# Quantitative Text Analysis

## Meeting 8

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# Unsupervised Machine Learning

# Machine Learning

- Supervised
    - An outcome variable is defined
    - Focus is on prediction
- Unsupervised
    - No outcome variable has been defined
    - Focus is on patterns

# Machine Learning

- Supervised
    - An outcome variable is defined
    - Focus is on prediction
- **Unsupervised**
    - **No outcome variable has been defined**
    - **Focus is on patterns**

# How to use the *supervised* methods?

- Easy
- At least conceptually
- ***Clear objective function***

# How to use the supervised methods?

$$Y = (y_1, y_2, \ldots, y_n)$$
$$X = (x_1, x_2, \ldots, x_n)$$
$$(y_1, x_1), (y_2, x_2), \ldots, (y_n, x_n)$$

Task to predict $\hat{y}$ as close to $y$

# How to use the supervised methods?

$$L(y, \hat{y}) = (y - \hat{y})^2$$

$$\hat{y} = \underset{\theta}{\operatorname{argmin}} \; E\left[L(model(\mathbf{x}, \theta), y)\right]$$

# How to use *unsupervised* learning

- Objective function?

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- Quantity of interest?

# How to use *unsupervised* learning

- Objective function?
- Quantity of interest?
- Objective function = your quantity of interest


LIGHTYEAR

# How to use *unsupervised* learning

- Objective function?
- Quantity of interest?
- Objective function = your quantity of interest
- ***This is difficult***

# Measurement

- A collection of quantitative or numerical data that describes a property of an object or event

# Measurement

- A collection of quantitative or numerical data that describes a property of an object or event
- What is the ***object***?

# Measurement

## In Social Science

- Operationalisation ➡ Data Collection ➡ Analyses ➡ Measurement
- The quantity of interest is ***extrinsic*** to the model

# Measurement

## In Computer Science

- Model Building ➡ Measurement of Performance
- The quantity of interest is ***intrinsic*** to the model

$$L(\theta, \hat{\theta}) = (\hat{\theta} - \theta)^2$$

Main quantity of
Interest for
computer science

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Means to an end
for social science

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Means to an end
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Main quantity of
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$$\hat{\theta} \approx \theta$$

What social
science wants

# Prediction vs. Inference

- Computer scientists often emphasise *prediction*
- Social scientists are often more interested in *inference*
- Vast, multidimensional parameter space = not suitable for inference
    - Good for prediction
- E.g., Turing test
    - Machine passes
    - *Why* does it pass/not pass

# Problems

- Translation of Social Science concepts
- Connecting Methods to Theory
- Difficult to understand what is being *measured*

# Unsupervised Learning Example

- Clustering algorithms are great tools
- Not well suitable for the “standard” social science paradigm
- Needs external validation, but there is no “best” method
- “Validation” based on “theory” or “expectation” leads to biases

# The paradigm

- Approximating a data-generating process

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- Approximating a data-generating process
- *Assumption*: there is one (and only one) “true” data-generating process
- It ***is*** the reality

# Sticking to the paradigm

- The “normal” paradigm works only if we assume that there is one “correct” classification
- Need to adapt to different methods
-

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- The “normal” paradigm works only if we assume that there is one “correct” classification
- Need to adapt to different methods
- Unsupervised methods are ***meaningless*** in conjunction with the “true” data-generating process assumption

# Focus on Discovery

# Objectives

- Descriptive analysis/Discriminating words:
    - What are the characteristics of a corpus? How do some documents compare to each other
    - Collocation analysis, readability scores, Cosine/Jaccard similarity
- Clustering and scaling:
    - What groups of documents are in the corpus? Can the documents be placed on a dimension?
    - Cluster analysis, principal component analysis, wordfish..
- Topic modeling:
    - What are the main themes in a corpus?
    - LDA, STM

# K-Means Clustering

- Simple(ish) algorithmic method
- Partitions the data into K non-overlapping clusters

# Setup

$$C_1, C_2, ..., C_k$$

$$C_1 \cup C_2 \cup \ldots \cup C_K = \{1, \ldots, n\}$$

$$C_k \cap C_{k'} = \emptyset \text{ for all } k \neq k'$$

# Assumption and task

- Optimal clustering solution is the one where ***within-cluster variation is as small as possible***

$$W(C_k)$$

$$\underset{C_1,\ldots,C_K}{\text{minimize}} \left\{ \sum_{k=1}^{K} W(C_k) \right\}$$

# Within cluster variation

$$W(C_k) = \frac{1}{|C_k|} \sum_{i,i' \in C_k} \sum_{j=1}^{p} (x_{ij} - x_{i'j})^2$$

# Algorithm

- Randomly assign cluster numbers (1 through K) for each observation
    - Iterate until no further changes to the cluster assignment:
    - For each cluster determine the centroid (average of all observations in the cluster)
    - Re-assign observations to a cluster with the closest centroid (calculated with a distance metric).

# Guarantees convergence at a local optimum

- Cannot guarantee the best solution
- But are rather good one
- Sensitive to random assignment at the start

# Cluster Algorithms Validation

- Data assumptions (think data generation)
- Internal validity (best results for the data)
- External validity (matches with pre-existing understanding of data)
- Cross-validity (similar results across similar datasets)
- You are the validation method

# Questions?

# Topic Modelling

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

- Latent semantic analysis
- Singular value decomposition
- Even clustering methods (like the one we just discussed)

# 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***

# Latent Dirichlet Allocation

- By modelling distributions of topics over words and words over documents, topic models identify the most discriminatory groups of documents automatically.
- Assumption: if a document is about a certain topic, one would expect words that are related to that topic to appear in the document more often than in documents that deal with other topics.

# Mixture Models

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

# Hierarchical Models

# Hierarchical Models

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

# Hierarchical Models

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

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

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

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

# Hierarchical Models

Likelihood Function

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

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

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

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

Prior Distribution of Parameters

# Hierarchical Models

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

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

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

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Hyperparameters

# LDA

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

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

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

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

# LDA

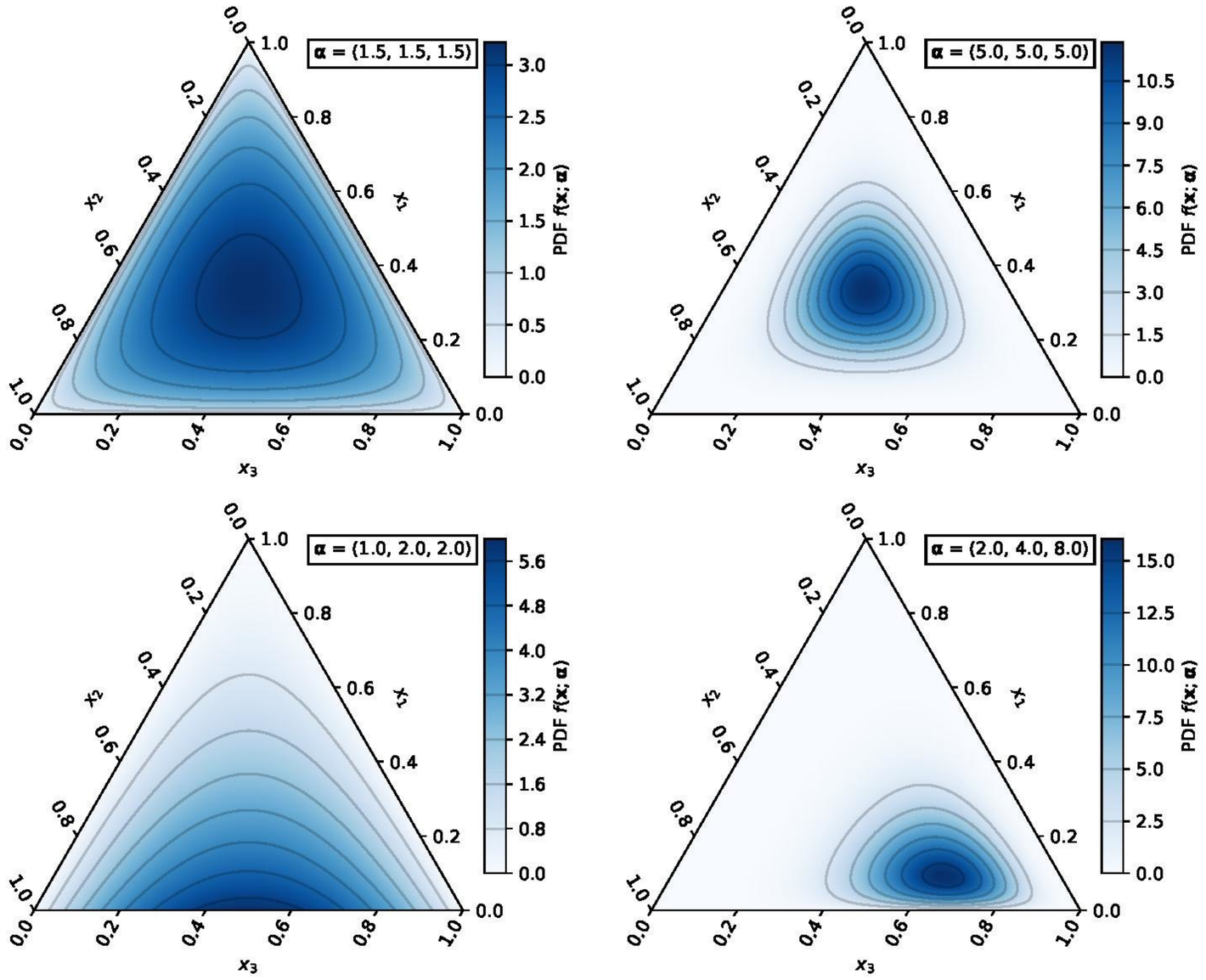
- θ_k is the topic-word distribution for topic k, representing the probability of each word given the topic.
- η_d is the document-topic distribution for document d, representing the probability of each topic in the document.
- z_d,w is the topic assignment for word w in document d, indicating which 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 $\alpha$ 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 $\beta$ 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.


α = (1.5, 1.5, 1.5)
α = (5.0, 5.0, 5.0)
α = (1.0, 2.0, 2.0)
α = (2.0, 4.0, 8.0)
x1
x2
x3
PDF f(x; α)

# Tricky to estimate

# Structural Topic Models (Roberts et al., 2014)

- Add additional distribution for additional structure in the text:

- Allows to add additional covariates to the estimation

# Validating topic models

- Tests of:
  - topic semantic validity: assess the extent to which the keywords within each topic have a coherent underlying meaning, and how these meanings behave across topics (e.g., Quinn et al., 2010, p. 210)
  - convergent validity: topic probabilities per document are compared with an external trusted variable like manual coding for the same documents (e.g., Guo et al., 2016)

- A possible validation workflow proposed by Maier et al. (2018): combi of quantitative topic summary metrics (e.g., NPMI; Lau et al., 2014) and human expert evaluations.

# Text scaling methods

- Attempts to fit documents into a unidimensional space
- Documents are “scaled” based on the frequency of used terms
- Assume “discriminating” words have a Poisson distribution

- “Ideological” successor to log odds ratio we’ve seen

# Wordfish (Slapin and Proksch 2008)

$$w_{ik} \sim \text{Poisson}(\lambda_{ik})$$

$$\lambda_{ik} = exp(\alpha_i + \psi_k + \beta_k \times \theta_i)$$

$\alpha_i$ Text size from type i

$\psi_k$ Frequency of word k

$\beta_k$ Discrimination power of word k

$\theta_i$ Ideological position of type i

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