

بِسْمِ اللَّهِ الرَّحْمَنِ الرَّحِيمِ

دورة "استرجاع المعلومات" باللغة العربية - صيف ٢٠٢١

Information Retrieval – Summer 2021



2. Indexing & Preprocessing

read

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Feedback on Yesterday's Lecture

- Mostly very positive!
 - detailed explanation, simplification
 - content well-organized, logical sequence, etc.
 - polls
- Speed, repetition
- Lab
- More material
- Taking questions





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Google supports Boolean retrieval.

- Yes
- No

Boolean retrieval is called "exact-match" because ...

- it returns documents that exactly satisfy the Boolean query.
- it returns documents that exactly satisfy the information need.
- it divides the collection into exactly two subsets of documents.

When we change our query after seeing the search results,

- we are actually changing our information need.
- we are representing the same information need but in a different way.
- either of the above cases can happen.

Today's Roadmap

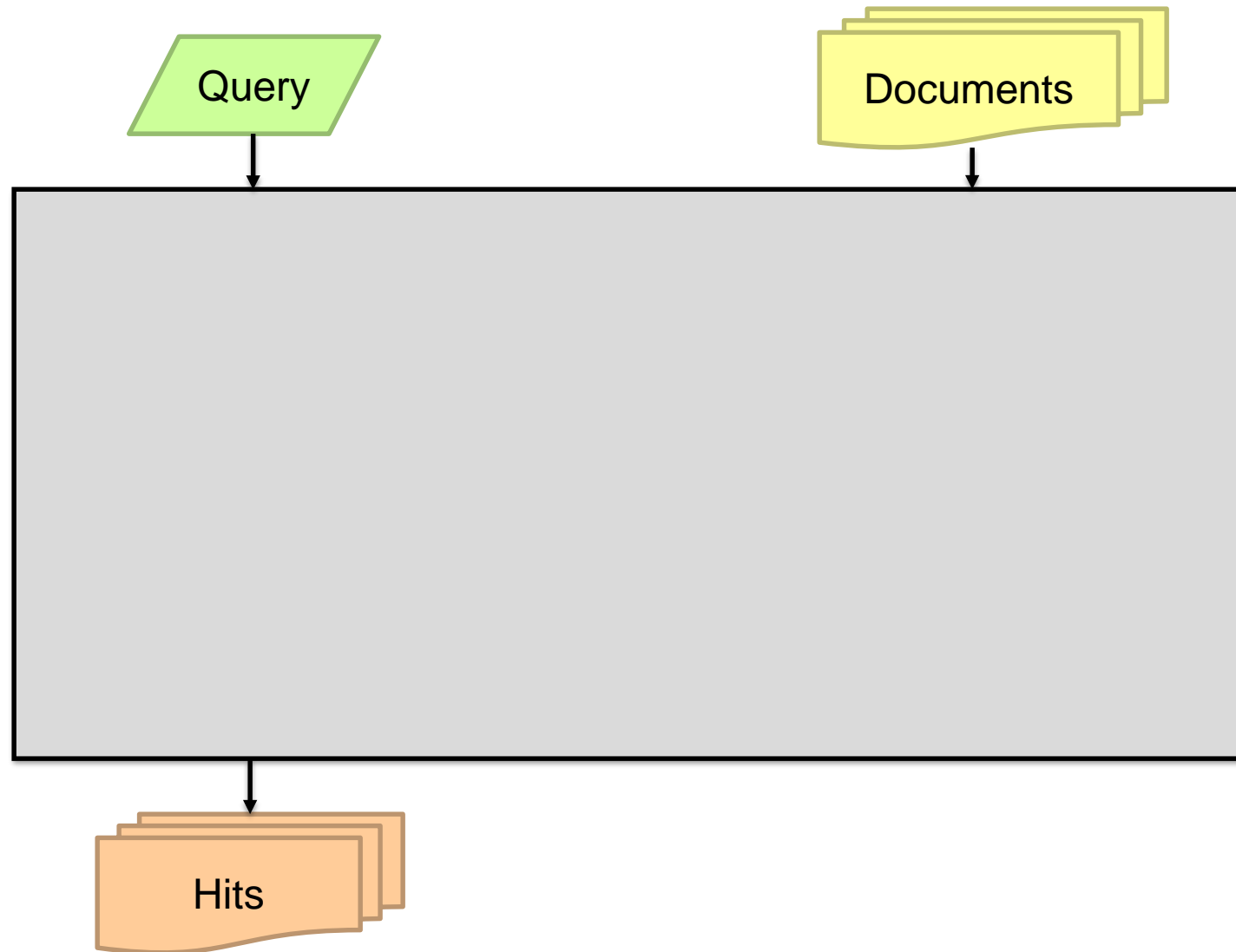
- The anatomy of a search engine
- Indexing
- Preprocessing



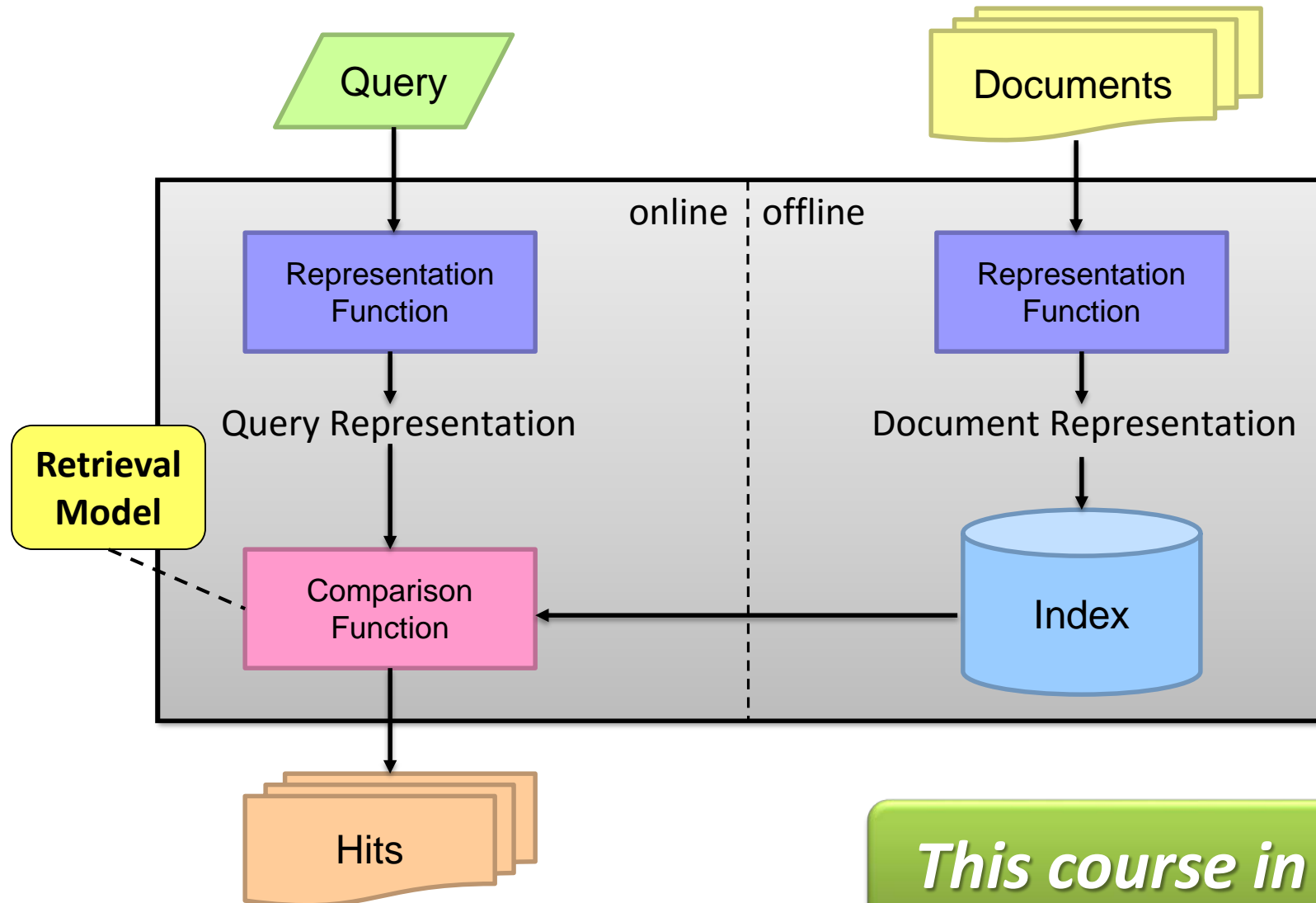


THE ANATOMY OF A SEARCH ENGINE

The IR Black Box

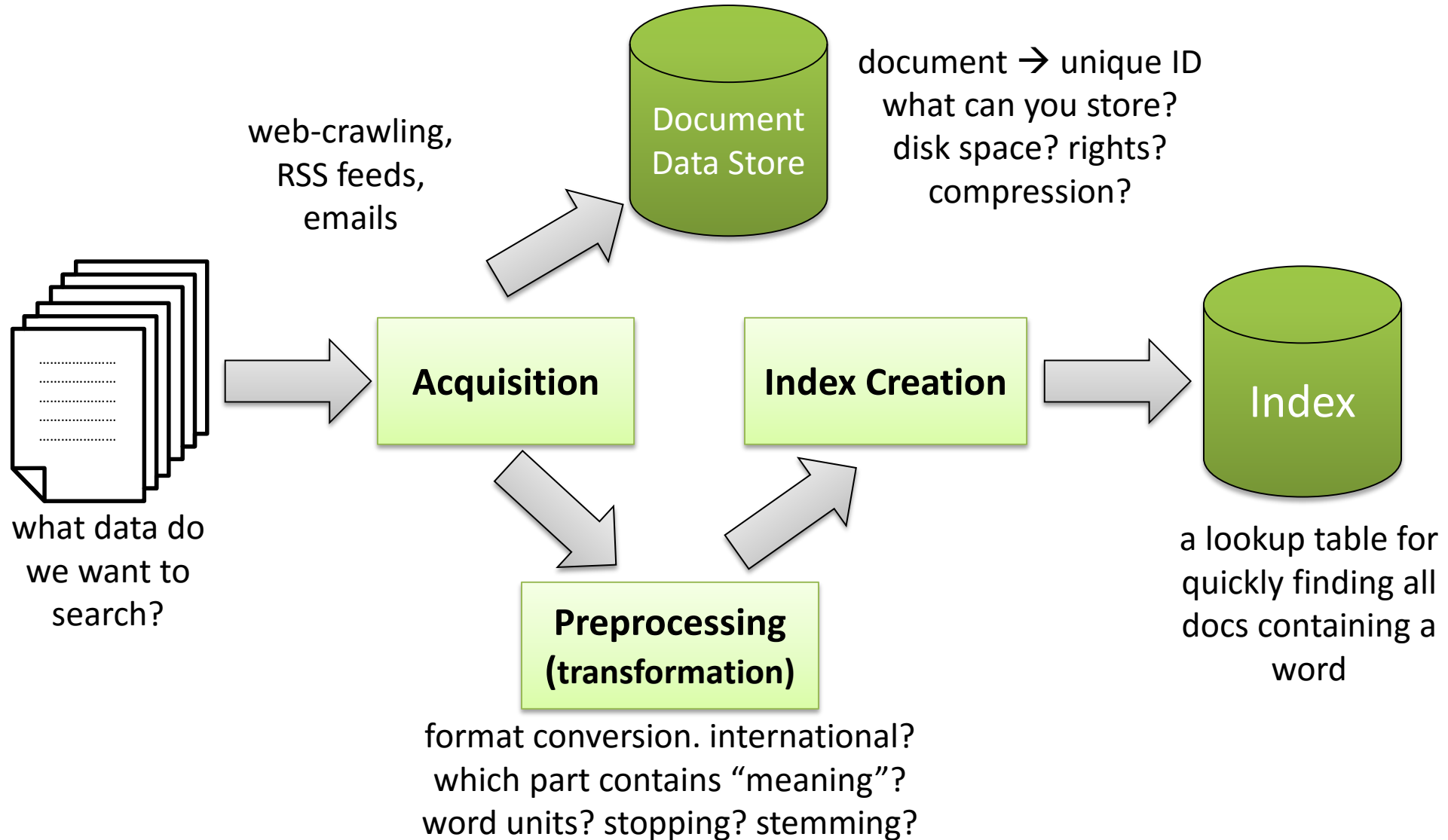


Inside the IR Black Box

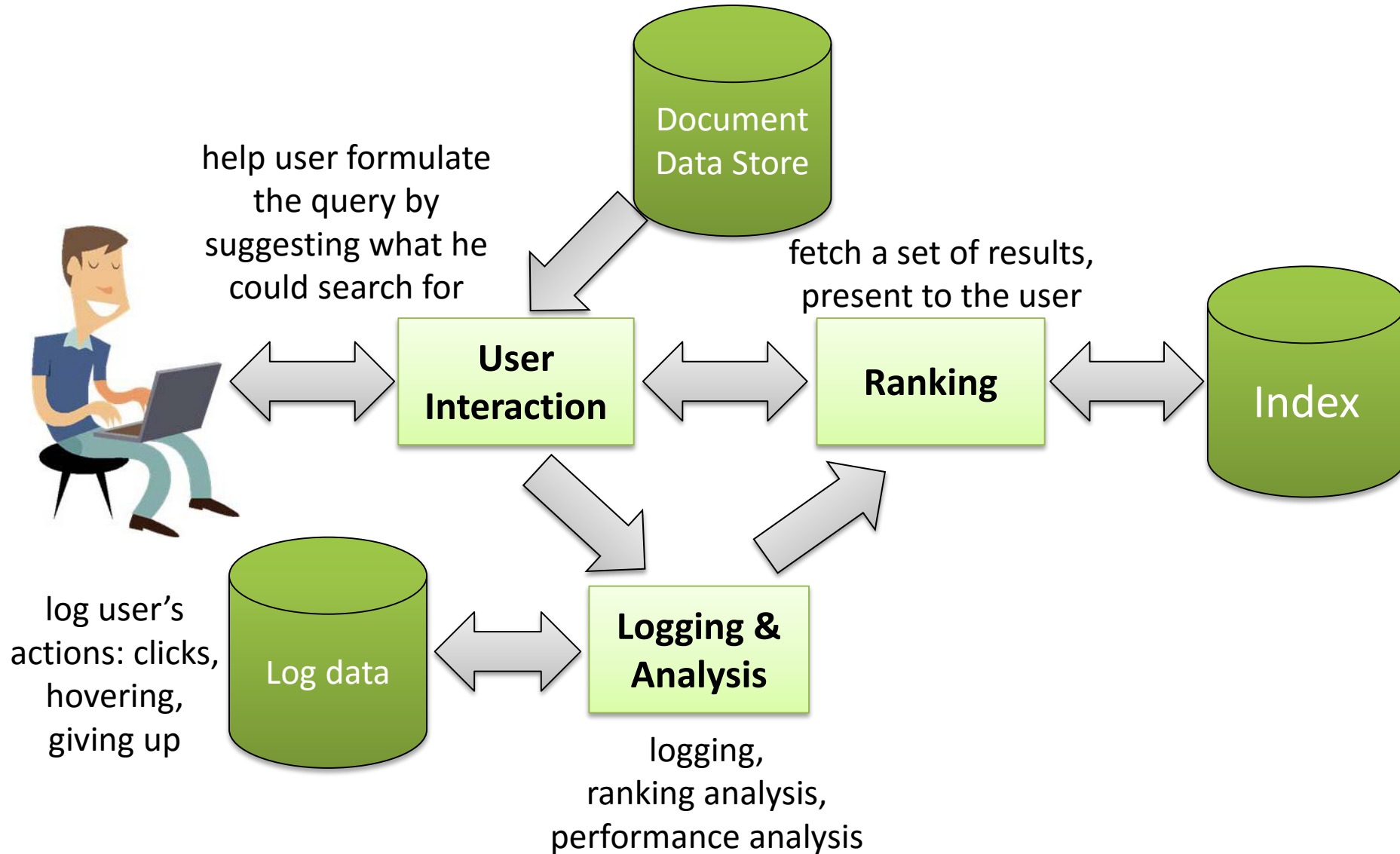


This course in 1 slide!

Indexing process (offline)



Search process (online)







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Indexing is done at query time only.

- Yes
- No, it is done only offline
- No, it is done both offline and online


Ranking is done ...

- offline
- online
- both offline and online



(SIMPLE) INDEXING

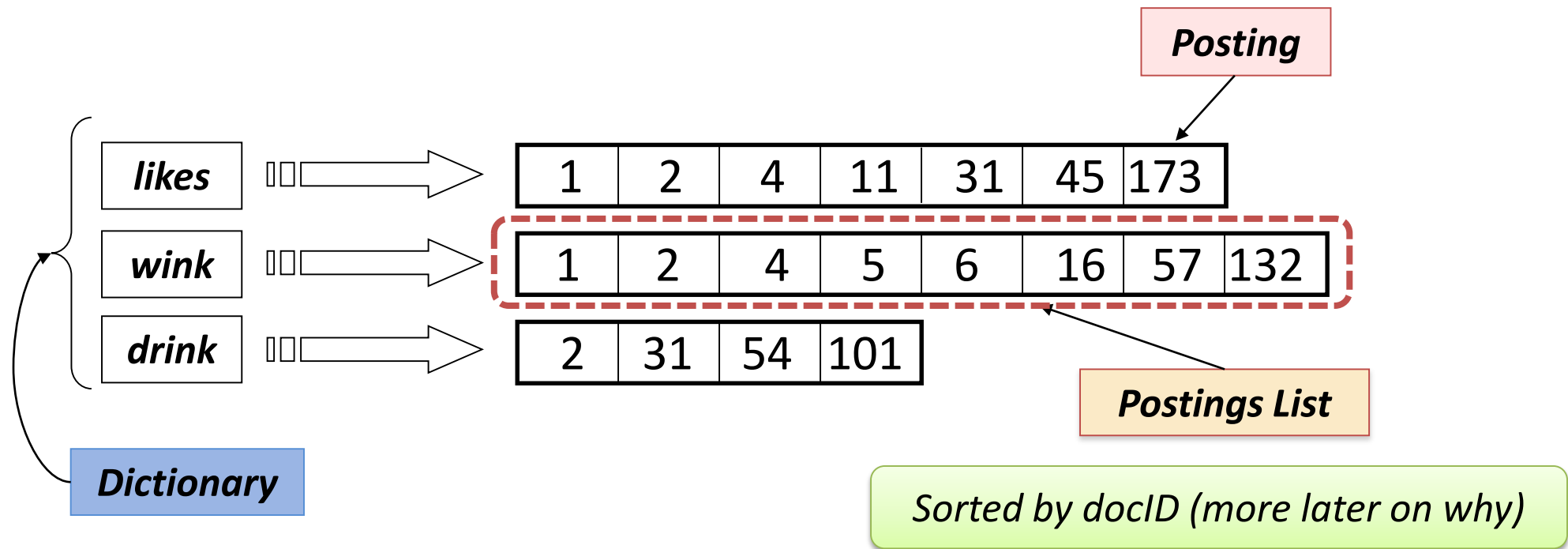
Bigger Collections ...

- Consider $N = 1$ million documents, each with about 1000 words.
- Say there are $M = 500\text{K}$ *distinct* terms among these.
- 500K x 1M term-doc incidence 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?

Inverted Index

- For each term t , we must store a list of all documents that contain t .
 - Identify each by a **docID**, a document serial number



Inverted Index Construction

Documents to be indexed



Tokenizer



Normalizer



Indexer



Token stream

*Preprocessing
(later today)*

Terms (modified tokens)

Inverted index

He likes to wink, he likes to drink.

He likes to wink he likes to drink

he like wink he like drink

he → 2 → 4 →

like → 1 → 2 →

wink → 3 → 9 →

Step 1: Term Sequence

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

Preprocess



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

Sequence of
(term, Doc ID) pairs

Step 2: Sorting

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

Preprocess



Term	docID
I	1
did	1
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julius	1
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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

Sequence of
(term, Doc ID) pairs

Core indexing step

**Sort by
term then
DocID**



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

Sorted Sequence of
(term, Doc ID) pairs

Step 3: Dictionary & Postings

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

Preprocess

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

Sequence of (term, Doc ID) pairs

Core indexing step
Sort by term then DocID

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

Sorted Sequence of (term, Doc ID) pairs

Dictionary & Postings

df information is added

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

Inverted Index

Indexing

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

Preprocess

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

Sequence of
(term, Doc ID) pairs

**Sort by
term then
DocID**

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

Sorted Sequence of
(term, Doc ID) pairs

**Dictionary
&
Postings**

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

Inverted Index

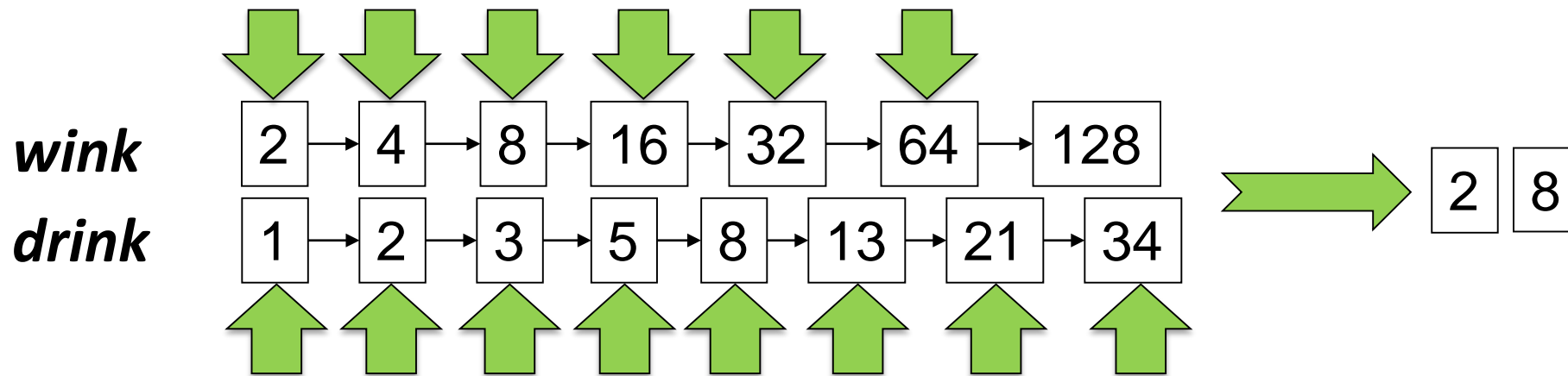
How do we index efficiently?

In IR2 course 😊

Query Processing: AND

○ Consider processing the query: **wink AND drink**

1. Locate **wink** in the Dictionary, Retrieve its postings
2. Locate **drink** in the Dictionary, Retrieve its postings
3. “Merge” the two postings lists



○ Complexity ?

○ Crucial: postings sorted by docID.


Intersecting Two Postings Lists: (a “merge” algorithm)

```
INTERSECT( $p_1, p_2$ )
1   $answer \leftarrow \langle \rangle$ 
2  while  $p_1 \neq \text{NIL}$  and  $p_2 \neq \text{NIL}$ 
3  do if  $\text{docID}(p_1) = \text{docID}(p_2)$ 
4      then  $\text{ADD}(answer, \text{docID}(p_1))$ 
5           $p_1 \leftarrow \text{next}(p_1)$ 
6           $p_2 \leftarrow \text{next}(p_2)$ 
7      else if  $\text{docID}(p_1) < \text{docID}(p_2)$ 
8          then  $p_1 \leftarrow \text{next}(p_1)$ 
9          else  $p_2 \leftarrow \text{next}(p_2)$ 
10 return  $answer$ 
```

Document-at-a-time

How to modify for OR?

Boolean Queries: More General Merges

- Adapt the merge for the queries: 
wink AND NOT drink
wink OR NOT drink
- What about an arbitrary Boolean formula?
(wink OR drink) AND (like OR NOT ink)





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In inverted index, we can get efficiently ...

- what terms appear in a specific document
- what documents have a specific term
- both of the above

One posting belongs to ...

- one term
- one document
- one term in one document



PROXIMITY QUERIES

Proximity Queries

- If 2 words are “near” each other in a document *d*, they might be more related than further words → *d* might be “*more relevant*”
- Ex: Find ***Gates NEAR/3 Microsoft.***

How can we support it?

Positional Indexes

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

<likes: 9347;

1: 7, 18, 33, 72, 86, 231;

2: 3, 149;

4: 17, 191, 291, 430, 434;

5: 363, 367, ...>

What's the biggest problem?

Positional Index Size

- You can compress position values/offsets
- Nevertheless, a positional index **expands postings storage** *substantially*
- Nevertheless, a positional index is **now standardly used** because of the power and usefulness of phrase and proximity queries ... whether used explicitly or implicitly in a ranking retrieval system.

Phrase Queries

- Want to be able to answer queries such as “*qatar university*” – as a phrase
- Thus the sentence “*I went to university in Qatar*” 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*

How can we support it using positional index?





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Phrase queries are special case of proximity queries

- Yes
- No

Proximity queries are Boolean queries

- more expensive than
- less expensive then
- of equal cost to

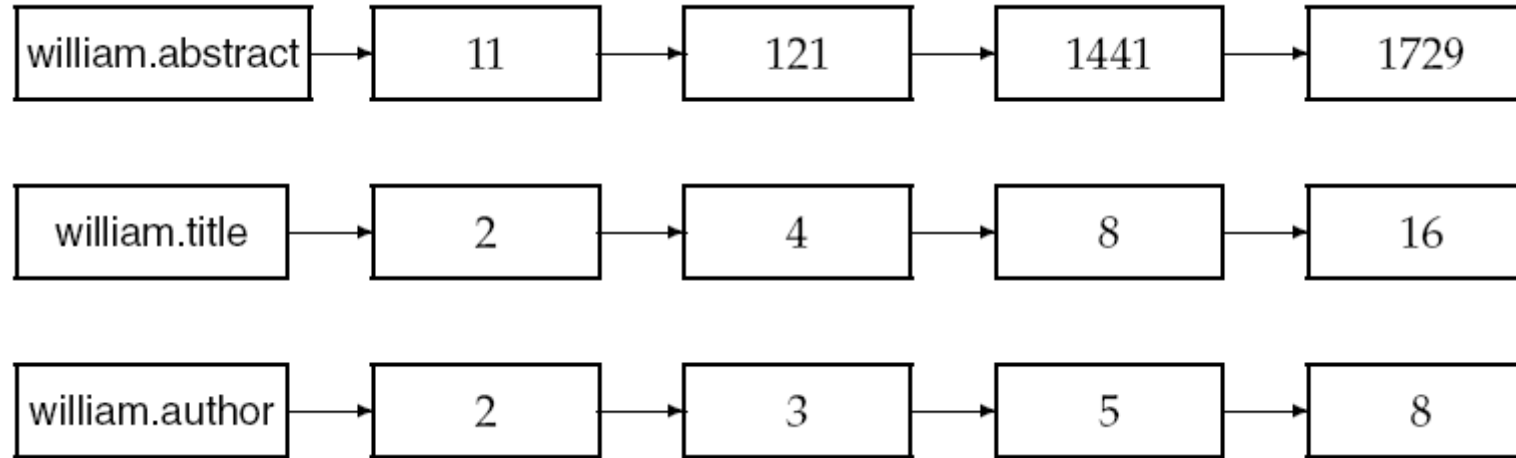


ZONES

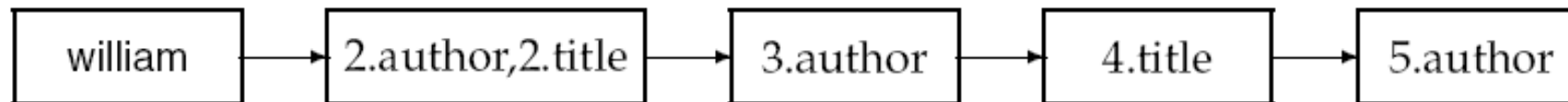
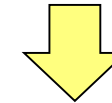
Zone

- A zone is a region of the doc that can contain an arbitrary amount of text e.g.,
 - Title
 - Abstract
 - References ...
- Build inverted indexes on zones as well to permit querying
 - e.g., find docs with *merchant* in the title zone and “*gentle rain*” in the body.

Example Zone Indexes



Encode zones in dictionary vs. postings.



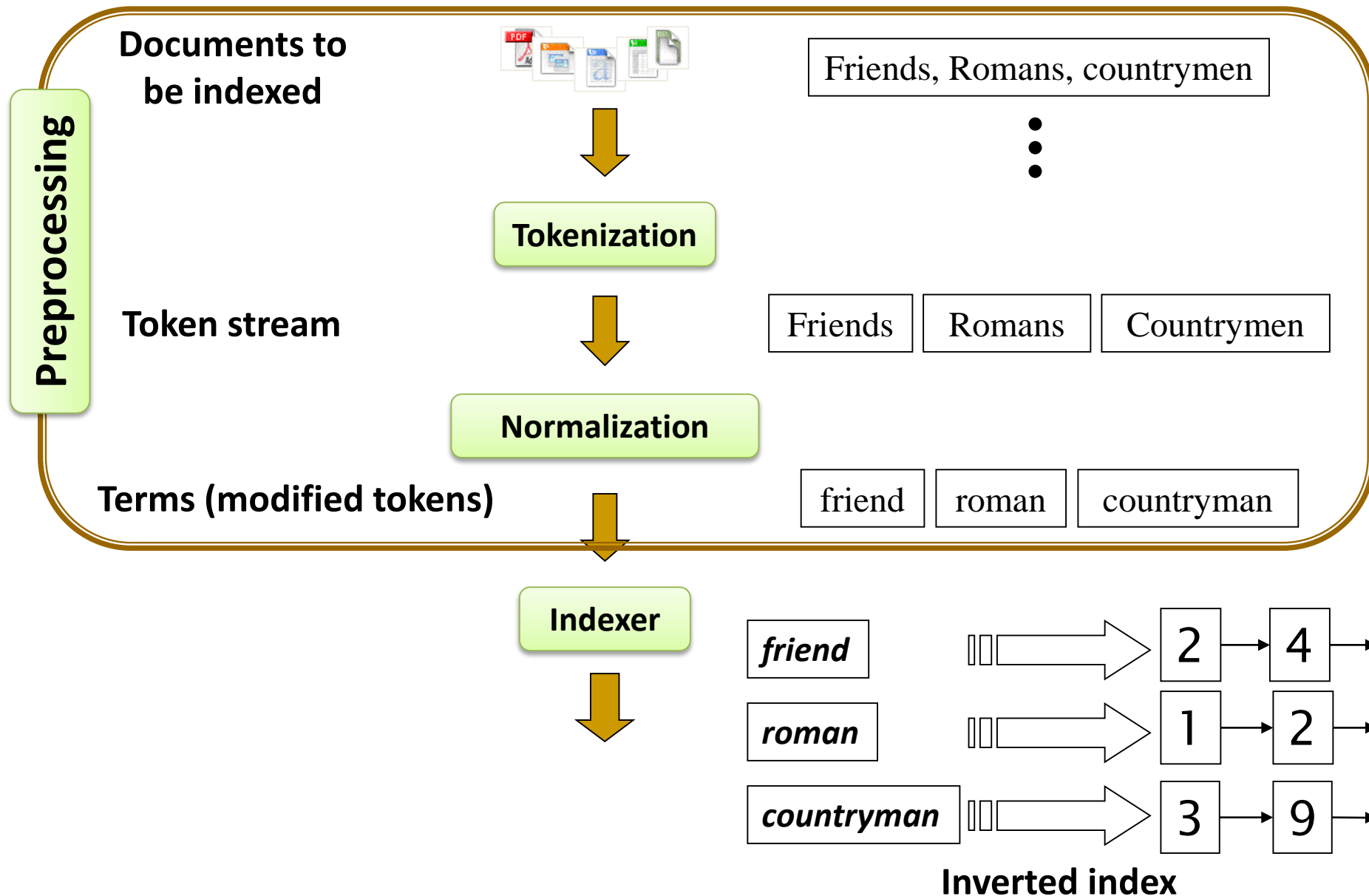


Today's Roadmap

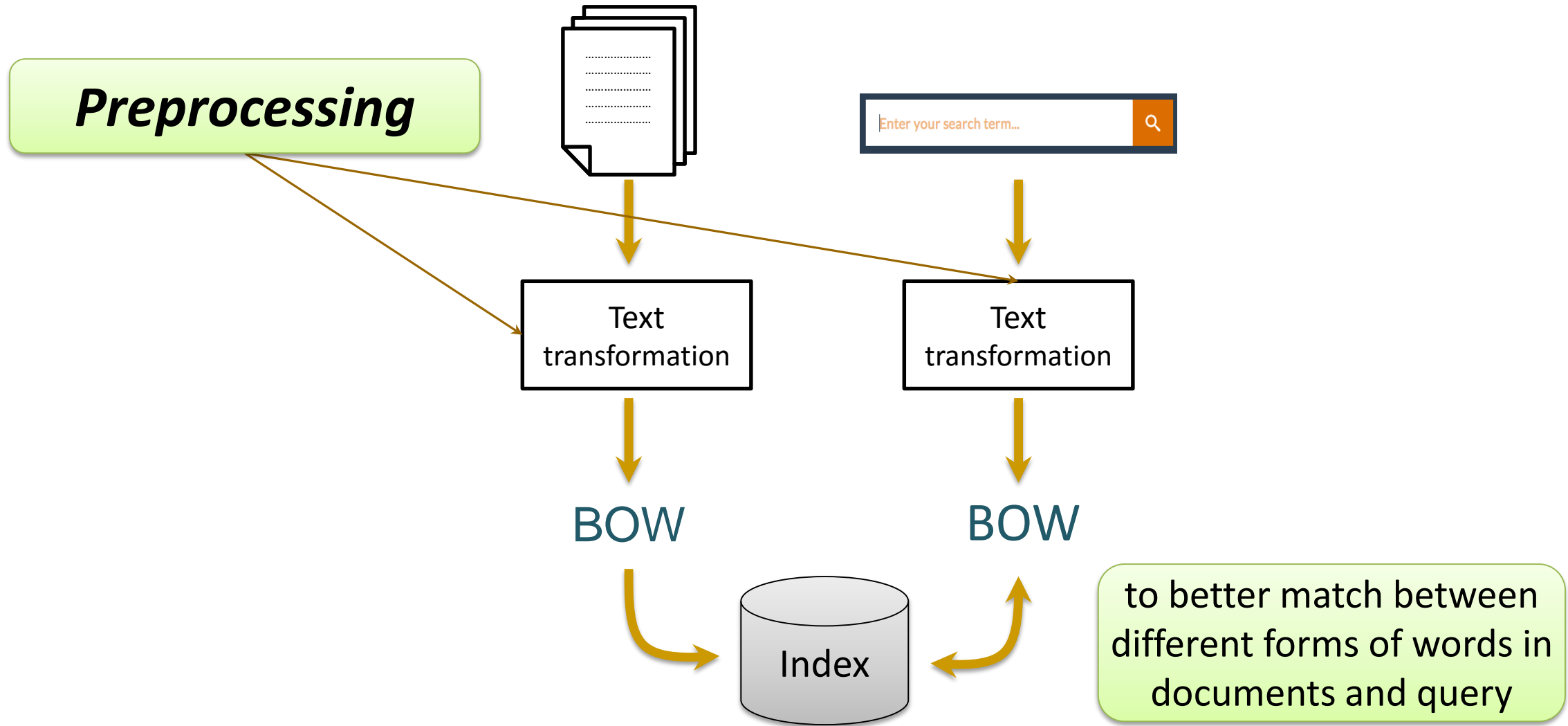
- The anatomy of a search engine
- Indexing
- Preprocessing



The Basic Indexing Pipeline



Preprocessing



Preprocessing Steps

1. Tokenization
2. Stopping
3. Stemming

Objective: identify the optimal form of the term to be indexed to achieve the best retrieval performance.

Before Tokenization ...

○ Encoding & Parsing a Document

- Which encoding/character set?
- What format? pdf/word/excel/html?
- What language?
- Each is classification problem
- BUT often done heuristically, by user selection, or by metadata

*Byte sequence →
Character sequence*

○ What is a Unit Document?

- A file? An email? A group of files (PPT)?
A book (a chapter/paragraph/sentence)?
- Understand collection, user, and usage patterns

Where to Stop?



TOKENIZATION

Tokenization

○ Sentence → tokenization (splitting) → tokens

○ Input: “*Friends, Romans and Countrymen*”

○ Output: Tokens

- *Friends*
- *Romans*
- *and*
- *Countrymen*

*But what are
valid tokens to emit?*

○ A **token** is an instance of a sequence of characters

○ Each such token is now a candidate for an index entry (**term**),
after further processing.

Issues in Tokenization

○ *Finland's capital* → *Finland? Finlands? Finland's?*

○ *Hewlett-Packard* → one token or two?

- *state-of-the-art*: break up hyphenated sequence.
- *co-education*
- *lowercase, lower-case, lower case ?*
- It can be effective to get the user to put in possible hyphens

○ *San Francisco*: one token or two?

- How do you decide it is one token?

○ Numbers?

- *3/20/91 Mar. 12, 1991 20/3/91*
- This course code is CMPT621
- *(800) 234-2333*

Issues in Tokenization

○ URLs:

- *<http://www.bbc.co.uk>*
- *<http://www.bbc.co.uk/news/world-europe-41376577>*

○ Social Media

- *Black lives matter*
- *#Black_lives_matter*
- *#BlackLivesMatter*
- *#blacklivesmatter*
- *@blacklivesmatter*

Language-dependent Issues

○ French

- *L'ensemble* → one token or two?
 - *L ? L' ? Le ?*
 - Want *l'ensemble* to match with *un ensemble*
 - Until at least 2003, it didn't on Google

○ German noun compounds are not segmented

- *Lebensversicherungsgesellschaftsangestellter*
- 'life insurance company employee'
- German retrieval systems benefit greatly from a **compound splitter** module
 - Can give a 15% performance boost for German

○ Chinese and Japanese have no spaces between words:

- 莎拉波娃现在居住在美国东南部的佛罗里达。
- Tokenization → Segmentation

Tokenization: common practice

- Just split at non-letter characters
- Add special cases if required
- Some applications have special setup
 - Social media: hashtags/mentions handled differently
 - URLs: no split, split at domain only, remove entirely!
 - Medical: proteins & diseases names



STOP WORD REMOVAL

Stopping (stop words removal)

- ~~This is a very~~ exciting lecture ~~on the~~ technologies ~~of~~ text
- **Stop words:** the most common words in collection
→ the, a, is, he, she, I, him, for, on, to, very, ...
- They have little semantic contribution
- They appear a lot \approx 30-40% of text
- New stop words appear in specific domains
 - e.g., “RT” in Tweets: *“RT @realDonaldTrump Mexico will ...”*
- Stop words
 - influence on sentence structure
 - less influence on topic (aboutness)

Stopping: always apply?

- Sometimes very important:

- Phrase queries: “Let it be”, “To be or not to be”
- Relational queries:
 - flights to Doha from London
 - flights from Doha to London

- In Web search, trend is to keep them:

- Good compression techniques means the space for including stop words in a system is small.
- Good query optimization techniques mean you pay little at query time for including stop words.

Stopping: common practice

- Common practice in many applications
 - remove stop words
- There are common stop words list for each language
 - NLTK (Python)
 - Lucene (Java)
 - <http://members.unine.ch/jacques.savoy/clef/index.html>
- There are special stop words list for some applications

How to create your own list?







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Can tokenization affect retrieval effectiveness?

- Yes
- No

Stop words should usually have very high document frequency

- Yes
- No



NORMALIZATION

Normalization

- **Objective** → make words with different surface forms look the same
- Document: “there are few CARS!!”
Query: “car”
should “car” match “CARS”?
- Sentence → tokenization → **tokens** → normalization → **terms** to be indexed (vocabulary/dictionary).

Case Folding

- “A” & “a” are different strings for computers
- Case folding: convert all letters to lower case
- CAR, Car, caR → car
- Windows → windows
 - should we do that?
 - Usually yes, users are so lazy
- Upper case in mid-sentence?
 - I bought it from **General Motors**
 - **Black** vs. **black**

Thesauri and Soundex

○ Do we handle synonyms?

- e.g., by hand-constructed equivalence classes
 - *car* = *automobile* *color* = *colour*
- We can rewrite to form equivalence-class terms
 - When the document contains *automobile*, index it under *car-automobile* (and vice-versa)
- Or we can expand a query
 - When the query contains *automobile*, look under *car* as well

○ What about spelling mistakes?

- One approach is soundex, which forms equivalence classes of words based on phonetic heuristics

Lemmatization

- Lemmatization implies doing “proper” reduction to the “base” or dictionary form, called **lemma**.
 - Morphological analysis
- Reduce inflectional/variant forms to base form
- e.g.,
 - *am, are, is* → *be*
 - *saw* → *see*
 - *car, cars, car's, cars'* → *car*

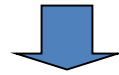
Stemming

- Search for: “play”
should it match: “plays”, “played”, “playing”, “player”?
- Many morphological variations of words
 - *inflectional* (plurals, tenses)
 - *derivational* (making verbs nouns, etc.)
- In most cases, aboutness does not change.
- Stemmers attempt to reduce morphological variations of words to a common **stem**.

Stemming

- “Stemming” suggests crude affix chopping
 - language dependent
 - e.g., *automate*, *automates*, *automatic*, *automation* all reduced to *automat*.

for example compressed and compression are both accepted as equivalent to compress.



for **exampl** **compress** and **compress** **ar** both **accept** as
equival to compress

Porter Stemmer

- Most common algorithm for stemming English
- Conventions + 5 phases of reductions
 - phases applied sequentially
 - each phase consists of a set of commands
- Example convention: *Of the rules in a compound command, select the one that applies to the longest suffix.*
- Example rules
 - *sses* → *ss* (processes → process)
 - *y* → *i* (reply → repli)
 - *ies* → *i* (replies → repli)
 - *tional* → *tion* (international → internation)
 - *(m>1)ement* → (replacement → replac), (cement → cement)

Stemming: is it really useful?

- Usually, it achieves 5-10% improvement in retrieval effectiveness, e.g. English.
- For highly inflected languages, it is more critical:
 - 30% improvement in Finnish IR
 - 50% improvement in Arabic IR

They are Ahmad's **children**
The **children** behaved well
Her **children** are cute
My **children** are funny
We have to save **our children**
Patents and **children** are happy
He loves **his children**
His **children** loves him

هؤلاء **أبناء** أحمد
الأبناء تصرفوا جيدا
أبناءها لطاف
أبنائي ظرفاء
علينا أن نحمي **أبناءنا**
الآباء والأبناء سعداء
هو يحب **أبناءه**
أبنائه يحبونه

Stemmed words are misspelled ?!

- repli, replac, suppli, inform retriev, anim
- These are not words anymore, these are terms.
- These terms are not seen by the user, but just used by the IR system (search engine).
- These represent the optimal form for a better match between different surface forms of a word.
 - e.g. replace, replaces, replaced, replacing, replacer, replacers, replacement, replacements → replac.





Same tokenization/normalization steps should be applied to documents and queries.

- Yes, always!
- No, they can be different of course

The dictionary in the index includes ...

- words
- tokens
- terms
- all of the above

Preprocessing: common practice

- Tokenization: split at non-letter characters
 - For tweets, you might want to keep “#” and “@”.
- Remove stop words
 - find a common list, and filter these words out.
- Apply case folding
- Apply Porter stemmer (or others for other languages)
 - Other stemmers are available, but Porter is the most famous with many implementations available in different programming languages.

Summary

○ Pre-processing:

- Tokenization → Stopping → Stemming

This is an **example sentence** of how the **pre-processing** is **applied** to **text** in **information retrieval**. It **includes**: **Tokenization**, **Stop Words Removal**, and **Stemming**



exampl sentenc pre process appli text inform retriev includ token
stop word remov stem



*How can we know
if a search engine is “good” or “bad”?*

