

# The Second-Moment Method

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# Markov's Inequality

Recall Markov's inequality:

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

Proof:

$$\begin{aligned}\mathbb{E}|X| &= \int_{\omega: |X| < t} |X| dP + \int_{\omega: |X| \geq t} |X| dP \\ &\geq 0 + t \cdot \Pr[|X| \geq t]\end{aligned}$$

# Markov's Inequality

What was special about the absolute value function?

- ① non-negative
- ② increasing

We can apply the same proof to other functions.

## Theorem

### *Chebyshev's Inequality*

$$\Pr[|X - \mathbb{E}X| \geq t] \leq \frac{\text{var}(X)}{t^2}$$

$$\text{var}(X) = \mathbb{E}[|X - \mathbb{E}X|^2] \geq t^2 \cdot \Pr[|X - \mathbb{E}X| \geq t]$$

# Chebyshev's Inequality

For example, if  $X$  has mean 3, variance 1, then the probability that  $X$  is more than 5 or less than 1 is bounded by  $1/4$ .

Is the bound a good bound for the Normal distribution?

Give an example of a random variable where the Chebyshev bound is tight.

# The Weak Law of Large Numbers

As an application of Chebyshev's Inequality, we can prove our first limit theorem.

## Theorem

*Let  $X_1, X_2, \dots$  be i.i.d. random variables with mean  $\mu$  and variance  $\sigma^2$ . Then for every  $\epsilon > 0$ ,*

$$\Pr \left[ \left| \frac{X_1 + \dots + X_n}{n} - \mu \right| > \epsilon \right] \rightarrow 0 \text{ as } n \rightarrow \infty$$

# The Weak Law of Large Numbers

Comments:

- What does the WLLN say about political polling, for instance?
- Are all of the conditions necessary?
- Why do we say 'Weak'?

# The Weak Law of Large Numbers

Proof: Let  $U_n = \frac{X_1 + \dots + X_n}{n}$  and calculate  $\mathbb{E}U_n$  and  $\text{var}(U_n)$

$$\mathbb{E}U_n = \mu$$

$$\text{var}(U_n) = \frac{1}{n^2} \sum \text{var}(X_i) = \frac{\sigma^2}{n}$$

Now apply Chebyshev:

$$\Pr \left[ \left| \frac{X_1 + \dots + X_n}{n} - \mu \right| > \epsilon \right] \leq \frac{\sigma^2}{\epsilon^2 n} \rightarrow 0 \text{ as } n \rightarrow \infty$$



# First-Moment Method

Let  $X$  be a counting r.v. If  $\mathbb{E}X \rightarrow 0$  as  $n \rightarrow \infty$ , then  $\Pr[X = 0] \rightarrow 1$ .

But what if  $\mathbb{E}X \rightarrow \infty$ ? Can we say that  $\Pr[X = 0] \rightarrow 0$ ?

No, not necessarily.

Example: Let  $X = n^2$  with probability  $1/n$  and 0 with probability  $1 - 1/n$ . Then  $X = 0$  whp, but  $\mathbb{E}X \rightarrow \infty$ .

# Counting Random Variables

If  $X$  is a counting random variable then by plugging in  $t = \mathbb{E}X$ ,

Lemma

$$\Pr[X = 0] \leq \frac{\text{var}(X)}{(\mathbb{E}X)^2}$$

In particular, if  $\mathbb{E}X \rightarrow \infty$  and  $\text{var}(X) = o((\mathbb{E}X)^2)$ , then  $X \geq 1$  whp.

## An Example

$m$  balls thrown randomly into  $n$  bins. We saw with the first-moment method that if  $m = (1 + \epsilon)n \log n$ , then whp there are no empty bins. But what if  $m = (1 - \epsilon)n \log n$ ?

Let  $X$  be the number of empty bins.

$$\mathbb{E}X = n \cdot \left(1 - \frac{1}{n}\right)^m$$

If  $m = (1 - \epsilon)n \log n$  then  $\mathbb{E}X \sim n^\epsilon \rightarrow \infty$ . But to conclude that  $X \geq 1$  whp, we need the second-moment method.

## Calculating the Variance

Let  $X = X_1 + X_2 + \cdots + X_n$ . Then

$$\text{var}(X) = \sum_{i=1}^n \text{var}(X_i) + \sum_{i \neq j} \text{cov}(X_i, X_j)$$

Let  $X_i$  be the indicator rv that the  $i$ th bin is empty.

## Upper Bounding the Variance

Since we just need an upper bound to apply Chebyshev's inequality, things become simpler.

First, since the  $X_i$ 's are indicator rv's,  $\text{var}(X_i) \leq \mathbb{E}X_i$  and  $\sum \text{var}(X_i) \leq \mathbb{E}X$ . Since  $\mathbb{E}X \rightarrow \infty$  for our choice of  $m$ ,

$$\sum \text{var}(X_i) = o((\mathbb{E}X)^2)$$

## Bounding the Covariances

We need to bound  $\sum_{i \neq j} \text{cov}(X_i, X_j)$ . Each of the terms are the same and there are  $n(n-1)$  of them.

$$\begin{aligned} \text{cov}(X_i, X_j) &= \mathbb{E}(X_i X_j) - \mathbb{E}X_i \mathbb{E}X_j \\ &= \Pr[\text{i and j empty}] - \Pr[\text{i empty}] \cdot \Pr[\text{j empty}] \\ &= \left(1 - \frac{2}{n}\right)^m - \left(1 - \frac{1}{n}\right)^{2m} \end{aligned}$$

We could calculate and show that this is small, but that is unnecessary: the covariance terms are negative.

We showed that for  $m = (1 - \epsilon)n \log n$ ,

$$\mathbb{E}X \rightarrow \infty$$

and

$$\text{var}(X) = o((\mathbb{E}X)^2)$$

Then using Chebyshev's inequality with  $t = \mathbb{E}X$ , we concluded that  $\Pr[X = 0] = o(1)$ .

# Applications of the 2nd Moment Method

- What's the 'typical' position of a simple random walk after  $n$  steps?
- What's the longest run of Heads in  $n$  flips of a fair coin?
- What is the maximum of  $n$  independent standard normal RV's?