Statistical Language Modeling for Information Access

Theory, day 1: Basics and practicalities

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Outline

1. **Introduction**
   Background
2. **A look ahead**
3. **Let's get to work**
   Basic language modeling
   Basic evaluation

Outline

Search

- Information avalanche
  - Internet
  - Intelligence
  - Scientific research (astronomy, biomedicine, humanities, …)
  - Cultural heritage
  - Desktop, Email, …
  - Enterprise, Business Intelligence
  - User generated content
  - …
- Not just growing, but growing at a growing pace
  - 1999: 250 megabytes per person for each man, woman, and child on earth
  - 2002: almost 800 MB of recorded information is produced per person
  - `http://www.sims.berkeley.edu/research/projects/how-much-info-2003/`
  - Today?

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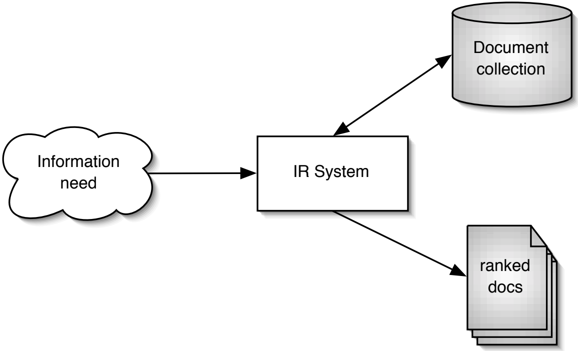
Thought Experiment

- Imagine that your are an information retrieval engine



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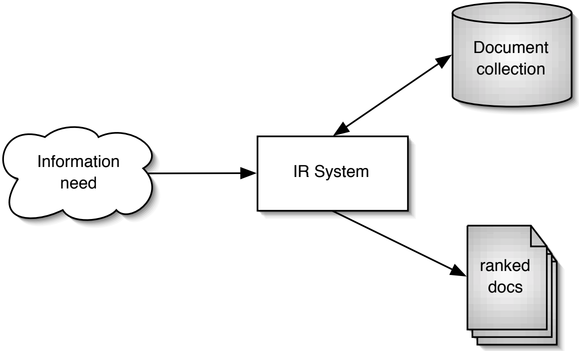

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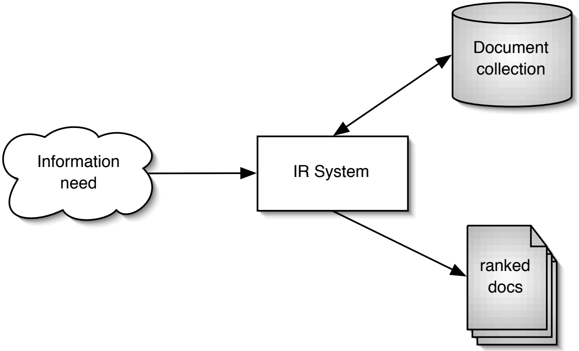

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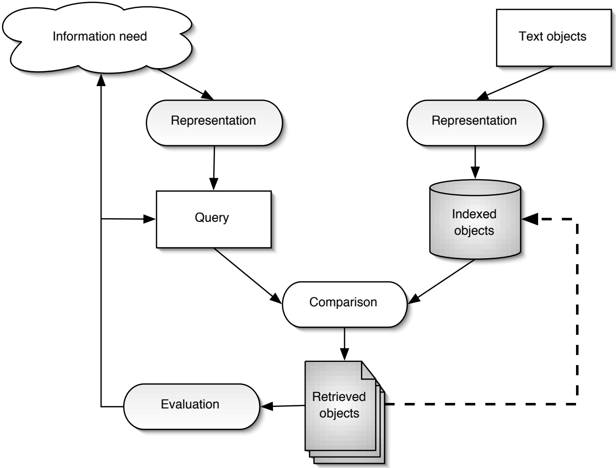

Basic Information Retrieval

- Given an information need, return suitable results
    - Document retrieval: Given a free text query, produce a list of documents ranked from most to least relevant
    - "Relevant" $\sim$ "about the same topic"
    - "About the same topic" $\sim$ "similarity"
- Basic idea at the heart of much work in IR
    - find words in docs
    - compare them to words in query
    - some words get a bigger weight than others
    - this approach is extremely effective!

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Basic Information Retrieval

- **Bag of words** representation of contents of documents
  - effective and popular approach, considers words without order or structure
  - look at all re-arrangments of newspaper headline
    - stocks fall on inflation fears
    - inflation stocks fall on fears
    - fall inflation stocks on fears
    - fall fears inflation stocks on
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  - what is the value/weight of a word?
  - how do we determine similarity?
  - can we get a formal/theoretical model for this?

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The Meaning of "Meaning"

- Meaning = use …
  - Observe language used in query
  - Observe language used in documents
  - Compare these observations
  - Count, count, count, …
- Other features used in query-document comparisons
  - Phrases
  - Link structure
  - Named entities (people, locations, times, organizations, products, …)
  - …
- Research into effectiveness, efficiency, and extending the ideas to new settings

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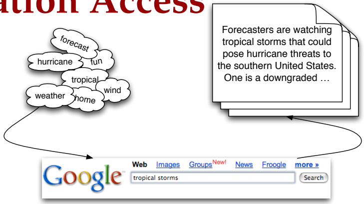

- Intuition
  - Users
    - Have a reasonable idea of terms that are likely to occur in documents of interest
    - Will choose query terms that distinguish these documents from others in the collection
- Language modeling approaches
  - Attempt to model query generation process
    - Different estimation methods, (in)dependence assumptions, …
  - Documents are ranked by probability that query would be observed as a random sample from the respective document model
    - Suitable variations for other retrieval tasks

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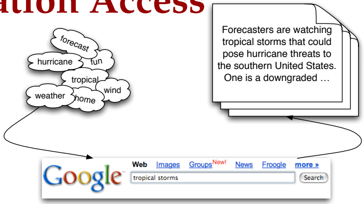

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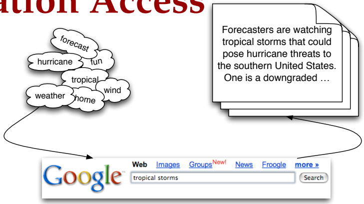

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IR Methodology

- But does it work?
- IR has a very heavy emphasis on experimental evaluation
  - Often comparative: given System A and System B, use a suitable test collection to score both, then analyze the differences (if any)
- Theory meets Experiment meets Practice
  - Real World Task™
    - → suitably abstracted into test collection
    - → devise, compare, improve models and algorithms
  - Test collection development often done as collaborative effort
  - Increasing awareness of need to supplement lab-based evaluations with user studies: it works, but do users become happier?

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Outline of the Course

Theory

- The course wiki
  - `http://www.science.uva.nl/~mdr/Teaching/Cordoba2011/`
  - SouthWestOfAmsterdam (case sensitive!)
- Day 1: general retrieval modeling and evaluation principles; introduction to language modeling
- Day 2: estimation, smoothing methods, mixture models, and applications to retrieving (semi)structured documents
- Day 3: incorporating symbolic knowledge, lexical relations and context within a language modeling setting
- Day 4: language modeling approaches to tasks at the interface of IR and IE; ongoing developments and prominent research questions

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Practical Component

- Aim: basic familiarity with Lemur
  - Language modeling toolkit developed at UMass
  - `http://lemurproject.org/tutorials/`
  - `http://ciir.cs.umass.edu/~strohman/indri`
- Higher aim: you should be able to run an information retrieval experiment using Lemur by the end of the week
  - Index, submit queries, generate results, evaluate the results, compare and analyse the outcomes, …

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Practical

- Day 1: Installing and Indexing
- Day 2: Retrieval and Evaluation
- Day 3: Retrieval Parameters
- Day 4: Pseudo Relevance Feedback; Additional bells, whistles and requests

Learning Goals

Things we want to get across

- Basic information retrieval, including evaluation methodology
- Basic language modeling for IR, applications of language modeling ideas to a broad range of information access tasks
- A sense of today's state of the art in language modeling in IR
- Hands-on experience with the Lemur, language modeling toolkit
- Familiarity with the basic "experimental loop" in IR

Who Are We?

- Maarten de Rijke
  - Worked in modal logic for 10 years, then switched to IR
  - Currently professor of "Information processing and Internet," leading an IR group of about 25 people (ILPS)
  - Main interests: intelligent information access, social media analysis, beyond relevance, beyond the ranked list, learning to rank
- Edgar Meij
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Some Elementary Material

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- Assume basic familiarity with statistics ("you can count")
- Bayes:
$$p(A|B) = \frac{p(B|A) \cdot p(A)}{p(B)}$$
- Maximum likelihood estimation: method used for fitting a mathematical model to some data; a way of tuning the free parameters of the model to provide a good fit
- Elementary notions about graphs
- Less than a tiny bit of XML, HTML
- Theory meets experiments meets application
- Search experience

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- Term frequency, (inverse) doc frequency, doc length normalization
- Term frequency (TF): frequency of word w in document d

$$tf_{w,d} = \frac{word\_count(w,d)}{word\_count(d)}$$

- Inverse document frequency (IDF):

$$\begin{aligned} df_w &= \text{number of docs in which } w \text{ appears} \\ idf_{w,d} &= \log\left(\frac{\text{number of docs}}{df_w}\right) \end{aligned}$$

- Weight of term w in doc d

$$weight_{w,d} = tf_{w,d} \cdot idf_{w,d}$$

- Baseline vector-based similarity

$$sim(q,d) = \frac{\sum_{w \text{ in } q} weight_{w,d} \cdot weight_{w,d}}{\sqrt{\sum_{w \text{ in } d} weight^2_{w,d}} \cdot \sqrt{\sum_{w \text{ in } q} weight^2_{w,q}}}$$

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Outline

Retrieval Based on Language Models

- Treat the generation of queries as a random process
- Approach
  - Infer a language model for each document.
  - Estimate the probability of generating the query according to each of these models.
  - Rank the documents according to these probabilities.
  - Usually a unigram estimate of words is used
- What's a language model? Probability distribution over strings
  - how likely is a given string (observation) in a given "language"
  - English: $p_1 > p_2 > p_3 > p_4$
    - $p_1 = P($"a quick brown fox"$)$
    - $p_2 = P($"fox a quick brown"$)$
    - $p_3 = P($"een snelle brown fox"$)$
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What's a Language Model?

- … depends on what "language" we are modeling
  - in much of IR $p_1 = p_2$
  - in some applications we may want p_3 to be high
- Notation
  - Convention: make explicit what we are modeling
    - M: "language" we are trying to model
    - s: observation (string of tokens from some vocabulary)
    - $P(s|M)$: probability of observing "s" in language M
  - What is M?
    - a "source" or "generator": a mechanism that spits out strings that are legal in the language
    - $P(s|M)$: probability of getting "s" during random sampling from M

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Language Modeling for IR

- Every document in a collection defines a "language"
  - consider all posssible sentences (strings) that author could have written down when creating some given document
  - some are perhaps more likely to occur than others
    - ... subject to topic, writing style, language, ...
  - $P(s|M_D)$: probability that author would write down string "s"
    - think of writing zillions of variations of a document and counting how many times we get "s"
- Suppose q is the user's query
  - what is the probability that author would write down "q"?
- Rank documents D in the collection by $P(q|M_D)$
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Other Apps: Same Idea

- Topic detection and tracking
  - query q can be topic description, or an on-topic story
  - documents with high $P(q|M_D)$ probably discuss the same topic
- Classification/filtering
  - query can be a set of training documents for a particular class
  - or testing docs can refelct observations from model of training set
- Cross-language retrieval
  - query can be in a different language from document collection
  - author could have written a document in a different language
- Multi-media retrieval
  - languages don't have to be textual (e.g., spoken or handwritten docs)
  - extends to images, sounds, video, preferences, hyerplinks, ...
- Expert finding
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  - languages don't have to be textual (e.g., spoken or handwritten docs)
  - extends to images, sounds, video, preferences, hyerplinks, …
- Expert finding
  - ?

Other Apps: Same Idea

- Topic detection and tracking
  - query q can be topic description, or an on-topic story
  - documents with high $P(q|M_D)$ probably discuss the same topic
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- Words are sampled independently from each other
  - metaphor: randomly pulling out words from an urn (with replacement)
  - joint probability decomposes into a product of marginals
  - estimation of probabilities: simple counting
- E.g., assume $M = \{R, B, R, B, Y, B, R, R, Y\}$ and q, the query, is $\{R, Y, R, B\}$
  - $P(q) = P(R) \cdot P(Y) \cdot P(R) \cdot P(B) = 4/9 \cdot 2/9 \cdot 4/9 \cdot 3/9$

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  - estimate a language model M_D for every document D in the collection
  - rank docs by the probability of "generating" the query

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- Drawbacks
  - no notion of relevance in the model: everything is random sampling
  - user feedback/query expansion not part of the model
    - examples of relevant documents cannot help us improve the language model M_D
    - the only option is augmenting the original query Q with extra terms
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- General problem
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  - maximum likelihood estimator and the zero frequency problem
  - discounting techniques
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Jelinek-Mercer Smoothing

- Correctly setting λ is very important
- Start simple
  - set λ to be a constant, independent of document, query
- Tune to optimize retrieval performance
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Things to Think About

- Text representation
  - What makes a "good" representation?
  - How is a representation generated from text?
  - What are retrievable objects and how are they organized?
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Outline

What's It All About … Relevance

- Relevance is difficult to define satisfactorily
- A relevant document is one judged useful in the context of a query
  - who judges? what is useful?
  - humans not very consistent
  - judgments depend on more than document and query
- With real collections, never know all relevant docs
- Assessing retrieval: boring and *very* time-consuming

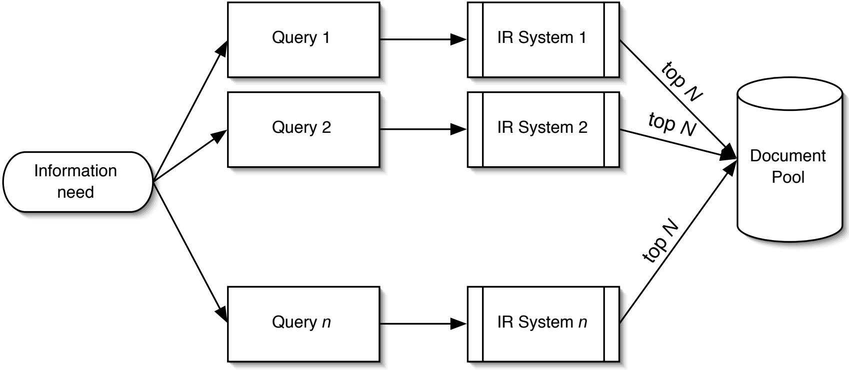
Test Collections

- Compare retrieval performance using a test collection
  - set of documents
  - set of queries
  - set of relevance judgments (which docs relevant to each query)
- To compare the performance of two techniques:
  - each technique used to evaluate test queries
  - results (set or ranked list) compared using performance measure
  - most common measures based on precision and recall
- Use multiple measures to get different views
  - test with multiple collections — performance is collection dependent

Finding Relevant Documents

- Question: did the system find **all** relevant material?
- To answer accurately, corpus needs complete judgments
  - i.e., "yes," "no," or some score for every query-document pair
- For small corpora, can review all docs for all queries
  - done for TDT collection of 60K docs as recently as 1998
- Not practical for large or medium-sized collections
  - TREC collections have millions of documents
- Other approaches that can be used
  - sampling, search-based, pooling

Finding Relevant Documents: Pooling



Precision and Recall

- Precision: fraction of retrieved documents that is relevant

$$precision = \frac{|relevant \cap retrieved|}{|retrieved|}$$

- Recall: fraction of the relevant documents that has been retrieved

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Precision and Recall

- P and R are well-defined for sets
- For ranked retrieval...
  - compute a P/R point for each relevant document
  - compute a value at fixed recall points (e.g., precision at 20% recall)
  - compute value at fixed rank cutoffs (e.g., precision at rank 20)
  - ...

Precision and Recall Example

Five relevant documents: 

- Ranking #1:

Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
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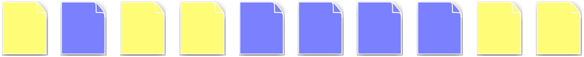

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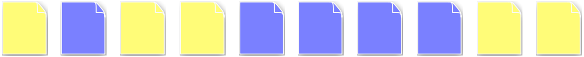

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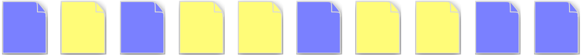

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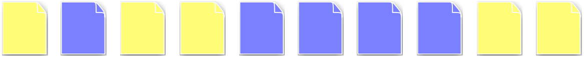

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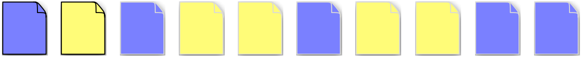

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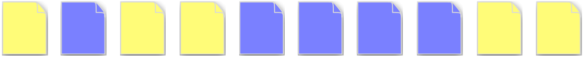

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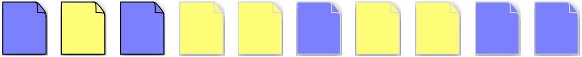

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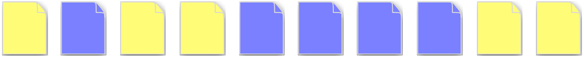
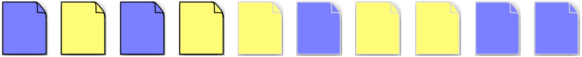


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

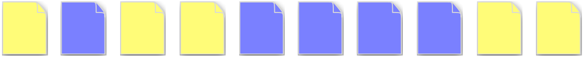
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

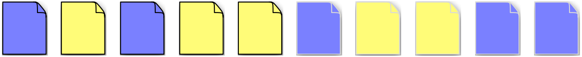


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

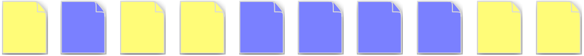
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

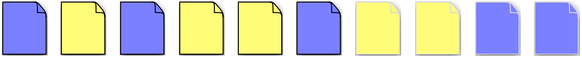


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

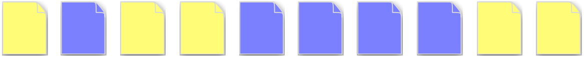
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

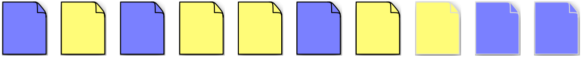


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

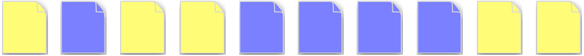
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

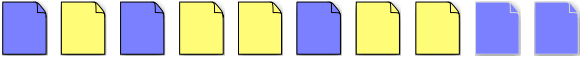


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

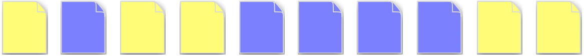
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

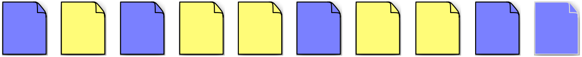


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

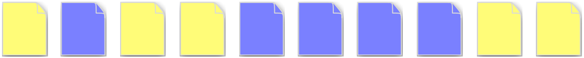
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	1.0
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

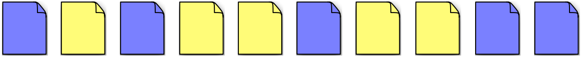


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

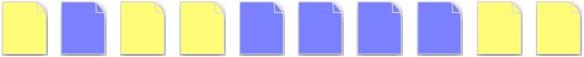
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

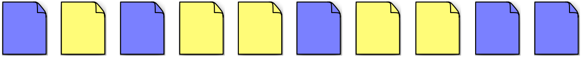


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

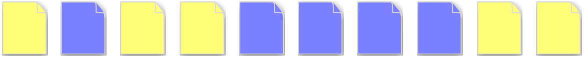
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

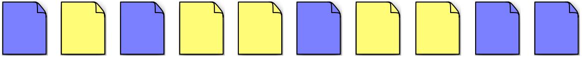


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

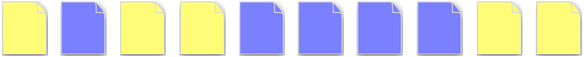
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:



Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

Five relevant documents:

- Ranking #1:

Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

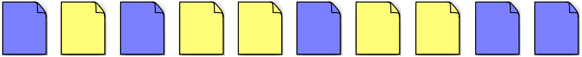
- Ranking #2:

Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

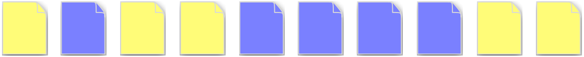
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

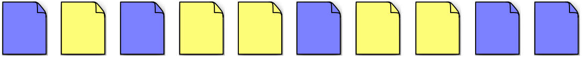


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

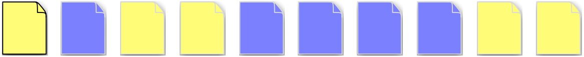
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

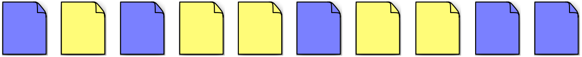


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

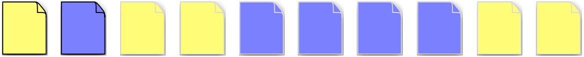
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

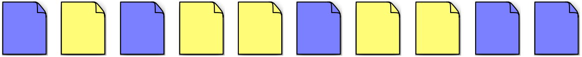


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

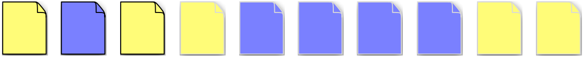
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

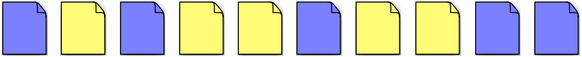


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

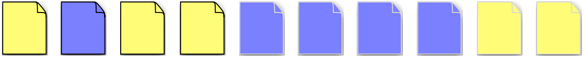
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

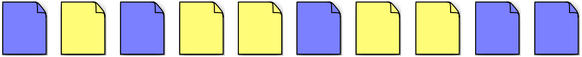


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

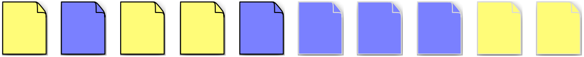
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

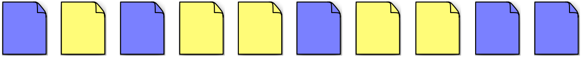


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

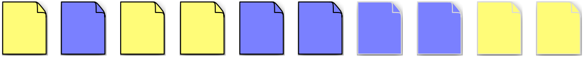
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

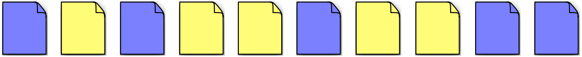


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

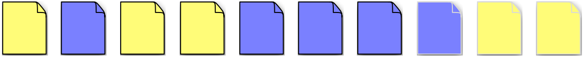
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

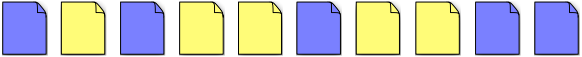


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	1.0	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

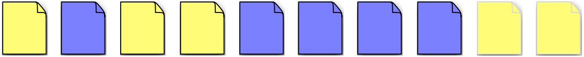
Five relevant documents: 

- Ranking #1:



Recall	**0.2**	0.2	**0.4**	0.4	0.4	**0.6**	0.6	0.6	**0.8**	**1.0**
Precision	1.0	0.5	0.67	0.5	0.4	0.5	0.43	0.38	0.44	0.5

- Ranking #2:

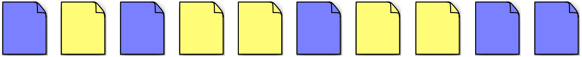


Recall	0.0	**0.2**	0.2	0.2	**0.4**	**0.6**	**0.8**	**1.0**	1.0	1.0
Precision	0.0	0.5	0.33	0.25	0.4	0.5	0.57	0.63	0.55	0.5

Precision and Recall Example

Five relevant documents: 

- Ranking #1:



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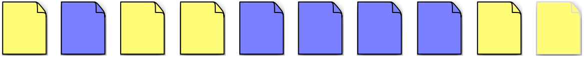
- Ranking #2:



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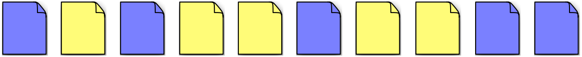

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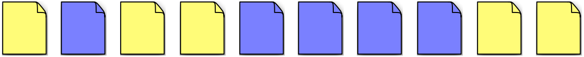

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Averaging

- Hard to compare P/R scores for individual queries
  - need to average over many queries
- Two main types of averaging
  - micro-average – each relevant doc is a point in the average
  - macro-average – each query is a point in the average (most common)
  - what does each tell someone evaluating a system?
- Why use one over the other?
- Also done with average precision value
  - called mean average precision (MAP)

Average Precision Again

- Average precision at standard recall points
- For a given query, compute P/R point for every relevant doc.
- Interpolate precision at standard recall levels
  - 11-pt is usually 100%, 90, 80, , 10, 0% (yes, 0% recall)
  - 3-pt is usually 75%, 50%, 25%
- Average over all queries to get average precision at each recall level
  - average over all recall levels to get a single result
  - called "interpolated average precision"

Some Other Single-Valued Measures

- F measure
  - $F = 1 - E$ often used (good results mean larger values of F)
  - $F1$ measure is popular: F with $\beta = 1$

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

$$F_1 = \frac{1}{1/P + 1/R}$$

- R-Precision
  - given a query Q compute the precision at rank $|relevant_Q|$, where $relevant_Q$ is the set of relevant docs for Q
- $p@n$
  - compute the precision at a fixed rank n for every query
  - useful for evaluating search engines

Known Item Search

- Site finding
  - a **site** is an organized collection of pages on a specific topic maintained by a single person or group
  - not the same thing as a domain (`cnn.com` has numerous sites)
- Topic can be very broad; examples from a query log:
  - *Where can I find Hotmail?*
  - *Where is the official Star Wars site?*
  - *Where is the fun site dating patterns analyzer?*
- Not known-item, but known answer (question answering)
  - *Who was Cleopatra?* or: *Where is the Taj Mahal?*
- Given a query, find **the** URL or **the** answer

Evaluating Known Item

- Usually only one possible answer (the site's page)
  - so recall is either zero or one
  - recall/precision graphs are not very interesting
- Instead measure the rank where the site's URL was found
  - sometimes scored as $\mathbf{1}/\boldsymbol{rank}$
  - when averaged over many queries, called "mean reciprocal rank" (MRR)

Significance Tests

- Are observed differences statistically different?
  - generally can't make assumptions about underlying distribution
  - single-valued measures are easier to use, but R/P is possible
- Sign test or Wilcoxon signed-ranks test are typical
  - sign test answers how often
  - Wilcoxon answers how much
- Bootstrapping methods
- Are observed differences detectable by users?

Sign Test Example

- For techniques A and B, compare average precision for each pair of results generated by queries in test collection
  - if difference is large enough, count as $+$ or $-$, otherwise ignore
  - use number of $+$'s and the number of significant differences to determine significance level
    - e.g. for 40 queries, technique A produced a better result than B 12 times, B was better than A 3 times, and 25 were the "same", $p < \mathbf{0.035}$ and technique A is significantly better than B
    - if $A > B$ 18 times and $B > A$ 9 times, $p < \mathbf{0.122}$ and A is not significantly better than B at the 5% level

Retrieval Evaluation with Incomplete Information

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  - I.e., what if the assumption that all relevant documents within a test collection have been identified and are present in the collection is incorrect?
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