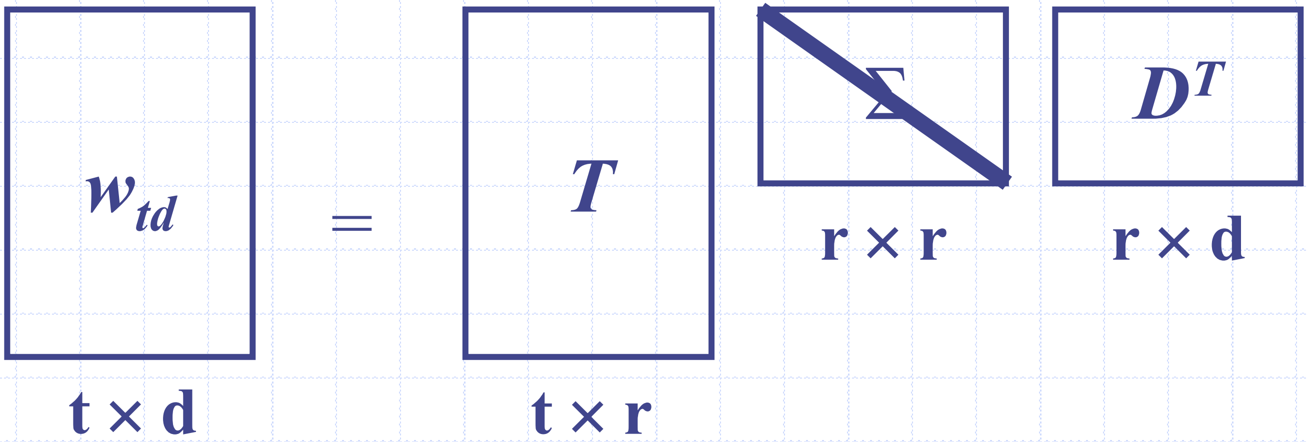
Latent Semantic Indexing

Thanks to Dr. Ian Soboroff

Issues: Vector Space Model

- Assumes terms are independent
  - Some terms are likely to appear together
    - synonyms, related words
    - spelling mistakes?
  - Terms can have different meanings depending on context
- Term-document matrix has very high dimensionality
  - are there really that many important features for each document and term?

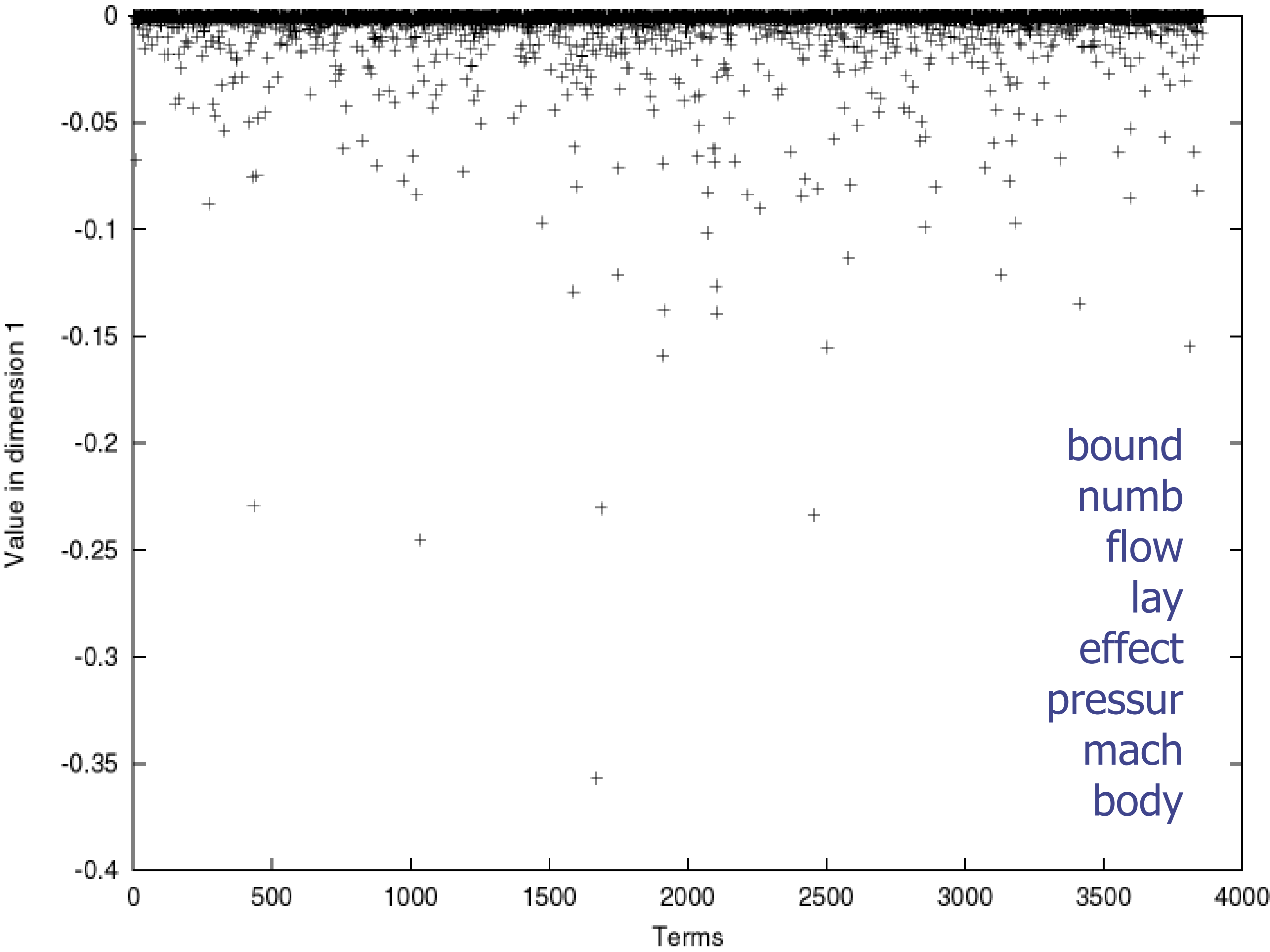
Latent Semantic Indexing



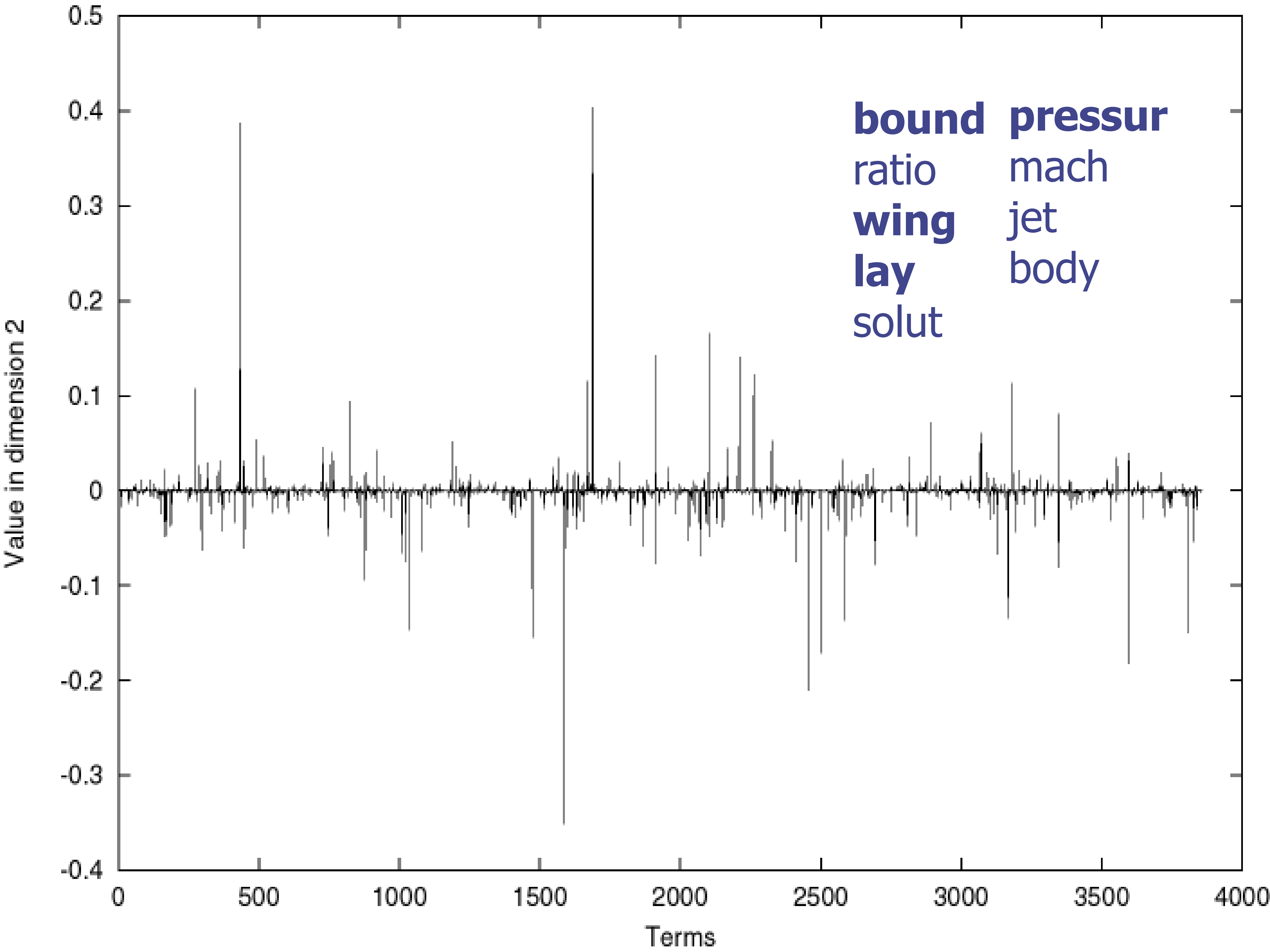
- Compute *singular value decomposition* of a term-document matrix
  - D, a representation of M in *r* dimensions
  - T, a matrix for transforming new documents
  - diagonal matrix Σ gives relative importance of dimensions

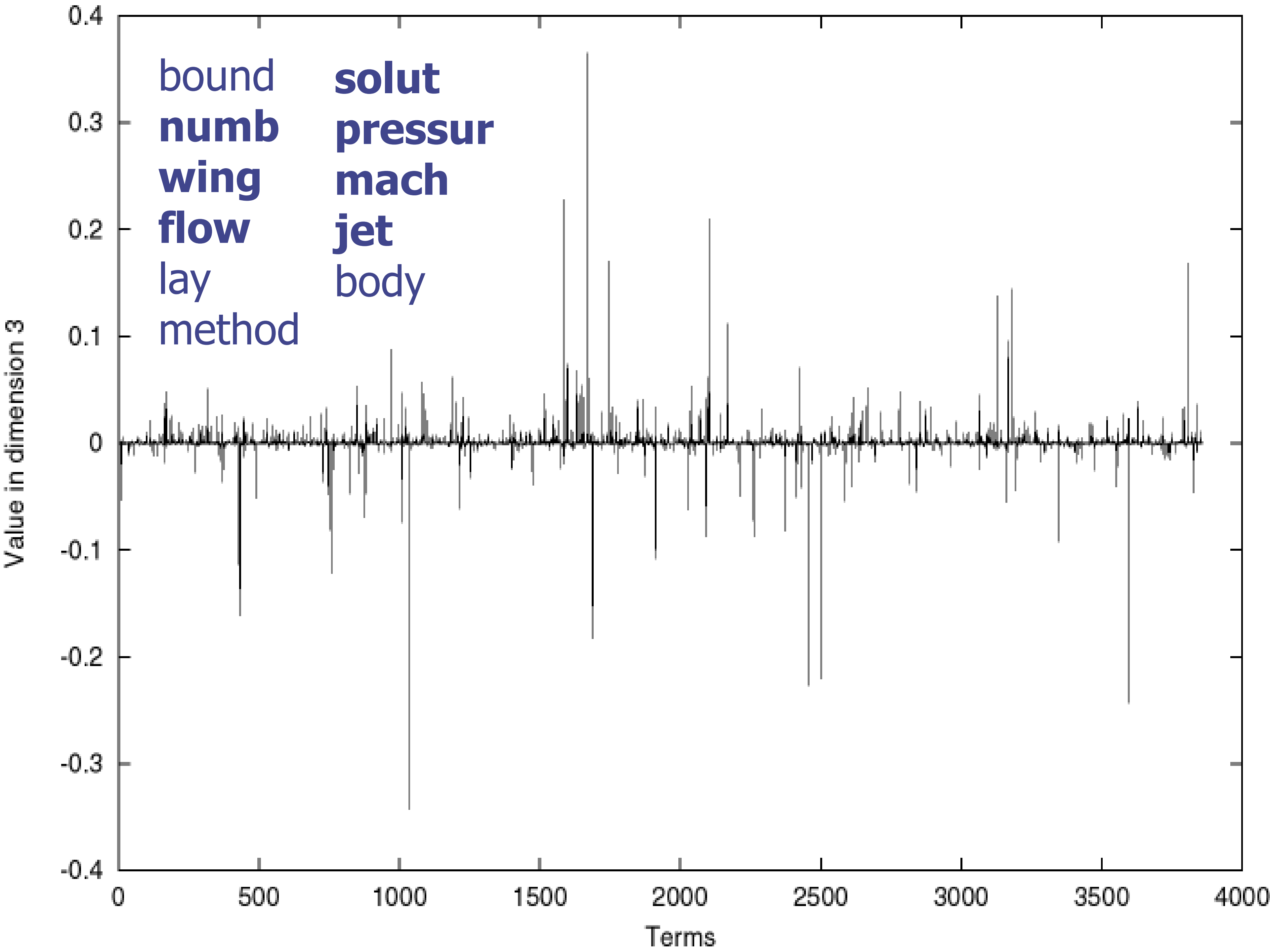
LSI Term matrix T

- T matrix
  - gives a vector for each term combo in LSI space
  - for a new document c, c'*T gives a new row in D
  - That is, "fold in" the new document into the LSI space, where c' is c transpose
- LSI is a rotation of the term-space
  - original matrix: terms are d-dimensional
  - new space has (maybe much) lower dimensionality
  - dimensions are groups of terms that tend to co-occur in the same documents
    - synonyms, contextually-related words, variant endings



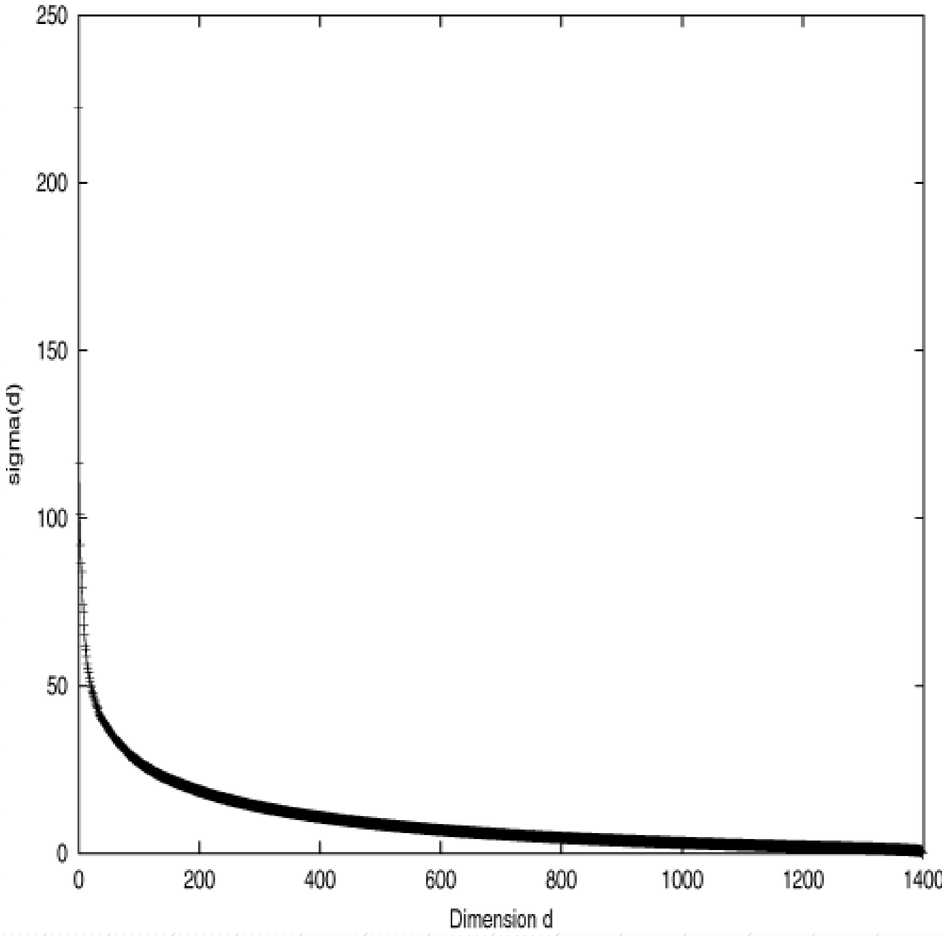
Value in dimension 1
Terms
0
-0.05
-0.1
-0.15
-0.2
-0.25
-0.3
-0.35
-0.4
0
500
1000
1500
2000
2500
3000
3500
4000
bound
numb
flow
lay
effect
pressur
mach
body


bound
ratio
wing
lay
solut
pressur
mach
jet
body
Value in dimension 2
Terms
0.5
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
0
500
1000
1500
2000
2500
3000
3500
4000

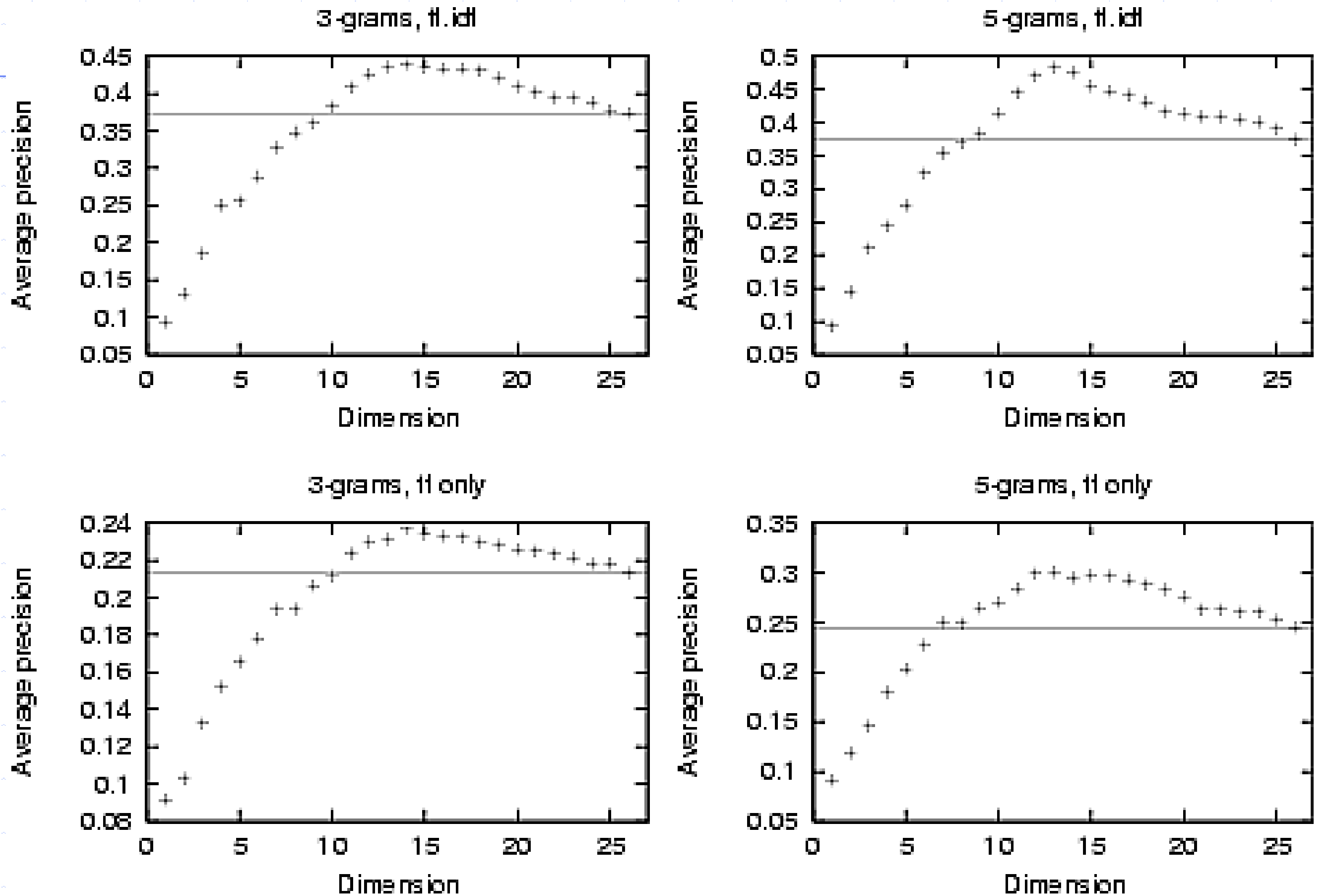

bound
numb
wing
flow
lay
method
solut
pressur
mach
jet
body
Value in dimension 3
Terms
0.4
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
-0.4
0
500
1000
1500
2000
2500
3000
3500
4000

Singular Values

- Σ gives an ordering to the dimensions
  - values tend to drop off very quickly
  - singular values at the lower right tail represent "noise"
  - cutting off low-value dimensions reduces noise and can improve performance



Truncating Dimensions in LSI



Document matrix D

- D matrix
  - coordinates of documents in LSI space
  - same dimensionality as T vectors
  - can compute the similarity between a term and a document

In the literature, the formula is often expressed M = $U\Sigma V^T$

Improved Retrieval with LSI

- New documents and queries are "folded in"
  - multiply vector by $T\Sigma^{-1}$
- Compute similarity for ranking as in VSM
  - compare queries and documents by dot-product
- Improvements come from
  - reduced noise
  - no need to stem terms (variants will co-occur)
  - no need for stop list
    - stop words are used uniformly throughout collection, so they tend to appear in the first dimension
  - No speed or space gains, though…

LSI in TREC-3

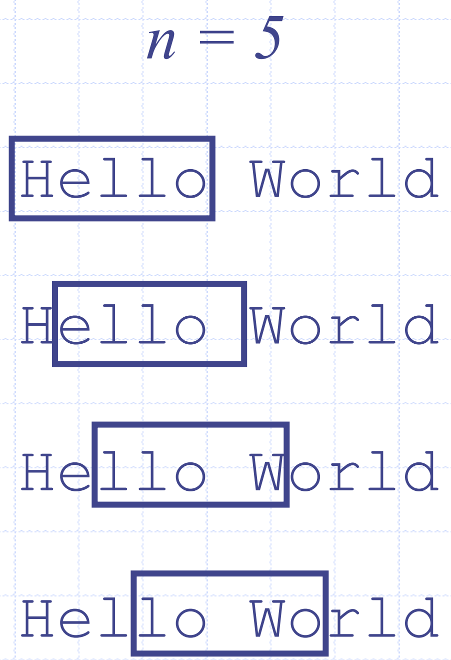
- LSI space computed from a sample of the document collection
- Documents and queries folded into LSI space for comparison
- Improvement in AP with LSI: 5%
  - Improvements up to 20% seen in smaller collections

Other LSI Applications

- Text classification
  - by topic
    - dimension reduction -> good for clustering
  - by language
    - languages have their own stop words
  - by writing style
- Information Filtering
- Cross-language retrieval

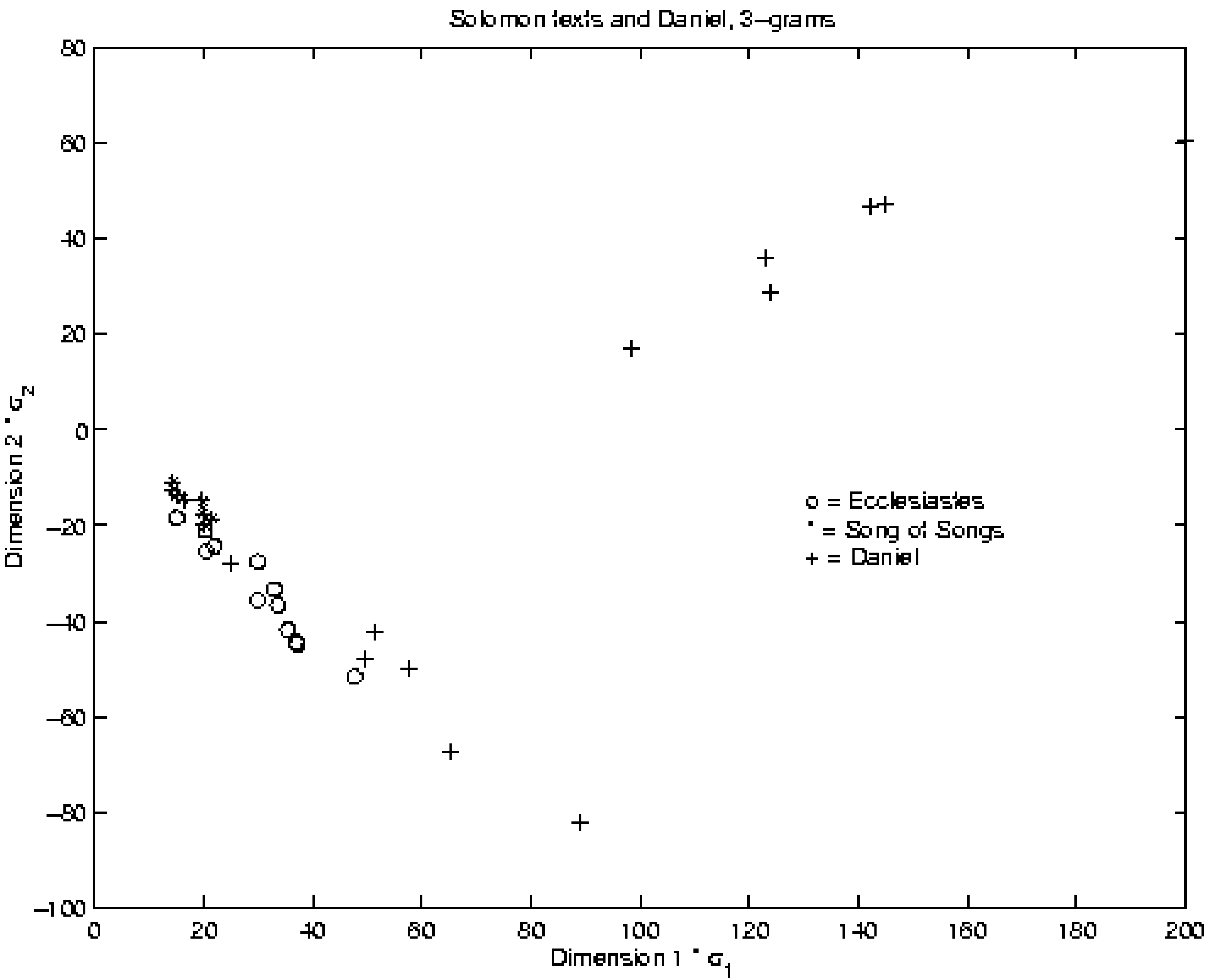
N-gram indexing recap

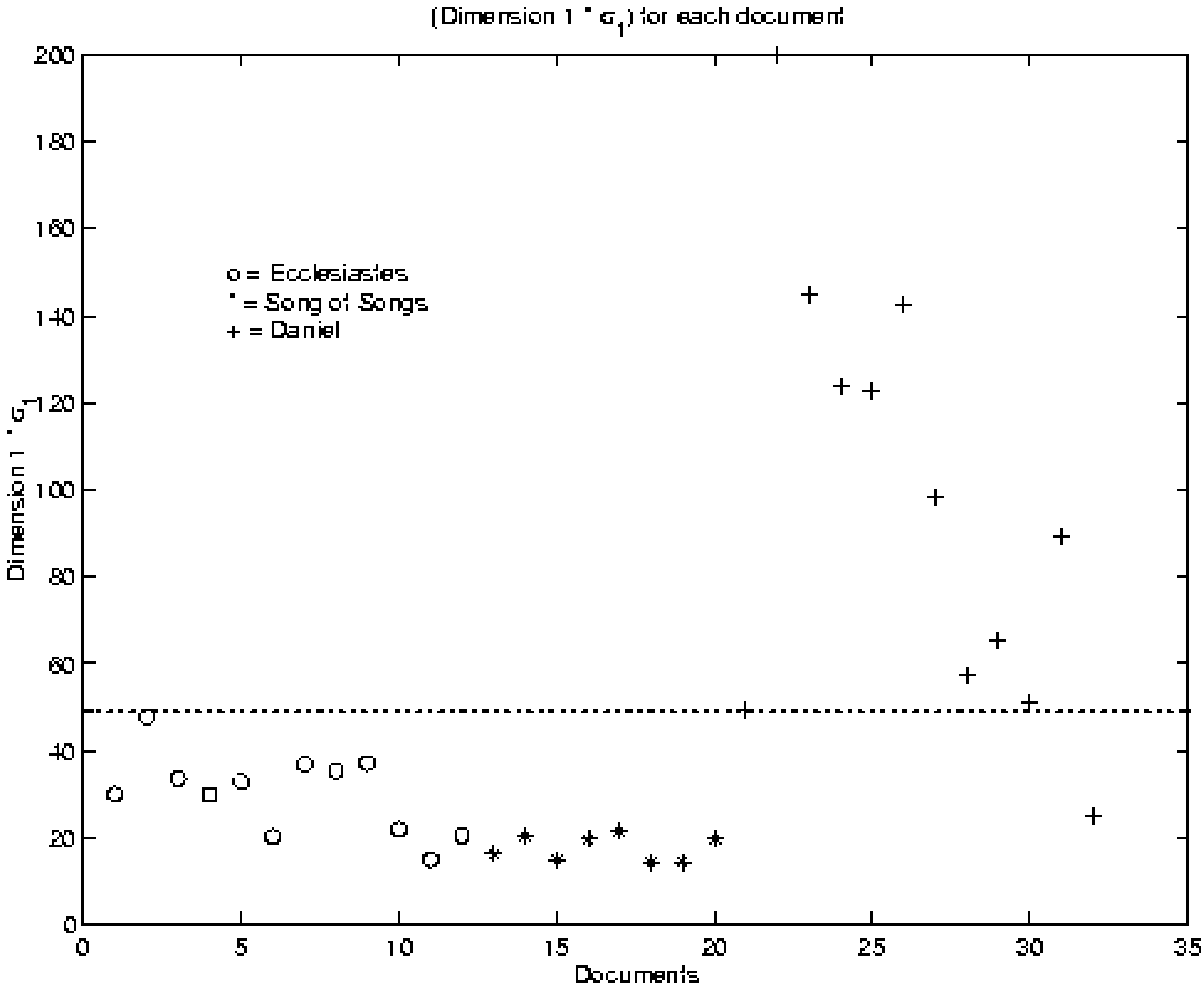
- Index all *n* character sequences
  - language-independent
  - resistant to noisy text
  - no stemming
  - easy to do
- Document ⇒ array of n-gram frequencies

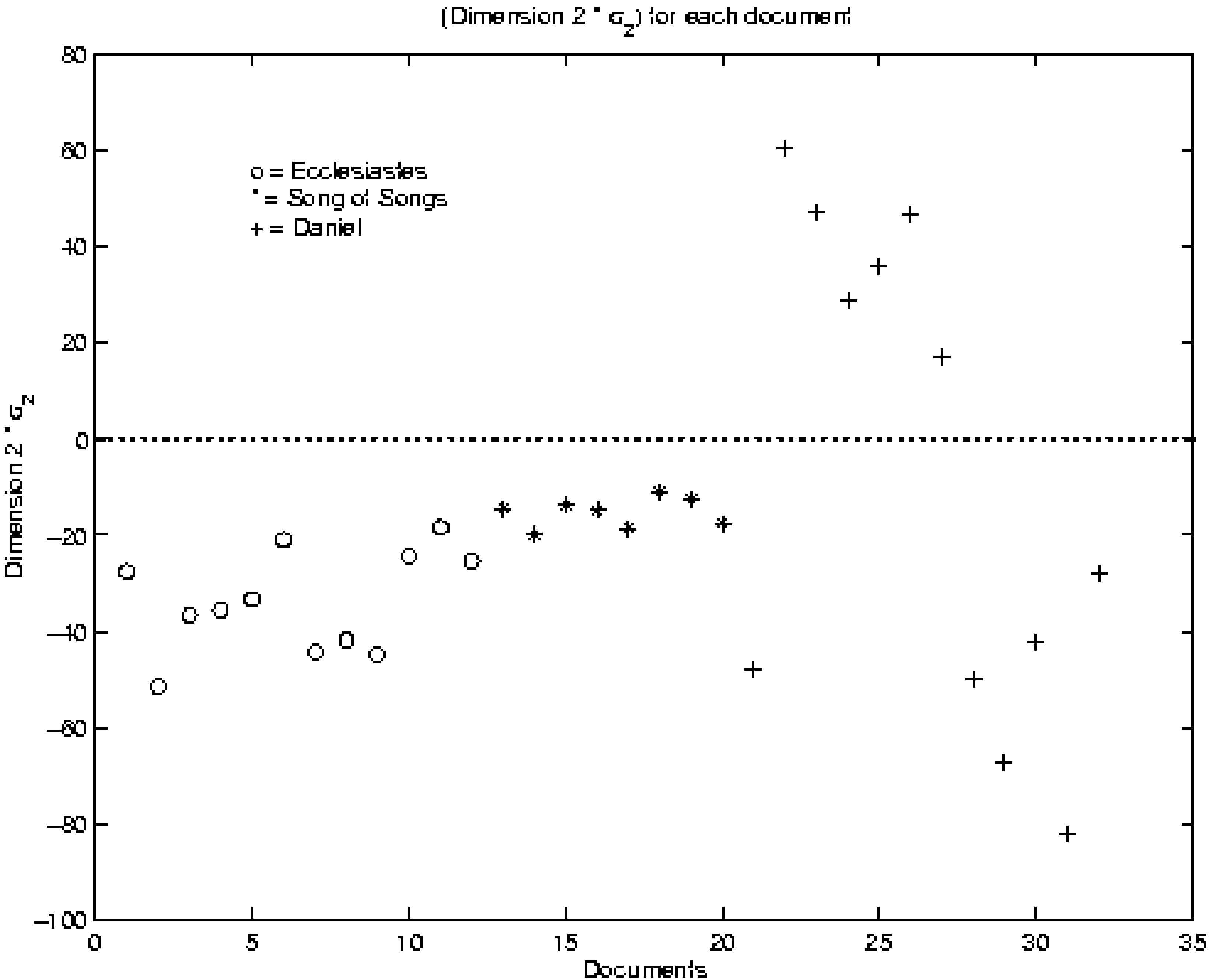


Why N-grams?

- N-grams capture pairs of words
  - Brings out phraseology and word choice
- LSI using n-grams might cluster documents by writing style and/or author
  - a lot of what makes style is word choices and stop word usage
- Small experiment
  - Three biblical Hebrew texts: Ecclesiastes, Song of Songs, Book of Daniel
  - used 3-grams in original Hebrew


Solomon texts and Daniel, 3−grams
Dimension 2 * σ_2
Dimension 1 * σ_1
o = Ecclesiastes
* = Song of Songs
+ = Daniel
80
60
40
20
0
−20
−40
−60
−80
−100
0
20
40
60
80
100
120
140
160
180
200


(Dimension 1 * σ_1) for each document
o = Ecclesiastes
* = Song of Songs
+ = Daniel
Dimension 1 * σ_1
Documents
0
20
40
60
80
100
120
140
160
180
200
0
5
10
15
20
25
30
35



(Dimension 2 * σz) for each document
o = Ecclesiastes
* = Song of Songs
+ = Daniel
Dimension 2 * σz
Documents
80
60
40
20
0
−20
−40
−60
−80
−100
0
5
10
15
20
25
30
35

Conclusion

- LSI can be a useful technique for reducing the dimensionality of an IR problem
  - reduction can improve effectiveness
  - reduction can find surprising relationships!
- SVD can be expensive to compute on large matrices
- Available tools for working with LSI
  - MATLAB or Octave (small data sets only)
  - Python package scipy.linalg