Leveraging Watch-time Feedback for Short-Video Recommendations: A Causal Labeling Framework

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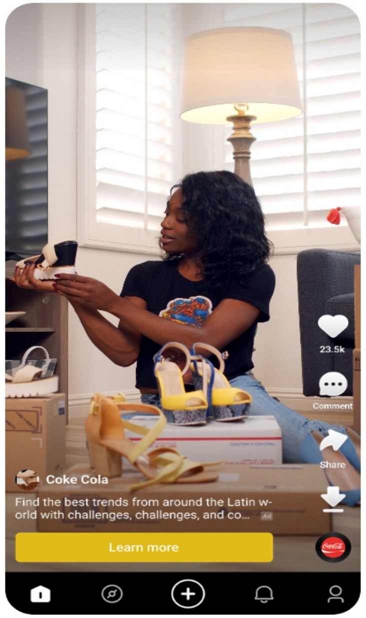
Short Video Recommendation

- Short-video content-sharing & Short-video Recommendation
  - Short-video applications, e.g., TikTok & Kuaishou **gain immense popularity**



KUAISHOU

366 million daily active users in China

Over 10 billion daily views

As well as,
Over 15 million short videos uploaded daily

Embrace All Lifestyles

  - Short video recommender system: **personalized video filtering**

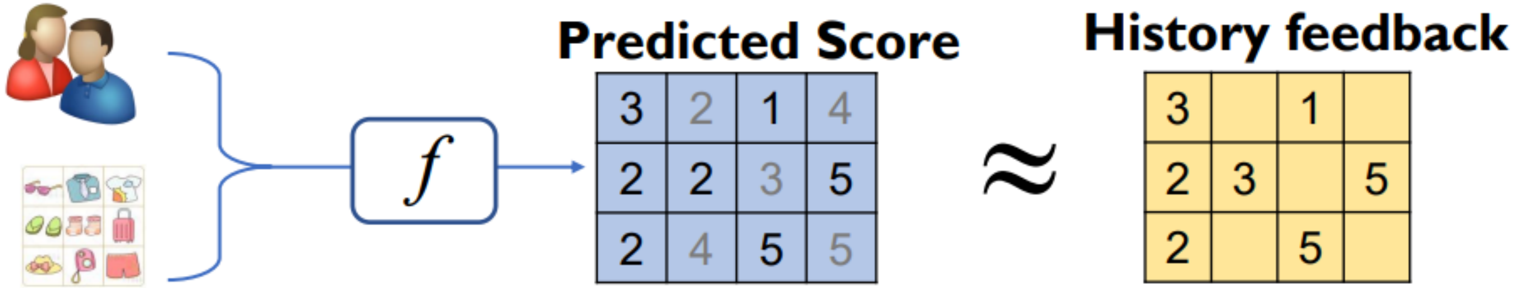
Video Ocean

Filtering
Based on history

User interested videos

Short Video Recommendation

- Recommender system
  - Fitting historical feedback data (**Click, Purchase**, ….) with a recommender model f



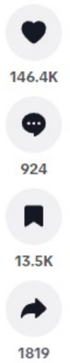
  - For video recommendation

Implicit feedback (main)

watch time

- Implicitly reflect user preference
- Existing for each interaction (**rich**)

Explicit feedback



like

comment

favorite

forward

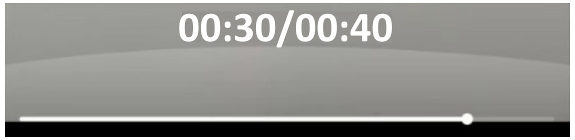
- reflect user preference explicitly
- **Limited availability!**

Labeling Short Video Recommendation

- Due to the limited availability of explicit feedback, recommender system construction highly relies on the watch time feedback
- However, **directly and merely use it as a label** is not enough to release its power:
    - #1: Watch time contains valuable semantic information:

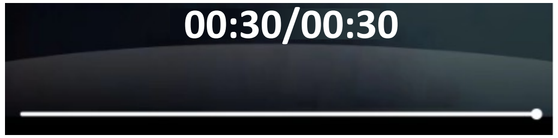
For example:

Normal watching



vs

Finish watching

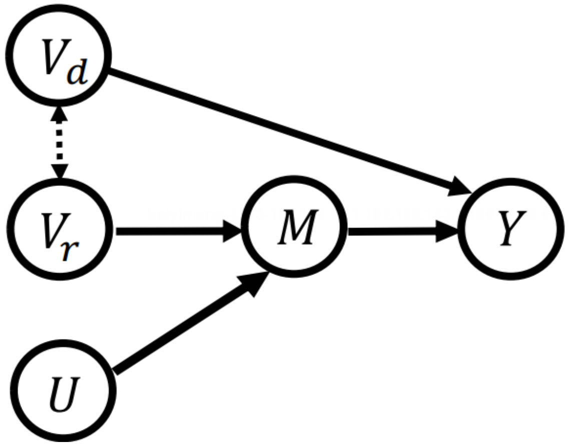


The same watch time, but the latter indicates relatively strong user preference

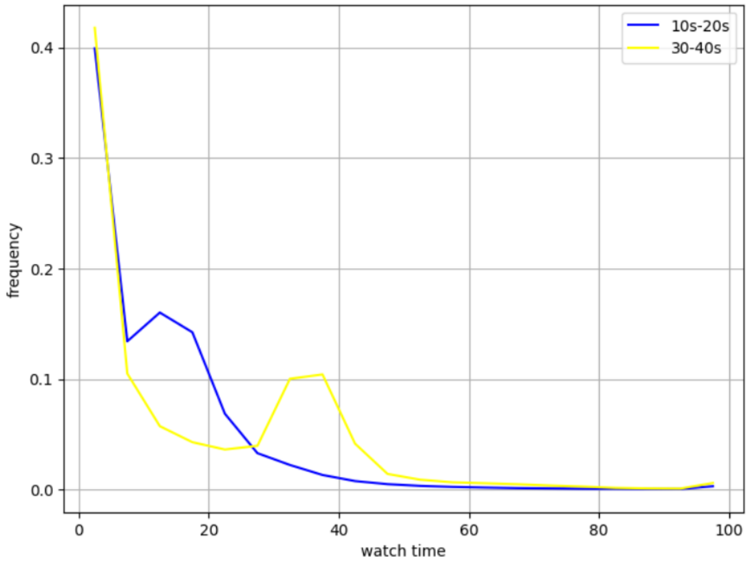
Direct labeling could not emphasize this!

Labeling in Short Video Recommendation

- However, **directly and merely use it as a label** is not enough to release its power:
  - #2: Using watch time as a direct label is susceptible to various biases, e.g., duration bias
    - Reason: watch time is not only determined by user-item matching but also video length



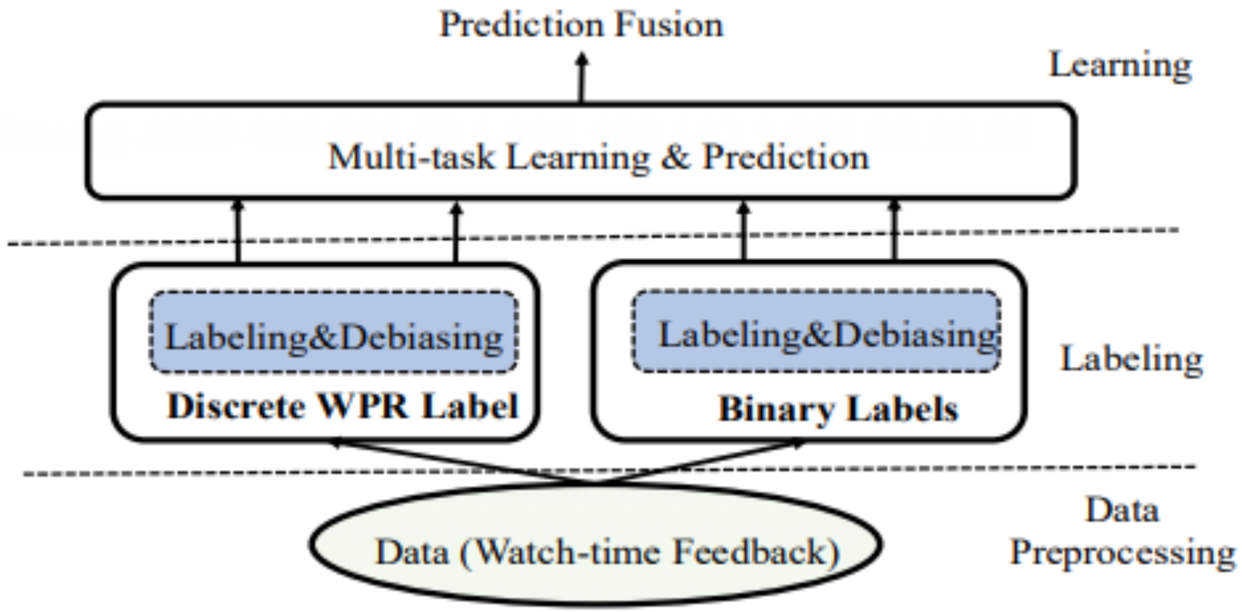
V_d: video duration
V_r: other video features
U: user
M: user-item matching
Y: watch time



This direct labeling method would lead to biased recommendation, e.g., amplifying the interest for shorter videos when using finishing playing

Debiased Multi-Semantic-Extracting Labeling Framework

- Our solution: **Debiased Multi-Semantic-Extracting** Labeling (**DML**) Framework
  - **Step 1(For chagllenge#1)**: convert watch-time to multiple labels, including
    - **Watch-time Percentile Rank labels**: for modeling watching time information
    - **Binary Playback progress-related labels**: modeling the playback-progress related information



- **For changllenge#2**: Causality-inspired Label debiasing:
  - Refine the converted labels for debiasing
  - Fully pre-processing, without modifying the modifying the model architecture and learning strategies

Debiased Multi-Semantic-Extracting Labeling Framework

- Watch-time Percentile Rank (WPR)
  - Watch time itself serves as a natural indicator, but it exhibits a **substantial range** and a **long-tail distribution**:

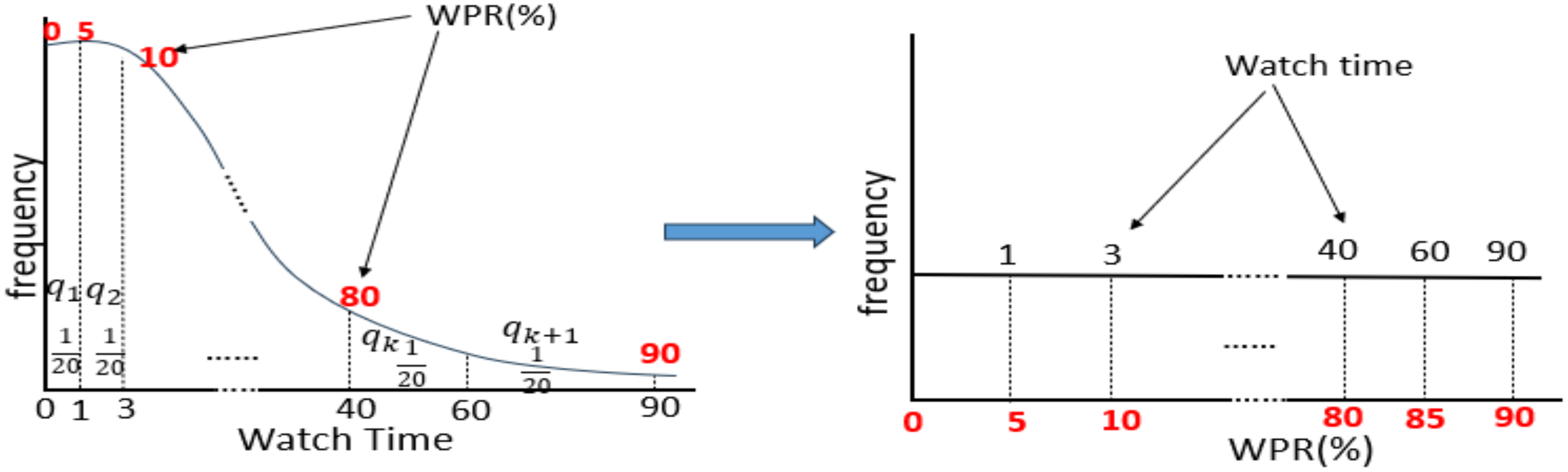
    E.g, in our scernarios, majority < 120 seconds, but certain outliers beyond an hour (repetitive playback)
  - Existing work points out that percentiles (specifical quantiles) are robust to outliers
  - This drives a "Watch-time Percentile Rank" label, which is range-limited and balanced:

rank all data $\mathcal{D}$ based on watch time feedback in ascending → split the ranked data into N groups $\{\mathcal{D}_n\}_{n=1}^{N}$, making sure $q_n/|\mathcal{D}|$ → for each $(x, y) \in \mathcal{D}_n$, WPR label $y_{wpr} = \sum_{n'=1}^{\mathrm{n}} q_{n'}$

We make: sure $\boldsymbol{q_1 \geq \cdots \geq q_N}$

Debiased Multi-Semantic-Extracting Labeling Framework

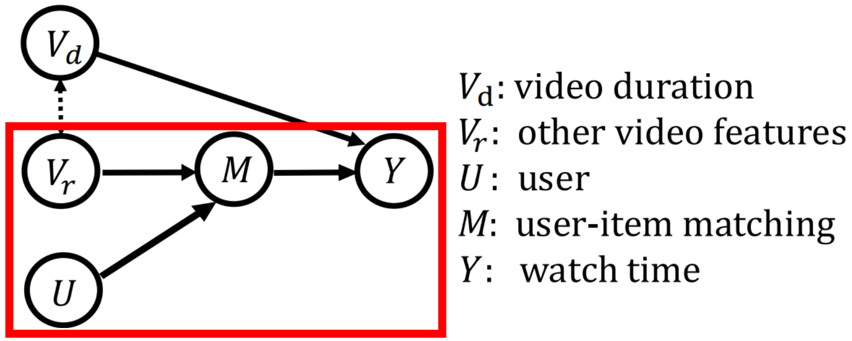
- Watch-time Percentile Rank (WPR)
  - Example: $q_1 = q_2 = \cdots = q_n$



  - When enforce $q_1 \geq \cdots \geq q_N$, becoming fine-grained imbalance, coarse-grained balance

Debiased Multi-Semantic-Extracting Labeling Framework

- Label debiasing for WPR
  - WPR would inherit the duration bias in watch time
  - Normal debasing: causal adjustment [1]
    - estimated preference as $\sum_{v_d \in \mathcal{V}_d} \boldsymbol{P(Y|U, V_r, v_d)} \boldsymbol{P(v_d)}$ to cut down the edge $V_d \to Y$



- **simulate the adjustment process: independently create WPR for different groups with different video durations**
  - Step1: Split samples into different groups by the video duration (Within each group, biased factors have an equal impact on all videos within the group)
  - Step2: Perform WPR generation process for each group ($\mathcal{D}^{v_d}$) ($\boldsymbol{M_2}$) (Among groups, similar label distributions, indicating similar influence.)

approximate the elimination of the impact of video duration on the label

He et al. Addressing Confounding Feature Issue for Causal Recommendation. TOIS 2023.

Debiased Multi-Semantic-Extracting Labeling Framework

- **Binary Labels**
  - Labels to represent different levels of playback progress beyond finishing view:
    - **Effective View:** $y_{ev} = \mathbb{I}(y \geq t_{50}(\mathcal{D}))$ (if the watch time on a video exceeds that of 50% of training example)
    - **Long View:** $y_{lv} = \mathbb{I}(y \geq t_{75}(\mathcal{D}))$(similar to effective view, 75% of training example)
- Debiasing for binary labels:
  - Duration Bias:
    - split groups by the **video duration ($\mathcal{D}^{v_d}$)**
    - $y_{ev}^{d} = \mathbb{I}(y \geq t_{50}(\mathcal{D}^{v_d}))$
  - Other biases: user-side/item-side factors play a similar causal role to the video duration, bringing bias

Split samples into groups by users ($\boldsymbol{D_u}$) | Split samples into different groups by items($\boldsymbol{D_i}$)

debiasing: $y_{ev}^{u} = \mathbb{I}(y \geq t_{50}(\mathcal{D}^{u}))$ 

item side: $y_{ev}^{v} = \mathbb{I}(y \geq t_{50}(\mathcal{D}^{v}))$ 

Experiments

- Dataset
  - Industrial data from Kuaishou

Data	Field	Size
Daily Log Info	Users	345.5 million
	Videos	45.1 million
	Samples	46.2 billion
	Average User Actions	133.7 / day
Historical Behaviors	Average User Behaviors	14.5 thousand
	Max User Behaviors	100 thousand

- Baselines
  - TR: traditional regression method using watch time as the label directly
  - WLR: Youtube Weighted Logistic Regression
  - OR: using ordinal regression to fit watch time
  - D2Q: using backdoor adjustment to address duration bias

All baselines are implemented on Kuaishou's multi-task learning framework, which means that there are other task like predicting "follows"

Experiments

- Offline evaluation (Watch time prediction)

Methods	AUC↑	GAUC↑	MAE↓	MAPE↓	RMSE↓
TR	0.6597	0.6397	24.1743	3.6892	45.4747
WLR	0.6711	0.6551	23.5743	3.1528	43.3776
OR	0.6727	0.6474	22.8930	3.5017	44.3891
D2Q	0.6732	0.6581	22.6728	2.7342	45.5293
DML	**0.6763**	**0.6617**	**21.7657**	**2.6039**	**42.7735**

  - DML outperforms all baselines on all metrics
  - D2Q outperforms other baselines in most of the metrics
  - TR exhibits the worst performance among all compared methods

- Online experiments:

Business Scenarios	Featured-Video Tab		Slide Tab	
	WT	AU	WT	AU
WLR	-	-	-	-
D2Q	+0.273%	+0.114%	+0.358%	+0.135%
DML(y_{wpr})	+0.694%	+0.207%	+0.648%	+0.228%
DML(y^d_{wpr})	+1.048%	+0.332%	+1.080%	+0.412%
DML(y^d_{wpr},$\{y^d_{ev}, y^v_{ev}, y^u_{ev}\}$)	+2.230%	+0.773%	+2.057%	+0.709%
DML(y^d_{wpr},$\{y^d_{lv}, y^v_{lv}, y^u_{lv}\}$)	+1.549%	+0.566%	+1.284%	+0.555%

Conclusion

- Debiased Multi-Semantic-Extracting Labeling Framework
  - Multi labels to release rich semantics in watch time
  - Causality-inspired debiasing at label level
  - Deployed in Kuaishou
- Focus on label re-definition and debiasing for recommendation
- Future work
  - Automating Label Definition
  - Make the generated labels better align with the platform goals
    - A paper about our preliminary attempt was accepted by WSDM 2024 and will be published to arxiv in the near future.

    LabelCraft: Empowering Short Video Recommendations with Automated Label Crafting

THANKS!