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Knowledge Representation for Emotion Intelligence

Shuo Wang

Supervised by Xiaofeng Meng[1]
Expected graduation date: June 2019
Information School
Renmin University of China
Beijing, China
wsterran@126.com

***abstract*—Emotion intelligence (EI) is a traditional topic for psychology, sociology, biology and medical science. Because emotion is related with the personality, interpersonal effect, social function, disease treatment, etc. Analyzing the emotion from the Web data by computer technology becomes more and more popular, and the scientists from the non-computer domains need more helpful computing models to deal with professional problems that are not traditional for computer science. Knowledge representation is a basic and possible solution as a bridge between emotion intelligence and artificial intelligence. For the sentiment words, word embedding can map the words to vectors that represent the semantic context of the words. Sentiment embedding based on the word embedding can capture both semantics and the emotion information. We have introduced two kinds of improving embedding methods (MEC and Emo2Vec) for the sentiment words embedding. For emotion structure based on the psychology of emotion, knowledge graph can represent the cognitive relations between different emotion types. The same emotional expressions can affect the reaction and behaviors of the recipient in different ways due to factors such as social relations, information processing, time pressure, etc. Knowledge graph can represent these complicated situations as the relations between the entities and attributes. Based on this graph, we make the inference or prediction of the emotion influence on decision making.**

Keywords—emotion intelligence, sentiment embedding, cognitive structure of emotion, knowledge graph

I. Motivation

Nowadays, hundreds of millions of people distribute their reviews or comments on products, offers and services through the online platforms such as Blogs, WeChat, QQ, discussion boards, etc. The internet merchants can mine the opinions from these data for recommending or improving the products. Additionally, there are many debates or comments on the news or hot events [16]. The public emotion or position can be analyzed from them. Generally speaking, sentiment analysis or opinion mining refers to the use of natural language processing, text analysis, computational linguistics, and biometrics to systematically identify, extract, quantify, and study affective states and subjective information. Therefore, such process is widely applied to reviews and survey responses, online and social medias, and healthcare application that range from marketing to customer service. However, most methods just give a score for evaluating the positive or negative sentiment, or sometimes their strength. This kind of analysis results only shows the emotion existence and its intensity, but we can not know what is the next. The reaction or behavior for the previous emotional expression is not mentioned, and the reason of the emotion generation is not considered.

In my research, the new research directions of sentiment embedding and knowledge graph for sentiment analysis and emotion inference are introduced. In order to make better use of the emotion intelligence theory, the problem is divided into two levels: instance level and concept level. For the instance level, the sentiment embedding method intends to solve the sentiment representation for words and sentences. For the concept level, knowledge graph builds a network to represent the emotion structure based on cognitive and appraisal theory, which can link the emotion type, emotion entity, emotion condition, emotion instances, etc. The instance level is the basis of the concept level. The analysis result from the instance level can be used as a part of the input for the concept level. The whole levels can store the knowledge of psychology emotion from instances to abstract concepts.

II. Background and Related Work

A. Sentiment Embedding

Sentiment analysis methods typically employ nature language processing technology with utilization of additional resources (e.g. sentiment- and emotion-based lexicons, sophisticated dictionaries and ontologies) to model the documents. Some document features such as the frequency and presence of terms and parts of speech, emotional words and phrases, and the existence of negations are identified towards a successful sentiment classification which can characterize the documents based on their polarity as negative, positive or neutral.

With the recent development of deep neural network in machine learning, the neural network language models have made great progress in natural language processing tasks. Word embedding methods generally use neural network architectures to learn the distribution vector representation of words by leveraging the context information in large corpora. In 2001, Bengio et al. used a neural network language model (NNLM) to learn word embeddings based on the preceding context of the words while learning the language model. The C&W [1] model extended the preceding context to both preceding and succeeding contexts that were the inputs for a convolutional network. In 2013, Mikolov et al. further proposed the Continuous Bag-of-Words (CBOW) and Skip-gram models [2] at the same time. They used a single layer architecture without the hidden layer to increase the training speed of the models. Levy and Goldberg and Pennington et

[1]WAMDM Lab, Information School, Renmin University of China, Beijing, 100872.

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al. [3] respectively indicated that the methods mentioned above generated the word embeddings based on linear and local contexts, and thus proposed dependency-based word embeddings and global word vectors (GloVe).

The models mentioned above only complete the word embeddings and do not detect the sentiment with the word embeddings. The common existing sentiment embedding is the use of polarity labels from the labeled corpora to guide the learning process. A semi-supervised method [4] provided by Maas et al. can capture both the semantic information from unlabeled data using a probabilistic model and the sentiment information from a labeled corpus using a prediction models for learning sentiment embeddings. Labutov and Lipson [5] transfered the source embedding to the targeting embedding with a fast method by optimizing the conditional likelihood of the polarity labels on a movie review dataset. Recent works focused on the distant supervision method which automatically collected the tweets for learning the neural network models of sentiment embeddings. Tang et al. created the sentiment embeddings based on the C&W models in learning word contexts. They gave the hybrid model (HyRank) [6] to combine the contexts of words and sentiment polarity of tweets.

B. Knowledge Integrated from Psychology of Emotion

There has been a wealth of research on emotions in psychology and cognitive science. The corresponding models or theories state the antecedents and consequents of emotions as well as their impact on the reaction or behaviors. Among emotion literatures, the cognitive appraisal theory is well known and most well researched. Appraisal theory was proposed [7] and developed [8] to explain how different emotions may emerge from the same event, in different individuals and on different occasions. Appraisal is a process that detects and assesses the significance of the environment for well-being [9]. Unlike other emotion theories that vaguely propose that cognitions contribute to emotions, appraisal theories specify the appraisal criteria or variables that are most important in differentiating emotions. Most appraisal theorists [10,11] propose that the appraisal variables include concerns, certainty, agency (event caused by oneself, someone else, or impersonal circumstances), and coping potential or control. In addition, the novelty, expectancy, urgency, intentionality, legitimacy, fairness and norm compatibility contribute to the differences in emotions. There is not complete agreement among appraisal theorists on the number and identity of these variables.

Appraisal theories describe not only the contents of appraisal, but also the underlying mechanisms of the process, the nature of the representations, and the degree of automaticity. Two or three underlying mechanisms are proposed in appraisal theory, endorsing a dual or triple mode view of appraisal. The dual mode [9,11] view consists of two parts including (a) a rule-based mechanism, consisting of the on-line computation of one or more appraisal values, and (b) an schematic mechanism, consisting of the activation of learned associations between representations of stimuli and previously stored appraisal outputs (individual values or entire patterns). Appraisal theory allows that various mechanisms can underlie appraisal and that they can operate on a wide range of representations: conceptual and propositional versus perceptual and embodied. Although the appraisal theories include appraisal as a component in the emotional episode, this component is assigned as a central role unlike other emotion theories, which means appraisal triggers and differentiates emotional episodes through synchronic changes in other components. Appraisal determines the intensity and quality of action tendencies, physiological responses, behaviors, and feelings.

C. Knowledge Graph

In recent years, many data publishers have relied on the benefits provided by the Semantic Web [13,14] for quickly publishing, parsing and processing data by machines. This development has been partially supported by the Linked Open Data (LOD) that is initiated with more than 80 billion published RDF triples. Such data has been mainly extracted from (semi-) structured sources such as relational databases, meta-data, Wikipedia infoboxes, HTML tables, etc. However, a huge amount of information is mainly stated as plain text without any structure or description. With the support of Natural Language Processing (NLP) and Information Extraction (IE), two main elements are extracted and annotated from text: named entities and semantic relations between them. Broadly speaking, the extraction of such elements is the main component of the task which is known as Knowledge Graph Construction (KGC) [15,17,18]. Knowledge graph serves as an integrated information repository that interlinks heterogeneous data from different domains. Generally, KGC processing consists of four steps [17,18]: entity linking, relation extraction, property linking and representation. The output of KGC is an RDF sets stored in graph databases for query and searching.

The graph structures can be used to facilitate the semantic queries and become the popular schema to explore the deep links between the entities. In the graph database, the domain data are represented as a network of nodes, relationships and properties. The universal schema focuses on the benefits of using latent features for increasing the coverage of knowledge bases (KBs). Link prediction on the KBs can generate the inference rules through Markov Logic, PRA and so on.

III. Proposed Research Methods

As mentioned above, most information exists in plain text including the emotion information. Firstly, the sentiment words need to be recognized and transferred into proper forms with representation learning that can capture both the semantics and sentiments or emotions. Secondly, the knowledge of emotions needs to be extracted from the text and be stored into the KBs based on the psychology of emotion theory (mainly from the appraisal theories). Lastly, the emotion reaction or behavior can be inferred on the emotion graph by taking advantage of the inference rules and link prediction methods.

In the first task, the goal is to use proper embedding technology for improving the sentiment analysis, which means recognizing the right emotional type or emotional intensity. For the second assignment, the knowledge graph is divided into two layers: instance layer and schema layer (or concept layer). The instance layer consists of the emotion examples that include emotional entities, emotional relations and their properties. The schema layer includes the emotion type, emotional mechanism, appraisal variables etc. At last, the new example can be transferred into the RDF form and aligned to the elements in the schema layer. The inference can be implemented through the mechanism or prediction fu-

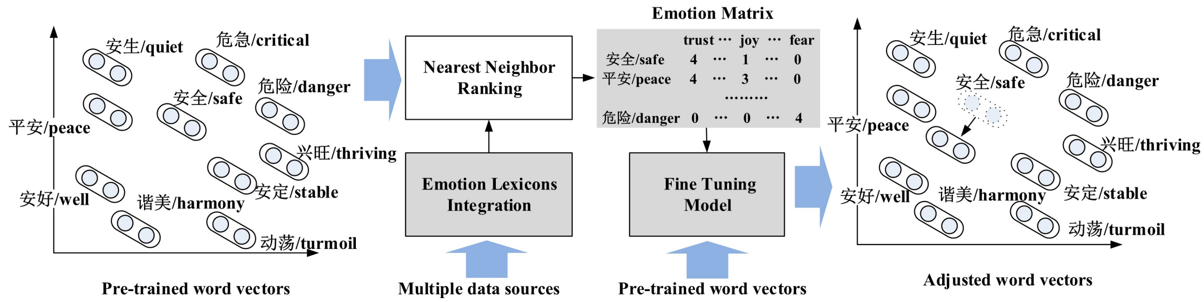

Fig. 1. The framework of multi-emotion category method

nction.

A. Sentiment Representation in Words Level

Given the lexicon based on Plutchik's wheel of emotions and a set of pre-trained word vectors, the proposed multi-emotion category method can adjust the pre-trained vectors of every word in the lexicon. As shown in Figure 1, the frame-work of multi-emotion category (MEC) method [15] is divided into three parts: lexicons integration, nearest neighbors ranking and fine-tuning model. The details of the three parts are described below.

For sentiment analysis, the unsupervised methods often rely on the documents statistical properties, NLP processes and existing lexicons. The most common labels are the negative and positive tags for the target words but the polarity emotion information is not enough for sentiment analysis. Some psychologists have provided several famous psychological theories for human emotions such as Paul Ekman, Carroll Izard, William McDougall, Robert Plutchik, etc. The emotion can be represented by multidimensional vector. I take advantage of Plutchik's wheel of emotions which can represent one word by 8-dimensional vector. There are several Chinese emotion lexicons (e.g. NTUSD, DUSD, HowNet, etc.) that have the different kinds of sentiment labels. The words disambiguation and alignment tools are used to integrate these lexicons into the rules of Plutchik's emotion theory. In this way, a new emotion lexicon which consists of 8-dimensional vector per emotion word is created for representing the emotion information and knowledge. The values of the vectors are normalized and the number of the words in this new lexicon is 14450.

And then the nearest neighbor ranking should be applied to select a set of words both semantically and emotionally similar to the target word for vector fine-tuning. The semantic vectors of the words are pretrained by word embedding method (e.g. Word2Vec, GloVe or others) and the sentiment vectors of the words are ready by the integration of emotion lexicons. This step ranks the semantically preordered words by distinguishing the emotional difference from each target word. For example, the target word is safe, and its top-10 nearest neighbors in semantics similarity are selected and ranked in descending order of the cosine similarities as follows, peace, danger, quiet, stable, critical, well, thriving, turmoil, harmony. It can be discovered that three dissimilar neighbors (danger, critical and turmoil) from the emotional view are negative in the neighbor list. The emotion vectors of the nearest neighbors are searched from the lexicon. The emotional distance between these neighbors and the target word can be calculated based on the Euclidean distance. The ranking results in emotional view are shown as follows, peace, harmony, quiet, stable, well, thriving, danger, critical, and turmoil. There are small changes for the emotionally similar neighbors in the order. On the contrary, the emotionally dissimilar neighbors are ranked lower because of the significant difference in distance.

At last, the fine-tuning model uses the results of the nearest neighbors ranking to assign different weights to the nearest neighbors and adjusts the target word vector to make it closer to its similar semantic and emotion neighbors and further away from the dissimilar emotion neighbors. At the same time, the adjusted vectors are not too far away from the original vectors. The fine-tuning model aims to minimize the distance between the pre-trained vector and its nearest neighbors based on an objective function which is defined as

$$\arg\min F(V) =$$

$$\arg\min \sum_{i=1}^{n}\left[p_1 dis\left(v_i^{s+1}, v_i^{s}\right) + p_2 \sum_{j=1}^{k} w_{ij} dis\left(v_j^{s+1}, v_j^{s}\right)\right]$$

where n denotes the number of vectors in $V = \{v_1, v_2, \ldots, v_n\}$, v_i denotes the target word vector, v_j denotes one vector of the top-k nearest neighbors, $dis(v_i, v_j)$ denotes the distance between two target word vector, w_{ij} denotes the weight of the vector v_j with respect to the target vector v_i, v^s and v^{s+1} respectively denotes the word vector in step s and step s+1. w_{ij} is the reciprocal rank of vector v_j in the ranking list generated by neighbors ranking step. We add a constraint to give a moving range for preventing too many words from being placed in the same location.

The MEC model also has several shortages: 1) its effect depends on the pretrained embedding results; 2) the context information of the sentiment words in the text is not considered into the embedding processing; 3) it needs to extend the classification model to multi-category tasks for describing the emotions more accurately. In order to improve the above shortcomings, I proposed a new method based on the word embedding named as Emo2Vec (Submitted for review) [19]. It does not need the pretrained word embedding but merges both semantics and sentiment at the same time in the embedding computation for the words. Under this tactics, the sentiment words and their context are embedding simultaneously to generate the vectors of words that contain both semantics and emotions. Specially, this embedding process takes advantage of the 8 dimension emotion vectors of the sentiment words, so the embedding results are adaptable for different tasks.

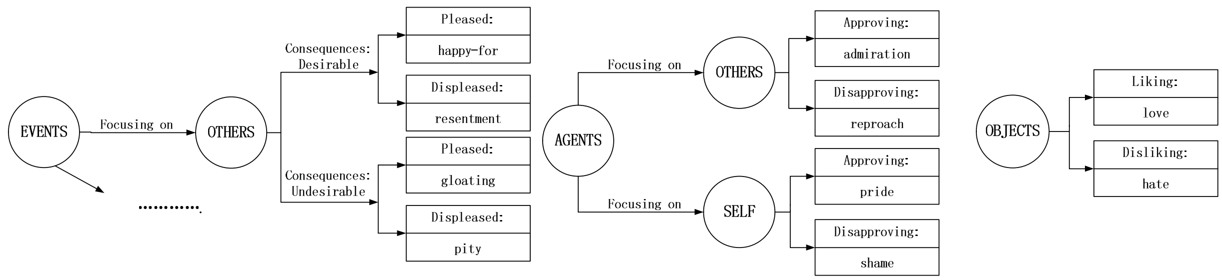

Fig. 2. Graph of the structure of emotion types in schema layer

B. Emotion Knowledge Graph Construction

Among the emotion literatures, the cognitive appraisal theory is the most well studied and in particularly, the OCC model presented by Ortony, Clore, and Collins [12] is widely used for emotion computation. This model argues that there are three major aspects of the world, or changes in the world, upon which one can focus, namely, events, agents, and objects. When one focuses on events, one does so because one is interested in their consequences. When one focuses on agents, one does so because of their actions. When one focuses on objects, one is interested in certain aspects of them. I build the schema layer of the emotional graph to represent the relation between the three aspects of worlds and emotion type as shown in Figure 2. Because the part of events is too large to shown in the paper, the objects and agents is shown completely in graph form. The emotion types include admiration, reproach, pride, shame, love, hate, etc. The concepts include events, objects, agents, emotion types, etc. The relations include "focusing-on", "Consequences", etc. The properties include "liking", "disliking", "approving", "disapproving", etc.

For the instance layer of the emotional graph, we can extract the entity and relation by named entity recognition and relation extraction method, and we also get emotion type through the method in word level. From the example (a), the emotion type can be identified by sentiment embedding. The entities include "man", "inheritance" and "unknown distant relative". The event is that a man gets a small inheritance. The man focuses on himself.

Example (a): The man was pleased when he realized he was to get a small inheritance from an unknown distant relative.

Example (b): Fred was happy for his friend Mary because she won a thousand dollars.

Example (c): Fred was jealous of his friend Mary because she won a thousand dollars.

C. Inference on Emotions

After constructing the schema layer based on the appraisal theories, we can map the instance to the concepts in this layer. Taking Example (b) and (c), the entities, events and focuses are same in them except the emotion type. When they are mapped into the concepts in schema layer, the properties of emotion types are different for the two examples, and the relations of consequences are also different. So the inference can be made for this situation. Fred is displeased for the event and desirable for it. If the background can be extended, we can assume that Fred and Mary be colleagues. The reason of displeased from Fred would probably be that Fred does not like Mary. This inference needs more variables in appraisal theories. Conversely, if we know that Fred likes Mary, we can infer that Fred should be happy for Mary when Mary won a thousand dollars. This process is the prediction of the emotion type. All the above examples is based on the rules represented by knowledge graph.

IV. EXPERIMENTS AND ANALYSIS

For the different levels of the emotion intelligence, I prepare different experiments settings. The datasets are also different for each assignments.

A. Experiments on Sentiment Embedding

The MEC method [15] is evaluated through a series of experiments on three datasets that include Chinese reviews on the hotels, English reviews on the movies, and Weibo Text of Sina website. The Weibo Text of Sina website has 14000 passages for training and 40000 passages for testing. Every passage consists of 4~7 sentences. The hotels review dataset consists of 3000 positive samples and 3000 negative samples. Each sample is one passage which consists of 1~10 sentences. The English movie reviews dataset is built by Cornell University that consists of 5331 positive snippets and 5331 negative snippets. We translated them into Chinese by Baidu Translator API.

The word embedding used for the experiments includes the conventional word embedding (Word2Vec), the sentiment embedding (HyRank), and our MEC methods (MEC(Word2Vec) and MEC(HyRank)). The classifiers used for the experiments include CNN and Bi-LSTM. These classify models are available on Github. Both the sentiment embedding and the proposed MEC method outperformed the conventional embedding because both of them brought the sentiment or emotion knowledge into the vector representations. The fine-tuning models improved both the conventional embedding and the sentiment embedding. Overall, MEC(Word2Vec) and MEC(HyRank) respectively improved Word2Vec and HyRank by 4.2% and 3.4% averaged on all datasets for Macro F1-score, and respectively improved the accuracy by 2.3% and 1.9%. Because the translation effect was not good enough for the classification and some translated words were not very consistent with Chinese idioms, the results of the reviews on movies were not as good as the other two datasets.

The Emo2Vec model not only can complete the above classification task, but also can cope with multi-category problem. The sentiment analysis need to classify the complicated classes for emotions, not just limited to positive and negative. Emo2Vec performs better than MEC in the classification accuracy on three datasets mentioned in MEC.

And it can complete the multi-class category on a Chinese dataset provided by NLPCC2014.

B. Experiments Setup and Analysis on EKG

Emotion Knowledge Graph (EKG) is divided into two parts, the schema layer (upper layer) and the instance layer (lower layer). The upper layer consists of the basic concepts corresponding to the appraisal theories. It was built manually based on the OCC model. The appraisal theories need some appraisal variables to differentiate the emotions. So one sentence as the examples mentioned in the previous section or several paragraphs without the story background can not take advantage of the schema layer to analyze the appraisal variables for emotions.

I use the drama works as the dataset that can set up the proper scenes for appraisal theories. The advantages of the drama is obvious to emotion analysis assignments: 1) the number of characters are limited and characters' relations are clear and stable; 2) the emotional episodes in dramas are clear and common sense; 3) the appraisal variables can be extracted easily from dramas and they can fit for the different needs from most appraisal theorists. However, the drama data don't have the standard labels or some evaluation metrics. So the experiment on dramas focuses on the effectiveness of the emotional inference based on appraisal theories. For example, the narration of Iago, a typical character in the drama of Othello, is collected for the emotional inference. The results of the inference clearly show the emotion types between Iago and other characters in the drama. Iago wants to become the deputy of General Othello, so he feels happy when he finds Cassio likes to talk with Tess Dimena. The knowledge graph can map the narration from Iago to the schema layer, and then find two paths for this event. One path leads to focus on the "self" which trigger the emotion type "hope" that means Iago hopes they keep talking or frequently talk to each other. The other path leads to focus on the "others" which result in "happy-for" that means Iago is pleased to this event. The same analysis can keep tracking the emotion changes when Iago faces Othello. Iago generates "admiration" to Othello because he married a beautiful wife. This emotion type is inferred by the agent focused on "others" in the graph. When Iago cheats Othello, the emotion type "pride" is predicted by the agent focused on the "self". In general, the prediction of the emotion type is good enough in the dramas.

V. CHALLENGE AND FUTURE WORK

With the development of the emotion intelligence, the appraisal variables are increased. For emotions in social interaction, the emotional competence is related with the friendship or partnership. The emotional effect also rely on the role that you play in the social interaction. For emotions in decision making, the goal activation is shaped by emotions. All these advances need to map onto the appraisal theories. So we should construct more complex model for the new discoveries in emotions.

The dramas provide a standard scene for the emotional inference based on the emotional knowledge graph. However, we need to apply the graph to solve the problems in the real life such as emotional management, decision control, sale scenario analysis, etc. So the data for these problems need to collect or build in future.

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