Graphical models:

- we have, in fact, been manipulating a probability model.
- There is value in seeing the model.
- Write X_i for a set of discrete random variables
- Obtain a graph $(V_i, E) = G$

each vertex is associated w/ an R.V.

- if the joint distribution

$$P(X_1 = x_a, X_2 = x_b, \ldots X_n = x_n)$$

can be factored as

$$P(X_1 = x_a, \ldots) = \prod_{C \in cl(G)} \varphi_c(X_c)$$

cliques

vars in a clique

Then

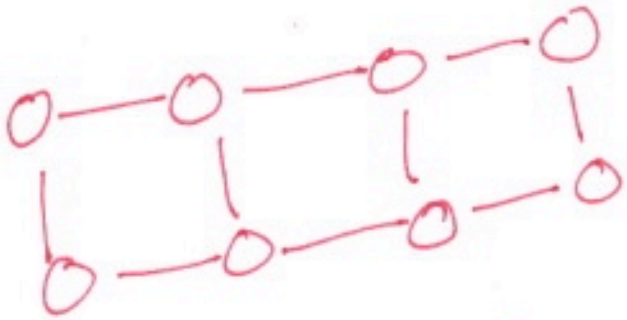
X is a Markov Random Field wrt G

(There are other kinds of MRF - we don't care)

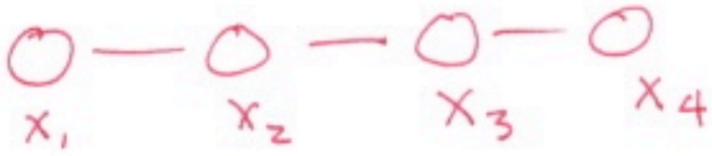
· We will focus on cases where cliques are edges.

eg

a model of a sequence!

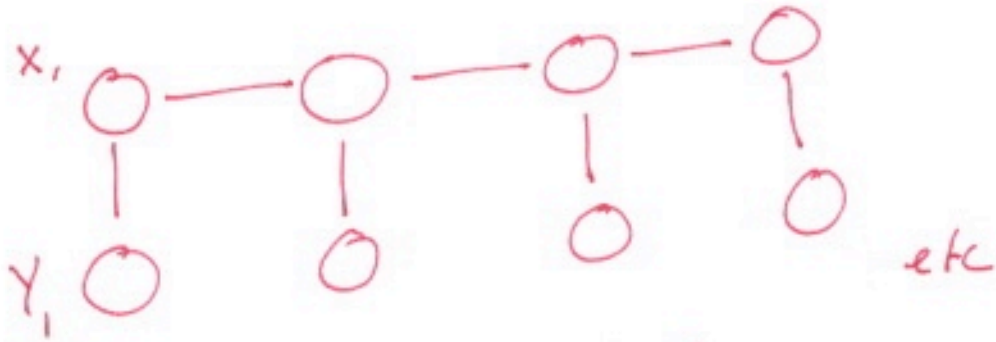


model of an image.



$$P(X_1, X_2, X_3, X_4) = \phi_a(X_1, X_2)\,\phi_b(X_2, X_3)\,\phi_c(X_3, X_4)$$

But what about measurements?



Now consider the joint of X, Y

$$P(X_1 \cdots Y_4) = \psi_a(X_1, Y_1)\,\varphi_a(X_1, X_2) \cdots$$

we know $Y_1 \cdots Y_4$

so $\psi_a(X_1, Y_1 = y_1)\,\varphi_a(X_1, X_2) \cdots$

Now

$\log P(X_1 \cdots Y_4)$

$= \log \psi_a(X_1, Y_1) + \log \psi_a(X_1, X_2) + \cdots$

(we've seen this! we know how to max (graph cut gives true for X_i binary approx otherwise)

These objects — MRF with some variables known — are known as Conditional Random Fields (CRF's).

Q: Other techniques to compute w/ CRF's?

(We <u>know</u> how to obtain an approx to

$$\max_X \log P(X, \cdots Y = y_n)$$