Extracting Implicit Aspects based on Latent Dirichlet Allocation

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1 RESEARCH PROBLEM

"What others think?" is the central to almost all human activities and is the key influencer of human behaviors (Fersini et al, 2016). For this reason, when people need to make a decision about which film is good or companies need to evaluate their products' weakness, they take into consideration the opinions of others.

With the rapid advances of the Internet, people have dramatically changed their way to gather others' opinion through the online review websites. These mediums have showed themselves as one of most popular channels with millions of users who share their opinions about they have purchased. Due to increase in user generated content on online review sites an important soure for data analysis can be provided. According to a survey conducted about 50% of the young population have been affected by these word of mouth data (Ha et al, 2015). So, for people there is no need to ask someone else about product they want to purchase and for companies there is no need to conduct surveys for their brands (Pawar et al, 2016). Beside all of them, for the same product there are huge amount of reviews on different web sites and to get the information they are interested in is very difficult and time consuming for average humans. Therefore, an automatic system is needed.

Sentiment analysis, which has been studied on since 1990's and in recent years has increasingly gained importance, is a study that analyses people's opinions and feelings toward products, companies, services and so on (Türkmen, 2016; Liu, 2012). Despite this short history, analyzing people's opinion and sentiment has been attracted to researchers and since then, many studies have been done. In these studies, sentiment analysis is realized at one of the three levels: document level, sentence level and aspect level sentiment analysis (Vinodhini and Chandrasekaran, 2012).

- **Document Level:** Essentially, with this level of analysis, the task of determining whether the given review is positive or negative. For instance given a restaurant review, the task is to learn general sentiment (good or bad) about this restaurant by using whole document.
- **Sentence Level:** Sentences are just short documents so there is in fact no key difference between sentence level and document level sentiment analysis. In this analysis the task is to learn general sentiment from every sentence separately.
- **Aspect Level:** As mentioned above, document and sentence level analysis give general sentiments about a product. Along with it is not correct to assume that if the result is negative; all the product specifications are weak. Accordingly it doesn't mean that all the product specifications are fine if the result is positive. So there is a need for finer-grained analysis. Aspect, which expresses sentiment, is anything that defines, completes a product; sentiment is positive or negative feeling about the aspect (Türkmen et al, 2016). In aspect level sentiment analysis sentiments are given separately for every aspect. For example given a restaurant review, instead of learning general sentiment for this restaurant, learning sentiments for aspects such as service, meal, etc. is proposed.

In sentiment analysis aspects are categorized as two types: explicit aspects and implicit aspects. If an aspect or its alternatives appears in a review this aspect is called explicit aspect. Conversely, if an aspect does not appear in the review but is implied by a sentiment this aspect is implicit. In the example below, the first sentence contains an explicit aspect "tuna". The second sentence the implicit aspect "price" is implied by using "cheap".

Example:

- The tuna is also very fresh, not so chewy.
- It's fairly cheap (for being so trendy).

For extracting explicit aspects there are four main methods tried in the literature: frequent noun and noun phrases based methods, rule based methods, supervised learning and topic models. On the other hand, implicit aspect extraction is tough task and many studies in the literarure ignore this phase. Regarding to aforementioned matters, we

Ekinci, E. and Omurca, S.
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In *Doctoral Consortium (DCAART 2017)*, pages 17-23

propose a implicit aspect extraction framework by using semantic similarity based topic model.

2 OUTLINE OF OBJECTIVES

The aspect based sentiment analysis studies are fundamentally focused on product aspects. Although in previous studies explicit aspect extraction has been studied intensely, on the contrary implicit aspect extraction has been studied limitedly. However implicit aspect extraction is the one of the important phase of the sentiment analysis studies for the following reasons. The sentence which only contains sentiment and aspect is unknown is not useful. More importantly, when the reviews are examined it can be clearly seen that number of implicit aspects in the sentences are enough to be considered for better sentiment analysis (Xu et al, 2015).

Probabilistic topic models are based on the idea that documents are mixtures of topics and a topic has a probability distribution over words (Stevyers and Griffiths, 2007). Actually, probabilistic topic model methods are defined as a group of algorithms that discover hidden thematic structure of document collections by mapping them into low dimensional space (Boyd-Graber and Blei, 2009). And a topic can be defined as a collection of words that frequently occur together and are related to the same subject. Latent Dirichlet Allocation (LDA), which is one of the simplest topic model, is emerging field in machine learning and text mining (Blei et al, 2004; Mei et al, 2007). The intuition behind LDA is that documents exhibit multiple topics. LDA, as a completely unsupervised method, is based on bag-of-words assumption. And the LDA model does not consider the semantic structure of the documents. This lack motivates our research.

The effectiveness and better generalization of the proposed framework we propose an unsupervised approach for implicit aspect extraction that is focused on the use of semantic similarity of documents for topic proportions and topic assignment. Furthermore, to encourage this Babelfy which carries out both multilingual word sense disambiguation and entity linking is used (Moro et al, 2014). Babelfy is based on the Babelnet, which is a integration of Wikipedia and WordNet, a multilingual semantic network (Navigli and Ponzetto, 2012). Babelfy is preferred for the concept extraction and by using these concepts semantic similarity of documents are calculated. The proposed framework will be tested on reviews of restaurants; also Jo and Oh (2011) used these reviews in English for ASUM.

It is planned to achieve the following objectives with our framework enabling aspect based sentiment analysis based on semantic similarity based topic model for implicit aspect extraction:

- Obtaining the reviews of restaurants and pre-processing these reviews using Stanford Natural Language Processing Tool,
- Determining noun phrases for extracting multi-word aspects from reviews by using Babelfy,
- Deciding parameters of LDA, applying the model to the reviews and extracting product aspects,
- Evaluating generalization performance of the model on the test data,
- Extracting concepts by using Babelfy and expanding reviews with these concepts,
- Calculating semantic similarity of reviews and using these obtained values for topic proportions and topic assignment in LDA,
- Evaluating generalization performance of the new model on the test data and comparing with LDA
- Extracting aspect sentiment pairs from reviews,
- Extracting implicit aspects by using aspect sentiment pairs,
- The efficiency of the proposed system will be examined.

3 STATE OF THE ART

In recent years, aspect based sentiment analysis studies have attracted more and more attention because for the first time in human history, a huge volume of opinionated data is obtained with new resources that have millions of users such as ecommerce and social media websites, blogs, dictionaries, news portals (Liu, 2012).

When the literature is evaluated it is shown that aspect extraction is one of the cornerstones of the sentiment analysis studies. To design a powerful sentiment analysis system, aspect extraction process should be carried out successfully (Ekinci et al, 2016). The first studies about this topic were made by Hu and Liu (2004). In their studies differences between explicit and implicit aspects were explained and only explicit aspect extraction was performed. Explicit aspects which are noun or noun phrases were extracted by using association rule mining. Popescu and Etzioni (2005) developed OPINE an unsupervised information extraction system to extract explicit aspects. They benefited from Pointwise Mutual Information for pruning aspects. Hu and Liu’s approach was further improved by Wei et al (2010) incorporating Semantic Based Refinement. The approach aims to use sentiments for successfully extracting explicit aspects. They used General Inquirer and Co-occurrence-based pruning, Opinion-based infrequent feature identification, Conjunction-based infrequent feature identification rules for aspect extraction and pruning.

Brody and Elhadad (2010) devised an unsupervised method, called Local LDA, for aspect extraction. For each aspect representative words were found by using Mutual Information. For example representative words for “meal” are “menu, fish, cuisine, and so on”. Conjunctions and negations were preferred for adjective extraction and they benefited from Conjunction Graph for determining polarities of adjectives. Li et al (2010) proposed two new methods, called Sentiment-LDA and Dependency-Sentiment-LDA. Sentiment-LDA is based on the idea that sentiments are related to topic. In Dependency-Sentiment-LDA, they integrated sentiment dependency to the topic model. Wang et al (2010) developed semi-supervised topic model Co-LDA. In Co-LDA, aspects and sentiments were modeled simultaneously. For this purpose the model is divided into two parts; sentiment LDA and topic LDA. Jo and Oh (2011) assumed that words in the same sentence are under the same topic with Sentence LDA. They after developed an advanced version of Sentence LDA, called Aspect and Sentiment Unification Model (ASUM). With ASUM aspects and sentiments were modeled together and aspect sentiment pairs were obtained. Xianghua et al (2013) utilized LDA to extract global topics for reviews in Chinese. They also utilized sliding window for local topics. For sentiment polarity they used Hownet lexicon. Ding et al (2013) composed Hierarchical Dirichlet Process-LDA (HDP-LDA). HDP-LDA differed from the LDA by automatic determination of topic counts. For determining sentiments they utilized lexicon. Bagheri et al (2013) devised Aspect Detection Model based LDA (ADM-LDA) which ignored bag of words and was based on Markov Chain. Wang et al (2014) proposed two new semi-supervised methods, called Fine-grained Label LDA (FL-LDA) and Unified Fine-grained Label LDA (UFL-LDA). FL-LDA utilized seed lexicon for aspects to extract aspects in the reviews. In UFL-LDA unlabeled documents were considered for high frequency aspects. Zheng et al (2014) devised Appraisal Expression Patterns LDA (AEP-LDA) for extracting product aspects from restaurant, hotel, MP3 player and camera reviews. The basic idea behind this model was that words in the same sentence were under the same topic. Aspects and sentiments were extracted simultaneously in this model. Like Bagheri et al (2013), Yin et al (2014) ignored bag of words in their LDA based approach, called Dependency-Topic-Affects-Sentiment-LDA (DTAS). Instead of bag of words they preferred Markov Chain. They assumed that sentiments in a sentence affected by sentence that contains sentence and the previous sentence.

In our thesis, we aim to extract implicit aspects so we also delve into literature in this subject area. Su et al (2008) used Mutual Reinforcement to expose hidden relation between aspect categories and group of sentiments. The hidden relation was presented by using bipartite graph. It was enough to create a connection between aspect and sentiment to be in the same sentence. The connection weight was determined by the total number of co-occurrence of them. Zhang et al (2012) preferred statistical methods for implicit aspects. They used PMI and frequency based collocation selection method for this purpose. Wang et al (2013) benefited from association rules for extraction of implicit aspects. By using five different association rules for aspects and sentiments new rules were extracted. From these rules implicit aspects were extracted by using frequency and PMI. Bagheri et al (2013) proposed graph-based scoring for implicit aspects. Relation between explicit aspects and sentiments was demonstrated with this graph. Xueke (2013) devised Joint Aspect/Sentiment Model (JAS) to remove deficiencies of LDA. By using aspect based sentiments were used for extraction of implicit aspects. Lau et al (2014) proposed LDA based fuzzy product ontologies for aspect based sentiment analysis. Both taxonomic (memory is a hardware) and non-taxonomic (bright flash) relations were extracted with this method. For non-taxonomic relations in sentences they benefited from Mutual Information. Poria et al (2014) presented rule based method for implicit aspects. They used explicit aspects and implicit aspect clues (IACs) for extraction of these aspects. IACs were adjectives and mapped to associated aspects category. Xu et al (2015) devised LDA based Explicit Topic Model, which was semi-supervised, for implicit aspects. The obtained results from this model was used in Support Vector Machines to extract implicit aspects from sentences.

4 METHODOLOGY

The thesis consists of ten steps as mentioned in the outline of the objectives section and is in the fourth step right now. The steps are explained in detailed and results are given for every steps below.

4.1 Dataset and Preprocessing

Reviews concerning 320 different restaurants from 4 different cities (Atlanta, Chicago, Los Angeles and New York City) are obtained from a web site[1]. This data set was used in Jo and Oh's (2011) study. The whole dataset consists of 25459 reviews in English but only 2647 reviews are used for this study. The summary of dataset depicted in Table 1.

Table 1: The summary of dataset.

Domain	Number of reviews	Average sentence count	Average word count
Restaurant	2647	12	187

After the dataset is obtained, for each of the word spell correction is applied. Spell correction is an important phase in sentiment analysis of word-of-mouth data and then stop words are eliminated. Stemming is also a crucial step. Stemming is used for reduces the different form of word to a single form. As the final phase of preprocessing, POS tagging is performed to assign parts of speech to token such as noun, adjective, verb, etc. For preprocessing steps Stanford NLP tool is used. There are 8603 different words in the reviews. Figure 1 is a part of an actual review and Figure 2 is the preprocessed version of this review.

> Had brunch with the girls today and we ordered the bottomless bubbly, mac and cheese, crab cakes benedict, penne, grilled cheeseee with tomato sauce and breakfast panini...

Figure 1: The actual review.

> brunch girl today order bottomless bubbly mac cheese crab cake benedict penne grilled cheese tomato sauce breakfast panini

Figure 2: The preprocessed review.

[1] http://uilab.kaist.ac.kr/research/WSDM11

4.2 Multi-word Aspects

In the reviews, some aspects have more than one single word. Aspect extraction is very important sentiment analysis, therefore, for an overall sentiment analysis of the reviews, multi-word aspects of the products must be detected. For this purpose, Babelfy, which is unified graph for word sense disambiguation and entity linking, is used (Moro et al, 2014). From reviews 2640 different multiword aspects are obtained such as, chicken salad, burgundy wine, flat iron steak and so on.

4.3 Latent Dirichlet Allocation

LDA is described as generative probabilistic model for collections of discrete data such as text corpora by Blei et al (2004). In LDA, generative model, which is a simple probabilistic procedure, specifies document creation by using latent variables (Stevyers and Griffiths, 2007; Jadhav 2014). With latent, it is desired to mean learning the meaning of the document by discovering latent topics (Mei et al, 2007). The basic intuition behind LDA is that documents exhibit multiple topics and topic has a probability distribution over words. LDA is completely unsupervised and is based on bag-of-words assumption. The generative model and posterior distribution of LDA is shown in Figure 3.

1. For each topic $k \in [1, K]$
   a. Randomly choose a distribution over words: $\varphi_k \sim Dirichlet(\beta)$
2. For each document $m \in [1, M]$
   a. Randomly choose a distribution over topics: $\theta_n \sim Dirichlet(\alpha)$
   b. For each word $w_n \in m$
      i. Randomly choose a topic from the distribution over topics: $z_{m,n} \sim Mult(\theta_m)$
      ii. Randomly choose a word from the corresponding distribution over the vocabulary: $w_{m,n} \sim Mult(\varphi_k, z_{m,n})$

Figure 3: Generative model for LDA.

Each documents are mixtures of topics and words in these documents are chosen one of these topics. And each topic has a distribution over words from a fixed vocabulary. Distribution over words and topic proportions are obtained with Dirichlet distribution. Dirichlet distribution is a the conjugate prior for the parameters of the multinomial distribution (Bishop, 2016).

The graphical model for LDA is given by using plate notation and is represented in Figure 4.

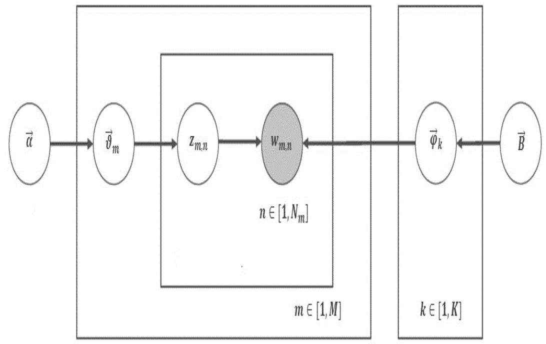

Figure 4: Graphical model for LDA.

In Figure 4 each nodes are random variables and directed edges are used to explain how these random variables are generated along with these edges. The observed node is shaded (words in the document) and hidden nodes are unshaded. In this model M is the total number of documents, K is the total number of topics. Number of words in document m is represented with N_m. α and β are Dirichlet parameters. θ_m is topic proportion in the documents and φ_k is distribution over words. According to graphical model the joint probability of observed and hidden random variables is given with Equation 1.

$$\left(\prod_{k=1}^{K} p(\varphi_k \mid \beta)\right)\left(\prod_{m=1}^{M} p(\theta_m \mid \alpha)\right)\left(\prod_{n=1}^{N} p(z_{m,n} \mid \theta_m) p(w_{m,n} \mid z_{m,n}, \varphi_k)\right) \quad (1)$$

The main purpose of GDA is to obtain model parameters and for model parameters posterior distribution in Equation 2 is used.

$$p(\varphi_{1:K}, \theta_{1:M}, z_{1:M} \mid w_{1:M}) = \frac{p(\varphi_{1:K}, \theta_{1:M}, z_{1:M}, w_{1:M})}{p(w_{1:M})} \quad (2)$$

Collapsed Gibbs Sampling algorithm is preferred for this posterior distribution.

4.4 Experimental Results

To apply LDA to reviews of restaurants firstly model parameters have to be specified. For $\alpha = 50/K$ and $\beta = 0.01$, which are recommended by Stevyers and Griffiths (2007), values are usually used. The number of topics is determined as $K = 100$ and 1000 iteration of the Collapsed Gibbs sampling algorithm have been performed. The extracted product aspects are given in Table 2.

Table 2: The extracted product aspects.

Breakfast	Dessert	Drink	Salad
toast	dessert	drink	salad
breakfast	chocolate	bar	goat cheese
egg	cream	cocktail	vinaigrette
banana	cookie	bartender	chicken
coffee	ice cream	martini	chicken salad
pancake	vanilla	round	protein
berry	rice	alcohol	chipotle
brioche	peanut	specialty	cucumber
fruit	mousse	tab	side
syrup	cod	vodka	lettuce

In Table 2 there are product aspects which are extracted from restaurant reviews. The extracted product features are examined for the validity of the proposed method. Three criteria are considered in the evaluation of these aspects: i) The aspects under the same topic should be compatible with each other, ii) aspects can be capture details in the reviews and iii) the most frequently discussed aspects in comments can be captured (Jo and Oh, 2011).

In order to measure the generalization performance of the model a measure of perplexity which is given in Equation 3. Perplexity is calculated over test data so 10% of reviews (260 reviews) are used as test data. The perplexity, used by convention in language modeling, is monotonically decreasing in the likelihood of the test data, and is algebraicly equivalent to the inverse of the geometric mean per-word likelihood (Blei et al 2004).

$$perplexity(D_{test}) = \exp\left\{-\frac{\sum_{d=1}^{M} \log p(w_d)}{\sum_{d=1}^{M} N_d}\right\} \quad (3)$$

The obtained results are given in Figure 5.

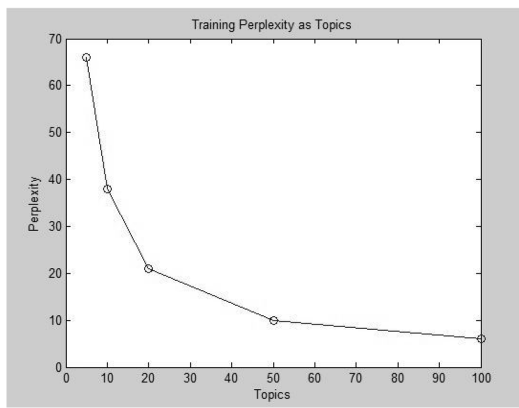

Figure 5: Perplexity results for reviews of restaurants.

As the obtained result is evaluated it can be clearly seen that the model has a good generalization performance.

5 EXPECTED OUTCOME

The outcomes of this study present implicit aspect extraction from reviews of restaurants in English. For this purpose a novel framework will be designed for implicit aspect extraction by using semantic similarity based LDA. For semantic similarity of reviews concepts, which are obtained by using Babelfy, will be extracted and these concepts will be represented in high dimensional space. The generalization performance of the proposed model will be compared with LDA.

6 STAGE OF THE RESEARCH

This paper provides with the background of the research that implicit aspect extraction from reviews in English. In this paper motivation and objectives of the research, literature review is given. The current stage of the research is focusing initially on the first forth stages.

The next stage we will plan to extract concepts by using Babelfy. These concepts will be used for semantic similarity of reviews. As a result, the goal of this stage is to organize topic proportions based on these similarity results. In this way, we aim to improve generalization performance of the LDA.

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