CARec: Content-Aware Point-of-Interest Recommendation via Adaptive Bayesian Personalized Ranking

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Abstract. Location-based social networks (LBSNs) offer researchers user-generated content data to study users' intrinsic patterns of preference. One important application of such study is to provide a personalized point-of-interest (POI) recommender system to improve users' experience in LBSNs. However, most of the existing methods provide limited improvements on POI recommendation because they separately employ textual sentiment or latent topic and ignore the mutual effect between them. In this paper, we propose a novel content-aware POI recommendation framework via an adaptive Bayesian Personalized Ranking. First, we make full use of users' check-in records and reviews to capture users' intrinsic preference (i.e., check-in, sentiment, and topic preferences). Then, by aggregating users' intrinsic preferences, we devise an adaptive Bayesian Personalized Ranking to generate the personalized ranked list of POIs for users. Finally, extensive experiments on two real-world datasets demonstrate that our framework significantly outperforms other state-of-the-art POI recommendation models in various metrics.

Keywords: POI Recommendation, Content-aware, Adaptive Ranking

1 Introduction

In recent years, the increasing popularity of mobile devices has made it easier for people to access the Internet. Now we can easily share our life through location-based social networks(LBSNs), such as Foursquare, Yelp and Facebook Places. When users visit Point-of-Interests (POIs) like parks, bars and restaurants, they make check-ins at POIs and leave texts to share their experience with social friends via mobile devices. The check-in data left at POIs contains rich information about user preference, which inspires researchers to study the POI recommendation task utilizing the data. POI recommendation has been a crucial demand in location-based services(LBS). It not only helps users to explore new POIs, but also has commercial usages like personalized advertising.

The aim of POI recommendation is to generate a ranked list of POIs that users might be interested in but have never visited. Traditional POI recommender systems try to capture intrinsic patterns of user preference by exploring different types of implicit feedback, e.g., check-in records, geographical information, social relations or temporal information. In recent years, user-generated texts have also attracted widespread attention because it's more explainable. Sentiment analysis and topic model are two important tools to analyse texts. [1] proposed a hybrid user location preference model to adjust users' check-in preference with sentiment scores. [2] [3] fused sentiment with other types of information like POI category to improve recommendation performance. However, these approaches provide limited improvements on POI recommendation because they cannot distinguish which part of the content is positive or negative. Topic model has also been applied to study content. [4] proposed a cross-region collaborative filtering method based on hidden topics about check-in records. [5] proposed a CoSoLoRec model, which applied an aggregated LDA model to associate users and POIs by latent topics. Nevertheless, these works model POI and user topic distribution separately and may not capture the mutual influence of the two distributions. Therefore, there seems a large marginal space left to improve the performance by synthetically considering multiple aspects of texts, i.e., latent topics, check-in frequency and textual sentiment to improve POI recommendation.

In this paper, we propose a **C**ontent-**A**ware Point-of-Interest **Rec**ommendation framework (called CARec), which utilizes texts by analysing sentiment and modeling topic distributions simultaneously. The preference inferred from texts is then combined with check-in preference and get an overall preference. CARec is composed of three modules: **check-in module**, **sentiment module** and **topic module**. For check-in module, users' intrinsic patterns of preference are modelled by probabilistic matrix factorization (PMF) [6]. PMF factorizes the user-POI check-in matrix into a low-dimensional vector space to acquire user and POI embeddings. For sentiment module, we adopt a natural language processing technology to analyse each piece of reviews and obtain users' sentiment

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score. For topic module, we extend the classic LDA to learn user topic distribution utilizing user documents and learn POI topic distribution utilizing both POI documents and features of historical visitors. According to previous work [7], directly optimizing for pairwise ranking like Bayesian Personalized Ranking (BPR) produces better performance than matrix factorization. Hence, by aggregating users' preferences generated by the above three modules, we propose a novel adaptive BPR to generate the personalized ranked list of POIs for users. We conduct experiments on two large-scale real-world datasets and the results show that our POI recommendation framework can produce better performance.

The main contributions of this paper can be summarized as follows:

1 We propose a novel content-aware POI recommendation framework (CARec) that makes full use of user-generated texts. To the best of our knowledge, this is the first work that mines texts in multiple aspects, i.e., latent topics, check-in frequency and textual sentiment.
2 We capture users' intrinsic patterns of preference on given POIs by modeling corresponding information separately.
3 We devise an adaptive Bayesian Personalized Ranking to generate the ranked list of POIs for users by aggregating various types of intrinsic preferences.
4 We evaluate our proposed framework on two real-world datasets and the experiment results demonstrate that our framework outperforms baseline methods in terms of various metrics.

The paper is organized as following: Section 2 describes some related works. Section 3 formulates the problem of our work and Section 4 presents our framework in detail. Section 5 reports experiement results on two real-world datasets and Section 6 concludes this paper.

2 Related Work

In this section, we introduce some researches related to our work: sentiment analysis-based POI recommendation methods, topic models in POI recommendation systems and ranking-based models.

Sentiment analysis-based methods extract user's sentiment preference from texts. [1] proposed a hybrid POI recommendation model by extracting users' sentiment preference from tips and combining check-in preference with sentiment preference. [3] obtained some high-quality features and inferred users' sentiment preference to these features to make recommendations. [2] studied users' sentiment preference together with topical aspect and spatial aspect. [8] studied content information for POI recommendation, which includes not only sentiment indications, but also POI properties and user interests.

Topic models in POI recommendation capture users' interests by modeling latent topics. Latent Dirichlet Allocation (LDA) is a model that has gained popularity as a tool for automatic corpus summarization and visualization [9]. [10] proposed LCA-LDA model by giving consideration to both personal interest and local preference. [4] proposed a cross-region collaborative filtering method based on hidden topics about check-in records to recommend new POIs. [5] leveraged a variant of LDA to extract the topics of users and POI from reviews to infer users' preference. [11] proposed a Social Topic model to capture both the social and topic aspects of user check-ins.

Bayesian Personalized Ranking (BPR) is a pairwise ranking method [7], which focuses on modeling the ranking of the feedbacks. It learns the ranking based on pairwise preference comparison over observed and unobserved feedbacks such that the Area Under the ROC Curves (AUC) can be maximized [12]. [13] [14] [15] extended BPR method by integrating different types of context. [15] proposed a personalized ranking framework with multiple sampling criteria, which is more flexible to incorporate multiple additional sources of information.

In this paper, the framework we propose is different from existing methods. First, our framework makes better use of contents by sentiment analysis together with user-sensitive topic model. Second, we make recommendations with an adaptive Bayesian Personalized Ranking model to achieve better performance.

3 Problem Defination

The aim of this work is to recommend POIs to users based on their check-ins and reviews. Let $\mathcal{U} = \{u_1,\ u_2,\ \dots\ ,u_m\}$ be the set of users and $\mathcal{V} = \{v_1,\ v_2,\ \dots\ ,v_n\}$ be the set of POIs. Each user u visited some POIs $\mathcal{V}_u^+$ historically and left some reviews $\mathcal{D}_u$. For convenience, we also define $\mathcal{V}_u^- = \{\ v \mid v \in \mathcal{V} \wedge v \notin \mathcal{V}_u^+\}$. All the reviews left at POI v is named $\mathcal{D}_v$. The authors of $\mathcal{D}_v$ are also known as the historical visitors of v, named $\mathcal{A}_v$. All the needed symbols in our work is shown in Table 1.

Table 1. Mathematical Notions

Symbol	Definition
u, $\mathcal{U}$	Individual user and set of users
v, $\mathcal{V}$	Individual POI and set of POIs
$\mathcal{V}_u^+$	Set of POIs u visited
$\mathcal{V}_u^-$	Set of POIs u has never visited
$\mathcal{A}_v$	Set of users visited v
$\mathcal{D}$	Set of reviews(document)
θ_u	topic distribution of user
π_v	topic distribution of POI

4 Recommendation Framework

In this section, we introduce details of CARec. Our framework consists of three modules: check-in module, sentiment module and topic module. The three modules explore three types of preference of each user, check-in preference $p_c(u, v)$ based on check-in records, sentiment preference $p_s(u, v)$ based on textual sentiment and topic preference $p_t(u, v)$ based on latent topic. The three types of preference are unified to an overall preference $p(u, v)$:

$$p(u, v) = p_s(u, v) \times p_t(u, v) \times p_c(u, v)$$

4.1 Check-in module

Check-in module aims to capture users' underlying patterns of preference with check-in records. We employ Probabilistic Matrix Factorization (PMF) [6] to factorize sparse user-POI check-in matrix $C_{m\times n}$ into user-latent space matrix $U_{m\times k}$ and POI-latent space matrix ${V_{n\times k}}^T$, where m and n are the number of users and POIs respectively, k is the dimension of latent space:

$$C_{m\times n} \approx U_{m\times k} \times V_{n\times k}^T$$

For the sparsity of check-in matrix, only observed check-ins are considered and the conditional probability of the observed check-ins are:

$$p(C \mid U, V, \sigma_C^2) = \prod_{i=1}^{m}\prod_{j=1}^{n} I_{ij}[\mathcal{N}(C_{i,j} \mid U_i \times V_j^T, \sigma_C^2)]$$

where I_{ij} is the indicator function: I_{ij}=1 if i checked-in at j, otherwise I_{ij}=0. $\mathcal{N}(x \mid \mu, \sigma^2)$ is Gaussian distribution with mean μ and variance σ^2. The Gaussian priors of U and V are:

$$p(U \mid \sigma_U^2) = \prod_{i=1}^{m}[\mathcal{N}(U_i \mid 0, \sigma_U^2\mathbf{I})]$$

$$p(V \mid \sigma_V^2) = \prod_{j=1}^{n}[\mathcal{N}(V_j \mid 0, \sigma_V^2\mathbf{I})]$$

We have posterior of U and V as follows according to bayesian inference:

$$p(U, V \mid C, \sigma_C^2, \sigma_U^2, \sigma_V^2) \propto p(C \mid U, V, \sigma_C^2)p(U \mid \sigma_U^2)p(V, \sigma_V^2) \quad (1)$$

Matrix U and matrix V are learned by maxmizing Eq. (1). The check-in preference of ith user u to jth POI v is:

$$p_c(u, v) = U_i \times V_j^T$$

4.2 Sentiment module

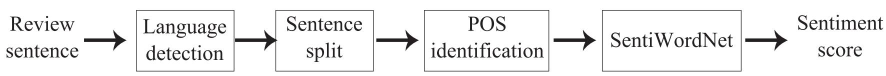
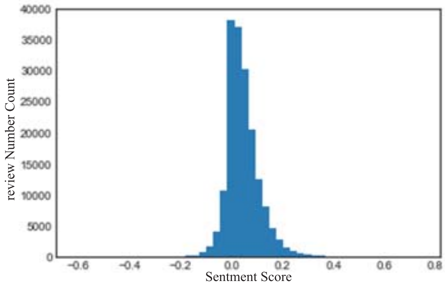


Fig. 1. Sentiment analysis of reviews

Sentiment module aims to find users' emotional feelings with reviews. The process flow can be seen in Fig.1. Firstly, the language detection component filters out non-English reviews. Then review sentences are split into words and the part-of-speech (POS) is identified. Finally, the sentiment score of a sentence is measured based on sentiment scores of words [16].

As can be seen in Fig.2, the distribution of sentiment scores are highly centralized around 0, which means most users expressed neutral sentiment. Thus we apply a mapping scheme for sentiment scores [1], as is presented in Fig.2. Similar to processing sparse check-in matrix, we apply PMF to infer sentiment preference $p_s(u,v)$. In this module, we use U_s and V_s to approximate user-POI sentiment preference matrix, the sentiment preference of the ith user u to jth POI v is:

$$p_s(u, v) = U_{si} \times V_{sj}^T$$



Sentiment Score	Mapped Score
[-1,-0.05]	1
[-0.05,-0.01]	2
[-0.01,0.01]	3
[-0.01,0.05]	4
[0.05, 1]	5

Fig. 2. Sentiment score distribution and mapping scheme

4.3 Topic Module

Topic module aims to model the topic distributions of users and POIs. Aggregated reviews are expected as the documents to model topic distributions. All reviews written by user u are aggregated as a user documenmt $\mathcal{D}_u$ and all reviews for POI v are aggregated as a POI document $\mathcal{D}_v$ [5].

User Topic Model. In user topic model, the generation of user document is modeled as a three-step process. First, for each user document, a topic distribution is sampled from a Dirichlet distribution. Second, for each word in user document, a single topic is chosen according to the sampled topic distribution. Finally, each word is sampled from the topic-word distribution of the topic. The flow of this process is shown in Fig.3. Each user is associated with topics following a multinomial distribution θ. Also, each topic is associated with words according to a multinomial distribution ϕ. Using gibbs sampling to sample and infer θ and ϕ, the topic distribution for u is θ_u:

$$\theta_{uk} = \frac{n_u^{(k)} + \alpha}{\sum_{k=1}^{K} (n_u^{(k)} + \alpha)}$$

where $n_u^{(k)}$ is the topic observation count for u, K is the number of latent topics. α is a hyperparameter.

POI Topic Model. POI topic model builds POI topic distributions leveraging both POI documents and topic distributions of historical visitors. As in Fig.4, for each topic sampled from θ, POI topic model enumerates all the historical visitors to decide the acceptance probability based on their interests. In this way, POI topic model captures the interests of historical visitor, and further reflects the features of intersted visitors. All the historical visitors are responsible to decide the acceptance probability a_{vk}:

$$a_{vk} = \frac{\sum_{u \in \mathcal{A}_v} \theta_{uk}}{|\mathcal{A}_v|}$$

Thus, the POI topic distribution π_v is:

$$\pi_{vk} = \frac{a_{vk}(n_v^{(k)} + \alpha)}{\sum_{k=1}^{K} (a_{vk}(n_v^{(k)} + \alpha))}$$

where $n_v^{(k)}$ is the topic observation count for v, K is the number of latent topics. User topic model and POI topic model have the same latent topic number K.

Finally, the topic preference of user u to POI v is:

$$p_t(u, v) = \theta_u \times \pi_v^T = \sum_{k=1}^{K} \theta_{uk} \times \pi_{vk}$$

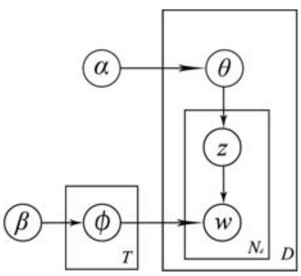


Fig. 3. User topic model

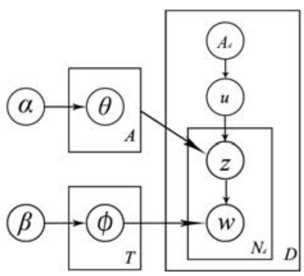


Fig. 4. POI topic model

4.4 Adaptive Bayesian Personalized Ranking

Algorithm 1: Learning Algorithm for ABPR

```
Input: users U, POIs V, visited POIs V_u^+ for each u ∈ U
Output: Θ = { P ∈ R^{m×k}, Q ∈ R^{n×k} }
initialization P ~ U(0,1), Q ~ U(0,1)
T ← 0 //iteration number
repeat
for T ← 1 to |U| do
    u ← uniformly sample from check-ins U
    i ← uniformly sample from observed check-ins V_u^+
    j,k ← uniformly sample from unobserved check-ins V_u^-
    if p(u,k) > p(u,j) then
        swap j and k
    end
    Compute gradients of P_u,Q_i,Q_j,Q_k;
    update parameters;
end
until convergence
```

We unify users' preference generated by the above three modules by Eq. (1). Then, we devise an adaptive Bayesian Personalized Ranking (ABPR) by using the overall preference score as its input. The ABPR is described in Algorithm 1:

ABPR swaps j and k adaptively if k is predicted more preference, so the pairwise ranking function of ABPR is:

$$\hat{r}_{u,i,j,k}(\Theta) = \hat{y}_{u,i} \succ \hat{y}_{u,j} \wedge \hat{y}_{u,j} \succ \hat{y}_{u,k} \tag{2}$$

ABPR aims to maxmize the AUC by learning the right ranking in Eq. (2). For each user $u \in \mathcal{U}$, the likelihood function of adaptive BPR is:

$$\mathcal{L}(\Theta) = \prod_{u\in\mathcal{U}} \Big(\prod_{i\in\mathcal{V}_u^+} \prod_{j\in\mathcal{V}_u^-} P(\hat{r}_{u,i} \succ \hat{r}_{u,j} \mid \Theta) \prod_{j\in\mathcal{V}_u^-} \prod_{k\in\mathcal{V}_u^-} P(\hat{r}_{u,j} \succ \hat{r}_{u,k} \mid \Theta) \Big)$$

We approximate the probability function using the sigmoid function σ(x) to optimise the AUC likelihood function, so that the likelihood function is differentialble. Then, the likelihood function is as follows:

$$\begin{aligned}\mathcal{J}(\Theta) = \arg\max_{\Theta} \sum_{u\in\mathcal{U}} \Bigg[& \sum_{i\in\mathcal{V}_u^+} \sum_{j\in\mathcal{V}_u^-} \ln(\sigma(\hat{r}_{u,i} - \hat{r}_{u,j})) + \\ & \sum_{j\in\mathcal{V}_u^-} \sum_{k\in\mathcal{V}_u^-} \ln(\sigma(\hat{r}_{u,j} - \hat{r}_{u,k})) \Bigg] - \\ & \lambda_p \sum_{u\in\mathcal{U}} \|P_u\|_F^2 - \lambda_q \sum_{i\in\mathcal{V}} \|Q_i\|_F^2\end{aligned}$$

where Θ is the set of all parameters to be optimised, including parameters of the latent factor of users $P \in \mathcal{R}^{m\times k}$ and POIs $Q \in \mathcal{R}^{n\times k}$, where k is the dimension of latent factors. λ_p and λ_q are regularization terms to avoid overfitting. $\|\cdot\|_F^2$ denotes the Frobenius norm.

Matrix factorization is applied to predict $\hat{r}_{u,i}$:

$$\hat{r}_{u,i} = P_u^T Q_i = \sum_{s=1}^{k} p_{u,s} \times q_{i,s} \tag{3}$$

Finally, we use Stochastic Gradient Descent(SGD) to find the local maximum of Eq. (3). The gradient of P_u, Q_i, Q_j, Q_k are as follows:

$$\frac{\partial\mathcal{J}}{\partial P_u} = \delta(\hat{r}_{u,j} - \hat{r}_{u,i})(Q_i - Q_j) + \delta(\hat{r}_{u,k} - \hat{r}_{u,j})(Q_j - Q_k) - \lambda_p P_u$$

$$\frac{\partial\mathcal{J}}{\partial Q_i} = \delta(\hat{r}_{u,j} - \hat{r}_{u,i}) P_u - \lambda_q Q_i$$

$$\frac{\partial\mathcal{J}}{\partial Q_j} = (\delta(\hat{r}_{u,k} - \hat{r}_{u,j}) - \delta(\hat{r}_{u,j} - \hat{r}_{u,i})) P_u - \lambda_q Q_j$$

$$\frac{\partial\mathcal{J}}{\partial Q_k} = -\delta(\hat{r}_{u,k} - \hat{r}_{u,j}) P_u - \lambda_q Q_k$$

Then parameters $\theta \in \Theta$ are updated with gradients above:

$$\theta^{(\mathcal{T}+1)} = \theta^{(\mathcal{T})} + \eta^{(\mathcal{T})} \cdot \frac{\partial\mathcal{J}}{\partial\theta}(\theta^{(\mathcal{T})})$$

5 Experiment

5.1 Dataset

We conduct our experiments on two publicly available large-scale LBSN datasets, Foursquare [17] and Yelp[1]. As the previous works [18] [19] [13] [14], we filter users who visited less than 10 POIs in Foursquare dataset (32

Table 2. Statistics of Datasets

	Foursquare	**Yelp**
Number of users	9728	5577
Number of POIs	12449	6900
Number of check-ins	177142	518186
Number of reviews	234793	542707
Density of user-POI matrix	0.15%	0.46%

in Yelp dataset), and POIs visited by less than 10 users (31 in Yelp dataset). Each dataset is split into trainset (80%) and testset(20%). The statistics information is shown in Table 2.

5.2 Evaluation Metrics

We utilize three popular metrics to evaluate the performance of the framework we proposed: precision (Pre@N), recall (Rec@N) and normalized discounted cumulative gain (NDCG@N) [20], where N is the number of recommended POIs. For each metric, we calculate the average performance of all users. For the limitation of space, we omit the details.

5.3 Baseline Methods

In order to demonstrate the benefits of our recommendation framework, we compare our method with the following baselines:

- **HPM-SC**: This is a hybrid recommendation model based on users' check-in preference and sentiment preference [1].
- **CoSoLoRec-T**: This is an aggregated topic model that leverages LDA to extract the topics of user and POI from reviews [5].
- **PMF**: This is a matrix factorization method, which is a popular collaborative filtering-based approach in recommendation systems [6].
- **UCF**: It is a typical memory-based collaborative filtering technique that makes recommendation based on a group of similar users [21] [22].
- **BPR-kNN**: It is a method that learns the symmetric item-correlation/item-similarity by the BPR optimization criterion [7].

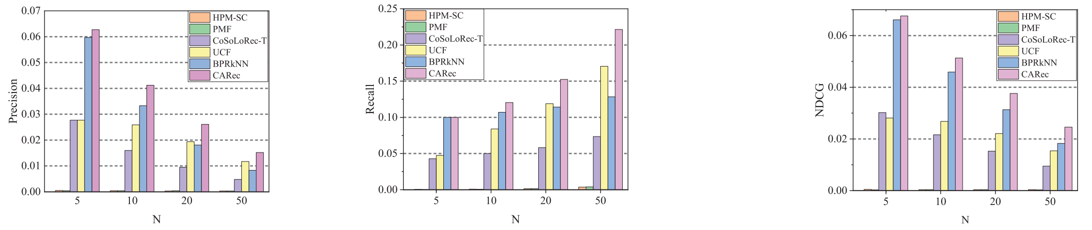
5.4 Parameter settings

For all the compared baselines, we adopt the optimal parameters reported in their works. In our experements, all critical parameters are tuned through cross-validation. PMF model has three parameters: number of latent factor K, α_U and α_V for initializing user-latent factor matrix and POI-latent factor matrix. In Foursquare, parameters for check-in module and sentiment module are K=50, α_U=0.15, α_V=0.2 and K=40, α_U=0.08, α_V=0.1. In topic model, the number of latent topic is 20. Parameters of adaptive BPR are K=30, λ_P=0.2, and λ_Q=0.1. In Yelp, parameters of check-in module and sentiment module are K=40, α_U=0.2, α_V=0.1 and K=50, α_U=0.2, α_V=0.2. In topic model, the number of latent topic is 20. Parameters of adaptive BPR are K=50, λ_P=0.2, and λ_Q=0.2.

5.5 Experimental results

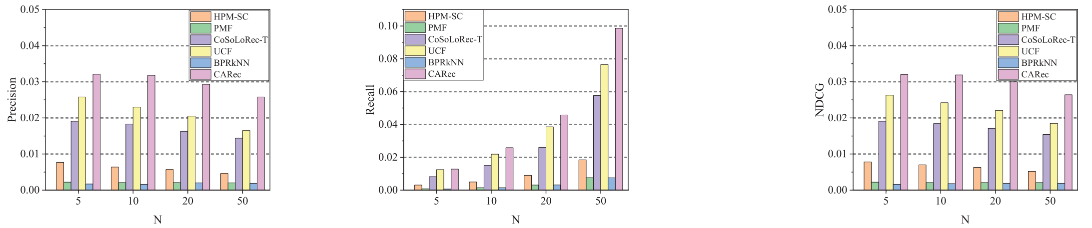
Performance Comparisons. The experimental results of each recommendation algorithm in terms of Pre@N, Rec@N, and NDCG@N on Foursquare and Yelp are reported in Fig.5 and Fig.6. By comparing all algorithms, we can see that our framework achieves the best performance in terms of all three metrics. For instance, compared with CoSoLoRec-T, UCF and BPR-kNN, our CARec gets an improvement by 126.35%, 126.35% and 5.03% in terms of Pre@5. Besides, recommendation precision of CARec is higher than CoSoLo-T by 123%, 91% ,70% and 158% when N is 5, 10, 20 and 50, respectively. CARec outperforms another topic model-based method, CoSoLoRec-T, indicating that considering visitors' topic distributions makes the POIs topic distribution better

[1] https://www.yelp.com/dataset



(a) Precision (b) Recall (c) NDCG

Fig. 5. Performance of baselines and CARec on Foursquare Dataset

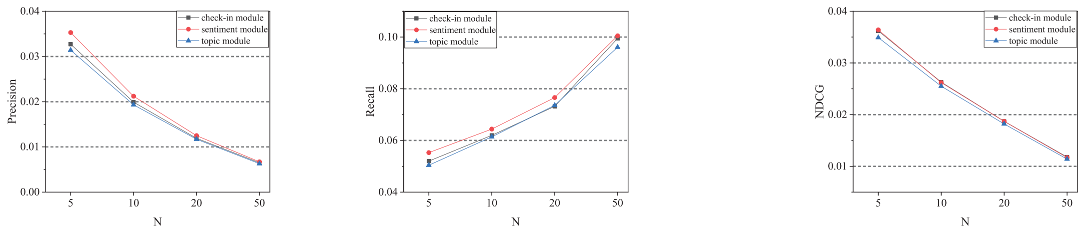


(a) Precision (b) Recall (c) NDCG

Fig. 6. Performance of baselines and CARec on Yelp Dataset

capture users' features. For BPR-ranking methods, CARec performs better than BPRkNN by 5%, 20.59%, 26.92% and 76.47% at Pre@5, Pre@10, Pre@20 and Pre@50 respectively. On the one hand, sentiment module provided extra information about user preference in CARec. On the other hand, our proposed adaptive Bayesian Personalized Ranking contributes to CARec by learning ranking of samples more effectively.

Comparing results in Fig.5 and Fig.6, we observe that CARec performs better on Fousquare dataset than Yelp. One possible reason is that Yelp has much lower repetitive check-in ratio (4%) than that in Foursquare dataset (32%), which means most users go to POIs for only once and left one piece of review. Low repetitive check-in ratio may result in two problems. First, most users have unfixed preferences when they go to a POI for the first time. For example, it is not clear whether they really like the food in a restaurant at the first visit. Because they only tried part of food here, thus they are more likely to express neutral reviews, which makes less



(a) Precision (b) Recall (c) NDCG

Fig. 7. Performance of Each CARec Module On Foursquare

sense in analysing preference. Second, low repetitive check-ins ratio leads to a phenomenon that a user's review to a certain POI is quite short, short texts make the result of sentiment analysis more likely to be inaccurate.

Performance of CARec modules. We also studied the performance of modules in CARec on Foursquare dataset. As can be seen Fig.7, check-in module has the second best performance in CARec. For example, it achieves 3.27%, 5.20% and 3.62% in terms of Pre@5, Rec@5 and NGCG@5, respectively. This result indicates that check-in preference has more contribution than topic preference in CARec. Sentiment module performs the best for all three metrics. For instance, in terms of Pre@5, it performs better than check-in module by 8% and better than topic module by 12%, respectively. This is because compared with check-in records and topic model, users' sentiment expressed in reviews are more explicit.

6 Conclusions

In this paper, we propose a novel content-aware POI recommendation framework, which utilizes users' check-in records and reviews to explore users' intrinsic patterns of preference. For obtaining check-in preference, we factorize the user-POI check-in matrix into a low-dimensional vector space to acquire user and POI embeddings. For sentiment preference, we adopt a natural language processing technology to analyse each piece of reviews and obtain users' sentiment score for POIs. For modeling topic preference, we learn user topic distribution utilizing user document and learn POI topic distribution utilizing both POI document and features of historical visitors. Finally, by aggregating the three types of users' intrinsic preferences, we devise an adaptive BPR to generate the personalized ranked list of POIs for users. Extensive experiments on real data demonstrate that our framework significantly outperforms other state-of-the-art POI recommendation models in different metrics.

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