

Lecture 1 - setup

Tuesday, January 7, 2020 14:23

- TODO: fill survey <http://bit.ly/IFT6132-W20> by Wednesday evening!

structured prediction basics & setup

Learning problem:

given a training dataset $D = (x^{(i)}, y^{(i)})_{i=1}^n$

$$\in X \quad \in \mathcal{Y}$$

goal: learn a prediction mapping $h_w: X \rightarrow \mathcal{Y}$

that has low classification error
generalization error

$$L(w; P) \triangleq \mathbb{E}_{(x,y) \sim P} [l(y, h_w(x))]$$

statistical decision loss / "risk" in ML
(Vapnik)

structured error function

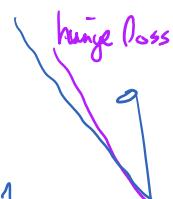
[see Lecture 4 & 5 of my PGM → review of statistical decision theory]

example of learning approach:

regularized ERM
"empirical risk minimization"

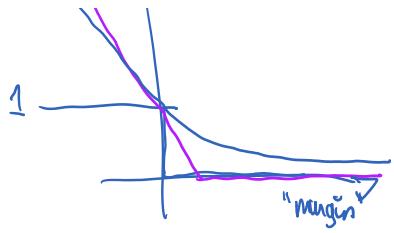
$$\hat{L}(w) = \frac{1}{n} \sum_{i=1}^n l(y^{(i)}, h_w(x^{(i)})) + R(w)$$

not diff. in w : non-convex
messy [NP hard to minimize in general]



→ replace \hat{L} with a surrogate loss / contrast fn.
ML statistics

$$\hat{\mathcal{L}}(w) = \frac{1}{n} \sum_{i=1}^n \mathcal{L}(x^{(i)}, y^{(i)}, w) + R(w)$$



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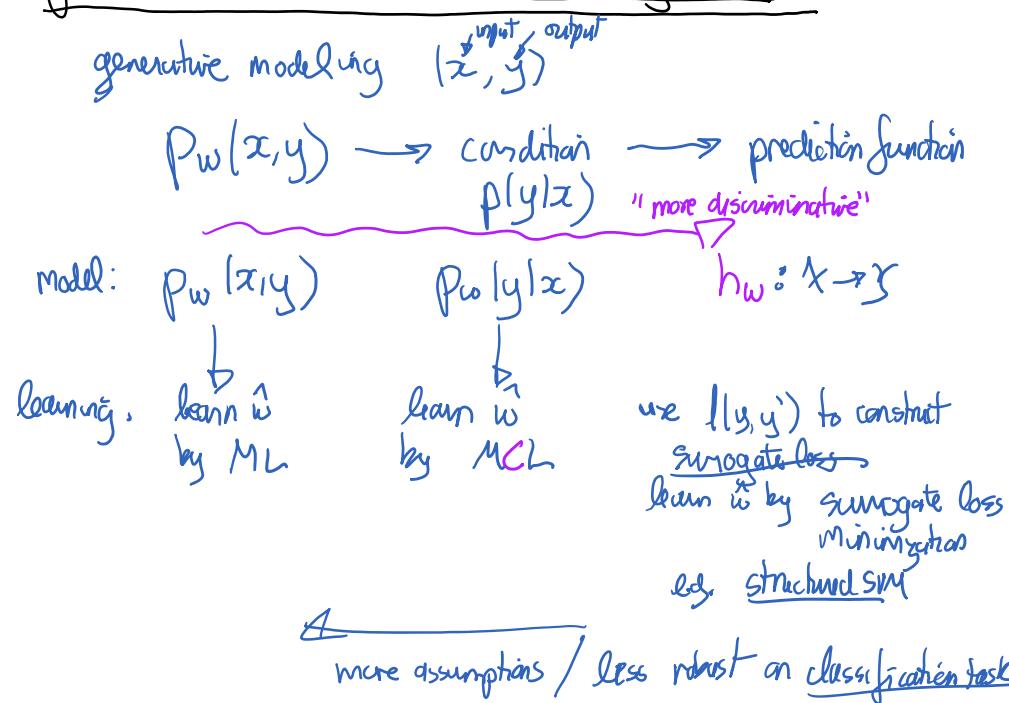
\mathcal{L} surrogate loss e.g. convex in w

- ↳ examples:
- structured hinge loss \rightarrow structured SVM
 - log-loss \rightarrow CRF

M-estimator in statistics

15h31

generative vs. discriminative learning continuum



Some important aspects of structured prediction (vs. binary classification)

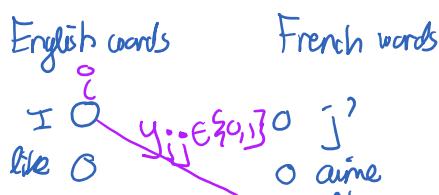
1) output space is usually exponentially big (ⁱⁿ natural size of input)

2) structured error function $\ell(y, y')$

3) sometimes constraints on pieces of y

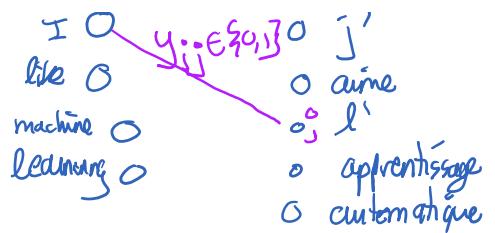
note: need an "encoding function" $y = (y_1, \dots, y_E) \in \mathbb{R}^E$

↳ consider word alignment example:



$$y = (y_{ij})_{(i,j) \in E} \in \{0, 1\}^{|E|}$$

↑
possible edges
(here, all pairs)



possible edges
(here, all pairs)

matching constraint $\left\{ \begin{array}{l} \sum_j y_{ij} \leq 1 \quad \forall i \\ \sum_i y_{ij} \leq 1 \quad \forall j \end{array} \right.$