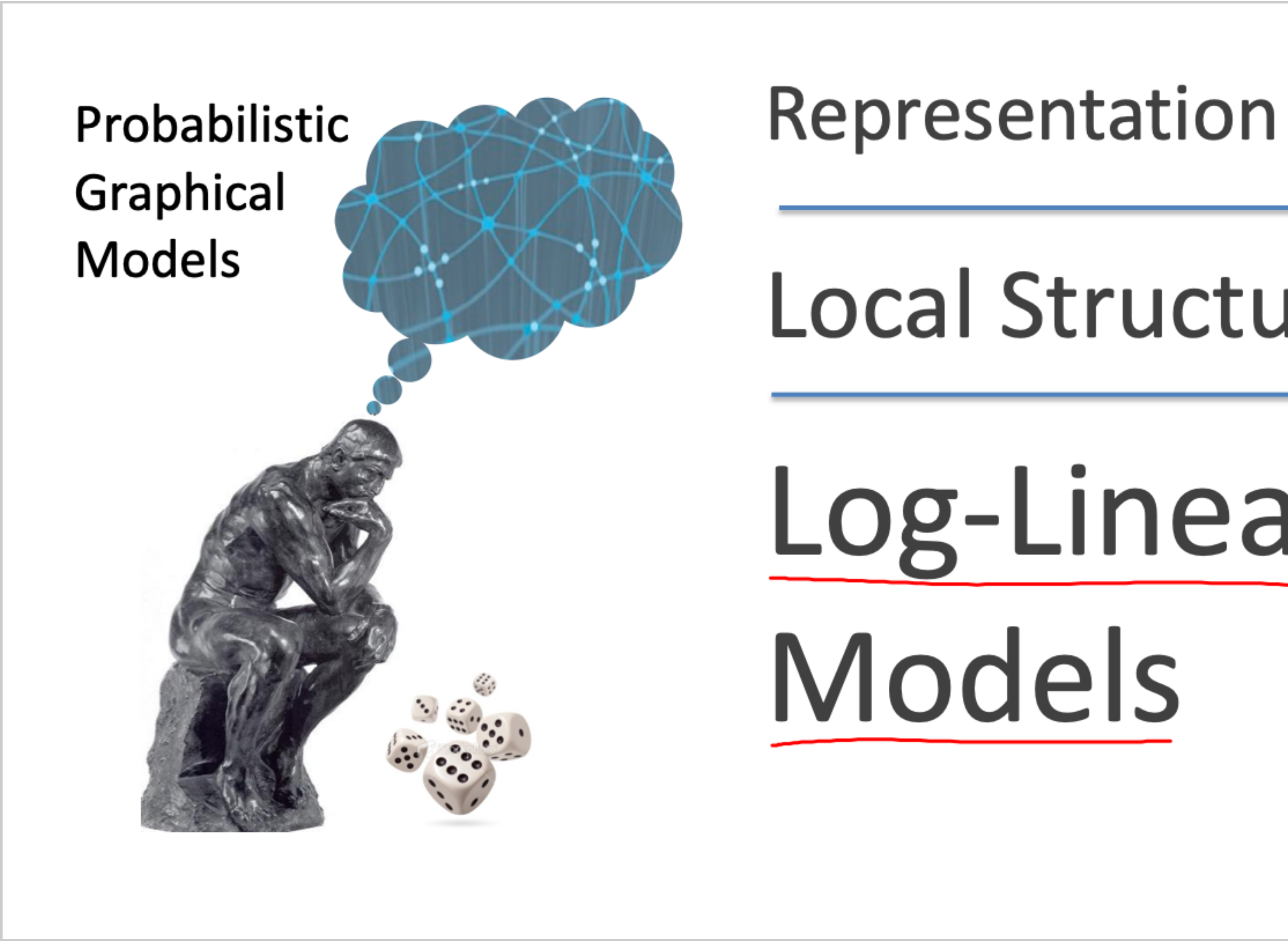
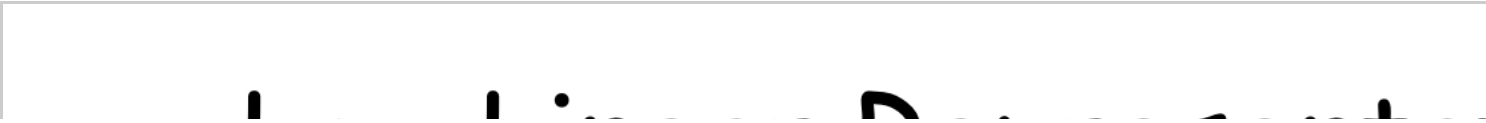
2.4.5-Repn-CPDs-loglinear

Tuesday, September 10, 2019 5:02 PM

2.4.5-Repn-CPDs...





ure

r

Log-Linear Representat

$$\tilde{P} = \prod_i \phi_i(\boldsymbol{D}_i) \Rightarrow \tilde{P} = \exp\left(-\sum_j \underset{\text{coefficie}}{w_j} f$$

$$\tilde{P} = \prod_j \exp\left(-w_j f\right.$$

fa

- Each feature f_j has a scope D_j
- Different features can have sam

Representing Table Fac

$$\phi(X_1, X_2) = \begin{pmatrix} a_{00} & a_{01} \\ a_{10} & a_{11} \end{pmatrix}$$

$$f_{12}^{00} = \mathbb{1}\{X_1 = 0, X$$

$$f_{12}^{01} = \mathbb{1}\{X_1 = 0, X_2$$

$$f_{12}^{10} = \mathbb{1}\{X_1 = 1, X_2$$

$$f_{12}^{11} = \mathbb{1}\{X_1 = 1, X_2$$

General representation

tion

linear

$${}_j(\boldsymbol{D}_j)\Big)$$

features

$${}_j(\boldsymbol{D}_j))$$

ctor

ne scope

tors

$${}_2 = 0\}$$

1

0

$${}_2 = 1\}$$

$${}_2 = 0\}$$

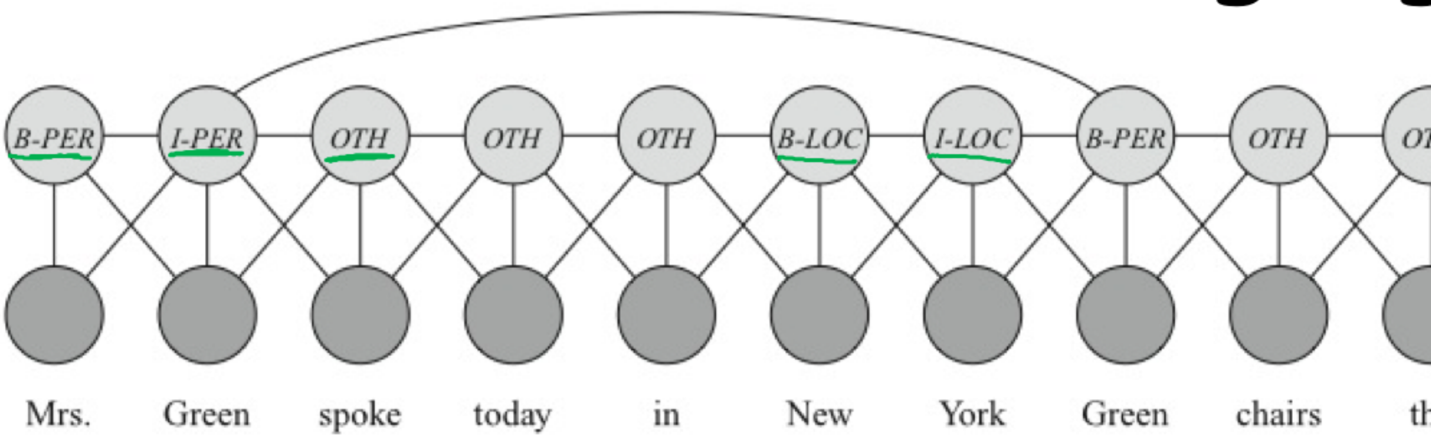
$${}_2 = 1\}$$

$\phi(X_1, X_2) = \exp(-\sum_{kl} w_{kl} f_{ij}^{kl}(X_1$

$w_{kl} = -\log a_{kl}$

exp(-w_{00}) whe
exp(-w_{01}) whe

Features for Languag



Features: word capitalized, word in atlas or name list, pr
"Mrs", next word is "Times", ...

$f(Y_i, X_i) = \mathbb{1}\{Y_i = \text{B person}, X_i \text{ is capitalized}\}$
$\mathbb{1}\{Y_i = \text{B\_loc}, X_i \text{ appears in Atlas}\}$

Ising Model

pai

$E(x_1, \ldots, x_n) = -\sum_{i<j} w_{i,j} \underbrace{x_i x_j}_{} - \sum_i$

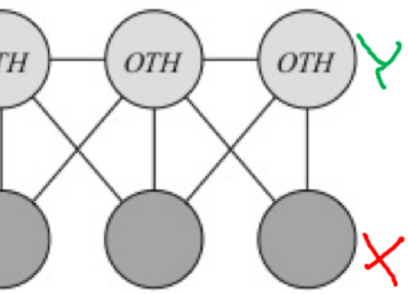
same
different

$${}_1, X_2))$$

n $x_1=0, x_2=0$

n $x_1=0, x_2=$

ge



evious word is

r wise

joint spins

$$u_i x_i$$

$$x_i \in \{-1, +1\} \quad f_{i,j}(X_i, X_j) = X_i \cdot X_j$$

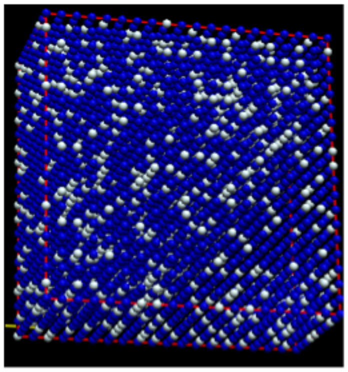
$$P(\boldsymbol{X}) \propto e^{-\frac{1}{T} E(\boldsymbol{X})}$$

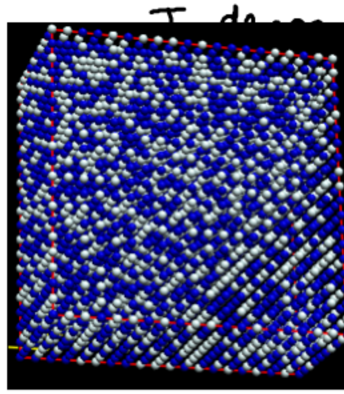
$\frac{w_{ij}}{T} \to 0$

T grows

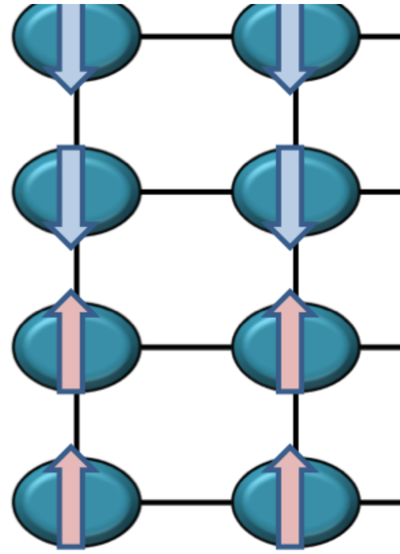
T decreases

low





high T



Metric MRFs

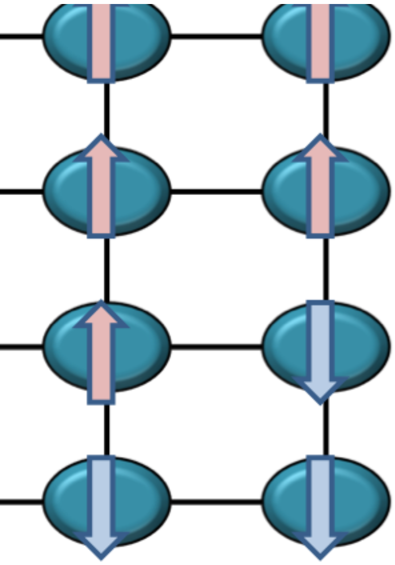
- All X_i take values in label space V

want X_i and X_j to take "similar" values

- Distance function $\mu : V \times V \to R^+$

metric

  - Reflexivity: $\mu(v,v) = 0$ for all v
  - Symmetry: $\mu(v_1,v_2) = \mu(v_2,v_1)$ for all v
  - Triangle inequality: $\mu(v_1,v_2) \leq \mu(v_1,v_3)$ for all v_1, v_2, v_3



v_1, v_2

semi metric

$) + \mu(v_3, v_2)$

Metric MRFs

- All X_i take values in label space V

X_i — X_j → want X_i and X_j to take "similar" values

- Distance function $\mu : V \times V \rightarrow R$

$$\underbrace{f_{i,j}(X_i, X_j)} = \mu(X_i, X_j)$$

lower

$$\underbrace{\exp\left(-w_{ij} f_{ij}(X_i, X_j)\right)} \qquad w_{ij} > 0$$

w_{ij}

highe

values of X_i and X_j far in μ → lower probab

Metric MRF Example

$$\mu(v_k, v_l) = \begin{cases} 0 & v_k = v_l \\ 1 & \text{otherwise} \end{cases}$$

$$\begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix}$$

$|v_k - v_l|$

distance

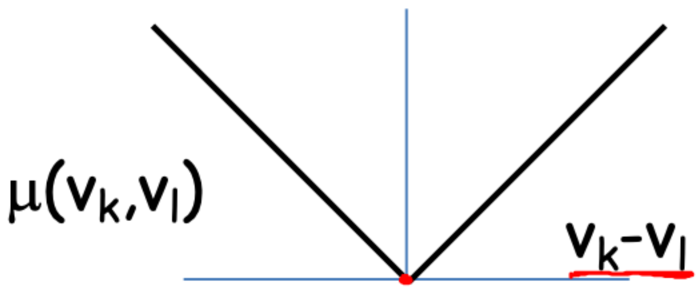
r

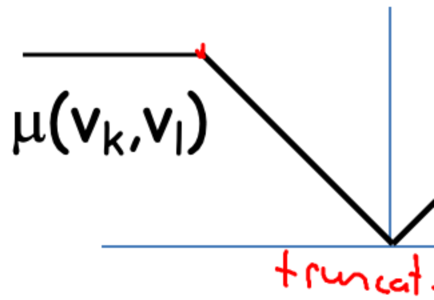
igher probability

ility

es

$$\begin{matrix} 1 & 1 \\ 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{matrix}\Bigg)$$

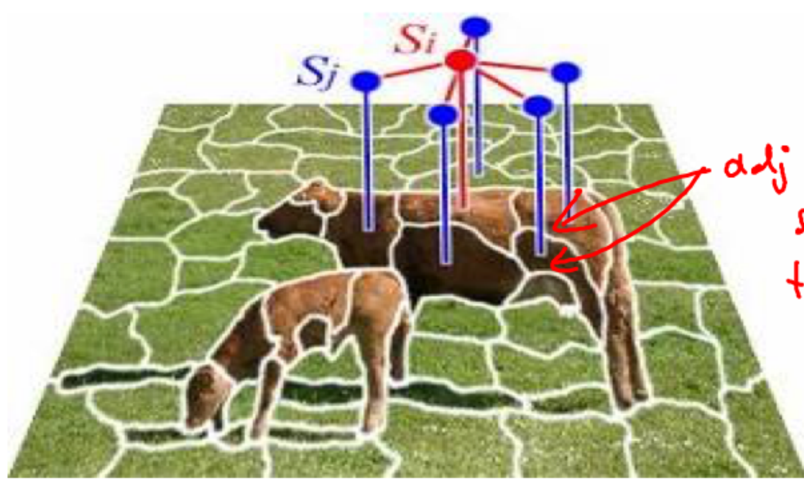




Metric MRF: Segmenta

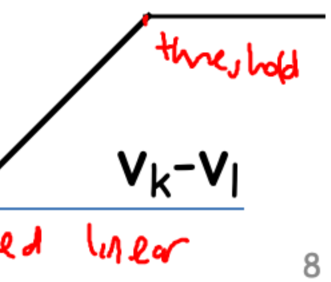
$$\mu(v_k,v_l) = \begin{cases} 0 & v_k = v_l \\ 1 & \text{otherwise} \end{cases}$$

$$\begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \\ 1 & 1 & 0 \\ 1 & 1 & 1 \end{pmatrix}$$



adjacent superpixels take same class

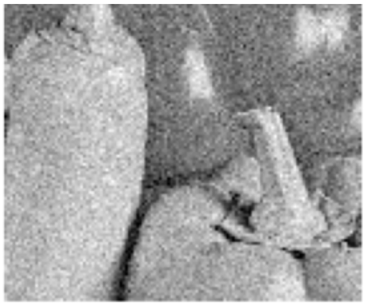
Metric MRF: Denoisin

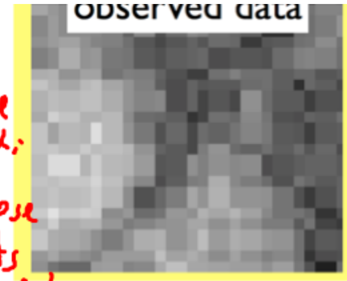


tion

$$\begin{matrix} 1 & 1 \\ 1 & 1 \\ 0 & 1 \\ 1 & 0 \end{matrix}\Bigg)$$

ng





Y_i close to X_i

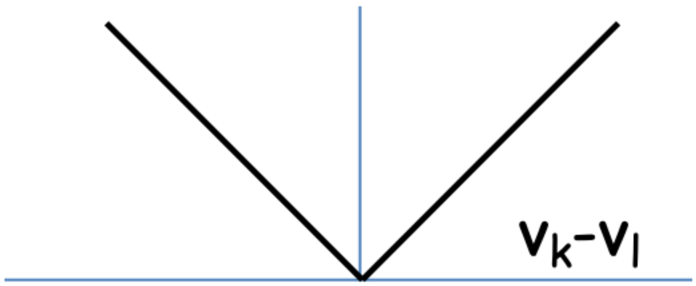
Y_i close to its neighbors

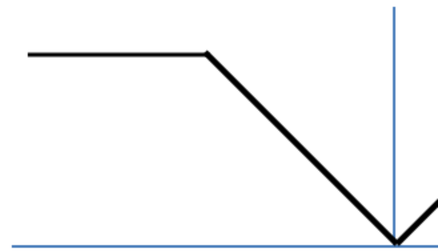
X noisy pixels

Y clean pixels

$\mu(v_k,v_l) = |v_k-v_l|$

$\mu(v_k,v_l) = \text{max}$





Similar idea for stereo reconstruction

$k(|v_k-v_l|,d)$