L15 – Week 8
Introduction to Statistical Learning Theory

CS 295 Optimization for Machine Learning

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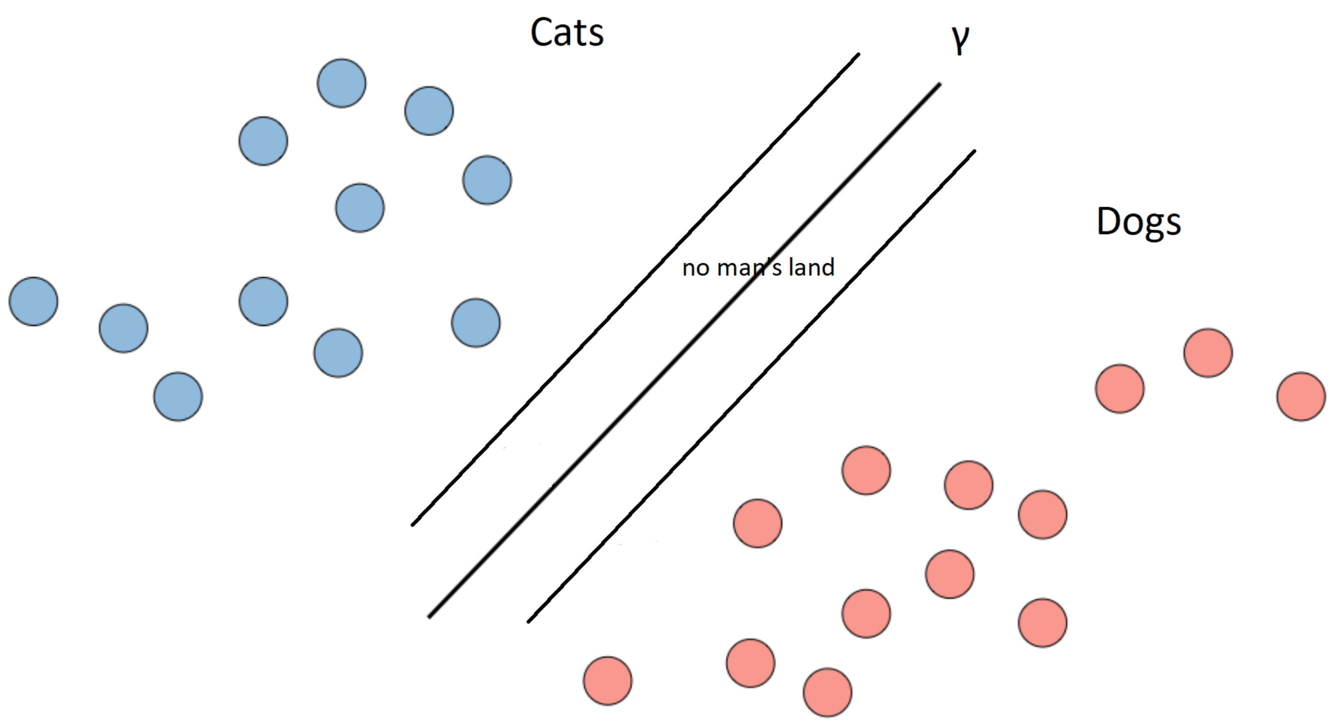
Linear Prediction



- Goal. Compute a vector w that separates the two classes.

The Perceptron Algorithm

Given $(x_1, y_1), \dots, (x_T, y_T) \in X \times \{\pm 1\}$ where we assume $||x_t|| = 1$ for all t.

Formally γ is defined

$$\gamma := \max_{w:\|w\|=1} \min_{i \in [T]} (y_i w^\top x_i)_+,$$

where $(a)_+ = \max(a, 0)$.

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Definition (Perceptron). *Consider the following iterative algorithm:*

1. Initialize $w_1 = 0$ (hypothesis)
2. On round t=1 … T
3. Consider (x_t, y_t) and form prediction $\hat{y}_t = \mathrm{sign}(w_t^\top x_t)$.
4. **If** $\hat{y}_t \neq y_t$
5. $w_{t+1} = w_t + y_t x_t$.
6. **Else** $w_{t+1} = w_t$.

Analysis of Perceptron

Theorem (# Corrections)**.** *Perceptron makes at most* $1/\gamma^2$ *mistakes and corrections on any sequence with margin* γ*.*

Proof. Let m the number of mistakes after T iterations. If a mistake is made at round t then

$$\|w_{t+1}\|_2^2 = \|w_t + y_t x_t\|_2^2$$

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$$

$$\boxed{\text{Therefore } \|w_T\|_2^2 \leq m.}$$

Analysis of Perceptron

Proof cont. Consider a vector w^* with margin γ.

By definition of γ for all t that there is a mistake

$$\boxed{\gamma \leq y_t {w^*}^\top x_t = {w^*}^\top (w_{t+1} - w_t).}$$

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By adding the above we also have that

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Therefore $m\gamma \leq \|w_T\|_2 \leq \sqrt{m}$.

Random Data and 0-1 loss function

What we really showed is that given $(x_1, y_1), \dots, (x_T, y_T) \in X \times \{\pm 1\}$ where we assume $||x_t|| = 1$ for all t it holds

$$\boxed{\sum_{t=1}^{T} \mathbf{1}_{y_t w_t^\top x_t \le 0} \le \frac{1}{\gamma^2}.}$$

Given $(x_1, y_1), \dots, (x_n, y_n) \in X \times \{\pm 1\}$ IID from some distribution P.

Run perceptron algorithm and consider $w_1, \dots, w_n$. Then choose w uniformly at random from $\{w_1, \dots, w_n\}$. This is good enough…

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Theorem (IID Data). *Let w be the choice of the algorithm. It holds that*

$$\mathbb{E}\left[\frac{1}{n}\sum_{i=1}^{n} \mathbf{1}_{y_i w^\top x_i \leq 0}\right] \leq \frac{1}{n}\mathbb{E}\left[\frac{1}{\gamma^2}\right].$$

Random Data and 0-1 loss function

Proof. We have proved from before that (and taking expectations)

$$\mathbb{E}\left[\frac{1}{n}\sum_{i=1}^{n}\mathbf{1}_{y_i w_i^\top x_i \leq 0}\right] \leq \mathbb{E}\left[\frac{1}{n\gamma^2}\right].$$

Let $S = ((x_1, y_1), ..., (x_n, y_n))$. The LHS can be expressed as

$$\mathbb{E}_\tau \mathbb{E}_S \left[\mathbf{1}_{y_\tau w_\tau^\top x_\tau \leq 0}\right] = \mathbb{E}_S \mathbb{E}_\tau \left[\mathbf{1}_{y_\tau w_\tau^\top x_\tau \leq 0}\right].$$

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Observe now that w_τ depends only on $(x_1, y_1), ..., (x_{\tau-1}, y_{\tau-1})$, hence

$$\mathbb{E}_S \mathbb{E}_\tau\left[\mathbf{1}_{y_\tau w_\tau^\top x_\tau \le 0}\right] = \mathbb{E}_S \mathbb{E}_\tau \mathbb{E}_{(x,y)\sim P}\left[\mathbf{1}_{y w_\tau^\top x \le 0}\right] = \mathbb{E}_S \mathbb{E}_\tau [L_{0-1}(w_\tau)]$$

Remark: If we keep iterating perceptron algorithm we finally get $L_{0-1}(w_T) = 0$ (how many steps?) where

$$L_{0-1}(w) = \frac{1}{n}\sum_i \mathbf{1}_{y_i w^\top x_i \le 0}$$

PAC Learning

Assume we are given:

- Domain set $\mathcal{X}$. Typically $\mathbb{R}^d$ or $\{0,1\}^d$. Think of 32x32 pixel images.
- Label set $\mathcal{Y}$, typically binary like $\{0,1\}$ or $\{-1,+1\}$.
- A concept class $\mathcal{C} = \{h : h : \mathcal{X} \to \mathcal{Y}\}$.

Given a learning problem, we analyse the performance of a learning algorithm:

- Training data $S = (x_1, y_1), ..., (x_m, y_m)$, where sample S was generated by drawing m IID samples from the distribution D.
- Output a hypothesis from a hypothesis class $\mathcal{H} = \{h : h : \mathcal{X} \to \mathcal{Y}\}$ of target functions.

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We measure the performance through generalization error that is

$$\mathrm{err}(h) = \mathbb{E}_{(x,y)\sim D}[\ell_{0-1}(h(x), y)].$$

PAC Learning

Definition (PAC learnable). *A concept class $\mathcal{C}$ of target functions is PAC learnable (w.r.t to $\mathcal{H}$) if there exists an algorithm A and function $m_{\mathcal{C}}^{A} : (0,1)^2 \to \mathbb{N}$ with the following property:*

Assume $S = ((x_1, y_1), ..., (x_m, y_m))$ is a sample of IID examples generated by some arbitrary distribution D such that $y_i = h(x_i)$ for some $h \in \mathcal{C}$ almost surely. If S is the input of A and $m > m_{\mathcal{C}}^{A}$ then the algorithm returns a hypothesis $h_S \in \mathcal{H}$ such that, with probability $1 - \delta$ (over the choice of the m training examples):

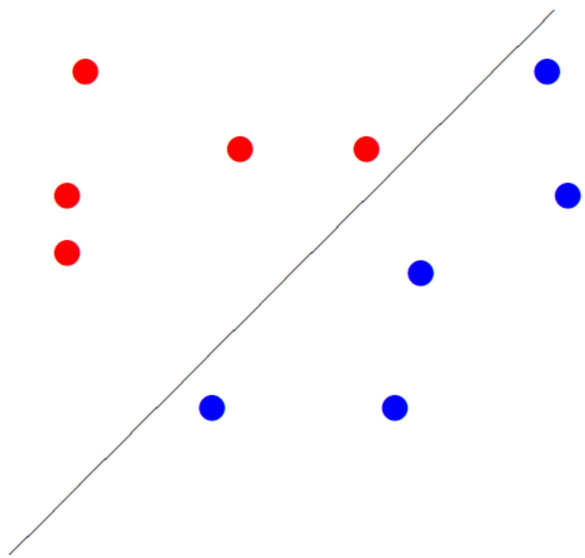
$$\mathrm{err}(h_S) < \epsilon$$

The function $m_{\mathcal{C}}^{A}$ is referred to as the sample complexity of algorithm A.

Examples

Example 2.2 (Half-spaces). *A second example that is of some importance is defined by hyperplane. Here we let the domain be $\chi = \mathbb{R}^d$ for some integer d. For every $\mathbf{w} \in \mathbb{R}^d$, induces a half space by consider all elements $\mathbf{x}$ such that $\mathbf{w} \cdot \mathbf{x} \geq 0$. Thus, we may consider the class of target functions described as follows*

$$\mathcal{C} = \{f_{\mathbf{w}} : \mathbf{w} \in \mathbb{R}^d, f_{\mathbf{w}}(x) = \mathrm{sign}(\mathbf{w} \cdot \mathbf{x})\}$$

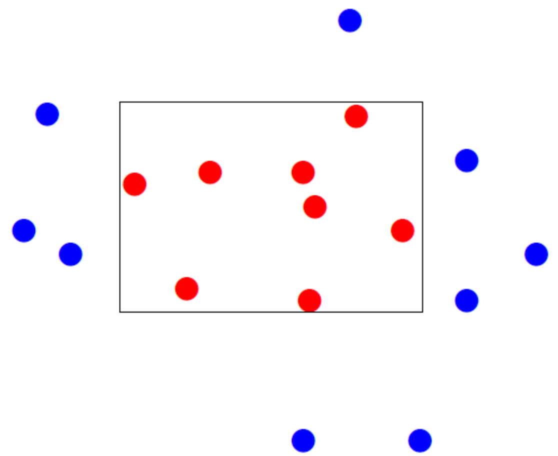


Examples

Example 2.1 (Axis Aligned Rectangles)**.** *The first example of a hypothesis class will be of rectangles aligned to the axis. Here we take the domain* $\chi = \mathbb{R}^2$ *and we let* $\mathcal{C}$ *include be defined by all rectangles that are aligned to the axis. Namely for every* (z_1, z_2, z_3, z_4) *consider the following function over the plane*

$$f_{z_1,z_2,z_3,z_4}(x_1, x_2) = \begin{cases} 1 & z_1 \leq x_1 \leq z_2,\ z_3 \leq x_2 \leq z_4 \\ 0 & \text{else} \end{cases}$$

Then $\mathcal{C} = \{f_{z_1,z_2,z_3,z_4} : (z_1, z_2, z_3, z_4) \in \mathbb{R}^4\}$.



ERM algorithm

Definition (ERM). *Empirical Risk Minimization algorithm is defined as follows:*

Return

$$\arg\min_{h \in \mathcal{H}} \mathrm{err}_s(h),$$

where $\mathrm{err}_s(h) = \frac{1}{m} \sum \ell_{0-1}(h(x_i), y_i)$

Theorem (Finite classes are PAC learnable). *Consider a finite class of target functions $\mathcal{H} = h_1, ..., h_t$ over a domain. Then if size of sample S is $m > \frac{2}{\epsilon^2} \log \frac{2|\mathcal{H}|}{\delta}$ then with probability $1 - \delta$ we have that*

$$\max_{h \in \mathcal{H}} |err_S(h) - err(h)| < \epsilon.$$

ERM algorithm analysis

Proof. Applying Hoeffding's inequality we obtain that for every S and fixed h since $\mathrm{err}_S(h)$ is sum of IID bernoulli with expectation $\mathrm{err}(h)$:

$$\Pr_S[|\mathrm{err}_S(h) - \mathrm{err}(h)| > \epsilon] \leq 2e^{-2m\epsilon^2}.$$

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What if the hypothesis class has infinite cardinality?

Conclusion

- Introduction to Statistical Learning.
  - Perceptron Algorithm.
  - Loss functions and PAC learning
  - ERM algorithm

- Next lecture we will talk about VC dimension.