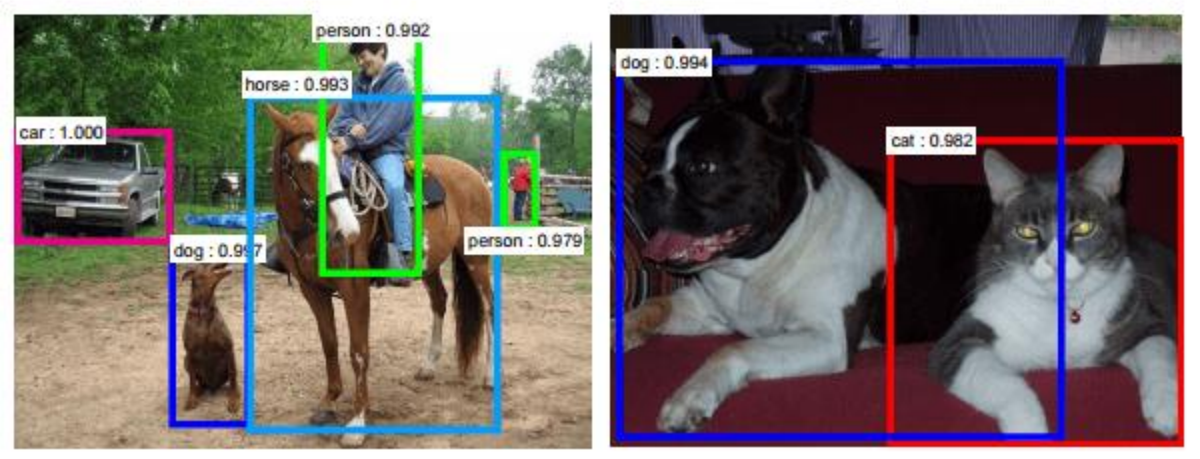
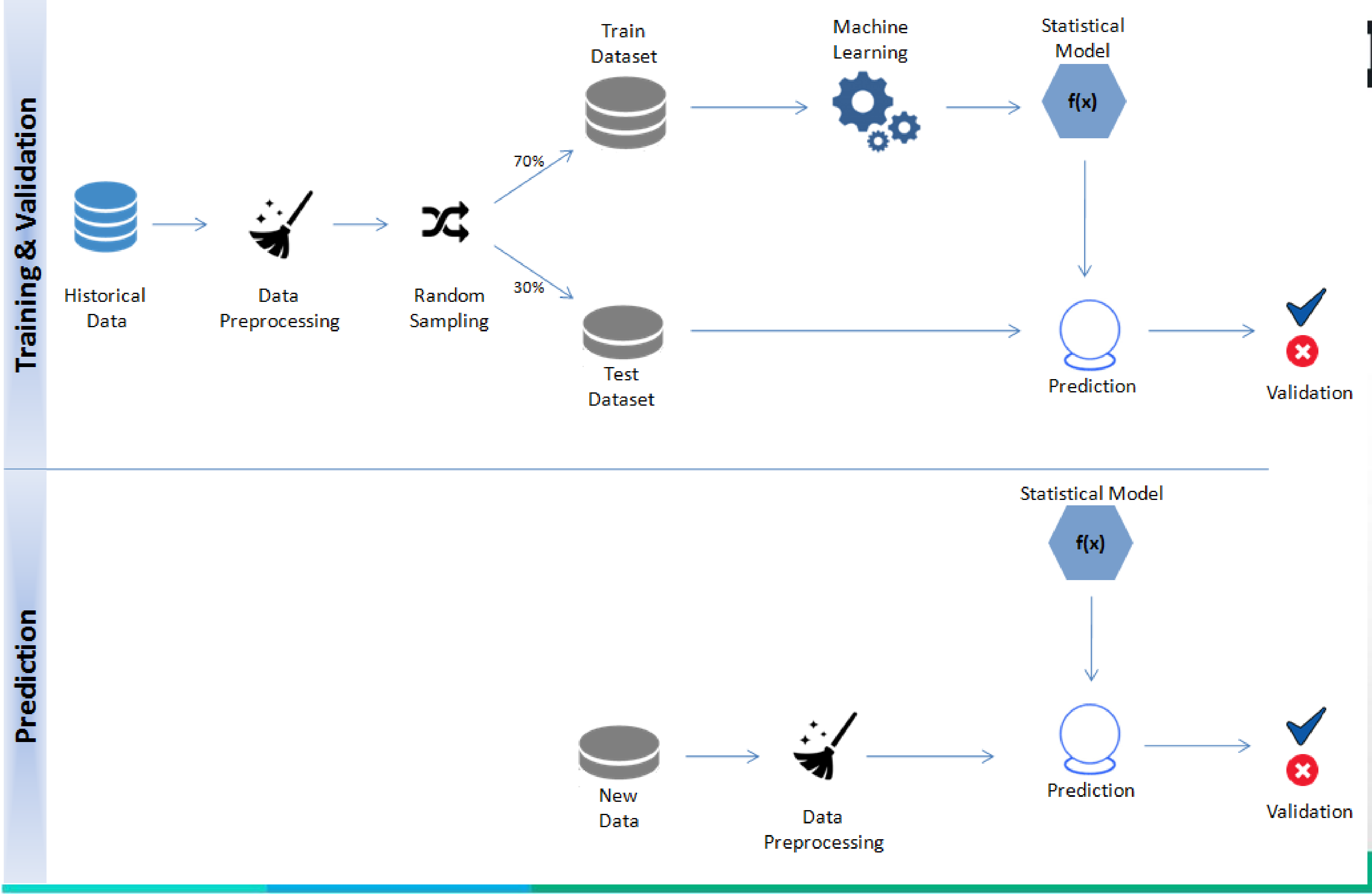
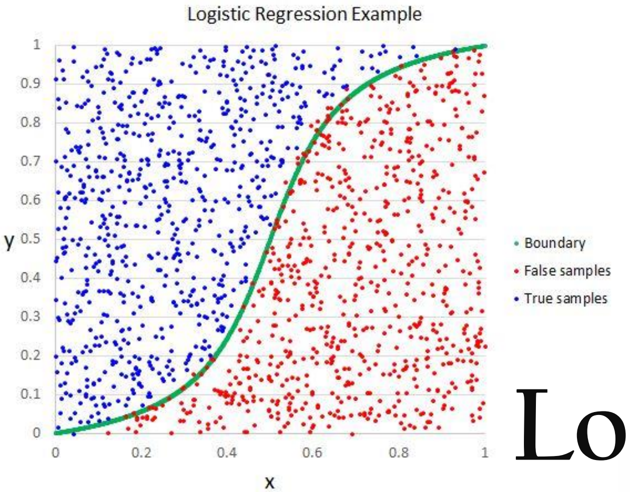
# Classification



| 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? |


Training & Validation
Historical Data
Data Preprocessing
Random Sampling
70%
30%
Train Dataset
Test Dataset
Machine Learning
Statistical Model
f(x)
Prediction
Validation
Prediction
Statistical Model
f(x)
New Data
Data Preprocessing
Prediction
Validation




# Logistic Regressions

## (Classification)

# Simple Linear Regression overview

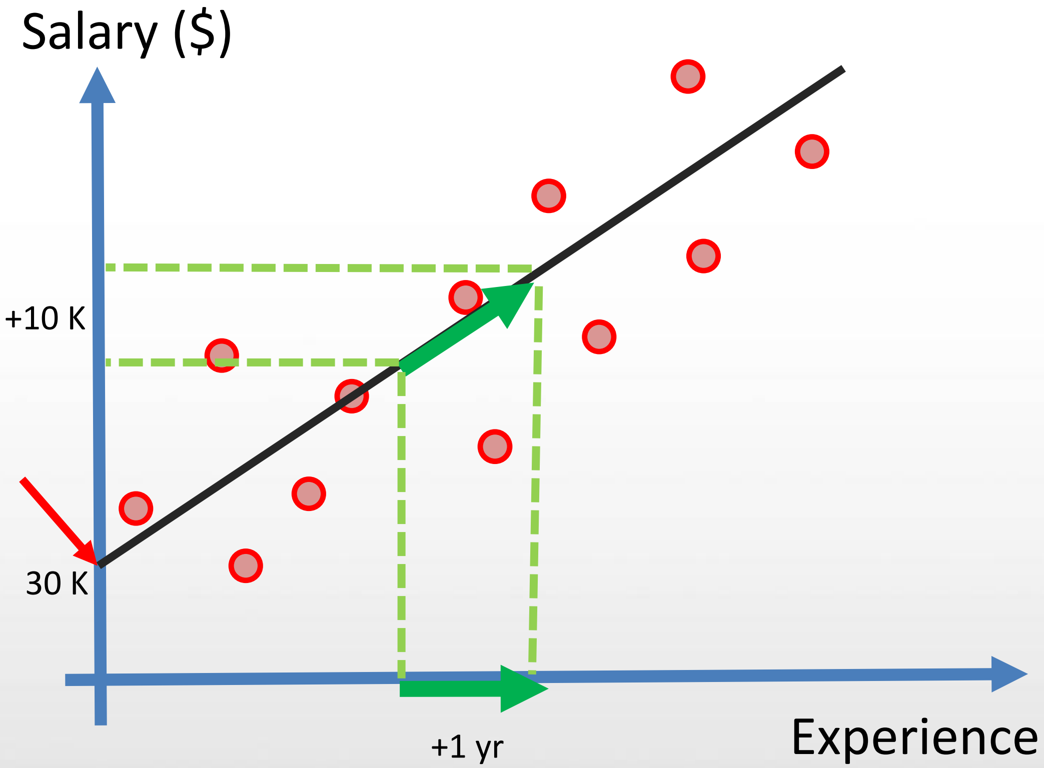
**Simple Linear Regression**

$$y = b_0 + b_1 * x_1$$

**Multiple Linear Regression**

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

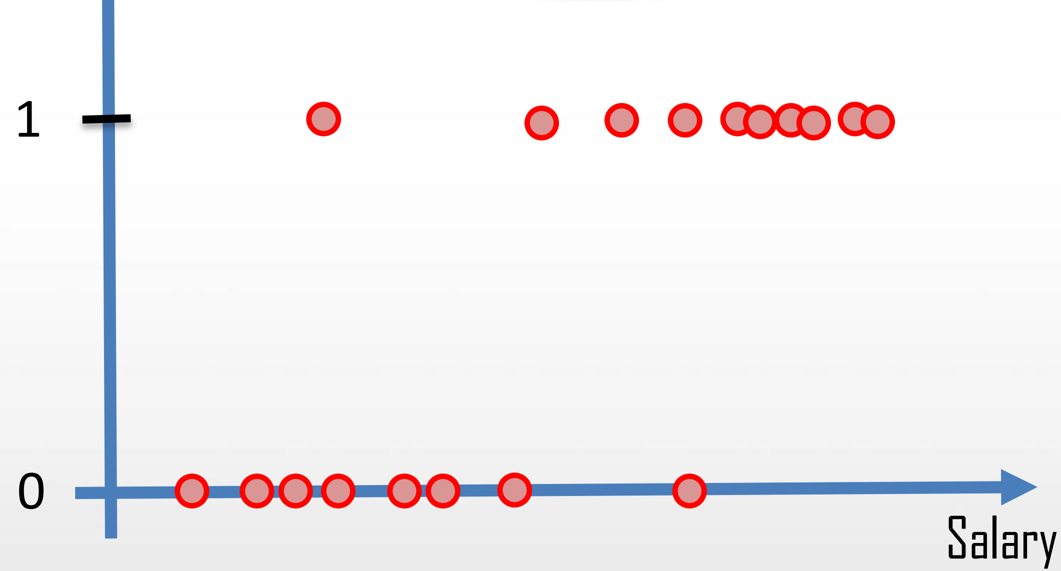
# Simple Linear Regression:




$$y = b_0 + b_1 \ast x_1$$

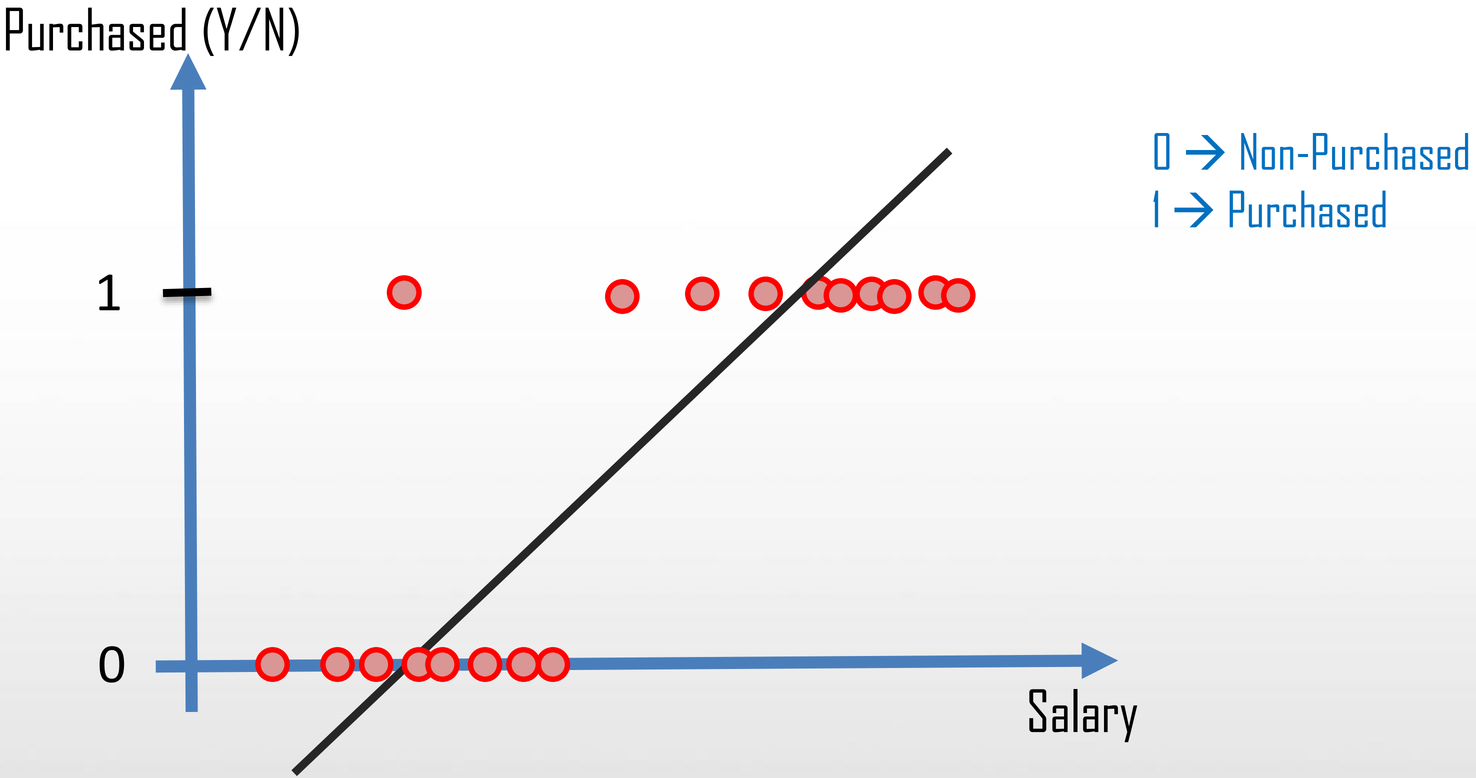
$$Salary = b_0 + b_1 \ast Experience$$

# Retail (Like hood to purchase)

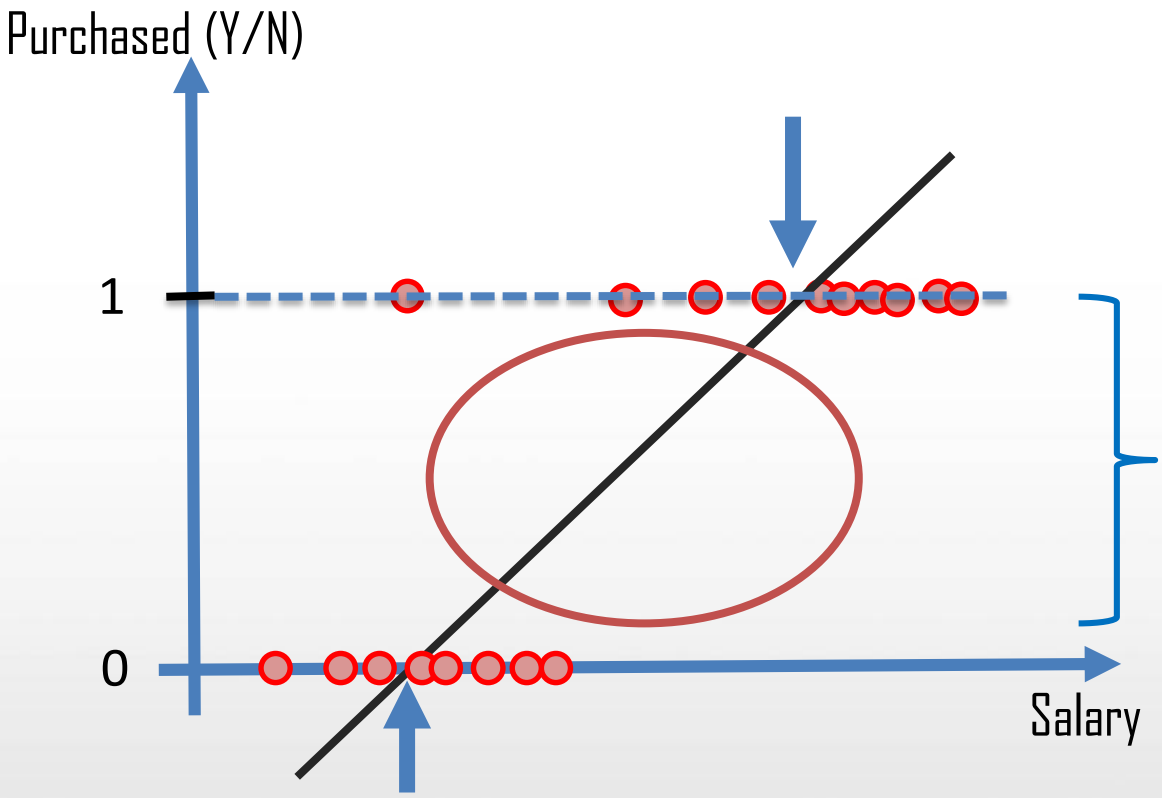



0 → Non-Purchased
1 → Purchased

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

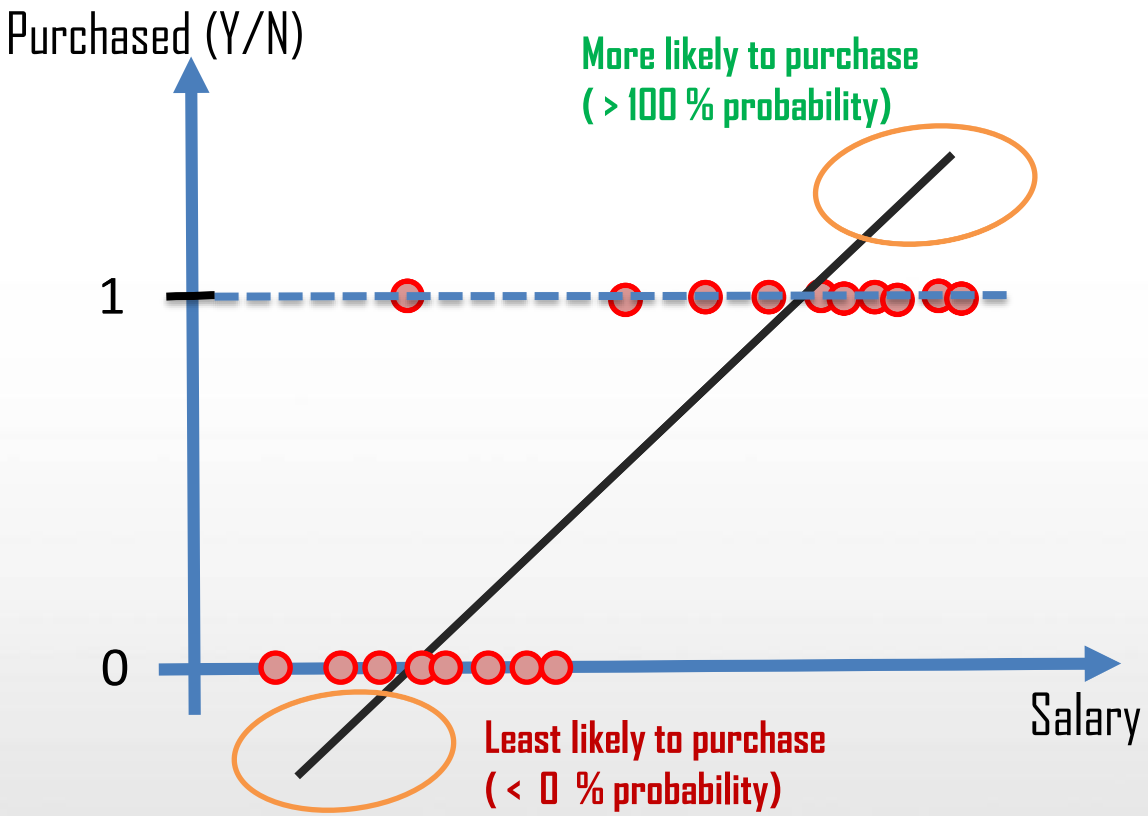


# Probability of Likely hood to purchase



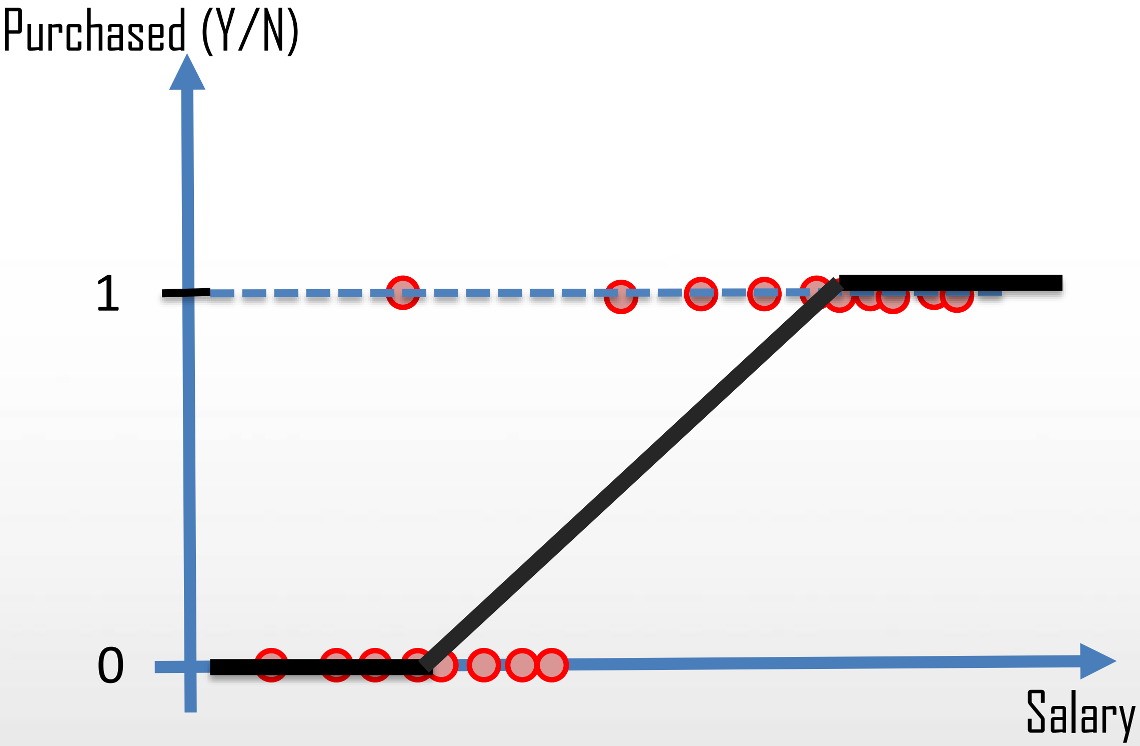

Gives probability scores,
- As "Salary" increases there is more likely hood that he/she can purchase a CAR

# 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



# Logistic Regression (Scientific Approach)


$$y = b_0 + b_1 * x_1$$

$$p = \frac{1}{1 + e^{-y}}$$

$$\log\left(\frac{p}{1-p}\right) = \boldsymbol{b_0 + b_1 * x_1}$$

# Logistic Regression (Scientific Approach)

- 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 $= \dfrac{\text{probability of event occurring}}{\text{probability of event } \textbf{not} \text{ occurring}}$"

Logits = log(Odd ratio)

# Logistic Regression (Scientific Approach)

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

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

From Linear Regression

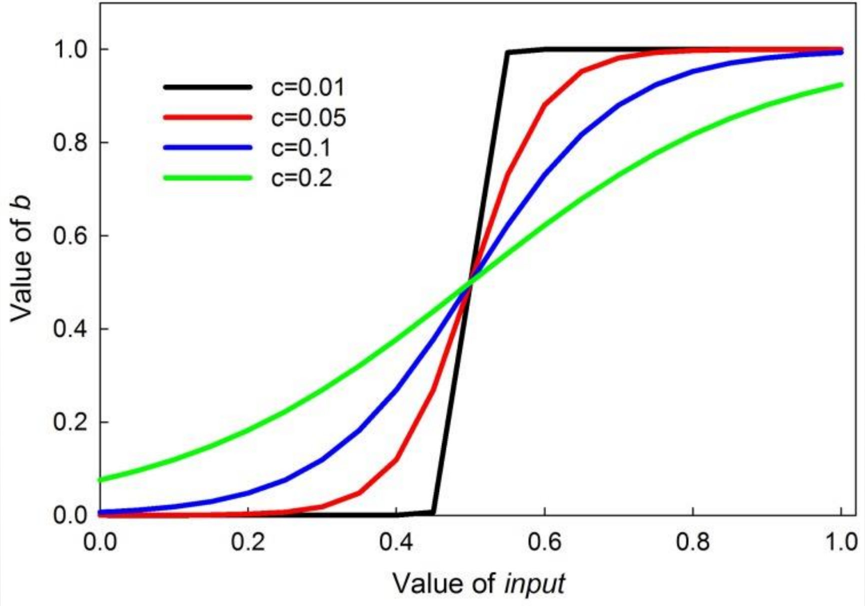
$$y = b_0 + b_1\ * x_1$$

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

# Logistic Regression (Scientific Approach)

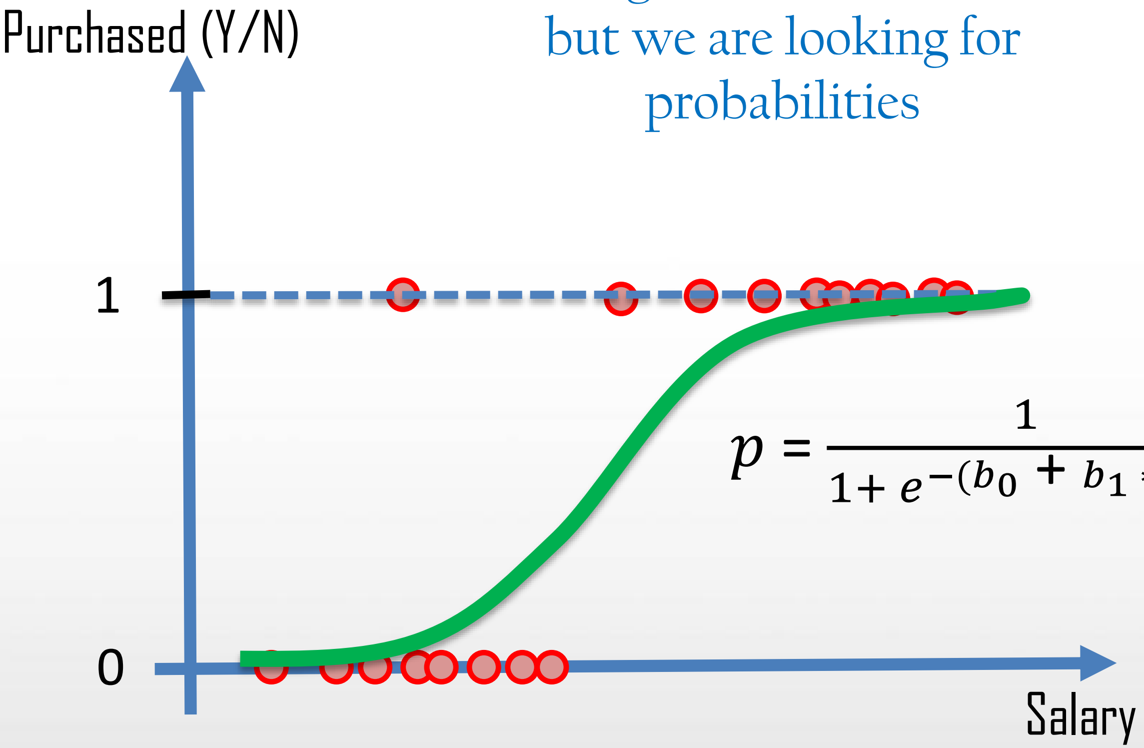
$$\log_e\left(\frac{P}{1-P}\right) = b_0 + b_1 * x_1$$

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



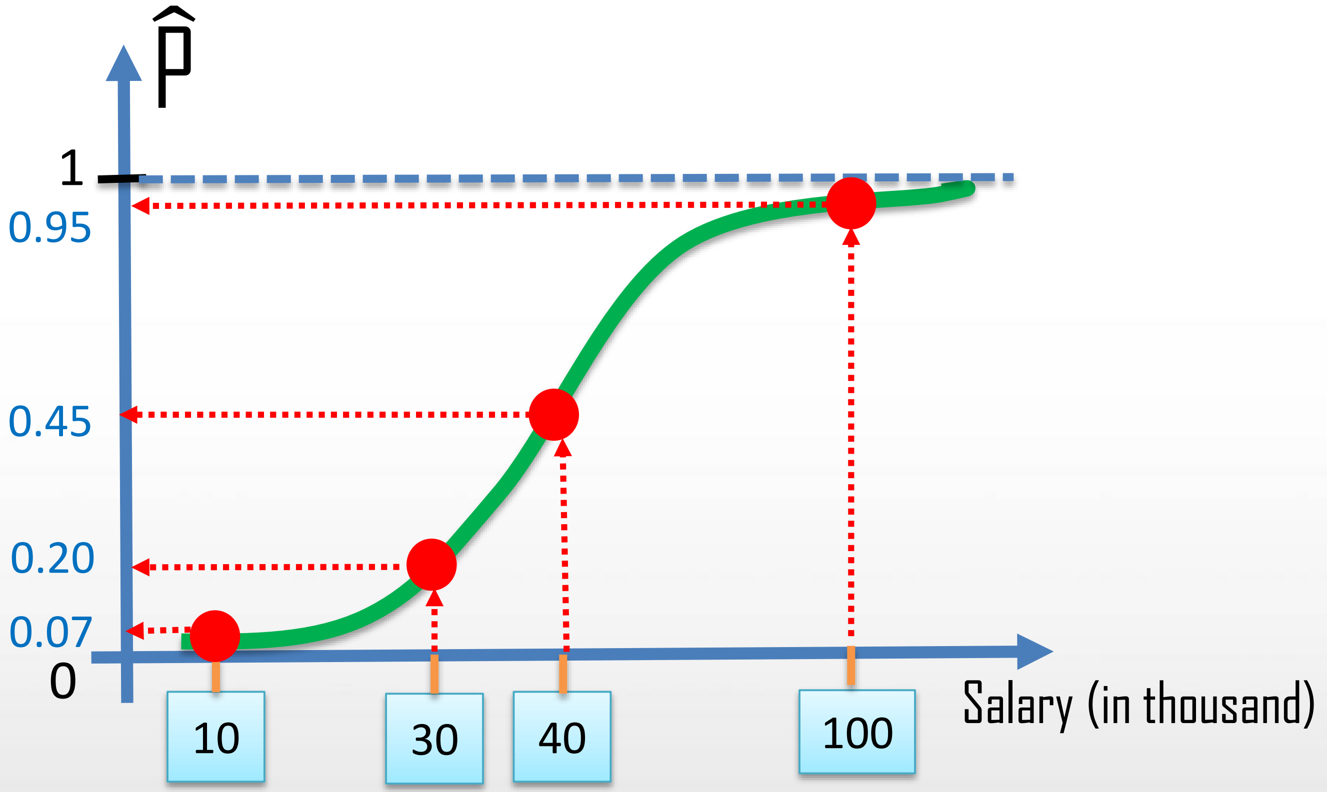
# Logistic Regression

Logistic regression is same as linear regression as best fit line but we are looking for probabilities

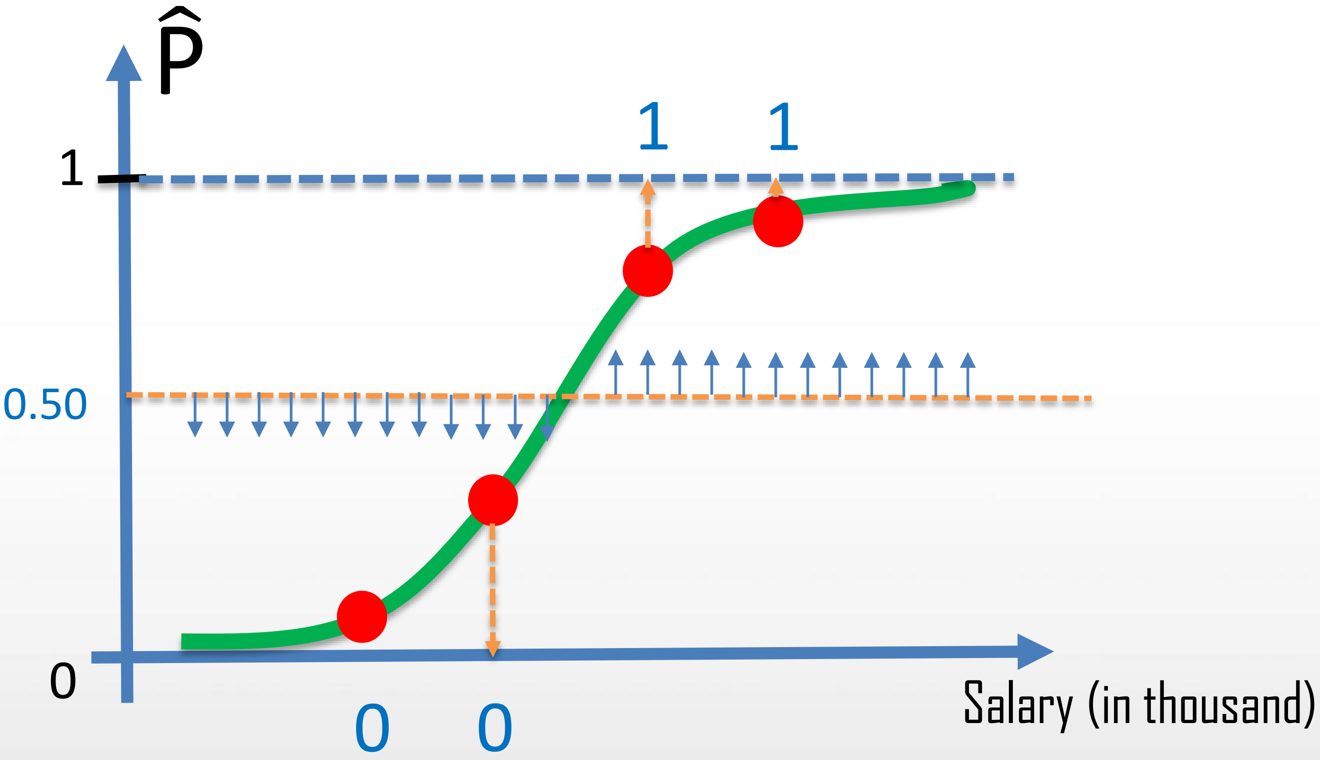



$$p = \frac{1}{1 + e^{-(b_0 + b_1 * x_1)}}$$

# 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

# IOTGYAN