Cooking Reviews Segmentation and Classification based on Deep Learning and Named Entity Detection

Randa Benkhelifa[1][a] and Nasria Bouhyaoui[2,1][b]
[1]Laboratoire de L'intelligence Artificielle et des Technologies de L'information, Université Kasdi Merbah, Route de Ghardaia BP.511, 30 000, Ouargla, Algeria
[2]Ecole Normale Supérieure de Ouargla, Ouargla, Algeria

Keywords: Text Segmentation, Text Classification, Online Social Network, YouTube, Cooking, Named Entity Detection, Sentiment Analysis.

Abstract: YouTube is one of the most used online social networking (OSN) websites for exchanging recipes. It allows uploading them, searching for, downloading, as well as rating and reviewing them. Sentiment analysis for food and cooking recipes comments is to identify what people think about such cooking recipe video through users' comments. Nowadays, users' give their opinion not only about recipes; they also evaluate the cook through their comments, where a cook's reputation can affect the users' opinion about his cooking recipes. Frequently, when a cook has a good reputation, his recipes receive a great success by people, and vice versa. In this paper, we propose a new approach that deal with the sentiment classification of cooking reviews. Firstly, we examine the benefit of performing named entity detection and conjunctions on our corpus for text segmentation in order to divide the comment on segments concerning the cook and segments concerning the recipe. Next, we make two sentiment classifications (about the cook and about the recipe). Finally, we incorporate the polarity of the cook sentiment classification in the recipe sentiment classification in order to analyse the effect of the opinion about the cook on the performance of the categorization of the shared cooking recipes comments in OSNs.

1 INTRODUCTION

Today, social networks such as Facebook, Twitter and YouTube have become an essential element in our daily life. Indeed, they are increasingly used to convey messages and ideas through generating tons of data on users and their interactions. The importance of this data is that it contains a good fraction of opinionated posts. Analyzing these posts can reveal how users feel about certain topics, or issues, events, products, people, recipes, etc. Sentiment analysis is the field that allows the treatment of users' emotions and feeling. The sentiment analysis is the process of determining whether a piece of subjective writing is positive or negative.

YouTube is a public video-sharing website where people can share their experience and opinions in order to maintain social relationships. One of the most popular videos is the cooking videos, where, people can upload, search for, download, as well as rate and review recipes. Sentiment analysis of food recipe comments is to identify what do people think about such cooking recipe video through user's comments (positive or negative comments), where it is interesting to predict their ratings automatically (Benkhelifa and Laallam, 2018).

Frequently, the user does not give his/her opinion only to evaluate the recipe; the user also gives his/her opinion to evaluate the chef or the cook who prepared this recipe. Sometimes, the judgment attributed to the person who cook effects the opinion about the cooking recipe.

Several papers over the years studied users' opinions based on the textual content shared by them in online social networks. The majority of the previews works (Benkhelifa and Laallam, 2018). The authors (Benkhelifa, et al., 2019) have focused on the

[a] https://orcid.org/0000-0002-5577-4332
[b] https://orcid.org/0000-0002-9810-3061

Benkhelifa, R. and Bouhyaoui, N.
Cooking Reviews Segmentation and Classification based on Deep Learning and Named Entity Detection.
DOI: 10.5220/0011542300003318
In *Proceedings of the 18th International Conference on Web Information Systems and Technologies (WEBIST 2022)*, pages 337-343
ISBN: 978-989-758-613-2; ISSN: 2184-3252

comments about the recipe ignoring user's opinion about the cook, which can play an important role in user opinion about the recipe.

In order to be able to process every part of opinion separately; a part concerning the recipe and a part concerning the cook, it is necessary to split the review on segments. Text segmentation is a method of splitting a document into smaller parts (Pak and Teh, 2018). This study is interested in only two types of entities, which are person and recipe. Concerning Person entity detection, lot of methods can be used to annotate them. To the best of our knowledge, there is no previous research concerning Recipe entities detection. Therefore, we have created a list that contains a great number of words concerning Recipe NE such as (recipe, food, ingredient, vegetables, cake, meat, meal, calorie, etc.).

In this paper, we propose a new approach, which segment the review social text into two parts: the part talking about recipe and the part talking about the cook. We examine the benefit of performing named entity recognition (NER) to an English corpus used for text segmentation. Next, we build two sentiment classifications, one for the recipe and the other for the cook. After that, we study the effects of incorporating the polarity of cook sentiment classification in recipes sentiment classification. Finally, the experiments show the impact of incorporating the opinion about the cook on the performance of the categorization of the shared cooking recipes comments in OSNs.

The remainder of this paper is as follows. In section 2, the related works are discussed. In section 3, we present our methodology including our proposed approach. The section 4 represents the details of the results applied to the dataset extracted from YouTube, and finally, we present a conclusion and perspectives in section 5..

2 RELATED WORKS

Online social networking has become a part of the daily routine of a huge number of persons (Benkhelifa and Bouhyaoui, 2021). Comments in social media has reached a great interest in several works on opinion mining and sentiment analysis.

2.1 Text Segmentation

Text segmentation is a traditional NLP task, which is widely used in text processing phase. It allows to automatically partitioning text into coherent segments or units. Each segment has its relevant significance. Those units can be categorized as word (Wu et al., 2007), (Liu and Chen, 2015), (Xia et al., 2009) and (Zhang et al., 2021), sentence (El-Shayeb et al., 2007), (Zhu et al., 2009), (Benkhelifa, et al., 2019) and (Wicks and Post, , 2021), topic (Fragkou, 2013), (Ehsan and Shakey, 2016), (Memon et al., 2021), (Lo et al., 2021), (Koshorek et al., 2018) and (Maraj et al., 2021) or any information unit depending on the text analysis task. The authors in (Memon et al., 2021) have proposed a new topic-modelling-based ensemble clustering approach, inducing the combination of text segmentation and text clustering. They have presented a cutting of a document into segments (i.e. sub-documents), wherein each sub-document is associated with exactly one sub-topic. The work in (Lo et al., 2021), the authors have built supervised neural text segmentation model in the educational domain. A novel supervised training procedure with a pre-labeled text corpus along with an improved neural Deep Learning model for improved predictions has been proposed in (Maraj et al., 2021).

Recently, in text segmentation, many works such as (Koshorek et al., 2018) and (Maraj et al., 2021) have focused on supervised methods, which this is formulated as a supervised learning problem (Koshorek et al., 2018). The supervised methods have solved two main drawbacks of the unsupervised algorithms, which are the difficulty of specializing for a given domain and in most cases, the unsupervised methods do not naturally deal with multi-scale issues.

In addition, sentiment analysis has used text segmentation in order to identify the polarity of each segment. The authors in (Zhu et al., 2009) and (Benkhelifa, et al., 2019) have used segmentation in their model to identify multiple polarities and aspects within one sentence. A novel method for aspect based sentiment analysis, with an adaptation of LDA Sentence Segmentation algorithm for product aspect extraction has been proposed in (Ozyurt and Akcayol, 2021).

One of the essential and basic tasks of information extraction and NLP is named entity recognition (NER). Hence, the term ‘Named Entity’, is now commonly used in NLP (Ramzi et al., 2017). NER is the task of extracting, locating and classifying named entities in a given piece of text. The named entity can be a proper noun, a numerical expression which represents type unit or monetary value, or a temporal value which represents time. The classification of a proper noun can be divided into three categories, namely a person, a location, or an organization.

2.2 Sentiment Classification

Recently, sentiment analysis is considered as the process of finding users opinion about a particular topic (Vijay et al., 2014). It performed on different domain data such as Movie (Zhang and Zhu, 2006), Books and Products (Dave et al., 2014), (Hu and Liu , 2004), (Tan and Na, 2017) , Restaurants (Jingjing et al., 2012), and cooking recipes (Liu, et al., 2014) (Ning et al., 2013) (Benkhelifa, et al., 2019) (Benkhelifa and Laallam, 2018), etc. The authors in (Pugsee and Niyomvanich, 2015) have shown that the reviews are the best rating predictors, in comparison to ingredients, preparation steps, and metadata. Based on users' reviews, various strategies for predicting recipe ratings has been explored by the authors in (Liu, et al., 2014). In order to improve the food recipes a suggestion analysis method is proposed by the authors in (Ning et al., 2013). A sentiment based rating approach for food recipes using sorts food recipes present on various websites from sentiments of review writers is proposed in (Rao and Kakkar, 2017). The work in (Bianchini, et al., 2017) propose a menu generation system is described, that takes into account both user's preferences and healthy nutrition habits. Another related research about food recipe comments (Benkhelifa and Laallam, 2018) has develop a real-time system to extract and classify the YouTube cooking recipes reviews automatically. This research has used the social media text characteristics to improve the system performance. The authors in (Benkhelifa, et al., 2019) has introduced a sentiment based real-time system which mines YouTube meta-data (Likes, Dislikes, views and comments) in order to extract important cooking recipes features and identify opinions polarity according to these extracted features. Here we are interested to show the effect of the cook's reputation on his cooking recipes reviews.

3 METHODOLOGY

The methodology followed in this work is presented in this section. We start by introducing the description of the process; how our method works.

3.1 Process

The process of the proposed approach is shown in Figure 1.

Our method separates the comment on two parts (cook's review part and cooking review) using text segmentation techniques. Then, we apply the

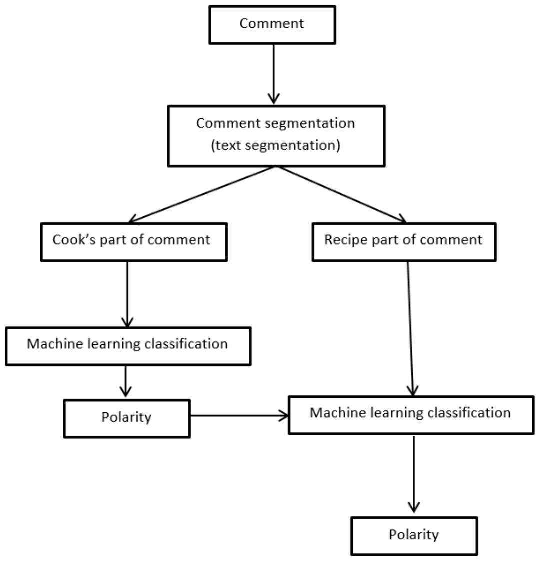

Figure 1: The process of the proposed approach.

sentiment classification on cook's part comment. The obtained polarity is combined to recipe review text for recipe sentiment classification.

Comment: it represents a short social text extracted from the well-known social network YouTube, where any person can access and express his/her opinion freely.

Comment segmentation: the segments of a comment are divided into two bags, cook's bag: this bag represents the text review concerning the cook, for example: "I love the way you cooked and smile amazing chef!". Where the second part represents recipe bag, which reflect the user's opinion about the recipe itself, for example: "I want to eat this, Looking delicious".

After that, we look for the polarity of the cook's part comments; the value of this polarity is included to the recipe sentiment classification process.

Here, we build the machine learning recipe sentiment classification, the classifiers are not based only on the textual content concerning the recipe they consider also the value of the polarity of the cook's parts of comment, this value is token as input of the classifier beside of the textual content.

3.2 Text Segmentation Approach

To build a robust system of comments segmentation, we propose to use a supervised segmentation based on named entity recognition. This study is interested in only two types of entities, which are person PER (representing the cook) and recipe REC. The other entities (that does not describe a person, or a recipe) including all other types of named entities NE such a location, an organization, etc. are not taken into account. Concerning Person entity detection, lot of methods can be used to annotate them. To the best of our knowledge, there is no previous research concerning Recipe entities detection. Therefore, we have created a list that contains a great number of words concerning Recipe NE such as (recipe, food, ingredient, vegetables, cake, meat, meal, calorie, etc.).

3.2.1 Text Segmentation Process

Our approach of segmentation is described by an Algorithm, which is constituted of the following steps as illustrated in Figure 2:

- Step 1: we use a separator segmentation: the comment is split according to the punctuation.
- Step 2: for each segment, we detect the NE. If the segment does not contain NE, we put it in the recipe bag. Else, if the segment contains only one type of NE, we put it in the bag of this entity type.
- Step 3: if the part of the comment contains more than one kind of named entity, we split this segment according to the conjunctions (except the “and” conjunction, which is removed in the preprocessing step). The result obtained could be two segments or more. In order to categorize each obtained segment into the adequate bag, we return to the step 2.

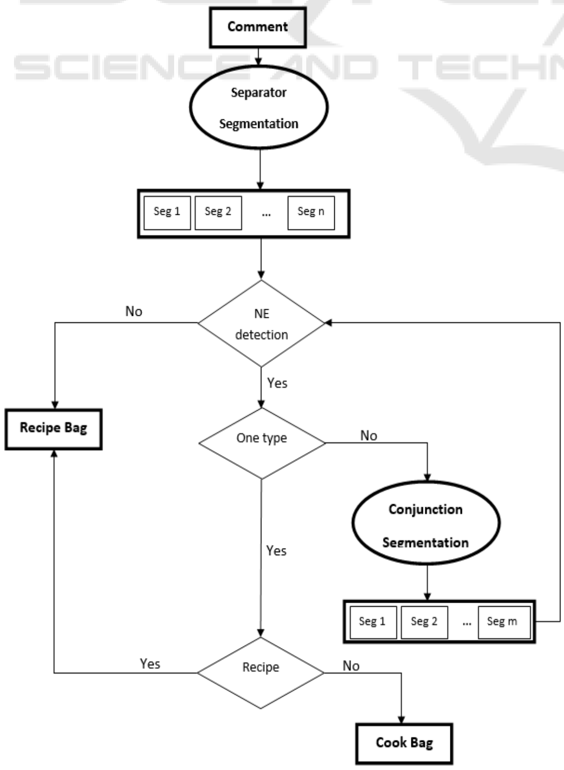

Figure 2: The process of comment segmentation.

- As an output, we get two sets (bags) of segments for each NE type (a cook’s bag and a recipe bag).

3.2.2 Text Segmentation Algorithm

Here, we give some notations. Suppose our dataset *D* has *n* Comments. Each comment c in C is segmented to a set of part (unit) *p* in *P*. Each unit *p* has a label *l* from $L=\{l_{per},l_{rec}\}$. Where l_{per} represents the unit talking about the cook, and l_{rec} is the label of the recipe unit.

```
Algorithm comment_segmentation{
Inputs: a set of comments C, a set of
parts P, boolean b, a set of Named
Entities NE, a set of labels L;
Output: a cook bag Pper, a recipe bag
Prec;
For each comment c in C Do {
        P= separator_segmantation(c);
        }

For each part p in P Do{
       b=Detect_entity(p);
       if b==no then{
           put p in Prec;
       }
       else{
           NE=annotate (p);
           if (same_label l(NE)==yes)
           then{
               if l(E)==REC then {
                  put p in Prec
               }
              else{
                  put p in Pper
                }
           }
           else{
              Conjunction segmentation;
              Goto line 10;
            }
}
Output (Prec, Pper);
}.
```

4 EXPERIMENTS

4.1 Dataset Collection and Construction

This section presents the dataset used in this work for both segmentation and classification. The main objective of this work is to segment and classify cooking reviews. Moreover, to study the effect of cook’s reputation on the users' opinion about his cooking recipes and to show how much it is important to consider this information in the classification process. YouTube comments are perfect for these due to their abundance and a short length. Moreover, YouTube is a popular video social network with a great diversity of users, which means that collecting a sufficiently large dataset with those characteristics on various topics is feasible. To ensure the consistency and the reliability of our proposed approaches, we tested our classification and method on a collection of 10000 recent texts of YouTube comments about videos of cooking recipes collected between (May and August 2016) from many YouTube videos. Three human annotators as following annotated these texts manually: for creating the training model of the sentiment classification (5000 positive and 5000 negative). Cooking recipe corpus and its annotations guideline had been originally defined in (Benkhelifa and Laallam, 2018).

4.2 Data Pre-processing

Preprocessing 1: it represents the prepressing, which is applied before the segmentation algorithm.

1. Removing {and}, in the most cases the conjunction “and” is used for listing several description of the same entity for example “she’s always happy and positive”.
2. Removing all words that can be annotated as Person but do not represent the cook and generally those words concern the comment author such as {I, My kids, My family, etc.}

Preprocessing 2: it represents the prepressing, which is applied before the classifications.

3. A term that appears less than three (3) times is removed;
4. Removing punctuation (.,!?) and symbols ([<>());
5. The stemmer employed is the lovenStemmer, which is used in the literature.

4.3 Evaluation Metrics

We adopt PK, the standard evaluation metric for text segmentation for reporting the results of the prosed text segmentation. PK score is the percentage of wrong predictions on whether or not the first and last sentence of a randomly sampled snippet of k sentences belong to the same segment. Following the previous works, we set k to the half of the average ground truth segment size of the dataset.

Evaluation metrics for sentiment classifications

We now evaluate the performance of our method by evaluating the performance of machine learning training models, F-Measure (F) is one of the standard metrics employed for evaluating our machine learning models, this metric includes two fundamental factors, i.e., precision (P) and recall (R), which are obtained from the following relations:

$$P=TP/(TP+FP) \quad (1)$$

$$R=TP/(TP+FN) \quad (2)$$

$$F1=2*R*P/(R+P) \quad (3)$$

5 RESULTS AND DISCUSSION

5.1 Text Segmentation Results

After the segmentation phase, we have gotten 12% of PK.

We did not compare the obtained PK result with the other researches, and this is because our main objective is not the comment segmentation. In this work, we are interested in the review sentiment classification. The classification process required the performing of text segmentation.

5.2 Sentiment Classification Results

Deep learning algorithms Convolutional Neural Networks (CNN), and Recurrent Neural Networks (LSTM, and bi-LSTM) are used for both sentiment classifications. The first layer of each of these models is a word embedding layer that turns sentences into a feature map.

We start by showing the results of the cook’s sentiment classification.

Table 1: Cook’s sentiment classification results.

	Measure		
Classifier	***P***	***R***	***F***
bi-LSTM	**0.923**	0.857	**0.888**
LSTM	0.888	0.843	0.865
CNN	0.86	**0.86**	0.86

The best F-measure result is 0.888. It has been gotten using bi-LSTM classifier.

Now, we show the results obtained by cooking recipes sentiment classification using three deep learning algorithms CNN, LSTM, and bi-LSTM with and without cook’s classification polarity.

TC: Textual Content.

OC: Opinion about cook.

Table 2: Recipe sentiment classification results.

	Features		Measure		
Classifier	***TC***	***OC***	***P***	***R***	***F***
CNN	•		0.789	0.788	0.786
CNN	•	•	0.82	0.82	0.82
Bi-LSTM	•		0.789	0.787	0.787
Bi-LSTM	•	•	0.83	0.826	0.825
LSTM	•		0.82	0.811	0.81
LSTM	•	•	**0.84**	**0.83**	**0.83**

Comparison between the Gotten Results.

The highest results we got are 0.84 in precision, 0.83 in recall and 0.83 in F measure including both recipe textual content and opinion about the cook using LSTM classifier. Firstly, we have based only on the textual content extracted comment concerning from recipes without considering the opinion about the cook, we got these classifiers precisions, recalls and F-measures respectively, 0.789, 0.788, and 0.786 using CNN, 0.789, 0.787, 0.787 using bi-LSTM and 0.82, 0.81, and 0.81 using LSTM.

Including opinion about the cook (polarity value) in the classification process, we remark an improvement of 0.031 in precision, 0.032 in recall and 0.034 in F-measure using CNN classifier, where using bi-LSTM, we got an improvement of 0.041 in precision, 0.039 in recall, and 0.04 in F-measure. The LSTM classifier has gotten an improvement of 0.02, 0.019 and 0.02 in precision, recall and F-measure respectively.

6 CONCLUSIONS AND FUTURE WORK

In this paper, we have focused on text segmentation and classification; we have proposed a new approach of cooking comments segmentation based on deep learning and NER. Where the segmentation has gotten good results. In addition, we have shown the impact of incorporating the opinions about the cook on the performance of the classification of the recipes comments extracted from YouTube. Thus, we conclude that this integration has a good impact and it plays a crucial role in improving the performance of the recipes comments classification.

Future works: As a future extension of this work, we plan to explore other characteristics for text segmentation. We will also propose other approaches, to improve the performance of OSNs text classification.

ACKNOWLEDGEMENTS

This work was financially supported by "La Direction Générale de la Recherche Scientifique et du Développement Technologique (DGRSDT)" of Algeria.

REFERENCES

Benkhelifa, R., & Laallam, F. Z. (2018, February). Opinion extraction and classification of real-time youtube cooking recipes comments. In *International Conference on Advanced Machine Learning Technologies and Applications* (pp. 395-404). Springer, Cham.

Benkhelifa, R., & Bouhyaoui, N. (2021). Deep approach based on user's profile analysis for capturing user's interests. In *International Conference on Artificial Intelligence and its Applications* (pp. 177-186). Springer, Cham.

Benkhelifa, R., Bouhyaoui, N., & Laallam, F. Z. (2019). A Real-Time Aspect-Based Sentiment Analysis System of YouTube Cooking Recipes. In *Machine Learning Paradigms: Theory and Application* (pp. 233-251). Springer, Cham.

Bianchini, D., De Antonellis, V., De Franceschi, N., & Melchiori, M. (2017). PREFer: A prescriptionbased food recommender system. Computer Standards & Interfaces, 54, 64-75.

Liu C, Guo C, Dakota D, Sridhar Rajagopalan,Wen Li, Sandra K¨ubler, (2014). "My Curiosity was Satisfied, but not in a GoodWay: Predicting User Ratings for Online Recipes", Proceedings of the Second Workshop on Natural Language Processing for Social Media (SocialNLP), pages 12–21, Dublin, Ireland.

Dave K, Lawrence S, Pennock D. (2003). "Mining the peanut gallery: opinion extraction and semantic classification of product reviews". Proceedings of the 12th international conference on World Wide Web, ACM, New York, NY, USA, WWW"03.

Hu M, Liu B. (2004). "Mining and summarizing customer reviews". Proceedings of the 10th ACM SIGKDD international conference on knowledge discovery and data mining. ACM, New York, NY, USA, KDD.

Jingjing Liu, Stephanie Seneff, and Victor Zue, 2012. "Harvesting and Summarizing User-Generated Content for Advanced Speech-Based HCI", IEEE Journal of Selected Topics in Signal Processing, Vol. 6, No. 8, pp.982-992.

Ning Yu, Desislava Zhekova, Can Liu, and Sandra K ubler. (2013). Do good recipes need butter Predicting user ratings of online recipes. In Proceedings of the IJCAI Workshop on Cooking with Computers, Beijing, China.

Pugsee P., and Niyomvanich M., (2015) "Suggestion Analysis for Food Recipe Improvement," Proceeding of the 2015 International Conference on Advanced

Informatics: Concepts, Theory and Application (ICAICTA).

Rao, S., & Kakkar, M. (2017). A rating approach based on sentiment analysis. In Cloud Computing, Data Science & Engineering-Confluence, 2017 7th International Conference on (pp. 557-562). IEEE.

Tan, S. S., & Na, J. C. (2017). Mining Semantic Patterns for Sentiment Analysis of Product Reviews. In International Conference on Theory and Practice of Digital Libraries (pp. 382-393). Springer, Cham.

Vijay B. Raut et al. (2014). “Survey on Opinion Mining and Summarization of User Reviews on Web,” (IJCSIT) International Journal of Computer Science and Information Technologies, Vol.5 (2), pp.1026- 1030.

Zhang X., and Zhu F., (2006). “The influence of Online consumer reviews on the demand for experience goods: The case of video games”, In 27th international conference on information systems (ICIS), Milwaukee,. AISPress, 2006.

Pak, I., & Teh, P. L. (2018). Text segmentation techniques: a critical review. *Innovative Computing, Optimization and Its Applications*, 167-181.

Memon, M. Q., Lu, Y., Chen, P., Memon, A., Pathan, M. S., & Zardari, Z. A. (2021). An ensemble clustering approach for topic discovery using implicit text segmentation. *Journal of Information Science*, *47*(4), 431-457.

Maraj, A., Martin, M. V., & Makrehchi, M. (2021). A More Effective Sentence-Wise Text Segmentation Approach Using BERT. In *International Conference on Document Analysis and Recognition* (pp. 236-250). Springer, Cham.

Lo, K., Jin, Y., Tan, W., Liu, M., Du, L., & Buntine, W. (2021). Transformer over Pre-trained Transformer for Neural Text Segmentation with Enhanced Topic Coherence. *arXiv preprint arXiv:2110.07160*.

Koshorek, O., Cohen, A., Mor, N., Rotman, M., & Berant, J. (2018). Text segmentation as a supervised learning task. *arXiv preprint arXiv:1803.09337*.

Zhang, D., Hu, Z., Li, S., Wu, H., Zhu, Q., & Zhou, G. (2021). More than Text: Multi-modal Chinese Word Segmentation. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 2: Short Papers)* (pp. 550-557).

Wicks, R., & Post, M. (2021). A unified approach to sentence segmentation of punctuated text in many languages. In *Proceedings of the 59th Annual Meeting of the Association for Computational Linguistics and the 11th International Joint Conference on Natural Language Processing (Volume 1: Long Papers)* (pp. 3995-4007).

Wu, Y., Zhang, Y., Luo, S. M., & Wang, X. J. (2007). Comprehensive information based semantic orientation identification. IEEE NLP-KE 2007 - Proc (pp. 274–279). Beijing: Int. Conf. Nat. Lang. Process. Knowl. Eng. IEEE.

Liu, S. M., & Chen, J.-H. (2015). A multi-label classification based approach for sentiment classification. Expert Systems with Applications, 42, 1083–1093.

Xia, Z., Suzhen, W., Mingzhu, X., & Yixin, Y. (2009). Chinese text sentiment classification based on granule network. In: 2009 IEEE International Conference on Granular Computing GRC 2009 (pp. 775−778). Nanchang: IEEE.

Fragkou, P. (2013). Text segmentation for language identification in Greek forums. In: Proceedings of Adaptation of Language Resources and Tools for Closely Related Languages and Language Variants (pp. 23–29). Hissar: Elsevier B.V.

Ehsan, N., & Shakery, A. (2016). Candidate document retrieval for cross-lingual plagiarism detection using two-level proximity information. Information Processing and Management, 52, 1004–1017.

Zhu J, Zhu M, Wang H, Tsou BK (2009) Aspect-based sentence segmentation for sentiment summarization. In: Proceeding 1st International CIKM Worshop. Top Analysis mass Open.— TSA’09 (pp. 65–72). Hong Kong: ACM New York, NY, USA ©2009.

El-Shayeb, M. A., El-Beltagy, S. R, & Rafea, A. (2007). Comparative analysis of different text segmentation algorithms on arabic news stories. In: IEEE International Conference on Information Reuse and Integration, Las Vegas (pp. 441–446).

Ramzi Salah, Lailatul Qadri Zakaria (2017) Arabic Rule-Based Named Entity Recognition Systems Progress and Challenges.

Ozyurt, B., & Akcayol, M. A. (2021). A new topic modeling based approach for aspect extraction in aspect based sentiment analysis: SS-LDA. *Expert Systems with Applications*, *168*, 114231.