A Comparison of SVD and NMF for Unsupervised Dimensionality Reduction

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Outline

- Introduction to Text Mining
- Singular Value Decomposition
- Non-negative Matrix Factorization
- Methods
- Results
- Conclusion

Text Mining

- What is Text Mining?
  - How is it different from Data Mining?
- Why is it hard?
  - Unstructured Texts
- What would we like to do with derived information?
  - Discover new details.
  - Form new facts.

Singular Value Decomposition

$$A_{n\times m} = U_{n\times r} S_{r\times r} (V_{m\times r})^T$$

$A_{n\times m}$: n documents, m terms

$U_{n\times r}$: n documents, r concepts

$S_{r\times r}$: r rank ("strength" of each concept)

$V_{m\times r}$: m terms, r concepts

Non-negative Matrix Factorization

- Given a nonnegative target matrix *A* of dimension *m x n*, NMF algorithms aim at finding a rank *k* approximation of the form:

$$A_{m\times n} \approx W_{m\times k} \times H_{k\times n}$$

  - where W and H are nonnegative matrices of dimensions *m x k* and *k x n,* respectively.
  - *W* is the basis matrix, whose columns are the basis components. *H* is the mixture coefficient matrix, whose columns contain the contribution of each basis component to the corresponding column of X.
- How is the rank chosen for NMF?

$$\min_{W,H} f(W,H) = \left\| A - (WH) \right\|^{\frac{1}{2}}$$

Methods

- **Gather Documents**
- **Structure Text (Preprocessing)**
- **Implement the Techniques**
- **Evaluate Performance**

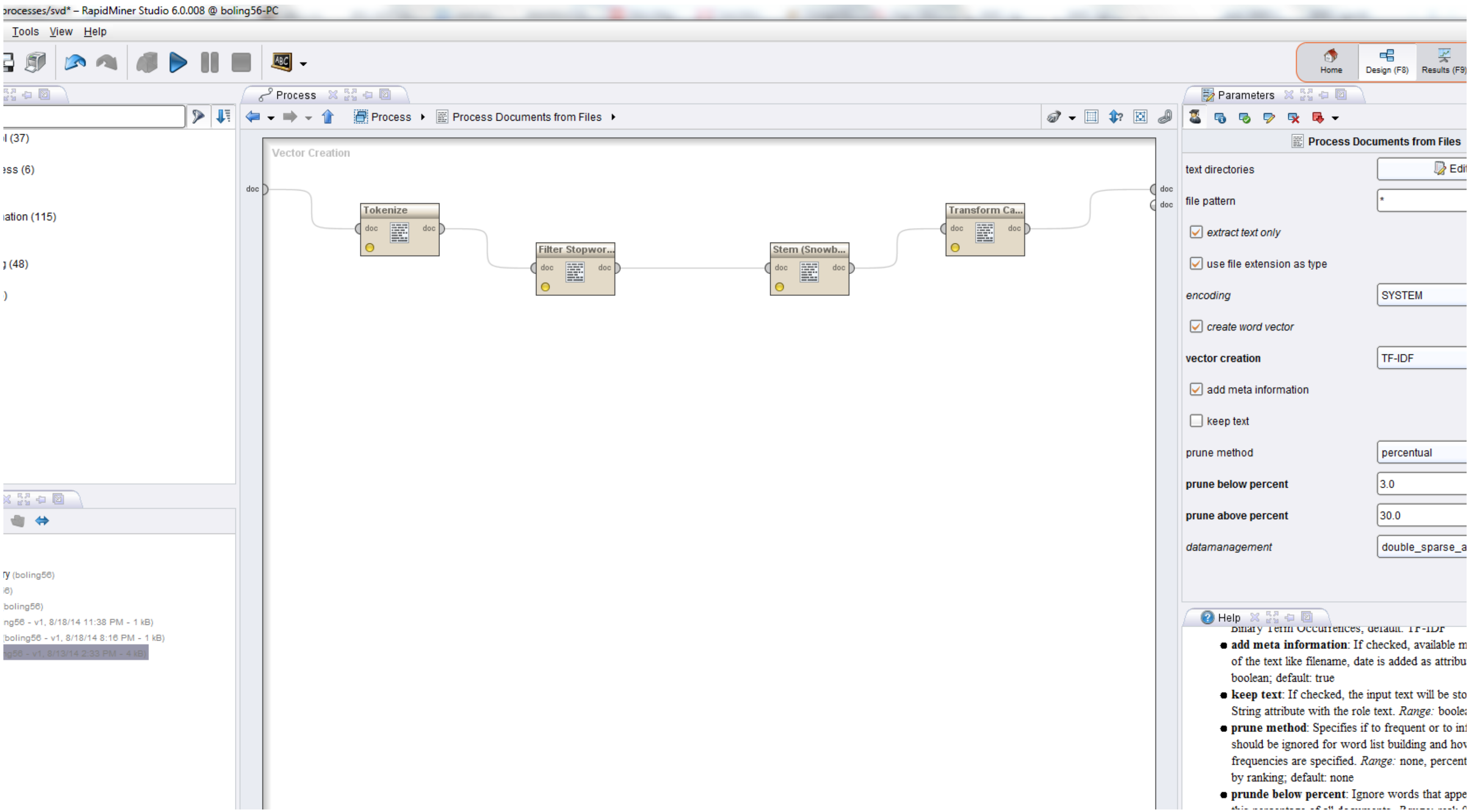
Methods

- We used the Pubmed Central Open Access Subset, which consists of 800,000+ full-text articles.
- Due to memory and space limitations, we did a keyword search on the data and found that 3,398 articles had the term “herbicides”.
- We preprocessed our dataset using RapidMiner and exported our preprocessed data to R.

Methods: Preprocessing Data

- Data Preparation
  - Tokenization
  - Filtering Stopwords and Length
  - Stemming (Snowball Stemming Algorithm)
  - Transform Cases (Lowercase letters)
- Pruning
  - Prune below 30%
  - Prune above 70%

Methods: Preprocessing Data



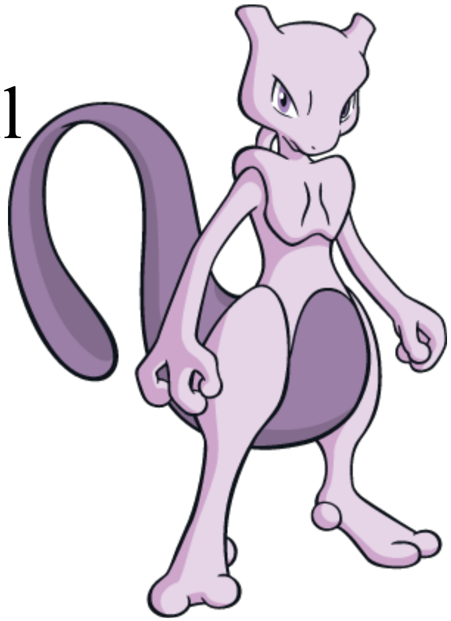
Methods: Term Weighting

- Term Frequency
  - It is the number of times that term *t* occurs in document *d*
  - Should we really use this?
- IDF Weighting
- Term Frequency-Inverse Document Frequency
  - Why Should We Use TF-IDF instead of TF?

Methods: Term Weighting

Assign to term *t* **a weight** in document *d* that is:

- highest when *t* occurs several times within a small number of documents.
  - We like to see rare things!
- lower when the term occurs fewer times in a document, or occurs in many documents.
- lowest when the term occurs in virtually all documents.



Reference: http://nlp.stanford.edu/IR-book/

Mewtwo image: http://images5.fanpop.com/image/polls/987000/987481_1333090091691_full.png

Low Rank Approximation in SVD

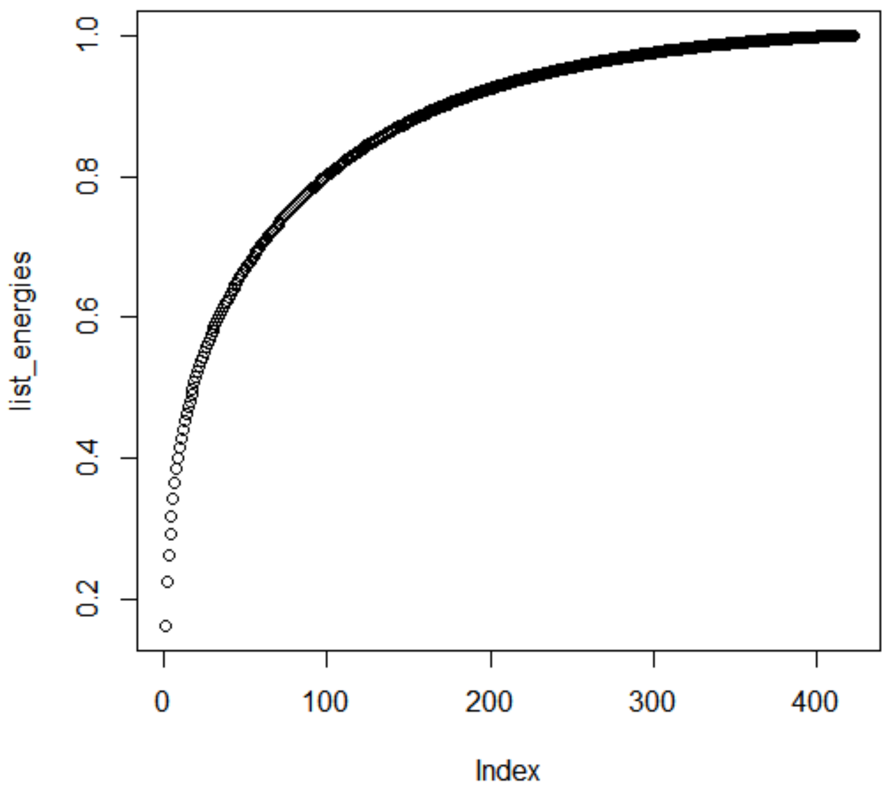
We retain k dimensions of matrix by computing the energy in . In order to retain 90% of the energy in , we compute and divide it by the total energy. This is defined as

$$E_k = \sum_{i=1}^{k} \sigma_{ii}^2$$

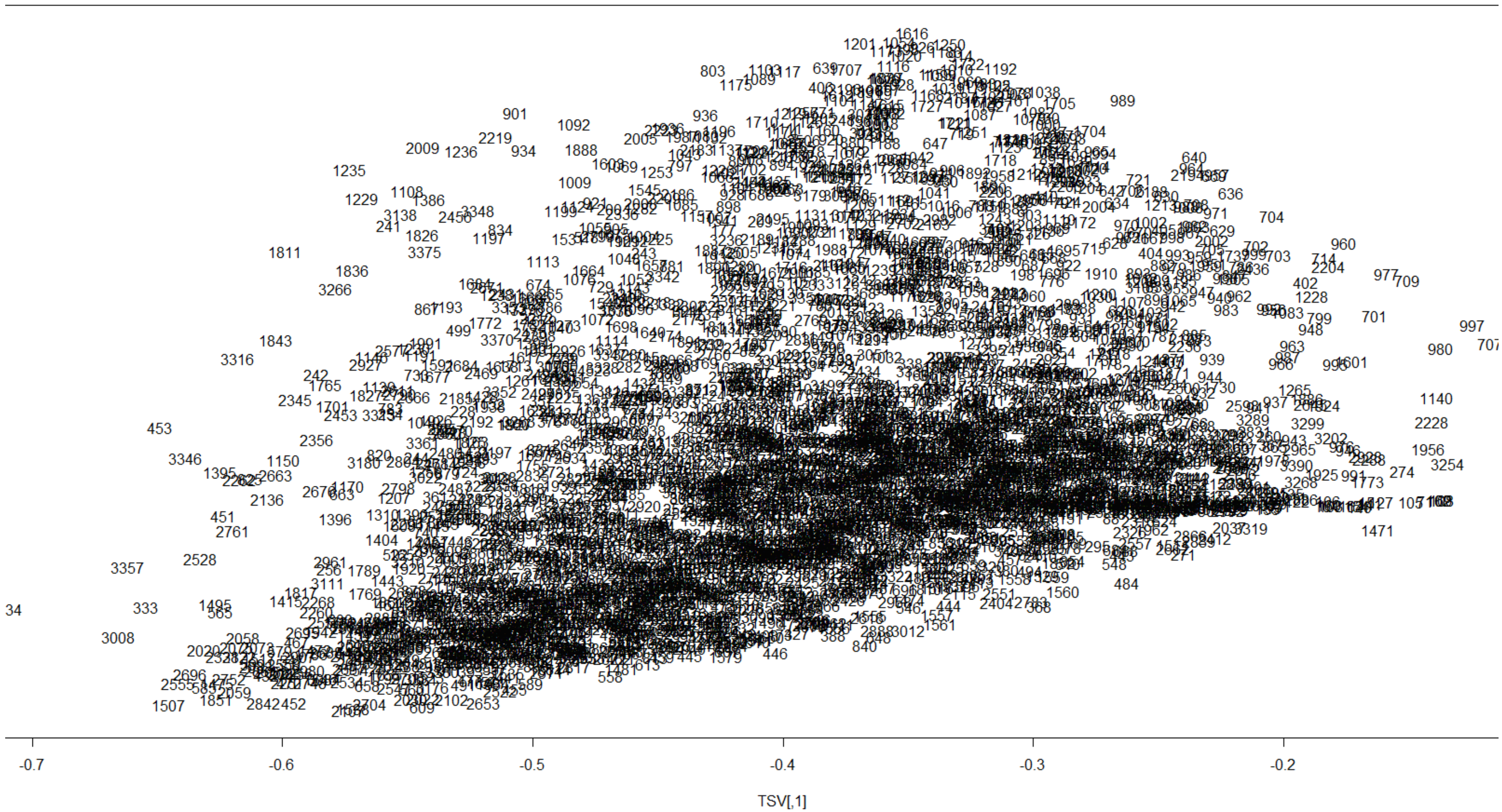
where k denotes the number of reduced dimensions and - σ_{ii} represents the singular values of Σ. By looking at all values of k, the retained energy is 90.0% at least $k = 172$.

$k = 172$	$k = 173$	$k = 174$	$k = 175$	$k = 176$	$k = 177$	$k = 178$	$k = 179$	$k = 180$	$k = 181$	$k = 182$
0.9006	0.9016	0.9026	0.9035	0.9044	0.9053	0.9062	0.9071	0.9080	0.9089	0.9097

“Energy” Plot for SVD



Document Similarity by VΣ



Comparing Approximation Errors Using **Frobenius Norm**

- Singular Value Decomposition

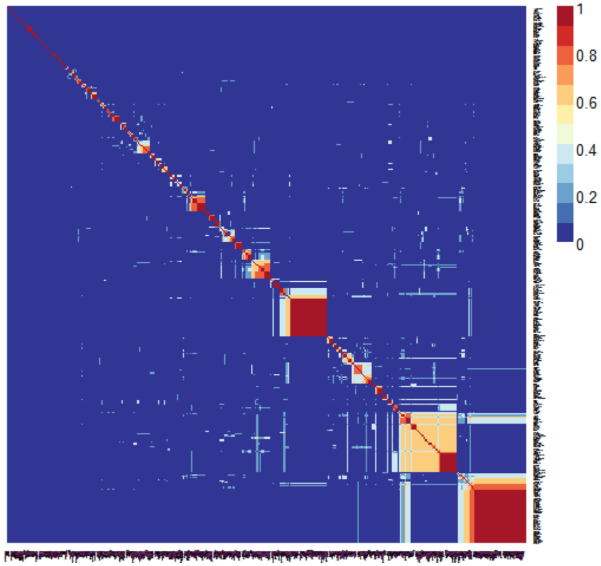
K= 170	K= 172	K= 175	K= 178	K= 182
18.54	18.37	18.11	17.84	17.50

- Non-negative Matrix Factorization

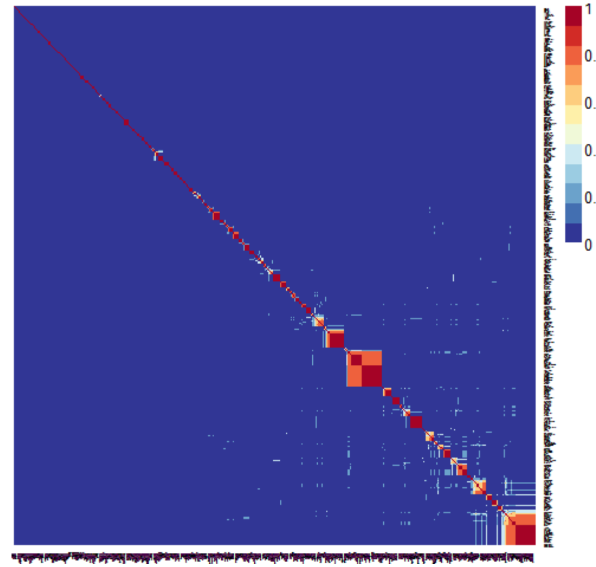
K=170	K=172	K=175	K=178	K=182
19.601	19.47	19.16	18.90	18.57

Consensus Maps for NMF

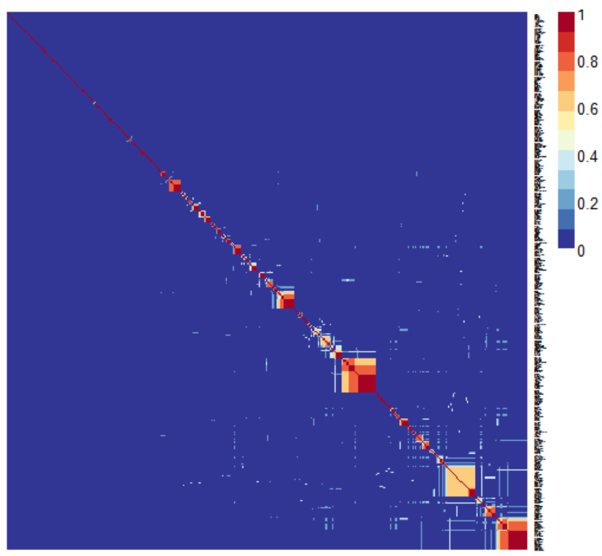
k = 100



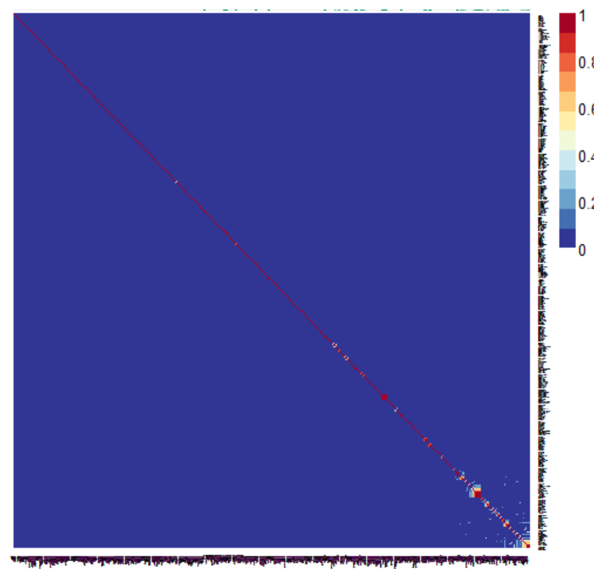
k = 175



k = 182



k = 375



Conclusion and Discussion

- Standard SVD produces a “deeper” factorization of the original data. Singular values come in handy when looking for valuable information.

- Standard NMF iteratively refines a solution, and one may choose to look at a lower rank, which is generally chosen so that $(n + m)r < nm$.

- NMF should be better in terms of its non-negativity constraints.

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