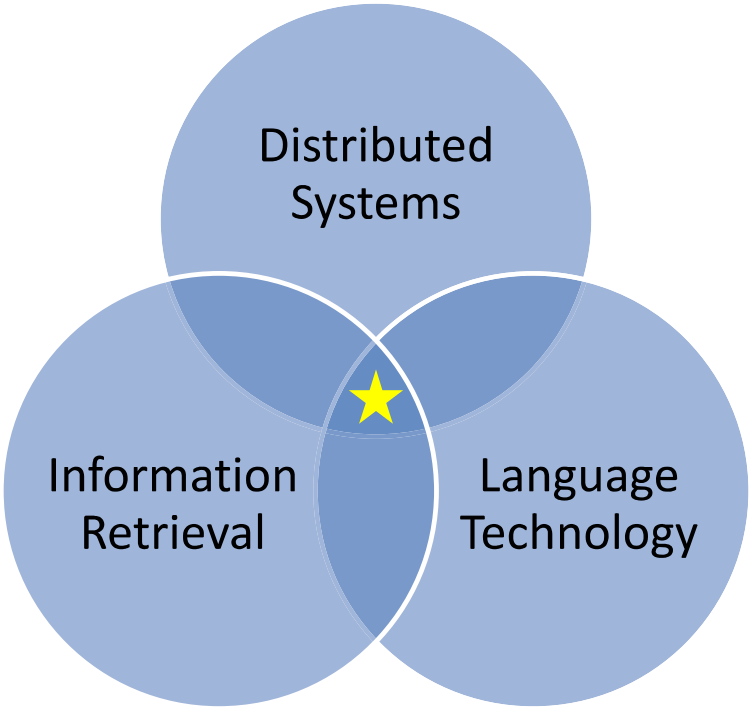
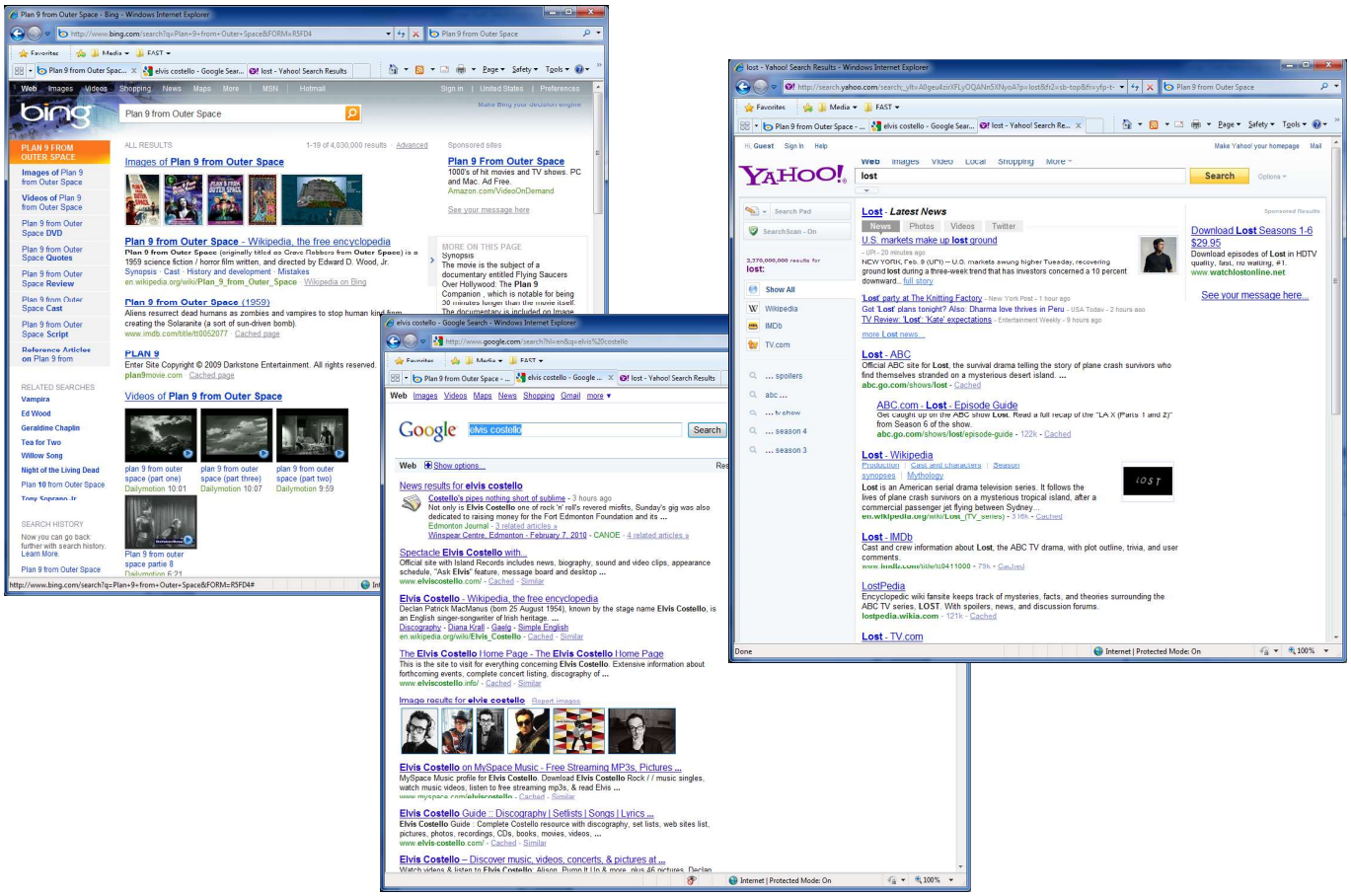
# The Sweetspot




SECRET SAUCE FACTORY

# Web Search


Plan 9 from Outer Space - Bing - Windows Internet Explorer
bing
Plan 9 from Outer Space
Images of Plan 9 from Outer Space
Plan 9 From Outer Space
Plan 9 from Outer Space - Wikipedia, the free encyclopedia
Videos of Plan 9 from Outer Space
elvis costello - Google Search - Windows Internet Explorer
Google
elvis costello
Search
News results for elvis costello
Elvis Costello - Wikipedia, the free encyclopedia
Elvis Costello on MySpace Music - Free Streaming MP3s, Pictures ...
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Lost - Wikipedia
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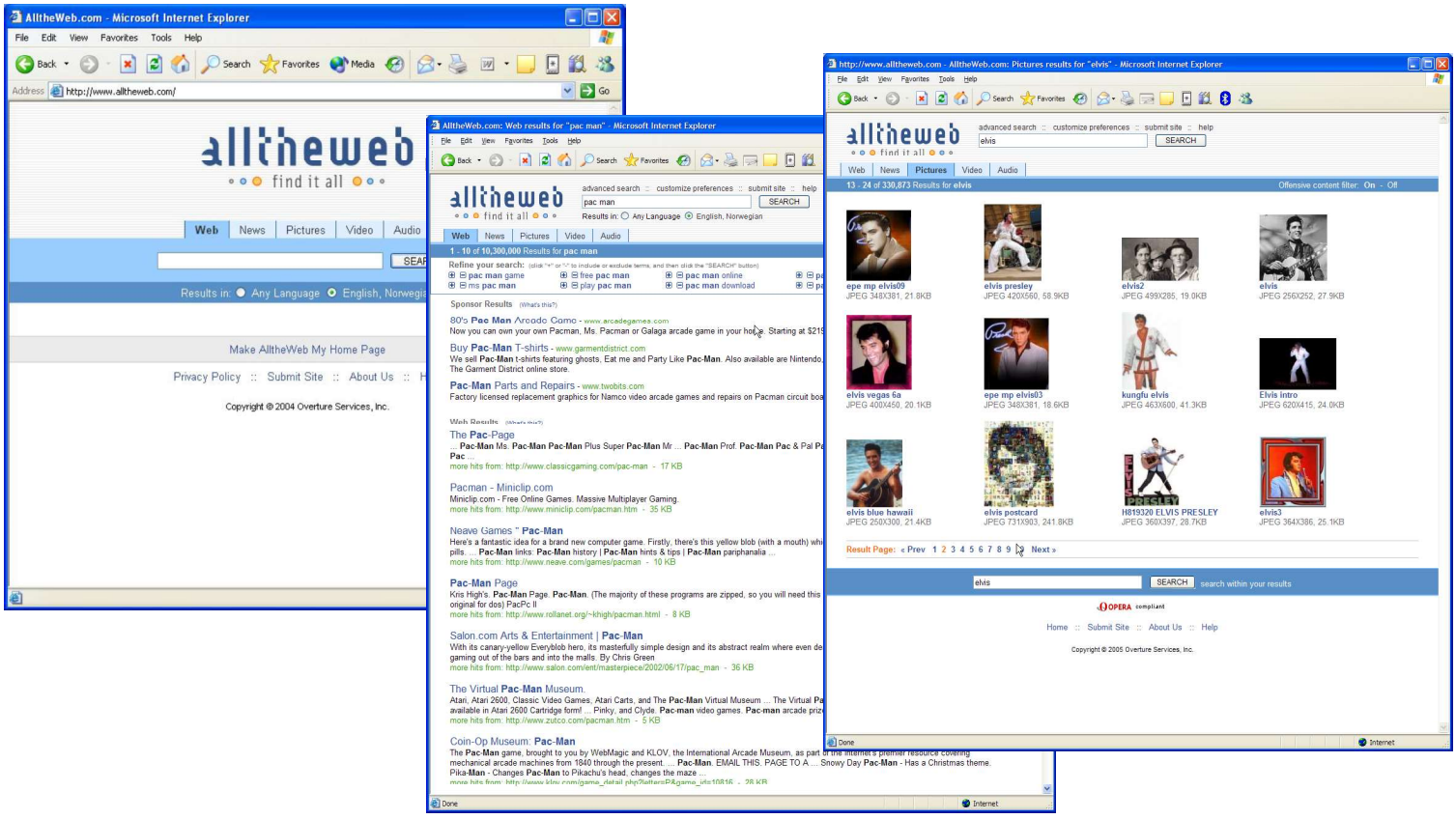
LostPedia
Lost - TV.com

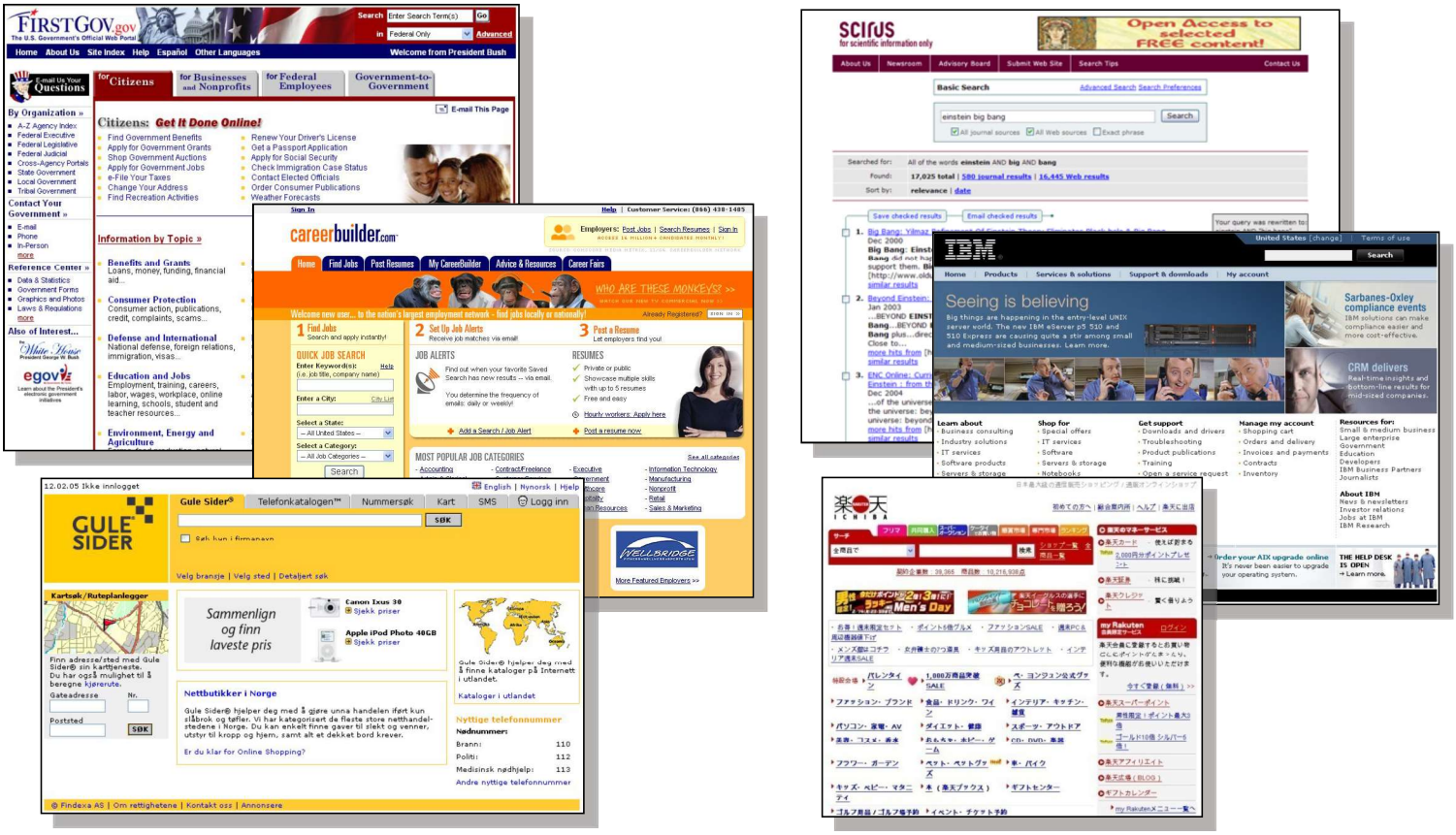
# alltheweb.com

1999-2003



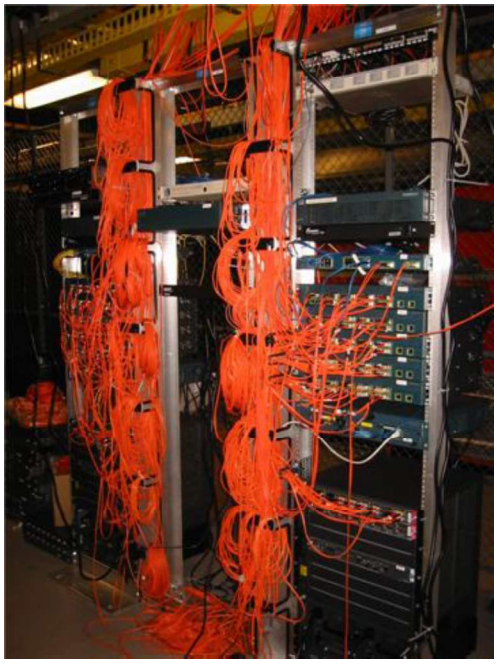
# Enterprise Search

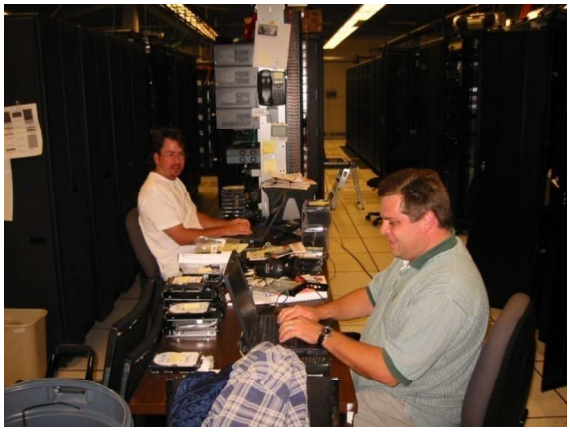
## Much more than intranets



# Data Centers

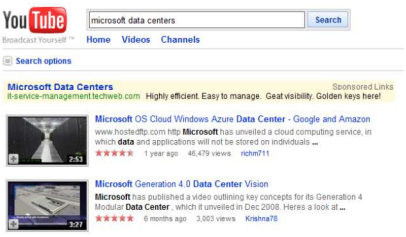
allltheweb.com 2000





# Data Centers

## Microsoft 2010

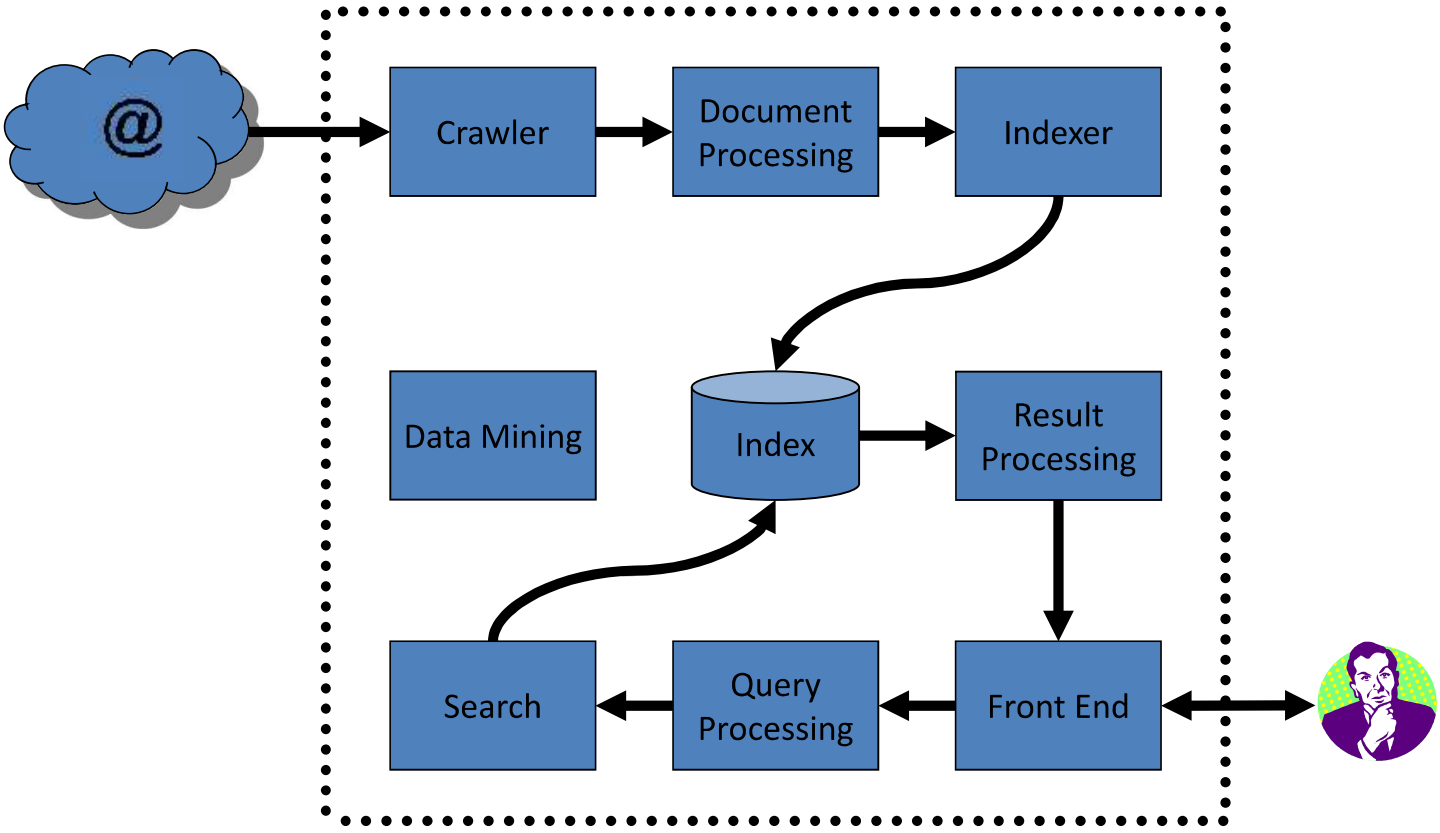




http://www.youtube.com/watch?v=K3b5Ca6lzqE

http://www.youtube.com/watch?v=PPnoKb9fTkA

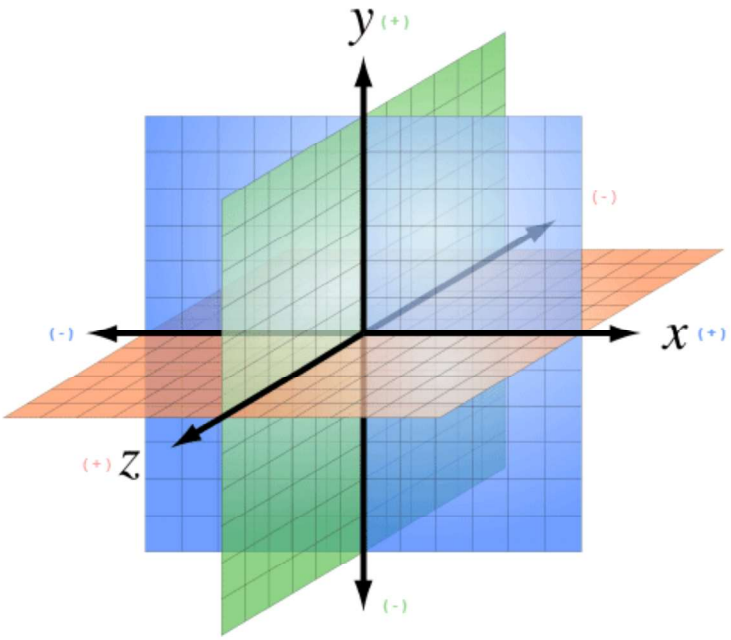
# Search Platform Anatomy

The 50,000 Foot View

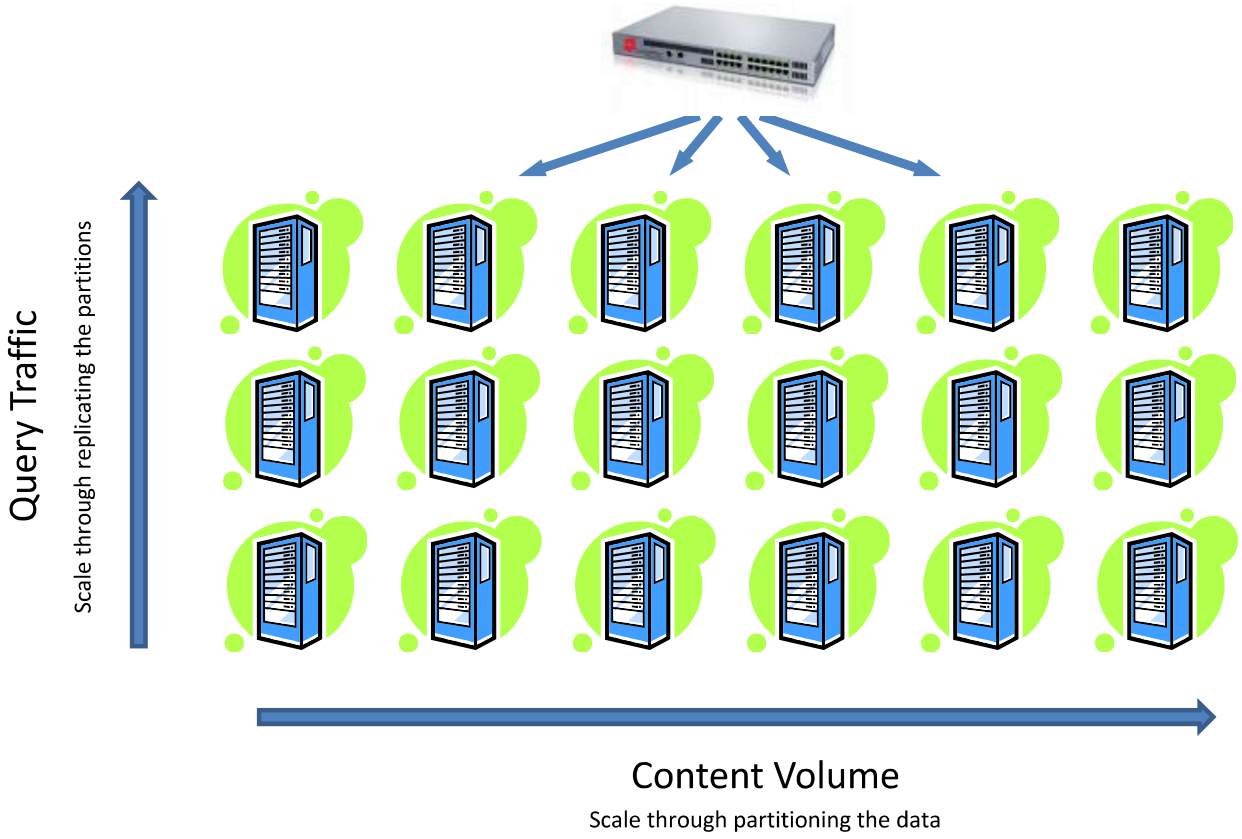


# Scaling

- **Content Volume**
  - How many documents are there?
  - How large are the documents?
- **Content Complexity**
  - How many fields does each document have?
  - How complex are the field structures?
- **Query Traffic**
  - How many queries per second are there?
  - What is the latency per query?
- **Update Frequency**
  - How often does the content change?
- **Indexing Latency**
  - How quickly must new data become searchable?
- **Query Complexity**
  - How many query terms are there?
  - What is the type and structure of the query terms?

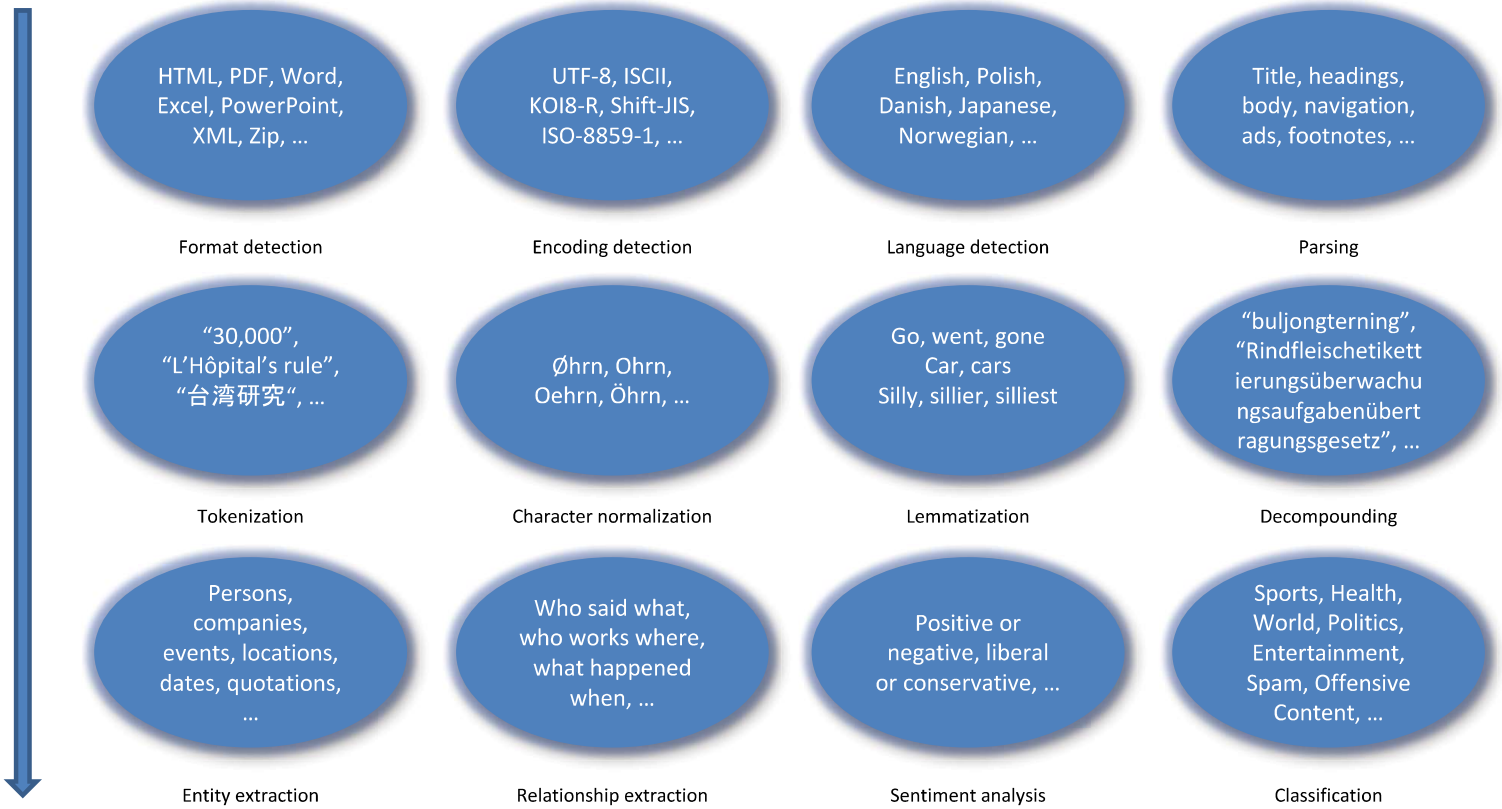


# Scaling

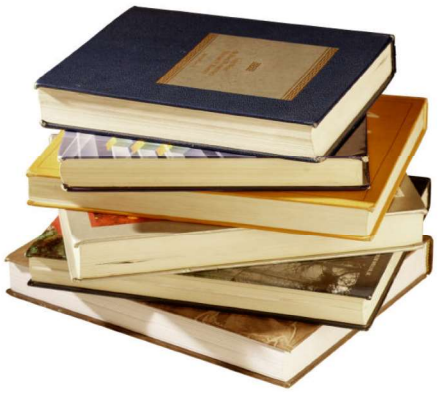

Query Traffic
Scale through replicating the partitions
Content Volume
Scale through partitioning the data

# Crawling The Web

# Processing The Content

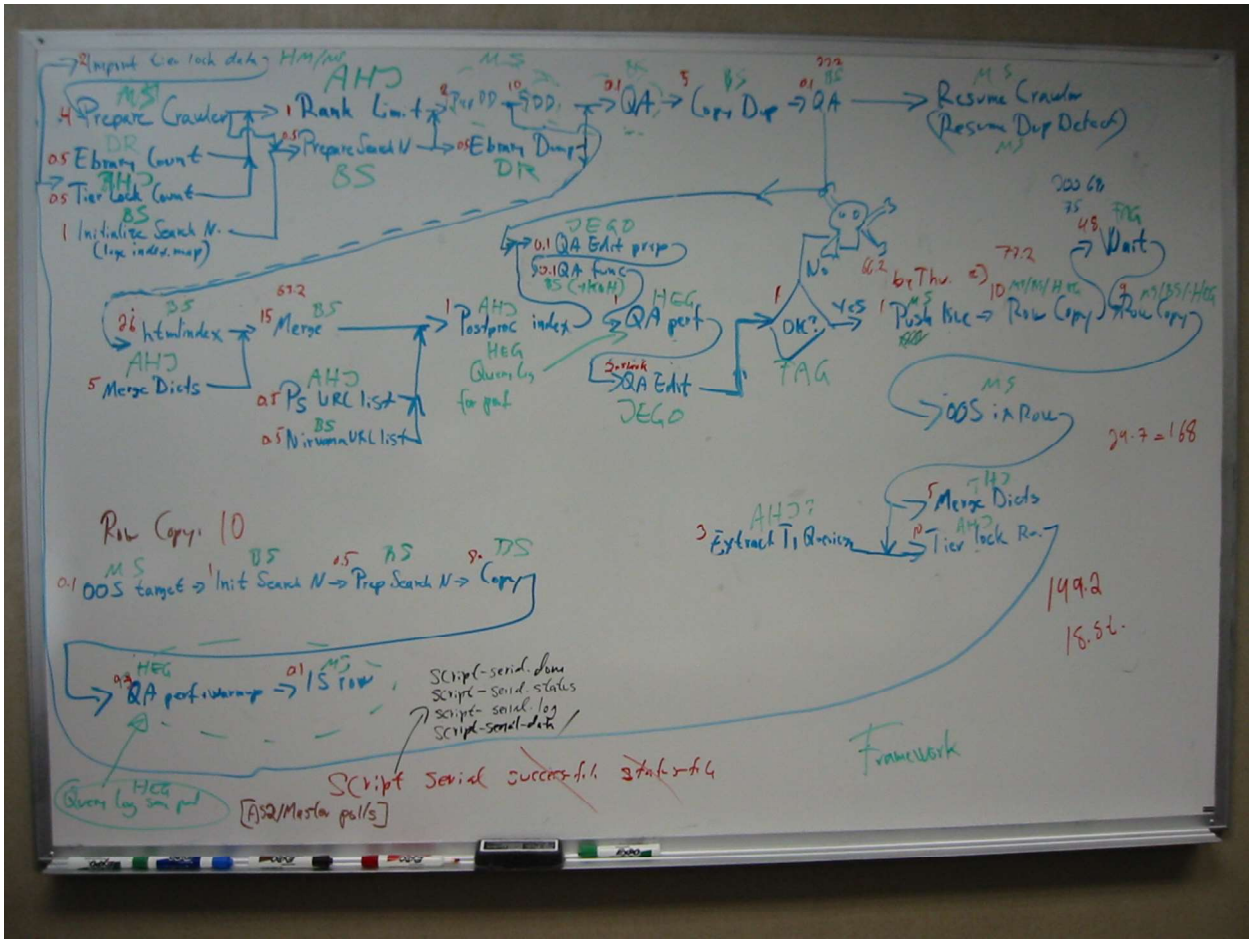


# Creating The Index

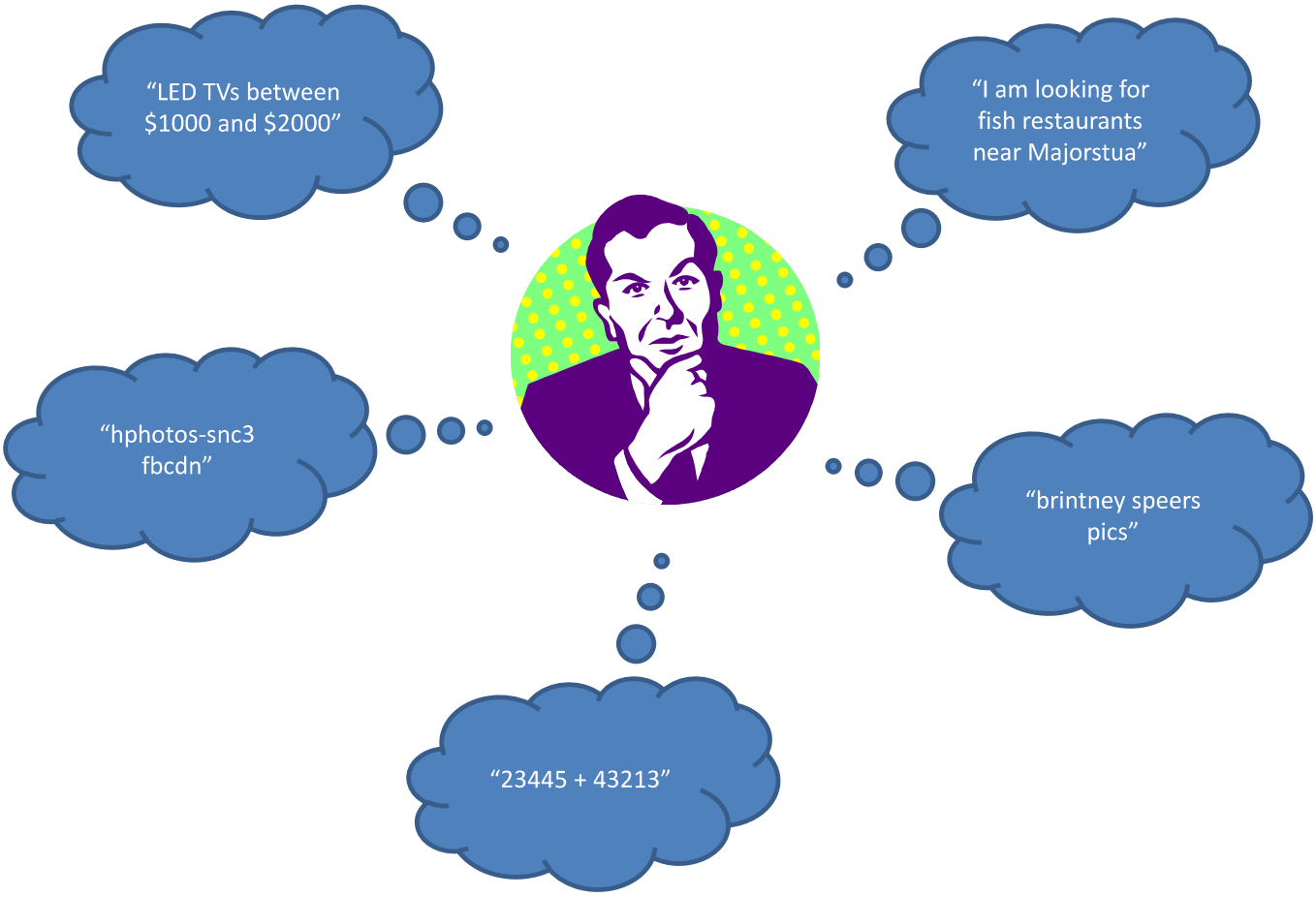


| Word | Document | Position |
|---|---|---|
| tea | 4 | 22 |
| | 4 | 32 |
| | 4 | 76 |
| | 8 | 3 |
| teacart | 8 | 7 |
| teach | 2 | 102 |
| | 2 | 233 |
| | 8 | 77 |
| teacher | 2 | 57 |

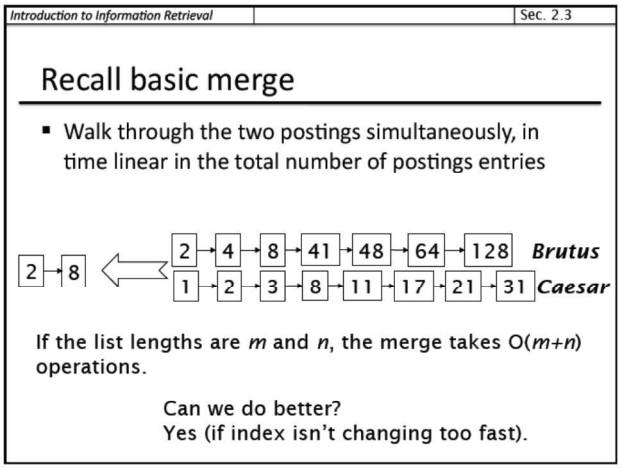
# Deploying The Index

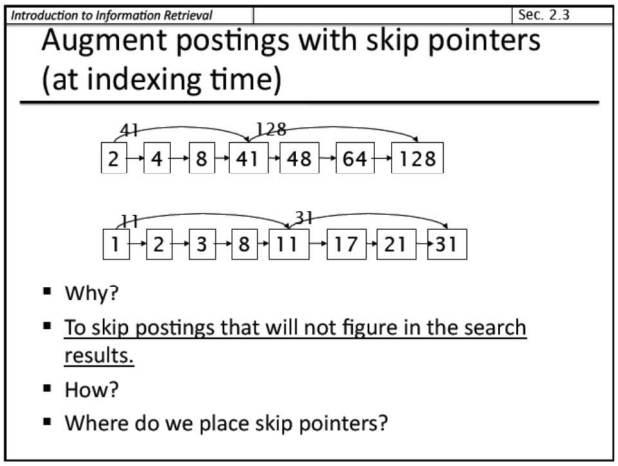


# Processing The Query



# Searching The Content

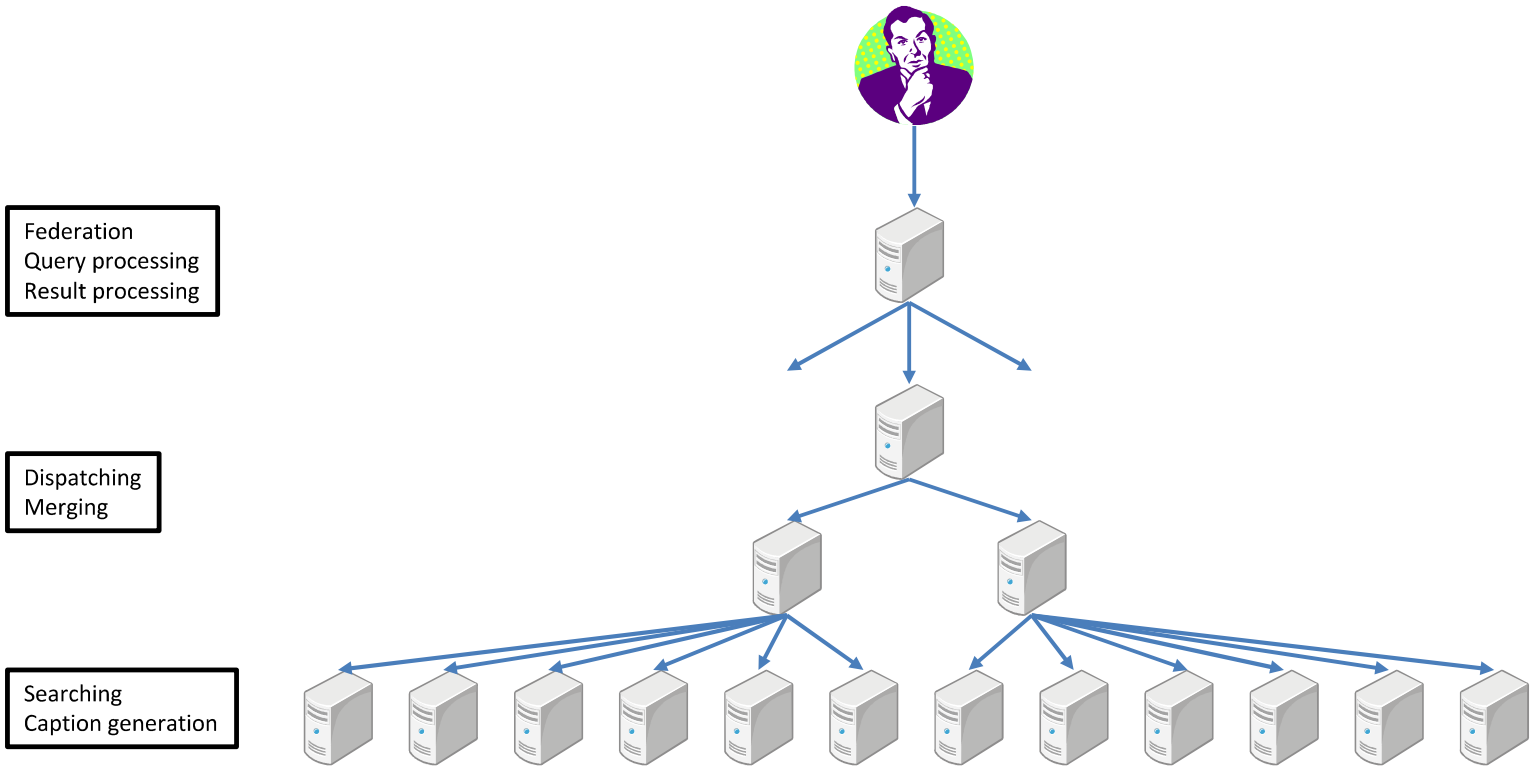



http://www.stanford.edu/class/cs276/handouts/lecture2-dictionary.pdf


Assess relevancy as we go along

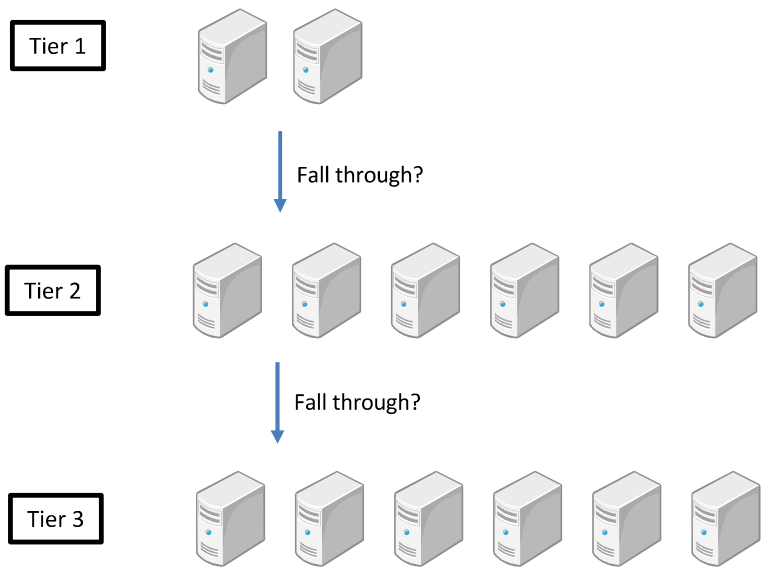
# Searching The Content




**“Divide and conquer”**

# Searching The Content

## Tiering

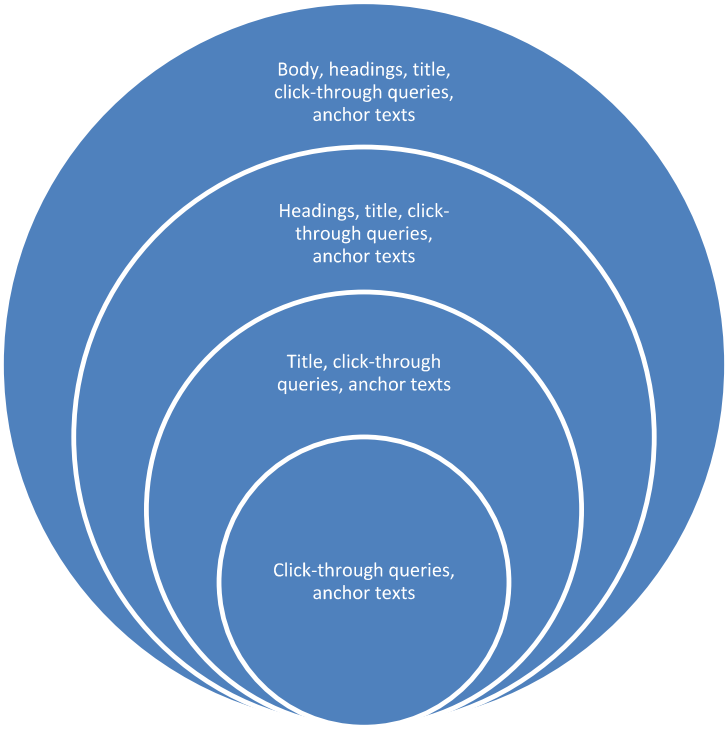



- Organize the search nodes in a row into multiple tiers
- Top tier nodes may have fewer documents and run on better hardware
- Keep the good stuff in the top tiers
- Only fall through to the lower tiers if not enough good hits are not found in the top tiers
- Analyze query logs to decide which documents that belong in which tiers

**“All search nodes are equal, but some are more equal than others”**

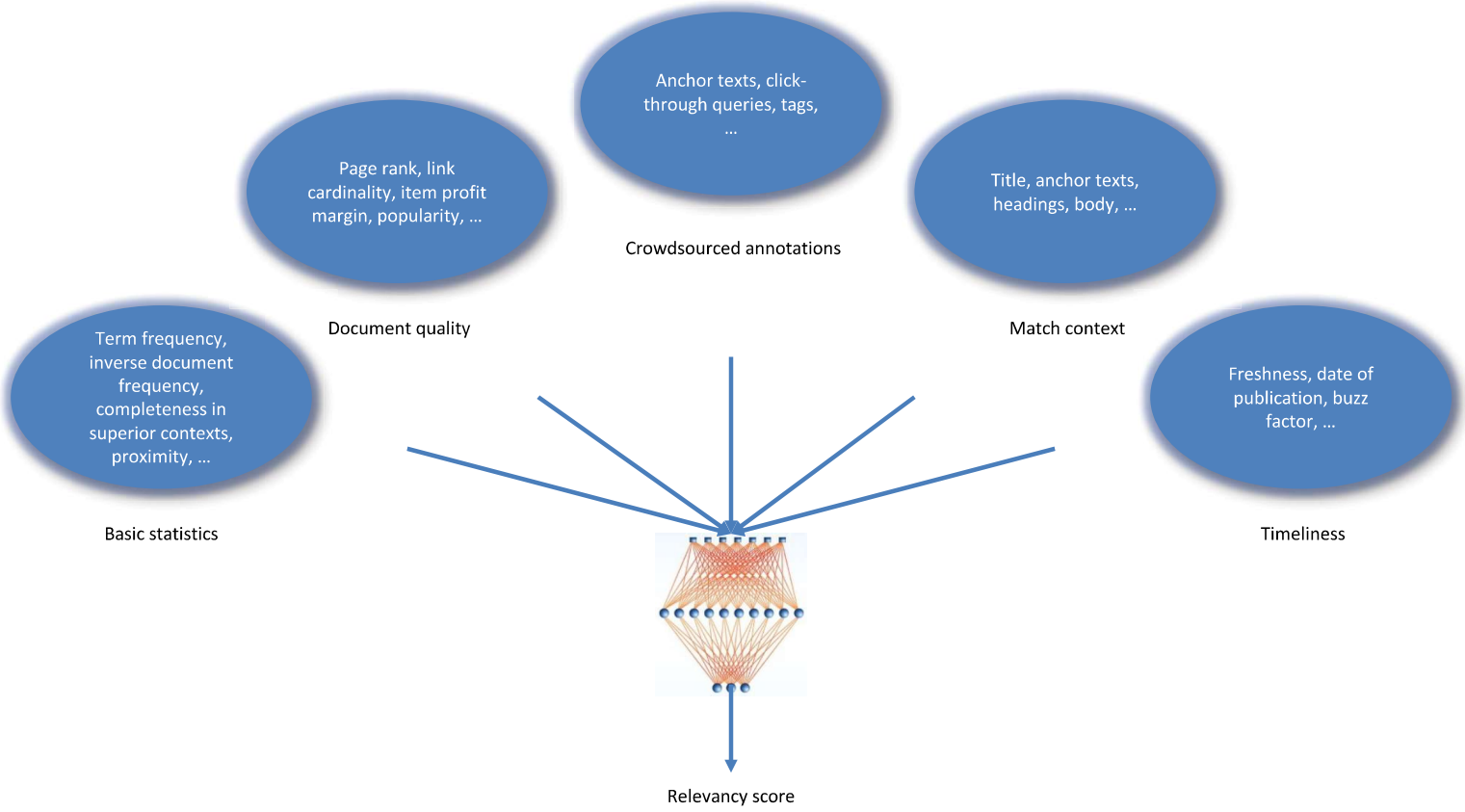
# Searching The Content

## Context Drilling




**“If the result set is too large, only consider the superior contexts”**

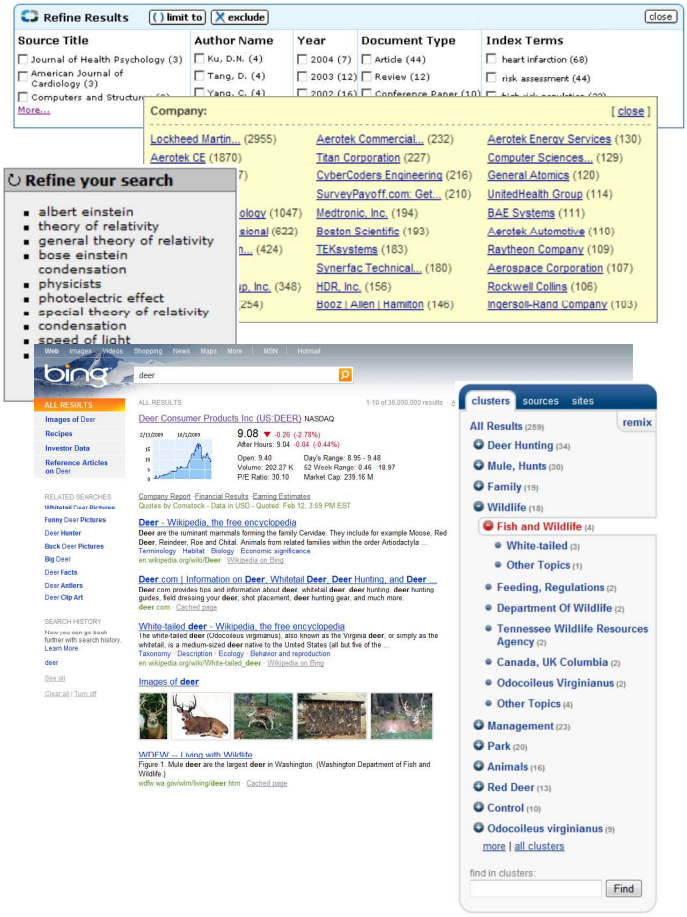
# Relevancy



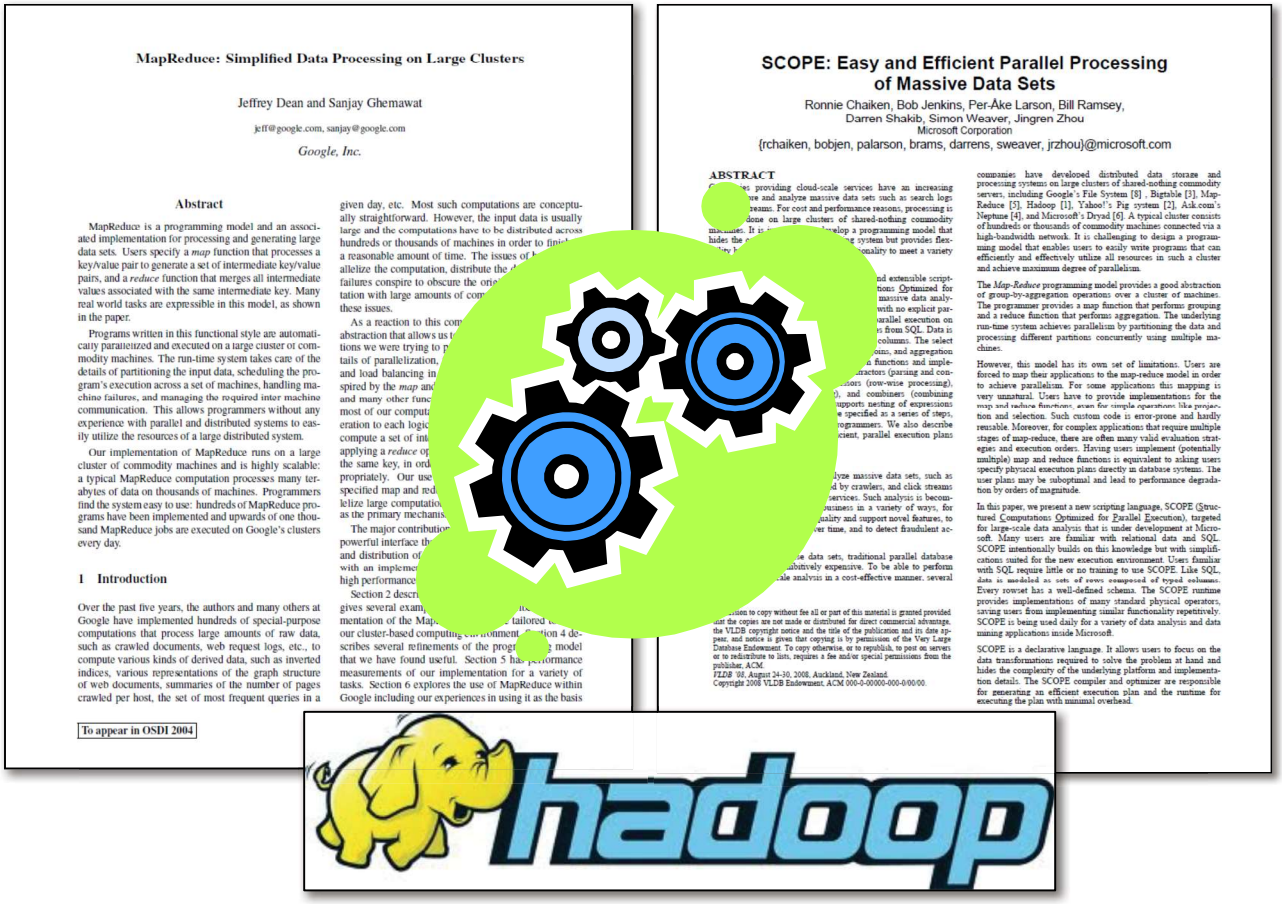

**“Maximize the normalized discounted cumulative gain (NDCG)”**

# Processing The Results

- **Faceted browsing**
  - What are the distributions of data across the various document fields?
  - “Local” versus “global” meta data
- **Result arbitration**
  - Which results from which sources should be displayed in a federation setting?
  - How should the SERP layout be rendered?
- **Unsupervised clustering**
  - Can we automatically organize the results set by grouping similar items together?
- **Last-minute security trimming**
  - Does the user still have access to each result?



# Data Mining


MapReduce: Simplified Data Processing on Large Clusters
Jeffrey Dean and Sanjay Ghemawat
jeff@google.com, sanjay@google.com
Google, Inc.
Abstract
MapReduce is a programming model and an associated implementation for processing and generating large data sets. Users specify a map function that processes a key/value pair to generate a set of intermediate key/value pairs, and a reduce function that merges all intermediate values associated with the same intermediate key. Many real world tasks are expressible in this model, as shown in the paper.
Programs written in this functional style are automatically parallelized and executed on a large cluster of commodity machines. The run-time system takes care of the details of partitioning the input data, scheduling the program's execution across a set of machines, handling machine failures, and managing the required inter-machine communication. This allows programmers without any experience with parallel and distributed systems to easily utilize the resources of a large distributed system.
Our implementation of MapReduce runs on a large cluster of commodity machines and is highly scalable: a typical MapReduce computation processes many terabytes of data on thousands of machines. Programmers find the system easy to use: hundreds of MapReduce programs have been implemented and upwards of one thousand MapReduce jobs are executed on Google's clusters every day.
1 Introduction
Over the past five years, the authors and many others at Google have implemented hundreds of special-purpose computations that process large amounts of raw data, such as crawled documents, web request logs, etc., to compute various kinds of derived data, such as inverted indices, various representations of the graph structure of web documents, summaries of the number of pages crawled per host, the set of most frequent queries in a
To appear in OSDI 2004
SCOPE: Easy and Efficient Parallel Processing of Massive Data Sets
Ronnie Chaiken, Bob Jenkins, Per-Åke Larson, Bill Ramsey,
Darren Shakib, Simon Weaver, Jingren Zhou
Microsoft Corporation
{rchaiken, bobjen, palarson, brams, darrens, sweaver, jrzhou}@microsoft.com
ABSTRACT
hadoop

# Applications

# Spellchecking

488941 britney spears
40134 brittany spears
36315 brittney spears
24342 britany spears
7331 britny spears
6633 briteny spears
2696 britteny spears
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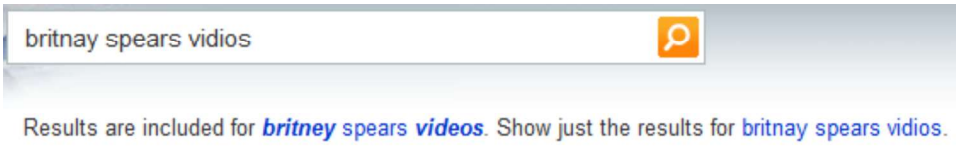
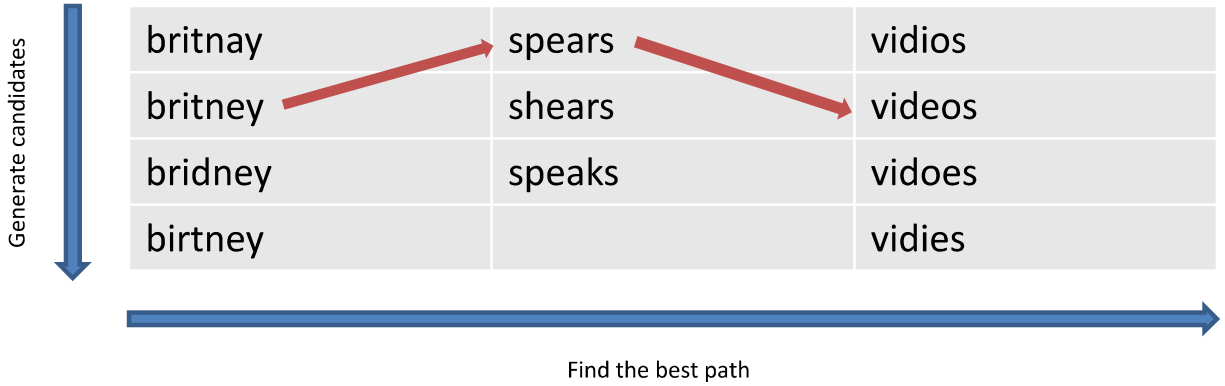
http://www.google.com/jobs/britney.html

# Spellchecking




1. Generate a set of candidates per query term using approximate matching techniques. Score each candidate according to, e.g., “distance” from the query term and usage frequency.

2. Find the best path in the lattice using the Viterbi algorithm. Use, e.g., candidate scores and bigram statistics to guide the search.

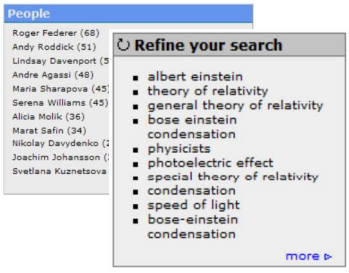
# Entity Extraction

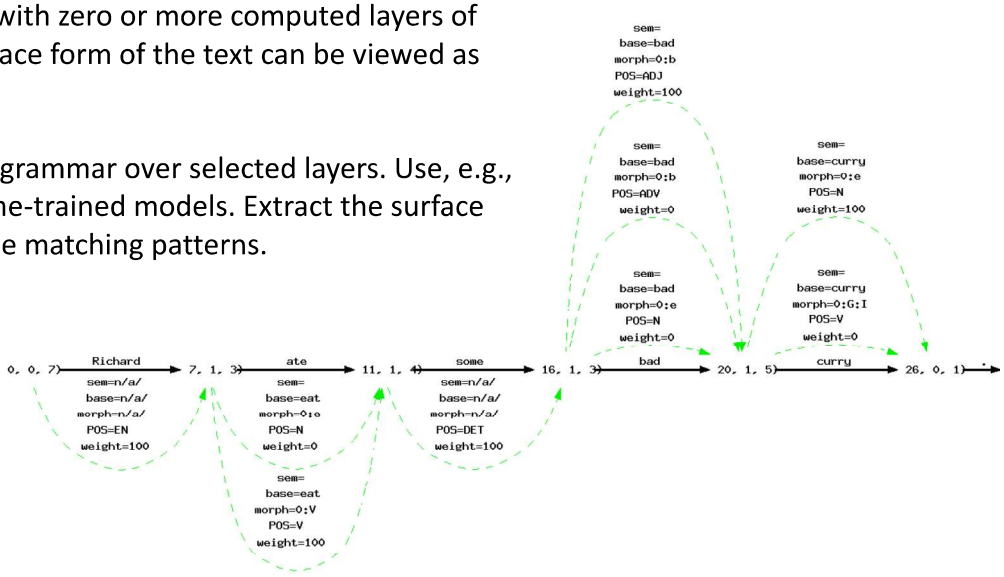
Levels of abstraction

| | | | | |
|---|---|---|---|---|
| … | … | … | … | … |
| MAN | | | | FOOD |
| N/proper | V/past/eat | DET | ADJ | N/singular |
| Richard | ate | some | bad | curry |

1. Logically annotate the text with zero or more computed layers of meta data. The original surface form of the text can be viewed as trivial meta data.

2. Apply a pattern matcher or grammar over selected layers. Use, e.g., handcrafted rules or machine-trained models. Extract the surface forms that correspond to the matching patterns.



# Sentiment Analysis

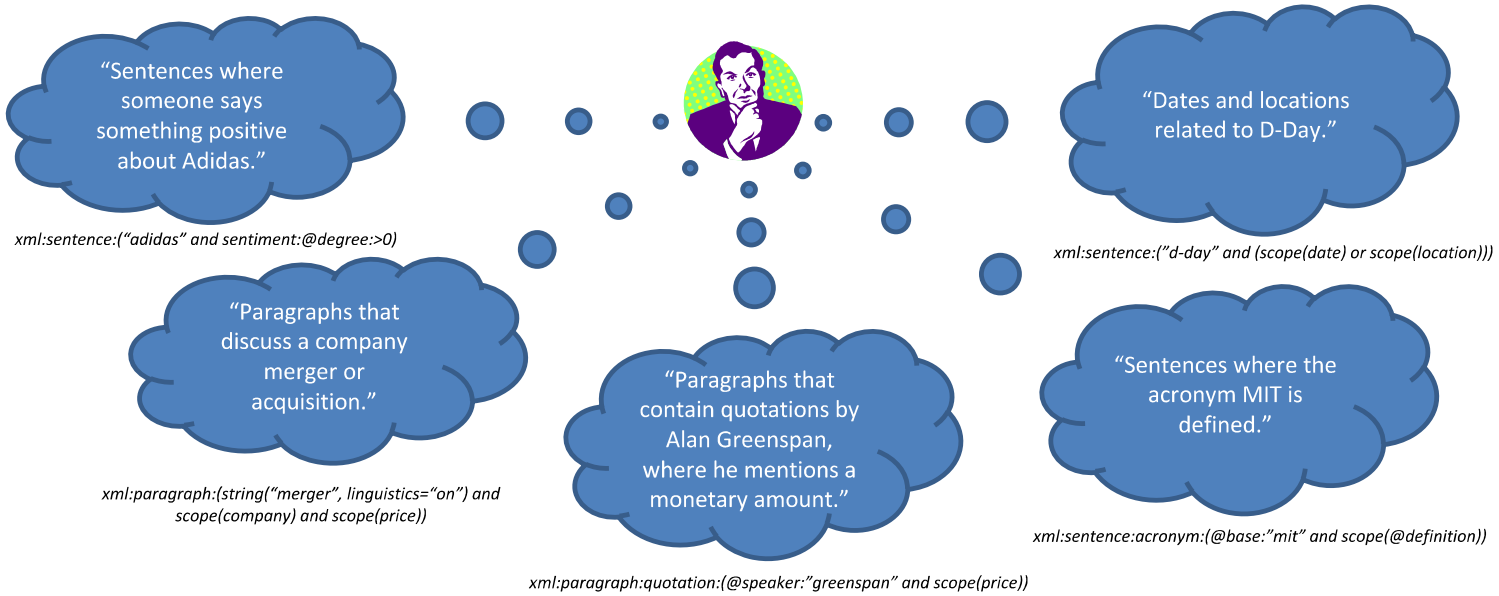

http://research.microsoft.com/en-us/projects/blews/

1. To construct a sentiment vocabulary, start by defining a small seed set of known polar opposites.

2. Expand the vocabulary by, e.g., looking at the context around the seeds in a training corpus.

3. Use the expanded vocabulary to build a classifier. Apply special heuristics to take care of, e.g., negations and irony.

# Contextual Search




Persons that appear in **documents** that contain the word *{soccer}*

| person@base |
|---|
| Jack Nicklaus (~10.0%) |
| Fred Davis (~10.0%) |
| Billie Jean King (~8.0%) |
| Richard Nixon (~8.0%) |
| John Wayne (~7.0%) |
| Margaret Smith (~7.0%) |
| Joe Frazier (~7.0%) |
| Irina Rodnina (~7.0%) |
| Mao Zedong (~6.0%) |
| Gordie Howe (~6.0%) |
| Richard M. Nixon (~6.0%) |
| More... |

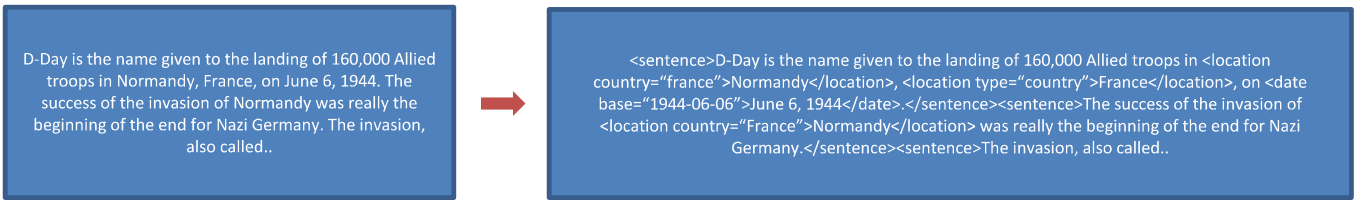
Example from Wikipedia

| person@base |
|---|
| Diego Maradona (~4.0%) |
| David Beckham (~4.0%) |
| Alan Shearer (~3.0%) |
| Michelle Akers (~3.0%) |
| Mia Hamm (~3.0%) |
| Eric Wynalda (~3.0%) |
| Freddy Adu (~3.0%) |
| Michel Platini (~2.0%) |
| Stanley Matthews (~2.0%) |
| Oliver Neuville (~2.0%) |
| Bobby Moore (~2.0%) |
| More... |

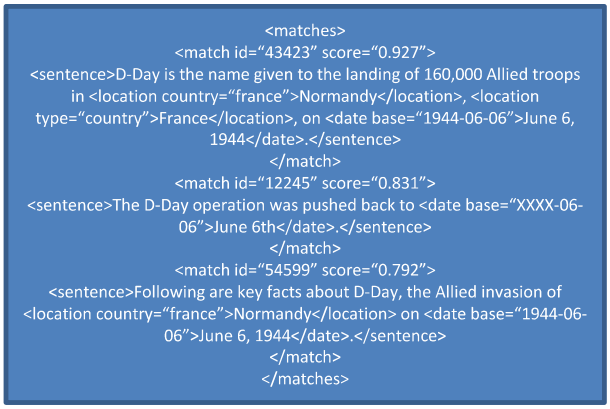
Persons that appear in **paragraphs** that contain the word *{soccer}*

# Contextual Search

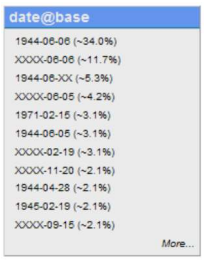
1. During content processing, identify structural and semantic regions of interest. Mark them up in context, possibly decorated with meta data.




2. Make all the marked-up data fully searchable in a way that preserves context and where retrieval can be constrained on both structure and content. Possibly translate natural language queries into suitable system queries.

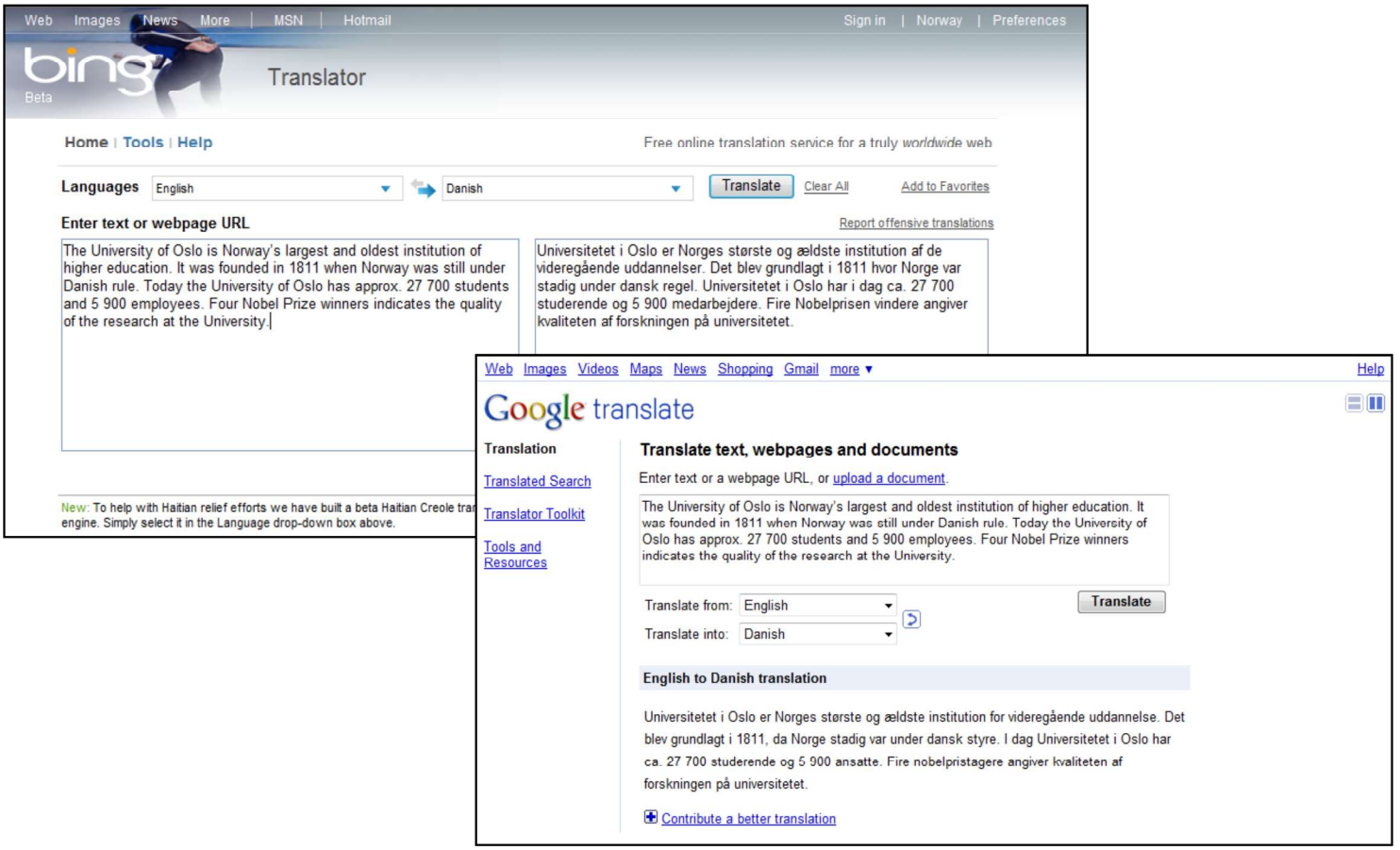




3. Aggregate data over the matching fragments and enable faceted browsing on a contextual level.

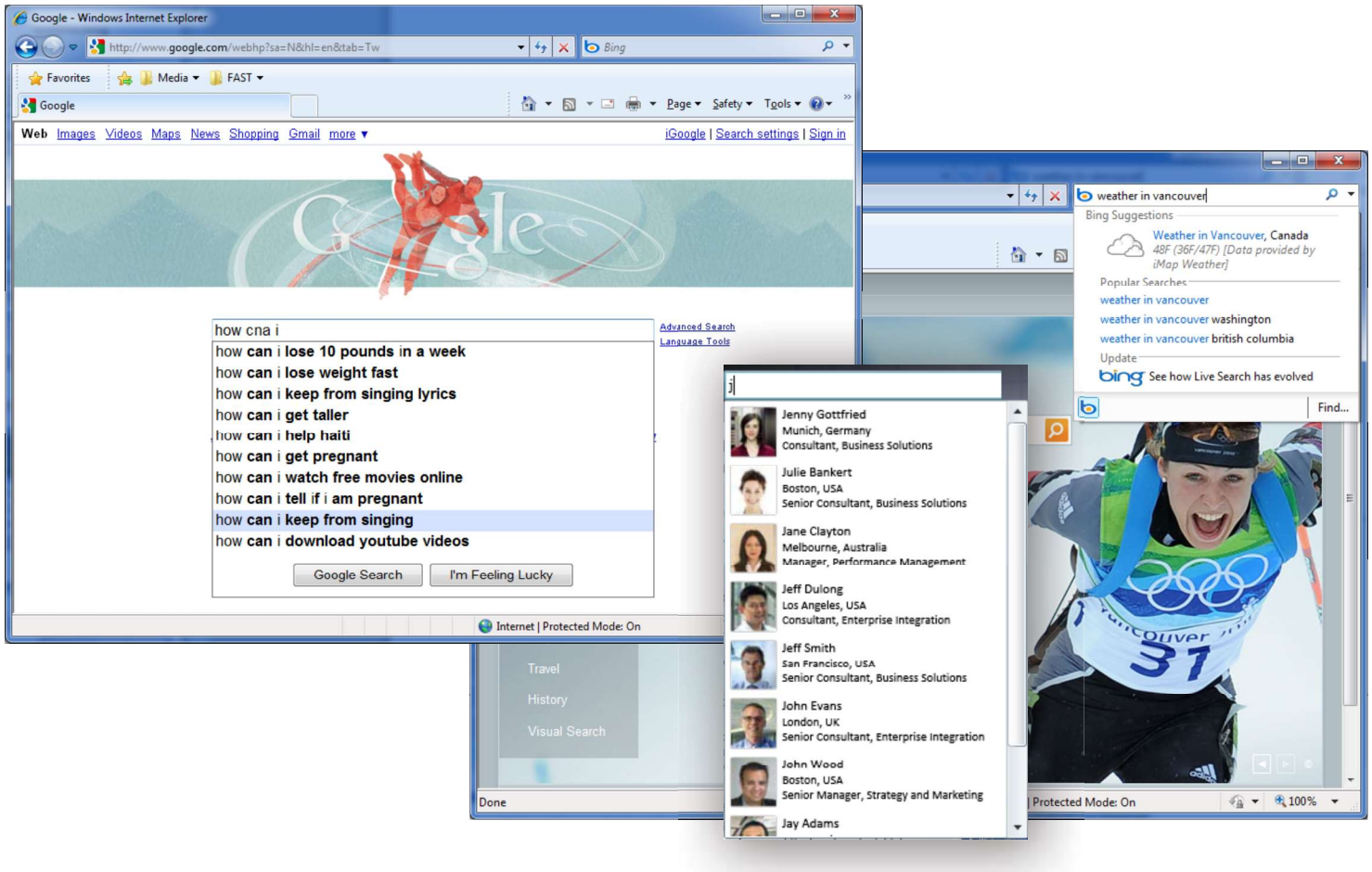



Example from Wikipedia

# Machine Translation



# Query Completion



# Caption Generation

- **Intra-document search**
  - Locate and rank relevant document fragments
  - But do it fast!
- **Perceived relevancy**
  - First impressions count
  - Can make or break a service
- **Trends towards richer captions**
  - Format-specific interactivity
  - Actionable elements