**IMPLEMENTATION**

**MODULES:**

* OSN System Construction Module
* Microblogging Feature Selection
* Learning Product Embeddings
* Cold-Start Product Recommendation

**MODULES DESCSRIPTION:**

**OSN System Construction Module**

* In the first module, we develop the Online Social Networking (OSN) system module. We build up the system with the feature of Online Social Networking. Where, this module is used for new user registrations and after registrations the users can login with their authentication.
* Where after the existing users can send messages to privately and publicly, options are built. Users can also share post with others. The user can able to search the other user profiles and public posts. In this module users can also accept and send friend requests.
* With all the basic feature of Online Social Networking System modules is build up in the initial module, to prove and evaluate our system features.
* Given an e-commerce website, with a set of its users, a set of products and purchase record matrix, each entry of which is a binary value indicating whether has purchased product. Each user is associated with a set of purchased products with the purchase timestamps. Furthermore, a small subset of users can be linked to their microblogging accounts (or other social network accounts).

**Microblogging Feature Selection**

* In this module, we develop the Microblogging Feature Selection. Prepare a list of potentially useful microblogging attributes and construct the microblogging feature vector for each linked user. Generate distributed feature representations using the information from all the users on the ecommerce website through deep learning. Learn the mapping function, which transforms the microblogging attribute information au to the distributed feature representations in the second step. It utilises the feature representation pairs of all the linked users as training data.
* A demographic profile (often shortened as “a demographic”) of a user such as sex, age and education can be used by ecommerce companies to provide better personalised services. We extract users’ demographic attributes from their public profiles. Demographic attributes have been shown to be very important in marketing, especially in product adoption for consumers

**Learning Product Embeddings**

* In the previous module, we develop the feature selection, but it is not straightforward to establish connections between users and products. Intuitively, users and products should be represented in the same feature space so that a user is closer to the products that he/she has purchased compared to those he/she has not. Inspired by the recently proposed methods in learning word embeddings, we propose to learn user embeddings or distributed representation of user in a similar way.
* Given a set of symbol sequences, a fixed-length vector representation for each symbol can be learned in a latent space by exploiting the context information among symbols, in which “similar” symbols will be mapped to nearby positions. If we treat each product ID as a word token, and convert the historical purchase records of a user into a timestamped sequence, we can then use the same methods to learn product embeddings. Unlike matrix factorization, the order of historical purchases from a user can be naturally captured.

**Cold-Start Product Recommendation**

* We used a local host based e-commerce dataset, which contains some user transaction records. Each transaction record consists of a user ID, a product ID and the purchase timestamp. We first group transaction records by user IDs and then obtain a list of purchased products for each user.
* For our methods, an important component is the embedding models, which can be set to two simple architectures, namely CBOW and Skip-gram. We empirically compare the results of our method ColdE using these two architectures, and find that the performance of using Skip-gram is slightly worse than that of using CBOW.