A Survey of Arabic Thematic Sentiment Analysis Based on Topic Modeling

Seham Basabain
ssbasabain@kau.edu.sa
Lecturer in Information Systems
Faculty of Computing
King AbdulAziz University
Jeddah, Saudi Arabia.

Abstract
The expansion of the world wide web has led to a huge amount of user generated content over different forums and social media platforms, these rich data resources offer the opportunity to reflect, and track changing public sentiments and help to develop proactive reactions strategies for decision and policy makers. Analysis of public emotions and opinions towards events and sentimental trends can help to address unforeseen areas of public concerns. The need of developing systems to analyze these sentiments and the topics behind them has emerged tremendously. While most existing works reported in the literature have been carried out in English, this paper, in contrast, aims to review recent research works in Arabic language in the field of thematic sentiment analysis and which techniques they have utilized to accomplish this task. The findings show that the prevailing techniques in Arabic topic-based sentiment analysis are based on traditional approaches and machine learning methods. In addition, it has been found that considerably limited recent studies have utilized deep learning approaches to build high performance models.
Keywords: *Sentiment Analysis, Arabic Natural Language Processing, Topic Modeling, LDA, Language modeling.*

1. Introduction

User generated content on the World Wide Web offers the opportunity to reflect and track changing public sentiments and help to develop proactive reactions strategies for decision and policy makers. Analysis of public emotions and opinions towards events and sentimental trends in these user generated data can help to address unforeseen areas of public concerns and develop a subjective language processing thematic analysis to predict emotions of the public in a particular piece of text (e.g., tweets) who are likely to experience disproportionate effects of events or products. This study was motivated by the fact that most of the work on subjective language processing was based on English, and not much attention was on Arabic language. Also, we believe that our results of public emotions towards different events which are basically defined as a "non-trivial thing that happens at a special date/time in a special location" [1], can provide a basis for decision making, and possible adjustments for events or products, instead of building surveys [2]. Sentiment analysis involves categorizing subjective opinions from unimodal or multimodal data to obtain predictions about sentiments, emotions, or state of mind towards predetermined target thematical topics of interest [3]. There is currently a growing interest in utilizing NLP techniques such as sentiment analysis/emotion prediction and topic modeling [4], in association with ML, to mine social media data. Such approaches are currently under-utilized in Arabic language, and there is significant potential in drawing on AI-enabled social-media analysis to inform public policy research. The work on Arabic sentiment analysis was introduced by [5], but comparing to English this field needs more development. Probably, this is due to the challenges pertaining the Arabic language such as multi dialects, complex language morphology, and lack of publicly available tools and resources [6]. To conduct a sentiment analysis task different approaches can be followed in the literature, most of these approaches are sentiment lexicon-based or ML approaches. Recently, the advancement of DL led to significant exploitation in NLP applications such as sentiment analysis task. Most of the work implemented DL in SA are for English language. Reviewing Arabic sentiment analysis literature reveals that out of 209 articles only six articles utilized DL approaches [7]. Most of these works do not implement the recently developed language models based on transformers.

2. Sentiment Analysis Systems

Recently with the rise of Web 2.0, social media platforms, and micro-blogging systems such as Twitter, the amount of textual data with embedded sentiments has tremendously increased. Thus, sentiment analysis has captured the interest of many researchers to build different models to automatically detect users' emotions from these data. Handling people's feedback and opinions is critical to different applications such as better product and advertisement recommendations for customers [8], and tracking emotions towards a specific service or event to take proper responses to keep them satisfied [9]. Social media platforms are rich data resources that also offer the opportunity to reflect, and track changing public sentiments and help to develop proactive reactions strategies for decision and policy makers. Analysis of public emotions and opinions towards events sentimental trends can help to address

Manuscript received September 5, 2021
Manuscript revised September 20, 2021
https://doi.org/10.22937/IJCSNS.2021.21.9.21

unforeseen areas of public concerns. The need of developing classification systems to analyze and handle these sentiments has emerged tremendously. Sentiment analysis or opinion mining is an NLP task concerned with detecting sentiments, emotions, or attitudes towards a certain target like an event, a product, a service, etc. It automatically identifies four components an entity, its aspect, an opinion holder, and opinions sentiment [7]. Textual modality can be used to extract subjectivity information that any emotional experience can arise. Emotion analysis is somehow distinguished from sentiment analysis when using text modality. In the prior, the focus is to extract multiple emotions categories from text (e.g., happiness, sadness, anger, or surprise), while in sentiment analysis the focus is to detect classical valence classification (positive, neutral, or negative) through text analysis [10]. The Application of sentiment analysis has three main levels of granularity based on the target text: document level, sentence level, and entity/aspect level [11]. Sentiment analysis task from a given text is usually a categorical classification task, given an input text, a classifier will predict the sentiment corresponding to this text. The classification process usually starts with the collection and pre-processing of the data to get the data ready for analysis. Then, a model is developed to extract information from these data [12]. To conduct a sentiment analysis task different approaches can be followed in the literature, most of these approaches are sentiment lexicon-based, ML approaches, or hybrid techniques that combine both lexicon-based methods and ML-based methods. The former approach exploits sentiment lexicons to calculate polarities of the extracted sentiment words, while the second aims to develop a new model utilizing traditional ML classifiers or deep learning algorithms, in this approach an annotated data is mapped to feature vectors and trained to build a model able to predict the class of unseen data [7]. Lexicon-based techniques can be dictionary-based or corpus-based. While traditional ML approach can be supervised using algorithms such as Naïve Bayes, neural networks, decision trees, or Support Vector Machine (SVM), unsupervised using clustering algorithms such as k-means [13] or semi-supervised using ensemble approaches such as Random forest, boosting, voting, bagging and stacking. An enhanced taxonomy on the classification of sentiment analysis methods is presented in Figure 1 adopted from [7], which can be adapted to other languages than English like Arabic.

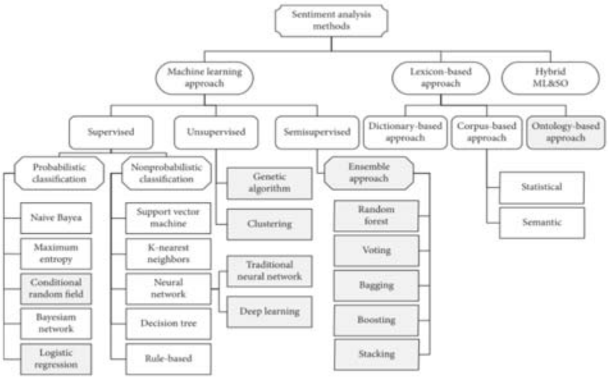

Figure 1 Taxonomy on Classification of Sentiment Analysis Methods

3. Sentiment Analysis in Arabic

Arabic content on the web by Arab users has significantly increased on numerous websites and social media platforms. sentiment analysis is not a trivial task, it involves categorizing subjective opinions from unimodal or multimodal data to obtain predictions about sentiments, emotions or state of mind towards predetermined target thematical topics of interest [3]. There is currently a growing interest in utilizing NLP techniques such as sentiment analysis/emotion prediction and topic modeling [4], in association with ML, to mine social media data. Such approaches are currently under-utilized in Arabic language, and there is significant potential in drawing on AI-enabled social-media analysis to inform public policy research. The work on Arabic sentiment analysis was introduced by [5], but comparing to English this field needs more development. Probably, this is due to the challenges pertaining the Arabic language such as multi dialects, complex language morphology, and lack of publicly available tools and resources [6]. Arabic is spoken in different regions in the world with different dialects, more than 250 million individuals in the Middle East and North Africa have Arabic as their first language. Also, it is the language of the Holy Quran the sacred book of all Muslims around the world. In Arabic written documents, different types of Arabic can be found. Classical Arabic (CA), this type is almost specific to the language used in the Holy Quran, which is based on the dialects of ancient Arab tribes. Another type is the Modern Standard Arabic (MSA), which is the formal type of today's written and spoken Arabic in media, books, papers, and radio. The last type is Colloquial Arabic, which is the Dialectal Arabic (DA) unique from one country to another and sometimes differs from one region to another in the same country, this type is usually used in social media and everyday life and incorporates its own lexicon [14]. Moreover, there is a recent social media trend where users tend to merge English letters and numbers to represent Arabic words. This type is referred to as Arabizi, an example of Arabizi is the word “7ar” which means “Hot” or “حار” pronounces as “Haar” where the number 7 refers to the letter “ح” sounds “Ha” and the remaining letters “ar” complete the pronunciation of the word. Arabic differs from other languages like English, that it is cursive means that words are composed by connecting letters, it also differs being written from right to left. Also, Arabic consists of twenty-eight letters with no capitalization. Writing letters in Arabic can be in different shapes depending on their location in the word, and these letters can be pronounced differently based on diacritics associate these letters in a word which drastically can lead to change the meaning of a word formulated with the same letters. For example, the two words “قَلْبْ” and “قَلَبَ” looking to be the same words but in fact, due to the different diacritics on each letter they become totally different in meanings where the first word means “heart” and the second word means “Flipped”. Moreover, nouns in Arabic have different formats for singular, dual, and plural, as well as pronouns, which vary between masculine and feminine. This complexity in the Arabic language has led to less progress in the Arabic NLP work such as sentiment analysis, although, in the last few years, more research and resources are freely available for this task especially after introducing the Arabic sentiment classification task as one of the shared tasks in the SemEval 2016 workshop [15]. But still, the progress can get even more challenging and harder when applied to Twitter data that are short and sparse without enough contextual information[16]. In addition, these short tweets constitute different sources of noise such as spelling and grammatical mistakes, Twitter-specific tokens like hashtags, and the use of different dialects and non-textual objects [17].

4. Topic Modeling

Topic modeling is an automatic word clustering machine learning technique for a set of documents to identify a set of patterns (topics) in the data based on statistical concepts, where each topic is defined as a distribution over a set of words. These sets of words are first assigned with random probabilities, then running a certain topic modeling algorithm, to update probabilities to infer the latent structure of topics in a document [18].

The modeling process follows unsupervised learning because unlike topic classification models, there is no need for predetermined tags or training data that has been previously labeled by humans [19].

A significant number of micro-blogs are communicated via social media platforms such as Twitter, these unstructured big data are considered a type of electronic word of mouth (eWOM) that several studies utilize to investigate sentiments in particular topics of interest. Thus, recently topic modeling gained great attention in last years as an established method to reveal and annotate large documents with thematic information in many fields like Information Retrieval (IR) and NLP [18]. Detecting topics from Twitter short text have different approaches: with word embeddings vs. without word embeddings, specified vs. unspecified, supervised vs. unsupervised (or semi-supervised), and online vs. offline approaches [1].

4.1 Topic Modeling Approaches

Traditional topic modeling approaches provide methods to identify word patterns that represent text documents and determine their relatedness using the Vector Space Model [20], in this model documents are represented as numeric features with the representation of the degree of similarity based on the distance between them with two different term weighing schemas, Term Frequency (TF) and Term Frequency-Inverse Document Frequency (TF-IDF) [21]. The commonly used language-specific text representation models are bag of words (BoW) representations [22] and Word Embeddings. While recent natural language processing approaches for topic analysis include: 1) latent Bayesian approaches such as Latent Dirichlet Allocation (LDA) and structured Topic Models (STM), 2) neural embedding approaches such as Word2vec, Tweet2vec, MUSE, and Universal Sentence Encoder (USE) [23].

In the first approach using Bayesian probabilities, the relationship is defined between words to latent variables (topics) which basically are probability distribution functions over a set of words. Although STM and LDA are generative unsupervised statistical models and have similar frameworks, STM extends LDA with the capability of observing which topics correlate to each other [19]. Though, LDA in different works has outperformed other models such as Latent Semantic Analysis (LSA) in many fields such as NLP [18]. LDA as one of the most popular topic modeling algorithms has the advantage of not requiring any prior training data and has the ability to discover topics in longer documents including adjectives and nouns. It also can obtain relations between topics in small documents like paragraphs and short sentences. Although, if small documents are used data aggregation is needed to avoid data sparsity. Moreover, the number of topics has to be predefined and has to be sufficient to avoid general topics if this number is small or overlapping topics if the selected number is too large [24].

Research on topic modeling employed different approaches to reveal and annotate large unstructured documents with thematic information. [22] developed a language-independent topic model that learns topics in one language (English) and using cross-lingual contextualized topic modeling with zero-shot learning to predict these topics from unseen documents in different languages (Italian, French, German, and Portuguese). All documents have the same content in different languages, and since all traditional methods are language-specific they replaced the input BOW representations with multilingual contextualized embeddings using SBERT pre-trained model. Their work was based on the Another work utilizing topic modeling is presented in [19], they extracted topics from tourists reviews using the STM approach. Since there is less research on emotions association in the field of tourism [25], constructed an emotion tourism model combining sentiment lexicons and LDA topic modeling. A recent study that combined emotion detection with topic clustering is done by [26], in their work they used the pre-trained BERT model to extract hidden emotional representations in the text along with an LDA topic model to cluster underlying topics. They calculated multi-labels emotional intensity of the sentence using a classification neural network.

4.2 Topic Modeling in Arabic

Although Arabic content is significantly increasing on the web, the application of topic modeling is still in its infancy [27], even though topic-based models outperform models that do not take underlying topics of texts into consideration [28]. Reviewing literature, very few works have been done for context information modeling for emotion detection. [28], analyzed tweets of people in the same community to explore the impact of external factors in emotions. They trained a model to detect underlying topics in tweets using Gated Recurrent Units (GRU) then proposed a Context-aware Gated Recurrent Units (C-GRU) that uses this contextual information (topics) and use them as an extra layer to classify emotions conveyed by the tweet. They also investigated transferring knowledge using supervised transfer learning, which could overcome the limitations of the conventional methods of topic detection that rely on words occurrences. Due to the shortness of tweets and sparseness in word occurrences, the traditional approach might be ineffective [1]. Topic modeling and event detection in Arabic have been presented in some significant works, [18] have applied a combined approach to cluster documents and topics and a dataset of Modern Standard Arabic (MSA) of 2700 news documents of different 9 topics. They have applied the LDA algorithm, the output probability of detected topics is then mean-normalized, and then the k-means clustering algorithm is applied. Their model was evaluated on 5 news datasets, with the result that combining LDA, and k-means outperforms using k-means solely. Another work that complies with the same finding that combining the k-means algorithm with LDA produces much higher performance results for clustering Arabic text documents is presented by [29], where they applied their system on Arabic new text from several websites. Other work by [30], presented a framework for Arabic event detection from social media, they have utilized over 16 million Arabic tweets. After these tweets are collected, they went through pre-processing, classification, (temporal, spatial, and textual) feature selection, topic clustering, and summarization. After that, they have applied LDA to compare their results, and found that LDA could not perform well on tweets due its shortness.

5. Topic-based Sentiment Analysis

The expansion of the world wide web has led to a huge amount of user generated content over different forums and social media platforms, these rich data resources offer the opportunity to reflect, and track changing public sentiments and help to develop proactive reactions strategies for decision and policy makers. Analysis of public emotions and opinions towards events and sentimental trends can help to address unforeseen areas of public concerns. Social media platforms such as Twitter provides rich sentimental discussed and debated social topics. We argue that such data provided by these platforms can provide significant social support with considerable spatiotemporal granularity, although this data is largely unstructured, with the application of established AI techniques such as NLP, machine learning (ML), and deep learning (DL) techniques it is amenable to analyze it on a large scale and identify trends in topics and public emotions [3]. Artificial intelligence (AI) can enable an instant analysis of public opinions and attitudes to a specific context. Different research works have applied these techniques to extract this information automatically, [25] have developed a sentiment classification model of tourism using a hybrid method to combine Naïve Bayes algorithm with tourism emotional lexicon, then an LDA topic model was used for corpus clustering to correct the classification model to generate a model suitable for multi-class topics. They argued that current models on sentiment analysis in the field of tourism are limited with classification accuracy need to be improved. [31] also contributed to the field of tourism topic-based sentiment analysis focusing on under-emphasized tourism locations to discover the latent topics using LDA and SVM algorithms for sentiment analysis. Their results show that combined different features enhanced performance in this task. Topic-based sentiment analysis aims to evaluate opinions and sentiments towards a specific event and extract the underlying topics discussed that event. Where events are basically defined as a “non-trivial thing that happens at a special date/time in a special location” [1]. This explains that recent research works on topic-based sentiment analysis were mostly on the outbreak pandemic of COVID-19 virus that invaded the world in late 2019 causing health and economic devastating situations. [32] utilized Twitter discussions to understand people’s opinions about the pandemic and their hidden topics of concern over a long period timeline in different locations, the study revealed twenty topics using LDA and analyzed changing sentiments and opinions on these topics over time with corresponding reasons behind the change along with spatial analysis to analyze top tweeting countries. Then a sentiment analysis was performed at both spatial/temporal levels. The study results showed that implementing pooling before applying LDA yields a more topic coherence and can significantly improve generated topic models. Another research work by (Abdulaziz *et al.*, 2021) also utilized tweets to extract topics discussed during two different periods of the Coronavirus and their corresponding sentiments, they have applied LDA for topic modeling and a lexicon-based approach for sentiment analysis. More works on Covid-19 were carried by [34] confirming that 60% of social media users has positive sentiments towards remote work during COVID-19, their work was based on using K-means, an unsupervised ML approach to identify topics related to remote work from collected tweets. And Naïve Bayes algorithm for sentiment analysis as a supervised method. [35] analysed topics and sentiment dynamics about COVID-19 in tweets to infer people's mental health. For generating topic models, they have used Dynamic Topic Model (DTM), while they utilized VADER a sentiment lexicon tool to infer the associated sentiment polarities in each topic.

6. Topic-based Sentiment Analysis in Arabic

Although topic modeling as an area of research has been actively evolving over the years, its application on the Arabic text is still lagging despite the increase of the Arabic content on the web. Recently, research works have implemented sentiment-topic modeling based on the insight that similar sentimental topics/events might trigger similar sentiments or opinions in the same public community. Where, a sentimental event is "an event that draws opinionated responses from the community" [36]. These works main objective was to detect the sentiment for a given topic and to understand the overall sentiment of an input document. Reviewing literature revealed very little work on this thematic sentiment analysis for the Arabic language combining two different text mining techniques of sentiment analysis and topic modeling [36] aimed at detecting sentimental events from Arabic tweets by associating a topic with a timeline frame that lists positive/negative frequencies of these topics over a period of time. [37] proposed a new approach of topic-based sentiment analysis through representing short texts based on concepts instead of terms assuming that terms belonging to the same topic share the same semantics in the dataset, this means that their corresponding concepts will also share the same semantics. Their main issue in short text conceptualization was the coverage ratio of Arabic semantic resources, therefore, they integrated LDA topic model as a tool to assist in bringing together terms with the same semantic links to their corresponding concepts after mapping terms to their corresponding concepts in BabelNet is not covered this is done until the nearest term in the same topic is mapped to a concept. They tested and evaluated their approach on the LARB dataset one of the largest sentiment analysis datasets for Arabic represented as a Bag of Concepts BoC, using machine learning algorithms for text categorization: Naïve Bayesian (NB), Decision Tree (DT), and Support Vector Machine (SVM) with promising results. Some studies used thematic sentiment analysis to determine the sentimental topics of discussion on Twitter Arabic datasets, [38] analyzed Arabic Moroccan tweets to identify sentiments and visualize the topics behind these tweets. For sentiment detection, they applied the Textblob library [39] a lexicon-based method that calculates the polarity score of the range [-1, 1] where negative polarities represent negative sentiment and positive polarities represent positive sentiment. For topic detection they have used two of the most popular algorithms: Non-negative Matrix Factorization (NMF) and Latent Dirichlet Allocation (LDA). Their results show that LDA outperformed NMF except with the runtime.

This study suggested to improve their approach of topic-based sentiment analysis by utilizing deep learning algorithms. (A. R. Alharbi et al., 2020), applied text classification on Arabic news web pages, their work relied on LDA and neural networks. They effectively eliminated the problem of documents representations using vector space model n-gram term-document vectors with their high dimensionality and lack of structure. Thus, they passed these vectors to the LDA algorithm for a better syntactic and semantic representation of text documents through extracting hidden topics from all the text documents where each subject is defined by the probability of the word spread to further express each text on the vectors of such topics. These probability dimensions are then fed to an Artificial Neural Network (ANN) to build a classification model. Their classification model was validated using the ten-fold cross validation strategy repeated two times resulting in 85.11% as the best accuracy result. Another study by [41], also applied a topic-based sentiment analysis on several Moroccan Facebook pages where they implemented a supervised approach using Naïve Bayes to extract the sentiments and an unsupervised approach using LDA algorithm to retrieve topics of the text, then they combined the two models in a semi-supervised approach to associate each topic to a specific sentiment. [16] used LDA along with other representation models such as Bag of Words (BoW), Latent Semantic Analysis (LSA) and Probabilistic Latent Semantic Analysis (PLSA) on Arabic sentiment analysis task. They evaluated their approach on a dataset collected from Twitter and found that BoW outperformed the other models.

Author	Dataset	Topic Modeling Technique	Sentiment Analysis Technique
[38]	Moroccan dialectal Arabic tweets	LDA, NMF	Textblob
[42]	News articles from Sahifat Sabaq, Was news, Maroof Craft websites	LDA	Artificial Neural Network (ANN)
[16]	MSA tweets	LDA, LSA, PLSA, BoW	Naïve Bayes (NB), Support Vector Machine (SVM)
[37]	Reviews from www.goodreads.com, LARB	LDA, BoC	Naïve Bayes (NB), Support Vector Machine (SVM) and Decision Trees (DT)
[41]	Moroccan dialectal Arabic from Facebook	LDA	Naïve Bayes (NB)

Table 1 Reviewed articles on Arabic Topic-based Sentiment Analysis

7. Discussion and Future Directions

The goal of this survey is to provide interested researchers an overview of current works dealing with Arabic thematic sentiment analysis from NLP perspective. Hence, literature was reviewed to explore techniques used in these studies, challenges, and limitations. Based on the papers reviewed, some future research directions and opportunities are listed below:

(i) A limited number of published papers in the field of Arabic thematic sentiment analysis indicates that this domain needs to gain more attention from multi-disciplinary researchers.

(ii) Arabic thematic sentiment analysis literature does not cover all types of Arabic dialects, there is a lack of standardized benchmark datasets for different dialects for this task, most of the work relied on self-collected data. Constructing and building a corpus freely available to the NLP research community will be a significant contribution and will unify the conducted experiments and obtained results.

(iii) Regarding computing techniques some methods are discussed heavily than others. For instance, supervised methods such as classification techniques were mainly utilized. This gives an opportunity for future work to explore new directions such as the emerging deep learning approaches.

(iv) Current research has limited domains explored, there is an opportunity for other significant domains like health care, education, and tourism to be investigated with the cooperation of field experts and NLP researchers.

(v) Topic modeling techniques utilized in the literature somehow relied on traditional approaches, a research opportunity for developing a language-independent topic model that learns topics in one language (English) for instance and using cross-lingual contextualized topic modeling with zero-shot learning to predict these topics from unseen documents in different languages such as Arabic. Since all traditional methods are language-specific researchers can replace the traditional input representations with multilingual contextualized embeddings e.g., multilingual SBERT pre-trained model.

(vi) Finally, future research activities in this field could establish multi-lingual corpus for this task.

8. Conclusion

In this review paper, we have investigated how recent Arabic research works have combined sentiment analysis techniques with topic modeling algorithms for analyzing Arabic text to extract trending topics and the sentiments they carry. From the review analysis, the most topic modeling approach used was LDA for topics and events extraction and grouping them into similar clusters. For sentiment analysis, most of the papers have applied traditional machine learning methods, although these models have performed significantly well, there is still a need to compare these techniques with established deep learning (DL) techniques to analyze sentiments and identify public emotions on a large scale. Also, future work needs to analyze different domains like education and tourism.

References

[1] Z. Mottaghinia, M.-R. Feizi-Derakhshi, L. Farzinvash, and P. Salehpour, 'A review of approaches for topic detection in Twitter', *J. Exp. Theor. Artif. Intell.*, pp. 1–27, Jun. 2020, doi: 10.1080/0952813X.2020.1785019.

[2] A. Alharbi, M. Taileb, and M. Kalkatawi, 'Deep learning in Arabic sentiment analysis: An overview', *J. Inf. Sci.*, vol. 47, no. 1, pp. 129–140, Feb. 2021, doi: 10.1177/0165551519865488.

[3] A. Hussain *et al.*, 'Artificial intelligence-enabled analysis of UK and US public attitudes on Facebook and Twitter towards COVID-19 vaccinations', *medRxiv*, 2020.

[4] X. Chen and H. Xie, 'A Structural Topic Modeling-Based Bibliometric Study of Sentiment Analysis Literature', *Cogn. Comput.*, vol. 12, no. 6, pp. 1097–1129, Nov. 2020, doi: 10.1007/s12559-020-09745-1.

[5] M. Abdul-Mageed, M. Diab, and M. Korayem, 'Subjectivity and sentiment analysis of modern standard Arabic', in *Proceedings of the 49th Annual Meeting of the Association for Computational Linguistics: Human Language Technologies*, 2011, pp. 587–591.

[6] S. Basabain, 'Text-based Arabic Emotion Detection Challenges and Effective Approaches: A Review of the State-of-the-Art', Mar. 2021.

[7] A. Ghallab, A. Mohsen, and Y. Ali, 'Arabic Sentiment Analysis: A Systematic Literature Review', *Appl. Comput. Intell. Soft Comput.*, vol. 2020, p. e7403128, Jan. 2020, doi: 10.1155/2020/7403128.

[8] S. M. Mohammad, Tony, and Yang, 'Tracking Sentiment in Mail: How Genders Differ on Emotional Axes', *ArXiv13096347 Cs*, Sep. 2013, Accessed: Feb. 03, 2021. [Online]. Available: http://arxiv.org/abs/1309.6347

[9] J. Li, Y. Rao, F. Jin, H. Chen, and X. Xiang, 'Multi-label maximum entropy model for social emotion classification over short text', *Neurocomputing*, vol. 210, pp. 247–256, Oct. 2016, doi: 10.1016/j.neucom.2016.03.088.

[10] T. Henriques, S. Silva, S. Brás, S. C. Soares, N. Almeida, and A. Teixeira, 'Emotionally-aware multimodal interfaces: Preliminary work on a generic affective modality', 2018, pp. 80–87.

[11] I. Abu Farha and W. Magdy, 'A comparative study of effective approaches for Arabic sentiment analysis', *Inf. Process. Manag.*, vol. 58, no. 2, Art. no. 2, Mar. 2021, doi: 10.1016/j.ipm.2020.102438.

[12] K. M. Nahar, M. Ra'ed, M. Al-Shannaq, M. Daradkeh, and R. Malkawi, 'Direct text classifier for thematic arabic discourse documents.', *Int Arab J Inf Technol*, vol. 17, no. 3, pp. 394–403, 2020.

[13] A. Alharbi, M. Taileb, and M. Kalkatawi, 'Deep learning in Arabic sentiment analysis: An overview', *J. Inf. Sci.*, vol. 47, no. 1, Art. no. 1, Feb. 2021, doi: 10.1177/0165551519865488.

[14] A. Althagafi, G. Althobaiti, H. Alhakami, and T. Alsubait, 'Arabic Tweets Sentiment Analysis about Online Learning during COVID-19 in Saudi Arabia', *Int. J. Adv. Comput. Sci. Appl.*, pp. 620–625, 2021.

[15] M. Gridach, H. Haddad, and H. Mulki, *Empirical Evaluation of Word Representations on Arabic Sentiment Analysis*. 2017.

[16] M. Bekkali, 'Arabic Sentiment Analysis using Different Representation Models', *Int. J. Emerg. Trends Eng. Res.*, vol. 8, Aug. 2020, doi: 10.30534/ijeter/2020/79872020.

[17] R. Baly *et al.*, 'OMAM at SemEval-2017 Task 4: Evaluation of English State-of-the-Art Sentiment Analysis Models for Arabic and a New Topic-based Model', in *Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017)*, Vancouver, Canada, Aug. 2017, pp. 603–610. doi: 10.18653/v1/S17-2099.

[18] M. Alhawarat and M. Hegazi, 'Revisiting K-Means and Topic Modeling, a Comparison Study to Cluster Arabic Documents', *IEEE Access*, vol. 6, pp. 42740–42749, 2018, doi: 10.1109/ACCESS.2018.2852648.

[19] E. Christodoulou, A. Gregoriades, M. Pampaka, and H. Herodotou, 'Combination of Topic Modelling and Decision Tree Classification for Tourist Destination Marketing', in *Advanced Information Systems Engineering Workshops*, Cham, 2020, pp. 95–108. doi: 10.1007/978-3-030-49165-9_9.

[20] G. Salton, A. Wong, and C.-S. Yang, 'A vector space model for automatic indexing', *Commun. ACM*, vol. 18, no. 11, pp. 613–620, 1975.

[21] H. M. Alghamdi and A. Selamat, 'Topic detections in Arabic Dark websites using improved Vector Space Model', in *2012 4th Conference on Data Mining and Optimization (DMO)*, Sep. 2012, pp. 6–12. doi: 10.1109/DMO.2012.6329790.

[22] F. Bianchi, S. Terragni, D. Hovy, D. Nozza, and E. Fersini, 'Cross-lingual Contextualized Topic Models with Zero-shot Learning', *ArXiv200407737 Cs*, Feb. 2021, Accessed: Mar. 05, 2021. [Online]. Available: http://arxiv.org/abs/2004.07737

[23] J. Brandt *et al.*, 'Identifying social media user demographics and topic diversity with computational social science: a case study of a major international policy forum', *J. Comput. Soc. Sci.*, vol. 3, no. 1, pp. 167–188, Apr. 2020, doi: 10.1007/s42001-019-00061-9.

[24] R. Albalawi, T. H. Yeap, and M. Benyoucef, 'Using topic modeling methods for short-text data: A comparative analysis', *Front. Artif. Intell.*, vol. 3, p. 42, 2020.

[25] B. Chen, L. Fan, and X. Fu, 'Sentiment Classification of Tourism Based on Rules and LDA Topic Model', in *2019 International Conference on Electronic Engineering and Informatics (EEI)*, 2019, pp. 471–475.

[26] F. Ding, X. Kang, S. Nishide, Z. Guan, and F. Ren, 'A fusion model for multi-label emotion classification based on BERT and topic clustering', in *International Symposium on Artificial Intelligence and Robotics 2020*, Oct. 2020, vol. 11574, p. 115740D. doi: 10.1117/12.2579255.

[27] A. Rafea and N. A. GabAllah, 'Topic Detection Approaches in Identifying Topics and Events from Arabic Corpora', *Procedia Comput. Sci.*, vol. 142, pp. 270–277, 2018, doi: 10.1016/j.procs.2018.10.492.

[28] A. E. Samy, S. R. El-Beltagy, and E. Hassanien, 'A Context Integrated Model for Multi-label Emotion Detection', in *Arabic Computational Linguistics*, vol. 142, K. Shaalan and S. R. ElBeltagy, Eds. Amsterdam: Elsevier Science Bv, 2018, pp. 61–71. doi: 10.1016/j.procs.2018.10.461.

[29] A. R. Alharbi, M. Hijji, and A. Aljaedi, 'Enhancing topic clustering for Arabic security news based on k-means and topic modelling', *IET Netw.*, 2021.

[30] N. Alsaedi, P. Burnap, and O. Rana, 'Sensing real-world events using Arabic Twitter posts', 2016.

[31] W. Shafqat and Y.-C. Byun, 'A recommendation mechanism for under-emphasized tourist spots using topic modeling and sentiment analysis', *Sustainability*, vol. 12, no. 1, p. 320, 2020.

[32] I. AlAgha, 'Topic Modeling and Sentiment Analysis of Twitter Discussions on COVID-19 from Spatial and Temporal Perspectives', *J. Inf. Sci. Theory Pract.*, vol. 9, no. 1, pp. 35–53, 2021.

[33] M. Abdulaziz, M. Alsolamy, A. Alotaibi, and A. Alabbas, 'Topic based Sentiment Analysis for COVID-19 Tweets'.

[34] S. Wrycza and J. Maślankowski, 'Social media users' opinions on remote work during the COVID-19 pandemic. Thematic and sentiment analysis', *Inf. Syst. Manag.*, vol. 37, no. 4, pp. 288–297, 2020.

[35] H. Yin, S. Yang, and J. Li, 'Detecting topic and sentiment dynamics due to COVID-19 pandemic using social media', in *International Conference on Advanced Data Mining and Applications*, 2020, pp. 610–623.

[36] M. Daoud and N. A. Daoud, 'Sentimental event detection from Arabic tweets', *Int. J. Bus. Intell. Data Min.*, vol. 17, no. 4, p. 471, 2020, doi: 10.1504/IJBIDM.2020.110378.

[37] M. Bekkali and A. Lachkar, 'Arabic Sentiment Analysis based on Topic Modeling', in *Proceedings of the New Challenges in Data Sciences: Acts of the Second Conference of the Moroccan Classification Society*, Kenitra Morocco, Mar. 2019, pp. 1–6. doi: 10.1145/3314074.3314091.

[38] N. Habbat, H. Anoun, and L. Hassouni, 'Topic Modeling and Sentiment Analysis with LDA and NMF on Moroccan Tweets', *Innov. Smart Cities Appl. Vol. 4*, vol. 183, p. 147, 2021.

[39] S. Loria, 'textblob Documentation', *Release 015*, vol. 2, 2018.

[40] A. R. Alharbi, S. D. Alharbi, A. Aljaedi, and O. Akanbi, 'Neural Networks Based on Latent Dirichlet Allocation For News Web Page Classifications', in *2020 IEEE 2nd International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, Sep. 2020, pp. 1–6. doi: 10.1109/IICAIET49801.2020.9257842.

[41] T. Zarra, R. Chiheb, R. Moumen, R. Faizi, and A. E. Afia, 'Topic and sentiment model applied to the colloquial Arabic: a case study of Maghrebi Arabic', in *Proceedings of the 2017 International Conference on Smart Digital Environment*, Rabat Morocco, Jul. 2017, pp. 174–181. doi: 10.1145/3128128.3128155.

[42] A. R. Alharbi, S. D. Alharbi, A. Aljaedi, and O. Akanbi, 'Neural Networks Based on Latent Dirichlet Allocation For News Web Page Classifications', in *2020 IEEE 2nd International Conference on Artificial Intelligence in Engineering and Technology (IICAIET)*, Sep. 2020, pp. 1–6. doi: 10.1109/IICAIET49801.2020.9257842.