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# ANALYSING NATURAL CALAMITY USING SOCIAL NETWORKS

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## Abstract:

Information generated by social networks demands effective recommender systems(twitter server) to give useful results. Earlier techniques become unqualified because they ignore social relation data; existing social recommendation approaches consider social network structure, but social contextual information has not been fully considered. It is significant and challenging to fuse social contextual factors(individual preference and interpersonal influence)which are derived from users' motivation of social behaviors into social recommendation. In this paper, we investigate the social recommendation problem on the basis of psychology and sociology studies.. We first present the particular importance of the two contextual factors in online behavior prediction. Then we propose a matrix factorization method to fuse them in latent space. We conduct experiments on both Facebook style bidirectional and Twitter style unidirectional social network datasets.

## Introduction:

Social network users produce large volumes of information, which makes

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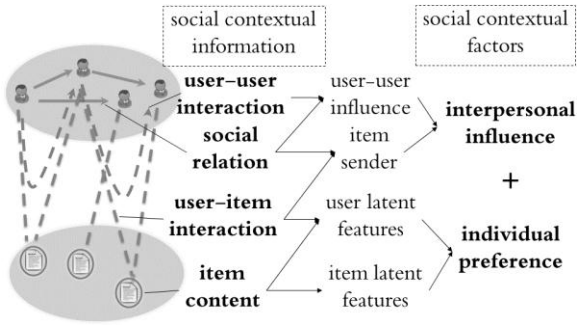
it necessary to utilize highly accurate recommender systems to support them in finding useful results. Earlier collaborative filtering techniques do not consider social relations, making them difficult to provide exact recommendations.Recently,proposed a framework of social recommender systems that made use of social relation data.However, in this work,both social relation structure and contextual factors are fully considered. It is significant and challenging to fuse social contextual factors from the contextual information and amalgamate them into a integrated recommendation framework.




**(Ref)** A novel framework for social recommendation. Meng Jiang,Peng Cui, Fei

(**Fig**)shows the entire social contextual information which can be derived from links on social networks.

In this paper we consider Twitter, when a user receives a tweet that is posted by one of his friends (the sender), he usually reads its content to see whether the item is interesting. We can get this knowledge from item content and user-item interaction information. In this situation, the user cares about who the sender is and whether the sender is a close friend or authoritative. If more than one friend sends him the same tweet, he may read it more responsively. This knowledge can be learnt from social relation and user-user interaction information. Both of these aspects are important for the user to decide whether to adopt (e.g., share, retweet) the item. The above can be viewed as two contextual factors namely individual preference and interpersonal influence.

Individual preference is indicated that individuals are to some extent influenced by others' behaviors, rather than making decisions independently.Interpersonal influence makes user behaviors more complex and thus increases the unpredictability of the item adoption.

Therefore, only when individual preference and interpersonal influence are properly fused into recommendation, uncertainity can be reduced and quality improves.

This framework is based on a probabilistic matrix factorization method to combine individual preference and interpersonal influence to improve the accuracy of social recommendation. More definitely, we factorize the user-item interaction matrix into two intermediated latent matrices including user-item influence matrix and user-item preference matrix, which are produced from threeobjective latent matrices: user latent feature matrix, item latent feature matrix, and user-user influence matrix. Moreover, as we can partially witness individual preference and interpersonal influence based on previous user-item and user-user interaction data.

## RELATED WORKS:

In this segment, we analysis several major approaches to recommendation methods. Content-based filtering and collaborative filtering have been widely used to help users find out the valuable information. Matrix factorization methods have been proposed for social recommendation due to their efficiency in dealing with large datasets.Content-based filtering introduces the basic idea of studying the item content for the ranking problem. It rank candidate items by how well they match the topic interest of the user as their preference. Collaborative filtering methods, which comprises of memory-based and model-based methods.The memory-based approaches calculate the similarity between all users based on their ratings of items. The model-based methods learn a model based on patterns recognized in the ratings of users. Collaborative filtering only utilizes user-item interaction information, but it is notuse full of social relation and social rich knowledge including user profiles and detailed item content.

## Model:

In this section, we introduce details of our social contextual model based on matrix factorization.First, we formally define the problem of social recommendation. In our model, we suppose that whether a user adopts an item on social networks is

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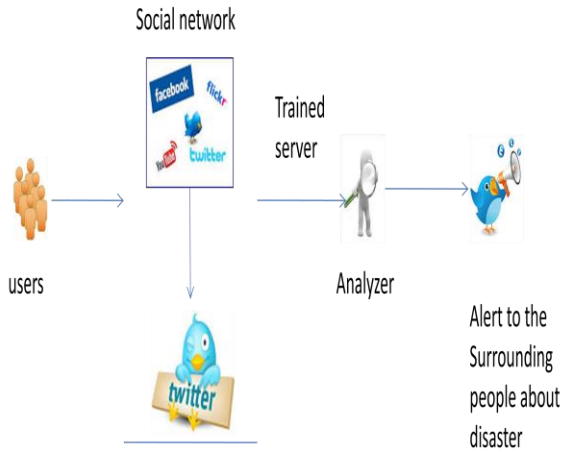
determined by three aspects:(1) item content: what the item tells about, (2) useritem interaction: what items the user likes, and (3) social relation and user-user interaction: who the senders are.The users can only receive items from their friends as social networks usually do. In our case, we know the item content, user behaviors over the items, and the interactions between users. From these previous data, we can derive the item content representation,individual preference,and interpersonal influence. We compute the user-user preference similarity matrix, item-item content similarity matrix, and user-user interaction matrix. Though the accuracy of similarity matrices depends on how LATENT ANALYSIS performs on previous data, it is fair towards competing methods in experiments to share knowledge from these matrices.

With the hypothesis that the similarities in observed spaces are consistent with the latent spaces, we regularize the three latent spaces by observed matrices (social contextual factors) in that: (1) the users that are similar in user latent space have similar preferences (2) the items that are similar in item latent space V have similar descriptive (3)high interpersonal influence in the influence latent space generates frequent interpersonal interactions;(4) the product of user latent space and item latent Space corresponds to the users' individual preference on the items; (5) the Hadamard product of interpersonal influence and individual preference is proportional to the probability of item adoptions.As the model performance is evaluated by root mean square error (RMSE) on the test set, we adopt a probabilistic linear model with Gaussian observation noise.




## Conclusion:

We conducted extensive experiments on two large real-world social network datasets, and showed that social contextual information can greatly boost the performance of

recommendation on social network datasets.The algorithm used in this project is general and can be easily adapted according to different real-world recommendation scenarios.

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