Foundations of Bayesian NLP

MSc Artificial Intelligence

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Institute for Logic, Language, and Computation

2018

The problem with MLE

Motivating example from Liang and Klein (2007)

- mixture of Gaussians trained via EM

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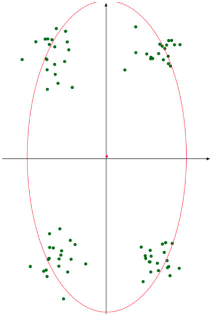

K	training log-likelihood	test log-likelihood
1	-364	

Example from Liang and Klein (2007): ACL tutorial on Structured Bayesian Nonparametric Models

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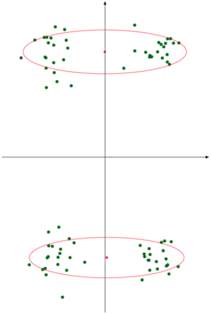

K	training log-likelihood	test log-likelihood
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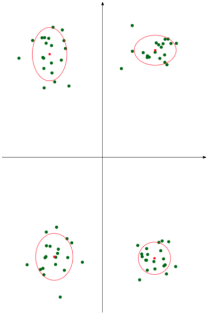

K	training log-likelihood	test log-likelihood
1	-364	
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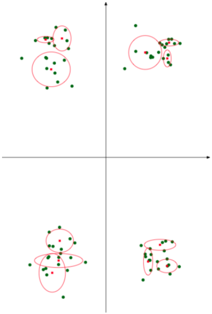

K	training log-likelihood	test log-likelihood
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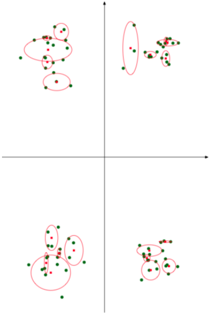

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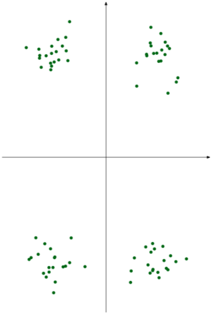

K	training log-likelihood	test log-likelihood
1	-364	-368
2	-204	-206
4	-82	-128
12	21	-147
20	86	-173

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- on heldout set
- preferably via cross-validation

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Can you see limitations of this approach?

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- on heldout set
- preferably via cross-validation

Can you see limitations of this approach?

- availability of data
- representativeness of heldout set
- discrete optimisation: combinatorial search over models

NLP1

Preliminaries

Bayesian modelling

Applications

Conventions

- N observations
  $\mathbf{x} = \langle x_1, \ldots, x_N \rangle$

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- Parameter vector
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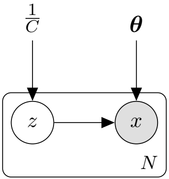
- Collection of parameter vectors
  $\boldsymbol{\theta} = \langle \theta^{(1)}, \ldots, \theta^{(C)} \rangle$

Mixture model



Let's assume x to be 1 of K, and z to be 1 of C

- categorical likelihood

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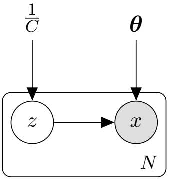

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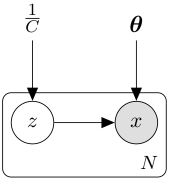

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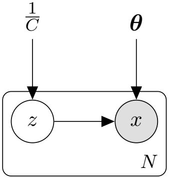

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$$Z_i \sim \mathcal{U}(C)$$

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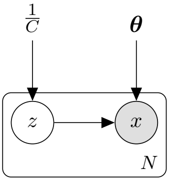

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$$\begin{aligned} Z_i &\sim \mathcal{U}(C) \\ X_i \mid \boldsymbol{\theta}, \mathbf{z}_{-i}, z_i = c &\sim \mathrm{Cat}(\theta^{(c)}) \end{aligned} \tag{1}$$

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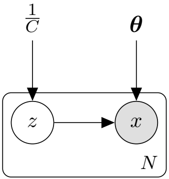

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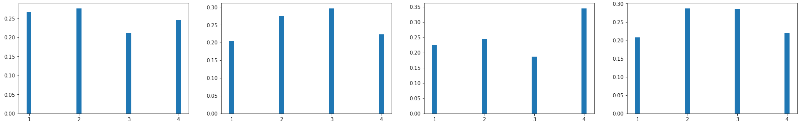
What is a sensible conditional distribution $X|\theta^{(c)} \sim \mathrm{Cat}(\theta^{(c)})$?

What makes a good conditional?

$c = 1$ (the blue cluster), $K = 4$



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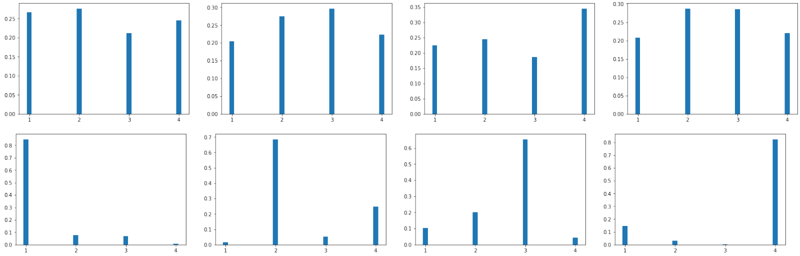

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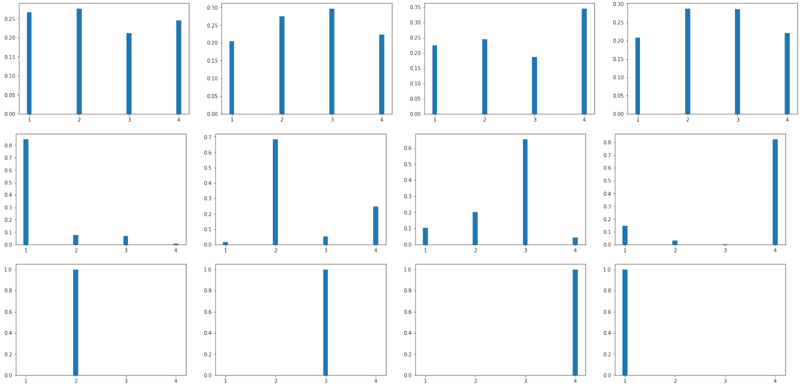

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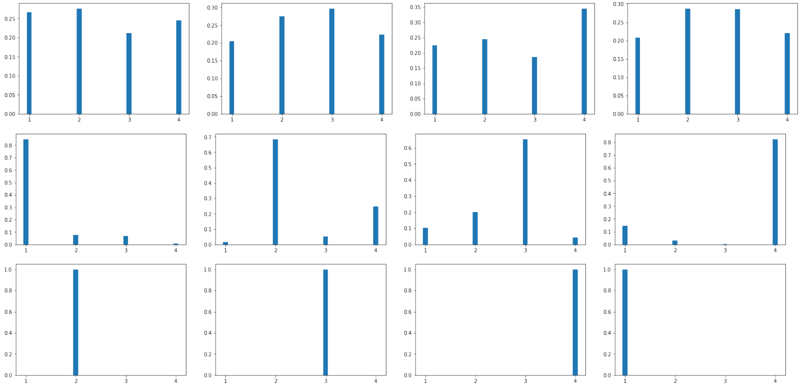

Can you make any assumptions before observing data?

Bayes rule

What does Bayes rule tell you?

$$\underbrace{P(h|d)}_{\text{posterior}} =$$

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- the posterior updates our beliefs about hypotheses **in light of** observed data.

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An optimisation problem based on the *(log-)likelihood function*

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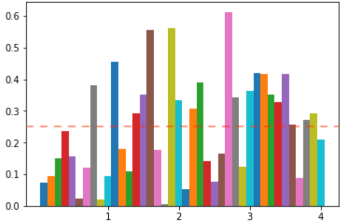
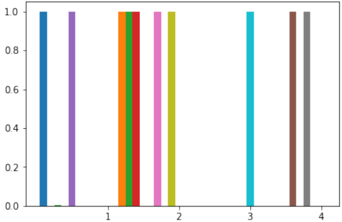
- local optimality guarantees;

All the same a priori

Before data, MLE is equally happy with the hypotheses on the left





Constraining MLE

Maximum a posteriori

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- that only covers the specification of a prior
- Bayesian modelling does not end at prior specification
  you need the crucial part: posterior inference

A Bayesian model

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- they are random variables much like data

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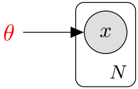
A Bayesian model

Frequentist



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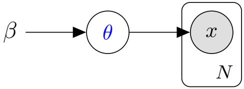

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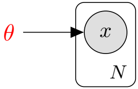

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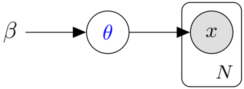

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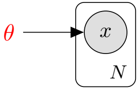

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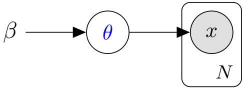

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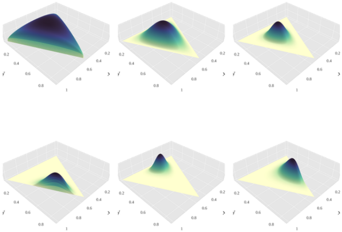
We will study an example that illustrates important concepts
Dirichlet-Multinomial model

Dirichlet distribution

A distribution over the open simplex of K-dimensional vectors

we denote the simplex by

$$\Delta_{K-1} = \left\{ \theta \in \mathbb{R}^K_{>0} : \sum_{k=1}^{K} \theta_k = 1 \right\} \subseteq \mathbb{R}^K_{>0} \tag{5}$$



Use this notebook and this wikipage to learn more

Count vector

For observations $\mathbf{x}$, where x_i is 1 of K
define $n^{(\mathbf{x})}$ as the K-dimensional vector such that

$$n_k = \sum_{i=1}^{N} [x_i = k] \tag{6}$$

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Example: for $K = 3$ and $N = 6$

$$\mathbf{x} = \langle x_1 = 2, x_2 = 3, x_3 = 1, x_4 = 2, x_5 = 2, x_6 = 3 \rangle$$

$$n^{(\mathbf{x})} =$$

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$$n^{(\mathbf{x})} = \langle n_1 = 1, n_2 = 3, n_3 = 2 \rangle$$

Gamma function

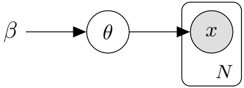
A generalisation of the factorial function to $\mathbb{R}$

$$\Gamma(z) = \int_0^\infty \epsilon^{z-1} \exp(-\epsilon) \mathrm{d}\epsilon \tag{7}$$

Properties

- $\Gamma(n) = (n-1)!$ for positive integer n
- $\Gamma(z) = (z-1)\Gamma(z-1)$

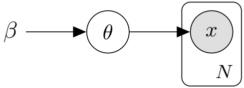
Dirchlet-Multinomial



Model

$$\begin{aligned} \theta|\beta &\sim \mathrm{Dir}(\beta) \\ X_i|\theta &\sim \mathrm{Cat}(\theta) \quad \text{for } i = 1, \ldots, N \end{aligned} \tag{8}$$

Dirchlet-Multinomial



Model

$$
\begin{aligned}
\theta|\beta &\sim \mathrm{Dir}(\beta) \\
X_i|\theta &\sim \mathrm{Cat}(\theta) \quad \text{for } i = 1, \ldots, N
\end{aligned} \tag{8}
$$

Joint distribution

$$
\begin{aligned}
P(\mathbf{x}, \theta|\beta) &= P(\theta)P(\mathbf{x}|\theta) \\
&= \mathrm{Dir}(\theta|\beta)\,\mathrm{Mult}(n^{(\mathbf{x})}|\theta, N)
\end{aligned} \tag{9}
$$

Multinomial likelihood

For $\theta \in \Delta_{K-1}$

$$P(\mathbf{x}|\theta) = \mathrm{Mult}(n^{(\mathbf{x})}|\theta, N)$$

Multinomial likelihood

For $\theta \in \Delta_{K-1}$

$$\begin{aligned} P(\mathbf{x}|\theta) &= \mathrm{Mult}(n^{(\mathbf{x})}|\theta, N) \\ &= \frac{N!}{\prod_{k=1}^{K} n_k!} \prod_{k=1}^{K} \theta_k^{n_k} \end{aligned}$$

Multinomial likelihood

For $\theta \in \Delta_{K-1}$

$$\begin{aligned} P(\mathbf{x}|\theta) &= \mathrm{Mult}(n^{(\mathbf{x})}|\theta, N) \\ &= \frac{N!}{\prod_{k=1}^{K} n_k!} \prod_{k=1}^{K} \theta_k^{n_k} \\ &= \frac{\Gamma(\sum_{k=1}^{K} n_k + 1)}{\prod_{k=1}^{K} \Gamma(n_k + 1)} \prod_{k=1}^{K} \theta_k^{n_k} \end{aligned}$$

Multinomial likelihood

For $\theta \in \Delta_{K-1}$

$$P(\mathbf{x}|\theta) = \mathrm{Mult}(n^{(\mathbf{x})}|\theta, N) = \frac{N!}{\prod_{k=1}^K n_k!} \prod_{k=1}^K \theta_k^{n_k} = \frac{\Gamma(\sum_{k=1}^K n_k + 1)}{\prod_{k=1}^K \Gamma(n_k + 1)} \prod_{k=1}^K \theta_k^{n_k} \tag{10}$$

Example: for $K = 3$ and $N = 6$

$$\theta = \langle \theta_1 = 0.2, \theta_2 = 0.3, \theta_3 = 0.5 \rangle$$
$$\mathbf{x} = \langle x_1 = 2, x_2 = 3, x_3 = 1, x_4 = 2, x_5 = 2, x_6 = 3 \rangle$$
$$n^{(\mathbf{x})} = \langle n_1 = 1, n_2 = 3, n_3 = 2 \rangle$$

$$P(\mathbf{x}|\theta) = \frac{\Gamma(\ldots)}{\prod \ldots} \theta_1^1 \times \theta_2^3 \times \theta_3^2$$

Dirichlet prior

For $\beta \in \mathbb{R}^K_{>0}$

$$\mathrm{Dir}(\theta|\beta) = \frac{\Gamma(\sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(\beta_k)} \prod_{k=1}^K \theta_k^{\beta_k - 1}$$

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&\propto \prod_{k=1}^K \theta_k^{\beta_k - 1}
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\end{aligned} \tag{11}$$

We call

$$\int_{\Delta_{K-1}} \prod_{k=1}^K \theta_k^{\beta_k - 1} = \frac{\prod_{k=1}^K \Gamma(\beta_k)}{\Gamma(\sum_{k=1}^K \beta_k)}$$

the *Dirichlet normaliser*

Posterior

$$P(\theta|\mathbf{x}, \beta) \propto$$

Posterior

$$P(\theta|\mathbf{x}, \beta) \propto P(\mathbf{x}|\theta)P(\theta|\beta)$$

Posterior

$$
\begin{aligned}
P(\theta|\mathbf{x},\beta) &\propto P(\mathbf{x}|\theta)P(\theta|\beta)\\
&\propto \underbrace{\frac{\Gamma(\sum_{k=1}^{K} n_k + 1)}{\prod_{k=1}^{K}\Gamma(n_k+1)} \prod_{k=1}^{K} \theta_k^{n_k}}_{\mathrm{Mult}(n^{(\mathbf{x})}|\theta)} \times
\end{aligned}
$$

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&\propto \prod_{k=1}^K \theta_k^{n_k} \times \prod_{k=1}^K \theta_k^{\beta_k - 1} \\
&= \prod_{k=1}^K \theta_k^{n_k + \beta_k - 1}
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&= \prod_{k=1}^K \theta_k^{n_k + \beta_k - 1} \propto \mathrm{Dir}(\theta|n^{(\mathbf{x})} + \beta)
\end{aligned}
$$

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P(\theta|\mathbf{x}, \beta) &\propto P(\mathbf{x}|\theta)P(\theta|\beta) \\
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\end{aligned}
$$

Thus

$$
P(\theta|\mathbf{x}, \beta) = \underbrace{\qquad\qquad}_{\frac{1}{\text{normaliser}} \text{ of } \mathrm{Dir}(n^{(\mathbf{x})}+\beta)} \prod_{k=1}^K \theta_k^{n_k + \beta_k - 1} \tag{12}
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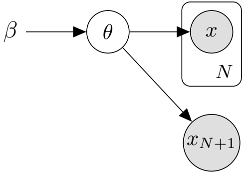
&\propto \prod_{k=1}^{K} \theta_k^{n_k} \times \prod_{k=1}^{K} \theta_k^{\beta_k - 1} \\
&= \prod_{k=1}^{K} \theta_k^{n_k + \beta_k - 1} \propto \mathrm{Dir}(\theta|n^{(\mathbf{x})} + \beta)
\end{aligned}
$$

Thus

$$
P(\theta|\mathbf{x}, \beta) = \underbrace{\frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)}}_{\frac{1}{\text{normaliser}} \text{ of } \mathrm{Dir}(n^{(\mathbf{x})}+\beta)} \prod_{k=1}^{K} \theta_k^{n_k + \beta_k - 1} \tag{12}
$$

Posterior predictive distribution

Suppose a new data point $x_{N+1} = j$ is available



$$P(x_{N+1} = j | \mathbf{x}, \beta) = \int_{\Delta_{K-1}} P(\theta, x_{N+1} | \mathbf{x}, \beta) \mathrm{d}\theta$$

x_{N+1} is independent of $\mathbf{x}$ given θ

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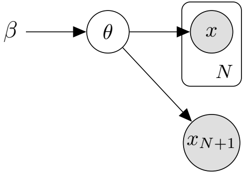

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} P(\theta, x_{N+1}|\mathbf{x}, \beta)\mathrm{d}\theta$$

$$= \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

x_{N+1} is independent of $\mathbf{x}$ given θ

Posterior predictive distribution (cont.)

Suppose a new data point $x_{N+1} = j$ is available

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

Posterior predictive distribution (cont.)

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$$= \int_{\Delta_{K-1}} \theta_j \times \qquad \mathrm{d}\theta$$

Posterior predictive distribution (cont.)

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$$= \int_{\Delta_{K-1}} \theta_j \times \underbrace{\frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)}}_{\text{constant wrt } \theta} \prod_{k=1}^{K} \theta_k^{n_k + \beta_k - 1} \mathrm{d}\theta$$

Posterior predictive distribution (cont.)

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Posterior predictive distribution (cont.)

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$$= \underbrace{\frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)}}_{\text{constant wrt } \theta} \int_{\Delta_{K-1}} \theta_j \times \underbrace{\theta_j^{n_j+\beta_j-1} \prod_{k \neq j} \theta_k^{n_k+\beta_k-1}}_{\prod_{k=1}^K \theta_k^{n_k+\beta_k-1}} \mathrm{d}\theta$$

Posterior predictive distribution (cont.)

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$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

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$$= \frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)} \int_{\Delta_{K-1}} \theta_j^{n_j+\beta_j} \prod_{k \neq j} \theta_k^{n_k+\beta_k-1} \mathrm{d}\theta$$

Posterior predictive distribution (cont.)

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \underbrace{\int_{\Delta_{K-1}} \theta_j^{n_j + \beta_j} \prod_{k \neq j} \theta_k^{n_k + \beta_k - 1} \mathrm{d}\theta}$$

Posterior predictive distribution (cont.)

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \underbrace{\int_{\Delta_{K-1}} \theta_j^{n_j+\beta_j} \prod_{k \neq j} \theta_k^{n_k+\beta_k-1} \mathrm{d}\theta}_{\text{Dir normaliser}}$$

Posterior predictive distribution (cont.)

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \underbrace{\int_{\Delta_{K-1}} \theta_j^{n_j + \beta_j} \prod_{k \neq j} \theta_k^{n_k + \beta_k - 1} \mathrm{d}\theta}_{\text{Dir normaliser}}$$

$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \overline{}$$

Posterior predictive distribution (cont.)

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

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$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \frac{\qquad}{\Gamma(N + \sum_{k=1}^{K} \beta_k + 1)}$$

Posterior predictive distribution (cont.)

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

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$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \frac{\Gamma(n_j + \beta_j + 1) \prod_{k \neq j} \Gamma(n_k + \beta_k)}{\Gamma(N + \sum_{k=1}^{K} \beta_k + 1)}$$

Posterior predictive distribution (cont.)

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \underbrace{\int_{\Delta_{K-1}} \theta_j^{n_j+\beta_j} \prod_{k \neq j} \theta_k^{n_k+\beta_k-1} \mathrm{d}\theta}_{\text{Dir normaliser}}$$

$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \frac{\Gamma(n_j + \beta_j + 1) \prod_{k \neq j} \Gamma(n_k + \beta_k)}{\Gamma(N + \sum_{k=1}^{K} \beta_k + 1)}$$

$$= \frac{\Gamma(N + \sum_{k=1}^{K} \beta_k)}{\prod_{k=1}^{K} \Gamma(n_k + \beta_k)} \frac{(n_j + \beta_j)\Gamma(n_j + \beta_j) \prod_{k \neq j} \Gamma(n_k + \beta_k)}{(N + \sum_{k=1}^{K} \beta_k)\Gamma(N + \sum_{k=1}^{K} \beta_k)}$$

Posterior predictive distribution (cont.)

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

$$= \frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)} \underbrace{\int_{\Delta_{K-1}} \theta_j^{n_j+\beta_j} \prod_{k \neq j} \theta_k^{n_k+\beta_k-1} \mathrm{d}\theta}_{\text{Dir normaliser}}$$

$$= \frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)} \frac{\Gamma(n_j + \beta_j + 1) \prod_{k \neq j} \Gamma(n_k + \beta_k)}{\Gamma(N + \sum_{k=1}^K \beta_k + 1)}$$

$$= \frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)} \frac{(n_j + \beta_j)\Gamma(n_j + \beta_j) \prod_{k \neq j} \Gamma(n_k + \beta_k)}{(N + \sum_{k=1}^K \beta_k)\Gamma(N + \sum_{k=1}^K \beta_k)}$$

$$= \frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)} \frac{(n_j + \beta_j)\Gamma(n_j + \beta_j) \prod_{k \neq j} \Gamma(n_k + \beta_k)}{(N + \sum_{k=1}^K \beta_k)\Gamma(N + \sum_{k=1}^K \beta_k)}$$

Posterior predictive distribution (cont.)

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \int_{\Delta_{K-1}} \underbrace{P(x_{N+1} = j|\theta)}_{\text{likelihood}} \underbrace{P(\theta|\mathbf{x}, \beta)}_{\text{posterior}} \mathrm{d}\theta$$

$$= \frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)} \underbrace{\int_{\Delta_{K-1}} \theta_j^{n_j+\beta_j} \prod_{k \neq j} \theta_k^{n_k+\beta_k-1} \mathrm{d}\theta}_{\text{Dir normaliser}}$$

$$= \frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)} \frac{\Gamma(n_j + \beta_j + 1) \prod_{k \neq j} \Gamma(n_k + \beta_k)}{\Gamma(N + \sum_{k=1}^K \beta_k + 1)}$$

$$= \frac{\Gamma(N + \sum_{k=1}^K \beta_k)}{\prod_{k=1}^K \Gamma(n_k + \beta_k)} \frac{(n_j + \beta_j)\Gamma(n_j + \beta_j) \prod_{k \neq j} \Gamma(n_k + \beta_k)}{(N + \sum_{k=1}^K \beta_k)\Gamma(N + \sum_{k=1}^K \beta_k)}$$

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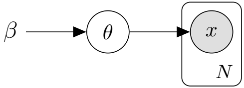
Dirchlet-Multinomial (overview)



Joint distribution

$$\begin{aligned} P(\mathbf{x}, \theta|\beta) &= P(\theta)P(\mathbf{x}|\theta) \\ &= \mathrm{Dir}(\theta|\beta)\,\mathrm{Mult}(n^{(\mathbf{x})}|\theta, N) \end{aligned} \tag{13}$$

Posterior

$$P(\theta|\mathbf{x}, \beta) = \mathrm{Dir}(\theta|n^{(\mathbf{x})} + \beta) \tag{14}$$

Predictive posterior

$$P(x_{N+1} = j|\mathbf{x}, \beta) = \frac{n_j + \beta_j}{N + \sum_{k=1}^{K} \beta_k} \tag{15}$$

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- MLE is memoryless: there is one fixed θ, no matter how much more data you see, θ will never change

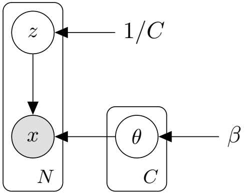
NLP1

Preliminaries

Bayesian modelling

Applications

Bayesian mixture model with categorical observations



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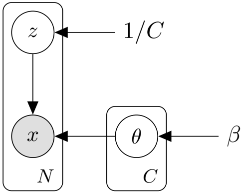

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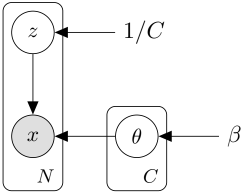

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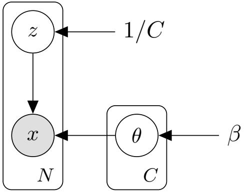

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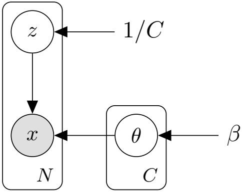

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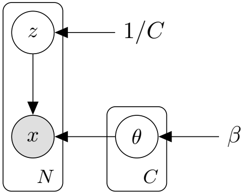

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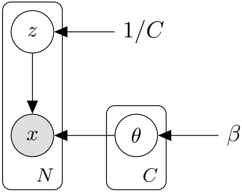

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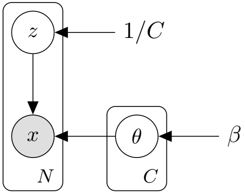

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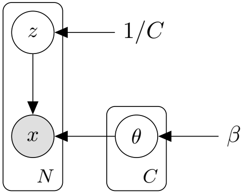

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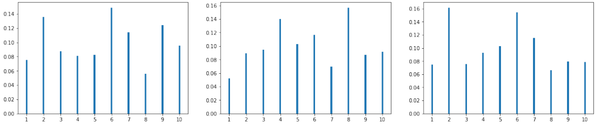
- what about preferring to use fewer components?

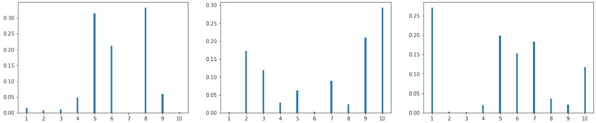
Sparse prior over mixing weights

Say we have 10 components, how do you want to use them?

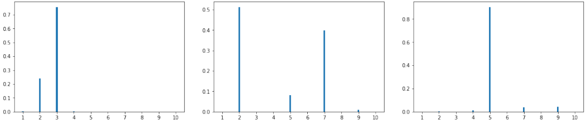
I couldn't care less



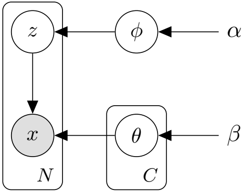
Sparingly



Like I pass students



Bayesian mixture model - Sparse prior over mixing weights



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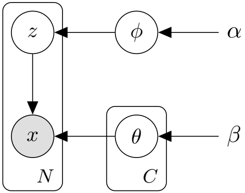

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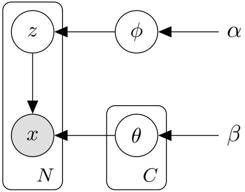

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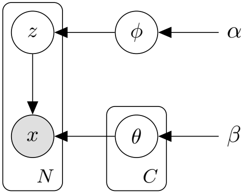

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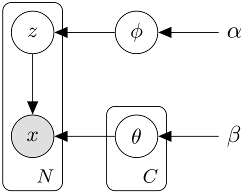

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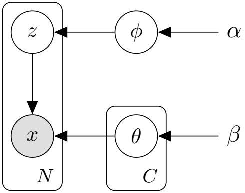

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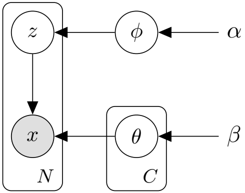

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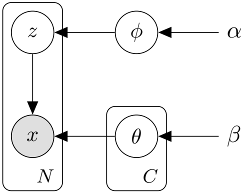

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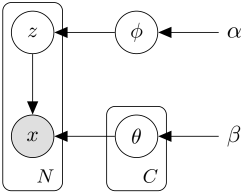

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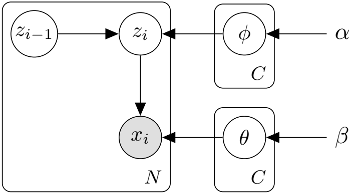
Bayesian HMM



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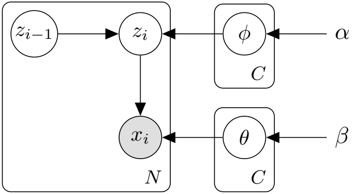

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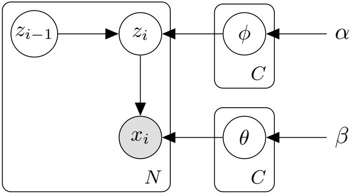

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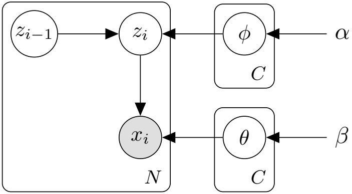

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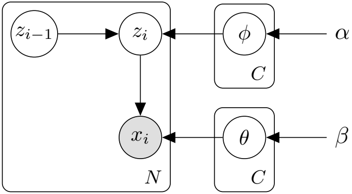

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- applying each of P_k in turn or choosing P_k at random produces a $\mathbf{P}$ that satisfies the necessary conditions

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When we have collected a large number T of samples

- we can summarise the distribution and/or make decisions

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For more, take ML4NLP ;D

References I