UNIVERSITY OF NAIROBI

SCHOOL OF COMPUTING AND INFORMATICS

CROSS DOMAIN ARGUMENTATION MINING BY LEARNING OVER SENTENCE STRUCTURE

BY

MOSES OMOLLO ODUMA

P52/86105/2016

SUPERVISOR

DR. ENG. LAWRENCE MUCHEMI

A RESEARCH PROJECT REPORT SUBMITTED IN PARTIAL FULFILLMENT FOR THE REQUIREMENTS OF AN AWARD OF THE DEGREE OF MASTER OF SCIENCE IN COMPUTATIONAL INTELLIGENCE OF THE UNIVERSITY OF NAIROBI

MAY, 2018

DECLARATION

I **Moses Omollo Oduma** do declare that this research project report is my original work and has not been presented for any award in any other university.

Moses Omollo Oduma Date

P52/86105/2016

I **Dr. Eng. Lawrence Muchemi** of the University of Nairobi do confirm that this research project report has been presented for examination with my approval as the University Supervisor

Dr. Eng. Lawrence Muchemi Date

School of Computing and Informatics

ACKNOWLEDGEMENT

I take this opportunity to thank the Almighty God for His providence throughout the my masters’ degree. I am thankful to my family members for the moral support they during the study. I am also grateful to my fellow students who were of great support and gave sound advice throughout my studies. I wish to appreciate my supervisor Dr. Lawrence Muchemi for his support and advice during this project. He gave me sound counsel of how to complete the project and was resourceful all throughout the project.

ABSTRACT

Argumentation mining is new field that cuts across many disciplines. Users in Natural Language Processing technologies are keen on presentation of text information in form or arguments due to the many potential applications that are available. For such users, identification of arguments and components that make up the arguments is of much interest since this reduces drastically the effort and resources needed to read through text data that come from many varied sources. There is already attempts to provide applications that are able to read text and identify the arguments in them and the components that make up those arguments. At the moment, tools available are still in research phase. However, use of Argument mining has been incorporated in some domains such as question answering applications and machine translation.

This study proposes the use of machine learning on structure of sentences in order to mine arguments from text. Sentence structure is used in the identification of arguments and later the components that make up such arguments.

In our approach, the machine learning models were created using one data source that contains essays. Evaluation was done on newly acquired data source to as to ascertain the performance of our approach on any new data. Various metrics for evaluation have been presented in this study and discussions on the same done. We have also developed a tool that can be used with any new data. In our tool, we have allowed a user to retrain the model in case of need. The tool provided has a graphical user interface that the user interacts with.

The tool developed in this study, separates the various components of arguments into two distinct categories.

Table of Contents

LIST OF ABBREVIATIONS

AM - Argumentation Mining

GUI - Graphical User Interface

IDE - Integrated Development Environment

JDK - Java Development Environment

NER - Named Entity Recognition

NLTK - Natural Language ToolKit

POS - Part of Speech

SBAR - Subordinate Clause

STS - Semantic Text Similarity

SVM - Support Vector Machine

TE - Textual Entailment

LIST OF FIGURES

LIST OF TABLES

CHAPTER ONE: INTRODUCTION

1.0. The Background

Argumentation mining(AM) is a multidisciplinary field that cuts across machine learning, natural language processing and computational linguistics. The aim of Argumentation mining is to extract structured argument data from unstructured text. Arguments are made up of claims (conclusion), evidences (premises) and an inference between the claim and evidences.

Argumentation Mining is related to the field of opinion mining and sentiment analysis. However, it has different goals from the two fields. Sentiment analysis aims at extracting the attitude, usually positive or negative or neutral, towards an object or a given aspect of the object while Opinion Mining aims at mining the viewpoints about the object or given aspects of the object (Budzynska & Villata 2017; Cabrio & Villata, 2012). On the other hand, Argumentation Mining provides reasons behind the viewpoints about the object or an aspect of the object.

Opinion mining, also called sentiment analysis, has been used to identify attitude towards a given subject or a given aspect of the subject (Villalba & Saint-Dizier, 2012). This attitude is often positive or negative. Opinions are subjective statements describing what a person believes or thinks about something and are usually not conclusive.

Argumentation mining aims at extracting structured argument data from unstructured text. Contrary to opinions, arguments are used to provide justifications towards a viewpoint or opinion and explanations their explanations. Arguments are used to convince the customers to accept a given viewpoint of a product. They are also used to convince the public to accept a particular opinion that is advance in the news and social media. Arguments are used in areas involving debating, dialogues, law and policy making.

There are two approaches to Argumentation Mining namely structural approaches and statistical approaches. Structural approaches explore use of grammars whereas statistical approaches makes use of Machine learning which includes both supervised and unsupervised learning algorithms.

Argumentation Mining has got applications in areas such as debating technologies, policy making, machine translation, information retrieval, text summarisation, recommender systems and question answering among other areas.

There have been some initial successes in argumentation mining. These include the IBM debating technologies which gave an initial system in which if given a controversial topic, the system would give the pros and cons of the topic based on Wikipedia pages (Aharoni et al, 2014) and MARGOT (**M**ining **ARG**uments fr**O**m **T**ext), the first online argumentation mining tool that is used to identify argumentative components of sentences, (Lippi & Torroni, 2016a).

1.1. Problem Statement

Arguments are made up of claims, evidences and inference between the claims and evidences with the heart of every argument being a single claim (Levy et al, 2014). Current approaches in argumentation mining have used corpora from single domain such as medical (Groza & Nagy, 2016), news (Sardianos et al, 2015), social media, wikipedia pages(Levy et al, 2014) among others. For instance, student essays are argumentative in nature and usually follow a given structure. The structure is usually such that the essays open with a claim in the first paragraph, followed by justifications of the claim in paragraphs that follow and reaffirmation of the claim in the last paragraph. The structure in essays usually does not apply in areas such as social media, Wikipedia articles and medical fields among others. The approaches used in such single domains have failed to generalize when applied in new unknown domains (Daxenberger et al, 2017). The performance of the methods has been very poor when subjected to new data.

1.2. Goal of the Study

The goal of this study was to classify whether a new sentence would be argumentative or not.

1.3 Research questions

1. How do we automatically create a pool of sentences (corpora) that contains argumentative sentences?
2. How do we design a model that can identify arguments from argumentative sentences?
3. How can we implement an argument mining tool for claim identification that generalizes in newly acquired data sets?
4. How do we evaluate the model designed in argument mining?

1.4. Scope and Limitations of the study

This study used annotated data that is already available in the public domain for use in research purposes. Such data sometime have less inter-annotator agreement. The study did not endeavor to correct any errors that might be noted due to varying inter annotator agreements.

1.5. Justification of the Study

This study was significant as follows.

1. The study provided a tool that enable the general community that is interested in argumentation to be able to extract claims from text originating in domains that were unknown beforehand.
2. This study advanced the need of commercialization of argumentation mining. This was done by providing methods that can generalize in new text corpora.
3. Researchers in the areas of language processing, argumentation and debating technologies.

CHAPTER TWO: LITERATURE REVIEW

2.0 Introduction

This section covers the literature relevant to the study. It opens by introducing arguments and the field of argumentation mining. It then covers the argumentation pipeline and the various approaches that have been used to handle various tasks of argumentation mining. The section closes by looking at the conceptual model for the study.

2.1 Arguments

An argument is made up of several statements. It can be defined as being made up of claim, evidence and the link or inference between the claim and evidence. In an argument, the claim is also referred to as the conclusion. The claim is usually supported by one or more evidences, also called premises. The link between the two is called the warrant or the inference and sometimes simply called the argument (Lippi & Torroni, 2015). It is what makes the argument complete.

In its simplest form, an argument is made up of a claim and one or more supporting premises which can be represented by a predicate as follows:

$$\text{Premise} \longrightarrow \text{Claim}$$

Figure 1: Simple Argument as predicate

Arguments, in most case, are usually identified by the presence of cue phrases which contain cue words. Such phrases will have the following patterns among others:

<claim> because <premise>.

Since <premise> it is feasible that <claim>.

<premise>. Therefore, <claim>.

However, not all arguments have the presence of cue words or phrases. Sometime, the cue phrases are also used in a misleading way. The following is an example of an argument without the use of a cue phrase.

> *"By wearing school uniforms, pupils are not able to develop their own style of fashion. Wearing school uniforms will have negative influence on the development of their characters."*

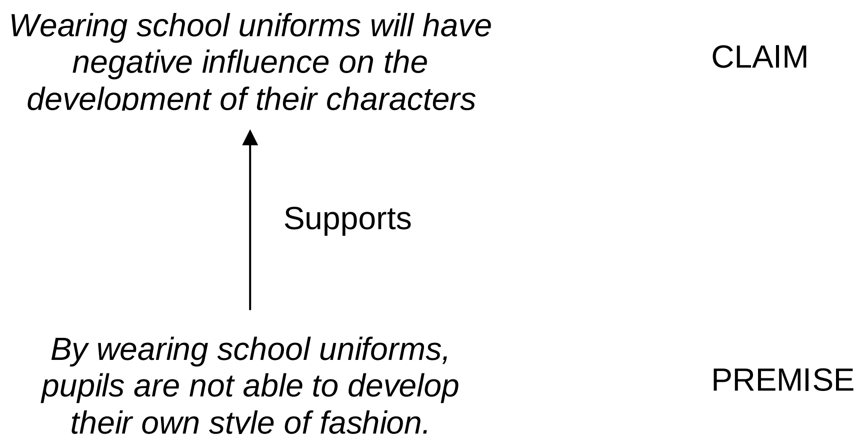

Figure 2: Example argument without cue words

2.2 Argumentation Mining

Argumentation mining is a field of study that aims at extracting structured argument data from unstructured text. Argumentation is a multi-discipline research field which studies debates and reasoning process. It spans across areas such as logic, philosophy, linguistics, computer science, law, dialectics, rhetoric, law and psychology (Lippi and Torroni, 2016; Bodanza, Tohmé & Auday, 2016). An argument can be defined as being made up of claim, evidence and the link or inference between the claim and evidence. In an argument, the claim is also referred to as the conclusion. The claim is usually supported by one or more evidences, also called premises. The link between the two is called the warrant or the inference and sometimes simply called the argument. It is what makes the argument complete.

The advancements in Artificial intelligence especially in the areas of knowledge representation and reasoning, and multi-agents systems has led to the rise of the field of computational linguistics (Lippi and Torroni, 2016). This led to initial works on systems that formulate convincing arguments towards a controversial topic (Aharoni et al, 2014). When supplied with a controversial topic, such systems would identify relevant claims and their supporting evidences from sources such as Wikipedia.

Argumentation is used in decision making where the arguments are used to support, contradict and explain given statements. In debating, argumentation is used in summarizing the debates, giving feedback to participants in debate and helping participants in finding weakness in other participants in the debates.

2.3 Argument Mining Pipeline

Common tasks in argument mining include detection of argumentative components, identification of component types and prediction of the argumentative structure. These tasks can be represented by the following pipeline (Lippi and Torroni, 2016).

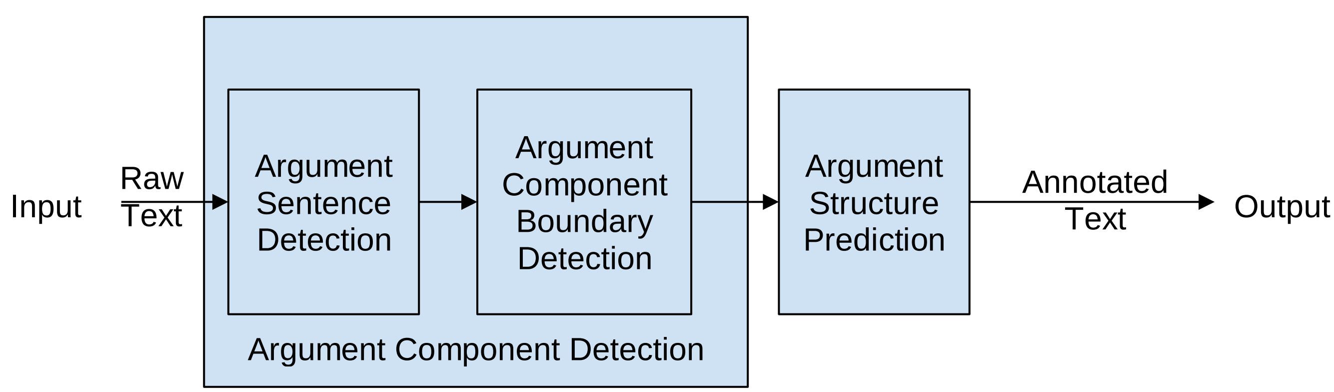

Figure 3: Argumentation Pipeline

Source: Lippi and Torroni (2016)

2.3.0 Argumentative sentence detection

This is the identification of sentence that make up an argument in a given text corpora. Arguments can be found in one sentence or can span several sentences. Arguments can also only form part of a sentence but not the whole sentence. There are two tasks associated with argumentative sentence detection namely claim detection and evidence detection(Lippi and Torroni, 2016).

Methods that have been proposed for argumentative sentence detection include the use of Machine Learning approaches, Text summarisation approaches and structural parsing of information.

2.3.0.1 Machine Learning

Machine Learning is the science which makes computers to learn without being explicitly programmed. It is a multi-disciplinary field that involves tools and ideas from computer science, probability and statistics, optimization and linear algebra. Machine learning has been applied in a number of fields one of which includes text analytics.

Several algorithms have been used in machine learning. These algorithms can be classified into either supervised algorithms or unsupervised algorithms or semi-supervised.

Supervised algorithms are where you have one or more inputs mapping to a given out and there exists a mapping function between inputs and outputs. Such algorithms include that which perform regression or classification tasks. Supervised machine learning tasks are performed by algorithms such as Support Vector Machines, Linear Regression and random forests.

In unsupervised machine learning, the inputs do not have corresponding outputs. Such algorithm are those that does clustering and association.

In Argumentation Mining, argumentative sentence identification can be treated as a binary classification problem where argumentative sentences are separated from non-argumentative sentences. This has made it possible to apply classifiers in a supervised environment. This approach has been used in identification of arguments from news, blogs and social media (Sardianos et al, 2015; Goudas et al, 2014).

2.3.0.2 **Text Summarisation**

Text summarization is condensing text into shorter forms while preserving its meaning. Two methods of text summarisation exists namely extractive text summarisation and abstractive text summarisation. With the growth of information, text summarisation techniques has been key in understanding the information in the large volume of data.

2.3.0.1.0 Extractive text summarization

Extractive summarisation is selecting important sentences from the original text and concatenating them to form a summary. Several methods exist for extractive summarisation (Gupta & Lehal, 2010). These include machine learning methods, cluster based approaches, term frequency-inverted document frequency(TF-IDF), cluster based approaches, Latent Semantic Analysis (LSA) based approaches and fuzzy logic among others.

Extractive summarisation methods has been used to identify sentences containing arguments. For instance, (Petasis & Karkaletsis, 2016) used graph based model, TextRank, to extract arguments from text. TextRank is a graph based ranking model that can be used to extract summary from documents by exploiting similarity among sentences based on their content.

Extractive text summarisation has also yielded good results in identification of arguments in news (Petasis & Karkaletsis, 2016).

2.3.0.1.1 Abstractive Text Summarisation

Abstractive Text Summarisation involves forming sentences which were previously not in the original document but using the words that were available in the document. Abstractive text summarisation has been used to address the weaknesses that are evident when extractive summarisation techniques are used. Such weaknesses include the length of sentences and the spread of information in text (Kasture et al, 2014). Some sentences are usually longer than average thus posing a challenge to extractive techniques. It is also noted that information tends to spread in an entire document or in several document. It therefore becomes difficult in using just a single sentence or a few sentences to summarise the whole document or any group of related documents. Abstractive techniques have been used in generating micro opinions from hotel reviews (Ganasen, 2010).

It is worth noting that based on the literature accessed, abstractive text summarisation techniques has not been explored in handling any tasks of argumentation mining.

2.3.0.3 Structural Parsing

Parsing is the process of structuring a representation of a natural language sentence usually in accordance with a given grammar. Natural language is made up of grammars which is ordered in a given order.

Lippi and Torroni (2015) argues that argumentative sentences have a common rhetoric structures with the structure having some common tag as the root. In their work, they use Parse Tree Kernels (PTK) to identify argumentative component of sentences. They used this approach to provide an online tool, MARGOT[1], which can be used to identify argumentative components of sentences.

2.3.1 **Text Segmentation**

Text segmentation is the process of dividing text into meaningful parts such as words, sentences and topics. It has been used in the area of sentiment analysis, opinion mining and argumentation mining. It has also formed part of both manual and automatic argumentation mining (Lawrence et al, 2014). In automatic argumentation mining, text segmentation is used to identify parts of the argument from the argumentative sentences. This includes the identification of claims and the related evidences.

Relational and structured output classifiers are often used in handling text segmentation. The classifiers such as Conditional Random Field (CRF), Hidden Markov models, Recurrent Neural Networks (RNN) and structured support vector machines (SVM) are some of the classifiers that have been used to handle text segmentation. For

[1] http://margot.disi.unibo.it/index.html

instance, Goudas et al(2014) combined text segmentation with CRF to extract premises(evidences) from argumentative sentences by exploiting the use of BIO representation. In this representation, B is the token at the start of the premise, I is the token within the premise other than the first token and O is any other tokens not within the premise.

Weakness of text segmentation approach is that it restricts usage in a broader context. For instance, a claim in one sentence can be a premise in another sentence in a different context. Also , a sentence which is not an argument in one context can be an argument in a different context (Lawrence et al, 2014).

2.3.2 **Argument Structure Prediction**

Structure prediction is telling how the various argumentative texts relate to each other. Arguments can either support each other or contradict each other. In real world, these relations are a network of supporting statements and attacking statements.

Several NLP techniques have been proposed for argument structure prediction. The methods such as Textual Entailments (TE) (Cabrio & Villata, 2012), use of discourse structures(Villalba & Saint-Dizier, 2012) and Semantic Text Similarity (STS) have been used to perform this task of the pipeline. In this task, it is always assumed that the claim always has an association with the evidence (Aharoni et al, 2015).

2.4 Conceptual Model

The following figure shows the proposed conceptual model for the research

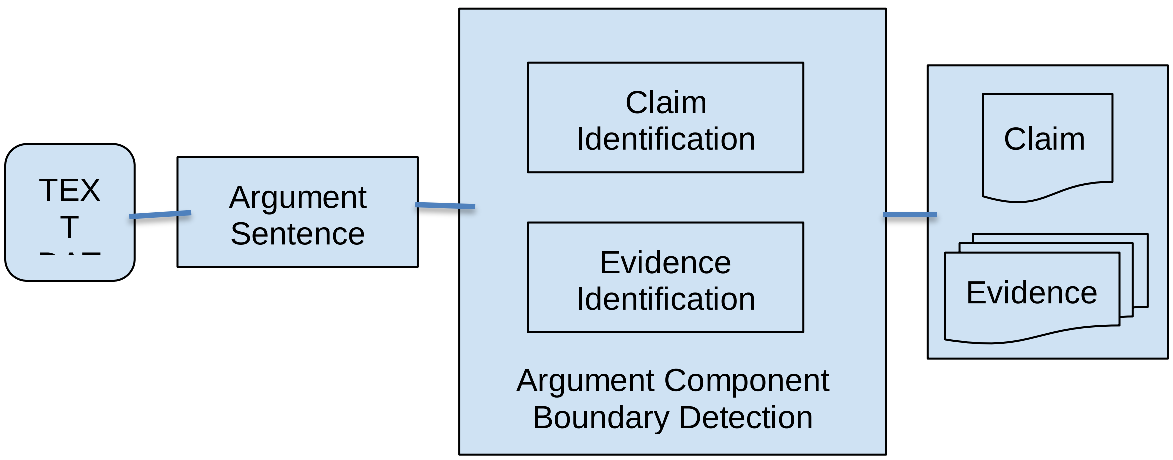

Figure 4: Conceptual Model

The following is the description of the conceptual model

Text Data - This was the input data which came from multiple source

Argument Sentence Detection - This process identified sentences that are considered argumentative. This included breaking up the input text data into sentences while taking care of all the punctuations used in the text input data.The sentences identified were identified to be argumentative or not.

Argument Component Boundary Detection - This part of the model identified the boundaries of the argumentative sentence and thus identifies the various components of the argument. These components are the claim and the various evidences. This is a sentence segmentation problem.

Output - These were sentences which have been classified as claims and evidences.

CHAPTER THREE: METHODOLOGY

3.0 Introduction

The research approach to this study was experimental setup which was be based on essays dataset. The source of data in this study was be data already available on the public domain and suitable for studies in argumentation mining.

3.1 Research Design

Experimental setup used in this study included Text Data input, Sentence Tokenization, Argumentative sentence detection, Sentence Segmentation and Claim identification. The experimental setup was such that one data set was used for the entire process. The data set which was used for the experimental setup was from essays. Once the process is complete including the claim identification, the process was applied to the data from essays. Sentence Tokenization, Argumentative sentence detection, Sentence Segmentation remained as is in the experimental setup when the new dataset from essays is used. However, to identify claim, the model trained on the first data set was then used against the new data sets acquired.

3.2 Data Collection

This research study used publicly available data that is already annotated for studies in the field of Argumentation Mining. Data used also included newly acquired data from news and customer reviews.

Argument Annotated Essays Corpus (AAEC), version 2 (Stab & Gurevych, 2017), was used in this study to develop the machine learning models. This dataset consists of argument annotated essays including argument components and argument relations. The dataset is made up of 402 essays, each of which has been annotated to contain one major claim, other claims, premises and relationships between argumentative components.

Additional data was extracted from two news websites: The Business Daily[2] and the Standard Media Group [3] site; and airline customers reviews data at SKYTRAX[4]. A total of 10 news articles were used and a total of 15 customer reviews were used in this work. Annotation of the additional data was achieved using MARGOT (Lippi & Torroni, 2016a). Since the tool provide data that belongs to both claims and premise instead of just one side, our analysis counted such data as both claim and premise.

3.4 Data Analysis Methods and Tools

Sentence Tokenization

Sentence tokenization was done using the NLTK sentence tokenizer which is provided in the nltk.tokenize package of NLTK. Sentence tokenization is the process of breaking down text data into individual sentences.

Argumentative sentence detection

Information Retrieval approaches was be used to identify argumentative sentences. The ranking method, TextRank was initially used to rank the sentences. Ranking methods are independent of the domain and does not need any training data. Ranking methods are used to find sentences that are related to most sentences in the given text. Petasis & Karkaletsis (2016) has shown that Ranking methods are related to Argumentation mining tasks. In their work, they showed that sentence that are ranked top are also argumentative. In my study, the top ranked sentences were studied in order to determine an appropriate cut off for the number of top ranked sentences.

Support Vector machine was also used in this work to identify the arguments. In this method, sentences were either classified as argumentative or not.

[2] https://www.businessdailyafrica.com/
[3] http://www.standardmedia.co.ke/
[4] http://www.airlinequality.com/

Sentence Segmentation

Sentence segmentation was used to detect the boundaries of argumentative component. Text Segmentation has applications in Named Entity Recognition (NER) problems (Lippi & Torroni, 2016b). In NER, chunking is used to identify boundaries of a Named Entity.

In this study, chunking was be used to identify various segments of the argumentative sentences. Chunking was implemented by breaking the sentences based on their structure and each broken point analyzed.

Claim identification

The classifier that was used in this study was Support Vector Machine (SVM). SVM is a discriminative algorithm and is better suited in classifying the sentences as either belonging to claim or evidence. To have training set of data, the segmented text was evaluated against the original annotated text input data to identify the texts that matches the claims. The training set was made of 50% of the entire segmented data. The SVM was trained 70% of the training data and tested on 30% of the training data.

The features that achieve high F Score measured was determined by looking at the linguistic structural characteristics of the of the segmented data. The results using both features were reported. All results using combined features was reported. Using the best features, the trained model was applied of the test data that was initially split from the training data.

3.5 System Design

3.5.0 Data Preparation and pre-processing

In this study, data preparation and pre-processing were done using the following steps

1. Removal of non-ascii characters – The data obtained had non-ascii characters and these were removed before any processing.
2. Sentence tokenisation – The obtained data was broken down into sentences. Sentences are usually made up of end of sentence markers such as full stops and question marks. Sentence tokenisation was done using sentence tokenizer.

3. Removal of unnecessary spaces – It was noted that the data that was used got unnecessary spaces especially before the end of sentence markers. Such unnecessary spaces were removed from the data.
4. Parsing the sentences to generate the constituency trees of the sentences
5. Creation of vector space model of the various components of the constituency trees. The vector space was based on the leaves of the constituency trees. This vector space was used to check the similarities between various sentence and was used to identify the argumentative sentences. It was also used to determine the components of argumentative sentences.

3.5.1 Sentence Classification

Sentence Classification is the initial process through which the input is processes. The text is split into sentences using NLTK sentence tokenizer. The split sentences are then classified as either argumentative or not. Argumentative sentences are those that contain the argument or part of the argument. The part of the argument can either be a premise or a claim.

3.5.2 Boundary Detection

Boundary detection is used to identify the start and end of claims and premises within the argumentative sentences. Features used for the boundary detection was based on the constituency trees of the sentences. Constituency trees were generated using Stanford constituency parser. Examples of constituency parse trees using two sentences from the essays corpus are as follows:

From this point of view, I firmly believe that we should attach more importance to cooperation during primary education.

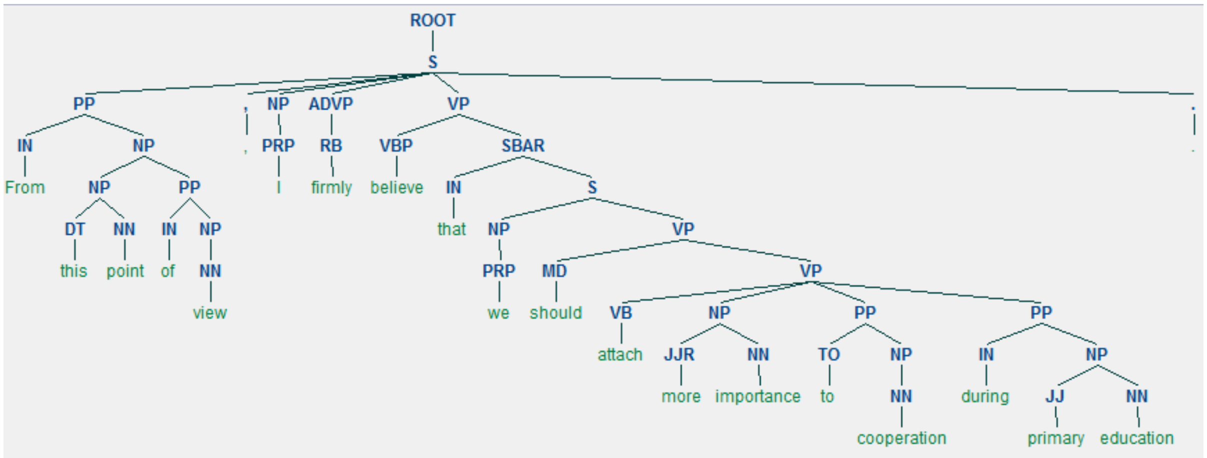

Figure 5: First Example of sentence structure

First of all, through cooperation, children can learn about interpersonal skills which are significant in the future life of all students.

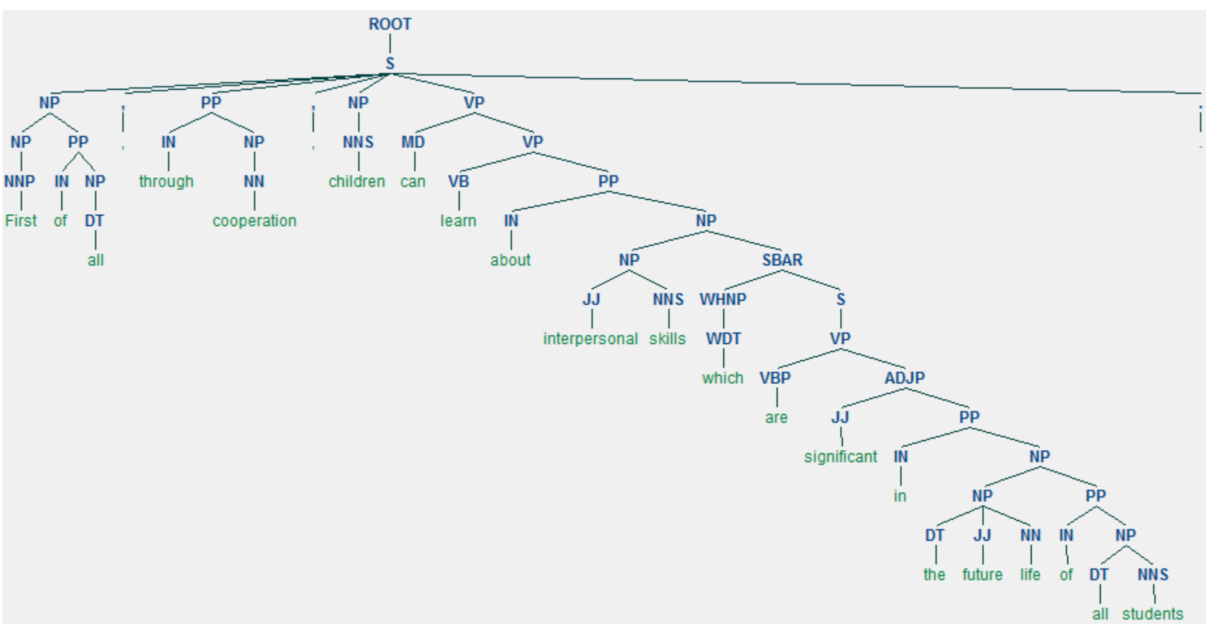

Figure 6: Second Example of sentence Structure

The conditions used to identify the boundaries were as follows:

1. The split components must be sentences by themselves.
2. Split components that were not sentences were discarded as not useful.
3. Each constituency tree was split into subtrees and leaves. The leaves at the subtrees were joined at S and SBAR nodes.

3.5.3 Overall System Architecture

The system implemented is available as a desktop application. The user submits a query in form of text. The user can either copy and paste text to the tool or browse the file which contains the text data.

The text data that is submitted by the user is processed using the argumentation mining pipeline (Figure 3).

Figure 7 shows the overall system architecture that was designed and implemented.

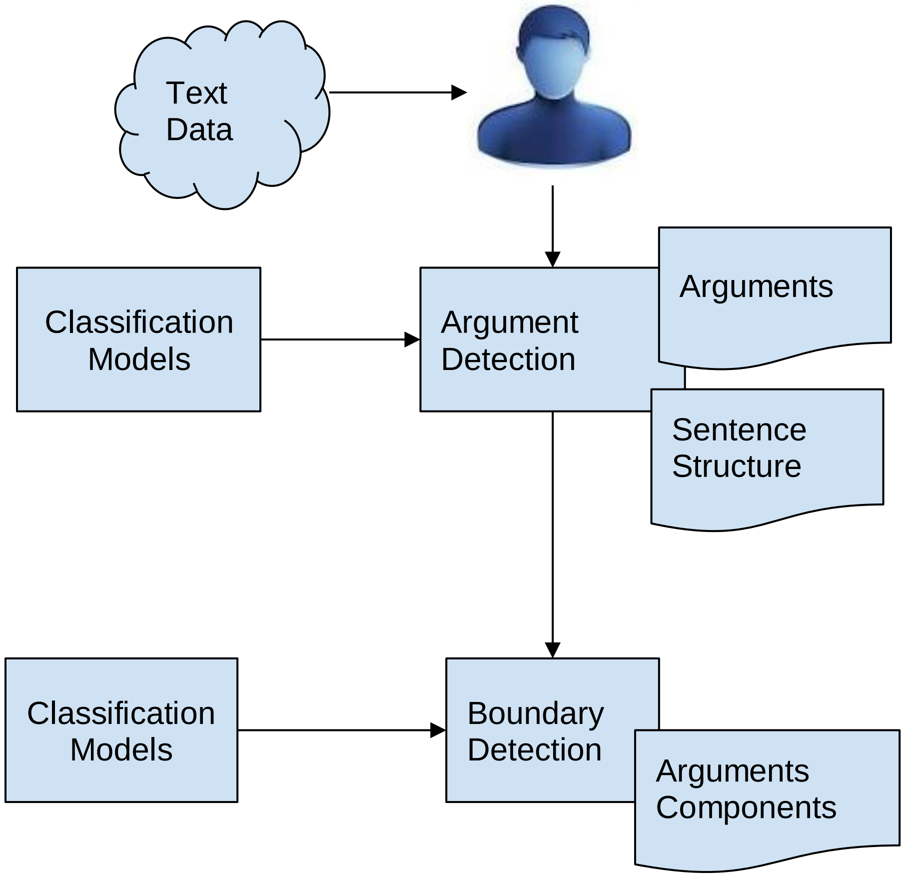

Figure 7: Overall Systems Architecture

Text Data – This is the input data provided by the user

Argument detection – This was the classification task that was used to divide the sentences into either argumentative or non-argumentative

Arguments – These were the output of the argument detection task that was used in the next part of the design.

Sentence Structure – The argumentative sentence was parsed into constituency tree and the structure used for boundary detection.

Classification Models – These are the machine learning models that were used to perform the tasks of argument detection and sentence boundary detection

Boundary Detection – This was the task of breaking up the sentence into various components. In this process, it was ensured that each resulting component was a sentence of its own. This is because either claim or premise of an argument needed to be a sentence by itself.

3.6 System Implementation

The system was implemented as a desktop application based on python programming language. Several modules were used to support the implementation.

3.6.1 Implementation Tools

Enthought Canopy

Enthought Canopy[5] is a comprehensive cross-platform IDE for scientific computing, with over 400 pre-built and tested packages for analysis and visualization of scientific data. These packages include those required for Natural Language processing tasks.The version used in the implementation of the research project was 2.1.3.

The Stanford Parser

The Stanford Parser is a statistical natural language parser built on Java programming language. A natural language parser is a program that works on the grammatical structure of sentences. Being a statistical parser, it uses the knowledge of human parsed sentences to provide the most likely analysis of any new text. The version of the parser used in this project was 3.8.0.

Java Development Kit (JDK)

This is a programming environment for building components and applications that use Java programming language. JDK is a requirement for the Stanford parser to be used. The version used in this project was 1.8.0.

Python

[5] https://www.enthought.com/

Python is a high level interpreted programming language. Interpreted programming languages are programming languages which execute instructions without compilation into machine language. Python 2.7 was used in the implementation of this research project.

Natural Language Toolkit (NLTK)

NLTK is a platform for building applications that work with human language data for text analysis. The version of NLTK used in this project was 3.4.2

Tkinter

The Graphical User Interface (GUI) was implemented using TKinter. It is the Python binding to the Tk GUI toolkit. Tk is an open source widget toolkit that provides a library of widgets for building a GUI for many programming languages.

3.7 User Interface Of Model

The user interface of the implemented design is shown in figure 8 below.

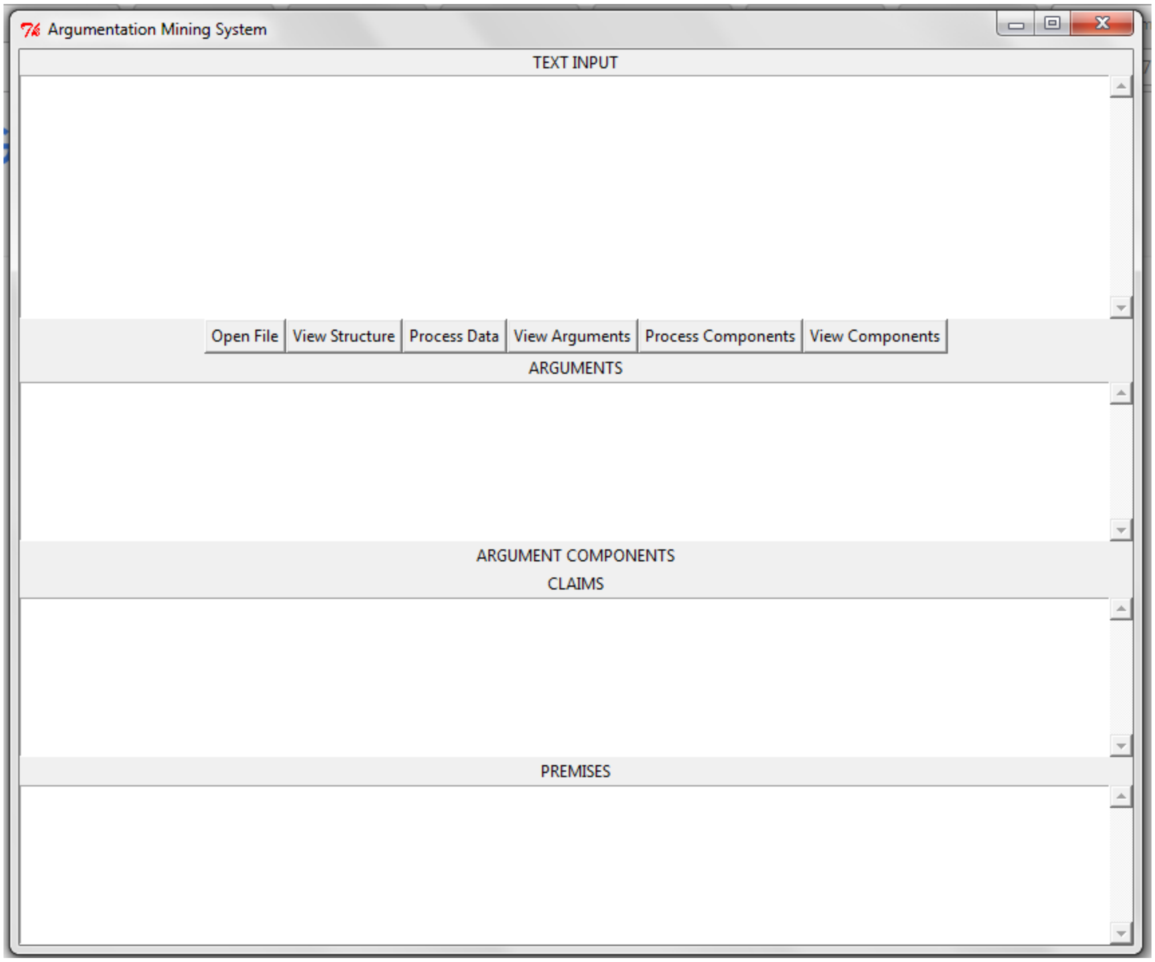

Figure 8: Graphical User Interface

Text Input - This is the text area where the text data is displayed. The user can either paste copied data to the area or load text data from file using the button labeled "Open File"

Open File - This button opens file on the local computer. The contents of the open file are displayed in the the Text Input area.

View Structure - This button enables the user to see the structure of the text data being displayed at the text input area. Illustration of this for one sentence is shown below:

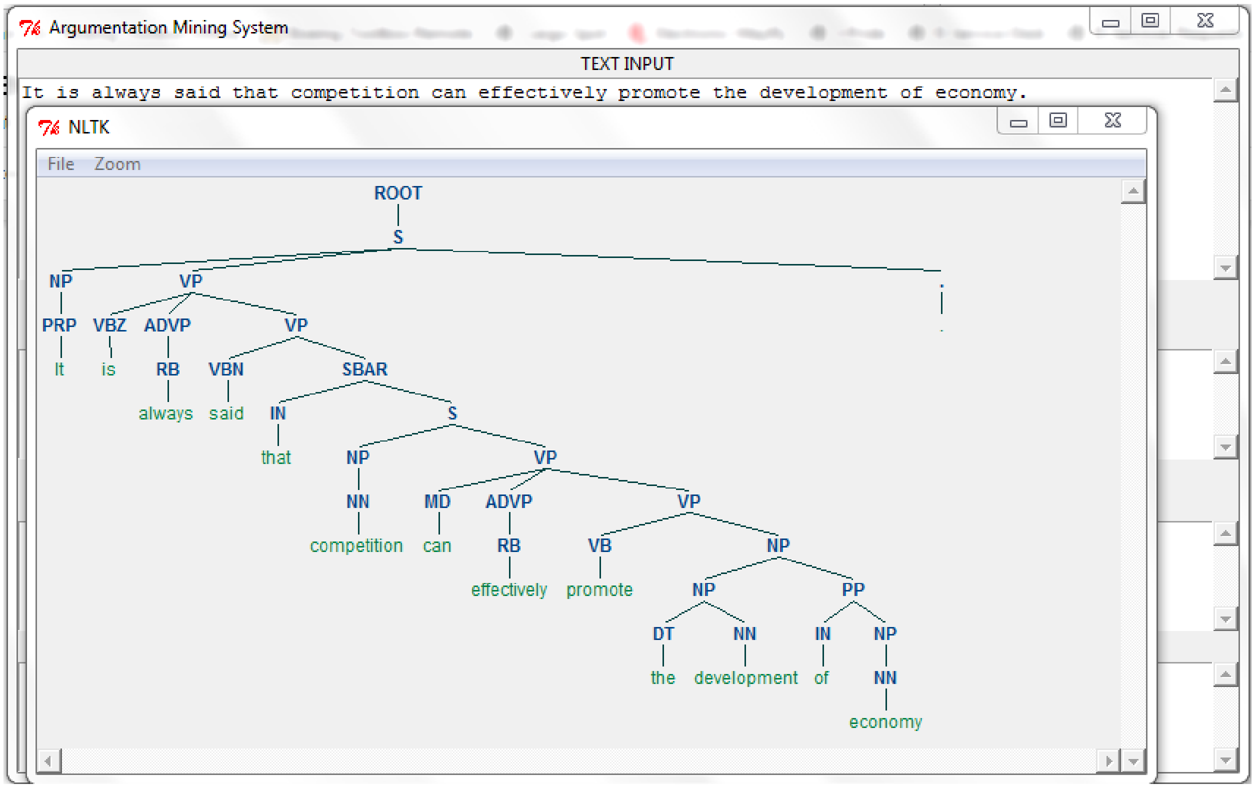

Figure 9: Sentence Structure from the GUI

Process Data - This button enables one to retrain the model using new data as input. The format of the input should made up of two columns with the separator being a tab. This is as shown in the table 6 below:

Column	**Data Type**	**Description**
1	Varchar(15)	Contains the label of whether the sentence is “Argument” or “NonArgument”
2	varchar(500)	The sentence that is classified as either “Argument” or “NonArgument”

Table 1: Data format training data for classification of arguments

View Arguments - This button enables the user to view the sentences that contain the arguments from the text input data.

Process Components - This button enables one to retrain the model for identifying the components of the sentence as either claim, premise or non of the two using new data as input. The format of the input should made up of two columns with the separator being a tab. This is as shown in the table below:

Column	**Data Type**	**Description**
1	Varchar(15)	Contains the label of whether the sentence is “Claim” or “Premise” or “Neither”
2	varchar(500)	The sentence that is classified as either “Claim” or “Premise” or “Neither”

Table 2: Data format training data for argument component identification

View Components - This button enables the user to view the components of the sentence that are claims of premises. The button detects the boundaries in the sentence and breaks the sentence into claims and premises.

Arguments - This is the text area which displays the argumentative sentences.

Claims - This text area displays the parts of the sentences that have been classified as claims.

Premises - This text area displays the parts of the sentences that have been classified as premises.

The figure below shows argument extracted from one paragraph of input data. It also illustrates the claims and premises extracted from the same piece of text.

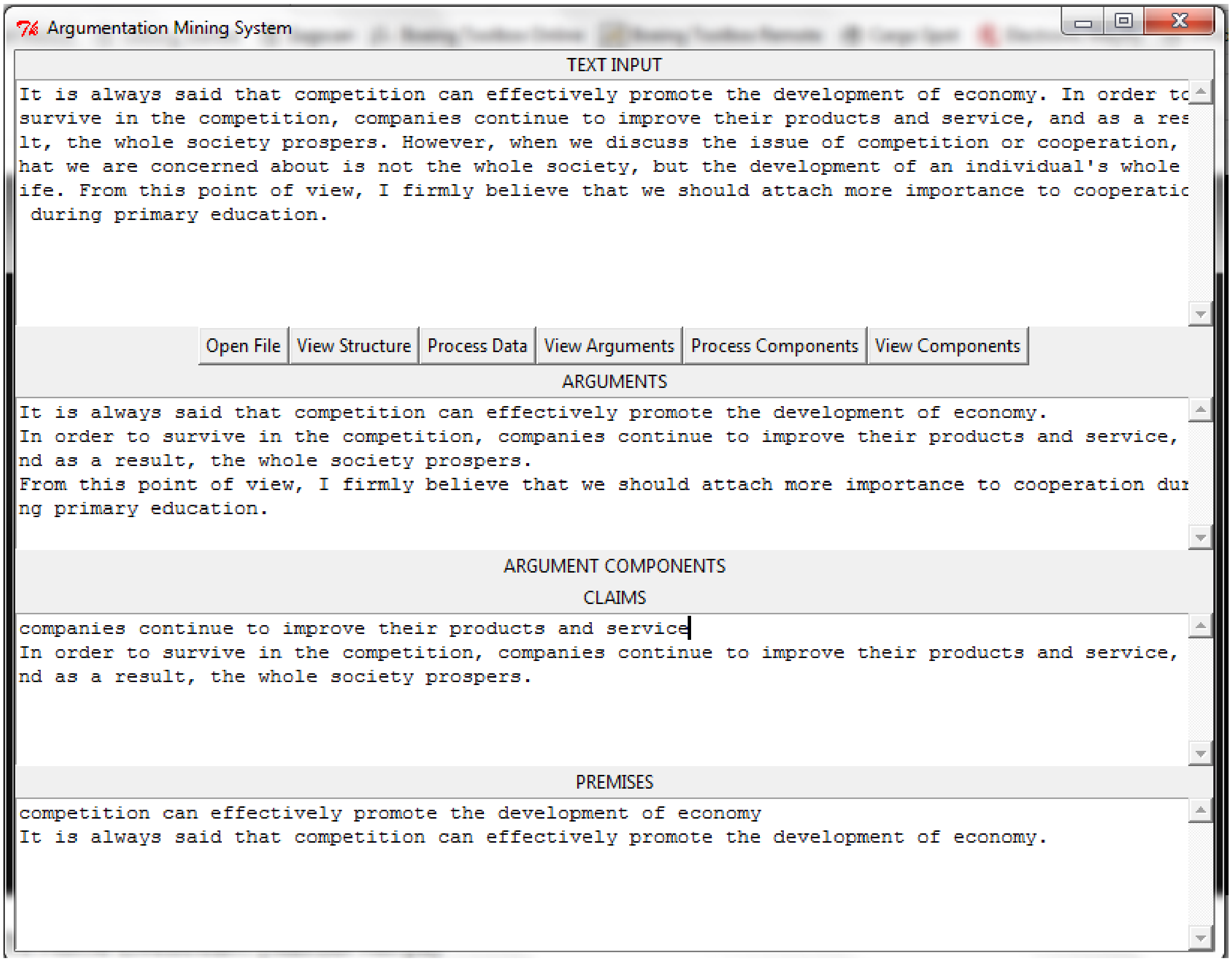

Figure 10: Example Argument mining in the GUI

CHAPTER 4: RESULTS AND DISCUSSIONS

4.0 Introduction

This section presents the results that were attained using the system that was built and based on the research objectives in chapter one. The section also discusses these results.

4.1 Presentation of results based on objectives

The results and discussions below have in presented in the chronological order such that the research questions in chapter one are answered.

4.1.0 Feature Selection

The training model was achieved by examining the features of the text data. The features that were considered in this research project included discourse indicators, part of speech (POS) tags, sequence of parts of speech tags, end of sentence markers, length of sentences and the sentence structure. The discourse markers that were used have been included in appendix 1.

Argument indicators - Argument indicators, also called discourse markers, are features that indicate the presence of an argument in a sentence. Some of the examples of argument indicators are words such as “deduce”, “because”, “therefore” among others.

Part-of-speech (POS) tags - POS tagging, also called grammatical tagging, is the categorisation of the various parts of speech into various tags based on the definition of the POS and the context in which it is used. The Penn treebank tagset was used to identify the various parts of speech.

End of sentence markers - This included the punctuations that mark the end of the sentence such as full stop (“.”) and question marks (“?”). It was noted that whenever the end of the sentence was incorporated as a feature, the training algorithm would overfit the data. This lead to a failure of the fit model to predict any new data that was not in the test set of the data. Due to this overfitting and failure to predict any new data set, the performance based on the end of the sentence markers is not reported in this study.

Sentence length - Sentences are made up of words and punctuation marks. The length of the sentence is the count of all the characters that make up the sentence.

Sentence structure - Sentences can be broken down into various parts such as noun phrases and verb phrases. These phrases can further be broken down so that a tree representation of a sentence is achieved. In the use of the sentence structure, the outermost leaves up to a level of two was consider. This can be represented in the diagram below:

The performance of these features was as shown in the table below:

Features	Precision	Accuracy	F1 Score
POS (Including count of occurrence)	74.4%	76.2%	75.0%
POS + Sentence structure	**78.6%**	**76.8%**	**77.0%**
POS + Discourse Indicator	74.0%	75.6%	74.6%
POS + Sentence length + Discourse Indicator	74.0%	75.6%	74.6%
POS + Sentence length	74.0%	75.6%	74.6%

Table 3: Performance of various features used in mining arguments

The best features above were used in both the classification of sentences into arguments or non-arguments and the identification of the various parts of the arguments which entailed identification of whether part of a sentence was a claim, a premise or neither. The performance of this has been shown in the table below:

Task	Precision	Accuracy	F1 Score
Sentence classification into argument and non-argument	78.6%	76.8%	77.0%
Claim and evidence identification	83.7%	67.6%	74.1%

Table 4: Performance of best model when used in argument mining and component identification

The results obtained shows that the use of discourse markers does not influence the performance of the model. When all features were looked, it was reported that the best performance was obtained when the sentence structure was incorporated with POS tags. This gave an F1 Score measure of 77% and accuracy of 76.8%. This accuracy was comparable to related similar work as shown in table 3.

Work	Accuracy
Habernal and Gurevych (2017).	75.4%
Stab and Gurevych (2017).	77.3%
Lippi and Torroni (2015)	71.4%
Our Work	76.8%

Table 5: Comparison of our work with other work in mining arguments

4.1.1 Boundary Detection for component identification

The boundary of the sentence was detected over the structure of the sentences. In the consideration of the structure of the sentence, various rules that apply to sentences were considered. These rules included the following:

1. Sentences are made up of phrases

2. Sentences can be made up of other sentences
3. A complete sentence is made up of end of sentence marks. This meant that for any split that was done, the split sentence would qualify as a complete sentence by simple addition of end of sentence mark
4. A sentence should be syntactically correct.

In our work, the sentence structure was analyzed using constituency based parse tree. The phrases were at S and SBAR nodes. In concurrence with Lippi and Torroni (2015), it was noted that SBAR nodes can form root of sentences by themselves. The structure was also broken at each leave and the output checked to ensure that it would be made up of a complete sentence. Any output that could not make up a sentence was discarded and not used in any evaluation.

4.2 Performance on new data sets

The model which was fit was run on three dataset: two newly acquired data set with one coming from news while the other customers review, and third dataset coming from already annotated data. The data from news was extracted from online news articles from https://www.businessdailyafrica.com/ and https://www.standardmedia.co.ke/. The reviews data was based on a sample of airlines reviews data available at SKYTRAX[6]. The third dataset was made of a subset of debates[7].

In order to evaluate the performance of our approach, annotation of the data collected was required. Annotation was however achieved using online tool for argumentation mining, MARGOT (Mining ARGuments frOm Text)[8]. The data annotated using the tool formed the baseline data and all evaluation from newly acquired data was done against this baseline data. This evaluation include the the measure of precision, recall and F1 Score measure. These three measures were computed as follows:

[6] http://www.airlinequality.com/review-pages/a-z-airline-reviews/

[7] https://www.uni-weimar.de/en/media/chairs/computer-science-department/webis/data/corpus-webis-debate-16

[8] http://margot.disi.unibo.it/index.html#

$$precision = \frac{|\{Relevant\ items\} \cap \{Retrieved\ items\}|}{|\{Retrieved\ items\}|}$$

$$Recall = \frac{|\{Relevant\ items\} \cap \{Retrieved\ items\}|}{|\{Relevant\ items\}|}$$

$$F_1 Score = \frac{2 \times Precision \times Recall}{Precision + Recall}$$

The performance of our tool against the baseline data was as shown in the table below for the argument classification task.

DATASET	**PRECISION**	**RECALL**	**F_1 SCORE**
News data	65.5%	59.4%	62.3%
Customers Reviews	20.4%	6.0%	9.0%
Debates	56.2%	64.9%	60.0%

Table 6: Performance of the model when used in new dataset acquired

4.3 Discussion of performance on new data set

Our tool had an almost similar F1 Score for both the news data and debates data when it came to the classification of the text into either argumentative or not. However, this was not the case with customers reviews data that was used. Unlike debates and news data, customer reviews tend to be shorter in length. This is shown in the table below.

DATASET	Average Words per sentence
News	22
Customer Reviews	18
Debate	25
Essays[9]	22

Table 7: Average sentence length for data sets used

The performance of our system can also be attributed to the different writing styles when customer reviews are compared to essays and debates. In customer reviews, the authors are usually free to write in whatever manner. Authors of reviews are usually not subject to strict language use and some authors would use, for instance, incorrect words and grammar. The authors would be less concerned about the syntactic correctness of the use of language. On the other hand, debates news and essays are structured. Authors of this usually organise their thoughts in such a manner that the they make sense and the objective of writing is also met. Authors of news, debates and essays tend to use correct syntax and there would be minimal errors in the use of language. These authors also do subject their work to reviews by other people before publishing their writings. This is contrary to customer reviews where authors write willingly and would rarely subject their writings for other parties to review before publishing them.

[9] Data used for creating the models

CHAPTER 5: CONCLUSIONS AND RECOMMENDATION

5.0 Conclusions

In this study we have proposed and demonstrated a way in which one can mine arguments and components that make up the arguments using machine learning algorithm that learns over the structure of sentences.

The experimental results show that this approach can successfully be used to mine arguments and components of the arguments achieve an F1 Score measure of 77% and 74.1% respectively. This is comparable to other approaches that have been used previously. In our approach, we trained our model based on already existing annotated data suitable for argumentation mining. We took a novel approach to annotate newly acquired data using existing argument mining tool. This approach eliminates the need for human annotators. This tool provided a baseline which was used to perform any evaluations on the newly acquired datasets.

The experimental results also showed that sentences broken at their leaves and joined back to the subordinate clauses (SBAR) or nodes with S formed good candidates for claims and premises in argumentation mining (Lippi and Torroni, 2015). We have also shown that argumentation mining in domains that have text data which is reviewed before publishing can use similar models to mine arguments and its components.

In this study, we also developed an application that uses the approach proposed in the study.

5.1 Challenges and limitations

Complexity of data: Since data was expressed in constituent trees, it was complex building a machine learning algorithm over the tree structure of sentences.

Limited Hardware resources: The hardware used could not allow for learn over a big array. The data was at some point expressed as an array.

Availability annotators: Annotation of text data requires experts in language. These experts need to be familiar with with the nature of arguments. These were not readily available within the available time.

5.2 Contributions of study

This study provided a tool that can be used to mine arguments. In our work, we demonstrated that we can use already available tools to annotate data we the tasks of argument mining.

We have also shown that argument mining can be achieved across domains that have similar writing styles.

5.3 Recommendation and future work

Future studies should focus on improving the performance of the approach on data coming from areas where writing styles is not strict such as the area of customer reviews and social media. There is also needing to improve the performance of our approach so that the such systems become more accurate. This will enhance movement towards commercialization of such systems.

REFERENCES

1. Aharoni, E., et al (2014). Claims on demand–an initial demonstration of a system for automatic detection and polarity identification of context dependent claims in massive corpora. *COLING 2014*, *6*.
2. Bodanza, G., Tohmé, F., & Auday, M. (2016). Collective argumentation: A survey of aggregation issues around argumentation frameworks. *Argument & Computation,* 1-34. doi:10.3233/aac-160014
3. Budzynska,K. and Villata,S (2017). Handbook of Formal Argumentation,chapter Processing Argumentation in Natural Language Texts. to appear.
4. Cabrio, E., & Villata, S. (2012, July). Combining textual entailment and argumentation theory for supporting online debates interactions. In *Proceedings of the 50th Annual Meeting of the Association for Computational Linguistics: Short Papers-Volume 2* (pp. 208-212). Association for Computational Linguistics.
5. Daxenberger, J., Eger, S., Habernal, I., Stab, C., & Gurevych, I. (2017). What is the Essence of a Claim? Cross-Domain Claim Identification. *arXiv preprint arXiv:1704.07203*.
6. Habernal, I., & Gurevych, I. (2017). Argumentation mining in user-generated web discourse. *Computational Linguistics*, *43*(1), 125-179.
7. Goudas, T., Louizos, C., Petasis, G., & Karkaletsis, V. (2014). Argument Extraction from News, Blogs, and Social Media. *Artificial Intelligence: Methods and Applications Lecture Notes in Computer Science,* 287-299. doi:10.1007/978-3-319-07064-3_23
8. Groza, A., & Nagy, M. M. (2016, September). Harmonization of conflicting medical opinions using argumentation protocols and textual entailment-a case study on Parkinson disease. In *Intelligent Computer Communication and Processing (ICCP), 2016 IEEE 12th International Conference on* (pp. 163-170). IEEE
9. Gupta, V., & Lehal, G. S. (2010). A Survey of Text Summarization Extractive Techniques. *Journal of Emerging Technologies in Web Intelligence,2*(3), 258-268. doi:10.4304/jetwi.2.3.258-268
10. Levy, R., Bilu, Y., Hershcovich, D., Aharoni, E., & Slonim, N. (2014). Context dependent claim detection.
11. Lippi, M., & Torroni, P. (2015, July). Context-Independent Claim Detection for Argument Mining. In *IJCAI* (Vol. 15, pp. 185-191).

12. Lippi, M., & Torroni, P. (2016a). MARGOT: A web server for argumentation mining. *Expert Systems with Applications*, *65*, 292-303.

13. Lippi, M., & Torroni, P. (2016b). Argumentation Mining: State of the Art and Emerging Trends. *ACM Transactions on Internet Technology,16*(2), 1-25. doi:10.1145/2850417

14. Petasis, G., & Karkaletsis, V. (2016). Identifying Argument Components through TextRank. *Proceedings of the Third Workshop on Argument Mining (ArgMining2016),* 96-102. doi:10.18653/v1/w16-2811

15. Rinott, R., Dankin, L., Perez, C. A., Khapra, M. M., Aharoni, E., & Slonim, N. (2015, September). Show Me Your Evidence-an Automatic Method for Context Dependent Evidence Detection. In *EMNLP* (pp. 440-450).

16. Sardianos, C., Katakis, I. M., Petasis, G., & Karkaletsis, V. (2015). Argument Extraction from News. *Proceedings of the 2nd Workshop on Argumentation Mining,* 56-66. doi:10.3115/v1/w15-0508

17. Stab, C., & Gurevych, I. (2017). Parsing argumentation structures in persuasive essays. Computational Linguistics.

18. Villalba, M. P. G., & Saint-Dizier, P. (2012). Some Facets of Argument Mining for Opinion Analysis. *COMMA*, *245*, 23-34.

19. Kohler, J., Khalid, A.-K., Wachsmuth, H., Hagen, M., & Stein, B. *Webis-Debate-16*. From Webis-Debate-16: https://www.uni-weimar.de/en/media/chairs/computer-science-department/webis/data/corpus-webis-debate-16/#webis-publications accessed on 25 April 2018

APPENDIX 1: Argument indicators

"Accordingly"

"Consequently"

"That","clearly"

"Entails"

"Hence"

"Implies"

"in short"

"in conclusion"

"it should be clear"

"points to the conclusions"

"So"

"the point I'm trying to make"

"Therefore"

"Thus"

"to sum up"

"we may deduce"

"As"

"besides"

"Because"

"Deduced"

"derived from"

"due to"

"For"

"Furthermore"

"in addition"

"in light of"

"in view of"

"indicated by"

"is supported by"

"may be inferred"

"Moreover"

"this can be seen from"

"Since"

"what's more"

APPENDIX 2: Reviews Used

1. The flight was good, the cabin crew were great and the food was good. However the seat button adjuster ref, seat 23J is depressed in the slot hence was unable to adjust my seat and get some sleep. Hope maintenance can get this sorted. Sometimes it took too long to clear tables after meals, this can be improved.
2. I travel almost every quarter between Lusaka and Nairobi and back, and my experience is good. The crew are courteous and friendly and helpful. One little disappointment though which I have experienced about twice is when the on Board duty free shop catalogue indicated there was a special offer of a perfume/cologne on sale, and when I asked for it I was told it was not available, and I also knew I was the first to ask amongst the passengers. The product this time on my return trip to Lusaka on Thursday 29th March, was a SAFARI cologne for men, by Ralph Lauren, advertised at a special price, but no product, and no apology in the catalogue.
3. I flew the route Kinshasa to Nairobi March 26 and back March 30. The flight-time is over 3 hours but Kenya Airways for whatever reason used the Embraer 190 which should be used only on short haul flights. Both times the cabin was full and there was not enough space in the overhead compartments for hand luggage. The seats are not comfortable and do not fully recline. It was not possible to work as the cabin was too noisy and crowded. Definitely I will choose Ethiopia Airlines, which uses a Boeing 787 for the flight to Addis Ababa and never Kenya Airways again.
4. A complete disappointment from start to finish. Delays can happen, but they should be communicated properly. The 45 min delay turned out to be over 2 hours. Cabin was untidy and dirty when joining the flight, which originated in Guangzhou, in Bangkok. The seat was spacious but lacked any privacy dividers or hoods, leaving one exposed to the frequent foot traffic walking up and down the cabin all night. Inflight catering in 'Premier World' was mediocre. No menu was handed to passengers. A cold chicken pie and some 'vegetarian' snack was offered alongside a small chocolate cake after take-off for this 8h30 overnight flight. No appetizer, no salad, no option of a warm meal, just some basic finger food. The crew had to be reminded to hand out the amenity kits which contain eyeshades, socks ear plugs, a pen and toothbrush. Cabin lights were dimmed but the crew didn't bother to close the curtains between the galley at the second door and the cabin, leaving the front section bright and uncomfortable. Landing in Nairobi was 1 hr 20 minutes behind schedule, ground staff made little effort to accommodate connecting passengers who missed their connection. Overall an underwhelming experience. For the same (or lower) price I would rather take in the 2 hour or so connection timw in Doha, Dubai or Abu Dhabi and fly with an airline which takes onboard service and passenger comfort seriously.
5. The ground staff was acting completely arbitrarily, and each of them had different rules. Our main problem with Kenya Airways was not on board, but with the ground staff. My husband (Ugandan) and I (German) were booked on a flight to Colombo in Sri Lanka. It was a one-way ticket. Since the Sri Lankan Visa is only for 30 days, I had another flight booked with Malaysian Airlines to Cambodia within that period. My husband and I both had E-Visas for Sri Lanka. So when we came to Entebbe Airport, the Kenya Airways Lady at the Check-In counter didn't let us board the

airplane. She claimed, that Ugandan citizens weren't allowed to go to Sri Lanka on an E-Visa (Our E-Visa was already granted and even certified by the Sri Lankan Embassy in Kampala). Also, she said that we had to have a flight from Sri Lanka back to our home countries and she couldn't let us go there on a one-way ticket. When I told her about our outbound flight with Malaysian, she said that there is "a rule, that every person has to return to their home countries within one year", so we had to show her a ticket back to our home countries, otherwhise she wouldn't check us in. As I said, she was acting totally arbitrarily. Unbelievable. So in the end I had to book a flight for each of us back to our home countries (which I of cause cancelled immediatly once arrived in Colombo). I did it right there and then at the airport, but she still had the opinion that our E-Visas weren't ok, so we missed the flight. Then, the lady took us to the Kenya Airways office at the airport and looked for another flight for us. But since "it was our mistake" that we missed it, we had to pay for the change fees. She then told us to go to the Sri Lankan High Comission in Kampala the next morning and apply for the normal visa. In general this lady was very rude, when I tried to explain to her that our E-Visas were already approved etc, she told me to shut up and that she was tired of dealing with people like us. So when we went to the embassy, we talked to the ambassador personally and he was completely shocked that they wouldn't let us board the airplane, since Ugandan citizens can go to Sri Lanka on an E-Visa and ours was already approved. He gave us his personal number, so that we could call im in case we would have any problems again. The next day the Check-In lady wasn't there and we had no problems to board the airplane, even though our visa was still the same and no one asked us for return tickets to our home countries. When I sent a customer complaint to the Kenya Airways Customer Service, they answered me that they received it and would forward it to someone from the Customer Service team. But after that, I didn't receive a reply for 1 month. So just recently I e-mailed them again, saying that I am still waiting for a reply, but nothing happend. I am deeply disappointed. This was my first experience with Kenya Airways, and it was the worst thing that ever happened to me in terms of flying. Never ever did I experience something like that with any other airline. I lost a lot of money and I didn't even receive an apologetic message from them, not even talking about compensation for the inconvenience. I would never recommend this airline to anyone! Don't fly with Kenya Airways if you don't want to have incidents like this, just save your time, money and energy and fly with other airlines like Qatar or Emirates.

6. Domestic Kenya Airways is surprisingly good. (I figured out the reason why. Big shots travel these routes together with tourists, so these are the folks that can cause trouble for management if it is not together). Service, check in, Safari Lounge, snacks/drinks are served on very short haul flights. Seamless check in service with Delta Airlines Elite Medallion Members is a excellent service Kenya Airways offers. On odd thing is: If you are connecting in Nairobi to a domestic destination, you have to exit the domestic area, then recheck everything again for your onwards domestic connection which adds to the hassle
7. The flight and boarding process for Kenya Airways was seamless. Being a Platinum member, Kenya Airways is very good at recognizing status, even at the Safari Lounge. I admit the new terminal gates are rather confusing in numbering. However,

the meals, etc were acceptable. Flight attendants were good too. While not at the standards of the Game Lodges and many restaurants in the country in terms of wait service, they were fine. The big issue with me was the seats, they were extremely uncomfortable in Economy. Even with a neck pillow, the seats were hard and cramped. This will become a challenge for passengers on their soon to start non-stop to New York, sitting 15.5 hours on these seats would not be something I would do. Would rather prefer the connection An odd thing happened when we arrived at Amsterdam, The flight was met by armed Dutch State Police going through Kenyan Passports with microscopes, a testament to how useless the Kenya Passports are nowadays due to the rampant corruption from Kenyan Immigration.

8. I rang Kenya Airways Office in London at about 8 pm to book a ticket for my 15 year old daughter to travel to Nairobi. The lady told me they don't take payment by phone. She needed to fax me a form to complete and return with Bank details. I told her I have never seen a Facsimile machine for over 15 years. She said she could not help if I had no access to fax machine. I rang 30 minutes later and a man answered. Quoted me a little lower price (for the same travel days) and was ready to take payment on phone and do the reservation. I told him I will call in ten minutes since I did not have my card ready. After 10 minutes another lady answered and quoted me a fare £200 higher. When I mentioned that I had been quoted a different fare just a few minutes before and wanted to speak to the guy, she said she did not know where he was. I rang first thing the following day and another lady did the booking by phone within a few minutes at a much lower fare without haggling. The issue of fax machine did not arise, and I wondered if each person on shift had their own rules. I am aware fare prices change but how they fluctuate upwards and downwards within minutes by margins of over £200 for the same day/time of travel is unbelivable.
9. I will never fly with Kenya Airways again! Or a heads up for anyone who is daft enough to fly Kenya Airways. They call themselves the Pride of Africa! I would like to challenge that and say they are the hustlers of Africa. They have left me stranded in Kenya with half my family on the flight and put a suspension on the last leg of my flight due to me missing one leg of my domestic internal flights. Even though I have fairly paid for all my seats on all the connecting flights. Speaking of the unhelpful customer services. I spent 30 mins on the phone, only to be placed on hold and eventually cut off with the issue unresolved. I then decided to go to the main office in Nairobi in hopes that something could be appeased only to find out that my only option is to book a new flight. My primary advice would be, never to fly with Kenya Airways, they have such nonsensical and unfair policies. If you are forced to fly Kenya Airways remember to take all your connecting flights and if you miss it for any unfortunate circumstance notify the airlines.
10. The Boeing 787 is a must try service on long range routes and they have great inflight service. I only got confused at the number of times cabin crew changed but still great, good food, great sleeper seat. I would fly again. Only let down ground crew especially in Guangzhou and Mombasa, difficult people.

APPENDIX 3: News Articles used

Article 1: https://www.standardmedia.co.ke/article/2001278234/invest-more-in-manufacturing-to-reverse-2017-downturn

Kenya's scorecard for last year is out, and the performance of the main sectors is not inspiring. There were fears that 2017 could easily be the worst year under President Uhuru Kenyatta, but not to the extent shown. We now know, from the Economic Survey 2018 report, that we are losing our most critical sectors; agriculture and manufacturing. Not even the vibrant financial services sector was spared, but the problem is fairly easy to diagnose and remedy, with broad proposals on patching up the interest rate regulations. National Treasury and Planning Cabinet Secretary Henry Rotich has said he is planning a range of amendments to address reduced access to credit while still ensuring that consumers are protected. Productivity from farms grew at a paltry 1.6 per cent, the slowest pace in over a decade, yet agriculture remains the biggest employer. Maize, tea, and coffee production fell even though high prices helped to compensate the shortfall, hence the marginal growth. Once again, dependence on rain exposed the economy to the ravages of the prolonged drought, which slashed harvests and sent food prices through the roof. Manufacturing has not been so sluggish since 2009, meaning that we are increasingly more reliant on imported products and, by extension, are exporting jobs. It has dawned on the Government that the trend is unsustainable if it is it achieve its dream of creating more jobs for our young adults joining the labour force and attaining middle-income status in a decade. Know if news is factual and true. Text 'NEWS' to 22840 and always receive verified news updates. However, what we are seeing are only statements of intent. These must be followed with deliberate and clear actionable plans that must be supported by funding if we are to expect any improvement. President Kenyatta has outlined his development agenda, narrowing it down to four pillars; affordable housing, food security, manufacturing, and universal healthcare. Private sector funding can help deal with the housing crisis if the Government provides an enabling environment to cushion investors and land. It is possible to revamp the public medical insurer and turning it into the National Health Insurance Fund to complement the investments in developing infrastructure in public hospitals. Attaining food security and expanding manufacturing would be the real test to President Kenyatta's legacy. Lessons can be taken from the past, when Kenya was food-reliant and systems in the agricultural sector worked. Extension officers would visit farms to teach best practices and arrest diseases before they became a crisis. Credit and certified inputs were readily available to farmers through the Agricultural Finance Corporation – before its plunder. All indications are that Kenya is now richer than ever before, meaning there would be no reason for not reverting to the structures that have worked before, with focus on the farmer. A pooling system for mechanisation of farming is one such initiative where specialised tools could be made available to groups to enhance their yields. It would be futile to allocate large budgets for agriculture, as we have seen with the Galana/Kulalu Food food security project that gobbled up billions of shillings and delivered little. With manufacturing, again, the priority should be small and medium enterprises that are currently stifled by layers of licensing regulations. Before we dream of building cars and heavy equipment, there are easier and more practical commodities that are consumed by the masses that we can manufacture locally. Policies that cushion small local industries from global competition should be put in place urgently, including heavy tariffs to discourage importation and spur manufacturing. Other more developed countries have embraced protectionism in attempts to protect their budding industries. Finally, we must acknowledge that we erred in closing down and 'upgrading' technical colleges into universities that are producing graduates the economy does not need. Perhaps we should consider reverting the polytechnics to middle-level training institutions with a bias to offering technical skills to support the manufacturing dream – rather than the thousands of degree holders who cannot do half the work of a diploma graduate.

Article 2: https://www.businessdailyafrica.com/analysis/ideas/Enact-law-to-save-global-brands-from-local-pirates/4259414-4535790-10dv1sf/index.html

Kenya has in the past 15 years undergone economic transformation that has seen phenomenal proliferation of shopping malls and trading centres as well as the entry of major global brands that were hitherto unknown in the country.

World-class multinationals in virtually all commercial sectors have also set up shop in Kenya, bringing along coveted brands.

One of the most unwelcome shocks that greets the arrival of such businesses in Kenya is the realisation that they cannot use their valued brands here because some 'enterprising' Kenyan has already obtained trade mark registration for the same.

What follows thereafter is either a bruising and expensive court battle or a negotiated settlement involving the re-purchase of the brand by its legitimate owner at a price that can only be described as extortionist or a ransom.

Protection of brands through registration is therefore an urgent imperative for any company contemplating doing business locally.

Kenya being a 'first-to file' country means that registration of trade marks is done on a 'first come first served' basis irrespective of whether the mark is registered, owned or used by another party outside Kenya. It all depends on who gets to the door of the Trade Marks Registry first.

This is why the Registry normally indicates in its database the precise time of the day when an application was received and paid for.

Kenyan law provides some respite to owners of what are called "well-known" trade marks. These are brands that have acquired such a high degree of distinctiveness that they have become household names. Examples of such marks include "Olympic", 'Google", "Coca Cola", "McDonalds", and "Nike", among others. Such brands enjoy protection under the law even if they are not locally registered.

The proprietor of a well-known mark can successfully challenge prior registration of the mark by a third party or resist attempts by such registered proprietor to stop the legitimate owner from using the mark in Kenya.

The burden of proving that one's mark is well-known lies upon the person claiming that the mark is well-known.

The World Intellectual Property Organisation (WIPO) has developed an elaborate criterion for determining whether a mark meets the required threshold of well-knownness.

The list of factors for consideration includes the degree of recognition of the brand by the relevant segment of consumers, level of advertising, promotion, sales volumes, among others. It must be a brand that requires no introduction to the relevant consumer.

The Achilles heel for owners of well-known brands is that the alleged notoriety of the mark must be within Kenya. The reputation of the brand outside Kenya is irrelevant. Therefore, a brand that has never been used in Kenya will not enjoy this privilege.

However, with the advent of the Internet and online shopping, this has become a spurious requirement considering that consumers in Kenya frequently encounter these brands online through advertisements, promotions and even purchases.

Courts in some jurisdictions like India have recognised the out-datedness of this threshold and determined that strong online presence of a brand would justify the recognition of a well-known

trade mark based on evidence that consumers in the local jurisdiction know the brand well even if the online sales may not be significant.
Kenyan trademarks law should be amended by removing the local notoriety requirement. This will adjust the law to the current business realities presented by technological advancement.
READ: Barclays' looming change of name to ABSA challenged
Apart from well-known marks there is another breed of brands, currently unknown under Kenyan law as ‘famous marks”. These are brands that are a notch higher than well-known marks.
They are superstar brands whose reputation is so high that their use by anyone in respect of any goods or services is likely to mislead consumers into believing that the product or service is provided by or associated with the owner of the famous brand.
The use of such mark on any goods or services amounts to taking an unfair advantage of the famous brand.
The protection of famous marks entitles their owners to ward off not only competitors who deal in similar goods/services but practically anyone else using the brand for any purpose whatsoever. The logic here is that such use dilutes the value of the brand.
In jurisdictions where famous trademarks are protected by legislation such as the US and the EU, the brands enjoy a broader degree of protection than well-known marks to the extent that their protection is not limited to any specific goods or services and do not need to have been used locally.
The law acknowledges that their fame transcends geographical boundaries.
Kenya has made the first baby steps in the right direction by introducing a provision in the Companies Act, 2015 which prohibits incorporation of a company under a name that constitutes the registered trade mark of a third party.
This law, while laudable, does not address the full spectrum of challenges faced by the owners of global brands that are routinely registered by pirates in Kenya prior to the arrival of the legitimate brands.
The enactment of a law that provides for the protection of famous marks would save Kenya from fast becoming a pirates’ den for global brands.

Article 3: https://www.businessdailyafrica.com/analysis/ideas/Steps-taken-to-plug-gaps-in-auditing-public-firms/4259414-4535804-hbqyw0/index.html

The industrial revolution and the subsequent growth of business activity is largely credited for the adoption of audit and audit methods.
While auditing procedures have been relied upon for a long time, the formal practice has been in existence for a relatively shorter period. This practice was fuelled by the financial crises of the early 20th century which questioned the role of audit in ensuring prudent risk management.
Following the stock market crash of 1929, auditing became an obligatory process in the United States and in many other jurisdictions around the world.
In the years that followed, auditing was streamlined, with the promulgation of the Accounting and Audit Oversight Standards by the Securities and Exchange Commission, following the enactment of the Securities and Exchange Act of 1934.
Firms were required to provide certain assurances about the information they submitted to ensure compliance with accounting standards. The process of verification of this information relied heavily on explanations provided by management, with little or no independent confirmation.
This has since evolved and today, there is great emphasis on independent verification of information provided by Management.

From a corporate governance perspective, there have been tremendous efforts towards building an appreciation of audit in the minds of the custodians of governance, especially for public companies.

Many jurisdictions around the world have made it a requirement for public companies to establish board audit committees with specific member constitution, requirements and responsibilities in respect of the external auditors.

READ: Court gives auditor-general free hand to audit military spending

Following a revision to the UK Corporate Governance Code in 2012, there is now a requirement for FTSE 350 companies to put the external audit assignment out to tender every 10 years.

This has been domesticated in Kenya through the Corporate Governance Code for Issuers of Securities to the Public which requires auditor rotation every six to nine years. These are just some among the many codes around the world which place specific requirements on audit and audit committee matters.

Audit committees play a vital role in ensuring the integrity of financial controls and integrated reporting and in the identification and management of financial risk.

The prominence of audit committees is demonstrated through the inclusion of the requirement for quoted firms to create audit committees by the Kenyan Companies' Act.

The only exception is where the quoted company is a subsidiary of another quoted company, in which case the parent company assumes the obligation to form the audit committee.

Failure by the directors of a quoted company to form an audit committee makes them liable to a fine of up to one million shillings.

The Act sets out the obligations of the audit committee of quoted companies to include the establishment of appropriate policies and strategies for corporate governance principles and to annually assess the extent to which the company has observed these policies and strategies.

In addition, the Capital Markets Authority in its Code of Corporate Governance for Issuers recommends that audit committees should have at least three independent and non-executive directors.

The code further recommends that at least one of the committee members be a holder of relevant professional qualification and be in good standing with their respective professional bodies.

The Companies Act also defines the obligations of both the board and company officers in regard to financial reporting and audit. Management of every company, particularly the chief executive officer and the chief finance officer, are required to keep proper accounting records.

Failure to fulfil this obligation could earn these officers a prison term of up to two years, and a fine of one million shillings which the company may be required to pay.

A similar obligation has been placed on the board of directors. Where directors fail to ensure proper preparation and audit of financial statements, they become liable to penalties of up to one million shillings.

In the spirit of the Code of Corporate Governance, companies should ensure compliance with all applicable laws, regulations, standards and internal policies.

Boards should establish internal procedures and monitoring systems to promote this by ensuring proper accounting records are kept and audited, and that the audit committee is properly constituted and executes its mandate as expected.

To respond to some of the shortcomings noted in corporate governance and financial reporting in the recent past, and to comply with the requirements of the IOSCO-Enhanced Multilateral Memorandum of Understanding (IOSCO-EMMoU), the authority is in discussions with the National Treasury to introduce a regime of approval of audit firms participating in the Capital Markets.

If adopted, approved auditors will have increased legal obligations to the authority and will be required to confirm the company's level of compliance with the Capital Markets Act, laws and regulations and the Code for Corporate Governance.

Article 4: https://www.businessdailyafrica.com/analysis/ideas/4259414-4532132-6mqeoy/index.html

In a week in which the 5th Devolution Conference in Kakamega hit social media headlines for the wrong reasons, it is ironical and fitting that this was also the week in which the real media story was about recently departed Kenneth Matiba, and the glowing tributes that have flowed for this successful government technocrat, astute businessman, fearless opposition leader, nationalist go-getter at heart.

Much is made of his brave, and almost successful, bid to be President in 1992. My thoughts this week, on observing the Devolution Conference (through the media, it must be said), is that, if real devolution had happened 40 or 50 years ago, Mr Matiba would have been exactly the Level 6 Governor, and future national leader, we truly need today. And Murang'a County would be on another development plane.

His demise is a reminder that our modern idea of "developmental" Kenya confuses celebrities for heroes, even as we "eat" our best and fete the rest.

Today, "making" money matters more than earning it. Yet, if we're talking what a national ethos could look like to Kenyans, Mr Matiba's life story is the place to start.

As a young Kenyan in the late 1980s and the 90s observing the relentless push for multi-party democracy, I was confused by this unusual politician who actually wanted to do the right thing.

Yet, as President Uhuru Kenyatta observed at Mr Matiba's first memorial service, we don't have leaders like that anymore.

Devolution, one of the products of that multi-party agitation of a generation ago, is seen as central to Kenya's development dream. Let's look at the Devolution Conference through a simple lens, the words, or tone, of its three main speakers.

President Kenyatta's high-tech opening address suggests that he is seriously taking a leaf out of the Jack Welch playbook.

To quote the iconic former head of US transnational General Electric, "Strategy is very straightforward. You pick a general direction and you implement like hell". This was very much Mr Kenyatta's tone as he outlined his "Big Four" agenda and its relevance to counties (or rather, counties' role in the "Big Four"). The time for action is now. "It's about results, not recommendations". A vibrant message, no less.

On the other hand, Opposition Leader Raila Odinga's address as guest speaker surprised many with his proposed three-tier 62 entity government, that is one national, 14 regional and 47 county governments.

READ: Governors need to face the poverty and graft problem

While some (read, Governors) were quick to rubbish this proposal, it is important to recall that, like every fundamental reform that Kenya needs, devolution is political first, and economic next.

In other words, inclusion and ethnic harmony are the prerequisite for county economic viability; for national progress and prosperity. This is the sort of proposal that requires welfare thinking (economics) before "bean counting" (accounting). An interesting message.

Deputy President William Ruto seems to have made a twin address, if immediate media reports are to be believed.

Officially, he spoke to challenges facing counties around budgeting and planning, own source (local) revenue collection, pending bills (expenditure management, procurement and commitment control), financial reporting and audit timeliness, and asset and liability verification, a task that remains incomplete since the advent of county government in 2013.

Unofficially, there were reported swipes against the proposed three-tier government, restructuring of the executive and constitutional change, and governors in their perpetual wars with county assemblies.

My take is that it is the politics that readers purchase in our competitive “breaking news” media space.
Indeed, as Chair of the Intergovernmental Budget and Economic Council (IBEC), a body responsible for national and county government consultations on budgetary and wider economic policy, as well as fiscal and debt matters, Mr Ruto actually “owns” the opportunity to lead a radical reform on the self-same county issues he highlighted in his speech.
Take planning and budgeting. This cannot work for results without transparent costing of programmes (or activities) across both levels of government based on a clear division of labour.
The stalemate we have reflects a national government that “owns” too much of the budget, and counties unproven in “value for money” spending.
Or own source revenue collection. Revenue comes from economic activity. Maybe it’s time to focus on the “E” (economic) in IBEC.
On reporting and auditing, is it not a crying shame that 2018/19 revenue shares to counties will be based on the 2013/14 accounts approved by Parliament? In whose interests are these audits and approvals so badly delayed? Pending bills. A proper IFMIS, anyone?
With smart thinking on these issues, IBEC could be a reform force for good.
Back to the beginning. The passing of a great leader in Kenneth Matiba reminds us of the past struggles that led to the great reform we call devolution, and the need for a forward path about doing the right thing.

Article 5: https://www.businessdailyafrica.com/analysis/ideas/complete-transition-to-seamless-mobile-money-platform/4259414-4547614-u9tmybz/index.html

The rapid evolution of technology in the last decade has spawned innovative services like mobile money, paving the way for the emergence of a digital economy.
Mobile money is no longer just about the traditional cash-in and cash-out transactions. It has grown to include paying bills, saving money, lending and enabling cross-border remittances.
Whereas Kenya and Africa lead the mobile money transformation, the story is promising globally. The GSMA 2017 State of the Industry Report on Mobile Money underlines the remarkable growth of mobile financial services.
About $1 billion is now transacted via mobile money daily, backed by an estimated 690 million registered users worldwide. An estimated 66 per cent of the combined population of adults in Rwanda, Tanzania, Uganda and Kenya are active mobile money users.
Mobile money has had an immense positive influence on the global push for financial inclusion.
It is also a facilitator of the digital economy, the latter described as the economic activity resulting from online transactions facilitated by devices like mobile phones and computers.
Mobile money is also a driver of financial inclusion, defined as access to financial services meeting one’s needs.
Financial inclusion has been identified as a critical factor in the realisation of Sustainable Development Goals (SDGs) to build prosperous and inclusive communities.
Mobile financial services have been identified as an enabler of SDGs, for instance, through creation of economic opportunities for women, affordable access to essential services like health and education, and poverty alleviation through increased uptake of financial services.
Lack of a seamless mobile money platform has, however, been touted as a major challenge to expansion of mobile financial services in Kenya.
The so-called wallet-to-wallet interoperability entails creating a platform for seamless money transactions via mobile phones — a critical ingredient in unlocking the transformative potential of the digital economy.
Fortunately, here in Kenya, wallet-to-wallet interoperability is becoming a reality.

Safaricom and Airtel have recently begun implementation after conducting a successful pilot run for wallet-to-wallet interoperability; Telkom Kenya is expected to join in due course. This marks a pivotal milestone in the country's quest for financial inclusion.
Interoperability, fully implemented, will also enhance market competitiveness and deliver value for consumers by way of lower cross-network money transfers. The government has strongly signalled support for the project.
Moreover, a market review report by consulting firm Analysys Mason flagging wallet-to-wallet interoperability as a key pre-requisite to enhanced competitiveness of mobile money services in Kenya appears to have been well-received by the ICT ministry.
But to achieve its purpose of delivering convenience and affordability to consumers, interoperability needs to rope in third parties like agents and merchants who play an instrumental role in the mobile money value chain.
The GSMA report reveals that agency fees account for more than half of the total revenues of the service provider.
Besides establishing the one-agent model, lowering agency-related costs will significantly help in growing the mobile money footprint.
Additionally, consumers stand to benefit from the lower cost of transactions.
READ: Kenya's mobile commerce deals pass Sh1 trillion mark
Service providers' margins will improve, hence providing incentives for investment in existing and new mobile money infrastructure and products.
The idea of a pre-funded account to settle inter-change fees has been mooted.
This, however, requires deeper interrogation to ensure that the final cost of having such an arrangement in place is not passed on to the consumer. Otherwise, this would defeat the essence of affordable and accessible digital financial services.
All in all, wallet-to-wallet interoperability will lead to the transformation of millions of lives in Kenya while also saving consumers the hassle of hopping from provider to provider.
The market is certainly ripe for a seamless mobile money platform going by the rapid uptake of mobile money services in Kenya.
I hope the Communications Authority of Kenya will prioritise this particular aspect when it makes public its final decision on the market review study by Analysys Mason later this month.

Article 6: https://www.businessdailyafrica.com/analysis/ideas/Higher-fuel-pump-prices-are-definitely-coming-soon/4259414-4551594-2vo1haz/index.html

We are sandwiched between two approaching realities, both of which will increase oil pump prices. Global oil prices are creeping towards $ 75 and when these are punched into the ERC price formula we shall see higher pump prices. Currently the pump prices reflect oil import costs of about $70.
The other factor is the indication in the 2018/19 budget proposals that petroleum products will from September this year bear a 16 per cent value added tax (VAT). This will apply on gross consumer prices which currently include other taxes and levies. For example pump prices of Sh100 per litre will automatically become Sh 116.
There is no indication that cooking gas and kerosene will be spared of VAT which means higher domestic energy costs. There are other unrelated proposals by petroleum authorities to increase kerosene import taxes to discourage adulteration of petrol and diesel with lower taxed kerosene.

The new petroleum VAT is one of the fiscal and financial policy conditionalities imposed on Kenya by the IMF and include the reversal of the controversial law on interest rate capping . Petroleum VAT was postponed two years ago, but this time around the Treasury may not be able to dodge it.
The petroleum VAT is intended to boost government revenues to rebalance the public debt, while also providing essential funding for the Big Four socio-economic agenda .
The combined impacts of the higher products import costs and VAT on consumers and the economy will be increased producer and consumer inflations . On the positive side, higher prices will definitely encourage energy use efficiency and conservation as discretionary consumption goes down especially among motorists.
Oil consumption in Kenya has increased by an annual average of 7.3 per cent since oil prices dropped from over $100 to a low of $25 in 2014 and back to above $70 in 2018 . The looming price hikes will likely reverse this trend as consumers change their consumption behaviour. If imports decrease, the strain on Kenya's balance of payments and trade will be lessened.
The firming up of global prices is due to varying factors which include genuine supply/demand shifts, geopolitical activities, and the ever-present commodity trade speculation. The main influence today is however the self-imposed curbs on oil production by OPEC oil producers and a number of non-OPEC countries including Russia.
Today, about one-third of total global oil production is by USA, Saudi Arabia and Russia with each producing an almost equal amount of about 10 million barrels per day. However the USA shale oil has become the swing supply and key influence on global oil prices.
At prices above $ 70 , the oil exploration and production activities which were hitherto abandoned or slowed down when prices slumped in 2014 , are now being resuscitated as break-even prices justify new investment decisions. This includes the onshore and deep-sea prospects and discoveries in Kenya.
The high prices will continue to encourage more investments and production. This will gradually depress prices with the consequence of reduced investments and production which will subsequently trigger price spikes.
The high global prices we are seeing today are part of this repetitive cycle. It is a roughly five-year cycle which has happened as far back as I can remember. It is this cyclic pattern that OPEC and its allies are trying to influence to create stability to oil revenues and their national budgets .
But other permanent structural shifts are taking place in global oil demands. Technology advancement is replacing oil demands with renewable energy, a trend that appears irreversible because of good economics and support for the wider climate change agenda. The renewable energy will continue to influence global oil demand, supply and prices.
Back to Kenya. We expect political debate on the impacts of the 16 per cent VAT on petroleum and why IMF should be dictating Kenya's economic policies.

Article 7: https://www.businessdailyafrica.com/corporate/shipping/Kenya-Railways-to-increase-SGR-freight-charges/4003122-4551380-hpsocuz/index.html

The Kenya Railways Corporation (KRC) is set to review the promotional freight charges on the standard gauge rail (SGR) upwards in the next two months as the State continues to woo shippers to embrace the multi-billion shilling investment.
Kenya Railways business, commercial and operations team leader James Siele told Shipping and Logistics that the rates will be adjusted again in July once the promotional tariff which was introduced in January comes to an end next month.
"We are working together with the Kenya Shippers Council and cargo owners to see how best we can adjust these rates. We cannot talk about the margins at this moment but all we know is that it will be in the best interest of the market," said Mr Siele.
Madaraka Express freight service customers have been enjoying the promotional tariff which was introduced in January.
The tariff was supposed to end on April 4, but towards the end of March, KRC extended it again until June 30.
This has seen SGR freighters pay a flat fee of Sh35,000 for a 20-foot container and Sh40,000 for a 40-foot container from Mombasa to Embakasi Inland Container Depot (ICD).
The Kenya Railways has also been charging Sh25,000 to transport a 20-foot container and Sh30,000 for a 40-foot container from ICD to Mombasa.
The rates, however, do not include the cost of handling cargo and returning empty containers.
"What we want is to have a sustained business so that we do not lose some of the gains we have made in as far as freight business is concerned in this country," said Mr Siele.
Plans by KRC to review special rates for SGR cargo come barely a few days after the Kenya Ports Authority (KPA) reduced the free storage period for containers at the Inland Container Depot in Embakasi, from 11 days to four days, in a move aimed at clearing a backlog of about 1,700 containers which were lying uncollected at the facility.
The move also comes in the midst of a row with freighters who have defied a government directive to transport their imported cargo through the standard gauge rail.

Article 8: https://www.standardmedia.co.ke/article/2001277987/devolution-is-a-success-story-more-yet-can-still-be-achieved

The fifth annual Governors Conference kicks off today in Kakamega. Ideally, the conferences give governors an opportunity to review their gains in the previous year and most importantly, where they have fallen short; how to stay ahead and remedies for the shortcomings. The rationale behind devolution was taking services closer to the people and allowing them to determine their own fate through constant engagement with their leaders. This type of participatory democracy allows the people to feel that they are directing their own destinies. Devolution was touted as a cure to the skewed allocation of resources. And by many accounts, it has achieved quite a lot; deviating from a governance system far away in Nairobi in which policy-makers formulated policies for places they knew nothing about with the resultant consequence that certain areas became more developed than others. In the formative years of devolution, the inevitable friction between the National Government, senators and governors nearly got us off to a bad start. Over the years though, most of the differences have been ironed out, paving way for speedy implementation of projects. Gains are discernible across the country. A testament that devolution is working well for us. Through it, we have showcased our diversity, strengthened our sovereignty and fostered stronger national values and ties. Some of the achievements include the building, specifically, of more hospitals to ensure people did not have to move long distances to get medical attention. All counties have so far purchased ambulances to boost their efforts in offering better healthcare in cases of medical emergency. Stay informed while on the go by subscribing to the Standard Group SMS service. Previously impassable roads have been upgraded, schools have acquired additional classrooms. Devolution has allowed the setting up of feeding programmes in some schools for children and the setting up of bursary schemes has proffered a critical lifeline to children from poor backgrounds. It was the beauty of devolution that saw Mandera County carry out its first ever Caesarean Section. Samburu County and Lamu County got their first tarmac roads. Thanks to devolution. Benefits that have accrued from devolution over the past four years are tangible. Having also dealt with the mistrust that initially existed between governors and Members of County Assemblies, many of whom took devolution to mean a quick ticket to riches, one feels the fresh breath of air. Indeed, the system offers a people-centred approach to leadership by emphasizing on participation and consultation and transparency and equility. No longer will Treasury mandarins dish out money as it pleases them. In a nutshell, it offers to redraw the past, by correcting its mistakes. But the sky remains the limit; a lot more still has to be achieved. However, going by the Auditor General's and Controller of Budget's reports that most of the more than Sh1 trillion disbursed to counties has been wasted or pilfered, it would seem like corruption too, has been devolved. This risks reversing the gains made so far. There have been some glaring hiccups too. Some of the devolved functions like health have posed a great challenge to the devolved units. Wildcat strikes and an exodus of doctors and nurses to the private sector have become the norm. This has been blamed on delayed salaries, poor remuneration and lack of medical supplies. Meanwhile, the Controller of Budgets decries the sharp drop in revenue collection within counties in the financial year 2017/2018. From a collection of Sh7 billion for the same period in the 2016/17 financial year, only Sh4.8 billion was collected this year. As such, besides the urgency in devising ways of streamlining revenue collection, counties need to come up with ways that maximize revenue generation, but that does not mean imposing more punitive taxation on citizens as happened in 2013. Most importantly, governors must work diligently to seal the loopholes through which public funds are lost and cure corruption. Extravagance and wastage within counties must be curbed and more emphasis placed on development and less on recurrent expenditure.

Article 9: https://www.standardmedia.co.ke/article/2001277389/how-sex-pests-easily-get-away-with-murder

When the musician Kemunto recently recounted her alleged rape, I was shocked to see so much victim bashing and shaming on Social Media, including questions about where, how and when. These reactions by Kenyans reminded me of what happened to my friend and colleague Jane (not her real name), a doctor who alleged she was raped by another doctor. With Jane's permission, I shared her story—albeit abstractly—in a professional group. I was appalled by the repeat of the classic script of victim-shaming and judging by many. When a doctor is raped... Sharing Jane's story, however, created a forum for women doctors to share their own experiences of abuse: sexist remarks, soft coercive invites for coffee or dinner, inappropriate touching, obscene text messages, unwanted hugging, grabbing, pinching and brushing their breast, and rape. Hearing other people's stories brought back memories of being raped as a child. I was between the ages of 11 and 14 years when the two gang rapes and the ongoing sexual abuse by my cousin took place. Poverty, life in the slums of Kibera, my mother's mental illness, and my family's isolation from our extended family and the community, all meant that I had no recourse, and my perpetrators would never face justice. No one listened to me when I spoke out. But compared to my teenage self, surely a prestigious doctor like Jane has mechanisms and structures of action. She can seek justice and has credibility and stature, just like I do now. Right? Wrong. Know if news is factual and true. When the law won't help I told Jane I would help her get legal support. She refused, remarking calmly: ''Stellah I am not ready to be dragged into legal-fights which will flood me with hurtful memories over and over in addition to being judged by the society- the how, when, where, questions, I am not ready to answer.'' If an educated woman like Jane doesn't feel confident coming forward, what hope is there for everyday Kenyan women? And if the medical field – one where doctors swear to do no harm - is fraught with abuse, what hope is there for other industries? Further, the very fact that there are no records of sexual offense cases in the medical sector in the first place, raises questions on how such cases are handled. We must change the way we process and investigate sexual offenses. First, we need better reporting procedures that do not involve reporting to harassers. In Jane's situation, for instance, the Human Resources contact to whom she would have been required to report, is a man who in the past has been accused of sexual harassment. Instead, people must have multiple options for reporting, including a gender-balanced panel to receive and process any complaints or accusations of sexual misconduct. These gender-balanced teams should receive comprehensive training on what constitutes sexual harassment, be able to investigate a reported allegation and present comprehensive reports that would bring to light the sexual offenses in the healthcare industry. Then, the process to collect evidence must be simplified. Right now, it is tedious and complex and a barrier for reporting. The complexity also makes it more likely for there to be errors in reporting. In a struggling healthcare system with other competing priorities, healthcare workers tasked to fill out the post-rape care forms often leave critical gaps that can potentially obstruct justice for survivors as the cases risk being thrown out of court because of lack of sufficient evidence. Having staff stationed at healthcare institutions serving specifically sexual assaulted patients will ensure that comprehensive reports are provided in line with recommendations and that the survivors get the help they need. We should also incorporate anonymous reporting options via a call line or SMS number. Special courts Lastly, the Judiciary could consider setting up a special court to offer the privacy lacking in the courts since as Jane pointed out, the constant public exposure during the case is traumatic, humiliating and damaging to not only the survivor but to his or her family. We cannot continue burying our heads in sand, assuming all is well when these evils happen in our medical institutions-silently being recorded only in the minds of the survivors. Leadership in the healthcare field can help prevent the occurrence of sexual abuse and rape by increasing knowledge and awareness of these issues and promoting positive social attitudes on the importance of consent. Men should be recognised as equal participants in these programmes while committing to serve as positive role models for other men to be intolerant of sexual abuses. Only then will we see a shift in the way we treat all women across Kenya—from the girls in the slums to medical doctors to celebrities.

Article 10: https://www.standardmedia.co.ke/article/2001276141/why-poverty-is-a-control-tool-of-the-political-elite

Both fact and legend agree that The Democratic Republic of Congo is potentially one of the richest countries on earth as far as natural resources are concerned. It is a place seemingly blessed with every type of mineral, yet consistently rated lowest on the UN Human Development Index, where even the more fortunate live in grinding poverty. This state of affairs is not by accident, it is a scheme by the elite to keep the multitudes in subjugation in perpetuity. This configuration is repeated all over the world, and Kenya is not in absolution. This is even more endemic where there are natural resources such as oil, gold, diamonds and the like, and a small privileged clique wants to keep a tight grip on them. The ruling elite knows that if they use the country's wealth to empower the people, the people will start demanding accountability, and this will jeopardize the "chose few." Kenya has done well as a non-mineral economy in Africa.

However, it has not been spared the jinx of subjugation by poverty. The ruling class likes it when people remain poor, because it is easy to control hungry people. It is easy to condition needy, hungry people like Ivan Pavlov’s dogs. It makes for high drama when mases of hungry people queue for hours to receive Sh100 from a politician, and even more incomprehensible because these masses are beholden of the same characters when it comes to voting day. We may not have stuck commercial oil, but in Kenya, politicians brandish the power of name dropping and the hawking of big dollar tenders in place of diamond and oil concessions to both local and international vendors in return for commissions. The net effect is that undeserving vendors end up bagging big dollar tenders, which they can’t deliver, or flounder with very substandard results to the detriment of the population while a small clique of politicians lounge in milk and honey. Avoid becoming a victim of Fake News. Chosen few In absolute monarchies like Saudi Arabia and Brunei, the oil feed belongs to a few princelings within reach of the throne. In Kenya, tenders and big government jobs are the preserve of those near the ruling elite. It is for this reason that the Auditor General has published audit reports that have shown Members of the National Assembly appointing their kin to CDF jobs, and in some absurd cases, their spouses. In one incongruity, a governor had appointed his mistress to the cabinet. This keeps many deserving people locked out from the government system as a deliberate commission; meritocracy has become unfashionable. United Nations special rapporteur Prof. Philip Alston has argued that the persistence of extreme poverty is a political choice made by those in power. This farcicality was bourgeoned by the 2010 constitution that made Kenyans “the most represented people in the world.” All these elected representatives have a feeling of entitlement, and that is why from Cabinet Secretaries, Members of parliament, Governors, and even MCAs, all feel entitled to overlap and obstruct in our highways. There is no bigger currency in Nairobi like that of dropping a name of some powerful politician. Deceit This false status cannot be sustained unless people are kept poor and hold those in positions of leadership in awe. As long as you will never bump into your local MP aboard the SGR to Mombasa, his name will forever be hallowed. Today, MCAs want to be picked by their chauffeured cars from the airport because they are “honorable.” Of course to the middleclass, this makes for high comedy and is an interminable source of social media ridicule. But the tragedy in a country with a social construct like Kenya is that the middle class is just a spectator class, yet they are the ones that sustain social expenditure by the government. Revenue authorities are yet to net revenue from low income earners, and therefore concentrate on salaried individuals and businesses. The richest of the rich pay nothing to run the country. Big business, like anywhere else in the world, don’t like paying taxes, and in nations like Kenya where political namedropping yields instant immunity, only SMEs pay meaningful tax to sustain government operations. On the other hand, the informal sector, the majority, is too messy and fragmented for revenue authorities to deal with. Yet, it is the masses in Kibera, Kawangware and Kariobangi that vote for politicians in droves, after inducements of small monies and “unga.” It is in these circumstances that the middle class becomes victim of a conspiracy between the very poor on the one hand, and the very rich and politicians on the other hand, yet it’s the middle class that sustains the two. I therefore submit that poverty is a political industry. Politicians will come up with “end poverty” white elephants projects, yet evidence has shown that all “poverty alleviating” schemes are perpetual, and politicians want it that way; it is their sustenance.