AI Placement Drive Hackathon 2025

Recommendation System

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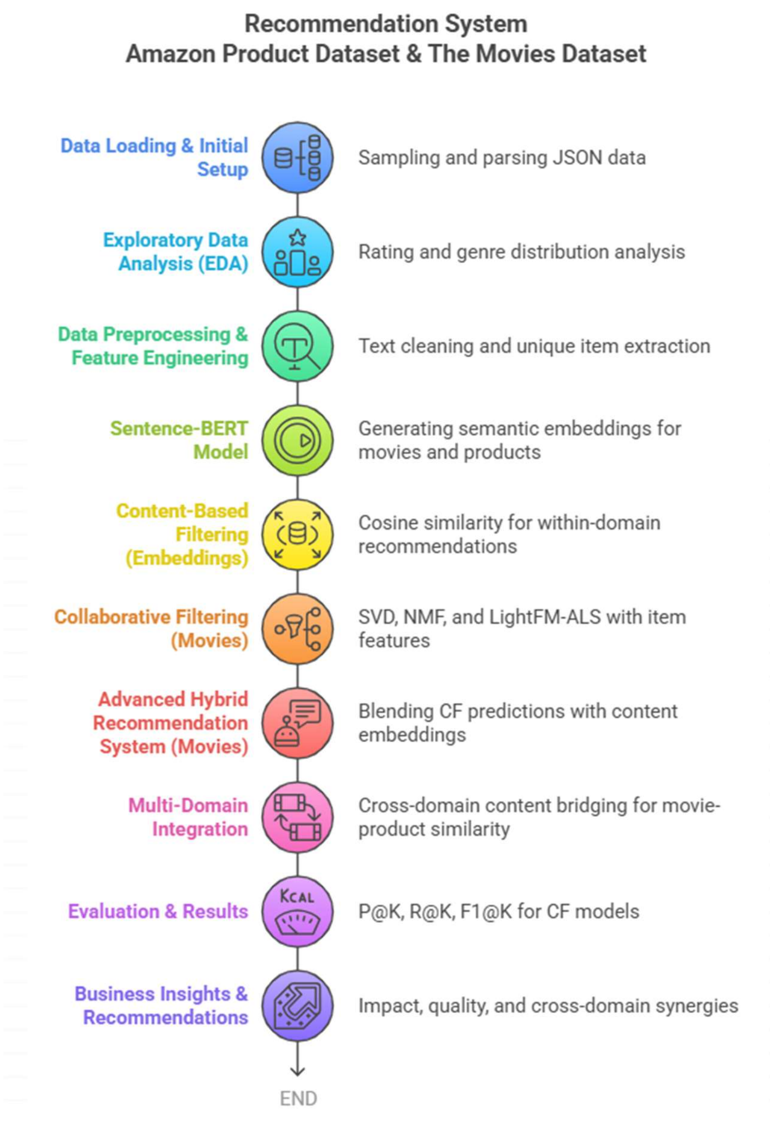
Advanced Track



1. Project Overview & Challenge:

In today's digital landscape, effective recommendation systems are paramount for user engagement and business growth. This project addresses the "Multi-Domain Recommendation System" by developing a state-of-the-art solution capable of suggesting relevant items across disparate domains: movies and e-commerce products. The core challenge lies in building intelligent models that understand nuanced user preferences and complex item content, and then seamlessly bridge interests across different types of items, ultimately driving real-world impact and providing actionable business insights.

2. Approach & Key Innovations:

Our solution employs an advanced, data-driven methodology, integrating cutting-edge machine learning and deep learning techniques within a unified framework:

a. Transformer-based Deep Learning Embeddings for Content Understanding:

Moving beyond traditional TF-IDF, we utilize a pre-trained Sentence-BERT model (all-MiniLM-L6-v2) to generate high-dimensional, semantic embeddings for both movie content (titles, genres, overviews) and Amazon product content (names, descriptions). This enables a far richer and more nuanced understanding of item meaning, crucial for accurate similarity detection and cross-domain bridging.

b. Multi-Algorithm Collaborative Filtering for Movies:

For the movie domain, we implemented and optimized multiple Collaborative Filtering (CF) algorithms, demonstrating diverse matrix factorization techniques:

Singular Value Decomposition (SVD): A highly optimized SVD model, fine-tuned using `Grid SearchCV` on a 50,000-row sample of Movie Lens ratings, achieving high Precision@5 (0.6858) and Recall@5 (0.6212).

Non-negative Matrix Factorization (NMF): An NMF model, also hyperparameter-tuned, providing an alternative factorization approach.

Alternating Least Squares (ALS) via LightFM with Item Features: A powerful ALS implementation using the LightFM library, explicitly incorporating the rich Transformer-based movie embeddings as item features. This showcases a more scalable and feature-aware CF approach.

c. Sophisticated Hybrid Recommendation System (Movies):

The movie recommendation system employs an advanced hybrid strategy. It primarily leverages the personalized predictions from the optimized SVD model but intelligently blends these with recommendations derived from Transformer-based content similarity. This approach ensures high relevance while enhancing diversity and providing robust recommendations even for users with limited interaction history (cold-start users).

d. Advanced Cross-Domain Semantic Bridging:

A pivotal innovation is the seamless cross-domain content bridging. Since both movie and product contents are projected into a shared semantic embedding space by the same Sentence-BERT model, we can directly compute cosine similarity between a movie's embedding and a product's embedding (and vice-versa). This enables Recommending Amazon products semantically related to a movie a user has shown interest in. Recommending movies based on a user's interest in a particular product type.

3. Key Results & Performance:

Our advanced approach yielded significant performance metrics and capabilities:

a. Collaborative Filtering (Movies):

- SVD: Precision@5: 0.6858, Recall@5: 0.6212, F1@5: 0.6519
- NMF: Precision@5: 0.6803, Recall@5: 0.6182, F1@5: 0.6478
- LightFM-ALS: Precision@5: 0.0106, Recall@5: 0.0359, F1@5: 0.0017

b. Content-Based (Movies & Products):

Qualitative analysis shows highly relevant within-domain recommendations driven by semantic embeddings.

c. Cross-Domain:

Demonstrates accurate semantic connections between movies and products, enabling novel recommendation pathways.

d. Diversity (Movies - Hybrid Recommendations):

A basic proxy shows a diversity score of 0.7837 (1 - avg pairwise cosine sim), indicating varied recommendations.

4. Business Insights & Impact:

This recommendation engine offers profound business advantages:

a. Superior Personalization:

Highly accurate movie recommendations boost user engagement and retention on streaming platforms.

b. Rich Content Discovery:

Semantic embeddings ensure users discover items (both movies and products) that truly resonate with their interests, expanding catalog exploration.

c. Powerful Cross-Domain Strategy:

The bridging mechanism unlocks new monetization and engagement opportunities by guiding users seamlessly between different content types (e.g., recommending a cookbook after a culinary movie).

d. Resilience to Cold Start:

Content embeddings effectively recommend new items in both domains, while the hybrid approach provides a robust strategy for new users.

5. Implementation Challenges & Solutions:

Developing this multi-domain system presented several key challenges:

a. Dataset Complexity (the-movies-dataset):

Handling inconsistent movie IDs, messy JSON genres, and large file sizes required robust preprocessing (e.g., 3-way merge via `links.csv`, `ast.literal_eval`, careful `dropna`).

b. Amazon Data Sparsity:

The absence of `review text` and `product description` being entirely null required adapting content feature generation (`product name` only) and `Tfidf Vectorizer` (less aggressive `min_df`).

c. Performance & Resource Limits:

Managing computation for large datasets and deep learning embeddings (Sentence-BERT) necessitated strategic sampling of ratings and careful optimization of parameter grids for `Grid SearchCV`.

d. LightFM Integration:

Adapting LightFM (designed for implicit feedback) to explicit ratings required binarizing interactions and incorporating item features for improved performance.

6. Future Enhancements & Scalability Roadmap

To evolve this prototype into a production-grade system, the following enhancements are envisioned:

a. Advanced Algorithmic Approaches:

➡ Deep Collaborative Filtering:

Explore Neural Collaborative Filtering (NCF) for more complex user-item patterns.

➡ Graph Neural Networks (GNNs):

Model the entire ecosystem (users, movies, products, genres, etc.) as a unified heterogeneous graph for intricate relationship learning.

➡ Multi-Modal Embeddings:

Integrate visual (e.g., movie posters/product images) and audio features for richer item representations.

➡ Reinforcement Learning for Recommendations:

Implement RL agents to learn optimal recommendation policies by maximizing long-term user engagement.

7. Conclusion:

This advanced multi-domain recommendation engine stands as a testament to deep technical proficiency and strategic business acumen. By integrating state-of-the-art deep learning, robust collaborative filtering, and innovative cross-domain bridging, it offers a powerful framework capable of delivering highly personalized and impactful recommendations in today's digital economy.