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AN AMPLE ANALYSIS ON EXTENDED LDA MODELS FOR ASPECT BASED REVIEW ANALYSIS

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Topic Modeling Algorithms (TMA) widely used in the field of Aspect Based Review Analysis and demonstrated good performance. The prime intuition behind topic models is that each document is a collection of some topics. A topic is a collection of words that represent the topic as a whole. TMA extract the 'latent' semantic topics and themes in a collection of documents. Latent Dirichlet Allocation (LDA) is the most popular TMA used in various text mining applications. In this study, we give deep insight on LDA and its combination with other approaches in Opinion Mining or Sentiment Analysis domain. The purpose of this paper is to provide an ample analysis of various extensions and combinations of LDA for optimizing the complete process of review miming.

Keywords: Topic Modeling Algorithm, Latent Dirichlet Allocation, Aspect Based Review Analysis, Opinion Mining, Text mining, Review Mining, Sentiment Analysis.

1. Introduction

In present digital era, people spend significant time on the Internet and prefer online services for purchasing various products and booking. As a result, a massive product review generated daily. These reviews are the prime source of information for manufacturers and customers to make appropriate marketing strategy, purchasing and production decisions. Last decade so many researchers have attracted in this direction and lot of work has been done at different levels of granularity of text reviews like word, sentence and document level. Document and sentence level analysis do not discover what exactly customers liked or not. Aspect Based Review Analysis (ABRA) goes one step further and analyzes the opinion with regard to individual product aspects. TMA especially LDA based methods are the very popular choice for feature or aspect extraction task. We have targeted applications of LDA in specifically ABRA. This paper summarizes various extensions of LDA and its combination with other approaches for the complete process of ABRA.

The remaining paper is organized as follows: basic terminologies and formal description of LDA model are presented in section 2. Section 3 discussed variations of LDA in ABRA. In section 4 comprehensive analysis of considered literature is done based on domain, datasets, methods, parameters and performance etc. Section 5 concluded the paper with future direction.

2. Basic Terminology and Formal Description of LDA

Topic extraction is of great importance in the area of review analysis. A lot of researchers have put forward a series of approaches to extract the hidden topics from the text such as TF-IDF, Matrix Factorization etc., among which the most popular one is the LDA.

[Blei et al. (2003)] have first tossed this and after that, so many extensions of LDA along with its applications in different domains have explored by the research community. LDA is a probabilistic generative model for text corpus at word and document level. The prime assumption of LDA is that documents are produced from a mixture of topics. These topics generate words based on their probability distribution. LDA obtain implicit correlations between words and topics and assign a probability to the unobserved documents by using inference algorithm.

Formally, we define the following terms:

Word : Basic unit from a vocabulary of size V.
Document : Sequence of N words. W= [w_1, w_2 ... w_n]
Corpus : Collection of M documents. D = [W_1, W_2 ...Wm]
Topic : Probability distribution over words or terms in a vocabulary.
θ and ϕ : Document-Topic and Topic-Word distribution respectively
α and β : Hyper parameters specifying the nature of the priors on θ and ϕ.

The LDA process consists of two parts: the first part is its generative process and the second part is its inference process. Description of generative process for LDA is as follows [Blei D. *et al*. (2010)]:

(1) Randomly choose a distribution over topics.
(2) For each word present in the given document:
   a. Randomly select a topic from the distribution over topics.
   b. Randomly select a word from the distribution over words related with selected topic.

LDA is a generative probabilistic model where generative process defined as a joint probability distribution over the observed and hidden variable. This conditional posterior distribution is used to infer the hidden variables given the observed variable. In LDA words of the documents are the observed variables and topic structure are the hidden variable [Blei *et al*. (2003), Blei D. *et al*. (2010)]. Figure 1 graphically represented LDA model.

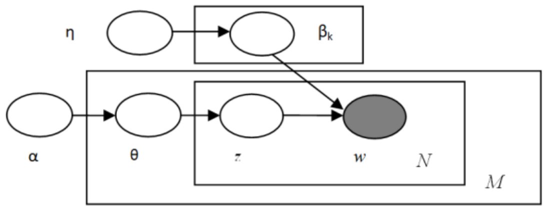


Fig1. Plate representation of LDA [Blei *et al*. (2003), Blei D. *et al*. (2010)]

Random variables are represented by circles and edges denote dependencies between variables. The observed variable is represented by a shaded circle and unobserved variables are shown by normal circles. Here words (w) of the documents are the observed variable and topic proportion (θ), assignments (z), topics (β) etc. are the latent variables. Plates (rectangular boxes) are representing replication. Plate N represents the documents and M represents topics and words within a document. The generative process of LDA is represented by following joint probability distribution:

$$\boldsymbol{P}\,(\boldsymbol{\beta}_{1:K}, \boldsymbol{\theta}_{1:D}, \boldsymbol{z}_{1:D}, \boldsymbol{w}_{1:D}) = \prod_{i=1}^{K} p(\beta_i) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n} \mid \theta_d) p(w_{d,n} \mid \beta_{1:K}, z_{d,n})\right) \quad (1)$$

Where:

$\beta_{1,k}$ = Topics where each β_k is the distribution over vocabulary.
θ_d = Topic proportion for the document d.
$\theta_{d,k}$ = Topic proportion for topic k in document d.
z_d = Topic assignment for d^{th} document.
$z_{d,n}$ = Topic assignment for n^{th} word in document d.
w_d = Observed words for document d.
$W_{d,n}$ = nth observed word for document.
N_d = Total number of words in document d.

In LDA parameter estimation is done to determine the values of parameters that maximize the probability of sample data. Inference algorithms evaluate hidden topics of unseen documents by using hidden topics of observed documents. Various inference algorithms like Gibbs Sampling (GS), Collapsed Gibbs Sampling (CGS), and Variation Expectation Maximization (EM) etc. are used for [Blei *et al*. (2003), Blei D. *et al*. (2010), Diya *et al.*(2013), Daud *et al.*(2010)] inference.

3. Variation of LDA for Textual Review Analysis

ABRA is the thrust area to work on. Aspect Extraction (AE) is the key part of ABRA. The performance of any ABRA algorithm is highly dependent on the AE. Topic Models are very popular methods for AE. Recently some of the topic models like LDA have got much attention from the research community. In the context of ABRA, Topic Models have shown very promising results in case of Un-Supervised and Semi-Supervised AE.

Few surveys are already presented [Diya *et al.*(2013), Daud *et al.*(2010), Jelisavčić *et al.*(2012), Alghamdi and Alfalqi (2015)] on TMA but we found that no one has targeted LDA in context ABRA. This comprehensive survey will complement previous ones and give deep insight about LDA in particular product review domain. Various available extensions of LDA are discussed here to find directions for further improvements. The latest survey presented in [Kumar *et al.* (2016)] talks about Swam Intelligence based approach and [Rana and Cheah (2016)] considered only aspect extraction in SA but exclude TMA.

3.1 Supervised LDA

Sentence-LDA (SLDA) is a probabilistic generative model. Aspect and Sentiment Unification Model (ASUM) is an extension of SLDA which integrates both aspect and sentiment [Jo and Oh (2011)]. The prime assumption of this model is that each sentence contains exactly one aspect so it split the sentence from punctuations and conjugations. SLDA generates one aspect for one sentence whereas ASUM gives different aspects of sentiments. The model may be utilized for aspect-based review summarization. It may also be applied to other types of data such as editorials, art critiques.

LDA and synonym lexicon based integrated approach for product aspect extraction from Chinese online review is presented [Baizhang et al (2013)]. This method creates a candidate feature set by identifying the noun and noun phrases using LDA which is reprocess with synonym lexicon to get extended feature set. Rule-based filtering is applied to get final feature set.

For sentiment analysis of tweets (short-texts), a LDA based Topic model is presented [Lim and Buntine (2014)]. It makes use of available auxiliary variables to improve ABRA. For incorporating a sentiment lexicon into the topic model a new formulation is used that automatically optimized using a tuning hyper parameter.

A hybrid LDA based on Deep Neural Network (DNN) is presented for learning and knowledge transfer [Zhang *et al.* (2016)]. This model used DNN for approximating LDA inference with fewer computations. This research indicates that transferring knowledge from Bayesian models to neural models is possible. A combination of Support Vector Machine (SVM) and LDA based TMA is proposed in [Uma and Karthiga (2015)]. In this method Term Frequency (TF)-Inverse Document Frequency (IDF) is calculated for pre-processed data and result is feed to LDA model. SVM is used for topic classifier which classifies the topics from each and every document.

3.2 Semi-Supervised LDA

A hybrid topic model Hierarchical Dirichlet Process (HDP) based on LDA is opted to determine aspects. This model differentiates between sentiment words and factual words. SentiWordNet is used as a knowledge base for the probability of sentiment distribution [Ding et al. (2013)]. Topic modeling through Double Latent Dirichlet Allocation (DLDA) model combines two methods in LDA named DLDA –I and DLDA-II. Their Key logic is to combine the sentiment with the topic model. Their model treats sentiment as equal to the topic but independent of the topic. Sentiment weight of words is evaluated and used to analyze the sentiment polarities. Entropy is used to optimize the Gibbs Sampling process calculation time [Chen *et al.* (2014)].

Topic Sentiment LDA (TSLDA) is another topic model used to predict the stock price movement by extracting the features of sentiments. This approach grabs the topic and sentiment at the same time [Nguyen and Shirai (2015)]. A semi-supervised LDA model presented for topic modeling [Wood *et al.* (2016)]. This model incorporates prior knowledge to guide the topic modeling process which improves the quality of the topics and of the topic labeling both.

3.3Un-Supervised LDA

For opinion mining of asymmetric collections, a new Maximum Entropy based Topic Model presented named CAMEL (Cross- collection Auto-labeled MaxEnt-LDA). It modeled both specific and common aspect along with integrating complementary information from different collections [Zuo *et al.* (2015)]. Sentence level is added in LDA to reduce arbitrariness. This algorithm can be applied on equal sized English and Chinese corpus to find out disparity among them [Liu (2016)]. For improving precision and speeds up the process of decision making a hybrid LDA based on Feature Ontology Tree (FOT) is derived. This model combines the features of both NLP and LDA with FOT [Santosh *et al.* (2016)].

Two different models named as Dirichlet multinomial topic model (LF-DMM) and latent feature vector representations of words (LF-LDA) are trained for very large corpora to improve the word-topic mapping learned on a smaller corpus [Nguyen *et al.* (2015)]. A model "lda2vec" is described using LDA topic modeling by [Moody and Christopher (2016)]. This model learns dense word vectors and used to build unsupervised document representations which have coherent topics.

4. Comprehensive analysis

In this section comprehensive analysis of ABRA using LDA based TMA is presented to give deep insight in the different element of the ABRA. Table 1 summarized the various approaches used by different researchers to perform different tasks of ABRA process.

Table1. Various tasks perform on using different approaches.

Authors and Reference	Approach	Task	Methods
Jo and Oh (2011)	S	AE and SA	S-LDA and ASUM
Ding et al. (2013)	SS	AE and SA	Hybrid LDA
Ma et al (2013)	SS	AE	LDA + Synonym Lexicon
Chen *et al. (*2014)	SS	AE and SA	Double LDA
Lim and Buntine (2014)	S	AE and SA	LDA + Sentiment Lexicon
Zuo *et al.* (2015)	US	AE and SA	LDA + Maximum Entropy
Zhang *et al.* (2016)	S	DC	LDA+ Deep Neural N/W
Uma *et al.* (2015)	S	AE and SC	LDA+ SVM
Nguyen *et al.* (2015)	SS	TE and SA	TSLDA
Liu (2016)	US	TE	LDA
Santosh *et al.* (2016)	US	AE	LDA + Feature Ontology Tree
Poria et al(2016)	SS	AE and AC	LDA+ Common Sense
Nguyen *et al.(*2015)	US	TE and TC	LF-LDA and LF-DMM
Moody *et al.* (2016)	US	TE	LDA+ Word Vector
Wood *et al.* (2016)	SS	TE and TL	LDA+ Prior Knowledge

S: Supervised, SS: Semi-supervised, US: Unsupervised, DC: Document Classification, SA: Sentiment Analysis SC: Sentiment Classification, TE: Topic Extraction, TL: Topic Labeling, TC: Topic Categorization

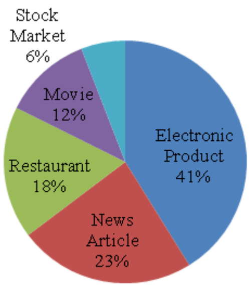
Supervised approaches used in [Jo and Oh (2011), Lim and Buntine (2014), Karami *et al.* (2015), Zhang *et al.* (2016), Uma and Karthiga (2015)] for aspect extraction and classification using sentiment lexicons like SentiWordNet etc. NN and SVM are used for classification in [Zhang *et al.* (2016), Uma and Karthiga (2015)]. Using Knowledge base with LDA some Semi Supervised approaches are presented in [Ding *et al.* (2013), Chen *et al.* (2014), Nguyen and Shirai (2015), Poria *et al.* (2016), Wood *et al.* (2016)]. Combining LDA with other approaches like Maximum Entropy, Feature Ontology and Vector representation [Zuo *et al.* (2015), Liu and Qihua (2016), Santosh *et al.* (2016), Nguyen *et al.* (2015), Moody and Christopher (2016)] few unsupervised methods are presented.

Table 2 summarizes the data sets used in various domains along with their source and short description.

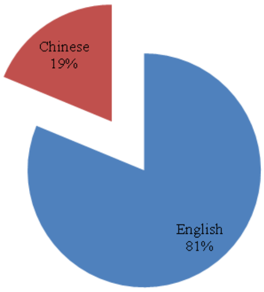
Table 2.Various Domain and Datasets Used.

Reference	**Domain**	**Dataset Detail**	**Language**	**Source of Data Set**
Jo and Oh (2011)	Electronics / Restaurant	22,000Electronics 30,000Restaurants	English	Amazon and Yelp3
Ding et al. (2013)	Restaurant	3400 sentences	English	City search New York
Ma et al (2013)	Camera and phone	17,000	Chinese	http://www.jd.com
Chen *et al. (*2014)	Movie Review	55385 with 27695(-) and 27690 (+)	Chinese	http://movie.douban.com/
Lim et al. (2014)	Electronic Camera, Mobile	Twitter 7 Tweets Sentiment140 tweets	English	snap.stanford.edu/ data/ twitter7 help.sentiment140.com
Zuo *et al.* (2015)	Electronic device	3000 Doc 50000 Sent 300000 word	English	Amazon
Zhang *et al.* (2016)	News Articles	21578 newswire 19,000 documents	English	Reuters-21578 20 Newsgroups
Uma et al. (2015)	Movie review	50k unsupervised	English	IMDB database
Nguyen et al (2015)	Stock Market	Historical Price Message Board	English	Yahoo Finance
Liu (2016)	Chinese corpus	1696 articles	Chinese	CCL
Santosh *et al.* (2016)	Electronic Product	100 review per cate.	English	Amazon.com, Cnet.com.
Poria et al(2016)	Hotel	235,793 reviews	English	TripAdvisor.com
Nguyen *et al.*(2015)	News Articles	19,000 documents and 32,600 RSS	English	20 Newsgroups TagMyNews news
Moody et al (2016)	News Articles	20,000 news doc	English	20Newsgroups, Hacker News
Wood *et al.* (2016)	News Articles	21578 newswire	English	Reuters

Analysis of Table 2 shows that most of the work has been done in product review domain. Figure 2(a) shows the distribution of various datasets domains. One more observation is that in most of the work English review are taken for processing. Figure 2(b) represents the distribution of language chosen by various articles.



(a)



(b)

Fig.2. (a) Datasets domains used for ABRA (b) Text Review Language used for ABRA

This is observed that 81% of articles chosen English text reviews for processing. Other language is Chinese which is used by 19% of articles. Amazon, Trip advisor, 20 Newsgroup are the very famous sources of review datasets.

Table 3 summarizes performance measure of various LDA based approaches used for ABRA. Approaches considered in the literature set different values of various parameters (K, α and β) and produce different performance in terms of F measure. In some literature only Qualitative Analysis is given. Different approaches use different evaluation parameters so the exact comparative analysis is not available.

Table3. Performance Analysis of various Approaches

Reference	**Approach**	**Parameter used**			**Inference method**	**Accuracy F measure**
		K_{max}	***α***	***β***		
Jo and Oh (2011)	S-LDA, ASUM	50	0.1	0.001	GS	0.78
Ding et al. (2013)	Hybrid LDA	50	0.001	0.5	GS	0.63
Ma et al (2013)	LDA, Synonym Lexi	50	0.1	0.01	GS	0.70
Chen *et al. (*2014)	DLDA-I,II	40	50/T	0.01	GS + ME	0.80(P)
Lim et al. (2014)	LDA, Sentiment Lexi	10	0.1	0.1	CGS	0.73
Zuo *et al.* (2015)	LDA + ME	20	*0.1*	0.01	CGS	NA
Zhang *et al.* (2016)	LDA+ NN	70	NA	NA	EM	NA
Uma et al. (2015)	LDA+ SVM	NA	NA	NA	SVM	NA
Nguyen et al (2015)	TS-LDA	90	0.1	0.01	CGS	0.56
Liu (2016)	LDA	50	0.1	0.1	GS	0.32
Santosh *et al.* (2016)	LDA + FOT	50	50/K	0.05	NA	0.90
Poria et al(2016)	LDA+ Common Sense	50	50/K	0.1	CGS	0.89
Nguyen *et al.(*2015)	LF-LDA + LF-DMM	80	0.1	0.01	GS	0.67
Moody et al (2016)	LDA+ Word vector	20	1/K	0.75	SGNS	0.60(TC)
Wood *et al.* (2016)	LDA+ Prior Knowl.	100	50/K	20/V	PMI	NA

From Table 3 some relation can be drawn between the values taken for α and β in different approaches. Document-topic density is represented by α and β represents topic-word density. For higher the value of α, documents should compose of more topics and for lower value of α, documents should contain fewer topics. Similarly, for higher the β, topics should compose of a large number of words in the corpus, and with the lower value of β, they should compose of few words. Selection of α and β can also improve the performance of LDA. Figure 3 represents values of α and β parameters in different variations of LDA.

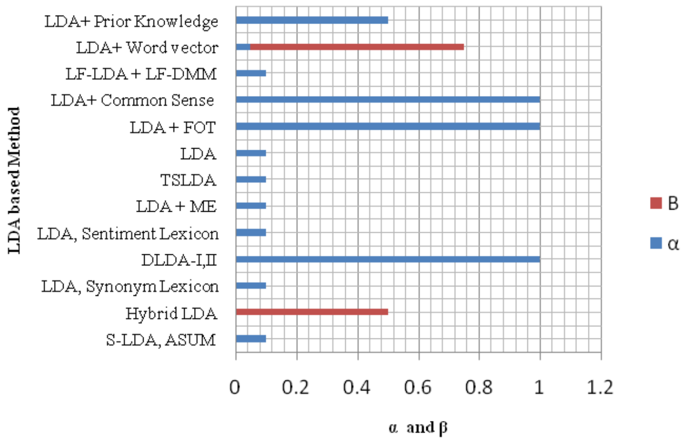


Fig.3. Parameter values (α and B) taken in different LDA extensions

In most of the approaches value of α is either 0.1 or 50/K where K is a number of topics. For β this value is 0.01. It is clear from above graph that proper selection of values of α and β is also one of the important factors in the performance of the LDA and its variations.

Table 3 also describing performance analysis and parameter values estimated in LDA with their Inference Method. Most of the considered articles have used F-score for their performance measure. In [Chen *et al.* (2014)] "Purity"(P) and in [Moody and Christopher (2016)] Topic Coherence (TC) parameter is used for the performance measure. In this study comparative performance analysis of various approaches is done the basis of F measure. Figure 4 represent the F-score for all approaches. It is clear from figure 4 that LDA alone cannot give higher F-measure and the performance of hybrid LDA is quite better.

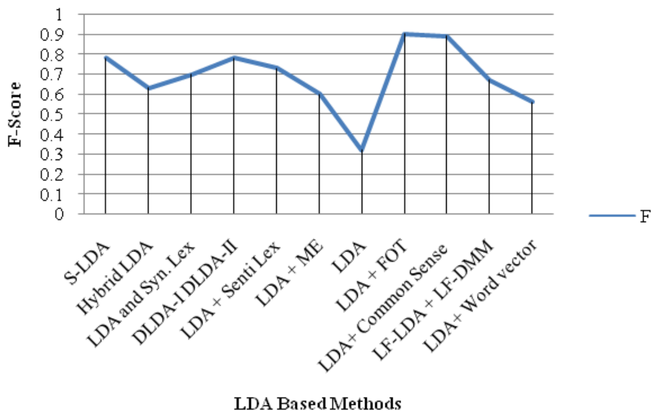


Fig.4. Performance Analysis for different Approached used

Average value of F-score for most of the considered methods is around 0.70 [Ding et al. (2013), Ma *et al.*(2013), Lim and Buntine (2014), Karami *et al.* (2015), Nguyen *et al.* (2015)]. LDA with FOT [Santosh *et al.*(2016)] and LDA with common sense knowledge [Poria *et al.* (2016)] have given the highest F-score among all approaches

In most of the considered articles experiment has been done on one or two datasets and performance evaluated. Variations are observed in performance for different domains. It shows that same method performs differently in the different domain. The reason is behind that some domains contain more complex or implicit aspect as compare to other. So for analysis same approach should be applied on the different dataset for examining its generic performance.

5. Conclusion and Future Directions

This survey paper presented an overview of various extensions of LDA for ABRA. More than 25 published and cited articles were categorized and summarized. These articles give the contribution to different sub tasks of ABRA. This analysis clarifies that LDA can be further modified to produce better result in textual review analysis. LDA has been applied to English reviews in most of the articles considered. Therefore application of LDA in other language reviews can be an open area of research. In Indian context, generalized LDA model is required to break the language barrier. Almost all articles have applied LDA on electronic product reviews, restaurant and movie reviews. So new categories can also be considered like Educational feedback, political review, medical document etc. For optimizing various parameters of LDA Genetic Algorithms may be used. Nature inspired approaches can combine with LDA for improve the complete process of ABRA.

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