on Gruber definition for ontology "ontology is an explicit specification of a conceptualization". They classified the ontologies based on their size, small- scale or large-scale. Often, large-scale ontologies represent distributed knowledge area within a problem domain (Seddiqui, M. H., & Aono, M. 2010).

2.4 Semantic Similarity and Relatedness Measures

According to literature, semantic measures can be classified in difference families based on their theoretical principles. We choose different measures to cover all kinds of semantic measures. The following will list two measures from each family.

1. Path Length Family

- Wu and Palmer Measure.
- Leacock & Chodorow Measure.

2. Information Content Family

- Resnik Measure.
- LIN Measure.

3. Semantic Relatedness Family

- LESK Measure.
- Hirst & St-Onge Measure.

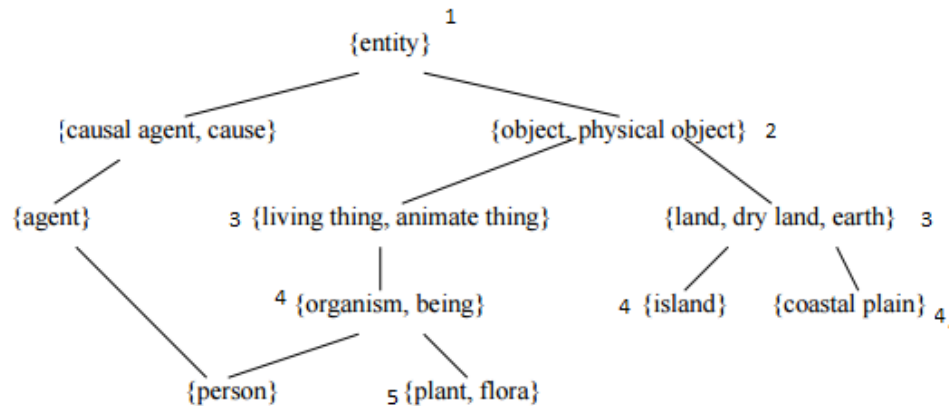


Figure 2.1: WordNet Hypernyms adapted from (Michelizzi, 2005)

2.4.1 Path Length Family

Path length similarity measures (also known as edge or node counting measures) compute the similarity between two concepts as a function of the length of the path linking the concepts and on the position of the concepts in the taxonomy. For example, (plant, flora) is closer to (living thing, animate thing) than it is to (land, dry land, earth). It can be seen as undirected graph. The greater the distance between two concepts, the less similar they are. Well known measures are Wu and Palmer and Leacock & Chodorow. Wu and Palmer similarity metric measure compute the depth of the two concepts while Leacock & Chodorow measure finds the shortest path between two concepts or terms using node counting (Michelizzi, 2005).

Wu and Palmer Measure

Michelizzi illustrate WuP similarity measure which is the depth of the two concepts and the depth of the least common subsumer (LCS).

The shared parent of two synsets is called subsumer. Baader et. al discussed LCS and shows that if we have two concepts, each concept represented by a node and both concepts shared the same ancestor. This relation is defined by is-a relationship. For example we can say that a car is an automobile and automobile is a vehicle. Also we can say boat is a vehicle. LCS and WuP measure are related to each other where the deeper the LCS is the larger the value of the measure (Baader et. al, 2007).

For example figure 3.4 the subsumers are (object, physical object) and (entity) for nodes (living thing, animate thing) and (land, dry land, earth). But to find the least common subsumer for these two nodes; we must search for the most specific subsumer of the two

synsets. Therefore, the LCS for these two synsets is (object, physical object) since its more specific than entity (Yang, 2015; Michelizzi, 2005).

$$Sim_{wup} = \frac{2 * depth(LCS)}{depth(concept_1) + depth(concept_2)} \dots\dots\dots (1)$$

Equation (1) shows how to calculate the WuP measure, which is the node depth of LCS for the two nodes divided by the sum of the depth of first node and the depth of the second node. Figure 3.4, to found the similarity of the two nodes (island) and (coastal plain) using WuP; the node counting (island) and (coastal plain) is 4 for both, the depth for their LCS which is (land, dry land, earth) is 3. Thus, the score using equation (1) is $\frac{2*3}{4+4}=0.75$.

Leacock & Chodorow Measure

LCH measure is another measure that uses the depth and the distance using nodes counting.

Equation (2) shows how to calculate the LCH measure.

$$Sim_{lch} = -log(\frac{dist_{node}(s_1, s_2)}{2 * D}) \dots\dots\dots (2)$$

Where S1 is the first concept, S2 is the second concept; dist is the distance between S1 and S2. D is the depth for a given taxonomy where the concepts are existing.

For example, using figure 3.4, the two synsets (island) and (coastal plain). The distance between them is 3, and the depth is 4. Thus, the score using measure LCH by equation (2) is:

$$-\log 3/(2 * 4) \approx 0.9808$$

2.4.2 Information Content Family

Information Content (IC) measures use the information content of concepts to measure the semantic similarity between two concepts. The information content value of the concept is calculated based on the frequency of the concepts, the concepts that occurs a lot have low information content. The concepts that have high information content are the concepts that rarely occur (Slimani, 2013).

Mathematically, the information content for a given concept can be calculated as equation (3):

$$IC(c) = -\log P(c) \quad \dots\dots\dots (3)$$

Where $P(c)$ is the probability of the concept c . “High information content means that the concept conveys a lot of meaning when it occurs in a text. A concept with high information content is very specific, but a concept with low information content is very general; therefore, information content corresponds to specificity” (Michelizzi, 2005).

Resnik Measure

Resnik measure is information content measure. It took into account the LCS information content which return the information content of the LCS of two concepts.

Equation (4) shows how to calculate Resnik measure.

$$Sim_{res} = IC(LCS) \dots\dots\dots (4)$$

LIN Measure

LIN measure which is building on Resnik's measure of similarity. To calculate the similarity between two concepts using LIN measure; the more these two concepts are similar to each other, the more they will have in common. When the two concepts are exactly the same concept, a LIN measure result is the maximum similarity.

Equation (5) shows how to calculate LIN measure. By equation (5), we can note that the similarity based on the information content for the least common subsumer. And the information content for both concepts. LIN measure and WuP measure look alike, but the WuP measure based on the depth of the LCS, where LIN measure based on the information content of LCS (Corley & Mihalcea, 2005; Michelizzi, 2005).

$$Sim_{lin} = \frac{2 * IC(LCS)}{IC(concept_1) + IC(concept_2)} \dots\dots\dots (5)$$

(Slimani, 2013; Baader et. al, 2007)

2.4.3 Semantic Relatedness Family

Semantic relatedness is a much broader notion than semantic similarity. For example, a tire is related to car, but the two are not very similar since a tire is not a type of a car nor is a car a type of tire. Well known measures are LESK and Hirst & St-Onge measures.

LESK Measure

LESK measure finds the relatedness of two concepts by defining a function of the overlapping between the corresponding definitions provided by a dictionary. It's based on the glosses of the synsets, where the synset that has gloss that contain a common words, they are more related to each other (Michelizzi, 2005).

Hirst & St-Onge Measure

HSO measure classifies relations in WordNet as having directions. "Its establishes the relatedness between two concepts by trying to find a path between them that is neither too long nor that changes directions too often" (Pedersen et al., 2004; Liu et al., 2011).

2.5 Summarization Evaluation Types

As discussed in previous sections, summarization is important in many fields like information retrieval. It can save time by reading the summary instead of reading the whole original text. Also it can speed up the information retrieval. The evaluation of summary quality is important and challenging task. Table 2.1 shows examples of methods used to evaluate the quality of the condensed text. These methods like sentence recall used exact matching among the original text and the condensed text. This research used semantic matching to evaluate the quality of the condensed text. To apply the semantic matching

technique; we used semantic measures which can be classified into semantic similarity and semantic relatedness.

Table 2.1: Example of Methods used to Evaluate the Condensed Text

Type of Evaluation	Author	Method	Procedure
Intrinsic	Jing et. al	Sentence recall	Using sentence recall to measure how much the summary contains the sentences from the text.
Intrinsic	Mani	Sentenced ranking	The summary is specified in term of ranking the sentences in terms of worthiness

Extrinsic	Morris et. al	Question answering	Also known as reading comprehension task. In this task human first read the full original text or summary for a given document, then the human answer a test of multiple question tests. By scoring the percentage of the correct answers.
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2.6 Tools Used

Many tools have been used in this research. Below is a brief description of each tool.

2.6.1 KAON Text2Onto Tool

KAON Text2Onto is a tool support the ontology engineering process by text mining techniques; we used this tool to extract the main concepts from each original text and condensed text. Figure 2.1 shows the front end of text2Onto. Each file is converted to text file and then uploaded it to get the concepts from both. (Maedche A., 2001)

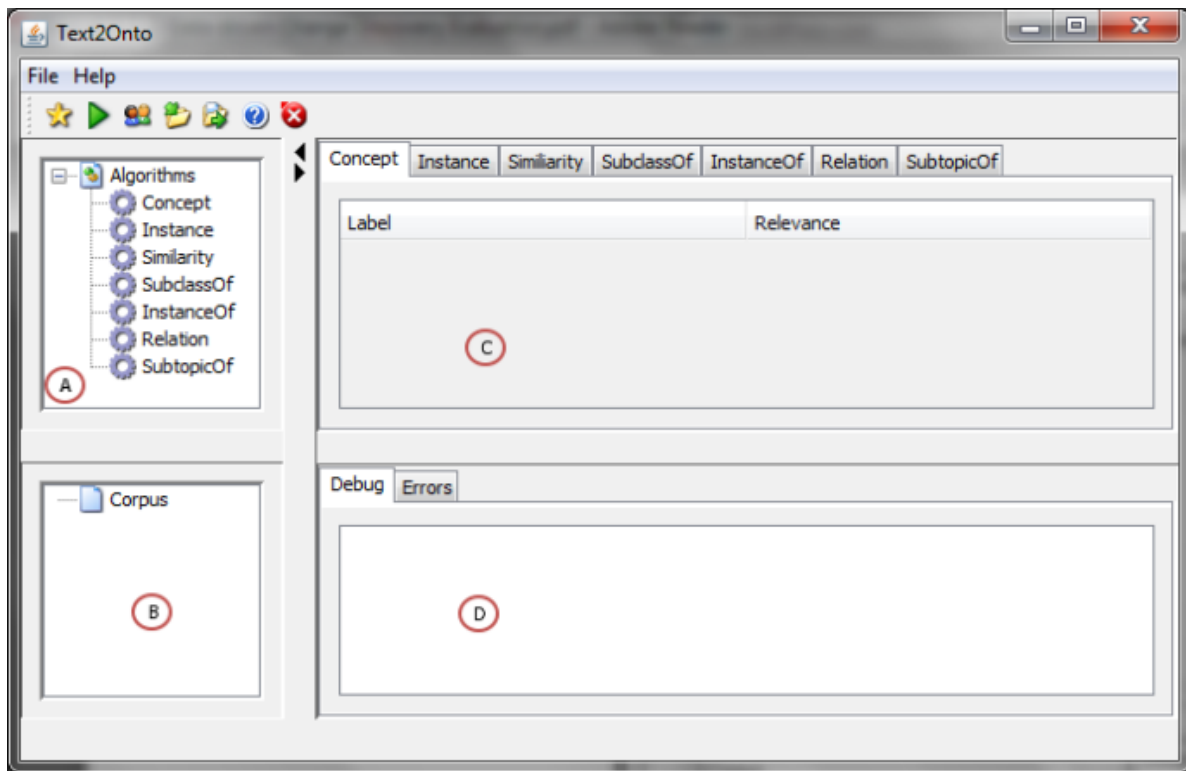


Figure 2.2: KOAN Text2Onto Front End

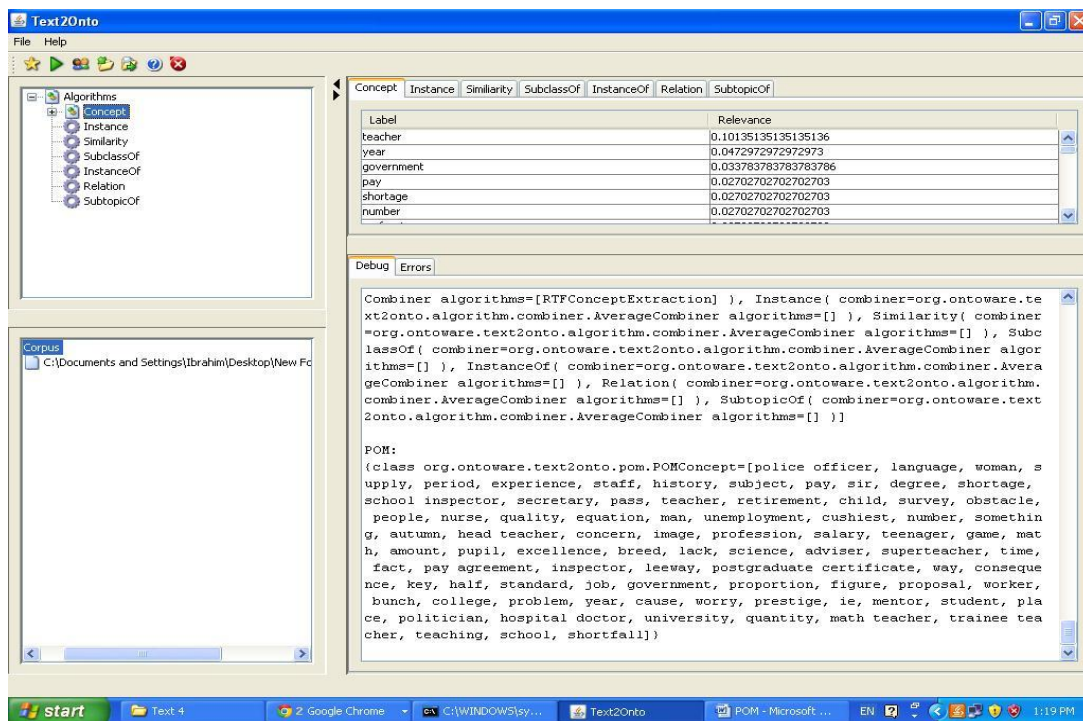



Figure 2.3: Concepts Extraction Example using KOAN Text2Onto

2.6.2 WordNet Similarity for Java (WS4J)

This tool WS4J⁵ provides a pure Java API for several semantic similarity and semantic relatedness measurements. The results are depends on WordNet relations between pairs of concepts. Figure 2.3 shows front end of WS4J. It provides matching for different semantic measures such as WuP, LCH, Resnik, LIN, HSO, and LESK.

WS4J Demo

WS4J (WordNet Similarity for Java) measures semantic similarity/relatedness between words.

WordNet loading status: 

Type in texts below, or use:

1.	Input mode	<input type="radio"/> Word <input checked="" type="radio"/> Sentence
2.	Sentence 1	<input type="text" value="the first sentence goes here"/>
3.	Sentence 2	<input type="text" value="the second sentence goes here"/>
4.	Submit	<input type="button" value="Calculate Semantic Similarity"/>

Figure 2.4: WS4J Tool Front End

WS4J provide two options of matching. First, by matching only two pairs of concepts and compute the semantic results of each measure. Second option, by matching set of concepts with another set of concepts and then computes the semantic results. This option can save time and effort; because it calculates the result for a number of concepts at once.

⁵ <http://ws4jdemo.appspot.com/>

CHAPTER THREE

Data Collection and Concepts Extraction

Overview

This chapter explains the methodology that the researcher has used. The steps of each phase of the methodology will be detailed. These steps are: data collection, concepts extraction, applying different semantic similarity and relatedness on the extracted concepts and evaluate the results of each measure by computing the error of each one. The aim is to match between original text and condensed text using coverage technique.

3.1 Introduction

The methodology of this research combined the quantitative and qualitative approach. Our methodology has been based on building several experiments to find the best semantic measure. The experiment part of the proposed work will be considered as quantitative. To be able to know the quality of the condensed text, we need human judgments. Thus, part of the evaluation process has been based on human. The other part is done by our experiment and this will depends on the error calculation which is the difference between the human result and measures results.

The main idea of this research is to find which semantic measures that give us the quality of the condensed text by extracting the main concepts for both condensed text and original text using KAON software; then matching those concepts by applying different types of semantic measures, through these measures the coverage will be defined. According to Kayed et al. using different measures will enable us to obtain “good concepts”. These concepts are not too generalized concepts neither too specified one (Kayed et al., 2013).

To evaluate our approach, an expert needed to evaluate the quality of condensed texts and these results will be compared with our results to see how much we are close to expert evaluation.

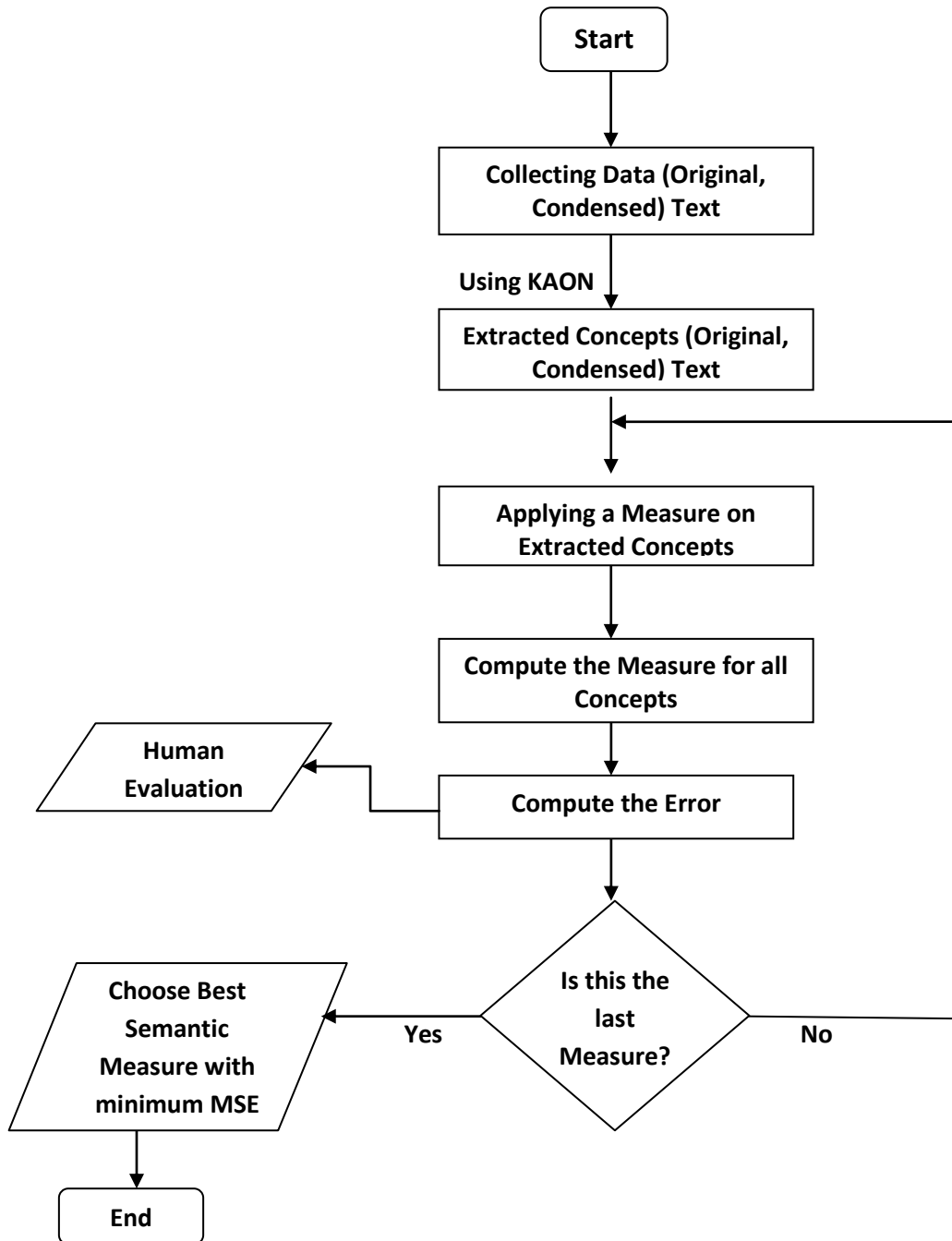


Figure 3.1: Flowchart of the Proposed Solution

The following will illustrate the main steps of the research methodology as showing in figure 3.1:

- 1- Collecting datasets.
- 2- Extracting the concepts.
- 3- Apply several semantic measures.
- 4- Evaluate the results.

The methodology will contain the following steps in details:

3.2 Data Collection (Data Samples)

To be able to apply our experiment, good data sets are needed. At the beginning we thought to use technical paper and its abstract, but we found that their abstract is very short and may not represent the whole paper. Therefore, we decide to look for a data where a condensed text and original text has been collected.

This research used a well-known benchmark (data samples) released on 2001 by NIST (National Institute of Standards and Technology) which is DUC⁶ (Document Understanding Conference). It contains seven datasets (DUC2001 to DUC2007). Lin & Moghaddas et al. discuss the validity of evaluation methods used in DUC. To get this data set, an assigned agreement is required. We sent the agreement to NIST and got the DUC datasets. *Refer to Appendix 1.*

The data set summaries are human generated summaries which are called reference summaries. The main purpose of this DUC is to evaluate the automatic summarization

⁶ <http://duc.nist.gov/>

techniques, by comparing the reference summary with automatic generated summary. DUC has different tasks and reference summaries are generated within a size limits. For task one, human must generate very short summary not longer than 75 bytes. This summary is called headline summary (like newspaper headline). But in task two, human must generate short summary not longer than 665 bytes (Lin, 2004; Moghadas et al., 2013).

The data sets contain news articles from New York Times newswire. It has different subject such as computer, health care, terrorism and political issues. To build our model, 34 sets have been chosen from DUC which contain short summary with its original text.

To evaluate our model, we choose other data sets and selected 14 sets which contain original text and condensed text. Like first data sets, these sets are articles from the Economist newspaper have different subjects such as medical science, teaching and social science. The condensed texts are automatic generated summary using lexical chains (Barzilay and Elhadad, 1999).

The original texts came with different sizes such as 3KB, 5KB, 8KB, 13KB20KB, but the condensed texts always come with fixed size 1 KB.

For example file named APW19981019.0098 (T1) original text size is 6KB and condensed text 1KB, where file named APW19981022.0269 (T2) original text size is 4KB and condensed text 1KB and so on.

Figure 3.2 illustrate a sample of original text and figure 3.3 illustrate a sample of condensed text from DUC:

```
<DOC>

<DOCNO> APW19981019.0098 </DOCNO>

<DOCTYPE> NEWS </DOCTYPE>

<TXTTYPE> NEWSWIRE </TXTTYPE>

<TEXT>

Britain has defense its arrest of Gen. Augusto Pinochet, with one lawmaker saying that Chile's claim that the former Chilean dictator has diplomatic immunity is ridiculous. Chilean officials, meanwhile, issued strong protests and sent a delegation to London on Sunday to argue for Pinochet's release. The former strongman's son vowed to hire top attorneys to defend his 82-year-old father, who ruled Chile with an iron fist for 17 years. British police arrested Pinochet in his bed Friday at a private London hospital in response to a request from Spain, which wants to question Pinochet about allegations of murder during the decade after he seized power in 1973. Pinochet had gone to the hospital to have a back operation Oct. 9. "The idea that such a brutal dictator as Pinochet should be claiming diplomatic immunity I think for most people in this country would be pretty gut-wrenching stuff," Trade Secretary Peter Mandelson said in a British Broadcasting Corp. television interview Sunday. Home Office Minister Alun Michael acknowledged Sunday that Pinochet entered Britain on a diplomatic passport, but said, "that does not necessarily convey diplomatic immunity." The Foreign Office said only government officials visiting on official business and accredited diplomats have immunity.

.
.
.
.
.

</TEXT>

</DOC>
```

Figure 3.2: Original Text Sample from DUC

Former Chilean dictator Augusto Pinochet has been arrested in London at the request of the Spanish government. Pinochet, in London for back surgery, was arrested in his hospital room. Spain is seeking extradition of Pinochet from London to Spain to face charges of murder in the deaths of Spanish citizens in Chile under Pinochet's rule in the 1970s and 80s. The arrest raised confusion in the international community as the legality of the move is debated. Pinochet supporters say that Pinochet's arrest is illegal, claiming he has diplomatic immunity. The final outcome of the extradition request lies with the Spanish courts.

Figure 3.3: Condensed Text Sample from DUC

3.3 Concept Extraction

After choosing original texts and condensed texts, the next step is extracting concepts from both texts. This is done using ontological tool KAON⁷. Each dataset is converted to text file then uploaded to KOAN program. For example the first file named APW19981019.0098 (T1), after upload the original text and extract concepts from it; the result was 135 concepts as for this file. Table 3.1 lists samples of these concepts. For more details table, *please see table Appendix 2*.

Table 3.1: Sample of Original Text Extracted Concepts

No.	Concept	No.	Concept	No.	Concept	No.	Concept	No.	Concept
1	Defense	28	prosecution	55	Order	82	Guard	109	Television
2	Minister	29	Institution	56	Advice	83	Stuff	110	Interview
3	Priest	30	Power	57	Government	84	Idea	111	Division
4	Magistrate	31	Abuse	58	Lawmaker	85	Business	112	Riot
5	Murder	32	Constitution	59	Bed	86	Army	113	Police
21
22
23	Boss	50	Caption	77	Diplomat	104	Demonstrator	131	Demonstration
24	Government	51	Capital	78	Policy	105	Operation	132	Anonymity
25	Official	52	Publicity	79	Trial	106	Official	133	Reign
26	Post	53	Patient	80	Black	107	Event	134	Hospital
27	Crime	54	Arrest	81	Police	108	Dissident	135	Protest

⁷ <http://kaon2.semanticweb.org/>

The extracting step has been done also on condensed text. The following table 3.2 shows the 20 extracted concepts.

Table 3.2: Sample of Condensed Text Extracted Concepts

No.	Concept	No.	Concept
1	Dictator	13	Outcome
2	Confusion	14	Request
3	Hospital	15	Charge
4	Arrest	16	Community
5	Murder	17	Surgery
6	Citizen	18	Death
7	Rule	19	Court
8	Legality	20	Government
9	Move		
10	Supporter		
11	Immunity		
12	Extradition		

This step has been repeated for all files. We have 34 files form the first data sets for both original text and condensed text, and 14 file form the second data sets.

Table 3.3 shows the number of extracted concepts for the first data sets. Table 3.4 shows the number of concepts for second data sets.

Table 3.3: Number of Extracted concepts of Original and Condensed Text from first Data Sets

No	Original Text File Name	Number of Original Concepts	Condensed Text File Name	Number of Condensed Concepts	Ratio between extracted concepts
1	APW19981019.009	135	D30003.M.100.T.C	20	15%
2	APW19981022.026	87	D30001.M.100.T.D	21	24%
3	APW19981030.079	131	D31022.M.100.T.C	21	16%
4	APW19981120.029	132	D30047.M.100.T.C	21	16%
5	APW19981202.127	101	D30022.M.100.T.D	16	16%
6	APW19981211.127	112	D30038.M.100.T.A	17	15%
7	APW19981212.016	184	D30053.M.100.T.B	20	11%
8	APW19981227.087	81	D30029.M.100.T.A	17	21%
9	NYT19981001.0379	397	D30027.M.100.T.C	24	6%
10	NYT19981003.0120	158	D30011.M.100.T.A	24	15%
11	NYT19981004.0102	193	D30015.M.100.T.A	19	10%
12	NYT19981010.0149	184	D30050.M.100.T.D	24	13%
13	NYT19981012.0334	221	D30036.M.100.T.D	16	7%
14	NYT19981012.0359	189	D31008.M.100.T.D	25	13%
15	NYT19981013.0354	176	D30006.M.100.T.C	26	15%
16	NYT19981013.0399	161	D31031.M.100.T.C	24	15%
17	NYT19981017.0027	127	D31026.M.100.T.C	19	15%
18	NYT19981018.0091	185	D31033.M.100.T.D	21	11%
19	NYT19981024.0050	208	D30048.M.100.T.C	22	11%
20	NYT19981104.0545	212	D30024.M.100.T.D	14	7%
21	NYT19981105.0538	194	D30008.M.100.T.D	18	9%
22	NYT19981107.0056	170	D31001.M.100.T.D	18	11%
23	NYT19981107.0251	93	D30010.M.100.T.D	17	18%
24	NYT19981114.0079	268	D30051.M.100.T.D	20	7%
25	NYT19981114.0129	185	D31013.M.100.T.D	19	10%
26	NYT19981121.0117	151	D30049.M.100.T.D	18	12%
27	NYT19981122.0163	194	D30026.M.100.T.D	25	13%
28	NYT19981126.0192	185	D30045.M.100.T.C	19	10%
29	NYT19981201.0444	155	D30005.M.100.T.C	17	11%
30	NYT19981204.0365	200	D30031.M.100.T.D	23	12%
31	NYT19981209.0451	268	D30017.M.100.T.A	23	9%
32	NYT19981219.0117	235	D30046.M.100.T.C	16	7%
33	NYT19981221.0377	178	D31050.M.100.T.E	23	13%
34	NYT19981223.0347	229	D30033.M.100.T.D	22	10%

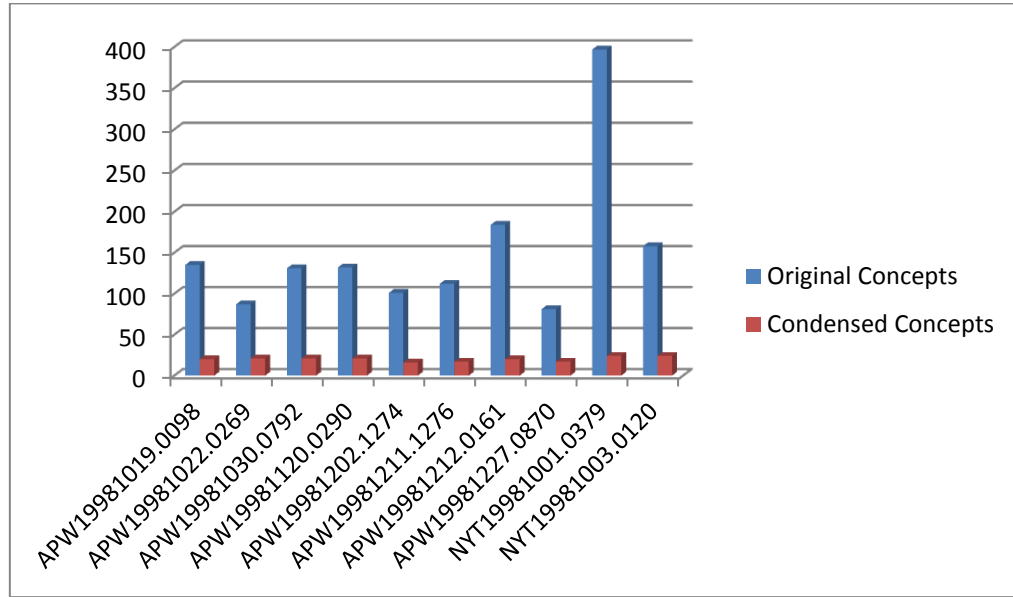


Figure 3.4: Sample of Extracted Concepts Percentage for First Data Set

Figure 3.4 shows an example of the ratio between the number of extracted concepts from the original text and number of extracted concepts from the condensed text. Data set summary size is less than 1KB (665 byte) and the original text size comes from 5KB to 20KB. From table 3.3, we can note the maximum ratio between the extracted concepts from the original text and the extracted concepts from the condensed text is 24% and the minimum is 6%. This is because of the variance between the size of the original text and the condensed text. Also when we extracted the concepts using KOAN, we used the default frequency of concepts which was (3). These two conditions have been applied on all data sets.

**Table 3.4: Number of Extracted concepts of Original and Condensed Text from
Second Data Sets**

No.	Original Text File Name	Number of Original Concepts	Condensed Text File Name	Number of Condensed Concepts	Ratio between extracted concepts
1	Text 1	114	Summary 1	23	20%
2	Text 2	228	Summary 2	30	13%
3	Text 3	91	Summary 3	16	18%
4	Text 4	89	Summary 4	15	17%
5	Text 5	53	Summary 5	15	28%
6	Text 6	87	Summary 6	9	10%
7	Text 7	127	Summary 7	24	19%
8	Text 8	86	Summary 8	14	16%
9	Text 9	79	Summary 9	23	29%
10	Text 10	121	Summary 10	15	12%
11	Text 11	176	Summary 11	40	23%
12	Text 12	335	Summary 12	40	12%
13	Text 13	60	Summary 13	10	17%
14	Text 14	88	Summary 14	32	32%

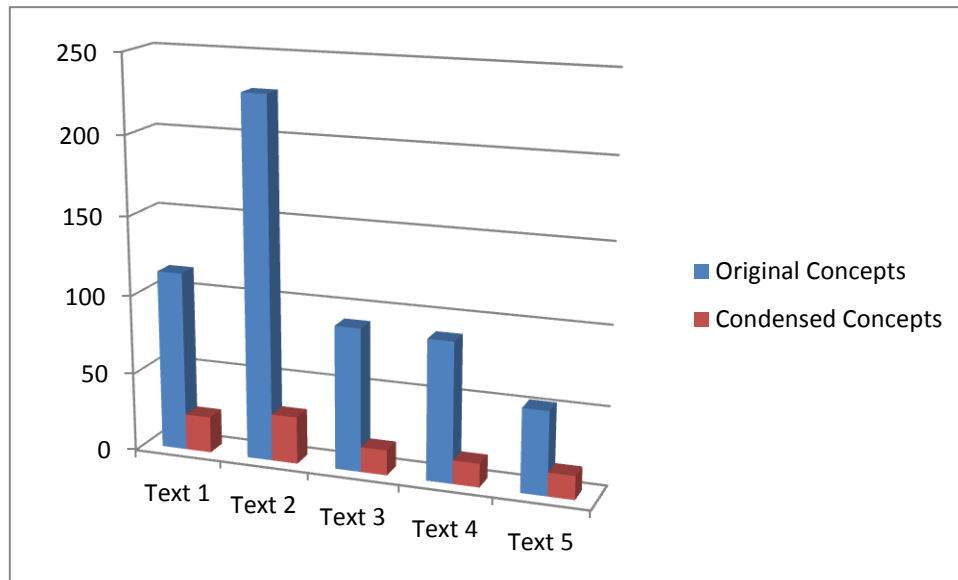


Figure 3.5: Sample of Extracted Concepts Percentage for Second Data Set

Figure 3.5 shows an example of ratio between number of extracted concepts from the original text and number of extracted concepts from the condensed text in second data set. From table 3.4, we can note the maximum ratio between the extracted concepts from the original text and the extracted concepts from the condensed text is 32% and the minimum is 10%, the average ratio is around 19%. When we extracted the concepts using KOAN, we used the default frequency of concepts which is (3). Also the condensed text size comes with fixed size 1KB, therefore; the condensed text size is the same for all data set.

3.4 Applying the Measures

This step took long time as we need to apply it for 34 file each file must apply six different measures. This is done using WS4J Demo software. The following part discusses in details

how we apply the measures. We choose file name (T1) as an example to explain our experiments.

3.4.1 Upload Concepts in WS4J

After extracting the concepts from each original text and condensed text, each file contains a number of concepts. For example, the first file (T1) contains 135 concepts from original text and 20 concepts from condensed text. WS4J⁸ has two inputs options, we choose to match a set of concepts at once because we got large number of concepts and this will save time and effort. Figure 3.4 shows how this is done. To calculate the semantic similarity for all the extracted concepts, we need to upload the 20 concepts and compare them with all the 135 concepts from the original text.

WS4J Demo

WS4J (WordNet Similarity for Java) measures semantic similarity/relatedness between words.

WordNet loading status: Loading

Type in texts below, or use: example words example sentences

1.	Input mode	<input type="radio"/> Word <input checked="" type="radio"/> Sentence
2.	Sentence 1	dictator confusion hospital room arrest murder citizen rule legality move supporter extradition request immunity extradition outcome request charge community surgery death court government
3.	Sentence 2	defense minister priest magistrate murder, day embassy police source insult team claim arrest warrant attorney envoy extradition request opinion term rally week boss government official post crime
4.	Submit	Calculate Semantic Similarity

Figure 3.6: Calculate Concepts Semantic Matching

⁸ <http://ws4jdemo.appspot.com/>

3.4.2 Calculate the Results for all Measures

After collecting data sets that contain both original text and condensed text. Then extract the concepts from each original text and condensed text. The next step is to match between the extracted concepts using different semantic measures. Table 3.5 clarifies a sample of using WuP measure for the first file T1. Columns represent the number of extracted Original Concepts (OC), where the table's rows represent the number of extracted Condensed Concepts (CC). Each file has six Semantic matching results using (WuP, LCH, LIN, Resnik, HSO, and LESK) measures. Each file has six tables. *For full table refer Appendix3.*

Table 3.5: Sample of Semantic Matching for WuP Results

OC	CC1	CC2	CC3	CC4	CC17	CC18	CC19	CC20
	dictator	Confusion	hospital	Arrest		Surgery	death	Court	Government
Defense	0.5556	0.6667	0.7778	0.6667	0.7778	0.625	0.8235	0.8
Minister	0.7273	0.6	0.4545	0.6	0.6667	0.5263	0.6667	0.6
Priest	0.7619	0.6667	0.4762	0.6667	0.4762	0.7143	0.6957	0.375
Magistrate	-	-	-	-	-	-	-	-
Murder	0.2	0.6667	0.2727	0.5455	0.5217	0.88	0.6087	0.5455
Day	0.7826	0.625	0.4762	0.625	0.4762	0.6667	0.6957	0.4286
Embassy	-	-	-	-	-	-	-	-
Police	0.2667	0.4	0.7059	0.4	0.3333	0.4286	0.7059	0.75
Source	0.8182	0.4444	0.6667	0.4444	0.6667	0.5714	0.7273	0.6
Insult	0.2857	0.6316	0.375	0.6316	0.7	0.5556	0.6	0.6316
Team	0.2857	0.4286	0.7059	0.4286	0.3529	0.4615	0.7059	0.75

For example : the two concept matching from the (T1) file , first condensed concept CC1 is *dictator* and first original concept OC1 is *defense*, the result as shown in the table 3.6 using WuP measure is: 0.5556.

Table 3.6: Two Concepts Matching Result

OC	CC1
	Dictator
Defense	0.5556

3.5 Evaluation

The evaluation process is to evaluate the quality of the condensed text by comparing it with the original text. Evaluation process first done by human then by comparing human evaluation and semantic measures evaluation then by calculating the errors of each measure and checking which measure that gives the minimum error. We will use descriptive statistical Mean Square Error (MSE) to evaluate the final results.

CHAPTER FOUR

Matching Process and Experiment

Overview

This chapter explains in details the proposed model. This is done after collecting the data sets and extracting main concepts from both condensed text and original text. The aim is to find which measure from semantic measures with a minimum error. The experiments are divided into two types of evaluations. In the first evaluation, the selected condensed texts have covered the original texts with 100%. In the second evaluation, expert evaluated the condensed text coverage for the original texts.

4.1 Proposed Model

Our proposed model contains the following phases:

1. Extracting concepts from the original text.
2. Extracting concepts from the condensed text.
3. Computing semantic measures among concepts.
4. Finding the best semantic measure with a minimum error.

The first and the second phase have been explained in chapter three. The following section will explain in details the semantic matching phase.

This research collected two data sets. For each set, we extracted the concepts from both original and condensed texts. In this phase, we are going to compare each concept from the original text with the concept from the condensed text. For example in file (T1), the extracted concepts from the original text were 135 concepts, and from the condensed text were 20 concepts. Table 4.1 shows an example of applying WuP measure on the 135 concepts against the 20 concepts for the original and condensed text respectively. The first

field of the table 4.1 represents the Original Concept (OC); in this example the concept is “defense”. The first row of the table 4.1 also represents the Condensed Concepts (CC) that has been extracted from the condensed text. For each concept from the 135 concepts we computed the WuP measure value. Table 4.1 represents a sample for this WuP measure. *For full results see appendix number 3.* This step has been repeated for all the files and for the six measures (34 files from first data sets and 14 files from second data sets).

**Table 4.1: Samples of Matching Original text Concepts with Condensed Concepts
using WuP**

OC	CC1	CC2	CC3	CC4		CC17	CC18	CC19	CC20
	dictator	Confusion	Hospital	arrest	surgery	death	Court	government
defense	0.5556	0.6667	0.7778	0.6667	0.7778	0.625	0.8235	0.8
minister	0.7273	0.6	0.4545	0.6	0.6667	0.5263	0.6667	0.6
priest	0.7619	0.6667	0.4762	0.6667	0.4762	0.7143	0.6957	0.375

Applying six semantic measures for 135*20 concepts for 5 acceptance rates produced more than 80,000 data items for only one file ($135*20*6*5=81,000$).

4.2 Calculate the Maximum for Each Concepts

The maximum is important to see how far these concepts are closed to each other. At first, we need to define the maximum value for each semantic measure (SM). Some semantic measures have maximum value such as WuP and LIN where they have “1” as a maximum

value while the maximum value of HSO measure is “16”. The other measures have no maximum value. The aim is to find how the condensed concepts best covered the original text concepts at a certain point. For example in the file (T1), the goal is to find how much the 20 condensed concepts cover the 135 original concepts. This is mean which concept from the 20 concepts that have the maximum matching value, and we can accept only if the maximum go beyond a certain point (cutting point). As table 4.2 shows that the maximum value is between original concepts “defense” and condensed concepts “charge” which has the value (0.8889) using WuP measure.

Table 4.2: Calculate Maximum Value Example using WuP

No	OC	CC1	CC2	CC15	CC16	CC17	CC18	CC19	CC20	MAX
		Dictator	confusion	charge	community	surgery	death	Court	Government	
1	defense	<u>0.5556</u>	<u>0.6667</u>	<u>.....</u>	<u>0.8889</u>	<u>0.75</u>	<u>0.7778</u>	<u>0.625</u>	<u>0.8235</u>	<u>0.8</u>	0.8889

4.3 Calculate the Maximum for Each Semantic Measure

As we discussed chapter three, semantic measures can be divided into semantic similarity measures and semantic relatedness measures. Some measures has maximum value (WuP, LIN, HSO) while other has no maximum value (LESK, LCH, Resnik). Measures such as WuP & LIN have a maximum value which is greater than or equal to zero and less than or equal to one. HSO measure has maximum value which is greater than or equal to zero and less than or equal to 16. We need the maximum value to calculate the value for each cutting points. Cutting point means that if semantic measures between two concepts above this

point; we will accept it otherwise if it's below this point, we reject it. There is a problem to define this; therefore, the maximum will help us to know if the result below this certain point the result is rejected. For example using WuP measure, the maximum value for this measure is "1". To calculate the number of accepted concepts for a certain point for example "50%". This means all the semantic matching results that have the maximum value above "0.50" is accepted, other matching results which is below "0.50" is rejected.

In the rest three measures (LESK, LCH, Resnik) there is no maximum value. Therefore, we cannot calculate the percentage of cutting point of each file. Thus, four different techniques are proposed to calculate the maximum number of each file. Then we can calculate the cutting point with a different percentage. Next part illustrates an explanation for each technique; we choose LESK measure to illustrate the techniques:

1) Max average:

We took the average of the maximum value for each original concepts (OC) and condensed concepts (CC).

For example file (T1), the original text has 135 extracted concepts and the condensed text has 20 extracted concepts. We compute the semantic matching for each OC with the CC. Then we calculated the maximum results. Thus, we will have 135 maximum for this file. After calculating the semantic measures results, we choose LESK measure to illustrate the example. The average value for all 135 maximums was 645 (LESK measure).

2) Trimming Max Average with 5%

We used the trimming method with 5% after sorting the semantic measure maximum from low to high.

For example in file (T1), the extracted concepts from the original file is 135 concepts and the extracted concepts from the condensed file is 20 concepts. We computed the semantic measures matching for all the extracted concepts, and then calculated the maximum results. The maximum values are sorted in ascending. 5% trimming from 135 is “7” concepts. Therefore, we removed 7 concepts from below and 7 concepts from above. Then, we calculate average of the remaining concepts “121 concepts” after trimming and the average was 300 (LESK measure).

3) Average for all results

This is done by calculating the average of semantic matching results for all the extracted concepts from the original text OC, and the extracted concepts from the condensed text CC.

We need to calculate the result as number of OC * number of CC for a given file.

For example in file name (T1) which we discussed before that it's contained 135 OC and 20 CC. So the result will be the average of $(135 * 20) = 2700$ and the value was 98 (LESK measure).

4) Trimming Average for all results with 5%

This technique is close to number two, but instead we sorted the concepts from high to low.

Then use trimming method with 5% percentage and chooses the first max after trimming.

For example in file name (T1) as explained before, the extracted concepts from the original file is 135 concepts and the extracted concepts from the condensed file is 20 concepts. The results from matching are 135 maximum values. The maximum values are sorted in descending way. 5% trimming from 135 is “7” concepts. Therefore, we removed 7 concepts from the above. The result of the first maximum value after trimming was 2595(LESK measure).

In all fourth methods, we got four values (645, 300, 98, and 2595). We need to choose neither not very high number nor small one because if we took the low value “98” most of the concepts will be included in our experiment. At the same time, if we took high value “2595” most of the concepts will be ignored and not included. So we decided to choose average value which is 300 as the maximum value for this file.

These techniques are tested for three measures (LESK, LCH, and Resnik). We found that the best technique is to calculate maximum is technique number two, which is trimming Max Average with 5%.

The Trimming Max Average with 5% is used for both first data sets and second data sets and for the three measures which we discussed before. Each set has different extracted original concepts. Therefore, the trimming with 5% value is depends on the number of the original text extracted concepts.

4.4 Semantic Matching with Different Cutting Points

This part explains why the researcher chooses different cutting points. Also discuss the result for each one. To accept how each two concepts are closed or far from each other; we need a cutting point. To find which cutting point is the best is critical. Therefore, we choose

five different points with different values (40%, 50%, 60%, 70%, and 80%) to accept or reject the matching results, and then apply them to all semantic measures. For each original text and its condensed we measure these cutting points for the six semantic measures. The equation (6) shows our own equation to calculate the acceptance rate for a certain measure. Therefore, in data set one we apply this for 34 files and for the six measures. Same done in data set two which has 14 files.

$$\text{Acceptance Rate \%} = \frac{\text{No. of concepts above cutting point \%}}{\text{No. of original Text concepts}} 100\% \quad \text{..... (6)}$$

Different cutting points are used to check the coverage of each condensed text. Each measure has five different cutting points. Next section illustrates an example for some of the semantic measure with different cutting points.

4.4.1 Examples of Different Acceptance Rate

Cutting point percentage calculation based on how the condensed concepts cover original concepts with threshold value. For example, first file (T1) from first data set; the result of cutting point 40% for WuP measure is 90.37. This is by calculating 40% from the maximum value of WuP measure. As discussed before, the maximum value for WuP is 1. Thus, for 40% the value is 0.40. That's mean all concepts with maximum is equal or greater than 0.40 is counted.

In the same file using cutting point 40% with WuP measure. This part illustrates how the calculation is done. The aim is to find how the condensed text covers the original text. The number of extracted concepts from condensed text is 20 concepts and number of extracted concepts from original text is 135. Therefore, we need to find how much these 20 CC

covered the OC which is 135. The researcher chooses different point to accept or reject the results. The total number of concepts which has a maximum value equal or greater than 0.40 is 122 concepts; this mean that the 20 condensed concepts is covered with 122 original concepts. To calculate the coverage percentage, we divided the covered concepts 122 by the total number of original text extracted concepts which are 135 concepts. The result using equation (6) is 90.37 as showing in table 4.3 for the first file using WuP measure. For the second file (T2), the result is 87.36.

$$\text{Acceptance Rate in 40\% (T1)} = \frac{122}{135} * 100\% = 90.37$$

Table 4.3: Sample of Result for Cutting Point 40% in WuP Measure

File Name	Text	OT size	CT size	40% cutting point
APW19981019.0098	T1	8 KB	1 KB	90.37
APW19981022.0269	T2	4KB	1 KB	87.36
APW19981030.0792	T3	5KB	1KB	86.26
APW19981120.0290	T4	5KB	1KB	87.88
...
...
...
NYT19981223.0347	T34	11KB	1KB	93.89

Table 4.3 presents a list of examples for data set one. Its show each file name and original text size” OT size” and condensed text size “CT size”. It also shows sample 40% cutting point result using WuP. We will discuss later how to calculate the average error for each cutting point.

Another walk through example for the first file (T1) but using another cutting point which is 70% using HSO measure. As explained previously, the maximum value for HSO is 16. Thus, we need to measure the degree of acceptance and rejection results to be above 70% cutting point, 70% from 16 is equal 11. This means all concepts with maximum are equal or greater than 11 are counted. The total number of concepts which has a maximum value above 11 is 20 concepts. This means that the 20 condensed concepts covered 20 original concepts. The result is 14.81 as showing in table 4.4 for the first file using HSO measure.

$$\text{Acceptance Rate in 70\% (T1)} = \frac{20}{135} * 100\% = 14.81$$

Table 4.4: Sample of Result for Cutting Point 70% in HSO Measure

File Name	Text	OT size	CT size	70% cutting point
APW19981019.0098	T1	8 KB	1 KB	14.81
APW19981022.0269	T2	4KB	1 KB	21.84
APW19981030.0792	T3	5KB	1KB	14.50
APW19981120.0290	T4	5KB	1KB	16.67
...
...
...
NYT19981223.0347	T34	11KB	1KB	3.93

4.4.2 Result for Different Cutting Point

This part shows why the researcher chooses different cutting point. For each file, six different measures are applied in the condensed text with five different cutting points. This mean that the experiments for the first data set which contain 34 set is (34*6*5=1020 experiments). For second data set which is 14 files (14*6*5=420 experiments).

Table 4.5 shows sample of results using different cutting points in WuP measure. By choosing high value cutting point such as 80%, this means that we need to high coverage between condensed text and original text. From table 4.5, we can notice that the lower cutting point value the higher result. For example first file (T1) using 40% cutting point; this mean all the maximum value that is above 0.40 is counted. The result was 90.37 (122 concepts that have value above 0.40 divided by the total number of original extracted concepts which is 135). While the result at the same file (T1) but using different cutting point 80% is 64.44 (87 concepts that have value above 0.8 divided by the total number of original extracted concepts 135).

Table 4.5: Sample of Result for all Cutting point in WuP Measure

File Name	Text	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point
APW19981019.0098	T1	90.37	90.37	90.37	87.41	64.44
APW19981022.0269	T2	87.36	87.36	86.21	80.46	60.92
APW19981030.0792	T3	86.26	86.26	83.97	79.39	62.60
APW19981120.0290	T4	87.88	87.12	84.85	79.55	66.67
...
...
...
NYT19981223.0347	T34	93.89	93.89	93.01	88.21	68.56

4.5 Two Cases

This research classifies the experiments in two parts. The classification is based on human evaluation of how much the condensed text covers its original text. First part, we consider the data sets' condensed text as an ideal, so we assume that the condensed text has covered the original text and all condensed text has 100% coverage. Second part, we considered that

this condensed text does not cover the original text and we need expert to evaluate the coverage of the condensed text. Expert evaluation divided into three categories (Good coverage “70% - 90%”, Medium coverage “60% - 75%”, and Bad coverage “40% - 55 %”). Next section will discuss in details each experiment.

4.5.1 Ideal Summaries

This part we considered the data sets’ condensed text as an ideal and no need for expert to evaluate it. Thus, we consider all human evaluation as 100 %. This mean that all the condensed text is covered the original text in data sets one. The aim is to explore which measure from the semantic measures that can give the minimum error. Through the results, we can find the best measure that can give minimum error in case we are sure that the condensed text is covered the original text. This is done only in data set one, as it’s considered as a reference or an ideal summary.

Table 4.6 shows sample of some results using WuP measure. It also represent human evaluation field. Through the table we can notice that human evaluation for all files is 100%. This is because we considered the summary as an ideal summary for each original text. Thus, we assume that all files has 100% coverage between the condensed text covered the original text. After that, we need to calculate the error between human and each cutting point. The error calculation is the difference between human and a given cutting point. The calculation as below:

$$\text{Error for a cutting point} = (\text{Human Evaluation} - \text{Cutting point result})^2 \dots \dots \dots (7)$$

For example in first file (T1), the result using WuP measure in cutting point 40% is 90.37. To calculate the error for cutting point 40% , the results is the difference between human evaluation which is 100 here and the result for error in 40% cutting point which is here 90.37. Thus the result for the error using WuP measure in 40% cutting point is:

$$\text{Error cutting point 40\%} = (100 - 90.37)^2 = 93$$

To be able to compute the mean square error, we record the error between the human evaluation and each cutting point result. This is done for different cutting points (40%, 50%, 60%, 70%, and 80%) and for each semantic measure (WuP, LCH, LIN, Resnik, HSO, and LESK). More details *refer to appendix 4*.

Table 4.6: Result for Cutting Point 40% in WuP with Human Evaluation 100%

File Name	Text	Human Ev. %	40% cutting point	ERROR 40%
APW19981019.0098	T1	100	90.37	93
APW19981022.0269	T2	100	87.36	160
APW19981030.0792	T3	100	86.26	189
APW19981120.0290	T4	100	87.88	147
...	...	100
...	...	100
...	...	100
NYT19981223.0347	T34	100	93.89	37

4.5.2 Different Evaluation Rates

In this part, an expert evaluation is needed to find whether if the condensed text covers its original text. We considered that condensed text does not cover the original text. That's

why; an expert evaluation is needed to evaluate how much the condensed text cover the original text. Expert evaluation divided into three categories:

Good coverage: 70% - 90%.

Medium coverage: 60% - 75%.

Bad coverage: 40% - 55%.

Original text files come with different sizes such as 4KB, 9KB, 15 KB and 20KB. But the condensed texts come with fixed size 1 KB. Because of that, an expert evaluation is important to find if the condensed text cover most content of the original text. By Good coverage we mean that the condensed text covers most of the content of its original text. In the other hand, bad coverage means that the condensed text does not cover the original text.

Table 4.7: Expert Evaluation Percentage for First Data Set

File Name	Text	OT size	CT size	Human Ev. %
APW19981019.0098	T1	8 KB	1 KB	70
APW19981022.0269	T2	4KB	1 KB	85
NYT19981114.0129	T25	15KB	1KB	55
APW19981120.0290	T4	5KB	1KB	80
NYT19981004.0102	T11	9KB	1KB	65
NYT19981001.0379	T9	20KB	1KB	40
...
...
NYT19981223.0347	T34	11KB	1KB	65

Table 4.7 present sample of expert evaluation percentage for first data set. It also shows each original text size (OT) and condensed text size (CT). For example first file (T1) with

8KB original text size and 1KB the condensed text size. The expert evaluation was 70%; this means when human compare the coverage between condensed text and original text, the result is the coverage is medium with 70%. While file (T9) the expert find the coverage of the condensed text is 40%, this means that the condensed text has a bad coverage comparing it with its original text.

The expert evaluation part is done for all 34 files from the first data sets and 14 file for the second data sets. In this experiment we need to find which measure can give a result that is closed to expert evaluation. And also which measure that can give the minimum. This experiment also needs different cutting point to compute the coverage of the condensed text.

Table 4.8: Result for Cutting Point 40% in WuP with Expert Evaluation Rates

File Name	Text	OT size	CT size	Human Ev. %	40% cutting point	ERROR 40%
APW19981019.0098	T1	8 KB	1 KB	70	90.37	415
APW19981022.0269	T2	4KB	1 KB	85	87.36	6
APW19981030.0792	T3	5KB	1KB	85	86.26	2
APW19981120.0290	T4	5KB	1KB	80	87.88	62
...
...
...
NYT19981223.0347	T34	11KB	1KB	65	93.89	834

Table 4.8 shows Result for cutting point 40% in WuP with Human Evaluation rate. To calculate the error for each cutting point we need to find the difference between human evaluation and the result for each cutting point. For example first file (T1); the expert evaluated the coverage of the condensed text by comparing with its original text. The

expert evaluation result was 70%. As discussed before, the calculation using WuP measure in cutting point 40% is 90.37. Therefore, the error between expert evaluation result and cutting point 40% result is the difference between both. The result is:

$$\text{Error in 40\%} = (70 - 90.37)^2 = 415$$

This calculation is the same as has been shown in the next file where the error is (6). This is done for all cutting points. For WuP measure, it has five different cutting points. Same is done for the other semantic measures. Through the results of these experiments, we need to find which measure from the six measures can give minimum error in a certain cutting point.

4.6 Experiment Result and Analysis

This research used Mean Square Error (MSE) to calculate the average error of each semantic measure. Each measure has different five cutting point, so each measure has five MSE result (Chai & Draxler, 2014).

$$\text{MSE} = \sum_n^1 \sqrt{\frac{(\text{Human Evaluation} - \text{Cutting point Result})^2}{n}} * 100\%$$

As discussed before, this research considered that the condensed texts cover its original text. Thus, in this part the expert evaluation for this part is 100%. The other part of experiment assumes that the condensed text does not cover the original text. Therefore, expert evaluation is needed. Results for expert evaluation come with different percentage

based on the coverage of the main content in condensed text. Next section explains the result for both parts.

Result for Ideal Summaries

As explained before, this research used six semantic measures (WuP, LCH, LIN, Resnik, HSO, and LESK) and five different cutting points (40%, 50%, 60%, 70%, and 80%). Each measure had five different results based on cutting point percentage. After we calculate the difference between expert evaluation and each measure result; Next step is to compute the average error for each measure in a given cutting point. Figure 4.1 present average errors for cutting point 40% for the six measures. Through the table we can note that WuP measure and LCH measure have lowest error with (12.22, 11.80). From results, we realized that measure that can give the minimum average error is LCH with (11.80) error. HSO measure gives the maximum error with (78.45). For the rest figures of all cutting points error, *refer to appendix no. 5*.

Table 4.9: Average MSE for 40% Cutting Point

Measures	Cutting point 40%
WuP	12.22
LCH	11.80
LIN	31.86
Resnik	18.38
HSO	78.45
LESK	42.27

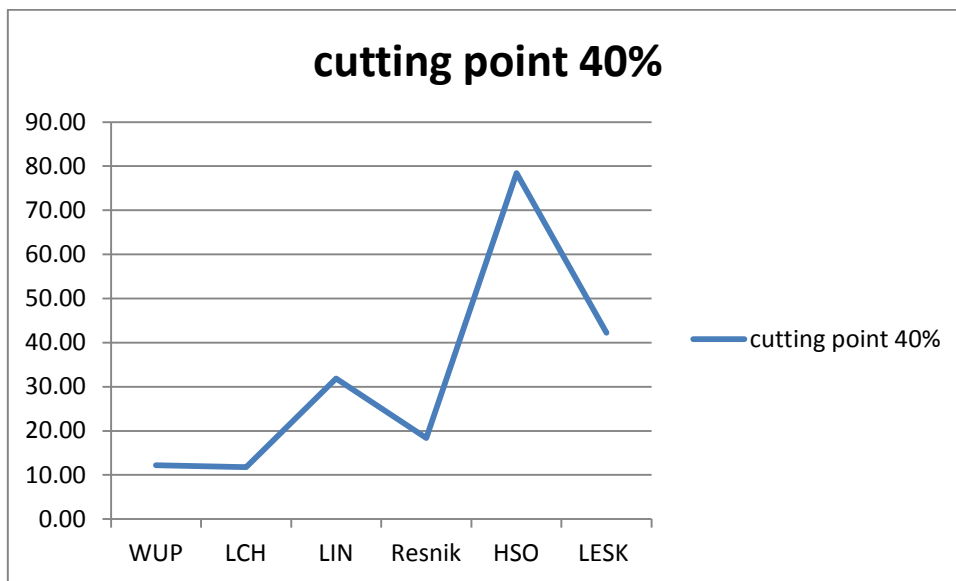


Figure 4.1: Average MSE for the 40% Cutting Point

Through table 4.10, we concluded that LCH measure is the best measure for cutting point 40%. This means if we have a condensed text and this condensed text has a high coverage of its original text; we can use LCH measure. We can note that LCH has the minimum error in most cases, also the average error for LCH between cutting point 40% (11.80) and cutting point 50 % (11.83) is insignificant.

Table 4.10: Average MSE for all Cutting Points

Measures	cutting point 40%	cutting point 50%	cutting point 60%	cutting point 70%	cutting point 80%
WuP	12.22	12.67	15.28	20.75	38.41
LCH	11.80	11.83	12.48	15.79	26.04
LIN	31.86	44.57	57.25	69.06	77.68
Resnik	18.38	20.46	25.46	31.79	40.31
HSO	78.45	87.98	87.98	87.98	87.98
LESK	42.27	50.10	56.15	61.51	66.14

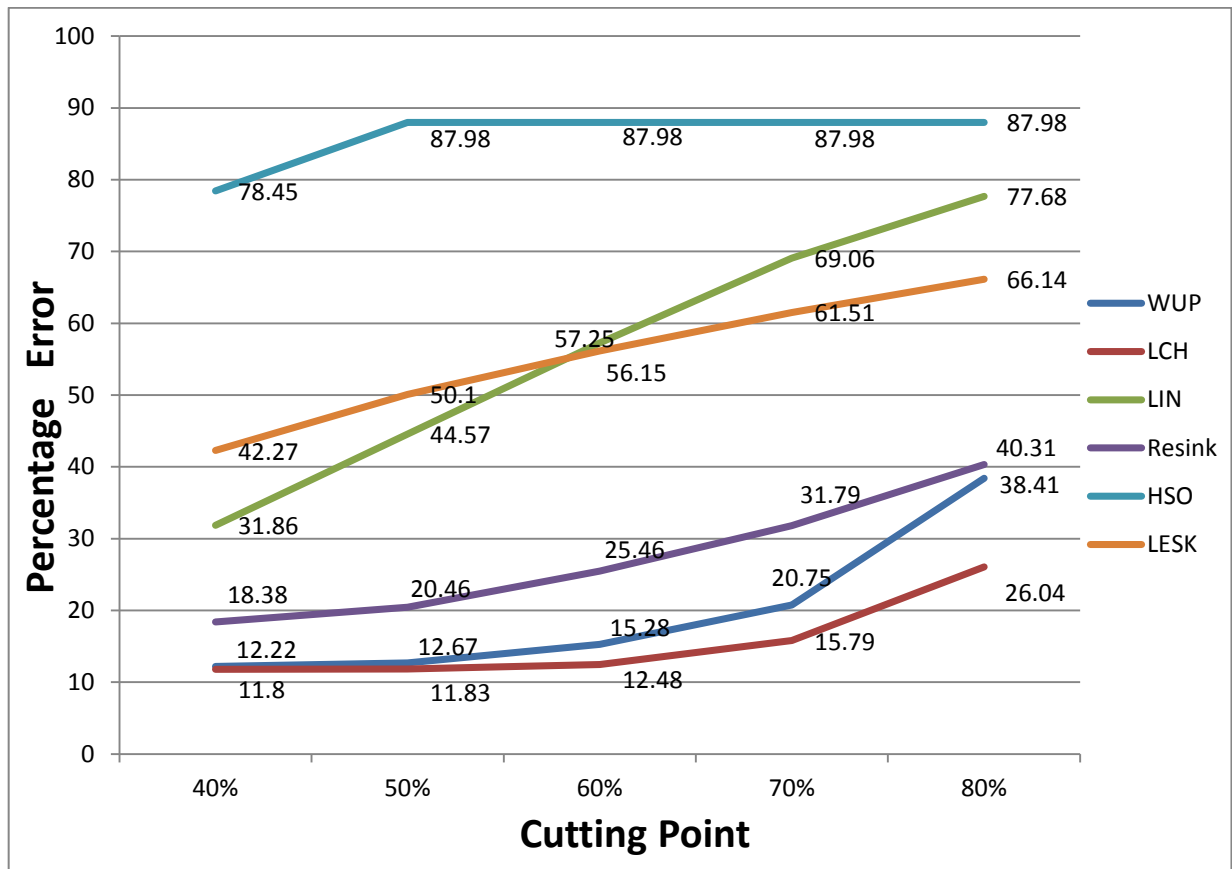


Figure 4.2: Average MSE for all Semantic Measures

Figure 4.2, shows that LCH measure is the best measure with minimum error. The figure also shows that there is a crossing point between LESK measure and LIN measure for the 60% cutting point. It's clear that LIN measure has error less than LESK. For example, for cutting point 40% LIN has 31.86 where LESK has 42.27. From that we concluded if we are looking for a generalized summary, cutting point is less than 60%, LIN gives minimum error comparing with LESK. However, if we are looking for a specific summary LESK gives minimum error comparing with LIN measure.

Results for different evaluation rates

As we discussed before, this experiment used expert evaluation to evaluate the quality of the condensed text. This is done by comparing the coverage with its condensed text. To compare the result of expert evaluation and our result; first we extracted the concepts from original text and condensed text, then applying the six semantic measures on the extracted concepts. Then we calculated the average error for each semantic measure. The results show that Resnik has the minimum error with 12.21% on average. Table 4.11 and figure 4.4 presents the results at cutting point 70%.

It's clear that Resnik measure has minimum error value.

Table 4.11: Average MSE for the 70% Cutting Point

Measures	cutting point 70%
WuP	16.24
LCH	19.32
LIN	40.62
Resnik	12.21
HSO	58.36
LESK	34.19

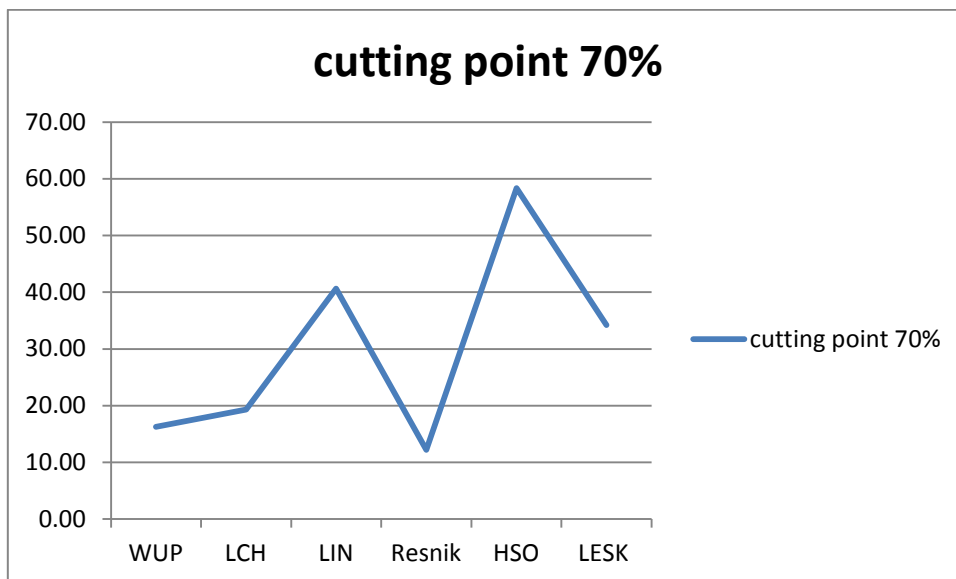


Figure 4.3: Average MSE for the 70% Cutting Point

Table 4.12: Average MSE for all Cutting Points

Measures	cutting point 40%	cutting point 50%	cutting point 60%	cutting point 70%	cutting point 80%
WuP	22.12	21.65	19.55	16.24	16.08
LCH	22.41	22.35	21.69	19.32	14.38
LIN	13.04	19.83	30.22	40.62	48.66
Resnik	17.21	16.24	13.17	12.21	15.96
HSO	49.23	58.36	58.36	58.36	58.36
LESK	20.24	25.26	29.72	34.19	38.39

Table 4.12 lists all results for all semantic measures using different cutting points. Through figure 4.4, we concluded that if we have a condensed text and we are not sure about the summary quality. We need an expert to evaluate it, to define whether the condensed text covers all the content of its original text.

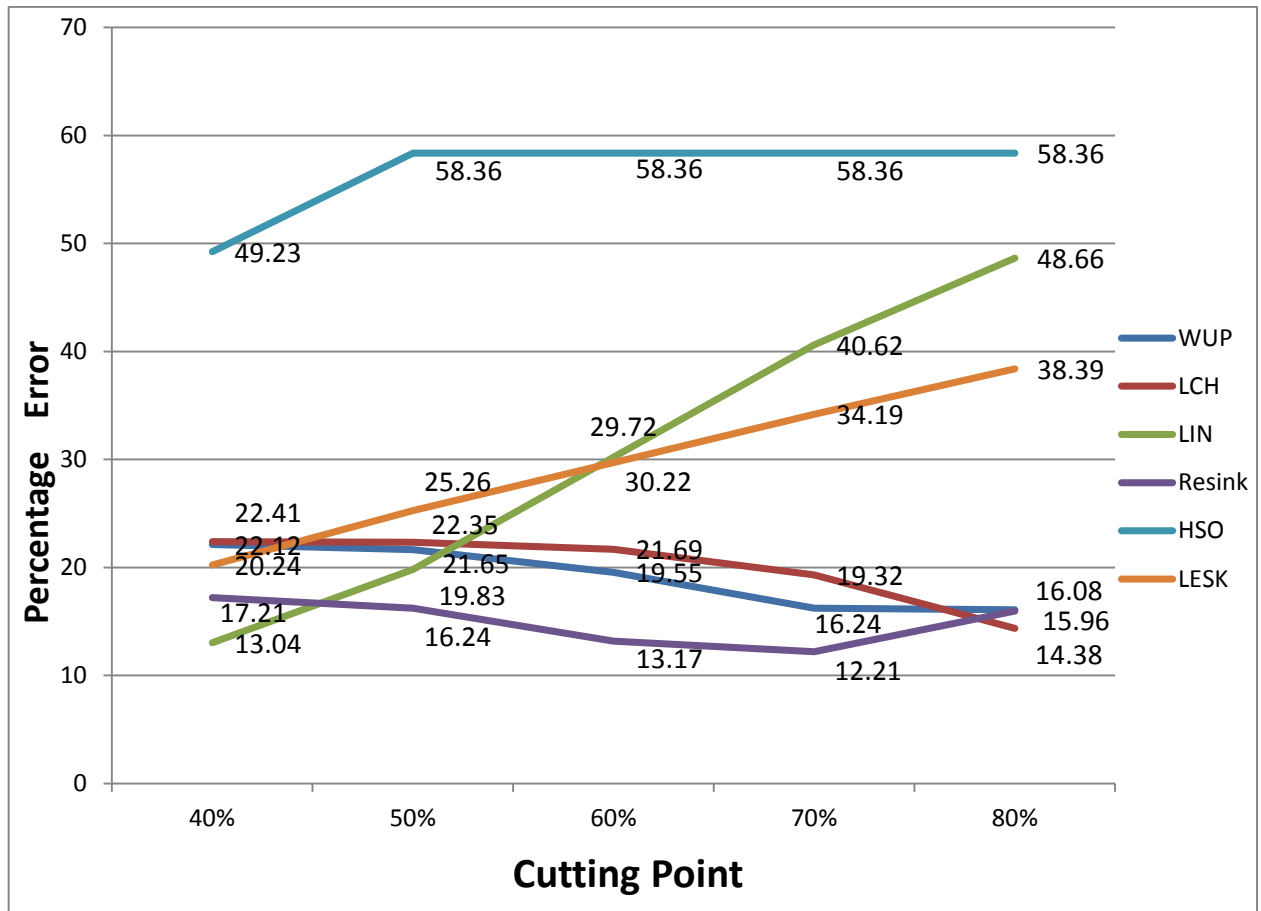


Figure 4.4: Average MSE for all Semantic Measures

From figure 4.4 shows that there are many crossing points between the measures. When the cutting point is less than 60%, i.e. the summary is very general, the error is not clear. However, when the cutting point is more than 60% the error become clear. For example, the crossing point for Resnik measure is (17.21) where LIN measure is (13.4) at cutting point 40%. This means if we are looking for a generalized summary LIN measure gives the

minimum error with MSE 13.4%. However, for a precise summary, Resnik has the minimum error in most cutting points.

Another crossing point is between LCH measure with average error (14.38) and WuP with average error (16.08). LCH and WuP are from the same family which is the path length. Both depend on calculating the depth between two concepts based on the node counting. The depth in given taxonomy is the length of the shortest path for two concepts between the root of the taxonomy and these concepts.

In the case of bad summaries; i.e. when the expert give 40% coverage In this case, this research recommends using LESK measure. Table 4.13 shows the results for all bad coverage from first data sets for (T9), column (H.E) shows the results of human evaluation which was (40%). It also shows the results for different acceptance rates used with the six semantic measures. Table 4.14 shows the result for the second data sets (T12). Both tables show that LESK measure gave the minimum error. Table 4.13 shows that LESK measure has the minimum error (3%). Table 4.14 shows that LESK measure has the minimum error (1%).

The results from table 4.13 and 4.14 show that LESK is the best measure to evaluate the bad coverage summary. We concluded that the semantic measures can be used to identify not only the good coverage but also the bad coverage.

Table 4.13: Result for Bad Coverage from First Data Sets

File Name	Text	OT size	H.E	40%	Cutting Points	80%	40%	Error	80%	SM
NYT19981001.0379	T9	20KB	40	90	64	2467	563	WuP
NYT19981001.0379	T9	20KB	40	84	61	1925	450	RES
NYT19981001.0379	T9	20KB	40	72	24	1011	266	LIN
NYT19981001.0379	T9	20KB	40	64	38	599	3	LESK
NYT19981001.0379	T9	20KB	40	90	79	2518	1489	LCH
NYT19981001.0379	T9	20KB	40	22	10	309	911	HSO

Table 4.14: Result for Bad Coverage from Second Data Sets

File Name	Text	OT size	H.E	60%	Cutting Points 70%	80%	Error 60%	70%	80%	SM
Text 12	T12	19KB	40	89	85	74	2397	2005	1158	WuP
Text 12	T12	19KB	40	79	74	68	1506	1158	787	RES
Text 12	T12	19KB	40	58	44	33	321	13	56	LIN
Text 12	T12	19KB	40	41	36	32	1	17	70	LESK
Text 12	T12	19KB	40	89	86	76	2426	2113	1326	LCH
Text 12	T12	19KB	40	18	18	18	475	475	475	HSO

4.7 Evaluate the Result using Second Data Set

This research used two data sets. The first data set contains 34 original texts and condensed texts. We apply our experiments in the first data set; but to evaluate the results, we used another data set which contains 14 original texts and 14 condensed texts. In this set, we assumed that the condensed text does not cover the original text. Therefore, an expert

evaluation is needed. All steps have been repeated as for the first data set. Then the error has been calculated by computing the difference between expert evaluation and the value of each measure. Table 4.13 and figure 4.5 show the average error using different semantic measures. The results show that Resnik measure is the best measure that gives minimum error 15.68% using cutting point 40%.

Table 4.15: Average MSE for all Cutting Points using Second Data sets

Measures	cutting point 40%	cutting point 50%	cutting point 60%	cutting point 70%	cutting point 80%
WuP	16.70	16.43	16.15	16.96	23.50
LCH	16.68	16.70	16.56	16.27	21.69
LIN	21.34	27.68	37.98	45.80	54.69
Resnik	15.68	15.77	17.22	21.38	29.79
HSO	49.50	59.79	57.79	59.79	59.79
LESK	39.53	44.86	49.46	52.37	54.15

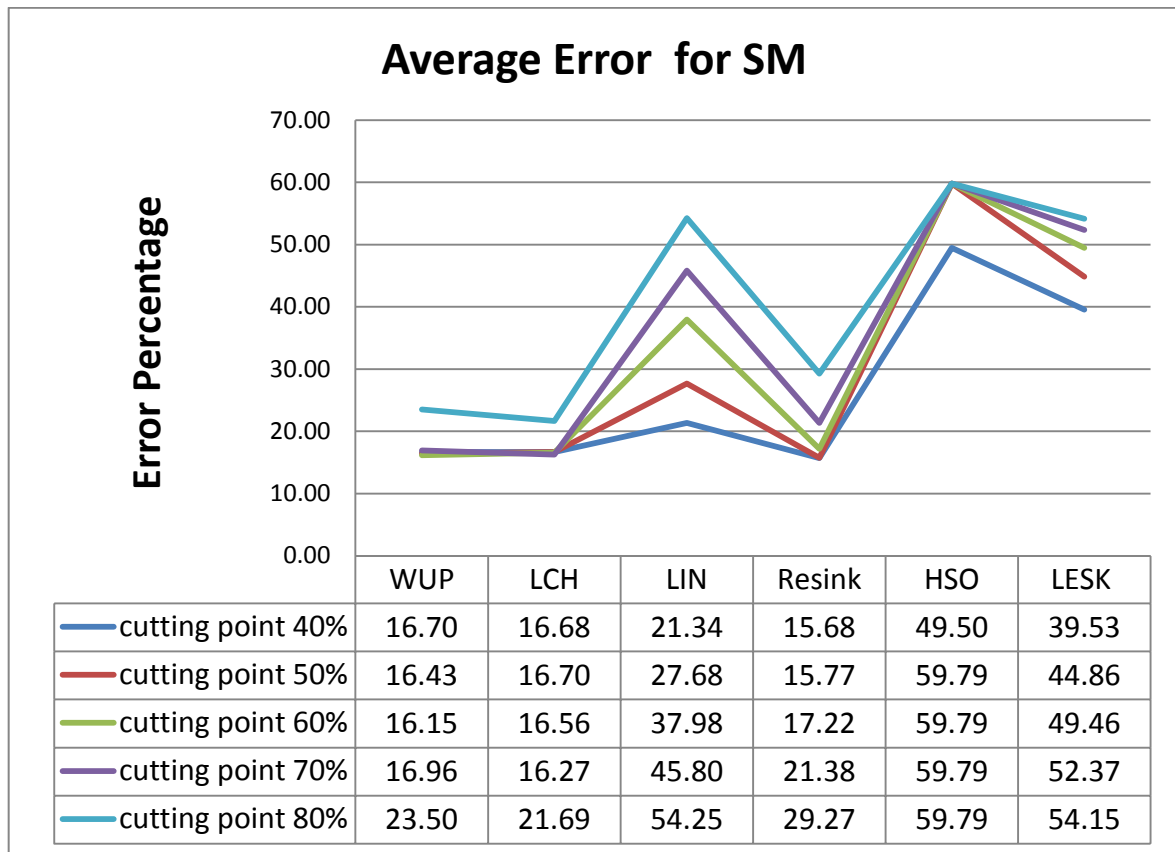


Figure 4.5: Average MSE for all Semantic Measures in Second Data Sets

CHAPTER FIVE

Conclusions and Future Work

Overview

This chapter summarizes the work done through this research. It discusses the conclusion from the results in both experiments. It also discusses future work.

5.1 Conclusion and Contributions

The thesis concluded in finding the best measure that can give a minimum error for measuring the quality of a condensed text. The results from first experiment showed that LCH measure has the minimum error comparing with other measures. This means that if you are sure that these summaries are the best ones for a given texts, you can use LCH to define how much the quality of these condensed texts.

However, if you believe that these summaries are not good ones and you need to find the quality of these summaries. Using Resnik measure will give the minimum error comparing it with other measures. Thus, Resnik is the best measure to define whether a condensed is covered or not.

This thesis also found out the best measure that can give the bad coverage of condensed text.

This means if we have a summary and we need to find out how much this summary is bad. LESK will give the minimum error. Thus, LESK is the best measure to define the worst (bad coverage) condensed text.

The above contributions can be summarized in one main point which is the semantic measures can be used to identify not only the good coverage but also the bad coverage.

The research evaluated the semantic measures and showed how these measures could be used to evaluate the quality of a condensed text. Also this research contributed in defining the best semantic measures with minimal error that defines how much a condensed text covers its original text.

The main steps for this research could be summarized in the following points:

- 1) This research studied how to find the quality of the condensed text using the semantic measures.
- 2) In order to study the quality of the condensed text. We used data sets that contain the original text with its condensed text. We collected data sets (first data set 34 files and second data set 14 files).
- 3) Extraction concepts from each condensed text and original text using KAON.
- 4) Semantic matching using six different measures (WuP, LCH, LIN, Resnik, HSO, and LESK). Each two measures belong to one family.
- 5) We calculated the coverage using different cutting point for each measure. By choosing different cutting point; we aim to find how closed the condensed text concepts from original text concepts.
- 6) The final results show that using a measure to define the coverage of the condensed text is based on the summary quality. We have three cases: if you are looking for the ideal summary, you can use LCH measure. If you are not sure from the quality of the condensed

text, you can use Resnik. If you are looking for a summary with a bad coverage, the measure that can tell that is LESK.

5.2 Future Work

There are several issues that can be explored further from this thesis. These are:

- 1) Possibility to use this approach to compare human generated summary and automatic generated summary. To compare among summaries, we need to extract the concepts from both human generated summary and automatic generated summary. Then, apply the semantic measures on the extracted concepts.
- 2) Using other semantic measures such as path measure, Jiang & Conrath measure and context Vectors measure.
- 3) Apply semantic measures for Arabic text. It's more difficult than English language because we must have an Arabic version of WordNet. Also, we need semantic measures that are designed to compute the similarity for Arabic concepts.
- 4) Use semantic measures to check relevancy and plagiarism. The plagiarism is already exist but with exact matching. Our idea is to apply the semantic matching using the semantic measures to check the relevancy and plagiarism.

References

- Alguliev, R., & Aliguliyev, R. (2007). Experimental investigating the F-measure as similarity measure for automatic text summarization. *Applied and Computational Mathematics*, Vol.6 (No.2), PP. 278-287.
- Al-Khiaty, M., & Ahmed, M. (2015). UML Class Diagrams: Similarity Aspects and Matching. *LNSE*, 4(1), 41-47. <http://dx.doi.org/10.7763/lmse.2015.v4.221>
- Baader, F., Sertkaya, B., & Turhan, A. (2007). Computing the least common subsumer w.r.t. a background terminology. *Journal of Applied Logic*, 5(3), 392-420. <http://dx.doi.org/10.1016/j.jal.2006.03.002>
- Barzilay, R., & Elhadad, M. (1999). Using lexical chains for text summarization. *Advances in Automatic Text Summarization*, PP. 111-121.
- Boon young, T., & Mingkhwan, A. (2015). Document Similarity using Computer Science Ontology based on Edge Counting and N-Grams, pp. 23-24.
- Buckley, J., Liu, G., Wang, R., & Zhou, H. (2011). A WordNet-based Semantic Similarity Measure Enhanced by Internet-based Knowledge. *In SEKE*, pp. 175-178.
- Chai, T., & Draxler, R. (2014). Root mean square error (RMSE) or mean absolute error (MAE) Arguments against avoiding RMSE in the literature. *Geoscientific Model Development*, 7(3), 1247-1250. <http://dx.doi.org/10.5194/gmd-7-1247-2014>.
- Corley, C., & Mihalcea, R. (2005). Measuring the semantic similarity of texts. *In Proceedings of The ACL Workshop On Empirical Modeling Of Semantic Equivalence And Entailment. Association for Computational Linguistics*.pp. 13-18.
- Fukusima, T., & Okumura, M. (2001). Text Summarization Challenge Text

Summarization Evaluation in Japan. *In Proceedings of The Workshop On Automatic Summarization. Pittsburgh, PA, USA.*

- Gupta, V. (2014). A Survey of Various Summary Evaluation Techniques. *International Journal of Advanced Research In Computer Science And Software Engineering, Vol. 4*(ISSN: 2320-088X).
- HOUSE, D., KLEIN, G., MANI, I., HIRSCHMAN, L., FIRMIN, T., & SUNDHEIM, B. (2002). SUMMAC: a text summarization evaluation. *Natural Language Engineering, 8*(01). <http://dx.doi.org/10.1017/s1351324901002741>
- Jiang, R., Dou, X., & Gan, M. (2013). From Ontology to Semantic Similarity: Calculation of Ontology-Based Semantic Similarity. *The Scientific World Journal, 2013*, 1-11. <http://dx.doi.org/10.1155/2013/793091>
- Kayed, A., Hirzallah, N., & Alharibat, M. (2013). Ontological Concepts Coverage Measure for Software- Component Description. *European Journal of Scientific Research, PP.77-99.*
- Kayed, A., Nizar, M., & Alfayoumi, M. (2010). Ontology concepts for requirements engineering process in e-government applications. *In Internet and Web Applications and Services (ICIW). Fifth International Conference on IEEE*, pp. 396-400.
- Lin, C. (2004). Looking for a few good metrics: ROUGE and its evaluation. *NTCIR Workshop.*
- Liu, G., Wang, R., Buckley, J., & Zhou, H. (2011). A WordNet-based Semantic Similarity Measure Enhanced by Internet-based Knowledge. *In SEKE*, pp. 175-178.
- Maedche, A., & Volz, R. (2001). The ontology extraction & maintenance framework Text-To-Onto. *In Proc. Workshop on Integrating Data Mining and Knowledge Management, USA*, 1-12.

- Mani, I. (2001a). Recent developments in text summarization. *Inproceedings of The Tenth International Conference On Information And Knowledge Management.ACM*, PP. 529-531.
- Mani, I. (2001b). Summarization Evaluation: An overview. *In proceedings of The Tenth International Conference on Information and Knowledge Management*.
- McInnes, B., & Pedersen, T. (2013). Evaluating measures of semantic similarity and relatedness to disambiguate terms in biomedical text. *Journal of Biomedical Informatics*, 46(6), 1116-1124. <http://dx.doi.org/10.1016/j.jbi.2013.08.008>
- Meng, L., Huang, R., & Gu, J. (2013). A review of semantic similarity measures in wordnet. *International Journal of Hybrid Information Technology*, Vol 6(1), PP. 1-12.
- Michelizzi, J. (2005). Semantic relatedness applied to all words sense disambiguation, (*Doctoral dissertation*), *University of Minnesota, Twin Cities*.
- Mittal, K., & Jain, A. (2015). WORD SENSE DISAMBIGUATION METHOD USING SEMANTIC SIMILARITY MEASURES AND OWA OPERATOR, *Vol.5, No.2*.
- Moghaddas, B., Kahani, M., Toosi, S., Pourmasoumi, A., & Estiri, A. (2013). Pasokh: A standard corpus for the evaluation of Persian text summarizers. *In Computer and Knowledge Engineering (ICCKE), 2013 3Th International Econference On IEEE*, pp. 471-475.
- Morris, A., Kasper, G., & Adams, D. (1992). The Effects and Limitations of Automated Text Condensing on Reading Comprehension Performance. *Information Systems Research*, 3(1), pp.17-35.
- Pedersen, T., Patwardhan, S., & Michelizzi, J. (2004). WordNet:: Similarity: measuring the relatedness of concepts. *Association for Computational Linguistics*, pp. 38-41.

- Seddiqui, M., & Aono, M. (2010). Metric of intrinsic information content for measuring semantic similarity in ontology. *In Proceedings Of The Seventh Asia-Pacific Conference On Conceptual Modelling, Vol. 110*, pp. 89-96.
- Slimani, T. (2013). Description and Evaluation of Semantic Similarity Measures Approaches. *International Journal of Computer Applications*, 80(10), 25-33. <http://dx.doi.org/10.5120/13897-1851>
- Steinberger, J., & Jezek, K. (2009). Evaluation measures for text summarization. *Computing and Informatics, Vol.28 (No.2)*, 1001-1026.

Appendix

Appendix

1. NIST assigned agreement

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2. Table of original extracted concepts in file.

No.	Concepts	No.	Concepts	No.	Concepts	No.	Concepts	No.	Concepts
1	Defense	28	Prosecution	55	Order	82	Guard	109	Television
2	Minister	29	Institution	56	Advice	83	Stuff	110	Interview
3	Priest	30	Power	57	Government	84	Idea	111	Division
4	Magistrate	31	Abuse	58	Lawmaker	85	Business	112	Riot
5	Murder	32	Constitution	59	Bed	86	Army	113	Police
6	Day	33	Statement	60	Result	87	People	114	Police
7	Embassy	34	Word	61	Water	88	Administration	115	Line
8	Police	35	Military	62	Cannon	89	Government	116	spokesman
9	Source	36	Support	63	Decade	90	Report	117	Response
10	Insult	37	Portrait	64	Application	91	Disappearance	118	Death
11	Team	38	Extradition	65	Regime	92	Passport	119	Pressure
12	Claim	39	Law	66	Delegation	93	Family	120	Release
13	Arrest	40	Protester	67	Place	94	Total	121	Injury
14	Warrant	41	Arrest	68	Politician	95	Police	122	Violation
15	Attorney	42	Opponent	69	Scene	96	Gas	123	Attitude
16	Envoy	43	Rightist	70	Decision	97	Allegation	124	Lobby
17	Extradition	44	Politician	71	Judge	98	News	125	Group
18	Request	45	Time	72	Evening	99	Court	126	Placard
19	Opinion	46	Amnesty	73	Dictator	100	Strongman	127	Bearing
20	Term	47	Month	74	Iron	101	Rights	128	Condition
21	Rally	48	Father	75	Fist	102	Abuse	129	Son
22	Week	49	Immunity	76	Visitor	103	Country	130	Year
23	Boss	50	Caption	77	Diplomat	104	Demonstrator	131	demonstration
24	Government	51	Capital	78	Policy	105	Operation	132	anonymity
25	Official	52	Publicity	79	Trial	106	Official	133	Reign
26	Post	53	Patient	80	Black	107	Event	134	Hospital
27	crime	54	Arrest	81	Police	108	Dissident	135	Protest

3. semantic matching results for T1

A) WuP Measure

No	OC	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9	CC10	CC11	CC12	CC13	CC14	CC15	CC16	CC17	CC18	CC19	CC20
		dictator	confusion	hospital	arrest	murder	citizen	rule	legality	move	supporter	immunity	extradition	outcome	request	charge	community	surgery	death	court	government
1	defense	<u>0.5556</u>	<u>0.6667</u>	<u>0.7778</u>	<u>0.6667</u>	<u>0.5455</u>	<u>0.5556</u>	<u>0.7778</u>	<u>0.4615</u>	<u>0.7778</u>	<u>0.7059</u>	<u>0.5455</u>	<u>0.6364</u>	<u>0.625</u>	<u>0.7778</u>	<u>0.8889</u>	<u>0.75</u>	<u>0.7778</u>	<u>0.625</u>	<u>0.8235</u>	<u>0.8</u>
2	minister	<u>0.7273</u>	<u>0.6</u>	<u>0.4545</u>	<u>0.6</u>	<u>0.5</u>	<u>0.7273</u>	<u>0.7</u>	<u>0.3333</u>	<u>0.7</u>	<u>0.7826</u>	<u>0.5</u>	<u>0.5</u>	<u>0.5263</u>	<u>0.6316</u>	<u>0.7</u>	<u>0.4</u>	<u>0.6667</u>	<u>0.5263</u>	<u>0.6667</u>	<u>0.6</u>
3	priest	<u>0.7619</u>	<u>0.6667</u>	<u>0.4762</u>	<u>0.6667</u>	<u>0.2857</u>	<u>0.7619</u>	<u>0.625</u>	<u>0.5333</u>	<u>0.3529</u>	<u>0.7619</u>	<u>0.6667</u>	<u>0.3</u>	<u>0.4286</u>	<u>0.4286</u>	<u>0.6957</u>	<u>0.5882</u>	<u>0.4762</u>	<u>0.7143</u>	<u>0.6957</u>	<u>0.375</u>
4	magistrate	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5	murder	<u>0.2</u>	<u>0.6667</u>	<u>0.7777</u>	<u>0.5455</u>	<u>1</u>	<u>0.2</u>	<u>0.5455</u>	<u>0.3</u>	<u>0.7273</u>	<u>0.2</u>	<u>0.7692</u>	<u>0.4615</u>	<u>0.4762</u>	<u>0.5714</u>	<u>0.5455</u>	<u>0.3333</u>	<u>0.5217</u>	<u>0.88</u>	<u>0.6087</u>	<u>0.5455</u>
6	day	<u>0.7826</u>	<u>0.625</u>	<u>0.4762</u>	<u>0.625</u>	<u>0.3158</u>	<u>0.7619</u>	<u>0.8</u>	<u>0.5333</u>	<u>0.4</u>	<u>0.7619</u>	<u>0.625</u>	<u>0.3333</u>	<u>0.4286</u>	<u>0.5</u>	<u>0.6957</u>	<u>0.5556</u>	<u>0.4762</u>	<u>0.6667</u>	<u>0.6957</u>	<u>0.4286</u>
7	embassy	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8	police	<u>0.2667</u>	<u>0.4</u>	<u>0.7059</u>	<u>0.4</u>	<u>0.2857</u>	<u>0.2667</u>	<u>0.4</u>	<u>0.4</u>	<u>0.3529</u>	<u>0.2667</u>	<u>0.4</u>	<u>0.3</u>	<u>0.375</u>	<u>0.4286</u>	<u>0.4</u>	<u>0.7059</u>	<u>0.3333</u>	<u>0.4286</u>	<u>0.7059</u>	<u>0.75</u>
9	source	<u>0.8182</u>	<u>0.4444</u>	<u>0.6667</u>	<u>0.4444</u>	<u>0.3636</u>	<u>0.8</u>	<u>0.7778</u>	<u>0.4</u>	<u>0.4444</u>	<u>0.8</u>	<u>0.4</u>	<u>0.381</u>	<u>0.6667</u>	<u>0.5714</u>	<u>0.7273</u>	<u>0.6667</u>	<u>0.6667</u>	<u>0.5714</u>	<u>0.7273</u>	<u>0.6</u>
10	insult	<u>0.2857</u>	<u>0.6316</u>	<u>0.375</u>	<u>0.6316</u>	<u>0.5217</u>	<u>0.2857</u>	<u>0.7368</u>	<u>0.4286</u>	<u>0.7368</u>	<u>0.2857</u>	<u>0.5217</u>	<u>0.5217</u>	<u>0.5556</u>	<u>0.7692</u>	<u>0.7368</u>	<u>0.5</u>	<u>0.7</u>	<u>0.5556</u>	<u>0.6</u>	<u>0.6316</u>
11	team	<u>0.2857</u>	<u>0.4286</u>	<u>0.7059</u>	<u>0.4286</u>	<u>0.3</u>	<u>0.2857</u>	<u>0.4286</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.2857</u>	<u>0.4286</u>	<u>0.3158</u>	<u>0.4</u>	<u>0.4615</u>	<u>0.4286</u>	<u>0.7059</u>	<u>0.3529</u>	<u>0.4615</u>	<u>0.7059</u>	<u>0.75</u>
12	claim	<u>0.2667</u>	<u>0.6667</u>	<u>0.3529</u>	<u>0.6667</u>	<u>0.5455</u>	<u>0.2667</u>	<u>0.8</u>	<u>0.4</u>	<u>0.7778</u>	<u>0.2667</u>	<u>0.5455</u>	<u>0.5455</u>	<u>0.5882</u>	<u>0.8571</u>	<u>0.8889</u>	<u>0.4615</u>	<u>0.7368</u>	<u>0.5882</u>	<u>0.6316</u>	<u>0.6667</u>
13	arrest	<u>0.2857</u>	<u>0.7143</u>	<u>0.375</u>	<u>1</u>	<u>0.5455</u>	<u>0.2857</u>	<u>0.6667</u>	<u>0.5714</u>	<u>0.6667</u>	<u>0.2857</u>	<u>0.7143</u>	<u>0.5455</u>	<u>0.5882</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.625</u>	<u>0.6316</u>	<u>0.7692</u>	<u>0.6316</u>	<u>0.6667</u>
14	warrant	<u>0.2857</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.4286</u>	<u>0.3</u>	<u>0.2857</u>	<u>0.7143</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.2857</u>	<u>0.4286</u>	<u>0.3158</u>	<u>0.4</u>	<u>0.7692</u>	<u>0.7059</u>	<u>0.5714</u>	<u>0.3529</u>	<u>0.4615</u>	<u>0.4</u>	<u>0.4</u>
15	attorney	<u>0.7619</u>	<u>0.2667</u>	<u>0.4762</u>	<u>0.2667</u>	<u>0.1905</u>	<u>0.7619</u>	<u>0.4348</u>	<u>0.2667</u>	<u>0.2353</u>	<u>0.7619</u>	<u>0.2667</u>	<u>0.2</u>	<u>0.4286</u>	<u>0.2857</u>	<u>0.6957</u>	<u>0.4211</u>	<u>0.4762</u>	<u>0.375</u>	<u>0.6957</u>	<u>0.25</u>
16	envoy	<u>0.75</u>	<u>0.3529</u>	<u>0.4545</u>	<u>0.3529</u>	<u>0.2609</u>	<u>0.7273</u>	<u>0.4706</u>	<u>0.3529</u>	<u>0.3158</u>	<u>0.7826</u>	<u>0.3529</u>	<u>0.2727</u>	<u>0.4</u>	<u>0.5</u>	<u>0.6667</u>	<u>0.4</u>	<u>0.4545</u>	<u>0.375</u>	<u>0.6667</u>	<u>0.3333</u>
17	extradition	<u>0.2105</u>	<u>0.5455</u>	<u>0.2857</u>	<u>0.5455</u>	<u>0.4615</u>	<u>0.2105</u>	<u>0.5455</u>	<u>0.3158</u>	<u>0.5455</u>	<u>0.2105</u>	<u>0.4615</u>	<u>1</u>	<u>0.5</u>	<u>0.5714</u>	<u>0.5455</u>	<u>0.3529</u>	<u>0.5217</u>	<u>0.5</u>	<u>0.5217</u>	<u>0.6364</u>
18	request	<u>0.3077</u>	<u>0.7059</u>	<u>0.4</u>	<u>0.7059</u>	<u>0.5714</u>	<u>0.3077</u>	<u>0.7692</u>	<u>0.4615</u>	<u>0.7059</u>	<u>0.3077</u>	<u>0.5714</u>	<u>0.5714</u>	<u>0.625</u>	<u>1</u>	<u>0.9412</u>	<u>0.5455</u>	<u>0.6667</u>	<u>0.625</u>	<u>0.6667</u>	<u>0.7059</u>
19	opinion	<u>0.3077</u>	<u>0.6316</u>	<u>0.4</u>	<u>0.6316</u>	<u>0.5217</u>	<u>0.3077</u>	<u>0.8235</u>	<u>0.4615</u>	<u>0.6316</u>	<u>0.3077</u>	<u>0.5217</u>	<u>0.6087</u>	<u>0.5882</u>	<u>0.8333</u>	<u>0.7143</u>	<u>0.5455</u>	<u>0.6</u>	<u>0.5882</u>	<u>0.6</u>	<u>0.7368</u>
20	term	<u>0.4545</u>	<u>0.4706</u>	<u>0.5455</u>	<u>0.4706</u>	<u>0.3478</u>	<u>0.4545</u>	<u>0.8421</u>	<u>0.4706</u>	<u>0.4211</u>	<u>0.5714</u>	<u>0.4706</u>	<u>0.3636</u>	<u>0.4444</u>	<u>0.7692</u>	<u>0.8</u>	<u>0.5714</u>	<u>0.5455</u>	<u>0.7692</u>	<u>0.5714</u>	<u>0.5714</u>
21	rally	<u>0.375</u>	<u>0.7059</u>	<u>0.625</u>	<u>0.7059</u>	<u>0.6087</u>	<u>0.375</u>	<u>0.7059</u>	<u>0.4286</u>	<u>0.7368</u>	<u>0.375</u>	<u>0.6087</u>	<u>0.6667</u>	<u>0.6667</u>	<u>0.75</u>	<u>0.7059</u>	<u>0.8571</u>	<u>0.6667</u>	<u>0.6667</u>	<u>0.8</u>	<u>0.8235</u>
22	week	<u>0.2857</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.4286</u>	<u>0.3</u>	<u>0.2857</u>	<u>0.8</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.2857</u>	<u>0.4286</u>	<u>0.3158</u>	<u>0.4</u>	<u>0.4615</u>	<u>0.4286</u>	<u>0.5</u>	<u>0.3529</u>	<u>0.5714</u>	<u>0.4</u>	<u>0.4</u>
23	boss	<u>0.8</u>	<u>0.2857</u>	<u>0.7368</u>	<u>0.2857</u>	<u>0.2</u>	<u>0.8</u>	<u>0.5714</u>	<u>0.2857</u>	<u>0.25</u>	<u>0.8</u>	<u>0.2857</u>	<u>0.2105</u>	<u>0.4615</u>	<u>0.3077</u>	<u>0.7273</u>	<u>0.4706</u>	<u>0.3668</u>	<u>0.4</u>	<u>0.7778</u>	<u>0.2667</u>
24	government	<u>0.2667</u>	<u>0.6667</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.5455</u>	<u>0.2667</u>	<u>0.6667</u>	<u>0.4</u>	<u>0.6667</u>	<u>0.2667</u>	<u>0.5455</u>	<u>0.6364</u>	<u>0.625</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.7059</u>	<u>0.75</u>	<u>0.625</u>	<u>0.9412</u>	<u>1</u>
25	official	<u>0.8</u>	<u>0.2857</u>	<u>0.5</u>	<u>0.2857</u>	<u>0.2</u>	<u>0.8</u>	<u>0.4545</u>	<u>0.2857</u>	<u>0.25</u>	<u>0.8571</u>	<u>0.2857</u>	<u>0.2105</u>	<u>0.4615</u>	<u>0.3077</u>	<u>0.7273</u>	<u>0.4444</u>	<u>0.5</u>	<u>0.4</u>	<u>0.7273</u>	<u>0.2667</u>
26	post	<u>0.7826</u>	<u>0.7059</u>	<u>0.6316</u>	<u>0.7059</u>	<u>0.64</u>	<u>0.7619</u>	<u>0.7778</u>	<u>0.4615</u>	<u>0.7778</u>	<u>0.8182</u>	<u>0.64</u>	<u>0.5714</u>	<u>0.625</u>	<u>0.75</u>	<u>0.7778</u>	<u>0.7273</u>	<u>0.7368</u>	<u>0.6667</u>	<u>0.6957</u>	<u>0.7059</u>
27	crime	<u>0.2353</u>	<u>0.6316</u>	<u>0.3158</u>	<u>0.6316</u>	<u>0.5217</u>	<u>0.2353</u>	<u>0.7368</u>	<u>0.3529</u>	<u>0.7368</u>	<u>0.2353</u>	<u>0.5217</u>	<u>0.5217</u>	<u>0.5556</u>	<u>0.6667</u>	<u>0.7368</u>	<u>0.4</u>	<u>0.7</u>	<u>0.5556</u>	<u>0.6</u>	<u>0.6316</u>
28	prosecution	<u>0.3077</u>	<u>0.6667</u>	<u>0.5333</u>	<u>0.6667</u>	<u>0.5455</u>	<u>0.3077</u>	<u>0.7778</u>	<u>0.4615</u>	<u>0.7778</u>	<u>0.3077</u>	<u>0.5455</u>	<u>0.5833</u>	<u>0.5882</u>	<u>0.7059</u>	<u>0.7778</u>	<u>0.7273</u>	<u>0.7368</u>	<u>0.5882</u>	<u>0.6316</u>	<u>0.7</u>
29	institution	<u>0.5263</u>	<u>0.7273</u>	<u>0.9524</u>	<u>0.6</u>	<u>0.75</u>	<u>0.5263</u>	<u>0.8</u>	<u>0.4286</u>	<u>0.8</u>	<u>0.6667</u>	<u>0.75</u>	<u>0.5</u>	<u>0.5263</u>	<u>0.6316</u>	<u>0.6</u>	<u>0.75</u>	<u>0.7368</u>	<u>0.7826</u>	<u>0.7778</u>	<u>0.8</u>
30	power	<u>0.7273</u>	<u>0.7692</u>	<u>0.6316</u>	<u>0.7692</u>	<u>0.4211</u>	<u>0.7273</u>	<u>0.7692</u>	<u>0.7692</u>	<u>0.5333</u>	<u>0.7273</u>	<u>0.8</u>	<u>0.4444</u>	<u>0.7143</u>	<u>0.5714</u>	<u>0.8235</u>	<u>0.6667</u>	<u>0.5263</u>	<u>0.8333</u>	<u>0.6667</u>	<u>0.75</u>

63	decade	<u>0.2857</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.2857</u>	<u>0.8</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.2857</u>	<u>0.4286</u>	<u>0.3158</u>	<u>0.4</u>	<u>0.4615</u>	<u>0.4286</u>	<u>0.5</u>	<u>0.3529</u>	<u>0.5714</u>	<u>0.4</u>	<u>0.4</u>	<u>0.6316</u>	<u>0.6667</u>
64	application	<u>0.5</u>	<u>0.7368</u>	<u>0.375</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.5</u>	<u>0.7778</u>	<u>0.4286</u>	<u>0.8235</u>	<u>0.5</u>	<u>0.6667</u>	<u>0.5714</u>	<u>0.625</u>	<u>0.9231</u>	<u>0.7778</u>	<u>0.5</u>	<u>0.7368</u>	<u>0.7</u>	<u>0.7778</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.6</u>
65	regime	<u>0.2667</u>	<u>0.4444</u>	<u>0.7059</u>	<u>0.4444</u>	<u>0.3636</u>	<u>0.2667</u>	<u>0.7778</u>	<u>0.4</u>	<u>0.4444</u>	<u>0.2667</u>	<u>0.4</u>	<u>0.381</u>	<u>0.4706</u>	<u>0.4706</u>	<u>0.4706</u>	<u>0.7059</u>	<u>0.5455</u>	<u>0.5263</u>	<u>0.9412</u>	<u>1</u>	<u>0.6667</u>	<u>0.7059</u>
66	delegation	<u>0.2857</u>	<u>0.6</u>	<u>0.75</u>	<u>0.6</u>	<u>0.5</u>	<u>0.2857</u>	<u>0.6</u>	<u>0.4286</u>	<u>0.6</u>	<u>0.2857</u>	<u>0.5</u>	<u>0.5833</u>	<u>0.5556</u>	<u>0.6316</u>	<u>0.6</u>	<u>0.75</u>	<u>0.5714</u>	<u>0.5556</u>	<u>0.75</u>	<u>0.8</u>	-	-
67	place	<u>0.4706</u>	<u>0.75</u>	<u>0.4706</u>	<u>0.7143</u>	<u>0.5455</u>	<u>0.4706</u>	<u>0.8</u>	<u>0.5714</u>	<u>0.7778</u>	<u>0.5</u>	<u>0.8571</u>	<u>0.5455</u>	<u>0.5882</u>	<u>0.7059</u>	<u>0.8182</u>	<u>0.75</u>	<u>0.7368</u>	<u>0.7692</u>	<u>0.8</u>	<u>0.6667</u>	<u>0.7778</u>	<u>0.7059</u>
68	politician	<u>0.8</u>	<u>0.2857</u>	<u>0.5</u>	<u>0.2857</u>	<u>0.2</u>	<u>0.8</u>	<u>0.4545</u>	<u>0.2857</u>	<u>0.25</u>	<u>0.8</u>	<u>0.2857</u>	<u>0.2105</u>	<u>0.4615</u>	<u>0.3077</u>	<u>0.7273</u>	<u>0.4444</u>	<u>0.5</u>	<u>0.4</u>	<u>0.7273</u>	<u>0.2667</u>	<u>0.6</u>	<u>0.3529</u>
69	scene	<u>0.5</u>	<u>0.7143</u>	<u>0.6</u>	<u>0.7143</u>	<u>0.4762</u>	<u>0.5</u>	<u>0.6667</u>	<u>0.5714</u>	<u>0.5882</u>	<u>0.6316</u>	<u>0.7143</u>	<u>0.5</u>	<u>0.75</u>	<u>0.625</u>	<u>0.7</u>	<u>0.75</u>	<u>0.6</u>	<u>0.7692</u>	<u>0.7368</u>	<u>0.625</u>	<u>0.6316</u>	<u>0.6364</u>
70	decision	<u>0.2857</u>	<u>0.7</u>	<u>0.375</u>	<u>0.6667</u>	<u>0.6364</u>	<u>0.2857</u>	<u>0.6667</u>	<u>0.5714</u>	<u>0.9474</u>	<u>0.2857</u>	<u>0.6364</u>	<u>0.5455</u>	<u>0.9412</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.5</u>	<u>0.6316</u>	<u>0.7059</u>	<u>0.7368</u>	<u>0.6667</u>	<u>0.5217</u>	<u>0.6364</u>
71	judge	<u>0.8</u>	<u>0.2857</u>	<u>0.5</u>	<u>0.2857</u>	<u>0.2</u>	<u>0.8</u>	<u>0.4545</u>	<u>0.2857</u>	<u>0.25</u>	<u>0.8182</u>	<u>0.2857</u>	<u>0.2105</u>	<u>0.4615</u>	<u>0.3077</u>	<u>0.7273</u>	<u>0.4444</u>	<u>0.5</u>	<u>0.4</u>	<u>0.7273</u>	<u>0.2667</u>	<u>0.7059</u>	<u>0.75</u>
72	evening	<u>0.2857</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.4286</u>	<u>0.3</u>	<u>0.2857</u>	<u>0.8</u>	<u>0.4286</u>	<u>0.375</u>	<u>0.2857</u>	<u>0.4286</u>	<u>0.3158</u>	<u>0.4</u>	<u>0.4615</u>	<u>0.4286</u>	<u>0.5</u>	<u>0.3529</u>	<u>0.5714</u>	<u>0.4</u>	<u>0.4</u>	<u>0.7619</u>	<u>0.2857</u>
73	dictator	<u>1</u>	<u>0.2857</u>	<u>0.5</u>	<u>0.2857</u>	<u>0.2</u>	<u>0.8</u>	<u>0.4545</u>	<u>0.2857</u>	<u>0.25</u>	<u>0.8</u>	<u>0.2857</u>	<u>0.2105</u>	<u>0.4615</u>	<u>0.3077</u>	<u>0.7273</u>	<u>0.4444</u>	<u>0.5</u>	<u>0.4</u>	<u>0.7273</u>	<u>0.2667</u>	<u>0.6316</u>	<u>0.6667</u>
74	iron	<u>0.5263</u>	<u>0.375</u>	<u>0.6316</u>	<u>0.375</u>	<u>0.2727</u>	<u>0.5263</u>	<u>0.6667</u>	<u>0.375</u>	<u>0.3333</u>	<u>0.6957</u>	<u>0.375</u>	<u>0.2857</u>	<u>0.4286</u>	<u>0.4</u>	<u>0.6316</u>	<u>0.5333</u>	<u>0.6316</u>	<u>0.4</u>	<u>0.6667</u>	<u>0.3529</u>	<u>0.8182</u>	<u>0.2857</u>
75	fist	<u>0.3529</u>	<u>0.2353</u>	<u>0.3</u>	<u>0.2353</u>	<u>0.1739</u>	<u>0.3529</u>	<u>0.2727</u>	<u>0.2353</u>	<u>0.2105</u>	<u>0.3529</u>	<u>0.2353</u>	<u>0.1818</u>	<u>0.375</u>	<u>0.25</u>	<u>0.3158</u>	<u>0.3333</u>	<u>0.3</u>	<u>0.3333</u>	<u>0.3158</u>	<u>0.2222</u>	<u>0.6957</u>	<u>0.25</u>
76	visitor	<u>0.8</u>	<u>0.2857</u>	<u>0.5</u>	<u>0.2857</u>	<u>0.2</u>	<u>0.8</u>	<u>0.4545</u>	<u>0.2857</u>	<u>0.25</u>	<u>0.8</u>	<u>0.2857</u>	<u>0.2105</u>	<u>0.4615</u>	<u>0.3077</u>	<u>0.7273</u>	<u>0.4444</u>	<u>0.5</u>	<u>0.4</u>	<u>0.7273</u>	<u>0.2667</u>	<u>0.7273</u>	<u>0.2667</u>
77	diplomat	<u>0.75</u>	<u>0.25</u>	<u>0.4545</u>	<u>0.25</u>	<u>0.1818</u>	<u>0.7273</u>	<u>0.4167</u>	<u>0.25</u>	<u>0.2222</u>	<u>0.8182</u>	<u>0.25</u>	<u>0.1905</u>	<u>0.4</u>	<u>0.2667</u>	<u>0.6667</u>	<u>0.4</u>	<u>0.4545</u>	<u>0.3529</u>	<u>0.6667</u>	<u>0.2353</u>	<u>0.5556</u>	<u>0.625</u>
78	policy	<u>0.2353</u>	<u>0.4211</u>	<u>0.3158</u>	<u>0.4211</u>	<u>0.3478</u>	<u>0.2353</u>	<u>0.7368</u>	<u>0.3529</u>	<u>0.4211</u>	<u>0.2353</u>	<u>0.3529</u>	<u>0.3636</u>	<u>0.4444</u>	<u>0.625</u>	<u>0.6667</u>	<u>0.4</u>	<u>0.5217</u>	<u>0.5</u>	<u>0.4</u>	<u>0.5714</u>	-	-
79	trial	<u>0.2667</u>	<u>0.6667</u>	<u>0.3529</u>	<u>0.6667</u>	<u>0.5455</u>	<u>0.2667</u>	<u>0.7778</u>	<u>0.4</u>	<u>0.7778</u>	<u>0.2667</u>	<u>0.5455</u>	<u>0.6087</u>	<u>0.7059</u>	<u>0.7059</u>	<u>0.7778</u>	<u>0.4615</u>	<u>0.7368</u>	<u>0.7059</u>	<u>0.6316</u>	<u>0.7368</u>	<u>0.4286</u>	<u>0.4286</u>
80	black	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
81	police	<u>0.2667</u>	<u>0.4</u>	<u>0.7059</u>	<u>0.4</u>	<u>0.2857</u>	<u>0.2667</u>	<u>0.4</u>	<u>0.4</u>	<u>0.3529</u>	<u>0.2667</u>	<u>0.4</u>	<u>0.3</u>	<u>0.375</u>	<u>0.4286</u>	<u>0.4</u>	<u>0.7059</u>	<u>0.3333</u>	<u>0.4286</u>	<u>0.7059</u>	<u>0.75</u>	<u>0.5217</u>	<u>0.5217</u>
82	guard	<u>0.7619</u>	<u>0.6316</u>	<u>0.6667</u>	<u>0.6316</u>	<u>0.5385</u>	<u>0.7619</u>	<u>0.7619</u>	<u>0.5333</u>	<u>0.8696</u>	<u>0.7619</u>	<u>0.625</u>	<u>0.5217</u>	<u>0.5556</u>	<u>0.6667</u>	<u>0.9091</u>	<u>0.6667</u>	<u>0.7</u>	<u>0.5714</u>	<u>0.8333</u>	<u>0.7059</u>	<u>0.6087</u>	<u>0.5455</u>
83	stuff	<u>0.5333</u>	<u>0.6154</u>	<u>0.5333</u>	<u>0.6154</u>	<u>0.381</u>	<u>0.5333</u>	<u>0.7143</u>	<u>0.7692</u>	<u>0.4706</u>	<u>0.5714</u>	<u>0.6154</u>	<u>0.4</u>	<u>0.5455</u>	<u>0.7692</u>	<u>0.8235</u>	<u>0.6154</u>	<u>0.5714</u>	<u>0.6667</u>	<u>0.5714</u>	<u>0.6316</u>	<u>0.6</u>	<u>0.6316</u>
84	idea	<u>0.2857</u>	<u>0.5</u>	<u>0.375</u>	<u>0.5</u>	<u>0.4</u>	<u>0.2857</u>	<u>0.875</u>	<u>0.4286</u>	<u>0.5</u>	<u>0.2857</u>	<u>0.4286</u>	<u>0.4211</u>	<u>0.5333</u>	<u>0.5714</u>	<u>0.5333</u>	<u>0.5</u>	<u>0.6</u>	<u>0.5882</u>	<u>0.4706</u>	<u>0.6667</u>	<u>0.8421</u>	<u>0.8889</u>
85	business	<u>0.3077</u>	<u>0.7059</u>	<u>0.7059</u>	<u>0.7059</u>	<u>0.5714</u>	<u>0.3077</u>	<u>0.8235</u>	<u>0.4615</u>	<u>0.8235</u>	<u>0.3077</u>	<u>0.5714</u>	<u>0.6957</u>	<u>0.625</u>	<u>0.75</u>	<u>0.8235</u>	<u>0.7273</u>	<u>0.7778</u>	<u>0.625</u>	<u>0.7059</u>	<u>0.75</u>	<u>0.4286</u>	<u>0.4286</u>
86	army	<u>0.2667</u>	<u>0.4</u>	<u>0.6667</u>	<u>0.4</u>	<u>0.2857</u>	<u>0.2667</u>	<u>0.4</u>	<u>0.4</u>	<u>0.3529</u>	<u>0.2667</u>	<u>0.4</u>	<u>0.3</u>	<u>0.375</u>	<u>0.4286</u>	<u>0.4</u>	<u>0.8</u>	<u>0.3333</u>	<u>0.4286</u>	<u>0.75</u>	<u>0.7059</u>	<u>0.7273</u>	<u>0.4706</u>
87	people	<u>0.3333</u>	<u>0.5</u>	<u>0.5714</u>	<u>0.5</u>	<u>0.3333</u>	<u>0.3333</u>	<u>0.5</u>	<u>0.5</u>	<u>0.4286</u>	<u>0.3333</u>	<u>0.5</u>	<u>0.3529</u>	<u>0.4615</u>	<u>0.5455</u>	<u>0.5</u>	<u>0.8</u>	<u>0.4</u>	<u>0.5455</u>	<u>0.6154</u>	<u>0.6154</u>	<u>0.6316</u>	<u>0.6667</u>
88	administration	<u>0.2857</u>	<u>0.6667</u>	<u>0.625</u>	<u>0.6667</u>	<u>0.5455</u>	<u>0.2857</u>	<u>0.7059</u>	<u>0.4286</u>	<u>0.6667</u>	<u>0.2857</u>	<u>0.5455</u>	<u>0.6364</u>	<u>0.625</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.7143</u>	<u>0.6316</u>	<u>0.625</u>	<u>0.6667</u>	<u>1</u>	<u>0.7059</u>	<u>0.75</u>
89	government	<u>0.2667</u>	<u>0.6667</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.5455</u>	<u>0.2667</u>	<u>0.6667</u>	<u>0.4</u>	<u>0.6667</u>	<u>0.2667</u>	<u>0.5455</u>	<u>0.6364</u>	<u>0.625</u>	<u>0.7059</u>	<u>0.6667</u>	<u>0.7059</u>	<u>0.75</u>	<u>0.625</u>	<u>0.9412</u>	<u>1</u>	<u>0.9412</u>	<u>1</u>
90	report	<u>0.2857</u>	<u>0.6667</u>	<u>0.375</u>	<u>0.6667</u>	<u>0.5455</u>	<u>0.2857</u>	<u>0.7143</u>	<u>0.4286</u>	<u>0.6667</u>	<u>0.2857</u>	<u>0.5455</u>	<u>0.5455</u>	<u>0.7059</u>	<u>0.8235</u>	<u>0.7778</u>	<u>0.5</u>	<u>0.6316</u>	<u>0.7059</u>	<u>0.6316</u>	<u>0.6667</u>	<u>0.7273</u>	<u>0.2667</u>
91	disappearance	<u>0.2857</u>	<u>0.7273</u>	<u>0.375</u>	<u>0.7059</u>	<u>0.8333</u>	<u>0.2857</u>	<u>0.7059</u>	<u>0.4286</u>	<u>0.8</u>	<u>0.2857</u>	<u>0.8333</u>	<u>0.5714</u>	<u>0.8</u>	<u>0.75</u>	<u>0.7059</u>	<u>0.5</u>	<u>0.6667</u>	<u>0.8696</u>	<u>0.6667</u>	<u>0.7059</u>	<u>0.8</u>	<u>0.2667</u>
92	passport	<u>0.2857</u>	<u>0.5714</u>	<u>0.375</u>	<u>0.5714</u>	<u>0.3</u>	<u>0.2857</u>	<u>0.6667</u>	<u>0.7143</u>	<u>0.375</u>	<u>0.2857</u>	<u>0.5714</u>	<u>0.3158</u>	<u>0.4</u>	<u>0.7143</u>	<u>0.625</u>	<u>0.5</u>	<u>0.3529</u>	<u>0.6154</u>	<u>0.4</u>	<u>0.4</u>	<u>0.5556</u>	<u>0.625</u>
93	family	<u>0.8</u>	<u>0.4615</u>	<u>0.7059</u>	<u>0.4615</u>	<u>0.3158</u>	<u>0.8</u>	<u>0.4615</u>	<u>0.4615</u>	<u>0.4</u>	<u>0.8</u>	<u>0.4615</u>	<u>0.3333</u>	<u>0.4615</u>	<u>0.5</u>	<u>0.7273</u>	<u>0.7273</u>	<u>0.5</u>	<u>0.5</u>	<u>0.7273</u>	<u>0.75</u>	<u>0.7059</u>	<u>0.375</u>
62	cannon	<u>0.4762</u>	<u>0.6957</u>	<u>0.5714</u>	<u>0.5714</u>	<u>0.64</u>	<u>0.4762</u>	<u>0.75</u>	<u>0.3158</u>	<u>0.8571</u>	<u>0.6364</u>	<u>0.64</u>	<u>0.48</u>	<u>0.5</u>	<u>0.6</u>	<u>0.5714</u>	<u>0.4211</u>	<u>0.5714</u>	<u>0.6667</u>	<u>0.6364</u>	<u>0.5714</u>	<u>0.6667</u>	<u>0.5714</u>

126	placard	0.3077	0.4615	0.4	0.4615	0.3158	0.3077	0.6154	0.4615	0.4	0.3077	0.4615	0.3333	0.4286	0.6667	0.5714	0.5455	0.375	0.5	0.4286	0.4286
127	bearing	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
128	condition	0.3077	0.8	0.4	0.7692	0.5455	0.3077	0.8889	0.6154	0.7778	0.3077	0.9231	0.5455	0.5882	0.7692	0.8	0.6667	0.8421	0.8333	0.6316	0.6667
129	son	0.7619	0.381	0.4762	0.381	0.32	0.7619	0.5714	0.3158	0.381	0.7619	0.32	0.3333	0.4286	0.4	0.6957	0.4211	0.48	0.4545	0.6957	0.5217
130	year	0.2857	0.4286	0.625	0.4286	0.3	0.2857	0.8	0.4286	0.375	0.2857	0.4286	0.3158	0.4	0.4615	0.4286	0.8571	0.3529	0.5714	0.8	0.6667
131	demonstration	0.3077	0.6316	0.4	0.6316	0.5217	0.3077	0.7	0.4615	0.7	0.3077	0.5217	0.6087	0.5882	0.6667	0.7	0.5455	0.6667	0.5882	0.6	0.7368
132	anonymity	0.25	0.625	0.3333	0.625	0.2727	0.25	0.5882	0.5	0.3333	0.25	0.625	0.2857	0.3529	0.4	0.5263	0.5556	0.3158	0.6667	0.3529	0.3529
133	reign	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
134	hospital	0.5	0.375	1	0.375	0.2727	0.5	0.5455	0.375	0.3333	0.6316	0.375	0.2857	0.375	0.4	0.5714	0.6667	0.7	0.4	0.8	0.7059
135	protest	0.2667	0.6667	0.3529	0.6667	0.5455	0.2667	0.6667	0.4	0.6667	0.2667	0.5455	0.6364	0.625	0.8235	0.7778	0.4615	0.6316	0.625	0.6316	0.7778

B) LCH measure

No	OC	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9	CC10	CC11	CC12	CC13	CC14	CC15	CC16	CC17	CC18	CC19	CC20
		dictator	confusion	hospital	arrest	murder	citizen	rule	legality	move	supporter	immunity	extradition	outcome	request	charge	community	surgery	death	court	government
1	defense	<u>1.4917</u>	<u>1.743</u>	<u>2.0794</u>	<u>1.743</u>	<u>1.291</u>	<u>1.4917</u>	<u>2.079</u>	<u>1.6094</u>	<u>2.079</u>	<u>1.8971</u>	<u>1.6094</u>	<u>1.4917</u>	<u>1.8971</u>	<u>2.0794</u>	<u>2.59</u>	<u>2.3026</u>	<u>2.0794</u>	<u>1.743</u>	<u>2.303</u>	<u>2.3026</u>
2	minister	<u>1.743</u>	<u>1.4917</u>	<u>1.1239</u>	<u>1.4917</u>	<u>1.1239</u>	<u>1.743</u>	<u>1.743</u>	<u>1.1239</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.1239</u>	<u>1.1239</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.291</u>	<u>1.6094</u>	<u>1.386</u>	<u>1.492</u>	<u>1.4917</u>
3	priest	<u>1.8971</u>	<u>1.8971</u>	<u>1.204</u>	<u>1.8971</u>	<u>0.9163</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.6094</u>	<u>1.204</u>	<u>1.8971</u>	<u>1.8971</u>	<u>0.9808</u>	<u>1.4917</u>	<u>1.4917</u>	<u>1.609</u>	<u>1.6094</u>	<u>1.204</u>	<u>2.079</u>	<u>1.609</u>	<u>1.291</u>
4	magistrate	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5	murder	<u>0.8557</u>	<u>1.4917</u>	<u>0.8557</u>	<u>1.291</u>	<u>3.6889</u>	<u>0.8557</u>	<u>1.291</u>	<u>0.9808</u>	<u>1.743</u>	<u>0.8557</u>	<u>1.743</u>	<u>0.9808</u>	<u>1.204</u>	<u>1.3863</u>	<u>1.291</u>	<u>1.1239</u>	<u>1.204</u>	<u>2.303</u>	<u>1.386</u>	<u>1.291</u>
6	day	<u>1.8971</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.0498</u>	<u>1.8971</u>	<u>2.303</u>	<u>1.6094</u>	<u>1.386</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.1239</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.609</u>	<u>1.8971</u>	<u>1.291</u>	<u>1.897</u>	<u>1.609</u>	<u>1.4917</u>
7	embassy	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8	police	<u>1.204</u>	<u>1.3863</u>	<u>1.8971</u>	<u>1.3863</u>	<u>0.9163</u>	<u>1.204</u>	<u>1.386</u>	<u>1.3863</u>	<u>1.204</u>	<u>1.204</u>	<u>1.3863</u>	<u>0.9808</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.386</u>	<u>1.8971</u>	<u>1.1239</u>	<u>1.492</u>	<u>1.897</u>	<u>2.0794</u>
9	source	<u>2.0794</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.4917</u>	<u>0.9808</u>	<u>2.0794</u>	<u>2.079</u>	<u>1.4917</u>	<u>1.291</u>	<u>2.0794</u>	<u>1.4917</u>	<u>1.0498</u>	<u>2.0794</u>	<u>1.743</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.743</u>	<u>1.897</u>	<u>1.4917</u>
10	insult	<u>1.291</u>	<u>1.6094</u>	<u>1.291</u>	<u>1.6094</u>	<u>1.204</u>	<u>1.291</u>	<u>2.079</u>	<u>1.4917</u>	<u>1.897</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.204</u>	<u>1.4917</u>	<u>2.3026</u>	<u>1.897</u>	<u>1.743</u>	<u>1.743</u>	<u>1.609</u>	<u>1.492</u>	<u>1.6094</u>
11	team	<u>1.291</u>	<u>1.4917</u>	<u>1.8971</u>	<u>1.4917</u>	<u>0.9808</u>	<u>1.291</u>	<u>1.492</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.0498</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.492</u>	<u>2.0794</u>	<u>1.204</u>	<u>1.609</u>	<u>1.897</u>	<u>2.0794</u>
12	claim	<u>1.204</u>	<u>1.743</u>	<u>1.204</u>	<u>1.743</u>	<u>1.291</u>	<u>1.204</u>	<u>2.079</u>	<u>1.3863</u>	<u>2.079</u>	<u>1.204</u>	<u>1.3863</u>	<u>1.291</u>	<u>1.6094</u>	<u>2.5903</u>	<u>2.59</u>	<u>1.6094</u>	<u>1.8971</u>	<u>1.609</u>	<u>1.609</u>	<u>1.743</u>
13	arrest	<u>1.291</u>	<u>2.0794</u>	<u>1.291</u>	<u>3.6889</u>	<u>1.291</u>	<u>1.291</u>	<u>1.897</u>	<u>1.743</u>	<u>1.743</u>	<u>1.291</u>	<u>2.0794</u>	<u>1.291</u>	<u>1.6094</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.743</u>	<u>1.6094</u>	<u>2.303</u>	<u>1.609</u>	<u>1.743</u>
14	warrant	<u>1.291</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.4917</u>	<u>0.9808</u>	<u>1.291</u>	<u>2.079</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.0498</u>	<u>1.3863</u>	<u>2.3026</u>	<u>1.897</u>	<u>1.743</u>	<u>1.204</u>	<u>1.609</u>	<u>1.386</u>	<u>1.3863</u>
15	attorney	<u>1.8971</u>	<u>1.204</u>	<u>1.204</u>	<u>1.204</u>	<u>0.7985</u>	<u>1.8971</u>	<u>1.204</u>	<u>1.204</u>	<u>1.05</u>	<u>1.8971</u>	<u>1.204</u>	<u>0.8557</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.609</u>	<u>1.3863</u>	<u>1.204</u>	<u>1.291</u>	<u>1.609</u>	<u>1.1239</u>
16	envoy	<u>1.743</u>	<u>1.204</u>	<u>1.1239</u>	<u>1.204</u>	<u>0.7985</u>	<u>1.743</u>	<u>1.386</u>	<u>1.204</u>	<u>1.05</u>	<u>1.8971</u>	<u>1.204</u>	<u>0.8557</u>	<u>1.3863</u>	<u>1.4917</u>	<u>1.492</u>	<u>1.3863</u>	<u>1.1239</u>	<u>1.291</u>	<u>1.492</u>	<u>1.1239</u>
17	extradition	<u>0.9163</u>	<u>1.291</u>	<u>0.9163</u>	<u>1.291</u>	<u>0.9808</u>	<u>0.9163</u>	<u>1.291</u>	<u>1.0498</u>	<u>1.291</u>	<u>0.9163</u>	<u>1.0498</u>	<u>3.6889</u>	<u>1.291</u>	<u>1.3863</u>	<u>1.291</u>	<u>1.204</u>	<u>1.204</u>	<u>1.291</u>	<u>1.204</u>	<u>1.4917</u>
18	request	<u>1.3863</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.3863</u>	<u>2.303</u>	<u>1.6094</u>	<u>1.897</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.743</u>	<u>3.6889</u>	<u>2.996</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.743</u>	<u>1.743</u>	<u>1.8971</u>
19	opinion	<u>1.3863</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.204</u>	<u>1.3863</u>	<u>2.303</u>	<u>1.6094</u>	<u>1.609</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.6094</u>	<u>2.5903</u>	<u>2.079</u>	<u>1.8971</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.492</u>	<u>1.8971</u>
20	term	<u>1.3863</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.0498</u>	<u>1.3863</u>	<u>2.303</u>	<u>1.6094</u>	<u>1.386</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.1239</u>	<u>1.4917</u>	<u>2.3026</u>	<u>2.303</u>	<u>1.8971</u>	<u>1.291</u>	<u>2.303</u>	<u>1.492</u>	<u>1.4917</u>
21	rally	<u>1.291</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.291</u>	<u>1.897</u>	<u>1.4917</u>	<u>1.897</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.6094</u>	<u>1.8971</u>	<u>2.0794</u>	<u>1.897</u>	<u>2.5903</u>	<u>1.743</u>	<u>1.897</u>	<u>2.303</u>	<u>2.3026</u>
22	week	<u>1.291</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.4917</u>	<u>0.9808</u>	<u>1.291</u>	<u>2.303</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.0498</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.492</u>	<u>1.743</u>	<u>1.204</u>	<u>1.743</u>	<u>1.386</u>	<u>1.3863</u>
23	boss	<u>2.0794</u>	<u>1.291</u>	<u>1.8971</u>	<u>1.291</u>	<u>0.8557</u>	<u>2.0794</u>	<u>1.386</u>	<u>1.291</u>	<u>1.124</u>	<u>2.0794</u>	<u>1.291</u>	<u>0.9163</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.4917</u>	<u>1.8971</u>	<u>1.386</u>	<u>2.079</u>	<u>1.204</u>
24	government	<u>1.204</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.291</u>	<u>1.204</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.204</u>	<u>1.3863</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.743</u>	<u>2.996</u>	<u>3.6889</u>
25	official	<u>2.0794</u>	<u>1.291</u>	<u>1.291</u>	<u>1.291</u>	<u>0.8557</u>	<u>2.0794</u>	<u>1.291</u>	<u>1.291</u>	<u>1.124</u>	<u>2.3026</u>	<u>1.291</u>	<u>0.9163</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.386</u>	<u>1.743</u>	<u>1.204</u>
26	post	<u>1.8971</u>	<u>1.8971</u>	<u>1.6094</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.8971</u>	<u>2.079</u>	<u>1.6094</u>	<u>2.079</u>	<u>2.0794</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.743</u>	<u>2.0794</u>	<u>2.079</u>	<u>2.3026</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.743</u>	<u>1.8971</u>
27	crime	<u>1.0498</u>	<u>1.6094</u>	<u>1.0498</u>	<u>1.6094</u>	<u>1.204</u>	<u>1.0498</u>	<u>1.897</u>	<u>1.204</u>	<u>1.897</u>	<u>1.0498</u>	<u>1.204</u>	<u>1.204</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.897</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.492</u>	<u>1.492</u>	<u>1.6094</u>
28	prosecution	<u>1.3863</u>	<u>1.743</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.291</u>	<u>1.3863</u>	<u>2.079</u>	<u>1.6094</u>	<u>2.079</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.291</u>	<u>1.6094</u>	<u>1.8971</u>	<u>2.079</u>	<u>2.3026</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.743</u>	<u>1.743</u>
29	institution	<u>1.3863</u>	<u>1.743</u>	<u>2.9957</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.3863</u>	<u>2.303</u>	<u>1.4917</u>	<u>2.079</u>	<u>1.743</u>	<u>1.743</u>	<u>1.1239</u>	<u>1.4917</u>	<u>1.6094</u>	<u>1.492</u>	<u>2.0794</u>	<u>1.8971</u>	<u>1.897</u>	<u>2.079</u>	<u>2.3026</u>
30	power	<u>2.0794</u>	<u>2.3026</u>	<u>1.6094</u>	<u>2.3026</u>	<u>1.204</u>	<u>2.0794</u>	<u>2.303</u>	<u>2.3026</u>	<u>1.609</u>	<u>2.0794</u>	<u>2.3026</u>	<u>1.291</u>	<u>2.0794</u>	<u>1.743</u>	<u>2.303</u>	<u>1.8971</u>	<u>1.4917</u>	<u>2.59</u>	<u>1.743</u>	<u>2.0794</u>
31	abuse	<u>1.291</u>	<u>1.743</u>	<u>1.291</u>	<u>1.743</u>	<u>1.291</u>	<u>1.291</u>	<u>2.079</u>	<u>1.4917</u>	<u>2.079</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.6094</u>	<u>2.3026</u>	<u>2.079</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.609</u>	<u>1.609</u>	<u>1.743</u>
32	constitution	<u>1.3863</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.8971</u>	<u>2.079</u>	<u>1.3863</u>	<u>2.0794</u>	<u>1.1239</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.609</u>	<u>1.8971</u>	<u>1.3863</u>	<u>2.079</u>	<u>1.609</u>	<u>1.4917</u>
33	statement	<u>1.3863</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.3863</u>	<u>2.303</u>	<u>1.6094</u>	<u>1.897</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.743</u>	<u>2.5903</u>	<u>2.59</u>	<u>1.8971</u>	<u>1.743</u>	<u>1.743</u>	<u>1.743</u>	<u>1.8971</u>
34	word	<u>1.291</u>	<u>1.743</u>	<u>1.291</u>	<u>1.743</u>	<u>1.291</u>	<u>1.291</u>	<u>2.079</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.6094</u>	<u>2.3026</u>	<u>2.303</u>	<u>1.8971</u>	<u>1.6094</u>	<u>1.609</u>	<u>1.609</u>	<u>1.743</u>
35	military	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
36	support	<u>1.3863</u>	<u>1.8971</u>	<u>1.8971</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.3863</u>	<u>2.303</u>	<u>1.3863</u>	<u>2.303</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.3863</u>	<u>1.743</u>	<u>2.0794</u>	<u>2.303</u>	<u>1.743</u>	<u>2.0794</u>	<u>1.743</u>	<u>2.079</u>	<u>1.8971</u>
37	portrait	<u>1.204</u>	<u>1.291</u>	<u>1.3863</u>	<u>1.291</u>	<u>0.8557</u>	<u>1.204</u>	<u>1.743</u>	<u>1.291</u>	<u>1.124</u>	<u>1.4917</u>	<u>1.291</u>	<u>0.9163</u>	<u>1.204</u>	<u>1.8971</u>	<u>1.897</u>	<u>1.4917</u>	<u>1.3863</u>	<u>1.386</u>	<u>1.492</u>	<u>1.204</u>
38	extradition	<u>0.9163</u>	<u>1.291</u>	<u>0.9163</u>	<u>1.291</u>	<u>0.9808</u>	<u>0.9163</u>	<u>1.291</u>	<u>1.0498</u>	<u>1.291</u>	<u>0.9163</u>	<u>1.0498</u>	<u>3.6889</u>	<u>1.291</u>	<u>1.3863</u>	<u>1.291</u>	<u>1.204</u>	<u>1.204</u>	<u>1.291</u>	<u>1.204</u>	<u>1.4917</u>
39	law	<u>1.3863</u>	<u>1.6094</u>	<u>1.8971</u>	<u>1.6094</u>	<u>1.1239</u>	<u>1.3863</u>	<u>2.996</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.1239</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.743</u>	<u>2.3026</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.897</u>	<u>2.0794</u>

40	protester	2.3026	1.3863	1.3863	1.3863	0.9163	2.3026	1.386	1.3863	1.204	2.3026	1.3863	0.9808	1.743	1.4917	1.897	1.6094	1.3863	1.492	1.897	1.291
41	arrest	1.291	2.0794	1.291	3.6889	1.743	1.291	1.897	1.743	1.291	1.743	1.291	0.9808	1.6094	1.8971	1.743	1.743	1.6094	1.492	1.609	1.743
42	opponent	2.3026	1.3863	1.3863	0.9163	2.3026	1.386	1.3863	1.204	2.3026	1.3863	0.9808	1.743	1.4917	1.897	1.6094	1.3863	1.492	2.079	1.291	
43	rightist	1.8971	1.204	1.204	0.7985	1.8971	1.204	1.204	1.05	1.8971	1.204	0.8557	1.4917	1.291	1.609	1.3863	1.204	1.291	1.609	1.1239	
44	politician	2.0794	1.291	1.291	0.8557	2.0794	1.291	1.291	1.124	2.0794	1.291	0.9163	1.6094	1.3863	1.743	1.4917	1.291	1.386	1.743	1.204	
45	time	1.4917	2.0794	1.4917	2.0794	1.204	1.4917	2.303	2.0794	1.609	1.4917	1.291	1.291	2.0794	1.8971	1.743	2.0794	1.4917	2.303	1.609	
46	amnesty	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
47	month	1.3863	1.6094	1.3863	1.6094	1.0498	1.3863	2.303	1.6094	1.386	1.3863	1.6094	1.1239	1.4917	1.743	1.609	1.8971	1.291	1.897	1.492	
48	father	2.0794	1.743	1.291	1.743	0.8557	2.0794	1.609	1.4917	1.124	2.0794	1.743	0.9163	1.6094	1.3863	1.743	1.4917	1.291	1.897	1.743	
49	immunity	1.291	2.0794	1.291	2.0794	1.743	1.291	2.303	1.743	1.291	1.743	1.291	1.3863	1.6094	1.609	1.743	1.204	2.303	1.386	1.3863	
50	caption	1.0498	1.6094	1.0498	1.6094	1.204	1.0498	1.609	1.204	1.609	1.0498	1.204	1.204	1.4917	2.0794	1.897	1.3863	1.4917	1.492	1.6094	
51	capital	1.3863	1.4917	1.6094	1.4917	0.9808	1.3863	1.492	1.4917	1.291	1.3863	1.4917	1.0498	1.4917	1.6094	2.079	1.8971	1.291	1.609	2.303	
52	publicity	1.3863	1.8971	1.3863	1.8971	1.0498	1.3863	2.303	2.3026	1.386	1.3863	1.8971	1.1239	1.4917	2.5903	2.079	1.8971	1.291	2.079	1.492	
53	patient	2.0794	1.291	1.291	0.8557	2.0794	1.291	1.291	1.124	2.0794	1.291	0.9163	1.6094	1.3863	1.743	1.743	1.291	1.386	1.743	1.3863	
54	arrest	1.291	2.0794	1.291	3.6889	1.291	1.291	1.897	1.743	1.743	1.291	2.0794	1.291	1.6094	1.8971	1.743	1.743	1.6094	2.303	1.609	
55	order	1.3863	2.3026	1.8971	1.291	1.3863	2.996	1.8971	2.079	1.3863	2.5903	1.291	1.291	1.6094	2.9957	2.59	2.3026	1.8971	2.59	1.897	
56	advice	1.291	1.4917	1.291	1.4917	0.9808	1.291	2.079	1.4917	1.291	1.291	1.4917	1.0498	1.3863	2.3026	1.897	1.743	1.204	1.609	1.386	
57	government	1.204	1.743	1.8971	1.743	1.291	1.204	1.743	1.3863	1.743	1.204	1.3863	1.4917	1.743	1.8971	1.743	1.8971	1.743	2.3026	3.6889	
58	lawmaker	2.0794	1.291	1.291	1.291	0.8557	2.0794	1.291	1.291	1.124	2.0794	1.291	0.9163	1.6094	1.3863	1.743	1.4917	1.291	1.386	1.743	
59	bed	1.6094	1.291	1.8971	1.291	0.8557	1.6094	1.609	1.291	1.124	2.0794	1.291	0.9163	1.6094	1.3863	1.743	1.743	1.8971	1.386	2.079	
60	result	1.6094	1.6094	1.291	1.6094	1.204	1.6094	2.079	1.4917	1.609	1.6094	1.4917	1.291	3.6889	2.3026	2.303	1.743	1.4917	2.079	1.492	
61	water	1.743	1.4917	1.743	1.4917	0.9808	1.743	1.492	1.4917	1.291	1.8971	1.4917	1.0498	1.8971	1.6094	1.897	1.743	1.743	1.609	1.897	
62	cannon	1.4917	1.6094	1.3863	1.3863	1.3863	1.4917	1.743	1.291	2.303	1.4917	1.3863	1.0498	1.6094	1.4917	1.386	1.4917	1.3863	1.492	1.492	
63	decade	1.291	1.4917	1.291	1.4917	0.9808	1.291	2.303	1.4917	1.291	1.291	1.4917	1.0498	1.3863	1.6094	1.492	1.743	1.204	1.386	1.3863	
64	application	1.4917	1.8971	1.291	1.8971	1.6094	1.4917	2.079	1.4917	2.303	1.4917	1.6094	1.3863	1.743	2.9957	2.079	1.743	1.8971	1.743	2.079	
65	regime	1.204	1.3863	1.8971	1.3863	0.9808	1.204	2.079	1.3863	1.291	1.204	1.3863	1.0498	1.3863	1.4917	1.386	1.8971	1.291	1.492	2.996	
66	delegation	1.291	1.4917	2.0794	1.4917	1.1239	1.291	1.492	1.4917	1.492	1.291	1.4917	1.291	1.4917	1.6094	1.492	2.0794	1.3863	1.609	2.079	
67	place	1.4917	2.0794	1.3863	2.0794	1.291	1.4917	2.303	1.743	2.079	1.4917	2.5903	1.291	1.743	1.8971	2.079	2.0794	1.8971	2.303	2.079	
68	politician	2.0794	1.291	1.291	1.291	0.8557	2.0794	1.291	1.291	1.124	2.0794	1.291	0.9163	1.6094	1.3863	1.743	1.4917	1.291	1.386	1.743	
69	scene	1.3863	2.0794	1.4917	2.0794	1.204	1.3863	1.897	1.743	1.609	1.6094	2.0794	1.291	2.0794	1.743	1.743	2.0794	1.4917	2.303	1.897	
70	decision	1.291	1.743	1.291	1.743	1.4917	1.291	1.743	1.743	2.996	1.291	1.743	1.291	2.9957	1.8971	1.743	1.743	1.6094	1.897	1.897	
71	judge	2.0794	1.291	1.291	1.291	0.8557	2.0794	1.291	1.291	1.124	2.0794	1.291	0.9163	1.6094	1.3863	1.743	1.4917	1.291	1.386	1.743	
72	evening	1.291	1.4917	1.291	1.4917	0.9808	1.291	2.303	1.4917	1.291	1.291	1.4917	1.0498	1.3863	1.6094	1.492	1.743	1.204	1.743	1.386	
73	dictator	3.6889	1.291	1.291	1.291	0.8557	2.0794	1.291	1.291	1.124	2.0794	1.291	0.9163	1.6094	1.3863	1.743	1.4917	1.291	1.386	1.743	
74	iron	1.3863	1.291	1.6094	1.291	0.8557	1.3863	1.609	1.291	1.124	1.743	1.291	0.9163	1.4917	1.3863	1.609	1.6094	1.6094	1.386	1.743	
75	list	1.204	1.0498	0.9808	1.0498	0.6931	1.204	1.05	1.0498	0.916	1.204	1.0498	0.7444	1.291	1.1239	1.05	1.204	0.9808	1.124	1.05	
76	visitor	2.0794	1.291	1.291	1.291	0.8557	2.0794	1.291	1.291	1.124	2.0794	1.291	0.9163	1.6094	1.3863	1.743	1.4917	1.291	1.386	1.743	
77	diplomat	1.743	1.1239	1.1239	1.1239	0.7444	1.743	1.124	1.1239	0.981	2.0794	1.1239	0.7985	1.3863	1.204	1.492	1.291	1.1239	1.204	1.492	
78	policy	1.0498	1.204	1.0498	1.204	0.9163	1.0498	1.897	1.204	1.204	1.0498	1.204	0.9808	1.291	1.743	1.743	1.3863	1.204	1.291	1.124	
79	trial	1.204	1.743	1.204	1.743	1.291	1.204	2.079	1.3863	2.079	1.204	1.3863	1.3863	1.8971	1.8971	2.079	1.6094	1.8971	1.897	1.8971	
80	black	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
81	police	1.204	1.3863	1.8971	1.3863	0.9163	1.204	1.386	1.3863	1.204	1.204	1.3863	0.9808	1.291	1.4917	1.386	1.8971	1.1239	1.492	1.897	
82	guard	1.8971	1.6094	1.743	1.6094	1.204	1.8971	1.897	1.6094	2.303	1.8971	1.743	1.204	1.4917	1.743	2.59	1.743	1.743	2.079	1.8971	
83	stuff	1.743	1.8971	1.6094	1.8971	1.0498	1.743	2.079	2.3026	1.386	1.743	1.8971	1.1239	1.8971	2.3026	2.303	1.6094	2.079	1.743	1.6094	
84	idea	1.291	1.4917	1.291	1.4917	1.1239	1.291	2.59	1.4917	1.492	1.291	1.4917	1.204	1.6094	1.743	1.609	1.743	1.4917	1.609	1.386	
85	business	1.3863	1.8971	1.8971	1.8971	1.3863	1.3863	2.303	1.6094	2.303	1.3863	1.6094	1.6094	1.743	2.0794	2.303	2.3026	2.0794	1.743	1.897	
86	army	1.204	1.3863	1.743	1.3863	0.9163	1.204	1.386	1.3863	1.204	1.204	1.3863	0.9808	1.291	1.4917	1.386	2.3026	1.1239	1.492	2.079	
87	people	1.4917	1.743	1.743	1.1239	1.1239	1.4917	1.743	1.743	1.492	1.4917	1.743	1.204	1.6094	1.8971	1.743	2.5903	1.3863	1.897	1.8971	
88	administration	1.291	1.743	1.743	1.743	1.291	1.291	1.897	1.4917	1.743	1.291	1.4917	1.4917	1.743	1.8971	1.743	2.0794	1.6094	1.743	3.6889	
89	government	1.204	1.743	1.8971	1.743	1.291	1.204	1.743	1.3863	1.743	1.204	1.3863	1.4917	1.743	1.8971	1.743	1.8971	1.743	2.996	3.6889	
90	report	1.291	1.743	1.291	1.743	1.291	1.291	2.079	1.4917	1.743	1.291	1.4917	1.291	1.8971	2.3026	2.079	1.743	1.6094	1.897	1.609	
91	disappearance	1.291	1.8971	1.291	1.8971	2.0794	1.291	1.897	1.4917	2.079	1.291	2.0794	1.3863	2.3026	2.0794	1.897	1.743	1.743	2.303	1.743	
92	passport	1.291	1.743	1.291	1.743	0.9808	1.291	1.897	2.0794	1.291	1.291	1.743	1.0498	1.3863	2.0794	1.743	1.743	1.204	1.897	1.386	
93	family	2.0794	1.6094	1.8971	1.6094	1.0498	2.0794	1.609	1.6094	1.386	2.0794	1.6094	1.1239	1.6094	1.743	1.743	2.3026	1.291	1.743	1.897	
94	total	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
95	police	1.204	1.3863	1.8971	1.3863	0.9163	1.204	1.386	1.3863	1.204	1.204	1.3863	0.9808	1.291	1.4917	1.386	1.8971	1.1239	1.492	1.897	
96	gas	1.6094	1.8971	1.291	1.8971	0.9163	1.6094	2.079	1.6094	1.204	1.6094	2.3026	0.9808	1.8971	1.4917	1.743	1.6094	1.291	2.079	1.386	
97	allegation	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
98	news	1.291	1.6094	1.291	1.6094	1.1239	1.291	2.079	1.8971	1.492											

102	abuse	<u>1.291</u>	<u>1.743</u>	<u>1.291</u>	<u>1.743</u>	<u>1.291</u>	<u>2.079</u>	<u>1.4917</u>	<u>2.079</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.6094</u>	<u>2.3026</u>	<u>2.079</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.609</u>	<u>1.609</u>	<u>1.743</u>
103	country	<u>1.4917</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.6094</u>	<u>1.0498</u>	<u>1.609</u>	<u>1.6094</u>	<u>1.386</u>	<u>1.4917</u>	<u>1.6094</u>	<u>1.1239</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.609</u>	<u>2.3026</u>	<u>1.3863</u>	<u>1.743</u>	<u>2.079</u>	<u>1.8971</u>
104	demonstrator	<u>1.8971</u>	<u>1.204</u>	<u>1.204</u>	<u>1.204</u>	<u>0.7985</u>	<u>1.8971</u>	<u>1.204</u>	<u>1.05</u>	<u>2.0794</u>	<u>1.204</u>	<u>0.8557</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.609</u>	<u>1.3863</u>	<u>1.204</u>	<u>1.291</u>	<u>1.609</u>	<u>1.1239</u>
105	operation	<u>1.743</u>	<u>2.0794</u>	<u>1.3863</u>	<u>2.0794</u>	<u>1.3863</u>	<u>1.743</u>	<u>2.303</u>	<u>1.743</u>	<u>2.303</u>	<u>2.0794</u>	<u>1.3863</u>	<u>2.3026</u>	<u>2.0794</u>	<u>2.59</u>	<u>1.8971</u>	<u>3.6889</u>	<u>2.303</u>	<u>1.743</u>	<u>1.8971</u>
106	official	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
107	event	<u>1.6094</u>	<u>2.0794</u>	<u>1.4917</u>	<u>2.0794</u>	<u>1.4917</u>	<u>1.6094</u>	<u>2.079</u>	<u>1.743</u>	<u>2.079</u>	<u>1.6094</u>	<u>1.6094</u>	<u>3.6889</u>	<u>2.3026</u>	<u>2.303</u>	<u>2.0794</u>	<u>1.8971</u>	<u>2.303</u>	<u>1.897</u>	<u>2.3026</u>
108	dissident	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
109	television	<u>1.204</u>	<u>0.9808</u>	<u>1.3863</u>	<u>0.9808</u>	<u>0.6444</u>	<u>1.204</u>	<u>1.386</u>	<u>0.9808</u>	<u>0.856</u>	<u>1.4917</u>	<u>0.9808</u>	<u>0.6931</u>	<u>1.204</u>	<u>1.0498</u>	<u>1.291</u>	<u>1.204</u>	<u>1.3863</u>	<u>1.05</u>	<u>1.492</u>
110	interview	<u>1.1239</u>	<u>1.4917</u>	<u>1.1239</u>	<u>1.4917</u>	<u>1.1239</u>	<u>1.1239</u>	<u>1.492</u>	<u>1.291</u>	<u>1.492</u>	<u>1.1239</u>	<u>1.291</u>	<u>1.1239</u>	<u>1.3863</u>	<u>2.079</u>	<u>1.4917</u>	<u>1.3863</u>	<u>1.386</u>	<u>1.386</u>	<u>1.4917</u>
111	division	<u>1.3863</u>	<u>2.0794</u>	<u>1.743</u>	<u>1.6094</u>	<u>1.4917</u>	<u>1.3863</u>	<u>2.59</u>	<u>1.6094</u>	<u>2.079</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.204</u>	<u>1.4917</u>	<u>2.0794</u>	<u>1.897</u>	<u>2.3026</u>	<u>1.743</u>	<u>1.743</u>	<u>1.8971</u>
112	riot	<u>1.291</u>	<u>2.5903</u>	<u>1.291</u>	<u>2.0794</u>	<u>1.3863</u>	<u>1.291</u>	<u>1.897</u>	<u>1.743</u>	<u>1.897</u>	<u>1.291</u>	<u>2.0794</u>	<u>1.204</u>	<u>1.4917</u>	<u>2.0794</u>	<u>1.743</u>	<u>1.4917</u>	<u>2.303</u>	<u>1.743</u>	<u>1.6094</u>
113	police	<u>1.204</u>	<u>1.3863</u>	<u>1.8971</u>	<u>1.3863</u>	<u>0.9163</u>	<u>1.204</u>	<u>1.386</u>	<u>1.3863</u>	<u>1.204</u>	<u>1.204</u>	<u>1.3863</u>	<u>0.9808</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.386</u>	<u>1.8971</u>	<u>1.1239</u>	<u>1.492</u>	<u>1.897</u>
114	police	<u>1.204</u>	<u>1.3863</u>	<u>1.8971</u>	<u>1.3863</u>	<u>0.9163</u>	<u>1.204</u>	<u>1.386</u>	<u>1.3863</u>	<u>1.204</u>	<u>1.204</u>	<u>1.3863</u>	<u>0.9808</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.386</u>	<u>1.8971</u>	<u>1.1239</u>	<u>1.492</u>	<u>1.897</u>
115	line	<u>1.6094</u>	<u>1.8971</u>	<u>1.8971</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.6094</u>	<u>2.303</u>	<u>1.8971</u>	<u>2.303</u>	<u>2.0794</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.743</u>	<u>2.0794</u>	<u>2.303</u>	<u>2.0794</u>	<u>2.079</u>	<u>2.079</u>	<u>1.8971</u>
116	spokesman	<u>1.8971</u>	<u>1.204</u>	<u>1.204</u>	<u>1.204</u>	<u>0.7985</u>	<u>1.8971</u>	<u>1.204</u>	<u>1.204</u>	<u>1.05</u>	<u>2.3026</u>	<u>1.204</u>	<u>0.8557</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.609</u>	<u>1.3863</u>	<u>1.204</u>	<u>1.291</u>	<u>1.609</u>
117	response	<u>1.4917</u>	<u>1.8971</u>	<u>1.291</u>	<u>1.8971</u>	<u>1.3863</u>	<u>1.4917</u>	<u>2.079</u>	<u>1.743</u>	<u>1.897</u>	<u>1.897</u>	<u>1.8971</u>	<u>1.3863</u>	<u>2.9957</u>	<u>2.5903</u>	<u>2.303</u>	<u>1.743</u>	<u>1.743</u>	<u>1.897</u>	<u>1.8971</u>
118	death	<u>1.3863</u>	<u>2.3026</u>	<u>1.3863</u>	<u>2.3026</u>	<u>2.3026</u>	<u>1.3863</u>	<u>2.079</u>	<u>1.8971</u>	<u>1.897</u>	<u>1.3863</u>	<u>2.3026</u>	<u>1.291</u>	<u>2.0794</u>	<u>1.743</u>	<u>1.897</u>	<u>1.4917</u>	<u>3.689</u>	<u>1.492</u>	<u>1.743</u>
119	pressure	<u>1.3863</u>	<u>1.743</u>	<u>1.1239</u>	<u>1.743</u>	<u>1.291</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.743</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.8971</u>	<u>1.291</u>	<u>2.0794</u>	<u>1.8971</u>	<u>2.303</u>	<u>1.4917</u>	<u>1.6094</u>	<u>2.079</u>	<u>1.743</u>
120	release	<u>1.6094</u>	<u>1.8971</u>	<u>1.6094</u>	<u>1.8971</u>	<u>2.0794</u>	<u>1.6094</u>	<u>2.303</u>	<u>1.3863</u>	<u>2.59</u>	<u>1.743</u>	<u>2.9957</u>	<u>1.3863</u>	<u>2.0794</u>	<u>2.0794</u>	<u>2.303</u>	<u>1.6094</u>	<u>2.996</u>	<u>1.897</u>	<u>1.8971</u>
121	injury	<u>1.1239</u>	<u>1.743</u>	<u>1.1239</u>	<u>1.743</u>	<u>1.291</u>	<u>1.1239</u>	<u>2.079</u>	<u>1.3863</u>	<u>2.079</u>	<u>1.1239</u>	<u>1.8971</u>	<u>1.291</u>	<u>1.6094</u>	<u>1.8971</u>	<u>2.079</u>	<u>1.4917</u>	<u>1.897</u>	<u>1.609</u>	<u>1.743</u>
122	violation	<u>1.1239</u>	<u>1.743</u>	<u>1.1239</u>	<u>1.743</u>	<u>1.291</u>	<u>1.1239</u>	<u>2.079</u>	<u>1.291</u>	<u>2.079</u>	<u>1.1239</u>	<u>1.291</u>	<u>1.6094</u>	<u>1.8971</u>	<u>2.079</u>	<u>1.4917</u>	<u>1.8971</u>	<u>1.609</u>	<u>1.609</u>	<u>1.743</u>
123	attitude	<u>1.3863</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.204</u>	<u>1.3863</u>	<u>2.303</u>	<u>1.743</u>	<u>1.609</u>	<u>1.3863</u>	<u>1.8971</u>	<u>1.291</u>	<u>1.743</u>	<u>1.743</u>	<u>1.743</u>	<u>1.4917</u>	<u>1.897</u>	<u>1.492</u>	<u>1.743</u>
124	lobby	<u>1.3863</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.6094</u>	<u>1.0498</u>	<u>1.3863</u>	<u>1.609</u>	<u>1.6094</u>	<u>1.386</u>	<u>1.6094</u>	<u>1.6094</u>	<u>1.1239</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.609</u>	<u>2.5903</u>	<u>1.743</u>	<u>2.59</u>	<u>1.8971</u>
125	group	<u>1.6094</u>	<u>1.8971</u>	<u>1.8971</u>	<u>1.8971</u>	<u>1.204</u>	<u>1.6094</u>	<u>1.897</u>	<u>1.8971</u>	<u>1.609</u>	<u>1.6094</u>	<u>1.8971</u>	<u>1.291</u>	<u>1.743</u>	<u>2.0794</u>	<u>1.897</u>	<u>2.9957</u>	<u>1.4917</u>	<u>2.079</u>	<u>2.0794</u>
126	placard	<u>1.3863</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.0498</u>	<u>1.3863</u>	<u>1.897</u>	<u>1.6094</u>	<u>1.386</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.4917</u>	<u>2.0794</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.291</u>	<u>1.743</u>	<u>1.492</u>	<u>1.4917</u>
127	bearing	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
128	condition	<u>1.3863</u>	<u>2.3026</u>	<u>1.3863</u>	<u>2.3026</u>	<u>1.291</u>	<u>1.3863</u>	<u>2.59</u>	<u>1.8971</u>	<u>2.079</u>	<u>1.3863</u>	<u>2.9957</u>	<u>1.291</u>	<u>1.6094</u>	<u>2.3026</u>	<u>2.303</u>	<u>1.8971</u>	<u>2.3026</u>	<u>2.59</u>	<u>1.609</u>
129	son	<u>1.8971</u>	<u>1.204</u>	<u>1.204</u>	<u>1.204</u>	<u>0.7985</u>	<u>1.8971</u>	<u>1.386</u>	<u>1.204</u>	<u>1.05</u>	<u>1.8971</u>	<u>1.204</u>	<u>0.8557</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.609</u>	<u>1.3863</u>	<u>1.204</u>	<u>1.291</u>	<u>1.609</u>
130	year	<u>1.291</u>	<u>1.4917</u>	<u>1.743</u>	<u>1.4917</u>	<u>0.9808</u>	<u>1.291</u>	<u>2.303</u>	<u>1.4917</u>	<u>1.291</u>	<u>1.291</u>	<u>1.4917</u>	<u>1.0498</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.492</u>	<u>2.5903</u>	<u>1.204</u>	<u>1.743</u>	<u>1.8971</u>
131	demonstration	<u>1.3863</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.204</u>	<u>1.3863</u>	<u>1.897</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.6094</u>	<u>1.3863</u>	<u>1.6094</u>	<u>2.0794</u>	<u>1.743</u>	<u>1.8971</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.8971</u>
132	anonymity	<u>1.1239</u>	<u>1.743</u>	<u>1.1239</u>	<u>1.743</u>	<u>0.8557</u>	<u>1.1239</u>	<u>1.609</u>	<u>1.4917</u>	<u>1.124</u>	<u>1.1239</u>	<u>1.743</u>	<u>0.9163</u>	<u>1.204</u>	<u>1.3863</u>	<u>1.386</u>	<u>1.4917</u>	<u>1.0498</u>	<u>1.897</u>	<u>1.204</u>
133	reign	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
134	hospital	<u>1.291</u>	<u>1.291</u>	<u>3.6889</u>	<u>1.291</u>	<u>0.8557</u>	<u>1.291</u>	<u>1.291</u>	<u>1.291</u>	<u>1.124</u>	<u>1.6094</u>	<u>1.291</u>	<u>0.9163</u>	<u>1.291</u>	<u>1.3863</u>	<u>1.386</u>	<u>1.743</u>	<u>1.386</u>	<u>2.079</u>	<u>1.8971</u>
135	protest	<u>1.204</u>	<u>1.743</u>	<u>1.204</u>	<u>1.743</u>	<u>1.291</u>	<u>1.204</u>	<u>1.743</u>	<u>1.3863</u>	<u>1.743</u>	<u>1.204</u>	<u>1.3863</u>	<u>1.4917</u>	<u>1.743</u>	<u>2.3026</u>	<u>2.079</u>	<u>1.6094</u>	<u>1.743</u>	<u>1.609</u>	<u>2.0794</u>

C) Resnik measure

No	OC	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9	CC10	CC11	CC12	CC13	CC14	CC15	CC16	CC17	CC18	CC19	CC20
		dictator	confusion	hospital	arrest	murder	citizen	rule	legality	move	supporter	immunity	extradition	outcome	request	charge	community	surgery	death	court	government
1	defense	<u>1.3696</u>	<u>2.6044</u>	<u>3.9425</u>	<u>2.6044</u>	<u>2.6044</u>	<u>1.3696</u>	<u>4.038</u>	<u>0.7794</u>	<u>3.3826</u>	<u>2.4934</u>	<u>2.6044</u>	<u>4.5251</u>	<u>4.093</u>	<u>5.4967</u>	<u>2.8145</u>	<u>3.8937</u>	<u>3.9425</u>	<u>4.093</u>	<u>3.9425</u>	<u>4.5251</u>
2	minister	<u>1.9033</u>	<u>2.6044</u>	<u>1.3696</u>	<u>2.6044</u>	<u>2.6044</u>	<u>1.9033</u>	<u>3.383</u>	<u>0.7794</u>	<u>3.3826</u>	<u>4.4837</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>2.6044</u>	<u>3.3826</u>	<u>1.1692</u>	<u>3.3826</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>
3	priest	<u>1.9033</u>	<u>3.1688</u>	<u>1.3696</u>	<u>3.1688</u>	<u>0.7794</u>	<u>1.9033</u>	<u>3.169</u>	<u>2.3982</u>	<u>0.7794</u>	<u>1.9033</u>	<u>3.1688</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>3.1688</u>	<u>3.1688</u>	<u>1.3696</u>	<u>3.1688</u>	<u>1.9033</u>	<u>0.7794</u>
4	magistrate	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5	murder	<u>0</u>	<u>4.5949</u>	<u>0.7794</u>	<u>2.6044</u>	<u>7.8339</u>	<u>0</u>	<u>2.604</u>	<u>0.7794</u>	<u>4.5949</u>	<u>0</u>	<u>6.883</u>	<u>2.6044</u>	<u>2.2541</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>7.4617</u>	<u>4.1005</u>	<u>2.6044</u>
6	day	<u>5.9193</u>	<u>3.1688</u>	<u>1.3696</u>	<u>3.1688</u>	<u>0.7794</u>	<u>1.9033</u>	<u>3.762</u>	<u>2.3982</u>	<u>0.7794</u>	<u>1.9033</u>	<u>3.1688</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>3.1688</u>	<u>3.1688</u>	<u>1.3696</u>	<u>3.1688</u>	<u>1.9033</u>	<u>0.7794</u>
7	embassy	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8	police	<u>0</u>	<u>0.7794</u>	<u>3.8937</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>0.779</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>3.8937</u>	<u>0.7794</u>	<u>0.7794</u>	<u>3.8937</u>	<u>3.8937</u>
9	source	<u>5.9193</u>	<u>1.7798</u>	<u>2.4934</u>	<u>1.7798</u>	<u>1.7798</u>	<u>1.9033</u>	<u>4.058</u>	<u>0.7794</u>	<u>1.7798</u>	<u>2.4934</u>	<u>1.7798</u>	<u>1.7798</u>	<u>4.093</u>	<u>3.0718</u>	<u>4.093</u>	<u>3.0088</u>	<u>3.3927</u>	<u>4.093</u>	<u>3.0088</u>	<u>3.3927</u>
10	insult	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>4.038</u>	<u>0.7794</u>	<u>3.3826</u>	<u>0</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>4.0382</u>	<u>4.0382</u>	<u>0.7794</u>	<u>3.3826</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>
11	team	<u>0</u>	<u>0.7794</u>	<u>3.8937</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>0.779</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>3.8937</u>	<u>0.7794</u>	<u>0.7794</u>	<u>3.8937</u>	<u>3.8937</u>
12	claim	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>4.555</u>	<u>0.7794</u>	<u>3.3826</u>	<u>0</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>7.584</u>	<u>7.5463</u>	<u>0.7794</u>	<u>3.3927</u>	<u>2.7753</u>	<u>2.6044</u>	<u>3.3927</u>
13	arrest	<u>0</u>	<u>3.1688</u>	<u>0.7794</u>	<u>10.667</u>	<u>2.6044</u>	<u>0</u>	<u>3.169</u>	<u>2.3982</u>	<u>2.6044</u>	<u>0</u>	<u>3.1688</u>	<u>2.6044</u>	<u>2.2541</u>	<u>2.6044</u>	<u>3.1688</u>	<u>3.1688</u>	<u>2.6044</u>	<u>3.1688</u>	<u>2.6044</u>	<u>2.6044</u>
14	warrant	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>4.038</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>4.0382</u>	<u>5.4027</u>	<u>3.1379</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>
15	attorney	<u>1.9033</u>	<u>0</u>	<u>1.3696</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>1.37</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>0</u>	<u>0</u>	<u>0.6144</u>	<u>0</u>	<u>1.9033</u>	<u>1.1692</u>	<u>1.3696</u>	<u>0.6144</u>	<u>1.9033</u>	<u>0</u>
16	envoy	<u>5.9193</u>	<u>0.7794</u>	<u>1.3696</u>	<u>0.7794</u>	<u>0.7794</u>	<u>1.9033</u>	<u>3.072</u>	<u>0.7794</u>	<u>0.7794</u>	<u>4.4837</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>3.0718</u>	<u>3.0718</u>	<u>1.1692</u>	<u>1.3696</u>	<u>0.7794</u>	<u>1.9033</u>	<u>0.7794</u>
17	extradition	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>2.604</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>0</u>	<u>2.2541</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>	<u>4.5251</u>
18	request	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>4.038</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>7.584</u>	<u>6.883</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>
19	opinion	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>4.058</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>4.5251</u>	<u>2.2541</u>	<u>4.0382</u>	<u>4.0382</u>	<u>0.7794</u>	<u>3.3927</u>	<u>2.7753</u>	<u>2.6044</u>	<u>4.5251</u>
20	term	<u>1.3696</u>	<u>2.3982</u>	<u>2.8722</u>	<u>2.3982</u>	<u>1.7798</u>	<u>1.3696</u>	<u>4.555</u>	<u>2.3982</u>	<u>1.7798</u>	<u>2.4934</u>	<u>2.3982</u>	<u>1.7798</u>	<u>1.7798</u>	<u>4.0382</u>	<u>4.9623</u>	<u>3.1379</u>	<u>3.3927</u>	<u>6.131</u>	<u>2.8722</u>	<u>3.3927</u>
21	rally	<u>0.6144</u>	<u>4.1005</u>	<u>3.5267</u>	<u>2.6044</u>	<u>4.1005</u>	<u>0.6144</u>	<u>2.604</u>	<u>0.7794</u>	<u>4.1005</u>	<u>0.6144</u>	<u>4.1005</u>	<u>4.5251</u>	<u>4.093</u>	<u>2.6044</u>	<u>4.093</u>	<u>5.4468</u>	<u>2.6044</u>	<u>4.1005</u>	<u>5.4468</u>	<u>4.5251</u>
22	week	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>3.762</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>2.9496</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>
23	boss	<u>1.9033</u>	<u>0</u>	<u>3.9425</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>2.493</u>	<u>0</u>	<u>0</u>	<u>2.4934</u>	<u>0</u>	<u>0</u>	<u>0.6144</u>	<u>0</u>	<u>2.4934</u>	<u>1.1692</u>	<u>3.9425</u>	<u>0.6144</u>	<u>3.9425</u>	<u>0</u>
24	government	<u>0</u>	<u>2.6044</u>	<u>3.8937</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>3.393</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>4.5251</u>	<u>2.2541</u>	<u>2.6044</u>	<u>2.6044</u>	<u>3.8937</u>	<u>6.8241</u>	<u>5.1285</u>	<u>6.3813</u>	<u>11.7658</u>
25	official	<u>1.9033</u>	<u>0</u>	<u>1.3696</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>1.37</u>	<u>0</u>	<u>0</u>	<u>4.4837</u>	<u>0</u>	<u>0</u>	<u>0.6144</u>	<u>0</u>	<u>1.9033</u>	<u>1.1692</u>	<u>1.3696</u>	<u>0.6144</u>	<u>1.9033</u>	<u>0</u>
26	post	<u>5.9193</u>	<u>4.5949</u>	<u>2.8722</u>	<u>2.6044</u>	<u>4.5949</u>	<u>1.9033</u>	<u>4.368</u>	<u>0.7794</u>	<u>4.5949</u>	<u>4.4837</u>	<u>4.5949</u>	<u>2.6044</u>	<u>2.2541</u>	<u>3.0718</u>	<u>3.3826</u>	<u>3.0088</u>	<u>3.3826</u>	<u>4.5949</u>	<u>4.1005</u>	<u>2.8722</u>
27	crime	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>3.383</u>	<u>0.7794</u>	<u>3.3826</u>	<u>0</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>2.6044</u>	<u>3.3826</u>	<u>0.7794</u>	<u>3.3826</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>
28	prosecution	<u>0</u>	<u>2.6044</u>	<u>2.8722</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>3.383</u>	<u>0.7794</u>	<u>3.3826</u>	<u>0</u>	<u>2.6044</u>	<u>4.5251</u>	<u>2.2541</u>	<u>2.6044</u>	<u>3.3826</u>	<u>2.8722</u>	<u>3.3826</u>	<u>2.6044</u>	<u>2.8722</u>	<u>4.5251</u>
29	institution	<u>1.3696</u>	<u>4.5949</u>	<u>8.3646</u>	<u>2.6044</u>	<u>5.6088</u>	<u>1.3696</u>	<u>7.576</u>	<u>0.7794</u>	<u>4.5949</u>	<u>2.4934</u>	<u>5.6088</u>	<u>2.6044</u>	<u>2.2541</u>	<u>2.6044</u>	<u>2.6044</u>	<u>3.8937</u>	<u>3.9425</u>	<u>5.6088</u>	<u>5.3823</u>	<u>3.8937</u>
30	power	<u>1.9033</u>	<u>3.1688</u>	<u>3.8937</u>	<u>3.1688</u>	<u>1.7798</u>	<u>1.9033</u>	<u>3.169</u>	<u>4.1033</u>	<u>1.7798</u>	<u>1.9033</u>	<u>7.6882</u>	<u>1.7798</u>	<u>4.5024</u>	<u>3.0718</u>	<u>4.8762</u>	<u>3.8937</u>	<u>2.7753</u>	<u>5.1285</u>	<u>3.8937</u>	<u>5.1285</u>
31	abuse	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>4.038</u>	<u>0.7794</u>	<u>3.3826</u>	<u>0</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>4.0382</u>	<u>4.0382</u>	<u>0.7794</u>	<u>3.3826</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>
32	constitution	<u>1.3696</u>	<u>4.5949</u>	<u>2.4934</u>	<u>2.6044</u>	<u>5.6088</u>	<u>1.3696</u>	<u>3.445</u>	<u>2.3982</u>	<u>4.5949</u>	<u>2.4934</u>	<u>5.6088</u>	<u>2.6044</u>	<u>2.2541</u>	<u>3.0718</u>	<u>3.0718</u>	<u>2.3982</u>	<u>2.6044</u>	<u>5.6088</u>	<u>4.1005</u>	<u>2.6044</u>
33	statement	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>4.038</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>5.4967</u>	<u>5.4967</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>
34	word	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>4.038</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>5.4967</u>	<u>7.7404</u>	<u>3.1379</u>	<u>3.3927</u>	<u>2.9496</u>	<u>2.6044</u>	<u>3.3927</u>
35	military	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-

36	support	<u>1.3696</u>	<u>2.6044</u>	<u>3.9425</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.2541</u>	<u>3.0718</u>	<u>6.7685</u>	<u>3.1379</u>	<u>3.9425</u>	<u>2.7753</u>	<u>3.9425</u>	<u>2.7753</u>
37	portrait	<u>1.3696</u>	<u>0.7794</u>	<u>2.4934</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>4.0382</u>	<u>4.9623</u>	<u>1.1692</u>	<u>2.4934</u>	<u>0.7794</u>	<u>2.4934</u>	<u>0.7794</u>
38	extradition	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>0</u>	<u>2.2541</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>	<u>4.5251</u>
39	law	<u>0</u>	<u>2.6044</u>	<u>3.8937</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>0</u>	<u>2.2541</u>	<u>3.0718</u>	<u>3.3826</u>	<u>3.8937</u>	<u>5.823</u>	<u>2.7753</u>	<u>3.8937</u>	<u>5.823</u>
40	protester	<u>1.9033</u>	<u>0</u>	<u>1.3696</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>0</u>	<u>0.6144</u>	<u>0</u>	<u>1.9033</u>	<u>1.1692</u>	<u>1.3696</u>	<u>0.6144</u>	<u>1.9033</u>	<u>0</u>
41	arrest	<u>0</u>	<u>3.1688</u>	<u>0.7794</u>	<u>10.667</u>	<u>2.6044</u>	<u>0</u>	<u>3.1688</u>	<u>2.2541</u>	<u>2.6044</u>	<u>3.1688</u>	<u>3.1688</u>	<u>2.6044</u>	<u>3.1688</u>	<u>2.6044</u>	<u>2.6044</u>
42	opponent	<u>1.9033</u>	<u>0</u>	<u>1.3696</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>0</u>	<u>0.6144</u>	<u>0</u>	<u>1.9033</u>	<u>1.1692</u>	<u>1.3696</u>	<u>0.6144</u>	<u>5.9912</u>	<u>0</u>
43	rightist	<u>1.9033</u>	<u>0</u>	<u>1.3696</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>0</u>	<u>0.6144</u>	<u>0</u>	<u>1.9033</u>	<u>1.1692</u>	<u>1.3696</u>	<u>0.6144</u>	<u>1.9033</u>	<u>0</u>
44	politician	<u>1.9033</u>	<u>0</u>	<u>1.3696</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>0</u>	<u>0.6144</u>	<u>0</u>	<u>1.9033</u>	<u>1.1692</u>	<u>1.3696</u>	<u>0.6144</u>	<u>1.9033</u>	<u>0</u>
45	time	<u>0</u>	<u>2.3982</u>	<u>0.7794</u>	<u>2.3982</u>	<u>2.2541</u>	<u>0</u>	<u>3.8895</u>	<u>2.2541</u>	<u>4.0796</u>	<u>2.2541</u>	<u>2.3982</u>	<u>2.7753</u>	<u>6.131</u>	<u>2.2541</u>	<u>2.7753</u>
46	amnesty	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>
47	month	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>2.9496</u>	<u>0.7794</u>	<u>0.7794</u>
48	father	<u>1.9033</u>	<u>3.1688</u>	<u>1.3696</u>	<u>3.1688</u>	<u>1.7798</u>	<u>1.9033</u>	<u>3.1688</u>	<u>1.7798</u>	<u>1.7798</u>	<u>3.6967</u>	<u>3.1688</u>	<u>3.3927</u>	<u>3.1688</u>	<u>1.9033</u>	<u>3.3927</u>
49	immunity	<u>0</u>	<u>4.5949</u>	<u>0.7794</u>	<u>3.1688</u>	<u>6.883</u>	<u>0</u>	<u>4.143</u>	<u>2.3982</u>	<u>4.5949</u>	<u>0</u>	<u>9.2008</u>	<u>2.6044</u>	<u>3.1688</u>	<u>6.883</u>	<u>4.1005</u>
50	caption	<u>0</u>	<u>2.6044</u>	<u>0.7794</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>3.072</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>	<u>2.6044</u>
51	capital	<u>1.3696</u>	<u>0.7794</u>	<u>3.8937</u>	<u>0.7794</u>	<u>0.7794</u>	<u>1.3696</u>	<u>3.072</u>	<u>0.7794</u>	<u>0.7794</u>	<u>2.4934</u>	<u>3.8937</u>	<u>2.4934</u>	<u>0.7794</u>	<u>6.3813</u>	<u>6.3813</u>
52	publicity	<u>0</u>	<u>2.3982</u>	<u>0.7794</u>	<u>2.3982</u>	<u>0.7794</u>	<u>0</u>	<u>4.038</u>	<u>4.033</u>	<u>0.7794</u>	<u>0</u>	<u>2.3982</u>	<u>0.7794</u>	<u>2.3982</u>	<u>0.7794</u>	<u>0.7794</u>
53	patient	<u>1.9033</u>	<u>0.7794</u>	<u>2.8722</u>	<u>0.7794</u>	<u>0.7794</u>	<u>1.9033</u>	<u>1.37</u>	<u>0.7794</u>	<u>0.7794</u>	<u>1.9033</u>	<u>2.8722</u>	<u>1.3696</u>	<u>0.7794</u>	<u>2.8722</u>	<u>2.8722</u>
54	arrest	<u>0</u>	<u>3.1688</u>	<u>0.7794</u>	<u>10.667</u>	<u>2.6044</u>	<u>0</u>	<u>3.169</u>	<u>2.3982</u>	<u>2.6044</u>	<u>0</u>	<u>3.1688</u>	<u>2.6044</u>	<u>3.1688</u>	<u>2.6044</u>	<u>2.6044</u>
55	order	<u>0</u>	<u>4.1426</u>	<u>5.6152</u>	<u>3.1688</u>	<u>2.6044</u>	<u>0</u>	<u>8.269</u>	<u>2.3982</u>	<u>3.3826</u>	<u>0</u>	<u>4.1426</u>	<u>2.6044</u>	<u>3.1688</u>	<u>3.8937</u>	<u>3.8937</u>
56	advice	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>4.038</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>	<u>0.7794</u>
57	government	<u>0</u>	<u>2.6044</u>	<u>3.8937</u>	<u>2.6044</u>	<u>2.6044</u>	<u>0</u>	<u>3.393</u>	<u>0.7794</u>	<u>2.6044</u>	<u>0</u>	<u>2.6044</u>	<u>4.5251</u>	<u>2.2541</u>	<u>6.3813</u>	<u>11.7658</u>
58	lawmaker	<u>1.9033</u>	<u>0</u>	<u>1.3696</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>1.37</u>	<u>0</u>	<u>0</u>	<u>1.9033</u>	<u>1.1692</u>	<u>1.3696</u>	<u>0.6144</u>	<u>1.9033</u>	<u>0</u>
59	bed	<u>1.3696</u>	<u>0</u>	<u>3.9425</u>	<u>0</u>	<u>0</u>	<u>1.3696</u>	<u>3.445</u>	<u>0</u>	<u>0</u>	<u>2.4934</u>	<u>3.6252</u>	<u>3.9425</u>	<u>0.6144</u>	<u>5.8659</u>	<u>0</u>
60	result	<u>0.6144</u>	<u>2.2541</u>	<u>2.8722</u>	<u>2.2541</u>	<u>2.2541</u>	<u>0.6144</u>	<u>4.038</u>	<u>0.7794</u>	<u>2.2541</u>	<u>0.6144</u>	<u>2.8722</u>	<u>2.2541</u>	<u>4.5024</u>	<u>2.8722</u>	<u>2.8722</u>
61	water	<u>1.3696</u>	<u>0.7794</u>	<u>2.4934</u>	<u>0.7794</u>	<u>0.7794</u>	<u>1.3696</u>	<u>2.493</u>	<u>0.7794</u>	<u>0.7794</u>	<u>2.4934</u>	<u>3.1379</u>	<u>2.4934</u>	<u>0.7794</u>	<u>2.4934</u>	<u>0.7794</u>
62	cannon	<u>1.3696</u>	<u>4.5949</u>	<u>2.4934</u>	<u>2.6044</u>	<u>4.5949</u>	<u>1.3696</u>	<u>5.436</u>	<u>0.7794</u>	<u>5.946</u>	<u>5.2675</u>	<u>1.1692</u>	<u>2.6044</u>	<u>4.5949</u>	<u>4.1005</u>	<u>2.6044</u>

63	decade	0	0.7794	0.7794	0.7794	0	3.762	0.7794	0.7794	0	0.7794	0.7794	0.7794	0.7794	0.7794	0.7794	2.9496	0.7794	0.7794
64	application	1.8747	4.1005	0.7794	2.6044	4.1005	1.8747	4.038	0.7794	4.1005	1.8747	4.1005	2.6044	2.2541	7.7584	4.7636	3.3826	4.1005	2.6044
65	regime	0	1.7798	3.8937	1.7798	1.7798	0	4.058	0.7794	1.7798	0	1.7798	1.7798	1.7798	1.7798	1.7798	3.3927	2.7753	6.3813
66	delegation	0	2.6044	3.8937	2.6044	2.6044	0	2.604	0.7794	2.6044	0	2.6044	4.5251	2.2541	2.6044	2.6044	2.6044	2.6044	6.1239
67	piece	1.1692	4.1426	1.1692	3.1688	2.6044	1.1692	4.143	2.3982	3.3826	1.1692	4.1426	2.6044	2.2541	3.0718	5.6559	3.3826	3.1688	2.7753
68	politician	1.9033	0	1.3696	0	0	1.9033	1.37	0	0	1.9033	0	0	0.6144	0	1.9033	1.1692	0.6144	0
69	scene	1.3696	4.6277	2.4934	3.1688	2.2541	1.3696	3.393	2.3982	2.2541	2.4934	3.1688	2.2541	4.0796	3.0718	5.5592	3.3927	4.0796	3.3927
70	decision	0	4.1005	0.7794	2.6044	4.1005	0	3.393	2.3982	7.1706	0	4.1005	2.6044	7.7053	2.6044	2.6044	2.3982	3.3927	4.1005
71	judge	1.9033	0	1.3696	0	0	1.9033	1.37	0	0	4.4837	0	0	0.6144	0	1.9033	1.1692	0.6144	1.9033
72	evening	0	0.7794	0.7794	0.7794	0.7794	0	3.762	0.7794	0.7794	0	0.7794	0.7794	0.7794	0.7794	0.7794	2.9496	0.7794	0.7794
73	dictator	10.38	0	1.3696	0	0	1.9033	1.37	0	0	1.9033	0	0	0.6144	0	1.9033	1.1692	0.6144	1.9033
74	iron	1.3696	0.7794	2.4934	0.7794	0.7794	1.3696	3.445	0.7794	0.7794	5.8125	0.7794	0.7794	0.7794	0.7794	3.9759	2.4934	0.7794	0.7794
75	fish	0.6144	0	0.6144	0	0	0.6144	0.614	0	0	0.6144	0	0	0.6144	0	0.6144	0.6144	0.6144	0
76	visitor	1.9033	0	1.3696	0	0	1.9033	1.37	0	0	1.9033	0	0	0.6144	0	1.9033	1.1692	0.6144	1.9033
77	diplomat	5.9193	0	1.3696	0	0	1.9033	1.37	0	0	4.4837	0	0	0.6144	0	1.9033	1.1692	0.6144	1.9033
78	policy	0	1.7798	0.7794	1.7798	1.7798	0	4.058	0.7794	1.7798	0	1.7798	1.7798	1.7798	4.0382	4.9623	0.7794	3.3927	3.3927
79	trial	0	2.6044	0.7794	2.6044	2.6044	0	3.383	0.7794	3.3826	0	2.6044	4.5251	4.0796	2.6044	3.3826	0.7794	3.3826	4.5251
80	black	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
81	police	0	0.7794	3.8937	0.7794	0.7794	0	0.779	0.7794	0.7794	0	0.7794	0.7794	0.7794	0.7794	0.7794	3.8937	0.7794	3.8937
82	guard	1.9033	4.1005	3.8937	2.6044	4.1005	1.9033	4.368	2.3982	7.5914	2.4934	4.1005	2.6044	2.2541	2.6044	8.8754	3.3826	4.1005	6.8531
83	stuff	1.1692	2.3982	1.1692	2.3982	1.7798	1.1692	4.038	4.1033	1.7798	1.1692	2.3982	1.7798	1.7798	4.0382	4.6453	3.1379	3.3927	1.7798
84	idea	0	1.7798	0.7794	1.7798	1.7798	0	4.058	0.7794	1.7798	0	1.7798	1.7798	1.7798	3.0718	3.0718	0.7794	3.3927	3.3927
85	business	0	2.6044	3.8937	2.6044	2.6044	0	3.393	0.7794	3.3826	0	2.6044	5.985	2.2541	2.6044	4.7636	3.8937	5.823	2.7753
86	army	0	0.7794	3.8937	0.7794	0.7794	0	0.779	0.7794	0.7794	0	0.7794	0.7794	0.7794	0.7794	0.7794	5.4468	0.7794	5.4468
87	people	0	0.7794	3.5267	0.7794	0.7794	0	0.779	0.7794	0.7794	0	0.7794	0.7794	0.7794	0.7794	0.7794	3.5267	0.7794	3.5267
88	administration	0	2.6044	3.5267	2.6044	2.6044	0	3.762	0.7794	3.3826	0	2.6044	4.5251	2.2541	2.6044	4.7636	3.5267	3.3826	9.1267
89	government	0	2.6044	3.8937	2.6044	2.6044	0	3.393	0.7794	2.6044	0	2.6044	4.5251	2.2541	2.6044	2.6044	3.8937	6.8241	11.7658
90	report	0	2.6044	0.7794	2.6044	2.6044	0	4.038	0.7794	2.6044	0	2.6044	2.6044	4.0796	5.8967	5.4967	0.7794	2.7753	2.7753
91	disappearance	0	4.5949	0.7794	2.6044	6.883	0	2.604	0.7794	4.5949	0	6.883	2.6044	4.0796	2.6044	2.6044	0.7794	2.6044	6.883
92	passport	0	2.3982	0.7794	2.3982	0.7794	0	4.038	4.1033	0.7794	0	2.3982	0.7794	0.7794	4.0382	4.0382	0.7794	2.3982	0.7794
93	family	1.9033	0.7794	3.8937	0.7794	0.7794	1.9033	1.37	0.7794	0.7794	1.9033	0.7794	0.7794	0.7794	0.7794	1.9033	3.8937	1.3696	3.8937
94	total	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
95	police	0	0.7794	3.8937	0.7794	0.7794	0	0.779	0.7794	0.7794	0	0.7794	0.7794	0.7794	0.7794	0.7794	3.8937	0.7794	3.8937

96	gas	1.3696	4.1426	2.4934	3.1688	0.7794	1.3696	4.143	2.3982	0.7794	2.4934	4.1426	0.7794	4.5024	0.7794	5.3672	3.1688	2.4934	4.7384	2.4934	0.7794
97	allegation	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
98	news	0	2.3982	0.7794	2.3982	2.2541	0	4.038	4.1033	2.2541	0	2.3982	2.2541	2.2541	4.0382	4.0382	2.3982	2.2541	2.3982	2.2541	
99	court	1.9033	4.1005	5.3823	2.6044	4.1005	1.9033	2.604	0.7794	4.1005	2.4934	4.1005	2.6044	2.2541	2.6044	2.6044	5.4468	5.8073	4.1005	11.073	
100	strongman	10.38	0	1.3696	0	0	1.9033	1.37	0	0	1.9033	0	0	0.6144	0	1.9033	1.1692	1.3696	0.6144	1.9033	
101	rights	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	
102	abuse	0	2.6044	0.7794	2.6044	2.6044	0	4.038	0.7794	3.3826	0	2.6044	2.6044	2.2541	4.0382	4.0382	0.7794	3.3826	2.6044	2.6044	
103	country	1.1692	0.7794	3.8937	0.7794	0.7794	1.1692	1.169	0.7794	0.7794	1.1692	0.7794	0.7794	0.7794	0.7794	1.1692	4.4243	1.1692	0.7794	4.679	
104	demonstrator	1.9033	0	1.3696	0	0	1.9033	1.37	0	0	4.4837	0	0	0.6144	0	1.9033	1.1692	1.3696	0.6144	1.9033	
105	operation	0.6144	3.1688	0.7794	3.1688	2.6044	0.6144	6.824	2.3982	3.3826	0.6144	3.1688	2.6044	4.093	2.6044	6.7685	3.1688	10.38	4.093	2.6044	
106	official	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
107	event	0.6144	4.1426	0.7794	3.1688	2.2541	0.6144	4.143	2.3982	2.2541	0.6144	4.1426	2.2541	6.2403	2.2541	4.8762	3.1688	2.2541	4.7384	2.2541	
108	dissident	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
109	television	1.3696	0	2.4934	0	0	1.3696	3.445	0	0	2.4934	0	0	0.6144	0	2.4934	1.1692	2.4934	0.6144	2.4934	
110	interview	0	2.6044	0.7794	2.6044	2.6044	0	3.072	0.7794	2.6044	0	2.6044	2.6044	2.2541	6.883	6.883	0.7794	2.6044	2.6044	2.6044	
111	division	0	7.131	3.8937	2.6044	4.5949	0	6.824	0.7794	4.5949	0	4.5949	2.6044	2.2541	5.4967	5.4967	3.8937	6.8241	4.5949	4.1005	
112	riot	0	7.6226	0.7794	3.1688	4.1005	0	4.038	2.3982	4.1005	0	4.1005	2.6044	2.2541	4.0382	4.0382	3.1688	3.3826	4.1005	4.1005	
113	police	0	0.7794	3.8937	0.7794	0.7794	0	0.779	0.7794	0.7794	0	0.7794	0.7794	0.7794	0.7794	0.7794	3.8937	0.7794	0.7794	3.8937	
114	police	0	0.7794	3.8937	0.7794	0.7794	0	0.779	0.7794	0.7794	0	0.7794	0.7794	0.7794	0.7794	0.7794	3.8937	0.7794	0.7794	3.8937	
115	line	1.3696	2.6044	3.8937	2.6044	2.6044	1.3696	4.368	2.3982	3.3826	5.5837	2.6044	4.5251	4.5024	3.0718	4.8762	3.8937	3.3826	4.7384	3.8937	
116	spokesman	1.9033	0	1.3696	0	0	1.9033	1.37	0	0	7.6549	0	0	0.6144	0	1.9033	1.1692	1.3696	0.6144	1.9033	
117	response	0.6144	2.6044	2.8722	2.6044	2.6044	0.6144	4.038	2.3982	2.6044	0.6144	3.8895	2.6044	6.2403	5.4967	5.4967	2.8722	2.6044	4.5024	2.8722	
118	death	0.6144	4.5949	0.7794	3.1688	7.4617	0.6144	3.169	2.3982	4.5949	0.6144	6.883	2.6044	4.5024	2.6044	4.7384	3.1688	2.7753	10.6671	4.1005	
119	pressure	0.6144	4.1426	0.7794	3.1688	2.6044	0.6144	4.143	4.1033	2.6044	0.6144	4.1426	2.6044	4.5024	2.6044	4.8762	3.1688	2.7753	4.7384	2.6044	
120	release	1.3696	4.5949	2.4934	2.6044	6.883	1.3696	4.368	0.7794	5.9546	5.5837	6.883	2.6044	4.093	4.0382	4.9623	1.1692	3.3826	7.9555	4.1005	
121	injury	0	4.1426	0.7794	3.1688	2.6044	0	4.143	2.3982	3.3826	0	4.1426	2.6044	4.093	2.6044	3.3826	3.1688	3.3826	5.8908	2.6044	
122	violation	0	2.6044	0.7794	2.6044	2.6044	0	3.383	0.7794	3.3826	0	2.6044	2.6044	2.2541	2.6044	3.3826	0.7794	3.3826	2.6044	2.6044	
123	attitude	0	2.6044	0.7794	2.6044	2.6044	0	3.383	2.3982	3.3826	0	3.8895	2.6044	2.2541	2.6044	3.3826	3.1379	3.3826	2.7753	2.6044	
124	lobby	1.3696	0.7794	3.9425	0.7794	0.7794	1.3696	2.493	0.7794	0.7794	2.4934	0.7794	0.7794	0.7794	0.7794	2.4934	3.8937	5.8073	0.7794	3.8937	
125	group	0.6144	0.7794	2.8722	0.7794	0.7794	0.6144	0.779	0.7794	0.7794	0.6144	0.7794	0.7794	0.7794	0.7794	0.7794	2.8722	0.7794	0.7794	2.8722	

D) LIN measure

No	QC	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9	CC10	CC11	CC12	CC13	CC14	CC15	CC16	CC17	CC18	CC19	CC20
		dictator	confusion	hospital	arrest	murder	citizen	rule	legality	move	supporter	immunity	extradition	outcome	request	charge	community	surgery	death	court	government
1	defense	<u>0.1404</u>	<u>0.0923</u>	<u>0.4508</u>	<u>0.2737</u>	<u>0.3117</u>	<u>0.1599</u>	<u>0.4661</u>	<u>0.0781</u>	<u>0.3512</u>	<u>0.1638</u>	<u>0.0862</u>	<u>0</u>	<u>0.4728</u>	<u>0.5895</u>	<u>0.7924</u>	<u>0.4209</u>	<u>0.3391</u>	<u>0.4286</u>	<u>0.4089</u>	<u>0.5027</u>
2	minister	<u>0.1993</u>	<u>0</u>	<u>0.1603</u>	<u>0</u>	<u>0</u>	<u>0.2276</u>	<u>0.1337</u>	<u>0</u>	<u>0</u>	<u>0.2334</u>	<u>0</u>	<u>0</u>	<u>0.0821</u>	<u>0</u>	<u>0.1858</u>	<u>0.4141</u>	<u>0</u>	<u>0.0734</u>	<u>0.1451</u>	<u>0</u>
3	priest	<u>0.2023</u>	<u>0.3855</u>	<u>0.1631</u>	<u>0.3318</u>	<u>0.0958</u>	<u>0.2316</u>	<u>0.3369</u>	<u>0.2459</u>	<u>0.1083</u>	<u>0.2375</u>	<u>0.3594</u>	<u>0</u>	<u>0.0966</u>	<u>0.1018</u>	<u>0.3443</u>	<u>0.3138</u>	<u>0.0829</u>	<u>0.3732</u>	<u>0.1473</u>	<u>0.1052</u>
4	magistrate	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
5	murder	<u>0</u>	<u>0.0984</u>	<u>0</u>	<u>0.2895</u>	<u>1</u>	<u>0</u>	<u>0.2211</u>	<u>0.0824</u>	<u>0.6665</u>	<u>0</u>	<u>0.0915</u>	<u>0</u>	<u>0.2901</u>	<u>0.3539</u>	<u>0.3095</u>	<u>0.1055</u>	<u>0.286</u>	<u>0.2884</u>	<u>0.0991</u>	<u>0.3071</u>
6	day	<u>0</u>	<u>0.1095</u>	<u>0</u>	<u>0.0951</u>	<u>0.1108</u>	<u>0</u>	<u>0.1075</u>	<u>0.0901</u>	<u>0.1279</u>	<u>0</u>	<u>0.101</u>	<u>0</u>	<u>0.1118</u>	<u>0.1188</u>	<u>0.1141</u>	<u>0.1183</u>	<u>0.0938</u>	<u>0.3931</u>	<u>0.1103</u>	<u>0.1235</u>
7	embassy	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8	police	<u>0</u>	<u>0.0982</u>	<u>0</u>	<u>0.0865</u>	<u>0.0992</u>	<u>0</u>	<u>0.0966</u>	<u>0.0823</u>	<u>0.1127</u>	<u>0</u>	<u>0.0913</u>	<u>0</u>	<u>0.1001</u>	<u>0.1056</u>	<u>0.1019</u>	<u>0.4762</u>	<u>0.0854</u>	<u>0.0995</u>	<u>0.4473</u>	<u>0.5463</u>
9	source	<u>0.1885</u>	<u>0.0906</u>	<u>0.2763</u>	<u>0.1839</u>	<u>0.209</u>	<u>0.2136</u>	<u>0.4583</u>	<u>0.0769</u>	<u>0.2349</u>	<u>0.2186</u>	<u>0.0847</u>	<u>0</u>	<u>0.2106</u>	<u>0.3623</u>	<u>0.3498</u>	<u>0.3655</u>	<u>0.1818</u>	<u>0.2794</u>	<u>0.3269</u>	<u>0.3505</u>
10	insult	<u>0</u>	<u>0.0817</u>	<u>0</u>	<u>0.2454</u>	<u>0.2755</u>	<u>0</u>	<u>0.4176</u>	<u>0.0704</u>	<u>0.3059</u>	<u>0</u>	<u>0.0769</u>	<u>0</u>	<u>0.2401</u>	<u>0.4289</u>	<u>0.4155</u>	<u>0.0866</u>	<u>0.3154</u>	<u>0.2389</u>	<u>0.0822</u>	<u>0.2579</u>
11	team	<u>0</u>	<u>0.1009</u>	<u>0</u>	<u>0.0885</u>	<u>0.102</u>	<u>0</u>	<u>0.0992</u>	<u>0.0842</u>	<u>0.1163</u>	<u>0</u>	<u>0.0936</u>	<u>0</u>	<u>0.1029</u>	<u>0.1088</u>	<u>0.1048</u>	<u>0.4903</u>	<u>0.0874</u>	<u>0.1023</u>	<u>0.4597</u>	<u>0.5631</u>
12	claim	<u>0</u>	<u>0.0944</u>	<u>0</u>	<u>0.2608</u>	<u>0.2951</u>	<u>0</u>	<u>0.4814</u>	<u>0.0796</u>	<u>0.3302</u>	<u>0</u>	<u>0.088</u>	<u>0</u>	<u>0.2572</u>	<u>0.824</u>	<u>0.5882</u>	<u>0.1009</u>	<u>0.3349</u>	<u>0.2602</u>	<u>0.095</u>	<u>0.3259</u>
13	arrest	<u>0</u>	<u>0.3394</u>	<u>0</u>	<u>1</u>	<u>0.2895</u>	<u>0</u>	<u>0.3011</u>	<u>0.2206</u>	<u>0.3233</u>	<u>0</u>	<u>0.319</u>	<u>0</u>	<u>0.2524</u>	<u>0.3057</u>	<u>0.307</u>	<u>0.2825</u>	<u>0.2536</u>	<u>0.3298</u>	<u>0.0864</u>	<u>0.2701</u>
14	warrant	<u>0</u>	<u>0.0848</u>	<u>0</u>	<u>0.0759</u>	<u>0.0856</u>	<u>0</u>	<u>0.4331</u>	<u>0.0727</u>	<u>0.0954</u>	<u>0</u>	<u>0.0796</u>	<u>0</u>	<u>0.0862</u>	<u>0.4453</u>	<u>0.4309</u>	<u>0.09</u>	<u>0.0751</u>	<u>0.0858</u>	<u>0.0853</u>	<u>0.093</u>
15	attorney	<u>0.206</u>	<u>0</u>	<u>0.1663</u>	<u>0</u>	<u>0</u>	<u>0.2363</u>	<u>0.1379</u>	<u>0</u>	<u>0</u>	<u>0.2426</u>	<u>0</u>	<u>0</u>	<u>0.0857</u>	<u>0</u>	<u>0.1916</u>	<u>0.139</u>	<u>0</u>	<u>0.0762</u>	<u>0.15</u>	<u>0</u>
16	envoy	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>
17	extradition	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>
18	request	<u>0</u>	<u>0.1047</u>	<u>0</u>	<u>0.3057</u>	<u>0.3539</u>	<u>0</u>	<u>0.5039</u>	<u>0.0868</u>	<u>0.4057</u>	<u>0</u>	<u>0.0969</u>	<u>0</u>	<u>0.309</u>	<u>1</u>	<u>0.5009</u>	<u>0.1128</u>	<u>0.3017</u>	<u>0.3071</u>	<u>0.1055</u>	<u>0.3254</u>
19	opinion	<u>0</u>	<u>0.1048</u>	<u>0</u>	<u>0.2588</u>	<u>0.2925</u>	<u>0</u>	<u>0.5279</u>	<u>0.0869</u>	<u>0.327</u>	<u>0</u>	<u>0.097</u>	<u>0</u>	<u>0.255</u>	<u>0.4783</u>	<u>0.4617</u>	<u>0.1129</u>	<u>0.2559</u>	<u>0.3165</u>	<u>0.1056</u>	<u>0.4738</u>
20	term	<u>0</u>	<u>0.0965</u>	<u>0</u>	<u>0.1709</u>	<u>0.1924</u>	<u>0</u>	<u>0.4751</u>	<u>0.0811</u>	<u>0.2142</u>	<u>0</u>	<u>0.0898</u>	<u>0</u>	<u>0.1937</u>	<u>0.4555</u>	<u>0.5412</u>	<u>0.3386</u>	<u>0.1691</u>	<u>0.339</u>	<u>0.2922</u>	<u>0.3259</u>
21	rally	<u>0</u>	<u>0.0817</u>	<u>0</u>	<u>0.2376</u>	<u>0.4184</u>	<u>0</u>	<u>0.1777</u>	<u>0.0704</u>	<u>0.4628</u>	<u>0</u>	<u>0.0769</u>	<u>0</u>	<u>0.2315</u>	<u>0.2793</u>	<u>0.2509</u>	<u>0.6049</u>	<u>0.2352</u>	<u>0.2305</u>	<u>0.5743</u>	<u>0.4041</u>
22	week	<u>0</u>	<u>0.1031</u>	<u>0</u>	<u>0.0902</u>	<u>0.1042</u>	<u>0</u>	<u>0.1013</u>	<u>0.0857</u>	<u>0.1192</u>	<u>0</u>	<u>0.0955</u>	<u>0</u>	<u>0.1051</u>	<u>0.1113</u>	<u>0.1072</u>	<u>0.1109</u>	<u>0.0891</u>	<u>0.3712</u>	<u>0.1038</u>	<u>0.1154</u>
23	boss	<u>0.1908</u>	<u>0</u>	<u>0.4057</u>	<u>0</u>	<u>0</u>	<u>0.2166</u>	<u>0.2184</u>	<u>0</u>	<u>0</u>	<u>0.2218</u>	<u>0</u>	<u>0</u>	<u>0.0777</u>	<u>0</u>	<u>0.1784</u>	<u>0.1279</u>	<u>0</u>	<u>0.0698</u>	<u>0.3714</u>	<u>0</u>
24	government	<u>0</u>	<u>0.1084</u>	<u>0</u>	<u>0.2701</u>	<u>0.3071</u>	<u>0</u>	<u>0.3636</u>	<u>0.0893</u>	<u>0.3454</u>	<u>0</u>	<u>0.1</u>	<u>0</u>	<u>0.2678</u>	<u>0.3254</u>	<u>0.2875</u>	<u>0.5296</u>	<u>0.267</u>	<u>0.4572</u>	<u>0.7486</u>	<u>1</u>
25	official	<u>0.2191</u>	<u>0</u>	<u>0.1783</u>	<u>0</u>	<u>0</u>	<u>0.2538</u>	<u>0.146</u>	<u>0</u>	<u>0</u>	<u>0.6148</u>	<u>0</u>	<u>0</u>	<u>0.0928</u>	<u>0</u>	<u>0.2029</u>	<u>0.1488</u>	<u>0</u>	<u>0.0818</u>	<u>0.1597</u>	<u>0</u>
26	post	<u>0.1373</u>	<u>0.0983</u>	<u>0.2781</u>	<u>0.2892</u>	<u>0.332</u>	<u>0.1559</u>	<u>0.4094</u>	<u>0.0824</u>	<u>0.3772</u>	<u>0.1596</u>	<u>0.0914</u>	<u>0</u>	<u>0.2898</u>	<u>0.3535</u>	<u>0.4016</u>	<u>0.315</u>	<u>0.371</u>	<u>0.2881</u>	<u>0.2859</u>	<u>0.3068</u>
27	crime	<u>0</u>	<u>0.0993</u>	<u>0</u>	<u>0.2919</u>	<u>0.3356</u>	<u>0</u>	<u>0.2231</u>	<u>0.0831</u>	<u>0.3818</u>	<u>0</u>	<u>0.0923</u>	<u>0</u>	<u>0.2929</u>	<u>0.3575</u>	<u>0.4055</u>	<u>0.1066</u>	<u>0.3744</u>	<u>0.2912</u>	<u>0.1</u>	<u>0.3098</u>
28	prosecution	<u>0</u>	<u>0.0835</u>	<u>0</u>	<u>0.2501</u>	<u>0.2815</u>	<u>0</u>	<u>0.188</u>	<u>0.0717</u>	<u>0.3134</u>	<u>0</u>	<u>0.0785</u>	<u>0</u>	<u>0.2454</u>	<u>0.2968</u>	<u>0.2649</u>	<u>0.3071</u>	<u>0.2475</u>	<u>0.2442</u>	<u>0.2922</u>	<u>0.4572</u>
29	institution	<u>0.1441</u>	<u>0.1145</u>	<u>0.879</u>	<u>0.2588</u>	<u>0.6299</u>	<u>0.1647</u>	<u>0.7563</u>	<u>0.0934</u>	<u>0.5769</u>	<u>0.1689</u>	<u>0.1052</u>	<u>0</u>	<u>0.255</u>	<u>0.309</u>	<u>0.2746</u>	<u>0.5619</u>	<u>0.2559</u>	<u>0.2537</u>	<u>0.5221</u>	<u>0.6491</u>
30	power	<u>0.1869</u>	<u>0.3606</u>	<u>0.1439</u>	<u>0.3132</u>	<u>0.2746</u>	<u>0.2119</u>	<u>0.4143</u>	<u>0.4744</u>	<u>0.3212</u>	<u>0.217</u>	<u>0.3377</u>	<u>0</u>	<u>0.5886</u>	<u>0.3638</u>	<u>0.5076</u>	<u>0.4007</u>	<u>0.2295</u>	<u>0.6494</u>	<u>0.38</u>	<u>0.6071</u>
31	abuse	<u>0</u>	<u>0.0906</u>	<u>0</u>	<u>0.2691</u>	<u>0.3058</u>	<u>0</u>	<u>0.4176</u>	<u>0.0769</u>	<u>0.3437</u>	<u>0</u>	<u>0.0847</u>	<u>0</u>	<u>0.2667</u>	<u>0.4289</u>	<u>0.4155</u>	<u>0.0966</u>	<u>0.3455</u>	<u>0.2652</u>	<u>0.0912</u>	<u>0.2842</u>
32	constitution	<u>0</u>	<u>0.2851</u>	<u>0</u>	<u>0.2729</u>	<u>0.669</u>	<u>0</u>	<u>0.3334</u>	<u>0.2411</u>	<u>0.6173</u>	<u>0</u>	<u>0.2661</u>	<u>0</u>	<u>0.271</u>	<u>0.3429</u>	<u>0.3317</u>	<u>0.233</u>	<u>0.2697</u>	<u>0.2762</u>	<u>0.0933</u>	<u>0.2884</u>
33	statement	<u>0</u>	<u>0.1202</u>	<u>0</u>	<u>0.2376</u>	<u>0.2658</u>	<u>0</u>	<u>0.6104</u>	<u>0.0972</u>	<u>0.2939</u>	<u>0</u>	<u>0.1101</u>	<u>0</u>	<u>0.2315</u>	<u>0.6349</u>	<u>0.7447</u>	<u>0.131</u>	<u>0.2352</u>	<u>0.2305</u>	<u>0.1212</u>	<u>0.2493</u>
34	word	<u>0</u>	<u>0.1112</u>	<u>0</u>	<u>0.2501</u>	<u>0.2815</u>	<u>0</u>	<u>0.4846</u>	<u>0.0912</u>	<u>0.3134</u>	<u>0</u>	<u>0.1024</u>	<u>0</u>	<u>0.2454</u>	<u>0.6264</u>	<u>0.5757</u>	<u>0.3827</u>	<u>0.2475</u>	<u>0.2949</u>	<u>0.112</u>	<u>0.3706</u>
35	military	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
36	support	<u>0.1565</u>	<u>0.0983</u>	<u>0.4397</u>	<u>0.2892</u>	<u>0.332</u>	<u>0.1811</u>	<u>0.4625</u>	<u>0.0824</u>	<u>0.3772</u>	<u>0.1862</u>	<u>0.0914</u>	<u>0</u>	<u>0.2898</u>	<u>0.3535</u>	<u>0.7247</u>	<u>0.3205</u>	<u>0.371</u>	<u>0.2881</u>	<u>0.3998</u>	<u>0.3068</u>
37	portrait	<u>0.1277</u>	<u>0.0835</u>	<u>0.2566</u>	<u>0.0749</u>	<u>0.0843</u>	<u>0.1436</u>	<u>0.4265</u>	<u>0.0717</u>	<u>0.0938</u>	<u>0.1468</u>	<u>0.0785</u>	<u>0</u>	<u>0.0848</u>	<u>0.4383</u>	<u>0.5215</u>	<u>0.1181</u>	<u>0.0741</u>	<u>0.0844</u>	<u>0.2349</u>	<u>0.0914</u>
38	extradition	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>
39	law	<u>0</u>	<u>0.102</u>	<u>0</u>	<u>0.2454</u>	<u>0.2755</u>	<u>0</u>	<u>0.9351</u>	<u>0.085</u>	<u>0.3059</u>	<u>0</u>	<u>0.0946</u>	<u>0</u>	<u>0.2401</u>	<u>0.3873</u>	<u>0.3731</u>	<u>0.4762</u>	<u>0.3154</u>	<u>0.29</u>	<u>0.4473</u>	<u>0.5733</u>
40	protester	<u>0.1885</u>	<u>0</u>	<u>0.1506</u>	<u>0</u>	<u>0</u>	<u>0.2136</u>	<u>0.1269</u>	<u>0</u>	<u>0</u>	<u>0.2186</u>	<u>0</u>	<u>0</u>	<u>0.0765</u>	<u>0</u>	<u>0.1763</u>	<u>0.1261</u>	<u>0</u>	<u>0.0688</u>	<u>0.1371</u>	<u>0</u>

41	arrest	0	0.3394	0	1	0.2895	0	0.3011	0.2206	0.3233	0	0.319	0	0.2524	0.3057	0.307	0.2825	0.2536	0.3298	0.0864	0.2701
42	opponent	0.206	0	0.1663	0	0	0.2363	0.1379	0	0	0.2426	0	0	0.0857	0	0.1916	0.139	0	0.0762	0.15	0
43	rightist	0.1908	0	0.1527	0	0	0.2166	0.1284	0	0	0.2218	0	0	0.0777	0	0.1784	0.1279	0	0.0698	0.1389	0
44	politician	0.2111	0	0.171	0	0	0.2431	0.141	0	0	0.2497	0	0	0.0884	0	0.196	0.1428	0	0.0783	0.1538	0
45	time	0	0.343	0	0.2881	0.3173	0	0.3546	0.2813	0.3657	0	0.316	0	0.5796	0.3401	0.3007	0.2703	0.2691	0.732	0.1124	0.3165
46	amnesty	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
47	month	0	0.1114	0	0.0965	0.1127	0	0.1093	0.0913	0.1305	0	0.1026	0	0.1138	0.1211	0.1162	0.1205	0.0952	0.3996	0.1122	0.126
48	father	0.2197	0.3322	0.1789	0.2915	0.1883	0.2546	0.3465	0.2166	0.2091	0.2619	0.3126	0	0.1896	0.1982	0.3393	0.2926	0.1659	0.323	0.1602	0.3196
49	immunity	0	0.4815	0	0.319	0.0915	0	0.4231	0.2366	0.1029	0	1	0	0.0922	0.0969	0.3305	0.3023	0.0796	0.3571	0.0912	0.1
50	caption	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
51	capital	0.1381	0.098	0.1568	0.0864	0.0991	0.1607	0.3066	0.0822	0.1126	0.1653	0.0912	0	0.0999	0.3147	0.6066	0.4747	0.0853	0.0994	0.5871	0.7312
52	publicity	0	0.0963	0	0.0649	0.0972	0	0.4901	0.0808	0.11	0	0.0895	0	0.0979	0.5058	0.4873	0.1029	0.0839	0.0974	0.0968	0.1068
53	patient	0.2134	0	0.1731	0	0	0.2461	0.1425	0	0	0.2529	0	0	0.0897	0	0.198	0.1445	0	0.0793	0.1555	0
54	arrest	0	0.3394	0	1	0.2895	0	0.3011	0.2206	0.3233	0	0.319	0	0.2524	0.3057	0.307	0.2825	0.2536	0.3298	0.0864	0.2701
55	order	0	0.4562	0	0.3381	0.3209	0	0.8255	0.2505	0.3629	0	0.428	0	0.28	0.7194	0.4012	0.8141	0.3391	0.3812	0.4268	0.5188
56	advice	0	0.0996	0	0.0876	0.1007	0	0.5077	0.0833	0.1147	0	0.0926	0	0.1016	0.5245	0.5047	0.1069	0.0865	0.101	0.1004	0.1112
57	government	0	0.1084	0	0.2701	0.3071	0	0.3636	0.0893	0.3454	0	0.1	0	0.2678	0.3254	0.2875	0.5296	0.267	0.4572	0.7486	1
58	lawmaker	0.1908	0	0.1608	0	0	0.2282	0.134	0	0	0.234	0	0	0.0824	0	0.1862	0.1344	0	0.0736	0.1455	0
59	bed	0.1516	0	0.3106	0	0	0.1746	0.3542	0	0	0.1793	0	0	0.0882	0	0.1408	0.3878	0	0.0782	0.5684	0
60	result	0.0739	0.0992	0.0841	0.2524	0.2901	0.0863	0.5033	0.083	0.33	0.0808	0.0922	0	1	0.5199	0.6149	0.1065	0.2493	0.6311	0.0999	0.2678
61	water	0.1277	0.1054	0.2566	0.092	0.1067	0.1436	0.2184	0.0873	0.1224	0.1468	0.0975	0	0.1076	0.1141	0.4418	0.3657	0.0908	0.1069	0.2349	0.1184
62	cannon	0.1404	0	0.2851	0	0	0.1599	0.3298	0	0	0.1638	0	0	0.08	0	0.1311	0.131	0	0.0716	0.2586	0
63	decade	0	0.0963	0	0.085	0.0973	0	0.0948	0.081	0.1103	0	0.0897	0	0.0981	0.1035	0.0999	0.1031	0.084	0.348	0.097	0.107
64	application	0	0.0965	0	0.2845	0.3258	0	0.4498	0.0811	0.3692	0	0.0898	0	0.2843	0.8895	0.5034	0.1033	0.365	0.2826	0.0971	0.3014
65	regime	0	0.1084	0	0.1624	0.1816	0	0.4004	0.0893	0.2009	0	0.1	0	0.1828	0.1909	0.1715	0.5296	0.1607	0.2474	0.7486	1
66	delegation	0	0.0788	0	0.0711	0.0795	0	0.0778	0.0683	0.088	0	0.0743	0	0.0801	0.0836	0.0812	0.3771	0.0704	0.0797	0.3588	0.4291
67	place	0.1378	0.4683	0.1564	0.3114	0.332	0.1602	0.4129	0.2311	0.3772	0.1649	0.4387	0	0.2898	0.3535	0.7198	0.4335	0.371	0.3476	0.5396	0.3068
68	politician	0.2111	0	0.171	0	0	0.2431	0.141	0	0	0.2497	0	0	0.0884	0	0.196	0.1428	0	0.0783	0.1538	0
69	scene	0.1373	0.3742	0.2781	0.3234	0.2689	0.1559	0.4115	0.2798	0.3028	0.1596	0.3495	0	0.4904	0.3495	0.5523	0.4352	0.2334	0.4878	0.4568	0.3741
70	decision	0	0.1027	0	0.3006	0.5466	0	0.4091	0.0854	0.9715	0	0.0952	0	0.8207	0.3706	0.3223	0.1105	0.2968	0.4324	0.1035	0.3721
71	judge	0.1951	0	0.1566	0	0	0.2722	0.1311	0	0	0.5364	0	0	0.08	0	0.1822	0.131	0	0.0716	0.1421	0
72	evening	0	0.0966	0	0.0853	0.0977	0	0.0951	0.0812	0.1107	0	0.09	0	0.0985	0.1038	0.1002	0.1035	0.0842	0.3491	0.0973	0.1074
73	dictator	1	0	0.1461	0	0	0.2071	0.1237	0	0	0.2118	0	0	0.0739	0	0.1719	0.1224	0	0.0668	0.1334	0
74	iron	0.1277	0.092	0.2566	0.0817	0.093	0.1436	0.3017	0.0779	0.1047	0.1468	0.086	0	0.0937	0.0986	0.3837	0.325	0.0807	0.0932	0.2349	0.1018
75	flist	0.0642	0	0.0717	0	0	0.0732	0.0598	0	0	0.0751	0	0	0.0819	0	0.0649	0.0702	0	0.0731	0.0649	0
76	visitor	0.2062	0	0.1666	0	0	0.2367	0.138	0	0	0.243	0	0	0.0858	0	0.1918	0.1392	0	0.0763	0.1502	0
77	diplomat	0.1928	0	0.1545	0	0	0.2191	0.1296	0	0	0.5208	0	0	0.0787	0	0.1801	0.1293	0	0.0706	0.1403	0
78	policy	0	0.1003	0	0.2012	0.2317	0	0.4855	0.0838	0.2639	0	0.0932	0	0.2336	0.4453	0.5295	0.1077	0.1987	0.305	0.1011	0.3694
79	trial	0	0.0991	0	0.2913	0.3348	0	0.3301	0.0829	0.3808	0	0.0921	0	0.2922	0.3566	0.4047	0.1063	0.3737	0.2905	0.0998	0.4332
80	black	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
81	police	0	0.0982	0	0.0865	0.0992	0	0.0966	0.0823	0.1127	0	0.0913	0	0.1001	0.1056	0.1019	0.4762	0.0854	0.0995	0.4473	0.5463

82	guard	<u>0.2023</u>	<u>0.2426</u>	<u>0.262</u>	<u>0.2588</u>	<u>0.4605</u>	<u>0.2316</u>	<u>0.3894</u>	<u>0.21</u>	<u>0.8644</u>	<u>0.2375</u>	<u>0.2288</u>	<u>0</u>	<u>0.255</u>	<u>0.309</u>	<u>0.8362</u>	<u>0.3916</u>	<u>0.3055</u>	<u>0.2537</u>	<u>0.3719</u>	<u>0.4462</u>
83	staff	<u>0.1194</u>	<u>0.2426</u>	<u>0.1331</u>	<u>0.2138</u>	<u>0.1763</u>	<u>0.1359</u>	<u>0.4031</u>	<u>0.3593</u>	<u>0.149</u>	<u>0.1393</u>	<u>0.2288</u>	<u>0</u>	<u>0.1276</u>	<u>0.4137</u>	<u>0.5261</u>	<u>0.4216</u>	<u>0.1047</u>	<u>0.2361</u>	<u>0.1257</u>	<u>0.1432</u>
84	idea	<u>0</u>	<u>0.1292</u>	<u>0</u>	<u>0.2504</u>	<u>0.2993</u>	<u>0</u>	<u>0.6459</u>	<u>0.103</u>	<u>0.3555</u>	<u>0</u>	<u>0.1176</u>	<u>0</u>	<u>0.3026</u>	<u>0.3387</u>	<u>0.3278</u>	<u>0.1418</u>	<u>0.2466</u>	<u>0.3769</u>	<u>0.1304</u>	<u>0.4774</u>
85	business	<u>0</u>	<u>0.1128</u>	<u>0</u>	<u>0.3261</u>	<u>0.3816</u>	<u>0</u>	<u>0.3176</u>	<u>0.0973</u>	<u>0.4425</u>	<u>0</u>	<u>0.1038</u>	<u>0</u>	<u>0.3334</u>	<u>0.4101</u>	<u>0.5105</u>	<u>0.5272</u>	<u>0.4177</u>	<u>0.3312</u>	<u>0.492</u>	<u>0.6072</u>
86	army	<u>0</u>	<u>0.1001</u>	<u>0</u>	<u>0.088</u>	<u>0.1013</u>	<u>0</u>	<u>0.0985</u>	<u>0.0837</u>	<u>0.1153</u>	<u>0</u>	<u>0.093</u>	<u>0</u>	<u>0.1021</u>	<u>0.1079</u>	<u>0.104</u>	<u>0.6049</u>	<u>0.0869</u>	<u>0.1015</u>	<u>0.5743</u>	<u>0.5585</u>
87	people	<u>0</u>	<u>0.1161</u>	<u>0</u>	<u>0.1001</u>	<u>0.1176</u>	<u>0</u>	<u>0.1139</u>	<u>0.0945</u>	<u>0.137</u>	<u>0</u>	<u>0.1066</u>	<u>0</u>	<u>0.1188</u>	<u>0.1267</u>	<u>0.1214</u>	<u>0.4648</u>	<u>0.0987</u>	<u>0.118</u>	<u>0.4314</u>	<u>0.4868</u>
88	administration	<u>0</u>	<u>0.0966</u>	<u>0</u>	<u>0.2701</u>	<u>0.3071</u>	<u>0</u>	<u>0.2046</u>	<u>0.0812</u>	<u>0.3454</u>	<u>0</u>	<u>0.09</u>	<u>0</u>	<u>0.2678</u>	<u>0.3254</u>	<u>0.4733</u>	<u>0.4682</u>	<u>0.3214</u>	<u>0.2973</u>	<u>0.4402</u>	<u>1</u>
89	government	<u>0</u>	<u>0.1084</u>	<u>0</u>	<u>0.2701</u>	<u>0.3071</u>	<u>0</u>	<u>0.3636</u>	<u>0.0893</u>	<u>0.3454</u>	<u>0</u>	<u>0.1</u>	<u>0</u>	<u>0.2678</u>	<u>0.3254</u>	<u>0.2875</u>	<u>0.5296</u>	<u>0.267</u>	<u>0.4572</u>	<u>0.7486</u>	<u>1</u>
90	report	<u>0</u>	<u>0.0991</u>	<u>0</u>	<u>0.2861</u>	<u>0.3279</u>	<u>0</u>	<u>0.4825</u>	<u>0.0829</u>	<u>0.3719</u>	<u>0</u>	<u>0.0921</u>	<u>0</u>	<u>0.4345</u>	<u>0.7361</u>	<u>0.4798</u>	<u>0.1063</u>	<u>0.2826</u>	<u>0.4324</u>	<u>0.0998</u>	<u>0.3032</u>
91	disappearance	<u>0</u>	<u>0.0848</u>	<u>0</u>	<u>0.2536</u>	<u>0.7024</u>	<u>0</u>	<u>0.1909</u>	<u>0.0777</u>	<u>0.5186</u>	<u>0</u>	<u>0.0796</u>	<u>0</u>	<u>0.4345</u>	<u>0.3017</u>	<u>0.2689</u>	<u>0.09</u>	<u>0.2509</u>	<u>0.4324</u>	<u>0.0853</u>	<u>0.267</u>
92	passport	<u>0</u>	<u>0.0817</u>	<u>0</u>	<u>0.0734</u>	<u>0.0824</u>	<u>0</u>	<u>0.4176</u>	<u>0.0704</u>	<u>0.0915</u>	<u>0</u>	<u>0.0769</u>	<u>0</u>	<u>0.083</u>	<u>0.4289</u>	<u>0.4155</u>	<u>0.0866</u>	<u>0.0727</u>	<u>0.0826</u>	<u>0.0822</u>	<u>0.0893</u>
93	family	<u>0.1774</u>	<u>0.101</u>	<u>0.1409</u>	<u>0.0887</u>	<u>0.1022</u>	<u>0.1995</u>	<u>0.1199</u>	<u>0.0843</u>	<u>0.1165</u>	<u>0.204</u>	<u>0.0938</u>	<u>0</u>	<u>0.103</u>	<u>0.109</u>	<u>0.1667</u>	<u>0.4903</u>	<u>0.0876</u>	<u>0.1024</u>	<u>0.4597</u>	<u>0.5631</u>
94	total	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
95	police	<u>0</u>	<u>0.0982</u>	<u>0</u>	<u>0.0865</u>	<u>0.0992</u>	<u>0</u>	<u>0.0966</u>	<u>0.0823</u>	<u>0.1127</u>	<u>0</u>	<u>0.0913</u>	<u>0</u>	<u>0.1001</u>	<u>0.1056</u>	<u>0.1019</u>	<u>0.4762</u>	<u>0.0854</u>	<u>0.0995</u>	<u>0.4473</u>	<u>0.5463</u>
96	gas	<u>0.1301</u>	<u>0.4191</u>	<u>0.262</u>	<u>0.2825</u>	<u>0.089</u>	<u>0.1467</u>	<u>0.3741</u>	<u>0.21</u>	<u>0.0997</u>	<u>0.15</u>	<u>0.3952</u>	<u>0</u>	<u>0.5886</u>	<u>0.0941</u>	<u>0.4932</u>	<u>0.3128</u>	<u>0.0777</u>	<u>0.5547</u>	<u>0.2395</u>	<u>0.097</u>
97	allegation	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
98	news	<u>0</u>	<u>0.0976</u>	<u>0</u>	<u>0.2195</u>	<u>0.2475</u>	<u>0</u>	<u>0.4977</u>	<u>0.0819</u>	<u>0.276</u>	<u>0</u>	<u>0.0908</u>	<u>0</u>	<u>0.2493</u>	<u>0.5138</u>	<u>0.4948</u>	<u>0.1046</u>	<u>0.2172</u>	<u>0.248</u>	<u>0.0983</u>	<u>0.2311</u>
99	court	<u>0.1334</u>	<u>0.098</u>	<u>0.5538</u>	<u>0.0864</u>	<u>0.0991</u>	<u>0.1508</u>	<u>0.2275</u>	<u>0.0822</u>	<u>0.1126</u>	<u>0.1543</u>	<u>0.0912</u>	<u>0</u>	<u>0.0999</u>	<u>0.1055</u>	<u>0.125</u>	<u>0.7345</u>	<u>0.0853</u>	<u>0.0994</u>	<u>1</u>	<u>0.7486</u>
100	strongman	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>	<u>0</u>
101	rights	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>
102	abuse	<u>0</u>	<u>0.0906</u>	<u>0</u>	<u>0.2691</u>	<u>0.3058</u>	<u>0</u>	<u>0.4176</u>	<u>0.0769</u>	<u>0.3437</u>	<u>0</u>	<u>0.0847</u>	<u>0</u>	<u>0.2667</u>	<u>0.4289</u>	<u>0.4155</u>	<u>0.0966</u>	<u>0.3455</u>	<u>0.2652</u>	<u>0.0912</u>	<u>0.2842</u>
103	country	<u>0.1488</u>	<u>0.1048</u>	<u>0.1707</u>	<u>0.0915</u>	<u>0.106</u>	<u>0.1753</u>	<u>0.1367</u>	<u>0.0869</u>	<u>0.1215</u>	<u>0.1809</u>	<u>0.097</u>	<u>0</u>	<u>0.1069</u>	<u>0.1133</u>	<u>0.1367</u>	<u>0.6103</u>	<u>0.0903</u>	<u>0.1063</u>	<u>0.4827</u>	<u>0.5874</u>
104	demonstrator	<u>0.1719</u>	<u>0</u>	<u>0.1361</u>	<u>0</u>	<u>0</u>	<u>0.1925</u>	<u>0.1164</u>	<u>0</u>	<u>0</u>	<u>0.1967</u>	<u>0</u>	<u>0</u>	<u>0.0682</u>	<u>0</u>	<u>0.1618</u>	<u>0.1141</u>	<u>0</u>	<u>0.0621</u>	<u>0.125</u>	<u>0</u>
105	operation	<u>0.0625</u>	<u>0.3666</u>	<u>0.0696</u>	<u>0.3177</u>	<u>0.3567</u>	<u>0.0711</u>	<u>0.4275</u>	<u>0.2357</u>	<u>0.4094</u>	<u>0.0728</u>	<u>0.3429</u>	<u>0</u>	<u>0.5274</u>	<u>0.3816</u>	<u>0.8589</u>	<u>0.3011</u>	<u>1</u>	<u>0.4729</u>	<u>0.1236</u>	<u>0.3732</u>
106	official	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
107	event	<u>0.0739</u>	<u>0.519</u>	<u>0.0841</u>	<u>0.3633</u>	<u>0.4469</u>	<u>0.0863</u>	<u>0.4518</u>	<u>0.252</u>	<u>0.5492</u>	<u>0.0888</u>	<u>0.4828</u>	<u>0</u>	<u>1</u>	<u>0.4934</u>	<u>0.5492</u>	<u>0.3213</u>	<u>0.3568</u>	<u>0.6311</u>	<u>0.1536</u>	<u>0.3961</u>
108	dissident	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
109	television	<u>0.1434</u>	<u>0</u>	<u>0.2919</u>	<u>0</u>	<u>0</u>	<u>0.1638</u>	<u>0.3363</u>	<u>0</u>	<u>0</u>	<u>0.1679</u>	<u>0</u>	<u>0</u>	<u>0.0821</u>	<u>0</u>	<u>0.1337</u>	<u>0.1341</u>	<u>0</u>	<u>0.0734</u>	<u>0.2642</u>	<u>0</u>
110	interview	<u>0</u>	<u>0.0875</u>	<u>0</u>	<u>0.2608</u>	<u>0.2951</u>	<u>0</u>	<u>0.3334</u>	<u>0.0746</u>	<u>0.302</u>	<u>0</u>	<u>0.082</u>	<u>0</u>	<u>0.2572</u>	<u>0.8242</u>	<u>0.3117</u>	<u>0.093</u>	<u>0.2579</u>	<u>0.2559</u>	<u>0.088</u>	<u>0.2749</u>

111	division	0	0.1079	0	0.2711	0.544	0	0.6091	0.089	0.6121	0	0.0996	0	0.2689	0.5895	0.2886	0.4992	0.268	0.3243	0.4676	0.5738
112	riot	0	0.0788	0	0.2376	0.4184	0	0.1777	0.0683	0.4628	0	0.0743	0	0.2315	0.2793	0.3259	0.0833	0.3055	0.2305	0.0793	0.2493
113	police	0	0.0982	0	0.0865	0.0992	0	0.0966	0.0823	0.1127	0	0.0913	0	0.1001	0.1056	0.1019	0.4762	0.0854	0.0995	0.4473	0.5463
114	police	0	0.0982	0	0.0865	0.0992	0	0.0966	0.0823	0.1127	0	0.0913	0	0.1001	0.1056	0.1019	0.4762	0.0854	0.0995	0.4473	0.5463
115	line	0.1471	0.323	0.3003	0.3261	0.3816	0.1686	0.4115	0.2677	0.4425	0.173	0.2989	0	0.5734	0.4101	0.4971	0.4629	0.4177	0.5418	0.4355	0.523
116	spokesman	0.1719	0	0.1361	0	0	0.1925	0.1164	0	0	0.7664	0	0	0.0682	0	0.1618	0.1141	0	0.0621	0.125	0
117	response	0.0673	0.0991	0.0757	0.2745	0.3127	0.0774	0.505	0.0829	0.3525	0.0795	0.0921	0	0.7996	0.7	0.6169	0.3071	0.2713	0.5176	0.2922	0.3165
118	death	0.0668	0.3829	0.075	0.3298	0.2884	0.0766	0.3349	0.2445	0.3279	0.0787	0.3571	0	0.6311	0.3071	0.5212	0.312	0.248	1	0.0994	0.4572
119	pressure	0.0695	0.4507	0.0784	0.3011	0.2925	0.0803	0.3991	0.4215	0.327	0.0825	0.4231	0	0.665	0.309	0.5587	0.2862	0.2559	0.6183	0.0957	0.2727
120	release	0.1346	0.0897	0.2719	0.2668	0.7281	0.1524	0.4176	0.0763	0.5397	0.1559	0.0839	0	0.4992	0.4289	0.5106	0.1251	0.2638	0.8263	0.2477	0.2816
121	injury	0	0.5268	0	0.3446	0.2755	0	0.4577	0.2552	0.3059	0	0.4896	0	0.4723	0.2901	0.3581	0.3252	0.3154	0.6244	0.0998	0.2579
122	violation	0	0.0875	0	0.2608	0.2951	0	0.1968	0.0746	0.3302	0	0.082	0	0.2572	0.3119	0.3596	0.093	0.3349	0.2559	0.088	0.2749
123	attitude	0	0.2987	0	0.2562	0.2658	0	0.3906	0.2508	0.2993	0	0.278	0	0.2609	0.2793	0.3259	0.242	0.3055	0.3342	0.1127	0.3448
124	lobby	0.1438	0	0.4628	0	0	0.1642	0.244	0	0	0.1684	0	0	0.0824	0	0.134	0.1344	0	0.0736	0.6168	0
125	group	0.0612	0.1433	0.0681	0.1196	0.1456	0.0695	0.1399	0.1118	0.1766	0.0711	0.1291	0	0.1474	0.1598	0.1514	0.5856	0.1176	0.1461	0.5335	0.6208
126	placard	0	0.0817	0	0.0734	0.0824	0	0.3176	0.0704	0.0915	0	0.0769	0	0.083	0.3262	0.3161	0.0866	0.0727	0.0826	0.0822	0.0893
127	bearing	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
128	condition	0	0.6821	0	0.4279	0.213	0	0.5705	0.3152	0.24	0	0.6209	0	0.2147	0.51	0.6036	0.3984	0.1849	0.4994	0.1295	0.2917
129	son	0.2116	0.0965	0.1715	0.1944	0.2226	0.2438	0.4072	0.0811	0.2523	0.2505	0.0898	0	0.2244	0.2367	0.2076	0.1432	0.1921	0.2949	0.1542	0.3706
130	year	0	0.1143	0	0.0987	0.1158	0	0.1122	0.0933	0.1346	0	0.1051	0	0.1169	0.1246	0.1194	0.6291	0.0974	0.4097	0.5961	0.4208
131	demonstration	0	0.1004	0	0.2947	0.3393	0	0.377	0.0839	0.3866	0	0.0932	0	0.2962	0.3892	0.4097	0.1078	0.378	0.2944	0.1011	0.4572
132	anonymity	0	0.3206	0	0.2825	0.0795	0	0.2862	0.21	0.088	0	0.3023	0	0.0801	0.0836	0.2915	0.2693	0.0704	0.312	0.0793	0.0859
133	reign	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
134	hospital	0.1461	0	1	0	0	0.1673	0.2477	0	0	0.1717	0	0	0.0841	0	0.1361	0.1369	0	0.075	0.5538	0
135	protest	0	0.0923	0	0.2737	0.3117	0	0.2076	0.0781	0.3512	0	0.0862	0	0.2719	0.6801	0.2915	0.0986	0.2705	0.2704	0.093	0.5027

E) HSO measure

No	OC	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9	CC10	CC11	CC12	CC13	CC14	CC15	CC16	CC17	CC18	CC19	CC20
		dictator	confusion	hospital	arrest	murder	citizen	rule	legality	move	supporter	immunity	extradition	outcome	request	charge	community	surgery	death	court	government
1	defense	0	0	3	0	0	0	3	0	3	2	0	0	2	3	5	4	3	0	4	4
2	minister	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
3	priest	2	2	0	2	0	2	0	0	0	2	2	0	0	0	0	0	0	3	0	0
4	magistrate	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
5	murder	0	0	0	0	16	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0
6	day	2	0	0	0	0	2	4	0	0	2	0	0	0	0	0	2	0	2	0	0
7	embassy	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
8	police	0	0	2	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	2	3
9	source	3	0	0	0	0	3	3	0	0	3	0	0	3	2	0	2	0	0	2	0
10	insult	0	0	0	0	0	0	3	0	2	0	0	0	0	4	2	0	0	0	0	0
11	team	0	0	4	0	0	0	0	0	0	0	0	0	0	0	0	3	0	0	3	3
12	claim	0	0	0	0	0	0	3	0	3	0	0	0	0	6	5	0	2	0	0	0
13	arrest	0	3	0	16	0	0	2	0	0	0	3	0	0	2	0	0	0	4	0	0
14	warrant	0	0	0	0	0	0	3	0	0	0	0	0	0	4	2	0	0	0	0	0
15	attorney	2	0	0	0	0	2	0	0	0	2	0	0	0	0	0	0	0	0	0	0
16	envoy	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0
17	extradition	0	0	0	0	0	0	0	0	0	0	0	16	0	0	0	0	0	0	0	0
18	request	0	2	0	2	0	0	4	0	2	0	0	0	0	16	4	2	2	0	0	2
19	opinion	0	0	0	0	0	0	4	0	0	0	0	0	0	5	3	2	0	0	0	2
20	term	0	0	0	0	0	0	4	0	0	0	0	0	0	4	4	2	0	4	0	0

F) LESK measure

No	OC	CC1	CC2	CC3	CC4	CC5	CC6	CC7	CC8	CC9	CC10	CC11	CC12	CC13	CC14	CC15	CC16	CC17	CC18	CC19	CC20
1	defense	<u>47</u>	<u>72</u>	<u>68</u>	<u>40</u>	<u>75</u>	<u>73</u>	<u>150</u>	<u>48</u>	<u>133</u>	<u>138</u>	<u>57</u>	<u>41</u>	<u>135</u>	<u>52</u>	<u>78</u>	<u>93</u>	<u>186</u>	<u>66</u>	<u>247</u>	<u>195</u>
2	minister	<u>56</u>	<u>48</u>	<u>56</u>	<u>21</u>	<u>60</u>	<u>95</u>	<u>64</u>	<u>22</u>	<u>58</u>	<u>120</u>	<u>34</u>	<u>29</u>	<u>52</u>	<u>43</u>	<u>62</u>	<u>58</u>	<u>78</u>	<u>43</u>	<u>93</u>	<u>109</u>
3	priest	<u>69</u>	<u>53</u>	<u>75</u>	<u>24</u>	<u>93</u>	<u>113</u>	<u>142</u>	<u>33</u>	<u>118</u>	<u>173</u>	<u>53</u>	<u>44</u>	<u>121</u>	<u>75</u>	<u>88</u>	<u>121</u>	<u>165</u>	<u>80</u>	<u>195</u>	<u>179</u>
4	magistrate	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>
5	murder	<u>54</u>	<u>57</u>	<u>55</u>	<u>29</u>	<u>1324</u>	<u>71</u>	<u>86</u>	<u>31</u>	<u>106</u>	<u>105</u>	<u>39</u>	<u>39</u>	<u>85</u>	<u>56</u>	<u>62</u>	<u>73</u>	<u>136</u>	<u>58</u>	<u>102</u>	<u>115</u>
6	day	<u>54</u>	<u>48</u>	<u>65</u>	<u>20</u>	<u>81</u>	<u>79</u>	<u>186</u>	<u>40</u>	<u>174</u>	<u>145</u>	<u>58</u>	<u>27</u>	<u>177</u>	<u>67</u>	<u>96</u>	<u>103</u>	<u>262</u>	<u>71</u>	<u>240</u>	<u>175</u>
7	embassy	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>
8	police	<u>43</u>	<u>48</u>	<u>56</u>	<u>24</u>	<u>56</u>	<u>70</u>	<u>85</u>	<u>33</u>	<u>69</u>	<u>95</u>	<u>40</u>	<u>31</u>	<u>69</u>	<u>51</u>	<u>66</u>	<u>96</u>	<u>90</u>	<u>54</u>	<u>123</u>	<u>127</u>
9	source	<u>46</u>	<u>40</u>	<u>50</u>	<u>23</u>	<u>50</u>	<u>78</u>	<u>67</u>	<u>26</u>	<u>72</u>	<u>102</u>	<u>34</u>	<u>29</u>	<u>70</u>	<u>46</u>	<u>63</u>	<u>57</u>	<u>87</u>	<u>58</u>	<u>70</u>	<u>90</u>
10	insult	<u>20</u>	<u>44</u>	<u>29</u>	<u>34</u>	<u>38</u>	<u>41</u>	<u>39</u>	<u>28</u>	<u>51</u>	<u>38</u>	<u>24</u>	<u>23</u>	<u>38</u>	<u>37</u>	<u>44</u>	<u>29</u>	<u>54</u>	<u>37</u>	<u>45</u>	<u>45</u>
11	team	<u>52</u>	<u>56</u>	<u>74</u>	<u>19</u>	<u>93</u>	<u>96</u>	<u>141</u>	<u>25</u>	<u>127</u>	<u>167</u>	<u>67</u>	<u>38</u>	<u>147</u>	<u>70</u>	<u>96</u>	<u>131</u>	<u>213</u>	<u>68</u>	<u>163</u>	<u>175</u>
12	claim	<u>22</u>	<u>39</u>	<u>31</u>	<u>23</u>	<u>40</u>	<u>49</u>	<u>52</u>	<u>37</u>	<u>47</u>	<u>45</u>	<u>30</u>	<u>26</u>	<u>41</u>	<u>31</u>	<u>196</u>	<u>39</u>	<u>56</u>	<u>38</u>	<u>57</u>	<u>64</u>
13	arrest	<u>10</u>	<u>35</u>	<u>14</u>	<u>411</u>	<u>29</u>	<u>23</u>	<u>40</u>	<u>14</u>	<u>49</u>	<u>21</u>	<u>25</u>	<u>18</u>	<u>25</u>	<u>24</u>	<u>29</u>	<u>20</u>	<u>36</u>	<u>39</u>	<u>21</u>	<u>44</u>
14	warrant	<u>48</u>	<u>45</u>	<u>56</u>	<u>15</u>	<u>73</u>	<u>71</u>	<u>79</u>	<u>30</u>	<u>76</u>	<u>100</u>	<u>37</u>	<u>28</u>	<u>76</u>	<u>50</u>	<u>61</u>	<u>74</u>	<u>112</u>	<u>62</u>	<u>135</u>	<u>100</u>
15	attorney	<u>87</u>	<u>60</u>	<u>71</u>	<u>28</u>	<u>99</u>	<u>104</u>	<u>125</u>	<u>45</u>	<u>126</u>	<u>159</u>	<u>56</u>	<u>41</u>	<u>126</u>	<u>70</u>	<u>87</u>	<u>119</u>	<u>168</u>	<u>86</u>	<u>225</u>	<u>184</u>
16	envoy	<u>29</u>	<u>26</u>	<u>22</u>	<u>12</u>	<u>31</u>	<u>49</u>	<u>32</u>	<u>13</u>	<u>24</u>	<u>64</u>	<u>15</u>	<u>18</u>	<u>17</u>	<u>19</u>	<u>35</u>	<u>24</u>	<u>27</u>	<u>19</u>	<u>27</u>	<u>34</u>
17	extradition	<u>17</u>	<u>32</u>	<u>25</u>	<u>18</u>	<u>39</u>	<u>52</u>	<u>36</u>	<u>21</u>	<u>37</u>	<u>45</u>	<u>21</u>	<u>650</u>	<u>38</u>	<u>27</u>	<u>35</u>	<u>31</u>	<u>53</u>	<u>39</u>	<u>41</u>	<u>48</u>
18	request	<u>31</u>	<u>36</u>	<u>48</u>	<u>24</u>	<u>56</u>	<u>53</u>	<u>64</u>	<u>31</u>	<u>73</u>	<u>81</u>	<u>35</u>	<u>27</u>	<u>67</u>	<u>1494</u>	<u>75</u>	<u>48</u>	<u>104</u>	<u>50</u>	<u>88</u>	<u>79</u>
19	opinion	<u>43</u>	<u>54</u>	<u>47</u>	<u>22</u>	<u>58</u>	<u>58</u>	<u>84</u>	<u>32</u>	<u>80</u>	<u>73</u>	<u>52</u>	<u>31</u>	<u>97</u>	<u>130</u>	<u>69</u>	<u>57</u>	<u>100</u>	<u>61</u>	<u>95</u>	<u>108</u>
20	term	<u>50</u>	<u>62</u>	<u>68</u>	<u>22</u>	<u>90</u>	<u>88</u>	<u>155</u>	<u>31</u>	<u>129</u>	<u>123</u>	<u>49</u>	<u>41</u>	<u>136</u>	<u>59</u>	<u>89</u>	<u>104</u>	<u>173</u>	<u>79</u>	<u>151</u>	<u>157</u>
21	rally	<u>21</u>	<u>23</u>	<u>23</u>	<u>15</u>	<u>26</u>	<u>32</u>	<u>42</u>	<u>16</u>	<u>36</u>	<u>29</u>	<u>17</u>	<u>16</u>	<u>21</u>	<u>20</u>	<u>27</u>	<u>110</u>	<u>41</u>	<u>18</u>	<u>53</u>	<u>48</u>
22	week	<u>32</u>	<u>45</u>	<u>49</u>	<u>19</u>	<u>51</u>	<u>55</u>	<u>79</u>	<u>25</u>	<u>58</u>	<u>62</u>	<u>38</u>	<u>30</u>	<u>56</u>	<u>43</u>	<u>55</u>	<u>56</u>	<u>80</u>	<u>51</u>	<u>88</u>	<u>75</u>
23	boss	<u>63</u>	<u>26</u>	<u>30</u>	<u>11</u>	<u>32</u>	<u>68</u>	<u>37</u>	<u>13</u>	<u>29</u>	<u>95</u>	<u>16</u>	<u>21</u>	<u>29</u>	<u>26</u>	<u>39</u>	<u>31</u>	<u>42</u>	<u>25</u>	<u>45</u>	<u>46</u>
24	government	<u>81</u>	<u>71</u>	<u>86</u>	<u>44</u>	<u>115</u>	<u>121</u>	<u>171</u>	<u>39</u>	<u>152</u>	<u>170</u>	<u>70</u>	<u>48</u>	<u>163</u>	<u>79</u>	<u>115</u>	<u>152</u>	<u>204</u>	<u>92</u>	<u>342</u>	<u>3878</u>
25	official	<u>78</u>	<u>48</u>	<u>77</u>	<u>19</u>	<u>82</u>	<u>125</u>	<u>162</u>	<u>28</u>	<u>181</u>	<u>254</u>	<u>60</u>	<u>35</u>	<u>202</u>	<u>60</u>	<u>110</u>	<u>111</u>	<u>293</u>	<u>75</u>	<u>247</u>	<u>207</u>
26	post	<u>55</u>	<u>61</u>	<u>65</u>	<u>41</u>	<u>94</u>	<u>84</u>	<u>137</u>	<u>28</u>	<u>184</u>	<u>144</u>	<u>54</u>	<u>38</u>	<u>160</u>	<u>67</u>	<u>96</u>	<u>95</u>	<u>279</u>	<u>71</u>	<u>155</u>	<u>154</u>
27	crime	<u>59</u>	<u>56</u>	<u>59</u>	<u>48</u>	<u>118</u>	<u>83</u>	<u>113</u>	<u>44</u>	<u>129</u>	<u>133</u>	<u>51</u>	<u>41</u>	<u>116</u>	<u>68</u>	<u>83</u>	<u>88</u>	<u>179</u>	<u>69</u>	<u>152</u>	<u>147</u>
28	prosecution	<u>42</u>	<u>58</u>	<u>67</u>	<u>26</u>	<u>88</u>	<u>80</u>	<u>72</u>	<u>39</u>	<u>70</u>	<u>87</u>	<u>37</u>	<u>47</u>	<u>68</u>	<u>55</u>	<u>77</u>	<u>73</u>	<u>93</u>	<u>59</u>	<u>112</u>	<u>97</u>
29	institution	<u>27</u>	<u>51</u>	<u>137</u>	<u>64</u>	<u>46</u>	<u>55</u>	<u>67</u>	<u>22</u>	<u>77</u>	<u>90</u>	<u>33</u>	<u>27</u>	<u>64</u>	<u>41</u>	<u>60</u>	<u>76</u>	<u>93</u>	<u>57</u>	<u>113</u>	<u>104</u>
30	power	<u>53</u>	<u>64</u>	<u>52</u>	<u>26</u>	<u>91</u>	<u>72</u>	<u>112</u>	<u>54</u>	<u>145</u>	<u>130</u>	<u>43</u>	<u>36</u>	<u>125</u>	<u>68</u>	<u>78</u>	<u>76</u>	<u>163</u>	<u>137</u>	<u>131</u>	<u>138</u>
31	abuse	<u>28</u>	<u>28</u>	<u>38</u>	<u>28</u>	<u>40</u>	<u>38</u>	<u>53</u>	<u>22</u>	<u>54</u>	<u>47</u>	<u>22</u>	<u>20</u>	<u>37</u>	<u>36</u>	<u>40</u>	<u>37</u>	<u>69</u>	<u>41</u>	<u>51</u>	<u>52</u>
32	constitution	<u>42</u>	<u>47</u>	<u>50</u>	<u>63</u>	<u>87</u>	<u>64</u>	<u>100</u>	<u>25</u>	<u>116</u>	<u>90</u>	<u>43</u>	<u>31</u>	<u>102</u>	<u>50</u>	<u>60</u>	<u>73</u>	<u>129</u>	<u>59</u>	<u>153</u>	<u>137</u>

33	statement	<u>52</u>	<u>62</u>	<u>69</u>	<u>25</u>	<u>80</u>	<u>86</u>	<u>165</u>	<u>34</u>	<u>170</u>	<u>161</u>	<u>77</u>	<u>45</u>	<u>208</u>	<u>150</u>	<u>409</u>	<u>100</u>	<u>298</u>	<u>85</u>	<u>191</u>	<u>176</u>
34	word	<u>60</u>	<u>64</u>	<u>76</u>	<u>30</u>	<u>102</u>	<u>99</u>	<u>237</u>	<u>42</u>	<u>233</u>	<u>204</u>	<u>89</u>	<u>42</u>	<u>247</u>	<u>96</u>	<u>126</u>	<u>151</u>	<u>393</u>	<u>108</u>	<u>238</u>	<u>192</u>
35	military	<u>20</u>	<u>29</u>	<u>29</u>	<u>12</u>	<u>24</u>	<u>38</u>	<u>37</u>	<u>21</u>	<u>34</u>	<u>45</u>	<u>19</u>	<u>17</u>	<u>45</u>	<u>27</u>	<u>32</u>	<u>27</u>	<u>61</u>	<u>29</u>	<u>51</u>	<u>42</u>
36	support	<u>46</u>	<u>52</u>	<u>75</u>	<u>43</u>	<u>81</u>	<u>92</u>	<u>177</u>	<u>33</u>	<u>224</u>	<u>238</u>	<u>54</u>	<u>43</u>	<u>201</u>	<u>68</u>	<u>117</u>	<u>93</u>	<u>345</u>	<u>77</u>	<u>186</u>	<u>155</u>
37	portrait	<u>28</u>	<u>43</u>	<u>34</u>	<u>15</u>	<u>48</u>	<u>57</u>	<u>45</u>	<u>18</u>	<u>42</u>	<u>55</u>	<u>21</u>	<u>29</u>	<u>36</u>	<u>30</u>	<u>63</u>	<u>38</u>	<u>54</u>	<u>31</u>	<u>48</u>	<u>52</u>
38	extradition	<u>17</u>	<u>32</u>	<u>25</u>	<u>18</u>	<u>39</u>	<u>52</u>	<u>36</u>	<u>21</u>	<u>37</u>	<u>45</u>	<u>21</u>	<u>650</u>	<u>38</u>	<u>27</u>	<u>35</u>	<u>31</u>	<u>53</u>	<u>39</u>	<u>41</u>	<u>48</u>
39	law	<u>72</u>	<u>77</u>	<u>85</u>	<u>25</u>	<u>106</u>	<u>104</u>	<u>788</u>	<u>43</u>	<u>273</u>	<u>214</u>	<u>91</u>	<u>38</u>	<u>295</u>	<u>88</u>	<u>147</u>	<u>136</u>	<u>520</u>	<u>102</u>	<u>266</u>	<u>233</u>
40	protester	<u>34</u>	<u>26</u>	<u>27</u>	<u>12</u>	<u>45</u>	<u>58</u>	<u>37</u>	<u>13</u>	<u>40</u>	<u>72</u>	<u>22</u>	<u>15</u>	<u>33</u>	<u>27</u>	<u>32</u>	<u>38</u>	<u>47</u>	<u>23</u>	<u>49</u>	<u>47</u>
41	arrest	<u>10</u>	<u>35</u>	<u>14</u>	<u>411</u>	<u>29</u>	<u>23</u>	<u>40</u>	<u>14</u>	<u>49</u>	<u>21</u>	<u>25</u>	<u>18</u>	<u>25</u>	<u>24</u>	<u>29</u>	<u>20</u>	<u>36</u>	<u>39</u>	<u>21</u>	<u>44</u>
42	opponent	<u>43</u>	<u>24</u>	<u>29</u>	<u>9</u>	<u>49</u>	<u>52</u>	<u>36</u>	<u>15</u>	<u>32</u>	<u>76</u>	<u>26</u>	<u>17</u>	<u>38</u>	<u>21</u>	<u>28</u>	<u>33</u>	<u>57</u>	<u>21</u>	<u>47</u>	<u>55</u>
43	rightist	<u>38</u>	<u>36</u>	<u>33</u>	<u>11</u>	<u>41</u>	<u>73</u>	<u>46</u>	<u>15</u>	<u>40</u>	<u>88</u>	<u>25</u>	<u>22</u>	<u>40</u>	<u>26</u>	<u>41</u>	<u>40</u>	<u>55</u>	<u>28</u>	<u>49</u>	<u>70</u>
44	politician	<u>102</u>	<u>52</u>	<u>73</u>	<u>16</u>	<u>86</u>	<u>123</u>	<u>170</u>	<u>23</u>	<u>174</u>	<u>219</u>	<u>48</u>	<u>28</u>	<u>205</u>	<u>63</u>	<u>98</u>	<u>108</u>	<u>276</u>	<u>63</u>	<u>243</u>	<u>188</u>
45	time	<u>42</u>	<u>46</u>	<u>40</u>	<u>23</u>	<u>62</u>	<u>60</u>	<u>111</u>	<u>41</u>	<u>106</u>	<u>103</u>	<u>68</u>	<u>27</u>	<u>113</u>	<u>52</u>	<u>71</u>	<u>78</u>	<u>149</u>	<u>59</u>	<u>138</u>	<u>125</u>
46	amnesty	<u>1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>
47	month	<u>40</u>	<u>49</u>	<u>48</u>	<u>23</u>	<u>54</u>	<u>64</u>	<u>87</u>	<u>30</u>	<u>61</u>	<u>72</u>	<u>41</u>	<u>35</u>	<u>61</u>	<u>39</u>	<u>64</u>	<u>62</u>	<u>104</u>	<u>59</u>	<u>79</u>	<u>91</u>
48	father	<u>66</u>	<u>38</u>	<u>53</u>	<u>24</u>	<u>69</u>	<u>73</u>	<u>126</u>	<u>28</u>	<u>120</u>	<u>131</u>	<u>41</u>	<u>27</u>	<u>129</u>	<u>51</u>	<u>65</u>	<u>110</u>	<u>167</u>	<u>57</u>	<u>204</u>	<u>165</u>
49	immunity	<u>31</u>	<u>34</u>	<u>38</u>	<u>25</u>	<u>39</u>	<u>50</u>	<u>58</u>	<u>29</u>	<u>50</u>	<u>61</u>	<u>2581</u>	<u>21</u>	<u>70</u>	<u>35</u>	<u>45</u>	<u>42</u>	<u>108</u>	<u>41</u>	<u>71</u>	<u>70</u>
50	caption	<u>32</u>	<u>39</u>	<u>44</u>	<u>17</u>	<u>46</u>	<u>46</u>	<u>70</u>	<u>20</u>	<u>56</u>	<u>55</u>	<u>32</u>	<u>27</u>	<u>53</u>	<u>37</u>	<u>42</u>	<u>54</u>	<u>71</u>	<u>38</u>	<u>62</u>	<u>71</u>
51	capital	<u>41</u>	<u>59</u>	<u>58</u>	<u>24</u>	<u>67</u>	<u>72</u>	<u>75</u>	<u>35</u>	<u>82</u>	<u>75</u>	<u>46</u>	<u>36</u>	<u>76</u>	<u>51</u>	<u>60</u>	<u>65</u>	<u>99</u>	<u>54</u>	<u>99</u>	<u>107</u>
52	publicity	<u>42</u>	<u>61</u>	<u>53</u>	<u>21</u>	<u>53</u>	<u>72</u>	<u>71</u>	<u>31</u>	<u>61</u>	<u>83</u>	<u>39</u>	<u>33</u>	<u>82</u>	<u>120</u>	<u>70</u>	<u>60</u>	<u>88</u>	<u>59</u>	<u>74</u>	<u>83</u>
53	patient	<u>68</u>	<u>57</u>	<u>70</u>	<u>20</u>	<u>88</u>	<u>141</u>	<u>87</u>	<u>17</u>	<u>83</u>	<u>171</u>	<u>52</u>	<u>35</u>	<u>82</u>	<u>52</u>	<u>68</u>	<u>83</u>	<u>125</u>	<u>60</u>	<u>107</u>	<u>123</u>
54	arrest	<u>10</u>	<u>35</u>	<u>14</u>	<u>411</u>	<u>29</u>	<u>23</u>	<u>40</u>	<u>14</u>	<u>49</u>	<u>21</u>	<u>25</u>	<u>18</u>	<u>25</u>	<u>24</u>	<u>29</u>	<u>20</u>	<u>36</u>	<u>39</u>	<u>21</u>	<u>44</u>
55	order	<u>54</u>	<u>62</u>	<u>77</u>	<u>52</u>	<u>86</u>	<u>94</u>	<u>180</u>	<u>37</u>	<u>131</u>	<u>139</u>	<u>63</u>	<u>39</u>	<u>126</u>	<u>136</u>	<u>105</u>	<u>150</u>	<u>179</u>	<u>138</u>	<u>179</u>	<u>154</u>
56	advice	<u>28</u>	<u>29</u>	<u>28</u>	<u>11</u>	<u>24</u>	<u>39</u>	<u>50</u>	<u>14</u>	<u>42</u>	<u>44</u>	<u>23</u>	<u>15</u>	<u>41</u>	<u>34</u>	<u>43</u>	<u>31</u>	<u>60</u>	<u>32</u>	<u>40</u>	<u>46</u>
57	government	<u>81</u>	<u>71</u>	<u>86</u>	<u>44</u>	<u>115</u>	<u>121</u>	<u>171</u>	<u>39</u>	<u>152</u>	<u>170</u>	<u>70</u>	<u>48</u>	<u>163</u>	<u>79</u>	<u>115</u>	<u>152</u>	<u>204</u>	<u>92</u>	<u>342</u>	<u>3878</u>
58	lawmaker	<u>60</u>	<u>28</u>	<u>32</u>	<u>9</u>	<u>32</u>	<u>59</u>	<u>39</u>	<u>18</u>	<u>31</u>	<u>78</u>	<u>22</u>	<u>18</u>	<u>25</u>	<u>21</u>	<u>41</u>	<u>31</u>	<u>45</u>	<u>26</u>	<u>48</u>	<u>45</u>
59	bed	<u>62</u>	<u>77</u>	<u>104</u>	<u>27</u>	<u>97</u>	<u>102</u>	<u>133</u>	<u>36</u>	<u>133</u>	<u>156</u>	<u>68</u>	<u>47</u>	<u>140</u>	<u>81</u>	<u>120</u>	<u>105</u>	<u>219</u>	<u>80</u>	<u>155</u>	<u>158</u>
60	result	<u>54</u>	<u>54</u>	<u>64</u>	<u>26</u>	<u>85</u>	<u>88</u>	<u>199</u>	<u>28</u>	<u>195</u>	<u>173</u>	<u>70</u>	<u>38</u>	<u>11245</u>	<u>67</u>	<u>104</u>	<u>105</u>	<u>256</u>	<u>83</u>	<u>186</u>	<u>163</u>
61	water	<u>87</u>	<u>86</u>	<u>91</u>	<u>26</u>	<u>106</u>	<u>111</u>	<u>183</u>	<u>37</u>	<u>202</u>	<u>166</u>	<u>95</u>	<u>47</u>	<u>212</u>	<u>72</u>	<u>119</u>	<u>123</u>	<u>313</u>	<u>100</u>	<u>206</u>	<u>188</u>
62	cannon	<u>25</u>	<u>35</u>	<u>37</u>	<u>28</u>	<u>44</u>	<u>54</u>	<u>71</u>	<u>26</u>	<u>59</u>	<u>66</u>	<u>50</u>	<u>33</u>	<u>60</u>	<u>42</u>	<u>45</u>	<u>53</u>	<u>116</u>	<u>58</u>	<u>72</u>	<u>77</u>

63	decade	<u>20</u>	<u>32</u>	<u>21</u>	<u>15</u>	<u>36</u>	<u>34</u>	<u>62</u>	<u>21</u>	<u>55</u>	<u>48</u>	<u>26</u>	<u>20</u>	<u>48</u>	<u>29</u>	<u>31</u>	<u>38</u>	<u>82</u>	<u>29</u>	<u>61</u>	<u>57</u>
64	application	<u>40</u>	<u>46</u>	<u>60</u>	<u>48</u>	<u>89</u>	<u>65</u>	<u>111</u>	<u>26</u>	<u>156</u>	<u>110</u>	<u>55</u>	<u>31</u>	<u>111</u>	<u>347</u>	<u>74</u>	<u>72</u>	<u>195</u>	<u>64</u>	<u>119</u>	<u>130</u>
65	regime	<u>81</u>	<u>71</u>	<u>86</u>	<u>35</u>	<u>115</u>	<u>121</u>	<u>171</u>	<u>39</u>	<u>152</u>	<u>170</u>	<u>70</u>	<u>48</u>	<u>163</u>	<u>79</u>	<u>115</u>	<u>152</u>	<u>204</u>	<u>92</u>	<u>342</u>	<u>3878</u>
66	delegation	<u>18</u>	<u>21</u>	<u>17</u>	<u>24</u>	<u>27</u>	<u>26</u>	<u>24</u>	<u>20</u>	<u>39</u>	<u>30</u>	<u>19</u>	<u>14</u>	<u>17</u>	<u>27</u>	<u>28</u>	<u>64</u>	<u>40</u>	<u>23</u>	<u>39</u>	<u>45</u>
67	place	<u>58</u>	<u>70</u>	<u>68</u>	<u>41</u>	<u>101</u>	<u>95</u>	<u>162</u>	<u>42</u>	<u>211</u>	<u>183</u>	<u>65</u>	<u>41</u>	<u>197</u>	<u>84</u>	<u>123</u>	<u>105</u>	<u>279</u>	<u>87</u>	<u>173</u>	<u>173</u>
68	politician	<u>102</u>	<u>52</u>	<u>73</u>	<u>16</u>	<u>86</u>	<u>123</u>	<u>170</u>	<u>23</u>	<u>174</u>	<u>219</u>	<u>48</u>	<u>28</u>	<u>205</u>	<u>63</u>	<u>98</u>	<u>108</u>	<u>276</u>	<u>63</u>	<u>243</u>	<u>188</u>
69	scene	<u>48</u>	<u>64</u>	<u>68</u>	<u>24</u>	<u>70</u>	<u>78</u>	<u>88</u>	<u>29</u>	<u>89</u>	<u>86</u>	<u>51</u>	<u>38</u>	<u>80</u>	<u>50</u>	<u>73</u>	<u>74</u>	<u>119</u>	<u>63</u>	<u>92</u>	<u>109</u>
70	decision	<u>27</u>	<u>46</u>	<u>37</u>	<u>61</u>	<u>76</u>	<u>49</u>	<u>51</u>	<u>29</u>	<u>184</u>	<u>60</u>	<u>32</u>	<u>27</u>	<u>143</u>	<u>56</u>	<u>58</u>	<u>44</u>	<u>106</u>	<u>59</u>	<u>64</u>	<u>78</u>
71	judge	<u>72</u>	<u>47</u>	<u>59</u>	<u>14</u>	<u>78</u>	<u>102</u>	<u>81</u>	<u>27</u>	<u>80</u>	<u>134</u>	<u>45</u>	<u>29</u>	<u>86</u>	<u>48</u>	<u>72</u>	<u>91</u>	<u>124</u>	<u>54</u>	<u>154</u>	<u>126</u>
72	evening	<u>22</u>	<u>29</u>	<u>26</u>	<u>23</u>	<u>37</u>	<u>39</u>	<u>56</u>	<u>20</u>	<u>48</u>	<u>50</u>	<u>34</u>	<u>26</u>	<u>48</u>	<u>34</u>	<u>42</u>	<u>51</u>	<u>67</u>	<u>41</u>	<u>55</u>	<u>68</u>
73	dictator	<u>2595</u>	<u>35</u>	<u>44</u>	<u>10</u>	<u>54</u>	<u>66</u>	<u>62</u>	<u>26</u>	<u>48</u>	<u>96</u>	<u>31</u>	<u>17</u>	<u>54</u>	<u>31</u>	<u>40</u>	<u>50</u>	<u>73</u>	<u>32</u>	<u>70</u>	<u>81</u>
74	iron	<u>55</u>	<u>63</u>	<u>75</u>	<u>26</u>	<u>68</u>	<u>79</u>	<u>114</u>	<u>30</u>	<u>89</u>	<u>89</u>	<u>75</u>	<u>31</u>	<u>110</u>	<u>57</u>	<u>74</u>	<u>79</u>	<u>156</u>	<u>69</u>	<u>135</u>	<u>134</u>
75	fist	<u>10</u>	<u>13</u>	<u>15</u>	<u>10</u>	<u>14</u>	<u>18</u>	<u>21</u>	<u>8</u>	<u>29</u>	<u>21</u>	<u>11</u>	<u>10</u>	<u>20</u>	<u>17</u>	<u>19</u>	<u>20</u>	<u>31</u>	<u>16</u>	<u>24</u>	<u>29</u>
76	visitor	<u>31</u>	<u>19</u>	<u>26</u>	<u>6</u>	<u>28</u>	<u>48</u>	<u>27</u>	<u>10</u>	<u>20</u>	<u>61</u>	<u>15</u>	<u>15</u>	<u>22</u>	<u>18</u>	<u>27</u>	<u>26</u>	<u>35</u>	<u>17</u>	<u>36</u>	<u>40</u>
77	diplomat	<u>96</u>	<u>42</u>	<u>53</u>	<u>16</u>	<u>74</u>	<u>83</u>	<u>144</u>	<u>23</u>	<u>137</u>	<u>158</u>	<u>39</u>	<u>34</u>	<u>151</u>	<u>45</u>	<u>71</u>	<u>103</u>	<u>224</u>	<u>62</u>	<u>230</u>	<u>179</u>
78	policy	<u>43</u>	<u>48</u>	<u>66</u>	<u>24</u>	<u>73</u>	<u>71</u>	<u>94</u>	<u>26</u>	<u>89</u>	<u>92</u>	<u>38</u>	<u>37</u>	<u>83</u>	<u>53</u>	<u>65</u>	<u>83</u>	<u>117</u>	<u>62</u>	<u>116</u>	<u>127</u>
79	trial	<u>74</u>	<u>90</u>	<u>84</u>	<u>33</u>	<u>120</u>	<u>107</u>	<u>138</u>	<u>58</u>	<u>123</u>	<u>129</u>	<u>74</u>	<u>58</u>	<u>128</u>	<u>82</u>	<u>98</u>	<u>95</u>	<u>177</u>	<u>89</u>	<u>176</u>	<u>165</u>
80	black	<u>24</u>	<u>37</u>	<u>31</u>	<u>15</u>	<u>34</u>	<u>44</u>	<u>49</u>	<u>86</u>	<u>43</u>	<u>55</u>	<u>25</u>	<u>22</u>	<u>38</u>	<u>32</u>	<u>35</u>	<u>51</u>	<u>67</u>	<u>36</u>	<u>55</u>	<u>61</u>
81	police	<u>43</u>	<u>48</u>	<u>56</u>	<u>24</u>	<u>56</u>	<u>70</u>	<u>85</u>	<u>33</u>	<u>69</u>	<u>95</u>	<u>40</u>	<u>31</u>	<u>69</u>	<u>51</u>	<u>66</u>	<u>96</u>	<u>90</u>	<u>54</u>	<u>123</u>	<u>127</u>
82	guard	<u>57</u>	<u>37</u>	<u>44</u>	<u>16</u>	<u>48</u>	<u>95</u>	<u>49</u>	<u>18</u>	<u>42</u>	<u>122</u>	<u>30</u>	<u>22</u>	<u>46</u>	<u>34</u>	<u>181</u>	<u>49</u>	<u>69</u>	<u>33</u>	<u>60</u>	<u>79</u>
83	stuff	<u>62</u>	<u>73</u>	<u>75</u>	<u>29</u>	<u>104</u>	<u>93</u>	<u>177</u>	<u>38</u>	<u>184</u>	<u>172</u>	<u>74</u>	<u>45</u>	<u>194</u>	<u>77</u>	<u>119</u>	<u>119</u>	<u>337</u>	<u>87</u>	<u>201</u>	<u>173</u>
84	idea	<u>37</u>	<u>51</u>	<u>45</u>	<u>24</u>	<u>54</u>	<u>60</u>	<u>182</u>	<u>32</u>	<u>89</u>	<u>97</u>	<u>48</u>	<u>28</u>	<u>109</u>	<u>60</u>	<u>84</u>	<u>65</u>	<u>128</u>	<u>60</u>	<u>99</u>	<u>108</u>
85	business	<u>53</u>	<u>60</u>	<u>76</u>	<u>28</u>	<u>88</u>	<u>76</u>	<u>104</u>	<u>34</u>	<u>105</u>	<u>108</u>	<u>51</u>	<u>37</u>	<u>105</u>	<u>66</u>	<u>100</u>	<u>92</u>	<u>136</u>	<u>61</u>	<u>135</u>	<u>172</u>
86	army	<u>49</u>	<u>53</u>	<u>70</u>	<u>24</u>	<u>56</u>	<u>65</u>	<u>92</u>	<u>27</u>	<u>86</u>	<u>121</u>	<u>48</u>	<u>36</u>	<u>78</u>	<u>52</u>	<u>67</u>	<u>81</u>	<u>114</u>	<u>59</u>	<u>196</u>	<u>170</u>
87	people	<u>68</u>	<u>56</u>	<u>71</u>	<u>28</u>	<u>108</u>	<u>321</u>	<u>169</u>	<u>34</u>	<u>158</u>	<u>162</u>	<u>54</u>	<u>52</u>	<u>178</u>	<u>77</u>	<u>97</u>	<u>186</u>	<u>228</u>	<u>67</u>	<u>200</u>	<u>209</u>
88	administration	<u>59</u>	<u>66</u>	<u>74</u>	<u>48</u>	<u>82</u>	<u>99</u>	<u>111</u>	<u>46</u>	<u>96</u>	<u>114</u>	<u>53</u>	<u>59</u>	<u>95</u>	<u>68</u>	<u>79</u>	<u>120</u>	<u>128</u>	<u>75</u>	<u>196</u>	<u>719</u>
89	government	<u>81</u>	<u>71</u>	<u>86</u>	<u>44</u>	<u>115</u>	<u>121</u>	<u>171</u>	<u>39</u>	<u>152</u>	<u>170</u>	<u>70</u>	<u>48</u>	<u>163</u>	<u>79</u>	<u>115</u>	<u>152</u>	<u>204</u>	<u>92</u>	<u>342</u>	<u>3878</u>
90	report	<u>42</u>	<u>44</u>	<u>49</u>	<u>45</u>	<u>79</u>	<u>61</u>	<u>91</u>	<u>28</u>	<u>84</u>	<u>88</u>	<u>49</u>	<u>34</u>	<u>93</u>	<u>61</u>	<u>73</u>	<u>76</u>	<u>135</u>	<u>64</u>	<u>102</u>	<u>126</u>
91	disappearance	<u>15</u>	<u>29</u>	<u>26</u>	<u>38</u>	<u>33</u>	<u>36</u>	<u>41</u>	<u>16</u>	<u>46</u>	<u>38</u>	<u>23</u>	<u>22</u>	<u>41</u>	<u>28</u>	<u>29</u>	<u>29</u>	<u>45</u>	<u>55</u>	<u>43</u>	<u>47</u>
92	passport	<u>24</u>	<u>29</u>	<u>29</u>	<u>15</u>	<u>32</u>	<u>47</u>	<u>42</u>	<u>19</u>	<u>36</u>	<u>41</u>	<u>29</u>	<u>21</u>	<u>38</u>	<u>27</u>	<u>40</u>	<u>33</u>	<u>52</u>	<u>27</u>	<u>52</u>	<u>56</u>
93	family	<u>60</u>	<u>51</u>	<u>67</u>	<u>17</u>	<u>85</u>	<u>79</u>	<u>123</u>	<u>29</u>	<u>124</u>	<u>117</u>	<u>46</u>	<u>33</u>	<u>132</u>	<u>49</u>	<u>79</u>	<u>115</u>	<u>178</u>	<u>72</u>	<u>195</u>	<u>135</u>

94	total	8	11	10	9	12	15	20	12	14	16	9	12	15	10	17	11	22	15	18	18
95	police	43	48	56	24	56	70	85	33	69	95	40	31	69	51	66	96	90	54	123	127
96	gas	62	67	77	30	93	102	195	36	191	181	78	34	224	77	120	120	338	85	225	184
97	allegation	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
98	news	28	36	35	24	33	42	57	30	53	53	29	20	56	28	53	45	80	41	59	70
99	court	70	60	109	21	102	120	186	47	164	197	69	41	186	88	115	156	250	85	7009	342
100	strongman	233	19	18	11	20	29	26	22	19	31	15	13	23	16	20	18	28	17	27	34
101	rights	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1	-1
102	abuse	28	28	38	28	40	38	53	22	54	47	22	20	37	36	40	37	69	41	51	52
103	country	83	82	81	33	108	116	196	37	246	196	75	50	254	76	113	145	434	89	267	218
104	demonstrator	34	23	27	10	32	33	31	13	28	47	21	15	24	20	28	38	40	15	48	40
105	operation	73	74	103	80	136	115	236	41	346	212	108	53	256	104	149	144	18283	107	250	204
106	official	20	19	21	8	24	32	27	33	28	46	23	17	29	24	24	19	48	19	40	40
107	event	54	55	64	25	85	88	199	28	195	173	70	39	11245	67	104	105	256	88	186	163
108	dissident	9	17	16	5	20	22	21	9	15	19	7	13	14	10	26	14	28	13	21	21
109	television	52	59	73	20	66	87	124	34	84	97	73	33	99	59	88	82	164	69	129	146
110	interview	24	38	31	15	35	46	38	20	39	46	25	23	31	26	39	32	47	31	43	45
111	division	46	52	72	61	86	65	168	30	120	107	45	39	128	59	75	123	193	77	148	245
112	riot	31	106	27	26	46	52	30	18	41	59	29	23	37	32	41	40	51	26	45	41
113	police	43	48	56	24	56	70	85	33	69	95	40	31	69	51	66	96	90	54	123	127
114	police	43	48	56	24	56	70	85	33	69	95	40	31	69	51	66	96	90	54	123	127
115	line	62	69	87	23	104	104	187	36	205	162	68	46	188	79	126	114	277	99	190	182
116	spokesman	8	5	6	2	6	10	7	3	6	15	7	4	5	6	7	6	11	7	11	11
117	response	50	56	55	30	78	87	130	36	144	143	82	33	150	108	92	89	205	82	161	145
118	death	32	46	47	39	58	59	72	26	71	75	41	39	83	50	69	59	107	1987	85	92
119	pressure	49	56	55	64	93	67	163	32	157	127	53	34	160	62	89	96	198	69	156	148
120	release	45	45	45	45	92	56	83	30	130	96	62	27	86	62	56	61	149	90	105	99
121	injury	57	68	58	29	103	88	137	32	170	150	67	33	182	67	98	86	295	71	170	157
122	violation	39	46	42	22	48	66	62	28	57	89	40	25	64	39	49	51	93	46	83	78
123	attitude	49	63	61	24	75	90	145	30	186	128	44	33	139	63	97	98	214	64	157	143
124	lobby	27	35	37	12	40	52	48	18	36	51	25	23	43	24	36	47	162	27	351	56
125	group	60	62	73	22	89	161	152	36	175	137	56	41	193	66	99	341	268	77	247	202

126	placard	<u>26</u>	<u>33</u>	<u>38</u>	<u>13</u>	<u>42</u>	<u>45</u>	<u>49</u>	<u>19</u>	<u>44</u>	<u>51</u>	<u>33</u>	<u>22</u>	<u>42</u>	<u>33</u>	<u>41</u>	<u>39</u>	<u>63</u>	<u>34</u>	<u>55</u>	<u>59</u>
127	bearing	<u>25</u>	<u>25</u>	<u>33</u>	<u>14</u>	<u>27</u>	<u>38</u>	<u>52</u>	<u>19</u>	<u>39</u>	<u>47</u>	<u>21</u>	<u>15</u>	<u>44</u>	<u>25</u>	<u>33</u>	<u>51</u>	<u>70</u>	<u>28</u>	<u>58</u>	<u>46</u>
128	condition	<u>64</u>	<u>83</u>	<u>75</u>	<u>49</u>	<u>94</u>	<u>111</u>	<u>214</u>	<u>40</u>	<u>260</u>	<u>200</u>	<u>205</u>	<u>42</u>	<u>250</u>	<u>68</u>	<u>121</u>	<u>126</u>	<u>476</u>	<u>169</u>	<u>216</u>	<u>201</u>
129	son	<u>34</u>	<u>29</u>	<u>35</u>	<u>18</u>	<u>40</u>	<u>41</u>	<u>52</u>	<u>17</u>	<u>43</u>	<u>52</u>	<u>27</u>	<u>20</u>	<u>49</u>	<u>33</u>	<u>35</u>	<u>46</u>	<u>60</u>	<u>37</u>	<u>63</u>	<u>70</u>
130	year	<u>42</u>	<u>53</u>	<u>51</u>	<u>25</u>	<u>55</u>	<u>64</u>	<u>89</u>	<u>33</u>	<u>87</u>	<u>81</u>	<u>45</u>	<u>36</u>	<u>77</u>	<u>51</u>	<u>74</u>	<u>121</u>	<u>110</u>	<u>62</u>	<u>103</u>	<u>109</u>
131	demonstration	<u>45</u>	<u>53</u>	<u>43</u>	<u>64</u>	<u>73</u>	<u>62</u>	<u>60</u>	<u>32</u>	<u>111</u>	<u>70</u>	<u>40</u>	<u>36</u>	<u>58</u>	<u>56</u>	<u>60</u>	<u>50</u>	<u>109</u>	<u>59</u>	<u>69</u>	<u>80</u>
132	anonymity	<u>4</u>	<u>19</u>	<u>5</u>	<u>27</u>	<u>9</u>	<u>10</u>	<u>22</u>	<u>5</u>	<u>11</u>	<u>9</u>	<u>13</u>	<u>6</u>	<u>9</u>	<u>8</u>	<u>9</u>	<u>8</u>	<u>10</u>	<u>15</u>	<u>8</u>	<u>15</u>
133	reign	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>	<u>-1</u>
134	hospital	<u>44</u>	<u>46</u>	<u>1614</u>	<u>14</u>	<u>55</u>	<u>65</u>	<u>64</u>	<u>20</u>	<u>56</u>	<u>81</u>	<u>38</u>	<u>25</u>	<u>64</u>	<u>48</u>	<u>64</u>	<u>70</u>	<u>159</u>	<u>47</u>	<u>109</u>	<u>86</u>
135	protest	<u>31</u>	<u>37</u>	<u>40</u>	<u>41</u>	<u>67</u>	<u>47</u>	<u>57</u>	<u>21</u>	<u>73</u>	<u>62</u>	<u>27</u>	<u>24</u>	<u>52</u>	<u>48</u>	<u>51</u>	<u>48</u>	<u>83</u>	<u>38</u>	<u>64</u>	<u>71</u>

4. Results for Ideal Summaries with different cutting points

” for full data, please contact the author email⁹”

a) WuP Results First Data

WuP with different cutting point														
File Name	Text	OT size	CT size	Human Ev.%	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
APW19981019.0098	T1	8 KB	1 KB	100	90.37	90.37	90.37	87.41	64.44	93	93	93	159	1264
APW19981022.0269	T2	4KB	1 KB	100	87.36	87.36	86.21	80.46	60.92	160	160	190	382	1527
APW19981030.0792	T3	5KB	1KB	100	86.26	86.26	83.97	79.39	62.60	189	189	257	425	1399
APW19981120.0290	T4	5KB	1KB	100	87.88	87.12	84.85	79.55	66.67	147	166	230	418	1111
APW19981202.1274	T5	5KB	1KB	100	88.12	88.12	88.12	86.14	61.39	141	141	141	192	1491
APW19981211.1276	T6	6KB	1KB	100	89.29	89.29	89.29	78.57	52.68	115	115	115	459	2239
APW19981212.0161	T7	6KB	1KB	100	85.33	85.33	84.78	79.35	60.33	215	215	232	427	1574
APW19981227.0870	T8	4KB	1KB	100	86.42	86.42	85.19	76.54	59.26	184	184	219	550	1660
NYT19981001.0379	T9	20KB	1KB	100	89.67	88.66	85.14	80.10	63.73	107	128	221	396	1316
NYT19981003.0120	T10	6KB	1KB	100	91.14	91.14	86.71	80.38	56.96	79	79	177	385	1852
NYT19981004.0102	T11	9KB	1KB	100	84.97	84.97	84.02	76.68	66.84	226	226	255	544	1100
NYT19981010.0149	T12	9KB	1KB	100	85.81	85.81	85.14	85.14	74.32	201	201	221	221	659
NYT19981012.0334	T13	10KB	1KB	100	84.62	83.26	76.47	71.49	48.87	237	280	554	813	2614
NYT19981012.0359	T14	9KB	1KB	100	85.19	84.13	78.84	75.13	55.56	219	252	448	618	1975
NYT19981013.0354	T15	8KB	1KB	100	92.61	92.05	90.91	84.09	75.00	55	63	83	253	625
NYT19981013.0399	T16	8KB	1KB	100	92.55	91.93	88.20	85.09	61.49	56	65	139	222	1483
NYT19981017.0027	T17	9KB	1KB	100	80.31	80.31	78.74	75.59	61.42	388	388	452	596	1489
NYT19981018.0091	T18	10KB	1KB	100	91.89	90.81	87.03	85.41	76.22	66	84	168	213	566
NYT19981024.0050	T19	11KB	1KB	100	92.79	92.79	84.62	78.85	59.62	52	52	237	447	1631
NYT19981104.0545	T20	11KB	1KB	100	82.55	81.13	78.77	72.64	51.42	305	356	451	748	2360
NYT19981105.0538	T21	8KB	1KB	100	90.72	90.21	86.60	78.87	58.25	86	96	180	447	1743
NYT19981107.0056	T22	7kb	1KB	100	85.88	85.29	84.12	78.82	54.71	199	216	252	448	2052
NYT19981107.0251	T23	5kb	1KB	100	86.02	86.02	86.02	79.57	66.67	195	195	195	417	1111
NYT19981114.0079	T24	13KB	1KB	100	88.43	88.43	85.45	78.36	57.46	134	134	212	468	1809
NYT19981114.0129	T25	15KB	1KB	100	92.43	91.35	89.73	85.95	71.89	57	75	105	198	790
NYT19981121.0117	T26	7KB	1KB	100	89.40	89.40	86.09	70.20	56.95	112	112	193	888	1853
NYT19981122.0163	T27	9KB	1KB	100	90.72	90.72	90.21	87.11	79.38	86	86	96	166	425
NYT19981126.0192	T28	9KB	1kb	100	92.43	91.35	89.73	85.95	71.89	57	75	105	198	790
NYT19981201.0444	T29	7KB	1KB	100	84.52	82.58	72.26	68.39	47.74	240	303	770	999	2731
NYT19981204.0365	T30	7KB	1KB	100	89.50	88.00	87.00	76.00	66.00	110	144	169	576	1156
NYT19981209.0451	T31	13KB	1KB	100	91.04	90.67	90.30	86.57	73.13	80	87	94	180	722
NYT19981219.0117	T32	13KB	1KB	100	82.13	81.70	77.45	71.49	44.26	319	335	509	813	3107
NYT19981221.0377	T33	8KB	1KB	100	88.76	88.76	88.76	84.83	69.10	126	126	126	230	955
NYT19981223.0347	T34	11KB	1KB	100	93.89	93.89	93.01	88.21	68.56	37	37	49	139	989
										149	161	233	430	1476
										12.22	12.67	15.28	20.75	38.41

⁹ Zainab_bayram@hotmail.com

b) LCH Results First Data

LCH with different cutting point														
File Name	Text	OT size	CT size	Human Ev. %	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
APW19981019.0098	T1	8 KB	1 KB	100	91.11	91.11	89.63	88.89	81.48	79	79	108	123	343
APW19981022.0269	T2	4KB	1 KB	100	87.36	87.36	86.21	80.46	71.26	160	160	190	382	826
APW19981030.0792	T3	5KB	1KB	100	86.26	86.26	86.26	82.44	74.05	189	189	189	308	674
APW19981120.0290	T4	5KB	1KB	100	87.88	87.88	87.88	84.09	62.88	147	147	147	253	1378
APW19981202.1274	T5	5KB	1KB	100	88.12	88.12	88.12	88.12	78.22	141	141	141	141	474
APW19981211.1276	T6	6KB	1KB	100	89.29	89.29	88.39	85.71	64.29	115	115	135	204	1276
APW19981212.0161	T7	6KB	1KB	100	88.59	88.59	88.04	84.24	78.26	130	130	143	248	473
APW19981227.0870	T8	4KB	1KB	100	86.42	86.42	85.19	81.48	70.37	184	184	219	343	878
NYT19981001.0379	T9	20KB	1KB	100	90.18	89.92	89.17	87.66	78.59	97	102	117	152	458
NYT19981003.0120	T10	6KB	1KB	100	91.77	91.77	91.77	89.87	83.54	68	68	68	103	271
NYT19981004.0102	T11	9KB	1KB	100	84.97	84.97	84.02	81.87	74.09	226	226	255	329	671
NYT19981010.0149	T12	9KB	1KB	100	85.81	85.81	85.14	84.46	71.62	201	201	221	242	805
NYT19981012.0334	T13	10KB	1KB	100	85.97	85.97	84.16	75.11	73.30	197	197	251	619	713
NYT19981012.0359	T14	9KB	1KB	100	86.24	86.24	84.13	80.42	69.31	189	189	252	383	942
NYT19981013.0354	T15	8KB	1KB	100	93.18	93.18	92.05	86.93	73.86	46	46	63	171	683
NYT19981013.0399	T16	8KB	1KB	100	92.55	92.55	92.55	91.30	79.50	56	56	56	76	420
NYT19981017.0027	T17	9KB	1KB	100	80.31	80.31	80.31	77.17	72.44	388	388	388	521	760
NYT19981018.0091	T18	10KB	1KB	100	92.97	92.97	91.89	86.49	76.22	49	49	66	183	566
NYT19981024.0050	T19	11KB	1KB	100	93.27	93.27	93.27	89.42	77.40	45	45	45	112	511
NYT19981104.0545	T20	11KB	1KB	100	82.55	82.55	82.55	79.25	69.81	305	305	305	431	911
NYT19981105.0538	T21	8KB	1KB	100	90.72	90.72	90.72	88.14	76.80	86	86	86	141	538
NYT19981107.0056	T22	7KB	1KB	100	87.06	87.06	86.47	83.53	70.59	167	167	183	271	865
NYT19981107.0251	T23	5KB	1KB	100	86.02	86.02	86.02	81.72	73.12	195	195	195	334	723
NYT19981114.0079	T24	13KB	1KB	100	88.43	88.43	88.43	85.07	67.16	134	134	134	223	1078
NYT19981114.0129	T25	15KB	1KB	100	92.43	91.89	89.19	86.49	84.86	57	66	117	183	229
NYT19981121.0117	T26	7KB	1KB	100	89.40	89.40	89.40	86.09	68.87	112	112	112	193	969
NYT19981122.0163	T27	9KB	1KB	100	90.72	90.72	90.21	83.51	75.26	86	86	96	272	612
NYT19981126.0192	T28	9KB	1KB	100	92.43	91.89	89.19	86.49	84.86	57	66	117	183	229
NYT19981201.0444	T29	7KB	1KB	100	87.10	87.10	87.10	79.35	71.61	166	166	166	426	806
NYT19981204.0365	T30	7KB	1KB	100	90.00	90.00	89.00	86.50	74.00	100	100	121	182	676
NYT19981209.0451	T31	13KB	1KB	100	91.04	91.04	89.93	88.06	70.90	80	80	101	143	847
NYT19981219.0117	T32	13KB	1KB	100	82.13	82.13	82.13	80.85	72.34	319	319	319	367	765
NYT19981221.0377	T33	8KB	1KB	100	88.76	88.76	87.64	86.52	79.78	126	126	153	182	409
NYT19981223.0347	T34	11KB	1KB	100	93.89	93.89	93.89	92.58	83.41	37	37	37	55	275
										139	140	156	249	678
										11.80	11.83	12.48	15.79	26.04

c) Resnik Results First Data

Resnik with different cutting point														
File Name	Text	OT size	CT size	Human Ev.	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
APW19981019.0098	T1	8 KB	1 KB	100	85.19	85.19	81.48	68.15	58.52	219	219	343	1015	1721
APW19981022.0269	T2	4KB	1 KB	100	85.06	82.76	79.31	71.26	60.92	223	297	428	826	1527
APW19981030.0792	T3	5KB	1KB	100	80.92	74.05	70.23	59.54	55.73	364	674	886	1637	1960
APW19981120.0290	T4	5KB	1KB	100	82.58	80.30	75.00	68.18	61.36	304	388	625	1012	1493
APW19981202.1274	T5	5KB	1KB	100	81.19	79.21	74.26	68.32	60.40	354	432	663	1004	1568
APW19981211.1276	T6	6KB	1KB	100	82.14	77.68	76.79	69.64	63.39	319	498	539	922	1340
APW19981212.0161	T7	6KB	1KB	100	79.35	75.00	73.91	65.76	58.15	427	625	681	1172	1751
APW19981227.0870	T8	4KB	1KB	100	83.95	79.01	72.84	67.90	51.85	258	440	738	1030	2318
NYT19981001.0379	T9	20KB	1KB	100	83.88	81.61	77.33	68.51	61.21	260	338	514	991	1505
NYT19981003.0120	T10	6KB	1KB	100	87.34	85.44	81.65	72.15	58.23	160	212	337	776	1745
NYT19981004.0102	T11	9KB	1KB	100	79.79	77.72	73.20	67.36	60.10	408	496	718	1066	1592
NYT19981010.0149	T12	9KB	1KB	100	78.38	77.03	73.65	67.57	65.54	467	528	694	1052	1187
NYT19981012.0334	T13	10KB	1KB	100	76.92	76.02	73.30	66.06	55.66	533	575	713	1152	1966
NYT19981012.0359	T14	9KB	1KB	100	80.42	78.84	74.07	70.37	58.73	383	448	672	878	1703
NYT19981013.0354	T15	8KB	1KB	100	86.36	85.23	70.45	70.45	64.20	186	218	873	873	1281
NYT19981013.0399	T16	8KB	1KB	100	87.58	86.34	83.23	73.29	57.76	154	187	281	713	1784
NYT19981017.0027	T17	9KB	1KB	100	75.59	74.02	69.29	64.57	54.33	596	675	943	1256	2086
NYT19981018.0091	T18	10KB	1KB	100	87.03	85.41	80.54	71.89	67.03	168	213	379	790	1087
NYT19981024.0050	T19	11KB	1KB	100	87.02	86.54	79.33	76.44	65.38	169	181	427	555	1198
NYT19981104.0545	T20	11KB	1KB	100	75.47	74.06	69.34	65.57	50.94	602	673	940	1186	2407
NYT19981105.0538	T21	8KB	1KB	100	84.02	82.99	76.29	66.49	53.61	255	289	562	1123	2152
NYT19981107.0056	T22	7kb	1KB	100	77.65	75.88	71.18	68.24	58.24	500	582	831	1009	1744
NYT19981107.0251	T23	5kb	1KB	100	79.57	77.42	72.04	63.44	55.91	417	510	782	1337	1944
NYT19981114.0079	T24	13KB	1KB	100	84.33	82.46	76.87	70.52	60.45	246	308	535	869	1564
NYT19981114.0129	T25	15KB	1KB	100	87.57	84.32	77.30	71.35	63.24	155	246	515	821	1351
NYT19981121.0117	T26	7KB	1KB	100	80.13	78.15	74.17	70.20	62.91	395	478	667	888	1375
NYT19981122.0163	T27	9KB	1KB	100	85.57	82.47	79.90	72.16	67.01	208	307	404	775	1088
NYT19981126.0192	T28	9KB	1kb	100	87.57	84.32	77.30	71.35	63.24	155	246	515	821	1351
NYT19981201.0444	T29	7KB	1KB	100	74.19	72.90	65.16	60.00	51.61	666	734	1214	1600	2341
NYT19981204.0365	T30	7KB	1KB	100	81.50	78.50	72.00	67.50	61.00	342	462	784	1056	1521
NYT19981209.0451	T31	13KB	1KB	100	84.33	83.58	77.61	71.27	65.30	246	270	501	825	1204
NYT19981219.0117	T32	13KB	1KB	100	74.04	72.77	67.66	63.83	59.57	674	742	1046	1308	1634
NYT19981221.0377	T33	8KB	1KB	100	78.65	77.53	71.91	66.85	62.36	456	505	789	1099	1417
NYT19981223.0347	T34	11KB	1KB	100	85.15	84.72	77.73	69.43	63.32	220	234	496	934	1346
										338	419	648	1011	1625
										18.38	20.46	25.46	31.79	40.31

d) LIN Results First Data

Lin with different cutting point														
File Name	Text	OT size	CT size	Human Ev.	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 40%
APW19981019.0098	T1	8 KB	1 KB	100	68.15	55.56	40.00	27.41	20.00	1015	1975	3600	5270	6400
APW19981022.0269	T2	4KB	1 KB	100	78.16	65.52	56.32	43.68	32.18	477	1189	1908	3172	4599
APW19981030.0792	T3	5KB	1KB	100	65.65	48.09	35.88	26.72	19.08	1180	2694	4112	5370	6547
APW19981120.0290	T4	5KB	1KB	100	71.21	56.06	43.94	31.06	25.00	829	1931	3143	4753	5625
APW19981202.1274	T5	5KB	1KB	100	78.22	66.34	52.48	35.64	27.72	474	1133	2259	4142	5224
APW19981211.1276	T6	6KB	1KB	100	58.93	43.75	32.14	25.00	20.54	1687	3164	4605	5625	6315
APW19981212.0161	T7	6KB	1KB	100	61.96	46.74	30.98	22.28	14.67	1447	2837	4764	6040	7281
APW19981227.0870	T8	4KB	1KB	100	69.14	49.38	44.44	27.16	20.99	953	2562	3086	5306	6243
NYT19981001.0379	T9	20KB	1KB	100	71.79	59.19	44.08	31.49	23.68	796	1665	3127	4694	5825
NYT19981003.0120	T10	6KB	1KB	100	68.99	55.06	37.34	24.68	15.82	962	2019	3926	5673	7086
NYT19981004.0102	T11	9KB	1KB	100	66.84	56.48	44.85	31.61	23.83	1100	1894	3042	4678	5801
NYT19981010.0149	T12	9KB	1KB	100	70.95	63.51	54.05	34.46	22.30	844	1331	2111	4296	6038
NYT19981012.0334	T13	10KB	1KB	100	62.90	48.87	34.84	23.53	14.93	1377	2614	4246	5848	7237
NYT19981012.0359	T14	9KB	1KB	100	67.72	52.91	35.45	27.51	20.63	1042	2217	4167	5254	6299
NYT19981013.0354	T15	8KB	1KB	100	78.98	67.05	56.25	47.73	37.50	442	1086	1914	2732	3906
NYT19981013.0399	T16	8KB	1KB	100	72.67	58.39	44.72	34.16	24.22	747	1732	3056	4335	5742
NYT19981017.0027	T17	9KB	1KB	100	65.35	51.18	39.37	29.92	19.69	1200	2383	3676	4911	6450
NYT19981018.0091	T18	10KB	1KB	100	77.84	68.65	58.38	45.41	34.59	491	983	1732	2981	4278
NYT19981024.0050	T19	11KB	1KB	100	74.52	59.13	44.23	31.25	22.60	649	1670	3110	4727	5991
NYT19981104.0545	T20	11KB	1KB	100	57.55	44.34	35.38	27.83	17.45	1802	3098	4176	5208	6814
NYT19981105.0538	T21	8KB	1KB	100	70.62	51.03	40.21	30.93	18.04	863	2398	3575	4771	6717
NYT19981107.0056	T22	7Kb	1KB	100	64.12	54.12	34.12	24.71	17.65	1288	2105	4340	5669	6782
NYT19981107.0251	T23	5Kb	1KB	100	67.74	54.84	39.78	30.11	20.43	1041	2040	3626	4885	6331
NYT19981114.0079	T24	13KB	1KB	100	63.81	51.87	38.43	27.99	18.66	1310	2317	3791	5186	6617
NYT19981114.0129	T25	15KB	1KB	100	74.05	61.62	51.89	35.14	23.24	673	1473	2314	4207	5892
NYT19981121.0117	T26	7KB	1KB	100	64.90	56.29	43.71	34.44	41.72	1232	1910	3169	4298	3396
NYT19981122.0163	T27	9KB	1KB	100	75.26	68.56	60.31	47.94	38.66	612	989	1575	2710	3763
NYT19981126.0192	T28	9KB	1Kb	100	74.05	61.62	51.89	35.14	23.24	673	1473	2314	4207	5892
NYT19981201.0444	T29	7KB	1KB	100	56.13	39.35	26.45	19.35	9.68	1925	3678	5409	6504	8158
NYT19981204.0365	T30	7KB	1KB	100	66.50	58.00	42.50	28.50	20.50	1122	1764	3306	5112	6320
NYT19981209.0451	T31	13KB	1KB	100	75.00	63.43	52.24	33.96	26.87	625	1337	2281	4362	5349
NYT19981219.0117	T32	13KB	1KB	100	57.87	46.81	35.32	22.98	11.91	1775	2829	4184	5932	7759
NYT19981221.0377	T33	8KB	1KB	100	69.10	60.11	46.07	32.58	23.60	955	1591	2909	4545	5838
NYT19981223.0347	T34	11KB	1KB	100	69.87	62.01	46.29	31.00	18.34	908	1443	2885	4760	6668
										1015	1986	3278	4770	6035
										31.86	44.57	57.25	69.06	77.68

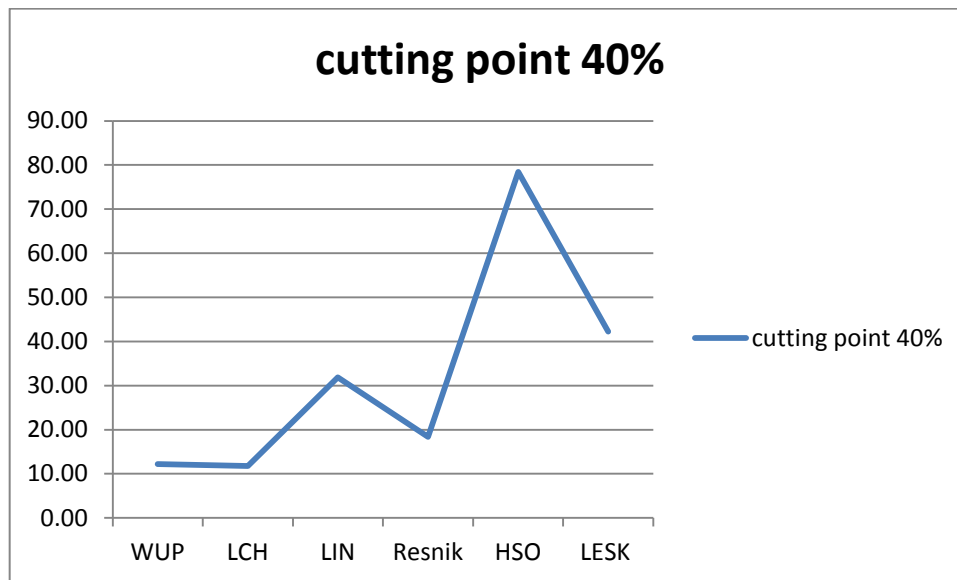
e) HSO Results First Data

HSO with different cutting point														
File Name	Text	OT size	CT size	Human Ev.	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
APW19981019.0098	T1	8 KB	1 KB	100	21.48	14.81	14.81	14.81	14.81	6165	7257	7257	7257	7257
APW19981022.0269	T2	4KB	1 KB	100	33.33	21.84	21.84	21.84	21.84	4444	6109	6109	6109	6109
APW19981030.0792	T3	5KB	1KB	100	24.43	14.50	14.50	14.50	14.50	5711	7310	7310	7310	7310
APW19981120.0290	T4	5KB	1KB	100	26.52	16.67	16.67	16.67	16.67	5400	6944	6944	6944	6944
APW19981202.1274	T5	5KB	1KB	100	30.69	9.90	9.90	9.90	9.90	4803	8118	8118	8118	8118
APW19981211.1276	T6	6KB	1KB	100	23.21	12.50	12.50	12.50	12.50	5896	7656	7656	7656	7656
APW19981212.0161	T7	6KB	1KB	100	13.04	7.07	7.07	7.07	7.07	7561	8637	8637	8637	8637
APW19981227.0870	T8	4KB	1KB	100	23.46	18.52	18.52	18.52	18.52	5859	6639	6639	6639	6639
NYT19981001.0379	T9	20KB	1KB	100	22.42	9.82	9.82	9.82	9.82	6019	8132	8132	8132	8132
NYT19981003.0120	T10	6KB	1KB	100	17.09	12.03	12.03	12.03	12.03	6874	7740	7740	7740	7740
NYT19981004.0102	T11	9KB	1KB	100	31.09	11.40	11.40	11.40	11.40	4749	7850	7850	7850	7850
NYT19981010.0149	T12	9KB	1KB	100	25.00	14.19	14.19	14.19	14.19	5625	7363	7363	7363	7363
NYT19981012.0334	T13	10KB	1KB	100	13.12	7.69	7.69	7.69	7.69	7548	8521	8521	8521	8521
NYT19981012.0359	T14	9KB	1KB	100	22.22	11.11	11.11	11.11	11.11	6049	7901	7901	7901	7901
NYT19981013.0354	T15	8KB	1KB	100	38.64	26.14	26.14	26.14	26.14	3765	5456	5456	5456	5456
NYT19981013.0399	T16	8KB	1KB	100	18.01	10.56	10.56	10.56	10.56	6722	8000	8000	8000	8000
NYT19981017.0027	T17	9KB	1KB	100	20.47	10.24	10.24	10.24	10.24	6325	8058	8058	8058	8058
NYT19981018.0091	T18	10KB	1KB	100	35.68	20.00	20.00	20.00	20.00	4138	6400	6400	6400	6400
NYT19981024.0050	T19	11KB	1KB	100	15.87	9.13	9.13	9.13	9.13	7079	8257	8257	8257	8257
NYT19981104.0545	T20	11KB	1KB	100	1.79	10.38	10.38	10.38	10.38	9645	8032	8032	8032	8032
NYT19981105.0538	T21	8KB	1KB	100	20.62	8.76	8.76	8.76	8.76	6301	8324	8324	8324	8324
NYT19981107.0056	T22	7Kb	1KB	100	21.76	11.18	11.18	11.18	11.18	6121	7890	7890	7890	7890
NYT19981107.0251	T23	5Kb	1KB	100	24.73	15.05	15.05	15.05	15.05	5665	7216	7216	7216	7216
NYT19981114.0079	T24	13KB	1KB	100	19.03	7.84	7.84	7.84	7.84	6556	8494	8494	8494	8494
NYT19981114.0129	T25	15KB	1KB	100	21.62	11.89	11.89	11.89	11.89	6143	7763	7763	7763	7763
NYT19981121.0117	T26	7KB	1KB	100	15.23	8.61	8.61	8.61	8.61	7186	8352	8352	8352	8352
NYT19981122.0163	T27	9KB	1KB	100	36.60	21.65	21.65	21.65	21.65	4020	6139	6139	6139	6139
NYT19981126.0192	T28	9KB	1Kb	100	21.62	11.89	11.89	11.89	11.89	6143	7763	7763	7763	7763
NYT19981201.0444	T29	7KB	1KB	100	9.03	3.87	3.87	3.87	3.87	8275	9241	9241	9241	9241
NYT19981204.0365	T30	7KB	1KB	100	19.00	11.50	11.50	11.50	11.50	6561	7832	7832	7832	7832
NYT19981209.0451	T31	13KB	1KB	100	29.10	15.67	15.67	15.67	15.67	5026	7111	7111	7111	7111
NYT19981219.0117	T32	13KB	1KB	100	14.04	3.83	3.83	3.83	3.83	7389	9249	9249	9249	9249
NYT19981221.0377	T33	8KB	1KB	100	20.22	9.55	9.55	9.55	9.55	6364	8181	8181	8181	8181
NYT19981223.0347	T34	11KB	1KB	100	15.72	3.93	3.93	3.93	3.93	7103	9229	9229	9229	9229
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										78.45	87.98	87.98	87.98	87.98

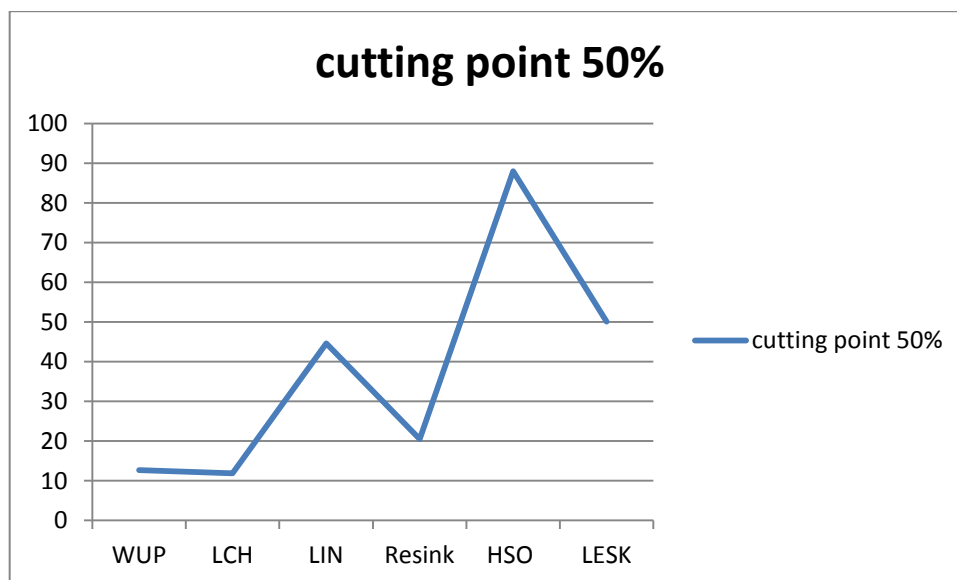
f) LESK Results First Data

LESK with different cutting point														
File Name	Text	OT size	CT size	Human Ev.	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
APW19981019.0098	T1	8 KB	1 KB	100	61.48	51.85	43.70	36.30	31.85	1484	2318	3169	4058	4644
APW19981022.0269	T2	4KB	1 KB	100	32.18	28.74	26.44	24.14	21.84	4599	5079	5412	5755	6109
APW19981030.0792	T3	5KB	1KB	100	43.51	37.40	32.06	29.77	22.14	3191	3918	4616	4932	6063
APW19981120.0290	T4	5KB	1KB	100	46.21	34.85	29.55	28.03	24.24	2893	4245	4964	5180	5739
APW19981202.1274	T5	5KB	1KB	100	64.36	57.43	50.50	45.54	41.58	1270	1813	2451	2965	3412
APW19981211.1276	T6	6KB	1KB	100	60.71	49.11	42.86	33.93	29.46	1543	2590	3265	4365	4975
APW19981212.0161	T7	6KB	1KB	100	71.74	61.41	53.80	46.20	40.76	799	1489	2134	2895	3509
APW19981227.0870	T8	4KB	1KB	100	53.09	44.44	38.27	34.57	30.86	2201	3086	3810	4281	4780
NYT19981001.0379	T9	20KB	1KB	100	64.48	54.41	49.62	42.07	38.29	1261	2079	2538	3356	3808
NYT19981003.0120	T10	6KB	1KB	100	59.49	48.73	41.14	35.44	29.75	1641	2628	3465	4168	4936
NYT19981004.0102	T11	9KB	1KB	100	62.69	53.37	46.39	42.49	37.82	1392	2175	2874	3308	3866
NYT19981010.0149	T12	9KB	1KB	100	53.38	45.95	39.86	35.81	29.73	2174	2922	3616	4120	4938
NYT19981012.0334	T13	10KB	1KB	100	61.99	54.75	46.15	42.53	37.56	1445	2047	2899	3302	3899
NYT19981012.0359	T14	9KB	1KB	100	49.21	42.86	38.62	32.28	26.98	2580	3265	3767	4587	5331
NYT19981013.0354	T15	8KB	1KB	100	43.75	35.80	32.39	31.25	27.27	3164	4122	4572	4727	5289
NYT19981013.0399	T16	8KB	1KB	100	64.60	57.14	52.17	45.34	38.51	1253	1837	2287	2988	3781
NYT19981017.0027	T17	9KB	1KB	100	52.76	49.61	41.73	36.22	32.28	2232	2540	3395	4068	4586
NYT19981018.0091	T18	10KB	1KB	100	54.59	45.41	38.38	31.35	28.11	2062	2981	3797	4713	5168
NYT19981024.0050	T19	11KB	1KB	100	71.15	60.10	51.44	45.19	42.79	832	1592	2358	3004	3273
NYT19981104.0545	T20	11KB	1KB	100	67.92	57.08	50.47	45.75	36.79	1029	1843	2453	2943	3995
NYT19981105.0538	T21	8KB	1KB	100	67.53	60.82	51.55	44.33	38.14	1055	1535	2348	3099	3826
NYT19981107.0056	T22	7Kb	1KB	100	62.35	50.59	47.65	42.94	35.88	1417	2442	2741	3256	4111
NYT19981107.0251	T23	5Kb	1KB	100	54.84	44.09	40.86	33.33	30.11	2040	3126	3498	4444	4885
NYT19981114.0079	T24	13KB	1KB	100	73.88	66.04	59.70	49.63	43.66	682	1153	1624	2537	3175
NYT19981114.0129	T25	15KB	1KB	100	58.38	50.27	44.86	38.92	36.22	1732	2473	3040	3731	4068
NYT19981121.0117	T26	7KB	1KB	100	65.56	56.29	47.68	40.40	33.77	1186	1910	2737	3552	4386
NYT19981122.0163	T27	9KB	1KB	100	37.63	31.96	28.87	26.80	25.77	3890	4630	5060	5358	5510
NYT19981126.0192	T28	9KB	1Kb	100	58.38	50.27	44.86	38.92	36.22	1732	2473	3040	3731	4068
NYT19981201.0444	T29	7KB	1KB	100	69.03	65.81	58.06	55.48	51.61	959	1169	1759	1982	2341
NYT19981204.0365	T30	7KB	1KB	100	57.00	51.50	44.50	34.50	29.50	1849	2352	3080	4290	4970
NYT19981209.0451	T31	13KB	1KB	100	49.63	44.40	38.43	32.84	28.73	2537	3091	3791	4511	5079
NYT19981219.0117	T32	13KB	1KB	100	73.19	63.40	52.77	48.09	41.70	719	1339	2231	2695	3399
NYT19981221.0377	T33	8KB	1KB	100	62.92	52.81	44.38	37.64	33.71	1375	2227	3093	3889	4395
NYT19981223.0347	T34	11KB	1KB	100	76.86	70.74	63.76	57.21	50.66	536	856	1314	1831	2435
										1787	2510	3153	3783	4375
										42.27	50.10	56.15	61.51	66.14

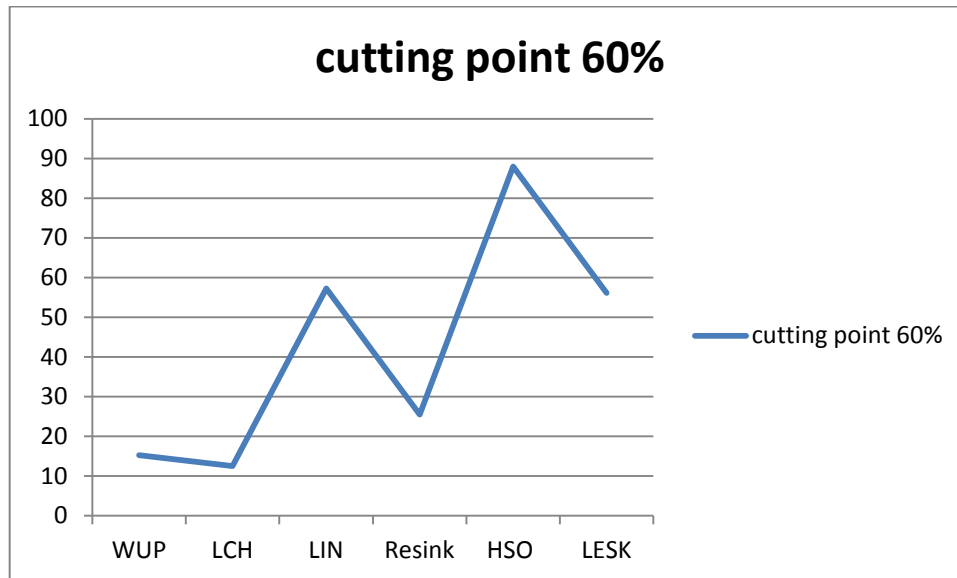
5. a) Cutting Point 40% figure



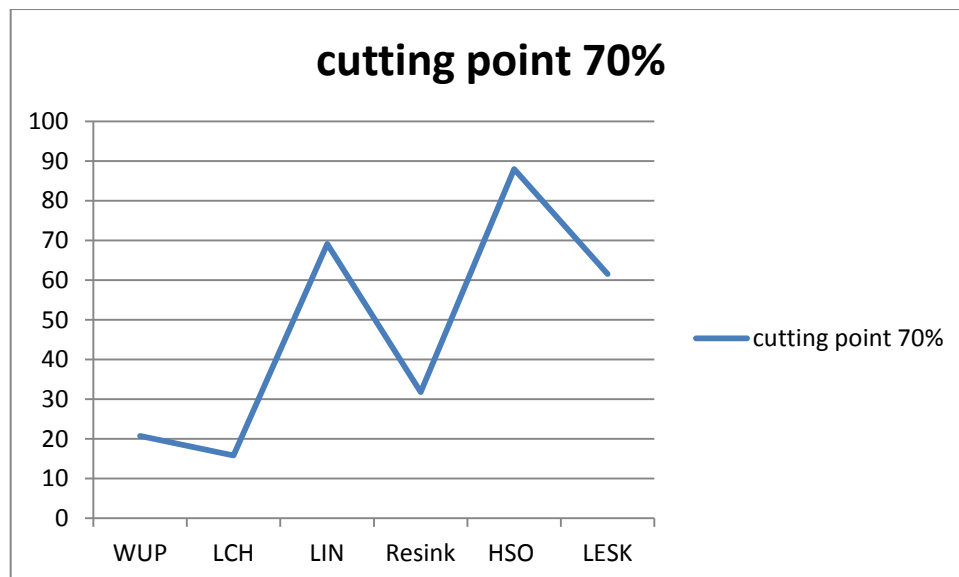
b) Cutting point 50% figure



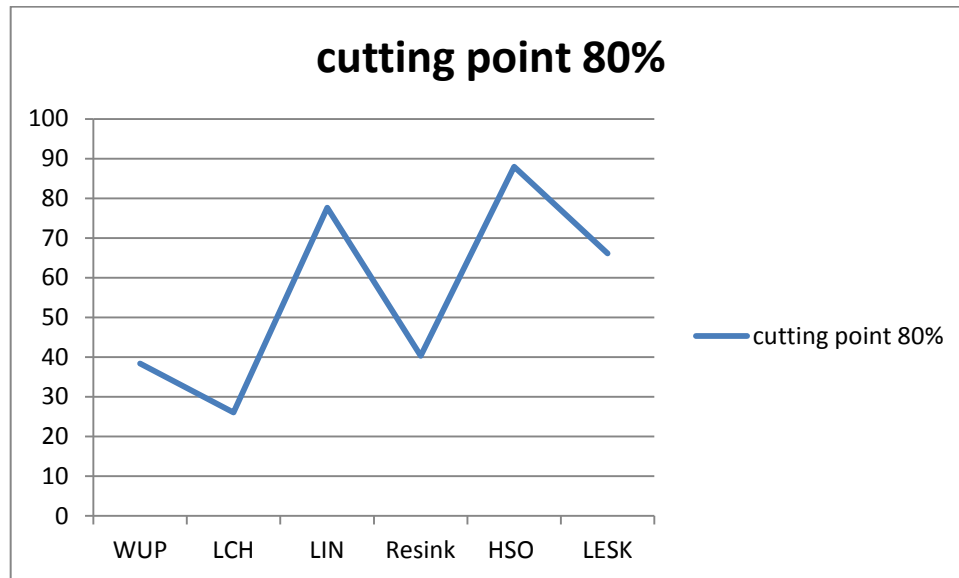
c) cutting point 60%



d) cutting point 70%



e) cutting point 80%



6. a) WuP results second data

WuP with different cutting point														
File Name	Text	OT size	CT size	Human Ev. %	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
Text1	T1	5 KB	1 KB	80	84	84	82	75	63	18	18	2	21	284
Text2	T2	11KB	1 KB	65	87	87	85	82	69	477	477	404	275	15
Text3	T3	4KB	1KB	85	88	87	86	74	64	8	3	1	129	452
Text4	T4	5KB	1KB	80	87	87	84	83	66	42	42	18	10	188
Text5	T5	3KB	1KB	90	81	81	81	79	66	79	79	79	116	574
Text6	T6	3KB	1KB	90	89	87	78	68	51	2	7	140	492	1554
Text7	T7	6KB	1KB	80	87	87	86	78	63	55	55	34	4	289
Text8	T8	3KB	1KB	90	78	78	76	72	62	146	146	208	321	805
Text9	T9	3KB	1KB	90	85	85	81	77	62	27	27	81	163	783
Text10	T10	5KB	1KB	80	91	91	90	88	68	119	119	102	58	150
Text11	T11	6KB	1KB	75	90	88	86	81	66	218	171	129	32	73
Text12	T12	19KB	1KB	40	90	90	89	85	74	2545	2545	2397	2005	1158
Text13	T13	3KB	1KB	90	87	85	83	70	53	11	25	44	400	1344
Text14	T14	5KB	1KB	75	88	83	78	76	67	156	63	12	1	63
										279	270	261	288	552
										16.70	16.43	16.15	16.96	23.50

b) LCH Results second data

LCH with different cutting point														
File Name	Text	OT size	CT size	Human Ev. %	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
Text 1	T1	5 KB	1 KB	80	86	86	83	74	64	36	36	11	40	255
Text 2	T2	11KB	1 KB	65	86	86	84	78	68	440	440	369	160	9
Text 3	T3	4KB	1KB	85	86	86	85	81	74	1	1	0	14	120
Text 4	T4	5KB	1KB	80	87	87	84	82	75	42	42	18	4	22
Text 5	T5	3KB	1KB	90	77	77	77	74	66	160	160	160	269	574
Text 6	T6	3KB	1KB	90	87	86	85	78	55	7	14	24	140	1213
Text 7	T7	6KB	1KB	80	86	86	83	75	65	34	34	12	27	214
Text 8	T8	3KB	1KB	90	77	77	76	76	58	176	176	208	208	1015
Text 9	T9	3KB	1KB	90	84	84	77	70	59	42	42	163	415	931
Text 10	T10	5KB	1KB	80	89	89	89	86	79	86	86	86	35	2
Text 11	T11	6KB	1KB	75	89	89	89	85	69	186	186	186	105	39
Text 12	T12	19KB	1KB	40	90	90	89	86	76	2515	2515	2426	2113	1326
Text 13	T13	3KB	1KB	90	83	83	82	77	62	44	44	69	178	803
Text 14	T14	5KB	1KB	75	86	86	85	75	67	129	129	105	0	63
										278	279	274	265	471
										16.68	16.70	16.56	16.27	21.69

c) LIN Results Second Data

Lin with different cutting point														
File Name	Text	OT size	CT size	Human Ev. %	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
Text 1	T1	5 KB	1 KB	80	69	62	49	43	36	115	314	953	1370	1939
Text 2	T2	11KB	1 KB	65	80	68	57	43	34	233	12	57	504	948
Text 3	T3	4KB	1KB	85	73	52	42	36	30	156	1112	1870	2375	3061
Text 4	T4	5KB	1KB	80	66	60	47	36	27	188	418	1076	1940	2813
Text 5	T5	3KB	1KB	90	64	55	42	36	25	668	1245	2351	2932	4287
Text 6	T6	3KB	1KB	90	62	54	37	28	24	780	1294	2832	3895	4338
Text 7	T7	6KB	1KB	80	77	64	54	43	28	8	263	659	1346	2750
Text 8	T8	3KB	1KB	90	57	48	42	33	20	1091	1791	2317	3300	4933
Text 9	T9	3KB	1KB	90	68	59	49	42	29	469	931	1651	2326	3707
Text 10	T10	5KB	1KB	80	72	58	38	26	15	66	491	1763	2957	4241
Text 11	T11	6KB	1KB	75	68	58	49	39	31	55	291	683	1281	1914
Text 12	T12	19KB	1KB	40	81	73	58	44	33	1697	1118	321	13	56
Text 13	T13	3KB	1KB	90	62	53	32	23	18	803	1344	3403	4444	5136
Text 14	T14	5KB	1KB	75	68	65	59	49	42	46	105	253	683	1086
										455	766	1442	2098	2943
										21.34	27.68	37.98	45.80	54.25

d) Resnik Results Second Data

Resnik with different cutting point														
File Name	Text	OT size	CT size	Human Ev.	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80
Text 1	T1	5 KB	1 KB	80	80	75	68	64	57	0	30	134	255	528
Text 2	T2	11KB	1 KB	65	80	78	75	66	60	233	171	100	2	29
Text 3	T3	4KB	1KB	85	85	82	70	57	53	0	7	215	776	1040
Text 4	T4	5KB	1KB	80	75	75	74	70	63	22	22	34	107	292
Text 5	T5	3KB	1KB	90	70	70	64	57	47	408	408	668	1115	1834
Text 6	T6	6KB	1KB	90	86	80	70	66	52	14	91	395	599	1465
Text 7	T7	6KB	1KB	80	81	81	76	72	61	1	1	19	70	345
Text 8	T8	3KB	1KB	90	74	71	69	57	45	243	364	458	1091	1994
Text 9	T9	3KB	1KB	90	84	78	75	71	53	42	133	235	365	1357
Text 10	T10	5KB	1KB	80	85	85	82	66	54	26	26	3	193	691
Text 11	T11	6KB	1KB	75	81	80	76	66	57	39	26	0	83	310
Text 12	T12	19KB	1KB	40	89	86	79	74	68	2367	2141	1506	1158	787
Text 13	T13	3KB	1KB	90	83	83	72	70	62	44	44	336	400	803
Text 14	T14	5KB	1KB	75	74	70	68	61	52	1	21	46	186	517
										246	249	296	457	857
										15.68	15.77	17.22	21.38	29.27

e) LESK Results Second Data

LESK with different cutting point														
File Name	Text	OT size	CT size	Human Ev.	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
Text 1	T1	5 KB	1 KB	80	36	29	27	26	22	1939	2606	2789	2882	3372
Text 2	T2	11KB	1 KB	65	50	44	39	31	28	225	447	674	1146	1396
Text 3	T3	4KB	1KB	85	37	30	23	22	22	2269	3061	3834	3972	3972
Text 4	T4	5KB	1KB	80	65	51	39	31	29	220	867	1654	2356	2579
Text 5	T5	3KB	1KB	90	38	32	26	25	25	2732	3355	4043	4287	4287
Text 6	T6	3KB	1KB	90	33	25	23	22	22	3211	4188	4491	4646	4646
Text 7	T7	6KB	1KB	80	39	35	32	29	28	1651	2057	2277	2587	2668
Text 8	T8	3KB	1KB	90	27	26	23	23	23	4001	4150	4455	4455	4455
Text 9	T9	3KB	1KB	90	38	33	32	29	28	2707	3259	3405	3707	3863
Text 10	T10	5KB	1KB	80	62	53	40	32	28	325	735	1627	2282	2694
Text 11	T11	6KB	1KB	75	54	47	40	35	30	442	807	1201	1627	2066
Text 12	T12	19KB	1KB	40	54	48	41	36	32	205	65	1	17	70
Text 13	T13	3KB	1KB	90	67	60	45	38	33	544	900	2025	2669	3211
Text 14	T14	5KB	1KB	75	38	34	33	33	33	1406	1674	1768	1768	1768
										1563	2012	2446	2743	2932
										39.53	44.86	49.46	52.37	54.15

f) HSO Results Second Data

HSO with different cutting point														
File Name	Text	OT size	CT size	Human Ev.	40% cutting point	50% cutting point	60% cutting point	70% cutting point	80% cutting point	ERROR 40%	ERROR 50%	ERROR 60%	ERROR 70%	ERROR 80%
Text 1	T1	5 KB	1 KB	80	36	25	25	25	25	1939	2977	2977	2977	2977
Text 2	T2	11KB	1 KB	65	39	19	19	19	19	674	2129	2129	2129	2129
Text 3	T3	4KB	1KB	85	29	20	20	20	20	3184	4254	4254	4254	4254
Text 4	T4	5KB	1KB	80	29	19	19	19	19	2579	3709	3709	3709	3709
Text 5	T5	3KB	1KB	90	38	25	25	25	25	2732	4287	4287	4287	4287
Text 6	T6	3KB	1KB	90	18	17	17	17	17	5128	5294	5294	5294	5294
Text 7	T7	6KB	1KB	80	43	24	24	24	24	1346	3178	3178	3178	3178
Text 8	T8	3KB	1KB	90	31	17	17	17	17	3435	5265	5265	5265	5265
Text 9	T9	3KB	1KB	90	39	27	27	27	27	2577	4022	4022	4022	4022
Text 10	T10	5KB	1KB	80	21	15	15	15	15	3424	4241	4241	4241	4241
Text 11	T11	6KB	1KB	75	34	21	21	21	21	1720	2914	2914	2914	2914
Text 12	T12	19KB	1KB	40	36	18	18	18	18	17	475	475	475	475
Text 13	T13	3KB	1KB	90	22	15	15	15	15	4669	5625	5625	5625	5625
Text 14	T14	5KB	1KB	75	45	34	34	34	34	873	1674	1674	1674	1674
										2450	3574	3574	3574	3574
										49.50	59.79	59.79	59.79	59.79