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Session-based sequential skip prediction

Idea: Recurrent neural networks (RNN) are being used for handling sequential data. The concept is, that the users actions share some intrinsic patterns which RNNs are able to model well. For every new session they are starting at the same point and try to model the user's actions over the course of the session. However, if additional information about the session is available a priori, the RNN cannot include it. The goal of this project is to create a neural network, which can incorporate such complementary information.

Method: We propose an architecture, which makes use of this additional information. By creating a parallel architecture, we can process the sequential information with an RNN, while processing the session-based information in a dense layer. The output of these two systems is then concatenated, before being processed through another dense layer and then sent to the output layer. The parallel architecture allows to benefit from the sequential structure of the RNN as well as from the computationally cheapness of using one wide layer.

Data set: The data set for testing the proposed neural network is provided by the *Spotify Sequential Skip Prediction Challenge*[1]. It includes 130 million of listening sessions with associated user actions. Furthermore, information about the 4 million songs include acoustic features and metadata of the tracks. The task of the challenge is to predict, which songs are skipped by the used. The prediction is carried out on the second half of the session, while full information about the first half is given.

Procedure: Firstly, we will preprocess the data, to bring in a suitable form for the neural network. Secondly, we will create the baseline RNN, including training and testing functionality. This allows to get used to the Leonhard environment. Thirdly, the proposed model will be implemented and tuned. And lastly, the model as well as the baselines will be tested and compared, such that an evaluation can be performed.

Baselines: Two baselines are used for measuring the performance of the proposed architecture. The first baseline is the best one, among the ones which are provided by the challenge. This baseline predicts the last action from the first half on all elements on the second half. The second baseline only uses a deep RNN.

Evaluation: The metric used for evaluating the proposed architecture is the mean average accuracy, which is also used for the challenge. So, for all sessions, the accuracy of the predictions will be calculated. These accuracies will then be averaged.

Literature: Recommender systems, in which the next user choice of item has to be predicted, feature similar architecture as session-based predictors. A broad overview over such systems using neural networks are given in (1). The session-based recommendation algorithms using deep learning are then compared to other machine learning algorithms in (2). In (3), the authors are proposing a conditioning input representation, by concatenating the hidden and output vectors with the complementary information vector. Furthermore, they also propose conditioning hidden dynamics, by adapting the hidden transitions depending on the complementary information. In (4) (5), the authors present a parallel structure to process user actions and complementary information in parallel. These last two papers use sequential complementary information, which is not provided by the data set. Furthermore, they predict only the next user action. In (6), the authors proposing a hierarchical RNN to create session-aware predictions, where they initialize the sessions with information of previous sessions of the same user. While user identification is not provided in the data set, the initialization of sessions with additional information is a similar task.

[1] https://www.crowdai.org/challenges/spotify-sequential-skip-prediction-challenge

References:

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