User Affinity Modeling: A Deep Learning Approach to Predicting Brand and Category Preferences from Interaction Dynamics

Course No. : AIMLCZG628T

Course Title: Dissertation

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BITS ID: 2023AC05492

Degree Program: M.Tech(AI & ML)

Research Area: E-Commerce

Dissertation / Project Work carried out at:
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November, 2025

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1. Broad Area of Work

1.1 The Imperative of Personalization in the Digital Ecosystem

In the contemporary digital landscape, the transition from mass-market, one-size-fits-all content to hyper-personalized, one-to-one user experiences represents a fundamental strategic shift.[1] Digital platforms, spanning e-commerce, content streaming, and social media, are no longer passive repositories of information but are increasingly sophisticated ecosystems designed to anticipate and cater to individual user needs. This paradigm is driven by the recognition that personalization is a critical engine for enhancing user engagement, improving conversion rates, and fostering long-term customer loyalty and retention.[3] By tailoring content, product recommendations, and user interfaces in real-time, businesses can create a more intuitive and satisfying customer journey, which in turn provides a significant competitive advantage in a crowded online marketplace.[3] Consequently, personalization has evolved from a supplementary feature into a core business strategy, essential for survival and growth in an environment where user attention is a finite and highly sought-after commodity.

The ability to predict what a user is most likely to respond to is paramount. By analyzing vast quantities of behavioral data—from clicks and views to purchases and search queries—organizations can move from a reactive to a proactive stance, anticipating user needs before they are explicitly stated.[3] This proactive anticipation streamlines processes, optimizes resource allocation, and enables personalization at a scale that would be manually impossible, ultimately leading to improved strategic decision-making and product development.[3] The success of this endeavor hinges on the quality and sophistication of the underlying predictive models that power these personalized experiences.

1.2 Introducing User Affinity Modeling

User Affinity Modeling is a predictive technique central to modern personalization, designed to quantify and forecast a user's latent interests and preferences based on their behavioral patterns.[3] The fundamental principle of affinity modeling is that the more a user interacts with items sharing specific attributes—such as a particular brand, category, color, or style—the stronger their affinity, or preference, for those attributes becomes.[1] This approach moves beyond simple item-to-item recommendations by focusing on the underlying metadata that connects products, allowing for a more nuanced and generalizable understanding of user taste.

This process begins by capturing every user engagement and collecting the associated product attribute values.[2] From this data, an "affinity score" is calculated and continuously updated. This score is a weighted measure that considers not only the frequency of interactions but also their type and recency. Different interactions are assigned weights corresponding to their assumed level of intent; for example, a purchase is a much stronger signal of affinity than a simple product view, and an "add to cart" action falls somewhere in between.[2] Recency is also a critical factor, as more recent interactions are typically more indicative of a user's current interests. The aggregation of these weighted, time-decayed scores across various attributes (e.g., brands, categories) forms a dynamic "affinity profile" for each user.[2] This profile provides a ranked list of a user's preferences, enabling systems to showcase products and content that are most likely to resonate at any given moment, thereby making recommendations more relevant and effective.[1]

2. Background

The central challenge this dissertation addresses is: **How can we accurately and scalably predict a user's latent and evolving affinities for specific brands and product categories, given a history of sparse and often implicit interaction data?** This problem is multifaceted and presents several significant technical hurdles that prevent straightforward solutions.

First, **Data Sparsity** is a pervasive issue in recommendation contexts. In most real-world scenarios, the user-item interaction matrix—a representation of which users have interacted with which items—is extremely sparse. The vast majority of users interact with only a minuscule fraction of the total available items, meaning most entries in the matrix are unknown.[6] This makes it difficult to find overlapping behavior between users or items, which is the foundation of many traditional recommendation algorithms.

Second, the **Cold-Start Problem** is a direct consequence of data sparsity. This challenge manifests in two forms: the new user problem and the new item problem. When a new user joins a platform, there is no interaction history upon which to base personalized recommendations. Similarly, when a new item is added to the catalog, it has no interaction data, making it invisible to models that rely on historical user behavior.[6] Effective affinity models must be able to gracefully handle these scenarios and provide reasonable predictions with limited information.

Third, **Dynamic Preferences** add a temporal dimension to the problem. User interests are not static; they evolve over time, influenced by seasonal trends, changing needs, or fleeting interests.[8] A model that treats all past interactions equally will fail to capture a user's current intent. Therefore, a successful affinity model must be able to recognize and adapt to these temporal shifts, giving appropriate weight to recent behavior while not entirely discarding long-term preferences.

Finally, the nature of **Implicit Feedback** introduces ambiguity. While explicit feedback like star ratings provides a clear signal of preference, most user interaction data is implicit—clicks, views, time spent on a page, and purchase history.[10] These signals are abundant but also "noisy." A click may not indicate genuine interest, and the absence of an interaction does not necessarily signify dislike. Interpreting these ambiguous signals to infer true user affinity is a critical and complex aspect of the modeling process.[9]

3. Objectives

To address the multifaceted problem statement, this dissertation seeks to answer the following specific research questions:

1. How do traditional collaborative filtering and matrix factorization models perform in the task of predicting brand and category affinity, and what are their inherent limitations when faced with sparse, dynamic data?

2. To what extent can sequential deep learning models, specifically Long Short-Term Memory (LSTM) networks, improve predictive accuracy by explicitly capturing the temporal order and dependencies within user interaction sequences?
3. Do state-of-the-art architectures, namely Transformers and Graph Neural Networks (GNNs), offer a significant performance advantage by modeling complex, long-range contextual dependencies and high-order relational structures, respectively?
4. What constitutes the most effective and fair evaluation protocol for rigorously comparing these diverse modeling paradigms in a realistic, offline recommendation scenario?

The primary contributions of this dissertation are:

- A comprehensive and structured literature review that synthesizes the evolution of user affinity modeling techniques, from foundational statistical methods to advanced deep learning architectures.
- An empirical, comparative evaluation of four distinct classes of models—collaborative filtering, matrix factorization, sequential deep learning, and graph-based deep learning—on a unified, large-scale, publicly available dataset.
- A detailed analysis of the practical trade-offs between these models, considering not only predictive accuracy but also architectural complexity, scalability, and their inherent ability to address key challenges like data sparsity and the cold-start problem.
- A discussion of best practices for data preprocessing, feature engineering, and the construction of appropriate data structures (matrices, sequences, graphs) for affinity modeling.

4. Scope of Work

4.1 Dataset Selection and Characterization

4.1.1 Survey of Publicly Available Datasets

The selection of an appropriate dataset is a foundational step that profoundly influences the scope and validity of any machine learning project. For the task of modeling brand and category affinity, the ideal dataset must be large-scale, contain explicit brand and category metadata, and include timestamps to enable sequential analysis. A survey of commonly used public datasets reveals several candidates:

- **Amazon Product Data:** This collection of datasets is exceptionally well-suited for this project. It is massive in scale, containing millions of users, items, and interactions. Crucially, it includes rich item metadata such as brand, category, price, and descriptive text, as well as user reviews and timestamps for each interaction.[11]
- **Yelp and Google Local Datasets:** These datasets are rich in user-generated reviews and ratings but are primarily focused on local businesses (restaurants, services) rather than consumer products. The concept of "brand" is less central, making them less ideal for this specific research question.[11]
- **MovieLens, Netflix, and Music Datasets:** These are classic benchmarks in the recommender systems community. However, they typically lack the explicit and structured brand and category metadata that is essential for this dissertation's focus. For example, while movie genres could be considered categories,

they do not map directly to the brand affinity problem in e-commerce.[12]

- **Specialized E-commerce Datasets:** Several datasets from e-commerce platforms like Retailrocket, Tmall, and Yoochoose are available. These are strong candidates as they often contain event-level data (view, add-to-cart, transaction), which is perfect for modeling different levels of user intent.[14]

4.1.2 Rationale for Selected Dataset

Based on the survey, the **Amazon Product Reviews** dataset (specifically a large product category like "Electronics" or "Clothing, Shoes and Jewelry") is selected for this project.[11] The rationale for this choice is threefold:

1. **Scale:** The dataset's immense size, with millions of users, items, and interactions, provides the statistical power necessary to train complex deep learning models and derive meaningful results.
2. **Rich Metadata:** It contains the precise features required for this study—explicit brand and category labels for each item, which are the direct targets of the affinity prediction task.
3. **Temporal Information:** Each interaction is timestamped, allowing for the chronological ordering of user histories, a prerequisite for training and evaluating sequential models like LSTMs and Transformers.

4.1.3 Exploratory Data Analysis (EDA)

Before model development, a thorough Exploratory Data Analysis (EDA) will be conducted to understand the fundamental properties and potential challenges of the selected dataset. This analysis will include:

- **Distribution Analysis:** Plotting histograms of user ratings, the number of interactions per user, and the number of interactions per item. This will likely reveal a "long-tail" distribution, where a small number of users and items are highly active, while the vast majority have very few interactions.
- **Sparsity Calculation:** Quantifying the sparsity of the user-item interaction matrix. This metric is critical as it formally defines the core challenge that the proposed models are designed to overcome.
- **Metadata Exploration:** Analyzing the distribution of brands and categories to identify popular and niche segments.

The key statistics derived from the EDA will be summarized to provide a quantitative snapshot of the problem space.

Statistic	**Value**
Number of Users	To be determined from EDA
Number of Items	To be determined from EDA

Number of Brands	To be determined from EDA
Number of Categories	To be determined from EDA
Total Interactions	To be determined from EDA
Timespan of Data	To be determined from EDA
Sparsity ($1 - \frac{\text{#Interactions}}{\text{#Users} \times \text{#Items}}$)	To be determined from EDA

Table 3.1: A template for summarizing the characteristics of the selected dataset. The values will be populated after conducting the Exploratory Data Analysis.

This table is foundational, as it quantitatively defines the scale and complexity of the modeling task. A high sparsity value, for instance, immediately justifies the necessity of moving beyond simple collaborative filtering toward more sophisticated latent factor and deep learning approaches capable of generalization.

4.2 Data Preprocessing and Feature Engineering

4.2.1 Handling Interaction Data

The raw dataset will undergo a series of preprocessing steps to prepare it for modeling. A key step is to define what constitutes a positive interaction. While explicit ratings (e.g., 4 or 5 stars) are strong positive signals, implicit feedback is more abundant. For this project, a user-item interaction will be considered positive if the user has purchased the item (inferred from a review being present). This creates a binary interaction signal, which is a common approach for modeling with implicit feedback.[10] Interactions will be filtered to ensure a minimum level of activity (e.g., users and items with at least 5 interactions) to reduce noise and improve model stability.

4.2.2 Feature Extraction and Encoding

All categorical features must be converted into a numerical format suitable for machine learning models. This involves:

- Creating contiguous integer mappings for user_id, item_id, brand, and category. This is essential for

creating embedding layers in the deep learning models.
- For the target prediction task, the goal will be to predict the brand_id and category_id of the next item a user will interact with.

4.2.3 Constructing Data Structures for Models

A critical aspect of the methodology is transforming the preprocessed data into the specific input structures required by each model architecture. This step highlights how the choice of data representation is inextricably linked to the modeling paradigm.

- **For Matrix Factorization:** The data will be structured as a user-item interaction matrix. Given the scale, this will be implemented as a sparse matrix (e.g., using scipy.sparse.coo_matrix), storing only the non-zero entries (user-item pairs with an interaction) to conserve memory.
- **For LSTM and Transformer Models:** The data will be transformed into sequences. For each user, their interactions will be sorted chronologically based on the timestamp. These sequences will then be padded or truncated to a fixed maximum length to enable batch processing. For each sequence, the task will be to predict the next item given the preceding items.
- **For the GNN Model:** The data will be used to construct a bipartite graph. User and item IDs will represent the nodes, and the interactions will form the edges connecting them. This graph will be represented using an adjacency list or a sparse adjacency matrix, which is the standard input format for GNN libraries like PyTorch Geometric.

4.3 Proposed Modeling Framework

This section details the specific architectures of the models that will be implemented and compared.

4.3.1 Baseline Models

Two foundational models will be implemented to serve as baselines for performance comparison:

- **Item-based Collaborative Filtering (Item-CF):** A memory-based model where the similarity between any two items is calculated using a metric like cosine similarity on the vectors of users who have interacted with them. Recommendations are generated by finding items similar to those in a user's history.
- **Matrix Factorization (MF):** A classic latent factor model, likely implemented using Singular Value Decomposition (SVD) or an optimization-based approach like Alternating Least Squares (ALS). This model will learn dense user and item embedding vectors and predict interaction scores based on their dot product.

4.3.2 Advanced Model Architectures

Three advanced deep learning models will be implemented to represent the state-of-the-art in sequential and graph-based recommendation.

- **LSTM-based Sequential Recommender:** The architecture will consist of an embedding layer to convert item IDs into dense vectors, followed by one or more LSTM layers. The LSTM will process the input sequence of item embeddings and output a final hidden state, which serves as a summary of the user's sequential preferences. This hidden state will then be fed into a fully connected layer with a softmax output to predict the probability distribution over all possible next items.[15]

- **Transformer-based Recommender (BERT4Rec):** This model will be implemented based on the architecture described in the BERT4Rec paper.[17] The input will consist of item embeddings summed with learned positional embeddings to retain sequence order. This will be followed by a stack of bidirectional Transformer encoder layers, each containing a multi-head self-attention mechanism and a feed-forward network. The model will be trained on the "Cloze" task, where it predicts masked items in the sequence, allowing it to learn deep bidirectional context.[18]
- **GNN-based Recommender (LightGCN):** A simple yet powerful GNN architecture, LightGCN, will be implemented.[19] This model starts with learnable embeddings for all users and items. It then performs multiple layers of graph propagation, where at each layer, a node's embedding is updated by taking a simple weighted average of the embeddings of its neighbors from the previous layer. The final prediction for a user-item pair is calculated as the dot product of their final embeddings after propagation, effectively capturing collaborative signals from high-order neighbors in the graph.[19]

5. Plan of Work

5.1 Evaluation Protocol

A robust and fair evaluation protocol is essential for drawing meaningful conclusions about the relative performance of different recommendation models. The protocol must simulate a realistic prediction scenario and employ metrics that accurately reflect the quality of a ranked list of recommendations.

5.1.1 Splitting Strategy

To evaluate the models' ability to predict future behavior, a **temporal splitting strategy** will be employed. This method is standard practice for evaluating sequential and time-aware recommendation systems. For each user in the dataset, their sequence of interactions will be ordered chronologically. The very last interaction will be assigned to the test set, the second-to-last interaction will be assigned to the validation set (for hyperparameter tuning), and all preceding interactions will form the training set. This ensures that the models are trained on past data and evaluated on their ability to predict genuinely future events, preventing any data leakage from the future into the training process.

5.2 Implementation Details

For the sake of reproducibility, all models will be implemented using widely adopted and well-maintained open-source libraries. The primary framework will be **PyTorch**. For the Transformer-based model, the **Transformers4Rec** library will be leveraged, as it provides optimized building blocks for applying Transformer architectures to recommendation tasks.[26] For the GNN-based model, the **PyTorch Geometric (PyG)** library will be used, which is a standard tool for implementing GNNs. All experiments will be conducted on a consistent hardware platform equipped with a high-performance GPU (e.g., NVIDIA A100 or V100) to ensure feasible training times for the deep learning models.

Hyperparameter tuning will be performed for each model using a systematic grid search or a more efficient method like Bayesian optimization. Key hyperparameters to be tuned include the latent embedding dimension, learning rate, batch size, number of layers (for deep models), number of attention heads (for the Transformer), and regularization strength. The optimal set of hyperparameters for each model will be selected based on its performance on the validation set, as measured by NDCG@10.

5.3 Qualitative Analysis and Case Studies

To provide a more intuitive and practical understanding of the models' behavior, the quantitative results will be supplemented with a qualitative analysis. This section will present case studies of a few selected users from the test set. For each user, their interaction history will be shown, followed by the top-10 brand/category recommendations generated by two or three key models (e.g., Matrix Factorization, LSTM, and BERT4Rec).

This comparative visualization will help illustrate the different characteristics of the models. For example, it might show that the MF model provides reasonable but generic recommendations based on overall popularity and user profile. The LSTM model might generate recommendations that are highly relevant to the user's most recent interactions, demonstrating its ability to capture short-term intent. The BERT4Rec model, in contrast, might produce a more diverse and nuanced list, picking up on more subtle, long-range patterns in the user's history. These concrete examples will make the abstract performance metrics more tangible and provide deeper insight into the qualitative differences between the modeling approaches.

5.4 Addressing Key Challenges

This section will revisit the core challenges outlined in the problem statement and analyze how effectively the evaluated models addressed them, using the experimental results as evidence.

- **Sparsity & Cold-Start:** While all models are affected by sparsity, their resilience varies. Traditional CF and MF models are particularly vulnerable. To empirically demonstrate this, a specific analysis will be conducted on a subset of "cold-start" users from the test set (e.g., users with fewer than 10 interactions in their training history). The performance of all models will be re-calculated on this subset. It is anticipated that the GNN model will show the least degradation in performance. This is because even a new user with a single interaction is connected to an item node in the graph. The GNN can then leverage the rich embedding of that item (which has been learned from all other users who interacted with it) to generate a reasonable initial embedding for the new user, thus offering a structural solution to the data scarcity problem.[20]
- **Dynamic Preferences:** The superior performance of the sequential models (LSTM and Transformer) over the static MF model will be presented as direct evidence of their ability to capture evolving user preferences. By processing interactions in chronological order, these models naturally learn to prioritize more recent signals of user intent, making their predictions more timely and relevant to the user's current context.

5.5 Limitations of the Study

A critical and transparent assessment of the study's limitations is crucial for maintaining academic integrity. The following limitations will be acknowledged and discussed:

- **Dataset Bias:** The chosen dataset, like any real-world dataset, is not free from inherent biases. **Popularity bias** is a significant concern, where popular items receive a disproportionate number of interactions and may be over-represented in the recommendations. **Selection bias** also exists, as users are only exposed to items presented by the platform's existing recommendation algorithm, creating a feedback loop.[9] This study does not explicitly implement debiasing techniques, and the results should be interpreted in this context.
- **Model Scope:** The study evaluates a representative but not exhaustive set of models. Many other architectures and variations exist within each paradigm (e.g., different GNN layers, other Transformer variants) that were not explored.
- **Computational Constraints:** The scale of hyperparameter tuning and model training was constrained by available computational resources. A more extensive search of the hyperparameter space might yield further performance improvements for some models.
- **Offline Evaluation:** The entire evaluation is conducted in an offline setting. It is a well-known issue in the field that improvements in offline metrics do not always translate to improvements in online business metrics (e.g., click-through rate, revenue) in a live A/B test. The results demonstrate predictive accuracy on a historical dataset, which is a strong but not definitive indicator of real-world performance.

5.6 Ethical Considerations and Broader Impact

The development and deployment of sophisticated user affinity models carry significant ethical responsibilities and have a broad societal impact that must be considered.

- **Privacy:** These models are trained on vast amounts of granular user interaction data. The collection, storage, and use of this data raise profound privacy concerns.[3] This section will emphasize the importance of adopting privacy-by-design principles, such as data anonymization, user consent, and providing users with transparent controls over their data and the ability to opt-out.[3]
- **Algorithmic Bias and Fairness:** Affinity models can inadvertently create and reinforce "filter bubbles" or "echo chambers," where users are only shown content that aligns with their existing preferences, limiting their exposure to diverse perspectives and new discoveries.[22] Furthermore, if the training data contains historical biases (e.g., certain demographic groups preferring certain brands), the model may learn and perpetuate these biases, potentially under-recommending products from minority-owned brands or to underserved user groups.
- **Impact on Consumer Choice:** A deeper discussion will be presented on the dual role of these models. While they aim to *predict* user preference, they also inevitably *shape* it. By curating the information environment for each user, these systems can influence purchasing decisions and cultural trends. This raises questions about consumer autonomy and the potential for these systems to limit serendipity—the joy of unexpected discovery—in favor of predictable relevance.[22]

5.8 Avenues for Future Research

Based on the findings and limitations of this study, several promising directions for future research can be identified:

- **Hybrid Models:** A compelling avenue for future work is the development of hybrid architectures that combine the strengths of different paradigms. For example, a model could use a GNN to learn rich, collaboratively-filtered user and item embeddings and then feed these embeddings as initial features into a Transformer to model the sequential dynamics of a user's session.

- **Cross-Domain Recommendation:** An interesting challenge is to explore the transferability of user affinity profiles. Future research could investigate whether a user's learned affinity for brands in one domain (e.g., fashion) can be used to bootstrap or improve recommendations in a related but distinct domain (e.g., cosmetics or home decor).
- **Explainability (XAI):** The most advanced models, like Transformers and GNNs, often function as "black boxes," making it difficult to understand the reasoning behind a specific recommendation.[29] Research into explainable AI for recommender systems is critical for building user trust and providing transparency. Future work could focus on adapting techniques like attention visualization or counterfactual explanations to these models.
- **Fairness and Diversity:** To counteract the homogenizing effect of filter bubbles, future research should focus on explicitly incorporating fairness and diversity objectives into the model's training process. This could involve adding terms to the loss function that penalize a lack of diversity in the recommended items or that ensure equitable exposure for items from different brands or categories.[22]

5.9 Project Timeline

Here is a proposed timeline for the project, commencing November 1, 2025.

Phase	Task	Duration	Start Date	End Date
1	Literature Review & Problem Refinement	2 Weeks	Nov 1, 2025	Nov 14, 2025
2	Data Acquisition, EDA, and Preprocessing	2 Weeks	Nov 15, 2025	Nov 28, 2025
3	Model Development & Implementation (Baselines, LSTM, Transformer, GNN)	4 Weeks	Nov 29, 2025	Dec 26, 2025
4	Experimentation & Hyperparameter Tuning	2 Weeks	Dec 27, 2026	Jan 9, 2026
5	Results Analysis, Interpretation & Case Studies	1 Weeks	Jan 10, 2026	Jan 16, 2026
6	Final Dissertation Writing, Review, and Submission	2 Weeks	Jan 17, 2026	Jan 31, 2026

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7. Particulars of the Supervisor and Examiner

	Supervisor	Additional Examiner
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8. Remarks of the Supervisor

This is a strong dissertation proposal. The topic is highly relevant, and your methodology, which compares foundational models against both sequential (LSTM/BERT4Rec) and graph-based (LightGCN) deep learning architectures, is an excellent way to address the research objectives. The plan to use a temporal split and robust ranking metrics like NDCG and MAP is solid.

My primary feedback concerns your accelerated timeline. Compressing this entire project—from data acquisition to final submission—into the 12 weeks between November 1st and January 31st is extremely ambitious. The "Model Development" and "Experimentation" phases, in particular, involve significant technical overhead.

Information about the Supervisor:

BIRLA INSTITUTE OF TECHNOLOGY & SCIENCE, PILANI
WORK INTEGRATED LEARNING PROGRAMMES (WILP) DIVISION
SECOND SEMESTER OF ACADEMIC YEAR 2024-2026

(INSERT COURSE NUMBER HERE) : (INSERT COURSE TITLE HERE) OUTLINE

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DISSERTATION / PROJECT / PROJECT WORK TITLE	User Affinity Modeling: A Deep Learning Approach to Predicting Brand and Category Preferences from Interaction Dynamics

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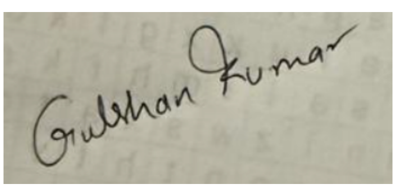		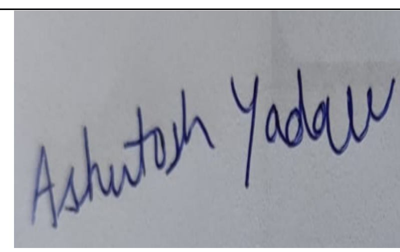
Signature of Student	**Signature of Supervisor**	**Signature of Additional Examiner**
Name: Gulshan Kumar	**Name: Archana Sinha**	**Name: Ashutosh Yadav**