| Variance |  |
| :---: | :---: |
| CS 70, Summer 2019 |  |
| Lecture 21, $7 / 30 / 19$ |  |
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## Definition of Variance

The key difference is the variance.
Variance is the expected "distance" to mean.
Let $X$ be a RV with $\mathbb{E}[X]=\mu$. Then:


## Two Games

Game 1: Flip a ${ }^{\text {ccoin }} 10$ times. For each Head you win 100. For each Tail, you lose 100.

Expected Winnings on Flip $i$ :


$$
\mathbb{E}\left[F_{i}\right]=100\left(\frac{1}{2}\right)+(-100)\left(\frac{1}{2}\right)=\underline{0}
$$

$\underbrace{\text { Expected Winnings After } 10 \text { Flips: }}$

$$
\mathbb{E}[F]=\sum_{i=1}^{10} \mathbb{E}\left[F_{i}\right]=0
$$

## Alternate Definition

We can use linearity of expectation to get an alternate form that is often easier to apply.
$\operatorname{Var}(X)=\mathbb{E}\left[X^{2}\right]-\mu^{2}$
$\mathbb{E}\left[(x-\mu)^{2}\right]=\mathbb{E}\left[x^{2}-2 \mu X+\mu^{2}\right]$
lineanty $=\mathbb{E}\left[x^{2}\right]-2 \mu \underbrace{\mathbb{E}[x]}_{\mu}+\mu^{2}$
$=\mathbb{E}\left[x^{2}\right]-\mu^{2}$

## Two Games fair

Game 2: Flip a coin 10 times. For each Head, you win 10000. For each Tail, you lose 10000.

Expected Winnings on Flip i:


$$
\mathbb{E}\left[F_{i}\right]=0=\frac{1}{2}(10000)+\frac{1}{2}(-10000)
$$

Expected Winnings After 10 Flips:

```
\mathbb{E}[F]=0
```

Q: Which game would you rather play?

## Variance: A Visual



## Variance of a Bernoulli

```
Let \(X \sim \operatorname{Bernoulli}(p)\).
Then \(\mathbb{E}[X]=\boldsymbol{p}\)
What is \(X^{2}\) ? \(\mathbb{E}\left[X^{2}\right]\) ?
```

```
\[
\begin{aligned}
& X^{2}=\left\{\begin{array}{lll|}
1 & w p & p \\
0 & w p & 1-p
\end{array} \left\lvert\, \begin{array}{c}
\mathbb{E}\left[x^{2}\right]=1 \cdot p+0 \cdot(1-p) \\
=p .
\end{array}\right.\right. \\
& \operatorname{Var}[X]=\mathbb{E}\left[X^{2}\right]-(\mathbb{E}[X])^{2}
\end{aligned}
\]
```


## Variance of a Geometric

Know the variance; proof optional, but good practice with manipulating RVs.

Let $X \sim \operatorname{Geometric}(p)$.
Strategy: Nice expression for $p \cdot \mathbb{E}\left[X^{2}\right]$
$\mathbb{E}\left[x^{2}\right]=1 \cdot p+4(1-p) p+9(1-p)^{2} p+$
$-\left[(1-p) \mathbb{E}\left[x^{2}\right]\right]=-\left[1(1-p) p+4(1-p)^{2} p\right]$
subtract from both sides
$p \mathbb{E}\left[x^{2}\right]=1 \cdot p+3(1-p) p+5(1-p)^{2} p+$
$=\left(2 \cdot p+4(1-p) p+6(1-p)^{2} p+\ldots\right)+\left(-p-(1-p) p-(1-p)^{2} p-\right)$

## Variance of a Dice Roll

What is the variance of a single 6 -sided dice roll?

$$
R=\text { value of a dice roll. }\{1,2,3,4,5,6\}
$$

What is $R^{2}$ ?

$$
R^{2}=\left\{\begin{array}{ccc}
1 & w p & \frac{1}{6} \\
4 & 11 & \frac{1}{6} \\
9 & \vdots & \vdots \\
16 & \vdots & \\
25 &
\end{array}\right.
$$

## Variance of a Geometric II

From the distribution of $X$, we know:
$\sum_{i=1}^{\infty} \mathbb{P}[x=i]=p+(1-p) p+(1-p)^{2} p+\ldots=1$
From $\mathbb{E}[X]$, we know:
$\mathbb{E}[x]=1 \cdot p+2 \cdot(1-p) p+3(1-p)^{2} p+\ldots$
(2)


## Variance of a Dice Roll

$$
\begin{aligned}
\mathbb{E}\left[R^{2}\right] & =\frac{1}{6}[\underbrace{1+4+9+16+25+36}_{10}] \\
& =\frac{1}{6}(91)
\end{aligned}
$$

$$
\operatorname{Var}(R)=\mathbb{E}\left[R^{2}\right]-(\mathbb{E}[R])^{2}
$$

$$
=\frac{91}{6}-\left(\frac{7}{2}\right)^{2}=
$$

(Notes.)

## Variance of a Geometric III

Recall $\mathbb{E}[X]=\frac{1}{p}$.
$\operatorname{var}(x)=\mathbb{E}\left[x^{2}\right]-(\underbrace{\mathbb{E}[x]})^{2}$

$$
=\frac{2-p}{p^{2}}-\frac{1}{p^{2}}=\frac{1-p}{p^{2}}
$$

## Variance of a Poisson

Same: know the variance; proof optional, but good practice with functions of RVs.

$$
\begin{aligned}
& \text { Let } X \sim \operatorname{Poisson}(\lambda) . \\
& \text { Strategy: Compute } \mathbb{E}[X(X-1)] \cdot \\
& \mathbb{E}[X(X-1)]=(\text { def }) \\
& \sum_{i=0}^{\infty} i(j=1) \cdot \frac{\lambda^{i}}{\frac{\mathbb{i} t}{(i-2)!} \cdot e^{-\lambda}}
\end{aligned}
$$

$=e^{-\lambda} \sum_{i=2}^{\infty} \frac{\lambda^{i}}{(i-2)!} \quad$ Taylor series
$=e^{-\lambda} \lambda^{2} \sum_{i=2}^{\infty} \frac{\lambda^{i-2}}{(i-2)!}$
$=e^{-\lambda}\left(\lambda^{2}\right)\left(e^{2}\right)=\lambda^{2}$

## Properties of Variance I: Scale

Let $X$ be a RV , and let $c \in \mathbb{R}$ be a constant.
Let $\mathbb{E}[X]=\mu$.
$\operatorname{Var}(c X)=c^{2} \cdot \operatorname{Var}(X)$
$\operatorname{Var}(c X)=\mathbb{E}\left[(c X)^{2}\right]-(\mathbb{E}[c X])^{2}$ lin.
$=\mathbb{E}\left[c^{2} X^{2}\right]-(c \mathbb{E}[X])^{2}$
$=c^{2} \mathbb{E}\left[X^{2}\right]-c^{2}(\mathbb{E}[X])^{2}$
$=c^{2} \operatorname{Var}(x)$

## Variance of a Poisson II

Use $\mathbb{E}[X(X-1)]$ to compute $\operatorname{Var}(X)$.

$$
\begin{aligned}
\operatorname{var}(x) & =\mathbb{E}\left[x^{2}\right]-(\mathbb{E}[x])^{2} \\
& =\underbrace{\mathbb{E}[x(x-1)]}_{\text {last slude }}+\underbrace{\mathbb{E}[x]}_{\text {yesterday }}-(\mathbb{E}[x])^{2} \\
& =x^{2}+\lambda-(\lambda)^{2}=\lambda
\end{aligned}
$$

## Properties of Variance II: Shift

Let $X$ be a RV , and let $c \in \mathbb{R}$ be a constant.
Let $E[X]=\mu$.
Then, let $\mu^{\prime}=\mathbb{E}[X+c]=y+c$
$\operatorname{Var}(X+c)=\operatorname{Var}(X)$
$\operatorname{var}(x+c)=\mathbb{E}\left[\left((x+c)-\mu^{\prime}\right)^{2}\right]$
$=\mathbb{E}\left[(x+x-\mu-x)^{2}\right]$
$=\mathbb{E}\left[(x-\mu)^{2}\right]=\operatorname{var}(x)$


Shift


## Break

Would you rather only wear sweatpants for the rest of your life, or never get to wear sweatpants ever again?

## Example: Shift It!

Consider the following RV:

$$
\begin{aligned}
& X= \begin{cases}1 & \text { w.p. } 0.4 \\
3 & \text { w.p. } 0.2 \\
5 & \text { w.p. } 0.4\end{cases} \\
& =\operatorname{Var}(x-3)
\end{aligned}
$$

What is $\operatorname{Var}(X)$ ? Shift it!

$$
x-3=\left\{\begin{array}{rll}
-2 & \text { wp. } & 0.4 \\
0 & \text { wp } & 0.2 \\
2 & \text { wp } & 0.4
\end{array} \left\lvert\, \begin{array}{l}
(x-3)^{2}= \begin{cases}4 & \text { wp } 0.8 \\
0 & \text { wp } 0.2\end{cases} \\
\\
\\
\\
\operatorname{Var}\left[(x-3)^{2}\right]=4 \cdot 0.0 .8+0 \cdot 0.2=3.2
\end{array}\right.\right.
$$

## Sum of Independent RVs

Let $X_{1}, \ldots, X_{n}$ be independent RVs. Then:

$$
\operatorname{Var}\left(X_{1}+\ldots+X_{n}\right)=\operatorname{Var}\left(X_{1}\right)+\ldots+\operatorname{Var}\left(X_{n}\right)
$$

Proof: Tomorrow!

## Today: Focus on applications.

## HW Mixups (Fixed Points)

(In notes.) $n$ students hand in HW. I mix up their HW randomly and return it, so that every possible mixup is equally likely.

Let $S=\#$ of students who get their own HW. Last time: defined $S_{i}=$ indicator for student $i$ gelting own HW.

$$
S_{i} \sim \operatorname{Ber}\left(\frac{1}{n}\right)^{J}
$$

Using linearity of expectation:
$\mathbb{E}[S]=\mathbb{E}\left[S_{1}+S_{2}+\ldots+S_{n}\right]=\mathbb{E}\left[S_{1}\right]+\mathbb{E}\left[S_{2}\right]+\ldots+\mathbb{E}\left[S_{n}\right]$ $=\frac{1}{n}(n)$ (1)

## Variance of a Binomial

Let $X \sim \operatorname{Bin}(n, p)$. Then,

$$
\begin{aligned}
& X=X_{1}+X_{2}+\ldots+X_{n} \\
& \text { Here, } X_{i} \sim \operatorname{Ber}(p) \quad X_{i} \text { ïd. } \\
& \operatorname{Var}(X)=\operatorname{Var}\left(X_{1}\right)+\operatorname{Var}\left(X_{2}\right)+\ldots+\operatorname{Var}\left(X_{n}\right) \\
& =n \cdot \operatorname{Var}\left(X_{1}\right) \quad X \sim \operatorname{Bin}(n, p) \\
& =\eta-\operatorname{Bin}(n, 1-p) \\
& \operatorname{Var}(X)=\operatorname{var}(Y)
\end{aligned}
$$

## HW Mixups II

Using our useful fact:
$\mathbb{E}\left[S^{2}\right]=\mathbb{E}\left[\left(S_{1}+S_{2}+\ldots+S_{n}\right)^{2}\right]$
$=\mathbb{E}\left[\sum_{i=1}^{n} S_{i}{ }^{2}+\sum_{i \neq j} S_{i} S_{j}\right]$
linearity:
$=\mathbb{E}\left[\sum_{i=1}^{n} S_{i}{ }^{2}\right]+\mathbb{E}\left[\sum_{i=j} S_{i} S_{j}\right]$
$=n \cdot \underbrace{\mathbb{E}\left[S_{1}{ }^{2}\right]}_{?}+n(n-1) \cdot \underbrace{\mathbb{E}\left[S_{1} S_{2}\right]}_{\text {? }}$

## Sum of Dependent RVs

Main strategy: linearity of expectation and indicator variables

## Useful Fact:

$$
\begin{aligned}
& \left(x_{1}+x_{2}+\ldots+x_{n}\right)^{2}= \\
& \quad\left(x_{1}+x_{2}+\ldots+x_{n}\right)\left(x_{1}+x_{2}+\ldots+x_{n}\right) \\
& = \\
& (\underbrace{x_{1}^{2}+x_{2}^{2}+\ldots+x_{n}^{2}}_{1})+(\underbrace{\left.x_{1} x_{2}+x_{1} x_{3}+\ldots+x_{n-1} x_{n}\right)}_{n(n-1)} \\
& =\sum_{i=1}^{n} x_{i}^{2}+\sum_{i \neq j} x_{i} x_{j} \text { alternate: } \sum_{i(l)} x_{i} x_{j}
\end{aligned}
$$

## HW Mixups III

What is $S_{i}^{2} ? \mathbb{E}\left[S_{i}^{2}\right]$ ?

$$
S_{1}^{2}=\left\{\left.\begin{array}{lll}
1 & \text { wp } \frac{1}{n} \\
0 & w p & 1-\frac{1}{n}
\end{array} \right\rvert\, \mathbb{E}\left[S_{1}^{2}\right]=\frac{1}{n}\right.
$$

For $i \neq j$, what is $S_{i} S_{j}$ ? $\mathbb{E}\left[S_{i} S_{j}\right]$ ?

## HW Mixups IV

Put it all together to compute $\operatorname{Var}(X)$.
$\operatorname{var}(x)=\mathbb{E}\left[x^{2}\right]-(\mathbb{E}[x])^{2}$
$=\underbrace{}_{n \in\left[S_{1}^{2}\right]+n(n-1) \mathbb{E}\left[S_{1} S_{2}\right]-(1)^{2}}$
$=n\left(\frac{1}{2}\right)+n(n-1) \frac{1}{n(n-1)}-1$
$=1$

## Summary

Today:

- Variance measures how far you deviate from mean
- Variance is additive for independent RVs proof to come tomorrow
- Use linearity of expectation and indicator variables

