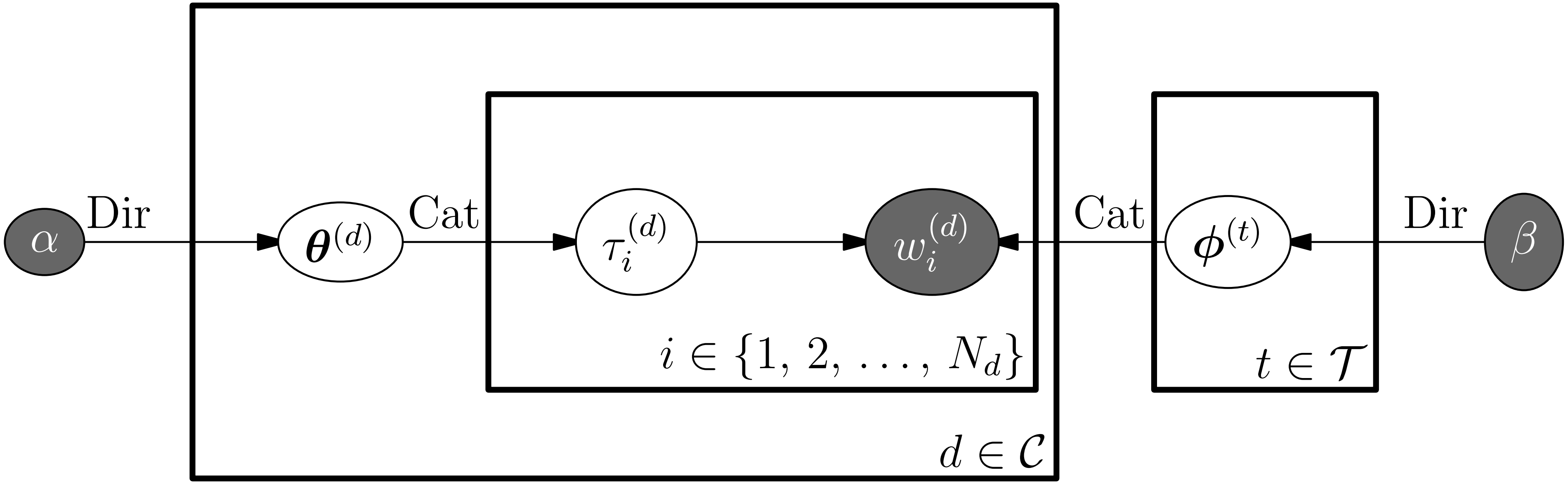
Advanced Machine Learning

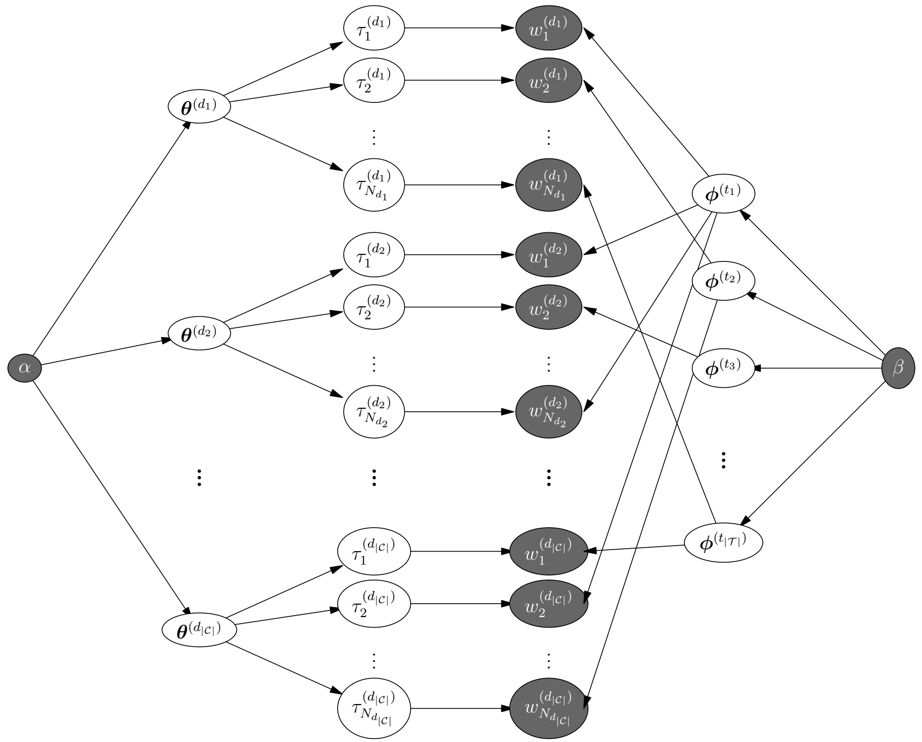
Graphical Models



Conditional Independence, Graphical models, LDA

Outline

1. **Graphical Models**
2. Cakes!
3. Latent Dirichlet Allocation



Graphical Models

- If we want to build large probabilistic inference systems
  - ⋆ AI Doctor
  - ⋆ Fault diagnostic system for a computer

  it is helpful to graphically represent causal connections

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Dependencies Between Variables

- In building a probabilistic model we want to know which random variables depend on each other directly and which don't
- Variables that don't will typically still be correlated
- If two random variables X and Y are correlated then
  - ⋆ X could affect Y
  - ⋆ Y could affect X
  - ⋆ X and Y could not influence each other, but both be affected by another random variable Z

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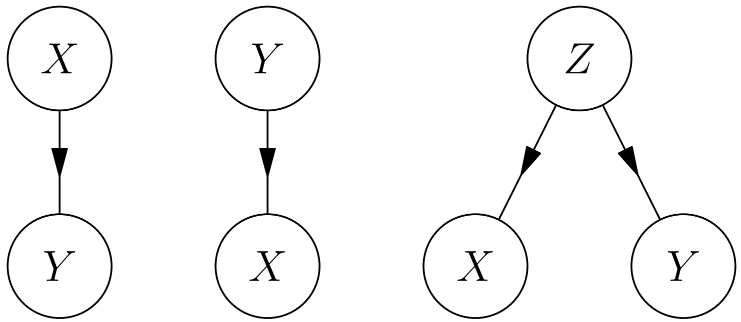
- We could represent the three conditions described above by



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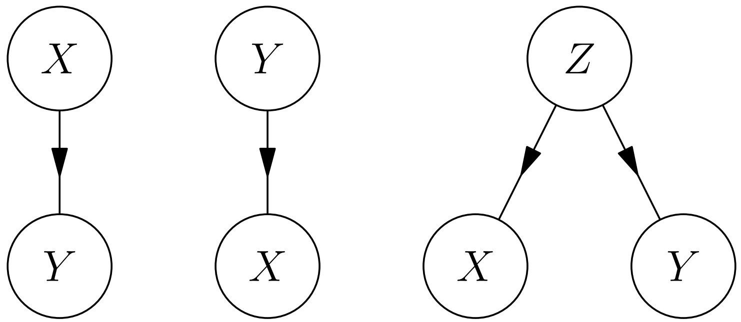

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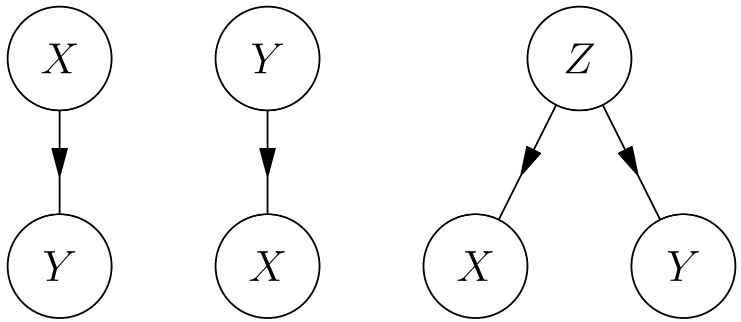

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Statistical Independence

- Two random variables are statistically independent if

$$\mathbb{P}(X, Y) = \mathbb{P}(X)\,\mathbb{P}(Y)$$

- Equally this implies $\mathbb{P}(X|Y) = \mathbb{P}(X)$ and $\mathbb{P}(Y|X) = \mathbb{P}(Y)$
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Conditional Independence

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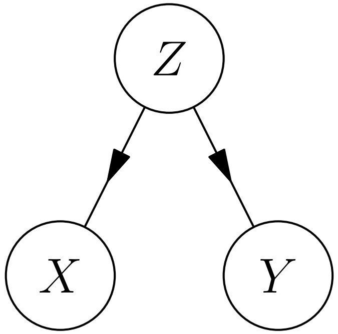

$$\mathbb{P}(X, Y|Z) = \mathbb{P}(X|Z)\, \mathbb{P}(Y|Z)$$

- Conditional independence implies that there is no direct causation

- But it doesn't imply zero correlation

- Conditional independence reduces computational complexity, e.g.

$$\mathbb{E}[X\,Y] = \sum_{X,Y,Z} X\,Y\,\mathbb{P}(X, Y, Z) = \sum_{Z} P(Z) \left(\sum_{X} X P(X|Z) \right) \left(\sum_{Y} Y P(Y|Z) \right)$$

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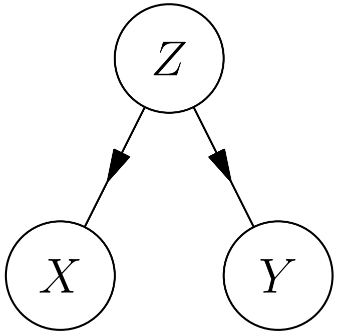

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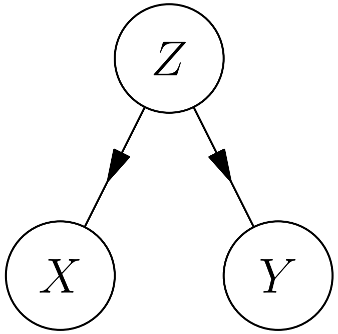

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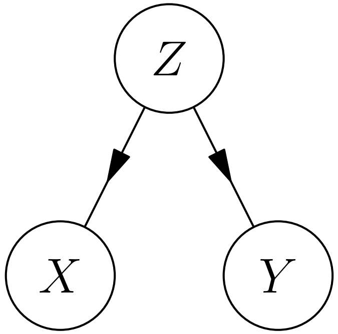

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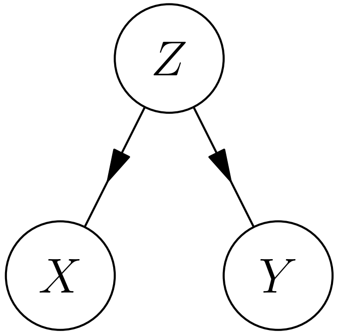

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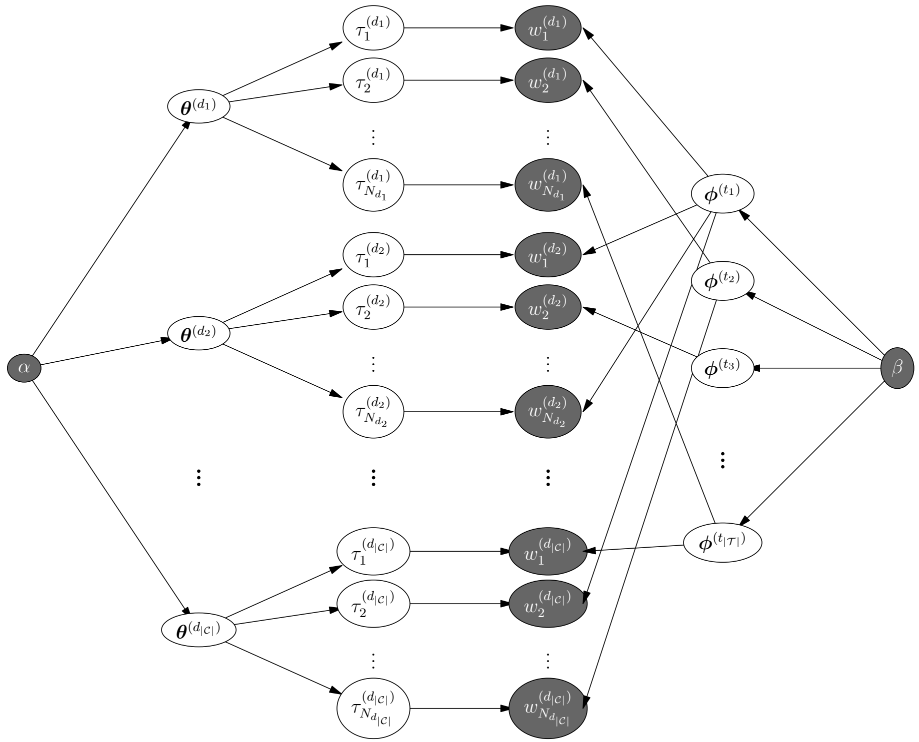

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- It illustrates some simple principles
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The Cake Scenario

- Abi and Ben both bake cakes and bring them into the coffee room
- Abi will bring in cakes 20% of the time: $\mathbb{P}(A=1)=0.2$
- Ben will bring in cakes 10% of the time: $\mathbb{P}(B=1)=0.1$
- 90% of the time if either Abi or Ben have put cakes in the coffee room there is some left when I enter
  $\mathbb{P}(C=1|A=1,B=0)=\mathbb{P}(C=1|A=0,B=1)=0.9$
- If they both make cake then there is always cake left
  $\mathbb{P}(C=1|A=1,B=1)=1$
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Computing with Probabilities

- Other probabilities I can deduce, e.g.
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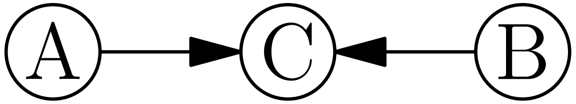

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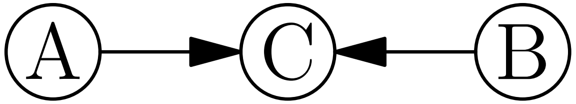

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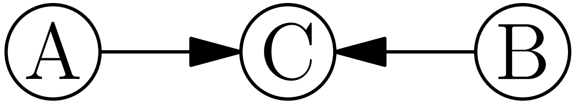

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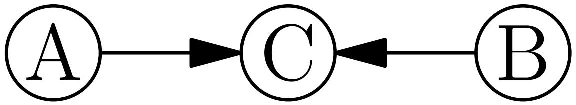

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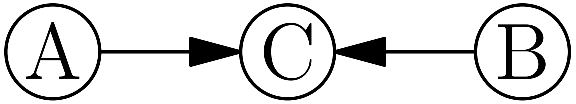

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Computing Expectations

- By using the joint probability and summing over all unknown quantities, we can compute expectations of anything we are interested in
- These sums are often sped up using knowledge of conditional independence
- To compute the probability of and event $\mathcal{E}$ we introduce an indicator function $[\![\mathcal{E}]\!]$ which is equal to 1 if the event happens and 0 otherwise
$$\mathbb{P}(\mathcal{E}) = \mathbb{E}[[\![\mathcal{E}]\!]]$$
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Are There Any Cakes Left?

- We can use our model to compute the probabilities of there being cakes in the coffee room

$$\begin{aligned}\mathbb{P}(C=1) &= \sum_{A,B,C\in\{0,1\}} [\![C=1]\!]\,\mathbb{P}(A,B,C)\\ &= \sum_{A,B\in\{0,1\}} \mathbb{P}(C=1|A,B)\,\mathbb{P}(A)\,\mathbb{P}(B) = 0.303\end{aligned}$$

- The probability that Abi baked a cake is just 0.2 and for Ben its 0.1 (which is what we assume at the start)

- The probability of them both baking on a particular day is 0.02

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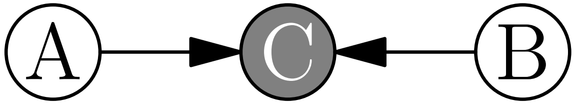
Making Observation

- Making observations changes probabilities
- In graphical models observed random variables are shaded



- The probabilities conditioned on C is given by

$$\mathbb{P}(A, B|C) = \frac{\mathbb{P}(A, B, C)}{\mathbb{P}(C)}$$

where

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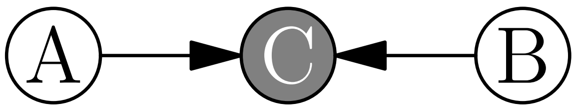
- In graphical models observed random variables are shaded



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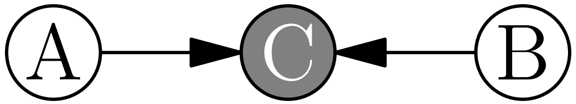

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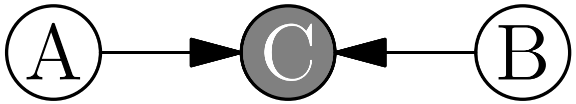

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- If we observe there are cakes

$$\mathbb{P}(A, B | C = 1) = \mathbb{P}(A, B, C = 1) / \mathbb{P}(C = 1)$$

- A straightforward if tedious calculation shows

$$\mathbb{P}(A = 1 | C = 1) = 0.630, \quad \mathbb{P}(B = 1 | C = 1) = 0.317$$
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Elaborate Cakes

- We can elaborate on our cake model
- We suppose that Dave likes cakes so if there is a cake in the coffee room there is a 80% chance that I will see him eating a cake: $\mathbb{P}(D=1|C=1)=0.8$
- Even if there are no cakes in the coffee room there is a 10% chance that Dave has bought his own cake: $\mathbb{P}(D=1|C=0)=0.1$
- Eli also likes cakes: there is a 60% chance that I will see her eating cakes if there are cakes in the coffee room: $\mathbb{P}(E=1|C=1)=0.6$
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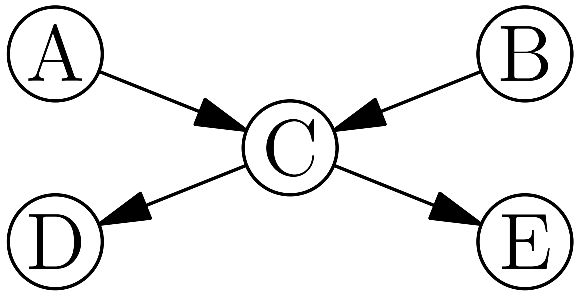

- This allows us to break down the joint probability

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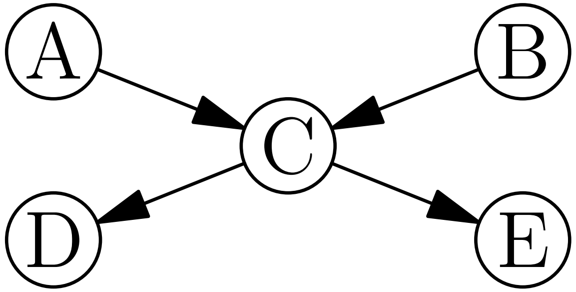

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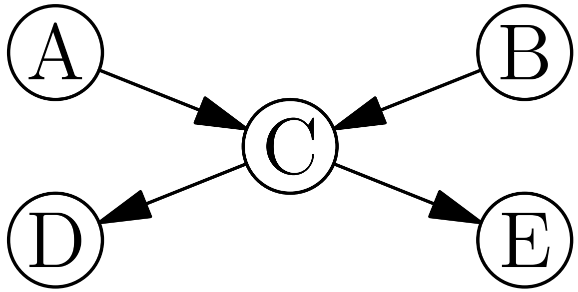

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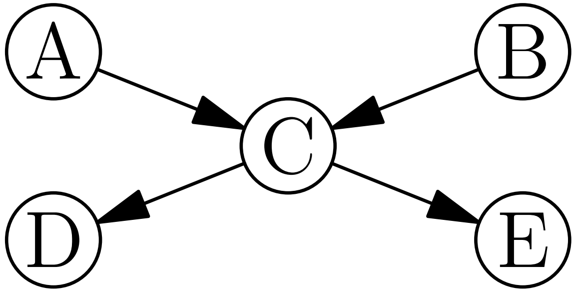

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Dependencies

- If we don't observe cakes then the probability of Dave and Eli eating cake are not independent

$$\mathbb{P}(D=1) = 0.3121, \qquad \mathbb{P}(E=1) = 0.1818$$
$$\mathbb{P}(D=1, E=1) = 0.14544$$

so $\mathbb{P}(D,E) \neq \mathbb{P}(D)\,\mathbb{P}(E)$

- This changes if we know there are cakes in the coffee room

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Graphical Model Frameworks

- There are sophisticated frameworks for computing probabilities in Bayesian Belief Networks efficiently
- If our graph is a tree then we can evaluate probabilities efficiently
- When there a loops (so that a random variable both influences and is influenced by another random variables) then exact evaluation of expectations requires exhaustive summing over variables
- There are various message passing algorithms designed to obtain approximations of expectations

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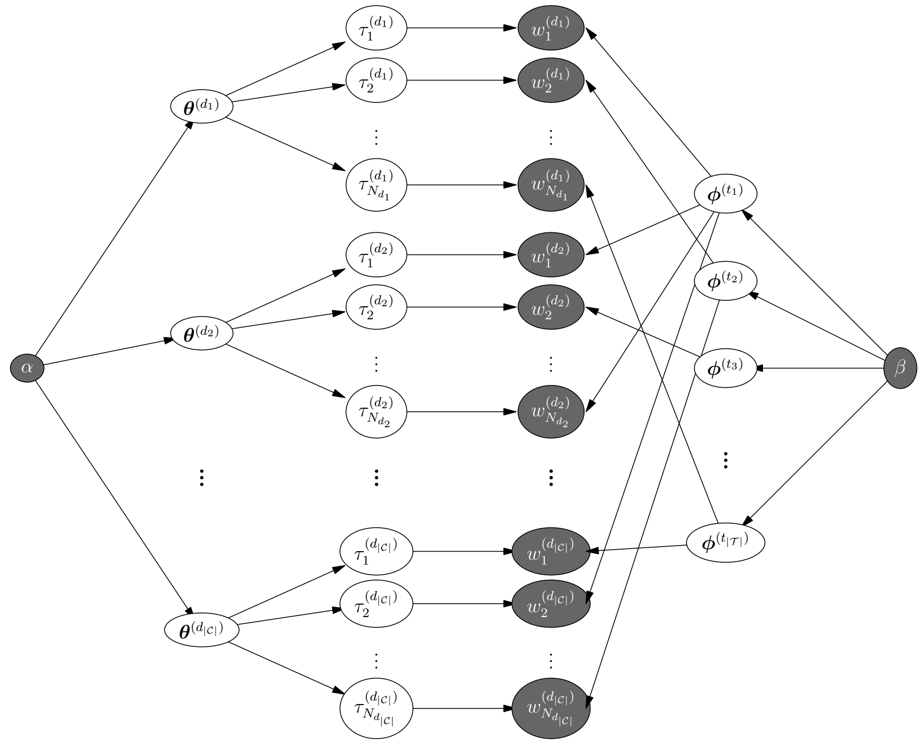
Outline

1. Graphical Models
2. Cakes!
3. **Latent Dirichlet Allocation**



Model for Documents

- We consider a model for the words in a set of documents (we ignore word order)
- We consider a corpus $\mathcal{C} = \{d_i | i = 1, 2, \ldots |\mathcal{C}|\}$
- With documents consisting of words

$$d = \left(w_1^{(d)}, w_2^{(d)}, \ldots, w_{N_d}^{(d)} \right)$$

- We assume that there is a set of topics $\mathcal{T} = \{t_1, t_2, \ldots, t_{|\mathcal{T}|}\}$
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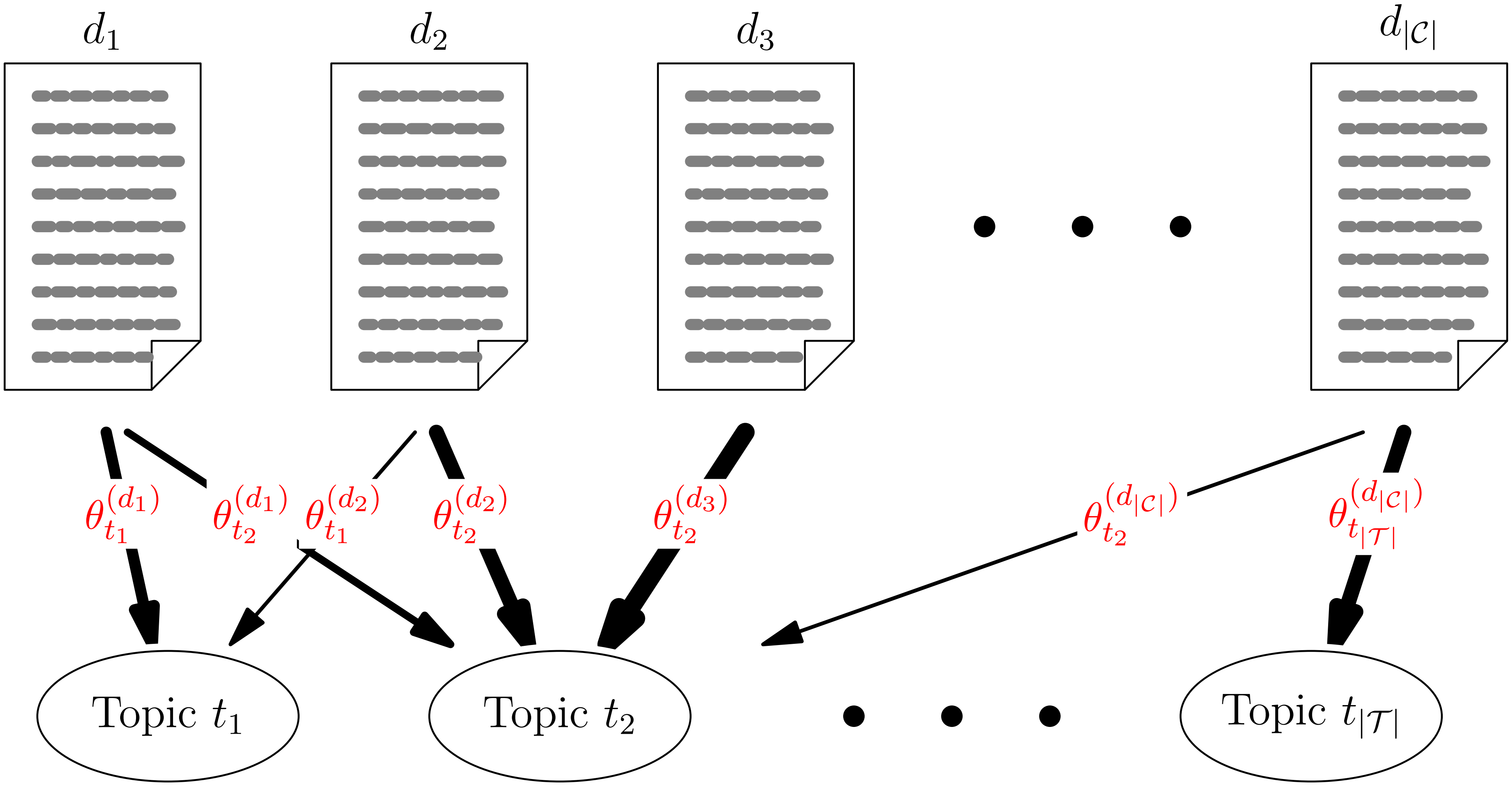
Documents and Topic

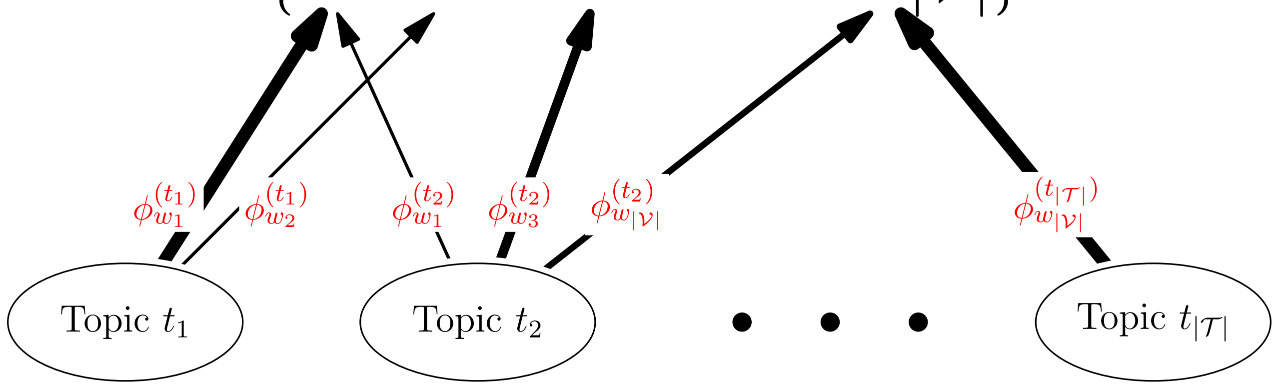


$$\boldsymbol{\theta}^{(d)} = (\theta_t^{(d)} | t \in \mathcal{T}) \qquad \theta_t^{(d)} \geq 0 \qquad \sum_{t=1}^{|\mathcal{T}|} \theta_t^{(d)} = 1$$

Words and Topic

- We associate a probability $\phi_w^{(t)}$ that a word, w, is related to a topic t

$$\mathcal{V} = \left\{w_1,\, w_2,\, w_3,\, \ldots,\, w_{|\mathcal{V}|}\right\}$$



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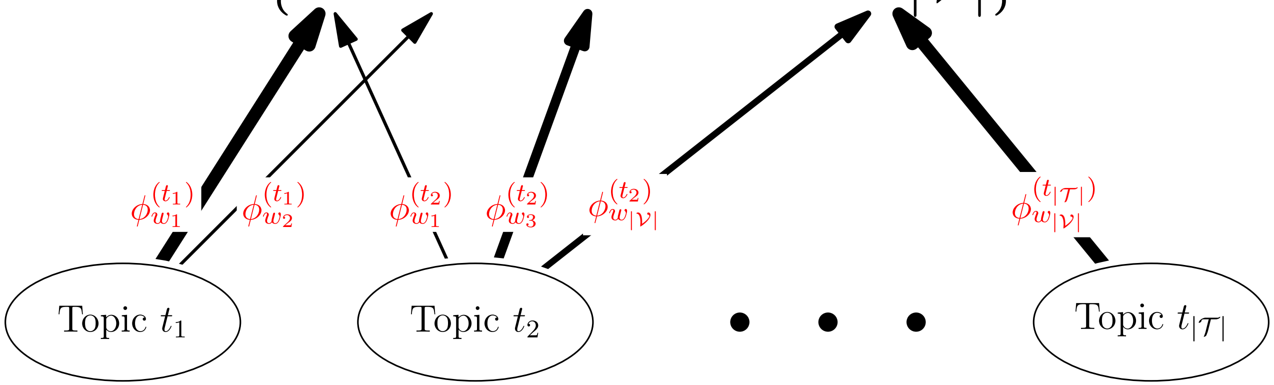

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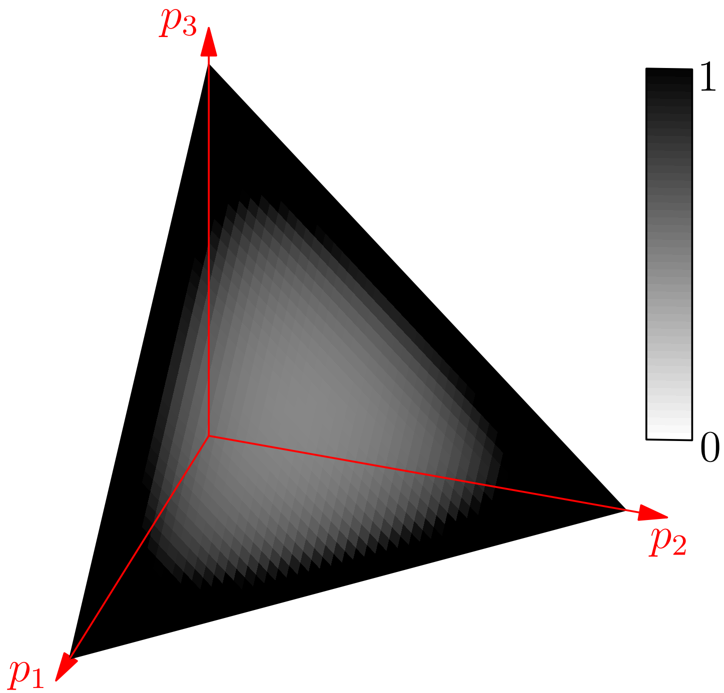
Dirichlet Allocation

- Most documents are predominantly about a few topics and most topic have a small number of words associated to them

- We can generate sparse vectors $\boldsymbol{\theta}^{(d)}$ and $\boldsymbol{\phi}^{(t)}$ from a Dirichlet distribution with small parameters $\boldsymbol{\alpha}$



$$\mathrm{Dir}(\boldsymbol{p}|\boldsymbol{\alpha}) = \Gamma\left(\sum_i \alpha_i\right) \prod_{i=1}^{n} \frac{p_i^{\alpha_i - 1}}{\Gamma(\alpha_i)}$$

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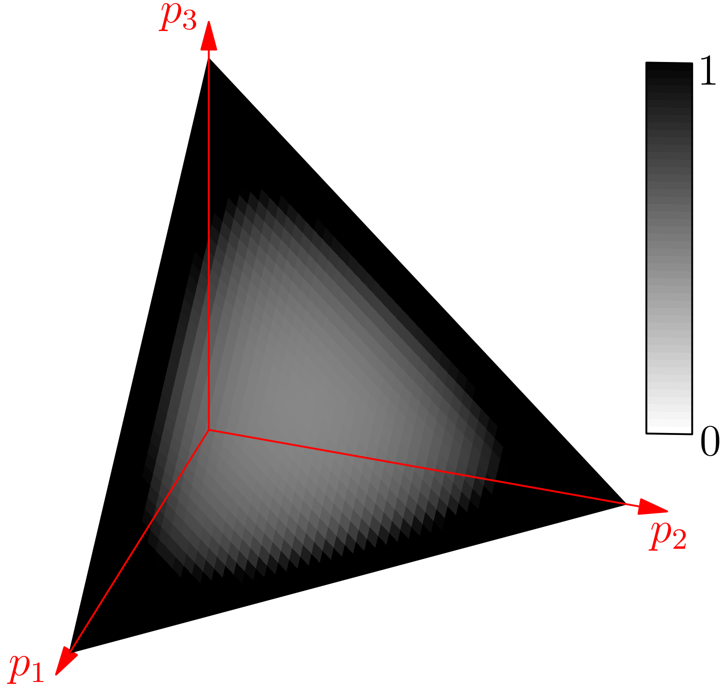

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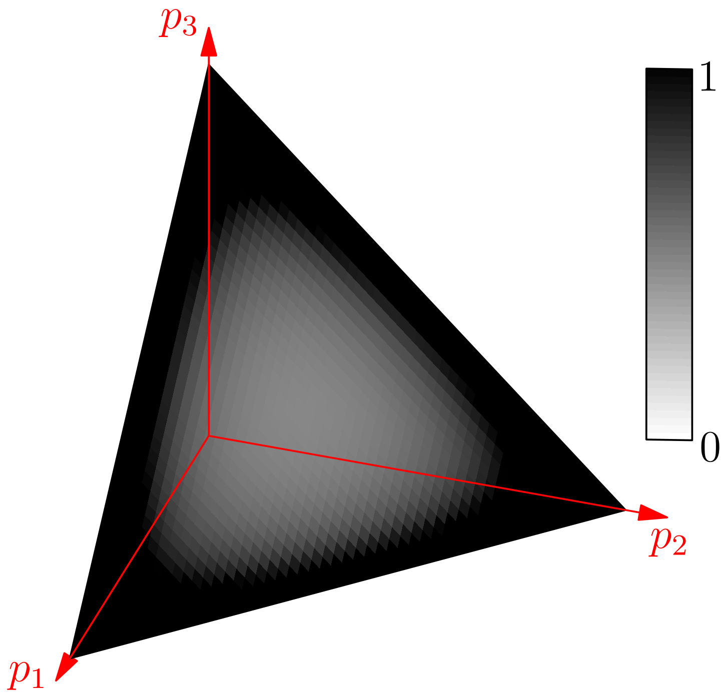

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LDA Graphical Model (version 1)

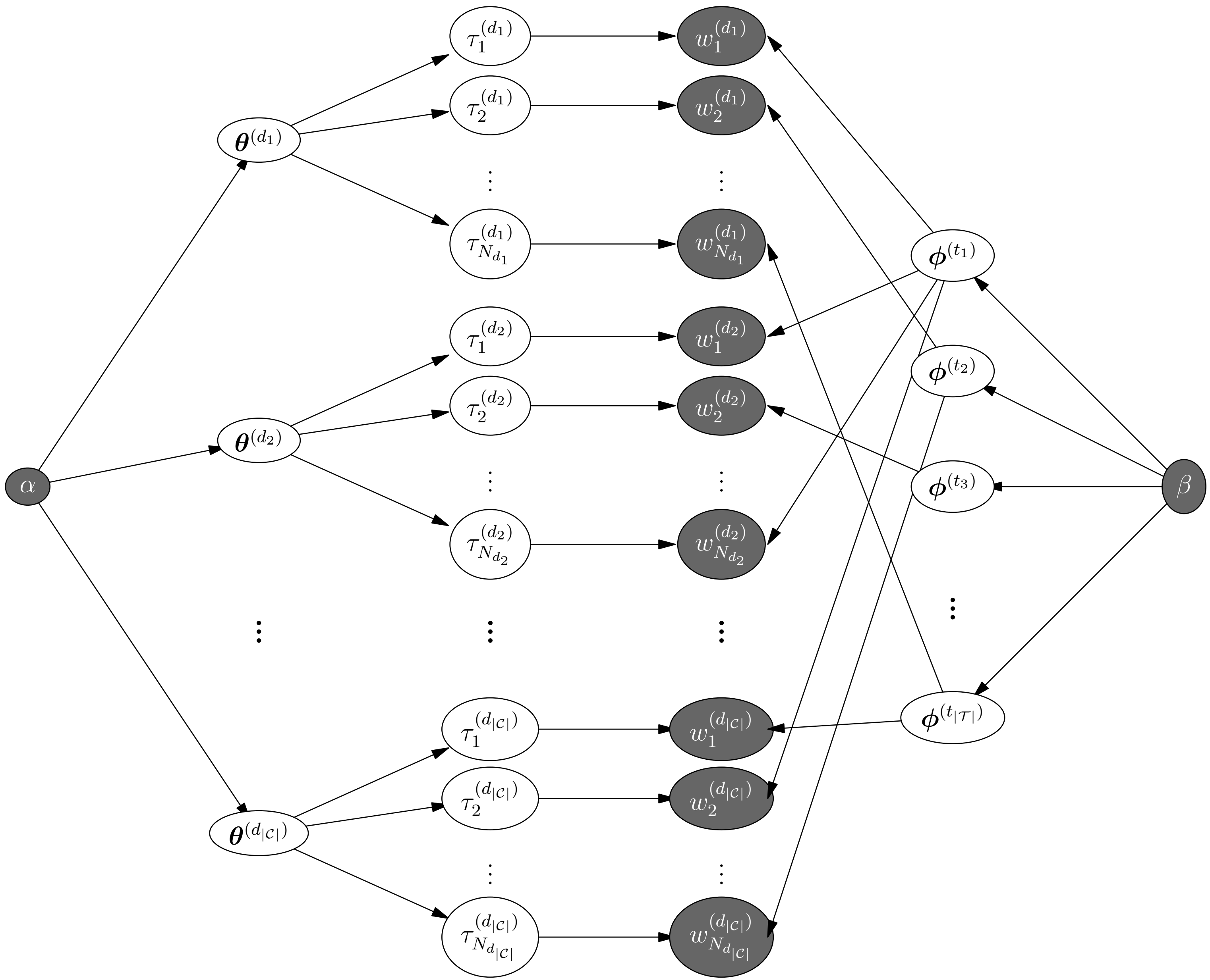

Plate Diagrams

- Drawing every random variable is tedious (and not really possible)
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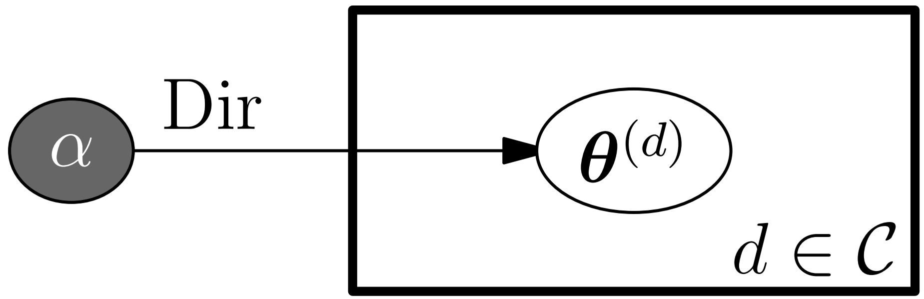

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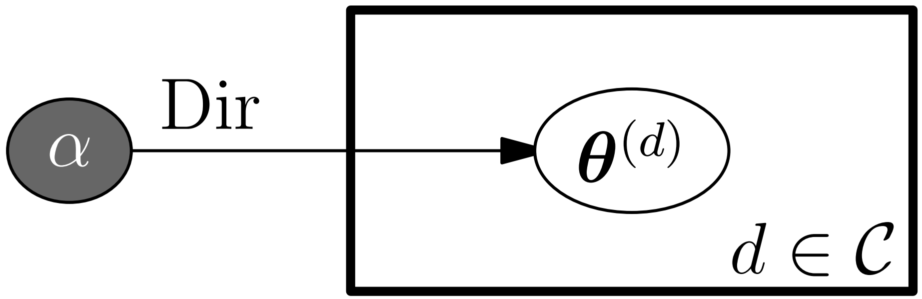

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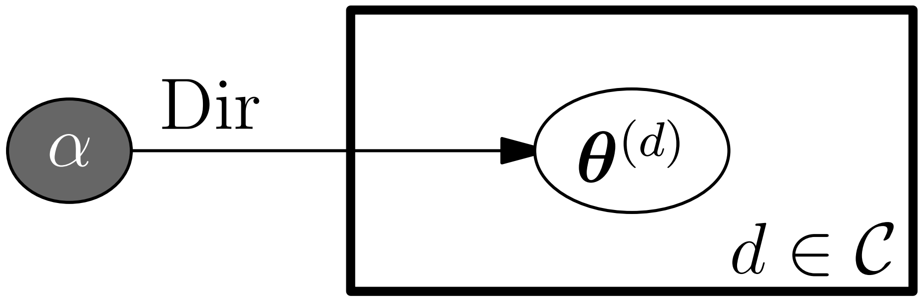

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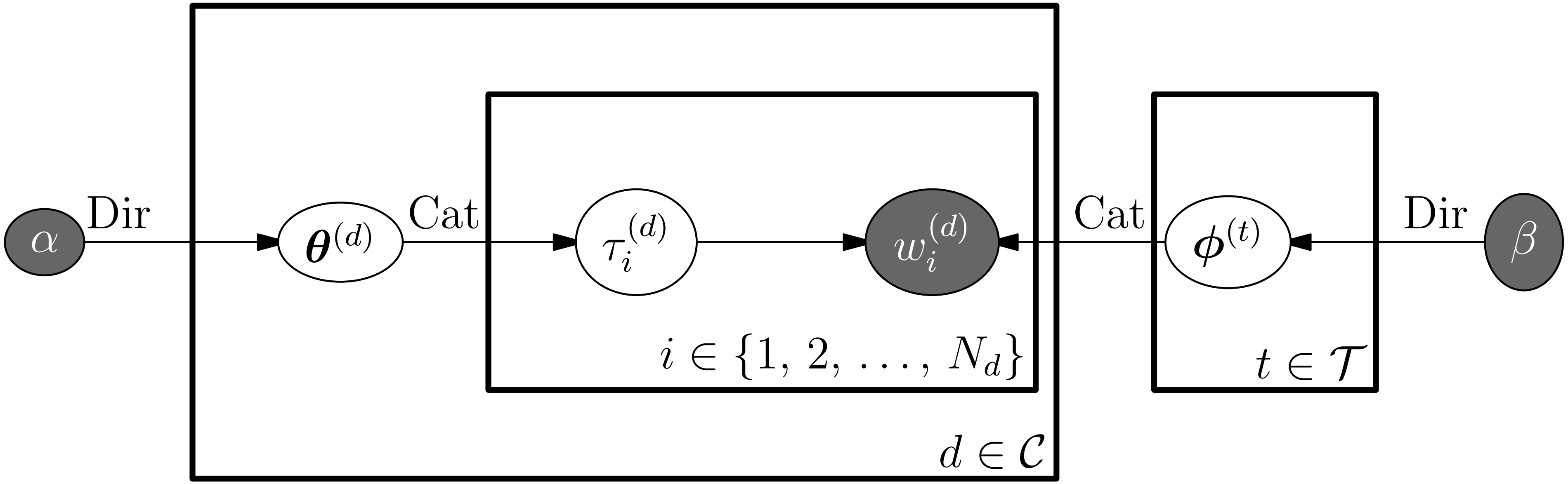
LDA Graphical Model (version 2)



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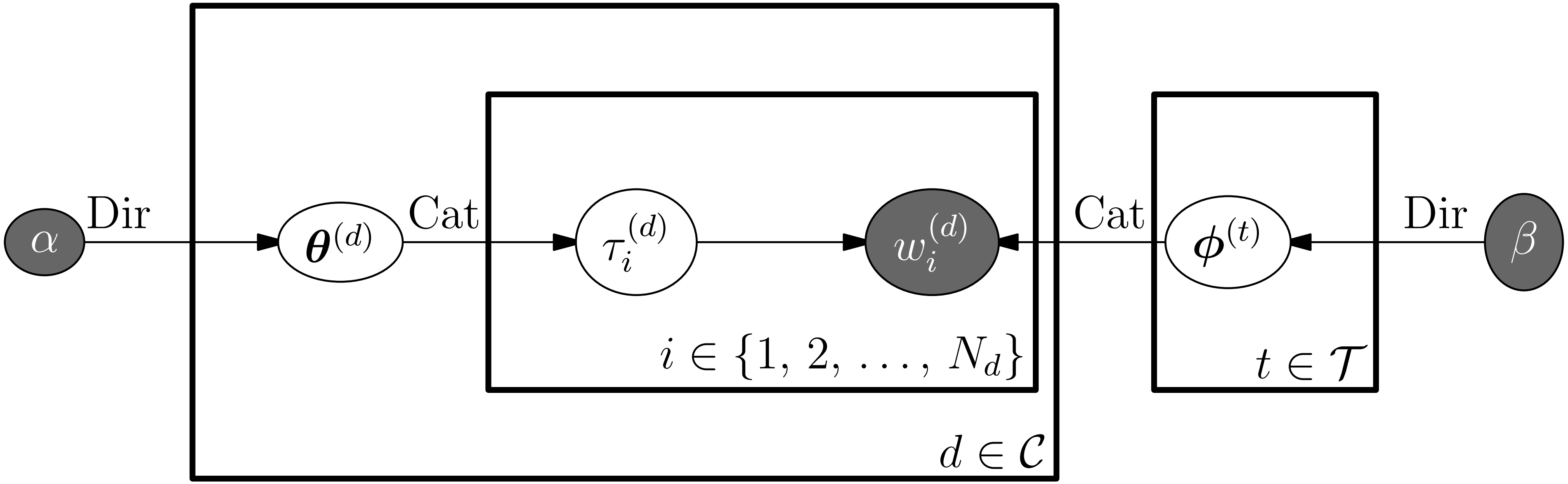

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Probabilistic Model

- The graphical Model is shorthand for the variables

$$\boldsymbol{W} = (\boldsymbol{w}^{(d)}|d \in \mathcal{C}) \quad \text{with} \quad \boldsymbol{w}^{(d)} = (w_1^{(d)}, w_2^{(d)}, \ldots, w_{N_d}^{(d)}), \quad \text{and} \quad w_i^{(d)} \in \mathcal{V}$$

$$\boldsymbol{T} = (\tau_i^{(d)}|d \in \mathcal{C} \ \wedge \ i \in \{1, 2, \ldots, N_d\}) \quad \text{with} \quad \tau_i^{(d)} \in \mathcal{T}$$

$$\boldsymbol{\Theta} = (\boldsymbol{\theta}^{(d)}|d \in \mathcal{C}) \quad \text{with} \quad \boldsymbol{\theta}^{(d)} = (\theta_t^{(d)}|t \in \mathcal{T}) \in \Lambda^{|\mathcal{T}|}$$

$$\boldsymbol{\Phi} = (\boldsymbol{\phi}^{(t)}|t \in \mathcal{T}) \quad \text{with} \quad \boldsymbol{\phi}^{(t)} = (\phi_w^{(t)}|w \in \mathcal{V}) \in \Lambda^{|\mathcal{V}|}$$

- Distributed according to

$$\mathbb{P}\left(\boldsymbol{W}, \boldsymbol{T}, \boldsymbol{\Theta}, \boldsymbol{\Phi} \middle| \alpha, \beta\right) = \left(\prod_{t \in \mathcal{T}} \mathrm{Dir}\left(\boldsymbol{\phi}^{(t)} \middle| \beta \boldsymbol{1}\right)\right) \left(\prod_{d \in \mathcal{C}} \mathrm{Dir}\left(\boldsymbol{\theta}^{(d)} \middle| \alpha \boldsymbol{1}\right) \prod_{i=1}^{N_d} \mathrm{Cat}\left(\tau_i^{(d)} \middle| \boldsymbol{\theta}^{(d)}\right) \mathrm{Cat}\left(w_i^{(d)} \middle| \boldsymbol{\phi}^{(\tau_i^{(d)})}\right)\right)$$

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- We are given the set of words $\boldsymbol{W}$ and don't really care about τ_i^d the topic associated with word i in document d
- But we are interested in the words associated with each topic $\boldsymbol{\phi}^{(t_i)}$
- And the topics associated with each document $\boldsymbol{\theta}^{(d)}$
- To compute them we need to sample the probability distribution
- One way to do this is using Monte Carlo methods (see next lecture)

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- This allows us to break down the joint probability of all the variables into conditional probabilities
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