

① Discrete Random Variables, PMF and CDF

② Expected Values and Variance *average.* *deviation from average.*

③ Discrete Distribution: Bernoulli, Binomial and Geometric

Discrete Random Variables, PMF and CDF

Motivating example: A fair dice is rolled 4 times.

Ω = set of all 4-tuples (x_1, x_2, x_3, x_4) with $x_i \in \{1, 2, 3, 4, 5, 6\}$.

Consider the following functions X and Y :

- X = **sum** of the rolls. E.g. $X((1, 2, 5, 6)) = \underline{1 + 2 + 5 + 6} = 14$.
- Y = **maximum** among the four numbers. E.g. $Y((1, 2, 5, 6)) = 6$. ✓

These functions are called random variables on Ω .

Calculus: $f(x) = x^2$

$$f: x \mapsto x^2$$

Probability:

$$X: \Omega \longrightarrow \mathbb{R}$$

$X: \omega \mapsto X(\omega)$ is a number.

A **random variable** on Ω is a **function** X that assigns a **real number** $X(\omega)$ to every outcome ω .

Random variables provide an efficient and intuitive way to specify events.

E.g. Using the random variable X above,

$$X = 5 \iff E = \{(1, 1, 1, 2), (1, 1, 2, 1), (1, 2, 1, 1), (2, 1, 1, 1)\} \subseteq \Omega$$

$$P(X=5) = P(E) = \frac{|E|}{|\Omega|}.$$

Example 1

A fair coin is tossed three times.

$$\Omega = \{HHH, HHT, HTH, THH, HTT, THT, TTH, TTT\}.$$

Consider the random variables X and Y defined by

- X = number of heads that occur
- Y = number of tails that occur

- $\mathbb{P}(X = \underline{3}) = \mathbb{P}(\{\underline{HHH}\}) = \frac{1}{8}. \quad \checkmark$
- $\mathbb{P}(\underline{X \leq 1}) = \mathbb{P}(\{\underline{HTT}, \underline{THT}, \underline{TTH}, \underline{TTT}\}) = \frac{4}{8}. \quad \checkmark$
- $\mathbb{P}(X \in \{\underline{0}, \underline{3}\}) = \mathbb{P}(\{\underline{HHH}, \underline{TTT}\}) = \frac{2}{8}. \quad \checkmark$
- $\mathbb{P}(\underline{X > Y}) = \mathbb{P}(\{\underline{HHH}, \underline{HHT}, \underline{HTH}, \underline{THH}\}) = \frac{4}{8}. \quad \checkmark$

Discrete Random Variables

A **discrete random variable** is a random variable whose set of possible values is finite or countably infinite.

↙
enumerate possibilities
one by one infinitely.

A dice is thrown repeatedly.

Consider the following random variables

- X : number of 6's among the first 10 throws
- Y : number of throws until the first 6 is thrown

Set of possible values of X : $\{\underline{0}, \underline{1}, \underline{2}, \dots, \underline{10}\}$ (finite set)

Set of possible values of Y : $\{\underline{1}, \underline{2}, \dots\}$ (countably infinite set)

$Y=1 \Leftrightarrow$ get "6" at 1st throw.
 $Y=2 \Leftrightarrow$ " " " 2nd throw but not 1st throw.

Let X be a discrete random variable. The **probability mass function (PMF)** of X is defined as

$$p_X(x) = \mathbb{P}(X = x)$$

x is a possible value

for all real numbers x .

Note:

- $p_X(x) = 0$ \Leftrightarrow x is not a possible value of X .
- the PMF of X uniquely determines the probabilities of all events involving X .
- sometimes we just write $p(x)$ instead of $p_X(x)$.

$$|\Omega| = 2 \times 2 \times 2 = 2^3 = 8$$

Example 2

A fair coin is tossed 3 times. Let X = number of heads that occur. The PMF is given by

x	0	1	2	3
$p(x)$	$\frac{1}{8}$	$\frac{3}{8}$	$\frac{3}{8}$	$\frac{1}{8}$



E.g. $x=2$ have 2 heads.
 $E = \{ HHT, HTH, THH \}$

$$P(X=2) = \frac{3}{8}$$



If X is a discrete random variable with PMF $p(x)$, then the **Cumulative Density Function (CDF)** of X is defined by

$$F(x) = \mathbb{P}(X \leq x) = \sum_{t \leq x} p(t), \quad -\infty < \underbrace{x}_{\text{circled}} < \infty \quad \checkmark$$

where the sum runs over all numbers $t \leq x$.

Example 3

A fair coin is tossed 3 times. Let X = number of heads that occur.

x	0	1	2	3
$p(x)$	$\frac{1}{8}$	$\frac{3}{8}$	$\frac{3}{8}$	$\frac{1}{8}$

} PMF

Let F be the CDF of X . Then

$$F(\underline{-1}) = \sum_{t \leq \underline{-1}} p(t) = 0. \quad \checkmark$$

$$F(\underline{0}) = \sum_{t \leq \underline{0}} p(t) = p(\underline{0}) = \frac{1}{8}. \quad \checkmark$$

$$F(\underline{1}) = \sum_{t \leq \underline{1}} p(t) = p(\underline{0}) + p(\underline{1}) = \frac{1}{8} + \frac{3}{8} = \frac{1}{2}. \quad \checkmark$$

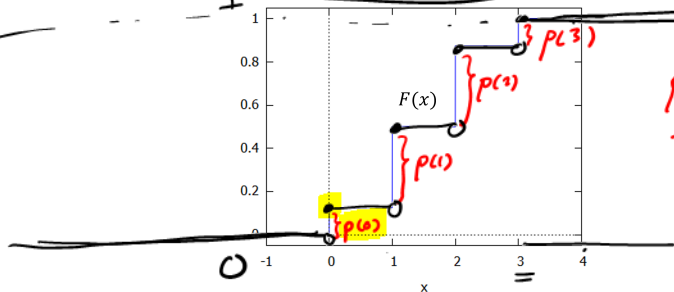
$$F(\underline{2}) = \sum_{t \leq \underline{2}} p(t) = p(\underline{0}) + p(\underline{1}) + p(\underline{2}) = \frac{1}{8} + \frac{3}{8} + \frac{3}{8} = \frac{7}{8}. \quad \checkmark$$

$$F(\underline{3}) = \sum_{t \leq \underline{3}} p(t) = p(0) + p(1) + p(2) + p(3) = \frac{1}{8} + \frac{3}{8} + \frac{3}{8} + \frac{1}{8} = 1. \quad \checkmark$$

$$F(c) = \sum_{t \leq c} p(t) = 0$$

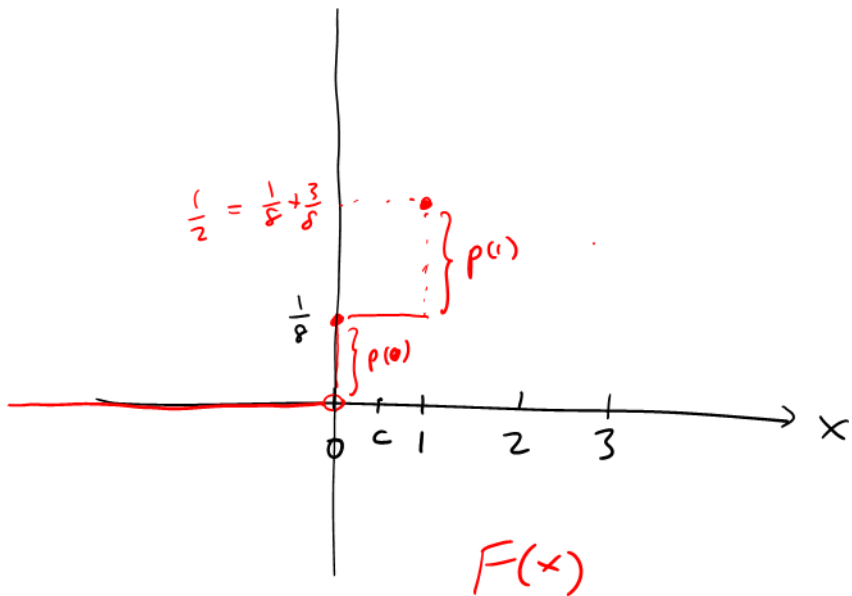
$\boxed{c < 0} \quad F(-0.01) = 0$

$$F(x) = \begin{cases} 0, & x < 0 \\ 1/8, & 0 \leq x < 1 \\ 1/2, & 1 \leq x < 2 \\ 7/8, & 2 \leq x < 3 \\ 1, & x \geq 3. \end{cases}$$



$$p(0) + p(1) + p(2) + p(3) = 1$$

Note: At every x with $p(x) > 0$ there is a jump by $p(x)$.



The CDF has the following properties:

- $F(x)$ is a non-decreasing function of x , for $-\infty < x < \infty$.
- $F(x)$ ranges from 0 to 1.
- If a is the minimum possible value of X , then $F(a) = p_X(a)$. If $c < a$ then $F(c) = 0$.
- If b is the maximum possible value of X , then $F(b) = 1$.
- Also called the distribution function.

weighted average.

Expected Values and Variance

If a fair coin is tossed 1000 times, we expect around 500 heads. ✓

If a dice is rolled 6000 times, around 1000 sixes are expected. ✓

Both statements can be expressed in terms of random variables:

- Let X be the number of heads among 1000 tosses. Then $\mathbb{E}[X]$ = 500
(expected value of X)
- Let Y be the number of sixes among 6000 throws. Then $\mathbb{E}[Y]$ = 1000

The definition of **expected values** formalizes this.

Expected Value of Random Variable

The **expected value** (or **mean**) of a **discrete** random variable X with PMF $p(x)$ is

$$\mathbb{E}[\underline{X}] = \sum_x \underline{x} \underline{p(x)}$$

where the sum runs over all numbers x with $p(x) > 0$.

Intuitive interpretation: $\mathbb{E}[X]$ is the sum of all possible values of X , weighted by their probabilities.

Remark: If c is a constant, then $\mathbb{E}[c]$ = c . ✓

Example 4

A fair coin is tossed 3 times. Let X = number of heads that occur.

$$x \quad 0 \quad 1 \quad 2 \quad 3 \quad \checkmark$$

$$p(x) \quad \frac{1}{8} \quad \frac{3}{8} \quad \frac{3}{8} \quad \frac{1}{8}$$

$$\mathbb{E}[X] = \sum_x xp(x) = 0 \cdot \frac{1}{8} + 1 \cdot \frac{3}{8} + 2 \cdot \frac{3}{8} + 3 \cdot \frac{1}{8} = \frac{12}{8} = \frac{3}{2} \quad \checkmark$$

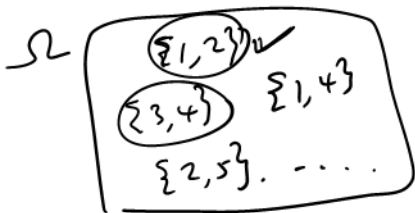


Example 5

Two balls are randomly selected **without** replacement from an urn containing 5 balls numbered 1 through 5. Let X denote the **larger number** among the **two balls** selected. Find $\mathbb{E}[X]$.

$\Omega = \{ \text{possible 2-combinations of } \{1, 2, 3, 4, 5\} \}$

$$|\Omega| = \binom{5}{2} = 10.$$



$$X(\{1, 2\}) = 2 \checkmark$$

$$X(\{3, 4\}) = 4 \checkmark$$

$$X(\{1, 4\}) = 4 \checkmark \text{ etc.}$$

PMF

x	(2)	(3)	4	5
$p(x)$	$\frac{1}{10}$	$\frac{2}{10}$	$\frac{3}{10}$	$\frac{4}{10}$

✓

1, 2, ..., $x-1$

$$P(X=\underline{x}) = \frac{|\{ \downarrow, x \}|}{10} = \frac{x-1}{10}$$

$$E[X] = \sum x p(x) = 2 \cdot \frac{1}{10} + 3 \cdot \frac{2}{10} + 4 \cdot \frac{3}{10} + 5 \cdot \frac{4}{10} = 4 \neq .$$

Expected Value of Function of Random Variable

Let X be a **discrete** random variable with PMF $p(x)$, and $g(X)$ be a function of X (e.g. $g(X) = X^2$, $g(X) = e^X$ etc.) Then

$$\mathbb{E}[g(X)] = \sum_x \underline{g(x)} \underline{p(x)}.$$

If $g(x) = X$ then $\mathbb{E}[g(x)] = \mathbb{E}[X]$

Example 6

A fair coin is tossed 3 times. Let X = number of heads that occur.

x	0	1	2	3
$p_X(x)$	$\frac{1}{8}$	$\frac{3}{8}$	$\frac{3}{8}$	$\frac{1}{8}$

$$g(X) = \underline{X^2} \quad \checkmark$$

$$\underline{\mathbb{E}[X^2]} = \sum_x x^2 p_X(x) = 0^2 \cdot \frac{1}{8} + 1^2 \cdot \frac{3}{8} + 2^2 \cdot \frac{3}{8} + 3^2 \cdot \frac{1}{8} = \frac{24}{8} = 3. \quad \checkmark$$

$$\mathbb{E}[X] = \underline{\underline{\left(\frac{3}{2}\right)}}$$

$$\mathbb{E}[X^2] \neq (\mathbb{E}[X])^2 \quad \checkmark$$

Linearity of Expected Values

Theorem 7 (Linearity of Expected Values)

Let X_1, \dots, X_n be random variables such that $\mathbb{E}[X_i]$ exists for all $i = 1, \dots, n$. Let a_1, \dots, a_n be real numbers (constants). Then

$$\mathbb{E}[a_1X_1 + \dots + a_nX_n] = a_1\mathbb{E}[X_1] + \dots + a_n\mathbb{E}[X_n].$$

Rules:

- constants can be pulled out of expected values
- expected value of a sum is the sum of expected values of the summands

Example 8

Suppose X , Y , Z are random variables with

$$\mathbb{E}[X] = -10, \quad \mathbb{E}[Y] = 20, \quad \mathbb{E}[Z] = 5000.$$

Then

$$\begin{aligned} \mathbb{E}[3X - 2Y + 5Z] &= 3\mathbb{E}[X] - 2\mathbb{E}[Y] + 5\mathbb{E}[Z] \\ &= 3(-10) - 2(20) + 5(5000) \\ &= 24930. \end{aligned}$$

Example 9

A firm purchases X number of computers each year, where X has the following probability distributions:

x	0	1	2	3
$f(x)$	$1/10$	$3/10$	$2/5$	$1/5$



If the cost of the computer is 1200 per unit and at the end of this year a rebate of $50X^2$ dollars will be issued, how much can this firm expect to spend on new computers during this year?

Give it a try!

$$\text{net Cost} = \underbrace{1200X - 50X^2}_{g(x)} \quad \checkmark$$

$$\begin{aligned}
 & E[1200X - 50X^2] \\
 &= 1200 \underline{E[X]} - 50 \underline{E[X^2]} \\
 &= 1200 \left(0 \cdot \frac{1}{10} + 1 \cdot \frac{3}{10} + 2 \cdot \frac{2}{5} + 3 \cdot \frac{1}{5} \right) \\
 &\quad - 50 \left(0^2 \cdot \frac{1}{10} + 1^2 \cdot \frac{3}{10} + 2^2 \cdot \frac{2}{5} + 3^2 \cdot \frac{1}{5} \right)
 \end{aligned}$$

$E[g(x)]$.

#.

Variance

The **variance** of a random variable X is defined as

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

x	0	1
$p(x)$	$\frac{1}{2}$	$\frac{1}{2}$

x	0	0.5	1
$p(x)$	$\frac{1}{4}$	$\frac{1}{2}$	$\frac{1}{4}$

Interpretation:

- $X - \mathbb{E}[X]$: deviation of X from its expected value
- $(X - \mathbb{E}[X])^2$: measures (squared) deviation from expected value
- $\mathbb{E}[(X - \mathbb{E}[X])^2]$ measure **average** (squared) deviation of X from its expected value. So variance measures how 'spread out' X is from its mean.

The **standard deviation** of a random variable X is defined as

$$\sigma_X = \sqrt{\text{Var}(X)}.$$



Theorem 10 (Formula for Variance)

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

Proof. Write $\underline{\underline{\mu}} = \underline{\underline{\mathbb{E}[X]}}$. Note that μ is a constant.

$$\begin{aligned}\text{Var}[X] &= \mathbb{E}[(X - \mu)^2] \quad \checkmark \\ &= \mathbb{E}[X^2 - 2\mu X + \mu^2] \quad \checkmark \\ &= \mathbb{E}[X^2] - 2\mu \underline{\underline{\mathbb{E}[X]}} + \mathbb{E}[\mu^2] \quad (\text{by linearity of expected values}) \\ &= \mathbb{E}[X^2] - 2\mu^2 + \mu^2 \quad (\text{expected value of constant}) \\ &= \mathbb{E}[X^2] - \mu^2 \quad \checkmark \\ &= \underline{\underline{\mathbb{E}[X^2]}} - (\mathbb{E}[X])^2. \quad \checkmark\end{aligned}$$



Discrete Distribution: Bernoulli, Binomial and Geometric

Bernoulli distribution

We say that a random variable X has a **Bernoulli distribution**, denoted by $X \sim \text{Bernoulli}(p)$ if X only takes value 0 (failure) and 1 (success) with $\mathbb{P}(X = 1) = p$. That is, its PMF is given by

x	0	1
$p(x)$	$1-p$	p

$$p(x) = \begin{cases} 1-p & \text{if } x = 0 \\ p & \text{if } x = 1 \\ 0 & \text{otherwise.} \end{cases}$$

Theorem 11 (Bernoulli)

If $X \sim \text{Bernoulli}(p)$, then

$$\mathbb{E}[X] = p, \quad \text{Var}[X] = p(1-p).$$

It follows that the standard deviation of X is $\sqrt{p(1-p)}$. ✓

$$\begin{aligned} \mathbb{E}[X] &= 0 \cdot (1-p) + 1 \cdot p \\ &= p \end{aligned}$$

$$\begin{aligned} \text{Var}[X] &= \mathbb{E}[X^2] - (\mathbb{E}[X])^2 \\ &= (0^2(1-p) + 1^2 \cdot p) - p^2 \\ &= p - p^2 \\ &= p(1-p). \end{aligned}$$

Some applications of Bernoulli distribution

- Experiments with only two outcomes, e.g. $X = 1$ if coin toss is head and $X = 0$ for tail ✓
- Yes-no-questions, e.g., $X = 1$ if person voted for candidate A and $X = 0$ otherwise ✓
- True-false conditions, e.g., $X = 1$ if total of 4 dice rolls is ≥ 20 and $X = 0$ otherwise

$$X = \begin{cases} 1 & \text{if } Y \geq 20 \\ 0 & \text{otherwise} \end{cases}$$

$$Y \geq 20.$$

Binomial distribution

A random variable X has a **Binomial distribution**, denoted by $X \sim \text{Binomial}(n, p)$ if X is a sum of n independent Bernoulli random variables $\text{Bernoulli}(p)$.

$$X = \sum_{i=1}^n X_i$$

$X_i \sim \text{Bernoulli}(p)$
 $E[X_i] = p$

Interpretation: X = number of successes among n independent experiments with success probability p .

Theorem 12 (Binomial distribution)

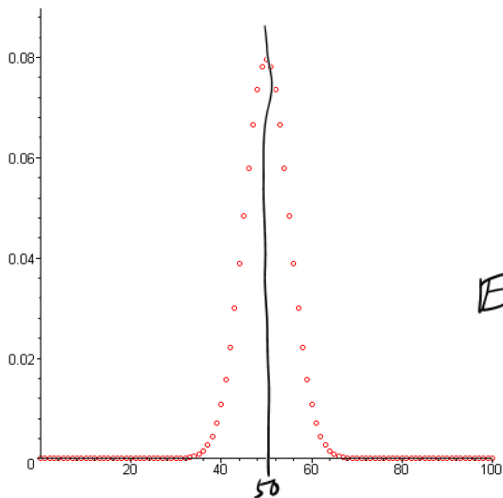
If $X \sim \text{Binomial}(n, p)$, then

probability have x number of successes (1) in n of the Bernoulli experiments.

$$\text{PMF: } \underline{p(x)} = \binom{n}{x} p^x (1-p)^{n-x}, \quad x = \underline{0, 1, \dots, n}.$$

$$\underline{E[X] = np}, \quad \underline{\text{Var}[X] = np(1-p)}.$$

$$\begin{aligned} E\left[\sum_{i=1}^n x_i\right] &= \sum_{i=1}^n E[x_i] \\ &= \sum_{i=1}^n p \\ &= np. \end{aligned}$$



PMF of Binomial(100,0.5)

$$\begin{aligned}
 E[X] &= np \\
 &= 100 \times 0.5 \\
 &= 50.
 \end{aligned}$$

n \downarrow \uparrow p
 $\overline{\quad}$

$$X = \sum_{i=1}^{10} X_i$$

$$X_i \sim \text{Bernoulli}\left(\frac{1}{6}\right)$$

$$X_i = \begin{cases} 1 & \text{if 6 occurs} \\ 0 & \text{otherwise} \end{cases}$$

Example 13

A dice is rolled 10 times. let X be the number of 6's rolled. Then

$$X \sim \text{Binomial}\left(\underline{10}, \underline{\frac{1}{6}}\right)$$

$$\underline{\mathbb{P}(X = 2)} = p(2) = \binom{10}{2} \left(\frac{1}{6}\right)^2 \left(\frac{5}{6}\right)^8 \approx 0.29.$$

$$\binom{n}{x} p^x (1-p)^{n-x}$$

Example 14

In a production line, 10% of the items produced are defective. In a particular test, (five items) are independently selected from the production line and are tested. Let X denote the number of defective items among the five items.

- (i) Find the expected value and variance of X .
- ~~(ii)~~ What is probability that at most one item is defective?

$$\text{Let } X_i = \begin{cases} 1 & \text{if } i\text{th item } \underline{\text{defective}}. \\ 0 & \text{otherwise.} \end{cases}$$
$$X = \sum_{i=1}^5 X_i \sim \text{Binomial}(5, 0.1) \quad \checkmark$$

$$E[X] = np$$

$$= 5 \times 0.1$$

$$= 0.5$$

$$\text{Var}[X] = np(1-p)$$

$$= 5 \times 0.1 \times 0.9$$

$$= 0.45.$$

$$P(X \leq 1) = P(X=0) + P(X=1)$$

$$= \binom{5}{0} (0.1)^0 0.9^5 + \binom{5}{1} 0.1^1 0.9^4$$

$$= 0.9180.$$

Geometric distribution

A random variable X has a **Geometric distribution**, denoted by $X \sim \text{Geom}(p)$, if X counts the number of experiments until the first success in a sequence of independent experiments with success probability p .

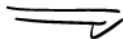
\downarrow
Bernoulli(p)

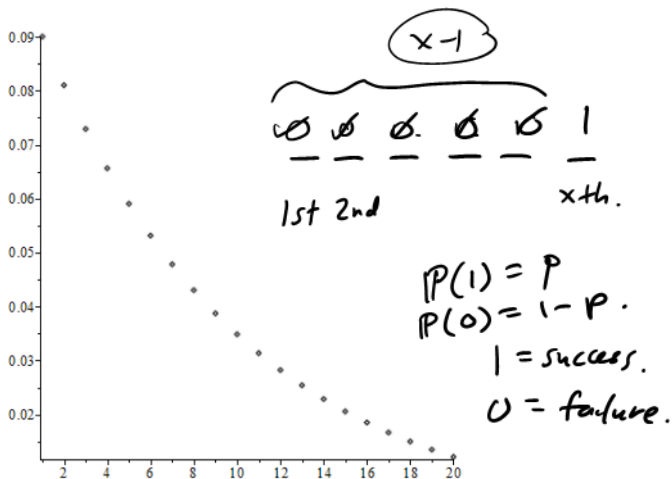
Theorem 15 (Geometric distribution)

If $X \sim \text{Geom}(p)$, then

$$\text{PMF: } p(x) = (1-p)^{x-1}p, \quad x = 1, 2, \dots,$$

$$\mathbb{E}[X] = \frac{1}{p}, \quad \text{Var}[X] = \frac{1-p}{p^2}.$$





PMF of Geom(0.1)



Example 16

A fair dice is rolled repeatedly. What is the probability that the 5th roll is the first roll for which a 1 or 6 occurs?

Bernoulli(p)

p = prob of getting
1 or 6

X = # roll until we get
1 or 6.

$$= \frac{2}{6} = \frac{1}{3}$$

$\sim \text{Geom}(p)$ $p = \frac{1}{3}$.

$$P(X=5) = (1-p)^4 p = \left(1 - \frac{1}{3}\right)^4 \left(\frac{1}{3}\right) \approx 0.066$$