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Evaluation of Society Response to Violence against Women in Turkey via Twitter using Topic Modeling

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Abstract

In recent times, people's reactions to violence against women, harassment and murder have been shared more and more, thanks to social media. This, in turn, led to the organization of people and increased awareness of violence against women. Inspired by this study, it focuses on subject modeling techniques to determine people's perspectives on violence against women, which is growing day by day. Opinions from users about violence against women are collected using the social media platform Twitter in order to analyze the reaction of the society. After the preprocessing stage, Turkish tweets are analyzed using Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), Hierarchical Dirichlet Process (HDP), Non-Negative Matrix Factorization (NMF) techniques. The results of the experiment show that the LDA technique significantly reveals the reaction of the society to violence against women and social awareness in Turkey.

1. Introduction

Violence against women is an important public health problem that can cause loss of workforce and even death in women and requires health care, as well as being a widespread social problem that is increasing day by day in society [1-2]. According to a report published by the World Health Organization in 2013 [3], approximately one-third (35%) of women worldwide experience physical and/or sexual violence. The same report also states that up to 38% of femicides worldwide are committed by a male partner. According to the 2002 report [4] in which the World Health Organization analyzed 48 studies conducted in different parts of the world, it was determined that 10-69% of women were exposed to physical violence by their husbands or partners at least once in their lives.

Social networks have a serious place in our daily life. Users evaluate their time using social platforms such as Twitter, Facebook or Instagram. For this reason, the continuous use of social media platforms by millions of people has become a common research area and data source for researchers. The main reason for this is that the data is published on these platforms in different types such as images, texts, videos, in large volumes, by millions of people at the same time. For this reason, researchers or institutions who see Twitter as a data source and advantage, or profit factor have sought different ways to analyze the data [5-6]. Therefore, in this paper, we propose to analyze the responses of women to violence against women by extracting the views of people on Twitter with topic modeling techniques.

Topic modeling is an unsupervised approach to finding groups of words called topics in a text document. These topics consist of words that often appear together and often share a common theme. Therefore, with a predefined set of words, these topics can be used as a group of words to best

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describe the entire document. Topic modeling facilitates us with different methods for organizing, understanding, and summarizing large collections of text data. In this study, Latent Semantic Analysis (LSA) [7-9], Latent Dirichlet Allocation (LDA) [10-12], Hierarchical Dirichlet Process (HDP) [13-15], Non-Negative Matrix Factorization (NMF) [16-18] methods are employed as topic modeling algorithms to determine people's perspective and requests on violence against women.

The remainder of this document is organized as follows: Chapter 2 provides a summary of work on issue modeling and machine learning approaches to violence issues. Chapter 3 explains the proposed framework. Chapters 4 and 5 present the experimental results and results, respectively.

2. Related Work

This section provides a brief summary of the limited computer science studies on violence against women.

In [19], Rodríguez-Rodríguez et. al propose to estimate and model gender-based violence (GBV) with the help of machine learning techniques. Authors evaluate the possibility of predicting the reports of gender violence with acceptable accuracy employing the most suitable technique for selecting variables and the most successful algorithm to get higher prediction performance. In order to demonstrate the effectiveness of the proposed model data set is gathered from January 2009 to September 2019 in Spain. Then, the training procedure is applied with Linear Regression (LR), Support Vector Machines (SVM), Random Forest (RF) and Gaussian Process (GP) models. Experiment results show that the combination of Multi-Objective Evolutionary Search Strategy (MOES) and RF is the best model for estimating GBV. In [20], Xue et. They evaluate the covert domestic violence epidemic during COVID-19 by presenting a broad analysis of the public discourse on domestic violence on Twitter. For this purpose, 1 million tweets about domestic violence and COVID-19 were collected between April 12 and July 16, 2020. Like our study, the authors focus on the unsupervised learning approach, using the Hidden Dirichlet Allocation (LDA) model to find prominent themes and topics. As a result of the study, the authors reveal 9 themes from nearly 1 million tweets about domestic violence and the COVID-19 pandemic. The results strikingly reflect the reason behind domestic violence and the COVID-19 pandemic.

In [21], Bello et. al concentrate on machine learning methodology to investigate the impact of gender-based violence in the Spain news media. Authors collect about 800,000 news from January 2005 to March 2020 by specifying class labels such as feminism, technology, economy, politics, etc. After determining the relation between news and GBV, two consecutive neural network models are applied. Experiment results indicate that there is a clear relationship between GBV news and public consciousness, the effect of mediatic GBV cases, and the intrinsic thematic relationship of GBV news. In [22], Amusa et. al propose to forecast the vulnerability of women to intimate partner violence (IPV) in South Africa by employing machine learning techniques. For this purpose, South African demographic and health survey dataset that is constructed with contribution of 1,816 ever-married women, carried out in the experiments. In addition to regression analysis, authors also focus on decision trees both classification and regression purpose, random forest, and gradient boosting techniques to determine patterns and relationships in the data set. Among these models, random forest exhibits the superior performance to find the correlation between IPV and the fear of the husband.

In [23], Xue et. al investigate domestic violence topics on Twitter with the help of data mining methods. Thus, the authors propose to explore hidden subjects and thematic structures among domestic violence-related texts on the Twitter platform. To analyze, 322,863 comments are gathered utilizing the “domestic violence” tag. To discover domestic violence topics, LDA approach is proposed. They conclude the study that the most common 20 pairs of words are “violence awareness,” “Greg Hardy,” “awareness month,” “victims domestic,” “stop domestic,” and “Ronda Rousey”. This work also demonstrates the viability of employing topic-modeling techniques for detecting gender-based violence data on Twitter. In [24], Frenda et. al propose to automatically identify misogyny and sexism on Twitter by analyzing online hate speech against women. For this purpose, authors classify English tweets as misogynistic and sexist. The authors conclude the paper that the proposed approach can determine the two sides of patriarchal behavior, misogyny, and sexism, evaluating three collections of English tweets, and acquiring promising results.

Our study differs from the aforementioned literature works in terms of analyzing violence against women with various topic modeling techniques such as Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), Hierarchical Dirichlet Process (HDP), Non-Negative Matrix Factorization (NMF) that provides the performance comparison. Moreover, this is the first attempt in terms of analyzing Turkish tweets related to violence against women and public awareness in Turkey by employing natural language processing techniques.

3. Proposed Framework

In this section of the study, topic modeling algorithms to be used in the construction of the proposed models, collection of the data set, pre-processing methods, and proposed model are mentioned.

3.1. Latent Semantic Analysis (LSA)

Latent Semantic Analysis, or LSA, is one of the fundamental methods in subject modeling. The main idea is to create a matrix of documents and terms and decompose it into a standalone document-subject matrix and a subject-term matrix. The first step is to create a document term matrix.

Given x documents and y words in the vocabulary, the x × y matrix can be constructed in which each row demonstrates a document, and each column indicates a word. In the plain version of LSA, each input can simply be a raw count of the number of times the j-th word seemed in the i-th document. In practice, however, raw counts do not work especially well because they do not account for the importance of each term in the document. For example, the term “5G” surely notifies more about the topics of a given document than the term “model.” Consequently, LSA models generally substitute raw counts in the document-term matrix with a term frequency-inverse document frequency (tf-idf) score.

Once getting the document-term matrix, it is come across that the matrix is quite sparse, rather noisy, and somewhat redundant across its many dimensions. Consequently, to discover the few latent topics that find the relations among the words and documents, it is required that to conduct dimensionality reduction on the x × y matrix. In this paper, dimension reduction is performed using truncated singular value decomposition (SVD), which is a technique in linear algebra that factorizes any matrix M into the product of 3 separate matrices: M=U × S × V where S is a diagonal matrix of the singular values of M. U means document-topic matrix, and V implies term-topic matrix. After that, cosine similarity is evaluated to assess the similarity of different documents, the similarity of different words and the similarity of terms and documents.

3.2. Latent Dirichlet Allocation (LDA)

Latent Dirichlet Allocation (LDA) is a generative statistical technique that allows clusters of observations to be identified by unobserved clusters, which explains why parts of the data are similar. For instance, if the observations are terms gathered into documents, it assumes that each document is a combination of a small number of topics and that the existence of each term is intrinsic to one of the topics of documents. Moreover, LDA is a kind of unsupervised learning technique that assesses documents as bag of words. That is, LDA ignores the order of terms in a document. LDA works by producing a document in two ways: choosing a set of topics and a set of words for each topic. Thus, there are 2 parts to be determined in LDA. The first one is that the terms/words that belong to a document. The second part is that the words that pertain to a topic or the probability of terms pertaining to a topic, that it is required to compute.

LDA demonstrates documents as a consolidation of topics. Likewise, a topic is a combination of words. If a word has a high probability of being in a topic, all the documents containing the word "w" will be more heavily involved with topic "t" as well. Like this, if the word "w" is not very possible to be in the topic "t", the documents which include the word "w" will be comprising very low probability of being in topic "t", because remnants of the words in the document "d" will pertain to some another topic and thence document "d" will have a higher probability for those topics. In the order to find the words that pertain to a topic or the probability of words pertaining to a topic, the proportion of words in document d that are assigned to topic t is calculated as a first step. This calculation finds how many terms pertain to the topic "t" for a given document "d". As a next step, the proportion of assignments to topic "t" over all documents is computed that come from the word "w". This presents how many documents are in topic "t" due to the word "w". Finally, the probability for the word "w" pertain to topic "t" is updated by multiplying the outputs of step 1 and step 2.

3.3. Hierarchical Dirichlet Process (HDP)

Standard parametric topic models such as LDA confront the difficulty of specifying the number of topics. The nonparametric topic modeling concept defeats this problem exploiting Bayesian nonparametric, in which the number of topics does not require to be specified previously and can be deduced from the data. The hierarchical Dirichlet Process which is an expansion of the LDA model can conduct as well as the best LDA model in terms of perplexity while doing so without any model selection process. The main structure stone of HDP is the Dirichlet process (DP), a probability distribution of discrete distributions over the topic space. Topic modeling necessitates the topics to be agreed upon both within each document and across different documents. In order to meet sharing topics across different documents, HDP extends the DP approach. This way, it is capable of topic sharing across different documents by putting into practice a shared DP prior to the basis distributions of the DPs for each document.

3.4. Nonnegative Matrix Factorization (NMF)

The non-negative matrix approach is a set of algorithms in multivariate analysis and linear algebra where a matrix M is generally resolvable into factors by providing two matrices N and R, with the characteristic that there are no negative elements in all three matrices. The non-negativity allows the result matrices simpler to examine. NMF is applied in such fields as astronomy, computer vision, document clustering, missing data imputation, chemometrics, audio signal processing, and bioinformatics, etc.

NMF is a kind of unsupervised machine learning like other topic modeling methods. The main cornerstone of unsupervised learning is the quantification of the distance between the elements. The distance between elements is calculated by different methods such as generalized Kullback–Leibler divergence, Frobenius norm, etc. Generalized Kullback–Leibler divergence, statistical measurement, is employed to quantify how one distribution is varied from another. If the value of divergence is less which means the value of Kullback–Leibler divergence is close to zero, the proximity of the correspondent terms increases.

In addition to generalized Kullback–Leibler divergence, Frobenius norm is also employed for NMF. In addition to generalized Kullback–Leibler divergence, Frobenius norm is also employed for NMF. Frobenius norm, aka euclidean norm, is described by the square root of sum of absolute squares of its elements. In topic modeling, non-negative matrix factorization, a statistical method, is applied for the purpose of decreasing the dimension of the input corpus. Thence, NMF employs the technique of factor analysis in order to ensure rather less weight to the terms with less coherency. Assume that, there is an input matrix M of shape a x b. Through NMF, M is factorized into two matrices namely, N and R, such that the dimension of N is a x b and that of R is c x d. In this situation, M demonstrates the term document matrix. This means each row of matrix R is a word embedding and each column of the matrix N shows the weight of each term obtained from each sentence. Thus, the relationship between words with each sentence is obtained semantically.

3.5. Proposed Model

In this section, we introduce the proposed framework for the purpose of evaluating society's reaction to violence against women in Turkey through Twitter using four different topic modeling techniques. As a first step, we focus on data gathering. In order to analyze the Turkish user comments related to violence against women, the dataset is constructed through the Twitter social media platform. For this purpose, different hashtags are determined and crawled employing Selenium crawler. Hashtags are chosen on words that evoke violence against women, and sometimes they are collected with the names of women who are the subject of women's murders. These include KadinaSiddeteHayir, KadinaSiddet, KadinCinayeti, KadinaSiddeteDurDe, İstanbulSözleşmesi, İstanbulSözleşmesiYaşatır, KadinaŞiddeteTepkisizKalma, KadinKatliamıVar, İstanbulSözleşmesiniUygula, İstanbulSözleşmesindenVazgeçmiyoruz hashtags, etc. In total, 67,751 Turkish comments are gathered utilizing more than 25 hashtags between June 2011 and December 2020. However, not enough comments are allowed to be taken by TwitterScraper and Twitter API, we focus on Selenium crawler. Thanks to the Selenium crawler, the limitation problem about downloading and gathering Turkish tweets from Twitter is overcome.

After gathering the raw dataset from Twitter, preprocessing step is initialized in order to clean noise from the dataset. Another reason behind performing pre-processing stage is to obtain more precise results. For this purpose, stop word elimination, removing hashtags, removing URLs, punctuation mark cleaning, removing non-alphanumeric symbols, and facial expression cleaning (emojis) are conducted. In this study, the process of dividing words into their roots (stemming) is not employed as a pre-processing technique, because when the word is separated into its root, it can lead to a positive change in meaning or a negative loss of meaning. For example, when we think of the word "ölmesin" (do not die), which is very related to the subject, the root of the word is "öl" (die). However, the original of the word contains the meaning of negativity. Loss of meaning occurs when the word is separated from other suffixes. This, in turn, can be misleading when society's response to violence against women wants to be measured. Because of this reason, stemming is not included in the pre-processing procedure.

After the pre-processing stage, the document-term matrix is separately constructed by employing the term-frequency (tf) approach for both unigrams and bigrams. Thence, each term or component demonstrates the count of each unigram or bigram that occurs in each of the Twitter comments. In modelling stage, four different topic models namely, latent semantic analysis (LSA), latent Dirichlet allocation (LDA), nonnegative matrix factorization (NMF), hierarchical Dirichlet process (HDP) are evaluated in order to detect the perception of society on violence against women in Turkey. Especially since literature studies on violence against women mostly focus on LDA or LSA models, we make a comprehensive comparison by including other models in this study. We also investigate the impact of other topic models on determining the reaction of society to violence against women in Turkey. In order to analyze the effect of topic modeling techniques, eight topics are assessed. To compare the performance of different models, topic coherence is evaluated as an evaluation metric. C_v coherence measure is employed in the experiments to demonstrate coherence value between topics. Moreover, hyperparameter tuning is performed in order to get the best results when alpha is 0.01, beta is 0.9, and number of topics is set to 8. All experiments are performed with Python programming language using 3.6.8 version. In addition to comparing different topic models in terms of topic coherence value, we also analyze the effect of unigrams and bigrams on the best performed topic model. As a first step, each model is assessed on unigram model. After determining best topic model, the effect of bigram is investigated. A general flow chart of the proposed model is presented in Figure 1.

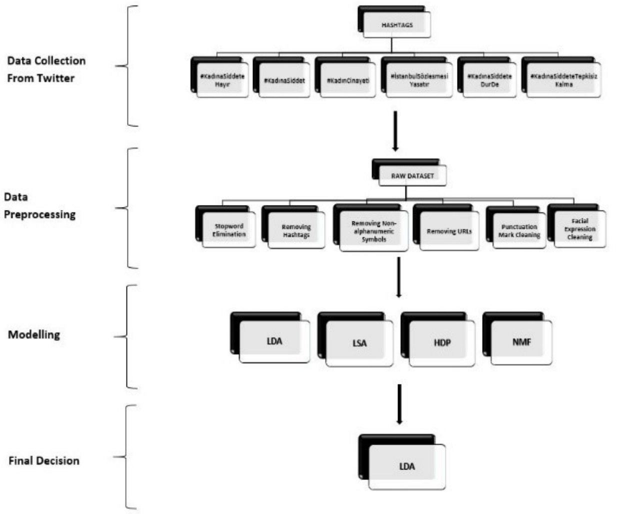

Figure 1. A general flow chart of the proposed model.

4. Experiment Results

In this section, we present the comprehensive experiment results. Our aim is to explore the conversations and discussions about violence against women in Turkey on Twitter. For this purpose, we utilize four different topic model techniques to analyze latent topics related to violence against women in a dataset of tweets. Especially, we aim to find answer several research questions with regard to Twitter postings that include violence against women.

i) What are the most common terms in the whole dataset?

ii) Are the terms about violence against women tend to comprise together?

iii) What topics about violence against women arise most constantly?

iv) On what topics does the whole data set center?

In this paper, we focus on eight topics to analyze the effect of topic modeling techniques. In order to compare the performance of different models, topic coherence is assessed as an evaluation criterion. Topic coherence estimates score a unique topic by assessing the degree of semantic similarity between high scoring terms in the matter. Thus, topic coherence value helps to allocate between those that are semantically interpretable ones and those that are outputs of statistical inference. C_v coherence measure is employed in the experiments to demonstrate coherence value between topics. C_v measure is based upon one-set partition of the top terms, a sliding window, and an implicit confirmation estimate that uses normalized pointwise mutual information (NPMI) and the cosine similarity.

In Figure 2, the topic coherence values for LSA model are presented. It is obviously seen that the coherence value of topic 4 is nearly 0.38. It is followed by topic 7, topic 5, topic 6, topic 8, topic 1, topic 3, and topic 2. However, topic 4 exhibits the best coherence value, it is not enough to demonstrate the degree of semantic similarity between high scoring terms in the topic. Topic 4 covers the following terms: “idam”, “kadınlar”, “ceza”, “ölmesin”, “müebbet”, “ağır”, “sözleşme”, “ölüm”, “cinayet”, “tecavüz”. Topic 2 includes “sözleşmesini”, “İstanbul”, “uygulayın”, “kadınların”, “koruyan”, “tbmm”, “adalet”, “sözleşmesi”, “uygulansın”, “bakanlık” terms. On the other hand, the poorest relation between terms in topic 2 is attracted the attention with 0.29 coherence value. This means that the topic 2 is not capable cover to distinguish topics in order to demonstrate semantically interpretable. When the meanings of the terms of topic 4 are analyzed compared to the terms of topic 2, it is not surprising that topic 4 has the highest coherence value. In Figure 3, word cloud representation of topic terms is also presented to observe the distribution of the terms by using LSA algorithm.

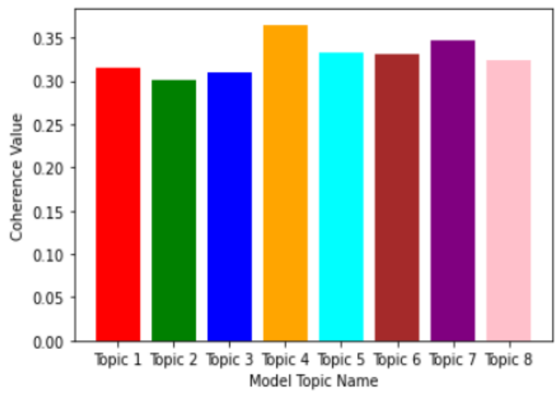

Figure 2. The chart of topic coherence values for LSA model.

Figure 3. The word cloud demonstration of topic terms for LSA model.

In Figure 4, the topic coherence results of HDP model are indicated. Although the coherence result of Topic 2 is superior compared to the other topics, HDP model is another poor method with roughly 0.38 coherence value when all topic models are considered. The HDP model performs like the LSA model in terms of coherence values. This means that the LSA and HDP model do not perform well enough semantically in terms of topics. Furthermore, HDP technique exhibits the poorest success when the performance of other topics is observed compared to LSA model. Topic 2 includes the following top ten words in terms of word scores: "uygulayın", "koruyan", "sözleşme", "kadın", "haksızlık", "bakanlık", "hadım", "İstanbul", "yaşamak", "şiddetin". Topic 2 is followed by topic 3, topic 4, topic 5, topic 6, topic 7, topic 8, and topic 1 in terms of coherence values. Topic 3 with nearly 0.33 coherence result includes the following terms: "anne", "kadın", "beyler", "şiddetin", "ölmesin", "koruyan", "sözleşmesi", "adalet", "uygulansın", "imza". When the terms are examined in topic 2, semantic similarity with words in topic 3 is observed, clearly. This is the indicator of high scoring words in both topics. Conversely, topic 1 demonstrates the worst coherence value result. When the terms are analyzed in topic 1, the semantic similarity between the terms is much lower than the other topics. These terms are "canı", "kampanyaya", "hak", "bıktık", "idam", "küçük", "şiddete", "sessiz", "artık", "ölmek". It is clearly seen that there is a low scoring words that mean the lower semantic similarity between terms located in topic 1 when the meanings of the words are assessed. In Figure 5, word cloud representation of topic terms is also presented to observe the distribution of the terms by using HDP technique.

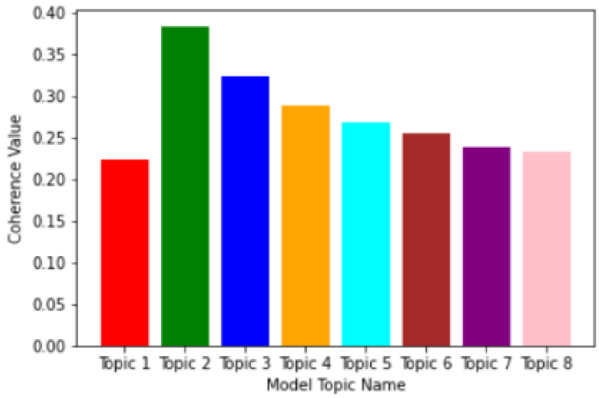

Figure 4. The chart of topic coherence values for HDP model.

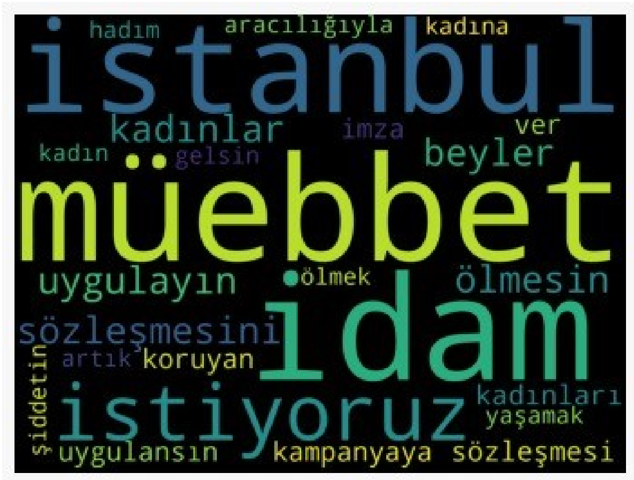

Figure 5. The word cloud demonstration of topic terms for HDP model.

In Figure 6, topic coherence results are demonstrated among eight topics with the usage of NMF model. NMF model is the second-best model with Topic 4 and nearly 0.50 score when coherence results are evaluated. Topic 4 is followed by Topic 5, Topic 6, Topic 7, Topic 3, Topic 8, Topic 2, Topic 1. NMF model ensures to separate semantically interpretable topics with the higher coherence value compared to the LSA and LDA for topic 4. NMF model is also competitive for topic 5, topic 6, topic 7, and topic 8 when LDA method is considered in terms of coherence values. When the performance of LSA and HDP is considered NMF is more suitable to evaluate of society response to violence against women in Turkey through Twitter in terms of both comparing coherence results and popular unigrams. The performance order of topic models can be summarized as when LDA is not considered yet: NMF> LSA> HDP. When the terms are analyzed in topic, semantic similarity with words in topic 3 is seen, obviously. This means that the high scoring words are presented in both topics. On the other hand, topic 1 shows the poorest coherence value. When the terms are analyzed in topic 1, the semantic similarity between the terms is much lower than the other topics. These terms are “kampanya”, “pazarlık”, “sözleşme”, “madde”, “bugün”, “ağustos”, “ceza”, “herkesten”, “İstanbul”, “kuvayi”. It is clearly seen that there are low scoring terms that mean the lower semantic similarity between words presented in topic 1 when the meanings of the words are evaluated. In Figure 7, word cloud representation of the topic terms is also presented to observe the distribution of the terms by using NMF technique.

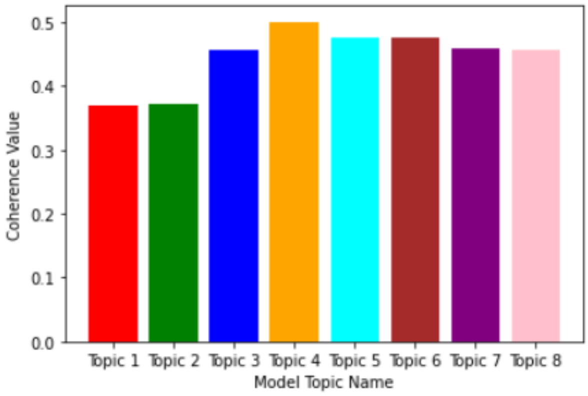

Figure 6. The chart of topic coherence values for NMF model.

Figure 7. The word cloud demonstration of topic terms for NMF model.

The experimental results show that the LDA model, among other subject models, shows remarkable results in terms of reflecting the society's reaction to violence against women and public awareness in Turkey. In Figure 8, topic coherence results are represented among eight topics. As clearly observed from Figure 8, Topic 2 indicates approximately 0.53 coherence value that outperforms the performance of the other topics. This means that the LDA model provides semantically interpretable subjects with a higher coherence result compared to other subject models. Topic 2 contains the following terms: “ceza”, “idam”, “müebbet”, “şiddet”, “ölüm”, “cinayetleri”, “kadınlar”, “sözleşmesi”, “uygulayın”, “İstanbul”. Topic 2 is followed by Topic 3 with 0.48 coherence value that is also competitive when the best results of LSA model is considered. Topic 3 covers the following terms: “şiddet”, “hayır”, “cinayet”, “uygula”, “kampanya”, “imza”, “adalet”, “istismar”, “müebbet”, “sözleşme”. When the words are analyzed in topic 3, semantic similarity with the terms in topic 2 attracts the attention that demonstrates high scoring terms in both topics. On the other hand, the poorest coherence value is exhibited by topic 1. When the terms are seen in topic 1, the semantic similarity between the words is much lower than the ones in the other topics. These words are “istiyoruz”, “kötü”, “hak”, “doğru”, “idam”, “beyler”, “gerek”, “kadın”, “yeter”, “basın”. It is obviously observed that there is a low scoring terms that reflects the lower semantic similarity between words located in topic 1 when the meanings of the terms are evaluated. When evaluating each topic modeling technique and coherence values between topics, it is seen that the LDA model mostly shows the best coherence value between topics except topic 4. It is followed by the NMF model for 5,6,7,8 topics and is highly competitive. This, in turn, shows that the semantic similarities of the words are greater in the topics involved in the NMF model, primarily after the LDA model. In this way, the topics extracted employing the LDA model and the words contained in it appear to be the model that mostly best reflects society's thoughts on violence against women in the Twitter environment.

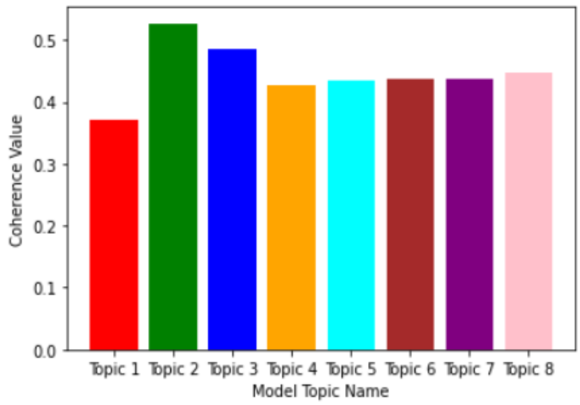

Figure 8. The chart of topic coherence values for LDA model.

Table 1 is presented to answer the question of what the most common terms in the entire data set are. In Table 1, the most significant five terms of related topics according to term scores with the usage of LDA model is represented. It is obviously seen that eight topics are comprised of similar contents. When topic 2 and topic 3 are considered, the terms located in the related topic are semantically more similar compared to the other topics. High scoring words in the topic through the level of semantic similarity also determine the distribution of words in the topic as presented Table 1. In this way, the experimental results are consistent when considering the consistency values of each subject. Moreover, we introduce the most common words related to violence against women in the whole dataset. In addition to the search keyword "kadinasiddet" (violence against women), the results indicate that popular unigrams for the LDA model are "müebbet", "ölüm", "ceza", "şiddet", "idam", "İstanbul", "kadın", "sözleşme", etc.

Table 1. Top five popular unigrams of related topics through LDA model.

Topics	Term1	Term2	Term3	Term4	Term5
1	kadın	istiyoruz	şiddet	yeter	erkek
2	idam	müebbet	ceza	kadın	adalet
3	şiddet	ölüm	cinayet	uygula	lanet
4	idam	şiddet	af	susma	istismar
5	İstanbul	uygula	sözleşme	çocuk	müebbet
6	istiyoruz	ölmesin	kadınlar	idam	yaşam
7	yeter	insanlık	kan	tutukla	ölüm
8	bela	ceza	Allah	lanet	idam

In Figure 9, word cloud representation of topic terms is also presented to show the distribution of the terms by using LDA algorithm.

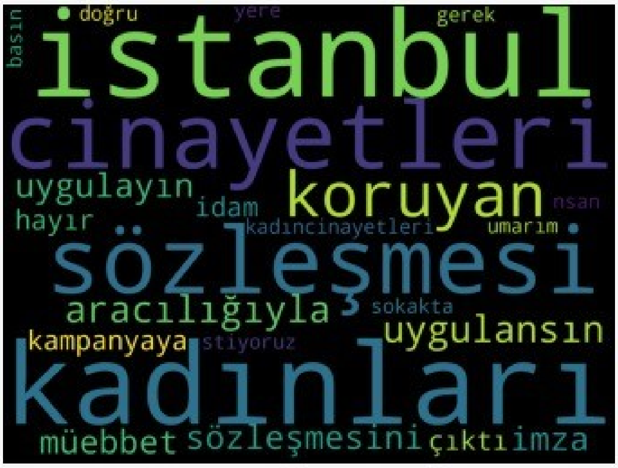

Figure 9. The word cloud demonstration of topic terms for LDA model.

In order to find the solution of the question whether violence against women related terms tend to comprise together, we focus on bigrams (pair of terms/words) and observe the impact of it on LDA model because the LDA model is the best among the other topic models. When we consider that bigram only ensures two concessive terms, regardless of the grammar construction and semantic content, then, it will be seen that some bigrams that are not listed in Table 2 such as "uygulayın kadınlar", "artık yaşamak" might not be self-explanatory. In Table 2, top ten popular and meaningful bigrams are listed in the data set. Top 10 common words with the highest percentage in all 16,672 bigrams are picked up. The remaining of the 16,672 bigrams constitute 76.32%. When the top ten popular bigrams are examined, most Turkish people express their opinion that violence against women should not go unpunished. We also observe that the idea of execution or life imprisonment outweighs it. Moreover, many users state that they want the contract to be valid for penalties. In this sense, our study clearly reveals the thoughts and reactions of the society on violence against women, which is the wound of many societies. LDA results express that many bigrams tend to comprise together among violence against women related tweets, such as "müebbet istiyoruz", "İstanbul sözleşmesi", "şiddete hayır", etc. Furthermore, the co-occurring terms are in common topics. For example, bigram "müebbet istiyoruz" can be in both topic 1 and topic 3.

Table 2. Top ten popular bigrams

Popular bigrams	Dataset (%)
Müebbet istiyoruz	5.24%
İstanbul sözleşmesi	3.82%
İdam istiyoruz	3.65%
Kadına şiddet	1.14%
Şiddete hayır	0.86%
Sözleşmeyi uygulayın	0.81%
Yaşamak istiyoruz	0.75%
Yeter artık	0.52%
Adalet nerede	0.35%
Kadın dayanışması	0.29%

It is difficult to compare the performance of our results with the other studies because of the lack of works with similar datasets, different topic modeling techniques, and various evaluation metrics. Our study differs from aforementioned literature works in terms of analyzing violence against to women with various topic modeling techniques such as Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), Hierarchical Dirichlet Process (HDP), Non-Negative Matrix Factorization (NMF) that provides the performance comparison. Moreover, this is the first attempt in terms of analyzing Turkish tweets related to violence against women and public awareness in Turkey by employing natural language processing techniques. Most of the literature studies on violence against someone [20,23] focus on to analyze the effect of only LDA model without comparing other methods which proves the contribution of the LDA model to extract the useful information from the document collection about violence subject. In [20], Xue et. al assess the hidden pandemic of family violence during COVID-19 via Twitter by employing LDA model. Authors conclude the study [20] that the results significantly reflect the reason behind domestic violence and the COVID-19 pandemic while our study centers on to expose the reaction of society to violence against women and public awareness in Turkey. Both studies emphasize that the LDA model is successful, while our study also reveals that the NMF model is very competitive when compared to LDA technique.

In [23], Xue et. al center on domestic violence topics on Twitter with the help of LDA technique. Thus, authors present to investigate hidden subjects and thematic structures among domestic violence-related texts on Twitter platform. In order to analyze domestic violence topics, LDA approach is proposed. They conclude the study that the most common 20 pairs of words are “violence awareness,” “greg hardy,” “awareness month,” “victims domestic,” “stop domestic,” and “ronda rousey”. Similar to study [20], authors focus on only LDA method to analyze the domestic violence related topics while our study intends to explore society response to violence against women in Turkey in addition to determine violence against women-related topics similar to other studies [20,23]. Moreover, we also evaluate the effect of LSA, HDP, and NMF models on violence against women unlike other studies. Our study reveals that tweets released from Twitter are a powerful indicator in order to reflect the thoughts and expectations of the society. Moreover, given the messages posted on Twitter about violence against women, it is clear that people often complain that there is no deterrent sanction against violence against women. For this reason, in the content of the posted messages, they often use words related to the sanctions or regulations that they want to be put into action.

5. Discussion and Conclusion

In this work, we focus on topic modeling models in order to analyze people's perception on violence against women, which is growing a little bit more every day. Opinions shared by users about violence against women are gathered employing social media platform Twitter for the purpose of analyzing pulse of the society. After pre-processing stage, Turkish tweets are analyzed by using Latent Semantic Analysis (LSA), Latent Dirichlet Allocation (LDA), Hierarchical Dirichlet Process (HDP), Non-Negative Matrix Factorization (NMF) techniques. In order to analyze aforementioned models, unigrams are evaluated. Experiment results demonstrate that LDA model maintains to allocate semantically explicable topics with the higher coherence result compared to the other topic models for unigrams. After determining the most suitable model for unigrams, we also investigate the impact of bigrams in order to assess the pulse of the society in terms of violence against women in Turkey. In order to demonstrate the effect of bigrams, LDA model is implemented. Experiment results demonstrate that LDA technique remarkably shows the pulse of the society to violence against to women and public awareness in Turkey for the usage of both unigrams and bigrams.

As a feature study, we aim to analyze the effect of bigrams in more detail and expand the study by evaluating trigrams.

Declaration of Ethical Standards

The authors of this article declare that the materials and methods used in this study do not require ethical committee permission and/or legal-special permission.

Conflict of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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