Are Neural Click Models Pointwise IPS Rankers?

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Motivation

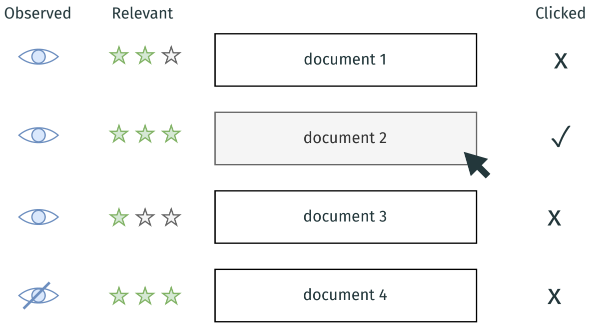
Unbiased LTR

Problem: Clicks are a biased indicator of item relevance [Craswell et al., 2008].

Unbiased LTR: Learn rankings from biased user interactions [Joachims et al., 2017].

Click biases:

- Selection bias
- **Position bias**
- Trust bias
- ...

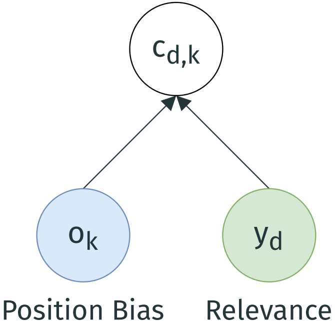


Probabilistic click models

Probabilistic click models [Chuklin et al., 2015]

- Generative models predicting biased click behavior.
- Bias and relevance are latent parameters jointly inferred using MLE.
- Pointwise rankers

Position-based Model (PBM)



Inverse-Propensity Scoring

Weight clicks to correct for position bias [Wang et al., 2016, Joachims et al., 2017].

- Decouples bias and relevance estimation.
- Generalizes over document features to require fewer observations of the same query-document pair.
- Introduced as pairwise / listwise rankers.

Two sides of the same coin?

- Same user models (PBM, Cascade).
- Introduction of neural click models that also use features [Guo et al., 2019].
- Introduction of pointwise IPS methods [Saito et al., 2020].

How do both approaches compare?

- Theoretically compare their ability for unbiased relevance estimation.
- Empirically on semi-synthetic click datasets used in ULTR.

Methods

Neural click model

Neural PBM

- Relevance of document d with features x_d: $\hat{y}_d = \sigma(g(\hat{y} \mid x_d))$.
- Position bias $\hat{o}_k$ at rank k.
- Predict clicks: $\hat{c}_{d,k} = \hat{o}_k \cdot \hat{y}_d$.

Inference using binary cross-entropy between predicted and observed clicks [Yan et al., 2022]:

$$\mathcal{L}_{\text{pbm}}(\hat{y}, \hat{o}) = -\sum_{(d,k) \in D} c_{d,k} \cdot \log(\hat{y}_d \cdot \hat{o}_k) + (1 - c_{d,k}) \cdot \log(1 - \hat{y}_d \cdot \hat{o}_k).$$

Inverse-propensity scoring

Pointwise IPS

- Relevance of document d with features x_d: $\hat{y}_d = \sigma(g(\hat{y} \mid x_d))$.

BCE loss weighting clicks inversely to the position bias [Saito et al., 2020]:

$$\mathcal{L}_{\text{ips}}(\hat{y}, \hat{o}) = -\sum_{(d,k)\in D} \frac{c_{d,k}}{\hat{o}_k} \cdot \log(\hat{y}_d) + (1 - \frac{c_{d,k}}{\hat{o}_k}) \cdot \log(1 - \hat{y}_d).$$

Comparing unbiasedness

- **IPS**: Saito et al. show that the pointwise IPS estimator is unbiased when correctly estimating position bias [Saito et al., 2020].
- **PBM with joint parameter inference**: Oosterhuis shows that click models jointly inferring bias and relevance are not always consistent estimators of document relevance [Oosterhuis, 2022].
- **PBM only inferring relevance?**

Click model only inferring relevance?

Find the ideal model that minimizes $\mathcal{L}_{\text{pbm}}$:

$$\begin{aligned}
\frac{\partial \mathcal{L}_{\text{pbm}}}{\partial \hat{y}} &= 0 \\
-\frac{c - \hat{o}\hat{y}}{\hat{y}(1 - \hat{o}\hat{y})} &= 0 \\
c - \hat{o}\hat{y} &= 0.
\end{aligned}$$

The click model also optimizes for unbiased relevance if $\forall k \in K, \hat{o}_k = o_k$

$$\hat{y} = \frac{\mathbb{E}_o\left[c\right]}{\hat{o}} = \frac{oy}{\hat{o}}.$$

Comparing loss magnitude

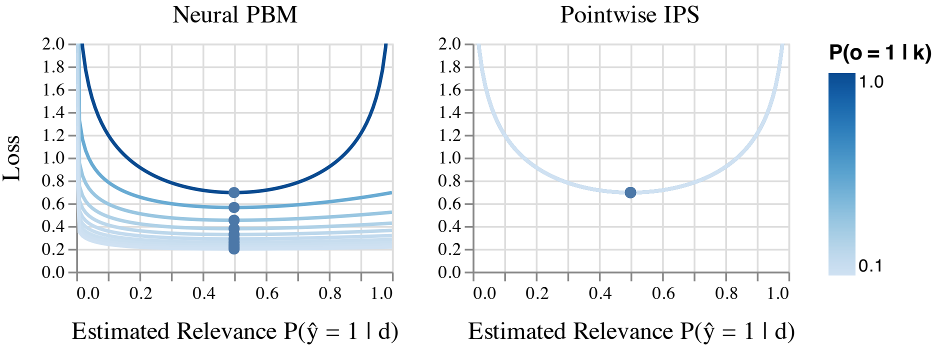


Figure 1: Loss for a single document of relevance $y_d = 0.5$ under increasing position bias.

Experiments

Experimental setup

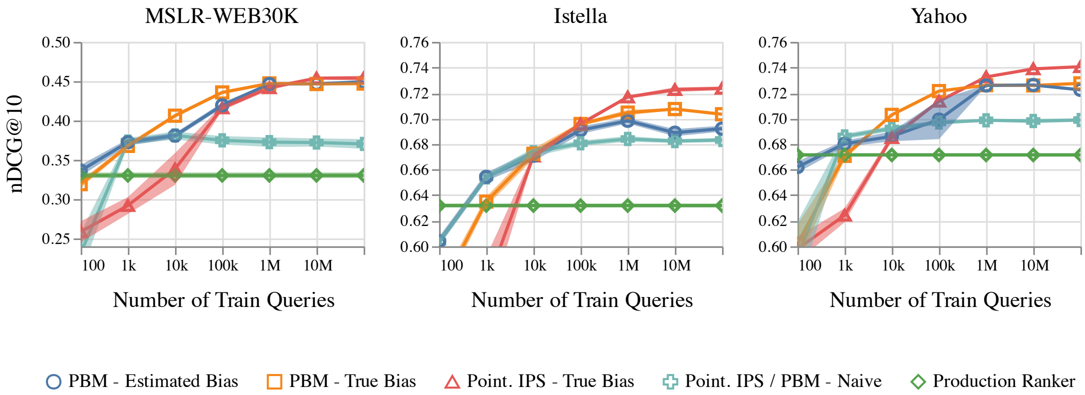
Semi-synthetic clicks on MSLR30K, Yahoo!, and Istella-S:

- Sample a query uniformly at random.
- Pre-rank documents with "production" ranker (LambdaMART, 20 train queries).
- Sample clicks using the PBM user model.

We simulate:

- **Position bias:** $o_k = (\frac{1}{1+k})^\eta$
- **Graded relevance:** $y_d = \epsilon + (1 - \epsilon) \cdot \frac{2^{s_d} - 1}{2^4 - 1}$, click noise $\epsilon = 0.1$.

Results

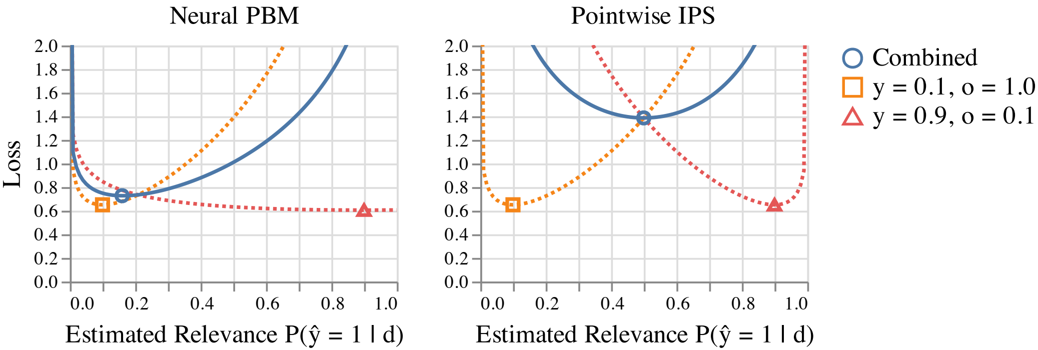


MSLR-WEB30K
Istella
Yahoo
nDCG@10
0.50
0.45
0.40
0.35
0.30
0.25
0.76
0.74
0.72
0.70
0.68
0.66
0.64
0.62
0.60
100
1k
10k
100k
1M
10M
Number of Train Queries
PBM - Estimated Bias
PBM - True Bias
Point. IPS - True Bias
Point. IPS / PBM - Naive
Production Ranker

Hypothesis I - Tuning?

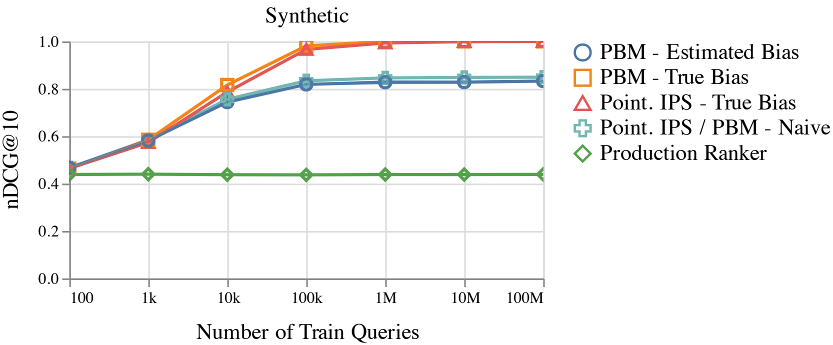
Hypothesis II - Does generalizing over features introduce bias?

Revisiting loss magnitude



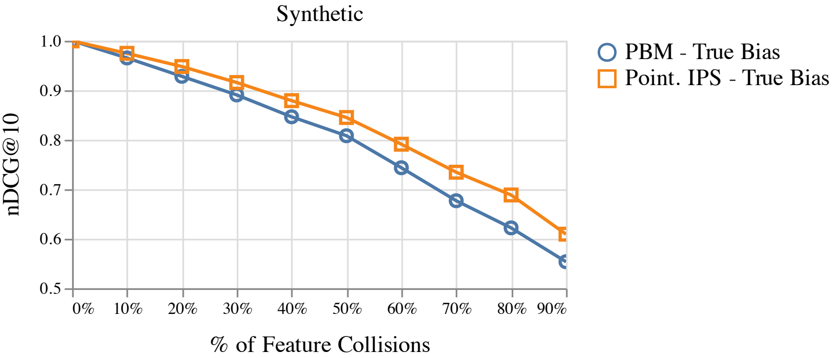
No shared features

Experiment I: One-hot encoded synthetic documents



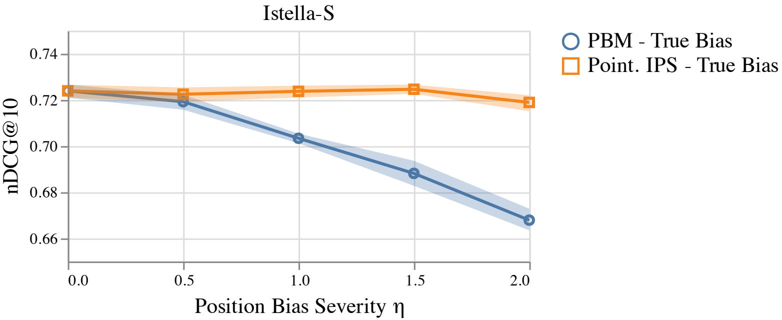
Randomly share features

Experiment II: Introduce feature collisions between synthetic documents



Mitigating known position bias

Experiment III: Increase the (known) position bias



Summary

- Both approaches optimize for unbiased document relevance **if the true position bias is known** and relevance is **estimated separately per query-document pair**.
- The neural click model seems to be **affected by (known) position bias** when generalizing over **shared, sometimes conflicting, document features**.

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https://github.com/philipphager/ultr-cm-vs-ips

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