Abstract

Recommender systems in location based social networks mainly take advantage of social and geographical influence in making personalized Points-of-interest (POI) recommendations. The social influence is obtained from social network friends or similar users based on matching visit history whilst the geographical influence is obtained from the geographical footprints users leave when they check-in at different POIs. However, this approach may fall short when a user moves to a new region where they have little or no activity history. We propose a location aware POI recommendation system that models user preferences mainly based on; user reviews and categories of POIs. We evaluate our algorithm on the Yelp dataset and the experimental results show that our algorithm achieves a better accuracy.

Keywords: Location Based Social Network, Point of Interest, Recommender Systems, Social Networks.

1. Introduction

The rapid growth of cities has led to an increase in the number of points of interest (POIs) such as; restaurants, theaters, stores, and hotels which provide some sort of entertainment and enrich peoples lives as well as providing us with more choices of life experiences than ever before. People are willing to explore the city and their neighborhood in their daily lives and decide which places to go according to their interest and various choices of POIs. However, because of the large number of possible POIs across cities, complexity of modern cities, and unfamiliarity to new individuals in these cities; finding a POI or making a satisfactory decision efficiently becomes a problem for people. Fortunately, advanced mobile devices embedded with wireless communication and location based social networks (LBSN) applications such as Foursquare, Yelp, and Facebook have become increasingly popular. These applications have become some of the most popular Internet applications and have attracted millions of users as they help solve the problem of finding possible places of interest in a specific area [1]. Through these applications individuals share their footprint, opinions, experiences and contribute assorted forms of location-specific multimedia content and may also declaring their presence by an action known...
as a check-in which is very helpful for individuals wishing to find new restaurants, events, bars, hotels and so on.

Nonetheless, despite the availability of information generally presented by LBSNs, a user is still subjected to an overwhelming amount of information which in most cases is biased by the popularity of a POI rather than individual preference. More specifically to this study, a user traveling or migrating to a new geographical region with no prior information about the new geographical region will have a hard time deciding which POI to visit aside from the tourist attractions. People are usually active only within small geographical regions within their home city. While it is easy to associate users when they visit similar sets of venues in the same geographical region, it is interesting and challenging to investigate ways to correlate users across different regions based on their local behavior. In this paper we propose New Region Location Recommender System (NRLRS), a system that makes relevant recommendations in a new location based on an individual's preferences discovered from their collective reviews and ratings obtained from their history data from previous regions visited.

2. Problem formulation

Suppose that there are $I$ users $U^{G_g} = \{u_1, u_2, \ldots, u_I\}$ and $J$ POIs $P^{G_g} = \{p_1, p_2, \ldots, p_J\}$ in a given geographical area $G_g$, where $G_g \in G: \{G_1, G_2, \ldots, G_g\}$ as set of geographical regions. Let $R^{G_g} \in R^{I \times J}$ denote a rating matrix from region $G_g$, where $R_{i,j}$ indicates rating of user $i$ on POI $j$ and zero is unknown or not rated. In LBSNs users are connected to each other explicitly (i.e. friendship) or implicitly through a similarity function creating similar user neighborhoods. For this $S^{G_g} \in R^{I \times K}$ denoting a user relationship (similarity in our cases) matrix where $S_{i,k}$ represents the strength of the relationship between $[0, 1]$. Users rate POIs and write reviews and thus each user is associated with a set of reviews. For this content we denote a $D^{G_g} \in R^{I \times W}$ given a vocabulary of words $W$, where $D_{i,w}$ represents the importance of a word $w \in W$ to user $i$ based on how often the user uses this word in expressing their preferences. In matrix $D$ we treat each user as a document and its content as all words that they have ever written that appear in vocabulary. Given $U^{G_g}, P^{G_g}, R^{G_g}, S^{G_g}, D^{G_g}$ where $g = 1, 2, 4 \ldots$. We aim to make personalized recommendation of locally interesting POI $\{p_1, p_2, \ldots, p_J\}$ in a region $G_a$ to users $\{u_1, u_2, \ldots, u_I\}$ from a region $G_b$ when they migrate to or visit region $G_a$ where $a$ is geographically different from $b$.

3. New Region Location Recommender

3.1. Baseline model: Latent factor Model

We adopt the latent factor model[2] based on matrix factorization as the baseline rating prediction model as follows;

\[
\text{rec}(u, p) = \alpha + \beta_i + \beta_j + U_i P_j
\]

where $\alpha$ is the global offset (average across the dataset), $\beta_i$ and $\beta_j$ are user and POI biases and $U_i = u_1, u_2, \ldots, u_i \in R^{I \times F}$ and $P_j = p_1, p_2, \ldots, p_j \in R^{F \times J}$ are $F$ - dimensional user and POI factors respectively. We consider $U_i$ as user preferences towards POIs and $P_j$ as POI properties.
hence the dot product $U_f, P_j$ matches the interaction between a user and POI. This gives us the following optimization problem:

$$
\min_{U_f, P_j, \phi} \sum_{(i,j) \in R} (R_{i,j} - \text{rec}(i, j))^2 + \lambda_1(||U_i||^2 + ||P_j||^2 + \beta_i^2 + \beta_j^2) \tag{2}
$$

where $i$ and $j$ have a non-zero $R_{i,j}$ rating in rating matrix $R$ and $\lambda_1$ are weights that control the capability of $U, P, \beta$ in order to avoid over-fitting at which we use $U_i, P_j, \beta_i$ and $\beta_j$ as smoothness regularization terms. Therefore, a user traveling to a different region will get a prediction of a locally interesting POI mainly influenced by the global offset and the users and items rating bias.

### 3.2. Integrating Rating with Review: Latent Dirichlet Allocation (LDA)

LDA uncovers hidden dimensions in a review text from which characteristics such as categories, quality and services of a POI reviewed by users can be deduced. We add an LDA component to our basic model as a regularizer so as to control $U_i$ (user latent vector) by giving us more information about the user. Therefore, our optimization problem changes to the following:

$$
\min_{U_f, P_j, \phi} \sum_{(i,j) \in R} (R_{i,j} - \text{rec}(i, j))^2 + \lambda_1(R) + \lambda_{\text{rev}} \sum_{u \in D} \sum_{v \in N_u} \log \theta_{u,v} \phi_{u,v} w_{u,v} \tag{3}
$$

where LDA parameters $\theta$ and $\phi$ denote the topic and word distributions, respectively; $w_{u,v}$ and $\theta_{u,v}$ are the $n^{th}$ word occurring in user $u$ and the corresponding topic, and $\lambda$ control contribution of the LDA regularization term addition effect of the user review. $R$ represents the regularization terms $||U_i||^2 + ||P_j||^2 + \beta_i^2 + \beta_j^2$. Ratings and reviews are fused through this transformation;

$$
\theta_{i,f} = \frac{\exp(\kappa U_{i,f})}{\sum_f \exp(\kappa U_{i,f})} \tag{4}
$$

where the parameter $\kappa$ is used to control the quality of the transformation being peaky and $\sum_f$ is the summation across each latent topics $f$. In this transformation we expect that the real valued parameters in the user preference vector $U_i$ associated with ratings to be transformed to the probabilistic ones $\theta_i$ associated with the reviews. We adopt the Hidden Factors as Topics (HFT) algorithm [3] as a component of our proposed system.

### 3.3. Integrating Social Influence

Most LBSNs recommendation system only consider direct friendships or users with physically overlapping visits to POI as a basis for social influence to improve accuracy [1][4][5][6][7]. However, they are less effective when a targeted user has very few social connection or location history. We use a weighted hierarchical category approach developed in [8] to model user preferences to form a basis for similarity comparison between users irrespective of their geographical region. We extend this similarity computation in [8] to add user reviews to add more descriptive understanding of a users preference. We use LDA Model to discover users to words interaction and we achieve the optimal solution using the Gibbs sampling. Using this similarity information we build our similarity matrix $S \in \mathbb{R}^{n \times k}$ containing similarity between any two users $i$ and $k$. This matrix assists us in providing additional information for building a neighborhood of similar users to offer social influence hence local opinion in a new geographical region unfamiliar to the
3.4. Integrating POI Characteristics

In LBSNs a POI characteristics affects its rating \([9][10][11]\). Therefore the more information we have about a POI the more accurate a recommendation of a particular POI. In this study, we assume a users rating to a given business is determined by its intrinsic and extrinsic characteristics of its geographical neighbors. Therefore, we divide the POI into latent factors of extrinsic properties \(Q \in R^F\) its geographical neighbors and latent factor of intrinsic properties \(D \in R^F\) its categories and rating of its neighbors.

Several studies \([4][8][12][13][14][15][16]\) have linked geographical influence to improving POI recommendation systems. Therefore, we incorporate the geographical neighborhood influence to improve the accuracy of business rating prediction. Let \(N_i\) be a set of geographical neighbors for a business \(i\), satisfying certain criterion selection (e.g. the top ten nearest neighbors). Let \(n \in N\) be neighbors of business \(i\). We consider POI category to be important because it gives an indication of the services or activities that take place or the way the business is conducted at a POI. We annotate the POI with a category information by integrating a category latent factor vector \(D \in R^F\) per category. This implies that similar category of POI tend to influence each others rating. This gives us our new prediction ratings computation;

\[
\text{rec}(u, p) = \alpha + \beta_i + \beta_j + U_i \cdot (P_j + \frac{\alpha_1}{|N_i|} \sum_{n \in N_i} Q_n + \frac{\alpha_2}{|D_j|} \sum_{c \in C_j} D_c)
\]

(6)

where \(\alpha_1\) and \(\alpha_2\) are weights that control the importance of the influence of the geographical neighborhood, and \(|N_i|\) and \(|D_j|\) denoting the cardinality of the set of neighbors. We add \(Q_n\) and \(D_c\) to the objective function as regularization terms as shown;

\[
\begin{align*}
\min_{U, P, \beta, \alpha} & \sum_{(i, j) \in R} (R_{i,j} - \text{rec}(i, j))^2 + \sum_{u \in D} \sum_{n \in N_u} \log \theta_{u,n} \Phi_{u,n} \\
& + \lambda_\text{rel} \sum_{k \in N(i)} (S_{i,k} - U_i^T H U_k) + \lambda_1 \|R\| + \lambda_2 (\|H\|)
\end{align*}
\]

(5)

where \(S_{i,k}\) is the similarity between two user \(i\) and \(k\), \(U\) is the user vector from the user latent factor matrix and \(H\) is the social correlation matrix. \(\lambda_\text{rel}, \lambda_1\) and \(\lambda_2\) are introduced as weights to control the contribution of the social correlation and over-fitting respectively.
to a great extent. We model popularity $p_j$ using [17] normalized popularity score and integrate it to our recommendation model as shown:

$$
rec(u, p) = \alpha + \beta_i + \gamma p_j + U_j, (P_j + \frac{\alpha_1}{|N_j|}) \sum_{i \in N_j} Q_n + \frac{\alpha_2}{|D_j|} \sum_{c \in C_j} D_c)
$$

(8)

where $\gamma$ controls the contribution of the popularity $p_j$ to the prediction rating.

4. Model training

Finally, our objective function that we wish to optimize in order to make accurate prediction is as follows.

$$
Y(\Theta, \Phi, z, \kappa) \triangleq \min_{U, P, \Theta, \Phi} \sum_{i \in R} (R_{i,j} - rec(i, j))^2 + \lambda \Omega(\Theta)
$$

rating error

$$
+ \lambda_{rec} \sum_{u \in D} \sum_{n \in N_u} \log \theta_{n} \phi_{n, u} + \lambda_{rel} \sum_{k \in N(i)} (S_{i,k} - U_k^J H U_k)
$$

local/social opinion

(9)

where $\text{argmin}_{\theta, \phi, z, k} Y(\Theta, \Phi, z, \kappa)$ is our objective function which we wish to minimize. $\Theta$ represents the parameter set $\{U, P, H, Q, D, \gamma\}$ i.e. the users, POI, social correlation, POI neighbor and category latent factors which are associated with the ratings and social relation and $\Phi$ represents the parameters $\{\theta, \phi\}$ associated with the review text. Parameter set $\{z, \kappa\}$ are the latent topics and controller for transformation between ratings and reviews. $\lambda \Omega(\Theta)$ are the regularization terms as follows:

$$
\lambda \Omega(\Theta) = \lambda(||\alpha||^2 + ||P||^2 + ||\beta||^2 + ||\gamma||^2 + \sum_{n \in N_j} ||Q_n||^2 + \sum_{c \in C_j} ||D_c||^2 + ||H||^2)
$$

(10)

We use stochastic gradient descent approach (GD) to find our optimal solution. The connection between ratings and social influence is the realized through the users latent feature space $U$, and ratings and reviews are linked through the transformation involving $U$ and $\theta$ through equation 4.

Our objective function optimal solution can be found by gradient descent and the latter by Gibbs sampling; so, we design a procedure alternating between following two steps;

$$
\text{update } \Theta^{new}, \Phi^{new}, k^{new} = \text{argmin}_{\theta, \phi, z, \kappa} Y(\Theta, \Phi, z, \kappa)
$$

(11)

sample $z_{n, d}$ with probability $z_{n, d} = f = \theta_{f, n}^{new}$

(12)

The first step Equation 11. we fix the sampling phase or topic assignments for each word in reviews corpus as we update the terms $\Theta, \Phi$ and $\kappa$ by gradient descent. $U$ and $\theta$ depend on each other; we fit only $U$ and then determine $\theta$ by equation 4. The second step equation 12, all parameters associated with reviews corpus $\theta$ and $\phi$ are fixed; then we sample topic assignments by iterating through all docs $d$ and each word within, setting $z_{n, d} = f$ with probability proportion to $\theta_{f, n} \theta_{f, n}$. This is similar to updating $z$ via LDA except that topic proportions $\theta$ are not sampled from a Dirichlet distribution, but instead are determined using equation 11. Finally, these two steps are repeated until a local optimum is reached.
5. Experimental results

In this section, we provide an empirical evaluation of the performances of the proposed model.

5.1. Experimental dataset

We evaluated our model using the Yelp Dataset Challenge\(^1\) comprising of; 2.2M reviews and 591K tips by 552K users for 77K businesses; 566K business attributes, e.g., hours, parking availability, ambience; Social network of 552K users for a total of 3.5M social edges; Aggregated check-ins over time for each of the 77K businesses; 200,000 pictures from the included businesses. This dataset is collected from 10 cities belonging to 4 countries. We selected Phoenix and Las Vegas based on their relatively larger amounts of ratings and reviews data coupled with a high number of overlapping users (users with activities in both cities). In our experiments target users are considered as the users from Phoenix with ratings in Las Vegas and vice versa. It should be noted that for simplicity we consider a city as our geographical region for testing. The dataset statistics for the two cities are shown in Table 1. The Yelp dataset provided does not explicitly contain a users home location or address. Therefore, users most active city is assumed to be users home location. A users activity refers to the total count of ratings and reviews left by the user at POIs in a given city. We use the local ratings/reviews as the training set, including 1-3 foreign reviews for our target users and use the remaining set of foreign ratings and reviews as test data.

| Statistic                      | Phoenix | Las Vegas |
|-------------------------------|---------|-----------|
| #users with review            | 65191   | 173703    |
| #Reviews/rating               | 219828  | 617352    |
| #Businesses                   | 8406    | 13592     |
| #users with review            | 65191   | 173703    |
| #Min/Max review per Business  | 1/1354  | Jan-37    |
| #foreign Reviews/ratings      | 78948   | 195205    |
| #Min/Max review per User      | 1/607   | 1/1126    |

5.2. Evaluation Metrics

We adopt the Mean Absolute Error (MAE) and normalized MAE (rMAE) to measure the accuracy of predicted ratings which measures the average absolute deviation between a predicted rating and the users true ratings. MAE is defined as follows;

\[
MAE = \frac{1}{|N|} \sum_{i \in P_j} |\hat{R}_{i,j} - R_{i,j}| \tag{13}
\]

where \(|N|\) denotes the number of tested ratings, \(R_{i,j}\) is the real rating, and \(\hat{R}_{i,j}\) is the predicted rating. This approach is used because the predicted rating values create an ordering across the items, predictive accuracy can also be used to measure the ability of a recommender system to rank items with respect to user preference\(^[1]\).

\(^1\)https://www.yelp.com/dataset_challenge
5.3. Experimental Evaluation

To evaluate the effectiveness of our proposed solution, we compare it with the following baseline approaches; User-KNN [18][19] and Item-KNN [18], we set the neighborhood size \( k = 150; \) User Cluster(UC)[4]; CKNN [5]; SVD++[20]; HFT[3]; and our model NRLRS. We use librec\(^2\) a recommendation system library in java for algorithms implementation and extension[21]. For all the latent factor models we set the default factor \( K = 10 \) otherwise stated. We set the learning rate \( \omega = 0.0005, \) momentum \( = 0.8 \) and the weights \( \lambda_{rel} = 0.0025 \) and \( \lambda_{rev} = 0.05 \). The results for the two cities in table 2 show the neighborhood models UKNN and IKNN as the least performing models. This is expected because when a user moves to a geographical region where they have little or no activity history due to limited information to match them with other users. Neighborhood approaches consider overlapping visited POI/items between users to determine similarity in preferences therefore this information is limited for a user with few ratings leading to a cold–start problem. CKNN and User Clusters methods performance is slightly better because in this approaches we incorporate users category preferences from previous cities activity history to build a user preferences. The latent factors models (HFT and NRLRS) outperform the neighborhood models because of ability to exploit and incorporate active users reviews from their previous geographical region into the new region. Our NRLRS incorporates variety information which helps us model POI properties and user preferences better for a new user in addition to integrating the neighborhood model feature of social influence. Different cities show different prediction accuracy values due to difference in the datasets statistics and patterns specific to individual cities, however the consistency in performance is shown across the different algorithms.

We test for performance of the latent factor models by varying the number of latent factors assigned. Thus, we adjust the number of latent factors and record the prediction accuracy results for each algorithm per city. This is tested with respect to the earlier wisdom that latent factor model tend to use more factors, hence an increase in the factors is expected to show an increment in ratings prediction[22]. We show the results in table 3. We use MAE to test the variation of the accuracy with the increase in the number of factors. The accuracy of SVD++, HFT and NRLRS do not show much variation with a change in the number of latent factors \( K \) and show stability across different size of \( K \). We adopt \( K = 10 \) as a default for experimental evaluation because it gives the best prediction results.

We further investigate the impact of social local opinion, POI properties and Reviews. We define

\[
\begin{array}{|c|c|c|c|c|}
\hline
\text{Algorithm} & \text{Phoenix} & \text{Las Vegas} \\
 & \text{MAE} & \text{rMAE} & \text{MAE} & \text{rMAE} \\
\hline
\text{UKNN} & 1.042772 & 0.983292 & 1.12693 & 1.058478 \\
\text{IKNN} & 1.045428 & 0.995892 & 1.123261 & 1.061438 \\
\text{UC} & 1.011951 & 0.968673 & 1.084291 & 1.054004 \\
\text{CKNN} & 1.040173 & 0.977881 & 1.125108 & 1.055962 \\
\text{SVD++} & 0.917106 & 0.893522 & 0.974019 & 0.949973 \\
\text{HFT} & 0.905218 & 0.877944 & 0.961174 & 0.935082 \\
\text{NRLRS} & 0.899781 & 0.870802 & 0.955040 & 0.929162 \\
\hline
\end{array}
\]

\(^2\)https://www.librec.net/
Table 3: Prediction Performance by varying number of latent factors (MAE)

| Factors (K) | Phoenix | Las Vegas |
|------------|---------|-----------|
|             | SVD++  | HFT      | NRLRS | SVD++  | HFT      | NRLRS |
| 5           | 0.916287 | 0.905274 | 0.899798 | 0.973807 | 0.961213 | 0.955177 |
| 10          | 0.917106 | 0.905218 | 0.899781 | 0.974019 | 0.961174 | 0.95504  |
| 20          | 0.917182 | 0.905291 | 0.899883 | 0.974787 | 0.961932 | 0.955783 |
| 50          | 0.917237 | 0.905233 | 0.899907 | 0.975496 | 0.962651 | 0.956517 |

Table 4: Impact of Components (MAE)

|                  | Phoenix | Las Vegas |
|------------------|---------|-----------|
| NRLRS/Rev        | 0.905218 | 0.904739  |
| NRLRS/Social     | 0.915097 | 0.915097  |
| NRLRS/Social/Rev | 0.901132 | 0.901132  |
| NRLRS/POI        | 0.899781 | 0.899781  |

our algorithms as followings; NRLRS/Rev: Consider all features but the reviews component, set \( \lambda_{rev} = 0 \); NRLRS/Social: Considers all feature but the Social Relations component, set \( \lambda_{rel} = 0 \); NRLRS/Social/Rev: Considers features all but the social relation and review features by setting \( \lambda_{rev} = 0 \) and \( \lambda_{rel} = 0 \); and NRLRS/POI: Considers all features but the POI properties by setting \( \alpha_1 = 0 \) and \( \alpha_2 = 0 \). We show the results in Table 4. Performance degrades when any of the components is eliminated demonstrating the importance of each components contribution to the entire model. We note that our model performance without the proposed integrated components shows a performance comparable to SVD++ algorithm across the two cities. Further, we note that reviews (NRLRS/Rev) show a very strong contribution as the performance of the algorithm significantly degrades when removed.

Our proposed model shows small improvements in the accuracy, they are significant in recommender systems, as [20] provides evidence that even a small improvement in a rating prediction error can affect the ordering of items and have significant impact on the quality of the top few presented recommendations and thus the overall performance of the recommender system.

6. Conclusion

We demonstrate that our proposed solution achieves a higher prediction accuracy than the current state of the art. This is especially true in our set context of exclusively considering users traveling to new geographical regions; in the case of our datasets Phoenix users traveling to Las Vegas and vice versa. Our algorithm outperforms the recommendation techniques from both cities.

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