Natural Language Processing
Session 6

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Session 6 Agenda

- Information retrieval and topic modeling
    - tf-idf weighting
    - LDA (Latent Dirichlet Allocation)
    - The Vector Space Model (VSM)
- Ranked retrieval
- Document summarization

Exercise 1: retrieve top 10 document most relevant to “Florida”

```
news_path = 'https://storage.googleapis.com/msca-bdp-data-open/news/news_some_company.json'

df = pd.read_json(news_path, orient='records', lines=True)
```

Exercise 2: identify top 10 document most relevant to “Florida” and not related to “Disney”

```
news_path = 'https://storage.googleapis.com/msca-bdp-data-open/news/news_some_company.json'

df = pd.read_json(news_path, orient='records', lines=True)
```

Keyword Extraction in Python

Introduction to
Information Retrieval

Introducing Information Retrieval and Web Search

Information Retrieval

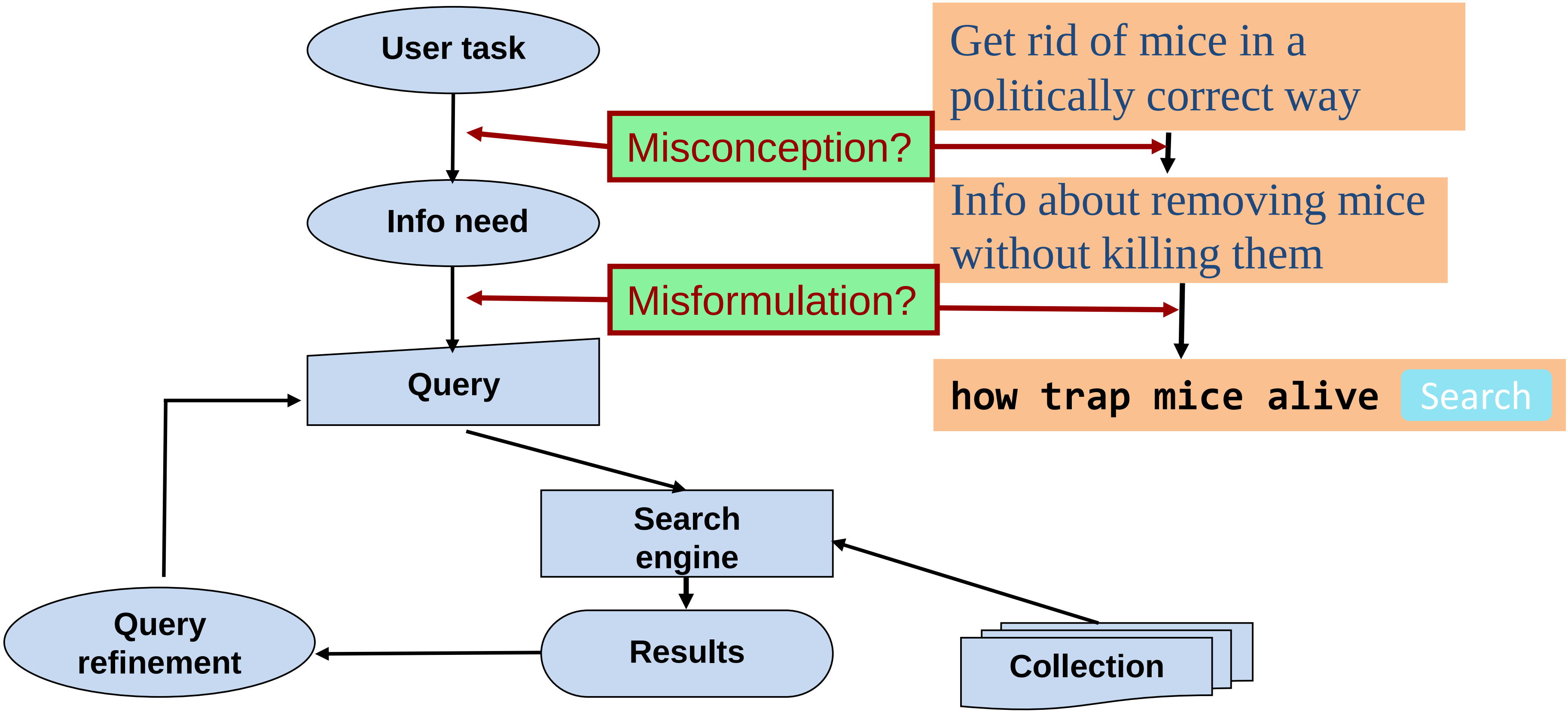
- Information Retrieval (IR) is finding material (usually documents) of an unstructured nature (usually text) that satisfies an information need from within large collections (usually stored on computers).

  - These days we frequently think first of web search, but there are many other cases:
    - E-mail search
    - Searching your laptop
    - Corporate knowledge bases
    - Legal information retrieval

Basic assumptions of Information Retrieval

- Collection: A set of documents
  - Assume it is a static collection for the moment
- Goal: Retrieve documents with information that is relevant to the user's information need and helps the user complete a task

The classic search model



How good are the retrieved docs?

- *Precision* : Fraction of retrieved docs that are relevant to the user's information need
- *Recall* : Fraction of relevant docs in collection that are retrieved

  - More precise definitions and measurements to follow later

Introduction to

Information Retrieval

Term-document incidence matrices

Unstructured data in 1620

- Which plays of Shakespeare contain the words ***Brutus*** *AND* ***Caesar*** but *NOT* ***Calpurnia***?
- One could `grep` all of Shakespeare's plays for ***Brutus*** and ***Caesar,*** then strip out lines containing ***Calpurnia***?
- Why is that not the answer?
  - Slow (for large corpora)
  - *NOT* ***Calpurnia*** is non-trivial
  - Other operations (e.g., find the word ***Romans*** near ***countrymen***) not feasible
  - Ranked retrieval (best documents to return)
    - Later lectures

Term-document incidence matrices

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

Brutus** AND **Caesar** BUT NOT **Calpurnia

1 if play contains word, 0 otherwise

Incidence vectors

- So we have a 0/1 vector for each term.
- To answer query: take the vectors for ***Brutus, Caesar*** and ***Calpurnia*** (complemented) ➔ bitwise *AND*.
  - 110100 *AND*
  - 110111 *AND*
  - 101111 =
  - **100100**

	Antony and Cleopatra	Julius Caesar	The Tempest	Hamlet	Othello	Macbeth
Antony	1	1	0	0	0	1
Brutus	1	1	0	1	0	0
Caesar	1	1	0	1	1	1
Calpurnia	0	1	0	0	0	0
Cleopatra	1	0	0	0	0	0
mercy	1	0	1	1	1	1
worser	1	0	1	1	1	0

Answers to query

- Antony and Cleopatra, Act III, Scene ii

Agrippa [Aside to DOMITIUS ENOBARBUS]: Why, Enobarbus,
When Antony found Julius ***Caesar*** dead,
He cried almost to roaring; and he wept
When at Philippi he found ***Brutus*** slain.

- Hamlet, Act III, Scene ii

Lord Polonius: I did enact Julius ***Caesar*** I was killed i' the
Capitol; ***Brutus*** killed me.

Bigger collections

- Consider N = 1 million documents, each with about 1000 words.
- Avg 6 bytes/word including spaces/punctuation
  - 6GB of data in the documents.
- Say there are M = 500K *distinct* terms among these.

Can’t build the matrix

- 500K x 1M matrix has half-a-trillion 0’s and 1’s.
- But it has no more than one billion 1’s.
  - matrix is extremely sparse.
- What’s a better representation?
  - We only record the 1 positions.

Why?

Introduction to

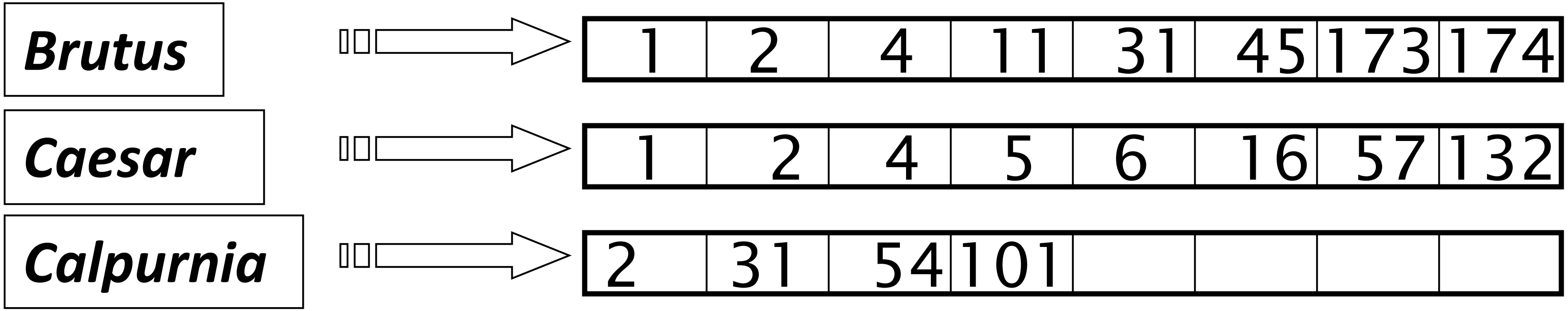
Information Retrieval

The Inverted Index

The key data structure underlying modern IR

Inverted index

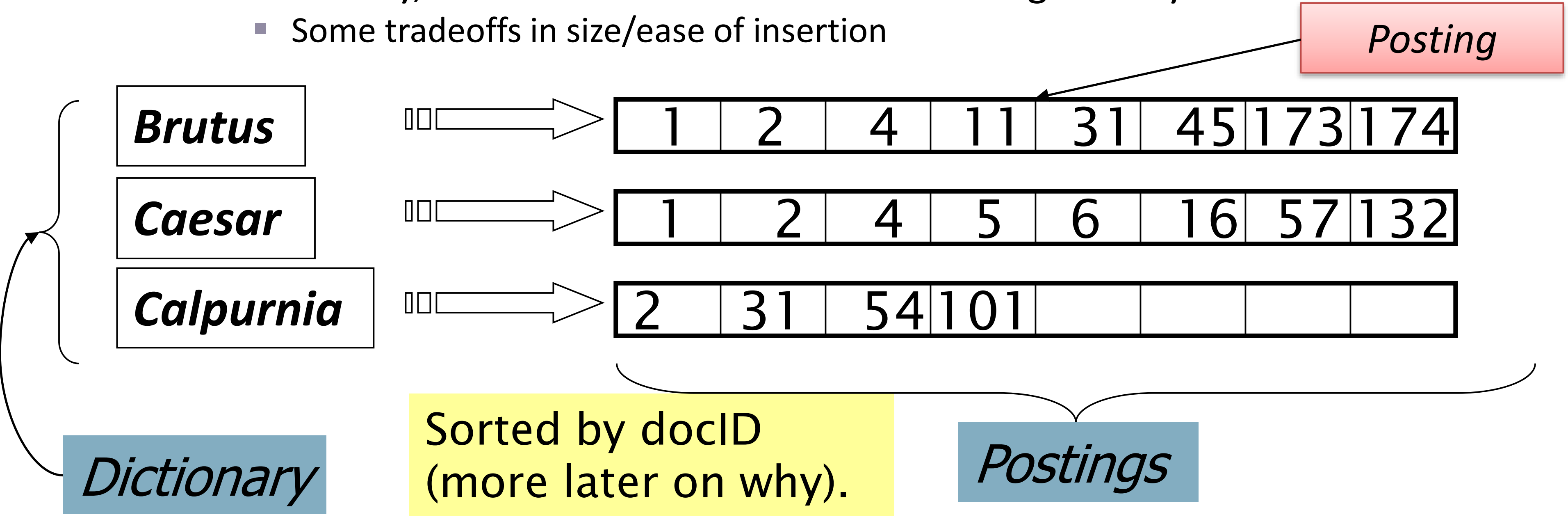
- For each term *t*, we must store a list of all documents that contain *t*.
  - Identify each doc by a **docID**, a document serial number
- Can we use fixed-size arrays for this?



What happens if the word ***Caesar*** is added to document 14?

Inverted index

- We need variable-size postings lists
  - On disk, a continuous run of postings is normal and best
  - In memory, can use linked lists or variable length arrays
    - Some tradeoffs in size/ease of insertion



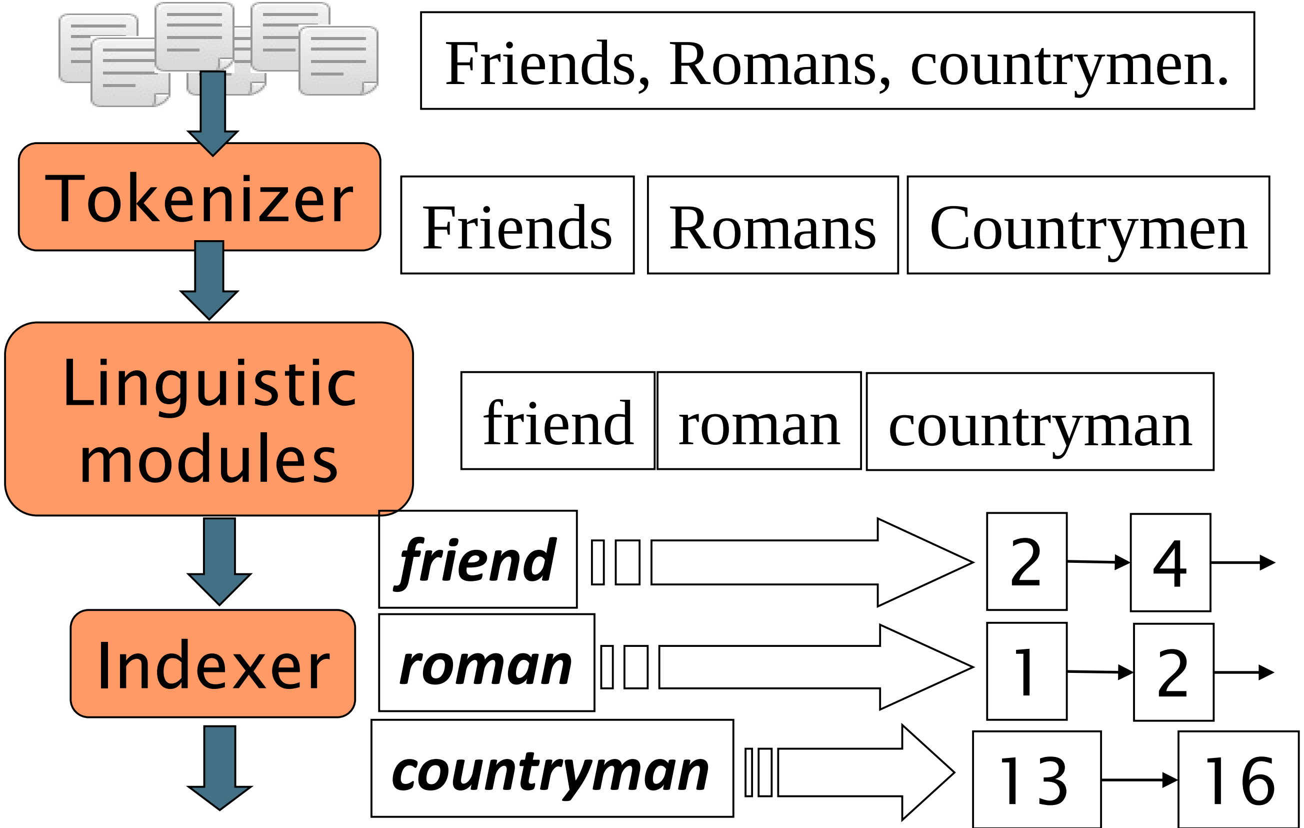
Inverted index construction

Documents to be indexed

Token stream

Modified tokens

Inverted index



Initial stages of text processing

- Tokenization
  - Cut character sequence into word tokens
    - Deal with ***"John's"***, ***a state-of-the-art solution***
- Normalization
  - Map text and query term to same form
    - You want ***U.S.A.*** and ***USA*** to match
- Stemming
  - We may wish different forms of a root to match
    - ***authorize***, ***authorization***
- Stop words
  - We may omit very common words (or not)
    - ***the, a, to, of***

Indexer steps: Token sequence

- Sequence of (Modified token, Document ID) pairs.

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

Term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Indexer steps: Sort

- Sort by terms
  - And then docID

Core indexing step

Term	docID
I	1
did	1
enact	1
julius	1
caesar	1
I	1
was	1
killed	1
i'	1
the	1
capitol	1
brutus	1
killed	1
me	1
so	2
let	2
it	2
be	2
with	2
caesar	2
the	2
noble	2
brutus	2
hath	2
told	2
you	2
caesar	2
was	2
ambitious	2

Term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

Indexer steps: Dictionary & Postings

- Multiple term entries in a single document are merged.
- Split into Dictionary and Postings
- Doc. frequency information is added.

Term	docID
ambitious	2
be	2
brutus	1
brutus	2
capitol	1
caesar	1
caesar	2
caesar	2
did	1
enact	1
hath	1
I	1
I	1
i'	1
it	2
julius	1
killed	1
killed	1
let	2
me	1
noble	2
so	2
the	1
the	2
told	2
you	2
was	1
was	2
with	2

term	doc. freq.	→	postings lists
ambitious	1	→	2
be	1	→	2
brutus	2	→	1 → 2
capitol	1	→	1
caesar	2	→	1 → 2
did	1	→	1
enact	1	→	1
hath	1	→	2
i	1	→	1
i'	1	→	1
it	1	→	2
julius	1	→	1
killed	1	→	1
let	1	→	2
me	1	→	1
noble	1	→	2
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

Why frequency?
Will discuss later.

Where do we pay in storage?

term	doc. freq.	→	postings lists
ambitious	1	→	2
be	1	→	2
brutus	2	→	1 → 2
capitol	1	→	1
caesar	2	→	1 → 2
did	1	→	1
enact	1	→	1
hath	1	→	2
i	1	→	1
i'	1	→	1
it	1	→	2
julius	1	→	1
killed	1	→	1
let	1	→	2
me	1	→	1
noble	1	→	2
so	1	→	2
the	2	→	1 → 2
told	1	→	2
you	1	→	2
was	2	→	1 → 2
with	1	→	2

Terms and counts

Lists of docIDs

Pointers

IR system implementation

- How do we index efficiently?
- How much storage do we need?

Introduction to

Information Retrieval

Phrase queries and positional indexes

Phrase queries

- We want to be able to answer queries such as ***"stanford university"*** – as a phrase
- Thus the sentence *"I went to university at Stanford"* is not a match.
  - The concept of phrase queries has proven easily understood by users; one of the few "advanced search" ideas that works
  - Many more queries are *implicit phrase queries*
- For this, it no longer suffices to store only

<*term* : *docs*> entries

A first attempt: Biword indexes

- Index every consecutive pair of terms in the text as a phrase
- For example the text "Friends, Romans, Countrymen" would generate the biwords
  - ***friends romans***
  - ***romans countrymen***
- Each of these biwords is now a dictionary term
- Two-word phrase query-processing is now immediate.

Longer phrase queries

- Longer phrases can be processed by breaking them down
- ***stanford university palo alto*** can be broken into the Boolean query on biwords:

stanford university *AND* ***university palo*** *AND* ***palo alto***

Without examining the documents, we cannot verify that the documents matching the above Boolean query do actually contain the original 4 word phrase

Can have false positives!

Issues for biword indexes

- False positives, as noted before
- Index blowup due to bigger dictionary
  - Infeasible for more than biwords, big even for them
- Biword indexes are not the standard solution (for all biwords) but can be part of a compound strategy

Solution 2: Positional indexes

- In the postings, store, for each ***term*** the position(s) in which tokens of it appear:

<***term,*** number of docs containing ***term***;
doc1: position1, position2 … ;
doc2: position1, position2 … ;
etc.>

Positional index example

<***be***: 993427;
1: 7, 18, 33, 72, 86, 231;
2: 3, 149;
4: 17, 191, 291, 430, 434;
5: 363, 367, …>

Which of docs 1,2,4,5 could contain "***to be or not to be***"?

- For phrase queries, we use a merge algorithm recursively at the document level
- But we now need to deal with more than just equality

Processing a phrase query

- Extract inverted index entries for each distinct term: ***to, be, or, not.***
- Merge their *doc:position* lists to enumerate all positions with "***to be or not to be***".
  - ***to****:*
    - *2*:1,17,74,222,551; *4*:8,16,190,429,433; *7*:13,23,191; ...
  - ***be****:*
    - *1*:17,19; *4*:17,191,291,430,434; *5*:14,19,101; ...
- Same general method for proximity searches

Proximity queries

- LIMIT! /3 STATUTE /3 FEDERAL /2 TORT
  - Again, here, /*k* means "within *k* words of".
- Clearly, positional indexes can be used for such queries; biword indexes cannot.
- Exercise: Adapt the linear merge of postings to handle proximity queries. Can you make it work for any value of *k*?
  - This is a little tricky to do correctly and efficiently
  - See Figure 2.12 of *IIR*

Introduction to

Information Retrieval

BM25, BM25F, and User Behavior

Okapi BM25 and BM25F

- BM25 “Best Match 25” (they had a bunch of tries!)
  - Developed in the context of the Okapi system
- The name of the actual ranking function is BM25
  - it is usually referred to as "Okapi BM25", since the Okapi information retrieval system, implemented at London's City University in the 1980s and 1990s, was the first system to implement this function.
- BM25 and its newer variants, e.g. BM25F (a version of BM25 that can take document structure and anchor text into account), are improving on the TF-IDF-like retrieval functions by incorporating normalization for *tf* using document length

Document length normalization

- Longer documents are likely to have larger tf_i values
- Why might documents be longer?
  - Verbosity: suggests observed tf_i too high
  - Larger scope: suggests observed tf_i may be right
- A real document collection probably has both effects
- … so should apply some kind of normalization

Exercise 3: what is this collection about: identify major themes and topics

```
df = pd.read_json(news_some_company.json, orient='records', lines=True)
```

Topic Modeling in Python

Exercise 4: summarize the content of collection in a few (5-10) sentences

```
df = pd.read_json(news_some_company.json, orient='records', lines=True)
```

Text Summarization in Python

Thank You!