



# Recomind:

Mindful Session Recommendations



# Agenda

- Introduction.
- Motivation.
- Dataset Statistics.
- Methodology.
- Experiment results.
- Discussion.
- Conclusion.





# Team Members

## Group 5

- Manar Elghobashy
- Yara Elzahy
- Adham Mokhtar
- Yara Hassan





# Introduction

Develop an effective session-based recommendation system for videos to predict the next items in a session, using the `sbr_data_IM` dataset. The system will leverage user items in sequence for personalized recommendations.



# Motivation

- Personalized Recommendations.
- Adaptation to Changing Preferences.
- Enhanced User Engagement.
- Relevance for Multiple Industries.



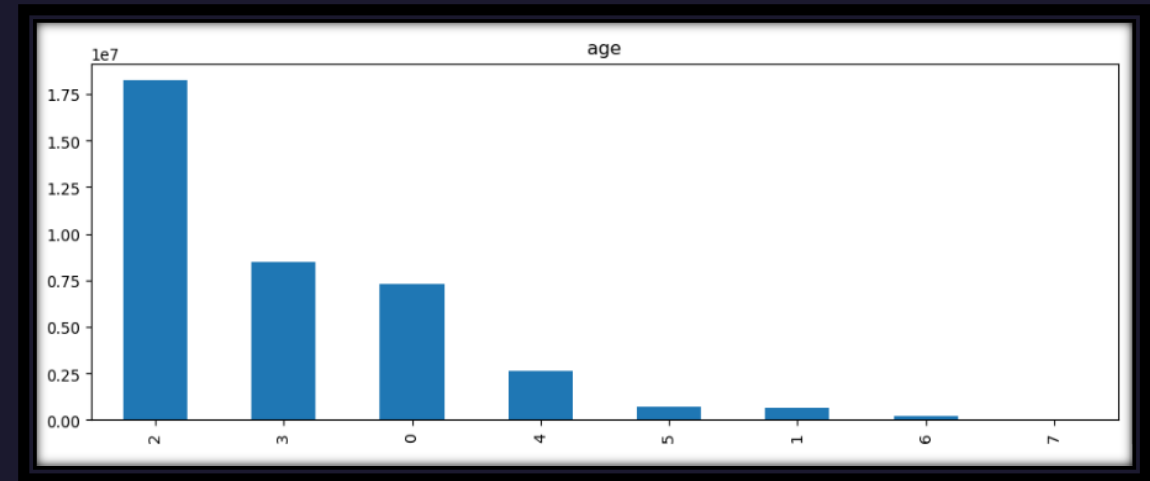
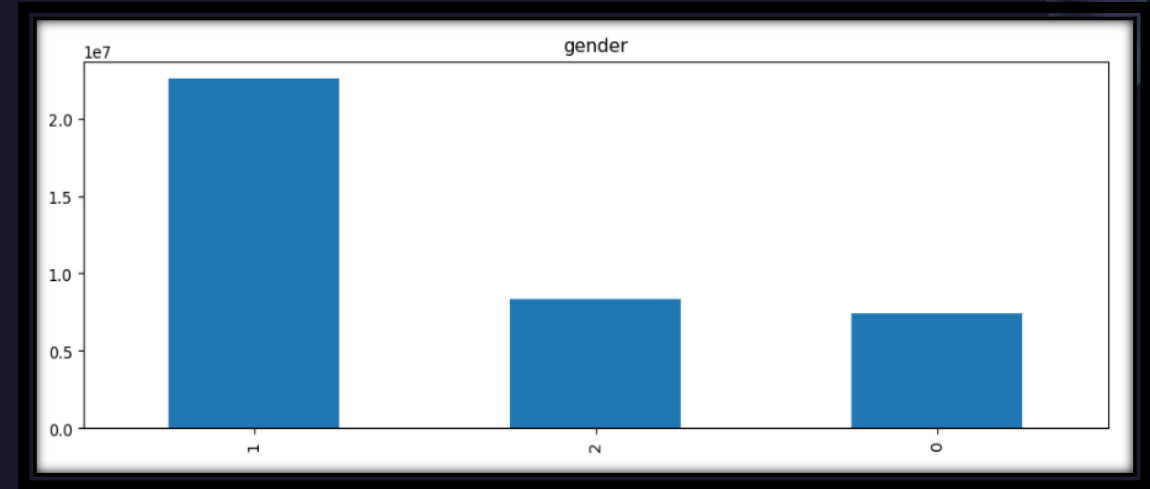


# Dataset

- The sbr\_data\_IM dataset is a preprocessed version of the Tenrec dataset, specifically derived from Qk\_video which was filtered upon clicked items.
- Our Dataset has 10 columns which includes user interactions with videos, such as clicks, follows, likes, shares, and video watching times. It also contains information on video categories, gender, and age of the users.

# Dataset Statistics

- Based on the data statistics, we decided to head our main focus on the Age and Gender
- Here's Why:
  1. Least Bias in feature selection: Compared to Like, Follow, Share, and Click.
  2. Improved Fairness: Reduces potential discrimination.
  3. Data Integrity: More reliable and inclusive results.
- And thus, we chose to split the data on the Age (0,3).



# Methodology

We explore and compare four SOTA recommender system models:

- Gru4Rec
- SasRec
- NextItNet
- Bert4Rec

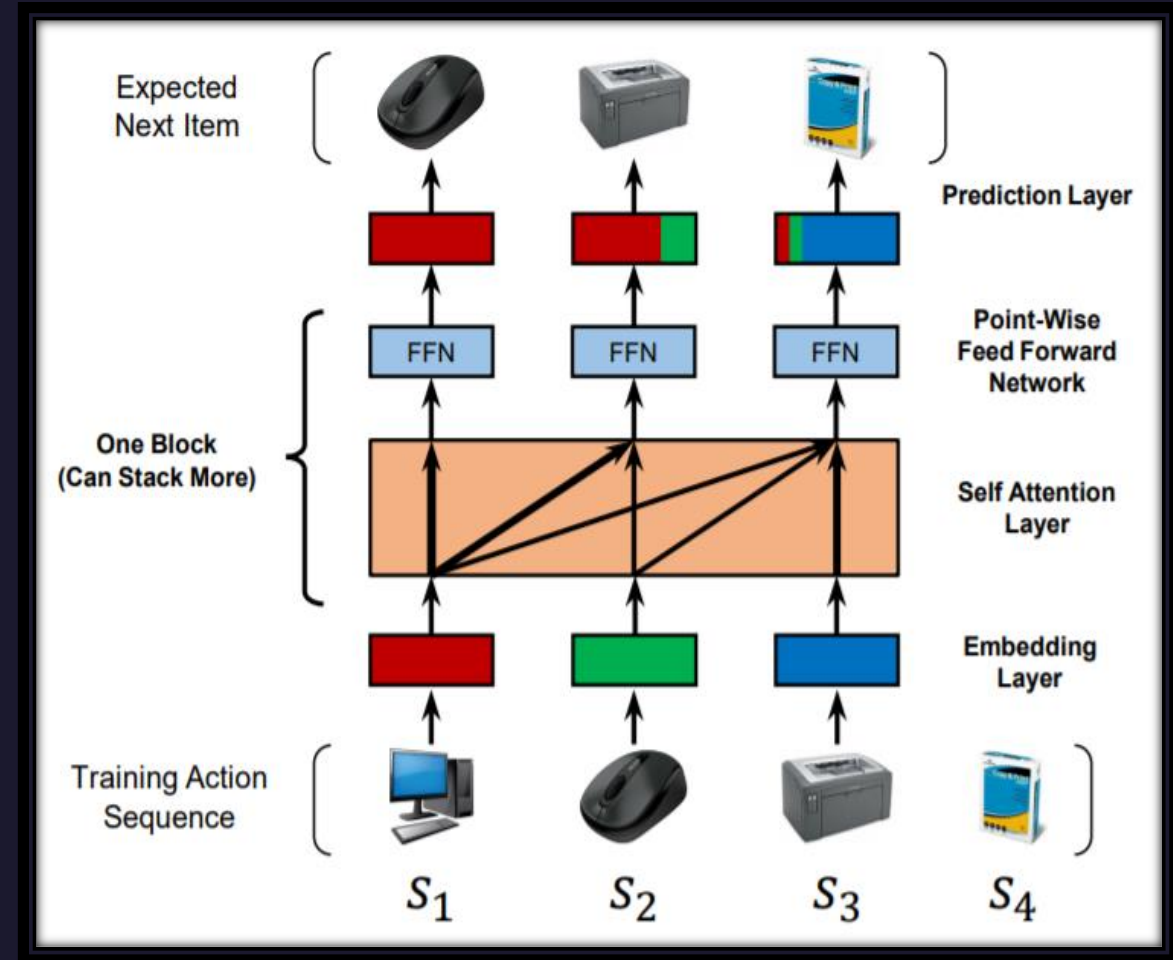


# SasRec

SASRec is a sequential recommendation model that uses self-attention mechanisms to capture long-range dependencies. It excels in providing accurate recommendations for sequential data.

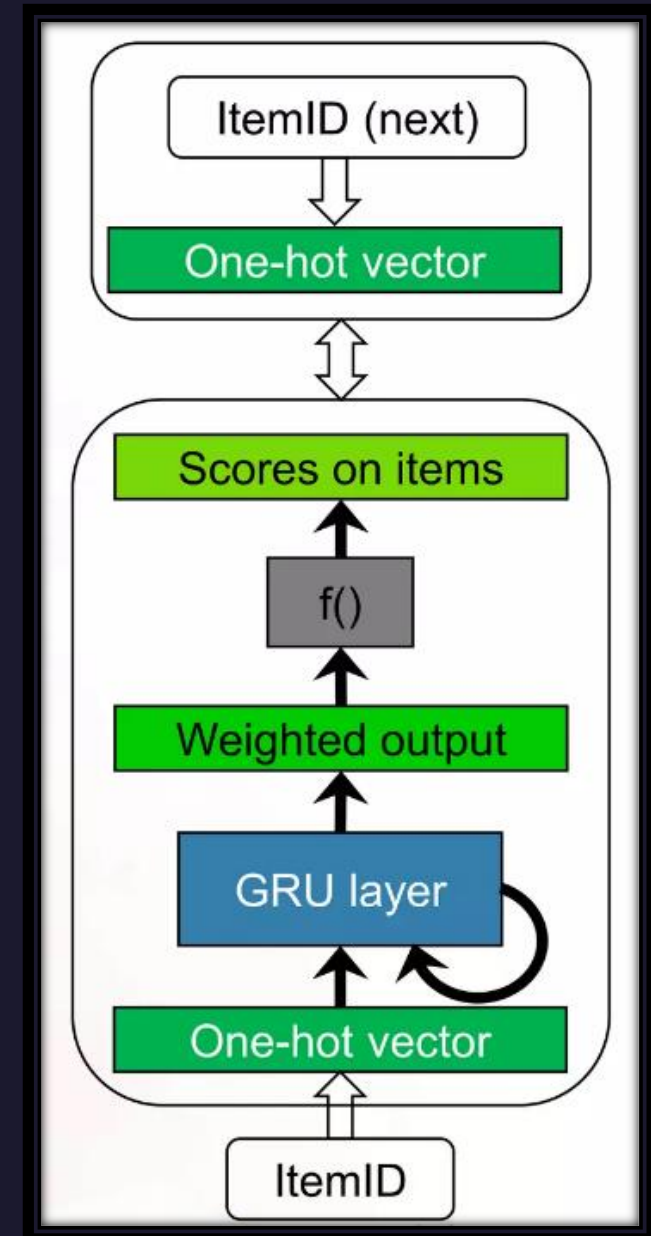
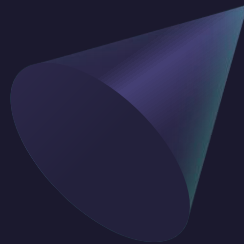
➤ Unique Characteristics:

1. Self-Attention Mechanism: Utilizes Transformer-inspired self-attention to capture item dependencies in sequences.
2. Efficient Long-Term Dependency Handling: Addresses vanishing gradient problem for handling long sequences.
3. Ideal for Session-Based Systems: Provides real-time, personalized recommendations from shorter user sessions.



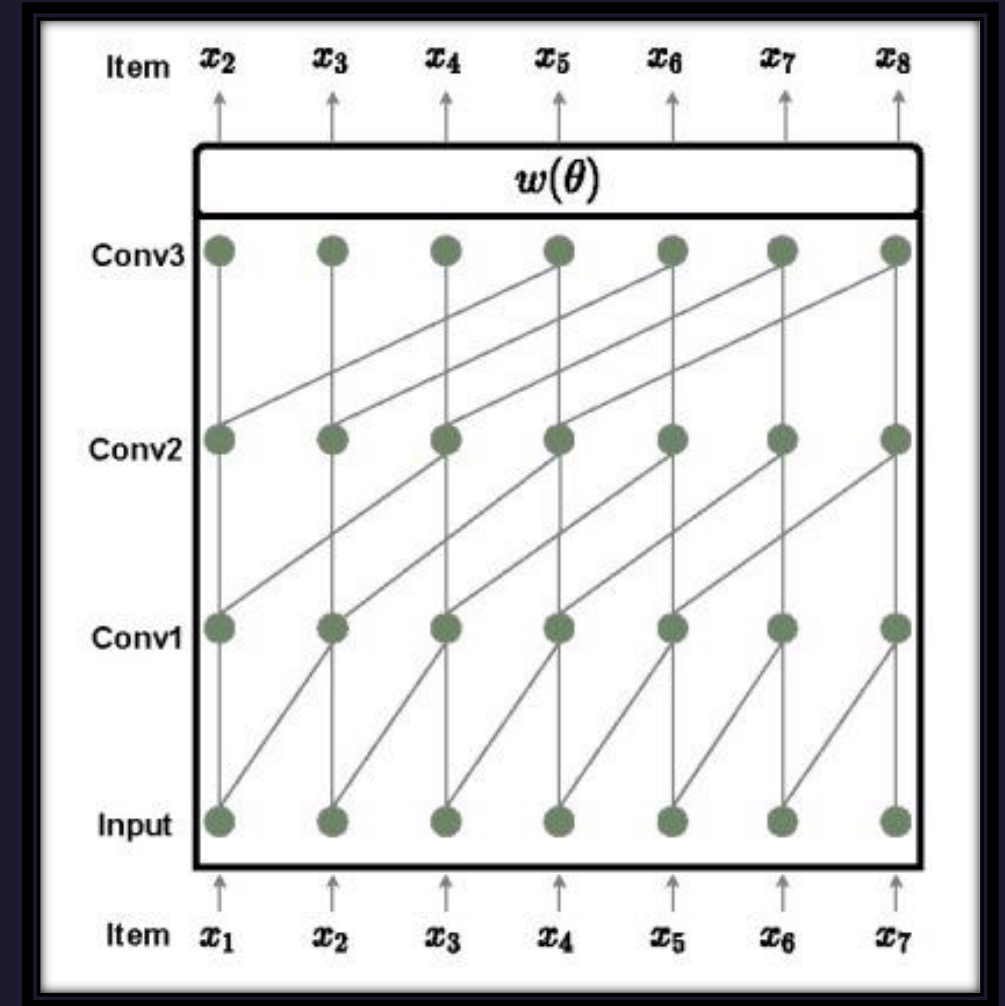
# Gru4Rec

- GRU4Rec is a powerful recurrent neural network-based model designed for sequential recommendation tasks. It effectively models user preferences over time, making it suitable for personalized and dynamic recommendations.
- Unique Characteristics:
  1. Sequence Modeling: GRU learns from sequential interactions, considering temporal order.
  2. No Explicit User Representation: Uses only session history, suitable for anonymous users.
  3. Real-time Recommendations: Fast training and inference, applicable for dynamic, real-time scenarios.



# NextItNet

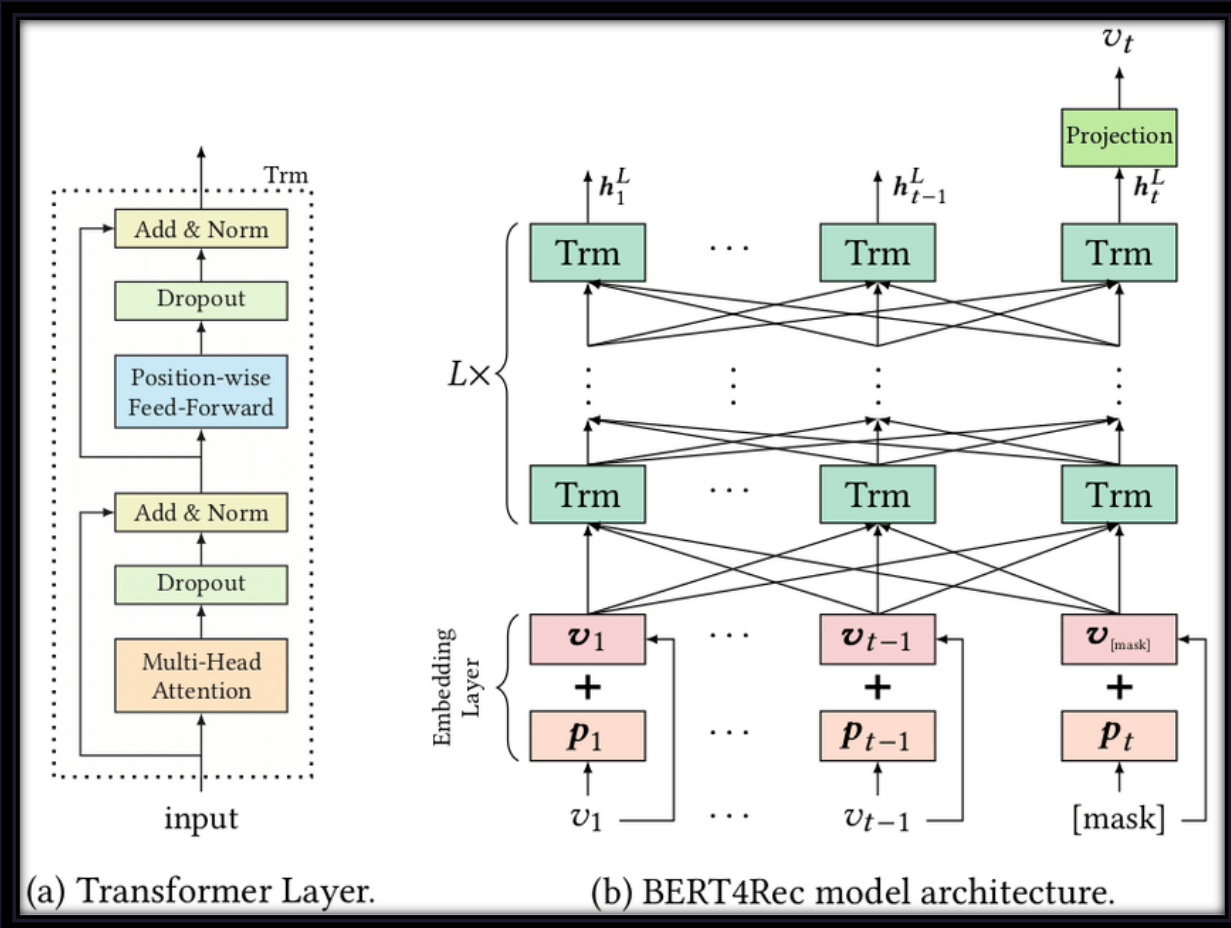
- NextItNet is a state-of-the-art model for session-based recommendation scenarios. Using dilated convolutions and residual blocks, it accurately predicts the next item a user is likely to interact with, showing promise for session-based recommendation tasks.
- Unique Characteristics:
  1. Autoregressive Generation with Temporal Encoding: Sequentially predicts items with temporal dynamics.
  2. Dilated Convolutional Neural Network (CNN): Efficiently captures long-range dependencies in sequential data without adding complexity to the model by using dilated convolutions.
  3. Next-Item Prediction: Contextually relevant recommendations for users.





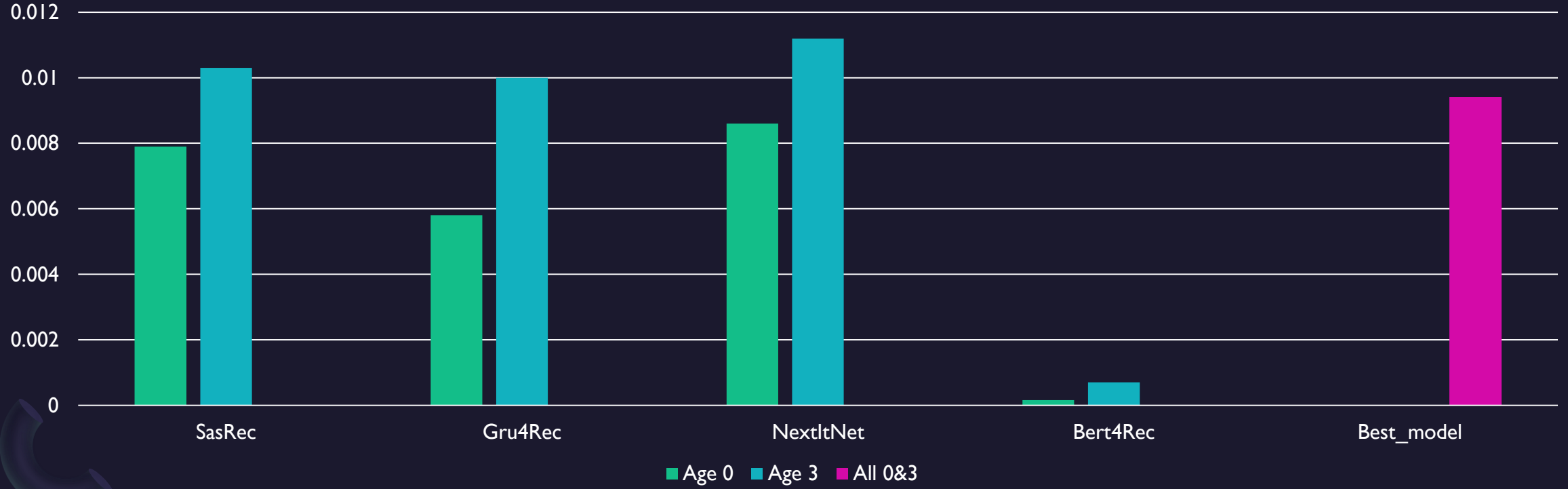
# Bert4Rec

- BERT4Rec is a recommender system model inspired by BERT, which captures item-item and user-item relationships effectively. It generates contextually rich recommendations considering historical and current user interactions.
- Unique Characteristics:
  1. Based on Transformer Architecture: Utilizes Transformer's self-attention mechanism for modeling item dependencies in sequential data.
  2. Handles Sequential and Multi-Modal Data: Can process user-item interactions and additional modalities like text or item attributes.
  3. Contextual Item Embeddings: Enhances accuracy with contextual item embeddings.



# Experiment results

NDCG@20 Results.



# Discussion

## EXPERIMENTS WITH AGE=3

- Nextinet model: Slightly good recommendations, NDCG@20 comparable to leaderboard. Improvement needed with tuning.
- Sasrec model: Improved training, moderate test performance, but room for enhancement.
- GRU4Rec model: Promising training, lacks validation consistency. Improve with hyperparameters and regularization.
- BERT4Rec model: Learned from data, poor validation (low recall/NDCG). Further experimentation needed.

## EXPERIMENTS WITH AGE=0

- Nextinet model: Positive learning from training, limited generalization (low recall/NDCG). Potential for future optimization.
- Sasrec model: Limited performance, needs refinement in metrics and configuration.
- GRU4Rec model: Trained 20 epochs, moderate validation. Improvement needed with hyperparameters and preprocessing.
- BERT4Rec model: Unstable training, extremely low recall/NDCG. Needs investigation and fixes.







# Conclusion

- The project's objective was to create an effective session-based recommendation system, providing personalized suggestions based on user behaviors in shorter sessions.
- NextItNet emerged as the best model for predicting Click-Through Rate (CTR) for users with age groups 0 and 3, achieving a commendable NDCG@20 score of 0.0094 on the sbr\_data\_IM dataset.

Thank You.