CA2Rec: Context-Aware Hotel Recommendation

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Abstract

The session-based and context-aware recommender system developed in this project allows us to reap the benefits of the consideration of dynamic interactions between users and items. For example, the developed system factorizes the user profiles, observable click behaviors, and the location contexts for learning session-based preferences in the domain of hotel recommendation. Doing so enables tracking of the changes in users' preferences over time, so that the system can adapts to these changes. Furthermore, mining the sequential patterns of user-item interactions is also beneficial to capture the characteristics of items which may attract attentions from broad costumers in a given context.

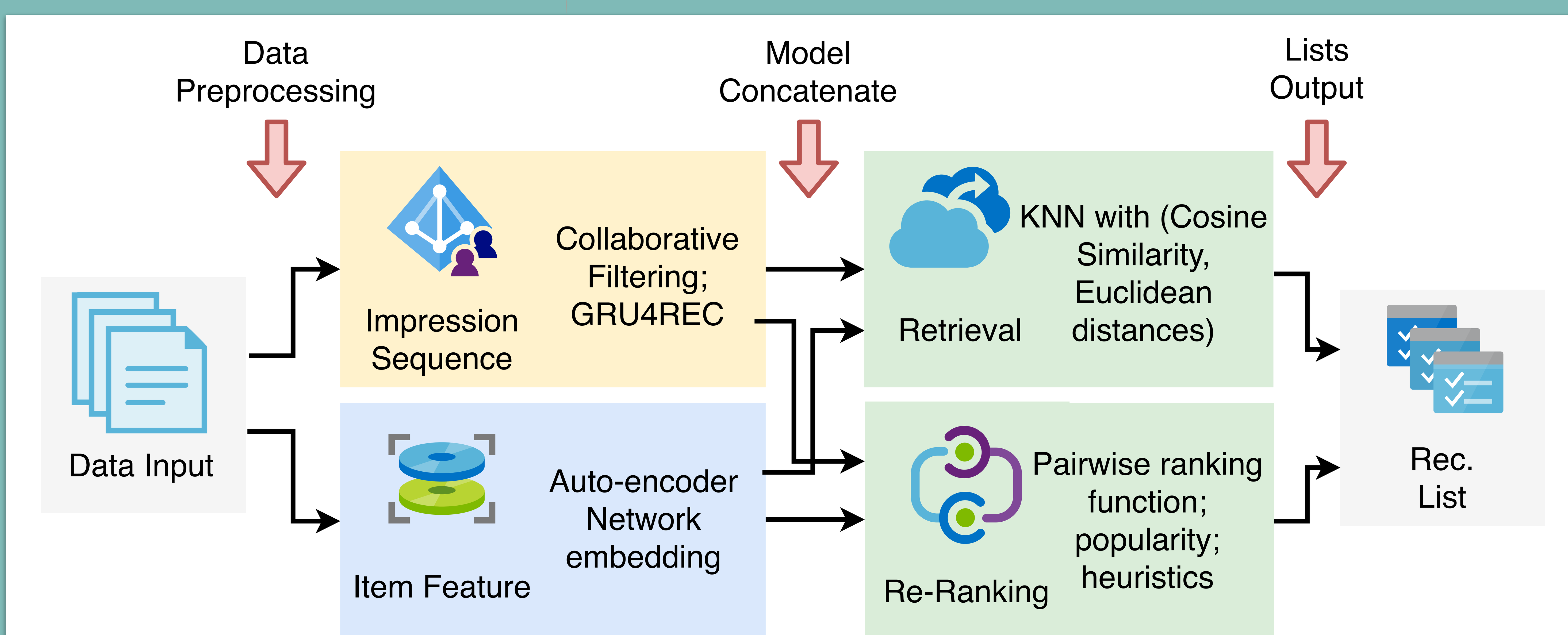
Recommendation

Time Series Feature Extraction

For extracting sequential behaviors of the users, we utilize **Recurrent Neural Network** to capture the time series features. We use a single layer **GRU** with **100** hidden unit and a **100 dimension embedding layer**. Similar to GRU4REC, we predict the next item user interacted with using the current item. The whole network was trained with **5 epochs.** We extracts the output of GRU hidden units to get the final feature vector.

Data Preparation

The dataset is obtained from Trivago 2019 RecSys Challenge. In training set, there are in total **582544** users, **927143** items and **15734730** events. We filter out sessions that only have less than 5 events. As a result, every event belong to one of **586363** sessions. Every event can have one of 10 possible action types such as interaction item info, interaction item image. Not every event associate with an item, some event may contain user input(e.g., search for poi). The final goal is to predict the item id when user performs **clickout** action.



Making a Recommendation

There are 3 stages operations for generating the final recommendation list:

- **Feature Concatenation and Normalization:** We concatenate all of the feature gained from Network Embedding, Autoencoder and GRU4Rec, then apply vector normalization for each items.
- **Generating Recommender List :** We generate the recommendation list by applying distance metrics (e.g, Euclidean Distance, Cosine Distance) to KNN retrieval.
- **List Re-ranking :** Then, we feed the list into re-ranking function (Trained by gradient boosting tree with pairwise ranking loss and heuristic labels such as popularity) to re-rank the final recommendation list.

Representation Learning on Graph

We construct a bipartite network based on three kind of interactions for modeling the user-item relations:

- **Interaction:** User interacts with item information including rating, info, image, deals.
- **ClickOut:** User makes a click-out on the item and gets forwarded to a partner website.
- **Search:** User searches for an accommodation.

This lead to a bipartite network with **2786609** edges, **717774** user nodes and **289506** item nodes. Then, we adopt DeepWalk and HopRec to learn the user and item feature vectors for further recommendation.

Experiment

We evaluate our method from two aspect with three kinds of metrics, where MRR is evaluated by each session, Precision and Recall are evaluated by user based on the sessions:

$$Recall = \frac{TruePositive}{TruePositive + FalseNegative} \qquad MRR = \frac{1}{|Q|}\sum_{i=1}^{|Q|}\frac{1}{rank_i} \qquad Precision = \frac{TruePositive}{TruePositive + FalsePositive}$$