UTILIZING AN ENTITY-LEVEL SEMANTIC ANALYSIS APPROACH TOWARDS ENHANCED POLICY MAKING

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ABSTRACT

The tremendous growth and usage of social media in modern societies have led to the production of an enormous real-time volume of social texts and posts, including tweets, that are being produced by users. These collections of social data can be potentially useful, but the extent of meaningful data in these collections is still of high research and business interest. One of the main elements in several application domains, such as policy making, addresses the scope of public opinion analysis. The latter is recently realized through sentiment analysis and Natural Language Processing (NLP), for identifying and extracting subjective information from raw texts. An additional challenge refers to the exploitation and correlation of the sentiment that can be derived for different entities into the same text or even a sentence to analyze the different sentiments that can be expressed for specific products, services, and topics by considering all available information that can be depicted within a text in a holistic way. Hence, this paper evaluates the utilization of an Entity-Level Sentiment Analysis (ELSA) approach on Twitter Data. The latter seeks to enhance the knowledge derived from tweets with the ultimate objective the overall enhancement of the policy making procedures of modern organizations and businesses.

KEYWORDS

Twitter Sentiment Analysis, Entity-Level Sentiment Analysis, Named Entity Recognition, Policy Making

1. INTRODUCTION

The last decade the user-generated opinionated data have shown a tremendous expansion through divergent sources such as blogs, online forums, social media platforms, and microblogging websites. A recent survey indicated that within 2021 there were 4.48 billion people actively using social media in the world, and this is an increase of 13.13% year-on-year from 3.69 billion in 2020, while in comparison with the active users back in 2015 there is an overall increase in users of 115.59% in just six years [1]. Such data contain opinions about any product, topic, service, trend, or any worldwide situation and, thus, can be effectively used by the policy makers for extracting valuable information from them or even facilitate the policy making procedures with the ultimate goal to enhance the final policies.

At the same time, the massive amount of data generated by users using social media platforms is the result of the integration of their background details and daily activities. This enormous volume of generated data known as "big data" has been intensively researched recently [2]. The

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term "big data" is globally used for describing a collection of datasets that are mainly characterized by high velocity, volume, and variety [3], hence their processing and analysis using traditional data processing techniques and approaches is a difficult and complex task [4]. In addition, the volume and ever-increasing amount of data produced, in the form of real-time data, has led the scientific and business communities to develop advanced big data applications through the utilization of Artificial Intelligence (AI) techniques and methods [5]. What is more, the overwhelming of data of unstructured data that are generated through conversations, opinions, texts or even posts on modern social media indicate the increasing need for the deployment and utilization of several sub-tasks in the field of Natural Language Processing (NLP) which can be found and received only in the form [6]. These types of data are usually difficult to manage, and as a result understanding and extracting valuable information and knowledge out of them is a demanding and challenging task.

Among the various sources of opinionated and unstructured data, Twitter is one of the top social platforms and a rich source of information as tweets are produced by its users on each topic. On top of this, Twitter recently announced its results for the fourth quarter and fiscal year 2021 where an annual revenue growth of 37% to $5.08 Billion and an average monetizable daily active usage (mDAU) growth of 13% to 217 million in Q4 were observed [7]. To this end, the analysis of the tweets that are generated from its users can play a vital role in the policies of each stakeholder. Twitter Sentiment Analysis aims to identify and analyze aggregated sentiments of people from opinionated microblogging data and plays an important role in identifying the individual's sentiment or opinion and their impact on society [8], thus it has become a key tool in social media marketing strategies and policy making procedures based on this information. Moreover, the last two years and especially due to the COVID-19 pandemic breakout it is emerging the need for the correct analysis of the sentiment of people and the protection of them from fake news, propaganda, and misleading information [9].

However, the texts of social media posts and tweets can have different sentiments for different products, events, and topic that can be reported into the same tweet or even into the same sentence. The latter indicates the need to also identify and extract key entities that can be detected into a single tweet and hence to provide the sentiment for this specific identified entity, thus utilizing the task of an Entity-Level Sentiment Analysis (ELSA) instead of a simple and vanilla Sentiment Analysis. At present, the most commonly used entity detection method is Named Entity Recognition (NER) and the existing techniques of NER are mainly divided into four types: methods based on rule and dictionaries [10], methods based on machine learning [11], methods based on deep learning [12], and methods based on hybrid approaches [13]. During the last years and based on the final achievements in the field of NLP mainly through the introduction of Transformers also the NER subtask has taken into advantage these latest advancements [14]. To this end, the utilization of NER subtask can enhance the Twitter Sentiment Analysis towards the final implementation of an ELSA approach to further enhance the policy making procedures based on the sentiments of several different and of high interest identified entities within the examined text.

The rest of the paper is organized as follows. Section 2 describes the related work and the recent advances in the fields of Sentiment Analysis and more specifically in the Entity-Level Sentiment Analysis task. In Section 3 the overall methodology and pipeline for the evaluation and the outcomes of ELSA approach in Tweets is being introduced. In addition, the proposed end-to-end pipeline followed during the experimental phase coupled with the utilization of the NER are also being examined and utilized to enhance the implementation and results of the ELSA task. Moreover, Section 4 presents the experimental results and includes a discussion over the final outcomes and the comparison between the results of the proposed ELSA pipeline. Finally, Section 5 concludes the paper and states the future work that will be implemented.

2. Related Work

The term "Sentiment Analysis" was firstly introduced at the early beginnings of the 21st century [15], using various developed standards to identify the emotion in a text, while the term opinion mining made its first appearance almost at the same time [16]. At its heart, Sentiment Analysis employs various NLP and Machine Learning techniques that are implemented to classify a text based on sentiments. The first attempts were made in the early 21st century where researchers aimed to classify long texts into categories according to the overall feeling they express [17] – [19]. Although Sentiment Analysis is one of the first tasks of NLP for which the research community had remarkable results, the evolution and wide use of Deep Neural Networks over the past years has led to the utilization of Neural Networks in Sentiment Analysis tasks. With the advances in the field of Deep Learning, many new algorithms have flourished which can enhance the task of Sentiment Analysis. Hence, recent research efforts are oriented towards the use of Neural Networks and Deep Learning (DL) techniques, such as Convolutional Neural Networks (CNNs) or Recurrent Neural Networks (RNNs), which have shown remarkable results, and which can be leveraged for the task of Sentiment Analysis [20] – [22]. While several techniques have been applied to the task of sentiment analysis, more work has been done recently to evaluate and recognize the sentiment of different entities or aspects in the text [23]. The applications for an accurate ELSA tool can help modern businesses and organizations to more accurately identify customer sentiments to products/services [24]. In this direction, authors in [25] have introduced and evaluated various Neural Network based approaches to tackle the task of entity-level sentiment analysis and to showcased that a bidirectional RNN outperformed all the other models that were implemented. What is more, several recent researches have introduced multi-entity sentiment analysis approaches completing the automatic recognition of multiple target entities and their corresponding sentiment polarities and achieving state-of-the-art performances indicating that the utilization of Neural Networks and Transformers can leverage the potentials of an ELSA approach [26] – [27].

Under the scopes of this research work the utilization and evaluation of an Entity-Level Sentiment Analysis (ELSA) mechanism aims to identify fine-grained opinion polarity towards specific entities and is a challenging and complex subtask of Sentiment Analysis due to additional target and entity level information and knowledge extraction that should be achieved from a given text/sentence. The main objective of this task is to classify the sentiments of a text concerning already identified and extracted entities from the NER task. Hence, in this research work the main goal is to utilize and take advantage of this approach to enhance the Twitter Sentiment Analysis task towards the implementation of an ELSA mechanism and further leverage the potentials of enhanced policies based on the outcomes of this approach.

3. Proposed Approach

The increasing interest and use of DL and the utilization of neural networks has enhanced NLP tasks along with other tasks and application of AI. The proposed methodology to evaluate ELSA involves two key elements. At first, the proposed ELSA approach and pipeline is being presented. Afterwards, the main techniques and approaches that utilized for performing the NER and ELSA are being presented in sub-sections of this section. In this context, this research work performs an initial utilization and evaluation of a complete ELSA pipeline and mechanism. The latter consists of several components that are being depicted in "Fig. 1" below. The proposed approach is further evaluated and implemented on a real-world scenario in the context of the PolicyCLOUD project [28] that seeks to support evidence-based elaboration and analysis of policies based on the utilization of several essential ingest and analytic functions that are built-in within the framework [29].

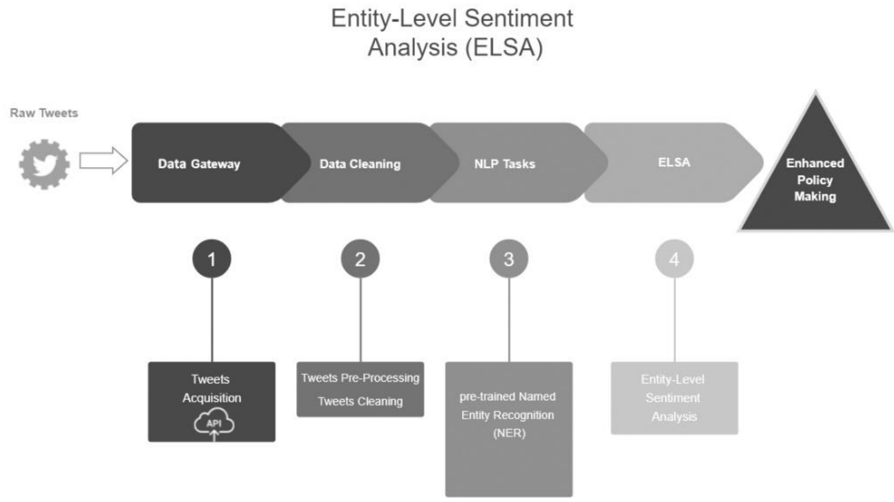

Figure 1. ELSA pipeline

As depicted in the above figure several subcomponents are integrated in the complete ELSA pipeline. More specifically, the first component that initializes also the overall process is the Data Gateways component, which through the utilization of a Twitter Microservice, acquires the Twitter data and further forward them to the overall ELSA pipeline throughout the usage and initialization of the Twitter API v0.2. Afterwards, the Data Cleaning component is responsible to perform the initial and necessary data pre-processing and cleaning on the collected tweets. Data obtained from twitter usually contains a lot of HTML tags, links, usernames, punctuations, emojis, hashtags etc., which get embedded in the original data. Thus, it is necessary to filter and delete all these entities. What is more, as the overall process deals with raw text several NLP subtasks were utilized to extract value and knowledge out of the raw tweets. To this end, tokenization, sentence identification and most importantly the task of Named Entity Recognition (NER) are being utilized. Finally, the last step of the proposed approach is the utilization of an Entity-Level Sentiment Analysis (ESLA) task to further extract the sentiment on specific identified entities.

3.1. Data Gateway

This paper mainly studies the tweet texts that have been fetched based on keywords related with wine products and brands. As mentioned above the research work presented in this paper is evaluated and implemented in the context of a project where one of the main use cases and scenarios is to identify customers sentiments related to various wine products to further enhance the advertising and organizational strategic policies related to these wines. The latter is being demonstrated through the utilization of a Twitter Microservice to fetch tweets based on three specific keywords related with wine products, “merlot”, “bordeaux”, and “cabernet”. What is more, it should be noted that the newly introduced Twitter API v2 sends by default only the “id” and the “text” attributes when a corresponding call is triggered. In the context of this work, more attributes and information for a tweet were selected to be gathered and analyzed. More specifically, the “lang”, “created_at”, “id_str”, “retweet_count”, “favorite_count”, “entities” and “geo” objects were added. A spanshot of tweet in JSON format is being depicted in “Fig. 2”, where all the related attributes and information concerning a collected Tweet are depicted. In addition, it should be noted that the already identified and provided entities from the Twitter are not sufficient to perform the ELSA mechanism as several PRODUCT entities are missing. For instance, as is being depicted in “Fig. 2” the only initial provided entity is the “Cabernet

Sauvignon", while the raw text also includes "Merlot", "Bordeaux" and "Sauvignon Franc" product entities. Hence, a custom NER approach should be at first implemented in order the proposed mechanism to be able to better extract all the related PRODUCT entities from the examined text.


```
{
  "created_at": "2022-02-22T08:33:52.000Z",
  "id": "1496040533617266689",
  "id_str": "1496040533617266689",
  "text": "RT @wine_is_art: Three Left Bank of #Bordeaux facts\n\n• It’s about powerful long-lived wines.\n•
    Cabernet Sauvignon is the main grape variety…",
  "entities": {
    "mentions": [
      {
        "start": 3,
        "end": 15,
        "username": "wine_is_art",
        "id": "1405297851484282883"
      }
    ],
    "annotations": [
      {
        "start": 95,
        "end": 112,
        "probability": 0.4336,
        "type": "Product",
        "normalized_text": "Cabernet Sauvignon"
      }
    ],
    "hashtags": [
      {
        "start": 36,
        "end": 45,
        "tag": "Bordeaux"
      }
    ]
  },
  "geo": null,
  "retweet_count": 1,
  "favorite_count": 0,
  "lang": "en"
},
```


Figure 2. A tweet snapshot

3.2. Data Cleaning

As concerns especially the twitter data before performing any DL technique the pre-processing of this raw text is a crucial and mandatory step as it can contain a lot of elements, from plain text, mentions, hashtags, links, emojis, and punctuations, to many other things. Hence, all these "noisy data" may need to be removed before proceeding to the further processing and analysis of the examined tweets. For the purposes of this task, filtering, and removal of punctuations, links, mentions and stopwords are being performed in the collected tweets.

```
'Three Left Bank of #Bordeaux facts\n\n• It’s about powerful long-lived
wines.\n• Cabernet Sauvignon is the main grape variety, but it’s often b
lended with Merlot and Cabernet Franc.\n• It’s home to the official 1855
Classification of the Médoc.\n\n#finewine https://t.co/8c7CKbZPXx'
```

```
'RT @KatieLopez98: New Wine Avaliable 2016 Arnaldo-Caprai Belcompare 🍇
IT https://t.co/BM7aEfCeKc\n\n#wine #Italy #vino #redwine #merlot #party
#Food #BAR #drink #friends'
```

Figure 3. Raw tweet examples

The abovementioned steps and phases for the pre-processing and cleaning of raw tweets have resulted in the cleaned tweet texts that are being depicted in "Fig. 4", which can be further processed and analyzed to implement the ELSA task.

```
'Three Left Bank Bordeaux facts It powerful long lived wines Cabernet Sa
uvignon main grape variety often blended Merlot Cabernet Franc It home o
fficial 1855 Classification Médoc finewine co / 8c7CKbZPXx'
'RT New Wine Avaliable 2016 Arnaldo Caprai Belcompare 🍇IT co / BM7aEfCe
Kc wine Italy vino redwine merlot party Food BAR drink friends'
```

Figure 4. Tweet texts after cleaning

3.3. Named Entity Recognition (NER)

The task of NER is a subtask of NLP that seeks to identify and label words or phrases in text that refer to a person, product, location, organization, or even quantity. Thus, under the scopes of the proposed ELSA pipeline the NER subtask is utilized to extract and classify named entities found in the examined tweets based on a specific dictionary listing the examined products for which the sentiment needs to be identified. This process is performed as an initial and mandatory step in the complete ELSA pipeline as this process facilitates the procedure of entity identification, which then will be scored with polarity. To implement this step the spaCy toolkit was utilized as basis. It is worth to mention that the NER pipeline that is being provided by this toolkit was first trained on specific train data to further fine tuning the overall process and focus on the identification of wine products entities. For instance, when utilized the spaCy NER pipeline without pre-training the “Bordeaux” entity was recognized as “GPE”, but after the manually pretraining of the NER pipeline it was identified correctly as “PRODUCT” in the examined tweets. Finally, the final annotation of the initial tweets with the already identified entities is implemented. The below figure depicts the final annotation of the original tweet based on the custom identified entities.

```
Three Left Bank Bordeaux facts It powerful long lived
wines Cabernet Sauvignon main grape variety often
blended Merlot Cabernet Franc It home official 1855
Classification Médoc finewine co / 8c7CKbZPXx
['Bordeaux', 'Cabernet Sauvignon', 'Merlot', 'Cabernet
Franc', 'Médoc']
```

Figure 5. NER output and annotation of text with identified PRODUCT entities

3.4. Entity-Level Sentiment Analysis (ELSA)

The ELSA mechanism that is being proposed in this research work seeks to enhance the Sentiment Analysis task within the project by filtering and providing the corresponding sentiments for identified and extracted entities in tweets, specifically for a scenario related to wine marketing policies. To this end, an ELSA approach was followed in respect of providing and end-to-end mechanism for the identification of sentiments of extracted entities from the step of NER. Under the scopes of this research work and within the framework of the project a ready-to-use Python library is utilized, the “aspect-based-sentiment-analysis” [31], as a first implementation and evaluation of an ELSA mechanism. The latter bases its functionality directly to BERT’s next-sentence prediction to formulate the task as a sequence-pair classification. As the project progress further research will be conducted in this respect and custom DL and Transformers based implementations and approaches will be followed.

4. EXPERIMENTAL RESULTS

This section presents the experimental results of the utilization of previously mentioned pipeline. For the purposes of this paper and the overall research, 2500 Tweets were collected through the utilization of the Data Gateway component with the keywords “merlot”, “bordeaux” and “cabernet” as filtering parameters, as they are highly, and worldwide recognized wine products and corresponding policies need to be applied by stakeholders within the framework of the project based on the analysis of the sentiment for these four specific products.

4.1. Evaluation Setup

Experiments were based on implementing the various NLP and Entity-Level Sentiment Analysis tasks with Python programming language and the utilization of Anaconda environment and IPython Notebook. Moreover, several tools and libraries of the Python language for the implementation of the abovementioned tasks were utilized. More specifically, to implement the initial processing of Twitter data the NLTK library was utilized, while for the NER subtask the spaCy tool was selected as the most appropriate. Further and custom implementations will be performed in later steps, as this is just a first of a series of implementations and evaluations between different tools and approaches of the integrated ELSA mechanism.

4.2. Twitter Entity-Level Sentiment Analysis

The proposed methodology and pipeline focuses on an Entity-Level Sentiment Analysis (ELSA) approach [32] - [33], in charge of providing “author sentiment towards various entities in text” as cited in [34], which can be considered as an intermediate granularity between sentence-level sentiment, “It's known that the entity discussed in the sentence and there is just one single opinion in each sentence” and aspect-level sentiment “people talk about entities that have many aspects (attributes) and they have a different opinion about each of the aspects”. In particular this approach aims to get the positive, negative and neutral opinions about different entities (all related to the wine domain) based on social media data. Targeted wine entities, such as the “cabernet”, the “bordeaux” and the “merlot”, have been identified well and their sentiments have been extracted in high accuracy by the utilized ELSA mechanism.

```
Sentiment.positive for "Bordeaux"
Scores (neutral/negative/positive): [0.245 0.068 0.687]
```

Importance 1.00 three left bank bordeaux facts • it ' powerful long lived wines • cabernet sauvignon main grape variety ' often blended merlot cabernet franc • it ' home official 1855 classification medoc finewine

Importance 0.87 three left bank bordeaux facts • it ' powerful long lived wines • cabernet sauvignon main grape variety ' often blended merlot cabernet franc • it ' home official 1855 classification medoc finewine

Importance 0.67 three left bank bordeaux facts • it ' powerful long lived wines • cabernet sauvignon main grape variety ' often blended merlot cabernet franc • it ' home official 1855 classification medoc finewine

Importance 0.56 three left bank bordeaux facts • it ' powerful long lived wines • cabernet sauvignon main grape variety ' often blended merlot cabernet franc • it ' home official 1855 classification medoc finewine

Importance 0.50 three left bank bordeaux facts • it ' powerful long lived wines • cabernet sauvignon main grape variety ' often blended merlot cabernet franc • it ' home official 1855 classification medoc finewine

Figure 6. Sample example of the utilization of absa tool on the examined tweet

As presented in the above figures the first conducted experiments and their outcomes through the utilization of this ELSA mechanism and tool have shown remarkable results. The appropriate wine products and their corresponding entities have been well identified and the sentiment for each of them has been recognized and extracted providing extra information and knowledge about the user-generated opinion even within a single tweet, as well as to the complete dataset of collected and examined tweets with the ultimate goal to enhance the policy making procedures. Moreover, Table 1 depicts the aggregated sentiment results for the identified PRODUCT entities in the total number of examined tweets. The latter indicates that users have a strong preference on "Cabernet Franc", and "Cabernet Sauvignon", while the "Merlot" product has the highest negative sentiment among the examined wines. Moreover, the nature of the word "Bordeaux", as it can represent a product, a location, a region or even a team, has resulted in a is highly neutral sentiment in contrary to the sentiments of the other examined products. Finally, the "Weiss bier" term also appears within the examined tweets and its sentiment is overall highly negative and is justified by the topic of the collected tweets. As was mentioned in the previous sections the collection of the examined tweets was based on the "merlot", "bordeaux", and "cabernet" keywords, thus probably these tweets have been generated from people with specific interest and taste for wine products rather than beer products. The outcomes of this analysis can leverage the potentials of enhanced policies and different marketing strategies and help policy maker to understand the behavioral and buying patterns of the customers better.

Table 1. Sentiment of different identified PRODUCT entities

PRODUCT entity	Positive	Negative	Neutral
Cabernet Franc	0.759	0.056	0.185
Cabernet Sauvignon	0.732	0.089	0.179
Bordeaux	0.577	0.115	0.308
Merlot	0.656	0.182	0.162
weiss bier	0.498	0.341	0.161

5. CONCLUSION

In this research work, a comparative analysis and evaluation of an end-to-end pipeline for implementing the ELSA task was introduced and analyzed to specify and indicate the increasing need of utilizing an Entity-Level Sentiment Analysis on tweets coupled with several subtasks of the NLP. Twitter is a popular social media platform, and it contains an abundance of information about various products, services, ideas, events and topics. Hence, data provided by this platform can be leveraged by companies, organizations, policy makers and individuals to get an overview of users' sentiments on specific products, services, and topics of discussion. To this end, the challenges of performing an end-to-end ELSA approach plays a vital role in the overall policy making procedures of the modern organizations. More specifically, the utilization of this approach can facilitate the understanding of trends and to correlate observed changes in sentiment towards products acceptance and analyze the impact of various marketing strategies and enable prompt reaction to expressed consumer feedback. Hence, the main scope of this research work is an initial examination and evaluation of an ELSA mechanism with emphasis on the utilization and evaluation of a pre-trained NER task and an ELSA tool.

The ELSA mechanism enhances the overall Sentiment Analysis task within the project by filtering and providing the corresponding sentiments for identified and extracted entities from collected tweets, specifically for a real-world scenario related to wine marketing policies. The complete ELSA pipeline proposed in this paper, will be further evaluated and applied in the context of a holistic environment for data-driven policy making as realized by the project, where data from four different languages (Bulgarian, Italian, Spanish and English) will be utilized and processed. The ELSA approach introduced in this paper will also be used in different scenarios within this project such as in the analysis and elaboration of various policies for municipalities where specific complaints and messages from citizens can be processed. In this context, specific sentiment can be recognized and extracted dedicated to a specific topic or issue. For instance, a unique post/compliance of a citizen can have different sentiment for the transportation issue (e.g., negative) but in parallel it can have the opposite sentiment for the road infrastructure issue (e.g., positive).

While the initial results of the proposed approach are very encouraging, further evaluation and research should be implemented. To this end, more experiments will be conducted as the project evolves and further evaluations and comparisons will be conducted based on the utilization of different approaches. In this direction, Transformer-based ELSA mechanisms will be developed and utilized rather than utilizing an existing tool as introduced under the scopes of this research work, as Transformers have shown remarkable results on the ELSA task [35]. Furthermore, in the future, further enhancements on the proposed approach will be implemented by leveraging different DL techniques and more specifically RNNs and Transformers to enhance the implemented tasks of NER and ELSA. More specifically, BERT models BERT models achieve state-of-the-art accuracy on NLP several tasks as compared to other RNN architectures [36] – [37], thus one of the first experiments of the future work will focus on leveraging a pre-trained BERT model to predict the different entities within a text.

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