① Probability Mass Functions (PMF)

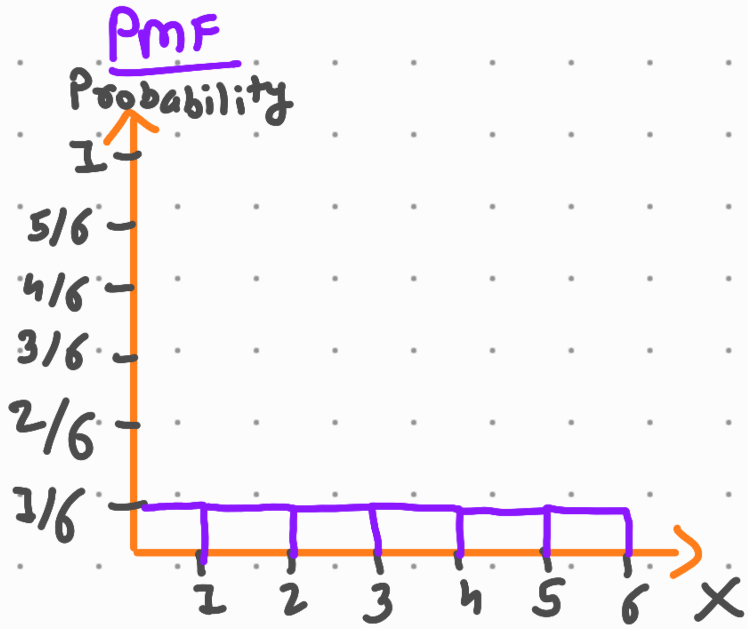
[Used for Discrete Random Variables]

e.g. Rolling a dice => {1, 2, 3, 4, 5, 6}

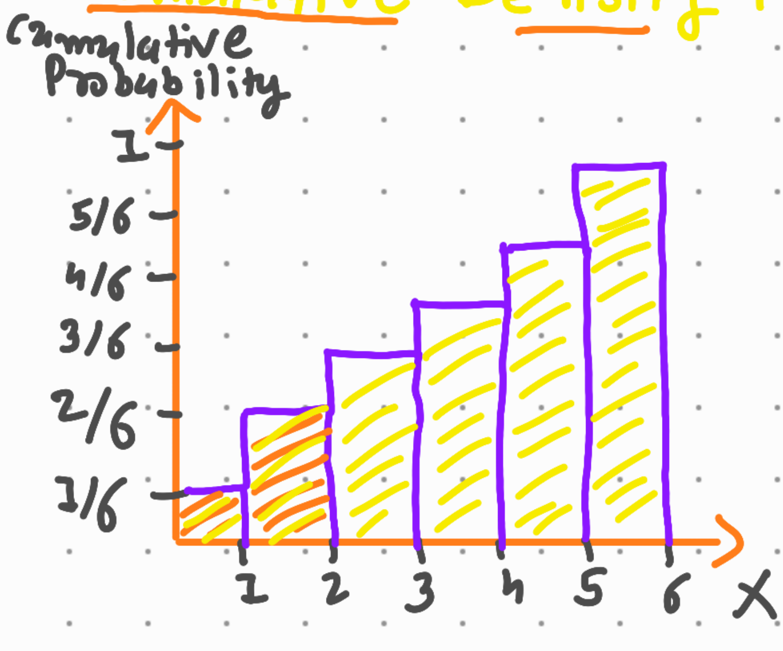
=> Fair dice

$P_r(1) = P_r(2) = P_r(3) = P_r(4) = P_r(5) =$

$P_r(6) = 1/6$



-> Cumulative Density Function (CDF)



$P_r(x \leq 2) = P_r(x=1) + P_r(x=2)$

$= 1/6 + 1/6$

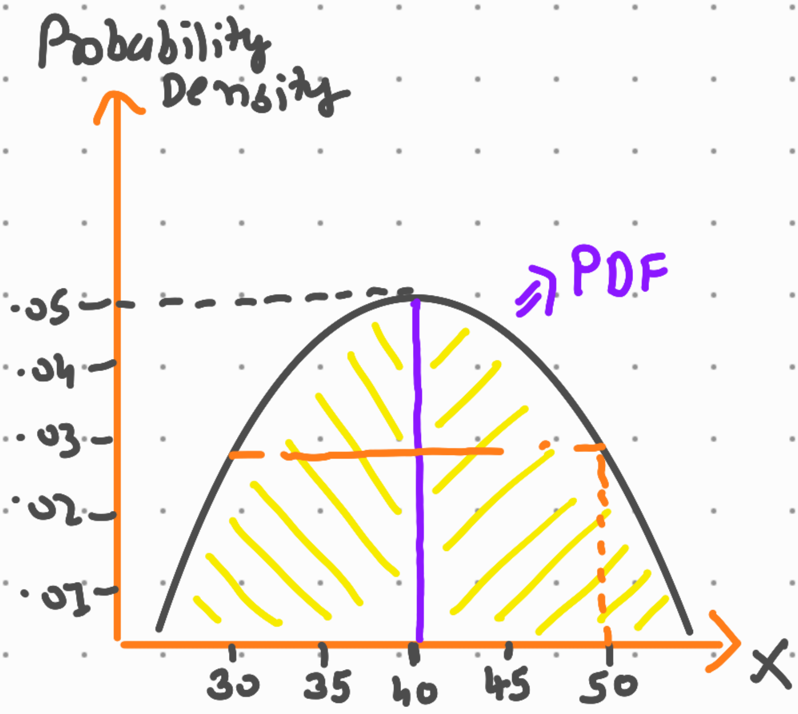
$= 2/6 = 1/3$

$$P_r(x \le 6) = P_r(x=1) + \dots + P_r(x=6)$$
$$= 1/6 + \dots + 1/6$$
$$= 6/6 = 1$$

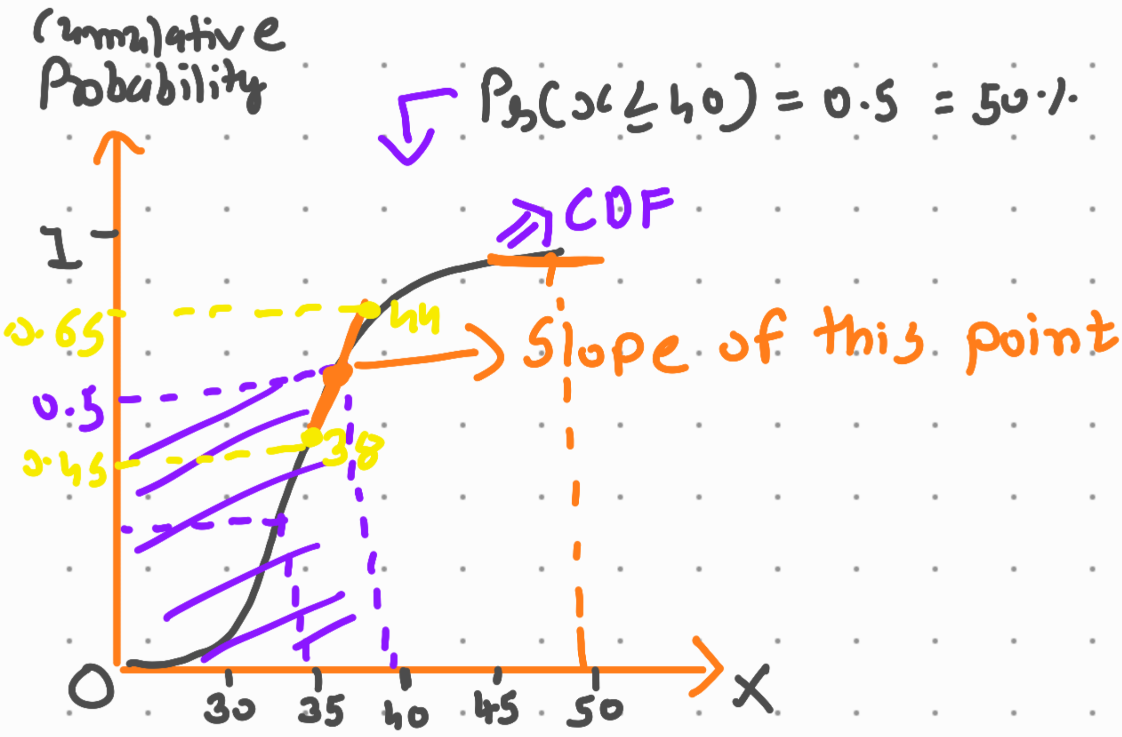
② Probability Density Function (PDF)

[Used for Continuous Random Variable]

e.g. $X = \text{Ages} = \{\dots\dots\}$

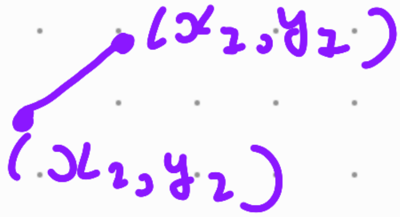


$P_r(x \le 40) = 0.5 = 50\%$



$$\text{Slope} = \left\{ \frac{0.65 - 0.45}{44 - 38} \right\} = 0.033$$

↳ Probability Density



$$\text{Slope} = \left[\frac{x_2 - x_1}{y_2 - y_1} \right]$$

= Gradient ⇒ Probability Density

→ Probability Density = Gradient of Cumulative Density function.

→ **PDF Properties**

① Always Non-Negativity

↳ $f(x) \geq 0$ for all x

② Total area under the PDF curve is equal to 1

$$\boxed{\int_{-\infty}^{\infty} f(x)\,dx = 1}$$

e.g.

→ With respect to different distribution $f(x)$ function is going to change.

Types of Probability Distribution

Dataset ⇒ Follows Distribution

① Bernouli Distribution

↳ Outcomes are Binary (PMF)

⇓

Discrete Random Variable

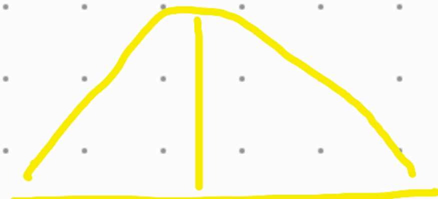
② Binomial Distribution ⇒ (PMF)

⇓

Discrete Random Variable

③ Normal/Gaussian Distribution

↳ (PDF) ⇒



⇓

Assumptions

④ Poisson Distribution ⇒ (PMF)

⑤ Log Normal Distribution ⇒ (PDF)

↳ Continuous Random Variable

⑥ Uniform Distribution => (PMF)

→ For every Distribution,

$$\boxed{\int_{-\infty}^{+\infty} f(x)\,dx = 1}$$

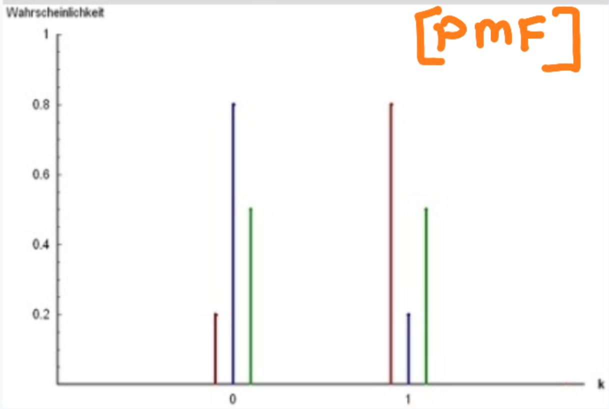
f(x) will be Different.

① Bernoulli Distribution

A discrete probability distribution wherein the random variable can only have 2 possible outcomes is known as a Bernoulli Distribution. If in a Bernoulli trial the random variable takes on the value of 1, it means that this is a success. The probability of success is given by p. Similarly, if the value of the random variable is 0, it indicates failure. The probability of failure is q or 1 - p. Bernoulli distribution can be used to derive a binomial distribution, geometric distribution, and negative binomial distribution.

Bernoulli distribution

Probability mass function



Three examples of Bernoulli distribution:

- $P(x=0) = 0.2$ and $P(x=1) = 0.8$
- $P(x=0) = 0.8$ and $P(x=1) = 0.2$
- $P(x=0) = 0.5$ and $P(x=1) = 0.5$

① Discrete Random Variable (PMF)

② Outcomes are Binary

e.g. Tossing a coin {H, T}

$Pr(x=H) = 0.5 = P$

$Pr(x=T) = 0.5$
$= 1 - Pr(x=H)$
$= q$

Person will Pass or Fail

$Pr(x=Pass) = 0.4$

$Pr(x=Fail) = 1 - 0.4 = 0.6$

$Pr(Success) \Rightarrow k=1$

$Pr(Fail) \Rightarrow k=2$

Parameters	$0 \leq p \leq 1$ $q = 1 - p$
Support	$k \in \{0, 1\}$

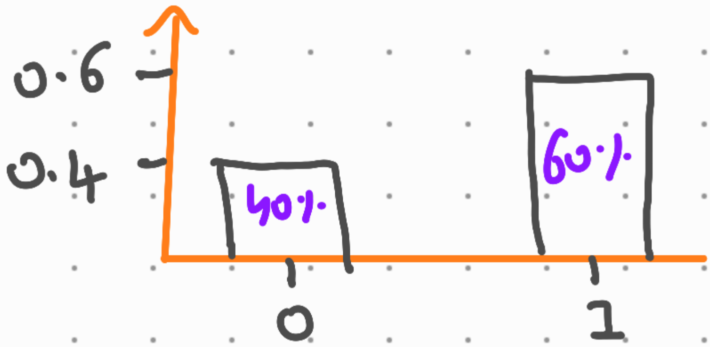
$\Rightarrow$ 2-Outcomes

PMF	$\begin{cases} q = 1 - p & \text{if } k = 0 \\ p & \text{if } k = 1 \end{cases}$
CDF	$\begin{cases} 0 & \text{if } k < 0 \\ 1 - p & \text{if } 0 \leq k < 1 \\ 1 & \text{if } k \geq 1 \end{cases}$
Mean	p
Median	$\begin{cases} 0 & \text{if } p < 1/2 \\ [0, 1] & \text{if } p = 1/2 \\ 1 & \text{if } p > 1/2 \end{cases}$
Mode	$\begin{cases} 0 & \text{if } p < 1/2 \\ 0, 1 & \text{if } p = 1/2 \\ 1 & \text{if } p > 1/2 \end{cases}$
Variance	$p(1 - p) = pq$

PMF

e.g. Company Launched a new Phone 'A'.

(k)
(1) Use => 60% => p
(0) Not Use => 40% => $q = 1 - p$



$$\boxed{PMF = p^{k} * (1-p)^{1-k}}$$ ⇒ Use to construct the distribution

if $k=1$

$$P_s(k=1) = p^{1}(1-p)^{1-1} = p$$

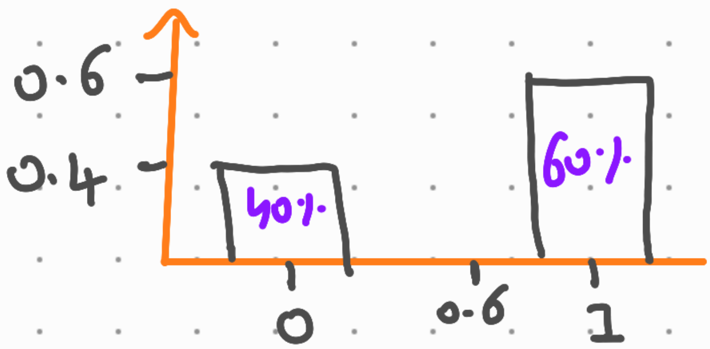
if $k=0$

$$P_s(k=0) = p^{0}(1-p)^{1-0} = 1-p = q$$

→ Simplified

$$PMF \begin{cases} q = 1-p & \text{if } k=0 \\ p & \text{if } k=1 \end{cases}$$

→ Mean



$$E(x) = \sum_{k=0}^{1} k \cdot p(k) \quad k \in \{0, 1\}$$

$= (0 \times 0.40) + (1 \times 0.60)$

$= 0 + 0.60$

$= 0.60$

$$\boxed{E(x) = p}$$

→ Median

$$\text{Median} \begin{cases} 0 & \text{if } p < 1/2 \\ [0, 1] & \text{if } p = 1/2 \\ 1 & \text{if } p > 1/2 \end{cases}$$

$$\left\{ \begin{array}{ll} \text{Median} = 0 & \text{if } q > p \\ \text{median} = 0.5 & \text{if } q = p \\ \text{median} = 1 & \text{if } q < p \end{array} \right\}$$

→ Mode

$p > q \Rightarrow p$ will be the mode

$\Rightarrow$ else q will be the mode

→ Variance

$K = 0$ and 1

$P_B(K=0) = 0.4 \to q$

$P_B(K=1) = 0.6 \to p$

$$\boxed{\sigma^2 = p(1-p) = pq}$$

$$\sigma^2 = 0.40(0-0.6)^2 + 0.6(1-0.6)^2$$

$$= 0.40(0.36) + 0.6(0.16)$$

$$\sigma^2 = 0.24$$

$$= pq$$

→ Standard Deviation

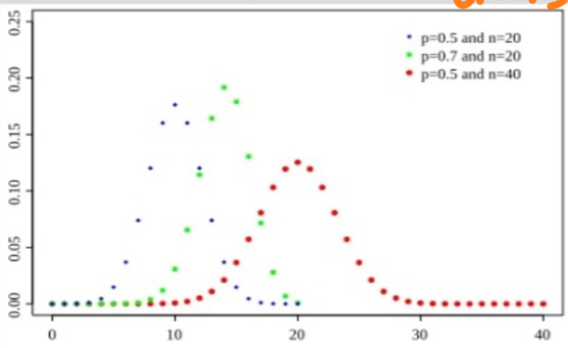
$$\boxed{\sigma = \sqrt{\sigma^2} = \sqrt{pq}}$$

② Binomial Distribution

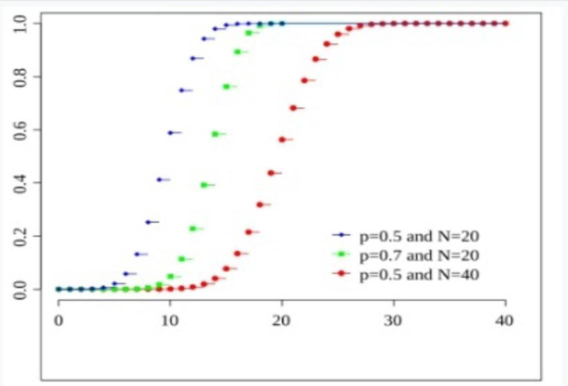
The binomial distribution with parameters n and p is the discrete probability distribution of the number of successes in a sequence of n independent experiments, each asking a yes–no question, and each with its own Boolean-valued outcome: success (with probability p) or failure (with probability q = 1-p). A single success/failure experiment is also called a Bernoulli trial or Bernoulli experiment, and a sequence of outcomes is called a Bernoulli process; for a single trial, i.e., n = 1, the binomial distribution is a Bernoulli distribution. The binomial distribution is the basis for the popular binomial test of statistical significance

Binomial distribution

Probability mass function (PMF)



Cumulative distribution function



Notation $B(n,p)$

Parameters	$n \in \{0,1,2,\ldots\}$ – number of trials $p \in [0,1]$ – success probability for each trial $q = 1 - p$
Support	$k \in \{0,1,\ldots,n\}$ – number of successes
PMF	$\binom{n}{k} p^k q^{n-k}$
CDF	$I_q(n - \lfloor k \rfloor, 1 + \lfloor k \rfloor)$ (the regularized incomplete beta function)
Mean	np
Median	$\lfloor np \rfloor$ or $\lceil np \rceil$
Mode	$\lfloor (n+1)p \rfloor$ or $\lceil (n+1)p \rceil - 1$
Variance	$npq = np(1-p)$
Skewness	$\frac{q-p}{\sqrt{npq}}$
Excess kurtosis	$\frac{1-6pq}{npq}$
Entropy	$\frac{1}{2}\log_2(2\pi e npq) + O\left(\frac{1}{n}\right)$ in shannons. For nats, use the natural log in the log.

1. Discrete Random Variable
2. Every outcome of the experiment is Binary
3. These experiment are performed for $\underline{n}$ trials

e.g. Tossing a coin for 10 times.

single $\rightarrow \{H, T\}$

$n = 10$

$\rightarrow$ Notation: $B(n, p)$

$\rightarrow$ Parameters: $n \in \{0, 1, 2, \dots, \}$

$\hookrightarrow$ no. of trials or experiment

$p \in [0, 1]$

$\hookrightarrow$ success probability for each trial

$q = 1 - p$

$\rightarrow$ Support: $K \in \{0, 1, 2, 3, \dots, n\}$

$\hookrightarrow$ Number of successes

PMF:

$$\boxed{\begin{aligned} P_r(K, n, p) &= {}^{n}C_{K}\, p^{K} (1-p)^{n-k} \\ &= {}^{n}C_{K}\, p^{K} q^{n-k} \end{aligned}}$$

for $k = 0, 1, 2, \ldots, n$ where

$$\boxed{{}^{n}C_{k} = \frac{n!}{k!\,(n-k)!}}$$ ⇒ Binomial Coefficient

Mean: $\boxed{n \cdot p}$

Variance: $\boxed{npq}$

Standard Deviation: $\boxed{\sqrt{npq}}$

e.g. ① Coin Flip

No of trials $(n) = 5$

Probability of success $(p) = 0.5$

No. of successes (k) = varies from 0 to 5

① What is the Probability of getting exactly 3 heads in 5 flips?

$n = 5$
$k = 3$

$P_3(k=3) = {}^5C_3\, 0.5^3 (1-0.5)^{5-3}$
$= 0.3125$ //

② Quality Control

Scenario = Inspecting 10 items in a factory where each item has a 10% chance of being defective.

No of trials $(n) = 10$

Probability of success $= 0.1$
(defective item)

No of successes (K) = varies from 0 to 10

(i) What is the probability of finding exactly 2 defective items in a sample of 10.

$$P_B(K=2) = {}^{10}C_2\, 0.1^2 (1-0.1)^8$$

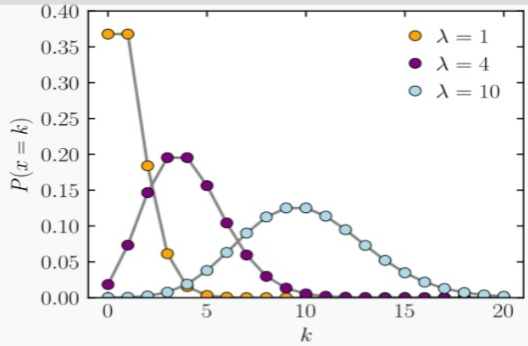
$$\simeq 1.937$$

③ Poisson Distribution

The Poisson distribution is a discrete probability distribution that expresses the probability of a given number of events occurring in a fixed interval of time if these events occur with a known constant mean rate and independently of the time since the last event.[1] It can also be used for the number of events in other types of intervals than time, and in dimension greater than 1 (e.g., number of events in a given area or volume).

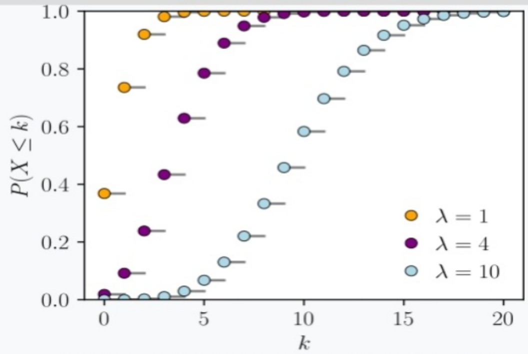
Poisson Distribution

Probability mass function



The horizontal axis is the index k, the number of occurrences. λ is the expected rate of occurrences. The vertical axis is the probability of k occurrences given λ. The function is defined only at integer values of k; the connecting lines are only guides for the eye.

Cumulative distribution function



The horizontal axis is the index k, the number of occurrences. The CDF is discontinuous at the integers of k and flat everywhere else because a variable that is Poisson distributed takes on only integer values.

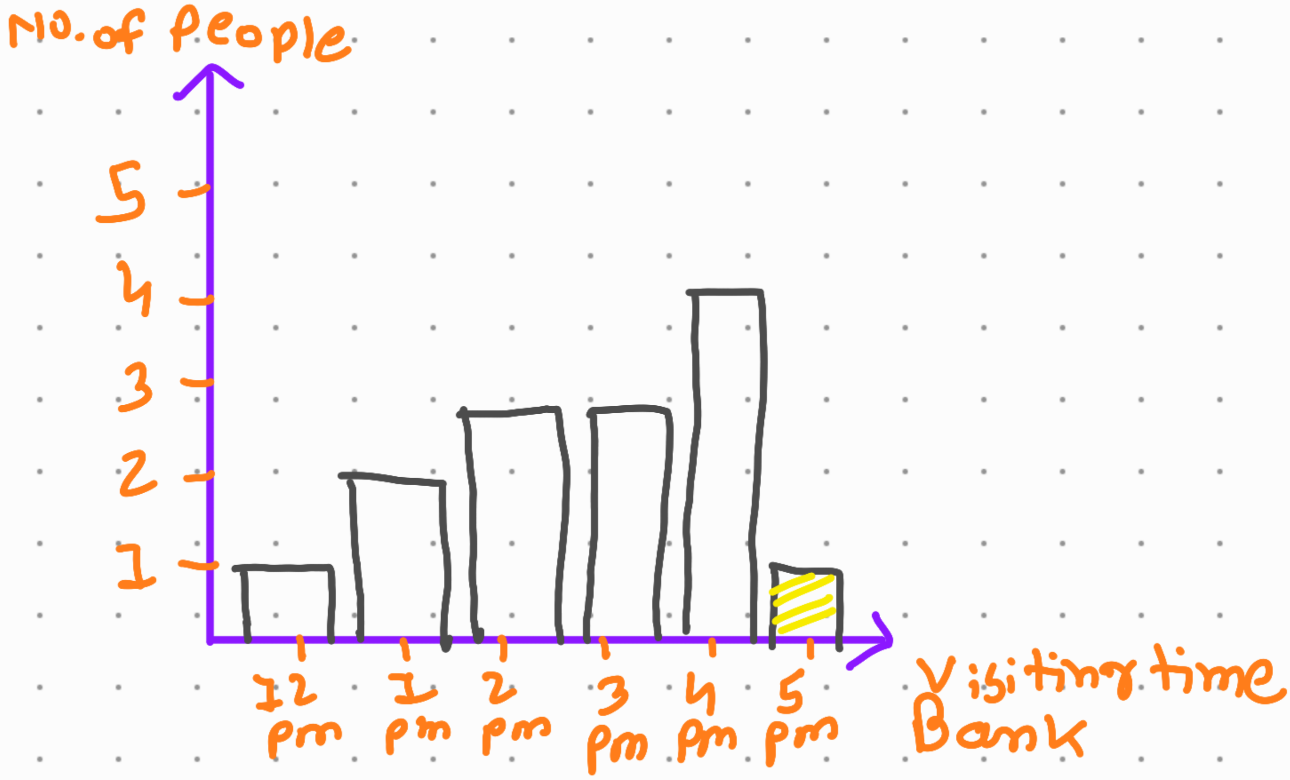
Notation	$\operatorname{Pois}(\lambda)$
Parameters	$\lambda \in (0, \infty)$ (rate)
Support	$k \in \mathbb{N}$ (Natural numbers starting from 0)
PMF	$\dfrac{\lambda^k e^{-\lambda}}{k!}$
CDF	$\dfrac{\Gamma(\lfloor k+1 \rfloor, \lambda)}{\lfloor k \rfloor !}$, or $e^{-\lambda} \sum_{j=0}^{\lfloor k \rfloor} \dfrac{\lambda^j}{j!}$, or $Q(\lfloor k+1 \rfloor, \lambda)$ (for $k \ge 0$, where $\Gamma(x, y)$ is the upper incomplete gamma function, $\lfloor k \rfloor$ is the floor function, and Q is the regularized gamma function)
Mean	λ
Median	$\approx \left\lfloor \lambda + \frac{1}{3} - \frac{1}{50\lambda} \right\rfloor$
Mode	$\lceil \lambda \rceil - 1, \lfloor \lambda \rfloor$
Variance	λ
Skewness	$\dfrac{1}{\sqrt{\lambda}}$
Excess kurtosis	$\dfrac{1}{\lambda}$
Entropy	$\lambda\Big[1 - \log(\lambda)\Big] + e^{-\lambda} \sum_{k=0}^{\infty} \dfrac{\lambda^k \log(k!)}{k!}$ or for large λ $\approx \frac{1}{2}\log(2\pi e \lambda) - \frac{1}{12\lambda} - \frac{1}{24\lambda^2} - \frac{19}{360\lambda^3} + \mathcal{O}\left(\frac{1}{\lambda^4}\right)$

① Discrete Random Variable (PMF)

② Describes the number of events occurring in a fix time intervals

e.g. ① No. of people visiting hospital every hour

② No. of people visiting banks every hour



$\lambda \Rightarrow$ Expected no. of events occurring at every time interval

PMF $\Rightarrow \dfrac{e^{-\lambda}\lambda^{x}}{x!}$ $\lambda = 3$

e.g.

$$P(x=5) = \frac{e^{-\lambda}\lambda^{x}}{x!} \quad (\lambda=3)$$

$$= \frac{e^{-3}3^{5}}{5!} = 0.101$$

$$= 10.1\%$$

Probability of Person visiting Bank at 4 & 5 hour =

$P_3(x=4) + P_3(x=5)$

Mean

$$\text{mean} = E(x) = \mu = \lambda * t$$

t = time interval

Variance

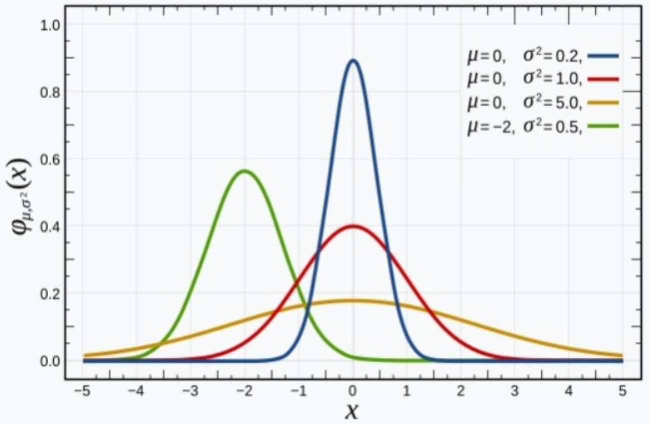
$$\text{Variance} = \lambda * t = \mu$$

(4) Normal / Gaussian Distribution

Normal distribution or Gaussian distribution is a type of continuous probability distribution for a real-valued random variable.

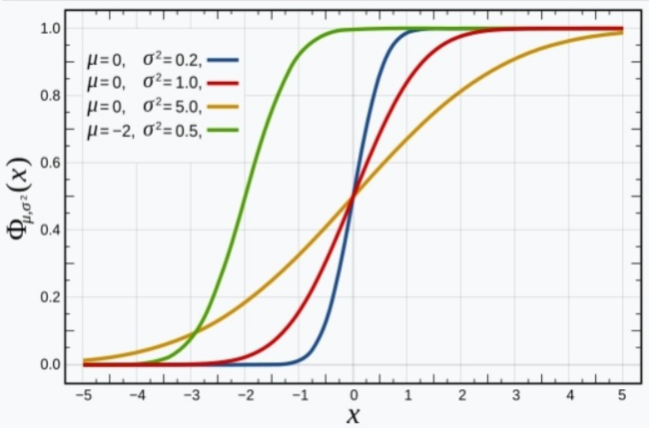
Normal distribution

Probability density function



The red curve is the *standard normal distribution*.

Cumulative distribution function

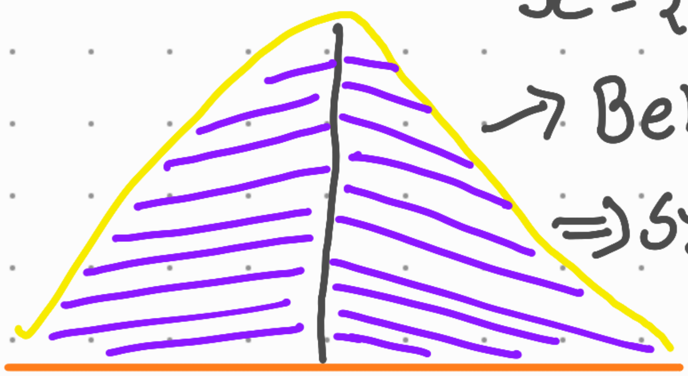


Notation $\mathcal{N}(\mu, \sigma^2)$

Parameters	$\mu \in \mathbb{R}$ = mean (location) $\sigma^2 \in \mathbb{R}_{>0}$ = variance (squared scale)
Support	$x \in \mathbb{R}$
PDF	$\frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$
CDF	$\Phi\left(\frac{x-\mu}{\sigma}\right) = \frac{1}{2}\left[1 + \operatorname{erf}\left(\frac{x-\mu}{\sigma\sqrt{2}}\right)\right]$
Quantile	$\mu + \sigma\sqrt{2}\operatorname{erf}^{-1}(2p-1)$
Mean	μ
Median	μ
Mode	μ
Variance	σ^2
MAD	$\sigma\sqrt{2/\pi}$
Skewness	0
Excess kurtosis	0
Entropy	$\frac{1}{2}\log(2\pi e \sigma^2)$

(1) Continuous Random Variable (PDF)

$x = \{ \ldots\ldots\ldots \}$



→ Bell Curve

⇒ Symmetric Distribution

$\boxed{\text{Mean} = \text{Median} = \text{Mode}}$

Notation $\Rightarrow N(\mu, \sigma^2)$

Parameters $\Rightarrow \mu \in R$ = mean

$\sigma^2 \in R > 0$ = Variance

$x \in R$

e.g. ① Weights of Students in a Class
② Heights of students in a Class

$\Rightarrow$ IRIS DATASET $\rightarrow$ Petal, Sepal Length
Petal, Sepal Width
$\rightarrow$ By this Predict Flower

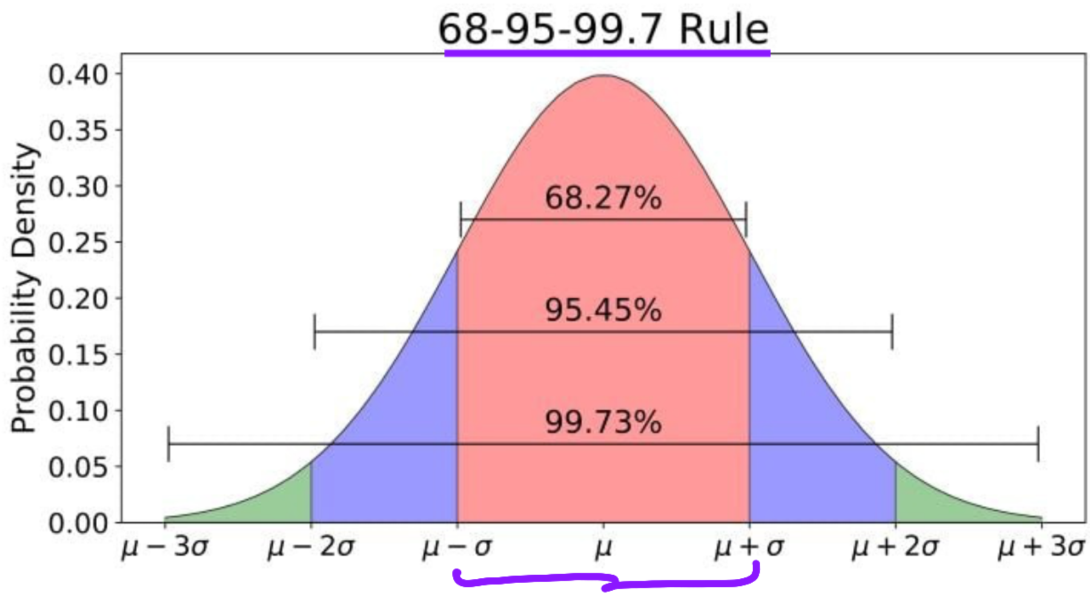
$$\boxed{\text{PDF} \Rightarrow \frac{1}{\sigma\sqrt{2\pi}} e^{-1/2\left(\frac{x_i-\mu}{\sigma}\right)^2}}$$

MEAN $\Rightarrow \mu = \sum_{i=1}^{n} \frac{x_i}{n}$

Variance $\Rightarrow \sigma^2 = \sum_{i=1}^{n} \frac{(x_i-\mu)^2}{n}$

Standard Deviation $\Rightarrow \sigma = \sqrt{\sigma^2}$

Emperical Rule of Normal / Gaussian Distⁿ



$x = \{ \ldots\ldots\ldots\ldots\ldots \}$

↳ Normal / Gaussian Distribution

Probability

$Pr(\mu - \sigma \le x \le \mu + \sigma) \approx 68\%$

$Pr(\mu - 2\sigma \le x \le \mu + 2\sigma) \approx 95\%$

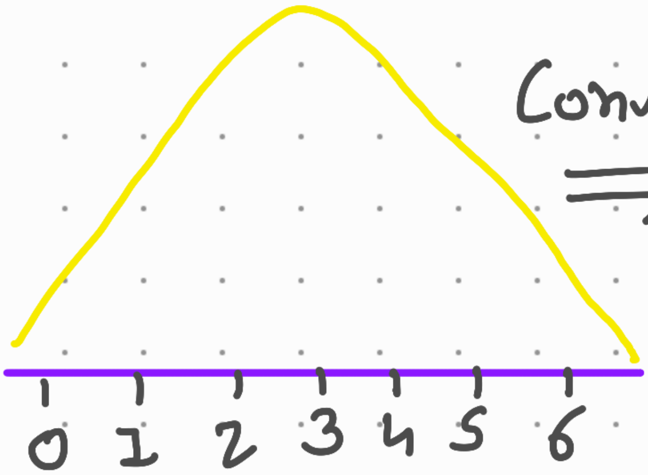
$Pr(\mu - 3\sigma \le x \le \mu + 3\sigma) \approx 99\%$

5 Standard Normal Distribution

$x = \{1, 2, 3, 4, 5\}$

$\mu = 3$

$\sigma = 1.414 \simeq 1$



Convert $\Longrightarrow$ $\mu = 0$, $\sigma = 1$

→ For Conversion we will use:

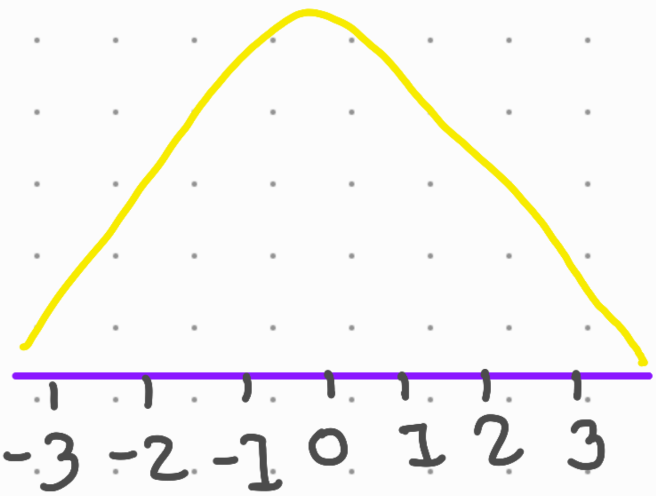
$$\boxed{\text{Z-Score} = \frac{x_i - \mu}{\sigma}}$$

1. $\frac{1-3}{1} = -2$
2. $\frac{2-3}{1} = -1$
3. $\frac{3-3}{1} = 0$
4. $\frac{4-3}{1} = 1$
5. $\frac{5-3}{1} = 2$

$y = \{-2, -1, 0, 1, 2\}$

Converted Distribution

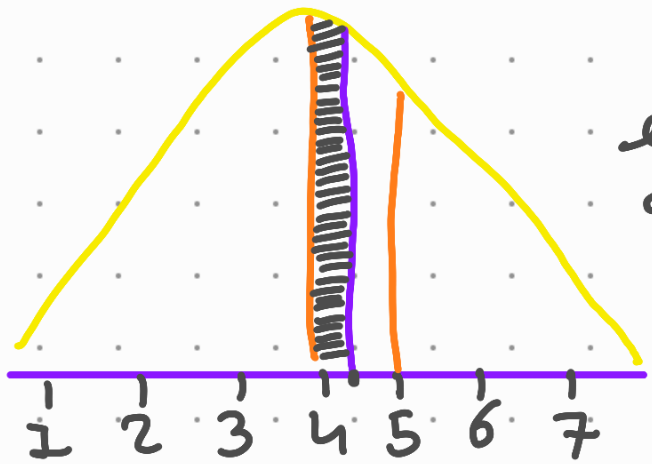
$y = \{-2, -1, 0, 1, 2\} \Rightarrow \boxed{\begin{matrix}\mu = 0 \\ \sigma = 1\end{matrix}}$



→ A Random Variable belongs to a Standard Normal Distribution if

$$\boxed{x \approx SND(\mu = 0, \sigma = 1)}$$

→ Importance of Z-score



$\mu = 4$
$\sigma = 1$

① How many standard Deviation 4.25 is away from the mean?

→ $x_i = 4.25$

$$\text{Z-score} = \frac{4.25-4}{1} = 0.25$$

→ Using Z-Table, area under curve of 0.25 can be found.

→ For ML Purpose, have to Bring all features in same unit scale.

⇓

e.g. Dataset

Age (Yrs)	Weight (Kgs)	Height (Cms)	Salary (INR)
24	70	176	40K
25	60	160	50K
26	55	150	60K
27	40	130	30K
30	30	175	20K
31	25	180	70 K
⇓	⇓	⇓	⇓

Standardization

$$\text{Z-score} = \frac{x_i - \mu_{age}}{\sigma} \quad \frac{x_i - \mu_w}{\sigma} \quad \frac{x_i - \mu_h}{\sigma} \quad \frac{x_i - \mu_s}{\sigma}$$

⑥ Uniform Distribution

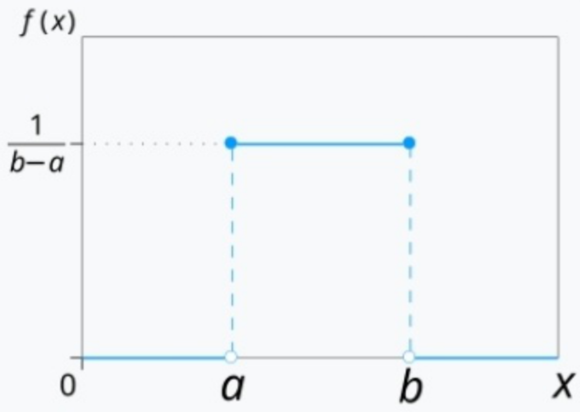
① Continuous Uniform Distribution (PDF)

② Discrete Uniform Distribution (PMF)

① Continuous Uniform Distribution (PDF)

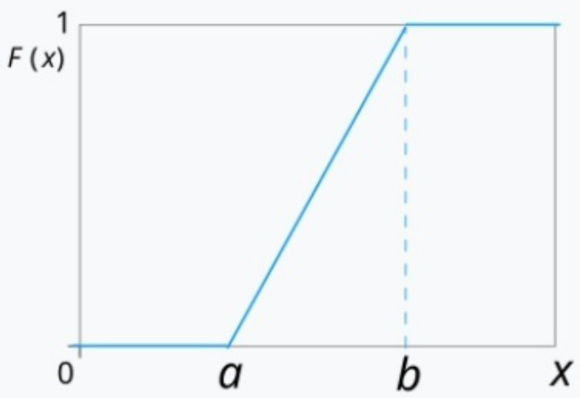
Continuous uniform

Probability density function



Using maximum convention

Cumulative distribution function



Notation $\mathcal{U}_{[a,b]}$

Parameters	$-\infty < a < b < \infty$
Support	$[a, b]$
PDF	$\begin{cases} \frac{1}{b-a} & \text{for } x \in [a,b] \\ 0 & \text{otherwise} \end{cases}$
CDF	$\begin{cases} 0 & \text{for } x < a \\ \frac{x-a}{b-a} & \text{for } x \in [a,b] \\ 1 & \text{for } x > b \end{cases}$
Mean	$\frac{1}{2}(a+b)$
Median	$\frac{1}{2}(a+b)$
Mode	any value in (a, b)
Variance	$\frac{1}{12}(b-a)^2$
MAD	$\frac{1}{4}(b-a)$
Skewness	0
Excess kurtosis	$-\frac{6}{5}$
Entropy	$\log(b-a)$
MGF	$\begin{cases} \frac{e^{tb}-e^{ta}}{t(b-a)} & \text{for } t \neq 0 \\ 1 & \text{for } t = 0 \end{cases}$
CF	$\begin{cases} \frac{e^{itb}-e^{ita}}{it(b-a)} & \text{for } t \neq 0 \\ 1 & \text{for } t = 0 \end{cases}$

The continuous uniform distributions or rectangular distributions are a family of symmetric probability distributions. Such a distribution describes an experiment where there is an arbitrary outcome that lies between certain bounds. The bounds are defined by the parameters, a and b, which are the minimum and maximum values.

→ Notation : $U(a, b)$

→ Parameters : $-\infty < a < b < \infty$

→ $PDF = \begin{cases} \frac{1}{b-a} & x \in [a, b] \\ 0 & \text{otherwise} \end{cases}$

$CDF = \begin{cases} 0 & \text{for } x < a \\ \frac{x-a}{b-a} & \text{for } x \in [a, b] \\ 1 & \text{for } x > b \end{cases}$

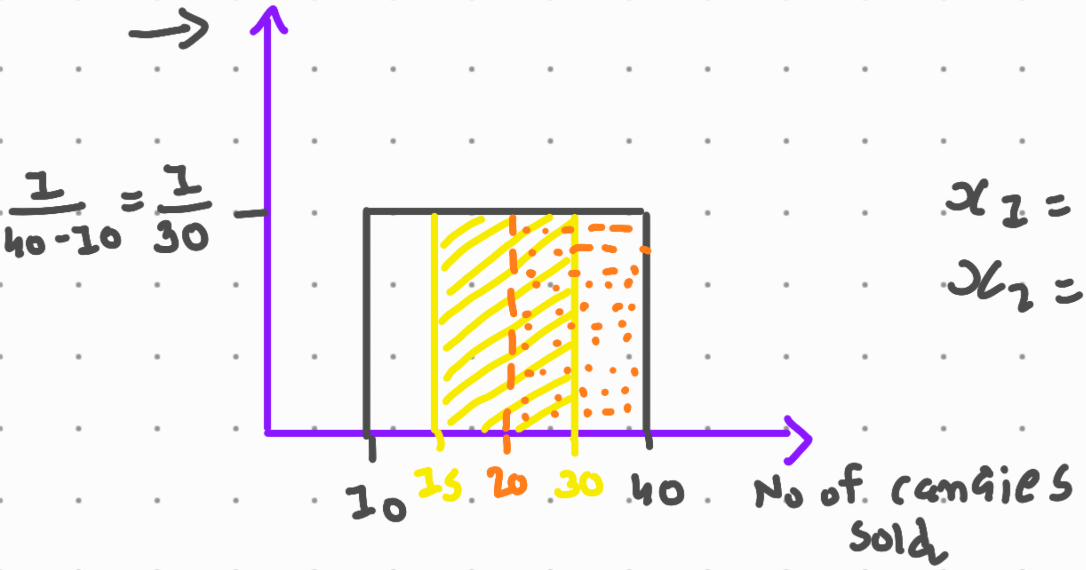
→ Mean $= \frac{1}{2}(a+b)$

Median $= \frac{1}{2}(a+b)$

Variance $= \frac{1}{12}(b-a)^2$

e.g. The number of candies sold daily at a shop is uniformly distributed with a maximum 40 candies and a minimum of 10

(i) Probability of daily sales to fall between 15 and 30 ?



$x_1 = 15$

$x_2 = 30$

$$P_r(15 \leq x \leq 30) = (x_2 - x_1) * \frac{1}{b-a}$$

$$= (30-15) * \frac{1}{30}$$

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

$$= 0.5 \; \boxed{= 50\%}$$

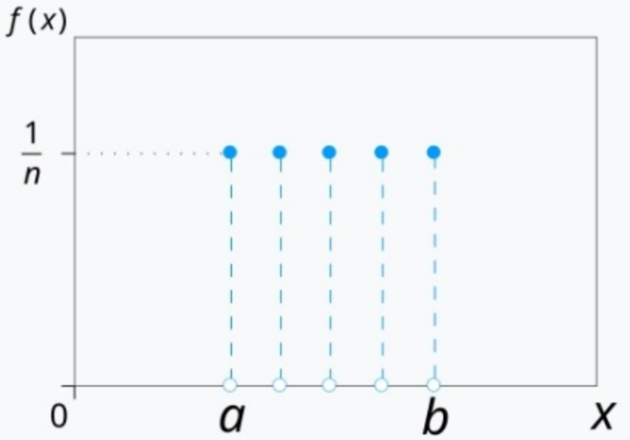
$$P_g(x \geq 20) = (40-20) * \frac{1}{30}$$

$$= 0.66 \; \boxed{= 66\%}$$

② Discrete Uniform Distribution (PMF)

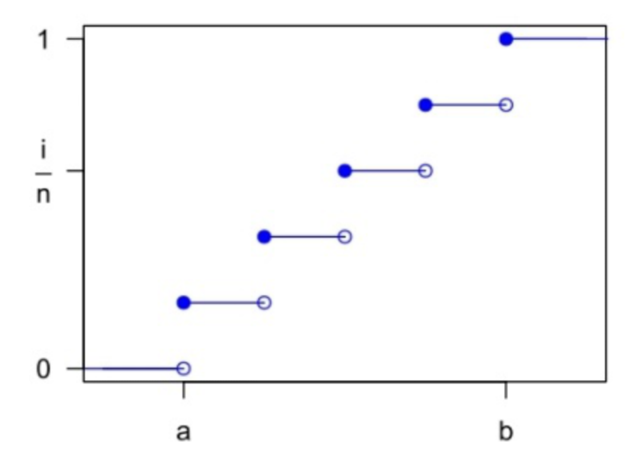
discrete uniform

Probability mass function



$n = 5$ where $n = b - a + 1$

Cumulative distribution function



Notation $\mathcal{U}\{a, b\}$ or $\mathrm{unif}\{a, b\}$

Parameters	a, b integers with $b \geq a$ $n = b - a + 1$
Support	$k \in \{a, a+1, \ldots, b-1, b\}$
PMF	$\frac{1}{n}$
CDF	$\frac{\lfloor k \rfloor - a + 1}{n}$
Mean	$\frac{a+b}{2}$
Median	$\frac{a+b}{2}$
Mode	N/A
Variance	$\frac{(b-a+1)^2 - 1}{12}$
Skewness	0
Excess kurtosis	$-\frac{6(n^2+1)}{5(n^2-1)}$
Entropy	$\ln(n)$
MGF	$\frac{e^{at} - e^{(b+1)t}}{n(1-e^t)}$
CF	$\frac{e^{iat} - e^{i(b+1)t}}{n(1-e^{it})}$
PGF	$\frac{z^a - z^{b+1}}{n(1-z)}$

The discrete uniform distribution is a symmetric probability distribution wherein a finite number of values are equally likely to be observed; every one of n values has equal probability 1/n. Another way of saying "discrete uniform distribution" would be "a known, finite number of outcomes equally likely to happen."

→ Notation: $U(a,b)$

→ Parameters: a, b where $b \geq a$

→ PMF = $\frac{1}{n}$

→ mean = median = $\frac{a+b}{2}$

e.g. Rolling a fair dice = $\{\overset{a}{1}, 2, 3, 4, 5, \overset{b}{6}\}$

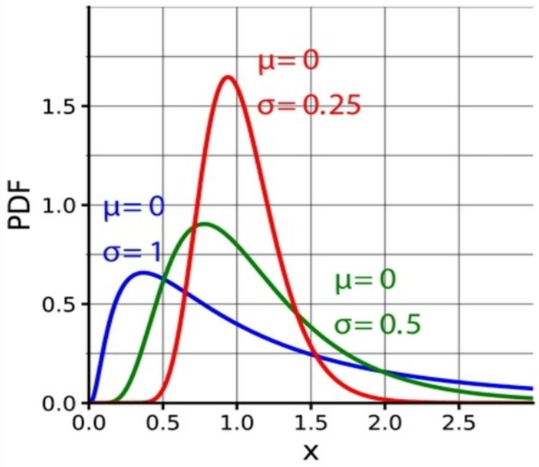
$n = b - a + 1 = 6 - 1 + 1 = 6$

$P_X = \frac{1}{n} \Rightarrow P_X(1) = \frac{1}{6}$

⑦ Log Normal Distribution

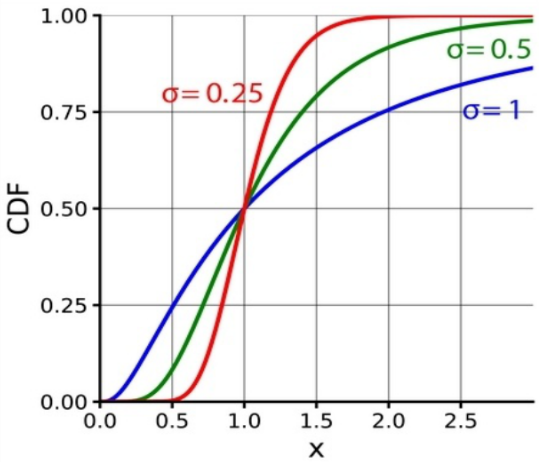
A Log-normal (or lognormal) distribution is a continuous probability distribution of a random variable whose logarithm is normally distributed. Thus, if the random variable X is log-normally distributed, then Y = ln(X) has a normal distribution.Equivalently, if Y has a normal distribution, then the exponential function of Y, X = exp(Y) , has a log-normal distribution.

Probability density function



Identical parameter μ but differing parameters σ

Cumulative distribution function



$\mu = 0$

Notation $\operatorname{Lognormal}(\mu, \sigma^2)$

Parameters	$\mu \in (-\infty, +\infty)$ (logarithm of location), $\sigma > 0$ (logarithm of scale)
Support	$x \in (0, +\infty)$
PDF	$\frac{1}{x\sigma\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu)^2}{2\sigma^2}\right)$
CDF	$\frac{1}{2}\left[1 + \operatorname{erf}\left(\frac{\ln x - \mu}{\sigma\sqrt{2}}\right)\right] = \Phi\left(\frac{\ln(x) - \mu}{\sigma}\right)$
Quantile	$\exp\left(\mu + \sqrt{2\sigma^2}\operatorname{erf}^{-1}(2p-1)\right)$
Mean	$\exp\left(\mu + \frac{\sigma^2}{2}\right)$
Median	$\exp(\mu)$
Mode	$\exp(\mu - \sigma^2)$
Variance	$[\exp(\sigma^2) - 1]\exp(2\mu + \sigma^2)$
Skewness	$[\exp(\sigma^2) + 2]\sqrt{\exp(\sigma^2) - 1}$
Excess kurtosis	$1 \exp(4\sigma^2) + 2\exp(3\sigma^2) + 3\exp(2\sigma^2) - 6$
Entropy	$\log_2\left(\sqrt{2\pi}\,\sigma\, e^{\mu + \frac{1}{2}}\right)$

Log Normal Distribution ⇒ Righ Skewed Distribution

$\mu = 0$ σ = will vary