SESSION-BASED PRODUCT RECOMMENDATION

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INTRODUCTION

Neiman Marcus is a Fashion Retailer selling luxury apparels & accessories via their proprietary website. Their website has many unregistered visitors, and they wish to improve personalized recommendations for these users. Recommending the right product helps cultivate brand loyalty, stimulates more site visits, and encourages more interactions with the brand. We implemented session-based recommender that relies heavily on the user's most recent interactions. We referenced the research paper **'Evaluation of Session-based Recommendation Algorithms'** by **Malte Ludewig and Dietmar Jannach.** Our experiments revealed that Gru4Rec, a complex approach based on deep neural networks, performed suitably well for product recommendation.

DATA

Data source: Kaggle RetailRocket Dataset
1,048,575 rows, 234,838 products

- **Timestamp**
- **Session ID**
- **Product ID**
- **Event (View/ AddToCart)**

Data preparation:

- Discard products with less than 6 occurrences
- Discard sessions with less than 3 products
- Divide user-activity into sessions based on a 30-minute threshold of inactivity

MODEL SELECTION - GRU4REC

Gru4Rec is a Recurrent Neural Network that predicts the next viewed product based on the current session. While the usage of RNNs for session-based, or more generally, sequential prediction problems is a natural choice, this particular network architecture, the choice of the loss functions, and the use of session-parallel mini-batches to speed up the training phase are key innovative elements of Gru4Rec approach.

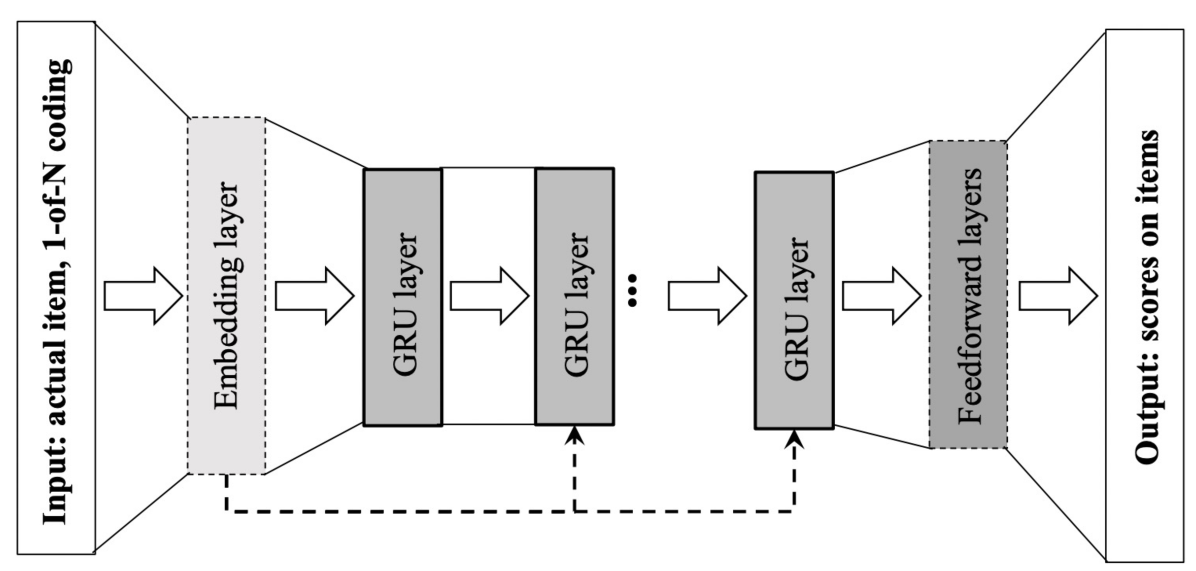
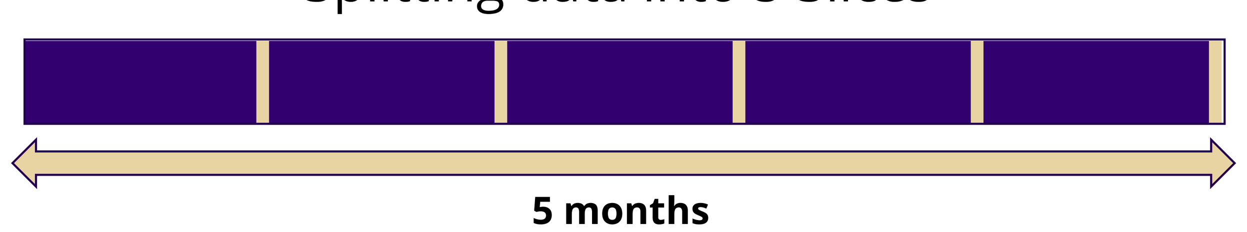


Figure 1: Architecture of the gru4rec neural network

APPROACH

Splitting data into 5 Slices



For each split:

- **Training Data – 25 days**
- **Testing Data – 2 days**

The 5 data slices allowed us to ensure multiple measurements of evaluation metrics with different test sets.

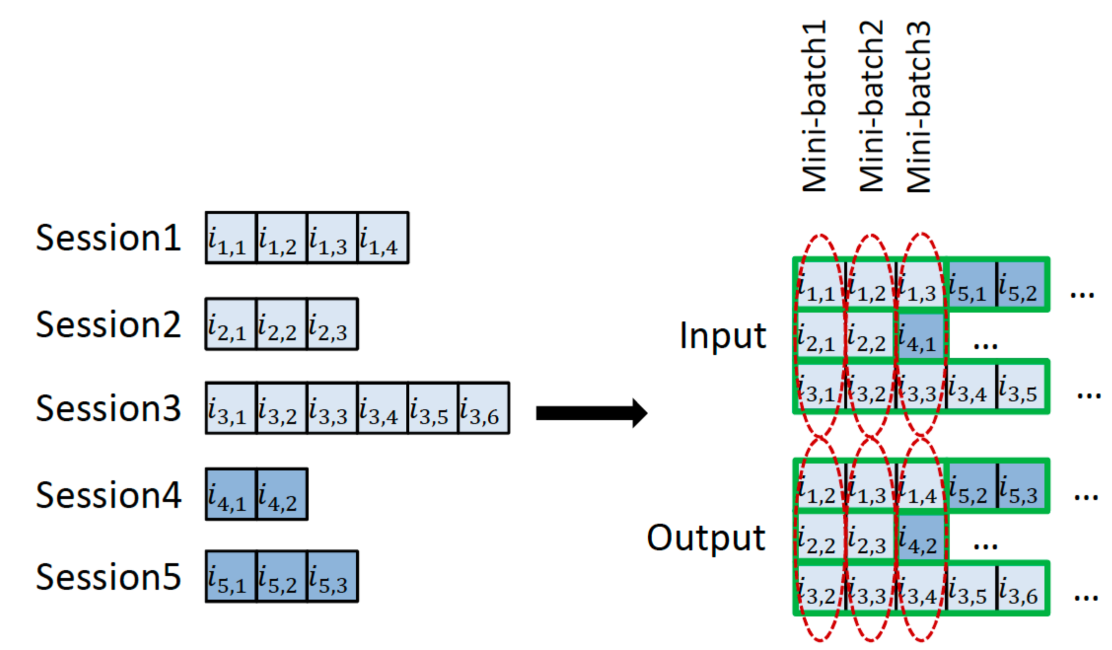


Figure 2: Illustration of the session-parallel mini-batch scheme of Gru4Rec we implemented

- The input of the network is formed by a single product, which is one-hot encoded in a vector representing the entire product space, and the output is a vector of similar shape that should give a ranking distribution for the subsequent product.
- While training and predicting with the help of this network architecture, the products of a session are fed into the network in the correct order and the hidden state of the GRUs is reset after a session ends.

Final Model Parameter Tuning:

We tried various combinations of hyperparameter values and obtained optimal results using the following hyperparameters.

Parameter	Value
Learning Rate	0.06
Loss Function	TOP1-max
Activation Function	ELU-0.50
Dropout Rate	0.20
Momentum	0.10

Table 1: Final Hyperparameter Tuning on Gru4Rec

RESULTS

Metrics	Our Model	Benchmark model
MRR@20	0.332	0.243
Hit Rate@20	0.573	0.480
Coverage@20	0.794	0.602
Popularity@20	0.032	0.060

Table 2: Comparing our model results with the benchmark model from Ludewig's research paper

- ✓ We reported four metrics computed from the top 20 recommended products.
- ✓ We reported the average of the metrics for all 5 slices.
- ✓ MRR (Mean Reciprocal Rank): Evaluates to what extent can the immediate next product in a session be predicted.

CONCLUSION

- We found a combination of optimal hyperparameter values that maximized our model's performance thereby improving the results found in Ludewig and Jannach's research paper
- This model can be utilized by Neiman Marcus along with their existing recommender models to improve personalization and product recommendations for unregistered users.

For more information, scan here to find the Project GitHub Repository.

SCAN ME