Behavior-Based Metrics

Praveen Chandar, Spotify

Explicit Feedback

- Ask users to learn about their experience with the system (surveys, ratings, etc.) or setup annotation tasks for humans to provide labels given data points.
- Limitations of explicit feedback
  - intrusive
  - expensive
  - might not reflect ***true*** user preference
  - might be infeasible for certain applications (e.g., personalization)

Implicit Feedback

- Infer user satisfaction from behavioral systems as they interact with the system.
- Advantages over explicit
  - collected in a natural setting
  - easy & inexpensive to collect
  - provides a direct measure of user preferences
- Limitation
  - can be noisy
  - biased

Mark Claypool et al. **Implicit Interest Indicators.** IUI 2001.
Diane Kelley et al. **Implicit feedback for inferring user preference: a bibliography.** SIGIR Fourm 2003.

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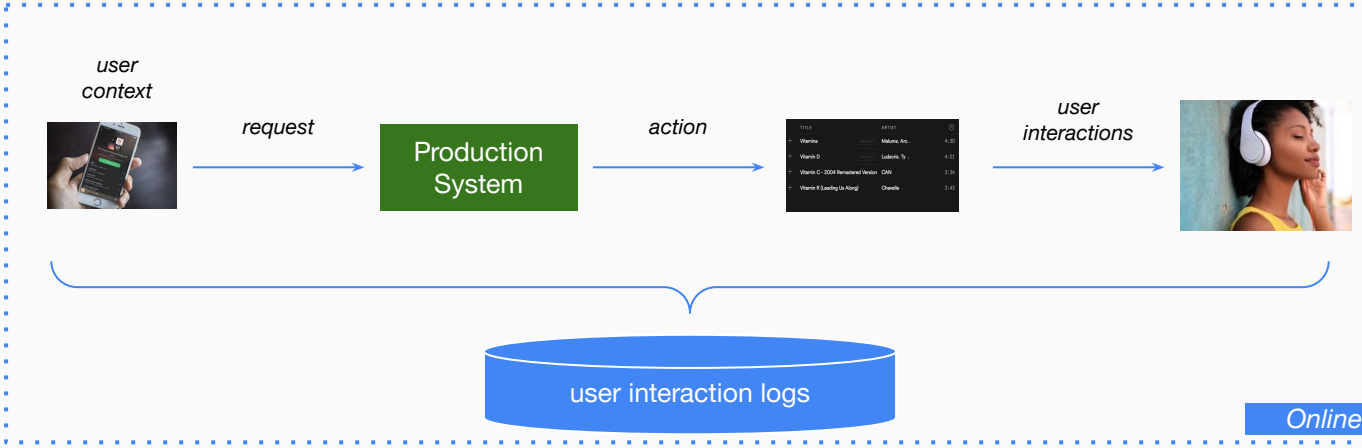
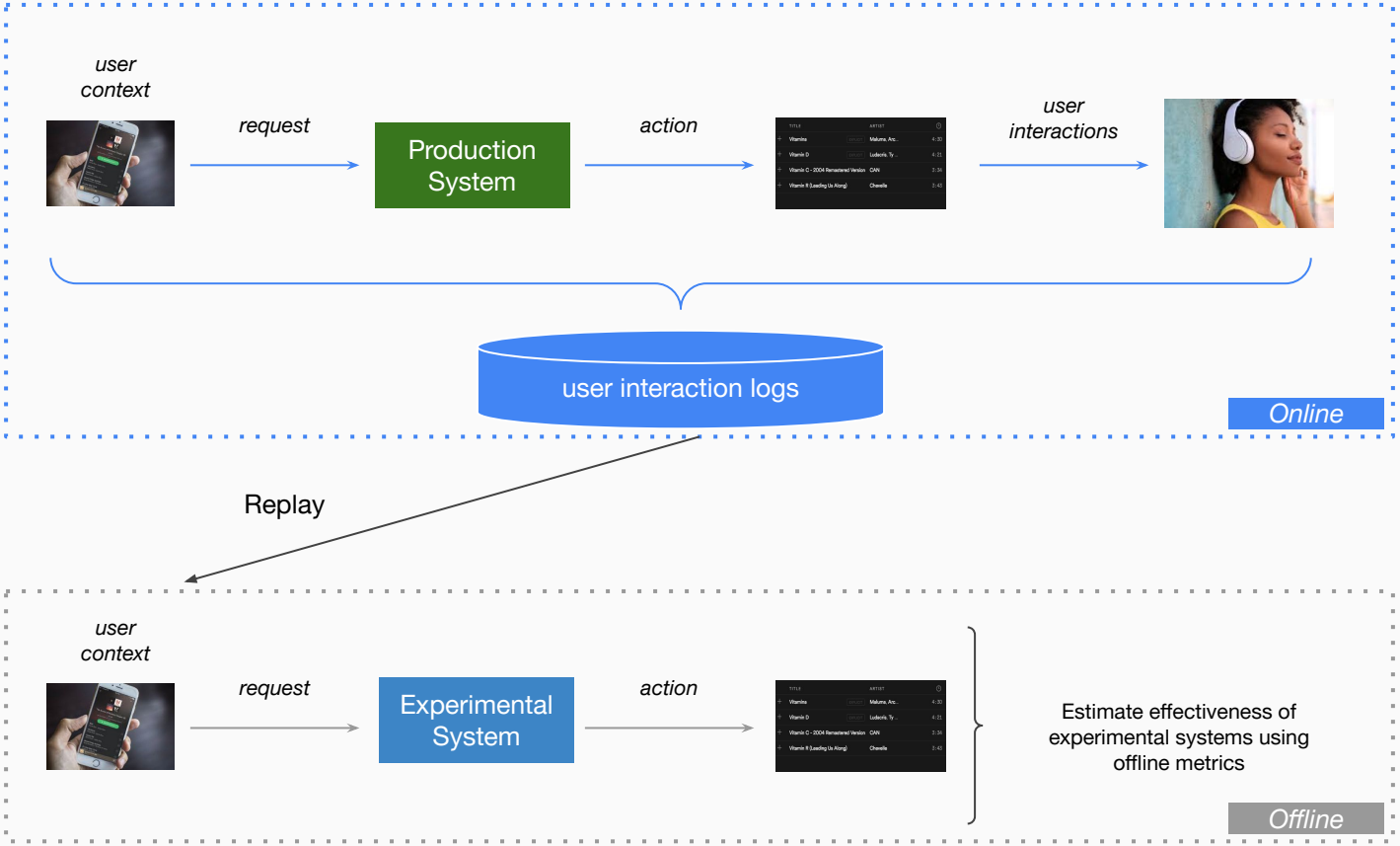
ML Evaluation Workflow



ML Evaluation Workflow

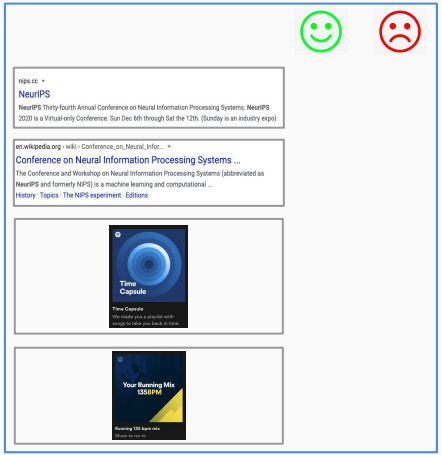


Categorizing Implicit Signals

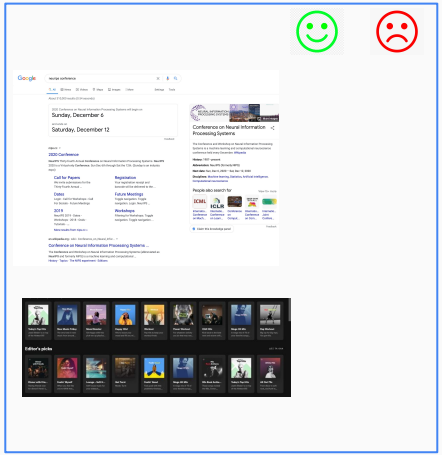
short-term

long-term

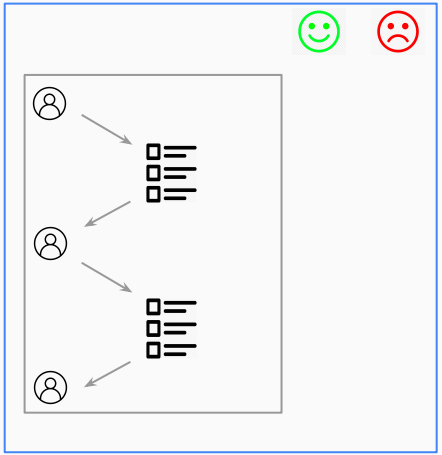
Item Level Feedback



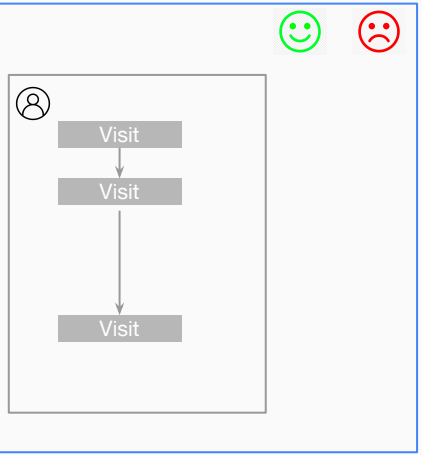
Page Level Feedback



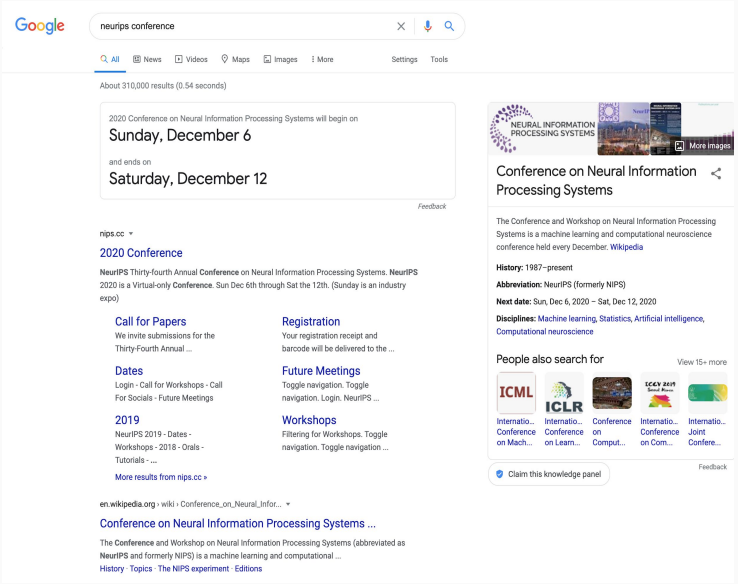
Session Level Feedback



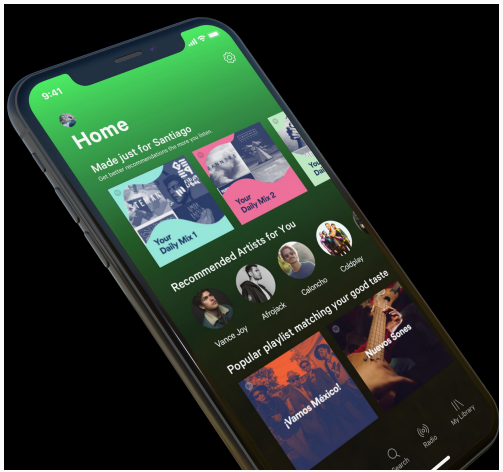
Intra-Session Feedback



Illustrative Examples



Web Search



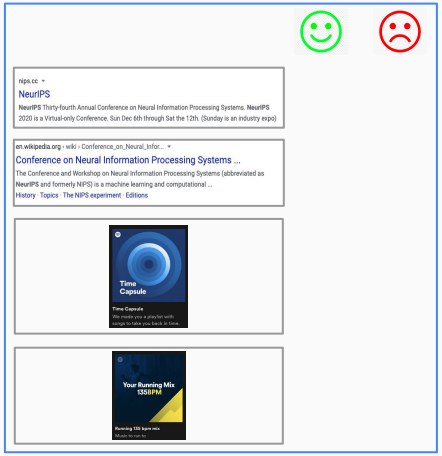
Music Recommendation

Item Level Feedback

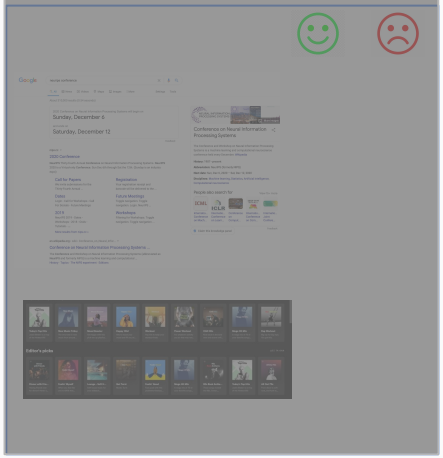
short-term

long-term

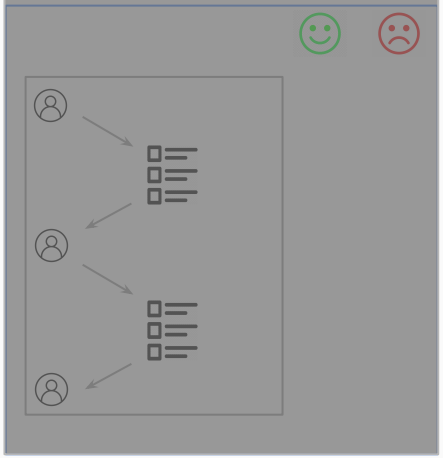
Item Level Feedback



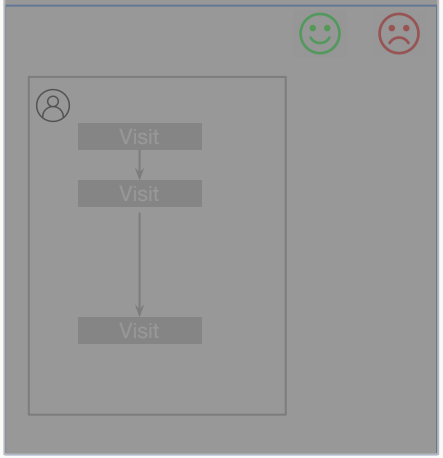
Page Level Feedback



Session Level Feedback

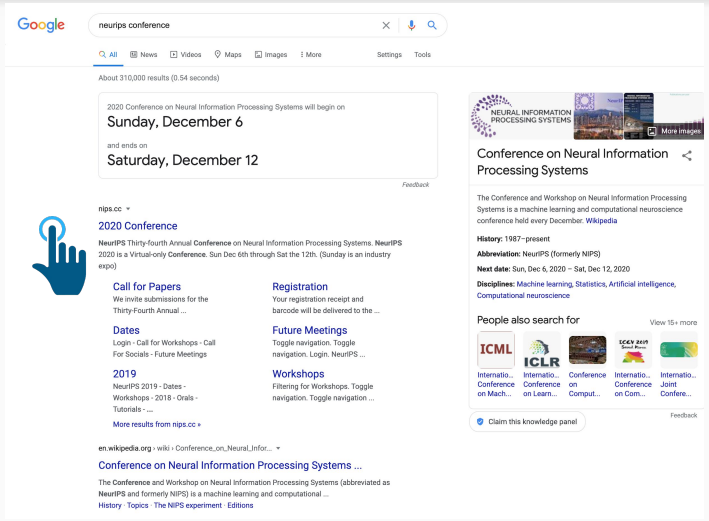


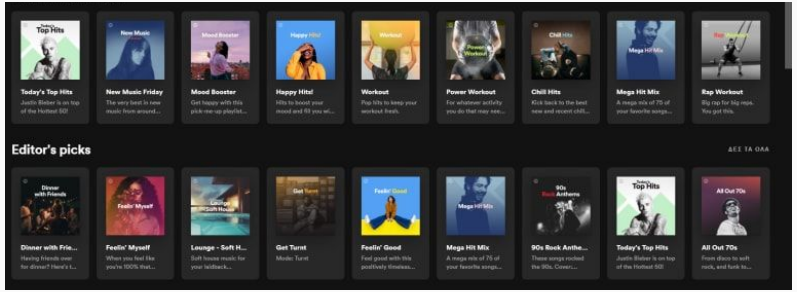
Intra-Session Feedback



Behavioral Signals: Clicks

- User ***clicks*** are widely used behavioral signal for predicting satisfaction but are often noisy.
- Clicks are useful for learning personalized ML models in several applications.
- We ***assume*** that users are not randomly clicking on items, but make a informed choice.
- Clicks are considered independent of other user actions and items.

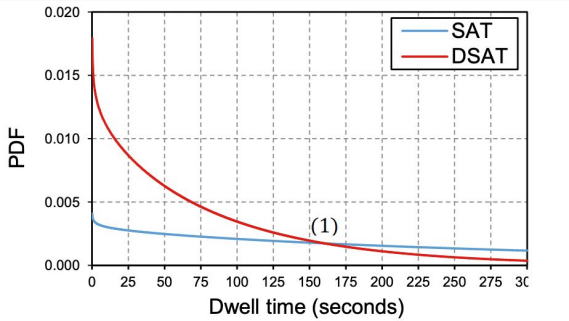




Thorsten Joachims. **Optimizing search engines using clickthrough data.** KDD 2007.

Behavioral Signals: Dwell Time

- ***Dwell Time*** is the time spent by the user on a page or item after clicking on it.
- Longer dwell time (30 secs or more in search applications) is one common approach to reduce noise in click signals.
- Empirical analyses have shown differences in dwell time distributions for satisfied & dissatisfied clicks.

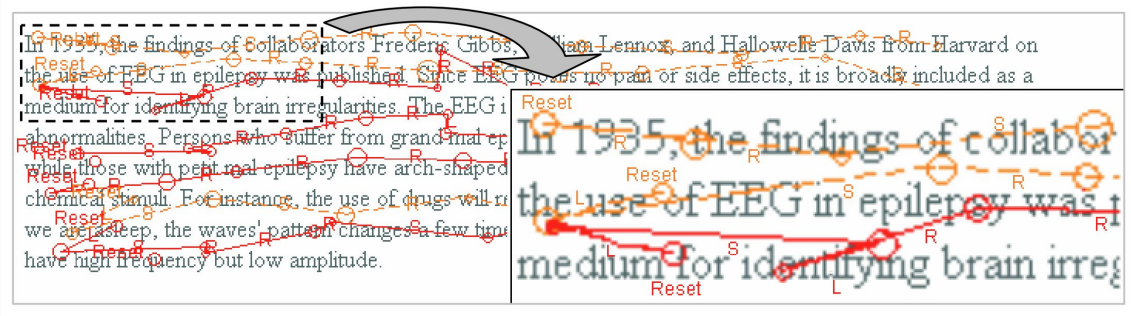


- Dwelling patterns are influenced by attributes of an item. For instance, sophisticated content (high reading level) requires more time.

Youngho Kim et al. **Modeling Dwell Time to Predict Click-level Satisfaction.** WSDM 2014.

Behavioral Signals: User Eye Movements

- User eye movement exhibits unique behavior when reading. The eye fixation and saccade could be used to infer satisfaction.
- ***Fixation***: 200-250 ms steady gaze at one point.
- ***Saccade:*** Rapid eye movement from one fixation to the next.



Georg Buscher et al. **Eye movements as implicit relevance feedback.** CHI 2008.

Behavioral Signals: Cursor Movements

- Collecting eye-tracking data can be intrusive and expensive.
- Studies have shown a correlation between ***cursor*** & ***gaze*** position.
- Signals from cursor movements can be combined to predict user satisfaction
  - ***Click-through rate***: % of clicks when item is shown
  - ***Hover rate***: % hover over items
  - ***Unclicked hover***: Time of hover over item w/o click

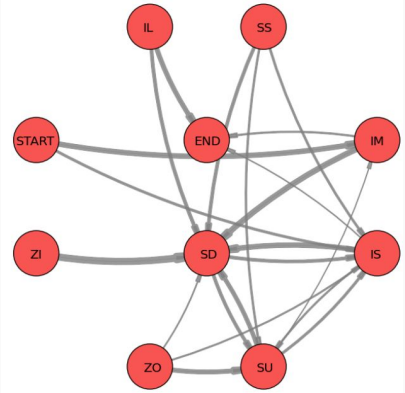
Click positions

Cursor movement positions

Jeff Huang, Ryen White and Susan Dumais. **No clicks, no problem: using cursor movements to understand and improve search.** CHI 2011.

Behavioral Signals: Touch Gestures on Mobile

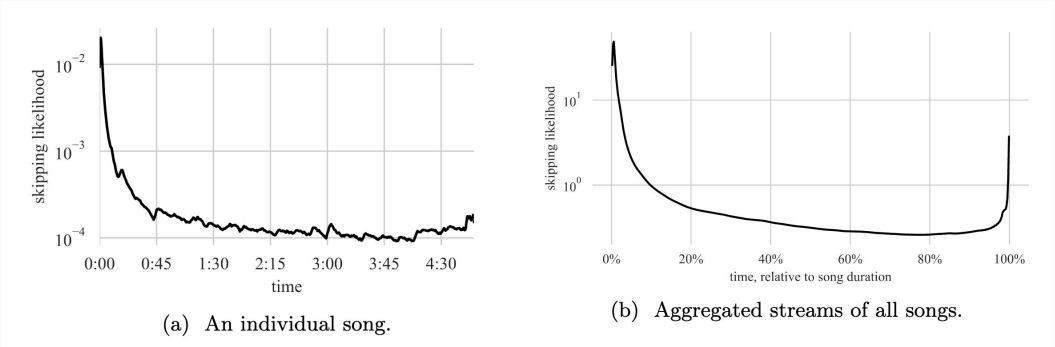
- Behavior modeling on mobile need to account for fine-grained user interactions such as
  - zooming in (ZI) and out (ZO)
  - swiping down (SD), up (SU), and horizontal (SS)
  - inactive short (IS), medium (IM), and long (IL)
- Markov state transitions can be used to predict likelihood of success for items (i.e., relevance of a page).



Qi Guo et al. **Mining touch interaction data on mobile devices to predict web search result relevance.** SIGIR 2013.

Behavioral Signals: Streams & Skip Behavior

- About 25% of streamed songs are skipped within first 5 secs and only about half of all songs are listened to in their entirety [*Lamere 2018*]
- There exists a correlations between skipping & musical structure and can be used to understand user satisfaction.



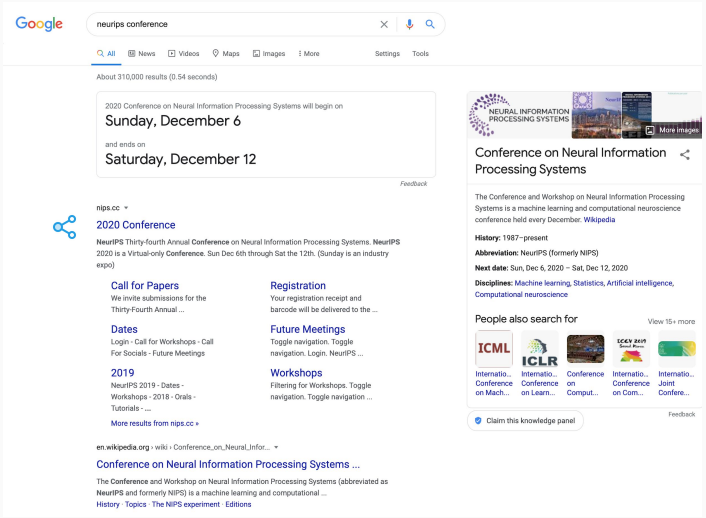
(a) An individual song.

(b) Aggregated streams of all songs.

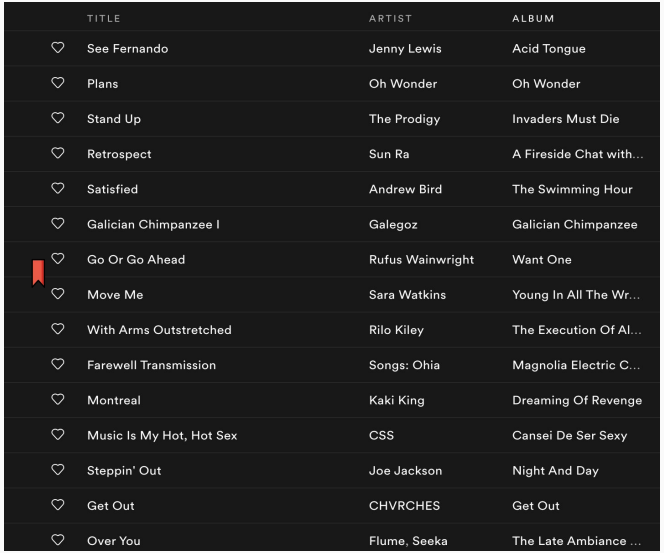
Nicola Montecchio et al. **The Skipping Behavior of Users of Music Streaming Services and its Relation to Musical Structure.** PLOS ONE 2020.

Behavioral Signals: Bookmarks, Saving & Shares

- Social interactions such as sharing with friends and followers could be used to measure satisfaction.



- Behavioral signals such as bookmarking, saving could measure satisfaction.

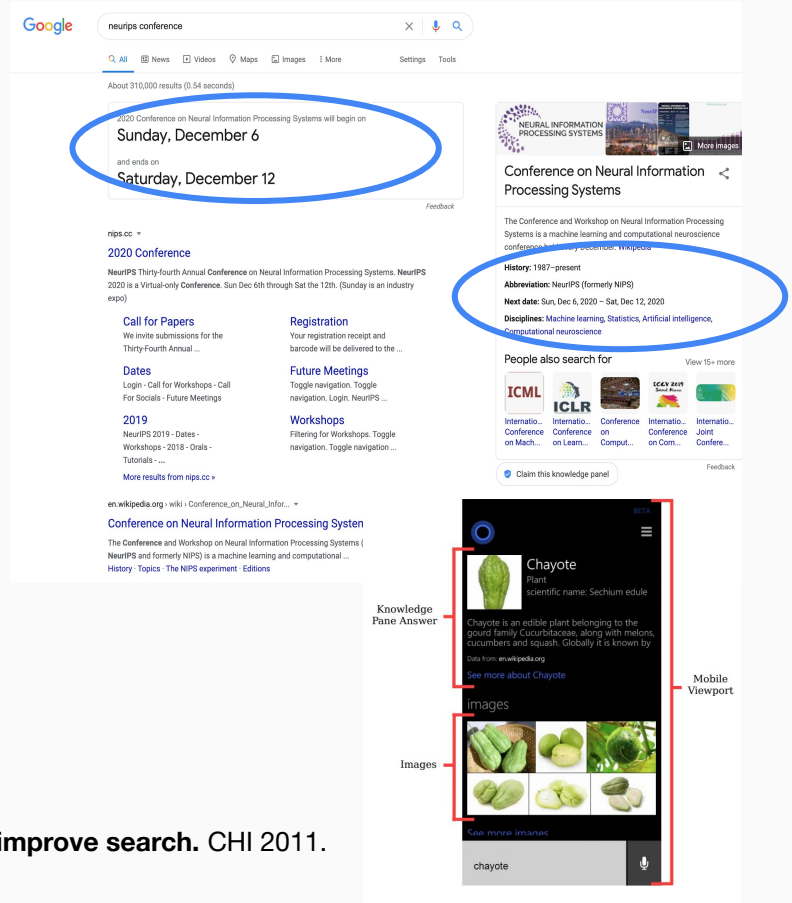


Jean Garcia-Gathright et al. **Understanding and Evaluating User Satisfaction with Music Discovery.** SIGIR 2018.

Anlei Dong et al. **Time is of the essence: improving recency ranking using Twitter data.** WWW 2010.

Good Abandonment

- Scenarios in which user does not interact with the results for a given request but are satisfied is referred to as ***good abandonment***.
- In contrast ***bad abandonment*** happens when user needs are not satisfied and results in no interaction with the results.
- Clicks and dwell time signals alone are often insufficient to distinguish between the two. The following signal have been used to predict ***good abandonment*** in mobile and desktop:
  - properties of the request
  - user session
  - gaze and viewport tracking



Jeff Huang et al. **No clicks, no problem: using cursor movements to understand and improve search.** CHI 2011.
Kyle Williams et al. **Detecting Good Abandonment in Mobile Search.** WWW 2016.

Summary: Item Level Feedback

Behavioral Signals

- Clicks
- Dwell Time
- Eye-Tracking
- Cursor Movements
- Gestures on Mobile
- Streams & Skip Behavior
- Bookmarks, Saving & Shares

User Intent / Goals

Context

Heterogeneity of Items

User

Summary: Item Level Feedback

Behavioral Signals

- Clicks
- Dwell Time
- Eye-Tracking
- Cursor Movements
- Gestures on Mobile
- Streams & Skip Behavior
- Bookmarks, Saving & Shares

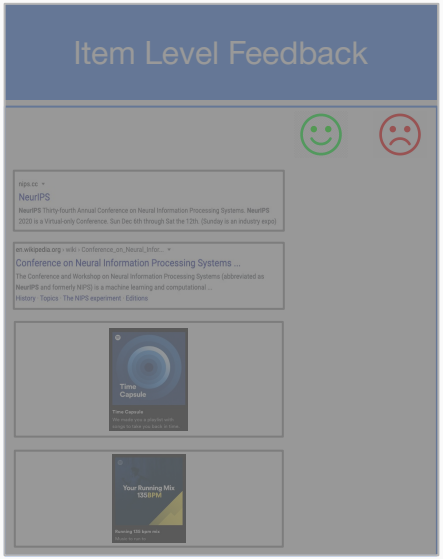
Offline metric validation

- AUC
- Precision
- Akaike Information criterion (AIC)
- Bayesian information criterion (BIC)

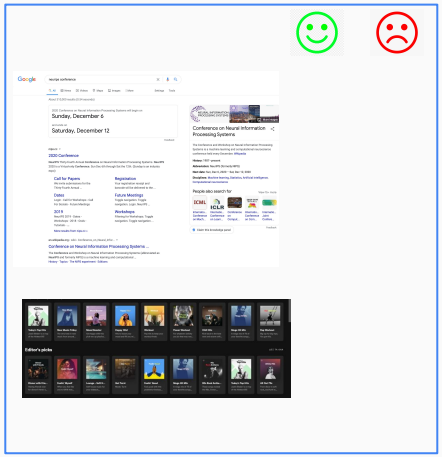
Page Level Feedback

short-term *long-term*

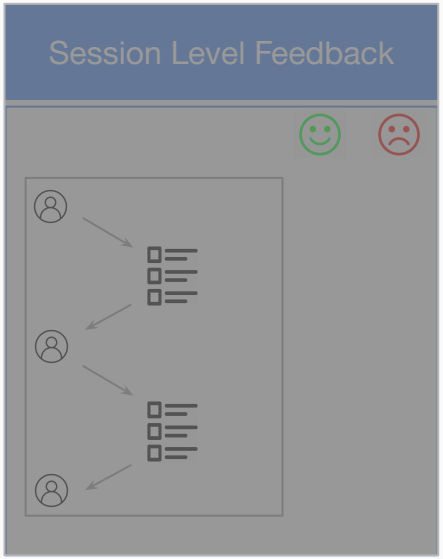
Item Level Feedback



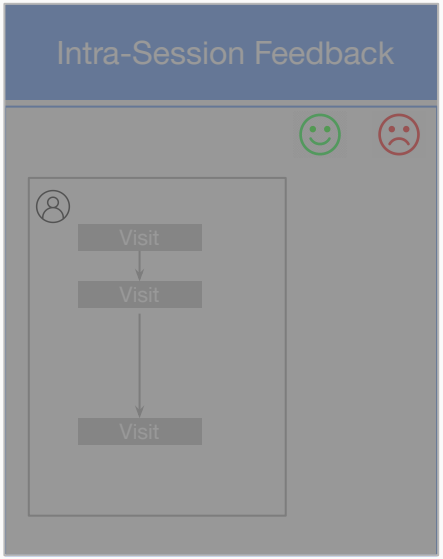
Page Level Feedback



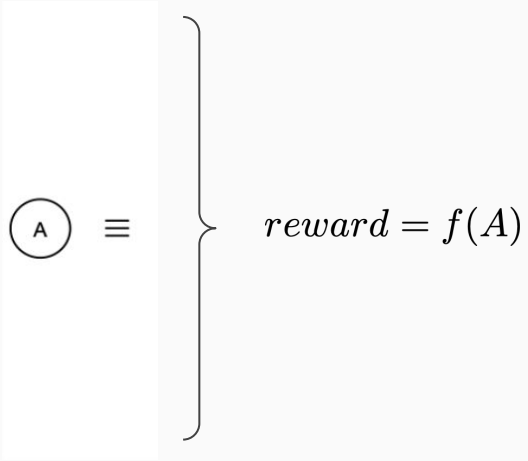
Session Level Feedback



Intra-Session Feedback



Whole Page Feedback

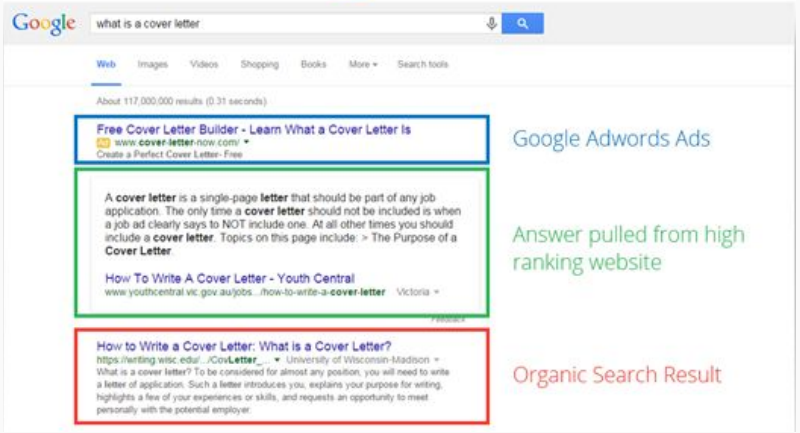


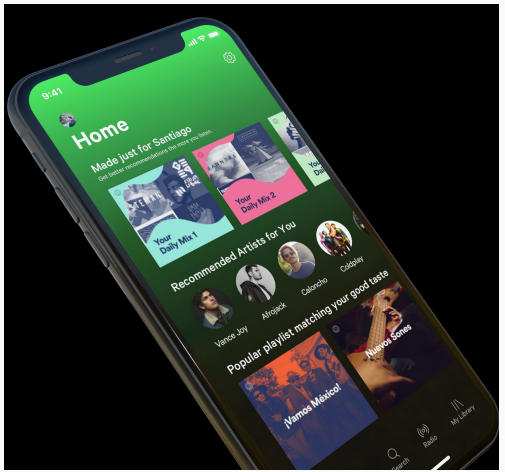
- In many application, a set of items are presented to the user for a given request.
- Whole-page feedback defines how well items presented on a page and its attributes satisfies the user request.

  Action → entire page
  Labels → success for the entire page

Peter Bailey et al. **Evaluating Whole-Page Relevance.** SIGIR 2010.

Whole Page Feedback: Examples





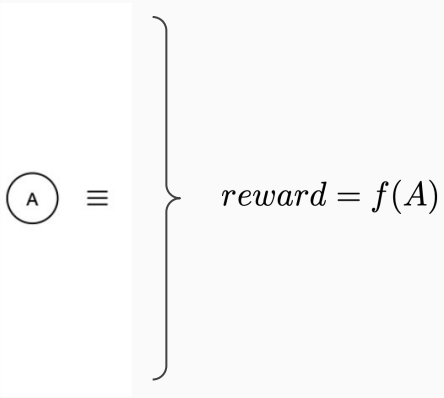
User Models for Whole Page Evaluation

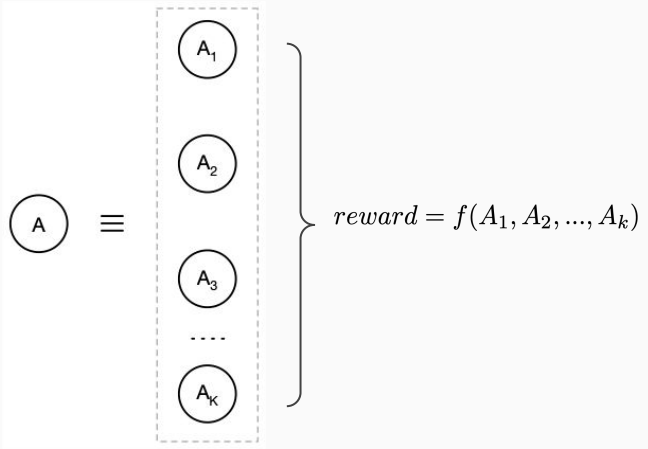
- While assigning labels/reward for the result page provides a holistic view of success, in several scenarios they are computed from rewards observed at the item-level.

  Action → decompose action into sub-actions
  Labels → aggregation of sub-action rewards

- However, the observed rewards at the item level could be biased due to various reasons relating to the characteristics of the page and ignoring them would lead to unreliable estimates.

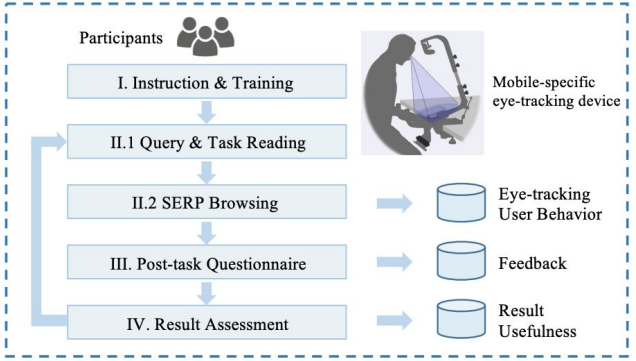
- This calls for the development of user behavioral models to accurately estimate a page-level reward



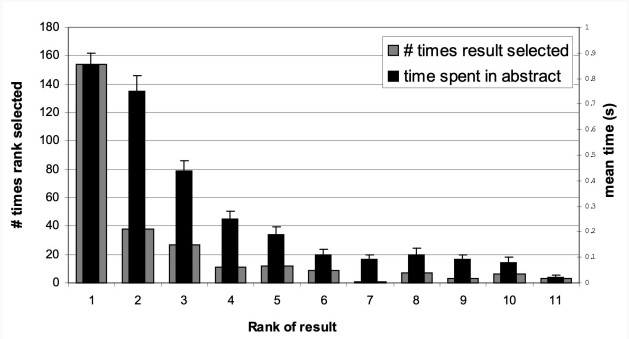


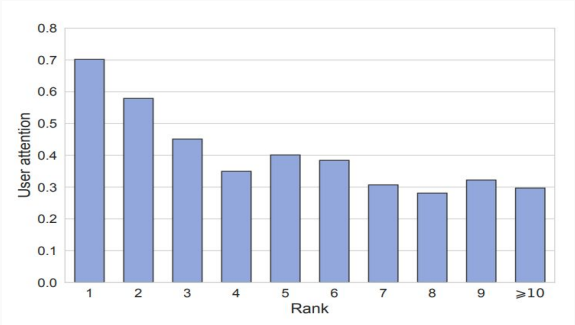
User Browsing Models: Position-Based Model

> How do users interact with the list of ranked results of search engines?
>
> Do they read the abstracts sequentially from top to bottom, or do they skip links?
>
> How many of the results do users evaluate before clicking on a link or reformulating the search?
>
> - *Granka et al. 2004*



User Attention per rank on ***Desktop*** vs. ***Mobile***

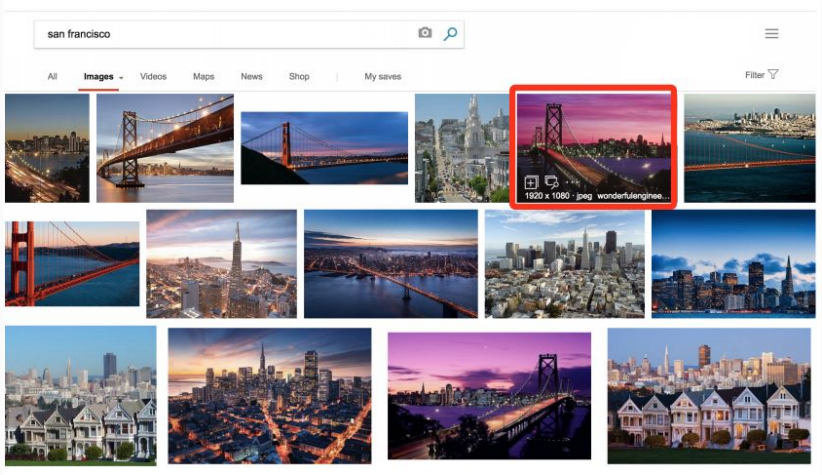




Laura A. Granka et al. **Eye-tracking analysis of user behavior in WWW search.** SIGIR 2004.
Yukun Zheng et al. **Investigating Examination Behavior in Mobile Search.** WSDM 2020.

Grid-based Model

- In movie recommendations, image search, etc., the results are presented in a grid view, and users examine them both vertically and horizontally.

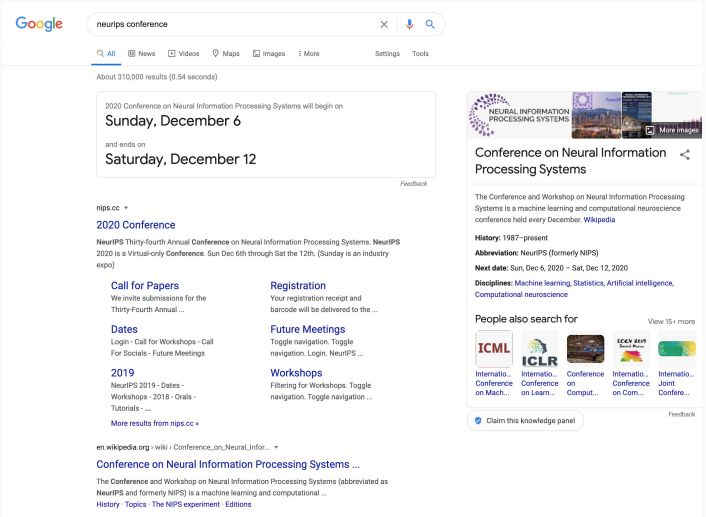


middle positions may attract more attention depending on the domain in grid-based layouts.

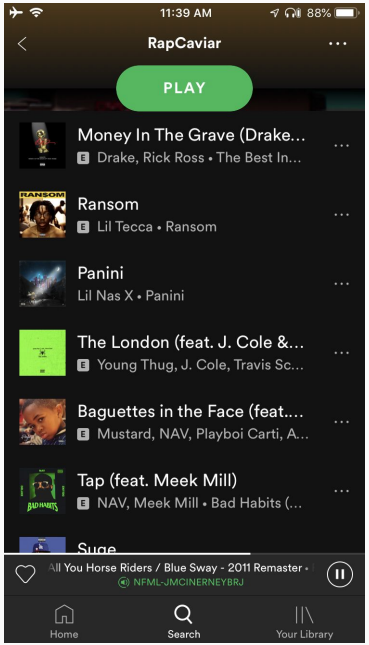
Xiaohui Xie et al. **Grid-based Evaluation Metrics for Web Image Search.** CIKM 2019.

User Browsing Models: Cascade Model

- Likelihood of a user examining a document at rank *i* depends on how satisfied they were with previously observed documents.



- Users' interaction with a track in a playlist could be influenced by previous track(s).

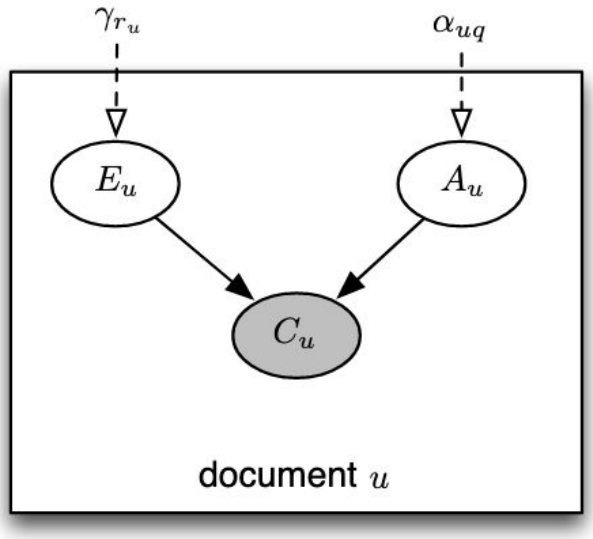


Olivier Chapelle et al. **Expected reciprocal rank for graded relevance.** CIKM 2009.

Click Models: Position-Based Model

- Click models is a way to represent user clicks that makes it easy to quantify user behavior. Many existing click models use probabilistic graphical models.
- A user examining an item at position r does not depend on examinations and clicks above r.
- Clicks depend on probability of examination & user-item attractiveness or ***utility***.

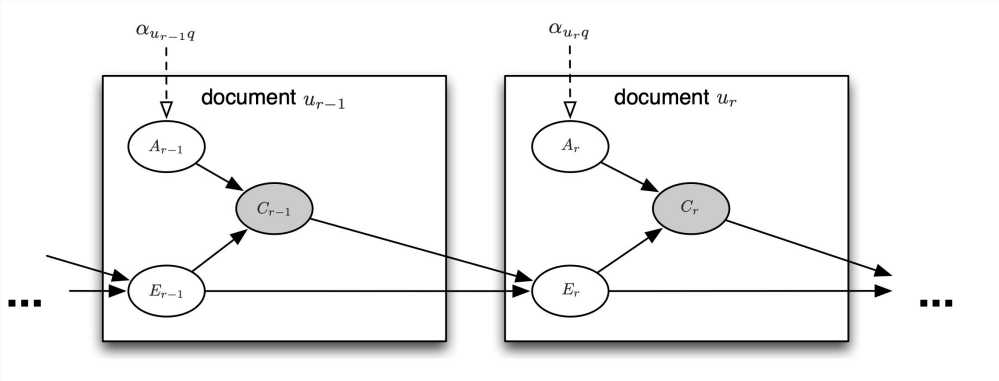
$$P(E_{r_u} = 1) = \gamma_{r_u}$$
$$P(A_u = 1) = \alpha_{uq}$$
$$P(C_u = 1) = P(E_{r_u} = 1) \cdot P(A_u = 1)$$



Aleksandr Chuklin, Ilya Markov, Maarten de Rijke. **Click Models for Web Search.** CIKM 2009.

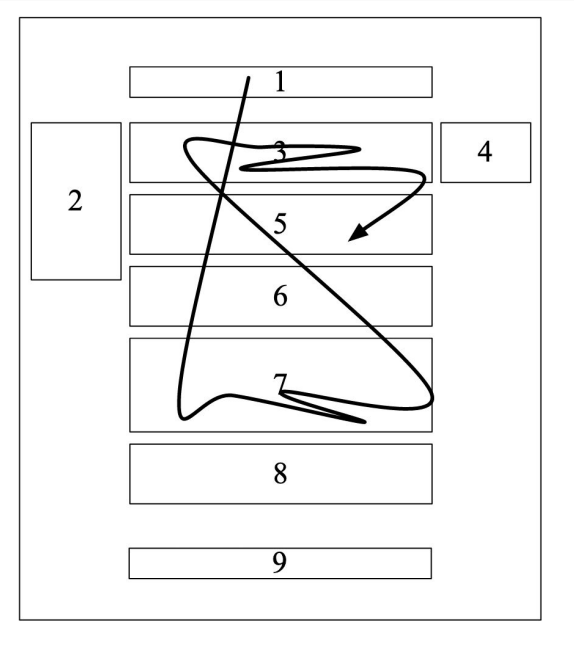
Click Models: Cascade Model

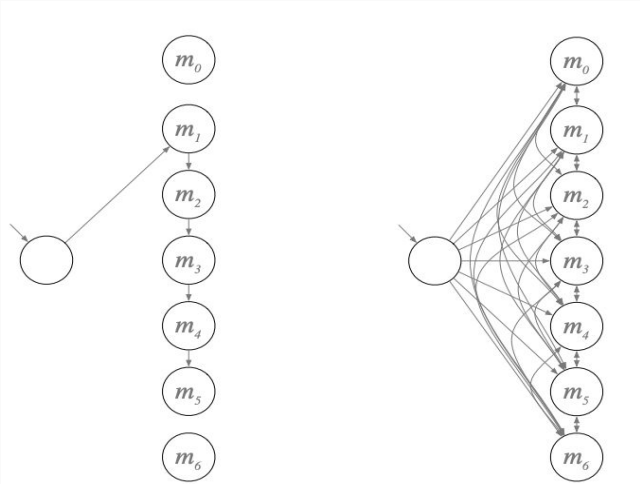
- Cascade dependency between clicks and previously examined items



Aleksandr Chuklin, Ilya Markov, Maarten de Rijke. **Click Models for Web Search.** CIKM 2009.

Browsing Models: Non-Sequential Examination Model





Fernando Diaz et al. **Robust models of mouse movement on dynamic web search results pages.** CIKM 2013.

Estimating Position Bias from Log Data

- ***Position Bias*** Higher ranked items are more likely to be examined resulting in higher interaction.

- Interventions to address position bias
  - Randomize items (if policy is not stochastic)
  - Aggregate interaction per position
  - Infer propensity of observation conditional on position

- Randomization Techniques
  - *Randomize Top K*
  - *Swap Method*
    Swap items from random position with pivot rank.
  - *Intervention Data*
    Exploit the randomness in historical intervention data (i.e., A/B tests).

Assumption

Probability of examination is dependent only on the rank of the item.

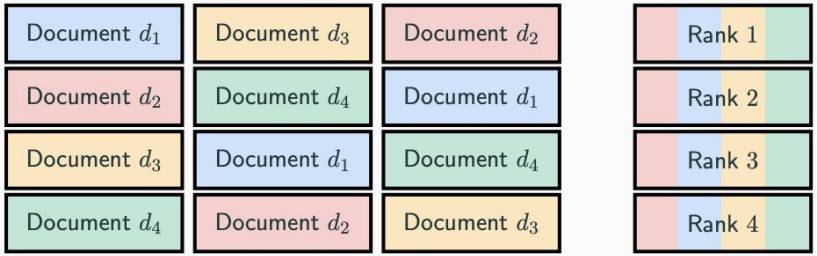


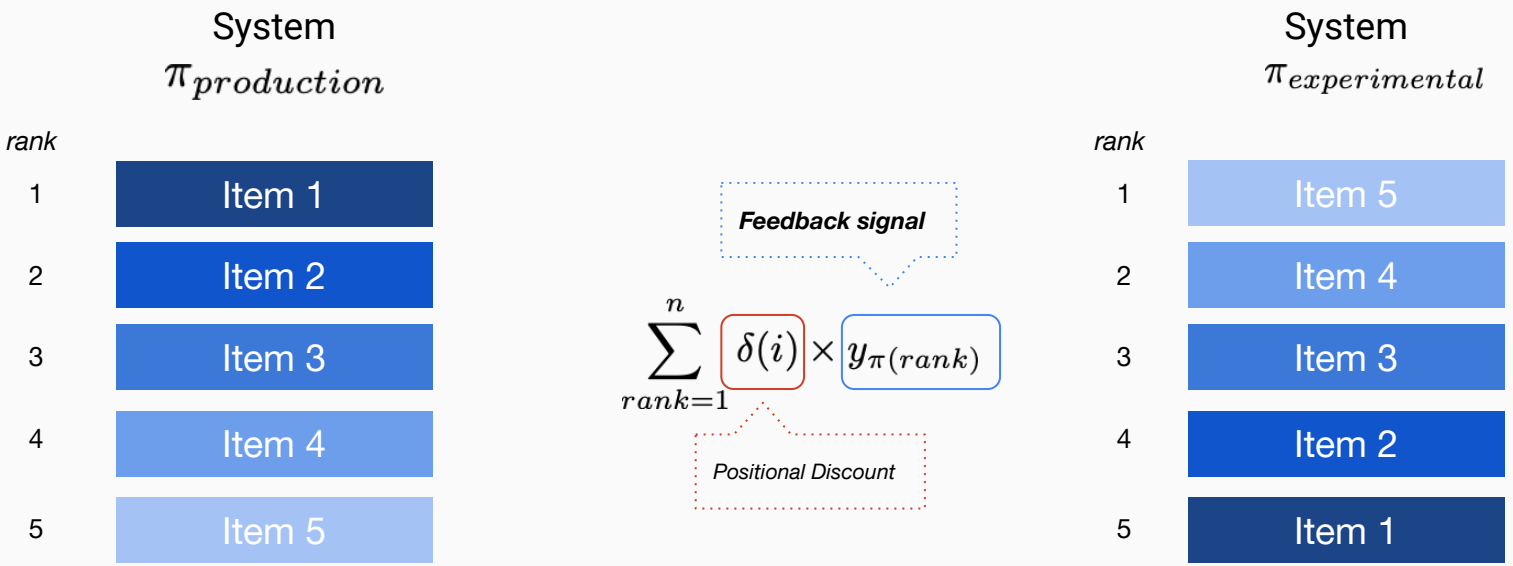
Figure Source: *Unbiased Learning to Rank: Counterfactual and Online Approaches*

Lihong Li et al. **Unbiased offline evaluation of contextual-bandit-based news article recommendation algorithms.** WSDM 2011
Xuanhui Wang et al. **Position Bias Estimation for Unbiased Learning to Rank in Personal Search.** WSDM 2018.
Aman Agarwal et al. **Estimating Position Bias without Intrusive Interventions.** WSDM 2019.

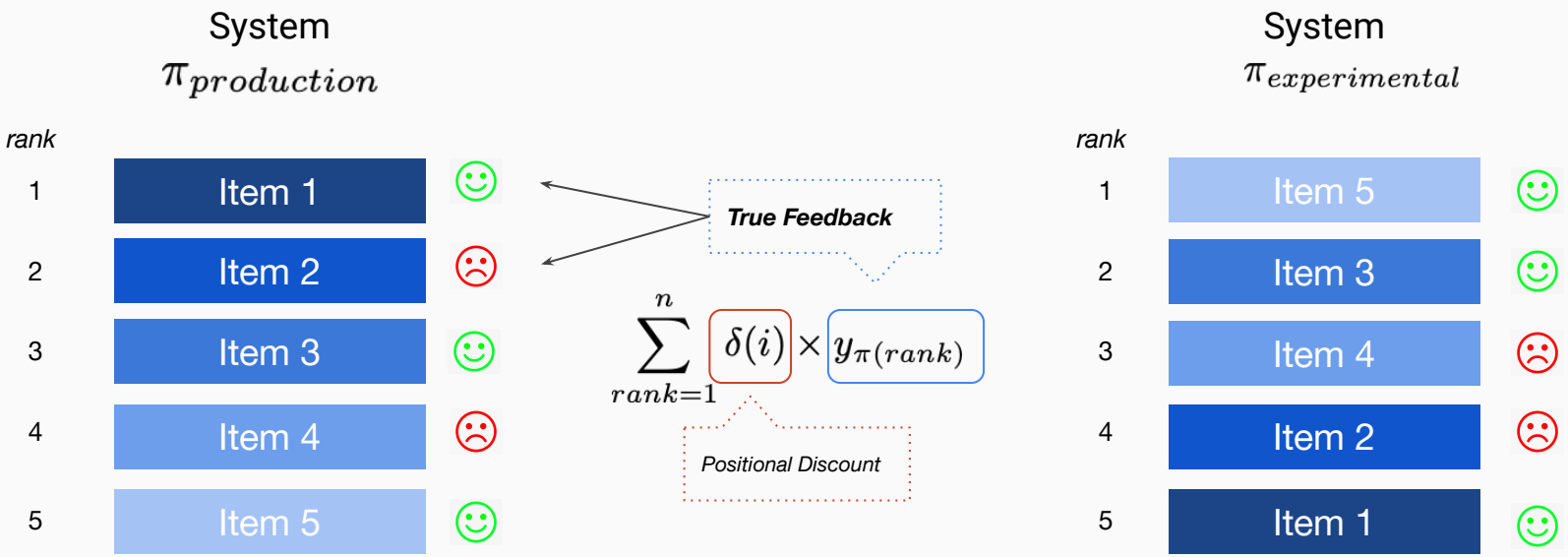
Counterfactual Evaluation from Log Data

Lihong Li et al. **Unbiased offline evaluation of contextual-bandit-based news article recommendation algorithms.** WSDM 2011

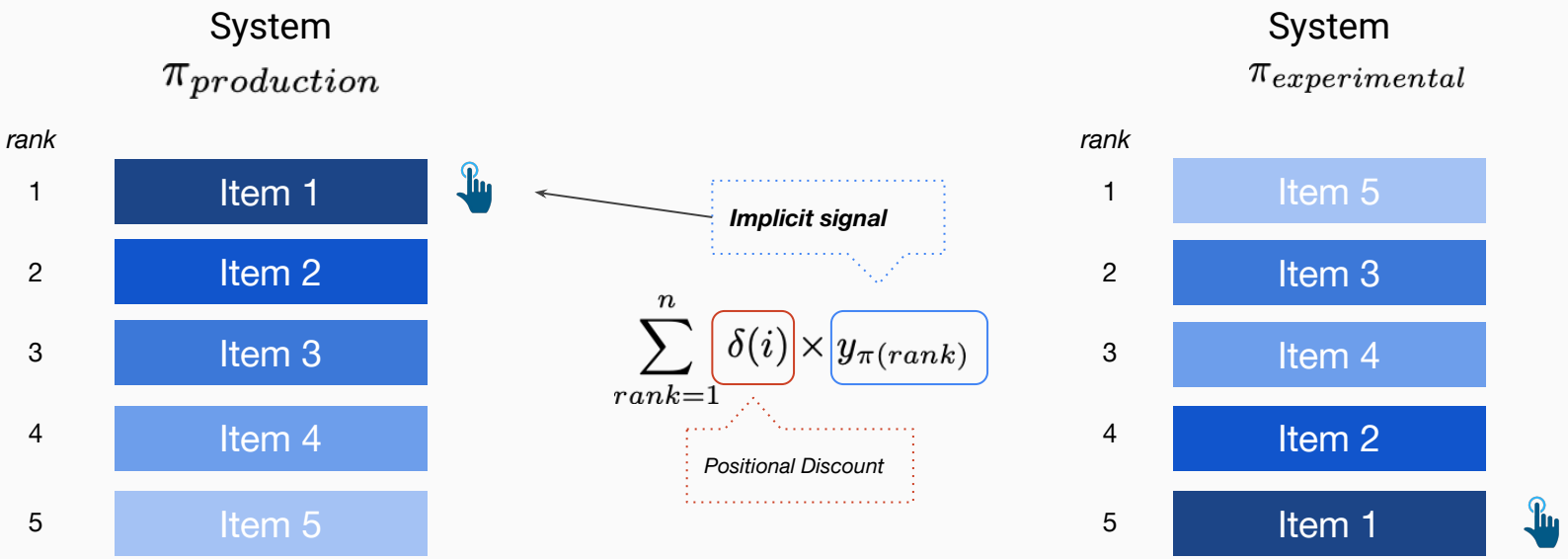
Counterfactual Evaluation from Log Data



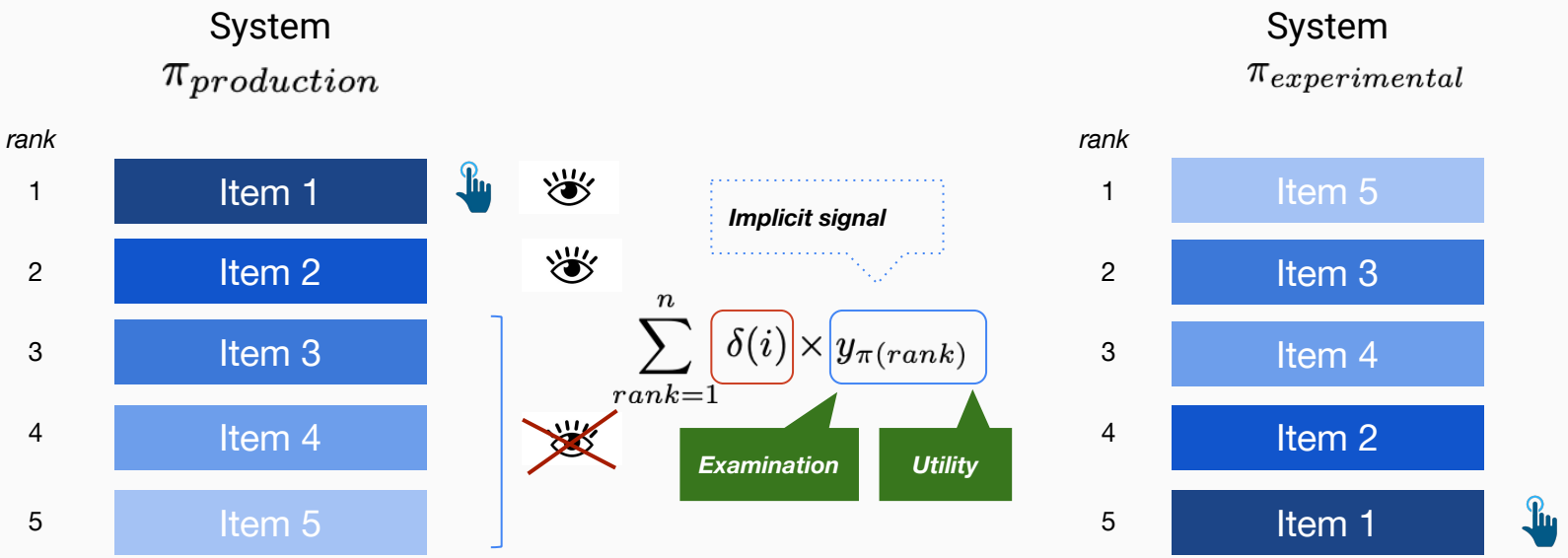
Counterfactual Evaluation from Log Data



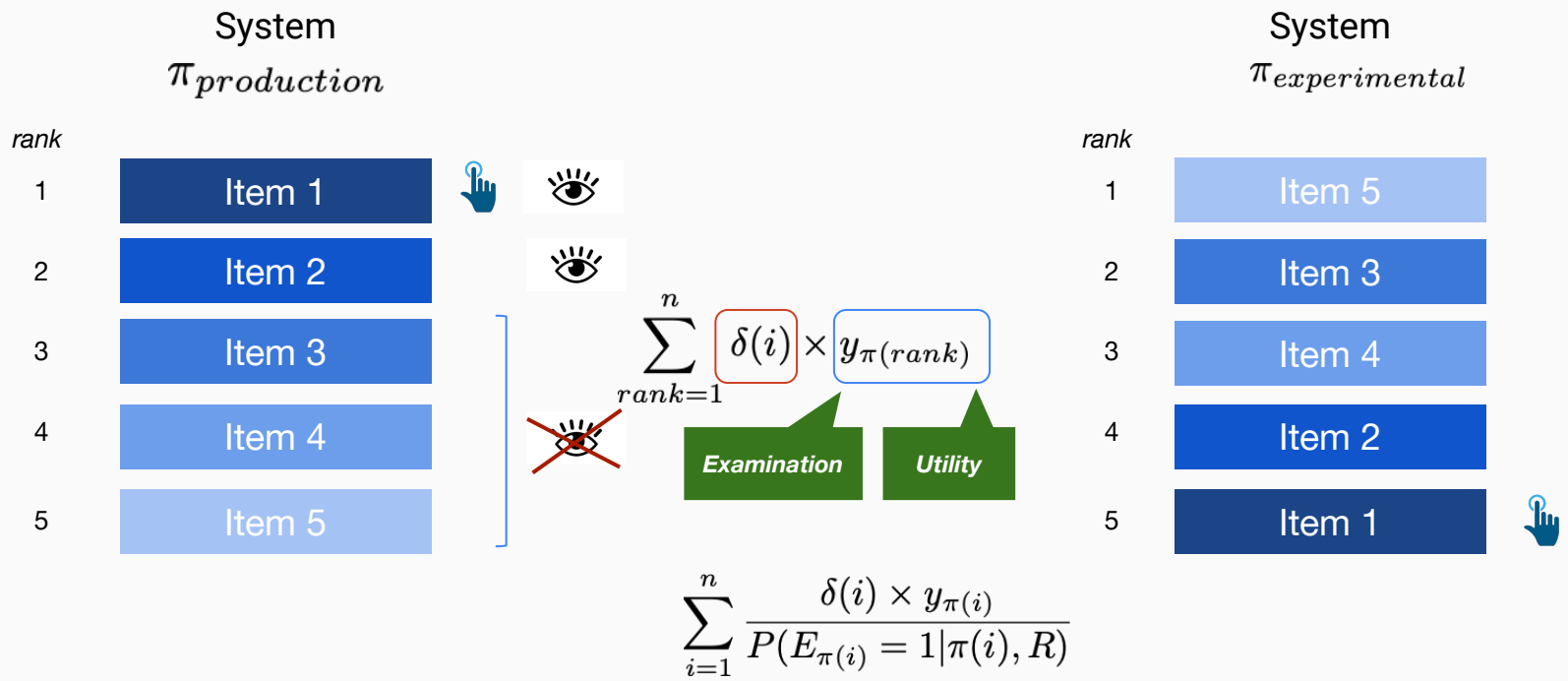
Counterfactual Evaluation from Log Data



Counterfactual Evaluation from Log Data

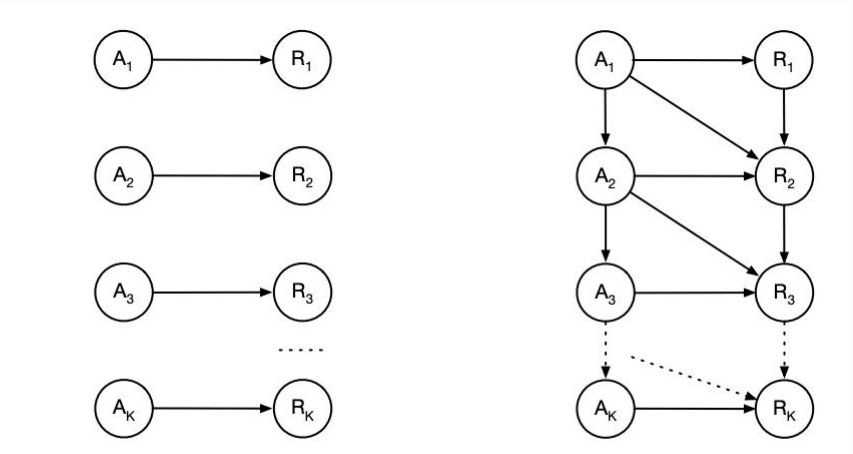


Counterfactual Evaluation from Log Data



Xuanhui Wang et al. **Learning to Rank with Selection Bias in Personal Search.** SIGIR 2016.
Thorsten Joachims et al. **Unbiased Learning-to-Rank with Biased Feedback** WSDM 2017.

Counterfactual Slate Evaluation



Linear Additive Rewards when sub-action rewards are not available.

Adith Swaminathan et al. **Off-policy evaluation for slate recommendation.** NeurIPS 2017.

Independence Assumption

Shaui Li et al. **Offline evaluation of ranking policies with click models**. KDD 2018.

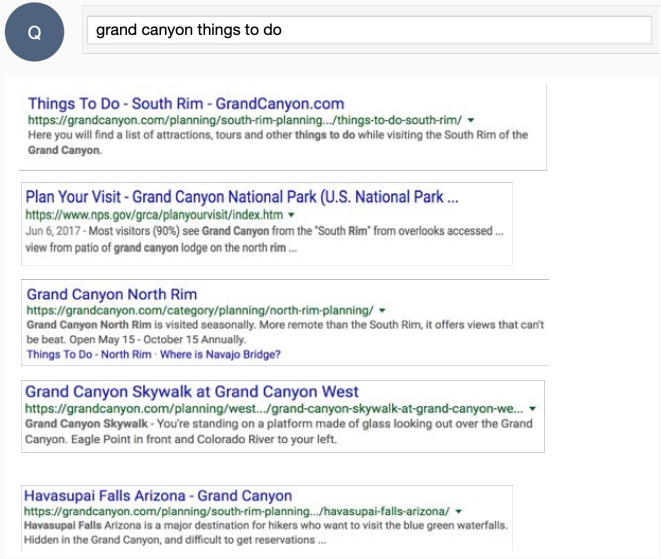
Sequential Reward Dependence Assumption

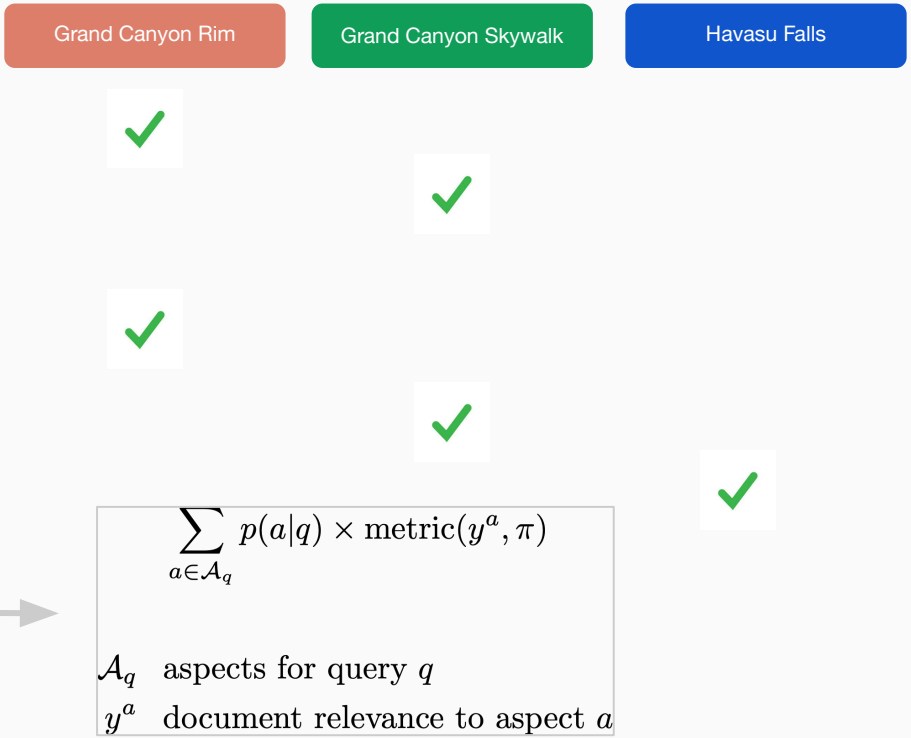
James McInerney et al. **Counterfactual Evaluation of Slate Recommendations with Sequential Reward Interactions** KDD 2020.

Counterfactual Evaluation: Grid-based & Beyond

- *Ruocheng Guo et al.* **Debiasing Grid-based Product Search in E-commerce.** KDD 2020.
- *Jiawei Chen et al.* **Bias and Debias in Recommender System: A Survey and Future Directions.** TKDE 2020

Novelty & Diversity in Rankings





A variation of rank-based metric that rewards novelty and penalizes diversity

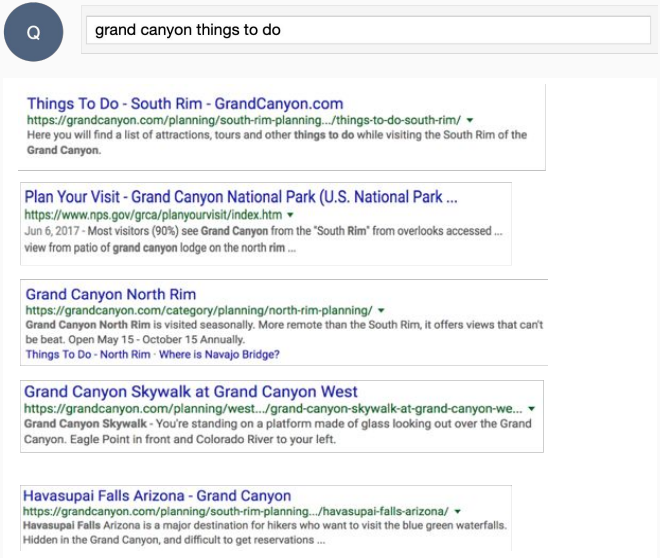
$$\sum_{a \in \mathcal{A}_q} p(a|q) \times \text{metric}(y^a, \pi)$$

$\mathcal{A}_q$ aspects for query q

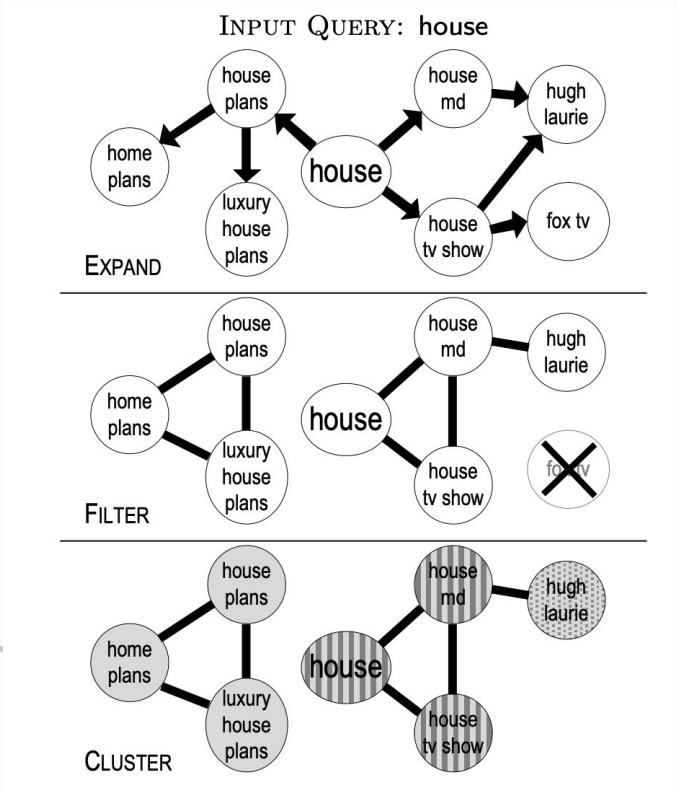
y^a document relevance to aspect a

Charles Clarke et al. **Novelty and Diversity in Information Retrieval Evaluation** SIGIR 2008.
Filip Radlinski et al. **Inferring Query Intent from Reformulations and Clicks.** WWW 2010.

Novelty & Diversity in Rankings



A variation of rank-based metric that rewards novelty and penalizes diversity

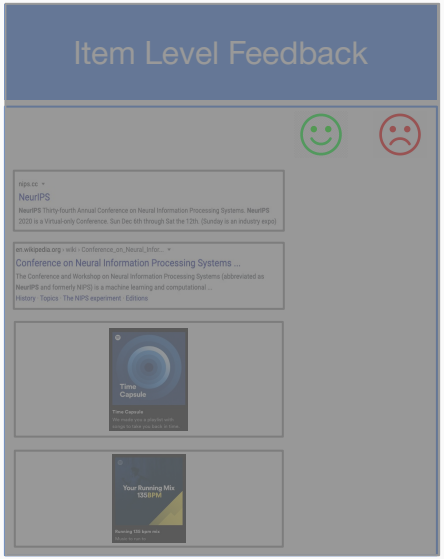


Charles Clarke et al. **Novelty and Diversity in Information Retrieval Evaluation** SIGIR 2008.
Filip Radlinski et al. **Inferring Query Intent from Reformulations and Clicks.** WWW 2010.

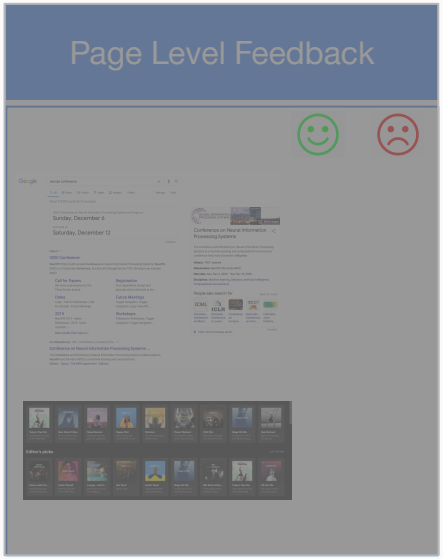
Session Level Feedback

short-term *long-term*

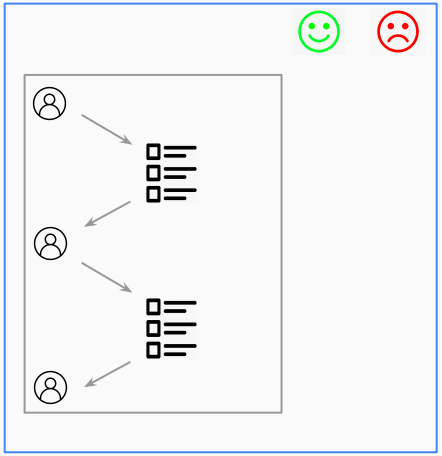
Item Level Feedback



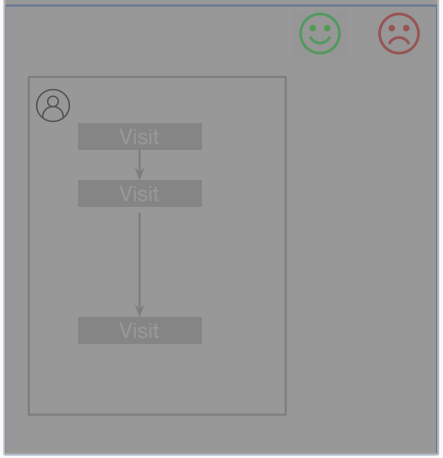
Page Level Feedback



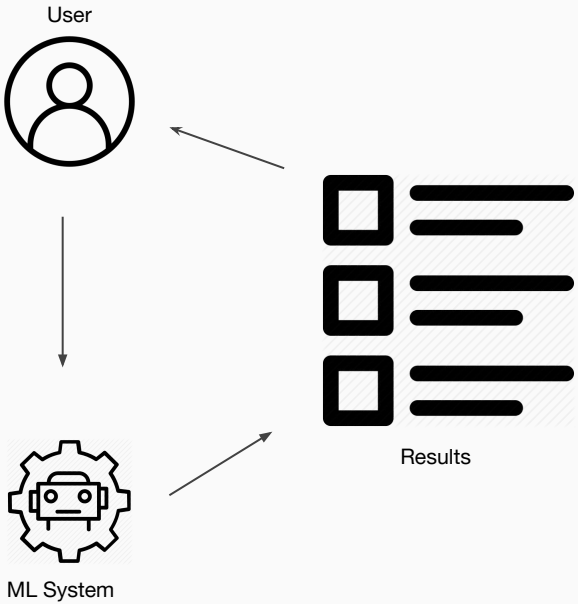
Session Level Feedback



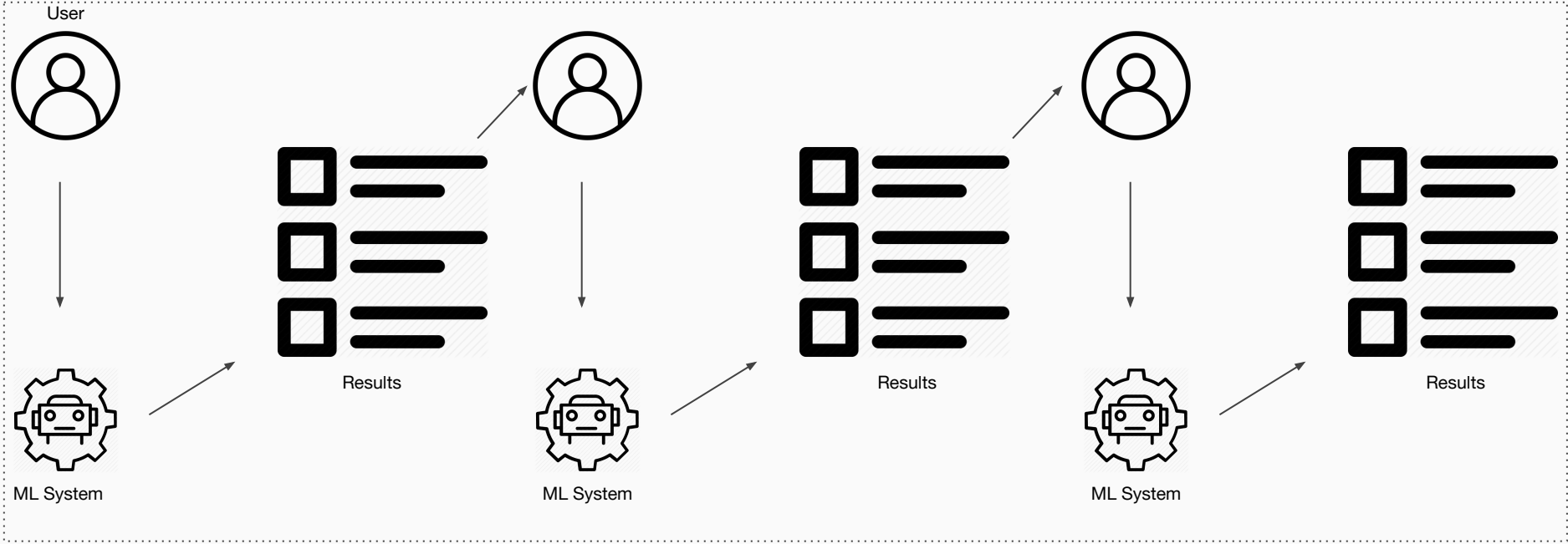
Intra-Session Feedback



Session Level Evaluation: Introduction

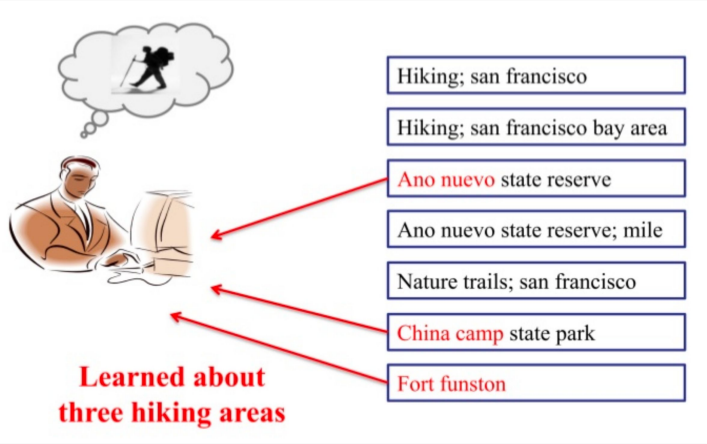


Session Level Evaluation: Introduction



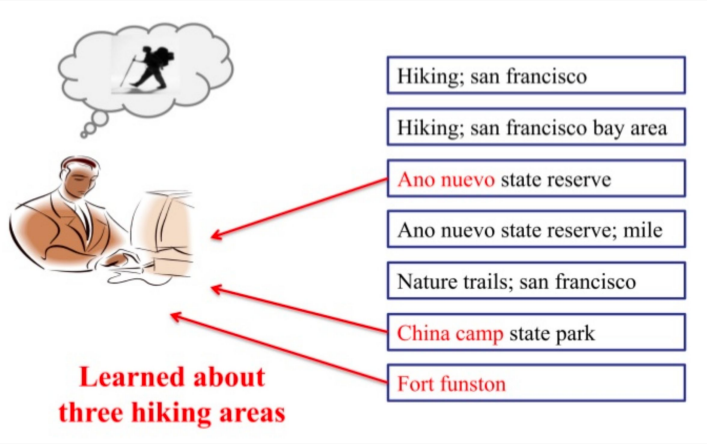
How do we evaluate the user experience over a session?

Session Level Evaluation: Examples



Rishabh Mehrotra et al. **Understanding & Inferring User Tasks and Need.** WWW 2018.

Session Level Evaluation: Examples

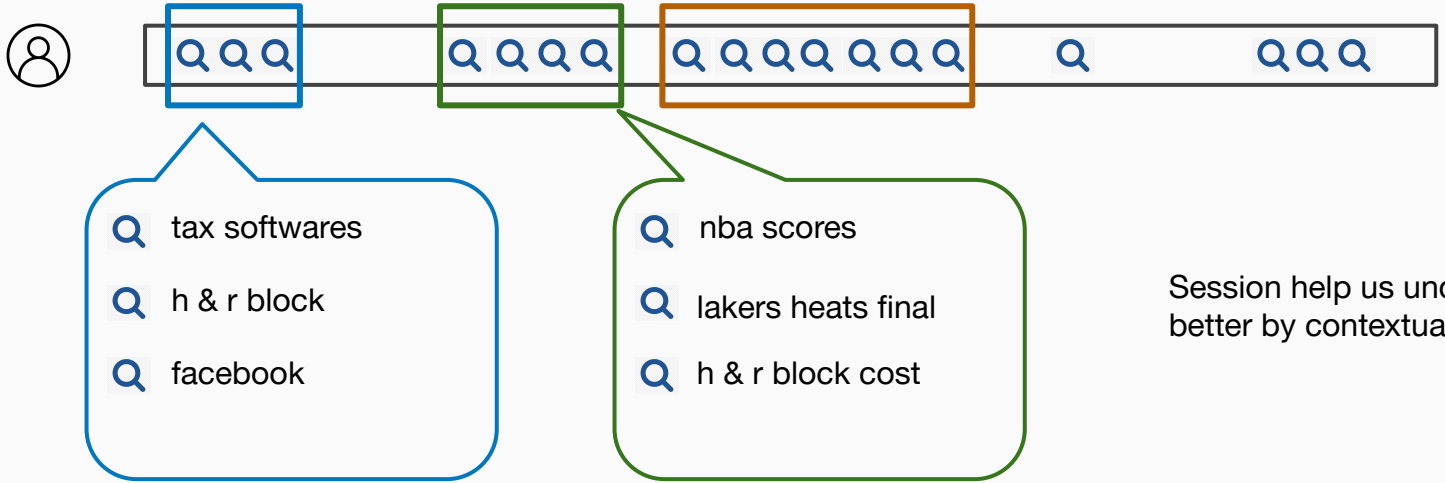


Rishabh Mehrotra et al. **Understanding & Inferring User Tasks and Need.** WWW 2018.
Shuo Zhang and Krisztian Balog. **Evaluating Conversational Recommender Systems via User Simulation.** KDD 2020.
Malte Ludewig and Dietmar Jannach. **Evaluation of session-based recommendation algorithms.** User Modeling and User Adapted Interaction 2018.

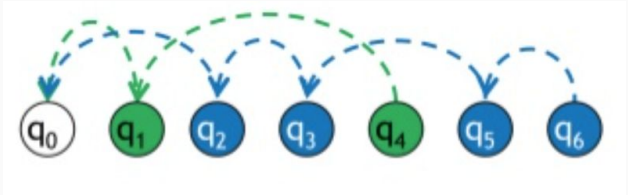
Identifying Sessions from Logs

time between requests
could be reasonable
proxies to identify sessions

Identifying Sessions from Logs



Session help us understand user goals better by contextualizing their requests.

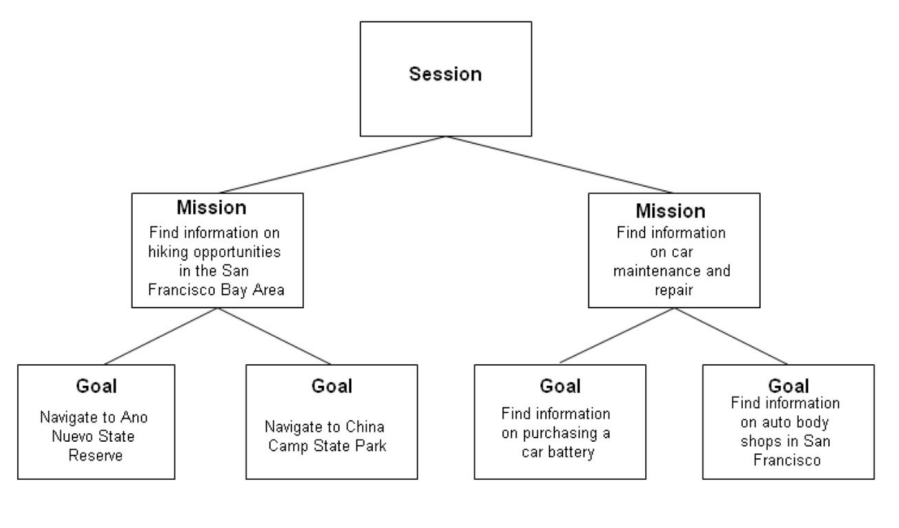


Sessions → User Goals

User Sessions
All user activity within a fixed time window.

User Goals
Atomic piece of user activity accomplished by issuing one or more requests to the system.

Web Search Example



Rosie Jones & Kristina Klinkner. **Beyond the Session Timeout: Automatic Hierarchical Segmentation of Search Topics in Query Logs.** CIKM 2008.
Julia Kiseleva et al. **Understanding User Satisfaction with Intelligent Assistants.** CHIIR 2016.

Identifying User Goals

QUERY and TIMESTAMP	GOAL #	MISSION #	DESCRIPTION
hiking; san francisco Tue Apr 17 23:43:17 2007 (4m 17s)	1	1	MISSION 1: Find info on hiking opportunities in and around San Francisco
hiking; san francisco bay area Tue Apr 17 23:47:34 2007 (4m 59s)	1	1	GOAL 1: Find info on hiking trails in San Francisco and the Bay Area
ano nuevo state reserve Tue Apr 17 23:52:33 2007 (7m 54s)	2	1	GOAL 2: Navigate to Ano Nuevo State Reserve and ↓nd out about distances
ano nuevo state reserve; miles Wed Apr 18 00:00:27 2007 (3m 34s)	2	1	
nature trails; san francisco Wed Apr 18 00:04:01 2007 (16m 15s)	1	1	
lobos creek trail Wed Apr 18 00:20:16 2007 (0m 3s)	3	1	GOAL 3: Navigate to Lobos Creek Trail
china camp state park; san rafael Wed Apr 18 00:20:19 2007 (2m 35s)	4	1	GOAL 4: Navigate to China Camp, San Rafael and ↓nd out about distances
china camp; miles Wed Apr 18 00:22:54 2007 (20m 2s)	4	1	
hike; san francisco Wed Apr 18 00:42:56 2007 (3m 19s)	1	1	
fort funston Wed Apr 18 00:46:15 2007 (1h 51m 26s)	5	1	GOAL 5: Navigate to Fort Funston
			MISSION 2: Find info on car maintenance and repair
brake pads Wed Apr 18 03:36:47 2007 (16m 36s)	6	2	GOAL 6: Find info on brake pads
auto repair Wed Apr 18 03:53:23 2007 (8m 0s)	7	2	GOAL 7: Find info on an auto body shop in San Francisco
auto body shop Wed Apr 18 04:01:23 2007 (3m 31s)	7	2	
batteries Wed Apr 18 04:04:54 2007 (0m 29s)	8	2	
car batteries Wed Apr 18 04:05:23 2007 (2m 8s)	8	2	GOAL 8: Find info on purchasing a car battery
auto body shop; san francisco Wed Apr 18 04:07:31 2007 (3m 33s)	7	2	
buy car battery online free shipping Wed Apr 18 04:11:04 2007	8	2	

Extracting Goals from User Logs in Search

About 75% of the user goals are accomplished by issuing queries across sessions.

Approaches to extracting user goals from log data:

- Clustering
- Structure Learning
- Hawkes Processes
- Entity-based Extraction

Rishabh Mehrotra et al. **Understanding & Inferring User Tasks and Need.** WWW 2018.

Why Sessions?

- Understand User Behavior
- Predict Success
- Validate Metrics

User Behavior: Modeling User Frustration

- Frustration is not the same as success.
- A user can be successful in accomplishing their task but still be frustrated with their experience.

What was the best selling TV in 2008?

television set sales 2008
"television set" sales 2008
"television" sales 2008
google trends
"television" sales statistics 2008

user got frustrated starting here

Extracted from an actual user study conducted at UMass

Henry Field et al. **Predicting Searcher Frustration.** SIGIR 2010.

User Behavior: Exploring vs. Struggling

Struggling Session

Query can you use h & r block software for more than one year

Query how do I file 2012 taxes on hr block
- **Click** http://www.hrblock.com

Query can you only use h & r block one year
- **Click** http://www.consumeraffairs.com/finance/hr_block_free.html
- **Click** http://financialsoft.about.com/od/taxcut/gr/HR-Block-At-Home-...

Query do I have to buy new tax software every year
- **Click** http://financialsoft.about.com/od/simpletips/f/upgrade_yearly.htm...
- **Click** http://askville.amazon.com/buy-version-Tax-Software-year/Answer...

END OF SESSION

Exploring Session

Query career development advice
- **Click** http://www.sooperarticles.com/business-articles/career-devel...

Query employment issues articles
- **Click** http://jobseekeradvice.com/category/employment-issues/...

Query professional career advice
- **Click** http://ezinearticles.com/?Career-Advice-and-Professional-Ment...
- **Click** http://askville.amazon.com/buy-version-Tax-Software-year/Answer...

Query what is a resume
- **Click** http://en.wikipedia.org/wiki/R%C3%A9sum%C3%A9...

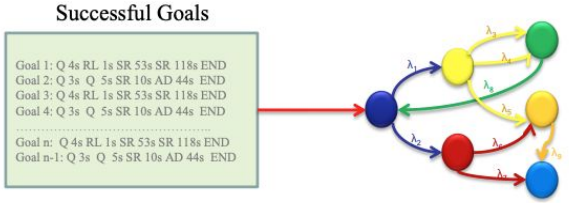
END OF SESSION

Ahmed Hassan et al. **Struggling or exploring?: disambiguating long search sessions.** WSDM 2014.

Success Prediction: Search Trails

Time	Query	# Clicks	Avg. Dwell Time
t_1	sea bass in oven	1	Short
t_2	baked sea bass	1	Short
t_3	baked sea bass recipe	6	Long

Table 1: Example of a Successful Goal



Time	Query	# Clicks	Avg. Dwell Time
t_1	gauage mod for rfactor	0	NA
t_2	gauges for rfactor	1	Short
t_3	new gauges for rfactor	0	NA
t_4	gauges mod for rf	0	NA
t_5	new tacks for rfactor	1	Short
t_6	rfactor gauge plugin	0	NA

Table 2: Example of an Unsuccessful Goal

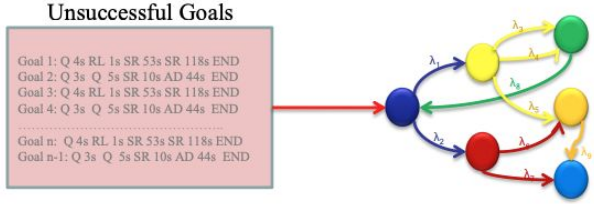


Figure Source: Understanding & Inferring User Tasks and Needs

Predict success with Markov chains by using time distributions to model each transition.

Ahmed Hassan et al. **Beyond DCG: User Behavior as a Predictor of a Successful Search.** WSDM 2014.

Metric Validation: Session Level Annotations

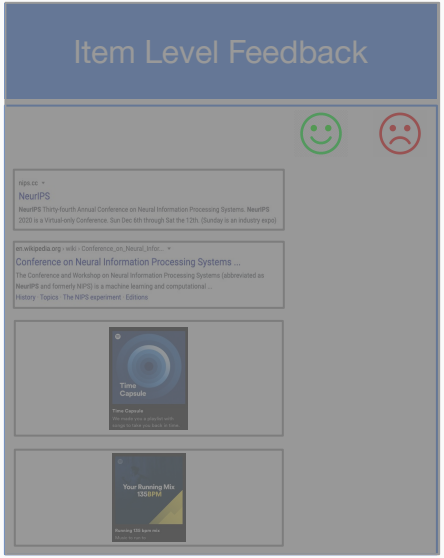
Table 3 A list of user actions that are included in utility. The row rank reflects a descending order in the absolute value of the weight associated with the events.

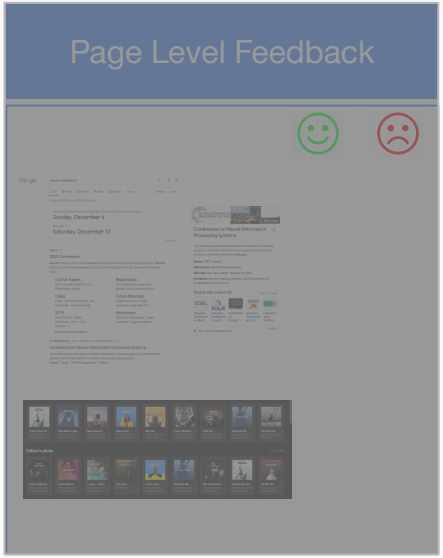
Events	Type
A click to an external page that is the last interaction in the user's session	strongly positive
A query issued by the user that is followed by a query that reformulates it	strongly negative
A click to an external page with a long dwelltime	positive
A click to an external page with a short dwelltime	negative
A query issued by the searcher that is not followed by a reformulation	weakly negative

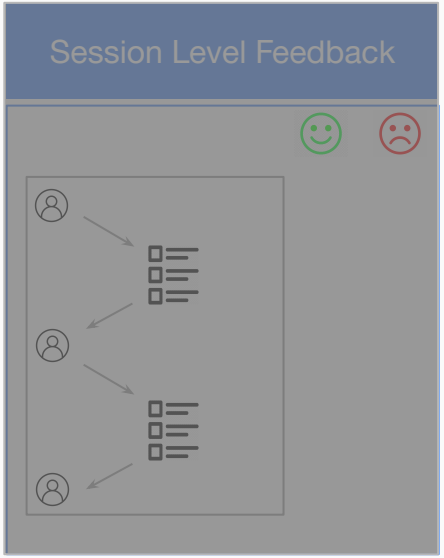
Ahmed Hassan et al. **Beyond Success Rate: Utility as a Search Quality Metric for Online Experiments.** WSDM 2014.

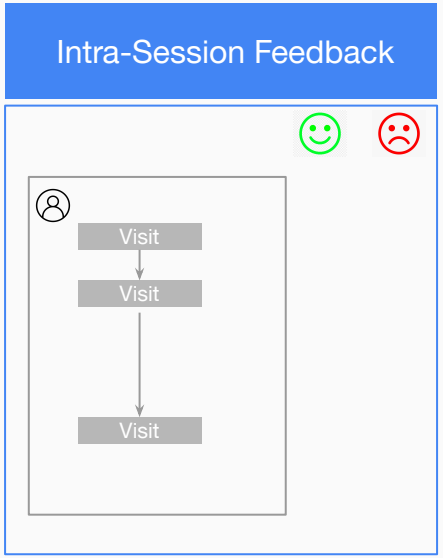
Inter-Session & Long-Term Feedback

short-term *long-term*









Inter-Session & Long-Term Feedback

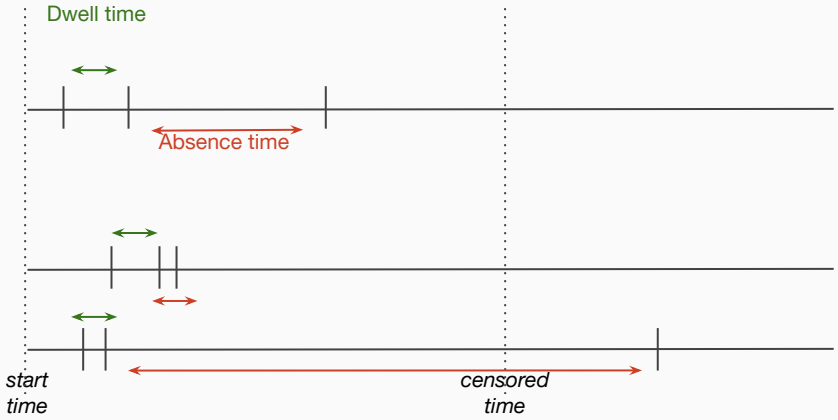
- Short-term metrics such as click can be misleading as they ignore user learning & novelty effects over time.

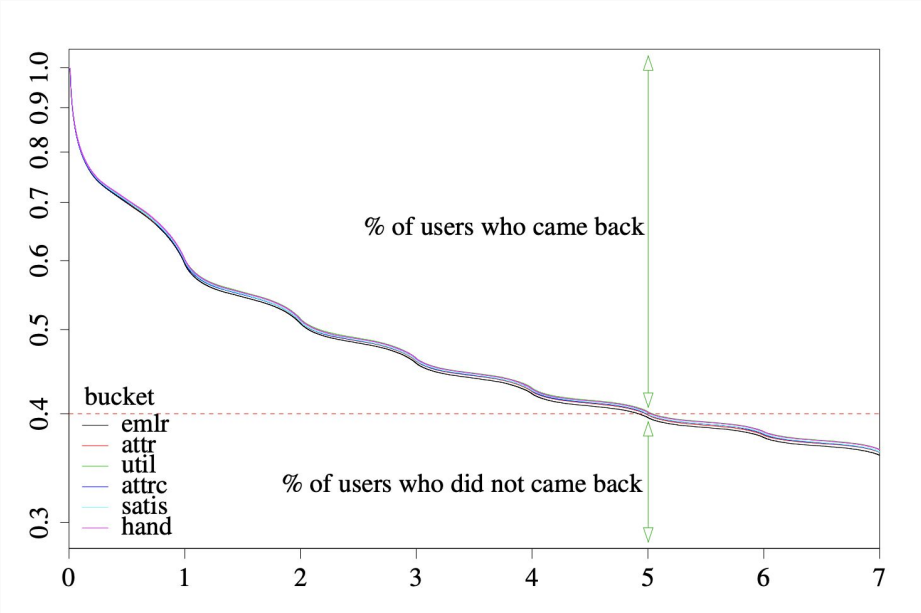
- Short-term signals ignore user's long-term goals/needs and a myopic view of success can result in "echo-chamber" effects or "filter bubbles". Kohavi et al. showed that optimizing for short-term improvements may be detrimental in the long-term.

- Measuring long-term success is challenging and complicated. We discuss two approaches
  - Predicted Metrics
  - Surrogates or Proxies

Inter-Session Feedback: Absence Time

- The time between successive sessions can be used to measure satisfactions (i.e., quicker the users return to the service → more satisfied).
- Modeling absence time using survival analysis (Cox model) to predict future outcome can be used to compare ML systems.

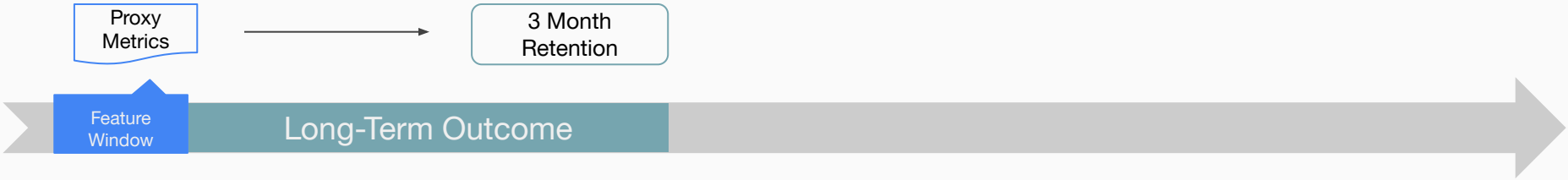




Georges Dupret and Mounia Lalmas. **Absence time and user engagement: evaluating ranking functions.** *WSDM 2013.*

Inter-Session Feedback: Surrogates & Proxies

- Satisfied users coming back to the service and re-engaging with the ML system is a reasonable proxy for long term success.
- One or more short-term metrics such as Clickthrough Rate, Session success can be used as proxies to estimate long-term outcomes (e.g. user retention).



Susan Athey, Raj Chetty, Guido W. Imbens, Hyunseung Kang. **The Surrogate Index: Combining Short-Term Proxies to Estimate Long-Term Treatment Effects More Rapidly and Precisely**. NBER 2019.

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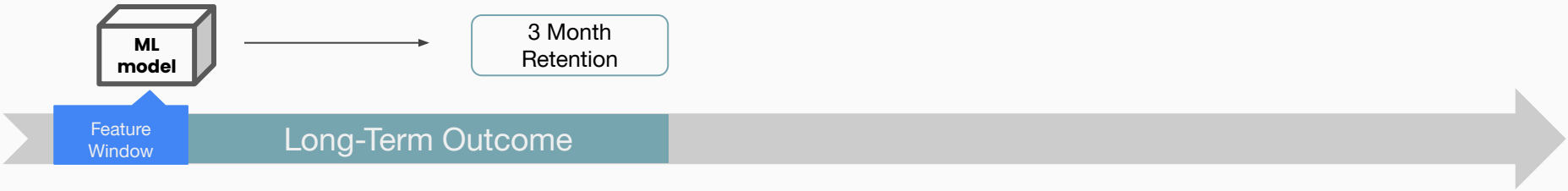
- One or more short-term metrics such as Clickthrough Rate, Session success can be used as proxies to estimate long-term outcomes (e.g. user retention).
- Alternatively, modeled metrics that predict long-term success could be used to compare ML systems.



Susan Athey, Raj Chetty, Guido W. Imbens, Hyunseung Kang. **The Surrogate Index: Combining Short-Term Proxies to Estimate Long-Term Treatment Effects More Rapidly and Precisely**. NBER 2019.

Additional Reading Materials and References

Relevant Tutorials

- Harrie Oosterhuis et al. **Unbiased Learning to Rank: Counterfactual and Online Approaches.** WWW 2020
- *Liangjie Hong & Mounia Lalmas* **Tutorial on Online User Engagement: Metrics and Optimization.** KDD 2020
- *Jean Garcia-Gathright et al.* **Mixed methods for evaluating user satisfaction.** RecSys 2019
- *Rishabh Mehotra et al.* **Understanding & Inferring User Tasks and Need**. WWW 2018.
- *Thorsten Joachims & Adith Swaminathan* **Tutorial on Counterfactual Evaluation and Learning**. SIGIR 2016
- *Aleksandr Chuklin et al.* **Click models for web search and their applications to IR.** WSDM 2016.
- *Et al.* **Challenges, Best Practices and Pitfalls in Evaluating Results of Online Controlled Experiments.** KDD 2019

Survey Papers

- *Jiawei Chen et al.* **Bias and Debias in Recommender System: A Survey and Future Directions.** TKDE 2020