MACHINE LEARNING

Celebrating 20 Years

A Larsen & Toubro Group Company

Corporate Facts

Among the top **20** Global IT services companies

With an annual revenue of **$970Mn**

260+ clients

Including **50+** Fortune 500 companies

43 sales offices across **27** countries in US, EMEA & APAC

20,000+ employees

Working out of **23** delivery centers

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Types of Machine Learning Algorithms:

- Supervised Learning
- Unsupervised Learning
- Reinforcement Learning

LTI

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CONTENT:

- REGRESSION (SIMPLE LINEAR REGRESSION, MULTIPLE LINEAR REGRESSION, POLYNOMIAL REGRESSION, SVR, DECISION TREE REGRESSION, RANDOM FOREST REGRESSION)
- ASSOCIATION RULE LEARNING (APRIORI, ECLAT)
- CLASSIFICATION (LOGISTIC REGRESSION, K-NN, SVN)

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SIMPLE LINEAR REGRESSION

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Regressions

Simple Linear Regression

Constant

Coefficient

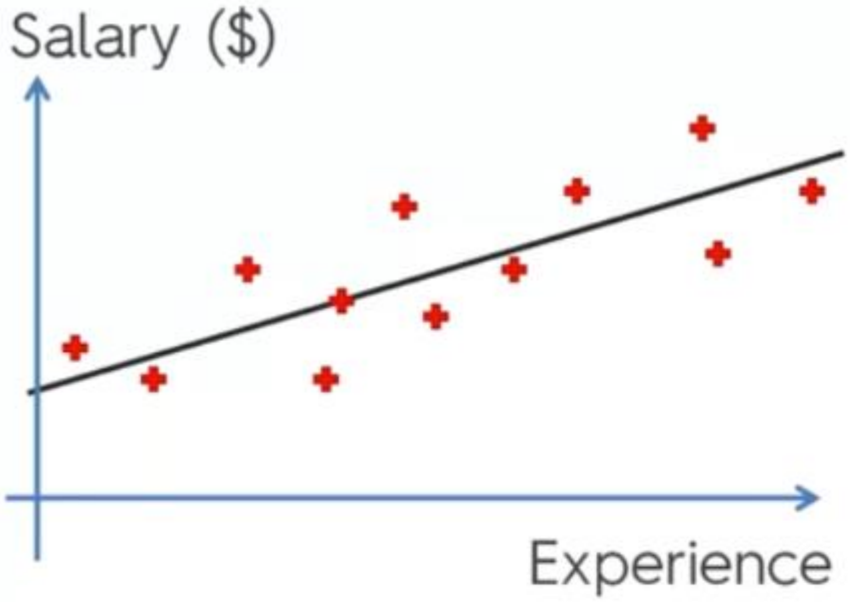
$$y = b_0 + b_1 * x_1$$

Dependent variable (DV)

Independent variable (IV)

Regressions

Simple Linear Regression:



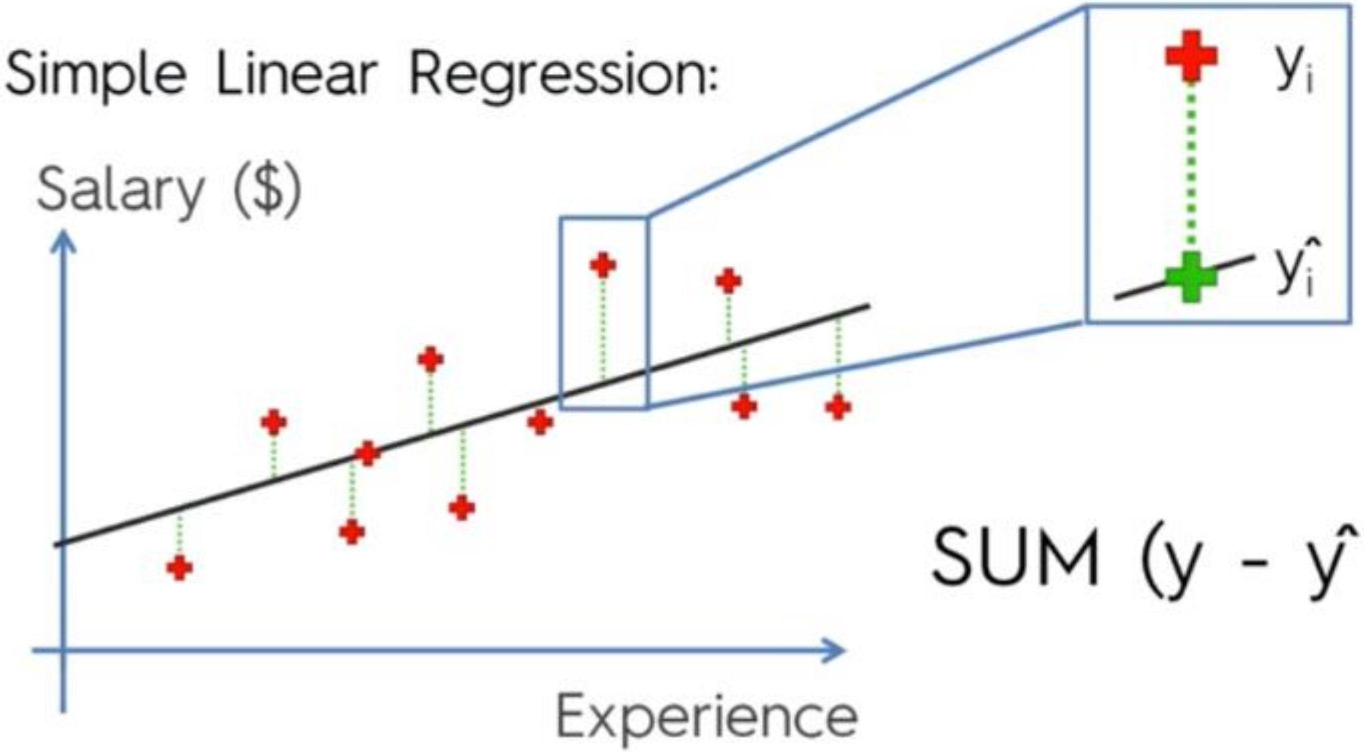
$$y = b_0 + b_1 * x$$

$$\downarrow$$

$$Salary = b_0 + b_1 * Experience$$

Ordinary Least Squares

Simple Linear Regression:



SUM $(y - \hat{y})^2$ -> min

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MULTIPLE LINEAR REGRESSION

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Regressions

Simple Linear Regression

$$y = b_0 + b_1 {*} x_1$$

Multiple Linear Regression

Dependent variable (DV)   Independent variables (IVs)

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

Constant

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Dummy Variables

Profit	R&D Spend	Admin	Marketing	State
192,261.83	165,349.20	136,897.80	471,784.10	New York
191,792.06	162,597.70	151,377.59	443,898.53	California
191,050.39	153,441.51	101,145.55	407,934.54	California
182,901.99	144,372.41	118,671.85	383,199.62	New York
166,187.94	142,107.34	91,391.77	366,168.42	California

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Dummy Variables

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192,261.83	165,349.20	136,897.80	471,784.10	New York
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182,901.99	144,372.41	118,671.85	383,199.62	New York
166,187.94	142,107.34	91,391.77	366,168.42	California

$$y = b_0 + b_1{}^*x_1 + b_2{}^*x_2 + b_3{}^*x_3 + \text{???}$$

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Dummy Variables

Dummy Variables

Profit	R&D Spend	Admin	Marketing	~~State~~	New York	California
192,261.83	165,349.20	136,897.80	471,784.10	~~New York~~	1	0
191,792.06	162,597.70	151,377.59	443,898.53	~~California~~	0	1
191,050.39	153,441.51	101,145.55	407,934.54	~~California~~	0	1
182,901.99	144,372.41	118,671.85	383,199.62	~~New York~~	1	0
166,187.94	142,107.34	91,391.77	366,168.42	~~California~~	0	1

$$y = b_0 + b_1{}^*x_1 + b_2{}^*x_2 + b_3{}^*x_3 + ??? + b_4{}^*D_1$$

Dummy Variable Trap

Profit	R&D Spend	Admin	Marketing	State
192,261.83	165,349.20	136,897.80	471,784.10	New York
191,792.06	162,597.70	151,377.59	443,898.53	California
191,050.39	153,441.51	101,145.55	407,934.54	California
182,901.99	144,372.41	118,671.85	383,199.62	New York
166,187.94	142,107.34	91,391.77	366,168.42	California

Dummy Variables

New York	California
1	0
0	1
0	1
1	0
0	1

$$y = b_0 + b_1{*}x_1 + b_2{*}x_2 + b_3{*}x_3 + b_4{*}D_1 + \cancel{b_5{*}D_2}$$

Always omit one dummy variable

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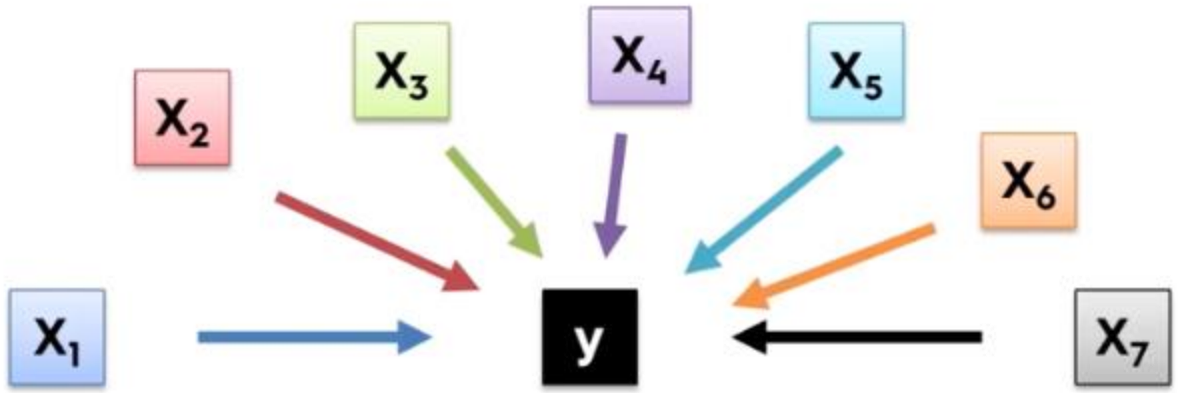
Building A Model



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Building A Model

5 methods of building models:

1. All-in
2. Backward Elimination
3. Forward Selection
4. Bidirectional Elimination
5. Score Comparison

Stepwise Regression

Building A Model

Backward Elimination

STEP 1: Select a significance level to stay in the model (e.g. SL = 0.05)

STEP 2: Fit the full model with all possible predictors

STEP 3: Consider the predictor with the <u>highest</u> P-value. If P > SL, go to STEP 4, otherwise go to FIN

STEP 4: Remove the predictor

STEP 5: Fit model without this variable*

Building A Model

Forward Selection

STEP 1: Select a significance level to enter the model (e.g. SL = 0.05)

STEP 2: Fit all simple regression models $\mathbf{y} \sim \mathbf{x_n}$ Select the one with the lowest P-value

STEP 3: Keep this variable and fit all possible models with one extra predictor added to the one(s) you already have

STEP 4: Consider the predictor with the lowest P-value. If P < SL, go to STEP 3, otherwise go to FIN

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Building A Model

Forward Selection

STEP 1: Select a significance level to enter the model (e.g. SL = 0.05)

STEP 2: Fit all simple regression models **$y \sim x_n$** Select the one with the lowest P-value

STEP 3: Keep this variable and fit all possible models with one extra predictor added to the one(s) you already have

STEP 4: Consider the predictor with the <u>lowest</u> P-value. If ~~P < SL~~, go to STEP 3, otherwise go to FIN

FIN: Keep the previous model

Building A Model

Bidirectional Elimination

STEP 1: Select a significance level to enter and to stay in the model
e.g.: SLENTER = 0.05, SLSTAY = 0.05

STEP 2: Perform the next step of Forward Selection (new variables must have: P < SLENTER to enter)

STEP 3: Perform ALL steps of Backward Elimination (old variables must have P < SLSTAY to stay)

STEP 4: No new variables can enter and no old variables can exit

FIN: Your Model Is Ready

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POLYNOMIAL REGRESSION

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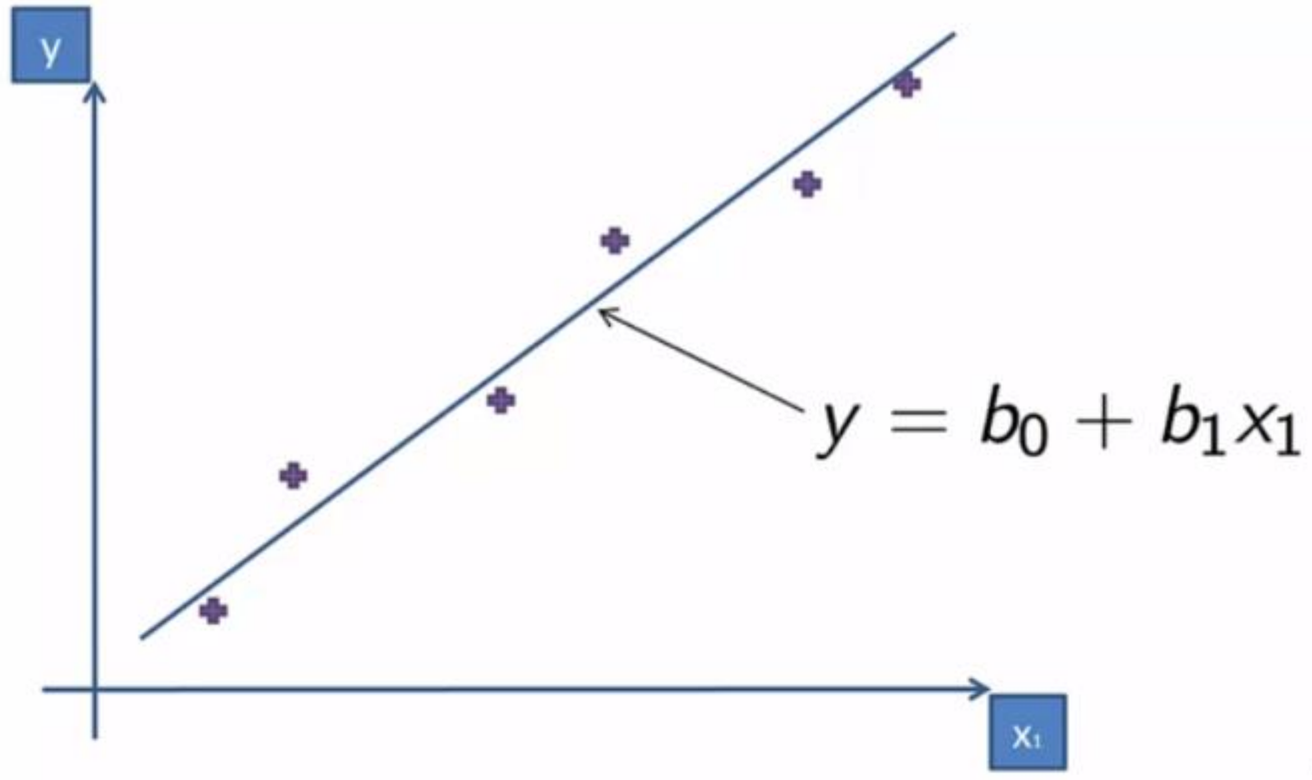
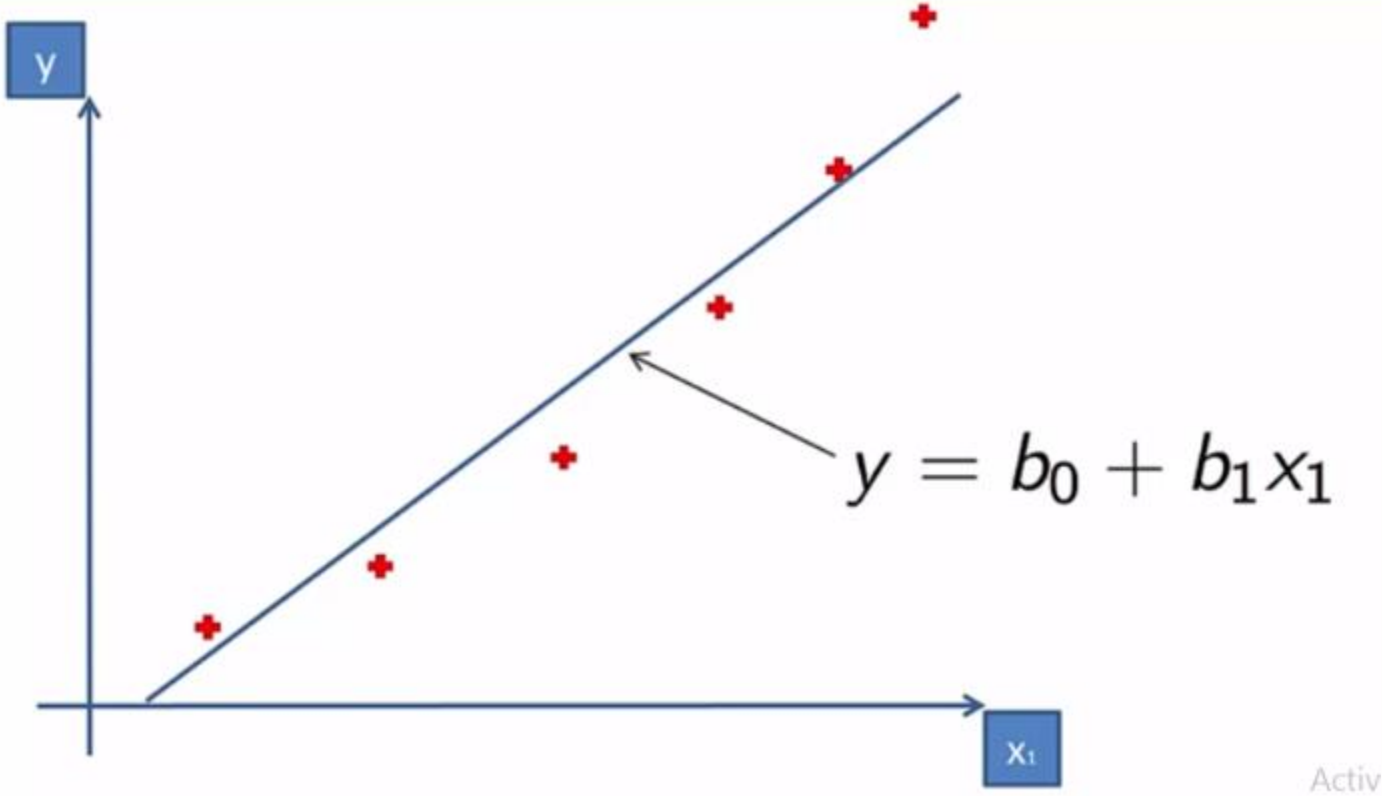
Regressions

Simple Linear Regression	$y = b_0 + b_1 x_1$
Multiple Linear Regression	$y = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_n x_n$
Polynomial Linear Regression	$y = b_0 + b_1 x_1 + b_2 x_1^2 + \ldots + b_n x_1^n$

Simple Linear Regression



Simple Linear Regression



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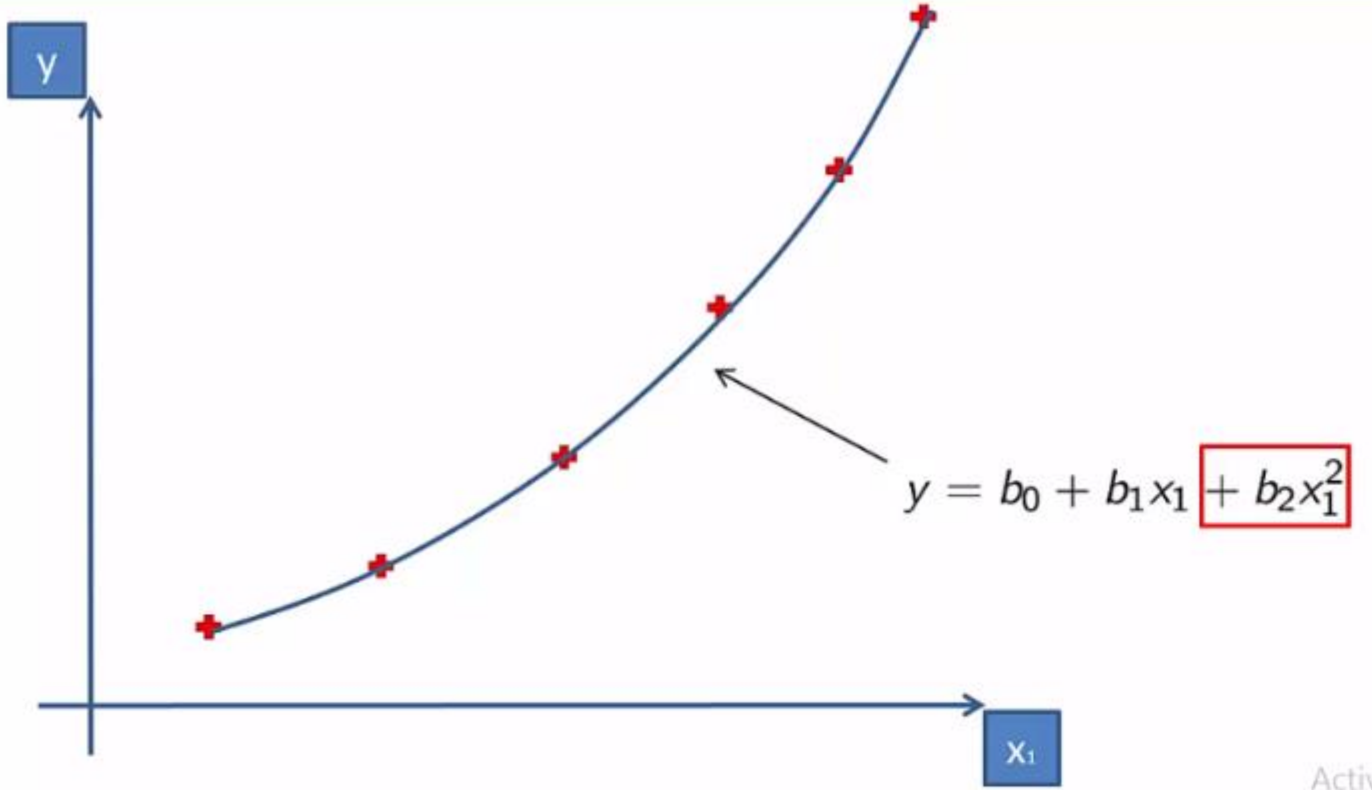
Polinomial Regression



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SVR

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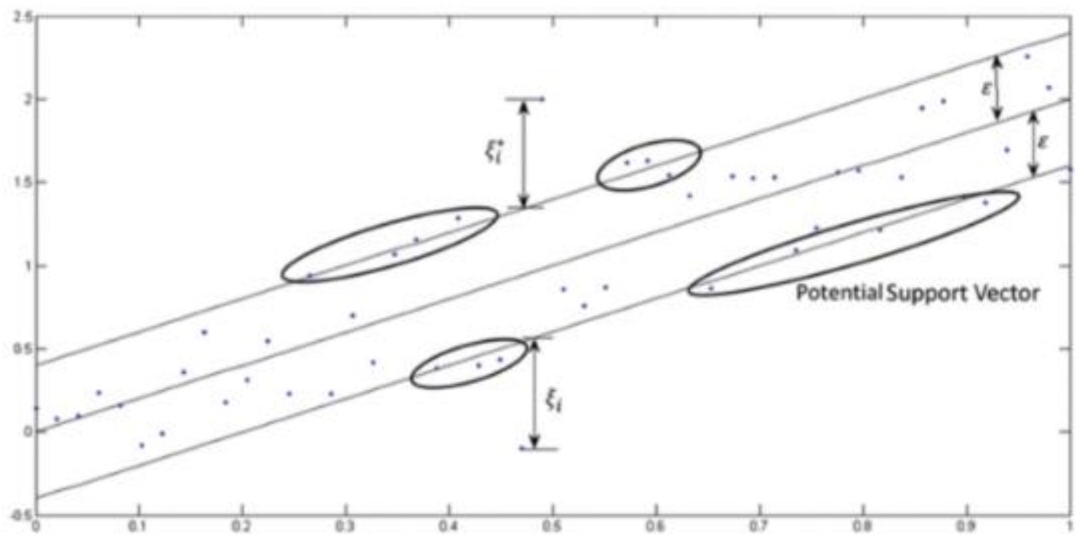
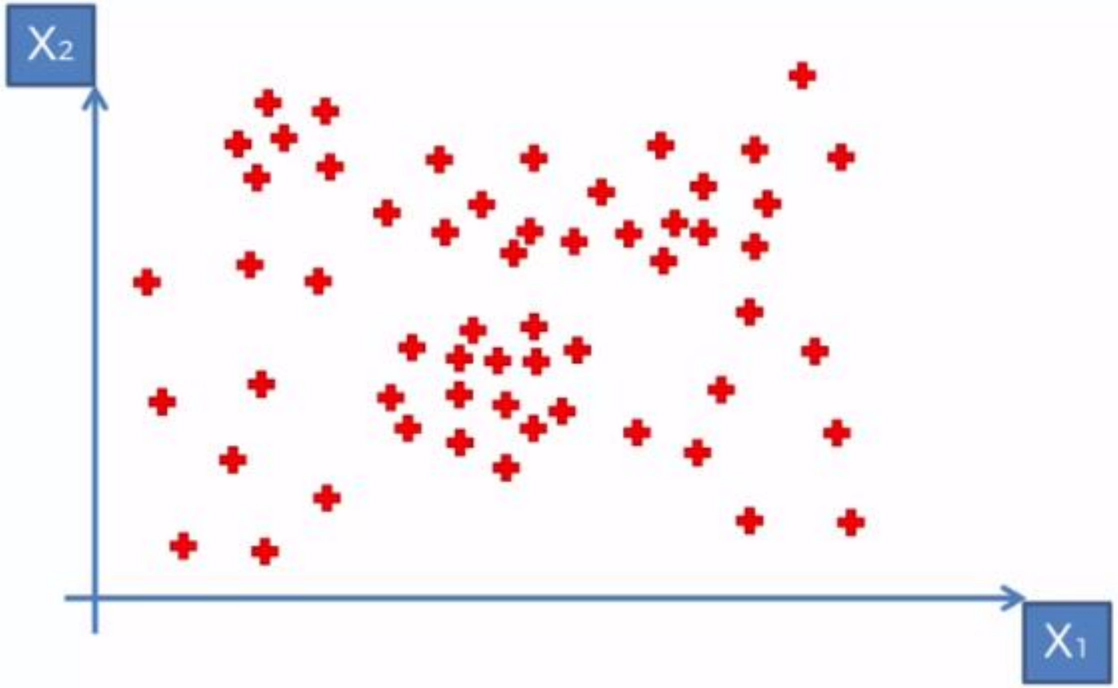
Support Vector Regression - SVR



DECISION TREE REGRESSION

Decision Tree Intuition



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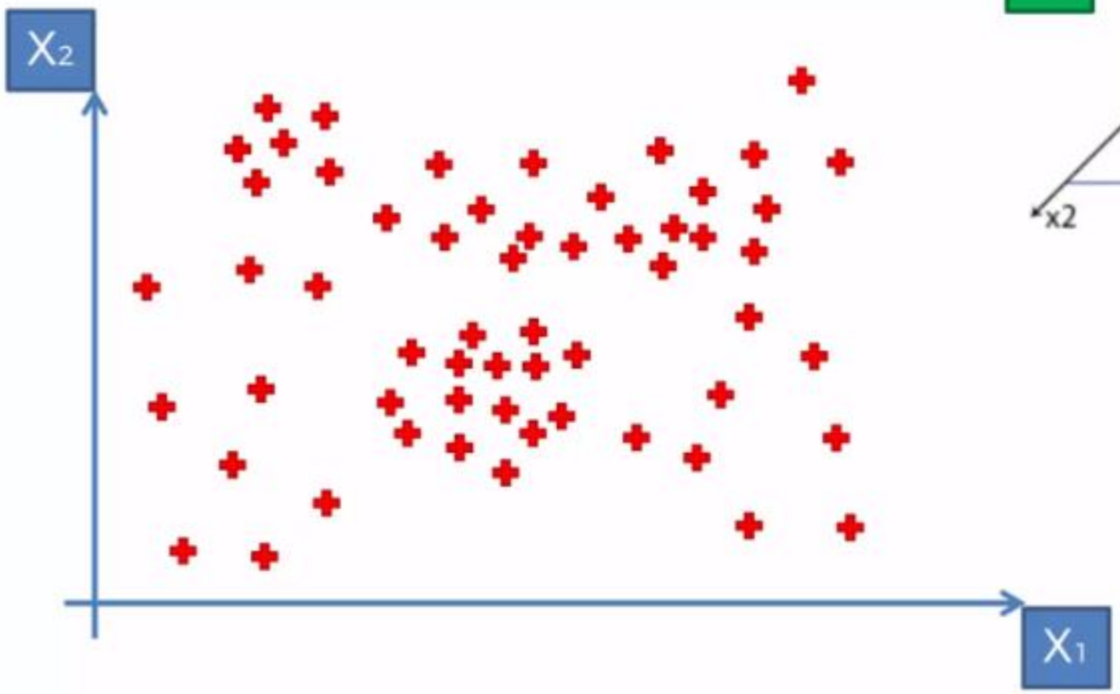
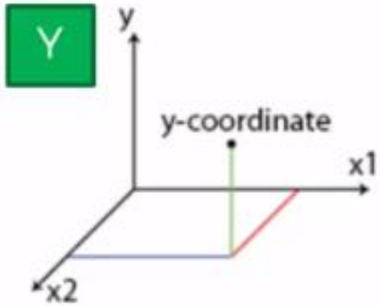
Decision Tree Intuition





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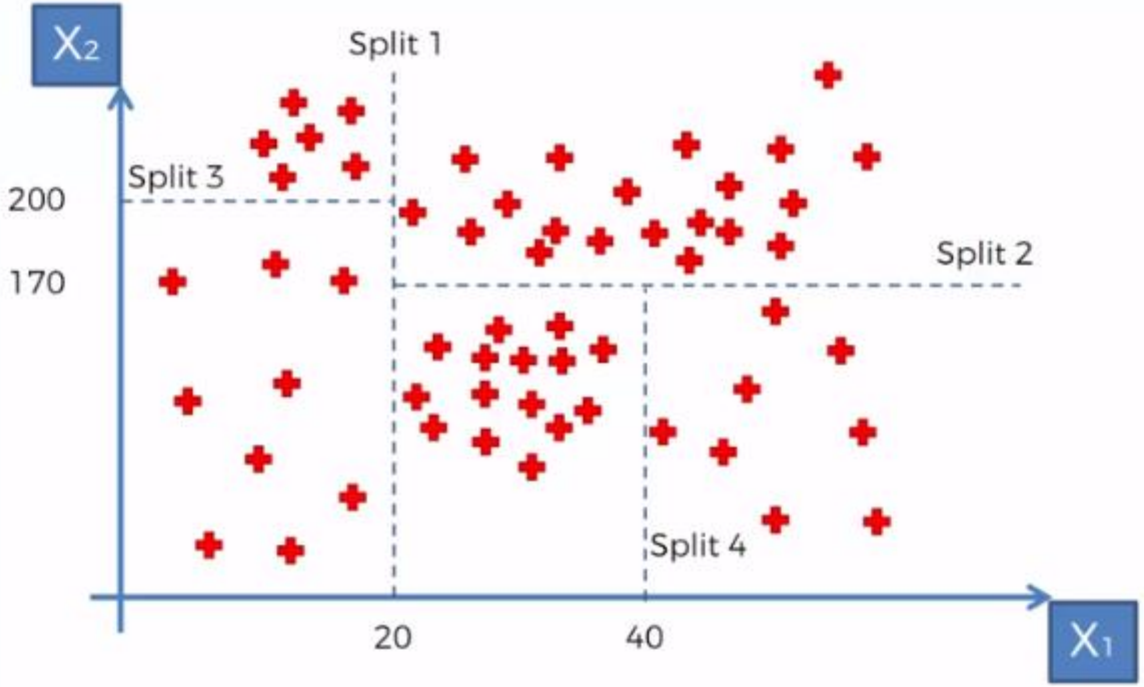
Decision Tree Intuition



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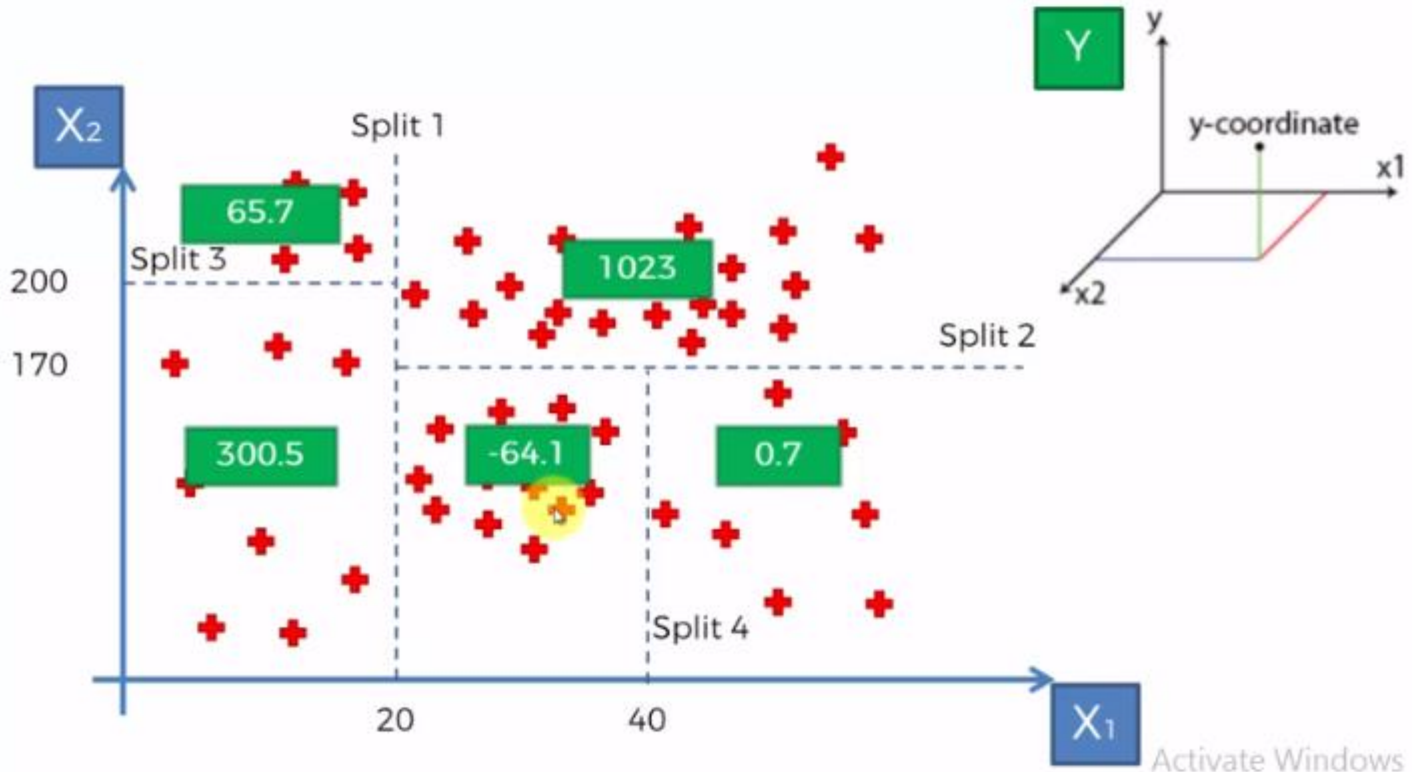
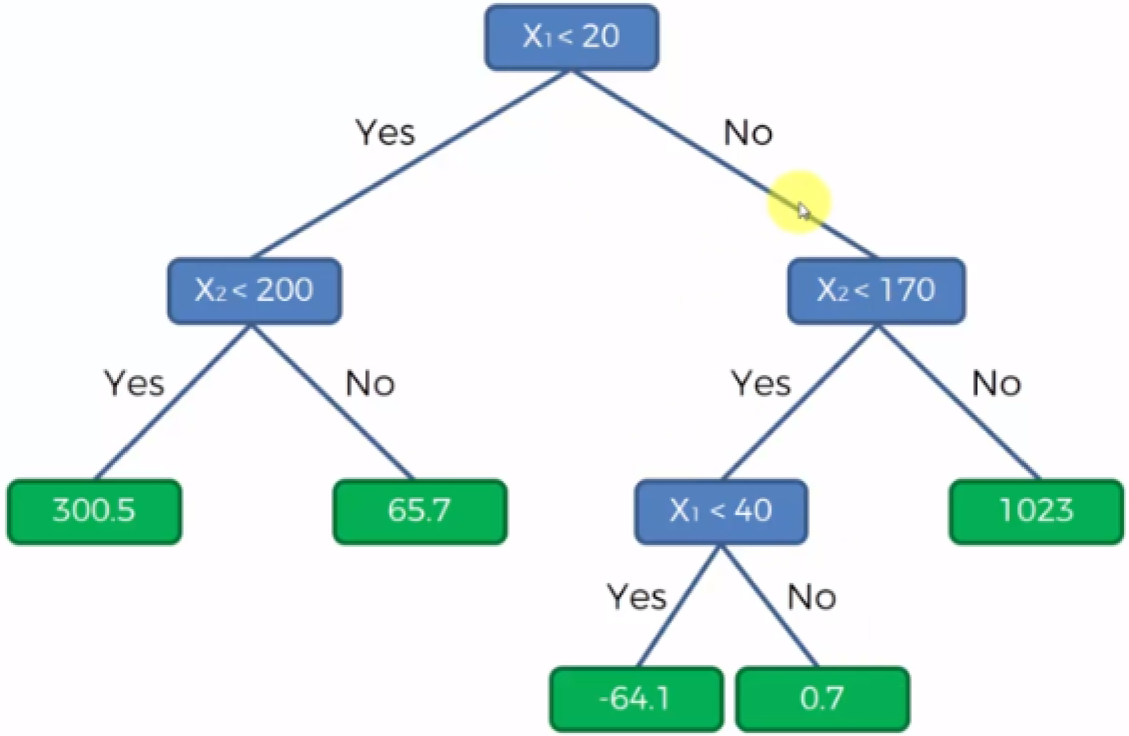
Decision Tree Intuition



Decision Tree Intuition



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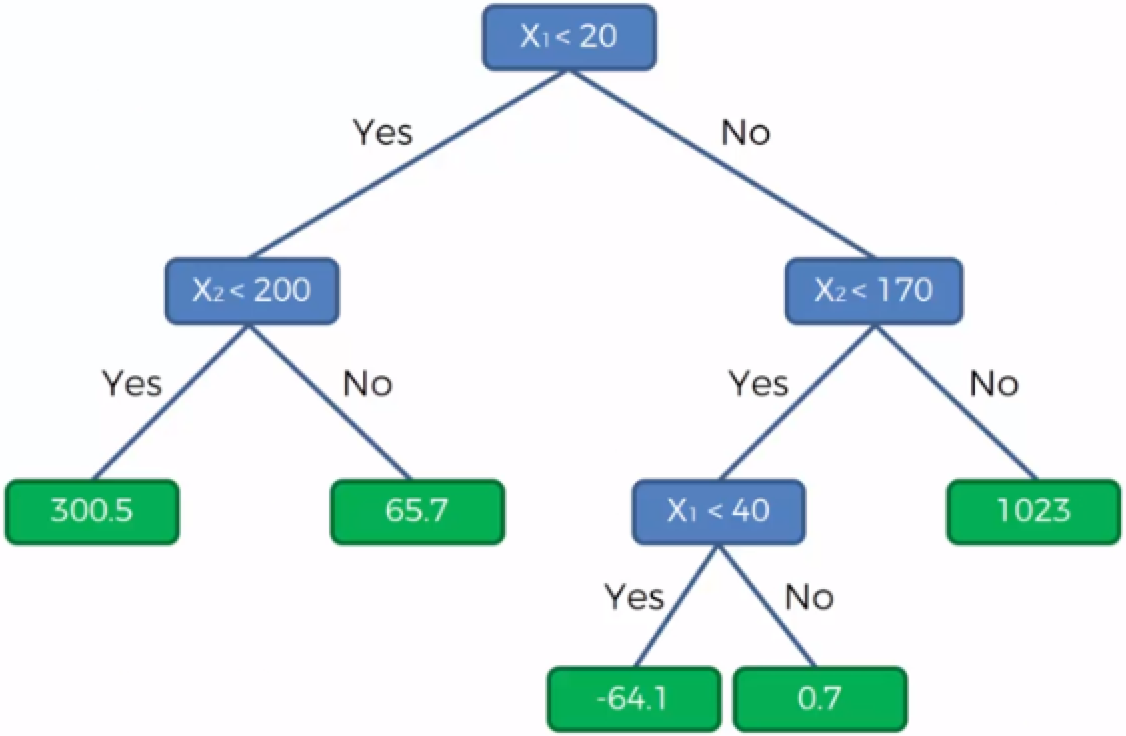
Decision Tree Intuition



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RANDOM FOREST REGRESSION

Random Forest Intuition

STEP 1: Pick at random K data points from the Training set.

⇩

STEP 2: Build the Decision Tree associated to these K data points.

⇩

STEP 3: Choose the number Ntree of trees you want to build and repeat STEPS 1 & 2

⇩

STEP 4: For a new data point, make each one of your Ntree trees predict the value of Y to for the data point in question, and assign the new data point the average across all of the predicted Y values.

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Random Forest Intuition

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APRIORI

ARL - What is it all about ?

ARL - What is it all about ?

People who bought also bought …

ARL - Movie Recommendation

User ID	Movies liked
46578	Movie1, Movie2, Movie3, Movie4
98989	Movie1, Movie2
71527	Movie1, Movie2, Movie4
78981	Movie1, Movie2
89192	Movie2, Movie4
61557	Movie1, Movie3

Potential Rules:

Movie1 → Movie2

Movie2 → Movie4

Movie1 → Movie3

ARL - Market Basket Optimisation

Transaction ID	Products purchased
46578	Burgers, French Fries, Vegetables
98989	Burgers, French Fries, Ketchup
71527	Vegetables, Fruits
78981	Pasta, Fruits, Butter, Vegetables
89192	Burgers, Pasta, French Fries
61557	Fruits, Orange Juice, Vegetables
87923	Burgers, French Fries, Ketchup, Mayo

Potential Rules:

Burgers ⇒ French Fries

Vegetables ⇒ Fruits

Burgers, French Fries ⇒ Ketchup

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Apriori - Support

Movie Recommendation: $$\text{support}(\boldsymbol{M}) = \frac{\#\ \text{user watchlists containing } \boldsymbol{M}}{\#\ \text{user watchlists}}$$

Market Basket Optimisation: $$\text{support}(\boldsymbol{I}) = \frac{\#\ \text{transactions containing } \boldsymbol{I}}{\#\ \text{transactions}}$$

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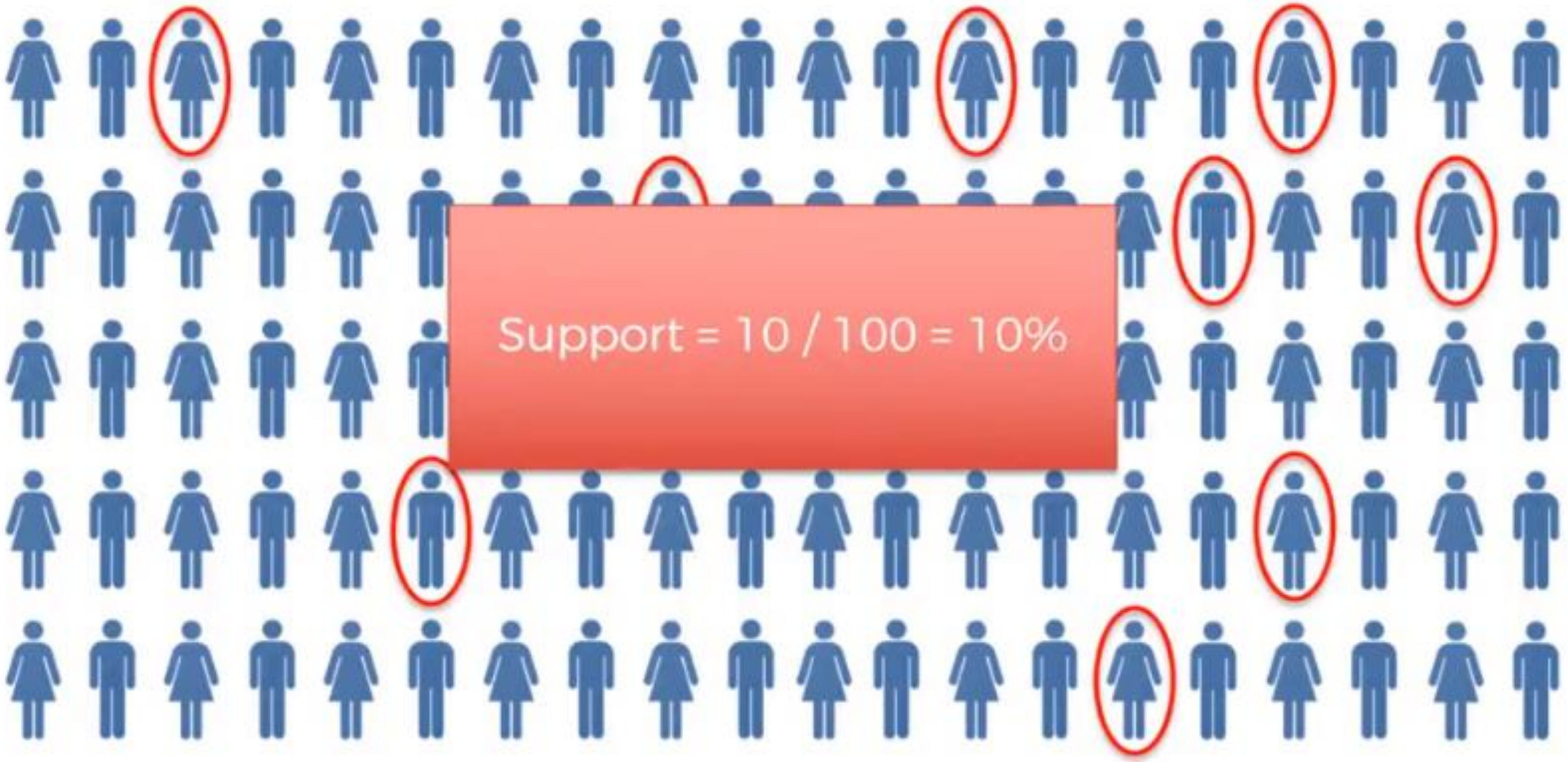
Apriori - Support



Apriori - Confidence

Movie Recommendation: $$\text{confidence}(M_1 \rightarrow M_2) = \frac{\#\text{ user watchlists containing } M_1 \text{ and } M_2}{\#\text{ user watchlists containing } M_1}$$

Market Basket Optimisation: $$\text{confidence}(I_1 \rightarrow I_2) = \frac{\#\text{ transactions containing } I_1 \text{ and } I_2}{\#\text{ transactions containing } I_1}$$

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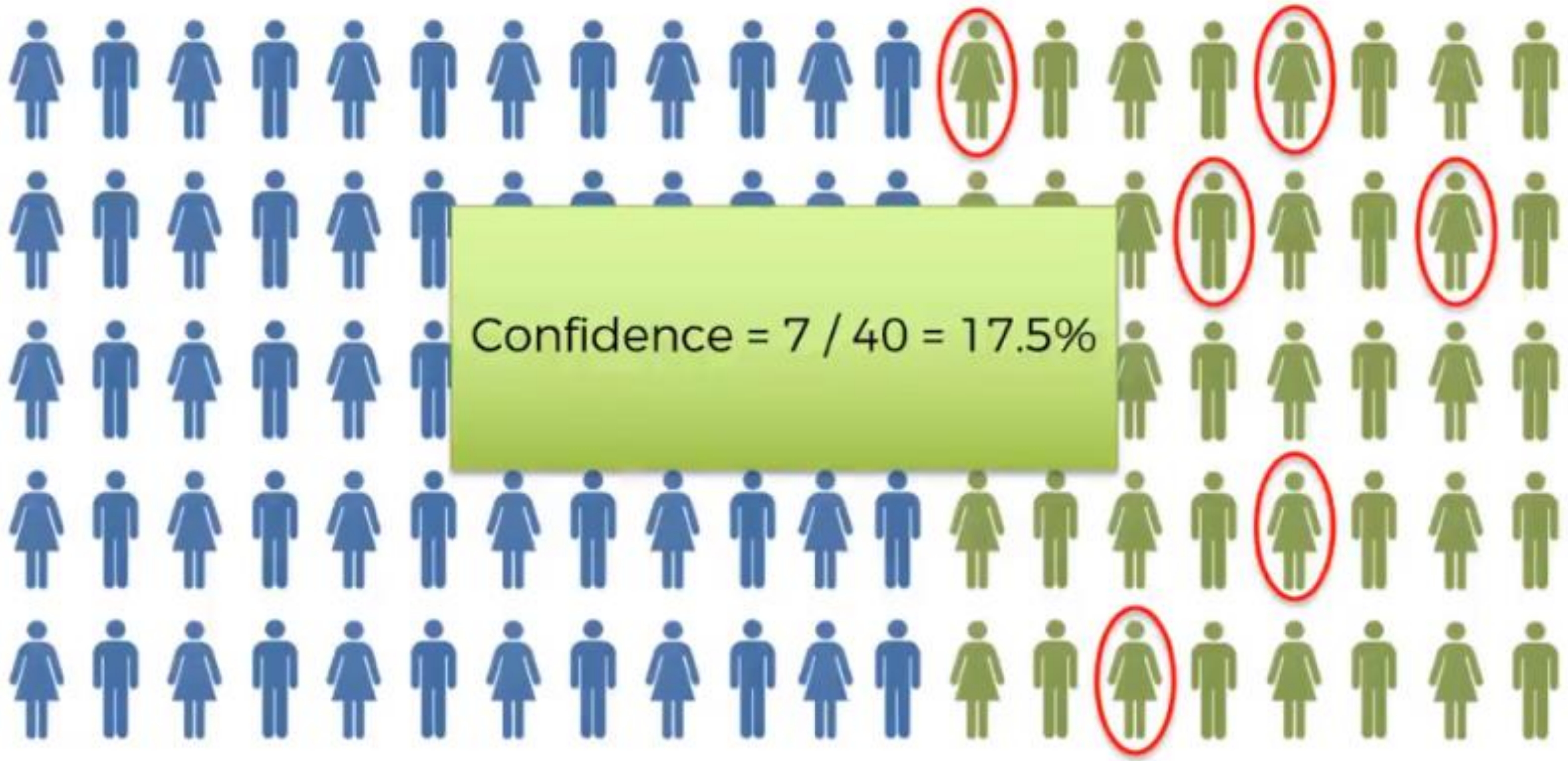
Apriori - Confidence

Apriori - Confidence



Apriori - Lift

Movie Recommendation: $$\text{lift}(M_1 \rightarrow M_2) = \frac{\text{confidence}(M_1 \rightarrow M_2)}{\text{support}(M_2)}$$

Market Basket Optimisation: $$\text{lift}(I_1 \rightarrow I_2) = \frac{\text{confidence}(I_1 \rightarrow I_2)}{\text{support}(I_2)}$$

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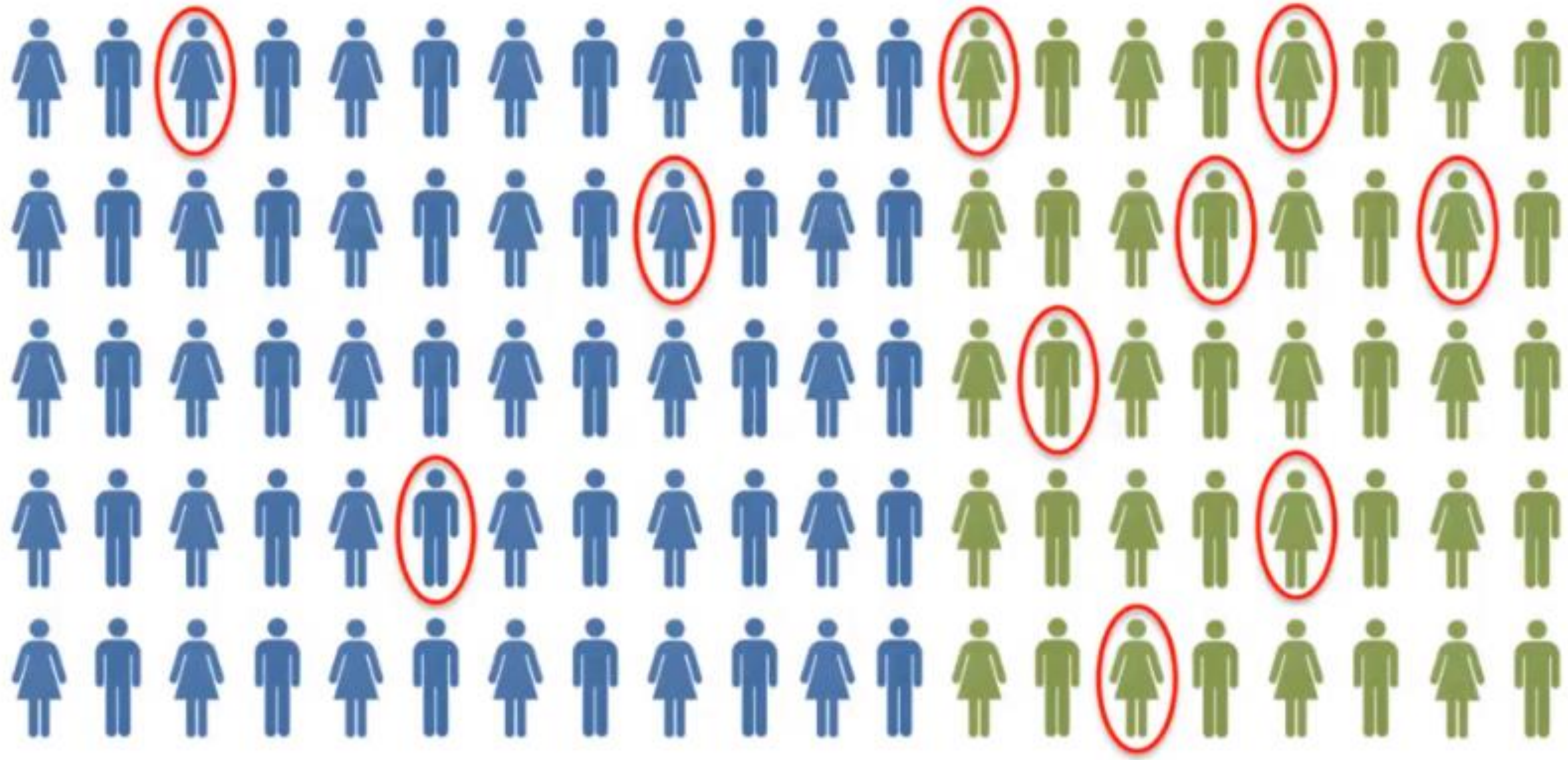
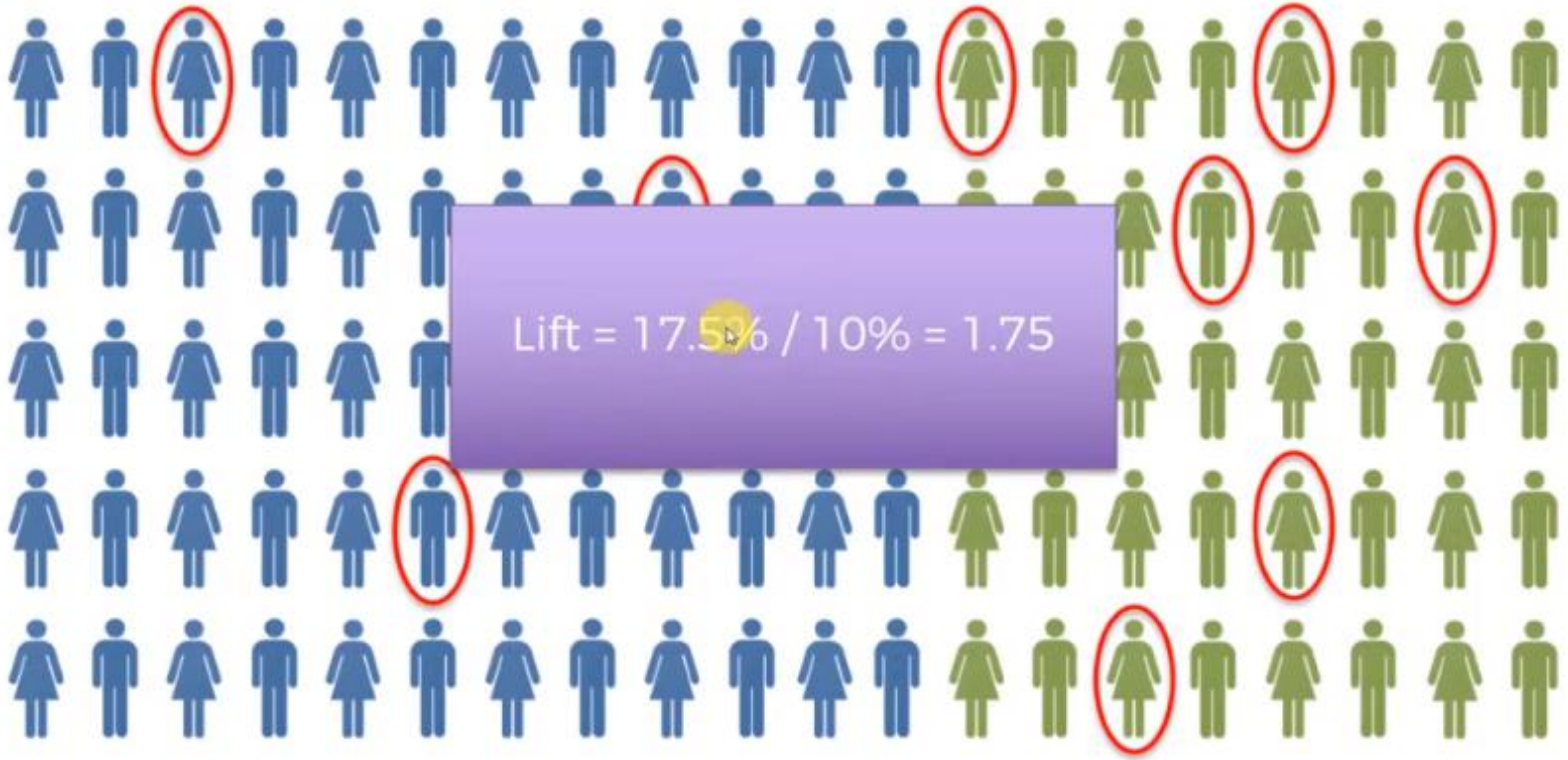
Apriori - Lift



Apriori - Lift



Apriori - Algorithm

Step 1: Set a minimum support and confidence

↓

Step 2: Take all the subsets in transactions having higher support than minimum support

↓

Step 3: Take all the rules of these subsets having higher confidence than minimum confidence

↓

Step 4: Sort the rules by decreasing lift

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ARL - Movie Recommendation

User ID	Movies liked
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89192	Movie2, Movie4
61557	Movie1, Movie3

Potential Rules:

Movie1 ⇒ Movie2

Movie2 ⇒ Movie4

Movie1 ⇒ Movie3

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ARL - Market Basket Optimisation

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Potential Rules:

Burgers ⇒ French Fries

Vegetables ⇒ Fruits

Burgers, French Fries ⇒ Ketchup

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ECLAT

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Eclat - Support

Movie Recommendation: $$\text{support}(\boldsymbol{M}) = \frac{\#\text{ user watchlists containing } \boldsymbol{M}}{\#\text{ user watchlists}}$$

Market Basket Optimisation: $$\text{support}(\boldsymbol{I}) = \frac{\#\text{ transactions containing } \boldsymbol{I}}{\#\text{ transactions}}$$

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Eclat - Algorithm

Step 1: Set a minimum support

↓

Step 2: Take all the subsets in transactions having higher support than minimum support

↓

Step 3: Sort these subsets by decreasing support

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LOGISTIC REGRESSION

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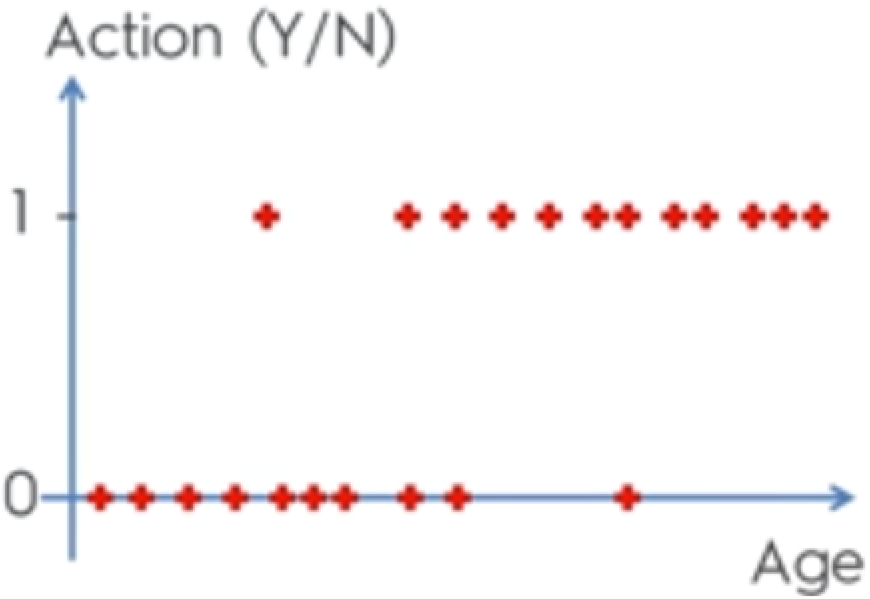
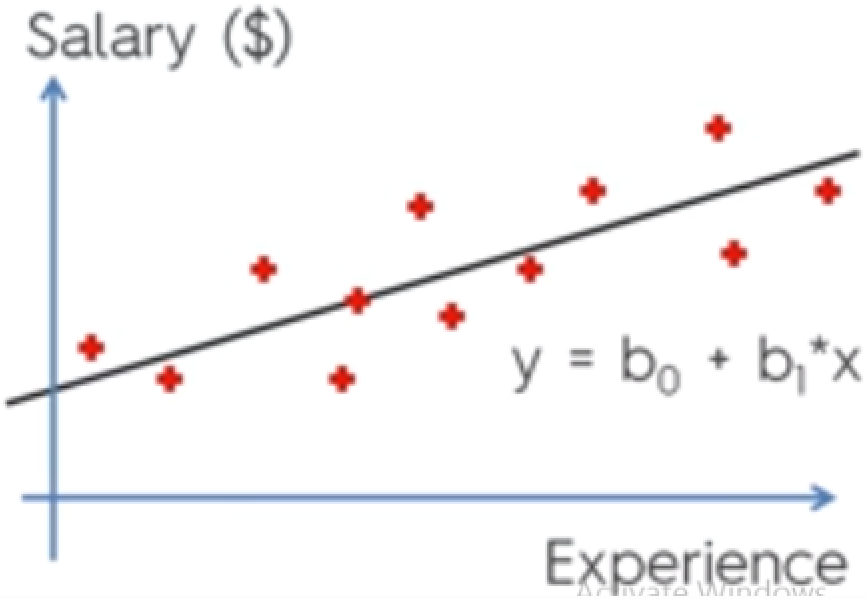
Logistic Regression

This is new:



We know this:



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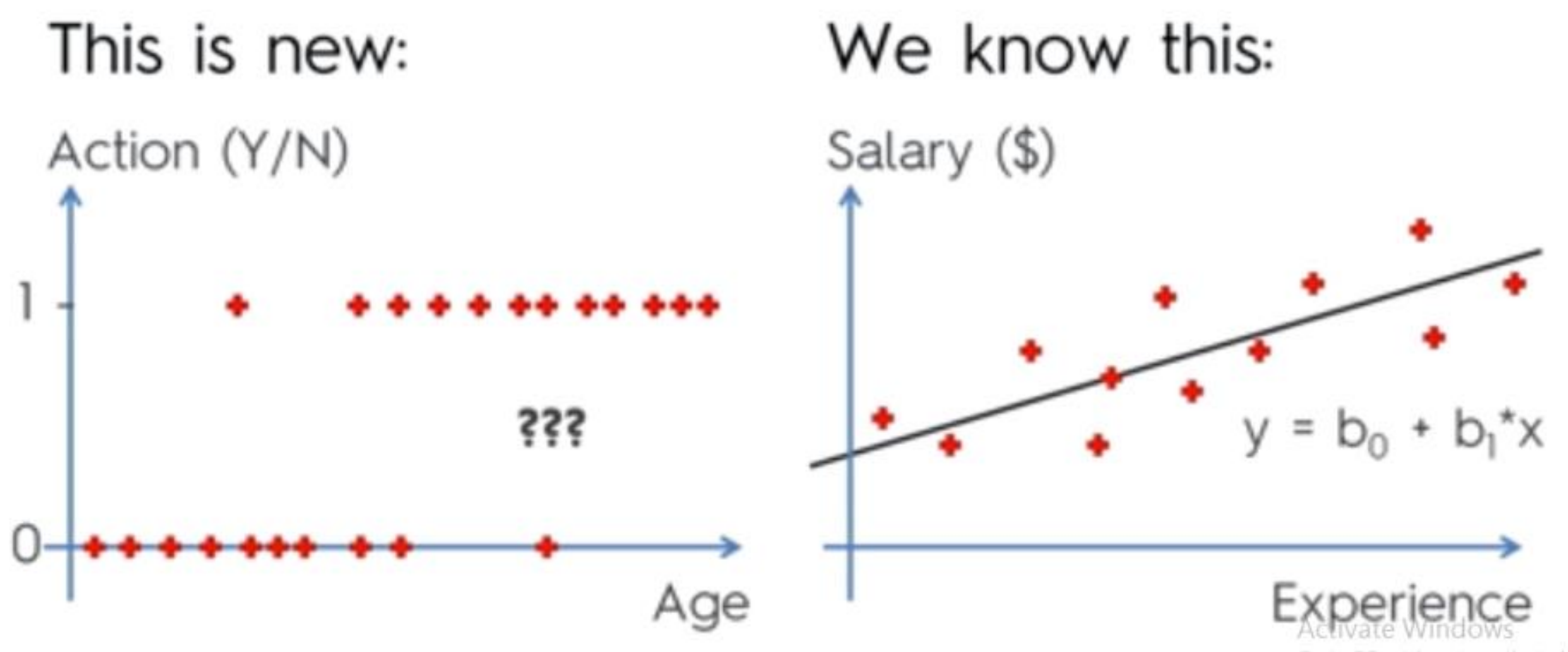
Logistic Regression



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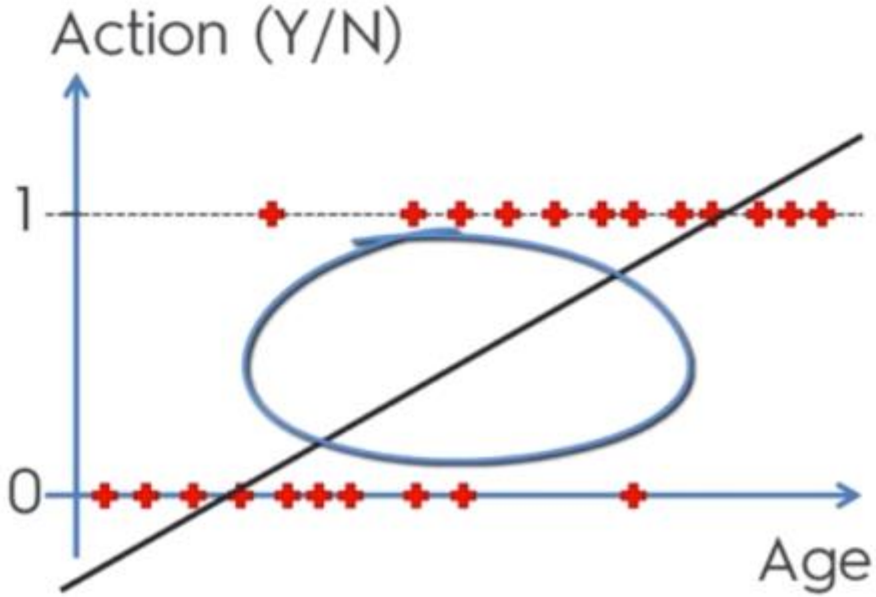
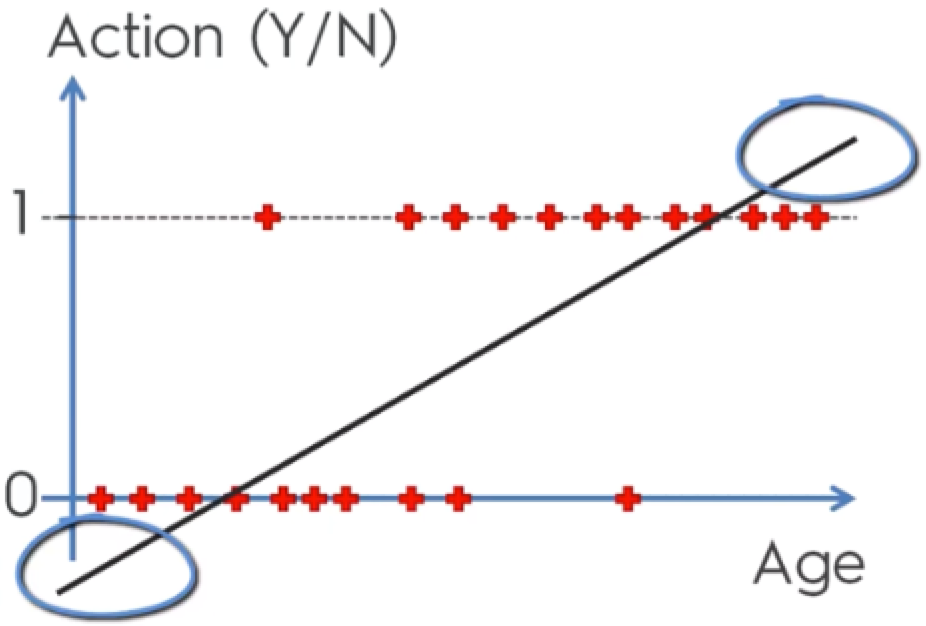
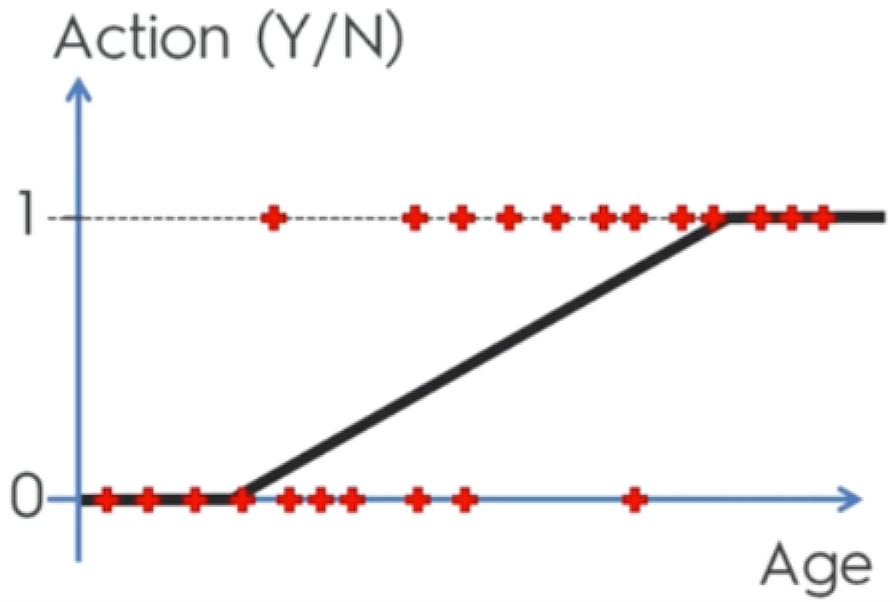
Logistic Regression



Logistic Regression



Logistic Regression



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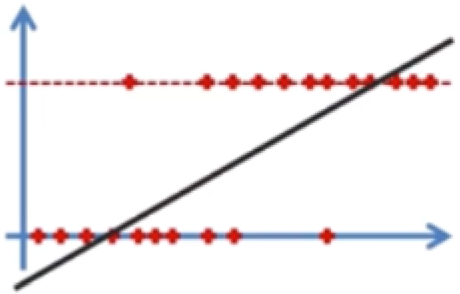
Logistic Regression

$$y = b_0 + b_1{}^{*}x$$

Sigmoid Function

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

$$\ln\left(\frac{p}{1-p}\right) = b_0 + b_1{}^{*}x$$



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Logistic Regression

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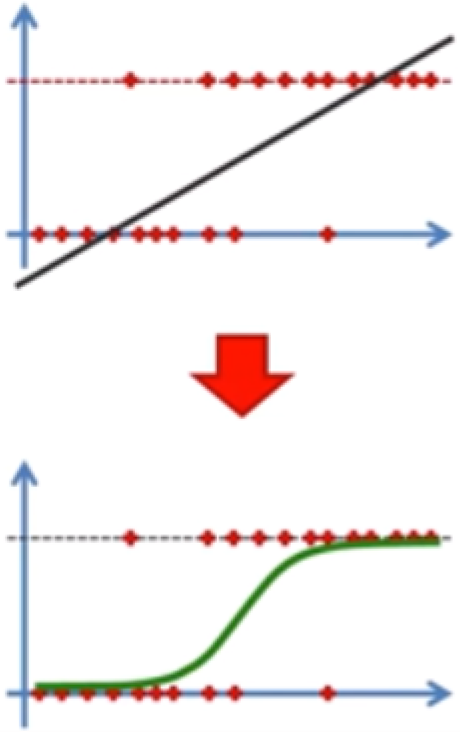
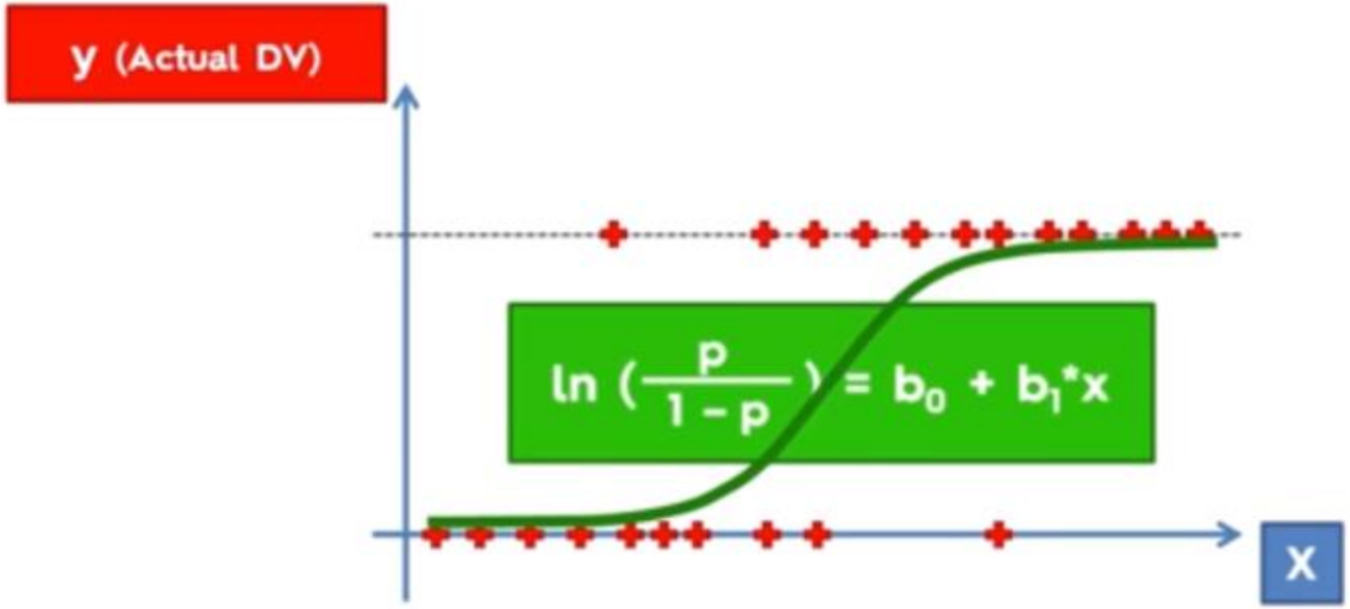
Sigmoid Function

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

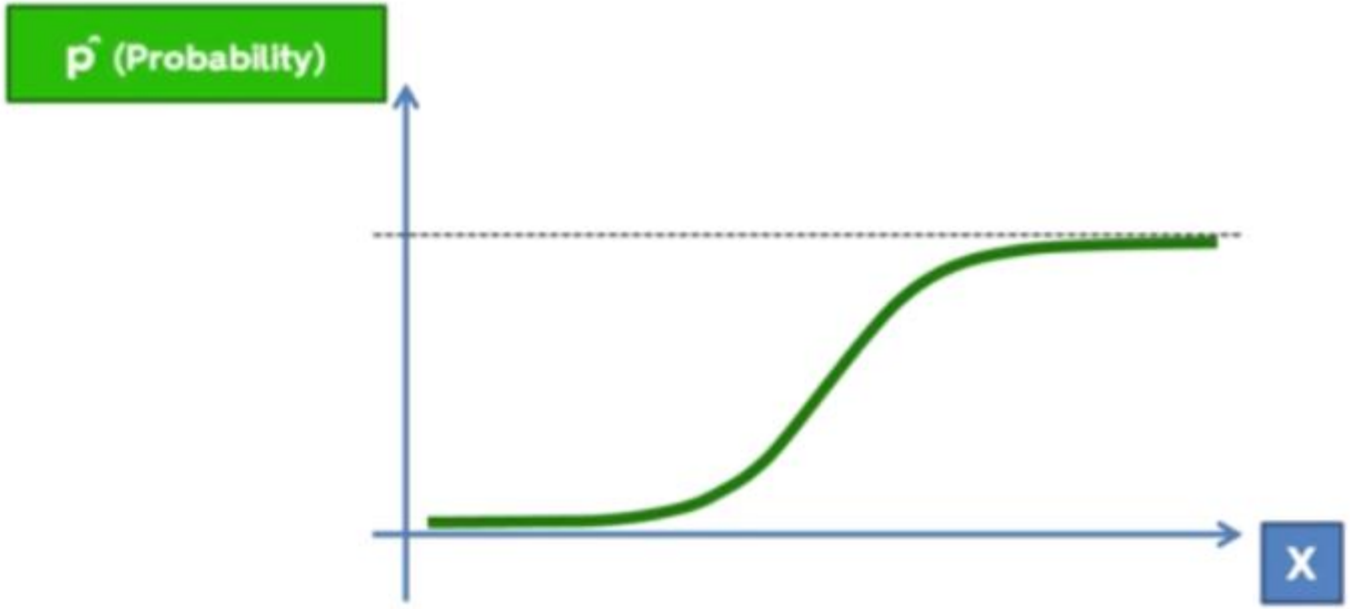
$$\ln\left(\frac{p}{1-p}\right) = b_0 + b_1{}^*x$$



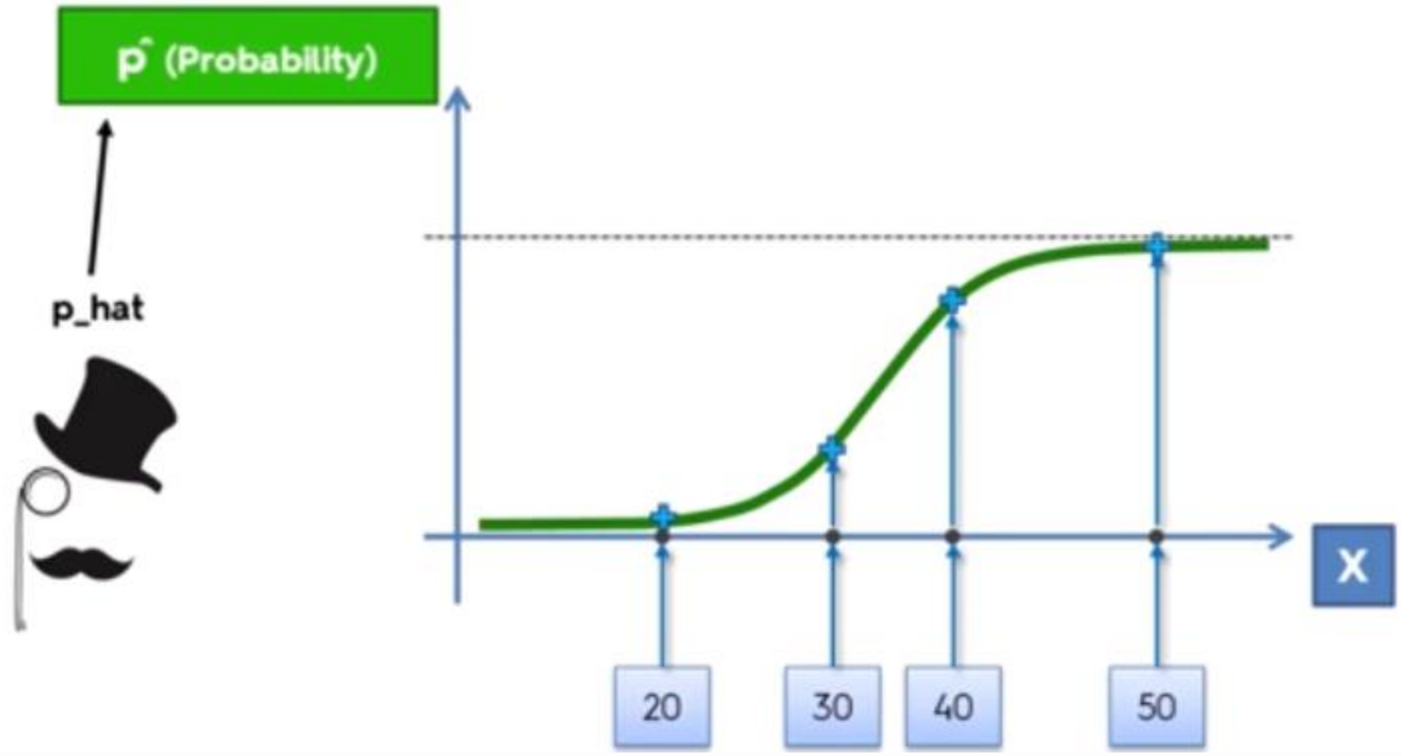
Logistic Regression



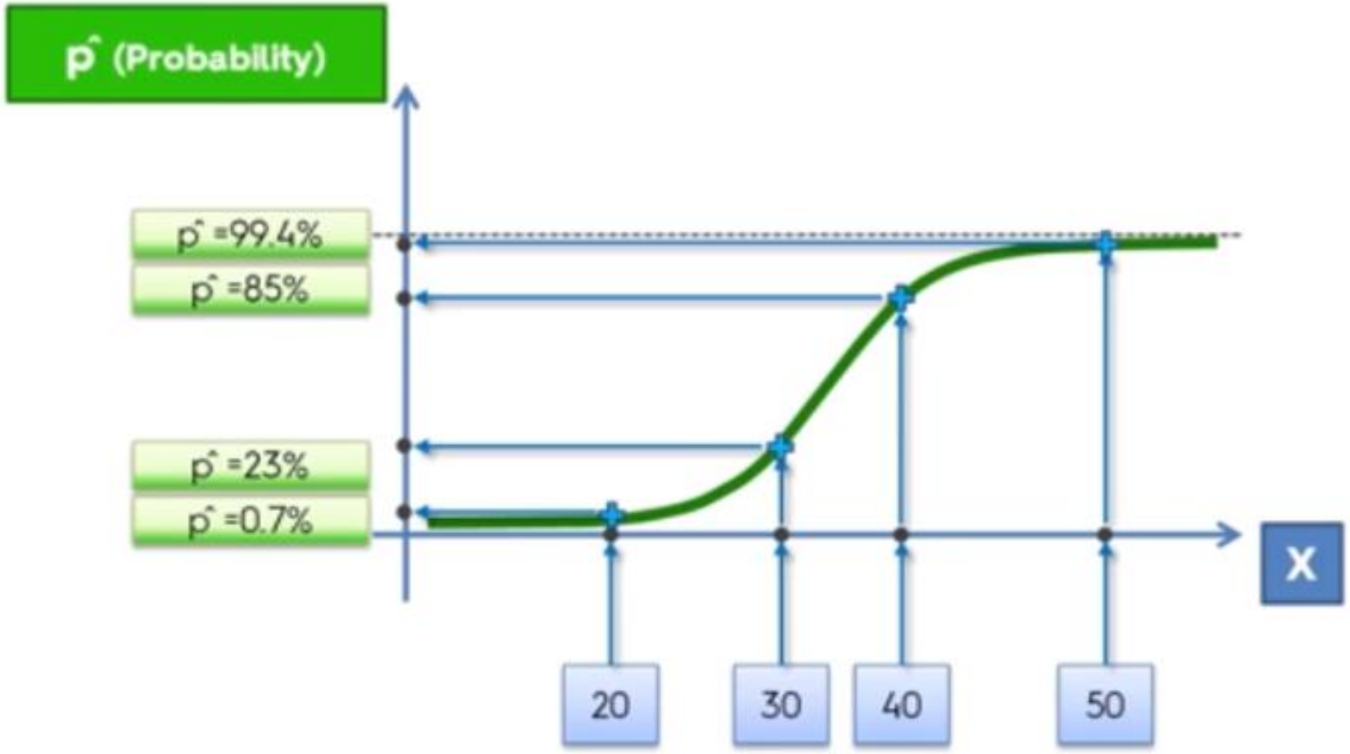
Logistic Regression



Logistic Regression



Logistic Regression



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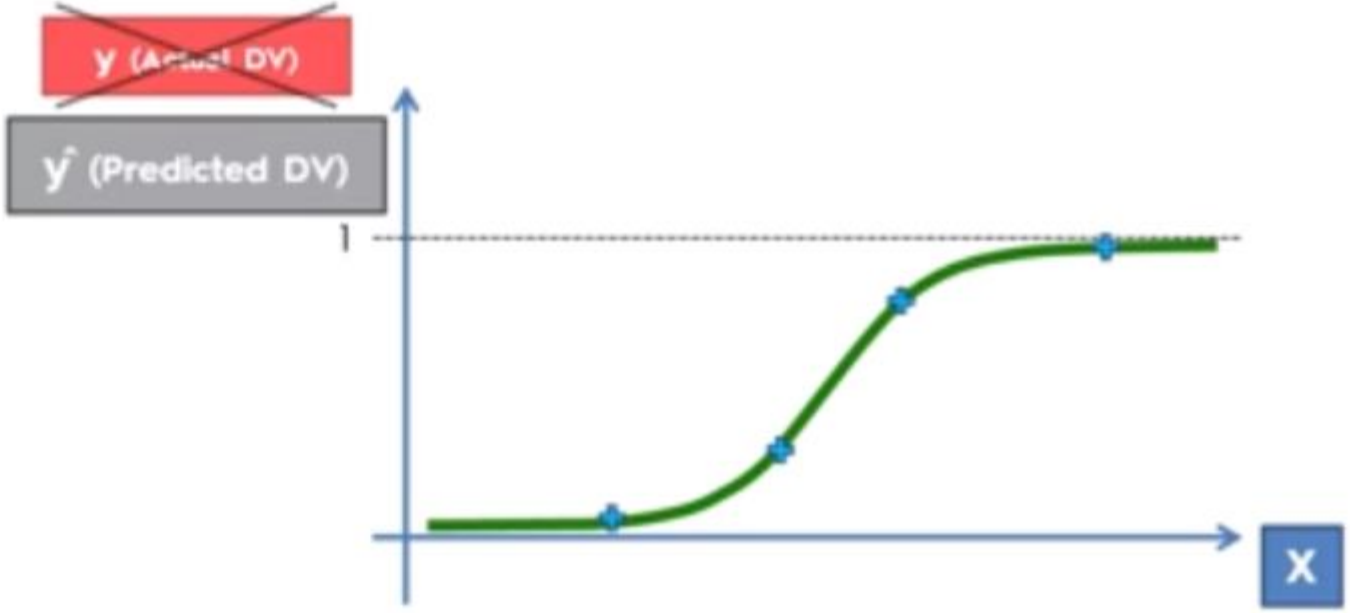
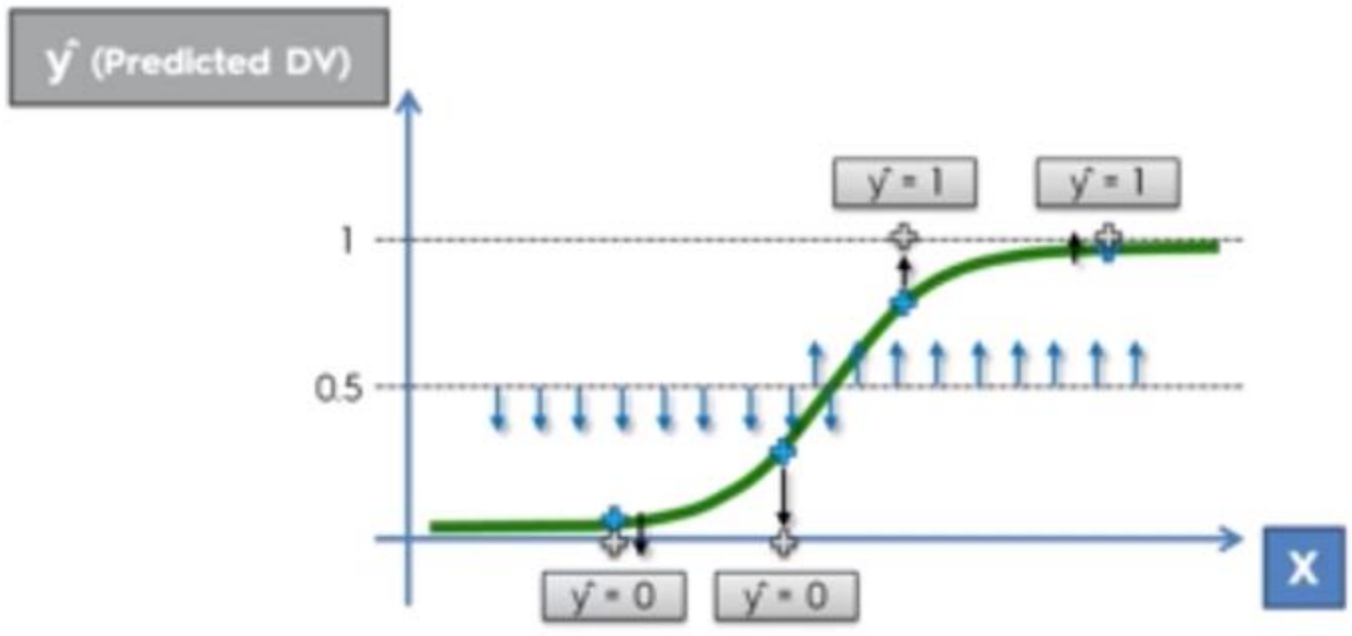
Logistic Regression

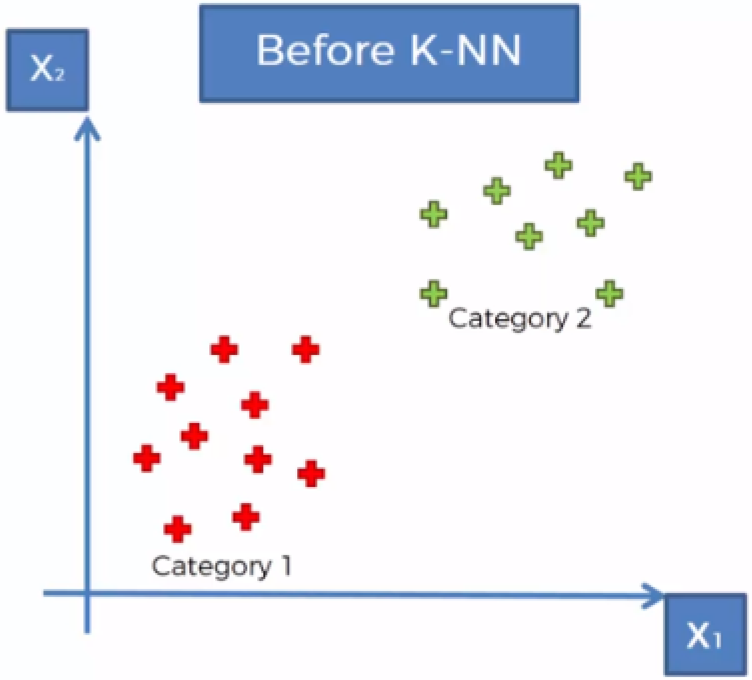


Logistic Regression

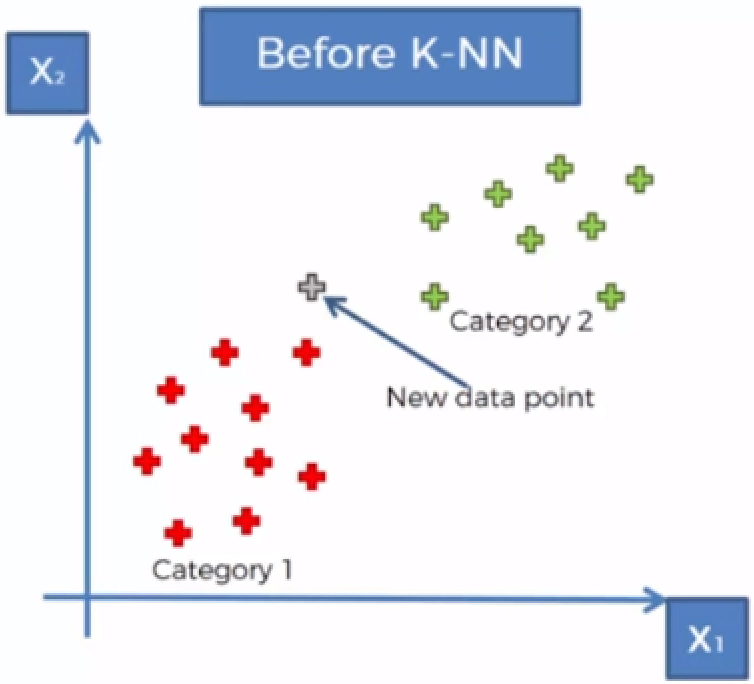


K-NN

What K-NN does for you



What K-NN does for you



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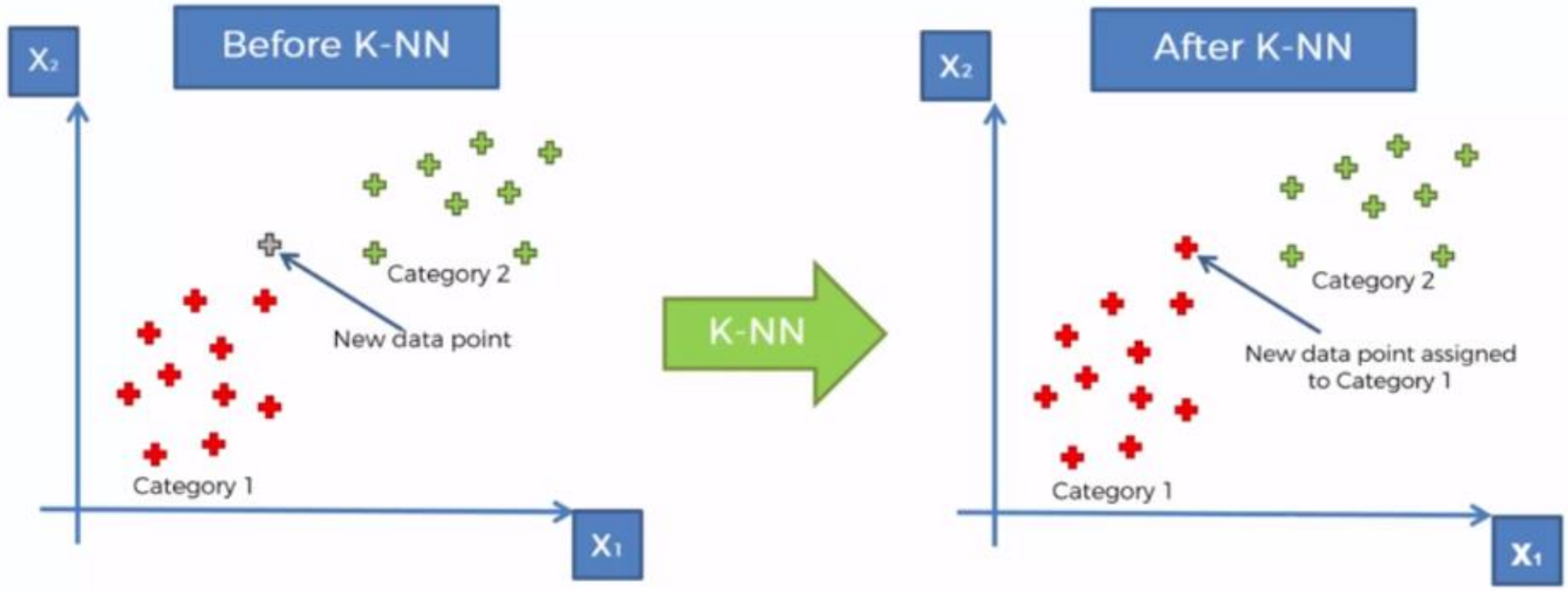
What K-NN does for you



How did it do that ?

STEP 1: Choose the number K of neighbors

⇩

STEP 2: Take the K nearest neighbors of the new data point, according to the Euclidean distance

⇩

STEP 3: Among these K neighbors, count the number of data points in each category

⇩

STEP 4: Assign the new data point to the category where you counted the most neighbors

⇩

Your Model is Ready

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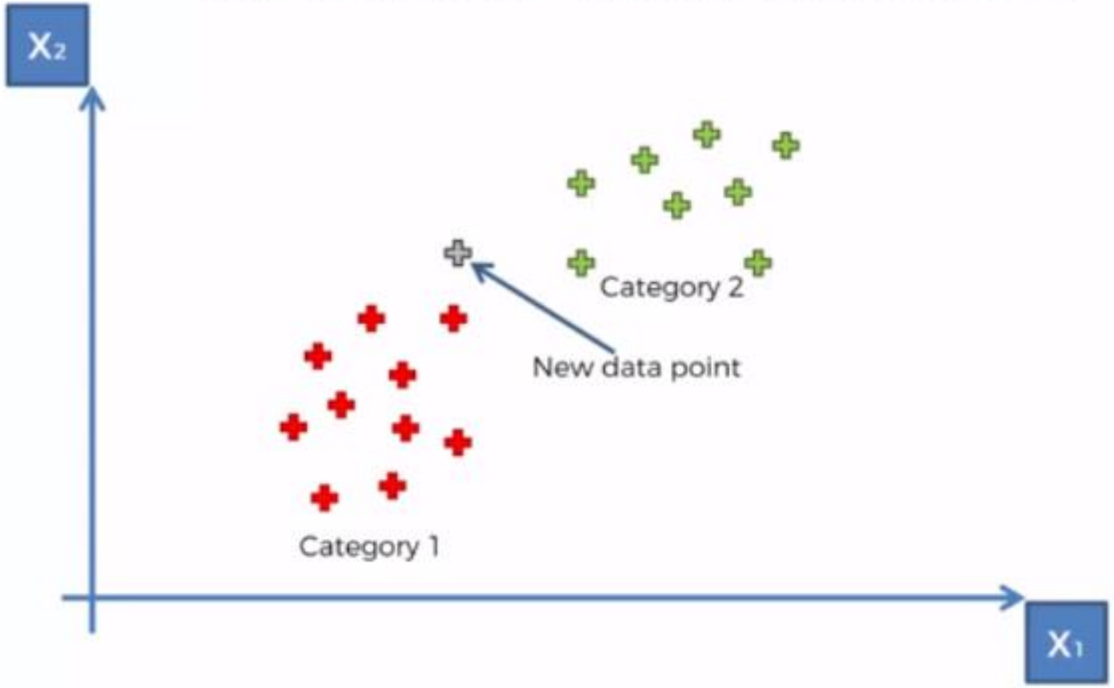
K-NN algorithm

STEP 1: Choose the number K of neighbors: K = 5



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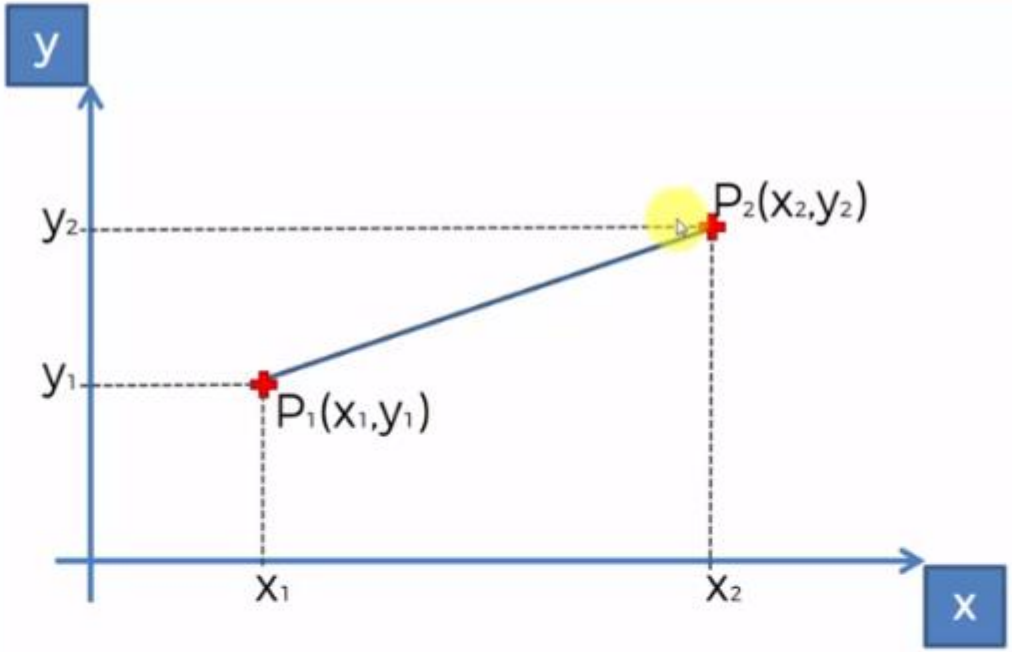
Euclidean Distance



$$\text{Euclidean Distance between } P_1 \text{ and } P_2 = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

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K-NN algorithm

STEP 2: Take the K = 5 nearest neighbors of the new data point, according to the Euclidean distance

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LTI

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K-NN algorithm

STEP 3: Among these K neighbors, count the number of data points in each category

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K-NN algorithm

STEP 3: Among these K neighbors, count the number of data points in each category

Category 1: 3 neighbors

Category 2: 2 neighbors

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K-NN algorithm

STEP 4: Assign the new data point to the category where you counted the most neighbors

Category 1: 3 neighbors

Category 2: 2 neighbors

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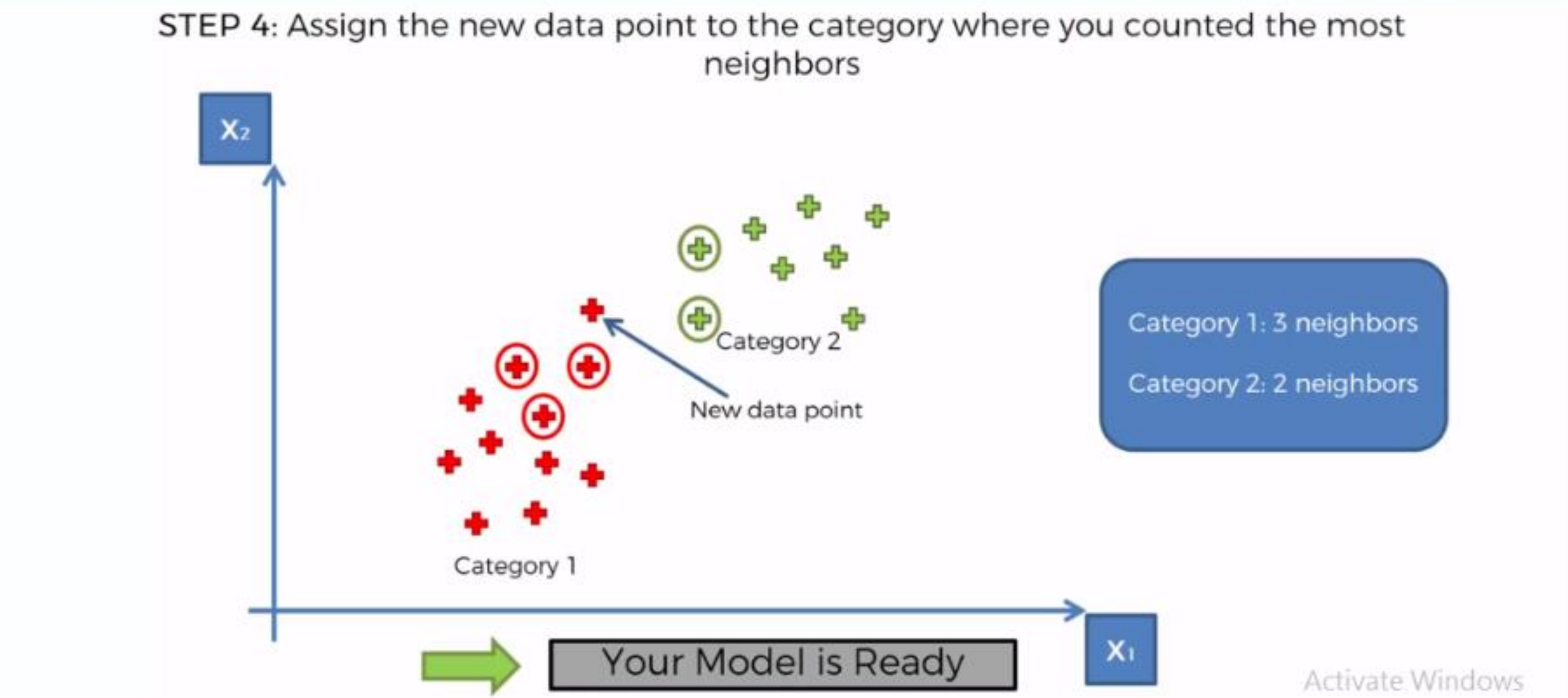
K-NN algorithm



SVM

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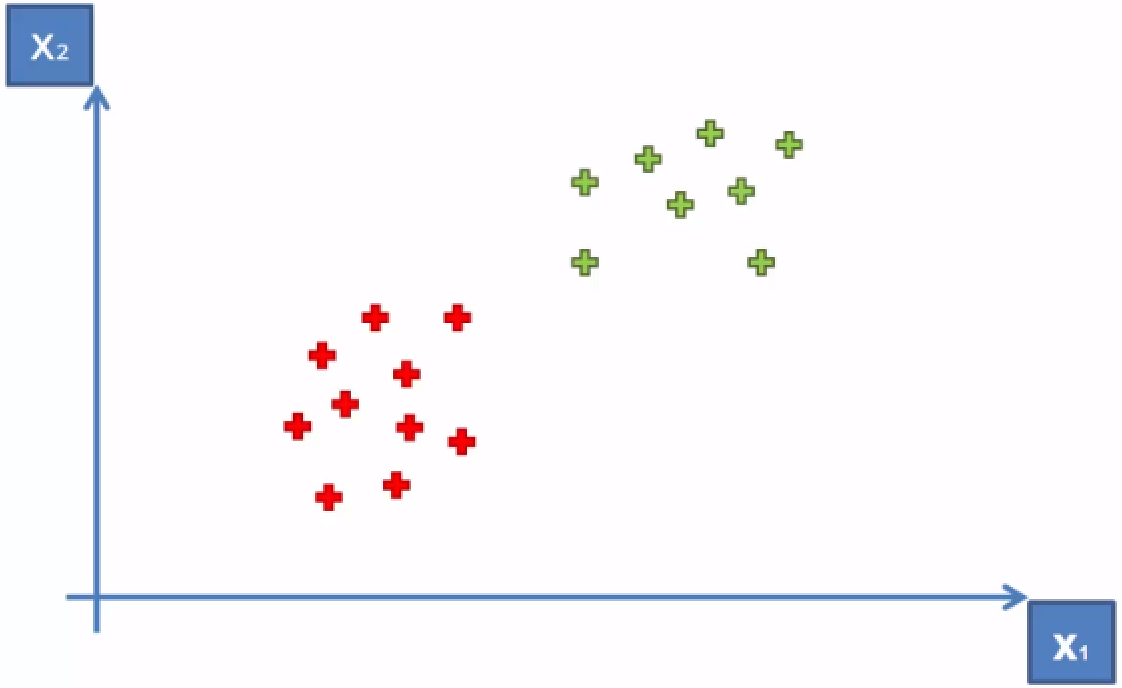
How to separate these points ?



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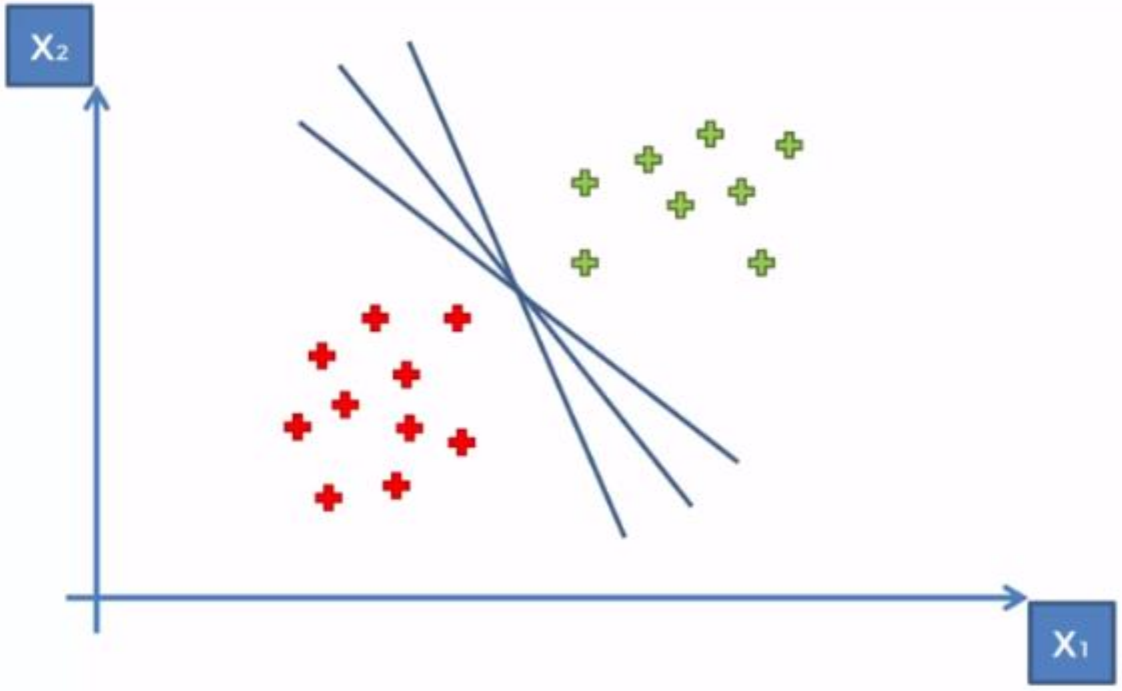
SVM



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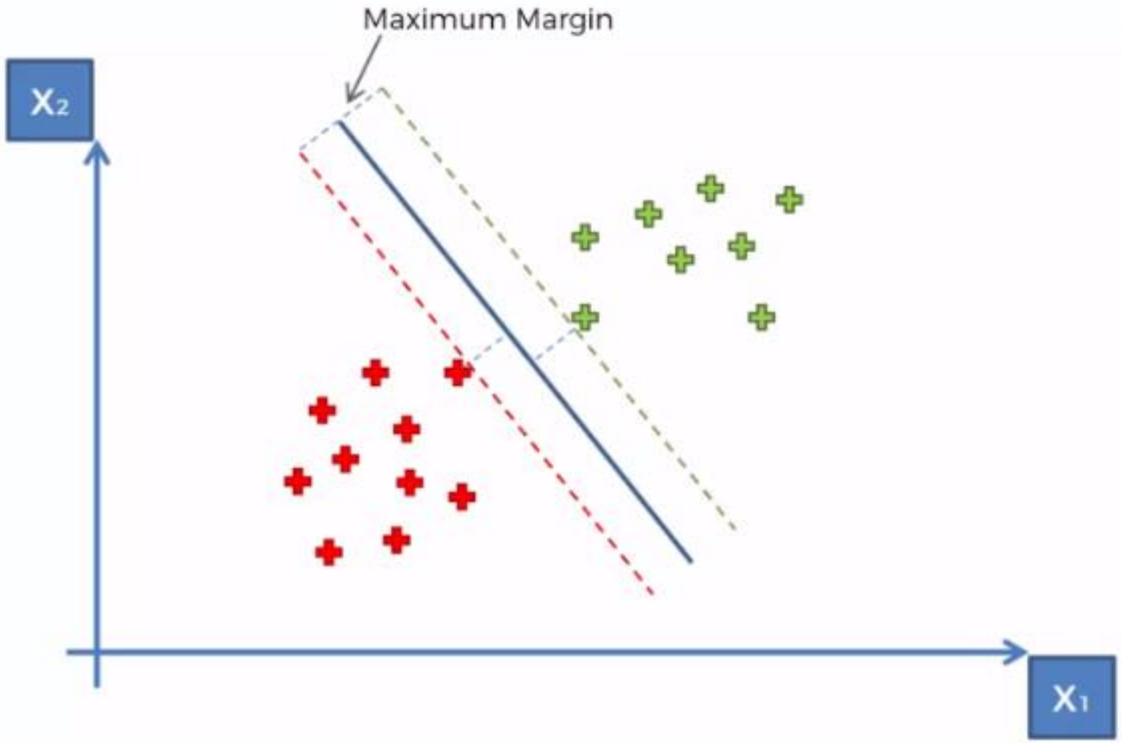
Maximum Margin



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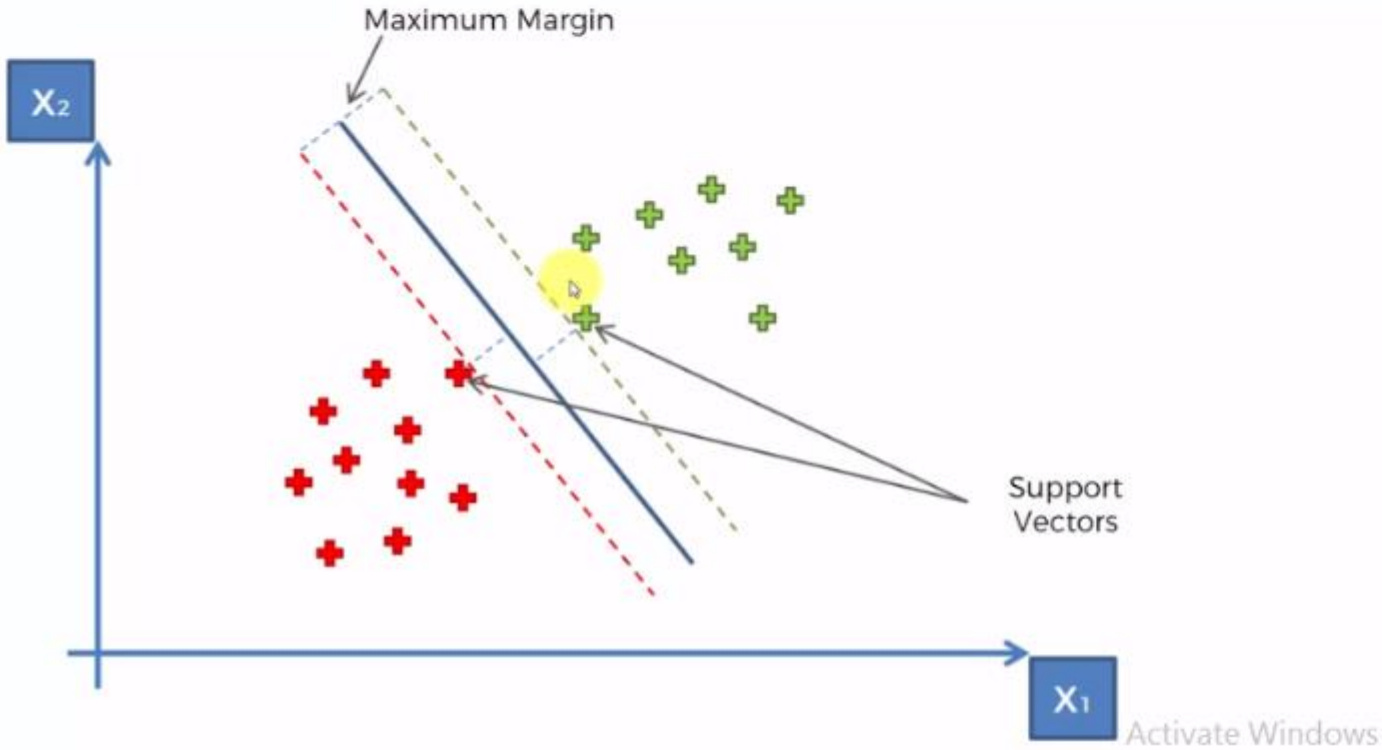
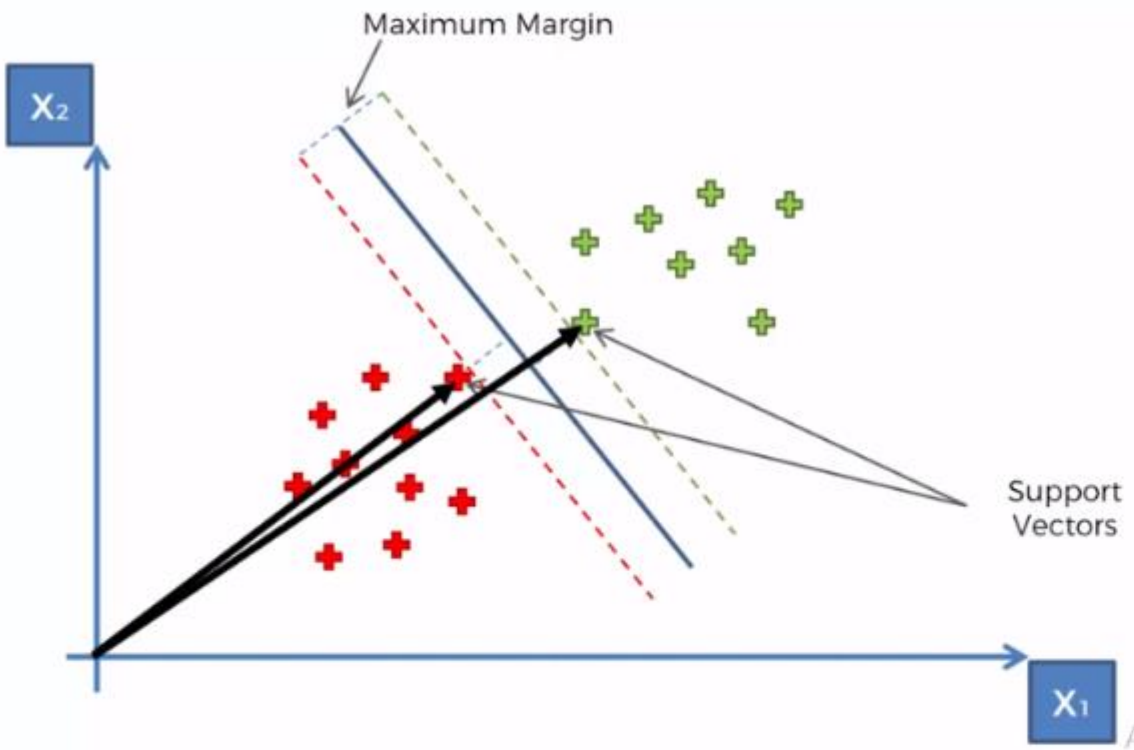
Support Vectors



Support Vectors



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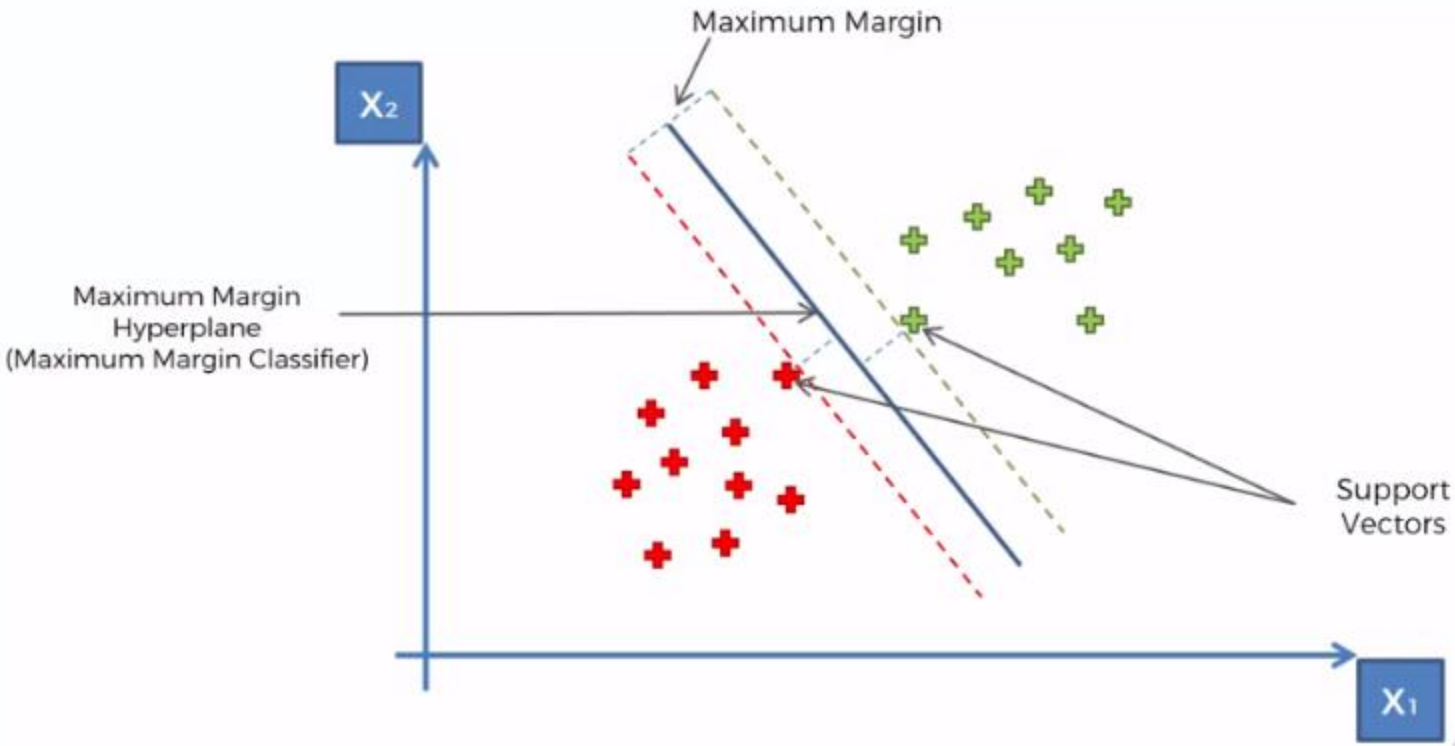
Hyperplanes



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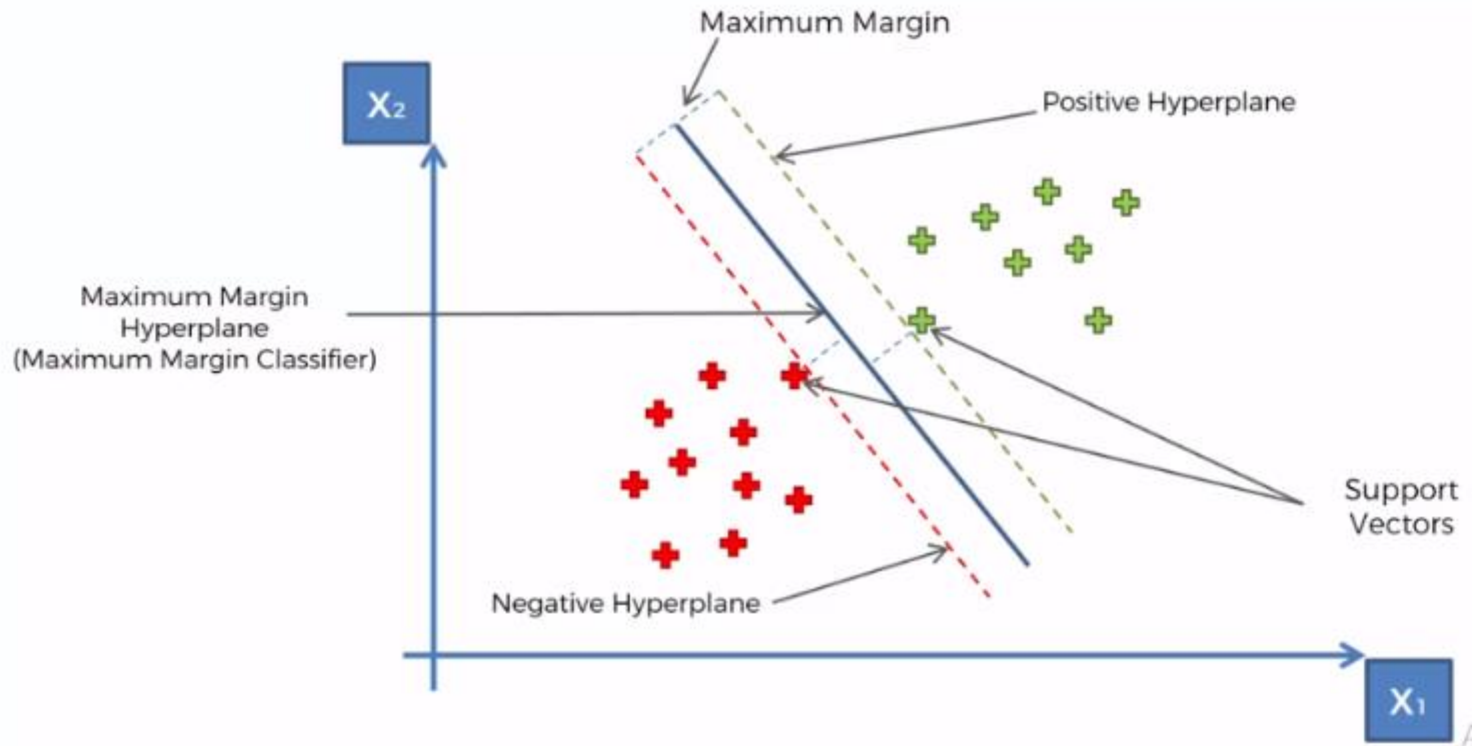
Hyperplanes



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What's So Special About SVMs?

What's So Special About SVMs?

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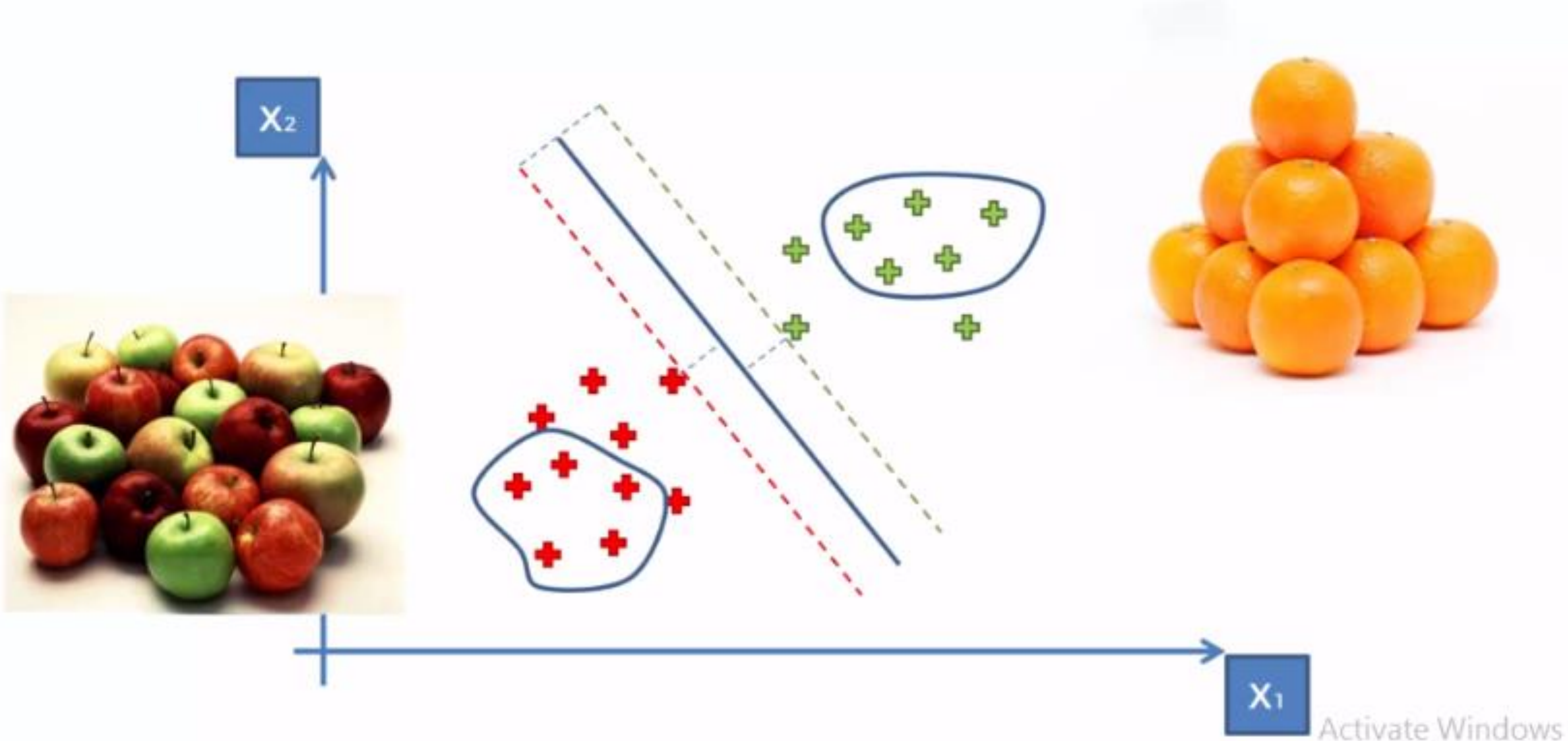
What's So Special About SVMs?



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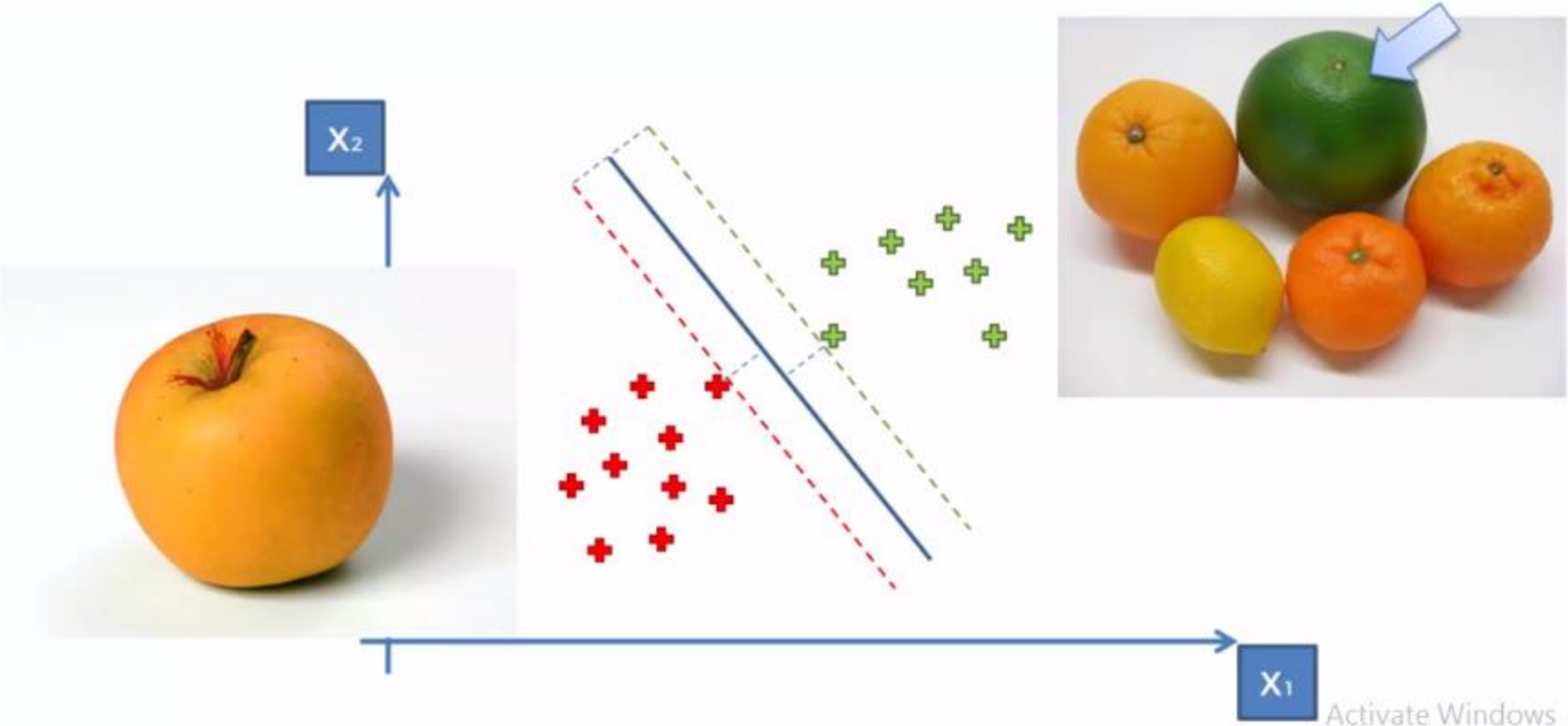
What's So Special About SVMs?



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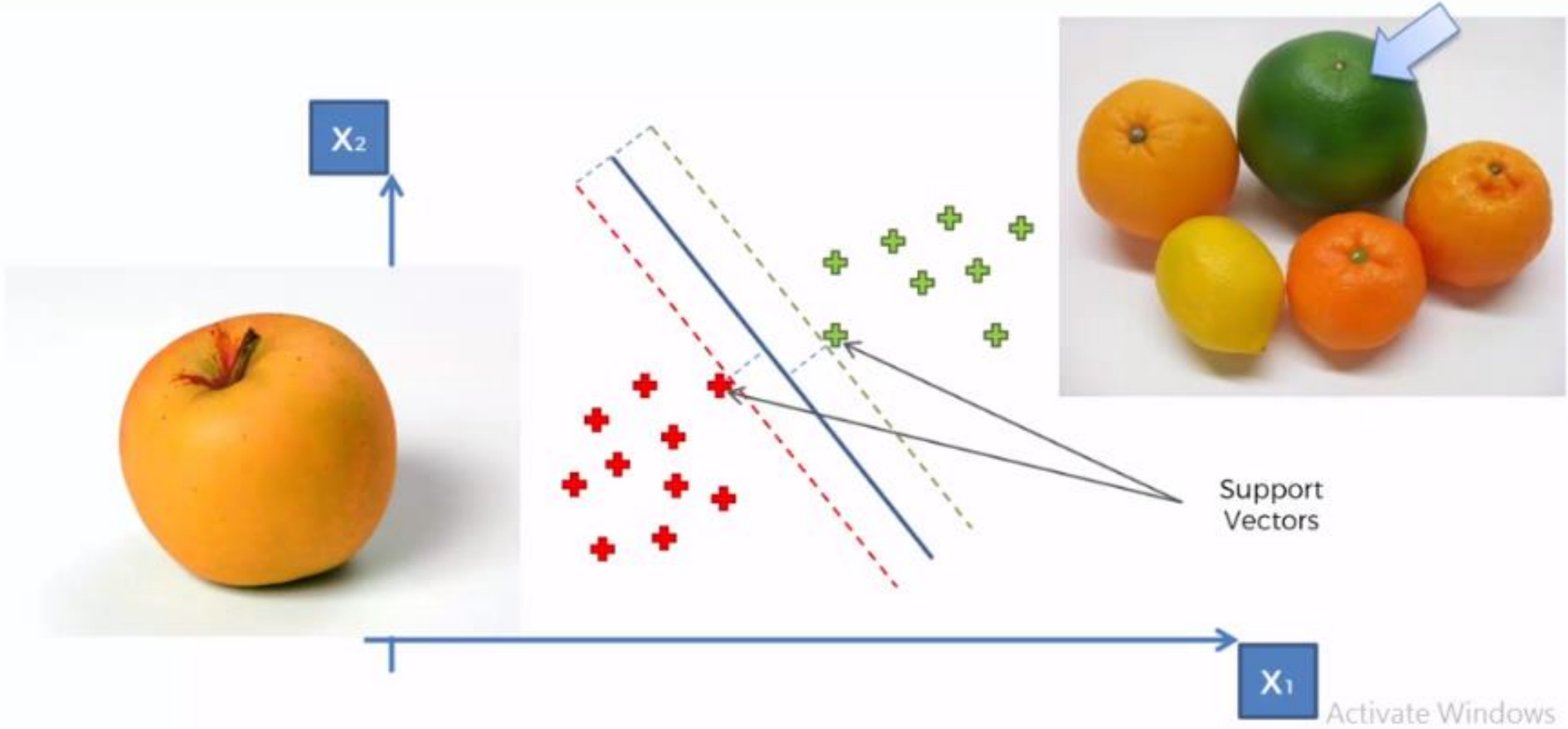
What's So Special About SVMs?



SOURCE(S):

Machine Learning by Kirill Eremenko and Hadelin de Ponteves

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THANK YOU