

Generating Personalised and Opinionated Review Summaries

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Abstract. This paper describes a novel approach for summarising user-generated reviews for the purpose of explaining recommendations. We demonstrate our approach using TripAdvisor reviews.

1 Introduction

Product reviews, that are written by real users, are now mainstream online. Sites like Amazon and TripAdvisor have collected thousands of reviews for all manner of products, and users are increasingly relying on these reviews make better choices [1]. However, there are so many reviews, some of which are quite long, and it is increasingly difficult for users to identify the relevant information for their needs [2]. Recently researchers have begun to explore the potential of such reviews in building recommender systems [3], identifying useful reviews [4], and using related techniques to help users write better reviews in the first place [5].

In this paper we explore how to exploit textual reviews to summarise product experiences that can explain recommendations. In particular we describe how we can profile a user based on the reviews that they have written, and identify product features that matter to them. And we explain how we can represent products in a similar fashion, by extracting opinions and sentiment information from their reviews. We then describe an initial approach to generating personalised product summaries for given user-product pairs on TripAdvisor data.

2 System Overview

This section describes our approach for generating personalised summaries that are tailored to a user's preferences, and non-personalised summaries that reflect the general opinion of users about a product.

2.1 Feature Extraction and Sentiment Classification

Inspired by the methods described in [6,7], we consider bi-gram features that conform to one of two part-of-speech (POS) co-location patterns: a noun preceded

by an adjective (*AN*) or by a noun (*NN*). Single noun features that frequently co-occur ($\geq 70\%$ of the time) with sentiment words in the same sentence are also considered [6].

To evaluate the sentiment of a given feature F_i in sentence S_j of review R_k , we identify the closest sentiment word w_{min} to F_i in S_j ; F_i is labelled as *neutral* if no sentiment words are present. In this context, sentiment words are those contained in the sentiment lexicon [6]. Next we extract the opinion pattern: the POS tags for w_{min} , F_i and any words that occur between them. After a pass over all features, the frequency of occurrence of all patterns is noted. For valid patterns (those which occur more than once) we assign sentiment to F_i based on that of w_{min} in the sentiment lexicon; sentiment is reversed if S_j contains a negation term within a 4-word distance of w_{min} . Features associated with invalid patterns are labelled as *neutral*.

2.2 Dataset and Feature Representation

Our corpus is taken from the hotel review site TripAdvisor.com. It contains 226,110 unique reviews written by 150,352 unique users for 2,500 hotels in 6 different cities. We mined over 270,000 unique features mention around 4,129,265 times using the process described in Section 2.1.

We propose two levels of features to represent users and hotels; these levels are determined by their similarity to amenities predefined on the TripAdvisor website. We obtain a set of **base features**, which are single-nouns and bi-gram noun phrases from the set of amenities that TripAdvisor uses to described hotels (e.g *fitness centre* and *wheelchair access*). We expect these features to be highly meaningful and familiar to users. We hypothesise that there is an extended bag of words that people use when talking about the same thing. For instance, a person talking about *'breakfast'* may use words like *'orange juice'* or *'buffet'*. The key thing to note is that these are *related* words, but not necessarily synonyms. We apply *k-Means* to base features and their corresponding sentences to find other co-occurring, related features. The k most co-occurring features are used to enhance the representation of each *base* feature as **expanded features**.

2.3 User Preferences and Hotel Profiles

Users normally talk about the things that matter to them in reviews. Therefore we assume that the preferences of each user consist of the features they mention in reviews and the relative frequency at which they mention them, which may indicate their relevance to the user. Hence we define the profile of a user as the set of all features mentioned by the user in reviews. Each feature in the set is tagged with the relative frequency with which it was mentioned in the user's reviews.

Similarly we define a hotel profile as a set of features mentioned by users about the hotel. Each feature in the set is tagged with its relative frequency and average sentiment score (a value in the range $[-1, +1]$).

2.4 Generating Summaries

To construct non-personalised summaries for a user-hotel pair, two hotel profiles are built using the base and expanded features respectively. Each feature is assigned a ranking score that is the product of its average sentiment and its normalised frequency. When the non-neutral features in the hotel profile are ranked by the ranking score, the top- n and bottom- n features form the pros and cons parts of the explanation respectively.

To generate a personalised summary for a user-hotel pair, two profiles are built each for users and hotels using the base and expanded features respectively. Each feature in the hotel profile is assigned a ranking score that is the product of its average sentiment and its normalised frequency. The ranking score of each feature in the hotel profile is updated by multiplying its original ranking score with its normalised frequency in the user profile. When the non-neutral features in the hotel profile are ranked by the updated ranking score, the top- n and bottom- n features form the pros and cons parts of the explanation respectively. In both explanation types, expanded features are mapped to their corresponding base features that are familiar to the user.

2.5 Examples

Earlier in 2.4, we described how we can model a user and hotel profile using base and expanded features. In Fig. 1 we show a fragment of the user and hotel profile used to generate the example summary in Fig. 2.

Hotel: <i>Auberge Discovery Bay Hong Kong</i>		User: <i>John M</i>	
Hotel Profile	Expanded Features	Base Features	Expanded Features
Free Breakfast	Bacon Apple Juice Blend Tea	Free Breakfast	Ace Cafea Bagel Brown Sauce
Business Centre	Meeting Staff Printer Scanner	Business Centre	Centre Work Trip Wireless Code
Shuttle Bus Service	Hopoff bus	Shuttle Bus Service	Station
...

Fig. 1. Snippet of a hotel and a user profile showing base and expanded features

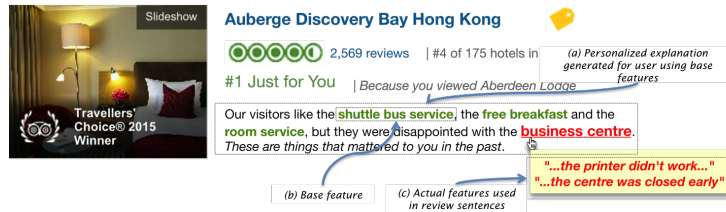


Fig. 2. An example of a personalised summary of hotel using profiles with base features.

Fig. 2 shows a screenshot of a personalised summary generated for a user-hotel pair. The pro features are highlighted in green, and the cons features in red.

We always present base features in the summaries regardless of how we choose to model the user and hotel profile. This is to avoid having too fine a level of granularity which might be unintuitive to users. Therefore *‘shuttle bus service’* is a pro feature of the hotel, ranked by the user’s preferences. The tooltips (see (c) in Fig. 2) display expanded features in snippets of sentences from reviews that are associated with the base feature in the summary. Here the reviewers have discussed the *‘printer’* not working, and the closing hours of the *‘centre’*; these have been summarised to *‘business centre’*

3 Conclusion

This paper presents a method for constructing personalised summaries of items based on opinions from textual reviews. With TripAdvisor data we show how the pros and cons of hotels can be explained to users using different feature representations. Our technique focuses on those features that users write about most frequently in their reviews. This forms the basis for prioritising features that are likely to be of interest to the user compared to non-personalised explanations, which focus on features that are commonplace for a hotel but may not be so relevant for an individual user. This work builds on related work in the area of opinion mining and recommender systems but considers a novel application in the form of explanation generation.

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