

Topic Models for Texts and Images in Representation Space

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Topic Models

Topics

gene 0.04
dna 0.02
genetic 0.01
...

life 0.02
evolve 0.01
organism 0.01
...

brain 0.04
neuron 0.02
nerve 0.01
...

data 0.02
number 0.02
computer 0.01
...

Documents

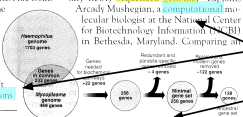
Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many **genes** does an **organism** need to survive? Last week at the genome meeting here,* two genome researchers with radically different approaches presented complementary views of the basic genes needed for **life**. One research team, using **computer** analyses to compare known **genomes**, concluded that today's **organisms** can be sustained with just 250 genes, and that the earliest life forms required a mere 128 **genes**. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those **predictions**

"are not all that far apart," especially in comparison to the 75,000 **genes** in the human genome, notes Siv Andersson, a geneticist at Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just a **genetic** numbers game, particularly as more and more **genomes** are completely sequenced and analyzed. "It may be a way of organizing any newly **sequenced genome**," explains

Arcady Mushegian, a **computational** molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

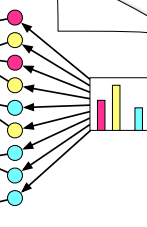


* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

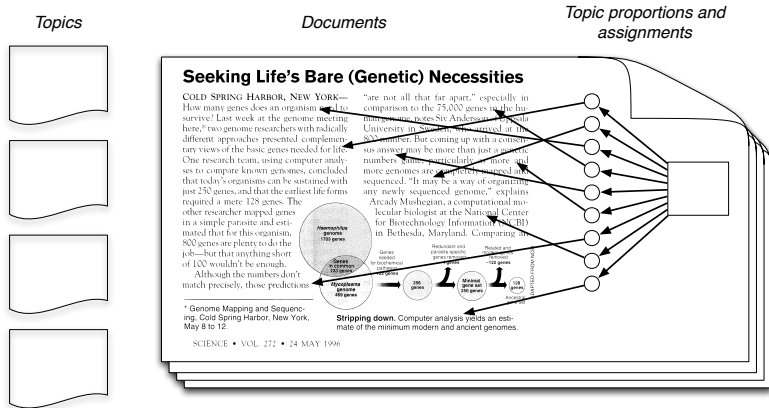
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Topic proportions and assignments



- LDA assumes that there are K topics shared by the collection.
- Each document exhibits the topics with different proportions.
- Each word is drawn from one topic.
- We discover the structure that best explain a corpus.

Latent Variable Models

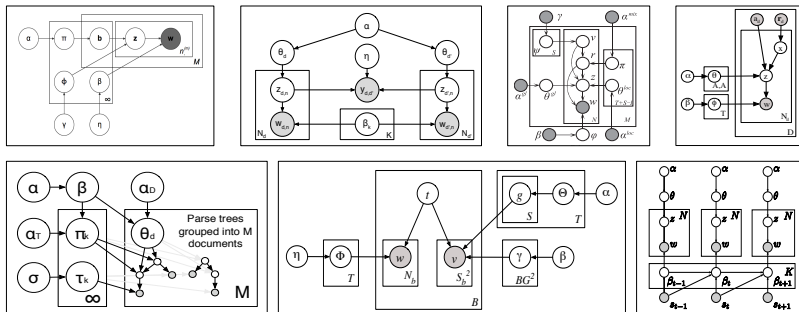


- Our goal is to **infer** the hidden variables
- I.e., compute their distribution conditioned on the documents

$$p(\text{topics, proportions, assignments} | \text{documents})$$

Slide stolen from D. Blei.

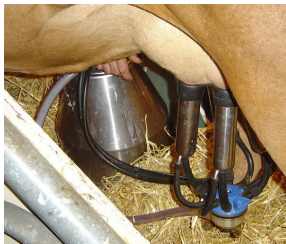
Bayesian Networks



Slide stolen from D. Blei.

- ▶ Shaded variables are *observed*, other variables are *hidden*.
- ▶ A model is our hypothesis for how data are generated.
- ▶ We *condition* on observations to update our hypothesis.

Multimodal Documents



A milking machine in action

farms also grow their own feed, typically including corn, alfalfa, and hay. This is fed directly to the cows, or stored as *silage* for use during the winter season. Additional dietary supplements are added to the feed to improve milk production. ^[10]

4.2 Poultry farms

Poultry farms are devoted to raising chickens (egg layers or broilers), turkeys, ducks, and other fowl, generally for



Typical cattle yard in Northern Iowa, USA

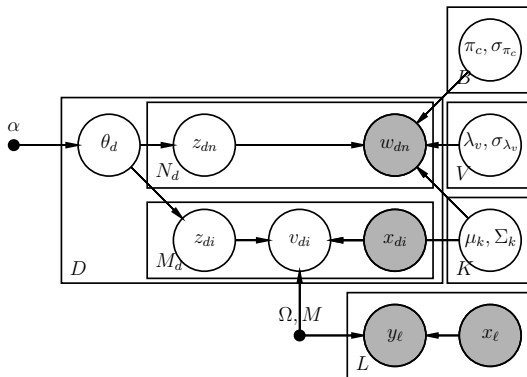
accompanied by the decoupling of political power from farm ownership.

5.1 Forms of ownership

In some societies (especially socialist and communist), *collective farming* is the norm, with either government ownership of the land or common ownership by a local group. Especially in societies without widespread industrialized farming, *tenant farming* and *sharecropping* are common; farmers either pay landowners for the right to use farmland or give up a portion of the crops.

- ▶ *We want to learn a topic model using text and images jointly.*
- ▶ Images and text complement each other.
- ▶ Captions aren't the whole story: cows in political contexts.

Gaussian Topic Models with CNNs



- Topics are (mixtures of) Gaussians.
- Words are latent vectors $\lambda_v \in \mathbb{R}^{D_w}$ using Bayesian word2vec.
- Images are latent vectors $v_{in} \in \mathbb{R}^{D_l}$ *conditioned* on raw images x_{di} . We have $v_{ni} \sim \mathcal{N}(MCNN_x(x_{ni}; \Omega), \Sigma)$ with Ω CNN parameters, M mapping to word vector space, and CNN_x feature representation output by CNN.

Variational Bayesian EM

To learn latent variable models, maximize the *marginal likelihood*

$$\max_{\theta} p(\mathbf{x}|\theta) = \int p(\mathbf{x}, \mathbf{z}|\theta) p(\mathbf{z}|\theta) d\mathbf{z}$$

This integral is intractable. Approximate instead with the *evidence lower bound (ELBO)*

$$\log p(\mathbf{x}|\theta) \geq E_{q(\mathbf{z}|\phi)} [\log p(\mathbf{x}, \mathbf{z}|\theta) - \log q(\mathbf{z}|\theta)] =: \mathcal{L}(\theta, \phi)$$

where $q(\mathbf{z}|\phi)$ is a simple *variational distribution* which approximates the posterior $p(\mathbf{z}|\mathbf{x}, \theta)$.

Variational Bayesian EM:

- ▶ E Step: Update $\phi^{(t+1)} \leftarrow \arg \max_{\phi} \mathcal{L}(\theta^{(t)}, \phi)$
- ▶ M Step: Update $\theta^{(t+1)} \leftarrow \arg \max_{\theta} \mathcal{L}(\theta, \phi^{(t)})$

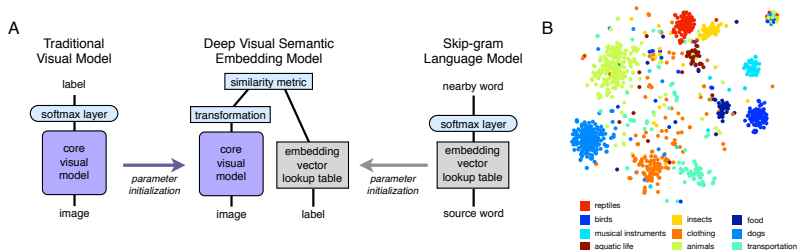
E step is variational Bayesian inference (Ranganath, Gerrish, and D. M. Blei, 2014; Wang and D. M. Blei, 2013). M step is learning (updating) a CNN with objective

$$\min_{\Omega} \sum_{\ell} L(y_{\ell}; \text{CNN}_y(x_{\ell}; \Omega)) + \frac{1}{2\sigma^2} \sum_{di} E_{q(v_{di}|\phi^{(t)})} [(v_{di} - \text{CNN}_x(x_{di}; \Omega))^2]$$

Why Do We Want to Do This?

- ▶ Constructing an unsupervised, non-discriminative, model
- ▶ Difficult to measure performance (Wallach et al., 2009)
- ▶ Unsupervised data can lead to better vector construction
- ▶ "...in general capture some distributional syntactic and semantic information." (Socher et al., 2013)
- ▶ Can this lead to a semantic understanding of multimodal data?

Related Methods



- ▶ Use Deep Boltzmann Machines (Srivastava and Salakhutdinov, 2014)
- ▶ Semi-supervised learning for effective generalization from smaller data sets (Kingma et al., 2014)
- ▶ Deep Visual-Semantic Embedding Model (DeViSE), use both unannotated text and trained image data for classification (Frome et al., 2013)

Implementation and Applications

- ▶ Image and text modalities: corpa with images, annotated images, images with captions
- ▶ Code EM algorithm with pretrained Caffe model and custom objective, compare with performing SGD on CNN and variational parameters jointly
- ▶ Explore other applications: modeling sub-topics, generalization to tangential classes, or image queries and search.
- ▶ Topic models also used for social networks and recommendation engines. Our method adds image features to those models.
- ▶ Compare with other algorithms

Thank You

► Questions?

References I

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