# Informatics 225
# Computer Science 221

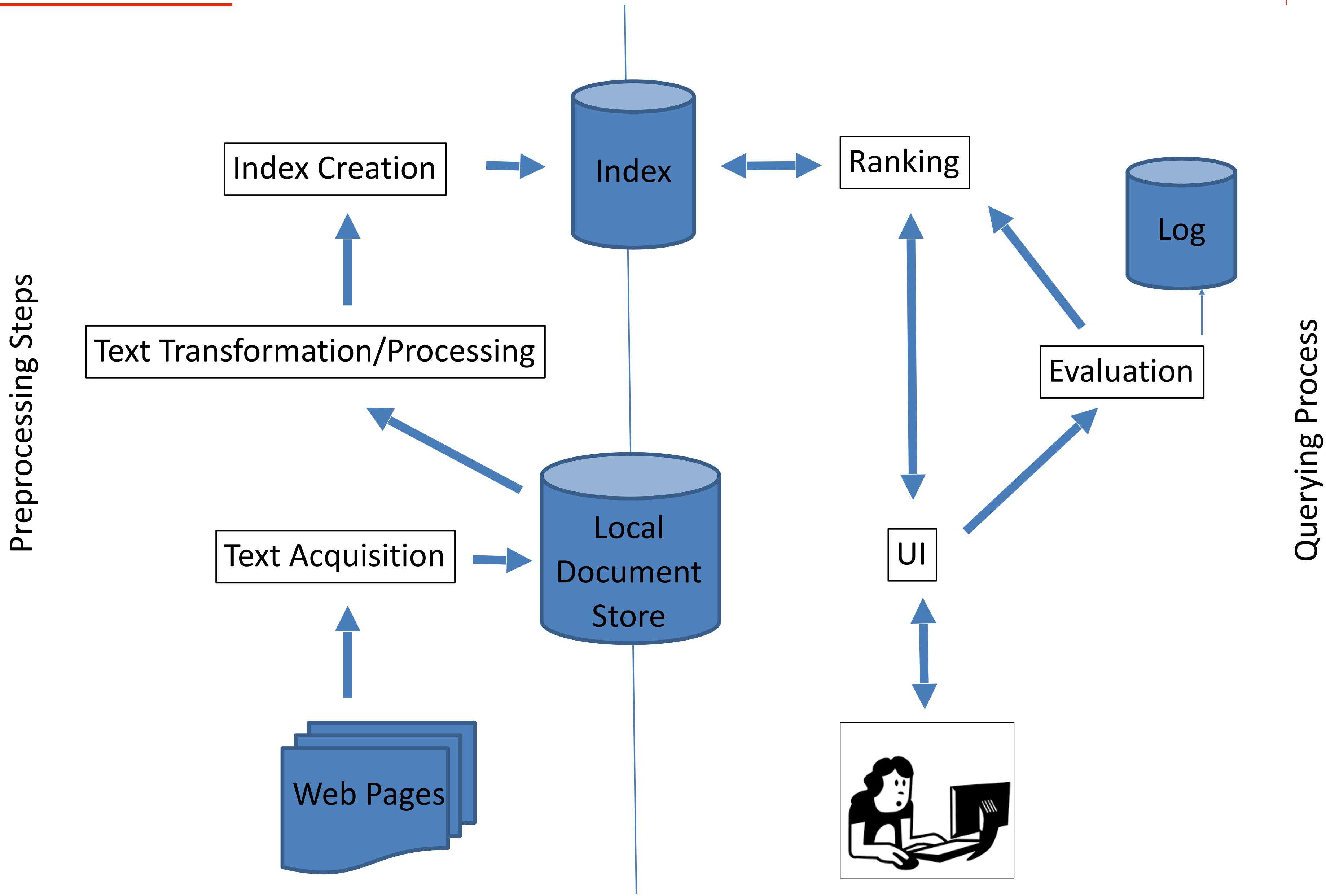
# Information Retrieval

Lecture 12



*These course materials borrow, with permission, from those of Prof. Cristina Videira Lopes, Prof. Alberto Krone-Martins, Addison Wesley 2008, Chris Manning, Pandu Nayak, Hinrich Schütze, Heike Adel, Sascha Rothe, Jerome H. Friedman, Robert Tibshirani, and Trevor Hastie. Powerpoint theme by Prof. André van der Hoek.*

# Architecture



# Detecting duplicates and removing noise

Information Retrieval

# Simhash

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- Simhash was introduced by Charikar, 2002 to combine the advantages of the word-based similarity measures with the efficiency of fingerprints based on hashing

  - *Similarity of pages measured by the cosine correlation is proportional to the number of bits that are the same in simhash fingerprints*

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(b) Words with weights

| | | | | | |
|---|---|---|---|---|---|
| tropical | 01100001 | fish | 10101011 | include | 11100110 |
| found | 00011110 | environments | 00101101 | around | 10001011 |
| world | 00101010 | including | 11000000 | both | 10101110 |
| freshwater | 00111111 | salt | 10110101 | water | 00100101 |
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| species | 1101111$\boxed{0}$ | | | | |

(c) 8 bit hash values

**3 = (2 -1 - 1 + 1 -1) + (2 + 1 -1 +1) + (-1 +1 -1 +1)**

1 -5 9 -9 3 1 3 $\boxed{3}$

(d) Vector $V$ formed by summing weights

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(c) 8 bit hash values

1  -5  9  -9  3  1  3  3

(d) Vector $V$ formed by summing weights

1  0  1  0  1  1  1  1

(e) 8-bit fingerprint formed from $V$

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- So, how similar are two text files A and B?
  - Compute the simhashes $H_A$ and $H_B$ for each text.

  - The similarity is simply the fraction of the bits that are the same over all n bits of the representation.

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- Are text A and text B near duplicates?
  - Define a threshold level τ.
  - If similarity is greater or equal than the threshold, they are near duplicates **under your definition of threshold.**

$$S_{A,B} \geq \tau \implies \text{A \& B are near duplicates}$$

# Removing noise

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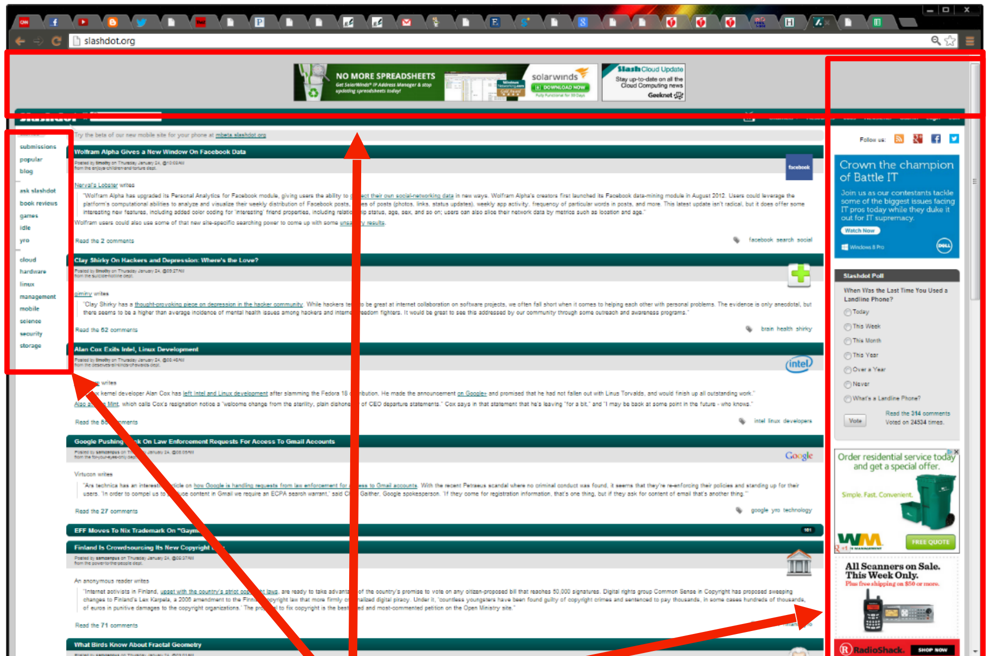
# Removing Noise

- Many web pages contain text, links, and pictures that are not directly related to the main content of the page

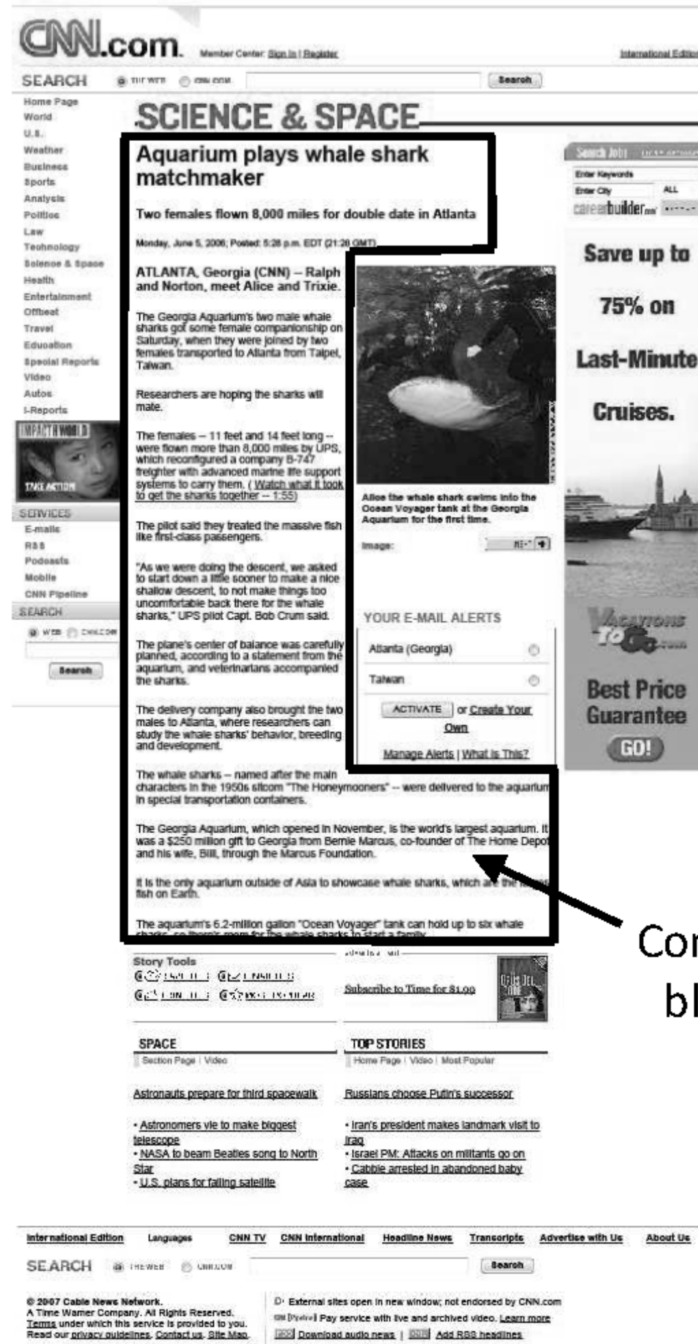
- This additional material is mostly *noise* that could negatively affect the ranking of the page

- Techniques have been developed to detect the content blocks in a web page
  - Non-content material is either ignored or reduced in importance in the indexing process

# Noise Example

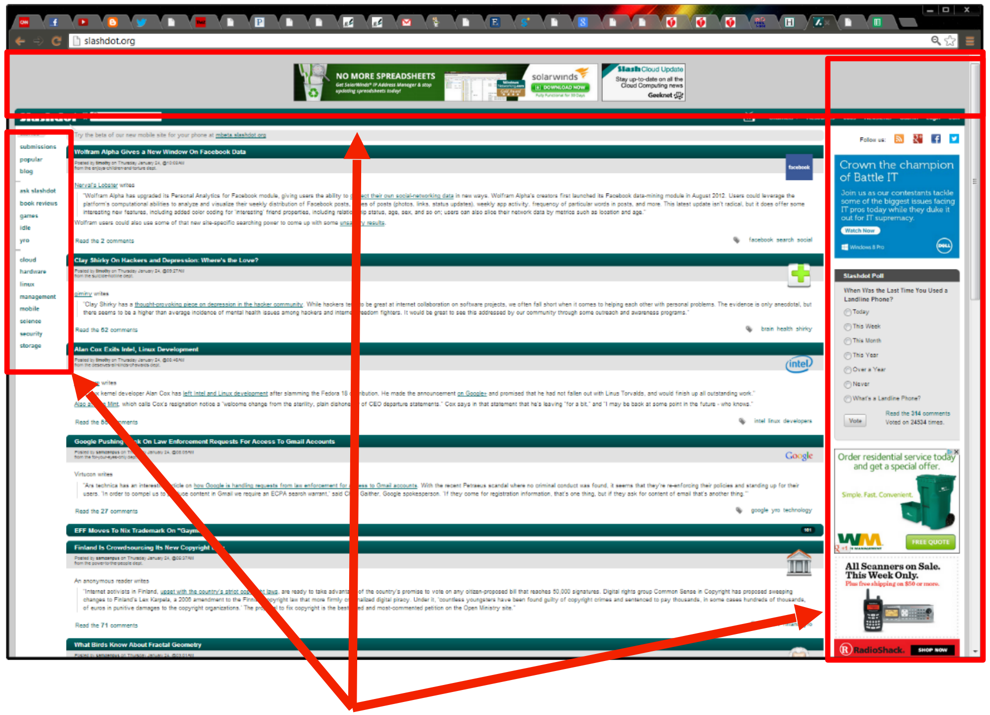



Noise blocks

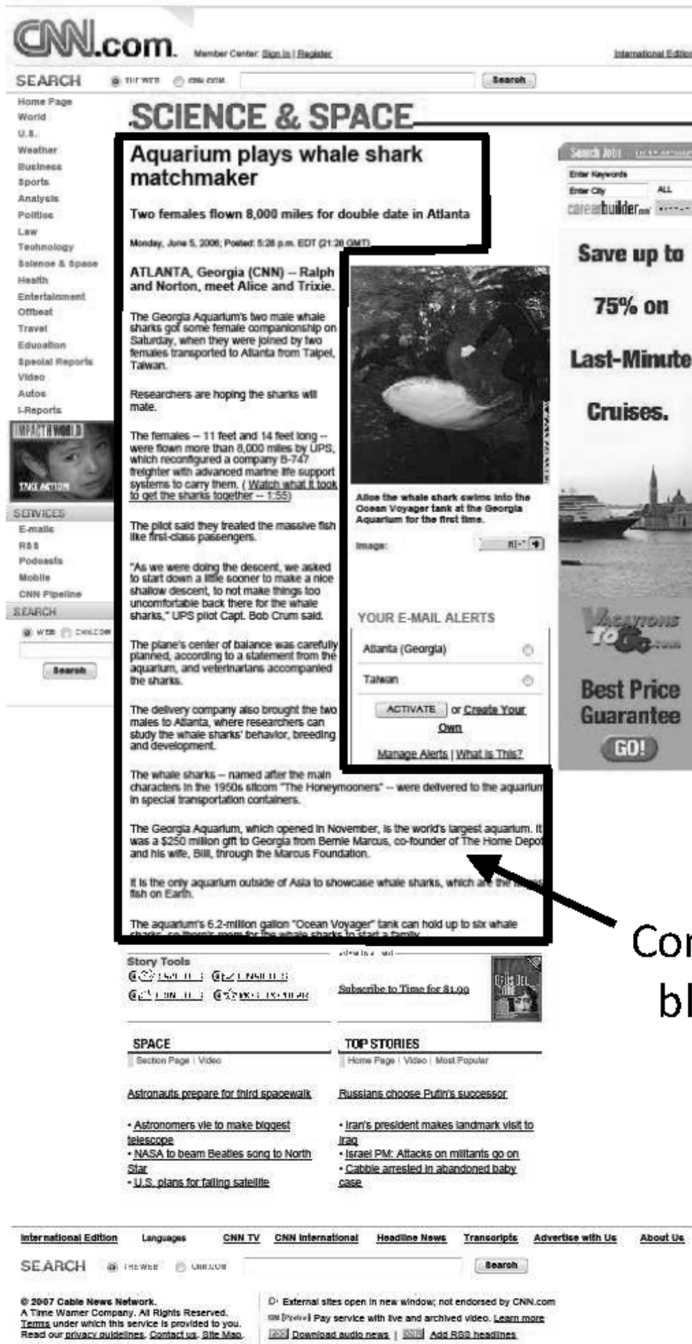



Content block

# Noise Example



Noise blocks

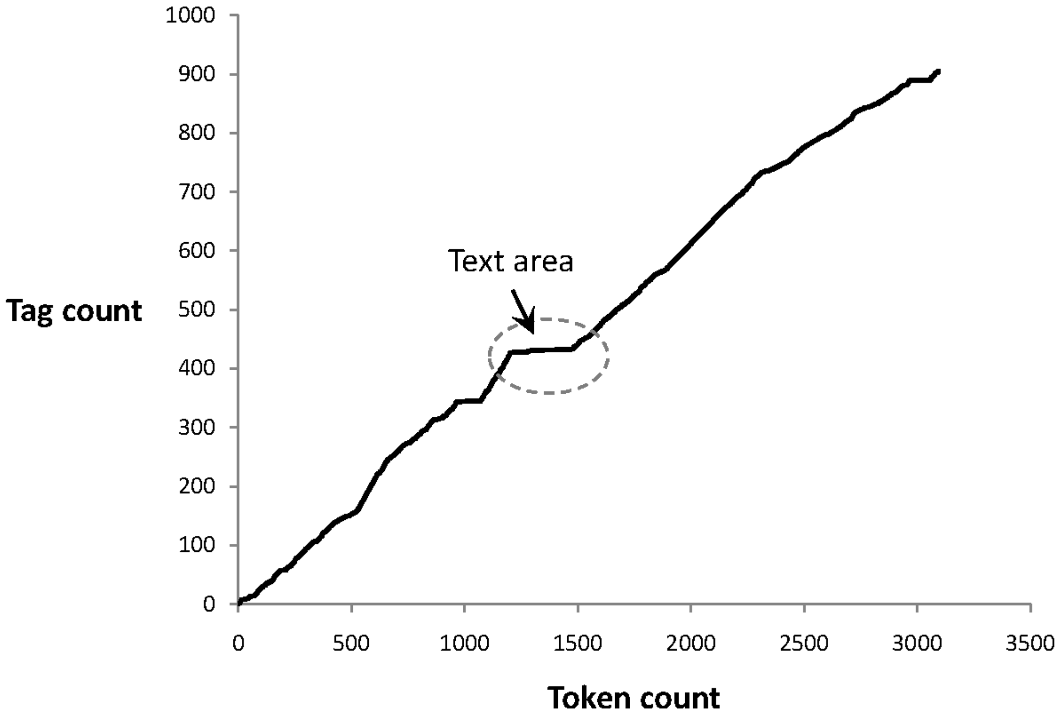


Content block

So how can you detect content?

# Finding Content Blocks

- Cumulative distribution of tags
  - Document slope curve (e.g. Finn, Kushmerick & Smyth, 2001)



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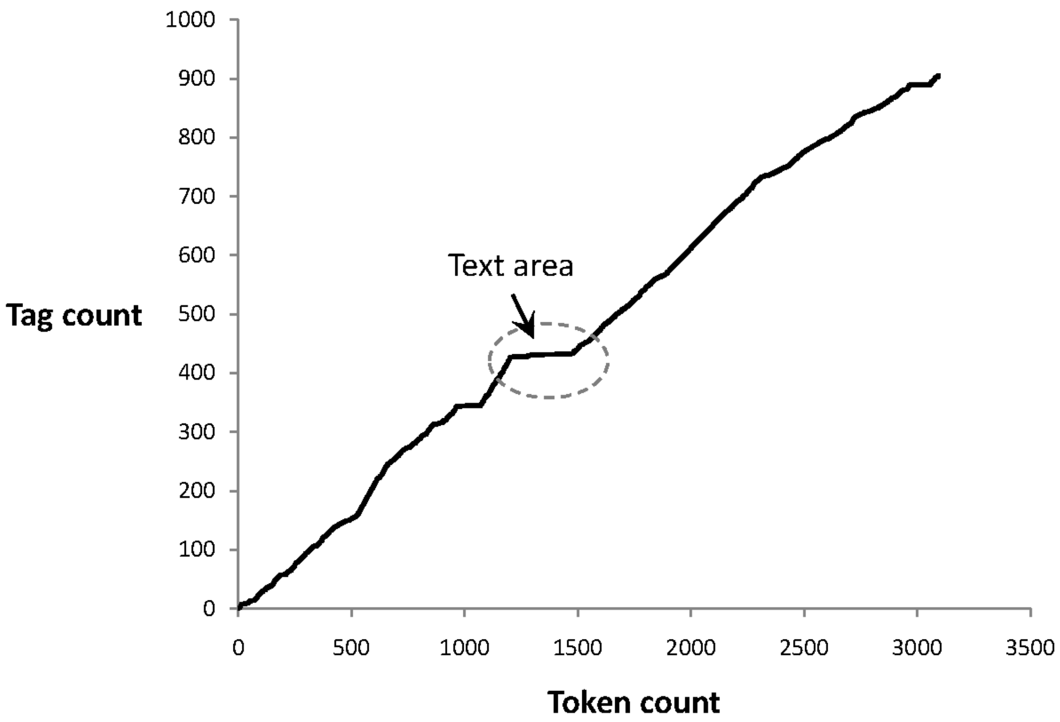


  – Main text content of the page corresponds to the "plateau" in the middle of the distribution

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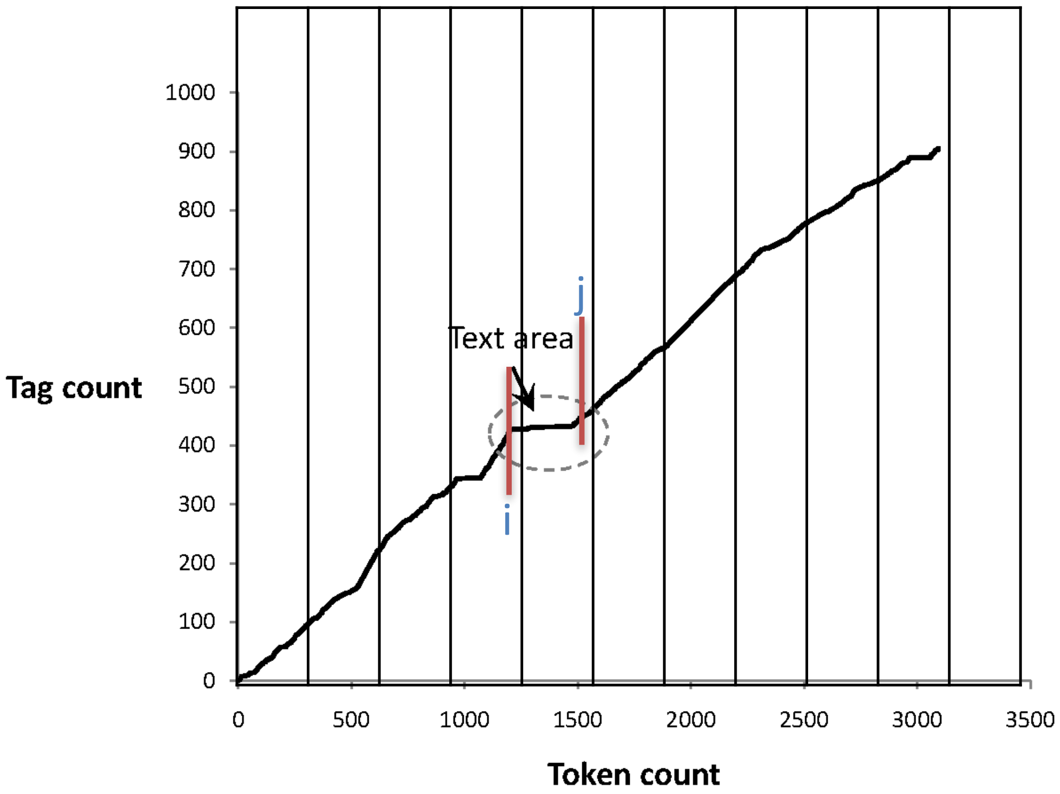
- Represent a **web page** as a **sequence** of **bits**, where $b_n = 1$ indicates that the ***n*th token is a tag**
- Optimization problem where we **find values of *i* and *j* to maximize** both the number of **tags below *i* and above *j* and** the number of **non-tag tokens between *i* and *j***
- i.e., find i and j that maximize

$$\sum_{n=0}^{i-1} b_n + \sum_{n=i}^{j} (1 - b_n) + \sum_{n=j+1}^{N-1} b_n$$

# Finding Content Blocks : Alternative

- Cumulative distribution of tags in the example web page

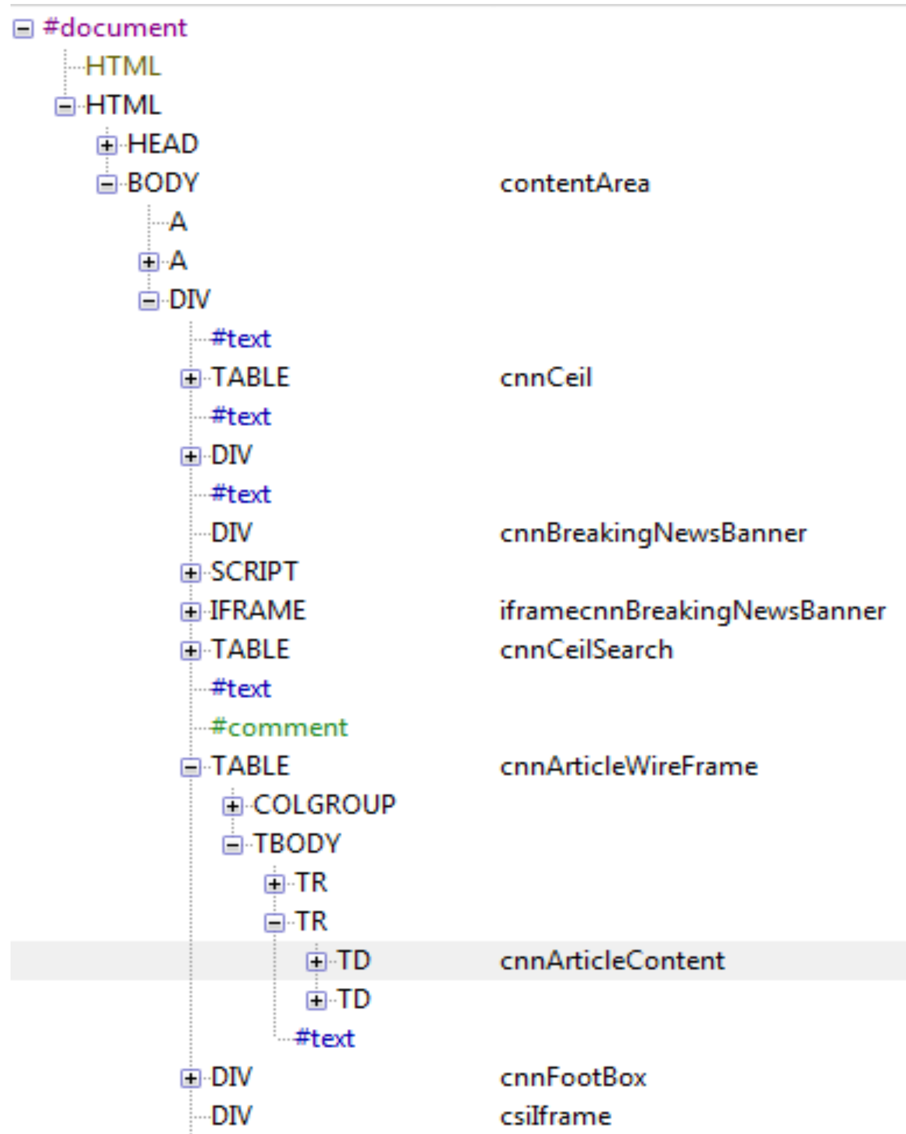



  - Determine the slope of the lines inside slices and iterate, reducing the slice size until you find zero slope windows.

# Finding Content Blocks

- Other approaches use Document Object Model (DOM) structure and visual (layout) features

- HTML parser:
  - HTML -> Document Object Model representation
  - Tree like structure



# Text processing : statistics

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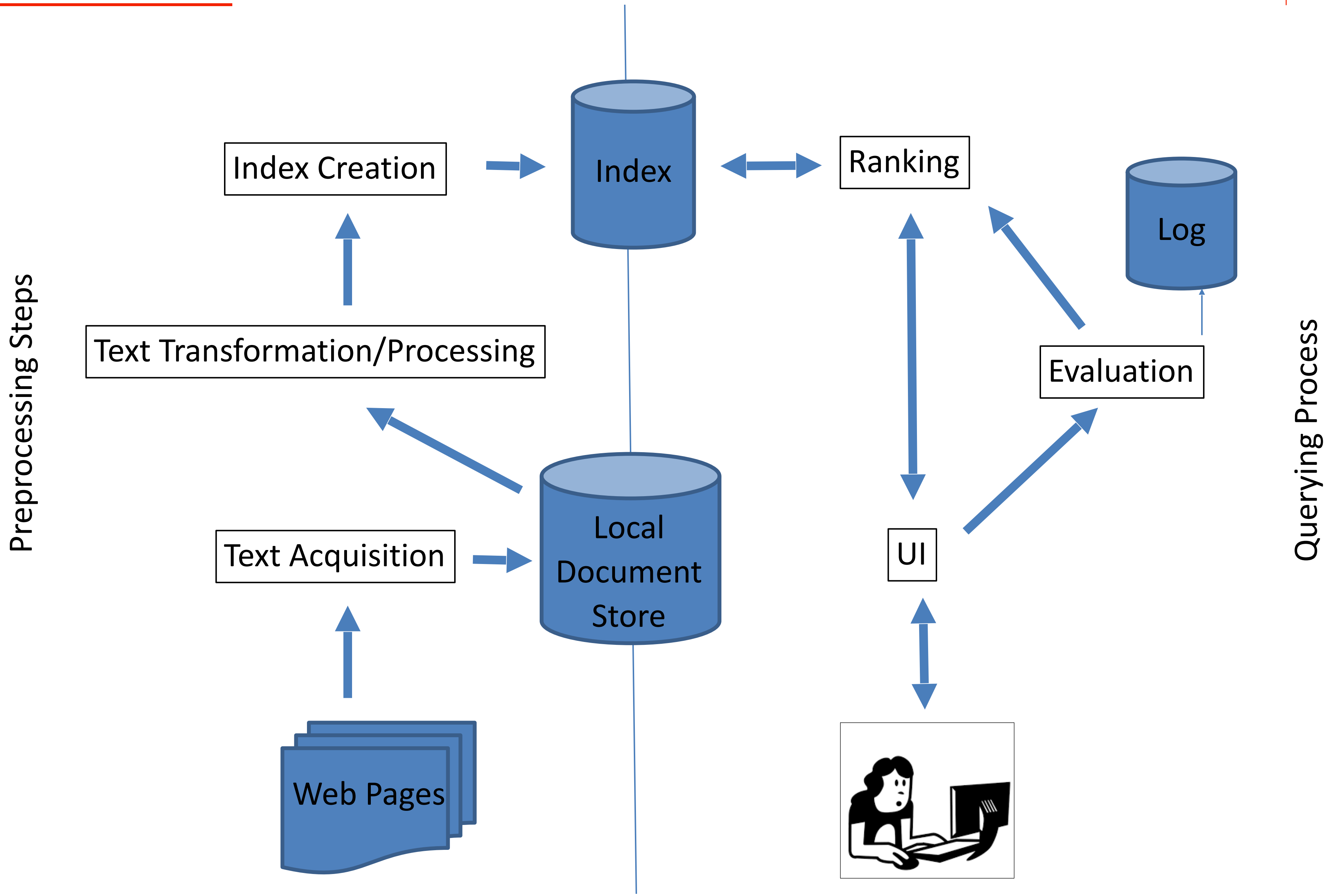
# Architecture



# Processing Text

- Essential step to convert documents to *index terms*

- Why?
  - In the context of web search matching the exact string of characters typed by the user is too restrictive
    - i.e., it doesn't work very well in terms of effectiveness (e.g. case sensitive searches *may or may not* be what you want)
  - Not all words are of equal value in a search
  - Sometimes not clear where words begin and end
    - Not even clear what a word is in some languages
      - e.g., Chinese, Korean

# Text Statistics

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- But many statistical characteristics of word occurrences are predictable!
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- But many statistical characteristics of word occurrences are predictable!
  - e.g., distribution of word counts
- Retrieval models and ranking algorithms depend **heavily** on statistical properties of words
  - e.g., *important words for retrieval tasks are words that occur often in documents but are not frequent in the corpus*

# Zipf’s Law

- Distribution of word frequencies is very *skewed*
  - a few words occur very often, many words hardly ever occur
  - e.g., two most common words (“the”, “of”) make up about 10% of all word occurrences in text documents!

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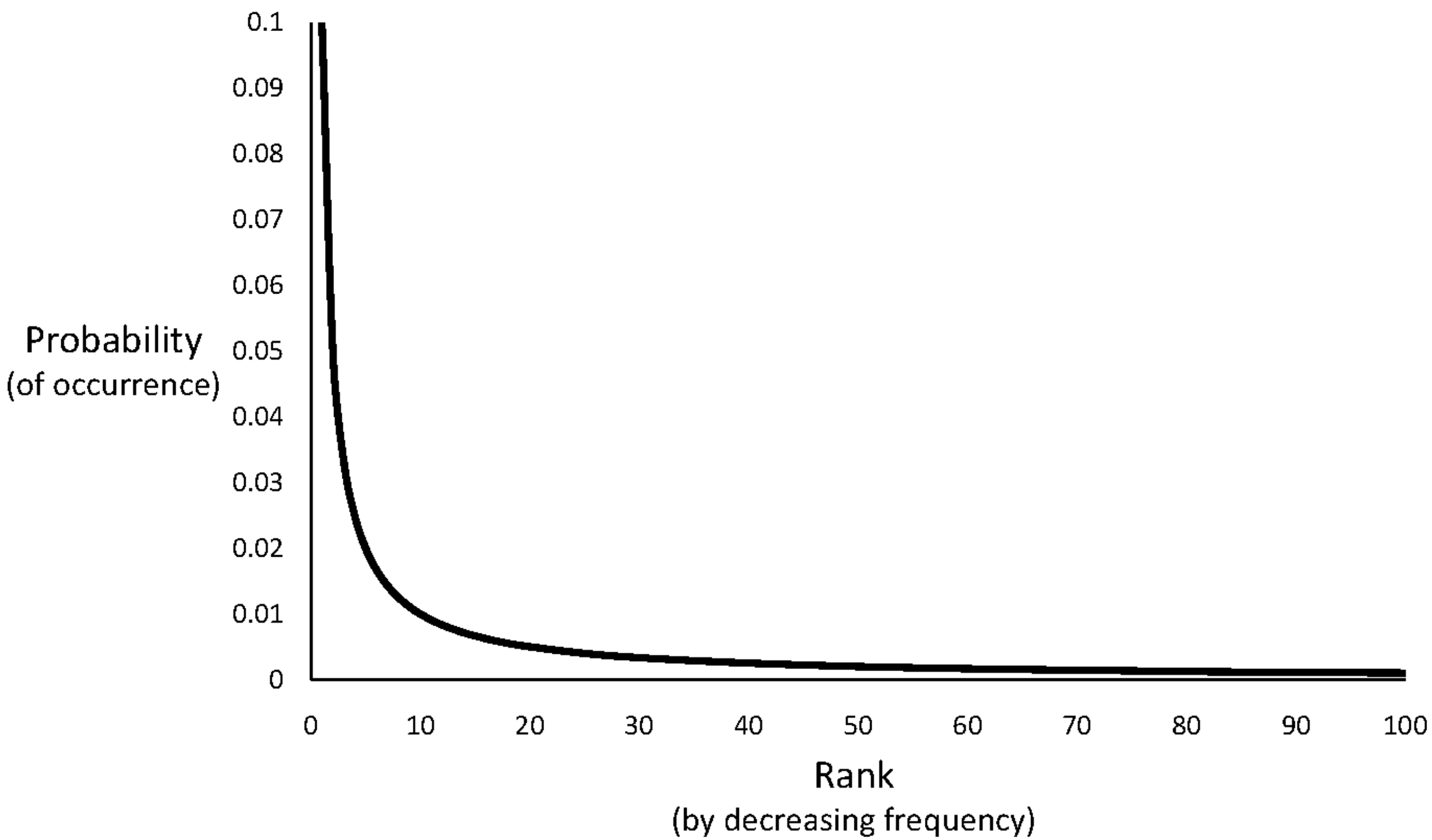
  - e.g., two most common words ("the", "of") make up about 10% of all word occurrences in text documents!
- Zipf's "law":
  - "The frequency of the r-th most common word is inversely proportional to r"
  - Or: the rank (*r*) of a word times its frequency (*f*) is ~ a constant (*k*)
    - assuming words are ranked in order of decreasing frequency
  - i.e., $r.f \approx$ k or $r.P_r \approx c$, where $P_r$ is probability of word occurrence and $c \approx 0.1$ for English

# Zipf’s Law for English



# News Collection (Associated Press 89) Statistics

| | |
|---|---|
| Total documents | 84,678 |
| Total word occurrences | 39,749,179 |
| Vocabulary size (unique words) | 198,763 |
| Words occurring > 1000 times | 4,169 |
| Words occurring once | 70,064 |

Biggest variations :

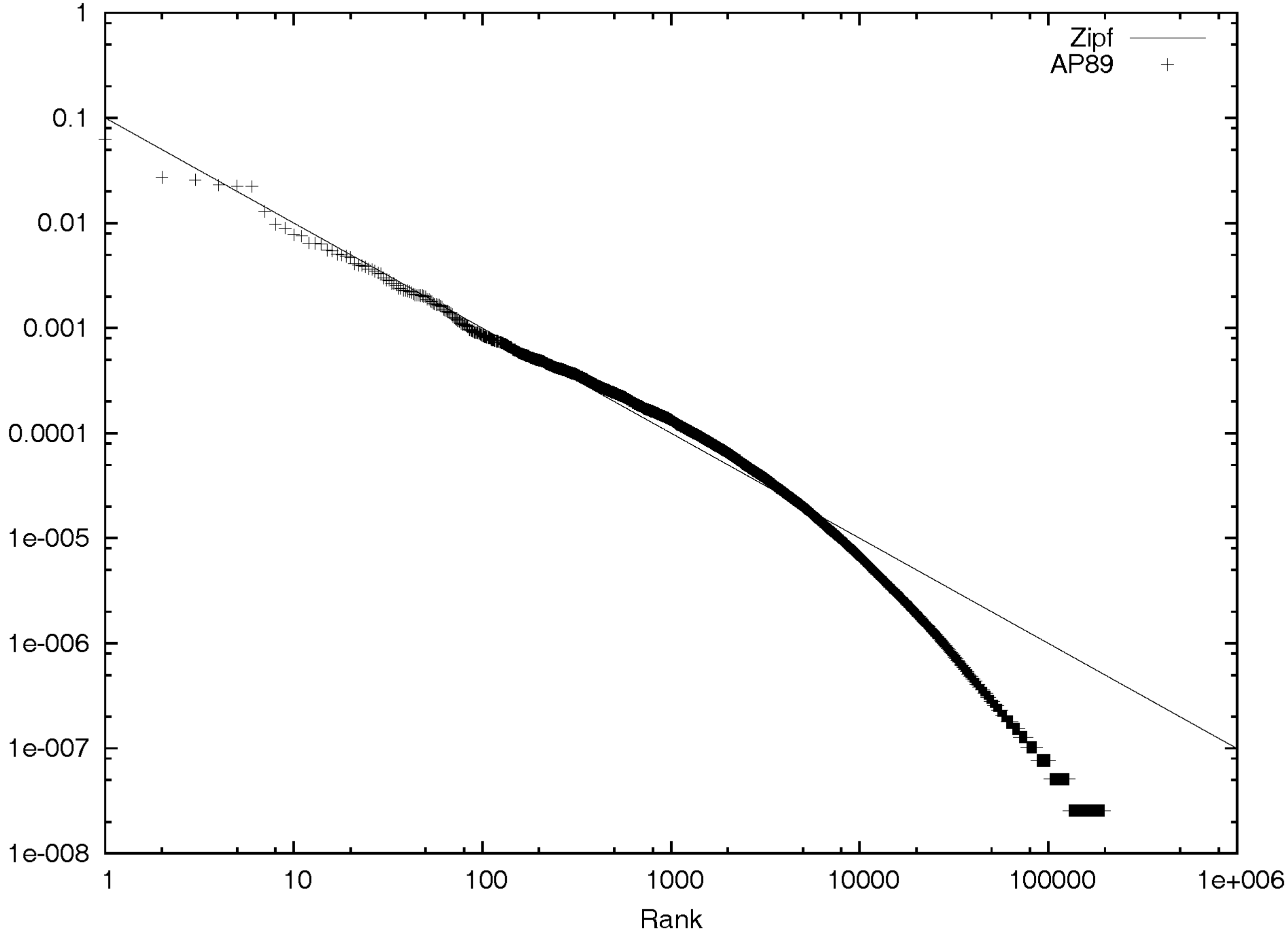
Highest frequency words

but if you keep digging…

| *Word* | *Freq.* | $r$ | $P_r(\%)$ | $r.P_r$ | *Word* | *Freq* | $r$ | $P_r(\%)$ | $r.P_r$ |
|---|---|---|---|---|---|---|---|---|---|
| the | 2,420,778 | 1 | 6.49 | 0.065 | has | 136,007 | 26 | 0.37 | 0.095 |
| of | 1,045,733 | 2 | 2.80 | 0.056 | are | 130,322 | 27 | 0.35 | 0.094 |
| to | 968,882 | 3 | 2.60 | 0.078 | not | 127,493 | 28 | 0.34 | 0.096 |
| a | 892,429 | 4 | 2.39 | 0.096 | who | 116,364 | 29 | 0.31 | 0.090 |
| and | 865,644 | 5 | 2.32 | 0.120 | they | 111,024 | 30 | 0.30 | 0.089 |
| in | 847,825 | 6 | 2.27 | 0.140 | its | 111,021 | 31 | 0.30 | 0.092 |
| said | 504,593 | 7 | 1.35 | 0.095 | had | 103,943 | 32 | 0.28 | 0.089 |
| for | 363,865 | 8 | 0.98 | 0.078 | will | 102,949 | 33 | 0.28 | 0.091 |
| that | 347,072 | 9 | 0.93 | 0.084 | would | 99,503 | 34 | 0.27 | 0.091 |
| was | 293,027 | 10 | 0.79 | 0.079 | about | 92,983 | 35 | 0.25 | 0.087 |
| on | 291,947 | 11 | 0.78 | 0.086 | i | 92,005 | 36 | 0.25 | 0.089 |
| he | 250,919 | 12 | 0.67 | 0.081 | been | 88,786 | 37 | 0.24 | 0.088 |
| is | 245,843 | 13 | 0.65 | 0.086 | this | 87,286 | 38 | 0.23 | 0.089 |
| with | 223,846 | 14 | 0.60 | 0.084 | their | 84,638 | 39 | 0.23 | 0.089 |
| at | 210,064 | 15 | 0.56 | 0.085 | new | 83,449 | 40 | 0.22 | 0.090 |
| by | 209,586 | 16 | 0.56 | 0.090 | or | 81,796 | 41 | 0.22 | 0.090 |
| it | 195,621 | 17 | 0.52 | 0.089 | which | 80,385 | 42 | 0.22 | 0.091 |
| from | 189,451 | 18 | 0.51 | 0.091 | we | 80,245 | 43 | 0.22 | 0.093 |
| as | 181,714 | 19 | 0.49 | 0.093 | more | 76,388 | 44 | 0.21 | 0.090 |
| be | 157,300 | 20 | 0.42 | 0.084 | after | 75,165 | 45 | 0.20 | 0.091 |
| were | 153,913 | 21 | 0.41 | 0.087 | us | 72,045 | 46 | 0.19 | 0.089 |
| an | 152,576 | 22 | 0.41 | 0.090 | percent | 71,956 | 47 | 0.19 | 0.091 |
| have | 149,749 | 23 | 0.40 | 0.092 | up | 71,082 | 48 | 0.19 | 0.092 |
| his | 142,285 | 24 | 0.38 | 0.092 | one | 70,266 | 49 | 0.19 | 0.092 |
| but | 140,880 | 25 | 0.38 | 0.094 | people | 68,988 | 50 | 0.19 | 0.093 |

AP89 most frequent words

# Zipf's Law for AP89




- Note problems at high and low frequencies

- Words that occur only once : *Hapax Legomena* (ἅπαξ λεγόμενον).