

$\bar{x} \mapsto y?$

Discriminative

$p(y|\bar{x})$

Generative

$p(y, \bar{x}) = p(y|\bar{x}) p(\bar{x})$

$p(y|\bar{x}) \propto p(y, \bar{x})$

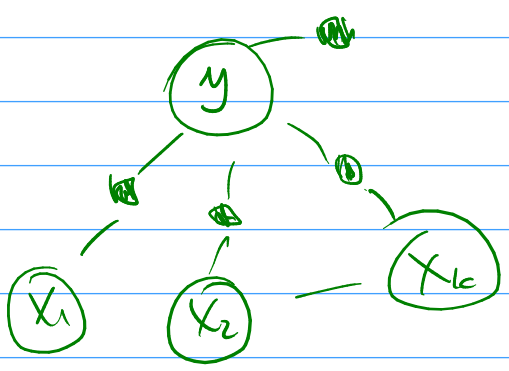
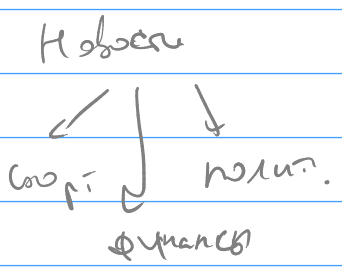
$p(y) p(\bar{x}|y)$

Logistic regression

$p(y|\bar{x}) = e^{\sum f_k(x,y) \theta_k}$

$p(y=t|\bar{x}) = \text{softmax}(e^{\bar{w}_t^T \bar{x}}) = \frac{e^{\bar{w}_t^T \bar{x}}}{\sum_{t'} e^{\bar{w}_{t'}^T \bar{x}}}$

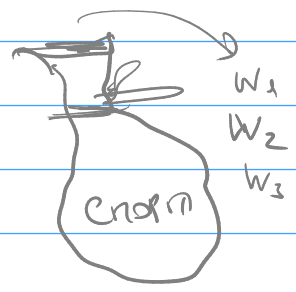
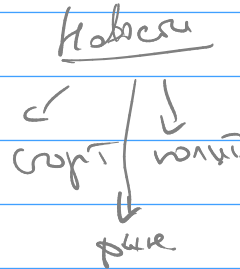
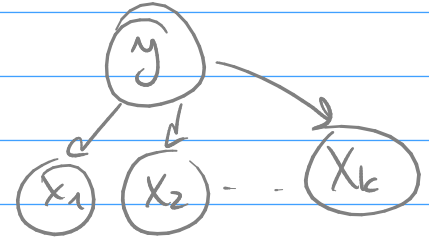
$= \frac{1}{z(\bar{x})} e^{w_{t1}^k x_1 + \dots + w_{tk}^k x_k} = \sum_t \sum_k [y=t] x_k w_{tk}$



Naive Bayes

$\bar{x} = (x_1 - x_k) \mapsto y$

$p(\bar{x}, y) = p(y) \cdot p(\bar{x}|y) = p(y) \prod_k p(x_k|y)$



$\frac{1}{z(\bar{x})} \prod_{s,k} e^{p(y=x_s) \theta_s}$

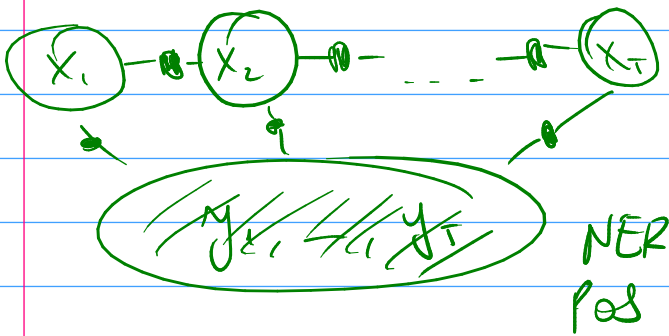
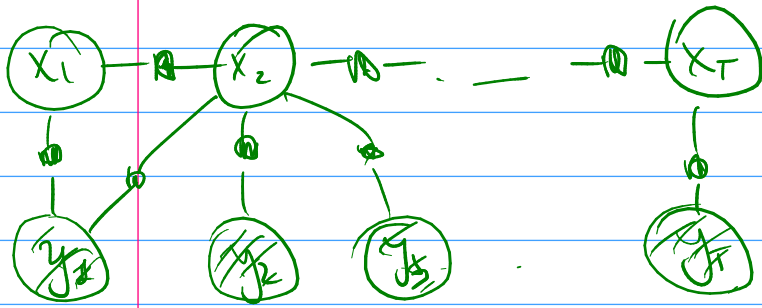
$p(\bar{x}, y) = \prod_t \pi_t^{[y=t]}$

$= e^{\sum_t [y=t] \ln \pi_t + \sum_{t,k} [x_k=w] \ln \theta_{wt}}$

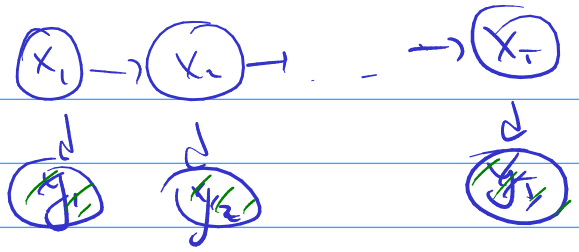
features $\ln \pi_t, \ln \theta_{wt}$

CRF conditional random fields
linear chain CRF

$p(\bar{x} | \bar{y})$



HMM



$p(\bar{x}, \bar{y}) = p(x_1) p(x_2 | x_1) p(y_1 | x_1) \dots$

$p(\bar{x} | \theta)$, $L(\theta) = \prod_{\bar{x} \in D} p(\bar{x} | \theta) \xrightarrow{\theta} \max$

$p(\theta) \prod_{\bar{x} \in D} p(\bar{x} | \theta) \xrightarrow{\theta} \max$

$p_{\text{model}}(\bar{x} | \theta) \approx p_{\text{data}}(\bar{x})$

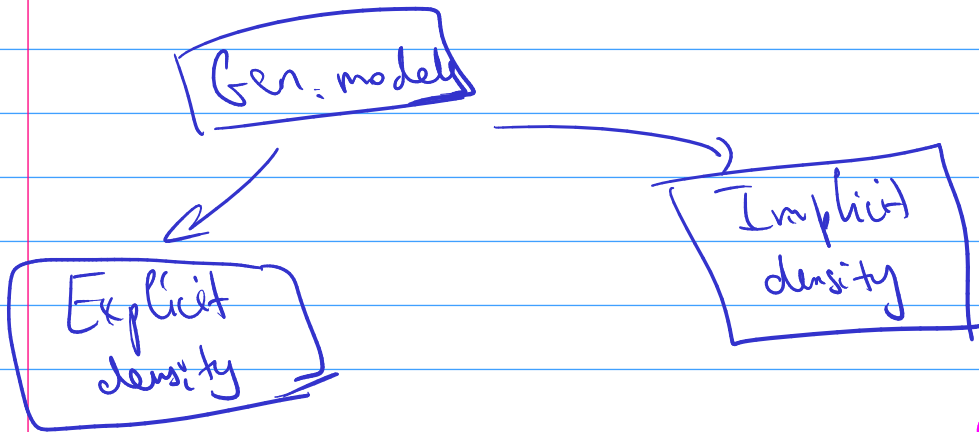
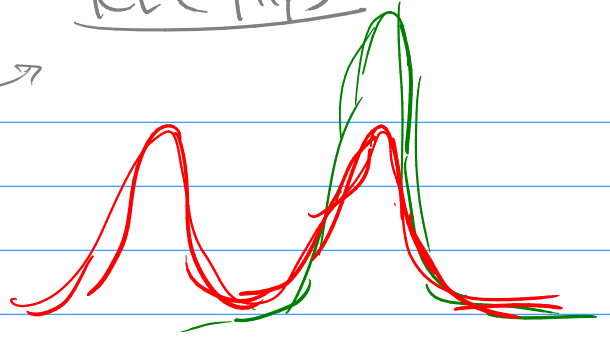
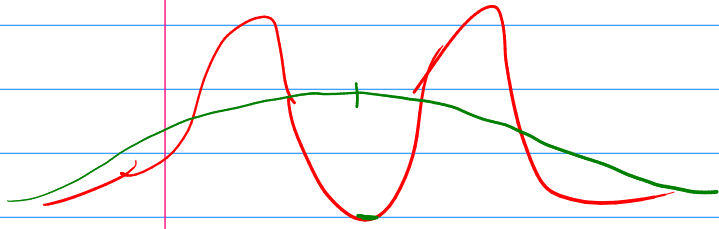
$\text{Unif}(D) = \text{Unif}(\{x_1, \dots, x_n\})$

$\text{KL}(p_{\text{data}} || p_{\text{model}}) = - \int p_{\text{data}}(\bar{x}) \ln \frac{p_{\text{model}}(\bar{x})}{p_{\text{data}}(\bar{x})} d\bar{x} =$

$= - \sum_n \left(\frac{1}{N} \right) \ln \frac{p_{\text{model}}(\bar{x})}{(1/N)} \longrightarrow \min p_{\text{model}}$

$$KL(p||q) = \int p \ln \frac{p}{q}$$

$$KL(q||p)$$

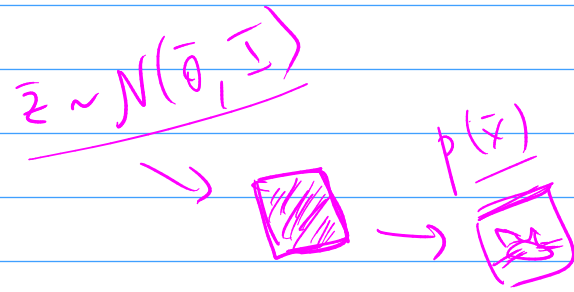


NB

$$p(\bar{x}, y) = p(y) \prod_k p(x_k | y)$$

HMM

$$p(\bar{x}, \bar{y}) = \dots$$

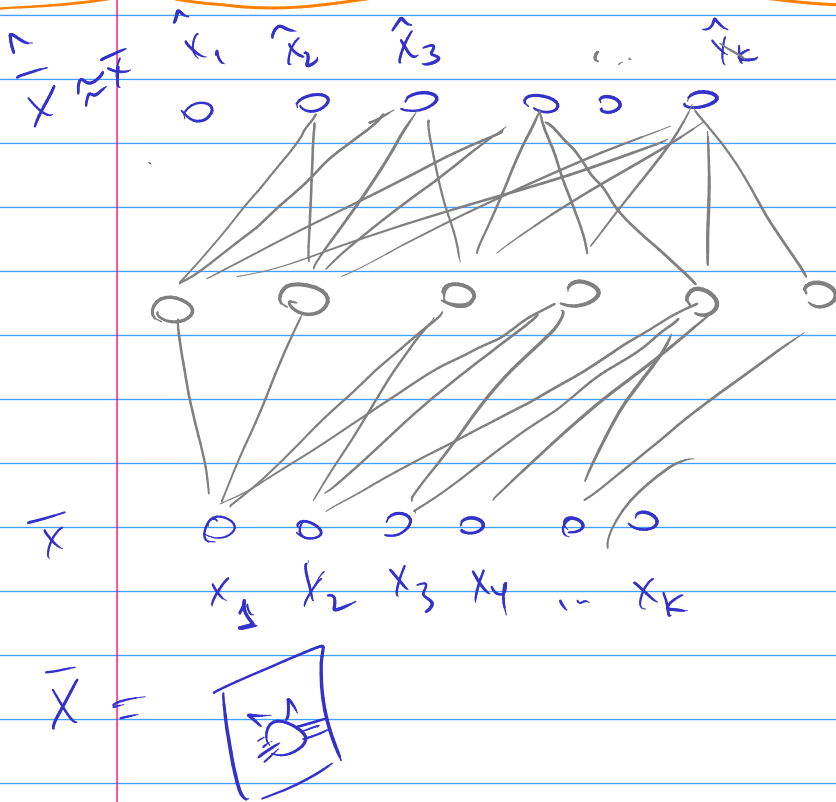
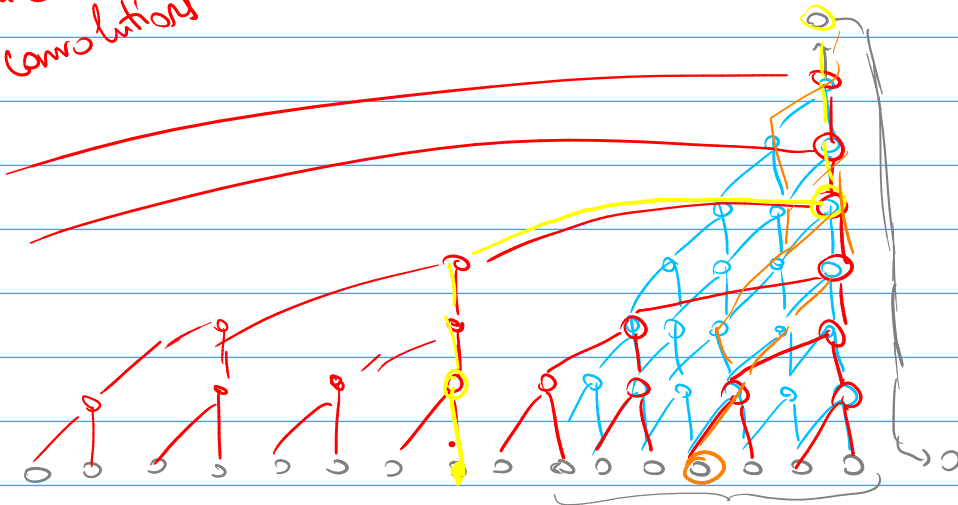


$$p(\bar{x}) = p(x_1) p(x_2 | x_1) p(x_3 | x_1, x_2) \dots p(x_n | x_1 \dots x_{n-1})$$

$$= \prod_k \underbrace{p(x_k | \bar{x}_{<k})}_{\approx NN}$$

$$p(\bar{x}_k | \bar{x}_{<k}) = p(\bar{x}_k | \bar{x}_{k-1}, \bar{h})$$

dilated
convolutions



MADE

$$p(\hat{x}) = \prod p(x_i | \mathcal{F}_i)$$

