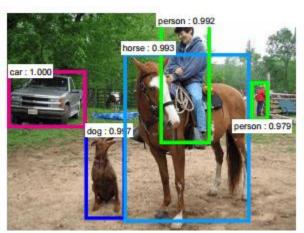
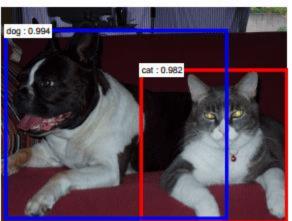
# Classification







Domain	Question		
Telecom	Is a customer likely to leave the network? (churn prediction)		
Retail	Is he a prospective customer? that is likelihood of purchase vs. non-purchase?		
Insurance	To issue insurance should a customer be sent for a medical checkup?		
Insurance	Will the customer renew the insurance?		
Banking	Will a customer default on the loan amount?		
Banking	Should a customer be given a loan?		
Manufacturing	Will the equipment fail?		
Health Care	Is the patient infected with a disease?		
Health Care	What type of disease does a patient have?		
Entertainment	What is the genre of music?		



New

Data

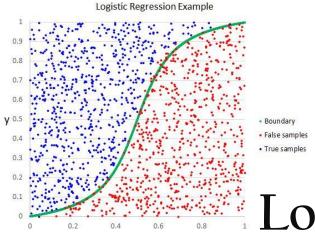
Data

Preprocessing



Validation

Prediction



# Logistic Regressions

(Classification)



#### Simple Linear Regression overview

Simple Linear Regression

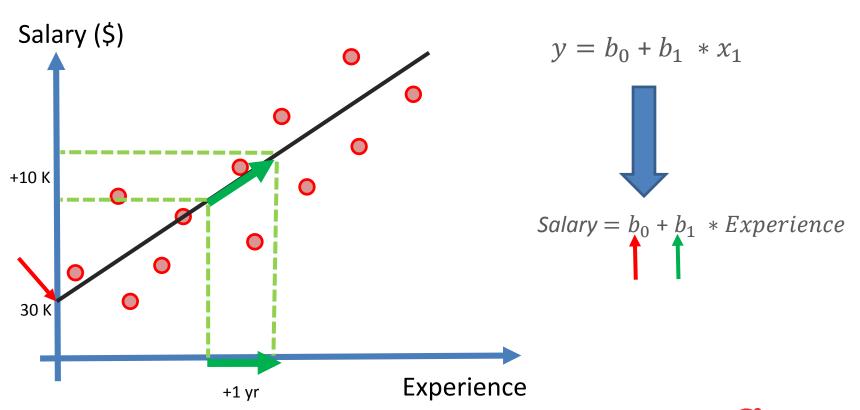
$$y = b_0 + b_1 * x_1$$

Multiple Linear Regression

$$y = b_0 + b_1 * x_1 + b_2 * x_2 + \dots + b_n * x_n$$



# Simple Linear Regression:

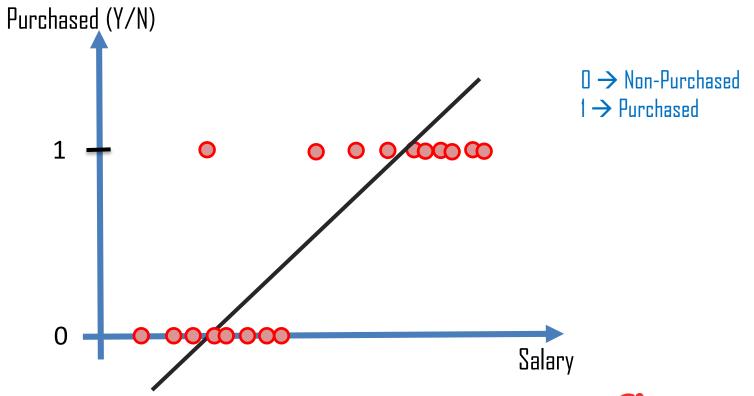




# Retail (Like hood to rchase) Purchased (Y/N) $\Pi \rightarrow Nnn-Purchased$ $1 \rightarrow Purchased$ 00000Salary

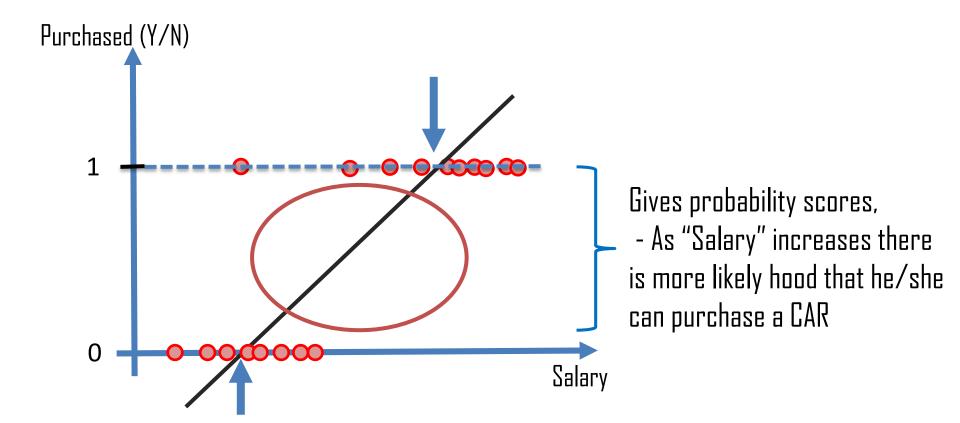


#### Linear Regression Prediction in Retail (Like hood to purchase)



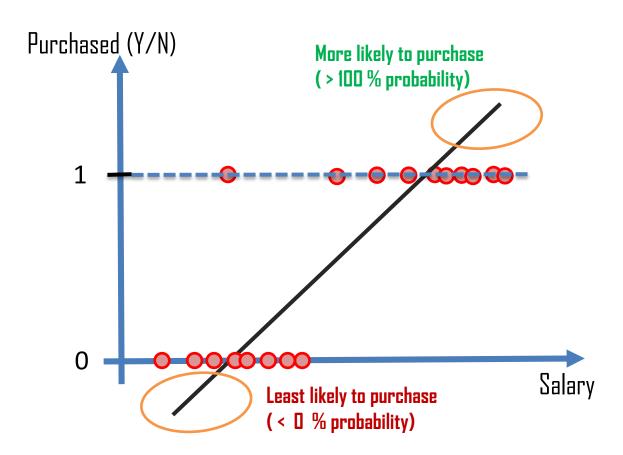


## Probability of Likely hood to purchase





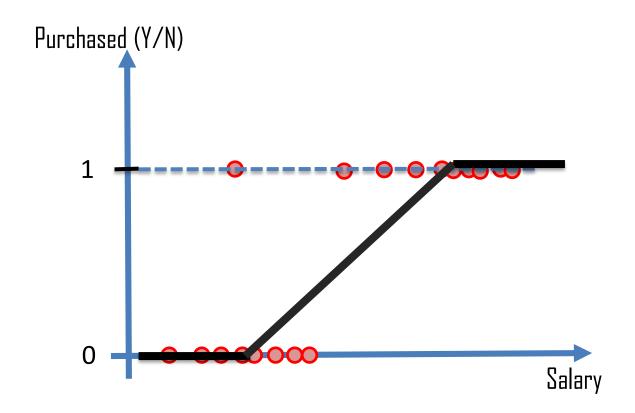
## Probability of Likely hood to purchase



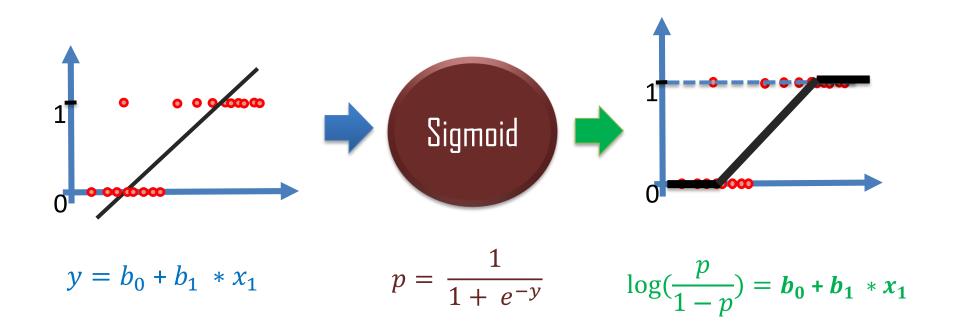
The Line above and below the probability limit is telling that there is more likely to purchased and not-purchased



## Logistic Regression









• Fundamental Idea is to introduce **sigmoid** or **Logit function** to regression equation.

Eq. of linear regression: 
$$y = b_0 + b_1 * x_1$$

Logistic regression can be explained better in odd ratios.

"Odd of an event occurring are defined = 
$$\frac{\text{probability of event occurring}}{\text{probability of event not occurring}}$$
"



odd ratio of purchased vs not purchased = 
$$\frac{P(y=1)}{1 - P(y-1)}$$

$$logits = y = log_e \left( \frac{P(y=1)}{1 - P(y-1)} \right)$$

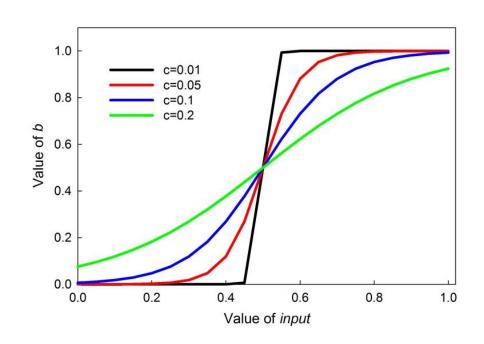
From Linear Regression

$$y = b_0 + b_1 * x_1$$

$$\log_e\left(\frac{P}{1-P}\right) = b_0 + b_1 * x_1$$

$$\log_e\left(\frac{P}{1-P}\right) = b_0 + b_1 * x_1$$

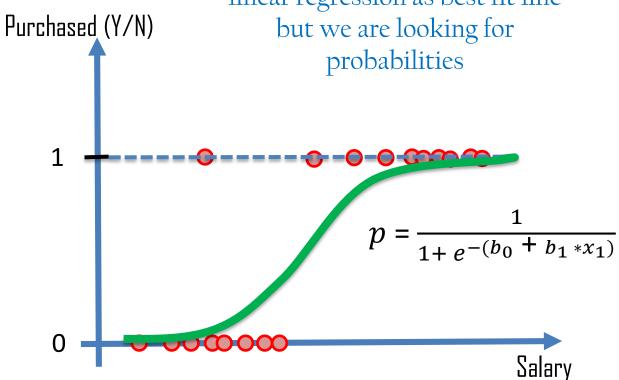
$$p = \frac{1}{1 + e^{-(b_0 + b_1 * x_1)}}$$



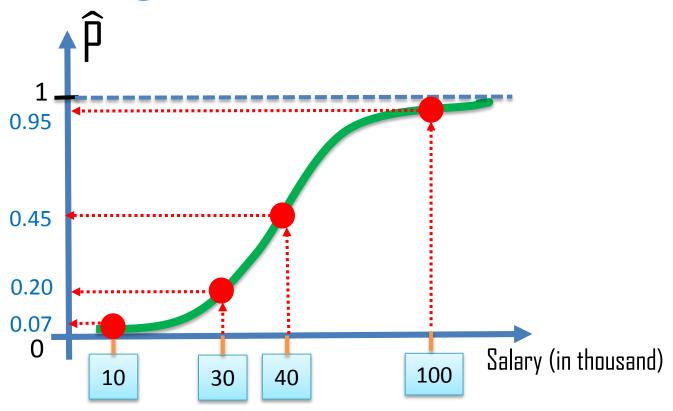


# Logistic Regression is same as

linear regression as best fit line

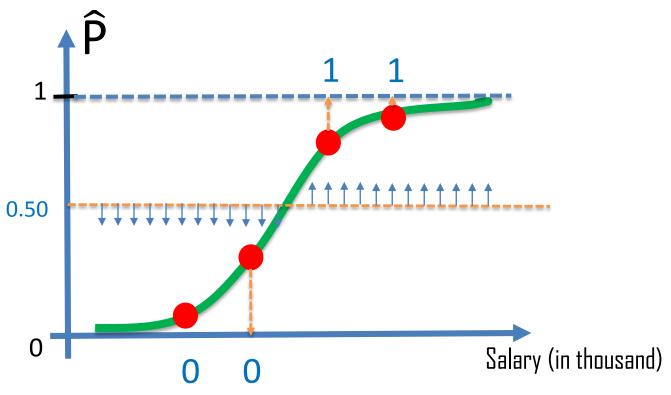


# Logistic Regression





# Logistic Regression





## Classification Model Performance

True Negatives (TN): Actual FALSE, which was predicted as FALSE

False Positives (FP): Actual FALSE, which was predicted as TRUE (Type I error)

False Negatives (FN): Actual TRUE, which was predicted as FALSE (Type II error)

True Positives (TP): Actual TRUE, which was predicted as TRUE



## Classification Performance Metric

Metric	Description	Formula
Accuracy	What % of the prediction were correct?	(TP + TN)/ (TP + TN + FP + FN)
Misclassification rate	What % of prediction were wrong ?	(FP + FN)/(TP + TN + FP + FN)
True Positive rate or Sensitivity or Recall	What % of positive classes did model catch ?	TP / (TP + FN)
False positive rate	What % of "No" were predicted "Yes"	FP / (FP + TN)
Specificity	What % of "No" were predicted "No"	TN / (TN + FP)
Precision (exactness)	what % of positive predictions were correct?	TP/(TP+FP)
F1 score	Weighted average of precision and recall	2*((precision * recall) / (precision + recall))



# Hands on Logistic Regression





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