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RECOMMENDED SENSITIVE LOCATIONS IN TEMPORARY NETWORK USING MATRIX CALCULATION

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ABSTRACT

Social recommendation is popular and successful among various urban sustainable applications like products recommendation, online sharing and shopping services. Users make use of these applications to form several implicit social networks through their daily social interactions. The users in such social networks can rate some interesting items and give comments. The majority of the existing studies investigate the rating prediction and recommendation of items based on user-item bipartite graph and user-user social graph, so called social recommendation. However, the spatial factor was not considered in their recommendation mechanisms. With the rapid development of the service of location-based social networks, the spatial information gradually affects the quality and correlation of rating and recommendation of items. This paper proposes spatial social union (SSU), an approach of similarity measurement between two users that integrates the interconnection among users, items and locations. The SSU-aware location-sensitive recommendation algorithm is then devised. This project evaluates and compares the proposed approach with the existing rating prediction and item recommendation algorithms. The results show that the proposed SSU-aware recommendation algorithm is more effective in recommending items with the better consideration of user's preference and location.

INTRODUCTION

The system is aimed at solving the recommendation problem and proposed a general framework for the recommendations on the Web. This framework is built upon the heat diffusion on both undirected graphs and directed graphs, and has several advantages. It is a general method, which can be utilized to many recommendation tasks on the Web and it can provide latent semantically relevant results to the original information need. This model provides a natural treatment for personalized recommendations. The designed recommendation algorithm is scalable to very large data sets. The system introduced a graph diffusion model for recommendation. It shows how to convert different Web data sources into correct graphs in the models; it conducts several experiments on query suggestions since Query Suggestion is a technique widely employed by commercial search engines to provide related queries to users' information need. Graph construction and Query Suggestion algorithm is used to provide related queries. Graph construction and Query suggestion algorithm is implemented. Similarity measure between two queries is also considered. Abbreviation based query suggestion is also considered. Personalized recommendations are given importance. Previous search query words are also taken into query suggestion calculation. The proposed methodology provides the following: Expansions of abbreviated query are considered and new search mechanism satisfies the user's information needs. And also unwanted Web page links are eliminated to better extent.

LITERATURE REVIEW

The authors **Eugene Agichtein, Eric Brill and Susan Dumais** showed that incorporating user behavior data can significantly improve ordering of top results in real web search setting. They examined alternatives for incorporating feedback into the ranking process and explore the contributions of user feedback compared to other common web search features. They reported results of a large scale evaluation over 3,000 queries and 12 million user interactions with a popular web search engine. They showed that incorporating implicit feedback can augment other features, improving the accuracy of a competitive web search ranking algorithms by as much as 31% relative to the original performance.

Recent work by **Joachims** and others exploring implicit feedback in controlled environments have shown the value of incorporating implicit feedback into the ranking process. Our motivation for that work is to understand how implicit feedback can be used in a large-scale operational environment to improve retrieval. While it is intuitive that user interactions with the web search engine should reveal at least some information that could be used for ranking, estimating user preferences in real web search settings is a challenging problem, since real user interactions tend to be more "noisy" than commonly assumed in the controlled settings of previous studies. Their paper explores whether implicit feedback can be helpful in realistic environments, where user feedback can be noisy (or adversarial) and a web search engine already uses hundreds of features and is heavily tuned.

Closely related to their work, **Joachims** collected implicit measures in place of explicit measures, introducing a technique based entirely on click through data to learn ranking functions. **Fox et al** explored the relationship between implicit and explicit measures in Web search, and developed Bayesian models to correlate implicit measures and explicit relevance judgments for both individual queries and search sessions. In this work considered a wide range of user behaviors (e.g., dwell time, scroll time, reformulation patterns) in addition to the popular click through behavior. However, the modeling effort was aimed at predicting explicit relevance judgments from implicit user actions and not specifically at learning ranking functions.

The authors **Nick Craswell and Martin Szummer** Search engines can record which documents were clicked for which query, and use these query-document pairs as 'soft' relevance judgments. However, compared to the true judgments, click logs give noisy and sparse relevance information. They applied a Markov random walk model to a large click log, producing a probabilistic ranking of documents for a given query. A key advantage of the model is its ability to retrieve relevant documents that have not yet been clicked for that query and rank those effectively. They conducted experiments on click logs from image search, comparing their ('backward') random walk model to a different ('forward') random walk, varying parameters such as walk length and self-transition probability. The most effective combination is a long backward walk with high self-transition probability.

Hang Cui, Ji-Rong Wen et al have been witnessing the explosive growth of information on the World Wide Web. People are relying more and more on the Web for their diverse needs of information. However, the Web is an information hotpot where innumerous authors have created and are creating their Web sites independently. The vocabularies of the authors vary greatly. There is an acute requirement for search engine technology to help users exploit such an extremely valuable resource.

EXISTING METHODOLOGY

The challenge of estimating the geo-location of an image using only its visual content has drawn increasing research attention over the past years. Work addressing this challenge has been pursued along two major directions: geo-constrained prediction, where the possible locations at which the target image could have been taken are limited to a defined geographic range or a set of predefined locations, and geo-unconstrained prediction, assuming that the target image could have been taken any where around the globe. We briefly elaborate on the reported

Projection of input data: It derives the user-item bipartite graph and user-location bipartite graph, respectively. Besides, the user-user social graph (G) from the social networks is derived.

Similarity measurement: Based on these derived graphs, similarity matrices between users can be constructed as simR (Rating), simA (User) and simD (Location).

Similarity aggregation: Further, It proposes an aggregation union, namely SSU which combines the various similarity matrices simR, simA and simD together and returns the similarity matrix between any two users.

Rating prediction and recommendation: At last, It adopts the finalized similarity matrix to predict the missing ratings and provide the recommendations in terms of similarity.

A. Geo-Constrained Content-Based Location Prediction

The approaches mentioned above served as a source of inspiration for the choice of visual features used in our own approach. The challenge we address is then how to deploy these

features effectively for image similarity assessment in a general case, i.e., when the target location is not constrained to a set of predefined locations typically characterized by specific visual scenery elements.

B. Content-Based Location Prediction Without Geo-Constraints

Compared to the effort that has been devoted to geo-constrained location prediction, there has been relatively less work dedicated to predicting locations at the global scale. This can be explained by the challenge of the task. If we consider all social images that have been taken at arbitrary locations around the world as candidate images representing the target location, the virtually infinite and, consequently, unknown range of the visual content covered by these images makes it difficult to define an effective strategy to assess their correspondence to the query image.

- All the records from the database are taken for matrix calculation and so importance is given to old products in the market also.
- Time interval based recommendations are not studied.
- New products launched in some locations and their recommendations by the web site itself are not included

PROPOSED METHODOLOGY

In addition with all the existing system mechanism, the proposed study also presents age group based similarity measurement. Here Similarity measurement based on users' ages is also taken into study as simA (Age) along with simR (Rating), simA (User) and simD (Location). And so, Rating prediction and recommendation adopts the finalized similarity matrix with including simA to predict the missing ratings and provide the recommendations. In addition, time intervals are taken for matrix calculation

A. Candidate Image Selection

Given a set of geo-tagged images crawled from the web, the goal of this step is to select those images that, based on their visual content, are most likely to have been taken at the same location as the query image. Since this set of candidate images serves as input for all further steps, the quality of this set is critical for the success of our approach.

Conceptually we search for invariant regions in the images and consider matches between invariant regions of two images as evidence that the images' visual content reflects the same location in the physical world, possibly captured under different conditions, e.g., capturing angle, scale or illumination. In order to identify the invariant regions and assess their matches, we use the standard bag-of-visual-words paradigm, which scales up well to a large-scale datasets.

B. Location Extraction

Given a ranked list of candidate images, the next step is to derive a set of candidate locations. Since multiple images from the list could have been taken at the same location, we propose a method that can gradually build the set from the geo-coordinates found by moving down the list. If new geo-coordinates are found within the distance of an already selected candidate location, the geo-coordinates of this location are updated by calculating the centroid of the geo-coordinates of all images at that location, otherwise a new candidate location is created. We set the distance such to meet the maximum allowed prediction deviation of the system and thus equal to the evaluation.

a. The number of top-ranked images in the list that we consider a reliable set of candidate images
b. The maximum number of candidate locations that we consider reliable to enter the selection process

C. Location Ranking

The step explained above could already be deployed to generate a ranked list of candidate locations, for instance by linking the rank of each candidate location to the rank of its image positioned highest in the list . However, this would make the GVR approach conceptually equal to the 1-NN category of approaches and would prevent it from making use of all the available information derived from the geo-visual context of the candidate locations and, consequently, from making more reliable predictions.

D. Reducing the Effect of High-Volume Uploads

The reliability of the candidate location list can be negatively influenced by the tendency of social media users to upload many images taken at the same location, for instance those related to a specific event attended and intensively photographed by a user. High-volume uploads of individual users damage prediction because they lead to a disproportionately high number of images in the set of a false location, which may overwhelm the otherwise lower visual similarity between images in that set and the query compared to the true location.

- Only time based selective records are taken from the database and so importance is not given to old products in the market.
- Time interval based recommendations are studied.
- New products launched in some locations and their recommendations by the web site itself are included.
- Age group wise similarity is also taken into consideration.

Experimental Results

1. **PROJECTION OF INPUT DATA**

COMMUNITY

In this module, the community id and name are added in 'Community' table. The details are displayed using data grid view control and modified if required.

USER

In this module, the user id and name are added in 'users' table. The details are displayed using data grid view control and modified if required.

ITEM

In this module, the item id and name are added in 'items' table. The details are displayed using data grid view control and modified if required.

LOCATION

In this module, the location id and name are added in 'location' table. The details are displayed using data grid view control and modified if required.

RATING

In this module ratings are added for the given user for the given item. The details are saved in 'ratings' table. The details are displayed using data grid view control and modified if required.

2. MATRIX CALCULATION

USER ITEM MATRIX (R)

In this module users are taken row wise, items are taken column wise and the matrix data is filled with rating values.

RATING SIMILARITY MATRIX simR

In this module rating similarity is calculated by users taken both row and column wise and matrix data is prepared which is the cosine similarity of user-item rating matrix R.

USER SIMILARITY MATRIX simA

In this module user similarity is calculated using M-FriendTNS: Modified-FriendTNS algorithm which takes a) user-user relationship matrix A and b) the number of users N as input. The output prepared is simA.

LOCATION SIMILARITY MATRIX simD

In this module location similarity is calculated by applying cosine similarity of D matrix (which is a matrix with users taken row wise and column wise).

FUTURE ENHANCEMENTS

At present, experimental results show that the SSU algorithm is more effective in predicting rating of items and recommending items in location-based ad-hoc social networks. As the dramatic growth of online social network sites continues, the social recommendation in location-based ad-hoc social networks is widely used everywhere.

In future, from a social sustainable perspective, the plan is to develop similar techniques in other urban sustainable applications, e.g. E-health field, to confirm that the approach is universally applicable in various domains. In addition, if the application is developed as web service, then it can be used in other projects also.

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