Advanced Text Analysis

Day 2 / Session 1

Petro Tolochko

Text Preprocessing

- Texts are ***highly*** dimensional
- When possible, it is nice to reduce this dimensionality
- Ideally, without losing too much information

Danny & Spirling, 2018

- Punctuation
- Numbers
- Lowercasing
- Stemming
- Stop-words
- N-grams
- Removal of words by frequency

Punctuation / Numbers / Lowercasing

- Fairly straightforward
- Often we don’t care about punctuation and/or numbers – so, might be better to remove them
- We probably do care about the letter case
    - To what extent?
    - Reduction in dimensions might be worth the reduction in accuracy
    - When would letter case be (un)important?

Stemming / Lemmatization

- A stem is the part of the word responsible for lexical meaning
- A stem is invariable part of the word under inflection
- “wait” is a stem of:
  - “Waiting”
  - “Waited”
  - “Waits”
- A lemma is the base / “original” part of the word
- Both are useful for dimension reduction and often produce similar results

Stop Words

- Words that are filtered out before the analysis begins
- Could be any type of words that you do not want in the analysis
- Usually, function words are used as stop words (FORESHADOWING…)
  - “The”
  - “Is”
  - “I”
  - “That”
  - etc.
- Domain-specific words are also often excluded from the analysis
- E.g., “Global Warming” in the corpus of texts about Global Warming

N-grams

- So far, we've only looked at "unigrams" – individual words
- Texts can be broken down into any n-gram sequences
- "I love ice-cream and bananas"
    - "I" "love" "ice-cream" "and" "bananas"
    - "I love" "love ice-cream" "ice-cream and" "and bananas"
    - 3-grams?

Removal of terms by frequency

- Further removal of dimensionality can be achieved by removing either very frequent or very infrequent terms
- If they are very frequent, they probably don’t carry much discriminating information for our analysis (think stopwords)
- If they are very infrequent, they probably carry a lot of discriminating information, but very low statistical power

Danny & Spirling, 2018

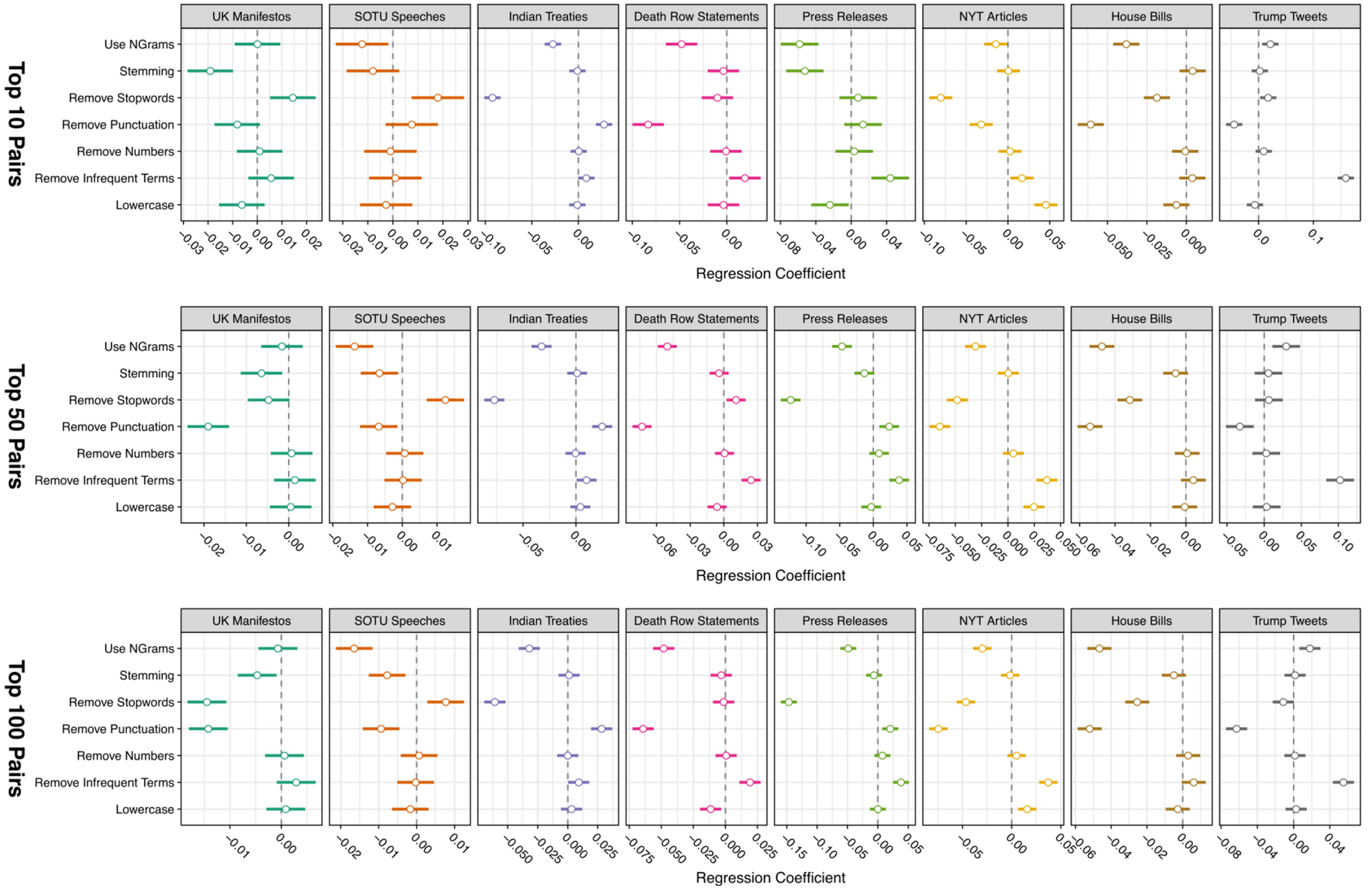

Figure 5. Regression results depicting the effects of each of the seven preprocessing steps on the `preText` score for that preprocessing combination.

Tf-idf

- We can do more than just count words
- We can transform these counts

- Use some sort of a weight in order to transform

- Term frequency inverse document frequency is one form of weighting

Term Frequency

$$tf(t,d) = \frac{f_{t,d}}{\sum_{t' \in d} f_{t',d}}$$

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Inverse Document Frequency

$$idf = log\frac{N}{n_j}$$

Number of Documents

Number of Documents where term j appears

tfidf

$$W_{ij} \times log\frac{N}{n_j}$$

What the hell?

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- ***Exactly!***
- Introduced in 1972 by a computer scientist (Spärck Jones, 1972)
- No theoretical justification
- Apart from “it seems to work…”

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- ***Exactly!***
- Introduced in 1972 by a computer scientist (Spärck Jones, 1972)
- No theoretical justification
- Apart from “it seems to work…”

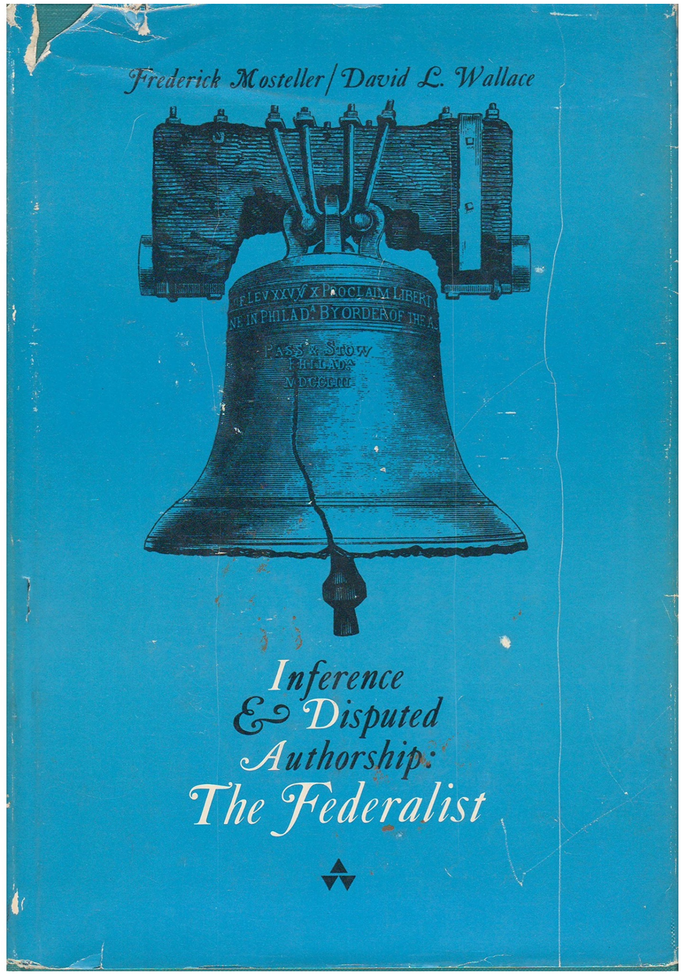
- Sometimes is does…

Log Odds / Log Odds Ratio

$$\log O_w^i = \log \frac{f_w^i}{1 - f_w^i}$$

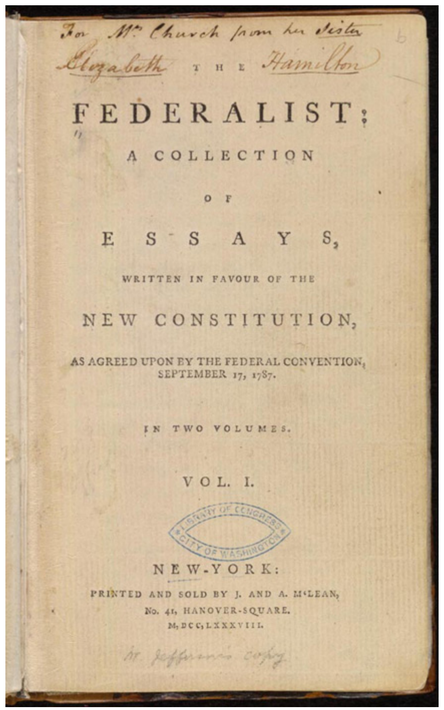
$$\log \frac{O_w^i}{O_w^j} = \log \frac{f_w^i}{1 - f_w^i} / \frac{f_w^j}{1 - f_w^j} = \log \frac{f_w^i}{1 - f_w^i} - log \frac{f_w^j}{1 - f_w^j}$$

Inference and Disputed Authorship: The Federalist



Frederick Mosteller &
David L. Wallace, 1963

One of the first (if not the first) text-as-data study



For Mrs Church from her sister
Elizabeth THE Hamilton

FEDERALIST:

A COLLECTION

OF

ESSAYS,

WRITTEN IN FAVOUR OF THE

NEW CONSTITUTION,

AS AGREED UPON BY THE FEDERAL CONVENTION,
SEPTEMBER 17, 1787.

IN TWO VOLUMES.

VOL. I.

NEW-YORK:

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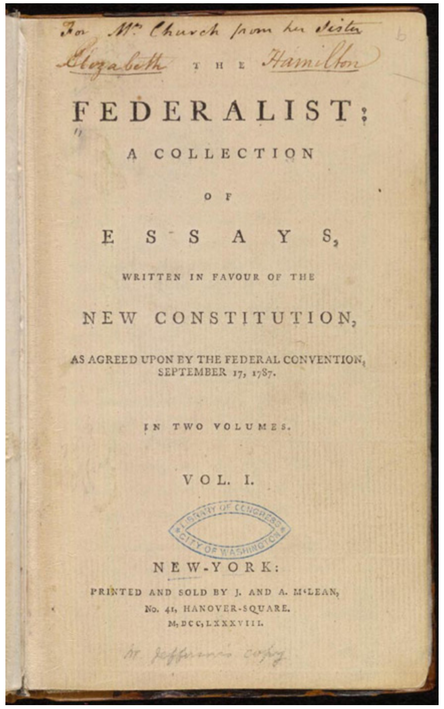
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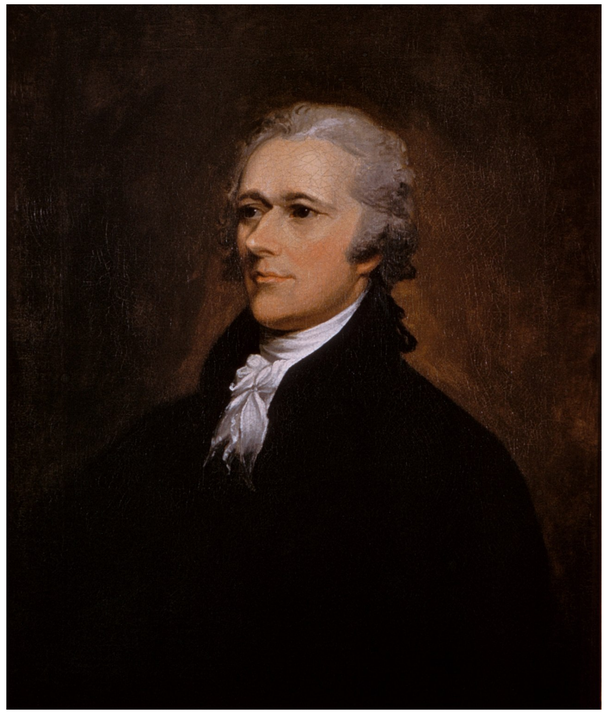
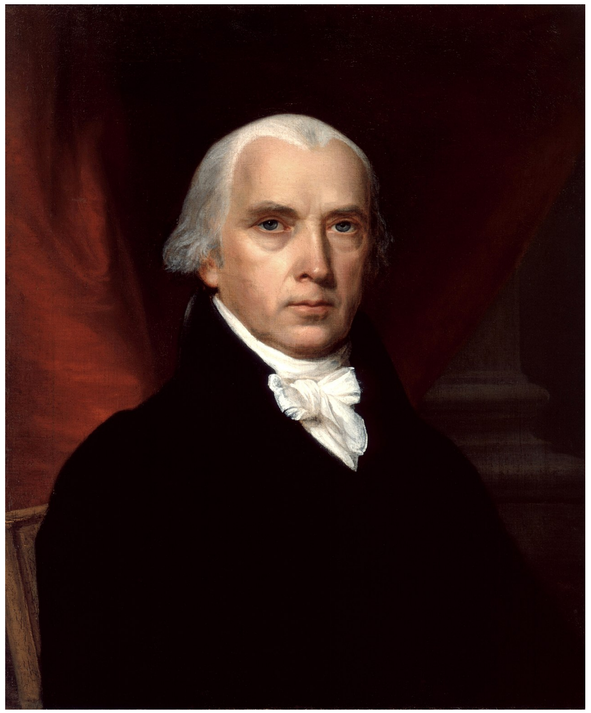
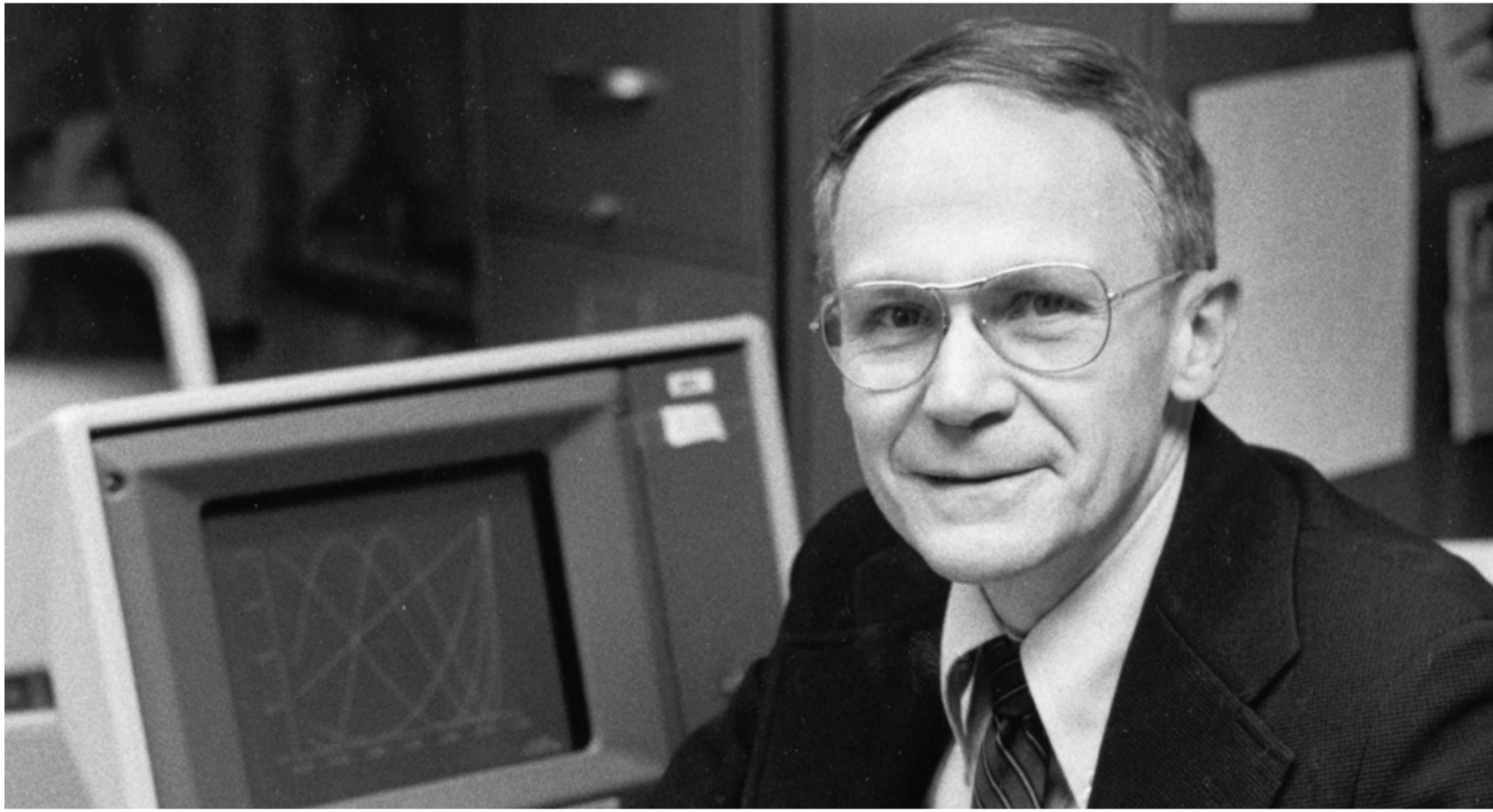




Who wrote them?

- 71 of the essays have a fairly certain authorship
- 12 are disputed
- Big historical debate as to how to ascribe authorship



Computer-assisted text analysis!

Computer-assisted text analysis…?

Dimension Reduction

- Remove all the stop-words!

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- Remove all the stop-words!
- Still… too many words!
-

Dimension Reduction

- Remove all the stop-words!
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- Remove all the words BUT the stop-words

Dimension Reduction

- Remove all the stop-words!
- Still… too many words!
- Remove all the words BUT the stop-words

- Maybe there is information in them!

Simplified example from Grimmer et al., 2022

- Focus on:
  - “Man”
  - “By”
  - “Upon”
- The rates with which the authors use these words may indicate authorship

Word Rates

	man	by	upon
Hamilton	102	859	374
Madison	17	474	7
Jay	0	82	1

Word Proportions

	man	by	upon
Hamilton	.076	.643	.28
Madison	.034	.952	.014
Jay	0	.988	.012

Word Proportions

Multinomial Model of Language

	man	by	upon
Hamilton	.076	.643	.28
Madison	.034	.952	.014
Jay	0	.988	.012

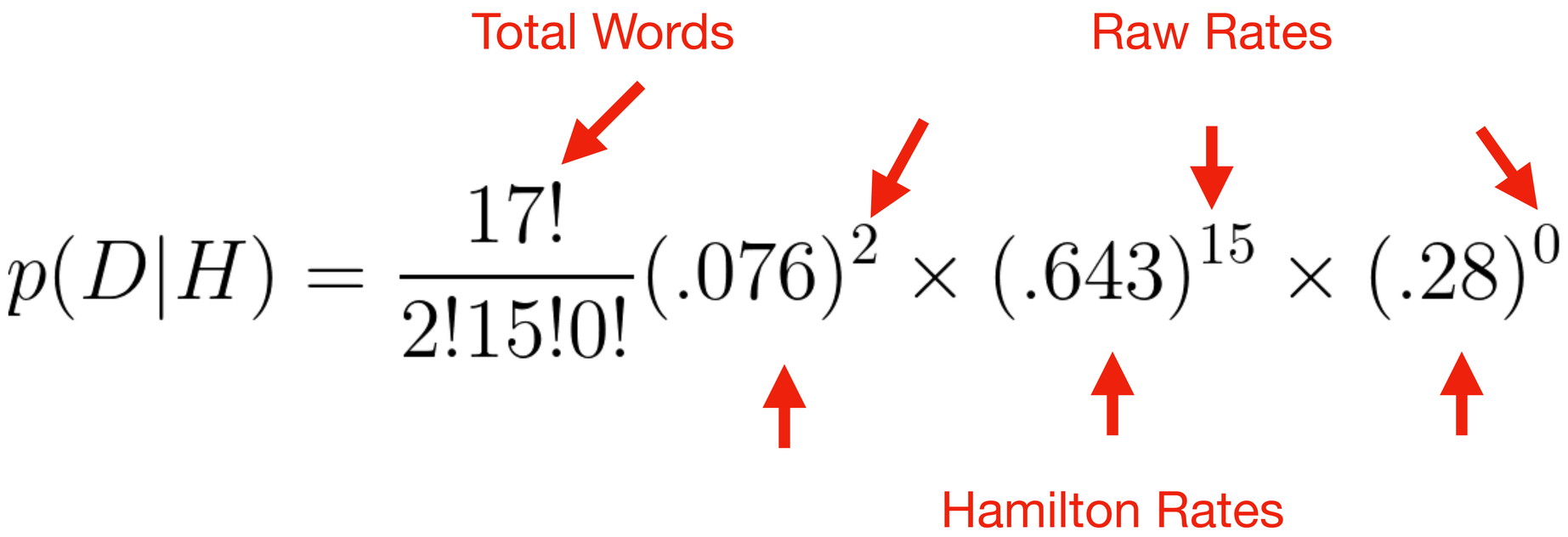
Disputed Paper

	man	by	upon
Disputed	2	15	0

Disputed Paper

$$p(D|H) = \frac{17!}{2!15!0!}(.076)^2 \times (.643)^{15} \times (.28)^0$$

Disputed Paper



Calculate Jay and Madison yourself

$$p(D|H) = \frac{17!}{2!15!0!}(.076)^2 \times (.643)^{15} \times (.28)^0 = .001$$

$$p(D|M) = \frac{17!}{2!15!0!}(.034)^2 \times (.952)^{15} \times (.014)^0 = .076$$

$$p(D|J) = \frac{17!}{2!15!0!}(0)^2 \times (.988)^{15} \times (.012)^0 = 0$$

Federalist Vector Space Model

- In the Markdown file…

Topic Modelling

- A model to discover latent topics
- Not synonymous with LDA
- LDA is one of topic models

- Latent semantic analysis
- Singular value decomposition

Latent Dirichlet Allocation

- Bayesian generative hierarchical model
- First introduced as a way to simultaneously model traits and genes (Pritchard, 2000)
- Adjusted for text analysis ML applications (Blei et al., 2003)

Latent Dirichlet Allocation

- Estimates a distribution of words across documents across latent topics
- A mixture model

Mixture Model

$$P(x) = \Sigma_{k=1}^{K} \pi_k \times P(x \mid \theta_k)$$

Mixture Model

$$P(x) = \Sigma_{k=1}^{K} \pi_k \times P(x \mid \theta_k)$$

- P(x) represents the probability density function (PDF) of the observed data point x
- K is the number of components in the mixture model
- π_k is the mixing proportion or weight assigned to the k-th component, representing the probability of a data point belonging to that component. These weights satisfy the condition $\Sigma_{k=1}^{K} \pi_k = 1$ and $0 \leq \pi_k \leq 1$
- P(x|θ_k) represents the conditional probability of observing data point x given the parameters θ_k of the k-th component distribution

Hierarchical Models

Hierarchical Models

Statistical Model

$$y = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k + \epsilon$$

Hierarchical Models

Statistical Model

$$y \sim Normal(\mu, \sigma)$$

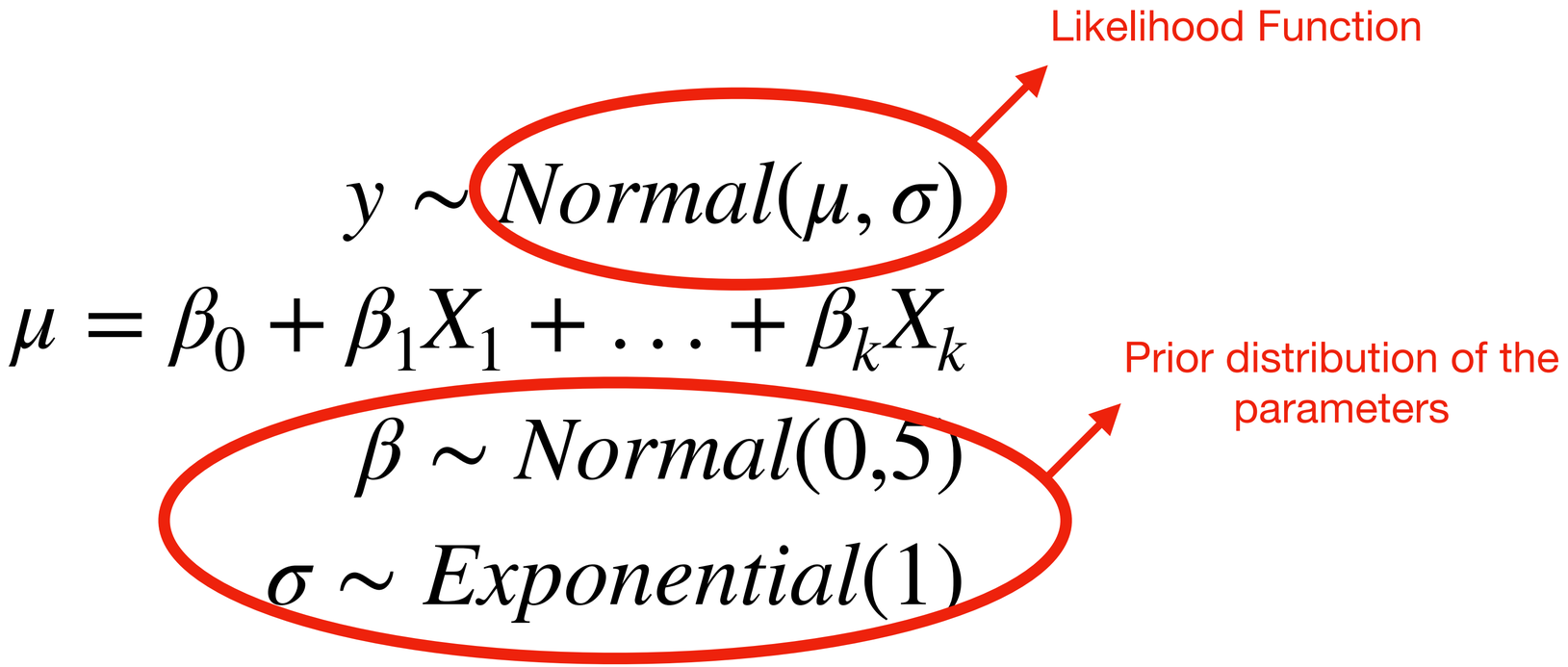
$$\mu = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k$$

$$\beta \sim Normal(0,5)$$

$$\sigma \sim Exponential(1)$$

Hierarchical Models

Statistical Model



Hierarchical Models

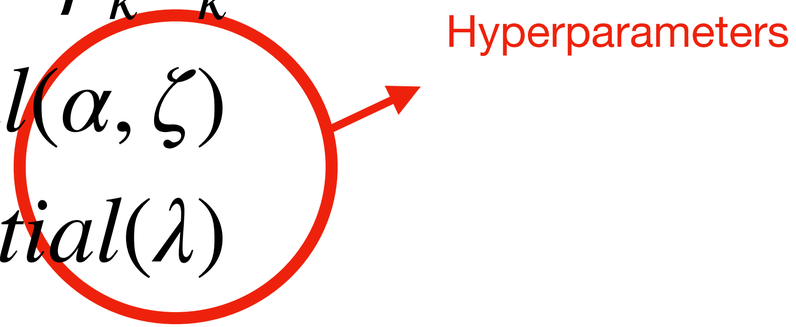
Statistical Model

$$y \sim Normal(\mu, \sigma)$$

$$\mu = \beta_0 + \beta_1 X_1 + \ldots + \beta_k X_k$$

$$\beta \sim Normal(\alpha, \zeta)$$

$$\sigma \sim Exponential(\lambda)$$



LDA

$$\theta_k \sim Dirichlet(\alpha) \quad \text{for each topic k}$$

$$\eta_d \sim Dirichlet(\beta) \quad \text{for each document d}$$

$$z_{d,w} \sim Multinomial(\eta_d) \quad \text{for each word w in document d}$$

$$x_{d,w} \sim Multinomial(\theta_{z_{d,w}}) \quad \text{for each word w in document d}$$

θ_k ~ Dirichlet(α), for each topic k,
η_d ~ Dirichlet(β), for each document d,
z_d,w ~ Multinomial(η_d), for each word w in document d,
x_d,w ~ Multinomial(θ_{z_d,w}), for each word w in document d.

LDA

- θ_k is the topic-word distribution for topic k, representing the probability of each word given the topic.
- η_d is the document-topic distribution for document d, representing the probability of each topic in the document.
- z_d,w is the topic assignment for word w in document d, indicating which topic generated the word.
- x_d,w is the observed word in document d.

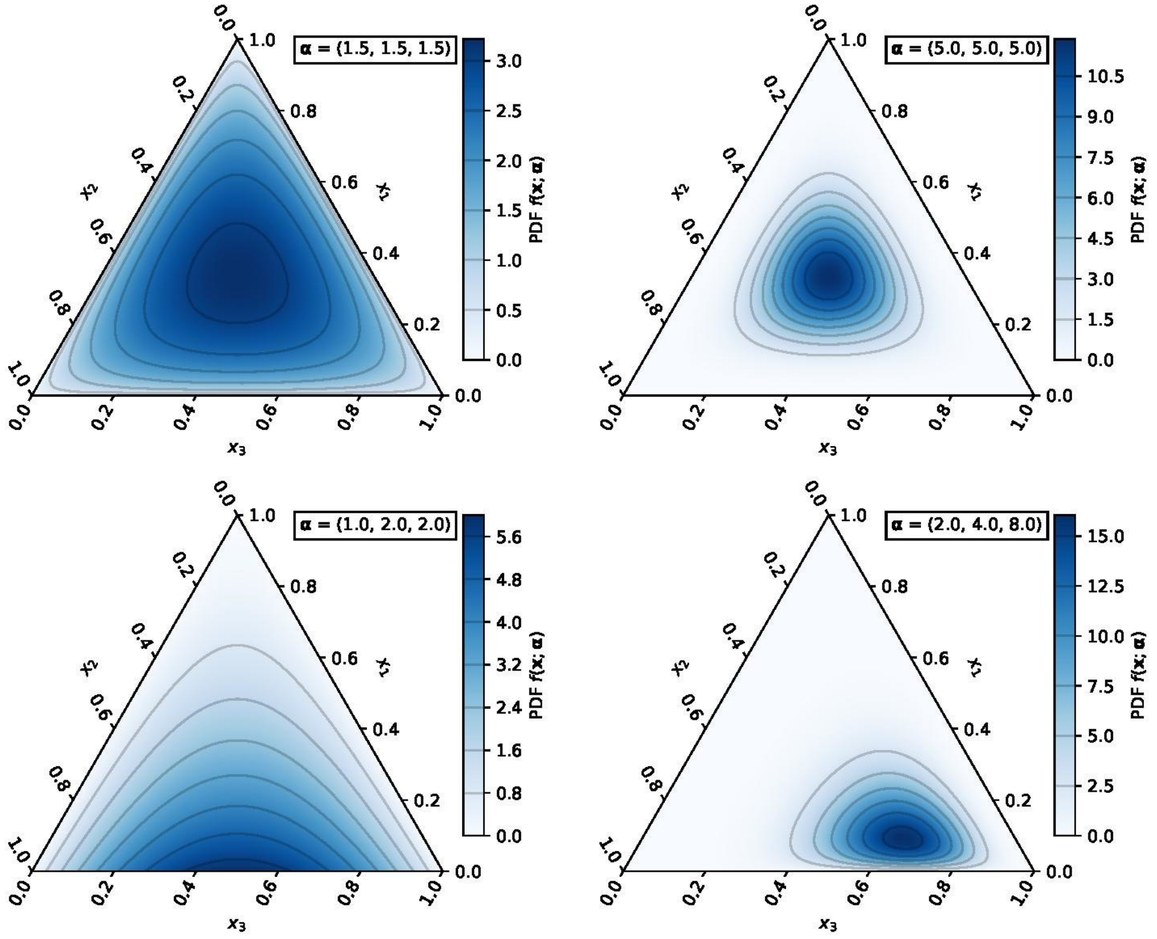
LDA

- For each topic $k \in \{1, ..., K\}$:
    - Draw a distribution over words $\theta_k \sim \text{Dirichlet}(\alpha)$, where α is a hyperparameter representing the topic-word prior.
    - For each document $d \in \{1, ..., D\}$:
    - Draw a distribution over topics $\eta_d \sim \text{Dirichlet}(\beta)$, where β is a hyperparameter representing the document-topic prior.
- For each word w in document d:
    - Draw a topic assignment $z_{d,w} \sim \text{Multinomial}(\eta_d)$, indicating which topic generated the word.
    - Draw a word $x_{d,w} \sim \text{Multinomial}(\theta_{z_{d,w}})$, indicating the specific word generated by the chosen topic.

LDA

- The goal of LDA is to infer the posterior distributions of the latent variables θ and η given the observed documents.
- Once the posterior distributions are estimated, LDA can be used to assign topics to new documents or extract the most probable words for each topic.

Dirichlet Prior



Validation of LDA

- Semantic Coherence
  - measures the degree to which the words within a topic are related and form a coherent theme
  - E.g., Pointwise Mutual Information
    - measures the association between two words based on their co-occurrence within a context window

Validation of LDA

- Exclusivity
  - the extent to which the words in a topic are specific to that topic and not shared across multiple topics
  - a topic should capture a distinct set of words that are less likely to appear in other topics

Validation of LDA

- ***Human Validation***