# BMI/CS 776 Lecture #30 Biomedical Text Mining

Colin Dewey (adapted from slides by Mark Craven) 2007.05.10

#### Some Important Text-Mining Problems

hypothesis generation

**Given**: biomedical objects/classes of interest (e.g. diseases & dietary factors)

**Do**: identify interesting, implied relationships among the objects

experiment annotation

Given: a set of genes/proteins exhibiting common behavior in an experiment

**Do**: identify commonalities among genes/proteins in the set

information extraction

Given: classes, relations of interest

Do: recognize and extract instances of the classes and relations from documents

#### Some Important Text-Mining Problems

document classification

Given: defined classes of interest

**Do**: assign documents to the relevant classes

ad-hoc retrieval

Given: a query

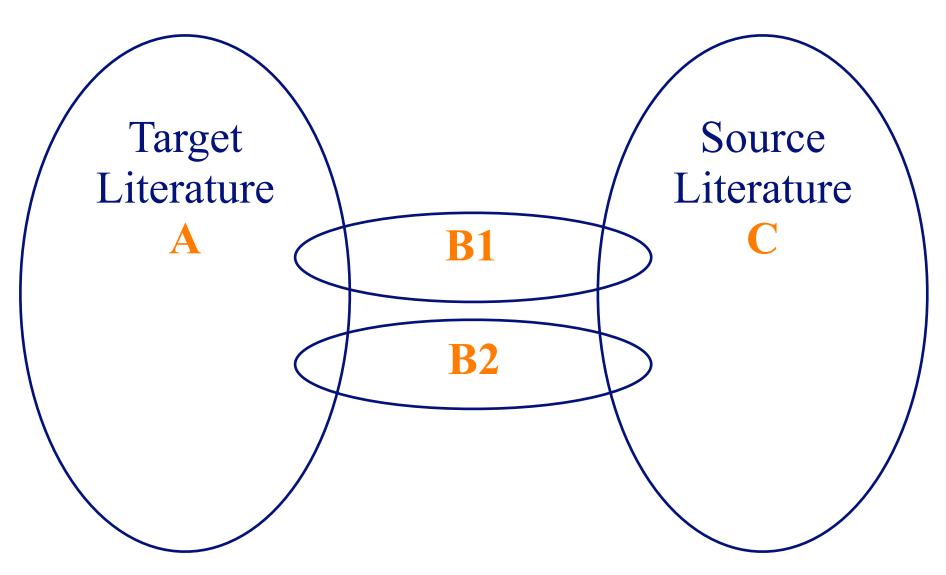
**Do**: return relevant documents/passages

- improving the accuracy of other inference tasks
  - querying with PSI-BLAST [Chang et al.]
  - predicting sub-cellular localization of proteins [Hoglund et al]
  - etc.

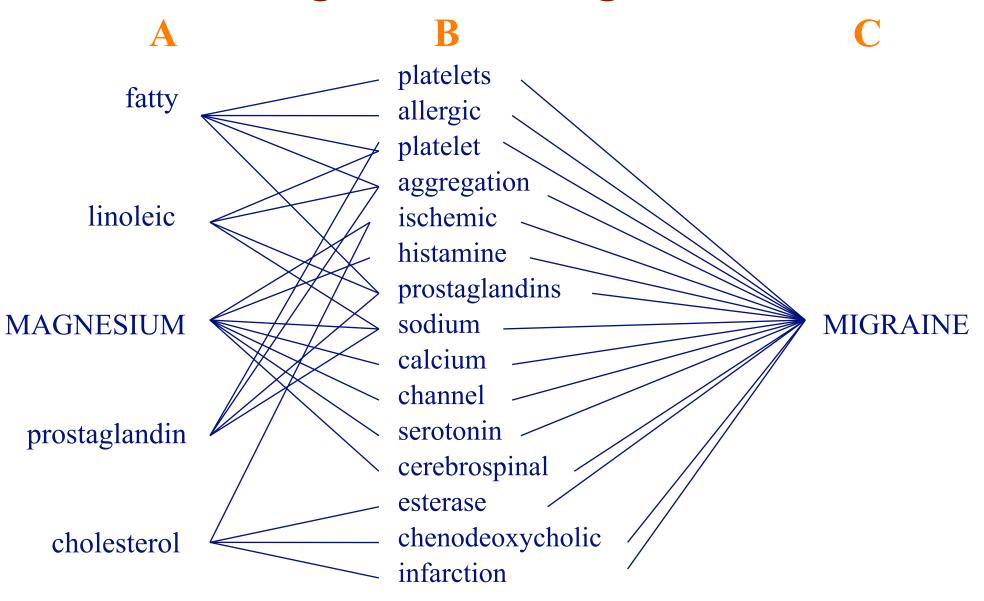
# Hypothesis Generation by Finding Complementary Literatures

- [Swanson & Smalheiser, Artificial Intelligence 91, 1997]
- ARROWSMITH aids in identifying relationships that are implicit, but not explicitly described, in the literature
- http://arrowsmith.psych.uic.edu/

# ARROWSMITH: Finding Complementary Literatures



#### ARROWSMITH Example: The Magnesium-Migraine Link



#### The ARROWSMITH Method

- given: query concept C (e.g. *migraine*)
- do:
  - run MEDLINE search on C
  - derive a set of words (B) from titles of returned articles;
     retain words
  - run MEDLINE search on each B word to assemble list of A words
  - rank A-C linkages by number of different intermediate B terms

# Restricting the Search in ARROWSMITH

- prune B list by
  - using a predefined *stop-list*("clinical", "comparative", "drugs",...)
  - having a <u>human</u> expert filter terms
- prune A list using *category restrictions* (e.g. dietary factors, toxins, etc.)
- prune C-B, B-A linkages by requiring:

$$Pr(B \mid C) > Pr(B)$$

$$Pr(A \mid B) > Pr(A)$$

Given a document with word C, do we see B more often than we'd expect by chance?

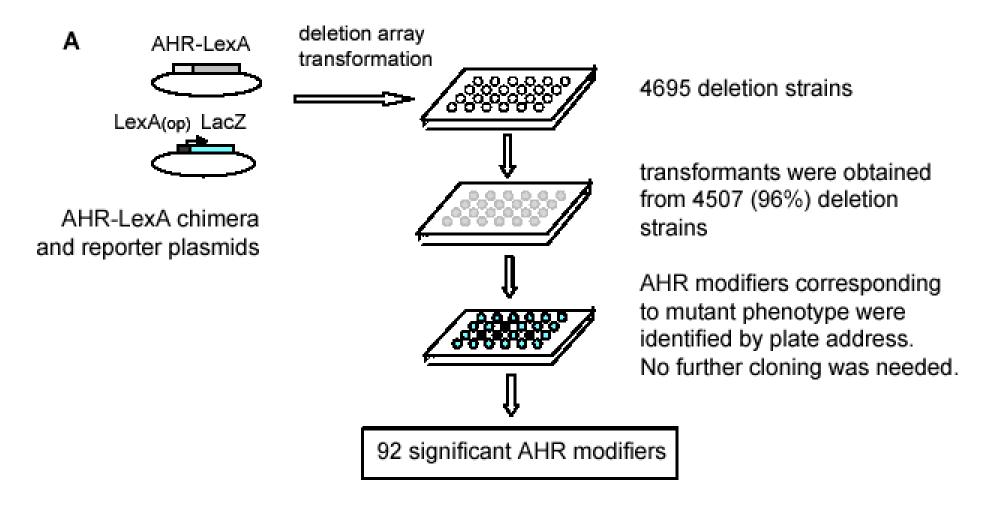
#### **ARROWSMITH Case Studies**

- indomethacin and Alzheimer's disease
- estrogen and Alzheimer's disease
- phospholipases and sleep
- etc.
- has led to hypotheses interesting enough to warrant further studies, peer-reviewed articles

#### Task: Automatic Annotation of Experiments

- Genes, Themes and Microarrays. Shatkay, Edwards, Wilbur & Boguski. *ISMB* 2000
- given: a set of genes with a "kernel" document for each
- return:
  - top-ranked words in theme for each gene
  - list of most similar genes, in terms of associated documents

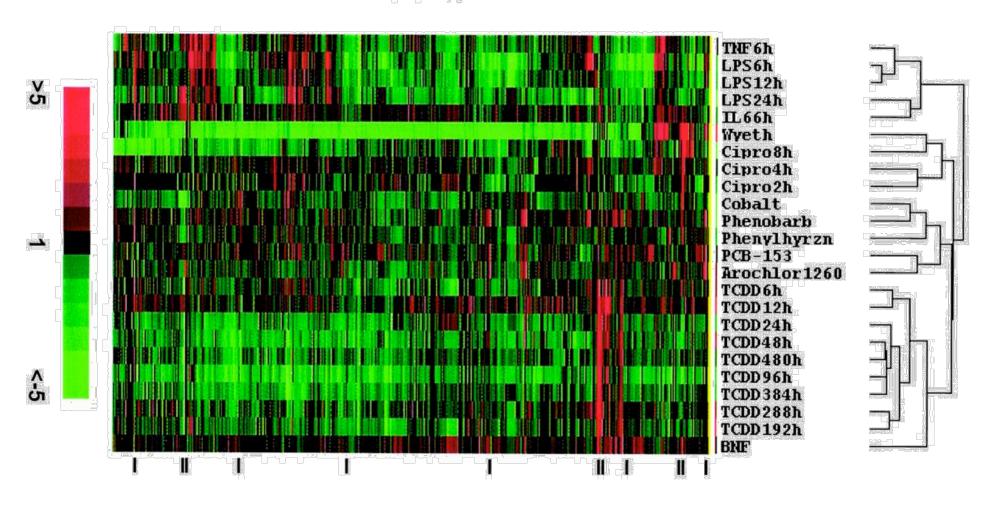
## High-throughput Experiment Example: Yao et al., *PLoS Biology* 2004



• Experiment identified 92 genes that, when knocked out, modify AHR signaling. What do they have in common?

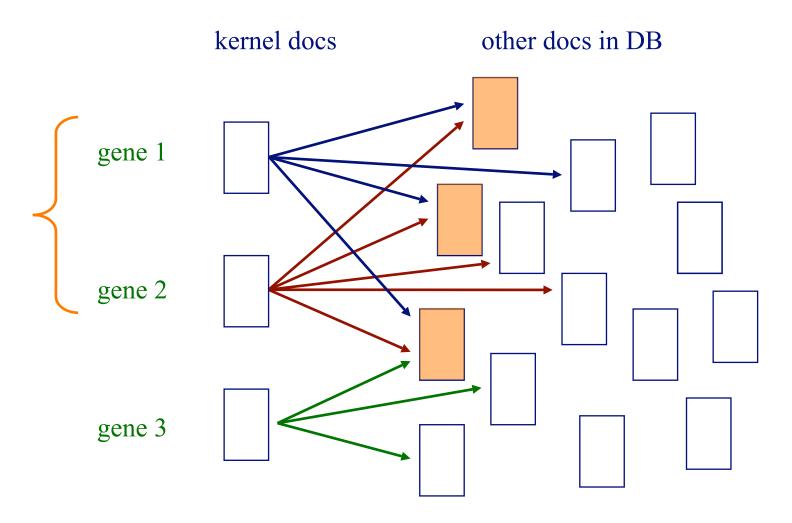
### High-throughput Experiment Example: Thomas et al., *Molecular Pharmacology* 2002

Genes



• In initial experiments, a mysterious set of genes that were upregulated in all treatments. What do they have in common?

#### Shatkay et al. Approach

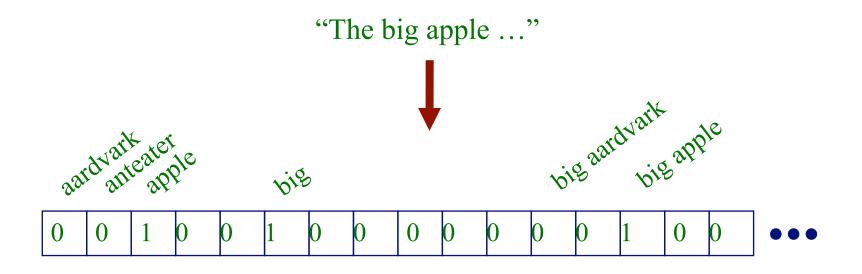


step 1: given kernel documents, find themes

step 2: given themes, find related genes

#### Representing Documents

- Shatkay et al. represent documents using fixed-length vectors
  - this is a common approach in many text processing systems (e.g. search engines)
- elements in vector represent occurrences of individual words (unigrams) and pairs of adjacent words (bigrams)



#### Themes

- a theme, T, is a set of documents discussing a common topic
- the occurrence of a given term  $t_i$  in a theme document d is represented by

$$p_i^T = \Pr(t_i \in d \mid d \in T)$$

• thus for every term in the vocabulary, we can characterize how likely it is to occur in a document on theme *T* 

#### Theme Example

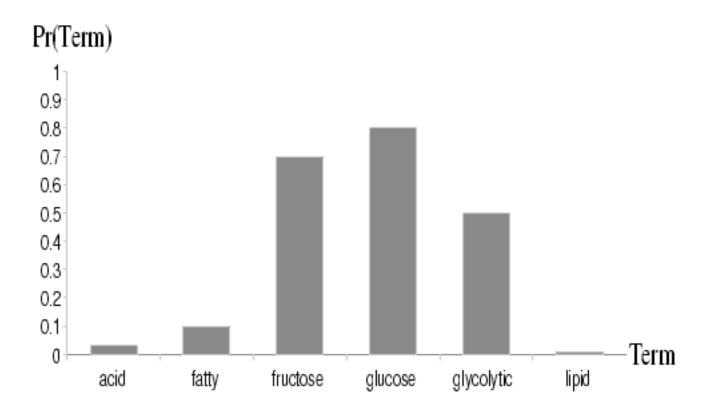


Figure from H. Shatkay et al., ISMB 2000

Theme = "Nutrition"

#### Other Parameters

- Shatkay et al. use similar parameters to represent
  - the occurrence of each term given that document d is not in the theme

$$q_i^T \equiv \Pr(t_i \in d \mid d \notin T)$$

 the occurrence of the term regardless of whether d is ontheme or off-theme

$$DB_i = \Pr(t_i \in d \mid d \in DB)$$

– the prob that a term occurrence,  $t_i$ , is best explained by DB probability or by on-theme/off-theme probabilities

$$\lambda$$

#### Model for "Generating" Documents

 we can think of the document vectors as having been generated from a model with these parameters

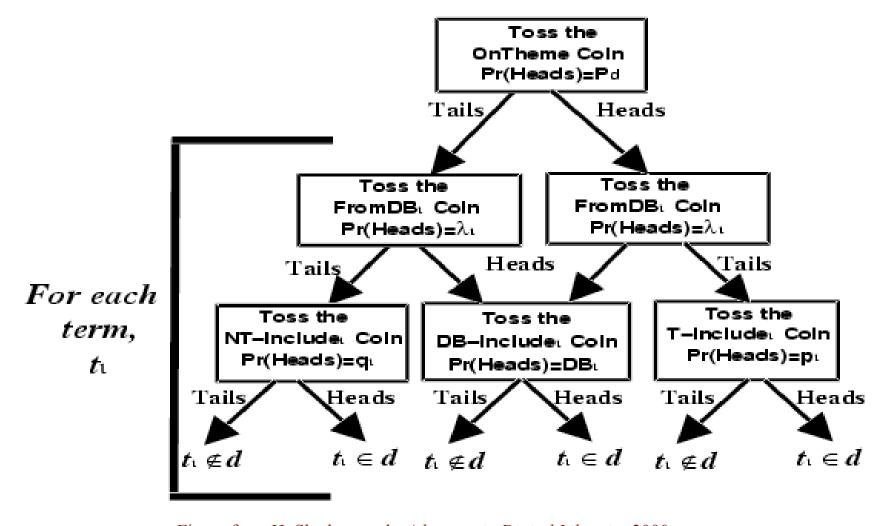


Figure from H. Shatkay et al., Advances in Digital Libraries 2000

#### Finding Themes

- given: a DB of documents and a "kernel" document
- do:
  - determine the parameters characterizing the theme T
  - determine the documents belonging to T
- if we knew the documents in *T*, it would be easy to determine the parameters
- if we knew the parameters, it would be easy to determine the documents in T
- but initially, we don't know either

#### Finding Themes

Shatkay et al. solve this problem using EM

E-step: compute likelihood for each document that it's in same theme as kernel

M-step: find new parameters that maximize the likelihood of this partition into theme/off-theme documents

#### Finding Themes: Output

- this EM process is run once for each gene/kernel document
- the results returned for each gene are  $-\text{ a list of the most highly weighted} \left(\frac{p_i^T}{q_i^T}\right) \text{words in the associated theme}$ 
  - a list of the most on-theme documents

#### Finding Themes: Example

• Shatkay et al. have applied this method to find themes in the AIDS literature [*Advances in Digital Libraries*, 2000]

Failure of screening to detect HIV in a foreign laborer who died of toxoplasmosis of the central nervous system.

AIDS-associated cytomegalovirus infection mimicking central nervous system tumors: a diagnostic challenge.

Chagasic granulomatous encephalitis in immunosuppressed patients. Computed tomography and magnetic resonance imaging findings.

Isolated homonymous lateral hemianopsia revealing central nervous system toxoplasmosis as the initial manifestation of AIDS.

Expression and antigenicity of human herpesvirus 8 encoded ORF59 protein in AIDS-associated Kaposi's sarcoma.

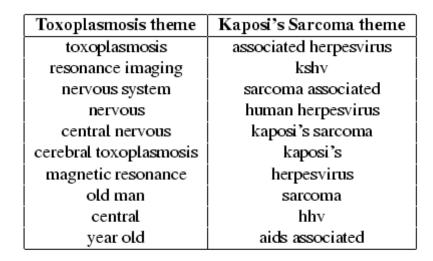
Primary intraosseous AIDS-associated Kaposi's sarcoma. Report of two cases with initial jaw involvement.

Expression of human herpesvirus-8 (HHV-8) encoded pathogenic genes in Kaposi's sarcoma (KS) primary lesions

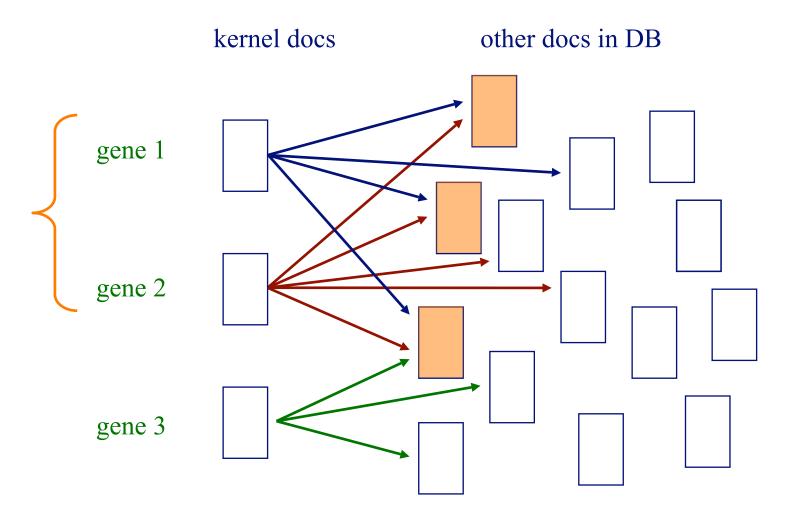
Further confirmation of the association of human herpesvirus 8 with Kaposi's sarcoma.

titles of top-4 documents for two themes

top-10 words for the themes



#### Finding Related Genes

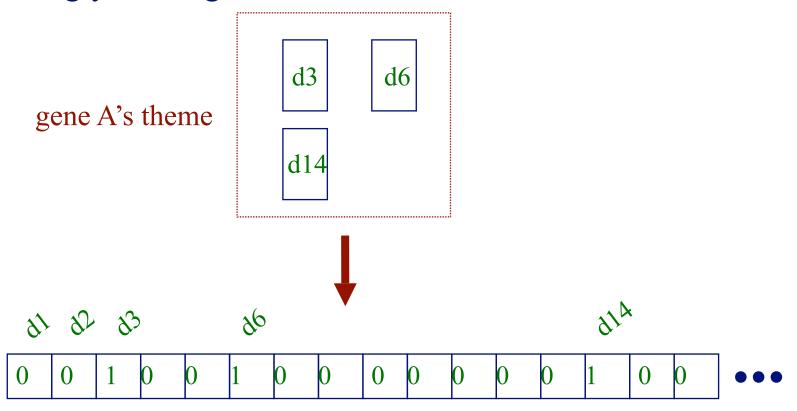


step 1: given kernel documents, find themes

step 2: given themes, find related genes

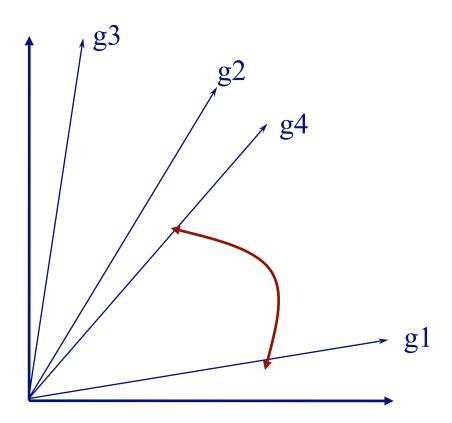
#### Representing Genes

- represent each gene using fixed-length vector in which each element corresponds to a document
- put a 1 in a given element if the associated document is strongly in the gene's theme



#### The Vector Space Model

- the similarity between two genes can be assessed by the similarity of their associated vectors
- this is a common method in information retrieval to assess document similarity; here we are assessing gene similarity



#### **Vector Similarity**

 one way to determine vector similarity is the cosine measure:

$$\cos(\vec{a}, \vec{b}) = \frac{\sum_{i} a_i b_i}{\sqrt{\sum_{i} a_i^2} \sqrt{\sum_{i} b_i^2}}$$

• if the vectors are normalized, we can simply take their dot product

#### Shatkay et al. Experiment

- analyzed 408 yeast genes
- documents = abstracts
- kernel documents: oldest reference for each gene in SGD
- database: 33,700 yeast-related documents

#### Shatkay et al. Experimental Results

Kernel (PMID,	Keywords	Assoc.	Function
Gene, Function)		Genes	
8702485	fatty acid,	OLE1	(Fatty Acid, Sterol. Met.)*
ELO1	fatty,	FAA4	Fatty Acid/Lipids/Sterols/Membranes
Fatty Acid/	lipids,	FAA3	Fatty Acid/Lipids/Sterols/Membranes
Lipids/	acid,	SUR2	Fatty Acid/Lipids/Sterols/Membranes
Sterols/	grown,	FAA1	Fatty Acid/Lipids/Sterols/Membranes
Membranes	medium,	ERG2	Fatty Acid/Lipids/Sterols/Membranes
	carbon,	PSD1	Fatty Acid/Lipids/Sterols/Membranes
	synthase,	CYB5	(Fatty Acid, Sterol. Met.)*
	strains,	PGM1	(Carbohydrates Met.)*
	deficient		
7651133	hexose,	HXT1	Nutrition
HXT7	glucose uptake,	RGT2	Nutrition
Nutrition	glucose conc.,	HXT4	Nutrition
	fructose,	HXT2	Nutrition
	glycolytic,	GLK1	Nutrition
	glucose,	SEO1	(Small Molecules Transport)*
	sugars,	PRB1	(Protein Degradation)*
	uptake,	AGP1	Nutrition
	aerobic,	ZRT1	Nutrition
	utilization	MIG2	(Carbohydrates Met.)*

Figure from H. Shatkay et al., ISMB 2000

# The Information Extraction Task: Named Entity Recognition

Analysis of Yeast PRP20 Mutations and Functional Complementation by the Human Homologue RCC1, a Protein Involved in the Control of Chromosome Condensation

Fleischmann M, Clark M, Forrester W, Wickens M, Nishimoto T, Aebi M

Mutations in the **PRP20** gene of yeast show a pleitropic phenotype, in which both mRNA metabolism and nuclear structure are affected. **SRM1** mutants, defective in the same gene, influence the signal transduction pathway for the **pheromone** response . . .

By immunofluorescence microscopy the PRP20 protein was localized in the nucleus. Expression of the RCC1 protein can complement the temperature-sensitive phenotype of PRP20 mutants, demonstrating the functional similarity of the yeast and mammalian proteins

- proteins
- small molecules
- methods
- cellular compartments

### The Information Extraction Task: Relation Extraction

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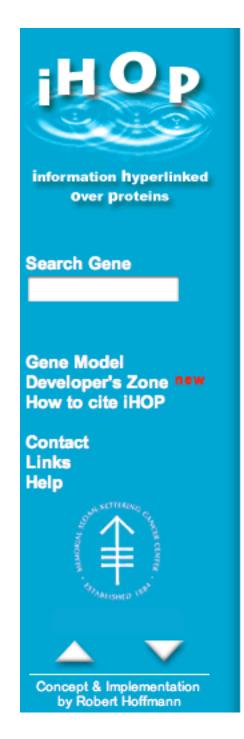
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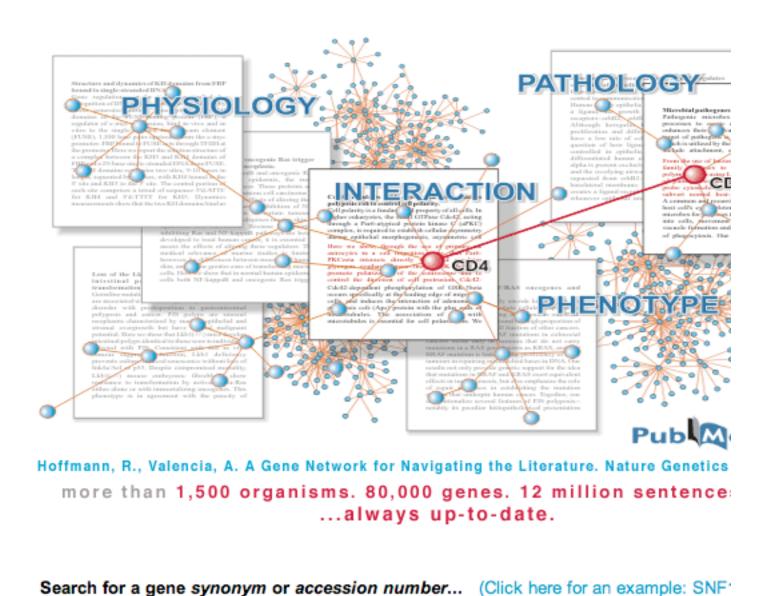
By immunofluorescence microscopy the <u>PRP20</u> protein was localized in the <u>nucleus</u>. Expression of the RCC1 protein can complement the temperature-sensitive phenotype of PRP20 mutants, demonstrating the functional similarity of the yeast and mammalian proteins

subcellular-localization(PRP20, nucleus)

#### Motivation for Information Extraction

- motivation for <u>named entity recognition</u>
  - better indexing of biomedical articles
  - assisting in relation extraction
- motivation for relation extraction
  - assisting in the construction and updating of databases
  - providing structured summaries for queries
    - What is known about protein X (subcellular & tissue localization, associations with diseases, interactions with drugs, ...)?
  - assisting scientific discovery by detecting previously unknown relationships, annotating experimental data





all fields

http://www.ihop-net.org/UniPub/iHOP/ 32

† in All organisms

# Task: Aiding Annotation of Gene/Protein Function

1. document filtering/classification

Given: article

**Do**: determine if it is relevant for curation of any genes in a particular category (GO, tumor biology, expression, etc.) (TREC Genomics Track in 2004, 2005)

2. annotation assignment

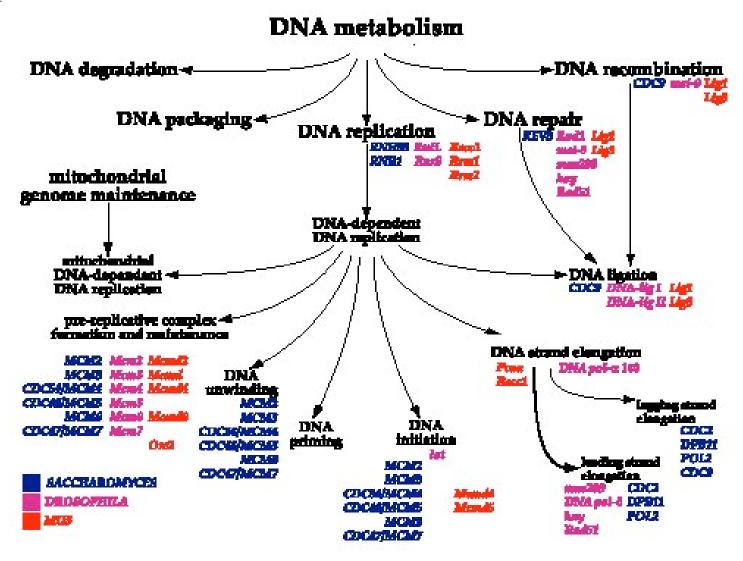
Given: article, gene

**Do**: return Gene Ontology concepts for the gene that are supported by the article

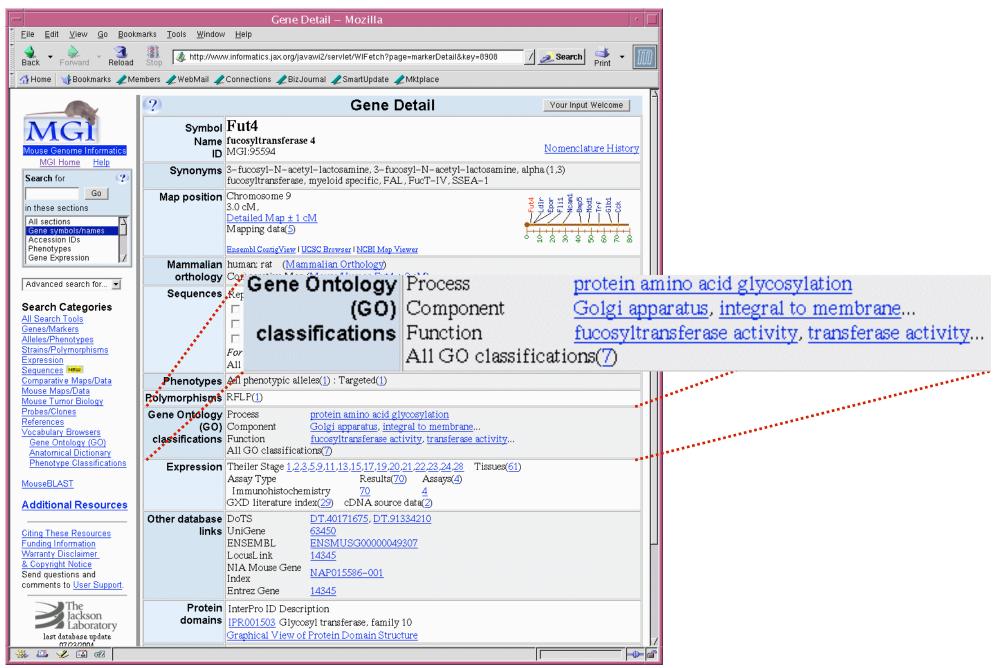
(BioCreative evaluation in 2003)

#### The Gene Ontology

• a controlled vocabulary of more than 17,600 concepts describing molecular functions, biological processes, and cellular components



#### Aiding Annotation: MGI Example



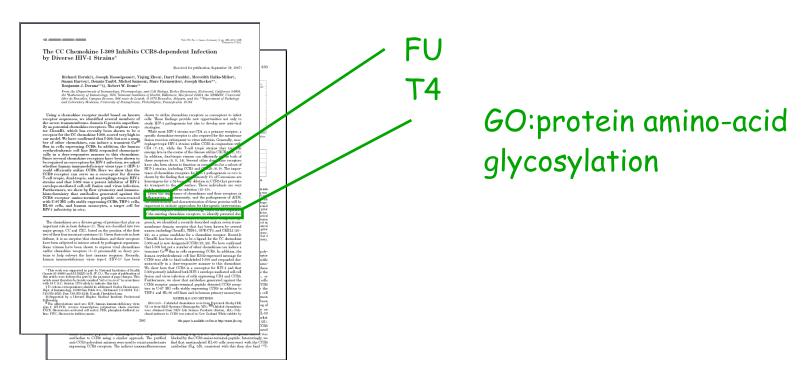
#### Annotating Genomes: MGI Example

• the current method for this annotation process...



## (Partially) Automating This Annotation Process

• first step: need to recognize references to gene names and GO concepts in text



• recall: more than 17,600 GO terms, tens of thousands of gene names plus variants of each

## Recognizing References to GO Terms in Text Passages

- it's not trivial to identify relevant references to GO concepts in the literature
- two examples of gene annotations and supporting passages:

(GO:0008285) negative regulation of cell proliferation

"...inhibition of cell proliferation..."

(GO:0007186) G-protein coupled receptor protein signaling pathway

"...in the signaling pathway, by receptor phosphorylation at the level of receptor/G protein coupling..."

# Recognizing References to GO Terms in Text Passages

• normalization using linguistic knowledge

```
inhibition of cell proliferation ⇒
 cell proliferation inhibition
 inhibits cell proliferation
```

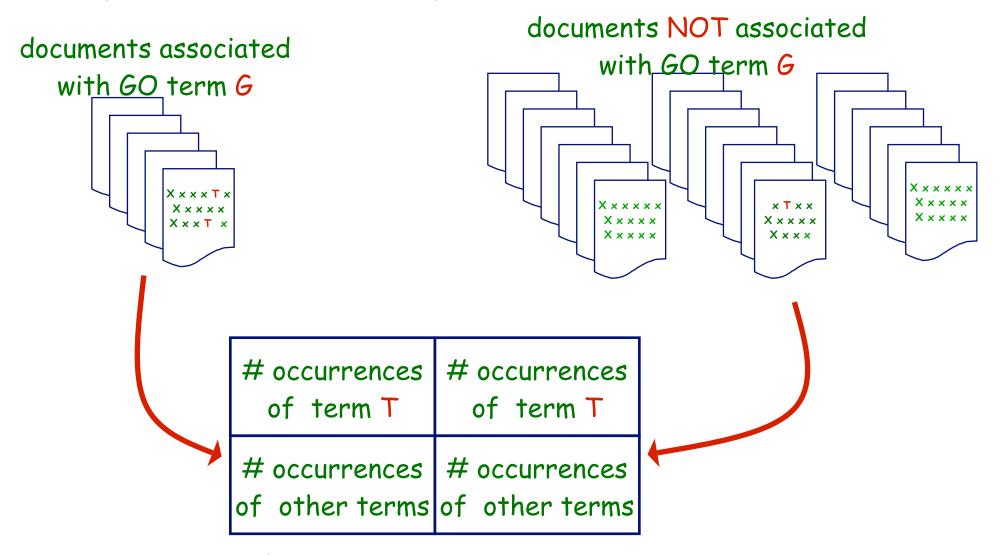
• matching on statistically associated terms; e.g. unigrams associated with sodium symporter activity

```
pantothenate
biotin
transporter
lipoate
smvt
uptake
sodium-depden
```

sodium-depdendent approximate string matching

# Identifying Terms Statistically Associated with GO Concepts

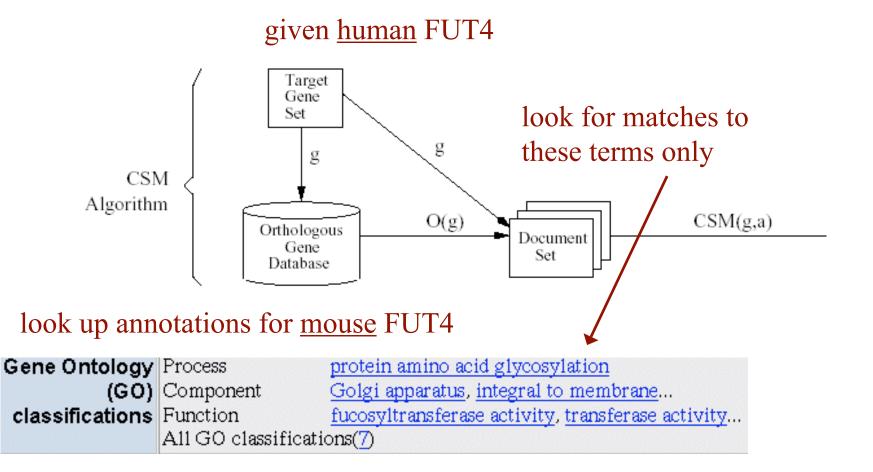
[Ray & Craven, BMC Bioinformatics 2005]



compute  $\chi^2$  value indicating association between T and G

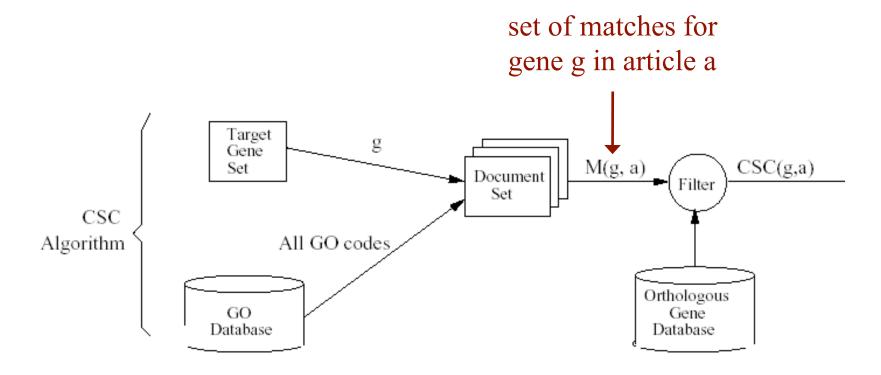
### Using Orthologous Genes in Annotation [Stoica & Hearst, *PSB* '06]

• *cross-species match* (CSM) method: look for GO matches only for concepts that have been used to annotate orthologous genes



### Using Orthologous Genes in Annotation [Stoica & Hearst, *PSB* '06]

• *cross-species correlation* (CSC) method: look for GO matches that correlate with concepts that have been used to annotate orthologous genes



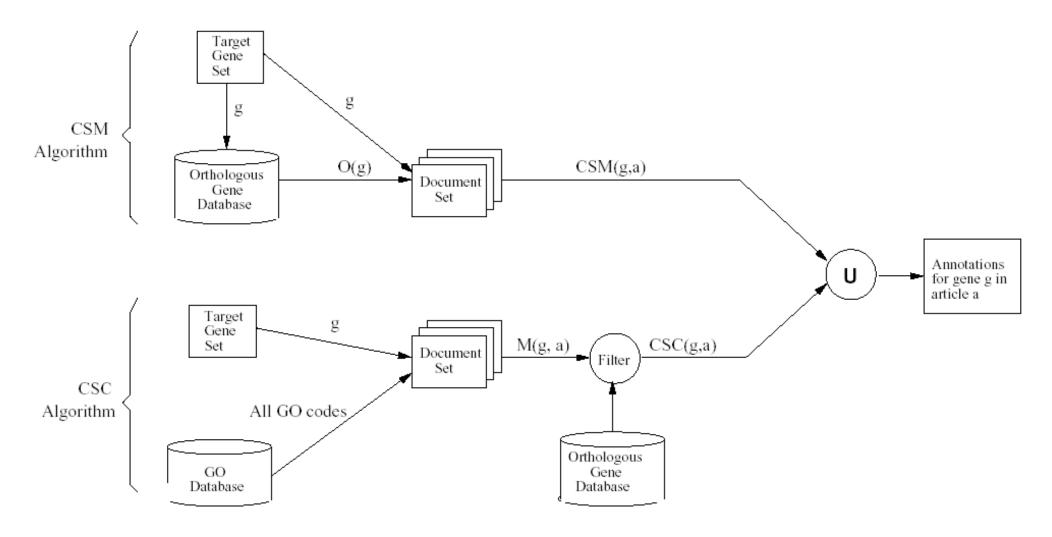
#### The CSC Algorithm

```
CSC(g,a) = \{\};
for every GO_1 in M(g,a) // set of matches for gene g in article a count = 0;
for every GO_2 in O(g) // concepts assigned to orthologs of g if ((\chi^2(GO_1,GO_2)>3.84)\&\&(GO_1\neq GO_2)) count + +;
if (count > p*o) // o is size of O(g), p is a specified fraction add GO_1 to CSC(g,a);
```

do concepts  $GO_1$  and  $GO_2$  tend to be associated with one another in annotations in the database?

### Using Orthologous Genes in Annotation [Stoica & Hearst, *PSB* '06]

full system takes union of CSM and CSC predictions



#### Stoica & Hearst Results

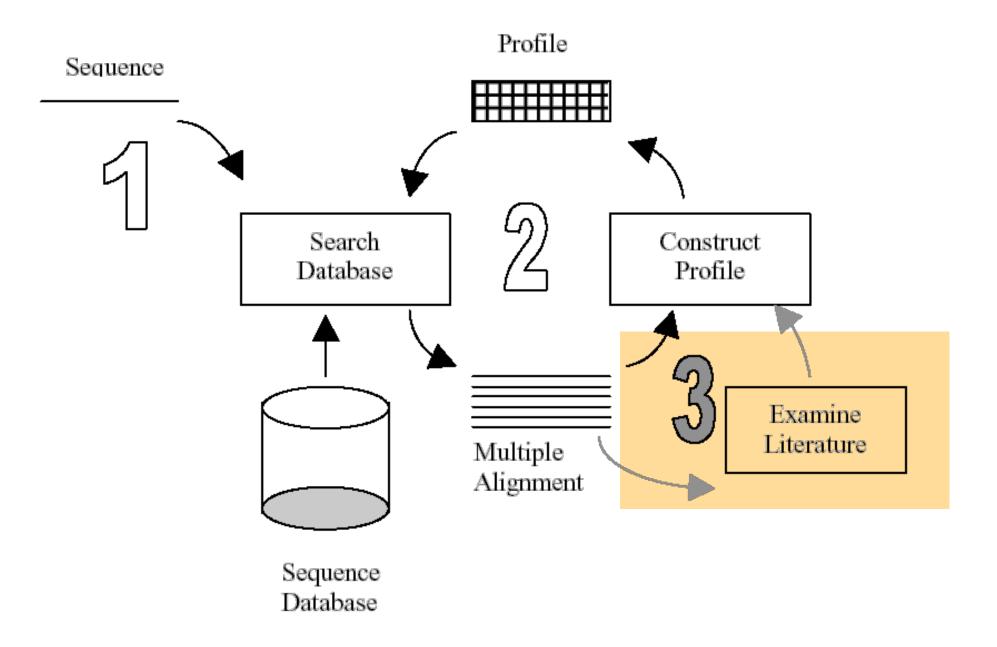
- annotate function on a test-set of 99 articles, 138 human genes
- stringent definition of a *correct* answer: passage references gene name and provides evidence for GO annotation at the right level of the hierarchy

System	Precision	TP (Recall)	F-measure
CSM	0.364	16 (0.068)	0.114
CSC	0.182	44 (0.185)	0.178
CSM + CSC	0.241	51 (0.215)	0.227
Ray and Craven <sup>23</sup>	0.213	52 (0.219)	0.216
Chiang and Yu <sup>7,8</sup>	0.327	37 (0.156)	0.211
Ehler and Ruch <sup>11</sup>	0.123	78 (0.329)	0.179
Couto et al. <sup>10</sup>	0.089	58 (0.245)	0.131
Verspoor et al. <sup>26</sup>	0.055	19 (0.080)	0.065
Rice et al. <sup>25</sup>	0.035	16 (0.068)	0.046

from BioCreative evaluation in 2003

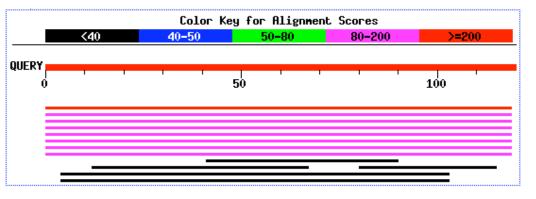
### Task: Augmenting PSI-BLAST with Text

[Chang et al., PSB '01]

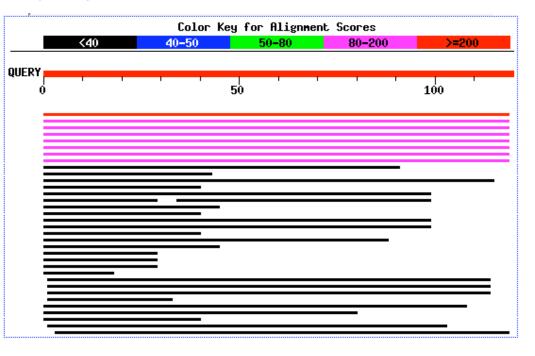


#### A PSI-BLAST Run Illustrated

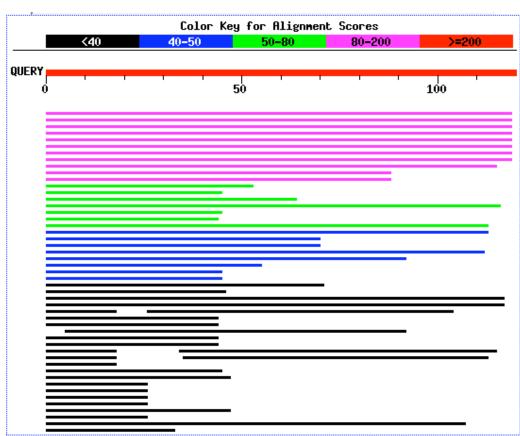
#### iteration 0



#### iteration 1



#### iteration 2



#### Augmenting PSI-BLAST with Text

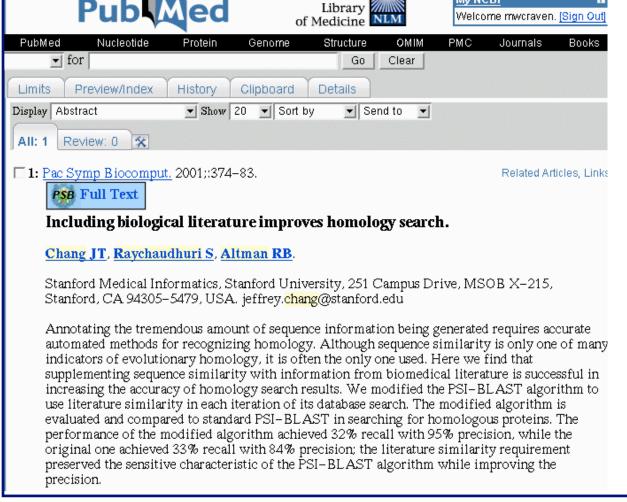
- PSI-BLAST often has greater sensitivity than BLAST
- but profile "drift" can occur, as the query is generalized
- key idea:
  - represent each protein with <u>text</u>, in addition to amino-acid sequence
  - discard proteins that have low text similarity to the query

### Calculating Text Similarity of Proteins

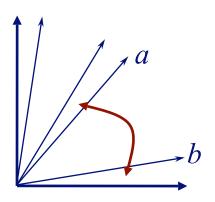
- for each protein, collect MEDLINE entries referenced in Swiss-Prot database
  - collect text in abstracts/MESH headings
  - drop low/high frequency words (associated with fewer than 3 or more than 85,000 sequences)
  - represent protein by vector of word-occurrence counts
- use cosine similarity to assess similarity of proteins
- drop proteins from profile whose similarity to query is below a specified threshold

### Calculating Text Similarity of Proteins

MV NCBI



National



$$\cos(\vec{a}, \vec{b}) = \frac{\sum_{i} a_i b_i}{\sqrt{\sum_{i} a_i^2} \sqrt{\sum_{i} b_i^2}}$$

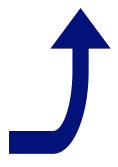


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Homolog

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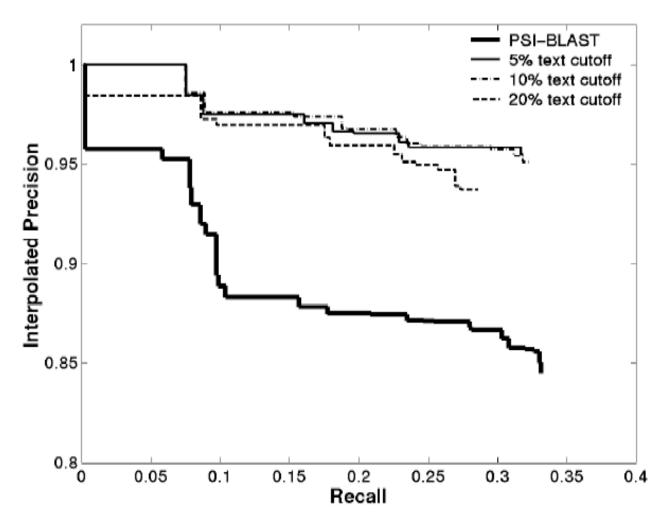


#### PSI-BLAST with Text Experiment

- assembled 54 families of homologous protein sequences
  - all proteins within a family have same structural (superfamily) classification in SCOP database
  - sequences have at least 4 associated abstracts in MEDLINE;
     linked from SwissProt
  - one query sequence per family the most divergent member of each family
- measured precision/recall for these queries using
  - PSI-BLAST
  - text-PSI-BLAST with different literature similarity thresholds

### Augmenting PSI-BLAST with Text

[Chang et al., PSB '01]



Most of the difference is explained by a few families for which ordinary PSI-BLAST didn't converge, but **text-**PSI-BLAST did