# Optimizing a Ranking System with User Interaction Logs

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December 15, 2020

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Based on the SIGIR 2019 Tutorial:
*Unbiased Learning to Rank: Counterfactual and Online Approaches*
*Harrie Oosterhuis, Rolf Jagerman, Maarten de Rijke*

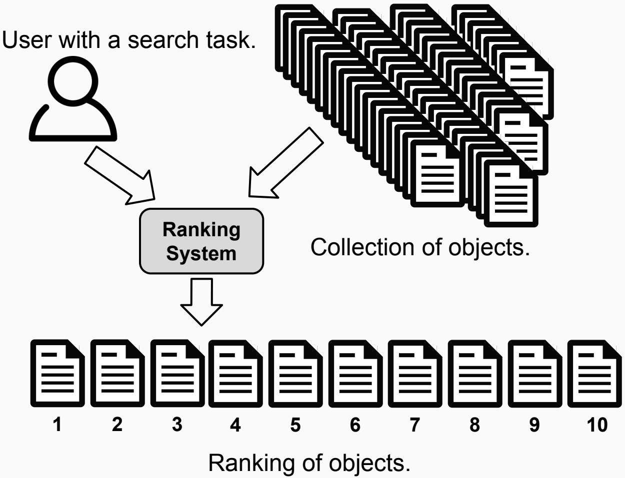
# Introduction: Ranking Systems

# Ranking Systems

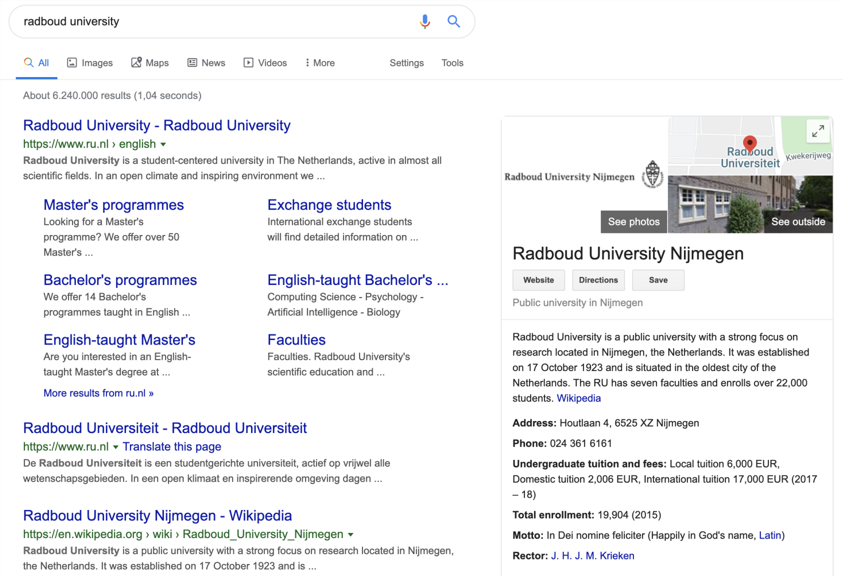
Let's go back to the beginning:

- Ranking systems are vital for **making large document collections accessible**.
- They can present users with **a small comprehensible selection** out of **millions of unordered results**.
- Search and recommendation are **practically everywhere**.

# Ranking Systems: Schematic Example



# Ranking Systems: Examples



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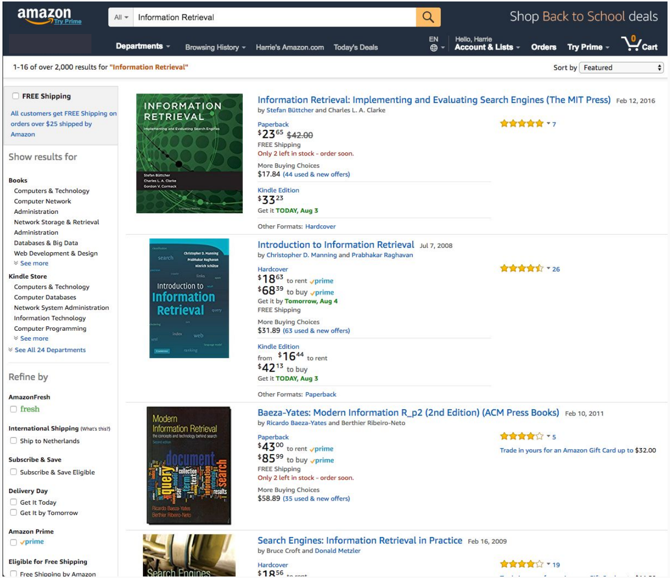

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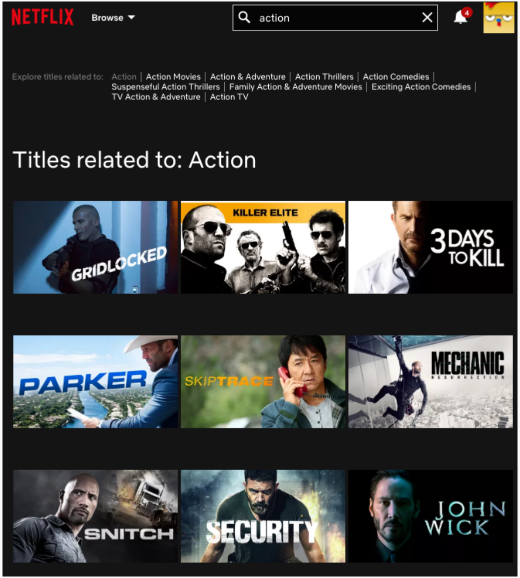
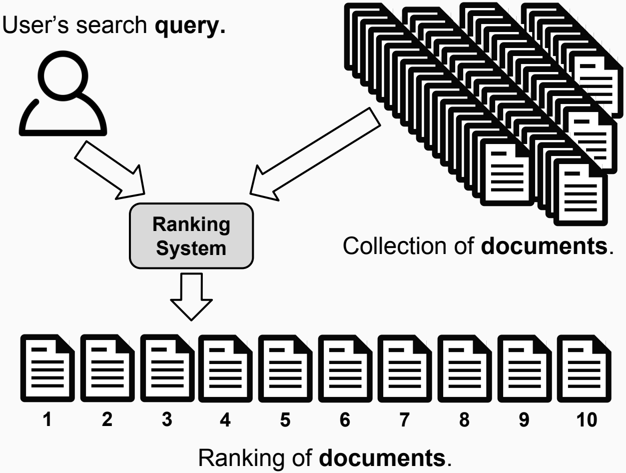


# Ranking Systems: Schematic Example Naming



# Supervised Learning to Rank

# Learning to Rank in Information Retrieval

**Learning to Rank** is a **core task** in informational retrieval:

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In **learning to rank**, we only care about the **ordering** according to $f_\theta$:

$$y(d_1) > y(d_2) \rightarrow f_\theta(d_1) > f_\theta(d_2).$$

# Supervised Learning to Rank

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## Supervised Learning to Rank

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Over the years several limitations of annotated datasets have become apparent,

**can you think of some limitations?**

# Limitations of the Annotated Datasets

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- **stationary**, cannot capture **future changes in relevancy** (Lefortier et al., 2014).
- **not necessarily aligned with actual user preferences** (Sanderson, 2010),

  i.e., annotators and users often disagree.

## Limitations of the Supervised Approach

Annotated datasets are **valuable** and have an **important place in research and development**.

However, the supervised approach is:

- **Unavailable** for practitioners without a **considerable budget**.
- **Impossible** for certain ranking problems.
- Often **misaligned** with *true* user preferences.

Therefore, there is a **need** for an **alternative** learning to rank approach.

# Learning from User Interactions

# Learning from User Interactions: Advantages

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- Interactions are **virtually free** if you have users.
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**User interactions** also bring their **own difficulties**:

- Interactions give **implicit feedback**.

## Learning from User Interactions: Difficulties

User interactions bring their **own difficulties**:

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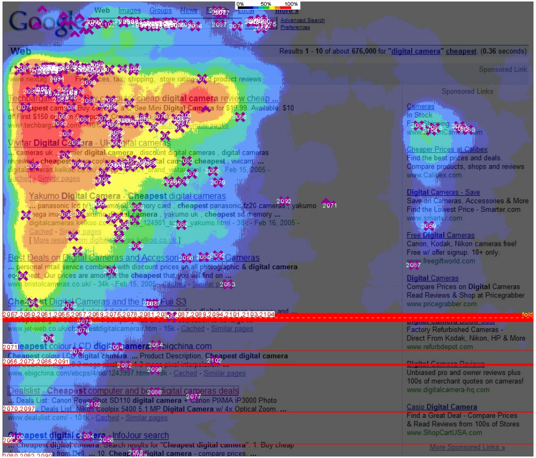
  - **Position bias: Higher ranked** documents get more attention.
  - **Item selection bias:** Interactions are **limited** to the **presented** documents.
  - **Presentation bias:** Results that are **presented differently** will be **treated differently**.
  - ...

# The Golden Triangle



# Learning from User Interactions: Goal

**Goal of unbiased learning to rank:**

- Optimize a ranker w.r.t. **relevance preferences** of users from their interactions.
- **Avoid** being **biased by other factors** that influence interactions.

# This Lecture

There are currently **two main approaches** to Unbiased Learning to Rank:

**Online Learning to Rank**

- Learning by **directly interacting with users.**
- Handle biases through **randomization of displayed results**.

**Counterfactual Learning to Rank**

- Learning from **historical interactions.**
- Use a **model of user behavior** to correct for biases.

We will discuss the latter.

# Counterfactual Evaluation

## Counterfactual Evaluation: Introduction

**Evaluation** is incredibly **important before deploying** a ranking system.

However, with the **limitations of annotated datasets**,
can we **evaluate** a ranker **without deploying** it or **annotated data**?

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However, with the **limitations of annotated datasets**,
can we **evaluate** a ranker **without deploying** it or **annotated data**?

**Counterfactual Evaluation**:
**Evaluate** a new ranking function $f_\theta$ using **historical interaction data** (e.g., clicks) collected from a previously deployed ranking function $f_{deploy}$.

## Counterfactual Evaluation: Full Information

If we **know** the **true relevance labels** ($y(d_i)$ for all $i$), we can compute any additive linearly decomposable IR metric as:

$$\Delta(f_\theta, D, y) = \sum_{d_i \in D} \lambda(\mathit{rank}(d_i \mid f_\theta, D)) \cdot y(d_i),$$

where $\lambda$ is a rank weighting function, e.g.,

$$\begin{aligned}
\text{Average Relevant Position} \quad & \mathit{ARP}: \lambda(r) = r, \\
\text{Discounted Cumulative Gain} \quad & \mathit{DCG}: \lambda(r) = \frac{1}{\log_2(1+r)}, \\
\text{Precision at } k \quad & \mathit{Prec@k}: \lambda(r) = \frac{\mathbf{1}[r \leq k]}{k}.
\end{aligned}$$

# Counterfactual Evaluation: Full Information

| | |
|---|---|
| $y(d_1) = 1$ | Document $d_1$ |
| $y(d_2) = 0$ | Document $d_2$ |
| $y(d_3) = 0$ | Document $d_3$ |
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# Counterfactual Evaluation: Partial Information

We often do not know the true relevance labels ($y(d_i)$), but can only observe implicit feedback in the form of, e.g., clicks:

- A click $c_i$ on document $d_i$ is a **biased and noisy indicator** that $d_i$ is relevant
- A missing click does **not** necessarily indicate non-relevance

# Counterfactual Evaluation: Clicks

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# Counterfactual Evaluation: Clicks

Remember that there are many reasons why a click on a document may **not** occur:

- **Relevance**: the document may not be relevant.
- **Observance**: the user may not have examined the document.
- **Miscellaneous**: various random reasons why a user may not click.

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- **Miscellaneous**: various random reasons why a user may not click.

Some of these reasons are considered to be:

- **Noise**: averaging over many clicks will remove their effect.
- **Bias**: averaging will **not** remove their effect.

# Counterfactual Evaluation: Examination User Model

If we **only** consider **examination** and **relevance**, a user click can be modelled by:

- The probability of document $d_i$ **being examined** $(o_i = 1)$ in a ranking $R$:

$$P(o_i = 1 \mid R, d_i)$$

- The probability of a **click** $c_i = 1$ on $d_i$ given its **relevance** $y(d_i)$ and whether it was **examined** $o_i$:

$$P(c_i = 1 \mid o_i, y(d_i))$$

- **Clicks only occur on examined documents**, thus the probability of a click in ranking $R$ is:

$$P(c_i = 1 \land o_i = 1 \mid y(d_i), R) = P(c_i = 1 \mid o_i = 1, y(d_i)) \cdot P(o_i = 1 \mid R, d_i)$$

# Counterfactual Evaluation: Naive Estimator

A **naive way** to estimate is to assume clicks are a unbiased relevance signal:

$$\Delta_{\mathit{NAIVE}}(f_\theta, D, c) = \sum_{d_i \in D} \lambda(\mathit{rank}(d_i \mid f_\theta, D)) \cdot c_i.$$

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Even if **no click noise** is present: $P(c_i = 1 \mid o_i = 1, y(d_i)) = y(d_i)$, this estimator is **biased** by the examination probabilities:

$$\begin{aligned}
\mathbb{E}_o[\Delta_{\mathit{NAIVE}}(f_\theta, D, c)] &= \mathbb{E}_o\Big[\sum_{d_i \in D} c_i \cdot \lambda(\mathit{rank}(d_i \mid f_\theta, D))\Big] \\
&= \mathbb{E}_o\Big[\sum_{d_i \in D} o_i \cdot y(d_i) \cdot \lambda(\mathit{rank}(d_i \mid f_\theta, D))\Big] \\
&= \sum_{d_i \in D} P(o_i = 1 \mid R, d_i) \cdot \lambda(\mathit{rank}(d_i \mid f_\theta, D)) \cdot y(d_i).
\end{aligned}$$

# Counterfactual Evaluation: Naive Estimator Bias

The biased estimator **weights documents** according to their **examination probabilities** in the ranking $R$ displayed during **logging**:

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**What effect does this have on the evaluation?**

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In rankings, **documents at higher ranks** are more likely to be examined: **position bias**.

Position bias causes **logging-policy-confirming** behavior:

- Documents displayed at **higher ranks during logging** are incorrectly considered as **more relevant**.

# Inverse Propensity Scoring

# Counterfactual Evaluation: Inverse Propensity Scoring

Counterfactual evaluation accounts for bias using **Inverse Propensity Scoring (IPS)**:

$$\Delta_{IPS}(f_\theta, D, c) = \sum_{d_i \in D} \frac{\lambda(\mathit{rank}(d_i \mid f_\theta, D))}{P(o_i = 1 \mid R, d_i)} \cdot c_i,$$

- $\lambda(\mathit{rank}(d_i \mid f_\theta, D))$: (weighted) rank of document $d_i$ by ranker $f_\theta$,
- $c_i$: observed click on the document in the log,
- $P(o_i = 1 \mid R, d_i)$: examination probability of $d_i$ in ranking $R$ displayed during logging.

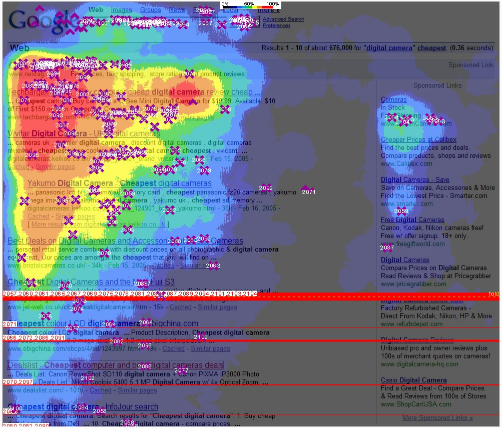
This is an **unbiased estimate** of any additive linearly decomposable IR metric.

# Counterfactual Evaluation: Proof of Unbiasedness

If no click noise is present, this provides an **unbiased estimate**:

$$
\begin{aligned}
\mathbb{E}_o[\Delta_{\mathit{IPS}}(f_\theta, D, c)] &= \mathbb{E}_o\left[\sum_{d_i \in D} \frac{\lambda(\mathit{rank}(d_i \mid f_\theta, D))}{P(o_i = 1 \mid R, d_i)} \cdot c_i\right] \\
&= \mathbb{E}_o\left[\sum_{d_i \in D} \frac{o_i \cdot \lambda(\mathit{rank}(d_i \mid f_\theta, D)) \cdot y(d_i)}{P(o_i = 1 \mid R, d_i)}\right] \\
&= \sum_{d_i \in D} \frac{P(o_i = 1 \mid R, d_i) \cdot \lambda(\mathit{rank}(d_i \mid f_\theta, D)) \cdot y(d_i)}{P(o_i = 1 \mid R, d_i)} \\
&= \sum_{d_i \in D} \lambda(\mathit{rank}(d_i \mid f_\theta, D)) \cdot y(d_i) \\
&= \Delta(f_\theta, D, y).
\end{aligned}
$$

# Remember the Golden Triangle?




The IPS estimator weights clicks inversely proportional to the examination probabilities.

Image source: `http://www.mediative.com/`

# Counterfactual Evaluation: Robustness of Noise

So far we have **assumed no click noise**: $P(c_i = 1 \mid o_i = 1, y(d_i)) = y(d_i)$.

However, the IPS approach still works without this assumption, as long as:

$$y(d_i) > y(d_j) \Leftrightarrow P(c_i = 1 \mid o_i, y(d_i)) > P(c_j = 1 \mid o_j, y(d_j)).$$

Since we can prove **relative differences** are inferred unbiasedly:

$$\mathbb{E}_{o,c}[\Delta_{\mathit{IPS}}(f_\theta, D, c)] > \mathbb{E}_{o,c}[\Delta_{\mathit{IPS}}(f_{\theta'}, D, c)] \Leftrightarrow \Delta(f_\theta, D) > \Delta(f_{\theta'}, D).$$

# Propensity-weighted Learning to Rank

# Propensity-weighted Learning to Rank (LTR)

The inverse-propensity-scored estimator can unbiasedly estimate performance:

$$\Delta_{\mathit{IPS}}(f_\theta, D, c) = \sum_{d_i \in D} \frac{\lambda(\mathit{rank}(d_i \mid f_\theta, D))}{P(o_i = 1 \mid R, d_i)} \cdot c_i.$$

How do we **optimize** for this **unbiased performance estimate**?

- It is **not differentiable**.
- **Common problem for all ranking metrics**.

# Upper Bound on Rank

Rank-SVM (Joachims, 2002) optimizes the following **differentiable upper bound**:

$$
\begin{aligned}
\mathit{rank}(d \mid f_\theta, D) &= \sum_{d' \in R} \mathbb{1}[f_\theta(d) \leq f_\theta(d')] \\
&\leq \sum_{d' \in R} \max(1 - (f_\theta(d) - f_\theta(d')), 0) = \overline{\mathit{rank}}(d \mid f_\theta, D).
\end{aligned}
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$$\leq \sum_{d' \in R} \max(1 - (f_\theta(d) - f_\theta(d')), 0) = \overline{\mathit{rank}}(d \mid f_\theta, D).$$

**Alternative choices** are possible, i.e., a **sigmoid-like bound** (with parameter $\sigma$):

$$\mathit{rank}(d \mid f_\theta, D) \leq \sum_{d' \in R} \log_2(1 + \exp^{-\sigma(f_\theta(d) - f_\theta(d'))}).$$

Commonly used for pairwise learning, LambdaMart (Burges, 2010), and Lambdaloss (Wang et al., 2018b).

# Propensity-weighted LTR: Average Relevance Position

Then for the Average Relevance Position metric:

$$\Delta_{\mathit{ARP}}(f_\theta, D, y) = \sum_{d_i \in D} \mathit{rank}(d_i \mid f_\theta, D) \cdot y(d_i).$$

This gives us an **unbiased estimator** and **upper bound**:

$$\begin{aligned}\Delta_{\mathit{ARP\text{-}IPS}}(f_\theta, D, c) &= \sum_{d_i \in D} \frac{\mathit{rank}(d_i \mid f_\theta, D)}{P(o_i = 1 \mid R, d_i)} \cdot c_i \\ &\leq \sum_{d_i \in D} \frac{\overline{\mathit{rank}}(d_i \mid f_\theta, D)}{P(o_i = 1 \mid R, d_i)} \cdot c_i,\end{aligned}$$

This upper bound is **differentiable** and **optimizable** by stochastic gradient descent or Quadratic Programming, i.e., Rank-SVM (Joachims, 2006).

## Propensity-weighted LTR: Additive Metrics

A similar approach can be applied to **additive metrics** (Agarwal et al., 2019).

If $\lambda$ is a **monotonically decreasing** function:

$$x \leq y \Rightarrow \lambda(x) \geq \lambda(y),$$

then:

$$\mathit{rank}(d \mid \cdot) \leq \overline{\mathit{rank}}(d \mid \cdot) \Rightarrow \lambda(\mathit{rank}(d \mid \cdot)) \geq \lambda(\overline{\mathit{rank}}(d \mid \cdot)).$$

This provides a **lower bound**, for instance for Discounted Cumulative Gain (DCG):

$$\frac{1}{\log_2(1 + \mathit{rank}(d \mid \cdot))} \geq \frac{1}{\log_2(1 + \overline{\mathit{rank}}(d \mid \cdot))}.$$

# Propensity-weighted LTR: Discounted Cumulative Gain

Then for the Discounted Cumulative Gain metric:

$$\Delta_{\mathit{DCG}}(f_\theta, D, y) = \sum_{d_i \in D} \log_2(1 + \mathit{rank}(d_i \mid f_\theta, D))^{-1} \cdot y(d_i).$$

This gives us an **unbiased estimator** and **lower bound**:

$$\begin{aligned}
\Delta_{\mathit{DCG\text{-}IPS}}(f_\theta, D, c) &= \sum_{d_i \in D} \frac{\log_2(1 + \mathit{rank}(d_i \mid f_\theta, D)^{-1}}{P(o_i = 1 \mid R, d_i)} \cdot c_i \\
&\geq \sum_{d_i \in D} \frac{\log_2(1 + \overline{\mathit{rank}}(d_i \mid f_\theta, D)^{-1}}{P(o_i = 1 \mid R, d_i)} \cdot c_i.
\end{aligned}$$

This lower bound is **differentiable** and **optimizable** by stochastic gradient descent or the Convex-Concave Procedure (Agarwal et al., 2019).

# Propensity-weighted LTR: Walkthrough

**Overview of the approach:**

- Obtain a **model of position bias**.
- Acquire a **large click-log**.
- Then for every click in the log:
  - Compute the **propensity of the click**:

$$P(o_i = 1 \mid R, d_i).$$

  - Calculate the **gradient** of the **bound** on the **unbiased estimator**:

$$\nabla_\theta \left[ \frac{\lambda(\overline{\mathit{rank}}(d_i \mid f_\theta, D))}{P(o_i = 1 \mid R, d_i)} \right].$$

  - **Update the model** $f_\theta$ by adding/subtracting the gradient.

## Propensity-weighted LTR: Semi-synthetic Experiments

Unbiased LTR methods are commonly **evaluated** through **semi-synthetic experiments** (Joachims, 2002; Agarwal et al., 2019; Jagerman et al., 2019).

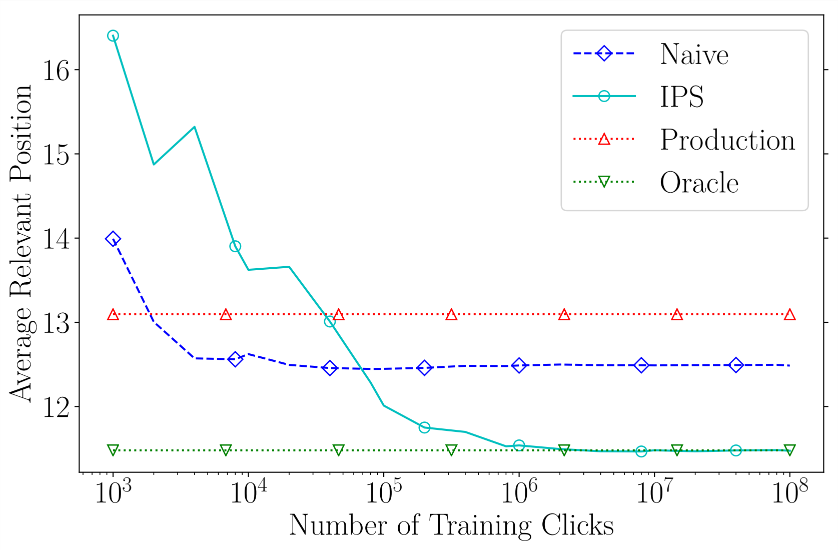
# Propensity-weighted LTR: Semi-synthetic Experiments

Unbiased LTR methods are commonly **evaluated** through **semi-synthetic experiments** (Joachims, 2002; Agarwal et al., 2019; Jagerman et al., 2019).

The experimental setup:

- Traditional LTR dataset, e.g., Yahoo! Webscope (Chapelle and Chang, 2011).
- Simulate queries by uniform sampling from the dataset.
- Create a ranking according to a baseline ranker.
- Simulate clicks by modelling:
    - **Click Noise**, e.g., 10% chance of clicking on a non-relevant document.
    - **Position Bias**, e.g., $P(o_i = 1 \mid R, d_i) = \frac{1}{\text{rank}(d|R)}$.
- Hyper-parameter tuning by unbiased evaluation methods.

# Propensity-weighted LTR: Results



# So far so good

So far we have seen how to:

- Perform **Counterfactual Evaluation** with **unbiased estimators**.
- Perform **Counterfactual LTR** by optimizing **unbiased estimators**.

**What essential part are we still missing?**

# Estimating Position Bias

Recall that position bias is a form of bias where higher positioned results are more likely to be observed and therefore clicked.

**Assumption**: The **observation probability** only depends on the rank of a document:

$$P(o_i = 1 \mid i).$$

The objective is now to **estimate**, for each rank $i$, the propensity $P(o_i = 1 \mid i)$.

# Estimating Position Bias

# Estimating Position Bias

So far we have seen how to:

- Perform **Counterfactual Evaluation** with **unbiased estimators**.
- Perform **Counterfactual LTR** by optimizing **unbiased estimators**.

At the core of these methods is the propensity score: $P(o_i = 1 \mid R, d_i)$, which helps remove bias from user interactions.

In this section, we will show how this **propensity score** can be **estimated** for a specific kind of bias: **position bias**.

# Estimating Position Bias

Recall that position bias is a form of bias where higher positioned results are more likely to be observed and therefore clicked.

**Assumption**: The **observation probability** only depends on the rank of a document:

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# Estimating Position Bias

RandTop-$n$ Algorithm:

Document $d_1$

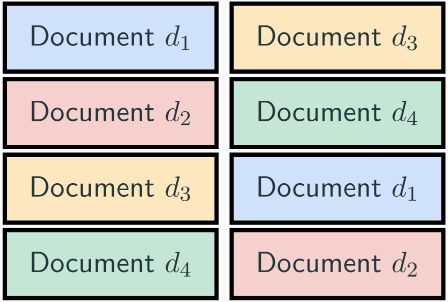
Document $d_2$

Document $d_3$

Document $d_4$

# Estimating Position Bias

RandTop-$n$ Algorithm:



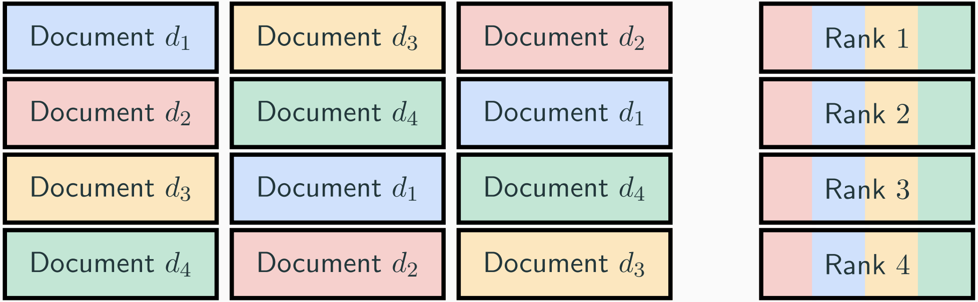
# Estimating Position Bias

RandTop-$n$ Algorithm:

| | | |
|---|---|---|
| Document $d_1$ | Document $d_3$ | Document $d_2$ |
| Document $d_2$ | Document $d_4$ | Document $d_1$ |
| Document $d_3$ | Document $d_1$ | Document $d_4$ |
| Document $d_4$ | Document $d_2$ | Document $d_3$ |

# Estimating Position Bias

RandTop-$n$ Algorithm:



# Estimating Position Bias

RandTop-$n$ Algorithm:

1. Repeat:
   - Randomly shuffle the top $n$ items
   - Record clicks
2. Aggregate clicks per rank
3. Normalize to obtain propensities $p_i \propto P(o_i \mid i)$

Note: we only need propensities proportional to the true observation probability for learning.

# Estimating Position Bias

Uniformly **randomizing** the top $n$ results may negatively impacts users during data logging.

There are various methods that minimize the impact to the user:

- RandPair: Choose a pivot rank $k$ and only swap a random other document with the document at this pivot rank (Joachims et al., 2017).
- Interventional Sets: Exploit inherent "randomness" in data coming from multiple rankers (e.g., A/B tests in production logs) (Agarwal et al., 2017).

# Estimating Position Bias Through Randomization

**What is the downside of estimating propensities through randomization?**

# Jointly Learning and Estimating

# Jointly Learning and Estimating

In the previous sections we have seen:

- Counterfactual ranker evaluation with unbiased estimators.
- Counterfactual LTR by optimizing unbiased estimators.
- Estimating propensity scores through randomization.

Instead of treating **propensity estimation** and **unbiased learning to rank** as two separate tasks, recent work has explored **jointly learning rankings and estimating propensities**.

# Jointly Learning and Estimating

Recall that the probability of a click can be decomposed as:

$$\underbrace{P(c_i = 1 \wedge o_i = 1 \mid y(d_i), R)}_{\text{click probability}} = \underbrace{P(c_i = 1 \mid o_i = 1, y(d_i))}_{\text{relevance probability}} \cdot \underbrace{P(o_i \mid R, d_i)}_{\text{observation probability}} .$$

In the previous sections we have seen that, if the **observation probability** is known, we can find an unbiased estimate of relevance via IPS.

# Jointly Learning and Estimating

It is possible to **jointly learn and estimate** by iterating two steps:

1. Learn an optimal ranker given a correct propensity model:

$$\underbrace{P(c_i = 1 \mid o_i = 1, y(d_i))}_{\text{relevance probability}} = \frac{P(c_i = 1 \wedge o_i = 1 \mid y(d_i), R)}{P(o_i \mid R, d_i)}.$$

2. Learn an optimal propensity model given a correct ranker:

$$\underbrace{P(o_i \mid R, d_i)}_{\text{observation probability}} = \frac{P(c_i = 1 \wedge o_i = 1 \mid y(d_i), R)}{P(c_i = 1 \mid o_i = 1, y(d_i))}.$$

## Jointly Learning and Estimating

- Given an accurate **model of relevance**, it is possible to find an accurate **propensity model**, and vice versa.
- This approach requires **no randomization**.
- Recent work has solved this via either an **Expectation-Maximization approach** (Wang et al. (2018a)) or a **Dual Learning Objective** (Ai et al. (2018)).

# Conclusion

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**In this lecture we discussed:**

- **User-interactions** on rankings are **very biased**.

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- **User-interactions** on rankings are **very biased**.
- **Counterfactual Learning to Rank:**
  - Unbiased learning from historical interaction logs.
  - Correct for position bias with inverse propensity scoring.
  - Requires an explicit user model.

# Conclusion

**In this lecture we discussed:**

- **User-interactions** on rankings are **very biased**.
- **Counterfactual Learning to Rank:**
  - Unbiased learning from historical interaction logs.
  - Correct for position bias with inverse propensity scoring.
  - Requires an explicit user model.
- Estimating **users' examination probabilities:**
  - Through randomization or joint learning.

# Future Directions

# Future Directions

- **Unbiased Learning to Rank for:**
  - Recommender systems (Schnabel et al., 2016).
  - Personalized rankings in search or recommendation.
- **Correcting for more biases:**
  - Presentation bias, a well known but unaddressed bias.
  - Social biases (fair/ethical A.I.) especially when ranking people.
- **Learning from other signals:**
  - Likes, dwell time, conversion, purchases, watch-time, etc.

This is an extremely active area of research!

# Questions and Answers

**Thank you for participating!**

# Notation

| Definition | Notation | Example |
|---|---|---|
| Query | $q$ | – |
| Candidate documents | $D$ | – |
| Document | $d \in D$ | – |
| Ranking | $R$ | $(R_1, R_2, \ldots, R_n)$ |
| Document at rank $i$ | $R_i$ | $R_i = d$ |
| Relevance | $y : D \to \mathbb{N}$ | $y(d) = 2$ |
| Ranker model with weights $\theta$ | $f_\theta : D \to \mathbb{R}$ | $f_\theta(d) = 0.75$ |
| Click | $c_i \in \{0, 1\}$ | – |
| Observation | $o_i \in \{0, 1\}$ | – |
| Rank of $d$ when $f_\theta$ ranks $D$ | $\mathit{rank}(d \mid f_\theta, D)$ | $\mathit{rank}(d \mid f_\theta, D) = 4$ |

# Notation Used in the Slides ii

| | | |
|---|---|---|
| Differentiable upper bound on $\mathit{rank}(d, \mid f_\theta, D)$ | $\overline{\mathit{rank}}(d, \mid f_\theta, D)$ | – |
| Average Relevant Position metric | $\mathit{ARP}$ | – |
| Discounted Cumulative Gain metric | $\mathit{DCG}$ | – |
| Precision at $k$ metric | $\mathit{Prec}@k$ | – |
| A performance measure or estimator | $\Delta$ | – |

# Resources i

- Tensorflow Learning to Rank, allows for inverse propensity scoring: `https://github.com/tensorflow/ranking`
- Inverse Propensity Scored Rank-SVM: `https://www.cs.cornell.edu/people/tj/svm_light/svm_proprank.html`
- Data and code for comparing counterfactual and online learning to rank `http://github.com/rjagerman/sigir2019-user-interactions`
- An older online learning to rank framework: Lerot `https://bitbucket.org/ilps/lerot/`

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# Acknowledgments

All content represents the opinion of the author(s), which is not necessarily shared or endorsed by their employers and/or sponsors.