

# Statistical Image Analysis

## Lecture 9: Image segmentation using MRFs

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### Example of discrete MRFs

A general MRF for lattices with first-order neighborhoods:

$$p(\mathbf{z}) = \frac{1}{Z} \exp \left( \sum_i \alpha_{z_i} + \frac{1}{2} \sum_i \sum_{j \in N_i} \beta_{z_i, z_j} \right).$$

Here  $\{\alpha_1, \dots, \alpha_K\}$  determines the prior probabilities for the  $K$  classes and  $\beta_{k,l}$  determines the interaction between class  $k$  and class  $l$ .

Common simplifications include assuming that

$$\beta_{k,l} = \begin{cases} \beta_k & \text{if } l = k \\ 0 & \text{otherwise} \end{cases} \quad \text{or} \quad \beta_{k,l} = \begin{cases} \beta & \text{if } l = k \\ 0 & \text{otherwise} \end{cases}$$

### Markov random field mixture models

- Hierarchical model for pixel values given classes:

$$\pi(\mathbf{Y}_i | z_i = k) \sim \mathbf{N}(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

$$\pi(z_i) = \begin{cases} \pi_1 & \text{if } z_i = 1 \\ \pi_2 & \text{if } z_i = 2 \\ \vdots & \\ \pi_K & \text{if } z_i = K \end{cases}$$

- Assuming independence between the pixels is not realistic!
- In a Markov random field mixture model, we use the model

$$\pi(\mathbf{Y}_i | z_i = k) \sim \mathbf{N}(\boldsymbol{\mu}_k, \boldsymbol{\Sigma}_k)$$

$$\mathbf{z} \sim \pi(\mathbf{z})$$

here  $\mathbf{z} = (z_1, \dots, z_n)$  is a random field that takes values in  $\{1, \dots, K\}$ , with density  $\pi(\mathbf{z})$ .

- Spatial dependencies modeled through  $\pi(\mathbf{z})$ .

### Conditional distributions

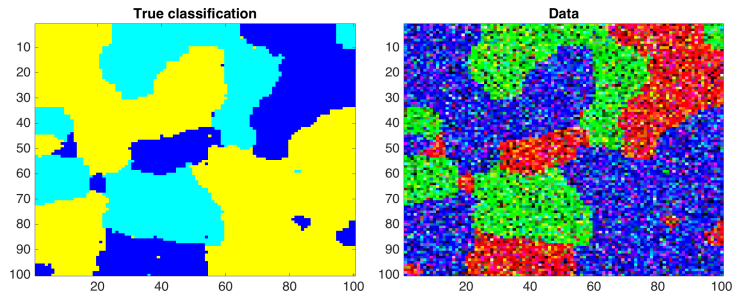
- The normalizing constant  $Z$  is intractable. However, the conditional distributions are simple:

$$p(z_i | \mathbf{z}_{-i}) = \frac{\exp(\alpha_{z_i} + \beta \sum_{j \in N_i} 1(z_j = z_j))}{\sum_k \exp(\alpha_k + \beta \sum_{j \in N_i} 1(z_j = k))}$$

- Since we have simple conditional distributions, we can sample the field using Gibbs sampling.
- Since we cannot compute  $Z$ , likelihood-based inference is difficult.
- A solution to this problem is to instead work with the pseudo-likelihood

$$\pi_p(\mathbf{z}) = \prod_i \pi(z_i | \mathbf{z}_{-i})$$

## Example data



Parameters:

$$\alpha_k = \frac{1}{3} \quad \beta = 2 \quad \Sigma_k = 0.2\mathbf{I}$$

$$\boldsymbol{\mu}_1 = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} \quad \boldsymbol{\mu}_2 = \begin{pmatrix} 0 \\ 1 \\ 0 \end{pmatrix} \quad \boldsymbol{\mu}_3 = \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}$$

