DEEP LEARNING-BASED STEAM STORE GAME RECOMMENDER SYSTEM

MSCA 31009 Machine Learning & Predictive Analytics
Final Project

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Agenda

- Problem Statement
- Data & Model Assumptions
- Exploratory Data Analysis
- Feature Engineering & Transformations
- Model Exploration
- Model Selection
- Hyperparameter Tuning
- Model Evaluation & Results
- Learnings & Future Work

Problem Statement

BACKGROUND AND CONTEXT

- **Steam Store**: A digital distribution platform for video games, offering a vast collection of games across various genres.
- **Features**: Includes community forums, game reviews, and multiplayer capabilities, enhancing user engagement and interaction.
- **User Base**: Boasts over **120 million** active users and a library of more than **30,000** games as of September 2021, providing a wide range of options for gamers to explore worldwide.

PROBLEMS AND QUESTIONS

- **Inadequate game recommender system**: The current Steam Store lacks an efficient recommendation system, resulting in users facing difficulties in discovering games that match their preferences.
- How can we leverage **user preferences** and **historical data** to create an accurate and personalized game recommender system on Steam Store?

RESOLUTION AND OBJECTIVE

- Develop and implement a **deep learning-based game recommender system** that utilizes advanced algorithms to analyze user preferences, historical data, and game features for accurate and personalized recommendations.

Data & Model Assumptions

DATA

- **Games**: Basic information about games, including ratings, pricing, and supported platforms (~50K).
- **Games Metadata**: Additional details about games such as descriptions and tags (~50K).
- **Users**: Includes information about user profiles, including the number of purchased products and published reviews (~7M).
- **Reviews**: Relationship between games and users, capturing user reviews and recommendations for specific products (~14M).

ASSUMPTIONS

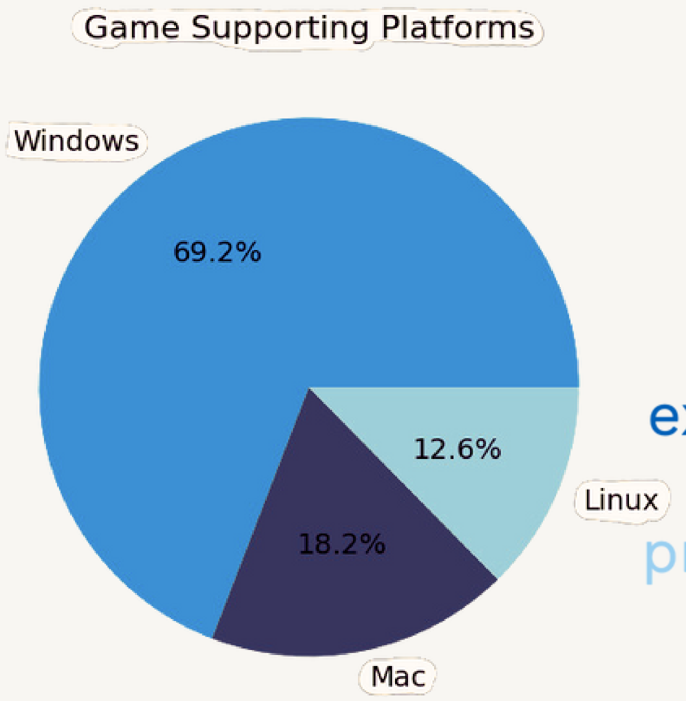
- **Accurate data representation:** The model assumes the provided data accurately represent user preferences and game information.
- **Reliable user feedback:** Users' purchasing decisions and reviews are assumed to reflect their genuine recommendations for experienced games.
- **Effective user-game modeling:** The model assumes successful capture and utilization of user-game relationships for accurate and personalized recommendations.

LIMITATIONS

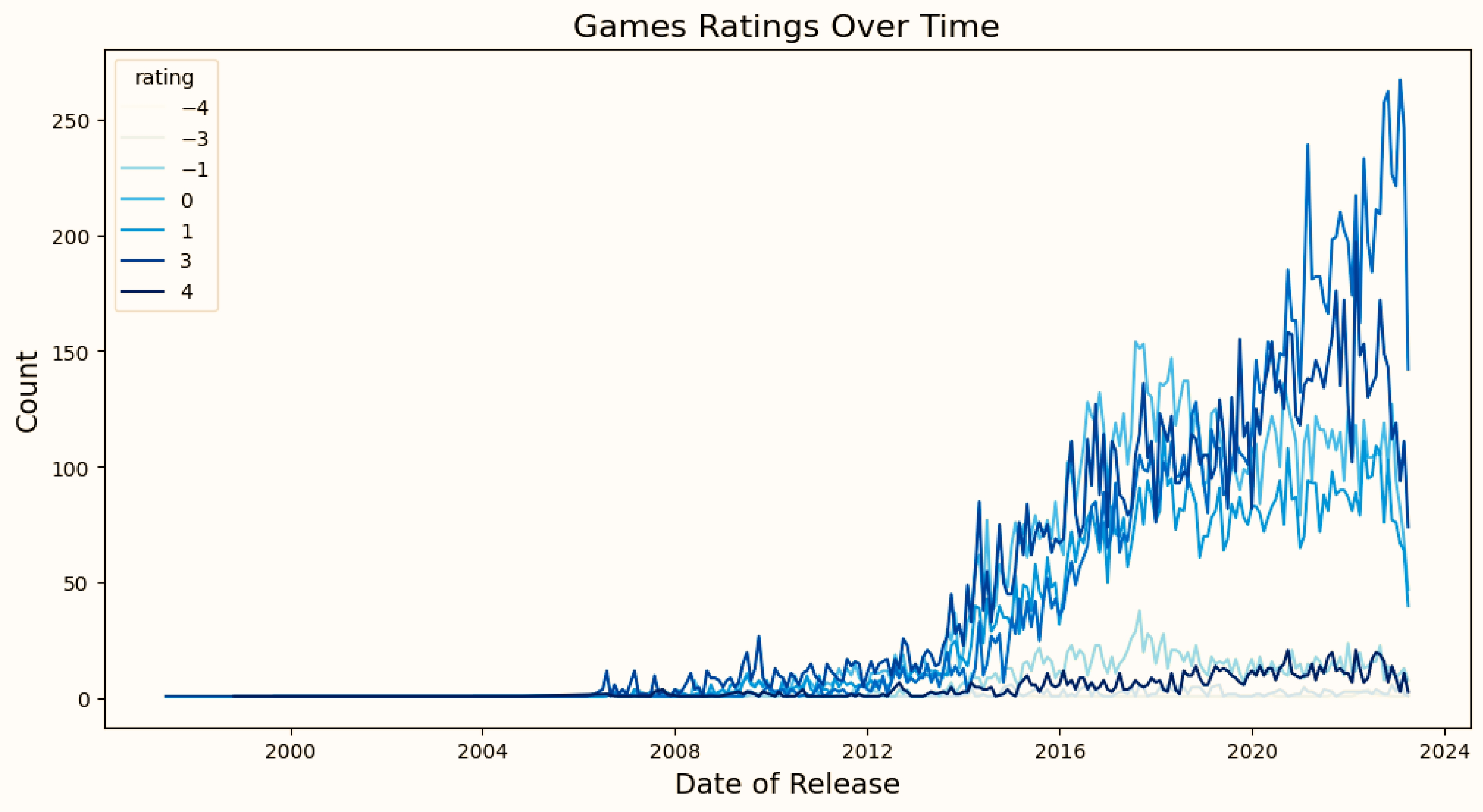
- **Incomplete data capture:** The available data may not fully capture the range of user preferences and game characteristics.
- **Limitations of historical user reviews:** Historical reviews may not accurately reflect current user preferences or trends.
- **Assumption of data influence:** The model assumes user preferences are solely influenced by the provided data, potentially overlooking external factors and individual context.

Exploratory Data Analysis

Games and Games Metadata

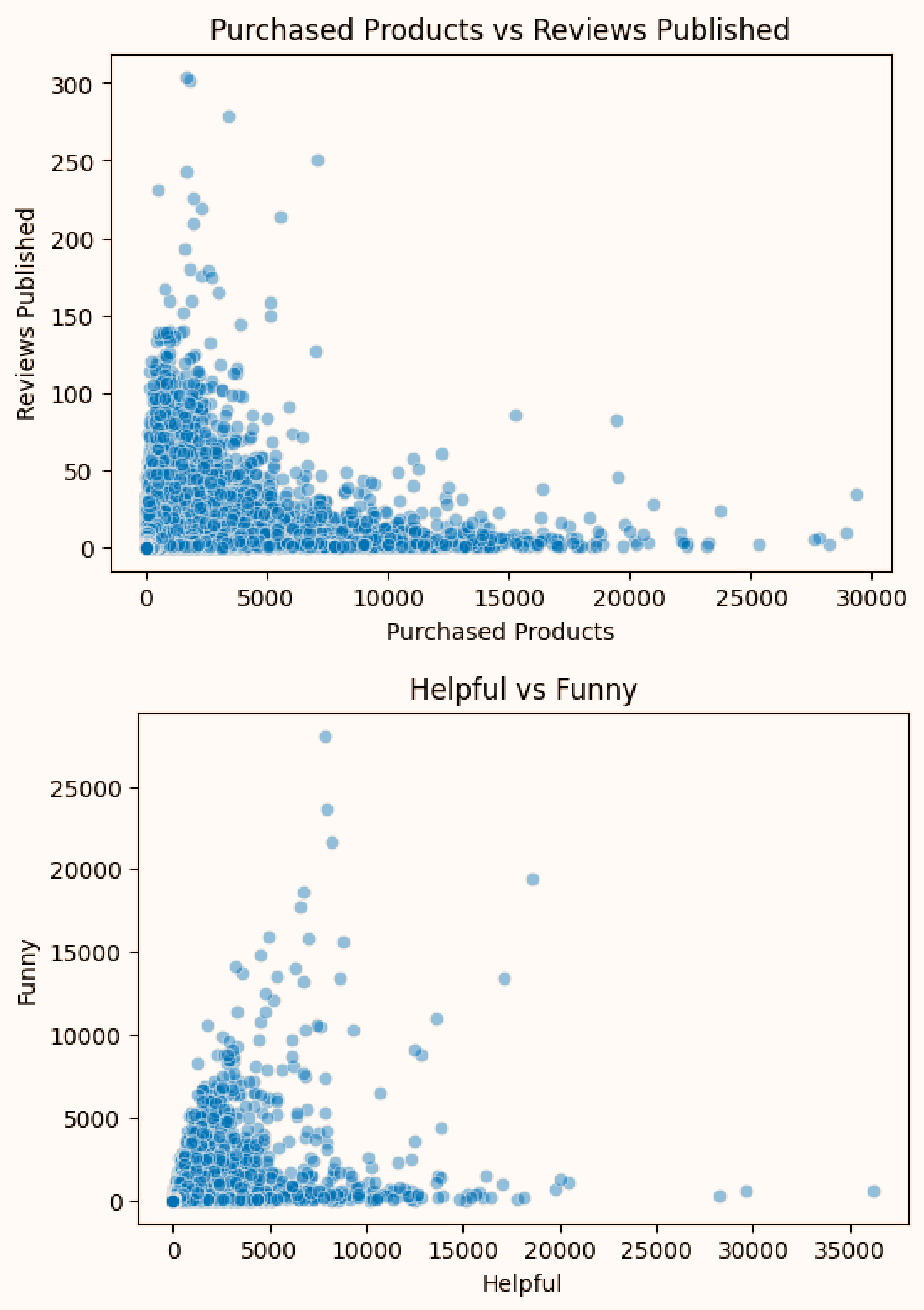


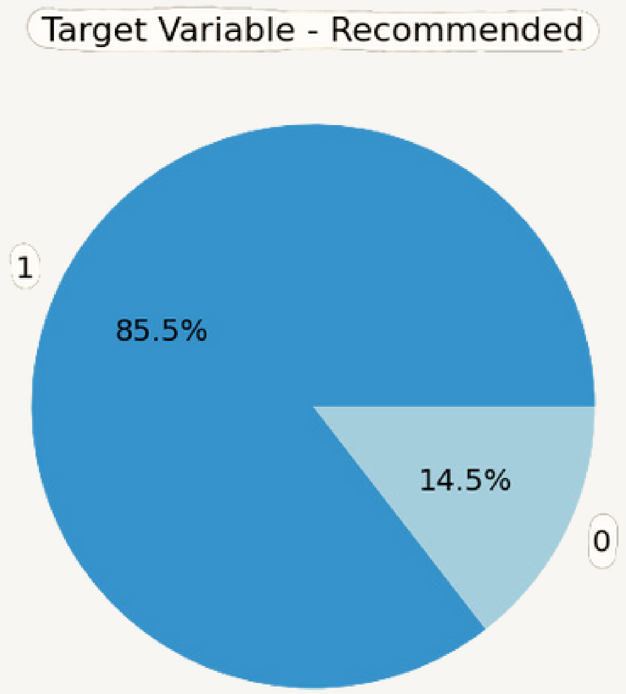
- **Platform Distribution**
  - The majority of games support Windows, followed by Mac and Linux.
  - ***Insight***: Consider platform preferences when designing the recommender system for personalized recommendations.
- **Popular Game Tags**
  - Top tags include anime, action, and horror.
  - ***Insight***: Incorporate user preferences for these popular tags to improve recommendation accuracy.
- **Game Rating Trends**
  - Ratings show overall positive sentiment and are increasing over time.
  - ***Insight***: Prioritize positive-rated games and leverage user feedback for more reliable recommendations.



Exploratory Data Analysis

Users and Reviews

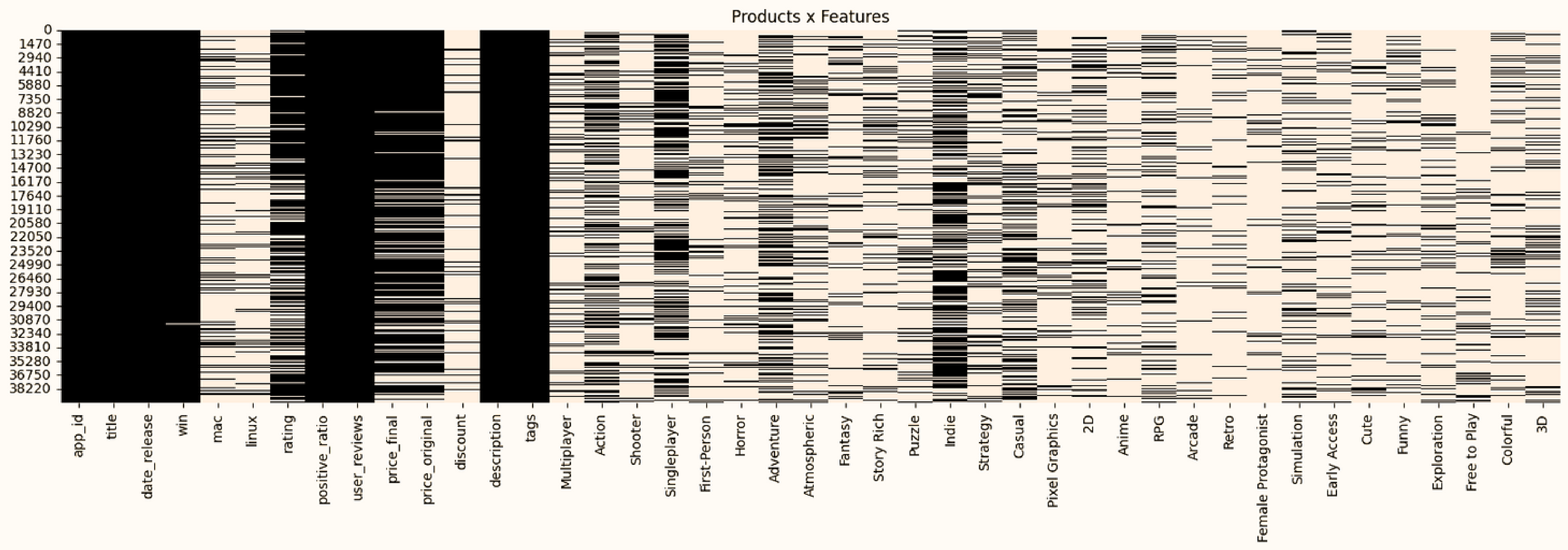




- **Purchased Products vs. Reviews Published**
  - A minor positive correlation was observed between purchases and user reviews.
  - ***Insight***: Users who purchase more products tend to be more active in providing reviews, which can be considered for personalized recommendations.
- **Helpful vs. Funny Ratings**
  - A minor positive correlation was found between helpfulness and funniness ratings.
  - ***Insight***: Consider ratings of helpfulness and funniness to enhance recommendation evaluation.
- **Imbalanced Target Variable (Recommended by User)**
  - A higher percentage of 1 (recommended) compared to 0 (not recommended).
  - ***Insight***: Addressing the class imbalance to ensure a fair representation of recommended and non-recommended games in the model. Proper resampling techniques and evaluation metrics can be employed to maintain model performance.

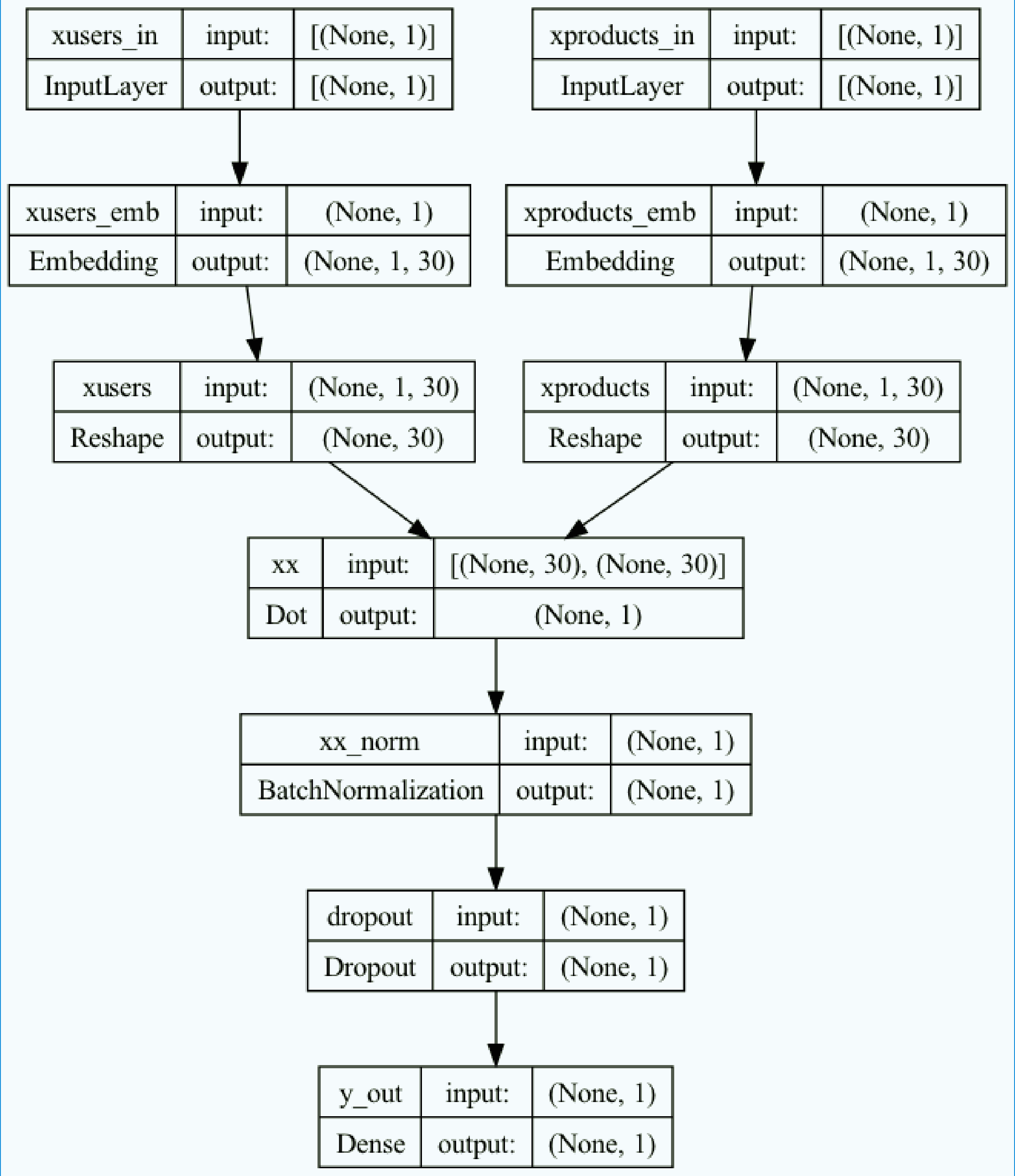
Feature Engineering & Transformations

- **Categorical Columns Encoding**: Encoded binary columns as 0s and 1s and scaled the rating column from -4 to 4 for standardized representation.
- **Top 30 Frequent Tags**: Selected and encoded the top 30 most frequent tags as new game features using binary encoding.
- **Standardization**: Applied MinMaxScalar to the feature-engineered games data for consistent scales.
- **Review Filtering**: Filtered user reviews to include only users who reviewed more than 1% of games to reduce data sparsity.
- **User-Game Interaction Matrix**: Created a user-game interaction matrix by pivoting the filtered reviews data where rows represent users and columns represent games.
- **Partitioning**: Split the user-game interaction matrix by columns (games) as train and test sets for predicting the recommendation of unseen games.
- **Oversampling**: Randomly sampled minority class (0) for the train set with a final class ratio of 1:1



Model Exploration

Content-Based Filtering &
Collaborative Filtering (CF) with Embeddings



CF WITH EMBEDDINGS

✚ Baseline Model: Content-Based Filtering

- Utilizes **game features** and user preferences for personalized recommendations.
- Overcomes **cold-start problems** by relying on game features, making it suitable for new users or games with limited data.
- Choosing content-based filtering as a **baseline model** allows for comparison against more advanced recommender systems

✚ Collaborative Filtering (CF) with Embeddings

- Leverages **user-item interactions** to capture the underlying patterns and preferences in the data.
- Captures intricate relationships between users and items by mapping them to a shared **latent space**.
- Handles data **sparsity issues** by learning representations that generalize well across users and items
- Incorporates **batch normalization layer** for improved model training, convergence, and regularization.

Model Exploration

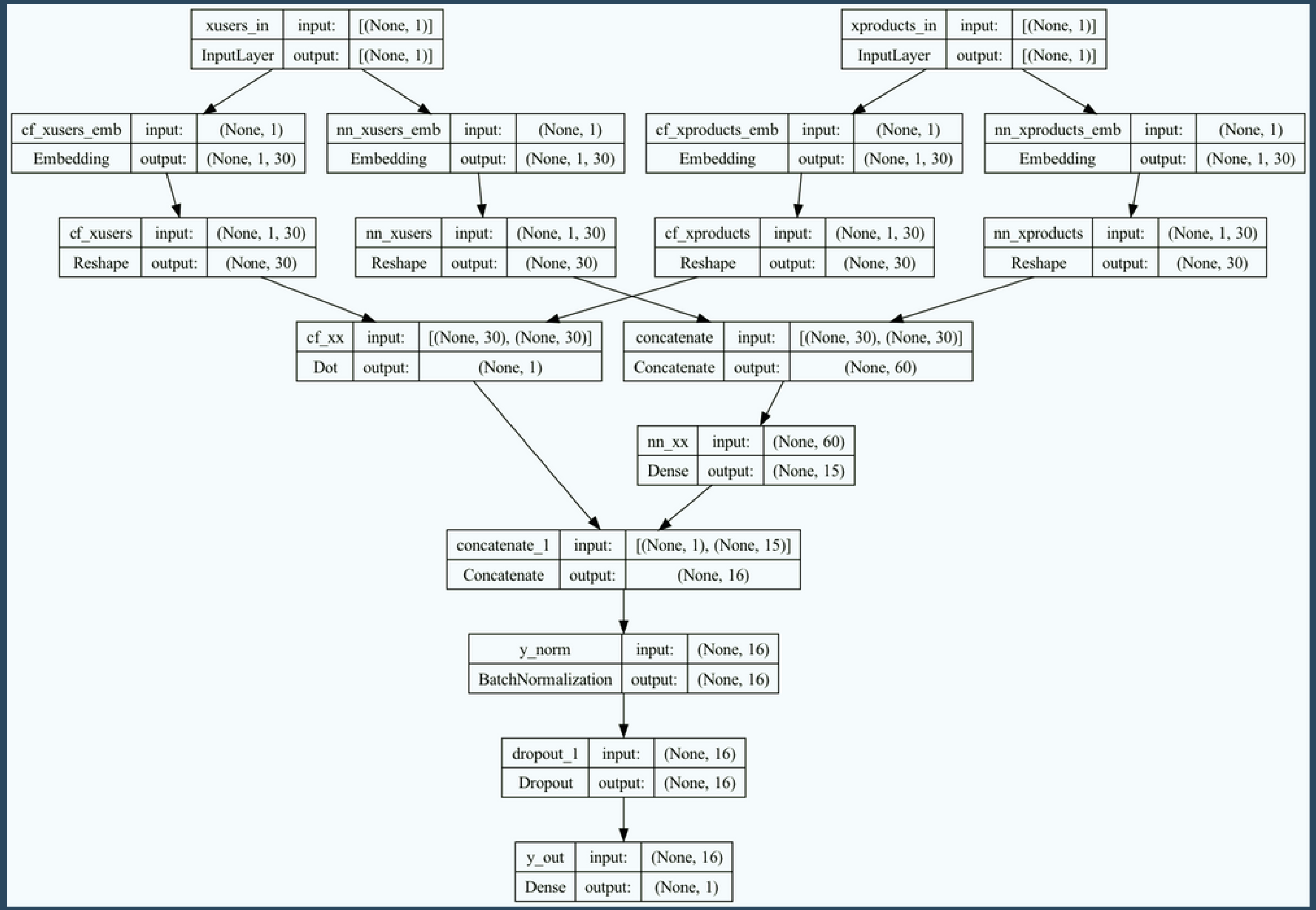
Neural Collaborative Filtering (NCF) & Hybrid Model

Neural Collaborative Filtering (NCF)

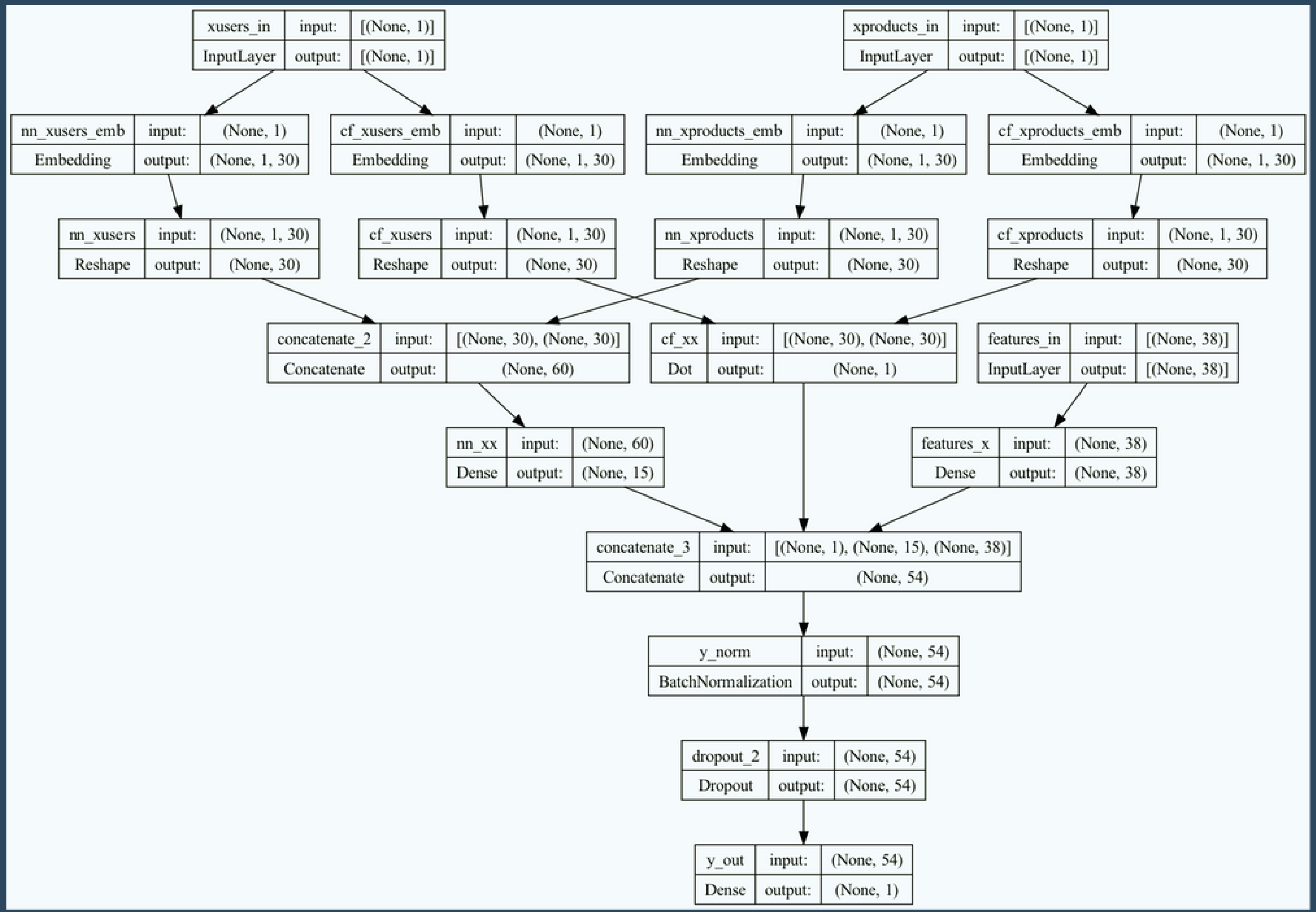
- Incorporates **neural networks** to model user-item interactions and enhance collaborative filtering for improved recommendation performance.

Hybrid: NCF with Content-Based Filtering

- Integrates **multiple recommendation techniques** including collaborative filtering, content-based filtering, and deep learning, to leverage their respective strengths.



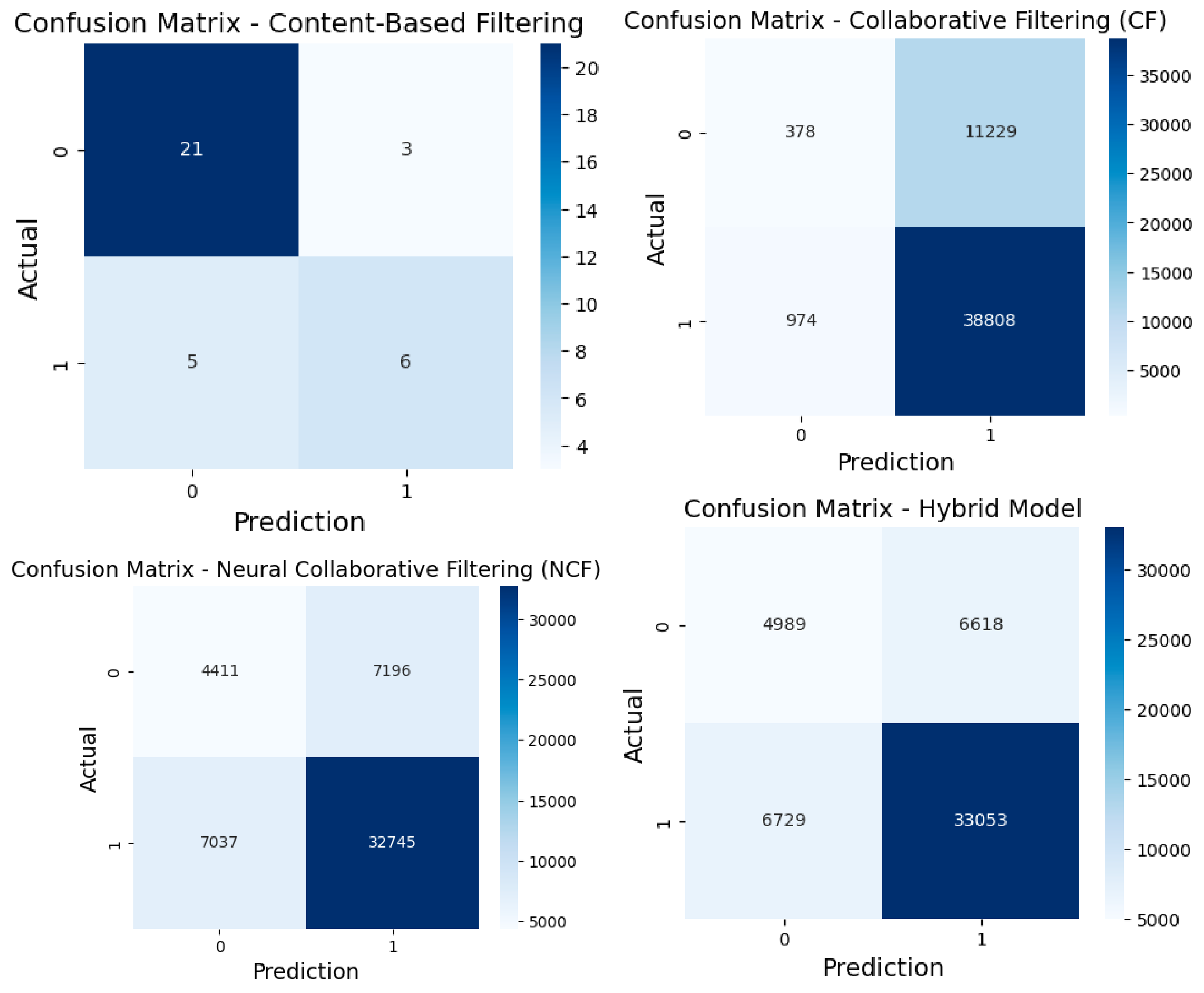
NEURAL COLLABORATIVE FILTERING (NCF)



HYBRID MODEL: NCF WITH CONTENT-BASED FILTERING

Model Selection

- Based on the confusion matrix and classification report, I choose the **Hybrid Model** as the final model since it has the highest training accuracy (84%), test accuracy (74%), precision, and recall.
- The Content-Based Filtering, Collaborative Filtering (CF), and Neural Collaborative Filtering (NCF) models have lower accuracy, precision, and recall. And they are all **severely overfitted**.
- All models were fitted with the **adamax** optimizer and **binary cross-entropy** loss function.
- I then improved the performance of the hybrid model by **tuning the hyperparameters**.



Hyperparameter Tuning

Tuning Hyperparameters for Hybrid Model Using
Random Search

BEST HYPERPARAMETERS

- Embedding Size: 30
- Batch Size: 64
- Epochs: 3

MODEL IMPROVEMENT

- Loss: 0.65 -> 0.54
- Accuracy: 0.74 -> 0.75
- Precision: 0.63 -> 0.64
- Recall: 0.63 -> 0.64
- F1 Score: 0.63 -> 0.64

EMBEDDING SIZE

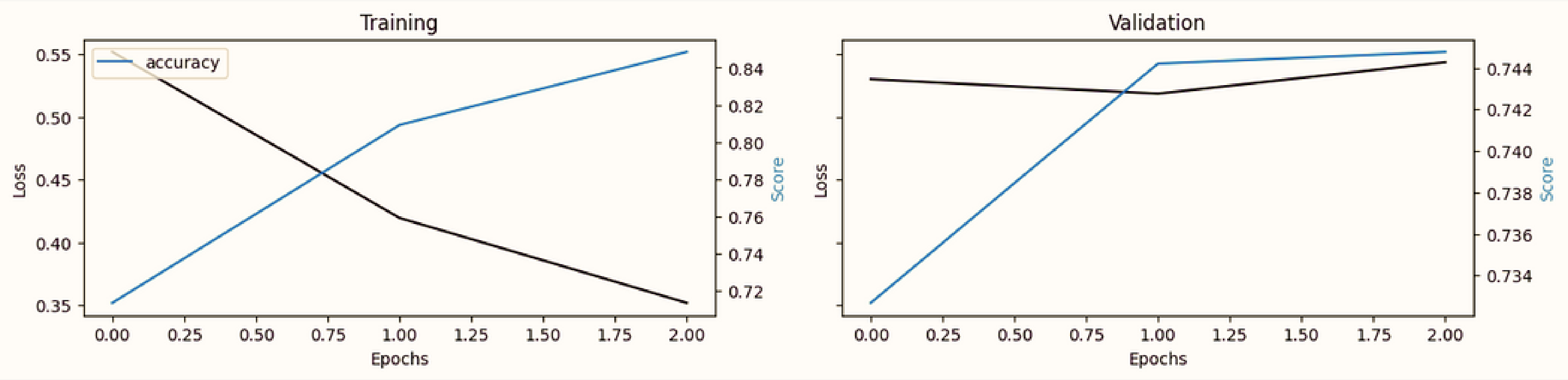
- Search Space: 10, 20, 30, 40, 50
- Increasing the embedding size can capture more complex patterns but may also increase the model's complexity and training time.

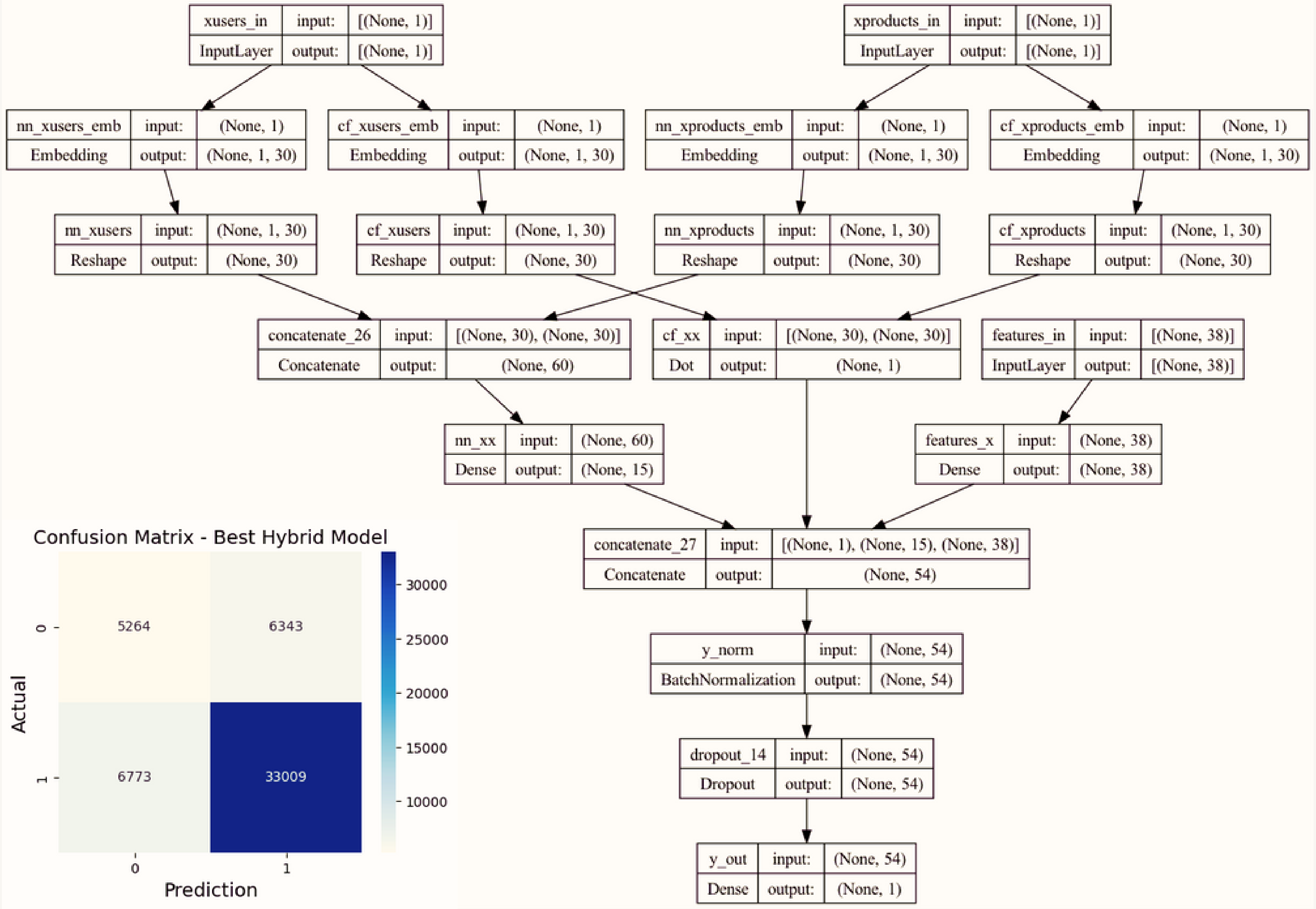
BATCH SIZE

- Search Space: 32, 64, 128, 256, 512
- Larger batch sizes can provide more stable gradient estimates and potentially faster training. However, excessively large batch sizes may lead to memory limitations or slower convergence.

EPOCHS

- Search Space: 3, 5, 7, 10, 15
- Increasing the number of epochs allows the model to see the data more times, potentially improving its ability to learn complex relationships but may lead to overfitting.





BEST HYBRID MODEL WITH EMBEDDING SIZE = 30

Model Evaluation & Results

BEST MODEL PERFORMANCE

- Test Loss: 0.54
- Test Accuracy: 0.75
- Training Accuracy: 0.81
- Precision: 0.64
- Recall: 0.64
- F1 Score: 0.64

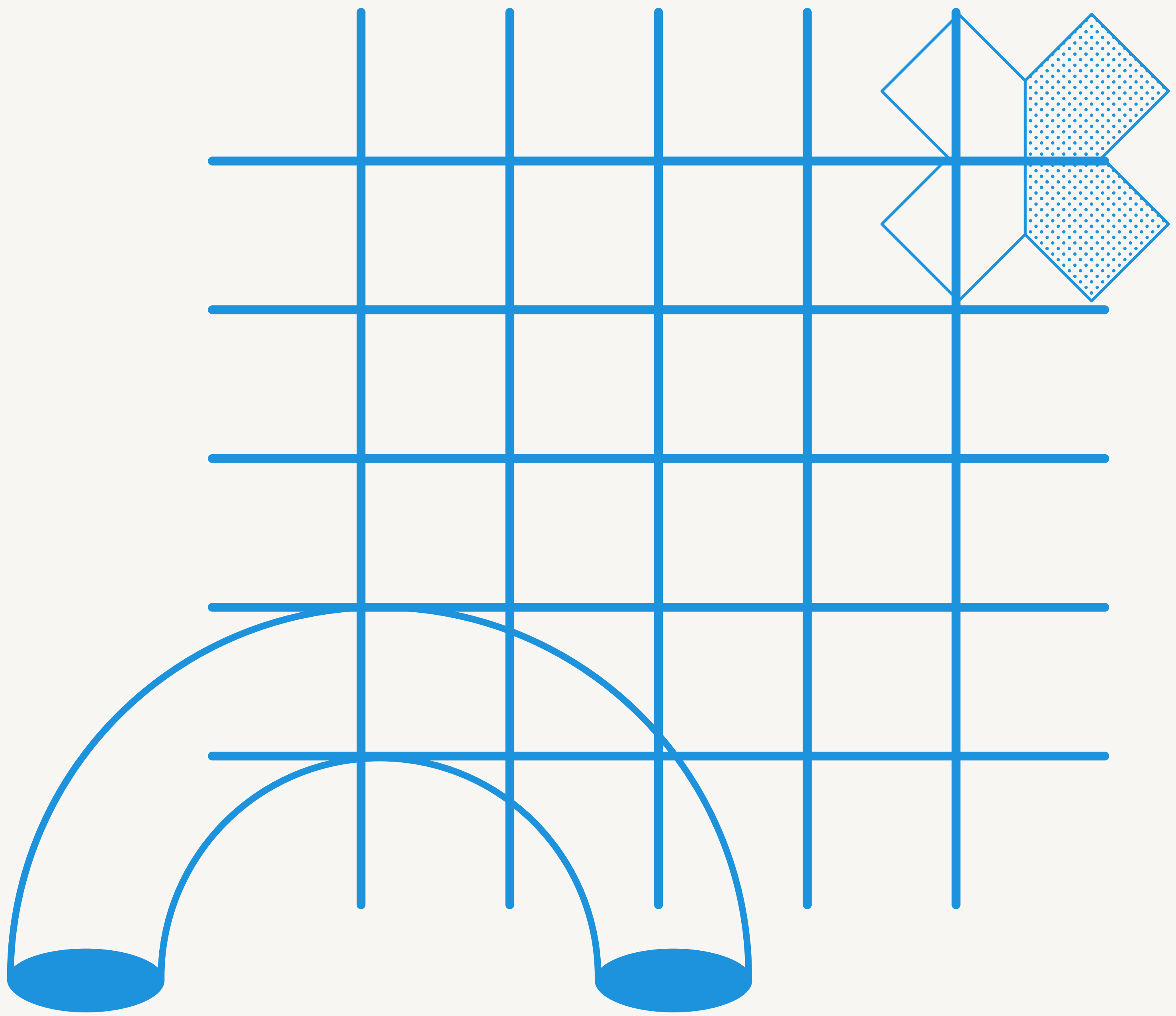
Learnings & Future Work

LEARNINGS FROM METHODOLOGY

- **Hybrid models improve recommendations:** Combining multiple techniques enhances accuracy and diversity.
- **Evaluation metrics guide model selection:** Choosing suitable metrics helps assess performance and select the best models.
- **Iterative refinement enhances performance:** Continuous experimentation and evaluation lead to improved recommendations.

FUTURE WORK

- **Incorporate Contextual information:** Personalize recommendations by considering factors like time, location, and user behavior.
- **Solve Cold-start problem:** Address the challenge of limited data for new users or items using content-based approaches and auxiliary information.
- **Utilize User feedback:** Incorporate explicit ratings and implicit interactions to refine the recommender system and enhance personalized recommendations.



Thank you!

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