Sentimental Causal Rule Discovery from Twitter

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Abstract—Sentiment analysis refers to the task of extracting the sentiment of people from textual data. This analysis can be employed to reflect the public's ideas about an issue stated in natural language text. On the other hand, causal rules are associations between different concepts in a context that one (or several concepts) cause(s) the other(s). In this paper, we propose a new concept "sentimental causal rules" which incorporate causal relationships among different aspects extracted from textual data and the sentiment towards those aspects. We also describe techniques to extract sentimental causal rules and show their effectiveness on Twitter as the data resource. As a case study, we investigated about the Kurdish issue in Turkey which is very important topic in our region causing heated debates that the governments need to follow. The experiments on Twitter data on the chosen case study suggest that sentimental causal rules are an effective way to summarize important aspects in textual data and to suggest causal relationships among those aspects which may lead to better policy making.

Index Terms-**Sentiment analysis, data mining, causal rules, sentimental causal rules, machine learning, Twitter**;

I. INTRODUCTION

Textual information entered by users in various media may contain their opinion which indicate the sentiment of the authors towards a specific issue. Opinions can be about issues such as a product, a service, or a political issue. To extract the opinions of people from text, one method is to manually analyse each piece of text which would certainly be time consuming. A more efficient method employs a mechanism that could automatically process the textual data using text mining techniques.

In this paper we propose the concept of "Sentimental Causal Rules" where causal rules based on various aspects extracted from textual data sources are associated with sentiment. We also propose sentimental causal rule discovery techniques which combine sentiment analysis and causal rule discovery. A more detailed and formal explanation of this concept is presented in sections III nd IV.

Sentiment analysis also possesses broad applicability in political issues which can be sensitive to a nation's welfare. One such political issue in Turkey, for example, is the conflict between Kurdish parties and the government of Turkey. This crucial issue has been discussed by many users in Twitter mostly in Turkish and somewhat in English. As looking at and processing those tweets manually is considerably time consuming, therefore the problem in this paper is tackled in a semi-automatic methodology to demonstrate the effectiveness of sentimental causal rules to process the tweets.

This paper proposes a four-fold methodology for sentimental causal rule discovery. The goal of the first step is to extract the aspect keywords from the tweets. The second step is extracting the causal association rules based on the previously extracted keywords. The goal of the third step is to facilitate automatic extraction of sentiment from textual data which results in automatically labelling each tweet as positive, negative, or neutral (objective). Finally the forth step assigns polarity values (percentages) to each aspect keyword and also each causal rule separately. Because of the short length of the tweets, usually the overall polarity of the tweet can be considered as the polarity of the aspects seen in the tweet. Our overall method for sentimental causal rule discovery method is presented in figure 1.
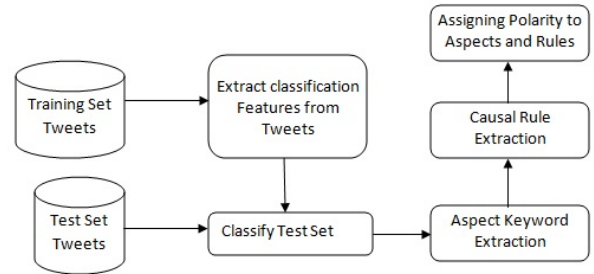

Fig. 1. The overall flowchart of our system for sentimental causal rule discovery

The majority of tweets about the Kurdish issue in Turkey is in Turkish but in this paper, we worked only on English tweets. For this purpose, the relatively small number of tweets downloaded -5000- reflects the homogeneity of tweets, i.e. Turkish tweets. We analysed the tweets by data mining and sentiment analysis techniques. First, we extracted keywords from all tweets which were later used in causal rule extraction. In other words, causal rules were extracted based on the keywords already obtained from the tweets. Then, we did sentiment analysis on tweets labelling them as positive, negative, or neutral. After extracting the aspect keywords, they helped to, then extract the aspect polarities, which means, for example, how much an aspect such as $Syria$ or a causal rule such as $student, Kurds \Rightarrow attack$ has gained positive or negative sentiment of users on Twitter.

With only pure sentiment analysis on tweet level, the results would be the percentage of positive, negative, or neutral tweets about our case study, which itself does not tell much. However, we sentimental causal rules we were able to see why and in which aspects hold positive or negative opinions by Twitter users.

II. Related Work

Investigating the attitudes of Twitter users on different issues is a new research area which has attracted many researchers. This section briefly summarizes the most relevant research on sentiment analysis in Twitter and also causal rule inference.

Designing online tools for sentiment analysis in Twitter is an interesting method of investigating the Twitter users' ideas. Sentiment140 [1] is one such free tool. This tool allows its users to discover the sentiment of a brand, product, or topic on Twitter. It classifies tweets about a topic (based on input keywords) into positive or negative, taking the advantage of machine learning methods such as Support Vector Machines. This tool uses features such as unigrams and bigrams, extracted from a tweet message. The contribution of this work can be the use of emoticons for distant supervised learning. The smiling emoticon :), for example, in a tweet indicates that it contains positive sentiment and :(indicates that the tweet contains negative sentiment. The designers propose this method to avoid the time spent for manually labelling the training data as positive or negative. In other words, all tweets in training data should have emoticons but for the test data, they are not mandatory.

Agarwal et. al. [2] also examine sentiment analysis on Twitter data. The authors experimented with three types of models: the unigram model, a feature based model, and a tree kernel based model. They assumed the unigram model as baseline. They investigated two kinds of models: tree kernel and feature based models and demonstrated that both these models outperform the unigram baseline.

Twitter can be employed to build a corpus for sentiment analysis and opinion mining purposes. An example of research for this purpose is by Pak and Paroubek [3]. In this work, the authors automatically collected a large number of tweets as a corpus. Then, they performed statistical linguistic analysis of the collected corpus. Thereafter, they classified to the tweets into positive, negative, or neutral. Their approach is based on the distribution of word frequencies in the corpus. TreeTagger was used for English to tag all the posts in the corpus. Pak and Paroubek took also advantage of the presence of n-grams as a binary feature in training the classifier.

A slightly different work has been accomplished by Kouloumpis et. al [4]. This work used a method for building a data model with Twitter hashtags. The features extracted from tweets include n-grams, POS tag of words, and using resources such as MPQA (Multi-Perspective-Question-Answering) subjectivity lexicon. After analysing the importance of all features, the authors conclude that POS features are less useful than others such as presence of intensifiers and positive/negative/neutral emoticons and abbreviations.

To our knowledge, very few works have been accomplished on sentiment analysis of Turkish political issues. One example is [5] which investigated the Turkish political news in media. In this work, unigrams and bigrams together with polar Turkish terms are used as classification features, which in turn are used to train a classifier to classify unlabelled documents. The authors used four different classifiers: Naive Bayes, Maximum Entropy, SVM and the character based N-Gram Language Model, and compared their efficiency with each other. They concluded that Maximum Entropy and N-Gram Language Model are more efficient than the SVM and the Nave Bayes classifiers. The classification accuracy in different cases are from 65% to 77%.

Apart from sentiment analysis research, several works have studied causal association rule mining. Some literature is concerned with discovering itemset patterns for the market basket analysis [6] [7]. In these papers, the authors searched for the nature of the relationships between the itemsets rather than merely extracting the statistical relationships between the itemsets, by using different algorithms such as CCC and CCU. [6] and [7] experimented on several data types and compared their results with each other. It was shown that finding causal models is applicable for large datasets and computationally faster. These works brought a new perspective to causal rule mining area.

A hybrid approach (the combination of constraint-based search and Bayesian methods) for discovering causal relations from sparse data, has been proposed by Dash and Druzdzel [8]. The algorithm used in this approach searches the space of equivalence classes of models (essential graphs) using heuristic techniques. Each essential graph is converted into a directed acyclic graph and scored using a Bayesian scoring metric. Two variants of the algorithm are developed and tested using data from randomly generated networks of sizes from 15 to 45 nodes with data sizes ranging from 250 to 2000 records. Both variations have been compared with each other; it was observed that in each experimental step, both variations of greedy search outperformed the previous (experimental) steps.

Mush research on text mining focuses on causal relations. They use hand-coded patterns to extract causation information from the text. One example has been done by Roxana Girju and Dan Moldovan [9]. The authors focused only on the causal relations and proposed a method for automatic detection of causation patterns. They accomplished a semi-automatic validation of ambiguous lexico-syntactic patterns referring to the causation. First, they discovered lexico-syntactic patterns that could express the causal relations; and then, the authors validated and ranked the ambiguous patterns acquired based on the semantic constraints on nouns and verbs. The method automatically discovers the applicable lexico-syntactic patterns referring to the causation and removes the ambiguity of the causal relationships obtained from the patterns in text. This work brought a considerable improvement in time and user work, compared to other previous attempts [10], [11].

To our knowledge the current work is the first one investigating Twitter user views using sentimental causal rules. Also we believe the case study used in this paper, Kurdish political issue in Turkey, is being processed for the first time through sentiment analysis and causal rule mining techniques.

III. SENTIMENTAL CAUSAL RULES

Causal rules, are association rules in which, one side of the association implies the other side based on the inductive reasoning mechanism. These rules show not only the dependency, but causality between different concepts (variables) in a context. For example in such a rule, $X, Y \rightarrow Z$, instead of saying that three variables, X, Y and Z are dependent, it is said that X and Y cause Z. A real example in marketing can be $soya, mushroom \rightarrow ketchup$ meaning that for people buying $soya$ and $mushroom$ causes buying also $ketchup$. But it does not imply that buying $ketchup$ causes also buying $soya$ and $mushroom$. This causality can also happen in political domain. For example $peace, Kurds \rightarrow live$ means that the result of making peace with $Kurds$ in Turkey will let them live (peacefully).

In this work, before extracting the causal rules, important aspect keywords (variables stated above) have been extracted (explained in section IV-A) from tweets to be used in causal rule extraction step. The results of aspect keyword extraction step is a set of keywords $(kw_1, kw_2, ...kw_n)$ as the important aspects of the political Kurdish issue in Turkey. We presented each tweet as a vector of aspect keywords $(ak_1, ak_2, ...ak_n)$, while n is the number of total aspect keywords which is 80. The value of ak_i for a tweet is 1 if the keyword kw_i has been seen in that tweet, and 0 otherwise. After feeding these vectors to our causal rule extractor (section IV-B), causal rules are extracted in the form of $ak_i, ak_j \rightarrow ak_k$ which indicates that existence of terms ak_i and ak_j in a tweet cause the existence of ak_k. The real example related to the subject of this paper can be the previously stated rule ($peace, Kurds \rightarrow live$).

Similar to each tweet or each aspect keyword in a tweet, causal rules can be polar. Extracting this polarity gives extra information as the attitude of the Twitter users about different aspects discussed in the tweets. For this reason, we investigated the polarity of each rule and extracted it via statistical methods; although other methods may work for it. This approach is explained in detail in subsection IV-D. The rule, $deal, Iran \Rightarrow Kurds$,for example, has been mostly seen in negative tweets, therefore, the label neg is assigned to it.

Apart from rule polarities, aspect polarities have been also investigated. The results of this investigation are presented in section V-B. The method for computing these polarities is again based on the occurrences of aspects in positive, negative or objective tweets. Based on our statistics, no general relation could be found between aspects and rule polarities. In other words, the aspects in different sides of a causal rule could have different polarities. This fact suggests that causal rules do not necessarily preserve the polarity of the aspects in two sides of the rule. A more detailed and step by step explanation of the sentimental causal rule discovery is given in the following section.

IV. SENTIMENTAL CAUSAL RULE EXTRACTION

In this section, the details of sentimental causal rule extraction from textual data is explained. First, Causal rules need to be extracted (step two) based on the aspect keywords that have already been extracted in step one. Apart from causal rules, sentiment analysis is accomplished on tweets which labels all (3000) tweets as positive, negative or objective (step three). The extracted causal rules take the advantage of sentimental analysis techniques, which in turn need extracting the polarity features from the tweets. The results obtained from the sentiment analysis step as the pos/neg/obj percentage of tweets, each rule has been extracted from, are used as criteria to classify the rules in three classes (step 4). Each step in this four-fold methodology is a subsection of this section.

A. Aspect Keywords Extraction

That a sentence can express an opinion which always contains an extractable target renders it useful in sentiment analysis. These targets often offer essential information or keywords relating to the content of the opinion. The term $Aspect$ in this work is assigned to those terms that are usually noun and carry a high importance in the above mentioned issue, such as $Syria$. Each aspect is an important feature related to the context, from which it has been extracted. In our research, we extracted the aspect keywords from the tweet set using a third party commercial service (www.alchemyapi.com), a cloud based text mining platform. The extraction process is accomplished by feeding the content of the subject tweet set to our Java based software whose keyword extraction feature has been built around the AlchemyApi's SDK.

For aspect keywords extraction in NLP, several techniques exist; the designers of AlchemyApi chose to take advantage of machine learning techniques and also the frequent nouns and phrases technique. The nouns can be identified using a POS tagger. In frequency based techniques, the most frequent words are specified and marked as aspects; Then the unrelated ones are removed after human evaluation. Although this method is simple, it is nonetheless quite effective. No further information is available regarding the keyword extraction method of this tool. After analysis of the tweet set, a group of 80 different keywords was reported; this group, in turn was used by our software utility to generate vectors for finding causal association rules using causal inference.

B. Causally Associative Rule Extraction

Association rule mining finds all the rules existing in the database that satisfy minimum support and confidence constraints. In the current study, instead of mere associations, we consider the problem of determining causal relationships between variables (aspect keywords) as they infer each other.

In many previous works on association rule mining, only pure association rules as the dependency between variables have been investigated; those works, however, did not extract the causalities from the extracted rules, such as variable X causes Y in $X \rightarrow Y$. Since this causality information can be quite useful in our case (Information extraction from political comments), we decided to use this technique.

In previous research on causal rule discovery, Bayesian analysis was the major method to extract the rules. In this method, causal Bayesian network is used as a network in

which, nodes represent the variables (attributes) and the arcs represent probabilistic dependence. The predecessors of a node (variable) is supposed to cause its associated nodes.

Constraint-based methods, on the other hand, can be an alternative to Bayesian methods. The PC and FCI algorithms [12] -two example algorithms of this method- use observational data -which has been already seen- to constrain the possible causal relationships between variables. Cooper [13] has described an algorithm called Local Causal Discovery (LCD) that is a special case of the PC and FCI algorithms.

The LCD (Local Causal Discovery) algorithm (Fig. IV-B) is a polynomial constraint based algorithm which uses the test of variable dependence and independence. The crucial part of this technique is Markov Condition [12]:

Definition (Markov Condition): let A be a node in a causal Bayesian network, and let B be any node that is not a descendant of A in the causal network. Then the Markov condition holds if A and B are independent, conditioned on the parents of A. Simply, any node in Bayesian network is conditionally independent of its non-descendants, given its parents.

$Input$: A vector of terms as the tweet, D and CD stand for *Dependence* and *Conditional Dependence* respectively
$Output$: list of possible causal relationships

    for all aspect keywords $ak_i \neq ak_j$
      if not $D(ak_i, ak_j)$
        for all aspect keywords ak_j not in (ak_i, ak_j)
          if $D(ak_i, ak_k)$ and $D(ak_j, ak_k)$ and $CD(ak_i, ak_j | ak_k)$
           output "ak_i and ak_j cause ak_k"

Fig. 2. LCD algorithm (Local Causal Discovery) for our case, adapted from [7]

Rule (CCU causality): Assuming that Markov Condition holds, the existence of causal relations can be investigated in tweets. Assume there are three variables (aspect keywords): X, Y and Z. Using the Chi-Square test [14], dependency between these variables can be figured out. For example, suppose that X and Y are dependent. Then it can be concluded that one is caused by the other (directly or indirectly) i.e, one is descendant of the other, or possibly the third variable cause both of them:
$X \rightarrow Y$, $Y \rightarrow X$ or $X \leftarrow Z \rightarrow Y$
If Z is dependent on both X and Y, then these three variables should be causally related. There are several possibilities for the structure of ordering these variables. Nonetheless, these conditions: X and Z are dependent, Y and Z are dependent but Y and Z are independent; however, they become dependent when conditioned on X, decrease the possibilities into one: $X \rightarrow Z \leftarrow Y$; which means that X and Y cause Z. This case has been used in our rule extraction method. Apart from methodology, some assumptions on dataset (tweets) have been considered:
$DiscreteVariables$: Every variable has binary value; the

word exists in a tweet or not.
$CausalFaithfulness$: If two word are causally related to each other, they have to be dependent. Reverse may not be true in general.
$NoSelectionBias$: The dataset is normally distributed.
Because $CausalRules$ concept has been already explained in detail in other papers such as [13], and it is only used in our work, we do not explain it more than this in this paper.

C. Sentiment Analysis of Tweets

There are three types of approaches to sentiment analysis: machine learning based, lexicon based and linguistic analysis based approaches [15]. In this work, we took advantage of first two methods. We did not analyse tweets linguistically. For example the the improvement in accuracy gained by considering the negation compared to the case without covering it, was very low (less than 1%), therefore we did not cover the negation problem. In supervised training based approaches, labelled reviews (tweets in this work) are used for training a classifier to distinguish between positive, negative, or neutral reviews, considering the extracted features. Then, given a sample review in testing phase, the same features are extracted and compared to the learned models of positive, negative, or neutral reviews.

The features used in this phase are based on the the average polarities and term frequencies of words in each tweet message, as summarized in Table I. The terms used in this table such as $polarity$ (numerical value indicating the positivity, negativity or neutrality of a review) and PMI (Pairwise Mutual Information) are explained more in IV-C2. Some of these features are well-known and used in the literature ([16], [17]) as well as our previous works [18] [19] [20] in a slightly different way, whereas, in this paper, the overall methodology for sentiment analysis is unique in its combined methodology. The first seventy features, F_1-F_{35} and F_{36} to F_{70}, are computed based on the presence of a set of positive and a set of negative seed words built by Hu and Liu [21] (called $SeedWordSet$ in this paper, including 2005 positive, and 4783 negative words) in different positions of tweets; while features F_{71} to F_{76} are computed using word polarities obtained from the SentiWordNet (SW) and the SenticNet (SN) -two known polarity resources in sentiment analysis- and PMI values of positive/negative seed words. Finally feature F_{77} is simply the occurrence of question mark ('?') in a tweet. A more precise explanation of features is presented in the following subsections.

1) Features Based on the Occurrences of seed words in different positions of the tweets (F_1-F_{70}): In this set of features, the number of positive and negative seed words in a tweet has been counted. In other words, for each tweet, a feature vector with 70 values has been built. The number 70 is chosen because no tweet in our set has more than 35 words (2 * 35 = 70). The value of each feature can be zero or one. The value 1 for i_{th} feature indicates that the i_{th} word in tweet is positive, if $i <= 35$ or it is negative, if $i > 35$. The positivity

Feature type	Feature name
features based on polar terms in different positions	F_1-F_{35}: positive terms in each position F_{36}-F_{70}: negative terms in each position
features based on polarity resources	F_{71}: avg. polarity of neg. terms in SW F_{72}: Avg. polarity of pos. terms in SW F_{73}: Avg. polarity of neg. terms in SN F_{74}: avg. polarity of pos. terms in SN F_{75}: avg. PMI value of pos. terms F_{76}: avg. PMI value of neg. terms F_{77}: occurrence of "?" in tweet

or negativity of a word or a set of words has been specified according to $SeedWordSet$.

2) Features Based on polarity resources (F_{71}-F_{76}): In SentiWordNet, three numerical values are assigned to each connotation of a word (or an expression): positivity, negativity or objectivity [22]. The summation of these three scores must equal to one which is presented in 1:

$$Pos.Score(w) + Neg.Score(w) + Obj.Score(w) = 1 \quad (1)$$

where *w* stands for a given word; and the three scores stand for its positivity, negativity or objectivity scores, respectively.

Furthermore, we define the polarity of a word w as:

$$Pol(w) = Pos.Score(w) - Neg.Score(w) \quad (2)$$

There are several senses and consequently polarity values (each value for each sense) for each word in SentiWordNet; to compute the polarity of a word in a context, we did not do word sense disambiguation because it is a different problem that not yet been completely solved. We employed the average polarity of all senses of a word in SentiWordNet as its overall polarity. Consequently, the average polarity of all words in a tweet as a review, r, denoted by $AP(r)$ is computed as in (3).

$$AP(r) = \frac{1}{|r|} \sum_{w_i \in r} Pol(w_i) \quad (3)$$

where $|r|$ is the number of words in review (tweet) r and $Pol(w_i)$ is the polarity of the word w_i as defined above.

Features F_{71} and F_{72} are based on the average polarity concept (AP): the average polarity of only the negative and only the positive words in a tweet, respectively. A word w is decided as positive if $Pol(w) > 0$, or otherwise decided as negative. Those words with $Pol(w) = 0$ are not considered in our work. The features F_{73} and F_{74} are computed in similar way to F_{71} and F_{72} using the SenticNet. However, in SenticNet, unlike SentiWordNet, there is only one numerical value between -1 and 1 assigned to a word or phrase as its overall polarity; therefore, we did not encounter issues such as word sense disambiguation like what we had in SentiWordNet. In SenticNet a word or a group of words is supposed to be negative if its overall polarity score is less than 0 or otherwise supposed positive. The words with polarity value of zero are not used n this work.

The last pair of features, F_{75} and F_{76} are computed using the PMI -Pairwise Mutual Information- of seed words in $SeedWordSet$. The formula used in computing the PMI value for each seed word is 4.

$$PMI(t_1, t_2) = \frac{P(t_1, t_2)}{P(t_1) * P(t_2)} \quad (4)$$

t_1 and t_2 are the terms that the PMI value is being computed for them. Here, t_1 is any of the seed words in $SeedWordSet$ and t_2 is any of the pure positive words such as $excellent$ or pure negative words such as $awful$. $P(t_i)$ is the probability of seeing t_i in a tweet and consequently $P(t_1, t_2)$ is the probability of seeing both t_1 and t_2 in a tweet. These probabilities have been computed using the tweets in training set.

We computed the PMI value of each positive seed word with very positive words and also the PMI value of each negative seed word with very negative words presented in Table II. The value assigned to each seed word in the $SeedWordSet$ is the average PMI value of that word with all negative or positive words in Table II. The computed values are used in the last pair of features F_{75} and F_{76}. These features are the average PMI values of seed words in the $SeedWordSet$ that have been seen in a tweets of training set.

pos. words	excellent, fantastic, good, outstanding, extraordinary
neg. words	awful, unpleasant, bad, sad, disgusting

Finally feature F_{77} is simply the occurrence of the question mark in a tweet. Usually tweets with question mark have more of a tendency to be neutral compared to those without question mark. Although this feature does not use any resource, it is placed among the second group of features to prevent adding a new feature group.

D. Assigning Polarity Values to Causal Rules

Based on the statistical processing of the tweets, we assigned three polarity values to each causal rule, which indicate how much a given rule has been extracted from positive, negative or objective tweets. As mentioned earlier, usually the overall (tweet level) polarity of the tweet can be considered as the polarity of the aspect(s) discussed in it. These scores are presented in results section (Table VI). Consequently we assign obj/pos/neg label to each rule if it satisfies one of the constraints below:

- else if $obj.score > (neg.score + pos.score)$ or $neg.score == pos.score$ then the rule is considered as $objective$.
- else if $(pos.score > neg.score)$ and $(pos.score > obj.score)$ then the rule is considered as $positive$.
- else if $(neg.score > pos.score)$ and $(neg.score > obj.score)$ then the rule is considered as $negative$.

The three scores mentioned above stand for the positivity, negativity and objectivity scores of each rule based on the

percentage of tweets it has been extracted. The proposed constraints for labelling is a suggested algorithm, while other methods such as strict threshold could be used; we chose the proposed one because it is more flexible than the strict threshold and also could generate more real results. In strict threshold method, similar to confidence and support values in association rule extraction, a threshold is set and those rules with higher scores than the threshold are used for some goal.

In most cases, rules are subjective and carry polar information, therefore the necessary condition for a rule to be objective is harder to satisfy ($obj.score > (neg.score + pos.score)$) than the conditions to be positive or negative. A rule is labelled as objective if its objectivity score is higher than the sum of both positivity and negativity scores or its positivity and negativity values are equal without regarding the objectivity score. But to be positive (or negative), having the maximum score as positive (or negative) is enough. Those rules that do not fit in any of the cases above, cannot be labelled in our method.

V. EXPERIMENTAL EVALUATION

In this section, the evaluation of proposed methodology explained in section IV-C has been presented including the dataset, results and discussion on results.

A. Data Sets

Twitter allows its users to post real time messages of 140 characters in length. The messages are called as tweets. Due to quick (time) and short nature of tweets, Twitter users often make spelling mistakes, use special characters to express special meanings and use emoticons to express feelings.

For this paper, tweets have been collected on three topics *Kurdish and Turkey*, *PKK* (Partiya Karker Kurdistan which means Kurdistan Worker's Party) and, *Kurdistan and Turkey* from a third party commercial service i.e. www.tweetarchivist.com. The data has been collected by capturing real-time tweets on a topic and archiving them. Neither kind of restriction such as language or location was imposed during the tweet collection process. The archive was made through collecting tweets in first three months of 2013 which resulted in around 10000 tweets in multiple languages. For this study, we sorted them and filtered only English tweets which resulted in around 5000. The filtered tweets were further analysed to remove scrap, irrelevant and duplicated tweets. The training dataset consisted about 2000 tweets. For the training data set each tweet was labelled manually as positive, negative or neutral. After training the classifier using the training set, we extracted another 1000 cleaned and unlabelled tweets and labelled them using the trained classifier.

Preprocessing of Tweets: Due to the nature of tweets, they need to be preprocessed to treat missing, incomplete or noisy data. To do so, tweets were passed through a Java utility created specifically for this goal. The preprocessing involves the following steps:

- Removal of URLs: some tweets contain URLs for hyper-linking different webpages. For sentiment analysis task,

they do not contribute; therefore they are removed from tweets.
- Removal of retweets: retweeting is the process of forwarding someone else's tweet and posting to contact list of forwarding person. Retweets are duplicates of original tweets; so, such tweets have to be identified and removed from the dataset.
- Treatment of special characters: special characters e.g. []()/!, have to be removed in the preprocessing step because they often are concatenated with words such as /begin ning/ which make the word of no use because of unavailability in the dictionary and failure to assign polarity to such words.
- Treatment of emoticons: tweets contain emoticons to express users' feelings, e.g. :-) for happiness and <3 for love. Emoticons play a vital role in decoding the exact sense of tweets. For this purpose, a dictionary of emoticons has been created by collecting 80 emoticons and their emotional state. Each occurrence of emoticon in a tweet has been replaced with its corresponding emotional state; e. g. <3 substituted with *love*. An alternative for this, is using classification features as the presence f each emoticon in tweets.
- Treatment of acronyms: a similar approach has been followed for treatment of acronyms. For acronym treatment, a dictionary of 500 acronyms had been created. The acronyms have been collected through the Internet resource (www.noslang.com). Each tweet has been processed to replace any acronym with its corresponding meaning e.g. lol replaced with laughing out loud or dah replaced with dumb as hell.

The sentiment analysis in tweets is a difficult task because 1) the length of tweets is short and 2) people usually do not express their ideas clearly in tweets about an issue; they rather use an informal language.

B. Results

The results obtained from our methodology can be categorized in different groups. All the results have been extracted from about 3000 English tweets. The first group is the accuracy of our sentiment analysis system. This accuracy is different for binary and ternary classifications, specially when different classifiers are used (Table III). These accuracies are computed using 5-fold cross validation on training data in Weka 3.6. Although the accuracy of the classification is less than ideal, however, it may worth to save the time spent on manually labelling the test tweets by automatic classification. We applied ternary classification on test data by Neural Networks (multilayer perceptron) classifier to predict the label of test set tweets.

The overall percentage of positive, negative or neutral tweets about the Kurdish political issue in Turkey is the next set of results which reflects the overall attitude of public. These percentages can be seen in Table IV. It seems that many users think negative rather than positive about the mentioned issue.

Classes	SVM	Logistic	NN
Binary	72	70	76
Ternary	67	64	68

Positive	Negative	Neutral
32	48	20

The third group of results is the keywords extracted from those tweets using an online keyword extractor (explained in IV-A). These keywords with the percentage of positive/negative/objective tweets including them are shown in Table V. These percentages indicate the percentage of pos/neg/obj tweets including each aspect keyword.

Finally, the association rules extracted from labelled tweets can bee seen in Table VI. In this table, support and confidence thresholds are taken as 0.004 and 0.2 respectively. The association rules revealed through causal inference provided useful insights into the overall summary and general sentiment of people about different aspects, discussed in tweet set. Based on rule labelling algorithm stated above, most of the rules presented in results section (Table VI) are labelled as negative because the negativity percentage of them are higher than the other scores. This negativity may be because no complete solution has been found for the Kurdish political issue in Turkey and it still remains as a negative issue in people's opinion. Several hypotheses can be extracted from those rules. Although some of these hypotheses may not be completely true, they can provide useful information for politicians.

- The rule $rebel, Kurds \Rightarrow withdraw$ may owe to the fact that the Kurdish rebel will cause them withdrawing from being under control of Turkish government. Based on our rule classification algorithm, this rule is classified as objective because $pos.score = neg.score$.
- association rules such as $deal, Kurds \Rightarrow Syria$, $Syria, fight \Rightarrow peace$, and $strategic, war \Rightarrow Syria$ encircle the group of tweets discussing about the impact of peace deal on the security situation of Syria. users comments and several news-tweets on Twitter argue that after evacuating Turkey, the rebel groups are moving to Syria and will operate there. This action will bring momentum to their strategic terror activities from now on for Syrian region. These rules mostly contain the negative keywords such as $fight$, $attack$ and $Syria$, which shows the negative attitude of Twitter users about this issue. Also two of these rules are classified a negative and one as positive.
- The rule $corridor, war \Rightarrow Syria$ has a means of the creation of Kurdish corridor in the region can be eased by fuelling war in Syria. This one is also classified as

negative. Syria is an strategic region in Kurdish issue because Kurds are the largest ethnic minority in Syria.

- The rule $Islam, Kurds \rightarrow attack$ suggests that some people blame Muslim Kurds to be the reason of potential war in Turkey. The high negativity percentage (100%) of this rule shows the pure negative attitude of Twitter about this this subject. On the other hand, the keyword $Islam$ has also higher negative score than positive which approves the mentioned assumption.
- The rule $student, kurd \Rightarrow attack$ implies that some Kurds force the students to participate in war against the Turkey. This issue had been mentioned in Turkish TV channels already. Not surprisingly this rule is fully negative.
- The rule $PKK, deal \Rightarrow peace$ suggests that the peace will come to the area if a debate process ($deal$) starts between two sides of this struggle ($Turkey$ and the PKK). The higher negative percentage of this rule indicates the negative attitude of people to make peace with the PKK.
- The rule $PKK, Kurdistan \Rightarrow deal$ indicated the fact that if PKK and Kurdish people can have their own $Kurdistan$ (country), the $peace\ deal$ will happen, however, this assumption is approached negatively by the users, based on the obtained pos/neg/obj percentages.
- A few association rules such as $deal, Iran \Rightarrow Kurds$ and $Iraq, Iran \Rightarrow Kurds$ indicate that the Kurdish issue in Turkey has dependency on the political involvement and internal situation of $Iraq$ and $Iran$. BAsed on the negativity scores of both rules, this point is also considered as negative.

aspect name	pos%	obj%	neg%
PKK	29	55	16
Turkey	33	46	21
Kurdish	31	47	22
rebel	58	28	14
Iran	17	70	13
Syria	17	61	22
Iraq	36	46	18
leader	54	24	22
peace	54	28	18
corridor	21	64	15
war	19	41	40
Islam	12	62	26
Process	52	32	16
Kurds	26	53	21
Withdraw	54	33	13
Fight	35	42	23
Strategic	21	48	31
Attack	6	88	6
student	20	66	14
Deal	15	72	13

VI. CONCLUSION AND FUTURE WORK

In this paper, we proposed the new concept of sentimental causal rules which consists of both sentiment analysis and

TABLE VI
ASSOCIATION RULES WITH THE PERCENTAGE OF POS./NEG/OBJ. SCORES
EXTRACTED BASED ON THE ASPECTS

Causal rule	pos	obj	neg	label
rebel, Kurds $\Rightarrow$ withdraw	50	0	50	obj
Syria, fight $\Rightarrow$ peace	33	50	17	pos
deal, Kurds $\Rightarrow$ Syria	6	5	89	neg
strategic, war $\Rightarrow$ Syria	29	29	42	neg
corridor, war $\Rightarrow$ Syria	29	29	42	neg
Islam, Kurds $\Rightarrow$ attack	0	0	100	neg
deal, Iran $\Rightarrow$ Kurds	6	6	88	neg
Iraq, Iran $\Rightarrow$ Kurds	4	10	86	neg
PKK, deal $\Rightarrow$ peace	22	7	71	neg
PKK, Kurdistan $\Rightarrow$ deal	15	13	72	neg
student, Kurds $\Rightarrow$ attack	0	0	100	neg

causal rule concepts. As the case study, we investigated the challenging problems between Turkish government and Kurdish parties. We investigated the ideas of Twitter users about this issue. A four-phase approach is proposed in this work: 1) aspect keywords extraction, 2) causal rules extraction based on aspect keywords already obtained from the tweets, 3) sentiment analysis on tweets and 4) assigning the polarity values to each aspect and also causal association rules. The achieved results, specially those related to the opinion of users about different aspects of the Kurdish issue in Turkey seem fairly well and approximate the current situation of Turkey. This paper reflects the ideas of Twitter users (mostly non-Turkish) about the above mentioned issue; Turkish people usually write their tweets in Turkish. These kind of works can help politicians know the ideas of people about different political issues. We will investigate Turkish tweets in this area in our future work. We found the sentiment analysis of tweets a difficult task mostly because of the short length of tweets, many junk words and inevitable syntax errors in them.

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