Information Retrieval

Foundational Concepts and Models

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ESSIR 2015 Tutorial
Based on joint material/discussions with Fei Cai, Aleksandr Chuklin, Katja Hofmann, Xinyi Li, Ilya Markov, Daan Odijk, Anne Schuth, Shimon Whiteson, Masrour Zoghi.
“Information retrieval (IR) is the activity of obtaining information resources relevant to an information need from a collection of information resources. Searches can be based on metadata or on full-text (or other content-based) indexing.” [1]
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Users and search engines the essential agents
- users’ information needs
- search engine results
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Users and search engines the essential agents
- users’ information needs
- search engine results

Search engine and users are agents that perform actions in response to each other: interactions, result list, interactions, result list, ...
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Information Retrieval
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Information Retrieval

The retrieval system

retrieval system

agent
The retrieval system
The retrieval system
The retrieval system

- Offline
- Online
- Front door

-ent-
The retrieval system
The retrieval system
The front door determines the user experience, produces search engine result page (SERP). Receives query, may return query auto completion suggestions. Receives other user signals (clicks, shares, ...). Should be connected to evaluation framework and to online module.
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Content crawling/ingestion
▶ Scheduling (freshness, e.g., based on social media) and discovery
Enriching
▶ Classification (spam, adult, . . . ), extraction (entities, multimedia, . . . ), and annotators (document expansion, translation, . . .
Aggregation of sources
▶ Interaction features (clicks, . . . ), social features (Twitter, . . .
▶ Graph-based computations (anchor text, PageRank, HITS, . . .
Indexing

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Information Retrieval
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Indexing
Query auto completion
▶ Down: Alterations (suggestions, translation, . . . ), classification (entities, intent, performance prediction, task detection, . . .)
▶ Up: SERP generation (snippet generation, device tailoring, answer insertion, suggestions, . . .)

Blender
▶ Down: ranker type and parameter selection (web, fresh, news, image, video, apps, social, . . .)
▶ Up: merging results (interleaving, diversity) and UX selection

Vertical ranking
▶ Hotfixes (personalized); compute Q+D features; apply rankers

Top-k retrieval
▶ Keyword matching, retrieval of document features
Query auto completion

Query understanding

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Top-k retrieval

- Keyword matching, retrieval of document features
Evaluation framework
Evaluation framework

Metrics
- Online, offline

Flighting
- Bucketing, A/B testing, interleaving

Learning

Logging

Annotations
- Experts, crowd
The big picture
The bigger picture
The biggest picture

retrieval system

user

agent

agent
Outline

1. Introduction
2. Front door
3. Offline
4. Online
5. Evaluation
6. Wrap-up
Front door
The front door determines the user experience, produces search engine result page (SERP).

Receives query, may return query auto completion suggestions.

Receives other user signals (clicks, shares, ...).
Search interface guidelines include:

- Offer efficient and informative feedback
- Balance user control with automated actions
- Reduce short-term memory load
- Provide shortcuts
- Reduce errors
- Recognize the importance of small details
- Recognize the importance of aesthetics

To design successful search user interfaces, understand human information seeking process, including strategies people employ when engaged in search

M. Hearst. *Search User Interfaces*, CUP, 2009
## User data

### User studies

**Controlled interpretation of behavior with detailed instrumentation**

<table>
<thead>
<tr>
<th>Observational</th>
<th>Experimental</th>
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<tbody>
<tr>
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*understand behavior contrast approaches*
Query auto completion

Helps users formulate query when they have an intent in mind but not a clear way to express it.

Typical query completion service of modern search engine takes initial characters entered by user and returns matching queries to automatically complete search clue.

Where offered, query completion is heavily used by visitors and highly influential on search results.

Useful and straightforward approach to rank QAC candidates is to use Maximum Likelihood Estimation (MLE) based on the past popularity of queries

- Assumes that the current query popularity distribution is the same as what was previously observed
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movie, christmas, MH370
Observations

- Recency; Whiting et al. (WWW '14)
- Specific temporal intervals; Shokouhi et al. (SIGIR '12)
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- Specific temporal intervals; Shokouhi et al. (SIGIR '12)

Predictions

- Time-series modeling; Shokouhi et al. (SIGIR '12)
- Regression; Whiting et al. (WWW '14)
Add personalization

QAC of typed prefix c **without logging in.**

QAC of typed prefix c **after logging in.**
Context-aware

- Previous queries; Bar-Yossef et al. (WWW ’11)
- Click graph; Cao et al. (KDD ’08)
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Learning to personalize

- Demographics + MPC + history; Shokouhi (SIGIR ’13)
- Query co-occurrence; Ozertem (SIGIR ’12)
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Trends at SIGIR ’15

- Semantics (distributed representations; Mitra, 2015)
- Adaptive models
Once we receive clicks, how can we make sense of it?

Click models

- Probabilistic graphical models of user interaction behavior
- (Chuklin et al., 2015)
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Click models

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Why?

- Understand users
- Simulate users
- Evaluate search
- Improve search
Random click model
Random click model

\[ P(C_u = 1) = \rho \]
CTR models

Rank-based CTR:

\[ P(C_r = 1) = \rho_r \]

Document-based CTR:

\[ P(C_u = 1) = \rho_{uq} \]
Position-based model
Position-based model

\[ P(C_u = 1) = P(E_u = 1) \cdot P(A_u = 1) \]
\[ P(A_u = 1) = \alpha_{uq} \]
\[ P(E_u = 1) = \gamma_{r_u} \]
Cascade model
\[ E_r = 1 \text{ and } A_r = 1 \iff C_r = 1 \]

\[ P(A_r = 1) = \alpha_{ur} q \]

\[ P(E_1 = 1) = 1 \]

\[ P(E_r = 1 \mid E_{r-1} = 0) = 0 \]

\[ P(E_r = 1 \mid C_{r-1} = 1) = 0 \]

\[ P(E_r = 1 \mid E_{r-1} = 1, C_{r-1} = 0) = 1 \]
Query suggestions

“Did you mean?”

- Catching zero result queries
- More popular queries

Most work on query suggestions exploits query logs.

- Exploiting consecutive queries during sessions combined with a content-based method using search frequency and query frequency (Zhang et al., 2006)
- Performing random walk on a bipartite graph consisting of queries and documents, with transition probabilities derived from the number of clicks between queries and documents: the click graph (Craswell et al., 2007)
- Query-flow graph inferred from reformulation patterns in search sessions, and uses random walk on the graph to obtain suggestions (Boldi et al., 2008)

Most of these developed and tested methods for so-called head queries.
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Click graph

- Bipartite with two types of nodes: queries and documents
- Edge connects a query and a document if a click for that query-document pair is observed
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Use to find query suggestions (given a query as input)

- Random walk on click graph
- Query-document transitions: prefer the most-clicked document for the query
- Document-query transitions: original model treats documents and queries symmetrically so prefers query with the most clicks
  - +: model will prefer to follow edges where we have the most evidence of relevance
  - -: model will prefer popular queries
Nodes are queries or images, edges indicate clicks. Images A and B are equidistant from the query ‘panda’ (distance=3), so retrieval based on a naive shortest-path algorithm could not distinguish them. Markov random walk approach sums over paths, so image A benefits from having 7 distinct paths of length 3. Nodes A and ‘panda’ are connected by a large “volume” of paths.

Query flow graph is a directed graph

- Nodes are queries
- Arcs are reformulations: non-symmetrical
- Arcs have annotations: frequencies, similarities, etc.
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Perform random walk to identify most probable suggestions

Recommendations for the query “apple” considering that the previous query was “banana” (top) or “beatles”? (bottom).
The query-flow graph also facilitates classifying types of reformulation behavior:

- **Parallel moves (50%–60%)**
  - *amsterdam → berlin*
  - *The most frequent class*

- **Specializations (30%–40%)**
  - *amsterdam soccer → amsterdam arena*

- **Generalizations (5%–10%)**
  - *amsterdam hotels → amsterdam*
  - Specialization and generalization frequently appear together in alternating order

- **Corrections (5%–10%)**
  - *masterdam → amsterdam*

---

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Offline
Offline vs. online

In computer science, algorithms that receive their input sequentially operate in an online modality.

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Batch or offline processing does not need human interaction.

- E.g., batch learning proceeds as follows:
  - Initialize the weights
  - Repeat the following steps:
    - Process all the training data
    - Update the weights
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**Typical offline computations in information retrieval**

- Any processing that is not query dependent (crawling, document enriching, aggregation, indexing, . . .)
Offline

Getting content
Document classification
Duplicate detection
Document enrichment
Content aggregation
Indexing
Getting content: many scenarios

- Desktop search
  - Recursive descent on file system

- Search on your phone
  - Recursive descent on file system (if battery permits?)

- Library search
  - Nightly ingestion

- Enterprise search
  - Nightly ingestion

- Twitter search
  - Near real-time availability

- Web search
  - Getting the content of the documents takes longer
  - Operate at variable speeds, with different priorities...
Crawling

- Initialize queue with URLs of known seed pages
- Repeat
  - Take URL from queue
  - Fetch and parse page
  - Extract URLs from page
  - Add URLs to queue

Fundamental assumption: The web is well linked.
Crawling

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What's wrong with this simple crawler?

- Scale: we need to distribute
- We cannot index everything: we need to select. How?
- Duplicates: need to integrate duplicate detection
- Spam and spider traps: need to integrate spam detection
- Politeness: we need to be “nice” and space out all requests for a site over a longer period (hours, days)
- Freshness: we need to re-crawl periodically
- Prioritize highly frequent re-crawls only for a small subset, frequent re-crawls for . . .
URL frontier

Data structure that holds and manages:

- URLs we have seen, but which have not been crawled yet
- Can include multiple pages from same host
- Avoid trying to fetch them all at the same time
- Keep all crawling threads busy

URL frontier: found but not yet crawled

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URLs crawled and parsed
**URL frontier**

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  - URLs we have seen, but which have not been crawled yet
  - Can include multiple pages from same host
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Basic crawling architecture

Duplicate detection

Duplicates occur in most collections of reasonable size

► But web is full of duplicated content, more so than many other collections
► Exact duplicates
  ● Easy to eliminate
  ● E.g., use hash/fingerprint
► Near-duplicates
  ● Abundant on the web
  ● Difficult to eliminate
► For the user, it is annoying to get a search result with near-identical documents
► Marginal relevance is zero: even a highly relevant document becomes non-relevant if it appears below a (near-)duplicate
Compute similarity with an edit-distance measure

We want “syntactic” (as opposed to semantic) similarity.

We do not consider documents near-duplicates if they have the same content, but express it with different words.

Use similarity threshold $\theta$ to decide “is/is not a near-duplicate”

- E.g., two documents are near-duplicates if similarity $> \theta = 80\%$. 
A **shingle** is simply a word n-gram.

Shingles are used as features to measure syntactic similarity of documents.

For example, for $n = 3$, “a rose is a rose is a rose” would be represented as this set of shingles:

\[
\{ \text{a-rose-is, rose-is-a, is-a-rose} \}
\]

We can map shingles to $1..2^m$ (e.g., $m = 64$) by fingerprinting.

Define the similarity of two documents as the Jaccard coefficient of their shingle sets.

For efficiency, define **sketches** (well chosen subsets of shingles) and compute Jaccard coefficient for two sketches.

- Index only document per equivalence class of similar documents
Spam detection

You have a page that will generate lots of revenue for you if people visit it

Therefore, you would like to direct visitors to this page.

One way of doing this: get your page ranked highly in search results

Exercise: How can I get my page ranked highly? (“Search engine optimization”)

You have a page that will generate lots of revenue for you if people visit it.

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One way of doing this: get your page ranked highly in search results.

Exercise: How can I get my page ranked highly? (“Search engine optimization”)

- Misleading meta-tags, excessive repetition
- Hidden text with colors, style sheet tricks etc.
- Used to be very effective, most search engines now catch these
Spam technique: Duplication

- Get good content from somewhere (steal it or produce it yourself)
- Publish a large number of slight variations of it
- And include profitable links to ads
Spam technique: Duplication

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Spam technique: Cloaking

- Serve fake content to search engine crawler
- So do we just penalize this always?
- No: legitimate uses (e.g., different content to US vs. European users)
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Spam technique: Link spam

- Create lots of links pointing to the page you want to promote
- Put these links on pages with high (or at least non-zero) PageRank
  - Newly registered domains (domain flooding): A set of pages that all point to each other to boost each other’s PageRank; Pay somebody to put your link on their highly ranked page; Leave comments that include the link on blogs
Gather content that appears to belong together

► Anchor text on the web
  • Anchor text is often a better description of a page’s content than the page itself
  • Anchor text can be weighted more highly than the text on the page

► Information around an entity (person, organization, location, cultural artefact, ...)
  • Large portion of queries are entity oriented
  • Information about “tail entities” is initially sparse (by definition) but may explode when entity hits the news
    — E.g., MH370, Ferguson, ...
  • Aggregate content from news, wikipedia, social, Twitter, ...
  • Spam, short-term interest, long-term interest
Inverted index construction

1. Collect the documents to be indexed:
   Friends, Romans, countrymen. So let it be with Caesar . . .

2. Tokenize the text, turning each document into a list of tokens:
   Friends Romans countrymen So . . .

3. Do linguistic preprocessing, producing a list of normalized tokens, which are the indexing terms:
   friend roman countryman so . . .

4. Index the documents that each term occurs in by creating an inverted index, consisting of a dictionary and postings.

Tokenization and preprocessing

**Doc 1.** I did enact Julius Caesar: I was killed i’ the Capitol; Brutus killed me.
**Doc 2.** So let it be with Caesar. The noble Brutus hath told you Caesar was ambitious:

**Doc 1.** i did enact julius caesar i was killed i’ the capitol brutus killed me
**Doc 2.** so let it be with caesar the noble brutus hath told you caesar was ambitious

Generate postings

<table>
<thead>
<tr>
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<th>docID</th>
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</thead>
<tbody>
<tr>
<td>i</td>
<td>1</td>
</tr>
<tr>
<td>did</td>
<td>1</td>
</tr>
<tr>
<td>enact</td>
<td>1</td>
</tr>
<tr>
<td>julius</td>
<td>1</td>
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<tr>
<td>caesar</td>
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<td>the</td>
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<td>1</td>
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<td>killed</td>
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Create postings lists, determine document frequency

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Split the result into dictionary and postings file

<table>
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<tr>
<th>Name</th>
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<th>Postings File</th>
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<td>Brutus</td>
<td>1 2 4 11 31 45 173 174</td>
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<tr>
<td>Caesar</td>
<td>1 2 4 5 6 16 57 132 ...</td>
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<tr>
<td>Calpurnia</td>
<td>2 31 54 101</td>
<td></td>
</tr>
</tbody>
</table>
Sort postings in memory (if infrastructure allows)

External sorting for disk-based set-ups

Distributed indexing for very large collections (MapReduce)

For dynamic collections, maintain main index on disk and separate auxiliary index in memory, search across both and merge results. Periodically merge auxiliary index into main index
The big picture
Break
Outline

1. Introduction
2. Front door
3. Offline
4. Online
5. Evaluation
6. Wrap-up
The big picture
Online
Query understanding

Blending

Vertical rankers

Top-k retrieval
Query understanding

Down

► Alterations
  • Confident suggestions, structured query generation, hotfixes (rules), advanced search syntax, query translation, qa understanding, stopword handling (term weighting)

► Classifiers
  • Query intent, topic, directly answerable, query performance prediction, language classifier, task detection, device detection

► Annotators
  • User modeling, localization, session, conversation?, entity extractors

► Aggregators
  • Query stats, tail/head
Query understanding

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Up

- SERP generation
  - Snippet generation, device tailoring, translation, answer insertion
With the help of intent identification, search engines can perform intent-aware result ranking, or provide accurate results for specific types of query

- If an image-oriented search intent is identified, invoke image search module so as to show a few image results along with general web results
  - Thessaloniki vs Thessaloniki image
With the help of intent identification, search engines can perform intent-aware result ranking, or provide accurate results for specific types of query.

- If an image-oriented search intent is identified, invoke image search module so as to show a few image results along with general web results
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Two main lines of work on intent identification, according to whether the intent label is predefined or not:

- Intent classification
- Intent discovery
Many flavors of intent classification

▶ Search goal
  - Navigational, informational, transactional

▶ Search task
  - “purchase computer”, “job-finding query”

▶ Semantic topics
  - “Cars”, “NBA” (DMOZ, ODP, Wikipedia)

▶ Vertical-oriented intents
  - Image, video, apps, . . .

▶ Time-sensitivity
  - News-sensitive queries

▶ Location-sensitivity
  - “coffee”
Classifying queries into pre-defined intent classes is challenging since queries are short and ambiguous.

Click-through data, session data, and search result data are widely used for the query classification tasks?

Generally, hand-crafted training data and hand-crafted intent inventory
Classifying queries into pre-defined intent classes is challenging since queries are short and ambiguous.

Click-through data, session data, and search result data are widely used for the query classification tasks?

Generally, hand-crafted training data and hand-crafted intent inventory

---

Image taken from D.E. Rose and D. Levinson. Understanding User Goals in Web Search. WWW '04, 2004
Intent discovery

► Another viewpoint of intent, not dependent on pre-defined intent categories

► Users with similar information needs click the same group of URLs, even though queries issued may vary
  - Query or URL clusters express highly similar information needs or intent.
  - Click-through bipartite graph often used in query clustering studies
  - A large fraction of queries follow some templates in most examined domains
    - Intent detection ~ a problem of template (or structure) detection among queries
    - Queries that fall into the same or synonymous templates are regarded as having the same intent
  - Alternatively, detect different intents of an ambiguous query through query refinements queries or the clicked URLs

► Intent is often assumed to be static
  - but see examples to come

► Intent is often assumed to be binary (yes or no) for a small number of intents
  - but see challenge to come
Shifting intents

▶ Radinsky et al. (2013)
  - When users' information needs change over time, ranking of results should also change to accommodate these needs

▶ Query “easter” at different times during year
  - Few weeks prior: *When?*
  - Few days prior: *What to do?*
  - During: *Meaning of easter*
Learning to detect intent shifts (Lefortier et al., 2014)

- Queries whose intent shifts from non-fresh to fresh
- Aggregated search approach to freshness
  - A “fresh” vertical
  - Fresh intent detector (MSE $\sim 0.025$)

- Intents may shift from non-fresh to fresh
  - $\sim 7\%$ of queries display a shift
  - Fresh intent detector needs time to catch up
  - On average 7.9h on a sample

- Can we do better?
  - Without throwing the fresh intent detector away
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- Can we do better?
  - Without throwing the fresh intent detector away
- Online exploration for quick adaptation
- Multi-armed bandits
  - Consider SERP as an action and consider only actions that integrate fresh results on SERP differently
  - Each action corresponds to deciding how many fresh results to integrate on SERP and where
- ExploreOnTop
  - Integrate one fresh result at the top of the SERP at the first position and gather user feedback and then re-estimate freshness
  - Reduce time delay by 57%, positive impact on 74% of SERPs, on average just 11 impressions of each selected query needed
Blender

Down (ranker parameterization)

▶ Ranker type selection
  - web, fresh, news, image, video, entity, apps

▶ Ranker parameter selection
  - production
  - for interleaving
  - for A/B testing

▶ Direct answers
  - Maps, facts, weather, qa...
Blender

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Up (SERP generation)

▶ Merging results
  - Interleaving
    - Diversity

▶ UX selection
  - For A/B testing
  - Production
  - KB panel (entity enrichment)

▶ Device tailoring
Diversity (Radlinski et al., 2009)

- **Extrinsic diversity**: diversity as uncertainty about the information need
  - Ambiguity: “jaguar”
  - Different aspects: “ebola”

- **Intrinsic diversity**: diversity as part of the information need
  - No single result that provides fully answers information need
  - User desires different views
  - User desires different options
  - Information need is to get an overview
  - Different results are needed from different sources to build confidence in correctness of answer
Diversity (Radlinski et al., 2009)

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Diversion (Bron et al., 2012, 2013)

▶ Study the search behavior of media studies scholars
Supports manual intrinsic diversity by offering a subjunctive interface through which researchers can compare alternative queries ("successor queries") around a topic of their interest ("initiator queries")?
Support for manual intrinsic diversity search?

Research questions may undergo changes during a research project:

- questions become more specific;
- additional questions are added;
- or a changed perspective in the research question?

Reasons for the changes in research questions: researchers learn about the availability of material, discover trends in the material or gain alternative views on a topic.
Vertical rankers

**Ranker**

- **hotfixes**
  - personalized
- **compute query document features**
  - geo spatial
  - bm25
  - ...
- **apply ranking model to**
  - query features
  - document features
  - query document features
So many criteria

- Aboutness
- Potential impact on reputation
- Importance
- Timeliness
- Quality
- Bias
- Fit with task/background
- Freshness
- Interestingness
- ...
Ranker development

- Traditionally, manual labor
- Think about what it means for a document to match a query
- Combination of term frequency, document frequency, document length E.g.,

\[
BM25(q, d) = \sum_{q_i \in q} \frac{idf(q_i) \cdot tf(q_i, d) \cdot (k_1 + 1)}{tf(q_i, d) + k_1 \cdot (1 - b + b \cdot \frac{dl}{avdl})} \cdot \frac{(k_3 + 1) \cdot qf(q_i, q)}{k_3 + qf(q_i, q)}
\]
So many rankers . . .

- **Content-based**
  - Boolean model, extended Boolean model, . . .
  - Vector space model, latent semantic indexing, . . .
  - BM25 model, statistical language model, . . .
  - Span-based model, distance-aggregation model, . . .

- **Structure-based**
  - Document structure
  - Site structure
  - Link structure

- **Based on interaction behavior**
  - Number of visits, . . .
  - Clicks, . . .
So many rankers . . .

▶ Content-based
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▶ Structure-based
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▶ ⇒ Documents represented by feature vectors
  - Features extracted for every query-document pair (e.g., score output by a traditional retrieval model)
  - Combine a large number of features
  - Incorporate new retrieval model by including the model’s output
• Least square retrieval function (TOIS 1989)
• Query refinement (WWW 2008)
• ListNet (ICML 2007)
• SVM-MAP (SIGIR 2007)
• Nested Ranker (SIGIR 2006)
• Pranking (NIPS 2002)
• LambdaRank (NIPS 2006)
• MPRank (ICML 2007)
• Frank (SIGIR 2007)
• MHR (SIGIR 2007)
• RankBoost (JMLR 2003)
• Learning to retrieval info (SCC 1995)
• LDM (SIGIR 2005)
• Large margin ranker (NIPS 2002)
• RankNet (ICML 2005)
• Ranking SVM (ICANN 1999)
• IRSVM (SIGIR 2006)
• Discriminative model for IR (SIGIR 2004)
• SVM Structure (JMLR 2005)
• OAP-BPM (ICML 2003)
• Subset Ranking (COLT 2006)
• GPRank (LR4IR 2007)
• QBRank (NIPS 2007)
• GBRank (SIGIR 2007)
• Constraint Ordinal Regression (ICML 2005)
• McRank (NIPS 2007)
• SoftRank (LR4IR 2007)
• AdaRank (SIGIR 2007)
• CCA (SIGIR 2007)
• ListMLE (ICML 2008)
• RankCosine (IPM 2007)
• Supervised Rank Aggregation (WWW 2007)
• Relational ranking (WWW 2008)
• Learning to order things (NIPS 1998)
• Round robin ranking (ECML 2003)
• …
<table>
<thead>
<tr>
<th>Category</th>
<th>Algorithms</th>
</tr>
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</table>
| **Pointwise approach** | **Regression-based**: Least square retrieval (TOIS 1989), Regression tree for ordinal class prediction (FI 2000), …
|                     | **Classification**: Discriminative model for IR (SIGIR 2004), …
|                     | **Ordinal regression**: Pranking (NIPS 2002), OAP-BPM (ECML 2003), Ranking with large margin principles (NIPS 2002), … |
| **Listwise approach** | **Non-measure specific**: ListNet (ICML 2007), ListMLE (ICML 2008), BoltzRank (ICML 2009), …
|                     | **Measure-specific**: AdaRank (SIGIR 2007), SVM-MAP (SIGIR 2007), SoftRank (LR4IR 2007), RankGP (LR4IR), … |
Ranker development

► Traditionally

- Train and tune offline, then deploy online
- Supervised learning paradigm
Ranker development

▶ Traditionally
- Train and tune offline, then deploy online
- Supervised learning paradigm

▶ Move away from supervised paradigm
- Weakly supervised rankers?
- A search engine that improves by being used, not in a supervised manner but in a weakly supervised way?
- Learn from the natural interactions with users
  - To evaluate rankers
  - To combine rankers
  - To create individual rankers
- Why is this a good idea
See Katja Hofmann’s lecture on Thursday
Top-k retrieval

Skipped.
Outline

1 Introduction

2 Front door

3 Offline

4 Online

5 Evaluation

6 Wrap-up
Evaluation framework
Evaluation framework ⇒ Experimental Framework

Metrics

Flighting

Learning

Logging

Annotations
Three families of evaluation method

▶ In the literature and in practice
  • Offline evaluation
  • User-study evaluation
  • Online evaluation

▶ Each method has advantages and disadvantages
Offline evaluation in 3 words

Collect a set of queries

For each query, describe the information being sought

Have assessors determine which documents are relevant

Evaluate systems based on the quality of their rankings

▶ Evaluation metric: describes quality of ranking with known relevant/non-relevant docs

Offline evaluation in 3 bullets

▶ Advantages

- the experimental condition is fixed; same queries, and same relevance judgements
- evaluations are reproducible; keeps us “honest”
- by experimenting on the same set of queries and judgements, we can better understand how system one system is better than another

Go and attend Stefano, Enrique, Julio and Evangelos’s lectures!
Offline evaluation in 3 bullets

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- by experimenting on the same set of queries and judgements, we can better understand how system one system is better than another

► Disadvantages

- Human assessors that judge documents relevant/non-relevant are expensive
- Human assessors are not the user; judgements are made ?out of context?
- Assumes that relevance is the same for every user

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User studies in 3 bullets

Provide a small set of users with several retrieval systems

Ask them to complete several (potentially different) search tasks

Learn about system performance by
  ▶ Observing what they do
  ▶ Asking why they did it
User studies in 3 bullets

▶ Advantages

• Very detailed data about users? reaction to systems
• In reality, a search is done to accomplish a higher-level task
• In user studies, this task can be manipulated and studied
• In other words, the experimental ?starting-point? need not be the query
User studies in 3 bullets

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• In other words, the experimental “starting-point” need not be the query

▶ Disadvantages

• User studies are expensive (pay users/subjects, scientist’s time, data coding)
• Difficult to generalize from small studies to broad populations
• The laboratory setting is not the user’s normal environment
• Need to re-run experiment every time a new system is considered

Go and attend Diane Kelly’s lecture!
Online evaluation in 3 words

See how normal users interact with your live retrieval system when just using it

Observe implicit behavior
  ▶ Clicks, skips, saves, forwards, bookmarks, “likes”, etc.

Try to infer differences in behavior from different flavors of the live system
  ▶ A/B testing
    • Have x% of query traffic use system A and y% of query traffic use system B
  ▶ Interleaving
    • Expose a combination of system versions to users
Online evaluation in 3 words

▶ Advantages

- System usage is naturalistic; users are situated in their natural context and often don’t know that a test is being conducted
- Evaluation can include lots of users

▶ Disadvantages

- Requires a service with lots of users (enough of them to potential hurt performance for some)
- This is often referred to as the “cold-start problem” requires a good understanding on how different implicit feedback signals predict positive and negative user experiences
- Experiments are difficult to repeat

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Online evaluation in 3 words

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Go and attend Katja Hofmann’s lecture!
Relative / SERP level

- A/B testing
- Interleaving
A/B testing

- Concept is trivial
  - Randomly split traffic between two (or more) versions
    - A (Control)
    - B (Treatment)
  - Collect metrics of interest
  - Analyze

- Must run statistical tests to confirm differences are not due to chance

- Best scientific way to prove causality, i.e., the changes in metrics are caused by changes introduced in the treatment(s)

Kohavi et al, 2009
Advantage of A/B testing

- When the variants run concurrently, only two things could explain a change in metrics:
  1. The “feature(s)” (A vs. B)
  2. Random chance
- Everything else happening affects both the variants
- For #2, conduct statistical tests for significance (“Student’s t-test”)
- A/B experiments are not the panacea for everything
  - Issues discussed in survey paper by Kohavi et al., 2009
Example

- (Kohavi et al., 2013)
- Clickthrough rate for search box and popular searches

Which one wins?

Kohavi et al, 2013
Beware

- Perform many sanity checks
- If something is “amazing,” find the flaw!
  - Examples
    - If you have a mandatory birth date field and people think it’s unnecessary, you’ll find lots of 11/11/11 or 01/01/01
    - If you have an optional drop down, do not default to the first alphabetical entry, or you’ll have lots of: jobs = Astronaut
    - For most web sites, traffic will spike between 1-2AM November 3, 2013, relative to the same hour a week prior. Why?

- Run an A/A test

- ...
Interleaving

Task
Combine hundreds of ranking features to get the best ranking for each search task / user

Approach

Today
Offline – use manual annotations for manual tuning or supervised learning,
problems: resources, fidelity, scale

Tomorrow?
Online – learn directly from natural user interactions with the search system
Learning from natural user interactions with an IR system (e.g., clicks on search results)

- Easy to collect while system operates
- Reflect natural user behavior and preferences
- Enable online learning

- Noisy
- Provide only relative preference indications

How can IR systems learn reliably and efficiently from noisy, relative feedback?
Approach – Overview

**Reinforcement Learning Approach**

- Learn by trying out actions (document lists), and observing feedback
- Follow a listwise learning approach (compare two ranking functions per round)
- Assume independent queries (contextual bandit problem)
Approach – Overview

Reinforcement Learning Approach

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1. Observe query
2. Generate result list
3. Infer feedback from clicks
4. Update retrieval function
Approach – Overview

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- How to reliably infer feedback?
- How to learn efficiently online?
Interleaved comparisons method — online evaluation

- **Goal:** Compare two result lists using click data
- **Procedure:**
  1. Generate interleaved result list (randomize per pair of ranks)
  2. Observe user clicks
  3. Credit clicks to original rankers to infer outcome

\[ o \in \{-1, 0, +1\} \]

Baseline: Team draft

- **Goal**: Compare two result lists using click data
- **Procedure**:
  1. Generate interleaved result list (randomize per pair of ranks)
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Baseline: Team draft

- **Goal:** Compare two result lists using click data
  - **Procedure:**
    1. Generate interleaved result list (randomize per pair of ranks)
    2. Observe user clicks
    3. Credit clicks to original rankers to infer outcome $o \in \{-1, 0, +1\}$

Key idea: Keep track of assignments (which list contributed which document)

Baseline: Team draft

- **Goal:** Compare two result lists using click data
- **Procedure:**
  1. Generate interleaved result list (randomize per pair of ranks)
  2. **Observe user clicks**
  3. Credit clicks to original rankers to infer outcome

\[ o \in \{-1, 0, +1\} \]

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Interleaving pros & cons

▶ Benefits

- A direct way to elicit user preferences
- More sensitive than many other online metrics
- Deals with issues of position bias and calibration
- Reusability recently addressed and partially solved

▶ Drawbacks

- Benchmark: No absolute number for benchmarking
- Interpretation: Unable to interpret much at the document-level, or about user behavior
Outline

1. Introduction
2. Front door
3. Offline
4. Online
5. Evaluation
6. Wrap-up
Wrap-up
The bigger picture
Responsible information retrieval

As user data becomes more and more important . . .

▶ Privacy
▶ Fairness
Responsible information retrieval

As user data becomes more and more important . . .

▶ Privacy
▶ Fairness

transgenders are

transgenders are **mentally ill**
transgenders are **sick**
transgenders are **annoying**
transgenders are **freaks**

Druk op Enter om te zoeken
Responsible information retrieval

As user data becomes more and more important …

► Privacy
► Fairness

► Accuracy
  • More dominant groups have bigger counts, more accurate estimates
Responsible information retrieval

As user data becomes more and more important . . .

▶ Privacy
▶ Fairness

▶ Accuracy
  ● More dominant groups have bigger counts, more accurate estimates

▶ Transparancy
  ● Let the system explain why it is showing certain results
Stuff you should work on

- Large-scale understanding of users and user behavior
- Higher level models of any aspect of search
- Online anything
- Responsible IR
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Resources

Text books

▶ M. Hearst. *Search User Interfaces*, CUP, 2009

Evaluation campaigns

Papers cited

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