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Multistage Model for Analysis of Opinions

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Abstract*— *The task of opinion mining has attracted interest during the last years. This is mainly due to the vast availability and value of opinions on-line and the easy access of data through conventional or intelligent crawlers. In order to utilize this information, algorithms make extensive use of word sets with known polarity. We consider the above issues by proposing an approach for a multistage model for analysis of opinions using sentiment orientation with conjunction and iteration at multilevel.

Keywords— Data mining, Opinion mining, supervised opinion mining, multistage opinion mining, iterative opinion mining.

I. INTRODUCTION

Social media websites like Twitter, Facebook etc. are a major hub for users to express their opinions online. On these social media sites, users post comments and opinions on various topics. Hence these sites become rich sources of information to mine for opinions and analyze user behavior and provide insights for:

- User behavior
- Product feedback
- User intentions
- Lead generation

Businesses spend an enormous amount of time and money to understand their customer opinions about their products and services. Thus Sentiment Analysis has become a hot research area since 2002. Sentiment Analysis is used to determine sentiments, emotions and attitudes of the user. The text used for analysis can range from big document (e.g. Product reviews from Amazon, blogs) to small status message (e.g. Tweets, Facebook comments).

Opinion mining is the field of study that analyses the people opinions, sentiments, appraisals and emotion towards the entities such as products, services. The main objective is to gathering the opinion about the products from the online review websites. The emergence of user-generated content via social media had an undeniable impact on the commercial environment. In fact, social media has shifted the content publishing from business towards the customer. With the explosive growth of social media for like microblogs, amazon, flipkart. On the web, individuals and organizations are increasingly using the content in these media for decision making. Each site typically contains a huge volume of opinion text. The average human reader will have difficulty in identifying the relevant sites and extracting and summarizing the opinions in them. So automated sentiment analysis systems are needed. In general, sentiment analysis has been classified at three levels. First level is document level, classifies whether a whole opinion document expresses a positive or negative opinion about the product. Second level is sentence level, classifies whether each sentence express a positive, negative or neutral opinion. Third level is aspect level, performs a fine grained classification of an opinion about the product. We are proposing a multistage iterative method for opinion word extraction .

II. RELATED WORK

In [1] a probabilistic method is presented that builds an opinion word lexicon. The method uses a set of opinion documents which is used as a biased sample and a set of relevant documents as a pool of opinions. In order to assess the effectiveness of the algorithm a dictionary made up of 8K words is used, built by [9, 10]. Certain probabilistic functions such as Information Content, Opinion Entropy and Average Opinion Entropy are used as extraction tools. The method is based upon the observation that nouns contain high information value, while adjectives, adverbs and verbs (usually opinion words) provide additional information to the context. Upon these observations and the probabilistic tools they extract the opinion word lexicon. The authors of [12] tackle the problem of opinion target orientation and summarization. The method uses an opinion lexicon [4] from WordNet. A list of content dependent opinion words such as nouns, verbs and word phrases that are joined together is utilized. The algorithm uses a score function, which is a formula that calculates opinion target orientation, by exploiting coexistence of 0opinion words and opinion targets in a sentence and the variance of distance among them. Linguistic patterns and syntactic conventions are used in order to boost the efficiency of the proposed method. [3] proposes an unsupervised lexicon building method for the detection of polar clauses0(clauses that can be classified as positive or negative) in order to acquire the minimum syntactic structures called \polar atoms" (words or phrases that can be classified as positive or negative opinion modifiers). This part of process

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includes a list of syntactic patterns that helps the identification of propositional sentences. Moreover the method uses an opinion lexicon and statistical metrics such as coherent precision and coherent density in order to acquire true polar atoms from fake ones. The authors of [7] exploit a model called partially supervised word alignment, which discovers alignment links between opinion targets and opinion modifiers that are connected in bipartite graph. Initially some high precision low recall syntactic patterns are used as training sets for generating initial partial alignment links. Then these initial links will be feeded into the alignment model. The selection of opinion target candidates is based upon a factor called confidence. Candidates with higher confidence will be extracted as the opinion targets.

Problem of Opinion mining can be categorized as sentiment classification [9] and feature based opinion mining. The problem of extracting the semantic orientation (SO) of a text (i.e., whether the text is positive or negative towards a particular subject matter) often takes as a starting point the problem of determining semantic orientation for individual words. The hypothesis is that, given the SO of relevant words in a text, we can determine the SO for the entire text. The Semantic orientation approach to Sentiment analysis is unsupervised learning because it does not require prior training in order to mine the data. Figure 6 has the details of the classification of approaches of semantic orientation.

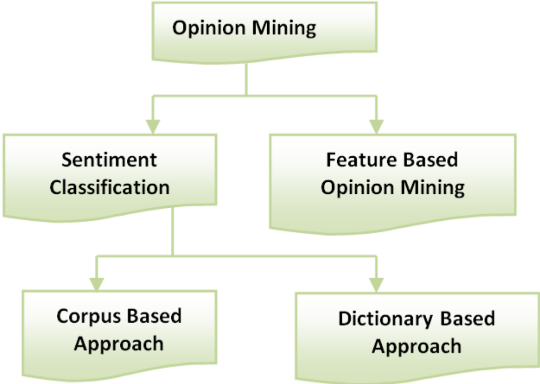

Fig. 1 Classification of approaches on semantic orientation

Major data mining techniques used to extract the knowledge and information are: generalization, classification, clustering, association rule mining, data visualization, neural networks, fuzzy logic, Bayesian networks, and genetic algorithm, decision tree. Figure 2 has the techniques of Opinion Mining.[13]

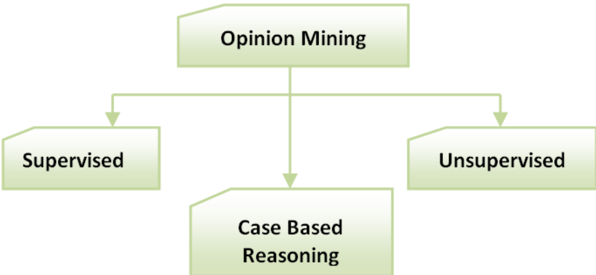

Fig. 2 Techniques of opinion mining

III. PROPOSED WORK

Our approach combines various components of the above methods, refines them and introduces new processes to overcome their disadvantages. We propose a hybrid multi-stage iterative approach for opinion extraction and semantic orientation. Our method utilizes iterative propagation and conjunction based method. This approach generates opinion words at every step which will treated as input for next stage. Proposed method is supervised and unsupervised both. It will have following phases:

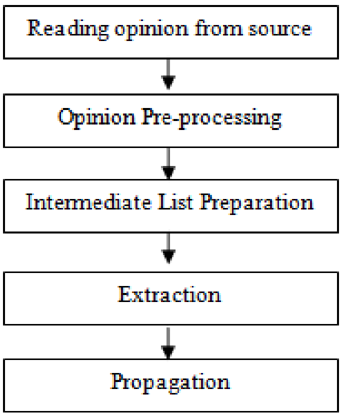

Fig. 3 Proposed Model

Before mining any , we perform certain pre-processing operations: - removal of stop words, change the upper case characters to lower case, perform stemming, removal of irrelevant or generic terms by comparing the distribution of terms within this domain corpus and in a more general collection of large set of random documents etc. Intermediate list preparation comprises a series of word sets like articles, verbs, comparatives, conjunctions, negations and pronouns. These words will constitute a main feed of the algorithm. We filter-out words from the Seed that don't appear in the corpus. In Seed list, the polarity of each word is provided. We apply polarity detection of opinions for finding positive and negative opinion. The double propagation process makes extensive use of all possible ways to discover new opinion words, but appears to have low precision (see Experimental Section). For this reason we apply a filtering procedure, namely opinion word validation. We employ two thresholds, the sentiment threshold and the frequency threshold. So we have both strategy supervised and unsupervised.

Extraction process is shown below:

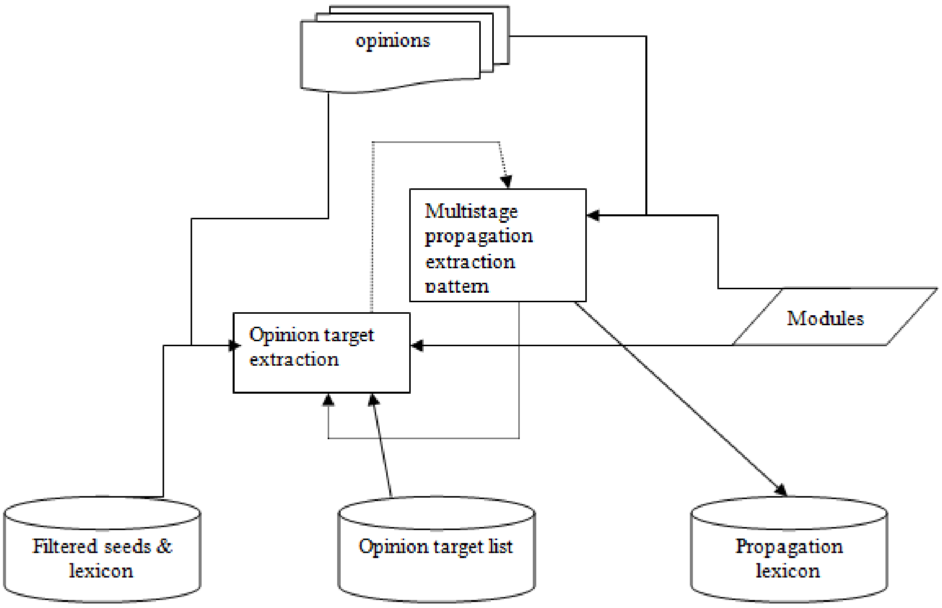

Fig 4 Proposed extraction process

IV. EXPERIMENTAL EVALUATION

Input is an excel file containing sample opinions with other information also like-

a. I mean how could a dining chair really go wrong? I don't know — I'm sure there are ways, but this one really doesn't do anything at all out of line. It's elegant, comfortable (nicely non-rigid), stacks efficiently, and doesn't break the bank. Good deal all round. Buy one. Or buy four. Or eight, if you got it like that.
b. We bought two of these grey chairs to go with the four white armless white dining chairs. They look absolutely perfect in our dining room. We have a modern home with a lot of antique pieces so it makes a nice eclectic mix. The chairs are very comfortable, well made, easy to care for. The delivery was prompt, and the pieces arrived in pristine condition.
c. Comfortable, great looking chairs. A great mix to our modern loft.
d. Chairs arrived in shorter time than expected. Incredibly crated and arrived blemish free. Chairs are most comfortable with an exquisite upholstery. Silver nailhead brads are well placed and the white coating thick and durable. Sturdy and comfortable --a great find. Contemporary yet timeless addition to our home.

With other information like http://www.pricegrabber.com/furniture/living-room-chairs++cb2-slim-white-chair/m-883068044/#_product_reviews

Opinion Directory will be like this-

Positive Polarity)

Sum:155 Words

elegant	[5.0] comfortable	[61.0] nicely	[4.0] efficiently	[1.0] good	[17.0] like	[25.0]
perfect	[19.0] modern	[22.0] nice	[18.0] well	[27.0] easy	[54.0] prompt	[1.0]
great	[62.0] incredibly	[3.0] free	[0.0] exquisite	[1.0] durable	[4.0] sturdy	[16.0]
gorgeous	[4.0] love	[67.0] shiny	[1.0] hot	[1.0] impressed	[1.0] awesome	[9.0]
fun	[-1.0] classic	[2.0] clear	[19.0] cleanliness	[1.0] transparent	[2.0] magical	[1.0]
support	[6.0] stunning	[1.0] happy	[10.0] best	[5.0] sleek	[13.0] versatile	[0.0]

(Negative Polarity)

Sum:103 Words

wrong	[-1.0] break	[-1.0] blemish	[-1.0] twist	[1.0] disgrace	[-1.0] disappointing	[-1.0]
nervous	[-3.0] illusion	[-4.0] bulkiness	[-1.0] butcher	[-1.0] dirt	[-1.0] scratch	[-2.0]
mistake	[-1.0] hate	[-1.0] repel	[-1.0] greasy	[0.0] expensive	[-12.0] afraid	[-1.0]
cheap	[-6.0] unexpected	[-3.0] downfall	[-1.0] scratched	[-1.0] scratches	[1.0] picky	[-1.0]
cramped	[-1.0] critical	[-1.0] sunk	[-1.0] problems	[0.0] bulky	[-1.0] problem	[2.0]
rough	[0.0] unnecessary	[1.0] awkward	[-1.0] tricky	[-1.0] incorrect	[-1.0] bump	[1.0]

Algorithmic analysis will be shown below between lexicon based and multistage based methods.

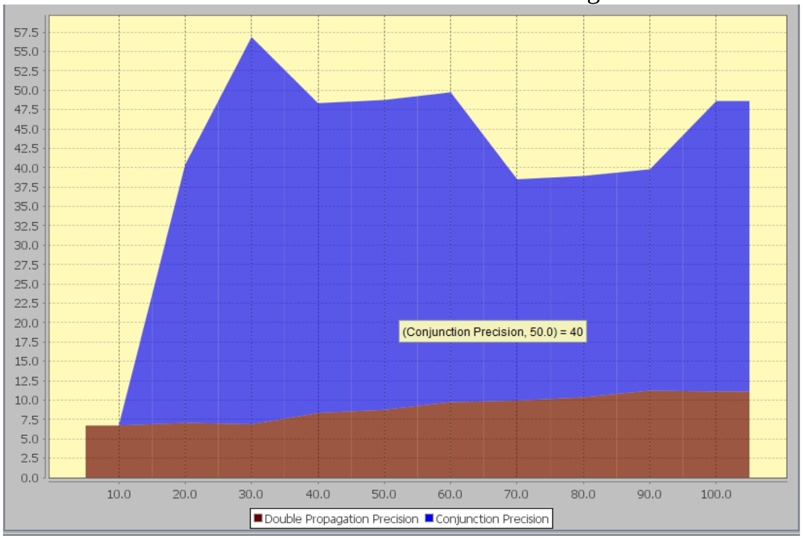

Fig 5 Precision matrix

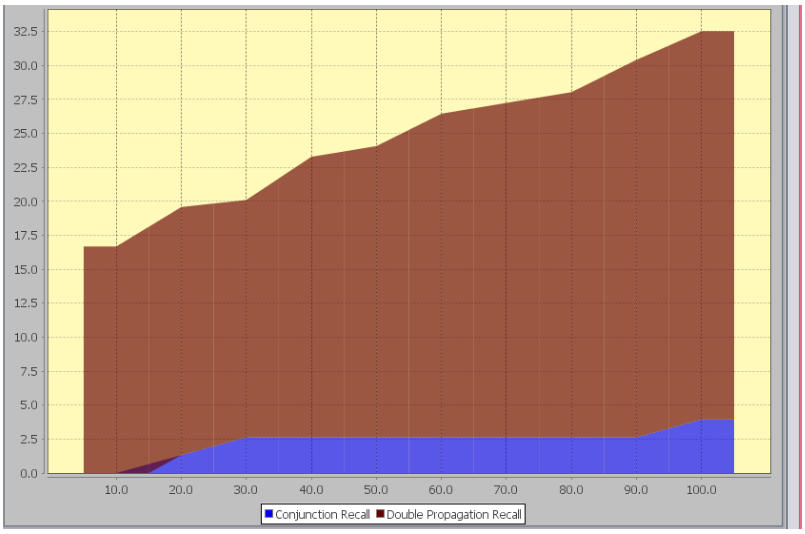

Fig 6 Racall Marics

V. CONCLUSION

We presented a multistage iterative method using supervised and unsupervised both approach for opinion word discovery. It consists of repeatedly discovering new opinion words. We follow language patterns and opinion-words opinion-targets relationships to identify new words. Word polarity is calculated automatically by following a set of polarity disambiguation procedures.

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