

## Probability

## 1. Markov's inequality

$$\Pr(X \geq t) \leq \frac{\mathbb{E}[X]}{t}$$

- a.
- b. The inequality is tight  $\rightarrow$  Cannot be improved
- c. Example)

$$\Pr(X \geq k\mathbb{E}[X]) \leq \frac{1}{k}$$

- i. Let  $X$  be a non-negative RV. Then,
- ii. For example  $X \sim \text{Bin}(1000, 0.1)$ .
- iii.  $X = \#$  heads of based on the coin where  $p = 0.1$
- iv. Then  $\mathbb{E}[X] = np = 1000 * 0.1 = 100$ .  $\rightarrow$  the expected value is non negative  $\rightarrow$  can apply markov's inequality
- v.  $\Pr(X=k) = nCk * (1-p)^{(1-k)} * (p)^k = nCk * (0.9)^{(1-k)} * (p)^k$
- vi. Markov's inequality:  $\Pr(X \geq 400) \leq \frac{1}{4}$
- vii. The bound is not tight, we can get much tighter bounds  $\rightarrow$  can make the upper bound smaller

## 2. Chebyshev's inequality

$$\Pr(|X - \mu| \geq t) \leq \frac{\sigma^2}{t^2}$$

- a. Let  $\mu = \mathbb{E}[X]$ ,  $\sigma^2 = \text{Var}[X]$ . Then
- b. Example 1:
  - i. Let's consider the same example as before, namely bound the head  $\Pr(X \geq 400)$  where  $X \sim \text{Bin}(1000, 0.1)$ .
  - ii.  $\text{Var}[X] = 1000 * 0.1 * 0.9 = 90$
  - iii.  $\Pr(X \geq 400) = \Pr(X - 100 \geq 300) \leq \Pr(|X - 100| \geq 300) \leq \frac{\text{Var}[X]}{300^2} = \frac{90}{300^2} = 0.001$
- c. Example 2:
  - i. Suppose that we toss a fair coin 100 times. What is the probability we see tails more than 60 times or less than 40 times?
  - ii.  $\Pr(X \leq 40 \cup X \geq 60) = \Pr(|X - 50| \geq 10) \leq \frac{25}{100} = \frac{1}{4}$

## 3. Weak law of large numbers

- a. Let  $X_1, X_2, \dots$  be a sequence of iid (independent identically distributed) RVs with mean  $\mu$ , and standard deviation  $\sigma$ . Consider the sum

$$S_n = X_1 + \dots + X_n$$

- b. Then as  $n \rightarrow \infty$ , for all  $\epsilon > 0$  the empirical average converges to  $\mu$  in probability.

$$\lim_{n \rightarrow \infty} \Pr\left(\left|\frac{S_n}{n} - \mu\right| > \epsilon\right) = 0.$$

- c.  $\rightarrow$  as you increase the number of trials, the estimate from the data you obtain will be closer to the true estimate

- d.  $\lim_{n \rightarrow \infty} \Pr(|S_n/n - \mu| > \epsilon) = 0$

$$\Pr(|S_n - \mu * n| > \epsilon * n) = 0$$

$$E(S_n) = E(\sum_{i=1}^n X_i) = \sum_{i=1}^n E(X_i) = n * \mu$$

$$\text{Var}(S_n) = n * \sigma^2$$

$$\Pr(|S_n - \mu * n| > \epsilon * n)$$

$$\Pr(|S_n - E(S_n)| > t) \leq n * \sigma^2 / (\epsilon^2 * n^2) \leq \sigma^2 / (\epsilon^2 * n)$$

$$\Pr\left(\left|\frac{S_n}{n} - \mu\right| > \epsilon\right) \leq \frac{\text{Var}(S_n/n)}{\epsilon^2} = \frac{\sigma^2}{n\epsilon^2} \rightarrow 0 \text{ as } n \rightarrow \infty$$

$$\text{As } n \rightarrow \infty, \Pr(|S_n - E(S_n)| > t) \leq 0$$

- e. Example 1:

- i. Consider rolling a regular die  $n$  times. Then by WLLN we obtain that sum of the first  $n$  rolls as  $n$  grows, for any  $\epsilon > 0$  satisfies

$$\Pr\left(\left|\frac{S_n}{n} - \frac{7}{2}\right| > \epsilon\right) \rightarrow 0$$

#### 4. Weak law of large numbers - Confidence intervals

- a. The proof of WLLN gives us a way to construct confidence intervals  
b. Specifically, if  $0 < \alpha < 1$ , we get the following confidence interval

$$\mu - \frac{\sigma}{\sqrt{\alpha n}} \leq \frac{S_n}{n} \leq \mu + \frac{\sigma}{\sqrt{\alpha n}} \text{ wp at least } 1 - \alpha$$

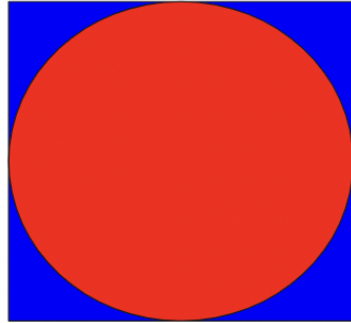
c.  $\Pr(|S_n/n - \mu| \geq \sigma/\sqrt{\alpha n})$

d.  $\Pr(|S_n - \mu * n| \geq \sigma * \sqrt{n}/\sqrt{\alpha})$

e.  $\Pr(|S_n - \mu * n| \geq \sigma * \sqrt{n}/\sqrt{\alpha}) \leq n * \sigma^2 / (\sigma^2 * n / \alpha) = \alpha$

#### 5. How to estimate pi?

- a. We generate a point uniformly at random within the unit square  $[0,1] * [0,1]$   
b. Let  $E$  be the event that the random point will fall within the circle. What is the probability of this event?



c.

$$\Pr(\mathcal{E}) = \frac{\text{circle area}}{\text{area of square}} = \frac{\pi r^2}{1 \times 1} = \frac{\pi}{4}$$

d.

e. Algorithm:

- i. We generate  $n$  random points  $(x_i, y_i)$  in the unit square  $[0,1] \times [0,1]$
- ii. We test for each point if it falls within the circle
- iii. Define  $S_n = \text{\#points inside the circle}$
- iv.  $E(S_n) = n * E[x_i] = n * \pi/4$   
 $\pi = 4 * E(S_n)/n$

$$\tilde{\pi} = 4 \frac{S_n}{n}$$

v. Let our  $\pi$  estimate be

vi. We can write the RV  $S_n$  as the sum of  $n$  independent Bernoulli variables

$$S_n = \sum_{i=1}^n X_i, \quad X_i = \begin{cases} 1 & \text{if } i\text{-th point inside circle} \\ 0 & \text{otherwise (o/w)} \end{cases}$$

vii.

viii.  $\text{Var}[S_n] = n * \pi/4 * (1 - \pi/4)$

ix.  $\Pr(|S_n/n - \pi/4| \geq \epsilon) \leq (\pi/4) * (1 - \pi/4) / (n\epsilon^2) < \beta$  (confidence interval value that we choose)

where  $\epsilon$  = accuracy

x. The above equation can be written as the following by flipping it

$\Pr(|S_n/n - \pi/4| \leq \epsilon) \geq 1 - \beta$  (that we chose above)

xi. Using Chebyshev's inequality, we get

$$\Pr\left(\left|\frac{X_1 + \dots + X_n}{n} - \frac{\pi}{4}\right| \geq \epsilon\right) \leq \frac{\pi/4(1 - \pi/4)}{n\epsilon^2} \leq \delta$$

xii. We can set  $\epsilon$  = accuracy,  $\beta$  = confidence interval value