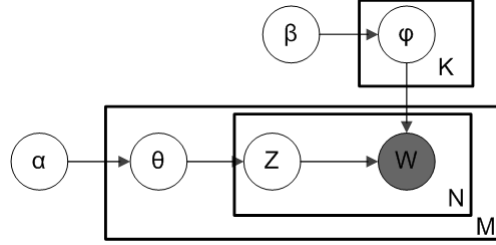


LDA Gibbs Sampling 详细推导过程, 2013.10.6, ys

作为基本的 topic model,熟悉 LDA 的推导过程还是很有必要的, 当掌握了它的推导过程后, 再遇到其他相关图模型的推断你就会觉得 ‘so easy!’。每次去推断别的模型, 总在脑袋里回味一下这个基本的 topic model 的推断过程, 趁现在跑程序总结下来, 分享学习, 做个记录, 也欢迎各位不吝赐教。

下文假定各位读者已经熟悉了 LDA 的先验分布假设, 生成过程等, 只给出了主要的公式推导流程。

0. 概率图模型如下图:



1. 首先给出联合概率: $p(\mathbf{w}, \mathbf{z} | \alpha, \beta) = p(\mathbf{w} | \mathbf{z}, \alpha, \beta) p(\mathbf{z} | \alpha, \beta) = p(\mathbf{w} | \mathbf{z}, \beta) p(\mathbf{z} | \alpha)$

*注: 当我们确定下来一个模型后, 首先计算它的联合概率, 这个是绝对不会错的, 在后续的采样中是很有用的。

• 1.1 第一项 $p(\mathbf{w} | \mathbf{z}, \beta)$:

$$\begin{aligned}
 p(\mathbf{w} | \mathbf{z}, \beta) &= \int p(\mathbf{w} | \mathbf{z}, \Phi) p(\Phi | \beta) d\Phi \\
 p(\mathbf{w} | \mathbf{z}, \Phi) &= \prod_{i=1}^{N \times M} \varphi_{z_i, w_i}^{n(z_i, w_i)} = \prod_{k=1}^K \prod_{t=1}^V \varphi_{k,t}^{n(k,t)} \\
 p(\Phi | \beta) &= \prod_{k=1}^K p(\varphi_k | \beta) = \prod_{k=1}^K \frac{\Gamma(\sum_{t=1}^V \beta_t)}{\prod_{t=1}^V \Gamma(\beta_t)} \prod_{t=1}^V \varphi_{k,t}^{\beta_t-1} \\
 \Rightarrow p(\mathbf{w} | \mathbf{z}, \beta) &= \int p(\mathbf{w} | \mathbf{z}, \Phi) p(\Phi | \beta) d\Phi \\
 &= \int \prod_{k=1}^K \prod_{t=1}^V \varphi_{k,t}^{n(k,t)} \cdot \prod_{k=1}^K \frac{\Gamma(\sum_{t=1}^V \beta_t)}{\prod_{t=1}^V \Gamma(\beta_t)} \prod_{t=1}^V \varphi_{k,t}^{\beta_t-1} d\varphi_{k,t} \\
 &= \int \prod_{k=1}^K \frac{\Gamma(\sum_{t=1}^V \beta_t)}{\prod_{t=1}^V \Gamma(\beta_t)} \prod_{t=1}^V \varphi_{k,t}^{n(k,t) + \beta_t - 1} d\varphi_{k,t} \\
 &= \int \prod_{k=1}^K \frac{\Delta(n_k + \beta)}{\Delta(\beta)} \frac{1}{\Delta(n_k + \beta)} \prod_{t=1}^V \varphi_{k,t}^{n(k,t) + \beta_t - 1} d\varphi_{k,t} \quad (\text{其中 } \frac{1}{\Delta(\beta)} = \frac{\Gamma(\sum_{t=1}^V \beta_t)}{\prod_{t=1}^V \Gamma(\beta_t)} \text{ (以下 } \Delta(\alpha) \text{ 类似)}) \\
 &= \prod_{k=1}^K \frac{\Delta(n_k + \beta)}{\Delta(\beta)} \quad (\text{利用 } \int \frac{1}{\Delta(n_k + \beta)} \prod_{t=1}^V \varphi_{k,t}^{n(k,t) + \beta_t - 1} d\varphi_{k,t} = 1)
 \end{aligned}$$

• 1.2 第二项 $p(\mathbf{z} | \alpha)$:

$$\begin{aligned}
 p(\mathbf{z} | \alpha) &= \int p(\mathbf{z} | \theta) p(\theta | \alpha) d\theta \\
 p(\mathbf{z} | \theta, \alpha) &= \prod_{i=1}^{N \times M} \theta_{d_i, z_i} = \prod_{d=1}^M \prod_{k=1}^K \theta_{d,k}^{n(d,k)} \\
 p(\theta | \alpha) &= \prod_{d=1}^M p(\theta_d | \alpha) = \prod_{d=1}^M \frac{\Gamma(\sum_{k=1}^K \alpha_k)}{\prod_{k=1}^K \Gamma(\alpha_k)} \prod_{k=1}^K \theta_{d,k}^{\alpha_k-1} \\
 \Rightarrow p(\mathbf{z} | \alpha) &= \int p(\mathbf{z} | \theta) p(\theta | \alpha) d\theta \\
 &= \int \prod_{d=1}^M \prod_{k=1}^K \theta_{d,k}^{n(d,k)} \cdot \prod_{d=1}^M \frac{\Gamma(\sum_{k=1}^K \alpha_k)}{\prod_{k=1}^K \Gamma(\alpha_k)} \prod_{k=1}^K \theta_{d,k}^{\alpha_k-1} d\theta_{d,k} \\
 &= \int \prod_{d=1}^M \frac{\Gamma(\sum_{k=1}^K \alpha_k)}{\prod_{k=1}^K \Gamma(\alpha_k)} \prod_{k=1}^K \theta_{d,k}^{n(d,k) + \alpha_k - 1} d\theta_{d,k} \\
 &= \prod_{d=1}^M \frac{\Delta(n_d + \alpha)}{\Delta(\alpha)} \quad (\text{同上述 } p(\mathbf{w} | \mathbf{z}, \beta) \text{ 的最后一步推导})
 \end{aligned}$$

• 1.3 联合 1.1, 1.2 有联合概率:

$$p(\mathbf{w}, \mathbf{z} | \alpha, \beta) = p(\mathbf{w} | \mathbf{z}, \alpha, \beta) p(\mathbf{z} | \alpha, \beta) = p(\mathbf{w} | \mathbf{z}, \beta) p(\mathbf{z} | \alpha) = \prod_{k=1}^K \frac{\Delta(n_k + \beta)}{\Delta(\beta)} \cdot \prod_{d=1}^M \frac{\Delta(n_d + \alpha)}{\Delta(\alpha)}$$

2. 计算采样的条件概率:第 i 个 word 的 topic 为 k 的概率 $p(z_i = k | z_{-i}, \mathbf{w}; \alpha, \beta)$

$$p(z_i = k | z_{-i}, \mathbf{w}; \alpha, \beta) = \frac{p(z_i = k, z_{-i}, \mathbf{w}; \alpha, \beta)}{p(z_{-i}, \mathbf{w}; \alpha, \beta)} \propto p(z_i = k, z_{-i}, \mathbf{w}; \alpha, \beta) = p(\mathbf{w} | z_i = k, z_{-i}; \alpha, \beta) \cdot p(z_i = k, z_{-i}; \alpha, \beta)$$

• 2.1 第一项 $p(\mathbf{w} | z_i = k, z_{-i}; \alpha, \beta)$ 分为两步走:

(1). 不包含第 i 个 word 及其所在 $z_i=k$ 的项:

$$\prod_{z=1, z \neq z_i}^K \frac{\Delta(n_{z,-i} + \beta)}{\Delta(\beta)}$$

(2). 第 i 个 word 所在的 $z_i=k$ 项:

$$\frac{\Delta(n_k + \beta)}{\Delta(\beta)}$$

(这里的 n_k 是包含了第 k 个 topic 下的 word 数目, 已经包含了第 i 个 word)。

由此有:

$$\begin{aligned} p(z_i = k | z_{-i}, \mathbf{w}; \alpha, \beta) &\propto p(\mathbf{w} | z_i = k, z_{-i}; \alpha, \beta) \\ &= \left(\prod_{z=1, z \neq k}^K \frac{\Delta(n_{z,-i} + \beta)}{\Delta(\beta)} \right) \cdot \frac{\Delta(n_k + \beta)}{\Delta(\beta)} \\ &= \prod_{z=1}^K \frac{\Delta(n_{z,-i} + \beta)}{\Delta(\beta)} \cdot \frac{\Delta(\beta)}{\Delta(n_{z=k,-i} + \beta)} \cdot \frac{\Delta(n_k + \beta)}{\Delta(\beta)} \propto \frac{\Delta(n_k + \beta)}{\Delta(n_{z=k,-i} + \beta)} \\ &= \frac{\Gamma(\sum_{t=1}^V (n_{k,-i}^t + \beta_t))}{\prod_{t=1}^V \Gamma(n_{k,-i}^t + \beta_t)} \cdot \frac{\prod_{t=1}^V \Gamma(n_k^t + \beta_t)}{\Gamma(\sum_{t=1}^V (n_k^t + \beta_t))} \quad (\text{利用 } \Gamma(a+1) = a\Gamma(a), \text{ 及 } n_k^t = n_{k,-i}^t + 1) \\ &= \frac{n_{k,-i}^t + \beta_t}{\sum_{t=1}^V (n_{k,-i}^t + \beta_t)} \end{aligned}$$

• 2.2 关于第二项 $p(z_i = k, z_{-i}; \alpha, \beta) = p(z_i = k, z_{-i}; \alpha)$ 同样分为两步走:

(1). 不包含第 i 个 word 所在的 doc di 项:

$$\prod_{d=1, d \neq d_i}^M \frac{\Delta(n_{d,-i} + \alpha)}{\Delta(\alpha)}$$

(2). 第 i 个 word 所在的项:

$$\frac{\Delta(n_{d_i} + \alpha)}{\Delta(\alpha)}$$

从而有

$$\begin{aligned} p(z_i = k, z_{-i}; \alpha, \beta) &= p(z_i = k, z_{-i}; \alpha) \\ &= \prod_{d=1, d \neq d_i}^M \frac{\Delta(n_{d,-i} + \alpha)}{\Delta(\alpha)} \cdot \frac{\Delta(n_{d_i} + \alpha)}{\Delta(\alpha)} \\ &= \prod_{d=1}^M \frac{\Delta(n_{d,-i} + \alpha)}{\Delta(\alpha)} \cdot \frac{\Delta(\alpha)}{\Delta(n_{d_i,-i} + \alpha)} \cdot \frac{\Delta(n_{d_i} + \alpha)}{\Delta(\alpha)} \quad (\text{注意此时在第一个分式中加入不含第 i 个 word 的 doc di}) \\ &= \frac{\Delta(n_{d_i} + \alpha)}{\Delta(n_{d_i,-i} + \alpha)} \\ &= \frac{\Gamma(\sum_{k=1}^K (n_{d_i,-i}^k + \alpha_k))}{\prod_{k=1}^K \Gamma(n_{d_i,-i}^k + \alpha_k)} \cdot \frac{\prod_{k=1}^K \Gamma(n_{d_i}^k + \alpha_k)}{\Gamma(\sum_{k=1}^K (n_{d_i}^k + \alpha_k))} \quad (\text{利用 } \Gamma(a+1) = a\Gamma(a), \text{ 及 } n_{d_i}^k = n_{d_i,-i}^k + 1) \\ &= \frac{n_{d_i,-i}^k + \alpha_k}{\sum_{k=1}^K (n_{d_i,-i}^k + \alpha_k)} \end{aligned}$$

• 2.3 联合 2.1, 2.2 从而有

$$p(z_i = k | z_{-i}, \mathbf{w}; \alpha, \beta) \propto p(\mathbf{w} | z_i = k, z_{-i}; \alpha, \beta) \cdot p(z_i = k, z_{-i}; \alpha, \beta) = \frac{n_{k,-i}^t + \beta_t}{\sum_{t=1}^V (n_{k,-i}^t + \beta_t)} \cdot \frac{n_{d_i,-i}^k + \alpha_k}{\sum_{k=1}^K (n_{d_i,-i}^k + \alpha_k)}$$