Topic Modeling

Comparison of methods for choosing an optimum value for the number of topics in an LDA model

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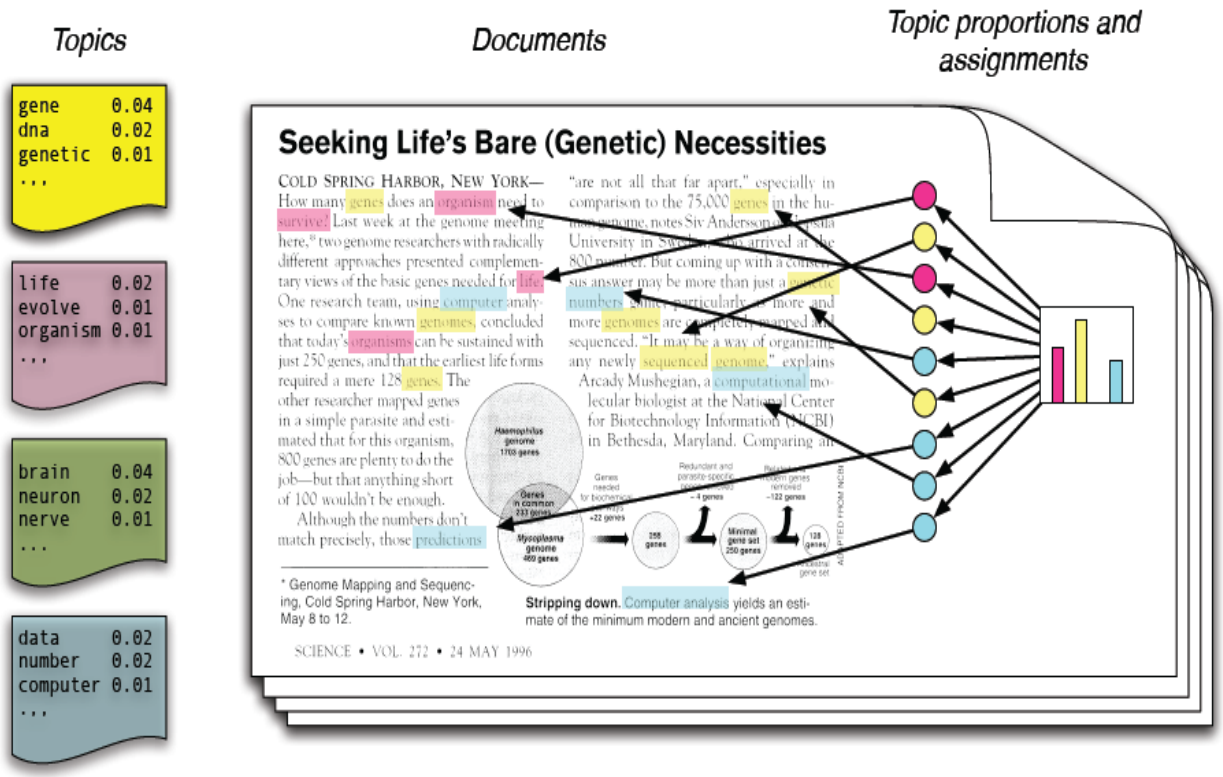
Outline

Introduction

Introduction: What is topic modeling?

- Unsupervised dimension reduction or clustering technique
- Assumes latent topics joining documents to words orthogonally
- Originally used with large corpuses of text data
- Recently applied to other big data including biomedical data sets

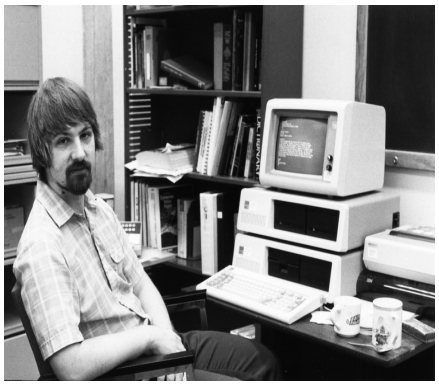
Introduction: What is topic modeling?



[0] Image credit Blei 2011

Methods leading to Latent Dirichlet Allocation

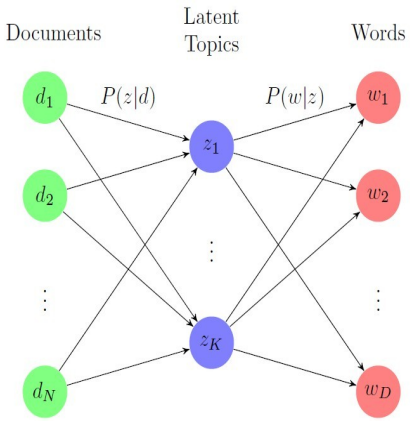
Latent Semantic Analysis (LSA)



- Deerwester et al. (1990)
- unsupervised text modeling technique
- term by document matrix
- orthogonal factors
- New indexing method found "promising"

[1] Photographic Archive, [apf12345], Special Collections Research Center, University of Chicago Library.

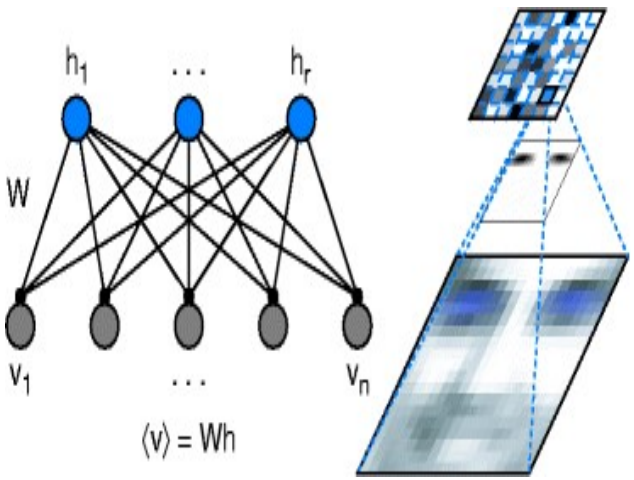
Probabilistic latent semantic indexing (pLSI, pLSA)



- Hofmann (1999)
- uses a mixture decomposition
- maximum likelihood model
- tempered expectation–maximization (EM) iterative algorithm

[2] Image credit: http://www.cnblogs.com/yuzhung/archive.html

Non-negative matrix factorizaton (NMF)

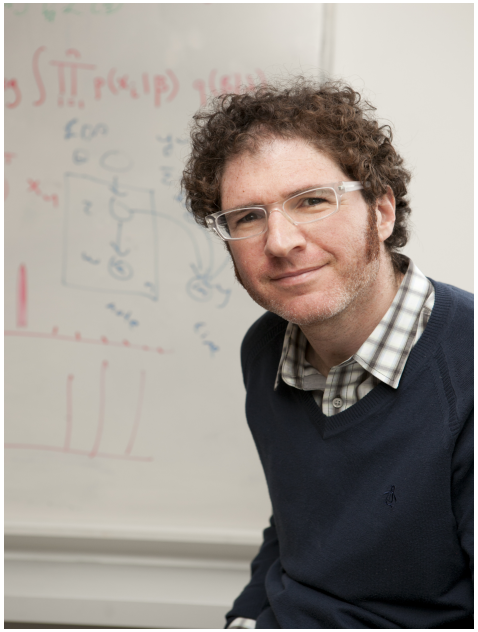


- Lee & Seung (1999)
- parts-based representation
- described as a neural network
- found by Ding (2008) to optimize the same objective function as pLSI

[1] Image credit Nature.com Lee & Seung (1999)

LDA and current trends

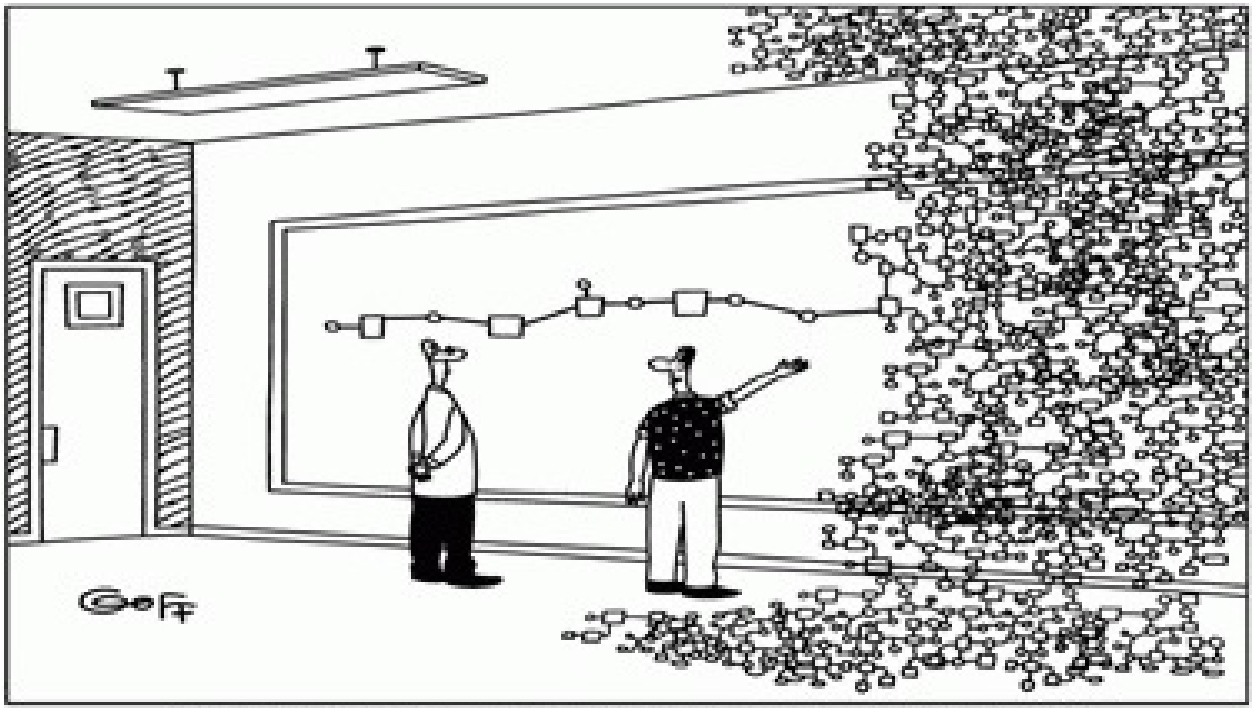
Latent Dirichlet allocation (LDA)



- Blei, Ng and Jordan (2003).
- document is finite mixture over topics
- topic is infinite mixture over probability distribution
- modeled using variational methods, EM algorithm

[2] Photo credit: Denise Applewhite

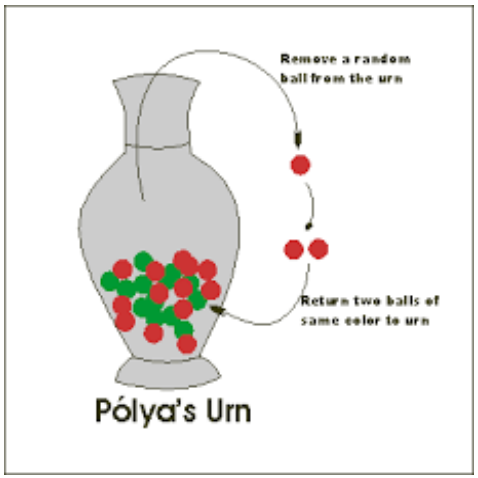
Expanding applications



"This is where the idea for the new EHR starts getting a little complicated."

[1] cldeanrobles.files.wordpress.com

Topic coherence & selecting the number of topics



- Pointwise Mutual Information (PMI), Newman et al. (2010)
- Generalized Pólya Urn model, Mimno et al. (2011)

[1] http://fac.ksu.edu.sa/raguech/blog/173205

Topic modeling using latent Dirichlet allocation

de Finetti's theorem and exchangeability

- Exchangeable random variables are conditionally independent, conditioned on some latent variable
- In topic modeling, words are conditionally independent, conditioned on topic

[1] http://www.novuslight.com.html

LDA hypothetical document generation

Representation $\sim$

1. A corpus consists of D documents
2. A document consists of N words from vocabulary of size V
3. Each word w_n is chosen from one of K topics.

LDA hypothetical document generation

1. Number of words (N) for document selected from Poisson, parameter ξ.
2. Multinomial probability vector θ length K selected from Dirichlet, parameter α
3. The nth word is chosen from the following process:

- Choose a topic, Z_n, from $Mult(1, \theta)$
- Choose a $V \times 1$ vector ϕ from $Dir(\beta_{Z_n})$
- Choose a word, w_n from $Mult(1, \phi)$

LDA hypothetical document generation

In this model

- w_{nj}=1 if the nth word is the jth in the vocabulary
- Z_{ni} = 1 if the nth word is in topic i
- w_{nj} is observed
- Z_{ni} is unobserved
- ϕ_{ij} =$p(w_{nj} = 1|z_{ni} = 1)$

LDA hypothetical document generation

As only one word occurs at each location in a document,

$$\sum_{i=1}^{K} z_{ni} = \sum_{j=1}^{V} w_{nj} = 1.$$

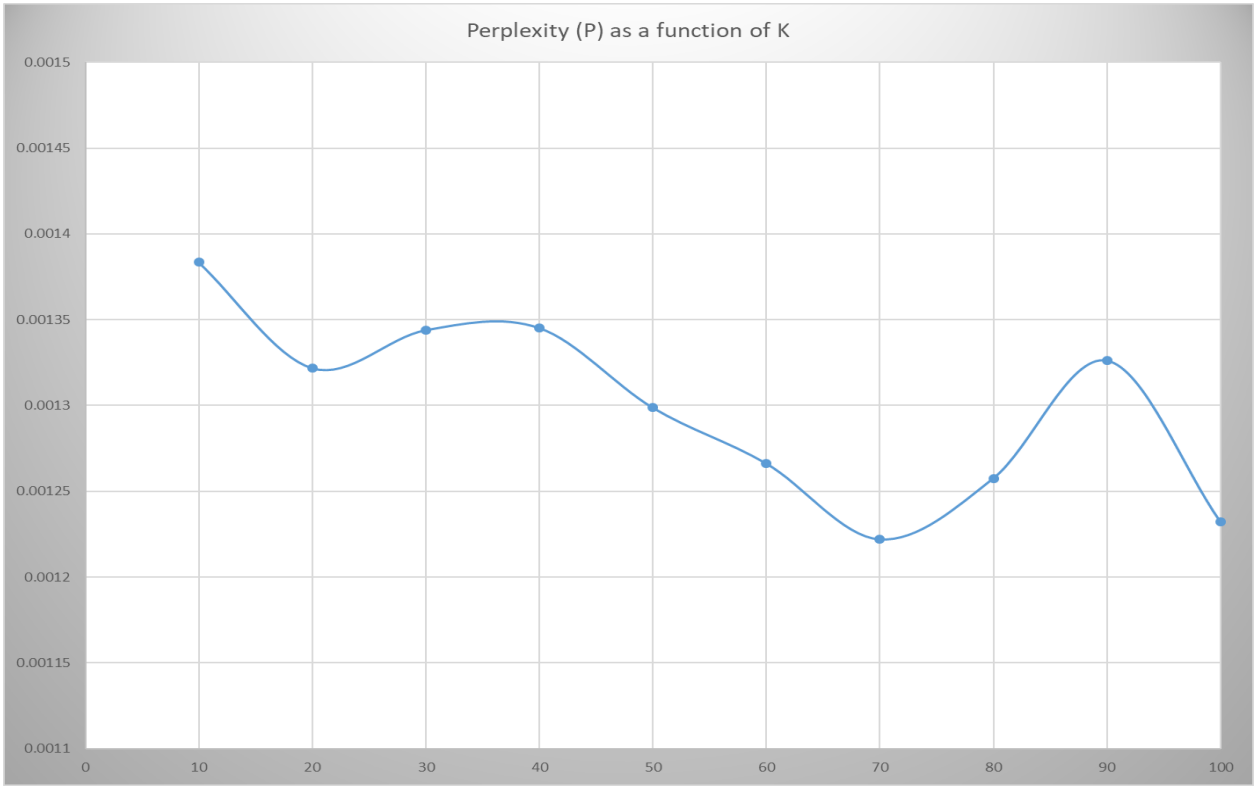
K optimization methods

Perplexity (P)

- Blei et al. (2003)
- Algebraic inverse of geometric mean per-word likelihood
- Lower perplexity scores indicate better performance
- Metric intrinsic to the LDA modeling process

$$P = \exp\left\{ -\frac{\sum_{d=1}^{D_M} \log P(\mathbf{w_d})}{\sum_{d=1}^{D_M} N_d} \right\}$$

Perplexity (P)



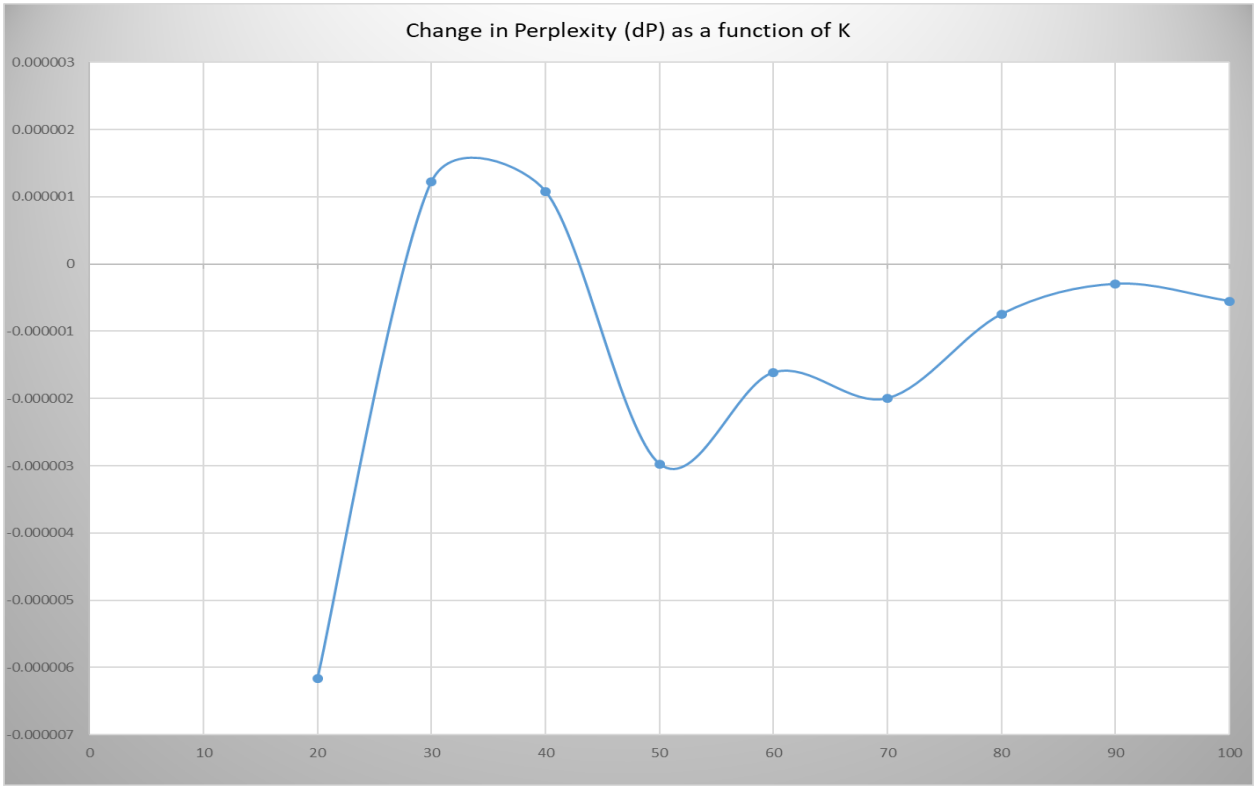
[1] Blei et al., 2003

Change in perplexity (dP)

- Zhao et al. (2015)
- Observed to be more stable and efficient as compared with raw peplexity

$$dP = \frac{P_{i+1} - P_i}{K_{i+1} - K_i}$$

Change in perplexity (dP)

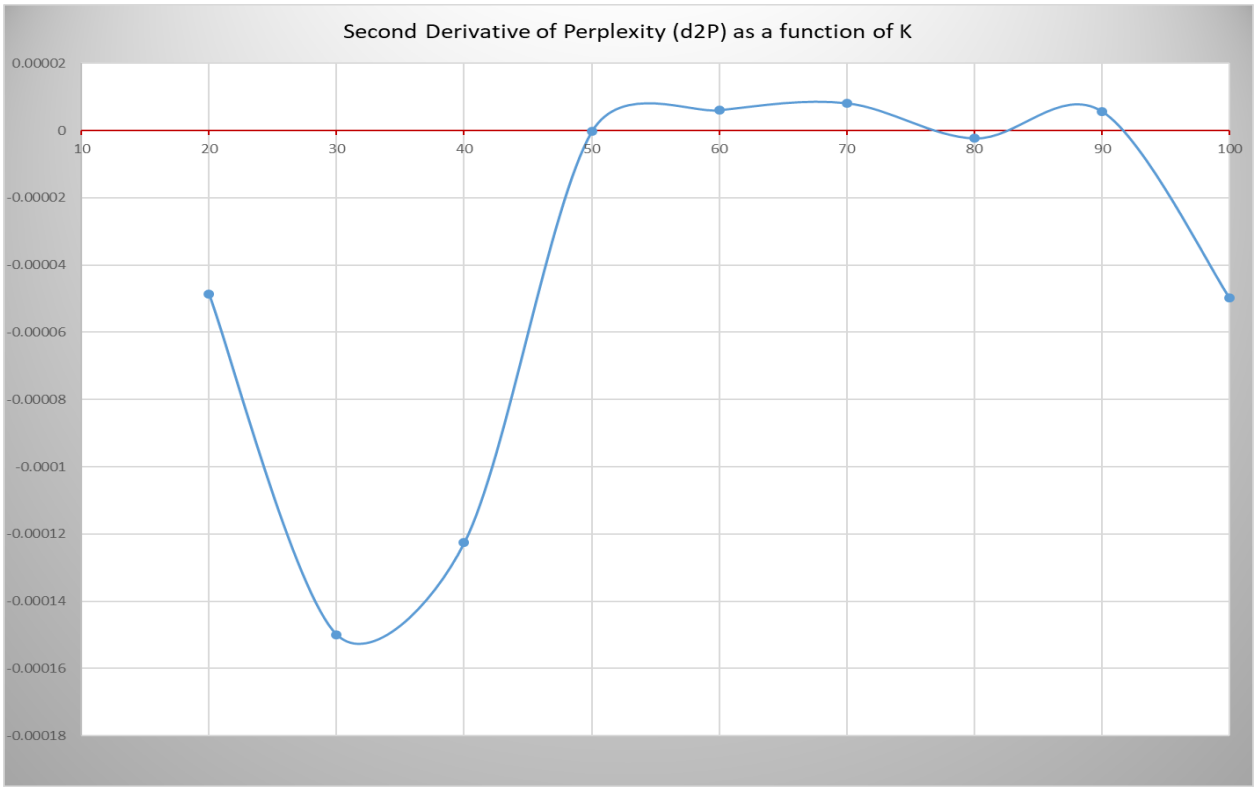


[1] Zhao et al., 2015

2nd derivative of perplexity (d2P)

- The zero line clarifies the change point described by Zhao et al.

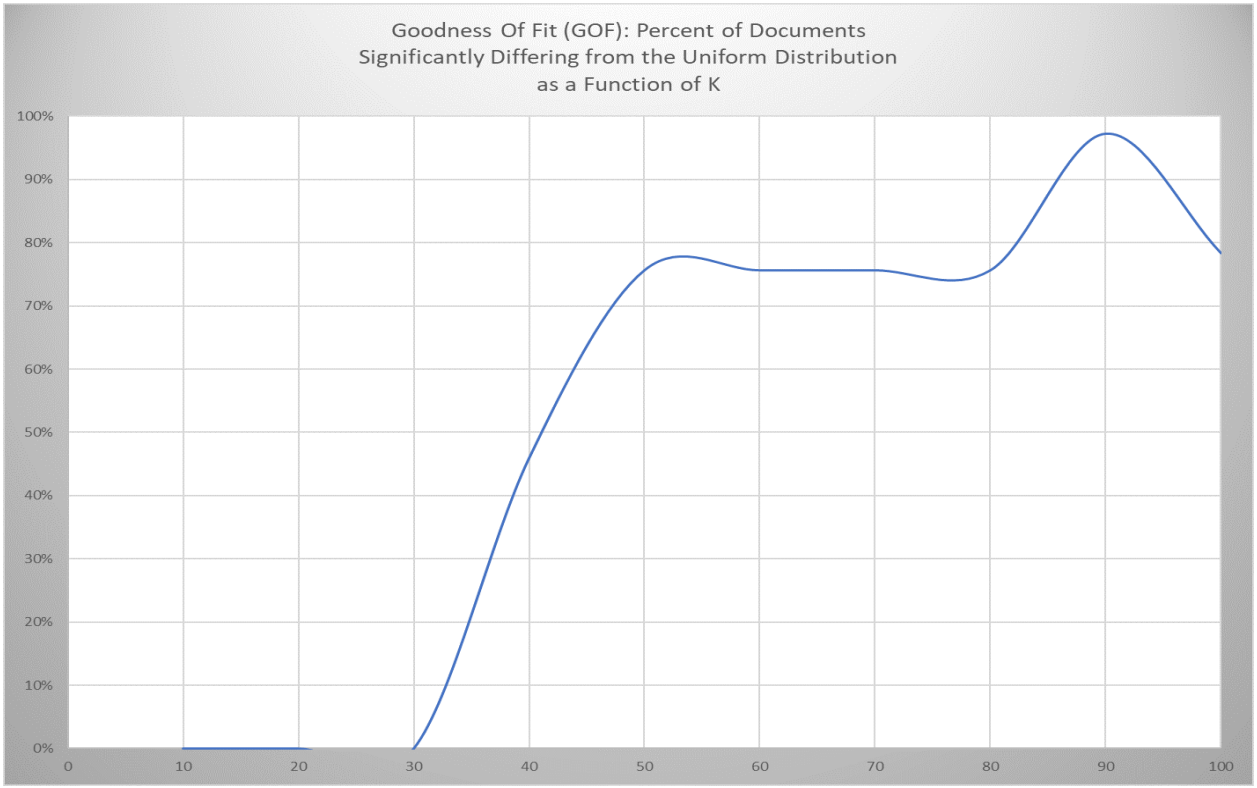
2nd derivative of perplexity (d2P)



Goodness Of Fit (GOF)

- Bowman, Chen and George (in press)
- Statistical analysis of model output
- Proportion of documents significantly different than random as metric to evaluate K
- H_0: Topic assignment not different from random (uniform) assignment

Goodness Of Fit (GOF)



[1] Bowman, Chen and George (in press)

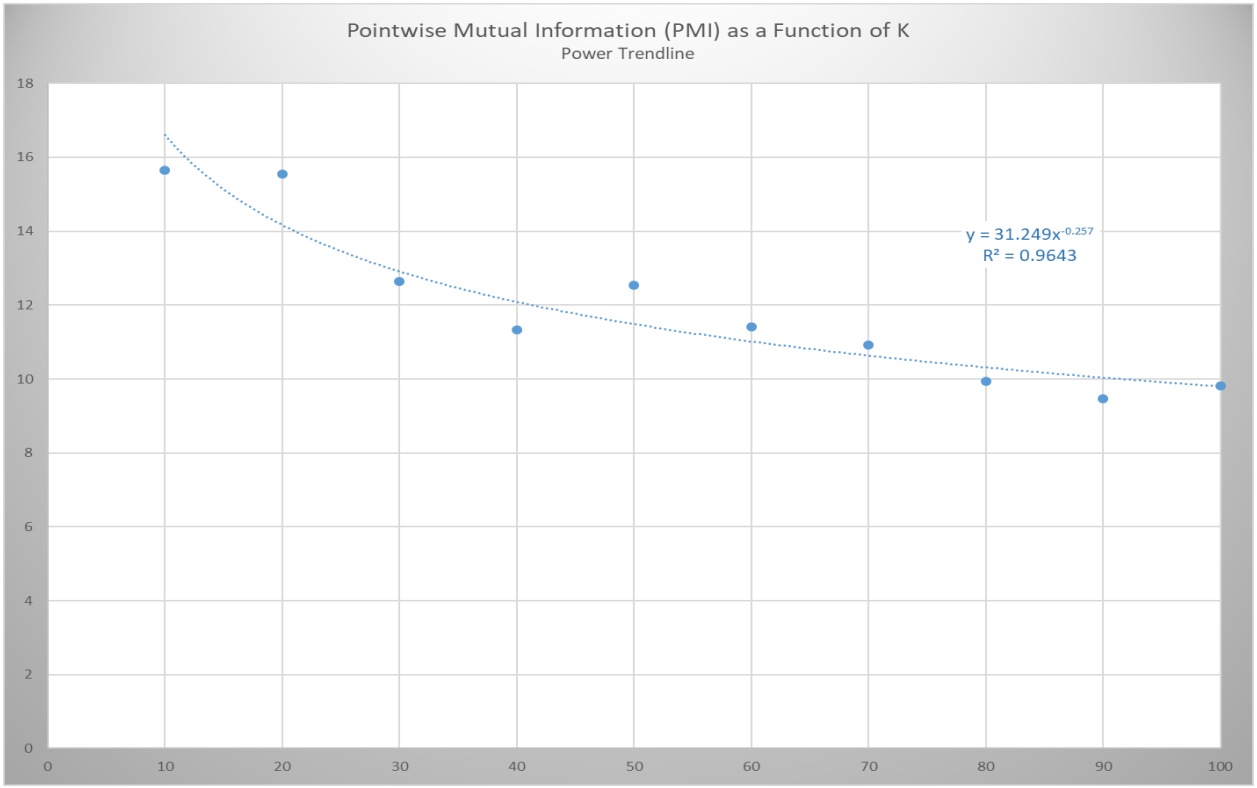
Pointwise Mutual Information (PMI)

$$\mathrm{PMI}(x,y) = \log \frac{p(x,y)}{p(x)p(y)}$$

- Newman et al. (2010)
- Extrinsic to modeling process
- Corroborated by human judgment

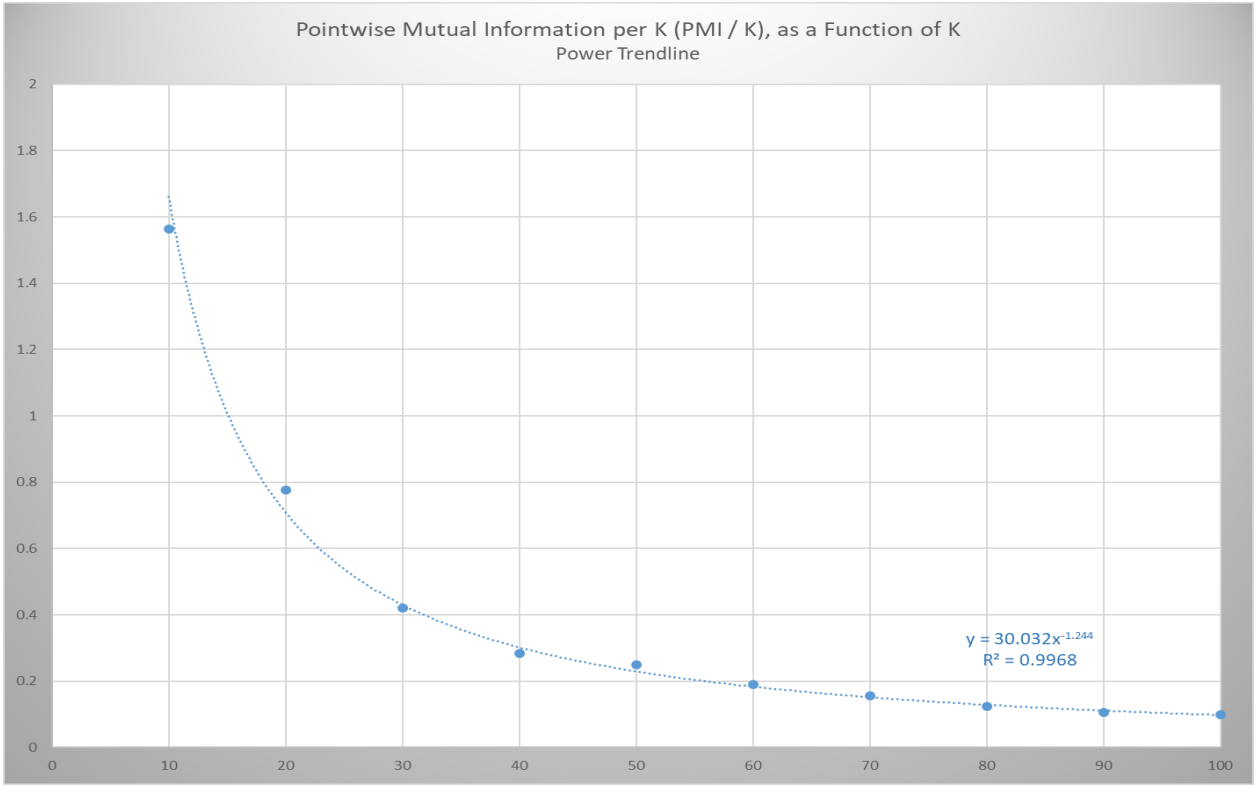
[1] Image credit: http://lintool.github.io/UMD-courses.html

Pointwise Mutual Information (PMI)

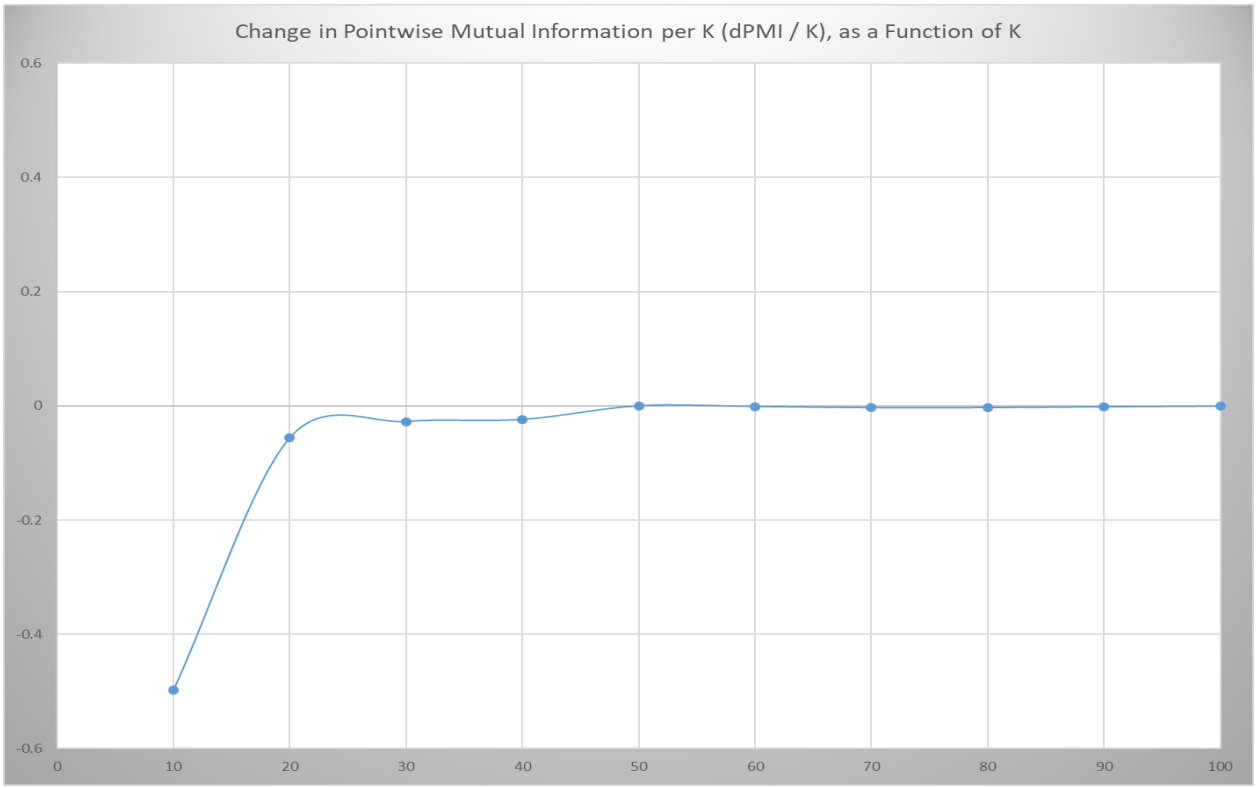


[1] Naraula et al., 2013

Pointwise Mutual Information per K (PMI / K)



Change in Pointwise Mutual Information per K (PMI / K)



Conclusion: Optimization method comparisons

- Methods of optimizing K do not converge
- Different optimization methods will be appropriate for differing purposes
- Judgment is called for

Thank you

$\sim$ *Thank you* $\sim$