Leveraging Aspect Phrase Embeddings for Cross-Domain Review Rating Prediction

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Abstract
Online review platforms are a popular way for users to post reviews by expressing their opinions towards a product or service, as well as they are valuable for other users and companies to find out the overall opinions of customers. These reviews tend to be accompanied by a rating, where the star rating has become the most common approach for users to give their feedback in a quantitative way, generally as a likert scale of 1-5 stars. In other social media platforms like Facebook or Twitter, an automated review rating prediction system can be useful to determine the rating that a user would have given to the product or service. Existing work on review rating prediction focuses on specific domains, such as restaurants or hotels. This, however, ignores the fact that some review domains which are less frequently rated, such as dentists, lack sufficient data to build a reliable prediction model. In this paper, we experiment on 12 datasets pertaining to 12 different review domains of varying level of popularity to assess the performance of predictions across different domains. We introduce a model that leverages aspect phrase embeddings extracted from the reviews, which enables the development of both in-domain and cross-domain review rating prediction systems. Our experiments show that both of our review rating prediction systems outperform all other baselines. The cross-domain review rating prediction system is particularly significant for the least popular review domains, where leveraging training data from other domains leads to remarkable improvements in performance. The in-domain review rating prediction system is instead more suitable for popular review domains, provided that a model built from training data pertaining to the target domain is more suitable when this data is abundant.

Introduction
In recent years, the advent and the prevalent popularisation of social media has led to a change in users’ habits of surfing the Internet (Kaplan & Haenlein, 2010; Quan-Haase & Young, 2010; Perrin, 2017). Since the emergence of social media platforms, Internet users are no longer limited to browsing online contents as mere readers, but they also have the possibility for contributing by expressing and sharing their opinions (Krumm, Davies, &
Narayanaswami, 2008). Users can freely post comments and share experiences on target entities such as products, businesses or events on online review platforms like Yelp.com or Amazon.com (Chatterjee, 2001; Ye, Law, & Gu, 2009). These reviews present the subjective opinions of people on products or businesses, which are invaluable for consumers and companies (Sparks & Browning, 2011). Given the volume of these reviews and the fact that they are spread on different sites across the Internet, makes it more challenging and costly to aggregate all the reviews on a particular product or business (Q. Zhang & Qu, 2013). To alleviate the cost of this task, there is a need to explore the development of automated review rating prediction systems.

The star rating system has become the de facto standard for assigning a rating to reviews online, where users can choose a number of stars, generally ranging from one to five, to score the extent to which they liked a product or business; a higher number of stars indicates that a user liked it (Moghaddam & Ester, 2013). Reviews by individual users can then be aggregated to get an overall picture of the extent to which people like a particular product or business. This enables both an ability for prospective customers to investigate reviews and ratings prior to paying for a product, as well as an ability for companies to mine online reviews associated with them to nowcast the public opinion on their products (Na et al., 2012). Some of these online reviews, such as those in Yelp or Amazon, are accompanied by a rating assigned by the user, which facilitates gathering comments from satisfied and unsatisfied customers. There are however many comments on the Web that do not have that information. For instance, reviews posted on Twitter, Facebook or a forum are only texts without a rating associated. Still, businesses are interested in capturing all those comments posted on different sites on the Web, hence broadening the information that they analyse. To mine those reviews lacking star ratings, one can build a classifier from datasets of reviews with star ratings. The classifier can then be applied to predict the rating of those text-only reviews. This is known as the review rating prediction task.

There has been work in the scientific literature looking at review rating prediction (Li et al., 2011; Fan & Khademi, 2014). This work has however been limited to predicting the ratings of reviews in very popular domains, such as restaurants (Ganu, Elhadad, & Marian, 2009) or hotels (Zhao, Qian, & Xie, 2016). For these domains, it is relatively easy to get a large-scale dataset from online sources for training a review rating prediction system. The task can however become more challenging for less popular domains, where the dearth of rated reviews available online inevitably means that the scarcity of labelled data available to train a rating prediction model will be rather limited. Moreover, the variance in vocabulary across different domains makes it more difficult to develop a prediction system that generalises to different domains; while one could use phrases like well written or entertaining book to express that they liked a book, one could then use totally different phrases such as careful treatment or clean office to indicate that they liked a dentist. Here we argue that these phrases, associated with different aspects that vary across domains, can be effectively leveraged for review rating prediction.

In this work, we are interested in exploring the ability to predict ratings for reviews pertaining to less popular domains, such as dentists or hair salons. To the best of our knowledge, review rating prediction for non-popular domains has not been tackled in previous work, and ours is the first attempt to do so. We propose to pursue the review rating prediction for non-popular domains by developing a cross-domain rating prediction system.
for the first time, where rated reviews from popular domains can be leveraged to build a model which can then be generalised to non-popular domains. To facilitate and ensure the effectiveness of building a model that will generalise to other domains, we propose an approach for generating aspect phrase embeddings and polarised aspect phrase embeddings, i.e. where phrases that vary across domains can be brought to a common semantic space by using word embeddings. We perform experiments with 12 datasets pertaining to 12 different types of businesses of different levels of popularity. Our analysis shows that, while an in-domain review rating prediction system is better for popular domains, for the least popular domains our cross-domain review rating prediction system leads to improved performance when we make use of aspect phrase embeddings. Different from an in-domain prediction system, our cross-domain system can be effectively applied to a wide range of product domains found on the Internet, which do not necessarily have proper review rating systems to collect labelled data from.

**Background: Review Rating Prediction vs Sentiment Analysis**

An effective and common way of extracting the value out of these comments is to perform sentiment analysis to mine and analyse textual information and sentimental orientation by identifying the users’ opinions and attitudes. The outcome of this sentiment analysis has a significant impact on business (Y. Liu, Bi, & Fan, 2017) and consumer decision-making (Cambria, Schuller, Xia, & Havasi, 2013). A study by (Anderson & Magruder, 2012) found that an “extra half-star rating causes restaurants to sell out 19 percentage points more frequently”. It can provide an informed awareness of public opinion on different matters, as well as it can increase a company’s market and social competitiveness. At the same time, the result of the analysis is also the reference basis for users to formulate reasonable consumption behaviour. Most sentiment classification experiments (B. Liu & Zhang, 2012) are defined as 2-way or 3-way classification tasks, where a text can labelled as expressing positive or negative sentiment (Balazs & Velásquez, 2016), with the addition of a third label neutral in many cases (Rosenthal, Farra, & Nakov, 2017).

There are three main levels of research on sentiment analysis: document level, sentence level and aspect level (Pang & Lee, 2008). Document-level sentiment analysis is the shallowest level of analysis in sentiment analysis. The premise of document-level sentiment analysis is that the entire text expresses only one sentiment, that is, positive or negative (Feldman, 2013). Compared with document-level sentiment analysis, sentence-level sentiment analysis has greatly improved the analysis granularity. It divides the entire text into sentences, and uses a single sentence as a unit of sentiment expression. The premise of sentence-level sentiment analysis is that a single sentence expresses only one emotion, that is, positive or negative (Feldman, 2013).

Different from the sentiment analysis task, the review rating prediction task consists in determining the score –as a rating between 1 and 5– that a user would give to a product or business, having the review text as input. While this may at first seem like a fine-grained sentiment analysis task, which is a translation of a textual view to a numerical perspective and consists in choosing one of five labels rather than three labels (positive, neutral, negative), there are three key characteristics that make the review rating prediction task different. First, the sentiment of a review is not necessarily the same as the rating, as a user may express a positive attitude when sharing a negative opinion of a business,
e.g. “I very much enjoyed my friend’s birthday celebration, however the food here is below standard and we won’t be coming back”. And second, a review tends to be relatively lengthy, discussing different aspects of a business, some of which may be more important than others towards the rating score, e.g. in a review saying that “the food was excellent and we loved the service, although that makes the place a bit pricey”, a user may end up giving it a relatively high score given that key aspects such as the food and the service were considered very positive. In addition, the review can discuss different aspects, and the set of aspects discussed in each review can vary, with some users not caring about certain aspects; e.g. one user focuses on food while another one focuses more on price (Ganu et al., 2009). Using the same star rating mode to express the score of specific feature can be more helpful to find users’ interest. Hence, we argue that a review rating prediction system needs to consider the opinions towards different aspects of a business. We achieve this by extracting aspect phrases mentioned in different sentences or segments of a review, which are then aggregated to determine the overall review rating.

Related Work

There has been a body of research in sentiment analysis in recent years (B. Liu & Zhang, 2012). This research has worked in different directions by looking into lexicon-based approaches (Hu & Liu, 2004), machine learning methods (Pang, Lee, & Vaithyanathan, 2002; Ye, Zhang, & Law, 2009) and deep learning techniques (Y. Wang, Huang, Zhao, et al., 2016; Poria et al., 2017). Research in sentiment analysis is also tackling data from many different sources, ranging from news articles (Ahmad, Cheng, & Almas, 2007) to tweets (Rosenthal et al., 2017). Work on sentiment analysis has also focused on a wide range of domains (Bollegala, Weir, & Carroll, 2013; Al-Moslmi, Omar, Abdullah, & Albaread, 2017), including popular domains such as politics or finances (Mullen & Malouf, 2006; Ahmad et al., 2007), but also less popular domains such as software or electronics (Pan, Ni, Sun, Yang, & Chen, 2010). Work on review rating prediction is however still in its infancy, where most of the work has only focused on reviews for popular domains such as hotels and restaurants, whereas other, less popular domains have not been studied.

Review rating prediction has commonly been regarded as a classification task, but also as a regression task on a few occasions (Li et al., 2011; Pang & Lee, 2005). The text of the review is the input that is consistently used by most existing works (Qu, Ifrim, & Weikum, 2010; Leung, Chan, & Chung, 2006), however many of them also incorporate other features extracted from the product being reviewed or from the user writing the review (Qu et al., 2010). Ganu et al. (Ganu et al., 2009) improved the review rating prediction accuracy by implementing new ad-hoc and regression-based recommendation measures, where the aspect of user reviews is considered; their study was however limited to only restaurant reviews and other domains were not studied. A novel kind of bag-of-opinions representation (Qu et al., 2010) was proposed and each opinion consists of three parts, namely a root term, a set of modifier terms from the same sentence, and one or more negation terms. This approach shows a better performance than prior state-of-the-art techniques for review rating prediction. Datasets including three review domains were used for their experiments, however they ran separate experiments for each domain and did not consider the case of domains lacking training data. Similarly, (H. Wang, Lu, & Zhai, 2010) performed experiments predicting the ratings of hotel reviews, using a regression model that
looked at different aspects discussed in a review, with the intuition that different aspects would have different levels of importance towards determining the rating.

Recent years have seen an active interest in researching approaches to review rating prediction, which are still limited to popular domains and do not consider the case of domains lacking training data. In a number of cases, features extracted from products and users are being used (Jin et al., 2016; Seo, Huang, Yang, & Liu, 2017b; B. Wang, Xiong, Huang, & Li, 2018), which limits the ability to apply a prediction system to new domains and to unseen products and users. (Tang, Qin, Liu, & Yang, 2015) studied different ways of combining features extracted from the review text and the user posting the review. They introduced the User-Word Composition Vector Model (UWCVM), which considers the user posting a review to determine the specific use that a user makes of each word. While this is a clever approach to consider differences across users, it also requires observing reviews posted by each user beforehand, and cannot easily generalise to new, unseen users, as well as to new review domains where we lack any information about those users. An approach that predicts review ratings from the review text alone is that by (Fan & Khademi, 2014). They performed a study of two kinds of features: bag-of-words representations of reviews, as well as part-of-speech tags of the words in the review. They studied how the top K keywords in a dataset contributed to the performance of the rating prediction system, finding that a multinomial logistic regression classifier using the top 100 keywords performed best. In this work, we implement and use this as a baseline classifier, along with another baseline classifier built from word embedding representations of review texts. Others such as (Titov & McDonald, 2008; Huang, Rogers, & Joo, 2014; Zhou, Wan, & Xiao, 2015; Vargas & Pardo, 2018) have used topic modelling techniques such as LDA or PLSA to identify the aspects that users discuss in restaurant reviews, however they did not study its effectiveness for review rating prediction.

The review rating prediction task is different from work on recommender systems (Resnick & Varian, 1997; Sarwar, Karypis, Konstan, & Riedl, 2000; Z. Zhang et al., 2013; Zheng, Noroozi, & Yu, 2017; Seo, Huang, Yang, & Liu, 2017a). While recommender systems generally aim to predict the extent to which a user may like a product before they even write a review of it, here we tackle the task of determining the number of stars that a user would give to an already written review. The review in various domains has been used in the previous studies like restaurants, movies and music (Ganu et al., 2009; Leung et al., 2006; Chen et al., 2011). Work on review rating prediction, as the one we tackle here, is useful to predict the rating that a user would give to online comments that do not have a rating, e.g. comments on Facebook or on a forum.

In this paper, we argue that a textual analysis of reviews needs to go beyond the sole exploration of the text as a whole, but also needs to look at the aspect phrases mentioned in the text, which contain the core opinionated comments. This is the case of good food for a restaurant or comfortable bed for a hotel. While these differ substantially across review domains, we propose to leverage aspect phrase embeddings to achieve representations of aspect phrases to enable generalisation. This allows us to perform cross-domain review rating experiments, where one can build a rating prediction model out of larger training data thanks to leveraging labelled data from other domains. To the best of our knowledge, ours is the first work to perform rating predictions for review domains with scarce training data, such as dentists, as well as the first to propose and test a cross-domain review rating
prediction system.

Datasets

To enable our analysis of review rating prediction over different domains, we make use of 12 different datasets, each associated with a different domain. We use three different data sources to generate our datasets: (1) a publicly available collection of 6 million reviews from Yelp\(^1\), (2) a collection of more than 142 million reviews from Amazon provided by (McAuley, Targett, Shi, & Van Den Hengel, 2015; He & McAuley, 2016), and (3) a collection of more than 24 million reviews retrieved from businesses listed in TripAdvisor’s top 500 cities. We filter 12 categories of reviews from these 3 datasets, which gives us 12 different datasets that enable us to experiment with review rating prediction over 12 different types of businesses and products. All of the datasets include both the review text and the review rating in a scale from 1 to 5. The use of a standardised 1-5 rating scale facilitates experimentation of rating prediction systems across domains.

Table 1 shows the list of 12 datasets we use for our experimentation. Our datasets comprise more than 58 million reviews overall, distributed across different types of businesses, where some businesses are far more popular than others. The number of reviews per type of business ranges from 22 million reviews for books to 36,000 reviews for dentists, showing a significant imbalance in the size and popularity of different domains. The variability of dataset sizes and popularity of review domains enables our analysis looking at the effect of the availability of large amounts of in-domain data for training.

| Business/Product | Source     | # Reviews    |
|------------------|------------|--------------|
| Books            | Amazon     | 22,507,155   |
| Restaurants      | TripAdvisor| 14,542,460   |
| Attractions      | TripAdvisor| 6,358,253    |
| Clothing         | Amazon     | 5,748,920    |
| Homeware         | Amazon     | 4,253,926    |
| Hotels           | TripAdvisor| 3,598,292    |
| Nightlife        | Yelp       | 877,352      |
| Events           | Yelp       | 387,087      |
| Casinos          | Yelp       | 115,703      |
| Hair salons      | Yelp       | 99,600       |
| Resorts          | Yelp       | 57,678       |
| Dentists         | Yelp       | 36,600       |
| TOTAL            | –          | 58,583,026   |

Table 1
Details of the 12 datasets, sorted by number of reviews. The number of reviews that each type of business/product receives varies drastically.

In Figure 1 we show a breakdown of the 1-5 star ratings for each dataset. We observe an overall tendency of assigning high ratings across most categories, except especially the cases of casinos and resorts, where the ratings are more evenly distributed. Most categories

\(^1\)https://www.yelp.com/dataset
show an upwards tendency with higher number of reviews for higher ratings, as is the case with attractions, books or restaurants. Interestingly, in the case of dentists and hair salons, the ratings that prevail are 1’s and 5’s, showing that users tend to either love or hate these services.

Methodology

One of the key challenges of dealing with reviews pertaining to different domains is that the vocabulary can vary significantly. We can expect that people will express that they like or dislike a product in different ways for different domains. For example, one may make a reference to *good food* when reviewing a restaurant, a *comfortable bed* for a hotel, an *inspiring novel* for a book and a *fun party* for an event. All of these could be deemed similarly positive for each domain, however without a proper method to capture these semantics, predictions made across domains may not be accurate enough. To tackle this problem, we propose to use aspect phrase embeddings.

Aspect Phrase Extraction and Representation

Different review domains tend to have different aspect categories associated with them. While one may care about *food quality* in restaurants, the focus is instead on the *engagement* when reviewing a book. Even if other aspect categories such as *price* are more widely generalisable across domains, most aspect categories and associated vocabulary vary across domains. In the first instance, we are interested in capturing those phrases associated with aspect categories, which we refer to aspect phrases. We define aspect phrases as tuples providing opinionated judgement of a particular aspect of a product, e.g. *excellent food* for restaurants or *interesting reading* for books. Once we have these tuples, in a second step
we use word embeddings to achieve a generalisable semantic representation of the aspect phrases.

**Aspect Phrase Extraction.** To extract the tuples conforming aspect phrases from the reviews, we rely on the assumption that these opinionated tuples will be made of (1) a sentiment word that judges it and (2) a non-sentiment word that refers to the object or action being judged. To restrict the context in which a tuple can be observed, we consider segments of the reviews, i.e. sentences or parts of sentences that are independent from each other. We perform the extraction of aspect phrases by following the next steps:

1. **POS tagging.** We extract the part-of-speech (POS) tags of all words in the reviews by using NLTK’s POS tagger (Bird & Loper, 2004), hence labelling each word as a noun, verb, adjective, adverb, etc.

2. **Identification of sentiment words.** We use the sentiment lexicon generated by (Hu & Liu, 2004), which provides a list of over 6,800 words associated with positive or negative sentiment. With this list, we tag matching keywords from reviews as being positive or negative.

3. **Segmentation of reviews.** We break down the reviews into segments. To identify the boundaries of segments, we rely on by punctuation signs (, . ; :) and coordinating conjunctions (for, and, nor, but, or, yet, so) as tokens indicating the end of a segment. Text at either side of these tokens are separated into different segments.

4. **Extraction of aspect phrases.** At this stage, we only act within the boundaries of each segment. Within each segment, we identify pairs of words made of (1) a sentiment word labelled as positive or negative and (2) a word labelled as noun or verb by the POS tagger and identified as a non-sentiment word, i.e. not matching any of the keywords in the sentiment lexicon. Each pair of words matching these criteria within a segment is extracted as an aspect phrase.

Through the process above, we extract aspect phrases for all review domains. Table 2 shows the most salient aspect phrases for each of the review domain. We observe that aspect phrases vary substantially across domains, with phrases referring to the *ease of use* for homeware, *comfort* for clothing, *food quality* for restaurants or *happy hour* for nightlife, among others.

**Aspect Phrase Representation.** Despite the ability of our method above to capture aspect phrases independent of the domain, these still vary in terms of vocabulary. To achieve semantic representations of aspect phrases extracted for different domains, we make use of Word2Vec word embeddings (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013). We train a word embedding model using the 58 million reviews in our datasets. This model is then used to achieve semantic representations of the aspect phrases with the following two variants;

- **Aspect phrase embeddings (APE):** we aggregate all the aspect phrases extracted for a review. We generated the embedding vector for each review by adding up the word embeddings for all words included in those phrases.
Polarised aspect phrase embeddings (PAPE): we aggregate the aspect phrases for a review in two separate groups, one containing positive phrases and the other containing negative phrases. Following the same method as for aspect phrase embeddings, here we generate a separate embedding representation for each group, which leads to an embedding representation for positive aspect phrases and another embedding representation for negative aspect phrases. We then concatenate both embeddings to get the combined vector.

Experiment Settings

Cross-validation. We perform different sets of experiments for comparing the performance of our rating prediction systems in in-domain and cross-domain settings for different domains. As we are interested in performing 10-fold cross-validation experiments for both settings, we randomly split the data available for each domain $d \in \{1..12\}$ into 10 equally sized folds, $f \in \{1..10\}$. Each time one of these folds is considered as the test data, $Test_{ij}$, while the training data depends on the setting, i.e. (1) $\sum_{f \in \{1..10\}, f \neq j, d = i} Train_{df}$ for in-domain experiments, and (2) $\sum_{d \in \{1..12\}, d \neq i, f = j} Train_{df}$ for cross-domain experiments. We ultimately average the performance scores across all 10 folds in each setting.

Classifiers. In setting up the experiments for our analysis, we tested all the classifiers proposed by (Fan & Khademi, 2014) and some more, including a multinomial logistic regression, a gaussian naive bayes classifier, support vector machines and random forests. Our experiments showed that the multinomial logistic regression was clearly and consistently the best classifier, and hence for the sake of clarity and brevity we report results using this classifier in the paper.

Features and baselines. We implement four different sets of features, which include two baselines and two methods that we propose:

- Baseline by (Fan & Khademi, 2014) (BL): the first baseline is the text-based review rating prediction system introduced by (Fan & Khademi, 2014). Their method
uses a selection of top K unigrams, given that other features such as part-of-speech
tags were not useful.

• **Baseline using Word Embeddings (w2v):** we implement a second baseline con-
sisting of a word embedding representation of the entire text of a review. We use the
word embedding model we trained from our review datasets.

• **Aspect Phrase Embeddings (APE):** we concatenate the word embedding vectors
obtained for the entire texts of reviews with the aspect phrase embeddings, i.e. word
embedding representations of the aspect phrases extracted from a review.

• **Polarised Aspect Phrase Embeddings (PAPE):** we concatenate the word em-
bedding vectors obtained for the entire texts of reviews with the polarised aspect
phrase embeddings, i.e. a concatenation of the word embedding representations of
positive aspect phrases and the word embedding representation of negative aspect
phrases.

**Evaluation**

The review rating prediction task can be considered as a rating task with five different
stars from 1 to 5. As a rating task, we need to consider the proximity between the predicted
and reference ratings. For instance, if the true star rating of a review is 4 stars, then the
predicted rating of 3 stars will be better than a predicted rating of 2 stars. To account for
the difference or error rate between the predicted and reference ratings, we rely on the two
metrics widely used in previous rating prediction work (Li et al., 2011), which include the
Root Mean Square Error (RMSE) (see Equation 1) and Mean Absolute Error (MAE) (see
Equation 2).

\[
\text{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} (\hat{y}_i - r_i)^2}{n}}
\]

\[
\text{MAE} = \frac{\sum_{i=1}^{n} |y_i - r_i|}{n}
\]

where:
- \( n \) denotes the total number of reviews in the test set.
- \( y_i \) is the predicted star rating for the \( i^{th} \) review.
- \( r_i \) is the real star rating given to the \( i^{th} \) review by the user.

We report both metrics for all our experiments, to facilitate comparison for future
work.

**Results**

The results are organised in two parts. First, we present and analyse results for
in-domain review rating prediction, where the training and test data belong to the same
domain. Then, we show and analyse the results for cross-domain review rating prediction,
where data from domains that differ from the test set is used for training. A comparison
of the performance on both settings enables us to assess the suitability of leveraging a
cross-domain classifier as well as the use of aspect phrase embeddings.
In-Domain Review Rating Prediction

Table 3 shows results for in-domain review rating prediction, where the training and test data belong to the same domain. Experiments are performed using 10-fold cross-validation within each of the 12 datasets. Note that lower scores indicate a smaller amount of error and hence better performance. These results show that both aspect phrase embeddings (APE) and polarised aspect phrase embeddings (PAPE) consistently outperform the sole use of word embeddings (w2v). Likewise, all these methods clearly outperform the baseline method (BL) by (Fan & Khademi, 2014) across all 12 domains, which emphasises the importance of using word embeddings for capturing semantics even when the experiments are within the same domain. A comparison between our two proposed methods using phrase embeddings shows that polarised phrase embeddings outperform phrase embeddings for the most popular review categories, whereas the difference is not so clear for less popular categories.

All in all, these results show that the use of either form of phrase embeddings leads to improvements in the review rating prediction when the training and test data belong to the same domain. The main goal of our work is however to show their effectiveness on cross-domain review rating prediction, which we discuss in the next section. The in-domain results presented in this section enable us to perform a comparison with the cross-domain results presented next.

| Category   | MAE  | RMSE  |
|------------|------|-------|
|            | BL   | w2v   | +ape | +pape |
| books      | 0.741 | 0.542 | 0.530 | 0.521 |
| restaurants| 0.811 | 0.484 | 0.471 | 0.466 |
| attractions| 0.715 | 0.567 | 0.554 | 0.549 |
| clothing   | 0.816 | 0.544 | 0.529 | 0.518 |
| homeware   | 0.850 | 0.581 | 0.563 | 0.543 |
| hotels     | 0.723 | 0.455 | 0.442 | 0.441 |
| nightlife  | 0.950 | 0.579 | 0.555 | 0.554 |
| events     | 0.955 | 0.595 | 0.565 | 0.568 |
| casinos    | 1.119 | 0.769 | 0.689 | 0.705 |
| hair salons| 0.615 | 0.410 | 0.405 | 0.414 |
| resorts    | 1.013 | 0.793 | 0.689 | 0.692 |
| dentists   | 0.525 | 0.322 | 0.317 | 0.324 |

Table 3
Results for in-domain review rating prediction. Categories are sorted in descending order by number of reviews, with the most popular review categories on top of the list.

Cross-Domain Review Rating Prediction

Table 4 shows results for cross-domain review rating prediction. While experiments are also performed using 10-fold cross-validation, we train the classifier for a particular domain using data from the other 11 datasets, i.e. simulating the scenario where we do not have any labelled data for the target domain. We also include results for the best performance for each review category when we train with data from the same domain,
which is represented as BID (best in-domain). This enables us to compare whether and the extent to which the use of out-of-domain data for training can help to improve the performance for each review category.

Results show a remarkable difference between popular and non-popular review categories. For the 6 most popular review categories (books, restaurants, attractions, clothing, homeware, hotels), the best performance is obtained by the best in-domain (BID) classifier, which indicates that for review categories with large amounts of training data, it is better to use in-domain data. However, when we look at the bottom 6 review categories (nightlife, events, casinos, hair salons, resorts, dentists), we observe that the cross-domain classifier leveraging out-of-domain data for training achieves higher performance. While the sole use of word embeddings (w2v) leads to improved performance for the least popular categories, the improvement is even better when we incorporate either phrase embeddings or polarised phrase embeddings. The results are also positive for the polarised aspect phrase embeddings (pape) over the aspect phrase embeddings (ape); even if the results are not better in 100% of the cases, PAPE tends to outperform APE in most cases, with just a small difference when APE is better, showing that one can rely on PAPE for all cases dealing with non-popular domains. These experiments show a clear shift in the performance of in-domain classifiers when the amount of training data decreases, encouraging the use of out-of-domain data for training in those cases.

Likewise, this motivates the use of the cross-domain classifier for new domains where no labelled data is available for training, for instance because reviews are collected from a website where no ratings are given by the user, such as Facebook, Twitter or comments on blogs.

|       | MAE        |       |       |       |       | RMSE        |       |       |       |       |
|-------|------------|-------|-------|-------|-------|------------|-------|-------|-------|-------|
|       | BID | w2v | +ape | +pape |       | BID | w2v | +ape | +pape |       |
| books | 0.521 | 0.725 | 0.691 | 0.672 |       | 1.023 | 1.354 | 1.307 | 1.278 |       |
| restaurants | 0.466 | 0.514 | 0.502 | 0.501 |       | 0.828 | 0.891 | 0.870 | 0.868 |       |
| attractions | 0.549 | 0.613 | 0.608 | 0.596 |       | 0.968 | 1.062 | 1.050 | 1.034 |       |
| clothing | 0.518 | 0.712 | 0.684 | 0.656 |       | 1.001 | 1.265 | 1.229 | 1.190 |       |
| homeware | 0.543 | 0.821 | 0.801 | 0.776 |       | 1.081 | 1.443 | 1.417 | 1.386 |       |
| hotels | 0.441 | 0.494 | 0.483 | 0.490 |       | 0.784 | 0.854 | 0.836 | 0.844 |       |
| nightlife | 0.554 | 0.541 | 0.530 | 0.524 |       | 0.958 | 0.937 | 0.921 | 0.912 |       |
| events | 0.565 | 0.543 | 0.525 | 0.521 |       | 1.004 | 0.973 | 0.943 | 0.936 |       |
| casinos | 0.689 | 0.652 | 0.630 | 0.623 |       | 1.118 | 1.081 | 1.048 | 1.039 |       |
| hair salons | 0.405 | 0.353 | 0.337 | 0.341 |       | 0.993 | 0.900 | 0.866 | 0.876 |       |
| resorts | 0.689 | 0.633 | 0.606 | 0.602 |       | 1.136 | 1.064 | 1.024 | 1.018 |       |
| dentists | 0.317 | 0.272 | 0.266 | 0.268 |       | 0.983 | 0.887 | 0.870 | 0.873 |       |

Table 4

Results for cross-domain review rating prediction. BID = best in-domain. Categories are sorted in descending order by number of reviews, with the most popular review categories on top of the list.
Conclusion

Review rating prediction has recently gained importance as a task that is related to opinion mining and sentiment analysis, however requiring aggregation of opinions towards different aspects within a review to predict a rating generally ranging from 1 to 5. Previous work on review rating prediction has however been limited to popular reviews domains, such as restaurants or hotels. Our paper intends to fill this gap by experimenting on 12 different datasets pertaining to 12 different review domains, of very different levels of popularity, and collected from different sources including Yelp, Amazon and TripAdvisor. Given that some of these review domains have very limited availability of labelled data for training, our aim has been to propose a cross-domain review rating prediction system that would perform well for those non-popular domains. Likewise, a cross-domain review rating prediction system can be used to predict ratings of reviews gathered from platforms where users do not assign ratings, such as Facebook or Twitter.

Our review rating prediction system leverages both POS taggers and sentiment lexicons to extract aspect phrases from reviews, i.e. phrases referring to different features of a business. To enable generalisation of aspect phrases to different domains, we make use of universal representations using word embeddings; we propose two different models for feature representations, (1) aspect phrase embeddings, which aggregate all aspect phrases of a review, and (2) polarised aspect phrase embeddings, which consider positive and negative aspect phrases separately to create an embedding representation for each. We compare our results with those of the best-performing classifier by (Fan & Khademi, 2014) and another baseline that uses word embedding representations of the entire review. We developed both in-domain and cross-domain review rating prediction systems following this methodology; this allows us to compare performance on in-domain and cross-domain experiments for different review domains.

Our experiments show that both of our methods leveraging phrase embeddings lead to improvements over the rest of the baseline methods, both in the in-domain and the cross-domain settings. Interestingly, a comparison of results for these two experiment settings shows that performance scores are higher for the in-domain classifier when we make predictions on the most popular domains, however the cross-domain classifier leads to substantial improvements for the least popular domains. Our results indicate that a classifier trained from in-domain data is more suitable for popular review domains, whereas unpopular review domains can be improved when out-of-domain data is used for training along with our aspect phrase embedding representation.

Future Work

While research in cross-domain review rating prediction is still in its infancy, there are a number of avenues that we identify for future research, including:

- **Implicit aspects**: Most of the existing research works focus only on the extraction of explicit aspect terms and ignore the implicit aspects. However, there are often many forms of implicit aspect terms in the review. In implicit expressions, adjectives and adverbs are the two most common types, since most of them describe some specific attributes of the entity.
• **Capturing user-specific expressions:** Different users tend to have different ways of expressing the same opinion. Sentiment terms are mostly achieved through adjectives and adverbs. However, some nouns (i.e., junk, rubbish) and verbs (i.e., enjoy, dislike) also express the sentiments of reviewers. In addition, sometimes the views of reviewers are expressed through the comparison of multiple sentences. The problem mainly needs to identify and mine the comparative sentences and objects.

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