# Text Analysis for Legal Practice (Class 2)

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2 Understanding your text data

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## Option 3: Difference in averages

- Normalize DTM from counts to proportions.
- For each word *p* in an arbitrary corpus *c*:

$$\mu_{\mathcal{D}} = rac{\sum_{i=1}^{N} \mathcal{D}_i}{T}$$

where  $p_i$  is the number of times a p appears in document i, N is the total number of documents in c and T is the total number of words in c.

 Take the difference between one author's proportion of a word and another's proportion of the same word.

$$heta_{
ho} = \mu_{
ho, Trum
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Find words with highest absolute difference.

# Differences in averages: Problems

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- Tasks: Identify authors of disputed papers.
- Method: Classify papers as Hamilton or Madison using dictionary methods.
- Training data → Hamilton, Madison are known to have authored.
- Test data → disputed (i.e. unlabeled) papers.
- Preprocessing:
  - Hamilton/Madison discuss similar themes.
  - Differ on the extent they use stop words.
  - Focus analysis on the stop words.

### Word Weights: Standardized Mean Difference

- For each word p, construct weight  $\theta_p$ ,  $\mu_{p,Hamilton} = \text{Rate}(p) \text{ in subcorpus of Hamilton docs}$   $\mu_{p,Madison} = \text{Rate}(p) \text{ in subcorpus of Madison docs}$   $\sigma_{p,Hamilton}^2 = \text{Var}(p) \text{ in subcorpus of Hamilton docs}$   $\sigma_{p,Madison}^2 = \text{Var}(p) \text{ in subcorpus of Madison docs}$
- We can then generate weight  $\theta_D$  as

$$heta_{
m p}=rac{\mu_{
m p,Hamilton}-\mu_{
m p,Madison}}{\sigma_{
m p,Hamilton}^2+\sigma_{
m p,Madison}^2}$$

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## Classification for determining authorship

 For each disputed document i, compute discrimination statistic.

$$Y_i = \sum_{p=1}^{p} \theta_p X_{ip}$$

- $Y_i \rightsquigarrow$  classification (linear discriminator)
  - Above midpoint in training set  $\rightsquigarrow$  Hamilton text.
  - Below midpoint in training set → Madison text.
- Findings: Madison is the author of the disputed federalist papers.

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Let's Program

Launch RStudio!

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