Contents

1 Introduction

1.1 Basic inequalities and theorems

Theorem 1.1 (Markov's inequality)**.** For a random variable X with $\mathbf{P}\{X < 0\} = 0$ and $t > 0$, we have

$$\mathbf{P}\{X \geq t\} \leq \frac{\mathbf{E}\,X}{t}.$$

Proof. In the first place, note that

$$\begin{aligned} X &= X \cdot \mathbb{1}_{\{X \geq t\}} + X \cdot \mathbb{1}_{\{X < t\}} \\ &\geq \ t \cdot \mathbb{1}_{\{X \geq t\}} + 0, \end{aligned}$$

and thus,

$$\mathbf{E}\,X \geq t \cdot \mathbf{E}\,\mathbb{1}_{\{X \geq t\}} = t \cdot \mathbf{P}\{X \geq t\}.$$

□

Theorem 1.2 (Chebyshev's inequality)**.** For $t > 0$, a random variable X with mean $\mu = \mathbf{E}\,X$ and variance $\sigma^2 = \mathbf{Var}\,X$, we have

$$\mathbf{P}\{|X - \mu| \geq t\} \leq \frac{\sigma^2}{t^2}.$$

Proof. We apply Markov's inequality to the non-negative random variable $Y = |X - \mu|^2$ in order to obtain the desired result

$$\mathbf{P}\{|X - \mu| \geq t\} = \mathbf{P}\{|X - \mu|^2 \geq t^2\} \leq \frac{\mathbf{E}\left[(X - \mu)^2\right]}{t^2} = \frac{\sigma^2}{t^2}.$$

□

1.2 Why bother?

The concentration inequalities are used to obtain information on how a random variable is distributed at some specific places of its domain. In the most common scenarios, these inequalities will be used to quantify how concentrated a random variable at its tails, for example,

$$\mathbf{P}\{|X - \mu| \geq t\} < f(t) << 1.$$

A concentration inequality is specially useful when this probability cannot be calculated at a low computational cost or estimated with high precision. The following will illustrate a case where using concentration inequalities achieves the best results.

1.2.1 Coin Tossing

A coin tossing game is fair if the chances of winning are equal to the chances of losing. We can verify from a sample of N games that the game is not rigged if the number of heads in the sample is not very distant from the average $N/2$. However, there's a chance that one may classify the coin as rigged, even when the coin is fair. By the *Law of Large Numbers*, we know that the larger the sample, the less likely it is to obtain a false positive. But let's ask ourselves how fast this probability converges to 0.

Let $S_N \sim \mathrm{Bi}(N, 1/2)$ denote the number of heads in a fair coin tossing game. Then,

$$\mu = \mathbf{E}\, S_N = \frac{N}{2}, \qquad \sigma^2 = \mathbf{Var}\, S_N = \frac{N}{4}.$$

For a fixed $\varepsilon > 0$, we may classify a coin tossing game as rigged if, after N trials, the ratio of heads vs tails in the sample is greater than $[1+\varepsilon : 1-\varepsilon]$, or similarly,

$$S_N \geq \mu + \frac{\varepsilon}{2} N = \frac{1+\varepsilon}{2} N.$$

It's clear that calculating the exact probability of the previous event for any N, ε is a very demanding task computationally. The Chebyshev's inequality 1.2 gives us a "good-enough" result for this problem,

$$\mathbf{P}\left\{S_N \geq \mu + \frac{\varepsilon}{2} N\right\} \leq \mathbf{P}\left\{|S_N - \mu| \geq \frac{\varepsilon}{2} N\right\} \leq \sigma^2 \frac{4}{\varepsilon^2 N^2} = \frac{1}{\varepsilon^2 N}.$$

Therefore, the probability of bad events tends to 0 at least linearly with the number of games.

1.2.2 Central Limit Theorem

The proof of the following three theorems can be found in Boucheron et al. (2003)

Theorem 1.3. Let X_i be a i.i.d. sample. Let $S_N = \sum_{i=1}^{N} X_i$, with mean $\mu = \mathbf{E}\, S_N$ and variance $\sigma^2 = \mathbf{Var}\, S_N$. If

$$Z_N = \frac{S_N - N \cdot \mathbf{E}\, X_i}{\sqrt{N \cdot \mathbf{Var}\, X_i}} = \frac{S_N - \mu}{\sqrt{N}\sigma},$$

then,

$$Z_N \to Z \sim \mathcal{N}(0,1), \text{ in distribution.}$$

□

Theorem 1.4 (Tails of the Normal Distribution)**.** Let $Z \sim \mathcal{N}(0,1)$, for $t > 0$ we have

$$\left(\frac{1}{t} - \frac{1}{t^3}\right) \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-t^2}{2}\right) \leq \mathbf{P}\{Z \geq t\} \leq \frac{1}{t} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-t^2}{2}\right).$$

□

With that in mind, we might naively assume that better bounds can be obtained by using the previous theorem. For a large enough N we can say that for the coin tossing,

$$Z_N = \frac{S_N - N/2}{\sqrt{N/4}}$$

$$\implies \mathbf{P}\left\{S_N \geq \frac{1+\varepsilon}{2} N\right\} = \mathbf{P}\left\{Z_N \geq \varepsilon\sqrt{N}\right\} \sim \mathbf{P}\left\{Z \geq \varepsilon\sqrt{N}\right\}.$$

However, this raises the question of whether we can draw the following conclusion from Theorem 1.4:

$$\mathbf{P}\left\{S_N \geq \frac{1+\varepsilon}{2} N\right\} \leq \frac{1}{\varepsilon\sqrt{N}} \frac{1}{\sqrt{2\pi}} \exp\left(\frac{-\varepsilon^2 \cdot N}{2}\right).$$

Unfortunately, the answer is no. The following theorem will show why.

Theorem 1.5 (Convergence Rate for Central Limit Theorem)**.** For Z_N, Z in Theorem 1.3, we have:

$$|\mathbf{P}\{Z_N \geq t\} - \mathbf{P}\{Z \geq t\}| = O(\tfrac{1}{\sqrt{N}}).$$

□

Since the approximation error is greater than the bound, the previous results cannot be taken into account.

In the context of coin tossing, this may not matter at all because the linear bound obtained using Chebyshev's inequality indicates that the probability of wrongly classifying a fair coin as a rigged coin converges at least linearly to zero. Even the Central Limit Theorem shows in a less precise way this convergence. However, for some specific problems in statistics, these basic tools are not precise enough to solve them. In the following chapters, we will show some examples were better crafted strategies are needed in order to get bounds to the tails of the random variables.

2 Exponential Inequalities

Even if we are satisfied with the linear convergence rate provided by Chebyshev's inequality, there are simple ways to improve this bound. The following result will provide the idea from which the exponential inequalities derive

Theorem 2.1 (MGF inequality)**.** Let X_i be independent random variables and let $S_N := \sum_{i=1}^N a_i X_i$. Let $\lambda > 0$ the following inequality holds,

$$\mathbf{P}\left\{S_N \geq t\right\} \leq e^{-\lambda t} \cdot \prod_{i=1}^N \mathbf{E}\, e^{\lambda a_i X_i}$$

Proof. Let $\lambda > 0$, using Markov's inequality (Theorem 1.1) we assert that since $x \mapsto e^{\lambda x}$ is a non-decreasing function,

$$\mathbf{P}\left\{S_N \geq t\right\} = \mathbf{P}\left\{e^{\lambda S_N} \geq e^{\lambda t}\right\} \leq e^{-\lambda t} \cdot \mathbf{E}\, \exp\left(\lambda \sum_{i=1}^N a_i X_i\right).$$

Since X_i are independent, the MGF of S_N is the product of MGFs of each X_i:

$$\mathbf{E}\, \exp\left(\lambda \sum_{i=1}^N a_i X_i\right) = \prod_{i=1}^N \mathbf{E}\, e^{\lambda a_i X_i}$$

$$\implies \mathbf{P}\left\{S_N \geq t\right\} \leq e^{-\lambda t} \cdot \prod_{i=1}^N \mathbf{E}\, e^{\lambda a_i X_i}.$$

□

The following two theorems are examples on how we can obtain tighter bounds than the ones provided by Chebyshev's inequality. In particular, these theorems are derived from the idea of the previous theorem and are considered as corollaries by some authors.

Theorem 2.2 (Chernoff's inequality)**.** Let $X_i \sim \mathrm{Be}(p_i)$ be independent random variables. Define $S_N = \sum_{i=1}^N X_i$ and let $\mu = \mathbf{E}\, S_N$. Then, for $t > \mu$, we have

$$\mathbf{P}\left\{S_N \geq t\right\} \leq \left(\frac{\mu}{t}\right)^t e^{-\mu+t}.$$

Proof. In the first place, use Theorem 2.1 to assert that for a $\lambda > 0$ that

$$\mathbf{P}\left\{S_N \geq t\right\} \leq e^{-\lambda t} \cdot \prod_{i=1}^N \mathbf{E}\, e^{\lambda X_i}$$

Now it is left to bound every X_i individually. Using the inequality $1 + x \le e^x$ we obtain

$$\mathbf{E}\, e^{\lambda X_i} = e^{\lambda} p_i + (1 - p_i) = 1 + (e^{\lambda} - 1)p_i \le \exp(e^{\lambda} - 1)e^{p_i}.$$

Finally, we plug this inequality on the equation to conclude that

$$e^{-\lambda t} \cdot \prod_{i=1}^{N} \mathbf{E}\, e^{\lambda X_i} \le e^{-\lambda t} \cdot \prod_{i=1}^{N} \exp((e^{\lambda} - 1)p_i) = e^{-\lambda t} \exp((e^{\lambda} - 1)\mu).$$

By using the substitution $\lambda = \ln(t/\mu)$ we obtain the desired result,

$$\mathbf{P}\{S_N \ge t\} \le \left(\frac{\mu}{t}\right)^t \exp\left(\frac{\mu t}{\mu} - \mu\right) = \left(\frac{\mu}{t}\right)^t e^{-\mu + t}.$$

□

Another exponential inequality that is derived using a similar technique is Hoeffding's inequality:

Theorem 2.3 (Hoeffding's inequality)**.** Let $X_1, \ldots, X_N$ be independent random variables, such that $X_i \in [a_i, b_i]$ for every $i = 1, \ldots, N$. Define $S_N = \sum_{i=1}^{N} X_i$ and let $\mu = \mathbf{E}\, S_N$. Then, for every $t > 0$, we have

$$\mathbf{P}\{S_N \ge \mu + t\} \le \exp\left(\frac{-2t^2}{\sum (a_i - b_i)^2}\right).$$

Proof. Since $x \mapsto e^x$ is a convex function, it follows that, for a random variable $X \in [a, b]$:

$$e^{\lambda X} \le \frac{e^{\lambda a}(b - X)}{b - a} + \frac{e^{\lambda b}(X - a)}{b - a}, \quad a \le b.$$

Next, take expectations on both hands of the equation to obtain:

$$\mathbf{E}\, e^{tX} \le \frac{(b - \mathbf{E}\, X) \cdot e^{\lambda a}}{b - a} - \frac{(\mathbf{E}\, X - a) \cdot e^{\lambda b}}{b - a}.$$

To simplify the expression, let $\alpha = (\mathbf{E}\, X - a)/(b - a)$, $\beta = (b - \mathbf{E}\, X)/(b - a)$ and $u = \lambda(b - a)$. Since $a < \mathbf{E}\, X < b$, it follows that α and β are positive. Also, note that,

$$\alpha + \beta = \frac{\mathbf{E}\, X - a}{b - a} + \frac{b - \mathbf{E}\, X}{b - a} = \frac{b - a}{b - a} = 1.$$

Now,

$$\ln \mathbf{E}\, e^{\lambda X} \le \ln(\beta e^{-\alpha u} + \alpha e^{\beta u}) = -\alpha u + \ln(\beta + \alpha e^{u}).$$

This function is differentiable with respect to u.

$$\begin{aligned} L(u) &= -\alpha u + \ln(\beta + \alpha e^{u}) \\ L'(u) &= -\alpha + \frac{\alpha}{\alpha + \beta e^{-u}} \\ L''(u) &= \frac{\alpha}{\alpha + \beta e^{-u}} \cdot \frac{\beta e^{-u}}{\alpha + \beta e^{-u}}. \end{aligned}$$

Note that if $x = \frac{\alpha}{\alpha+\beta e^{-u}} \leq 1$, then $L''(u) = x(1-x) \leq \frac{1}{4}$. Remember that $\alpha + \beta = 1$. Now, by expanding the Taylor series we obtain,

$$\begin{aligned} L(u) &= L(0) + uL'(0) + \frac{1}{2}u^2 L''(u) \\ &= \ln(\beta+\alpha) + u\left(-\alpha + \frac{\alpha}{\alpha+\beta}\right) + \frac{1}{2}u^2 L''(u) \\ &= \frac{1}{2}u^2 L''(u) \\ &\leq \frac{1}{8}\lambda^2 (b-a)^2. \end{aligned} \tag{$\star$}$$

Finally, use the inequality from Theorem 2.1 to conclude that

$$\begin{aligned} \mathbf{P}\{S_N - \mu \geq t\} \quad &\leq \quad e^{-\lambda t} \prod_{i=1}^{N} \mathbf{E}\, e^{\lambda X_i} \\ &\leq^{(\star)} e^{-\lambda t} \exp\left(\frac{1}{8} t^2 \sum_{i=1}^{N} (b_i - a_i)^2\right) \end{aligned}$$

□

Corollary 2.3.1. Let $X_1, \ldots, X_N$ be independent random Bernoulli variables such that $X_i \sim \mathrm{Be}(p_i)$, then

$$\mathbf{P}\left\{\sum_{i=1}^{N}(X_i - p_i) \geq t\right\} \leq \exp\left(\frac{-2t^2}{N}\right).$$

. □

Returning to the coin tossing problem, we can now make a stronger assertion of the rate of convergence of a false negative classification using Hoeffding inequality:

$$\mathbf{P}\left\{S_N - \frac{N}{2} \geq \frac{\varepsilon}{2} N\right\} \leq \exp\left(-\varepsilon N\right).$$

However, this raises the question of which of the previous inequalities is better for a given problem. In the previous case, we chose Hoeffding's inequality, but when dealing with any specific problem, one needs to determine the criteria for deciding whether it's more appropriate to use Chernoff, Hoeffding, or any other inequality. In the following section, we will try to identify situations where one of these inequalities is more suitable than the other.

2.1 Which inequality is better?

Let's start with a small improvement of the Chebyshev's bound for the one-sided tails

Theorem 2.4 (Cantelli's Inequality)**.** For $t > 0$, a random variable X with mean $\mu = \mathbf{E}\, X$ and variance $\sigma^2 = \mathbf{Var}\, X$, we have

$$\mathbf{P}\{X - \mu \geq t\} \leq \frac{\sigma^2}{t^2 + \sigma^2}.$$

Proof. In the first place note that,

$$\mathbf{P}\{Y \geq s\} \leq \mathbf{P}\{Y \geq s\} + \mathbf{P}\{Y \leq s\} = \mathbf{P}\{|Y| \geq s\} = \mathbf{P}\{Y^2 \geq s^2\}. \qquad (\star)$$

Let $u \geq 0$, define $Y = X - \mu + u$ and $s = t + u$ to obtain

$$\mathbf{P}\{X - \mu \geq t\} = \mathbf{P}\{X - \mu + u \geq t + u\} = \mathbf{P}\{Y \geq s\}.$$

We use $(\star)$ and Markov's inequality (1.1) on Y^2 to conclude,

$$\mathbf{P}\{Y \geq s\} \overset{(\star)}{\leq} \mathbf{P}\{Y^2 \geq s^2\} \overset{(1.1)}{\leq} \frac{\mathbf{E}\left[(X - \mu + u)^2\right]}{(t + u)^2}.$$

By linearity of expectation,

$$\mathbf{E}\left[(X - \mu + u)^2\right] = \mathbf{E}\left[(X - \mu)^2\right] + 2u \cdot \underbrace{\mathbf{E}\,(X - \mu)}_{0} + E(u^2) = \sigma^2 + u^2.$$

Finally, we choose an optimal $u = \frac{\sigma^2}{t}$ to conclude

$$\mathbf{P}\{X - \mu \geq t\} \leq \frac{\sigma^2 + u^2}{(t + u)^2} = \frac{\sigma^2 + \sigma^4/t^2}{(t + \sigma^2/t)^2} = \frac{\sigma^2(\frac{t^2+\sigma^2}{t^2})}{(\frac{t^2+\sigma^2}{t})^2} = \frac{\sigma^2}{t^2 + \sigma^2}$$

$\square$

On the other hand, the two-sided tail inequality, Cantelli's inequality is not always better than Chebyshev,

Corollary 2.4.1 (Two-sided Cantelli inequality)**.**

$$\mathbf{P}\{|X - \mu| \geq t\} \leq \frac{2\sigma^2}{t^2 + \sigma^2}.$$

In fact, this bound is only better than Chebyshev's $t^2 + \sigma^2 \leq 2t^2$, or equivalently, when $\sigma^2 \leq t^2$. However, in this case both inequalities give bounds greater than 1, and thus, are useless. Therefore, we conclude that in general Chebyshev's is better for two-sided tails and Cantelli's for one-sided tails.

2.2 Uniform Law of Large Numbers

For any probability measure P on the real line and $t > \in \mathbb{R}$, define P_n as the empirical probability measure obtain from an independent sample $X_1, \ldots, X_n$ of P, that is:

$$P_n(t) = n^{-1} \cdot \sum_{i=1}^{n} \mathbb{1}_{\{X_i < t\}}.$$

From the law of large numbers we know that for a fixed t, $P_n(t)$ converges to $P(t)$ with probability 1. However we can formulate a stronger statement on this convergence. The first application of concentration inequalities we are going to explore is the uniform law of large numbers, which states the following:

Theorem 2.5 (Glivenko-Cantelli Theorem)**.** For P, P_n and t from above,

$$\|P_n - P\| = \sup_{t \in \mathbb{Q}} |P_n(t) - P(t)| \xrightarrow{p} 0.$$

Proof. The proof, adapted from Pollard (2012), consists of 5 steps. At first instance, the author clarifies that we must stablish the condition of $t \in \mathbb{Q}$ to avoid problems with measurability. The author later proves that the theorem is true for any $t \in \mathbb{R}$, but for practical purposes, we will only prove it for rationals. Another remark the author makes is that this result from the real line can be later generalized for some classes of polynomials, and we will cover more about this in section 5.

First Symmetrization

In the first place, define P'_n as the empirical measure obtained from an independent copy of the sample $X'_1, \ldots, X'_n$ of P. Note that for any fixed t, $P_n(t)$ and $P'_n(t)$ are random variables derived from their respective samples which have:

$$\mathbf{E}\, P_n(t) = \mathbf{E}\, P'_n(t) = P(t), \quad \mathbf{Var}\, P_n(t) = \mathbf{Var}\, P'_n(t) = P(t)$$

We will bound the concentration of $\|P_n - P'_n\|$ first, which will later result in a bound for $\|P_n - P\|$ according to the following lemma:

For now, fix $\varepsilon > 0$, and keep in mind the values $Z = P_n - P$, $Z' = P'_n - P$, $\alpha = \frac{1}{2}\varepsilon$ and $\beta = \frac{1}{2}$.

Lemma 2.6. Let $\{Z(t)\}_{t \in T}$ and $\{Z'(t)\}_{t \in T}$ be independent stochastic processes under the same set of indices T. Also, assume that there exist $\alpha, \beta > 0$ such that

$$\mathbf{P}\left\{\sup_{t \in T} |Z(t)| \leq \alpha\right\} \geq \beta.$$

It follows that, for any $\varepsilon > 0$,

$$\mathbf{P}\left\{\sup_{t \in T} |Z(t)| > \varepsilon\right\} \leq \beta^{-1} \mathbf{P}\left\{\sup_{t \in T} |Z(t) - Z'(t)| > \varepsilon - \alpha\right\}.$$

Proof. Since Z, Z' are independent, it follows from the hypothesis that for any index $\tau \in T$,

$$\mathbf{P}\{|Z'(\tau)| \leq \alpha | Z\} = \mathbf{P}\{|Z'(\tau)| \leq \alpha\} \geq \mathbf{P}\left\{\sup_{t\in T} |Z'(t)| \leq \alpha\right\} \geq \beta.$$

Now, fix τ such that $|Z(\tau)| > \varepsilon$ and use the previous inequality to conclude,

$$\begin{aligned}
\beta \cdot \mathbf{P}\left\{\sup_{t\in T} |Z(t)| > \varepsilon\right\} &\leq \mathbf{P}\{|Z'(\tau)| \leq \alpha\} \cdot \mathbf{P}\{|Z(\tau)| > \varepsilon\} \\
\text{(Z, Z' are independent)} &= \mathbf{P}\{|Z'(\tau)| \leq \alpha,\ |Z(\tau)| > \varepsilon\} \\
&\leq \mathbf{P}\{|Z(\tau) - Z'(\tau)| > \varepsilon - \alpha\} \\
\textbf{TODO:}\text{ why?} &\leq \mathbf{P}\left\{\sup_{t\in T} |Z(t) - Z'(t)| > \varepsilon - \alpha\right\}.
\end{aligned}$$

□

Using Chevyshev's inequality (1.2) we know that the hypothesis is satisfied for the values of α and β we chose:

$$\forall t \in T : \mathbf{P}\left\{|Z'(t)| \leq \alpha\right\} = \mathbf{P}\{|P_n(t) - P(t)| \leq \varepsilon\} \geq \frac{1}{2} = \beta, \quad \text{if } n \geq 8\varepsilon^{-2}$$

Therefore, using the previous lemma, we conclude that

$$\mathbf{P}\{\|P_n - P\| > \varepsilon\} \leq 2\mathbf{P}\{\|P_n - P'_n\| > \tfrac{1}{2}\varepsilon\}, \quad \text{if } n \geq 8\varepsilon^{-2}.$$

Second Symmetrization

The following trick will allow us to stop considering all of the $2n$ from the previous symmetrization, and will help us to create a simpler random variable. Let $\sigma_1, \ldots, \sigma_n$ be Rademacher random variables, that is $\mathbf{P}\{\sigma_i = 1\} = \mathbf{P}\{\sigma_i = -1\} = 1/2$. Let $Y_i = \mathbb{1}_{\{X_i < t\}} - \mathbb{1}_{\{X_i < t\}}$, and note that,

$$P\{Y_i = 1\} = P\{Y_i = -1\} = \frac{1}{2}\left(1 - \mathbf{P}\{Y_i = 0\}\right).$$

Since σ_i is independent of Y_i, it follows that

$$\begin{aligned}
P\{\sigma_i Y_i = 1\} &= \mathbf{P}\{Y_i = 1, \sigma_i = 1\} + \mathbf{P}\{Y_i = -1, \sigma_i = -1\} \\
&= \frac{1}{2}\mathbf{P}\{Y_i = 1\} + \frac{1}{2}\mathbf{P}\{Y_i = -1\} \\
&= \mathbf{P}\{Y_i = 1\}
\end{aligned}$$

$$\implies P\{\sigma_i Y_i = \pm 1\} = P\{Y_i = \pm 1\}, \quad P\{\sigma_i Y_i = 0\} = P\{Y_i = 0\}$$

Therefore, we won't alter the distribution of Y_i when multiplying by σ_i

$$\implies Y_i \sim \sigma_i Y_i.$$

It follows that since $P_n - P_n' = n^{-1} \sum_{i \leq n} Y_i$,

$$\begin{aligned}
\mathbf{P}\{\|P_n - P_n'\| > \tfrac{1}{2}\varepsilon\} &= \mathbf{P}\left\{\sup_{t \in \mathbb{Q}} \left| n^{-1} \sum_{i=1}^{n} \sigma_i Y_i \right| > \tfrac{1}{2}\varepsilon \right\} \\
&\leq \mathbf{P}\left\{\sup_{t \in \mathbb{Q}} \left| n^{-1} \sum_{i=1}^{n} \sigma_i \mathbb{1}_{\{X_i < t\}} \right| > \tfrac{1}{2}\varepsilon \right\} \\
&\quad + \mathbf{P}\left\{\sup_{t \in \mathbb{Q}} \left| n^{-1} \sum_{i=1}^{n} \sigma_i \mathbb{1}_{\{X_i' < t\}} \right| > \tfrac{1}{2}\varepsilon \right\} \\
&= 2\mathbf{P}\{\|\tilde{P}_n\| > \tfrac{1}{4}\varepsilon\}.
\end{aligned}$$

where $\tilde{P}_n = n^{-1} \sum_{i \leq n} \sigma_i \mathbb{1}_{\{X_i < t\}}$. Then, from the previous section we can conclude that for $n \geq 8\varepsilon^{-2}$,

$$\mathbf{P}\{\|P_n - P\| > \varepsilon\} \leq 4\mathbf{P}\{\|\tilde{P}_n\| > \tfrac{1}{4}\varepsilon\}$$

$\square$

3 Application to Estimation of Data Dimension

3.1 Chernoff-Okamoto Inequalities

Applying Markov's Inequality to $Y = e^{uX}$, we can assert that

$$\mathbf{P}\{X \geq \lambda + t\} \leq e^{-u(\lambda+t)}\mathbf{E}\, e^{uX} = e^{-u(\lambda+t)}(1-p+pe^u)^n.$$

The right hand equation is minimized when,

$$e^u = \frac{\lambda + t}{(n-\lambda-t)} \cdot \frac{1-p}{p}.$$

Therefore, for $0 \leq t \leq n - \lambda$,

$$\mathbf{P}\{X \geq \lambda + t\} \leq \left(\frac{\lambda}{\lambda+t}\right)^{\lambda+t}\left(\frac{n-\lambda}{n-\lambda-t}\right)^{n-\lambda-t} \tag{3.1}$$

Theorem 3.1. Let X be random variable with the binomial distribution $\mathrm{Bi}(n,p)$ with $\lambda := np = \mathbf{E}\, X$, then for $t \geq 0$,

$$\mathbf{P}\{X \geq \lambda + t\} \leq \exp\left(-\frac{t^2}{2(\lambda + t/3)}\right) \tag{3.2}$$

$$\mathbf{P}\{X \leq \lambda - t\} \leq \exp\left(-\frac{t^2}{2\lambda}\right) \tag{3.3}$$

Used in: Theorem 3.3

Proof. (**TODO** I've already written the proof on paper) □

The article Díaz et al. (2019) explains how we can estimate the dimension d of a manifold M embedded on a Euclidean space of dimension m, say $\mathbb{R}^m$. First, we are going to introduce the method they used, and then, we will show how does the exponential inequalities can be used to prove two important results in the paper. The procedure starts with an example on a uniformly distributed sample on a d-sphere $\mathbb{S}^{d-1} \subset \mathbb{R}^d$, but will be later generalized for samples of any distribution on any manifold.

In the first place, let $Z_1, \ldots, Z_k$ be a i.i.d. sample uniformly distributed on $\mathbb{S}^{d-1}$. Then, we have the following formula for the variance of the angles between $Z_i, Z_j, i \neq j$:

$$\beta_d := \mathbf{Var}\left(\arccos\langle Z_i, Z_j\rangle\right) = \begin{cases} \dfrac{\pi^2}{4} - 2\displaystyle\sum_{j=1}^{k}(2j-1)^{-2}, & \text{if } d = 2k+1 \text{ is odd,} \\ \dfrac{\pi^2}{12} - 2\displaystyle\sum_{j=1}^{k}(2j)^{-2}, & \text{if } d = 2k+2 \text{ is even.} \end{cases} \tag{3.4}$$

The previous formula for the angle variance is proven in Díaz et al. (2019). In order to give more insight on how we will be choosing an estimator $\widehat{d}$ of the dimension of the sphere, consider the following theorem.

Theorem 3.2 (Bounds for β_d)**.** For every $d > 1$,

$$\frac{1}{d} \leq \beta_d \leq \frac{1}{d-1}.$$

. □

Knowing that for every $d > 1$, β_d is in the interval $[\frac{1}{d}, \frac{1}{d-1}]$, one can guess the dimension of the sphere by estimating β_d, and then, taking d from the lower bound of the interval where our estimator is. Since β_d is the variance of the angles in our sphere, our best choice for an estimator is the angle's sample variance,

$$U_k = \binom{k}{2}^{-1} \sum_{i<j\leq k} \left(\arccos\langle Z_i, Z_j\rangle - \frac{\pi^2}{2}\right)^2. \tag{3.5}$$

In Proposition 1. of Díaz et al. (2019) the authors prove that it's the Minimum Variance Unbiased Estimator for β_d on the unit sphere.

Furthermore, the authors also prove that this result can be generalized for any manifold with samples of any distribution. Let $X_1, \ldots, X_n$ be a i.i.d. sample from a random distribution P on a manifold $M \subset \mathbb{R}^m$, and let $p \in M$ a point. For $C > 0 \in \mathbb{R}$, let $k = \lceil C\ln(n)\rceil$ and define $R(n) = L_{k+1}(p)$ as the distance between p and its $(k+1)$-nearest neighbor. W.L.O.G. assume that $p = 0 \in M$ and that $X_1, \ldots, X_k$ are the k-nearest neighbors of p. Additionally, for the following theorem to be true, we requiere that at any neighborhood of p, the probability in that neighborhood is greater than 0.

The following theorem uses a special inequality from Chernoff-Okamoto, and it's crucial in the idea behind this generalization.

Theorem 3.3 (Bound k-neighbors)**.** For any sufficiently large $C > 0$, we have that, there exists n_0 such that, with probability 1, for every $n \geq n_0$,

$$R(n) \leq f_{p,P,C}(n) = O(\sqrt[d]{\ln(n)/n}), \tag{3.6}$$

where the function $f_{p,P,C}$ is a deterministic function which depends on p, P and C.

. □

The following theorem, although it does not require concentration inequalities, is important for connecting the idea of the previous theorem to the main frame. Let $\pi : R^m \to T_pM$ be the orthogonal projection on the Tangent Space of M at p. Also, define $W_i := \pi(X_i)$ and then normalize,

$$Z_i := \frac{X_i}{\|X_i\|}, \quad \widehat{W_i} := \frac{W_i}{\|W_i\|}. \tag{3.7}$$

Theorem 3.4 (Projection Distance Bounds)**.** For any $i < j \leq n$,

(i) $\|X_i - \pi(X_i)\| = O(\|\pi(X_i)\|^2)$ (3.8)

(ii) $\|Z_i - \widehat{W_i}\| = O(\|\pi(X_i)\|)$ (3.9)

(iii) The inner products (cosine of angles) can be bounded as it follows:

$$|\langle Z_i, Z_j\rangle - \langle \widehat{W_i}, \widehat{W_j}\rangle| \leq Kr, \tag{3.10}$$

for a constant $K \in \mathbb{R}$, whenever $r \geq \max(\|\pi(X_i)\|, \|\pi(X_j)\|)$.

. □

What follows is that if we know $W_1, \ldots, W_k$ are behaved similar to a uniformly distributed sample on the sphere $\mathbb{S}^d$, then, $Z_1, \ldots, Z_k$ (the normalized k-nearest neighbors of p) also behave like they are uniformly distributed on $\mathbb{S}^d$. The following theorem is made by combining the ideas of the previous theorems.

Theorem 3.5 (Projection's Angle Variance Statistic)**.** For $k = O(\ln n)$, let

$$V_{k,n} = \binom{k}{2}^{-1} \sum_{i<j\leq k} \left(\arccos\left\langle \widehat{W_i}, \widehat{W_j}\right\rangle - \frac{\pi^2}{2}\right)^2, \tag{3.11}$$

and let $U_{k,n} = U_k$ from equation 3.5. The following statements hold

(i) $k|U_{k,n} - V_{k,n}| \overset{n\to\infty}{\longrightarrow} 0$, in probability. (3.12)

(ii) $\mathbf{E}\,|U_{k,n} - V_{k,n}| \overset{n\to\infty}{\longrightarrow} 0$.

. □

This last theorem is as far as this document is planned to cover. However, the last result in the paper provides the main statement. It says that if we estimate β_d as we did with $U_{k,n}$ from 3.5, and then, extract $\widehat{d}$ from the interval where $U_{k,n}$ is located, it follows that,

Theorem 3.6 (Consistency)**.** When $n \to \infty$,

$$\mathbf{P}\{\widehat{d} \neq d\} \to 0.$$

3.2 Proofs

Proof Theorem 3.2: The even and the odd cases must be distinguished:

(1): When $d = 2k + 2$ is even: In the first place, remember that,

$$\lim_{k \to \infty} \sum_{j=1}^{k} j^{-2} = \frac{\pi^2}{6}.$$

It follows that

$$\begin{aligned} \beta_d &= \frac{\pi^2}{12} - 2 \sum_{j=1}^{k} (2j)^{-2} = \frac{\pi^2}{12} - \frac{1}{2} \sum_{j=1}^{k} j^{-2} \\ &= \frac{1}{2} \sum_{j=k+1}^{\infty} j^{-2}. \end{aligned}$$

Since $(j^{-2})_{j \in \mathbb{N}}$ is a monotonically decreasing sequence, it follows that

$$\begin{aligned} \frac{1}{d} = \frac{1}{2k+2} &= \frac{1}{2} \int_{k+1}^{\infty} x^{-2} dx \\ \leq \quad \beta_d \quad &\leq \frac{1}{2} \int_{k+1/2}^{\infty} x^{-2} dx \\ = \frac{1}{2k+1} &= \frac{1}{d-1}. \end{aligned}$$

(2): When $d = 2k + 3$ is odd: On the other hand, note that

$$\begin{aligned} \lim_{k \to \infty} \sum_{j=1}^{k} (2j-1)^{-2} &= \lim_{k \to \infty} \sum_{j=1}^{2k-1} j^{-2} - \sum_{j=1}^{k-1} (2j)^{-2} \\ &= \lim_{k \to \infty} \sum_{j=1}^{2k-1} j^{-2} - \frac{1}{4} \sum_{j=1}^{k-1} j^{-2} \\ &= \frac{\pi^2}{6} - \frac{\pi^2}{24} = \frac{\pi^2}{8} \end{aligned}$$

Then,

$$\begin{aligned} \beta_d &= \frac{\pi^2}{4} - 2 \sum_{j=1}^{k} (2j-1)^{-2} \\ &= 2 \sum_{j=k+1}^{\infty} (2j-1)^{-2}. \end{aligned}$$

Using a similar argument we conclude that

$$\begin{aligned} \frac{1}{d} = \frac{1}{2k+1} &= 2\int_{k+1}^{\infty} (2x-1)^{-2}dx \\ \leq \quad \beta_d \quad &\leq 2\int_{k+1/2}^{\infty} (2x-1)^{-2}dx \\ &= \frac{1}{2k+2} = \frac{1}{d-1}. \end{aligned}$$

$\square$

Proof Theorem 3.3: The volume of a d-sphere of radius r is equal to:

$$v_d r^d = \frac{\pi^{d/2}}{\Gamma(\frac{n}{2}+1)} r^d.$$

Where v_d is the volume of the unit d-sphere. For the assumptions we made on P and M around $p = 0$, we can say that for any $r > 0$, there's a percent (greater than 0) of the sample that is within a range r from p. This proportion is subordinated only by the volume of a d-sphere of radius r and a constant $\alpha := \alpha(P)$ that depends on the distribution P:

$$\rho = \mathbf{P}\{X \in M : |X| < r\} \geq \alpha v_d r^d > 0.$$

We can now define a binomial process based on how many neighbors does p has within a range r. Let $N = N_r \sim \mathrm{Bi}(n, \rho)$ be the number of neighbors, using Theorem 3.1 with $\lambda = n\rho$ and $t = \frac{\lambda}{2}$ we obtain,

$$\mathbf{P}\{N \leq \lambda - t\} = \mathbf{P}\{2N \leq \lambda\} \leq \exp(-\lambda/8).$$

Since $n(\alpha v_d r^d) \leq n\rho = \lambda$, it follows that, by choosing $r(n)$ such that

$$r(n) = \left(\frac{C}{\alpha v_d} \cdot \frac{\ln n}{n}\right)^{1/d} = O(\sqrt[d]{\ln(n)/n}), \qquad (\star)$$

and thus,

$$C \ln n = n(\alpha v_d r(n)^d) \leq \lambda,$$

we obtain:

$$P\{2N \leq C \ln n\} \leq \mathbf{P}\{2N \leq \lambda\},$$

and,

$$\exp(-\lambda/8) \leq \exp\left(\frac{-C\ln n}{8}\right) = n^{-C/8}.$$

Therefore,

$$P\{2N \leq C \ln n\} \leq n^{-C/8}.$$

Finally, with this last expression we proved that if $k = \frac{C}{2} \ln n$, then the k-neighbors of p are contained in the ball of radius $r(n)$ with a probability that converges exponentially to 1. $\square$

4 Applications to graph theory

4.1 The Azuma-Hoeffding Inequality

Definition 4.1. A sequence $X_0, \ldots, X_n$ of random variables is consider a **martingale** if, for every $i \leq n$,

$$\mathbf{E}\left[X_{i+1} | X_i, \ldots, X_0\right] = X_i$$

The random graph $G(n, p)$ has n labeled vertices and produces an edge between 2 of them with probability p. Let $v_1, \ldots, v_n$ denote the vertices and $e_1, \ldots, e_m$ the potential $\binom{n}{2}$ edges with the indicator function:

$$\mathbb{1}_{e_k \in G} = \begin{cases} 1, & e_k \in G \\ 0, & \text{otherwise} \end{cases}$$

An edge exposure martingale is a sequence of random variables defined as the expected value of a function $f(G)$ which depends on the information of the first j potential edges:

$$X_j = \mathbf{E}\left[f(G) \mid \mathbb{1}_{e_1 \in G}, \ldots, \mathbb{1}_{e_j \in G}\right]$$

Since all of the graph information is contained in its edges, the sequence transitions from no information: $X_0 = E(f(G))$, to the true value of the function: $X_m = f(G)$. Similarly, one can define a martingale which depends on how many vertices are revealed. The vertex exposure martingale is defined as it follows,

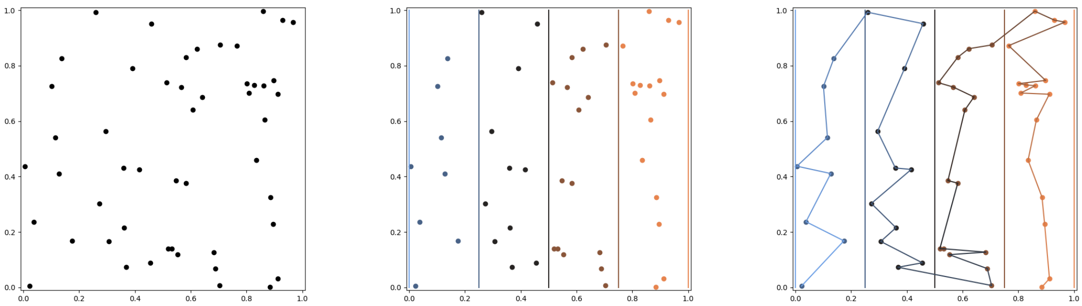
$$X_i = \mathbf{E}\left[f(G) \mid \mathbb{1}_{\{v_k, v_j\}},\ k, j \leq i\right]$$

In the following section we are going to present an application of the Azuma-Hoeffding inequality to prove the convergence to the mean of a linear approximation algorithm for the *Travelling Salesman Problem.*

4.2 An heuristic algorithm for the Travelling Salesman Problem

Let $X_1, \ldots, X_N$ be a sample of N uniformly distributed points in a compact square $[0, L] \times [0, L]$. The algorithm divides this square in M stripes of width L/M each. Then, it connects each of the points in each of the stripes vertically and connects the top-most of one stripe with the top-most of the next one (or viceversa as the image below shows).

In the reference Gzyl et al. (1990) the authors assert that by choosing a number of stripes $M^* = \lfloor 0.58 N^{1/2} \rfloor$, one can achieve the best result in comparison to the real TSP



(a) Uniform sample (b) Divide in M stripes (c) Join points vertically

solution. If t_N is the TSP solution distance for our sample and d_N is the algorithm's answer with the optimal M^*, then the error is asymptotically:

$$\frac{d_N - t_N}{t_N} \approx 0.23.$$

The result that we are going to prove is that d_N converges with an exponential rate to its mean. To prove our point, we are going to modify the algorithm's trajectory as it follows. Let e_N be trajectory distance that for any empty stripe in the plane we sum the length of its diagonal $\sqrt{L^2 + L^2/M^2}$ and then it skips the empty stripe. When there are no empty stripes $e_N = d_N$ and the probability that any given stripe is empty converges exponentially to 0:

$$\begin{aligned}
(1 - 1/M)^N &= \left(1 - 0.58^{-1} N^{-1/2}\right)^N \\
&= \left((1 - 1/M)^M\right)^{0.58^{-1} N^{1/2}} \\
&\sim \exp(-0.58^{-1} N^{1/2}).
\end{aligned}$$

Let $\mathcal{A}_i := \sigma\{X_1, \ldots, X_i\}$ be the sigma algebra corresponding to revealing the first i points, $\mathcal{A}_0 = \{\emptyset, [0, L]^2\}$. The expected value of the trajectory e_N given that we only know the positions of the first i points in the sample is $\mathbf{E}\left(e_N | \mathcal{A}_i\right)$. Define

$$Z_i = \mathbf{E}\left(e_N | \mathcal{A}_i\right) - \mathbf{E}\left(e_N | \mathcal{A}_{i-1}\right),$$

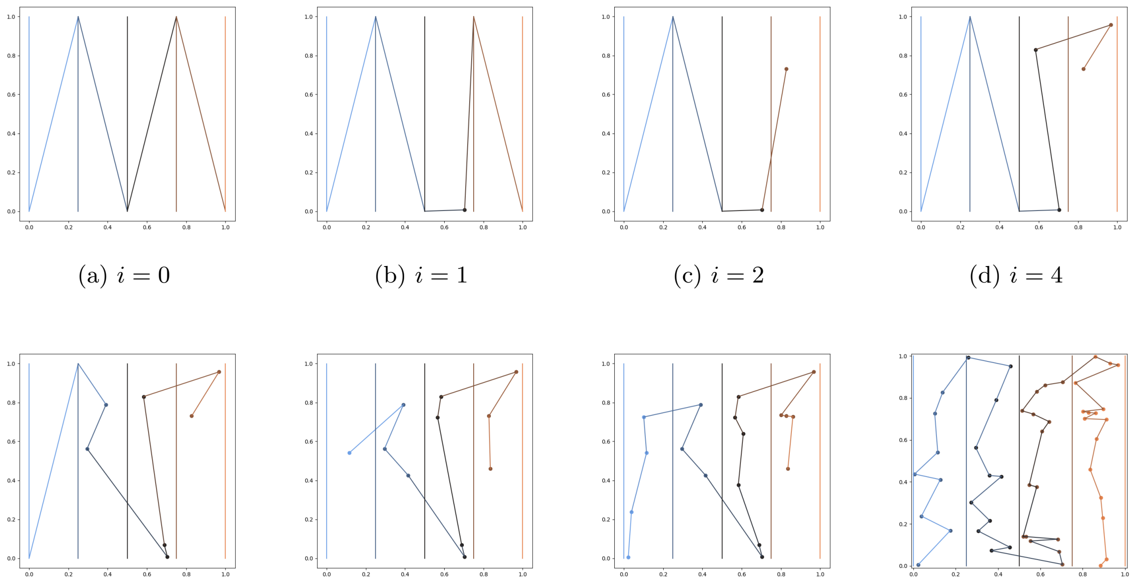
As the difference of this expectations when we reveal 1 more point. Note that since

$$\mathbf{E}\left(Z_i | \mathcal{A}_i\right) = \mathbf{E}\left(e_N | \mathcal{A}_i, \mathcal{A}_i\right) - \mathbf{E}\left(e_N | \mathcal{A}_{i-1}, A_i\right) = \mathbf{E}\left(e_N | \mathcal{A}_i\right) - \mathbf{E}\left(e_N | \mathcal{A}_i\right) = 0,$$

The $Z_i's$ form a vertex exposure martingale sequence.

Define $e_N^{[i]}$ as the distance of the trajectory when we remove the i-th point from the sample. Intuitively from the figure above and the triangle inequality, we can obtain

$$e_N^{[i]} \leq e_N \leq e_N + 2L/M,$$



(a) $i = 0$ (b) $i = 1$ (c) $i = 2$ (d) $i = 4$

(e) $i = 7$ (f) $i = 12$ (g) $i = 18$ (h) $i = N = 50$

Figure 4.1: Evolution of the vertex exposure martingale

meaning that revealing one point cannot increase more than 2 widths the distance of the trajectory. Thus,

$$\|Z_i\|_\infty = \sup_{X_1,\ldots,X_N} \|\mathbf{E}\left(e_N|\mathcal{A}_i\right) - \mathbf{E}\left(e_N|\mathcal{A}_{i-1}\right)\| \leq 2L/M.$$

On the other hand, by telescopic sums we obtain that

$$e_N - Ee_N = \mathbf{E}\left(e_N|\mathcal{A}_N\right) - \mathbf{E}\left(e_N|\mathcal{A}_0\right) = \sum_{i=1}^{N} Z_i.$$

Therefore, by the Azuma-Hoeffding inequality,

$$\mathbf{P}\{|e_N - Ee_N| > t\} \leq 2\exp\left(\frac{-t^2}{2}\sum_{i=1}^{N}\|Z_i\|_\infty^2\right).$$

Finally,

$$\sum_{i=1}^{N}\|Z_i\|_\infty^2 \leq \frac{4NL^2}{M^2},$$

which implies that

$$\mathbf{P}\{|e_N - Ee_N| > t\} \leq 2\exp\left(\frac{-t^2}{2}\sum_{i=1}^{N}\frac{4NL^2}{M^2}\right) \sim e^{-t^2KN},$$

for some $K \in \mathbb{R}^+$.

5 Applications to Vapnik–Chervonenkis theory

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