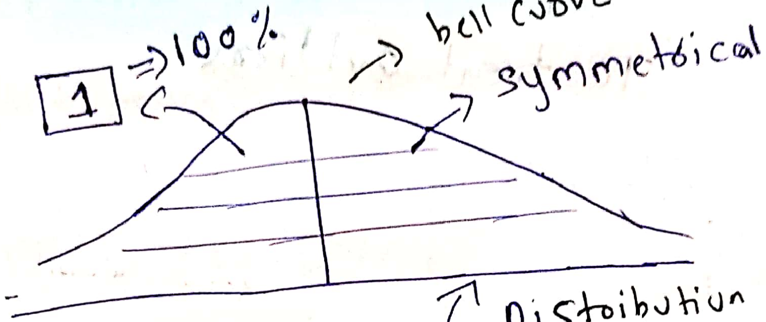
* Hare Krishna *

Statistics

1. Normal distribution
2. Standard Normal distribution
3. Z - score
4. Normalization
5. log - Normal distribution

1. Normal Distribution: / Gaussian



Age, weight, height ↗ Distribution

⇒ Doctors

⇑

Domain Expertise

Kernal density estimator

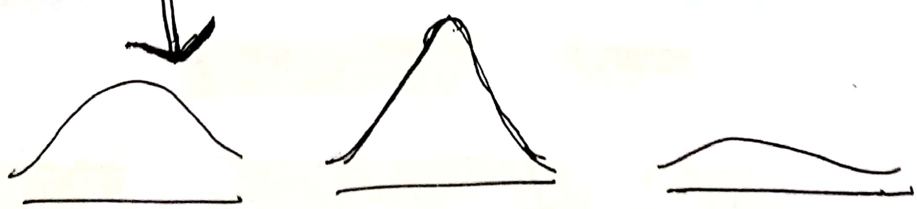
kde

IRIS DATASET ⇐

Petal length, sepal length, Petal width, sepal width

⇓

Gaussian Distribution



[Emperical Rule of Normal Distribution]

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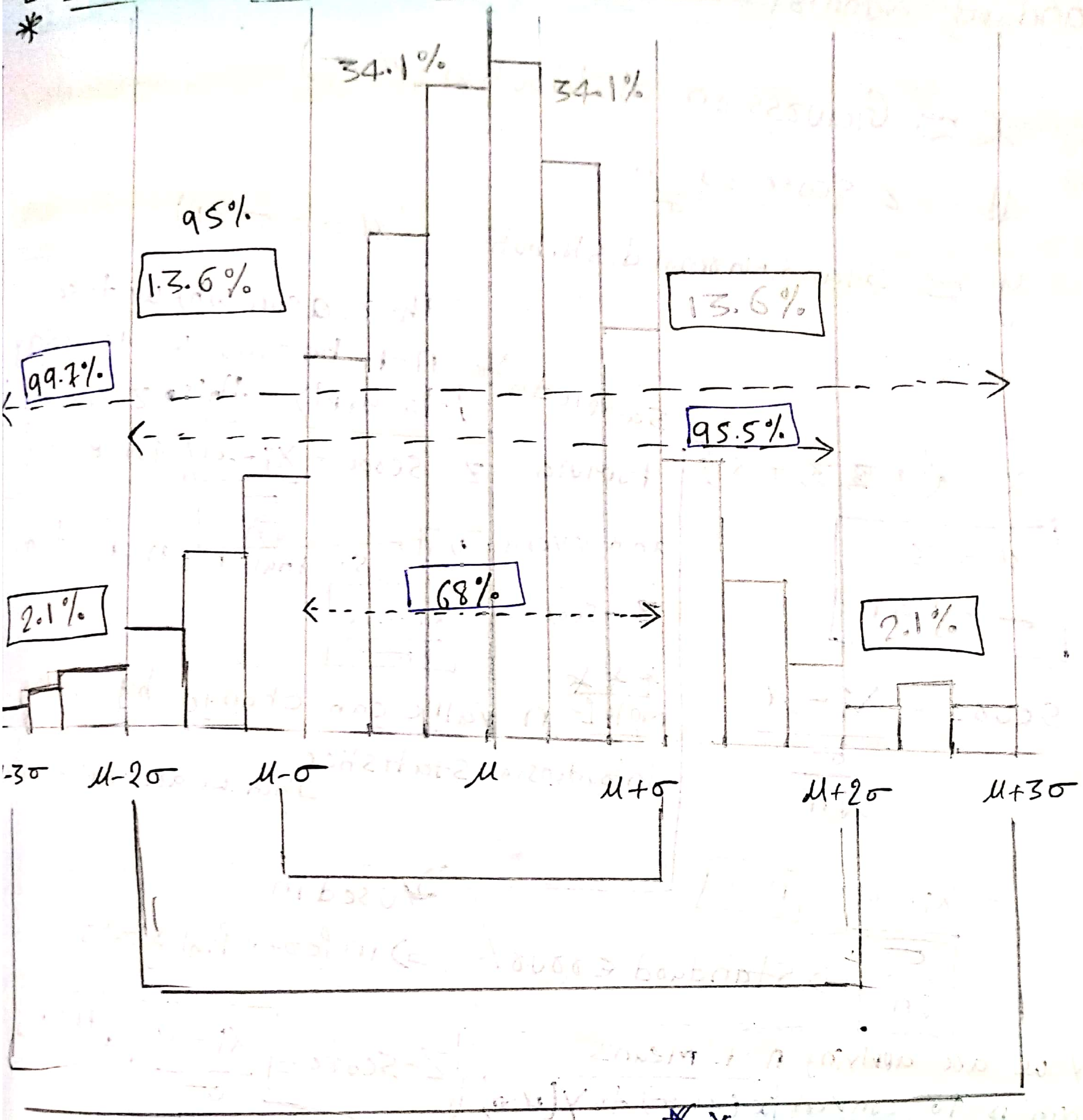


Q-Q plot.

⇓

distribution is Gaussian (or) NOT ?

** Emperical formula **

⇕

68 – 95 – 99.7 %

rule

68 – 95 – 99.7%

Standard Normal distribution:

$X \approx$ Gaussian distribution (μ, σ)

$\Downarrow$ $Z\text{-score} = \frac{x_i - \mu}{\sigma}$

$Y \approx$ Stand Normal distribution $(\mu = 0, \sigma = 1)$

Ex:

$X = \{1, 2, 3, 4, 5\}$ — Sample data

$$\boxed{\mu = 3 \quad \sigma = 1.41}$$

$$Z\text{-score} = \frac{x_i - \mu}{\frac{\sigma}{\sqrt{n}}}$$

$$= \frac{x_i - \mu}{\boxed{\frac{\sigma}{\sqrt{n}}}} \quad \boxed{n=1}$$

$\boxed{\frac{\sigma}{\sqrt{n}}}$ ⇒ Standard Error

The reason why we take $n=1$ because we are going to apply this Z-score formula $\boxed{Z\text{-score} = \frac{x_i - \mu}{\frac{\sigma}{\sqrt{n}}}}$ for each and every value so that my $n=1$ then

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

*** Note:- n value can change by using infradensial statistics. when we are implimentin

used in ⇒ inferential stats

Why we are applying $n=1$. mean's our aim is to convert $\boxed{x(\mu, \sigma) \text{ to } Y(\mu=0, \sigma=1)}$

$Z\text{-score} = \boxed{\frac{x_i - \mu}{\sigma}}$ $\boxed{n=1}$

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

$\mu = 3, \ \sigma = 1.414$

$= \frac{1-3}{1.414} = -1.414$

-3 -2 -1 0 1 2 3

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

$Y = \{-1.414, -0.707, 0, 0.707, 1.414\}$

1 is converted to $= -1.414$

2 is converted to $= -0.707$

3 is converted to $= 0$

4 is " " 0.707

i.e 5 is con $= 1.414$

why? We are converting Gaussian distribution (μ, σ)

to stand Normal distribution $(\mu = 0, \sigma = 1)$

lets say i have 3 features (Age, weight, height)

- height → calculated by (cm)
- weight → calculated by (kg)
- Age → calculated by (Years)

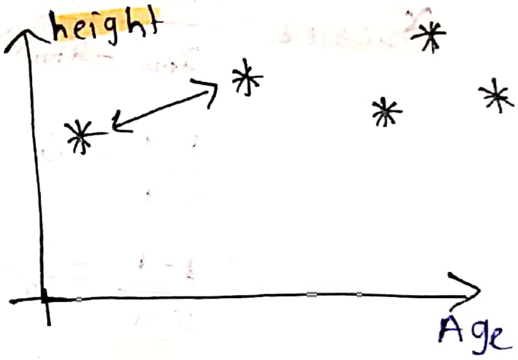
Age (Years)	weight (Kg)	(height) (cm)
24	72	150
26	78	160
32	84	165
33	92	170
34	87	150
28	83	180
24	80	175

at end of the day at Machine learning

Algorithm ⇒ mathematical model

math equations ⇓

Mathematical calculation Time ↑↑



Same scale

what if iam trying to bring the data set with in the same scale

this is advantage

beacuse of this calculation this will be fast

let take Age and apply Z-score formula then value will range b/w 0 - 3 $\mu = 1$

Similar to weight & height

at the end of the day if i probabily populated all My data Points will be in the Same scale

This entire Process is called [Standardization]

Feacture Scalling

Normalization ⇒ Standardization {z-score}

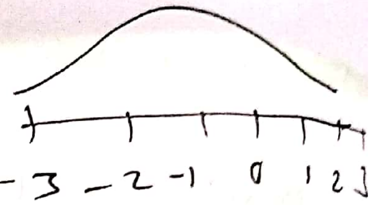
Normalization

⇓

(we give the range [0, 1]

Standardization {z-score}

$\boxed{\mu = 0, \sigma = 1}$



99.7%

[-3 ⟷ 3]

in Normalization we try to normalize the value b/w [lower scale ⟷ higher scale]

① Min max Scalar :- [0-1]

formula:-

$$x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$$

$$= \frac{1-1}{5-1} = 0$$

$$= \frac{2-1}{5-1} = \frac{1}{4}$$

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

$$= \frac{4-1}{5-1} = \frac{3}{4}$$

$$= \frac{5-1}{5-1} = \frac{4}{4}$$

X	⇒ Y
1	0
2	0.25
3	0.5
4	0.75
5	1

$\boxed{0 \text{ to } 1}$

we apply this in deep learning and some parts of machine learning,

X	⇒ Y	Y'
1	0	-1.414
2	0.25	-0.707
3	0.5	0
4	0.75	0.707
5	1	1.414

$\boxed{\text{image} = 0.255}$

Deep learning:-

Pixels range = $\boxed{0-255}$

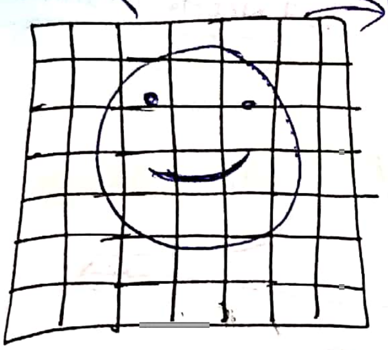
↓

converting these pixels rang to $\boxed{0-1}$

⇓

this process is called Normalization

pixels



$\boxed{0-255} \xrightarrow{\text{converting}} \boxed{0-1}$ → Normalization.

pixel-range

Normalization mean scaling down the values to $\boxed{0-1}$ is called Normalization. by (min max scaler) → technique.

Standatization:-

by using Z- score forum, Z- score ⇒ $\frac{x_i - \mu}{\sigma}$

we are able to convert.

x ⇒ Normal distribution (μ, σ)

⇓ ⇒ Z- score

Y ⇒ SND $(\mu = 0, \sigma = 1)$

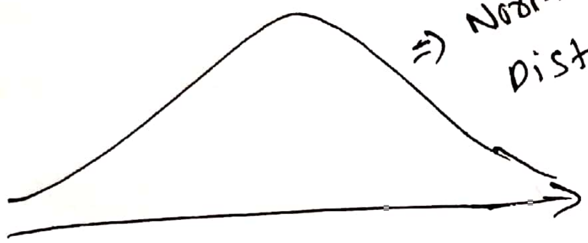
why we do this? :- Bring down the features to the same scale so that the calculation will be Easy.

Min Max Scaler $\Longleftrightarrow$ Standardization

$\Downarrow$ ML $\qquad\qquad$ $\Downarrow$ ML

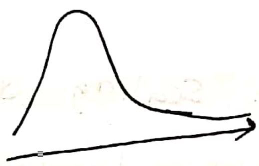
ML = Machine learning

① log Normal distribution:-

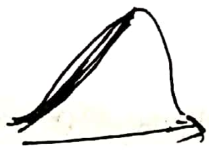


⇒ Normal / Gausian Distribution

log Normal distribution

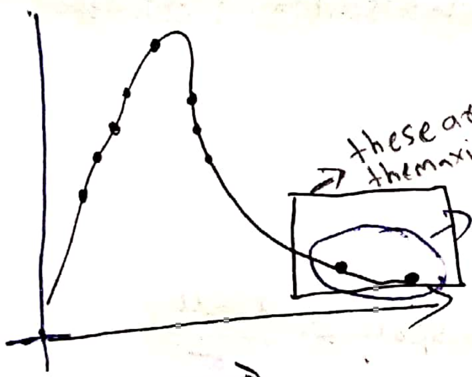


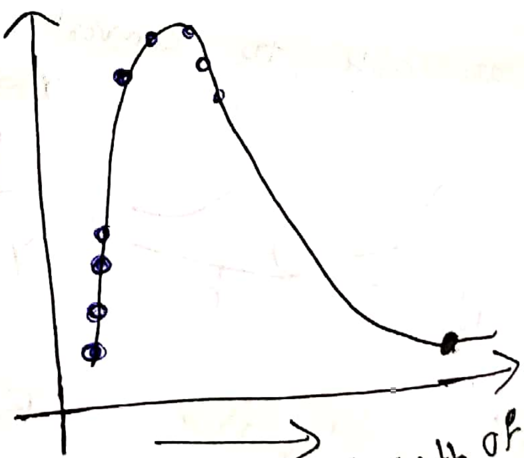
Right squed

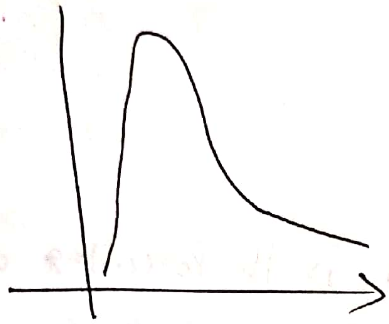


left-squed

log Normal distribution:

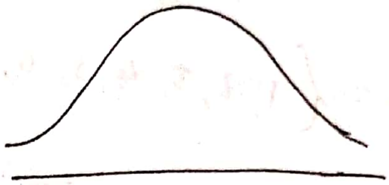






(ln) natural log = $\log_e$

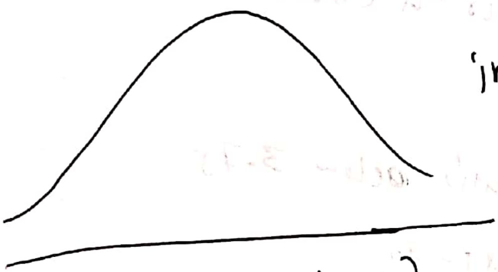
$y = \ln(x)$



$x \approx$ log normal distribution.

if the random variable X is ~~long~~ log-normally distributed, then $Y = \ln(x)$ has a normal distribution

$\Downarrow$ inverse

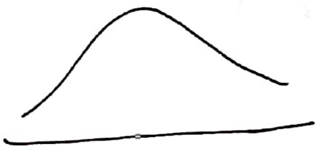


$X \approx ND(\mu, \sigma)$

$\Rightarrow$ antilog $\Downarrow$ $\exp(x)$ $\Downarrow$ Y

$\boxed{X \approx LND}$ $\Rightarrow \log_e(x) \Rightarrow$

$\Leftarrow$ $\boxed{\text{QQ plot}}$



$\Rightarrow y = \exp(x) \Rightarrow$