# Location Recommendation Using Content Aware Collaborative Filtering

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***Abstract* -** The Location recommendation plays an essential role in helping people find interesting places. Although recent researchers has studied how to advise places with social and geographical information, some of which have dealt with the problem of starting the new cold users. Because mobility records are often shared on social networks, semantic information can be used to address this challenge. There the typical method is to place them in collaborative content-based filters based on explicit reviews using machine learning, but require a positive design samples for a better learning performance, since the positive user preference is not observable in human mobility. However, previous studies have demonstrated empirically that sampling-based methods do not work well. To this end, we propose a system based on implicit scalable comments Content-based collaborative filtering framework (ICCF) to incorporate semantic content and avoid negative sampling using machine learning. We also establish its relationship with the factorization of the plate matrix plating. Finally, we evaluated ICCF with a large-scale hotel data set in which users have text and content profiles. The results show that ICCF surpasses many competitors' baselines and that user information is not only effective for improving recommendations, but also for managing cold start scenarios.

**Keywords-** **I**mplicit and Explicit feedback, Hotel recommendation, social network, collaborative filtering.

## I. Introduction

As we think about the title of this paper is related to Recommender System which is part of the Data mining technique. Recommendation systems use different technologies, but they can be classified into two categories: collaborative and content-based filtering systems. Content-based systems examine the properties of articles and recommend articles similar to those that the user has preferred in the past. They model the taste of a user by building a user profile based on the properties of the elements that users like and using the profile to calculate the similarity with the new elements. We recommend location that are more similar to the user's profile. Recommender systems, on the other hand, ignore the properties of the articles and base their recommendations on community preferences. They recommend the elements that users with similar tastes and preferences have liked in the past. Two users are considered similar if they have many elements in common.

One of the main problems of recommendation systems is the problem of cold start, i.e. when a new article or user is introduced into the system. In this study we focused on the problem of producing effective recommendations for new articles: the cold starting article. Collaborative filtering systems suffer from this problem because they depend on previous user ratings. Content-based approaches, on the other hand, can still produce recommendations using article descriptions and are the default solution for cold-starting the article. However, they tend to get less accuracy and, in practice, are rarely the only option.

The problem of cold start of the article is of great practical importance Portability due to two main reasons. First, modern online the platforms have hundreds of new articles every day and actively recommending them is essential to keep users continuously busy. Second, collaborative filtering methods are at the core of most recommendation engines since then tend to achieve the accuracy of the state of the art. However, to produce recommendations with the predicted accuracy that require that items be qualified by a sufficient number of users. Therefore, it is essential for any collaborative adviser to reach this state as soon as possible. Having methods that producing precise recommendations for new articles will allow enough comments to be collected in a short period of time, Make effective recommendations on collaboration possible.

In this paper, we focus on providing location recommendations novel scalable Implicit-feedback based Content-aware Collaborative Filtering (ICCF) framework. Avoid sampling negative positions by considering all positions not visited as negative and proposing a low weight configuration, with a classification, to the preference trust model. This sparse weighing and weighting configuration not only assigns a large amount of confidence to the visited and unvisited positions, but also includes three different weighting schemes previously developed for locations.

## II. Related Work

1. X. Liu, Y. Liu, and X. Li describe the "Exploring the context of locations for personalized Location recommendations". In this paper, we decouple the process of jointly learning latent representations of users and locations into two separated components: learning location latent representations using the Skip-gram model, and learning user latent representations Using C-WARP loss [1].

2. Shuyao Qi, Dingming Wu, and Nikos Mamoulis describe that ," Location Aware Keyword Query Suggestion Based on Document Proximity" In this paper, we proposed an LKS framework providing keyword suggestions that are relevant to the user information needs and at the same time can retrieve relevant documents Near the user location [2].

3. H. Li, R. Hong, D. Lian, Z. Wu, M. Wang, and Y. Ge describe the "A relaxed ranking-based factor model for recommender system from implicit feedback," in this paper, we propose a relaxed ranking-based algorithm for item recommendation with implicit feedback, and design a smooth and scalable optimization method for model's parameter Estimation [3].

4. D. Lian, Y. Ge, N. J. Yuan, X. Xie, and H. Xiong describe the "Sparse Bayesian collaborative filtering for implicit feedback," In this paper, we proposed a sparse Bayesian collaborative filtering algorithm best tailored to implicit feedback, And developed a scalable optimization algorithm for jointly learning latent factors and hyper parameters [4].

5. X. He, H. Zhang, M.-Y. Kan, and T.-S. Chua describe the "Fast matrix factorization for online recommendation with implicit feedback," We study the problem of learning MF models from implicit feedback. In contrast to previous work that applied a uniform weight on missing data, we propose to weight Missing data based on the popularity of items. To address the key efficiency challenge in optimization, we develop a new learning algorithm which effectively learns Parameters by performing coordinate descent with memorization [5].

## III. EXISTING SYSTEM

Lot of work has been done in this field because of its extensive usage and applications. In this section, some of the approaches which have been implemented to achieve the same purpose are mentioned. These works are majorly differentiated by the algorithm for recommendation systems.

In another research, general location route planning cannot well meet users' personal requirements. Personalized recommendation recommends the POIs and routes by mining user's travel records. The most famous method is location-based matrix factorization. To similar social users are measured based on the location co-occurrence of previously visited POIs. Then POIs are ranked based on similar users' visiting records. Recently, static topic model is employed to model travel preferences by extracting travel topics from past traveling behaviours which can contribute to similar user identification. However, the travel preferences are not obtained accurately, because static topic model consider all travel histories of a user as one document drawn from a set of static topics, which ignores the evolutions of topics and travel preferences.

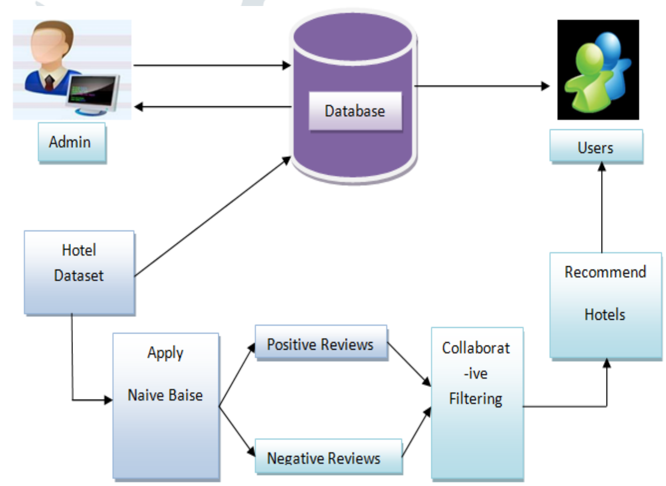
As my point of view when I studied the papers the issues are related to recommendation systems. The challenge is to addressing cold start problem from explicit and implicit feedback is based on the detection of recommendation between users and location with similar preference.

## IV. PROPOSED SYSTEM

As we studied then we want to propose content aware collaborative filtering is propose the integration of implicit and explicit feedback based recommendation, firstly find nearby locations i.e. hotels and then to recommend to user based on both feedback and achieve the high accuracy and also remove cold-start problem in recommendation system.

In this system, particular Recommendation of places for new users. Some popular recommendation frameworks, have been recently Proposed, but designed on the basis of explicit feedback with favourite samples both positively and negatively. Such as Only the preferred samples are implicitly provided in a positive way. Feedback data while it is not practical to treat all unvisited locations as negative, feeding the data on mobility together. With user information and location in these explicit comments Frames require pseudo-negative drawings. From places not visited. The samples and the lack of different levels of trust cannot allow them to get the comparable top-k recommendation.

### A. *System Diagram:*




### B. *Algorithms:*

**1. Naive Bayes**

Steps:

1. Given training dataset D which consists of documents belonging to different class say Class A and Class B
2. Calculate the prior probability of class A=number of objects of class A/total number of objects

Calculate the prior probability of class B=number of objects of class B/total number of objects

3. Find NI, the total no of frequency of each class
   Na=the total no of frequency of class A
   Nb=the total no of frequency of class B
4. Find conditional probability of keyword occurrence given a class:
   P (value 1/Class A) =count/ni (A)
   P (value 1/Class B) =count/ni (B)
   P (value 2/Class A) =count/ni (A)
   P (value 2/Class B) =count/ni (B)
   …………………………………..
   …………………………………..
   …………………………………..
   P (value n/Class B) =count/ni (B)
5. Avoid zero frequency problems by applying uniform distribution
6. Classify Document C based on the probability p(C/W)
   a. Find P (A/W) =P (A)*P (value 1/Class A)* P (value 2/Class A)……. P(value n /Class A)
   b. Find P (B/W) =P (B)*P (value 1/Class B)* P(value 2/Class B)……. P(value n /Class B)
7. Assign document to class that has higher probability.

**2. Content Aware collaborative filtering:**

- Content-aware collaborative filtering is the integration of content-based recommendation and collaborative filtering.
- Our proposed algorithm targets content-aware collaborative filtering from implicit feedback and successfully addresses the disadvantages by treating the items not preferred by users as negative while assigning them a lower confidence for negative preference and achieving linear time optimization.
- Accuracy is high.

Steps:

1. Given data of M users visiting N Locations
2. Location recommendation first converts it into a user-location frequency matrix
3. $C \epsilon N^{M*N}$
4. Each entry $C_{\iota,\mu}$ indicating the visit frequency of a user u to location i.
5. $\mathcal{R} \in \{0,1\}^{M*N}$ Is a preference matrix, for which each entry $r_{u,i}$ is set to 1.
6. If the user u has visited the location i otherwise is set to 0.
7. Weighed matrix factorization being performed on the preference matrix R.
8. Maps both users and locations into a joint latent space of $K \ll \min(M,N)$ dimension
9. Where, each user and each location is represented by user latent factor $p_u$ and location latent factor $q_i$.
10. Preference $r_{u,i}$ of a user u for a location i is estimated.

## V. Result and Discussion

Experimental evaluation is done to compare the proposed system with the existing system for evaluating the performance. The simulation is to platform used is built using Java framework (version JDK 8) on Windows platform. The system does not require any specific hardware to run; any standard machine is capable of running the application.

The experimental result evaluation, we have notation as follows:

TP: True positive (correctly predicted number of instance)

FP: False positive (incorrectly predicted number of instance),

TN: True negative (correctly predicted the number of instances as not required)

FN false negative (incorrectly predicted the number of instances as not required),

On the basis of this parameter, we can calculate six measurements

TPR=TP/TP+FN

FPR=FP/FP+FN

Accuracy = TP+TN÷TP+FP+TN+FN

Precision = TP ÷TP+FP

Recall= TP÷TP+FN

F1-Measure = 2×Precision×Recall ÷Precision+ Recall.

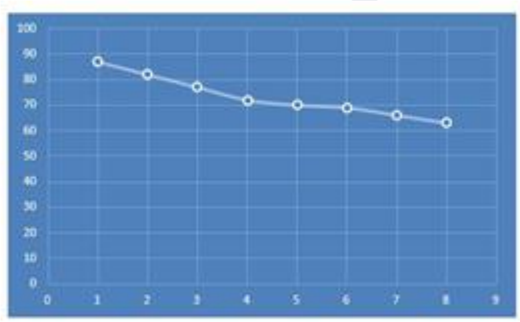


**Fig. Analysis Graph**

| Sr. No. | Framework | Accuracy |
|---|---|---|
| 1 | ICCF | 87% |
| 2 | ICF | 82% |
| 3 | geoMF | 77% |
| 4 | GRMF | 72% |
| 5 | IRENMF | 70% |
| 6 | LibFM-1 | 69% |
| 7 | LibFM-3 | 66% |
| 8 | LibFM-10 | 63% |

**Table. Comparison Table**

CONCLUSION:

In this Paper, we propose a new framework for collaborative filtering based on explicit and implicit feedback set of data and develop the coordinates of the offspring for effective learning of parameters. We establish the close relationship of matrix graphical factorization and shows that user functions really improve mobility Similarity between users. So we apply proposed system for the Location recommendation on a large-scale LBSN data set. our the results of the experiment indicate that proposed system is greater than five competing baselines, including two leading positions recommendation and factoring algorithms based on the ranking machine. When comparing different weighting schemes for negative preference of the unvisited places, we observe that the user-oriented scheme is superior to that oriented to the element scheme, and that the sparse configuration and rank one significantly improves the performance of the recommendation.

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