THE HONG KONG POLYTECHNIC UNIVERSITY
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Data Exploring & Extracting @ PolyU (DEEP Lab)

# Temporal Augmented Graph Neural Networks for Session-Based Recommendations

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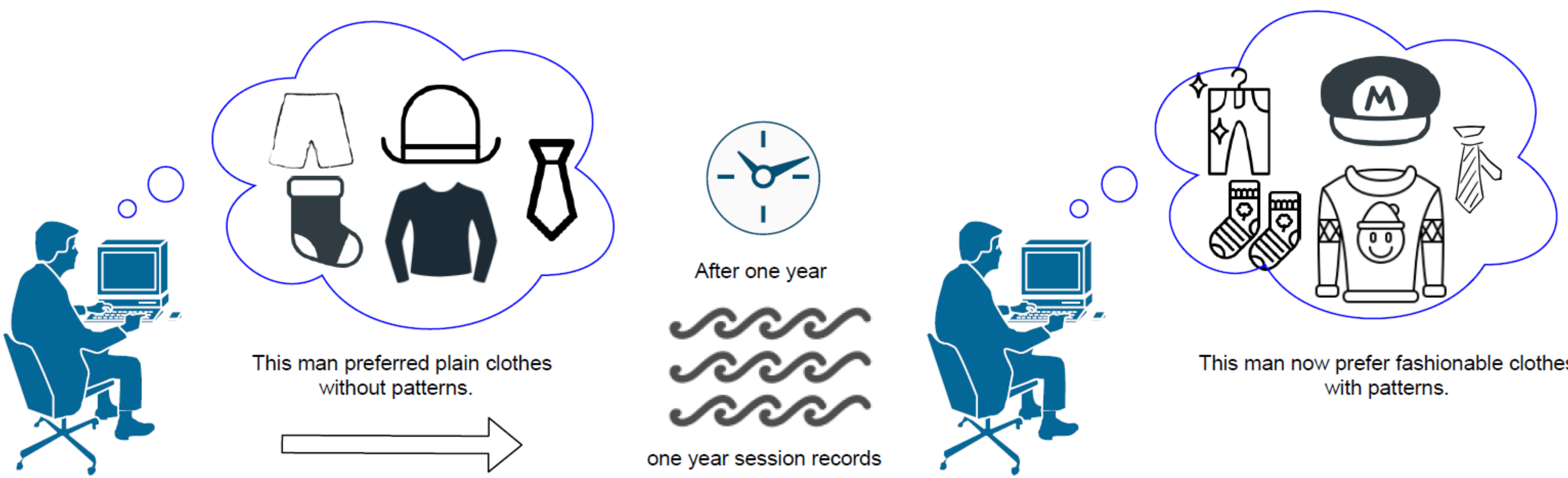
SIGIR 2021, Virtual Event

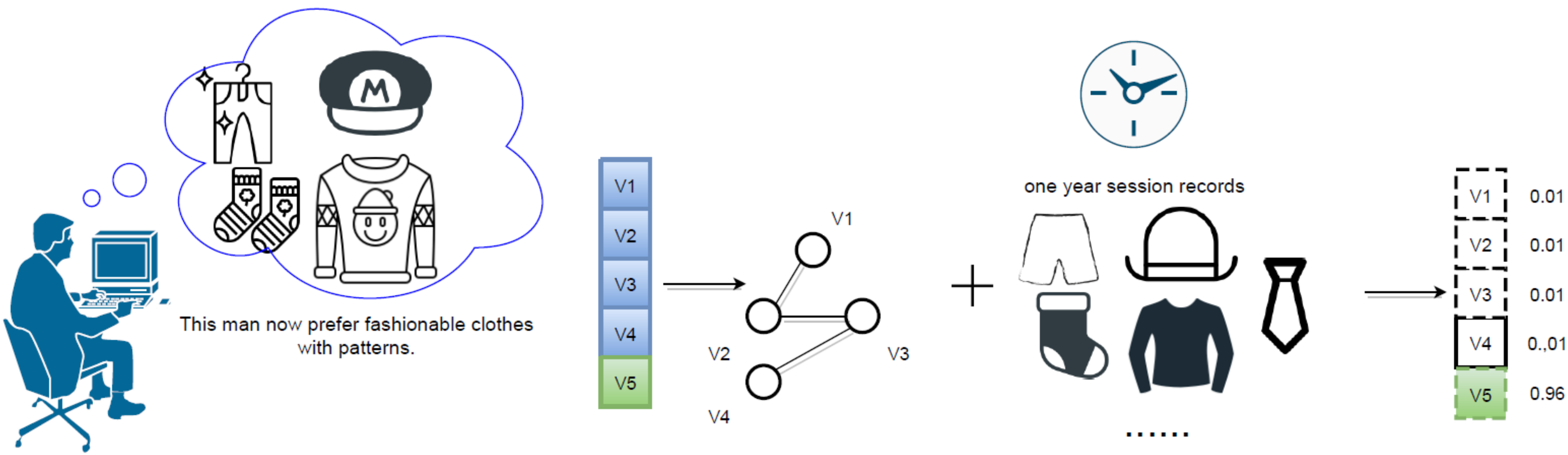
# Dynamic User Interest

- **Definition** : Session-based recommendation aims to predict the next item clicked by an anonymous user.
- Numerous historical session records have been accumulated, and user interests would drift when the time span is large

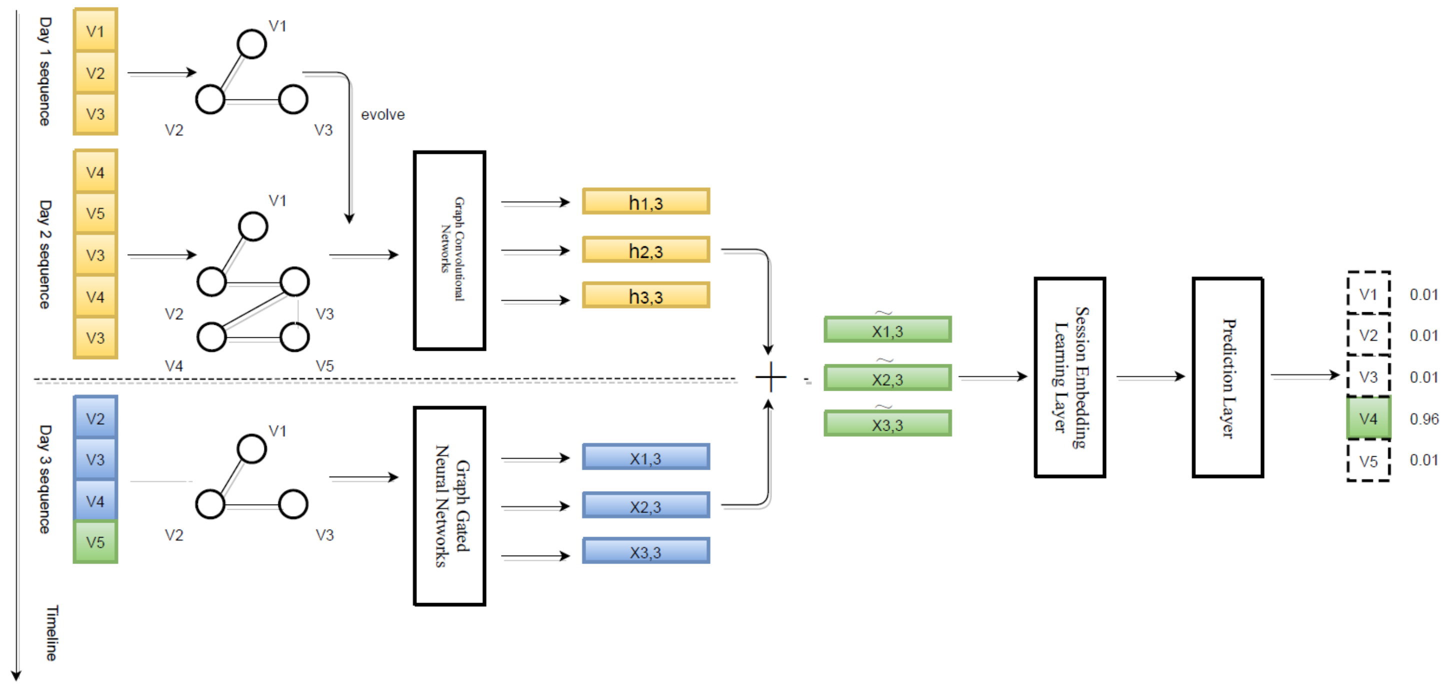


# Dynamic User Interest

- Modeling all historical sessions at one time or conducting offline retraining regularly is not efficient.
- We aim to
  - Propose a memory efficient model which could process continuously growing session records.
  - Track the latest overall user interest in time.



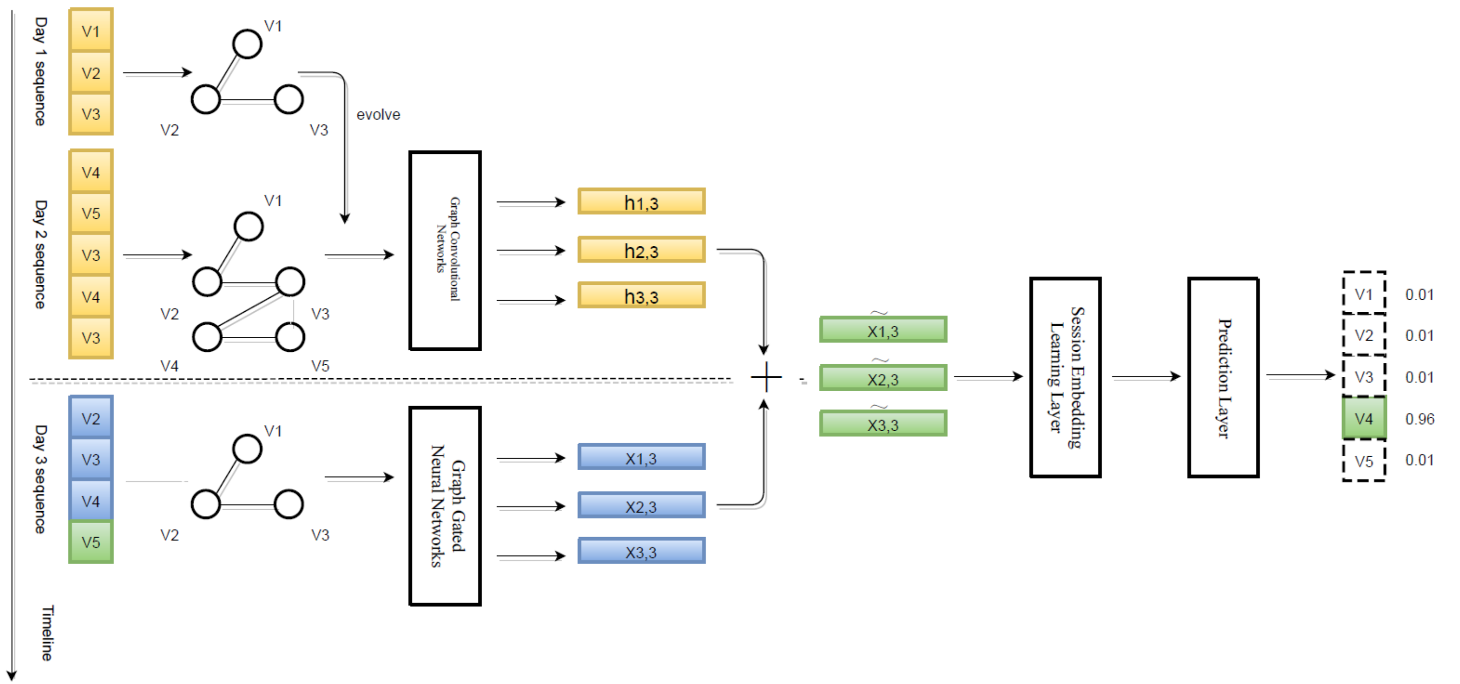
# TASREC Framework




- ➢ To infer the target item for a session in day $t$ $(e.g., t = 3)$, we construct the session graph and apply GGNN on it.

- ➢ To utilize day 1 and day 2 data, we construct a temporal graph in an iterative way and GCN is utilized to learn the high-order item interactions.

# TASREC Framework




- ➢ Given two embeddings for an item, we add them together and the attention mechanism is utilized to summarize the session.
- ➢ The prediction layer will generate scores for each candidate item.

# Experimental Settings

- Remove sessions with less than 2 interacted behaviors and delete items with less than 5 interactions.

- Given a session record $s = \{i_1, i_2, \dots, i_l\}_{t=2}^{l}$, we generate a set of training samples $\{(i_1, \dots, i_{t-1}), i_t\}$.

- To simulate the temporal training environment, we split data of the first $\frac{5}{6}$ and the last $\frac{1}{6}$ days into training and testing sets.

- Two categories of baselines
  - Static model: GRU4REC, SR-GNN, and LESSR
  - Temporal model: CSRM

# Experimental Results

| Method | Aotm | | | Diginetica | | | Retailrocket | | |
|---|---|---|---|---|---|---|---|---|---|
| | Recall@20 | Recall@50 | NDCG@100 | Recall@20 | Recall@50 | NDCG@100 | Recall@10 | Recall@20 | NDCG@100 |
| GRU4REC | 1.70 | 3.64 | 1.32 | 28.90 | 40.02 | 15.66 | 17.41 | 23.11 | 12.75 |
| SR-GNN | 3.82 | 6.94 | 2.73 | 48.74 | 65.37 | 28.41 | 36.34 | 45.58 | 28.93 |
| CSRM | <u>3.97</u> | <u>7.30</u> | <u>2.86</u> | 48.88 | <u>66.90</u> | 28.34 | 37.43 | <u>47.56</u> | 28.43 |
| LESSR | 3.11 | 5.58 | 2.31 | <u>49.59</u> | 66.12 | <u>29.03</u> | <u>37.97</u> | 46.59 | <u>29.84</u> |
| TASRec | **4.42** | **7.71** | **3.08** | **50.39** | **67.27** | **29.48** | **39.08** | **48.16** | **30.36** |
| Improv. | **11.34%** | **5.62%** | **7.69%** | **1.61%** | **0.55%** | **1.55%** | **2.92%** | **1.26%** | **1.74%** |

| Model | Recall@10 | Recall@20 | Recall@50 | NDCG@100 |
|---|---|---|---|---|
| TASRec-temp | 36.73 | 46.65 | 58.40 | 27.55 |
| TASRec-base | 36.60 | 45.45 | 56.49 | 28.84 |
| TASRec | **39.08** | **48.16** | **59.48** | **30.36** |

- TASRec performs consistently better than other baselines across three datasets.
- TASRec achieves significantly better performance than its two variants