Deep Processing QA & Information Retrieval

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NLP Systems and Applications
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Roadmap

- PowerAnswer-2: Deep processing Q/A
- Problem:
  - Matching Topics and Documents
- Methods:
  - Vector Space Model
- Retrieval evaluation

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: “Above median”: 53.4% main

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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- Single, basic referent:

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Q27.2	Who is her coach?
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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?
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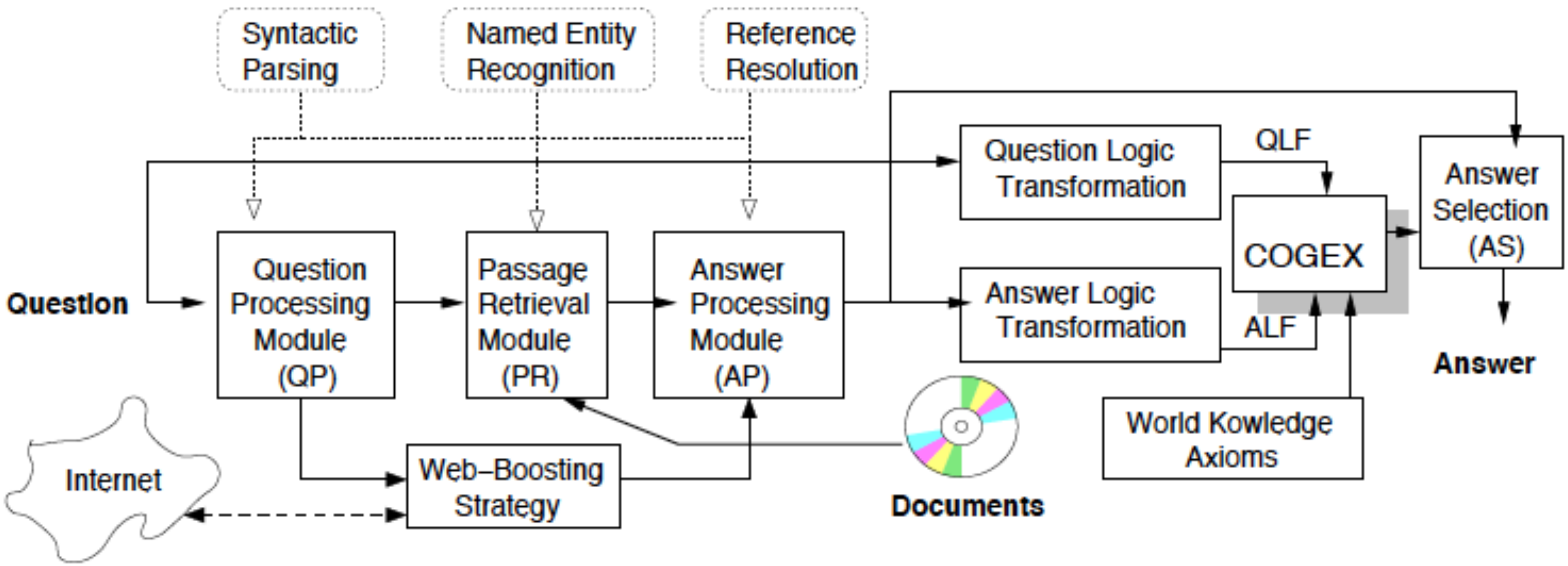
  - Most teams concatenate

PowerAnswer-2

- Factoid QA system:



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

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  - Reweighting improves
- Web-boosting improves significantly: 20%

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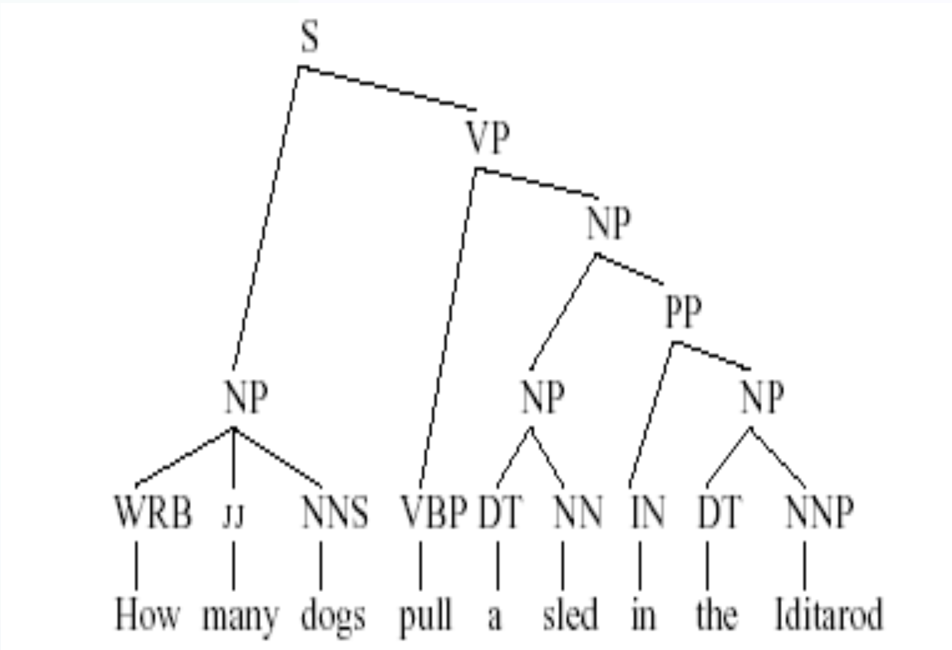
- Coreference resolution links entity references
- Translate to full logical form
  - As close as possible to syntax

Syntax to Logical Form



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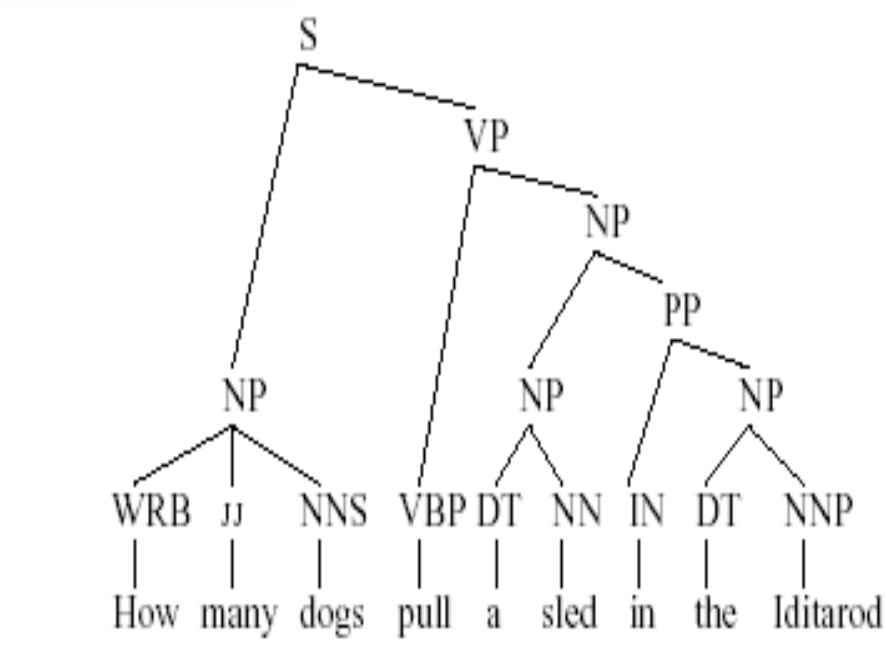

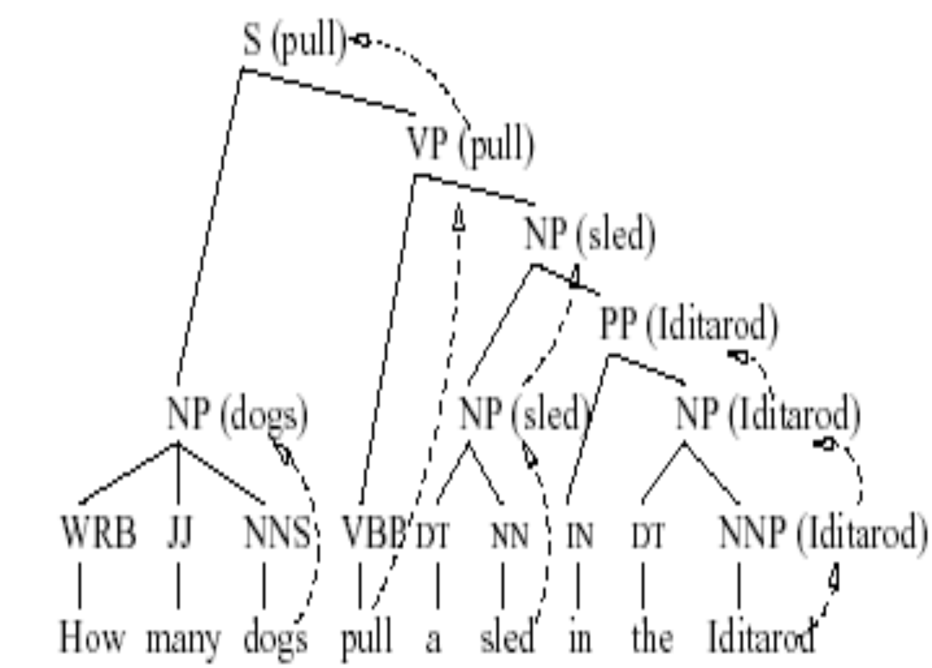

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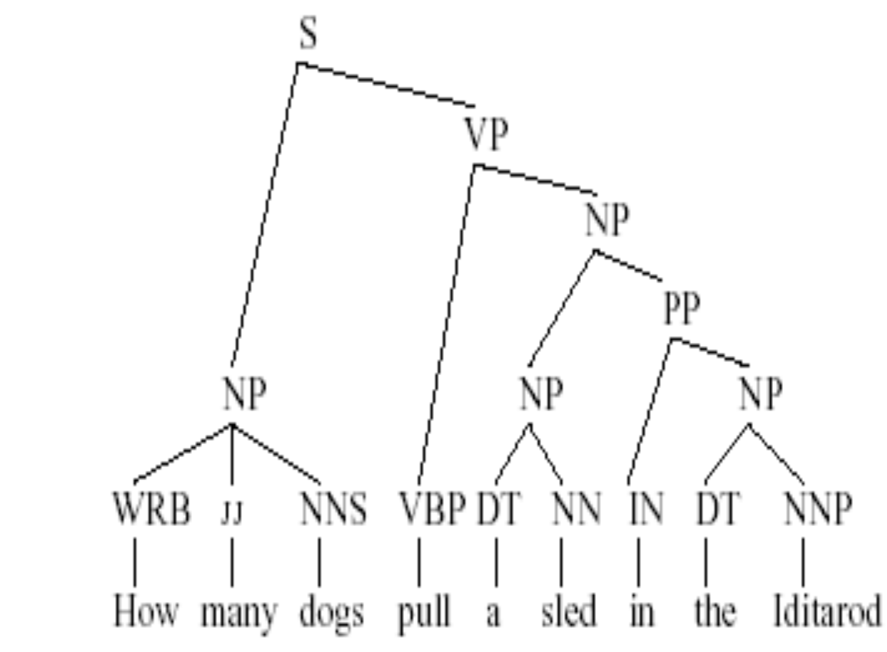

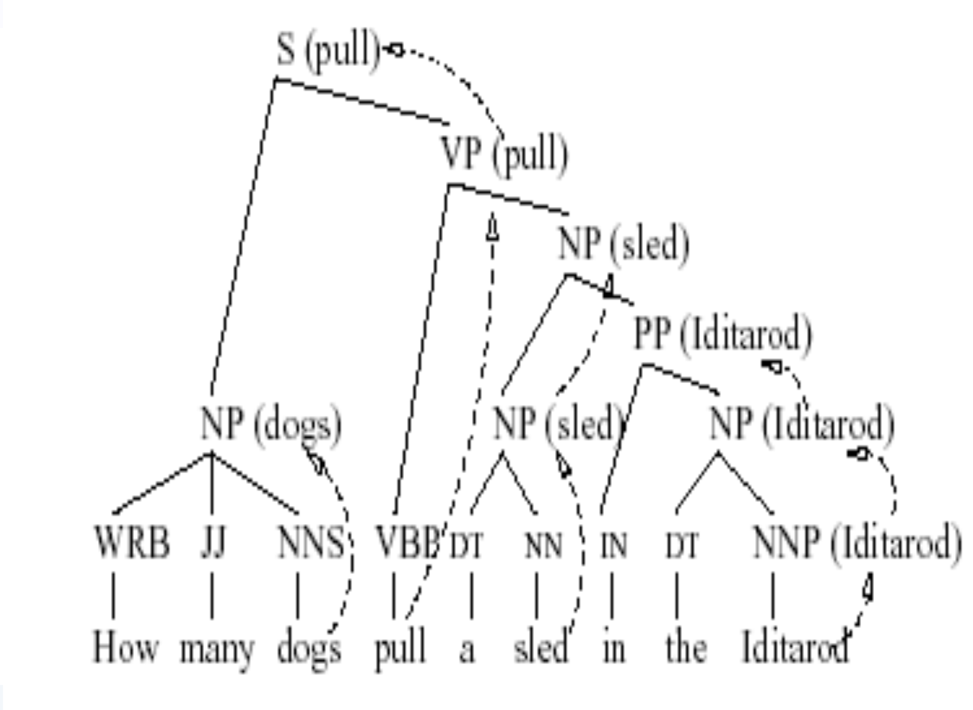

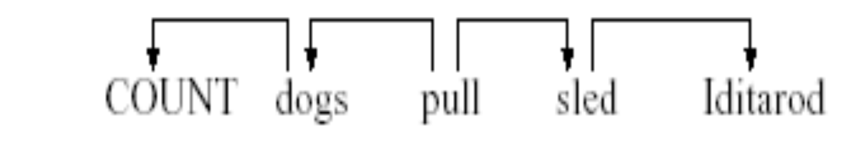

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  - Yields 12% improvement in accuracy!

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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.

Matching Topics and Documents

- Two main perspectives:
  - Pre-defined, fixed, finite topics:
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- Two main perspectives:
  - Pre-defined, fixed, finite topics:
    - "Text Classification"
  - Arbitrary topics, typically defined by statement of information need (aka query)
    - "Information Retrieval"
      - Ad-hoc retrieval

Information Retrieval Components

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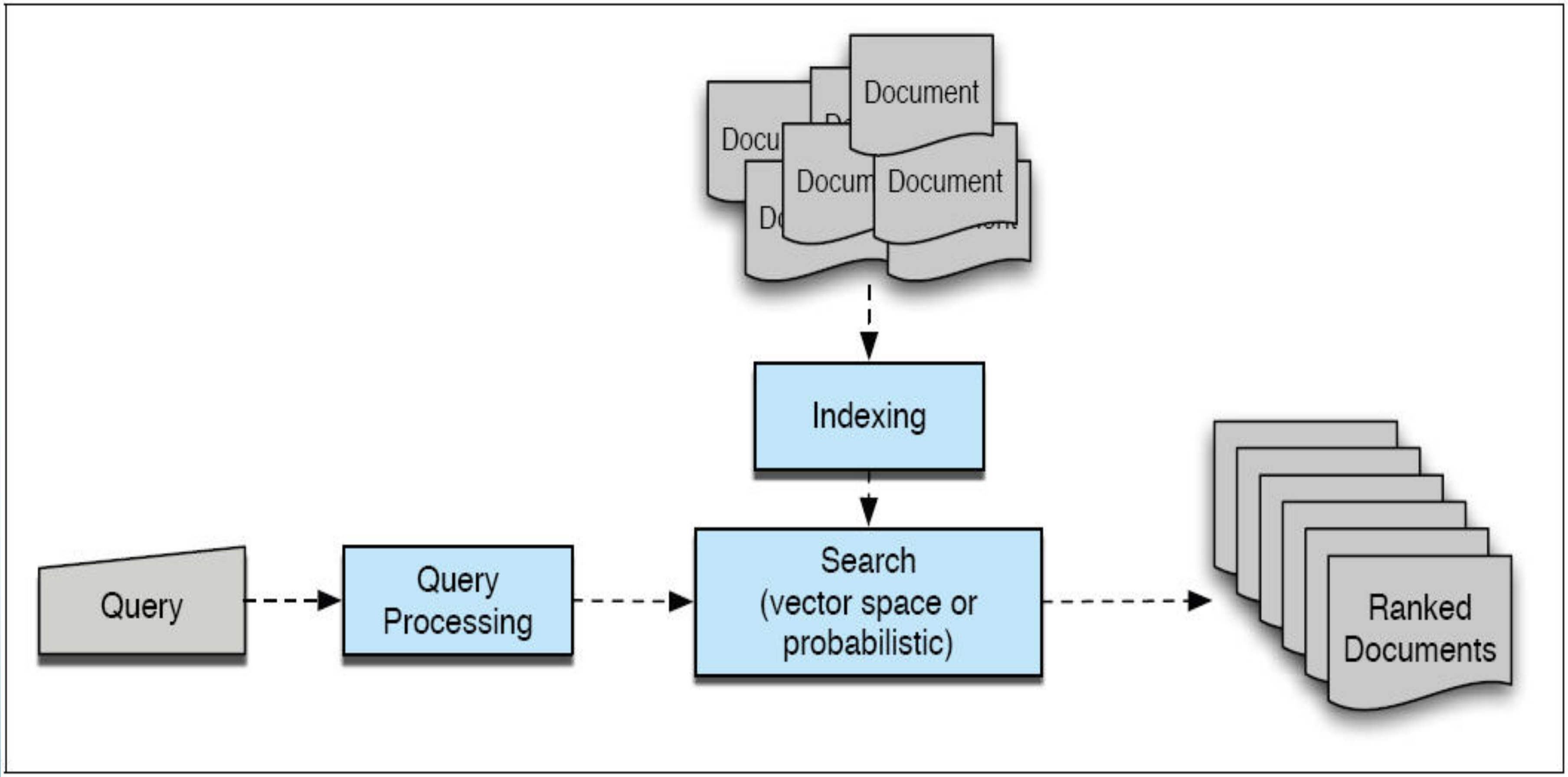
    - Words, or phrases

Information Retrieval Architecture



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  - E.g. $\vec{d}_j = (w_{1,j}, w_{2,j}, \ldots, w_{N,j}); \vec{q}_k = (w_{1,k}, w_{2,k}, \ldots, w_{N,k})$
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    - # 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)

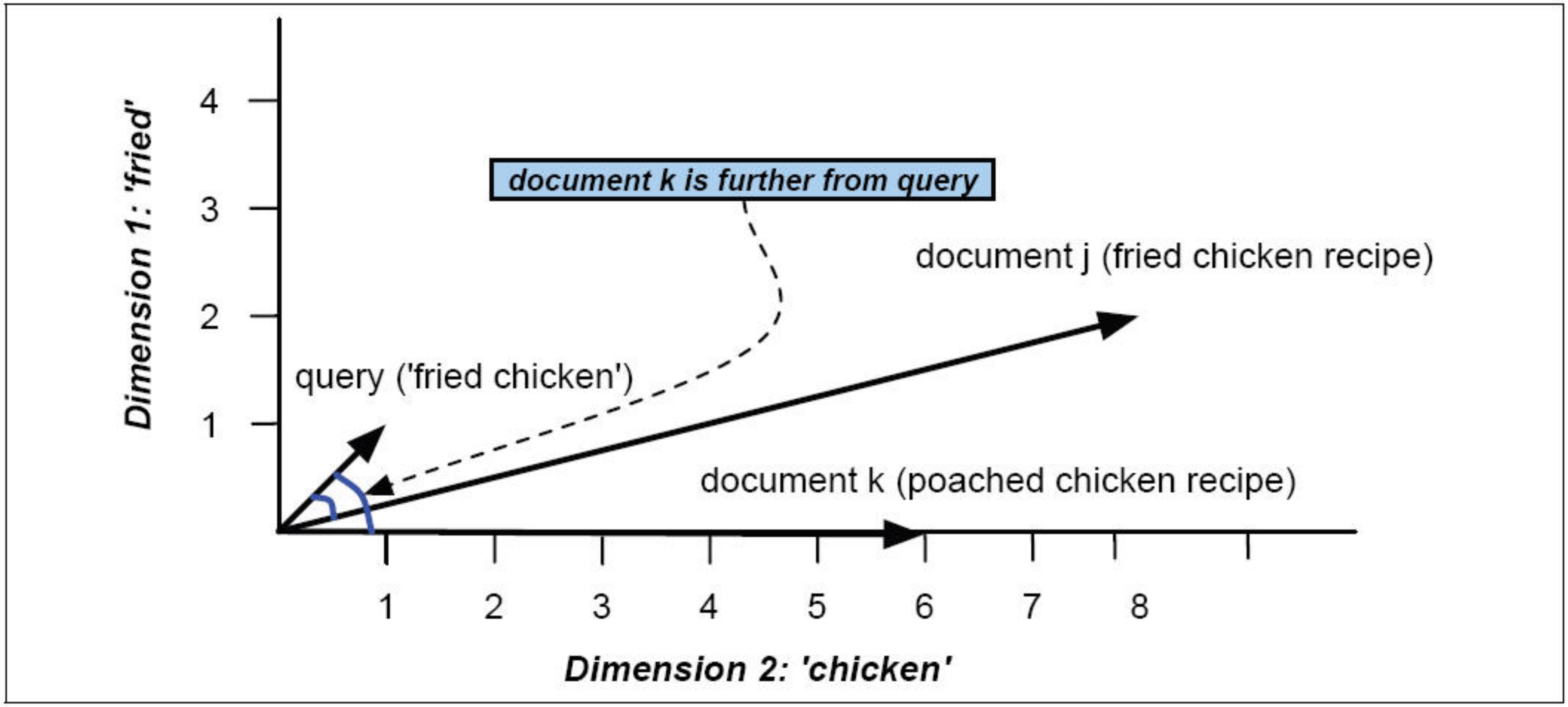
Vector Space Model (II)

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

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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

Rank-specific P & R

- $\text{Precision}_{\text{rank}}$: based on fraction of reldocs at rank
- $\text{Recall}_{\text{rank}}$: similarly

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- Precision_{rank}: based on fraction of reldocs at rank
- Recall_{rank}: similarly
- Note: Recall is non-decreasing; Precision varies

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- Note: Recall is non-decreasing; Precision varies
- Issue: too many numbers; no holistic view

Rank-specific P & R

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- $\text{Recall}_{\text{rank}}$: similarly
- 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:

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

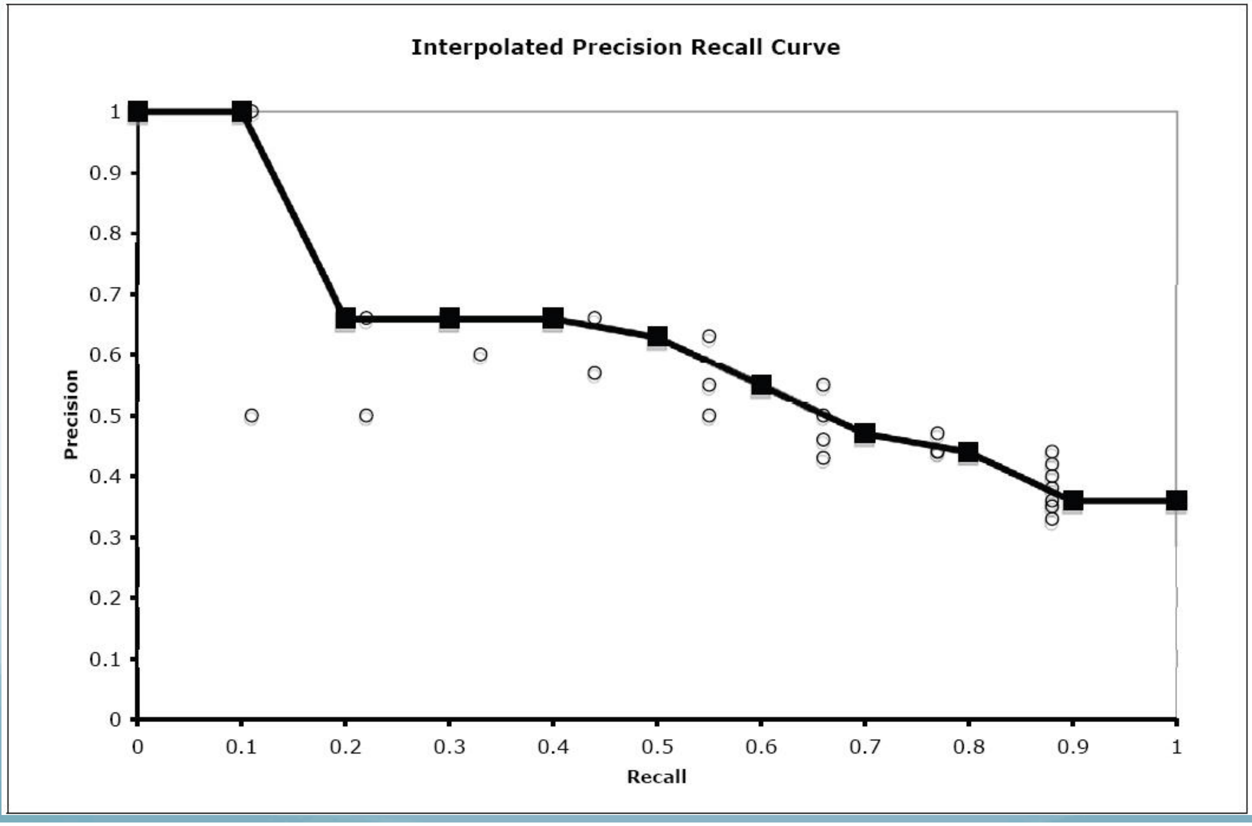
    - Can smooth variations in precision

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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    - Precision-oriented measure
- 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)