Text as Data - Modelado de Tópicos

Ciencia de Datos y Econometría Aplicada

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Modelos de Tópicos

- El texto es de dimensionalidad muy alta
- Algunas veces un modelo factorial no supervisado es una estrategia popular y útil con datos de texto
- Puedes primero ajustar un modelo factorial a un corpus gigante y usar estos factores para aprendizaje supervisado en un subconjunto de documentos etiquetados.
- La reducción de dimensionalidad no supervisada facilita el aprendizaje supervisado

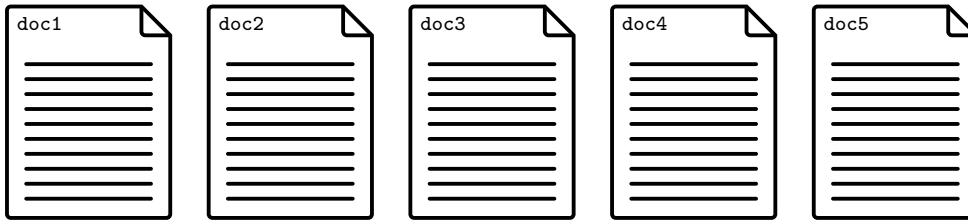
Modelos de Tópicos

LDA: Resumen

- El enfoque de usar PCA para factorizar texto era común antes de los años 2000.
- Las versiones de este algoritmo se denominaban bajo la etiqueta de análisis semántico latente.
- Sin embargo, esto cambió con la introducción del modelado de tópicos, también conocido como Asignación Latente de Dirichlet (LDA), por Blei et al. en 2003.
- Estos autores propusieron tomar en serio la representación de bolsa de palabras y modelar los conteos de tokens como realizaciones de un marco probabilístico.

Topic Models

El Problema



Topic Models

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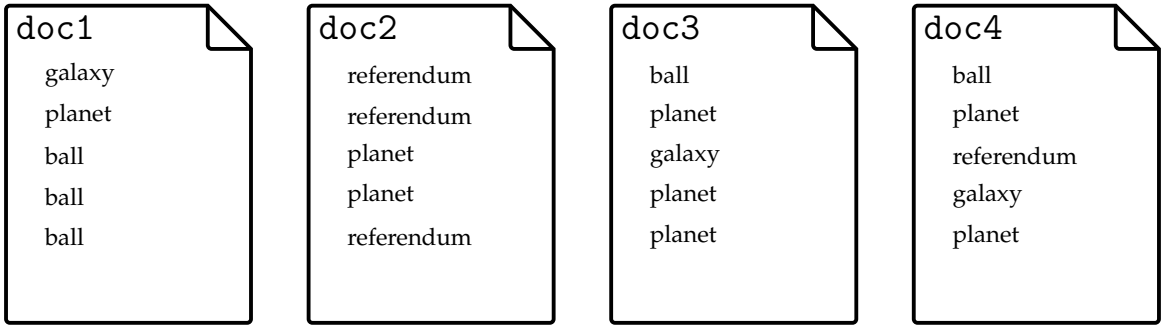
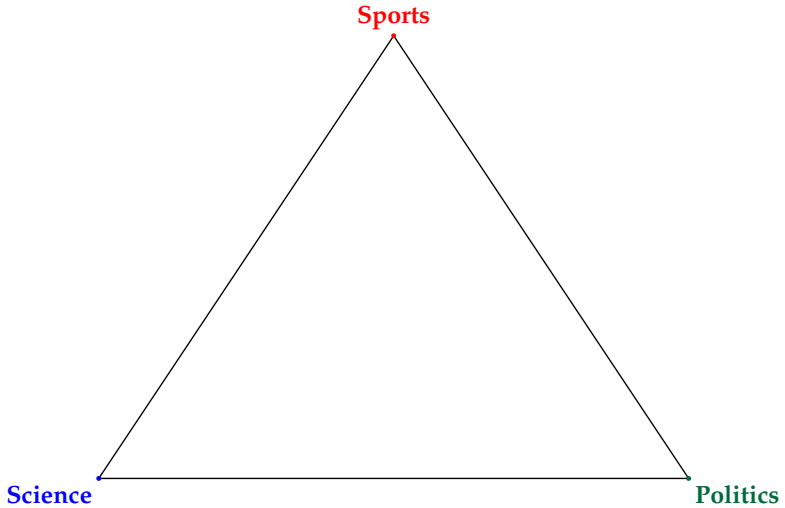


Topic Models

Latent Dirichlet Allocation



Topic Models

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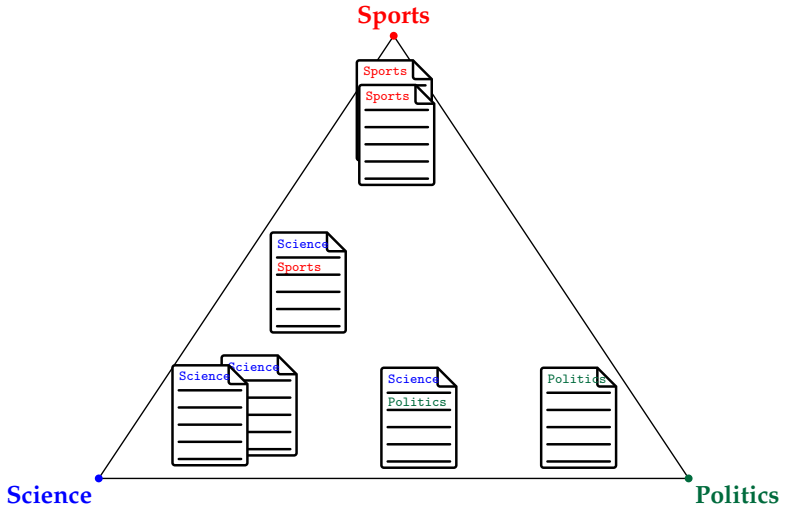

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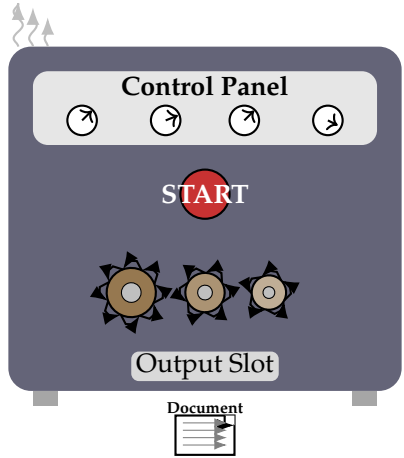
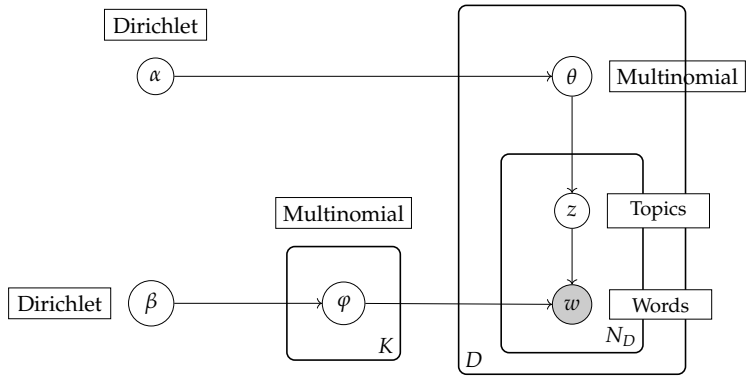


Topic Models

Latent Dirichlet Allocation: Blueprint



Topic Models

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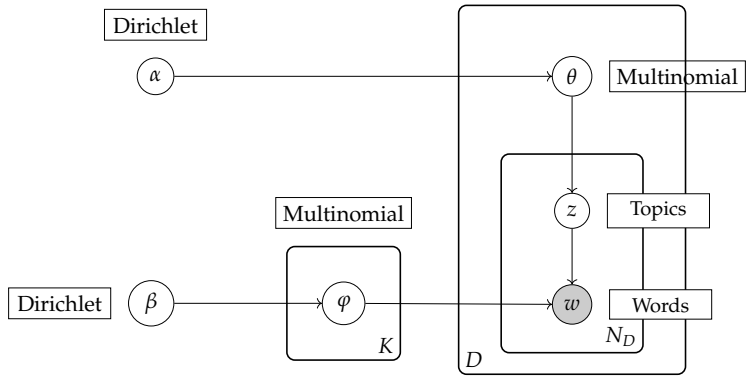

$$P(W, Z, \theta, \varphi; \alpha, \beta) = \prod_{j=1}^{M} P(\theta_j; \alpha) \prod_{i=1}^{K} P(\varphi_i; \beta) \prod_{t=1}^{N} P(Z_{j,t} \mid \theta_j) P(W_{j,t} \mid \varphi Z_{j,t})$$

Topic Models

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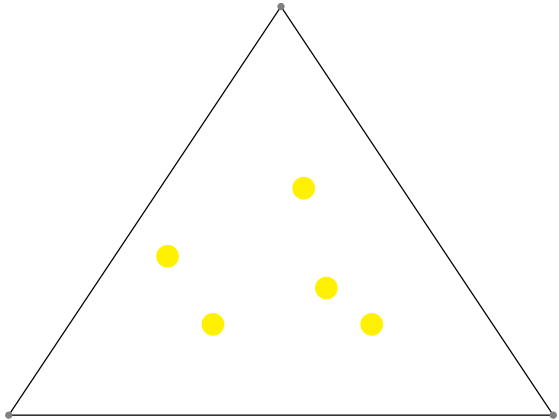
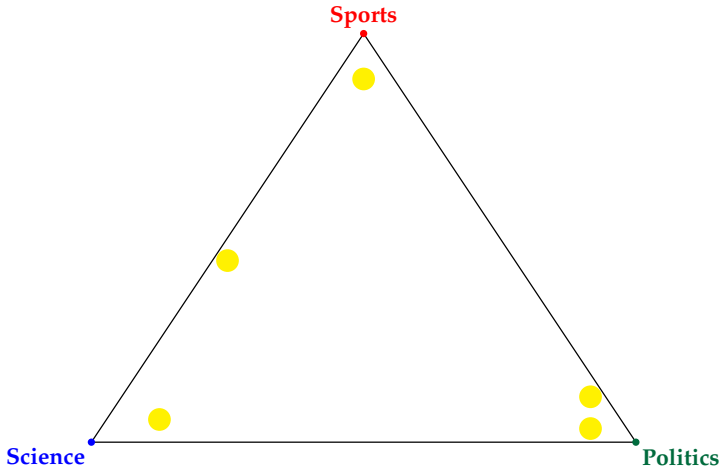
Topic Models

Dirichlet Distributions



Topic Models

Dirichlet Distributions



Topic Models

Dirichlet Distributions

- The Dirichlet distribution lives on something called the $(K-1)$**-simplex**. For our triangular house (when $K = 3$):

$$\Delta^{K-1} = \left\{ \boldsymbol{\theta} \in \mathbb{R}^K : \theta_k \geq 0 \; \forall k, \sum_{k=1}^{K} \theta_k = 1 \right\}$$

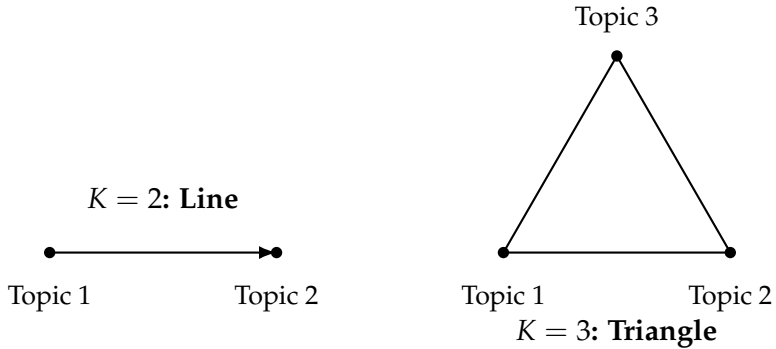
- This just says: $\boldsymbol{\theta}$ is a vector of K non-negative numbers that sum to 1
- We write $\boldsymbol{\theta} \sim \text{Dir}(\boldsymbol{\alpha})$ where $\boldsymbol{\alpha} = (\alpha_1, \ldots, \alpha_K)$ is the concentration vector.
- **The probability density function is:**

$$f(\boldsymbol{\theta} \mid \boldsymbol{\alpha}) = \frac{1}{B(\boldsymbol{\alpha})} \prod_{k=1}^{K} \theta_k^{\alpha_k - 1}$$

- where $B(\boldsymbol{\alpha}) = \frac{\prod_{k=1}^{K} \Gamma(\alpha_k)}{\Gamma(\alpha_0)}$ and $\alpha_0 = \sum_{k=1}^{K} \alpha_k$.
- $B(\boldsymbol{\alpha})$ is just a normalizing constant that ensures probabilities sum to 1.

Topic Models

Dirichlet Distributions



Topic Models

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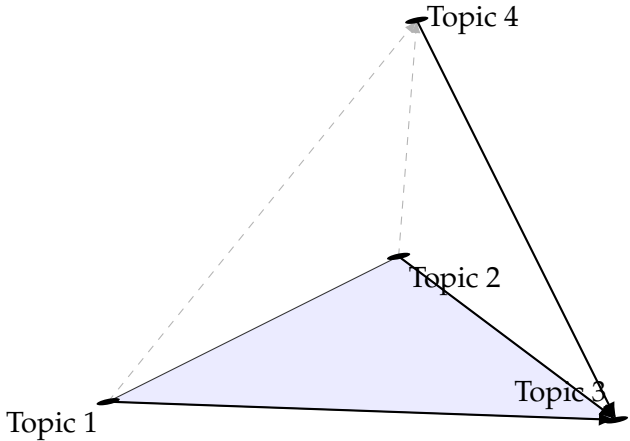


Figure 1: A tetrahedron for $K = 4$ topics. For $K > 4$, we enter higher dimensions!

Topic Models

Two Dirichlet Distributions in LDA

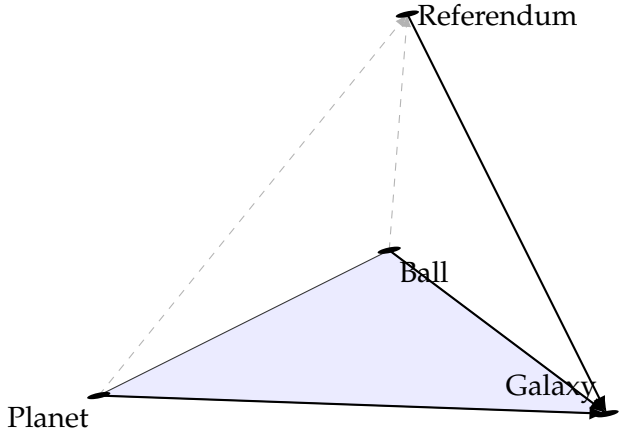
$$P(W, Z, \theta, \varphi; \alpha, \beta) = \prod_{j=1}^{M} P(\theta_j; \alpha) \prod_{i=1}^{K} P(\varphi_i; \beta) \prod_{t=1}^{N} P(Z_{j,t} \mid \theta_j) P(W_{j,t} \mid \varphi Z_{j,t})$$

LDA actually uses the Dirichlet distribution **twice**:

1. **Document-Topic distribution** ($\boldsymbol{\theta} \sim \text{Dir}(\boldsymbol{\alpha})$):
   - Lives on a triangle with corners = topics (Sports, Science, Politics)
   - Each point = a document's topic mixture
   - Usually sparse ($\alpha < 1$) because documents focus on one or two topics
2. **Topic-Word distribution** ($\boldsymbol{\varphi} \sim \text{Dir}(\boldsymbol{\beta})$):
   - Lives on a tetrahedron with corners = words (ball, planet, galaxy, referendum)
   - Each point = a topic's word distribution

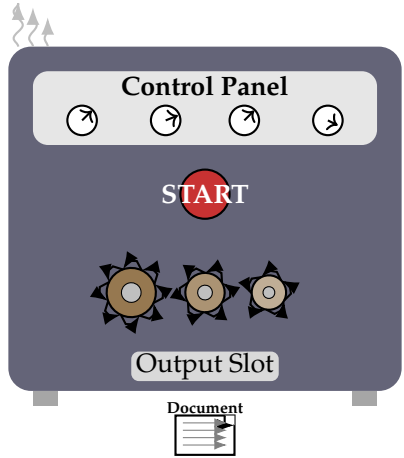
Topic Models

Two Dirichlet Distributions in LDA



Topic Models

LDA



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Topic Models: Examples LDA