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Information Retrieval

Document Understanding

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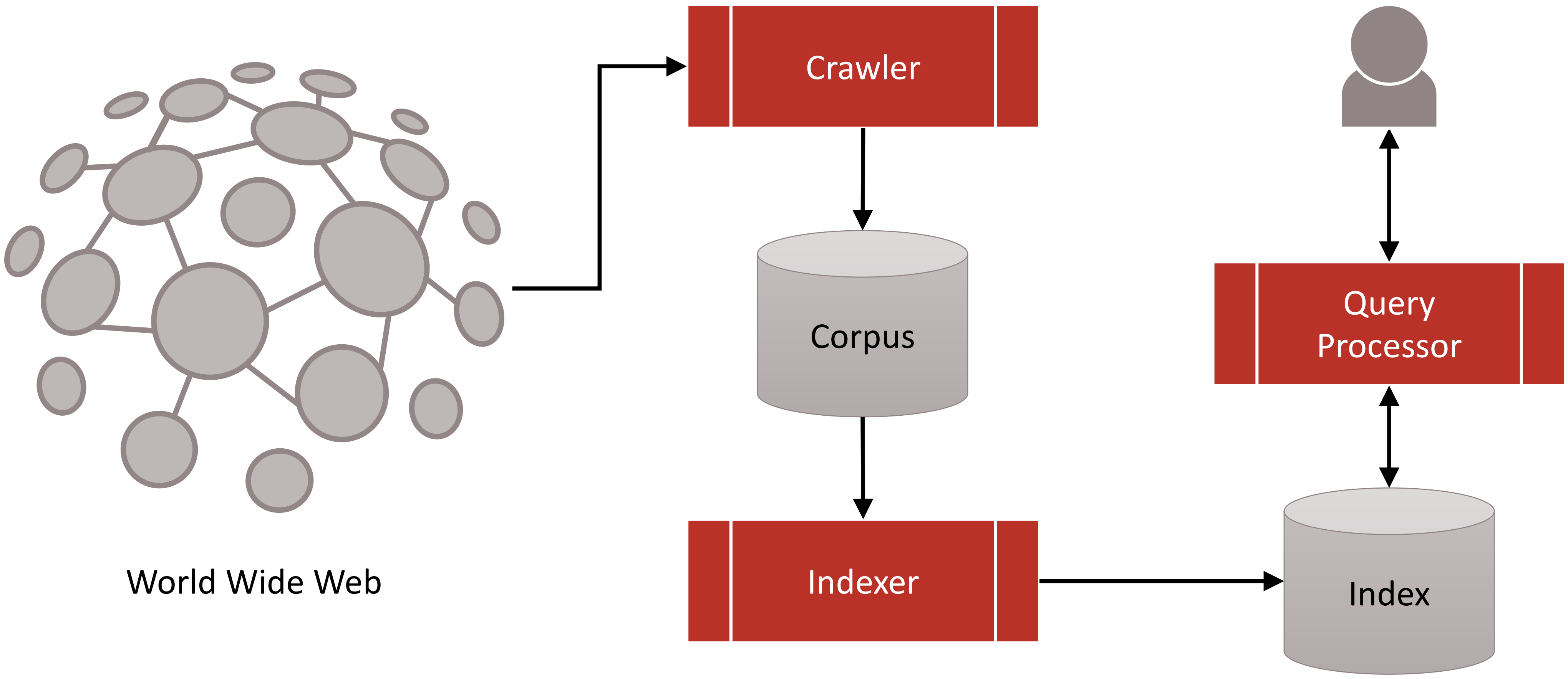
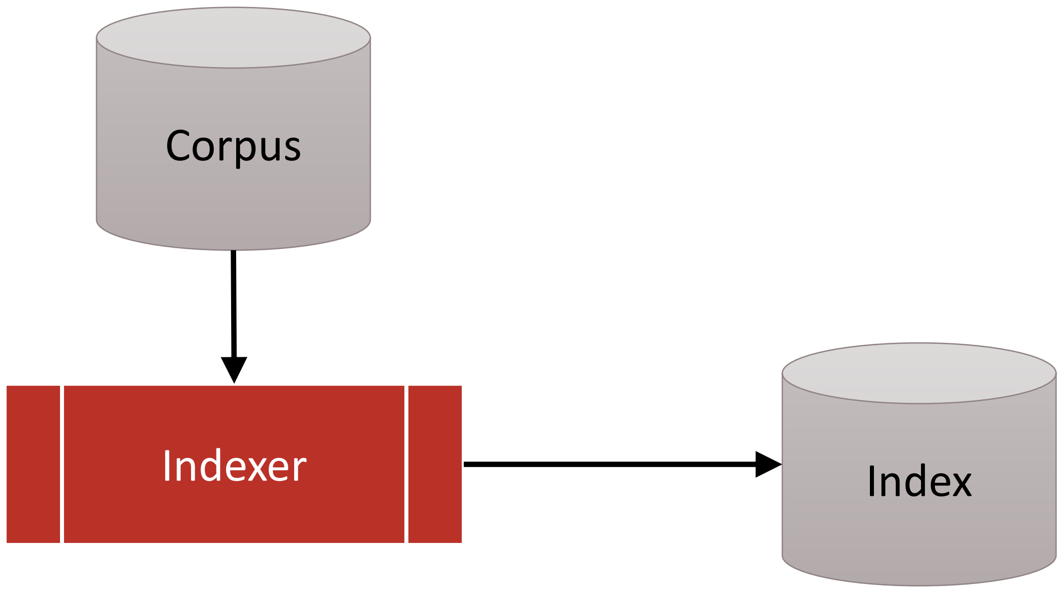
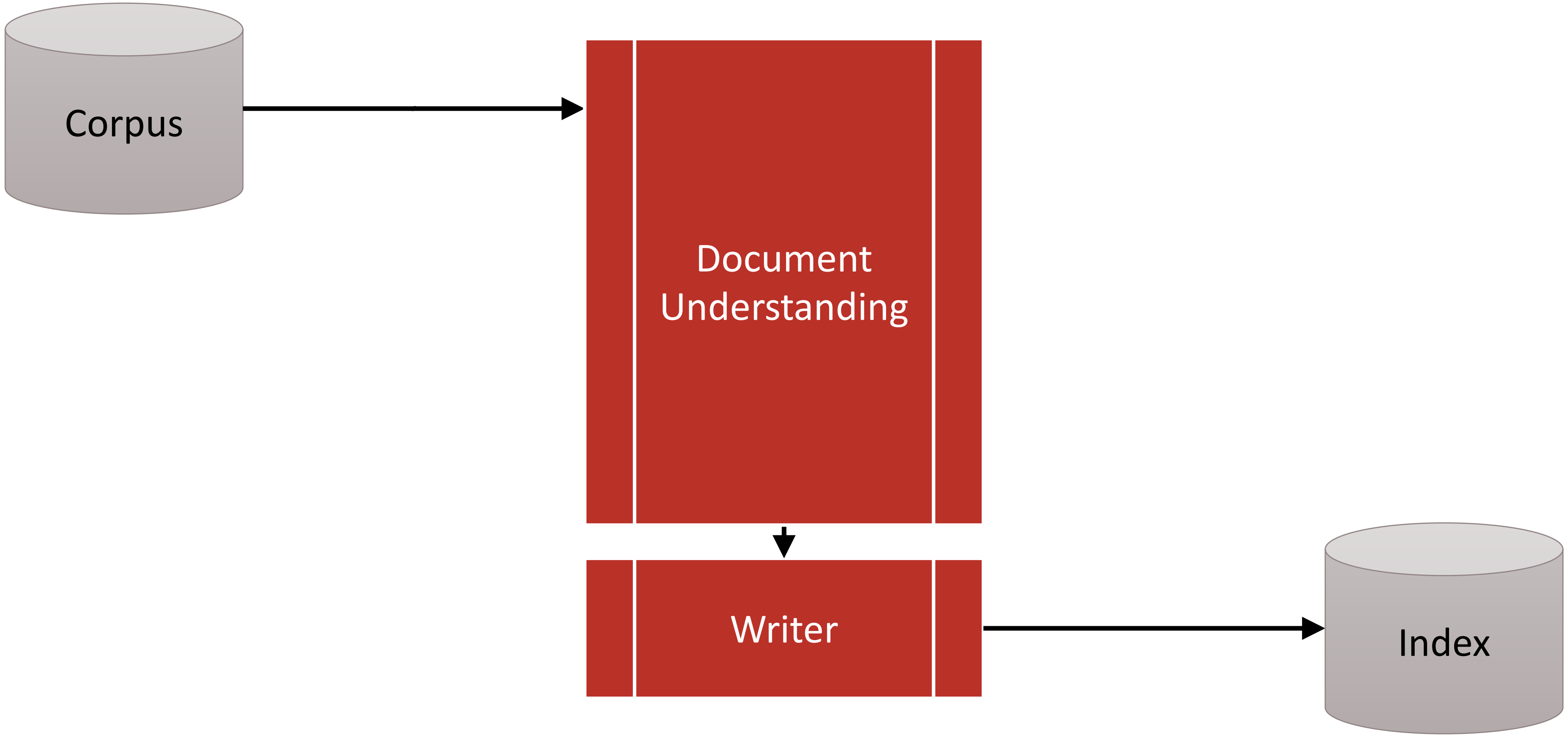
Search components



Search components



Indexing overview



Document understanding

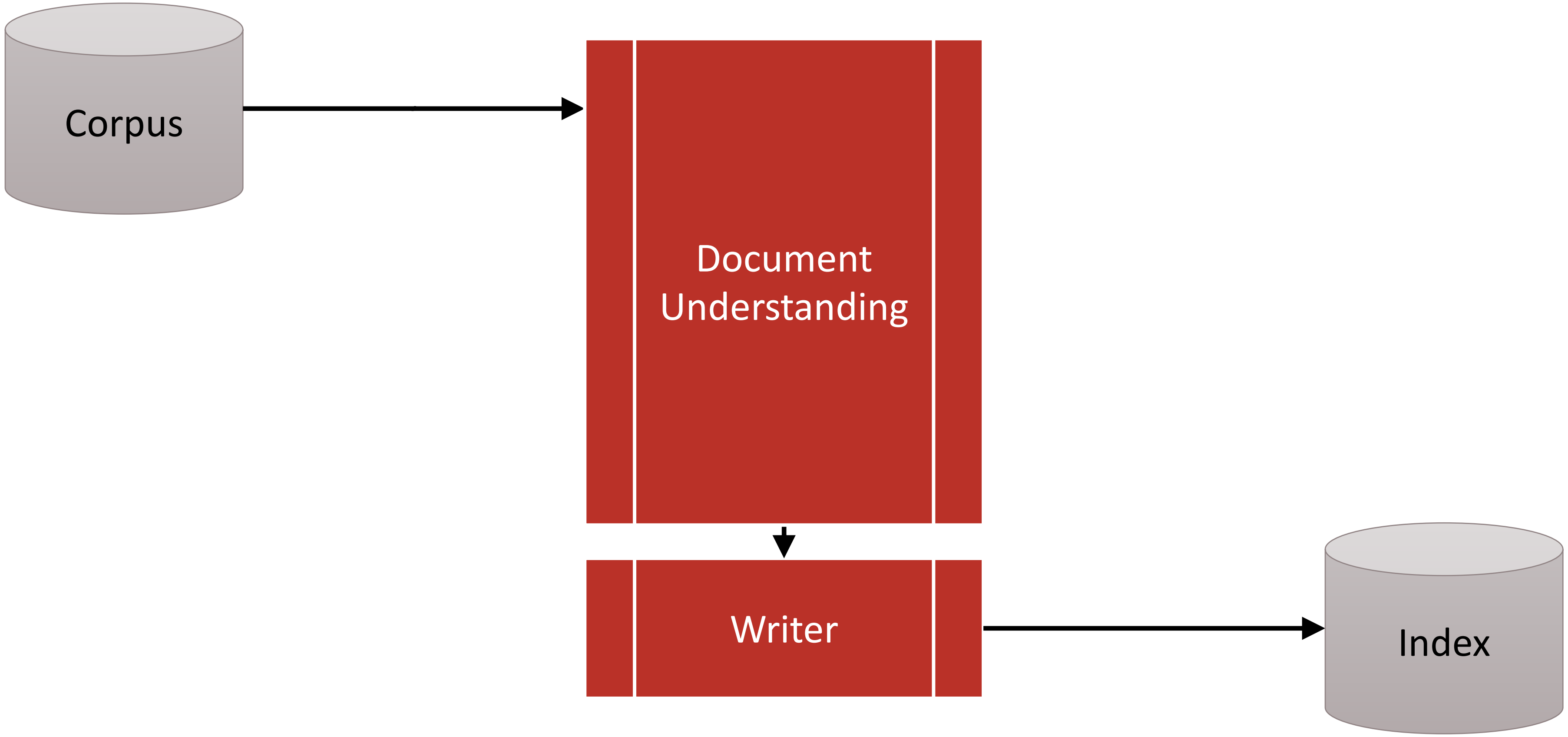
Making sense of text is a challenging task

- Not always clear what a document is
- Not always clear what a term is

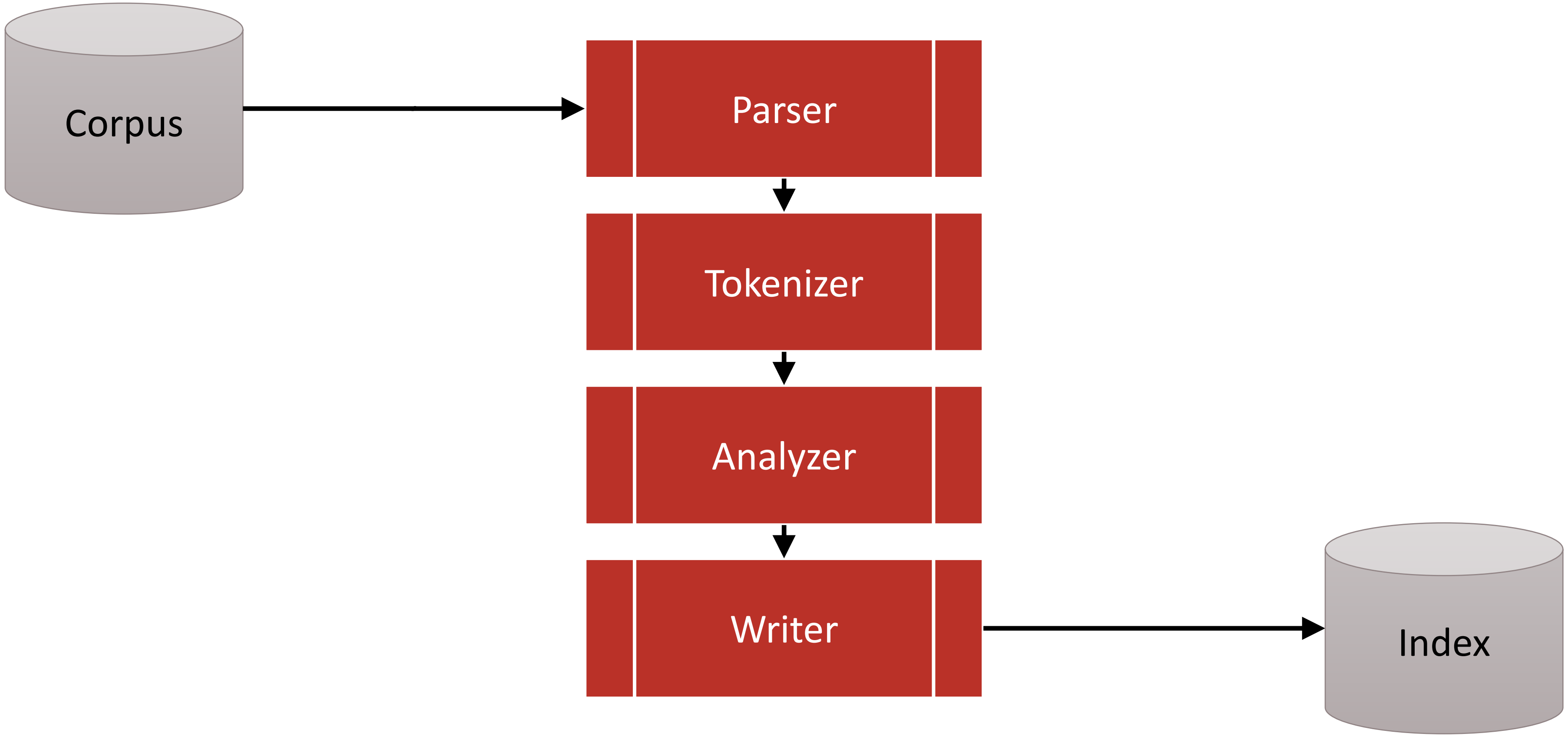
Matching exact strings is too restrictive

- Not all words are of equal value in a search

Indexing overview



Indexing overview



Document parsing

We previously assumed

- We know what a document is
- We can “machine-read” each document

This can be complex in reality…

What is a document?

Or, in IR parlance, what is our retrieval unit?

- A single file?
- How about an email with 5 attachments?
- Or a book with 15 chapters?

What content types will be accepted?

- text/html? application/pdf? application/msword?

How to read a document?

Must handle structure

- Text vs. binary, plain text vs. markup

It ain’t always beautiful

```
<div id="foo">
  <div id="bar">
    <span>Test</span>
</div>
```

How to read a document?

Must handle encoding

- Translate between bits and characters

Sometimes, multiple, ill-specified ones

ノーベル平和賞を受賞したワンガリ・マータイさんが名
誉会長を務めるMOTTA I NA Iキャンペーンの一環として、
毎日新聞社とマガジンハウスは「私の、もったいない」
を募集します。皆様が日ごろ「もったいない」と感じて
実践していることや、それにまつわるエピソードを800字
以内の文章にまとめ、簡単な写真、イラスト、図などを
添えて10月20日までにお送りください。大賞受賞者には5
0万円相当の旅行券とエコ製品2点の副賞が贈られます

Document tokenization

All along the watchtower
Princes kept the view
While all the women came and went
Barefoot servants, too
Outside in the cold distance
A wildcat did growl
Two riders were approaching
And the wind began to howl

all	while
along	all
the	the
watchtower	women
princes	came
kept	and
the	went
view	…

How to tokenize?

One simple strategy (early IR systems)

- Any sequence of 3+ alphanumeric characters
- Terminated by a space or other special character
- Upper-case changed to lower-case

What could go wrong?

What could go wrong?

Bigcorp's 2007 bi-annual report showed profits of 10%.

↳ bigcorp s 2007 bi annual report showed profits of 10

↳ bigcorp 2007 annual report showed profits

Too much information lost

- Small tokenization decisions can have a major impact on the effectiveness of some queries

Token length

Small words tend to be poorly discriminative

- a, an, be, of, to…

But they can also aid disambiguation

- ben e king, el paso, master p, world war ii

And even be crucial for matching

- xp, ma, pm, gm, j lo, c

Special characters

Apostrophes can be a part of a word, a part of a possessive, or just a mistake

- rosie o'donnell, can't, don't, 80's, master's degree

Accents and diacritics can change meaning

- résumé vs. resume, cocô vs. coco

Special characters

Periods can occur in numbers, abbreviations, URLs, ends of sentences, and other situations

- I.B.M., Ph.D., cs.umass.edu, F.E.A.R.

Hyphens are often not needed

- e-bay, wal-mart, active-x, cd-rom, t-shirts

Numbers and lowercasing

Numbers can be important, including decimals

◦ nokia 3250, top 10 courses, united 93, quicktime 6.5

Lowercasing can change meaning

◦ Bush vs. bush, Apple vs. apple

Non-delimited tokens

How to tokenize this?

White House aides wrestle with Trump’s comments

How about these?

whitehouse.gov, #ImpeachTrump

And this?!?!

莎拉波娃现在居住在美国东南部的佛罗里达

Token analysis

Discriminative power

Equivalence classing

Phrasing

Scoping

Discriminative power

Tropical fish are generally those fish found in aquatic tropical environments around the world, including both freshwater and saltwater species.

Document frequency (in millions)

saltwater	46	and	25,270
freshwater	95	in	25,270
aquatic	118	the	25,270
species	377	are	15,830

Stopping

Discard poorly discriminative words (aka ***stopwords***)

- a, an, and, are, as, at, be, by, for, from, has, he, in, is, it, its, not, of, on, or, that, the, to, was, were, will, with

Can be standardized or automatically derived

- Can be domain-specific (e.g. ”click” for anchor text)

Stopping

Reduce index space and response time

- May improve effectiveness

Discouraged in modern search engines

- Stopwords can be important in combinations

  To be, or not to be: that is the question.

  ↳ question

Equivalence classing

Reduce words to a canonical form

- Lexical equivalence
- Phonetic equivalence
- Semantic equivalence

Lexical equivalence

Many morphological variations of words

- Inflectional (e.g., plurals, tenses)
- Derivational (e.g., making verbs into nouns)

In most cases, these have very similar meanings

- swimming, swam → swim

Stemming

Reduce morphological variations to a stem

- Usually involves removing suffixes

Crude approximation of a principled lemmatization

- Ignores grammatical category
- Ignores surrounding context

Runs ***much*** faster!

Porter’s stemmer

A set of sequentially applied rules

Rule	**Example**
SSES → SS	caresses → caress
IES → I	ponies → poni
SS → SS	caress → caress
S →	cats → cat

Stemming effectiveness

Stemming usually improves recall

- But can potentially hurt precision

False positive equivalence

- universal, university, universe → univers

False negative equivalence

- alumnus → alumnu, alumni → alumni

Phonetic and semantic equivalence

Phonetic equivalence

- Reduce similar-sounding words to same form (e.g., Hermann ↔ Herman)

Semantic equivalence

- Reduce multiple surface forms to same entity (e.g., car ↔ automobile)

Phrasing

Many queries are 2-3 word phrases

- [bob dylan lyrics]

More precise than single words

- Documents with “bob dylan” vs. “bob” and “dylan”

Less ambiguous

- “big apple” vs. “apple”

Phrasing

Two broad strategies

- Syntactic phrasing
- Statistical phrasing

Syntactic phrasing

Part-of-speech (POS) taggers can label words according to their syntactic role in natural language

- e.g., NN (singular noun), NNS (plural noun), VB (verb), VBD (verb, past tense), VBN (verb, past participle)

Phrases can be identified as simple noun groups

- Sequences of nouns, adjectives followed by nouns…

POS tagging example

Document will describe marketing strategies carried out by U.S. companies for their agricultural chemicals.

↳ Document/NN will/MD describe/VB marketing/NN strategies/NNS carried/VBD out/IN by/IN U.S./NNP companies/NNS for/IN their/PRP agricultural/JJ chemicals/NNS ./.

POS tagging example

Document will describe marketing strategies carried out by U.S. companies for their agricultural chemicals.

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Statistical phrasing

POS tagging is too slow for large collections

- Do we need a full syntactic analysis?

Simpler definition: phrases as n-grams

- Unigram: single words
- Bigram: 2-word sequence
- Trigram: 3-word sequence

Statistical phrasing

N-gram frequencies form a Zipf distribution

- Some very frequent, lots less frequent
- Frequent n-grams tend to be meaningful phrases

Could index all n-grams up to a specified length

- Much faster than POS tagging
- Uses a lot of storage

Statistical phrasing

Google n-grams
[Franz and Brants, 2006]

# tokens	1,024,908,267,229
# sentences	95,119,665,584
# 1-grams	**13,588,391**
# 2-grams	314,843,401
# 3-grams	977,069,902
# 4-grams	1,313,818,354
# 5-grams	1,176,470,663

Scoping

Documents often have structure

- HTML tags (e.g., h1, h2, p, a)

Not all parts are equally important

- Document title, URL, metadata, body sections

Can record the scope of word occurrences

- Enable scoped queries and structural ranking models

Summary

Document understanding improves representation

- Matching things rather than strings

Lots of important decisions

- May not know what’s best at indexing time

Keep it simple, but keep it all!

- Index everything, defer complexity to querying time

Summary

Indexing vs. querying

- Stopping
- Equivalence classing
- Phrasing
- Scoping

- Query relaxation
- Query expansion
- Query segmentation
- Query scoping

References

[Search Engines: Information Retrieval in Practice](), Ch. 4
Croft et al., 2009

[Introduction to Information Retrieval](), Ch. 2
Manning et al., 2008

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Coming next...

Document Indexing

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