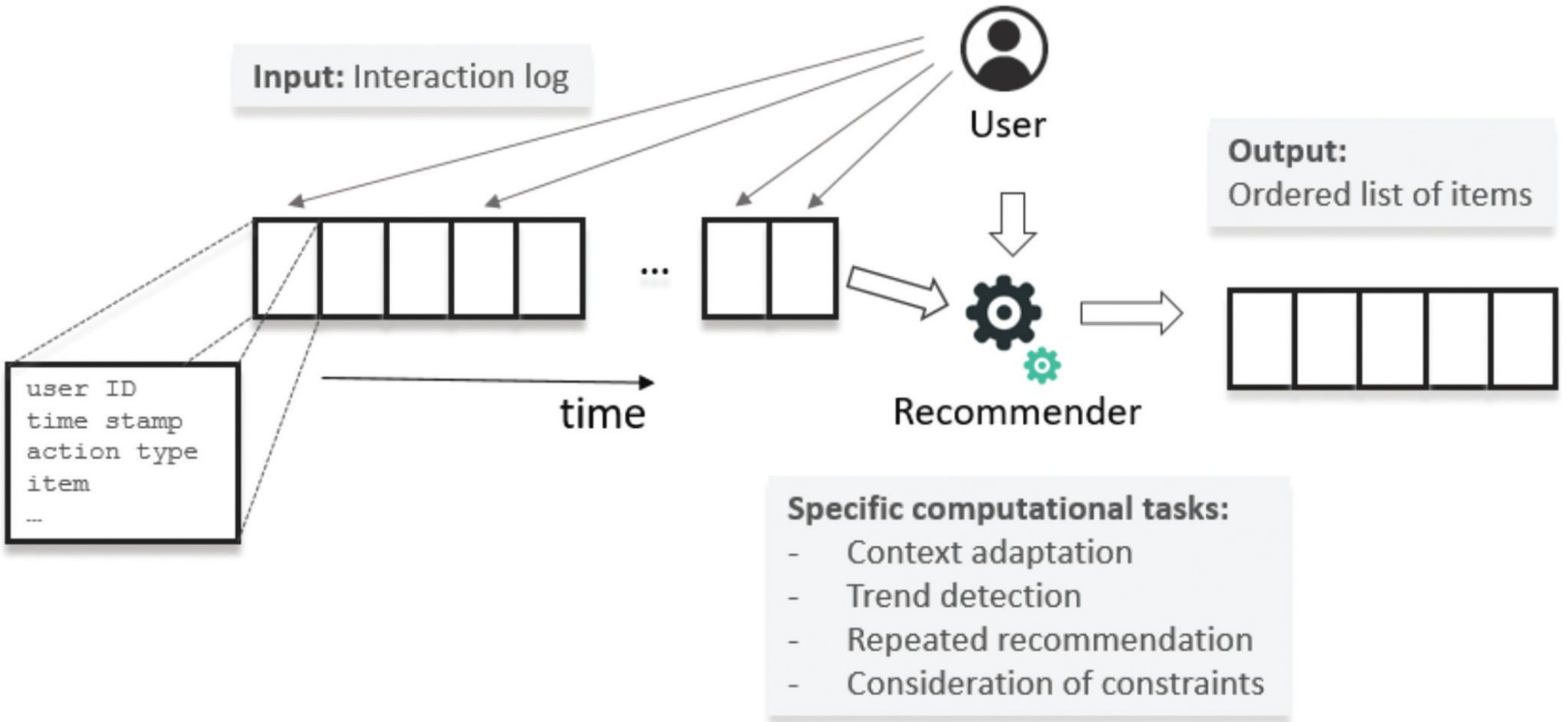
Lecture 27

- Sequential Recommendations

IT492: Recommendation Systems (AY 2023/24) — **Dr. Arpit Rana**

Sequence-aware Recommendation



Sequence-aware Recommendation

Inputs

- An ordered and often timestamped list of past user actions.
- Users can be already known by the system or anonymous ones (not logged in).
- In most application scenarios, each action will have an assigned action type (e.g., item-view, item-purchase, add-to-cart).
- Additional information might be available that describes further details of an action. For example,
  - whether an item was discounted when the action took place,
  - the users (e.g., demographics), or
  - the items (e.g., metadata features).

Sequence-aware Recommendation

Outputs

- An ordered list of items -
  - can be considered as a set of alternatives for the user (traditional rank sensitive list of items), or
  - consider all recommendations and do this in the provided order (a sequence of tracks in music recommendation)

Sequence-aware Recommendation

Categorization based on Long- and Short- term Interactions

- *Last-N Interactions-Based Recommendation*: only the last N user actions are considered to predict the next item to recommend
- *Session-Based Recommendation*: the sequence of user actions is limited to a session
- *Session-Aware Recommendation*: we have knowledge both about the users' actions in the last session and about their past behavior.

Sequence-aware Recommendation

Main Tasks

- *Context Adaptation*: finding alternatives, complements, or continuations
- *Trend Detection*: community trend (out-of-fashion) or individual trend (interest drift)
- *Repeated Recommendation*: repeated purchase of consumables, can be reminded at the right time (similar to proactive recommendation)
- *Consideration of Order Constraints and Sequential Patterns*: the order of objects—either in the logs, in the current session, or in the recommendations—can play a role.

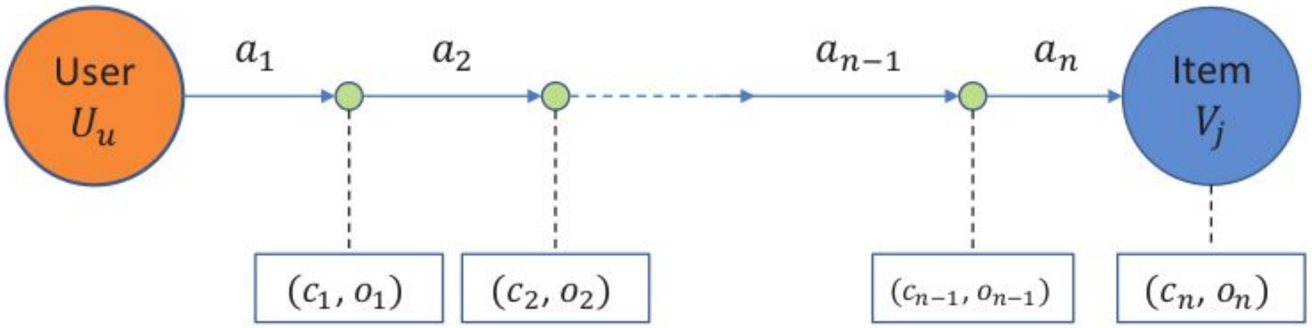
Sequential Recommendations

Sequence modeling techniques aim to learn models from past user actions to predict future ones.

- A ***behavior object*** refers to the items or services that a user chooses to interact with, which is usually presented as an ID of an item or a set of items.
  - It may be also associated with other information including text descriptions, images and interaction time.
- A ***behavior type*** refers to the way that a user interacts with items or services, including search, click, add-to-cart, buy, share, etc.

Sequential Recommendations

A schematic diagram of the sequential recommendation.



c_i: behavior type, o_i: behavior object.

A behavior a_i is represented by a 2-tuple, i.e., $a_i = (c_i, o_i)$. A behavior sequence (i.e., behavior trajectory) is a list of 2-tuples in the order of time.

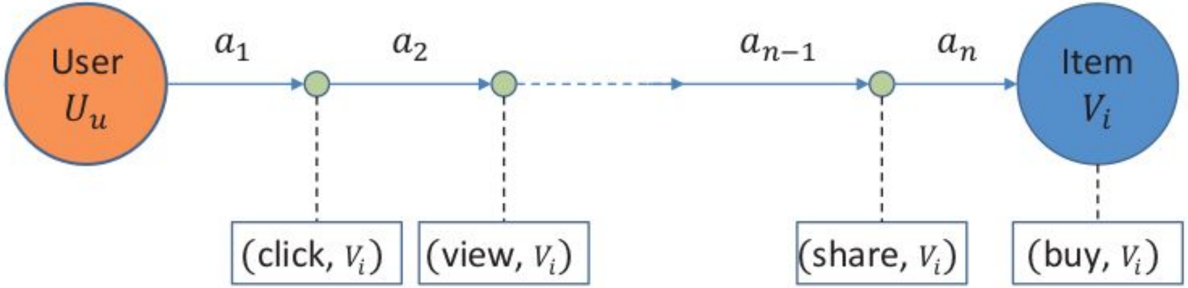
Sequential Recommendations

A system which takes a user's behavior trajectories as input, and then adopts recommendation algorithms to recommend appropriate items or services to the user.

- The input behavior sequence $\{a_1, a_2, a_3, \ldots, a_t\}$ is *polymorphic*, which can thus be divided into three types:
    - experience-based,
    - transaction-based and
    - interaction-based behavior sequence

Experience-based Sequential Recommendations

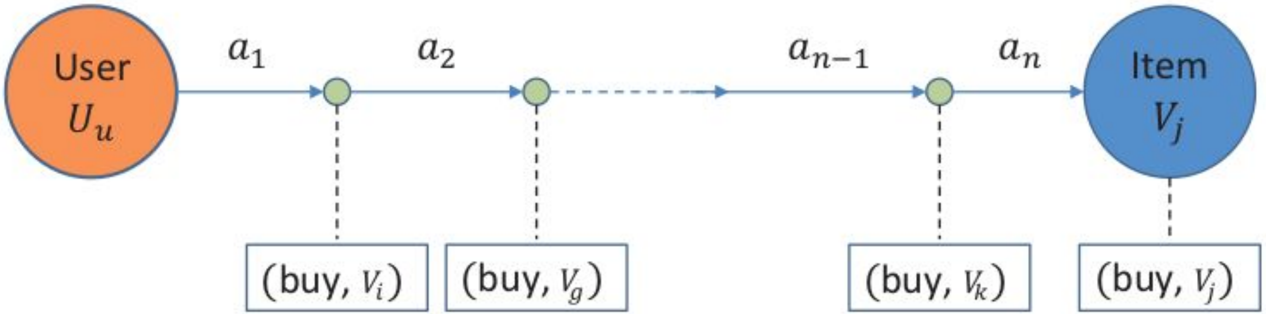
In an experience-based behavior sequence, a user may interact with a same object (e.g., item v_i) multiple times by different behavior types.



- For this type of behavior sequence, a model is expected to capture a user's underlying intentions indicated by different behavior types.
- The goal here is to predict the next behavior type that the user will exert given an item.

Transaction-based Sequential Recommendations

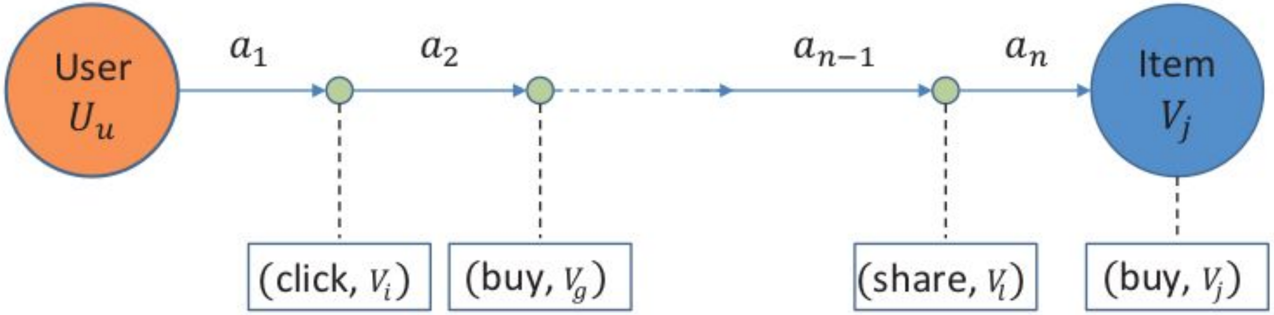
A transaction-based behavior sequence records a series of different behavior objects that a user interacts with, but with a same behavior type (i.e., buy).



- The goal of a sequential recommender system is to recommend the next object (item) that a user will buy in view of the historical transactions of the user.

Interaction-based Sequential Recommendations

A interaction-based behavior sequence consists of different behavior objects and different behavior types simultaneously.

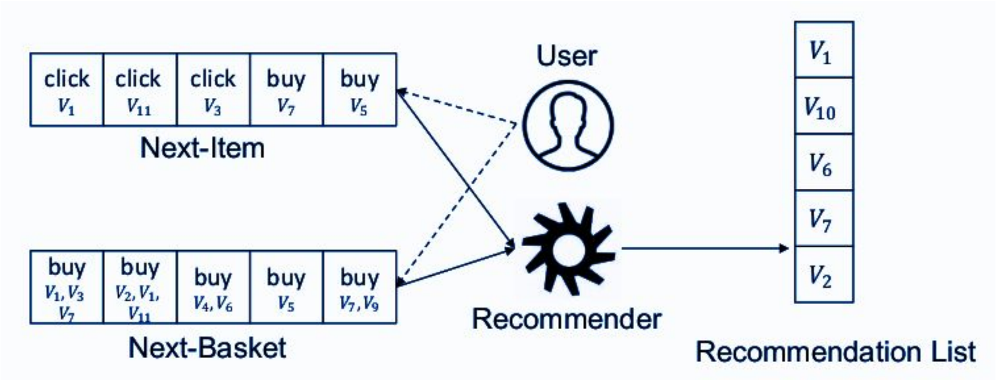


- Model understands different user intents expressed by different behavior types and preferences implied by different behavior objects

- Its major goal is to predict the next behavior object that a user will interact with.

Sequential Recommendations

There are two representative tasks in the literature: next-item recommendation and next-basket recommendation.



- In next-item recommendation, a behavior contains only one object (i.e., item), which could be a product, a song, a movie, or a location.
- In contrast, in next-basket recommendation, a behavior contains more than one object.

Sequential Recommendations

Models for Sequential Recommendations

- These models belong to the following categories:
  - Markov Models (First-order and Higher-order Markov chains),
  - Reinforcement Learning (MDPs, Contextual bandits), and
  - Recurrent Neural Networks (LSTM, GRU4Rec)
  - Advanced Models (BERT4Rec, Attention-based)

Models for Sequential Recommendations

Markov Models

- They consider sequential data as a stochastic process over discrete random variables (or states).

- The Markov property limits the dependencies of the future to a finite history.

- In sequence-aware recommender systems, the Markov property translates into assuming that the next user actions depend only on a limited number of the most recent preceding actions. For example,
  - In first-order Markov Chains (MCs) the transition probability of every state depends only on the previous state.
  - Higher-order MCs use longer temporal dependencies to model more complex relationships between the states.

Models for Sequential Recommendations

Reinforcement Learning

- These techniques learn by interacting with the environment, and are sequential in nature.
- In a recommendation scenario, the interaction consists of a recommendation of an item to the user (the action) for which the system then receives a feedback (the reward). For example,
    - In the music domain, the system recommends a song and monitors if the user listens to or skips the recommended song.
    - In this example, we assign a positive reward if the user listens to the song and zero otherwise.
    - The goal of the system is to maximize the cumulative reward computed over a number of interactions.

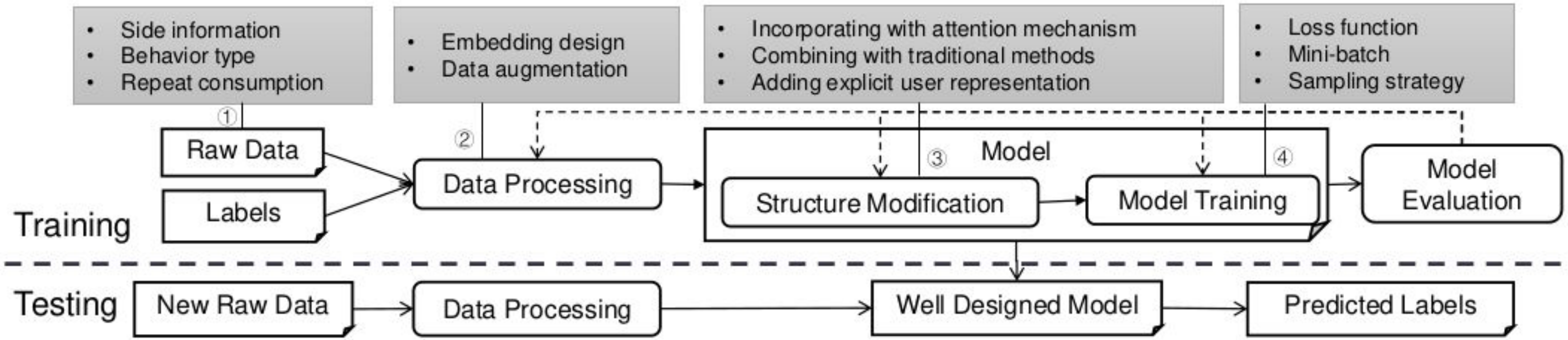
Models for Sequential Recommendations

Recurrent Neural Networks

- At each timestep, the hidden state of the RNN is computed from the current input in the sequence and the hidden state from the last step.
- The hidden state is then used to predict the probability of the next items in the sequence.
- The recurrent feedback mechanism memorizes the influence of each past data sample in the hidden state of the RNN, hence overcoming the fundamental limitation of MCs.
- RNNs are therefore well suited for modeling the complex dynamics in user action sequences.
- Variants of RNNs such as Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU4Rec) are important.

Models for Sequential Recommendations

The diagram shows the training and testing process of a sequential recommender system using advanced models.



- **End of the Course !!**