# Review of Selected Topics in Probability Expectation 

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Lecture 5

## Expectation

...or mean value, expected value, 1st moment.
Definition (Expectation)
The expectation of a random variable $X$ is the number

$$
\begin{align*}
\mathbb{E}[X] & \stackrel{\text { def }}{=} \sum_{x \in \mathcal{A}_{X}} x \operatorname{Pr}(X=x) \quad \text { (if } X \text { is discrete) }  \tag{1}\\
& \stackrel{\text { def }}{=} \int_{-\infty}^{\infty} x f(x) d x \quad \text { (if } X \text { is continuous) } \tag{2}
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Quiz: $\mathbb{E}[X] \in \mathcal{A}_{X}$ ? Answer:

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$$

Quiz: $\mathbb{E}[X] \in \mathcal{A}_{X}$ ? Answer: No, it is just a weighted sum of the values of $X$ !

## Definitions and Properties of Expectation

- $\mathbb{E}[c \cdot X]=c \mathbb{E}[X]$, for any constant $c$.
- Theorem (Linearity of Expectation)

For any random variables $X, Y, \mathbb{E}[X+Y]=\mathbb{E}[X]+\mathbb{E}[Y]$.

- For any real function $g(\cdot)$ defined on $\mathcal{A}_{X}$, $\mathbb{E}[g(X)]=\sum_{x \in \mathcal{A}_{X}} g(x) \operatorname{Pr}(X=x)$.
- For any two independent random variables $X, Y$, $\mathbb{E}[X \cdot Y]=\mathbb{E}[X] \mathbb{E}[Y]$.
- There is at least one value $a_{\jmath} \in \mathcal{A}_{X}$ such that $a_{\jmath} \geq \mathbb{E}[X]$.


## First Order Concentration - Markov's Inequality

Question: Suppose we flip a coin 50 times and let $X$ be the number of times it turned up heads. How much is the probability that $X>47$ ?

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Theorem (Markov's Inequality)
For any positive random variable $X$, and $t>0$

$$
\begin{equation*}
\operatorname{Pr}(X \geq t) \leq \frac{\mathbb{E}[X]}{t} \tag{3}
\end{equation*}
$$

Proof (discrete case).

$$
\begin{aligned}
\mathbb{E}[X] & =\sum_{x \in \mathcal{A}_{x}} x \operatorname{Pr}(X=x) \geq \sum_{x \geq t} x \operatorname{Pr}(X=x) \\
& \geq \sum_{x \geq t} t \operatorname{Pr}(X=x)=
\end{aligned}
$$

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& \geq \sum_{x \geq t} t \operatorname{Pr}(X=x)=t \operatorname{Pr}(X \geq t) .
\end{aligned}
$$

## Variance

Example: Let $W=0$ with probability 1 ,

$$
Y= \begin{cases}+1 & \text {,with probability } \frac{1}{2} \\ -1 & \text {,with probability } \frac{1}{2} .\end{cases}
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and

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X= \begin{cases}+100 & \text {,with probability } \frac{1}{2} \\ -100 & \text {,with probability } \frac{1}{2}\end{cases}
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These are different, but have the same expectation.
Definition (Variance)
The variance of a random variable $X$ is the number

$$
\begin{equation*}
\operatorname{Var}(X) \stackrel{\text { def }}{=} \mathbb{E}\left[(X-\mu)^{2}\right] \tag{4}
\end{equation*}
$$

where $\mu=\mathbb{E}[X]$. The typical deviation of $X$ is defined as

$$
\begin{equation*}
\sigma \stackrel{\text { def }}{=} \sqrt{\operatorname{Var}(X)} \tag{5}
\end{equation*}
$$

## Properties of Variance

- $\operatorname{Var}(X) \geq 0$.
- $\operatorname{Var}(X)=\mathbb{E}\left[X^{2}\right]-\mathbb{E}^{2}[X]$.
- $\operatorname{Var}(a X+b)=a^{2} \operatorname{Var}(X)$, for any constants $a, b$.
- If $X, Y$ are independent, then $\operatorname{Var}(X+Y)=\operatorname{Var}(X)+\operatorname{Var}(Y)$. Note: The inverse does not hold!


## Covariance

## Definition (Covariance)

The covariance of two random variables $X, Y$ is

$$
\begin{align*}
\operatorname{Cov}(X, Y) & \stackrel{\text { def }}{=} \mathbb{E}\left[\left(X-\mu_{X}\right)\left(Y-\mu_{Y}\right)\right]  \tag{6}\\
& =\mathbb{E}[X Y]-\mathbb{E}[X] \mathbb{E}[Y]
\end{align*}
$$

,where $\mu_{X}=\mathbb{E}[X]$ and $\mu_{Y}=\mathbb{E}[Y]$.
Intuition: The covariance is a measure of the dependency of two variables. It can take negative values (can you find an example?).

## Properties of Covariance

- If $X$ is independent of $Y, \operatorname{Cov}(X, Y)=0$. Note: The inverse does not hold! (Homework: Find an example!)
- $\operatorname{Cov}(X, Y)=\operatorname{Cov}(Y, X)$ (symmetry).
- $\operatorname{Cov}(X, X)=\operatorname{Var}(X)$.
- (variance of sum)

$$
\begin{aligned}
\operatorname{Var}\left(\sum_{i=1}^{n} X_{i}\right) & =\sum_{i, j} \operatorname{Cov}\left(X_{i}, X_{j}\right) \\
& =\sum_{i} \operatorname{Var}\left(X_{i}\right)+\sum_{i} \sum_{j \neq i} \operatorname{Cov}\left(X_{i}, X_{j}\right) .
\end{aligned}
$$

## Chebyshev's Inequality

Theorem (Chebyshev's Inequality)
For any random variable $X$ and any $k>0$

$$
\begin{equation*}
\operatorname{Pr}(|X-\mathbb{E}[X]| \geq k) \leq \frac{\operatorname{Var}(X)}{k^{2}} \tag{7}
\end{equation*}
$$

Proof. Similar to the proof of Markov's inequality.
Note: Chebyshev's inequality gives stronger bounds than Markov's inequality, at the cost of more complex computations. Intuitively, the more information we have from higher moments (i.e. $\mathbb{E}\left[X^{i}\right]$, for $i \in \mathbb{N}$ ), the more we can say for a distribution (more on this later...).

## Quiz

For some fixed $k>0$, let

$$
X= \begin{cases}k & , \text { with probability } \frac{1}{2 k^{2}} \\ 0 & , \text { with probability } 1-\frac{1}{k^{2}} \\ -k & , \text { with probability } \phi\end{cases}
$$

What are is the exact value and the upper bounds we can get for $\operatorname{Pr}(|X| \geq k)$ using Markov's and Chebyshev's inequality respectively?
(a) $\frac{1}{2}, 1$ and $\frac{1}{k^{2}}$
(b) $\frac{1}{k^{2}}$, inconclusive and $\frac{1}{k^{2}}$
(c) $\frac{1}{2}, 0$ and $\frac{1}{2}$
(d) none of the above

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Answer: (b)

## Conditional Expectation

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Let $X, Y$ two random variables. The conditional expectation of $X$, given $Y=y$ is the function of $y$

$$
\begin{aligned}
\mathbb{E}[X \mid Y=y] & \stackrel{\text { def }}{=} \sum_{x \in \mathcal{A}_{X}} x \cdot \operatorname{Pr}(X=x \mid Y=y) \quad \text { (if } X \text { is discrete) } \\
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$$

- If $X, Y$ are independent, then $\mathbb{E}[X \mid Y=y]=\mathbb{E}[X]$
- $\mathbb{E}[\mathbb{E}[X \mid Y]]=\mathbb{E}[X]$ (Exercise: Prove this!)


## Homework

Investigate the discrete distributions

- Binomial
- Geometric
- Poisson
and the continuous distributions
- Uniform
- Exponential
in terms of Expectation, Variance.


## Further reading

S. Ross. A first course in probability:

Chapter 4, "Random Variables"
Chapter 5, "Continuous Random Variables"
Chapter 6, "Jointly Distributed Random Variables" Chapter 7, "Properties of Expectation"

