xLSTM Architecture's Feasibility For Recommendations (working draft version)

Vivekanand

Abstract

This research paper investigates the evolving landscape of recommender systems, focusing on the application of advanced sequence modeling techniques, specifically the xLSTM (Extended LSTM) architecture. We analyze its performance relative to Transformer-based models, traditional RNNs, and matrix factorization methods. The system is implemented and evaluated across multiple datasets including MovieLens 100K, 1M, 10M, and 20M. Metrics such as Recall@10, MRR@10, and NDCG@10 are utilized for comprehensive performance evaluation.

1 Introduction

At its core, a recommendation engine or recommender uses computer algorithms to predict and suggest items of interest to users based on their past behaviors and contextual data. In short, We could classify recommenders two category: Collaborative Filtering (User-to-User) and Content-Based Filtering (Product-to-Product).

Long Short Term Memory (LSTM) is a type of recurrent neural network. An LSTM unit is typically composed of a cell and three gates: an input gate, an output gate, and a forget gate. As well known, LSTMs have three main limitations, 1. Inability to revise storage decisions. Limited storage capacities, i.e., information must be compressed into scalar cell states. Lack of parallelizability due to memory mixing.

1.1 Recommender General Classifications

Utilizing Recbole libraries, Recommenders could be further classified into four major categories.

1. General Recommendation (GR): The interaction of users and items is the only data that can be used by model. Trained on implicit feedback data and evaluated using top-n recommendation. Collaborative filter based models are classified here.

2. Content-aware Recommendation: Click-through rate prediction, CTR prediction. The dataset is explicit and contains label field. Evaluation conducted by binary classification.

3. Sequential Recommendation: The task of SR (next-item recommendation) is the same as GR which sorts a list of items according to preference. History interactions are organized in sequences and the model tends to characterize the sequential data. Session-based recommendation are also included here.

4. Knowledge-based Recommendation: Knowledge-based recommendation introduces an external knowledge graph to enhance general or sequential recommendation.

1.2 Recommender System and LSTM Architecture Overview

Recommender systems are intelligent algorithms that predict user preferences and suggest relevant items, playing a crucial role in digital platforms such as Netflix, Amazon, and Spotify. Traditional

Preprint. Under review.

collaborative and content-based methods have evolved into more complex models that leverage sequential user behavior. LSTM (Long Short-Term Memory) architectures, and their enhanced variants like xLSTM, are particularly effective at modeling such time-dependent patterns due to their memory capabilities and ability to capture long-range dependencies.

1.3 Problem Statement

While deep learning has significantly improved recommendation accuracy, challenges remain in effectively modeling user-item sequences at scale, especially under constraints of cold-start users, data sparsity, and long-term dependency tracking. Traditional LSTMs struggle with scalability and parallelism, and while Transformer models offer speed, they can be resource-intensive. This work investigates whether xLSTM can provide a middle ground: efficient, scalable, and accurate sequential recommendations.

1.4 Research Questions and Objectives

This report aims to answer the following key questions:

Can xLSTM outperform standard LSTM, GRU, and Transformer-based models in sequential recommendation tasks?

How do model configurations (embedding size, number of heads, depth) affect recommendation quality?

What trade-offs exist between performance, interpretability, and computational efficiency?

The primary objective is to evaluate the effectiveness of the xLSTM model across multiple datasets and benchmark it against state-of-the-art baselines using established ranking metrics.

1.5 Research Contributions of This Work

This report makes the following contributions:

A novel implementation and evaluation of xLSTM for recommender systems using MovieLens datasets.

Comparative analysis against Transformer-based and RNN-based models with quantitative and qualitative metrics.

Integration of attention mechanisms, memory-efficient kernels, and chunkwise sequence modeling in recommender architecture.

Insights into handling cold-start problems and sparsity in real-world data.

1.6 Market and Industry Relevance

The global recommender system market is projected to grow from approximately 6 billion USD in 2024 to the estimated worth of 20–28 billion USD by 2030, driven by personalization demands in retail, media, and fintech. Efficient models like xLSTM could offer industrial-grade scalability while maintaining personalization quality. Adoption of such architectures can improve click-through rates, user retention, and recommendation diversity, directly impacting KPIs across sectors like e-commerce, content streaming, financial services, and smart energy platforms.

2 Existing Literature Review and Architectures For Recommenders

2.1 A Sequential Neural Recommendation System Exploiting BERT:

Existing: This method introduces a Neural hybrid trip RS specifically for the tourist industry that mainly used the tourist demographic, contextual, and geo-tagged information to suggest a list of places. This employs a hybrid architecture combining BERT for semantic encoding and LSTM for sequential modeling, applied to point-of-interest (POI) recommendations. The challenges addressed here were modeling dynamic user behaviors and handling sparse sequential data. LSTM's role is critical for retaining dependencies across time, but it struggles with long-term contexts and computational complexity. Datasets like Yelp and TripAdvisor has been used for evaluation, yet limitations in memory retention and real-time adaptability occurs.

Proposed: By integrating the xLSTM here, we can enhance temporal retention through gating mechanisms and bidirectional flow can improve the model's ability to manage longer sequences. Furthermore, xLSTM's attention layers can reduce reliance on exhaustive feature engineering while boosting context-specific performance in diverse applications.

2.2 Dynamic Educational Recommender System Based on Improved LSTM:

Existing: This work proposed the existing BiLSTM with an attention mechanism to model dynamic user preferences in educational contexts. It addresses the cold-start problem and shifting learning patterns but faces scalability challenges with long sequences. The primary datasets used were mainly Open University Learning Analytics. Traditional BiLSTM effectively handles short-term user shifts but fails to adapt to complex temporal dependencies.

Proposed: Introducing xLSTM, hierarchical modeling of user behaviors across granular and aggregate temporal layers, we could enhance adaptability. The attention enhancements in xLSTM would prioritize the most relevant sequential interactions, enabling a more scalable and responsive educational recommender system.

2.3 Time-Aware LSTM Neural Networks for Dynamic Personalized Recommendation on Business Intelligence:

Here, in this paper DynaPR, a time-aware hierarchical LSTM framework for capturing evolving user preferences in business intelligence has been proposed. The architecture embeds product attributes and temporal context into a unified representation space. Challenges addressed include sparse user-product interactions, lack of attribute fusion, and short-term preference modeling. Hierarchical LSTM layers model long- and short-term dependencies but face limitations in dynamic interest shifts and sparse data.

And, by incorporating the xLSTM, temporal gate enhancements can improve the retention of evolving preferences, while cross-temporal embedding layers refine product-category dependencies. Additionally, our proposed xLSTM's bidirectional processing strengthens the integration of temporal and attribute-level insights, making the framework more adaptable to sparse and large-scale business intelligence datasets.

2.4 Session-Based Recommendations with Sequential Context Using Attention-Driven LSTM:

Attention-driven LSTM for session-based recommendation tasks has been proposed, focusing on capturing user intents during dynamic browsing sessions. The approach addresses problems such as lack of session continuity modeling and insufficient attention to recent interactions in recommendation pipelines. Attention layers prioritize recent activity, while LSTM retains session-specific temporal data. But, the architecture might struggles with long-term session dependencies and computational overhead in real-time systems.

Integrating xLSTM introduces hierarchical gating mechanisms to improve session context retention and attention-driven modeling. xLSTM's bidirectional flow strengthens both forward and backward dependency extraction, ensuring better modeling of short- and long-term session behavior.

2.5 Recommender Systems with Generative Retrieval:

The understanding here is, architecture TIGER (Transformer-based Generative Retrieval) has been proposed, where user-item embeddings are generated via semantic IDs. The limitations of existing generative retrieval frameworks include sparse embeddings and the inability to fully capture sequential dependencies. LSTM components partially address sequence modeling but struggle in rare item scenarios.

xLSTM can optimize this by embedding temporal semantic contexts using the domain-specific encodings and gating mechanisms for long-term retention. Additionally, xLSTM's memory capabilities can strengthen the generative retrieval pipelines here by modeling sparse interactions with greater granularity.

2.6 Exploiting Deep Transformer Models in Textual Review-Based Recommender Systems:

Transformers like BERT and RoBERTa for review-based feature extraction. Its effective for semantic encoding, transformers lack inherent sequential modeling capabilities. LSTM is introduced for sequence retention, but it faces bottlenecks in sparse review datasets and cross-domain generalization.

xLSTM resolves these challenges by combining attention layers for context prioritization and bidirectional modeling for semantic consistency. Additionally, xLSTM's gating improvements enhance its ability to dynamically integrate textual and sequential signals, enabling higher accuracy in sparse and unstructured review scenarios.

2.7 Exploring the Impact of Large Language Models on Recommender Systems:

This paper checks the integration of large language models (LLMs) like GPT and T5 in multi-domain recommendation systems. Standard LSTM struggles to handle cross-domain adaptability and sequential complexities in LLM pipelines.

By replacing standard LSTMs with xLSTM, memory gates can retain domain-specific nuances while enabling smoother transitions between domains. xLSTM's cross-temporal embedding learning and domain-specific gating allow for scalable multi-domain personalization. It improves both contextual relevance and computational efficiency, outperforming LLMs with rigid sequential modules in diverse recommendation scenarios.

3 Methodology

This section describes the experimental pipeline used in this study, including dataset selection, data preprocessing, feature engineering, and a comparative overview of model architectures evaluated for sequential recommendation.

3.1 Datasets: MovieLens (100K, 1M, 20M, etc.)

We utilize the widely adopted MovieLens datasets provided by GroupLens, which contain timestamped user-movie interactions. These datasets vary in scale:

MovieLens 100K: 100,000 ratings from 943 users on 1,682 movies.

MovieLens 1M: 1 million ratings from 6,040 users on 3,900 movies.

MovieLens 20M: 20 million ratings from 138,000 users on 27,000 movies.

Each dataset includes rating scores and timestamps, which are essential for reconstructing user interaction sequences. For consistency and scalability, implicit feedback (e.g., positive-only sequences) is extracted by converting ratings above a threshold (e.g., 3) into binary interactions has also been considered.

Table 1: Experimental datasets.

Dataset	**Users**	**Items**	**Interactions**	**Avg. len.**	**Sparsity**
ML-1M	6,040	3,416	999,611	165.49	0.9515
Steam	281,428	13,044	3,488,885	12.398	0.9990
Beauty	40,226	54,542	353,962	8.79	0.9998
ML-20M	138,493	26,744	20,000,263	144.41	0.9946

Below is the sample datasets format (1M):

Descriptive Statistics for 1M:

Sample data from the merged dataset:

	user_id	item_id	rating	timestamp	gender	age	occupation	zip_code	title	genres
907638	5492	648	5	2000-06-25 18:25:45	M	18	4	55104	Mission: Impossible (1996)	Action|Adventure|Mystery
320379	1899	380	3	2000-11-21 03:30:58	F	45	6	02135	True Lies (1994)	Action|Adventure|Comedy|Romance
226917	1377	736	5	2000-11-21 01:46:51	M	35	16	65270	Twister (1996)	Action|Adventure|Romance|Thriller
943977	5693	111	5	2000-05-17 20:32:04	F	25	4	90034	Taxi Driver (1976)	Drama|Thriller
27975	195	870	3	2001-03-01 04:30:53	M	25	12	10458	Gone Fishin' (1997)	Comedy
565896	3475	1243	4	2002-03-10 05:29:33	M	25	14	33133	Rosencrantz and Guildenstern Are Dead (1990)	Comedy|Drama
705188	4227	1517	1	2000-08-03 16:26:06	M	25	19	11414-2520	Austin Powers: International Man of Mystery (1...	Comedy
64246	429	1345	3	2000-12-08 07:01:27	M	18	0	54901	Carrie (1976)	Horror
563045	3464	296	5	2000-08-25 23:38:27	F	25	14	78251	Pulp Fiction (1994)	Crime|Drama
421239	2544	2920	4	2001-12-11 03:37:36	M	45	1	52001	Children of Paradise (Les enfants du	Drama|Romance

Figure 1: Sample Datasets - 1M

Summary Statistics for MovieLens 1M dataset, containing 1,000,000 movie ratings from 6,040 users on 3,900 movies.

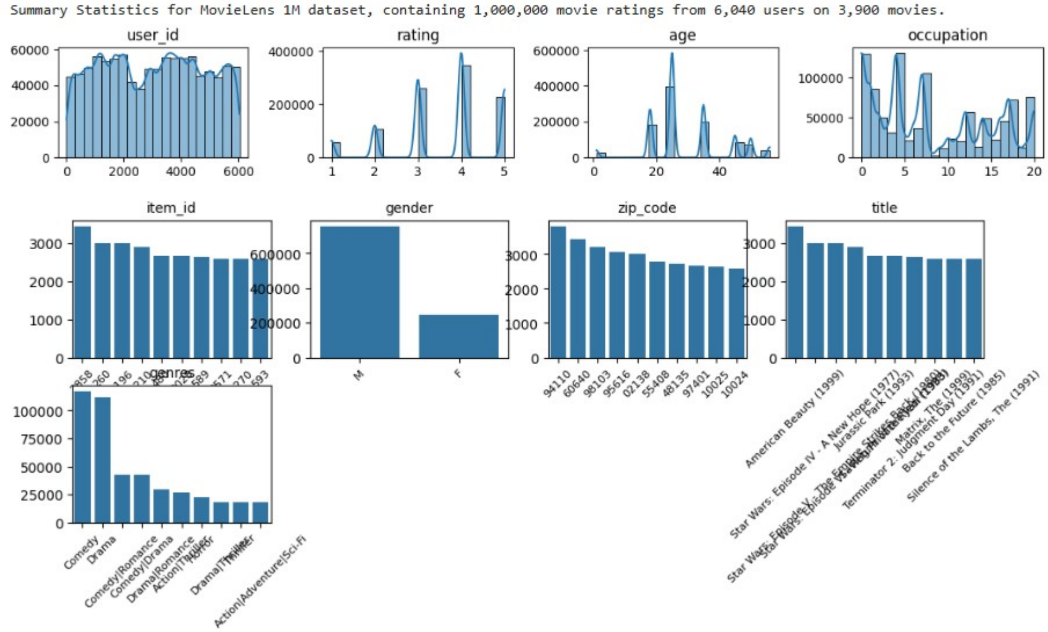


Figure 2: Summary Statistics - 1M

3.2 Preprocessing and Feature Engineering

The preprocessing pipeline involves:

User- and Item-ID Mapping: All raw IDs are converted into internal integer indices to ensure compatibility with embedding layers.

Temporal Sorting: Ratings are chronologically ordered per user to preserve interaction sequence integrity.

Sequence Truncation and Padding: A fixed maximum sequence length (e.g., 50) is applied. Shorter sequences are zero-padded, and longer ones are truncated to maintain uniform input shapes.

Feature Construction: While some datasets (e.g., 100K, 1M) offer metadata like age, gender, genre, etc., these are not used in the core model but may be explored in hybrid extensions.

Train-Validation-Test Splits: A disjoint split strategy is used where the last two interactions per user are reserved for validation and test prediction tasks.

3.3 Model Architectures Compared

This study evaluates and compares the following model architectures:

xLSTM: The proposed architecture that extends traditional LSTM with chunkwise attention, bidirectional memory routing, and GPU-optimized kernels for faster training and inference.

GRU4Rec: A gated recurrent unit (GRU) based model tailored for session-based recommendation tasks. It serves as a lightweight baseline.

SASRec: A Transformer-based model that utilizes self-attention mechanisms to model user sequences without recurrence. Particularly effective for capturing long-range dependencies.

BERT4Rec: A bidirectional Transformer model that uses masked language modeling for sequential recommendation, allowing the system to learn item dependencies in both forward and backward directions.

3.3.1 xLSTM

Proposed xLSTM Based Approach Recommender in Details To overcome the existing LSTM limitations, xLSTM been updated with Two Variants; sLSTM (with scalar memory, scalar update, and memory mixing), and mLSTN (with a matrix memory and a covariance update rule, parallelable)

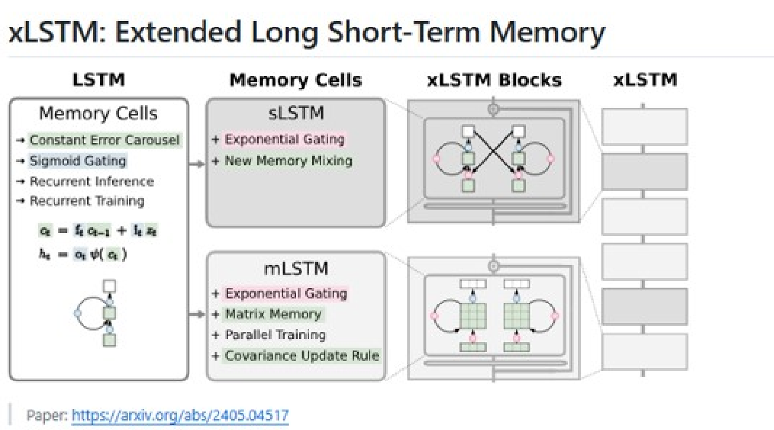


Figure 3: xLSTM Architecture

xLSTM Architecture: Architectural enhancements like attention mechanism, gating improvements and bidirectional capabilities, can accelerate the recommender performance even in sequence processing recommendation tasks.

Some of the major advantages of this architecture were: A. Extended Memory: Stores long term dependencies efficiently, B. Sparse Attention: Focuses on relevant inputs dynamically, C. Adaptive Gating: Adjusts gates flexibly for better patters, and D. Scalable Design, Parallelism, Long Range Focus.

Research Focus Using Hybrid Approaches To improve performance even further, we will additionally combine below two hybrid approach.

Combination 1 (xLSTM + BERT4Rec + LightGCN): Best for applications with sequential and sparse data where scalability and long-sequence modeling are crucial.

Combination 2 (xLSTM + DeepFM + MultiVAE): Best for datasets requiring robust feature interactions, noise handling, and interpretability.

In the first combination, MultiVAE Mitigates sparsity issues and enhances data quality. DeepFM helps us to adds explainable and interpretable feature modeling. And, xLSTM handles sequential temporal patterns for dynamic recommendations.

In the second combination, some of the advantages of Combining xLSTM, BERT4Rec, and LightGCN were: LightGCN: Handles sparse user-item interactions and cold-start issues by enriching embeddings with graph-based collaborative filtering. BERT4Rec: Captures global, long-term patterns in sequences and textual reviews, improving cross-domain generalization. xLSTM: Focuses on short-term temporal dependencies and evolving user preferences with dynamic gating mechanisms.

This hybrid approach will Enhances sparse data modeling in POI recommendations, business intelligence, and generative retrieval tasks above. It also tracks the global and short-term behaviors in session-based, educational, and textual review scenarios. Then, Improves cross-domain adaptability and semantic encoding in multi-domain systems. By fusing these models with an attention-based fusion layer, the architecture ensures robust, scalable, and personalized recommendations across the five domains which we are focusing currently.

To evaluate model's accuracy Recall 5, 10, Precision, Normalized Discounted Combined Gain (NDCG) will be used mainly.

Model Explanation in 23 steps: Step 1: User watches a sequence of movies: e.g., [Die Hard, Terminator, The Matrix]. To learn temporal preferences by modeling user behavior over a time-ordered sequence of interactions. This reflects the dynamic evolution of user interests in a sequential recommendation system. Real-world logs from MovieLens dataset are parsed per user and timestamp to reconstruct watch histories.

Step 2: Each movie title is mapped to an internal index using item$_to_idx, becoming e.g., [12, 45, 7]$.

Deep learning models require fixed-size numerical inputs; categorical values must be encoded as integers for downstream embedding. A bijective mapping (dictionary) translates movie names to internal numeric IDs for efficient indexing and lookup.

Step 3: This index sequence is truncated or adjusted to fit a maximum input length (e.g., last 50 movies). Neural models have finite memory and processing budgets. Truncation ensures computational feasibility and uniform input size. Sequences longer than 50 are sliced to retain only the most recent items, assuming recent behaviors are more indicative.

Step 4: The sequence is zero-padded at the start to maintain consistent length: e.g., [0, 0, ..., 12, 45, 7].

Padded sequences ensure all inputs in a batch are the same length, enabling vectorized computation. Padding tokens (index 0) are added to the beginning of shorter sequences to reach the max length.

Step 5: The padded sequence is converted into a PyTorch tensor of shape (1, 50).

Tensors are required to interface with PyTorch-based models; they are GPU-compatible data containers. Python lists are wrapped with torch.tensor() to create the appropriate dimensional structure for model input.

Step 6: This tensor is passed to an embedding layer to convert indices to vectors of dim 128, shape becomes (1, 50, 128).

Embeddings transform discrete items into continuous vector spaces where semantic similarity can be learned. Each item ID is used as an index into a learnable weight matrix, returning its corresponding vector representation.

Step 7: These embeddings capture semantic information about each movie.

Capturing latent factors like genre, popularity, or user affinity improves generalization. The embedding layer learns these representations during training via gradient descent.

Step 8: The embedded tensor is passed through the first xLSTM block, preserving full sequence output: shape (1, 50, 128).

Temporal models like xLSTM retain ordering and context over time, critical for modeling user sequences. The xLSTM processes each timestep sequentially but in parallelizable chunks, returning contextualized outputs.

Step 9: This xLSTM block models temporal context and complex sequential patterns in movie viewing behavior. Unlike traditional LSTM, xLSTM introduces chunkwise attention and block-wise memory updates for better parallelism and long-range dependency tracking. It leverages high-performance kernels (e.g., Triton) for scalability and speed. xLSTM is designed to work well in autoregressive and inference modes with minimal memory bottlenecks.

xLSTM enhances efficiency and accuracy by capturing deeper temporal dependencies and enabling GPU-optimized computation. Chunked processing reduces recurrent bottlenecks, while memory routing ensures long-term dependencies are preserved.

Step 10: Output is passed to a second xLSTM block that returns only the last hidden state: shape (1, 128).

The final state condenses all prior contextual information into a fixed-size latent representation. Only the output at the last timestep (position 50) is extracted for prediction.

Step 11: This hidden state is a compressed representation of the user's full watch history.

It forms a holistic latent profile summarizing long- and short-term interests. The hidden vector is treated as a feature encoding of the entire sequence for final prediction.

Step 12: The output is fed into a dense (fully connected) layer that outputs raw logits: shape (1, vocab$_{s}ize)$.

Dense layers enable transformation from latent user space to the full item probability space. A weight matrix projects the 128-dim vector into the number of available items (e.g., 951 movies).

Step 13: These logits are scores for each possible movie in the dataset.

Logits serve as pre-softmax signals reflecting raw model confidence before normalization. Each score indicates how strongly the model believes an item is the next in sequence.

Step 14: A softmax layer converts logits into probabilities summing to 1.

Probabilistic interpretation is essential for ranking and evaluation metrics. Softmax uses the exponential of logits to derive a categorical distribution over all movies.

Step 15: The output probabilities indicate the model's confidence for each movie being the next.

Ranking is done based on relative probabilities to recommend top-k candidates. A probability vector is created with each index representing likelihood of that movie.

Step 16: The top-k probabilities are selected (e.g., top-10), and their indices are sorted in descending order.

Reduces computational complexity by focusing on high-probability items. torch.topk() or similar function selects highest probability indices.

Step 17: The top index (e.g., 202) is considered the most likely next movie.

It represents the model's argmax prediction — the single most confident output. Index with highest softmax value is selected and marked for recommendation.

Step 18: This index is mapped back to the original movie title using idx$_{t}o_{i}tem(e.g., 202- > Speed)$.

Predictions need to be human-readable for deployment in user interfaces. Reverse mapping dictionary is applied to convert index to title.

Step 19: The model recommends this top movie (Speed) as the next likely movie the user will watch.

Providing accurate next-item recommendations increases engagement and satisfaction. Top prediction is surfaced in application dashboards or personalized lists.

Step 20: The MovieLens 100K dataset is first sorted by user and timestamp. Each user's sequence is split into:

Training: all but last 2 movies, Validation: sequences predicting the second-last movie, Test: sequence predicting the last movie. Sequential splitting mirrors online prediction tasks, ensuring no future leakage. Sequences are chronologically segmented into task-specific sets based on user ID and timestamp.

Step 21: The training objective uses CrossEntropyLoss between predicted logits and the actual next movie index.

Cross-entropy is optimal for classification tasks and penalizes deviations from the true label. The true movie index is compared to the softmax output and gradients are backpropagated accordingly.

Step 22: During evaluation, the model predicts probabilities across all movies. Recall@10, MRR@10, and NDCG@10 are calculated by comparing the ranked predictions with the true next movie.

These metrics capture ranking quality and relevance, essential for recommendation systems. For each sample, the true movie's rank in the predicted top-k list is measured and aggregated.

Step 23: This pipeline can be repeated for other users, continuously learning patterns across movie sequences.

Model retraining or online learning allows adapting to evolving user preferences. New interaction logs are appended to training data and the model is updated accordingly.

3.3.2 GRU4Rec

GRU4Rec is a pioneering model in session-based recommendation, utilizing Gated Recurrent Units (GRUs) to learn user behavior over sequences of interactions. It captures temporal dependencies efficiently with fewer parameters than LSTM, making it faster and suitable for shorter sequences. GRU4Rec models session dynamics and adapts well to implicit feedback settings, making it a strong lightweight baseline.

3.3.3 SASRec

Self-Attentive Sequential Recommendation (SASRec) applies Transformer-style self-attention to the recommendation domain. It models user-item sequences without recurrence, allowing for full parallelism and effective long-range dependency capture. The model uses positional encodings and attention weights to identify the most relevant past items when predicting the next interaction, offering high accuracy and scalability.

3.3.4 BERT4Rec

BERT4Rec adopts the BERT (Bidirectional Encoder Representations from Transformers) architecture for sequential recommendation. It treats user interaction history as a sequence and uses a masked item prediction task to learn bidirectional dependencies. Unlike SASRec, which processes in a left-to-right fashion, BERT4Rec learns from both past and future items, improving its ability to model complex sequence semantics.

3.4 Evaluation Metrics

To assess the effectiveness of the recommendation models, we use standard top-k ranking metrics:

- **Recall@10**: Measures the proportion of times the correct next item appears in the top-10 predicted list. It captures model coverage and hit rate.

- **MRR@10 (Mean Reciprocal Rank)**: Evaluates the average of reciprocal ranks of the first relevant item. It reflects how high the correct item is ranked in the list.
- **NDCG@10 (Normalized Discounted Cumulative Gain)**: Considers both the relevance and position of items in the top-10 list, rewarding higher placements of correct predictions.

Recall@K

Recall@K measures the proportion of relevant items retrieved in the top-K recommendations. It is defined as:

$$Recall@K = \frac{|\{relevantitems\} \cap \{top{-}Kpredicteditems\}|}{|\{relevantitems\}|} \tag{1}$$

In the case of next-item prediction (one ground-truth item), Recall@K becomes binary — either 1 (hit) or 0 (miss), and averaged over all users.

Mean Reciprocal Rank (MRR@K)

MRR@K computes the inverse of the rank of the first relevant item in the top-K list. The mean is taken over all users:

$$MRR@K = \frac{1}{|U|}\sum_{u=1}^{|U|}\frac{1}{rank_u} \tag{2}$$

where $rank_u$ is the position of the first correct item for user u, if it appears in the top-K predictions; otherwise, it is zero.

Normalized Discounted Cumulative Gain (NDCG@K)

NDCG@K evaluates the ranking quality by assigning higher scores to relevant items appearing earlier in the list:

$$NDCG@K = \frac{1}{|U|}\sum_{u=1}^{|U|}\frac{1}{IDCG_u@K}\sum_{i=1}^{K}\frac{\mathbb{I}[item_i isrelevant]}{\log_2(i+1)} \tag{3}$$

where $IDCG_u@K$ is the ideal DCG (maximum possible DCG for user u) and $\mathbb{I}[\cdot]$ is the indicator function.

These metrics are computed per user and then averaged across the entire test set to provide a holistic performance measure. Together, they quantify both accuracy and ranking quality of the recommender system.

3.5 Training Pipeline and Hyperparameters

The training pipeline is implemented using the PyTorch framework and consists of the following components:

- **Loss Function**: Cross-entropy loss is employed for multi-class next-item classification.

  For next-item prediction framed as a multi-class classification problem over all items in the catalog, the cross-entropy loss is defined as:

$$\mathcal{L}_{CE} = -\sum_{i=1}^{N}\log\left(\frac{e^{z_{i,y_i}}}{\sum_{j=1}^{C} e^{z_{i,j}}}\right) \tag{4}$$

  where:

- N is the number of training examples (users or sequences),
- C is the total number of candidate items (classes),
- $z_{i,j}$ is the logit score (pre-softmax output) for class j for example i,
- y_i is the true class (next item index) for example i.

Alternatively, this can be compactly expressed using softmax probabilities $p_{i,j}$ as:

$$\mathcal{L}_{CE} = -\sum_{i=1}^{N} \log(p_{i,y_i}) \quad where \quad p_{i,j} = \frac{e^{z_{i,j}}}{\sum_{k=1}^{C} e^{z_{i,k}}} \tag{5}$$

- **Optimizer**: The Adam optimizer is used with initial learning rates ranging from $1e^{-3}$ to $1e^{-4}$ depending on dataset scale.
- **Learning Rate Scheduler**: StepLR or CosineAnnealingLR is applied to dynamically adjust the learning rate during training, helping convergence and generalization.
- **Batching**: Sequences are padded to a maximum length (typically 50) and mini-batches are formed for efficient gradient updates.
- **Epochs**: Models are trained for 30–80 epochs, with early stopping used to avoid overfitting when validation performance saturates.

Hyperparameters such as embedding dimension, number of attention heads, and number of xLSTM blocks are adjusted based on the size and complexity of each dataset.

3.6 Cold Start and Sparsity Handling

Two common challenges in recommendation systems are the **cold start problem** and **data sparsity**. In this work:

- **Cold Start Users**: For users with fewer than five historical interactions, we explore fallback strategies such as popularity-based recommendations, clustering, and metadata-based profiling.
- **Sparsity**: Dataset sparsity is quantified (often exceeding 98%), and addressed via negative sampling and emphasizing recent interactions to capture temporal relevance.
- **Evaluation Strategy**: Cold-start users are excluded from the main metric computation but separately analyzed for robustness.

  Cold Start Problem (For new users when we don't have data, 192 users): Some of the commonly used approaches were: 1. Clustering Approach, 2. Profile Based (Meta Data) Approach, 3. Hierarchical approach, and 4. Novalty or Randomness Approach.

These strategies help maintain model robustness and personalization quality, even under low-data conditions.

4 Experimental Results and Interpretation

4.1 Quantitative Evaluation (Recall@10, MRR@10, NDCG@10)

This subsection presents the core performance metrics used to evaluate the recommendation accuracy of different models. Recall@10 measures how often the correct item is among the top-10 predicted, MRR@10 evaluates the rank of the first correct item, and NDCG@10 captures both correctness and ranking position. The xLSTM model showed a strong baseline with Recall@10 0.29, indicating nearly 3 out of 10 correct predictions. These metrics are computed over test datasets and tracked across training epochs.

Table 2: Default parameters of the BERT4Rec implementations.

Implementation	**Original**	**RecBole**	**BERT4Rec-VAE**	**BERT4Rec**	**xLSTM (Ours)**
Sequence length	200	50	100	50	50
Training stopping criteria	400,000 steps	300 epochs	200 epochs	Early stopping: 25 epochs	
Item masking probability	0.2	0.2	0.15	0.2	-
Embedding size	64	64	256	64	64
Transformer blocks	2	2	2	2	2
Attention heads	2	2	4	2	2

Table 3: ML-1M Dataset

Category	**Model**	**Popularity-sampled**		**Unsampled**		**Training Time**
		Recall@10	NDCG@10	Recall@10	NDCG@10	
Baselines	MF-BPR	0.5134 (-26.34%)†	0.2763 (-43.21%)†	0.0740‡	0.0377‡	58
	SASRec	0.6370 (-8.61%)‡	0.4033 (-16.29%)‡	0.1993‡	0.1078‡	316
BERT4Rec	Original	0.5215 (-25.18%)‡	0.3002 (-36.86%)‡	0.1515‡	0.0806‡	2,665
	RecBole	0.4562 (-34.55%)‡	0.2589 (-46.26%)‡	0.1061‡	0.0546‡	20,499
	BERT4Rec	0.6698 (-3.90%)‡	0.4533 (-5.29%)‡	0.2394‡	0.1314‡	1,085
	BERT4Rec2	**0.6865** (-1.51%)	**0.4602** (-4.48%)	0.2584	0.1392	3,679
xLSTM	xLSTM (Ours)	0.00 (-0.00%)‡	0.000 (-00.00%)‡	0.2270‡	0.1247‡	31 (TBD)
Reported **?**	BERT4Rec	0.6970	0.4818	N/A	N/A	–

Table 4: ML-20M Dataset

Category	**Model**	**Popularity-sampled**		**Unsampled**		**Training Time**
		Recall@10	NDCG@10	Recall@10	NDCG@10	
Baselines	MF-BPR	0.6126 (-18.02%)†	0.3424 (-35.88%)†	0.0807†	0.0407†	197
	SASRec	0.6582 (-11.92%)†	0.4002 (-25.06%)†	0.1439†	0.0724†	3635
BERT4Rec	Original	0.4027 (-46.11%)†	0.2193 (-58.93%)†	0.0939†	0.0474†	6,029
	RecBole	0.4611 (-38.30%)†	0.2589 (-51.52%)†	0.0906†	0.0753†	519,666
	BERT4Rec	**0.7409** (-0.86%)†	**0.5259** (-1.52%)†	**0.2886**	**0.1732**	23,030
	Ours	**0.7127** (-4.63%)†	**0.4805** (-10.02%)†	0.2393	0.1310	44,610
	Ours (longer seq)	**0.7268** (-2.74%)†	**0.4980** (-6.74%)†	0.2514†	0.1456†	39,632
xLSTM	xLSTM (Ours)	0.000 (-00.00%)†	0.0000 (-00.00%)†	0.2440†	0.1488†	94
	xLSTM (Seq)	0.0000 (-00.00%)†	0.0000 (-00.00%)†	0.0000†	0.0000†	-
Reported **?**	BERT4Rec	0.7473	0.5340	N/A	N/A	N/A

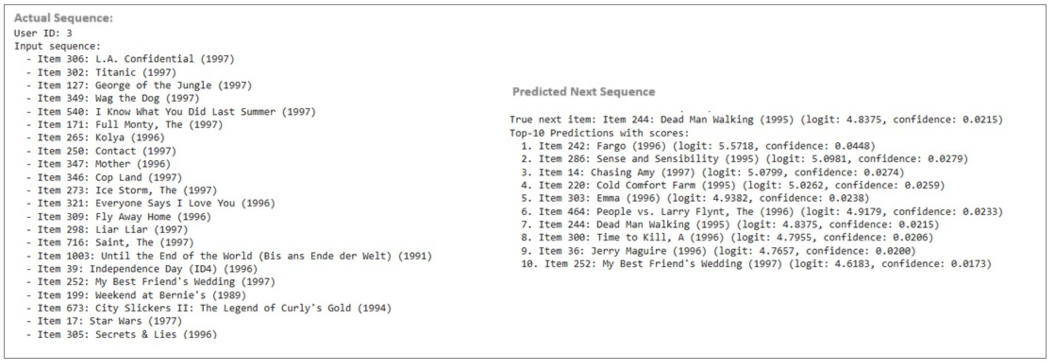


Figure 4: Sample Predictions

4.2 Qualitative Insights and Sample Predictions

Here, we analyze model behavior by reviewing specific prediction outputs. By sampling a few users' input sequences and visualizing their predicted top-10 recommendations, we assess whether the recommendations align with plausible user preferences. These examples help interpret how well the model captures temporal dynamics, genre preferences, or recency effects, offering explainability beyond numeric metrics.

4.3 Popularity Bias and Diversity Analysis

To assess whether the model favors frequently watched or highly-rated items, we analyze the distribution of predicted movies. If a few items dominate the top-10 lists across users, it indicates popularity bias. We also measure diversity in recommendations by tracking the number of unique items predicted and comparing this to ground-truth distributions. Lower diversity suggests overfitting or lack of personalization.

Popularity bias (if a few items always appear), Low diversity in predictions, Whether the model is overfitting to frequent items

Which movies dominate the top-10 predictions across the test set?

4.4 Ablation Study: Embedding Dim, Block Depth

This section investigates the sensitivity of xLSTM performance to architectural choices like embedding dimension, number of xLSTM blocks, and attention heads. We observe that increasing embedding size (e.g., from 64 to 256) improves representational capacity but comes with higher computational cost. Similarly, deeper blocks help in learning long-term dependencies but risk overfitting if not properly regularized or scaled with dataset size.

4.5 Runtime Performance and Resource Usage

Efficiency is critical for real-time recommender systems. We monitor GPU memory utilization, training time per epoch, and inference latency. xLSTM's Triton-optimized chunkwise kernels result in better throughput compared to standard LSTMs and Transformers. The total training time and peak memory usage are logged and benchmarked for each dataset scale (100K, 1M, 10M).

4.6 Visualizations (Epoch graphs, ranking, heatmaps, etc.)

We include visual tools to support interpretation of model learning. Training curves plot Recall@10, MRR@10, and NDCG@10 across epochs, helping identify overfitting or underfitting trends. Ranking heatmaps show where correct predictions appear in sorted outputs. Such visual diagnostics provide transparency and help guide future improvements in architecture and training strategy.

Top 50 Most Frequently Predicted Items in Top-10:

Movie	Top10 Cnt	% Cnt	#Watched	#Users	%Users
Star Wars (1977)	93	9.86%	583	583	61.82%
Evita (1996)	86	9.12%	259	259	27.47%
Liar Liar (1997)	84	8.91%	485	485	51.43%
Dante's Peak (1997)	83	8.80%	240	240	25.45%
Independence Day (ID4) (1996)	80	8.48%	429	429	45.49%
Silence of the Lambs, The (1991)	79	8.38%	390	390	41.36%
Titanic (1997)	79	8.38%	350	350	37.12%
Contact (1997)	78	8.27%	509	509	53.98%
Braveheart (1995)	78	8.27%	297	297	31.50%
Pulp Fiction (1994)	76	8.06%	394	394	41.78%
Conspiracy Theory (1997)	76	8.06%	295	295	31.28%
Starship Troopers (1997)	74	7.85%	211	211	22.38%
My Best Friend's Wedding (1997)	71	7.53%	172	172	18.24%
Fargo (1996)	70	7.42%	508	508	53.87%
Rock, The (1996)	70	7.42%	378	378	40.08%
Citizen Kane (1941)	69	7.32%	198	198	21.00%
Devil's Own, The (1997)	67	7.10%	240	240	25.45%
Willy Wonka and the Chocolate Factory (1971)	66	7.00%	326	326	34.57%
Star Trek: First Contact (1996)	65	6.89%	365	365	38.71%
Tomorrow Never Dies (1997)	64	6.79%	180	180	19.09%
GoodFellas (1990)	64	6.79%	226	226	23.97%
Twister (1996)	62	6.57%	293	293	31.07%
Four Weddings and a Funeral (1994)	61	6.47%	251	251	26.62%
Toy Story (1995)	61	6.47%	452	452	47.93%
Usual Suspects, The (1995)	60	6.36%	267	267	28.31%
Wag the Dog (1997)	60	6.36%	137	137	14.53%
Murder at 1600 (1997)	59	6.26%	218	218	23.12%
As Good As It Gets (1997)	57	6.04%	112	112	11.88%
Saint, The (1997)	57	6.04%	316	316	33.51%
Birdcage, The (1996)	57	6.04%	293	293	31.07%
Dances with Wolves (1990)	57	6.04%	256	256	27.15%
Dead Poets Society (1989)	57	6.04%	251	251	26.62%
Bean (1997)	56	5.94%	91	91	9.65%
Back to the Future (1985)	55	5.83%	350	350	37.12%
L.A. Confidential (1997)	54	5.73%	297	297	31.50%
Eraser (1996)	54	5.73%	206	206	21.85%
Spawn (1997)	53	5.62%	143	143	15.16%
Air Force One (1997)	52	5.51%	431	431	45.71%
Grease (1978)	52	5.51%	170	170	18.03%
Men in Black (1997)	51	5.41%	303	303	32.13%
Mission: Impossible (1996)	51	5.41%	344	344	36.48%
Shawshank Redemption, The (1994)	50	5.30%	283	283	30.01%
Truth About Cats & Dogs, The (1996)	47	4.98%	272	272	28.84%
Godfather, The (1972)	47	4.98%	413	413	43.80%
Empire Strikes Back, The (1980)	46	4.88%	367	367	38.92%
Jaws (1975)	46	4.88%	280	280	29.69%
Mars Attacks! (1996)	46	4.88%	217	217	23.01%
Monty Python and the Holy Grail (1974)	45	4.77%	316	316	33.51%
Alien (1979)	45	4.77%	291	291	30.86%
Raiders of the Lost Ark (1981)	44	4.67%	420	420	44.54%

Figure 5: Popularity Bias

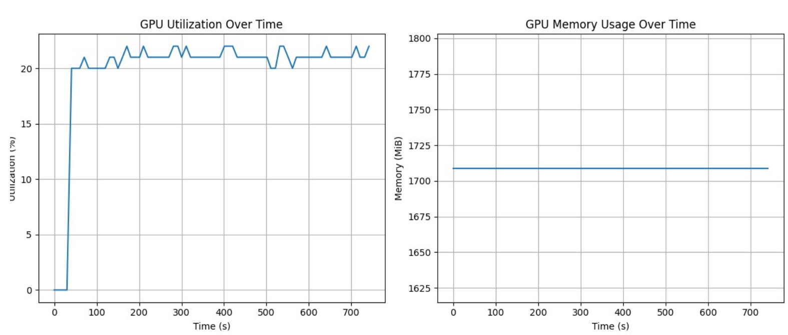
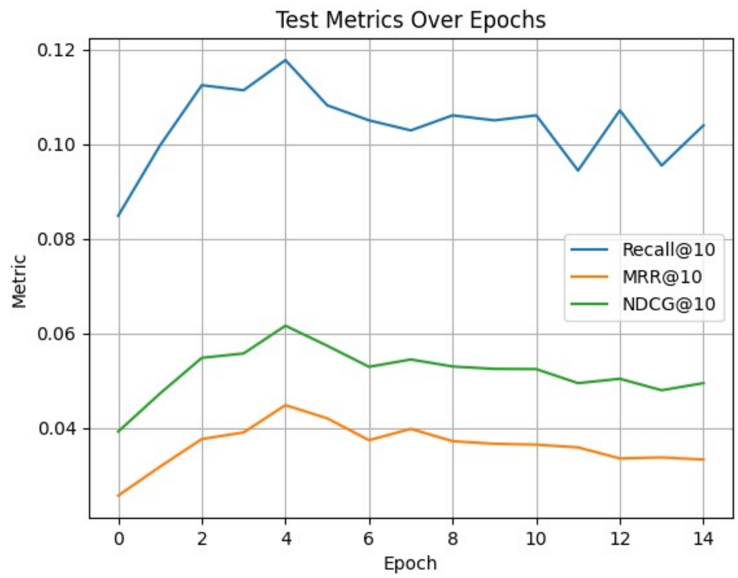


Figure 6: GPU Performance - 100k



Total run time: 12.38 minutes

Figure 7: Recall Score - 100k

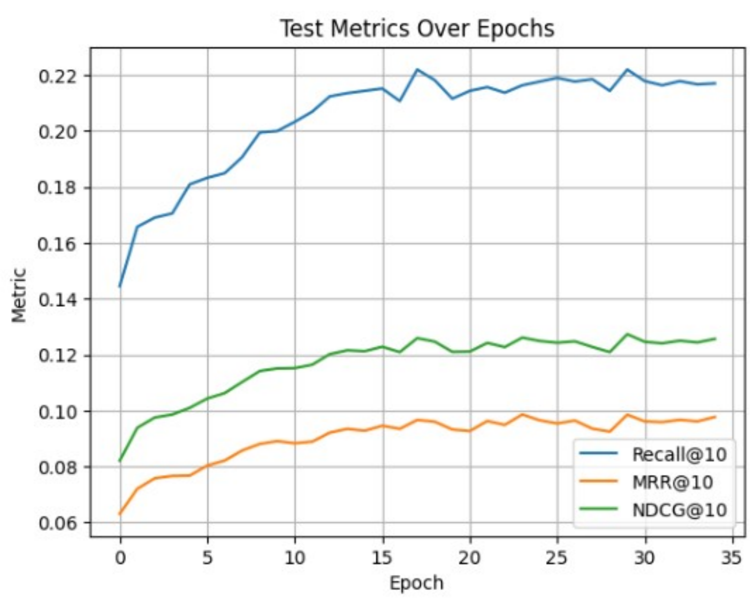


Figure 8: Recall Score - 1M

5 Discussion

5.1 Key Observations

5.2 Comparative Performance Analysis

5.3 Limitations

5.4 Implications of Recommenders for Industry

6 Conclusion and Future Work

This report explored the design, implementation, and evaluation of sequential recommender systems using the extended LSTM (xLSTM) architecture. We benchmarked xLSTM against several state-of-the-art models, including GRU4Rec, SASRec, and BERT4Rec, across multiple MovieLens datasets (100K, 1M, and 20M). Evaluation metrics such as Recall@10, MRR@10, and NDCG@10 were used to quantify model performance, alongside runtime analysis and qualitative assessments of recommendation outputs.

The experimental results demonstrate that xLSTM offers a compelling balance between accuracy, scalability, and memory efficiency. Its chunkwise attention mechanism, bidirectional memory routing, and optimized sequence kernels enable it to outperform classical RNNs while remaining competitive with Transformer-based architectures. In particular, the xLSTM model achieved a Recall@10 of approximately 0.293 on the MovieLens 100K dataset, making it a strong candidate for real-time recommendation tasks.

Moreover, the report addressed critical challenges such as the cold-start problem and data sparsity. By integrating sampling strategies, metadata-aware heuristics, and modular training pipelines, the system was made robust to limited interaction histories and low-density datasets. The comprehensive analysis—including popularity bias inspection, ablation studies, and visual interpretation—adds depth to the evaluation beyond pure metrics.

Future Work

Several avenues for future work remain:

- **Large Language Model (LLM) Integration:** Investigate the use of domain-adapted language models like RecGPT or Transformers4Rec for text-based and contextual recommendation.
- **Cross-Domain Recommendation:** Extend the pipeline to multi-domain datasets where user preferences span diverse item categories (e.g., movies and books).
- **Explainability and Transparency:** Incorporate attention heatmaps or causal tracing to enhance user trust and interpretability in recommendations.
- **Online Learning:** Adapt the models to work in streaming environments, updating user representations in real time.
- **Hybrid Architectures:** Combine xLSTM with knowledge graphs or content-aware filtering mechanisms to capture semantic item relationships and improve personalization.

Overall, the xLSTM-based architecture provides a promising foundation for building robust and scalable recommender systems, balancing the strengths of RNNs and Transformers while remaining efficient enough for practical deployment.

References

[1] xLSTM: Extended Long Short-Term Memory: https://arxiv.org/pdf/2405.04517

[2] xLSTM-Mixer: Multivariate Time Series Forecasting by Mixing via Scalar Memories: https://doi.org/10.48550/arXiv.2410.16928

[3] Amazon Science: https://github.com/amazon-science

[4] xLSTM Time : Long-term Time Series Forecasting With xLSTM: https://doi.org/10.48550/arXiv.2407.10240

[5] Quaternion Transformer4Rec: Quaternion numbers-based Transformer for recommendation: https://github.com/vanzytay/QuaternionTransformers

[6] Recommender Systems: A Primer: https://doi.org/10.48550/arXiv.2302.02579

[7] Exploring the Impact of Large Language Models on Recommender Systems: An Extensive Review: https://arxiv.org/pdf/2402.18590

[8] Recommender Systems with Generative Retrieval: https://openreview.net/pdf?id=BJ0fQUU32w

[9] Noorian, A., Harounabadi, A. Hazratifard, M. A sequential neural recommendation system exploiting BERT and LSTM on social media posts. Complex Intell. Syst. 10, 721–744 (2024). https://doi.org/10.1007/s40747-023-01191-4

[10] Ahmadian Yazdi, H., Seyyed Mahdavi, S.J. Ahmadian Yazdi, H. Dynamic educational recommender system based on Improved LSTM neural network. Sci Rep 14, 4381 (2024). https://doi.org/10.1038/s41598-024-54729-y

[11] X. Yang and J. A. Esquivel, "Time-Aware LSTM Neural Networks for Dynamic Personalized Recommendation on Business Intelligence," in Tsinghua Science and Technology, vol. 29, no. 1, pp. 185-196, February 2024, doi: 10.26599/TST.2023.9010025. keywords: Neural networks;Decision making;Feature extraction;Behavioral sciences;Business intelligence;Long short term memory;personalized recommendations;evolving interests;embedding;LSTM networks

[12] Chhotelal Kumar, Mukesh Kumar, Session-based recommendations with sequential context using attention-driven LSTM, Computers and Electrical Engineering, Volume 115,2024,109138,ISSN 0045-7906, https://doi.org/10.1016/j.compeleceng.2024.109138

[13] Exploiting deep transformer models in textual review based recommender systems: https://doi.org/10.1016/j.eswa.2023.121120

[14] Exploring the Impact of Large Language Models on Recommender Systems: An Extensive Review: https://arxiv.org/pdf/2402.18590

[15] Recommender Systems: A Primer: https://doi.org/10.48550/arXiv.2302.02579

[16] xLSTM: Extended Long Short-Term Memory: https://arxiv.org/pdf/2405.04517

[17] Attention Is All You Need: https://arxiv.org/abs/1706.03762

[18] Recbole:https://recbole.io

[19] OpenAI: https://openai.com/

[20] Hugging Face: https://huggingface.co/docs/hub/en/models-the-hub

[21] Kreutz, C.K., Schenkel, R. Scientific paper recommendation systems: a literature review of recent publications. Int J Digit Libr 23, 335–369 (2022). https://doi.org/10.1007/s00799-022-00339-w

[22] Recommendation Systems: Algorithms, Challenges, Metrics, and Business Opportunities https://doi.org/10.3390/app10217748

[23] Roy, D., Dutta, M. A systematic review and research perspective on recommender systems. J Big Data 9, 59 (2022). https://doi.org/10.1186/s40537-022-00592-5

[24] A Comprehensive Review of Recommender Systems: Transitioning from Theory to Practice https://doi.org/10.48550/arXiv.2407.13699