Information Retrieval

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Roadmap

- Information Retrieval
  - Vector Space Model
  - Term Selection & Weighting
  - Evaluation

  - Refinements: Query Expansion
    - Resource-based
    - Retrieval-based

  - Refinements: Passage Retrieval
    - Passage reranking

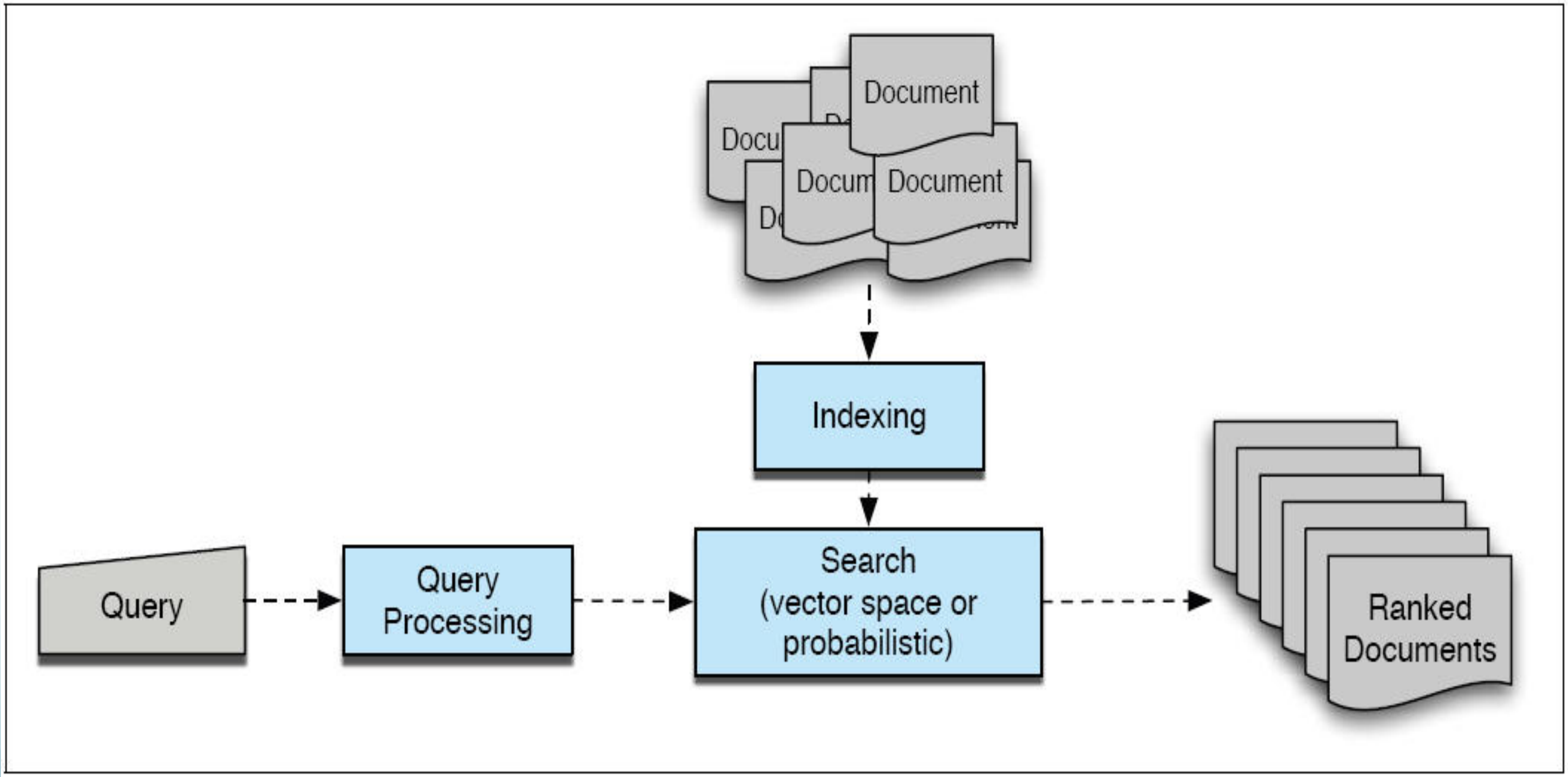
Matching Topics and Documents

- Two main perspectives:
  - Pre-defined, fixed, finite topics:
    - "Text Classification"
  - Arbitrary topics, typically defined by statement of information need (aka query)
    - "Information Retrieval"
      - Ad-hoc retrieval

Information Retrieval Components

- Document collection:
  - Used to satisfy user requests, collection of:
  - Documents:
    - Basic unit available for retrieval
      - Typically: Newspaper story, encyclopedia entry
      - Alternatively: paragraphs, sentences; web page, site
- Query:
  - Specification of information need
- Terms:
  - Minimal units for query/document
    - Words, or phrases

Information Retrieval Architecture



Vector Space Model

- Basic representation:
  - Document and query semantics defined by their terms
  - Typically ignore any syntax
    - Bag-of-words (or Bag-of-terms)
      - Dog bites man == Man bites dog

- Represent documents and queries as
  - Vectors of term-based features
  - E.g. $\vec{d}_j = (w_{1,j}, w_{2,j}, \ldots, w_{N,j}); \vec{q}_k = (w_{1,k}, w_{2,k}, \ldots, w_{N,k})$
  - *N:*
    - # of terms in vocabulary of collection: Problem?

Representation

- Solution 1:
  - Binary features:
    - w=1 if term present, 0 otherwise
  - Similarity:
    - Number of terms in common
    - Dot product

$$sim(\vec{q}_k, \vec{d}_j) = \sum_{i=1}^{N} w_{i,k} w_{i,j}$$

- Issues?

VSM Weights

- What should the weights be?
- "Aboutness"
  - To what degree is this term what document is about?
  - Within document measure
  - Term frequency (tf): # occurrences of t in doc j
- Examples:
  - Terms: chicken, fried, oil, pepper
  - D1: fried chicken recipe: (8, 2, 7,4)
  - D2: poached chick recipe: (6, 0, 0, 0)
  - Q: fried chicken: (1, 1, 0, 0)

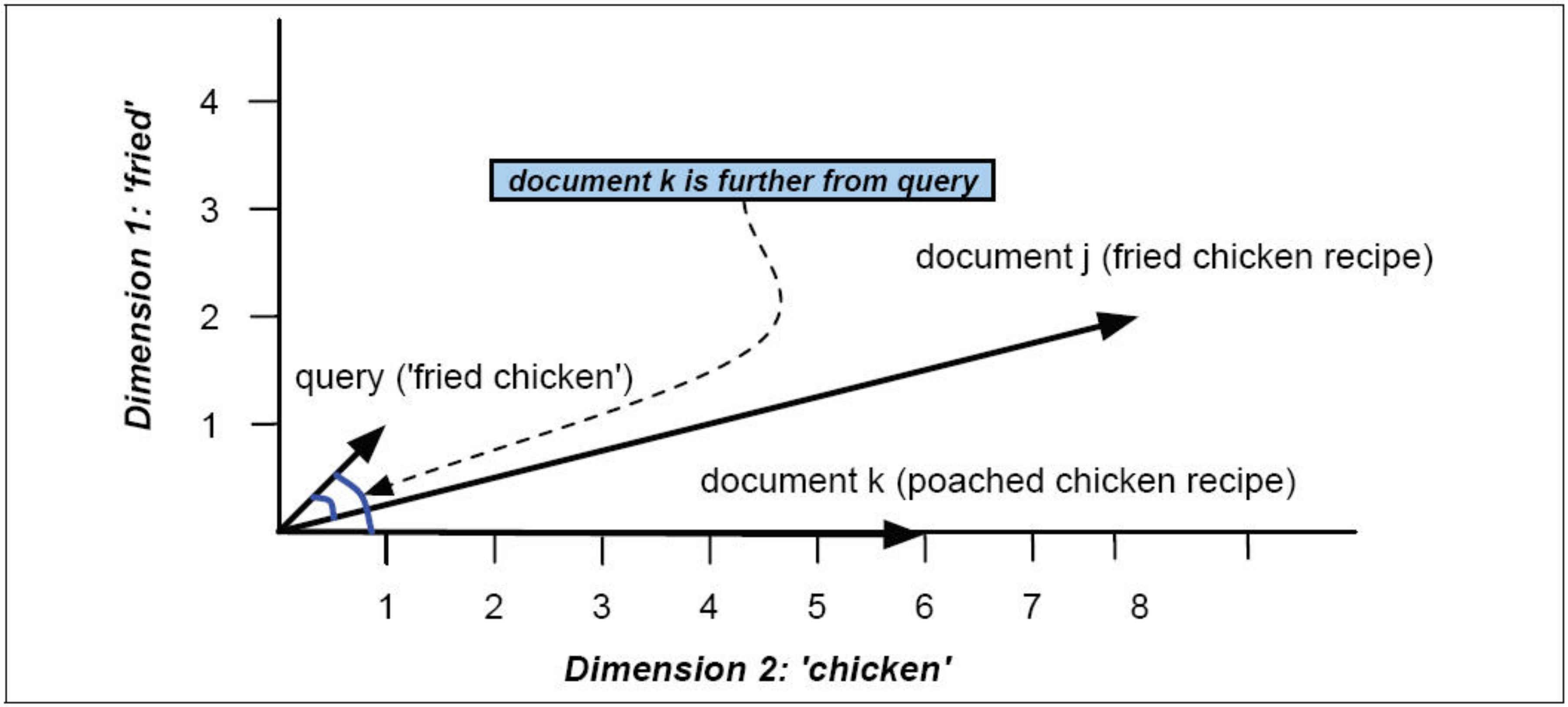
Vector Space Model (II)

- Documents & queries:
  - Document collection: term-by-document matrix

$$A = \begin{pmatrix} 8 & 6 \\ 2 & 0 \\ 7 & 0 \\ 4 & 0 \end{pmatrix}$$

  - View as vector in multidimensional space
    - Nearby vectors are related
  - Normalize for vector length

Vector Space Model



Vector Similarity Computation

- Normalization:
  - Improve over dot product
    - Capture weights
    - Compensate for document length
  - Cosine similarity

$$sim(\vec{q}_k, \vec{d}_j) = \frac{\sum_{i=1}^{N} w_{i,k} w_{i,j}}{\sqrt{\sum_{i=1}^{N} w_{i,k}^2}\sqrt{\sum_{i=1}^{N} w_{i,j}^2}}$$

    - Identical vectors:

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    - Identical vectors: 1
    - No overlap: 0

Term Weighting Redux

- "Aboutness"
  - Term frequency (tf): # occurrences of t in doc j
    - Chicken: 6; Fried: 1 vs Chicken: 1; Fried: 6
- Question: what about 'Representative' vs 'Giffords'?
- "Specificity"
  - How surprised are you to see this term?
  - Collection frequency
  - Inverse document frequency (idf):

$$idf_i = \log\left(\frac{N}{n_i}\right) \qquad w_{i,j} = tf_{i,j} \times idf_i$$

Tf-idf Similarity

- Variants of tf-idf prevalent in most VSM

$$sim(\vec{q},\vec{d}) = \frac{\sum_{w \in q,d} tf_{w,q} tf_{w,d} (idf_w)^2}{\sqrt{\sum_{q_i \in q} (tf_{q_i,q} idf_{q_i})^2} \sqrt{\sum_{d_i \in d} (tf_{d_i,d} idf_{d_i})^2}}$$

Term Selection

- Selection:
  - Some terms are truly useless
    - Too frequent:
      - Appear in most documents
    - Little/no semantic content
      - Function words
        - E.g. the, a, and,…
  - Indexing inefficiency:
    - Store in inverted index:
      - For each term, identify documents where it appears
      - ‘the’: every document is a candidate match
- Remove ‘stop words’ based on list
  - Usually document-frequency based

Term Creation

- Too many surface forms for same concepts
  - E.g. inflections of words: verb conjugations, plural
    - Process, processing, processed
    - Same concept, separated by inflection
- Stem terms:
  - Treat all forms as same underlying
    - E.g., ‘processing’ -> ‘process’; ‘Beijing’ -> ‘Beije’
- Issues:
  - Can be too aggressive
    - AIDS, aids -> aid; stock, stocks, stockings -> stock

Evaluating IR

- Basic measures: Precision and Recall
- Relevance judgments:
  - For a query, returned document is relevant or non-relevant
    - Typically binary relevance: 0/1
  - T: returned documents; U: true relevant documents
  - R: returned relevant documents
  - N: returned non-relevant documents

$$\Pr ecision = \frac{|R|}{|T|}; \operatorname{Re} call = \frac{|R|}{|U|}$$

Evaluating IR

- Issue: Ranked retrieval
  - Return top 1K documents: ‘best’ first
  - 10 relevant documents returned:
    - In first 10 positions?
    - In last 10 positions?
    - Score by precision and recall – which is better?
      - Identical !!!
      - Correspond to intuition? NO!

- Need rank-sensitive measures

Rank-specific P & R

Rank	Judgment	Precision_{Rank}	Recall_{Rank}
1	R	1.0	.11
2	N	.50	.11
3	R	.66	.22
4	N	.50	.22
5	R	.60	.33
6	R	.66	.44
7	N	.57	.44
8	R	.63	.55
9	N	.55	.55
10	N	.50	.55
11	R	.55	.66
12	N	.50	.66
13	N	.46	.66
14	N	.43	.66
15	R	.47	.77
16	N	.44	.77
17	N	.44	.77
18	R	.44	.88
19	N	.42	.88
20	N	.40	.88
21	N	.38	.88
22	N	.36	.88
23	N	.35	.88
24	N	.33	.88
25	R	.36	1.0

Rank-specific P & R

- Precision_{rank}: based on fraction of reldocs at rank
- Recall_{rank}: similarly
- Note: Recall is non-decreasing; Precision varies
- Issue: too many numbers; no holistic view
  - Typically, compute precision at 11 fixed levels of recall
  - Interpolated precision:

$$IntPrecision(r) = \max_{i>=r} Precision(i)$$

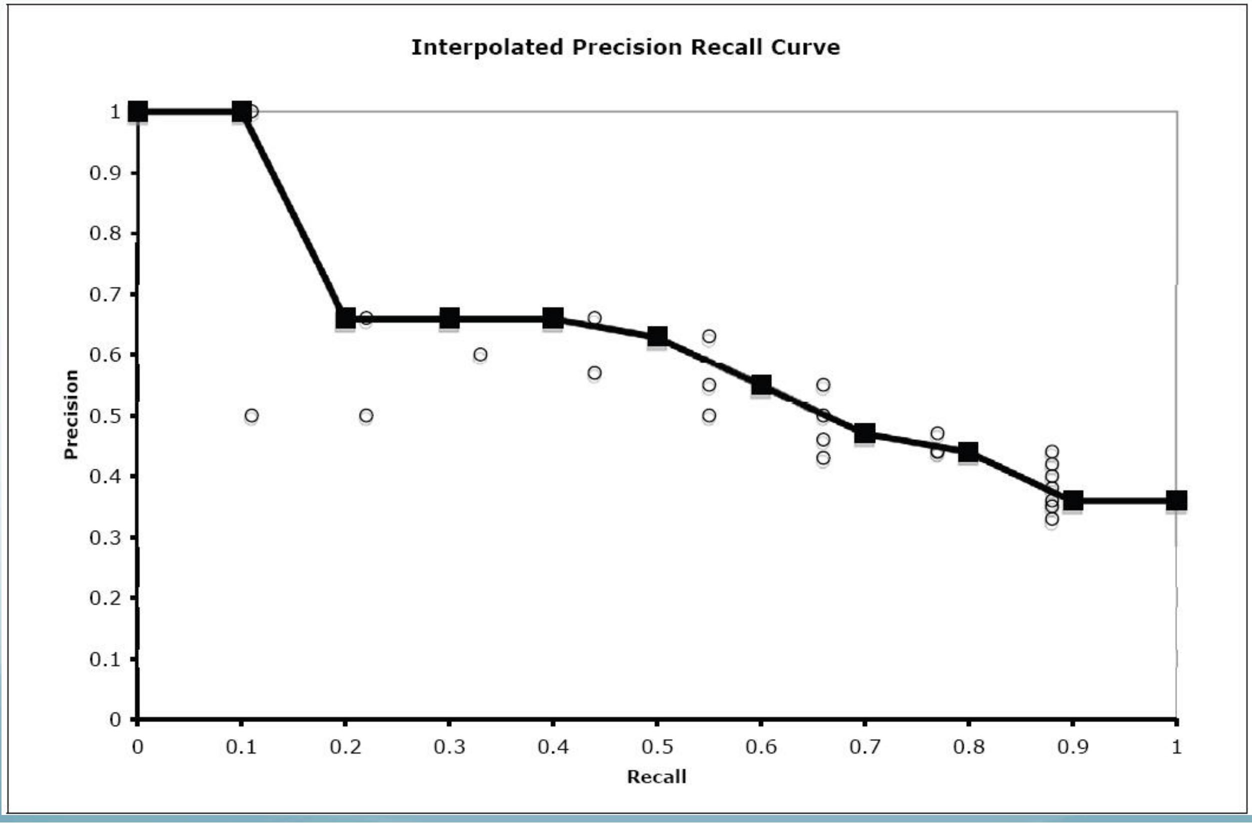
    - Can smooth variations in precision

Interpolated Precision

Interpolated Precision	Recall
1.0	0.0
1.0	.10
.66	.20
.66	.30
.66	.40
.63	.50
.55	.60
.47	.70
.44	.80
.36	.90
.36	1.0

Comparing Systems

- Create graph of precision vs recall
  - Averaged over queries
  - Compare graphs



Mean Average Precision (MAP)

- Traverse ranked document list:
  - Compute precision each time relevant doc found
    - Average precision up to some fixed cutoff
    - R_r: set of relevant documents at or above r
    - Precision(d) : precision at rank when doc d found

$$\frac{1}{|R_r|}\sum_{d \in R_r} \mathrm{Pr}\,ecision_r(d)$$

- Mean Average Precision: 0.6
    - Compute average of all queries of these averages
    - Precision-oriented measure

- Single crisp measure: common TREC Ad-hoc