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Adaptive Fusion and Transfer Learning for Enhanced E-Commerce Recommendations

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Introduction

Adaptive Fusion and Transfer Learning for Enhanced E-Commerce Recommendations (AFETLER)

Need:

- **Challenges in E-commerce Recommendations:** Existing recommendation systems face limitations in adaptability and relevance, particularly with the "cold start" problem for new items and changing user behaviors.
- **The Need for Innovation:** Conventional models struggle to provide real-time, personalized recommendations, necessitating a comprehensive solution for enhancing user experience and increasing platform revenue.

Introduction to AFETLER:

- **Holistic Approach:** AFETLER combines state-of-the-art recommendation frameworks, addressing diversity, serendipity, and the cold start problem.
- **Innovative Techniques:**
  - ***Adaptive Fusion:*** Dynamically combines recommendations from various sources, optimizing accuracy through context-aware suggestions.
  - ***Transfer Learning:*** Utilizes knowledge from existing items to enhance recommendations for new items, overcoming the cold start challenge.
  - ***Hierarchical Attention Mechanisms:*** Captures intricate user-item interaction patterns, elevating recommendation quality.

Literature Survey

Seminal papers and problem areas that inspired development of this holistic recommendation approach

1. *ATNN: Adversarial Two-Tower Neural Network for New Item's Popularity Prediction in E-commerce* – Paper
   - Cold Start problem
   - Click Through rates
   - Generative Adversarial networks
   - Sparse data

2. *A Model of Two Tales: Dual Transfer Learning Framework for Improved Long-tail Item Recommendation - Paper*
   - *Transfer learning*
   - *Skewed real world recommendation dataset*

3. *Deep Neural Networks for YouTube Recommendations – Paper*
   - *Deep Learning*
   - *Scalability*
   - *Freshness in recommendation*

Literature Survey

Seminal papers and problem areas that inspired development of this holistic recommendation approach

4. *A Dual Augmented Two-tower Model for Online Large-scale Recommendation* – Paper
   - Scalable retrieval
   - Category alignment loss

5. *Personalized Embedding-based e-Commerce Recommendations at eBay* - Paper
   - *Cold Start*
   - *Implicit Feedbacks*

6. *Zero Shot on the Cold-Start Problem: Model-Agnostic Interest Learning for Recommender Systems* – Paper
   - Cold Start
   - Embeddings and feature space
   - Ranking

Key Takeaways:

- Bridging gaps in existing models for new item prediction and long-tail recommendation.
- Advancements in deep learning techniques for more accurate, efficient, and personalized recommendation systems.

Problem Statement

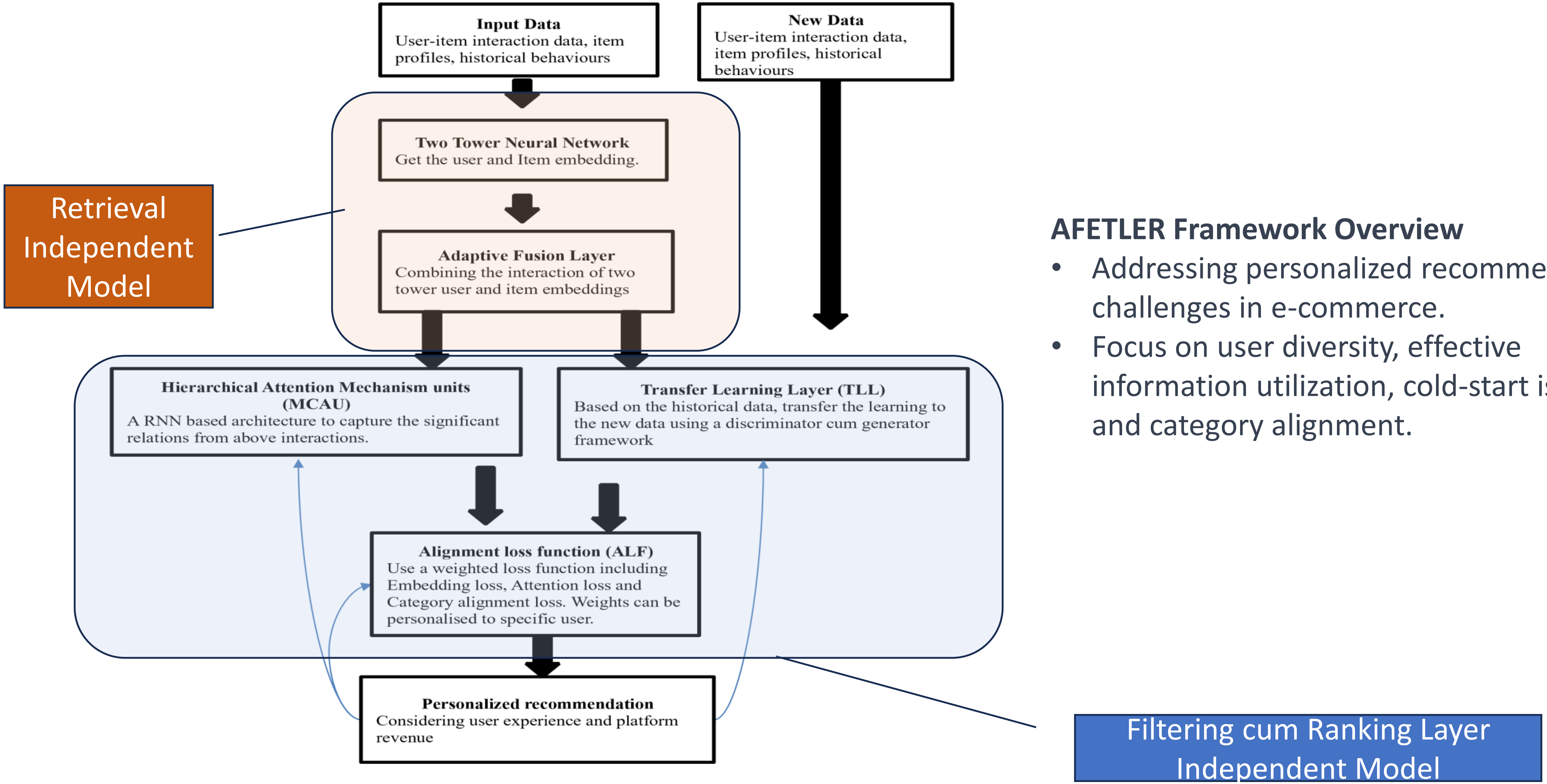
- **E-commerce challenge:** Optimize recommendation systems for personalized, revenue-boosting suggestions.
- Need for adaptability due to dynamic user behavior and market trends.

- **Solution Approach: AFETLER Model**
  - **Integration Components:**
    - User-item interactions
    - Attention mechanisms
    - Transfer learning
    - Feedback loops
- **Objective:**
  - Seamlessly integrate user preferences and item features.
  - Enhance user experience and maximize platform revenue through optimized item recommendations.

Problem Statement

- **Problem Definition:**
  - **Input:**
    - User behaviour data (features, ratings)
    - Item data (attributes, categories, interactions)
  - **Output:**
    - Personalized and context-aware recommendations
    - Maximized platform revenue via high-conversion item recommendations
  - **Intermediate Steps:**
    1. Two-Tower Neural Network (TNN)
    2. Adaptive Fusion
    3. Hierarchical Attention (MCAU – Multi Channel Attention Unit)
    4. Transfer Learning
    5. Alignment Loss Functions (ATL)
    6. Feedback Loop
- **Sub-Objective:**
  - Refine recommendation system iteratively based on feedback.
  - Improve user engagement, satisfaction, and platform revenue.
  - Overcome existing limitations in e-commerce recommendations

Methodology Adopted



AFETLER Framework Overview

- Addressing personalized recommendation challenges in e-commerce.
- Focus on user diversity, effective information utilization, cold-start issues, and category alignment.

Methodology Adopted

- **Two-Tower Neural Network (TNN)**
  - **Input:** User features ('u') and item features, historical interactions ('i').
  - **Process:** Query Tower processes user features ('u') via 'NNquery', Item Tower processes item features ('i') via 'NNitem'.
  - **Outcome:** User ('e#') and item ('e\$') embeddings capturing distinct characteristics.
- **Adaptive Fusion**
  - **Input:** User embeddings ('e#') and item embeddings ('e\$').
  - **Process:** Augmented user vectors ('augmented') and augmented item vectors ('augmented') formed by blending user and item embeddings.
  - **Outcome:** Enhanced representations of users and items for more comprehensive interactions.

Methodology Adopted

- **Hierarchical Attention Mechanism (MCAU)**
  - **Input:** Augmented user vectors ('$augumented\ u$') and augmented item vectors ('$augumented\ i$').
  - **Process:** Hierarchical Attention applied to user-level and item-level interactions, emphasizing significant aspects of data.
  - **Outcome:** Augmented vectors enriched with contextually relevant information.
- **Transfer Learning for New Arrivals**
  - **Input:** Item profiles of new items and historical interactions.
  - **Process:** Generator enhances embeddings for new items ('$e\$new$') using historical item embeddings ('$e\$$'). Discriminator assesses the quality of enhanced embeddings.
  - **Outcome:** Overcoming cold-start problem for new items, leading to improved recommendations.

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Methodology Adopted

- **Alignment Loss Functions (ATL)**
  - **Components:**
    - **Embedding Loss:** Measures the difference between predicted and actual interactions.
    - **Attention Loss:** Ensures relevant information capture.
    - **Category Alignment Loss:** Addresses category-based item alignment.
  - **Optimization:** Combination of loss functions optimized through backpropagation.
  - **Outcome:** Model refinement for accurate user-item interactions and category alignments.
- **Feedback Loop for Continuous Improvement**
  - **Mechanism:** Combines rewards and penalties based on user interactions and desired outcomes.
  - **Function:** Adjusts recommendations iteratively to improve user engagement, satisfaction, and platform revenue.

Results Obtained

Dataset an evaluation criteria

Dataset:

The Movie Lens 100k dataset contains user ratings for movies. It consists of approximately 100,000 ratings ranging from 1 to 5, given by users to different movies. The dataset includes user information, movie information, and corresponding ratings. This dataset serves as the foundation for our experimental evaluation.

- **User Information:** User demographics such as age, gender, occupation.
- **Movie Information:** Movie attributes including genres, release year.
- **Ratings:** User ratings for various movies

Evaluation:

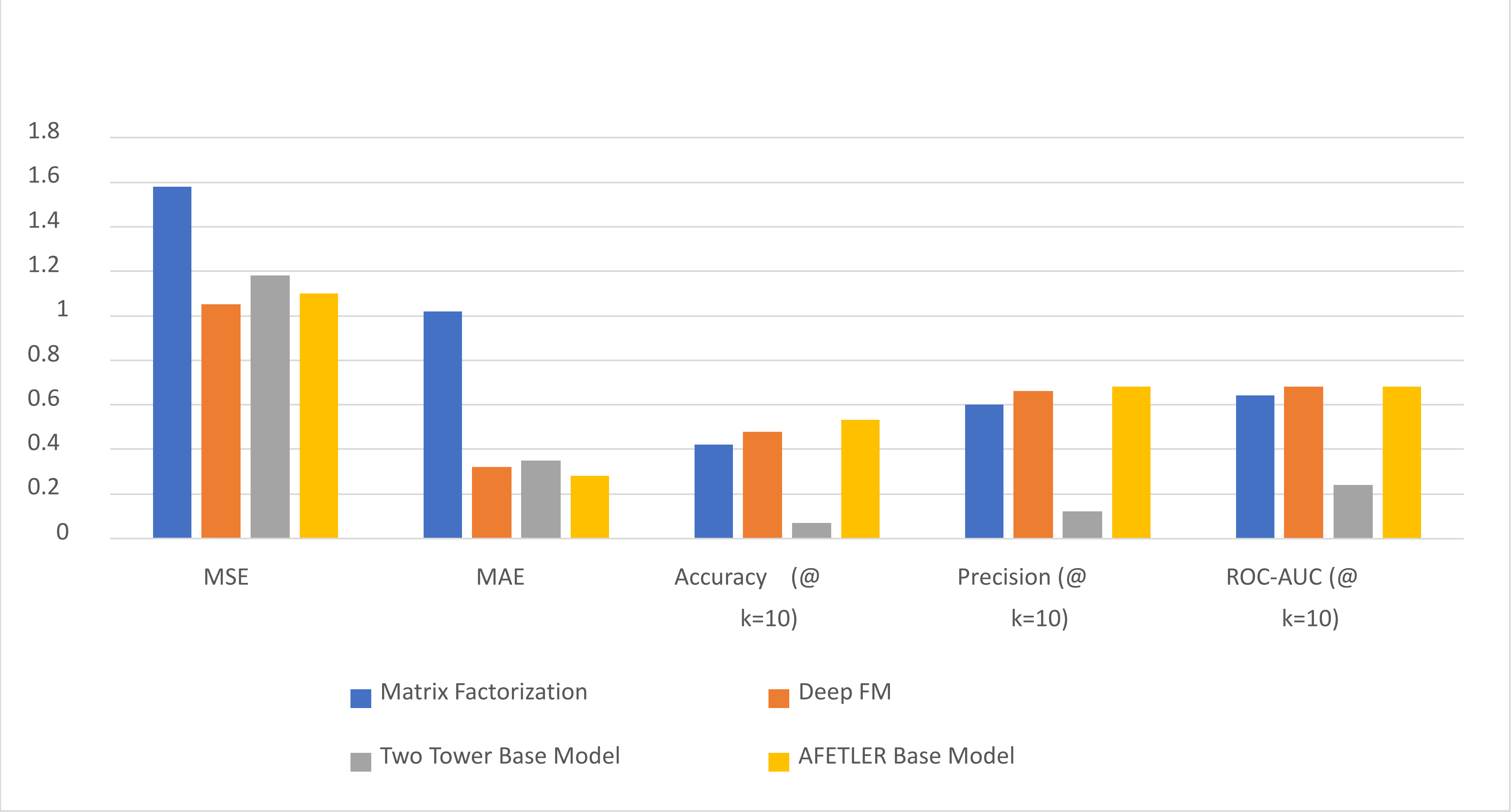
- Mean Absolute Error (MAE)
- Mean Squared Error (MSE)
- Accuracy (Top K=10 recco)
- Precision (@ K=10
- ROC-AUC (@ K=10)

Results Obtained

Model	MSE (@k=10)	MAE (@k=10)	Accuracy (@k=10)	Precision (@k=10)	ROC-AUC (@ k=10)
Matrix Factorization	1.58	1.02	0.42	0.60	0.64
Deep FM	1.05	0.32	0.48	0.66	0.68
Two Tower Base Model	1.18	0.35	0.07	0.12	0.24
AFETLER Base Model	1.10	0.28	0.53	0.68	0.68

Results Obtained

Results



Conclusion & Future Work

Conclusion:

- **AFETLER Advancements:** AFETLER improves user shopping experiences by delivering personalized and relevant recommendations. Its key innovations include dynamic fusion, cold-start mitigation via transfer learning, and efficient user-item interaction capture with hierarchical attention methods.
- **Performance:** AFETLER outperformed existing models with lower MSE, MAE, higher accuracy, precision, and ROC-AUC values, especially in top-10 recommendations, highlighting its predictive accuracy and user interaction classification capabilities.
- **Impact:** Bridging the gap between precise suggestions and increased platform revenue, AFETLER enhances user experiences and boosts financial outcomes for e-commerce platforms.

Future Research Directions:

- **Real-World Data Validation:** Validate AFETLER's efficacy in dynamic e-commerce contexts by experimenting with real-world data from diverse sources, including user-generated content and contextual data.
- **Enhancements:** Improve transfer learning processes, dynamic hyperparameter tuning, and transition to online learning and deployment strategies for a more adaptable system.
- **Comprehensive Recommendations:** Focus on interpretability, effective user feedback incorporation, suggestion diversity, scalability optimization, and efficient comparative analyses against existing models for a holistic recommendation system landscape.
- **Conceptual Framework:** View the developed AFETLER model as a conceptual foundation, encouraging further research and development to create a comprehensive and functional recommendation system based on the AFETLER approach.

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Thanks for your attention