

# Neural networks

Conditional random fields - Markov network

# LINEAR CHAN CRF

**Topics:** factor, sufficient statistic

- With hidden units, the CRF factors could be:

$$\Psi_f(\mathbf{y}, \mathbf{X}) = \begin{cases} \phi_f(y_k, \mathbf{x}_{k-1}) = \exp(a^{(L+1, -1)}(\mathbf{x}_{k-1})_{y_k}) \\ \phi_f(y_k, \mathbf{x}_k) = \exp(a^{(L+1, 0)}(\mathbf{x}_k)_{y_k}) \\ \phi_f(y_k, \mathbf{x}_{k+1}) = \exp(a^{(L+1, +1)}(\mathbf{x}_{k+1})_{y_k}) \\ \phi_f(y_k, y_{k+1}) = \exp(V_{y_k, y_{k+1}}) \end{cases}$$

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unary factors

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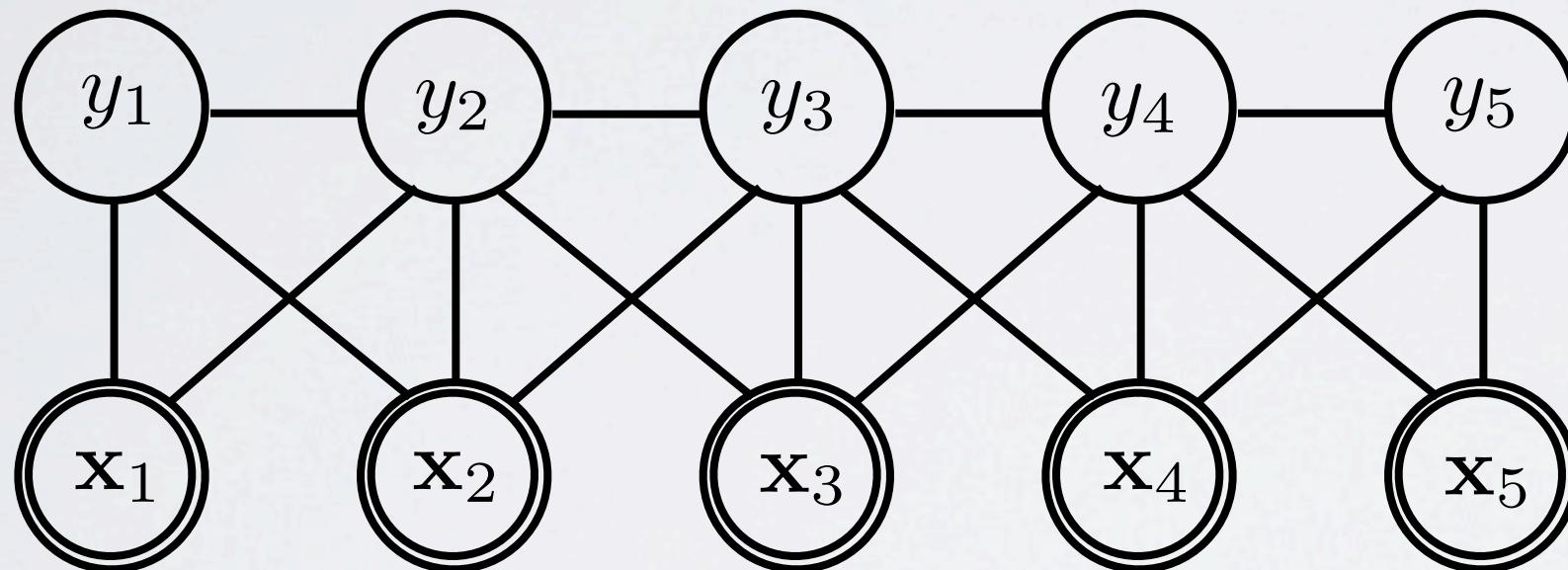
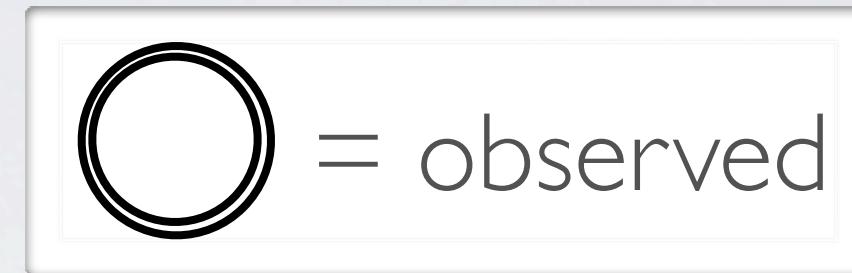
$$\Psi_f(\mathbf{y}, \mathbf{X}) = \begin{cases} \text{unary factors} \\ \phi_f(y_k, \mathbf{x}_{k-1}) = \exp(a^{(L+1, -1)}(\mathbf{x}_{k-1})_{y_k}) \\ \phi_f(y_k, \mathbf{x}_k) = \exp(a^{(L+1, 0)}(\mathbf{x}_k)_{y_k}) \\ \phi_f(y_k, \mathbf{x}_{k+1}) = \exp(a^{(L+1, +1)}(\mathbf{x}_{k+1})_{y_k}) \\ \phi_f(y_k, y_{k+1}) = \exp(V_{y_k, y_{k+1}}) \\ \text{pairwise factors} \end{cases}$$

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# MARKOV NETWORK VISUALIZATION

**Topics:** Markov network

- Illustration for  $K=5$

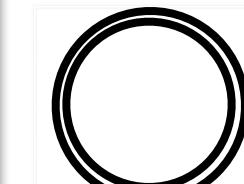


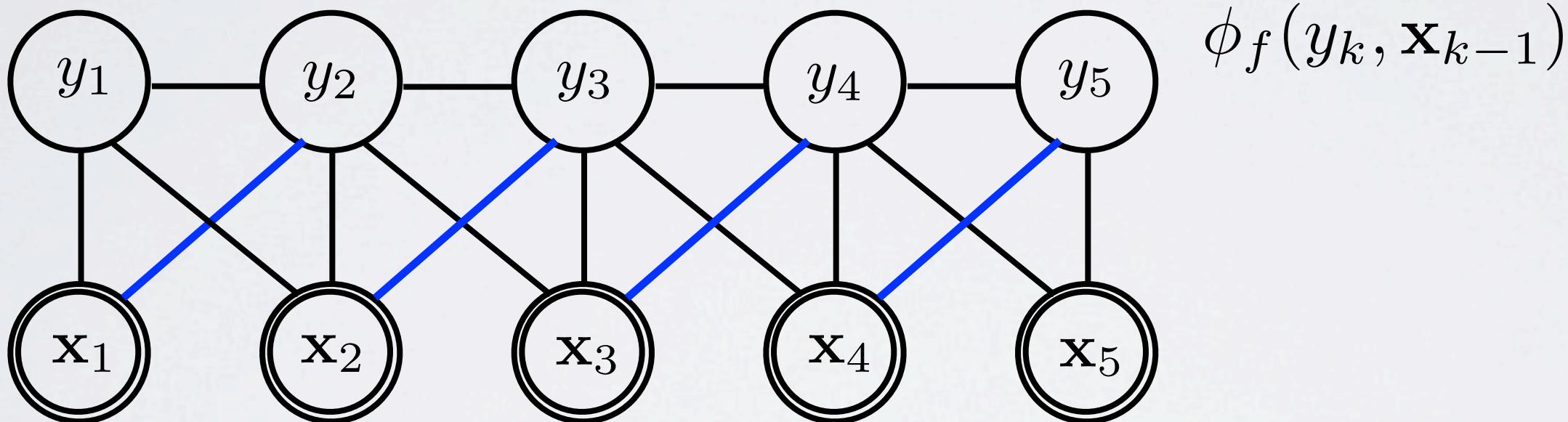
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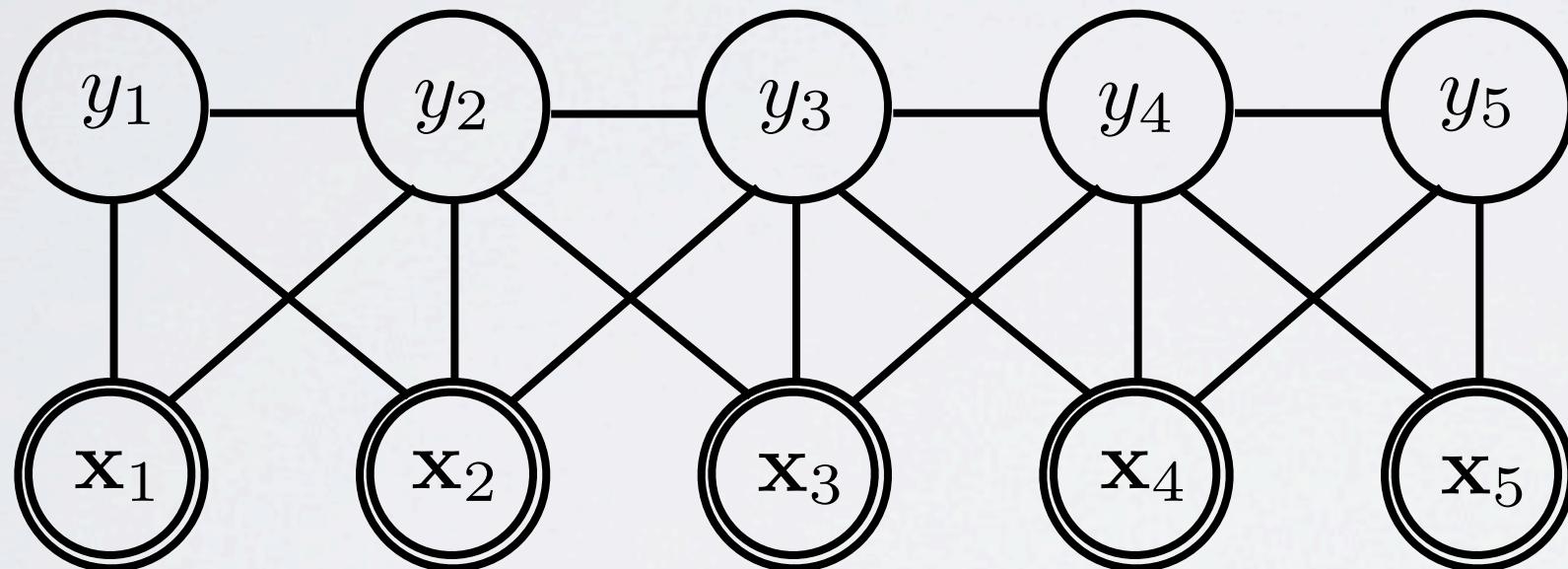
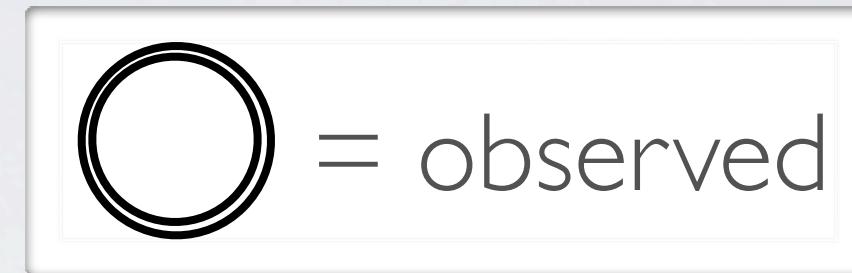


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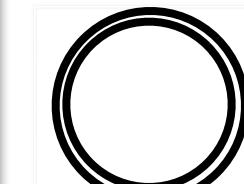


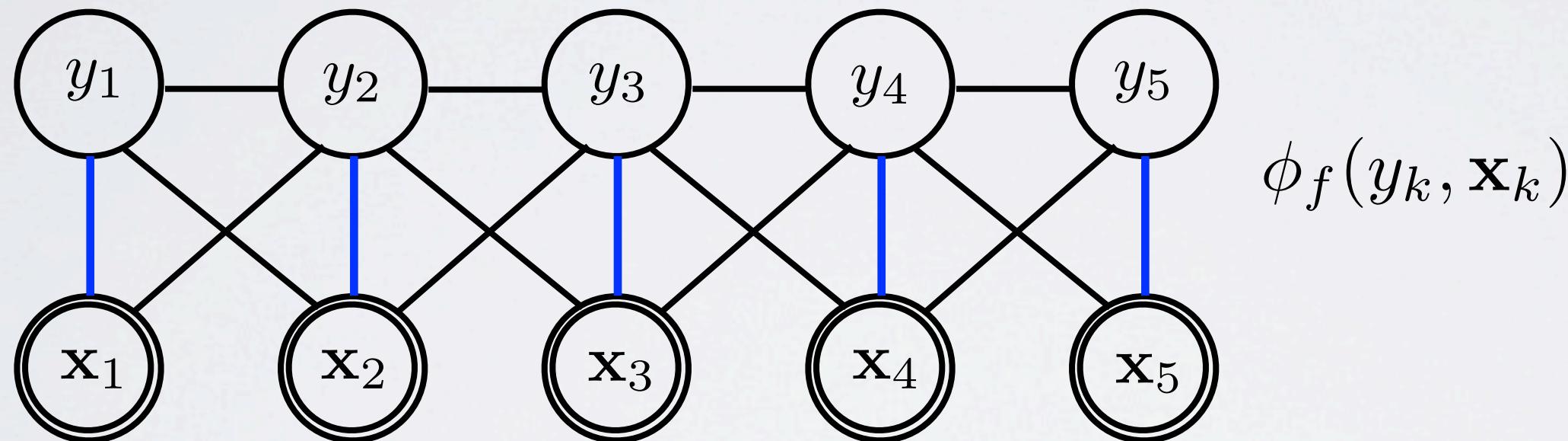
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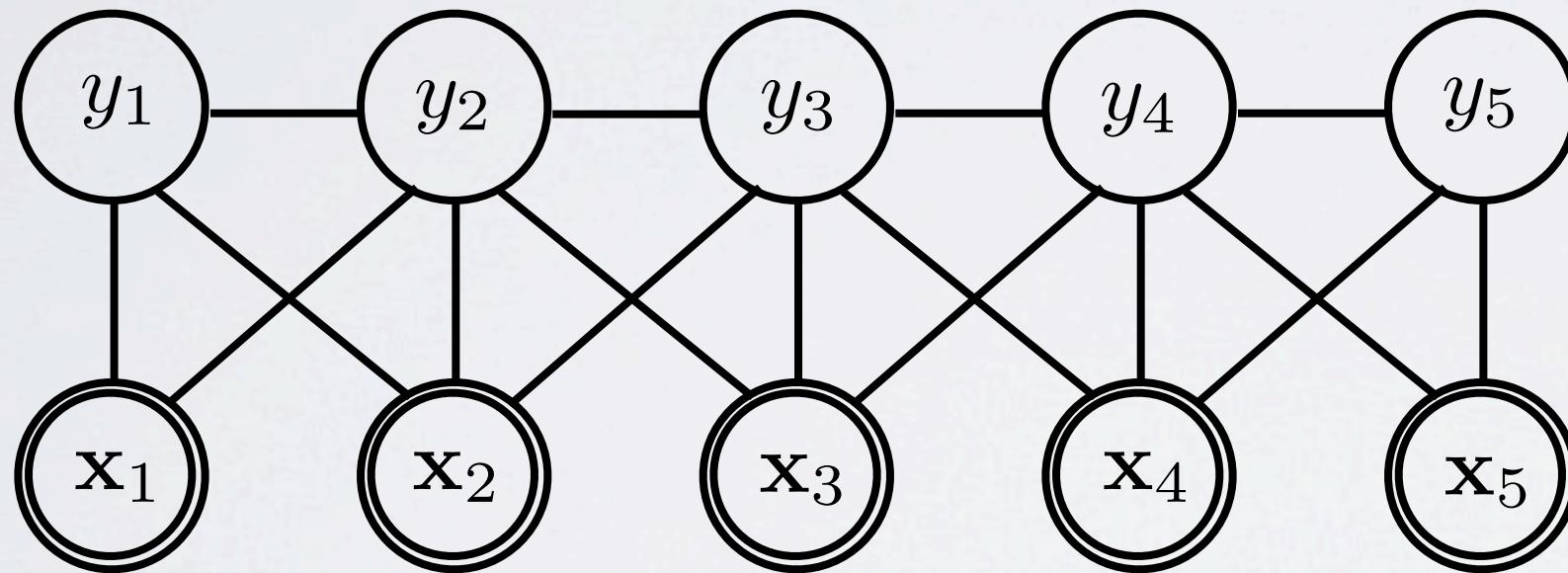
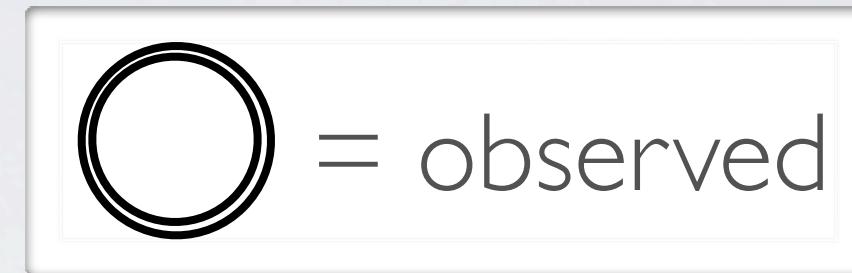


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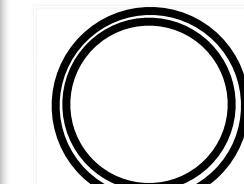


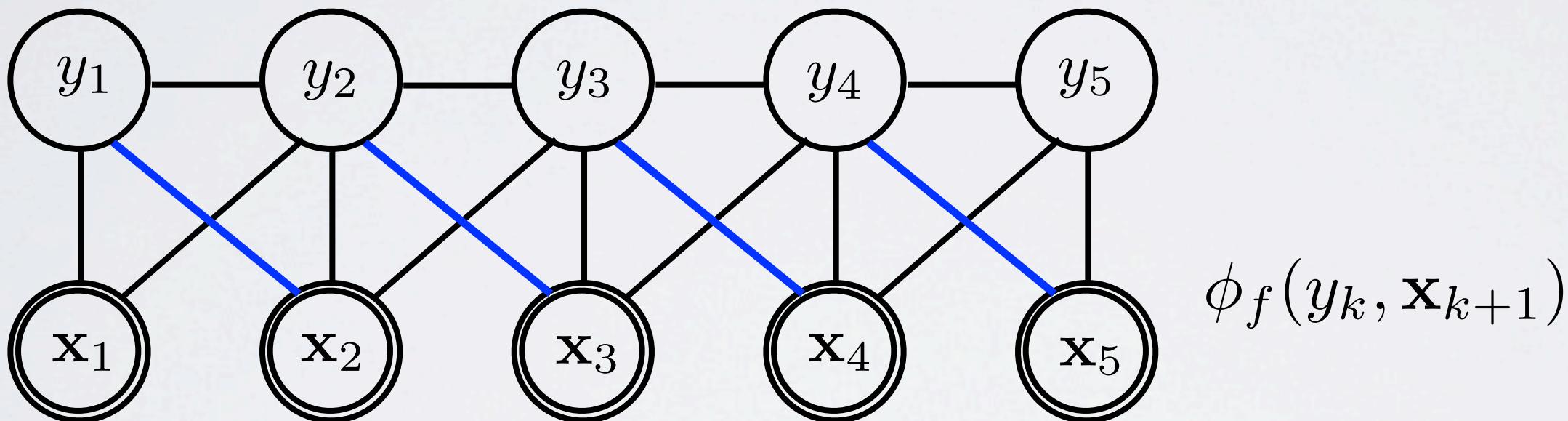
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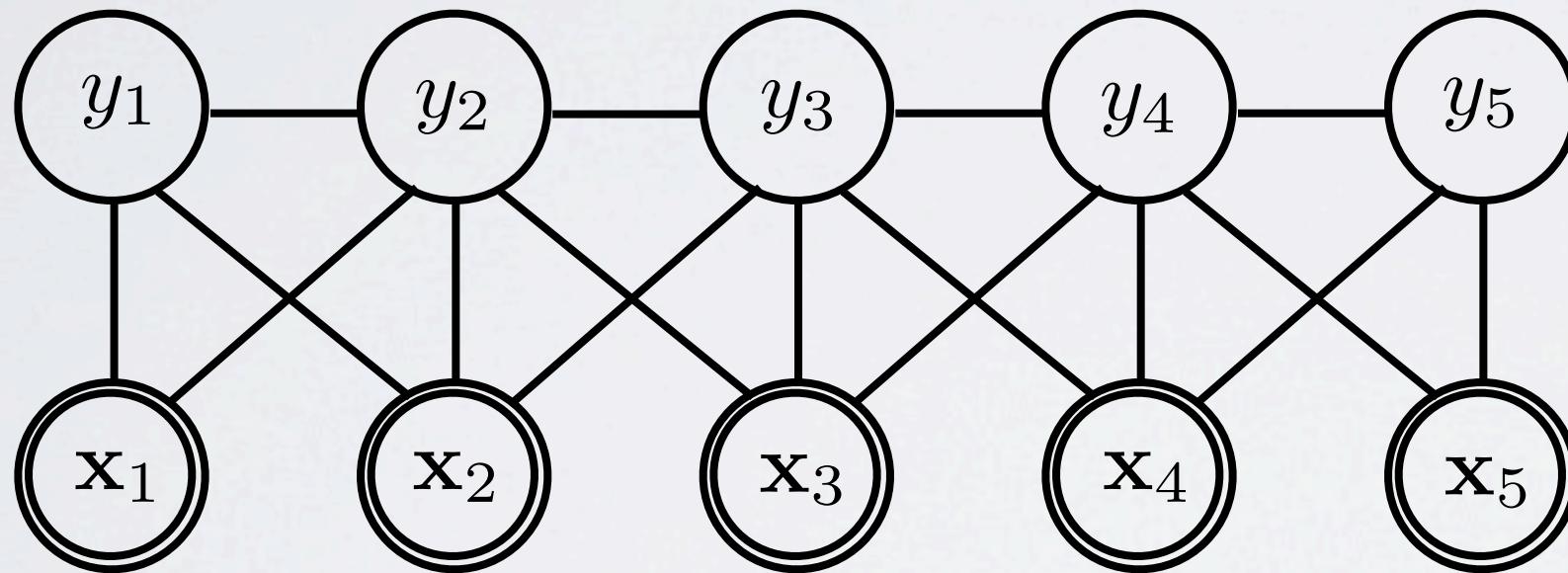
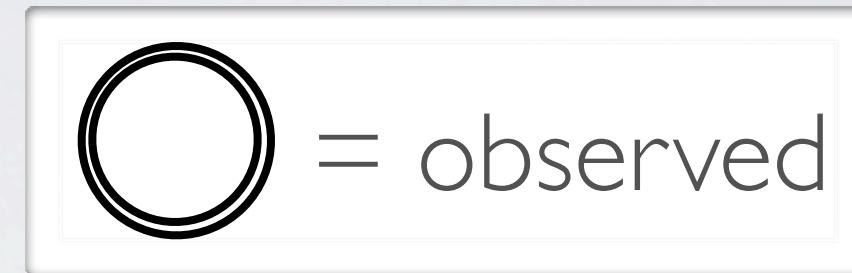


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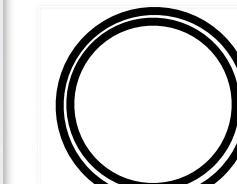


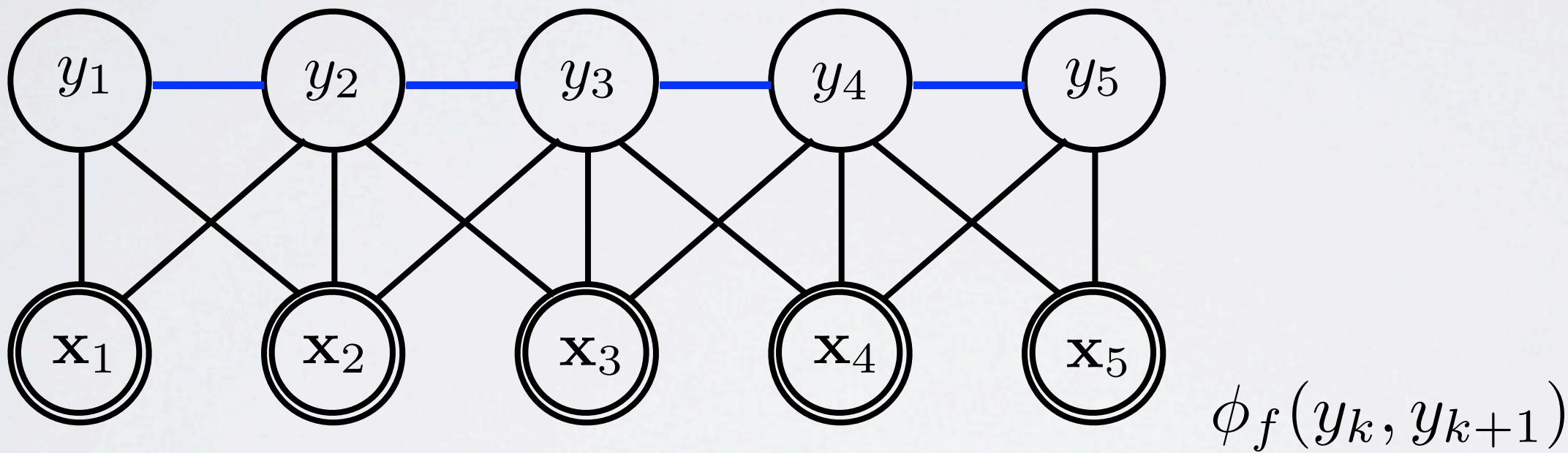
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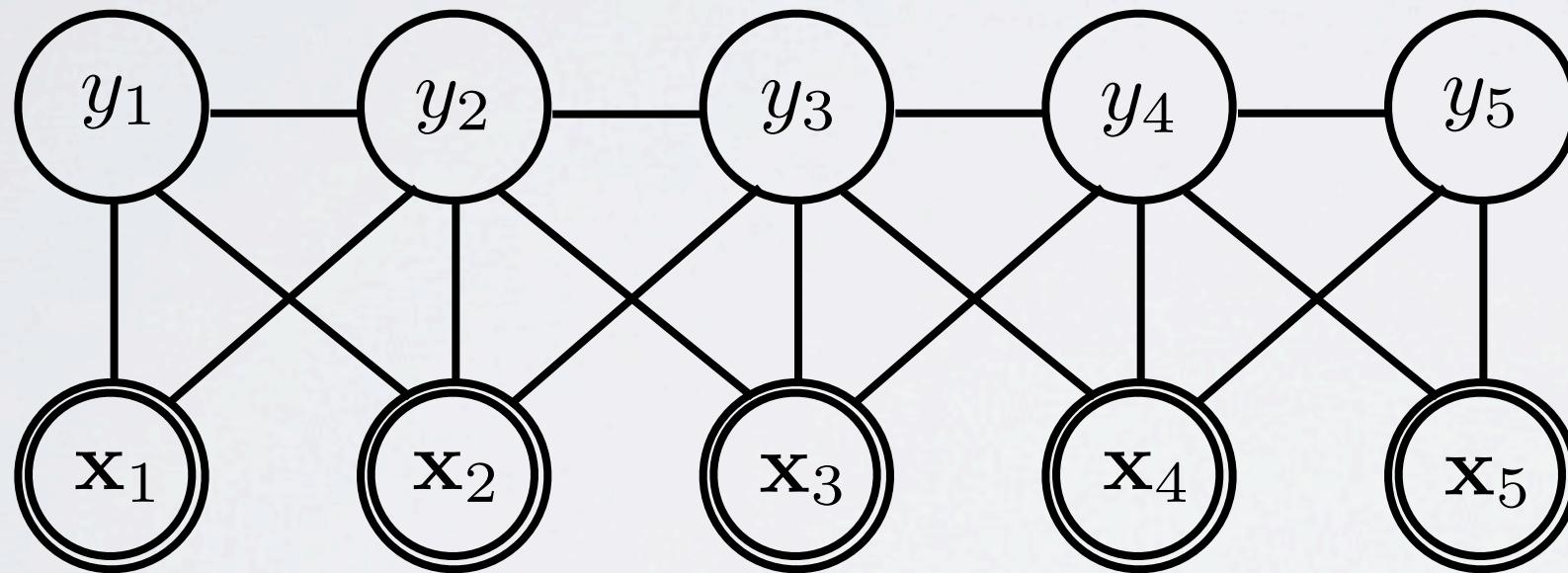
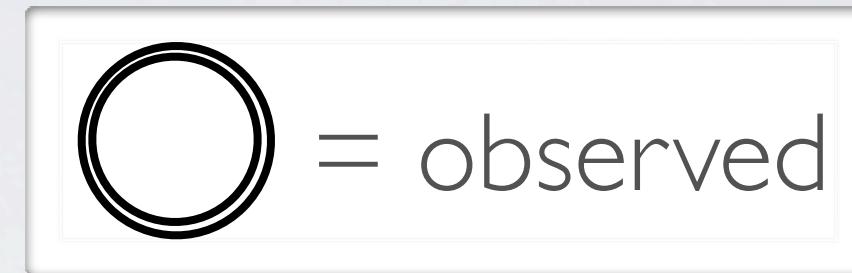


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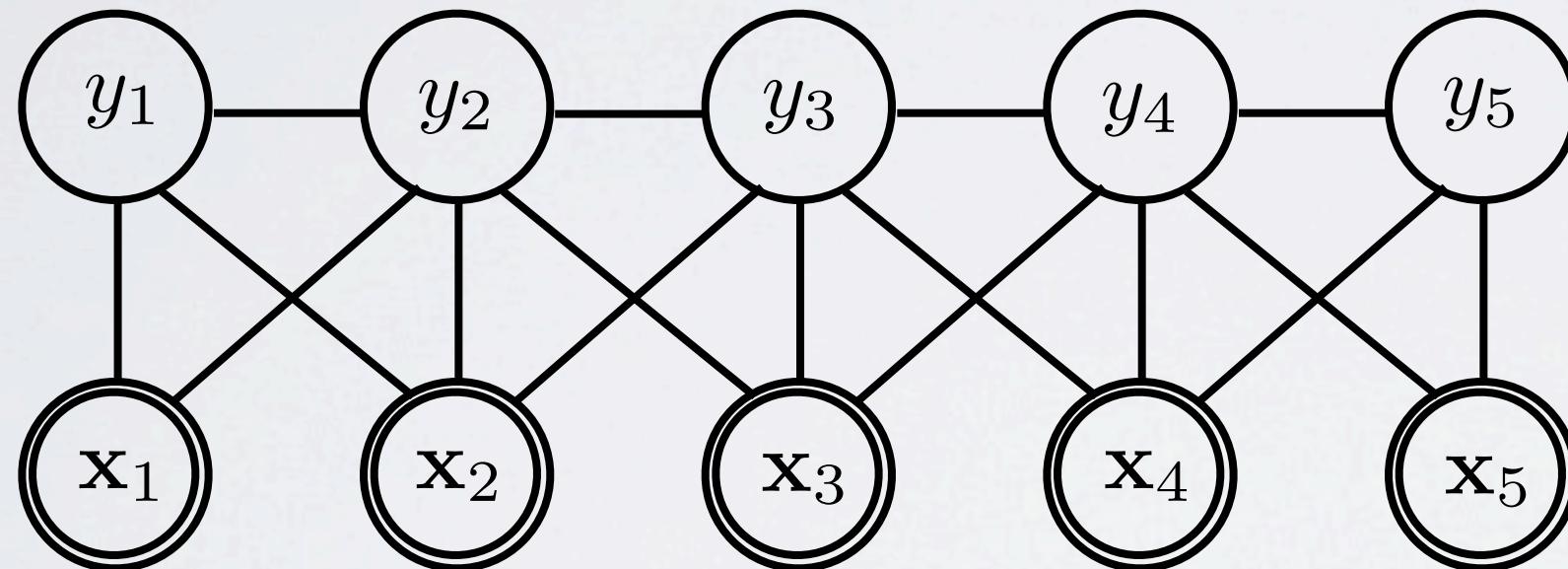
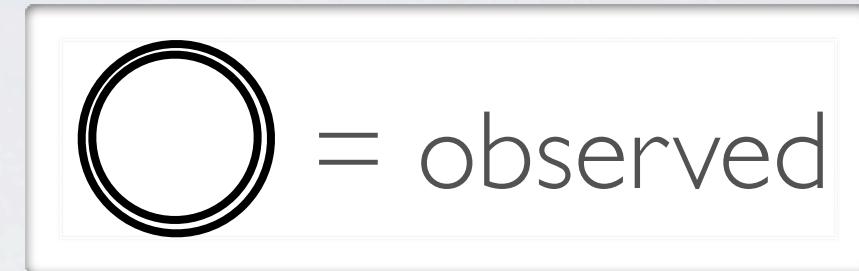


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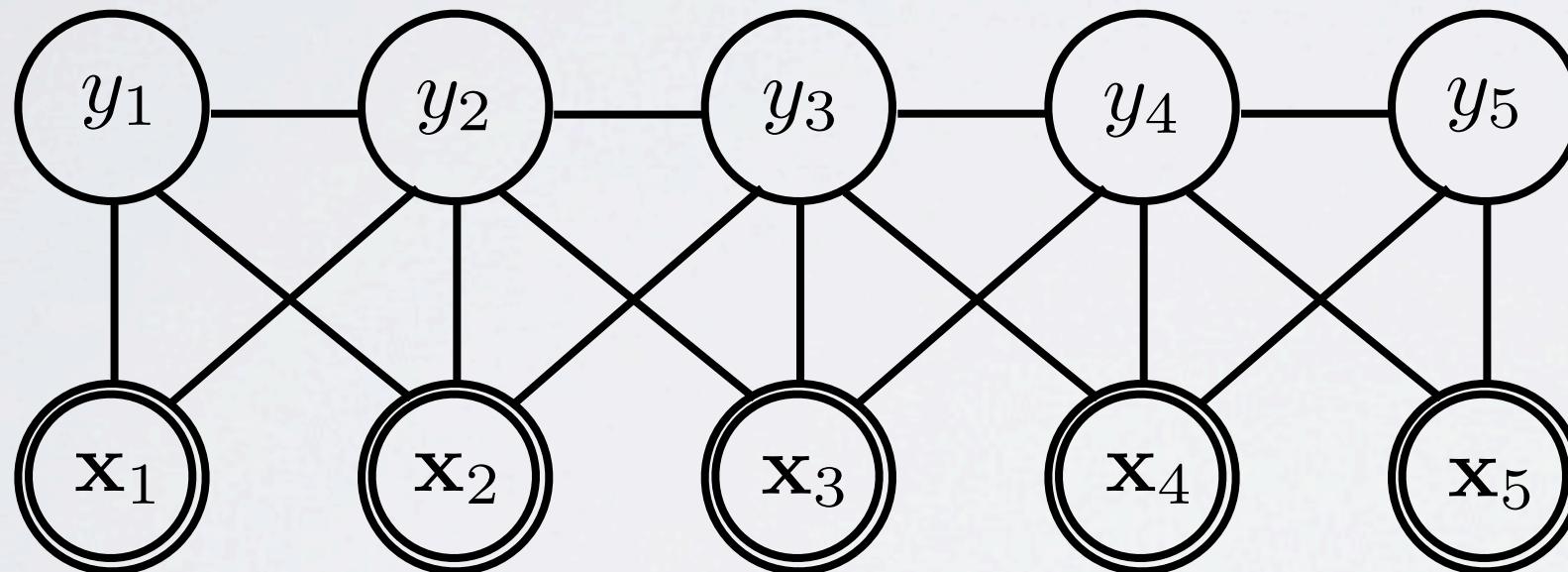
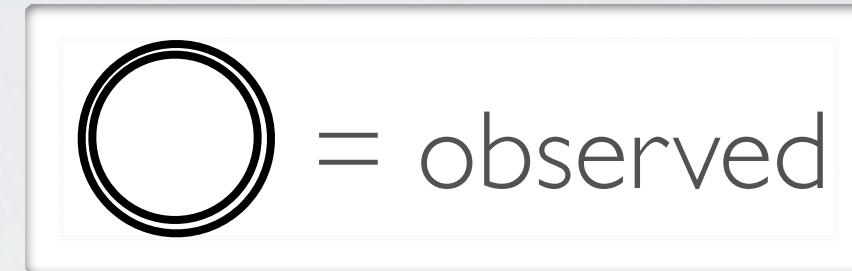


- Local Markov property
  - ▶ each node is independent of other nodes **given** its neighbors

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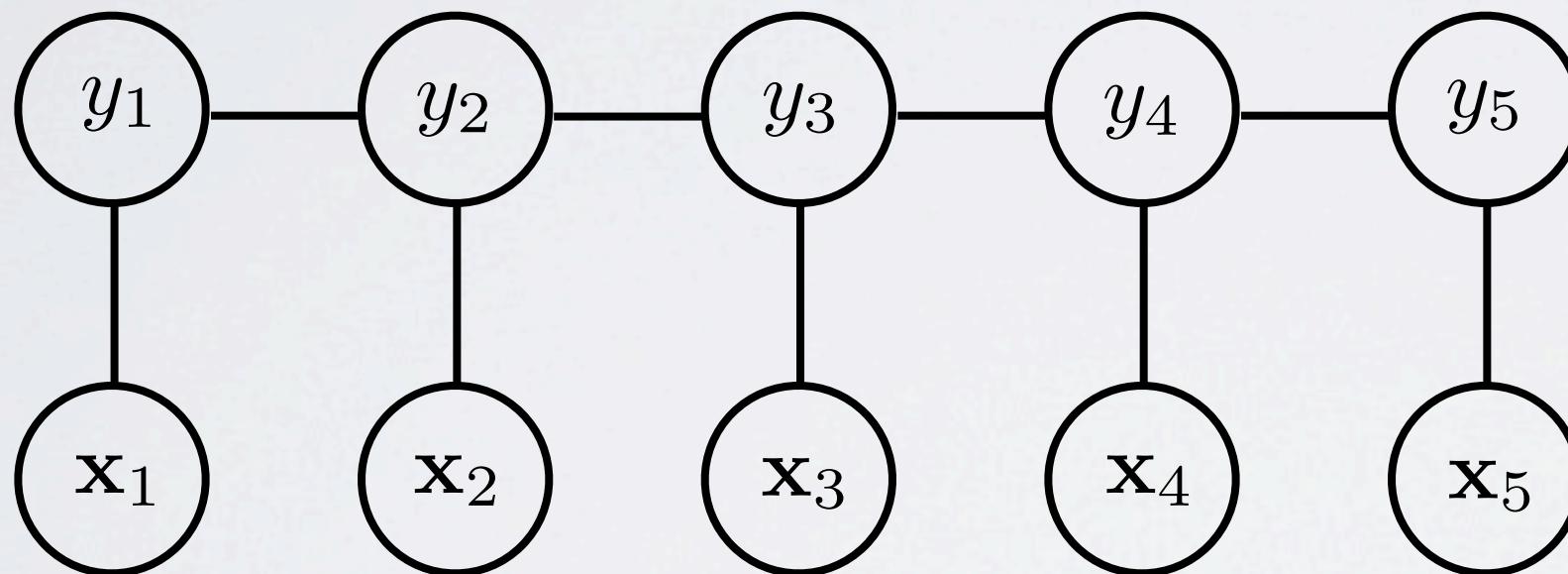


- General conditional independence
  - ▶ two nodes are conditionally independent if all paths between them contain at least one of the conditioning node

# DIRECTED VS. UNDIRECTED

**Topics:** undirected graphical model, directed graphical model

- CRF is an undirected graphical model

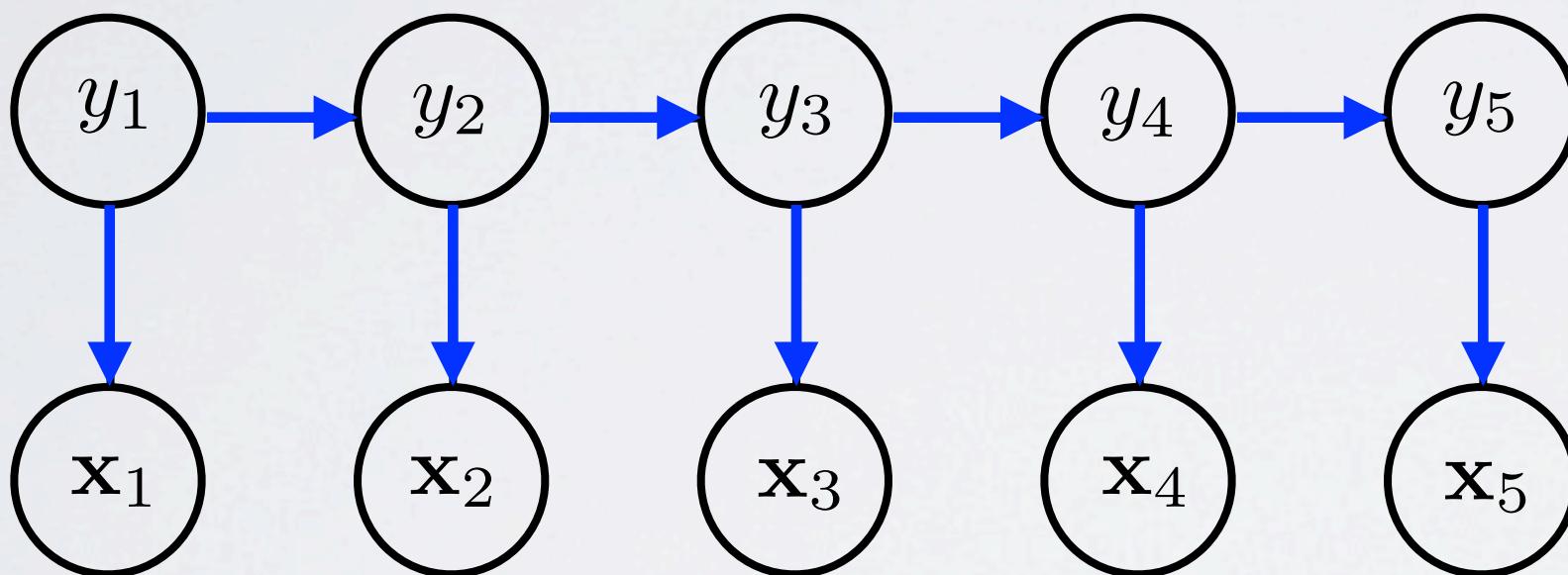


$$\left. \begin{array}{l} \phi_f(y_k, \mathbf{x}_k) \\ \phi_f(y_k, y_{k+1}) \end{array} \right\} \text{only need to be non-negative}$$

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- HMM is a directed graphical model



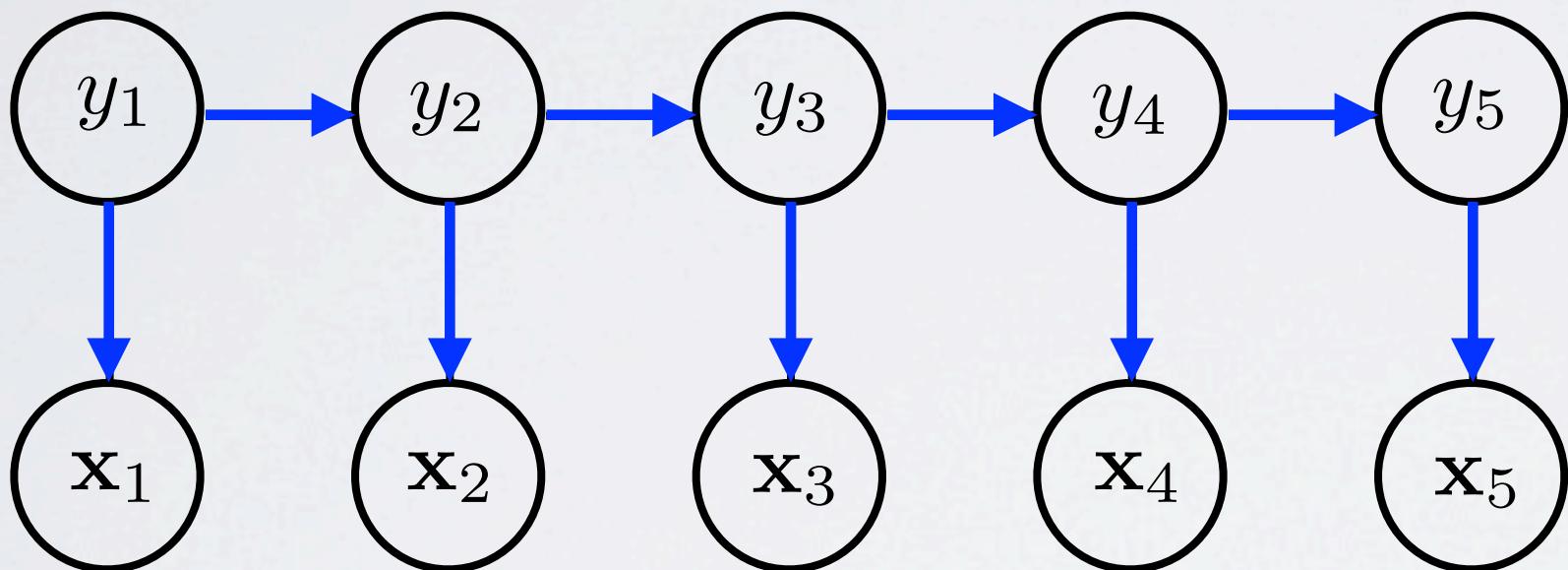
$$\phi_f(y_k, \mathbf{x}_k)$$

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$$\phi_f(y_k, \mathbf{x}_k) = p(\mathbf{x}_k | y_k)$$

$$\phi_f(y_k, y_{k+1}) = p(y_{k+1} | y_k)$$