# Strategies for QA & Information Retrieval

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NLP Systems and Applications
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# Roadmap

- Shallow and Deep processing for Q/A
  - AskMSR, ARANEA: Shallow processing Q/A
    - Wrap-up
  - PowerAnswer-2: Deep processing Q/A

- Information Retrieval:
  - Problem:
    - Matching Topics and Documents
  - Methods:
    - Vector Space Model
  - Retrieval evaluation

# Redundancy-based Answer Extraction

- Prior processing:
  - Question formulation
  - Web search
  - Retrieve snippets – top 100
- N-grams:
  - Generation
  - Voting
  - Filtering
  - Combining
  - Scoring
  - Reranking

# N-gram Filtering

- Throws out ‘blatant’ errors
  - Conservative or aggressive?
    - Conservative: can’t recover error
- Question-type-neutral filters:
  - Exclude if begin/end with stopword
  - Exclude if contain words from question, except
    - ‘Focus words’ : e.g. units
- Question-type-specific filters:
  - ‘how far’, ‘how fast’: exclude if no numeric
  - ‘who’,’where’: exclude if not NE (first & last caps)

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  - E.g. ‘what year ‘ -> must be acceptable date year
- Example after filtering:
  - Who was the first person to run a sub-four-minute mile?

| Candidate | Score |
|---|---|
| Bannister | 137 |
| Roger | 114 |
| Roger Bannister | 103 |
| English | 26 |
| ... | ... |

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- Possible issues:
  - Bad units: Roger Bannister was – blocked by filters
    - Also, increments score so long bad spans lower
- Improves significantly

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| Sir Roger Bannister | 280 |
| Bannister Sir Roger | 278 |
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- Promote best answer candidates:
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  - Use answer type specific forms to raise matches
    - E.g. ‘where’ -> boosts ‘city, state’

- Small improvement depending on answer type

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- Does require some form of ‘answer projection’
  - Map web information to TREC document

# Deliverable #2

- Baseline end-to-end Q/A system:
  - Redundancy-based with answer projection

  also viewed as
  - Retrieval with web-based boosting

- Implementation: Main components
  - (Suggested) Basic redundancy approach
  - Basic retrieval approach (IR next lecture)

# Data

- Questions:
  - XML formatted questions and question series
- Answers:
  - Answer ‘patterns’ with evidence documents
- Training/Devtext/Evaltest:
  - Training: Thru 2005
  - Devtest: 2006
  - Held-out: …
- Will be in /dropbox directory on patas
- Documents:
  - AQUAINT news corpus data with minimal markup

# PowerAnswer2

- Language Computer Corp.
  - Lots of UT Dallas affiliates
- Tasks: factoid questions
- Major novel components:
  - Web-boosting of results
  - COGEX logic prover
  - Temporal event processing
  - Extended semantic chains
- Results: Best factoid system: 0.713 (vs 0.666, 03.329)

# Challenges: Co-reference

- Single, basic referent:

| Target 27 - *Jennifer Capriati* | |
|---|---|
| Q27.2 | Who is her coach? |
| Q27.3 | Where does she live? |

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| --- | --- |
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- Multiple possible antecedents:
  - Depends on previous correct answers

| Target 136 - *Shiite* | |
| --- | --- |
| Q136.1 | Who was the first Imam of the Shiite sect of Islam? |
| Q136.2 | Where is his tomb? |
| Q136.3 | What was this person's relationship to the Prophet Mohammad? |
| Q136.4 | Who was the third Imam of Shiite Muslims? |
| Q136.5 | When did he die? |

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  - Establish question context, constraints

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- Least shallow approach:
  - Heuristic reference resolution

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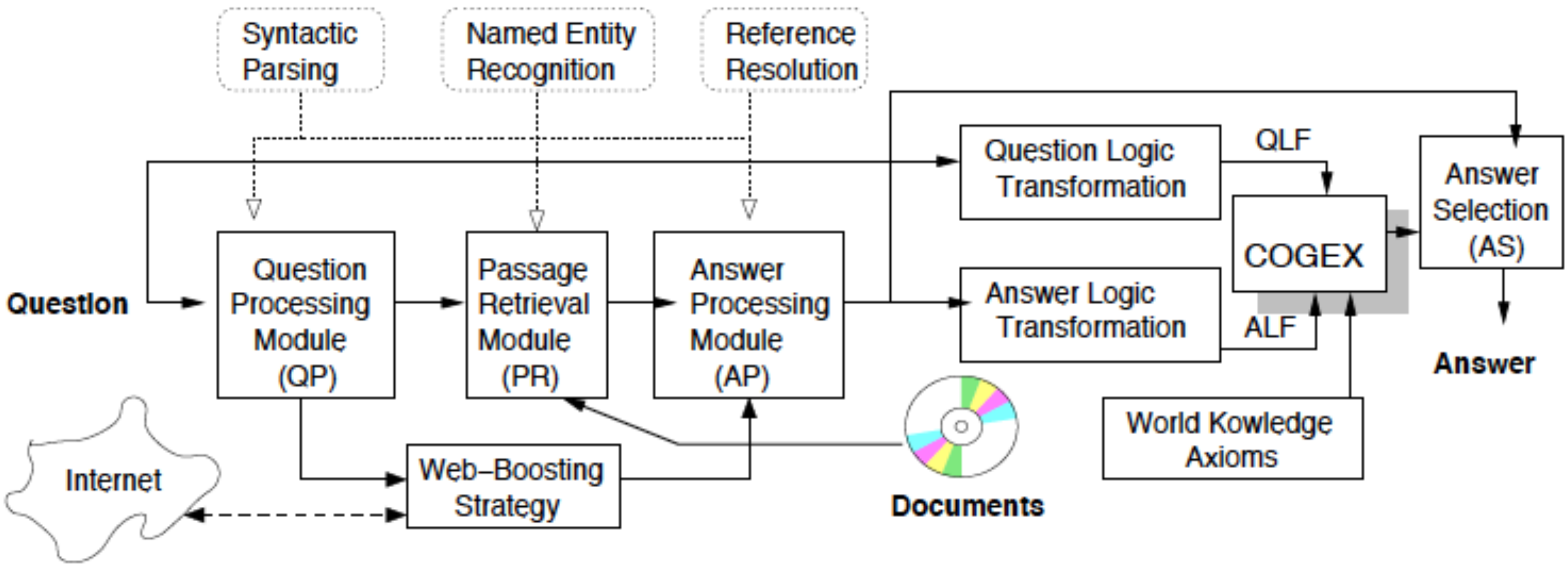
    - When was the band formed?
      - Wouldn't replace 'the band'
  - Most teams concatenate

# PowerAnswer-2

- Factoid QA system:



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- Complex components:
  - COGEX abductive prover
  - Word knowledge, semantics:
    - Extended WordNet, etc
  - Temporal processing

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- Intuition:
  - Common terms in search likely to be answer
  - QA answer search too focused on query terms
  - Reweighting improves
- Web-boosting improves significantly: 20%

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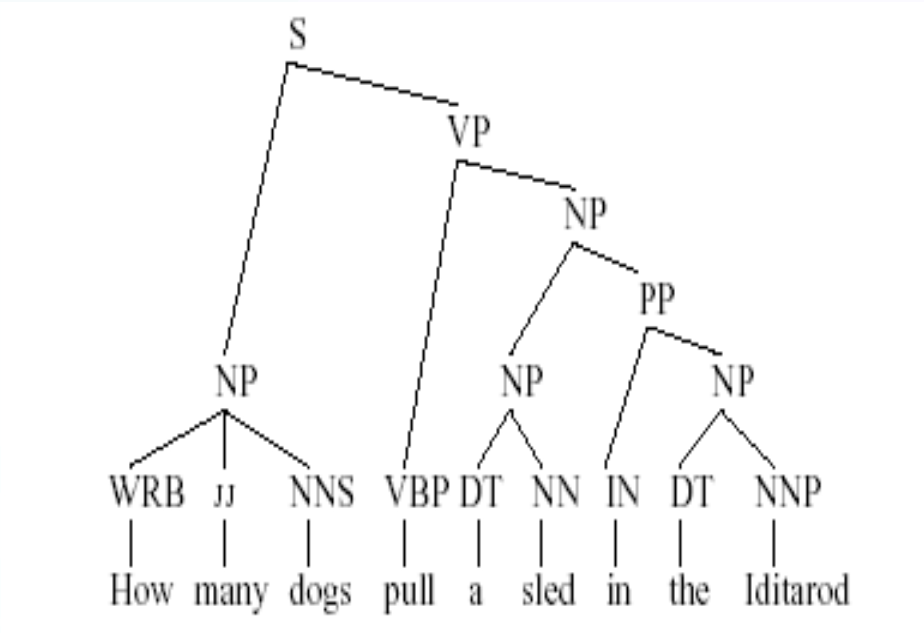
- Coreference resolution links entity references
- Translate to full logical form
  - As close as possible to syntax

# Syntax to Logical Form



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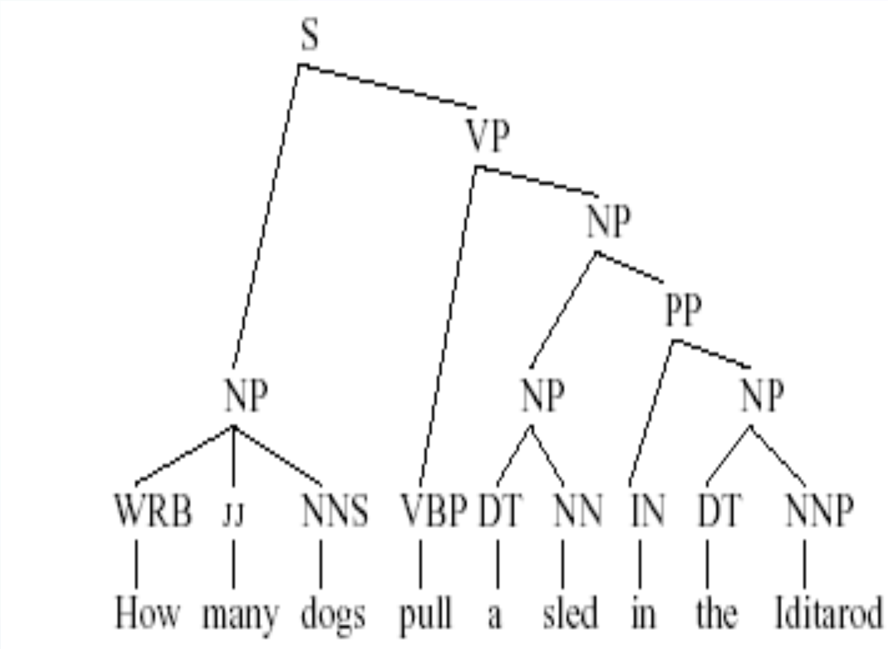


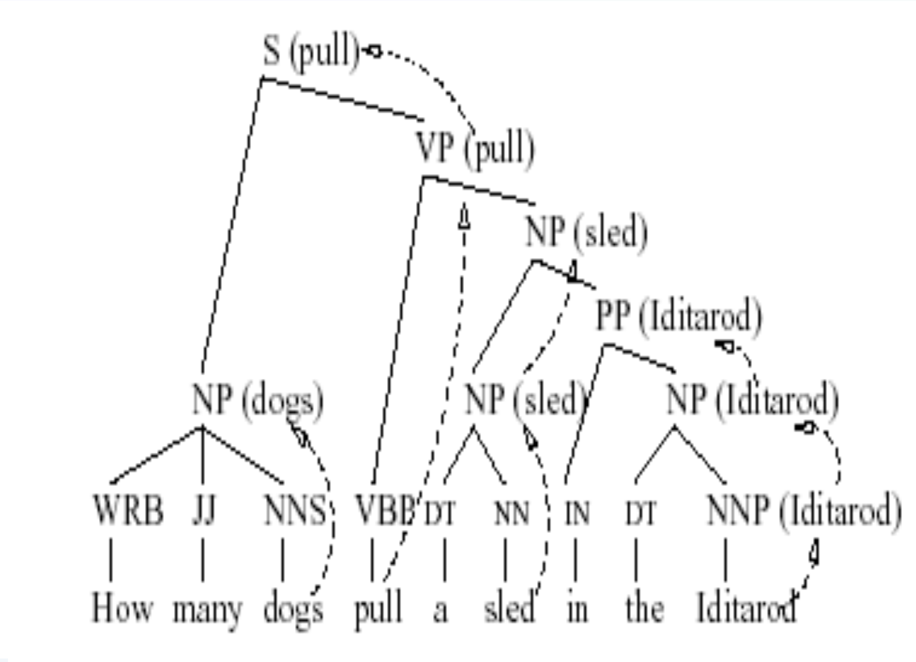

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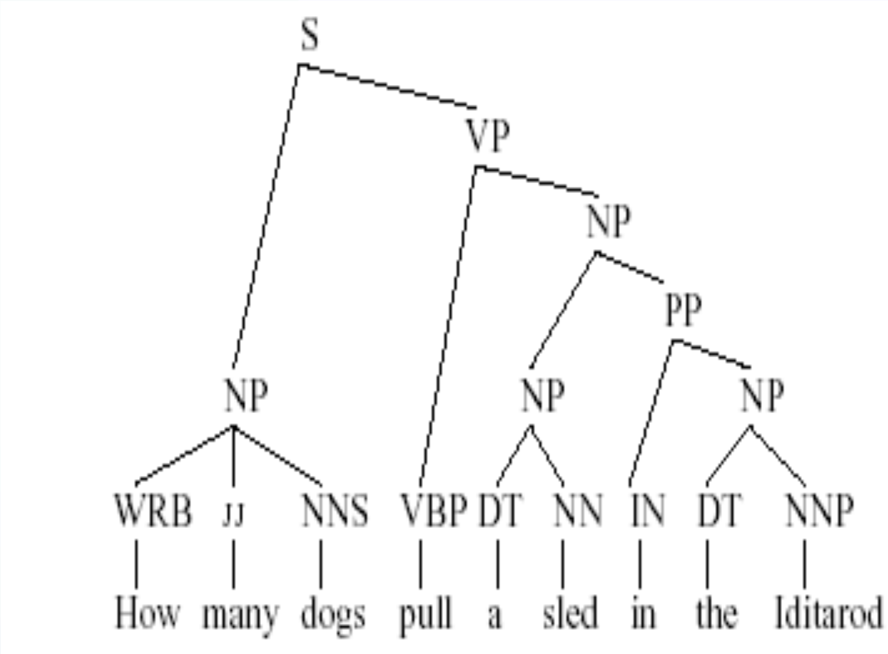


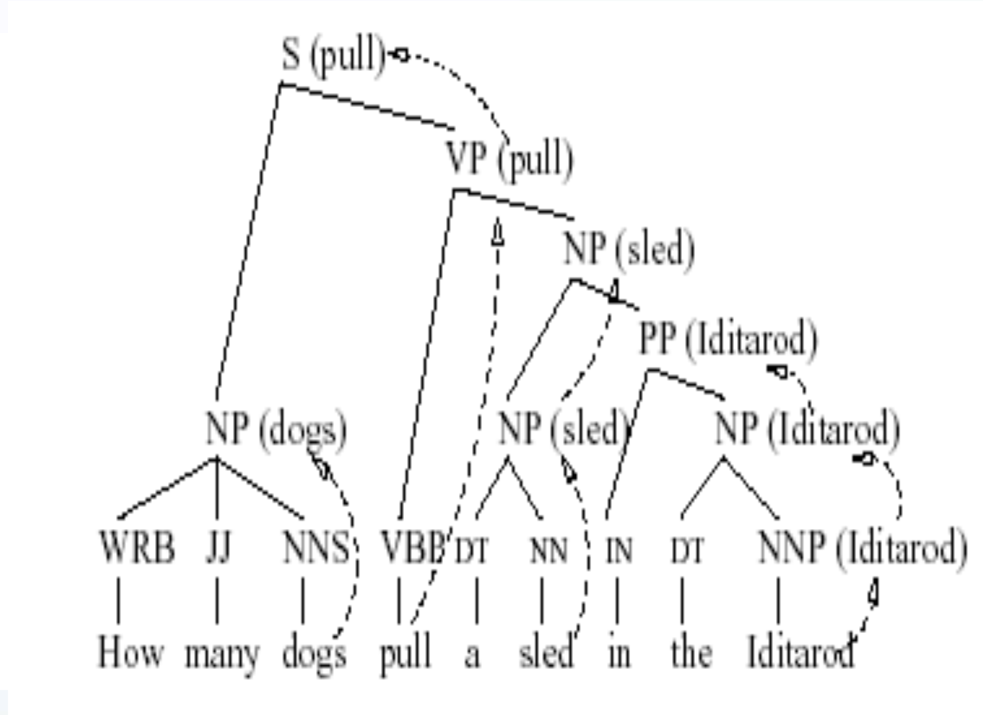


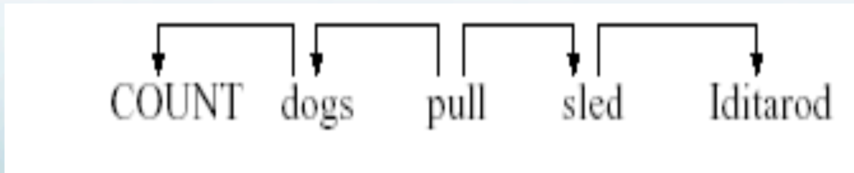

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- *Q: When was the internal combustion engine invented?*
- *A: The first internal-combustion engine was built in 1867.*
- Yields 12% improvement in accuracy!

# Example

- How hot does the inside of an active volcano get?
- Get(TEMPERATURE, inside(active(volcano)))
- "lava fragments belched out of the mountain were as hot as 300 degrees Fahrenheit"
- Fragments(lava,TEMPERATURE(degrees(300)), belched(out, mountain))
  - Volcano ISA mountain; lava ISPARTOF volcano
  - Lava inside volcano
  - Fragments of lava HAVEPROPERTIESOF lava
- Knowledge derived from WordNet to proof 'axioms'

Ex. Due to D. Jurafsky

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- Improves only by 2%
  - Mostly captured by surface forms

# Results

| | PowerAnswer-2 |
|---|---|
| Factoid | 0.713 |
| List | 0.468 |
| Other | 0.228 |
| Overall | 0.534 |

Table 2: Results in the main task.

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    - "Text Classification"
  - Arbitrary topics, typically defined by statement of information need (aka query)
    - "Information Retrieval"
      - Ad-hoc retrieval

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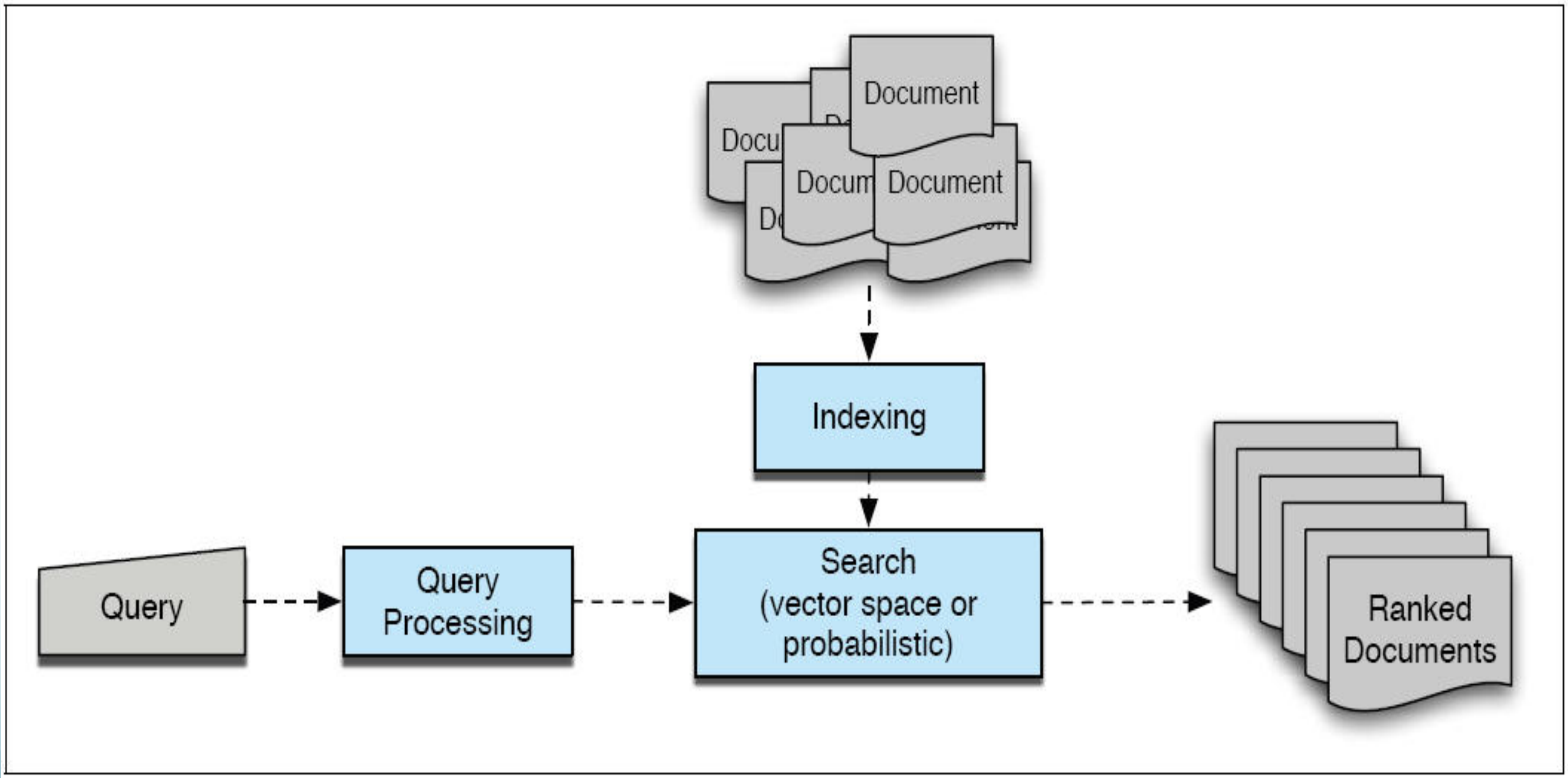
  - Minimal units for query/document
    - Words, or phrases

# Information Retrieval Architecture



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  - *N:*
    - # of terms in vocabulary of collection: Problem?

# Representation

- Solution 1:
  - Binary features:
    - w=1 if term present, 0 otherwise
  - Similarity:
    - Number of terms in common
    - Dot product

$$sim(\vec{q}_k, \vec{d}_j) = \sum_{i=1}^{N} w_{i,k} w_{i,j}$$

- Issues?

# VSM Weights

- What should the weights be?
- "Aboutness"
  - To what degree is this term what document is about?
  - Within document measure
  - Term frequency (tf): # occurrences of t in doc j
- Examples:
  - Terms: chicken, fried, oil, pepper
  - D1: fried chicken recipe: (8, 2, 7,4)
  - D2: poached chick recipe: (6, 0, 0, 0)
  - Q: fried chicken: (1, 1, 0, 0)

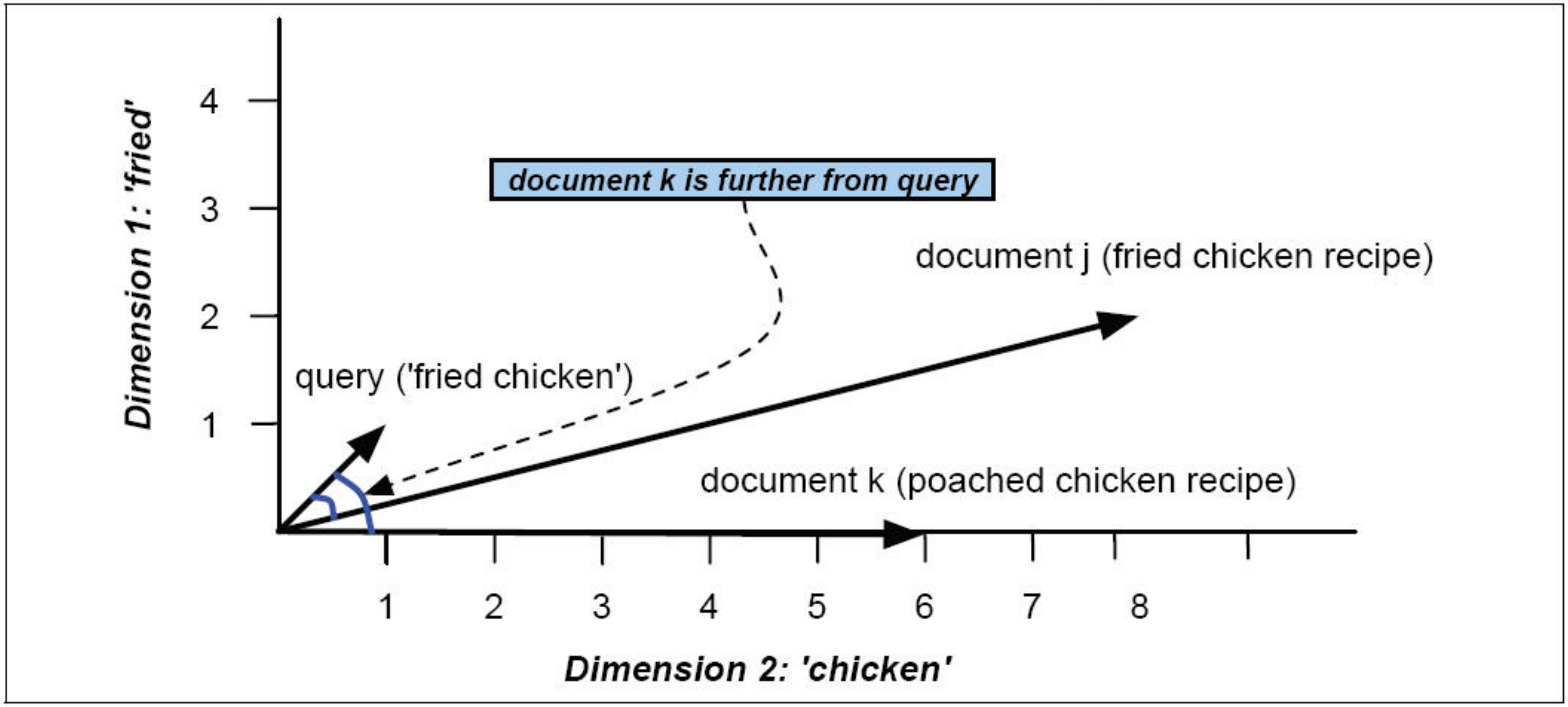
# Vector Space Model (II)

- Documents & queries:
  - Document collection: term-by-document matrix

$$A = \begin{pmatrix} 8 & 6 \\ 2 & 0 \\ 7 & 0 \\ 4 & 0 \end{pmatrix}$$

  - View as vector in multidimensional space
    - Nearby vectors are related
  - Normalize for vector length

# Vector Space Model



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    - Identical vectors: 1
    - No overlap:

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    - Identical vectors: 1
    - No overlap: 0

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# Tf-idf Similarity

- Variants of tf-idf prevalent in most VSM

$$sim(\vec{q},\vec{d}) = \frac{\sum_{w \in q,d} tf_{w,q} tf_{w,d} (idf_w)^2}{\sqrt{\sum_{q_i \in q} (tf_{q_i,q} idf_{q_i})^2} \sqrt{\sum_{d_i \in d} (tf_{d_i,d} idf_{d_i})^2}}$$

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- Remove 'stop words' based on list
  - Usually document-frequency based

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- Issues:
  - Can be too aggressive
    - AIDS, aids -> aid; stock, stocks, stockings -> stock

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$$\Pr ecision = \frac{|R|}{|T|}; \operatorname{Re} call = \frac{|R|}{|U|}$$

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- Need rank-sensitive measures

# Rank-specific P & R

| Rank | Judgment | $Precision_{Rank}$ | $Recall_{Rank}$ |
|---|---|---|---|
| 1 | R | 1.0 | .11 |
| 2 | N | .50 | .11 |
| 3 | R | .66 | .22 |
| 4 | N | .50 | .22 |
| 5 | R | .60 | .33 |
| 6 | R | .66 | .44 |
| 7 | N | .57 | .44 |
| 8 | R | .63 | .55 |
| 9 | N | .55 | .55 |
| 10 | N | .50 | .55 |
| 11 | R | .55 | .66 |
| 12 | N | .50 | .66 |
| 13 | N | .46 | .66 |
| 14 | N | .43 | .66 |
| 15 | R | .47 | .77 |
| 16 | N | .44 | .77 |
| 17 | N | .44 | .77 |
| 18 | R | .44 | .88 |
| 19 | N | .42 | .88 |
| 20 | N | .40 | .88 |
| 21 | N | .38 | .88 |
| 22 | N | .36 | .88 |
| 23 | N | .35 | .88 |
| 24 | N | .33 | .88 |
| 25 | R | .36 | 1.0 |

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- $Precision_{rank}$: based on fraction of reldocs at rank
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- Note: Recall is non-decreasing; Precision varies
- Issue: too many numbers; no holistic view
  - Typically, compute precision at 11 fixed levels of recall
  - Interpolated precision:

$$IntPrecision(r) = \max_{i>=r} Precision(i)$$

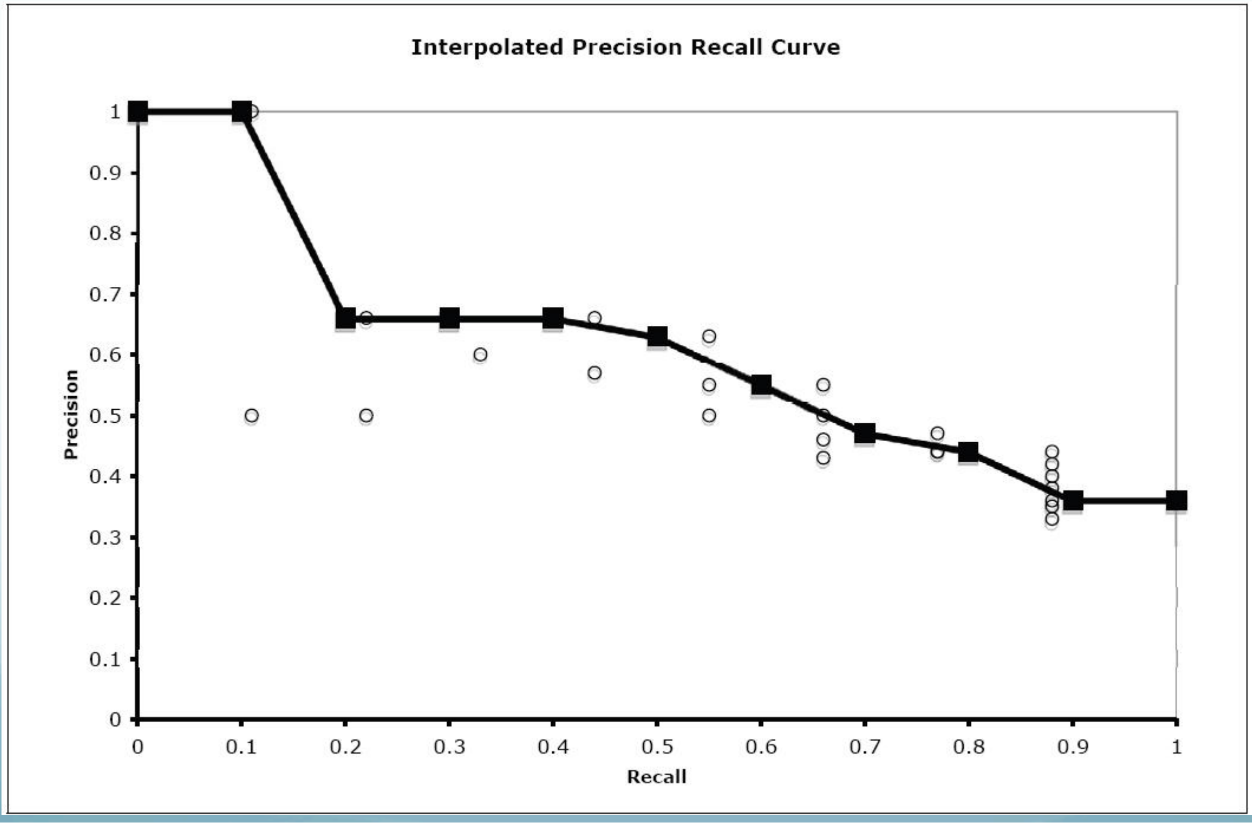
    - Can smooth variations in precision

# Interpolated Precision

| Interpolated Precision | Recall |
|---|---|
| 1.0 | 0.0 |
| 1.0 | .10 |
| .66 | .20 |
| .66 | .30 |
| .66 | .40 |
| .63 | .50 |
| .55 | .60 |
| .47 | .70 |
| .44 | .80 |
| .36 | .90 |
| .36 | 1.0 |

# Comparing Systems

- Create graph of precision vs recall
  - Averaged over queries
  - Compare graphs



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- Single crisp measure: common TREC Ad-hoc

# Roadmap

- Retrieval systems
- Improving document retrieval
  - Compression & Expansion techniques
- Passage retrieval:
  - Contrasting techniques
  - Interactions with document retreival

# Retrieval Systems

- Three available systems
  - Lucene: Apache
    - Boolean systems with Vector Space Ranking
    - Provides basic CLI/API (Java, Python)

  - Indri/Lemur: Umass /CMU
    - Language Modeling system  (best ad-hoc)
    - ‘Structured query language
      - Weighting,
    - Provides both CLI/API (C++,Java)

  - Managing Gigabytes (MG):
    - Straightforward VSM

# Retrieval System Basics

- Main components:
  - Document indexing
    - Reads document text
      - Performs basic analysis
        - Minimally – tokenization, stopping, case folding
        - Potentially stemming, semantics, phrasing, etc
    - Builds index representation

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    - Builds index representation
  - Query processing and retrieval
    - Analyzes query (similar to document)
      - Incorporates any additional term weighting, etc
    - Retrieves based on query content
      - Returns ranked document list

# Example (I/L)

- indri-5.0/buildindex/IndriBuildIndex parameter_file
  - XML parameter file specifies:
    - Minimally:
      - Index: path to output
      - Corpus (+): path to corpus, corpus type
    - Optionally:
      - Stemmer, field information
- indri-5.0/runquery/IndriRunQuery query_parameter_file -count=1000 \

  -index=/path/to/index -trecFormat=true > result_file

  Parameter file: formatted queries w/query #

# Lucene

- Collection of classes to support IR
  - Less directly linked to TREC
    - E.g. query, doc readers
- IndexWriter class
  - Builds, extends index
  - Applies analyzers to content
    - SimpleAnalyzer: stops, case folds, tokenizes
    - Also Stemmer classes, other langs, etc
- Classes to read, search, analyze index
- QueryParser parses query (fields, boosting, regexp)