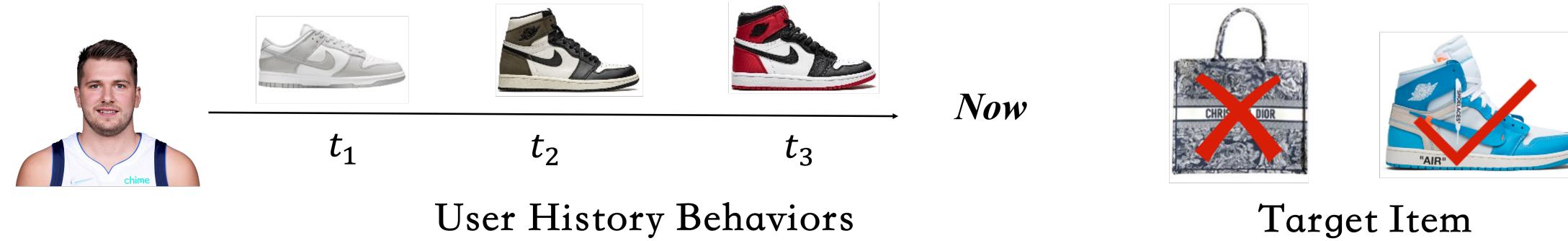


## User Interest Modeling

User interest modeling based on her history behaviors has been a hot research topic in recommender systems. There should be both semantic and temporal correlation between behaviors and the target.

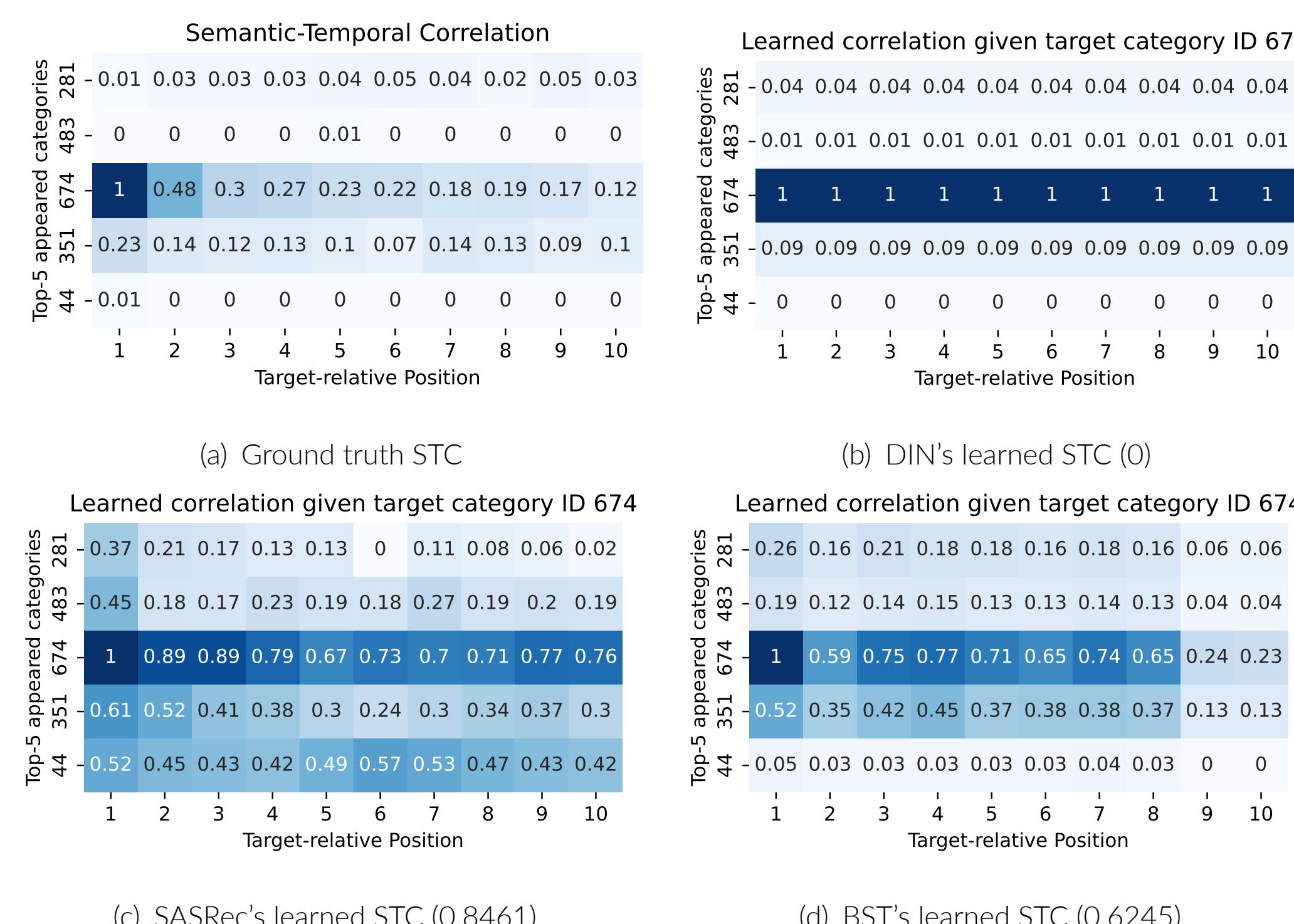


## How do Existing Method Learn Semantic-Temporal Correlation?

**Definition (Category-wise Target-aware Correlation (CTC)).** CTC is defined as the mutual information between behaviors with category  $c_i$  whilst occurring at position  $p$ , and the user response label on the target item with category  $c_t$ . Formally,

$$\text{Cor} = \text{MI} (\mathcal{X}_{C(X)=c_i \wedge P(X)=p}, \mathcal{Y}_{C(Y)=c_t}), \quad (1)$$

where  $C(\cdot)$ ,  $P(\cdot)$  denotes the category or position of the behavior or target.

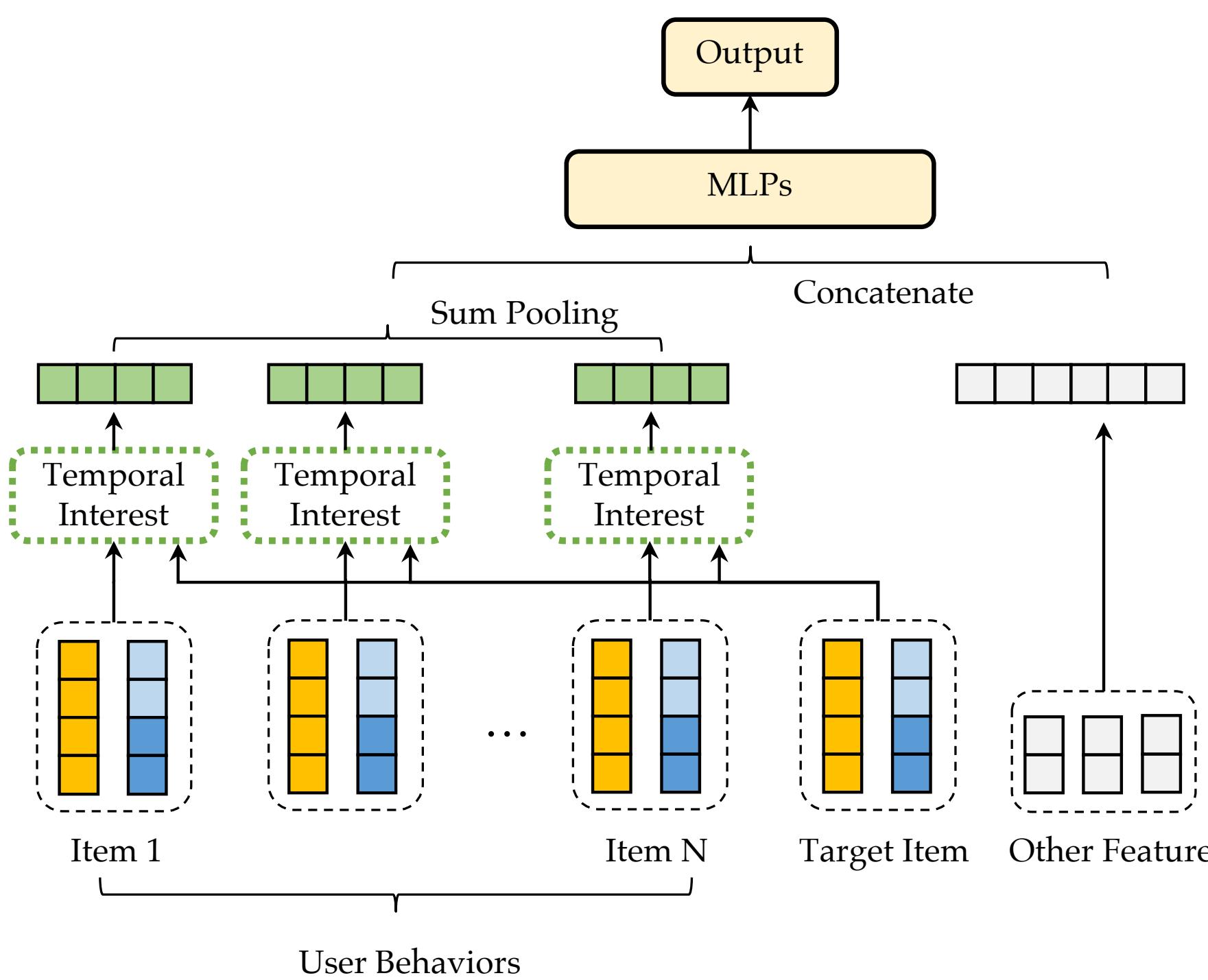


We observe **strong semantic-temporal correlations** between behaviors and the target:

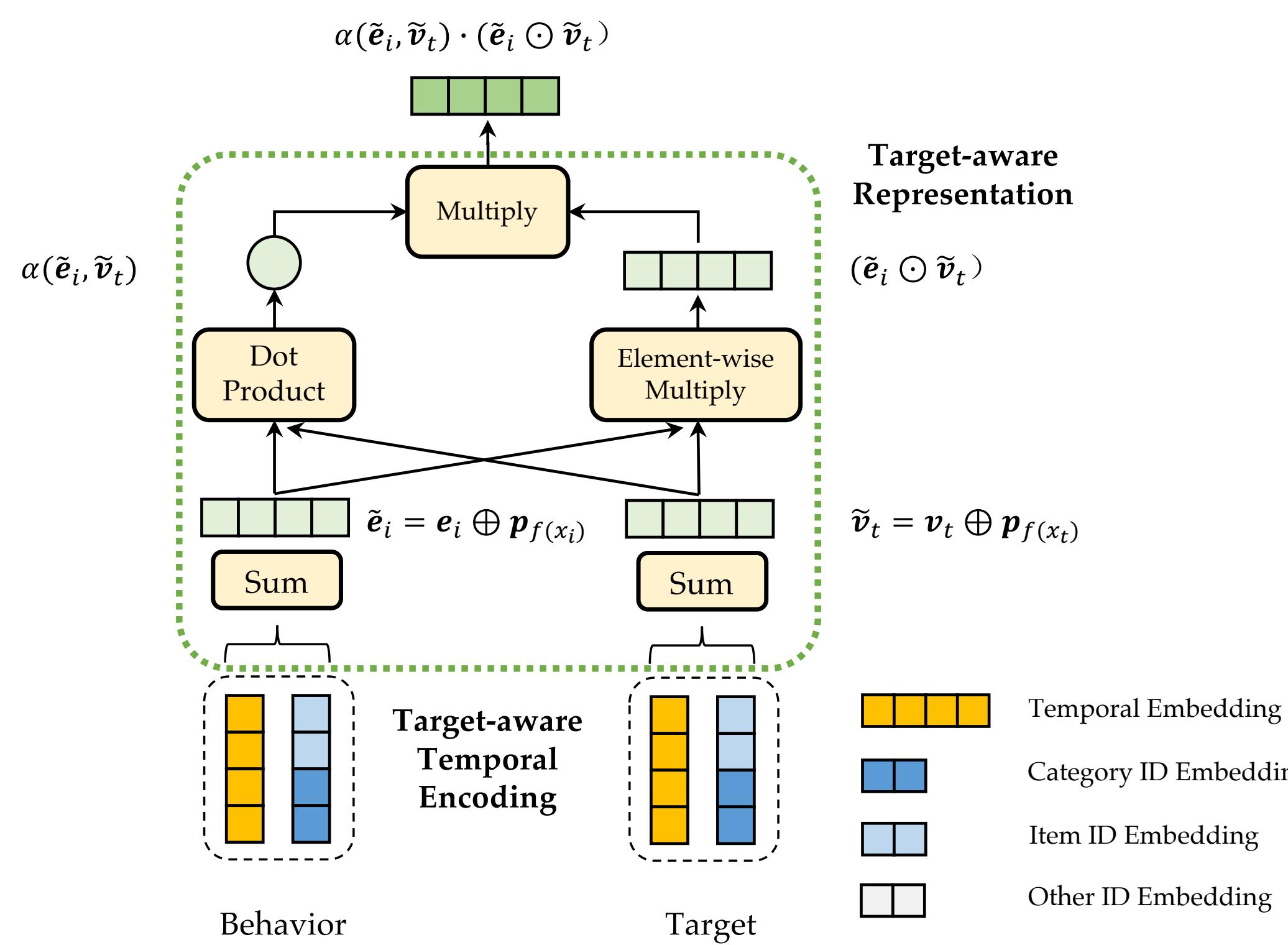
**semantic pattern between matching categories:** behaviors belonging to the same category as the target exhibit a higher degree of correlation than other categories.

**temporal decaying pattern:** among the semantically correlated behaviors, there is a compelling correlation decrease from the most recent behaviors to the oldest ones.

## Temporal Interest Network



## Temporal Interest Module



In order to conduct 4-way interaction over the quadruplet (behavior semantics, target semantics, behavior temporal, target temporal) to capture the semantic-temporal correlation, we propose TIM, which consists of a) **Target-aware Temporal Encoding (TTE)**: TTE preserves the temporal information of behaviors regarding the target. b) **Target-aware Attention (TA)** and c) **Target-aware Representation (TR)** over the temporally encoded behaviors and target.

$$u_{\text{TIN}} = \sum_{i \in \mathcal{H}} \underbrace{\alpha(\tilde{e}_i, \tilde{v}_t)}_{\text{TTE}} \cdot \underbrace{(\tilde{e}_i \odot \tilde{v}_t)}_{\text{TA}} \quad (2)$$

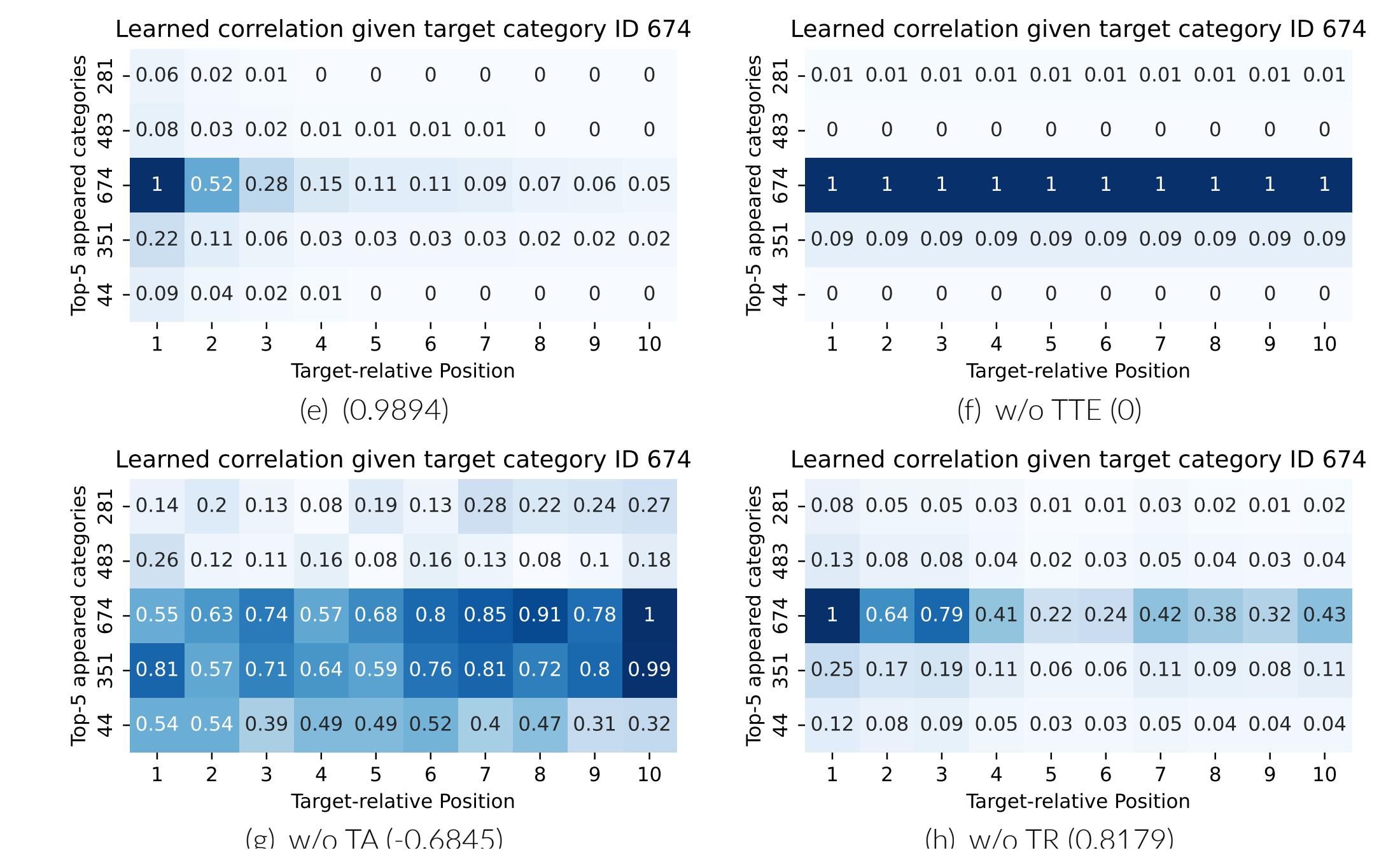
## Performance Evaluation

Table 1. Models with the same background color have the same component code.

Model	Code	Amazon			Alibaba				
		Logloss	$\Delta\%$	GAUC	$\Delta\%$	Logloss	$\Delta\%$	GAUC	$\Delta\%$
Avg Pooling & Concat	XXX	0.4908 (1E-3)	-	0.8445 (2E-3)	-	0.1969 (1E-3)	-	0.6074 (4E-4)	-
Avg Pooling & Product	XXV	0.4824 (5E-4)	-1.71	0.8523 (8E-4)	+0.92	0.1960 (1E-3)	-0.46	0.6106 (9E-4)	+0.53
DIN'	XVX	0.4803 (9E-4)	-2.14	0.8536 (4E-4)	+1.08	0.1962 (1E-3)	-0.36	0.6096 (6E-4)	+0.36
DIN	XV✓	0.4703 (2E-3)	-4.18	0.8590 (1E-3)	+1.72	0.1963 (1E-3)	-0.30	0.6113 (4E-4)	+0.64
GRU4Rec	VX✓	0.4766 (2E-3)	-2.89	0.8574 (2E-3)	+1.53	0.1972 (1E-3)	+0.15	0.6091 (4E-4)	+0.28
SASRec	VX✓	0.4837 (7E-3)	-1.45	0.8497 (4E-3)	+0.62	0.1959 (8E-4)	-0.51	0.6091 (4E-4)	+0.28
BERT4Rec	VX✓	0.4833 (5E-3)	-1.53	0.8501 (2E-3)	+0.66	0.1961 (1E-3)	-0.41	0.6096 (9E-4)	+0.36
DIEN	VJX	0.4807 (8E-3)	-2.06	0.8590 (1E-3)	+1.72	0.1973 (9E-4)	+0.20	0.6108 (6E-4)	+0.56
DSIN	VVX	0.4726 (2E-3)	-3.71	0.8592 (1E-3)	+1.74	0.1964 (2E-3)	-0.25	0.6106 (9E-4)	+0.53
BST	VVX	0.4850 (5E-4)	-1.18	0.8500 (9E-4)	+0.65	0.1959 (2E-3)	-0.51	0.6096 (6E-4)	+0.36
	VV✓	<b>0.4636 (3E-3)</b>	-5.54	<b>0.8629 (9E-4)</b>	+2.18	<b>0.1954 (2E-3)</b>	-0.76	<b>0.6144 (4E-4)</b>	+1.15
w/o TTE	XV✓	0.4752 (2E-3)	-3.18	0.8544 (8E-4)	+1.17	0.1963 (1E-3)	-0.30	0.6135 (7E-4)	+1.00
w/o TA	VX✓	0.4758 (3E-3)	-3.06	0.8566 (1E-3)	+1.43	0.1960 (7E-4)	-0.46	0.6094 (8E-4)	+0.33
w/o TR	VV✓	0.4743 (2E-3)	-3.36	0.8576 (9E-4)	+1.55	0.1965 (2E-3)	-0.20	0.6127 (1E-3)	+0.87

TIN has been successfully deployed to the pCTR and pLTV models on many Tencent Ads scenarios, including Wechat Moments, Channel, Tencent Video, Tencent News.

## TIN Captures Semantic-Temporal Correlation Decently



## Connections to Existing Methods

Model	Temporal Information?	How	TA	Attention	TR Representation	Notes on Representation
Avg Pooling & Concat	X	-	X	-	$gMLP([e_i, v_t])$	-
Avg Pooling & Product	X	-	X	-	$gMLP([e_i, v_t, e_i \odot v_t])$	-
DIN'	X	-	✓	$\sigma([e_i, v_t])$	$gMLP([e_i, v_t, e_i \odot v_t])$	Concat & MLP's hard to learn dot product?
DIN	X	-	✓	$\sigma([e_i, v_t])$	$gMLP([e_i, v_t, e_i \odot v_t])$	According to code released by the authors.
SIM	✓	TTE-T	✓	$\sigma([e_i, v_t])$	$gMLP([e_i, v_t])$	Concat & MLP's hard to learn dot product?
GRU4Rec	✓	GRU	X	-	$\sigma(h_t, v_t)$	According to open source code.
SASRec	✓	COE	X	-	$\sigma(e_i^V, v_t)$	According to Eqn. $r_{t,i} = F_t^T N_i^T$ ?
BERT4Rec	✓	COE	X	-	$\sigma(e_i^V, v_t)$	According to Eqn.(7) in?
ExtLayer	✓	AUGRU	X	-	-	-
EvoLayer	✓	AUGRU	✓	$\sigma(h_t, v_t)$	$gMLP([h_t, v_t])$	-
DSIN	✓	Bi-LSTM & COE	✓	$\sigma(e_i^K, v_t^K)$	$gMLP([e_i^K, v_t^K])$	Concat & MLP's hard to learn dot product?
BST	✓	COE	✓	$\sigma(e_i^K, v_t^K)$	$gMLP([e_i^K, v_t^K])$	Concat & MLP's hard to learn dot product?
w/o TTE	✓	TTE	✓	$\sigma(e_i, v_t)$	$gMLP([e_i, v_t, e_i \odot v_t])$	-
w/o TA	X	-	✓	$\sigma(e_i, v_t)$	$gMLP([e_i, v_t, e_i \odot v_t])$	-
w/o TR	✓	TTE	X	✓	$gMLP([e_i, v_t])$	-

All existing methods lack one or several of the three components (Temporal Information, Target-aware Attention and Target-aware Representation), making them fail to learn the semantic-temporal correlation.