Comparing Word Occurrances across Documents: Information Retrieval, Terminology Extraction, etc.

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Outline

- Classifying Documents
  - Viewing “subject” of a document as a function of the set of words contained in the document
  - Similar documents → similar word distribution
- Search Query
  - Find document that is similar to query
- Terminology Extraction
  - Find words and word sequences that are significant, i.e., are valid search terms
- Other areas:
  - Cluster “similar documents”: topic modeling, sublanguage identification, …

Ad Hoc Information Retrieval

- Model of document = unordered set of ***terms*** contained in that document (ignore word order)
  - Term = word, bigram, trigram, noun group, or other small unit of consecutive items
- Query = user input, typically a set of terms
- Collection = set of documents that system
- Goal find documents that are "closest" to query

Vector Model

- Model documents and queries as vectors
- Feature values filled by the weight of terms
  - Values also called dimensions
- Example:
  - Terms: potato chip, chicken, sesame seed, coconut milk
  - Vector for query about Thai soups $\vec{S} = (0,20,2,100)$
  - Vector for chicken and coconut soup recipe
    - $\vec{S} = (0,40,0,100)$
  - Vector for chicken noodle soup recipe $\vec{S} = (0,20,0,0)$
- IR task: find documents that most closely "match" query
  - Matching via similarity metric defined on pairs of vectors
- Weights and Similarity Scores need to be defined

TFIDF = Common Weight for Vector

- Term Frequency – number of times term ***t*** occurs in document
- Inverse Document Frequency: Reciprocal of portion of large document set that contain term ***t***, normalized with log function:

$$\log\left(\frac{NumberOfDocuments}{NumberOfDocumentsContaining(t)}\right)$$

- TFIDF(t) = TF(t) × IDF(t)
  - Scores terms highly that occur frequently in a document or query
  - Scores terms highly that are infrequent in collection

Example: *coconut milk* vs. *tablespoon*

- ***coconut milk***
  - occurs ~ 3 times in chicken and coconut soup recipe
    - Term frequency = 3
  - occurs in 4 out of 10,000 documents in collection
  - inverse document frequency = log(10000/4) = log(2500) = 7.82
  - TFIDF = 3 × 7.82 = 23.46
- ***tablespoon***
  - occurs 4 times in chicken and coconut soup recipe
    - Term frequency = 4
  - occurs in 1200 out of 10,000 documents in corpus
  - inverse document frequency = log(10000/1200) = log(8.33) = 2.12
  - TFIDF = 4 × 2.12 = 8.48
- ***coconut milk*** is more highly weighted for Thai Soup recipes than ***tablespoon***
- Note: Suitability of query term may depend on the nature of the collection
  - Is this a collection of recipes? – ***tablespoon*** not good search term
  - Is collection diverse: instructions, news, …? – tablespoon may be good search term

Cosine Similarity: Common Similarity Score

$$Similarity(A, B) = \frac{\sum_i a_i \times b_i}{\sqrt{\sum_i a_i^2 \times \sum_i b_i^2}}$$

- Cosine of the Angle Between the Vectors
- Numerator is Dot Product, Denominator is a normalizing factor, based on lengths of vectors
- If a query is A and a document is B
  - Cosine similarity high if values of a and b are similar

Example

- Vectors have values corresponding to terms:
  - potato chip, chicken, sesame seed, coconut milk, ground beef
- 2 Queries
  - Q1 chicken, coconut milk: (0,5,0,5,0)
  - Q2 ground beef, potato chip: (4,0,0,0,7)
- 2 Documents
  - D1 Chicken and Coconut Soup Recipe: (0,7,0,9,0)
  - D2 Hamburger Recipe: (3,0,2,0,9)
- Cosign similarities
  -

	Q1	Q2
D1	99.2	0
D2	0	95.9

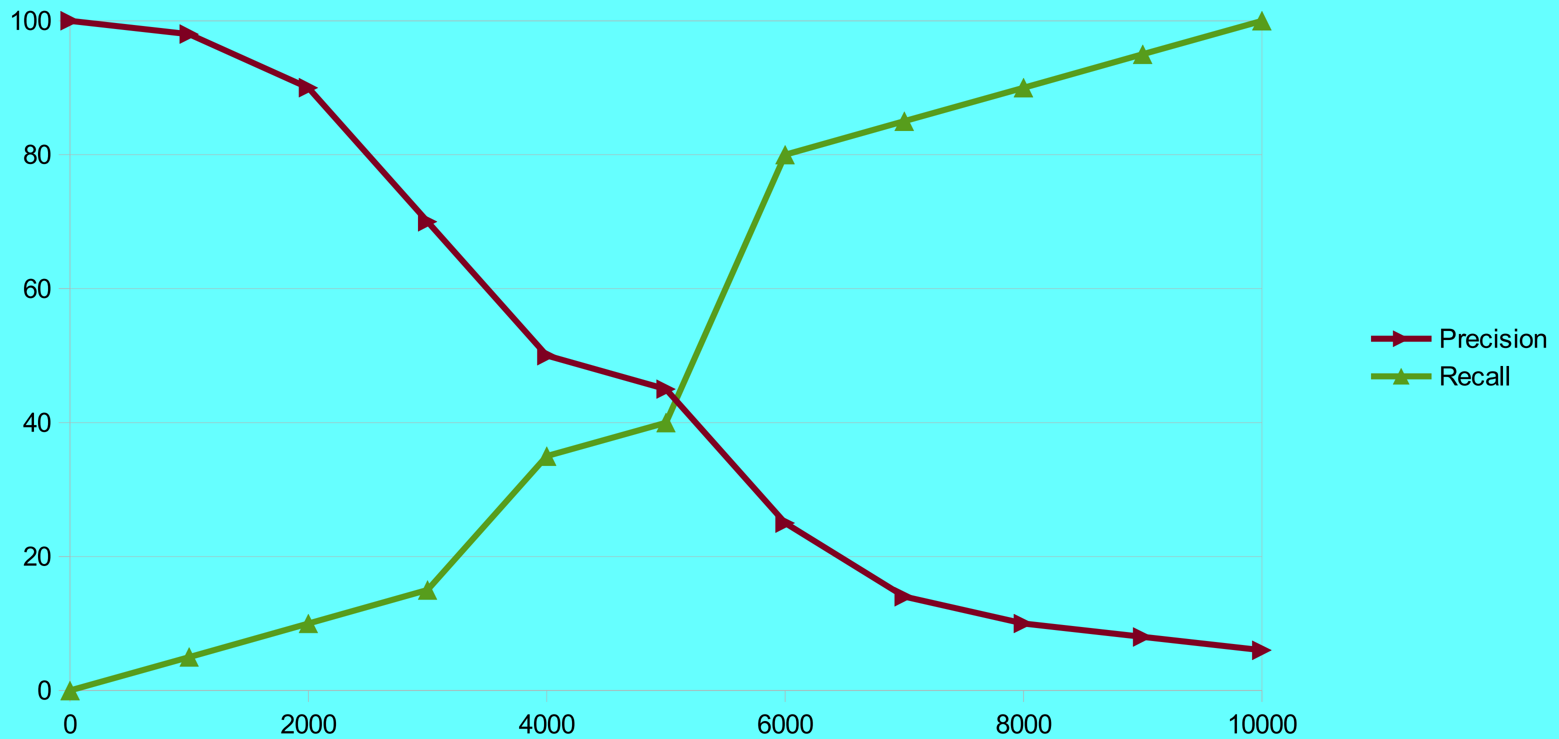
Other Factors

- Many more terms (possibly thousands) represented in each vector
- More weights, normalizations, etc.
- Other similarity measures and weighting functions
- Lists of “stop words”, e.g., ***the, a, in, to, does***, …
- Stemming procedures that consider some terms to be the same, e.g., *[cat, cats], [analyze, analyzes, analyzed, analysis, analyse,...]*
- Identifying other similar words, e.g., synonyms
  - query expansion, term clustering, ...
- Systems identify word sequences as terms: N-grams or chunking

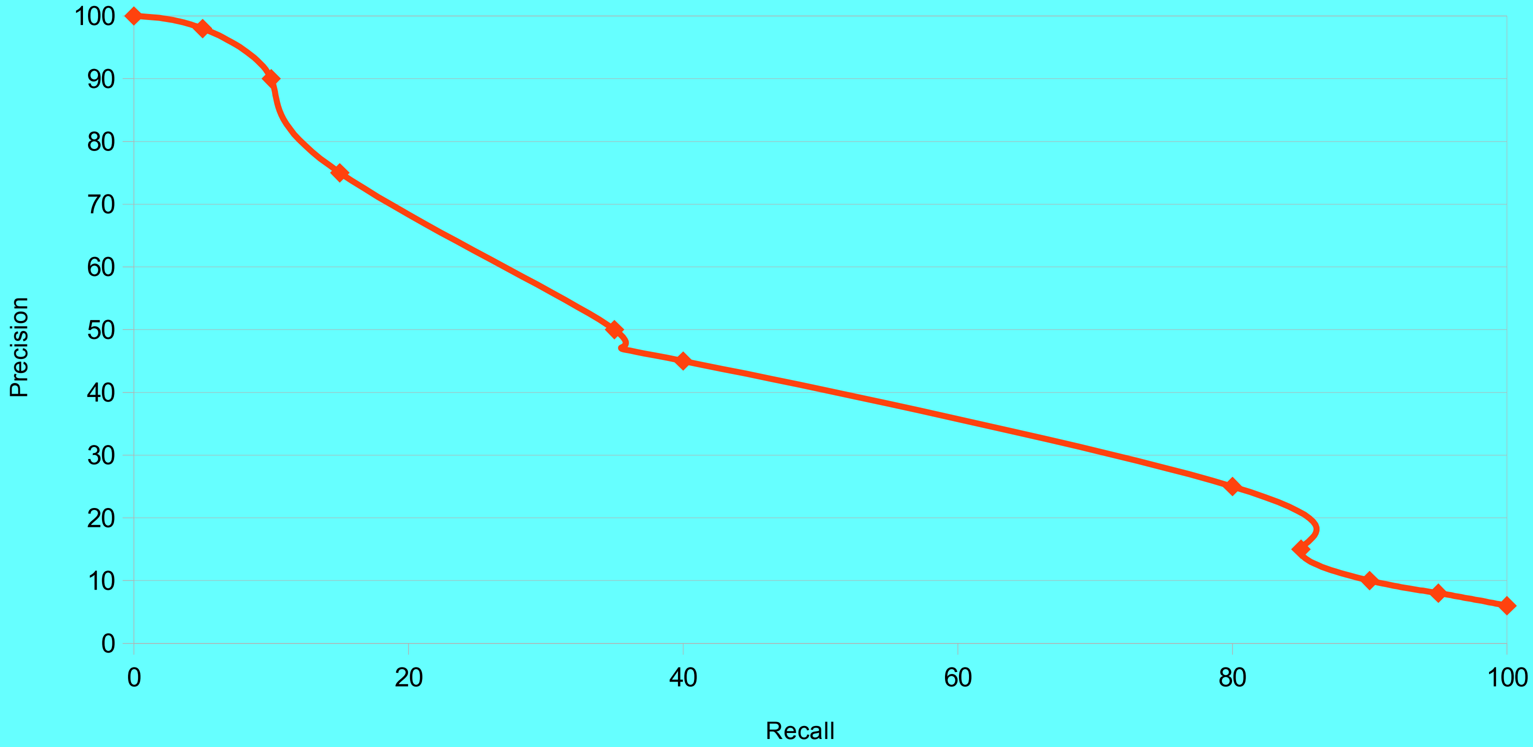
Evaluation of Doc Extraction

- Output = A Ranked List of Documents
  - Some high-ranked errors “worse” than low-ranked
  - Ranking makes relevant/irrelevant distinction subtle
  - Mean Average Precision (MAP): average precision weighted by rank
- Too Expensive to Create Gold Standard Manually
  - Collections can be millions or billions of documents
  - Precision can be approximated by taking samples of the text or evaluating the top N ranked terms manually.
  - Recall can also be approximated by some sort of sampling, e.g., only manually evaluating a subset of the colleciton
- Precision/Recall tradeoff curves based on numbers in the ranking
  - Typically, precision goes down and recall goes up as more documents in the ranking are considered

Sample Precision/Recall Tradeoff Based on Number of Search Results



Precision/Recall Curve



Final Remarks about Document Retrieval

- **TFIDF weighting + Cosine similarity**
  - **standard in IR document retrieval for over 50 years**
- **Web Search Engines**
  - **use these methods to identify relevant documents**
  - **they use other metrics, e.g., PageRank, to rank documents by their "importance"**
- **Some areas of Opinion/Sentiment Extraction**
  - **Similar methods applied to differentiating positive/negative opinions in documents**
  - **More Difficult**
  - **Same terms linked to positive/negative in different contexts**
    - **low, high, small, large, thin, thick, visible, loud, soft, …**
      - ***high/low quality, high/low interest, high/low resolution***

Terminology Talk

- Do Terminology Talk Now

Homework

- Jurafsky and Martin Chapter 23.1
- Meyers, et. al. 2015 paper (optional)
  - Paper Download: http://ceur-ws.org/Vol-1384/paper5.pdf
  - Code Available from github:
    - https://github.com/AdamMeyers/The_Termolator
    - https://github.com/ivanhe/termolator/
- Information Retrieval programming assignment:
  - TBA
  - Due March 17, 2016