

DUALRec: A Hybrid Sequential and Language Model Framework for Context-Aware Movie Recommendation

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WHAT IS RECOMMENDER?

'A recommendation engine, also called a recommender, is an artificial intelligence (AI) system that suggests items to a user. Recommendation systems rely on big data analytics and machine learning (ML) algorithms to find patterns in user behavior data and recommend relevant items based on those patterns.' -- IBM (2024)

DUALREC FRAMEWORK

multi-modal LSTM + LLM Semantic Reasoning = Enhanced Personalized Recommendations

Dataset

- **MovieLens 1M dataset**
- Stable benchmark dataset with 1 million ratings from 6000 users on 4000 movies.
- Each rating entry includes user ID, movie ID, rating value (1–5), movie titles, movie genres, and timestamp.

Development Environment & LLM Selection

Coding:

- Google Colab Pro
- A100 GPU
- 40GB GPU RAM
- Python 3

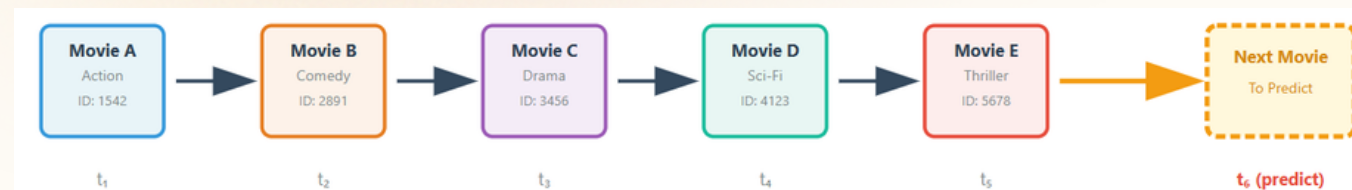
LLM Slection:

- DeepSeek V3–685B
- Mistral 8B
- DeepSeek–R1–Distill–Qwen–1.5B (for finetuning)
- Mistral 7B (for finetuning)

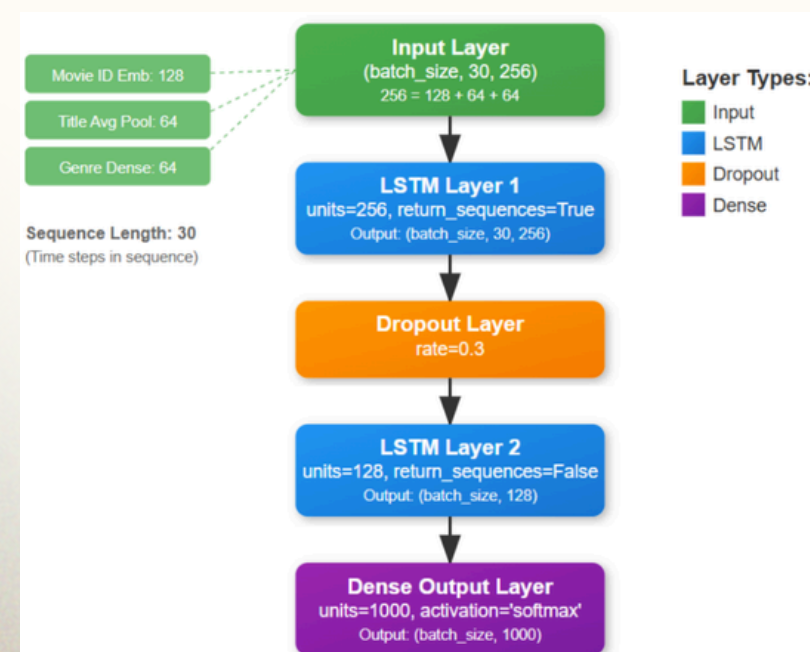
Data manipulation

- Movie filtering: Top 1,000 most frequently watched movies
- Movie ID → 128-dim embeddings
- Tokenized titles (Keras Tokenizer)
- Multi-label genre information– 18 movie genres
- Data split: 70% train / 15% validation / 15% test

Model Stage 1– Sequential Behaviour Modelling



- Group interactions by user and sort chronologically
- Create sequences of 30 consecutive movies with the 31st as target
- Tokenize movie titles (max 10 tokens) → 64-dim embeddings → global average pooling
- Generate 30 sequences per user using sliding window approach
- Genre as binary multi-hot vectors, 18 categories



- **Input:** Sequence of $30 \times d$ (where d = combined feature dimensions)
- **Layer 1:** 256 units, returns sequences (local dependencies)
- **Layer 2:** 128 units, final hidden state, return global representation of user long-term preference.
- **Dropout:** 0.3 for both layers
- **Output:** Softmax over 1K movies → top-1 prediction

Model Stage 2– LLM based recommendation generation

Stage 1 LSTM Output

Top-1 Prediction

Mission to Mars (2000)

Recent Viewing History (Last 5 Movies)

- Bug's Life, A (1998)
Animation, Children's, Comedy
- Antz (1998)
Animation, Children's
- Hercules (1997)
Adventure, Animation, Children's, Comedy, Musical
- Mulan (1998)
Animation, Children's
- Pocahontas (1995)
Animation, Children's, Musical, Romance

Below is a user's movie watching history:

- Bug's Life, A (1998) (Animation, Children's, Comedy)
- Antz (1998) (Animation, Children's)
- Hercules (1997) (Adventure, Animation, Children's, Comedy, Musical)
- Mulan (1998) (Animation, Children's)
- Pocahontas (1995) (Animation, Children's, Musical, Romance)

Based on this, the system (LSTM) recommends:

Mission to Mars (2000).

Now, as a helpful assistant, recommend 3 more full movie titles with release years and genres that this user would likely enjoy next.

LLM
Semantic Reasoning
Natural Language Generation

Example LLM Recommendations:

Based on the user's preference for animated, family-friendly films with adventurous and musical elements, here are three recommendations that align with their viewing history:

1. Tarzan (1999) Genres: Animation, Adventure, Children's, Musical
2. The Emperor's New Groove (2000) Genres: Animation, Adventure, Children's, Comedy
3. Lilo & Stitch (2002) Genres: Animation, Children's, Comedy, Science Fiction

- **Free form text generation**
- Structured prompts, no settled list of movies to choose for recommendation

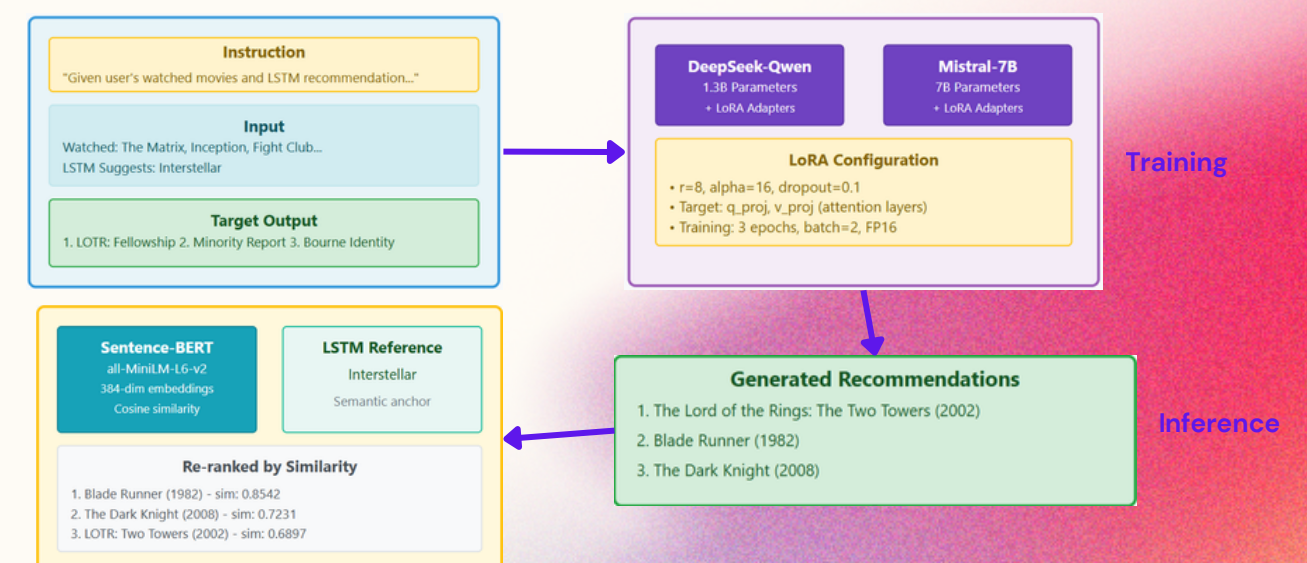
Model Stage 3– LoRA Fine-Tuning and Post-Generation Optimization

Method:

- Low-Rank Adaptation (LoRA) for parameter efficient fine tuning
- Two model variants (DeepSeek–Qwen 1.3B and Mistral–7B)
- **Instruction-following text generation**

Finetuning Data Construction Process:

- For each user, take first 5 movie viewing sequence as input
- Use the last 5 movies the user actually watched as the supervised learning window
- Combined with top-1 prediction from Stage 1 LSTM



Result & Discussion

- **Base Model Quality > Fine-tuning:** DeepSeek V3 (pre-trained) outperformed fine-tuned DeepSeek–Qwen
- **Instruction-Following Architecture Advantage:** Mistral–7B achieved highest HR@1 and NDCG@1
- **Parameter Efficiency:** Fine-tuned Mistral–7B > Mistral–8B. Task-specific adaptation more effective than scaling model size
- **Limited Top-K Improvement:** Minimal HR@1 → HR@5 gains across DUALRec variants
- **Traditional models (NARM, STAMP):** Optimize discriminative spread across candidates
- **LLM-based:** Generate semantically cohesive but homogeneous recommendations

Model	HR@1	HR@5	NDCG@1	NDCG@5
MostPop	0.0004	0.0070	0.0004	0.0053
SLIM	0.1270	0.3600	0.1270	0.2530
FPMC	0.1132	0.3748	0.1132	0.2464
NARM	0.1692	0.5230	0.1692	0.3501
STAMP	0.1584	0.5078	0.1584	0.3367
GCE-GNN	0.1312	0.4748	0.1312	0.3044
MCPRN	0.1434	0.4758	0.1434	0.3157
HIDE	0.1498	0.4998	0.1498	0.3256
Atten-Mixer	0.1490	0.4932	0.1490	0.3216
UniSRec	0.0508	0.2508	0.0508	0.1459
NIR	0.0572	0.2326	0.0572	0.1436
DUALRec – DS V3	0.1371	0.1425	0.1371	0.1406
DUALRec – Mistral 8B	0.0810	0.0907	0.0810	0.0871
DUALRec – DS Qwen Finetuned	0.0583	0.0605	0.0583	0.0597
DUALRec – Mistral 7B Finetuned	0.1847	0.2214	0.1847	0.2078

