

AdKDD 2020

On the Effectiveness of Self-supervised Pre-training for Modeling User Behavior Sequences

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Unity Technologies

Agenda

Mobile Game Advertising

Sequential Representation Learning

Self-supervised Pre-training

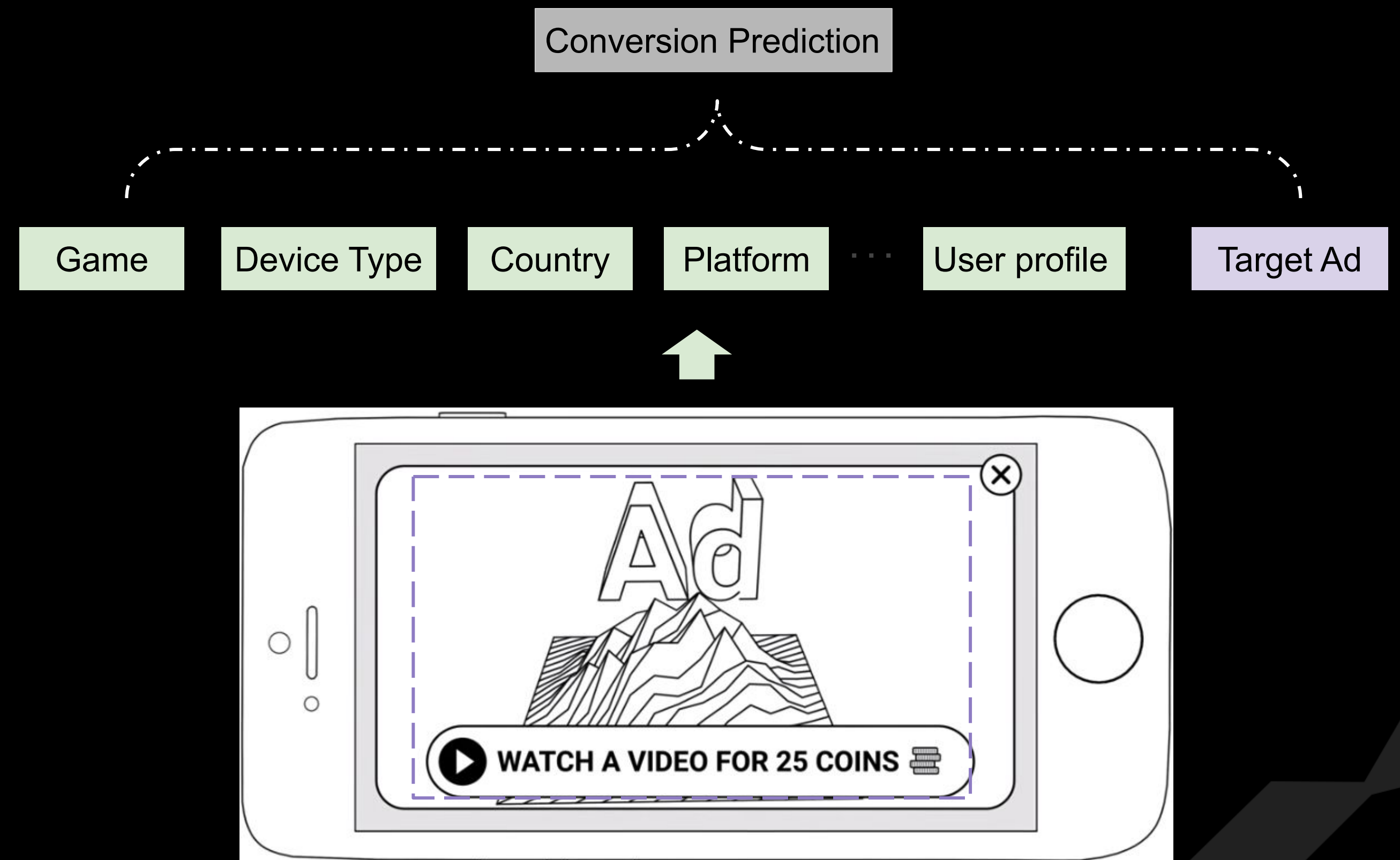
Knowledge Transfer to Downstream Task

Experiments

Conclusion

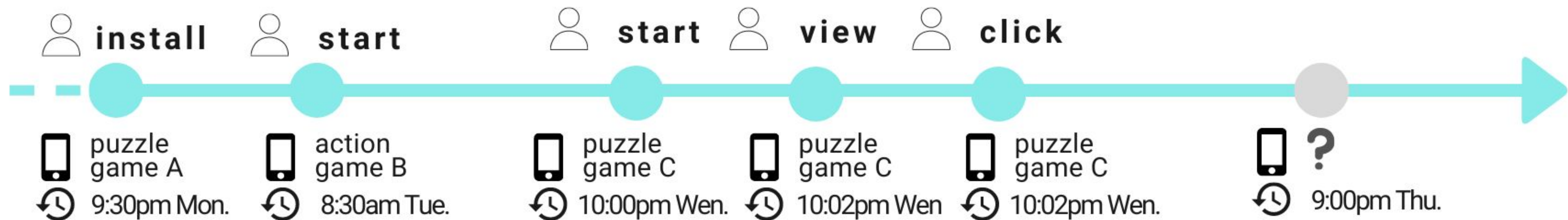
Mobile Game Advertising

- Unity Ad
 - Game Monetization Solution
 - Optimize the conversion prediction accuracy
 - Show the most valuable ads to wide variety of users



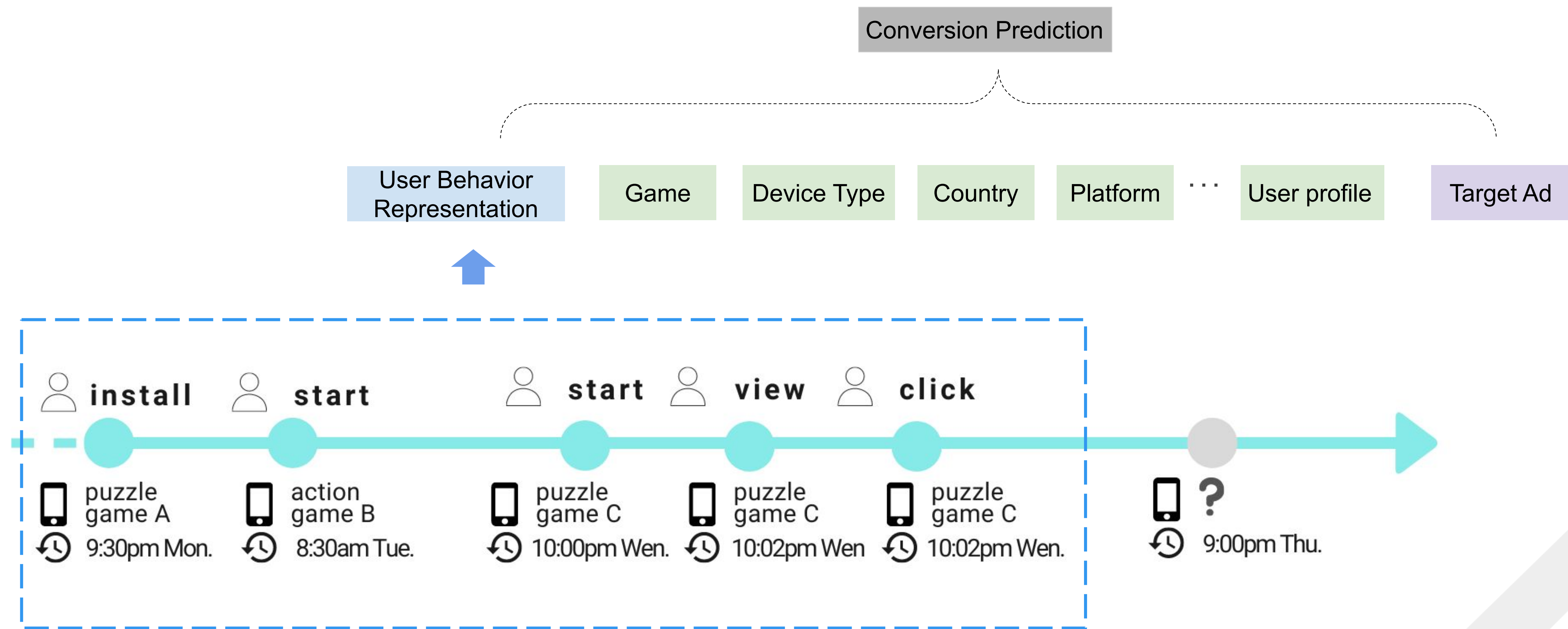
User Behavior Sequence

User historical behavior is crucial to improve conversion prediction



User Behavior Sequence

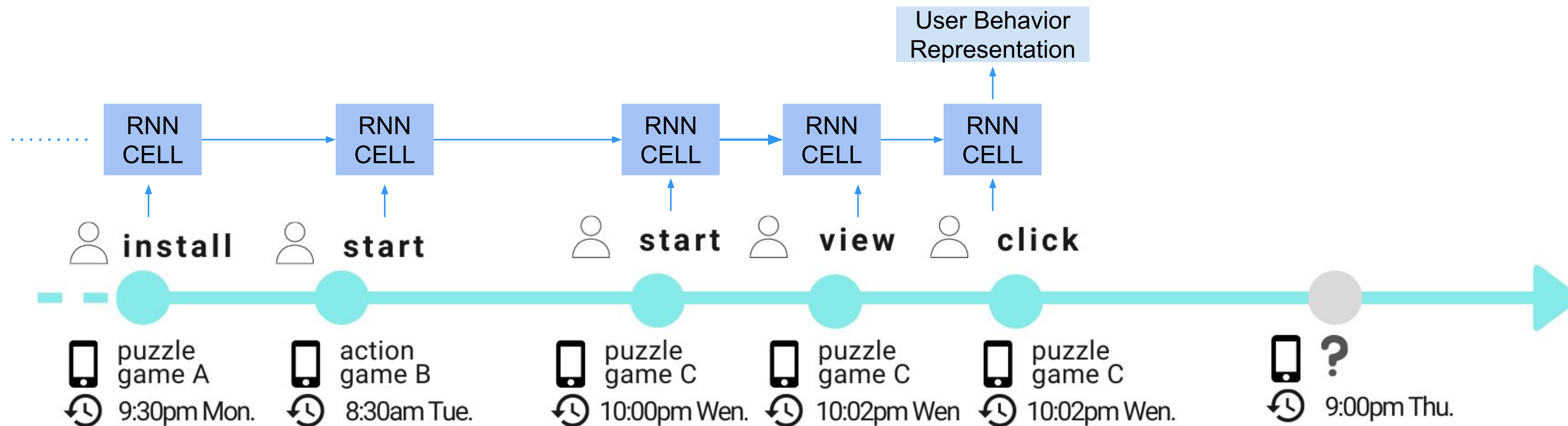
Encode user behavior sequence into meaningful representation



Sequential Representation Learning

Challenges

- Learn on outcomes (installs)
 - Installs are sparse
 - Ignore other signals about user's journey to conversion
- Predict next items
 - Items are many
 - User historical sequence could be noisy



Self-supervised Pre-training

Self-supervised learning

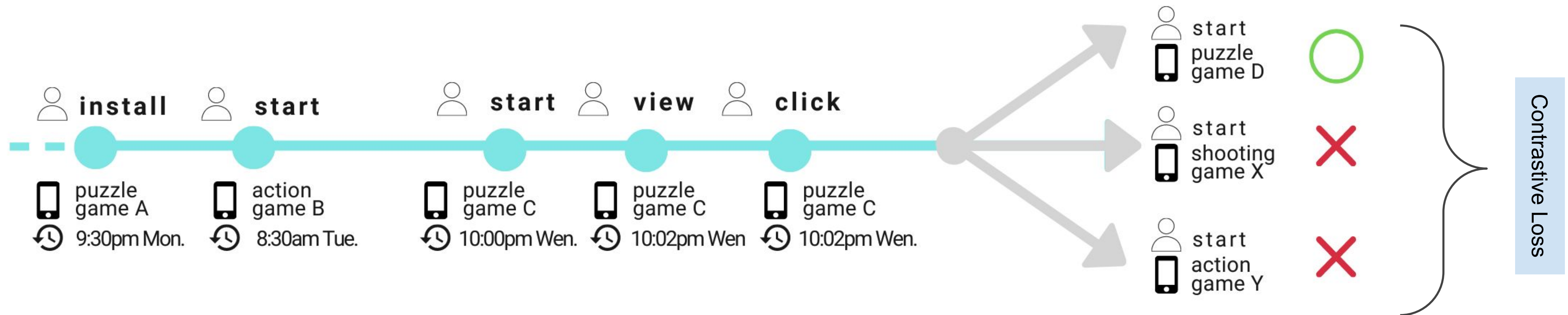
- Extract useful information from the data itself without any labels

Motivations

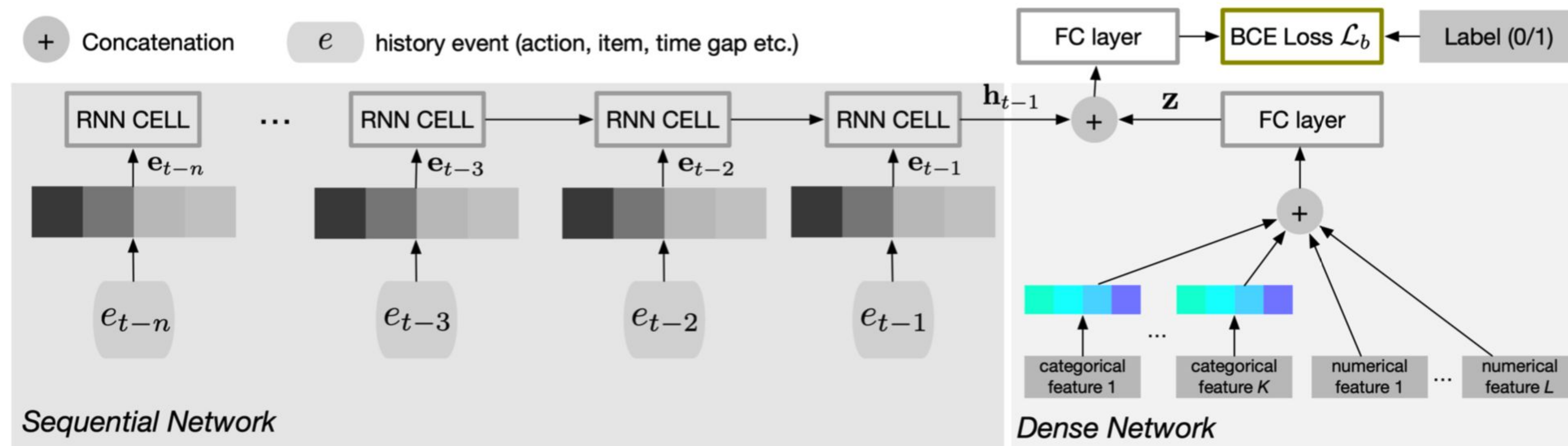
- Pre-train the representation with the most updated history without waiting for conversion windows
- The downstream task - conversion prediction does not train from scratch

Pre-text Task

Predicting the relative probability of the correct next item instead of reconstructing the exact next item



Knowledge Transfer to Downstream Task

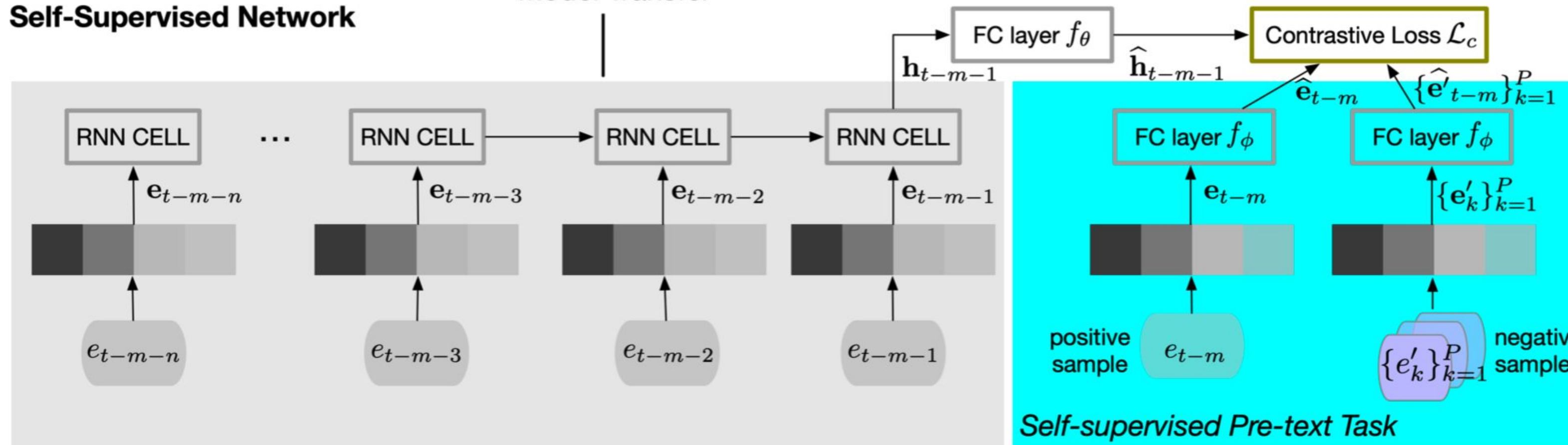


$$\mathcal{L}_b = -y_i \log \sigma(\mathbf{g}_i) - (1 - y_i) \log (1 - \sigma(\mathbf{g}_i))$$

Conversion Prediction Network

Self-Supervised Network

Model Transfer



$$\mathcal{L}_c = -\log \frac{\exp(\hat{\mathbf{h}}_{i,t-m-1} \cdot \hat{\mathbf{e}}_{i,t-m})}{\exp(\hat{\mathbf{h}}_{i,t-m-1} \cdot \hat{\mathbf{e}}_{i,t-m}) + \sum_{k=1}^P \exp(\hat{\mathbf{h}}_{i,t-m-1} \cdot \hat{\mathbf{e}}'_k)}$$

Experiment Settings

Data

- One month of user behavior history
- Most updated 30 events

Network

- Dense + RNN with GRU
- Optimizer: Adam (learning rate: 0.001)
- Batch size: 5,000

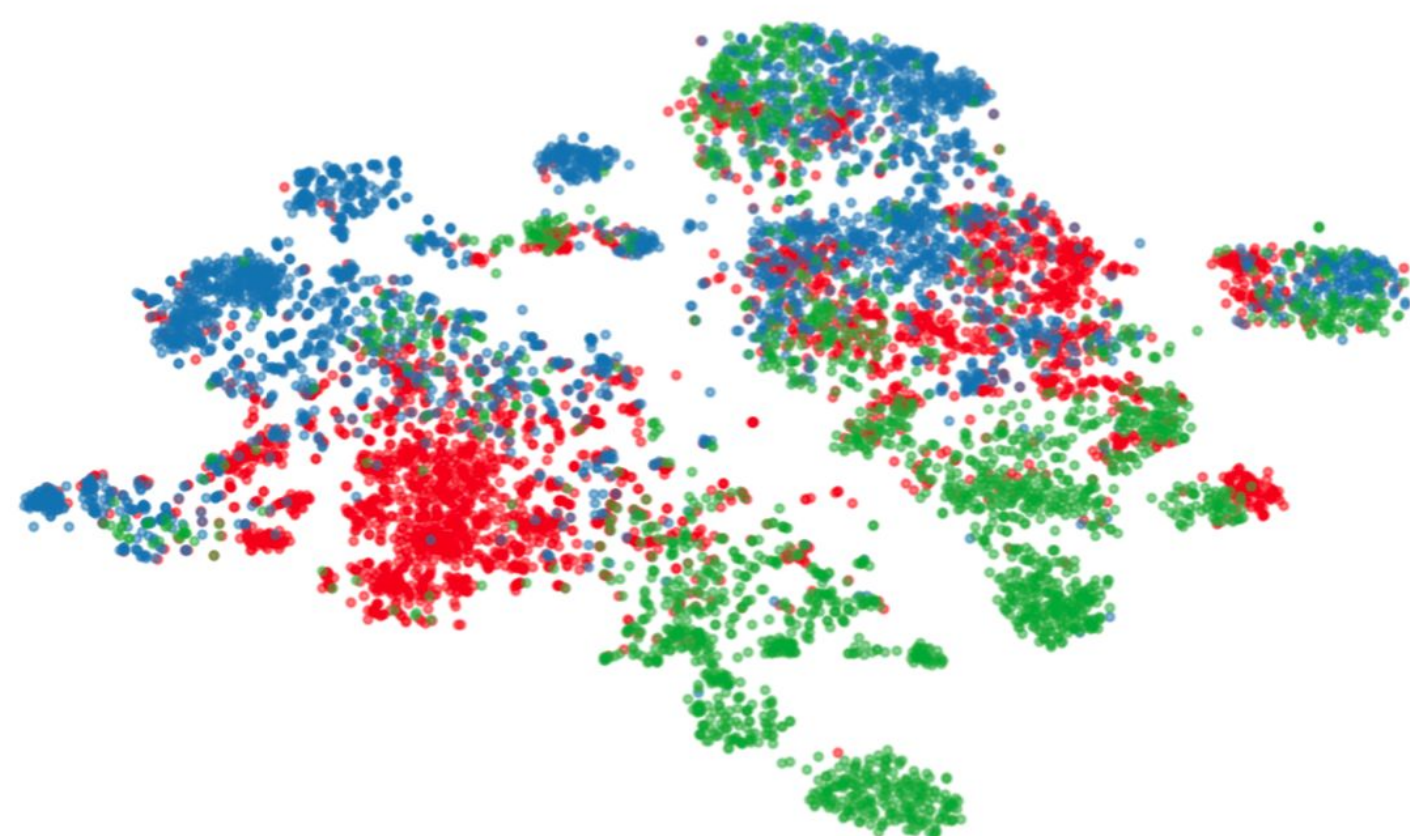
Evaluation Metrics

- Log-loss
- AUC

training data size	20,000,000
validation data size	4,000,000
test data size	4,000,000
average sequence length	23.3
number of unique target items	2974

Visualization and Linear evaluation

Visualize pre-trained sequence representations for four target items (2,000 samples are selected)



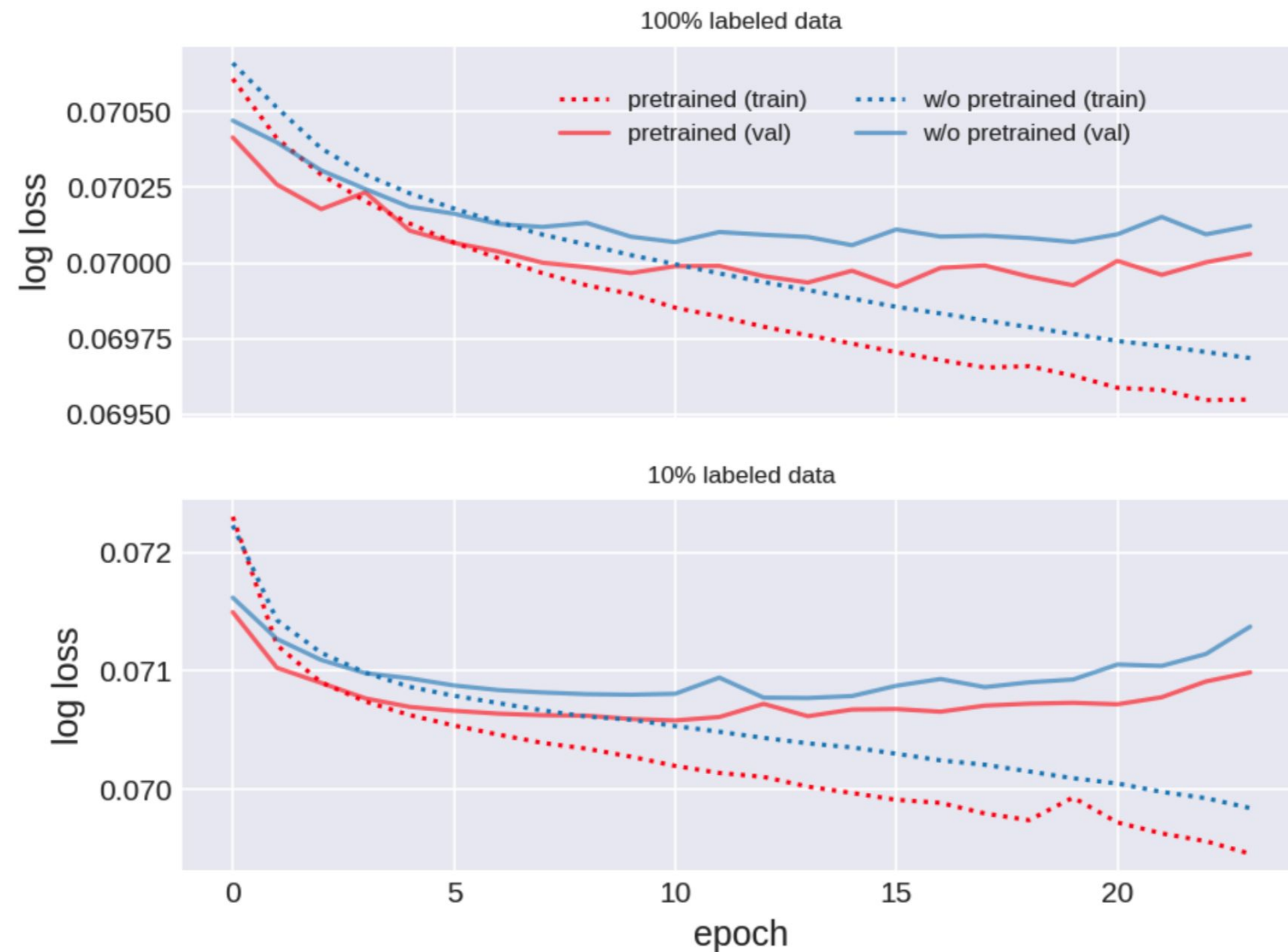
Compare log-loss and AUC for models with and w/o pre-training

Test case	Pre-trained	Log loss	Impr	AUC	RelaImpr
Linear evaluation		0.07188		0.7701	
	✓	0.07105	1.15%	0.7831	4.81%
Full labeled data		0.06934	3.53%	0.8048	12.85%
	✓	0.06924	3.67%	0.8062	13.37%

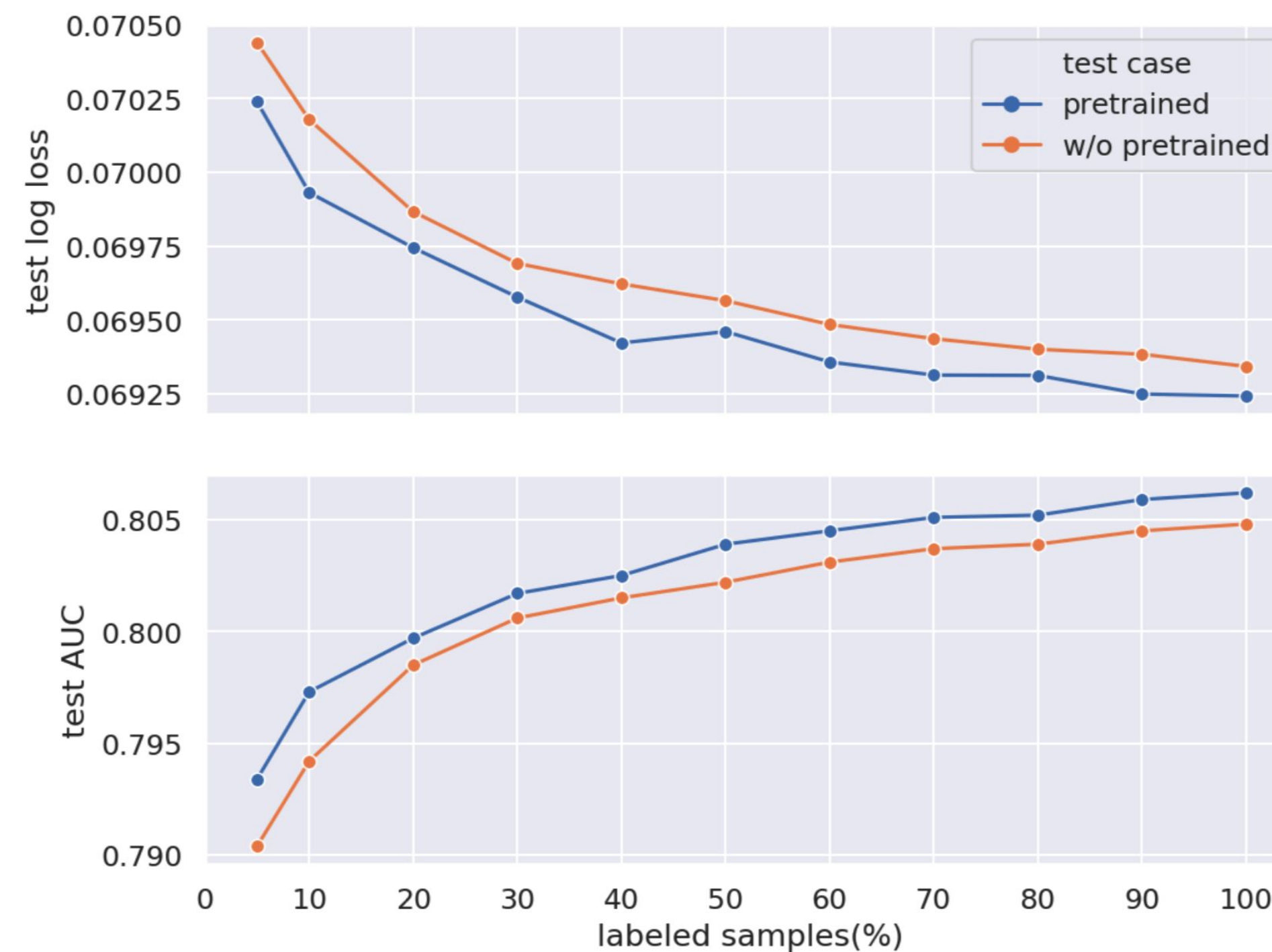
Training with Different Proportions of labeled samples

- Information gain from pre-training is large when labeled data is sparse
- Achieve comparable log-loss and AUC with pre-training with less labeled data

Training and validation curves



Test log loss and AUC

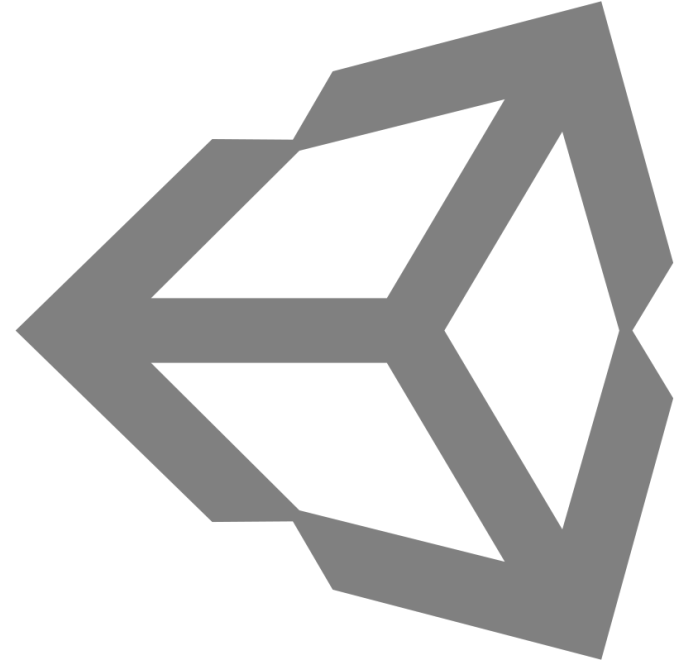


Conclusion

Introduce a self-supervised pre-training scheme for modeling user behavior sequence in conversion prediction task

Models with the proposed self-supervised pre-training scheme converge quicker, achieve better log-loss and AUC score, and are label efficient

Other more efficient pre-text tasks of self-supervised learning can be further researched in the future



Thank You!

