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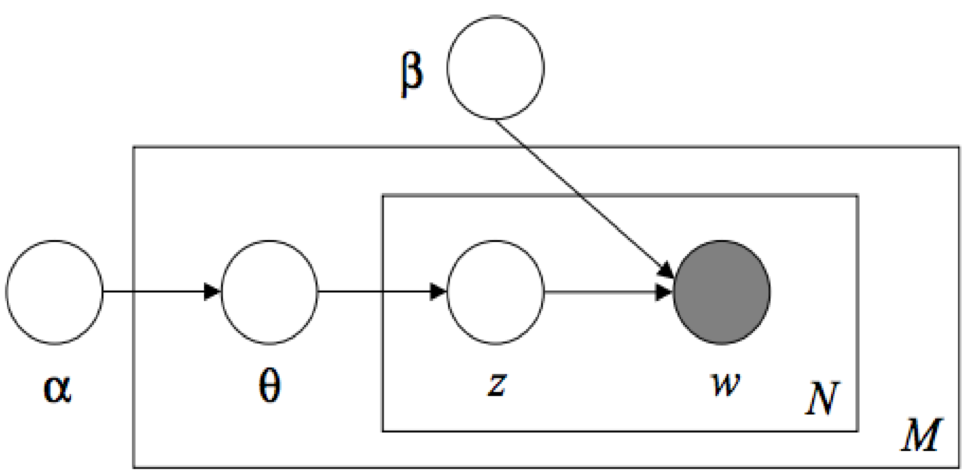
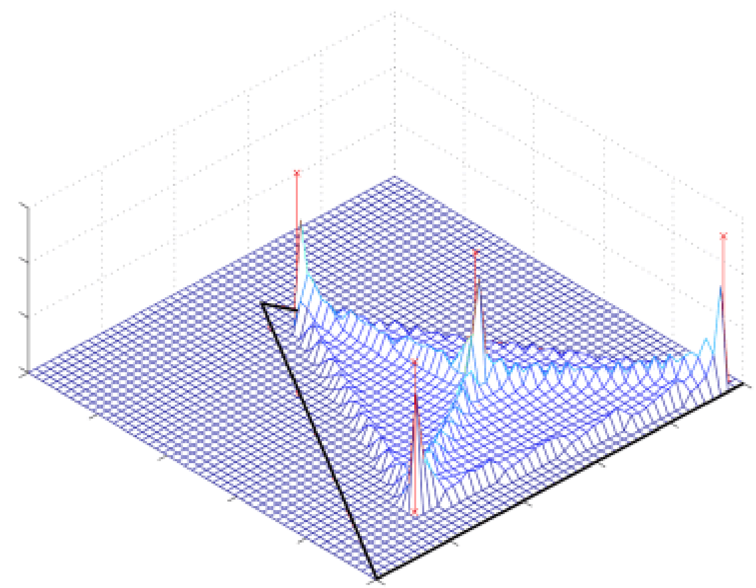
Topic Recognition
Latent Dirichlet Allocation

Algorithmic Methods in the Humanities · June 23, 2016

Florian Becker

INSTITUTE OF THEORETICAL INFORMATICS · ALGORITHMICS GROUP





More and more text

http://www.passion-estampes.com/npe/newsletter-francois-schuiten.html

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Mass production of text:

- $>$ 4000 peer-reviewed papers / day
- nearly 3 million blog posts / day
- 500 million tweets / day

(Probabilistic) Topic Models - Intro

- Automatically extract **topics** from documents
- Organizing and searching of large collections of text

(Probabilistic) Topic Models - Intro

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Algorithm: Corpus $\rightarrow$ Topics

Input	corpus, int K (number of topics)
Output	K topics

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Distribution over words

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Distribution over words

0.15*algorithm
0.1*complexity
0.05*program
0.05*turing
...
...

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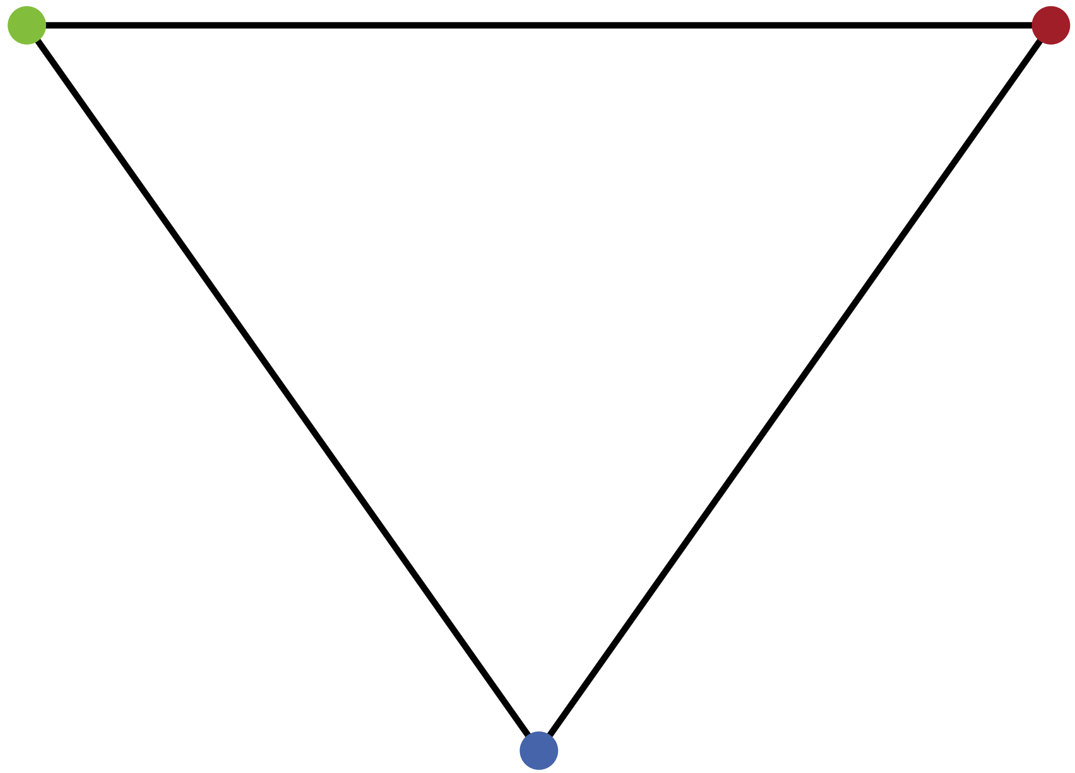
Topic Simplex

A document is a distribution over topics



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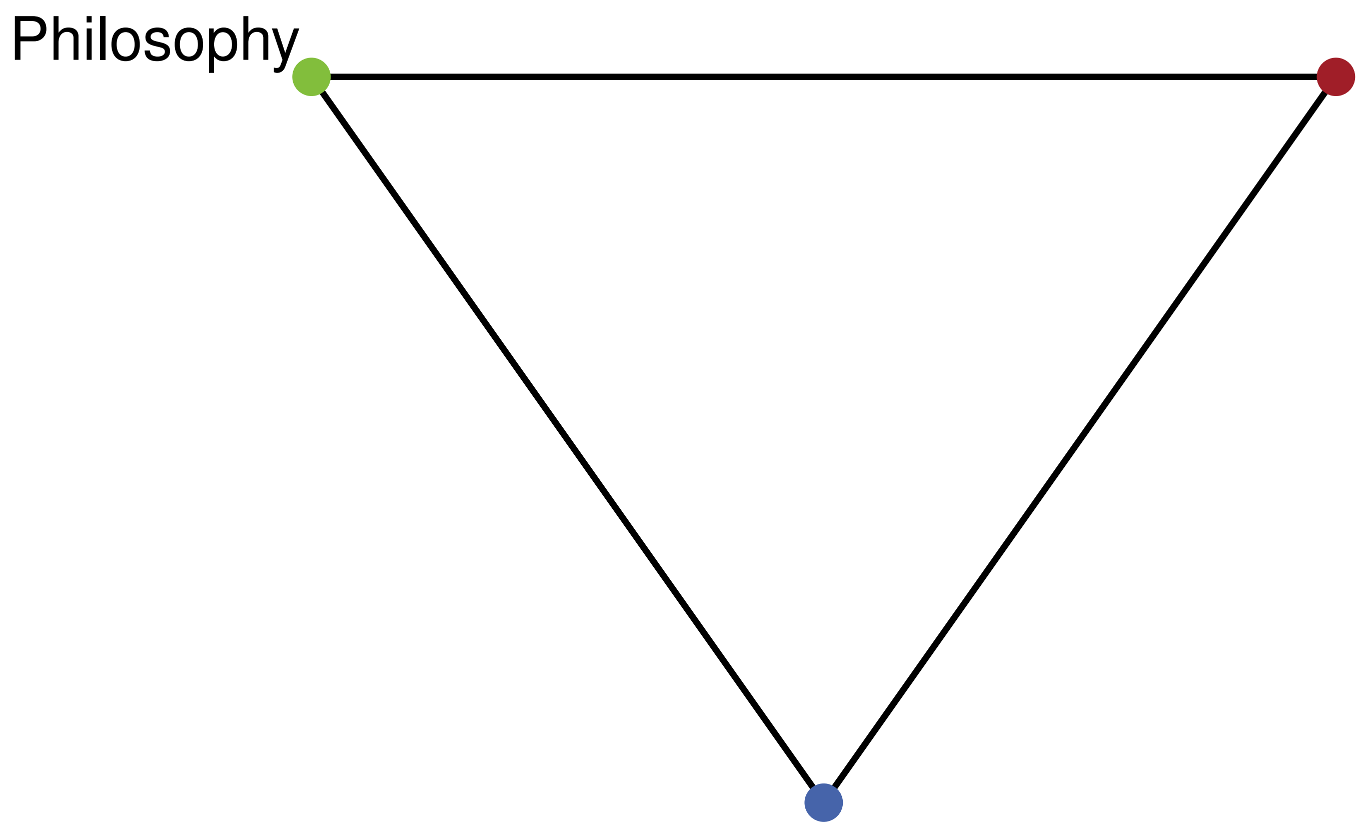

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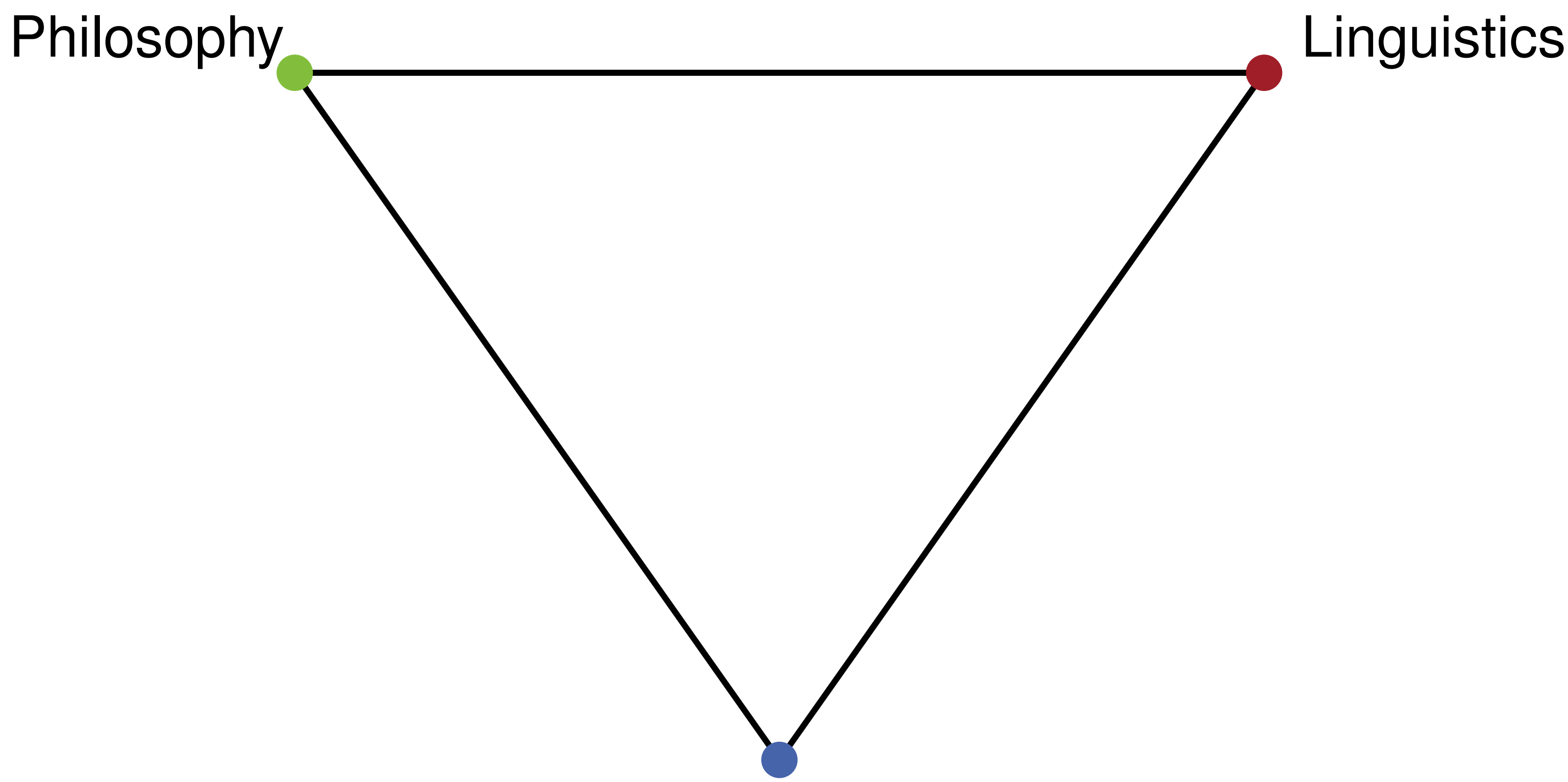

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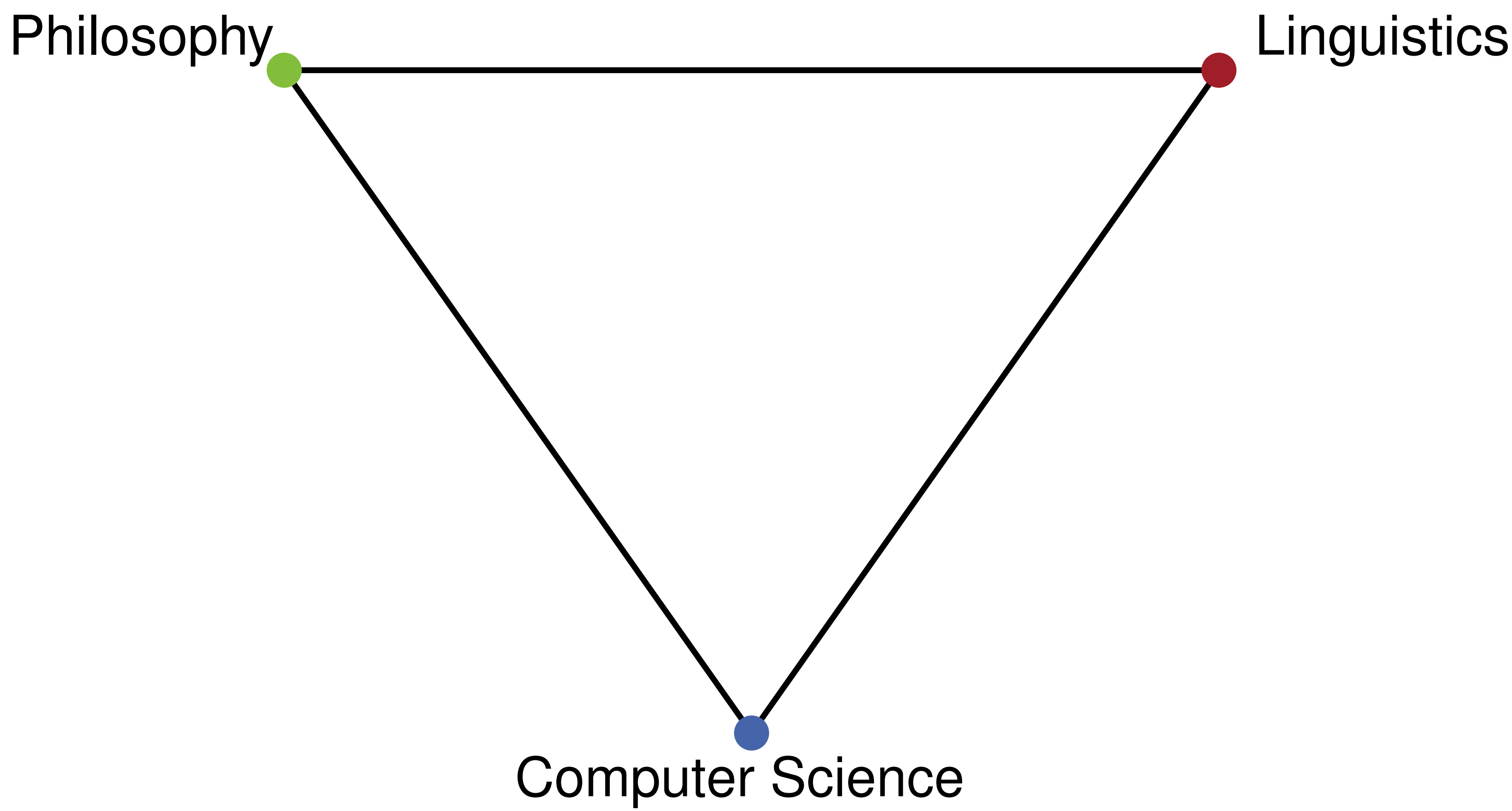

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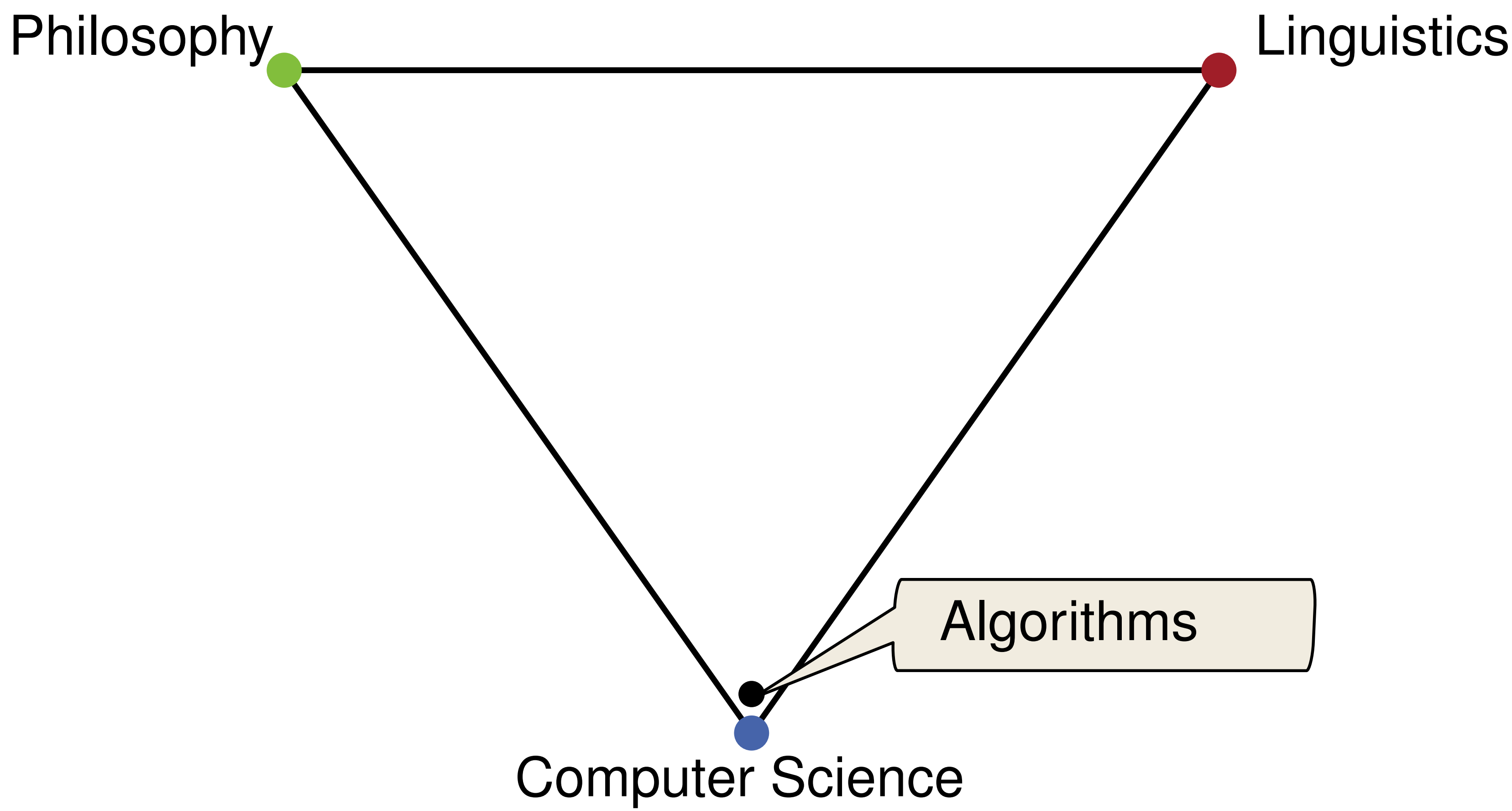

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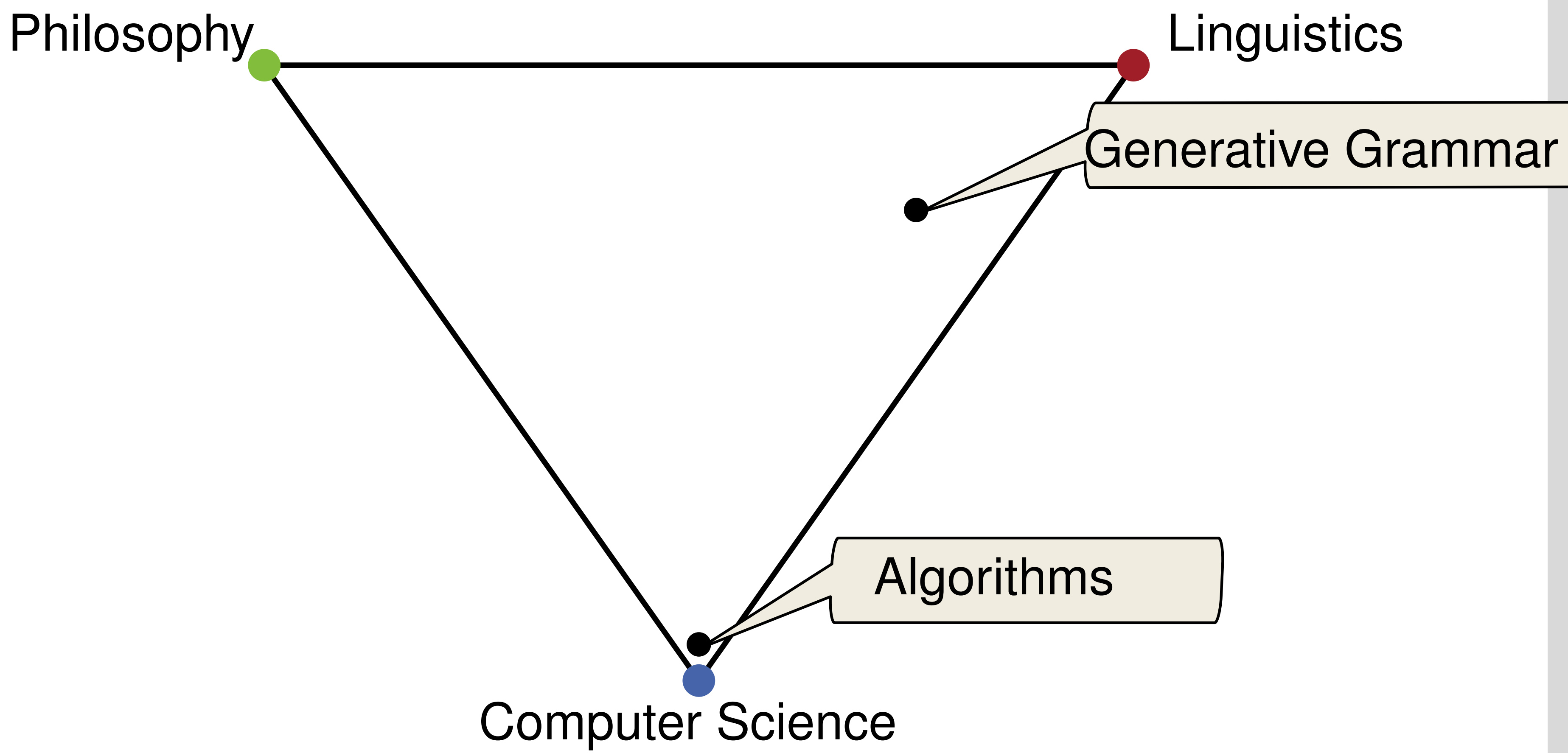

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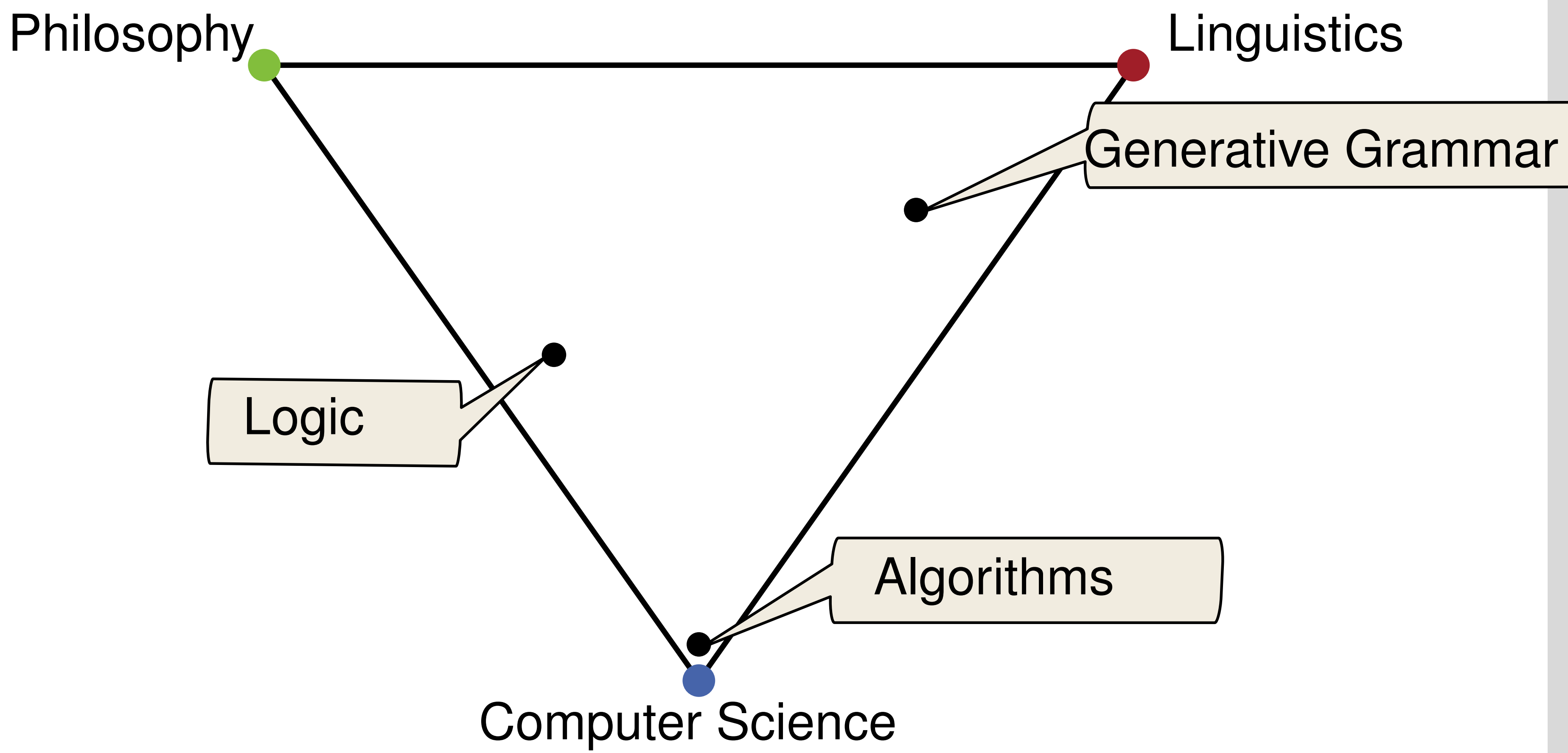

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Outline

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Latent Dirichlet Allocation: What does it do?

Outline

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Latent Dirichlet Allocation: What does it do?

- Assumptions
- Generative Process
- Dirichlet Distribution

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Demo

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Latent Dirichlet Allocation: How does it do it?

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Latent Dirichlet Allocation: How does it do it?

- Inference
- Gibbs Sampling

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Latent Dirichlet Allocation: What does it do?

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Latent Dirichlet Allocation: How does it do it?

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Conclusion

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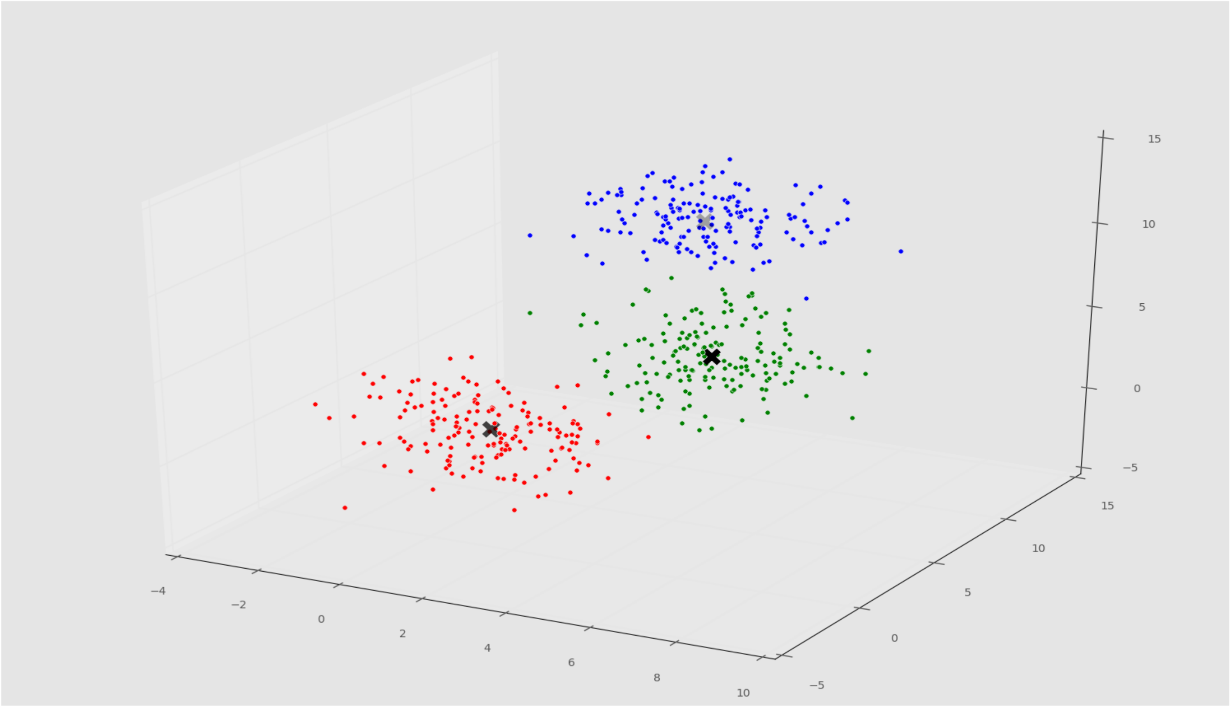
Latent Dirichlet Allocation

Latent Dirichlet Allocation

- Unsupervised Learning Model
- Finding clusters of similar texts
- Generative Model



Latent Dirichlet Allocation

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Assumptions

- A document is represented as a bag of words
- A document is about multiple topics
- A topic is a distribution over words
- Order of documents in corpus does not matter
- Every document is generated by a **generative process**

Generative Process

Algorithm: Generative Process

1. Choose $\theta_i \sim \text{Dir}(\alpha)$,
2. Choose $\varphi_k \sim \text{Dir}(\beta)$
3. For each of the word positions i, j
   (a) Choose a topic $z_{i,j} \sim \text{Multinomial}(\theta_i)$.
   (b) Choose a word $w_{i,j} \sim \text{Multinomial}(\varphi_{z_{i,j}})$

$j \in \{1, \ldots, N_i\}$, and $i \in \{1, \ldots, D\}$

N_i - Number of words in document i
D - Number of documents

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Dirichlet Distribution

Binomial Distribution $\rightarrow$ Multinomial Distribution $\rightarrow$ Dirichlet Distribution

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Dirichlet Distribution

Binomial Distribution $\rightarrow$ Multinomial Distribution $\rightarrow$ Dirichlet Distribution

Binomial Distribution (PMF)

$$f(k; n, p) = \Pr(X = k) = \binom{n}{k} p^k (1-p)^{n-k}$$

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Dirichlet Distribution

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Binomial Distribution (PMF)

$$f(k; n, p) = \Pr(X = k) = \binom{n}{k} p^k (1 - p)^{n-k}$$

success/failure experiments
Example: fair coin, 6 tosses

Probability of 5 heads?

$$\Pr(5 \text{ heads}) = f(5) = \Pr(X = 5) = \binom{6}{5} 0.5^5 (1 - 0.5)^{6-5} \approx 0.09375$$

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Dirichlet Distribution

Multinomial Distribution (PMF)

$$f(x_1, \ldots, x_k; n, p_1, \ldots, p_k) = \frac{n!}{x_1! \cdots x_k!} p_1^{x_1} \cdots p_k^{x_k}$$

Dirichlet Distribution

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Some event with 3 outcomes: $X = [x_1, x_2, x_3]$

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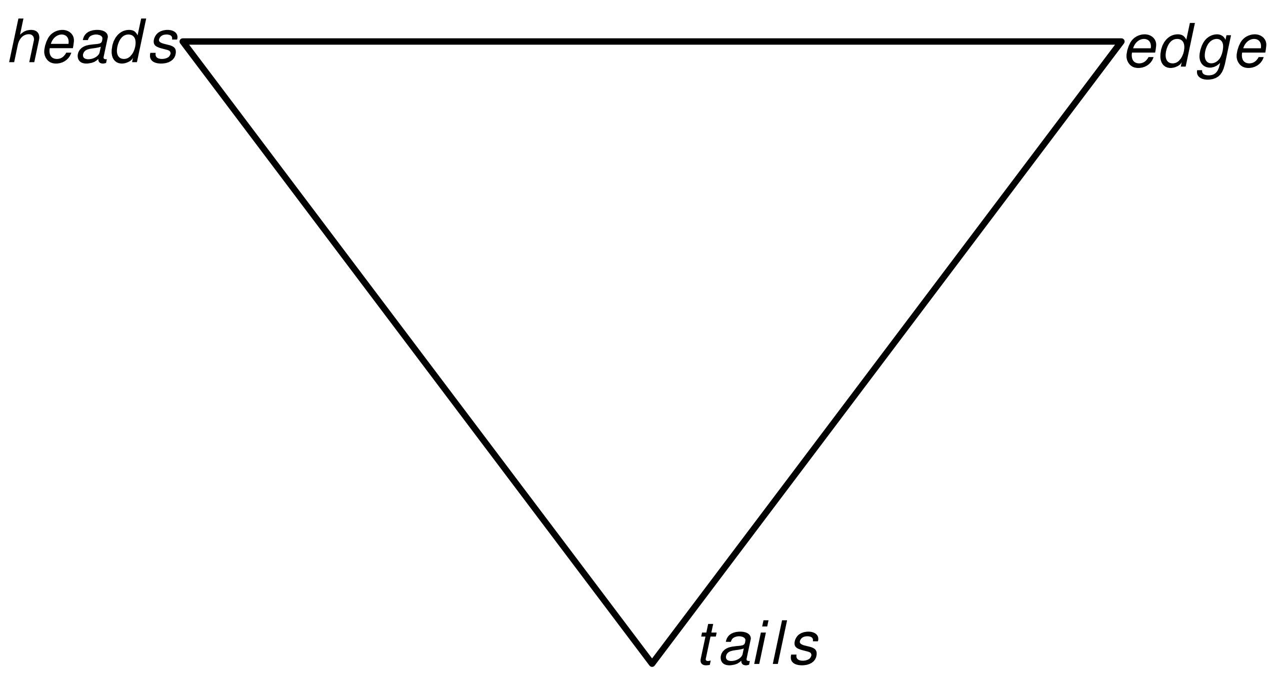

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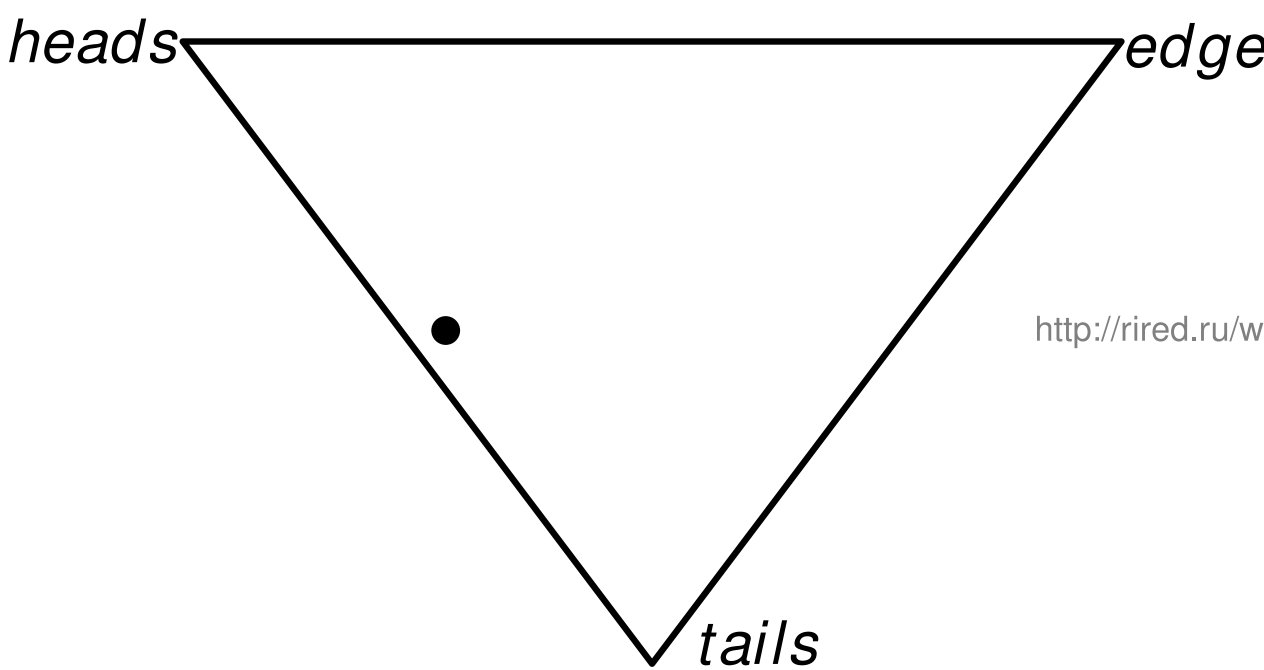

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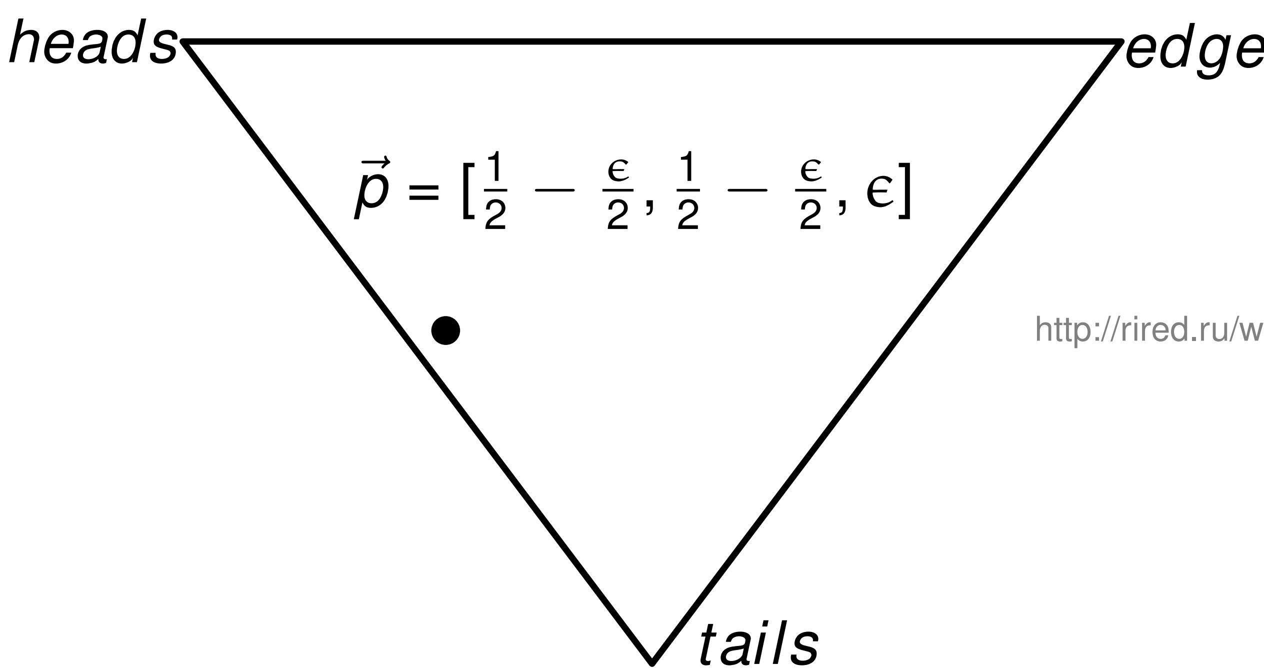

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Dirichlet Distribution

The Dirichlet distribution $Dir(\alpha)$ is a distribution over the space of multinomial distributions.

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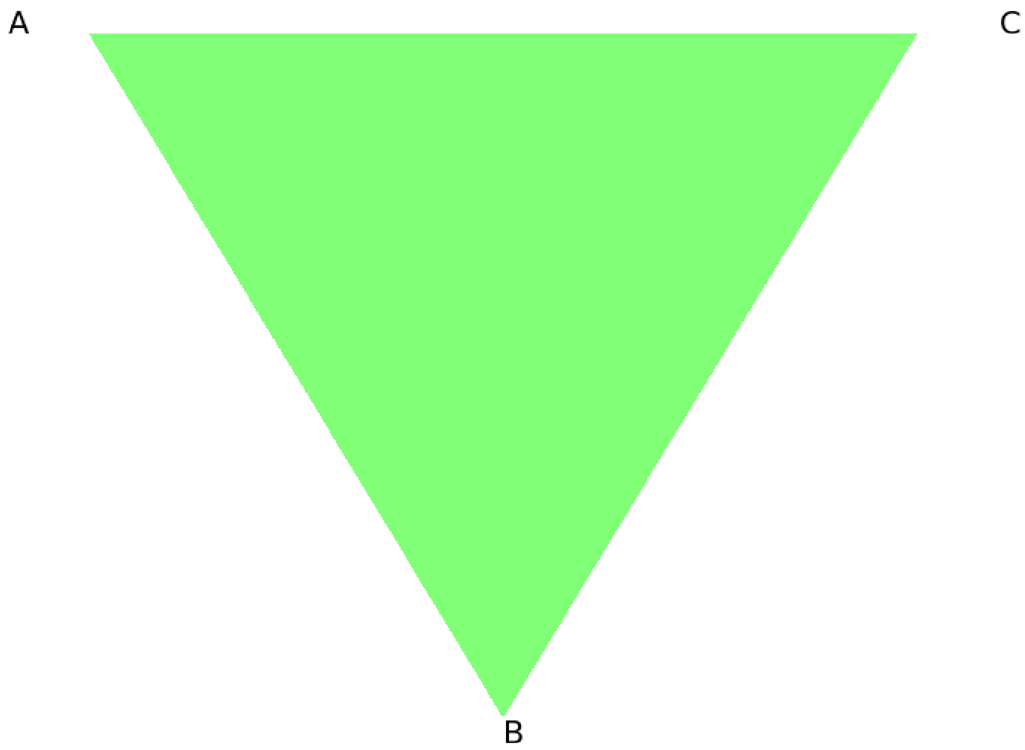
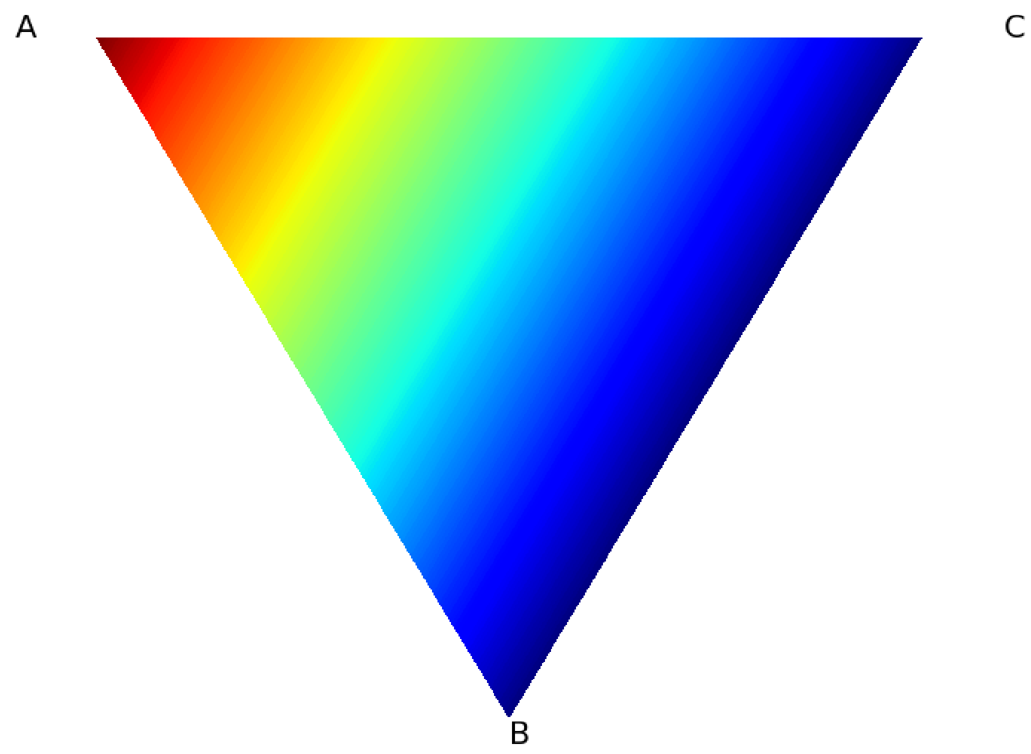
$\alpha = [1, 1, 1]$



Dirichlet Distribution

The Dirichlet distribution $Dir(\alpha)$ is a distribution over the space of multinomial distributions.

$\alpha = [2, 1, 1]$



Dirichlet Distribution

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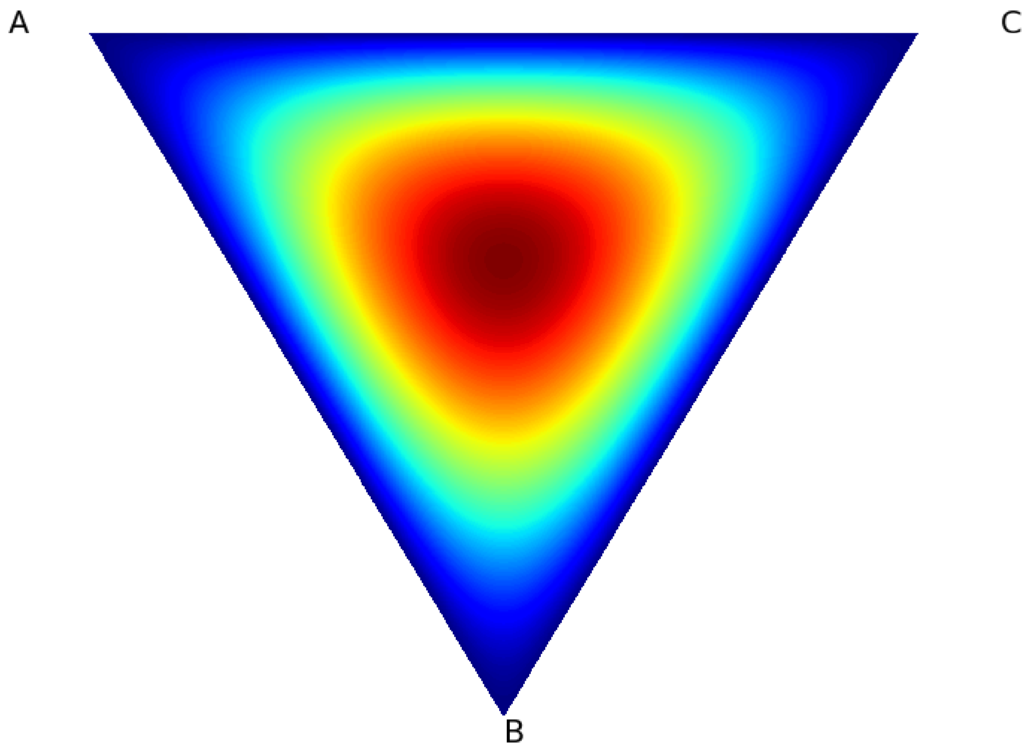
$\alpha = [2, 2, 2]$



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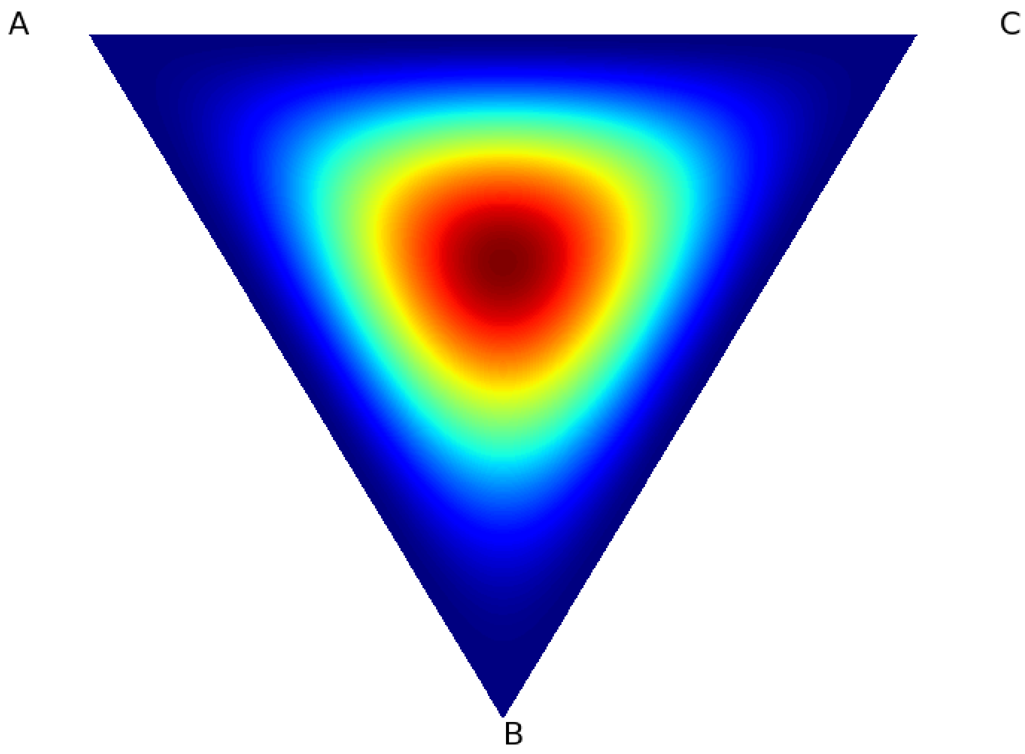
The Dirichlet distribution $Dir(\alpha)$ is a distribution over the space of multinomial distributions.

$\alpha = [3, 3, 3]$



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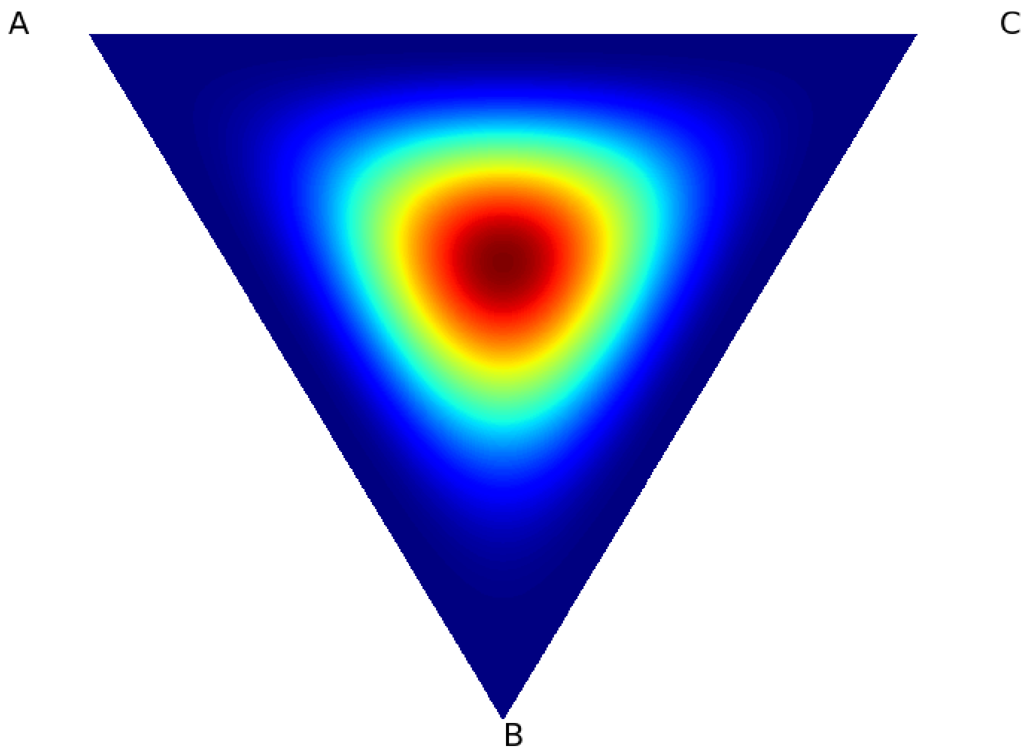
$\alpha = [4, 4, 4]$



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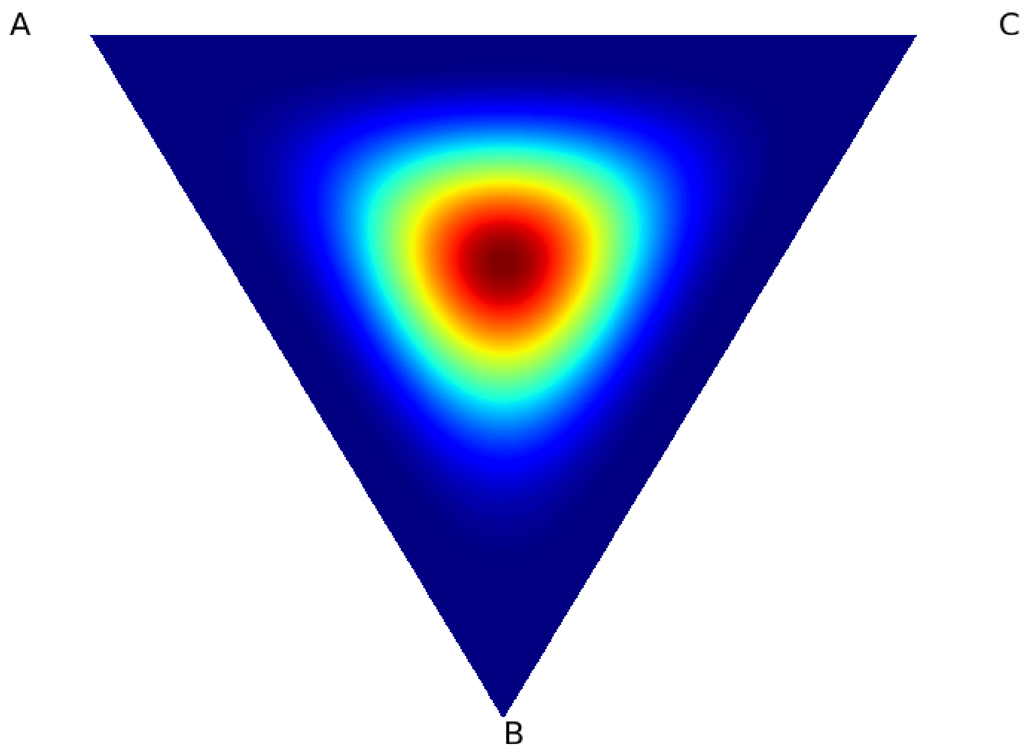
$\alpha = [5, 5, 5]$



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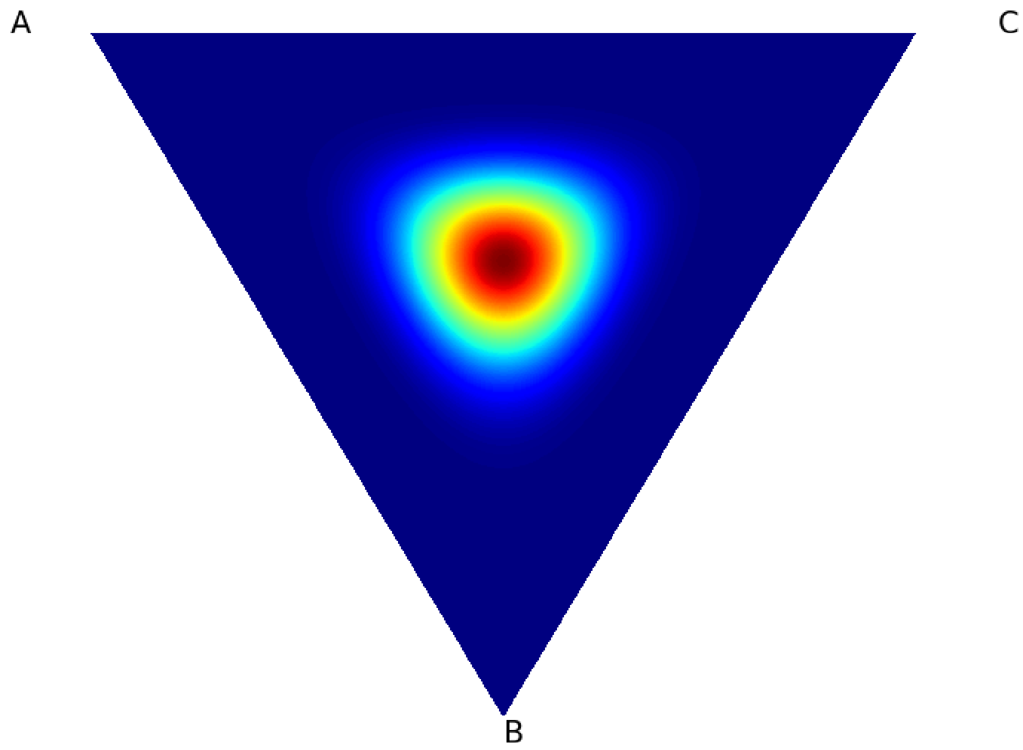
$\alpha = [10, 10, 10]$



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$\alpha = [0.9, 0.9, 0.9]$

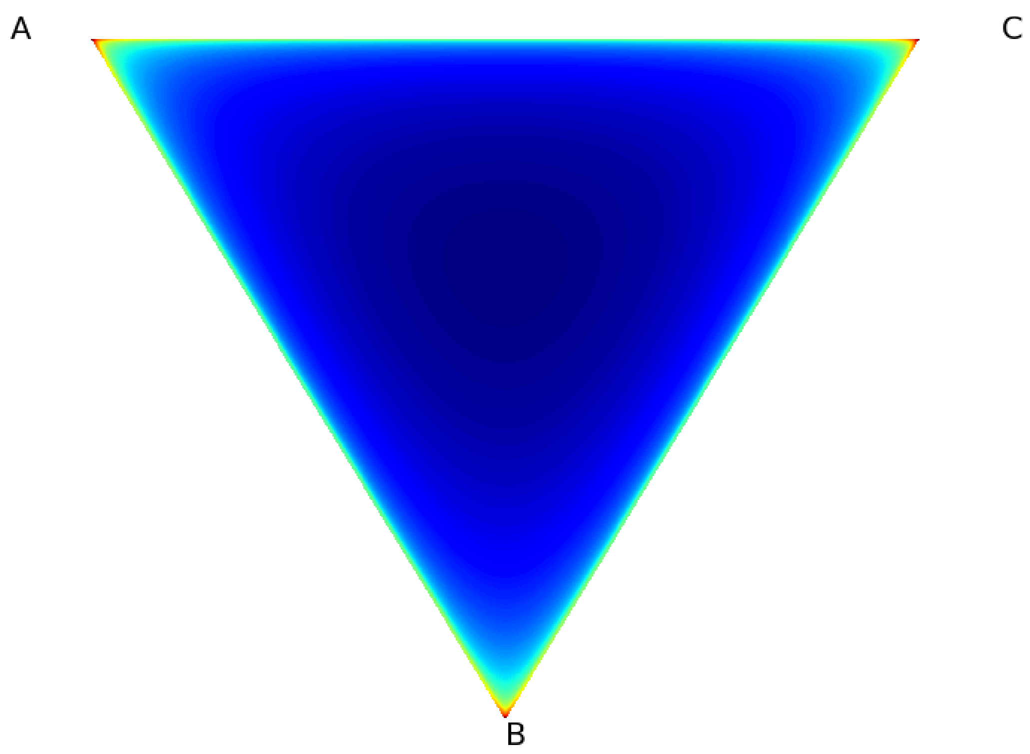

Plate Notation

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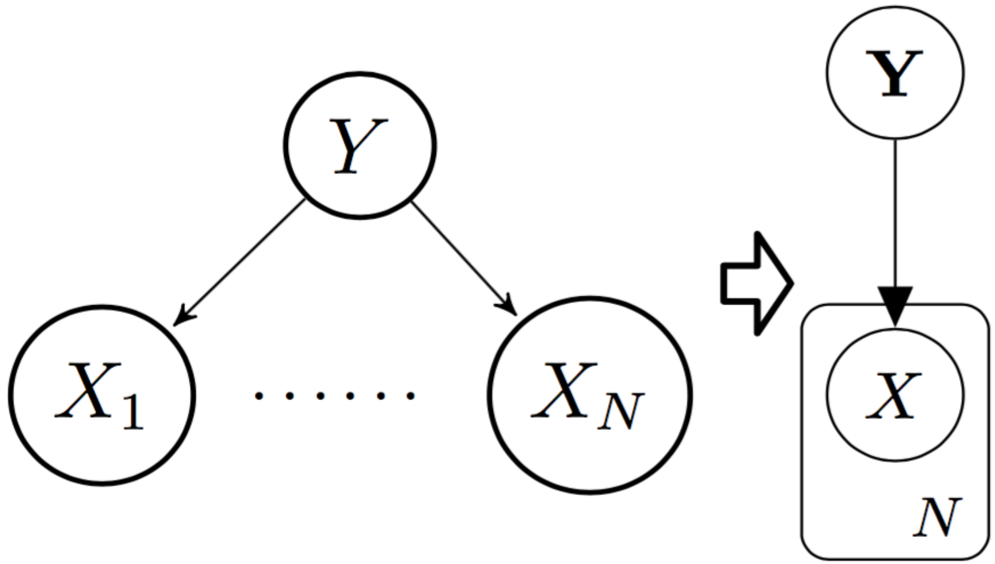

- Vertex $\equiv$ random variable
- Edge $\equiv$ dependence

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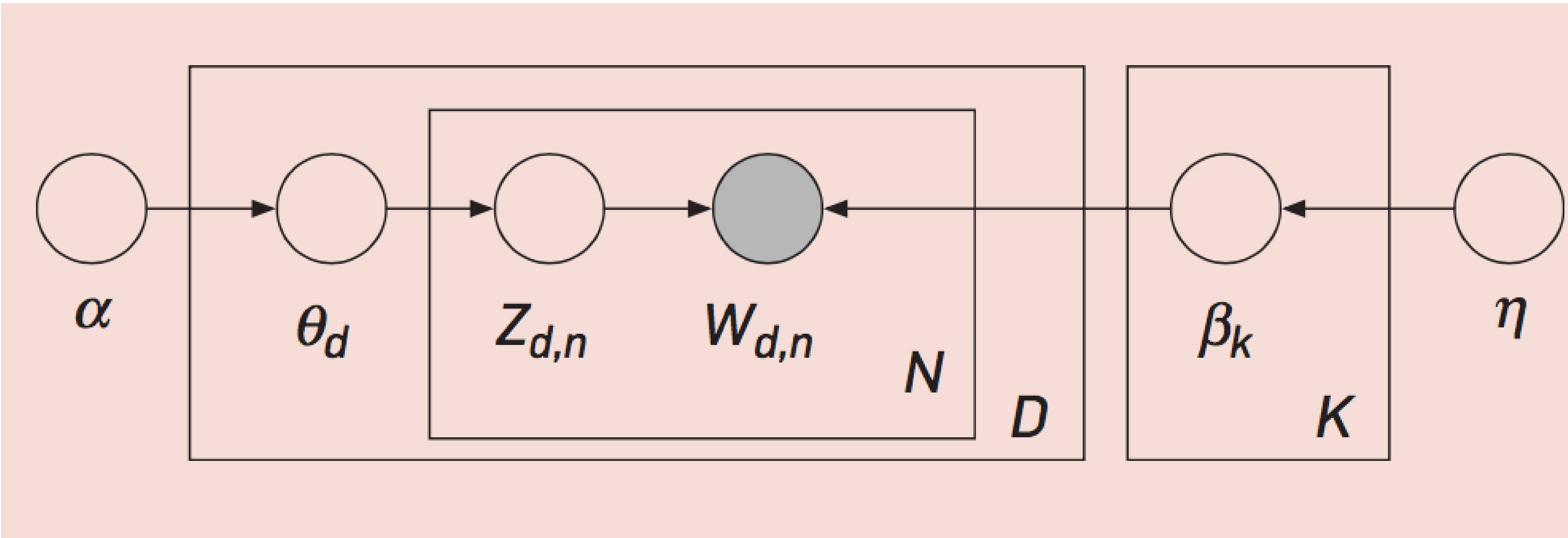
Plate Notation: LDA



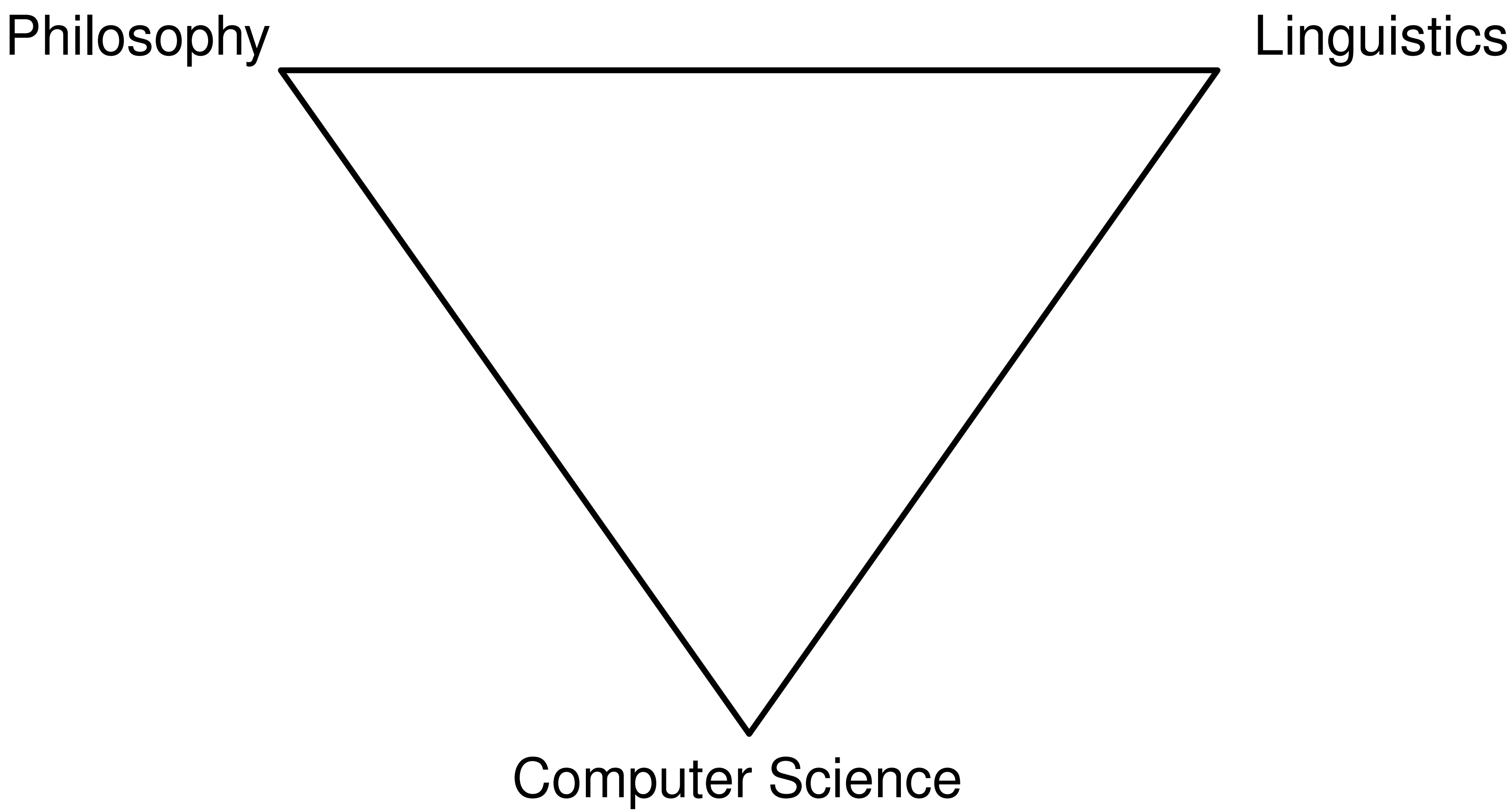
α - Dirichlet parameterization

β_k - topics (dist. over words)

θ_d - topic proportions for d^{th} document

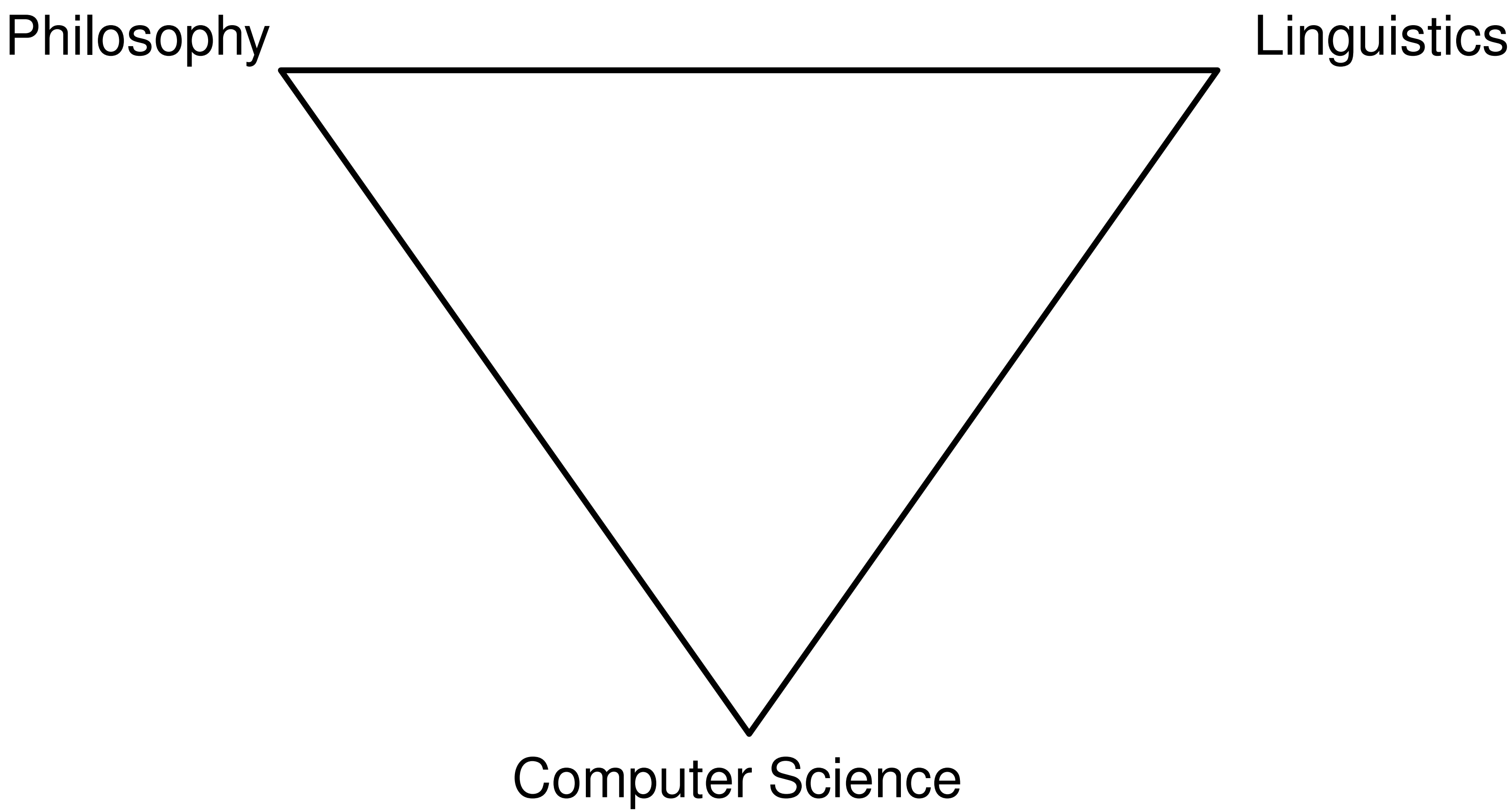
$z_{d,n}$ - topic assignment for n^{th} word in d^{th} document

LDA: Demo



LDA: Demo

Depending on how the corpus changes. . .



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LDA and Inference

- Goal: Automatically discover topics from a collection of documents
- Only documents themselves are *observed*
- topics, per-document topic distributions, and the per-document per-word topic assignments is *hidden*

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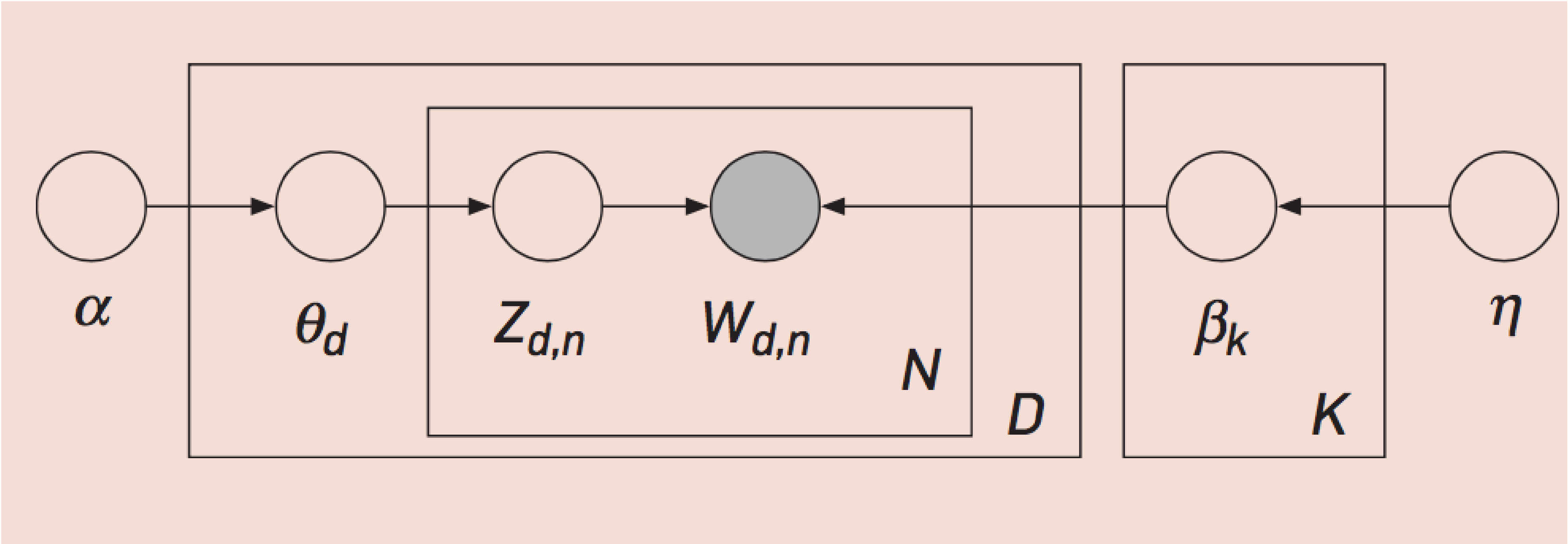

Inference

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How to infer latent variables?

Inference

How to infer latent variables?

$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D} | w_{1:D}) = \frac{p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D})}{p(w_{1:D})}$$

β_k - topics (dist. over words)
θ_d - topic proportions for d^{th} document
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w_d - observed words

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marginal probability

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Inference

Problem: Marginal probability is intractable to compute

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Inference

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Could only be computed theoretically:
Sum the joint distribution over every possible instance of the hidden topic structure.

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Inference

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In other words: Sum over all possible ways of assigning each observed word of the collection to one of the topics.

Inference

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Sum the joint distribution over every possible instance of the hidden topic structure.

In other words: Sum over all possible ways of assigning each observed word of the collection to one of the topics.

$\Rightarrow$ Approximation !

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Gibbs Sampling

- used for Bayesian inference
- randomized algorithm
- Markov Chain Monte Carlo Algorithm
- Method to find (good) topics

Gibbs Sampling - Example

Text mining algorithms can be used to find structure in text corpora like Plato's *dialogues*

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Gibbs Sampling - Example

Text mining algorithms can be used to find structure in text corpora like Plato's *dialogues*

-	-	-	-	-	-	-
text	mining	algorithms	structure	corpora	Aristotle	dialogues

Gibbs Sampling - Example

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Text mining algorithms can be used to find structure in text corpora like Plato's *dialogues*

1. Randomly assign words to topics

1	3	2	1	2	1	2
text	mining	algorithms	structure	corpora	Plato	dialogues

Gibbs Sampling - Example

Text mining algorithms can be used to find structure in text corpora like Plato's *dialogues*

1. Randomly assign words to topics

1	3	2	1	2	1	2
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2. Do this for all documents in corpus

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Gibbs Sampling - Example

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Gibbs Sampling - Example

1	3	2	1	2	1	2
text	mining	algorithms	structure	corpora	Plato	dialogues

	1	**2**	**3**
text	65	54	59
mining	21	4	12
algorithms	100	74	122
structure	20	12	14
corpora	5	2	12
Plato	35	33	42
dialogues	24	27	31

Gibbs Sampling - Example

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Counts from **all** documents

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Gibbs Sampling - Example

sample word *algorithm*

1	3	???	1	2	1	2
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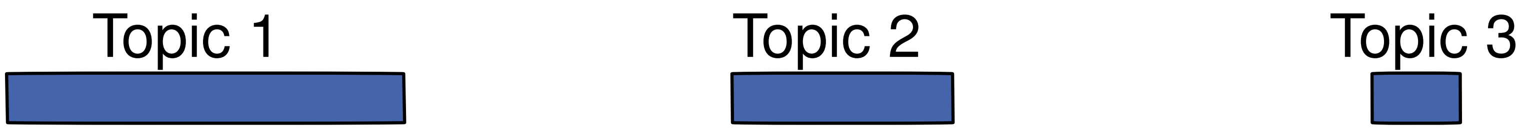
3. Topic distribution in this document



Gibbs Sampling - Example

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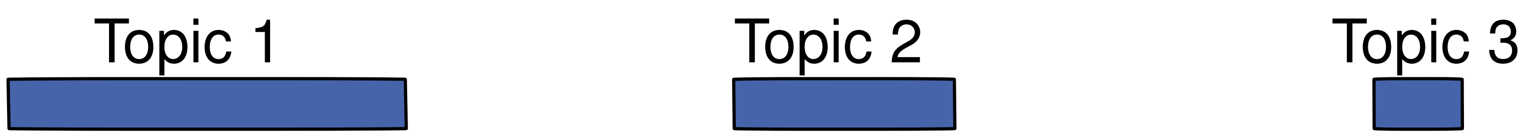

4. Word distribution over topics

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Gibbs Sampling - Example

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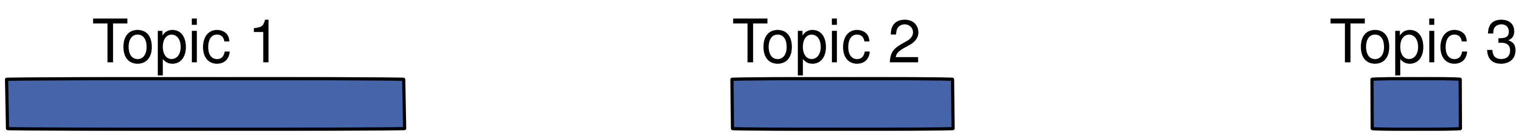

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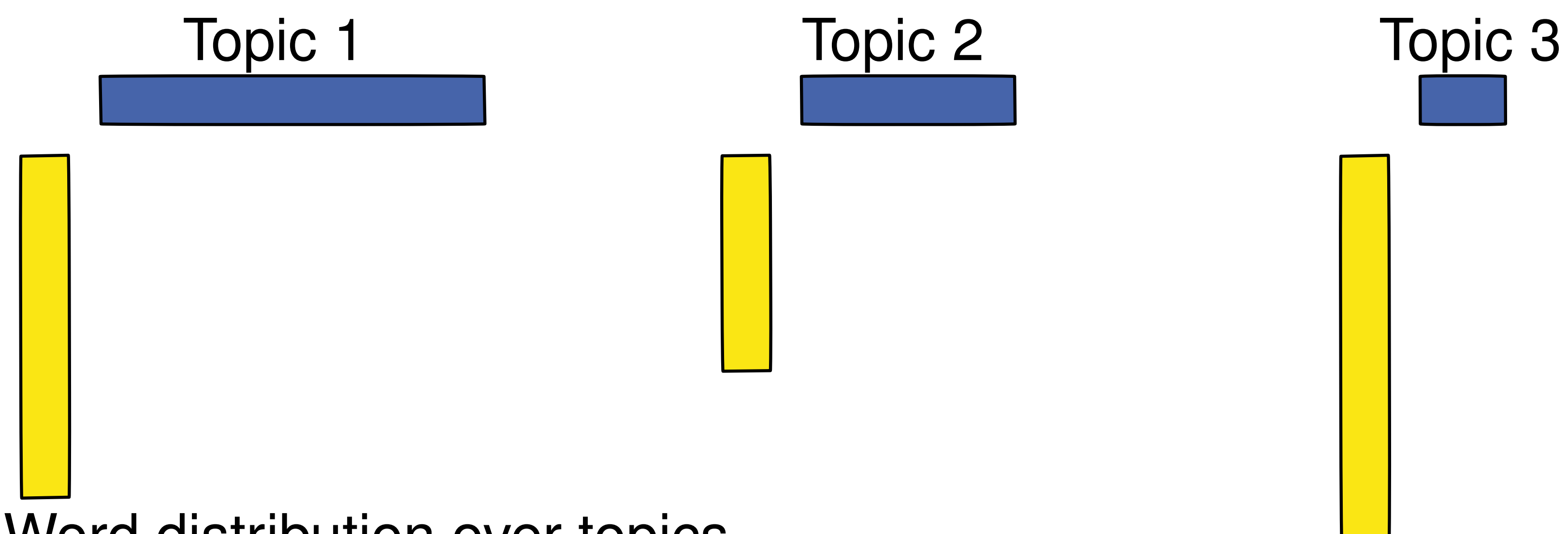

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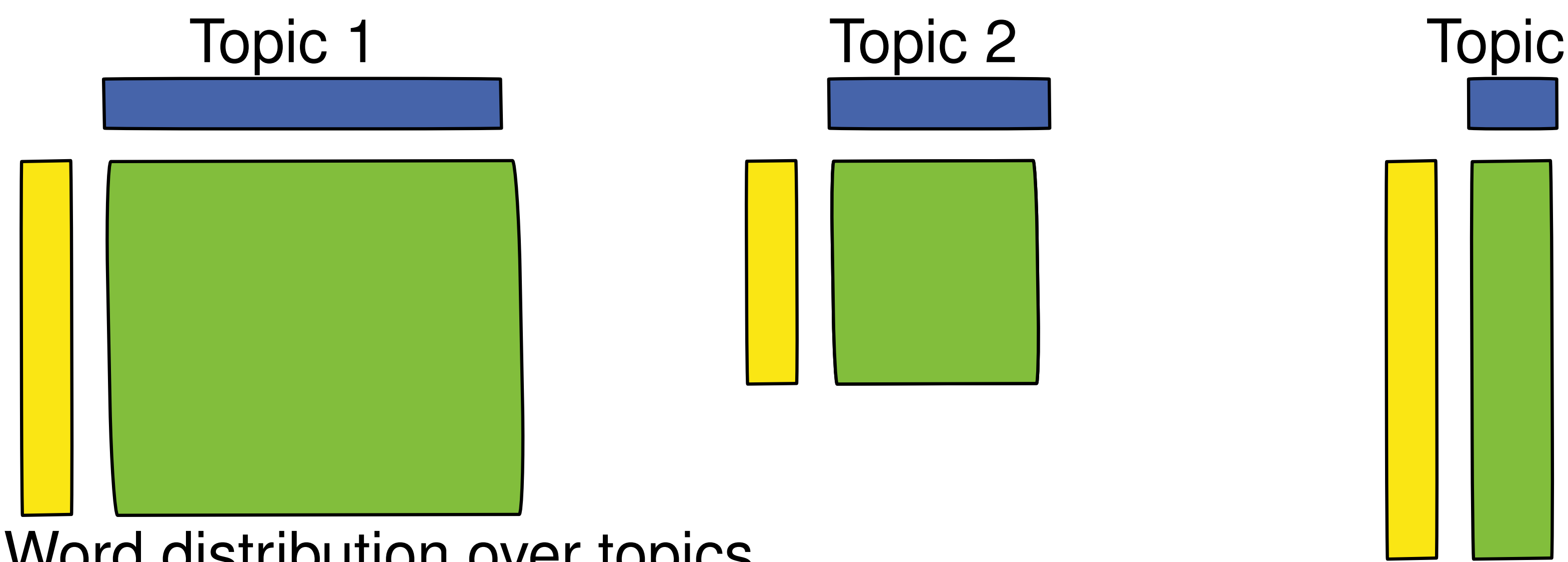

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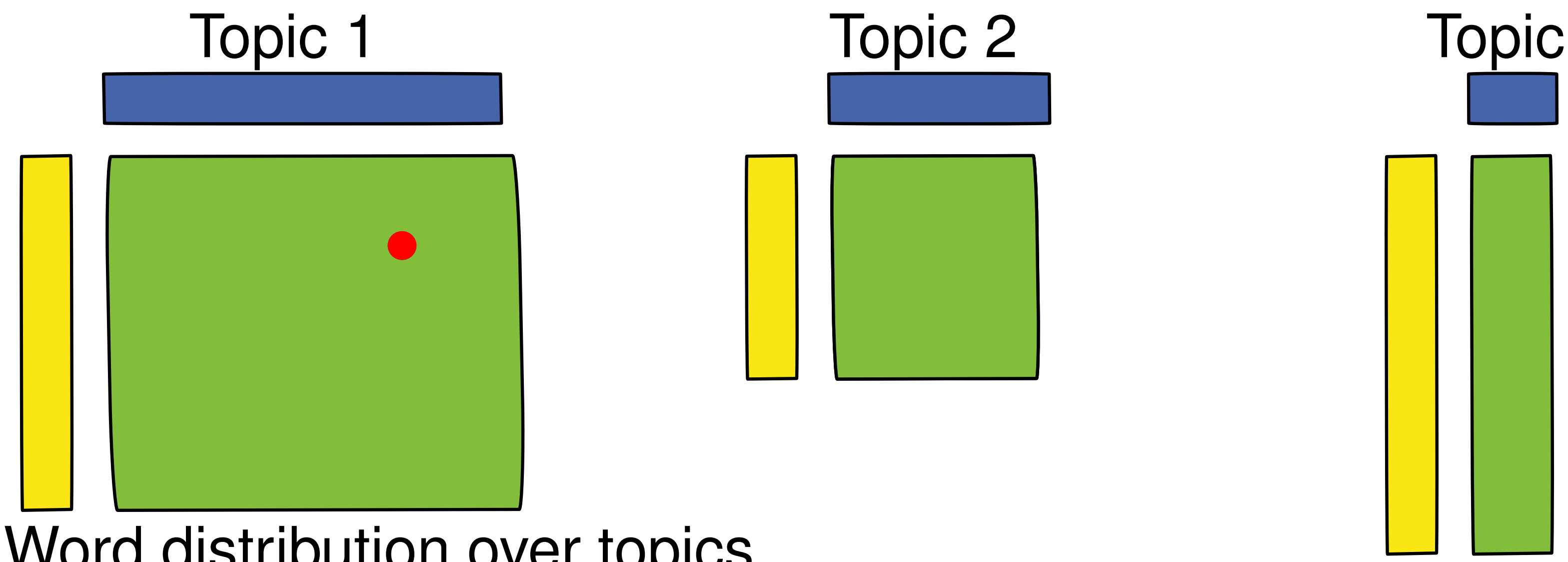

4. Word distribution over topics
5. Sample according to green area

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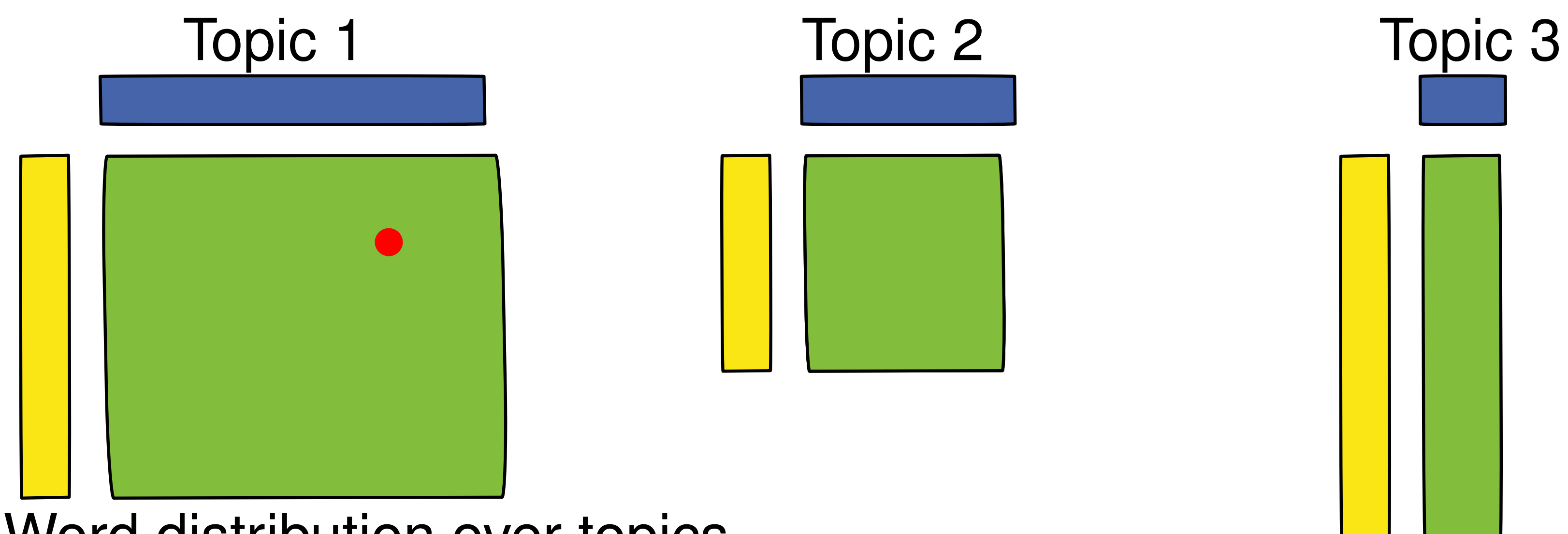
Gibbs Sampling - Example

reassign to Topic 1

1	3	**1**	1	2	1	2
text	mining	algorithms	structure	corpora	Plato	dialogues

3. Topic distribution in this document



4. Word distribution over topics
5. Sample according to green area

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Conclusion - Take home message

Wrap up

Conclusion - Take home message

Wrap up

- Topic models find the hidden topical patterns that pervade a unstructured collection of text
  - Generative process as a model of how texts are composed
  - Words are **allocated** according a Dirichlet distribution over topics

Conclusion - Take home message

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Wrap up

- Topic models find the hidden topical patterns that pervade a unstructured collection of text
  - Generative process as a model of how texts are composed
  - Words are **allocated** according a Dirichlet distribution over topics
- Inference
  - Gibbs sampling can be used for approximating the hidden variables

Resources

- http://www.cs.columbia.edu/ blei/
- Blei, David M., Andrew Y. Ng, and Michael I. Jordan. ”Latent dirichlet allocation.” the Journal of machine Learning research 3 (2003): 993-1022. APA
- Porteous, Ian, et al. ”Fast collapsed gibbs sampling for latent dirichlet allocation.” Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining. ACM, 2008.