Dual Learning Algorithm for Delayed Conversions

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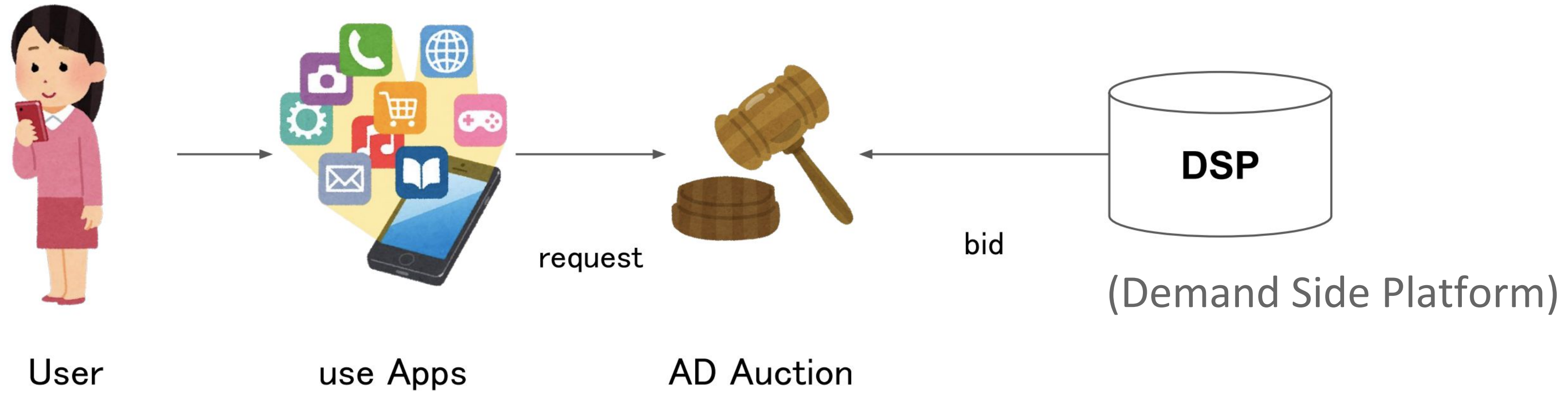
AI Lab

CVR prediction in Real-Time Bidding (RTB)

- In online advertising, DSP participates in ad auction to obtain ad impression
- **The optimal bid price in the auction is user's conversion rate (auction theory result)**



The ideal loss function in predicting CVR

To predict CVR, one wants to minimize the following **ideal loss function**

$$\mathcal{L}_{ideal}^{CVR}(f) = \mathbb{E}_{(X,Y)}\left[\underline{Y}\,\delta^{(1)}(f(X)) + (1-\underline{Y})\,\delta^{(0)}(f(X))\right]$$

True Conversion Label

The ideal loss function in predicting CVR

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CVR Predictor

(machine learning)

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(local) loss functions

example) cross-entropy loss

$$\delta^{(1)}(f) = -\log(f(X)),\ \ \delta^{(0)}(f) = -\log(1-f(X))$$

The delayed feedback issue in CVR prediction

It is desirable to optimize the ideal loss function to predict CVR (empirical risk minimization; ERM)

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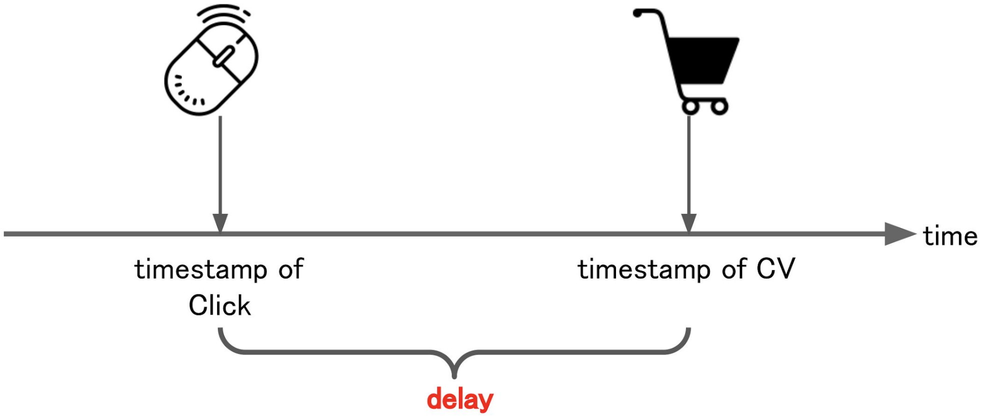
However, the delayed feedback issue emerges here



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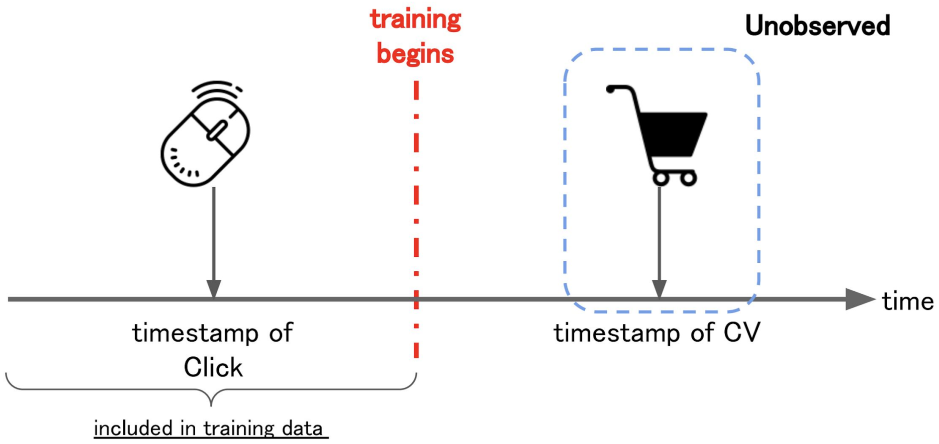
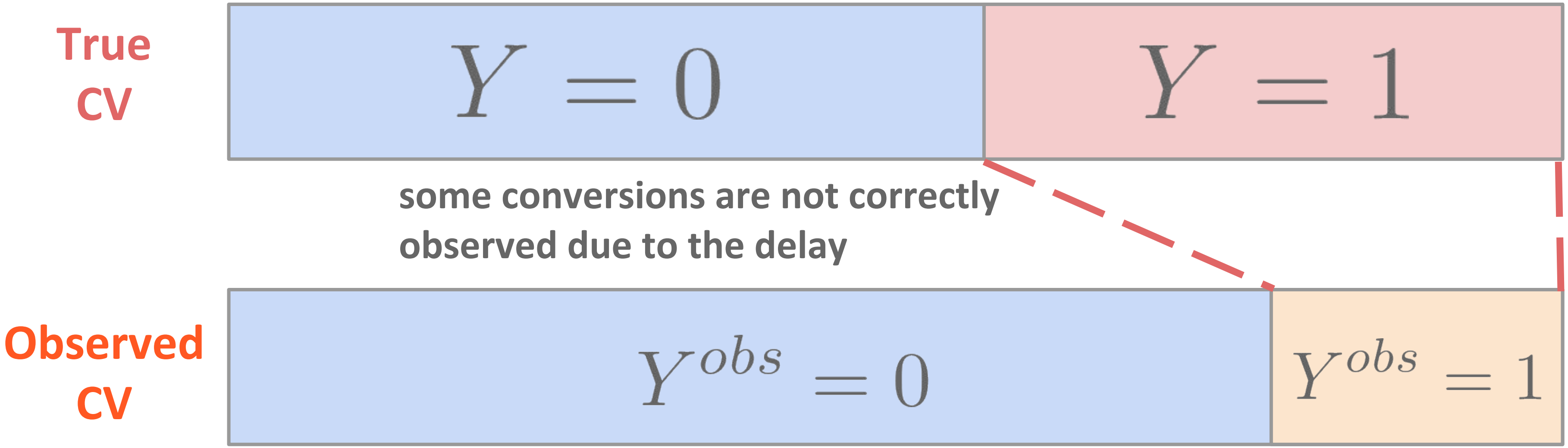


The delayed feedback issue in CVR prediction

As a result, there is a critical difference beteween

the **true conversion label** and the **observed conversion label**



Modeling Observed Conversions

To understand difficulties in modeling delayed feedback, we used the following probabilistic model

$$Y^{obs} = O_i \cdot Y_i$$

Observed Conversion Label

True Conversion Label (prediction target)

Modeling Observed Conversions

To understand difficulties in modeling delayed feedback, we used the following probabilistic model

$$Y^{obs} = O_i \cdot Y_i$$

Observation indicator:

whether the true conversion is observed or not

Challenge 1: positive-unlabeled (PU) problem

$$Y^{obs} = O_i \cdot Y_i$$

Only **positive-side feedback is observed**,

and the **negative feedback is always unobserved**

$$Y^{obs} = 0 \not\Rightarrow Y = 0$$

The unobservation of a conversion — **doesn't imply** — **The user will not convert eventually**

Challenge 2: missing-not-at-random (MNAR) problem

Some positive conversions are much more frequently observed

$$P\left(Y_i^{obs}=1 \mid X_i, E_i\right)=\underline{\theta\left(X_i, E_i\right)} \cdot \gamma\left(X_i\right)$$

not uniform among ad requests

propensity score $\theta\left(X_i, E_i\right)=P(O_i=1 \mid X_i, E_i)$

CVR $\gamma\left(X_i\right)=P(Y_i=1 \mid X_i)$

Naive Approach: Directly Imputing Observed Conversions

A simple way to predict CVR is naive direct imputation

ideal loss

$$\frac{1}{n}\sum_{i=1}^{n}\left[\underline{Y_i} \cdot \delta_i^{(1)} + (1 - \underline{Y_i}) \cdot \delta_i^{(0)}\right]$$

↓

naive loss

$$\frac{1}{n}\sum_{i=1}^{n}\left[\underline{Y_i^{obs}} \cdot \delta_i^{(1)} + (1 - \underline{Y_i^{obs}}) \cdot \delta_i^{(0)}\right]$$

Naive Approach: Directly Imputing Observed Conversions

Naive loss is biased because it ignores critical challenges

$$\underbrace{\mathbb{E}\left[\text{naive loss}\right]}_{\text{The expectation of the naive loss}} \neq \underbrace{\mathcal{L}_{ideal}(f)}_{\text{The ideal loss function}}$$

Naive loss fails to approximate the ideal loss

Existing Methods

- **Delayed Feedback Model (Chapelle. 2014)**
  - addresses PU problem by EM-like procedure
  - based on parametric assumption on delay distribution
  - does not consider missing-not-at-radodom problem

- **Importance Weighting Methods (Ketena et al., 2019)**
  - addresses MNAR problem by importance weighting
  - does not tackle the positive-unlabeled problem

Our Approach: Unbiased Estimation of Ideal Loss Function

We propose the **first unbiased estimator** combining **inverse propensity weighting** & **positive-unlabeled learning**

ideal loss

$$\frac{1}{n}\sum_{i=1}^{n}\left[\underline{Y_i}\cdot\delta_i^{(1)}+(1-\underline{Y_i})\cdot\delta_i^{(0)}\right]$$

IPS loss

$$\frac{1}{n}\sum_{i=1}^{n}\left[\frac{Y_i^{obs}}{\underline{\theta(X_i,E_i)}}\delta_i^{(1)}+\left(1-\frac{Y_i^{obs}}{\underline{\theta(X_i,E_i)}}\right)\delta_i^{(0)}\right]$$

Our Approach: Unbiased Estimation of Ideal Loss Function

We propose the **first unbiased estimator** combining

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$$\frac{1}{n}\sum_{i=1}^{n}\left[\frac{Y_i^{obs}}{\theta(X_i, E_i)}\delta_i^{(1)} + \left(1 - \frac{Y_i^{obs}}{\theta(X_i, E_i)}\right)\delta_i^{(0)}\right]$$

The basic idea:

upweight conversions having fewer chances to be observed

Our Approach: Unbiased Estimation of Ideal Loss Function

This estimator is proven to be **theoretically unbiased for the ideal loss function**

$$\mathbb{E}[\ \mathrm{IPS\ loss}] = \mathcal{L}_{ideal}(f)$$

The proposed loss function | **The ideal loss function**

The IPS loss successfully approximates the ideal loss

Our Approach: Unbiased Estimation of Ideal Loss Function

This estimator is proven to be **theoretically unbiased for the ideal loss function**

$$\frac{1}{n}\sum_{i=1}^{n}\left[\frac{Y_i^{obs}}{\theta(X_i, E_i)}\delta_i^{(1)} + \left(1 - \frac{Y_i^{obs}}{\theta(X_i, E_i)}\right)\delta_i^{(0)}\right]$$

But, how to estimate the propensity score from data?

Our Approach: Unbiased Estimation of Ideal Loss Function

We can follow the same logic to estimate propensity score with a theoretical garuntee

ideal loss for propensity estimation

$$\frac{1}{n}\sum_{i=1}^{n}\left[O_i \cdot \delta_i^{(1)} + (1 - O_i) \cdot \delta_i^{(0)}\right]$$

ICVR loss

$$\frac{1}{n}\sum_{i=1}^{n}\left[\frac{Y_i^{obs}}{\gamma(X_i)}\delta_i^{(1)} + \left(1 - \frac{Y_i^{obs}}{\gamma(X_i)}\right)\delta_i^{(0)}\right]$$

Our algorithm: Dual Learning Algorithm for Delayed Feedback

Update CVR predictor (f) based on the IPS loss

$$\frac{1}{n}\sum_{i=1}^{n}\left[\frac{Y_i^{obs}}{g(X_i, E_i)}\delta_i^{(1)} + \left(1 - \frac{Y_i^{obs}}{g(X_i, E_i)}\right)\delta_i^{(0)}\right]$$

Update propensity estimator (g) based on the ICVR loss

$$\frac{1}{n}\sum_{i=1}^{n}\left[\frac{Y_i^{obs}}{f(X_i)}\delta_i^{(1)} + \left(1 - \frac{Y_i^{obs}}{f(X_i)}\right)\delta_i^{(0)}\right]$$

Experiment: Setups

We generated a synthetic dataset:

- 100,000 samples and 30 features
- follows our probabilistic model on delayed feedback
- different delay distributions: exponential or normal

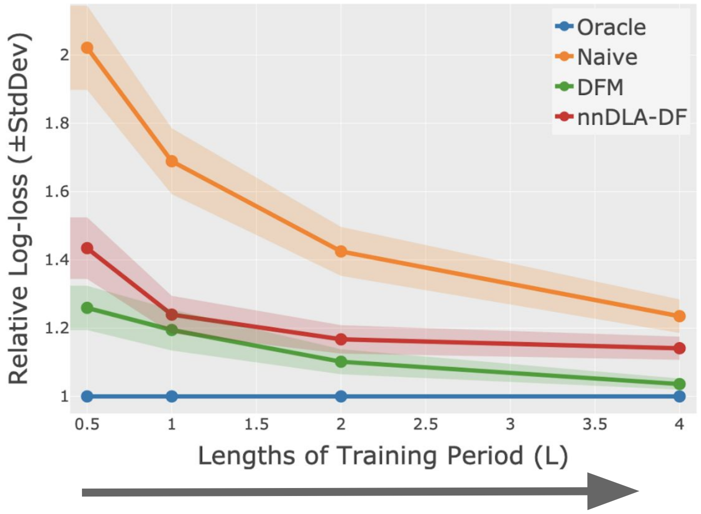
We tested the following methods:

Naive, DFM (Chappelle. 2014), DLA-DF (ours), and Oracle (reference)

Experiment: Results

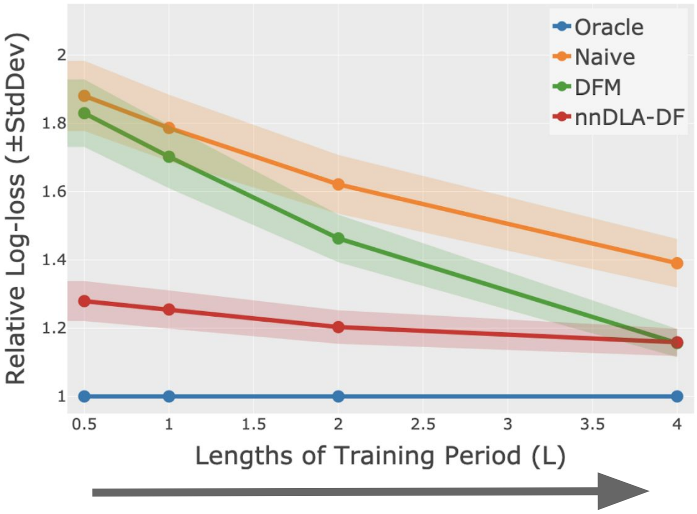
Our method (red) is robust to the delay distribution

delay distribution: **exponential**



smaller bias in log data

delay distribution: **normal**



smaller bias in log data

Conclusions

- In predicting CVR, naively using observed conversions might lead to sub-optimal predictions due to the conversion delay
- It is essential to address both positive-unlabeled and missing-not-at-random problems
- We proposed dual learning algorithm that simultaneously addresses the challenges with theoretical guarantees

Thank you for listening!

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