Computer Science Department
University of Crete

Opinion Mining on Parliamentary Commentaries, using Machine Learning.

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Computer Science Department
UNIVERSITY OF CRETE
Heraklion, Greece 2015

Graduate thesis 2015

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Abstract

Natural Language Processing is a scientific field in the area of Computer Science, which seeks a better correlation between natural language and computers. In fact Natural Language Processing is a wide scientific field in which technologies such as “Machine Translation”, “Named Entity Recognition and Disambiguation”, “Sentiment Analysis” and more are included. This Thesis seeks a better approach in order to export information from plain texts, which basically contain civil placements on consultation laws issued by the Greek Government. Attempted to export proposals - counterproposal of the authors and also the arguments that the authors expressed. Finally attempted to export the entire view of the author summarized in a word “Positive” or “Negative”, according to the opinion that the author expressed in the text. To export of these data is made entirely by analysing texts through a three step process (which will be explained in detail in the following chapter of this Thesis) and implementing techniques from the wide spectrum of NLP (such as Information Retrieval, Part-Of-Speech Tagging, Sentiment Analysis, etc.). The results show that we can create realistic methods in order to export this type of Semantic Information. Recently the research community gives more interesting on this subject, because ic could be exploited in a number of other areas outside the field of Computer Science (eg. Journalism, Politics, etc.).

Keywords: argument extraction, sentiment, machine learning, suggestion extraction, POS Tagging, opinion mining, natural language processing.

Declaration of Authorship

We declare that this thesis titled, “Natural Languages Processing on Parliamentary Commentaries, using Machine Learning.” and the work presented in it are our own. We confirm that:

- This work was done wholly or mainly while in candidature for a research degree at this University.
- Where any part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution, this has been clearly stated.
- Where we have consulted the published work of others, this is always clearly at-tributed.
- Where we have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely our own work.
- We have acknowledged all main sources of help.
- Where the thesis is based on work done by ourselfs jointly with others, we have made clear exactly what was done by others and what I have contributed ourselves.

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Name ____________________ Sign ____________________

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Name ____________________ Sign ____________________

Acknowledgements

TODO

Name Familyname, Gothenburg, Month Year

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TODO

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TODO

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TODO

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TODO

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$$f(t) = \begin{cases} 1, & t < 1 \\ t^2 & t \geq 1 \end{cases} \tag{2.1}$$

3
Methods

In this chapter, we will thoroughly analyse the ways with which the three processing stages which were presented in the previous units, were implemented.

In order to describe in the best possible way the process that was followed, a detailed description of the dataset which was used will be given, as well as of the features that characterise it. Then, we will describe the relational database model which we used to store the information from the texts (dataset). Finally, for each one of the process stages, we will describe the methodology with which each matter was approached.

3.1 Preparing the Dataset

In this part of the methodology, the features of the used dataset (3.1.1) will be described in detail. Some information on the way of choosing data (3.1.2) will be described as well. Next, the way of data mining from the Greek Open Government platform[1] (3.1.3) and finally, the Entity-Relation Model (3.1.4) of the database which was used to store the data will also be described.

3.1.1 Dataset

As it has already been mentioned in some points of this Thesis, the data that were used have been taken from the Greek Open Government platform, which constitutes a platform of electronic consultation of citizens on texts, more specifically on laws and decrees that the Greek Government issues. These data are open and accessible to everyone.

In this section, the basic features of the studied texts will be described. The reason why this section comes first in this part of the methodology, is that the very nature of these texts (they are basically users' comments to the online service), created many problems in their analysis.

As it has already been mentioned, the texts that were studied feature several oddities, some of which made the process of analysing them difficult.

[1] http://www.opengov.gr

- Initially, the first that we can notice is that the length of the texts is relatively short. To be precise, it is rare for them to be longer than 3000 characters (approximately 200 words, 80% of the texts). The length of the text did not affect all the stages of the analysis. The biggest difficulty appeared in the effort to extract the degree of the writer's agreement with the initial text (more details will be given later).

- A second remark is the fact that the texts that were studied do not consist an official text. By the term "official", we want first to declare that the texts are made up of users' comments in an online service and secondly, that they contain many errors (spelling etc). This created many difficulties in the studying of these comments. The first difficulty had to do with the tools needed in order to conduct the overall analysis of each text. The basic idea was that the tools had to be tolerant when it came to errors, at least up to a degree.

  Some very usual errors are:
  1. spelling errors
  2. absence of some letters in a word
  3. letter transposition in a word
  4. use only of capital letters
  5. absence of punctuation
  6. wrong sentence separation (there was no gap after the dot)
  7. some more errors that will not be mentioned for ease of reference

- One more issue is that there are many times when syntactic structure errors are spotted. This problem is directly connected to the use of POS-Tagger for the syntactic analysis (parsing) of texts. This issue affects, to some degree, the extrapolation of arguments and of proposals and counter proposals that the user makes.

- Another feature is that the texts are entirely in Greek. This problem is more serious, because there are no tools which we needed at some point of the analysis, that support the Greek Language. Subsequently, as we will see later on, there was the need to resort to some compromising solutions.

- One last issue that is worth mentioning, which constitutes a more qualitative feature, at least in the whole of texts that were studied, is the fact that the majority of users who wrote a comment are "annoyed". This "annoyance" stems from the fact that the texts that are under discussion contain laws and presidential decrees that, essentially, lead to a decrease in public spending towards the citizens. This "annoyance" is noted almost in the entire dataset that we studied. The problem is that the texts in which the writers agree with the initial text are limited. As a result, this issue complicates the process of acknowledging, if the writer agrees with the initial text.

3.1.2 Choosing Set of Documents

To continue the process, we randomly chose five different bills that contained a significant amount of users' replies. Afterwards, we selected a few, trying to eliminate the replies that we did not want to process. For example:

- replies that only contained one sentence
- replies in greeklish

Next, we limited the dataset so as to contain a number of approximately two hundred replies. This total is the final dataset that was studied and on which the conclusions for all the processing stages were based.

3.1.3 Finalizing the Dataset

The last step for the creation of the final dataset was the data mining from the Greek Open Government platform[2] (the website for public consultation on laws). This process was simple enough, since the service provides the users with the option to locally store all the comments that have been posted for each law or decree. The data were in excel file format, providing for each comment the following meta-data:

- the Law Article which was commented
- an id for each comment
- the name of the user-commenter
- the date

These data were later stored in the database which was created for the storage of data that were collected in all the stages of processing.

3.1.4 Database

In order to store the database, an MySQL[3] Database was created, whose Entity-Relation Model[4] can be presented in the following layout.

[2] http://www.opengov.gr

[3] https://www.mysql.com

[4] https://en.wikipedia.org/wiki/Entity%E2%80%93relationship_model

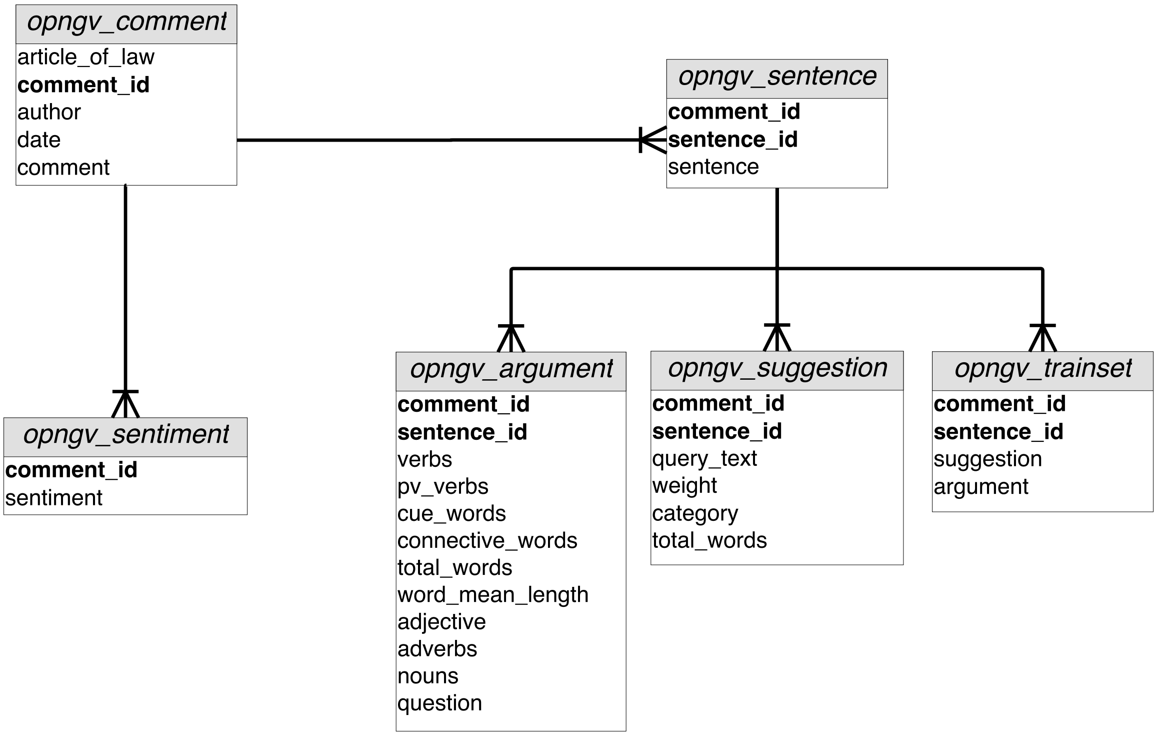


Figure 3.1: Entity - Relation Model

In the above layout, we can see the Entity-Relation Model that was used for storing data. The keys for each table of data have been marked with bold.

3.1.5 Building a Trainset

One last element that deals with the chapter on dataset, is characterising a total of sentences if each one of them contains an Argument or a Suggestion. We should note here that sentence separation will be analysed thoroughly later. The Train set that we created, as we will see in the chapters that follow, is needed so that the machine learning algorithms can become train, as well as to achieve a better evaluation. The set of sentences that was created contains approximately one thousand sentences.

3.2 Argument Extraction

At this point, the process with which the Argument Extraction was carried out on the whole of the texts will be described. The process is based on three stages:

- Selecting Argument Markers (3.2.1).
- POS-Tagging the set of documents (3.2.2).
- Applying machine learning to the Argument Markers (3.2.3).

Each one of the three stages will be explained right away.

3.2.1 Selecting Argument Markers

This step, in essence, constitutes the selection process of certain “criteria” that will help us define what an argument is. Essentially, this process constituted the hardest part in the whole Argument Extraction stage. This step, by extension, was performed only once.

Having studied enough from Related Work (which was mentioned to a great extent above), it was clear that in order to extract the arguments from the texts that we had available we would have to apply some Machine Learning process. Therefore, it is now clearer that at this step (3.2.1), we had to define some parameters which will define with a relative clarity whether a sentence is an argument or not.

But before we get in the process of searching for these variables, we had one more difficulty to face. Even though it sounds relatively easy to recognise the arguments in a text, in reality it was a rather difficult process. There was great difficulty for the whole team that is working on this Project to agree on whether a sentence contains an argument or not. After a lot of discussion, we ended up with the following definition:

Sentence is likely to contain an argument if it contains the following markers:

- *The sentence provides a context clue from which we can interpret that the writer expresses an opinion.*
- *The sentence is explanatory, which means that the writer wants either to further explain or support an opinion.*

If there is any of the above markers in a sentence, then this sentence can be characterised as an argument (Argumentative sentence). Even with the above two conventions, in some cases it is still difficult to determine whether a sentence is an argument. More precisely, another convention has been set, with which we made an effort to exclude the sentences that are interrogative. The reason is that usually, interrogative sentences are likely to express irony. In our dataset this was actually very usual.

Having set the above conventions, we studied a total of Argumentative Sentences, in order to be able to track down “Argument Markers”. In essence, we looked for parts of speech (for example the number of verbs, number of adjectives and more), as well as other variables that often appear in this type of sentences. These variables were to be used in the next steps and especially in the step where the “Machine Learning” process is applied

From the study that was conducted, also combining Related work, we ended up with the following variables:

- **Number of Verbs:** In many studies which have been conducted in the past, it was noted that verbs are closely linked to arguments. To be precise, verbs express action. Another characteristic is that verbs syntactically compose a sentence or, a little more arbitrarily, verbs enrich a sentence. Consequently, it was noted that the sentences which contain arguments usually have a larger number of verbs.
- **missing:**
- **Key Words:** This variable refers to the number of words that were traced in a group of words that we created. This group contains words that are used when someone tries to explain or support an opinion. For example, in this group there are the words consider, believe, admit, suppose, think, must, consequently, since, until, because, namely.
- **Number of Connective Words:** This variable counts the number of linking words that were found in a sentence. In essence, this number has a direct relation to the next variable which shows the total number of words. The idea of counting the length of a sentence lies to the fact that usually, longer sentences are more likely to contain arguments. Especially when the studied dataset contains texts with arguments and political discussion.
- **Total Number of Words:** respectively with the previous variable.
- **Average Number of Letters in a Word:** This variable came up from the bibliography that we had available. It has been noted that this variable, especially in texts that contain political discussion, can help in a significant way to track arguments.
- **Number of Adjectives:** It is the number of arguments that were found in a sentence. The logic behind this variable is the same with the “Number of Verbs” variable logic.
- **Number of Adverbs:** It came up after studying the bibliography and it states the number of adverbs in a sentence.
- **Number of Nouns:** The role of this variable is equivalent to the “Number of Adjectives” variable.
- **A Boolean Variable that States Whether a Sentence is Interrogative:** The need for this variable was explained thoroughly above.

3.2.2 POS-Tagging

In this part we will analyse the second step in the process of argument extraction from a text. Unlike the previous step (3.2.1), the execution of this step is essential for every new step we wish to analyse.

As it has already been mentioned above (2.2), the POS-Tagging procedure has as goal to analyse the grammar of the text, as well as to extract an output which will contain a recognition of what part of speech each word is. Clearly, this process is very important for Argument Extraction because it constitutes the way with which all parts of speech will be detected.

3.2.2.1 POS-Tagger

In this Thesis, “ILSP POS-Tagger[5]” was used, which was created by the “Institute of Language and Speech processing[6]”.

3.2.2.2 POS-Tagger Output

From the outputs supported by POS-Tagger that we had available, we have chosen the “xceslemma” option, with which-apart from POS-Tagging, Lemmatization can also be accomplished. We will need the latter in the next unit that we are going to study. The output given is in XML format. An example can be seen below:

```
<?xml version=’1.0’ encoding=’UTF−8’?>
<cesDoc xmlns="http://www.xces.org/schema/2003" version="0.4">
  <text>
    <body>
      <p id="p1">
        <s id="s1">
          <t id="t1" word="..." tag="AtDfNeSgNm" lemma="..."/>
          <t id="t2" word="..." tag="RgFwOr" lemma="..."/>
          <t id="t3" word="..." tag="PnReNe03SgNmXx" lemma="..."/>
          <t id="t4" word="..." tag="VbMnIdPr03SgXxIpPvXx" lemma="..."/>
          <t id="t5" word="..." tag="VbMnIdPr03SgXxIpPvXx" lemma="..."/>
          <t id="t6" word="..." tag="AsPpSp" lemma="..."/>
          <t id="t7" word="..." tag="NoCmFeSgAc" lemma="..."/>
          <t id="t8" word="..." tag="RgFwOr" lemma="..."/>
          <t id="t9" word="..." tag="PTERM_P" lemma="..."/>
        </s>
      </p>
    </body>
  </text>
</cesDoc>
```

The text that was given as input was *“The output which is given is in XML format”*. We note that for every word of the text, the following information is given:

- **Id:** an auto increment identifier given in every word of the text
- **Word:** the initial word of the text

[5] http://nlp.ilsp.gr/soaplab2-axis/

[6] http://www.ilsp.gr/en

- **Tag:** the Grammar concerning the particular word. For example, verbs start with “Vb” and nouns with “No”. The whole tagset can be found here `http://nlp.ilsp.gr/nlp/tagset_examples/tagset_en/`
- **Lemma:** it is the dictionary entry of each word. For example, we note that the verb “given” has “give” as its lemma.

3.2.2.3 Parsing XML File

TODO

3.2.2.4 Uploading to Database

TODO

```
INSERT INTO opngv_argument VALUES (values..)
```

3.2.3 Apply Machine Learning

TODO

3.2.3.1 Selecting Train and Test Set

TODO

```
SELECT
        opngv_argument.verbs,
        opngv_argument.pv_verbs,
        opngv_argument.cue_words,
        opngv_argument.connective_words,
        opngv_argument.total_words,
        opngv_argument.word_mean_length,
        opngv_argument.adjective,
        opngv_argument.adverbs,
        opngv_argument.noons,
        opngv_argument.question,
        opngv_trainset.Argument
FROM
        opngv_sentence
        INNER JOIN opngv_argument
                ON opngv_sentence.comment_id = opngv_argument.comment_id
                AND opngv_sentence.sentence_id = opngv_argument.sentence_id
        INNER JOIN opngv_trainset
                ON opngv_sentence.comment_id = opngv_trainset.comment_id
                AND opngv_sentence.sentence_id = opngv_trainset.sentence_id
```

TODO

3.2.3.2 Machine Learning Process

TODO

3.2.3.3 Machine Learning Algorithms

TODO

“Weka is a collection of machine learning algorithms for data mining tasks. The algorithms can either be applied directly to a dataset or called from your own Java code. Weka contains tools for data pre-processing, classification, regression, clustering, association rules, and visualization. It is also well-suited for developing new machine learning schemes.”

3.3 Suggestion Extraction

TODO

3.3.1 Selecting Suggestion Markers

TODO

```
<?xml version='1.0' encoding='UTF-8'?>
<cesDoc xmlns="http://www.xces.org/schema/2003" version="0.4">
  <text>
    <body>
      <p id="p1">
        <s id="s1" casing="lowercase">
          <t id="t1" word="..." tag="VbIsIdPr03SgXxIpAvXx" lemma="..."/>
          <t id="t2" word="..." tag="PtSj" lemma="..."/>
          <t id="t3" word="..." tag="VbMnIdXx03SgXxPePvXx" lemma="..."/>
          <t id="t4" word="..." tag="NoCmFeSgNm" lemma="..."/>
          <t id="t5" word="..." tag="AsPpPaFeSgAc" lemma="..."/>
          <t id="t6" word="..." tag="NoCmFeSgAc" lemma="..."/>
          <t id="t7" word="..." tag="DIG" lemma="..."/>
          <t id="t8" word="..." tag="AtDfMaSgGe" lemma="..."/>
          <t id="t9" word="..." tag="NoCmMaSgGe" lemma="..."/>
          <t id="t10" word="..." tag="PTERM_P" lemma="..."/>
        </s>
      </p>
    </body>
  </text>
</cesDoc>
```

TODO

3.3.2 POS-Tagging and Lemmatization the set of Documents

TODO

3.3.3 Apply Information Retrieval Methods in order to find the Suggestions

TODO

3.3.4 Adding additional features for the optimization of Machine Learning Processs

TODO

3.3.5 Apply Machine Learning

TODO

3.3.5.1 Selecting Train and Test Set

TODO

```
SELECT
        opngv_suggestion.weight,
        opngv_suggestion.category,
        opngv_suggestion.total_words,
        opngv_trainset.Suggestion
FROM
        opngv_sentence
        INNER JOIN opngv_suggestion
                ON opngv_sentence.comment_id = opngv_suggestion.comment_id
                AND opngv_sentence.sentence_id = opngv_suggestion.sentence_id
        INNER JOIN opngv_trainset
                ON opngv_sentence.comment_id = opngv_trainset.comment_id
                AND opngv_sentence.sentence_id = opngv_trainset.sentence_id
ORDER BY
        opngv_trainset.Suggestion DESC
LIMIT 366
```

TODO

3.3.5.2 Machine Learning Process

TODO

3.3.5.3 Machine Learning Algorithms

TODO

3.4 Overall Opinion Extraction

TODO

3.4.1 Translate Documents to English

TODO

3.4.2 Perform Sentiment Analysis

TODO

- **SentiStrength[7]:** *"SentiStrength estimates the strength of positive and negative sentiment in short texts, even for informal language. It has human-level accuracy for short social web texts in English, except political texts. SentiStrength reports two sentiment strengths:*

  - *-1 (not negative) to -5 (extremely negative)*
  - *1 (not positive) to 5 (extremely positive)*

  Why does it use two scores? Because research from psychology has revealed that we process positive and negative sentiment in parallel - hence mixed emotions. SentiStrength can also report binary (positive/negative), trinary (positive/negative/neutral) and single scale (-4 to +4) results."

- **Sentiment Analysis with Python NLTK Text Classification[8]:** *"Sentiment analysis using a NLTK 2.0.4 powered text classification process. It can tell you whether it thinks the text you enter below expresses positive sentiment, negative sentiment, or if it's neutral. Using hierarchical classification, neutrality is determined first, and sentiment polarity is determined second, but only if the text is not neutral."*

[7] `http://sentistrength.wlv.ac.uk`

[8] `http://text-processing.com/docs/sentiment.html`

4

Evaluation and Results

TODO

4.1 Argument Extraction

TODO

4.1.1 Argument Markers

TODO

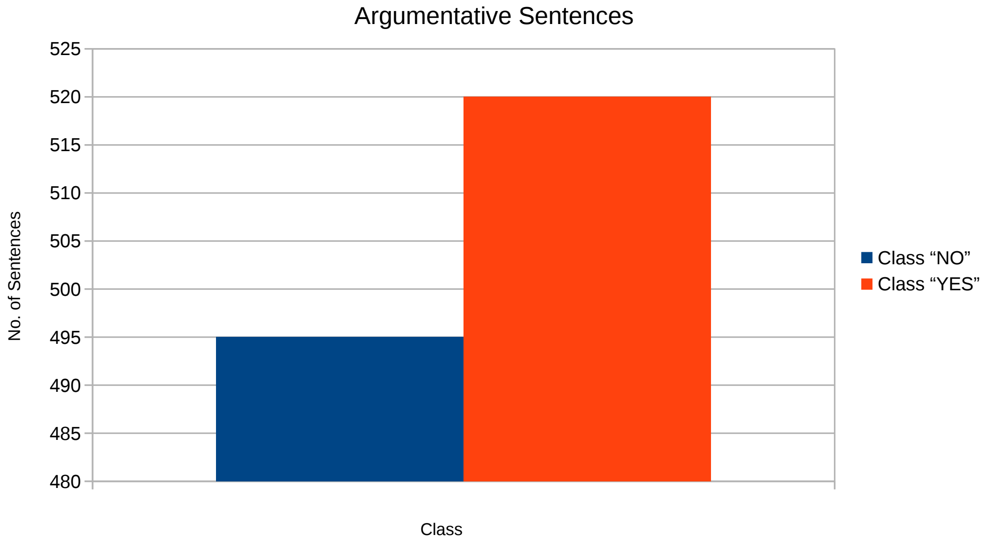


Figure 4.1: Argumentative Sentences in Train Set.

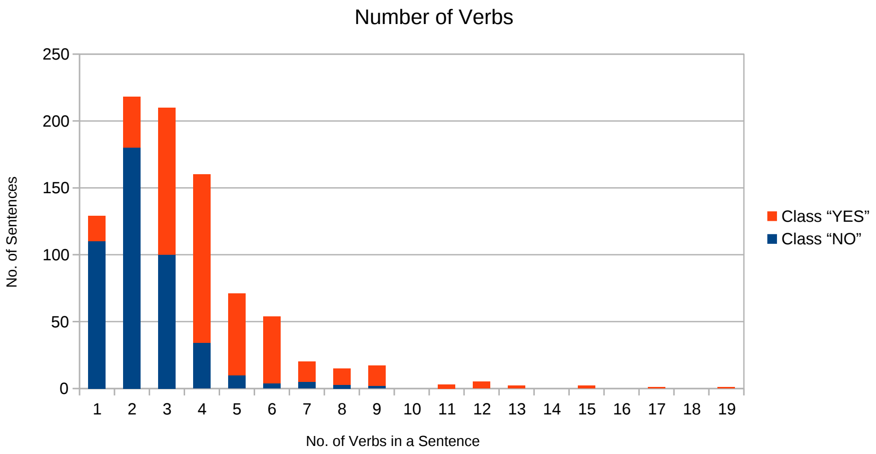


Figure 4.2: Argument Marker - Number of Verbs in a Sentence.

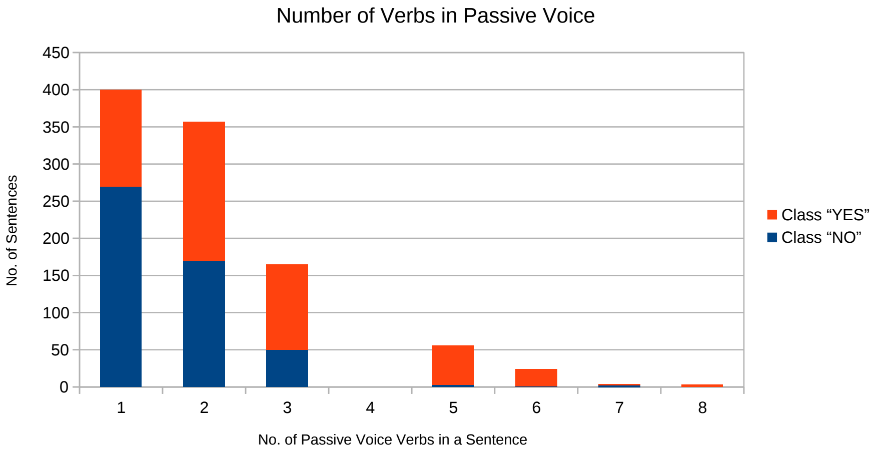


Figure 4.3: Argument Marker - Number of Verbs in Passive Voice in a Sentence.

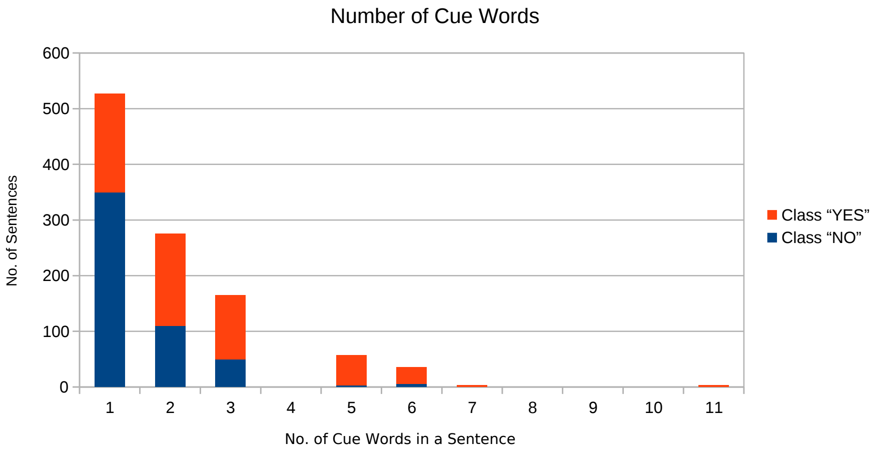


Figure 4.4: Argument Marker - Number of Cue Words in a Sentence.

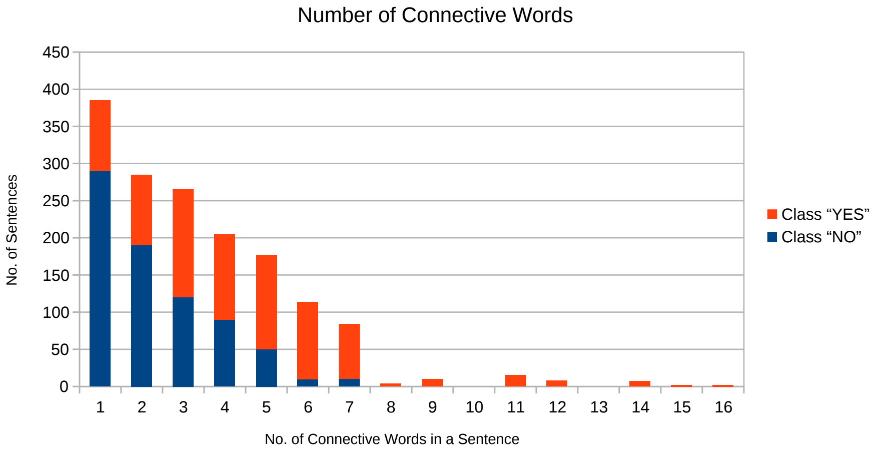


Figure 4.5: Argument Marker - Number of Connective Words in a Sentence.

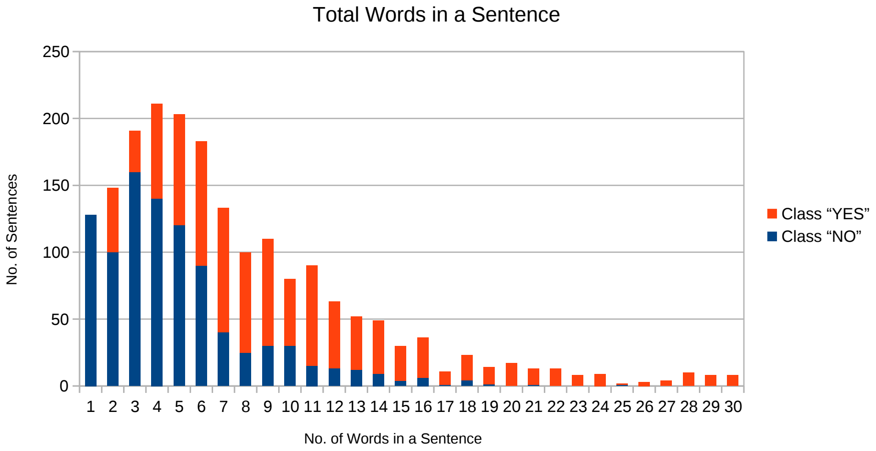


Figure 4.6: Argument Marker - Total words in a Sentence.

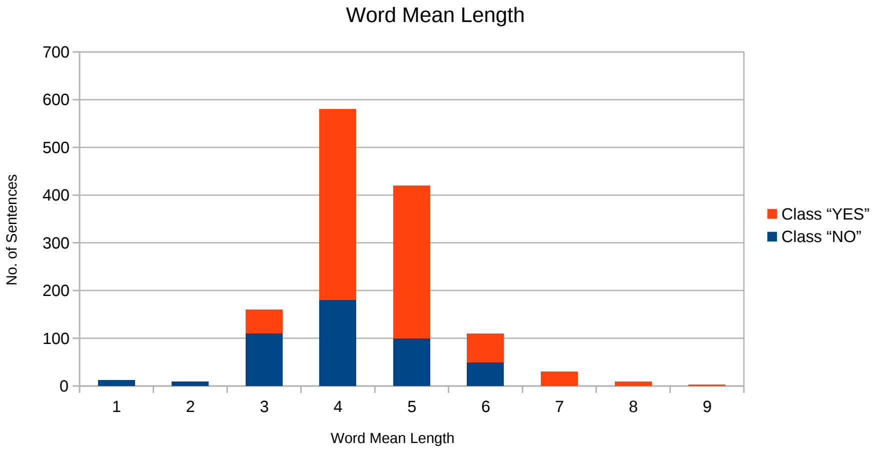


Figure 4.7: Argument Marker - Word Mean Length.

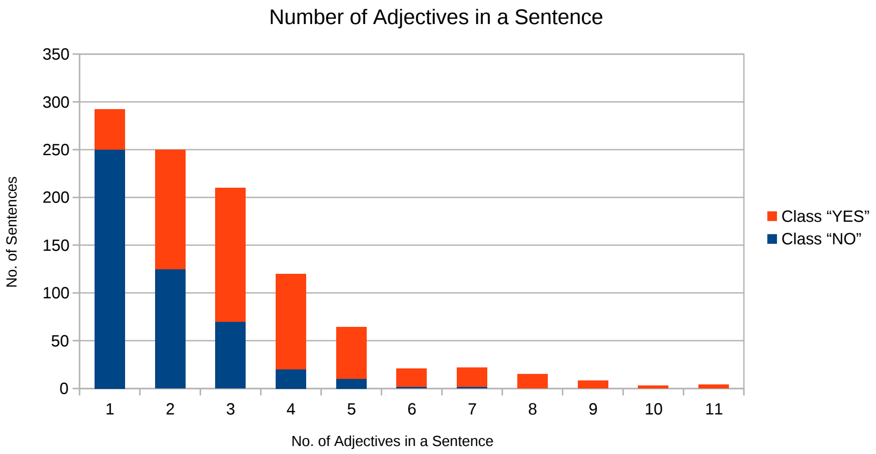


Figure 4.8: Argument Marker - Number of Adjectives in a Sentence.

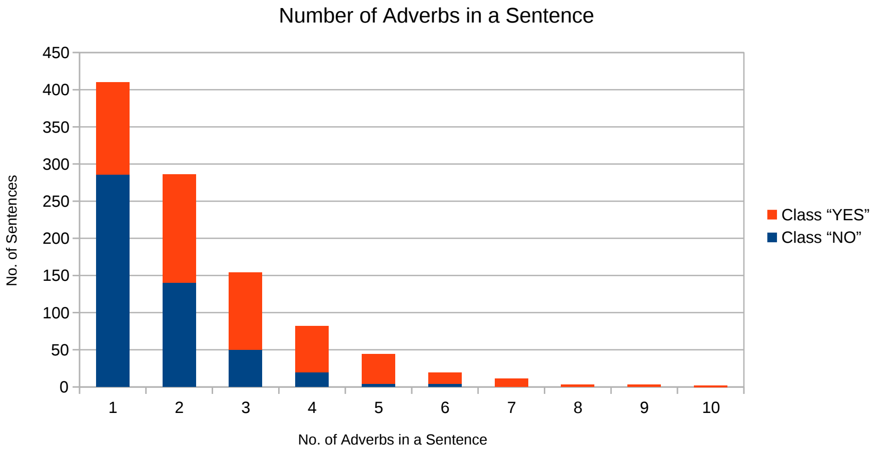


Figure 4.9: Argument Marker - Number of Adverbs in a Sentence.

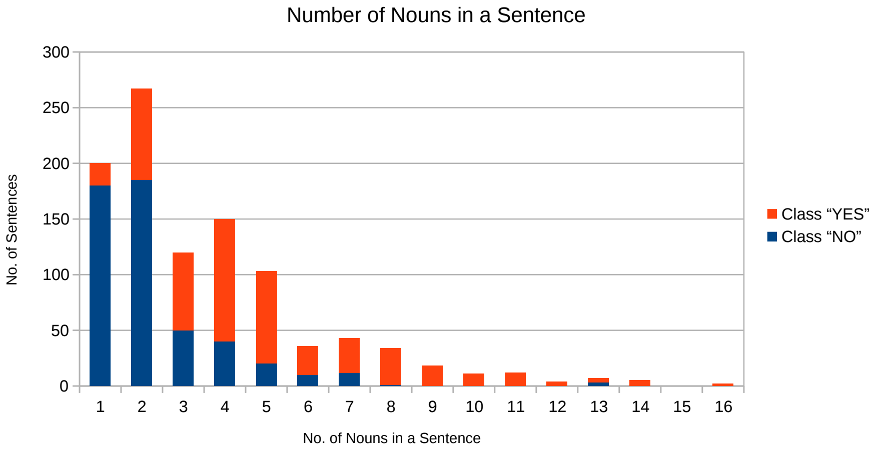


Figure 4.10: Argument Marker - Number of Nouns in a Sentence.

4.1.2 Algorithms used in Machine Learning Procedure

TODO

Table 4.1: Detailed Accuracy for Class “No” (Argument Extraction).

Algorithm	Precision	Recall	F-Measure
SVM	*0.815*	*0.830*	**0.823**
Random Forest	**0.818**	*0.818*	*0.818*
Native Bayes	*0.718*	**0.899**	*0.798*
Logistic Regression	*0.801*	*0.819*	*0.819*

Table 4.2: Detailed Accuracy for Class “Yes” (Argument Extraction).

Algorithm	Precision	Recall	F-Measure
SVM	*0.836*	*0.821*	**0.828**
Random Forest	*0.827*	**0.827**	*0.827*
Native Bayes	**0.873**	*0.663*	*0.754*
Logistic Regression	*0.837*	*0.802*	*0.819*

Table 4.3: Weighted Average on both Classes (Argument Extraction).

Algorithm	Precision	Recall	F-Measure
SVM	**0.826**	**0.826**	**0.826**
Random Forest	*0.823*	*0.823*	*0.823*
Native Bayes	*0.797*	*0.778*	*0.776*
Logistic Regression	*0.820*	*0.819*	*0.819*

TODO

Table 4.4: Additional Statistical Information (Argument Extraction).

	Frequenncy	Percentage
Correctly Classified Instances	*838*	*82.56%*
Incorrectly Classified Instances	*177*	*17.4383*
Kappa statistic	*0.6512*	-
Mean absolute error	*0.1744*	-
Root mean squared error	*0.4176*	-
Relative absolute error	-	*34.90%*
Root relative squared error	-	*83.54%*
Coverage of cases (0.95 level)	-	*82.56%*
Mean rel. region size (0.95 level)	-	*50%*
Total Number of Instances	*1015*	-

4.1.3 Information about the Train Set

TODO

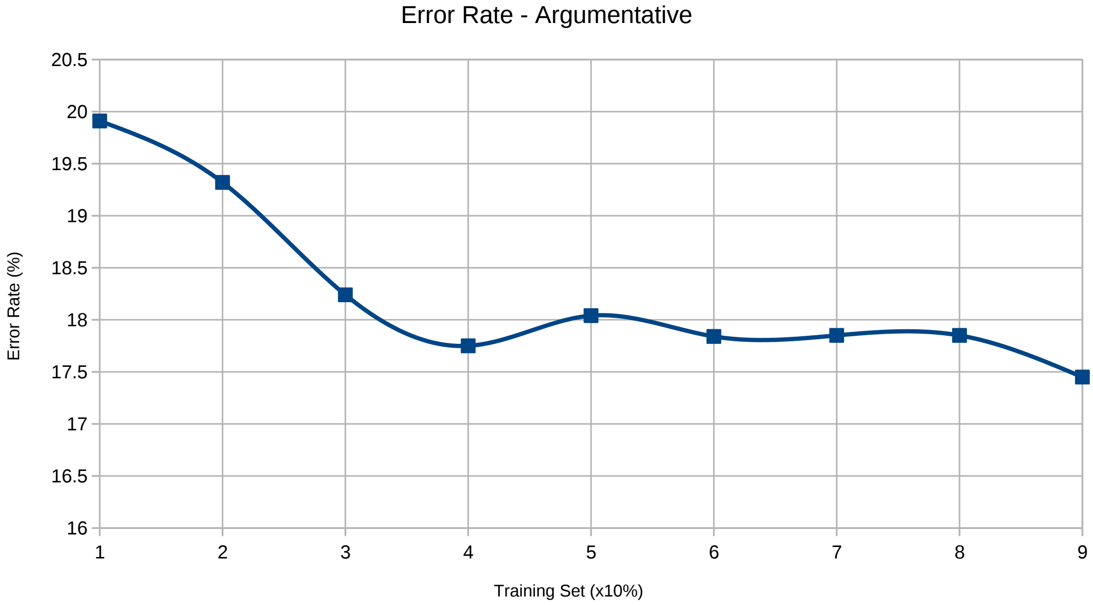


Figure 4.11: Error Rate of Argumentative Sentence Classification.

4.2 Suggestion Extraction

TODO

4.2.1 “10 Fold Cross Validation” on Train Set

TODO

Table 4.5: Detailed Accuracy for Class “No” (Suggestion Extraction).

Algorithm	Precision	Recall	F-Measure
J48	*0.881*	*0.923*	*0.901*
Random Forest	*0.890*	*0.915*	*0.902*
Native Bayes	**0.912**	*0.915*	*0.604*
SVM	*0.839*	**0.989**	**0.908**

Table 4.6: Detailed Accuracy for Class “Yes” (Suggestion Extraction).

Algorithm	Precision	Recall	F-Measure
J48	*0.552*	*0.432*	*0.485*
Random Forest	*0.556*	*0.489*	*0.519*
Native Bayes	*0.608*	**0.601**	**0.604**
SVM	**0.735**	*0.137*	*0.230*

Table 4.7: Weighted Average on both Classes (Suggestion Extraction).

Algorithm	Precision	Recall	F-Measure
J48	*0.822*	*0.834*	*0.826*
Random Forest	*0.830*	*0.837*	*0.833*
Native Bayes	**0.858**	**0.858**	**0.858**
SVM	*0.820*	*0.835*	*0.786*

TODO

Table 4.8: Additional Statistical Information (Suggestion Extraction).

	Frequenncy	Percentage
Correctly Classified Instances	*871*	*85.81%*
Incorrectly Classified Instances	*144*	*14.19%*
Kappa statistic	*0.518*	-
Mean absolute error	*0.1901*	-
Root mean squared error	*0.3382*	-
Relative absolute error	-	*64.21%*
Root relative squared error	-	*87.98%*
Coverage of cases (0.95 level)	-	*95.67%*
Mean rel. region size (0.95 level)	-	*70.64%*
Total Number of Instances	*1015*	-

4.2.2 Equivalent Train Set

TODO

Table 4.9: Detailed Accuracy for Class “No” (Suggestion Extraction, using Equivalent Train Set).

Algorithm	**Precision**	**Recall**	**F-Measure**
J48	*0.940*	*0.810*	*0.870*
Random Forest	**0.996**	*0.810*	**0.893**
Native Bayes	*0.941*	**0.828**	*0.881*
SVM	*0.939*	*0.819*	*0.875*

Table 4.10: Detailed Accuracy for Class “Yes” (Suggestion Extraction, using Equivalent Train Set).

Algorithm	**Precision**	**Recall**	**F-Measure**
J48	*0.470*	*0.765*	*0.582*
Random Forest	**0.533**	**0.984**	**0.641**
Native Bayes	*0.495*	*0.765*	*0.601*
SVM	*0.479*	*0.760*	*0.588*

Table 4.11: Weighted Average on both Classes (Suggestion Extraction, using Equivalent Train Set).

Algorithm	**Precision**	**Recall**	**F-Measure**
J48	*0.855*	*0.802*	*0.818*
Random Forest	**0.912**	**0.841**	**0.857**
Native Bayes	*0.861*	*0.817*	*0.831*
SVM	*0.856*	*0.808*	*0.823*

TODO

Table 4.12: Additional Statistical Information (Suggestion Extraction, using Equivalent Train Set).

	Frequenncy	**Percentage**
Correctly Classified Instances	*854*	*84.14%*
Incorrectly Classified Instances	*161*	*15.86%*
Kappa statistic	*0.5966*	-
Mean absolute error	*0.2273*	-
Root mean squared error	*0.3467*	-
Relative absolute error	-	*47.98%*
Root relative squared error	-	*73.02%*
Coverage of cases (0.95 level)	-	*97.14%*
Mean rel. region size (0.95 level)	-	*83.00%*
Total Number of Instances	*1015*	-

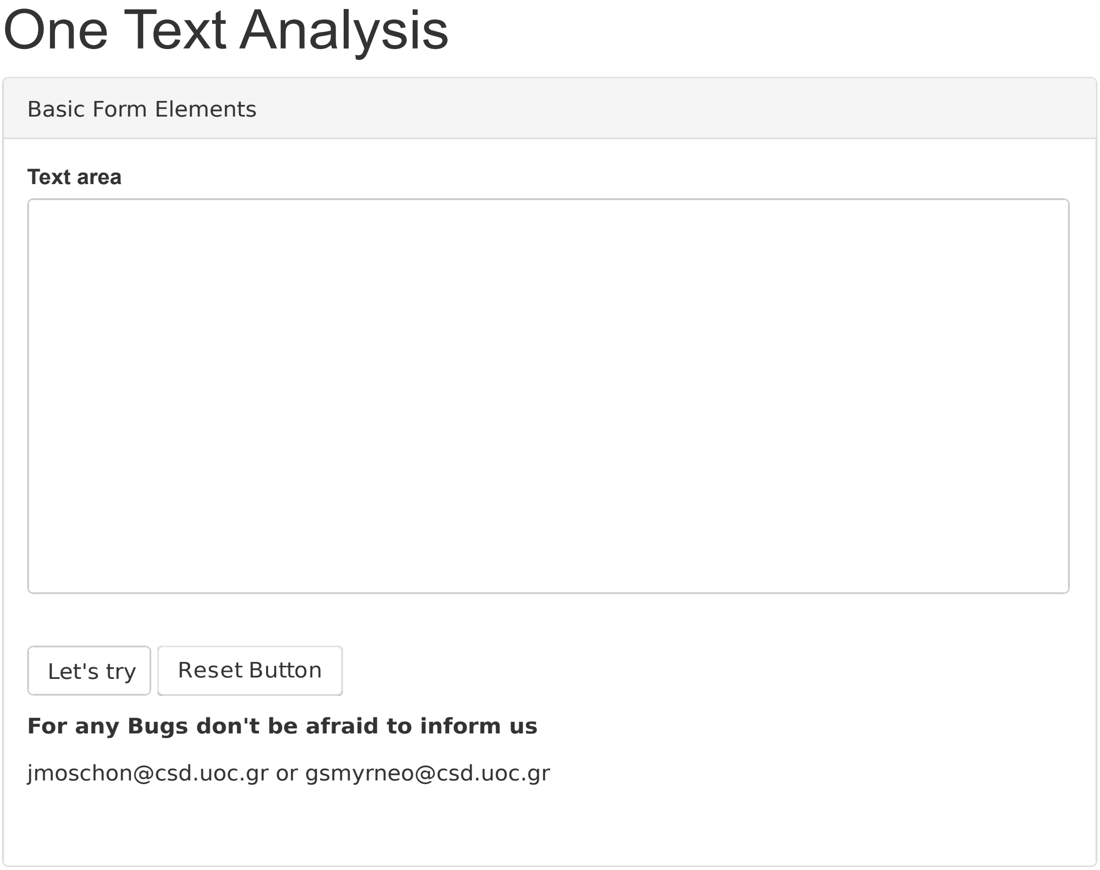
4.3 Overall Opinion Extraction

TODO

5

Demo Application

TODO



One Text Analysis

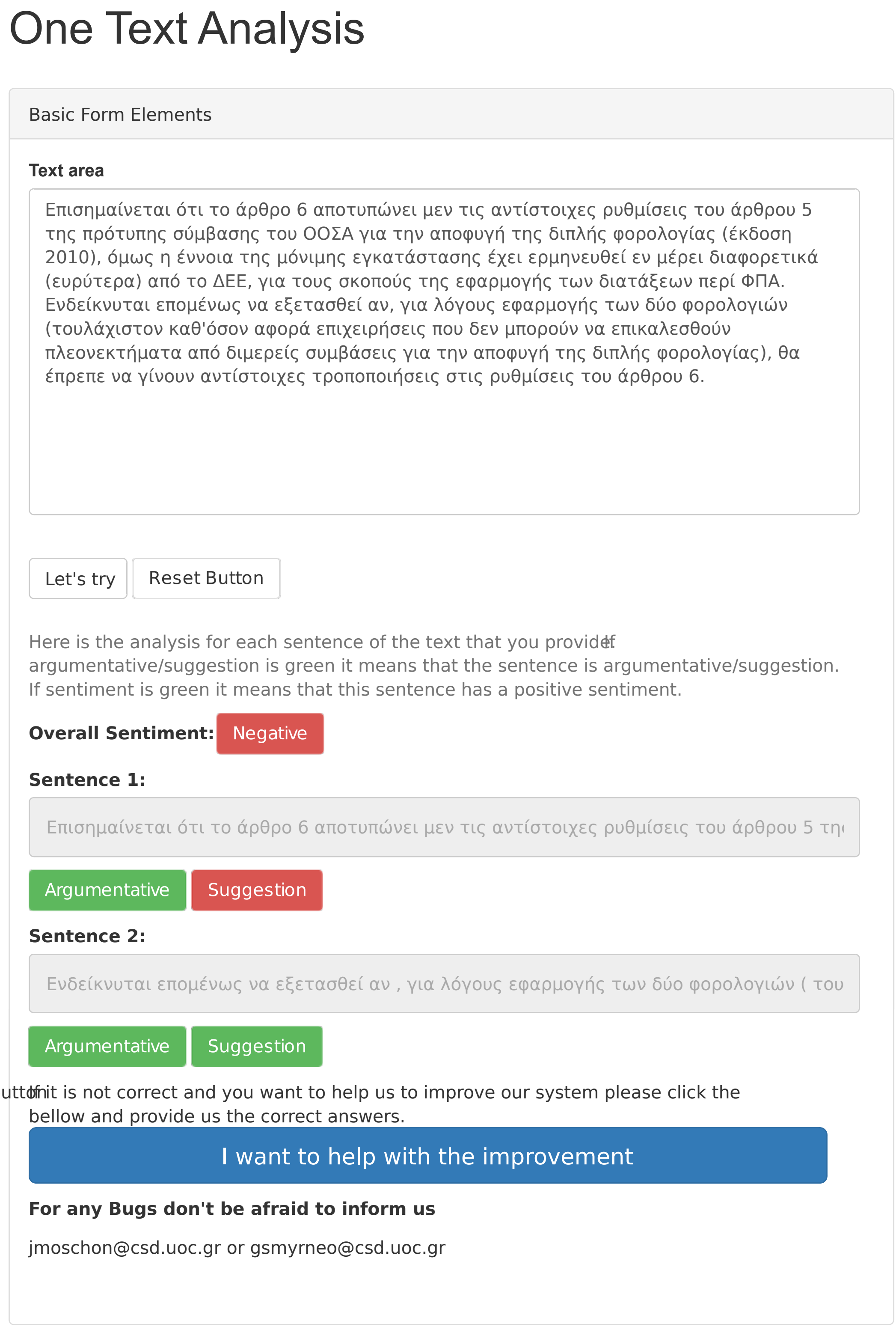
Basic Form Elements

Text area

For any Bugs don't be afraid to inform us

jmoschon@csd.uoc.gr or gsmyrneo@csd.uoc.gr

TODO



One Text Analysis

Επισημαίνεται ότι το άρθρο 6 αποτυπώνει μεν τις αντίστοιχες ρυθμίσεις του άρθρου 5 της πρότυπης σύμβασης του ΟΟΣΑ για την αποφυγή της διπλής φορολογίας (έκδοση 2010), όμως η έννοια της μόνιμης εγκατάστασης έχει ερμηνευθεί εν μέρει διαφορετικά (ευρύτερα) από το ΔΕΕ, για τους σκοπούς της εφαρμογής των διατάξεων περί ΦΠΑ. Ενδείκνυται επομένως να εξετασθεί αν, για λόγους εφαρμογής των δύο φορολογιών (τουλάχιστον καθ'όσον αφορά επιχειρήσεις που δεν μπορούν να επικαλεσθούν πλεονεκτήματα από διμερείς συμβάσεις για την αποφυγή της διπλής φορολογίας), θα έπρεπε να γίνουν αντίστοιχες τροποποιήσεις στις ρυθμίσεις του άρθρου 6.

Here is the analysis for each sentence of the text that you provided. If argumentative/suggestion is green it means that the sentence is argumentative/suggestion. If sentiment is green it means that this sentence has a positive sentiment.

Overall Sentiment: 🟥 Negative

Sentence 1:

Επισημαίνεται ότι το άρθρο 6 αποτυπώνει μεν τις αντίστοιχες ρυθμίσεις του άρθρου 5 τη

🟩 Argumentative 🟥 Suggestion

Sentence 2:

Ενδείκνυται επομένως να εξετασθεί αν , για λόγους εφαρμογής των δύο φορολογιών (του

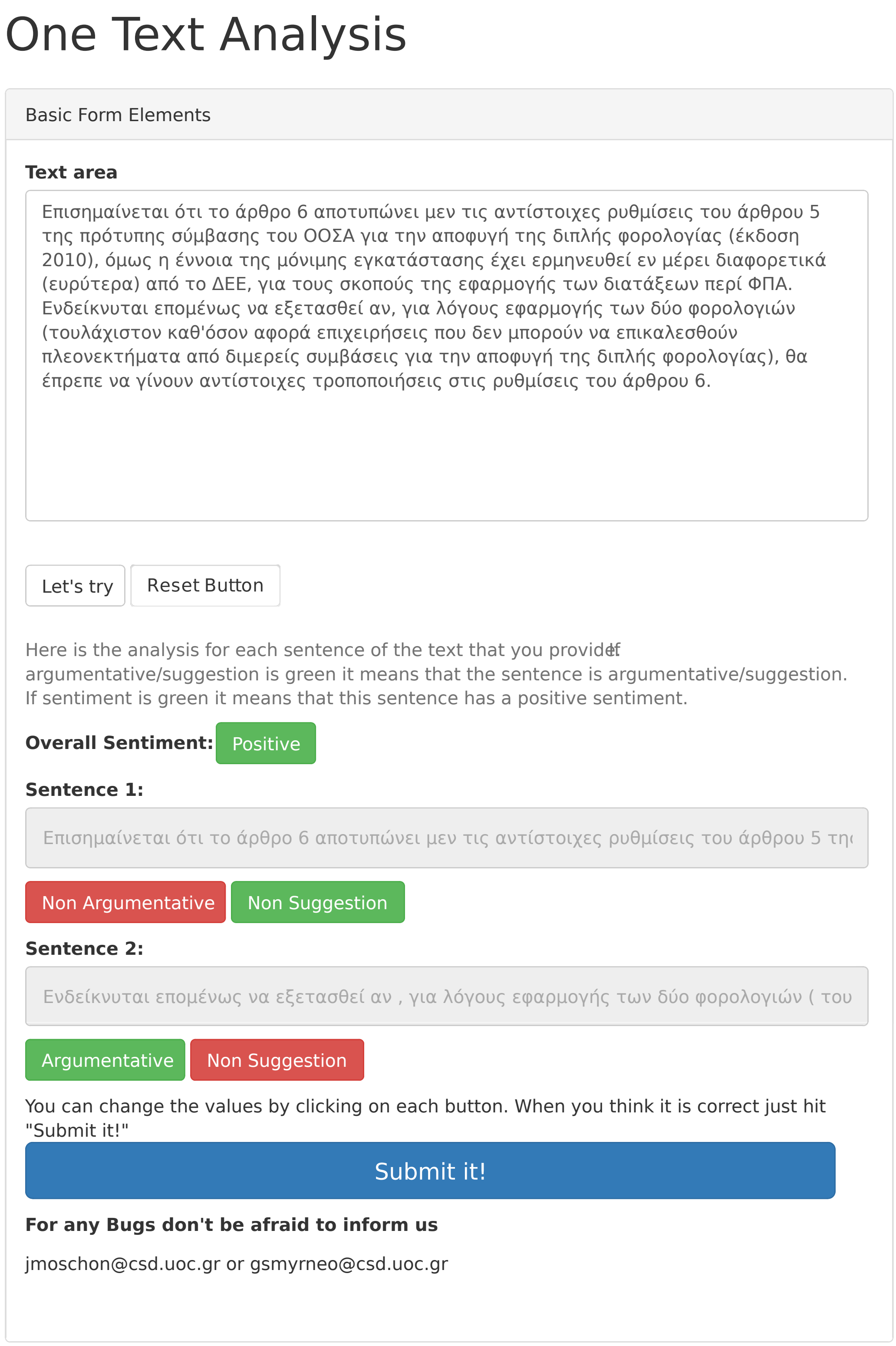
🟩 Argumentative 🟩 Suggestion

If it is not correct and you want to help us to improve our system please click the button bellow and provide us the correct answers.

For any Bugs don't be afraid to inform us

jmoschon@csd.uoc.gr or gsmyrneo@csd.uoc.gr

TODO



One Text Analysis

Basic Form Elements

Text area

Επισημαίνεται ότι το άρθρο 6 αποτυπώνει μεν τις αντίστοιχες ρυθμίσεις του άρθρου 5 της πρότυπης σύμβασης του ΟΟΣΑ για την αποφυγή της διπλής φορολογίας (έκδοση 2010), όμως η έννοια της μόνιμης εγκατάστασης έχει ερμηνευθεί εν μέρει διαφορετικά (ευρύτερα) από το ΔΕΕ, για τους σκοπούς της εφαρμογής των διατάξεων περί ΦΠΑ. Ενδείκνυται επομένως να εξετασθεί αν, για λόγους εφαρμογής των δύο φορολογιών (τουλάχιστον καθ'όσον αφορά επιχειρήσεις που δεν μπορούν να επικαλεσθούν πλεονεκτήματα από διμερείς συμβάσεις για την αποφυγή της διπλής φορολογίας), θα έπρεπε να γίνουν αντίστοιχες τροποποιήσεις στις ρυθμίσεις του άρθρου 6.

Here is the analysis for each sentence of the text that you provided If argumentative/suggestion is green it means that the sentence is argumentative/suggestion. If sentiment is green it means that this sentence has a positive sentiment.

Overall Sentiment: Positive

Sentence 1:

Επισημαίνεται ότι το άρθρο 6 αποτυπώνει μεν τις αντίστοιχες ρυθμίσεις του άρθρου 5 τη

Non Argumentative | Non Suggestion

Sentence 2:

Ενδείκνυται επομένως να εξετασθεί αν , για λόγους εφαρμογής των δύο φορολογιών (του

Argumentative | Non Suggestion

You can change the values by clicking on each button. When you think it is correct just hit "Submit it!"

For any Bugs don't be afraid to inform us

jmoschon@csd.uoc.gr or gsmyrneo@csd.uoc.gr

TODO

6

Conclusion

Lorem ipsum dolor sit amet, consectetur adipisicing elit, sed do eiusmod tempor incididunt ut labore et dolore magna aliqua. Ut enim ad minim veniam, quis nostrud exercitation ullamco laboris nisi ut aliquip ex ea commodo consequat. Duis aute irure dolor in reprehenderit in voluptate velit esse cillum dolore eu fugiat nulla pariatur. Excepteur sint occaecat cupidatat non proident, sunt in culpa qui officia deserunt mollit anim id est laborum.

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