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Multi-aspect Sentiment Analysis with Topic Models Modeling

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Abstract—We have tried to examine the viability of topic model based methodologies to two multi-aspect sentiment analysis tasks: multi- aspect sentence labeling and multi-aspect rating prediction. For one of the tasks of sentence labeling, we propose a weakly-supervised approach that utilizes only minimal prior knowledge—in the form of seed words— to uphold an immediate correspondence between topics and aspects. This correspondence will be utilized to name sentences with execution that approaches a fully supervised standard. For multi-aspect rating prediction, we find that general evaluations can be utilized as a part of conjunction with our sentence labeling to accomplish sensible execution contrasted with a fully supervised baseline. At the point when highest level perspective evaluations are accessible, we find that topic model based characteristics can be utilized to enhance unsophisticated supervised pattern execution, in concurrence with past multi-aspect rating prediction work...

Keywords- Sentiment Analysis with Multiple Aspects, topic modeling;

I. INTRODUCTION

The constantly expanding prominence of sites that characteristic client created conclusions (e.g., TripAdvisor.com) has prompted a richness of client audits that are regularly excessively various for a client to peruse. Subsequently, there is a developing need for frameworks that can naturally concentrate, assess and present notions in ways that are both useful and simple for a client to decipher.

Early methodologies to this issue [1]–[4] have concentrated on deciding either the general extremity (i.e., positive or negative) or the estimation rating (e.g., one-to-five stars) of a surve. Be that as it may, just acknowledging coarse general appraisals neglects to enough speak to the different potential extents on which a substance might be explored.. For example, while the following review from TRIPADVISOR.com might express an overall sentiment rating of 3-stars, it additionally expresses a positive opinion toward the restaurant's food, as well as negative opinions toward the restaurant's ambiance and service:

"The sustenance was great, however it assumed control thirty minutes to be situated, and the administration was horrible. The room was exceptionally boisterous and frosty wind blew in from a shade beside our table. Pastries were great, but since of [the] poor administration, I'm not certain we'll ever retreat!"

Looking beyond just overall ratings is important for users, too, because they are likely to differ in how much value they ascribe to each of these distinct aspects. For example, while a gourmand may forgive a restaurant's poor ambiance, they may be uncompromising when it comes to food quality. Accordingly, a new branch of sentiment analysis has emerged, called MULTI-ASPECT SENTIMENT ANALYSIS, that aims to take into account these various, potentially related aspects often discussed within a single review.

Recently, several topic modeling approaches based on Latent Dirichlet Allocation (LDA) [5] have been proposed for multi-aspect sentiment analysis tasks [6]–[8]. These approaches use variations of LDA to uncover latent topics in a document collection, with the hopes that these topics will correspond to rateable aspects for the entity under review.

For multi-aspect sentence labeling, we propose a weakly supervised topic modeling approach (see Section III-A1) that uses minimal prior knowledge in the form of seed words to encourage a correspondence between topics and ratable aspects. We find that these models generally perform quite well (see Section VI-A), and that the best of these models performs comparably to a supervised approach.

For multi-aspect rating prediction, we consider two set- tings. In the first, we assume that aspect-ratings are unavail- able, but find (in Section VI-B) that by leveraging overall ratings in conjunction with our multi-aspect sentence label- ing approach, we can produce significant improvements over an aspect-blind baseline. In our second setting, we use gold-standard aspect-ratings to train supervised classifiers both with and without topic model based features.

We find (in Section VI-C) that these additional features improve perfor- mance over an online supervised baseline (Perceptron Rank). However, this improvement is diminished when a more competitive supervised baseline is used instead (Support- Vector Regression)—a finding not previously acknowledged.

For both assignments, we inspect and analyze two sorts of topic models (see Section IV): LDA, and Segmented Topic Models (STM)—an as of late proposed [9] topic model that, to date, has not been connected to sentiment analysis errands.

At last, we perform our examinations using far reaching dataset (see Section V-A) from region (hotels). Especially, we survey our data hailing from Tripadvisor.

II. RELATED WORK

While sentiment analysis has been mulled over widely for quite a while [10], most methodologies have concentrated on document- level overall sentiment. As of late, there has been a developing enthusiasm toward sentiment analysis at better levels of granularity, and particularly approaches that consider the multi- aspect nature of numerous sentiment analysis tasks.

A. Multi-aspect Sentiment analysis

Early multi-aspect work concentrated on making aspect-based audit outlines utilizing mined item emphasizes [11]–[13]. More late work [14], [15] has likewise started modeling implied aspects. For instance, [16] create an aspect-based survey summarization framework that concentrates and totals aspects and their relating sentiments.

Late work has likewise started to take a gander at multi-aspect rating prediction. [17] present the Good Grief algorithm, which together takes in positioning models for unique aspects utilizing an online Perceptron Rank (Prank) [18] algorithm. [19] and [20] bootstrap aspect terms with seed words for unsupervised multi-aspect opinion polling and probabilistic rating regression, separately. [21] incorporate a document-level HMM model to enhance both multi-aspect rating prediction and aspect-based sentiment summarization.

B.Multi-aspect Topic Models

While early generative approaches to sentimenent analysis tasks focused only on latent topics [22]–[24], recently work has begun to additionally model multiple aspects present in a single document. For example, [7] present Multi-grain LDA (MG-LDA), in which review-specific elements and ratable aspects are modeled by global and local topics, respectively. [6] introduce Local-LDA, a sentence-level LDA that discovers ratable aspects in reviews. [8] present MaxEnt-LDA, a maximum entropy hybrid model that discovers both aspects and aspect-specific opinion words.

However, the mapping between topics and aspects in these models is still largely implicit, which can be burdensome when working with different parameterizations or datasets. [25] integrate ground-truth aspect ratings into MG-LDA to force topics to correlate directly with aspects. However, their approach requires gold-standard aspect ratings. In contrast, in this work we both consider settings in which aspect ratings are available (see Section III-B), and settings in which they are unavailable (see Section III-A).

III.MULTI-ASPECT SENTIMENT ANALYSIS TASKS

A. Multi-aspect Sentence Labeling

The first phase of multi-aspect sentiment analysis is aspect identification and mention extraction. This step identifies the relevant aspects for a rated entity and extracts all textual mentions associated with those aspects [25].

In this work, we consider a limited version of the aspect identification and mention extraction task, which we call multi-aspect sentence labeling. In our limited setting, we assume that aspects are fixed—e.g., food, service, and ambiance for restaurant reviews—and that it is sufficient to identify a single aspect for each sentence in a document.

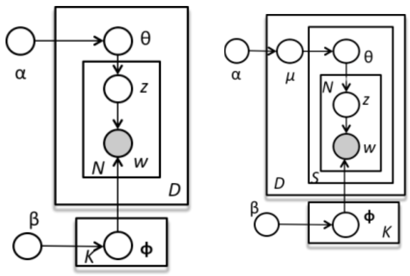
In particular, we evaluate 4 topic models, weakly supervised with aspect-specific seed words (see Section III-A1), and label each sentence according to its latent topic distribution. Formally, for each sentence s and topic k, we calculate the probability, p_k^s, of words in s assigned to k, averaged over n samples, and use arg $\max_k$ p_k^s as the label for s.

1) Weak Supervision with Minimal Prior Knowledge: To encourage topic models to learn latent topics that correlate directly with aspects, we augment them with a weak supervised signal in the form of aspect-specific seed words. Rather than directly using the seed words to do bootstrapping, as in [19] and [20], we use them to define an asymmetric prior on the word-topic distributions. This approach guides the latent topic learning towards more coherent aspect-specific topics, while also allowing us to utilize large-scale unlabeled data. For example, we define our prior knowledge (seed words) for the original LDA model as a conjugate Dirichlet prior to the multinomial word-topic distributions φ. By integrating with the symmetric smoothing prior β, we define a combined conjugate prior for each seed word w in $\varphi \sim \mathrm{Dir}(\{\beta + C_w\}_{w \in V})$, where C_w can be interpreted as an equivalent sample size—i.e., the impact of our asymmetric prior is equivalent to adding C_w pseudo counts to the sufficient statistics of the topic to which w belongs. When we do not have prior knowledge for a word w, we set $C_w = 0$.

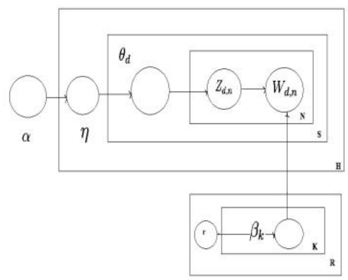
B. Multi-aspect Rating prediction

The second phase of multi-aspect sentiment analysis is multi-aspect rating prediction [7], [17], [20], [21]—in which each aspect of a document is assigned polar (i.e., positive, negative, neutral), numeric, or “star” (i.e., 1-5) ratings.

Specifically, we consider two settings: (1) multi-aspect rating prediction with indirect supervision, and (2) supervised multi-aspect rating prediction. In (1), aspect ratings are predicted based only on the text and overall rating of each review. Specifically, we train a regression model on the given overall ratings and, for each aspect, apply the model to the corresponding aspect-labeled sentences (see Section III-A). In (2), the supervised multi-aspect rating prediction setting, we augment and compare standard supervised regression learners with features derived from unsupervised topic



(a) LDA. (b) STM



(C) Plate Notation for Proposed Method

Figure 1. Plate notations for topic models described in Section IV.

models (without seed words). Following [7], we create features based on the output of each topic model by concatenating standard n-gram features with their associated sentence-level topic assignments, and then evaluate super vised classifiers trained on those features.

IV. TOPIC MODELS

In their most basic form, topic models exploit word co-occurrence information to capture latent topics in a corpus. Approaches to both tasks described in Section III use these latent topics to model multiple aspects within a document, however the quality of these topics varies depending on the topic model used. In this work we consider 4 topic models, described here. Graphical representations for each of these models appear in Figure 1, in plate notation.

1) LDA and Local LDA: The first two topic models that we consider are based on Latent Dirichlet Allocation (LDA) [5]. LDA is a probabilistic generative model in which documents are represented as mixtures over latent topics. Formally, LDA assumes that a corpus is generated according to the following generative story line:

- For each topic k:
  - Choose word-topic mixture: $\varphi_k \sim \mathrm{Dir}(\beta)$
    - ∗ Choose topic: $z_{d,w} \sim \theta_d$
      - ∗ Choose word: $w \sim \varphi_{z_{d,w}}$

While LDA can effectively model word co-occurrence at the document level, [6] argue that review aspects are more likely to be discovered from sentence-level word co-occurrence information. They propose Local LDA, in which sentences are modeled as documents are in standard LDA.

2) Multi-grain LDA: In response to limitations of standard LDA for multi-aspect work, [7] propose Multi-Grain LDA (MG-LDA). MG-LDA jointly models document-specific themes (global topics), and themes that are common throughout the corpus intended to correspond to ratable aspects, called local topics. Additionally, while the distribution over global topics is fixed for a given document (review), local topic proportions are varied across the document according to sentence-level sliding windows. Formally, each document d is generated as follows:

- Choose global topic proportions: $\theta^{gl} \sim \mathrm{Dir}(\alpha^{gl})$
- For each sliding window v of size T :
  - Choose local topic proportions: $\theta^{loc}_{d,v} \sim \mathrm{Dir}(\alpha^{loc})$
  - Choose granularity mixture: $\pi_{d,v} \sim \mathrm{Beta}(\alpha^{mix})$
- For each sentence s:
  - Choose window proportions: $\psi_{d,s} \sim \mathrm{Dir}(\gamma)$
- For each word w in sentence s of document d:
  - Choose sliding window: $v_{d,w} \sim \psi_{d,s}$
  - Choose granularity: $r_{d,w} \sim \pi_{d,v_{d,w}}$
  - Choose topic: $z_{d,w} \sim \{\theta^{gl}, \theta^{loc}_{d,v}\}_{r_{d,w}}$
  - Choose word: $w \sim \varphi_{z_{d,w}}$
- For each document d:
  - Choose document topic proportions: $\theta_d \sim \mathrm{Dir}(\alpha)$
  - For each word w in document d:

When T = 1, MG-LDA generalizes to a combination of standard and Local LDA, where α^{mix} regulates the tradeoff between document- and sentence-level topic proportions.

3) Segmented Topic Model: Lastly, we introduce the Segmented Topic Model (STM) [9], which jointly models document- and sentence-level topic proportions using a two- parameter Poisson Dirichlet Process (PDP). Documents d are generated as follows:

- Choose document topic proportions: $\theta_d \sim \mathrm{Dir}(\alpha)$
- For each sentence s:
  - Choose topic proportions: $\theta_s \sim \mathrm{PDP}(\theta_d, a, b)$
- For each word w in sentence s:
  - Choose topic: $z_{d,w} \sim \theta_s$

– Choose word: $w \sim \varphi_{z_{d,w}}$

STM can be considered an extension of Local LDA that additionally considers document-level topic distributions in- duced from the individual sentence-level topic distributions.

4) Inference: While exact inference for the models just presented is largely intractable [5], approximate techniques such as variational inference or Gibbs sampling can be used instead. Following [26], we use a collapsed Gibbs sampling

approach for inference.[1] The exact sampling algorithms are excluded for brevity. We instead refer the reader to [26] for the LDA and Local LDA sampler, [7] for the MG-LDA sampler, and [9] for the STM sampler.

V. EXPERIMENTAL SETUP

A. Dataset and Preprocessing

Tasks and models discussed in Section III and Section IV are evaluated on Trip advisor datasets.

We evaluate multi-aspect rating prediction on [20]'s TripAdvisor hotel review corpus. For each review, this corpus contains an associated overall rating, as well as ratings for 7 aspects: value, room, location, cleanliness, check-in/front desk, service, and business services. After removing reviews missing any of the first 6 aspect-ratings, and (as before) excluded reviews that were too short or too long, we were left with 66,512 reviews.

Datasets were tokenized and sentence split using the Stanford POS Tagger [28]. For topic models, we removed

Table V

singleton words, and stop words not appearing in the senti- ment lexicon introduced by [29]. We have used a java program to split the review corpus data into individual Author based and put them into the single data file. This will play a vital role in proving the authenticity and liability of the users over longer period of time. This will also help us understand the user behavior and linguistic use.

We have used the open source tool Mallet to perform the task of topic modeling. Mallet provides the all the necessary functionalities for the same.

VI. RESULTS AND DISCUSSION

Results are given in term of precision (P), recall (R), and F-1 score in Table I. The majority baseline labels all sentences according to the most common aspect label, food.

Following results show that the Efficacy of the sentiment analysis can be improved using the suggested plate notations. Several other alternative methods can be suggested for the same. The above results are obtained by applying the changes suggested in the LDA available in mallet and also changing the parameters for the same

A	B	C	D	E	F	G	H	I	J	K	L	M	N
	ACCURACY	VALUE			SERVICES			BUSINESS SERVICES			FRONT DESK		
		P	R	F1	P	R	F1	P	R	F1	P	R	F1
MAJORITY	0.595	0.595	1	0.746	0	0	0	0	0	0	0	0	0
LDA	0.477	0.646	0.554	0.597	0.469	0.494	0.481	0.234	0.249	0.245	0.378	0.398	0.383
STM	0.794	0.952	0.776	0.856	0.674	0.759	0.714	0.656	0.676	0.663	0.432	0.454	0.444
OUR APPROACH	0.845	0.89	0.874	0.879	0.71	0.82	0.789	0.64	0.7	0.653	0.45	0.51	0.495

Table I: Comparison of different attributes between already existing approach and Proposed Method

These results might be clarified as takes after. Since most sentences typically concentrate on only one or two aspects, sentence level word co-event data is more proper than document-level co-events for contemplating aspects. For sure, while an audit may discuss a few aspects at the same time, the document-level word co-event will most likely be unable to well recognize the individual aspects from one another.

VII. CONCLUSION

We explore the part of unsupervised and weakly supervised topic modeling methodologies to multi-aspect sentiment analysis. We demonstrate that weakly supervised topic models perform well on multi-aspect sentence labeling

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