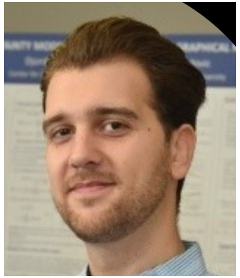
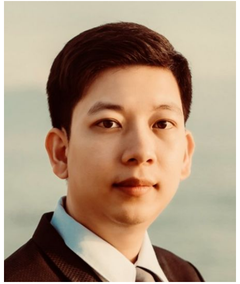
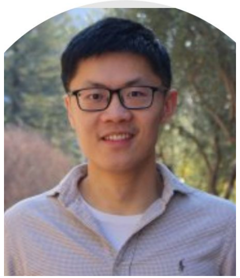
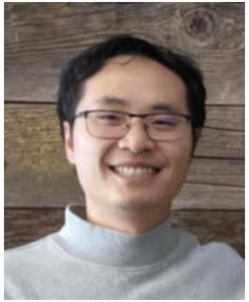
Mitigating Position Bias in Click Predictor Models:
A Novel Downsampling Approach for Enhanced Accuracy and Efficiency

AdKDD 2025 - Toronto Canada









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Outline

- Position Bias
- Existing Methods and Limitations
- New downsampling method
- Offline Experiments
- Online Experiments
- Conclusion

Position Bias

Display position affects the probability of engagement for the item. In particular,

- Top-ranked items are much more likely to be clicked/purchased
- Higher trust for the top ranked items
- People lost patience after scrolling for a while, leading to lower PTR/CTR of lower ranked items even if they might be relevant.

Image source: https://research.google/pubs/pub34378/ [1]

Let k be the position, d be the document (i.e. item) and q be the query.

$$\underbrace{P(C=1 \mid k,d,q)}_{\substack{\text{Probability of Engagement} \\ \Uparrow \\ \text{CTR of item d at position k}}} = \underbrace{P(E=1 \mid k,q)}_{\substack{\text{Probability of Item Seen} \\ \Uparrow \\ \text{Position-k CTR}}} \cdot \underbrace{P(R=1 \mid d,q)}_{\substack{\text{Probability of Item is Relevant} \\ \Uparrow \\ \text{Position-1 CTR of item d}}}$$

Existing Methods: Limitations

Methods

- Model(position_k, query, items, contexts) = click_value_at_position_k
- Model(position_k_prior, query, items, contexts) = click_value_at_position_k
- Model_position_bias(position_k)*Model(query, items, contexts) = click_value_at_position_k
- Impression weightings and Loss Modification
- Etc.
- Inverse propensity model

Limits

- Using all data points ⇒ Sampling if large datasets ⇒ Downsampling ⇒ Loss of information
- Position bias issue still exists
- Heavy training process

New Downsampling Method

- Ob 1: Position-1 - (almost) no position bias issue
- Ob 2: Position Bias ⇒ CTRs of positions are different
- Ob 3: CTRs of Slots are roughly equal if good Ads/ Items are randomly distributed and no position bias

Example:

1. Large eCommerce platforms: many good competitors and good ads
2. Ads ranked by expected revenue, i.e. pCTR*BidValue.

- Key Idea: **filter out negative samples at lower positions to make theirs position CTRs equal to position-1 CTR**
- Advantages:

1. Smaller training dataset
2. Position bias issue is solved in simple way ⇒ No heavy training process or complex training algorithms

Offline Experiments

	AUC	Logloss	Bias
Model without any position bias methods	0.00000	0.00000	0.00000
Model with position prior	0.01349	-0.00799	-0.67149
Model with position k as a feature	0.01547	-0.00855	-0.60399
Model with downsampling dataset	0.01354	-0.00807	-0.65636
Model with downsampling dataset and position k as a feature	0.01575	-0.00859	-0.60500

Table 5: Comparative analysis of performance models.

$$\text{Bias} = \sum_{i=1}^{N} p_i / \sum_{i=1}^{N} y_i$$

where y_i is the actual label (0 or 1), p_i is the predicted probability, and N is the number of samples.

Depth	AUC	Logloss	Bias	Model Size (Mb)
05	0.000000	0.000000	0.000000	1.9
10	0.000725	-0.000010	-0.007141	24.9
15	0.002273	-0.000233	-0.007849	112.0

Table 4: Differences in performance metrics for model depths 10 and 15 compared to depth 5. The differences are calculated by subtracting the metrics of depth 5 from those of depths 10 and 15. A positive difference in AUC indicates improved performance, while a negative difference in Logloss and Bias suggests better performance.

Online Experiments

- 3-week AB test: 1-week for calibration and 2-week AB test
- 1-week for calibration because Model with position prior is **BIASED** if no calibration
- Model with position prior and Model with position as a feature are **BIASED** if no calibration.

  Reason: Algorithmic position debias may not work well with with unseen items because the do not impose any lower and upper bounds on ads' CTRs when they have no position bias issues
- Model with downsampling dataset and Model with downsampling dataset and position k as a feature are **NOT BIASED**

  Reason: We impose our own view about position CTR on each data points in training dataset, i.e. we impose a lower and upper bounds on ads' CTRs when they have no position bias issues.

AUC	Logloss	Bias	CTR	STR	GMB
+2.3%	-3.8%	+77.84%	+7.72%	+14.5%	+18.10%

Table 6: Relative Enhancement of Model with downsampling dataset and position k as a feature Compared to Model with position prior (95% Statistical Confidence)

Conclusion

- New downsampling method $\Rightarrow$ all position CTRs = position-1 CTR
- Small training dataset
- Simple training processes and algorithms
- Solving position bias issue well

Thank you very much for your intention :)

Typical Mathematical Formulation

Let k be the position, d be the document (i.e. item) and q be the query.

$$\underbrace{P(C = 1 \mid k, d, q)}_{\text{Probability of Engagement}} = \underbrace{P(E = 1 \mid k, q)}_{\text{Probability of Item Seen}} \cdot \underbrace{P(R = 1 \mid d, q)}_{\text{Probability of Item is Relevant}}$$

CTR of item d at position k

Position-k CTR

Position-1 CTR of item d