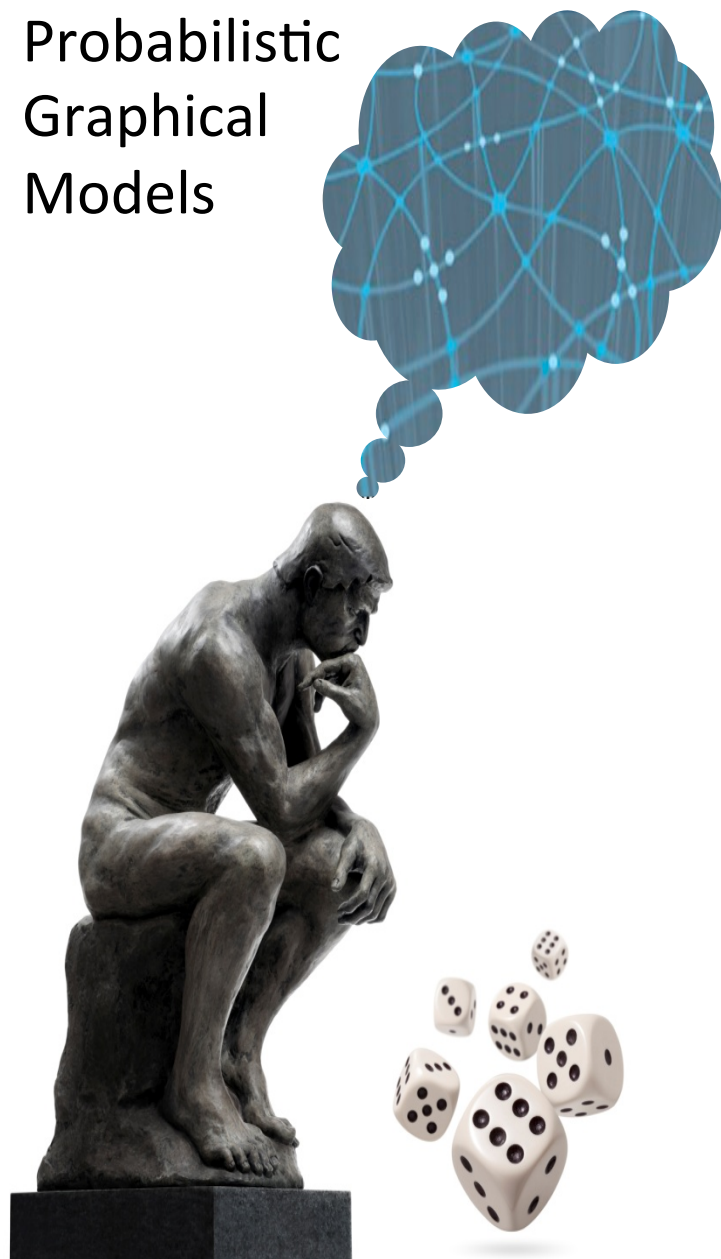


Probabilistic  
Graphical  
Models



Inference

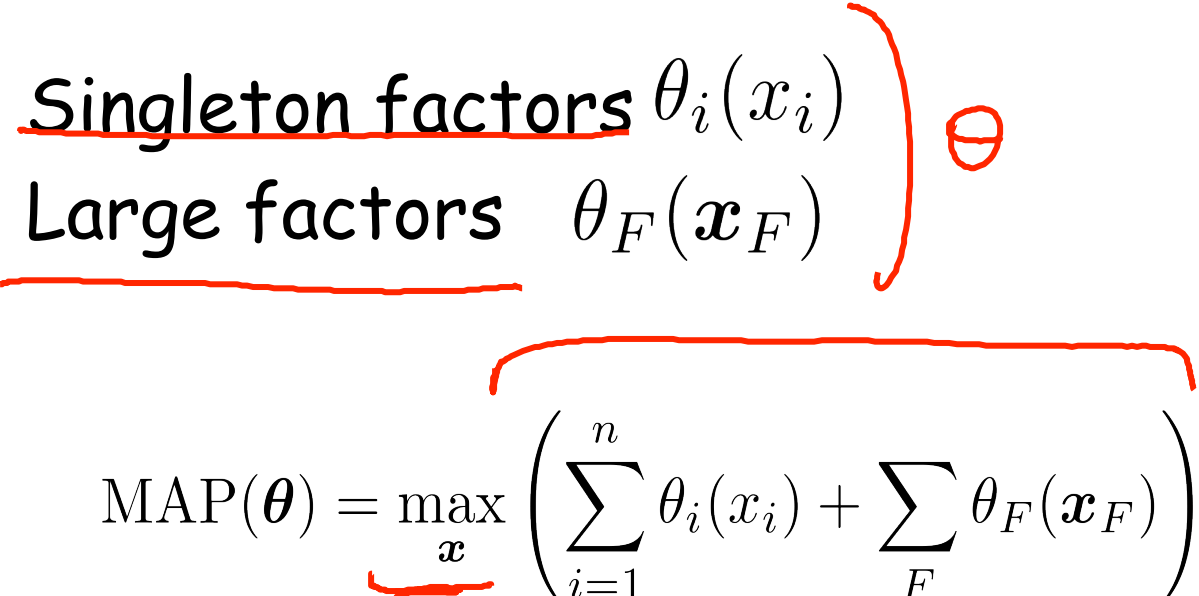
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MAP

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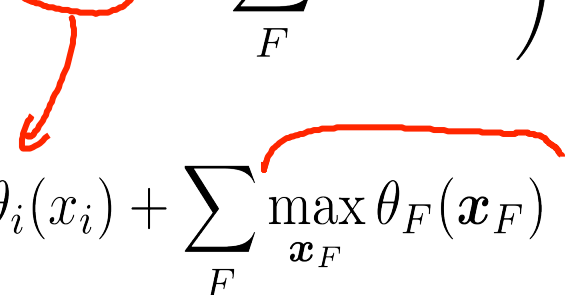
Dual  
Decomposition

# Problem Formulation

- Singleton factors  $\theta_i(x_i)$
  - Large factors  $\theta_F(\mathbf{x}_F)$
- 

$$\text{MAP}(\boldsymbol{\theta}) = \max_{\mathbf{x}} \left( \sum_{i=1}^n \theta_i(x_i) + \sum_F \theta_F(\mathbf{x}_F) \right)$$

# Divide and Conquer

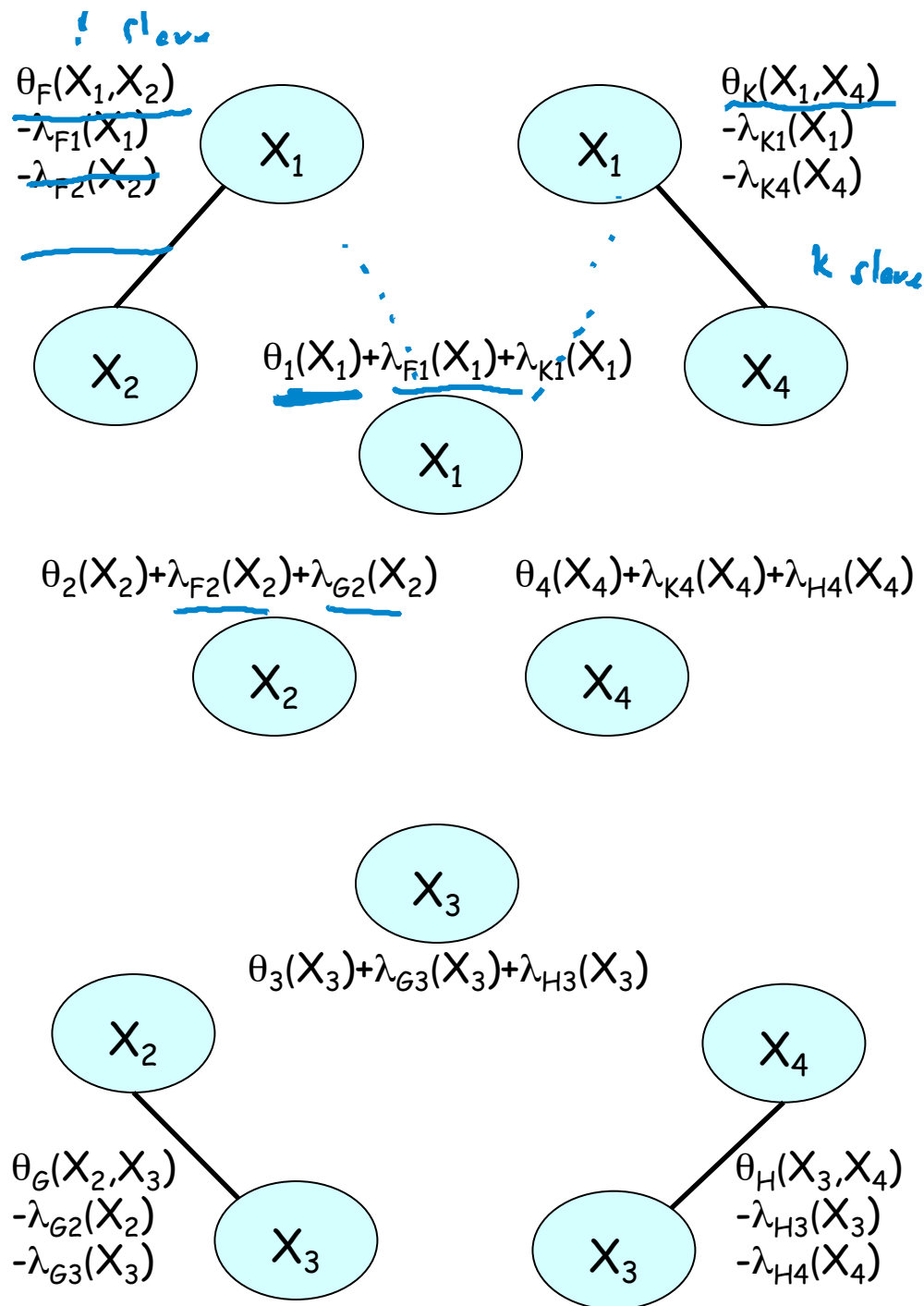
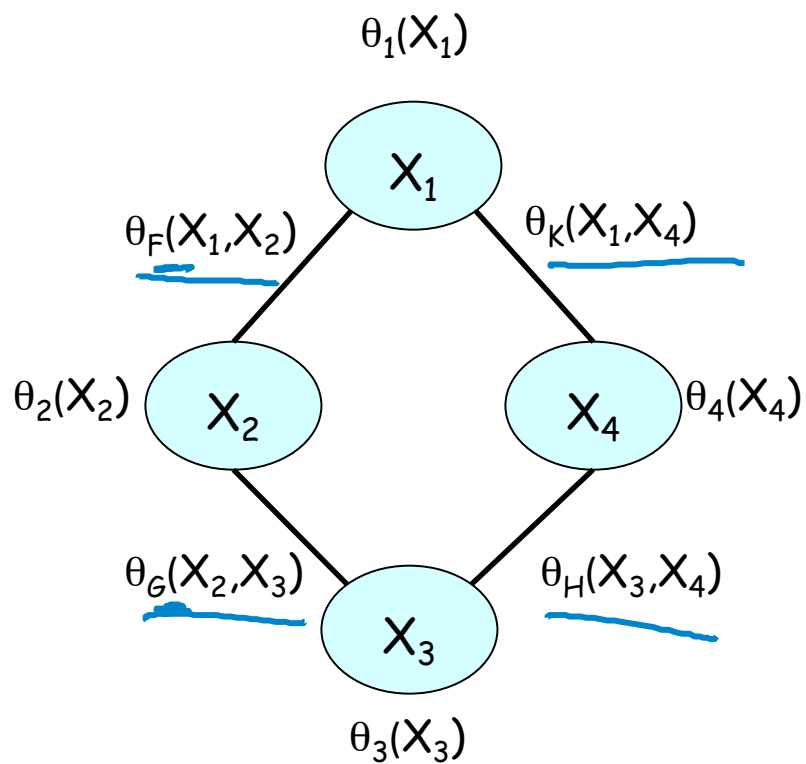
$$\text{MAP}(\boldsymbol{\theta}) = \max_{\boldsymbol{x}} \left( \sum_{i=1}^n \theta_i(x_i) + \sum_F \theta_F(\boldsymbol{x}_F) \right)$$
$$\sum_{i=1}^n \max_{x_i} \theta_i(x_i) + \sum_F \max_{\boldsymbol{x}_F} \theta_F(\boldsymbol{x}_F)$$
A red arrow points from the term  $\theta_i(x_i)$  in the first equation to the  $\max_{x_i} \theta_i(x_i)$  term in the second equation. A red bracket is placed over the  $\max_{\boldsymbol{x}_F} \theta_F(\boldsymbol{x}_F)$  term in the second equation.

*local decision making*

# Divide and Conquer

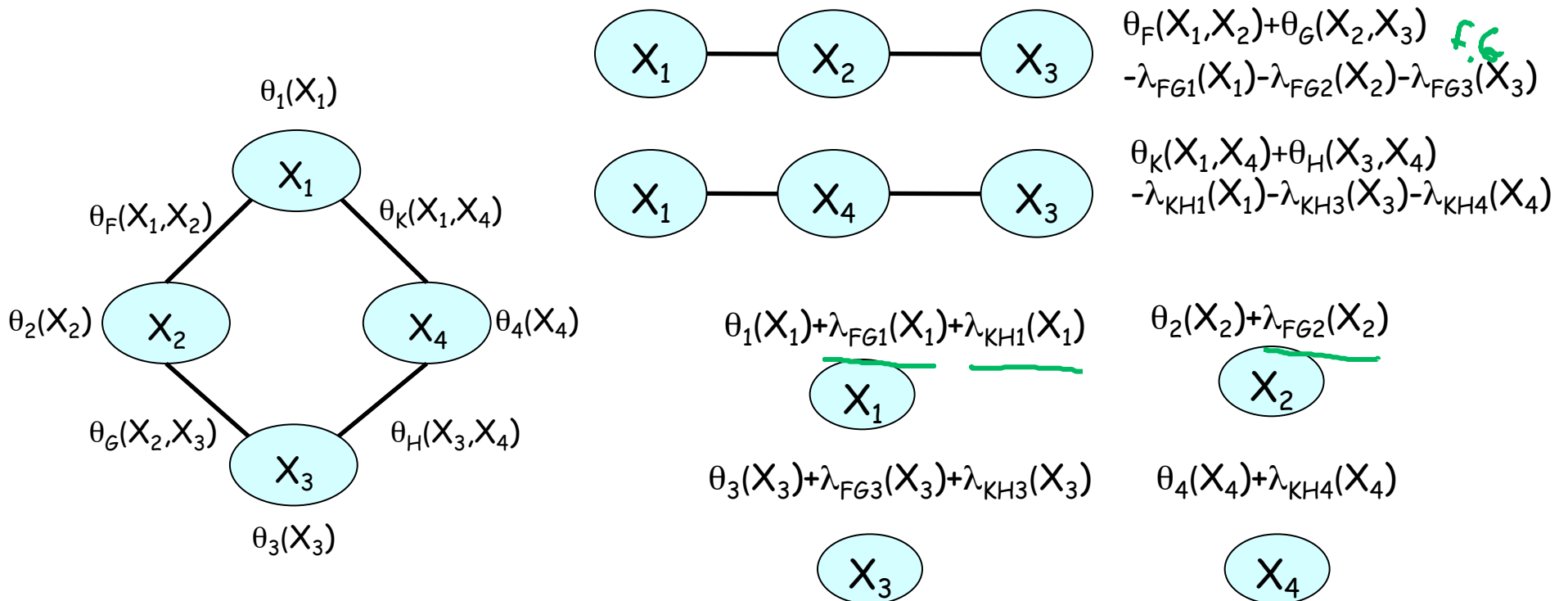
$$\begin{aligned}
 \text{MAP}(\boldsymbol{\theta}) &= \max_{\mathbf{x}} \left( \sum_{i=1}^n \theta_i(x_i) + \sum_F \theta_F(\mathbf{x}_F) \right) \\
 &= \max_{\mathbf{x}} \left( \sum_{i=1}^n (\underbrace{\theta_i(x_i)}_{i \text{ slave}} + \underbrace{\sum_{F:i \in F} \lambda_{Fi}(x_i)}_{i \in F}) + \sum_F (\underbrace{\theta_F(\mathbf{x}_F)}_{f \text{ slave}} - \underbrace{\sum_{i \in F} \lambda_{Fi}(x_i)}_{\substack{\text{agree} \\ \text{with } i \text{ slaves}}}) \right) \\
 &\quad \text{messages between } f \text{ and } i \\
 L(\boldsymbol{\lambda}) &= \sum_{i=1}^n \max_{x_i} \left( \theta_i(x_i) + \sum_{F:i \in F} \lambda_{Fi}(x_i) \right) + \sum_F \max_{\mathbf{x}_F} \left( \theta_F(\mathbf{x}_F) - \sum_{i \in F} \lambda_{Fi}(x_i) \right) \\
 &\quad \bar{\theta}_i^\lambda \qquad \bar{\theta}_F^\lambda
 \end{aligned}$$

$L(\boldsymbol{\lambda})$  is upper bound on MAP( $\boldsymbol{\theta}$ ) for any setting of  $\boldsymbol{\lambda}$ 's



# Divide and Conquer

- Slaves don't have to be factors in original model
  - Subsets of factors that admit tractable solution to local maximization task



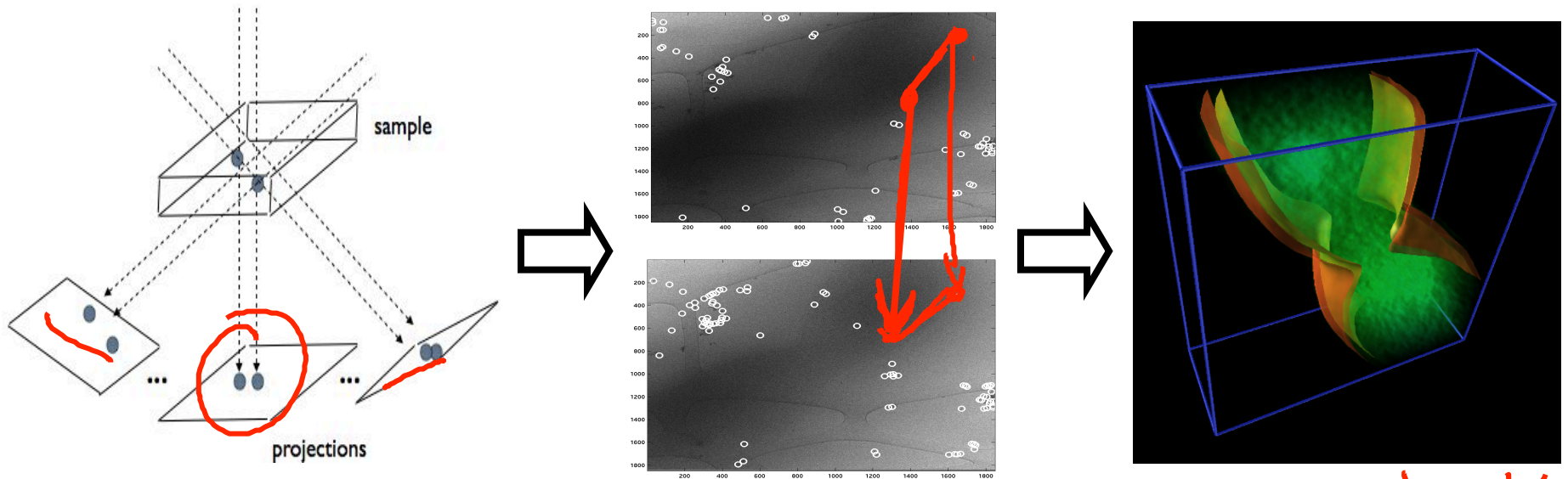
# Divide and Conquer

- In pairwise networks, often divide factors into set of disjoint trees
  - Each edge factor assigned to exactly one tree
- Other tractable classes of factor sets
  - Matchings
  - Associative models
  - ...

# Example: 3D Cell Reconstruction

correspond tilt  
images

compute 3D  
reconstruction



- Matching weights: similarity of location and local neighborhood appearance
- Pairwise potentials: approximate preservation of relative marker positions across images

Duchi, Tarlow, Elidan, and Koller, NIPS 2006. Amat, Moussavi, Comolli, Elidan, Downing, Horowitz, Journal of Structural Biology, 2006.