Recommender Systems

Lecture 4: Generative approaches to recommender systems

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Where are we?

- **Lecture 1**
  - Introduction to RecSys
- **Lecture 2**
  - Evaluation in RecSys
- **Lecture 3**
  - a. Sequential RecSys
  - b. Large Language Model-based RecSys
- **Lecture 4**
  - a. Generative models in RecSys
  - b. Case studies in GenRec

Acknowledgements

This lecture is based on a number of published papers.

Part 1
Generative models in recommender system

Generative models in RecSys

- Generative models are used in multiple ways:
  - VAE for embedding generation
  - Language models for review/explanation generation
  - RAG for text-to-item generation

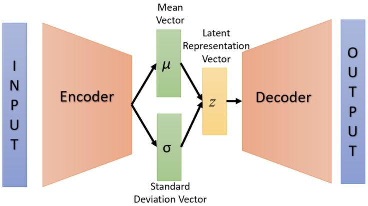

Figure 1: VAE-based recommender systems [Fraihat et al., 2024]

Generative models in RecSys

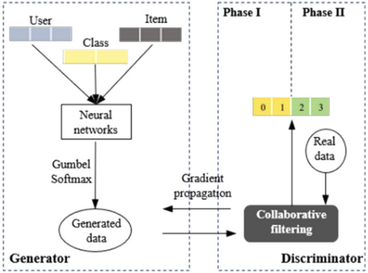

Figure 2: The generative model constructs data [Wang et al., 2019]

- The core mechanism of most modern recommendation models—including matrix factorization and deep learning approaches—relies on **matching user and item embeddings** in a latent space

Limitations of embedding-based recommenders

- Tightly coupled with the indexing structure
- Matching is limited to item-level semantic similarity (e.g., a simple matching function over fixed-length embedding vectors)

Is this simple fixed-length embedding interaction truly enough for recommendation?

Terminology clarification

- **Embedding-based methods using generative structure models (GenStruct):** Use generative models to learn user/item representations or assist in reranking, but still rely on embedding matching
- **Generative recommendation (GenRec):** User history $\rightarrow$ next item identifier
- **Generative information retrieval (GenIR):** Query $\rightarrow$ relevant document identifier
- *Note:* Some papers use "generative recommendation" broadly to include both GenStruct and GenRec above

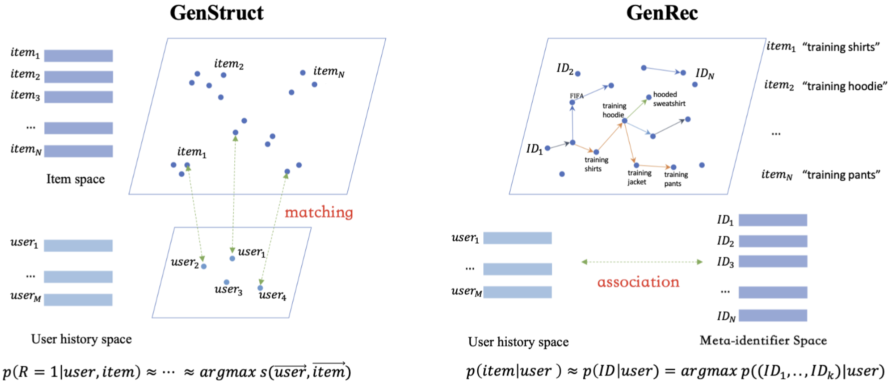

Figure 3: Mechanism: matching vs. association / generation

Definition: Generative recommendation (GenRec)

- **Definition:** A recommendation paradigm where the model directly **generates item identifiers** (ID) given a user's interaction history [Rajput et al., 2023]
- The task is cast as a sequence-to-sequence generation problem:
  - Input: user interaction sequence
  - Output: next item ID
- No explicit index is required

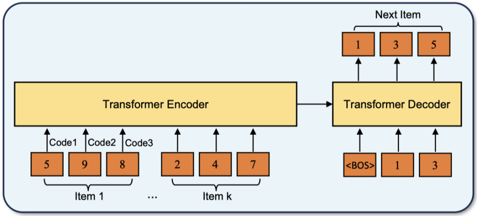

Figure 4: The GenRec model generates the next item ID [Zhu et al., 2024]

From generative retrieval to generative recommendation

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- **Why it matters:**
  - Moves beyond index-based retrieval
  - Enables end-to-end learning with strong generalization

From generative retrieval to generative recommendation

- **Generative information retrieval (GenIR):** A GenIR model directly generates relevant document identifiers in a sequence-to-sequence fashion, for a query
- **Why it matters:**
  - Moves beyond index-based retrieval
  - Enables end-to-end learning with strong generalization
- **Inspiration for GenRec:**
  - Items $\equiv$ documents
  - User history $\equiv$ query
  - Next-item prediction $\equiv$ identifier generation

Advantages of GenRec [Rajput et al., 2023]

- **Unified paradigm:** Item corpus is indexed implicitly via a generative model
- **Flexible conditioning:** Easily incorporate user history, context, and auxiliary information as prompt input
- ...

Q&A

Questions, . . .

Basic workflow of GenRec models

Basic pipeline

- Input: tokenized user interaction history
- Output: item ID via autoregressive decoding
- Model architecture: encoder-decoder

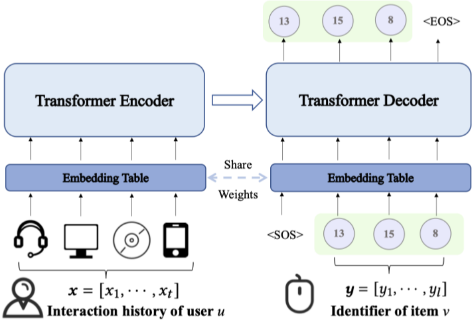

Figure 5: GenRec pipeline [Si et al., 2024]

Identifiers in GenRec

- **What is an identifier?** A unique, textual representation of an item (e.g., "item_12345"), used as the decoding target

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- **Why identifiers?**
  - Serve as a symbolic reference to items in the catalog
  - Make it possible to reframe recommendation as a sequence generation problem

Identifiers in GenRec

- **What is an identifier?** A unique, textual representation of an item (e.g., "item_12345"), used as the decoding target
- **Why identifiers?**
  - Serve as a symbolic reference to items in the catalog
  - Make it possible to reframe recommendation as a sequence generation problem
- **Output format:** Generated as token sequences (e.g., "item", "_", "12", "345")

Examples

- Random identifiers [Geng et al., 2022]
  - Semantically meaningless: the token structure contains no information about item content (e.g., "item_12345")
  - The model should learn to map user history to arbitrary string tokens
  - Harder to generalize, especially to unseen or cold-start items [Rajput et al., 2023]
- Semantic identifiers [Rajput et al., 2023]
  - Residual quantization codes
  - Improving learnability and generalization

Training

- Given the user history, the model learns to maximize the likelihood of the next item identifier

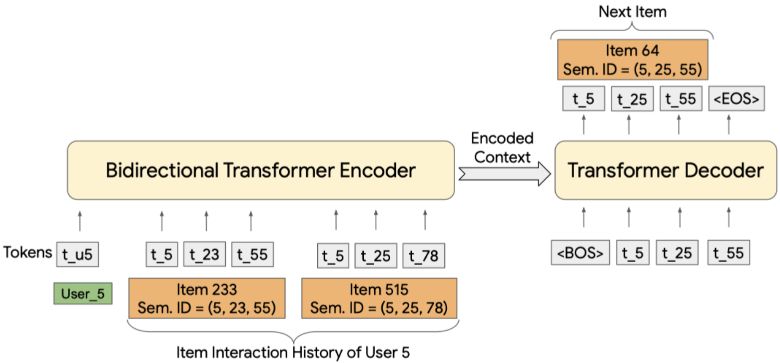

Figure 6: Training illustration [Rajput et al., 2023]

Inference

- Beam / greedy search

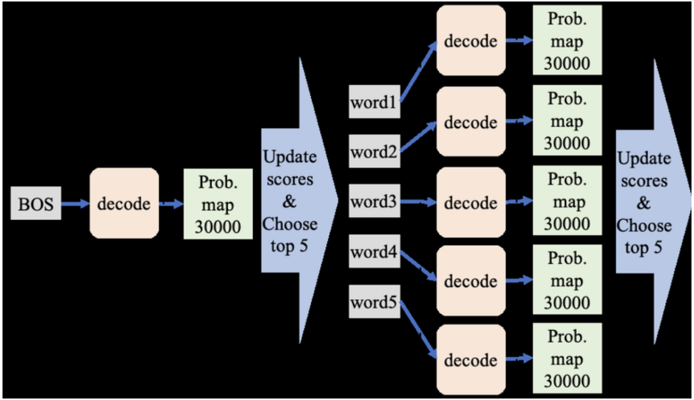

Figure 7: Beam search illustration [Li et al., 2020]

Inference

- Constrained beam search: ensure only valid IDs
- Prefix tree structure:
  - Nodes are annotated with tokens from the vocabulary
  - For each node, its children indicate all the allowed continuations from the prefix defined traversing the trie from the root to it

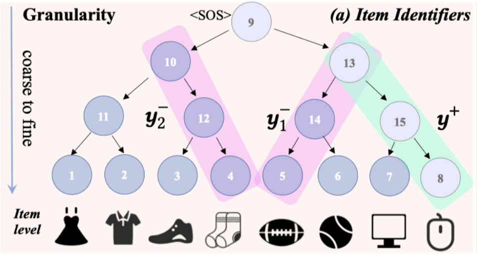

Figure 8: Constrained decoding with a prefix tree [Si et al., 2024]

Recent advances in GenRec

Roadmap

P5

[Geng et al., 2022]

(Randomly IDs)

Roadmap

P5 [Geng et al., 2022] → **TIGER** [Rajput et al., 2023]

(Randomly IDs) (RQ codes as IDs)

Roadmap

P5 [Geng et al., 2022] → **TIGER** [Rajput et al., 2023] → **SEATER** [Si et al., 2024]

(Randomly IDs)

(RQ codes as IDs)

(Tree-structured IDs
and contrastive ranking)

Roadmap

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[Geng et al., 2022]

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EAGER

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(Integrating user behaviour
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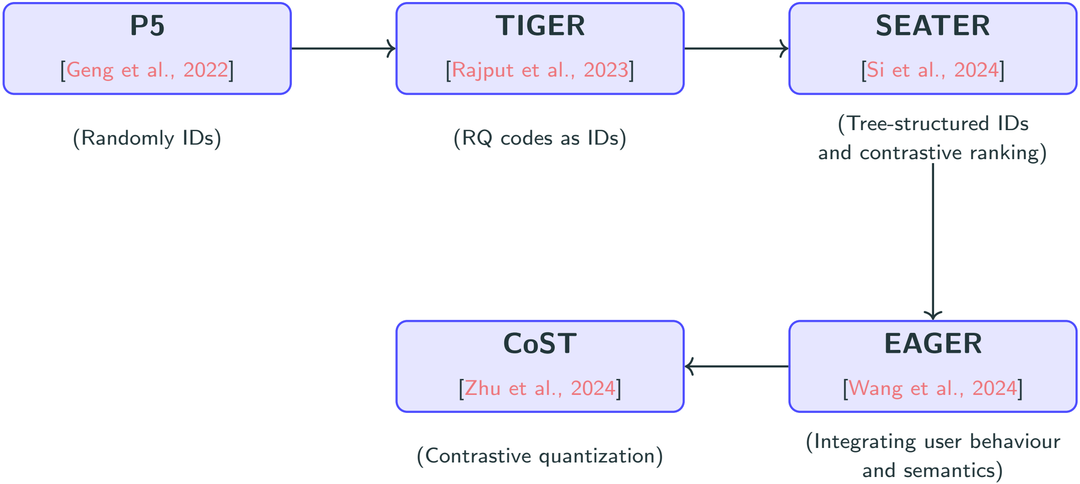
Roadmap


P5
[Geng et al., 2022]
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←

MQL4GRec
[Si et al., 2024]
(Generative multi-modal
recommendation)

Part 2
Case studies in GenRec: TIGER and SEATER

Recommender systems with generative retrieval

TIGER [Rajput et al., 2023]

- **T**oken-based **I**tem **G**eneration for **E**nd-to-end **R**ecommendation (TIGER)
- **Key idea:** Reformulate recommendation as sequence-to-sequence generation
- Uses a shared encoder-decoder architecture, trained to decode item IDs

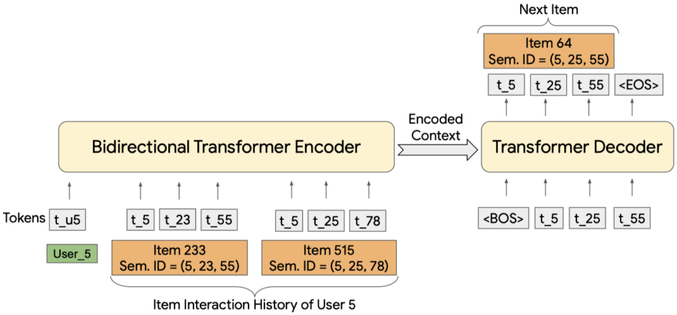

Figure 9: TIGER overview [Rajput et al., 2023]

Identifier

- **Goal:** Represent each item with a structured, semantically meaningful identifier
- **Steps:**
  - Encode (Sentence-T5) item metadata into dense vectors
  - Apply **residual quantization** (RQ) $\rightarrow$ a sequence of discrete tokens

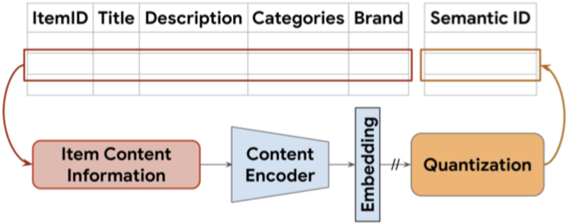

Figure 10: ID generation [Rajput et al., 2023]

Why semantic item IDs matter

- Arbitrary IDs (e.g., item123) are difficult to be learned, since there is a big semantic gap between the model vocabulary and IDs
- Semantic IDs provide structured, informative targets for generative modeling
- Advantages:
  - Generalization: Easier for models to decode and recover unseen or rare items
  - Compositionality: Token overlap reflects semantic similarity across items

Training pipeline

- **Stage 1: Train the VAE-based ID generator**
  - Item metadata $\rightarrow$ encode $\rightarrow$ RQ
- **Stage 2: Generate item IDs**
  - Each item is assigned a multi-token ID from learned codebooks
  - IDs are fixed and used as targets in next stage
- **Stage 3: Train the GenRec model**
  - Autoregressive model trained to predict next item's ID based on user history

Training the VAE-based ID generator

- **Step 1: Encode item metadata**
  - Metadata (title, category, etc.) encoded to a dense vector z via an encoder.
- **Step 2: Initialize residual**
  - Initialize residual $r_1 = z$

Training the VAE-based ID generator

- **Step 3: Iterative quantization**
  - For each level $i = 1$ to m:
    - Select the closest codeword c_i from codebook $\mathcal{V}_i$:

$$c_i = \arg\min_{v \in \mathcal{V}_i} \|r_i - v\|$$

    - Update residual: $r_{i+1} = r_i - c_i$

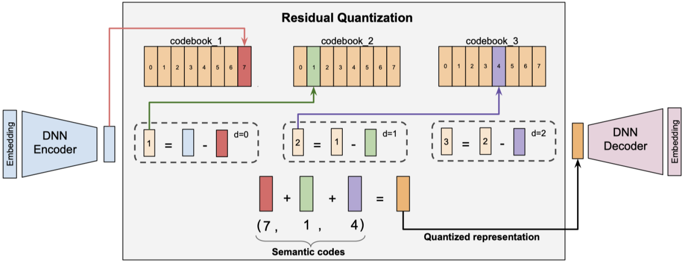

Figure 11: RQ pipeline

Training the VAE-based ID generator

- **Step 4: Form IDs**
  - The item ID is the token sequence: $[c_1, c_2, ..., c_m]$
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$$\mathcal{L}_{\text{VAE}} = \mathcal{L}_{\text{recon}} + \beta \cdot \text{KL}(q(z|x)||p(z))$$

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- Once trained, the encoder + RQ is used to generate IDs for downstream training

Training the GenRec model

- **Input:** A sequence of previously interacted item IDs
- **Target:** The ID tokens of the next item
- **Training strategy:**
  - Teacher forcing
  - Use cross-entropy loss on token prediction (MLE)

Inference

- Beam search or greedy decoding
- Post-processing: Map generated ID tokens back to item via lookup table or similarity match
- Flexible decoding: Support diverse decoding (e.g., sampling, diverse beam)

Results

- Evaluated on Amazon Product Recommendation datasets (Books, Beauty, etc.)
- Compared against:
  - Traditional RecSys (SASRec, GRU4Rec)
  - Retrieval+Generation (Two-stage)
- TIGER outperforms the GenRec baseline P5

Limitations of TIGER

- Token-based decoding still struggles with:
  - **Out-of-catalog items**
  - **No structural encoding** of topic hierarchy or semantic relations
- No explicit modeling of:
  - **Fairness, diversity**, or long-tail bias
  - Personalized decoding strategies
  - **Discriminative training signals**

Q&A

Questions, . . .

Generative retrieval with semantic tree-structured identifiers and contrastive learning

SEATER [Si et al., 2024]

- **S**emantic tr**E**e-based gener**A**tive re**T**ri**E**val with cont**R**astive learning (SEATER)
- Compared to TIGER:
  - TIGER uses flat semantic IDs; SEATER introduces tree structure
  - SEATER unifies generative & contrastive signals

Tree-structured item IDs

- **Idea:** Use tree-structured identifiers to reflect topic granularity
- Balanced K-ary tree structure
- **Benefits:**
  - Identifiers encode semantic hierarchy
  - Better generalization and interpretability

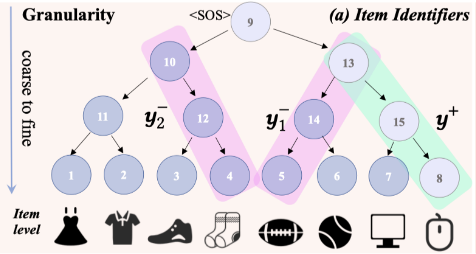

Figure 12: Tree-structured IDs [Si et al., 2024]

Constructing tree-structured IDs

- **Input:** Item embedding retrieved from pretrained SASRec model
- Apply m-level RQ to encode the item embedding into a discrete token sequence
- **Balanced k-ary tree structure:**
  - Each level corresponds to a specific semantic granularity
  - The token path forms a leaf-to-root path in a semantic tree
  - Token space partitioned into subtrees (e.g., genre $\rightarrow$ subgenre $\rightarrow$ item)

Training: Generation loss

- **Backbone**: T5
- **Input:** User history sequence
- **Target:** Structured ID tokens
- **Objective**: MLE loss/ cross-entropy loss

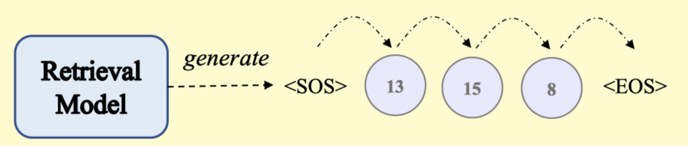

Figure 13: MLE loss [Si et al., 2024]

Training: Alignment loss

- The parent token should align closely with the centroid of its child tokens
- This loss pulls the representations of tokens with parent-child relationships closer and pushes the representations of unrelated tokens apart

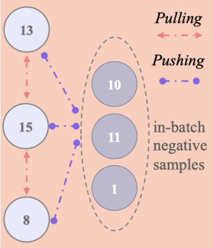

Figure 14: Alignment loss [Si et al., 2024]

Training: Ranking contrastive loss

- **Goal:** Train the model to distinguish similar IDs by learning hierarchical structure
- **The intuition**: longer shared prefixes → more similar items in the hierarchy
- **Approach:**
  - Select sampled item ID with varying prefix lengths shared with the true ID
  - Use triplet contrastive loss to let the decoder learn ranking preferences based on these prefix overlaps

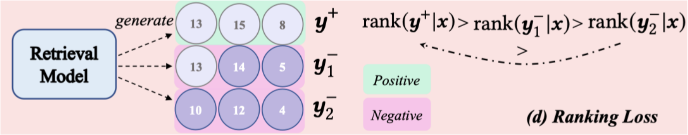

Figure 15: Ranking loss [Si et al., 2024]

Training: Total loss

- Combine three objectives with tuned weights:

$$\mathcal{L} = \mathcal{L}_{\text{gen}} + \lambda_{\text{a}} \cdot \mathcal{L}_{\text{align}} + \lambda_{\text{r}} \cdot \mathcal{L}_{\text{rank}}$$

Results

- Datasets: Yelp, Books, News, Micro-video
- **Findings:**
  - SEATER outperforms TIGER
  - Tree structure + ranking contrastive loss improves both generalization and robustness.

Limitations

- **Limitations:**
  - Tree-based IDs still require careful design — poor trees lead to bad generalization
  - Does not yet support real-time dynamic index updates
  - High training complexity due to hybrid loss terms
- **Future work:**
  - Explore neural tree construction (learnable hierarchies)
  - Integrate reinforcement signals for better decoding feedback
  - Apply to recommendation and multi-modal retrieval

Q&A

Questions,. . .

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