

Tutorial: Markov Chain Monte Carlo (MCMC)

Maximum likelihood estimation for Markov chains

- We use MLE to estimate A from data $\mathcal{D} = \{x^{(1)}, \dots, x^{(M)}\}$.
- Likelihood of any particular sentence $x^{(i)}$ of length T_i :

$$p(x^{(i)}|\theta) = \prod_{j=1}^K \pi_j^{\mathbb{1}[x_1^{(i)}=j]} \prod_{t=2}^{T_i} \prod_{j=1}^K \prod_{k=1}^K A_{jk}^{\mathbb{1}[x_t^{(i)}=k, x_{t-1}^{(i)}=j]}$$

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- Log-likelihood of \mathcal{D} (all sentences treated as independent):

$$\log p(\mathcal{D}|\theta) = \sum_{i=1}^N \log p(x^{(i)}|\theta) = \sum_j N_j^1 \log \pi_j + \sum_j \sum_k N_{jk} \log A_{jk}$$

- where we define the counts:

$$N_j^1 = \sum_{i=1}^N \mathbb{1}[x_1^{(i)} = j], \quad N_{jk} = \sum_{i=1}^N \sum_{t=1}^{T_i-1} \mathbb{1}[x_t^{(i)} = j, x_{t+1}^{(i)} = k].$$

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- The MLE is given as:

$$\hat{\pi}_j = \frac{N_j^1}{\sum_j N_j^1}$$

$$\hat{A}_{jk} = \frac{N_{jk}}{\sum_k N_{jk}}.$$