Can POI Recommendation methods perform well on Travel Social Network datasets ?

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1 INTRODUCTION

One of the services that most benefited from the internet expansion and use of summarization techniques was the tourism [Yoo et al. 2016]. Given the amount of data produced in Travel Social Networks (TSN) and Location Based Social Networks (LBSN), as TripAdvisor, Yelp, Gowalla and Foursquare, several works has used these platform data to recommend Points-Of-Interest (POI) to users [Qian et al. 2019], Successive POI-Recommendation [Ying et al. 2019; Zhao et al. 2019] and Trip Planning Recommendation [Gavalas et al. 2015; Kotiloglu et al. 2017].

One aspect that is usually left aside in POI recommendation works is the fact that LBSN and TSN has different appeal towards the users. LBSN has the intuit of the user share in real time the users current place, making check-ins and a quick review of a place. In TSN platforms the intuit is that the user describes his experience in a trip producing a more detailed review, given a more broad view of the visited place. Hence, in LBSN in amount of data created is more quantitative, while the generated data in TSN platforms is much more qualitative.

By taken this in consideration, in this work we propose a study over POI recommendation literature proposals that use LBSN datasets, evaluating it performance over adapted TSN datasets. Our main goal is to evaluated these methods are suited for different datasets, if using classic recommendation approaches, as Collaborative Filtering (CF) and Contend Based (CB) it is possible to out perform POI Recommendation approaches, and lastly if using descriptive features in the classic approaches is possible to enhance it performance. To guide our work we focus on the following research questions:

(1) How baseline algorithms perform over the proposed datasets ?
(2) By using Users historic from other cities it is possible increase the model results ?

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To perform this work we gathered data from TripAdvisor (a TSN). The data is gathered from a small Brazilian city: Tiradentes, Minas Gerais. This city was chosen due the fact that it economy is based on tourism, and the fact that it is a challenge to perform well based on very few data by user, making even harder to achieve good results.

2 RELATED WORK

In this section we review relevant works on POI Recommendation. We discuss the subcategories of POI recommendation, discussing the data used and how we can adapt literature approaches to our proposal.

2.1 POI Recommendation

POI recommendation addresses the problem of discovering relations between users and places, helping people to discover attractive locations, even were the user is in a unknown place [Yin et al. 2016]. Basically, given a user u and a item i, we want to discover what is the relevance of i for u.

Currently, in the literature there are several proposed approaches tackling the POI Recommendation problem. These works, mostly focus on using data from the so-called LBSN. These datasets, are widely used given the amount of instances available, and due the fact that most of them have few features **(user, local id, timestamp and geo-coordinates)**, which decreases the cost of pre-processing the data. Over these datasets distinct approaches have been proposed as Collaborative Filtering [Ye et al. 2011; Zhang et al. 2014], Matrix Factorization [Li et al. 2015; Lian et al. 2014], Hybrids [Cheng et al. 2012; Ye et al. 2011] and considering different aspects to enhance the quality of predictions as geographical [Cheng et al. 2012; Ye et al. 2011], social [Zhang et al. 2014], temporal [Gao et al. 2013] and categorical [Zhang and Chow 2015] contexts.

Different from LBSN, TSN data, has a more descriptive data from places and users. This data when applied in a context based recommender can be very useful to discovering what characteristics a place most have to a user to enjoy it. While in LBSN is possible to see the human mobility in real time, TSN will be enable to verify what a user like in a finer granularity.

3 PROPOSED SOLUTION

In this section we show the proposed solution showing the datasets collected, the algorithms used in the process, the evaluation procedure and metrics.

3.1 Dataset Gathered

To perform this work, first we implement a data crawler that gathers data from TripAdvisor [1]. For this work we gathered all the data available of the city Tiradentes, Minas Gerais. With this crawler, it was possible the following fields: Attractions, Restaurants, Vacation

[1]https://tripadvisor.com.br/

# of users	22389
# of places	355
# of Instances in Tiradentes	58905
# of Instances outside Tiradentes	993718
# of Restaurants	147
# of Hotels and Vacation Rentals	172
# of Attractions	36

Table 1. Dataset description

Baseline	**Description**
USG *	Combination of User-Based CF and Friend Based CF [Ye et al. 2011].
LORE *	Combination of Kernel Density Estimation, Friend Based CF e Additive Markov Chain [Zhang et al. 2014].
LFBCA *	Combination of graphs and user based CF [Wang et al. 2013].
MGMPFM *	Combination of Poisson Factor Model and Multi-Center Gaussian Model [Cheng et al. 2012].
GeoSoca *	Combination of Kernel Density Estimation and Complex Networks algorithms [Zhang and Chow 2015].
KNN (User/Item)	Classic memory based CF Algorithm
SVD	Classic model based CF Algorithm
SVD++	Implementation of the FunkSVD [Kurucz et al. 2007]
NMF	Perform matrix factorization over the data, not accepting negative values

Table 2. Baselines used in our experimental evaluation

Rentals and Hotels. Besides that we also gathered all the Tiradentes visitors historic in other cities. In the Table 1, we show the attributes of the dataset gathered.

3.2 Baselines

To evaluate the performance of LBSN based POI recommender systems over TSN datasets, we compare different algorithms modeled to perform POI recommendation. The algorithms were selected by it code availability.

In the Table 2, is possible to see the baselines used and their description. With a * we have the baselines that has as original input LBSN datasets. To test the quality of these algorithm with TSN datasets, we adapt the datasets having the same formats. It is high-valued, that some of the properties that are present on LBSN could not be captured in the conversion of the data. LBSN has timestamps with check-ins real of each pair user item. In TSN we do not have this data. Having only the month and year of visit. To overcome this problem we define the first day of the month-year of visit, as the user-item timestamp of the TSN dataset.

We also do not have the friendship connection, which is used in some of the baselines to perform the so-called Friend Based CF. In this case, we set a friendship connection between two users if the users has visited at least one equal place one equal place in the evaluation city (Tiradentes).

Lastly, we high-value that the output given by the LBSN baselines is in a ranking format, were this ranking is sorted by the importance of a item to a given user. The value of importance ranges between 0 1. Thus, to transform it to ranting values, we multiply the importance score by 5.

3.3 Evaluation Procedure

To evaluate our approach, we use two procedure. First, when not using any user historic, a temporal k-fold, using all data of the target city. We do not perform any interaction filter over the city

Parameters	**Evaluation without historic**	**Evaluation with historic**
# folds	5	5
Dataset	City complete dataset	City complete dataset + 50 thousand historic instances
User Interaction Filter	Not used	10

Table 3. Evaluation Procedure

dataset given the users cold-start users the mean rating of a place normalized by z-score.

When evaluating the second RQ raised, besides using Tiradentes complete data, we also use the city visitors historic. As the users historic is much larger outside Tiradentes and we do not had enough computer power to train with all data, we train the model with smaller samples of the historic data (50000 instances). To make a fair comparison not have the results attached to a sample, we perform 50 executions of the algorithm using different samples to ensure our results. We also make a interaction filter over the historic dataset, getting only users which have visit at least 10 different places outside Tiradentes.

The Table 3, summarize our evaluation procedure.

Lastly, to evaluate the quality of the algorithms we use a regression metric root mean squared and evaluate the correlation between the rankings given by the algorithm and the user real ranking.

4 EXPERIMENTAL RESULTS

In this section, we present and evaluate the results of the tested algorithms, answering the research questions raised.

4.1 Algorithms Performance

In 4, it is possible to see the results achieved by the algorithms. In blue, we have the algorithms which have the best results for a given metric. In red, we have the worst results of each metric.

As it is possible to see, the algorithm with the best result is SVD. While the worst results are attached to USG, which is a LBSN POI recommender. By looking more close to the results is also possible to see that the literature baselines has worse results when compared to more simple baselines.

Analyzing the RMSE results, it is possible to see that the baseline algorithms, with exception of LFBCA, has worse results even compared with a random approach. Our hypothesises, is that given that LFBCA is a more simple approach, the algorithm could capture better the data aching in "better" results.

It is high-valued, that the baseline algorithms do not has a good performance in general, hence, facilitating for answering the Research Question: **How baseline algorithms perform over the proposed datasets ?**: Do not perform good, even when compared to basic baselines. We believe that some factors influence on the bad results of the baseline algorithms: (*i*) We do not had friendship data, so we infer, (*ii*) Some of the algorithms consider a temporal influence which could not be capture by our data and (*iii*) We make a adaptation of the output, which was originally a ranking, and we transform it on a regression.

To answer our second research question, we took a different approach **By using Users historic from other cities it is possible increase the model results ?**. Given that the baseline algorithms do not had a good performance, we focused on the basic baselines

Metric	KNN-Item	KNN-User	NMF	Random	SVD	SVD++	GEOSOCA	LFBCA	LORE	MGMPFM	USG
RMSE	0.913998	0.895091	0.928738	1.159130	0.848212	0.849928	1.554764	1.118597	1.524624	1.752802	1.826574
RMSE Std.	0.025785	0.021046	0.024355	0.023175	0.023511	0.023912	0.106238	0.058000	0.090516	0.127101	0.131034
Spearman	0.347885	0.350182	0.344278	0.017279	0.177728	0.175904	0.288226	0.281352	0.269024	0.267195	0.272604
Spearman Std.	0.013332	0.015357	0.009107	0.012398	0.030077	0.022815	0.029594	0.011758	0.020714	0.016592	0.015047

Table 4. Results of the algorithms using only Tiradentes data

Metric	KNN-Item	KNN-User	NMF	Random	SVD	SVD++
RMSE	0.977155	0.952007	1.004757	1.207418	0.871085	0.871131
RMSE std	0.032462	0.029787	0.036425	0.025782	0.028373	0.028499

Table 5. Results of the algorithms using Tiradentes and the user historic in other cities

to evaluate if the historic factor could have a influence on the users results. In Table 5, we show the historic results.

Through the Table 5, we see that the best algorithm as in the first evaluation is the Matrix Factorization Approach **SVD**. However, the algorithm do not have a better performance when dealing with the user outside data. Even tough, this results are not conclusive, we believe that the historic data only added a small noise in the algorithm, hence, the techniques have a small variation when evaluating RMSE. Thus answering the Research Question **By using Users historic from other cities it is possible increase the model results ?**, in our experiments it was not possible to see a significant increase or decrease of the results. We suppose that by using Content Based Recommender System, the historic data would have a bigger role, given that it would be possible to retrieve similar places to those already visited by the user.

5 CONCLUSIONS

In this work, we proposed a study over POI Recommendation approaches. In our study we compare different techniques that aim to suggest places to user visit. However, some of this algorithms are tailored for specific datasets, from the so-called Location Based Social Networks. Our research question that guided our work, focus on evaluating if this algorithms would also work on Travel Social Networks (TSN) datasets. Through our work, it was possible to verify that this algorithms do not work well on TSN datasets. We believe that this techniques do not work so well for several reasons, between then we high-value the data modeling and the output given by the algorithm and adapted by us. In our second research question we evaluated the impact of user historic on the recommendation. Our results show that the historic do not have a significant impact of the results, however, we believe that if used a Content Based approach, we would have better results. Has future works, we plan to identify the reasons why the literature datasets do not perform well in TSN datasets, also implement a content based technique to extract more of the data we have and lastly expand the amount of cities considered in the evaluation.

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