

Opinion Recommendation using Neural Memory Model

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Abstract

We present opinion recommendation, a novel task of jointly predicting a custom review with a rating score that a certain user would give to a certain product or service, given existing reviews and rating scores to the product or service by other users, and the reviews that the user has given to other products and services. A characteristic of opinion recommendation is the reliance of multiple data sources for multi-task joint learning, which is the strength of neural models. We use a single neural network to model users and products, capturing their correlation and generating customised product representations using a deep memory network, from which customised ratings and reviews are constructed jointly. Results show that our opinion recommendation system gives ratings that are closer to real user ratings on Yelp.com data compared with Yelp’s own ratings, and our methods give better results compared to several pipelines baselines using state-of-the-art sentiment rating and summarization systems.

1 Introduction

Offering a channel for customers to share opinions and give scores to products and services, review websites have become a highly influential information source that customers refer to for making purchase decisions. Popular examples include IMDB¹ on the movie domain, Epinions² on the product domain, and Yelp³ on the service domain. Figure 1 shows a screenshot of a restaurant review page on Yelp.com, which offers two main types of

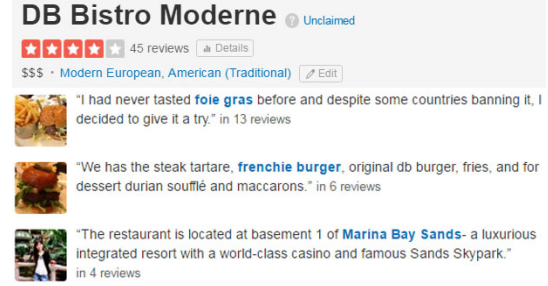


Figure 1: A restaurant review on Yelp.com.

information. First, an overall rating score is given under the restaurant name; second, detailed user reviews are listed below the rating.

Though offering a useful overview and details about a product or service, such information has several limitations. First, the overall rating is general and not necessarily agreeable to the taste of individual customers. Being a simple reflection of all customer scores, it serves an average customer well, but can be rather inaccurate for individuals. For example, the authors themselves often find highly rated movies being tedious. Second, there can be hundreds of reviews for a product or service, which makes it infeasible for exhaustive reading. It would be useful to have a brief summary of all reviews, which ideally should be customized to the reader.

We investigate the feasibility of a model that addresses the limitations above. There are two sources of information that the model should collect to achieve its goal, namely information on the *target product*, and information about the *user*. The former can be obtained from reviews written by other customers about the target product, and the latter can be obtained from the reviews that the user has written for other products and services. Given the above two sources of information, the model should generate a *customized score* of the product that the user is likely to give after trying, as well as a *customized review* that the user would

¹<http://www.imdb.com/>

²<http://epinions.com/>

³<https://www.yelp.com/>

have written for the target product.

We refer to the task above using the term **opinion recommendation**, which is a new task, yet closely related to several existing lines of work in NLP. The first is *sentiment analysis* (Hu and Liu, 2004; Pang and Lee, 2008), which is to give a rating score based on a customer review. Our task is different in that we aim to predict user rating scores of new product, instead of predicting the opinion score of existing reviews. The second is *opinion summarization* (Nishikawa et al., 2010; Wang and Ling, 2016), which is to generate a summary based on reviews of a product. A major difference between our task and this task is that the summary must be customized to a certain user, and a rating score must additionally be given. The third is *recommendation* (Su and Khoshgof-taar, 2009; Yang et al., 2014), which is to give a ranking score for a certain product or service based on the purchase history of the user and other customers who have purchased the target product. Our task is different in the source of input, which is *textual* customer reviews and ratings rather than *numerical* purchase history.

There are three types of inputs for our task, namely the reviews of the target product, the reviews of the user on other products, and other users reviews on other products, and two types of outputs, namely a customized rating score and a customized review. The ideal solution should consider the interaction between all given types of information, jointly predicting the two types of outputs. This poses significant challenges to statistical models, which require manually defined features to capture relevant patterns from training data. Deep learning is a relatively more feasible choice, offering viabilities of information fusion by fully connected hidden layers (Collobert et al., 2011; Henderson et al., 2013). We leverage this advantage in building our model.

In particular, we use a recurrent neural network to model the semantic content of each review. A neural network is used to consolidate existing reviews for the target product, serving the role of a *product model*. In addition, a *user model* is built by consolidating the reviews of the given user into a single vector form. Third, to address potential sparsity of a user’s history reviews, neighbor users are identified by collaborative filtering (Ding et al., 2006), and a vector representation is learned by using a neural *neighborhood model*, which consoli-

dates their history reviews. Finally, a deep memory network is utilized to find the association between the user and target product, jointly yielding the rating score and customised review.

Experiments on a Yelp dataset show that the model outperforms several pipelined baselines using state-of-the-art techniques. In particular, review scores given by the opinion recordation system are closer to real user review scores compared to the review scores which Yelp assigns to target products. Our code is released at <http://github.com/anonymous>.

2 Related Work

Sentiment Analysis. Our task is related to document-level sentiment classification (Pang and Lee, 2008), which is to infer the sentiment polarity of a given document. Recently, various neural network models are used to capture the sentimental information automatically, including convolutional neural networks (Kim, 2014), recursive neural network (Socher et al., 2013) and recurrent neural network (Teng et al., 2016; Tai et al., 2015), which have been shown to achieve competitive results across different benchmarks. Different from binary classification, review rating prediction aims to predict the numeric rating of a given review. Pang and Lee (2005) pioneered this task by regarding it as a classification/regression problem. Most subsequent work focuses on designing effective textual features of reviews (Qu et al., 2010; Li et al., 2011; Wan, 2013). Recently, Tang et al. (2015) proposed a neural network model to predict the rating score by using both lexical semantic and user model.

Beyond textual features, user information is also investigated in the literature of sentiment analysis. For example, Gao et al. (2013) developed user-specific features to capture user leniency, and Li et al. (2014) incorporated textual topic and user-word factors through topic modeling. For integrating user information into neural network models, Tang et al. (2015) predicted the rating score given a review by using both lexical semantic information and a user embedding model. Chen et al. (2016b) proposed a neural network to incorporate global user and product information for sentiment classification via an attention mechanism.

Different from the above research on sentiment analysis, which focuses on predicting the opinion on existing reviews. Our task is to recommend the

score that a user would give to a new product *without* knowing his review text. The difference originates from the object, previous research aims to predict opinions on reviewed products, while our task is to recommend opinion on new products, which the user has not reviewed.

Opinion Summarization. Our work also overlaps with to the area of opinion summarization, which constructs natural language summaries for multiple product reviews (Hu and Liu, 2004). Most previous work extracts opinion words and aspect terms. Typical approaches include association mining of frequent candidate aspects (Hu and Liu, 2004; Qiu et al., 2011), sequence labeling based methods (Jakob and Gurevych, 2010; Yang and Cardie, 2013), as well as topic modeling techniques (Lin and He, 2009). Recently, word embeddings and recurrent neural networks are also used to extract aspect terms (Irsoy and Cardie, 2014; Liu et al., 2015).

Aspect term extraction approaches lack critical information for a user to understand how an aspect receives a particular rating. To address this, Nishikawa et al. (2010) generated summaries by selecting and ordering sentences taken from multiple review texts according to affirmativeness and readability of the sentence order. Wang and Liu (2011) adopted both sentence-ranking and graph-based methods to extract summaries on an opinion conversation dataset. While all the methods above are *extractive*, Ganesan et al. (2010) presented a graph-based summarization framework to generate concise abstractive summaries of highly redundant opinions, and Wang and Ling (2016) used an attention-based neural network model to absorb information from multiple text units and generate summaries of movie reviews.

Different from the above research on opinion summarization, we generate a *customized* review to a certain user, and a rating score must be additionally given.

Recommendation. Recommendation systems suggest to a user new products and services that might be of their interest. There are two main approaches, which are content-based and collaborative-filtering (CF) based (Adomavicius and Tuzhilin, 2005; Yang et al., 2014), respectively. Most existing social recommendation systems are CF-based, and can be further grouped into model-based CF and neighborhood-based CF (Kantor et al., 2011; Su and Khoshgoftaar,

2009). Matrix Factorization (MF) is one of the most popular models for CF. In recent MF-based social recommendation works, user-user social trust information is integrated with user-item feedback history (e.g., ratings, clicks, purchases) to improve the accuracy of traditional recommendation systems, which only factorize user-item feedback data (Ding et al., 2006; Koren, 2008; He et al., 2016).

There has been work integrating sentiment analysis and recommendation systems, which use recommendation strategies such as matrix factorization to improve the performance of sentiment analysis (Leung et al., 2006; Singh et al., 2011). These methods typically use ensemble learning (Singh et al., 2011) or probabilistic graph models (Wu and Ester, 2015). For example, Zhang et al. (2014) who proposed a factor graph model to recommend opinion rating scores by using explicit product features as hidden variables.

Different from the above research on recommendation systems, which utilize numerical purchase history between users and products, we work with textual information. In addition, recommendation systems only predict a rating score, while our system generates also a customized review, which is more informative.

Neural Network Models. Multi-task learning has been recognised as a strength of neural network models for natural language processing (Collobert et al., 2011; Henderson et al., 2013; Zhang and Weiss, 2016; Chen et al., 2016a), where hidden feature layers are shared between different tasks that have common basis. Our work can be regarded as an instance of such multi-tasks learning via shared parameters, which has been widely used in the research community recently.

Dynamic memory network models are inspired by neural turing machines (Graves et al., 2014), and have been applied for NLP tasks such as question answering (Sukhbaatar et al., 2015; Kumar et al., 2016), language modeling (Tran et al., 2016) and machine translation (Wang et al., 2016). It is typically used to find abstract semantic representations of texts towards certain tasks, which are consistent with our main need, namely abstracting the representation of a product that is biased towards the taste of a certain user.

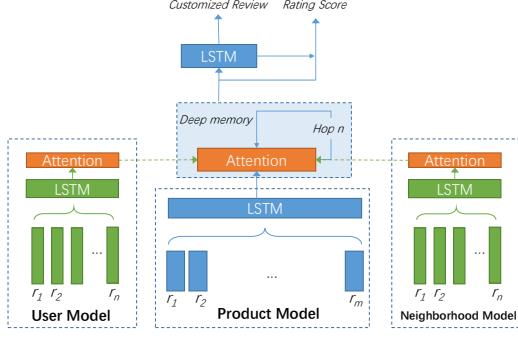


Figure 2: Overview of proposed model.

3 Model

Formally, the input to our model is a tuple $\langle R_T, R_U, R_N \rangle$, where $R_T = \{r_{T_1}, r_{T_2}, \dots, r_{T_{n_t}}\}$ is the set of existing reviews of a target product, $R_U = \{r_{U_1}, r_{U_2}, \dots, r_{U_{n_u}}\}$ is the set of user's history reviews, and $R_N = \{r_{N_1}, r_{N_2}, \dots, r_{N_{n_n}}\}$ is the set of the user's neighborhood reviews. All the reviews are sorted with temporal order. The output is a pair $\langle Y_S, Y_R \rangle$, where Y_S is a real number between 0 and 5 representing the rating score of the target product, and Y_R is a customised review.

For capturing both general and personalized information, we first build a *product model*, a *user model*, and a *neighborhood model*, respectively, and then use a memory network model to integrate these three types of information, constructing a *customized product model*. Finally, we predict a customized rating score and a review collectively using neural stacking. The overall architecture of the model is shown in Figure 2.

3.1 Review Model

A customer review is the foundation of our model, based on which we derive representations of both a user and a target product. In particular, a user profile can be achieved by modeling all the reviews of the user R_U , and a target product profile can be obtained by using all existing reviews of the product R_T . We use the average of word embeddings to model a review. Formally, given a review $r = \{x_1, x_2, \dots, x_m\}$, where m is the length of the review, each word x_k is represented with a K -dimensional embedding e_k^w (Mikolov et al., 2013). We use the $\sum_k (e_k^w)/m$ for the representation of the review e_r^d .

3.2 User Model

A standard LSTM (Hochreiter and Schmidhuber, 1997) without coupled input and forget gates or

peephole connections is used to learn the hidden states of the reviews. Denoting the recurrent function at step t as $\text{LSTM}(x_t, h_{t-1})$, we obtain a sequence of hidden state vectors $\{h_{U_1}, h_{U_2}, \dots, h_{U_{n_u}}\}$ recurrently by feeding $\{e^d(r_{U_1}), e^d(r_{U_2}), \dots, e^d(r_{U_{n_u}})\}$ as inputs, where $h_{U_i} = \text{LSTM}(e^d(r_{U_i}), h_{U_{i-1}})$. The initial state and all stand LSTM parameters are randomly initialized and tuned during training.

Not all reviews contribute equally to the representation of a user. We introduce an attention mechanism (Bahdanau et al., 2014; Yang et al., 2016) to extract the reviews that are relatively more important, and aggregate the representation of reviews to form a vector. Taking the hidden state $\{h_{U_1}, \dots, h_{U_2}, \dots, h_{U_{n_u}}\}$ of user model as input, the attention model outputs, a continuous vector $v_U \in \mathbb{R}^{d \times 1}$, which is computed as a weighted sum of each hidden state h_{U_i} , namely

$$v_U = \sum_i^{n_u} \alpha_i h_{U_i} \quad (1)$$

where n_u is the hidden variable size, $\alpha_i \in [0, 1]$ is the weight of h_{U_i} , and $\sum_i \alpha_i = 1$.

For each piece of hidden state h_{U_i} , the scoring function is calculated by

$$u_i = \tanh(W_U h_{U_i} + b_U) \quad (2)$$

$$\alpha_i = \frac{\exp(u_i)}{\sum_j \exp(u_j)} \quad (3)$$

where W_U and b_U are model parameters. The attention vector v_U is used to represent the *User Model*.

3.3 Finding Neighbor Users

We use neighborhood reviews to improve the user model, since a user may not have sufficient reviews to construct a reliable model. Here a neighbor refers to a user that has similar tastes to the target user (Koren, 2008; Desrosiers and Karypis, 2011). The same as the user model, we construct the *neighborhood model* v_N using the neighborhood reviews $R_N = \{r_{N_1}, r_{N_2}, \dots, r_{N_{n_n}}\}$ with an attention recurrent network.

A key issue in building the neighborhood model is how to find neighbors of a certain user. In this study, we use matrix factorization (Koren, 2008) to detect neighbors, which is a standard approach for recommendation (Ding et al., 2006; Li et al., 2009;

He et al., 2016). In particular, users' rating scores of products are used to build a product-users matrix $M \in \mathbb{R}^{n_t \times n_u}$ with n_t products and n_u users. We approximate it using three factors, which specify soft membership of products and users (Ding et al., 2006) by finding:

$$\begin{aligned} \min_{F, S, T} \|M - FST^T\| \\ \text{s.t. } S \geq 0, F \geq 0, T \geq 0 \end{aligned} \quad (4)$$

where $F \in \mathbb{R}^{n_t \times K}$ represents the posterior probability of K topic clusters for each product; $S \in \mathbb{R}^{K \times K}$ encodes the distribution of each topic k ; and $T \in \mathbb{R}^{K \times n_u}$ indicates the posterior probability of K topic clusters for each user.

As a result of matrix factorization, we directly obtain the probability of each user on each topic from the person-topic matrix T . To infer T , the optimization problem in Eq.4 can be solved using the following updating rule:

$$T_{jk} \leftarrow T_{jk} \frac{(M^T F S)_{jk}}{(T T^T M^T F S)_{jk}} \quad (5)$$

Obtaining the user-topic matrix T , we measure the implicit connection between two users using:

$$\text{sim}(i, j) = \sum_{k=1}^K T_{ik} T_{jk} \quad (6)$$

where $\text{sim}(i, j)$ measure the implicit connection degree between users i and j . If $\text{sim}(i, j)$ is higher than a threshold η , we consider user j as the neighbor of user i .

3.4 Product Model

Given the representations of existing reviews $\{e(r_{T_1}), e(r_{T_2}), \dots, e(r_{T_{n_t}})\}$ of the product, we use a LSTM to model their temporal orders, obtaining a sequence of hidden state vectors $h_T = \{h_{T_1}, h_{T_2}, \dots, h_{T_{n_t}}\}$ by recurrently feeding $\{e(r_{T_1}), e(r_{T_2}), \dots, e(r_{T_{n_t}})\}$ as inputs. The hidden state vectors h_T are used to represent the product.

3.5 Customized Product Model

We use the user representation v_U and the neighbour representation v_N to transform the target product representation $h_T = \{h_{T_1}, h_{T_2}, \dots, h_{T_{n_t}}\}$ into a customised product representation v_C , which is tailored to the taste of the user. In particular, a dynamic memory network (Sukhbaatar

et al., 2015; Xiong et al., 2016) is utilized to iteratively find increasingly abstract representations of h_t , by injecting v_U and v_N information.

The memory model consists of multiple dynamic computational layers (hops), each of which contains an attention layer and a linear layer. In the first computational layer (hop 1), we take the hidden variables h_{T_i} ($0 \leq i \leq n_t$) of product model as input, adaptively selecting important evidences through one attention layer using v_U and v_N . The output of the attention layer gives a linear interpolation of h_T , and the result is considered as input to the next layer (hop 2). In the same way, we stack multiple hops and run the steps multiple times, so that more abstract representations of the target product can be derived.

The attention model outputs a continuous vector $v_C \in \mathbb{R}^{d \times 1}$, which is computed as a weighted sum of h_{T_i} ($0 \leq i \leq n_t$), namely

$$v_C = \sum_i^{n_t} \beta_i h_{T_i} \quad (7)$$

where n_t is the hidden variable size, $\beta_i \in [0, 1]$ is the weight of h_{T_i} , and $\sum_i \beta_i = 1$. For each piece of hidden state h_{T_i} , we use a feed forward neural network to compute its semantic relatedness with the abstract representation v_C . The scoring function is calculated as follows at hop t :

$$\begin{aligned} u_i^t = \tanh(W_T h_{T_i} + W_C v_C^{t-1} \\ + W_U v_U + W_N v_N + b) \end{aligned} \quad (8)$$

$$\beta_i^t = \frac{\exp(u_i^t)}{\sum_j \exp(u_j^t)} \quad (9)$$

The vector v_C is used to represent the customized product model. At the first hop, we define $V_C^0 = \sum_n h_{T_i}/n$.

The product model h_{T_i} ($0 \leq i \leq n_t$) represents salient information of existing reviews in their temporal order, they do not reflect the taste of a particular user. We use the customised product model to integrate user information and product information (as reflected by the product model), resulting in a single vector that represents a customised product. From this vector we are able to synthesis both a customised review and a customised rating score.

3.6 Customized Review Generation

The goal of customized review generation is to generate a review Y_R from the customized product representation v_C , composed by a sequence of

words y_{R_1}, \dots, y_{R_n} . We decompose the prediction of Y_R into a sequence of word-level predictions:

$$\log P(Y_R|v_C) = \sum_j P(y_{R_j}|y_{R_1}, \dots, y_{R_{j-1}}, v_C) \quad (10)$$

where each word y_{R_j} is predicted conditional on the previously generated $y_{R_1}, \dots, y_{R_{j-1}}$ and the input v_C . The probability is estimated by using standard word softmax:

$$P(y_{R_j}|y_{R_1}, \dots, y_{R_{j-1}}, v_C) = \text{softmax}(h_{R_j}) \quad (11)$$

where h_{R_j} is the hidden state variable at timestamp j , which is modeled as $LSTM(u_{j-1}, h_{R_j})$. Here a LSTM is used to generate a new state h_{R_j} from the representation of the previous state $h_{R_{j-1}}$ and u_{j-1} . u_{j-1} is the concatenation of previously generated word $y_{R_{j-1}}$ and the input representation of customized model v_C .

3.7 Customized Opinion Rating Prediction

We consider two factors for customised opinion rating, namely existing review scores and the customised product representation v_C . A baseline rating system such as Yelp.com uses only the former information, typically by taking the average of existing review scores. Such a baseline gives an empirical square error of 1.28 (out of 5) in our experiments, when compared with a test set of individual user ratings, which reflects the variance in user tastes. In order to integrate user preferences into the rating, we instead take a weighted average of existing ratings cores, so that the scores of reviews that are closer to the user preference are given higher weights.

As a second factor, we calculate a review score independently according to the customised representation v_c of existing reviews, without considering review scores. The motivation is two fold. First, existing reviews can be relatively few, and hence using their scores alone might not be sufficient for a confident score. Second, existing ratings can be all different from a users personal rating, if the existing reviews do not come from the user's neighbours. As a result, using the average or weighted average of existing reviews, the personalised user rating might not be reached.

Formally, given the rating scores s_1, s_2, \dots, s_n of existing reviews, and the the customized prod-

uct representation v_C , we calculate:

$$Y_S = \sum_i^n \alpha_i \cdot s_i + \mu \tanh(W_S v_C + b_S) \quad (12)$$

In the left term $\sum_i^n \alpha_i \cdot s_i$, we use attention weights α_i to measure the important of each rating score s_i . The right term $\tanh(W_S v_C + b_S)$ is a review-based shift, weighted by μ .

Since the result of customized review generation can be helpful for rating score prediction, we use neural stacking additionally feeding the last hidden state h_{R_n} of review generation model as input for Y_S prediction, resulting in

$$Y_S = \sum_i^n \alpha_i \cdot s_i + \mu \tanh(W_S(v_C \oplus h_{R_n}) + b_S) \quad (13)$$

where \oplus denotes vector concatenation.

3.8 Training

For our task, there are two joint training objectives, for review scoring and review summarisation, respectively. The loss function for the former is defined as:

$$L(\Theta) = \sum_{i=1}^N (Y_{S_i}^* - Y_{S_i})^2 + \frac{\lambda}{2} \|\Theta\|^2 \quad (14)$$

where $Y_{S_i}^*$ is the predicted rating score, Y_{S_i} is the rating score in the training data, Θ is the set of model parameters and λ is a parameter for L2 regularization.

We train the customized review generation model by maximizing the log probability of Eq.10 (Sutskever et al., 2014; Rush et al., 2015). Standard back propagation is performed to optimize parameters, where gradients also propagate from the scoring objective to the review generation objective due to neural stacking (Eq.13). We apply online training, where model parameters are optimized by using Adagrad (Duchi et al., 2011). For all LSTM models, we empirically set the size of the hidden layers to 128. We train word embeddings using the *Skip-gram* algorithm (Mikolov et al., 2013)⁴, using a window size of 5 and vector size of 128. In order to avoid over-fitting, dropout (Hinton et al., 2012) is used for word embedding with a ratio of 0.2. The neighbor similarity threshold η is set to 0.25.

⁴ <https://code.google.com/p/word2vec/>

	Amount
Business	15,584
Review	334,997
User	303,032

Table 1: Statistics of the dataset.

4 Experiments

4.1 Experimental Settings

Our data are collected from the yelp academic dataset⁵, provided by Yelp.com, a popular restaurant review website. The data set contains three types of objects: *business*, *user*, and *review*, where business objects contain basic information about local businesses (i.e. restaurants), review objects contain review texts and star rating, and user objects contain aggregate information about a single user across all of Yelp. Table 1 illustrates the general statistics of the dataset.

For evaluating our model, we choose 4,755 user-product pairs from the dataset. For each pair, the existing reviews of the target service (restaurant) are used for the product model. The rating score given by each user to the target service is considered as the gold customized rating score, and the review of the target service given by each user is used as the gold-standard customized review for the user. The remaining reviews of each user are used for training the user model. We use 3,000 user-product pairs to train the model, 1,000 pairs as testing data, and remaining data for development.

We use the ROUGE-1.5.5 (Lin, 2004) toolkit for evaluating the performance of customized review generation, and report unigram overlap (ROUGE-1) as a means of assessing informativeness. We use Mean Square Error (MSE) (Wan, 2013; Tang et al., 2015) is used as the evaluation metric for measuring the performance of customized rating score prediction. MSE penalizes more severe errors more heavily.

4.2 Development Experiments

4.2.1 Ablation Test

Effects of various configurations of our model, are shown on Table 2, where *Joint* is the full model of this paper, *-user* ablates the user model, *-neighbor* ablates the neighbor model, *-rating* is a single-task model that generates a review without the rating

	Rating	Generation
Joint	0.904	0.267
-user	1.254	0.220
-neighbor	1.162	0.245
-user,-neighbor	1.342	0.205
-rating	-	0.254
-generation	1.042	-

Table 2: Feature ablation tests.

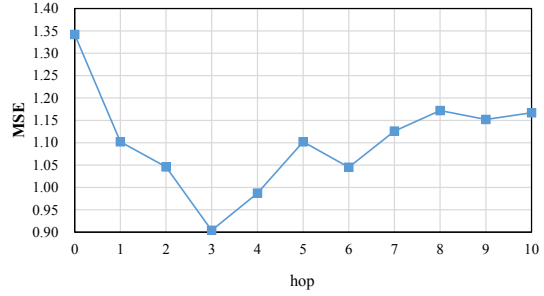


Figure 3: Influence of hops.

score, and *-generation* generates only the rating score.

By comparing “Joint” and “-user,-neighbor”, we can find that customized information have significant influence on both the rating and review generation results ($p - value < 0.01$ using t -test). In addition, comparison between “-Joint” and “-user”, and between “-user” and “-user, -neighbor” shows that both the user information and the neighbour user information of the user are effective for improving the results. A users neighbours can indeed alleviate scarcity of user reviews.

Finally, comparison between “Joint” and “-generation”, and between “Joint” and “-rating” shows that multi-task learning by parameter sharing is highly useful.

4.2.2 Influence of Hops

We show the influence of hops of memory network for rating prediction on Figure 3. Note that, the model would only consider the general product reviews (*-user*, *-neighbor*), when $hop = 0$. From the figure we can find that, when $hop = 3$, the performance is the best. It indicates that multiple hops can capture more abstract evidences from external memory to improve the performance. However, too many hops leads to over-fitting, thereby harms the performance. As a result, we choose 3 as the number of hops in our final test.

⁵https://www.yelp.com/academic_dataset

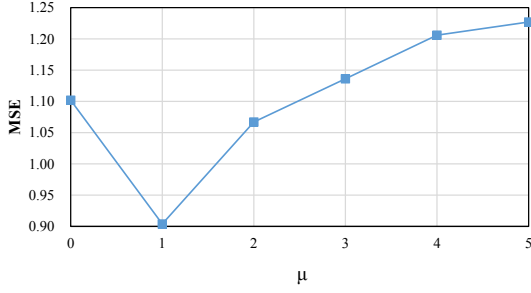


Figure 4: Influence of bias score.

4.2.3 Influence of μ

We show the influence of the bias weight parameter μ for rating prediction in Figure 4. With μ being 0, the model uses the weighted sum of existing reviews to score the product. When μ is very large, the system tends to use only the customized product representation v_c to score the product, hence ignoring existing review scores, which are a useful source of information. Our results show that when μ is 1, the performance is optimal, thus indicating both existing review scores and review contents are equally useful.

4.3 Final Results

We show the final results for opinion recommendation, comparing our proposed model with the following state-of-the-art baseline systems:

- *RS-Average* is the widely-adopted baseline (e.g., by Yelp.com), using the averaged review scores as the final score.
- *RS-Linear* estimates the rating score that a user would give by $s_{ui} = s_{all} + s_u + s_i$ (Ricci et al., 2011), where s_u and s_i are the training deviations of the user u and the product i , respectively.
- *RS-Item* applies k NN to estimate the rating score (Sarwar et al., 2001). We choose the cosine similarity between v_c to measure the distance between product.
- *RS-MF* is a state-of-the-art recommendation model, which uses matrix factorisation to predict rating score (Ding et al., 2006; Li et al., 2009; He et al., 2016).
- *Sum-Opinosis* uses a graph-based framework to generate abstractive summarisation given redundant opinions (Ganesan et al., 2010).

	Rating	Generation
RS-Average	1.280	-
RS-Linear	1.234	-
RS-Item	1.364	-
RS-MF	1.143	-
Sum-Opinosis	-	0.183
Sum-LSTM-Att	-	0.196
Joint	1.023	0.250

Table 3: Final results.

- *Sum-LSTM-Att* is a state-of-the-art neural abstractive summariser, which uses an attentional neural model to consolidate information from multiple text sources, generating summaries using LSTM decoding (Rush et al., 2015; Wang and Ling, 2016).

All the baseline models are single-task models, without considering rating and summarisation prediction jointly. The results are shown in Table 3. Our model (“Joint”) significantly outperforms both “RS-Average” and “RS-Linear” (p -value < 0.01 using t -test), which demonstrates the strength of opinion recommendation, which leverages user characteristics for calculating a rating score for the user.

Our proposed model also significantly outperforms state-of-the-art recommendation systems (RS-Item and RS-MF) (p -value < 0.01 using t -test), indicating that textual information are a useful addition to the rating scores themselves for recommending a product.

Finally, comparison between our proposed model and state-of-the-art summarisation techniques (Sum-Opinosis and Sum-LSTM-Att) shows the advantage of leveraging user information to enhance customised review generation, and also the strength of joint learning.

5 Conclusion

We presented a dynamic memory model for opinion recommendation, a novel task of jointly predicting the review and rating score that a certain user would give to a certain product or service. In particular, a deep memory network was utilized to find the association between the user and the product, jointly yielding the rating score and customised review. Results show that our methods are better results compared to several pipelines baselines using state-of-the-art sentiment rating and summarisation systems.

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