Introduction to Information Retrieval

http://informationretrieval.org

IIR 8: Evaluation & Result Summaries

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Overview

1 Recap
2 Unranked evaluation
3 Ranked evaluation
4 Evaluation benchmarks
5 Result summaries
Outline

1 Recap

2 Unranked evaluation

3 Ranked evaluation

4 Evaluation benchmarks

5 Result summaries
Looking vs. Clicking

- Users view results one and two more often / thoroughly
- Users click most frequently on result one
Pivot normalization

Relevance vs Retrieval with cosine normalization

source: Lillian Lee
Now we also need term frequencies in the index.

- **Brutus** → 1,2 7,3 83,1 87,2 ...
- **Caesar** → 1,1 5,1 13,1 17,1 ...
- **Calpurnia** → 7,1 8,2 40,1 97,3
Use heap for selecting the top $k$ in ranking

- A heap efficiently implements a priority queue.
- Takes $O(N)$ operations to construct (where $N$ is the number of documents) . . .
- . . . then each of $k$ winners can be read off in $O(k \log k)$ steps.
- Allows to rank in time linear in $N$ (for small $k$ and large $N$) – as opposed to $O(N \log N)$.
Binary max heap
Outline

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Measures for a search engine

- How fast does it index
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  - Number of documents/bytes per hour
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- How fast does it search
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- How fast does it search
  - Latency as a function of index size / queries per second
- What is the cost per query?
  - Given certain requirements, e.g., a 20-billion-page index
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- How can we quantify user happiness?
Who is the user?

- Who is the user we are trying to make happy?
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  - Enterprise: CEO. Employees are more productive because they find right away what they are looking for. **Measure:** profit of the company
Most common definition of user happiness: Relevance

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- But has been very successful in IR.
Relevance: query vs. information need

- Relevance to *what?*
Relevance: query vs. information need

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- Take 1: relevance to the query
Relevance: query vs. information need

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- **Query** $q$: WINE AND RED AND WHITE AND HEART AND ATTACK
- Consider document $d'$: *He then launched into the heart of his speech and attacked the wine industry lobby for downplaying the role of red and white wine in drunk driving.*
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- $d'$ is relevant to the query $q$ ...
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Relevance: query vs. information need

- $d'$ is relevant to the query $q$ . . .
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- User happiness can only be measured by relevance to an information need, not by relevance to queries.
Relevance: query vs. information need

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- User happiness can only be measured by relevance to an information need, not by relevance to queries.
- Our terminology is sloppy in these slides and in IIR: we talk about query-document relevance judgments even though we mean information-need-document relevance judgments.
Precision and recall

- Precision \((P)\) is the fraction of retrieved documents that are relevant

\[
\text{Precision} = \frac{\#(\text{relevant items retrieved})}{\#(\text{retrieved items})} = P(\text{relevant|retrieved})
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## Precision and recall

<table>
<thead>
<tr>
<th></th>
<th>Relevant</th>
<th>Nonrelevant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Retrieved</td>
<td>true positives (TP)</td>
<td>false positives (FP)</td>
</tr>
<tr>
<td>Not retrieved</td>
<td>false negatives (FN)</td>
<td>true negatives (TN)</td>
</tr>
</tbody>
</table>

\[
P = \frac{TP}{TP + FP}\]

\[
R = \frac{TP}{TP + FN}\]
Why do we use complex measures like precision and recall?
Accuracy

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- Why not something simple like accuracy?
Recap
Unranked evaluation
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Evaluation benchmarks
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Accuracy

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- Accuracy is the fraction of decisions (relevant/nonrelevant) that are correct.
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- Accuracy is the fraction of decisions (relevant/nonrelevant) that are correct.
- In terms of the contingency table above, accuracy = \( \frac{TP + TN}{TP + FP + FN + TN} \).
Why do we use complex measures like precision and recall?
Why not something simple like accuracy?
Accuracy is the fraction of decisions (relevant/nonrelevant) that are correct.
In terms of the contingency table above, accuracy = \( \frac{TP + TN}{TP + FP + FN + TN} \).
Why is accuracy not a useful measure for web information retrieval?
Why not just use accuracy?
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Search for:  

0 matching results found.

• Simple trick to maximize accuracy in IR: always say no and return nothing
Why not just use accuracy?

0 matching results found.

- Simple trick to maximize accuracy in IR: always say no and return nothing
- You then get 99.99% accuracy on most queries.
Why not just use accuracy?

- Simple trick to maximize accuracy in IR: always say no and return nothing.
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- Searchers on the web (and in IR in general) want to find something and have a certain tolerance for junk.
Simple trick to maximize accuracy in IR: always say no and return nothing.
You then get 99.99% accuracy on most queries.
Searchers on the web (and in IR in general) want to find something and have a certain tolerance for junk.
Accuracy is not a good measure of user happiness, we’ll use precision and recall instead.
Difficulties in using precision/recall

- We should always average over a large set of queries.
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We need relevance judgments for information-need-document pairs – but they are expensive to produce.
Difficulties in using precision/recall

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  - There is no such thing as a “typical” or “representative” query.
- We need relevance judgments for information-need-document pairs – but they are expensive to produce.
- For alternatives to using precision/recall and having to produce relevance judgments – see end of this lecture.
Precision/recall tradeoff

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- You can increase recall by returning more docs.
- Recall is a non-decreasing function of the number of docs retrieved.
- A system that returns all docs has 100% recall!
- The converse is also true (usually): It’s easy to get high precision for very low recall.
- Suppose the document with the largest score is relevant. How can we maximize precision?
A combined measure: $F$

- $F$ allows us to trade off precision against recall.
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- $F$ allows us to trade off precision against recall.

\[ F = \frac{1}{\alpha \frac{1}{P} + (1 - \alpha) \frac{1}{R}} = \frac{(\beta^2 + 1)PR}{\beta^2 P + R} \]

where \[ \beta^2 = \frac{1 - \alpha}{\alpha} \]
A combined measure: $F$

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- $\alpha \in [0, 1]$ and thus $\beta^2 \in [0, \infty]$
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- Most frequently used: balanced $F$ with $\beta = 1$ or $\alpha = 0.5$
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- $\alpha \in [0, 1]$ and thus $\beta^2 \in [0, \infty]$  
- Most frequently used: balanced $F$ with $\beta = 1$ or $\alpha = 0.5$
  - This is the harmonic mean of $P$ and $R$: $\frac{1}{\hat{F}} = \frac{1}{2} (\frac{1}{P} + \frac{1}{R})$
A combined measure: $F$

- $F$ allows us to trade off precision against recall.

$$F = \frac{1}{\alpha \frac{1}{P} + (1 - \alpha) \frac{1}{R}} = \frac{(\beta^2 + 1)PR}{\beta^2 P + R}$$

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- Most frequently used: balanced $F$ with $\beta = 1$ or $\alpha = 0.5$
  - This is the harmonic mean of $P$ and $R$:  
    $$\frac{1}{F} = \frac{1}{2} \left( \frac{1}{P} + \frac{1}{R} \right)$$
- What value range of $\beta$ do I choose for weighting recall higher than precision?
### F: Example

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<thead>
<tr>
<th></th>
<th>relevant</th>
<th>not relevant</th>
</tr>
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<tbody>
<tr>
<td>retrieved</td>
<td>18</td>
<td>2</td>
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<tr>
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$F_1$?
$F_1$ and other averages
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We can view the harmonic mean as a kind of soft minimum.
F: Why harmonic mean?

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- Taking the minimum achieves this.
- But minimum is not smooth and hard to weight.
- $F$ (harmonic mean) is a kind of smooth minimum.
Precision-recall curve

- Precision/recall/F are measures for unranked sets.
Precision-recall curve

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- We can easily turn set measures into measures of ranked lists.
Precision-recall curve

- Precision/recall/F are measures for **unranked sets**.
- We can easily turn set measures into measures of **ranked lists**.
- Just compute the set measure for each “prefix”: the top 1, top 2, top 3, top 4 etc results.
Precision/recall/F are measures for unranked sets.

We can easily turn set measures into measures of ranked lists.

Just compute the set measure for each “prefix”: the top 1, top 2, top 3, top 4 etc results

Doing this for precision and recall gives you a precision-recall curve.
A precision-recall curve
A precision-recall curve

- Each point corresponds to a result for the top $k$ ranked hits ($k = 1, 2, 3, 4, \ldots$).
A precision-recall curve

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- **Interpolation (in red):** Take maximum of all future points
A precision-recall curve

- Each point corresponds to a result for the top $k$ ranked hits ($k = 1, 2, 3, 4, \ldots$).
- Interpolation (in red): Take maximum of all future points.
- Rationale for interpolation: The user is willing to look at more stuff if both precision and recall get better.
## 11-point interpolated average precision

<table>
<thead>
<tr>
<th>Recall</th>
<th>Interpolated Precision</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0</td>
<td>1.00</td>
</tr>
<tr>
<td>0.1</td>
<td>0.67</td>
</tr>
<tr>
<td>0.2</td>
<td>0.63</td>
</tr>
<tr>
<td>0.3</td>
<td>0.55</td>
</tr>
<tr>
<td>0.4</td>
<td>0.45</td>
</tr>
<tr>
<td>0.5</td>
<td>0.41</td>
</tr>
<tr>
<td>0.6</td>
<td>0.36</td>
</tr>
<tr>
<td>0.7</td>
<td>0.29</td>
</tr>
<tr>
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</tr>
<tr>
<td>0.9</td>
<td>0.10</td>
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11-point average: \( \approx 0.425 \)
11-point interpolated average precision

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11-point average: \( \approx 0.425 \)

How can precision at 0.0 be \( > 0 \)?
Averaged 11-point precision/recall graph
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- Compute interpolated precision at recall levels 0.0, 0.1, 0.2, ...
Averaged 11-point precision/recall graph

- Compute interpolated precision at recall levels 0.0, 0.1, 0.2, …
- Do this for each of the queries in the evaluation benchmark
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- Compute interpolated precision at recall levels 0.0, 0.1, 0.2, …
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- Average over queries
Averaged 11-point precision/recall graph

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- This measure measures performance at all recall levels.
Compute interpolated precision at recall levels 0.0, 0.1, 0.2, …
Do this for each of the queries in the evaluation benchmark
Average over queries
This measure measures performance at all recall levels.
The curve is typical of performance levels at TREC.
ROC curve
ROC curve

- Similar to precision-recall graph
ROC curve

- Similar to precision-recall graph
- But we are only interested in the small area in the lower left corner.
Similar to precision-recall graph
- But we are only interested in the small area in the lower left corner.
- Precision-recall graph “blows up” this area.
Variance of measures like precision/recall

- For a test collection, it is usual that a system does crummily on some information needs (e.g., $P = 0.2$ at $R = 0.1$) and excellently on others (e.g., $P = 0.95$ at $R = 0.1$).
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- Indeed, it is usually the case that the variance of the same system across queries is much greater than the variance of different systems on the same query.
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- Indeed, it is usually the case that the variance of the same system across queries is much greater than the variance of different systems on the same query.
- That is, there are easy information needs and hard ones.
What we need for a benchmark

- A collection of documents
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A collection of documents
- Documents must be representative of the documents we expect to see in reality.
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    - Kappa measure in a few slides
Standard relevance benchmark: Cranfield

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- Late 1950s, UK
- 1398 abstracts of aerodynamics journal articles, a set of 225 queries, exhaustive relevance judgments of all query-document-pairs
- Too small, too untypical for serious IR evaluation today
Standard relevance benchmark: TREC

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- Rather, NIST assessors’ relevance judgments are available only for the documents that were among the top \( k \) returned for some system which was entered in the TREC evaluation for which the information need was developed.
Standard relevance benchmarks: Others

- GOV2
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  - 25 million web pages
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  - But still 3 orders of magnitude smaller than what Google/Yahoo/MSN index
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\[
\kappa = \frac{P(A) - P(E)}{1 - P(E)}
\]
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$$\kappa = \frac{P(A) - P(E)}{1 - P(E)}$$

- $\kappa =$? for (i) chance agreement (ii) total agreement
Kappa measure (2)

- Values of $\kappa$ in the interval $[2/3, 1.0]$ are seen as acceptable.
Kappa measure (2)

- Values of $\kappa$ in the interval $[2/3, 1.0]$ are seen as acceptable.
- With smaller values: need to redesign relevance assessment methodology used etc.
Calculating the kappa statistic

<table>
<thead>
<tr>
<th>Judge 1</th>
<th>Yes</th>
<th>No</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes</td>
<td>300</td>
<td>20</td>
<td>320</td>
</tr>
<tr>
<td>No</td>
<td>10</td>
<td>70</td>
<td>80</td>
</tr>
<tr>
<td>Total</td>
<td>310</td>
<td>90</td>
<td>400</td>
</tr>
</tbody>
</table>

Observed proportion of the times the judges agreed

\[ P(A) = (300 + 70)/400 = 370/400 = 0.925 \]

Pooled marginals

\[ P(\text{nonrelevant}) = (80 + 90)/(400 + 400) = 170/800 = 0.2125 \]
\[ P(\text{relevant}) = (320 + 310)/(400 + 400) = 630/800 = 0.7878 \]

Probability that the two judges agreed by chance

\[ P(E) = P(\text{nonrelevant})^2 + P(\text{relevant})^2 = 0.2125^2 + 0.7878^2 = 0.665 \]

Kappa statistic

\[ \kappa = (P(A) - P(E))/(1 - P(E)) = (0.925 - 0.665)/(1 - 0.665) = 0.776 \]
Calculating the kappa statistic

<table>
<thead>
<tr>
<th>Judge 2 Relevance</th>
<th>Yes</th>
<th>No</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
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\[ \kappa = \frac{P(A) - P(E)}{1 - P(E)} = \frac{0.925 - 0.665}{1 - 0.665} = 0.776 \]
(still in acceptable range)
### Interjudge agreement at TREC

<table>
<thead>
<tr>
<th>information need</th>
<th>number of docs judged</th>
<th>disagreements</th>
<th>NR</th>
<th>R</th>
</tr>
</thead>
<tbody>
<tr>
<td>51</td>
<td>211</td>
<td>6</td>
<td>4</td>
<td>2</td>
</tr>
<tr>
<td>62</td>
<td>400</td>
<td>157</td>
<td>149</td>
<td>8</td>
</tr>
<tr>
<td>67</td>
<td>400</td>
<td>68</td>
<td>37</td>
<td>31</td>
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<td>95</td>
<td>400</td>
<td>110</td>
<td>108</td>
<td>2</td>
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<tr>
<td>127</td>
<td>400</td>
<td>106</td>
<td>12</td>
<td>94</td>
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Impact of interjudge disagreement

- Judges disagree a lot. Does that mean that the results of information retrieval experiments are meaningless?
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- No.
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- Supposes we want to know if algorithm A is better than algorithm B
- An information retrieval experiment will give us a reliable answer to this question.
We’ve defined relevance for an isolated query-document pair.
Critique of pure relevance

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- Alternative definition: marginal relevance
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- Why?
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Evaluation at large search engines

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- Search engines often use precision at top $k$, e.g., $k = 10$ . . .
- . . . or measures that reward you more for getting rank 1 right than for getting rank 10 right.
- Search engines also use non-relevance-based measures.
  - Example 1: clickthrough on first result
  - Not very reliable if you look at a single clickthrough (you may realize after clicking that the summary was misleading and the document is nonrelevant) . . .
  - . . . but pretty reliable in the aggregate.
  - Example 2: Ongoing studies of user behavior in the lab – recall last lecture
  - Example 3: A/B testing
A/B testing

- Purpose: Test a single innovation
A/B testing

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A/B testing

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- **Probably** the evaluation methodology that large search engines trust most
- **Variant:** Give users the option to switch to new algorithm/interface
How do we present results to the user?

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- How should each document in the list be described?
- This description is crucial.
- User can identify good hits (= relevant hits) based on description.
- No need to “click” on all documents sequentially
Doc description in result list

- Most commonly: doc title, url, some metadata ...
Doc description in result list

- Most commonly: doc title, url, some metadata . . .
- . . . and a summary
Doc description in result list

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- . . . and a summary
- How do we “compute” the summary?
Summaries

- Two basic kinds: (i) static (ii) dynamic
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- A static summary of a document is always the same, regardless of the query that hit the document.
- Dynamic summaries are query-dependent. They attempt to explain why the document was retrieved for the query at hand.
Static summaries

- In typical systems, the static summary is a subset of the document.
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Simplest heuristic: the first 50 or so words of the document.
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- Most sophisticated: complex NLP to synthesize/generate a summary
  - For most IR applications: not quite ready for prime time yet
Dynamic summaries

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- Prefer snippets in which query terms occurred as a phrase
- Prefer snippets in which query terms occurred jointly in a small window
- The summary that is computed this way gives the entire content of the window – all terms, not just the query terms.
Query: “new guinea economic development”

Snippets (in bold) that were extracted from a document: ... **In recent years, Papua New Guinea has faced severe economic difficulties and** economic growth has slowed, partly as a result of weak governance and civil war, and partly as a result of external factors such as the Bougainville civil war which led to the closure in 1989 of the Panguna mine (at that time the most important foreign exchange earner and contributor to Government finances), the Asian financial crisis, a decline in the prices of gold and copper, and a fall in the production of oil. **PNG’s economic development record over the past few years is evidence that** governance issues underly many of the country’s problems. Good governance, which may be defined as the transparent and accountable management of human, natural, economic and financial resources for the purposes of equitable and sustainable development, flows from proper public sector management, efficient fiscal and accounting mechanisms, and a willingness to make service delivery a priority in practice. ...
Google examples for dynamic summaries
Generating dynamic summaries

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- Don’t cache very long documents – just cache a short prefix
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Dynamic summaries

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- Ideally: the snippet should answer the query, so we don’t have to look at the document.
- Dynamic summaries are a big part of user happiness because
  - We can quickly scan them to find the relevant document we then click on.
  - In many cases, we don’t have to click at all and save time.
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- Google VP of Engineering on search quality evaluation at Google