ATHENS UNIVERSITY OF ECONOMICS AND BUSINESS

BACHELOR RESEARCH ASSIGNMENT

Argument Mining

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Contents

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List of Abbreviations

SVM	**S**upport **V**ector **M**achine
LR	**L**ogistic **R**egression
NB	**N**aive **B**ayes classifier
RF	**R**andom **F**orest
RNN	**R**ecurrent **N**eural **N**etworks for Language Models
RF	**R**andom **F**orest
CRF	**C**onditional **R**andom **F**orest
ML	**M**aximum **L**ikelihood
TES	**T**extual **E**ntailment **S**uites
P	**P**arsing Using a Context-Free Grammar
LSTM	**L**ong **S**hort-**t**erm **M**emory
POS	**P**art **O**f **S**peech

Chapter 1

Introduction

1.1 Definition

Argument mining is a relatively new research field in natural language processing. The aim of this research is the auto detection and identification of argumentative structures expressed in text. In order to perform extraction and evaluation of arguments, computer science and artificial intelligence is used.

An argument is a group of premises conducted to support a claim (Palau and Moens, 2009). When it comes to real world, arguments are hardly identified even by experts (Lippi and Torroni, 2015). The ambiguity of natural language, the implicit content, the different ways of expressing and the complex structure of arguments are the main reasons why argument mining is a challenging research field. Labeled corpora are scarce which is a fact that slows down field's potential growth (Lippi and Torroni, 2015).

The purpose of argument mining is to understand what kind of views have been expressed in the examined text and why they are held. Argument mining has derived from opinion mining and sentiment analysis research area, in which the only goal is to understand the opinions about a certain topic (Lawrence and Reed, 2015).

1.2 Research Goal

My research goal is to identify argumentative statements by using two different approaches; the structural approach which is based on hand coded rules and the statistical approach, which based on supervised and deep learning algorithms.

The structural approach uses lexical cues that have been identified by linguists as signs of argumentative speech. As an example, words such as "because", "therefore", "in order to" are common cues of arguments. However, these argumentative patterns are rarely used in practice, since human discourse involves a lot of information which is being implied rather than being explicitly stated.

On the other hand, the statistical approach relies on examples of pieces of text that have been manually labeled as argumentative or non-argumentative. These are used for training models in order to automatically identify arguments in free text without the use of predefined lexical cues and rules. The challenging part is the construction of a manually annotated data-set, given the fact that a large amount of data are required for training such models.

The fundamental research questions that will be addressed in this assignment are the following:

- To what extent are the lexical rules drafted by a structural approach capable of successfully identifying arguments in existing resources of labeled data?

- Do the statistical approaches outperform these results?

1.3 Assignment's Structure

This paper of research is organized into 6 chapters. Chapter 2 presents the state of the art in argument mining, and introduces the two different approaches; the structural and the machine learning approach. Chapters 3 and 4 describe in detail the methods and results of both approaches implemented in the scope of this study. Chapter 5 contains the corpora created for the supervised algorithm, while chapter 6 concludes with a look to future work.

Chapter 2

State-of-the-Art

Arguments do not have a universally accepted definition; though there are plenty of well-described proposals. According to (Walton, 2009), an argument is a group of statements which splits into three portions, which are conclusion, set of premises, and an inference leading from premises to conclusion. These concepts have been widely accepted in literature, but they are defined in slightly different ways. Conclusions are also referred to as claims, premises as evidence or reasons, while the link between claims and evidence is the argument (Lippi and Torroni, 2015).

A claim is supported or argued by one or more premises and it is the main part of an argumentative text. Claims are controversial in terms of validity and need premises to endorse readers' acceptance (Stab and Gurevych, 2014). Argumentation schemes and their common patterns provide a way to both identify and determine arguments (Lawrence and Reed, 2015).

The term of argumentation used to be connected with the process of argument construction (Lippi and Torroni, 2016). After the emergence of text mining procedures, this term defines the process of argument identification in text (Lippi and Torroni, 2016). The research field of argument mining is about the automatic recognition of argumentative structures expressed in natural language texts. Argument mining utilizes methods and techniques used in natural language processing, such as machine learning and sentiment analysis (Lippi and Torroni, 2015).

In general, argument mining procedure is separated into linguistic and computational part, as described in figure 2.1. Regarding the linguistic part, large corpora of manually annotated argument data are being created based on a common agreement among annotators about argument's structure. On the other hand, the computational part is separated into two main styles of automation, the structural and the statistical approach. (Budzynska and Villata, 2015)

In **structural or grammar approach**, linguists aim to retrieve lexical patterns, rules or categories while annotating a training corpus. For example, it might be noticed that words like "because", "since", "however" are signs of arguments inside a specific corpus (Budzynska and Villata, 2015). These signs are called indicators, and point out the connection between claims and premises inside a text (Lawrence and Reed, 2015). Indicators are declared as linguistic expressions that connect statements and provide an unambiguous recognition of argumentative structure (Webber, Egg, and Kordoni, 2012).

A lot of research has been applied in order to be found words and expressions revealing argumentative structure (Van Eemeren, Houtlosser, and Henkemans, 2007, Knott and Dale, 1994). Apart from indicators, other structural techniques have been applied for argument mining. Such techniques are argumentation schemes (Feng and Hirst, 2011), dialogical context (Budzynska et al., 2014), and semantic context (Cabrio and Villata, 2012) or a combination of them.

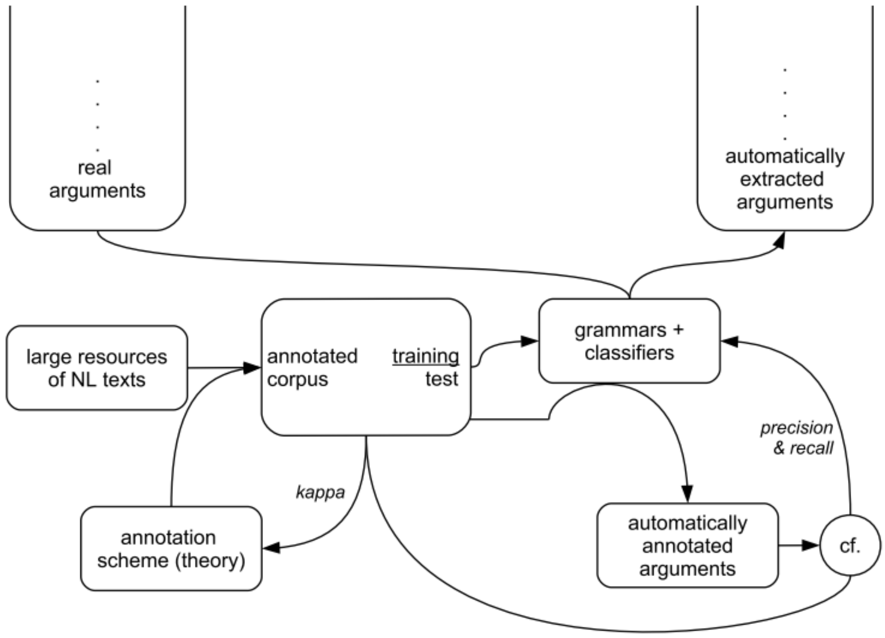


FIGURE 2.1: Natural language processing techniques
Source: Budzynska and Villata, 2015

In **statistical approach**, linguists are replaced by algorithms. These algorithms are basically classifiers developed for automating the argument annotation procedure (Budzynska and Villata, 2015). The first attempts for the before mentioned automation were made in (Moens et al., 2007), in which text is separated into sentences, and then each sentence is classified as argumentative or non-argumentative based on its lexical or syntactic features. As a result, (Palau and Moens, 2009) presented an additional separation of argumentative sentences as premises or conclusions. As regards the automatic recognition of argumentative schemes, it was introduced in (Walton, 2011) and it was based on the idea of connecting each scheme with a group of indicators. The paper's proposal is first indicating the arguments included in text, and then matching them to a given list of argument schemes. (Feng and Hirst, 2011) classifies annotated argumentation structures into a list of five common argumentation schemes. In (Lippi and Torroni, 2015), the authors describe a framework for claim detection in unstructured data-sets without any contextual information. Because arguments are often expressed through rhetorical structures, the previously mentioned framework was built based on an SVM classifier which captures similarities among parse trees via Tree Kernels. This method is used for measuring likeliness of two trees regarding their common substructures. Furthermore, Habernal and Gurevych (Habernalt and Gurevych, 2016) try to evaluate argument convincingness by assessing their qualitative properties. Using an annotated corpus of 26,000 sentences, their purpose is to predict which argument is more convincing between a pair of arguments and to rank arguments regarding the topic and their convincingness, through the usage of SVM and LSTM algorithms.

Various traditional machine learning algorithms have been employed in the context of argument mining (Figure 2.2). More specifically, most of the algorithms that have been implemented are Support Vector Machines (Mochales and Moens, 2011; Park and Cardie, 2015; Stab and Gurevych, 2014; Eckle-Kohler, Kluge, and Gurevych, 2015), Logistic Regression (Levy et al., 2014; Rinott et al., 2015), Naive Bayes classifiers (Mochales and Moens, 2011; Biran and Rambow, 2011; Park and Cardie, 2015; Eckle-Kohler, Kluge, and Gurevych, 2015), Maximum Entropy classifiers (Mochales and Moens, 2011), and Decision Trees and Random Forests (Stab and Gurevych, 2014; Eckle-Kohler, Kluge, and Gurevych, 2015). All mentioned classifiers are trained in labeled corpora. Thus, some parts of the annotated text are given, alongside with the associated label, and during training stage a model is being produced. This model is used to perform predictions on new unlabeled text. (Lippi and Torroni, 2016)

	SC							BD		SP			
System	SVM	LR	NB	ME	DT	RF	RNN	CRF	ML	TES	P	SVM	NB
Eckle-Kohler et al. [2015]	X		X			X							
Lippi and Torroni [2015]	X												
Rinott et al. [2015]		X											
Sardianos et al. [2015]	X						X	X					
Boltuzic and Snajder [2014]										X		X	
Goudas et al. [2014]	X							X					
Levy et al. [2014]		X							X				
Stab and Gurevych [2014b]	X		X		X	X						X	
Cabrio and Villata [2012a]										X			
Rooney et al. [2012]	X												
Biran and Rambow [2011]			X								X		X
Mochales Palau and Moens [2011]	X		X	X							X		

FIGURE 2.2: Machine learning algorithms that have been used for argument mining
Source: Lippi and Torroni, 2016

Despite the fact that researchers have tried to make a comparison between these algorithms, there is no clear proof of which classifier is more appropriate for argumentation mining. In fact, most of the research efforts have been settled down on finding appropriate features for improving performance instead of implementing new specifically designed models and algorithms for solving argument identification problem (Lippi and Torroni, 2016).

To sum up, a number of different approaches have been applied to argument identification problem. The research community solutions are ranging from linguistic techniques (Garcia Villalba and Saint-Dizier, 2012) and topic modeling (John Lawrence, Chris Reed, Colin Allen, Simon McAlister, Andrew Ravenscroft, 2014), to supervised machine learning algorithms(firstly implemented by Moens et al., 2007).

Chapter 3

Methods

In this research paper, we attempt to apply two different approaches for recognizing argumentative sentences. These approaches cover both a structured methodology, which is related to the selection of hand-coded linguistic rules, and a statistical one, that includes the implementation of supervised algorithms; namely, Random Forest classifier and sequence classification with LSTM.

3.1 Structural Approach

The structural approach is based on lexical cues, rules or patterns for identifying arguments inside a given text. These cues are also referred to as argument indicators, since they are connecting claims and premises, signaling argumentative relations.

Argumentative Indicators based on (Knott and Dale, 1994)							
Indicator	POS	Indicator	POS	Indicator	POS	Indicator	POS
even though	none	first	adv	against	none	last	adv
naturally	none	most	{"[a-z]*ly": "adv"}	if	none	(T | t)(he more).+?(the more)	none
once more	none	more	{"[a-z]*ly": "adv"}	once again	none	(T | t)(he more).+?(the less)	none
surely	none	second	adv	so	mark	third	adv
should say	none	too	(too)($ | [\\.])	might say	none	may say	none
could say	none	while	mark	as a start	none	in order to	none
still	adv	that is	none	since	mark	yet	(Y | y)(et)[^\\.].
that	mark	above all	none	actually	none	after all	none
afterwards	none	all in all	none	also	none	although	none
anyway	none	as a consequence	none	as a result	none	at any rate	none
at first blush	none	at first view	none	at the outset	none	because	none
by comparison	none	by the same token	none	certainly	none	consequently	none
correspondingly	none	despite the fact that	none	either	none	equally	none
even then	none	every time	none	except insofar as	none	firstly	none
for a start	none	for instance	none	further	none	for the simple reason	none
accordingly	none	admittedly	none	after that	none	all the same	none
alternatively	none	always assuming that	none	as	none	as a corollary	none
at first	none	at first sight	none	at the moment when	none	at the same time	none
but	none	by contrast	none	by the way	none	clearly	none
conversely	none	despite that	none	essentially	none	even so	none
eventually	none	except	none	finally	none	first of all	none
for example	none	for one thing	none	for this reason	none	furthermore	none
hence	none	in actual fact	none	in any case	none	in conclusion	none
in fact	none	in other words	none	in short	none	in sum	none
incidentally	none	instead	none	merely because	none	just as	none
meanwhile	none	it might appear that	none	as long as	none	as well	none
notably	none	moreover	none	of course	none	nevertheless	none
on one hand	none	not only	none	now that	none	no doubt	none
on the grounds that	none	on the assumption that	none	on the one side	none	on the other side	none
plainly	none	otherwise	none	so that	none	providing that	none
such that	none	secondly	none	sure enough	none	simply because	none
thereafter	none	summing up	none	therefore	none	suppose that	none
thirdly	none	the fact is that	none	to be sure	none	though	none
to sum up	none	to conclude	none	undoubtedly	none	to take an example	none
whenever	none	to the extent that	none	whereas	none	what is more	none
wherever	none	for the reason that	none	besides	none	(E | e)(ither).+?(or)	none
in one hand	none	(N | n)(either).+?(nor)	none	on one side	none	in this case	none
in point of fact	none	as a matter of fact	non	provided that	none	presumably	none
rather than	none	regardless	none	as an example	none	simply	none
in order that	none						

A list of indicators were extracted from the corpus created by (Knott and Dale, 1994). This corpus includes often-used words or phrases in arguments according to paper's authors. Based on these words, a dictionary was developed containing as keys the extracted words, and as values, their specific part of speech in argumentative sentences. It needs to be mentioned that words, considered by us as usual or non-usual in argumentative structures, were added or removed respectively from the dictionary. For this purpose, there were created five methods in Python for paper's extraction, modification, as well as dictionary's creation (Appendix 6). The indicators that demonstrate the previously referred dictionary is presented in the table above.

Apart from dictionary's development, a way to handle and encapsulate corpora into the same format was necessary, and the code developed for this purpose is shown in Appendix 7. Each data-set was differently displayed, from unstructured text to sentence labeled data. This is the reason why there was created a *datasets.ini* file containing information about data, for example the number of column indicating the sentence or/and the label, which sheet includes the desired data, or which is the data-set's path. The key of each record was the name of every corpora as it was saved in local file. So, depending on the data-set's type (excel, csv or txt file) and its configurations, other actions were applied in order to returned a list of sentences and their labels in case corpora was annotated.

By using the previously created dictionary and corpora handler, argument identification had to take place (Appendix 8). For this reason, part of speech tagging was necessary, so as a sentence's words and their POS to be compared to those words included in the dictionary. Statements tokenization was achieved through the usage of a library called *spaCy*, which is an open-source NLP library written in Python and Cython, and it was selected due to its performance and efficiency comparing to other libraries. If any of matches between the dictionary and a given sentence occur, the sentence is characterized as argumentative, otherwise as non-argumentative. As regards the labeled corpora, the algorithm's outcomes and the given labels, which is considered to be the truth, are correlated so as four counters to be calculated; False Positives, False Negatives, True Positives and True Negatives. These counters are used for measuring accuracy that is a metric for reviewing algorithm's results, which will be used and described at Chapter 5.

3.2 Statistical Approach

The statistical approach is relying on algorithms developed for automating the argument annotation process. These algorithms receive as input, a representation of data that can be understood by computers. For this reason, textual data of our corpora need to be transformed into numeric tensors. (Chollet, 2017)

Text is considered as a form of sequence data, and tokens are the different units into which a text can be split. These units can be either words, characters or n-grams (Chollet, 2017). After text tokenization, the next step is connecting numeric vectors with the occurred tokens. Then, the sequences of vectors instead of words is fed into the selected algorithm.

There are a variety of ways for vector and token association. Two and the most known ones for forms of sequence data are the one-hot encodingText and word-embedding methods (Chollet, 2017), which will be used in the implemented algorithms later on.

As regards one-hot encodingText is a basic way to transform tokens into vectors. Every word is connected with a unique integer index, which is turned into a binary vector of vocabulary's size. Another version of this method is the one-hot hashing trick, which is used when vocabulary's unique tokens are too much that is difficult to be handled. This approach hashes words into a fixed-sized vector through a hashing function, rather than allocating an index to each word, and then creating a dictionary for these indexes. The disadvantages of this method is the hash collisions, and in general the inability of word's correlation that leads to high dimentionality. (Chollet, 2017)

Word embedding, or dense word vectors, is another popular way to associate vectors with words. In contrast with one-hot encodingText, this technique has low-dimensionality and float vectors. Furthermore, dense word vectors are trained by the data provided, and thus packing more and more data into the same dimensions. This is achieved by minimizing the geometric distance between related words, like synonyms, while maximizing it when words have different semantic (Chollet, 2017).

The implemented algorithms for argument mining problem are the Random Forest classification algorithm, using one-hot encodingText, and the LSTM-RNN algorithm, using word embedding method. The annotation of argumentative and non-argumentative sentences can be considered as a binary classification in Random Forest (Stab and Gurevych, 2014) or a statistical structure mapping of written language in LSTM (Chollet, 2017).

3.2.1 Random Forest Classification Algorithm

The Random Forest algorithm is a collection of decision trees, where each one of them are slightly different from the others either by selecting the data-points or by selecting different features (Müller and Guido, 2016). Every decision tree, built during the training period, predicts to which class a specific input is more suitable (argument or non-argument). After this process is completed, the chosen prediction for each sentence is the one that has the majority of votes across the decision trees. Chollet, 2017

By using the `sklearn.ensemble` library, a Random Forest classification algorithm was implemented (Appendix 9). First of all, an annotated corpora containing both argumentative and non-argumentative sentences is loaded and features regarding how many words, punctuation characters and uppercase characters were created (see Chapter 5). Afterwords, the sentences were tokenized in order to be transformed into a format that computer can understand, as mentioned before. For the tokenization `OneHotEncoder` of `sklearn.preprocessing` library was used. The corpora was seperated into a training and a test set of data, and then model was defined and trained using the train data. Finally, the model is tested and a matrix showing the real and the predicted data was presented in a heatmap plot.

The model is applied by using two different methods for training. The one method is using the features created, like in (Lawrence and Reed, 2016), while the other is by using the tokenized sentences.

3.2.2 LSTM-RNN Algorithm

Deep learning in natural-language processing problems is aiming to identify patterns of words or sentences (Chollet, 2017). The most appropriate deep learning model for sequence data processing, like sequences of words in our case, is the Recurrent Neural Network algorithm. RNN is a neural network algorithm that is implementing internal iterations. The RNN resets its state every time a new independent process occurs, which means that each sequence is a different data input to the network. However, network include loops over each sequence's elements. RNN includes the so-called LSTM layer. The Long Short-Term Memory algorithm was developed by Hochreiter and Schmidhuber in 1997, and the purpose of creation was to solve the "vanishing-gradient problem" of SimpleRNN algorithm. LSTM is basically allowing previous information to be re-injected across different timesteps. (Chollet, 2017)

By using the tensorFlow keras API, an LSTM algorithm was conducted and implemented (Appendix 10). First of all, the corpora created in Chapter 4 is loaded, and data applied to one list of sentences and one list of labels. Following, the corpora is split into a training and a testing data-set. Furthermore, the lists of trained sentences were tokenized, taking into account only the first ten-thousand most frequent words. The lists of the occurred trained sequences, which are basically lists of integers after the tokenization process, are transformed into a two-dimensions numpy array that has a shape of (number of sequences, number of timesteps). The number of timesteps is basically the length of the longest sequence. It has to be mentioned that shorter sequences are padded with values at the end, so every sequence has the same shape.

As regards word embedding, Global Vectors for Word Representation (*Glove*) was used, which is a file containing 100-dimensional pre-computed embedding vectors for 400,000 of English words. This file helped in building an index that associates words with number vectors, and through which an embedding matrix of shape (max_words= 10000, embedding_dim = 100) was created and loaded in Embedding layer later on. The Embedding layer is a dictionary-like that maps integer indexes for certain words to dense vectors, and it is the first layer of our model. The second layer applies to LSTM method, while the third layer of Dense was added to end our stack of layers with an equal number of units and classes created. After constructing our model, we are freezing the Embedding layer to avoid deleting what has already been learned.

Finally, the model was trained based on the training data, which are explicitly separated into training and validation samples used for learning word embedding based on our corpora. The last step is testing the model on the test data by firstly tokenizing the sentences, and then evaluating the results occurred.

Chapter 4

Data Curation

In order to successfully apply the statistical learning approach, a well-structured training data-set is needed. In this section, the process of data curation is elaborated so as both argumentative and non-argumentative sentences to be found.

Most of the argumentative sentences included in our corpora were found on two IBM data-sets created for this purpose (Table 4.1), and are about three main topics; Video Games, Democracy and Multiculturalism. It has to be mentioned that some of the data were duplicated, and thus Python code of Appendix 2 was created so as to be removed.

Source Data	file	Total Data	Duplicated	Arguments	Non-Arguments
Aharoni et al., 2014a	CDEdata.xls	1292	967	325	-
Bar-Haim et al., 2017	claim_stance_dataset_v1	2394	56	2366	-

TABLE 4.1: Argumentative Data Used

However, the exploitation of the existing annotated data-sets regarding argument detection has the obstacle of lacking non-argumentative instances. The previously mentioned IBM corpora contain only phrases that have been manually annotated as positive instances of arguments. This means that it is impossible to train a supervised algorithm in classifying non-arguments without any negative examples.

So, our purpose was to gather an equal number of argumentative and non-argumentative sentences that have the same context with the curated data of IBM. Therefore, plain text referring to Video Games was found in additional IBM data-sets. These raw data files were split into sentences, and each of these sentences was labeled as argument or non-argument by authors of this research paper, and the Table 4.2 depicts the results. The data referred as "Not used" were blank or incomplete lines.

The non-arguments collected were not enough, thus it was decided to scrap data from Wikipedia articles. The topics of these articles were similar to the previously gathered data, and more specifically about Video games, Democracy and Multiculturalism. The code used for the scraping process, as weel as the scraped pages, are aligned at Appendix 1.

Source Data	file	Total Data	Not Used	Arguments	Non-Arguments
Mirkin et al., 2017	asr/DJ_1_ban-video-games_pro.wav.asr.txt	9	3	5	1
Mirkin et al., 2017	asr/EH_1_ban-video-games_pro.wav.asr.txt	20	3	12	5
Mirkin et al., 2017	asr/HE_1_ban-video-games_pro.wav.asr.txt	21	1	12	8
Mirkin et al., 2017	asr/SN_1_video-games_pro.wav.asr.txt	28	10	15	3
Mirkin et al., 2017	asr/TL_1_ban-video-games_pro.wav.asr.txt	19	6	8	5
Mirkin et al., 2017	asr/YB_1_ban-video-games_pro.wav.asr.txt	19	4	7	8
Aharoni et al., 2014a	wiki12_articles/Gender _representation_in_video_games	39	4	5	30

TABLE 4.2: Argumentative and Non-Argumentative Data Used

Assuming that Wikipedia articles' authors are objective and do not express their point of view, most of the data scraped were included as non-arguments in the data-set. It has to be mentioned that the data collected from this procedure were previously checked from the python code-described in the Chapter 3 (Appendix 6). The sentences classified as non-arguments were added to the created data-set, while the others were considered as ambiguous (Table 4.3).

Topic of Wikipedia	Total Data	Not Used	Controversial sentences	Non-Arguments
Early Hstory of video games	143	19	59	65
Fourth generation of video game consoles	65	6	32	27
Game Boy	84	22	23	39
Game design	223	32	71	120
Game	191	28	89	74
Gaming Computer '	129	8	62	59
Gaming disorder	12	6	-	6
History of video games	604	70	224	310
Home computer	359	236	54	69
Nintendo	393	70	133	190
PC game	248	60	87	101
Video game	434	82	154	198
Video game addiction in China	58	4	9	45
Video game addiction	257	138	70	49
Video game console	337	261	41	35
Video game culture	292	74	104	114
Video game development	446	229	102	115
Video game industry	275	49	91	135
Video game music	460	176	146	138
Video game programmer	164	19	72	82
Video game-related health problems	52	7	22	23
Video gaming in Japan	300	102	82	116
Video gaming in the United States	119	31	27	61
The Game Awards	36	2	18	16
Multicultural transruption	45	3	20	22
Multicultural and diversity management	41	7	17	17
Multicultural education	248	28	104	116
Multiculturalism in Australia	156	37	55	54
Criticism of multiculturalis	237	56	96	85
Cultural pluralism	28	7	12	9
Multiculturalism in Canada	205	28	84	93
Multiculturalism	449	62	160	227
Democracy Index	59	18	17	24
Direct democracy	162	22	59	81
Types of democracy	25	7	9	9
Representative democracy	56	7	26	23
Criticism of democracy	191	102	55	34
Athenian democracy	335	41	147	147
History of democracy	394	81	126	187
Democracy	452	71	193	188

TABLE 4.3: Non-Argumentative Data Used & Controversial Sentences

The previously described data were concatenated (Appendix 3), so as to be used in the statistical approach algorithms. The corpora is composed by both arguments and non-arguments (Table 4.3).

Argumentative and No-Argumentative Data Used				
File	Total Data	Arguments	Non-Arguments	False-Positive Arguments
dataset.csv	6318	2755	3563	-
found_fp.csv	2952	-	-	2952

TABLE 4.4: Data included in our corpora

As regards the ambiguous sentences of Wikipedia articles that was mentioned before, they were all saved in a file named `found_ambiguous.csv` (Appendix 4). This file indicates all the keywords responsible for these controversial results. The indicators- described in the previous Chapter and found in Wikipedia articles- were counted using code of Appendix 5, and the following table was the outcome of that enumeration.

Indicator Found	Number of Sentences	Indicator Found	Number of Sentences
as	**968**	**that**	**542**
also	**440**	**because**	**121**
as well	**101**	**for example**	**92**
(E | e)(ither).+?(or)	44	as a result	23
because	**121**	notably	13
for instance	17	**but**	**326**
that is	40	**while**	**197**
actually	26	against	3
still	85	so that	12
though	87	besides	4
furthermore	13	eventually	41
more +	**40**	either	53
clearly	5	**if**	**107**
since	34	on the grounds that	3
although	85	third	6
consequently	4	as a consequence	2
rather than	66	instead	42
nevertheless	9	except	5
otherwise	12	in fact	10
too	3	not only	22
on one side	1	simply	26
moreover	9	hence	4
therefore	25	every time	1
in other words	4	despite the fact that	2
in order to	43	as	9
at the same time	7	of course	2
finally	13	as an example	2
first	29	even though	14
lastly	3	equally	7
whereas	13	(T | t)(he more).+?(the more)	2
regardless	7	for this reason	2
simply because	1	by contrast	3
naturally	4	at any rate	1
in short	2	in this case	3
such that	5	essentially	5
(N | n)(either).+?(nor)	4	whenever	4
second	5	as long as	2
even then	3	as a matter of fact	1
accordingly	3	provided that	1
conversely	3	alternatively	3
afterwards	6	thereafter	1
meanwhile	10	once again	3
once more	1	above all	1
by comparison	1	surely	2
undoubtedly	2	on the one side	1
at first	1	presumably	2
after all	1	what is more	1
certainly	1	anyway	1
so	16	most	22
further	**53**		

TABLE 4.5: Indicators found in Wikipedia articles

The goal of this process was to test in Wikipedia articles the argumentative indicators included in the Chapter 3's dictionary, and upon cross-examination to remove indicators that do not usually reveal argumentative sentences. Based on the Table 4.5, the indicators marked as bold are the ones found in the majority of Wikipedia sentences. More than 10% of each indicator's sentences was examined by the authors of this research papers, and the keywords, that did not usually pointed out argumentative statements and removed from the dictionary, are represented in the following. The annotations are described in detail inside the file `Results/found_ambiguous_results_annotated.xlsx`.

Indicator	Total Number of Sentences	Number of Sentences Examined	Arguments	Non-Argument	Depending on the context	Removed from the dictionary
as	968	131	22	98	11	Yes
that	542	91	20	54	17	Yes
also	440	64	8	46	10	Yes
but	326	50	7	36	7	Yes
while	197	35	6	24	5	Yes
because	121	33	20	10	3	No
if	107	20	6	12	2	No
as well	101	20	5	14	1	No
for example	92	8	5	3	0	No
further	53	20	4	15	1	Yes
against	51	21	3	16	2	Yes
more +a dverb in 'ly'	40	16	4	12	0	No

TABLE 4.6: Indicators found in Wikipedia articles

It was also observed that the following indicators were used in combination with punctuation, and that's why they were modified into the formats of the table 4.7.

Indicator	Modified to
while	, while
that is	, that is,
still	, still
as a result	as a result,

TABLE 4.7: Indicators found in Wikipedia articles

Chapter 5

Results

Results for both structured and statistical implementations presented in Chapter 3, are applied to a set of corpora in order to be evaluated.

5.1 Structural Approach

The structural approach described in previous chapters is being assessed into this section. For this purpose, the code of Appendix 8 alongside with two IBM corpora was applied. It has to be mentioned that these two IBM corpora include only argumentative sentences, and we aim to check how many of those arguments will be identified correctly by our algorithm.

The metric of accuracy was used in order to evaluate the indicators selected for recognizing argumentative sentences, while precision, recall and f1 score did not have value because of the non-arguments lack. For measuring accuracy, four counters were used; **true positives** (tp) is counting the times both algorithm and analyst labeled a sentence as argumentative, **true negatives** (tn) how often both algorithm and analyst labeled as non-argumentative, **false positive** (fp) the times the algorithm assigned as argumentative a sentence that expert recognized as non-argumentative, **false negative** (fn) how many times human identified a sentence as argumentative while algorithm did not.

- **Accuracy** represents the percentage of correctly classified sentences:

$$A = \frac{tp + tn}{tp + tn + fp + fn}$$

- **Precision** indicates the times of correctly identification instances:

$$P = \frac{tp}{tp + fp}$$

- **Recall** measures the times algorithm missed out arguments:

$$R = \frac{tp}{tp + fn}$$

- **F1 Score** presents the mean of precision and recall:

$$F = \frac{2 * P * R}{P + R}$$

Source Data	**file**	**Accuracy**
Bar-Haim et al., 2017	claim_stance_dataset_v1	17.50%
Aharoni et al., 2014b	CDEdata.xls1.00.1480.25	14.81%

TABLE 5.1: Results of Structural Approach

Structural approach seems not to be able to capture a variety of argumentative structures. This is beacause, argumentative patterns are rarely used in practice, since human discourse involves a lot of information which is being implied rather than being explicitly stated.

5.2 Statistical Approach

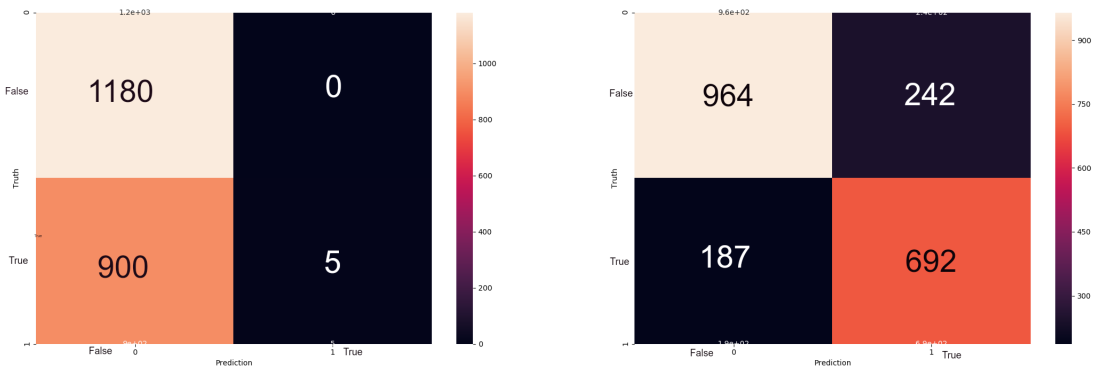
5.2.1 Random Forest Algorithm

Supervised machine learning algorithms need a number of labeled data in order to be trained. That was the reason corpora of Chapter 4 was created, and used in the implantation of Random Forest classifier algorithm (Appendix 9). A number of 33% of the data used to train the model, while the rest of them to evaluate the results.

It has to be mentioned that two methods were used for argument's classification. The first one was by tokenizing the sentences, so as to be in a format that a computer can understand, and then training the model based on the tokenized sentences. This method had an accuracy of **56.83%**, precision **100%**, recall **0.55%**, f1 score **71.13%**, and the results are displayed in the heatmap of figure 5.1 (A). Based on the results, it seems that Random Forest trained by tokenized sentencses is not recognizing argumentative sentences. That's why we implemented another technique in which we determined some features of each sentence ,and then feed the algorithm with these features instead of the sentences. In this way the accuracy increased to **79.42%**, while precision is **74.08%**, recall **78.72%**, f1 score **76.33%** , and it deprecates to the heatmap of figure 5.1 (B). The results of the first approach are not that high, and that is probably because of the unique words.

The features used for classification are the following based on the paper (Lawrence and Reed, 2016):

- **Word Counter**: the number of words in a sentence
- **Uppercase Characters Counter**: the number of uppercase characters found
- **Punctuation or Special Characters Counter**: the number of presence punctuation characters like " "



(A) Classification based on the sentences

(B) Classification based on features

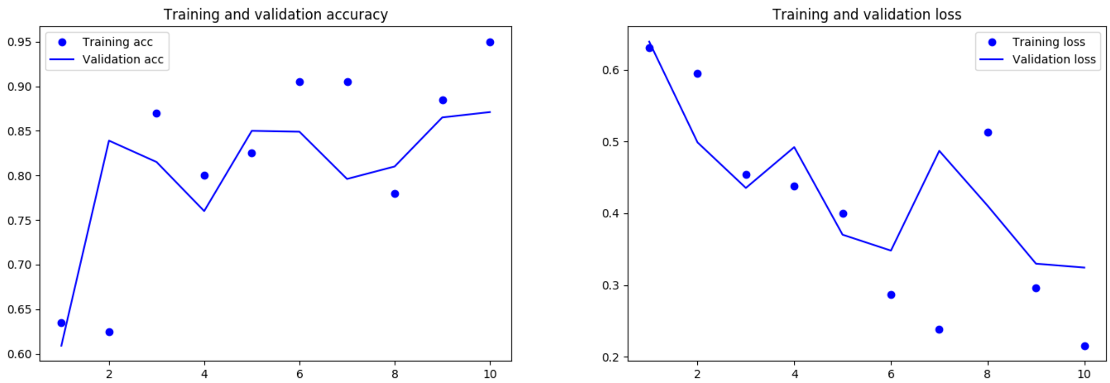
FIGURE 5.1: Predicted and Real results of Random Forest classification algorithm

As the results of table 5.1 reveal, Random Forest implements well when features are used for each of sentence. Machine learning approach seems to be a better fit for identifying arguments than lexical rules.

5.2.2 LSTM-RNN Algorithm

The LSTM-RNN algorithm described in previous chapters is being assessed into this section. For this purpose, the code of Appendix 10 alongside with the data-set described in Chapter 4 was executed.

The data-set used contains an equal number of argumentative and non-argumentative sentences, as well as their labels. The twenty percent of the data were used for training the model, while the rest of them for evaluating it. The model's performance over time is represented in the following plots by using the metrics of accuracy and loss.



(A) (B)

FIGURE 5.2: Training and validation accuracy and loss when using pre-trained word embeddings

After testing the algorithm in test data, the following results occurred with an accuracy of **85.36%**, precision **78.15%**, recall **88.90%**, f1 score **82.61%**. These results lead to a conclusion that LSTM-RNN algorithm seems to be more appropriate for argument mining problems, comparing to Random Forest and the Structural approach examined in the previous section.

```
Found 10823 unique tokens.
Shape of data tensor: (5054, 235)
Shape of label tensor: (5054,)
Found 400000 word vectors.

Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, None, 100)         1000000
_________________________________________________________________
lstm (LSTM)                  (None, 100)               80400
_________________________________________________________________
dense (Dense)                (None, 1)                 101
=================================================================
Total params: 1,080,501
Trainable params: 1,080,501
Non-trainable params: 0
_________________________________________________________________
None

Train on 200 samples, validate on 1000 samples
Epoch 1/10
200/200 [==============================] - 2s 10ms/sample - loss: 0.6307 - acc: 0.6350 -
    f1_m: 0.3386 - precision_m: 0.9722 - recall_m: 0.2519 - val_loss: 0.6393 - val_acc:
    0.6090 - val_f1_m: 0.6948 - val_precision_m: 0.5351 - val_recall_m: 0.9980
Epoch 2/10
```

```
200/200 [==============================] - 2s 9ms/sample - loss: 0.5955 - acc: 0.6250 -
    f1_m: 0.4697 - precision_m: 0.7757 - recall_m: 0.5645 - val_loss: 0.4988 - val_acc:
    0.8390 - val_f1_m: 0.8320 - val_precision_m: 0.7773 - val_recall_m: 0.8969
Epoch 3/10
200/200 [==============================] - 1s 7ms/sample - loss: 0.4542 - acc: 0.8700 -
    f1_m: 0.8178 - precision_m: 0.8778 - recall_m: 0.7895 - val_loss: 0.4353 - val_acc:
    0.8150 - val_f1_m: 0.8213 - val_precision_m: 0.7220 - val_recall_m: 0.9551
Epoch 4/10
200/200 [==============================] - 1s 7ms/sample - loss: 0.4383 - acc: 0.8000 -
    f1_m: 0.7469 - precision_m: 0.8571 - recall_m: 0.7411 - val_loss: 0.4922 - val_acc:
    0.7600 - val_f1_m: 0.7883 - val_precision_m: 0.6582 - val_recall_m: 0.9867
Epoch 5/10
200/200 [==============================] - 1s 7ms/sample - loss: 0.3999 - acc: 0.8250 -
    f1_m: 0.8295 - precision_m: 0.8415 - recall_m: 0.8676 - val_loss: 0.3702 - val_acc:
    0.8500 - val_f1_m: 0.8494 - val_precision_m: 0.7830 - val_recall_m: 0.9289
Epoch 6/10
200/200 [==============================] - 1s 6ms/sample - loss: 0.2866 - acc: 0.9050 -
    f1_m: 0.8928 - precision_m: 0.8759 - recall_m: 0.9155 - val_loss: 0.3480 - val_acc:
    0.8490 - val_f1_m: 0.8474 - val_precision_m: 0.7793 - val_recall_m: 0.9292
Epoch 7/10
200/200 [==============================] - 1s 7ms/sample - loss: 0.2383 - acc: 0.9050 -
    f1_m: 0.9028 - precision_m: 0.8486 - recall_m: 0.9646 - val_loss: 0.4870 - val_acc:
    0.7960 - val_f1_m: 0.7277 - val_precision_m: 0.9137 - val_recall_m: 0.6066
Epoch 8/10
200/200 [==============================] - 1s 6ms/sample - loss: 0.5132 - acc: 0.7800 -
    f1_m: 0.7525 - precision_m: 0.7843 - recall_m: 0.8197 - val_loss: 0.4105 - val_acc:
    0.8100 - val_f1_m: 0.7571 - val_precision_m: 0.8881 - val_recall_m: 0.6615
Epoch 9/10
200/200 [==============================] - 1s 6ms/sample - loss: 0.2962 - acc: 0.8850 -
    f1_m: 0.8746 - precision_m: 0.9322 - recall_m: 0.8448 - val_loss: 0.3297 - val_acc:
    0.8650 - val_f1_m: 0.8500 - val_precision_m: 0.8417 - val_recall_m: 0.8593
Epoch 10/10
200/200 [==============================] - 1s 6ms/sample - loss: 0.2154 - acc: 0.9500 -
    f1_m: 0.9505 - precision_m: 0.9344 - recall_m: 0.9677 - val_loss: 0.3243 - val_acc:
    0.8710 - val_f1_m: 0.8628 - val_precision_m: 0.8376 - val_recall_m: 0.8928
1264/1264 [==============================] - 1s 938us/sample - loss: 0.3474 - acc: 0.8536 -
     f1_m: 0.8261 - precision_m: 0.7815 - recall_m: 0.8890
Accuracy: 85.36%
Precision: 78.15%
Recall: 88.90%
F1 score: 82.61%
```

Chapter 6

Conclusion

I have implemented three separate argument mining techniques, applicable to both structural and statistical approach. For the **structural approach**, there was created a dictionary of lexical cues that usually characterize argumentative structures based on (Knott and Dale, 1994). The algorithm created was tested in two IBM corpora containing only argumentative sentences, the accuracy seems to be around **15 to 17 %**. As regards the statistical approach, a corpora has to be curated in order to include both argumentative and non-argumentative instances. That is why Wikipedia articles were scrapped assuming that there are no arguments included, and the sentences gathered were cross-checked by the algorithm created for the structural approach. Every sentence that did not have argumentative cues, based on the algorithm, was added to the corpora as non-argumentative, while the others considered as ambiguous and were checked by two annotators so as to remove misleading indicators of dictionary. Afterwards, two algorithms were built by using as training data a part of this corpora. **Random forest classification algorithm** was approached by two different methods of training. The first technique was by using the tokenized sentences which leads to an accuracy of **56.83%**, precision **100%**, recall **0.55%**, f1 score **71.13%**, while the second was by using features like counter of words, uppercase and punctuation characters that have an accuracy of **79.42%**, precision **74.08%**, recall **78.72%**, and f1 score **76.33%**. Finally, the other algorithm of statistical approach that was built is the **LSTM-RNN** that concludes to an accuracy of **85.44%**, precision of **78.15%**, recall of **88.90%**, f1 score of **82.61%**.

As the results of both structural and statistical algorithms reveal, linguistic rules are not capable of successfully identifying arguments. On the other hand, learning algorithms are a better fit to argument mining, with the most accurate one to be the LSTM-RNN algorithm. One of the main goals as regarding future work is to apply the algorithms built in a fully annotated data-set found in GitHub's issues.

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Appendicies

Appendicies 1

Scrap Data from Wikipedia

```
import urllib.request
import re
from inscriptis import get_text


def wiki(theme):
  url = "https://en.wikipedia.org/wiki/" + theme
  html = urllib.request.urlopen(url).read().decode('utf-8')

  text = get_text(html)

  with open('../datasets/wiki_' + theme + '.txt', 'w') as out:
    for row in text.split('\n'):
      if len(row) >= 80 and not row[0].isdigit() and not row[1].isdigit() and not row[2] ==
      '*':
        row = re.sub(r'\[\d+]', '', row)
        row = row.rstrip('\n')
        out.write(row)
        out.write('\n')


if __name__ == '__main__':

  # Video games topic
  wiki('Video_game-related_health_problems')
  wiki('Video_game_addiction_in_China')
  wiki('Video_game_addiction')
  wiki('Gaming_disorder')
  wiki('2017_in_video_gaming')
  wiki('2019_in_video_gaming')
  wiki('History_of_video_games')
  wiki('PC_game')
  wiki('Video_game_culture')
  wiki('Gaming_computer')
  wiki('Video_game_console')
  wiki('Video_game')
  wiki('Video_gaming_in_the_United_States')
  wiki('Video_game_music')
  wiki('Video_game_industry')
  wiki('Video_game_development')
  wiki('Game_design')
  wiki('Video_game_programmer')
  wiki('Early_history_of_video_games')
  wiki('Video_gaming_in_Japan')
  wiki('Video_game_crash_of_1983')
  wiki('Sixth_generation_of_video_game_consoles')
  wiki('Video_gaming_in_China')
  wiki('1980s_in_video_gaming')
  wiki('Home_computer')
  wiki('Nintendo')
  wiki('Game_Boy')
  wiki('Fourth_generation_of_video_game_consoles')
  wiki('Game')
  wiki('The_Game_Awards')

  # Democracy topic
  wiki('Democracy')
```

```
wiki('History_of_democracy')
wiki('Athenian_democracy')
wiki('Representative democracy')
wiki('Direct_democracy')
wiki('Types_of_democracy')
wiki('Democracy_Index')
wiki('Criticism_of_democracy')

# Multiculturalism
wiki('Multiculturalism')
wiki('Criticism_of_multiculturalism')
wiki('Cultural_pluralism')
wiki('Multiculturalism_in_Canada')
wiki('Multicultural_education')
wiki('Multicultural_and_diversity_management')
wiki('Multiculturalism_in_Australia')
wiki('Multicultural_transruption')

```

Appendicies 2

Remove Duplicate Sentences

```python
import os

FILE_PATH = os.path.abspath(os.path.dirname(__file__))


def remove_duplicate_rows(file_name):
  sentences = []

  with open(os.path.join(FILE_PATH, '../Results/' + file_name), mode='r') as txt_file:
    reader = txt_file.read()

    for sentence in reader.split("\n"):
      sentences.append(sentence)

  with open ( os.path.join ( FILE_PATH, '../Results/new_' + file_name ), mode='w' ) as
    txt_file_new:
    for i in range(len(sentences)):
      if i == 0:
        txt_file_new.write(sentences[i])
        txt_file_new.write("\n")
      elif i < len(sentences) and sentences[i] != sentences[i-1]:
        txt_file_new.write(sentences[i])
        txt_file_new.write("\n")


if __name__ == '__main__':
  remove_duplicate_rows('CDEdata.csv')
```

Appendicies 3

Concat Results of checked Data

```
import os
import glob
import csv

FILE_PATH = os.path.abspath(os.path.dirname(__file__))


def combine_results():

  csvfiles = glob.glob(FILE_PATH + '/../Results/checked/*.csv')
  dataset = csv.writer(open(FILE_PATH + '/../Results/dataset.csv', 'w'), delimiter=',')

  for files in csvfiles:
    rd = csv.reader(open(files, 'r'))

    for row in rd:
      if 'wiki' in files:
        if "False" in row:
          dataset.writerow(row)
      else:
        if "True" or "False" in row:
          dataset.writerow(row)


def find_ambiguous():

  csvfiles = glob.glob(FILE_PATH + '/../Results/checked/*.csv')
  found_ambiguous = csv.writer(open(FILE_PATH + '/../Results/found_ambiguous.csv', 'w'),
    delimiter=',')

  for files in csvfiles:
    rd = csv.reader(open(files, 'r'))

    for row in rd:
      if 'wiki' in files:
        if "True" in row:
          found_ambiguous.writerow(row)


if __name__ == '__main__':
  combine_results()
  find_ambiguous()
```

Appendicies 4

Gather Ambiguous Sentences found in Wiki articles

4.1 ../Results/found_ambiguous_results.csv

In the **terminal** type:

```
$python3 getAmbiguousSentences.py > ../Results/found_ambiguous_results.csv
```

4.2 getAmbiguousSentences.py

```
import json
from configParser import choose_function
from getArguments import spaCy, pos_tagged, check_regex

"""
Description: by using a dictionary that includes words often used
in arguments, it is identified if given sentences are
arguments or not. Part of speech tagging from spaCy is used
for this purpose as well and it is imported by getArguments.py file.
"""


def check_dictionary(doc, dictionary):
  """None
  This function checks if any of the words in the sentence exists
   in the dictionary given. If it does, then it is checked if
   this word's part of speech match with its value given in
   dictionary. If they match, then the word is added in a
   list named keyword_found.

  :param doc: pos tagged sentence from spacy function
  :param dictionary: dictionary that has as keywords words
    and as value their part of speech
  :return: keywords found in the given sentence
  """

  keyword_found = []

  for key, value in dictionary.items():
    if check_regex(doc, key) is not None:
      if len(value) == 1:
        for key2 in value:
          if checz_regex(doc, key + ' ' + key2) is not None
           and check_regex(doc, key2) is not None and
           pos_tagged(doc, check_regex(doc, key2).text) is not 'None':
            if value[key2] == pos_tagged(doc, check_regex(doc, key2).text)[1] or \
             value[key2] == pos_tagged(doc, check_regex(doc, key2).text)[2]:
              keyword_found.append(key + " " + key2)
      elif value == 'none':
        keyword_found.append(key)
      elif len(value) != 1 and check_regex(doc, value)
       is not None:
```

```
        keyword_found.append(key)
      elif pos_tagged(doc, key)[1] == value or \
       pos_tagged(doc, key)[2] == value:
        keyword_found.append(key)

  return keyword_found


if __name__ == '__main__':

  with open('../dict/dictionary.json', 'r') as dict:
    dictionary = json.load(dict)

  sentences = choose_function("found_ambiguous.csv")

  if sentences != 'No dataset found':
    for sentence in sentences:

      print('"' + str(sentence[0]).strip('b') + '",' +
        str(check_dictionary(spaCy(sentence[0]), dictionary))

  else:
    print(sentences)
```

Appendicies 5

Enumerate ambiguous sentences

```
import os
import csv
import json

FILE_PATH = os.path.abspath(os.path.dirname(__file__))


def enumerate_ambiguous(file_name):
  with open('../dict/dictionary.json', 'r') as dict:
    dictionary = json.load(dict)

    with open(os.path.join(FILE_PATH, '../Results/' + file_name), mode='r', encoding='utf-8') as file:
      reader = csv.reader(file)
      counters = {}

      count = 0
      count_rows = 0

      for row in reader:
        firstArgumentWordFlag = False

        count_rows += 1
        # first cell includes sentences, not keywords
        for column in row[1:]:

          if firstArgumentWordFlag == False:
            testStr = "['"
            if column.startswith(testStr):
              firstArgumentWordFlag = True
            else:
              continue

          column = column.strip("['] ")
          column = column.strip('"')

          if column in dictionary:
            count += 1
            if column in counters:
              counters[column] += 1
            else:
              counters[column] = 1
          else:
            if ' + ' in column:
              count += 1
              firstPart = column.split(" + ")[0]

              if firstPart in counters:
                counters[firstPart] += 1
              else:
                counters[firstPart] = 0
            else:
              print(row)
              print('Not found: ', column)

  save_array_to_csv(counters)
```

```python

def save_array_to_csv(my_dict):
  with open(FILE_PATH + '/../Results/found_Ambiguous_keywords.csv', 'w', newline='') as f:
    w = csv.writer(f)
    w.writerows(my_dict.items())


if __name__ == '__main__':
  enumerate_ambiguous('found_ambiguous_results.csv')
```

Appendicies 6

Extract keywords from pdf

```
"""
Description: extract words which are often used in arguments
(based on a paper),and create a dictionary based on these words
(key of the dict) and their specific, if they have one, part
of speech (value of the dict) in arguments
"""

import json
import textract
import os
import csv

FILE_PATH = os.path.abspath(os.path.dirname(__file__))  # path of this file


def extract_data():
  """
  By using textract library, this function extracts the whole pdf file

  pdf: paper called 'Using Linguistic Phenomena to Motivate a Set
  of Coherence Relations'
  """

  text = textract.process(os.path.join(FILE_PATH,
  "../Reading/cues-UsingLinguisticPhenomenaMotivateCoherenceRelations_Knott93.pdf"))
  save(text)


def save(text):
  """
  This function saves extracted text to a csv file
  """
  if not os.path.exists("../dict" ):
    os.makedirs("../dict")

  with open(os.path.join(FILE_PATH, "../dict/data.csv"),
   mode='wb') as csv_file:
    csv_file.write(text)

  modify_csv_file("../dict/data.csv")  # modify extracted text


def modify_csv_file(data):
  """
  This function modifies csv file in order to keep those words
  we are interested in
  """

  flag = 0

  with open(os.path.join(FILE_PATH, data)) as inp:
    reader = csv.reader(inp)

    with open(os.path.join(FILE_PATH, "../dict/data2.csv"),
     mode='w') as out:
      for row in reader:
        if len(row) > 0 and row[0] == "Phrase":
```

```
          flag = 1
          continue
        if len(row) == 0 or row[0].isdigit():
          flag = 0
        if flag == 1 and len(row) > 0:
          out.write(row[0])
          out.write("\n")
  check_words("../dict/data2.csv", "../dict/data.csv")


def check_words(data2, data):
  """
  This function adds or removes words that considered as useful
  or not
  """

  exclude_words = ['after', 'and', 'as soon as', 'before',
          'at first', 'at first sight', 'earlier',
          'fisrt of all', 'for', 'inasmuch as',
          'later', 'much sooner', 'not because',
          'now', 'if not', 'if so',
          'in the beginning', 'in the end',
          'in the meantime', 'in turn',
          'much later', 'not', 'notwithstanding that',
          'suppose', 'the more often', 'this time',
          'presumably because', 'when', 'where',
          'previously', 'regardless of that', 'rather',
          'after that', 'as', 'simply because', 'then',
          'true', 'until', 'again', 'and/or', 'or',
          'else', 'even']

  include_words = ['for the reason that', 'besides',
          '(E|e)(ither).+?(or)','(N|n)(either).+?(nor)',
          'in one hand', 'in this case',  'on one side',
          'as a matter of fact', 'in point of fact',
          'presumably', 'provided that',
          'regardless', 'rather than', 'simply',
          'as an example', 'in addition']

  test_words = {'even though': 'none', 'first': 'adv',
        'against': 'none', 'last': 'adv',
        'more': {'[a-z]*ly': 'adv'},
        'most': {'[a-z]*ly': 'adv'}, 'if': 'none',
        '(T|t)(he more).+?(the more)': 'none',
        '(T|t)(he more).+?(the less)': 'none',
        'naturally': 'none', 'once again': 'none',
        'once more': 'none', 'surely': 'none',
        'second': 'adv', 'so': 'mark', 'third': 'adv',
        'too': '(too)($|[\.])', 'should say': 'none',
        'might say': 'none', 'may say': 'none',
        'could say': 'none', 'while': 'mark',
        'as a start': 'none', 'in order to': 'none',
        'in order that': 'none', 'still': 'adv',
        'that is': 'none', 'since': 'mark',
        'yet': '(Y|y)(et)[^\.].', 'that': 'mark'}

  with open(os.path.join(FILE_PATH, data2), 'r') as inp, \
    open(os.path.join(FILE_PATH, data), 'w') as out:

    for row in csv.reader(inp):
      if row[0] in exclude_words:
        continue
      else:
        out.write(row[0])
        out.write("\n")

    for word in include_words:
      out.write(word)
      out.write("\n")

  create_dictionary("../dict/data.csv", test_words)

```

```python

def create_dictionary(data, test_words):
  """
  This function creates a .json file that includes a dictionary of
  the words from the csv file created before and some additional
  words for testing
  """

  dictionary = test_words

  with open(os.path.join(FILE_PATH, data), 'r') as inp:

    for row in csv.reader(inp):
      if "\x05" in row[0]:
        row[0] = row[0].replace('\x05', 'fi')  # correct words from pdf extraction

      if row[0] in test_words.keys():
        continue
      else:
        dictionary.update({row[0]: 'none'})

  with open('../dict/dictionary.json', 'w') as dict:
    json.dump(dictionary, dict)


if __name__ == '__main__':
  extract_data()
```

Appendicies 7

Load Data-sets based on their configurations

```
from xlrd import open_workbook
import configparser
import os
import re
import csv

FILE_PATH = os.path.abspath(os.path.dirname(__file__))


def py23_str(value):
  """
  This function tries to convert a string to unicode. Because
  of the fact that this conversion differ from python 3
  to python 2, here are checked both possibilities so as
  the program to run in both python 3 and 2.

  :param value: sentence to be converted from string to unicode
  :return: converted input
  """

  try:  # Python 2
    return unicode(value, errors='ignore', encoding='utf-8')
  except NameError:  # Python 3
    try:
      return str(value, errors='ignore', encoding='utf-8')
    except TypeError:  # Wasn't a bytes object, no need to decode
      return str(value)


def get_sentences_csv(dataset_number):
  """
  This function reads files with .csv extension

  :dataset_number: number that refers to order (starts from 0)
  of a dataset in datasets.ini

  :return: a list of sentences
  """
  sentences = []

  path, _, column, is_argument = get_parameters_dataset(dataset_number)

  with open(os.path.join(FILE_PATH, path), mode='r') as dataset:
    reader = csv.reader(dataset)
    for sentence in reader:
      if is_argument is not None:
        sentences.append([str(sentence[int(column)]), str(sentence[int(is_argument)])])
      else:
        sentences.append([str(sentence[int(column)]), 'True'])

  sentences.pop(0)
  return sentences

```

```
def get_sentences_xls(dataset_number):
  """
  This function reads files with .xls extension

  :dataset_number: number that refers to order (starts from 0)
  of a dataset in datasets.ini
  :return: a list of sentences
  """
  sentences = []

  path, sheet, column, is_argument = get_parameters_dataset(dataset_number)

  reader = open_workbook(path, on_demand=True)
  sheet = reader.sheet_by_name(sheet)
  if is_argument is not None:
    for cell, cell2 in zip(sheet.col(int(column)), sheet.col(int(is_argument))):
      sentences.append([cell.value.encode("utf-8"), cell2.value.encode("utf-8")])
  else:
    for cell in sheet.col(int(column)):
      sentences.append([cell.value.encode("utf-8"), 'True'])

  sentences.pop(0)
  return sentences


def get_sentences_txt(dataset_number):
  """
  This function reads files with .txt or none extension

  :dataset_number: number that refers to order (starts from 0)
           of a dataset in datasets.ini

  :return: a list of sentences
  """
  sentences = []

  path, _,  _, _ = get_parameters_dataset(dataset_number)

  with open(os.path.join(FILE_PATH, path), mode='r') as txt_file:
    reader = txt_file.read()

    for sentence in reader.split('.'):
      sentences.append([sentence])

  return sentences


def get_parameters_dataset(dataset):
  """
  This function gets the arguments of a specific dataset from datasets.ini

  :dataset: number that refers to order (starts from 0)
        of a dataset or the name of dataset in datasets.ini
  :return: section['path'] + file_name: path of dataset
  sheet: sheet that data are in it if it is an .xls file
  column: column of sentences to be identified as arguments or not
  is_argument: column which reveals if a specific sentence is
         an argument or not
  """
  dataset_number, config = check_validity_of_dataset(dataset)

  section = config.sections()[dataset_number]  # each section is a name of a file with data
  section = config[section]
  file_name = re.match(r".*: (.*)>", str(section), re.MULTILINE)
  file_name = file_name.group(1)

  try:
    sheet = section['sheet']
  except KeyError:
    sheet = None

```

```
    try:
        is_argument = section['is_argument']
    except KeyError:
        is_argument = None

    try:
        column = section['column']
    except KeyError:
        column = None

    return section['path'] + file_name, sheet, column, is_argument


def check_validity_of_dataset(dataset):
    """
    This function checks of a dataset exists in dataset.ini or not

    :dataset: number that refers to order (starts from 0) of
    a dataset or the name of dataset in datasets.ini
    :return: dataset_number: returns the order of given
    dataset in datasets.ini config: returns object config
    from datasets.ini
    """
    config = configparser.ConfigParser()
    config.read('../datasets/datasets.ini')

    if dataset in config:
        dataset_number = config.sections().index(dataset)
    elif dataset < len(config.sections()):
        dataset_number = dataset

    return dataset_number, config


def choose_function(dataset):
    """
    This function checks the extension of a datasets and chooses
    an appropriate method to read the file

    :dataset: number that refers to order (starts from 0)
    of a dataset or the name of dataset in datasets.ini
    :return: a list of sentences if dataset exits
    otherwise 'No dataset found'
    """

    try:
        dataset_number = int(check_validity_of_dataset(dataset)[0])

        try:
            _, extension = dataset.rsplit('.', 1)
        except ValueError:
            extension = None

        if extension == 'xls':
            return get_sentences_xls(dataset_number)
        elif extension == 'csv':
            return get_sentences_csv(dataset_number)
        elif extension == 'txt' or extension is None:
            return get_sentences_txt(dataset_number)

    except TypeError:
        return 'No dataset found'
```

Appendicies 8

Find Argumentative Sentences

```python
import json
import spacy
from __future__ import division
from configParser import choose_function, os, py23_str, re

"""
Description: by using a dictionary that includes words often used
in arguments, this file identifies if given sentences are
arguments or not. Part of speech tagging from spaCy is used
for this purpose as well.
"""

FILE_PATH = os.path.abspath(os.path.dirname(__file__))

tp = 0
tn = 0
fp = 0
fn = 0


def spaCy(sentence):
  """
  By using spaCy, this function gets a sentence and returns every
  word's part of speech

  :param sentence: input to be tokenized
  :return: tokenized sentence
  """

  nlp = spacy.load('en')
  doc = nlp(py23_str(sentence))

  return doc


def pos_tagged(doc, word):
  """
  This function gets a tagged sentence from spaCy and a specific
  word and return its part of speech and its dependency

  :param doc: pos tagged sentence from spacy function
  :param word: a word that we are interested to learn its part of
    speech
  :return: word, its part of speech(pos) and its dependence in the
    given sentence or None
  """

  word = word.lower()

  for token in doc:
    if token.text.lower() == word:
      return [token.text, token.pos_.lower(), token.dep_.lower()]

  return 'None'


def check_regex(doc_regex, regex):
```

```
    """
    By using spaCy's function called match, this function is
    checking if a specific regular expression is represented
    by a given sentence

    :param doc_regex: pos tagged sentence from spacy function
    :param regex: a regular expression
    :return: the part of the sentence that is indicated in the given
      regex otherwise None
    """

    regex = re.compile(r''+regex)

    for match in re.finditer(regex, doc_regex.text.lower()):
      start, end = match.span()  # get matched indices
      word_found = doc_regex.char_span(start, end)  # create Span from indices

      return word_found

    return None


def check_dictionary(doc, dictionary):
    """
    This function checks if any of the words in the sentence exists
     in the dictionary given. If it does, then it is checked if
     this word's part of speech match with its value given in
     dictionary. If they match, then the word is added in a
     list named keyword_found.

    :param doc: pos tagged sentence from spacy function
    :param dictionary: dictionary that has as keywords words
      and as value their part of speech
    :return: True if the list keyword_found is not empty or False
         if it is empty
    """

    keyword_found = []

    for key, value in dictionary.items():
      if check_regex(doc, key) is not None:
        if len(value) == 1:
          for key2 in value:
            if checz_regex(doc, key + ' ' + key2) is not None
             and check_regex(doc, key2) is not None and
             pos_tagged(doc, check_regex(doc, key2).text) is not 'None':
              if value[key2] == pos_tagged(doc, check_regex(doc, key2).text)[1] or \
               value[key2] == pos_tagged(doc, check_regex(doc, key2).text)[2]:
                keyword_found.append(key + " + " + key2)
        elif value == 'none':
          keyword_found.append(key)
        elif len(value) != 1 and check_regex(doc, value)
         is not None:
          keyword_found.append(key)
        elif pos_tagged(doc, key)[1] == value or \
         pos_tagged(doc, key)[2] == value:
          keyword_found.append(key)

    if len(keyword_found) != 0:
      return 'True'
    else:
      return 'False'


def check_validity(real_value, given_value):
    """
    This function checks if two given values match

    :param real_value:  real value is the result of check_dictionary
      function
    :param given_value: given value is the value given by analysts
      into dataset
```

```
  :return: Correct results if they match or Wrong results if they
    do not match
  """
  global tn, tp, fn, fp

  if real_value in given_value:
    if real_value == 'True':
      tp = tp + 1
    else:
      tn = tn + 1
    return "Correct results"
  else:
    if real_value == 'False':
      fp = fp + 1
    else:
      fn = fn + 1
    return "Wrong results"


def precision():
  if (tp + fp) != 0:
    return tp/(tp + fp)
  else:
    return "Integer division by zero"


def recall():
  if (tp + fn) != 0:
    return tp/(tp + fn)
  else:
    return "Integer division by zero"


def f1_score(precision, recall):
  if (precision + recall) != 0:
    return 2 * (precision * recall) / (precision + recall)
  else:
    return "Integer division by zero"


if __name__ == '__main__':

  with open('../dict/dictionary.json', 'r') as dict:
    dictionary = json.load(dict)

  sentences = choose_function("found_fp.csv")
  labeled_data = False

  if sentences != 'No dataset found':
        for sentence in sentences:

      if len(sentence) == 2:
        print('"' + str(sentence[0]).strip('b') + '",' + 'True') # for csv
        # print ( str ( sentence[0] ).strip ( 'b' ) + ',' + 'True' )
        labeled_data = True

      else:
        print('"' + str(sentence[0]).strip('b') + '",' +
         check_dictionary(spaCy(sentence[0]), dictionary)) # for csv

  else:
    print(sentences)
```

Appendicies 9

Statistical Approach: Random Forest algorithm

```
import pandas as pd
import seaborn as sn
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import string
import csv
import os
import numpy as np


"""
Description: implementing Random Forest classifier model
to an annotated corpora that contains
both argumentative and none sentences
"""

FILE_PATH = os.path.abspath(os.path.dirname(__file__))  # path of this file


def load_dataset(path):
  """
  Loading dataset of a given path, and creating features based on the sentences given.
  The first feature is a counter of words included in each sentence,
  the second feature is a counter of uppercase characters, while
  the third feature is a counter of special characters (punction)
  :param path: full path of dataset
  :return: a list of sentences and their labels, and a set of features
  """

  # load & prepare data
  with open(path, 'r') as file:
    dataset = csv.reader(file, delimiter=",")
    df = pd.DataFrame(dataset)

  del df[2]  # column full of non labels = df[1]
  df[1] = [len(sentences.split()) for sentences in df[0]]  # Word Count'
  df[2] = [sum(char.isupper() for char in sentence) \
      for sentence in df[0]]  # 'Uppercase Char Count'

  df[3] = [sum(char in string.punctuation for char in sentence) \
      for sentence in df[0]]  # 'Special Char Count'
  df[4] = pd.factorize(labels)[0]  # switch False to 0 and True to 1

  return df


def tokenize_sentences(df):
  """
  Tokenizing raw sentences by using One-hot encoding
  into a format that a computer can understand
```

```

    :param df: the dataframe that includes 4 columns
          [sentences, word Counter, uppercase counter,
          special char counter, label]
    :return: tokenized sentences, labels
    """
    vectorizer = OneHotEncoder(handle_unknown='ignore')
    vectorizer.fit([[line.strip()] for line in df[0]])
    sentences = vectorizer.transform([[line.strip()] for line in df[0]]).toarray()

    # sentences = vectorizer.fit_transform(df[0])
    labels = df[4]
    return sentences, labels


def define_model(x_train, y_train):
    """
    This function defines and trains the Random Forest model

    :param x_train: the training sentences
    :param y_train: the sentences' labels
    :return: trained model
    """
    model = RandomForestClassifier()
    model.fit(x_train, y_train)
    return model


def precision(tp, fp):
    if (tp + fp) != 0:
        return tp/(tp + fp)
    else:
        return "Integer division by zero"


def recall(tp, fn):
    if (tp + fn) != 0:
        return tp/(tp + fn)
    else:
        return "Integer division by zero"


def f1_score(precision, recall):
    if type(recall) != str and type(precision) != str and (precision + recall) != 0:
        return 2 * (precision * recall) / (precision + recall)
    else:
        return "Integer division by zero"


def testing_model(model, x_test, y_test):
    """
    This function evaluates the model on the test set

    :param model: trained model
    :param x_test: the testing set of sentences
    :param y_test: the sentences' labels
    :return: a matrix of the predicted and real values
    """
    score = model.score(x_test, y_test)
    print("Accuracy: %.2f%%" % (score * 100))

    y_predicted = model.predict(x_test)
    cm = confusion_matrix(y_test, y_predicted)

    fp = cm[0][1]
    fn = cm[1][0]
    tp = cm[1][1]

    prec = precision(tp, fp)
    rec = recall(tp, fn)

    print("Precision: %.2f%%" % (prec * 100))
```

```python
    print("Recall: %.2f%%" % (rec * 100))
    print("F1 Score: %.2f%%" % (f1_score(prec, rec) * 100) )

    print(cm)
    return cm


def plot_results(cm):
    """
    This function is showing a heatmap plot based on
    the values of the confusion matrix that contains
    the real an predicted values.
    :param cm: matrix of both real and predicted values
    """
    plt.figure(figsize=(10, 7))
    sn.heatmap(cm, annot=True)
    plt.xlabel('Prediction')
    plt.ylabel('Truth')
    plt.show()


if __name__ == '__main__':
    df = load_dataset('../Results/dataset.csv')
    sentences, labels = tokenize_sentences(df)

    #  using features instead of the sentences
    #
    features = np.asarray(df[df.columns[1:4]].values)
    # split dataset into test and train data
    x_train, x_test, y_train, y_test = \
      train_test_split(features, labels, test_size=0.33)

    model = define_model(x_train, y_train)
    cm = testing_model(model, x_test, y_test)
    plot_results(cm)

    #  using sentences without their features
    #
    # split dataset into test and train data
    x_train, x_test, y_train, y_test = train_test_split(sentences, labels, test_size=0.33)

    model = define_model(x_train, y_train)
    cm = testing_model(model, x_test, y_test)
    plot_results(cm)
```

Appendicies 10

Statistical Approach: LSTM-RNN algorithm

```
import csv
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from tensorflow.python.keras.preprocessing.text import Tokenizer
from tensorflow.python.keras.preprocessing.sequence \
  import pad_sequences
from tensorflow.python.keras.layers import Dense, LSTM, Embedding
from tensorflow.python.keras.models import Sequential
from keras import backend

"""
Description: implement lstm model to an annotated corpora
that contains both argumentative and none sentences
"""

# path of this file
FILE_PATH = os.path.abspath(os.path.dirname(__file__))


def load_dataset(path):
  """
  Loading dataset of a given path
  :param path: full path of dataset
  :return: a list of sentences and their labels
  """

  # load & prepare data
  with open(path, 'r') as file:
    dataset = csv.reader(file, delimiter=",")
    df = pd.DataFrame(dataset)

  del df[2]  # column full of none

  df[1] = pd.factorize(df[1])[0]  # False switched to 0 and True to 1
  texts = list(df[0].values)
  labels = list(df[1])

  return texts, labels


def get_tokenized_text(max_words, texts_train):
  """
  Tokenizing raw sentences.
  :param max_words: considering only the top max_words of dataset
            (most frequent ones)
  :param texts_train: sentences to for tokenization
  :return: tokenizer, sequences, word_index
  """
  tokenizer = Tokenizer(num_words=max_words)
  tokenizer.fit_on_texts(texts_train)
```

```
    sequences = tokenizer.texts_to_sequences(texts_train)
    word_index = tokenizer.word_index

    print('Found %s unique tokens.' % len(word_index))
    return tokenizer, sequences, word_index


def pad_sentences(sequences, labels_train):
    """
    This function transforms a list of num_sentences sequences
    (lists of integers) into a 2D Numpy array of shape
    (num_sentnece, num_timesteps).
    The num_timesteps is either the maxlen argument if provided,
    or the length of the longest sequence otherwise.
    Sequences that are shorter than num_timesteps are padded
    with value at the end.

    :param sequences: list of tokenized sentences
    :param labels_train: list of sequences' labels
    :return: a 2D Numpy array of sentences and labels
    """
    data = pad_sequences(sequences)
    labels_train = np.asarray(labels_train)
    print('Shape of data tensor:', data.shape)
    print('Shape of label tensor:', labels_train.shape)

    # Splits the data into a training set and a validation set,
    # but first shuffles the data
    indices = np.arange(data.shape[0])
    np.random.shuffle(indices)
    data = data[indices]
    labels_train = labels_train[indices]

    return data, labels_train


def word_embedding(glove_file, max_words, word_index):
    """
    Parsing the GloVe's word-embeddings file in order
    to build an index that maps words (as strings)
    to their vector representation (as number vectors),
    and then build an embedding matrix that will
    be loaded into an Embedding layer later on.

    :param glove_file: path of Glove's word-embedding
    :param max_words: considering only the top max_words
              of dataset (most frequent ones)
    :param word_index: index of words after tokenization
    :return: embedding_dim, embedding_matrix
         of shape (max_words, embedding_dim)
    """

    embeddings_index = {}
    f = open(os.path.join(FILE_PATH, glove_file))
    for line in f:
      values = line.split()
      word = values[0]
      coefs = np.asarray(values[1:], dtype='float32')
      embeddings_index[word] = coefs
    f.close()
    print('Found %s word vectors.' % len(embeddings_index))

    embedding_dim = 100
    embedding_matrix = np.zeros((max_words, embedding_dim))
    for word, i in word_index.items():
      if i < max_words:
        embedding_vector = embeddings_index.get(word)
        if embedding_vector is not None:
          # Words not found in the embedding
          # index will be all zeros.
          embedding_matrix[i] = embedding_vector

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    return embedding_dim, embedding_matrix


def lstm_model(max_words, embedding_dim, embedding_matrix):
    """
    This function defines the model and
    loads pretrained word embedding into the Embedding layer

    :param max_words: considering only the top max_words
              of dataset (most frequent ones)
    :param embedding_dim: number of embedding dimensions used
    :param embedding_matrix: a matrix of shape shape
                 (max_words, embedding_dim)
    :return: the defined model
    """

    # define model
    model = Sequential()
    model.add(Embedding(max_words, embedding_dim))
    model.add(LSTM(100))
    model.add(Dense(1, activation='sigmoid'))
    print(model.summary())

    # Loading pretrained word embeddings into the Embedding layer
    model.layers[0].set_weights([embedding_matrix])
    model.layers[0].trainable = False

    return model


def recall_m(y_true, y_pred):
    """
    Calculating recall metric

    :param y_true: the real value of a sentence
    :param y_pred: the estimated value of a sentence
    :return: recall metric
    """
    true_positives = backend.sum(backend.round(backend.clip(y_true * y_pred, 0, 1)))
    possible_positives = backend.sum(backend.round(backend.clip(y_true, 0, 1)))
    recall = true_positives / (possible_positives + backend.epsilon())
    return recall


def precision_m(y_true, y_pred):
    """
    Calculating precision metric

    :param y_true: the real value of a sentence
    :param y_pred: the estimated value of a sentence
    :return: precision metric
    """
    true_positives = backend.sum(backend.round(backend.clip(y_true * y_pred, 0, 1)))
    predicted_positives = backend.sum(backend.round(backend.clip(y_pred, 0, 1)))
    precision = true_positives / (predicted_positives + backend.epsilon())
    return precision


def f1_m(y_true, y_pred):
    """
    Calculating F1 Score metric

    :param y_true: the real value of a sentence
    :param y_pred: the estimated value of a sentence
    :return: f1_score metric
    """
    precision = precision_m(y_true, y_pred)
    recall = recall_m(y_true, y_pred)
    return 2 * ((precision * recall) / (precision + recall + backend.epsilon()))


def training_model(x_train, y_train, x_val, y_val, model):
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    """
    This function is responsible for compiling and
    training the model

    :param x_train: sentences for training model (200 sentences)
    :param y_train: labels of training sentences
    :param x_val: sentences for validating trained model
            (1000 sentences)
    :param y_val: labels of validation sentences
    :param model: defined model
    :return: historing of training, trained model
    """

    model.compile(loss='binary_crossentropy', optimizer='rmsprop',
            metrics=['accuracy'])
    history = model.fit(x_train, y_train, epochs=10, batch_size=128,
              validation_data=(x_val, y_val))
    model.save_weights('pre_trained_glove_model.h5')

    return history, model


def plotting_results(history):
    """
    This function is showing plots of the training and
    validation results based on accuracy and loss metrics.

    :param history: history of training procedure
    """
    acc = history.history['acc']
    val_acc = history.history['val_acc']
    loss = history.history['loss']
    val_loss = history.history['val_loss']
    epochs = range(1, len(acc) + 1)

    plt.plot(epochs, acc, 'bo', label='Training acc')
    plt.plot(epochs, val_acc, 'b', label='Validation acc')
    plt.title('Training and validation accuracy')
    plt.legend()
    plt.figure()

    plt.plot(epochs, loss, 'bo', label='Training loss')
    plt.plot(epochs, val_loss, 'b', label='Validation loss')
    plt.title('Training and validation loss')
    plt.legend()
    plt.show()


def testing_model(texts_test, labels_test, tokenizer, model):
    """
    This function tokenizes the data of test set,
    and evaluates the model on the test set

    :param texts_test: sentences for testing model
    :param labels_test: labels of the testing sentences
    :param tokenizer: tokenizer
    :param model: trained model
    :return: accuracy of the created model
    """

    # Tokenizing the data of the test set
    sequences = tokenizer.texts_to_sequences(texts_test)
    x_test = pad_sequences(sequences)
    y_test = np.asarray(labels_test)

    # Evaluating the model on the test set
    model.load_weights('pre_trained_glove_model.h5')
    loss, accuracy, f1_score, precision, recall = model.evaluate(x_test, y_test)

    print("Accuracy: %.2f%%" % (accuracy * 100))
    print("Precision: %.2f%%" % (precision * 100))
    print("Recall: %.2f%%" % (recall * 100))
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  print("F1 score: %.2f%%" % (f1_score * 100))


def main():
  texts, labels = load_dataset('../Results/dataset.csv')
  texts_train, texts_test, labels_train, labels_test = \
    train_test_split(texts, labels, test_size=0.2)

  max_words = 10000  # Considers only the top 10,000 words
             # in the dataset
  training_samples = 200
  validation_samples = 1000\usepackage{xcolor}
  \definecolor{maroon}{cmyk}{0, 0.87, 0.68, 0.32}
  \definecolor{halfgray}{gray}{0.55}
  \definecolor{ipython_frame}{RGB}{207, 207, 207}
  \definecolor{ipython_bg}{RGB}{247, 247, 247}
  \definecolor{ipython_red}{RGB}{186, 33, 33}
  \definecolor{ipython_green}{RGB}{0, 128, 0}
  \definecolor{ipython_cyan}{RGB}{64, 128, 128}
  \definecolor{ipython_purple}{RGB}{170, 34, 255}

  tokenizer, sequences, word_index = \
    get_tokenized_text(max_words, texts_train)
  data, labels_train = pad_sentences(sequences, labels_train)

  x_train = data[:training_samples]
  y_train = labels_train[:training_samples]
  x_val = \
    data[training_samples: training_samples + validation_samples]
  y_val = \
    labels_train[training_samples: training_samples + validation_samples]

  embedding_dim, embedding_matrix \
  = word_embedding('../Reading/glove.6B/glove.6B.100d.txt', \
          max_words, word_index)

  model = lstm_model(max_words, embedding_dim, embedding_matrix)
  history, model = training_model(x_train, y_train, \
                 x_val, y_val, model)
  plotting_results(history)
  testing_model(texts_test, labels_test, tokenizer, model)


if __name__ == '__main__':
  main()
```