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Extractive and Abstractive Sentence Labelling of Sentiment-bearing Topics

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Abstract

This paper tackles the problem of automatically labelling sentiment-bearing topics with descriptive sentence labels. We propose two approaches to the problem, one extractive and the other abstractive. Both approaches rely on a novel mechanism to automatically learn the relevance of each sentence in a corpus to sentiment-bearing topics extracted from that corpus. The extractive approach uses a sentence ranking algorithm for label selection which for the first time jointly optimises topic–sentence relevance as well as aspect–sentiment co-coverage. The abstractive approach instead addresses aspect–sentiment co-coverage by using sentence fusion to generate a sentential label that includes relevant content from multiple sentences. To our knowledge, we are the first to study the problem of labelling sentiment-bearing topics. Our experimental results on three real-world datasets show that both the extractive and abstractive approaches outperform four strong baselines in terms of facilitating topic understanding and interpretation. In addition, when comparing extractive and abstractive labels, abstractive labels are able to provide more topic information coverage given the same label length constraint. Despite having 16% average on grammatical scores below fully extracted human-written sentences, the abstractive fusion generates topic labels can synthesise rich information needed for sentiment-bearing topic interpretations.

Keywords automatic topic labelling, topic model

1 Introduction

Probabilistic topic models such as latent Dirichlet allocation (LDA) [1] capture the thematic properties of documents by modelling texts as a mixture of distributions over words, known as topics. The words under each topic tend to co-occur together and consequently are thematically related to one another. These topics can therefore be used as a lens for exploring and understanding large archives of unstructured text. Since the introduction of LDA, many extensions have been proposed, an important one being the Joint Sentiment-Topic (JST) model that aims to mine and uncover rich opinion structures from opinionated documents [2]. This work has spurred subsequent research in developing variants of sentiment topic models for a range of opinion mining tasks such as aspect-based sentiment analysis [3], contrastive opinion mining [4], and the analysis of sentiment and topic dynamics [5].

JST is a hierarchical topic model which can detect sentiment and topic simultaneously from opinionated documents. The hidden topics discovered, therefore, are essentially sentiment-bearing topics resembling opinions. This is a key difference compared to the standard topics extracted by LDA which only express thematic information. We exemplify this difference using two topic examples shown in Table 1, where each topic is summarised using the ten topic words with the highest marginal probability. By examining

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the topic words, we see that the terms of the LDA topic are recognisably about the theme “computer technology”, whereas the terms of the JST topic capture opinions relating to “unsatisfactory online shopping experience”.

Although sentiment topic models have become an increasingly popular tool for exploring and understanding opinions from text, existing models all share some noticeable drawbacks which can significantly limit their usefulness and effectiveness. First, applying sentiment topic models for exploratory purposes requires unfolding the meaning of the topics discovered, which, so far, relies entirely on manual interpretation. However, it is generally difficult for a non-expert user to understand a topic based only on its multinomial distribution, especially when the user is not familiar with the source collection [6]. The second limitation lies in these models’ inability to facilitate accurate opinion and sentiment understanding, which is crucial for many applications. The issue stems from the fact that, although the topic words of sentiment-bearing topics collectively express opinions, only a limited understanding of these opinions is possible by examining a list of topic words. Using the JST topic in Table 1 as an example, through manual examination one can interpret that this topic expresses opinions relating to an “unsatisfactory online shopping experience”, but it is impossible to gain any deeper insight, e.g. whether the sentiment unhappy is being expressed about the product being ordered or about Amazon’s policies.

Remarkably, there is no existing work that has studied the problem of automatic labelling of sentiment-bearing topics. Substantial work on automatic topic labelling exists, but has focused on labelling standard topics discovered by LDA to facilitate the interpretation of topics discovered. These works note that standard topics mainly express thematic information [7] and that most of the high ranking topic terms are nouns, and therefore aim to extract phrasal labels that capture this thematic association to the topic terms. In contrast, the top terms of sentiment-bearing topics consist of a good mixture of nouns, verbs, and adjectives resembling opinions rather than themes [2, 8, 9]. Existing topic labelling approaches engineered for standard LDA topic are intrinsically unsuited to labelling sentiment-bearing topics as they provide no mechanism for modelling opinionated content.

In this paper, we formally study the problem of automatically labelling sentiment-bearing topics extracted by the JST model [2]. In contrast to existing approaches which generate topic labels in the form of either a single term [10], a small set of terms (e.g. the top-n topic words) [11], or phrases [7], we choose the sentence as the label modality to facilitate interpretation of the opinions encoded in sentiment-bearing topics. Specifically, we propose two novel approaches for automatically generating sentence labels that can facilitate understanding and interpretation of multinomial sentiment-bearing topics extracted by JST, one extractive and the other abstractive. Both approaches rely on a novel mechanism to automatically learn the relevance of each sentence in a corpus to sentiment-bearing topics extracted from that corpus. The extractive approach uses a sentence ranking algorithm for label selection which for the first time jointly optimises this sentence relevance and aspect–sentiment co-coverage. The abstractive approach provides an alternate solution to aspect–sentiment co-coverage by using sentence fusion to generate a sentential label that includes relevant content from multiple sentences.

We compare the effectiveness of our sentence based topic labelling approaches against four strong baselines, including two sentence label baselines and two topic labelling systems which have been widely benchmarked in the literature [6, 7]. Experimental results on three real-world datasets show that the labels generated by our approaches are more effective than all the baselines in terms of facilitating sentiment-bearing topic understanding and interpretation. To summarise, our contributions in this paper are three-fold: (i) we introduce a novel mechanism which can automatically learn the relevance to sentiment-bearing topics of the underlying sentences in a corpus; (ii) we design an effective sentence label selection criteria which jointly considers relevance to the topic as well as aspect and sentiment co-coverage; (iii) we explore two sentence fusion methods for generating abstractive sentence label which can enhance topic coverage by including information from multiple sentences.

To our knowledge, we are the first to study the problem of labelling sentiment-bearing topics. We describe related work in Section 2, followed by our labelling method in Section 3, experimental design in Section 4, results in Section 5 and conclusions in Section 6.
2 Related Work

Since its introduction, latent Dirichlet allocation (LDA) has become a popular tool for unsupervised analysis of text, providing both a predictive model of future text and a latent topic representation of the corpus. The latter property of topic models has enabled exploration and digestion of large text corpora through the extracted thematic structure represented as a multinomial distribution over words. Still, a major obstacle to applying LDA is the need to manually interpret the topics, which is generally difficult, especially for non-expert users. This has in turn motivated a number of approaches to automatically generating meaningful labels that facilitate topic understanding.

2.1 Automatic Topic Labelling

Automatically learning topic labels from data. In early work, Mei et al. [6] proposed generating topic labels using either bigrams or noun phrases extracted from a corpus and ranked the relevance of candidate labels to a given topic using KL divergence. Candidate labels were scored using relevance functions which minimised the similarity distance between the candidate labels and the topic words. The top-ranked candidate label was then chosen as the topic’s label. Mao et al. [12] labelled hierarchical topics by investigating the sibling and parent-child relations among the topics. Their approach followed a similar paradigm to [6], which ranked candidate labels by measuring the relevance of the labels to a reference corpus using Jensen-Shannon divergence. More recently, Cano et al. [11] proposed an approach to labeling topics based on multi-document summarisation. They measured the term relevance of documents to topics and generated topic label candidates based on the summarisation of a topic’s relevant documents.

Automatic topic labelling leveraging external sources. Another type of approach in automatic topic labelling leverages external sources, e.g., Wikipedia or DBpedia [10, 13, 14]. Lau et al. [10] proposed selecting the most representative term from a topic as its label by computing the similarity between each word and all others in the topic. Several sources of information were used to identify the best label, including pointwise mutual information scores, WordNet hypernymy relations, and distributional similarity. These features were combined in a re-ranking model. In a follow-up work, Lau et al. [13] generated label candidates for a topic based on top-ranking topic terms and titles of Wikipedia articles. They then built a Support Vector Regression (SVR) model for ranking the label candidates. Other researchers [14] proposed using graph centrality measures to identify DBpedia concepts that are related to the topic words as their topic labels. More recently, Aletras et al. [7] proposed generating topic labels of multiple modalities, i.e., both textual and images labels. To generate textual label candidates, they used the top-7 topic terms to search Wikipedia and Google to collect article titles which were subsequently chunk parsed. The image labels were generated by first querying the top-n topic terms to the Bing search engine. The top-n candidate images retrieved were then ranked with PageRank and the image with the highest PageRank score was selected as the topic label.

To summarise, the topic labelling approaches in the above-mentioned works were engineered for labelling standard LDA topics rather than sentiment-bearing topics, and mostly fall into one of the following linguistic modalities: a single term [10], a small set of terms (e.g., the top-n topic words) [10], or phrases [7, 13]. These linguistic modalities, while sufficient for expressing facet subjects of standard topics, are inadequate to express complete thoughts or opinions due to their linguistic constraints, i.e. lacking a subject, a predicate or both. Our goal is to address this gap and study the problem of automatically labelling sentiment-bearing topics with more appropriate and descriptive sentence labels.

2.2 Sentence Fusion

Sentence fusion is a text-to-text generation technique that transforms overlapping information from a cluster of similar sentences into a single sentence. Barzilay and McKeown [15] introduced a sentence fusion framework which borrows the idea of multi-document summarisation. Their approach provides a means to capture the main information in a cluster of related sentences in comparison to the common method which just selects the sentence closest to the centroid. Approaches to sentence fusion typically use dependency graphs to produce an intermediary syntactic representation of the information in a cluster of sentences [15–17]. The graph is then linearised in different ways to generate fused sentences, which are then ranked using a language model or language-specific heuristics to filter out ill-formed sentences [18]. This type of approaches of fusing sentences mimics the strategies used by humans as reported in the analysis of human-generated summaries in [19]. The sentence fusion task has since widened to encompass other variants such as combining two sentences to produce a single sentence that either con-
veys only the common information between two sentences, or contains all information in one or two sentences, but without redundancy [17, 20–23]. More recent work on sentence fusion considers not only pairs of sentences but also larger sentence clusters using multi-sentence compression [24–26].

The most popular strategy for fusion relies on merging the dependency trees of input sentences to produce a graph representation will be linearised in a separate stage [15–17, 23]. In contrast, multi-sentence compression techniques for sentence clusters generate output sentences as high-scoring paths in a weighted bigram graph [24–26]. Another variation of the fusion task uses the set theoretic concepts of union and intersection fusion [20], which forgo the problem of identifying relevance and are thus less dependent on the context. These approaches extend fusion task that only uses the intersection of sentences [15], although both approaches point out the similar view that the best linearisation with a language model usually produces low rankings and not be able to deal with word order, agreement and sub-categorisation constraint.

3 Methodology

The goal of our work is to develop automatic approaches for labelling multinomial sentiment-bearing topics with descriptive sentence labels. We first briefly introduce the JST model used for extracting sentiment-bearing topics, and then proceed to describe the proposed approaches for sentence label generation. It should be noted that our approaches do not have any specific dependencies on the JST model, and thus they are general enough to be directly applied to any other sentiment topic model variants that generate multinomial topics as output.

3.1 Preliminaries of the JST Model

The graphical model of JST is shown in Figure 1, in which $D$ denotes a collection of documents, $N_d$ a sequence of words in document $d$, $S$ the number of sentiment labels, $T$ the total number of topics, and $\{\alpha, \beta, \gamma\}$ the Dirichlet hyperparameters (cf. [2] for details). The formal definition of the generative process in JST corresponding to the graphical model shown in Figure 1 is as follows. First, one draws a sentiment label $l$ from the per-document sentiment proportion $\pi_d$. Following that, one draws a topic label $z$ from the per-docuent topic proportion $\theta_{l,d}$ conditioned on sentiment label $l$. Finally, one draws a word from the per-corpus word distribution $\varphi_{l,z}$ conditioned on both the sentiment label $l$ and topic label $z$.

$$\pi_d \sim \text{Dir}(\alpha)$$

$$\theta_{l,d} \sim \text{Dir}(\beta)$$

$$\varphi_{l,z} \sim \text{Dir}(\gamma)$$

$$w_i \sim \text{Mult}(\varphi_{l,z})$$

The problem to be solved by the JST model is the posterior inference of the variables, which determine the hidden sentiment-bearing topic structures that can best explain the observed set of documents. Formally, a sentiment-bearing topic is represented by a multinomial distribution over words denoted as $p(w|l, z) = \varphi_{w,l,z}$, where $w$, $l$, and $z$ represent the word, sentiment label and topic label indices, respectively. In particular, the approximated per-corpus sentiment-topic word distribution is

$$\varphi_{l,w,z} = \frac{N_{l,w,z} + \beta}{N_{l,z} + V\beta},$$

where $V$ is the corpus vocabulary size, $N_{l,w,z}$ is the number of times word $w$ appeared in topic $z$ with sentiment label $l$, $N_{l,z}$ is the number of times words are assigned to $z$ and $l$. Recalling that $\varphi_{w,l,z}$ is a multinomial distribution, we have $\sum_{w \in V} \varphi_{w,l,z} = 1$.

3.2 Modelling the Relevance between Sentiment-bearing Topics and Sentences

The original JST model can only learn topic–word and topic–document associations as it operates on bag-of-words features at the document-level, with the corpus sentence struc-
ture being ignored. Therefore, we propose a new computational mechanism that can uncover the relevance to a sentiment-bearing topic of the underlying sentences in the corpus. To achieve this, we first preserve the sentence structure information for each document during the corpus preprocessing step (see Section 4 for more details). Second, modelling topic-sentence relevance is essentially equivalent to calculating the probability of a sentence given a sentiment-bearing topic \( p(\text{sent} | l, z) \), i.e., the likelihood of a sentence (from the corpus) associating with a given sentiment-bearing topic. The posterior inference of JST, based on Gibbs sampling [2, 27], can recover the hidden sentiment label and topic-label assignments for each word in the corpus. Such label-word assignment information provides a means to re-assembling the relevance between a word and a sentiment-bearing topic. By leveraging the sentence structure information and gathering the label assignment statistics for each word of a sentence, we can derive the probability of a sentence given a sentiment-bearing topic as

\[
p(\text{sent} | l, z) = \frac{p(l, z | \text{sent}) \cdot p(\text{sent})}{p(l, z)} \\
\propto p(l, z | \text{sent}) \cdot p(\text{sent}),
\]

(2)

where

\[
p(l, z | \text{sent}) = \sum_{w \in \text{sent}} \varphi_{l, z, w} \\
p(\text{sent}) = \sum_{l} \sum_{z} \sum_{w} \varphi_{l, z, w}.
\]

(3)

Note that the per-corpus sentiment-topic-word distribution \( \varphi_{w,i,z} \) defined in Eq. 1, is obtained via the posterior inference using Gibbs sampling. Also \( p(l, z) \) is discounted as it is a constant when comparing sentential labels for the same sentiment-bearing topic. A summary of our mechanism of calculating \( p(\text{sent} | l, z) \) is given in Algorithm 1.

3.3 Extractive labelling of sentiment-bearing topics

Given a sentiment-bearing topic, one intuitive approach for selecting the most representative sentence label is to rank the sentences in the corpus according to the topic-sentence relevance probability \( p(\text{sent} | l, z) \) derived in the previous section. One can then select the sentence with the highest probability as a label for the topic. We found that a high-degree of relevance, however, cannot be taken as the only criterion for label selection as it might result in the selection of short sentences that do not provide enough information about the topic or that cover either thematic or sentiment information alone. To address these issues and to select the most representative sentence labels covering sentiment-coupled aspects which reveal opinions, it is important to consider the occurrences of both aspect and sentiment, and the balance between them. To this end, we designed a sentiment label selection criterion which jointly considers relevance as well as aspect and sentiment co-coverage. This provides the basis for building an algorithm for ranking sentence labels in terms of how well they can describe the opinion encoded in a sentiment-bearing topic.

Given a sentiment-bearing topic, we define the sentence scoring function below:

\[
L(s | t_{l, z}) = \alpha \cdot \text{Rel}(s | t_{l,z}) + (1 - \alpha) \cdot \text{Cov}(s | t_{l,z}).
\]

(5)

Here, \( \text{Rel}(s | t_{l,z}) \) is the relevance score between a sentence \( s \) and a given sentiment-bearing topic \( t_{l,z} \) as described in Section 2. \( \text{Cov}(s | t_{l,z}) \), the aspect and sentiment co-coverage score, encodes two heuristics: (i) sentence labels covering either sentiment or aspects information alone will be significantly down-weighted; and (ii) labels which cover salient aspects of the topic coupled with sentiment will be given high weightage. Parameter \( \alpha \) sets the relative contributions of relevance and the co-coverage of aspect and sentiment, and was empirically set to 0.4. Let \( i \) be a word from sentence \( s, a_i \) a binary variable that indicates whether word \( i \) is an aspect word, \( o_i \) a binary variable that indicates whether word \( i \) is a sentiment word, \( w_{i,l,z} \) the importance weight of word \( i \) given topic \( t_{l,z} \), and \( t'_{i,l,z,n} \) a binary variable which indicates the presence of word \( i \) in the top-\( n \) words of sentiment-bearing topic \( t_{l,z} \). Formally, the aspect and sentiment co-coverage score is formulated as

\[
\text{Cov}(s | t_{l,z}) = \frac{2 \cdot A(s | t_{l,z}) \cdot S(s | t_{l,z})}{A(s | t_{l,z}) + S(s | t_{l,z})}
\]

(6)

\[
A(s | t_{l,z}) = \sum_{i \in s} w_{i,l,z} \cdot a_{i,l} \cdot t'_{i,l,z,n}
\]

(7)
where the weight $w_{t_{i},z}$ essentially equals to $\varphi_{t_{i},z}$, i.e., the marginal probability of word $i$ given a sentiment-bearing topic $t_{i,z}$. We identify whether word $i$ is an aspect word or a sentiment word as follows. In the preprocessing, we perform parts of speech (POS) tagging on the experimental datasets (detailed in Section 4). Words tagged as nouns are regarded as aspects words whereas sentiment words are the ones that have appeared in the MPQA sentiment lexicon\(^1\). Recalling that a multinomial topic is represented by its top-$n$ topic words with the highest marginal probability, we further constrain that word $i$ must also appear in the top-$n$ topic words of sentiment-bearing topic $t_{i,z}$. This ensures that a good sentence label should cover as many important sentiment coupled aspects of a topic as possible. In the case where a sentence contains either aspect or sentiment information alone (i.e., $A(s|t_{i,z}) = 0$ or $S(s|t_{i,z}) = 0$), the resulting aspect and sentiment co-coverage score would be zero, thus down-weighting the corresponding sentence. Finally, a sentence label $\hat{s}$ for a sentiment-bearing topic $t_{i,z}$ can be obtained by:

$$\hat{s} = \arg\max_s L(s|t_{i,z}).$$  \hfill (9)

### 3.4 Abstractive topic labelling with multi-sentence compression

Our second type of approach to topic labelling employs sentence fusion techniques for generating abstractive labels. We hypothesise that abstractive sentence labels would be more succinct by removing redundant information of input sentences, while maintaining the essence of sentiment-bearing topics as much as possible. Specifically, we explore two well established sentence fusion algorithms [24, 25] for the fusion task, both of which search for an optimal weighting function in noisy graphs to identify readable and informative compressions.

#### 3.4.1 Word graph-based multi-sentence compression

Our first sentence fusion approach (named PathGraph) extends the algorithm of Filippova [24] to produce well punctuated and informative compression. Taking the sentences extracted in Section 2 as input, we build a word graph from a set of related sentences $S = \{s_1, s_2, \ldots, s_n\}$, by iteratively adding sentences to it. Figure 2 is an illustration of the word graph constructed from the four sentences below. For clarity, edge weights are omitted, and italicised fragments from the sentences are replaced with dots.

1. It was easy to set up and use.
2. Easy manual and set up.
3. It was a super easy setup.
4. The D-Link DP-300U was very easy to set up.

The word graph is constructed as follows. First, the first sentence is added to the graph represented by a string of word nodes plus the start and the end symbols, i.e., the start and end nodes in Figure 2. A word from the remaining sentences is mapped onto an existing node in the graph if they have the same lowercased word form and part of speech (POS), in addition to that there is no word from the sentence that is already mapped onto the node. A new node is created if there is no suitable candidate node in the word graph. Words are added to the graph in the three steps: (i) non-stopwords for which no candidate exists in the graph or for which a non-ambiguous mapping is possible; (ii) non-stopwords for which there are several possible candidates in the graph or which appear more than once in the sentence; and finally (iii) stopwords.

In the original algorithm of Filippova [24], punctuation marks are excluded [24]. We add an additional step to generate well-punctuated compressions by adding punctuation marks in the graph following [25], and select the candidate that has the same immediate context if the mapping is ambiguous. Once all the words from a sentence are added to the graph, words adjacent in the sentence are connected with directed edges, where the edge weights are calculated using the weighting function defined in Eq. 10 and Eq. 11.

$$w(i, j) = \frac{\text{coherence}(i, j)}{\text{freq}(i) \times \text{freq}(j)}$$ \hfill (10)

$$\text{coherence}(i, j) = \frac{\text{freq}(i) + \text{freq}(j)}{\sum_{s \in S} \text{dist}(s, i, j)}$$ \hfill (11)

Here freq$(j)$ is the number of words mapped to the node $j$. The function dist$(s, i, j)$ refers to the distance between the offset positions of words $i$ and $j$ in sentence $s$. The purpose of this function is two-fold: (i) to generate a grammatical compression, it favours links between words which often occur in this order (see Eq. 11); (ii) to generate an informative compression, it promotes paths passing via salient nodes.

To produce more informative sentences which maximise the range of topics they cover, we further make use of the top-15 topic words extracted by JST. The rationale behind is that topic words can capture the gist of documents, and thus can be used to better generate sentences that convey the gist.

\(^{1}\) http://www.cs.pitt.edu/mpqa/
of the set of related sentences. To do so, we added syntactic constraints in the path selection process to filter all the paths which do not contain any topic words (among the top-15 topic words) for the topic being labelled, which do not pass a verb node and which are shorter than eight words. Finally, the remaining paths are re-ranked by normalising the total path weight over its length.

3.4.2 Word graph compression by keyphrases relevance

The second sentence fusion algorithm (named Keyphrase) extends the work of [25], which is similar to GraphPath but differs in that it re-ranks the generated compressions according to the number relevant keyphrases a sentence compression contains. Specifically, keyphrases are extracted from the cluster of related sentences in two steps. First, a weighted graph is constructed from the set of related sentences, where nodes represent tuples consisting of lowercased words as well as their corresponding parts of speech. Two nodes are connected if their corresponding lexical units co-occur within a sentence. TextRank [28] is then applied to compute a salience score for each node. The second step generates and scores keyphrase candidates. A candidate keyphrase \( k \) is scored by summing the salience scores of the words it contains and normalising by its length (i.e., Eq. 12).

\[
\text{score}(k) = \frac{\sum_{w \in k} \text{TextRank}(w)}{\text{length}(k) + 1} \tag{12}
\]

During the path selection process, we apply the same syntactic constraints as used for GraphPath, i.e., a candidate path must contain at least one top-15 topic words, one verb node, and satisfy the path length requirement. Finally, all candidate paths are re-ranked by normalising the total path weight over its compression length multiplied by the sum of the scores of the keyphrases it contains. The score of a sentence compression \( c \) is finally given by:

\[
\text{score}(c) = \frac{\sum_{i,j \in \text{path}(c)} w_{(i,j)} \times \sum_{k \in c} \text{score}(k)}{\text{length}(c)} \tag{13}
\]

where \( w_{(i,j)} \) is the edge weight defined in Eq. 10.

4 Experimental Setup

4.1 Dataset

We evaluated the effectiveness of the sentence label selected by our approach on three real-world datasets. Two datasets are publicly available, i.e., Amazon reviews for kitchen and electronic products, where each dataset contains 1000 positive and 1000 negative reviews\(^2\) [29]. We have also collected a movie review dataset for Internal Affairs and The Departed from IMDB\(^3\). These two movies virtually share the same storyline but with different casts and productions: Internal Affairs is a 2002 Hong Kong movie, while The Departed is a 2006 Hollywood movie.

4.2 Implementation Details

In the JST model implementation, we set the symmetric prior \( \beta = 0.01 \) [27], the symmetric prior \( \lambda = (0.05 \times L)/S \), where \( L \) is the average of the document length, \( S \) the is total number

\(^2\) https://www.cs.jhu.edu/~mdredze/datasets/sentiment/

\(^3\) http://www.imdb.com/
Table 2: Dataset statistics.

| Dataset   | total # of doc. | avg. # of words | avg. # of sentences | Vocab. size |
|-----------|-----------------|-----------------|---------------------|-------------|
| Kitchen   | 2,000           | 25              | 4                   | 2,450       |
| Electronics | 2,000           | 25              | 4                   | 2,317       |
| IMDb      | 1,383           | 118             | 13                  | 14,337      |

Table 3: Human evaluation based on Top-1 average rating.

| Domain       | Mei07 | Aletras14 | Top-prob | Centroid | Sent-label |
|--------------|-------|-----------|----------|----------|------------|
| Kitchen      | 0.31  | 1.29      | 0.64     | 1.79     | 1.81       |
| Electronics  | 0.32  | 2.13      | 0.83     | 1.33     | 2.48       |
| IMDb         | 0.36  | 1.73      | 0.69     | 1.67     | 2.58       |
| Average      | 0.39  | 1.72      | 0.72     | 1.59     | 2.29       |

Table 4: Average label length across three datasets.

| Avg. label length | Mei07 | Aletras14 | Top-prob | Centroid | Sent-label |
|-------------------|-------|-----------|----------|----------|------------|
| 6                 | 6.80  | 6.83      | 23.80    | 12.70    |            |

of sentiment labels, and the value of 0.05 on average allocates 5 percent of probability mass for mixing. The asymmetric prior $\alpha$ is learned directly from data using maximum-likelihood estimation [30] and updated every 50 iterations during the Gibbs sampling procedure. We empirically set the model with 2 sentiment labels and 10 topics for each sentiment label, resulting in 20 sentiment-bearing topics in total for each of the three evaluation datasets. In the preprocessing, we first performed automatic sentence segmentation on the experimental datasets in order to preserve the sentence structure information of each document, followed by parts of speech tagging on the datasets using the Stanford POS tagger [31]. Punctuation, numbers, and non-alphabet characters were then removed and all words were lowercased. Finally, we trained JST models with the preprocessed corpus following the standard procedures described in [2], with the MPQA lexicon [32] being incorporated as prior information for model learning.

4.3 Baselines

Top probability (Top-prob). The first baseline is to select the sentence with highest topic relevance probability $p(sent|l, z)$ according to the JST model, as described in Section 2.

Centroid. The second baseline is a centroid based sentence label. For each sentiment-bearing topic, we first construct a sentence cluster consists of the top 150 most relevant sentences for the given topic, ranked based on the topic relevance probability $p(sent|l, z)$. Next, for each of the sentence in the cluster, we compute the cosine similarity between the sentence and the remaining sentences in the cluster. Finally, the sentence with the highest cosine similarity score is picked as the topic label. This is a stronger baseline as it selects a sentence representative of multiple high probability sentences.

Phrase/bigram baselines. In addition to the two sentential baselines, we also compare our approach to two systems which have been widely bench-marked in the topic labelling task, namely, Mei07 [6] and Aletras14 [33]. Note that Mei07 is our re-implementation which generates bigram labels, while Aletras14 is the original implementation kindly provided by the authors which generates phrase labels. For both, we selected the top three bigrams/phrases for inclusion in the label.

5 Experimental Results

We evaluated our extractive topic labelling approach through an experiment where participants rated labeled topics generated by our approaches as well as two baselines and two competitor systems in Section 5.1. For the evaluation of our abstractive labelling approach, we added an additional Grammaticality measure as one of the evaluations for the label generated using the abstractive approach. The description of the evaluation is detailed in Section 5.2.

5.1 Evaluation of extractive sentence labelling

Evaluation Task. For each sentiment-bearing topic, annotators were provided with the top 10 topic words with the highest marginal probability and the labels generated by each system. They were then asked to judge the quality of each label on a 4-point Likert Scale: 3-Very good label, an excellent description of the topic; 2-Reasonable label, but does not completely capture the topic; 1-Label is semantically related to the topic, but would not make a good topic label; and 0-Label is completely inappropriate, and unrelated to the topic. The most relevant review of the sentiment-bearing topic (calculated using $p(d|l, z)$, the probability of a document given a sentiment-bearing topic) was also provided to annotators so

4) http://www.nltk.org/
that they can have a better context for topic understanding. To ensure there was no bias introduced in this step, we checked whether the most relevant review contains our sentence label. This only occurred in 7.5% of cases. For the remaining 92.5%, sentence labels appeared in only the second to the fifth most relevant reviews, not shown to the user. This suggests that our experience is not bias towards our system and that the most relevant review does not necessarily contain the most representative sentence label.

We recruited 30 Computing Science postgraduate students to participate in the evaluation task. Recalling that 20 sentiment-bearing topics were extracted for each dataset and that there are 5 systems to compare (i.e., our proposed approach and the four baselines) and 3 datasets, the total number of labels to rate is 300. To avoid the evaluation task being overly long, we broke the evaluation task into 3 sessions carried out on different days, with each session evaluating labels from one dataset only. Completing one session took around 18 minutes for each participant on average.

**Human Evaluation.** We report results using the Top-1 average rating [13], which is the average human rating (based on the Likert Scale) assigned to the best candidate labels selected by each of the approaches, and the higher rating will indicate a better overall quality of a label. Table 3 shows the Top-1 average ratings for each approach (with our approach denoted as Sent-label). The sentence labels generated by our approach outperforms all baselines significantly (two-tailed paired t-test; \( p < 0.001 \) in all cases). Furthermore, as shown in Table 4, the label selected by our approach also keeps a good balance of information-richness and brevity, in contrast to the other two sentiment baselines that favour either very short or very long sentences. To measure inter-annotator agreement (IAA), we first calculated Spearman’s \( \rho \) between the ratings given by an annotator and the average ratings from all other annotators for the labels corresponding to the same topic. We then averaged the \( \rho \) across annotators, topics, and datasets, resulting in an average \( \rho = 0.73 \), a good IAA.

We want to stress that these baselines are fair. To our knowledge, we are the first to study the problem of labelling sentiment-bearing topics, so there is no directly comparable system available which can generate sentence labelling for sentiment-bearing topics. In the past, top-\( n \) topic terms have been commonly used for manually interpreting sentiment-bearing topics for a variety of sentiment-topic models (i.e., it’s not just exclusively used for standard topic models), and that is why we propose an automatic labelling approach here. For the phrase label baselines, they can capture a fair amount of sentiment information from sentiment-bearing topics based on the adjective/adverb phrases extracted. The sentence label baselines are also strong baselines as they both make use of the probability distributions from the JST model, with the centroid baseline further addressing the diversity issue.

**Qualitative analysis.** Table 5 shows six sentiment-bearing topics for the Kitchen, Electronics and IMDb dataset extracted by JST. For each topic, we also show the top-3 labels generated by Mei07 and Aletras14, two baselines (i.e., Centroid, Top-prob), and the sentence label generated by our approach (Sent-label). It can be seen from the table that the sentence labels generated by our approach generally capture the opinions encoded in the sentiment-bearing topics quite well; whereas in quite a few cases the labels generated by Mei07 and Aletras14 either only capture the thematic information of the topics (e.g., Noise-cancelling headphones) or merely sentiment information (e.g., very good).

Our labelling approach also shows better performance than the sentential baselines. For instance, both sentential baselines were unable to adequately interpret the negative sentiment-bearing topics in the Kitchen dataset. For example, the Centroid baseline “I ordered ... received only the bottom piece,” captures the thematic information (i.e., product) but fails to capture the sentiment information (e.g., worth). The Top-prob baseline captures negative sentiment information (i.e., disappointed) but does not include any thematic information (e.g., money, product). A user who read the Top-prob baseline (i.e., “Here’s why I am sorely disappointed”) is likely to have some confusions in understanding what causes the disappointment in the label, e.g., whether it is due to money or product. Our approach (i.e., Sent-label) also performs better in the Electronics dataset by giving more descriptive information about products. Take the positive sentiment-bearing topics for example, the labels generated by Mei07 and Aletras14 capture two different thematic aspects i.e., sound and headphones, respectively. For the Top-prob label, it captures positive sentiment about sound quality, whereas the Centroid baseline label seems less relevant to the topic. In contrast, our proposed approach shows that the topic conveys the opinion of iPod sound quality being amazing.

To summarise, our experimental results show that our extractive sentence labelling approach outperforms four strong baselines and demonstrates the effectiveness of our sentence labels in facilitating topic understanding and interpretation.
### Table 5: Labelling examples for sentiment-bearing topics.

| Topic words | Positive Topics | Negative Topics |
|-------------|-----------------|-----------------|
| **Kitchen** | Very good well really nice price quality set little happy | Money don't product disappointed back waste without very worth make |
| Mei07       | Are very; a very; very good | The money; money on; you will |
| Aletras14   | Prices and quality; nice guy; coin grading | Food waste; zero waste; waste your money |
| Top-prob    | Well worth every penny. | Here's why I am sorely disappointed. |
| Centroid    | I got this for the dogs and they seem to like it. | I ordered the product and when I opened the box I found that I received only the bottom piece. |
| Sent-label  | Nice little toaster with good price. | Totally dissatisfy with this product and it's damn waste of money. |

| Topic words | **Electronics** sound headphones music ear noise cord ipod pair quality head | Receiver slightly laser pointer green serious blocks kensington delormes beam |
|-------------|---------------------------------|---------------------------------|
| Mei07       | The sound; The sound; sound is | Pointer is; of this; laser pointer |
| Aletras14   | Noise-cancelling headphones; Previous Bose headphones; Bose headphones | Laser safety; Laser pointer; Laser diode |
| Top-prob    | They have very good sound quality. | I made the mistake to buy the Kensington laser pointer before this one. |
| Centroid    | I just leave the mounts in place on the windshields of both cars and move the Nuvi and power cord to whichever car I am using at the moment. | I can maybe prefer a bit the ergonomy of the Kensington together with the very practical possibility to store the USB receiver inside the unit but this is probably just my taste and the hiro is quite comfortable either and lighter. |
| Sent-label  | The output of sound quality from an ipod is amazing. | The Kensington laser pointer is slightly expensive. |

| Topic words | **IMDb** without no want clever intelligent surely play offer effective puts | Language use vulgar blood used excessive dialog foul us realism |
|-------------|---------------------------------|---------------------------------|
| Mei07       | Is one; that it; that there | Violence and; of violence; terms of |
| Aletras14   | Flying Spaghetti Monster; Expelled: No Intelligence Allowed; Prayer | Vampire: The Masquerade ? Bloodlines; Monkeys in Chinese culture; Chavacano |
| Top-prob    | But what would Lucifer be without his collaborators. | But the story flows well as does the violence. |
| Centroid    | The Departed is without doubt the best picture of the year and never fails to entertain. | It's far too graphically violent for teenagers, including images of heads being shot and spurting blood, limbs being broken, etc. |
| Sent-label  | If you want to see an intelligent, memorable thriller, watch The Departed. | The movie includes some overdone foul language and violent scenes. |

### 5.2 Evaluation of abstractive sentence labelling

To evaluate the effectiveness of the abstractive labels, we compare the compressions generated by GraphPath and Keyphrase against the extractive label (Sent-label) in terms of grammaticality and informativity. In the evaluation, ten raters who are native speakers were presented with a list of top-10 topic words along with one label generated from the following labelling approaches (i.e., Sent-label, PathGraph and Keyphrase) in a random order. For each label, raters were asked to rate the label fluency and the label coverage using the topic words as guidance. In addition, raters were explicitly asked to ignore lack of capitalisation while evaluating grammaticality. The grammaticality of the labels are rated on a 3-points Likert scale: 2-good sentence, if the label is a complete grammatical sentence; 1-almost, if the label can be understood but requires minor editing, e.g. one mistake in articles; 0-ungrammatical, if it is none of the above. In terms of informativity, labels were rated using the same 4-points Likert scale as specified in Section 5.1.

Table 6 shows labelling examples based on extractive (Sent-label) and abstractive approaches for two sentiment-bearing topics extracted from the Kitchen dataset. Table 7 presents the average grammaticality scores of the sentence labels generated by three different approaches. Unsurprisingly, Sent-label achieves the highest grammaticality score (16% higher than Keyphrase) as its labels are the original sentences extracted from the corpus. Although the abstractive methods have lower grammaticality scores, almost 60% of the sentences generated by the Keyphrase algorithm are perfectly grammatical. When comparing the abstractive methods, it is observed that the grammaticality score of Keyphrase is slightly higher than that of PathGraph. This is probably due to the fact that Keyphrase compression generates shorter sentence labels than PathGraph (cf. Table 8). Table 9 shows
Table 6: Labelling examples based on extractive (Sent-label) and abstractive approach for sentiment-bearing topics.

| Positive Topic | Negative Topic |
|----------------|----------------|
| Topic words    |                |
| pan heat cooking oven stick pans cook stainless food surface | money dont  product disappointed back waste without very worth make |
| Sent-label     |                |
| I would have opted for the aluminum as that was what I had but my husband bought the stainless steel. | Totally dissatisfy with this product and it’s damn waste of money. |
| PathGraph      |                |
| i would have opted for the aluminum as that was i had but my husband bought the stainless steels great too of course but this is a worthy and earthy alternative. | it was so not worth your money! |
| Keyphrase      |                |
| it is a good quality stainless and that is important. | very disappointed in product. |

Table 7: Human evaluation ratings for grammaticality, expressed on a scale of 0 to 2. The average ratings over all fusions (Avg.) are also reported.

| System     | Grammatically |
|------------|---------------|
|            | 0  | 1  | 2  | Avg. |
| PathGraph  | 7% | 45%| 47%| 1.40 |
| Keyphrase  | 7% | 35%| 57%| 1.49 |
| Sent-label | 0% | 19%| 79%| 1.80 |

Table 8: Average label length of extractive and abstractive labels across three datasets.

|          | Sent-label | PathGraph | Keyphrase |
|----------|------------|-----------|-----------|
| Avg. label length | 12.70 | 13.87 | 9.90 |

To summarise, based on the experimental results we see that the Keyphrase algorithm outperforms the PathGraph algorithm in terms of both grammaticality and informativity. In addition, the abstractive labels generated based on the compression algorithms are more informative than the extractive label, with some cost of reduced grammaticality.

Table 9: Human evaluation between extractive and abstractive labels based on Top-1 average rating.

| Domain        | Sent-label | PathGraph | Keyphrase |
|---------------|------------|-----------|-----------|
| Kitchen       | 2.00       | 2.10      | 2.47      |
| Electronics   | 1.85       | 1.82      | 2.10      |
| IMDb          | 2.14       | 1.92      | 2.61      |
| Average       | 1.90       | 1.94      | 2.39      |

6 Conclusion and Future Work

This paper tackles the problem of automatically labelling sentiment-bearing topics with descriptive sentence labels. We propose two approaches to the problem, one extractive and the other abstractive. Both approaches rely on a novel mechanism to automatically learn the relevance of each sentence in a corpus to sentiment-bearing topics extracted from that corpus. To our knowledge, we are the first to study the problem of labelling sentiment-bearing topics. Our experimental results on three real-world datasets show that both the extractive and abstractive approaches outperform four strong baselines in terms of facilitating topic understanding and interpretation. In addition, when comparing extractive and abstractive labels, abstractive labels are able to provide more topic information coverage given the same label length constraint. Despite having 16% average on grammatical scores below fully extracted human-written sentences, the abstractive fusion generates topic labels can synthesise information needed for sentiment-bearing topic interpretations. It should also be noted that our approach does not have any specific dependencies on the JST model, and thus it is general enough to be directly applied to any other sentiment topic model variants which generate multinomial topics as output.

In the future, we would like to extend our work for opinion summarisation. One natural way of achieving this is to summarises documents through the propagation of the document-topic and topic-sentence associations learned from our framework.

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