HiCaPS: Hierarchical Contextual POI Sequence Recommender

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ABSTRACT

The Point-of-Interest (POI) preference of a user varies by locality, item type, and the co-visitors, e.g., $user_1$ and $user_2$ can have closest preference on *food* items but not on *historic* sites, etc. A locality can have different preference trends (e.g., popular for food, recreation, etc.) and a user's preference can span across multiple such trends. A good recommender should also exploit the aggregated locality preference trends. Most of the existing studies group items by category or global user preferences which might not be relevant for locality-based aggregated preferences. We propose **HiCaPS** (**Hi**erarchical **C**ontextual **P**OI **S**equence Recommender) that formulates user preferences as hierarchical structure and presents a hierarchy aggregation technique for POI recommendation. The top level of locality hierarchy contains preferred k items from a set of users and the subsequent levels contain preference wise subsets. The core contributions of this paper are: (i) it formulates user preferences as a preference hierarchy, presents a technique to aggregate preference hierarchies of a similar users, and models the target users' preference in terms of aggregated trend in a locality, (ii) it contextually exploits the aggregated trend to generate personalized POI sequences, and (iii) it extensively evaluates the proposed model with two real-world datasets and demonstrates performance gain (0.03 - 0.28 on pair F-score, 0.006 - 5.91 on diversity, 0.0349 - 17.51 on displacement, and 0.114 - 0.289 on NDCG) over baseline models.

CCS CONCEPTS

• **Information systems → Location based services**;

KEYWORDS

Hierarchical recommender; Social Networks; POI Recommender

ACM Reference Format:
Ramesh Baral, S. S. Iyengar, Tao Li, XiaoLong Zhu. 2018. HiCaPS: Hierarchical Contextual POI Sequence Recommender. In *Proceedings of 26th ACM SIGSPATIAL International Conference on Advances in Geographic Information Systems (SIGSPATIAL '18).* ACM, New York, NY, USA, 4 pages. https://doi.org/10.1145/3274895.3274925

SIGSPATIAL '18, November 6–9, 2018, Seattle, WA, USA

ACM ISBN 978-1-4503-5889-7/18/11…$15.00
https://doi.org/10.1145/3274895.3274925

1 INTRODUCTION

The POI check-ins are influenced by many contexts [1, 2], such as visit locality, co-visitors (e.g., friend, family, etc.), time of day, etc. The existing systems focus on categorical or global consumption hierarchy which needs to be extensive to incorporate the user preferences. The extensive global hierarchies are not only difficult to obtain but are also difficult to model and computationally expensive. This can be handled by segregating the hierarchy to semantical subsets of items. We attempt to address the contextual and locality preferences by modeling user preferences using the locality they visit. Figure 1a presents the scenario where preferences of user u_1 matches with u_2 and u_3 for *item type2* and with u_2 and u_6 for *item type1* but not with u_2 for *item type3*. For POI domain, the region/locality based separation represents locality specific set of POIs that have similar trend of attractions. In this paper, we exploit such semantic hierarchy for POI sequence recommendation. Such hierarchies can be adapted by many interesting applications, e.g., *personalization*, *question answering*, *knowledge discovery*, *preference-based association mining* (e.g., upper level of hierarchy can yield generic rules as: "20% of users who visited a *Restaurant* are most likely to visit a *Coffee Shop*"and the lower levels yield specific rules, such as "10% of users who visited "*Townhouse Grill*" (a restaurant) are most likely to visit the "*Starbucks*" (a coffee shop)").

Unlike the traditional categorical hierarchy of items, we represent the user preferences as hierarchical structures where the top level contains the k preferred items for a set of users and the lower levels contain their subsets. For a target user, the closest matching k clusters of former visitors in a locality are discovered. The hierarchical preferences of these clusters are generated, aggregated, and used for recommendation. The main contributions of this paper are: (i) it models the user locality preferences as hierarchical structure, (ii) it presents a hierarchy aggregation technique to model the aggregated preferences of multiple sets of users in a locality and contextually exploits the aggregated hierarchy for POI sequence recommendation, and (iii) it demonstrates the efficiency of proposed model with pair F-score, diversity, displacement, and NDCG metrics on two real-world datasets.

2 RELATED RESEARCH

Most of the existing studies exploited collaborative filtering [3], apriori principle [3], matrix factorization [4], topic-modeling [5], tree-based approaches [6], and neural networks [7]. Wang et al. [8] handled crowd constraints (e.g., peak hours of POIs) by extending the Ant Colony Optimization algorithm. The ranking model [9] personalized travel sequences in different seasons by merging textual data and viewpoint information extracted from images but ignored social and temporal preferences. Lim et al. [10] exploited

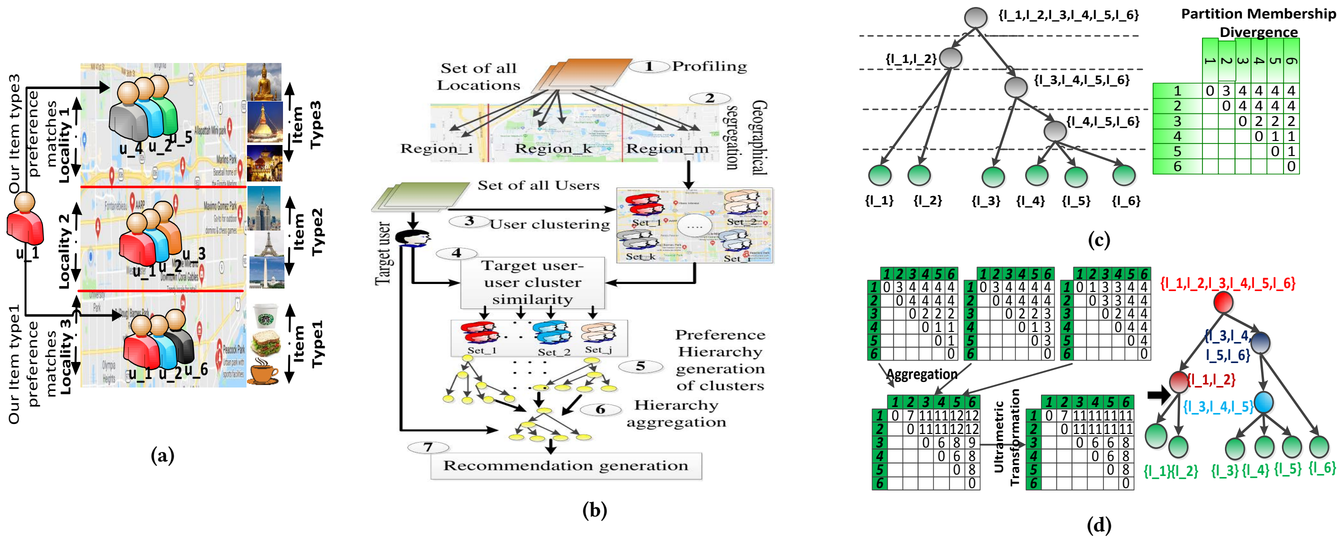

Figure 1: (a) user locality preferences, (b) high level overview of HiCaPS, (c) dendrogram descriptor and PMD derivation, (d) PMD aggregation and ultrametric transformation

Terms	Definition
$V_i = (l_i, a_i, d_i)$	check-in triplet for POI (l_i), arrival time (a_i), and departure time (d_i)
$\mid V_{u,i} \mid$	no. of check-ins of user u to POI i
$U, L, l.cat, u_f$	users, locations, category of location l, friends of user u
$ST(i) = \frac{1}{\lvert U\rvert} \sum_{\substack{u \in U \\ i \in L_u}} \frac{1}{\lvert V_{u,i}\rvert} \sum_{l \in V_{u,i}} (a_{l+1} - TT(l, l+1) - a_l)$	average stay time to POI i, $TT(a, b)$ is travel time between POI a and b
$AST(u, i) = (1-\alpha) * \sum_{i \in L_u} \frac{ST'(i)}{\lvert V'_{u,i}\rvert} + \alpha * \sum_{\substack{l \in L_u \\ l.cat = i.cat}} \frac{ST'(l)}{\lvert V'_{u,l}\rvert}$	aggregate stay time by category influence
$AST(u, i) = (1-\psi_1) * AST(u, i) + \psi_* \sum_{k \in u_f} AST(k, i)$	aggregate stay time by social influence
$PS(u, l, t) = \beta * \{(1-\theta) * \sum_{l \in L} \frac{\lvert V'_{u,l,t}\rvert}{\lvert V'_{u,l}\rvert} + \theta * \sum_{\substack{l' \in L \\ l'.cat = l.cat}} \frac{\lvert V'_{u,l',t}\rvert}{\lvert V'_{u,l'}\rvert}\} + (1-\beta) * AST(u, l)$	preference score of a user to a POI l at time t
$P(u, l, t) = PS(u, l, t) * (1 - \frac{1}{m} \sum_{i=1}^{m} Const_i(l, p))$	constraints penalized preference score, $Const_i(l, p)$ is normalized numeric measure of i^{th} constraint between locations p and l
θ, γ, β	constants between 0 and 1

Table 1: Terms used in the paper

geo-tagged images and contexts, such as visit duration, users' preferences, and start/end POIs to define time-based user preferences but ignored the categorical, temporal, and social constraints. A probabilistic model [11] used Rank-SVM to rank the items and used Markov model to predict the transition between POIs. Most of the existing studies have exploited few contexts and have focused on personalized POI visit durations. To the best of our knowledge, none of the previous studies have exploited locality-based hierarchical preference aggregation for contextual POI sequence generation.

3 METHODOLOGY

The terms used are defined in Table 1 and the high-level overview of proposed model is shown in Figure 1b and are defined next:

User and Location Profiling: A location profile is concatenation of the category vector $\langle c_1, c_2, .., c_i \rangle$, distance vector $\langle d_1, d_2, .., d_j \rangle$, and time vector $\langle t_1, t_2, .., t_k \rangle$. The vector value depends on its type (e.g., index of t_1 has the frequency of check-ins at time t_1 on this place, index of c_1 is set to 1(0) if the place is (is not) of category c_1, distance vectors use values as 1 Km, 5 Km, 10 Km, and more than 10 Km, time vector uses hourly values) and are normalized before concatenation. The user profiles are obtained similarly and contain the element's relevant frequency, e.g., c_1 represents the number of check-ins of the user to category c_1, etc. As a user preference varies by aspects (e.g., "Distance" over "Price"), they are weighted (using the frequency of check-ins). The preference of a user on feature f_i is defined as $pref(u, f_i) = \frac{\lvert V_u \rvert}{\phi(u, f_i)}$, where $\lvert V_u \rvert$ is the total visits made by user u and $\phi(u, f_i)$ is the count of unique feature f_i from her visits. For a group $G = \{(u_1, w_1), (u_2, w_2), ..., (u_m, w_m)\}$, where each pair represents a user's profile and the preference of a user to the group G, the aggregated profile $\mathcal{P}(G)$ is defined as: $\mathcal{P}(G) = \frac{1}{m}(\frac{w_1}{w} u_1 + \frac{w_2}{w} u_2 + \ldots + \frac{w_m}{w} u_m)$, where w_i is the fraction of check-ins from u_i that contribute to the group G, and $w = \sum_{i=1}^{m} w_i$. As user preferences vary by regions, we define user clusters for each region and incorporate preferences of users on the regions.

Geographical clustering: Inspired from [12], we divide locations into L uniform grids $\mathbb{L} = \{g_1, g_2, .., g_L\}$using Haversine Formula.

User clustering for each region: The visitors of each region are soft clustered to model the check-in preferences of similar users. A Gaussian mixture model is used to define a probabilistic model for cluster membership of each object as: $p(x_i \mid K) = \sum_{k=1}^{K} \pi_k g_k(x_i)$, where $g_k(x_i) = \mathcal{N}(x_i \mid \mu_k, \mathrm{Cov}_k)$ is the Gaussian distribution with mean μ_k and covariance matrix Cov_k, π_k is the prior distribution, K is the number of clusters, and $\sum_k \pi_k = 1$. Each of the Gaussian distribution component represents a locality of user activity and the mean value denotes the latitude and longitude of the locality center which can be user's favorite place. The parameters of the model and the membership can be determined by maximizing: $l(K) = \sum_{i=1}^{n} log(p(x_i \mid K))$ by *Expectation-Maximization (EM)* algorithm.

Target user and user cluster similarity: It is computed using cosine similarity between user profile and cluster profile.

Hierarchy of user clusters: Given a set of places in a region, the hierarchy represents check-in preferences of a user cluster and a node of the hierarchy represents some implicit preference association. Inspired from [13], the hierarchy is created using the conditional mutual information (CMI) metric [14] which gives the expected value of the mutual information of POI X and Y on the cluster C_i as: $CMI(X;Y|C_i) = H(X,C_i)+H(Y,C_i)-H(X,Y,C_i)-H(C_i)$, where the function $H(.)$ denotes an entropy. $H(X,C_i)$ is the fraction of check-ins to POI X that are contributed by members of C_i, $p(X,C_i) = (\alpha + \sum_{u \in C_i} \mid V_{u,X} \mid)/(\alpha * N + \mid V_X \mid)$ and $H(X,C_i) = -p(X,C_i)\log_2(p(X,C_i))$, where $\alpha > 0$ is a smoothing factor, N is the total number of users. $H(X,Y,C_i)$ depends on fraction of check-ins from members of C_i who have visited both X and Y. $H(C_i) = -p(C_i)\log_2(p(C_i))$, where $p(C_i) = \frac{1}{K}$ and K is the number of user clusters to be used. The CMI metric of a user cluster facilitates incorporation of the cluster preference to X and Y and can be transformed into region/locality specific places similarity matrix by setting the diagonal entries to 1 and normalizing other entries. The hierarchy of a cluster is obtained by complete link clustering because it is less susceptible to noise and outliers.

Algorithm 1 FindTransitiveDissimilarityMatrix

```
Input G: a pair-wise distance matrix, Output H: minimum transitive dissimilarity matrix closure of G, Initialize H to G
for k=1 to N do
    for i=1 to N do
        for j =1 to N do
            H_{i,j} = min(H_{i,j}, max(H_{i,k}, H_{j,k}))
```

Hierarchy aggregation: For a target user, the hierarchies of top-k matching clusters are ensembled. Among many popular descriptors, partition membership divergence (PMD) which gives the number of partitions in which the two objects in the hierarchy are not assigned together to a group is better [15]. Figure 1c illustrates the PMD computation of a hierarchical structure. The element-wise aggregated PMD (see Figure 1d) might not be ultrametric (a special property that is more strict than triangle inequality) and might not merge the closest clusters, yielding an incorrect topology. To get a correct topology, we need to transform it into an ultrametric form which is an approximation of the distance matrix that can be derived from the aggregated PMD. Any distance matrix $dist_{ij}$ is ultrametric *iff* the following conditions hold: (i) non-negativity ($a \neq b, dist(a,b) > 0$), (ii) symmetry ($dist(a,b) = dist(b,a)$), and (iii) ultrametricity ($dist(a,c) \leq \max(dist(a,b), dist(b,c))$). The hierarchical clustering merges closest clusters C_i and C_j if:

$$dist(C_i, C_j) \leq min(dist(C_i, C_k), dist(C_j, C_k)), \quad (1)$$

$\implies \forall_{i,j,k}, min(dist(C_i,C_k), dist(C_j,C_k) \leq dist(C_i \cup C_j, C_k)$. This reducibility condition [16] illustrates that the merge takes place between closest pairs and maintains the initial merge order. As long as the reducibility condition is satisfied, the updated dissimilarities satisfy the ultra-metric inequality [16]:

$$dist(x_i, x_j) \leq max(dist(x_i, x_k), dist(x_j, x_k), \forall_{x_i, x_j, x_k \in X}. \quad (2)$$

We use the concept of transitive dissimilarity of any path P_{ij} between vertices V_i and V_j as:

$$T(P_{ij}) = max(dist(i, k_1), .., dist(k_{n-1}, k_n), dist(k_n, j)) \quad (3)$$

and the minimal transitive dissimilarity as the minimum of transitive dissimilarity among all paths between vertices V_i and V_j as: $m_{ij} = \min_{P_{ij}}(T(P_{ij}))$. The minimal transitive dissimilarity between any two vertices satisfy ultrametric inequality [17]. As minimal transitive dissimilarity satisfies ultrametric inequality: $m_{ij} \leq max(m_{ik}, m_{jk}), \forall_{i,j,k}$ [13], we use modified Floyd-Warshall algorithm [18] to find the new transitive dissimilarity matrix that is closest approximation of the original matrix and is ultrametric. Algorithm 1 shows the transformation of aggregated PMD matrix. Figure 1d shows the aggregation and ultrametric transformation.

Recommendation generation: The ensembled hierarchy for a region is traversed to find the best match between the target user profile, current context, and the items at each level. Given a user's current location, first the k-nearest regions are identified. The trees of these regions are then traversed using the current context and preference score of the user. From the best matching leaf node (i.e. a set of locations that satisfy the context across the path/branch with maximum score), the location with highest preference score is added to the sequence. The items already added to sequence are ignored. One option is to perform DFS (depth first search) on the same hierarchy to generate all items in the sequence (known as **HiCaPSI**). As removing an item from the item pool can effect the user clusters, we can repeat user clustering, hierarchy generation and hierarchy aggregation (known as **HiCaPSII**).

Models		Precision Pair	Recall Pair	Pair-F1	Diver-sity	Displa-cement	NDCG@10
Weeplaces	Popularity	0.30000	0.16666	0.21428	1.20000	23.30785	0.2867
	Apriori	0.46079	0.23088	0.30762	1.90000	13.00000	0.2921
	Markov	0.49411	0.24711	0.32945	2.50000	11.72130	0.2979
	HITS [19]	0.49981	0.27336	0.35342	4.00000	10.55233	0.3107
	HGMF [20]	0.60000	0.39011	0.47280	6.39700	8.62700	0.4210
	HiCaPSI	0.62422	0.41970	0.50192	**7.11820**	8.22990	0.5565
	HiCaPSII	0.67771	0.43100	**0.52690**	7.09120	**7.77014**	**0.5771**
Gowalla	Popularity	0.36442	0.20010	0.25834	3.20000	25.22877	0.2885
	Apriori	0.46922	0.24276	0.31997	3.33500	13.00000	0.2973
	POI-Markov	0.49993	0.24981	0.33314	3.50000	11.22113	0.2989
	HITS [19]	0.50653	0.27993	0.36058	4.00000	11.11224	0.3137
	HGMF [20]	0.56555	0.40831	0.47423	6.33830	9.50310	0.4251
	HiCaPSI	0.60914	0.43000	0.50412	8.44765	7.77669	0.5625
	HiCaPSII	0.67112	0.44462	**0.53487**	**8.45001**	**7.71001**	**0.5791**

Table 2: Performance of models with different metrics

4 EVALUATION

The dataset[1] was collected from two popular LBSNs - Weeplace and Gowalla. The former has 7,658,368 check-ins from 15,799 users on 971,309 different locations and the latter has 36,001,959 check-ins from 319,063 users on 2,844,076 locations. We used the **pairs-F1** [11] metrics that considers both the POI identity and its order by using the F1 score of every pair of POIs in a sequence: $pairs{-}F1 = \frac{2 * P_{PAIR} * R_{PAIR}}{P_{PAIR} + R_{PAIR}}$, where P_{PAIR} is precision and R_{PAIR} is recall of the ordered POI pairs. The **displacement** measures the distance between predicted sequence (seq_a) and actual sequence (seq_e): Displacement $(seq_a, seq_e) = \sum_{i=1}^{|seq_e|} \mid \text{Distance}(seq_{a_i}, seq_{e_i}) \mid$. The **diversity** of locations measures the categorical similarity (i.e. Similarity is 1 if two places have same category and 0 otherwise). More diversity implies more POI categories: Diversity $(c_1, c_2, ..., c_n) = (\sum_{i=1}^{n} \sum_{j=i+1}^{n} (1 - \text{Similarity } (c_i, c_j)))/(\frac{n}{2} * (n-1))$.

[1] http://www.yongliu.org/datasets/

Evaluation Baselines: 1) *Popularity*: It selects the POI with highest check-in frequency, (2) *Markov Model*: It uses first order Markov Chain on Laplace smoothed state-transition matrix and initial probability matrix derived from check-in data and personalized for each user, (3) *Apriori* [3, 21]: The most frequently checked-in place of a user is used as a starting point and places within a threshold distance (ϵ) are used to get candidate sets. The top-k trips with: (i) ≤8 hours travel time (lower travel times preferred) and (ii) higher trip score (i.e. preference scores, see Table 1) (4) *HITS* [19]: The locality preferences are incorporated by hierarchically organizing locations into regions. The inference is made from the adjacency matrix between users and POIs for the region. The score of a sequence is determined using the hub scores of visitors of the sequence and authority scores of POIs weighted by the probability that people would consider the sequence. (5) HGMF [20] modeled the hierarchical relation between user and item latent factors.

Experimental Results and Discussion: A 5-fold cross validation-based pair F-score, diversity, displacement, and NDCG performance is shown in Table 2, and the diversity and displacement trend with increasing sequence length is shown in Figure 2. The non-personalized models (Popularity and Apriori) performed low. The Markov model relied on one previous check-in data to determine next location and was not able to fully model the check-in sequence generation. However, it outperformed Popularity and Apriori models which is due to the personalization implied from separate initial-probability and state-transition tables for each user. The HITS model outperformed Markov model. As it relied on separation of places into regions and authority and hub scores of places and users within the regions, its performance depends on the region generation approach. We used a radius of 10 Km from a specified location to generate such regions. Its performance with the radius of 5 Km and 15 Km was on par with Popularity model. **HiCaPSII** outperformed all other models except HiCaPSI in diversity on Weeplace dataset.

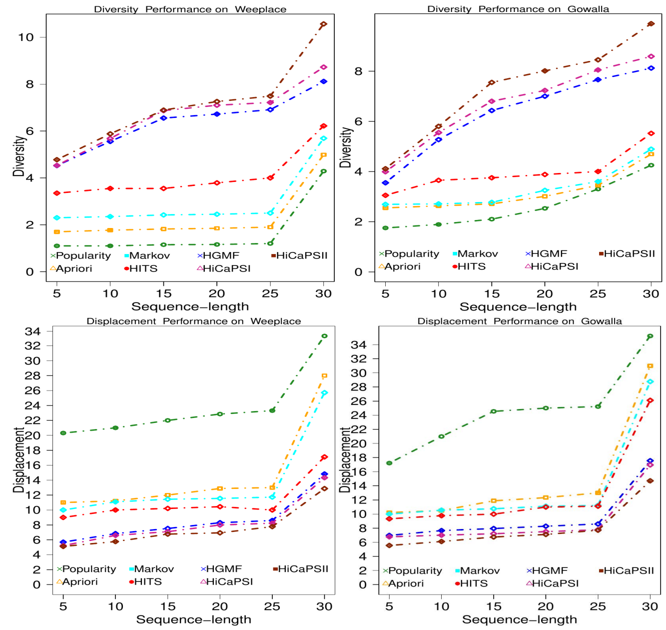

Figure 2: Diversity and Displacement trends of models

5 CONCLUSION AND FUTURE WORK

We formulated contextual and locality-based preferences as a hierarchy, presented hierarchy aggregation technique to model the preference trend of locality and incorporated different contexts for POI sequence generation. The evaluation metrics demonstrated efficiency of proposed models on two real-world datasets. As a future work, we would like to incorporate image and text attributes and also extend the model for knowledge discovery process.

Acknowledgment: This research is partially supported by U.S. Army Research Lab with grant no. W911NF-12-R-0012 and by FIU Dissertation Year Fellowship.

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