Recap:

Binary classification: Outputs (Yes, No)

Actual \ Predicted (n=165)	NO	YES
NO	50	10
YES	5	100

n=165

4 terms:

True positive : 100

True Negatives : 50

False Positives : 10

False Negatives : 5

$\overline{165}$

Accuracy: $\frac{T.P. + T.N.}{n \text{ (Total Sample)}}$

Error metrics and keywords:

$= \frac{100 + 50}{165} = 90.9\% \approx 91\%$

Area under the curve: (AUC)

(Binary classification) [Yes, No]

N or P, P or N

[Dog, Cat]

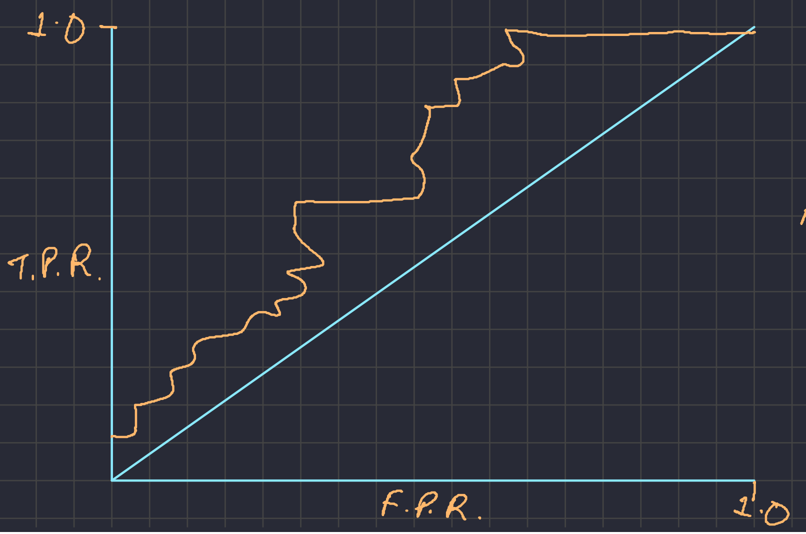
[True, false]

AUC of a classifier:

1.) True positive rate (Sensitivity): $\frac{T.P.}{(F.N. + T.P.)}$

2.) True Negative Rate (Specificity): $\frac{T.N.}{(T.N. + F.P.)}$

3.) False positive Rate : $\frac{F.P.}{T.N. + F.P.}$



AUC:

Range: [0 – 1]

→ Precision: (No. of correct positive results / No. of positive results predicted)

$$P = \frac{T.P.}{T.P. + F.P.}$$

→ Recall: (No. of correct positive results / No. of all samples that should have been positive)

$$\text{Recall}: \underbrace{\frac{T.P.}{\underset{(yes)}{T.P.} + \underset{(yes)}{F.N.}}}$$

Important:

F1 score:
$$F1 = 2 * \frac{1}{\frac{1}{\text{precision}} + \frac{1}{\text{recall}}}$$

Mean Absolute Error: |ytest − predictions|

$$M.A.E. = \frac{1}{N}\sum_{i=1}^{N} \overbrace{|y_i - \hat{y}_i|}^{\text{unit}}$$

y_i → actual value
$\hat{y}_i$ → model's prediction

$$\sqrt{\frac{(y_i - \hat{y}_i)^2}{N}}$$

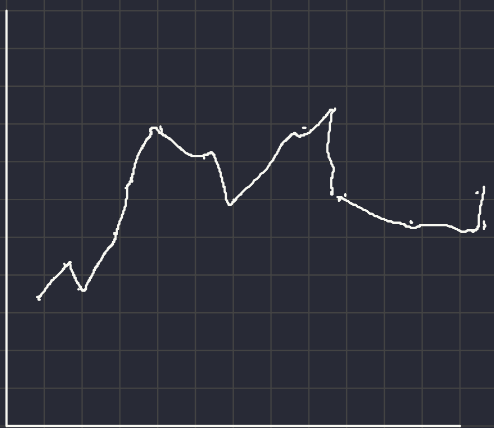
Mean squared error:
$$\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \quad \text{unit}^2$$

y_i → actual value
$\hat{y}_i$ → prediction made

magnitude is squared.
unit is squared.

$$R.M.S.E. = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2}$$

unit^2 → unit
magnitude



line graph

correlation: [−1, 1]
continuous range of [−1, 1]

−ve corr ⟹ $V_1 \uparrow$; $V_2 \downarrow$
+ve corr ⟹ $V_1 \uparrow$; $V_2 \uparrow$

Two values
V_1 ; V_2 $\quad C(V_1, V_2) = 0$ no corr.
if $C(V_1, V_2) = -1$ neg. corr
if $C(V_1, V_2) = 1$ pos. corr

$c\,[-0.88]$ feature 1 feature 2 +ve or −ve

% survival ↑ ↓ Male 3-class ticket

$c\,[0.91]$ Child class − 1

if $c(f_1, f_2)$ positive
then $f_1\uparrow$ means
$f_2\uparrow$

if $c(f_1, f_2)$ negative
then $f_1\uparrow$ means
$f_2\downarrow$ and
vice-versa

Simple linear regression

$x \longrightarrow$ Trained model (Single-Regressor) $\longrightarrow y$

T.V. Sales ?

{ one feature
one label }

Multiple L.R

T.V. $x_1 \longrightarrow$
Radio $x_2 \longrightarrow$ Trained model (Multi-Regressor) $\longrightarrow y$ Sales ?
Newspaper $x_3 \longrightarrow$

{ multiple features
single prediction }