

Predicting Search Satisfaction Metrics with Interleaved Comparisons

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Filip Radlinski

Beer&Tech, Criteo, October 28, 2015

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Search is not just

Google

werd in 1989 opgericht in het oude stadshart van Haarlem en ontpopte zich ...

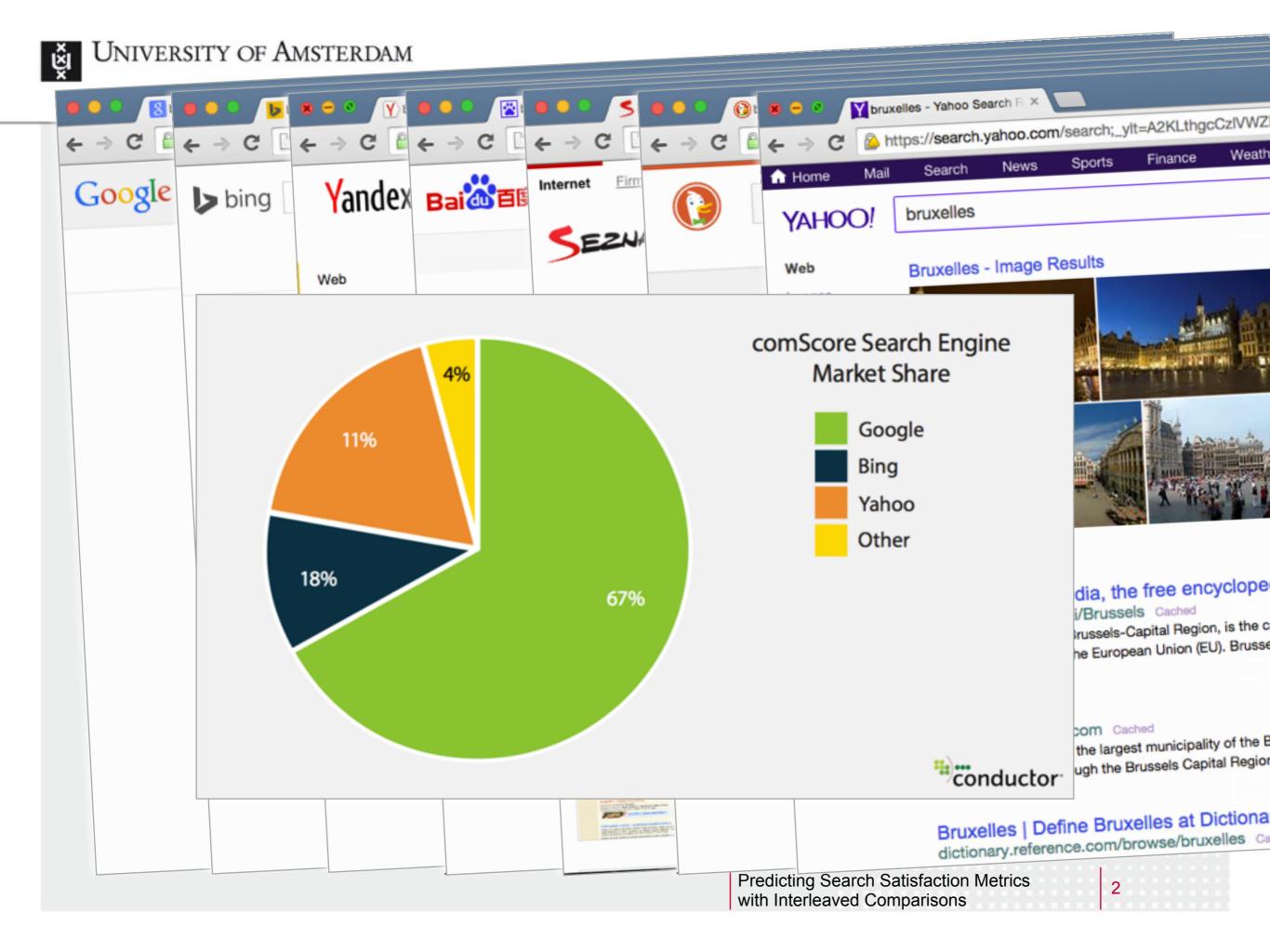
Cafe Bruxelles: Home

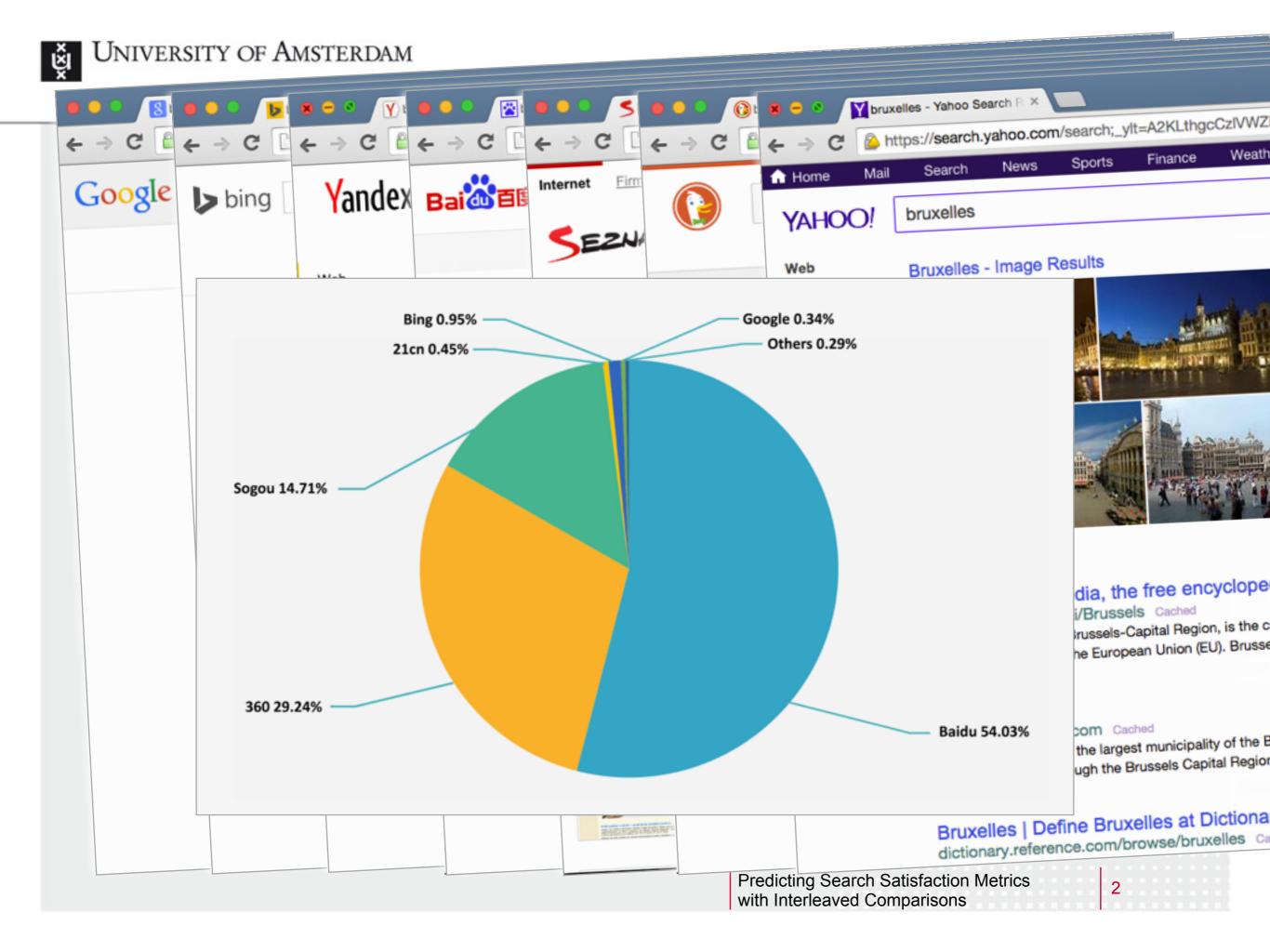
www.cafebruxelles.nl/home/ - Translate this page Home. Beste Gast, Welkom bij Bruxelles!! Wel bekend en geliefd in Haarlem vanwege haar gezellige ongedwongen sfeer en het bonte gezelschap aan ...

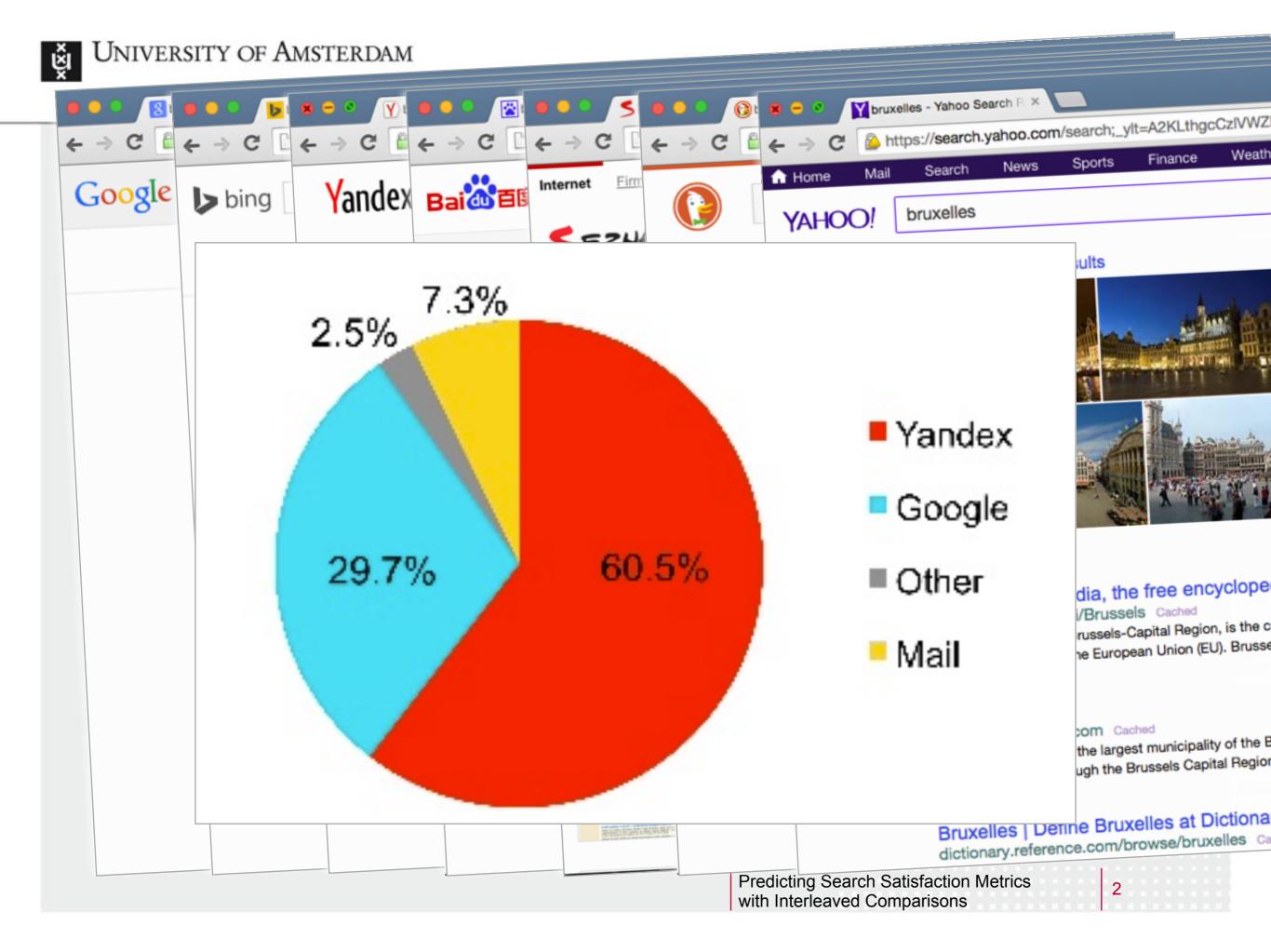
> **Predicting Search Satisfaction Metrics** with Interleaved Comparisons

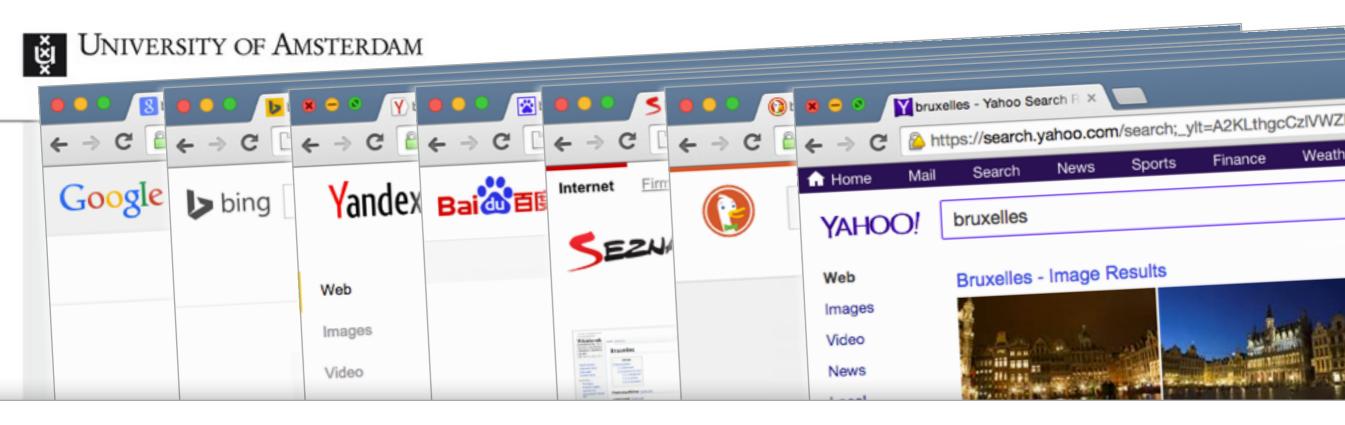


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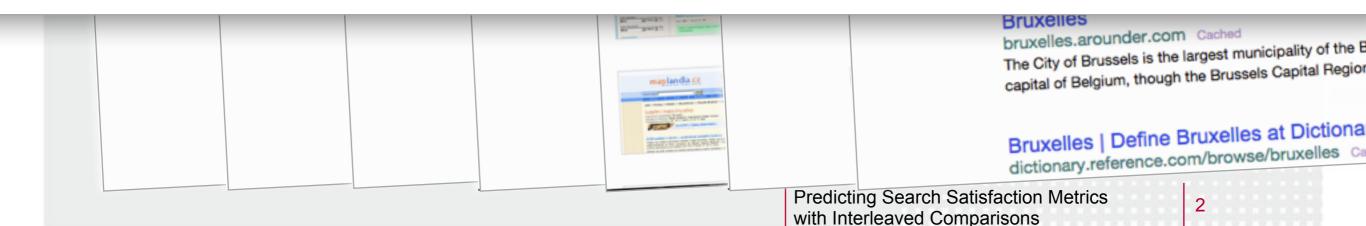


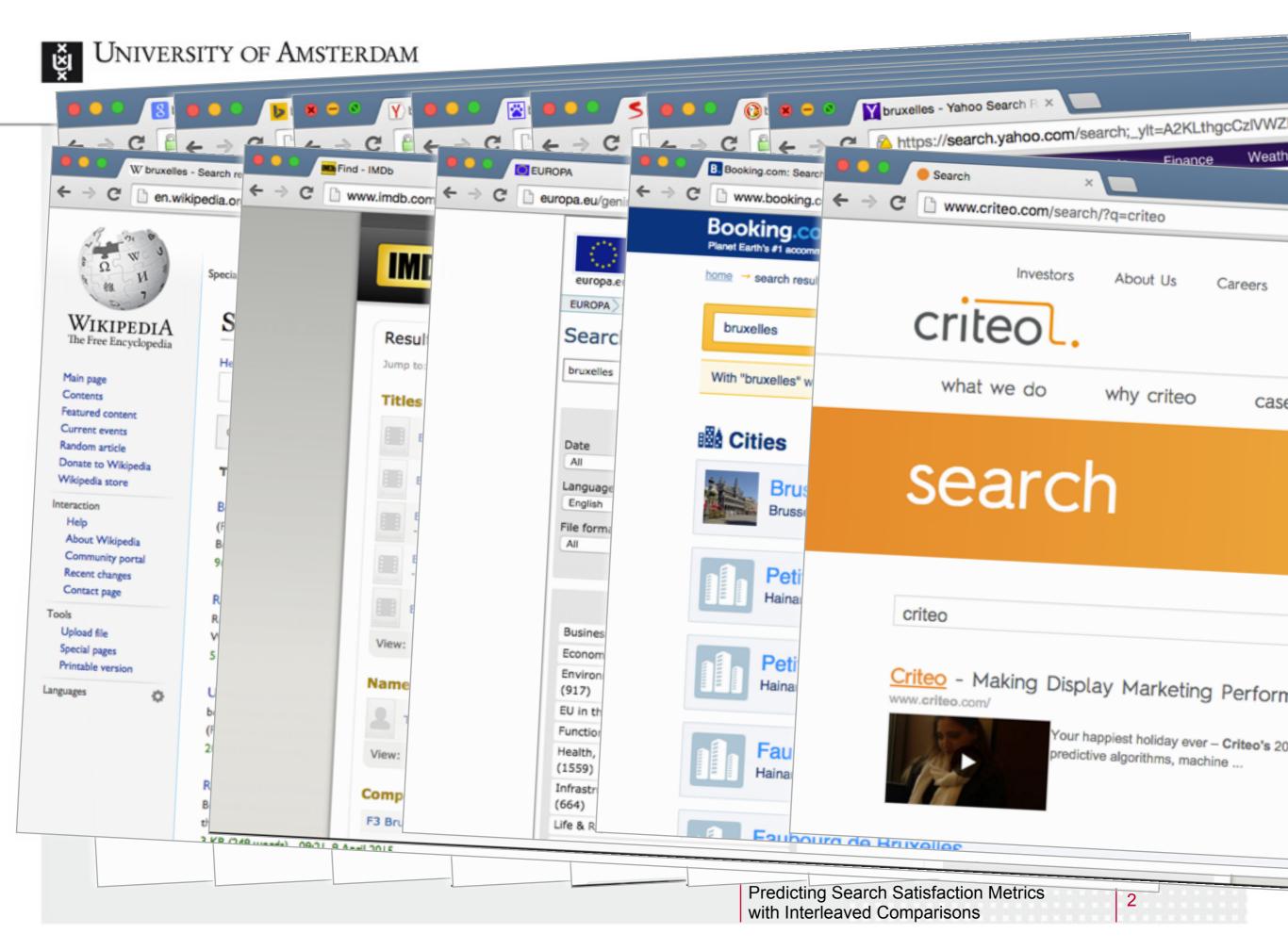


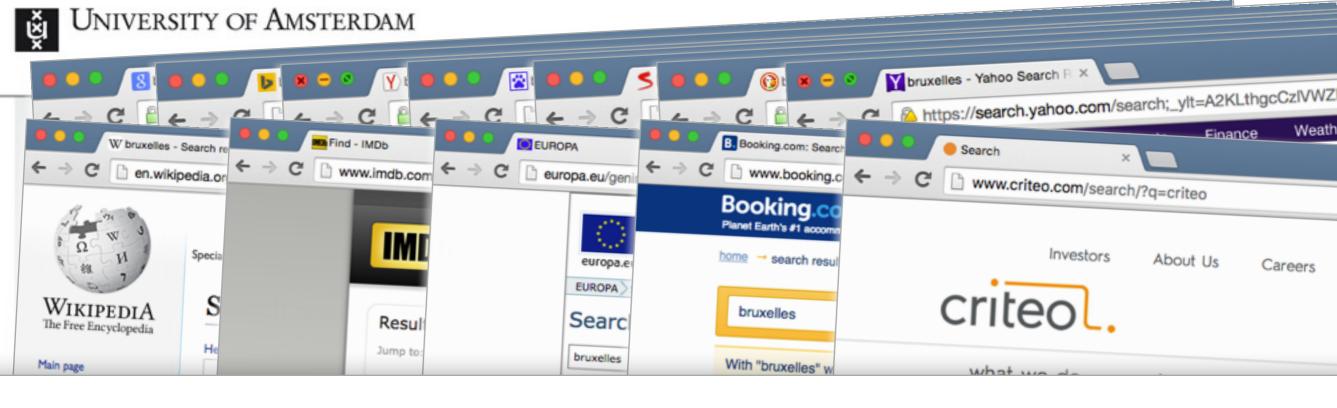




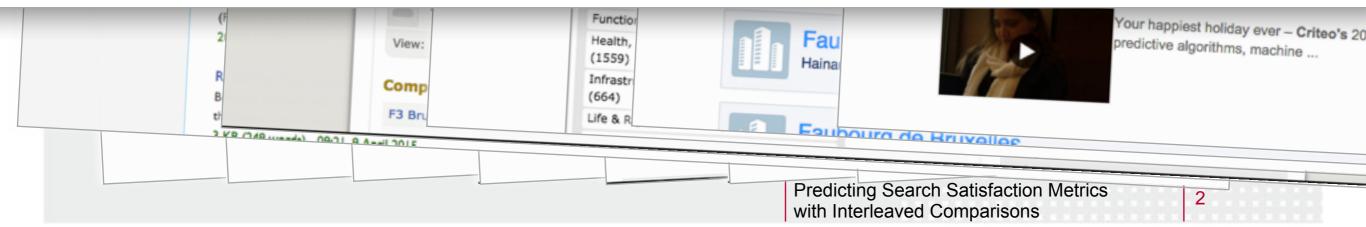
Search is not just web search

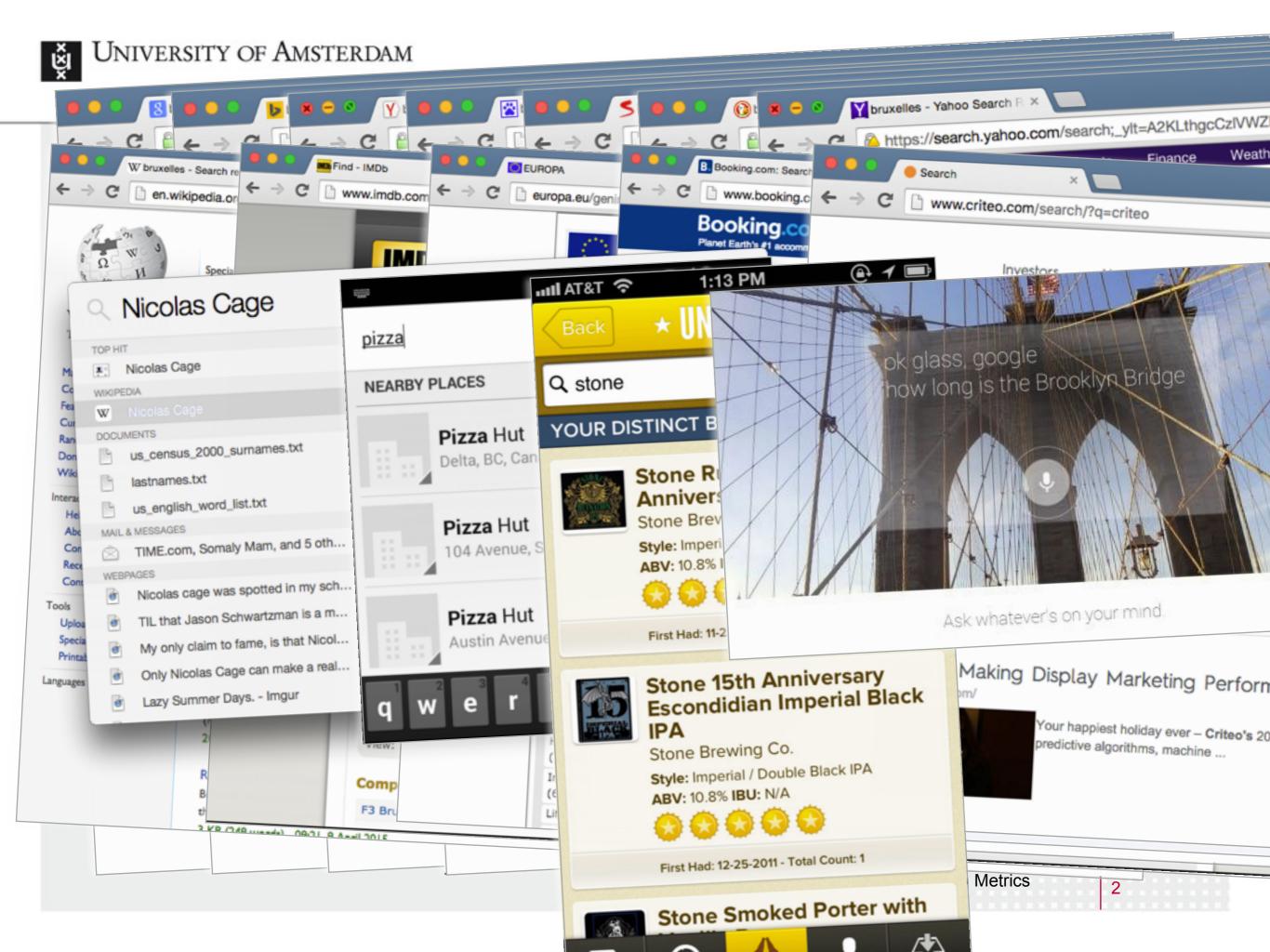


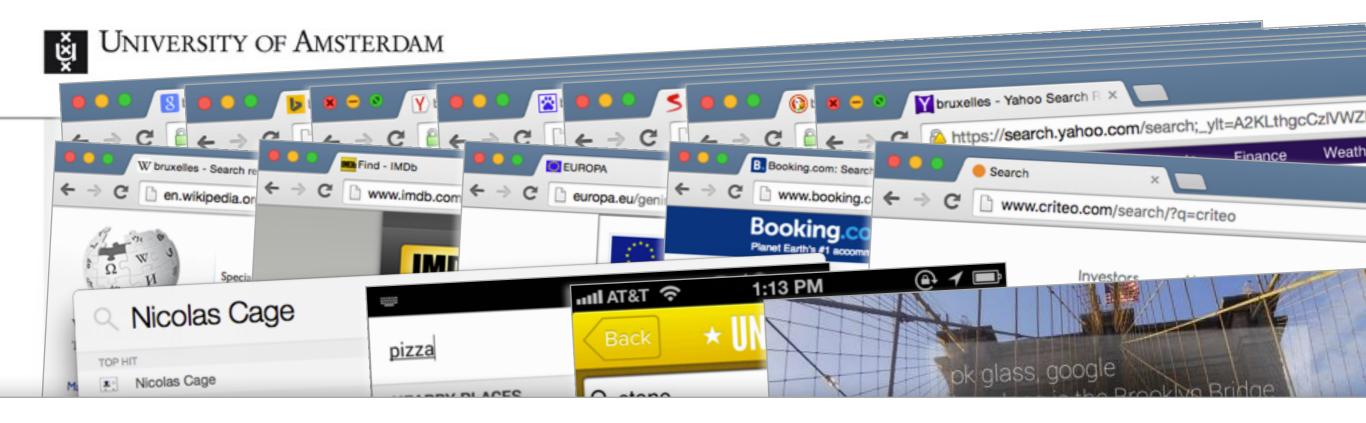




Search is not just in a browser







Search is everywhere

2 view:	IPA Stone Brewing Co.	Your happiest holiday ever – Criteo's 2 predictive algorithms, machine
R Comp B t F3 Bru 2 KP (249 wards) 09:21 9 April 2015	Stone Dretning Style: Imperial / Double Black IPA ABV: 10.8% IBU: N/A Lin Control Control	
	First Had: 12-25-2011 - Total Count: 1	Metrics 2
	Stone Smoked Porter wit	



Motivation - Search

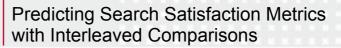
Half the world's population uses web search



Motivation - Search

Half the world's population uses web search

Web search is trusted more than traditional media

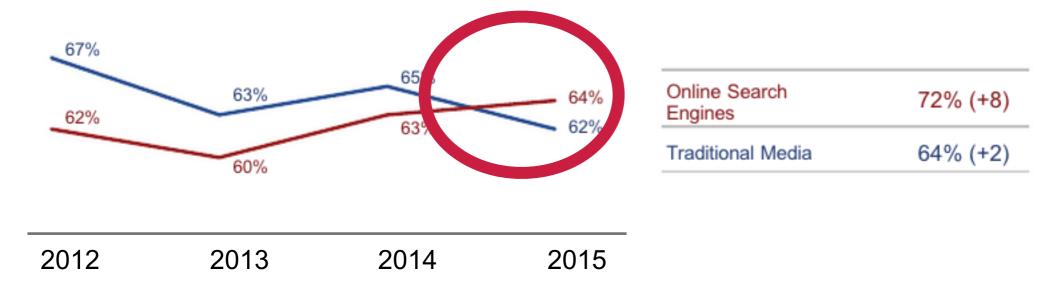




Motivation - Search

MEDIA SOURCES: SEARCH ENGINES NOW MOST TRUSTED

Trust in each source for general news and information (20-country global data)



2015 | Trust Barometer

Predicting Search Satisfaction Metrics
with Interleaved Comparisons



Motivation - Search

MEDIA SOURCES: SEARCH ENGINES NOW MOST TRUSTED

Trust in each source for general news and information (20-country global data).

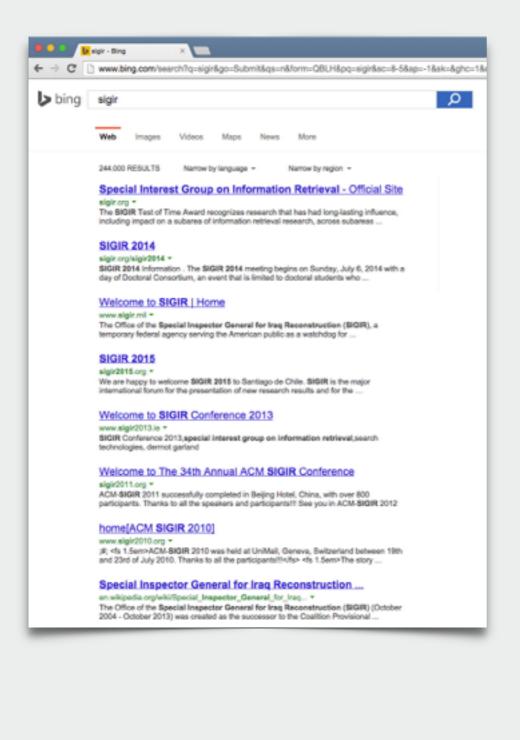
It matters whether search performs well

2015 | Trust Barometer

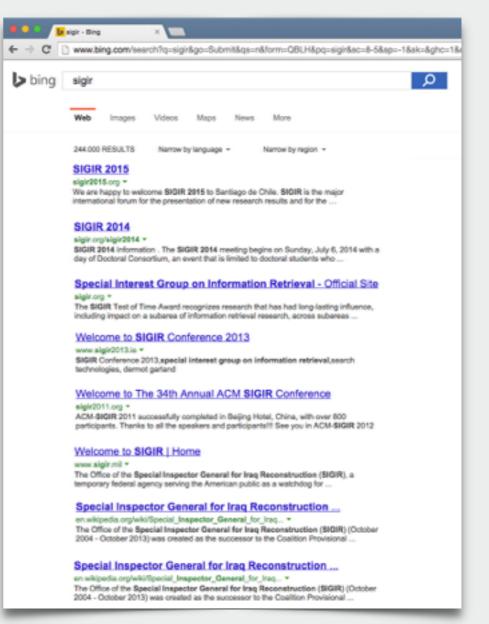




Motivation - Evaluation







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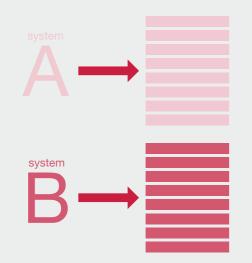


Motivation - Evaluation



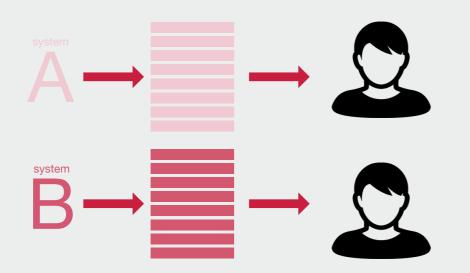


Motivation - AB Testing





Motivation - **AB Testing**



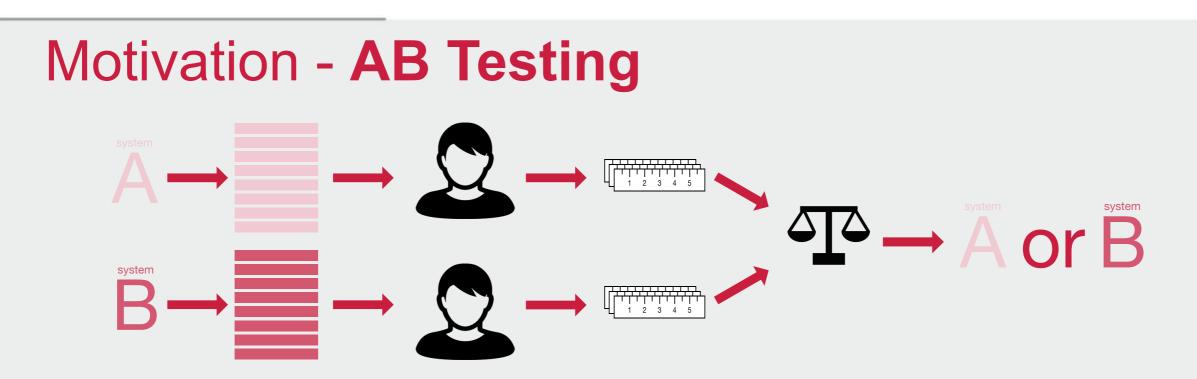
User population divided into two groups





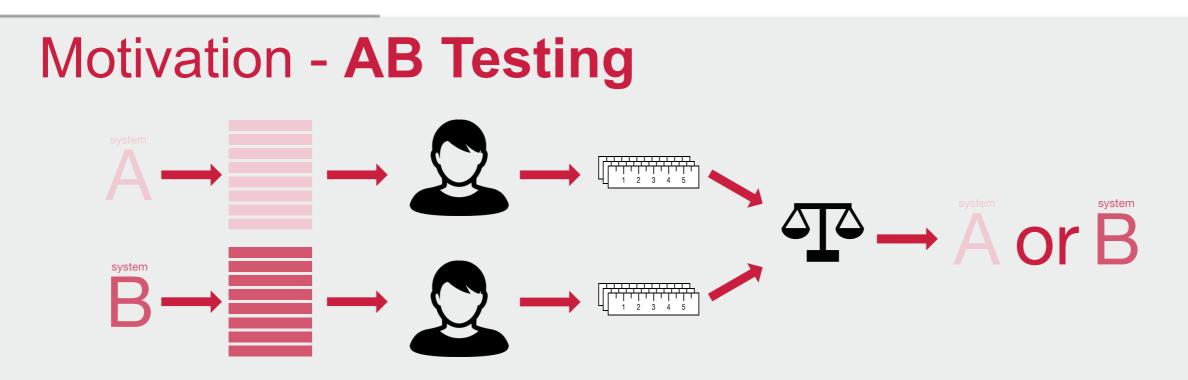
User population divided into two groups Trusted and sophisticated metrics





User population divided into two groups
 Trusted and sophisticated metrics
 Difference in metric value indicates the winner

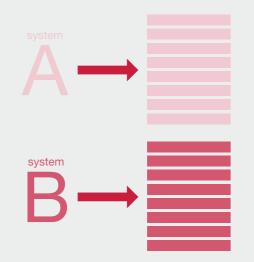




- User population divided into two groups
- Trusted and sophisticated metrics
- Difference in metric value indicates the winner
- Between subject design
 - Differences between users and their queries
 - Low sensitivity, millions of queries

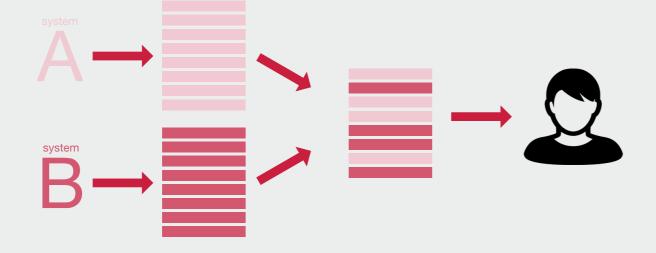


Motivation - Interleaving



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Motivation - Interleaving



All users see both systems



Motivation - Interleaving

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All users see both systems

Simple metric: system with more clicks wins

Motivation - Interleaving

$\stackrel{\text{system}}{B} \rightarrow \stackrel{\text{system}}{B} \rightarrow \stackrel{\text{system$

- All users see both systems
- Simple metric: system with more clicks wins
- Within subject design
 - Both systems now cater for every user
 - High sensitivity, 10-100x less queries needed (compared to AB Testing)

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Motivation - Team Draft Interleaving (TDI)

	B
doc 1	doc 2
doc 2	doc 4
doc 3	doc 7
doc 4	doc 1
doc 5	doc 3

F. Radlinski, M. Kurup, and T. Joachims. How does clickthrough data reflect retrieval quality? In CIKM'08. 2008

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Motivation - Team Draft Interleaving (TDI) A B





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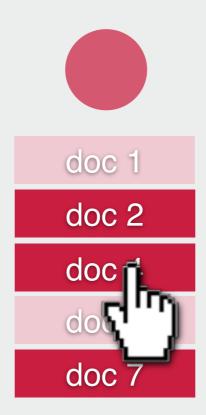


Motivation - Team Draft Interleaving (TDI) A B





Motivation - Team Draft Interleaving (TDI) A B





Motivation - Team Draft Interleaving (TDI)

Infer winner: B > A

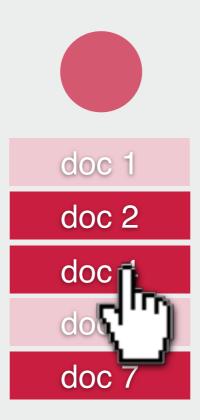




Motivation - Team Draft Interleaving (TDI)

Infer winner: B > A

Count fraction of wins over many queries



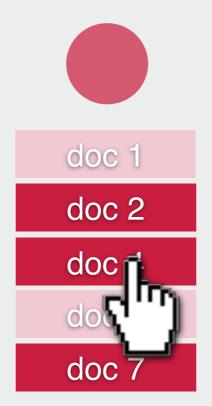


Motivation - Team Draft Interleaving (TDI)

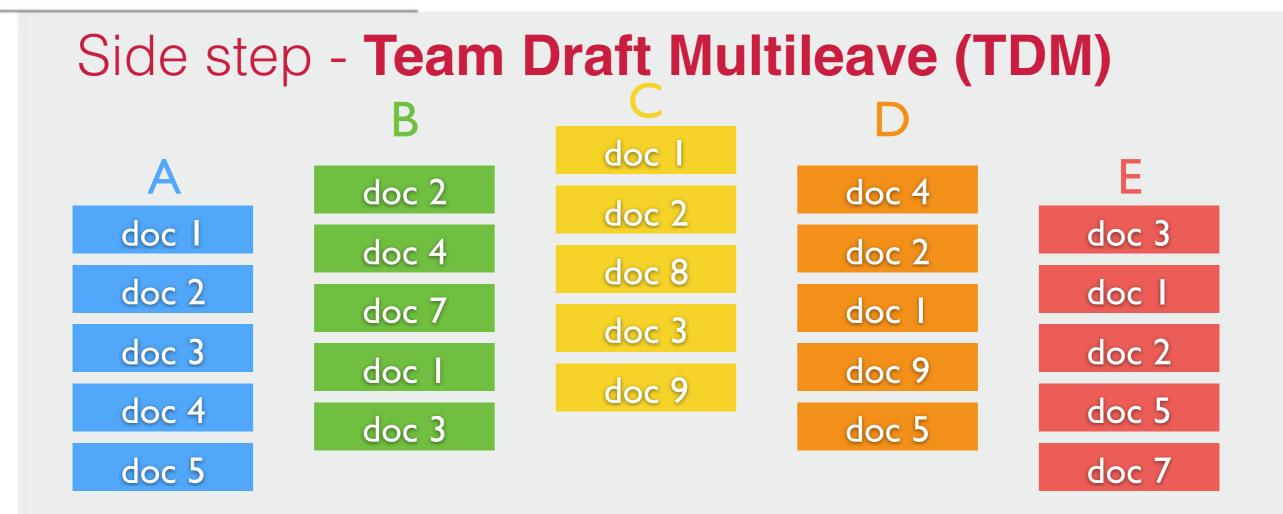
Infer winner: B > A

Count fraction of wins over many queries

- Well tested in practice
 - Used at Bing, Yandex, Seznam

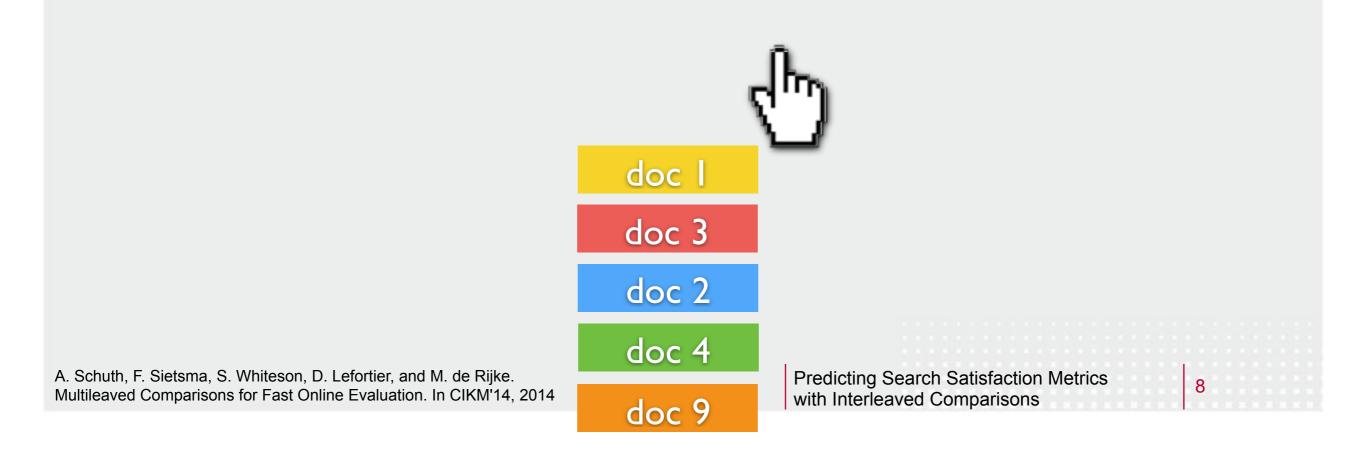


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Side step - Team Draft Multileave (TDM) B C D E





Side step - Team Draft Multileave (TDM) B A * Infer ranking over systems: A & E > B & C & D



A. Schuth, F. Sietsma, S. Whiteson, D. Lefortier, and M. de Rijke. Multileaved Comparisons for Fast Online Evaluation. In CIKM'14, 2014

Predicting Search Satisfaction Metrics with Interleaved Comparisons



Side step - Team Draft Multileave (TDM) B C D A E * Infer ranking over systems: A & E > B & C & D

Aggregate rankings over many queries





Side step - Team Draft Multileave (TDM) B C D E

Infer ranking over systems: A & E > B & C & D
 Aggregate rankings over many queries
 Many less queries required

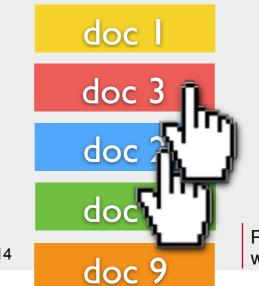


Predicting Search Satisfaction Metrics with Interleaved Comparisons



Side step - Team Draft Multileave (TDM) B C D E

- Infer ranking over systems: A & E > B & C & D
- Aggregate rankings over many queries
- Many less queries required
 - Relative to when all systems would be compared pairwise





Side step - Team Draft Multileave (TDM) R F

- Infer ranking over systems: A & E > B & C & D
- Aggregate rankings over many queries
- Many less queries required
 - Relative to when all systems would be compared pairwise
- But not tested in practice (yet)

A. Schuth, F. Sietsma, S. Whiteson, D. Lefortier, and M. de Rijke.

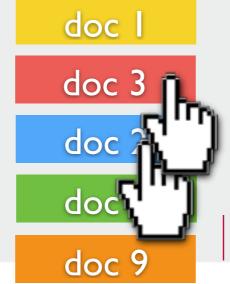




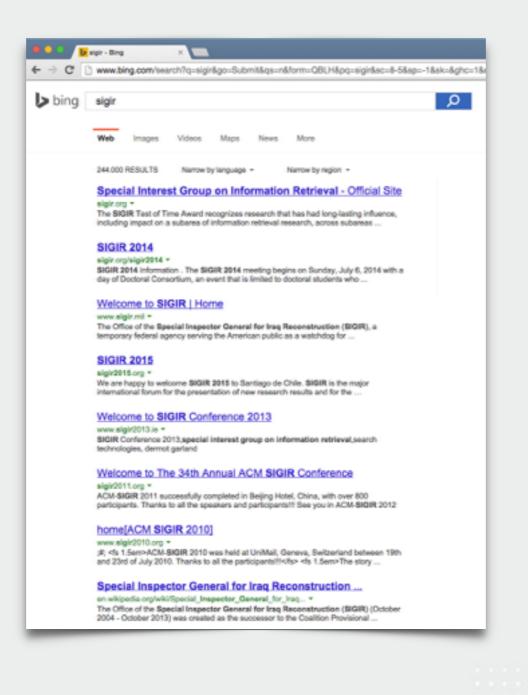
UNIVERSITY OF AMSTERDAM Not used in the rest of this work

Side step - Team Draft Multileave (TDM) B C D E

- Infer ranking over systems: A & E > B & C & D
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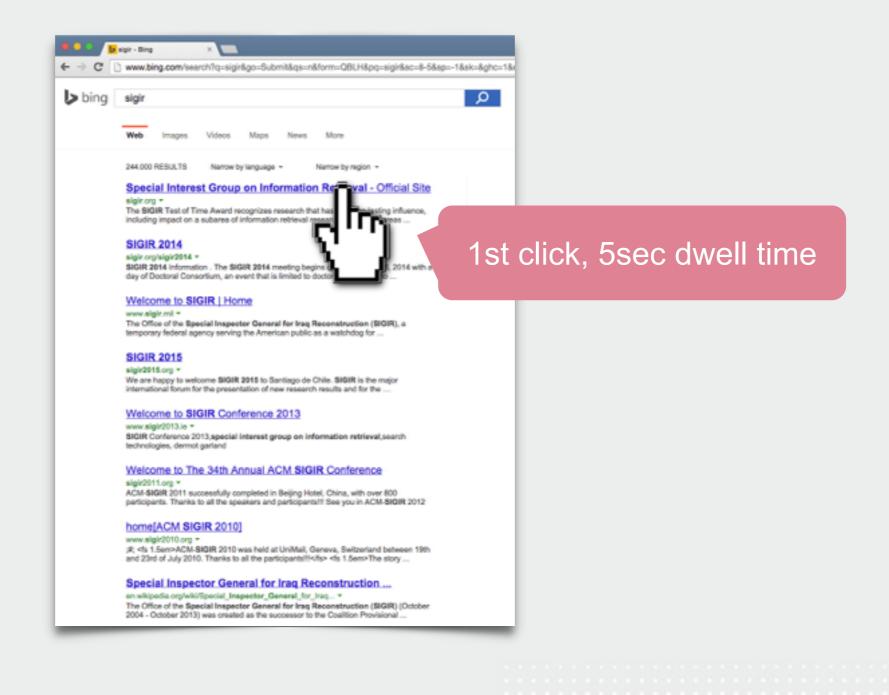


Motivation - AB Testing - As a Gold Standard



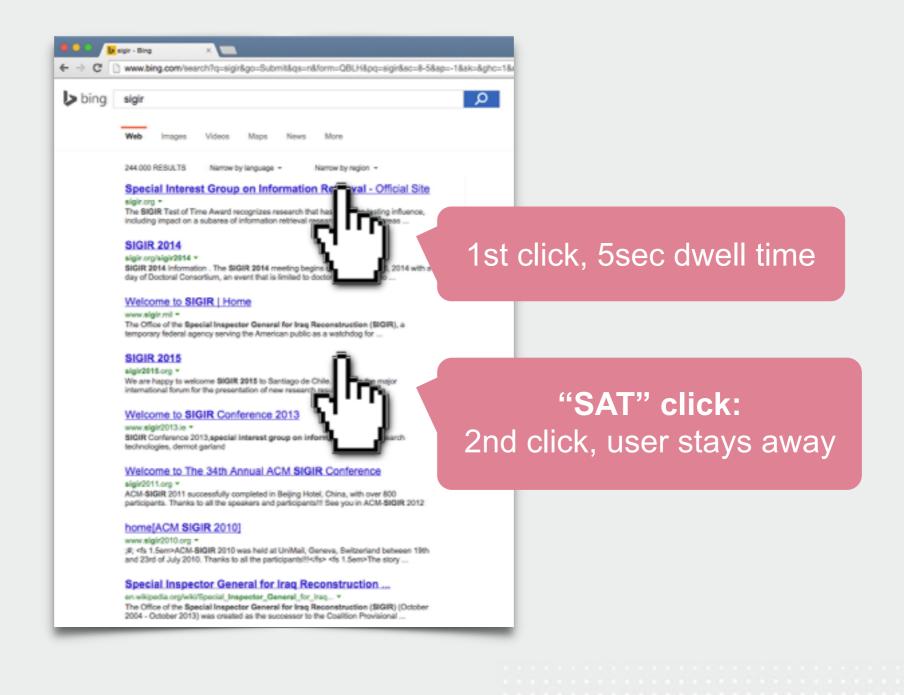
Predicting Search Satisfaction Metrics with Interleaved Comparisons

Motivation - AB Testing - As a Gold Standard



Predicting Search Satisfaction Metrics with Interleaved Comparisons

Motivation - AB Testing - As a Gold Standard



Predicting Search Satisfaction Metrics with Interleaved Comparisons



Motivation - AB Testing - Metrics

AB Metric Description

Predicting Search Satisfaction Metrics with Interleaved Comparisons



Motivation - AB Testing - Metrics

AB Metric	Description
AB	Fraction queries with at least one click

Predicting Search Satisfaction Metrics	
with Interleaved Comparisons	



Motivation - AB Testing - Metrics

AB Metric	Description
AB	Fraction queries with at least one click
AB@1	Fraction queries with at least one click on 1st position



Motivation - AB Testing - Metrics

AB Metric	Description	
AB	Fraction queries with at least one click	
AB@1	Fraction queries with at least one click on 1st positic	Classifier predicting SAT probability
ABs	Fraction queries with at least one SAT click	with a threshold



Motivation - AB Testing - Metrics

AB Metric	Description	
AB	Fraction queries with at least one click	
AB@1	Fraction queries with at least one click on 1st positic	Classifier predicting SAT probability
ABs	Fraction queries with at least one SAT click	with a threshold
ABs@1	Fraction queries with at least one SAT click on 1st po	osition



Motivation - AB Testing - Metrics

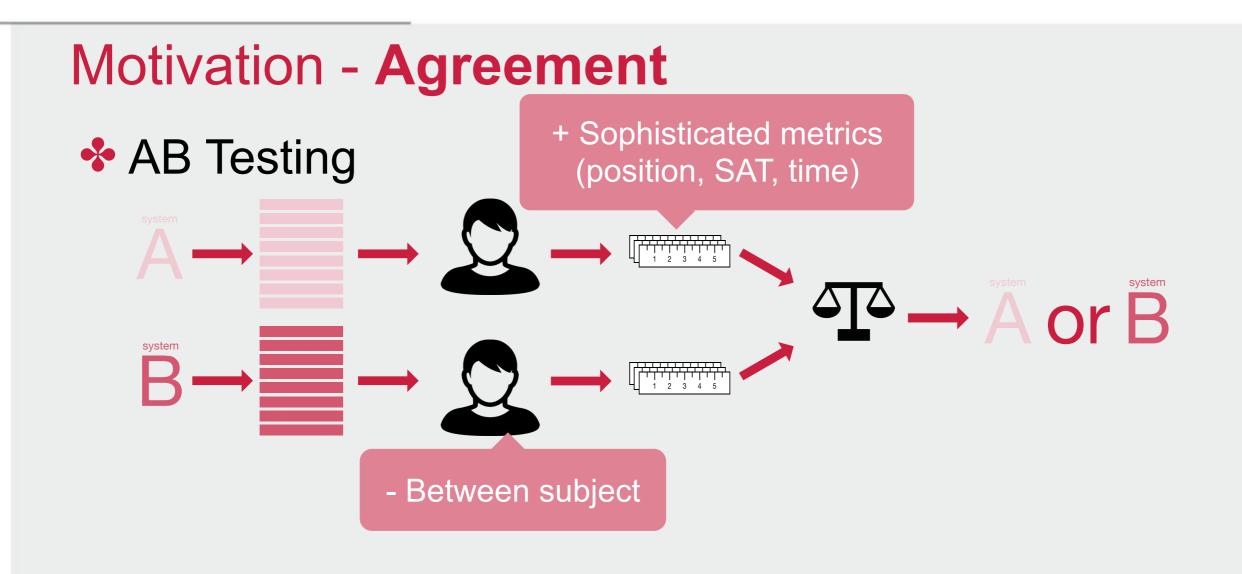
AB Metric	Description		
AB	Fraction queries with at least one click		
AB@1	Fraction queries with at least one click on 1st positic	Classifier pre	
ABs	Fraction queries with at least one SAT click	with a three	
ABs@1	Fraction queries with at least one SAT click on 1st po	osition	
ABT	Time from the query issue until first click		



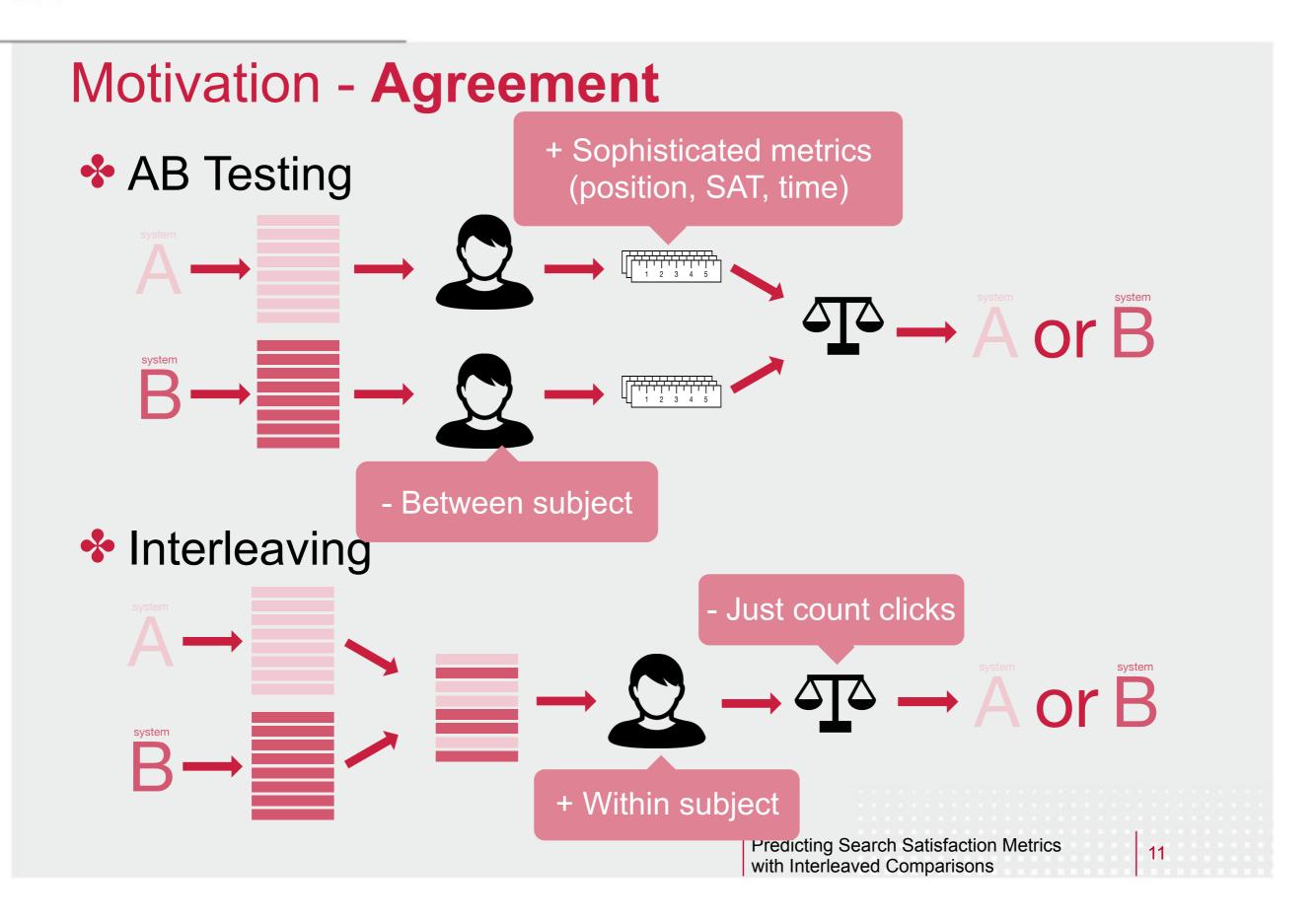
Motivation - AB Testing - Metrics

AB Metric	Description	
AB	Fraction queries with at least one click	
AB@1	Fraction queries with at least one click on 1st positic Classifier pre	
ABs	Fraction queries with at least one SAT click with a three	
AB _s @1	Fraction queries with at least one SAT click on 1st position	
ABT	Time from the query issue until first click	
AB⊤@1	Time from the query issue until first click on 1st position	
AB _{T,S}	Time from the query issue until first SAT click	
AB _{T,S} @1	Time from the query issue until first SAT click on 1st position	

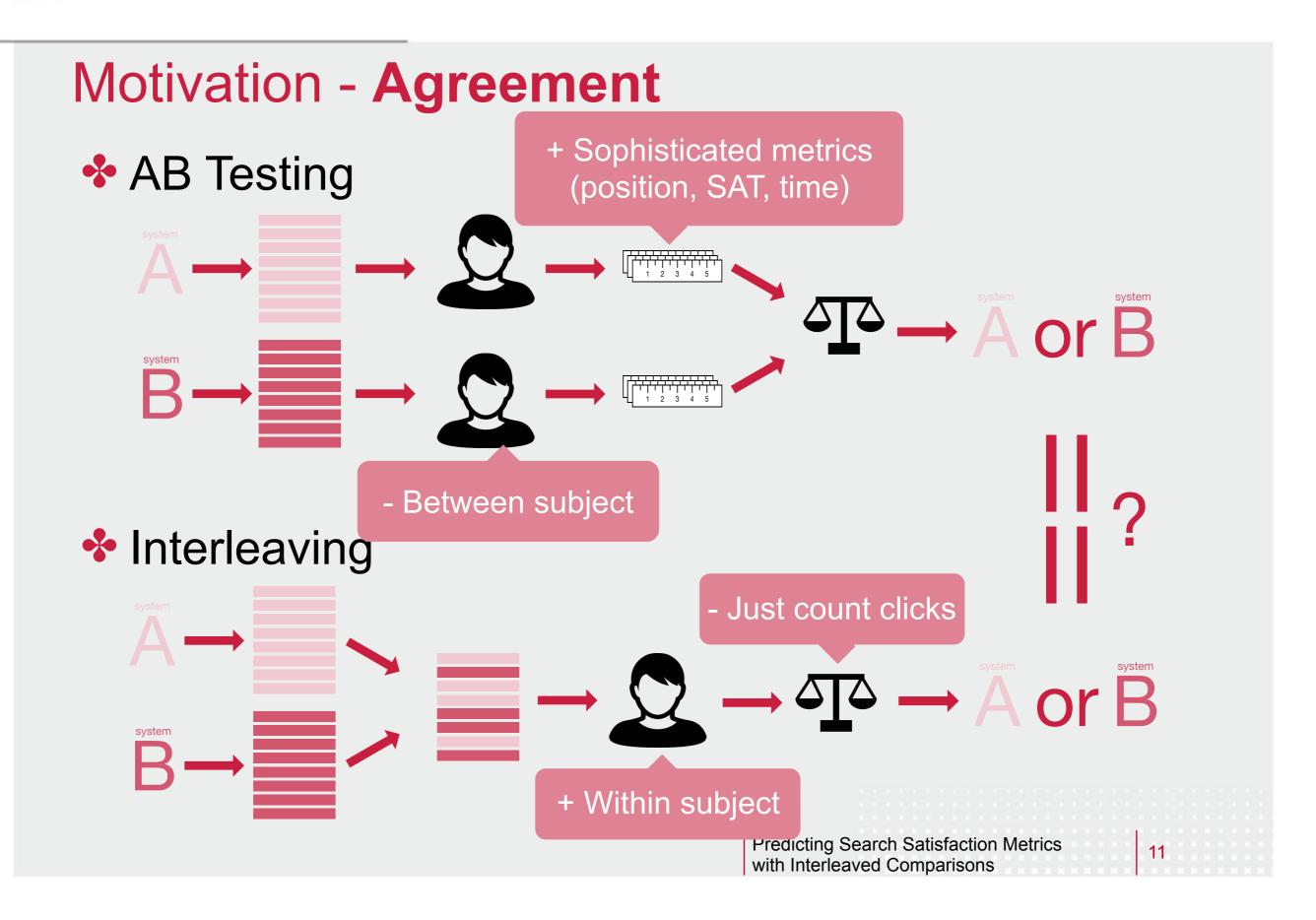
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Outline

Motivation **Data + analysis** Methods + results Conclusions



Predicting Search Satisfaction Metrics	
with Interleaved Comparisons	

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Data - Properties

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Data - Properties

38 ranker pairs

AB Tested + Interleaved (TDI)

Data - Properties

- AB Tested + Interleaved (TDI)
- only ranking changes

- AB Tested + Interleaved (TDI)
- only ranking changes
- bing.com, web, desktop

- AB Tested + Interleaved (TDI)
- only ranking changes
- bing.com, web, desktop
- 9 months in 2014

- AB Tested + Interleaved (TDI)
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- bing.com, web, desktop
- 9 months in 2014
- United States locale

38 ranker pairs

- AB Tested + Interleaved (TDI)
- only ranking changes
- bing.com, web, desktop
- 9 months in 2014
- United States locale

Click volume

38 ranker pairs

- AB Tested + Interleaved (TDI)
- only ranking changes
- bing.com, web, desktop
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- United States locale

Click volume

AB: ~1 week, high volume

38 ranker pairs

- AB Tested + Interleaved (TDI)
- only ranking changes
- bing.com, web, desktop
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- United States locale

Click volume

- AB: ~1 week, high volume
- Interleaving: ~4 days, low volume

38 ranker pairs

- AB Tested + Interleaved (TDI) *
- only ranking changes *
- bing.com, web, desktop *
- 9 months in 2014
- United States locale

Click volume

- AB: ~1 week, high volume *
- Interleaving: ~4 days, **low** volume *
- ~80 times more queries for AB



38 ranker pairs

- AB Tested + Interleaved (TDI)
- only ranking changes
- bing.com, web, desktop
- 9 months in 2014
- United States locale

Click volume

- AB: ~1 week, high volume
- Interleaving: ~4 days, low volume
- ~80 times more queries for AB
- ~3 billion clicks

38 ranker pairs

- AB Tested + Interleaved (TDI)
- only ranking changes
- bing.com, web, desktop
- 9 months in 2014
- United States locale

Click volume

- AB: ~1 week, high volume
- Interleaving: ~4 days, low volume
- ~80 times more queries for AB
- ~3 billion clicks

These are our datapoints

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Predicting Search Satisfaction Metrics

with Interleaved Comparisons



Data - Analysis - Agreement

Interleaving (TDI) does not agree well with AB metrics

AB Metric	Interleaving (TDI)
AB	0.63

Predicting Search Satisfaction Metrics
with Interleaved Comparisons

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Data - Analysis - Agreement

Interleaving (TDI) does not agree well with AB metrics

AB Metric	Interleaving (TDI)	
AB	0.63	
AB@1	0.71 Significantly	
AB _S	0.71 different from	
AB _s @1	0.76 random	
ABT	0.53	
AB _T @1	0.45	
AB _{T,S}	0.47	
AB _{T,S} @1	0.42	

Predicting Search Satisfaction Metrics	S
with Interleaved Comparisons	



Data - Analysis - Sensitivity (Power)

How many queries are required for statistically significant conclusions?

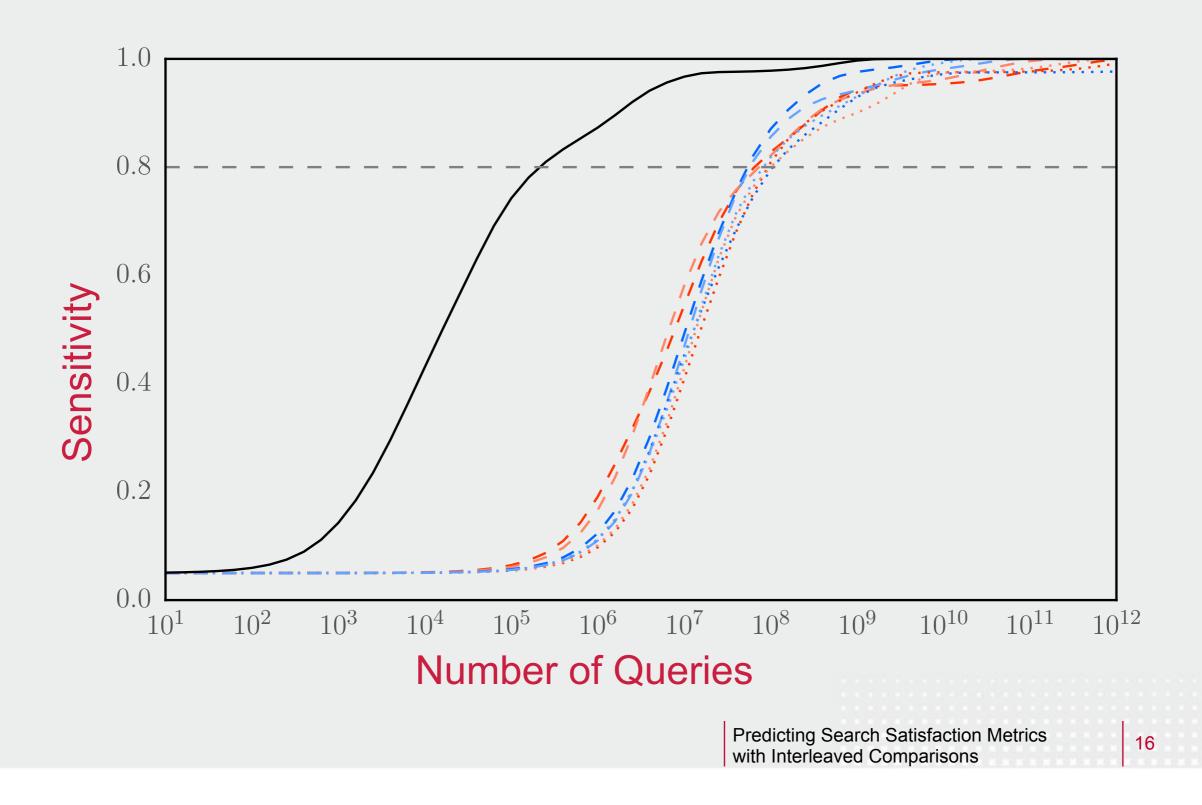


Data - Analysis - Sensitivity (Power)

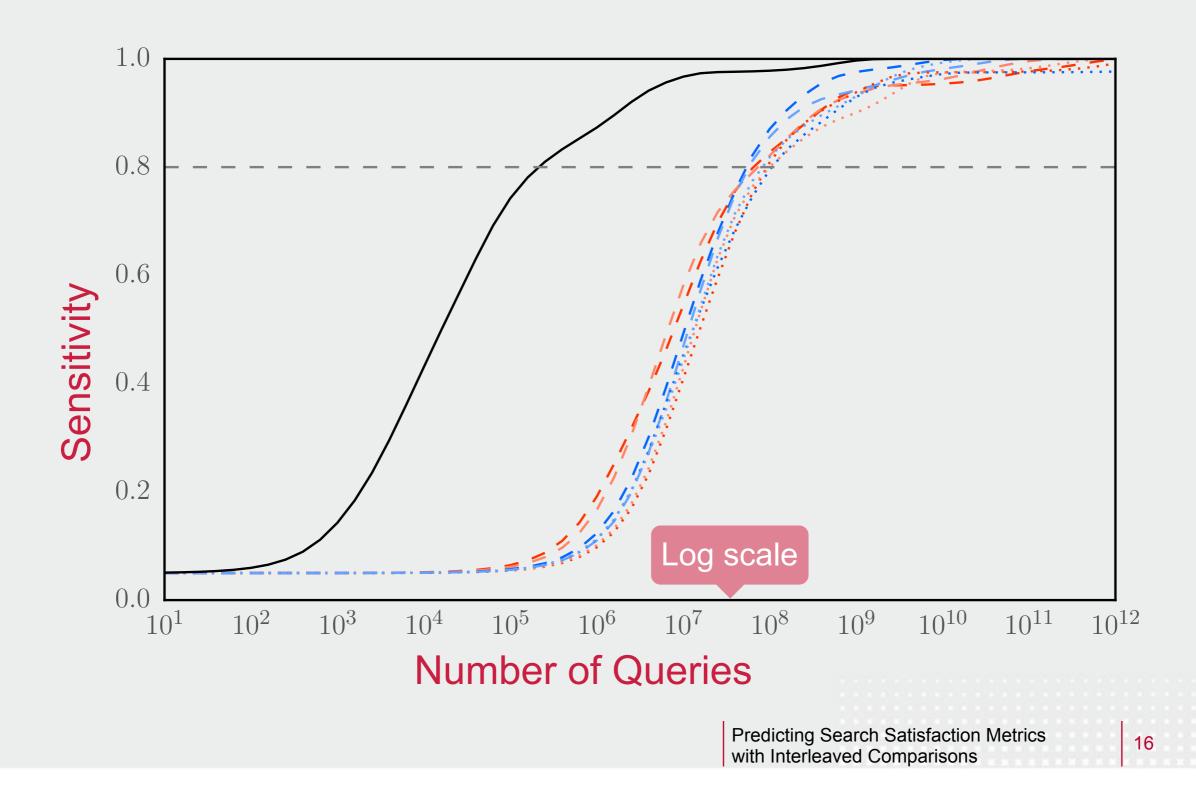
How many queries are required for statistically significant conclusions?

- Sensitivity (power) analysis
 - alpha=0.05, two sided
 - AB Testing: independent t-test
 - Interleaving (TDI): paired t-test

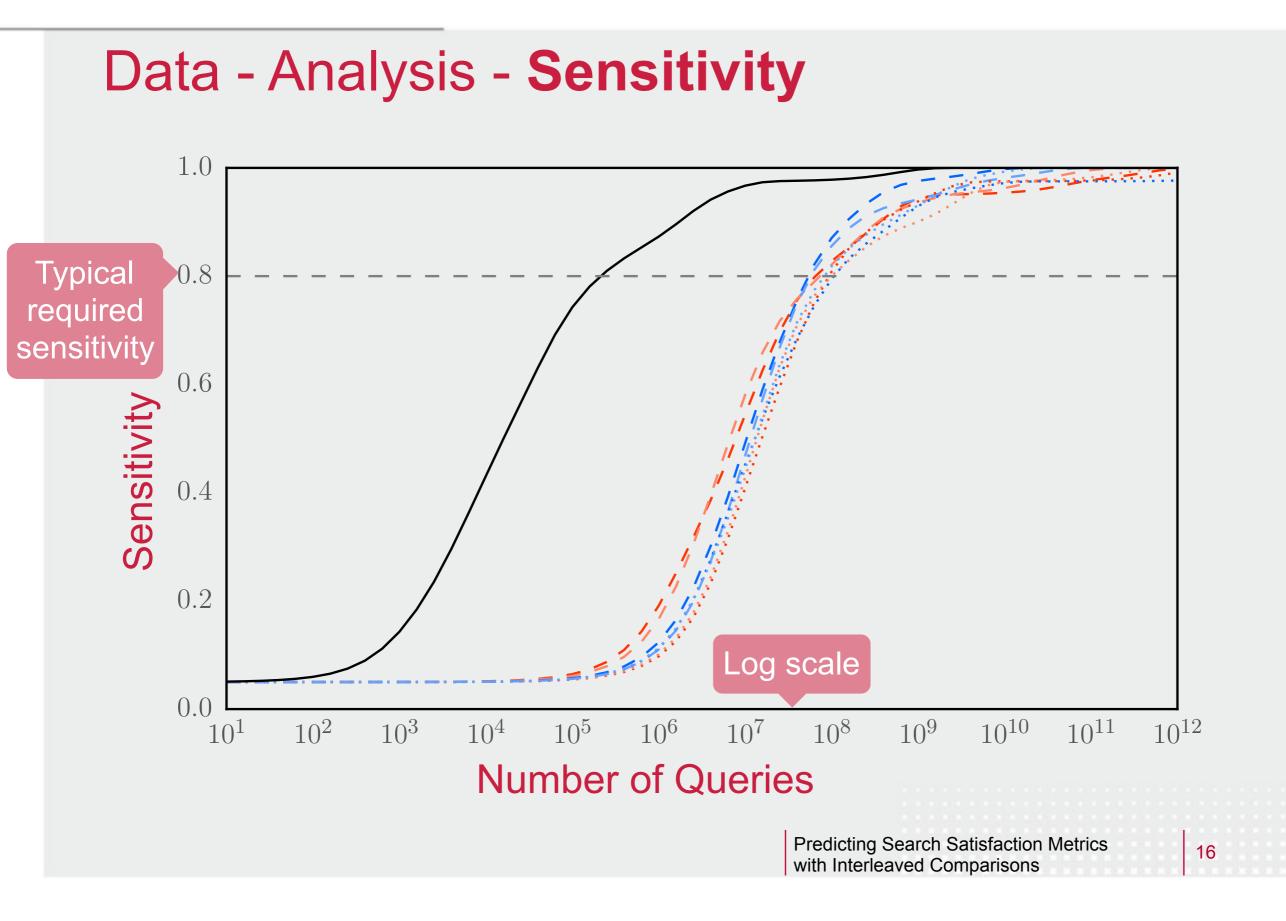
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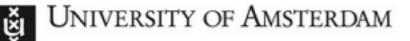


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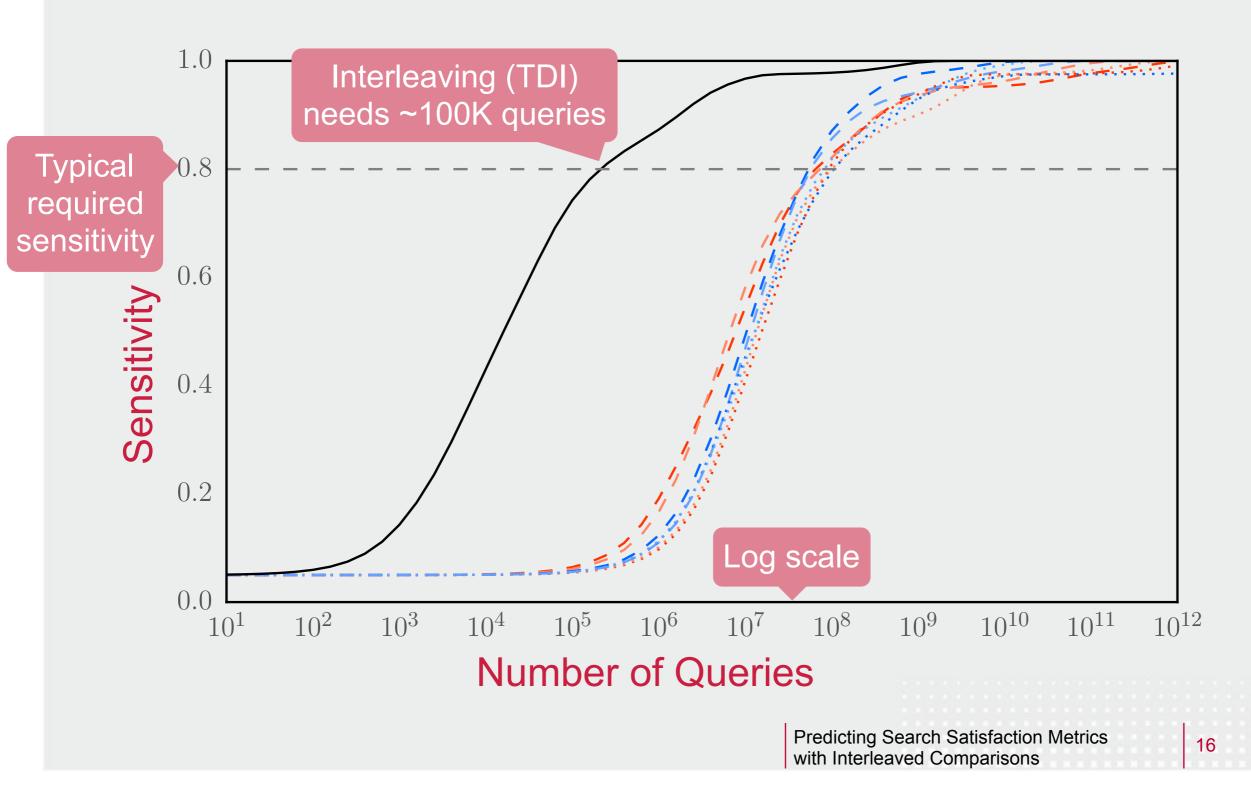


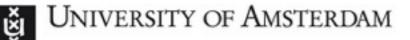
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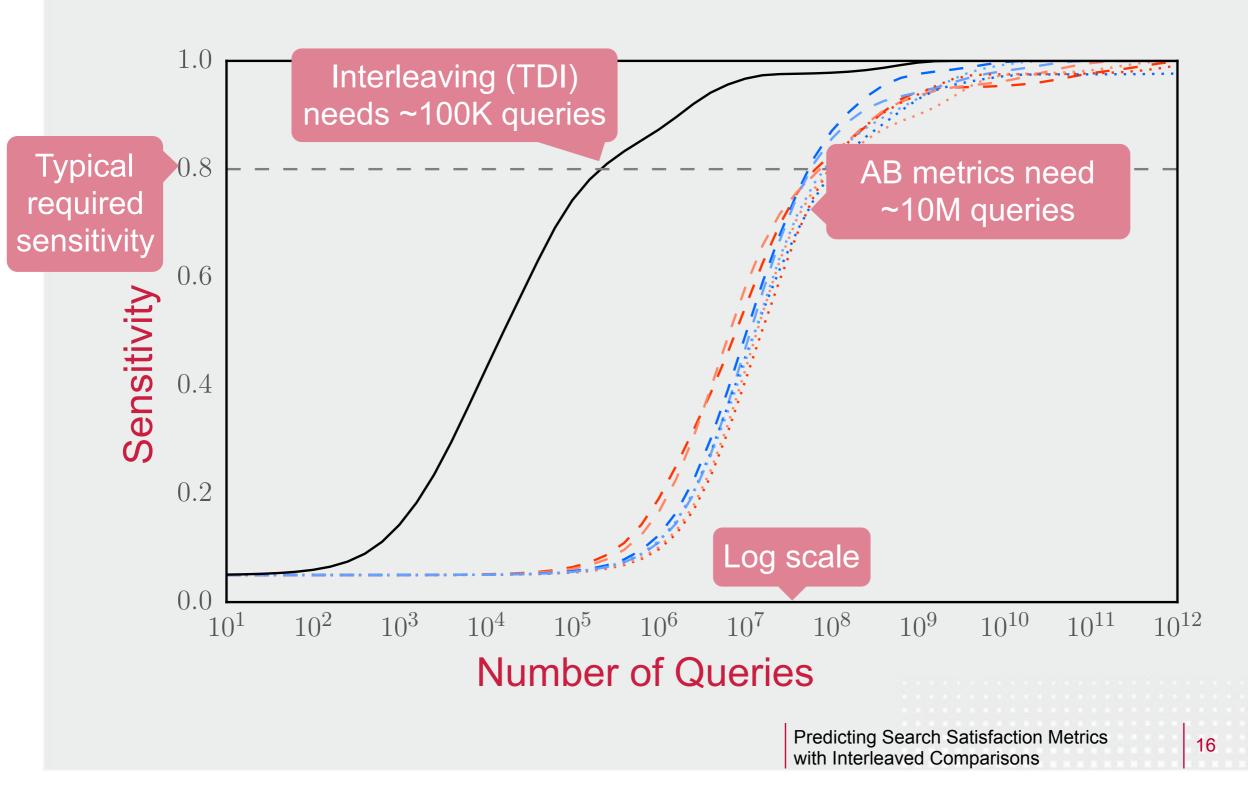




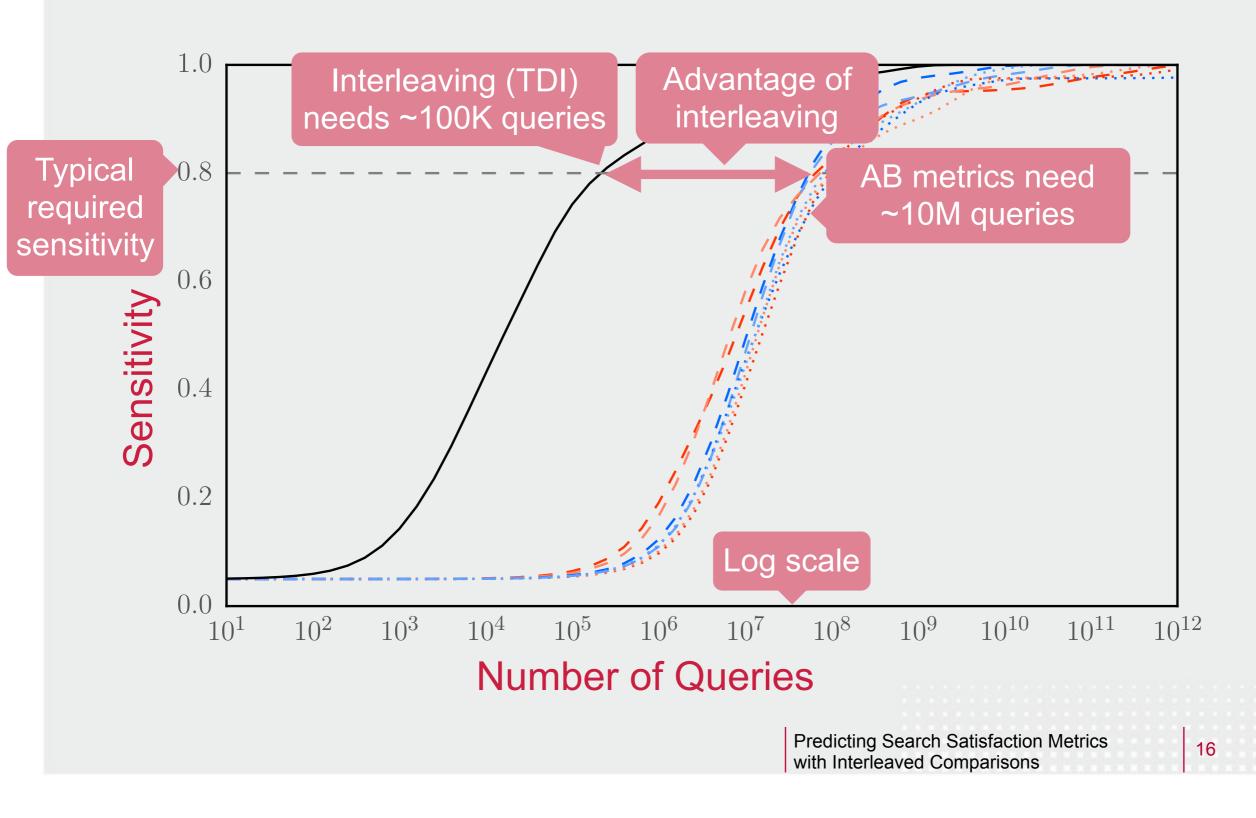




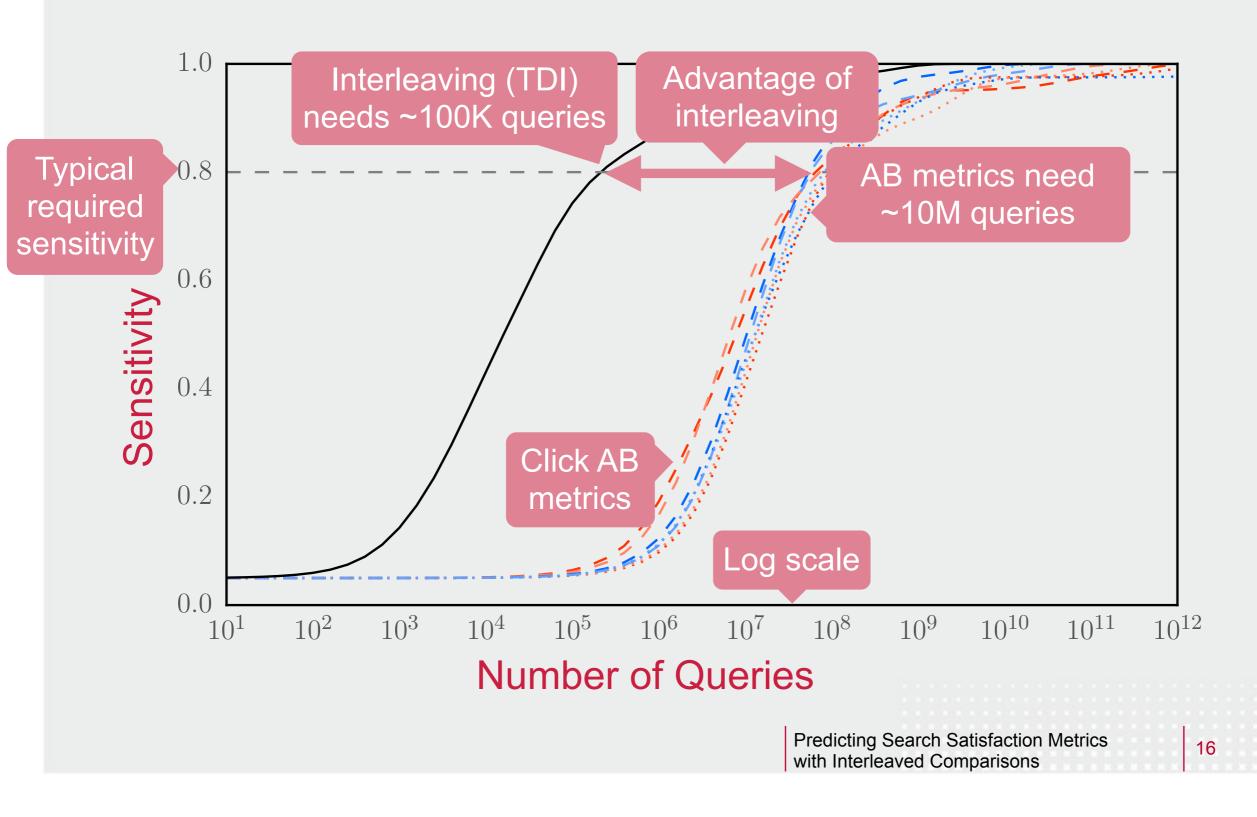


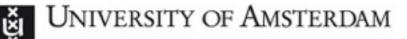




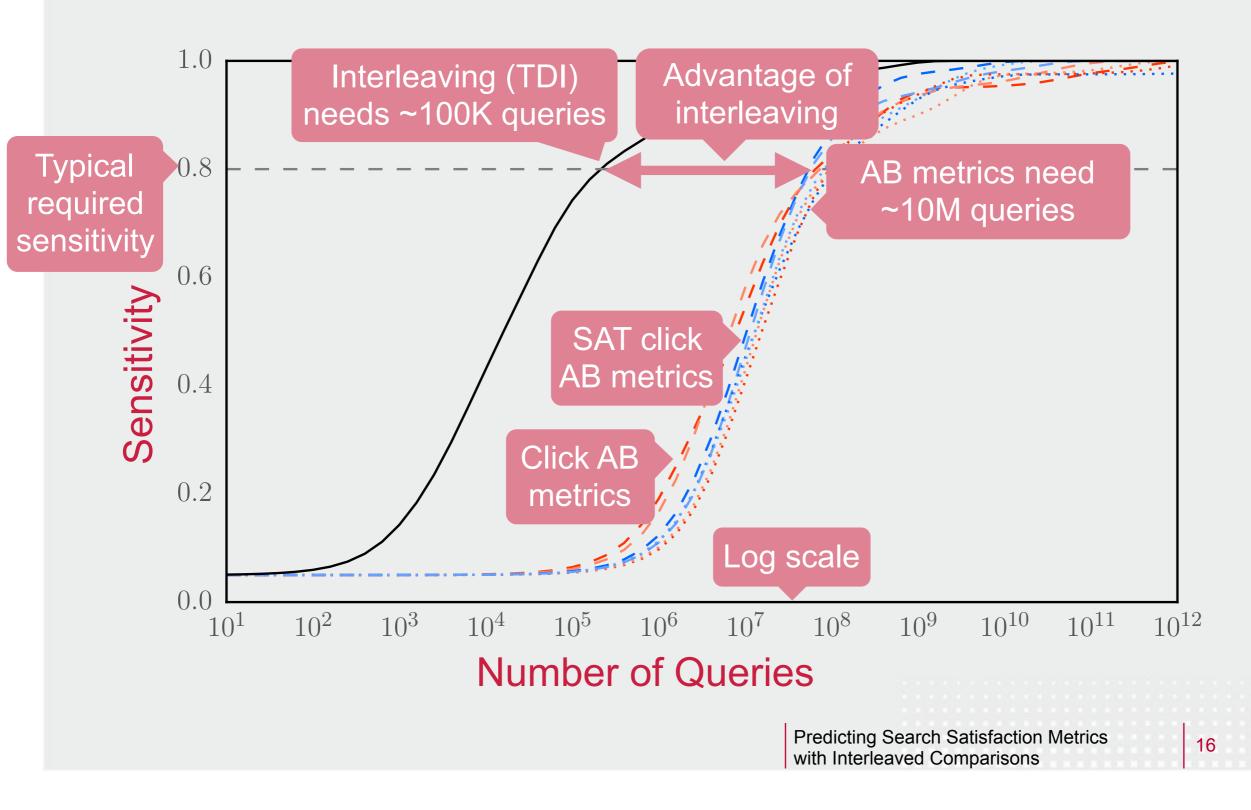


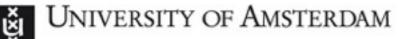


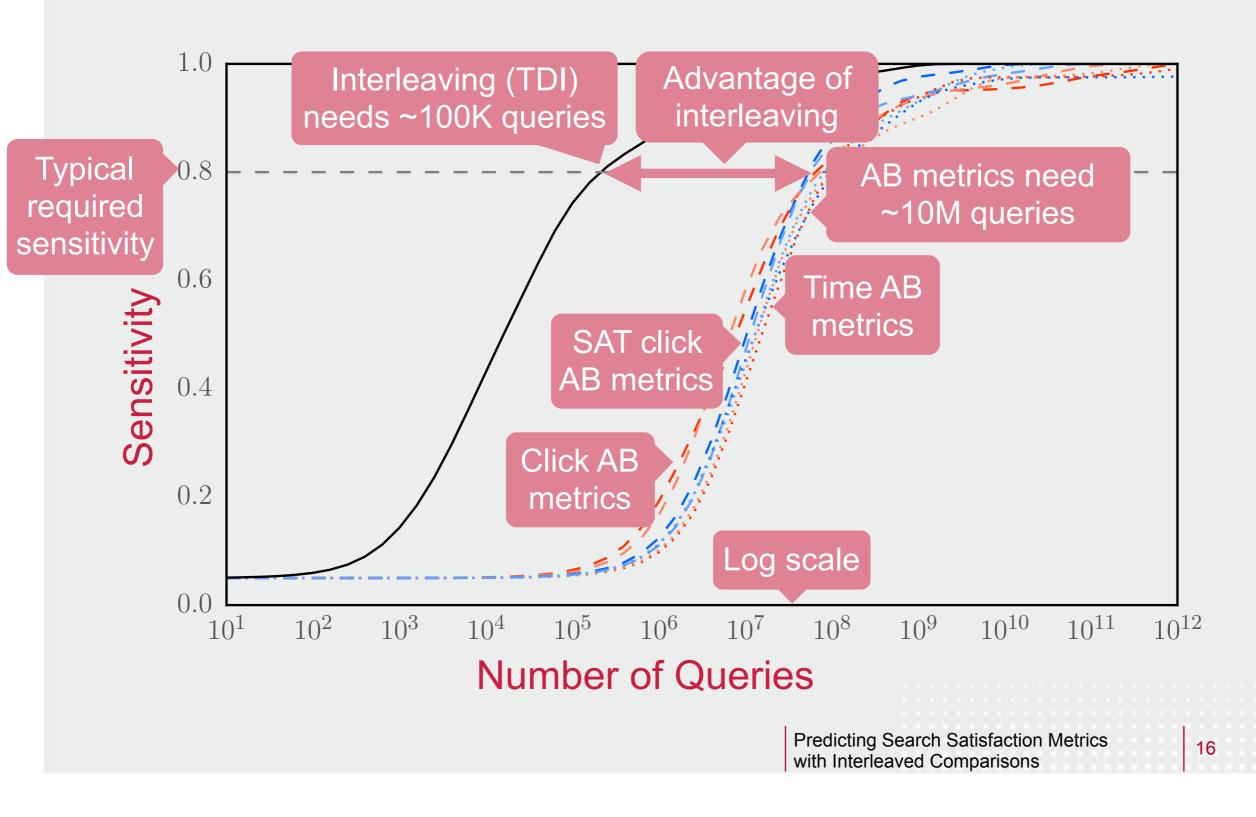










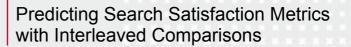




Predicting Search Satisfaction Metrics	
with Interleaved Comparisons	



AB Testing has low sensitivity



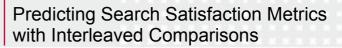


AB Testing has low sensitivity Interleaving (TDI) has high sensitivity (10-100x AB)





AB Testing has low sensitivity Interleaving (TDI) has high sensitivity (10-100x AB) Interleaving (TDI) has low agreement with AB metrics



17



AB Testing has low sensitivity Interleaving (TDI) has high sensitivity (10-100x AB) Interleaving (TDI) has low agreement with AB metrics

We aim to Improve interleaving (TDI) to increase agreement with a given AB metric while maintaining sensitivity

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Data - Analysis - Aim

	Sensitivity	Agreement with AB
	(required #queries)	(prefer same ranker)
AB Testing	~10M 🗴	~90%

Predicting Search Satisfaction Metrics
with Interleaved Comparisons



Data - Analysis - Aim

	Sensitivity	Agreement with AB
	(required #queries)	(prefer same ranker)
AB Testing	~10M 🚫	~90%
Interleaving (TDI)	~100K 📀	~60%



Data - Analysis - Aim

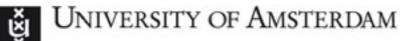
	Sensitivity	Agreement with AB
	(required #queries)	(prefer same ranker)
AB Testing	~10M 🚫	~90%
Interleaving (TDI)	~100K 📀	~60%
Improved Interleaving (TDI)	~100K ? ⊘	~90% ? 🐼

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Outline

Motivation Data + analysis **Methods + results** Conclusions



Methods

1. Matching AB Metrics

2. Parameterized Credit Functions

3. Combined Credit Functions





Interleaving traditionally counts all clicks





Interleaving traditionally counts all clicks Instead of counting all clicks ...





Interleaving traditionally counts all clicks Instead of counting all clicks ...

... we propose to match AB metrics



Interleaving traditionally counts all clicks Instead of counting all clicks ...

- ... we propose to match AB metrics
 - Count only certain clicks



- Interleaving traditionally counts all clicks
 Instead of counting all clicks ...
- ... we propose to match AB metrics
 - Count only certain clicks
 - @1



- Interleaving traditionally counts all clicks
 Instead of counting all clicks ...
- ... we propose to match AB metrics
 - Count only certain clicks
 - @1
 - SAT



(a)1

SAT

Methods - Matching AB Metric

Interleaving traditionally counts all clicks Instead of counting all clicks ...

... we propose to match AB metrics

Count only certain clicks

Filter out clicks, can reduce sensitivity

Predicting Search Satisfaction Metrics with Interleaved Comparisons



(a)1

SAT

Methods - Matching AB Metric

Interleaving traditionally counts all clicks Instead of counting all clicks ...

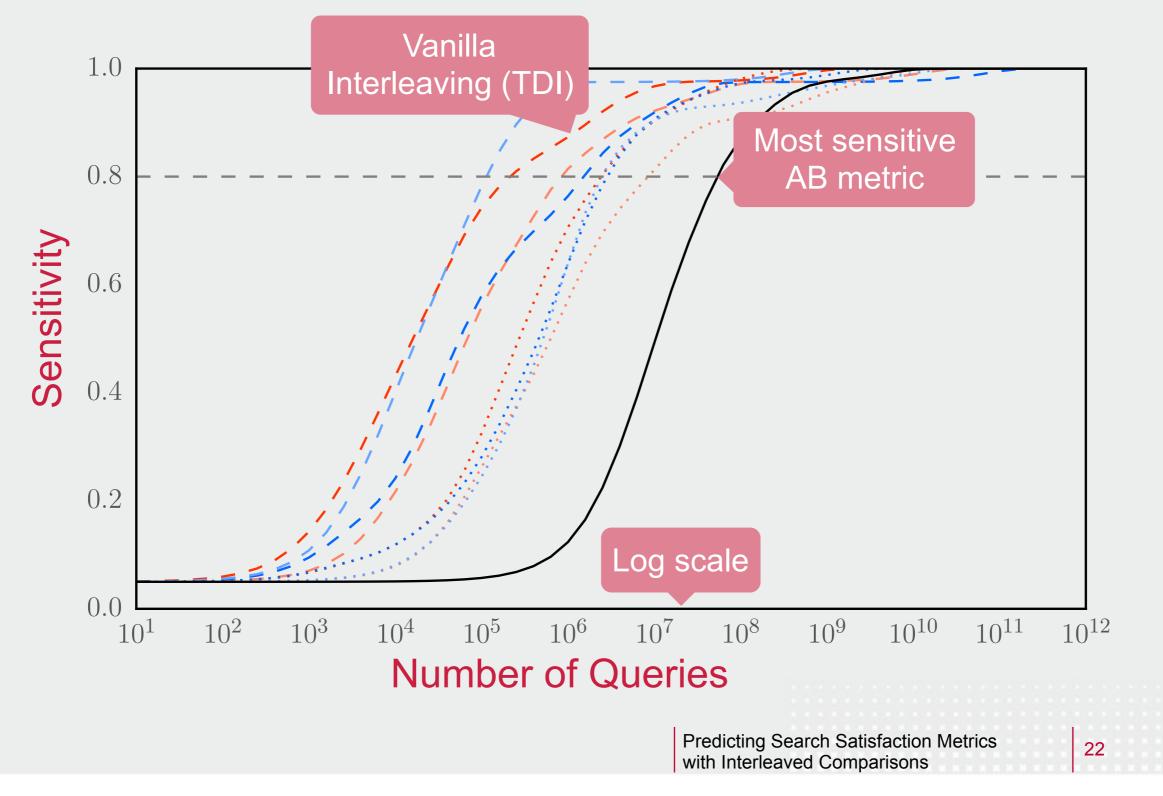
... we propose to match AB metrics

Count only certain clicks

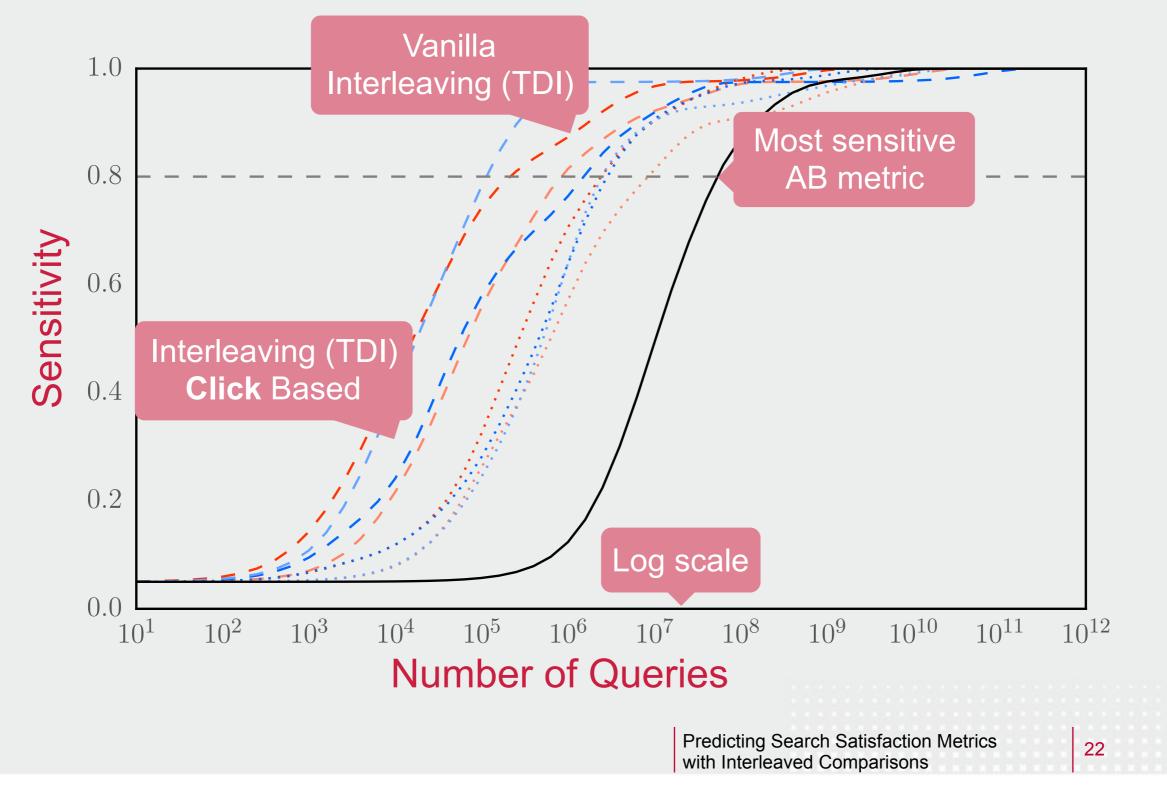
Filter out clicks, can reduce sensitivity

Measure time to click

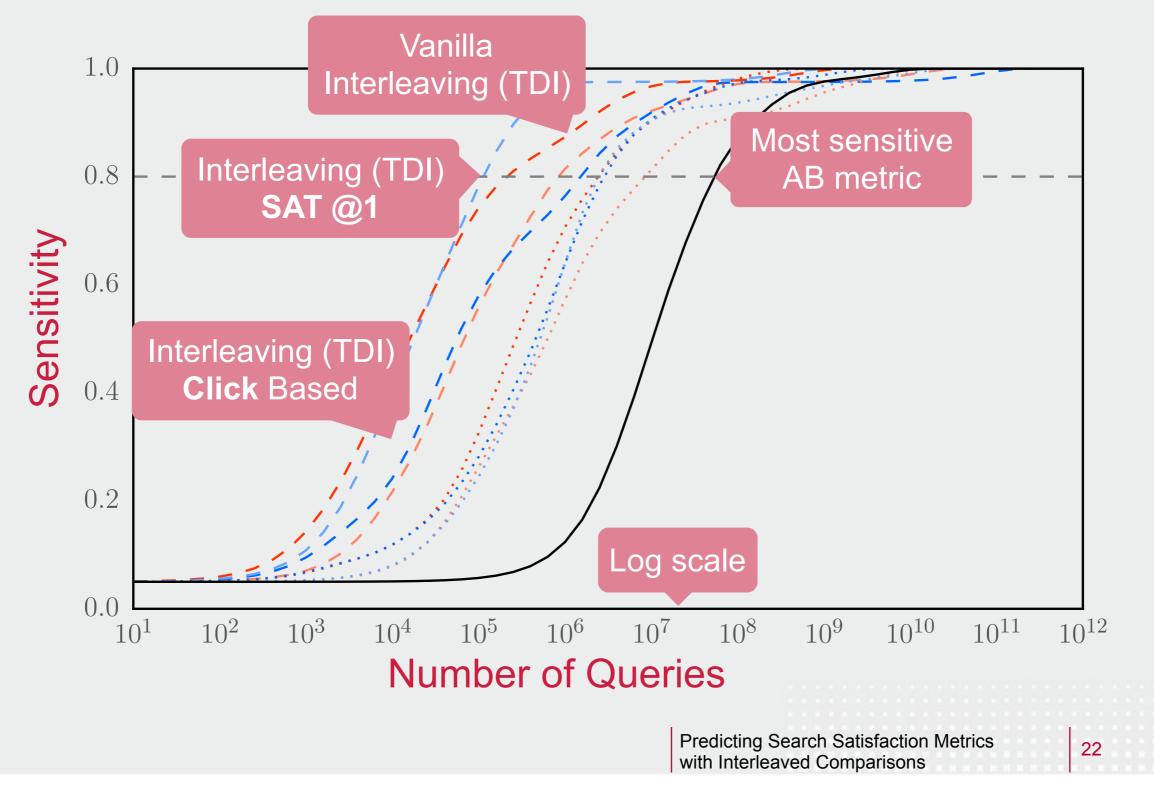
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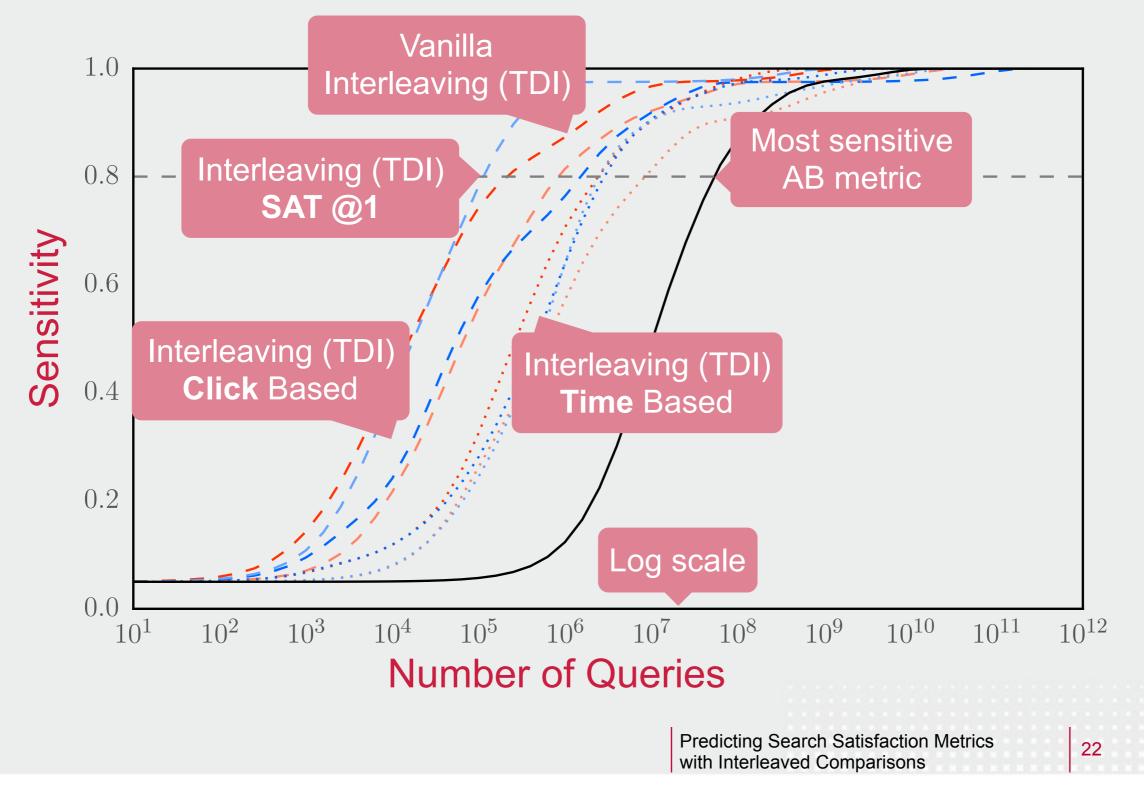


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Methods - Matching AB metric - Agreement

Vanill	a interle	aving
	TDI	
AB	0.63	matching AB metric
AB@1	0.71	
ABs	0.71	
AB _s @1	0.76	
ABT	0.53	
AB _T @1	0.45	
AB _{T,S}	0.47	
AB _{T,S} @1	0.42	

Predicting Search Satisfaction Metrics	
with Interleaved Comparisons	



Methods - Matching AB metric - Agreement

Vanilla interleaving

	TDI	TDI@1	TDIs	TDI _s @1	TDIT	TDI _T @1	TDI _{T,S}	TDI _{T,S} @1
AB	0.63							
AB@1	0.71	0.68						
ABs	0.71		0.87					
AB _s @1	0.76			0.63				
ABT	0.53				0.71			
AB _T @1	0.45					0.58		
AB _{T,S}	0.47						0.58	
AB _{T,S} @1	0.42							0.58



Methods - Matching AB metric - Agreement

Vanilla interleaving

	TDI	TDI@1	TDIs	TDI _s @1	TDIT	TDI⊤@1	TDI _{T,S}	TDI _{T,S} @1
AB	0.63	0.66	0.84	0.66	0.61	0.61	0.58	0.53
AB@1	0.71	0.68	0.76	0.63	0.63	0.47	0.55	0.55
ABs	0.71	0.68	0.87	0.68	0.68	0.58	0.61	0.55
AB _s @1	0.76	0.68	0.82	0.63	0.74	0.53	0.61	0.50
ABT	0.53	0.55	0.47	0.55	0.71	0.55	0.68	0.58
AB _T @1	0.45	0.47	0.45	0.58	0.63	0.58	0.61	0.62
AB _{T,S}	0.47	0.55	0.53	0.71	0.66	0.66	0.58	0.53
AB _{T,S} @1	0.42	0.50	0.53	0.66	0.61	0.66	0.58	0.58

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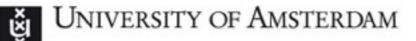
Methods - Matching AB metric - Agreement

Vanilla interleaving

	TDI	TDI@1	TDIs	TDI _s @1	TDIT	TDI⊤@1	TDI _{T,S}	TDI _{T,S} @1
AB	0.63	0.66	0.84	0.66	0.61	0.61	0.58	0.53
AB@1	0.71	0.68	0.76	0.63	0.63	0.47	0.55	0.55
ABs	0.71	0.68	0.87	0.68	0.68	0.58	0.61	0.55
AB _s @1	0.76	0.68	0.82	0.63	0.74	0.53	0.61	0.50
ABT	0.53	0.55	0.47	0.55	0.71	0.55	0.68	0.58
AB _T @1	0.45	0.47	0.45	0.58	0.63	0.58	0.61	0.62
AB _{T,S}	0.47	0.55	0.53	0.71	0.66	0.66	0.58	0.53
AB _{T,S} @1	0.42	0.50	0.53	0.66	0.61	0.66	0.58	0.58

Highest agreement not on diagonal

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Methods

Matching AB Metrics Parameterized Credit Functions Combined Credit Functions





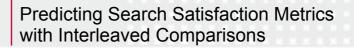
We aim to increase agreement



Remember, we have a model that predicts **SAT probability**

We aim to increase agreement
 Parameterize TDI with a SAT threshold t_s

TDIs^{ts} and TDI_{T,S}^{ts}





Remember, we have a model that predicts **SAT probability**

We aim to increase agreement
 Parameterize TDI with a SAT threshold t_s

TDIsts and TDIT,sts

Click based

Time based

Predicting Search Satisfaction Metrics with Interleaved Comparisons



We aim to increase agreement

Remember, we have a model that predicts SAT probability

- Parameterize TDI with a SAT threshold ts
 - TDI_S^{ts} and TDI_{T,S}^{ts}

Click based

Time based

Filter out non SAT clicks, can reduce sensitivity





Remember, we have a model that predicts SAT probability

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 Parameterize TDI with a SAT threshold t_s
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Find optimal threshold t_s

Maximize agreement for each AB metric



We aim to increase agreement

Remember, we have a model that predicts **SAT probability**

- Parameterize TDI with a SAT threshold ts
 - TDIs^{ts} and TDI_{T,S}^{ts}

Click based

Time based

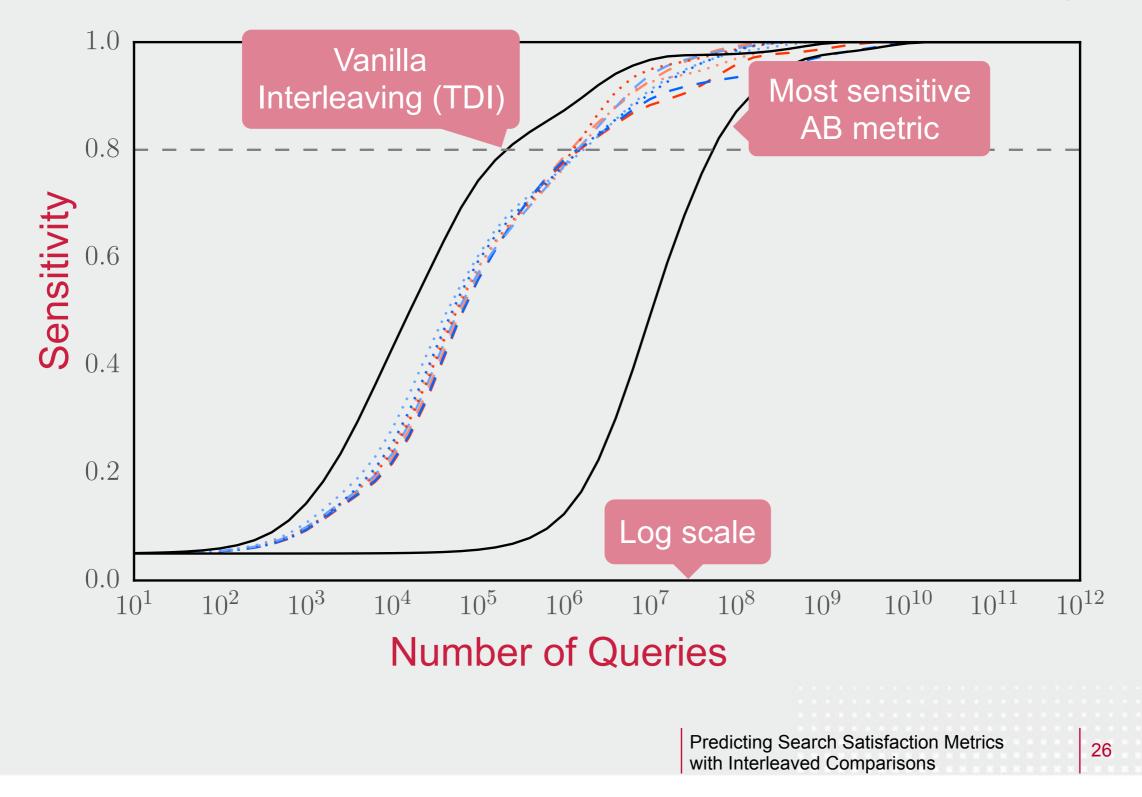
Filter out non SAT clicks, can reduce sensitivity

Find optimal threshold t_s

- Maximize agreement for each AB metric
- Repeat n=100 times:
 - Take bootstrap sample
 - Grid search to find t_s that maximizes agreement
 - Report performance on "out of bag" sample

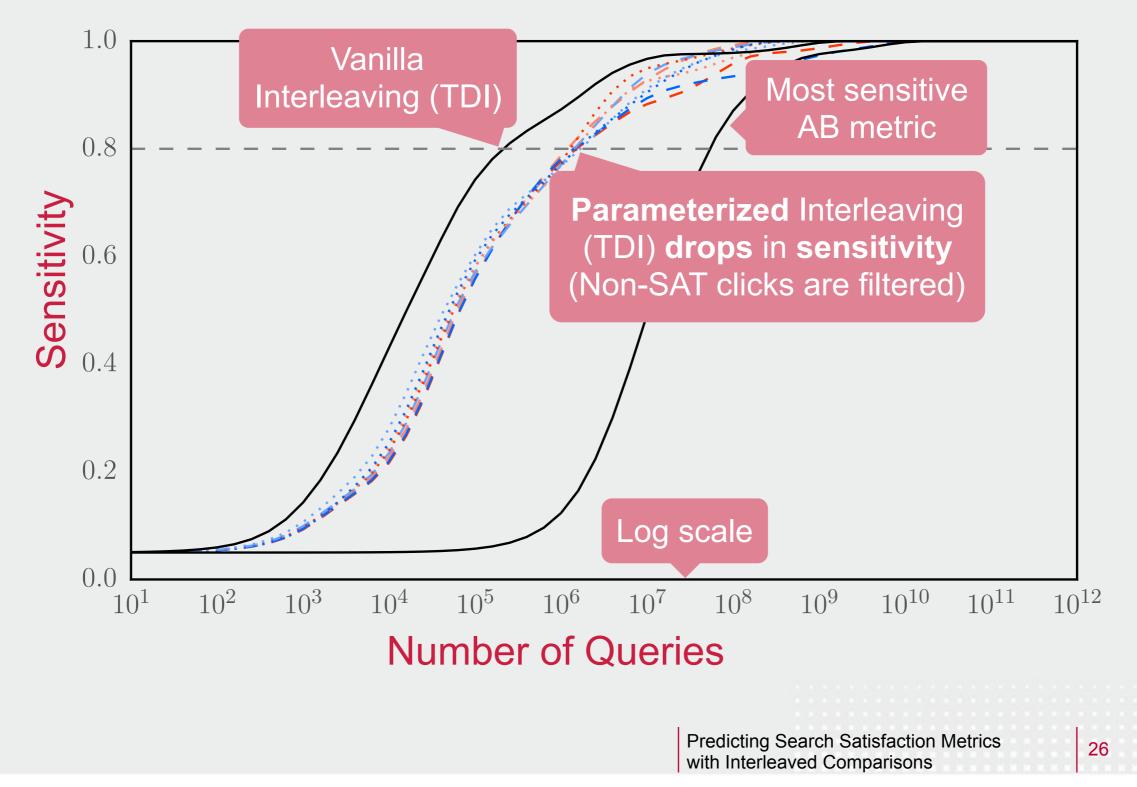
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Methods - Parametrized Credit - Sensitivity



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Methods - Parametrized Credit - Sensitivity





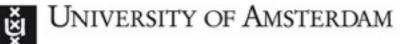
	Vanilla
AB Metric	TDI
AB	0.63
AB@1	0.71
ABs	0.71
AB _s @1	0.76
ABT	0.53
AB _T @1	0.45
AB _{T,S}	0.47
AB _{T,S} @1	0.42



	Vanilla	Click based
AB Metric	TDI	TDIs ^{ts}
AB	0.63	0.82
AB@1	0.71	
ABs	0.71	
AB _s @1	0.76	
ABT	0.53	
AB _T @1	0.45	
AB _{T,S}	0.47	
AB _{T,S} @1	0.42	



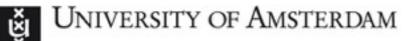
	Vanilla	Click based
AB Metric	TDI	TDI _S ts
AB	0.63	0.82
AB@1	0.71	0.79
ABs	0.71	0.84
AB _s @1	0.76	0.84
ABT	0.53	0.47
AB _T @1	0.45	0.49
AB _{T,S}	0.47	0.46
AB _{T,S} @1	0.42	0.52



	Vanilla	Click based	Time based
AB Metric	TDI	TDIs ^{ts}	TDI _{T,S} ts
AB	0.63	0.82	0.53
AB@1	0.71	0.79	0.54
ABs	0.71	0.84	0.48
AB _s @1	0.76	0.84	0.48
ABT	0.53	0.47	0.67
AB _T @1	0.45	0.49	0.62
AB _{T,S}	0.47	0.46	0.61
AB _{T,S} @1	0.42	0.52	0.62



	Vanilla	Click based	Time based
AB Metric	TDI	TDIs ^{ts}	TDI _{T,S} ts
AB	0.63	0.82	0.53
AB@1	0.71	0.79	0.54
ABs	0.71	0.84	0.48
AB _s @1	0.76	0.84	0.48
ABT	0.53	0.47	0.67
AB _T @1	0.45	0.49	0.62
AB _{T,S}	0.47	0.46	0.61
AB _{T,S} @1	0.42	0.52	0.62



Methods

1. Matching AB Metrics

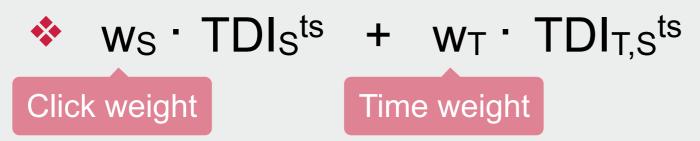
2. Parameterized Credit Functions

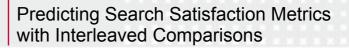
3. Combined Credit Functions





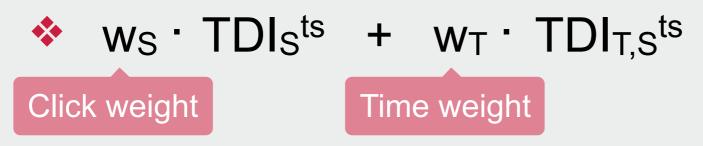
Combine parameterized credit functions







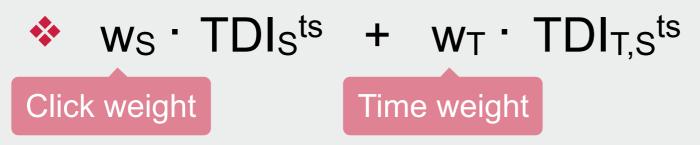
Combine parameterized credit functions



- Find optimal weights
 - Maximizing agreement



Combine parameterized credit functions



- Find optimal weights
 - Maximizing agreement
- Using the same maximization procedure
 - Bootstrap sample, parameter sweep



Methods - Combined Credit - Agreement

AB Metric	TDI
AB	0.63
AB@1	0.71
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AB _s @1	0.76
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AB _{T,S}	0.47
AB _{T,S} @1	0.42



Methods - Combined Credit - Agreement

		TDI _{T,S} W	Click weight	Time weight
AB Metric	TDI	agreement	Ws	ŴŢ
AB	0.63	0.84	1.00	0.00
AB@1	0.71			
AB _S	0.71			
AB _s @1	0.76			
ABT	0.53			
AB _T @1	0.45			
AB _{T,S}	0.47			
AB _{T,S} @1	0.42			



Methods - Combined Credit - Agreement

		TDI _{T,S} W	Click weight	Time weight
AB Metric	TDI	agreement	Ws	WT
AB	0.63	0.84	1.00	0.00
AB@1	0.71	0.75	1.00	0.05
AB _S	0.71	0.85	1.00	0.00
AB _s @1	0.76	0.83	1.00	0.02
ABT	0.53	0.68	0.99	0.90
AB _T @1	0.45	0.56	0.96	0.79
AB _{T,S}	0.47	0.63	0.91	0.88
AB _{T,S} @1	0.42	0.50	0.06	0.25



Methods - Combined Credit - Agreement

		TDI _{T,S} W	Click weight	Time weight
AB Metric	TDI	agreement	Ws	ŴŢ
AB	0.63	0.84	1.00	0.00
AB@1	0.71	0.75	1.00	0.05
AB _S	0.71	0.85	1.00	0.00
AB _s @1	0.76	0.83	1.00	0.02
ABT	0.53	0.68	0.99	0.90
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AB _{T,S}	0.47	0.63	0.91	0.88
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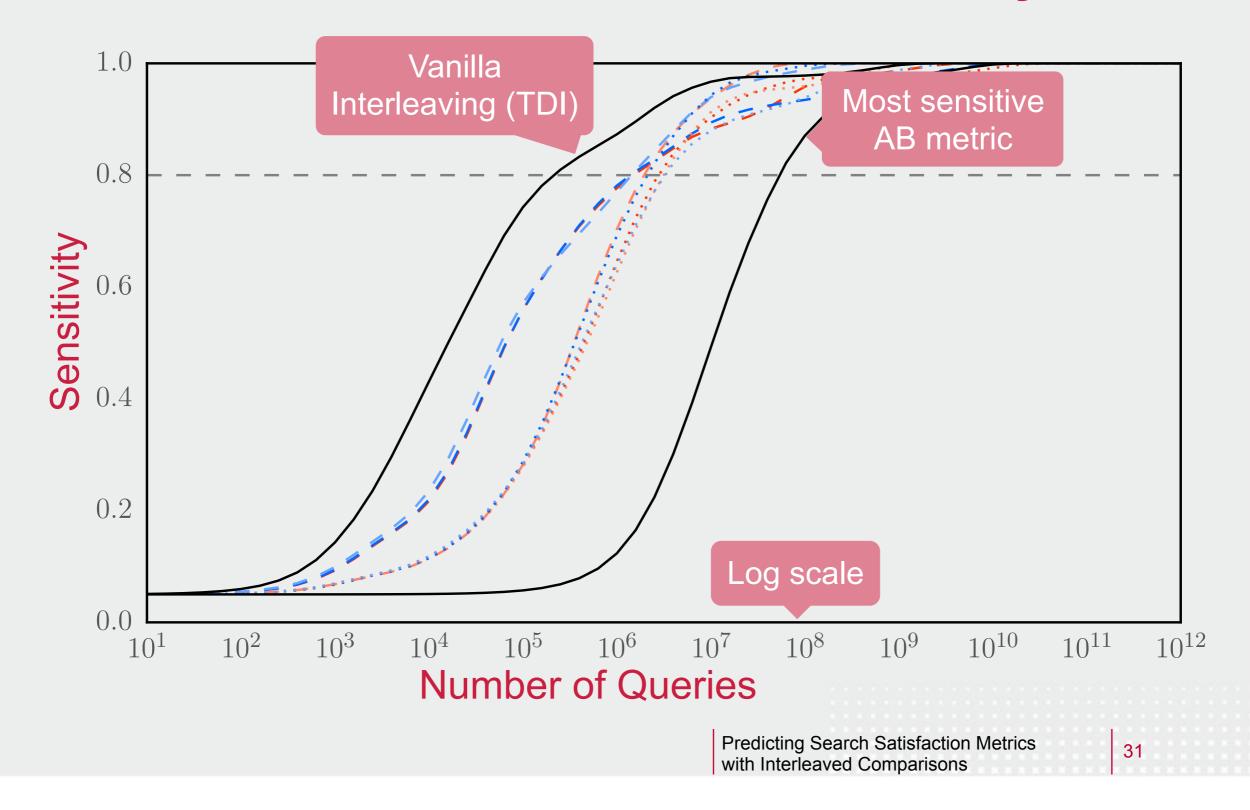


Methods - Combined Credit - Agreement

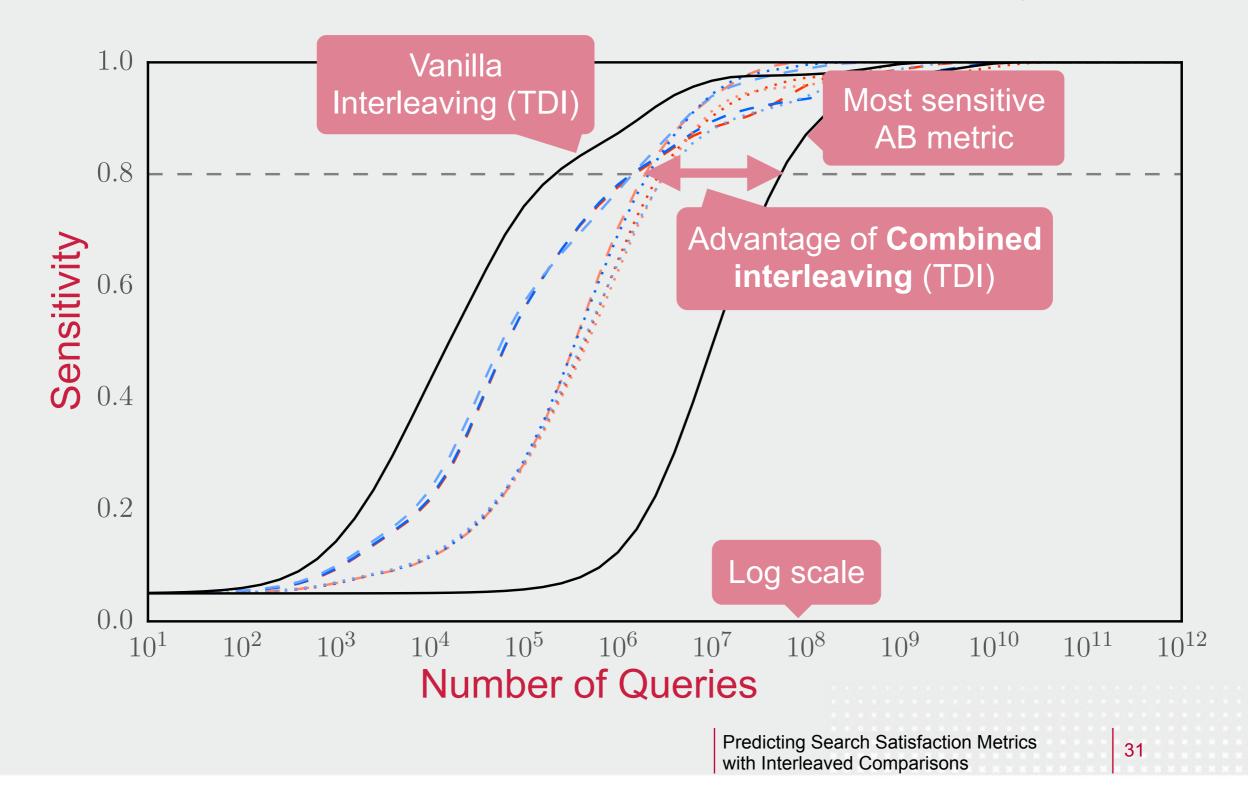
		TDI _{T,S} W	Click weight	Time weight
AB Metric	TDI	agreement	Ws	ŴŢ
AB	0.63	0.84	1.00	0.00
AB@1	0.71	0.75	1.00	0.05
AB _S	0.71	0.85	1.00	0.00
AB _s @1	0.76	0.83	1.00	0.02
ABT	0.53	0.68	0.99	0.90
AB _T @1	0.45	0.56	0.96	0.79
AB _{T,S}	0.47	0.63	0.91	0.88
AB _{T,S} @1	0.42	0.50	0.06	0.25

All significantly better than TDI

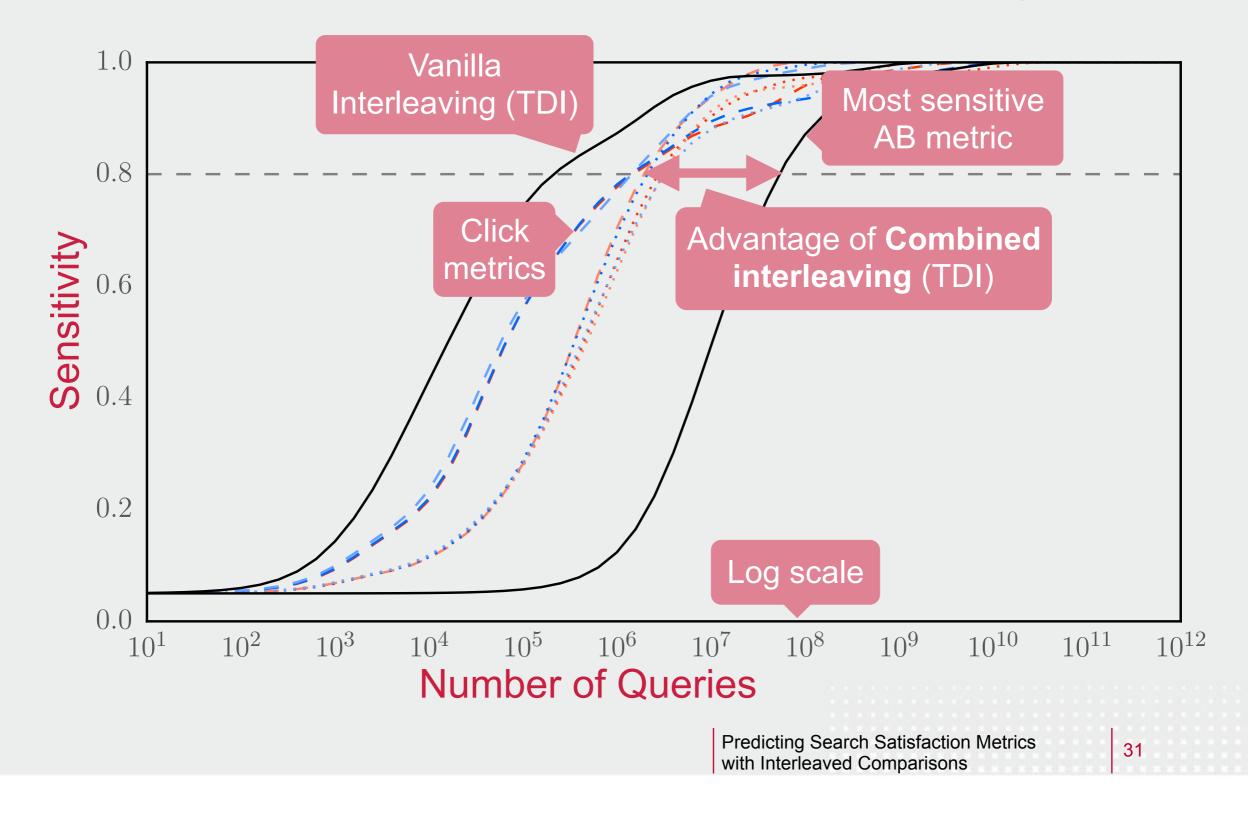
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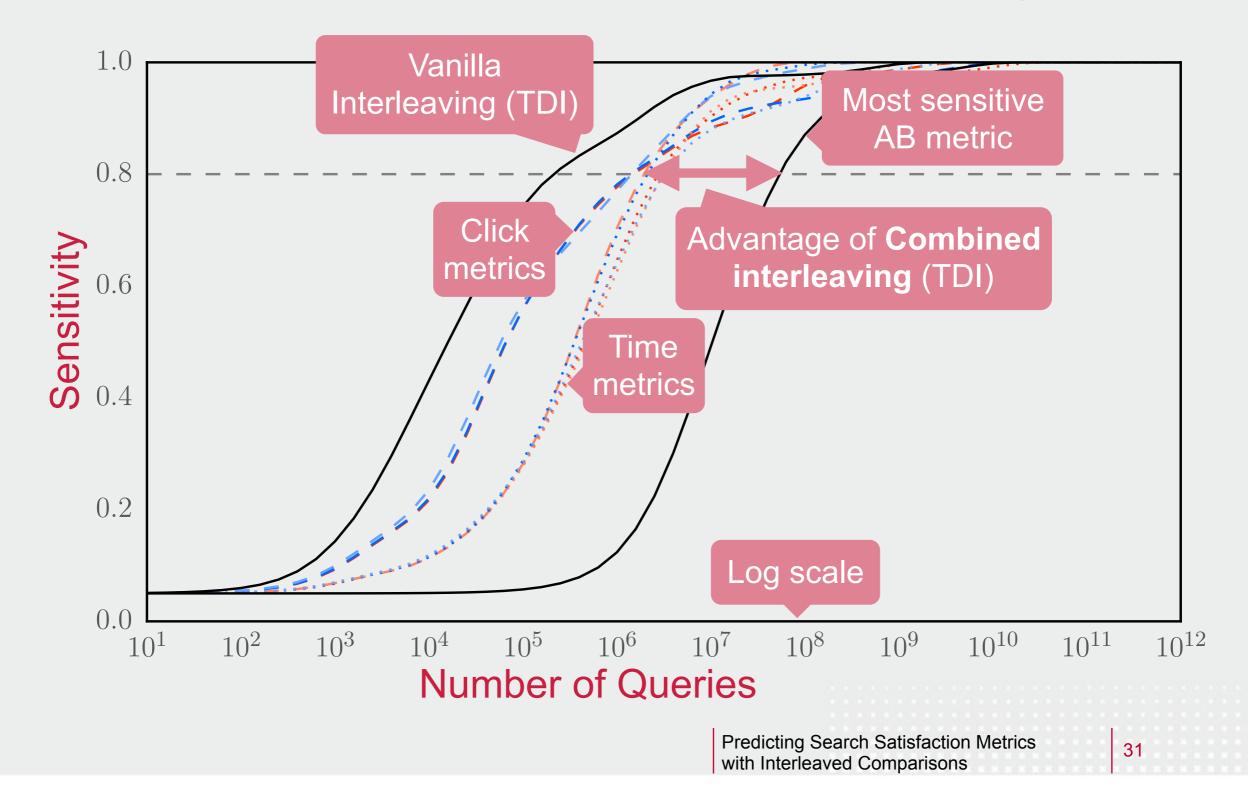
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Outline

Motivation Data + analysis Methods + results **Conclusions**



Conclusions - Data Analysis



Conclusions - Data Analysis

Sensitivity:

Confirming earlier findings

AB Testing is 10-100x less sensitive than Interleaving



Conclusions - Data Analysis

Sensitivity:

Confirming earlier findings

- AB Testing is 10-100x less sensitive than Interleaving
- Agreement

New insight

Between AB Testing and Interleaving (TDI) is low: <76%</p>



Conclusions - Methods



Conclusions - Methods

Interleaving (TDI) with just credit matching AB metrics Unpredictable performance





Conclusions - Methods

Interleaving (TDI) with just credit matching AB metrics Unpredictable performance

Interleaving (TDI) with parameterized credit functions

Improvements for some AB metrics

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Conclusions - Methods

Interleaving (TDI) with just credit matching AB metrics Unpredictable performance

Interleaving (TDI) with parameterized credit functions Improvements for some AB metrics

Interleaving (TDI) with combined credit functions Improvements for all AB metrics

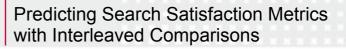




Consider even richer user signals (sessions, task level features)



- Consider even richer user signals (sessions, task level features)
- Take magnitude and uncertainty of AB metric differences into account



35



- Consider even richer user signals (sessions, task level features)
- Take magnitude and uncertainty of AB metric differences into account
- Understanding of where and why agreement is low or high



- Consider even richer user signals (sessions, task level features)
- Take magnitude and uncertainty of AB metric differences into account
- Understanding of where and why agreement is low or high
- Apply to other types of ranking systems



Predicting Search Satisfaction Metrics with Interleaved Comparisons

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Richer user signals in interleaving

- Richer user signals in interleaving
- Agreement of interleaving with an AB metric can be made as high as 87%

- Richer user signals in interleaving
- Agreement of interleaving with an AB metric can be made as high as 87%
- While maintaining high sensitivity of interleaving

- Richer user signals in interleaving
- Agreement of interleaving with an AB metric can be made as high as 87%
- While maintaining high sensitivity of interleaving
- Weak signals can be measured with a strong (but biased) proxy

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- Agreement of interleaving with an AB metric can be made as high as 87%
- While maintaining high sensitivity of interleaving
- Weak signals can be measured with a strong (but biased) proxy

