Topic Modeling in Sentiment Analysis: A Systematic Review

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Abstract. With the expansion and acceptance of Word Wide Web, sentiment analysis has become progressively popular research area in information retrieval and web data analysis. Due to the huge amount of user-generated contents over blogs, forums, social media, etc., sentiment analysis has attracted researchers both in academia and industry, since it deals with the extraction of opinions and sentiments. In this paper, we have presented a review of topic modeling, especially LDA-based techniques, in sentiment analysis. We have presented a detailed analysis of diverse approaches and techniques, and compared the accuracy of different systems among them. The results of different approaches have been summarized, analyzed and presented in a sophisticated fashion. This is the really effort to explore different topic modeling techniques in the capacity of sentiment analysis and imparting a comprehensive comparison among them.

Keywords: *aspect-based sentiment analysis; aspect extraction; grouping synonyms; LDA; topic modeling*.

1 Introduction

With the emergence of World Wide Web (WWW) during the last two decades, WWW has become the leading source of information. This source of information contains enormous amount of human generated reviews on products, services, government policies, social issues, religion, etc. on different blogs, social media, chat forums, manufacturer's or distributor's websites. These reviews not only help people to make a choice for buying some specific product or surfing to get better services, but also give a vibrant idea to manufacturers about their products or services. For any customer or manufacturer, this is almost impossible to read and analyze all these reviews manually and build a decision upon it.

Sentiment analysis or opinion mining deals with the extraction of opinions/sentiments from user generated text and have attracted the researchers from academia as well as from industry during the last decade [1,2]. Different approaches have been proposed, but aspect-based sentiment analysis has attracted the most. It focused on extraction of aspects from the customer

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reviews and ranking them as positive or negative. There are three main tasks of aspect-based sentiment analysis: (1) extracting and categorizing aspects into similar classes; (2) determining the polarity of opinion words for specific aspect; and (3) summarization and visualization of aspects along with their positive or negative opinions [3,4]. The first task is the most crucial task and most of the researchers have focused on this task. In this literature review, we have presented an analysis of different topic modeling techniques, proposed for the extraction and categorization of aspects into similar classes.

2 Review Methodology

From the last recent years, topic modeling has been widely used for the extraction of aspects and their categorization from online reviews [5]. This opens a new horizon for research in the domain of sentiment analysis. Topic modeling approaches extract aspects from customer reviews and categorize these aspects into similar classes simultaneously and therefore, proved the importance and significance in aspect-based sentiment analysis. Hence, in this section, most recent and related work will be discussed on topic modeling, based on systematic literature review (SLR).

2.1 Research Questions

Finding the right questions for research is the key to understand the impact and importance of topic modeling in sentiment analysis. The main purpose of this SLR is to identify the techniques and methods for the extraction and categorization of aspects from customer reviews using topic modeling. The Population, Intervention, Outcome, Context (PIOC) criteria [6] was adopted to identify and formalize the questions, as summarized in Table 1.

Table 1 Summary of PIOC.

Population	**Online reviews**
Intervention	Aspect extraction from customer reviews using topic modeling
Outcomes	Accuracy of aspect extraction and categorization
Context	Aspect-based sentiment analysis

On the basis of PIOC, following research questions were identified:

Q1 : What topic modeling techniques are there for aspect extraction?
Q1a : What kinds of datasets are being used for these techniques?

Q1b : How successful are these techniques for both explicit and implicit aspect extraction?
Q1c : What is the overall performance of aspect extraction using topic modeling?
Q2 : How efficient are these techniques to group similar aspects?

2.2 Search Strategy

A well-planed and organized search strategy plays a key role in a SLR, so that every relevant work can be identified in the research results. This is the reason, to answer the research questions an extensive search was applied for the relevant research papers.

Following is the search string:

(topic modeling) AND (aspect extraction OR feature extraction OR sentiment analysis OR opinion mining OR aspect-based sentiment analysis) AND/OR (customer reviews OR online reviews)

The following decisions were adopted for the search strategy:

Search database: IEEE Explore, Science direct, Springer link, ACM digital directory, Google scholar.
Search items: Journal articles and conference papers
Search applied on: Full text
Publication period: 2010 to 2014.

This research covers the publications during the period of 2010 to 2014. Any paper published before of or after this period is not included.

2.3 Study Selection

Due to the above mentioned search strategy, a vast variety of research papers were identified. All the irrelevant papers were excluded after analyzing the abstract. This process reduces the number of candidate papers. Furthermore, the number of candidate papers was condensed after reading the full text.

For the selection of relevant papers, following inclusion and exclusion criteria were adopted throughout the process.

Inclusion criteria:

1. Aspect-based sentiment analysis
2. Focusing on topic modeling for aspect extraction
3. Topic identification in online reviews

4. Aspect extraction through topic modeling in customer reviews
5. Aspect categorization
6. Using domain knowledge in topic modeling
7. Explicit and implicit aspect extraction
8. Focused on online reviews

Exclusion criteria:

1. Document or sentence level sentiment analysis
2. Aspect extraction without topic modeling
3. Sentiment analysis on social media
4. Aspect extraction other than online reviews
5. Sentiment polarity identification
6. Aspect summarization

2.4 Results on SLR

In this SLR, aspect extraction and categorization through topic modeling has been investigated. The search for the relevant papers covered the period between 2010 and 2014. After the extensive search, 16 studies were selected to answer the research questions (RQs) mentioned in this review. Following are the findings which can clear the answers of the review questions:

(RQ1) *There are two main techniques used for the topic modeling: Probabilistic Latent Semantic Analysis (pLSA) [7] and Latent Dirichlet Allocation (LDA) [8]. Among these techniques, LDA has been widely used for the extraction of aspects from online reviews.*

Building on LDA, different supervised, semi and un-supervised approaches have been proposed incorporation with other techniques. These techniques will be discussed in details in the section 4. Table 2 showed a detailed summary of these approaches.

(RQ1a) *Studies reviewed, in this paper, used online customer reviews for the aspect extraction. These reviews were collected from different websites and contain different language datasets.*

Most of the approaches, reviewed in this study, used English language datasets except structural learning model [9], which used datasets in Chinese for the evaluation. Cross-Lingual Joint Aspect/Sentiment (CLJAS)[10] used more than five different language datasets, which belong to Chinese, French, German, Spanish, Italian and Dutch languages. Majority of the datasets, used for evaluations, belong to hotels, restaurants or product domains except for CLJAS which used multiple domain datasets for the aspect extraction. The details of the datasets, used by topic modeling techniques, have been elaborated in Table 2.

(RQ1b) *Topic modeling techniques have shown significance achievement for the extraction of explicit aspect. But, these approaches do not articulate any clue for the extraction of implicit aspects.*

In topic modeling, each aspect is considered as a topic, which has some correlation with the given domain. These topics are expressed in the form of explicit words, because only those topics could be identified which exist in the review. For example in this sentence: "The phone is great but the battery life is too short", there are two aspects which will be discovered as topics by topic modeling. These are phone and battery life. Both of these words are explicitly mentioned in the sentence. Therefore, topic modeling techniques can easily identify such kind of topics.

On the other hand, implicit aspects are not expressed by conventional means. Consider the review: "It's light enough to carry all day without bother". In this review, there is no explicit word which represents any aspect, but it still holds the aspect weight which is implicit in this review. As there is no word which could be a potential topic in this review, topic modeling techniques cannot give any notion to how to identify these implicit aspects. Only Joint Aspect/sentiment (JAS) model [11] provides the details for the extraction of implicit aspects, but they used topic modeling to extract explicit aspects and sentiments, and then used these extracted sentiment lexicon to further identify the implicit aspects.

(RQ1c) *It is difficult to build an overall judgment for the performance of topic modeling techniques. This is due to the diversity of datasets, domains and approaches adopted for the evaluation.*

Although topic modeling has proved its significance for the aspect extraction in sentiment analysis, perhaps this is very difficult to compare all these techniques and reach a single decision for the overall performance. Many approaches have focused on single domain knowledge and use this knowledge to extract aspects from a specific domain. But, on the other hand, some approaches have used multi-domain knowledge to extract aspects and used one domain's knowledge in other domains. Also, due to the vast diversity in datasets, it cannot be claimed that one approach performed well in one domain will also produce same performance in other domain without conducting extensive experiments.

This has been observed that, supervised or semi-supervised techniques perform better than the unsupervised techniques due the trained datasets. Therefore, the evaluation analysis of different techniques has been explained in the results and discussion section, which discusses and elaborates the comparison of techniques with the same slants.

Table 2 Summary of topic modeling techniques.

Study	Language	Approach	Domain
Fang and Huang [9]	Chinese	Supervised	Restaurant
CLJAS [10]	Multi-language	Unsupervised	Multi domain
JAS [11]	English	Supervised	Restaurant Hotel
Brody and Elhadad [14]	English	Unsupervised	Restaurant Hotel
MaxEnt-LDA [15]	English	Unsupervised	Restaurant Hotel
ASUM [16]	English	Unsupervised	Restaurant Electronic
ME-SAS [18]	English	Semi-supervised	Hotels
HASM [19]	English	Supervised	Laptops Digital SLRs
ADM-LDA [20]	English	Unsupervised	Product
UFL-LDA [22]	English	Semi-supervised	Camera Hotel
MDK-LDA [23]	English	Semi-supervised	Product
GK-LDA [24]	English	Semi-supervised	Product
MC-LDA [25]	English	Semi-supervised	Product
AKL [26]	English	Unsupervised	Product
LTM [29]	English	Unsupervised	Product
AMC [30]	English	Unsupervised	Product

(RQ2) *Topic modeling is not only capable of extracting topics, but also group similar terms under a single topic in a particular domain.*

Topic modeling techniques search the document for discovering the topics. In customer reviews, these topics are aspects and there could be many words which were used for the same aspect. For example, in the domain of mobile phone, LCD and screen referred to same aspect. Similarly, picture and movie are the synonyms in the movie domain, but these are not representing same aspect in the camera domain where these both are different aspects. In camera domain photo and picture are the synonyms of each other.

Traditional dictionary based approaches do not perform well in such scenarios, but topic modeling is a principle approach to group similar terms into topics. Topic modeling techniques discover those topics which are relevant to the domain and for each topic there could be more than one terms in the document. Therefore, topic modeling has proved its significance to group similar topics [12].

3 Topic Modeling in Sentiment Analysis

In this section, those techniques have been discussed which use topic modeling for the extraction and categorization of aspect from online reviews. There are two basic methodologies for topic modeling, pLSA and LDA. But pLSA method is inherently transductive, i.e. to apply the learned knowledge there is no direct method [5]. Therefore, very few studies have focused on pLSA, like Moghaddam and Ester [13]. They extended pLSA for aspect extraction and rating from reviews by incorporating latent rating information of reviews. Most of the research focused on LDA-based techniques, therefore, in this section; only those techniques have been deliberated which used LDA-based methodologies for aspect extraction.

3.1 LDA-Based Topic Modeling

For the extraction of aspects from reviews, Brody and Elhadad [14] proposed an unsupervised local topic model technique. This technique focused on a small number of topics and relied on the sentence level. They treated each sentence as a document and apply standard LDA on each sentence. The output of the model was the aspects, which were identified from each sentence. Also, they presented a method to automatically identify positive and negative adjectives as opinions using polarity propagation, rather than using the manual seed words.

Zhao, *et al.* [15] proposed hybrid topic-based model MaxEnt-LDA, which incorporates maximum entropy along with topic modeling to identify aspects and opinions together. The model was semi-supervised and not only extracted adjectives as opinions but also allowed non-adjective opinion words. Similarly, Jo and Oh [16] proposed two models to identify aspects and grouping them simultaneously. They observed that in any sentence all the aspects represent same topic. The first model Sentence-LDA (SLDA) identified aspects that match the details of reviews at sentence level. The second model was an extension of previous model which was Aspect and Sentiment Unification Model (ASUM) and identified the aspects along with the sentiments which modify a particular aspect.

In sentiment analysis problems, opinion words played a very vital role. These words express the sentiments of users for a particular aspect. But the opinion words can also affect the aspects and same word can signify different meanings for different aspects. For example, in hotel reviews, word “large” can express positive sentiment for room aspect but on the other hand same word can express negative sentiment for noise aspect. This idea was used by Xu, *et al.* [17] and Xueke, *et al.* [11] to propose a Joint Aspect/Sentiment (JAS) model which extract aspects from reviews and generates the aspect-dependent sentiment lexicons. They extended LDA for the purpose of aspect extraction and the opinion words, modifying the aspects, were extracted. Also they further used the same opinion words to extract the implicit aspects.

Fang and Huang [9] proposed structural learning model which incorporates struct-SVM and latent discriminate method to not only finding the aspects but also clustering them in groups for Chinese restaurant reviews. They identified the sentences which contain aspects, and computed the subjectivity and polarity score with respect to aspects jointly. To extract aspects from sentences, they adopted a rule-based approach.

Mukherjee and Liu [18] proposed two semi-supervised models to extract and grouping aspects which represent same semantics for hotel reviews. Both techniques were based on statistical models to extract and categorize aspects, while providing some seed words as input. The first model was Seeded aspect and sentiment (SAS) model while the second one was the improved version of SAS by employing maximum entropy (ME-SAS). But to train ME-SAS there was no need for the manual labeled data.

Hierarchical Aspect Sentiment Model (HASM) [19] identified the hierarchical structure among aspect and sentiment words within the review sentences. The defined structure was a nested tree where roots and nodes form a sub-tree and each root represent an aspect and children of that root represent the sentiments over that particular aspect. This nested nature of the tree helped to distinguish among aspect topics and sentiment polar topics. The tree was capable of identifying more than two sentiments over an aspect in one review. The distribution of words in tree was used to identify the polarity of sentiments or aspect for the given review.

Bagheri, *et al.* [20] considered the each word in the sentence as a state of Markov chain [21]. The subsequent words in the chain to any other word are more likely to have the same topic. By assuming these properties, they proposed Aspect Detection Model based on LDA (ADM-LDA) to extract the aspects from the documents by unsupervised means.

Cross-Lingual Joint Aspect/Sentiment (CLJAS) [10] model extracts aspects and sentiments from two different languages simultaneously. It was assumed that, the reviews shared the same topic distribution over different languages. This property helped to assign topics of the reviews which in this case remain same. Once the topic was assigned, a dictionary based translation was used to exploit correspondence between languages to find the semantically aligned topic distribution. The proposed model was based on LDA topic model. The model first identified aspects and sentiments from reviews and then these aspect/sentiment words were used to assign polarity.

Wang, *et al.* [22] proposed two semi-supervised LDA techniques to extract and group product aspects from the online reviews. They generated a seed list from E-commerce website and used this prior knowledge about the product to extract aspects. They proposed Fine-grained Labeled LDA (FL-LDA) which used these seed words to identify those words which were related to them. FL-LDA not only identifies the semantically related aspects to the seeded list but also grouped them together into similar clusters. Furthermore, to identify those aspects which were not extracted through FL-LDA but were frequently used in the reviews, Unified Fine-grained LDA (UFL-LDA) was proposed to tackle such aspects.

3.2 Knowledge-Based Topic Modeling

In the domain of product reviews, the aspect price is very common among the products and all the products have this aspect. Similarly, in the electronic devices the aspect battery is common in all the products and in mobiles, screen and sound are the common aspects among different products. This shared knowledge is very useful to identify shared aspects and extract them from the documents.

Therefore, Chen, *et al.* [23] proposed a knowledge based system MDK-LDA (LDA with Multi-Domain Knowledge). A word in a different domain may have more than one meaning, even in the same domain there could be more than one senses of a single word. Therefore, they took inputs from the users to handle such kind of words. The focus of the research was the must-link state i.e. the set of words which are frequent must be present in the same document. Furthermore, Chen, *et al.* [24] build a General Knowledge LDA (GK-LDA) model to identify the wrong knowledge by exploiting lexical semantic relations which was learnt by MDK-LDA. This model also deals with only must-link states. The previous two models learn knowledge from the multiple domains but the focus of both approaches was the must-link and they do not consider the cannot-link. To overcome these issues, Chen, *et al.* [25] proposed the MC-LDA (LDA with m-set and c-set) which not only extract knowledge from different domains but also identified the wrong knowledge, which was extracted on both must-link and cannot-link states.

The first self-learning knowledge-based system was proposed by Chen, *et al.* [26], which learn knowledge from the set of domains which share same kind of aspects and used this knowledge to improve the aspect extraction. The system learned knowledge without any manual interference as the previous knowledge-based systems do. An unsupervised approach, to learn quality knowledge from multiple domains and extract the aspects with the guidance of learnt knowledge, was proposed. The proposed method was AKL (Automated Knowledge LDA) which based on the traditional topic-base model LDA. By applying AKL on each domain, a set of topics was obtained. From this set, to find the terms which appear together in multiple domains, they used Frequent Pattern Mining (FPM) [27]. Furthermore, these patterns or knowledge were used to extract aspects from the reviews. As the knowledge obtained may contain errors, the Blocked Gibbs Sampler [28] was adopted, which dynamically balanced the use of extracted knowledge and information in the corpus.

The above approach AKL was followed by Chen and Liu [29] to propose Lifelong Topic Model (LTM). LTM model had the additional mechanism to re-extract the knowledge from the domains and again learn from this knowledge to extract aspects from the reviews. Therefore, the model was called lifelong model as it can mine the documents again to extract knowledge as needed by the model. The previous work for extracting knowledge from different domains only focused must-link relations and did not cover the cannot-link relation. Therefore, Chen, *et al.* [30] proposed a lifelong model which covered the both links to extract knowledge from multiple domains. The model was called Automatically generated Must-link and Cannot-link (AMC).

4 Results and Discussion

This section covers the analysis of overall performance of different topic-based techniques, which covers the aspect extraction accuracy as reported by different studies. Assembling a comparison among different methodologies is unpractical due to the diverse characteristics of the datasets, domains and languages. Therefore, we have tried to compare those approaches which have relatively similar datasets and used same language. Where possible, a sharp analysis of some diverse methods has been conducted. Figure 1 summarized the overall studies reviewed in this paper.

A total of 16 existing studies were selected for the analysis of topic modeling in sentiment analysis. The Figure 1 shows that most of the studies focused on unsupervised approaches and semi-supervised approaches. This shows the importance of self-learning models making significant contribution to the literature.

Table 3 elaborates the accuracy parameters, used for the analysis, of the performance of different LDA-based techniques. Knowledge-based approaches used precision @n (p@n) parameter to identify topics, where n is the rank position of the topic. While in other approaches, the accuracy parameter is the overall precision of the system. CLJAS and UFL-LDA have no values for any parameter because they did not report any performance measure for aspect identification.

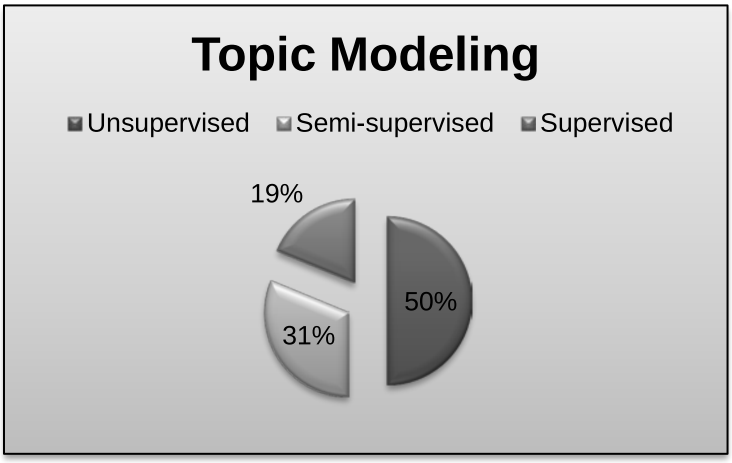

Figure 1 Distribution of all approaches for Topic modeling.

In Table 3, all the values are the average values because multiple review datasets from different domains were used for the evaluation e.g. in AMC 10 and in AKL 4 different datasets were used.

Table 3 Aspect extraction accuracy of LDA-based techniques.

Study	Precision	Precision@5	Precision@10
Brody and Elhadad	0.868	X	X
MaxEnt-LDA	0.808	X	X
ASUM	0.850	X	X
JAS	0.808	X	X
Fang and Huang	0.941	X	X
ME-SAS	0.880	X	X
HASM	0.860	X	X
ADM-LDA	0.851	X	X
CLJAS	X	X	X
UFL-LDA	X	X	X
MDK-LDA	X	0.900	0.780
GK-LDA	X	0.925	0.860
MC-LDA	X	0.957	0.900
AKL	X	0.900	0.832
LTM	X	0.840	0.570
LTM*	X	0.880	0.820
AMC	X	0.916	0.71

For the comparison of different approaches, we took the accuracy of different approaches reported in the studies as in Table 3. In Figure 2, the accuracy in the form of precision is presented and calculated the average precision where experiments were conducted on more than one datasets. This gives an overall performance for that approach. For Figures 3, 4 and 5, there are two precisions i.e. p@5 and p@10, using the values of n as 5 and 10, as reported in the studies. These precisions are again calculated as average precision of all the datasets. The reason to calculate the average precision is that, in some datasets the precision reported is very high and it is not compulsory that other approaches have used the same dataset. Therefore, buy calculating the average precision, it is quite reasonable to compare different approaches and the analysis will not be biased.

In Figure 2, the comparison of LDA-based models has been elaborated. In this evaluation, CLJAS and UFL-LDA approaches are not included. Because, CLJAS does not focused on single language and domain, and this is not possible to compare this methodology with single language approaches. UFL-LDA does not give any clear measurement or accuracy for the aspect extraction and also used online product information which makes UFL-LDA different from all other techniques. The major focus of the research was on the grouping of similar aspects.

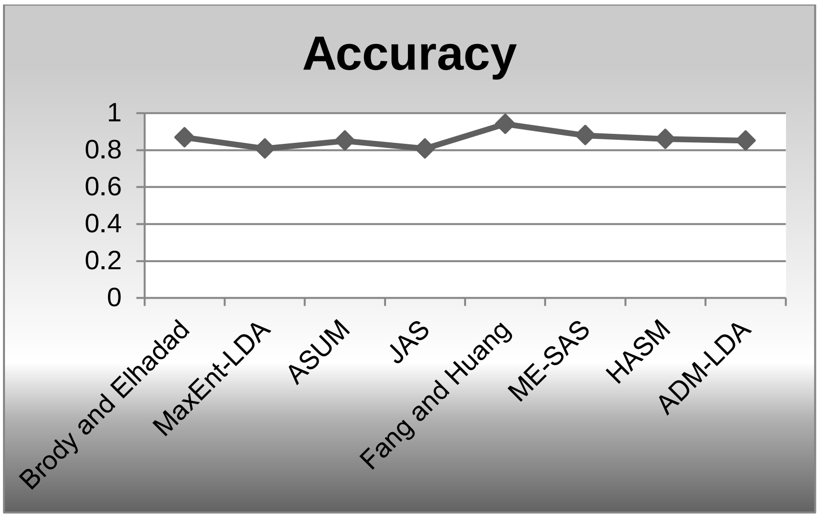

Figure 2 Accuracy of LDA-based models.

In Figure 2, Brody and Elhadad, MaxEnt-LDA, ASUM and ADM-LDA are the unsupervised approaches, while JAS, Fang and Huang, and HASM are supervised and ME-SAS is semi-supervised. The graph clearly shows that the approach adopted by Fang and Huang out forms the rest of the methodologies. But, this approach was applied on the Chinese reviews while the rest of the approaches were applied on English language reviews. From the rest of the approaches, ME-SAS produced the best result among all.

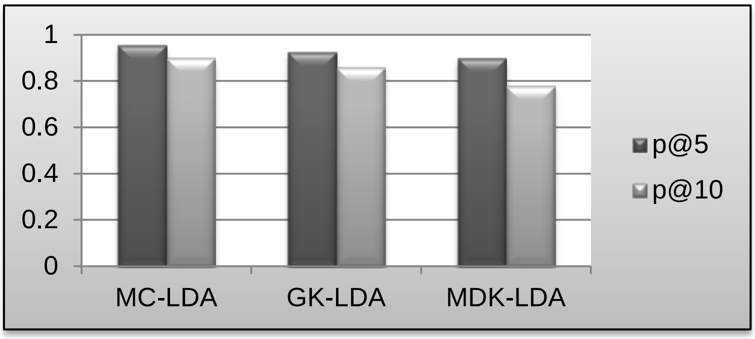

Figure 3 Aspect extraction accuracy of Knowledge-based semi-supervised approaches.

Figure 3 illustrates the comparison of knowledge-based approaches. These all are semi-supervised and focused on product domain as explained in Table 2. The experiments were conducted in the studies on different product reviews. The precisions shown in Figure 3 are the average precisions of all the products for each approach. MDK-LDA exploit knowledge from multiple domains using cannot-link while GK-LDA using must-link. But on the other hand, MC-LDA covered both cannot-link and must-link and also identified the wrong knowledge. Therefore, the overall performance is better than the other two models. These models cannot be compared with the other approaches in Figure2, because these models use shared knowledge of different domains to identify the aspects while other approaches do not use such shared knowledge.

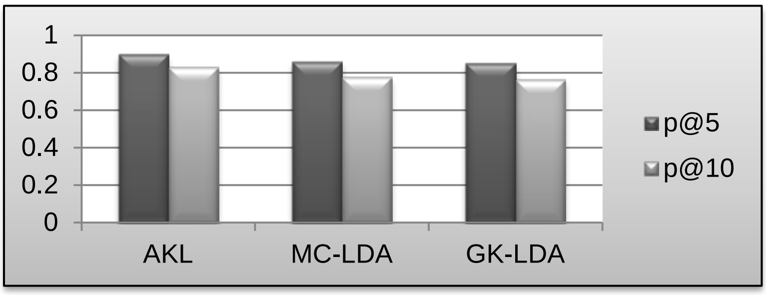

Figure 4 Aspect extraction accuracy of Knowledge-based unsupervised approaches.

MC-LDA, GK-LDA and MDK-LDA required knowledge as user's input to learn from different domains and has a high precision reported. But in Figure 4, when compared to AKL, which is a totally self-learning model and does not required any input knowledge, the precision was dropped. This is due the reason that the knowledge provided as input to both MC-LDA and GK-LDA was the knowledge learnt by AKL. Therefore, when same knowledge was provided to AKL, it performs better then MC-LDA and GK-LDA. This proves the significance of self-learning approaches i.e. when user provides knowledge as input to MC-LDA and GK-LDA, they performed significantly well but when they were provided the knowledge learn by AKL, the performance of these techniques falls. Therefore, AKL performed better for the automatic knowledge learning.

Although, AKL, GK-LDA and MC-LDA can learn knowledge, either as user provided input or by automatically extracting knowledge, but LTM and AMC can re-extract knowledge from domains where required and re-use the new knowledge for the identification of topics. This makes them lifelong learning models and therefore, cannot be compared directly with the previous approaches. Therefore, in Figure 5, the comparison between lifelong learning models has been elaborated. In the diagram, this is clear that AMC outperforms LTM but very close to LTM*. This is because, in Figure 5 LTM used AMC knowledge provided as input to LTM, hence its performance dropped. On other hand, LTM* used its own knowledge to extract aspects and performs better. But again, both LTM and LTM* have poor precision as compared to AMC. Because, AMC tackles both must and cannot-links while LTM can mine knowledge with must-link only.

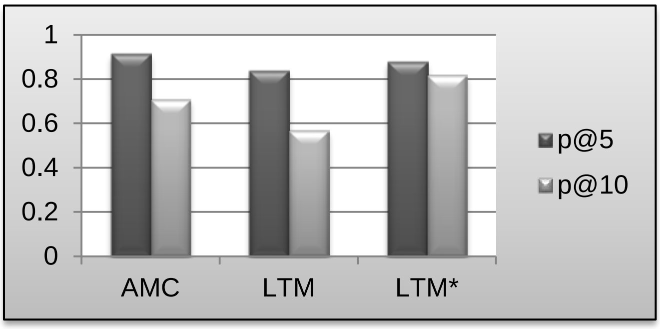

Figure 5 Comparing accuracy of aspect extraction among AMC and LTM.

The comparison of accuracies of all the approaches was accomplished due to the availability of the results and consistency between domain, language and results. But, this is not possible in the case of aspect categorization, to conduct a comparison of all the approaches. There is no common benchmark in the studies, building upon we can conduct a comparison. Also, different approaches can produce different number of clusters on the same datasets. Therefore, a sharp analysis of topic coherence for knowledge-based approaches has been elaborated in Figure 6 [24].

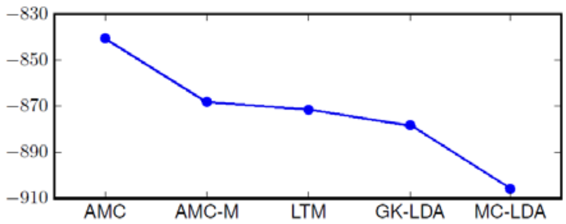

Figure 6 Topic coherence.

In Figure 3, MC-LDA performed better than GK-LDA but for topic coherence it performed very poor as in Figure 6. This is because MC-LDA is not capable to deal with the large number of cannot-links. While, on the other hand GK-LDA tackles cannot-link efficiently. From the diagram, it is clear that AMC performed better than all other approaches. But, let us take a look at Figure 7, when the AMC knowledge was provided to LTM as input, LTM performed poor. But when LTM used its own learned knowledge, LTM provide better coherent topics as compared to AMC, as shown in Figure 7 by LTM*. This clears that, the knowledge provided to the system plays a very important role for the accuracy of the system.

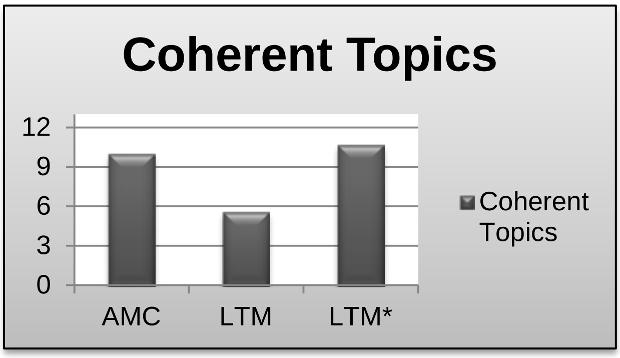

Figure 7 Comparison of coherent topics for AMC and LTM.

5 Conclusion

In this paper, we have systematically reviewed topic modeling in the area of sentiment analysis and presented extensive comparative evaluations of different approaches. From the analysis, the effectiveness of topic modeling for the aspect extraction and categorization has been demonstrated. Although, some approaches have not focused on grouping synonyms like ME-SAS, but most of them used LDA-based techniques for aspect extraction and groping them into similar clusters simultaneously.

Although, topic modeling has performed significantly well, but there is a need to compare these techniques with other aspect-based sentiment analysis techniques. By doing this, we can technically compare the results and effectiveness of different approaches. In sentiment analysis, implicit aspect played a very important role and affects the accuracy of the system. Except JAS no approach has focused on the identification of implicit aspects. Even JAS did not use LDA for the identification of implicit aspects. LDA-based models can extract only those topics which appeared in the document frequently. Therefore, LDA-based approaches are not able to handle implicit aspects.

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