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SDS 384 11: Theoretical Statistics

Lecture 11: Uniform Law of Large Numbers

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Uniform convergence of CDFs

- Given $X_1, \ldots, X_n \overset{\text{iid}}{\sim} F$, where F is the CDF of some unknown density.
- A natural estimate of F is given by

$$\hat{F}_n(t) := \frac{1}{n} \sum_{i=1}^{n} 1_{-\infty,t}(X_i)$$

- $1_{-\infty,t}$ is the indicator function for $\{x \leq t\}$
- $\hat{F}_n(t)$ is the empirical CDF.
- Note that this is unbiased since $E[\hat{F}_n(t)] = F(t)$

Law of large numbers

- For any fixed $t \in \mathbb{R}$, LLN states that $\hat{F}_n(t) \xrightarrow{P} F(t)$

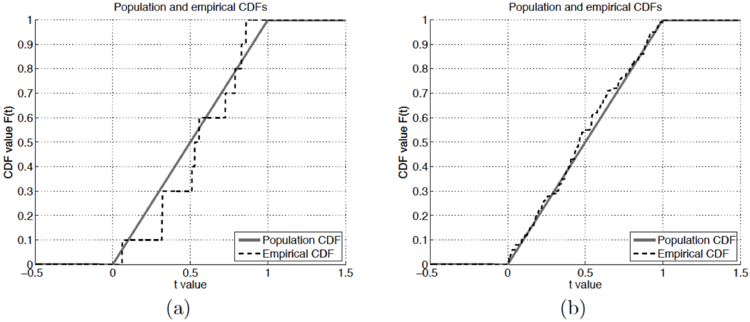

Figure 4-1. Plots of population and empirical CDF functions for the uniform distribution on $[0, 1]$. (a) Empirical CDF based on $n = 10$ samples. (b) Empirical CDF based on $n = 100$ samples.

[Taken from Martin Wainwright's book]

Why the empirical CDF?

- A statistical functional maps a CDF to a real number.
- Say you want to estimate a statistical functional $\gamma(F)$
- A natural estimator uses the "plug in" principle, i.e. $\gamma(\hat{F}_n)$
- Understanding the properties of the empirical CDF will help us understand why this plug in estimator is a good estimator.

Examples of functionals-expectation

Example

Given some integrable function g, the expectation functional is given by

$$\gamma_g(F) := \int g(x)dF(x)$$

- Let $g(x) := x$
- $\gamma_g(F) = E[X]$
- $\gamma_g(\hat{F}_n) = \frac{1}{n}\sum_{i=1}^{n} X_i$, which is the sample average.
- For general g, $\gamma_g(\hat{F}_n) = \frac{1}{n}\sum_{i=1}^{n} g(X_i)$

Examples of functionals-quantile

Example

Given some $\alpha \in [0,1]$, the quantile functional Q_α is given by

$$Q_\alpha(F) := \inf\{t \in \mathbb{R} | F(t) \geq \alpha\}$$

- The median corresponds to the special case $\alpha = 1/2$
- The plug in estimator is given by the sample quantile.

$$Q_\alpha(\hat{F}_n) = \inf\{t \in \mathbb{R} | \hat{F}_n(t) \geq \alpha\}.$$

- The question is whether the estimate converges in some sense to the truth.
    - Note that the above function is nonlinear and so we cannot use law of large numbers to show consistency.

How do we measure consistency?

- First define $\|F - G\|_\infty := \sup_{t \in \mathbb{R}} |G(t) - F(t)|$ to measure the distance between two CDF's F and G.
- Now define continuity of a functional w.r.t this norm.
- We will say that γ is continuous at F in the sup-norm if

$$\forall \epsilon > 0, \exists \delta > 0, \text{ s.t. } \|G - F\|_\infty \leq \delta \Rightarrow |\gamma(G) - \gamma(F)| \leq \epsilon.$$

- This essentially means that in order to show consistency of a plug-in estimator we need to show that $\|\hat{F}_n - F\|_\infty$ converges to zero.

The Glivenko Cantelli theorem

Theorem

For any distribution the empirical CDF $\hat{F}_n$ is a strongly consistent estimator of the population CDF F in the uniform norm, i.e.

$$\|\hat{F}_n - F\|_\infty \overset{a.s.}{\to} 0.$$

- We prove this later.

General function classes

- Consider the function class $\mathcal{F}$ of integrable real-valued functions.
- Let $\|P_n - P\|_{\mathcal{F}} := \sup_{f \in \mathcal{F}} |\frac{1}{n} \sum_i f(X_i) - E[f]|$

Definition

We say that $\mathcal{F}$ is a **Glivenko-Cantelli** class for P if $\|P_n - P\|_{\mathcal{F}}$ converges to zero in probability as $n \to \infty$.

- Can also be defined in a stronger sense.
- We say that $\mathcal{F}$ satisfies the strong **Glivenko-Cantelli** law if the above quantity converges to zero a.s.

The classical Glivenko Cantelli theorem

- Consider the function class $\mathcal{F}$ of indicator functions of the form $\mathcal{F} := \{I_{(-\infty,t]}(.)|t \in \mathbb{R}\}$.
- For a fixed $t \in \mathbb{R}$, $E[I_{(-\infty,t]}(X)] = P(X \leq t) = F(t)$
- So the classical GC theorem corresponds to a strong uniform law for the above class.

Failure of the uniform law

Example

Let $\mathcal{S}$ be the class of all subsets of $[0,1]$ such that the subset S has a finite number of elements. Now consider $\mathcal{F}_{\mathcal{S}} := \{1_S(.) | S \in \mathcal{S}\}$. Let $X_i \overset{\text{iid}}{\sim} P$ s.t. P is a distribution over $[0,1]$ and P has no atoms, i.e. $P(\{x\}) = 0, \forall x \in [0,1]$. This class is not a GC class for P.

- First note that $P[S] = 0, \forall S \in \mathcal{S}$.
- Let $X = \{X_1, \dots, X_n\}$
- We see that $X \in \mathcal{S}$, and $P_n[X] = 1$.
- $\sup_{S \in \mathcal{S}} |P_n[S] - P[S]| = 1 - 0 = 1$

Coming back to functionals

- We saw that functionals help us look at quantities like quantiles, means, etc. But is that all?
- As it turns out they help enormously for empirical risk minimization too.
- Consider the indexed family of probability distributions $\mathcal{P}_\Theta := \{P_\theta | \theta \in \Theta\}$
- Let $X = \{X_1, \ldots, X_n\} \overset{\text{iid}}{\sim} P_\theta^*$, where $\theta^* \in \Theta$
- This θ^* could lie in some d dimensional space
  - Take for example the problem of estimating the means of a Mixture of Gaussians.
- This θ^* could also be lying in some function class, which will give us a non-parametric estimation problem.

Estimating the true θ^*

- In these cases, we estimate θ^* by minimizing a loss function of the form $\mathcal{L}_\theta(x)$ which measures how well P_θ represents or fits the unknown distributions.
- Empirical risk minimization is based on the objective function, also known as the **empirical risk**

$$\hat{R}_n(\theta, \theta^*) = \frac{1}{n} \sum_i \mathcal{L}_\theta(X_i)$$

- The population risk is given by

$$R(\theta, \theta^*) := \underbrace{E_{\theta*}}_{E_{X_1 \sim P_{\theta*}}} [\mathcal{L}_\theta(X_1)]$$

Empirical risk minimization

- Sometimes, we minimize empirical risk over some subset $\Theta_0 \in \Theta$, to get $\hat{\theta}$
- The statistical question is how small is the **excess risk** $R(\hat{\theta}, \theta^*) - \inf_{\theta \in \Theta_0} R(\theta, \theta^*)$
- Now we will look at some examples

Example: Maximum Likelihood

Example

Consider a family of distributions $\{P_\theta, \theta \in \Theta\}$, each with a strictly positive density p_θ. Now suppose that we are given $X_1, \ldots, X_n \overset{\text{iid}}{\sim} P_{\theta*}$. We would like to estimate the unknown parameter θ. In order to do so, we consider the objective function

$$.\mathcal{L}_\theta(x) := \log \frac{p_{\theta*}(x)}{p_\theta(x)}$$

- The maximum likelihood estimate is indeed

$$\hat{\theta} = \arg\min_{\theta \in \Theta} \frac{1}{n} \sum_i \mathcal{L}_\theta(X_i).$$

- The population risk is $R(\theta, \theta^*) = E_{\theta*} \log \frac{p_{\theta*}(X)}{p_\theta(X)}$, which is the KL divergence between the fitted and true densities.

Example: binary classification

Example

You observe n i.i.d samples $(X_i, Y_i) \in \mathbb{R}^d \times \{-1, 1\}$, where X_i is a set of d features, and Y_i corresponds to the label. One can assume that $X_i \sim P_X$ and $Y_i \sim P_{Y|X=X_i}$. In this context we want to estimate some function $f : \mathbb{R}^d \to \{-1, 1\}$ which minimizes the probability of misclassification. We use

$$\mathcal{L}_f(x, y) := \begin{cases} 1 & \text{If } f(x) = y \\ 0 & \text{Otherwise} \end{cases}$$

Empirical risk minimization

- For equally probable classes, the Bayes classifier f^* is given by:

$$f^*(x) := \begin{cases} 1 & \text{If } P(Y=1|X=x) \geq P(Y=-1|X=x) \\ -1 & \text{If } P(Y=1|X=x) < P(Y=-1|X=x) \end{cases}$$

- In practice, since the odds ratio is unknown, we often minimize:

$$\hat{R}_n(f, f^*) = \sum_{i=1}^{n} 1_{f(X_i) \neq Y_i}.$$

- The above is also the training error rate.
- Typically we minimize the above over some restricted set of decision rules.

Empirical risk minimization

- Our goal is to understand the behavior of the excess risk.
- Recall that we want to bound $R(\hat{\theta}, \theta^*) - \inf_{\theta \in \Theta_0} R(\theta, \theta^*)$, aka, $\delta R(\hat{\theta}, \theta^*)$.
- Assume for convenience that the infimum over $\theta \in \Theta_0$ is achieved at $\theta_0 \in \Theta_0$.
- $\delta R(\hat{\theta}, \theta^*)$ equals

$$\underbrace{R(\hat{\theta}, \theta^*) - \hat{R}_n(\hat{\theta}, \theta^*)}_{T_1} + \underbrace{\hat{R}_n(\hat{\theta}, \theta^*) - \hat{R}_n(\theta_0, \theta^*)}_{T_2 < 0} + \underbrace{\hat{R}_n(\theta_0, \theta^*) - R(\theta_0, \theta^*)}_{T_3} \tag{1}$$

- T_3 is just the deviation of a sum of bounded and iid random variables from its expectation. So this can be easily bounded using tools like Hoeffding etc.

Empirical risk minimization

- $T_3 = \frac{1}{n}\sum_i \mathcal{L}_{\theta_0}(X_i) - E[\mathcal{L}_{\theta_0}(X_i)]$
  - When $\mathcal{L}$ is a bounded loss function, we can use techniques we have learned so far.
- Lets look at $-T_1 = \frac{1}{n}\sum_i \mathcal{L}_{\hat{\theta}}(X_i) - E[\mathcal{L}_{\hat{\theta}}(X_i)]$
- This again is much harder to analyze since $\hat{\theta}$ is a function of $X_1, \ldots, X_n$.
- Typically we bound this using

$$T_1 \leq \sup_{\theta \in \Theta_0} \left| \frac{1}{n}\sum_i \mathcal{L}_{\theta}(X_i) - E[\mathcal{L}_{\theta}(X_i)] \right| =: \|\hat{P}_n - P\|_{\mathcal{L}(\Theta_0)}$$

- Where $\mathcal{L}(\Theta_0)$ is the loss class $\{\mathcal{L}_\theta | \theta \in \Theta_0\}$

Empirical Risk Minimization

- $T_3 = \frac{1}{n}\sum_i \mathcal{L}_{\theta_0}(X_i) - E[\mathcal{L}_{\theta_0}(X_i)] \leq \|\hat{P}_n - P\|_{\mathcal{L}(\Theta_0)}$
- $\delta R(\hat{\theta}, \theta^*) \leq 2\|\hat{P}_n - P\|_{\mathcal{L}(\Theta_0)}$
- Now we will establish an uniform law of large numbers for the loss class $\mathcal{L}(\Theta_0)$