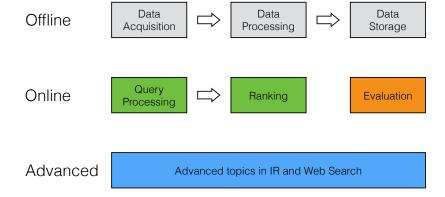
# Information Retrieval Online Evaluation and Statistical Testing

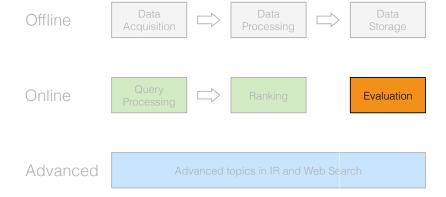
Ilya Markov i.markov@uva.nl

University of Amsterdam

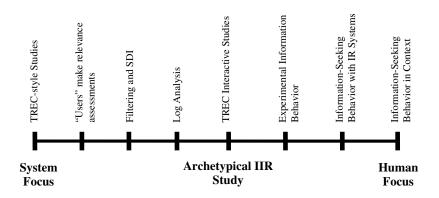
#### Course overview



#### This lecture

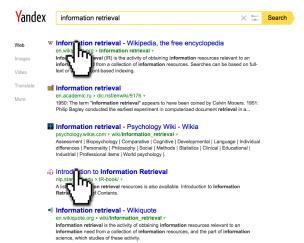


# Taxonomy of evaluation approaches



Diane Kelly, "Methods for Evaluating Interactive Information Retrieval Systems with Users"

#### Online scenario



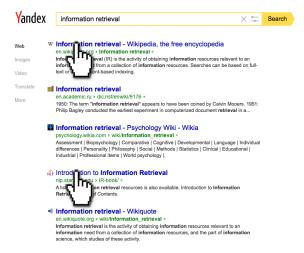
#### Outline

- Online evaluation
  - Online metrics
  - Between-subject experiments
  - Within-subject experiments
  - Summary
- 2 Hypothesis testing

#### Outline

- 1 Online evaluation
  - Online metrics
  - Between-subject experiments
  - Within-subject experiments
  - Summary

# Which user-generated signals indicate search quality?



Ilya Markov

#### Classification of online measures

Evaluation Method	Absolute	Relative	
Item Level	Click-through rate,	Click-skip,	
SERP Level	Abandonment rate,	A/B Testing, Interleaving,	

Evangelos Kanoulas, "A Short Survey on Online and Offline Methods for Search Quality Evaluation"

#### Online metrics

Type of interaction	Metric	Good	Bad
Clicks	Click-through rate Click rank (reciprocal rank) Abandonment	$\uparrow \\ \downarrow \\ \downarrow$	<b>↓ ↑ ↑</b>
Time	Dwell time Time to first click Time to last click	↑ ↓ ↑	<b>↓ ↑ ↓</b>
Queries	Number of reformulations Number of abandoned queries	<b>+ + +</b>	<b>†</b>

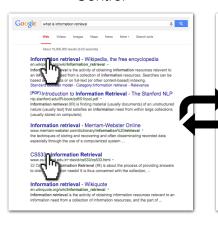
Hypothesis testing

#### Outline

- 1 Online evaluation
  - Online metrics
  - Between-subject experiments
  - Within-subject experiments
  - Summary

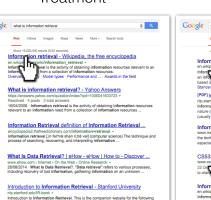
#### A/B testing

#### Control



#### Treatment

book, Christopher D. Manning, Prabhakar Raghavan and Hinrich Schütze ...



Ilya Markov

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Information Retrieval

informa

# A/B testing

- Set the current search system as control
- 2 Set an alternative search system as treatment
- 3 Assign 0.5%-1.0% of users to each of these systems
- 4 Record user interactions with these systems during time period T
- 5 Compare the systems using online metrics
- 6 Choose a winner based on one or several metrics

# A/B testing, practical considerations

- Choosing metrics
- Control extraneous factors
- Estimate adequate sample size
- Novelty impact
- Etc.

# A/B testing discussion

- Pros
  - Can evaluate anything
  - Using any online metric
- Cons
  - High variance between users
  - Not very sensitive
  - Needs lots of observations

Hypothesis testing

#### Outline

- 1 Online evaluation
  - Online metrics
  - Between-subject experiments
  - Within-subject experiments
  - Summary

## Interleaving

- Given a user's query, produce two rankings (current and alternative)
- Merge the rankings into a single ranking using a mixing policy
- 3 Present the merged ranking to a user and collect interactions (see online metrics)
- 4 Choose a winning ranking using a scoring rule
- 5 Repeat steps 1-4 until a clear winner is identified

#### Team draft interleaving



P<sup>PST</sup> Search Engines that Learn from Implicit Feedback - Depar... www.rs.ng.rik\*-redocurses/Orln/Loachins-Search-Engines.pdf \* by T.Joochins - Clade by felf - Reliabed articles Aug 2, 2007 - search-engines present results heavily bisses a user's. Search-engine loss provide a - Intel engineers who search fleet commer interest for.

5 Alternative Search Engines That Respect Your Privacy - Ho... www.bevigoek.com,...5 alternative search engines that respect you p., \* May 9, 2012 - Google, Bing, Yahoo - all the major search engines took you search.



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| www.cs.rug.nli~costcourses/Critif/Joechins-Search-Engines.pdf \* by T-Joechins-Cled by 161 - Related articles

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A Search Engine the striker/cockhirms.org\* - Examples of implicit feedbac The ability to learn enables - 5 Alternative Search www.howtopeek.com/.../5-May 9, 2012 - Googe, Bing, you, and it discards user ag

Search Engines that

Port Search Engines

www.cs.rug.ni/~roe/course

by T Josephins - Cited by 16

Aug 2, 2007 - search engin

logs provide a ... that employ





# Team draft interleaving

- Mixing policy: each ranker selects its highest ranked document that is not yet in the combined list
- Scoring rule: a ranker is preferred if its results get more clicks

# Other interleaving methods

- Probabilistic interleaving
- Optimized interleaving
- Multileaving

## Interleaving discussion

- Pros
  - No variance due to different users
  - Highly sensitive
  - Needs much fewer observations compared to A/B testing
- Cons
  - Can only use document-level metrics

Hypothesis testing

#### Outline

- 1 Online evaluation
  - Online metrics
  - Between-subject experiments
  - Within-subject experiments
  - Summary

## Online evaluation summary

- Online metrics
- Between-subject experiments A/B testing
- Within-subject experiments interleaving

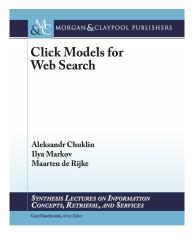
## What are the advantages of online evaluation?

- Based on real users
- Cheap as it uses a running search system

## What are the disadvantages of online evaluation?

- Online metrics are difficult to interpret
- May disturb users
- Cannot run too many experiments in parallel
- User search interactions are biased

#### Click models



http://clickmodels.weebly.com/the-book.html

#### Materials

K. Hofmann, L. Li, F. Radlinski

Online Evaluation for Information Retrieval

Foundations and Trends in Information Retrieval, 2016

Description

# **Evaluating efficiency**

Motrie neme

Metric name	Description
Elapsed indexing time	Measures the amount of time necessary to build a
	document index on a particular system.
Indexing processor time	Measures the CPU seconds used in building a docu-
	ment index. This is similar to elapsed time, but does
	not count time waiting for I/O or speed gains from
	parallelism.
Query throughput	Number of queries processed per second.
Query latency	The amount of time a user must wait after issuing a
	query before receiving a response, measured in mil-
	liseconds. This can be measured using the mean, but
	is often more instructive when used with the median
	or a percentile bound.
Indexing temporary space	Amount of temporary disk space used while creating
	an index.
Index size	Amount of storage necessary to store the index files.

Croft et al., "Search Engines, Information Retrieval in Practice"

Hypothesis testing

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#### Outline

- 1 Online evaluation
- 2 Hypothesis testing
  - Basics
  - Hypothesis testing in IR

#### Example

Query	Α	В	B-A
1	25	35	10
2	43	84	41
3	39	15	-24
4	75	75	0
5	43	68	25
6	15	85	70
7	20	80	60
8	52	50	-2
9	49	58	9
10	50	75	25

- How can we be sure that B is better than A?
- Test statistical significance (hypothesis testing)

Croft et al., "Search Engines, Information Retrieval in Practice"

Hypothesis testing

#### Outline

- 2 Hypothesis testing
  - Basics
  - Hypothesis testing in IR

# Test procedure

- ① Set null hypothesis  $H_0$
- 2 Set alternative hypothesis  $H_1$
- 3 Collect sample data  $\mathbf{X} = \{X_1, \dots, X_n\}$ 
  - **X** is **unlikely** under  $H_0 \Longrightarrow$  reject  $H_0$  in favor of  $H_1$
  - **X** is **not unlikely** under  $H_0 \Longrightarrow$  no evidence against  $H_0$
  - ... but this is not an evidence in favor of  $H_0!$

#### Example

- **1**  $H_0: p_{head} = 0.8$
- **2**  $H_1: p_{head} \neq 0.8$
- 3 Perform 10 tosses, observe 4 heads

$$\frac{n!}{h!(n-h)!}p^h(1-p)^{n-h} = \frac{10!}{4!6!}0.8^40.2^6 = 0.005$$

4 Perform 10 tosses, observe 7 heads

$$\frac{10!}{7!3!}0.8^70.2^3 = 0.201$$

# Test procedure (cont'd)

- Consider a statistical model
- ② Set  $H_0$  and  $H_1$
- 3 Choose a test statistics  $T(X_1, \ldots, X_n)$
- $\bullet$  Choose a critical region C (discussed next)
- Decision rule
  - $T \in C \Longrightarrow \text{reject } H_0 \text{ in favor of } H_1$
  - $T \notin C \Longrightarrow$  fail to reject  $H_0$

Ilya Markov

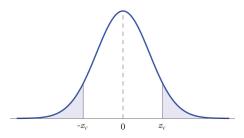
# Example (cont'd)

- $H_0$ :  $p_{head} = 0.8$
- $H_1: p_{head} \neq 0.8$
- Sample mean  $\overline{X} = \frac{1}{n} \sum_{i=1}^{n} X_i$

• For large enough 
$$n$$

- For large enough n  $\overline{X} \mid H_0 \sim \mathcal{N}(0.8, \sigma^2/n)$
- Test statistics  $T = \frac{\overline{X} 0.8}{\sigma / \sqrt{n}} \sim \mathcal{N}(0, 1)$
- Critical region

$$C = (-\infty, -z_c] \cup [z_c, \infty)$$



- $P(T \in C|H_0) \leq \alpha$
- $\alpha$  size, usually  $\in \{0.01, 0.05\}$
- For  $\alpha = 0.05$ ,  $z_{\alpha/2} = 1.96$

Picture taken from http://2012books.lardbucket.org/books/beginning-statistics/ s09-04-areas-of-tails-of-distribution.html

# Example (cont'd)

#### Reject $H_0$ if

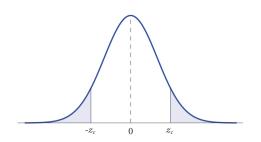
• 
$$T \leq -z_{\alpha/2}$$
,  $T \geq z_{\alpha/2}$ 

• 
$$\overline{X} \le -z_{\alpha/2} \cdot \sigma/\sqrt{n} + 0.8$$
,  
 $\overline{X} \ge z_{\alpha/2} \cdot \sigma/\sqrt{n} + 0.8$ 

Alternatively, reject  $H_0$  if

• 
$$p = P(|T| > T_{obs} | H_0) \le \alpha$$

p-value



Test statistics and *p*-value can be calculated using any statistical software, e.g., R

#### **Errors**

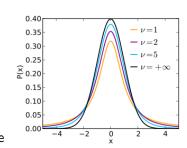
	$H_0$ is false	H₀ is true
Reject H <sub>0</sub>	power	type I error $(\alpha)$
Not reject $H_0$	type II error	

#### Outline

- 2 Hypothesis testing
  - Basics
  - Hypothesis testing in IR

#### T-test

- ① Get measurements for systems A and B  $M(A) \sim \mathcal{N}(\mu_A, \sigma^2), M(B) \sim \mathcal{N}(\mu_B, \sigma^2)$
- **2**  $H_0: \mu_A = \mu_B$
- **3**  $H_1: \mu_A \neq \mu_B$
- $T = \frac{\overline{A} \overline{B}}{\hat{\sigma} / \sqrt{n}} \sim T^{(n-1)} -$ Student's t-distribution
- **S** Use standard hypothesis testing procedure with  $\alpha \in \{0.01, 0.05\}$



Picture taken from https://en.wikipedia.org/wiki/Student%27s\_t-distribution

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#### T-test example

Query	Α	В	B-A
1	25	35	10
2	43	84	41
3	39	15	-24
4	75	75	0
5	43	68	25
6	15	85	70
7	20	80	60
8	52	50	-2
9	49	58	9
10	50	75	25

$$\overline{B} - \overline{A} = 21.4$$

• 
$$\hat{\sigma} = 29.1$$

$$T = \frac{21.4}{29.1/\sqrt{10}} = 2.33$$

• 
$$p = P(|T| > 2.33 | H_0) = 0.02$$

• If 
$$\alpha = 0.05$$
, reject  $H_0$ 

• If 
$$\alpha = 0.01$$
, do not reject  $H_0$ 

Croft et al., "Search Engines, Information Retrieval in Practice"

# Wilcoxon signed-ranks test

- Get measurements for systems A and B
- ② For each item i, compute  $|m_{A,i} m_{B,i}|$  and  $sgn(m_{A,i} m_{B,i})$
- 3 Exclude items with  $|m_{A,i} m_{B,i}| = 0$
- ullet Order the remaining  $N_{nz}$  items based on  $|m_{A,i}-m_{B,i}|$
- **5** Assign ranks  $R_i$  from smallest to largest
- 6 Compute the test statistics

$$W = \sum_{i=1}^{N_{nz}} [sgn(m_{A,i} - m_{B,i}) \cdot R_i]$$

- **7** For large  $N_{nz}$ ,  $W \sim \mathcal{N}$
- **8** Use standard hypothesis testing procedure with  $\alpha \in \{0.05, 0.01\}$

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# Wilcoxon test example

Query	Α	В	B-A
1	25	35	10
2	43	84	41
3	39	15	-24
4	75	75	0
5	43	68	25
6	15	85	70
7	20	80	60
8	52	50	-2
9	49	58	9
10	50	75	25

- Ranked non-zero differences2, 9, 10, 24, 25, 25, 41, 60, 70
- Signed ranks
  -1, +2, +3, -4, +5.5, +5.5, +7,
  +8, +9
- W = 35
- $p = P(|W| > 35 | H_0) = 0.025$
- If  $\alpha = 0.05$ , reject  $H_0$
- If  $\alpha = 0.01$ , do not reject  $H_0$

Croft et al., "Search Engines, Information Retrieval in Practice"

# Hypothesis testing summary

- IR must use statistical testing
- The most common and one of the most powerful is the paired t-test

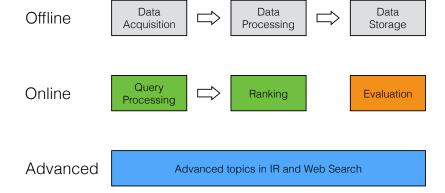
#### **Materials**

M. Smucker, J. Allan, B. Carterette

A Comparison of Statistical Significance Tests for Information Retrieval Evaluation

Proceedings of CIKM, pages 623–632, 2007

#### Course overview



# See you tomorrow at 14:30

