Lifelong Sequential Modeling for User Response Prediction

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May 2019

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User Response Prediction

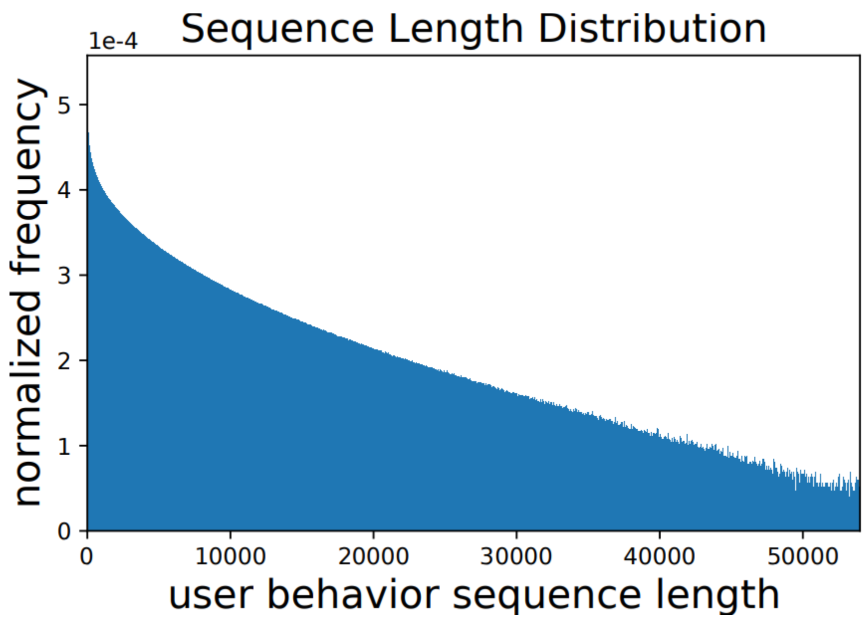
- Predict the probability of positive user response
  - Feature $\boldsymbol{x}$, including side-information and previous behaviors
  - Label y
  - Output $\Pr(y=1|\boldsymbol{x})$

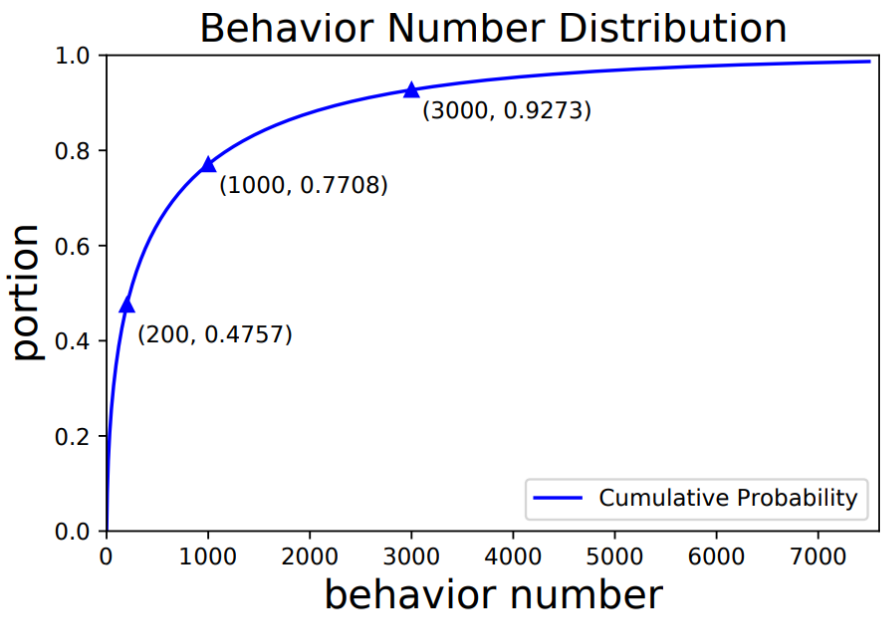
Response Type	Prediction Goal	Abbreviation
Click	Click-through Rate	CTR
Conversion	Conversion Rate	CVR

Sequential Modeling for User Behaviors

- Sequential user modeling
  - Conduct a comprehensive **user profiling** with the **historical user behaviors** and other side information and represent it in a unified framework.
- Usage
  - User targeting in online advertising
  - User behavior prediction
- Characteristics of user behaviors
  - Intrinsic and multi-facet user interests
  - Dynamic user interests and tastes
  - Multi-scale *sequential dependency* within behavior history

Analysis of User Behaviors (Alibaba)





Related Works

- Aggregation-base methods: w/o considering sequential dependencies
  - Matrix factorization (KDD’09)
  - SVD and other variants (KDD’09, KDD’13)
- State-based methods: simple state and transition assumption
  - Markov chain models (WWW’10, ICDM’16, RecSys’16)
- Deep learning methods: cannot handle long-term behavior sequences
  - Recurrent neural network models (ICLR’16, CIKM’18)
  - Convolutional neural network models (WSDM’18)

Lifelong Sequential Modeling

- Definition of Lifelong Sequential Modeling (LSM)
  - LSM is a process of continuous (online) user modeling with sequential pattern mining upon the lifelong user behavior history.

- Characteristics
  - supports **lifelong** memorization of user behavior patterns
  - conducts a **comprehensive** user modeling of intrinsic and dynamic user interests
  - continuous **adaptation** to the up-to-date user behaviors

Framework of LSM

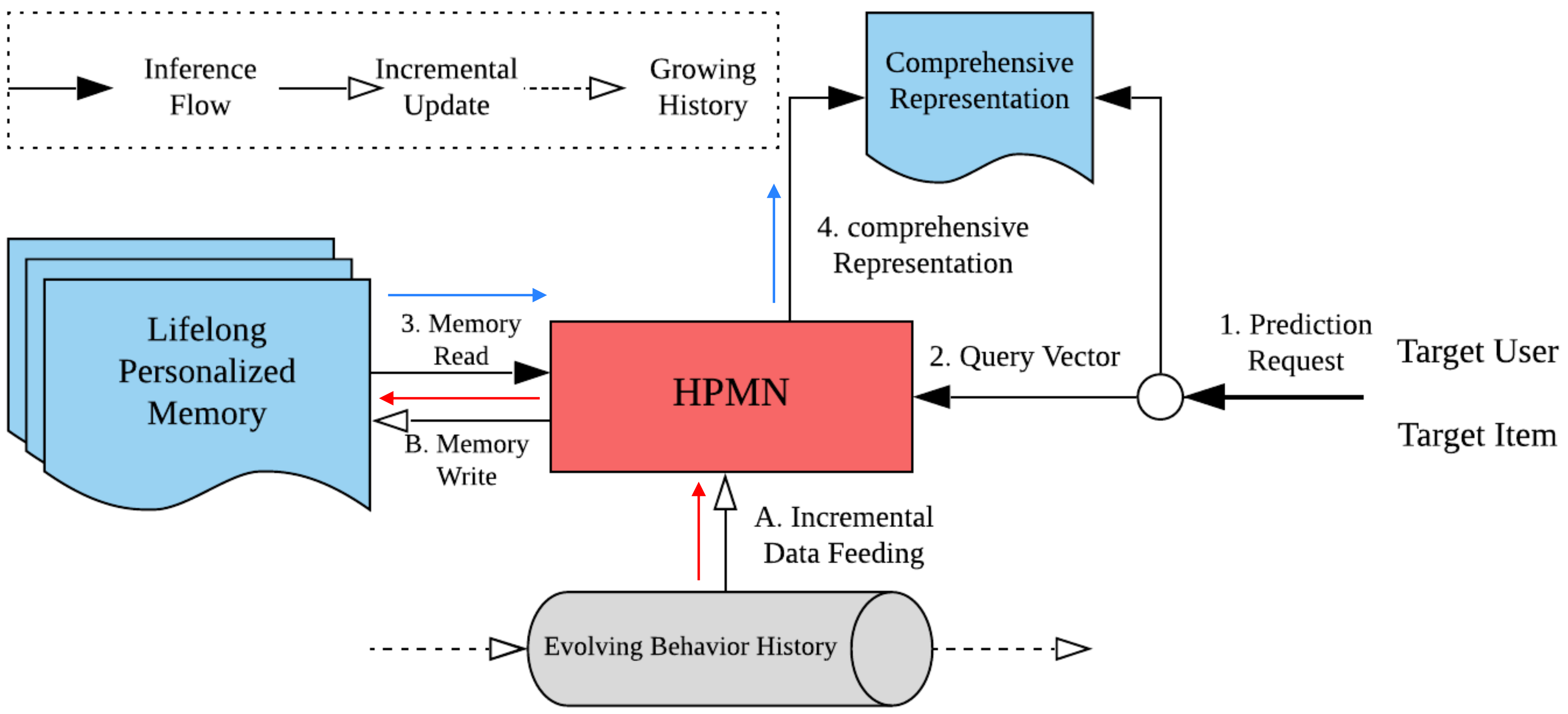


Figure 2: The LSM framework.

HPMN Model

- Hierarchical Periodical Memory Network, HPMN

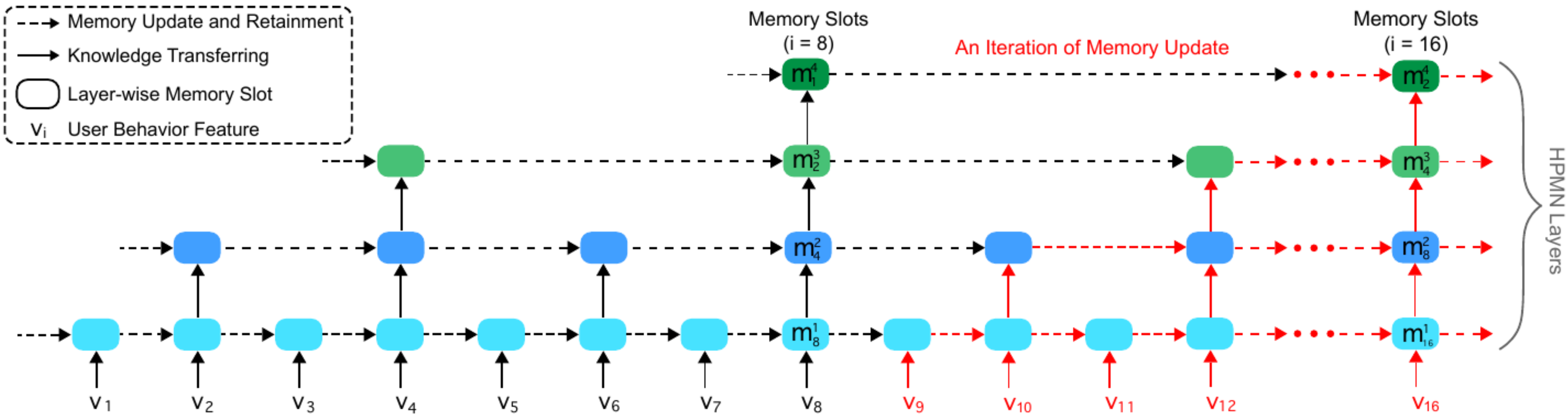


Figure 3: The framework of HPMN model with four layers maintaining user memory in four ($D = 4$) memory slots. The update period t^j of j-th layer follows an exponential sequence $\{2^{j-1}\}_{j=1}^{D}$ as an example. The red part means the incremental updating mechanism; the dotted line means the periodic memorization and forgetting.

User Response Prediction

- Real-time query only on the maintained user memory
  - w/o inference over the whole user behavior sequence online

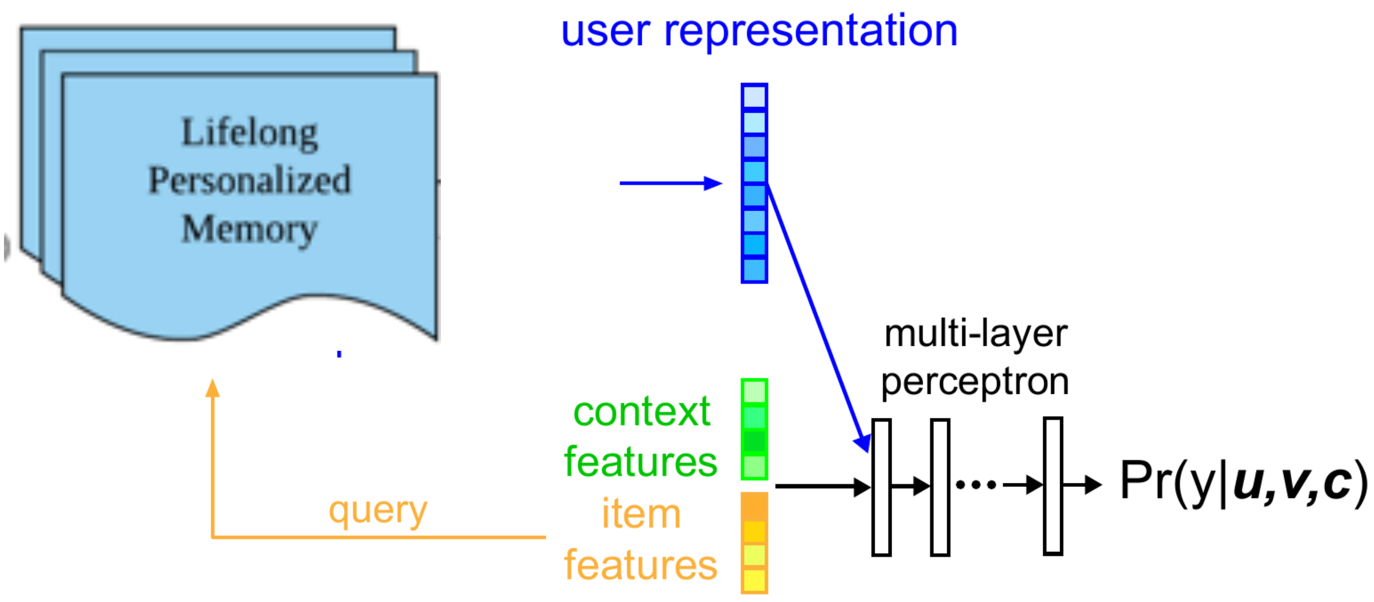


Figure 4: The overall user response prediction.

R/W Operations

- The content in the j-th memory slot at step i
  - $\{\boldsymbol{m}_i^j\}_{j=1}^D$
- Memory query and attentional reading
  - Given the query vector of the target item $\boldsymbol{v}$
  - Calculate the attention weight $w^j = E(\boldsymbol{m}^j, \boldsymbol{v})$ for each j-th memory slot
  - User representation $\boldsymbol{r} = \sum_j^D w^j \cdot \boldsymbol{m}^j$ at step i
- Periodical and gate-based (soft) writing

$$\boldsymbol{m}_i^j = \begin{cases} g^j\left(\boldsymbol{m}_i^{j-1}, \boldsymbol{m}_{i-1}^j\right) & \text{if } i \bmod t^j = 0\,, \\ \boldsymbol{m}_{i-1}^j & \text{otherwise}\,, \end{cases}$$

HPMN Model Training

- Offline model training
- Online memory maintaining

- Loss functions
  - Cross entropy loss
  - Memory covariance regularization
    - To enlarge covariance between each pair of memory slots
    - Help deal with multi-facet user interests
  - Parameter regularization

Experiment Setup

- Datasets

Table 2: The dataset statistics. T: length of the whole lifelong sequence (maximal length in the dataset). s: length of recent behavior sequence.

Dataset	Amazon	Taobao	XLong
User #	192,403	987,994	20,000
Item #	63,001	4,162,024	3,269,017
s	10	44	232
T	100	300	1,000

short → long
Sequence length

- Evaluation metrics
  - AUC
  - Log-loss

Compared Models

1. Aggregation-based methods
   1. DNN: utilizes sum-pooling for user behaviors
   2. SVD++: latent factor model
2. Short-term behavior modeling methods
   1. GRU4Rec: recurrent neural network model
   2. Caser: convolutional neural network model
   3. DIEN: dual RNN model w/ attention mechanism
   4. RUM: key-value memory network model
3. Long-term behavior modeling methods
   1. LSTM: long-short term memory model
   2. SHAN: hierarchical attention-based model
   3. HPMN: our model

Experiment Results

Table 4: Performance Comparison. (* indicates p-value < 10^{-6} in the significance test. ↑ and ↓ indicates the *performance* over lifelong sequences (with length T) is better or worse than the same model over short sequences (with length s). AUC: the higher, the better; Log-loss: the lower, the better. The second best performance of each metric is underlined.)

Model Group	Model	Len.	AUC Amazon	AUC Taobao	AUC XLong	Log-loss Amazon	Log-loss Taobao	Log-loss XLong
Group 2	GRU4Rec	s	0.7669	0.8431	0.8716	0.5650	0.4867	0.4583
	Caser	s	0.7509	0.8260	0.8467	0.5795	0.5094	0.4955
	DIEN	s	0.7725	0.8914	<u>0.8725</u>	0.5604	0.4184	<u>0.4515</u>
	RUM	s	0.7434	0.8327	0.8512	0.5819	0.5400	0.4931
Group 1	DNN	T	0.7546	0.7460	0.8152	0.6869	0.5681	0.5365
	SVD++	T	0.7155	0.8371	0.8008	0.6216	0.8371	1.7054
Group 2	GRU4Rec	T	0.7760 ↑	0.8471 ↑	0.8702 ↓	0.5569 ↑	0.4827 ↑	0.4630 ↓
	Caser	T	0.7582 ↑	0.8745 ↑	0.8390 ↓	0.5704 ↑	0.4550 ↑	0.5050 ↓
	DIEN	T	<u>0.7770</u> ↑	<u>0.8934</u> ↑	0.8716 ↓	<u>0.5564</u> ↑	<u>0.4155</u> ↑	0.4559 ↓
	RUM	T	0.7464 ↑	0.8370 ↑	0.8649 ↑	0.6301 ↓	0.4966 ↑	0.4620 ↑
Group 3	LSTM	T	0.7765	0.8681	0.8686	0.5612	0.4603	0.4570
	SHAN	T	0.7763	0.8828	0.8369	0.5595	0.4318	0.5000
	HPMN	T	**0.7809***	**0.9240***	**0.8929***	**0.5535***	**0.3487***	**0.4150***

Visualized Analysis

Conclusion

- First work proposes lifelong sequential modeling
- Construct hierarchical periodical memory network to model long-term sequential dependency
- Dynamic read-write operations
- Significantly improved the performance

- Acknowledgement
  - Alibaba Innovation Research (AIR)
  - National Natural Science Foundation of China

Alibaba Group