User Activity Modeling under Inflated Distribution

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Abstract

User activity modeling serves as an effective approach to reflect Daily Active Users (DAU) levels by forecasting users' prospective behavioral engagement. In industrial practice, particularly in user active days prediction tasks, the data demonstrates extreme distributional imbalance. Specifically, completely inactive and fully active users constitute the vast majority, resulting in a highly skewed phenomenon known as a two-sided inflated distribution. Existing methods either rely on the assumption of a normal distribution, neglecting the optimization objectives to focus purely on designing complex model architectures for user feature extraction, which renders them ineffective in non-normally distributed real-world industrial scenarios, or they have explored modeling non-normal distributions, but still struggle to directly operate on the discrete data space in user activity modeling and mitigate the two-sided inflation prevalent in industrial data. Based on this finding, we propose a simple yet effective user activity modeling method under two-sided inflated distribution. Specifically, we decompose the problem into two objectives: first, modeling whether the target is at an inflated point; and second, modeling the distribution when the target is not at an endpoint. Finally, we apply this modeling approach to uplift modeling. Extensive offline evaluations and online A/B tests on Douyin platforms, involving over 1 billion users, demonstrate the effectiveness of the proposed method.

CCS Concepts

• **Information systems → Information retrieval**; • **Computing methodologies → Machine learning**; • **Applied computing → Electronic commerce**.

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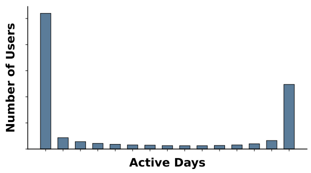
1 Introduction

In industrial recommendation and e-commerce platforms, maximizing Daily Active Users (DAU) is essential for maintaining platform health [4, 38, 39]. Achieving this relies on precise user activity modeling to quantitatively forecast a user's future behavioral feedback. Accurately forecasting user activity enables platforms to design appropriate recommendation strategies, such as targeted push notifications, personalized content delivery, and promotional campaigns, thereby maximizing overall gross revenue and significantly enhancing user retention and experience, and ultimately driving DAU growth.

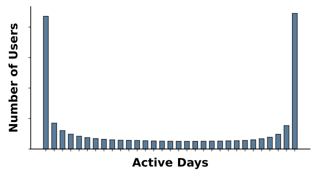
To enhance the capability of user activity modeling, existing works have primarily focused on designing sophisticated model architectures, including decoupled attention, asynchronous caching, and stacking fine-tuning [2, 14, 18, 26]. With the impressive advances in deep learning, these complex architectural designs have gathered increasing attention and achieved significant improvements in various industrial downstream tasks [28, 36, 40]. Despite these advances in model structure, loss function design has been overlooked in existing methods.

In industrial user active days prediction, a ubiquitous phenomenon is that the target data typically exhibits a two-sided inflated distribution, which specifically manifests here as a heavily two-sided inflated distribution. For example, as shown in Figure 1, users' active days for both 14 days (Lifetime 14, LT14) and 30 days (Lifetime 30, LT30) on the Douyin[1] platform show that most users are

[1]https://www.douyin.com/



(a) Douyin active days in 14-day window.



(b) Douyin active days in 30-day window.

Figure 1: Active Days (LT14/30) of the Douyin platforms involving over 1 billion users: The number of active days per user over a 14/30-day window, capturing user stickiness and retention.

either completely inactive or fully active at both extremes. Meanwhile, on other platforms like Toutiao[2] and Doubao[3], we observe a similar two-sided inflated distribution, further confirming that this extreme data inflation is a widespread characteristic across various industrial applications.

Based on this observation, directly adopting the Mean Square Error-based or the Gaussian Mixture Model-based loss function to train the uplift prediction model will lead to sub-optimal performance [41]. While existing works have proposed generalized zero-inflation strategies for modeling non-normal distributions [3, 6, 19, 33], they still struggle to directly operate on the discrete data space inherent in user activity modeling and mitigate the two-sided inflation prevalent in industrial data.

To bridge this gap, we propose a simple yet effective method for user activity modeling. Specifically, we decompose the problem into the following two objectives: first, we aim to train a multi-class classification model to predict if the user will fall into the inflated point; secondly, we model the distribution if the user is not at endpoints. Note that this method can not only address the distribution inflation problem but can also overcome the data imbalance. Finally, we apply this modeling approach to uplift modeling. The main contributions are as follows:

- We identify the prevalence of multiple point-inflation phenomena in industrial data distributions, which has been overlooked in existing user activity modeling research.
- We propose a generalized user activity modeling framework tailored to address the data imbalance inherent in two-sided inflated distributions.
- We evaluated the proposed method through large-scale online A/B testing on two platforms with a user base exceeding 1 billion. Currently, the method is fully deployed and serves the complete main traffic on these platforms.

2 Related Work

2.1 User Activity Modeling

User active days refer to the dates on which a user has engaged in valid sessions, such as logging in or browsing on the platform [15]. Early research on modeling user active days within specific time windows relied on statistical analysis to capture temporal dynamics and periodic patterns [22, 25]. With the advancement of deep learning techniques, more modeling approaches based on recurrent neural networks [24], graph neural networks [29], or mixture of experts [21] have been proposed. Although these deep models possess strong representational capabilities for complex temporal patterns in user activity behavior, they pay insufficient attention to the specific distribution characteristics of point-inflation in user active days. Consequently, their prediction accuracy for user active days at inflated points is relatively poor.

2.2 Distribution Modeling

Generalized distribution modeling serves as a crucial theoretical foundation for user activity modeling. Beyond applying common probabilistic distribution models, researchers have proposed complex parametric models such as Gaussian mixture models [41], as well as nonparametric methods like Bayesian approaches [1, 20] to capture the complexity of user behavior. Although these methods may possess desirable theoretical properties, when applied to user activity modeling, they often fail to capture the complex distribution of two-sided inflation.

2.3 Uplift Modeling

Uplift modeling estimates heterogeneous treatment effects to distinguish treatment-driven conversions from natural ones [23, 27, 34, 42], and is tightly connected to causal debiasing in recommender systems [9, 11, 31, 35]. Core approaches include meta-learners and their deep extensions [5, 44], tree-based uplift methods [23, 27], doubly robust and causal balancing techniques [7, 8, 12, 45], and counterfactual learning [13, 16, 30, 32]. Recent work further tackles practical issues such as propensity bias [37, 43], noisy labels [17], and missing-not-at-random data [10, 46]. Our work addresses the overlooked distributional challenge of two-sided inflation in user activity targets within the uplift framework.

3 Methods

3.1 Notation and setup

Following the notations in fundamental uplift modeling, we use X_i ($i \in \{1, \dots, N\}$) to represent the user features, Y_i ($i \in \{1, \dots, N\}$) to represent the objective, such as user click days, user click frequency, or life-time. In addition, we use T_i to represent the treatment for user i. The treatment T_i takes values among a pre-defined set $\{0, 1, \dots, T_0\}$ while Y_i is from 0 to the right point k. For illustrative purposes, we assume that there is two-sided inflation, i.e., the distribution is inflated at $Y = 0$ and $Y = k$.

3.2 The Proposed Two-Sided Inflated Loss (TSIL)

The overall framework of the proposed TSIL model is based on the widely used X-Net structure [44]. The core of TSIL is two hierarchical prediction subtasks. As shown in Figure 2, the overall structure of TSIL consists of a shared bottom representation layer, two task-specific transformer encoders, and a loss fusion layer.

3.2.1 *Task 1: Three-Class Classification.*

To capture the two-sided inflated characteristic, we first design a three-class classification subtask to model the probability of Y falling into three intervals

[2] https://www.toutiao.com/
[3] https://www.doubao.com/

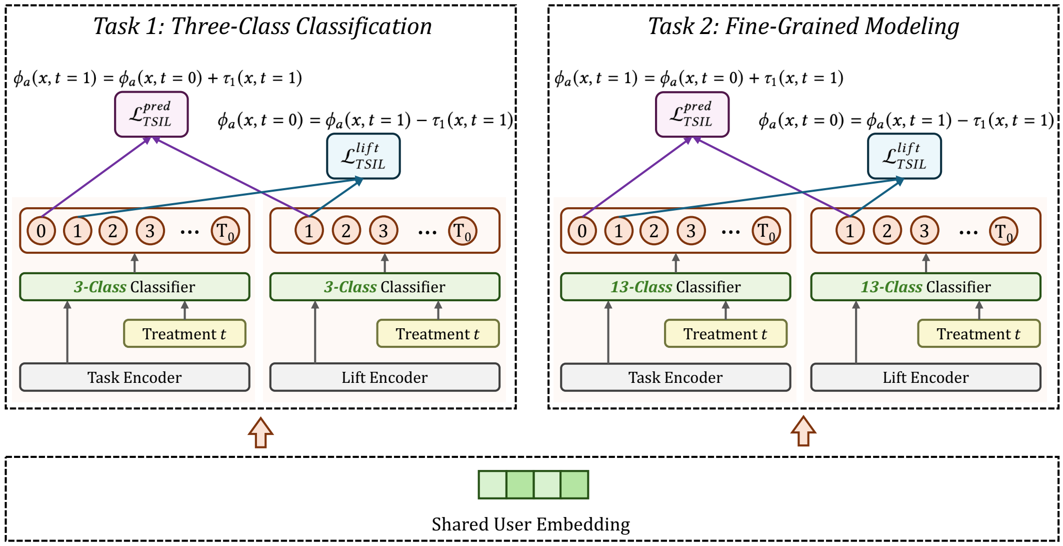


Figure 2: Overview of the model structure. Task 1 classifies users into three activity categories ($A \in \{0, 1, 2\}$); Task 2 models the discrete active-day distribution for middle-active users ($A = 1$). Both tasks share a bottom embedding layer and each contains a Task Encoder and a Lift Encoder.

based on an indicator $A \in \{0, 1, 2\}$, where:

$$\begin{cases} A = 0 \Leftrightarrow Y = 0 \quad \text{(inactive users)} \\ A = 1 \Leftrightarrow 0 < Y < 14 \quad \text{(middle active users)} \\ A = 2 \Leftrightarrow Y = 14 \quad \text{(fully active users)} \end{cases} .$$

We denote $\phi_a(x, t) = P(A = a|x, t)$ as the probability of user x falling into interval a under treatment t, with the constraint $\sum_{a=0}^{2} \phi_a(x, t) = 1$. In our model, $\phi_a(x, t) = P(A = a|x, t)$ is predicted by a task-specific transformer encoder.

3.2.2 Task 2: Fine-Grained Modeling. For the middle active user group ($A = 1$), we design a fine-grained probability modeling subtask to capture the discrete distribution of active days. We denote $p_{k,t} = P(Y = k|x, t, A = 1)$ as the probability that the user's active days is k ($k \in \{1, \ldots, 13\}$) under treatment t, with the constraint $\sum_{k=1}^{13} p_{k,t} = 1$. The probability $p_{k,t}$ is predicted by another task-specific transformer encoder, which shares the bottom layer with Task 1 to reduce parameters and capture feature commonality.

3.2.3 Loss Function Design. We design a **loss function** combining a standard cross entropy loss to train the task 1 classifier, the negative log-likelihood loss for probability modeling of the two subtasks, and regression loss for numerical active days value prediction. The total loss function is:

$$\mathcal{L}_{TSIL} = \mathcal{L}_{CE} + \mathcal{L}_{NLL} + \mathcal{L}_{Reg}.$$

Cross-Entropy Loss ($\mathcal{L}_{CE}$). The three-class probability classifier is trained by the following standardized cross-entropy loss:
$\mathcal{L}_{CE} = -\frac{1}{N} \sum_{i=1}^{N} \sum_{a=0}^{2} \mathbb{I}(A_i = a) \cdot \log(\phi_a(x_i, t_i))$,where $\mathbb{I}(\cdot)$ is the indicator function.

Negative Log-Likelihood Loss ($\mathcal{L}_{NLL}$). The NLL loss models the joint probability of the observed active days values (A, Y) (where $Y = 0$ for $A = 0$, $Y = k$ for $A = 1$, $Y = 14$ for $A = 2$). The joint probability is:

$$\begin{cases} P(A = 0, Y = 0) = \phi_0(x, t) \\ P(A = 1, Y = k) = \phi_1(x, t) \cdot p_{k,t} \\ P(A = 2, Y = 14) = \phi_2(x, t) \end{cases} .$$

The NLL loss is then defined as:

$$\mathcal{L}_{NLL} = -\mathbb{I}(Y = 0, A = 0) \log \phi_0(x, t) - \mathbb{I}(Y = 14, A = 2) \log \phi_2(x, t) - \mathbb{I}(Y = k, A = 1) \log \left(\phi_1(x, t) \cdot p_{k,t}\right).$$

Regression Loss ($\mathcal{L}_{Reg}$). The regression loss is designed to improve the prediction accuracy of the active days value, which is:

$$\mathcal{L}_{Reg} = \left(\phi_1(x, t) \sum_{k=1}^{13} k \cdot p_{k,t} + 14 \cdot \phi_2(x, t) - Y\right)^2 ,$$

where the predicted value is the mathematical expectation of active days, which combines the results of Task 1 and Task 2.

3.2.4 Adaptation to X-Net Structure. In practice, the ultimate goal is to estimate the causal effect of a treatment on user activity, i.e., uplift modeling (see Subsection 2.3). We therefore adopt X-Net [44], a widely used uplift architecture, as the backbone to illustrate how TSIL integrates into this framework. Specifically, the TSIL model adopts a multi-tower structure with the prediction head and uplift head. Raw user features X and treatment features T are first encoded by the shared bottom transformer, generating unified embeddings. Then, prediction encoders directly output $\phi_a(x, t) = P(A = a|x, t)$ (Task 1) and $p_{k,t} = P(Y = k|x, t, A = 1)$ (Task 2), while lift encoders estimate treatment effects $\tau_1(x, t) = P(A = a|x, t) - P(A = a|x, t = 0)$ and $\tau_2(x, t) = P(Y = k|x, t, A = 1) - P(Y = k|x, t = 0, A = 1)$, quantifying difference between $T = t$ (treatment) and $T = 0$ (control).

Therefore, there are two possible ways to compute each prediction. For the treatment group with $T > 0$, taking $\phi_a(x, t = 1)$ as an

Table 1: Performance comparison on public datasets. Bold indicates the best result; underline indicates the second best. ↑ means higher is better; ↓ means lower is better.

Dataset	Method	AUC↑	Spearman↑	MAPE↓
Kaggle Shopper	MSE	0.6578	0.2919	0.0803
	ZILN	0.6793	<u>0.3150</u>	0.0732
	GMM	<u>0.6802</u>	0.3144	<u>0.0645</u>
	Ours	**0.7007**	**0.3174**	**0.0192**
KDD CUP 98	MSE	0.4774	0.0071	0.1045
	ZILN	0.5320	0.0084	0.0858
	GMM	<u>0.5420</u>	<u>0.0090</u>	<u>0.0731</u>
	Ours	**0.5547**	**0.0110**	**0.0522**

example, we can (1) directly use the prediction head to compute, or (2) compute as $\phi_a(x, t=1) = \phi_a(x, t=0) + \tau_1(x, t=1)$. Meanwhile, for the control group with $T = 0$, taking $\phi_a(x, t=0)$ as an example, besides directly using the prediction head, we can use $\phi_a(x, t=0) = \phi_a(x, t=1) - \tau_1(x, t=1)$ to compute.

Therefore, the final loss function includes two parts, $\mathcal{L}_{TSIL}^{pred}$, which directly uses the prediction head to compute, and $\mathcal{L}_{TSIL}^{lift}$, which includes the lift head to compute. In addition, we use multi-task learning to train models, and each output is activated via elu + 1 to ensure non-negativity.

4 Experiment

To demonstrate the effectiveness of the proposed method, we conduct offline experiments on both public and industrial datasets. In addition, we conduct online A/B tests involving over 1 billion users on Douyin.

4.1 Dataset and Task Description

To comprehensively evaluate the proposed TSIL method, we conduct experiments on both public datasets and an industrial dataset.

Public Datasets. Following ZILN [33], we use two public LTV prediction benchmarks: **Kaggle Shopper**[4] (311K customers, predicting 12-month purchase value) and **KDD CUP 98**[5] (200K donors, predicting donation amount).

Industrial Dataset. The **Douyin** dataset is collected via a push notification RCT with 20.59 million users. Control and treatment groups received zero and predefined-frequency notifications, respectively. We recorded 14-day active days (LT14).

For all datasets, we stratify each target into three categories ($A \in \{0, 1, 2\}$): $A = 0$ for the left inflated point ($Y = 0$), $A = 2$ for the right inflated point ($Y = k$), and $A = 1$ for the middle region ($0 < Y < k$).

4.2 Offline Experiments

4.2.1 Experiment Details. **Baseline.** We compare our method against the following baselines under the same model architecture: (1) **MSE**, a standard regression model trained with mean squared error loss; (2) **ZILN** [33], a zero-inflated lognormal model that handles zero inflation by combining a binary classifier with a lognormal distribution for positive values; and (3) **GMM** [41], a Gaussian mixture model-based loss that models the target distribution as a mixture of Gaussian components.

[4]https://www.kaggle.com/c/acquire-valued-shoppers-challenge
[5]https://kdd.ics.uci.edu/databases/kddcup98/kddcup98.html

Table 2: The AUUC and Calibration in Douyin.

Dataset	Metric	MSE	GMM	Ours
Douyin	AUUC	0.9552	0.9602	**0.9660**
	Calibration	**0.9827**	0.4557	1.0849

Table 3: Ablation study of loss components on public datasets.

Dataset	Variant	AUC↑	Spearman↑	MAPE↓
Kaggle Shopper	w/o NLL + Reg	0.6726	0.2922	0.0722
	w/o NLL	0.6877	0.3071	0.0552
	w/o Reg	0.6925	0.3157	0.0233
	All (Ours)	**0.7007**	**0.3174**	**0.0192**
KDD CUP 98	w/o NLL + Reg	0.5390	0.0074	0.0764
	w/o NLL	0.5400	0.0082	0.0779
	w/o Reg	0.5409	0.0090	0.0622
	All (Ours)	**0.5547**	**0.0110**	**0.0522**

Evaluation Metrics. For the public datasets, following prior work [33], we adopt three complementary metrics: (1) **Area Under the Curve (AUC)↑** (higher is better), measuring the model's discriminative ability in ranking users by predicted values; (2) **Spearman Correlation↑** (higher is better), capturing the monotonic rank association between predicted and actual values; and (3) **Mean Absolute Percentage Error (MAPE)↓** (lower is better), measuring the decile-level mean absolute percentage error for model calibration.

For the industrial dataset, we evaluate performance via two metrics: (1) **Area Under the Uplift Curve (AUUC)↑** (higher is better) computes the normalized area under the cumulative gain curve sorted by predicted uplift. (2) **Calibration Ratio** (closer to 1 is better) compares predicted to actual effects, and deviations indicate over- or under-estimation.

4.2.2 Performance Comparison. Table 1 and Table 2 present the offline prediction performance on public benchmarks and the Douyin industrial dataset, respectively. On the public datasets, the proposed TSIL method achieves the best performance across all metrics, consistently outperforming all baselines in both ranking quality and calibration accuracy. On the Douyin industrial dataset, TSIL similarly achieves the highest AUUC and the most proper calibration among all compared methods, confirming its effectiveness at billion-scale deployment. Among baselines, MSE performs worst due to its implicit normality assumption; ZILN [33] improves by modeling zero inflation but only addresses the left endpoint; GMM [41] further advances with mixture components yet still lacks explicit handling of two-sided inflation. TSIL's advantage stems from capturing probability mass at both inflated endpoints, while the fine-grained modeling accurately characterizes middle-region users.

4.2.3 Ablation Study. Table 3 investigates the roles of each loss component in our method: (1) **w/o NLL + Reg** retains only $\mathcal{L}_{\text{CE}}$,

Table 4: Performance of MAE across different subgroups in public datasets.

Dataset	Method	$A=0$	$A=1$	$A=2$
Kaggle Shopper	MSE	37.769	28.118	35.792
	ZILN	<u>29.979</u>	27.081	<u>31.229</u>
	GMM	34.769	<u>26.505</u>	31.371
	Ours	**28.990**	**25.710**	**28.712**
KDD CUP 98	MSE	0.758	0.625	1.280
	ZILN	<u>0.692</u>	0.619	1.144
	GMM	0.703	<u>0.608</u>	<u>0.953</u>
	Ours	**0.638**	**0.606**	**0.899**

Table 5: Performance of AUUC and Calibration metrics across different user activity subgroups in Douyin.

Activity	Metric	Baseline	Ours
Overall	AUUC	0.9552	**0.9660**
	Calibration	**0.9827**	1.0849
$A=0$	AUUC	0.8792	**0.9145**
	Calibration	0.3926	**0.9832**
$A=1$	AUUC	0.8699	**0.8714**
	Calibration	**0.9462**	1.0725
$A=2$	AUUC	0.9488	**0.9495**
	Calibration	1.1005	**1.0098**

which yields the weakest ranking quality across both datasets. (2) **w/o NLL** uses $\mathcal{L}_{\text{CE}} + \mathcal{L}_{\text{Reg}}$, removing the fine-grained distribution modeling. While it improves over the CE-only variant, ranking quality remains limited. (3) **w/o Reg** uses $\mathcal{L}_{\text{CE}} + \mathcal{L}_{\text{NLL}}$, removing regression regularization. This variant achieves competitive ranking but higher prediction error. (4) **All (Ours)** integrates all three components and achieves the best performance across all metrics. The improvement indicates that $\mathcal{L}_{\text{NLL}}$ and $\mathcal{L}_{\text{Reg}}$ work synergistically.

4.2.4 In-Depth Analysis on Inflated Point. Table 4 and Table 5 further decompose performance across user activity subgroups. Our method achieves the lowest MAE on all three subgroups of both public datasets, and yields steady AUUC improvements on Douyin with substantially better Calibration, especially for inactive users ($A=0$) where the baseline severely underestimates. These results provide empirical evidence supporting our claim that existing deep models have insufficient prediction accuracy at inflated points, and demonstrate the effectiveness of our method at inflated points.

4.3 Online A/B Test Experiments

4.3.1 Experiment Details. In the online A/B testing, we evaluate performance via three metrics: (1) **Active days (R_g)**: The relative change ($\times 10^{-4}$) in user active days versus the baseline. (2) **Cost (R_c)**: The relative change in sent notifications. (3) **Return on Investment (ROI)**: Evaluates resource efficiency defined as $ROI = \frac{1+R_g}{1+R_c}$. We record the cumulative relative changes for these metrics at Days 4, 7, and 10.

Table 6: Online A/B test results across user activity subgroups in Douyin.

Activity	Active days (1e-4)	Cost	ROI
Day4			
Overall	+0.410% ± 0.630%	-0.099% ± 0.026%	+0.509%
$A=0$	+29.550% ± 16.640%	+9.951% ± 0.140%	**+17.822%**
$A=1$	+0.570% ± 5.360%	+0.018% ± 0.070%	+0.553%
$A=2$	-0.030% ± 0.600%	-0.571% ± 0.040%	+0.549%
Day7			
Overall	+0.770% ± 0.570%	-0.076% ± 0.026%	+0.847%
$A=0$	+32.910% ± 14.430%	+10.381% ± 0.138%	**+20.409%**
$A=1$	+1.610% ± 5.360%	-0.002% ± 0.070%	+1.610%
$A=2$	+0.080% ± 0.560%	-0.567% ± 0.043%	+0.655%
Day10			
Overall	+0.760% ± 0.560%	+0.002% ± 0.025%	+0.758%
$A=0$	+40.390% ± 13.690%	+12.945% ± 0.130%	**+24.302%**
$A=1$	+1.210% ± 4.320%	-0.020% ± 0.071%	+1.231%
$A=2$	-0.020% ± 0.570%	-0.631% ± 0.033%	+0.613%

4.3.2 Results Analysis. Table 6 details the performance comparison in the online A/B testing, and we report the relative changes for each metric along with their corresponding confidence intervals. Specifically, our proposed method demonstrates superiority in three main aspects: (1) Regarding the improvement in user active days, a routine industrial iteration typically yields an average increase of $0.2\%\times 10^{-4}$, **our method significantly exceeds average increase**, achieving substantial increases in both active days and ROI; (2) Our method achieves precise offline calibration for inactive users ($A=0$) as indicated in Table 2, effectively correcting the severe underestimation of the MSE baseline, and guided our online strategy to increase notifications for $A=0$ users; although this required reallocating limited notification capacity from the $A=1$ and $A=2$ groups to the $A=0$ group, the ROI still realized positive growth across all scenarios, **proving the strong consistency between our offline modeling and online experimental results**. (3) Our method consistently outperforms the baseline across all evaluated time windows (Day 4, Day 7, and Day 10) and user groups, **showing its robust stability and sustained effectiveness over time**.

5 Conclusion

In this paper, we introduced a novel Two-Sided Inflated Loss (TSIL) framework for industrial user activity modeling, which effectively addresses the severe two-sided inflated distribution prevalent in real-world data. Our method decomposes prediction into an end-point classification subtask and a fine-grained distribution subtask for middle-active users. Extensive offline and online A/B experiments on billion-scale platforms validate TSIL's effectiveness, and the method is fully deployed on Douyin.

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