DIGMN: Dynamic Intent Guided Meta Network for Differentiated User Engagement Forecasting in Online Professional Social Platforms

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Reported by Zhaoze Gao

1. Introduction

2. Approach

3. Experiments

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Introduction

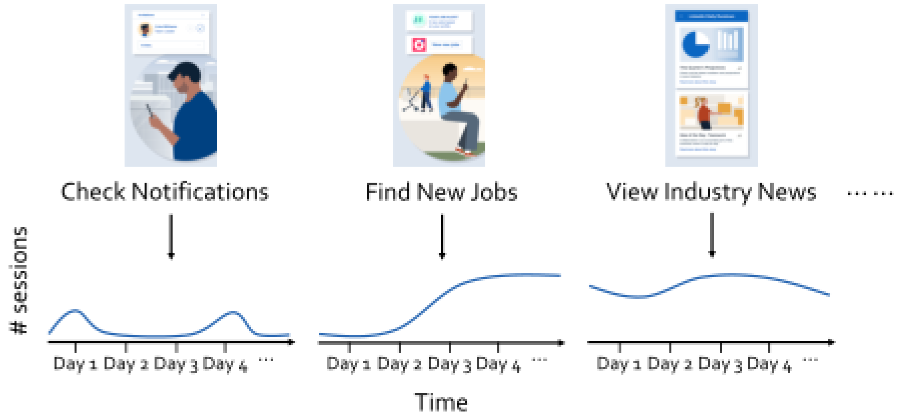
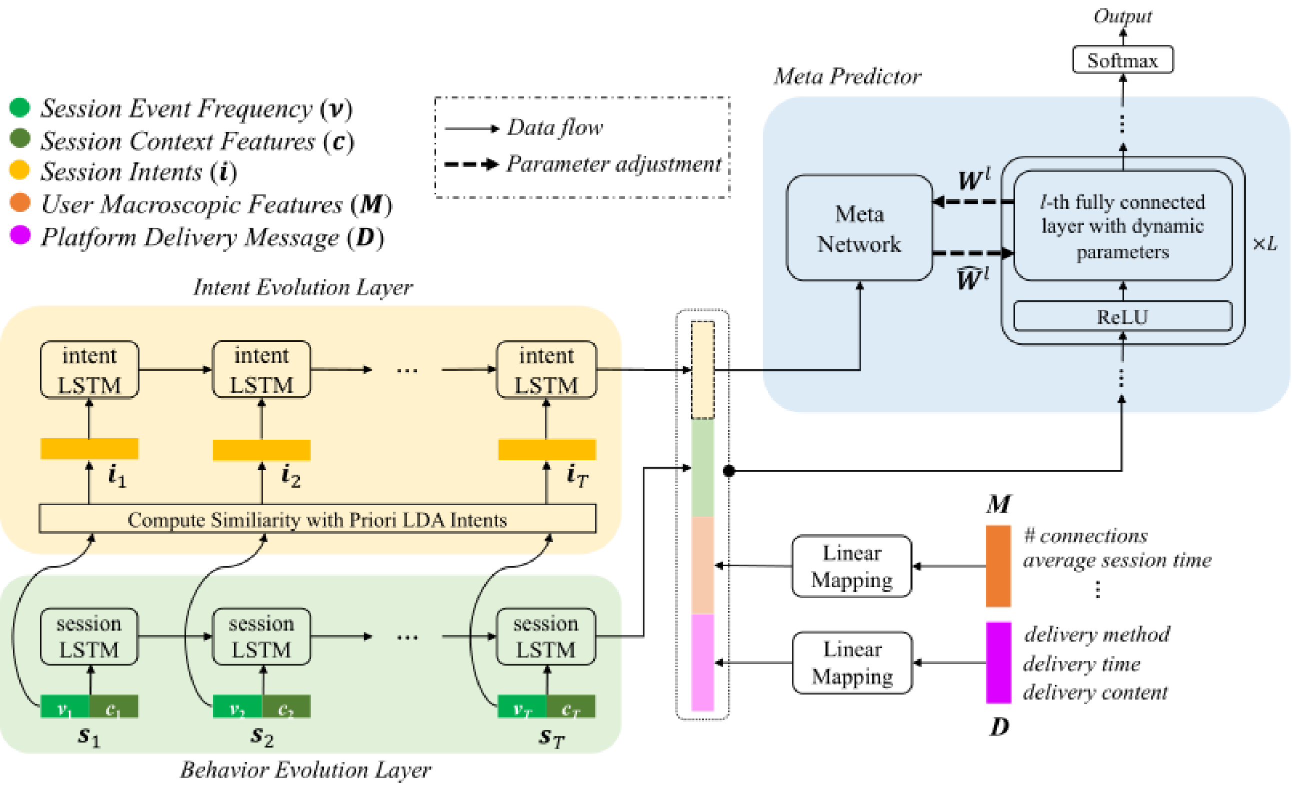


Figure 1: Example of different user engagement patterns with different user intents.

Dynamic Intent Guided Meta Network (DIGMN), which can explicitly model user intent varying with time and perform differentiated user engagement forecasting.

Approach



$$U = \{u_1, u_2, ..., u_N\}$$

$$I = \{i_1, i_2, ..., i_M\}$$

User event. $e = (u, i, t)$

User session. $\mathcal{S} = (u, c, \mathcal{E})$

User engagement. $\bar{s} = \frac{\#\ valid\ sessions}{\#\ total\ days}$ $\bar{d} = \frac{\#\ active\ days}{\#\ total\ days}$

Platform actions. $\mathcal{D} = (u, w, r, t)$

$$\Pr(y_u | M_u, S_u, D_u, ; \Theta) \quad (1)$$

user's macroscopic features M_u (e.g., the number of connections, the average number of sessions per day in the past period), session

$S_u = < \mathcal{S}_1, \mathcal{S}_2, ..., \mathcal{S}_T >$ T is the number of sessions

the latest platform delivery message D_u

Approach

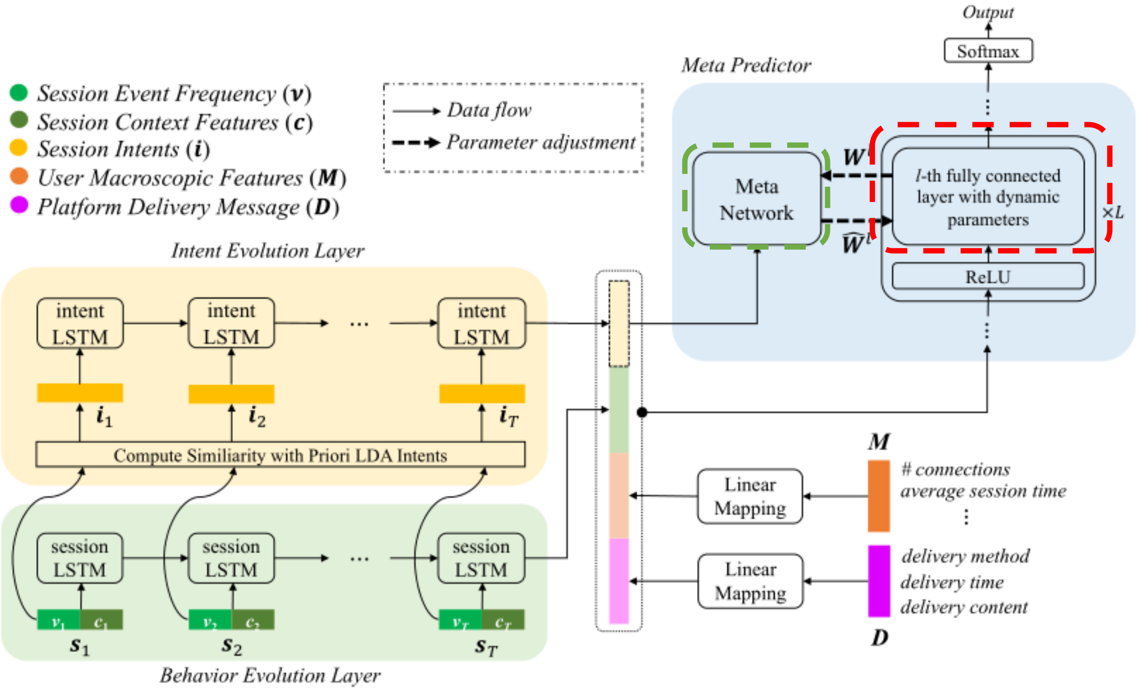


Figure 3: The framework of our proposed model. It consists of three main components: behavior evolution layer, intent evolution layer and a meta predictor.

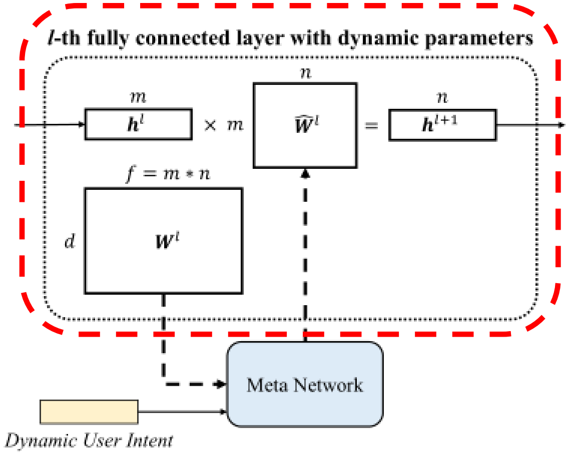


Figure 4: The l-th fully connected layers with dynamic parameters.

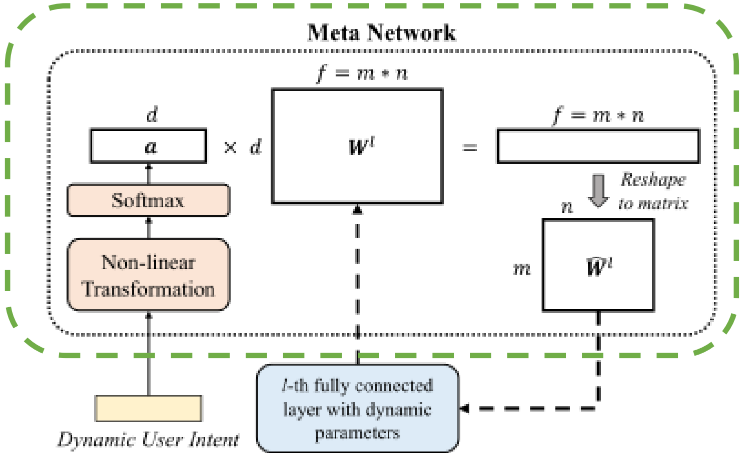
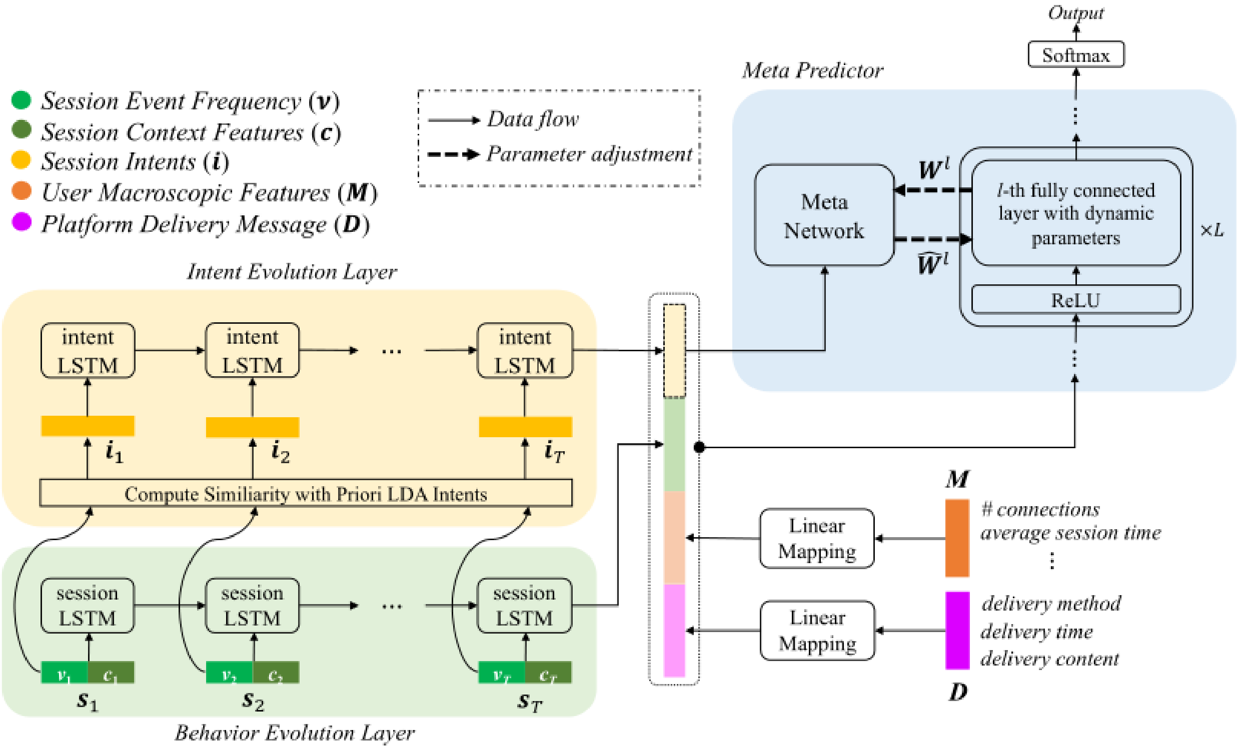


Figure 5: Meta Network.

Approach



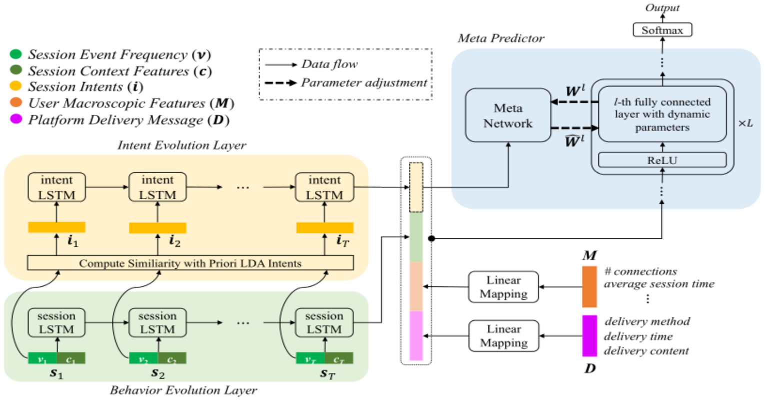
$$i_k = \frac{\boldsymbol{v} \cdot \boldsymbol{t}_k}{||\boldsymbol{v}|| \times ||\boldsymbol{t}_k||} \quad (2)$$

$$\boldsymbol{y} = F(\boldsymbol{x}, \Theta) \quad (3)$$

$$\boldsymbol{y} = F(\boldsymbol{x}, \Theta^*) = F(\boldsymbol{x}, \phi(\boldsymbol{x}, \Theta)) \quad (4)$$

$$\boldsymbol{h}^{l+1} = \widehat{\boldsymbol{W}}^l \cdot \boldsymbol{h}^l + \hat{\boldsymbol{b}}^l \quad (5)$$

Approach



$$a = \mathrm{Softmax}(W_2(\mathrm{ReLU}(W_1\tilde{i} + b_1)) + b_2)$$
$$s.t. \sum_{i=1}^{d} a_i = 1, 0 < a_i < 1 \tag{6}$$

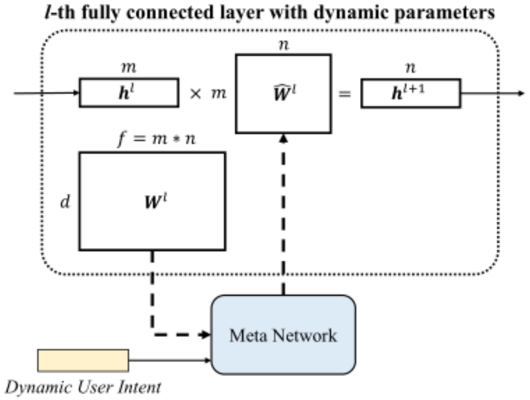


Figure 4: The l-th fully connected layers with dynamic parameters.

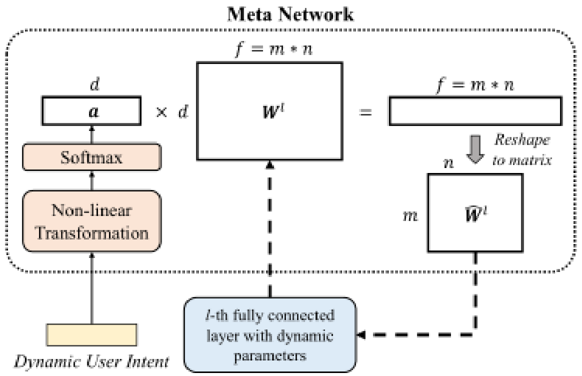


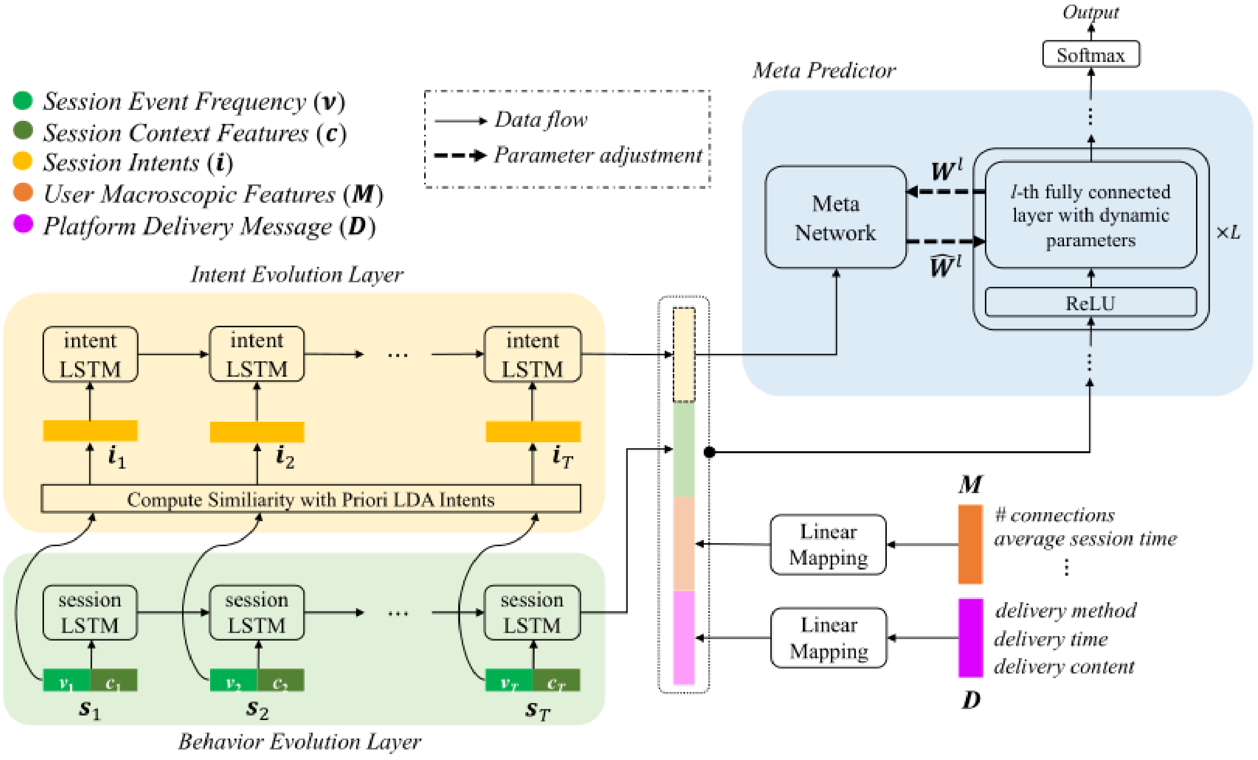
Figure 5: Meta Network.

$$\widehat{W}^l = \mathrm{Reshape}(a^T W^l) = \mathrm{Reshape}(\sum_{i=1}^{d} a_i W_i^l) \tag{7}$$
$$W_1^l, W_2^l, ..., W_d^l \in \mathbb{R}^{(m*n)}$$
$$W^l = [W_1^l, W_2^l, ..., W_d^l]^T \in \mathbb{R}^{d\times(m*n)}$$

$$\lambda \cdot ||(W^l(W^l)^T - I)||_F^2 \tag{8}$$

$$\mathcal{L}_R = \sum_{l=1}^{L} ||(W^l(W^l)^T - I) \odot (1 - I)||_F^2 \tag{9}$$

Approach



$$\mathcal{L}_C = -\frac{1}{n}\sum_i \sum_c y_{ic} \log(\hat{y}_{ic}) \quad (10)$$

$$\mathcal{L} = \mathcal{L}_C + \beta \cdot \mathcal{L}_R \quad (11)$$

Experiments

Table 1: Types of user events we collect on the platform.

Event ID	Event Type	Explanation
1	Feed	view and react to updates
2	Search	search for members, jobs, or other
3	View Profile	view profiles of members or companies
4	Jobs	view or apply for jobs
5	PYMK	invite members to build connections
6	Notification	check notifications
7	Message	check or send messages
8	Edit Profile	edit personal profile
9	Share Content	share content
10	Follow	follow members, companies, or other

Experiments

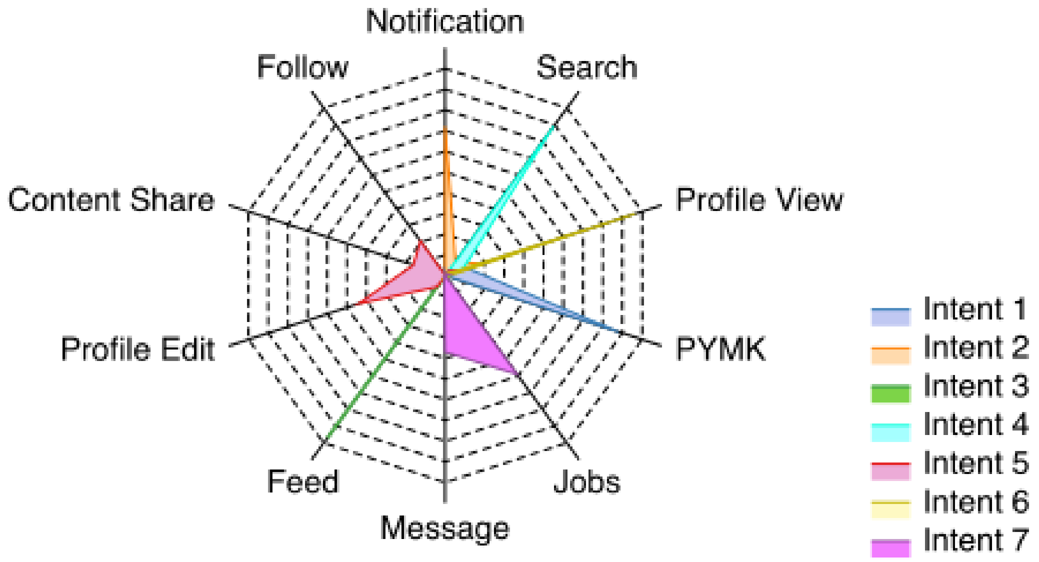


Figure 2: Basic user intents. There are 7 basic intents obtained by LDA, and we show the event weights that compose them.

Experiments

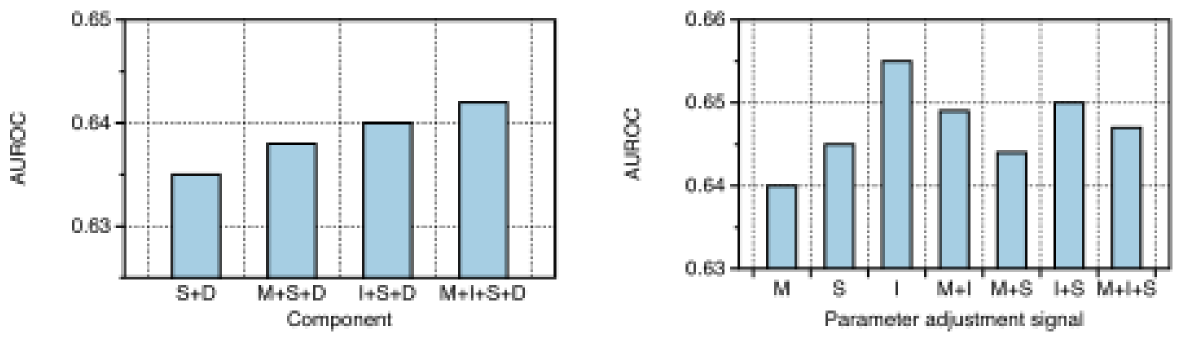
Table 2: Labels of user engagement forecasting tasks.

Day-level Task	Session-level Task
$y = \begin{cases} -1, & \bar{d}_h > \bar{d}_f \\ 0, & \bar{d}_h = \bar{d}_f \\ 1, & \bar{d}_h < \bar{d}_f \end{cases}$	$y = \begin{cases} 0, & \bar{s}_h > \bar{s}_f \\ 1, & \bar{s}_h \leq \bar{s}_f \end{cases}$

Table 3: Performance comparison on the classification of user engagement trends at the day-level and the session-level.

Model \ Task	Day-level Macro F1-Score	Session-level AUROC
Feature-based model		
LR	0.446 ± 0.000	0.561 ± 0.000
XGBoost	0.460 ± 0.001	0.569 ± 0.001
End-to-end neural network model		
MLP	0.463 ± 0.002	0.571 ± 0.002
Activity LSTM	0.518 ± 0.001	0.605 ± 0.001
Temporal GCN-LSTM	0.522 ± 0.002	0.600 ± 0.003
Deep Multi-channel	0.575 ± 0.002	0.633 ± 0.002
DIGMN (ours)	$\mathbf{0.592 \pm 0.001}$	$\mathbf{0.655 \pm 0.001}$
Improvements	2.96%	3.48%

Experiments

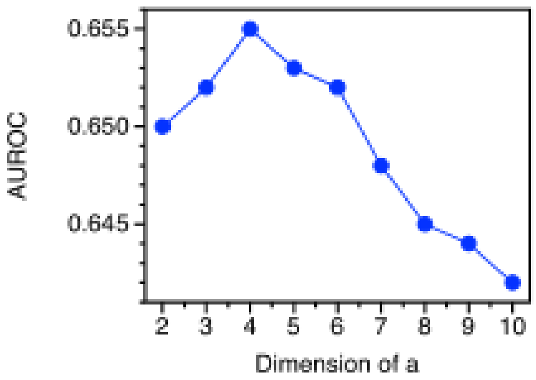


(a) Ablation study on different model components.

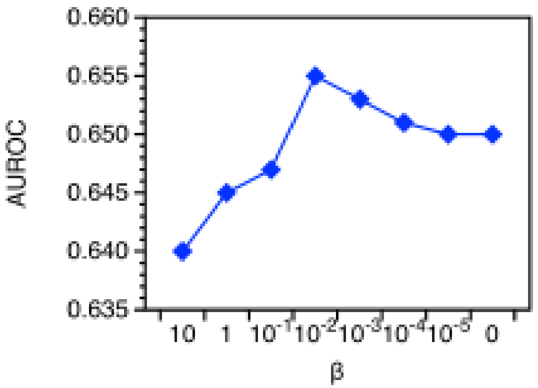
(b) Ablation study on different parameter adjustment signal of DIGMN.

Figure 6: Ablation study of components and different parameter adjustment signal. M, D, S, I **represent macroscopic features, the latest platform delivery message, session features and intent features respectively.**

Experiments



(a) Prediction performance of different dimension of $\boldsymbol{a}$.



(b) Prediction performance of different β.

Figure 7: Hyperparameter sensitivity.

Experiments

Table 5: Prediction performance of different L.

# FC-D Layers	# Hidden Units	AUROC
$L = 1$	-	0.645 ± 0.001
$L = 2$	{64}	0.651 ± 0.001
$L = 3$	{64,32}	0.655 ± 0.001
$L = 4$	{64,32,32}	0.652 ± 0.001
$L = 5$	{64,32,32,32}	0.646 ± 0.002

Table 6: Prediction performance of different methods to extract session intents.

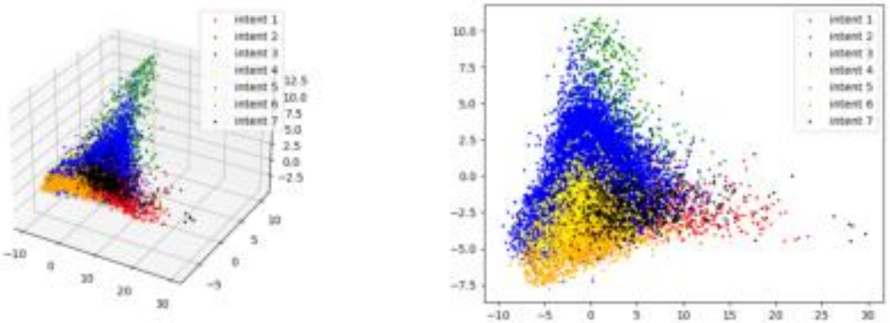
Methods to extract session intents	AUROC
End-to-end learning	0.644 ± 0.001
Prior intents	0.655 ± 0.001

Experiments

Table 4: Performance comparison of DIGMN with dynamic predictor and DIGMN with static predictor.

Model \ Task	# Hidden Units in Predictor	Day-level		Session-level	
		Macro F1-Score	# Parameters	AUROC	# Parameters
DIGMN (Static)	{64, 32}	0.580 ± 0.001	18.8K	0.642 ± 0.001	18.7K
DIGMN (Static)	{160, 96}	0.585 ± 0.001	38.6K	0.645 ± 0.002	38.5K
DIGMN (Dynamic)	{64, 32}	0.592 ± 0.001	40.8K	0.655 ± 0.001	40.7K

Experiments



(a) The distribution of user dynamic intent in to 3-dimensional space.

(b) The distribution of user dynamic intent in to 2-dimensional space.

Figure 8: The visualization of dynamic user intent representation. We apply zero-mean normalization to the input high-dimensional vectors before using PCA for dimension reduction.

Thank you！