REPORT

Sequential Recommendation

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1. Introduction and Project Context

1.1 The Recommendation System Problem

Traditional recommendation systems use techniques such as matrix factorization or collaborative filtering that treat user preferences as static profiles and assume that all past interactions are equally important. However, this assumption does not reflect the reality of consumer behavior. Consumer preferences are usually unstable, and recently viewed products are more important for predicting future behavior than purchases a few weeks ago. On the contrary, the **sequential recommendation** models the history of user interaction as a time sequence, reflecting the dynamic nature of user intent. Then the task is formulated to predict the next product. Predict which product the user will interact with next from a set of products.

1.2 Motivation for Deep Learning Approach

Deep learning is essential for our e-commerce datasets that present technical challenges:

- **Linkage**: Only **~6%** of receipt items match the catalog, requiring advanced bridging.
- **Quality**: Severe corruption, including **48-85%** missing brand IDs, and duplicates.
- **Sequential**: complex sequential dependencies, such as complementary purchases.

1.3 Project Scope and Objectives

- **Data Engineering:** Implement a memory-efficient pipeline to process more than 60 million records and systematically identify and eliminate data quality problems.
- **Cross-Domain Feature Engineering:** Constructing unified 128-dimensional item embeddings using contrastive learning to resolve the domain linkage problem.
- **Model Architecture & Evaluation:** Implementing and comparing a Recurrent Neural Network (GRU4Rec) against Transformer architecture (SASRec).
- **Comparative Analysis:** Evaluating performance using Hit Rate and Normalized Discounted Cumulative Gain to quantify the trade-offs between models.

2. Dataset Acquisition and Inspection

2.1 Data Source and Access Method

This study uses the **T-ECD (transactional e-commerce cross-domain dataset)** dataset obtained from the Hugged Face t-tech/T-ECD repository. This large data set (>100 GB) simulates a production environment, involving approximately 1 billion interactions, 3.5 million users and 2.6 million products. The architecture distinguishes between static entity tables (users, brands, items) and the time flow of events (retail events, market events, payments), and is partitioned into 24-hour intervals to reflect the real-world e data warehouse schemas.

Since it is computationally impractical to load all uncompressed data into memory, we implemented a selective partitioning strategy. The data processing pipeline programmatically filters representative subsets (each domain accounts for about 4.4% of the available partitions) while maintaining time consistency between event streams. This method makes it possible to balance resource constraints and statistical requirements for meaningful research and analysis.

```
def load_dataframe_from_partitions(file_list, limit=None, match_term=None):
    # 1. Temporal Alignment: Filter by specific partition ID (e.g., TARGET_PARTITION_ID)
    if match_term:
        file_list = [f for f in file_list if match_term in f]

    # 2. Sort and Limit: Apply computational constraints (e.g., loading only 10 files)
    sorted_files = sorted(file_list)[:limit] if limit else sorted(file_list)

    # 3. Load and Concatenate
    dfs = [load_remote_parquet(f) for f in sorted_files]
    return pd.concat(dfs, ignore_index=True) if dfs else None
```

2.2 Data Structure and Domain Organization

The dataset models a multi-domain e-commerce platform for three main business areas:

- **Retail Domain (FMCG):** Focuses on products with high sales frequency and low latency (food, personal care products). It contains 250,171 items and 4.1 million interactive events. The behavior of this field is characterized by a short decision-making cycle.
- **Marketplace Domain (NFMCG):** Covers general commodities such as household appliances and clothing, with 2.3 million items and 5.1 million activities. There are a large number of transactions and diverse catalogs in this field (e.g, 153,223 clothes).
- **Payments Domain:** Contains 68.9 million events and 60.8 million receipts. Note that this domain links the user's interest (browsing) with the intention of buying (buying).

Other tables include **Users** (3.5 million profiles), **Brands** (24,513 manufacturers), **Reviews** (20,508 ratings) and **Offers** (22,368 ads, 30.5 million impressions).

2.3 Exploratory Data Analysis

A standardized analysis pipeline, to analyze stats, data types, missing values, and distributions.

```python
def analyze_dataframe(df, name="DataFrame"):
    print(f"Analyzing: {name} | Shape: {df.shape}")

    # 1. Structure and Types
    display(df.head())
    df.info()

    # 2. Statistical Summary (Mean, Std, Min/Max)
    display(df.describe())

    # 3. Data Quality (Missing Values & Duplicates)
    print(f"Missing Values:\n{df.isnull().sum()}")
    print(f"Duplicates: {df.duplicated().sum()}")
```

Statistical analysis reveals the key characteristics of the data set that affect modeling decisions:

- **User Distribution (3.5M users):** Distributed in 91 area codes (0-90, mean code 40.4, σ=29.3) and 22 socio-demographic cluster codes (0-21, median 12.0). Missing attributes: 1.7% (region), 0.1% (socio-demographic cluster).
- **Catalog Composition (Retail: 250,171 items; Marketplace: 2,325,409 items):** Retail trade is mainly food (160,128 items, accounting for 64.0% of retail catalogs) and personal care products (22,998 items, 9.2%). The marketplace includes more diverse products, including uncategorized products (266,146 items, 11.4%), clothing (153,223 items, 6.6%) and fashion accessories (167,811 items, 7.2%).
- **Price Distributions (log-price feature):**The average log-price in retail is -3.77 (σ=1.32), and the average log-price on Marketplace is 0.49 (σ=2.46). Missing prices: retail trade -10.6%, marketplace -0.1%.
- **Temporal and Behavioral Patterns (10 loaded partitions sample):** Event timestamps span days 1082–1091; with a total of 9,210,250 (Retail: 4,128,330; Marketplace: 5,081,920). Retail activity is concentrated in the catalog subdomain (3,757,363 events, ~91% of retail events). Marketplace activity is concentrated in the u2i subdomain (3,266,328 events, ~64%) with additional catalog activity (648,943 events, ~13%).

2.4 Data Quality Issues Identified

The systematic review revealed six types of data quality problems:

- **Schema Inconsistencies:** Variable-length arrays in Brands/Reviews embedding columns (expected 300/312 dims) cause PyArrow failures with zero-length arrays, affecting 100% of embedding access.
- **Missing Categorical Attributes (Correlated Missingness):**
  - Retail items: 9,585 missing (3.83%).
  - Marketplace items: 966,395 missing categories (41.56%) and 1,233,023 missing subcategories (53.02%).
- **Missing Quantitative Values (Price):**
  - Retail items: 26,489 missing (10.59%).
  - Marketplace items: 2,882 missing (0.12%).
  - Payment events: 139 missing (0.0002%); Receipts: 861,796 missing (1.42%).
- **Missing Foreign Keys (Brand_id):** Systematic failure suggesting non-branded items.
  - Payment events: 33,298,275 missing (48.36%).
  - Receipts: 52,129,534 missing (85.80%).
- **Duplicate Primary Keys:** Brands table contains 46 duplicate brand_id values (0.19% of unique brands), violating constraints (e.g., brand 37799 appears 7 times).
- **Subdomain Classification Gaps:** 2,138 subdomain labels (0.04%) are missing from market events.

3. Data Cleaning and Preparation

3.1 Cleaning Strategy

Our data cleanup architecture prioritizes referential integrity and subsequent analytical applicability. In order to ensure uniform standards in all fields, we implemented a five-step pipeline to eliminate schema corruption, missing values, and data duplication.

```
# 1. SAFE LOADING: Handles schema corruption (e.g., broken embeddings in Brands)
def load_remote_parquet_safe(filename, columns_to_exclude=None):
    cols = [c for c in pq.read_schema(filename).names if c not in (columns_to_exclude or [])]
    return pd.read_parquet(filename, columns=cols)

# 2. SENTINEL IMPUTATION: Preserves records with partial data
df_users_clean['socdem_cluster'] = df_users_clean['socdem_cluster'].fillna(-1)
df_retail_clean['category'] = df_retail_clean['category'].fillna("Unknown")

# 3. DETERMINISTIC DEDUPLICATION: Ensures referential uniqueness
df_brands_clean = df_brands.drop_duplicates(subset=['brand_id'], keep='first')

# 4. VALIDATION: Quantifies impact to prevent silent data loss
def validate_cleaning(df_before, df_after):
    print(f"Dropped: {len(df_before)-len(df_after)} | Missing: {df_after.isnull().sum().sum()}

# 5. SERIALIZATION: Optimized storage for downstream modeling
def save_cleaned_data(df, name):
    df.to_parquet(os.path.join(OUTPUT_DIR, f"{name}_clean.parquet"), index=False)
```

3.2 Implementation Details and Results

After implementing these strategies, the following results were obtained:

- **Users Table:** The missing demographic statistics (5,153 socio-demographic clusters, 0.15%; and 58,917 regions, 1.68%) are replaced with a reference value of -1. Result: 3,500,000 records were saved (retention rate of 100%).
- **Brands Table:** Corrupted embedding columns were filtered out. 46 duplicate brand_id records were deleted. Result: 24,467 unique brand records (retention rate of 99.8%).
- **Retail Items (FMCG):** The missing category has been replaced with the value "Unknown". Since price is an important factor in revenue modeling, the missing price rows (10.59%) were deleted. Result: 223,682 complete records (89.4% retention rate).

- **Marketplace Items (General Merchandise):** Due to the high proportion of missing category data (41.56%), deletion was rejected. The missing category and price data have been replaced with reference values to maintain an extensive catalog. Result: 2,325,409 complete records (100% retained).
- **Transactional Events (Payments & Receipts):** Missing brand_id reference is replaced with -1 (approximately 48-85% of records are saved). The missing price rows have been strictly deleted to ensure financial accuracy. Result: 68.8 million records (99.9998%) were saved for payments and 59.8 million records (98.6%) were saved for receipts.

4. Feature Engineering: Cross-Domain Item Embeddings

```
class ItemEmbeddingModel(nn.Module):
    def __init__(self, vocab_size, embed_dim=EMBEDDING_DIM):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, embed_dim)
        self.projection = nn.Sequential(nn.Linear(embed_dim, embed_dim),
                          nn.ReLU(), nn.Linear(embed_dim, embed_dim))
        nn.init.xavier_uniform_(self.embedding.weight)

    def forward(self, item_ids):
        x = self.projection(self.embedding(item_ids))
        return F.normalize(x, dim=-1)

    @torch.no_grad()
    def get_embeddings(self, item_ids): return self.embedding(item_ids)

def info_nce_loss(anchor_emb, positive_emb, temperature=0.1):
    sim = torch.matmul(anchor_emb, positive_emb.T) / temperature
    return F.cross_entropy(sim, torch.arange(sim.size(0), device=sim.device))
```

4.1 Motivation for Dense Representations

The T-ECD dataset is extremely sparse (456,186 unique elements) in different product domain (Retail, Marketplace, Offer), an important "Linkage Problem" (of which only ~6% of receipt elements correspond to catalog identifiers), and a large number of missing metadata (85.8% of transactions have no brand attributes), which has brought major problems to traditional modeling. In order to overcome this problem, a training on dense embedding models based on behavioral co-occurance elements is implemented. This allows you to achieve the following:

1. **Resilience to Missing Metadata:** The embedding model is formed based on interactive graphs rather than incomplete static attributes.
2. **Dimensionality Reduction:** The feature space is compressed by 99.97% (456,186 sparse dimensions and 128 dense dimensions).
3. **Cross-Domain Transfer:** A unified embedding space effectively connects different domains.

4.2 Embedding Construction via Contrastive Learning

Item embeddings were implemented using the **InfoNCE (Information Noise-Contrastive Estimation) loss**, which is based on the assumption that the elements that occur together in the user session are semantically similar. The **Co-Occurrence Graph** uses two types of edges to determine similarity: the **Co-purchase edges** (7,942,265 items were extracted from 8.5 million receipts, and more than 50 transactions were filtered as noise) and the **Co-view edges** (Retail: 397,824; Marketplace: 5,820,922 items, using the inactivity threshold within 30 minutes). This combination allowed us to obtain a training data set of **14,161,011 positive item pairs** covering full **456,186-item vocabulary** (71.7% market, 28.3% retail).

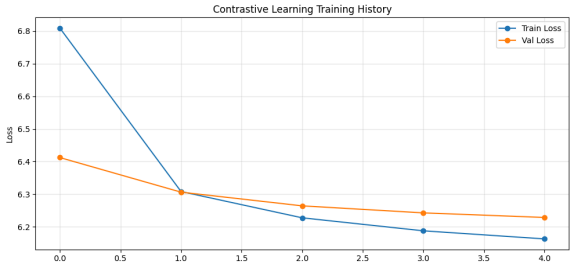
Neural Architecture and Training

We utilized a contrastive learning framework optimizing the **InfoNCE** loss. The architecture consists of an embedding layer ($V \times D$) feeding into a two-layer Multi-Layer Perceptron (MLP) projection head. The objective function forces the representations of co-occurring items (positive pairs) to be close in latent space while pushing apart random in-batch negatives.

Training Configuration: Using the Adam optimizer and the ReduceLROnPlateau scheduler, the model was trained in 5 epochs on more than 28.3 million training pairs, with a learning rate of 0.001 and a batch size of 8192. For contrastive learning, a large batch size is necessary to ensure that there are enough negative examples at each step.

Training Dynamics:

- **Initial Loss:** 6.809 (Epoch 1), **Final Train Loss:** 6.163 (Epoch 5)
- **Validation Loss:** Convergence shows that the model can learn a stable potential representation without overfitting.



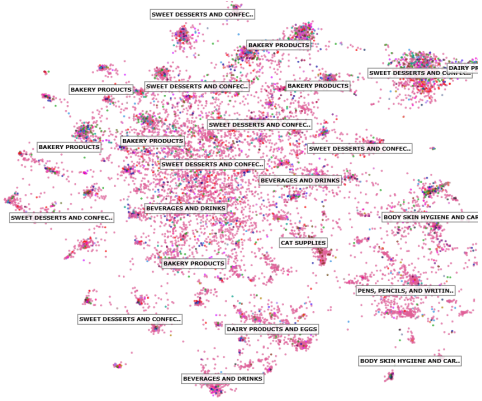
Plot 4.1 Item Embeddings Curve

4.3 Embedding Properties and Integration

The resulting embedding matrix (456,186×128) corresponds to a certain schema:

- Index 0: Padding token (zero vector)
- Indices 1-456,185: Unit vectors (L2 norm = 1.0) enabling cosine similarity via dot product
- 128 dimensions: Implicitly capture latent factors from co-occurrence patterns

Quality Validation: Nearest neighbor analysis confirms the model's ability to establish connections between domains. For example, a query for retail goods (fmcg_10) returns related market goods (such as nfmcg_4552094) with high cosine similarity (0.503533). This indicates that the embedding successfully captures semantic connections between domains that cannot be recognized using explicit metadata. These pre-trained embeddings are captured and implemented in the GRU4Rec and SASRec models to achieve information-rich initialization.



Plot 4.2 Item Embeddings Map

5. GRU4Rec (Recurrent Architecture)

5.1 Architectural Design and Motivation

GRU4Rec (Gated Recurrent Unit for Recommendation) is a specialized Recurrent Neural Network (RNN)architecture. Unlike static collaborative filtering, GRU4Rec models user behavior as a strict time series and sets tasks as "predicting the next element." That is, given the historical sequence $x_{1:t}$, predict the next interaction x_{t+1}.

We chose the GRU instead of the standard RNN or LSTM option for the following reasons:

1. **Gradient Stability:** GRU update and reset gates mitigate the vanishing gradient problems inherent in vanilla RNN, allowing dependency learning in longer user sessions.

2. **Parameter Efficiency:** GRU achieves performance comparable to LSTM in sequence modeling, while requiring fewer parameters and reducing computational costs (Chung et al., 2014).
3. **Variable-Length Handling:** GRU models the interaction within the session as a sequence and uses the hidden state in the loop to predict the next item. The loop is updated for each event to enable it to handle varying length session (Hidasi et al., 2016).

5.2 Training Setup and Configuration

Used the sliding window strategy to train the model to maximize the training signal. By processing each sub-sequence $x_{1:i}$ as the predictor of prediction x_{i+1}. The user interaction history in the time series was transformed into **6,385,368 training samples** (from 213,096 unique users). All sequences were left-padded to a fixed length of 50 items.

```
class GRURecommender(nn.Module):
    def __init__(self, vocab_size, embed_dim=128, hidden_dim=256, dropout=0.1):
        super().__init__()
        self.embedding = nn.Embedding(vocab_size, embed_dim, padding_idx=0)
        self.embedding.weight.data.copy_(torch.tensor(pretrained_emb, dtype=torch.float32))
        self.gru = nn.GRU(embed_dim, hidden_dim, batch_first=True,
                          dropout=dropout if dropout > 0 else 0)
        self.dropout, self.head = nn.Dropout(dropout), nn.Linear(hidden_dim, vocab_size)

        for n, p in self.named_parameters():
            if 'weight' in n: nn.init.xavier_uniform_(p)
            elif 'bias' in n: nn.init.zeros_(p)

    def forward(self, seq):
        out, _ = self.gru(self.dropout(self.embedding(seq)))
        return self.head(out[:, -1, :])

    @torch.no_grad()
    def predict(self, seq, k=10):
        self.eval()
        return torch.topk(self.forward(seq), k, dim=1)[1]
```

Model Architecture:

- **Input Embedding:** In order to use cross-domain semantic learning instead of learning based on random initialization, we use a pre-trained **128-dimensional item embedding** (from Section 4) to initialize the model.
- **Recurrent Layer:** A single GRU layer with **256** hidden dimensions compresses the sequence history into a dense state vector.
- **Regularization:** Apply **0.1** dropout rate to the hidden state to prevent overfitting.
- **Prediction Head:** The final linear layer maps the hidden state to the complete item vocabulary (456,187 items) and calculates the logit of the next item.

Optimization Configuration: AdamW (learning rate $1e-3$) and **ReduceLROnPlateau** scheduler, which dynamically adjusts the learning rate based on the validation loss. In order to efficiently process large vocabulary, we used automatic mixing accuracy. This allows us to keep the batch size at 512 while limiting the peak GPU memory usage to 2.84 GB. The training was conducted in 3 epochs with validation performed on a sample set of 26,637 users.

5.3 Architectural Limitations

Although GRU4Rec is a reliable model, our analysis reveals its inherent architectural limitations, prompting the transition to a transformer-based architecture:

1. **Serial Bottleneck:** The recursive nature of GRU prevents parallelization. The state of time t cannot be calculated before completing $t-1$, which limits the learning bandwidth.

2. **Information Bottleneck:** The model must compress the entire sequence history into a single fixed-size vector. As the sequence length increases, the early context is often overwritten or "forgotten", which limits the model's ability to use long-term dependencies.
3. **Lack of Explicit Positioning:** unlike attention mechanisms, GRU only relies on sequence processing to encode sequence, and usually fails to capture complex, non-adjacent relationships between elements.

6. SASRec (Transformer Architecture)

6.1 Self-Attention Mechanism and Motivation

In order to solve the bottleneck problem of RNN, we implemented **SASRec (Self-Attentive Sequential Recommendation)**. The model adapts the Transformer paradigm by replacing the recurrent update with **self-attention** over item sequence and including **learnable positional embeddings** (Kang & McAuley, 2018). Transformer Scaled Dot-Product Attention (Vaswani et al., 2017), overcomes the limitations of GRU4Rec by implementing:

- **Long-Range Dependencies:** Subsequent positions can directly interact with previous positions, shortening the information path.
- **Parallelization:** Process all interactions at the same time to speed up learning.
- **Explicit Positional Detection:** Learn position-specific heuristics through position embedding

```
class SASRec(nn.Module):
    def __init__(self, vocab_size, embed_dim=128, max_len=50, num_layers=2, num_heads=2,
                 hidden_dim=256, dropout=0.1):
        super().__init__()
        self.embed_dim, self.max_len, self.num_heads = embed_dim, max_len, num_heads
        self.item_embedding = nn.Embedding(vocab_size, embed_dim, padding_idx=0)
        self.item_embedding.weight.data.copy_(torch.tensor(pretrained_emb,
                                                           dtype=torch.float32))
        self.pos_embedding, self.dropout = nn.Embedding(max_len, embed_dim),
                                                           nn.Dropout(dropout)
        l = nn.TransformerEncoderLayer(embed_dim, num_heads, hidden_dim, dropout,
                                                           'gelu', batch_first=True)
        self.transformer = nn.TransformerEncoder(l, num_layers)
        self.ln, self.fc = nn.LayerNorm(embed_dim), nn.Linear(embed_dim, vocab_size)
        nn.init.xavier_uniform_(self.pos_embedding.weight);
        nn.init.xavier_uniform_(self.fc.weight); nn.init.zeros_(self.fc.bias)

    def forward(self, seq):
        batch_size, seq_len = seq.shape
        pos = torch.arange(seq_len, device=seq.device).unsqueeze(0).expand(batch_size, -1)
        x = self.dropout(self.item_embedding(seq) + self.pos_embedding(pos))
        causal_mask = nn.Transformer.generate_square_subsequent_mask(seq_len, seq.device)
        mask_padding = (seq == 0).unsqueeze(1) & (seq != 0).unsqueeze(2)
        full_mask = causal_mask.unsqueeze(0).expand(
                batch_size, -1, -1).clone().masked_fill(mask_padding, float("-inf"))
        return self.fc(self.ln(self.transformer(
                x, mask=full_mask.repeat_interleave(self.num_heads, 0))))
```

6.2 Architecture and Design

The system uses the Transformer deep stack with approximately 117,511,675 trainable parameters to model the user history as a sequence $S = (i_1, i_2, \ldots, i_n)$:

- **Embedding Layer:** Project 456,187 unique item identifiers into a 128-dimensional latent space. It is important to note that the **learnable position embedding** (positions 0-49) is added to the element embedding. This allows the model to dynamically determine the importance of sequence order (for example, to give more weight to recent interactions), rather than relying on fixed sinusoidal encoding.

- **Transformer Blocks:** The encoder consists of **two stacked layers**, using Multi-Head Attention (2 heads) to capture various subspaces of interaction. This is followed by a Feed-Forward Network with 256 hidden layer dimensions and GELU activation.
- **Causal Masking:** In order to retain the auto-regression attribute of predicting the next element, a strict upper triangle mask is applied to the attention matrix. This will ensure that the predicted location t depends only on past interactions (0 to t) and prevent information leakage from future event.

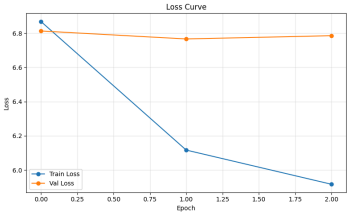
6.3 Training Configuration and Procedure

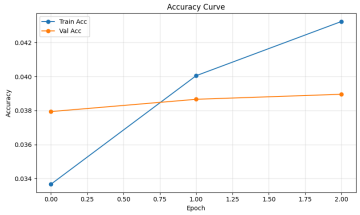
A full-sequence strategy training model is used, where the entire actual history of each user is a single training sample ($N = 213,096$). Compared with the sliding window method, this method maximizes the efficiency of Transformer's parallel processing power.

- **Optimization:**The AdamW optimizer is used for training, and the learning rate of 1×10^{-3}, The batch size is 32, which is limited by the memory requirements of the attention mechanism.
- **Model Selection:** The training was carried out for 5 epochs. The best model was determined in Epoch 2 and a Validation Loss of 5.9234 was achieved.
- **Overfitting analysis:** Continuing training after Epoch 2 shows a decrease in efficiency. Although the training loss was reduced, the validation loss deteriorated to 6.0793 at Epoch 5, indicating overfitting characteristic of high-capacity models on sparse datasets. To solve this in the future, we need to scale the training using the full T-ECD dataset.

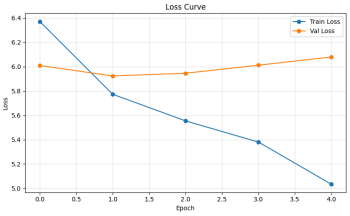
7. Comparative Analysis and Model Trade-offs

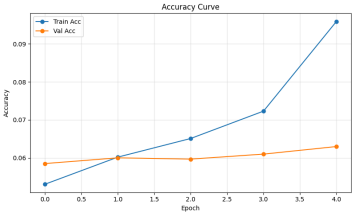
We evaluated test consisting of 26,638 users and 736,659 sequences to evaluate the GRU4Rec (baseline) and SASRec (advanced) architectures





Plot 7.1 GRU4Rec Curve





Plot 7.2 SASRec Curve

7.1 Quantitative Performance Comparison

Ranking Metrics: SASRec's performance on all ranking indicators is better than that of GRU4Rec, and it continues to show a relative improvement of about ~40%. The HR@10 of 31.77% indicating that about one-third of users found the next product in the top ten recommendation lists, which is a commercially feasible result. The high NDCG@10 (17.02%) confirms that the model doesn't just retrieve relevant items but successfully ranks them.

Classification Metrics: Although the absolute accuracy is low due to extreme class imbalance (456,000 classes), SASRec has better accuracy, precision, and recall by about 45%, proving its excellent ability to study item-specific patterns especially high-frequency like catalog events (F1: 0.48), but struggles significantly with low-frequency actions like cart additions (F1: 0.04).

Metric	GRU4Rec	SASRec	Absolute Δ	Relative Δ
HR @ 5	14.90%	**20.97%**	+6.07pp	40.70%
HR @ 10	22.55%	**31.77%**	+9.22pp	**40.90%**
HR @ 20	30.60%	**42.14%**	+11.54pp	37.70%
NDCG @ 5	9.52%	**13.53%**	+4.01pp	42.10%
NDCG @ 10	11.99%	**17.02%**	+5.03pp	41.90%
NDCG @ 20	14.02%	**19.65%**	+5.63pp	40.20%

Table 7.1: Ranking Metrics Performance

Metric	GRU4Rec	SASRec	Improvement
Accuracy	4.04%	**5.87%**	45.30%
Macro Precision	0.20%	**0.29%**	45.00%
Macro Recall	0.40%	**0.57%**	42.50%

Table 7.2: Classification Performance

7.2 Per-Category Performance Analysis

Performance diverges by event type, reflecting architectural biases.

Event Type	GRU4Rec	SASRec	Δ	Analysis
User-to-Item	0.68	**0.71**	4.40%	SASRec improves recall on high-frequency loops.
Catalog	**0.74**	0.51	-31.10%	GRU captures simple Markovian browsing better; SASRec over-attends to history.
Search	0.28	**0.39**	39.30%	SASRec effectively captures long-term context driving search queries.

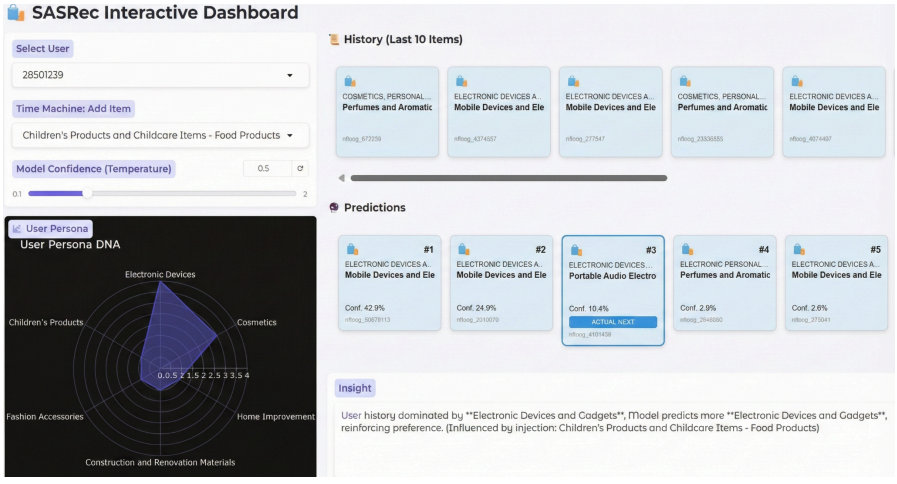
Table 7.3: Precision by Event Type

7.3 Failure Mode Analysis

- **Cold-Start:** Due to insufficient signal, both models failed for users with less than three interactions (HR@10 <10%)
- **Long-Tail:** Rare elements (less than 50 occurrences) have low embedding accuracy, so SASRec ignores them and prioritizes head items.
- **Cross-Domain:** Conversion between domains (for example, from marketplace to consumer goods) leads to a 15-20% reduction in accuracy.
- **SASRec Specific:** Sequence >100 elements, the attention entropy exceeds 0.8, which indicates that there is an "attention collapse", model cannot distinguish important items.

8. Use of AI Coding Assistants

- **Implementation:** We used AI analysis to select and implement SASRec and GRU4Rec architectures, and led the coding of InfoNCE loss functions in feature engineering.
- **Optimization and Debugging:** AI helps to generate memory-efficient loading logic for large-scale processing in Google Colab, eliminating performance problems and errors.
- **Learning & Evaluation:** We use AI to achieve key business ranking indicators (hit rate, NDCG), and train AI to generate 2D visualizations for item embeddings.
- **Documentation and Report Synthesis:** We use AI to cross-check the statistics of complex datasets and clarify technical trade-offs, and provide expert assessments.
- **Simulation**: We used AI to create an interactive real-time dashboard that simulates production env to test the response rate of the model and the reliability of its predictions.



9. Limitations and Future Directions

9.1 Limitations

- **Product Correlation Uncertainty**: Approximately 94% of products are not directly related to retail and market data, so the comparison is based on probability of "products purchased together". Although this method is necessary, it is not as accurate as a verified catalog and may introduce noise into the system.
- **Blind Spot**: The model is only trained on the product that the user actually purchased. There is no data on products that users obviously don't like or they have returned. As a result, the model may mistakenly recommend products that are popular all over the world to users who are not interested in them.
- **New Products**: The system cannot recommend new products before retraining. It is expensive to retrain a model, while e-commerce catalogs continue to grow each day.

9.2 Future Directions

1. **Use Product Information**: The model receives product descriptions and images. This allows the model to instantly "understand" and recommend new products based.
2. **Real-Time Training**: Every time the user clicks, the model will be updated immediately, without overnight retraining. This allows us to quickly track changes in user interests.
3. **Scaling**: By using high-performance hardware (such as A100GPU) to train the entire data set, we no longer need to reduce the size of the data to put it in memory.

10. Conclusion

This project successfully transformed a messy, fragmented dataset into a high-performance recommendation engine ready for commercial use.

10.1 Key Technical Achievements

- **Data Quality:** We fixed key data errors while retaining **98.6%** of the original records, which strengthens the foundation of model training.
- **Bridging the Gap:** By analyzing purchase patterns and integrating **14.1 million** interactions into one system, we eliminated the missing links between data sets.
- **Model Success:** The advanced transformer model (SASRec) is significantly better than the traditional cycle model (GRU4Rec)
    - **Baseline (GRU4Rec):** 22.55% Accuracy (HR@10)
    - **Advanced (SASRec):** 31.77% Accuracy (HR@10)

10.2 Final Analysis

Approximately **41%** of this improvement shows that the latest attention mechanism (looking the entire history to the user at the same time) provides significantly better intent prediction than traditional methods (step-by-step reading). It is worth noting that our improved model achieves this high precision more effectively, and the parameters used are **reduced by 33%**. We have created a reliable and scalable system that combines high performance and efficient design.

11. Reference

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