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IN4325

# Query Autocompletion and Interactive IR

# The big picture

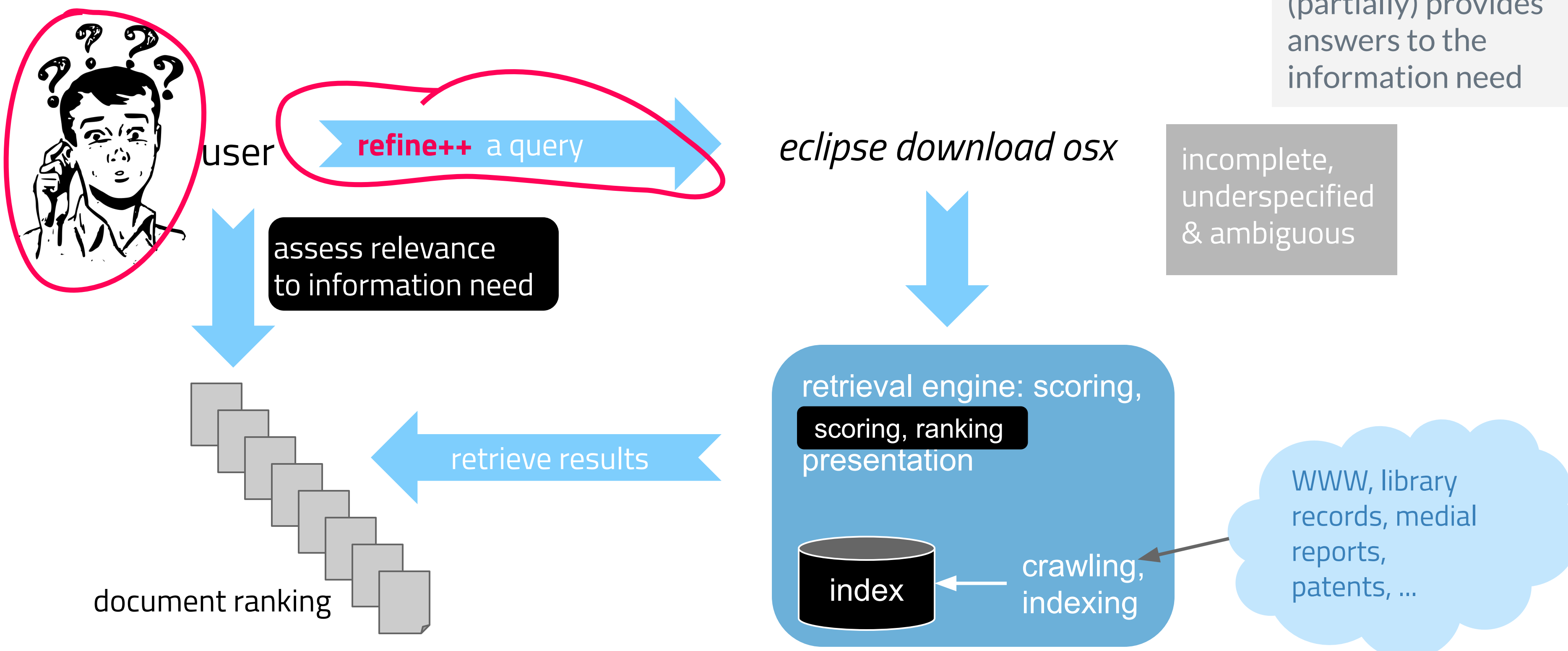
# The essence of IR

**Information need**
Topic the user wants to know more about

**Query**
Translation of need into an input for the search engine

**Relevance**
A document is relevant if it (partially) provides answers to the information need

**Information need**: *Looks like I need Eclipse for this job. Where can I download the latest beta version for macOS Sierra?*



# Query autocompletion

## Interactive query expansion

*Select the term(s) to augment your original query with.*

## Query suggestions

*Select the complete query to replace your original query with.*

## Query autocompletion

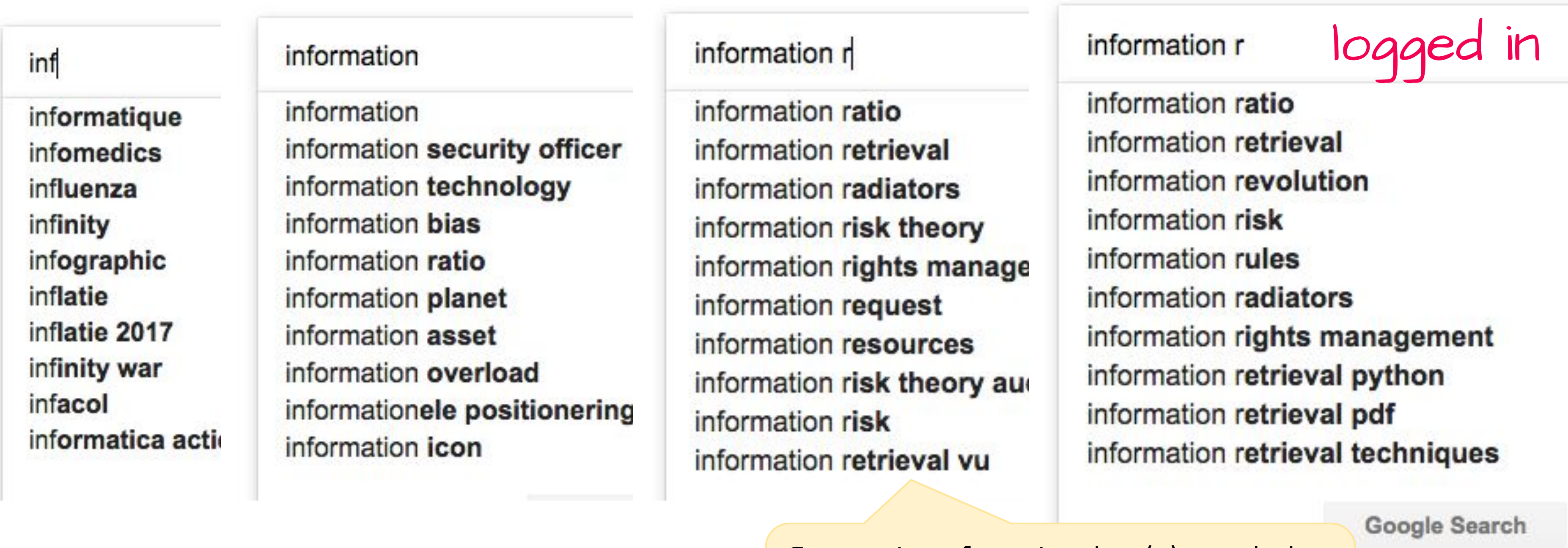
*Select the complete query to replace your original query with whilst typing.*

## Related queries

*Select the complete query to replace your original query with. May deviate away from your original intent!*

Last time

# Overview



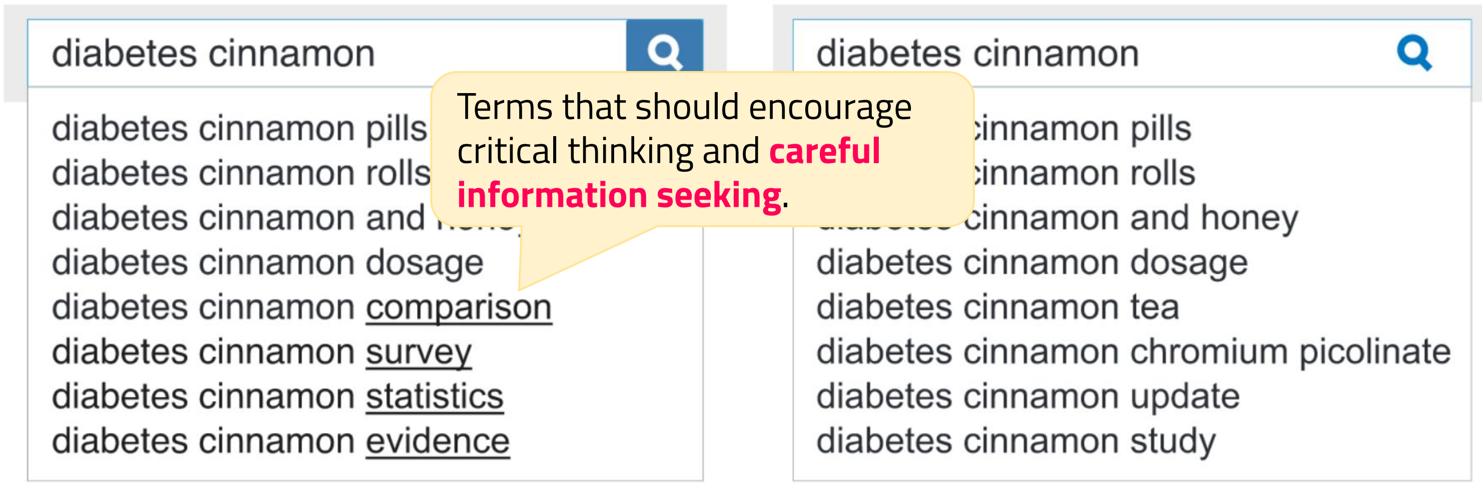

Suggestion of queries that (1) match the user's information needs and (2) yield a high-quality result ranking.

Goals:

1. Reduce query entry time
2. Prepare results in advance of query submission
3. Help users formulate a more precise query

Requires the search system to infer the user's *intent*.

# CHIIR 2018: query priming study




(1) QAC with query priming (2) Conventional QAC

Findings:

1. With priming, users issue more queries
2. With priming, users (re)-visit the SERP more often
3. The priming effect varies relative to users' educational backgrounds (benefits highly educated users)

https://dl.acm.org/citation.cfm?id=3176377

# Query-log based Query autocompletion

# Task

Given the current prefix (=query string the user has typed in so far), rank all possible candidates* (=complete queries).

Display the top ranked candidates to the user.

*assume for now that we have that list available

Previously

# Two strong baselines

Assumptions:

1. Access to a query log and document clicks
2. Access to a corpus
3. Access to a user's past queries

**Most popular ranker**

Query candidates are ranked according to their past popularity

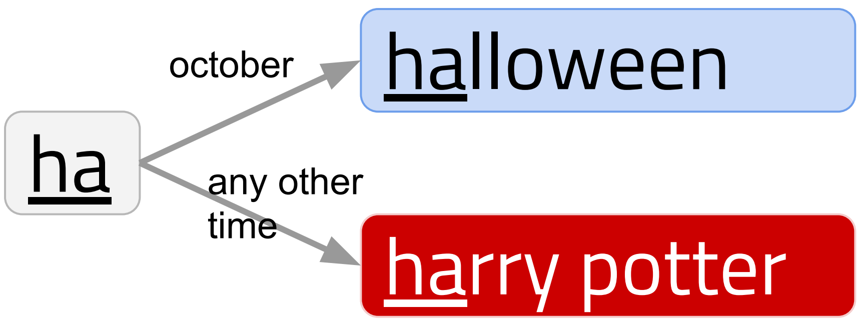
**Clicked documents ranker**

Cosine similarity between a user's profile (previously clicked docs by that user) and the candidate query profile (previously clicked docs across all users for that query)

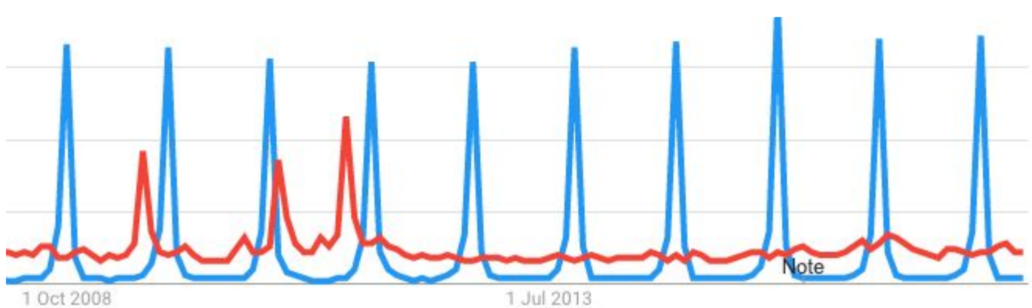
https://dl.acm.org/citation.cfm?id=2348364

Previously

# Time-sensitive query autocompletion




Approach: apply time-series modeling and rank candidates according to their forecasted frequencies



# Web search engines are not everything …

Large user base

Assumptions:

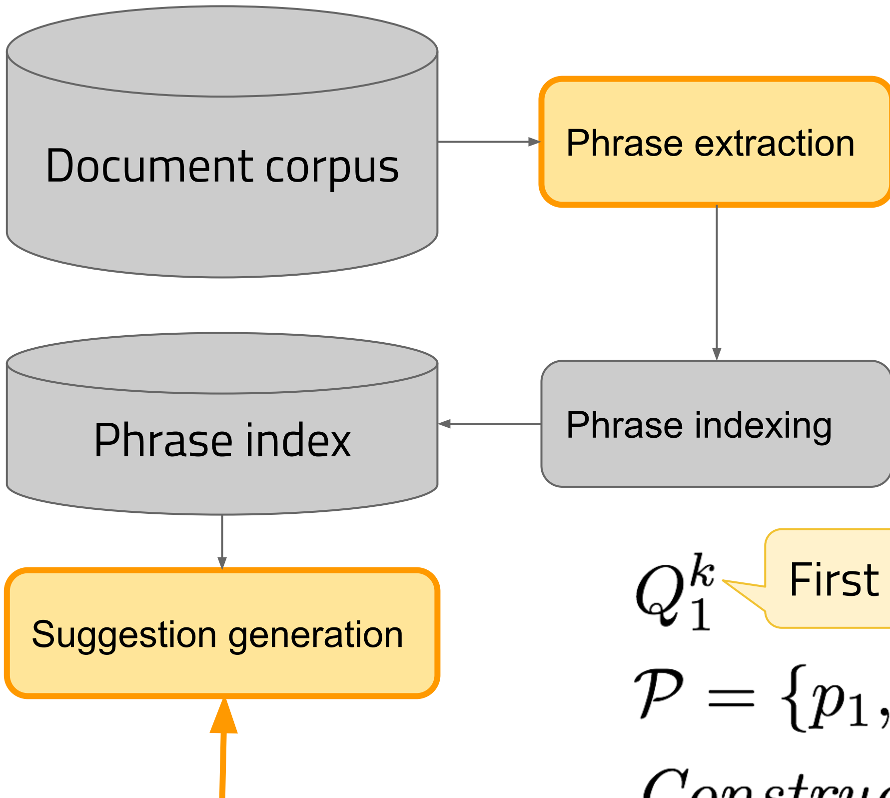
1. **Access to a query log and document clicks**
2. Access to a corpus always possible
3. **Access to a user's past queries**

What about search in specialized domains or personal search systems (PIM)?

# Corpus-based Query autocompletion

https://dl.acm.org/citation.cfm?id=2010023

# Corpus-based query suggestions




- N-grams: unigrams, bigrams, trigrams
- Skip over stopwords when generating phrases

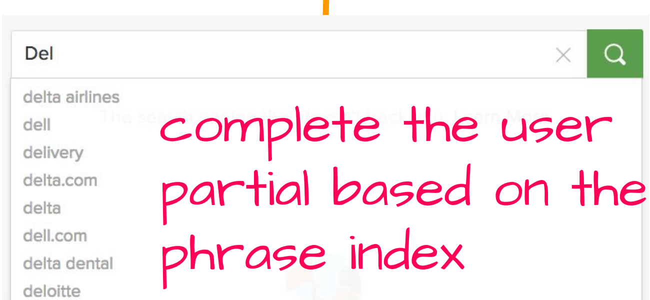
$Q_1^k$ First $k$ characters typed

$\mathcal{P} = \{p_1, .., p_n\}$ Set of all extracted phrases

$$Construct\ S \subset \mathcal{P},\ such\ that\ each$$

$$s \in S\ is\ a\ possible\ completion\ of\ Q_1^k$$

$$P(p_i | Q_1^k)$$




complete the user partial based on the phrase index

https://dl.acm.org/citation.cfm?id=2010023

# Corpus-based query suggestions

$P(p_i|Q_1^k)$ Probability that the user will type $p_i$ given her first $k$ typed characters

$Q_1^k = \underline{Q_c} + \underline{Q_t}$ Completed word(s) plus word the user is currently typing

$$P(p_i|Q_1^k) = \frac{P(p_i) \times P(Q_1^k|p_i)}{P(Q_1^k)}$$ according to Bayes' theorem

$$= \frac{P(p_i) \times P(Q_t|p_i) \times P(Q_c|p_i)}{P(Q_1^k)}$$ Simplifying assumption: conditional independence

$$P(p_i)P(Q_t|p_i) = P(p_i, Q_t) = P(Q_t)P(p_i|Q_t)$$

$$= \frac{\cancel{P(Q_t)} \times P(p_i|Q_t) \times P(Q_c|p_i)}{\cancel{P(Q_1^k)}}$$

Remains static for all $p_i$

$$\stackrel{rank}{=} P(p_i|Q_t) \times P(Q_c|p_i)$$

https://dl.acm.org/citation.cfm?id=2010023

# Corpus-based query suggestions

$$P(p_i|Q_1^k) \overset{rank}{=} P(p_i|Q_t) \times P(Q_c|p_i)$$

Phrase that contains the completed word $c_i$

Phrase selection probability

Phrase-query correlation
`bill gate*` vs. `india gate*`
Context is needed!

$$P(p_{ij}|Q_t) = P(c_i|Q_t) \times P(p_{ij}|c_i)$$

Term completion probability; $c_i$ is a possible word completion

Term to phrase probability

$$P(Q_c|p_i) = \frac{P(Q_c, p_i)}{P(p_i)}$$

Estimated based on corpus statistics; to avoid data sparseness, we simplify to the bag of words approach, i.e. search queries `linux install firefox` `install firefox linux` `firefox install linux` are treated in the same way.

Assumption: phrases in the corpus that are more important have a higher chance of being used by the user for querying. Estimated based on corpus statistics.

# Corpus-based query suggestions

## Data sets

**TREC**: 200K news articles by the Financial Times published between 1991-1994, 40 test queries

**Ubuntu**: 100K discussion threads, 40 test queries

Given a complete query, retain only the first keyword (Type-A) or the first keyword plus $k>2$ characters (Type-B)

## Baseline

**SimSearch**: search the phrase index for all phrases containing the partial user query; rank them in order of decreasing corpus frequency

`Radioactive waste`
(TREC Topic 387)

`Radioactive`
(Type-A)

`Radioactive was`
(Type-B)

https://dl.acm.org/citation.cfm?id=2010023

What are good metrics?

# Corpus-based query suggestions

## Data sets

**TREC**: 200K news articles by the Financial Times published between 1991-1994

## Baseline

**SimSearch**: search the phrase index for all phrases containing the partial user query; rank them in order of decreasing corpus frequency

presented approach

| Query = mount | | | Query = falkland | | |
|---|---|---|---|---|---|
| **SimSearch** | **CompSearch** | **Prob** | **SimSearch** | **CompSearch** | **Prob** |
| mount | mount | mount | falklands | falklands | falklands |
| mounted | mounted | unable to mount | falkland | falkland | falklands war |
| mounting | mounting | mount point type | falkland islands | falklanders | falkland islands |
| mounts | mounts | sudo mount | falklands war | | falklands conflict |
| sudo mount | mountpoint | able to mount | falklands conflict | | 1982 falklands |
| unable to mount | mountcifs | mountpoint | 1982 falklands | | 1982 falklands conflict |
| system mount | mountable | try to mount | falkland islands government | | falkland islands government |
| file system mount | mounter | mount the drive | 1982 falklands conflict | | falklands war in 1982 |
| mount point type | mountunmount | mount the partition | falkland arms | | 1982 falklands war |
| system mount point type | mountpoints | file system mount | falklanders | | invasion of the falklands |

https://dl.acm.org/citation.cfm?id=2010023

12 assessors (colleagues), majority vote on top 10 suggestions

# Corpus-based query suggestions

| Rating | Meaning |
|---|---|
| Y | Yes, a meaningful suggestion |
| N | No, not a meaningful suggestion, or badly formed as a query |
| D | An (almost) duplicate suggestion, conveys no new information |
| ?? | Not sure |

presented approach

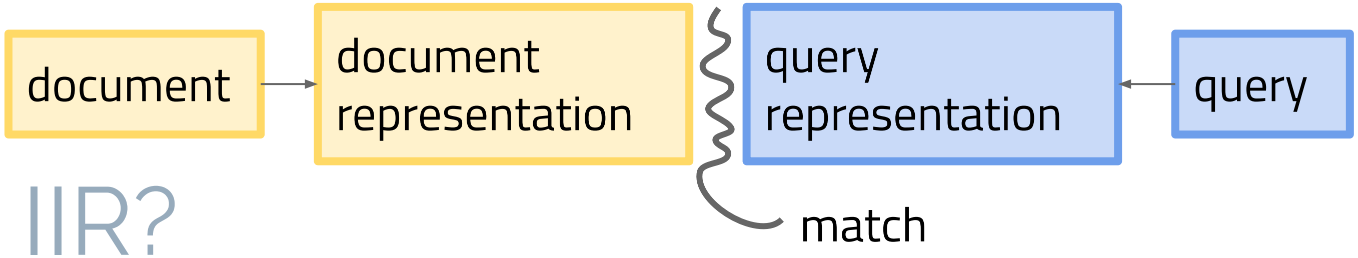
| Ubuntu | | | |
|---|---|---|---|
| | SimSearch | CompSearch | Probabilistic |
| Type-A | 1.00 | 1.00 | 1.00 |
| Type-B | 0.75 | $1.00^{s}$ | $1.00^{s}$ |
| Overall | 0.875 | $1.00^{s}$ | $1.00^{s}$ |
| **TREC** | | | |
| | SimSearch | CompSearch | Probabilistic |
| Type-A | 1.00 | 1.00 | 1.00 |
| Type-B | 0.15 | $0.95^{S}$ | $1.00^{S}$ |
| Overall | 0.575 | $0.975^{S}$ | $1.00^{S}$ |

Success rate: at least one meaningful suggestion for the partial query

**Table 4: Success Rate of different query suggestion methods for the two datasets. Superscripts s and S indicate statistically significant improvements over SimSearch with $p < 0.05$ and $p < 0.01$, respectively (one-tailed t-test).**

# Interactive Information Retrieval

*“classic” IR model*




# What is IIR?

*" The area of interactive information retrieval covers research related to* ***studying*** *and* ***assisting*** *these diverse end users of information access and retrieval systems."*
(Ian Ruthven)

*" In interactive information retrieval,* ***users are typically studied*** *along with their interactions with systems and information."*
(Diane Kelly)

*“... the interactive approach to IR has led to a f****ocus on the user-oriented activities*** *of query formulation and reformulation, and inspection and judgement of retrieved items ...”* (Nick Belkin)

# From past to present

Many (many!) models have been proposed over the years. This is only a small selection.

Conceptual, observational and empirical work

Bates' berrypicking

Kuhlthau's ISP

Fuhr's IPRP

Search Economic Theory

Information Foraging Theory

approximately equivalent

Mathematical models of information seeking and search

- Observe users
- Propose a model that *describes* the observations well and has intuitive appeal

- Narrow down the 'search space' of **testable hypotheses**
- Pick the most promising hypotheses
- Design & execute user studies to (in)validate the hypotheses

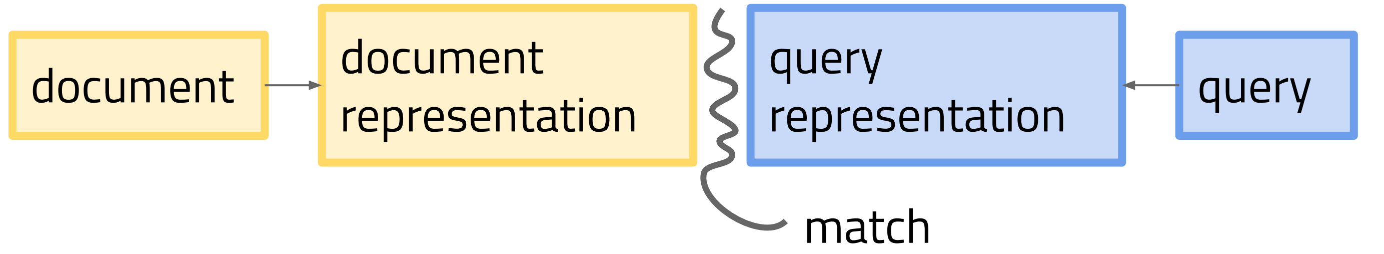
Most often in IR when we talk about models we mean retrieval models.

Not now though!

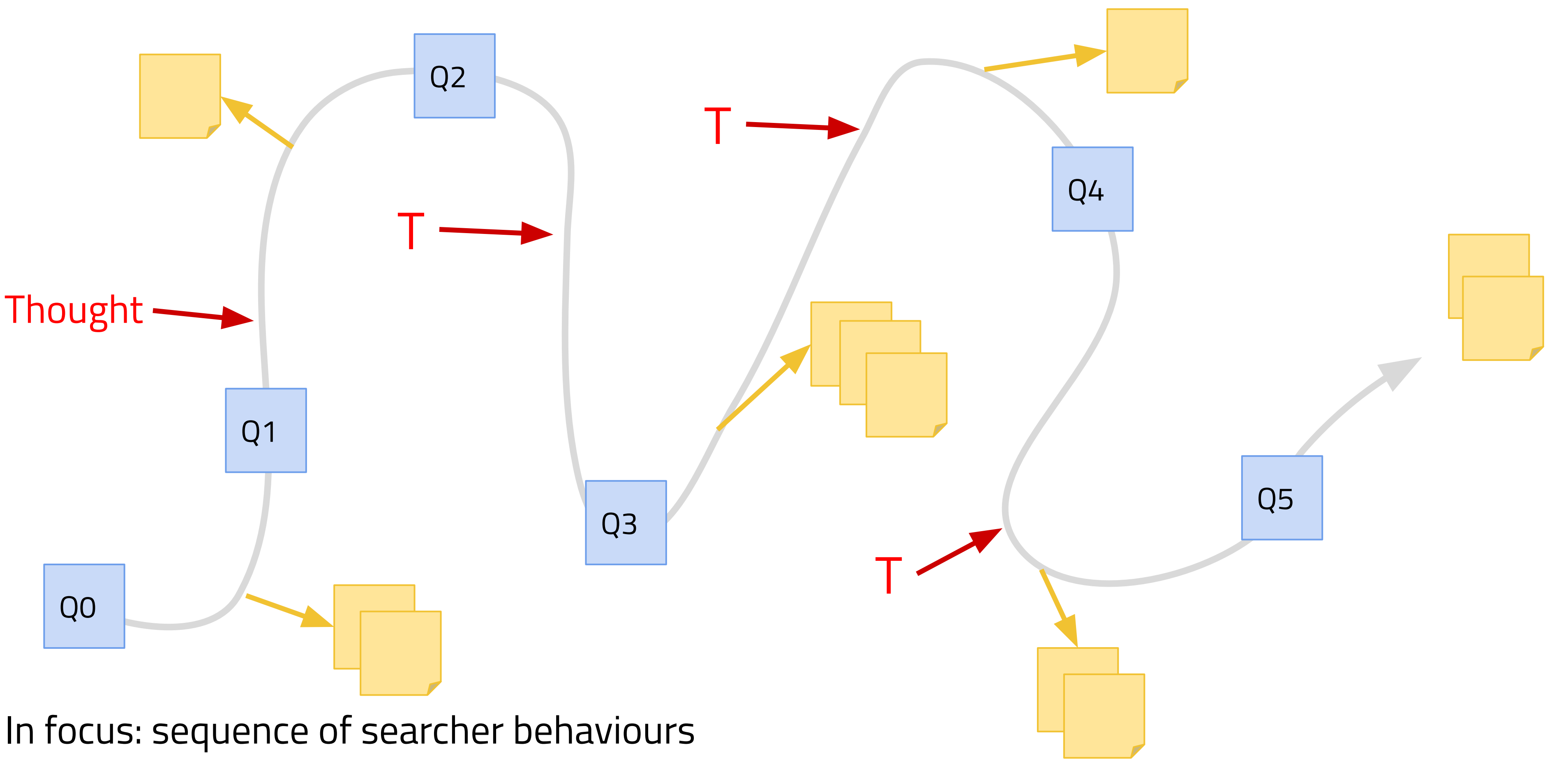
Now: models for interactive information seeking and retrieval

# Two early models of IIR

*“classic” IR model*




# Bates’ berrypicking model (1989)




In focus: sequence of searcher behaviours
Based on intuitions, informal observations

https://www.emeraldinsight.com/doi/pdfplus/10.1108/eb024320

# Bates' berrypicking model (1989)

- Information needs **evolve over time**, they are not static throughout the search

- Users frequently start their search with just one sub-topic of a broader topic

- Each found piece of information can result in new ideas and search directions

- A query is not satisfied by a final retrieved set of documents, but by a **series of selections** of bits of information at each stage of the evolving search

bit-at-a-time retrieval ***= berrypicking***

flickr@calliope

https://www.emeraldinsight.com/doi/pdfplus/10.1108/eb024320

# Kuhlthau's Information Search Process model (1988)

Model designed based on **observations** of **high school students**' application of library skills (i.e. qualitative research)

Motivation: "*Findings are needed that define the **experience** of people in an information search from their **own perspective**.*"

Systematic development of theory

Goal: **grounded theory** of the library search process


flickr@juanillooo

# Kuhlthau's Information Search Process model (1988)

Exploratory study based on:

- Observations in the natural setting (school library)
- Interviews (45 minutes)
- Journals (diaries)
- Search logs
- Time lines
- Flow charts
- Assessed writing probes

Participants: 26 college-bound high school seniors

Assignment: write a paper

*Describe how you felt when the teacher announced the research assignment.*

*Describe how and why you chose your topic.*

*How did you know when your search was completed?*

*What did you find most difficult about your search?*

# Kuhlthau's Information Search Process model (1988)

Six stages

| Task initiation | Topic selection | Prefocus exploration | Focus formulation | Information collection | Search closure |
|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| Feelings (affective) | uncertainty | optimism | confusion, frustration, doubt | clarity | sense of direction, confidence | relief |

Thoughts (cognitive)

ambiguity → specificity

→ increased interest

Actions (physical)

seeking relevant information → seeking pertinent information

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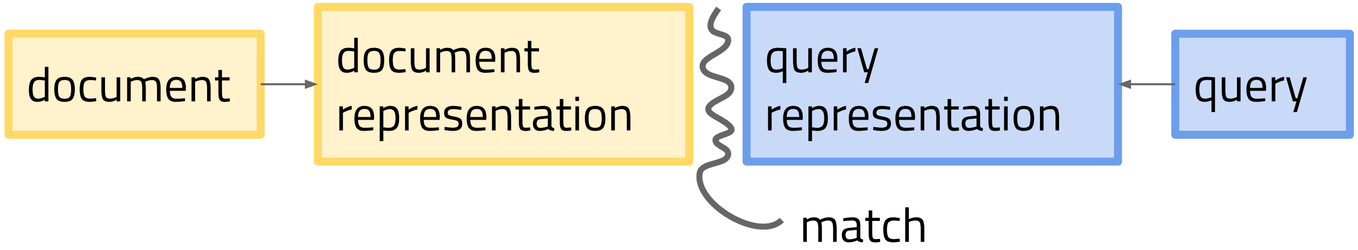
Hidden from any IR system we know today ...

# One of today's prevalent IIR modeling approaches

*"classic" IR model*




# Predictive models are needed

- Observational studies and descriptive models allow us to think but not to reason about interactive IR design decisions

e.g. is it better to show 20 query autocompletion items or just 3?

http://tiny.cc/4s2vlz

- Interactive IR experiments have shown that system effectiveness and **user performance** do not necessarily correlate

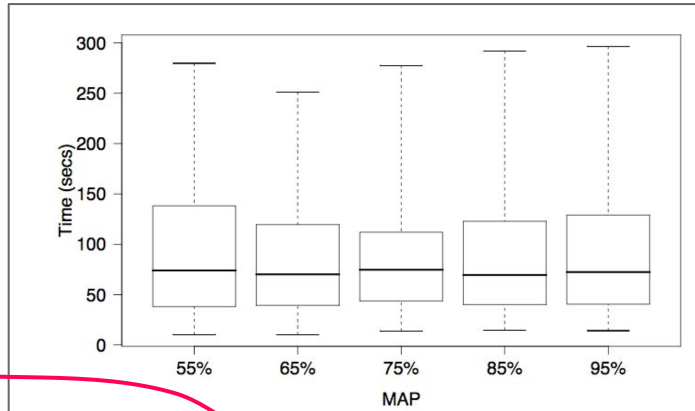



**Figure 3: Time taken to find the first relevant document versus the mean average precision of the system used.**

space of all possible UI changes

UIs predicted to be useful by a model

# Economic models of interaction

(Azzopardi et al, 2011-today)

Focus on understanding/predicting the behaviour of economic agents within an environment.

Economics is a field ripe with predictive models of costs and benefits; can we make use of them?

User interactions re-interpreted:

- Users take **actions** to advance towards their **goals**
- Each action has a **cost** (time, effort, cognitive load, etc.)
- An action may or may not lead to a **benefit** (saving time, finding new information, etc.)


Tutorial: http://zuccon.net/publications/azzopardi-zuccon-2017-tutorial-economics.pdf

# Economic models of interaction

(Azzopardi et al, 2011-today)

Representation of reality in an abstracted form; requires assumptions.

Having formulated a **mathematical model**, we can examine what actions:

- accrue the **most benefits** for a given cost
- incur the **least cost** for a given benefit level
- a rational user should take (given a task, interface, context, constraints) to achieve **optimal** results

# Economic models of interaction

(Azzopardi et al,  2011-today)

Assumptions:

- Economic agents are **rational** and attempt to maximize their benefits

- Economic agents can **adapt** their strategies towards the optimal course of interaction

Let's look at an (I)IR example!

# Building economic models

iterate

1. Describe the problem context (who/what/how)
2. Specify the cost and benefit functions (keep it simple and then refine)
3. Solve the model (analytically, computationally, or graphically)
4. Use the model to generate hypotheses about behaviours (how do different variables influence interaction and behaviour)
5. Compare the predictions with observations in the literature and/or experimental data (model as a guide and evidence that [in]validates our models, leading to refinement)

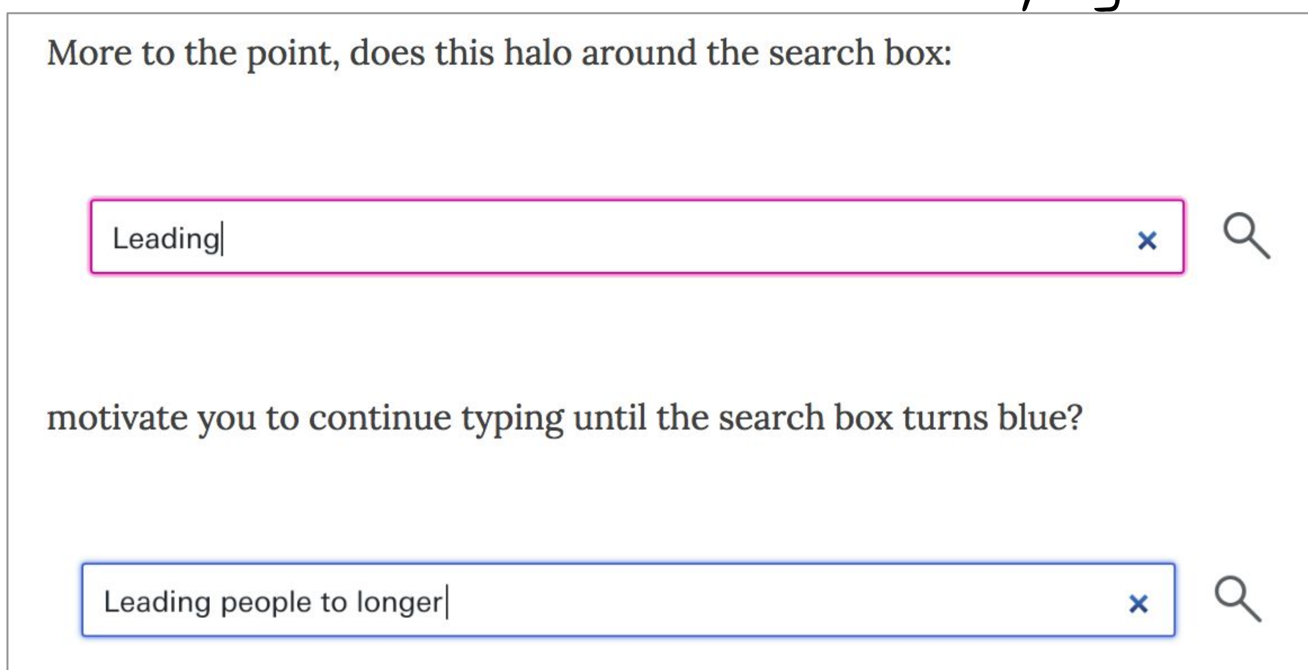
# Economic model of querying

Goal: a model that describes the relationship between the length of the query and the costs/benefits of the query given its length

How about trying this?

Longer queries tend to lead to better results; users do not use long queries.

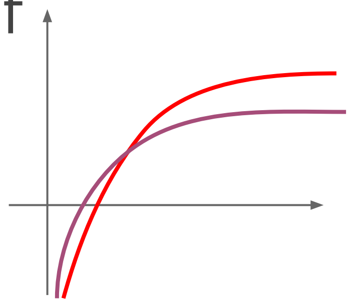
Can we incentivize them?



# Economic model of querying

Goal: a model that describes the relationship between the length of the query $\mathbf{W}$ (in words) and the costs/benefits of the query given its length.

Modeling assumption: cost/benefit are a function of query length alone.



$$\underline{b(\mathbf{W})} = \mathbf{k} \times \log_a(\mathbf{W} + \mathbf{1})$$

benefit function

Diminishing returns ($\mathbf{a}$ determines steepness) as the length increases with $\mathbf{k}$ as scaling factor (e.g. SE quality).

$$\underline{c(\mathbf{W})} = \mathbf{W} \times \mathbf{c_w}$$

cost function
(i.e. the effort in querying)

Effort to enter one word.

# Economic model of querying

Given the cost and benefit functions, we can compute the **profit (net benefit)** that the user receives for a query of length $\mathbf{W}$:

$$\pi = b(\mathbf{W}) - c(\mathbf{W}) = \mathbf{k} \times log_a(\mathbf{W} + \mathbf{1}) - \mathbf{W} \times \mathbf{c_w}$$

Which query length maximizes the user's net benefit? Differentiate with respect to $\mathbf{W}$ and solve:

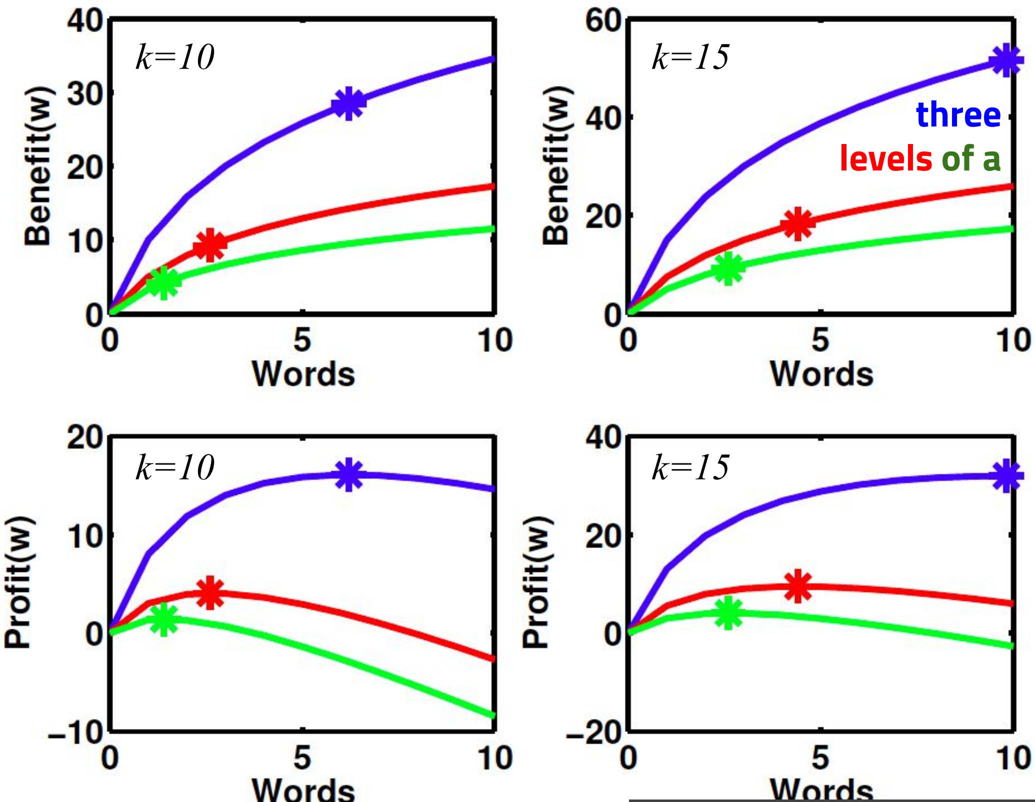
$$\frac{\partial \pi}{\partial \mathbf{W}} = \frac{\mathbf{k}}{\log \mathbf{a}} \times \frac{\mathbf{1}}{\mathbf{W} + \mathbf{1}} - \mathbf{c_w} = 0$$

$$\mathbf{W}^* = \frac{\mathbf{k}}{\mathbf{c_w} \times \log \mathbf{a}} - \mathbf{1}$$

# Economic model of querying

$$\mathbf{W}^* = \frac{\mathbf{k}}{\mathbf{c_w} \times \log \mathbf{a}} - \mathbf{1}$$

What does the model say about:
query halo effect
query autocompletion




Hypotheses based on this model:

- As the system performance ($\mathbf{k}$) increases, the query length increases
- If additional terms provide less and less benefit ($\mathbf{a}$ increases), queries decrease in length
- With decreasing cost of entering a word ($\mathbf{c_w}$), users tend to pose longer queries

# Economic models of interaction

(Azzopardi et al., 2011-today)

Challenges:

- **Estimation of costs and benefits** and their respective units (temporal, fiscal, satisfaction, enjoyment, ...)
- Assumption that users seek to max. their benefit
- Is the model sufficiently realistic wrt. user and environment?
- **Design of experiments**

# Thanks for your Attention!

Any questions?

Feel free to drop me a line:

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