Lecture 11: Computational Learning Theory

PAC Learning

Computational Learning Theory

- So far our questions were of the form — Given m samples iid from a distribution $\mathbb{P}_x$, can we upper bound the error as $\epsilon = O(m^{-\alpha})$?

Computational Learning Theory

- So far our questions were of the form — Given m samples iid from a distribution $\mathbb{P}_x$, can we upper bound the error as $\epsilon = O(m^{-\alpha})$?
- In particular, we have discussed how to use properties of the distribution to give better statistical "rates".

Computational Learning Theory

- So far our questions were of the form — Given m samples iid from a distribution $\mathbb{P}_x$, can we upper bound the error as $\epsilon = O(m^{-\alpha})$?
- In particular, we have discussed how to use properties of the distribution to give better statistical "rates".
- [Today] In Computational Learning Theory, we will treat the learning algorithm as a computational process. This requires making a few things explicit (Discuss in pairs what they can be):

Computational Learning Theory

- So far our questions were of the form — Given m samples iid from a distribution $\mathbb{P}_x$, can we upper bound the error as $\epsilon = O(m^{-\alpha})$?
- In particular, we have discussed how to use properties of the distribution to give better statistical "rates".
- [Today] In Computational Learning Theory, we will treat the learning algorithm as a computational process. This requires making a few things explicit (Discuss in pairs what they can be):
  - How does the algorithm "interact" with the distribution ?

Computational Learning Theory

- So far our questions were of the form — Given m samples iid from a distribution $\mathbb{P}_x$, can we upper bound the error as $\epsilon = O(m^{-\alpha})$?
- In particular, we have discussed how to use properties of the distribution to give better statistical "rates".
- [Today] In Computational Learning Theory, we will treat the learning algorithm as a computational process. This requires making a few things explicit (Discuss in pairs what they can be):
  - How does the algorithm "interact" with the distribution ?
  - What information does the algorithm have about the "learning problem" ?

Computational Learning Theory

- So far our questions were of the form — Given m samples iid from a distribution $\mathbb{P}_x$, can we upper bound the error as $\epsilon = O(m^{-\alpha})$?
- In particular, we have discussed how to use properties of the distribution to give better statistical "rates".
- [Today] In Computational Learning Theory, we will treat the learning algorithm as a computational process. This requires making a few things explicit (Discuss in pairs what they can be):
  - How does the algorithm "interact" with the distribution ?
  - What information does the algorithm have about the "learning problem" ?
  - How "long" is the algorithm allowed to run etc ?

Computational Learning Theory

- So far our questions were of the form — Given m samples iid from a distribution $\mathbb{P}_x$, can we upper bound the error as $\epsilon = O(m^{-\alpha})$?
- In particular, we have discussed how to use properties of the distribution to give better statistical "rates".
- [Today] In Computational Learning Theory, we will treat the learning algorithm as a computational process. This requires making a few things explicit (Discuss in pairs what they can be):
  - How does the algorithm "interact" with the distribution ?
  - What information does the algorithm have about the "learning problem" ?
  - How "long" is the algorithm allowed to run etc ?
  - How will the output estimator be "represented" ?

Computational Learning Theory

- So far our questions were of the form — Given m samples iid from a distribution $\mathbb{P}_x$, can we upper bound the error as $\epsilon = O(m^{-\alpha})$?
- In particular, we have discussed how to use properties of the distribution to give better statistical "rates".
- [Today] In Computational Learning Theory, we will treat the learning algorithm as a computational process. This requires making a few things explicit (Discuss in pairs what they can be):
  - How does the algorithm "interact" with the distribution ?
  - What information does the algorithm have about the "learning problem" ?
  - How "long" is the algorithm allowed to run etc ?
  - How will the output estimator be "represented" ?

Finally, this proposes an answer to the question what can be "learned" under various restrictions.

Binary classification Setting

Some terminologies

- Instance space: $\mathcal{X}$ e.g. $\mathbb{R}^2, \{0,1\}^d, \mathbb{R}^d$ etc.
- Label space: $\mathcal{Y} = +1, -1$
- Hypothesis/Concept classes are represented by : $\mathcal{C}, \mathcal{H}, \mathcal{F}$. They are sets of maps from $\mathcal{X}$ to $\mathcal{Y}$. (In other words, classes of labelling functions) E.g.
  - CONJUNCTIONS e.g. $x_1 \wedge x_3 \wedge x_5$
  - DISJUNCTIONS e.g. $x_2 \vee x_3 \vee x_5$
  - Linear halfspaces e.g. $\sum_{i=1}^{d} w_i x_i \geq b$
- Data Distribition $\mathbb{P}_x$ over $\mathcal{X}$
- Example Oracle: An oracle $\mathrm{Ex}\left(c; \mathbb{P}_x\right)$ that samples $x \sim \mathbb{P}_x$ and returns $(x, c(x))$.
- Target Concept Refer to c as the "target concept" (ground truth).

Learning Algorithm

- Learning algorithm An algorithm $\mathcal{A}$
  - for learning concept class $\mathcal{C}$
  - with hypothesis class $\mathcal{H}$
  - can call the example oracle $\mathrm{Ex}(c; \mathbb{P}_x)$ many times
  - and must return some $h \in \mathcal{H}$.
- Two sources of randomisation :
  - **Randomness from data**Inherently, due to the randomisation of $\mathrm{Ex}(c; \mathbb{P}_x)$, $\mathcal{A}$ is always randomised. This randomness is from $\mathbb{P}_x$.
  - **Randomness from algorithm** After receiving data from $\mathrm{Ex}(c; \mathbb{P}_x)$, $\mathcal{A}$ can flip and unbiased coin and introduce further randomness into the algorithm. Let the joint distribution over $\mathbb{P}_x$ and internal coin flips of $\mathcal{A}$ be $\mathbb{P}$.

Probably Approximately Correct Learnability: Attempt 1

Definition (PAC learning)

A concept class $\mathcal{C}$ is PAC learnable with hypothesis class $\mathcal{H}$ if there exists a learning algorithm $\mathcal{A}$ such that for all distributions $\mathbb{P}_x$, concept $c \in \mathcal{C}$, and $\epsilon, \delta > 0$, if $\mathcal{A}$ is given access to $\mathrm{Ex}\left(c; \mathbb{P}_x\right)$ and knows ϵ, δ, $\mathcal{A}$ returns $h \in \mathcal{H}$ such that with probability at least $1 - \delta$, over inner randomisation of $\mathrm{Ex}\left(c; \mathbb{P}_x\right)$ and $\mathcal{A}$ we have that $\mathbb{P}_x[h(x) \neq c(x)] \leq \epsilon$.

- If $\mathcal{A}$ runs in time poly $\left(\frac{1}{\epsilon}, \frac{1}{\delta}\right)$ then $\mathcal{C}$ is **efficiently PAC learnable**.
- If $\mathcal{C}$ is learnable with $\mathcal{H} = \mathcal{C}$, then we say $\mathcal{C}$ is **proper learnable** Otherwise, it is referred to as **improper learnable** We will focus on proper PAC learnability for now.
- Number of times $\mathcal{A}$ calls $\mathrm{Ex}\left(c; \mathbb{P}_x\right)$ is equal to the sample size m
- So far, we have written ϵ as function of m i.e. $\epsilon(m, \delta)$ is the error rate. m is the sample size or the smallest possible m is the sample complexity.

Understanding the definition

What are some things or questions that stand out to you about learnability in this definition ?

- **Efficiency**
  - What is one unit of time ?
  - What are possible reasons of inefficiency ?
  - What kinds of computational constraints are required on h ?
- **Available information to $\mathcal{A}$**
  - What does $\mathcal{A}$ know and what does $\mathcal{A}$ not know ?
  - What are some possible changes to $\mathrm{Ex}\left(c; \mathbb{P}_x\right)$ that can simulate real environments ? How can they change a class' learnability ?

Discuss in pairs

Understanding the definition

- Efficiency.
  - What is one unit of time ?
    Call to $\mathrm{Ex}(c; \mathbb{P}_x)$ takes unit time. The algorithm is run on a turing machine.
  - What are possible reasons of inefficiency ?
    Exponential sample complexity or exponential running time.
  - What kinds of computational constraints are required on h ?
    h needs to be poly evaluable, otherwise trivial
- Available information
  - What does $\mathcal{A}$ know and what does $\mathcal{A}$ not know ?
    Knows $\mathcal{C}$ but not c. Does not know $\mathbb{P}_x$.
  - What are some changes to $\mathrm{Ex}(c; \mathbb{P}_x)$ that can simulate real environments ?
    Noisy Oracle (RCN, Massart, Tsybakov), Positive/Negative only, Membership Query, Statistical Query
- It attempts to separate the two things
  - Having sufficient data
  - Being able to compute the estimator/hypothesis from the data

Learning Axis-Aligned Rectangles

- Let $\mathcal{X} = \mathbb{R}^2, \mathcal{Y} = \{+1, 0\}$
- $\mathcal{C}$ is the class of Axis-Aligned Rectangle Classifiers. A concept $c \in \mathcal{C}$ labels $x \in \mathcal{X}$ positive $(+1)$ if x lies inside the rectangle and 0 o.w.

Theorem

The concept class of axis aligned rectangles is efficiently proper PAC learnable.

Proof:

- Algorithm $\mathcal{A}$ chooses $m = \frac{4}{\epsilon} \log\left(\frac{4}{\delta}\right)$, queries $\mathrm{Ex}\left(c; \mathbb{P}_x\right)$ m times and outputs the smallest axis-aligned rectangle R' that contains all $+$ve points.
- Let R be the target rectangle. Choose 4 regions T_1, T_2, T_3, T_4 along the inner sides of R such that each region has mass $\frac{\epsilon}{4}$ under $\mathbb{P}_x$. Note that if $\mathrm{Ex}\left(c; \mathbb{P}_x\right)$ returns at least one point in all of these regions with probability greater than $1 - \delta$, it suffices for us.
- Let A_i be the event that $\mathrm{Ex}\left(c; \mathbb{P}_x\right)$ upon m calls does not return any point in T_i. Show $\mathbb{P}[\bigcup_i A_i] \leq 4 \exp\left(-\frac{m\epsilon}{4}\right)$
- Setting $m = \frac{4}{\epsilon} \log\left(\frac{4}{\delta}\right)$ completes the proof.

Probably Approximately Correct Learnability: Attempt 2

Issue: Previous definition does not account for the size of the concept class or the instance space.

- **Representation scheme for concept class**: $\rho : (\Sigma \cup \mathbb{R})^* \to \mathcal{C}$ is a representation scheme for $\mathcal{C}$. e.g. $\rho((x_1, y_1), (x_2, y_2)) =$ axis-aligned rectangle with bottom left corner at (x_1, y_1) and top right corner in (x_2, y_2). (Unit cost to represent alphabets in Σ and numbers in $\mathbb{R}$)
- **Size of representations** The function $\mathrm{size} : (\Sigma \cup \mathbb{R})^* \to \mathbb{N}$ measures the size of a representation in $(\Sigma \cup \mathbb{R})^*$.
- **Size of concept**: A size of a concept is the minimum size over all representations in that representation scheme
$\mathrm{size}(c) = \min_{\sigma : \rho(\sigma) = c} .\mathrm{size}(\sigma)$

What are some examples where the choice of ρ affects the size of a concept?

- **Instance size**: Instances $x \in \mathcal{X}$ also has an associated size e.g. memory to store. We denote $\mathcal{X}_d$ as an instance space where all $x \in \mathcal{X}_d$ has size d.

What are some examples of sizes of instance spaces?

Often these are clear from context but sometimes need further thought.

Probably Approximately Correct Learnability: Attempt II

For $d \geq 1$, let $\mathcal{C}_d$ be a concept class over $\mathcal{X}_d$. Consider instance space $\mathcal{X} = \bigcup_{d=1}^{\infty} \mathcal{X}_d$ and the corresponding concept class $\mathcal{C} = \bigcup_{d=1}^{\infty} \mathcal{C}_d$.

Definition (PAC learning)

A concept class $\mathcal{C}$ is PAC learnable with hypothesis class $\mathcal{H}$ if there exists a learning algorithm $\mathcal{A}$ such that for all $d > 0$, all distributions $\mathbb{P}_x$ over $\mathcal{X}_d$, concept $c \in \mathcal{C}_d$, and $\epsilon, \delta > 0$, if $\mathcal{A}$ is given access to $\mathrm{Ex}(c; \mathbb{P}_x)$ and knows ϵ, δ, size(c), and d, $\mathcal{A}$ returns $h \in \mathcal{H}$ such that with probability at least $1 - \delta$, over inner randomisation of $\mathrm{Ex}(c; \mathbb{P}_x)$ and $\mathcal{A}$ we have that $\mathbb{P}_x[h(x) \neq c(x)] \leq \epsilon$.

Efficient PAC learnability: $\mathcal{A}$ should run in time polynomial in $\frac{1}{\epsilon}$, $\frac{1}{\delta}$, size(c), and d. Usually size(c) is bounded by some polynomial in d and hence can be ignored.

Learning CONJUNCTIONS

Now we will see an example of PAC Learning Attempt II

- Let $\mathcal{X}_d = \{0,1\}^d$, $\mathcal{Y} = \{0,1\}$
- $\mathrm{CONJUNCTIONS}_d$ over d boolean variables $z_1, \ldots, z_d$
  - **literal** is a variable or its negation
  - **conjunction** is an AND of literals.
- A conjunction can be represented with two sets $P, N \subseteq [d]$

$$c_{P,N} = \bigwedge_{i \in P} z_i \wedge \bigwedge_{j \in N} \bar{z}_j$$

- The class of $\mathrm{CONJUNCTIONS}_d$ is the set of all conjunctions.

$$\mathrm{CONJUNCTIONS}_d = \{c_{P,N} | P, N \subseteq [d]\}$$

- Note an efficient representation scheme: size $c_{P,N} \leq d$

Theorem (learning conjunctions)

The concept class $\mathcal{C} = \bigcup_{d \geq 1} \mathit{CONJUNCTIONS}_d$ is efficiently PAC learnable.

Proof of learning conjunctions

Proof Let c^* be the target concept. The proof follows these three steps

- **Algorithm** Fix $m \geq \frac{2d}{\epsilon} \log\left(\frac{2d}{\delta}\right)$ and run the following algorithm.
  - Start with $c_{[d],[d]}$; call $\mathrm{Ex}\left(c^*; \mathcal{D}\right)$ m times.
  - For every +ve example, eliminate all literals from $c_{[d],[d]}$ that cause it to be zero. Return the resultant conjunction h.

- **"Correct"** Call a literal ℓ "bad" if $\mathbb{P}_x[c^*(x) = 1 \wedge \ell(x) = 0] \geq \frac{\epsilon}{2d}$.
  - Note by construction, $\mathbb{P}_x[h(x) \neq c^*(x)] = \mathbb{P}_x[h(x) = 0 \wedge c(x) = 1]$.
  - Let B be the set of bad literals and h contain no literals in B. Then, $\mathbb{P}_x[h(x) = 0 \wedge c(x) = 1] \leq \sum_{\ell \in \bar{B}} \mathbb{P}_x[h(x) = 0 \wedge \ell(x) = 1] \leq \epsilon$

- **"Approximately"** Now, we need to prove that h contains no bad literals. Let A_ℓ be the event that ℓ is not eliminated by the algorithm after m calls
  - Bound $\mathbb{P}[A_\ell] \leq (1 - \frac{\epsilon}{2d})^m \leq \exp(-\frac{\epsilon m}{2d})$.
  - $\mathbb{P}\,[\text{at least 1 "bad" literal remain}] \leq \mathbb{P}\left[\bigcup_{\ell \in B} A_\ell\right] \leq \sum_{\ell=0}^{2d} \exp(-\frac{\epsilon m}{2d})$
  - Use $m \geq \frac{2d}{\epsilon} \log\left(\frac{2d}{\delta}\right)$ to show that all bad literals are eliminated with probability $1 - \delta$.

Exercise: Learning k-CNF

A different approach to proving learnability — By Reduction

- Let $\mathcal{X}_d = \{0,1\}^d$, $\mathcal{Y} = \{0,1\}$
- $\mathrm{k\text{-}CNF}_d$ over d boolean variables.
  - Set of k-tuples $S = \{S^1, \ldots S^p\}$. $\forall i: \; S^i \subset [d]$ and $\left|S^i\right| = k$.
  - $c_S(x) = \bigwedge_{i=1}^{p} (\bigvee_{j=1}^{k} x \left[S_j^i\right])$

Theorem (learning k-CNF)

The concept class $\mathcal{C} = \bigcup_{d \geq 1} k\text{-}CNF_d$ is efficiently PAC learnable.

Proof by Reduction We need the concept of *monotone conjunctions*. *Monotone conjunctions* are conjunctions without negated literals.

- **Step 1: (Reduction)** Show these exist: instance space Z_k, a map $\phi : \{0,1\}^d \to Z_k$, and a bijection φ between $\mathrm{k\text{-}CNF}_d$ and monotone conjunctions on Z_k.
- **Step 2: (Algorithm)** Show that the algorithm for learning conjunctions also learns monotone conjunctions. Hence, $\mathcal{C}$ is PAC learnable.
- **Step 3: (Reduction is polynomial)** Show that ϕ, ϕ^{-1}, and φ are polynomially evaluable and thus $\mathcal{C}$ is efficiently PAC learnable.