Conditional Random Field

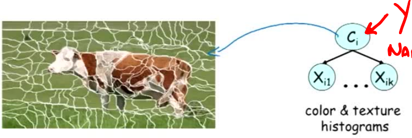
Task-specific prediction

we always have the same type of variables always
The same type of problem

	X input VARS	Y Target VARS
Image Segmentation	Pixel values Processed features	class for every pixel, Grass, sky cow, water
Text Processing	words in sentence	labels of words, person, location, organization

Correlated features

Correlated Features



Y

Naive Bayes
Features Are independent given a label
-Add edges is hard
-Densly connected

Alternative
Model only $P(Y|X)$

Daphne Koller

CRF

$\Phi = \{\underbrace{\phi_1}_{\text{Factor}}(\underbrace{D_1}_{\text{scope}}) \dots \phi_K(D_K)\}$ Gibbs distribution

$\tilde{P}_\Phi(X, Y) = \prod_{i=1}^{K} \phi_i(D_i)$ ← multiply

unnormalized measure

$Z_\Phi(X) = \sum_Y \tilde{P}_\Phi(X, Y)$

$\tilde{P}_\Phi(Y|X) = \frac{1}{Z_\Phi(X)} \tilde{P}_\Phi(X, Y)$

$x^0 y^0$ — $/Z(x^0)$
$x^0 y^1$ — $/Z(x^0)$
+
$x^1 y^0$ — $/Z(x^1)$
$x^1 y^1$ — $/Z(x^1)$
+

family of conditional distributions

$$\phi_i(X_i, Y) = \exp\{w_i \mathbb{1}\{X_i = 1, Y = 1\}\}$$ Logistic Model

indicator Function

$\phi_i(x_i, Y=1) = \exp\{w_i x_i\}$

$\phi_i(x_i, Y=0) = \exp\{0\} = 1$

$\tilde{P}_\phi(x, Y=1) = \exp\{\sum_i (w_i x_i)\}$

$\tilde{P}_\phi(x, Y=0) = 1 \cdot 1 \dots 1 = 1$

$$P_\phi(Y=1, X) = \frac{\overbrace{\exp\{\sum_i (w_i x_i)\}}^{P(Y=1,X)}}{\underbrace{1}_{P(Y=0,X)} + \underbrace{\exp\{\sum_i (w_i x_i)\}}_{P(Y=1,X)}} = \frac{e^z}{1+e^z}$$