

Quantitative Text Analysis

Meeting 8: Unsupervised Machine Learning

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Overview

- From Supervised to Unsupervised Learning
- Measurement and the Quantity of Interest
- Clustering
- Topic Models (LDA and STM)
- Text Scaling (Wordfish)
- Validation and Interpretation

Machine Learning Paradigms

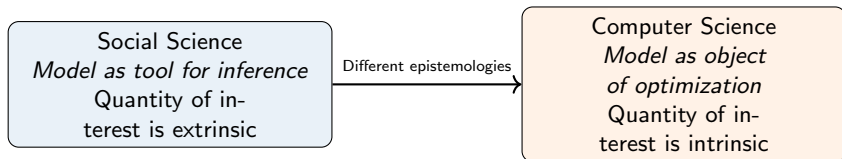
Supervised

- Outcome variable defined
- Focus: prediction and accuracy
- Objective function clear

Unsupervised

- No predefined labels
- Focus: structure discovery
- Objective = quantity of interest

Measurement and Paradigms



What is Measurement?

- Measurement = the process of assigning numbers (or symbols) to phenomena according to rules.
- Involves three linked steps:
 - **Conceptualization:** What do we want to capture?
 - **Operationalization:** How can we represent it empirically?
 - **Quantification:** How do we express it numerically?
- Measurement always implies a mapping between *theoretical constructs* and *observed data*.

Measurement in Social Science

- Measurement is often **theory-driven**.
- The goal is to capture latent constructs (e.g., trust, ideology, polarization).
- Accuracy means: correspondence between the *measure* and the *theoretical concept*.
- Model \Rightarrow means to an end (a tool to understand the construct).

Focus: Construct validity and interpretability.

Measurement in Computer Science

- Measurement is typically **data-driven**.
- The model itself produces measurable quantities (loss, accuracy, error).
- Accuracy means: minimizing difference between \hat{y} and y (or optimizing an objective function).
- Model \Rightarrow end in itself (the metric is *intrinsic* to the model).

Focus: Optimization and predictive performance.

What Is an Objective Function?

- In machine learning, the **objective function** defines what the model tries to achieve.
- It translates a goal into something computable.
- Examples:
 - Linear regression: minimize squared error $(y - \hat{y})^2$
 - K-means: minimize within-cluster variance
 - PCA: minimize reconstruction error
- **Think of it as:** the model's "definition of success."

Objective Function vs. Quantity of Interest

Computer Science

- Objective function = quantity of interest
- “Success” is defined by minimizing loss
- Example: clustering minimizes distance

Social Science

- Quantity of interest is *theoretical*
- “Success” = capturing a latent construct
- Example: clustering may reflect norms, roles, or ideologies

In social science, we care about meaning, not just optimization.

Examples of Objective Functions

Model	Objective Function	Goal
Linear Regression	$\min (y - \hat{y})^2$	Fit predictions
K-Means	$\min \sum_i x_i - \mu_{c_i} ^2$	Compact clusters
PCA	$\min X - X_{approx} ^2$	Reduce dimensions
LDA	$\max P(w, z \alpha, \beta)$	Infer latent topics
Wordfish	$\max L(\alpha, \psi, \beta, \omega)$	Position texts

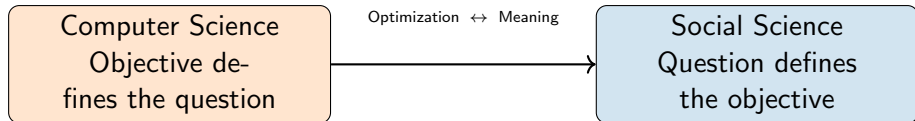
Key insight: each method measures something *different* because its objective differs.

Why the Objective Function Matters

- Defines what the model “cares about”.
- Different objectives \Rightarrow different structures discovered.
- If the objective does not align with theory, results can mislead.

Good measurement = alignment between objective and theory.

Two Ways of Defining the Objective



What Does $\hat{\theta}$ Mean?

- Every model estimates parameters $\hat{\theta}$: coefficients, embeddings, topic proportions, etc.
- But the role of $\hat{\theta}$ differs across disciplines:
 - In **computer science**: $\hat{\theta}$ is a *means* — it helps minimize a loss function.
 - In **social science**: $\hat{\theta}$ is the *quantity of interest* — what we want to understand and interpret.

$\hat{\theta}$ in Two Paradigms

Computer Science

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

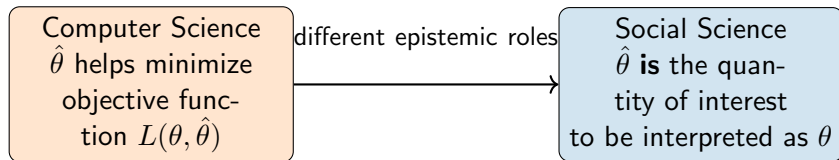
- Goal: make predictions accurate.
- $\hat{\theta}$ has no meaning beyond performance.
- Once optimized, the parameters can be ignored.

Social Science

$\hat{\theta}$ is evidence about the world.

- Goal: explain.
- $\hat{\theta}$ approximates the theoretical construct θ .
- $\hat{\theta} \approx \theta$ is the research objective.

Two Roles of $\hat{\theta}$



Same symbol, opposite direction of reasoning.

Two Views on Learning and Measurement

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What social science wants

Focus on Discovery

Unsupervised methods shift our goal

From: Estimating \hat{y} as close to y as possible

To: Discovering latent structure, clusters, or dimensions

Prediction vs Inference

- **Prediction:** How well does the model reproduce unseen data?
- **Inference:** What do parameters tell us about the world?
- Large parameter spaces \Rightarrow poor inference, good prediction

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$$L(X, \hat{S})$$

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In unsupervised learning, the objective function itself becomes the measure.

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- **Translation of social science concepts** Machine learning measures patterns, not constructs.
- **Connecting methods to theory** Models optimize statistical objectives, not theoretical meanings.
- **Difficult to understand what is being measured** Without a clear mapping between theory and model, \hat{S} may have no interpretable referent.

Unsupervised Learning Example

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- Yet they don't fit well with the *standard* social science paradigm:
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- “Validation” based on theory or expectation can introduce confirmation bias.

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- The goal is to **approximate the data-generating process**.
- *Assumption*: there exists one (and only one) “true” data-generating process.
- This assumption implies that “truth” exists and can be recovered.

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- Unsupervised methods violate this assumption: they discover **multiple** plausible structures.
- Therefore, unsupervised models are **meaningless** if interpreted under the “true model” assumption.
- We need a new epistemology: *discovery-oriented*, not truth-oriented.

From Truth to Discovery

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In unsupervised learning, meaning is not recovered, it is constructed.

Epistemology of Discovery

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Discovery = modeling as a form of measurement.

Questions?

Families of Unsupervised Methods

- **Clustering:**

Find groups of similar items.

Examples: K-Means, Hierarchical Clustering.

- **Topic Modeling:**

Find latent themes in text.

Examples: Latent Dirichlet Allocation (LDA), Structural Topic Model (STM).

- **Scaling:**

Place items along latent dimensions.

Example: Wordfish (Slapin & Proksch, 2008).

K-Means Clustering

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

K-Means Clustering

$$C_1, C_2, \dots, C_K$$

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Each observation belongs to exactly one cluster.
Clusters are non-overlapping and collectively exhaustive.

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Intuition: assign points to clusters so that each cluster is as compact as possible.

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K-Means converges to a local optimum, not necessarily the global one.

Choosing the Number of Clusters

- **Elbow method:** plot WCSS vs. K
- **Silhouette score:** average distance to own cluster vs others
- **Theory-informed:** choose K based on expected structure

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- **Cross-validity:** stability across similar datasets or time periods.
- **You are the validation method.**
Interpretation and theory provide the ultimate validation.
- Validation moves from *data-fit* to *meaning-fit*.

Topic Models

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- Topic modeling is a **family of models**, not a single algorithm.
- **Latent Dirichlet Allocation (LDA)** is one of several topic models.
- Other approaches include:
 - Latent Semantic Analysis (LSA)
 - Singular Value Decomposition (SVD)
 - Clustering-based topic discovery

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- Originally introduced to model *population structure* in genetics (Pritchard, Stephens & Donnelly, 2000).
- Adapted to text analysis as a probabilistic topic model (Blei, Ng & Jordan, 2003).
- Each document is modeled as a *mixture of topics*, and each topic as a *distribution over words*.

Latent Dirichlet Allocation (LDA)

- Goal: discover latent topics that generate observed words.
- Assumption: documents are mixtures of topics; topics are distributions of words.

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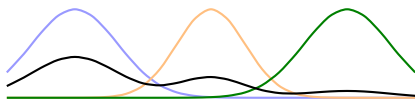
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Example: a document can be 70% about politics, 20% about health, 10% about sports.

Mixture Model



Observed data = weighted combination of latent distributions

Hierarchical Models

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In hierarchical (Bayesian) models, coefficients are random variables with their own probability distributions.

Hierarchical Models

$$y \sim \text{Normal}(\mu, \sigma)$$

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

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Likelihood: $y \sim \text{Normal}(\mu, \sigma)$: how data are generated.

Priors: β, σ have their own distributions.

The model is hierarchical because parameters depend on other parameters.

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Hierarchical Models: Hyperparameters

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The numbers $(0, 5)$ and (1) are **hyperparameters**: they define the prior distributions for model parameters.

In LDA, the Dirichlet priors α and β play this same role.

They control how concentrated or diffuse the topic and document distributions are.

LDA Formalized

Generative process:

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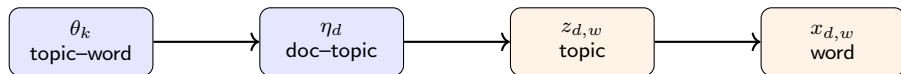
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Formally: $P(\theta, \eta, z \mid x, \alpha, \beta)$

LDA Generative Process



Model first draws topic-word distributions, then document-topic mixtures, assigns topics to words, and generates observed words.

LDA in Words

- ① For each topic k , draw word distribution $\theta_k \sim \text{Dir}(\alpha)$
- ② For each document d , draw topic mixture $\eta_d \sim \text{Dir}(\beta)$
- ③ For each word:
 - Choose topic $z_{d,w} \sim \text{Mult}(\eta_d)$
 - Choose word $x_{d,w} \sim \text{Mult}(\theta_{z_{d,w}})$

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- **High α** : all θ_k similar (uniform).
Low α : few θ_k dominate (sparse distribution).

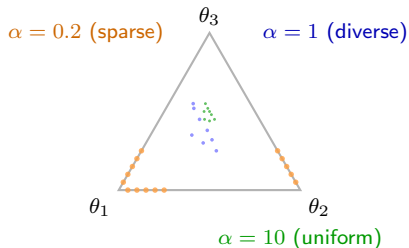
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- Parameterized by $\boldsymbol{\alpha} = (\alpha_1, \dots, \alpha_K)$, which control how concentrated or spread out the probabilities are.
- **High α** : all θ_k similar (uniform).
- **Low α** : few θ_k dominate (sparse distribution).
- In LDA, Dirichlet priors control how concentrated topics or words are.

Visualizing the Dirichlet Distribution



Smaller $\alpha \rightarrow$ more peaked; larger $\alpha \rightarrow$ more uniform.
Each dot is a draw $(\theta_1, \theta_2, \theta_3)$ lying on the simplex.

Dirichlet in LDA

Variable	Drawn from	Meaning
η_d	$\text{Dirichlet}(\beta)$	Topic distribution for document d
θ_k	$\text{Dirichlet}(\alpha)$	Word distribution for topic k

Dirichlet priors define the diversity or sparsity of topics and words.

Interpreting α and β in Topic Models

- α (**document–topic prior**): controls how many topics appear per document.
 - Low $\alpha \rightarrow$ each document dominated by few topics (sparse).
 - High $\alpha \rightarrow$ documents mix many topics (diffuse).

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 - High $\alpha \rightarrow$ documents mix many topics (diffuse).
- β (**topic–word prior**): controls how many words dominate each topic.
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Interpreting α and β in Topic Models

- α (**document–topic prior**): controls how many topics appear per document.
 - Low $\alpha \rightarrow$ each document dominated by few topics (sparse).
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- In practice: $\alpha, \beta < 1$ yield more interpretable, “focused” topic models.

α shapes documents; β shapes topics.

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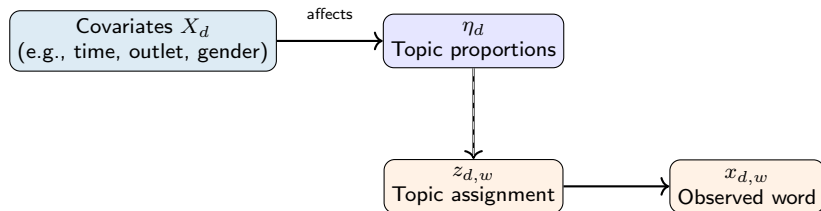
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- Enables inference: how topics vary by time, source, gender, ideology, etc.

How STM Extends LDA



STM extends LDA by adding document-level structure:

*Covariates influence which topics appear (**prevalence**) and how topics are expressed (**content**).*

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- Without validation, unsupervised results are **artifacts of the algorithm**.

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- **Interpretive validity:** the researcher's qualitative assessment of meaning —
You are the validation method.

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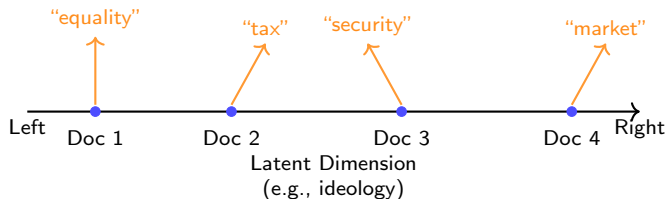
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- **Human-in-the-loop validation:**
Experts or crowdsourced coders rate interpretability and label consistency.

Text Scaling Methods

- Place documents on latent dimensions (e.g., ideology).
- Use discriminating word frequencies as anchors.

Text Scaling



*Documents are positioned along a latent dimension according to word usage.
Discriminating words push documents toward one end or the other.*

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- **Scale invariance:** only relative positions matter, the scale's origin is arbitrary.

Wordfish as a Hierarchical Model (Slapin & Proksch, 2008)

Likelihood:

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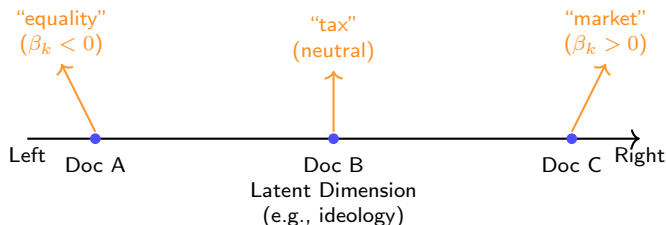
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Wordfish estimates document positions ω_i and word discriminations β_k jointly.

How Wordfish Links Words and Documents



Words with positive β_k pull documents to the right; words with negative β_k pull them to the left.

Estimated ω_i summarize these directional tendencies.

Summary: Comparing Unsupervised Methods

	Goal	Output	Example
Clustering	Grouping	Cluster labels	K-means
Topic Modeling	Thematic discovery	Topic-word probs	LDA / STM
Scaling	Latent dimension	Position scores	Wordfish

What Unsupervised Learning Does (and Doesn't Do)

- **Discovers structure**, it does not define it.
- **Measures relationships**, not “truth”.
- Depends on **assumptions about meaning, similarity, and latent space**.
- **Useful for exploration and theory building**, not just prediction.

Unsupervised learning helps us see structure we didn't know was there, but we still have to interpret what that structure means.

Each method is a different kind of measurement, and every measurement is a theoretical exercise.

Questions?