Intent Classification using Feature Sets for Domestic Violence Discourse on Social Media

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Abstract—Domestic Violence against women is now recognized to be a serious and widespread problem worldwide. Domestic Violence and Abuse is at the root of so many issues in society and considered as the societal tabooed topic. Fortunately, with the popularity of social media, social welfare communities and victim support groups facilitate the victims to share their abusive stories and allow others to give advice and help victims. Hence, in order to offer the immediate resources for those needs, the specific messages from the victims need to be alarmed from other messages. In this paper, we regard intention mining as a binary classification problem (abuse or advice) with the use-case of abuse discourse. To address this problem, we extract rich feature sets from the raw corpus, using psycholinguistic clues and textual features by term-class interaction method. Machine learning algorithms are used to predict the accuracy of the classifiers between two different feature sets. Our experimental results with high classification accuracy give a promising solution to understand a big social problem through big social media and its use in serving information needs of various community welfare organizations.

Index Terms—Domestic Violence, Social Media, classification, abuse, machine learning

I. INTRODUCTION

Domestic Violence (DV) is a global issue of pandemic proportions and vulnerable to any age group, culture, socioeconomic group, and education level. The World Health Organization estimates that 35% of women worldwide have experienced Intimate Partner Violence (IPV) [1]. IPV refers not only to physical, but it also includes sexual, verbal, psychological and financial [2]. DV has severe and persistent effects on physical health and also have a cumulative impact on women mental health [3]. Hence, there is a burning need to better characterize and understand DV, to provide appropriate resources for victims and efficiently implement control measures.

People are increasingly using social media platforms, such as Twitter and Facebook. They share their thoughts and opinions of daily activities and happenings on these sites in a naturalistic setting. Thus generates massive amount of user data discussing various topics, even the socially stigmatized context and society tabooed topics like DV. Victims experiencing abuse are in need of earlier access to specialized DV services such as health care, crisis support, legal guidance and so on. They may not have the option or unaware to seek help directly. In social media, many social welfare and non profit organizations are encouraging the victims and survivors of DV to express their feelings and share their experience of being in an abusive relationship. Hence the social support groups for a good social cause play a leading role in creating awareness promotion and leveraging various dimensions of social support like emotional, instrumental, and informational support to the victims. When the victims seek help, it is important for those groups to identify those critical posts and provide a clear call-to-response help with more immediate impact. From the citizen-generated data, social welfare organizations with limited resources are trying to incorporate information nuggets to enrich their decision support system [4].

Intent mining provides insights that are not explicitly available from the user generated data. Intent is defined as a purposeful action and this can help to identify actionable information [5] [6]. Intent classification (focused on future action) is a form of text classification. In our work, we can apply intent classification to classify the user posts into any of the two classes as abuse or advice. If the user shared their life experience of abusive relationship, that post is classified in “abuse” class. Instead, if the post relates to awareness promotion, giving advice or opinion, it is to be classified in “advice/opinion” class.

From the table [1], we can clearly understand that the posts 2 and 4 describe the story about abusive relationship. The post 2 is shared by DV survivor and post 4 is shared by victim’s friend. The post 1 has some awareness promotion in it and post 3 expresses one’s thought/advice. Hence, they are classified as opinion/advice. Thus, our research question is “How to mine relevant social intent from an ambiguous and proliferation of unstructured textual data in abuse discourse?” By notion, the relevant intent classes meet actionable information needs of an organization in a given context [4]. There is no chance of helping the victim or victim’s family, if the message is unnoticed or ignored. Thus the paper focuses to identify abuse related posts and turn that knowledge into action that will help the victims of abuse. Thus the intent classification system in turn provide an actionable knowledge, which helps the society in turn.

With the proliferation of unstructured data, text classification or text categorization has found many applications...
in topic classification, sentiment analysis, authorship identification, spam detection, and so on. We observed two key challenges with intent classification on our DV discourse. First, informal language use in short-text messages creates ambiguity to interpret user expressions and thus weakening term-class relationships. Second, sparsity of instances of specific intent classes in the corpus creates data imbalance. In the binary classification, both intent classes may co-occur within a single message. For instance, post 1 in table I may be classified into class abuse instead of class advice, as the text contains keyword abuse. Hence in our work, intent classification exploits a rich feature representation for learning, created by using knowledge sources from psycholinguistics features, and also the textual features from the underlying post. We extract the texts relating to DV from Facebook, because it allows for long text discussion and therefore use of standard English is more common. Facebook allows users to comment on posts, providing them with the ability to share their stories about abusive life pattern, give advice, and provide support. The two contributions of this work are as follows:

- Constructing the two different and efficient feature sets by analysing the psycholinguistic dimensions and the textual features of the user postings on Facebook.
- Evaluating the classifiers performance for identifying texts by constructing and comparing the two different feature set from DV discourse.

Analysis of the linguistic structures embedded in these posts instances provides insight the victims of domestic abuse report their personal story and they need emergency support. Trained classifiers agree with these linguistic structures, adding evidence that these social media texts provide valuable insights into DV. Intent mining classification can help to design efficient cooperative information systems between citizens and organizations for serving organizational information needs and help the victims in need.

The structure of the paper is as follows. In Section II the related work is discussed. Section III defines the problem statement and experimental analysis is discussed in Section IV. Section V discusses feature extraction method in detail and Section VI explains about classifiers and evaluation metrics. Prediction results are discussed in Section VII. Finally, Section VIII discusses about the conclusion.

II. RELATED WORK

With the increasing popularity of social media, the amount of information now available to decisive moment is massive. The sheer overwhelm of social media data makes it to be the one of Big Data’s most significant sources [7] [8]. Several research studies focused on social media to analyse and predict real world activities like user sentiment analysis, opinion mining on political campaigns [9] [10], natural disasters [11], epidemic surveillance [12], event detection [13], tourism [14] [15], e-healthcare services [16] [17] and so on. In the other hand, some studies dealt with security and privacy issues [18] [19] [20] [21] [22]. as the increasing sophistication of social media data is posing substantial threats to users privacy. In contrast to traditional media, social media becomes a fast reaching data source to share the opinions and thoughts in online immediately with a status update. Hence, this becomes an efficient platform for researchers to detect real world events in informational retrieval and decision making.

Recent studies have predicted mental health conditions by analysing textual features [23] [24] [25]. For this kind of prediction, two main characteristics such as topics and language styles expressed via text have been popularly investigated. For identifying depression, linguistic styles such as an expression of sadness or the use of swear words have been used as the cues [26].

Linguistic Inquiry and Word Count (LIWC) [27] has been commonly used to capture language characteristics and they are considered to be influential predictors of depression-related disorders and mental health [28] [29]. Popular Bayesian probabilistic modelling tools, such as Latent Dirichlet allocation (LDA) are used to extract the topics [30]. LDA and its variants have been used previously to discover several mental ailments discussed in millions of tweets [31]. The authors [32] used standard n-gram features, submission length and author attributes to classify a Reddit submission as high or low level self-disclosure. Another study states that, support seeking in stigmatized context of sexual abuse on Reddit and investigated the use of throw away accounts in the aspects of support seeking, anonymity and first time disclosures [33]. Most relevantly, Schrading et al. [34] analyzed the lexical

| S.No | POST | CLASS |
|------|------|-------|
| 1    | To understand why people stay in abusive relationships. Visit the link. | advice/opinion |
| 2    | If I could go back to the day that I was bickering with my first husband. Nothing serious just small disagreement. I was 8 months pregnant walked in the kitchen to get a drink and boom he was hiding and waiting. It took one punch to my head I fell backwards out unconscious in a pool of blood. | abuse |
| 3    | Negative emotions like hatred destroy our peace of mind. Guide your- self to find peace and healing within you and other people. Hope we become better people to love and share the best in us Bless. | advice/opinion |
| 4    | Yesterday I lost a loving and dear sweet friend. Her life was cut short by the monster she once-Loved and called her husband. | abuse |

TABLE I
EXAMPLE POSTS AND ITS ASSOCIATED INTENT CLASS
structures of the tweet to predict whether a victim was about staying or leaving an abusive relationship.

Though, the majority of studies assessing the role of Twitter, Facebook, and Reddit for the enormous new findings, there is limited research that focuses on online DV disclosures. Hence, this is the first study to conduct an intent classification of Facebook content that relates to abuse discourse.

III. PROBLEM STATEMENT

Let \( B = \{ m_i | 1 \leq i \leq n \} \) denote the corpus of all \( n \) Facebook posts, each post \( m_i \) is a facebook post generated in DV community pages, and \( L = \{ L_j | j = <abuse>, <advice/opinion> \} \) is a set of binary classes.

For each given post \( m_i \in B \), predict an intent class in \( L \) based on textual features \( f_j \) extracted from post: \( F(m_i) = [f_1(m_i), ..., f_j(m_i)] \ldots 1 \leq j \leq p \).

To characterize the difference between two classes of DV dataset, two feature sets are extracted.

- LIWC Features: Psycholinguistic knowledge based on LIWC [16] are used as feature sets. These features differentiate the semantic-syntactic patterns and informational context of two different classes of abuse and advice. Thus training the classifiers for intent classification and improve the accuracy.

- Term based model: Feature sets are build based on textual features derived from Term-Class interaction with chi-square metric [24] to synthesize a more accurate classification procedure.

The model for the current study is illustrated in Fig. 1 and in the following sections, we describe the components of this model.

IV. EXPERIMENTAL ANALYSIS

Effective intent mining on social media data is demanding due to ambiguity in interpretation of the textual data, and its sparsity of relevant behaviour [4]. In this paper, we address the binary classification of intent with a use-case of DV data generated in Facebook. This study uses machine learning approaches to discriminate the online posts into two categories based on two different feature set approaches. The first approach which is explained in section IV-A exploits the use of psycholinguistic features generated with LIWC [27] and has the advantage to achieve higher accuracy and also being computationally efficient. Another approach explained in section IV-B constructs the feature set based on bag-of-tokens [35], which uses tf.idf approach combined with chi-squared algorithm [36]. Thus, the classifier is finally trained with higher accuracy based on the constructed feature set.

A. Data Collection

For the current study, we extracted the data from Facebook pages which is focusing on specific theme like DV using NCapture [37]. The dataset contains 8856 posts and 28873 comments and extracted posts are ranging from historical to current date (2014 to 2017). The data extracted contains information about post content, user name, link description, comments and extracted posts are ranging from historical to current date (2014 to 2017). The data extracted contains information about post content, user name, link description, comment text, commenter username, created time, and likes. Table II illustrates our dataset details.

B. Extracting Gold Standard Labels

Two of the authors annotated a random sample of 1135 posts to classify the corpus and labelled them as abuse and opinion/advice based on textual information. Hence 510 posts are classified in first class, i.e. 45% and 625 posts are labelled in second class which is 55%. The kappa’s coefficient was good between the authors and it was 0.85. To measure the “inter-rater reliability”, a statistical measure Kappa coefficient is used to measure the degree of agreement between two users. Any discrepancies between the authors are clarified after further discussion.

C. Data Pre-processing

For the effective analysis, text pre-processing is the most important step, as it removes noise that produces negatives effects and degrades performance. High quality information and features are extracted by incorporating some pre-processing techniques like stop word removal and some normalization techniques like stemming, lemmatization and so on. First, we removed stop words that are not included for the content analysis. Stop word lists contain common English words like articles, prepositions, conjunctions, pronouns, etc., Few examples are the, a, an, the, in, and at. Next, pre-processing step is lemmatization. This is used to reduce more inflectional forms of words into a more limited form of canonical forms. This helps to standardize terms appearance and to reduce data sparseness. For example, the following terms such as

| DV Page Source Name       | Posts | Comments | Page Likes |
|--------------------------|-------|----------|------------|
| Stop DV                  | 3597  | 13462    | 63k        |
| DV Survivors             | 2816  | 8415     | 32k        |
| Stop DV against Women    | 516   | 2802     | 7.5k       |
| DV Awareness Month       | 1927  | 4194     | 15k        |
physically assaulted, physically assaults and physically assaul-
ting are all lemmatized to “physical assault”. Similarly
physically abusing, physically abused, physically abuses are
all lemmatized to “physical abuse”.

V. FEATURE EXTRACTION

Feature Extraction is one of the most important steps in
data mining and knowledge discovery. The idea is to select
the best features $f_j$ that improve the classification accuracy. In
the following sections [V-A] and [V-B] the two different feature
extraction techniques used in this work is discussed.

A. Methodology 1: Psycholinguistic Features Analysis

We examine and analysed the proportions of word usage
in psycholinguistic categories as defined in the LIWC 2015
package [27]. The LIWC analyses text on a word-by-word
basis and calculates the percentages of words that match
particular word categories.

For each given post $m_i \epsilon B$ corpus, predict an intent class in
$\mathcal{L}$ based on LIWC features extracted from post $m_i$ defined as
$F^{(m_i)} = \left[ f_j^{(m_i)} \right]_{j \in \mathcal{L}}, \quad 1 \leq j \leq p \right]$. Here $f_j^{(m_i)}$ denotes the
quantity of specific psycholinguistic feature $j$ in post $m_i \epsilon B$

LIWC package is a psycholinguistic lexicon created by
psychologists with focus on identifying the various emotional,
cognitive, and linguistic components present in individuals
verbal or written communication. For each input of a post, it
returns more than 70 output variables with higher level
hierarchy of psycholinguistic features such as

- linguistic dimensions, other grammar, informal language
- temporal, affective, social processes
- cognitive, biological, perceptual processes
- personal concerns, drives, relativity.

These higher level categories are further specialized in sub-
categories such as in

- biological processes - body, sexual, health and ingestion.
- affective processes - positive emotion, negative emotion and
  negative emotion further sub-classified as anger, anxiety, and sadness.
- drives - affiliation, achievement, power, regard, and risk.

For evaluating the prediction accuracy of psycholinguistic
features, each individual facebook post is converted to a vector
of 70 output numerical variables, as mentioned above. Each
output variable represents the frequency distribution of the
appearance of those categories appeared in the specific post.
Each word in the post could fit some categories and not fit into
some categories. Hence, there would be the huge difference
between the posts, to which category it belong. For instance,
the following post “Please view, share and is possible donate.
We appreciate your support! ” has higher value of ‘positive
emotion’ (36.36%), ‘focus present’ (36.36%), ‘you’ (9.09%),
‘social’ (27.27%) and has (0%) for the categories such as
‘negative emotion’, ‘shehe’, ‘bio’, ‘body’. The above post falls
into “advice/opinion” category, as it creates a good social
cause and for fund-raising, and also has higher percentage
of positive expression and present focus in it. In contrast,

| Category | Dimension | Example words |
|----------|-----------|---------------|
| LIWC FEATURES AND THE EXAMPLE WORDS USED IN OUR DATASET |
| Linguistic Dimensions | personal pronouns (I, you, shehe) | I, you, he, she, his, him, her, herself |
| Time orientations | focuspast | broke, ran, accepted |
| Biological Processes | body, sexual health | massacre, injury, rat |
| Psychological Processes | posemo | hope, share, support, take |
| | negemo | threat, lose, hate |
| | anxiety | threat, misery, worry |
| | anger | sucks, hate, yell |
| | sad | miss, lose, suffer, overwhelm |
| Personal Concern | death | die, murder, kill, suicide, bury |

The post “He is just an evil, greedy, arrogant little man” has
higher percentage of ‘negative emotion’(40%), ‘anger’ (10%) ,
‘male’(20%), ‘shehe’(10%) and (0%) of ‘posemo’, ‘you’,
‘death’. This post falls into “abuse” class, as woman explaining
about her abusive partner and the post carries a lot of negative
emotion in it.

1) Most informative features and analysis: We only se-
lected the top-most informative 15 features, as shown in table
III to perform the binary classification task. We selected those
features based on the mean value of all the posts, which
is defined in table [V]. We selected the feature sets that are
strong predictors of two classes such as “advice/opinion” and
“abuse”.

LIWC sub-categories such as ‘negative emotion’, ‘anger’,
‘shehe’, ‘focuspast’ are features with higher mean value and
good prediction level for “abuse” category. ‘Positive emo-
tion’, ‘focus present’, ‘you’, ‘focus future’ sub-categories,
as expected, are good predictors for “opinion/advice” class.
Another important prediction is that ‘health’, ‘sexual issues’,
and personal concern such as ‘death’ are as good predictors
for “abuse” class. The results infer that, because of the abusive
cycle, most of the victims suffer from severe health issues and
also death. Further analysis show that posts related to “abuse”
category are often self-reflective, with more words related to
personal pronouns i.e, usage of more pronouns such as ‘I’ and
shehe’, when describing their life experience about violence,
whereas in the “opinion/advice” category, 2nd person usage
‘you’ is higher, when giving advice or sharing opinion to
other people. It is important to compare the time orientations,
the posts of “abuse” category are more focused on ‘past’
and contains negative emotions with expression of ‘anxiety’,
‘angry’ and ‘sad’. On the other hand, the “advice” category
contains more of positive emotion, as sharing of good thoughts
and opinions and more time orientated towards ‘present’ and
‘future’.

The posts related to “abuse” category has higher mean
values of the corresponding features such as ‘I’, ‘shehe’,
‘focuspast’, ‘body’, ‘sexual’, ‘health’, ‘death’ and ‘negative
emotions’. The posts related to “opinion/advice” scores high
in features such as you, focuspresent, focusfuture, posemo. For
eg., if we consider Shehe feature, the posts belongs to “abuse”
category have the highest mean value of 10.98, whereas the
posts of “opinion/advice” category have the lowest mean value of 0.39. This implies, when the victims post their story, they need to say more about the abuser and thus used more third person pronoun ‘shehe’. In the “opinion/advice” class, the people just express their thoughts and not necessarily use third person pronoun.

B. Methodology 2: tf.idf approach with chi-squared metric ($\chi^2$ Statistic) as feature selection parameter

- In Term Document Matrix $TM(D \times T)$ dimension, $D$ indicates the total number of posts and $T$ indicates no. of terms. Thus $TM_{ij}$ indicates the corresponding tf.idf matrix. Two common features such as TF and IDF used, where $TF(t, p)$ represents the number of times the term $t$ appears in post $p$ and $DF(t)$ denotes the number of posts contain term $t$.

$TF.IDF(t, p)$ weighting scheme improves the discriminative power, where $TF.IDF(t, p) = TF(t, p)IDF(t)$ with $IDF(t) = \log\frac{N}{DF(t)}$ is the inverse document frequency. In this work, a term $t$ will be selected if it has high $DF(t)$ value and high average values of $TF(t, p)$ and thus high $TF.IDF(t, p)$ across all $D$ Facebook posts over a threshold. Term-Class interaction based selection method is also used which capture the dependence between terms and corresponding class labels during the feature selection process.

- The feature selection technique based on chi-squared on the entire term document matrix $TM(D \times T)$ is used to compute chi-squared value corresponding to each word. The Chi-square statistical test has been widely accepted as a statistical hypothesis test to evaluate the dependency among two variables [24]. In natural language processing, Chi-squared is generally used to measure the degree of dependence between term $t$ and label $l$ and compared to the distribution with one degree of freedom. The expression for ($\chi^2$ Statistic) is defined as

$$\chi^2(t,l) = \frac{(P(N-MQ))^2}{(P+M)(Q+N)(P+Q)(M+N)}$$  \hspace{1cm} (1)

Where $D$= the total number of posts.

$P$ = the number of posts of label $l$ containing term $t$.

$Q$= number of posts containing $t$ occurring without $l$.

$M$= number of label $l$ occurring without $t$.

$N$ = number of posts of other classes without $t$.

VI. Classifiers and Evaluation Metrics

We now pursue the use of supervised learning to construct classifiers trained to predict the class label of the posts. Although we analysed results for both all dimension-inclusive and dimension-reduced cases, we employ principal component analysis (PCA) to avoid over-fitting for all the classifiers. We compare several different classifiers such as Support Vector Machine, k-Nearest Neighbor, Naive bayes, and Decision Tree to empirically determine the best suitable classification technique. The problem of binary text classification problem is generally defined as follows:

Our training set corpus $B = m_1, m_2, ..., m_n$ of $n$ posts, such that each post $m_i$ is labelled with a class of either $L = l_1$ or $l_2$. The task of a classifier $f$ is to find the corresponding label for each post.

$$f : BeL \rightarrow f = l$$  \hspace{1cm} (2)

For all of our analyses, we use 10-fold cross validation and leave one out methods to assess the effectiveness of the model.

- Support Vector Machines (SVM): a non-probabilistic generalized and linear binary classifier [38]. This maps an input feature vector into a higher dimensional space and find a hyperplane that separates the data into two classes with the maximal margin between the closest samples in each class.

- Naive Bayes (NB): a probabilistic method [39] for text classification is familiar for its robustness and relative simplicity. This classifier constructs the conditional probability distributions of underlying features given a class label from the training data only. The classification on unseen data is then performed by comparing the class likelihoods [40] [41].

- Decision Tree (DT): an interpretable classifier [42] creates the hierarchical tree of the training instances, in which a condition on the feature value is used to divide the data hierarchically. For the classification of text documents, the conditions on decision tree nodes are commonly defined in terms and a node may be subdivided to its children based on the presence or absence of a particular term in the document. Ensemble methods use multiple learning algorithms of decision tree for better predictive performance [43] [44] [45].

- k-Nearest Neighbor (k-NN): a proximity-based classifier [46] use distance-based measures i.e., the documents which belong to the same class are more likely similar or close to each other based on the similarity measures. The classification of the test document is reported from the class labels of the k nearest similar documents in the training set.

| Features          | Abuse ($\mu$) | Advice($\mu$) | Abuse ($\sigma$) | Advice ($\sigma$) |
|-------------------|---------------|---------------|------------------|-------------------|
| I                 | 3.15          | 2.02          | 1.01             | 0.61              |
| You               | 0.99          | 4.01          | 1.19             | 0.03              |
| Shehe             | 10.98         | 0.39          | 2.07             | 10.73             |
| Focuspast         | 7.99          | 0.10          | 4.78             | 1.55              |
| Focuspresent      | 7.11          | 14.34         | 0.65             | 0.09              |
| Focusfuture       | 0.96          | 1.35          | 2.28             | 0.57              |
| Body              | 0.84          | 0.42          | 0.58             | 0.14              |
| Sexual            | 0.34          | 0.09          |                  |                   |

TABLE IV

MEAN SCORES OF PSYCHOLINGUISTIC PROCESSES (LIWC) FOR THE POSTS OF 2 CATEGORIES
TABLE V
CONFUSION MATRIX OF VARIOUS COMBINATIONS OF LIWC FEATURES

| SVM Classifier features set                               | Precision (%) | Recall (%) | F-Measure (%) | Accuracy (%) |
|-----------------------------------------------------------|---------------|------------|---------------|--------------|
| Linguistic Dimensions (3 features)                        | 96            | 91         | 93            | 94           |
| Time orientations (3 features)                            | 98            | 86         | 91            | 92           |
| Biological Processes + personal concern (4 features)      | 89            | 42         | 57            | 68           |
| Psychological Processes (5 features)                      | 83            | 86         | 84            | 84           |
| Selected LIWC features (15 features)                      | 97            | 96         | 96            | 97           |

We have performed various runs with different feature set in the above defined classifiers. We used the common metrics such as Precision, Recall, F-Measure, and Accuracy to evaluate the classification performance. Precision measures the percentage of the Facebook posts that the classifier predicted (i.e., the classifier labeled as positive) that are in fact positive (i.e., are positive according to the human gold labels). Recall measures the percentage of posts actually present in the gold label that were correctly identified by the Classifier. F-measure comes from a weighted harmonic mean of precision and recall. Accuracy calculates the percentage of correctly classified posts versus. Number of total posts. All the metrics are defined as follows.

\[
\text{Precision} (P) = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalsePositive}} \tag{3}
\]

\[
\text{Recall} (R) = \frac{\text{TruePositive}}{\text{TruePositive} + \text{FalseNegative}} \tag{4}
\]

\[
F - \text{Measure} = \frac{2PR}{P + R} \tag{5}
\]

\[
\text{Accuracy} = \frac{\text{TruePositive} + \text{TrueNegative}}{\text{TruePositive} + \text{TrueNegative} + \text{FalsePositive} + \text{FalseNegative}} \tag{6}
\]

VII. PREDICTION RESULTS AND DISCUSSION

A. LIWC analysis

Our chosen most informative features of LIWC have higher accuracy in prediction of two different classes abuse and advice. Among all the classifiers, SVM outperforms all the other classifiers. The classification accuracy of SVM, kNN and decision tree are 97%, 95.3%, 95.1% respectively.

Table V and Fig. 2 show the various evaluation metrics of SVM classifier with the combination of various selected features. Higher the value of accuracy, the selected features are very good in prediction of classes of our model.

Parallel coordinates plot as shown in Fig. 3 with all the selected features that separates the class value best. For example, “posemo, focuspresent, you” are the features best classifying the class to be in “advice/opinion”, which is plotted in blue color. The orange color plot explains the class to be in “abuse”, with the selective features such as “shehe, focuspast and death”. We can understand that, when the victim or survivor posts about abusive experience, they use more past tense and health concern. ‘Shehe’ notion also widely used to represent the abuser. Whereas, in the case of advice/opinion category, the linguistic style contain present tense and future tense, as it is more focused on future life and well-being.

B. Term-Class Interaction model

Our final model contains 300 features based on tf.idf vector and the total number of features is reduced to top 250 features based on the chi-squared value. Hence the feature space is significantly reduced. Finally standard Classifiers such as naive-bayes and k-NN are applied to classify the posts in the corresponding class and the results of the classifiers are compared with respect to standard evaluation metrics precision, recall and accuracy. Among the validation methods of leave one out and k folds cross validation, 10 folds cross validation is used in the final model for the better evaluation of the predictive accuracy. Our result in Fig. 4 shows that classification accuracy of NB is 82% with 10 folds cross validation, which outperforms the classification accuracy of kNN.
The term-class interaction values using chi-squared test is shown in Table [VI]. We can clearly see from Table [VI] that terms, such as share, support, page, thank, are highly associated with class “opinion/advice”, whereas the terms, such as kill, husband, murder, leave, are more dependent with the class “abuse”.

Utilizing the property of $\chi^2$ statistic, it is inferred that higher the $\chi^2$ value of term $t$, indicates the higher likelihood of occurrence in the class $c$. Thus we use $\chi^2$ metric to weight the context words in the tf.idf model. The key aspect is that words with higher $\chi^2$ statistics tend to be keywords for class identification. Hence we applied chi-square statistical test to select the lexicon that particularly correlates to the specific class identification task for user posts. In this work, words that are likely to be valuable for the classification task are more heavily weighted based on $\chi^2$ metric, and hence reducing the disturbance of the noise words which are not helpful comparatively to the later task. The Fig. [5] shows, each term’s probability in predicting the corresponding class. For example, the words, such as share and support belongs to class “advice/opinion” (which is represented as 0). The words, such as kill, murder, leave, predicts the text to be in abuse class (represented as 1).

VIII. Conclusion

The results of this study demonstrated that the linguistic dimensions and textual features discussed in the user posts have the potential to classify the text into appropriate class. The experimental results highlighted that psycholinguistic clues have strong indicative powers in the prediction of posts than textual features. By interpreting the use of proposed intent mining classification models, social support groups on Facebook can quickly identify DV victims via text posted on Facebook and appropriate support can be provided.

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