Leveraging Instrumental Variables in Online Advertising Auctions: Robust Click-Through Rate Prediction

August 12, 2024

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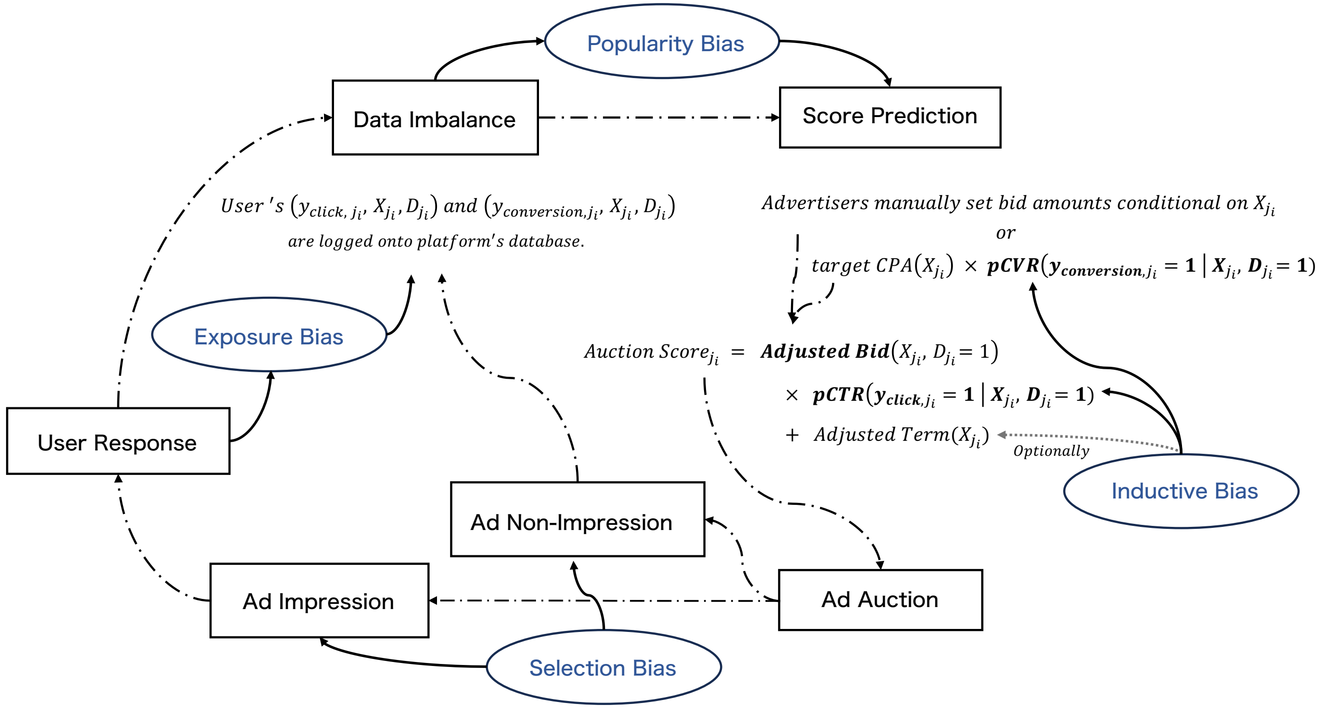
Index

Problem & Key Contributions

- In online ad auctions, selection bias remains even if the prediction of user response is unbiased.
- At the same time, the cold-start problem worsens predictions for ads with few displays.
- We identify valid instrumental variables (IVs) and adapt predictions accordingly.
- Experiments show that IVs-based prediction is especially effective in cold-start scenarios, with further improvements when considering IV heterogeneity.

Bias Loop in Online Advertising Auctions

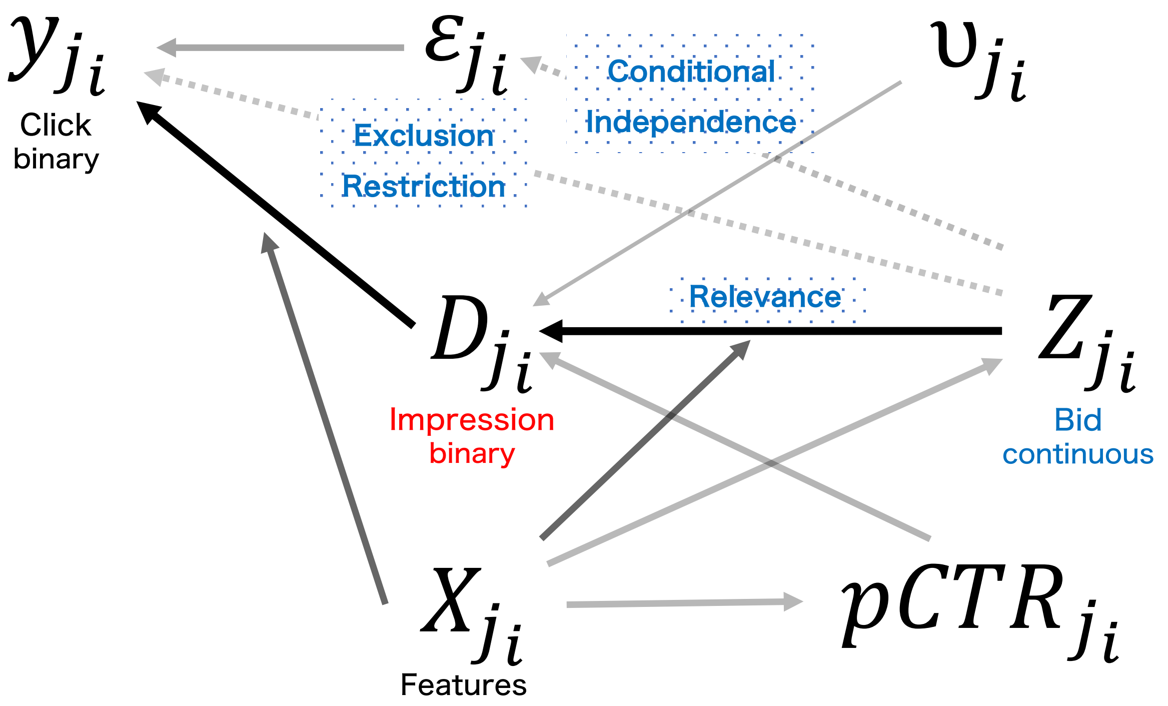
- Before finding reasonable IVs, organize the process of data generation in online ad auctions.
- It has been previously pointed out that there is a bias toward advertisements that are more likely to win impressions.
- We point out that the generation of selection bias is also attributed to a user response prediction model including omitted variable bias.



Identification of Instrumental Variables

- Advertisers set bids based on targeting, using either manual or automatic methods.
- Targeting variables ensure IVs meet conditional independence and account for user response heterogeneity.

- The relevance of IVs to display probability varies with targeting due to varying auction competition.
- Leveraging this, we test the effectiveness of our method that explicitly incorporates IV heterogeneity in experiments.



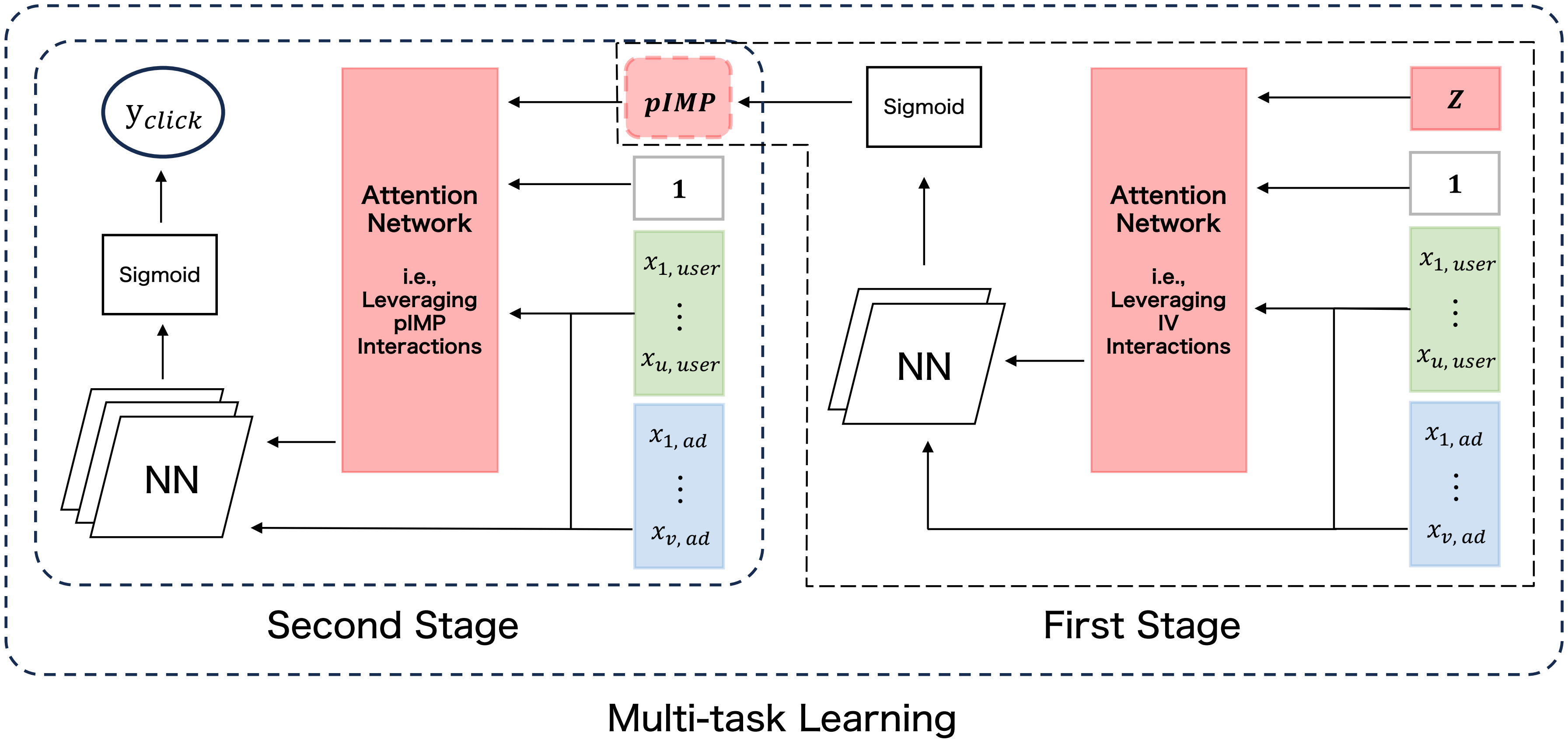
Methods – (1)

- Adopt one-way inference with multi-task learning instead of two-stage estimation with IVs. Loss function for its objectives is:

$$Loss_{pCTR} = Loss_{pCTR} \times 1_{\{D_l=1\}}$$

- We employ an attention network to test the concept of incorporating heterogeneity in IVs.
- Similarly, in the modeling of outcomes, we employ an attention network to explicitly incorporate heterogeneity in treatment effects.

Methods – (2)



y_{click}
Sigmoid
NN
Attention Network
i.e., Leveraging pIMP Interactions
$pIMP$
1
$x_{1,\,user}$
$x_{u,\,user}$
$x_{1,\,ad}$
$x_{v,\,ad}$
Sigmoid
NN
Attention Network
i.e., Leveraging IV Interactions
Z
1
$x_{1,\,user}$
$x_{u,\,user}$
$x_{1,\,ad}$
$x_{v,\,ad}$
Second Stage
First Stage
Multi-task Learning

Experiments - Simulation

- Ablation study:
  - In simulation: Naïve, IV-BS, UB-IPS
  - In real datasets: Naïve, IV-BS, IV-FS, IV-SSFS, UB-IPS

- In simulation datasets:
  - For training: confounded displayed datasets including 5,000 records
  - For validation: independently displayed data including 50,000 records
  - Evaluated at each quantiles of extent of confoundedness

Experiments - Real Datasets & Evaluation Scores

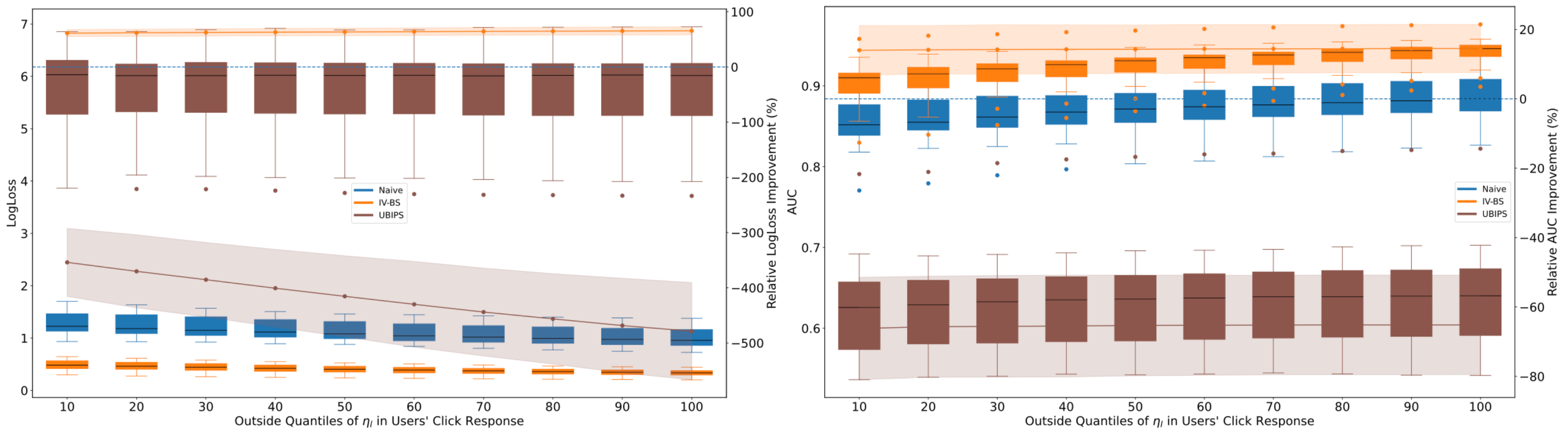
- In real datasets:
  - For training: 7 days period data including 50,000 records
  - For validation: a day after the training days including 2 million records, advertising of which is independently displayed.
  - Evaluated at each quantiles of ads' previous displayed number.

- Evaluation scores:

$$\text{Relative LogLoss} = \frac{\text{Naive LogLoss} - \text{Compared LogLoss}}{\text{Naive LogLoss}} \times 100,$$

$$\text{Relative AUC} = \left(\frac{\text{Compared AUC} - 0.5}{\text{Naive AUC} - 0.5} - 1\right) \times 100.$$

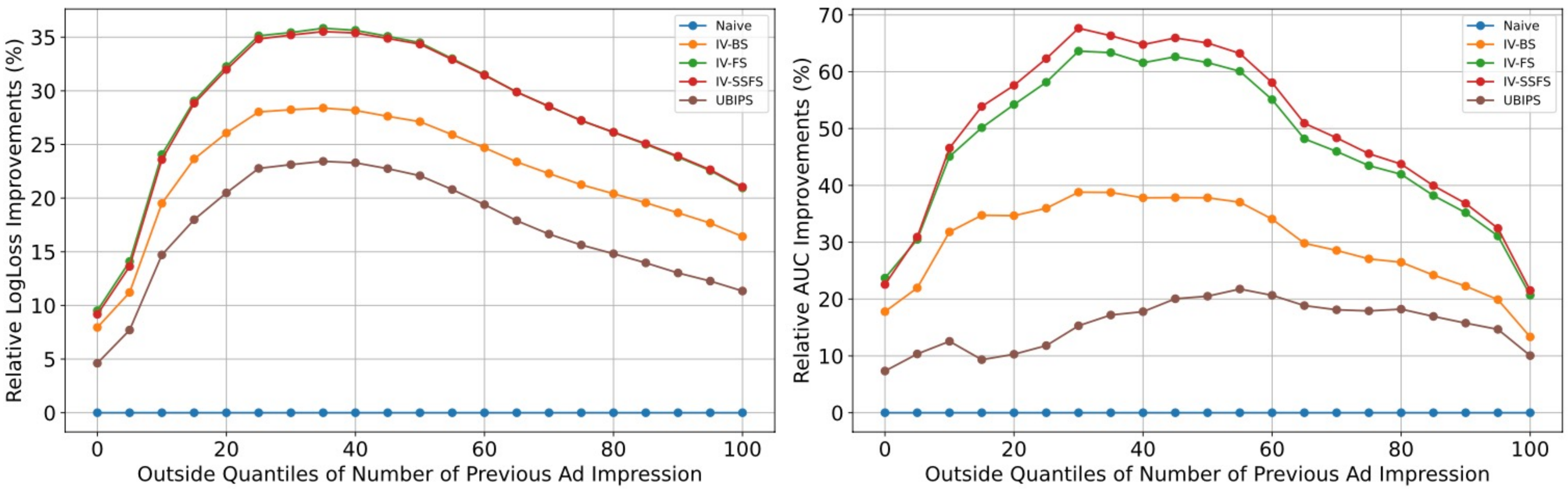
Results - Simulation



(a) LogLoss & Relative LogLoss **(b) AUC & Relative AUC**

Figure 4: Simulation: Performance scores at each outside quantile of η_l. Box plots show actual scores. Line plots show relative scores, with the bold line as the mean and shaded area showing replication variation.

Results – Real datasets



(a) Relative LogLoss **(b) Relative AUC**

Figure 5: Real data: Performance scores at each quantile of previous ad impressions.

Conclusion

- Instrumental variables (IVs) method in online ad auctions works well in predicting user outcomes by mitigating selection bias
- IVs heterogeneity works particularly well

- Evaluation of prediction and auction mechanism in bias loops, including other exposure or popularity bias than selection bias, matter.
- Interactions with IVs using graph neural networks can be effective.