Geographical Diversification in POI Recommendation: Toward Improved Coverage on Interested Areas

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ABSTRACT

In recommending POIs(Point-Of-Interests), factors such as the diversity of the recommended POIs are as important as accuracy for providing a satisfactory recommendation. Although existing diversification methods can help POI recommender systems suggest more diverse POIs, they lack "geographical diversification," which results in the concentration of the supposedly "diverse" recommended POIs on "a small portion" in areas where the target-user is most active. This is caused by the neglect of POI locations in the diversification, i.e., existing diversification methods try to diversify the categories of recommended items. However, geographical diversification is essential for users whose activity interests comprise many sub-areas and who require a variety of recommended POIs encompassing all their activity interests. In this paper, we propose a novel *proportional geographical diversification* method that recommends a variety of POIs located in the activity district of a user such that the variety of sub-areas in the district is proportional to the frequency of his/her activity in each sub-area. We compare the performance of the proposed method with existing diversification methods using real datasets. The evaluation result shows that no method except the proposed one can significantly increase geographical diversity at the expense of tolerable accuracy loss.

CCS CONCEPTS

• **Information systems → Information retrieval diversity**;

KEYWORDS

POI recommendation; Diversity; Geographical diversity;

ACM Reference format:
Jungkyu Han and Hayato Yamana. 2017. Geographical Diversification in POI Recommendation: Toward Improved Coverage on Interested Areas. In *Proceedings of RecSys'17, August 27–31, 2017, Como, Italy, ,* 5 pages.
DOI: http://dx.doi.org/10.1145/3109859.3109884

1 INTRODUCTION

While recommending items, the diversity of the recommended items is as important as the recommendation accuracy. For instance, books that span a variety of categories (genres) would interest an user more than books from a single popular category[30]. In recommending POIs(Point-Of-Interests), in addition to the diversity of POI categories, *geographical diversification (geo-diversifiation)* or the diversity of POI locations can also be considered. For example, when a user visits both a shopping area and an office area habitually, recommending POIs from both areas is better than recommending POIs from only one of the areas.

Geo-diversity is particularly useful in recommending POIs that are located in a user's activity districts such as near his/her workplace or along his/her commute line that consists of many sub-areas frequently visited by the user. Because of routine visits to activity districts[6], the various sub-areas in the district have similar visit probability regardless of the user's current location. Therefore, recommending POIs that are located near the current location - a popular form of mobile application - is less useful. Instead, recommending POIs by assuming that the user interest is distributed over many sub-areas in the district achieves a more satisfactory result. In contrast, a recommender that merely recommends POIs from only a small portion of the sub-areas will lose user interest. Although existing diversification methods[30][7][19] are capable of diversifying the category of POIs, they lack "geo-diversification," which results in the concentration of supposedly "diverse" recommended POIs on "a small portion" of the sub-areas where the target-user is most active.

To address the problem, we propose a novel *proportional geographical diversification* method that recommends a variety of POIs located in an user's activity district such that the variety of sub-areas located in a district is proportional to the frequency of user activity in each sub-area. The proposed technique can also be applied to any POI recommender system that has already been deployed.

We describe related work in Section 2. A detailed description of geographic diversification is provided in Section 3. We report the evaluation results and conclude our paper in Section 4 and Section 5, respectively.

2 RELATED WORK

Our study is related to POI recommendation and recommendation result diversification. In this section, we briefly describe POI recommendation studies followed by a review of the current diversification methods.

POI recommendation: Most POI recommendation methods integrate aspects unique to POI with memory-based [24][27][26] or model-based Collaborative Filtering (CF) [5][15][8][16][10][25]. More specifically, aspects such as *user activity density over areas* [24][28][5][15][27], *suitable time of visit for each POI*[8][26], visiting trend of the public in each visited area[16][10][25], and social

RecSys'17, August 27–31, 2017, Como, Italy

DOI: http://dx.doi.org/10.1145/3109859.3109884

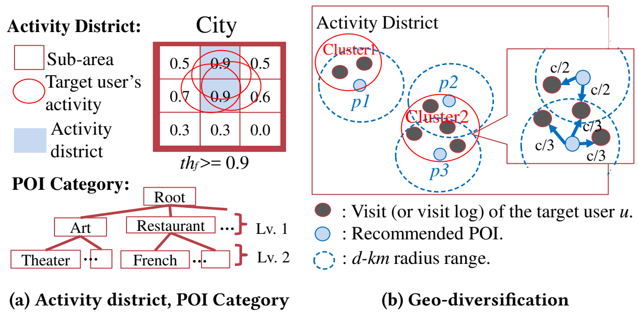

Figure 1: Activity district, POI category, and Geo-Div.

connections [24][28][5] were studied to improve POI recommendation performance. The above mentioned aspects were integrated with the design and evaluated with regard to improving the recommendation accuracy. Therefore, it is not clear if the existing POI recommendation studies can be directly applied to the geo-diversification problem that we are attempting to solve.

Result diversification: The concept of result diversification has been introduced to recommendation systems from the field of IR [30][22].

Re-ordering methods[30][7][19][2][12][3] achieve diversification by re-ordering the items in the recommendation list(*RecList*). An ordered RecList of the n items calculated from a base recommender is re-ordered on the basis of a given diversification objective, and then, the top-k ($k < n$) items in the re-ordered list are presented to the user as the final RecList. Since re-ordering methods are mainly designed for item "category" diversification, they are not directly applicable to "location" diversification. A specific group of re-ordering methods[30][2][3] that are based on pair-wise item distance can be applied to the location diversification objective by defining the "distance" as the geographic distance between two POIs. However, as a result, these methods simply recommend POIs that are located far from each other.

Modification of the CF algorithms to handle diversity has been proposed[11][17][1][18][21][23]. For instance, *Hurley et al.* [11] proposed a personalized ranking method that incorporates pair-wise dissimilarity of the items in the RecList. Graph-based diversification methods[13] and clustering-based diversification methods[29][14] that adopt graph and clustering algorithms, respectively, for recommended item diversification were also studied. However, these studies also did not consider the location of items. Furthermore, the cost incurred in applying these techniques to POI recommender systems that have already been deployed is high in comparison to applying re-ordering methods because "core" recommender algorithms must be modified.

3 GEOGRAPHICAL DIVERSIFICATION

In this section, we first define the important terms that are used in the following discussion, and then describe the proposed geo-diversification. We use lower case u to refer to the recommendation target user. Hereafter, *RecPOIs* represent individual POIs that need to be recommended, and *RecList* refers to the entire list of POIs to be recommended.

3.1 Activity district and POI recommendation

We first define u's activity district that indicates the set of the sub-areas frequently visited by u. In other words, the activity district represents the set of sub-areas where u's activity density is greater than a pre-defined threshold.

Sub-area: Sub-area $\boldsymbol{a}$ **indicates a 0.5** $\boldsymbol{km} \times$ **0.5** $\boldsymbol{km}$ **squared area** that covers a partial geographic area of a given city (ct). Upper case A indicates the set of all non-overlapping sub-areas that satisfy $ct = \sum_{a \in A} a$.

Activity Density: Activity density $\boldsymbol{\hat{d}_{u,a} \in [0,1]}$ in Eq.(1) indicates the estimated value of how frequently u visits a sub-area a, normalized for each u. Therefore, $\hat{d}_{u,a}$ becomes 1 (or 0) iff a is the most frequent (or rarest) visited sub-area of u. Here, $d_{u,a}$ in Eq.(1) indicates u's visit-probability density to a, which is calculated by using an Adaptive Density Kernel [28].

$$\hat{d}_{u,a} = \frac{log(d_{u,a} - \min_{a' \in A} d_{u,a'} + 1)}{log(\max_{a' \in A} d_{u,a'} - \min_{a' \in A} d_{u,a'} + 1)} \tag{1}$$

Activity District: We formally define the **activity district for each** $\boldsymbol{u}$ **as** $\boldsymbol{AD_u = \{a \in A | \hat{d}_{u,a} \geq th_f\}}$, as shown in the upper part of Figure 1a. RecPOIs are selected from the POIs located in $\forall a \in AD_u$. The goal of using AD_u is to find out all the sub-areas where u visits with some frequency. If th_f is too large, only one sub-area is selected. On the other hand, if th_f is too small, all the sub-areas in the city are selected. We empirically use $th_f = 0.9$ after manually evaluating the distribution of u's visit logs and the corresponding AD_u of randomly sampled users.

POI recommendation: A POI recommendation for u indicates a suggestion made to u that consists of k POIs selected from the POIs located in $\boldsymbol{AD_u}$.

3.2 Proportional geo-diversification

To achieve geo-diversification, **(R1)** the RecPOIs should be positioned in locations that are near to those visited by u. In addition, **(R2)** the ratio of the RecPOIs in some location should be proportional to the ratio of u's visits to the nearby locations. As shown in Figure 1b, we recommend three POIs to u who visited Cluster1 twice and Cluster2 four times, one POI was located close to Cluster1 and two POIs were located close to Cluster2.

To realize (R1) and (R2), we assign a distributable cover value c to each recommendable POI. When a POI p is considered as a RecPOI, c of p is evenly divided and distributed to each of u's visits located nearby (in the callout in Figure 1b). For each visit, if there are multiple RecPOIs located nearby, the distributed values from the RecPOIs are accumulated. In the ideal case, by recommending POIs that make all accumulated values on the visits equal, we can roughly satisfy (R1) and (R2) because the same proportion of RecPOIs are located nearby for each visit.

Alg. 1 and Table 1 describe the details of the aforementioned distribution procedure and the adopted symbols, respectively. A log $l \in < user, time, POI >$ is maintained on geographic space by using the location of POI in l. We use raw logs instead of activity density in Eq.(1) for each sub-area because sub-area based averaging is too

Table 1: Symbols

SYM	Explanation	SYM	Explanation
T_u	The set of u's visit logs located in AD_u.	s_l	The accumulated cover value on visit log l.
$R_{k,u}$	The set of k RecPOIs for u.	n_{NR}	The accumulated cover value could not be distributed to none of visit logs
d_p	The d-km radius range from POI p.	c_p	The cover value c possesed by POI p.
k	The number of RecPOIs.	v_l	The accumulated cover value on visit log l in the ideal case. $\forall_{l \in T_u} v_l = 1$.

Algorithm 1 Distributing c of each RecPOI to the user visits

procedure DISTRIBUTE-$c(T_u, R_{k,u}, d, k)$
Output: s_l and v_l for each $l \in T_u$, and n_{NR};
$\forall_{l \in T_u}(s_l \leftarrow 0, v_l \leftarrow 1)$, $n_{NR} \leftarrow 0$, $\forall_{p \in R_{k,u}} c_p \leftarrow |T_u| / k$;
for each POI $p \in R_{k,u}$ **do**
$loglist \leftarrow getLogs\_In\_Range\_d_p(d_p, T_u)$;
$count \leftarrow getTheNumberOfLogs(loglist)$;
if $count < 1$ **then** $n_{NR} \leftarrow n_{NR} + c_p/|T_u|$;
else, **for** each l in $loglist$ **do** $s_l \leftarrow s_l + c_p/count$;

coarse to locate RecPOIs.

To measure the uniformness of the cover value distribution over $\forall_{l \in T_u} s_l$, we use the proportionality metric PR_g (Eq.(2), $PR_g \in [0.0, 1.0]$) proposed by *Dang et al.*[7]. PR_g is the complement of the disproportionality metric DP_g (Eq.(3)) divided by its possible maximum value. Both the metrics are calculated using the result of Alg.1. Here, we write only $R_{k,u}$ in the input parentheses of the metrics for representing the expression concisely. Owing to the initial value assigned to c_p in Alg. 1, $\forall_{l \in T_u} v_l = 1$. f_l indicates the validity flag of disproportionality for log l. The value of f_l is 1 if $v_l \geq s_l$ and 0 otherwise. When the values of c_ps from all RecPOIs $p \in R_{k,u}$ are not uniformly distributed over the logs $l \in T_u$, DP_g becomes to 1, and hence, PR_g approaches 0.

$$PR_g(R_{k,u}) = 1 - DP_g(R_{k,u})/(|T_u| + 1/2) \quad (2)$$

$$DP_g(R_{k,u}) = \sum_{l \in T_u} f_l \cdot (v_l - s_l)^2 + n_{NR}^2/2 \quad (3)$$

3.3 Objective Function

In most of the re-ordering algorithms described in Section 2, re-ordering is carried out by greedy selection; the item(POI) that achieves maximum increment of the diversification objective at a given selection trial is selected from the item list calculated by a base recommender and then placed in the tail of the RecList[30][7][19]. We adopt re-ordering as it decouples diversification from the base recommender, and therefore is flexible enough to apply to already deployed POI recommender systems.

Eq.(4) represents the diversification objective of our proposed method. $rel(i)$ indicates the relevance score for POI i and $div_g(i, R)$ indicates the $PR_g(R_{k,u})$ increment by adding i to the RecList R at a given time point. For $rel(i)$, we use the score calculated for i by the base recommender. $\lambda \in [0.0, 1.0]$ denotes the diversity weight.

$$obj_{GeoD}(i, R) = rel(i)^{1-\lambda} \cdot div_g(i, R)^{\lambda} \quad (4)$$

$$div_g(i, R) = max(0, PR_g(\{i\} \cup R) - PR_g(R)) \quad (5)$$

4 EVALUATION

4.1 Dataset and Algorithms

For evaluation, we tested POI recommendations for the cities of Phoenix and Las Vegas in the USA using publicly available *Yelp Dataset Challenge* [1]. We selected cities that had the largest portions of visit logs in the dataset. POIs visited by less than five users were discarded from the dataset. Furthermore, only visit logs by users who had at least 20 visit logs in the target city were considered such users are more likely to have many sub-areas. As a result 20,723 POIs and 472,972 visit logs from 8,341 users for Phoenix, and 6,725 POIs and 197,368 visit logs from 8,812 users for Las Vegas were used.

The dataset provides a hierarchical category of POIs as shown in the bottom part of Figure 1a. We use the Lv.2 category in the category tree. For the distance of the two categories of POI i and j, we use Eq.(6) proposed by *Castillo et al.*[4]. cat_i indicates the category that i belongs to, and $sp(cat_i, cat_j)$ indicates the length of the shortest path between category cat_i and cat_j in the category tree. When more than one category is assigned to i or j, we take the minimum value of $sp(cat_i, cat_j)$ from all possible combinations.

$$dissim_{cat}(i, j) = 1 - 1/(1 + sp(cat_i, cat_j)) \quad (6)$$

The evaluation was carried out using 3-fold cross validation. The POIs that appear in u's training set or the POIs that are not located in AD_u are discarded from u's test set. In the test, for each u, a RecList is calculated from the POIs located in AD_u. As a result, on average, 7,217 users in Phoenix and 2,454 users in Las Vegas got recommendations in a single validation. Using re-ordering methods described in Section 2, a base recommender calculates n POIs for u, and then k out of the n calculated POIs are recommended by a given diversification method. We use $n = 80$, $k = 20$, and $d = 0.5km$ for re-ordering and *geo-diversity*.

We used *Ye et al.*'s method[24] as the base POI recommender (**Geo_UCF**) tuned to maximize the Recall metric[9]. We selected the algorithm because Geo_UCF is a pioneering work in POI recommendation that is referred by many other works and shows better accuracy(Recall) in our pre-evaluation as compared to other state-of-the-art proposals[28][10]. With respect to diversification, we evaluated two state-of-the-art category diversification methods, *Vargas et al.*[19] (**Binom**) and *Dang et al.*[7](**PM2**), list diversification methods based on pair-wise item dissimilarity in the RecList (**LD-cat** and **LD-geo**, the objective function is found in Eq.(2) of [19]), and our proposed method(**Geo-div**). LD-cat uses category distance in Eq.(6), and LD-dist uses km as the distance between the locations of two POI i, j to calculate pairwise item dissimilarity. For comparison, we also evaluate the random recommender (**Random**), which recommends POIs randomly and the popularity recommender (**Pop**), which recommends top-k popular POIs.

4.2 Evaluation Metric

We evaluate the algorithms using five metrics: *Recall@x*[9], *ILD@x*[30], *EPC@x*[20], *PRg@x*(Eq.(2)), and *PRg-r@x*. These metrics are calculated for each test user and, except for *PRg-r@x*, the average values obtained for all the test users are reported for each metric. For

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

PRg-r@x, the average of test users whose *PRg-r@x* value is greater than zero is reported.

Recall@x is an accuracy metric. In Eq.(7), GT indicates the set of the all ground truth POIs and RET_x represents the set of ground truth POIs included in the top-x POIs in the RecList. *ILD@x*(Eq.(8), a variation of ILS in [30]) measures pairwise category dissimilarity of the top-x POIs in the RecList. R_x in Eq.(8) indicates the set of the top-x POIs in the RecList. We measure two versions of ILD: $ILD_{cat}@x$ used Eq.(6) and $ILD_{geo}@x$ used km distance as $dissim(i, j)$, respectively. *EPC@x* is a novelty metric proposed by *Vargas et al.*[20]. A high *EPC@x* value indicates that the less-popular ground-truth POIs are located in the top part of the top-x POIs in the RecList. *PRg@x* indicates the value of PR_g calculated with the top-x POIs in the RecList. *PRg-r@x* carried out the same calculation as *PRg@x*, but with the ground truth POIs in the top-x POIs in the RecList. All of the metrics except for *ILD-geo* are in the [0.0, 1.0] range, where a value of 1 indicates the best performance in each metric.

$$Recall@x = |RET_x|/|GT| \tag{7}$$

$$ILD@x = \sum_{i,j \in R_x \wedge i \neq j} dissim(i, j)/(|R_x| \cdot (|R_x| - 1)) \tag{8}$$

4.3 Results and Discussion

The results are shown in Table 2. The two cities show similar trends. Owing to space limitations we only report the results from Phoenix. For the algorithms that control the weight ([0.0, 1.0]) on the diversification, we list the results of 0.5 and 0.9 except for LD-cat that showed nearly identical performance from a weight of 0.5. We also report the performance of Geo_UCF(**Geo_UCF_PRg**) tuned for maximizing *PRg@x* using increased weight on the estimated visit probability of u at a given POI location. When we compare Random, Pop, Geo_UCF, and Geo_UCF_PRg, Random achieves the highest *ILD-cat*, *ILD-geo*, and *EPC* owing to the randomly selected POIs, but has the lowest *Recall*. Pop has lower *ILD-geo*, and a *PRg* similar to that of Random. The performance of Pop indicates a concentration of the RecPOIs in a small portion of the area, and RecPOIs do not cover all the locations visited by u. The higher *Recall* and *PRg* measures in Geo_UCF and Geo_UCF_PRg as compared to the other two show the usefulness of personalization. However, interestingly, Geo_UCF_PRg has the lowest *ILD-geo* amongst all the evaluated algorithms despite its high *PRg*. One possible explanation is that Geo_UCF_PRg concentrates the RecPOIs in a small portion of u's active areas.

Among the diversification algorithms, PM achieves high *Recall* and *EPC*, but has low *ILD-cat*. Binom achieves both high *Recall* and high *ILD-cat* but has low *EPC*. The high *EPC* of PM is achieved because PM recommends POIs in the preferable categories of u, and the preferable categories deviated somewhat from the categories that popular POIs included. However, the concentration on the preferable categories lowered *ILD-cat*. Binom avoids over-concentration on certain categories, in other words, recommends POIs in less preferable categories, which results in high *ILD-cat* but low *EPC*. LD-cat and LD-geo work well in their objective and showed good performance in *ILD-cat* and *ILD-geo* metrices, respectively.

Table 2: Experimental results (Phoenix)

Alg.	***Recall@5***	***ILD-(cat,geo)@5***	***EPC@5***	***PRg@5***	**PRg-r@5**
Random	0.006	**0.387, 1.851**	**0.796**	0.301	0.157
Pop	0.054	0.314, 1.394	0.211	0.306	0.158
Geo_UCF[24]	**0.067**	0.303, 1.382	0.372	0.420	0.202
Geo_UCF_PRg[24]	0.062	0.314, 1.047	0.445	**0.518**	**0.251**
PM2[7]	0.057	0.286, 1.519	0.510	0.426	0.189
Binom(0.5)[19]	**0.067**	0.321, 1.388	0.375	0.421	0.201
Binom(0.9)	0.065	0.374, 1.424	0.395	0.424	0.197
LD-cat(0.5)[Eq.(3) of [19]]	0.062	**0.400**, 1.445	0.402	0.427	0.196
LD-geo(0.5)[Eq.(3) of [19]]	0.047	0.340, 2.573	0.407	0.329	0.146
LD-geo(0.9)	0.039	0.350, **2.594**	0.420	0.308	0.133
Geo-Div(0.5)	0.060	0.322, 1.650	0.475	0.719	0.271
Geo-Div(0.9)	0.054	0.333, 1.821	**0.524**	**0.812**	**0.280**
Alg.	***Recall@10***	***ILD-(cat,geo)@10***	***EPC@10***	***PRg@10***	**PRg-r@10**
Random	0.012	**0.387, 1.853**	**0.795**	0.394	0.126
Pop	0.092	0.320, 1.485	0.292	0.412	0.146
Geo_UCF	**0.111**	0.316, 1.431	0.428	0.516	0.173
Geo_UCF_PRg	0.101	0.327, 1.064	0.489	**0.594**	**0.203**
PM2	0.098	0.292, 1.537	0.539	0.525	0.164
Binom(0.5)	**0.110**	0.325, 1.435	0.429	0.516	0.173
Binom(0.9)	0.105	0.367, 1.468	0.446	0.524	0.171
LD-cat(0.5)	0.093	**0.400**, 1.504	0.465	0.535	0.167
LD-geo(0.5)	0.086	0.344, 2.162	0.458	0.466	0.134
LD-geo(0.9)	0.066	0.355, **2.181**	0.480	0.441	0.117
Geo-Div(0.5)	0.095	0.336, 1.654	0.524	0.867	**0.222**
Geo-Div(0.9)	0.089	0.342, 1.673	**0.563**	**0.888**	0.220
Alg.	***Recall@20***	***ILD(cat,geo)@20***	***EPC@20***	***PRg@20***	**PRg-r@20**
Random	0.024	**0.388, 1.855**	**0.795**	0.462	0.097
Pop	0.151	0.333, 1.526	0.375	0.477	0.122
Geo_UCF	**0.178**	0.330, 1.482	0.489	0.588	0.141
Geo_UCF_PRg)	0.154	0.343, 1.081	0.534	**0.647**	**0.155**
PM2	0.164	0.300, 1.556	0.576	0.594	0.135
Binom(0.5)	**0.177**	0.333, 1.481	0.489	0.589	0.141
Binom(0.9)	0.165	0.357, 1.495	0.494	0.595	0.138
LD-cat(0.5)	0.130	**0.398**, 1.520	0.514	0.619	0.130
LD-geo(0.5)	0.152	0.346, 1.894	0.505	0.571	0.123
LD-geo(0.9)	0.121	0.356, **1.916**	0.530	0.558	0.108
Geo-Div(0.5)	0.155	0.345, 1.587	0.562	**0.875**	**0.165**
Geo-Div(0.9)	0.149	0.347, 1.584	**0.590**	**0.875**	0.161

*The value in () in Alg. column indicates the adopted diversification weight.
**Bold faced in Alg. column indicates the proposed method and the best performance in other columns.
***Avg. and Med. of $|AD_u|$ for all target users in Phoenix are 103 and 86 respectively.

None of the diversification methods significantly improve *PRg* in comparison with Geo_UCF except for Geo-Div. High *PRg* and *PRg-r* of Geo-Div support Geo-Div's superiority, not only in terms of *PRg* that improves RecPOIs, but also on *PRg* improvement exhibited by the accurately predicted POIs. Although LD-geo has the highest *ILD-geo*, it cannot achieve high *PRg* improvement because LD-geo simply recommends POIs that are located far from each other. The *Recall* of Geo-Div(0.5) is not significantly lower than that of the other diversification methods, and is greater than that of Pop. Geo-Div also has high *EPC*. One possible explanation is that Geo-Div recommends POIs from a variety of areas, and therefore avoids recommending many popular RecPOIs located in a small portion of popular areas. The results show that Geo-Div is one of the best options when we need geo-diversification in POI recommendation. However, Geo-Div does not consider category diversification, and therefore does not significantly improve *ILD-cat*.

5 CONCLUSION

In this paper, we introduced the concept of geo-diversification and proposed a geo-diversification method for POI recommendation. Experimental results showed that our method achieves superior geo-diversification at the expense of tolerable accuracy loss. In future studies, we will carry out user studies to understand user perception about geo-diversification. We also plan on reinterpreting existing concepts of diversity in the context of POI recommendation and integrating the concepts on geo-diversification.

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