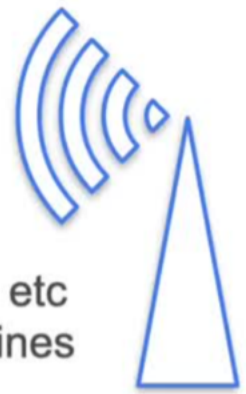
Day - 58, Jan - 27, 2025 (Magh 14, 2081 B.S.)

A Communication Problem

Communication channel

Noise
Interference from other devices
Obstructions like walls, trees, etc.
Atmospheric conditions: rain, humidity, etc
Electrical interference, i.e. from power lines
Others



Message sent: 10010

Message Recieved:
10010 + Z

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Dispersion of Noise Signal.

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Chi-Square Distribution

Z

What is the **power** of the noise in the channe

$$W = Z^2$$

The communication channel has noise with a standard normal distribution

What is the distribution of W?

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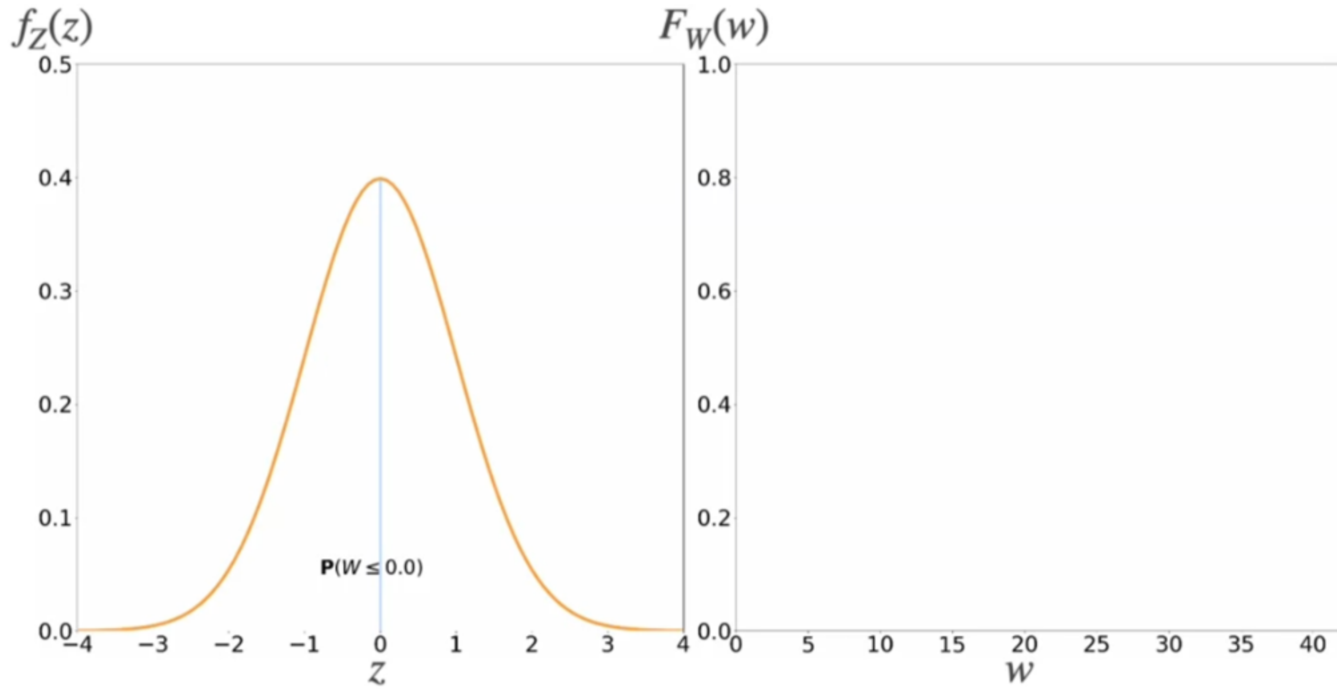
⇒ We assume the noise 'Z' follows the normalization [0,1] and viewing the graph we get,

Chi Square Distribution



$F_W(w) = P(W \le w)$

$\Rightarrow P(Z^2 \le w)$

$\Rightarrow P(|Z| \le \sqrt{w})$

$\Rightarrow P(-\sqrt{w} \le Z \le \sqrt{w})$

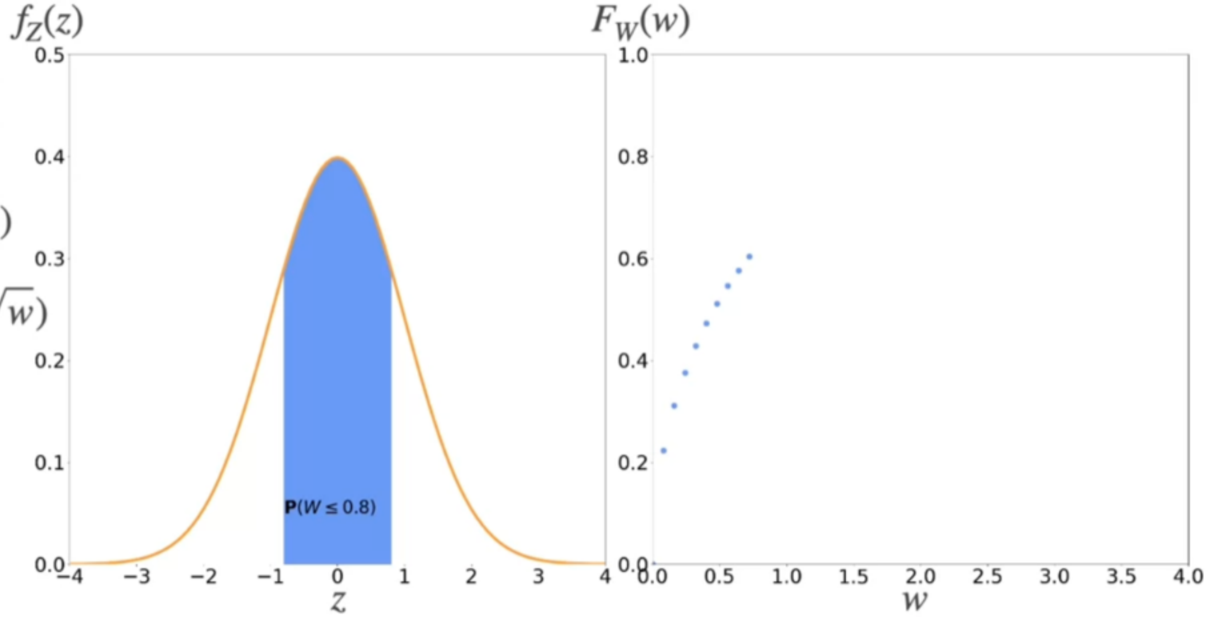
Let's try to see it graphically. Each value of W can be achieved with two different values of Z, which are negative square root of W, and square root of W, even more, the probability that capital W's and W is the area under the PDF curve on the Gaussian between these two numbers. You can get the CDF for W by finding these areas for each possible value W. Notice that for small values of W, you gain area at a much quicker rate. This is because the Gaussian distribution concentrates probability around 0. This is known as the Chi-squared distribution with one degree of freedom.

Sum of Squared of Independent Standard Normal Random Variables distribution is Chi-Squared Distribution.

Chi Square Distribution

1

$$F_W(w) = \mathbf{P}(W \le w)$$
$$= \mathbf{P}(Z^2 \le w)$$
$$= \mathbf{P}(|Z| \le \sqrt{w})$$
$$= \mathbf{P}(-\sqrt{w} \le Z \le \sqrt{w})$$



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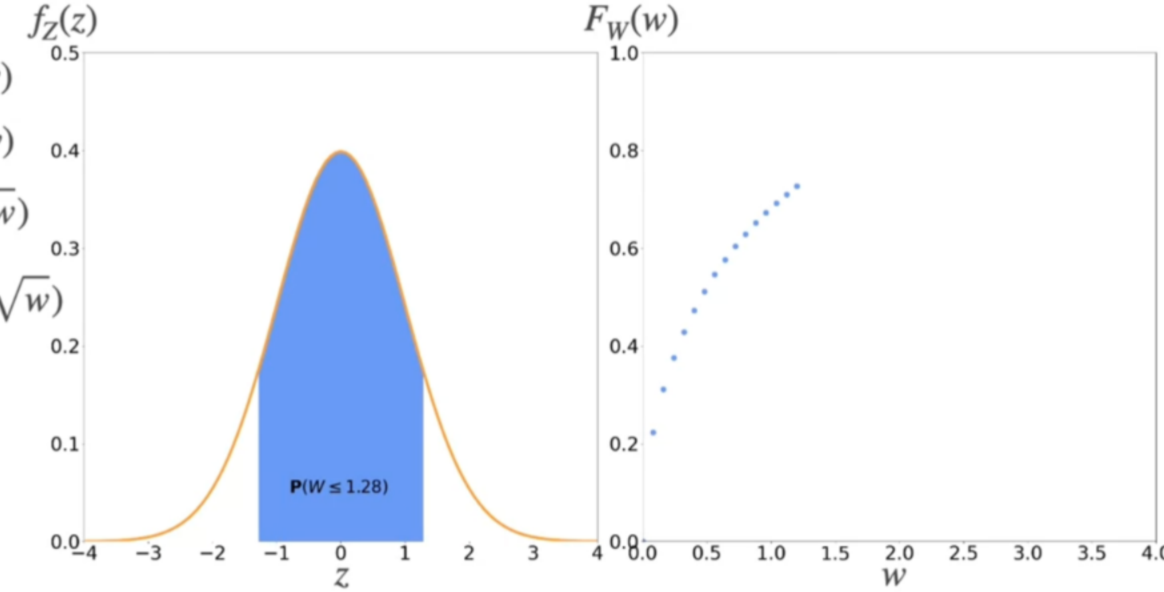
Chi Square Distribution

2

$$F_W(w) = \mathbf{P}(W \le w)$$
$$= \mathbf{P}(Z^2 \le w)$$
$$= \mathbf{P}(|Z| \le \sqrt{w})$$
$$= \mathbf{P}(-\sqrt{w} \le Z \le \sqrt{w})$$



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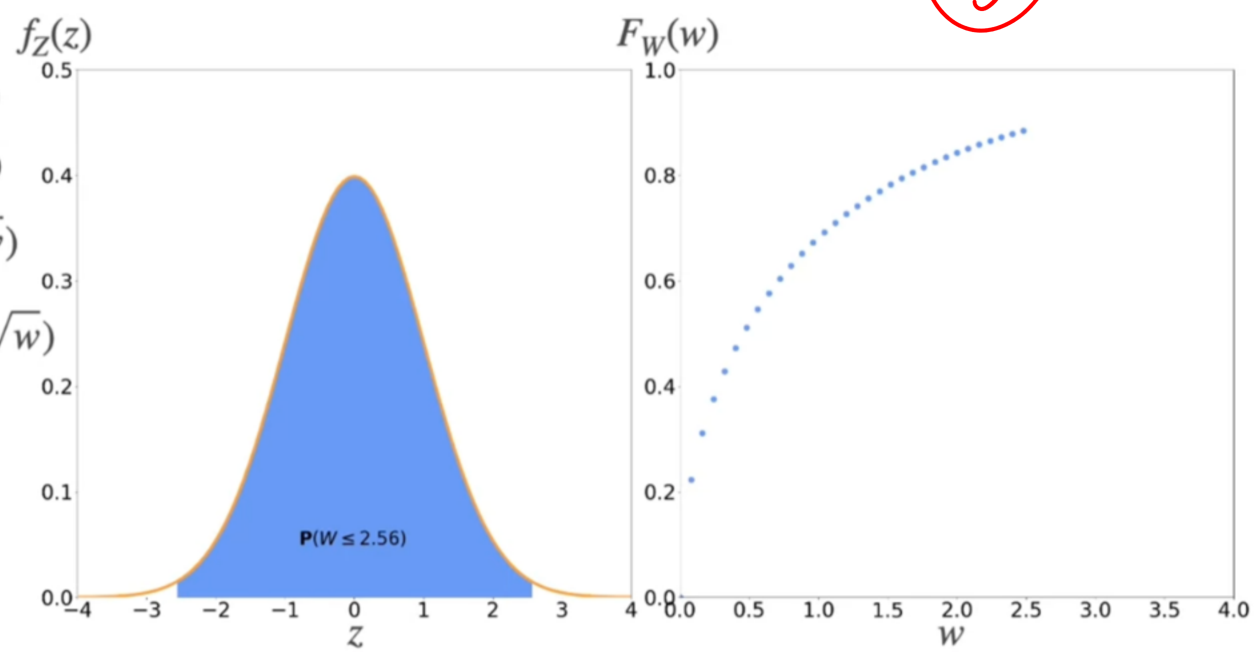
Chi Square Distribution

3

$$F_W(w) = \mathbf{P}(W \le w)$$
$$= \mathbf{P}(Z^2 \le w)$$
$$= \mathbf{P}(|Z| \le \sqrt{w})$$
$$= \mathbf{P}(-\sqrt{w} \le Z \le \sqrt{w})$$



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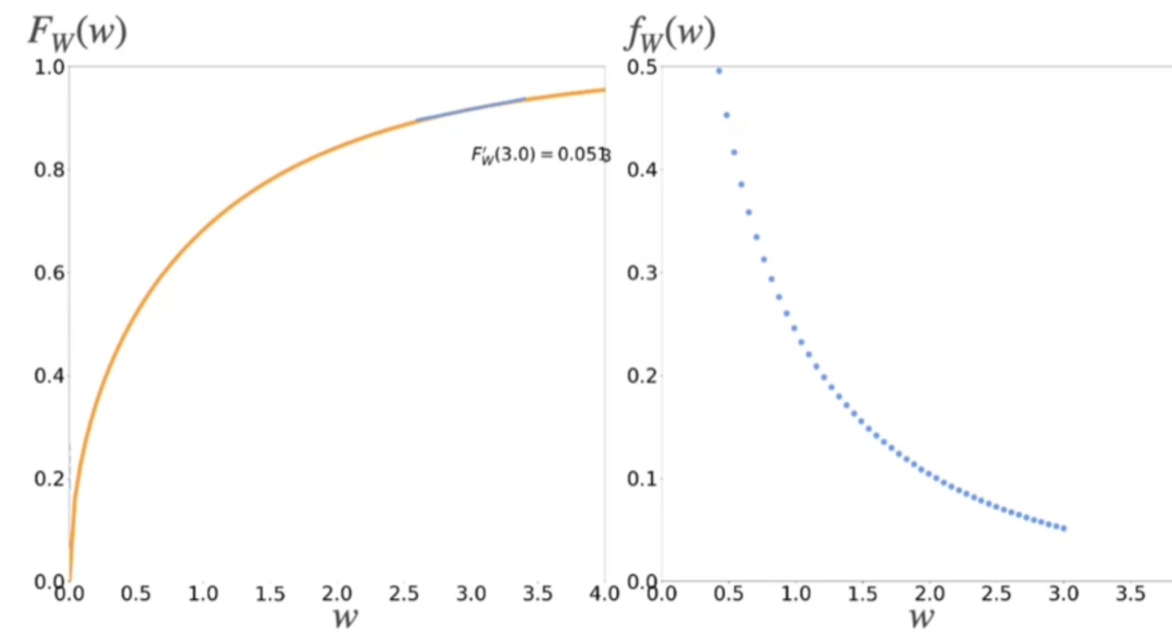
Chi Square Distribution

$$f_W(w) = F'_W(w)$$



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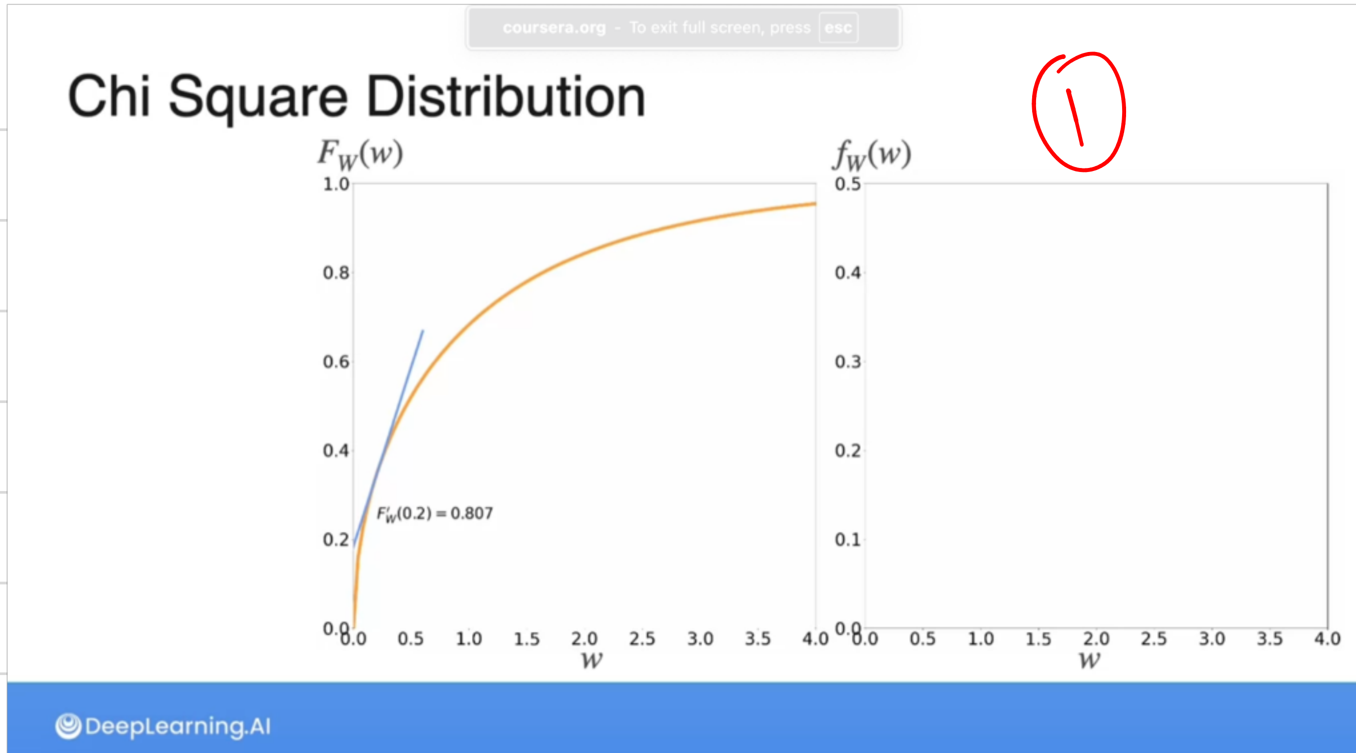
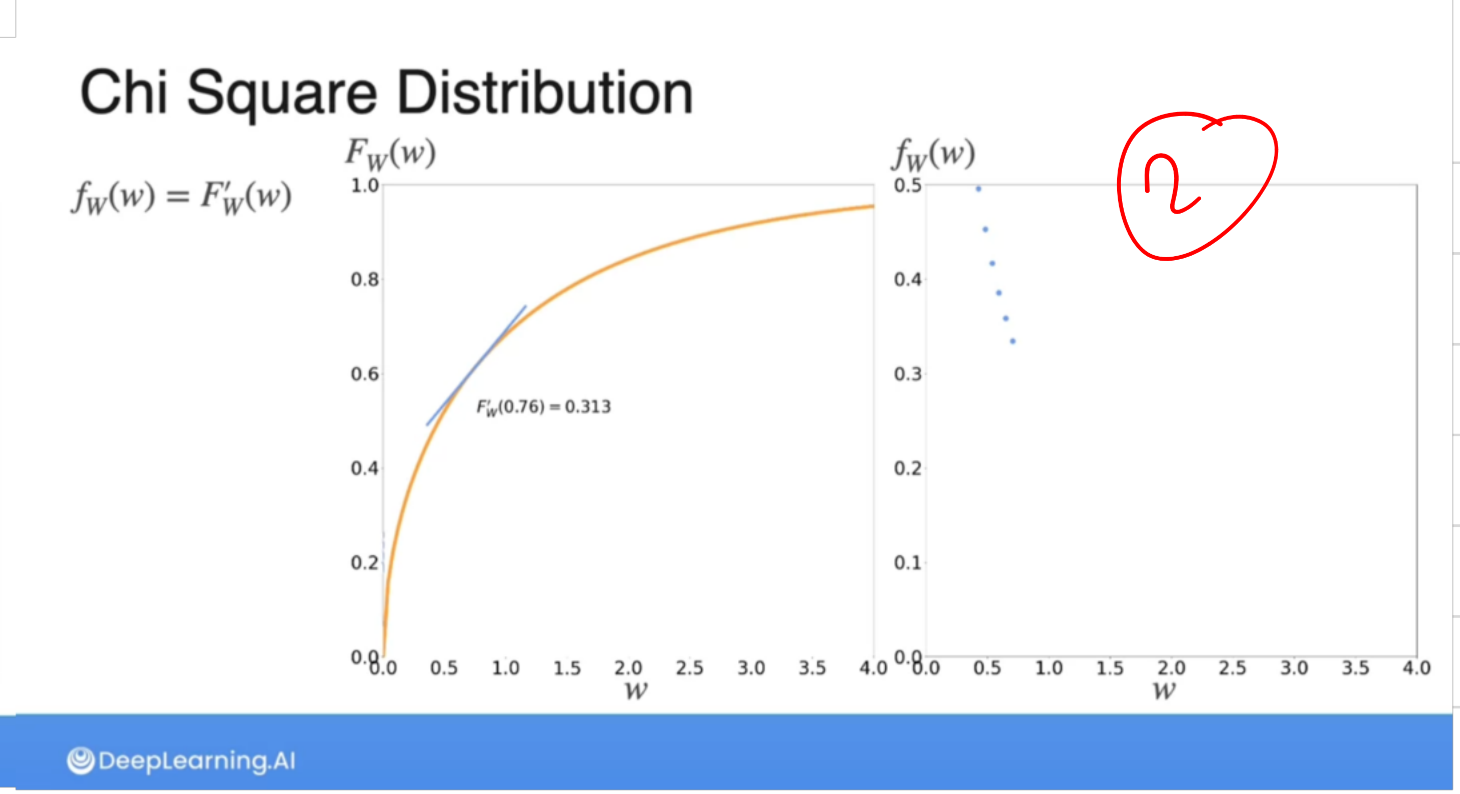
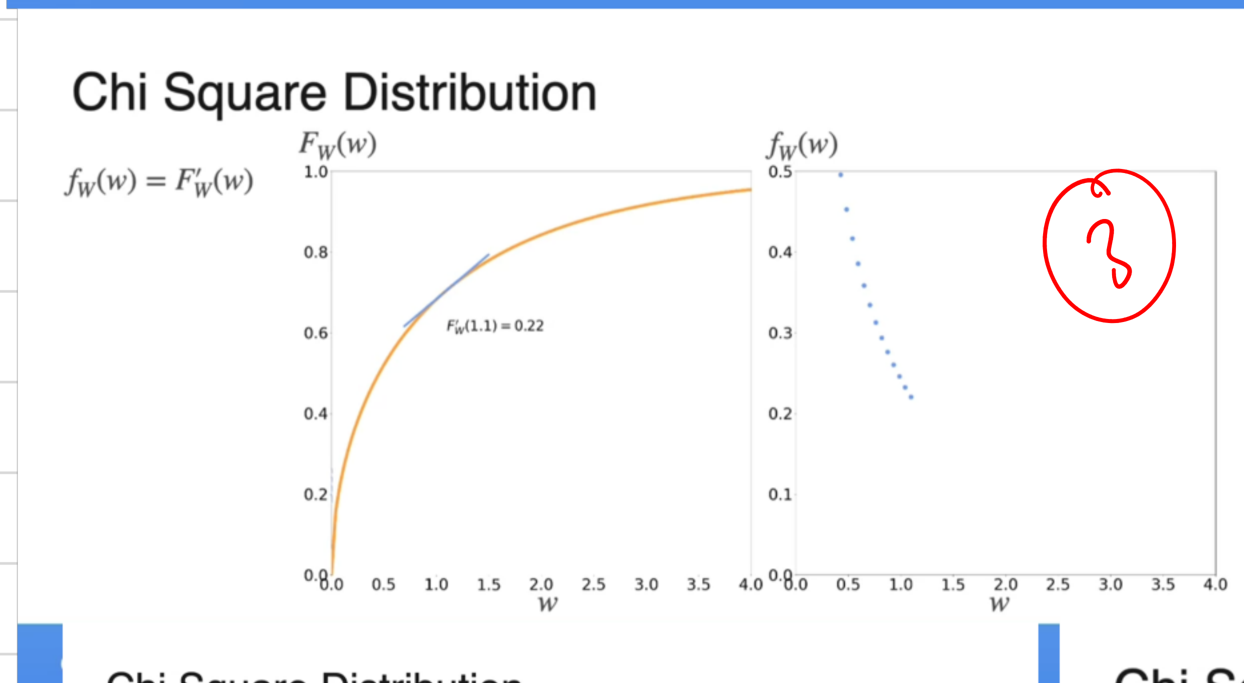
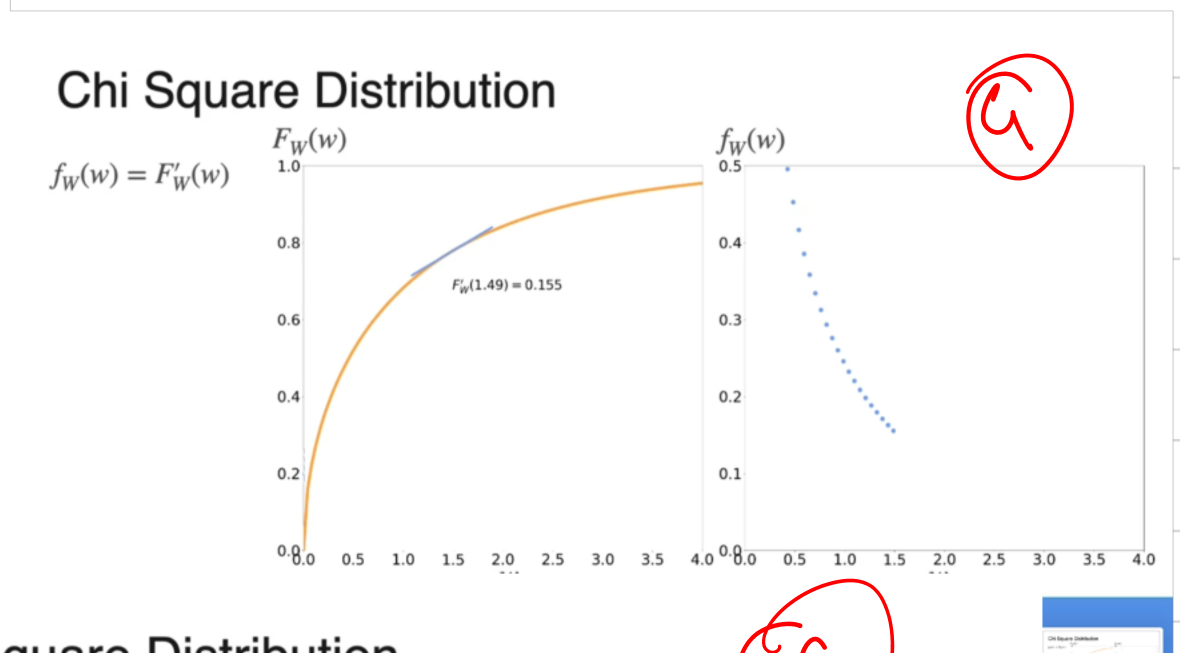
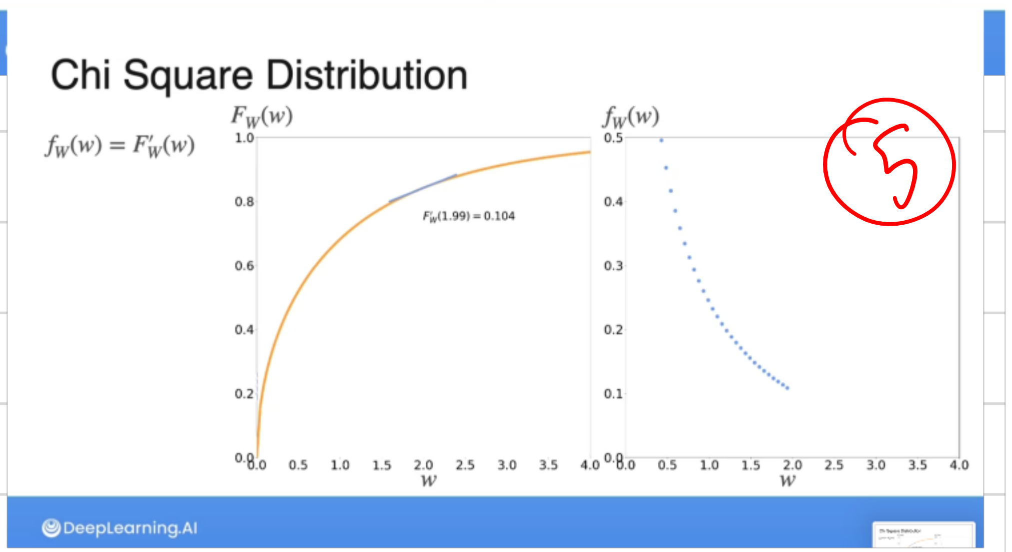
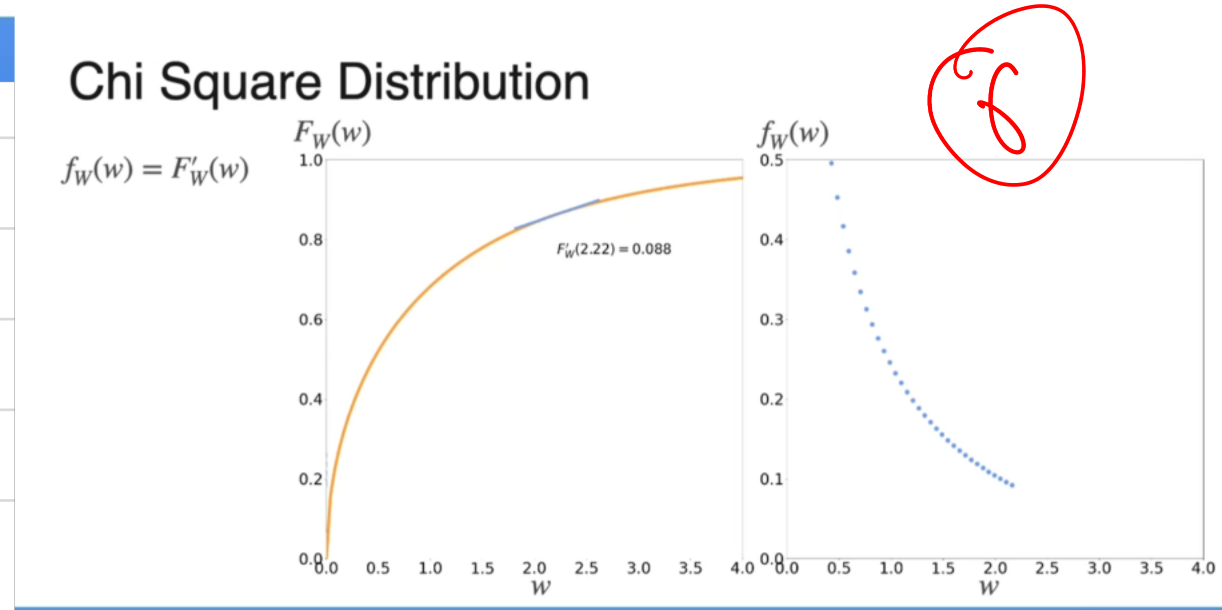








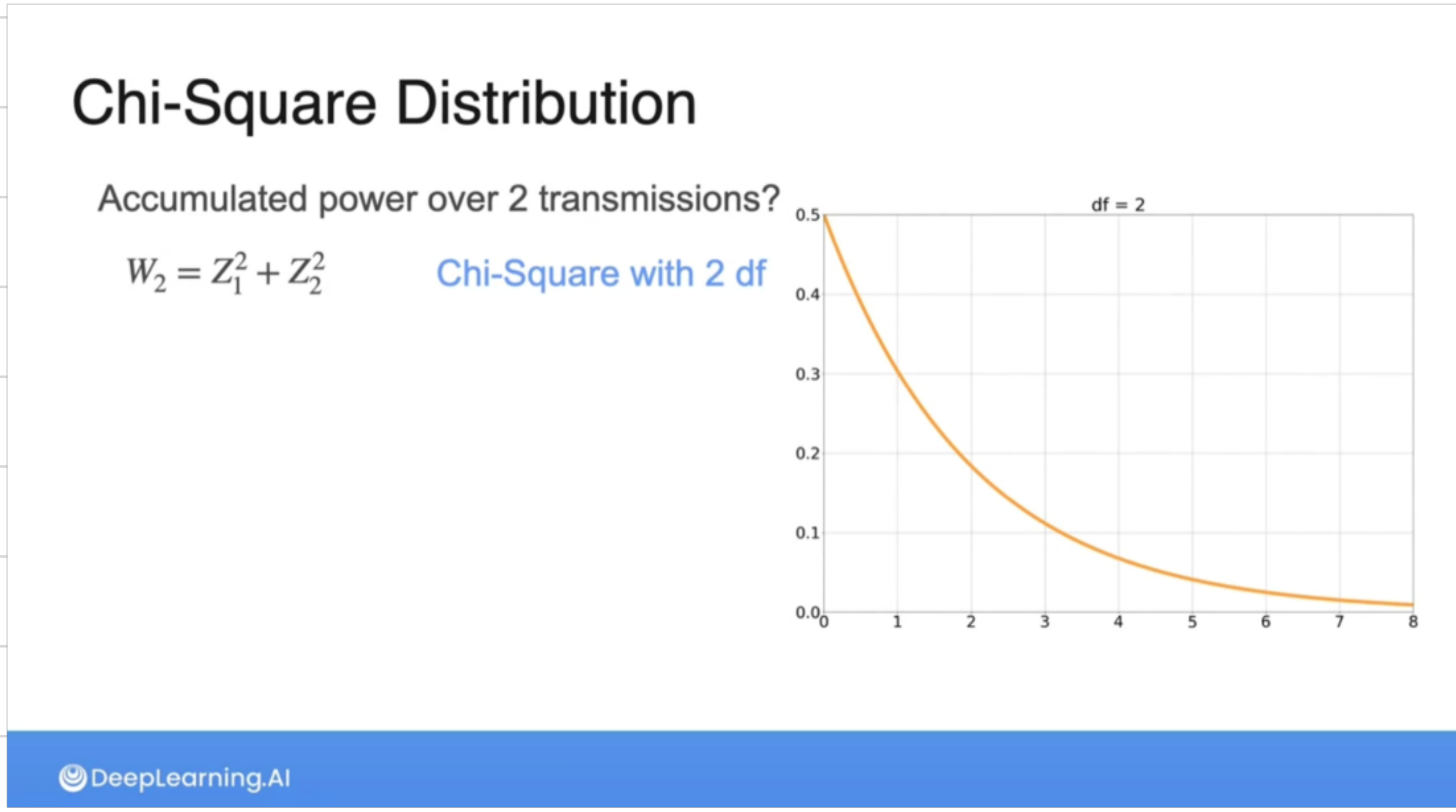


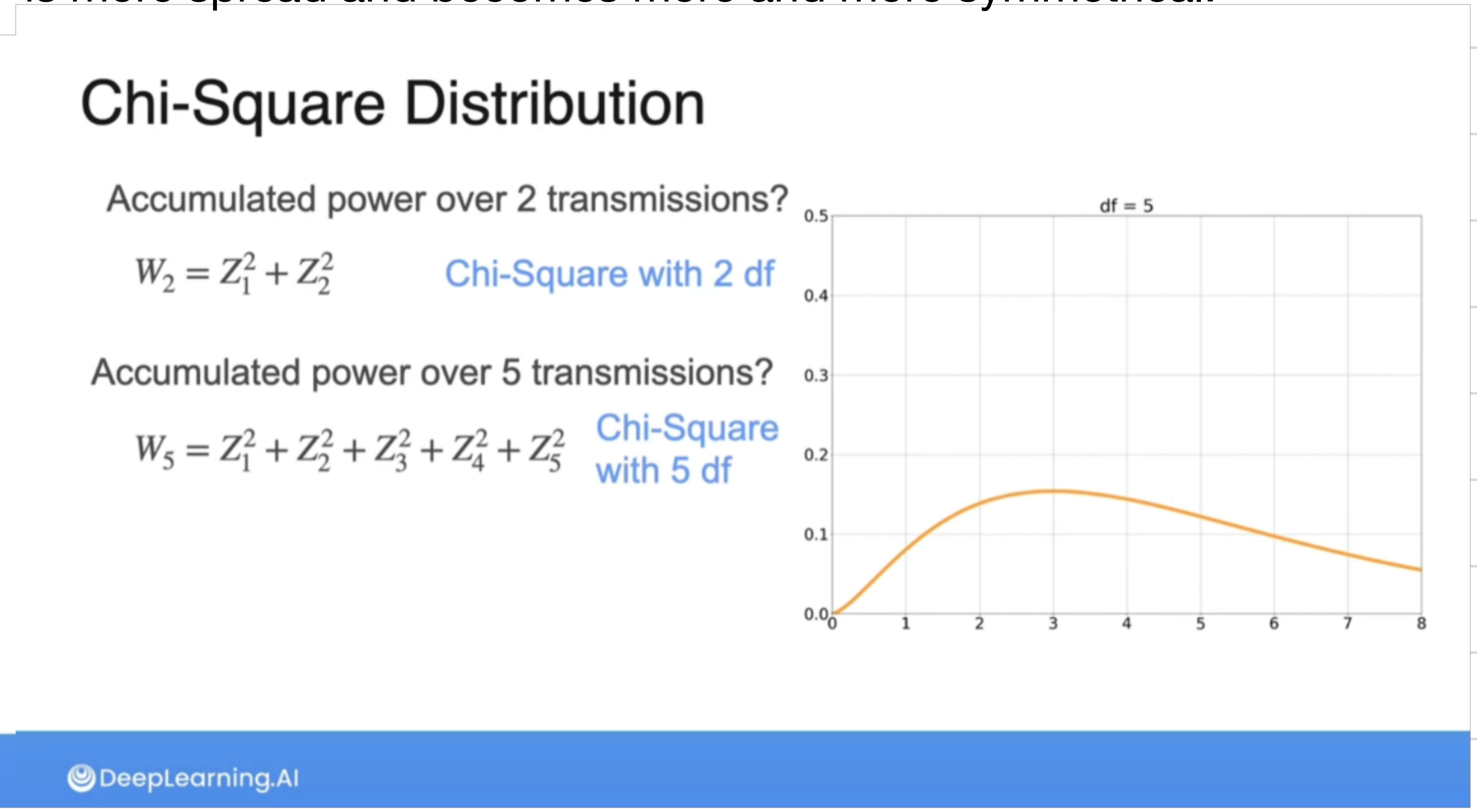


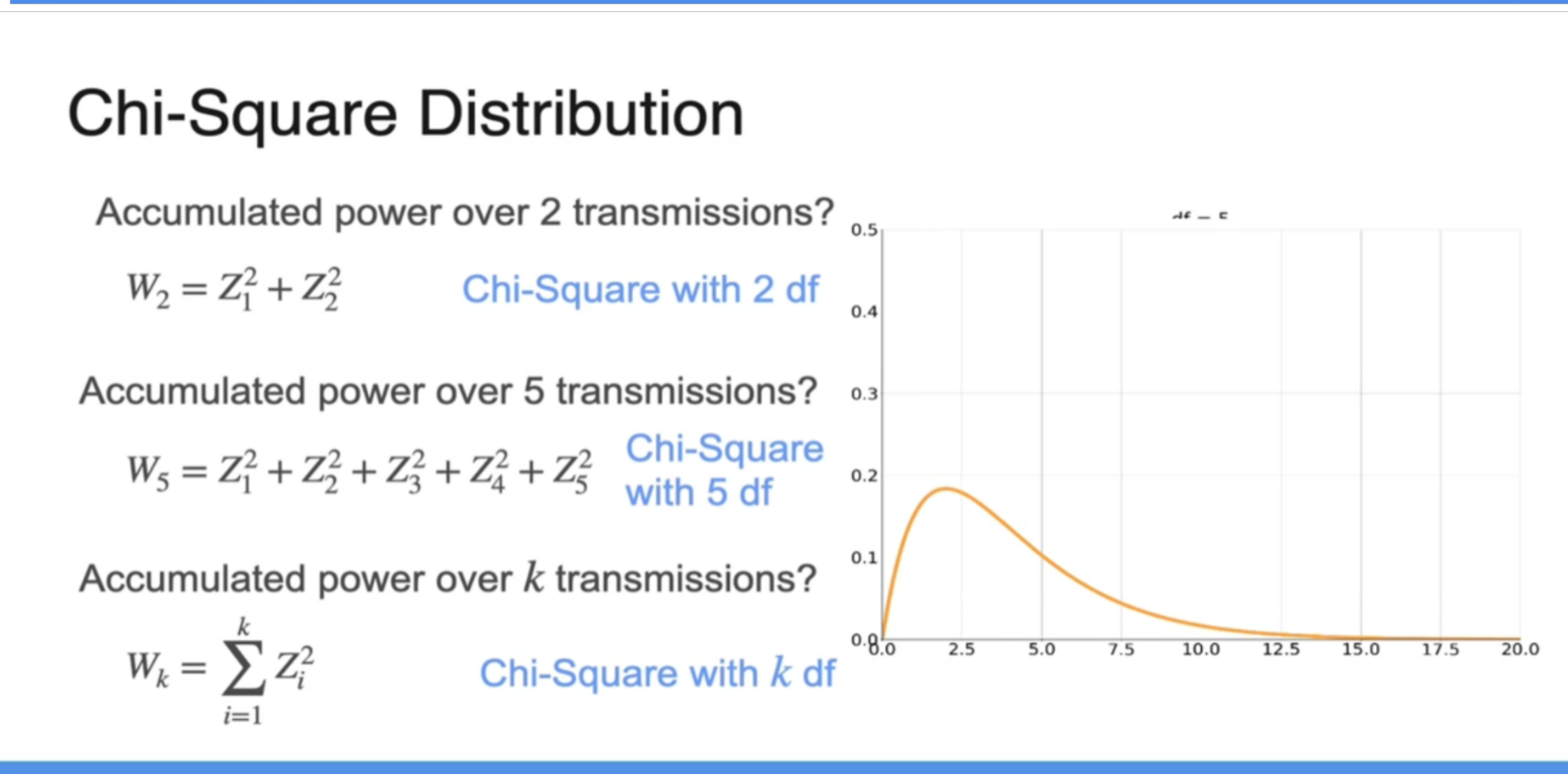
derivative of CDF ?

Slope :

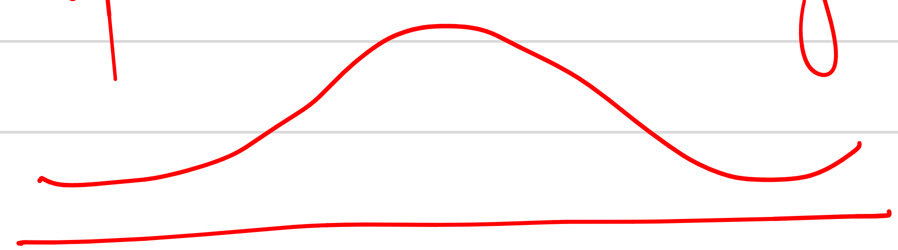
Well, notice that again, this is the sum of many independent standard normal variables squared and is set to follow a Chi-square distribution with k degrees of freedom and notice that as k increases, the PDF is more spread and becomes more and more symmetrical.





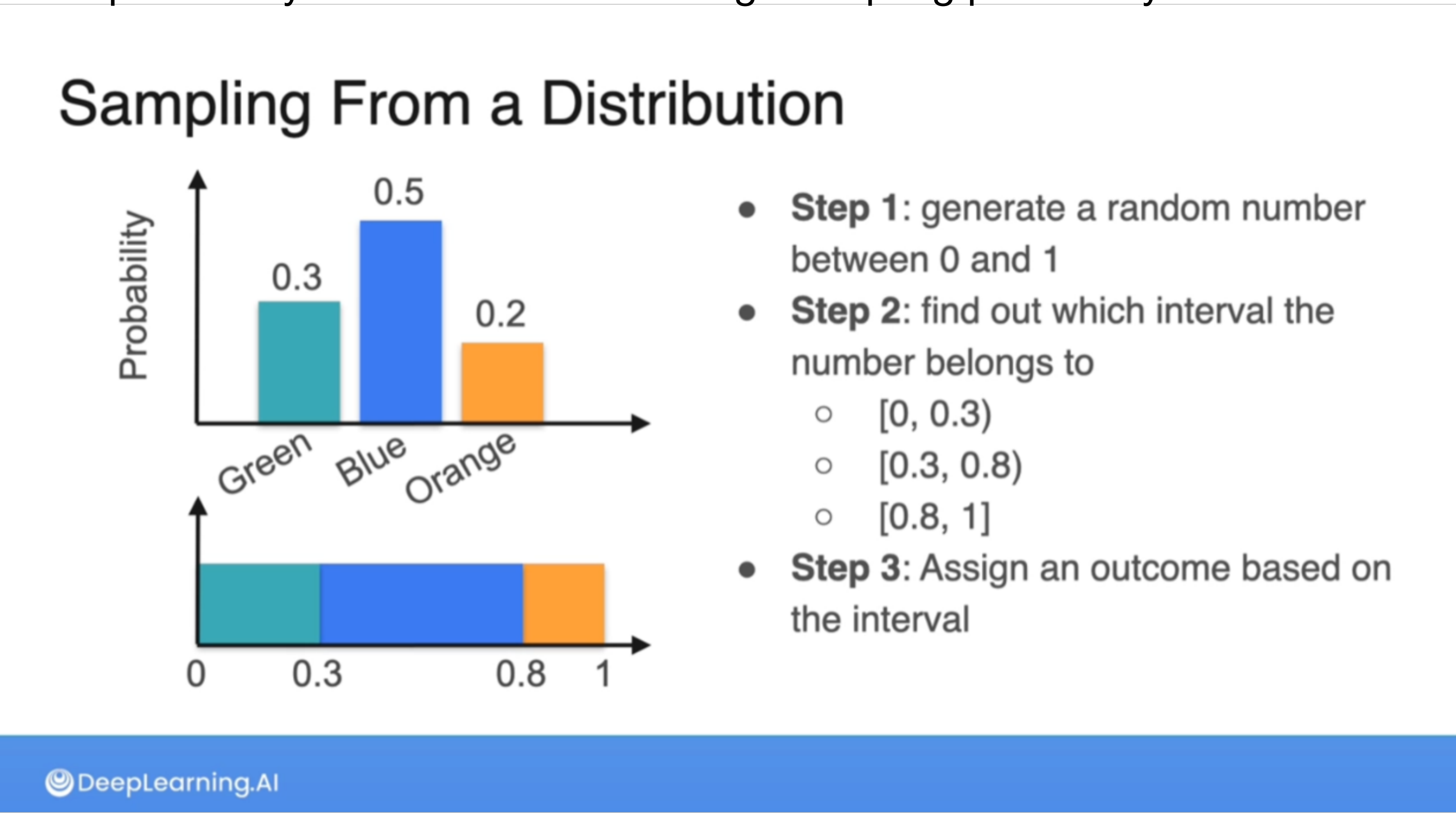


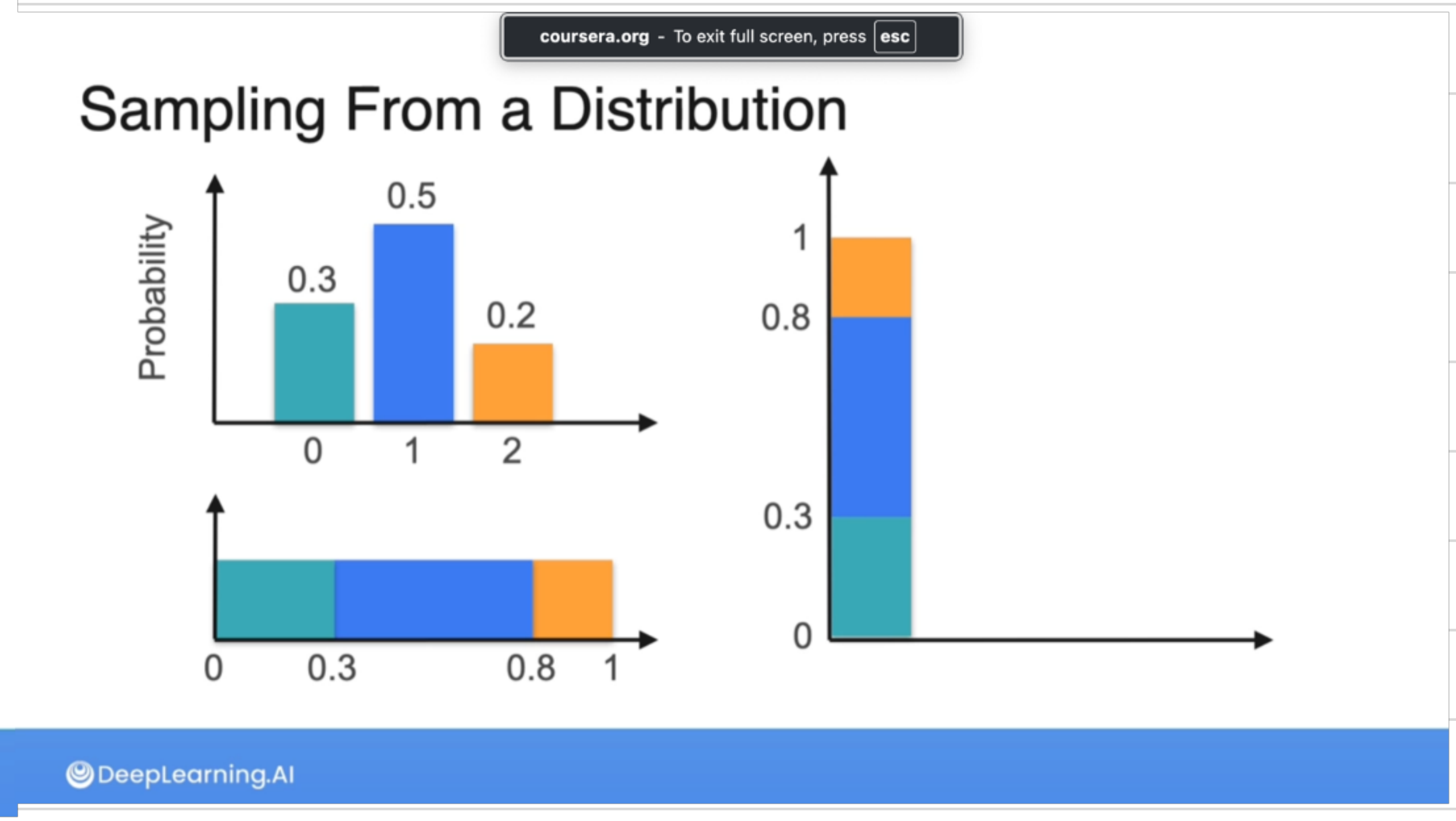
K degrees of freedom increases the PDF becomes more spread and more symmetrical.



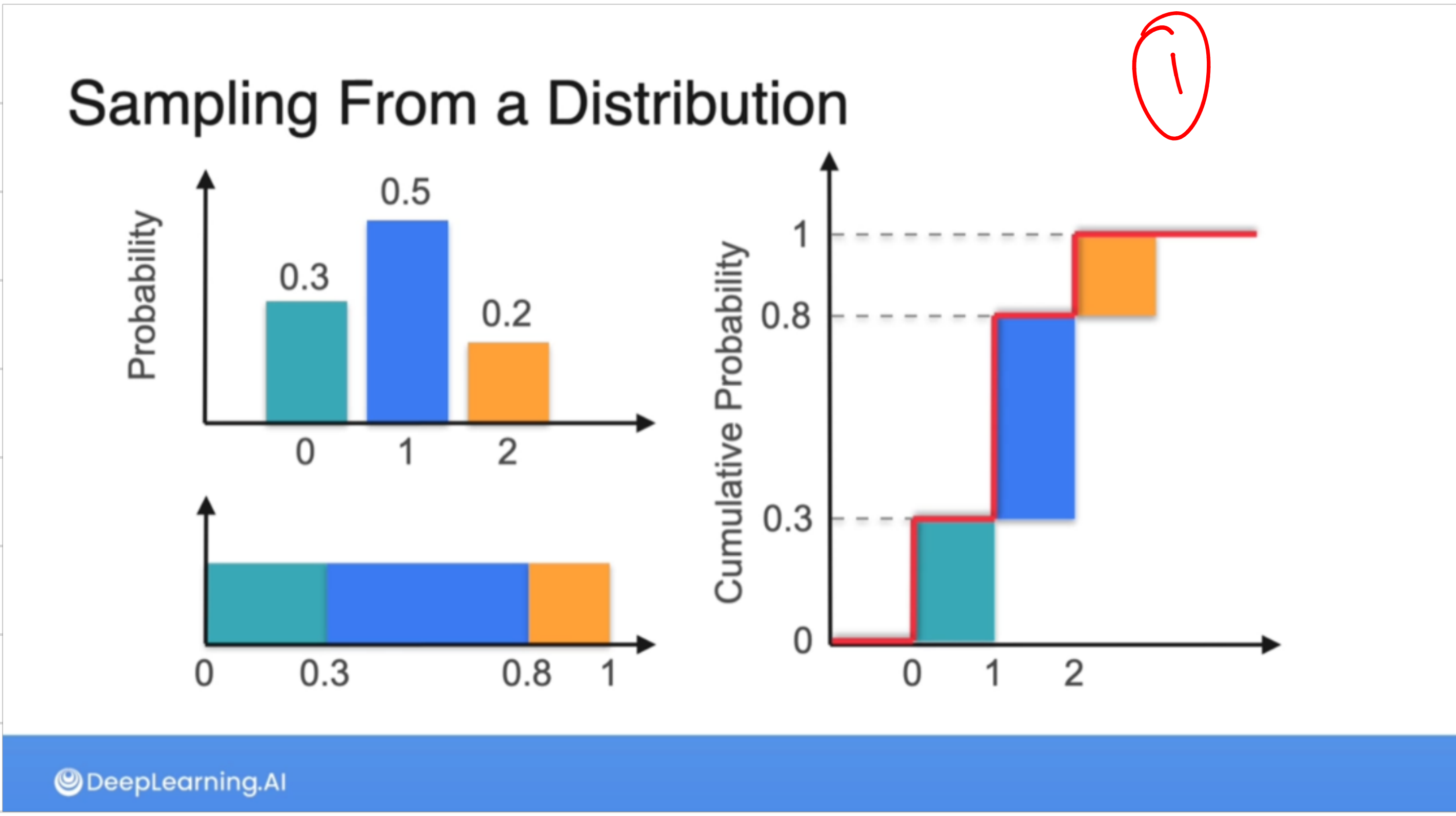
Sampling from Distributions:

- By sampling, I mean picking points that have the probabilities given by the original distribution. So this is a very important concept in probability and in machine learning. Sampling probability distribution.





In the fig Xx it is difficult to compute CDF of Normal distribution, so the Gray level represents Interval and we take Uniform points and find the Probability distribution.


Sampling From a Distribution
①
Probability
0.3
0.5
0.2
0
1
2
0
0.3
0.8
1
Cumulative Probability
1
0.8
0.3
0
0
1
2
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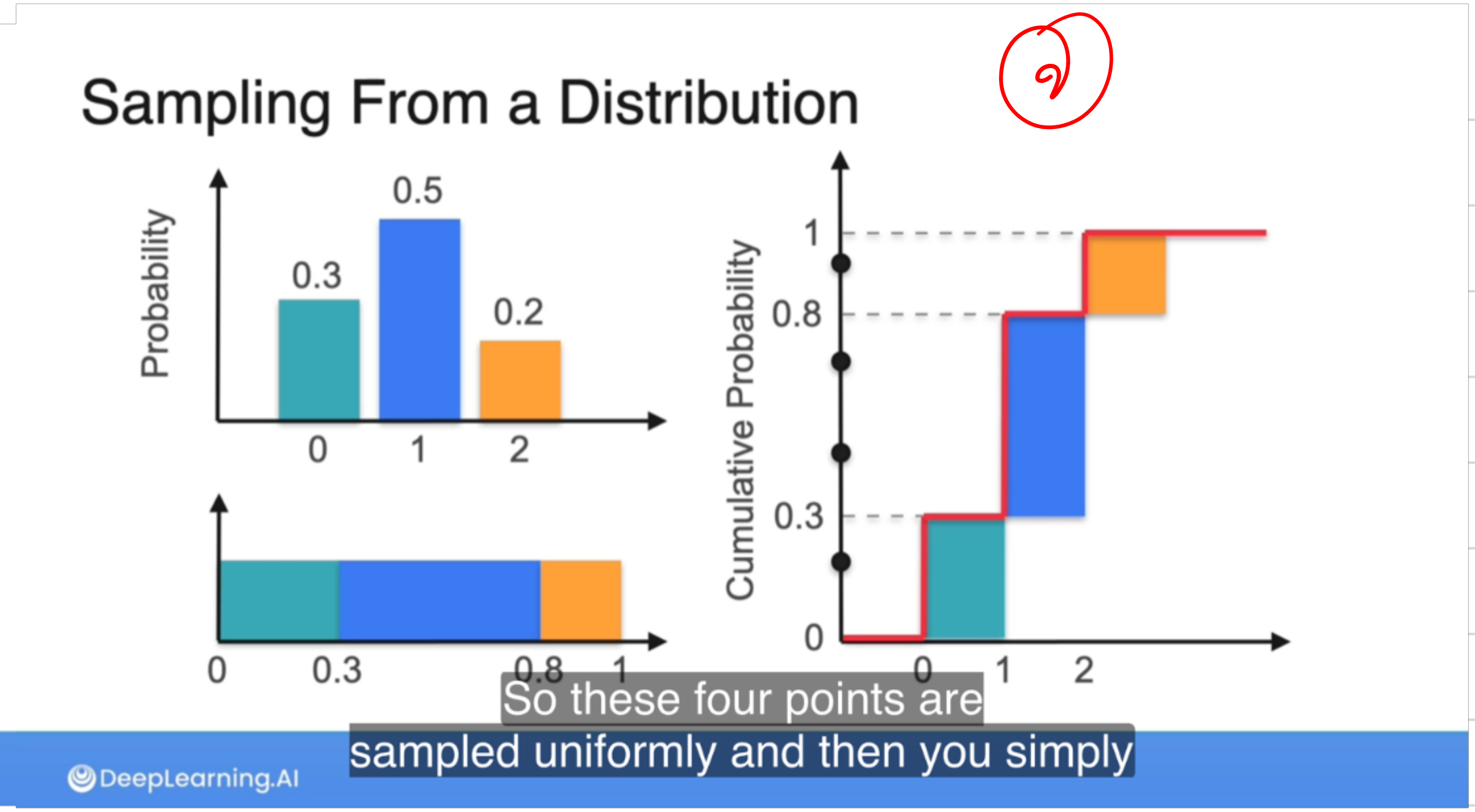
Sampling From a Distribution
②
Probability
0.3
0.5
0.2
0
1
2
0
0.3
0.8
1
Cumulative Probability
1
0.8
0.3
0
0
1
2
So these four points are
sampled uniformly and then you simply
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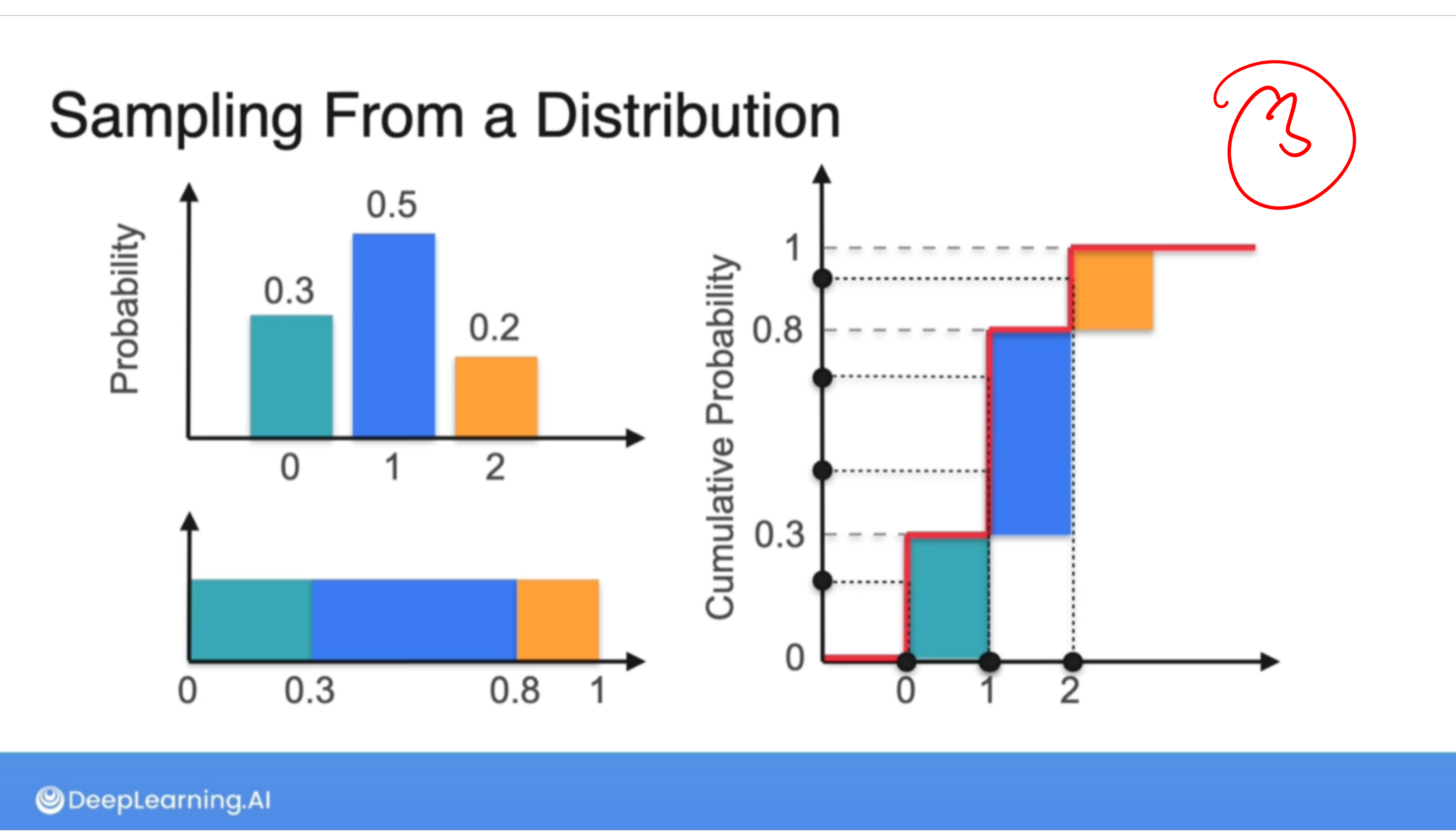
Sampling From a Distribution
③
Probability
0.3
0.5
0.2
0
1
2
0
0.3
0.8
1
Cumulative Probability
1
0.8
0.3
0
0
1
2
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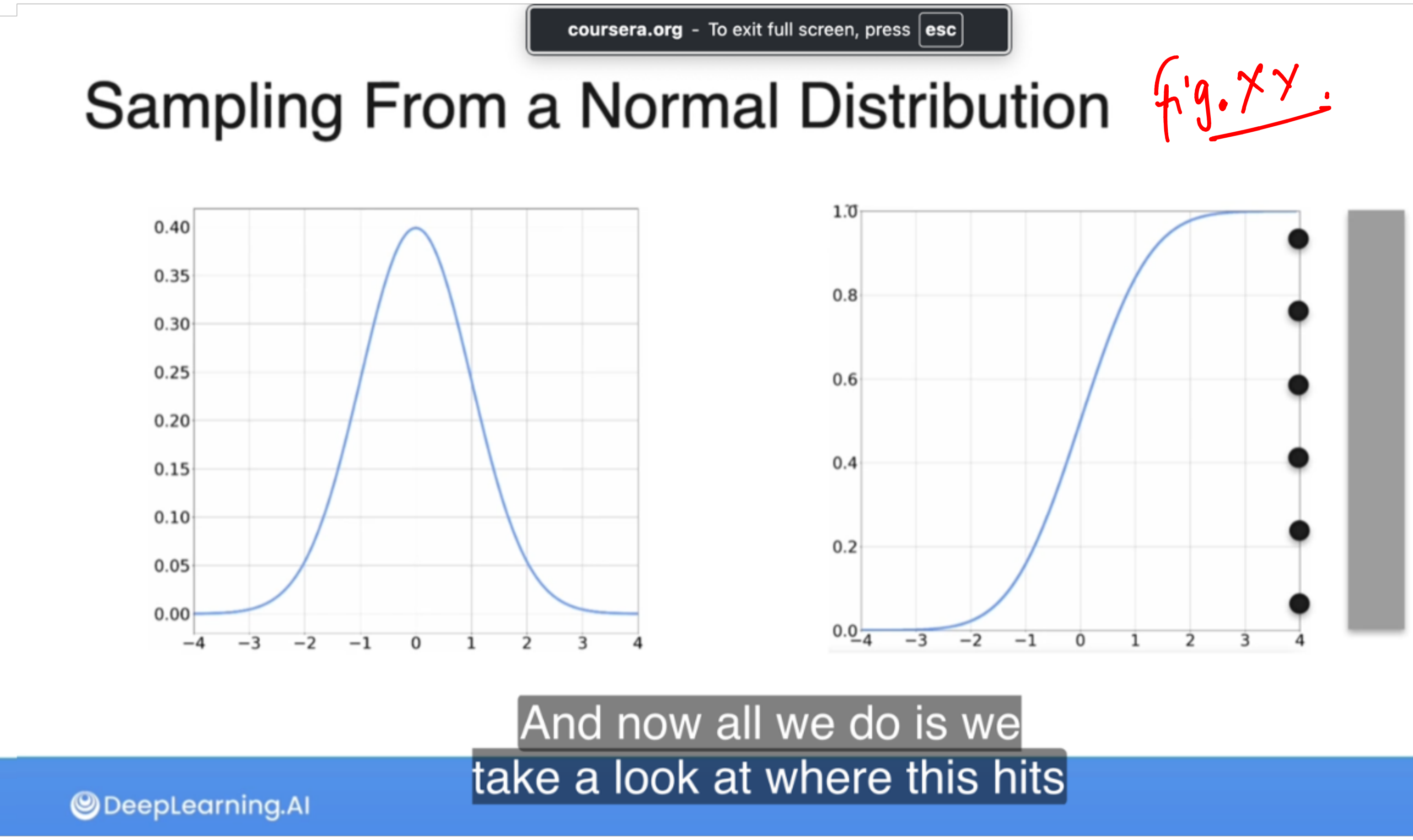
Sampling From a Normal Distribution
fig.xy.
0.40
0.35
0.30
0.25
0.20
0.15
0.10
0.05
0.00
−4
−3
−2
−1
0
1
2
3
4
1.0
0.8
0.6
0.4
0.2
0.0
And now all we do is we
take a look at where this hits
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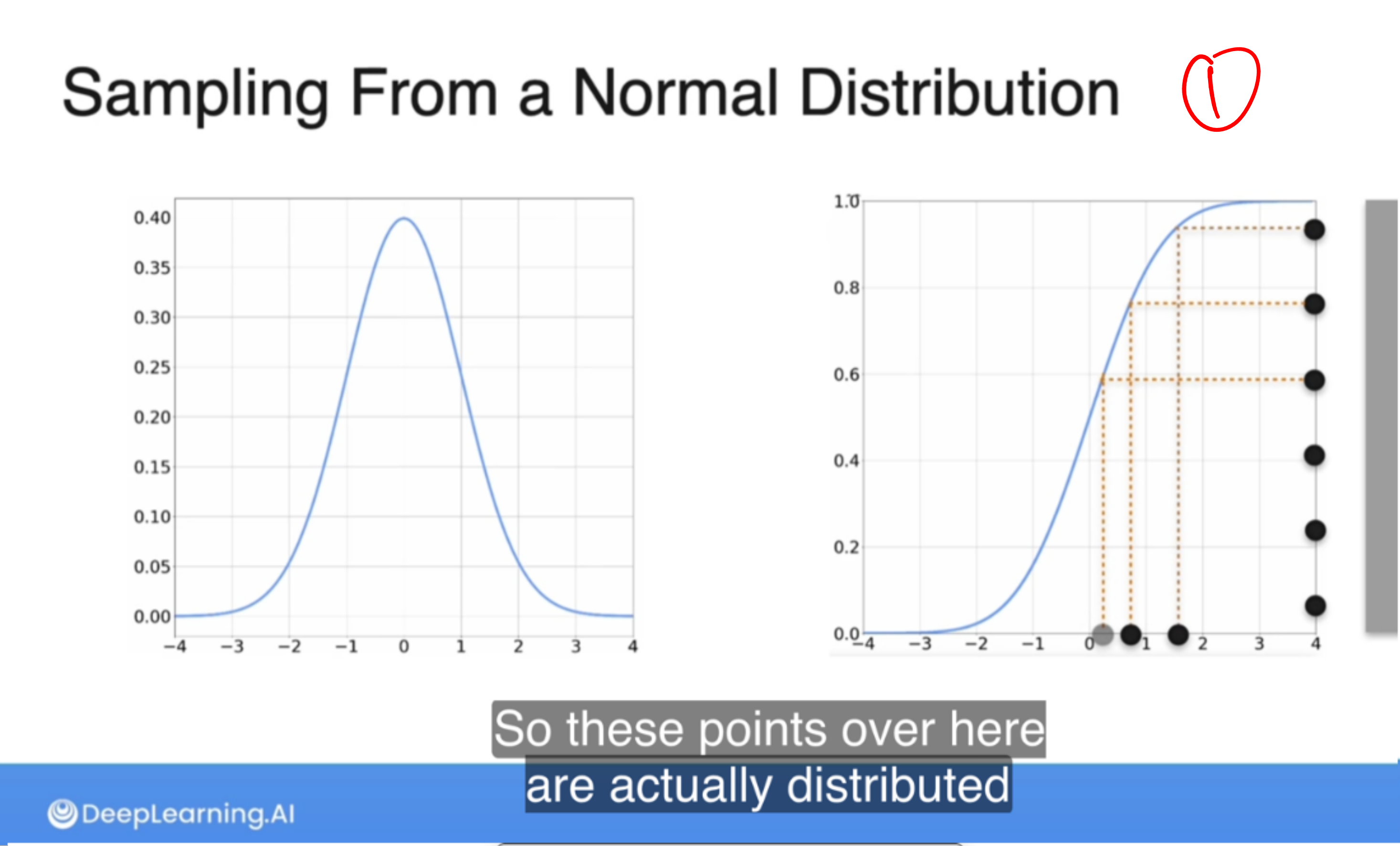
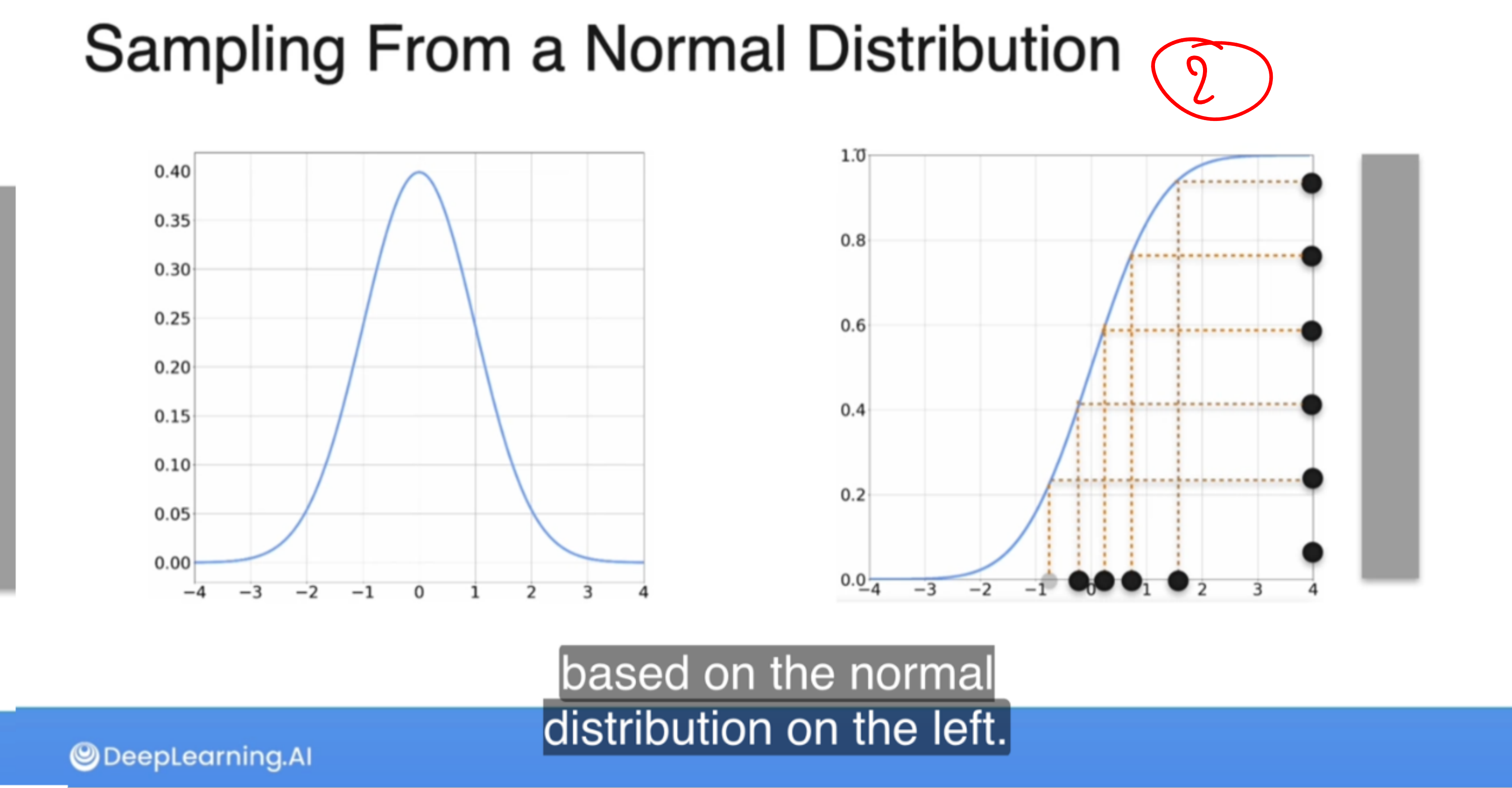
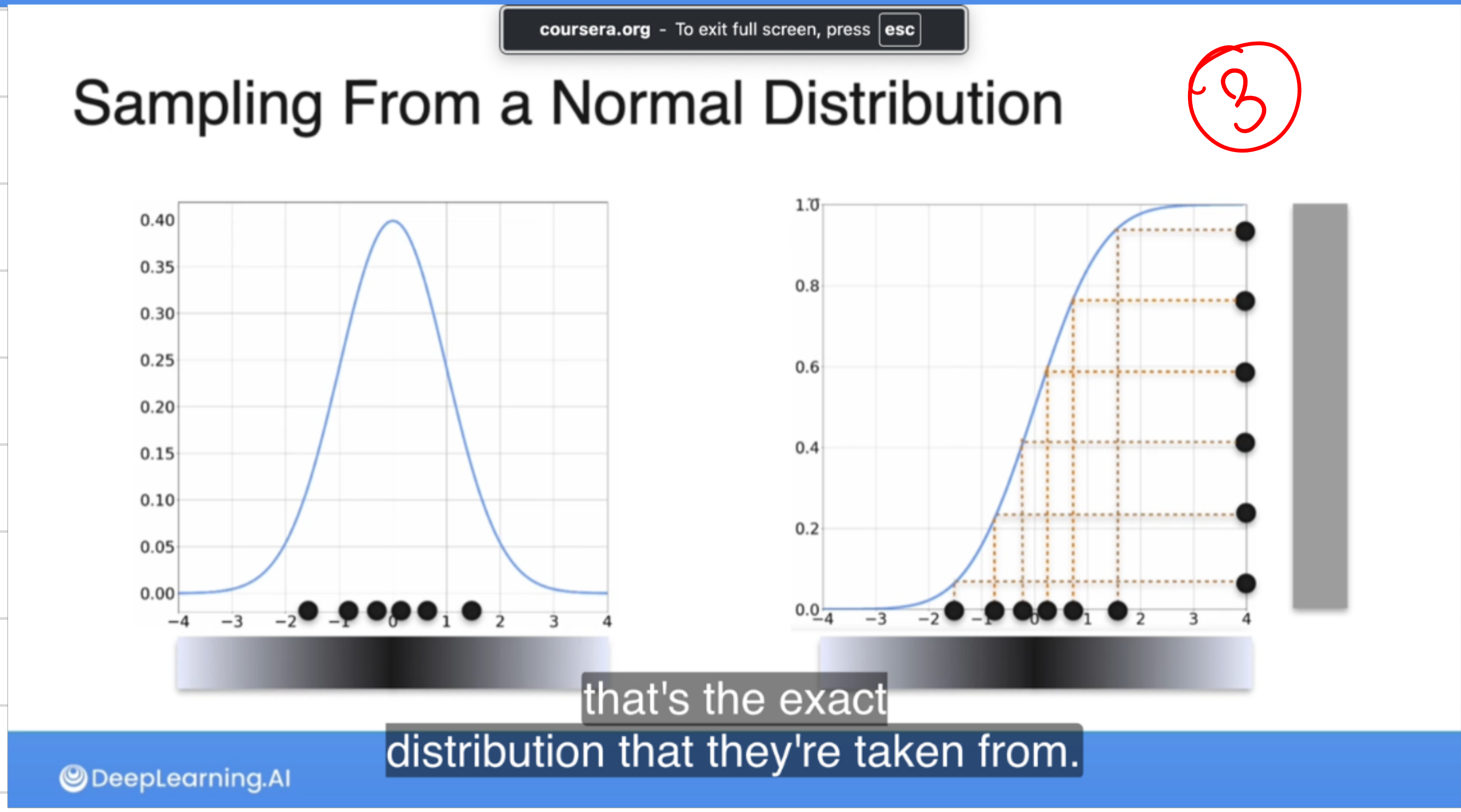
1



2



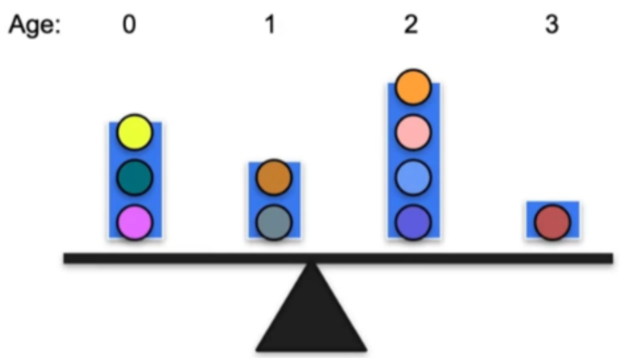
3



Expected Value (E(x))

Mean, Median and Mode describe the central distribution of data.

Mean: Example



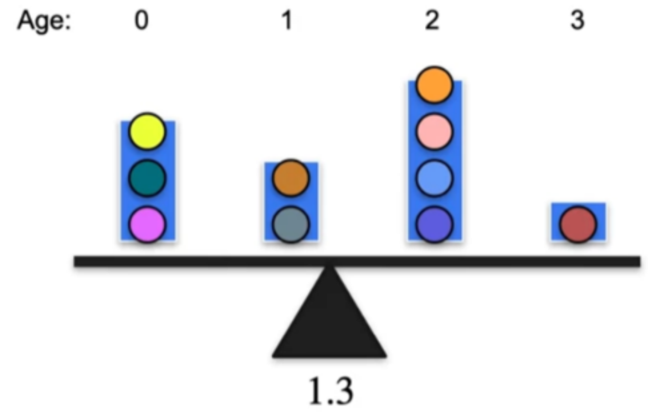
$$\frac{0+0+0+1+1+2+2+2+2+3}{10}$$

$$=\frac{13}{10}$$

$$=1.3$$

This sums up to 13
over 10 which equals 1.3.

Children in a Room



$$\frac{0+0+0+1+1+2+2+2+2+3}{10}$$

$$=\frac{13}{10}=1.3$$

$$=\frac{3\cdot 0+2\cdot 1+4\cdot 2+1\cdot 3}{10}$$

Weighted average

$$=\frac{3}{10}\cdot 0+\frac{2}{10}\cdot 1+\frac{4}{10}\cdot 2+\frac{1}{10}\cdot 3=1.3$$

is the weighted average of the
values of the variable where the

Expected Value: Motivation Example 1

You play a game with a friend

You win 10 dollars

You win nothing

Long term: $0.5\cdot\$10\ +0.5\cdot\$0=\$5$ ⇨ You expect to win \$5 on average

$\mathbb{E}[X]=5$

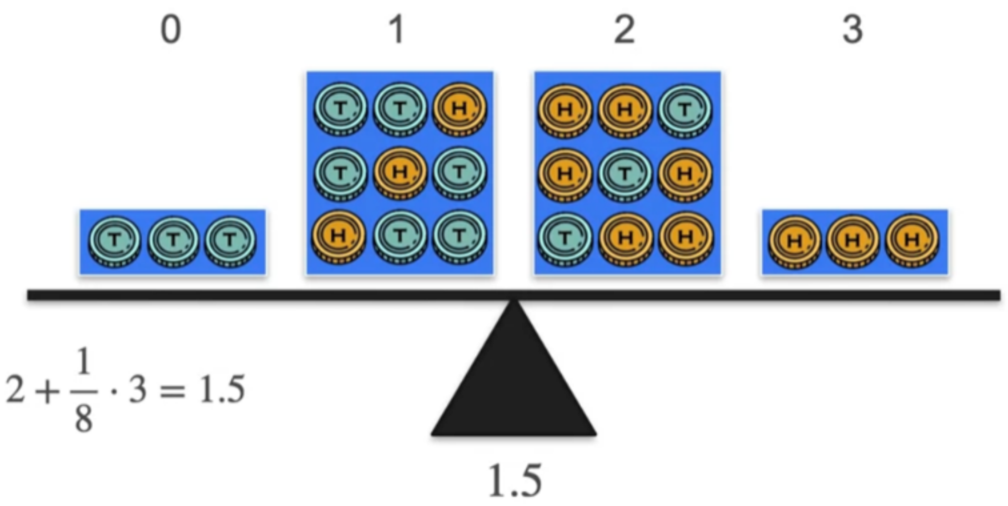
Expected Value: Motivation Example 1

Expected Value: Motivation Example 2

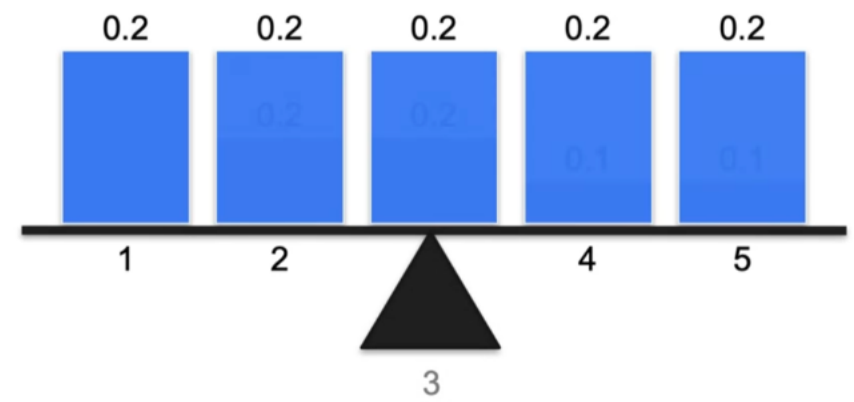
X: Number of heads

$\mathbb{E}[X] = 1.5$

$$\mathbb{E}[X] = \frac{1}{8}\cdot 0 + \frac{3}{8}\cdot 1 + \frac{3}{8}\cdot 2 + \frac{1}{8}\cdot 3 = 1.5$$



Expected Value . Ideal case.



In the case of PMF

$P_X(x) = P(X = x)$

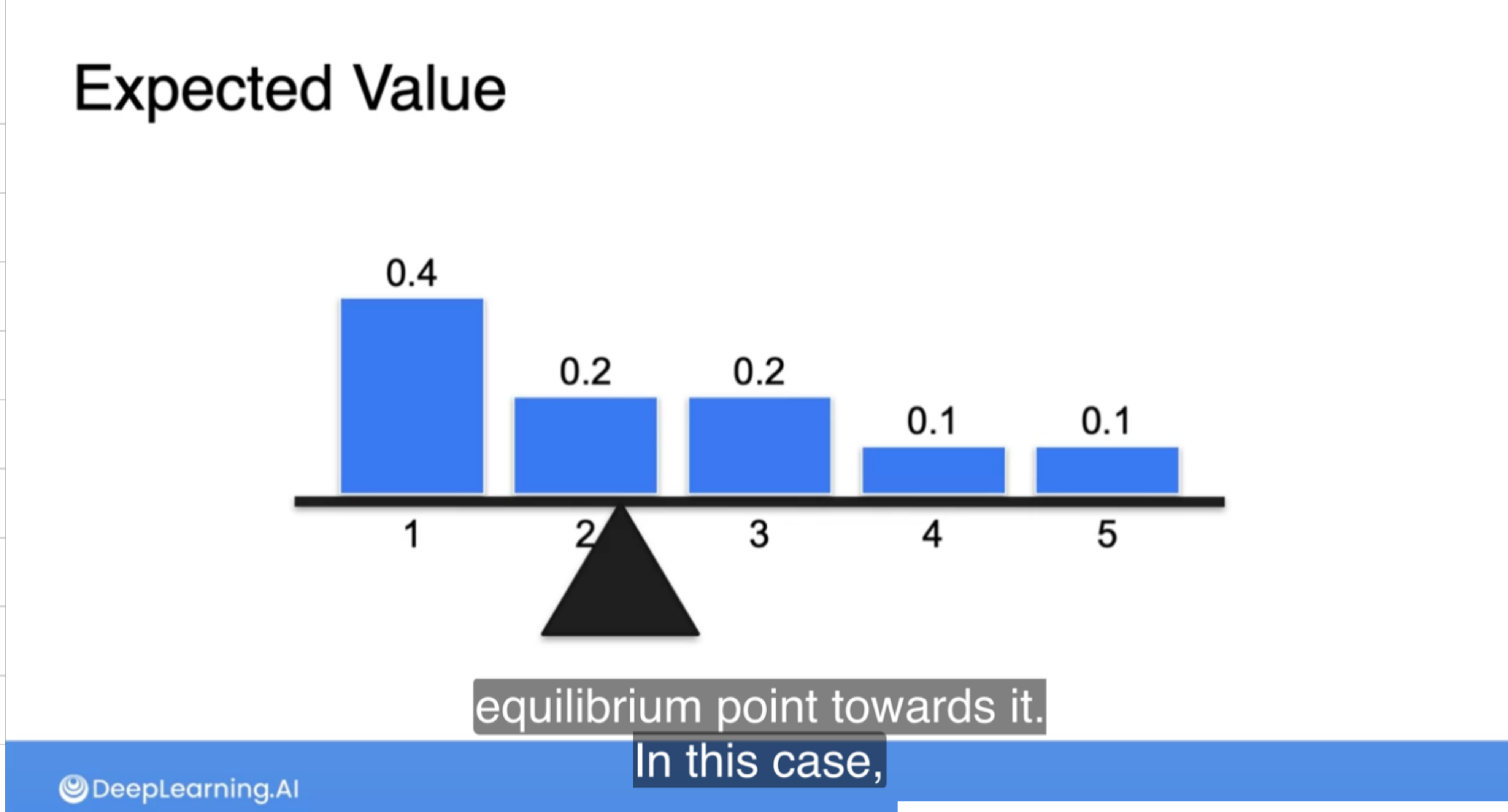
$E[X] = \sum_x x P_X(x)$.

Expected Value: Discrete Case

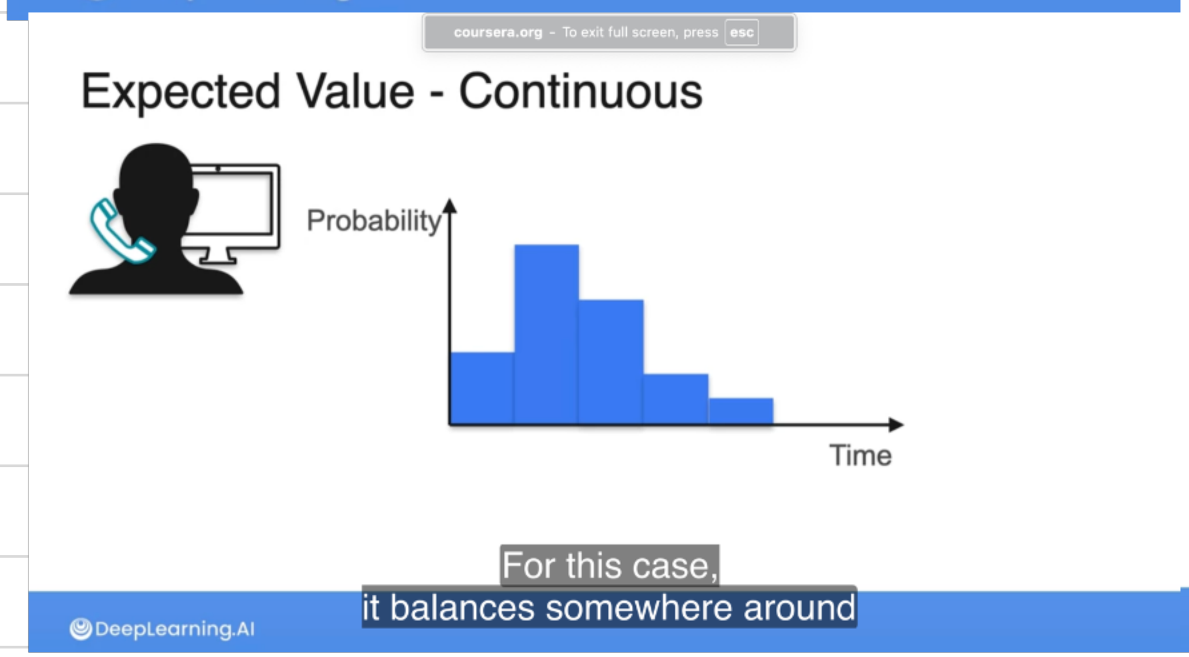
X a discrete random variable

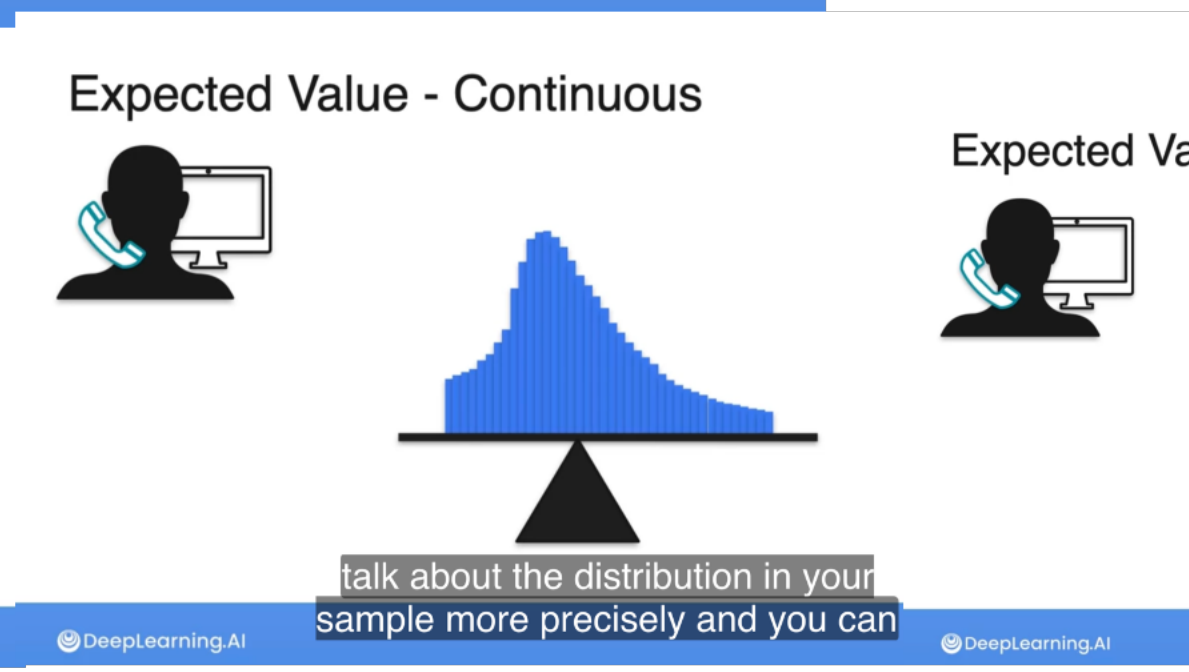
PMF of X
$p_X(x) = \mathbf{P}(X = x)$

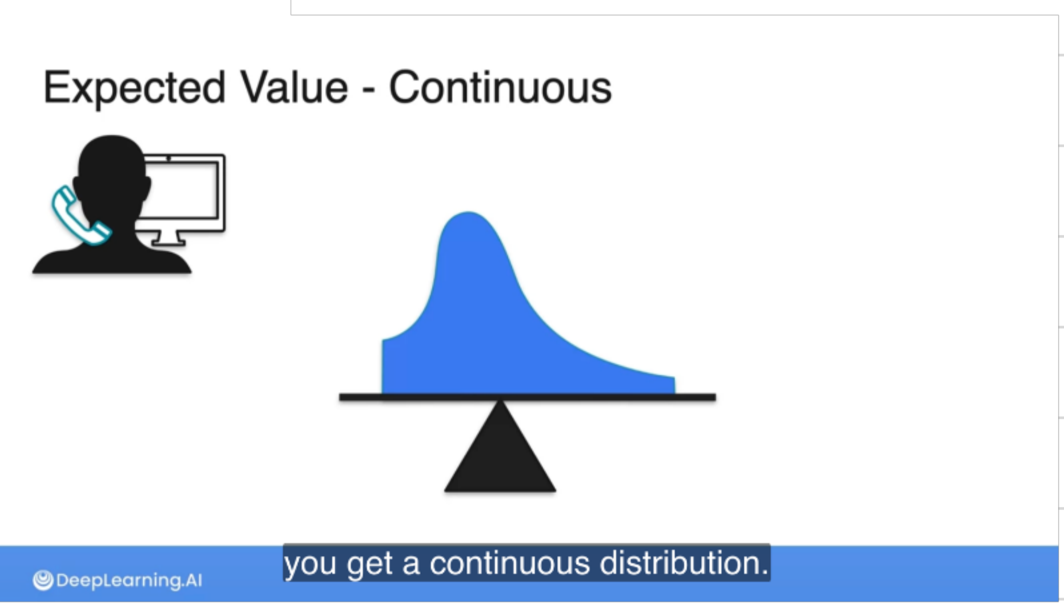
$$\mathbb{E}[X] = \sum_x x\, p_X(x)$$



We can't just increase one probability without adjusting (increase or decrease) other







Expected Value - Continuous

1

Discrete random variables	Continuous random variables
$\mathbb{E}[X] = \sum_x x\, p_X(x)$	$\int_{-\infty}^{\infty} x \cdot f_X(x)\, dx$
Weighted using PMF	Weighted using PDF

the possible values of x, but in the discrete case you weight the sum

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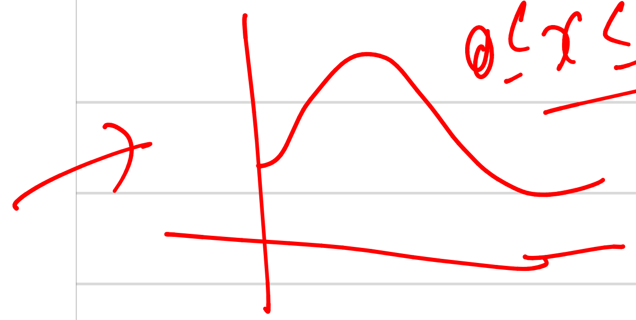

$a \le x \le b$ .. → PDF

E[x]

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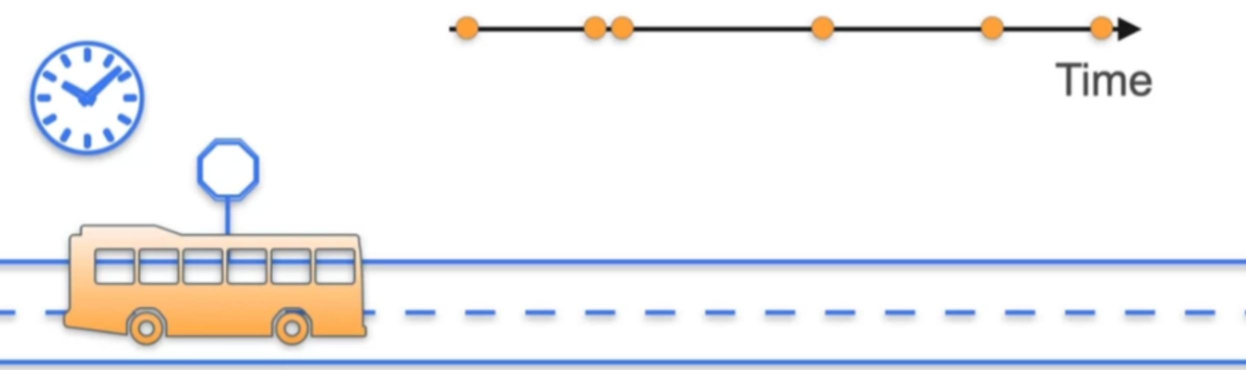
Expected Value

2

Tracking/keeping records

Waiting Time
15 min
32 min
58 min
1 min
47 min
14 min

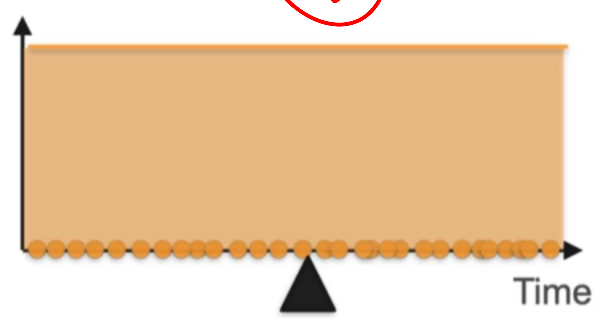


Expected Value

3

Waiting Time
15 min
32 min
58 min
1 min
47 min
14 min
37 min
8 min
29 min
55 min
...

Average = 30



point can land pretty much anywhere in that interval equally.

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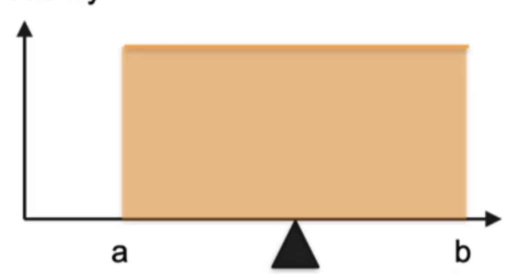
Expected Value: Uniform Distribution

4

$$\text{Average} = \frac{a+b}{2}$$



balancing it in the middle which is the point a

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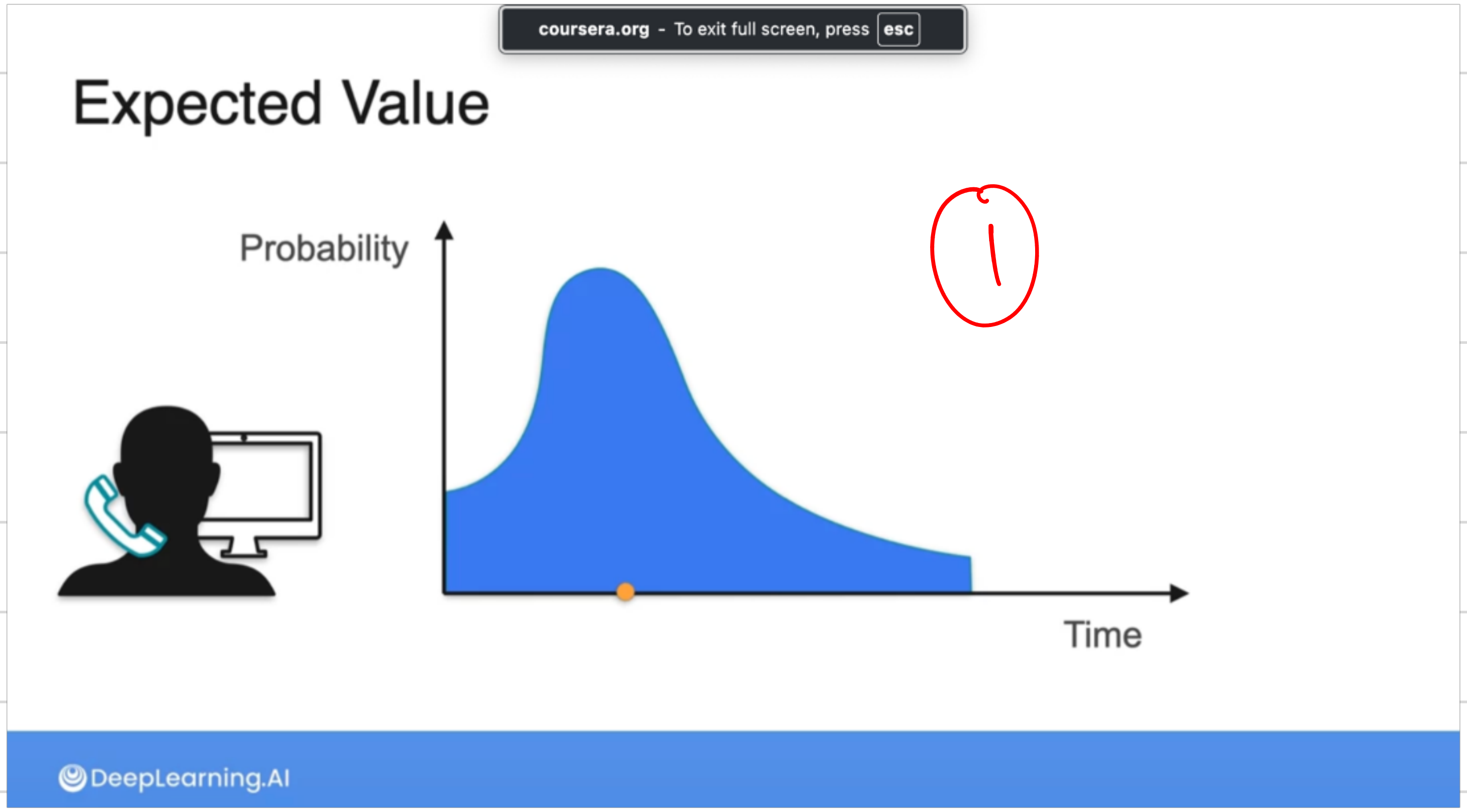
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Expected Value
1
Probability
Time
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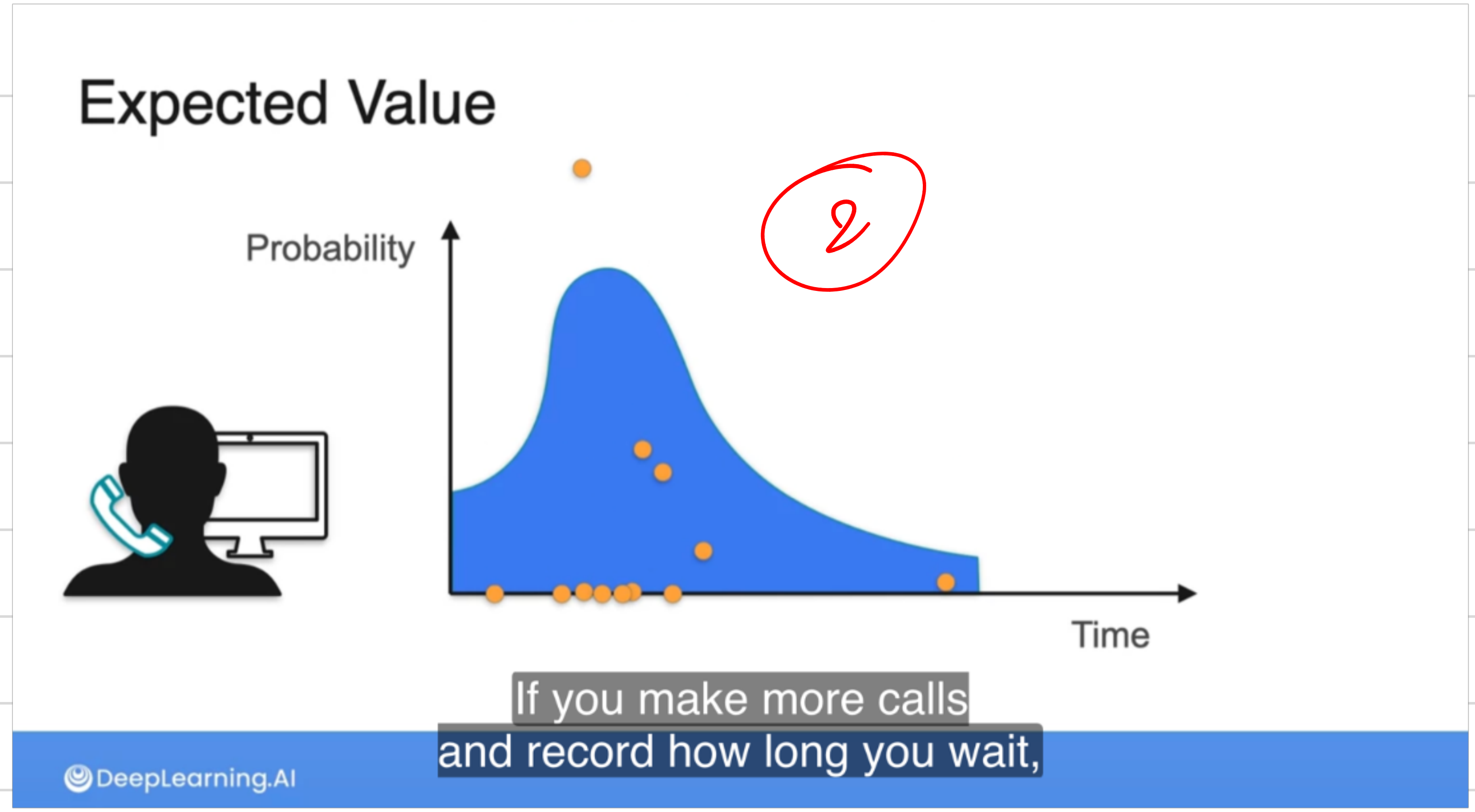
Expected Value
2
Probability
Time
If you make more calls
and record how long you wait,
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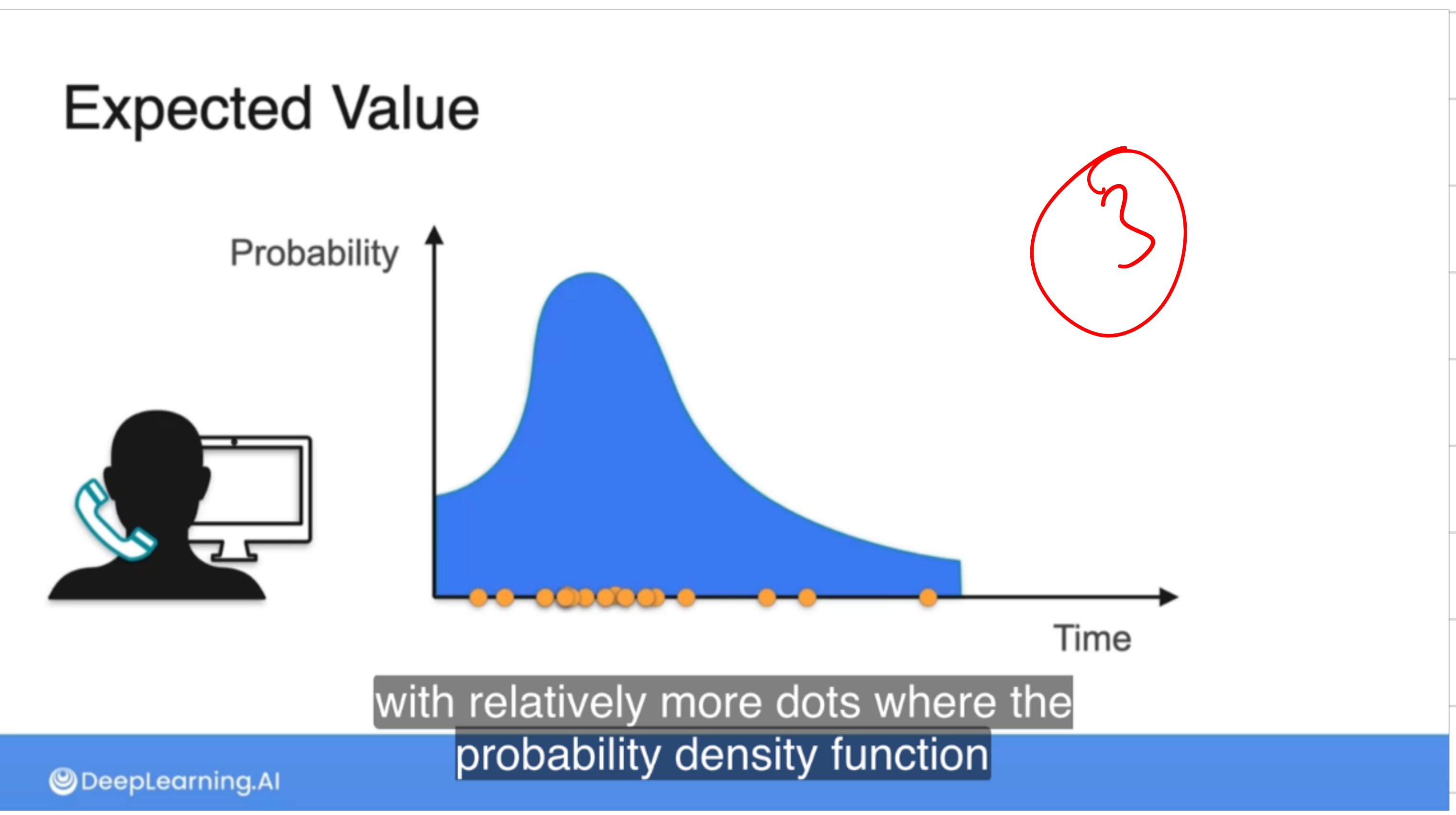
Expected Value
3
Probability
Time
with relatively more dots where the
probability density function
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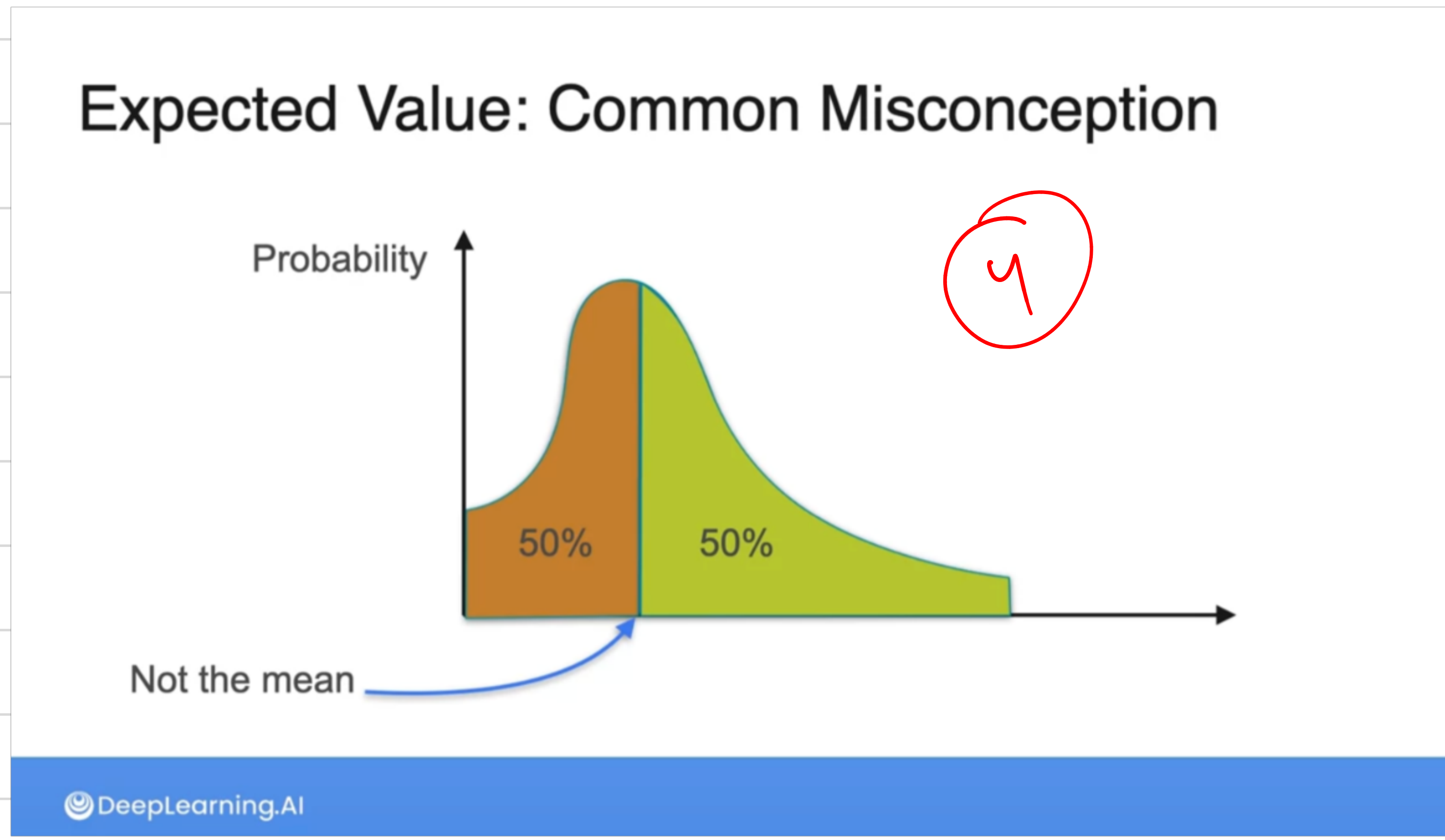
Expected Value: Common Misconception
4
Probability
50%
50%
Not the mean
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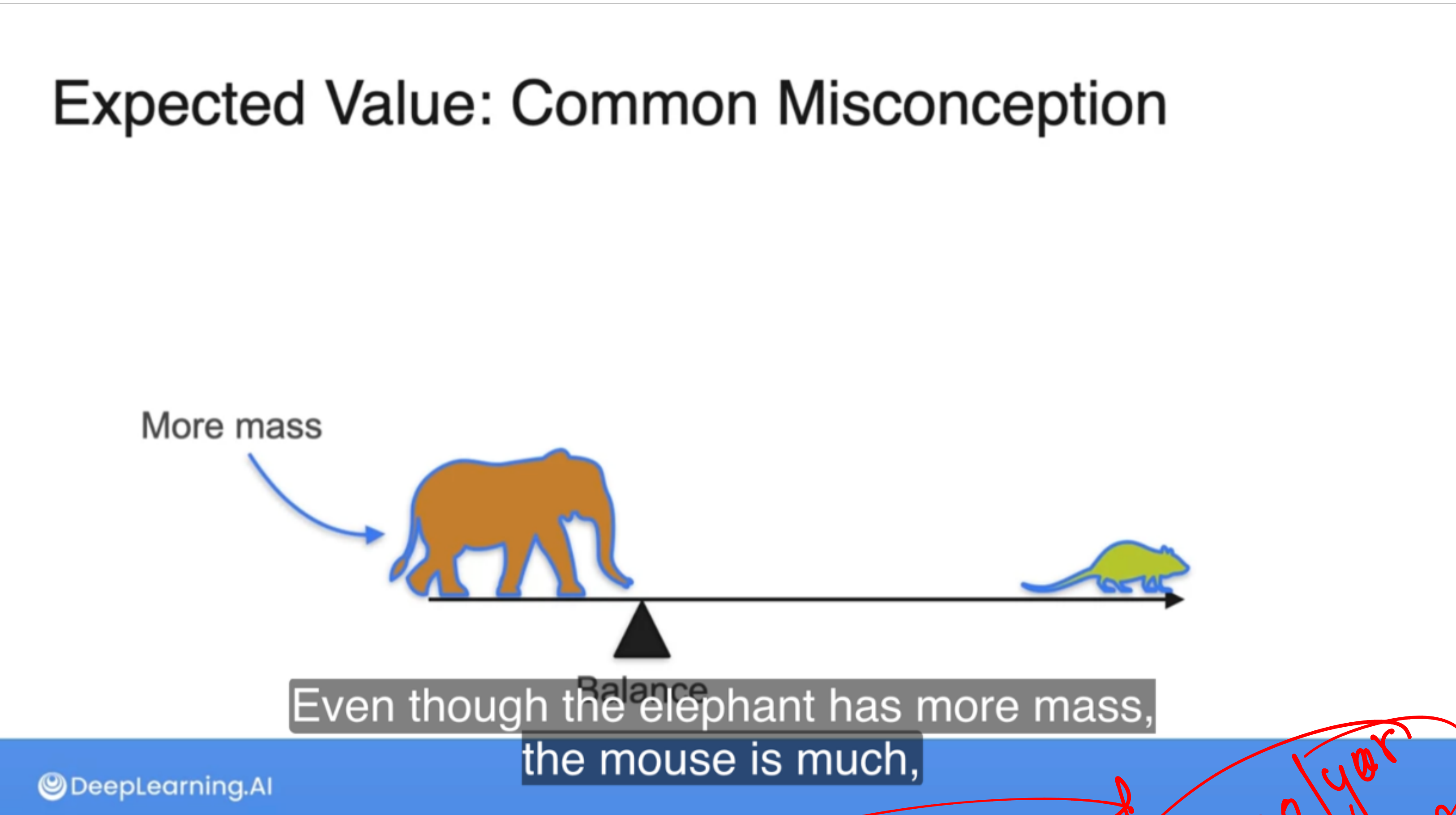
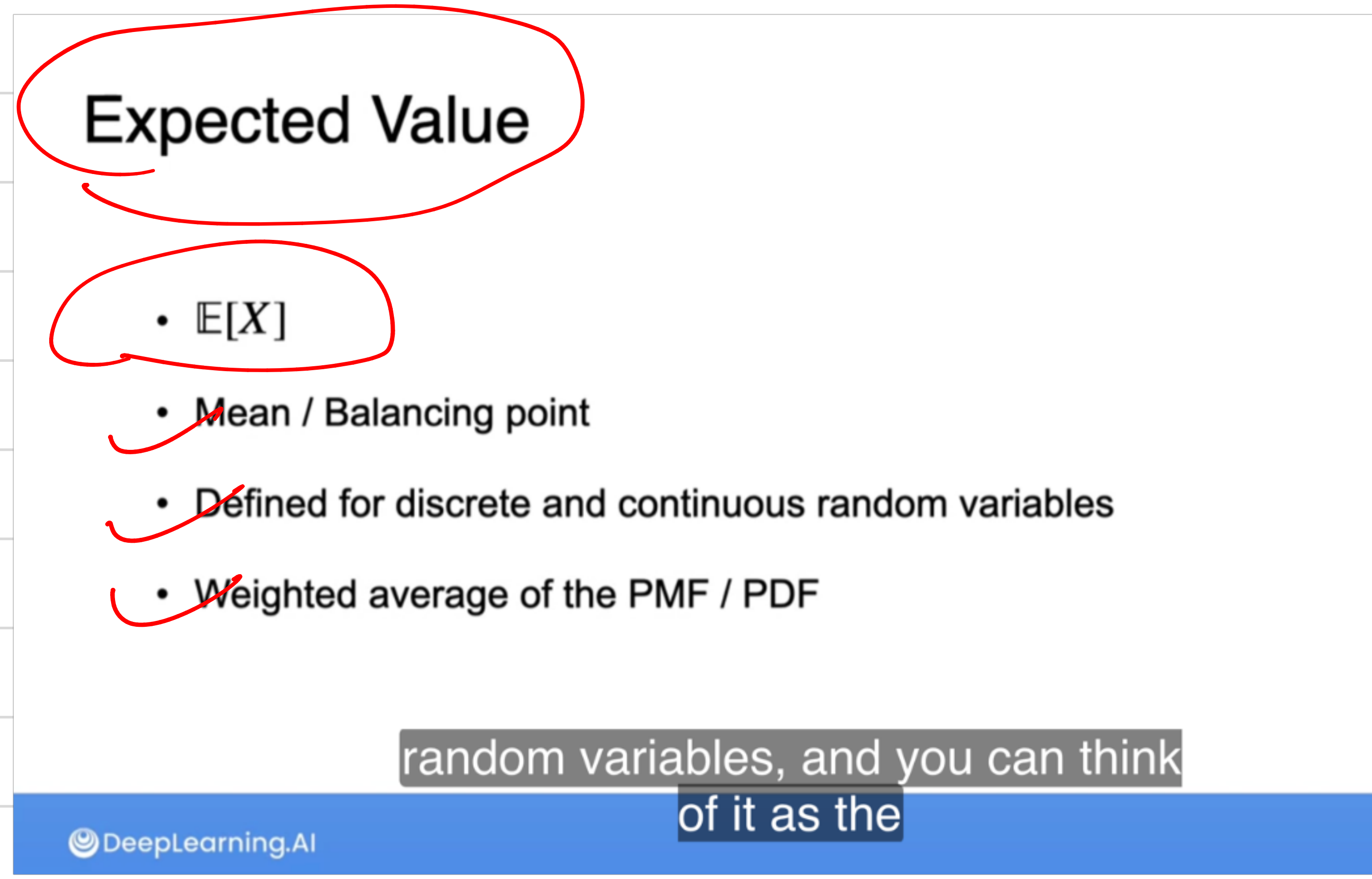
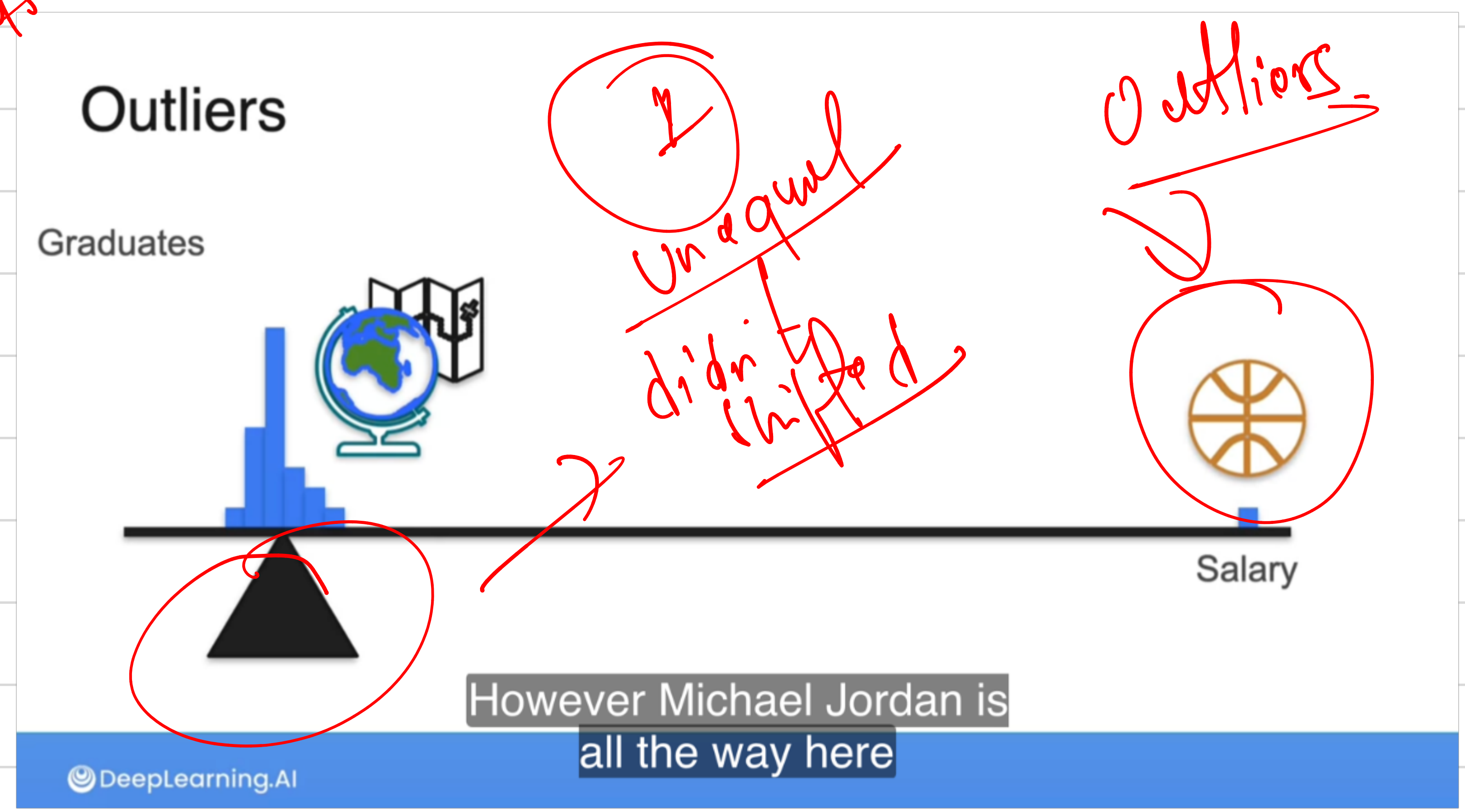




Outliers Concept:

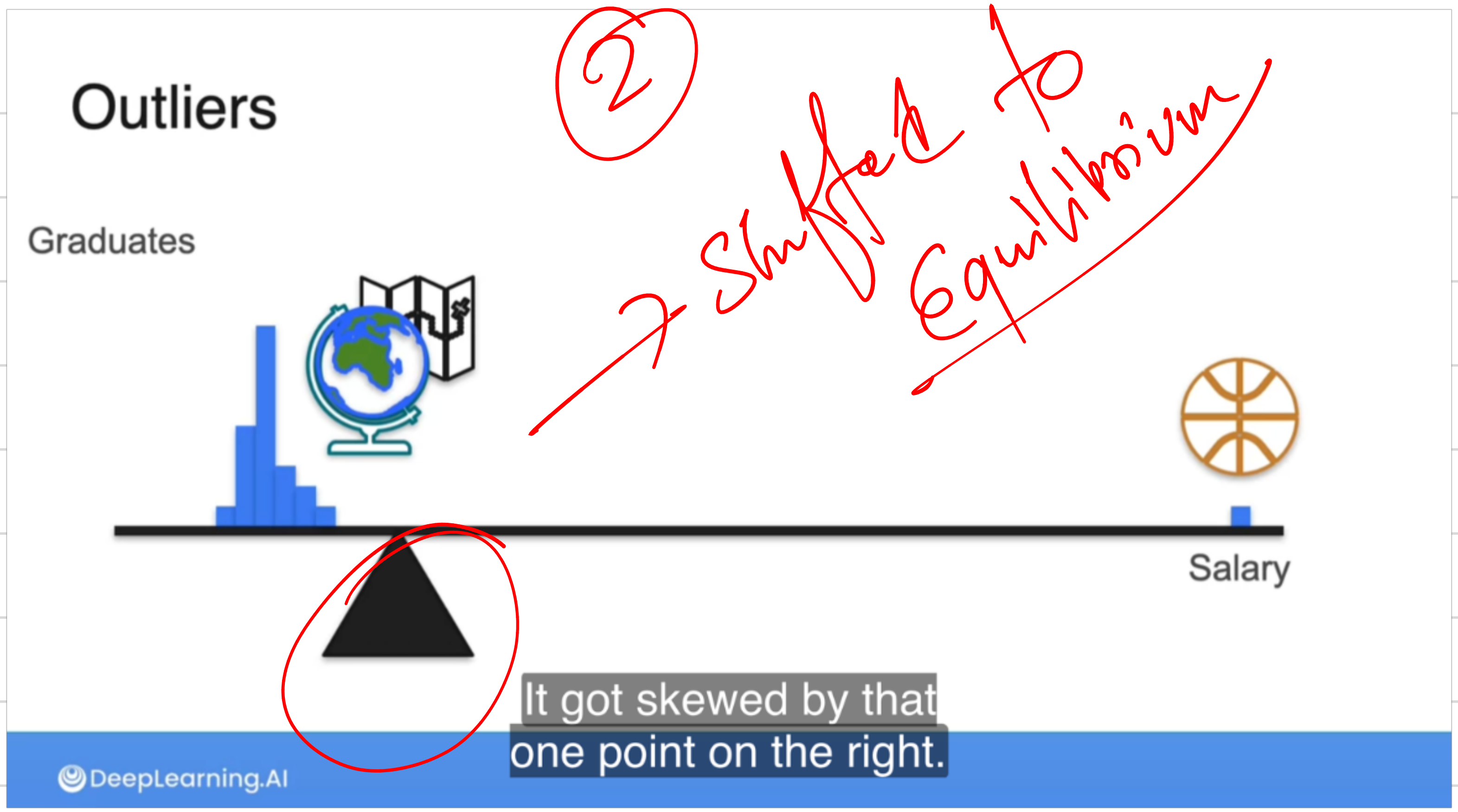
5, 6, 7, 8, 100

Outliers: Similarly Among Graduates Suppose others diff B.S. Whereas one earns around 35000-45000/ 750000/year



1 Unequal didn't shifted

Outliers


Outliers
② → Shifted to Equilibrium
Graduates
Salary
It got skewed by that
one point on the right.
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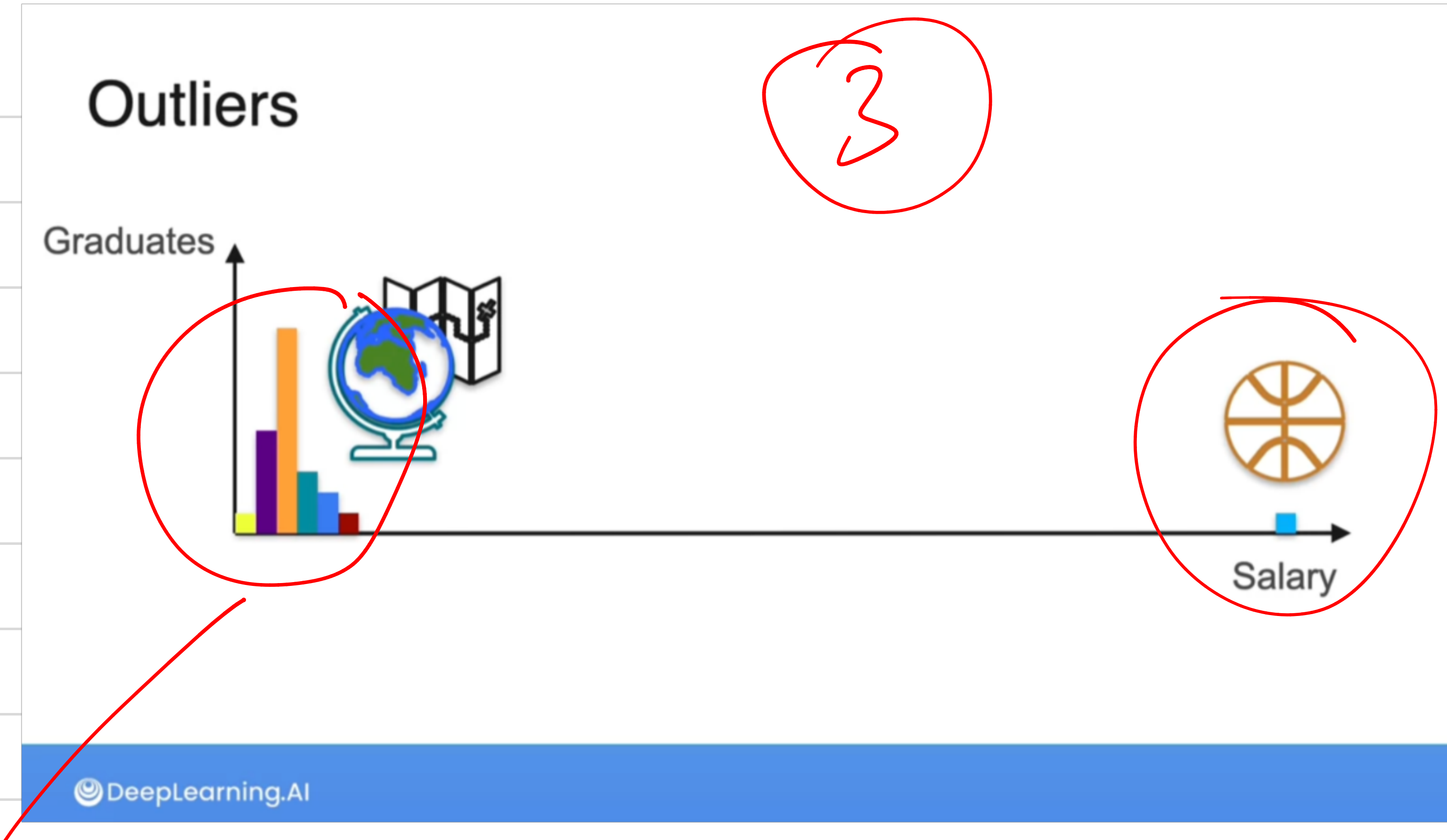
Outliers
③
Graduates
Salary
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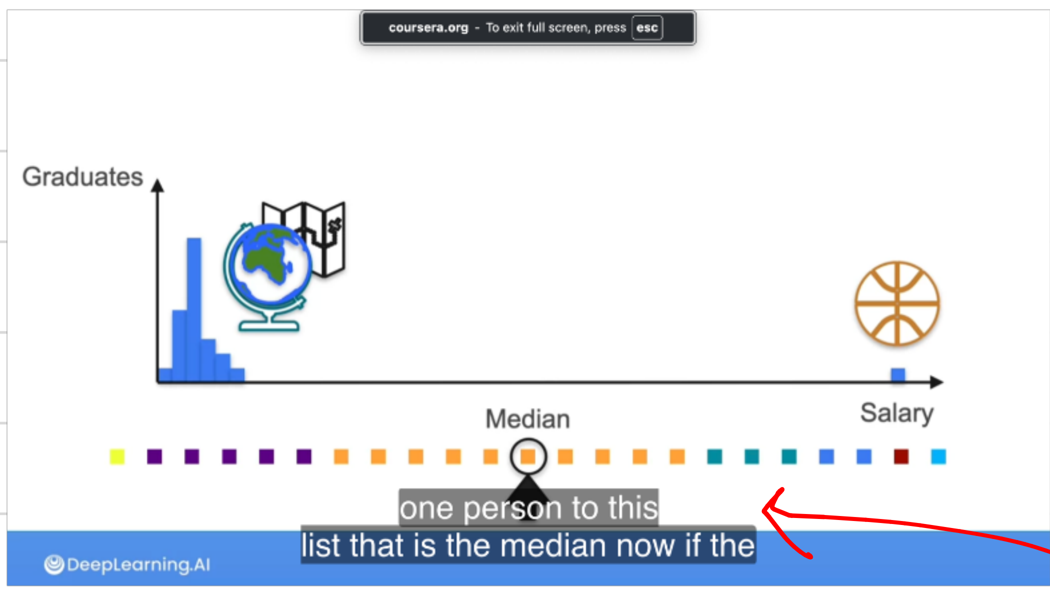
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Graduates
Median
Salary
one person to this
list that is the median now if the
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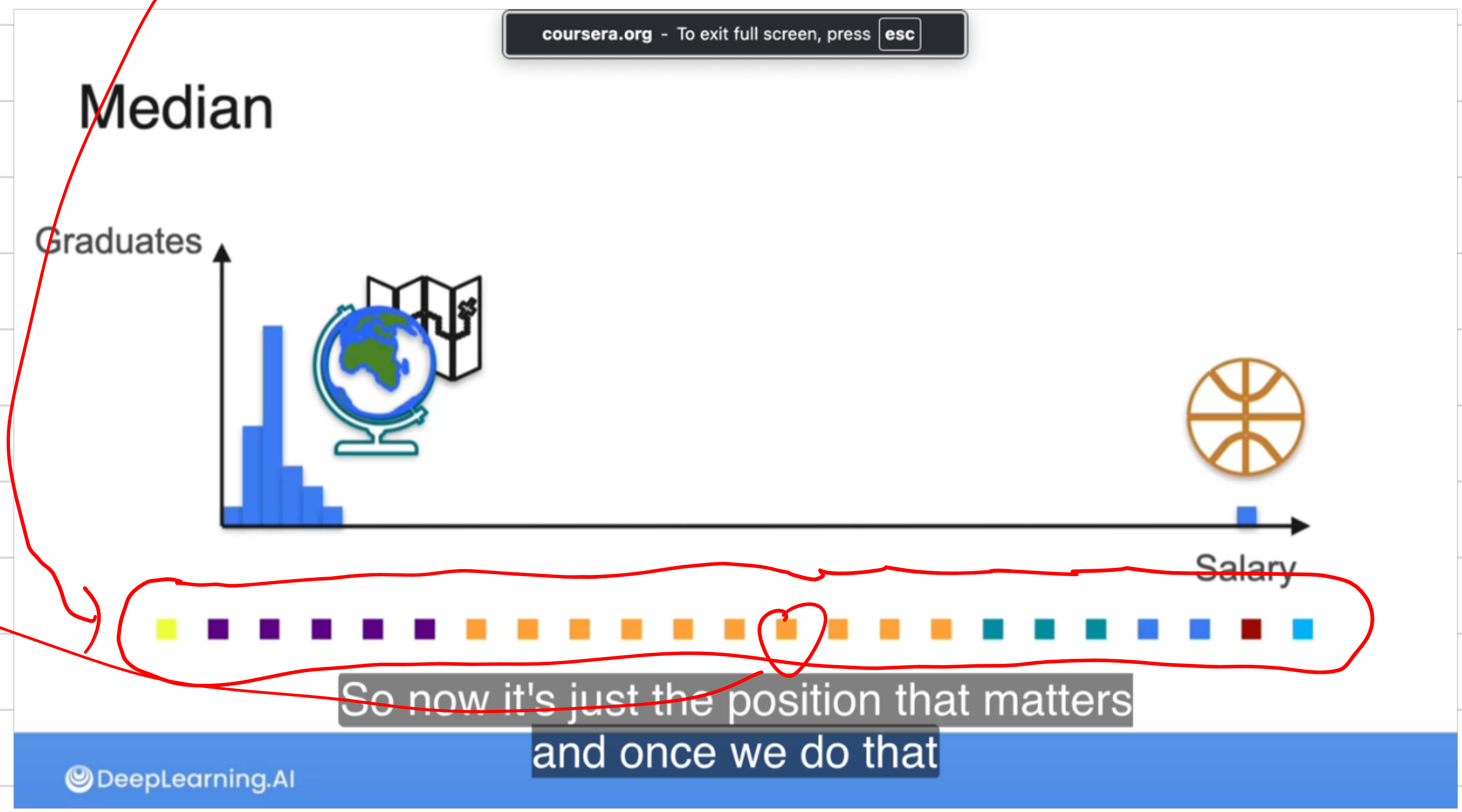
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Median
Graduates
Salary
So now it's just the position that matters
and once we do that
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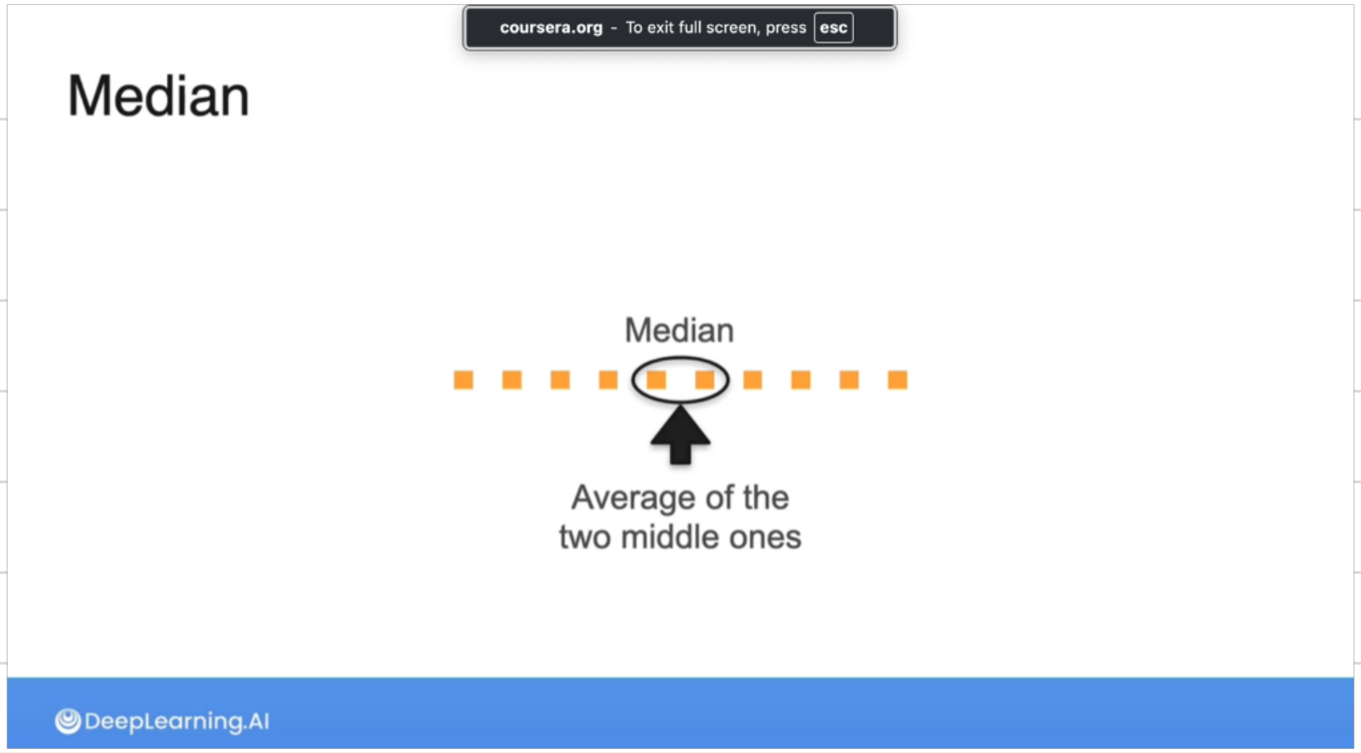
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Median
Median
Average of the
two middle ones
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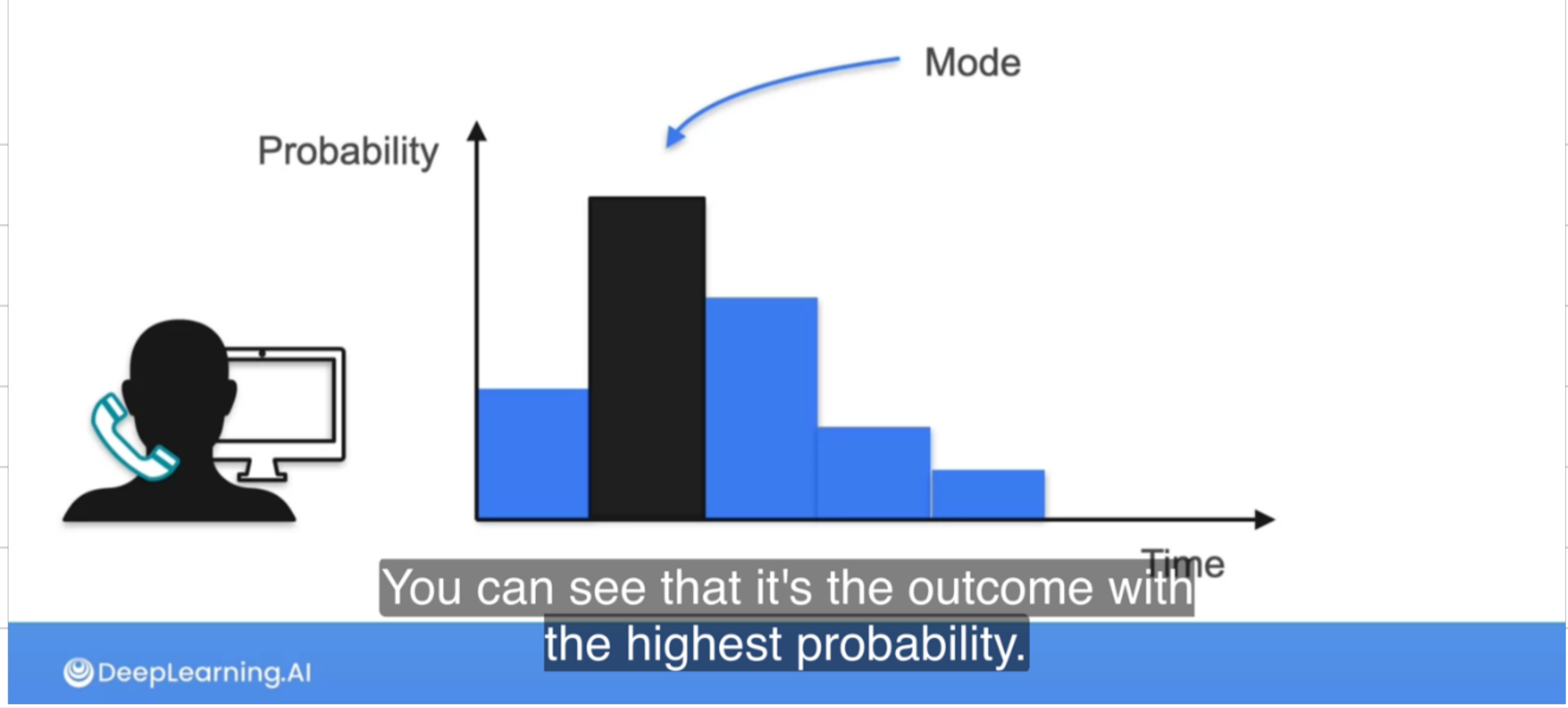
Mode
Probability
Time
You can see that it's the outcome with
the highest probability.
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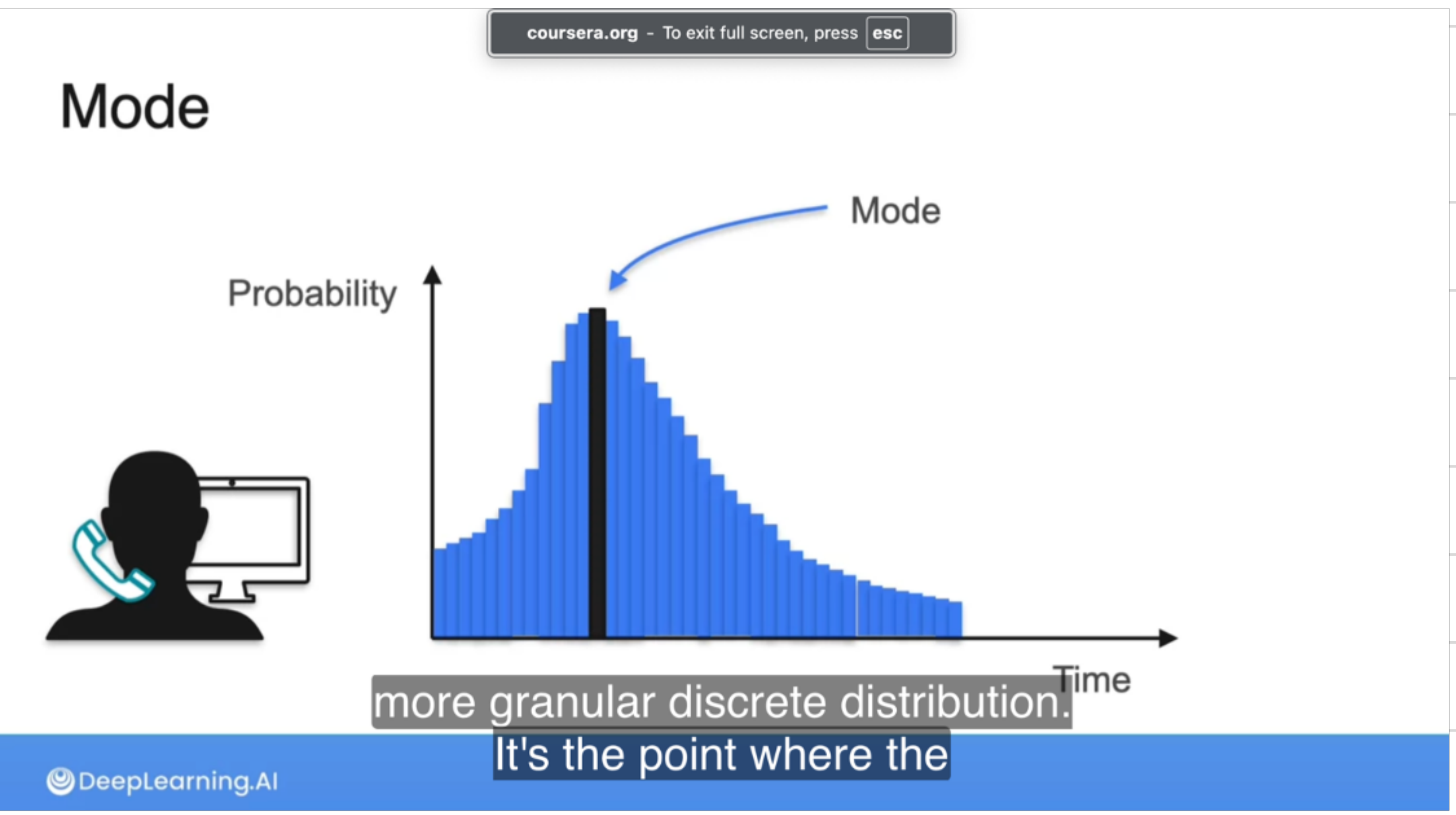
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Mode
Mode
Probability
Time
more granular discrete distribution.
It's the point where the
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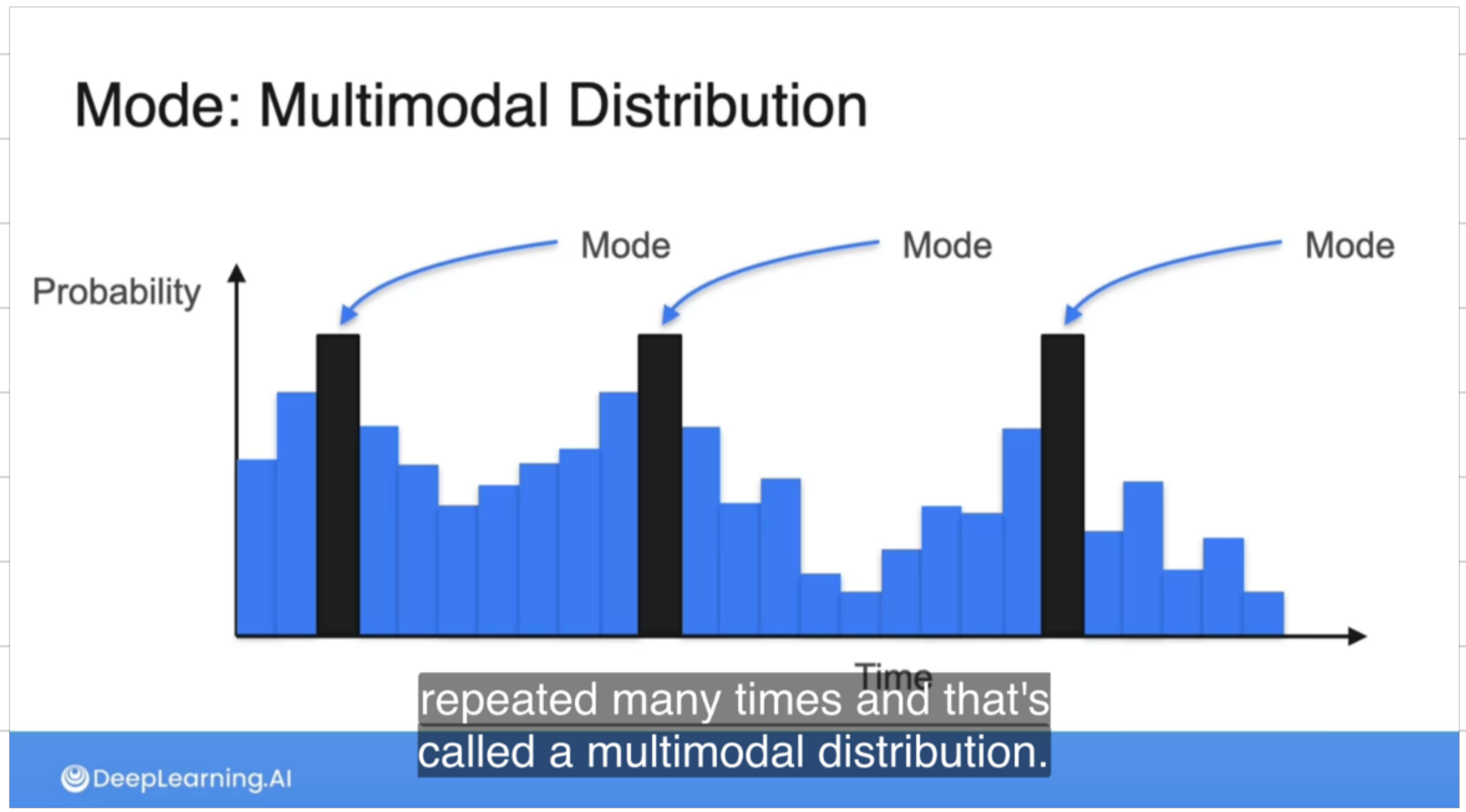
Mode: Multimodal Distribution
Mode
Mode
Mode
Probability
Time
repeated many times and that's
called a multimodal distribution.
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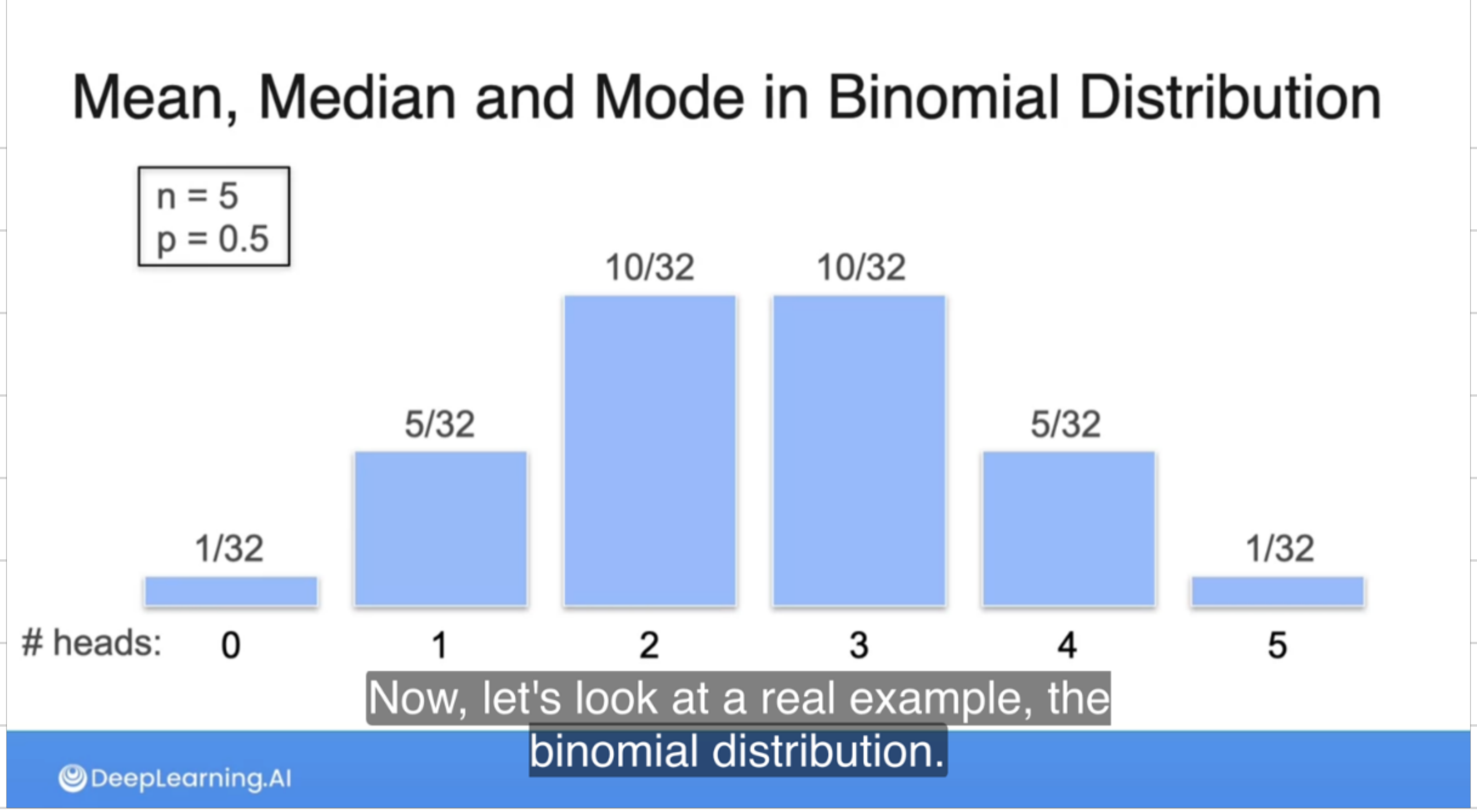
Mean, Median and Mode in Binomial Distribution
n = 5
p = 0.5
1/32
5/32
10/32
10/32
5/32
1/32
heads: 0 1 2 3 4 5
Now, let's look at a real example, the
binomial distribution.
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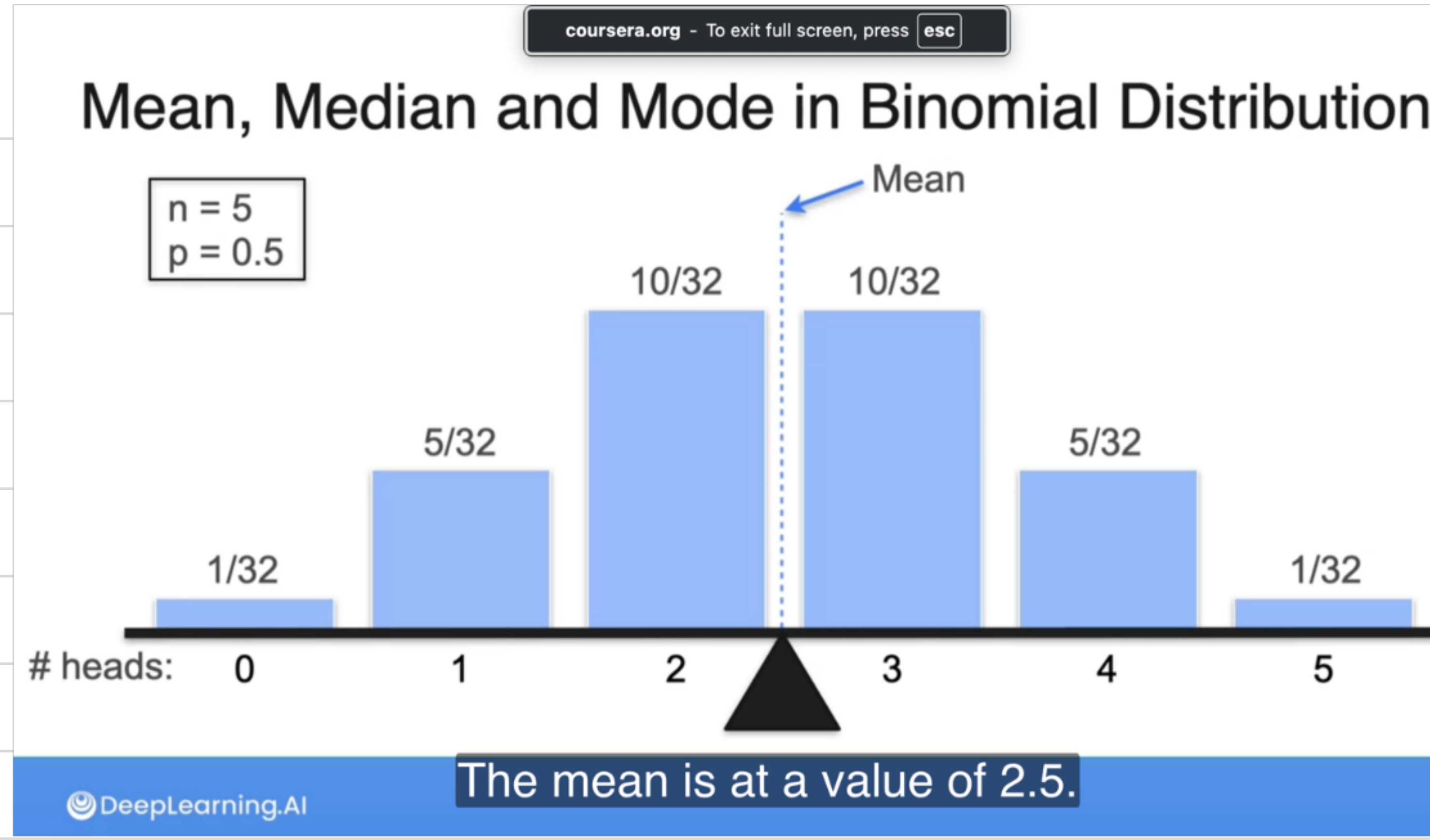
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Mean, Median and Mode in Binomial Distribution
Mean
n = 5
p = 0.5
1/32
5/32
10/32
10/32
5/32
1/32
heads: 0 1 2 3 4 5
The mean is at a value of 2.5.
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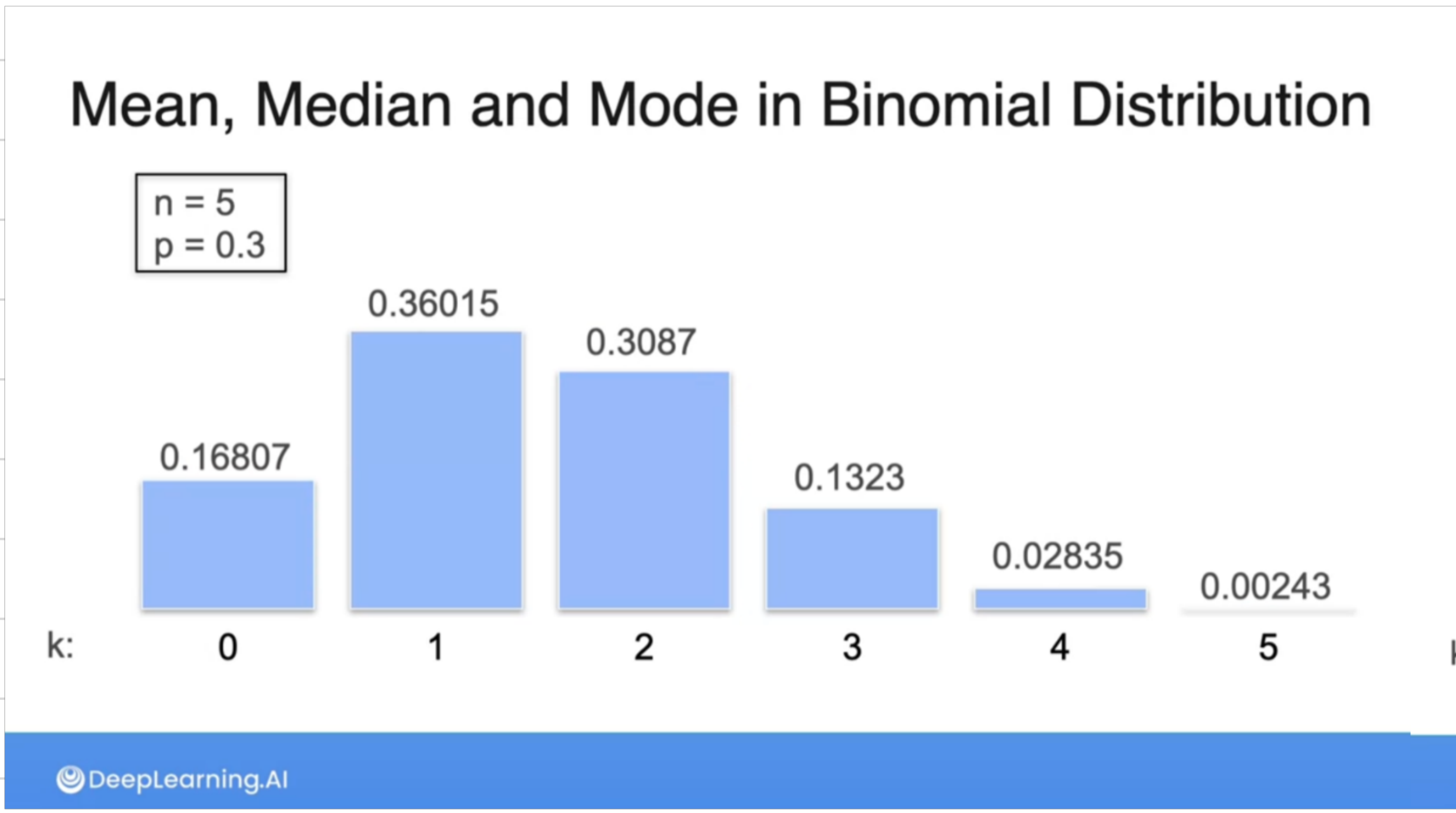
Mean, Median and Mode in Binomial Distribution
n = 5
p = 0.3
0.16807
0.36015
0.3087
0.1323
0.02835
0.00243
k: 0 1 2 3 4 5
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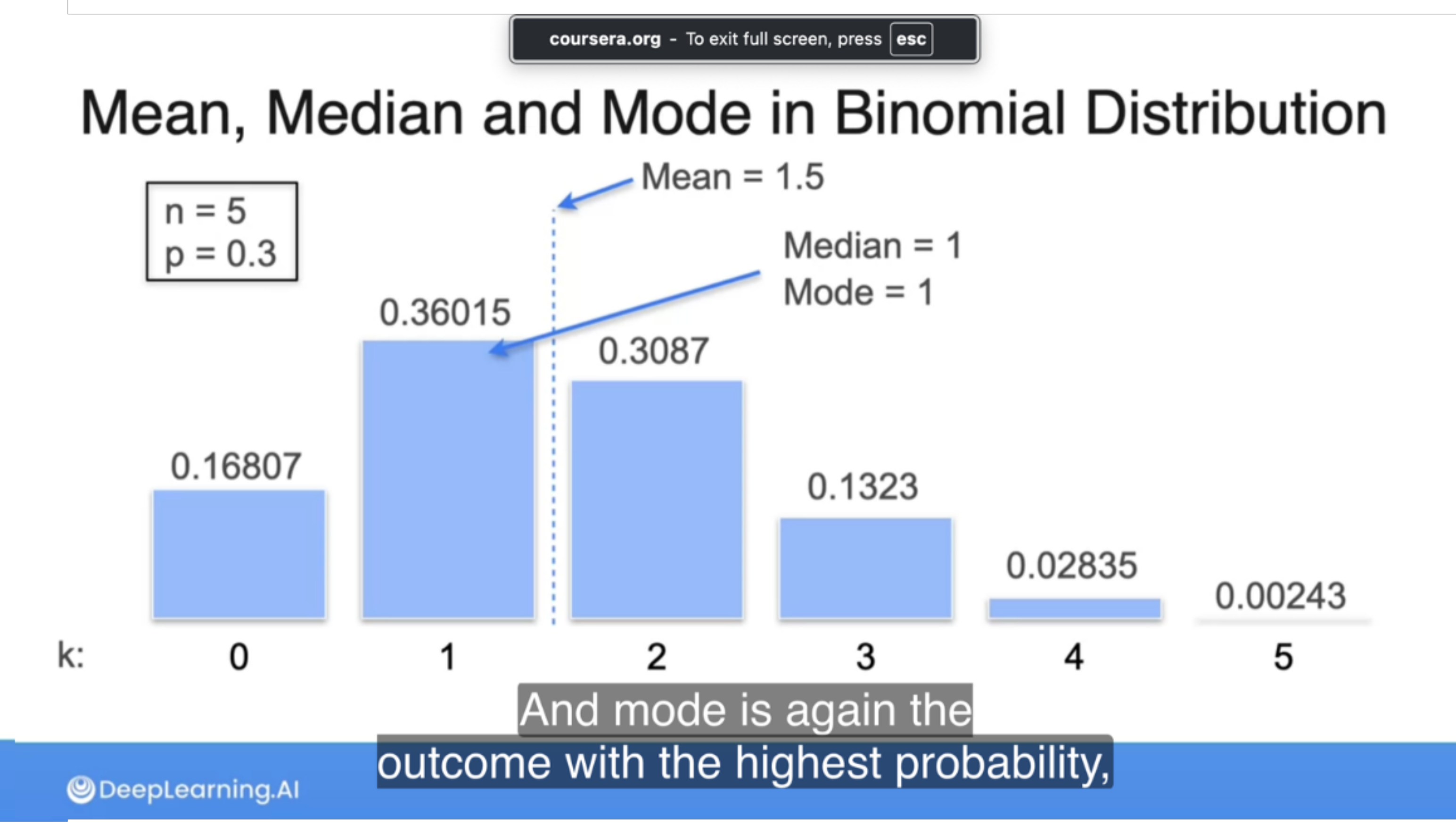
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Mean, Median and Mode in Binomial Distribution
Mean = 1.5
Median = 1
Mode = 1
n = 5
p = 0.3
0.16807
0.36015
0.3087
0.1323
0.02835
0.00243
k: 0 1 2 3 4 5
And mode is again the
outcome with the highest probability,
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$\sigma \Rightarrow$ Flatness or Spread.

$\mu \Rightarrow$ Highest of Center Peakness

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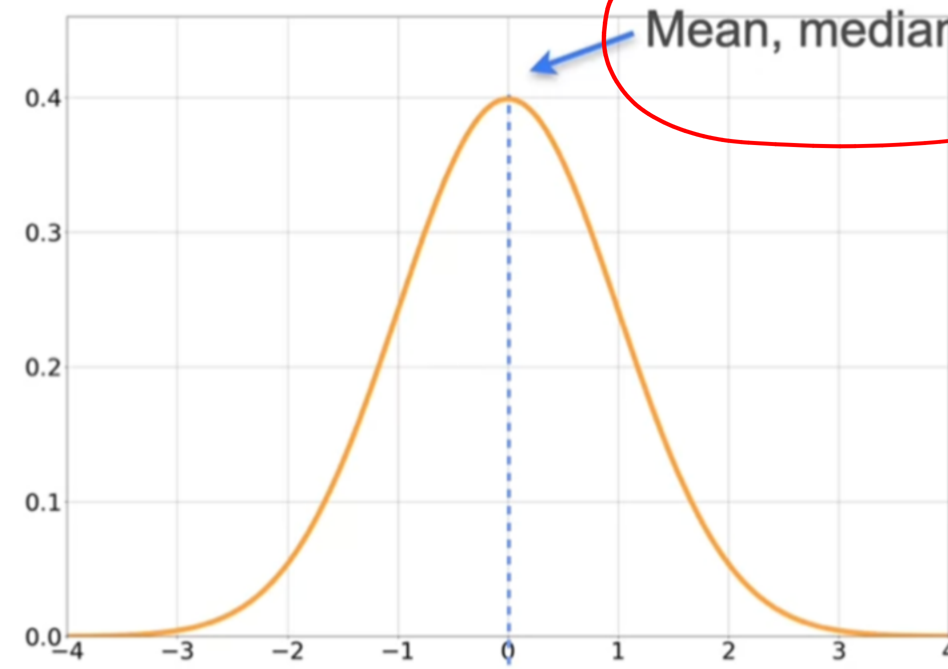
Mean, Median and Mode in Normal Distribution



which is the highest one.
So for a normal distribution,

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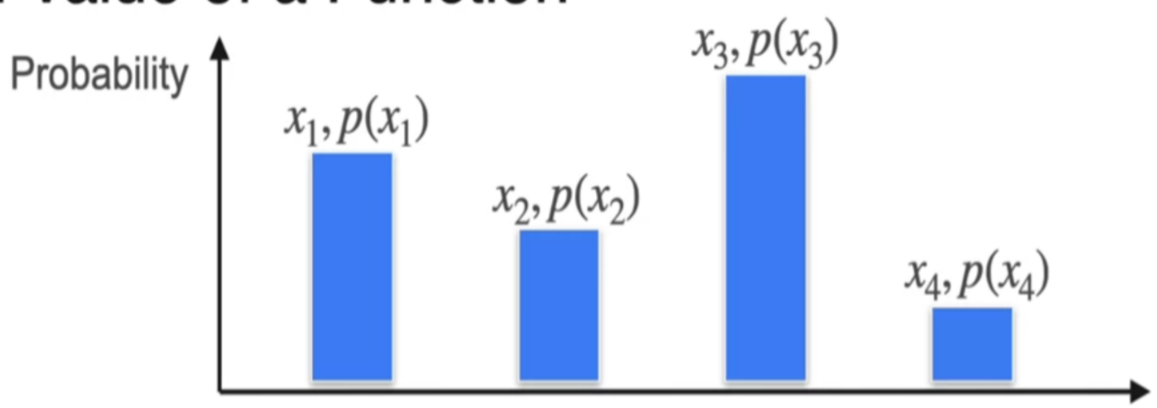
Expected Value of a Function



$$\mathbb{E}[X] = x_1 p(x_1) + x_2 p(x_2) + x_3 p(x_3) + x_4 p(x_4)$$

$$E[g(X)] = g(x_1)p(x_1) + g(x_2)p(x_2) + g(x_3)p(x_3) + g(x_4)p(x_4)$$

You just replace the x

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$$E[X] = x_1 p(x_1) + x_2 p(x_2) + x_3 p(x_3) + x_4 p(x_4)$$

replace x_i with $g(x_i)$

Expected Value of a Function

Probability:	1/6	1/6	1/6	1/6	1/6	1/6
Roll:	1	2	3	4	5	6
Square:	1	4	9	16	25	36

1

What is the fair price to pay for this game?

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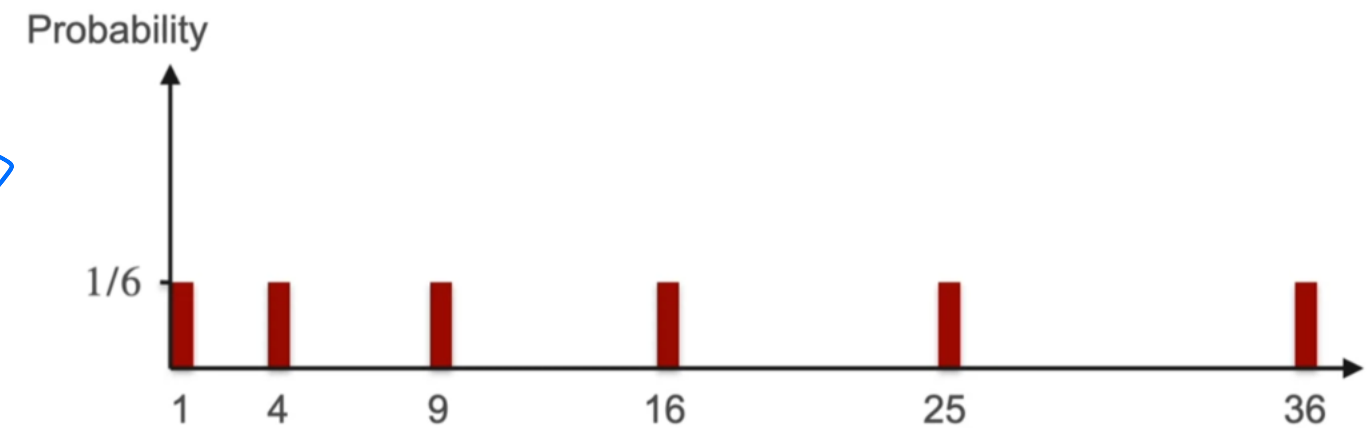
Expected Value of a Function



2

You can plot the distribution of

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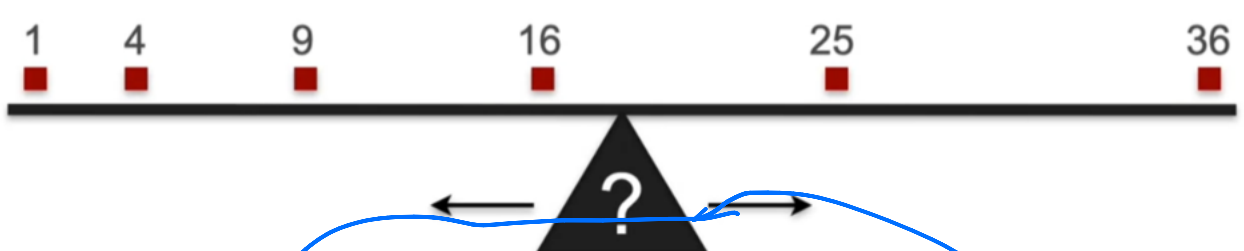
Expected Value of a Function

3



you can simply take the average of these numbers,

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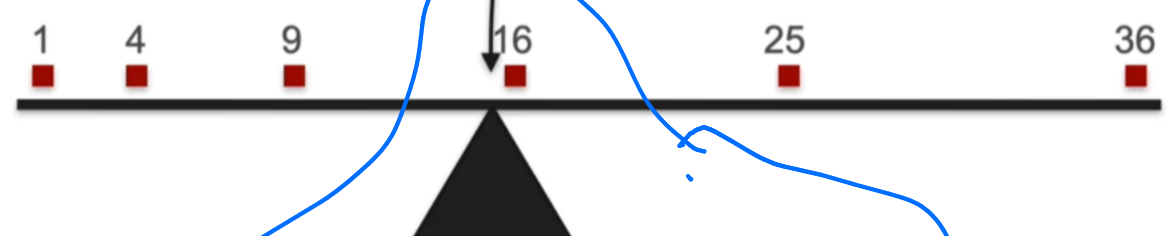
Expected Value of a Function

4

$$\frac{1+4+9+16+25+36}{6} = \frac{91}{6} = \frac{1^2}{6} + \frac{2^2}{6} + \frac{3^2}{6} + \frac{4^2}{6} + \frac{5^2}{6} + \frac{6^2}{6}$$

$$= \mathbb{E}\left[X^2\right]$$



You have actually calculated the expected value of x^2.

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Expectation of Linear Function

Probability:	1/6	1/6	1/6	1/6	1/6	1/6
Roll:	1	2	3	4	5	6
Double:	2	4	6	8	10	12
Wins	-3	-2	-1	0	1	2

Which means your wins are -3,

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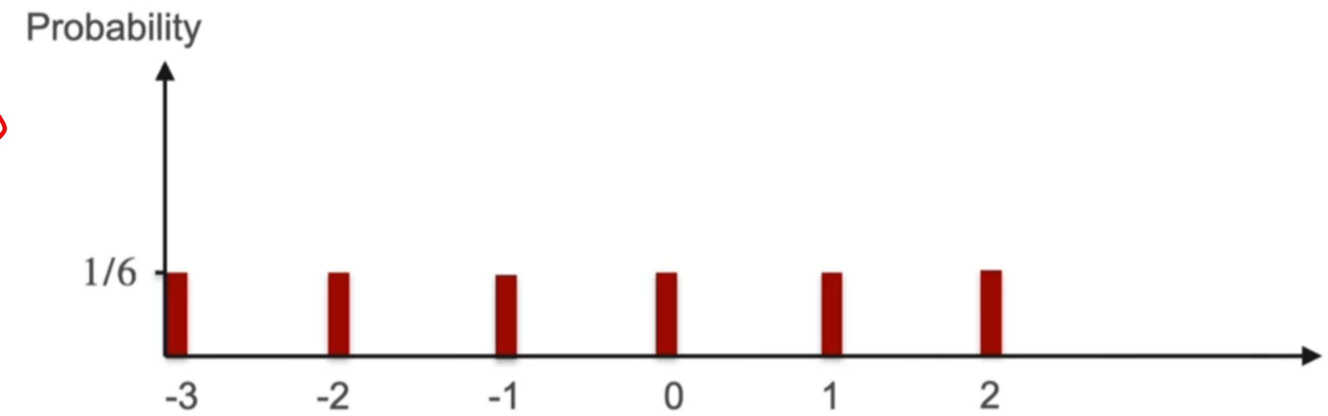
Expected Value of a Function



your payoffs and try to balance it on a scale,

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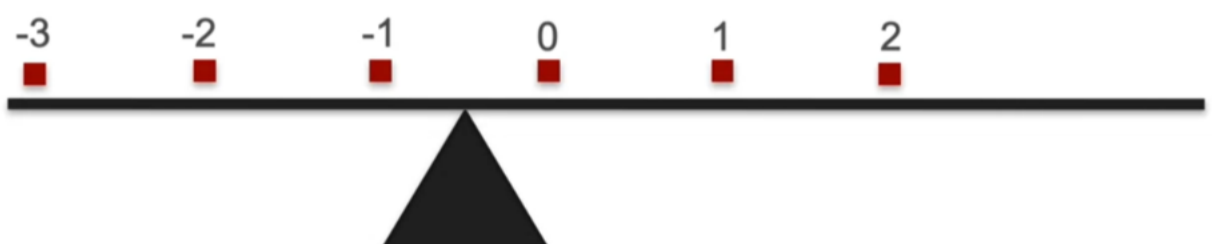
Expected Value of a Function

$$\frac{(2\cdot 1-5)+(2\cdot 2-5)+(2\cdot 3-5)+(2\cdot 4-5)+(2\cdot 5-5)+(2\cdot 6-5)}{6} = \frac{-3}{6} = -0.5$$



the value rolled minus the five dollars you started with.

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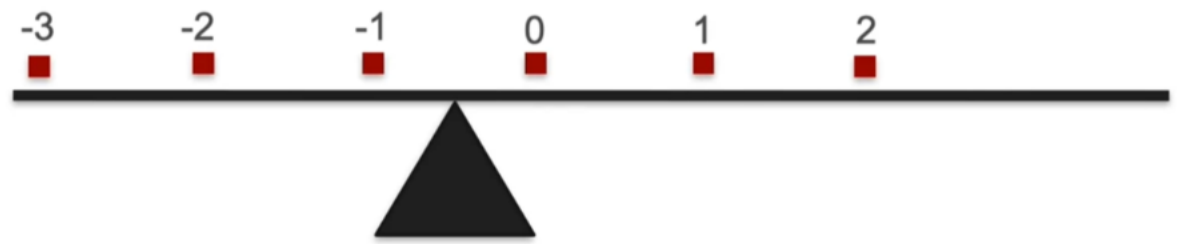
Expected Value of a Function

$$2\cdot\underbrace{\boxed{\frac{(1+2+3+4+5+6)}{6}}}_{\mathbb{E}[X]} + (-5) = \frac{-3}{6} = -0.5$$



Now, 1+2+3+4+5+6/6 is simply

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We can use any numbers in a and b

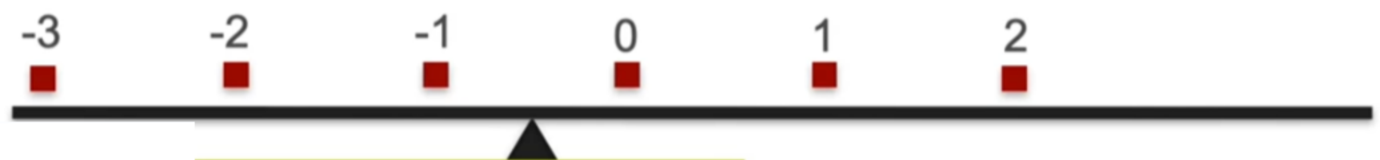
Therefore, we can use any values for 'a' and 'b' to create different linear transformations of the expected value, each with its own scaling and shifting effects.

Expected Value of a Function

$$\mathbb{E}[2 \cdot X + (-5)] = 2 \cdot \boxed{\frac{(1+2+3+4+5+6)}{6}} + (-5) = \frac{-3}{6} = -0.5$$

$\mathbb{E}[X]$

$$= 2 \cdot \mathbb{E}[X] + (-5)$$



In general: $\mathbb{E}[aX + b] = a\mathbb{E}[X] + b$ → $\mathbb{E}[aX] = a\mathbb{E}[X]$

But also the expected value of a

Sum of Expectations

Win $1

Win nothing

Win $1 $2 $3 $4 $5 $6

$\mathbb{E}[X_{coin}] = \$0.5$ $\quad$ $\mathbb{E}[X_{dice}] = \$3.5$

$$\mathbb{E}[X] = \mathbb{E}[X_{coin}] + \mathbb{E}[X_{dice}] = \$0.5 + \$3.5 = \$4$$

In general: $\mathbb{E}[X_1 + X_2] = \mathbb{E}[X_1] + \mathbb{E}[X_2]$

the variables is equal to the sum of the expectations.

$E[X_1 + X_2] = E[X_1] + E[X_2]$

[coin].

Win → 1/2

Case → 21/6 [Dice]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Sum of Expectations
Aamina
Aaron
Abigail
1
Expected number of correct assignments?
Bo Bleepityblop
8 billion people
Bo Bleepityblop who's going to be given their own name.
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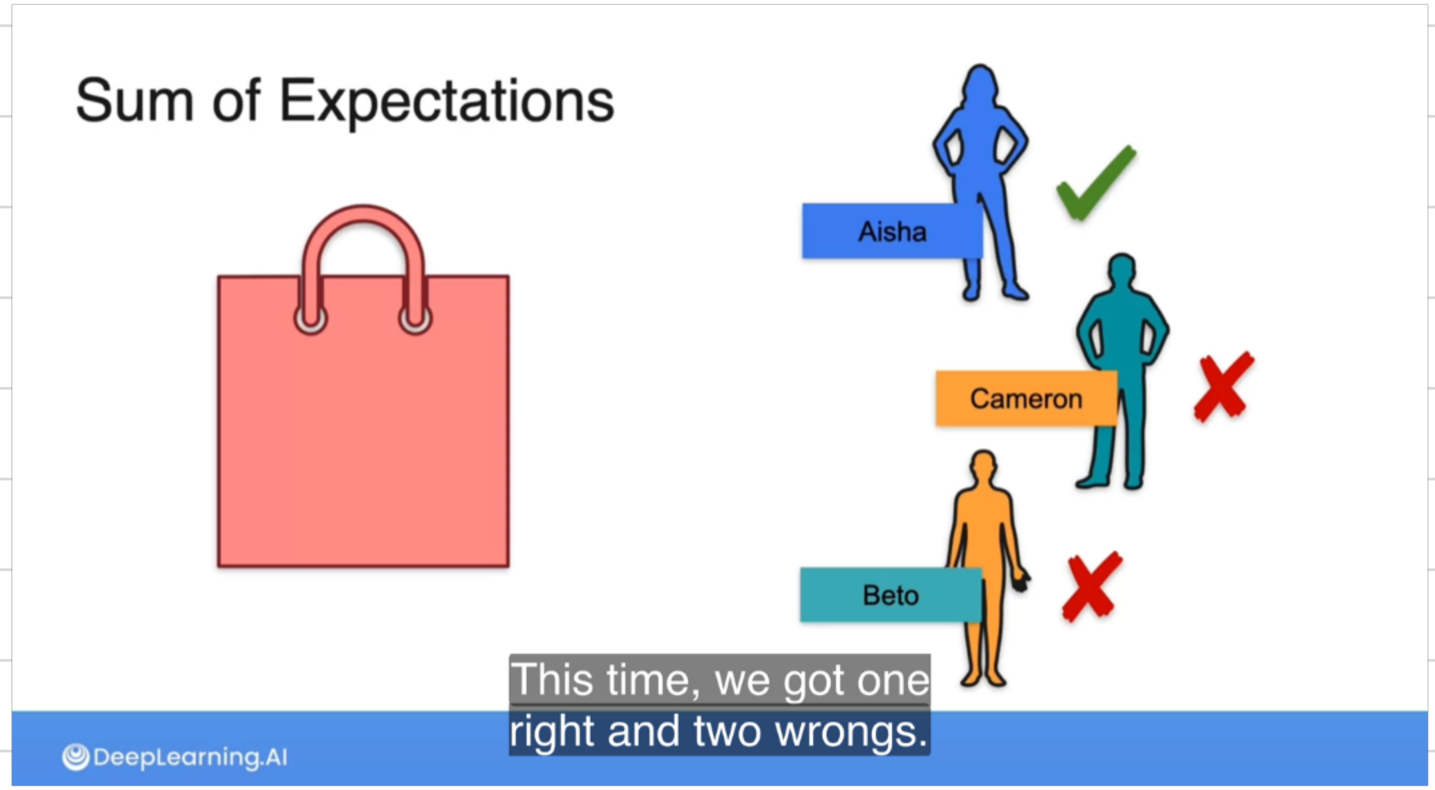
Sum of Expectations
Aisha
Cameron
Beto
This time, we got one right and two wrongs.
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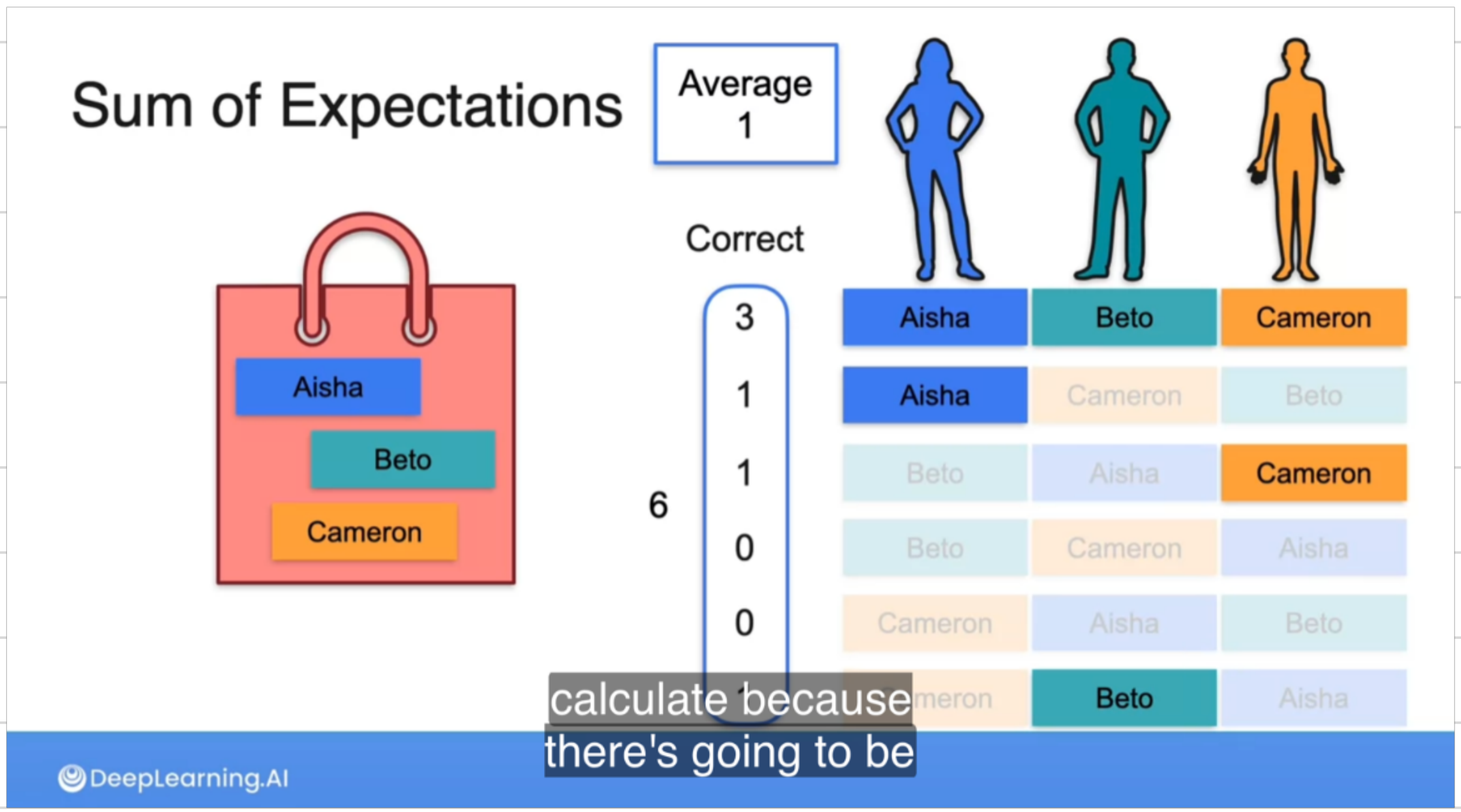
Sum of Expectations
Average 1
Aisha
Beto
Cameron
Correct
3 Aisha Beto Cameron
1 Aisha Cameron Beto
6
1 Beto Aisha Cameron
0 Beto Cameron Aisha
0 Cameron Aisha Beto
Beto Aisha
calculate because there's going to be
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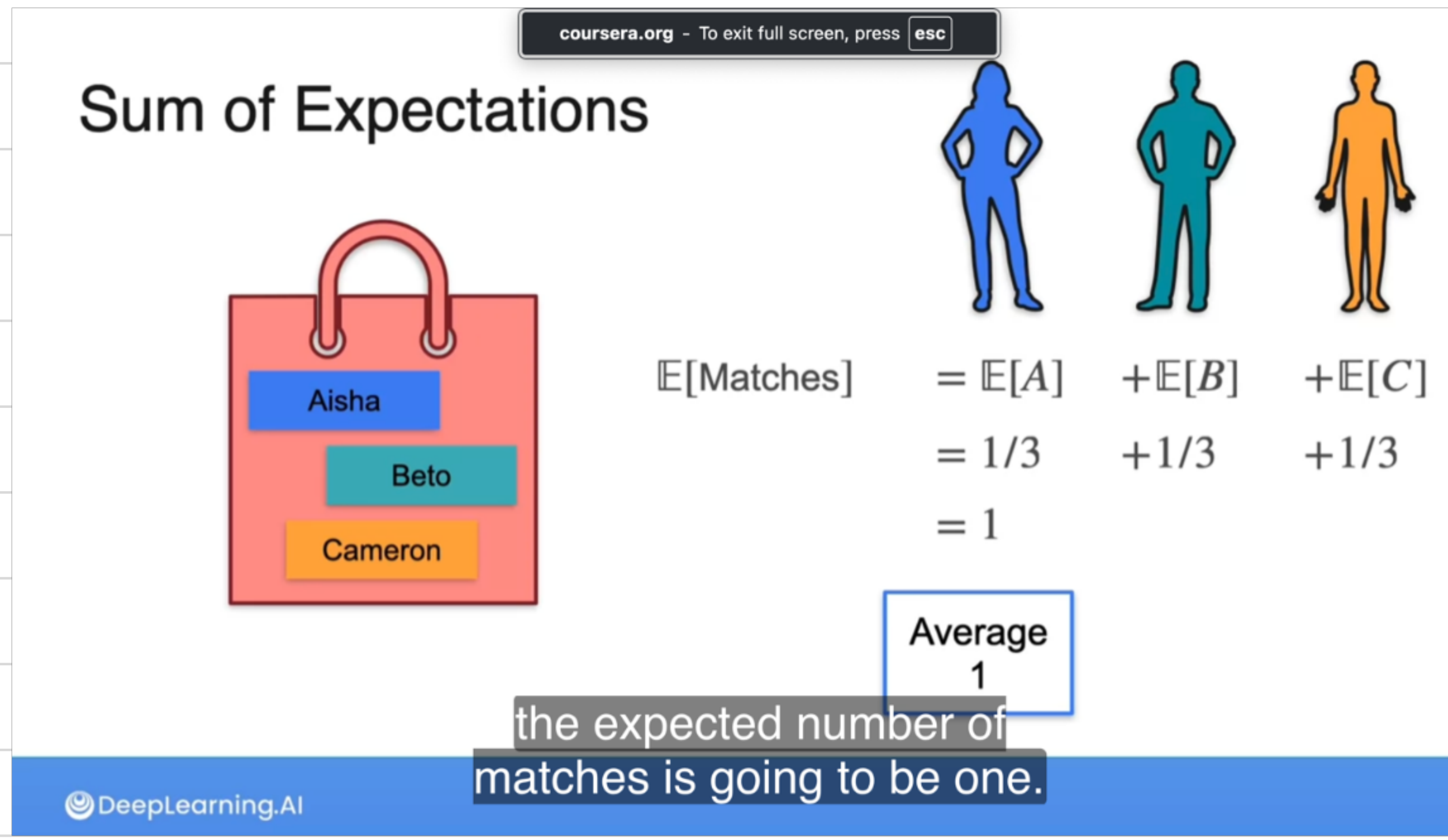
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Sum of Expectations
Aisha
Beto
Cameron
$\mathbb{E}[\text{Matches}] = \mathbb{E}[A] + \mathbb{E}[B] + \mathbb{E}[C]$
$= 1/3 + 1/3 + 1/3$
$= 1$
Average 1
the expected number of matches is going to be one.
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Sum of Expectations

n people (n = 8 billion)

$$\mathbb{E}\,[\text{Matches}] = \mathbb{E}\left[X_{\text{person}_1}\right] + \mathbb{E}\left[X_{\text{person}_2}\right] + \ldots + \mathbb{E}\left[X_{\text{person}_n}\right] = \frac{1}{n} + \frac{1}{n} + \cdots + \frac{1}{n}$$

$$= n \cdot \frac{1}{n} = 1$$

In general:
$\mathbb{E}\left[X_1 + X_2 + \ldots + X_n\right] = \mathbb{E}\left[X_1\right] + \mathbb{E}\left[X_2\right] + \ldots + \mathbb{E}\left[X_n\right]$

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So, the Sum of Expectations is 1 Among n people 8 = billion.

Variance:

So it turns out that expected value, although it tells us a lot about the distribution, it doesn't tell us the whole story. For example, two distributions may have the same expected value, but one of them can be very narrow and the other one can be very wide. This is captured by something called the variance

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Variance Motivation: Fair Price To Play the Game

You play a game with a friend

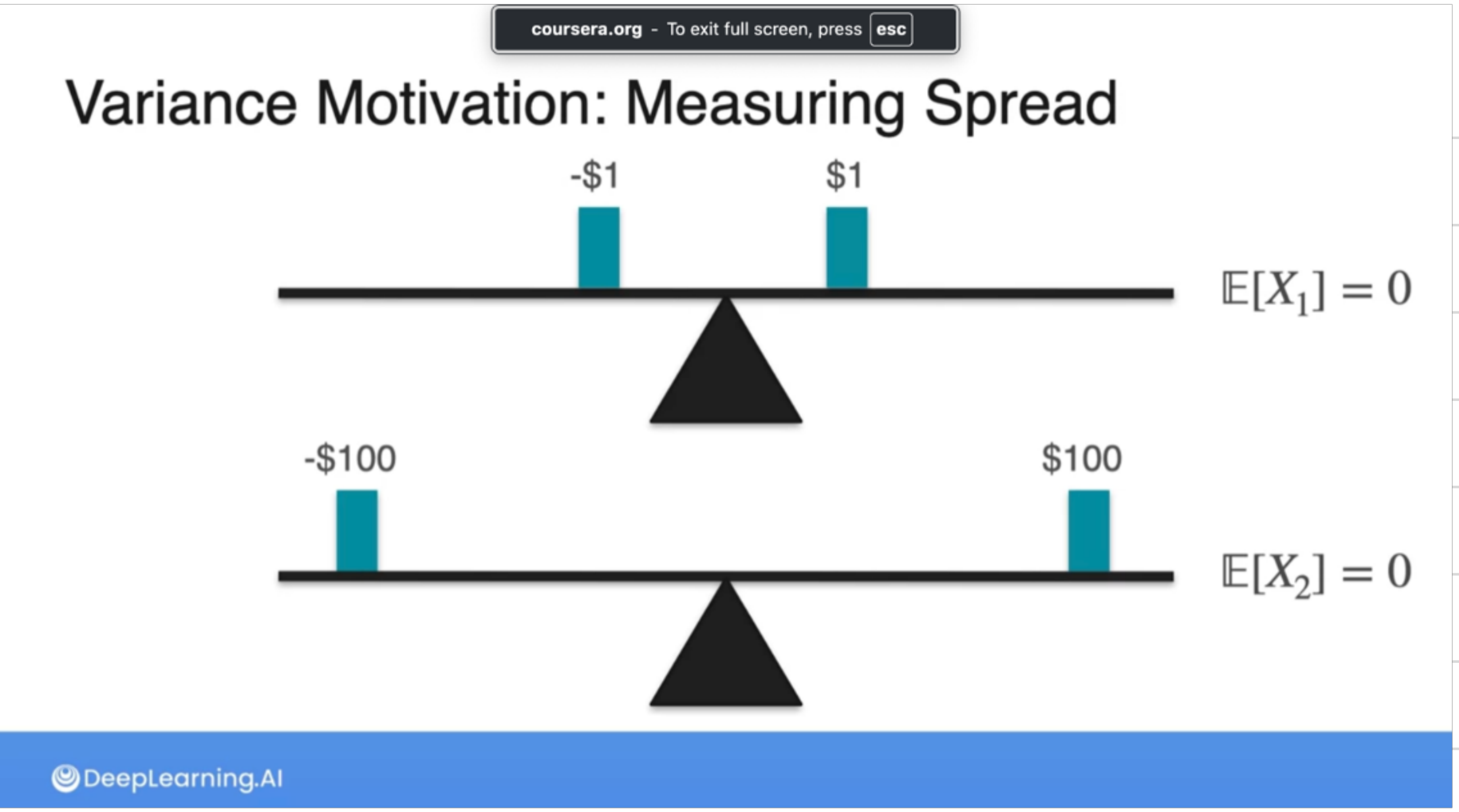
H You win 100 dollars

T You lose 100 dollars

Game cost:

$0

What is the fair amount of money to pay to play this game?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Variance Motivation: Measuring Spread
-$1
$1
$\mathbb{E}[X_1] = 0$
-$100
$100
$\mathbb{E}[X_2] = 0$
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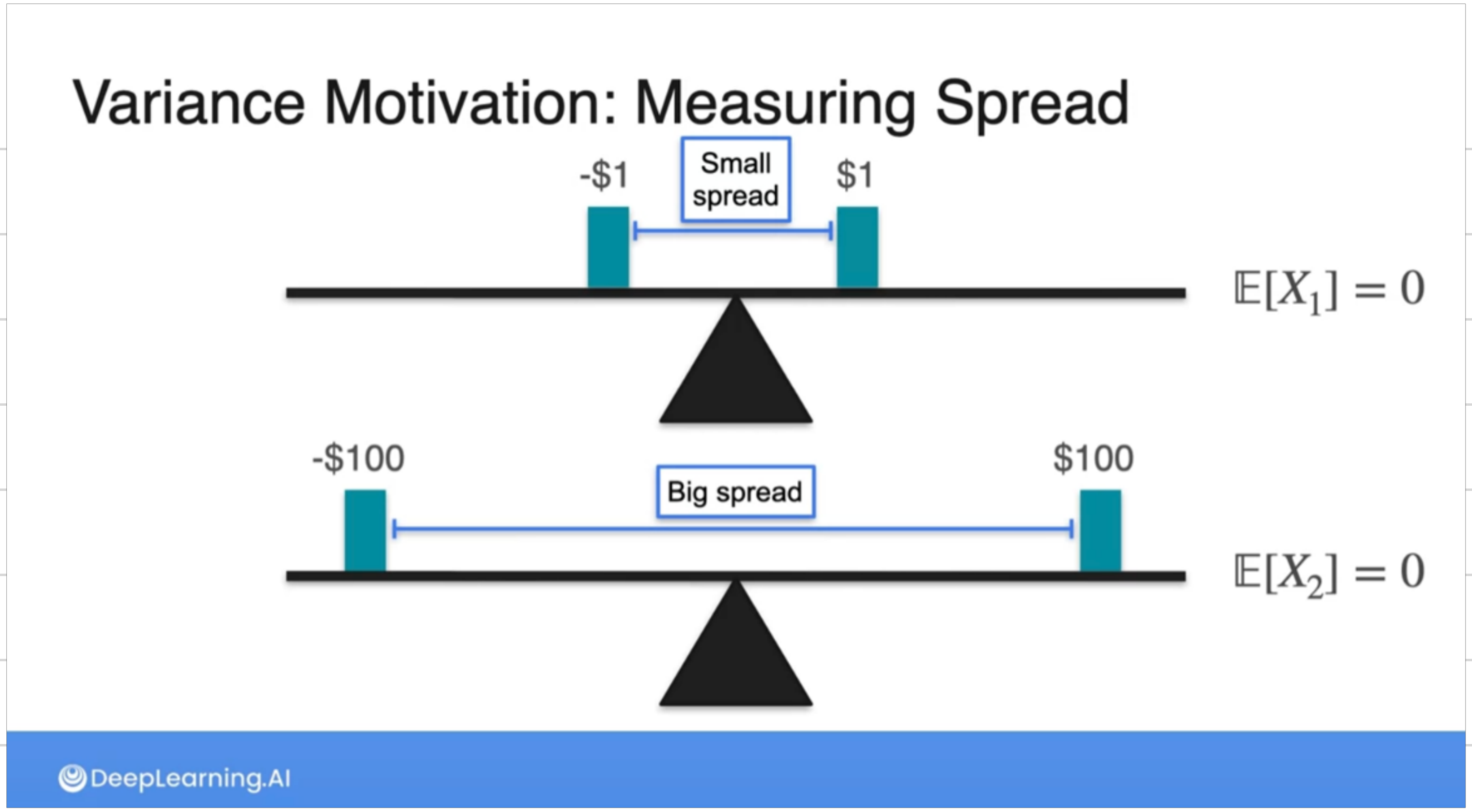
Variance Motivation: Measuring Spread
-$1
Small spread
$1
$\mathbb{E}[X_1] = 0$
-$100
Big spread
$100
$\mathbb{E}[X_2] = 0$
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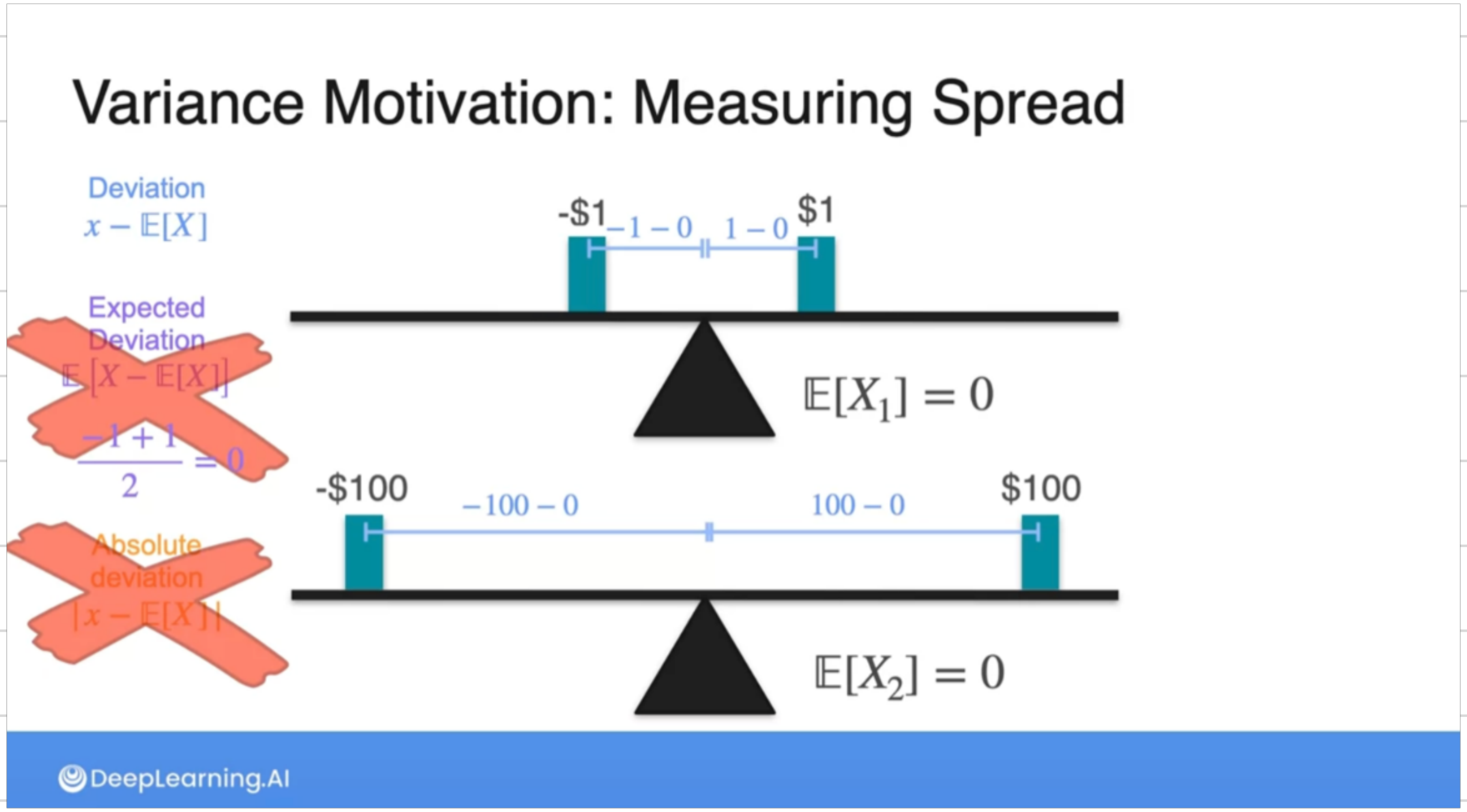
Variance Motivation: Measuring Spread
Deviation
$x - \mathbb{E}[X]$
Expected Deviation
$\mathbb{E}[X - \mathbb{E}[X]]$
$\frac{-1+1}{2} = 0$
Absolute deviation
$|x - \mathbb{E}[X]|$
-$1
$-1-0$
$1-0$
$1
$\mathbb{E}[X_1] = 0$
-$100
$-100-0$
$100-0$
$100
$\mathbb{E}[X_2] = 0$
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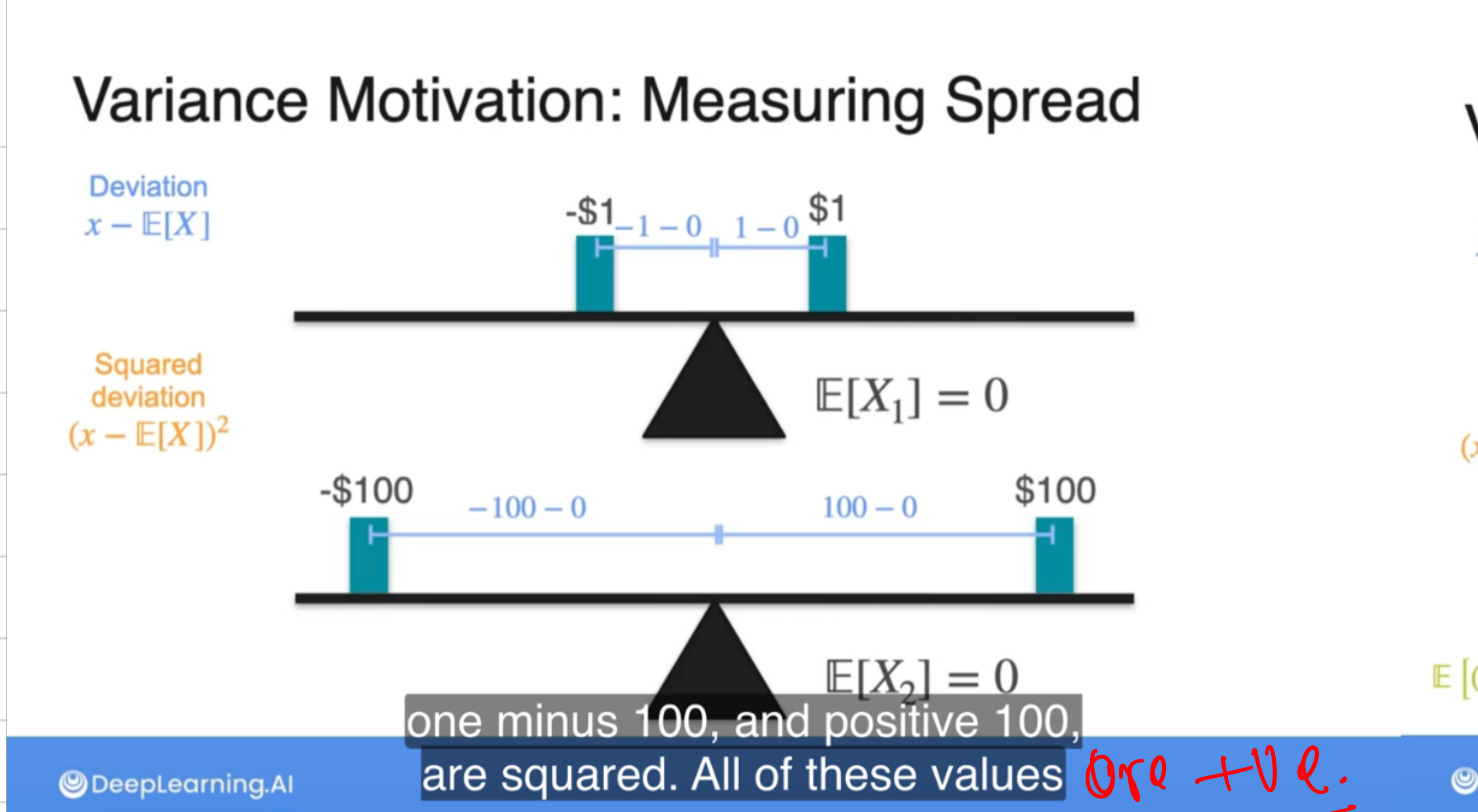
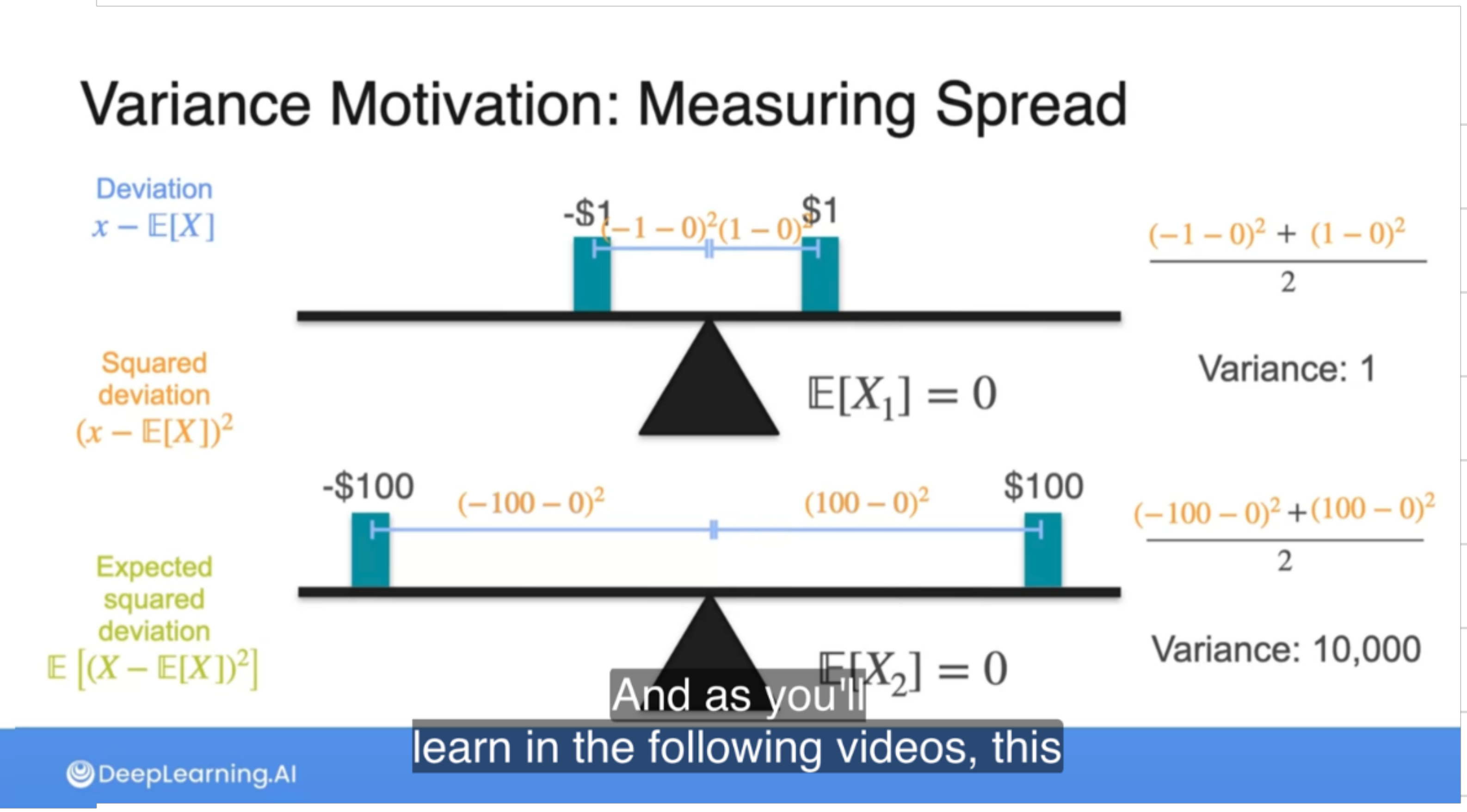


are +ve.



Variance Formula

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

1. Find X's mean
2. Find the deviation from that mean for every value of X
3. Square those deviations
4. Average those squared deviations

"Average squared deviation"

Hence, we always use squared deviations instead of Absolute Deviation only.

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Variance Motivation: Centering With Mean

1

Game 1

H You win 2 dollars

T You lose 2 dollars

Game 2

H You win 3 dollars

T You lose 1 dollar

They have the same variance

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Variance Motivation: Centering With Mean

2

Game 1

H You win 2 dollars

T You lose 2 dollars

$$\mathbb{E}[X_1] = \frac{1}{2}\cdot(-2) + \frac{1}{2}\cdot 2 = 0$$

Game 2

H You win 3 dollars

T You lose 1 dollar

$$\mathbb{E}[X_2] = \frac{1}{2}\cdot(-1) + \frac{1}{2}\cdot 3 = 1$$

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Variance Motivation: Centering With Mean

3

Game 1

H You win 2 dollars

T You lose 2 dollars

$$\mathbb{E}[X_1] = 0 \qquad \frac{1}{2}(-2-0)^2 + \frac{1}{2}(2-0)^2 = 4$$

Different price, but same spread

Game 2

H You win 3 dollars

T You lose 1 dollar

$$\mathbb{E}[X_2] = 1 \qquad \frac{1}{2}(-1-1)^2 + \frac{1}{2}(3-1)^2 = 4$$

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Both have same Spread or Variance.

Variance Formula

$$Var(X) = \mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{E}[X^2 - 2\mathbb{E}[X]X + \mathbb{E}[X]^2]$$

$\mathbb{E}[\text{constant} \cdot X] = \text{constant} \cdot \mathbb{E}[X]$

$\mathbb{E}[X+Y] = \mathbb{E}[X] + \mathbb{E}[Y]$

$$= \mathbb{E}[X^2] - \mathbb{E}[2\mathbb{E}[X]X] + \mathbb{E}[\mathbb{E}[X]^2]$$

$\mathbb{E}[X]$ is a constant

$\mathbb{E}[\text{constant}] = \text{constant}$

$$= \mathbb{E}[X^2] - 2\mathbb{E}[X]\,\mathbb{E}[X] + \mathbb{E}[X]^2$$

$$= \mathbb{E}[X^2] - 2\mathbb{E}[X]^2 + \mathbb{E}[X]^2$$

$$= \mathbb{E}[X^2] - \mathbb{E}[X]^2$$

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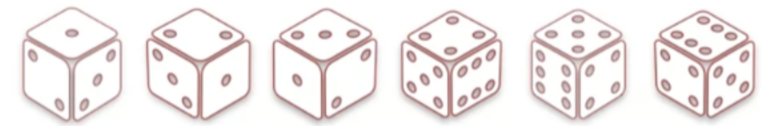
Properties of the Variance

Probability:	1/6	1/6	1/6	1/6	1/6	1/6
Roll:	1	2	3	4	5	6
Win Double:	\$2	\$4	\$6	\$8	\$10	\$12
Net Amount:	-\$3	-\$1	\$1	\$3	\$5	\$7



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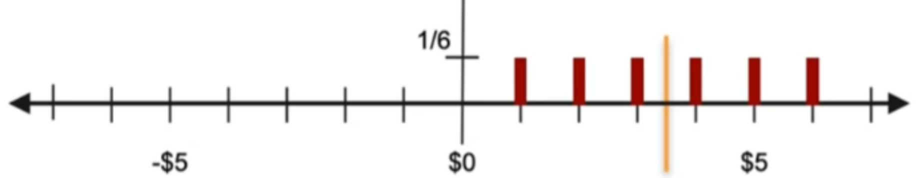
Properties of the Variance

$$Var(aX + b) = a^2 Var(X)$$

Variance: "Average squared deviation"

Dice roll is random variable: X

$\mathbb{E}[X] = 3.5$



Net winnings is random variable: $Y = 2X - 5$

$Var(Y) = Var(2X - 5) = 4Var(X)$

$\mathbb{E}[Y] = 2$

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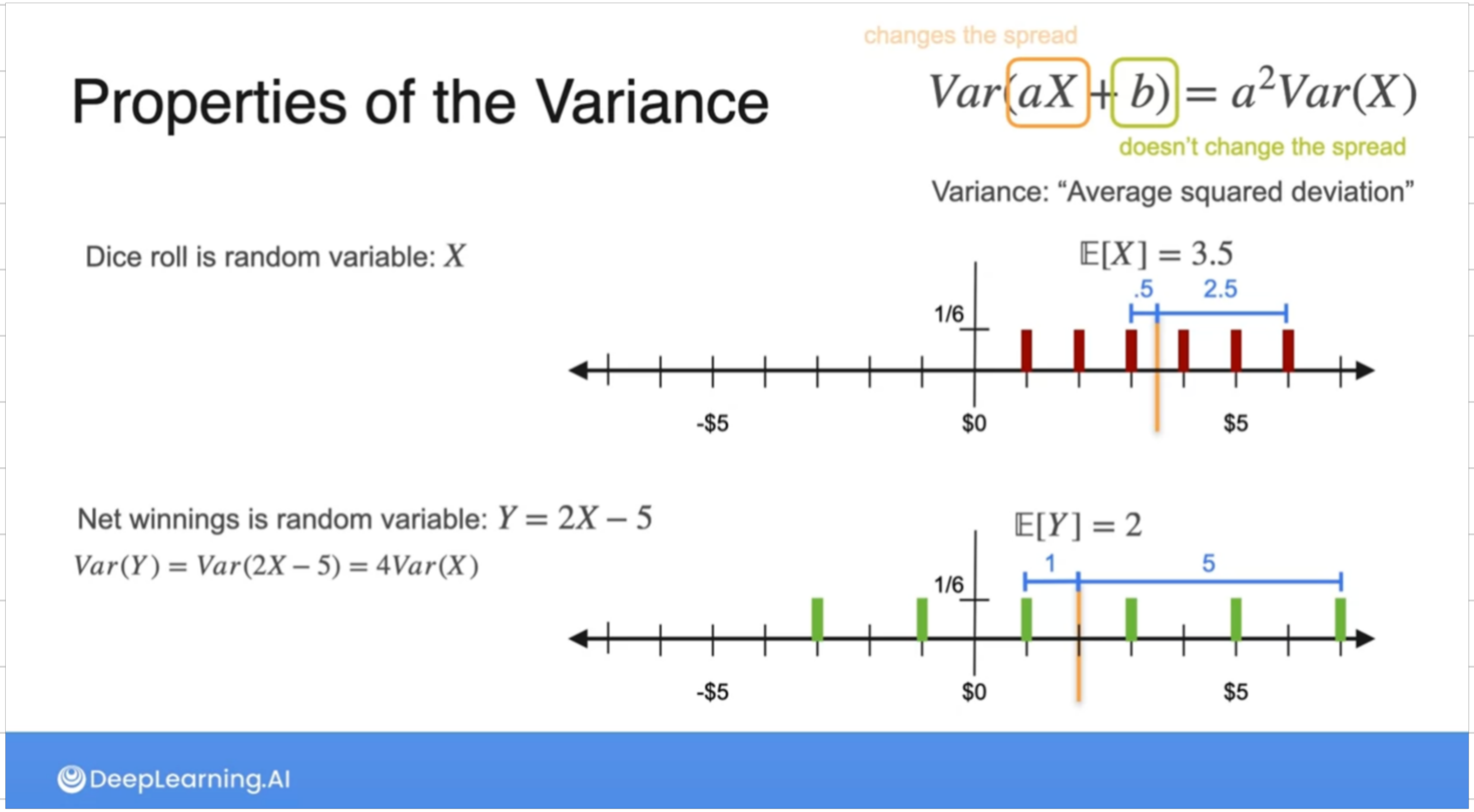
So, the $a=2$ and $b=-5$ for this case and the formula is

$$Var(aX+b) = a^2\,Var(x)$$



So, Next is Standard Deviation?

So the variance is a pretty useful way to measure the spread of a distribution. However, it has one small drawback, the units. Imagine if your distribution has, for example, the height of people. So, these heights are measured in meters or feet, and the expected value is also measured in meters or feet. However, the variance is measured in meters squared or feet squared. And this is not useful. So what do we do? We take the square root, we call that the standard deviation. So the standard deviation is a pretty useful way to measure the spread of a distribution using the same units of the distribution

Standard Deviation

$$\underbrace{\boxed{Var(X)}}^{m^2} = \mathbb{E}[(X-\mu)^2] = \overbrace{\boxed{\mathbb{E}[X^2]}}^{m^2} - \overbrace{\boxed{\mathbb{E}[X]^2}}^{m^2}$$

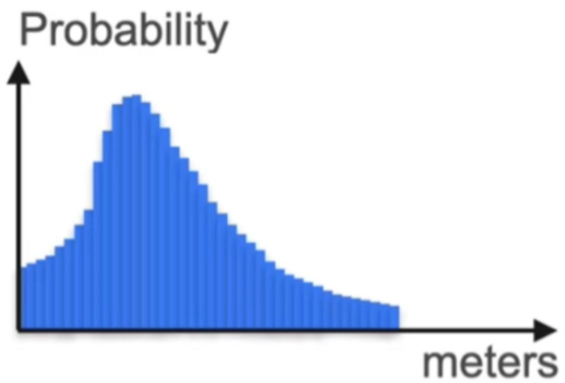
Say X is measured in meters.

Then $\mathbb{E}[X]$ is measured in meters.

Then $Var(X)$ is measured in meters^2.

Then $\sqrt{Var(X)}$ is measured in meters.

Let's call $std(X) = \sqrt{Var(X)}$, the *standard deviation* of X



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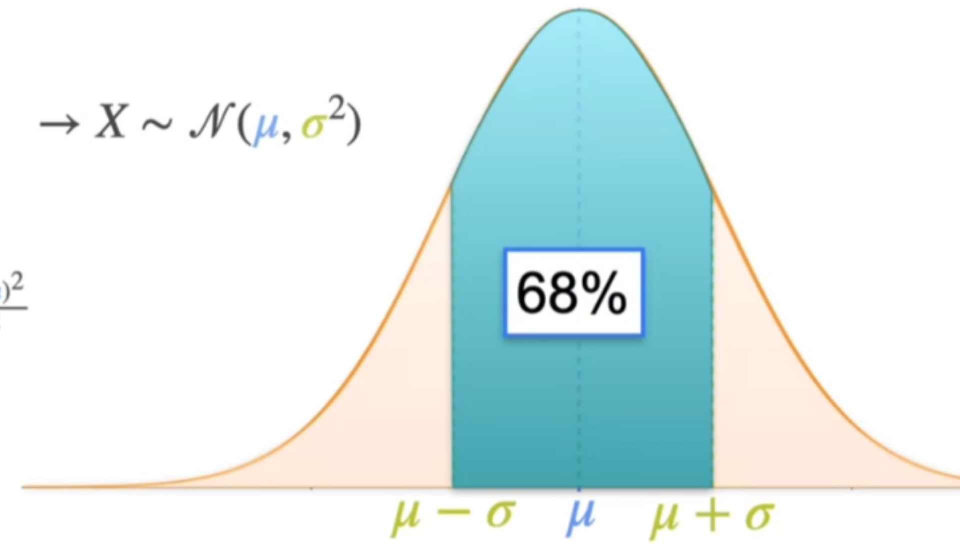
Normal Distribution: 68-95-99.7 Rule

Parameters:
- μ: center of the bell
- σ: spread of the bell

$\rightarrow X \sim \mathcal{N}(\mu, \sigma^2)$

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}$$



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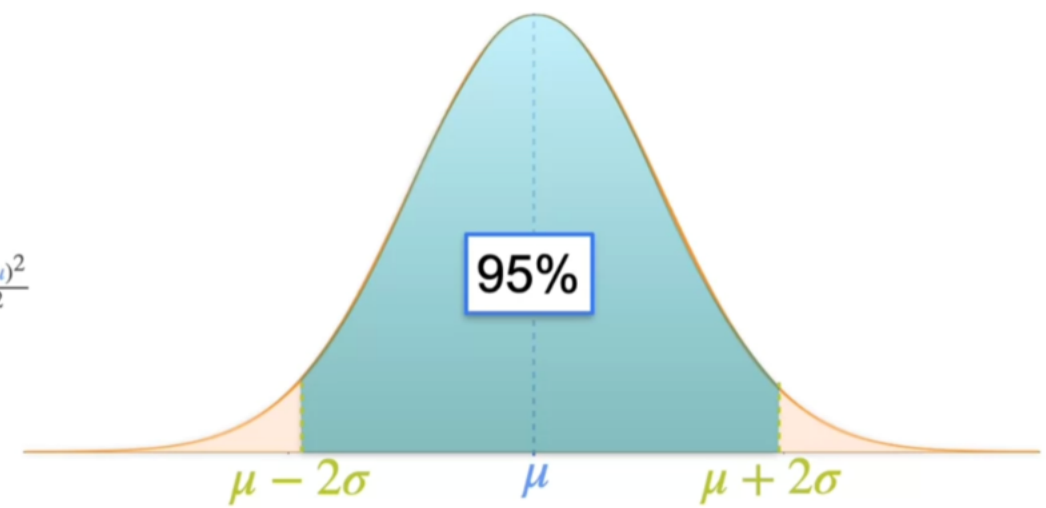
Let's Evaluate the Gaussian Distribution (Probability distribution)

Normal Distribution: 68-95-99.7 Rule

Parameters:
- μ: center of the bell
- σ: spread of the bell

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}$$



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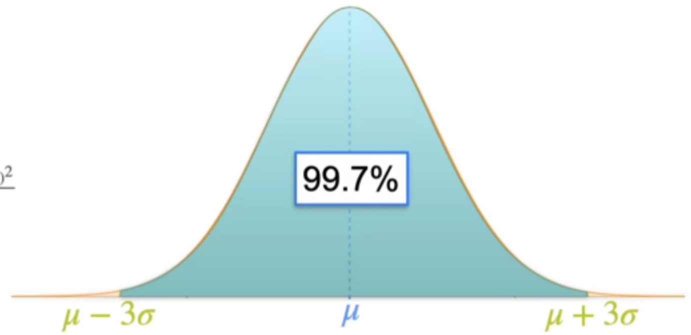
Normal Distribution: 68-95-99.7 Rule

Parameters:
- μ: center of the bell
- σ: spread of the bell

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}$$



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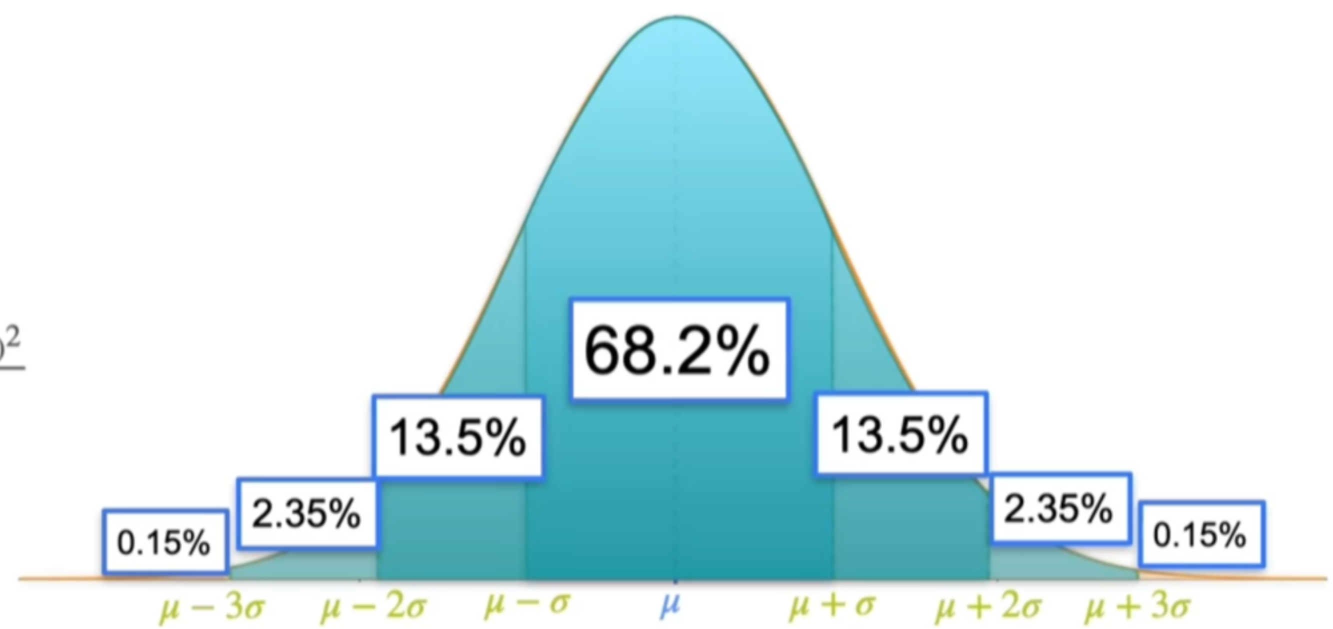
Normal Distribution: 68-95-99.7 Rule

Parameters:
- μ: center of the bell
- σ: spread of the bell

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}}$$



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