Analyzing emotion based movie recommender system using fuzzy emotion features

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ORIGINAL RESEARCH

Analyzing emotion based movie recommender system using fuzzy emotion features

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Abstract User generated contents like reviews and comments contain both the information about a given product and also the opinions asserted by the user. With the surge in internet usage, there is a cascade of user generated data such a reviews and comments. People share their experiences, opinions, sentiments and emotions by writing reviews and comments for products they purchase online or after watching a movie, reading books etc. These user generated data contains emotion lexicons such as happiness, sadness, and surprise. Analysis of such emotion can provide a new aspect for recommending new items based on their emotional preferences. In this work, we extract the emotions from this user generated data using the lexical ontology, WordNet and information from the domain of psychology. These extracted emotions can be used for recommendations. Evaluation on emotion prediction further verifies the effectiveness of the proposed model in comparison to traditional rating based item similarity model. We further compare this with fuzziness in emotion features.

Keywords Collaborative recommender system · Content based recommender system · Emotion analysis · WorldNet

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1 Introduction

Recommender system study patterns of activities of users, analyzes it and then anticipate their preferences among a set of items. Recommender system uses technology that can broadly be classified into two categories: content and collaborative filtering. Content based model (CBR) works by analyzing and examining properties about the items to make predictions. Collaborative model (CF) finds similarity of users or items to make predictions about what a user may like. CF approaches utilize the *wisdom of crowds* to recommend items according to the preferences of users with similar tastes and preferences [1]. Among these, traditional memory-based CF techniques find similar users based on their ratings for different items. These similar users form the basis of user based recommender system. Model-based CF approach analyzes the rating pattern to precompute a model to recommend items. Based on features and content of the items liked by the items, CBR systems finds similar items with same features or attributes to recommend new items [2]. Both CF and CBR approaches suffer some limitations. CF based recommender systems typically encounter the problems of (1) sparse rating as many users don't rate items and (2) cold start problem. Cold start problem is of two types: new user cold start problem and new item cold start problem. New user cold start problem occurs when a new use who has not rated any item enters a recommender system. New item cold start problem occurs when a new item that is not rated by other users is added to the system. On the other hand CBR only suffers from new user problem where there is no information about his like/dislike. Due to these limitation both CF and CBR fail to generate reliable recommendations [1]. Due to sparse user-item rating matrices nearest neighbors or nearest items are difficult to identify. This leads to poor recommendations [3].

In this paper we propose a new item based recommender system using both CF and CBF based approaches to recommend items using emotions. With advent of Web 2.0, users express their interests and tastes through feedbacks, reviews, comments etc., in social media. Many E-commerce sites store these feedbacks from multiple domains and try to suggest items from various domains that users may likely to be interested in for better recommendations. Emotions are intense feeling that are directed by something's or someone. Reviews and comments of an item act as a content from which emotions are extracted. These emotions act as link to generate item–item similarity. Then using item based collaborative filtering recommendations are performed. We compared our approach with other approaches that used item–item similarity using cosine based and conditional probability based similarity.

2 Related work

Traditional approaches for recommender systems utilizes content of items, demographic information of users or user-item rating for building recommender systems [4–6]. User based CF recommender systems uses user ratings for items to find similar users that like/dislike similar items.in the past. It then analyzes the neighborhood to recommend new items to a new user. The major limitation of this user based recommender system is that in many cases it is difficult to find neighbors due to lack of user-item rating. Second problem is related to scalability. With increase in number of users and items, the computations grow linearly, increasing the complexity and time for recommendation. Item-based recommendation approach computes similarity between the items for recommendations. In this approach, relation or similarity between the items are identified such as purchasing history or ratings given to the items. If a user likes and so purchases an item, she may often purchase another similar item [4, 7].

With the advent of Web 2.0, social networks and user-contributed information have become important sources of information that have largely contributed to recommender systems especially in e-commerce sites. Shi [8] in her paper surveys different sources of side information like reviews and comments that are freely written text, multimedia content, tags, geotag, that stretch beyond the rating matrix to remove sparsity.

In many research areas, emotion is a significant contextual factor in a variety of personalized and adaptive systems such as searching results [9], modeling user behavior [10], opinion mining and sentiment analysis [11], and information access and retrieval [12].

Emotions are widely being used in recommender system nowadays. In [12] movies are recommended to users by analyzing and modeling the user's mood. Kaminskas and Ricci [13] in their work recommend music for as user as he/she visits places of interest. The social tags acts as a link that represent the user's emotional state. Geneva Emotional Music Scale (GEMS) model is used to attach emotion tags based on social tag to music. Baldoni et al. [14], in his work also uses emotions from item annotations in social tagging systems. In our work, we used the approach as in [15] for automatic analysis of emotions from user generated text. In our work we used reviews of items to compile, emotion lexicon using Parrott's 2001 categorization of emotions from field of psychology [16] and WordNet [17]. A set of basic emotions are extracted from reviews thus building the emotion profile of items. This emotion profile act as a link for finding similar items with similar emotion profile. Then CF based approach is used for recommendations.

3 Emotion analysis of reviews

This section discusses how to extract various emotions that are expressed in user generated text gathered from reviews from the movie domain. Based on what users write in reviews after watching a movie, emotion profiles of all movies are created.

3.1 Compiling emotion lexicon

Emotions are defined as a "mental state that arises spontaneously rather than through conscious effort and is often accompanied by physiological changes" [18]. For analysis of emotion extracted from user generated content, we used the emotion lexicons using WorldNet as compiled in work [15]. In this work the knowledge from field of psychology, Parrott's 2001 categorization of emotions (which categorizes basic emotions as primary, secondary and tertiary in a hierarchical organization) is used. In the first step lexicon corresponding to six basic emotions i.e., love, anger, fear, joy, sadness and surprise is build. The corresponding primary, secondary and tertiary emotions keywords and their synonyms from WorldNet are added to their respective lexicons and are assigned different weights. For emotion E_k, the weight for a keyword *kw* is represented by $EmW(kw,k)$. The compiled emotion lexicon contains in all a total of 1377 keywords as mentioned in the paper [15].

3.2 Preprocessing of source

It is very important to preprocess the corpus containing reviews and comments from the two sources to extract appropriate content and filter out the inappropriate. Due to unpredictability of people writing reviews and comments after watching a movie or reading a book, reviewers may write words having mixed casing. Hence in first step reviews/comments are tokenized, and then converted to lower case so that irrespective of their casing, all match to their corresponding emotion. Stemming is performed to reduce the tokens to their root word like 'happier', 'happily', 'happiness' to root word 'happy'.

3.3 Emotion profiling of movie based on reviews

The emotion profile of any movie represents the cumulative strength of every emotion as computed by the emotion profiling of all the available reviews of a movie. The complete procedure for the emotion profiling is described as follows:

A given review R may convey one or more emotions. For this task, a previously compiled emotion lexicon is utilized that broadly categorizes into six basic emotions—joy, sadness, fear, anger, surprise and love [15] Let E_K represent an emotion of category k, where $k \in \{1.0.6\}$ representing the six basic emotions. A review reflects a camouflage of emotions. In the beginning, the emotion strengths for all six emotions are initialized to zero. Each word of the review acts as a tokenω. As review is read one token a time, ω is matched with the lexicons of each of the six emotion categories. If ω is found in *Lexicon* (E_K), the value of emotion strength for emotion E_K is incremented by the token's corresponding emotion weight $EmW(\omega,k)$. After reading and processing all tokens of the review, the emotion strengths of each of the emotions will indicate the emotion profile of the review. Thus emotion profile of movie l is $E_l=\{E_1, E_2, E_3, E_4, E_5, E_6\}$.

4 Items based Top N recommendation

Finding similar items is the most important step in item based Top N recommendation model.

4.1 Measuring similarity between items

4.1.1 Rating based item similarity

In this approach the similarity between two items is computed using cosine based similarity of the rated items x and y. Each item is represented as a vector in the user space where the vector contains the set of ratings of an item given by different users. Then the cosine similarity is computed between these vectors [7]. Formally, if R is $n \times m$ user-item matrix where n is number of users and m is the number of items, then the similarity between two items x_i and y_i is defined as the cosine of the n dimensional vectors corresponding to the x_i and y_i column of matrix R" where i is the common user. The similarity between these vectors is given by:

$$CosSim(x, y) = \frac{\sum_i x_i y_i}{\sqrt{\sum_i x_i^2}\sqrt{\sum_i y_i^2}} \tag{1}$$

From Eq. (1), it is clear that if two items are rated similarly by different users, the items are similar. This basically shows that similarity between two movies will be higher if each user that like one movie (hence rated it higher) also likes other movie.

4.1.2 Emotion based item similarity

After generating the emotion profile of an item, the similarity between the two items is computed using Kullback–Leibler Divergence (KLD). "KLD also known as the relative entropy is a measure of how different two probability distributions are from each other" [19]. The smaller the relative entropy, the more similar the distribution of emotions of two different items". But in our approach degree of similarity between two profiles must be symmetric. We therefore use the symmetric KLD divergence [20] which is computed as:

$$KL(P, Q) = \sum\left((P(i) - Q(i))\ln\frac{p(i)}{Q(i)}\right) \tag{2}$$

The lesser the divergence between two items, the more similar they are. So for each item we sort the items in ascending order to find Top N most similar items.

4.2 Generating recommendations

For each user who like a set of I items. For each item c candidate item in I, Top N items similar to c are added in the basket with their computed similarities to candidate item c. Then based on the computed similarity, items from the basket are sorted in non-increasing order and first N items are recommended for Top N recommendation [7].

5 Fuzzy emotion features

As discussed in last section, the use of different emotion features can be used for finding items with similar emotion features for recommendations. However, there is a certain degree of vagueness and blurring boundaries between the lexicons of these categorical emotion features. Rusell [21] asserted that "each emotion word, can be considered a label for a fuzzy set, defined as a class without sharp boundaries in which there is gradual but specifiable transition from membership to non-membership". Such an observation for emotion bearing words is consistent with the view that fuzziness is characteristic of natural language categories [22]. Thus each emotion state has a value specifying with it a grade of membership in each fuzzy set that corresponds to an emotion label. Zadeh proposed fuzzy logic as extension of classical set theory to model real world problems in a realistic manner [23].

Saraswat et al. [24] in their work exploited the inherent vagueness in emotional features for recommendation using fuzzy emotion features for movie domain. Here we take each emotion category as a linguistic variable and compare taking emotion as fuzzy feature with our approach.

6 Experiments and results

This section evaluates the performance of emotion based recommender system with rating based cosine item similarity. We then also compute the accuracy using Fuzzy emotion category for Top 10 recommendations using different Models such as Gaussian, Trapezoid and Triangle.

6.1 Data sets

In our experiments we conduct experiments using movies real work datasets from[1] MovieLens. We exploit the MovieLens 100 K version of the dataset for our experiments consisting of 943 users and 1581 items. It already has active users who have rated more than 20 movies and frequently reviewed movies. All review files from Movielens are pre-processed using the Python Natural Language Toolkit.

6.2 Experimental design and metrics

The goal of our experiments is to evaluate the performance of the emotion based top-N recommendations and compare with rating based cosine item similarity.

The Movielens dataset is split into a training and test set. One of nonzero entry of each row that means (that user has not rated) to be part of test set and the training set consists of other remaining non-zero entry. We then evaluate the quality of the top-N recommendations. Items that are rated more than 3 by a user are assumed as being liked by the user. For each user using the items present in the training set as the basket, we obtained the top-N recommendations. The training set is used to build similarity model.

The experimental analysis comparing rating based cosine similarity and emotion based item similarity is presented in the Table 1. Prediction accuracy is compared for the given approaches in Table 1 for top ten

Table 1 Prediction accuracy for Top 10 recommendations

	Rating based Cosine item similarity	Emotion based item similarity
Accuracy	0.289	0.612

Table 2 Prediction accuracy for Top N recommendations

	Rating based Cosine item similarity	Emotion based item similarity
Top 10	0.289	0.612
Top 15	0.268	0.631
Top 20	0.250	0.653
Top 25	0.246	0.671

recommendations. It depicts that prediction accuracy of emotion based Top N recommendation algorithm is far better than cosine based item to item similarity recommendation. This indicates that emotion extracted from reviews and comments act as an important feature for recommendation. Table 2 shows the variation of prediction accuracy with increase in number of recommendation. As N increases, there is slight decrease in accuracy whereas for emotion based item similarity prediction accuracy slightly increases. This is because as N increases as item list have common items. Results are depicted graphically in Fig. 1.

6.3 Results using fuzzy emotion features

We have also conducted experiments for showing prediction accuracy using fuzzy emotion features.

Since the emotion lexicon set contains overlapping words such as shock is present in lexicon of both anger and fear, we use fuzzy set theory proposed by Zadeh [25]. We used the R package *'frbs''* V3.1-0 [26] available in CRAN repository to implement Wang and Mendel's technique for generating fuzzy rules [27]. Movies who are given ratings

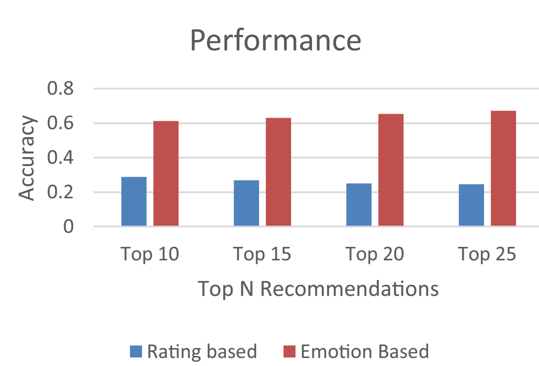

Fig. 1 Prediction accuracy for Top N recommendations

[1] MovieLens Dataset: http://grouplens.org/datasets/movielens/.

greater than 3 are assumed to be liked by the user and movies with ratings 1 and 2 are disliked by user. We do not consider ambiguous 3 rating. Zadeh implication generated 42 fuzzy rules for classifying each movie as liked or disliked based on its emotion content. Two of the rules generated based on three linguistic variable i.e., "small", "medium" and "large" are shown below.

Rule 1 IF love is small and joy is small and surprise is small and anger is small and sad is large and fear is small THEN class is 1

Rule 2 IF love is medium and joy is medium and surprise is small and anger is small and sad is small and fear is small THEN class is 2. Table 3 depicts the performance of fuzzy emotion features using different Models like Guassian, Trapezoid and Triangle using various Linguistic variable for Top 10 recommendations. The experimental results as shown in Table 4 compares rating based and emotion based item similarity with Guassian based fuzzy emotion features. As depicted in Table 4, prediction accuracy decreases from 0.612 to 0.51 (using Guassian Model) for Top 10 recommendations. But using fuzzy emotion features, prediction accuracy is better than rating based cosine item similarity. For top-N recommendations prediction accuracy decreases with fuzzy emotion features but is better than rating based similarity

Table 3 Impact of fuzzy emotion features on movie recommender system

Model	MF	Accuracy
Fuzzy Model	Gaussian	0.48
#Linguistic Variable = 3	Trapezoid	0.49
	Triangle	0.49
Fuzzy Model	Gaussian	0.51
#Linguistic Variable = 5	Trapezoid	0.49
	Triangle	0.49
Fuzzy Model	Gaussian	0.48
#Linguistic Variable = 7	Trapezoid	0.49
	Triangle	0.49

Table 4 Comparison of Guassian based fuzzy emotion features with rating based and emotion based movie recommender system

	Rating based Cosine item similarity	Emotion based item similarity	Gaussian fuzzy emotion features
Top 10	0.289	0.612	0.510
Top 15	0.268	0.631	0.513
Top 20	0.250	0.653	0.541
Top 25	0.246	0.671	0.551

7 Conclusions

This paper, presents and analyses top–N recommendation model based on emotion analysis of the reviews of the item. We compared our emotion based method with rating based cosine item to item similarity model. Our results show that emotion based item similarity provide more accurate recommendation than rating based cosine item similarity. In future we will use emotions as a link between domains for cross domain recommendation system. We then using fuzzy rule based framework based on Mamdani's model using Wang and Mendel learning technique to generate the fuzzy IF–Then rules from the training data. Results conclude that fuzzy emotion features do not increase the prediction accuracy as compared to discrete emotion features. For future work, algorithms can be formulated to extract emotions of items from different sources and also propose new approaches for recommendations.

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