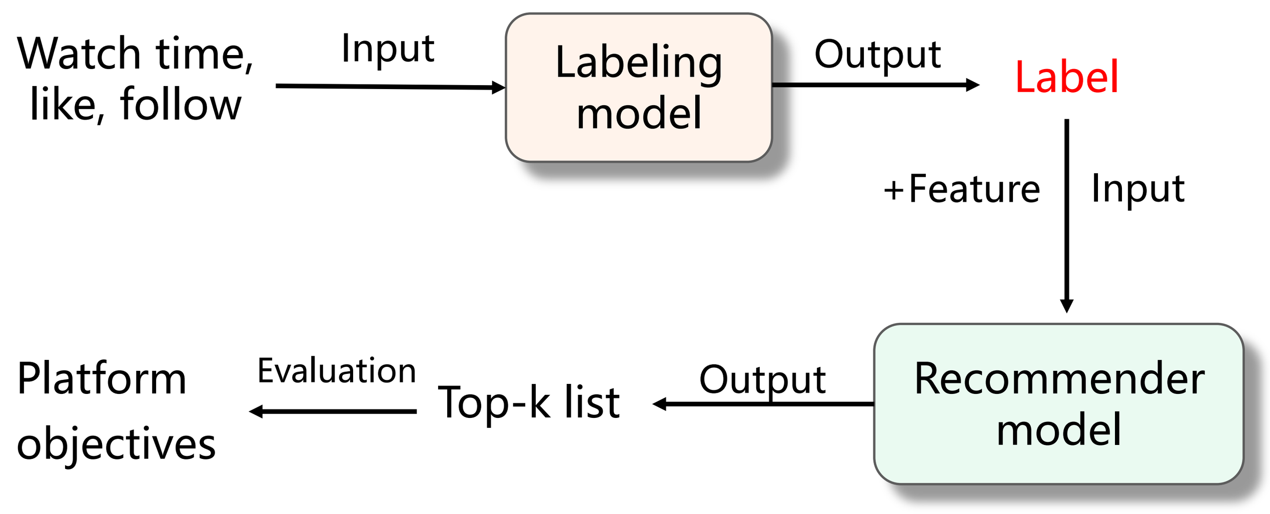
LabelCraft: Empowering Short Video Recommendations with Automated Label Crafting

Yimeng Bai[1], Yang Zhang[1], Jing Lu[2], Jianxin Chang[2], Xiaoxue Zang[2], Yanan Niu[2], Yang Song[2], Fuli Feng[1]
[1]University of Science and Technology of China, Hefei, China [2]Kuaishou Technology, Beijing, China
baiyimeng@mail.ustc.edu.cn, zy2015@mail.ustc.edu.cn

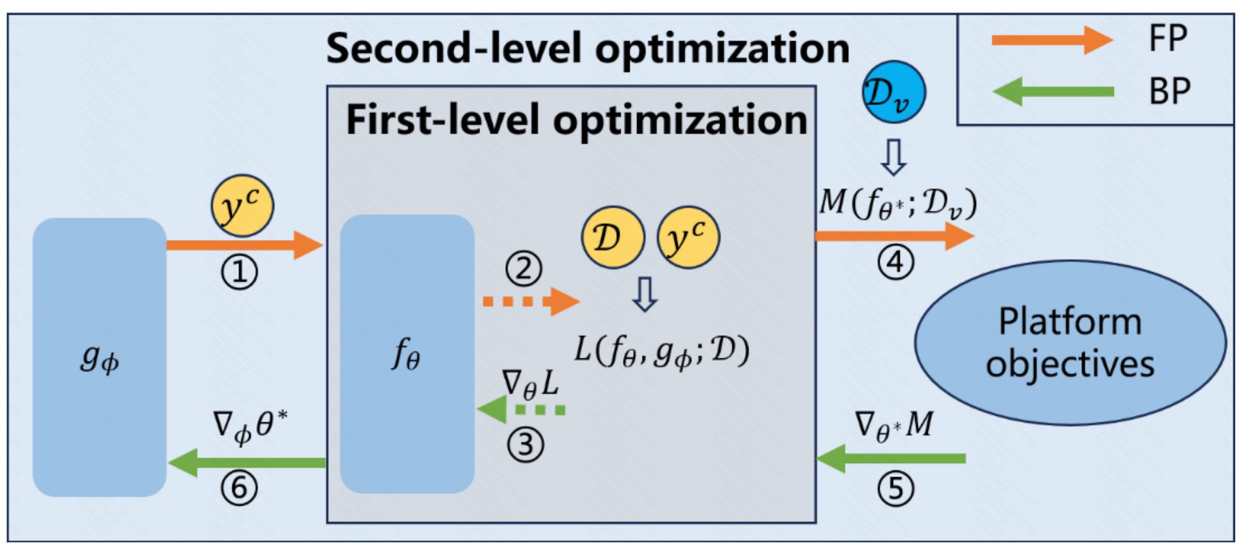
Short video recommendations often face limitations due to the quality of user feedback, which may not accurately depict user interests. To tackle this challenge, a new task has emerged: generating more dependable labels from original feedback. Existing label generation methods rely on manual rules, demanding substantial human effort and potentially misaligning with the desired objectives of the platform. To transcend these constraints, we introduce *LabelCraft*, a novel automated label generation method explicitly optimizing pivotal operational metrics for platform success. By formulating label generation as a higher-level optimization problem above recommender model optimization, LabelCraft introduces a trainable labeling model for automatic label mechanism modeling. Through meta-learning techniques, LabelCraft effectively addresses the bi-level optimization hurdle posed by the recommender and labeling models, enabling the automatic acquisition of intricate label generation mechanisms. Extensive experiments on real-world datasets corroborate LabelCraft's excellence across varied operational metrics, encompassing usage time, user engagement, and retention. Codes are available at https://github.com/baiyimeng/LabelCraft.

Introduction



- The task of **label generation** from user feedback is crucial for building effective short video recommender systems due to the unreliability of raw feedback.
- Previous research in short video recommendations has mainly relied on rule-based strategies for label generation, which require significant **manual effort** and may **not consistently align** with operational metrics.
- We pursue **automated label crafting** by reframing it as an optimization problem aligned with platform objectives, enabling a learning-based approach that eliminates manual creation of labeling rules and considers more factors.
- In this work, we propose **LabelCraft**, an automated label generation approach that optimizes multiple platform objectives through a **trainable labeling model**. By formulating the learning process as a **bi-level optimization** problem and employing **meta-learning** techniques, LabelCraft leads to the acquisition of increasingly sophisticated mechanisms for label generation.
- We validate its effectiveness on real-world datasets, consistently achieving favorable outcomes in terms of **user usage time**, **engagement**, and **retention**.

Methodlogy



Bi-level Optimization

$$\max_{\phi} M(f_{\theta^*}; \mathcal{D}_v) \Longrightarrow \text{Align with platform objectives}$$

$$s.t. \quad \theta^* = \arg\min_{\theta} L(f_\theta, g_\phi; \mathcal{D}), \Longrightarrow \text{Fit generated labels}$$

Recommender model *Labeling model*

Learning Strategy

Algorithm 1: Training of LabelCraft

Input: Recommender model f_θ, labeling model g_ϕ, training dataset $\mathcal{D}$, hold-out dataset $\mathcal{D}_v$, recommender learning rate η_1 for f_θ, and learning rate η_2 for g_ϕ.

Initialize ϕ and θ randomly;
while *Stop condition is not reached* **do**
  // Step 1 (update of ϕ);
  Compute θ' with $\theta' = \theta - \eta_1 \nabla_\theta L(f_\theta, g_\phi; \mathcal{D})$,
  Update ϕ according to $\phi \leftarrow \phi + \eta_2 \nabla_\phi M(f_{\theta'}; \mathcal{D}_v)$,
  // Step 2 (update of θ);
  Update θ according to Equation $\theta \leftarrow \theta - \eta_1 \nabla_\theta L(f_\theta, g_\phi; \mathcal{D})$,
end
return f_θ, g_ϕ

Meta learning

Platform Objectives

From *SOFT* top-k operator

$$M_1(f_\theta; \mathcal{D}_v) = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \sum_{(x,y) \in \mathcal{D}_v^u} \frac{\boxed{\alpha_{u,x}}}{k} scale(y_w),$$

$$M_2(f_\theta; \mathcal{D}_v) = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \sum_{(x,y) \in \mathcal{D}_v^u} \frac{\boxed{\alpha_{u,x}}}{k} \delta(sum(\boldsymbol{y}_e)),$$

$$M_3(f_\theta; \mathcal{D}_v) = \frac{1}{|\mathcal{U}|} \sum_{u \in \mathcal{U}} \left(\sum_{(x,y) \in \mathcal{D}_v^u} \frac{\boxed{\alpha_{u,x}}}{k} (scale(x_d) - E_{w,k})^2 \right)^{-1/2}$$

Evaluate alignment to platform objectives by **top-k list metrics**

Scaling scheme

$$scale(y_w) = \begin{cases} \frac{y_w}{w_\beta}\beta', & \text{if } 0 \le y_w \le w_\beta, \\ 1 - (1-\beta')\frac{w_{max} - y_w}{w_{max} - w_\beta}, & \text{else} \end{cases}$$

Dynamic balancing

$$M(f_\theta; \mathcal{D}_v) = \sum_{i=1}^{3} softmax(-\tau M_i(f_\theta; \mathcal{D}_v)) \cdot M_i(f_\theta; \mathcal{D}_v),$$

Experiment

- Dataset: Kuaishou, Wechat
- Baselines:
  - Direct: WT, EF
  - Manual: PC, PCR, D2Q, DVR
  - Multi-task: WT+EF, D2Q+EF, DVR+EF
- Feedback:
  - watch time
  - explicit feedback(like follow comment)
- Evaluation metrics (from NDCG@k):

$$\text{NWTG@}k = \frac{\text{WTG@}k}{\text{WTG}'\text{@}k}, \quad \text{WTG@}k = \sum_{i=1}^{k} \frac{y_w^i}{\log_2(i+1)}, \quad \text{NEG@}k = \frac{\text{EG@}k}{\text{EG}'\text{@}k}, \quad \text{EG@}k = \sum_{i=1}^{k} \frac{\delta(sum(\boldsymbol{y}_e^i))}{\log_2(i+1)},$$

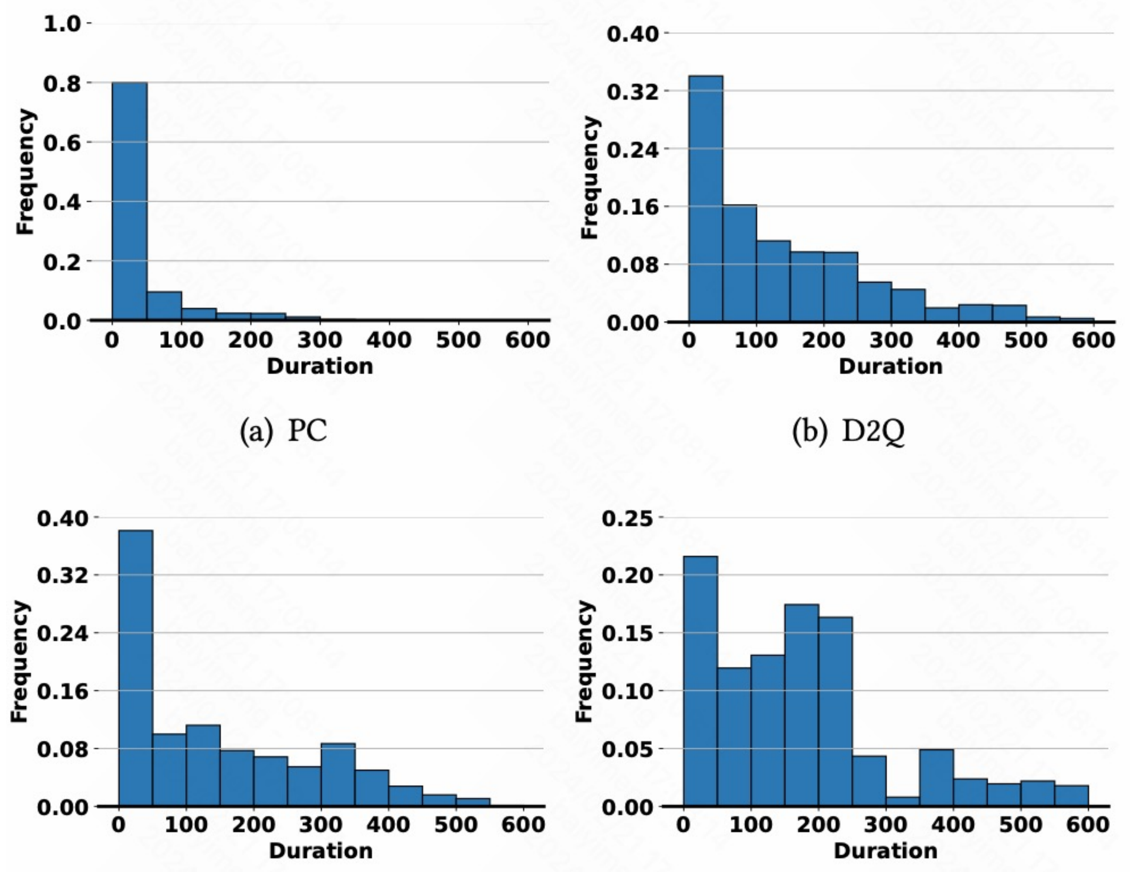
- **Performance comparison**

Method	Kuaishou					
	NWTG@10	RI	DS@10	RI	NEG@10	RI
PC	0.2121	41.6%	15	792.1%	0.7902	3.3%
PCR	0.2493	20.5%	67	105.9%	0.8005	2.0%
WT	0.2939	2.2%	113	21.6%	0.7991	2.2%
D2Q	0.2722	10.4%	122	12.4%	0.7949	2.7%
DVR	0.2814	6.7%	135	1.8%	0.7866	3.8%
EF	0.2557	17.5%	113	21.2%	0.8097	0.8%
WT+EF	0.2631	14.2%	119	15.5%	0.8000	2.1%
D2Q+EF	0.2800	7.3%	111	23.4%	0.7896	3.4%
DVR+EF	0.2876	4.4%	124	10.9%	0.7862	3.9%
LabelCraft	**0.3003**	-	**137**	-	**0.8165**	-

Method	Wechat					
	NWTG@10	RI	DS@10	RI	NEG@10	RI
PC	0.4563	39.0%	10	134.4%	0.7776	7.2%
PCR	0.4125	53.8%	12	100.3%	0.8109	2.8%
WT	0.4972	27.6%	15	58.7%	0.8201	1.7%
D2Q	0.6202	2.3%	23	6.8%	0.8191	1.8%
DVR	0.5300	19.7%	18	32.2%	0.8219	1.4%
EF	0.4593	38.1%	15	65.6%	0.8261	0.9%
WT+EF	0.5195	22.1%	21	17.4%	0.8205	1.6%
D2Q+EF	0.5790	9.5%	22	12.8%	0.8197	1.7%
DVR+EF	0.5698	11.3%	22	11.0%	0.8232	1.3%
LabelCraft	**0.6343**	-	**24**	-	**0.8338**	-

- LabelCraft consistently exhibits superior performance compared to the baselines across all evaluated aspects.
- This consistent superiority emphasizes the remarkable alignment between the labels generated by LabelCraft and the multi-aspect platform objectives.

- **Debiasing performance**



(a) PC (b) D2Q (c) DVR (d) LabelCraft

- When the platform objective is appropriately designed to be free of biases, it could guide the labeling model to generate bias-free labels.

Conclusion

- This study highlights the problem of **automatically generating reliable labels** from raw feedback in the realm of short video recommendations.
- We propose LabelCraft, an innovative framework for automated labeling that formulates the label generation process as an explicit optimization problem. By learning a labeling model **aligned with the platform objectives**, LabelCraft demonstrates promising results in generating better labels, as evidenced by comprehensive experiments conducted on real data from popular platforms.
- However, industrial scenarios often involve numerous and complex platform objectives. Hence, future work aims to develop labeling methods capable of simultaneously aligning with **more complex objectives**.
- Meanwhile, we plan to **decouple** the learning of the labeling model from the recommendation learning process to enhance the transferability of the generated labels, enabling their compatibility across diverse model types.