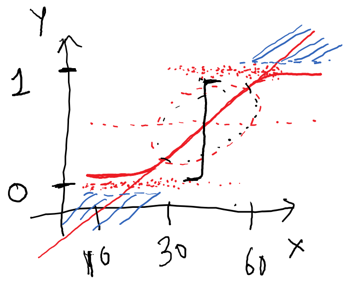
08 February 2018 13:48

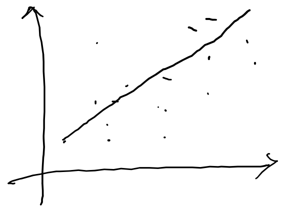
Logistic Regression

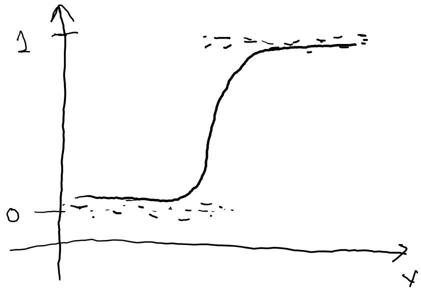
→ Dichotomous o/p

→ 1/0 , Yes/No

Prob







→ S-shaped curve

→ Sigmoid Curve $\Rightarrow f(x) = p = \dfrac{e^{y}}{1+e^{y}}$

We need $y = mx + c \to$ glm

$y = \beta_0 + \beta_1 x_1$

$\boxed{p + q = 1}$

$\Rightarrow p = \dfrac{e^{\beta_0+\beta_1 x_1}}{1+e^{\beta_0+\beta_1 x_1}} = f(x) \Rightarrow$ ✱

$\Rightarrow$ $\boxed{\text{Odds Ratio}}$ $\Rightarrow \dfrac{\text{Prob of event Occouring}}{\text{Prob of event Not occuring}} = \left(\dfrac{p}{1-p}\right) = S$

$$\frac{e^{y}/1+e^{y}}{1-e^{y}/1+e^{y}} = \frac{e^{y}/\cancel{1+e^{y}}}{\frac{1+e^{y}-e^{y}}{\cancel{1+e^{y}}}} = e^{y} = S = e^{b_0+b_1x_1}$$

Take log

log of odds Ratio

→ Logit fn.

$$\boxed{\underbrace{\log(S)}_{y} = b_0 + b_1 x_1 = b_0 + b_1 x_1 + \ldots + b_k x_k}$$

Keyword → glm(. ~ .)

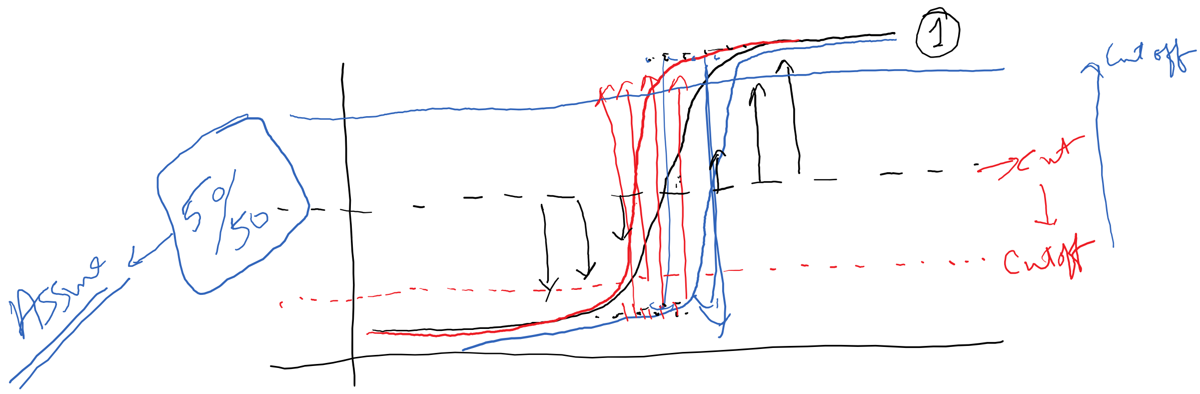
$$S = \frac{p}{1-p} = e^{y} \Rightarrow \log(S) = \log\left(\frac{p}{1-p}\right) = y = \beta_0 + \beta_1 x_1$$

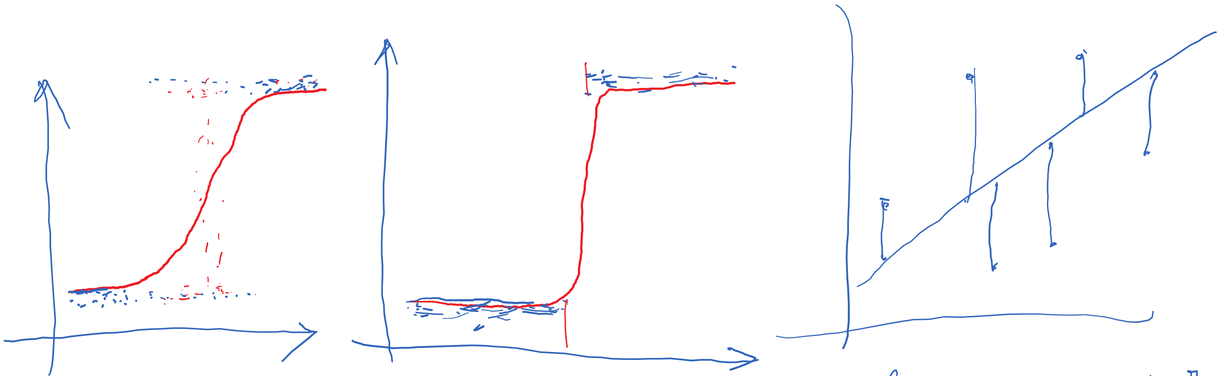
→ When my log(s) is +ve → probability of success is > 50%

(82) . . . 1 . /50 $\log\left(\frac{20}{80}\right) = -0.6$

$\log\left(\frac{80}{20}\right) = 0.6$ $\log\left(\frac{50}{50}\right) : 0$ $\log\left(\frac{20}{80}\right) = -0.6$

1 ← Prob of success prob of failure → 0





Maximum likelihood of points occurance Least square error ✗

→ Fischer Score → Iterations needed to reach Max likelihood

Performance of logistic model

1 → AIC 2 → Null & Residual deviance 3 → Confusion Matrix

→ AIC → Akaike Information Criteria → Counterpart of R^2 ↑

→ $\boxed{\text{lesser the better}}$ ↓

→ Null deviance → Response predicted by the model with "Intercept" ONLY

better

→ Null deviance → Response predicted by the model with "Intercept ONLY"

$y = \ln(s) = b_0$ lesser the better

→ Residual deviance → Response predicted by the model on "Adding" Independent variables

lesser the better $y = \ln(s) = b_0 + b_1x_1 + b_2x_2 \cdots b_kx_k$

Confusion matrix → Accuracy of the model & Avoid overfitting

		Predicted	
		good	bad
Actual	good	True +ve (d)	False -ve (c)
	bad	False +ve (b)	True -ve (a)

Type 2

Type 1

$$\text{Accuracy} = \left[\frac{T{+ve} + \text{True}{-ve}}{T{+ve} + T{-ve} + F{+ve} + F{-ve}}\right]$$

→ Sensitivity & Specificity (Recall)

TNR → Specificity $= \frac{A}{A+B}$

FPR → 1 - specificity $= \frac{B}{A+B}$

Sum to 1.

TPR → Sensitivity $= D/(C+D)$

FNR → $= C/(C+D)$

Sum to 1.

		Prediction	
		good	bad
Actual	good	T + (D)	F − (C)
	bad	F + (B)	T − (A)

$$FPR = \frac{B}{A+B}$$

$$TNR \rightarrow \frac{A}{(A+B)}$$

$$FNR = \frac{C}{C+D}$$

$$TPR = D/_{C+D}$$

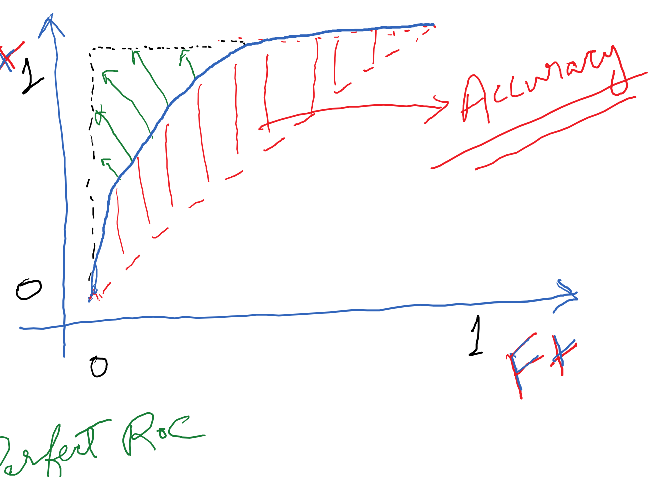
TPR →	How many	+ve out of	all +ve →	predicting Correctly
FPR →		−ve	−ve	Incorrectly
TNR →		−ve	−ve	Correctly
FNR →		+ve	+ve	Incorrectly

ROC → Reciver operator Curve → Summarize the model performance

Assume $P > 0.5$ → Focus on +ve

→ Area under the curve

= Accuracy ↑ → better.



Perfect ROC