

Week 6: Forecasting (Predictive Analytics) in Supply Chains (SCs)

Presented by:

Dr. Mehdi Rajabi Asadabadi



Predictive Analytics



Predictive analytics focus on **using historical data** to identify patterns enabling the **prediction of the future**.

The identified pattern or trend from historical data is represented by a **mathematical model**.

This model can then be used to predict future events based on the previous data and the new data.



Predictive Analytics Models

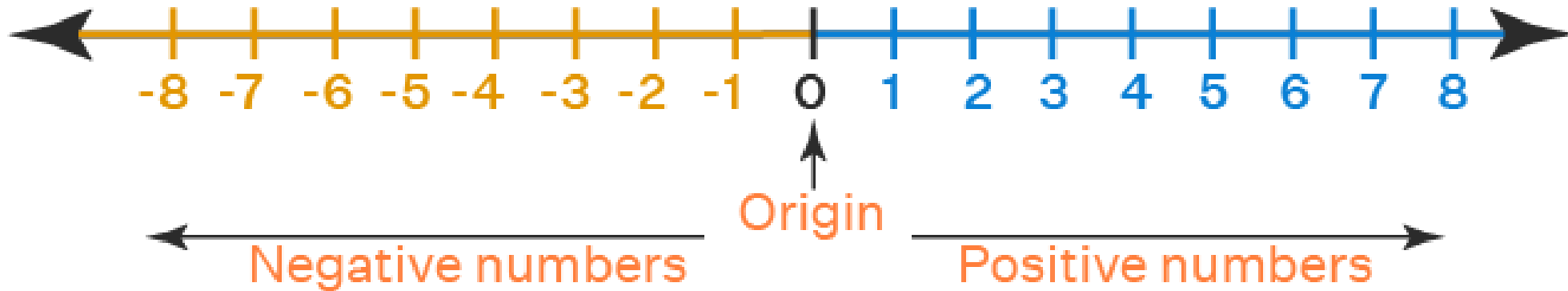
Classification:

Classification is the process of creating a set of classes for data, based on the existing data.

Predictive Analytics Models

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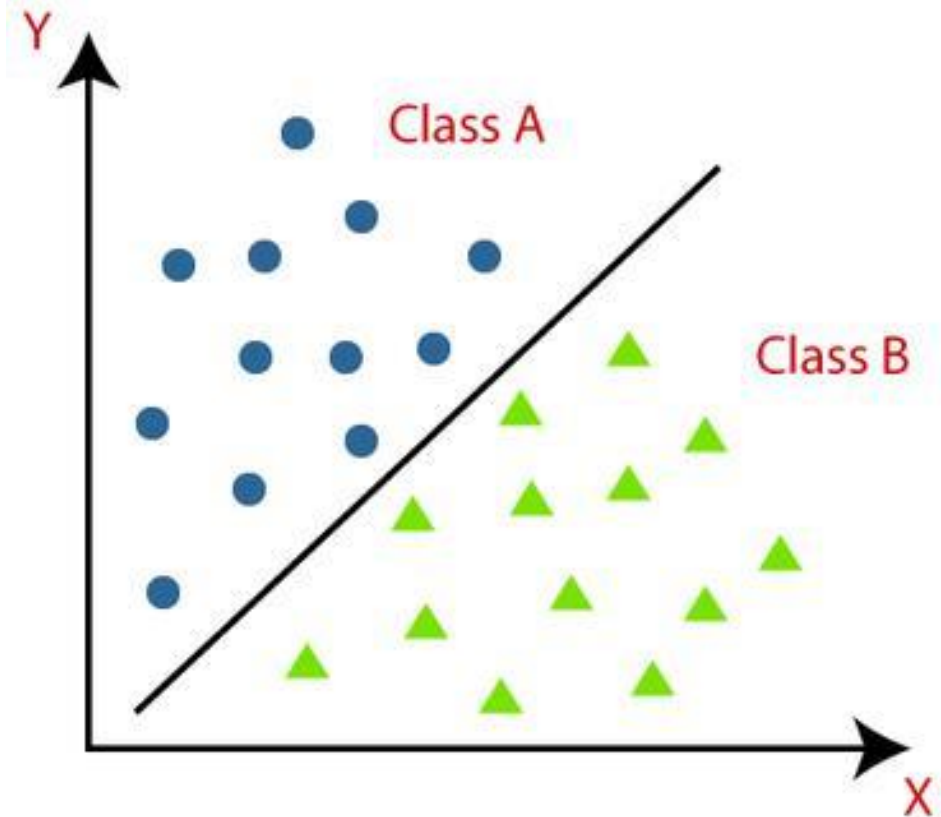
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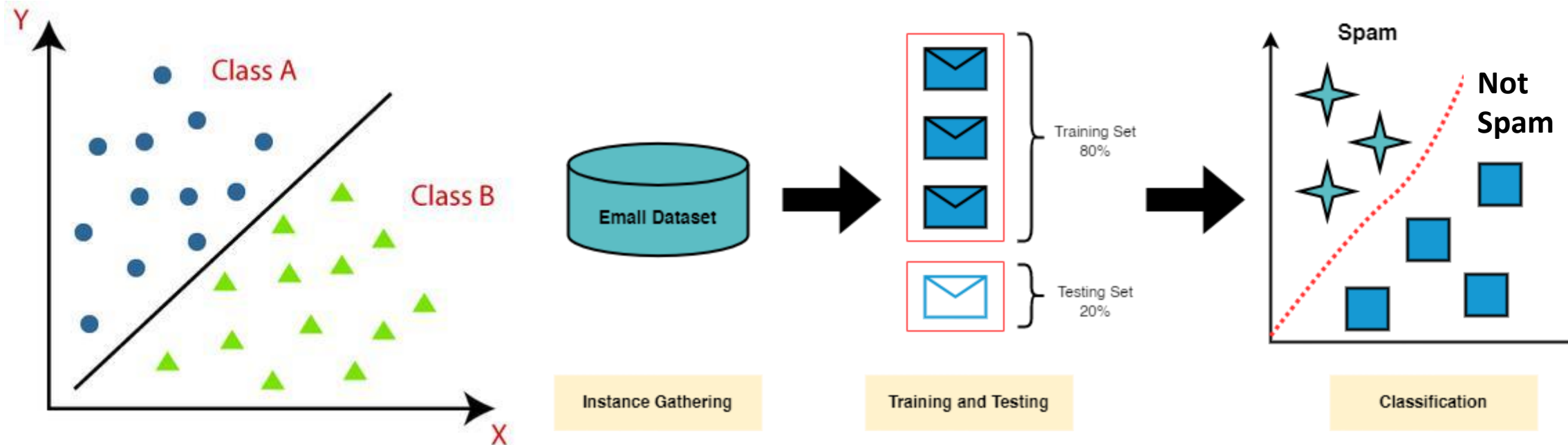


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Binary classification:

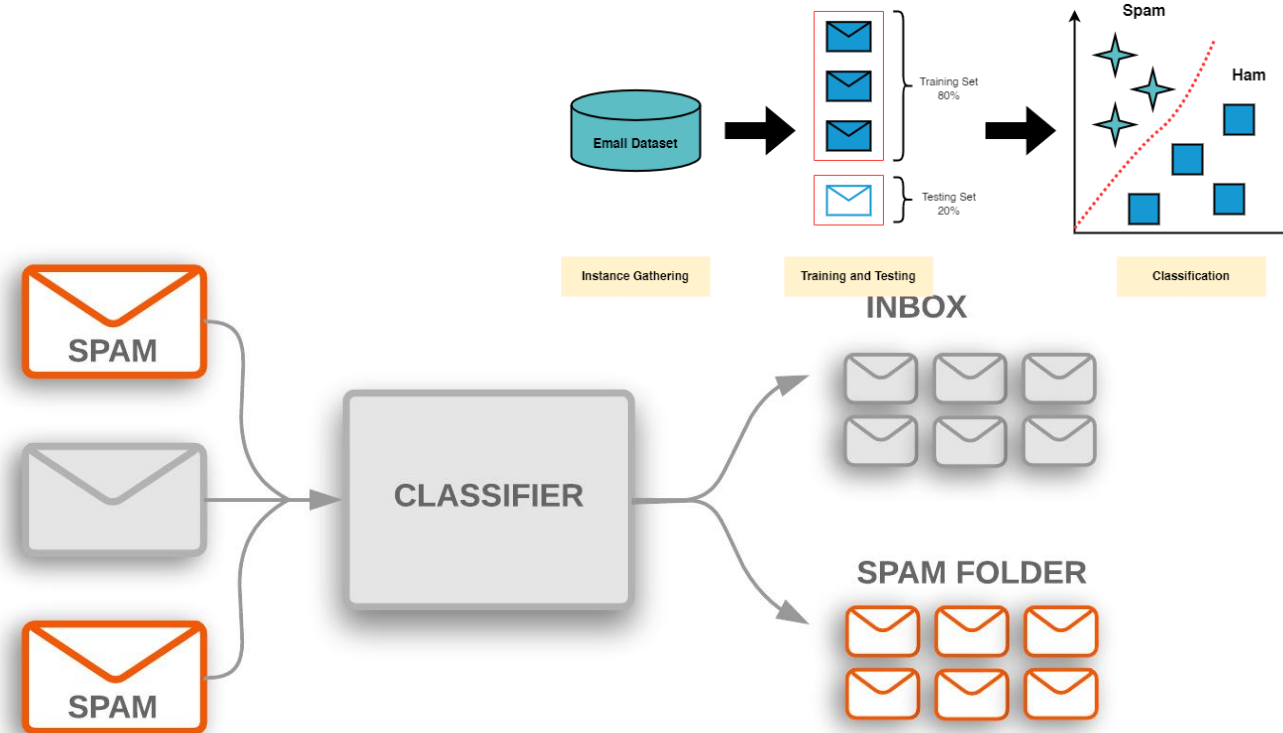
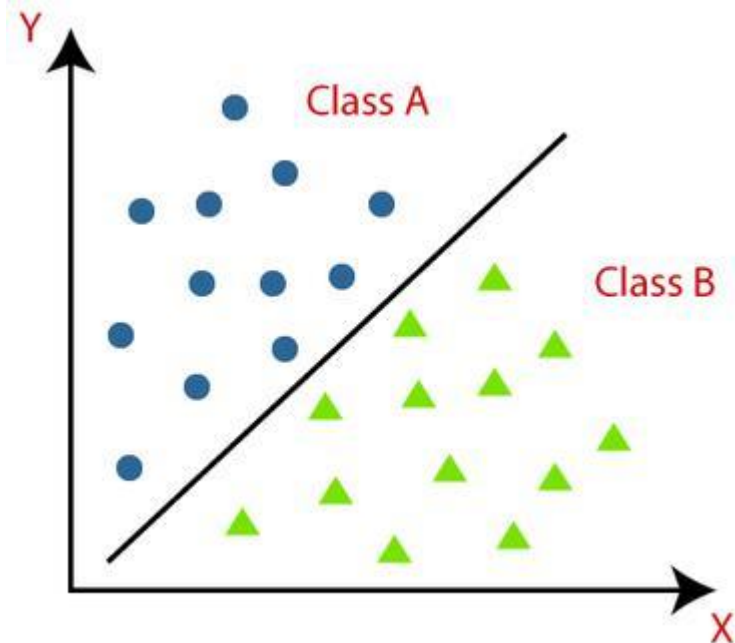


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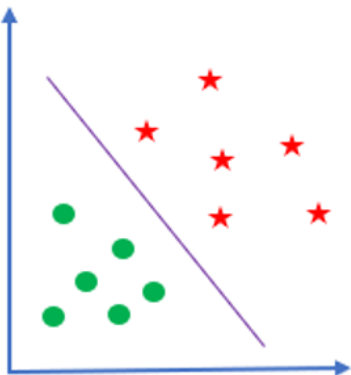
Predictive Analytics Models

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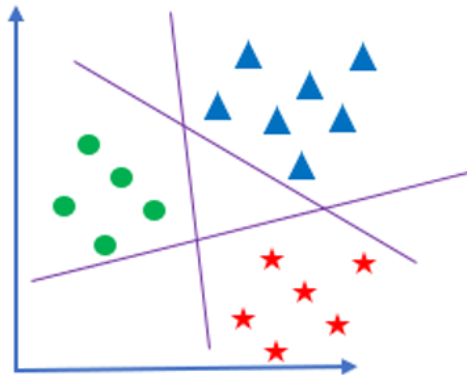
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Multiclass classification:

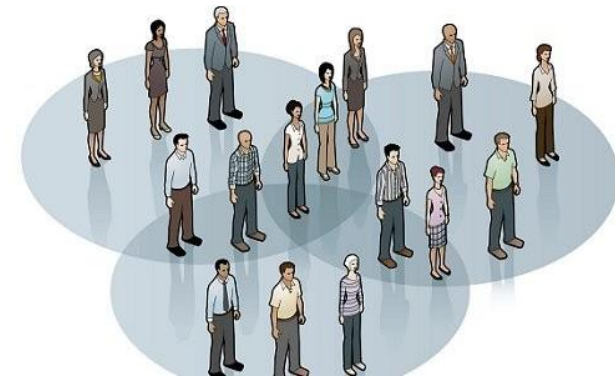
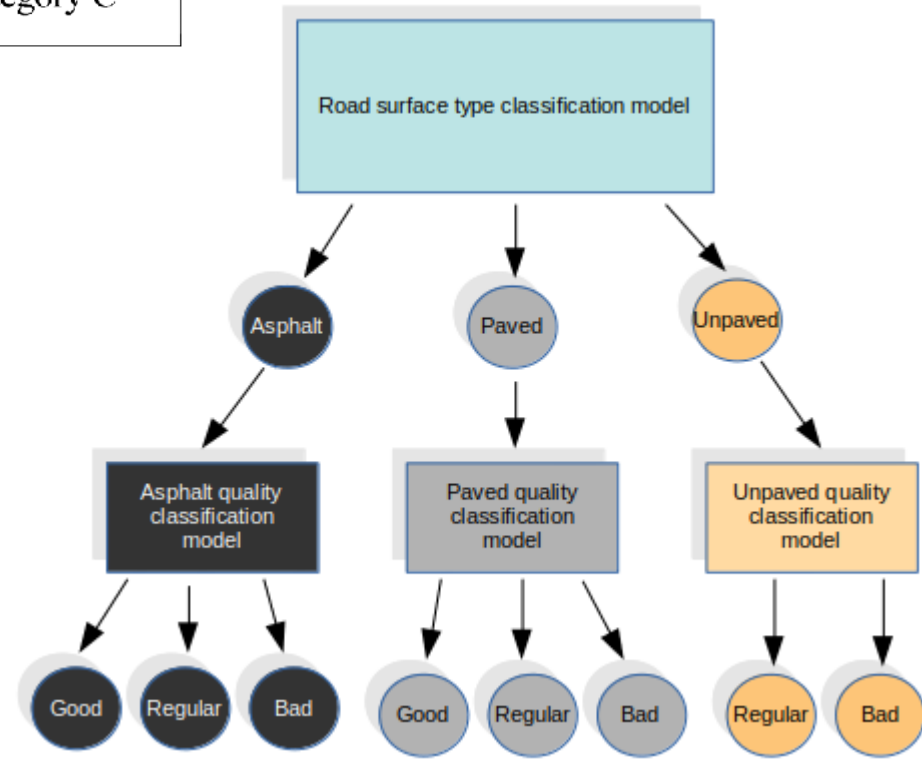
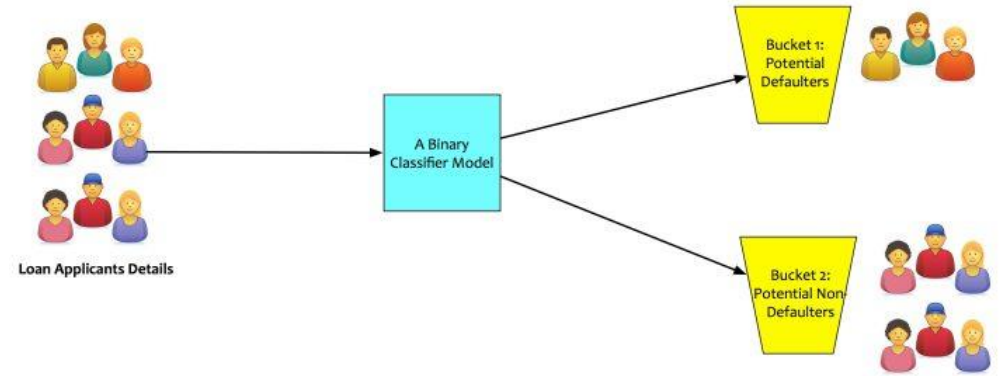
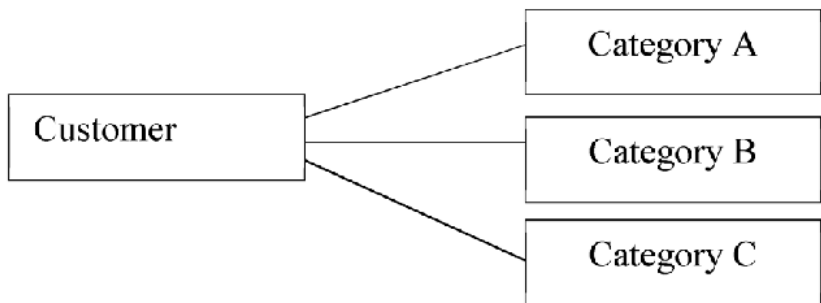
Binary classification



Multi-class classification



| | | SEVERITY → | | |
|--------------|---|-----------------|-----------------|-----------------|
| | | 1 | 2 | 3 |
| LIKELIHOOD ↓ | 1 | LOW - 1 - | LOW - 2 - | MEDIUM - 3 - |
| | 2 | LOW - 2 - | MEDIUM - 4 - | HIGH - 6 - |
| | 3 | MEDIUM - 3 - | HIGH - 6 - | HIGH - 9 - |



Predictive Analytics Models

Classification:

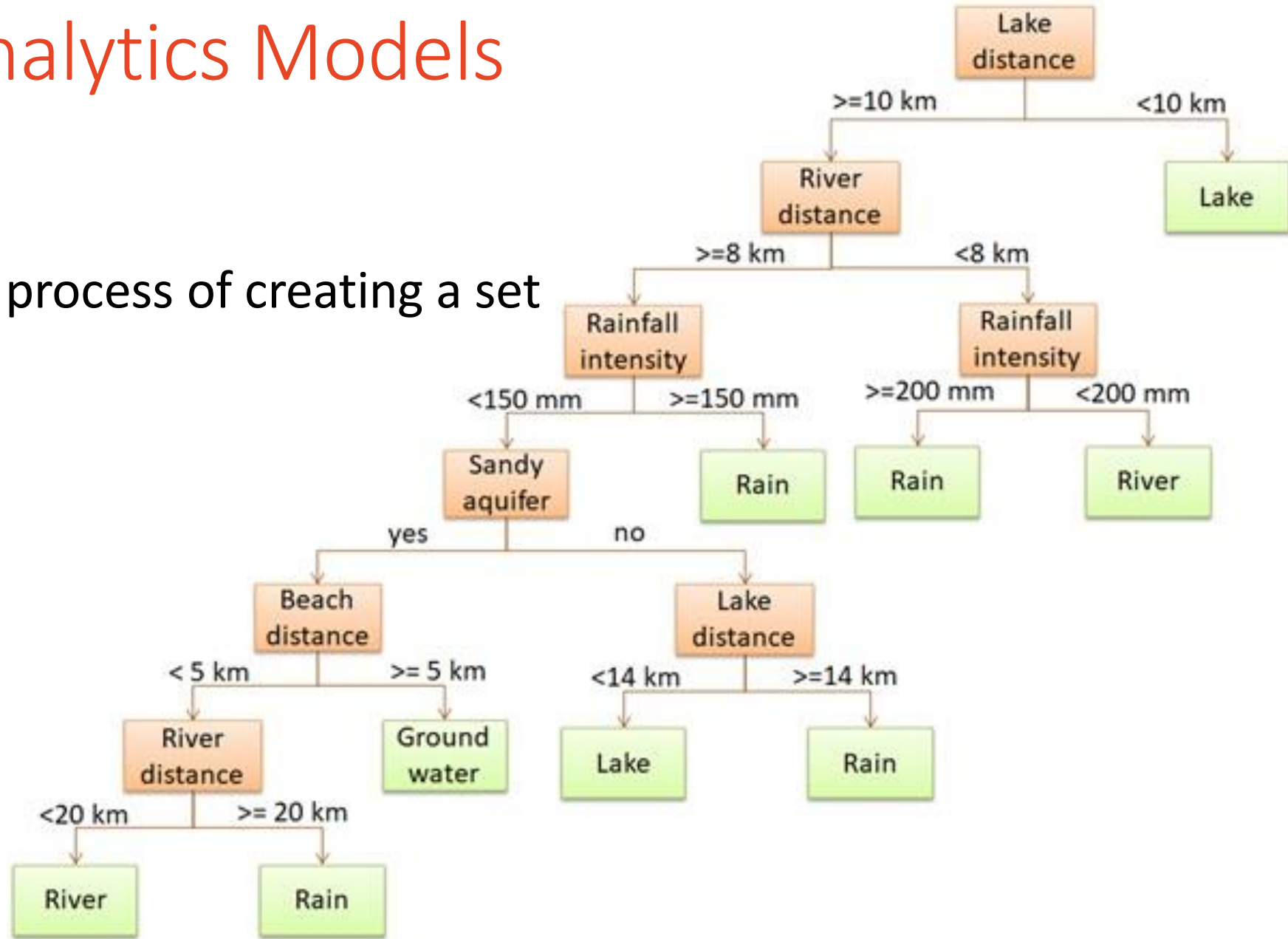
Classification is the process of creating a set of classes for data based on the existing data.

Predictive Analytics Models

Classification:

Classification is the process of creating a set of classes for data

Decision trees



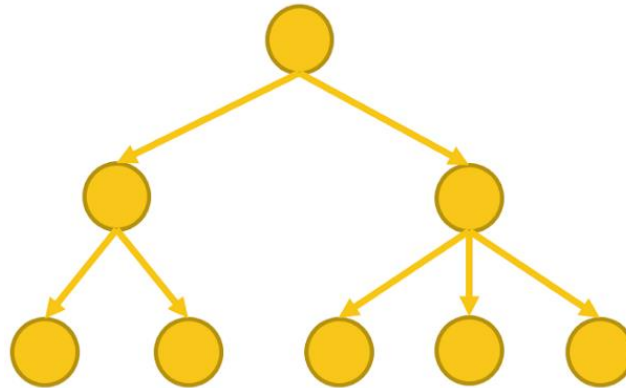
Predictive Analytics Models

Classification:

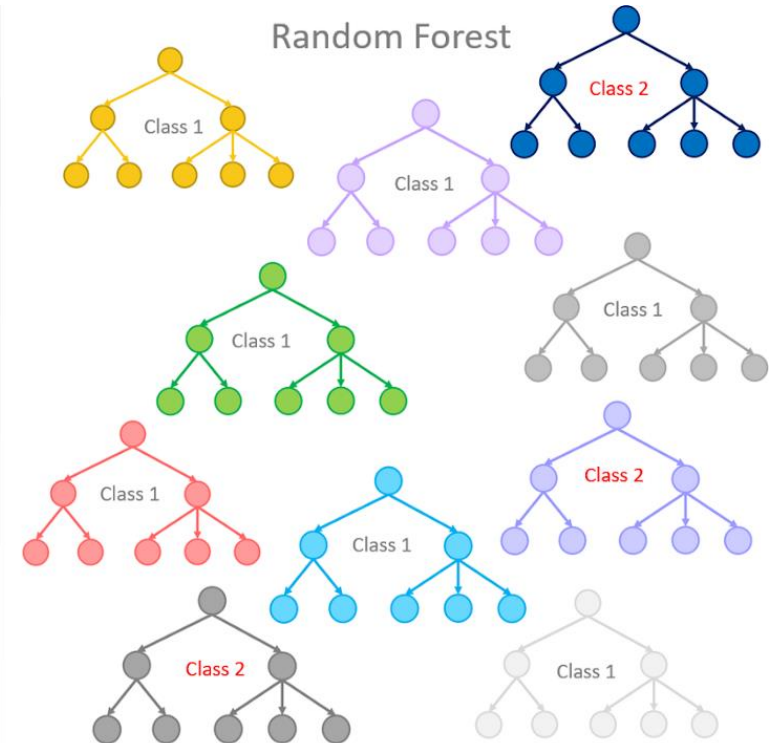
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Decision trees
Random forest

Single Decision Tree



Random Forest



Predictive Analytics Models

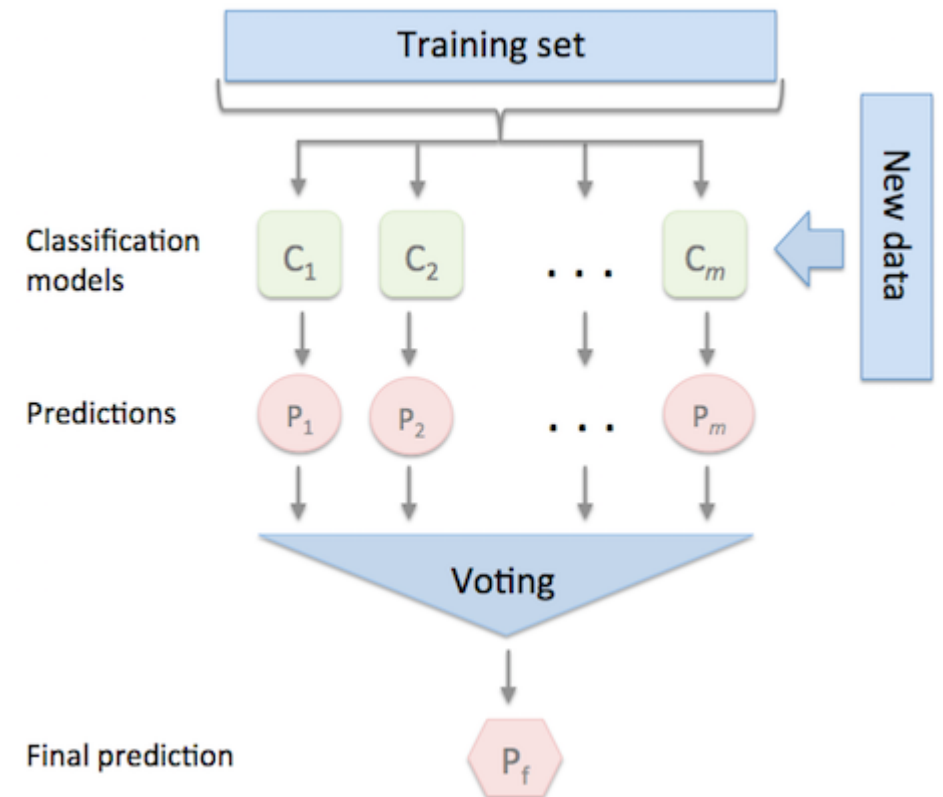
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Decision trees

Random forest

Voting classifiers



Predictive Analytics Models

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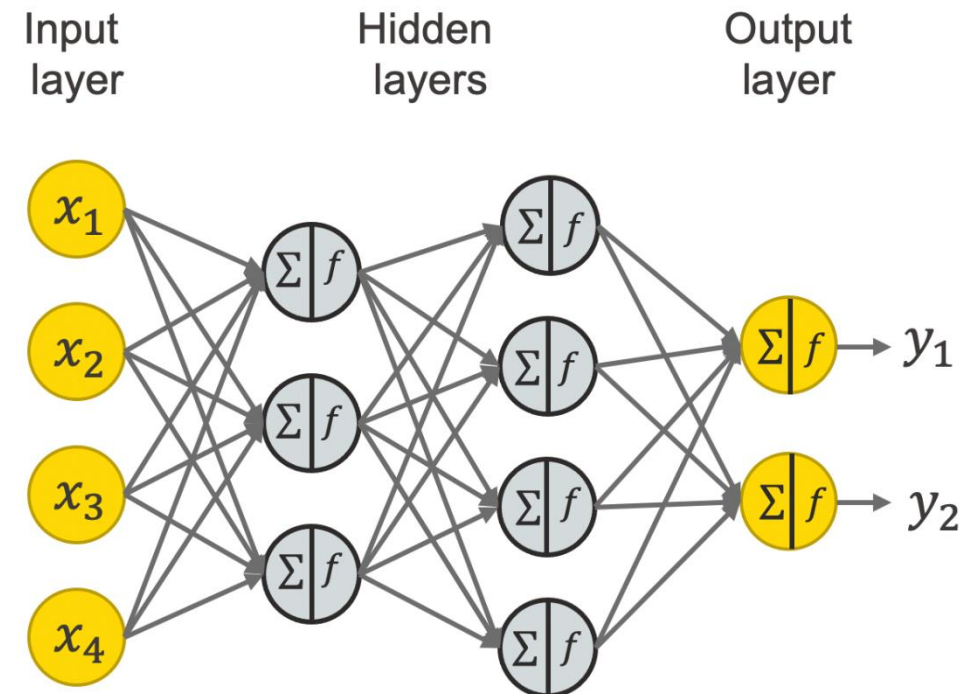
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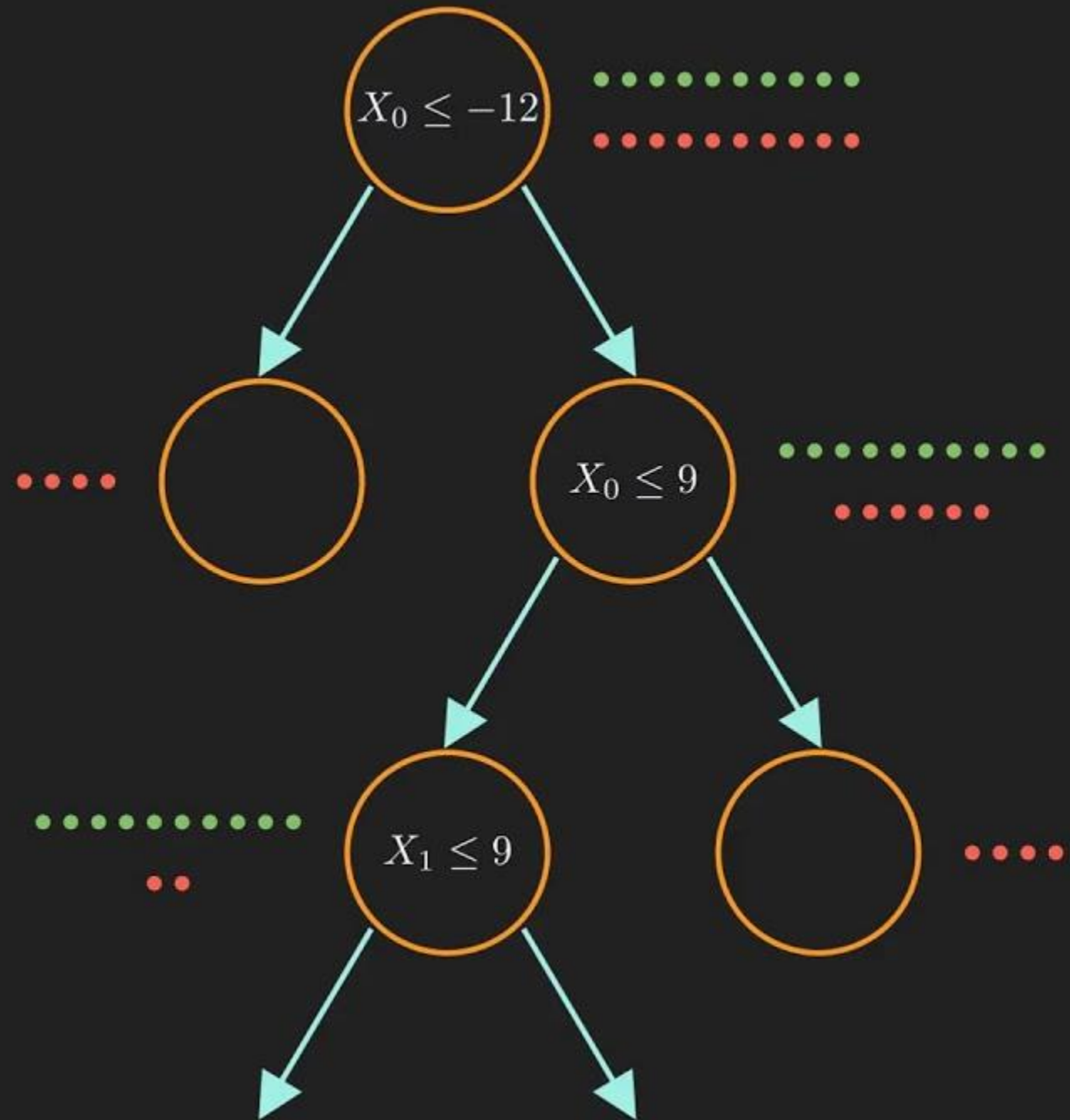
Voting classifiers

Neural networks and deep learning

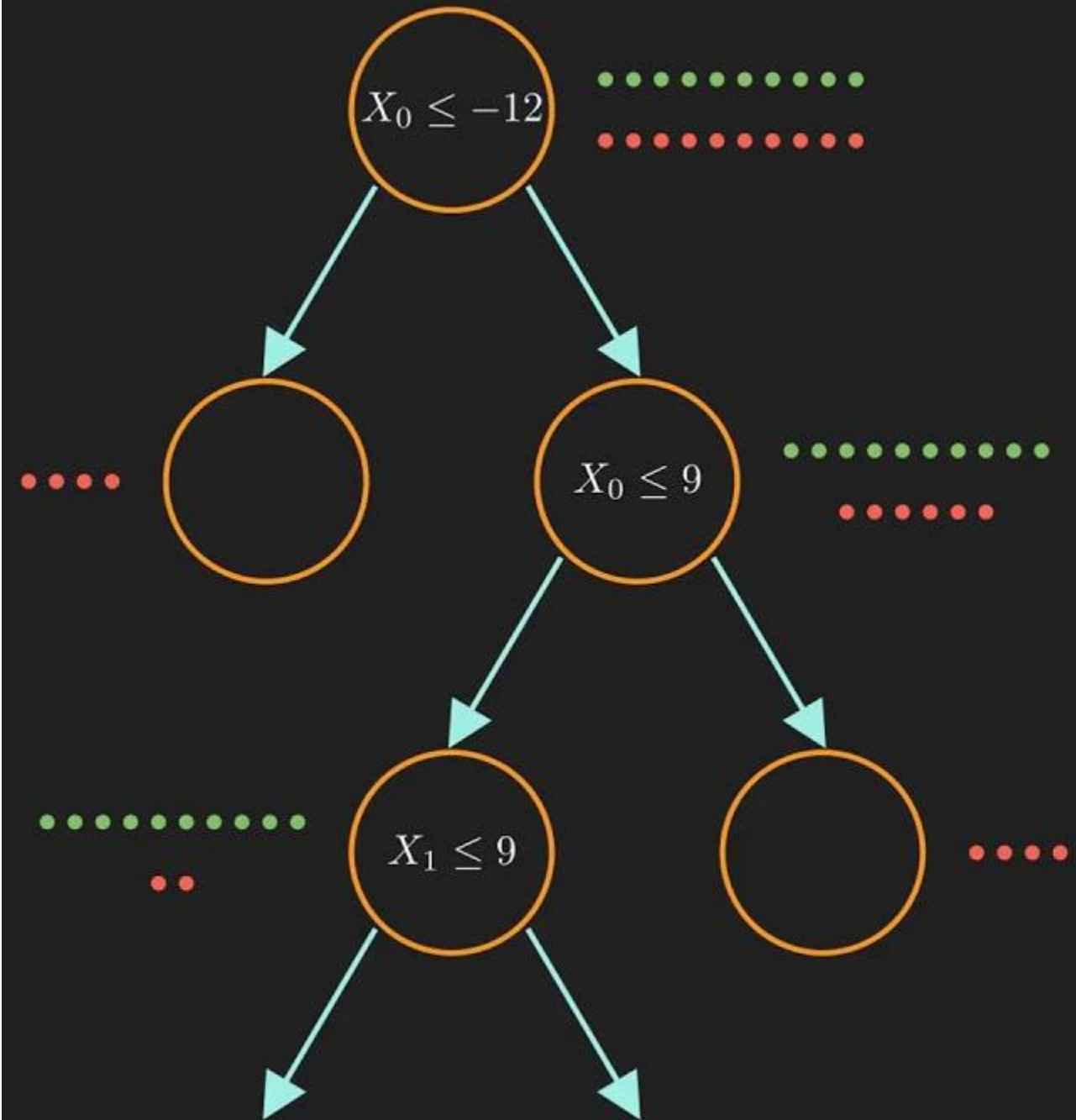
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Decision Tree Classifier



- A decision tree is essentially an **upside-down tree shaped diagram used to classify**.
- It is a predictive model **based on a branching series of Boolean tests (often) and non-Boolean tests**.
- It has a **root node** which is the **starting point of the decision tree**.
- **Splitting or branching** is the process of dividing a node into **two or more sub-nodes**.
- Nodes have **sub-nodes and leaf/terminal nodes**, which are the ones without a split.
- **Sub-nodes** of a specific node is known as **child nodes** and the node is known as **parent node**.

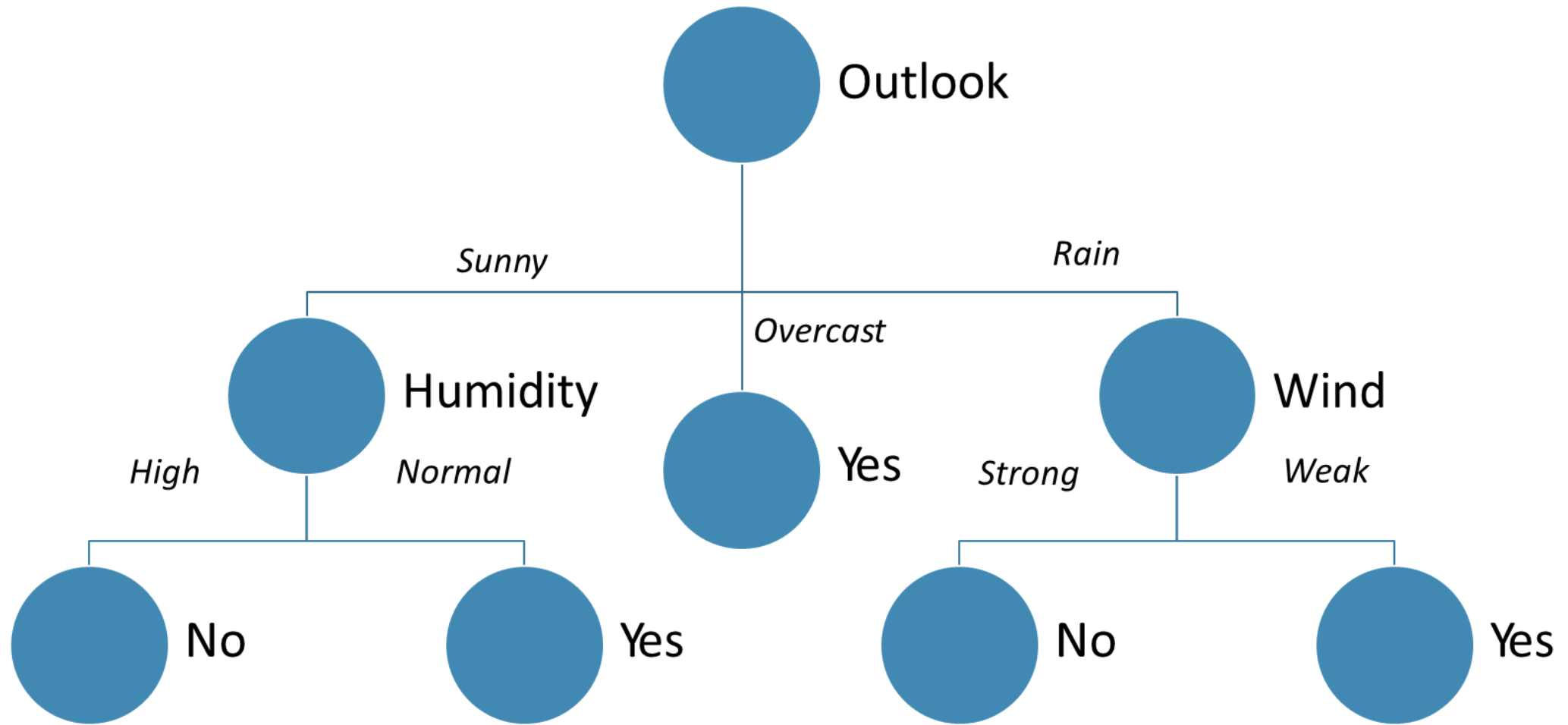


| features or attributes | | | | decision |
|------------------------|------|----------|--------|--------------|
| Outlook | Temp | Humidity | Windy | Play Tennis? |
| Sunny | Hot | High | Weak | No |
| Sunny | Hot | High | Strong | No |
| Overcast | Hot | High | Weak | Yes |
| Rain | Mild | High | Weak | Yes |
| Rain | Cool | Normal | Weak | Yes |
| Rain | Cool | Normal | Strong | No |
| Overcast | Cool | Normal | Strong | Yes |
| Sunny | Mild | High | Weak | No |
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| Rain | Mild | High | Strong | No |

Decision Tree

| features or attributes | | | | decision/classes |
|------------------------|------|----------|--------|------------------|
| Outlook | Temp | Humidity | Windy | Play Tennis? |
| Sunny | Hot | High | Weak | No |
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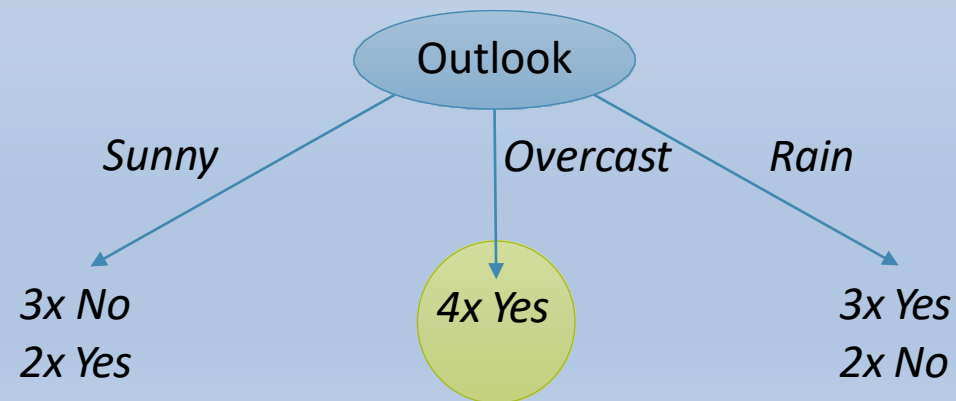
Decision Tree Classification



Decision Tree Classification

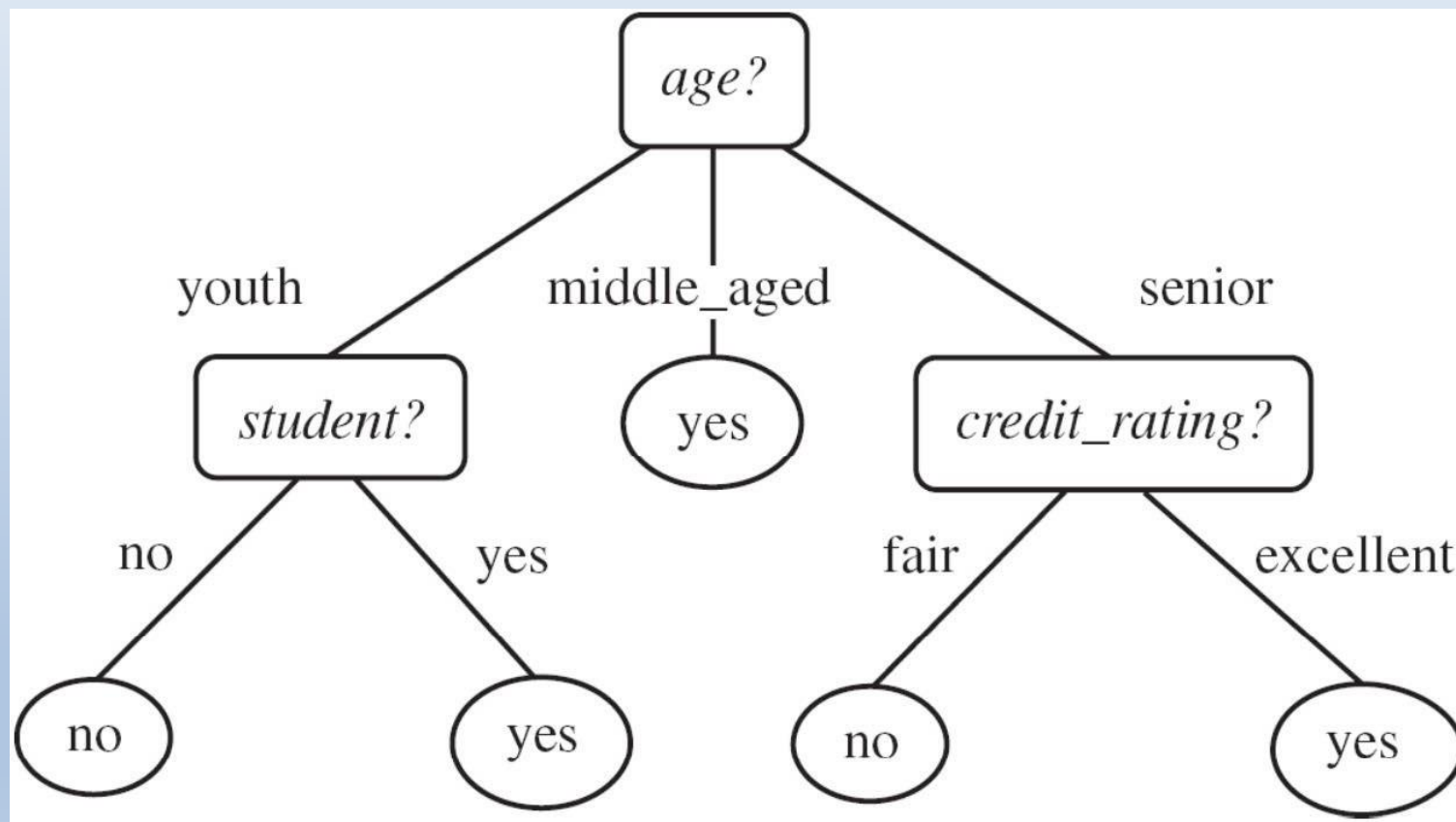
How do you build a decision tree?

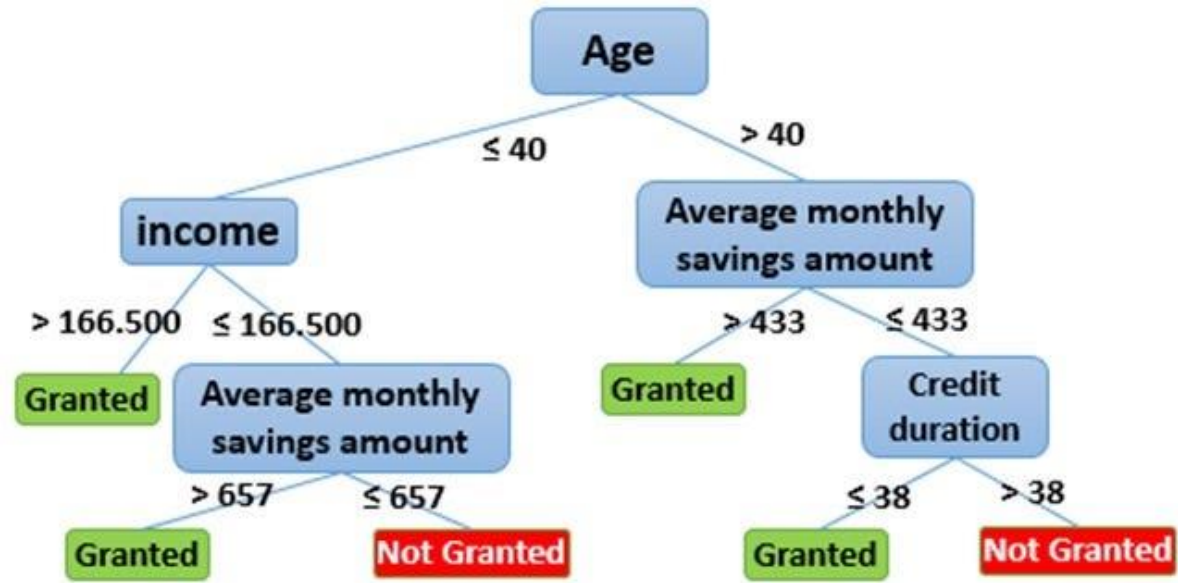
- Select an attribute (A)
 - Which attribute is the best? Impurity or information gain can be used
- For each value of A, create a partition.
- If training samples are perfectly classified, then stop – otherwise recursively iterate over the new child nodes



Example: Classifying potential customers using a decision tree

| <i>RID</i> | <i>age</i> | <i>income</i> | <i>student</i> | <i>credit_rating</i> | <i>Class: buys_computer</i> |
|------------|-------------|---------------|----------------|----------------------|-----------------------------|
| 1 | youth | high | no | fair | no |
| 2 | youth | high | no | excellent | no |
| 3 | middle_aged | high | no | fair | yes |
| 4 | senior | medium | no | fair | yes |
| 5 | senior | low | yes | fair | yes |
| 6 | senior | low | yes | excellent | no |
| 7 | middle_aged | low | yes | excellent | yes |
| 8 | youth | medium | no | fair | no |
| 9 | youth | low | yes | fair | yes |
| 10 | senior | medium | yes | fair | yes |
| 11 | youth | medium | yes | excellent | yes |
| 12 | middle_aged | medium | no | excellent | yes |
| 13 | middle_aged | high | yes | fair | yes |
| 14 | senior | medium | no | excellent | no |





Home Loan Approval

Figure 2

Example Decision Tree:
Should we develop a new
product or consolidate?

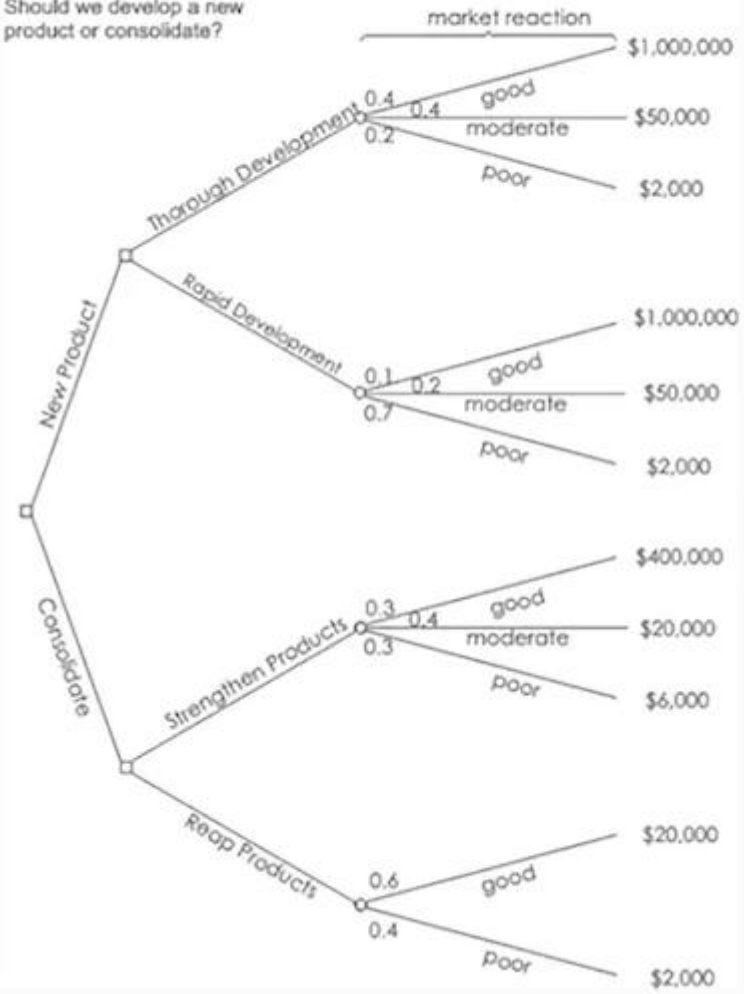


Figure 2

Example Decision Tree:
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product or consolidate?

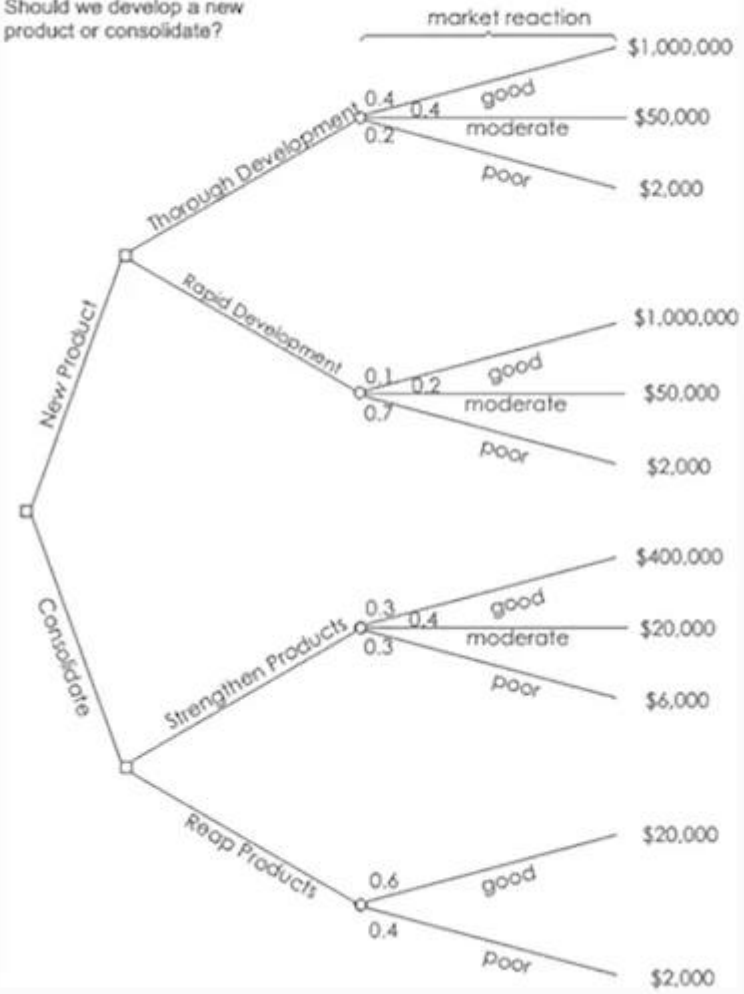


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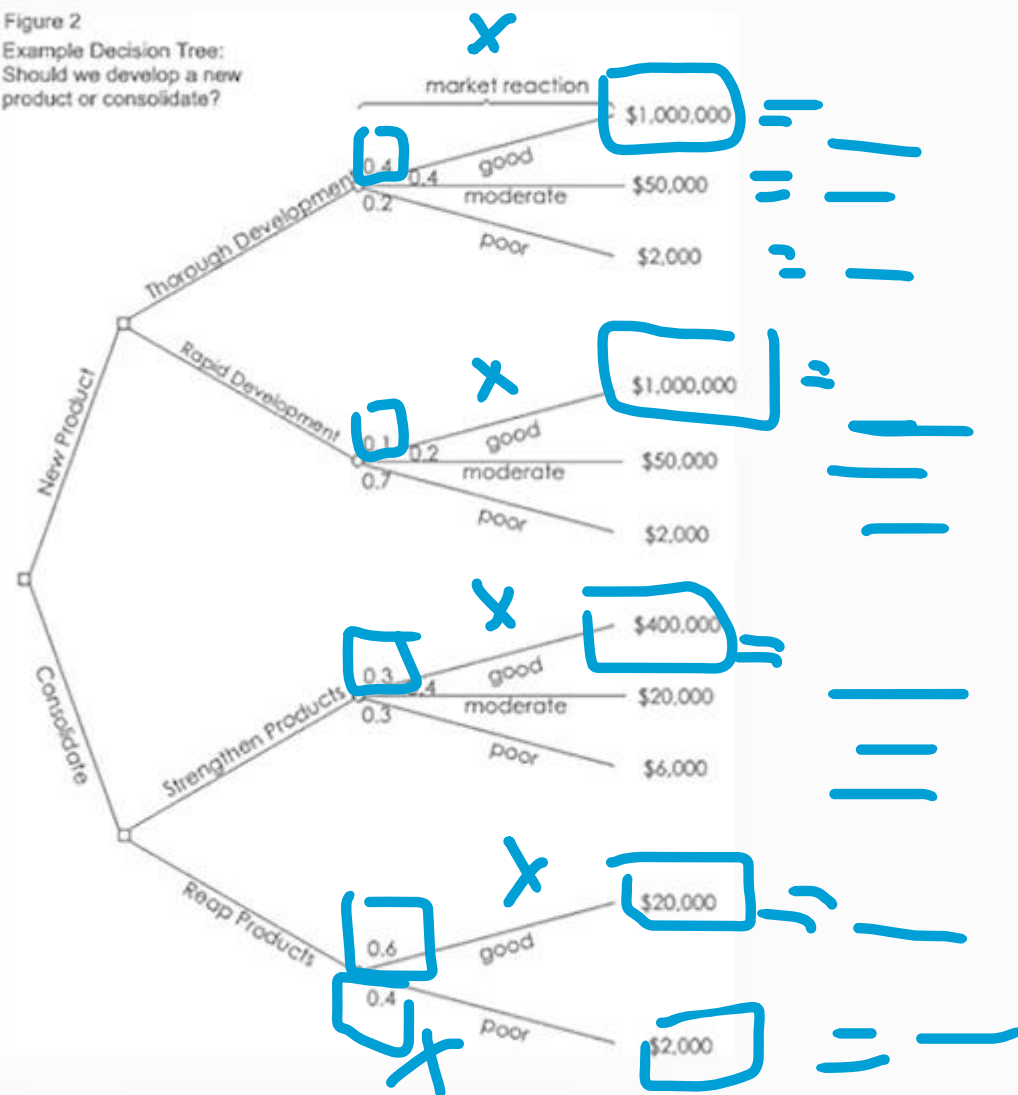


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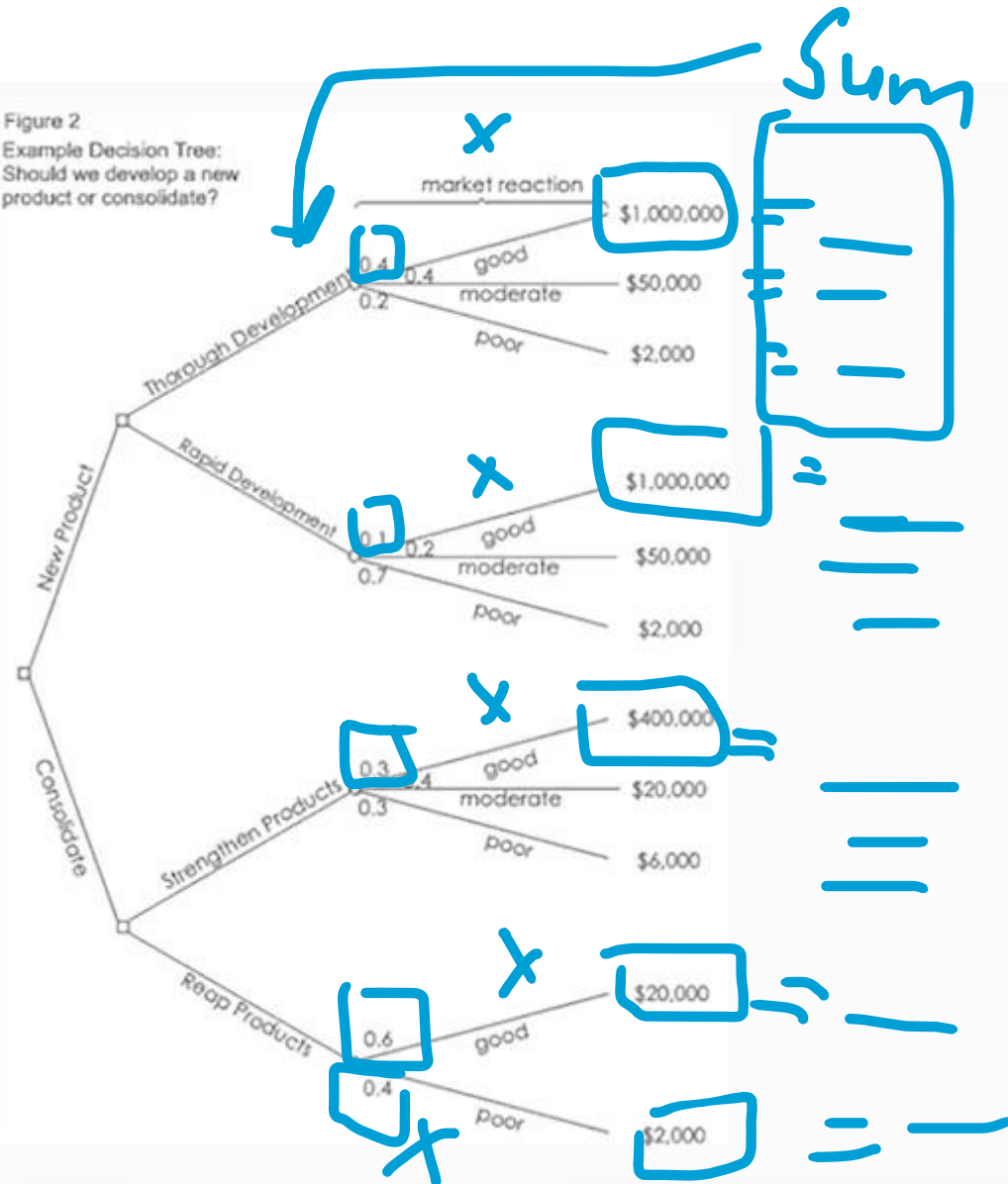


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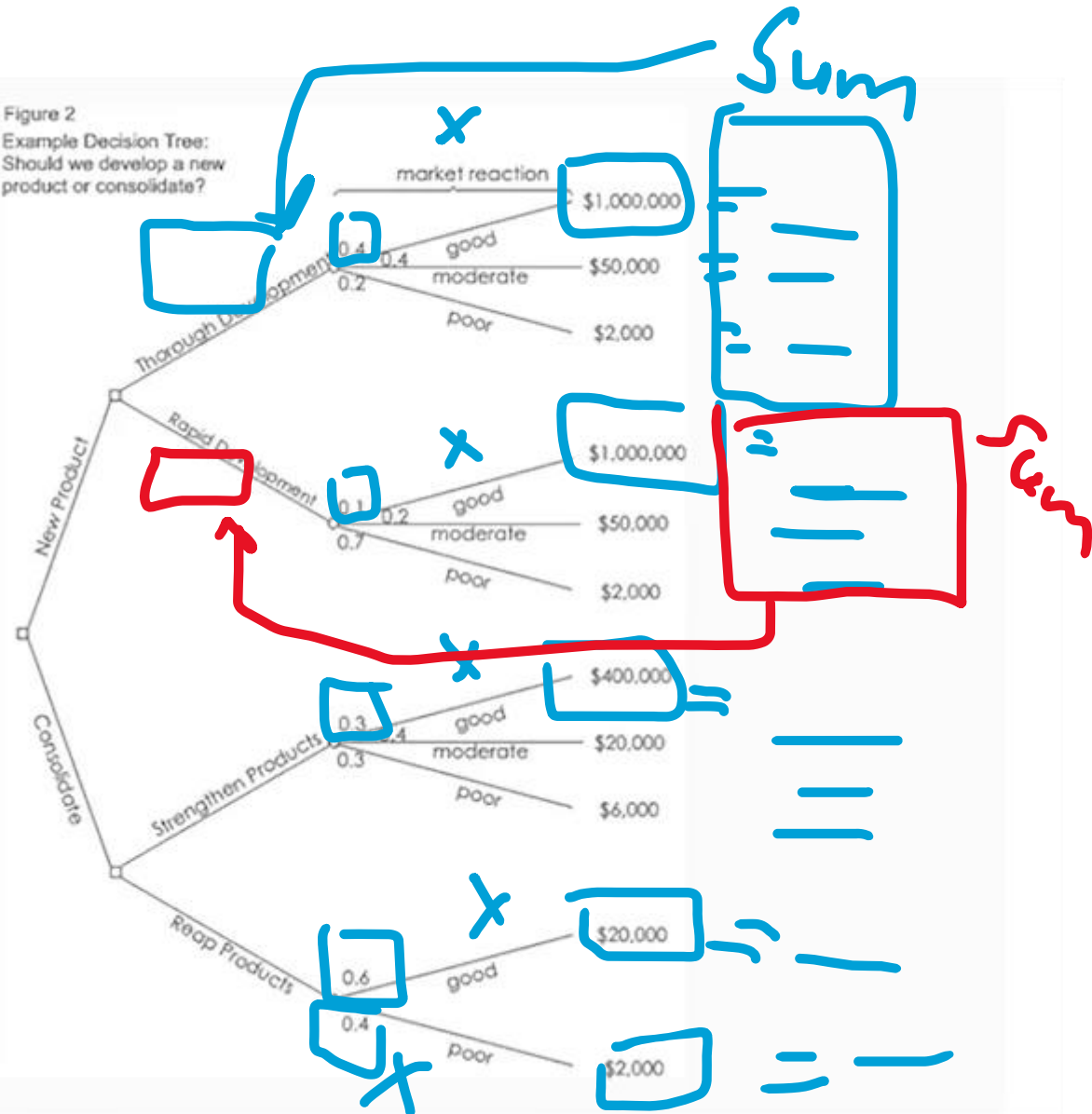
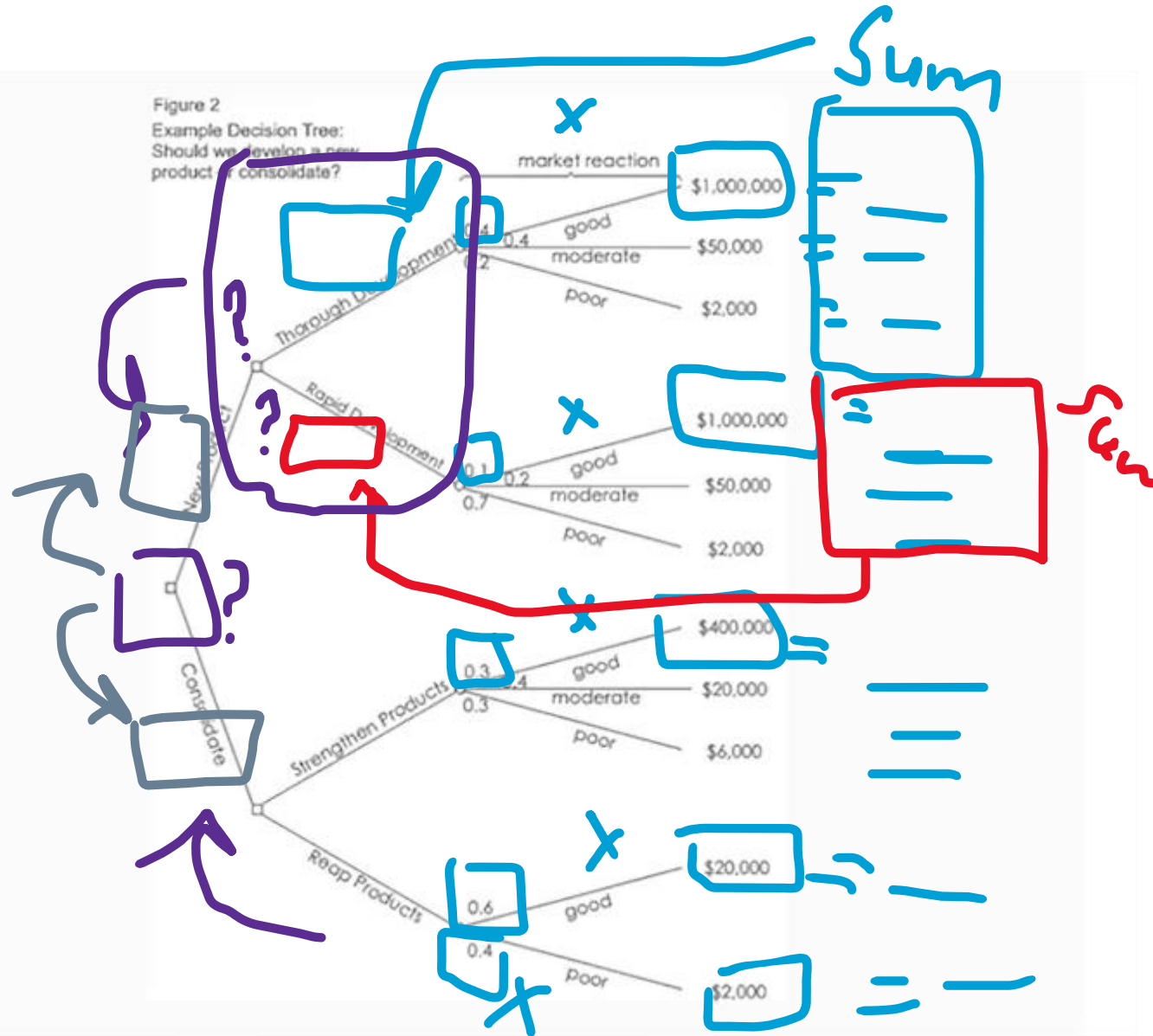


Figure 2
Example Decision Tree:
Should we develop a new
product or consolidate?





With limited attributes, it is possible to do the graphing of decision tree by hand, in other cases, it may become really time consuming and confusing.

Later in your jobs, if you wanted to use decision tree, remember that there are automated tools to do decision tree for you.

Applications of Classification Techniques

- **Financial markets** – ex: stock price prediction
- **Marketing** – next best offer prediction
- **Web Analytics** – ‘customer like you also purchased x,y,z’
- **Credit Modelling** – will you get approved for a credit card?
- **Medicine** – predicting the likely protein to bind to a virus
- **Social/Political Science** – predicting who wins the next US election
- **Automotive Industry** – Autopilot

Predictive Analytics Models in Supply Chains

- **Classification**

Classification is a mathematical model that can differentiate **between two or more outcomes**. For instance, using the historical data of a supplier, and setting some decision attributes, the decision of ‘**whether to sign a contract with this supplier?**’ can be answered by a classification model. Managers can be provided with such classification models to assist their decisions.

- **Regression**

As opposed to predicting a decision, regression focus on **predicting an unknown future value using available data**. For instance, **given the bitcoin prices for the last year, ‘what will be the price next week?’** can be answered by a regression model. Managers can be provided with the predicted value of these models to assist their decisions.

- **Other models (Clustering, Time Series, Forecasting, and similar)**

The background of the slide features a dark green grid with a white ECG line. Faint green text labels for ECG leads are visible: 'aVR', 'V1', 'II', 'aVL', 'V2', 'III', 'aVF', 'V3', and 'VI'.

Chapter 1: Classification Models

Chapter 2: Learning how to
Formulate a Regression Model

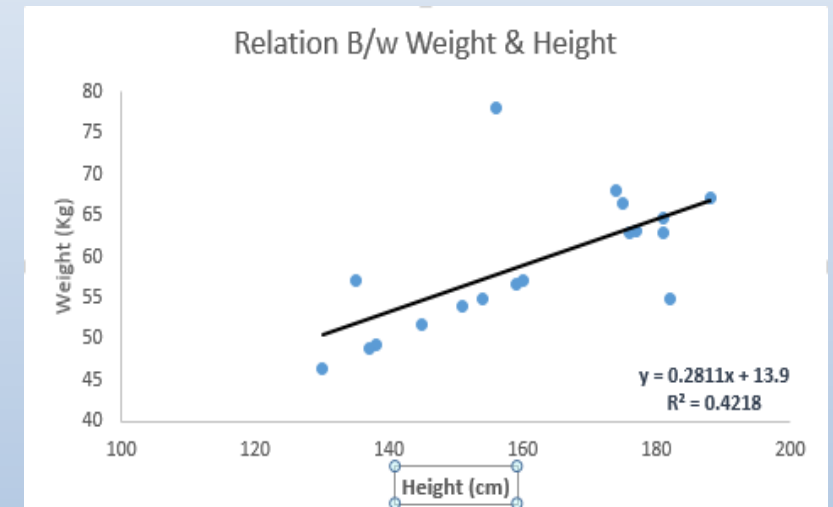
Chapter 3: Utilising Regression
Models to Forecast Demand

Regression

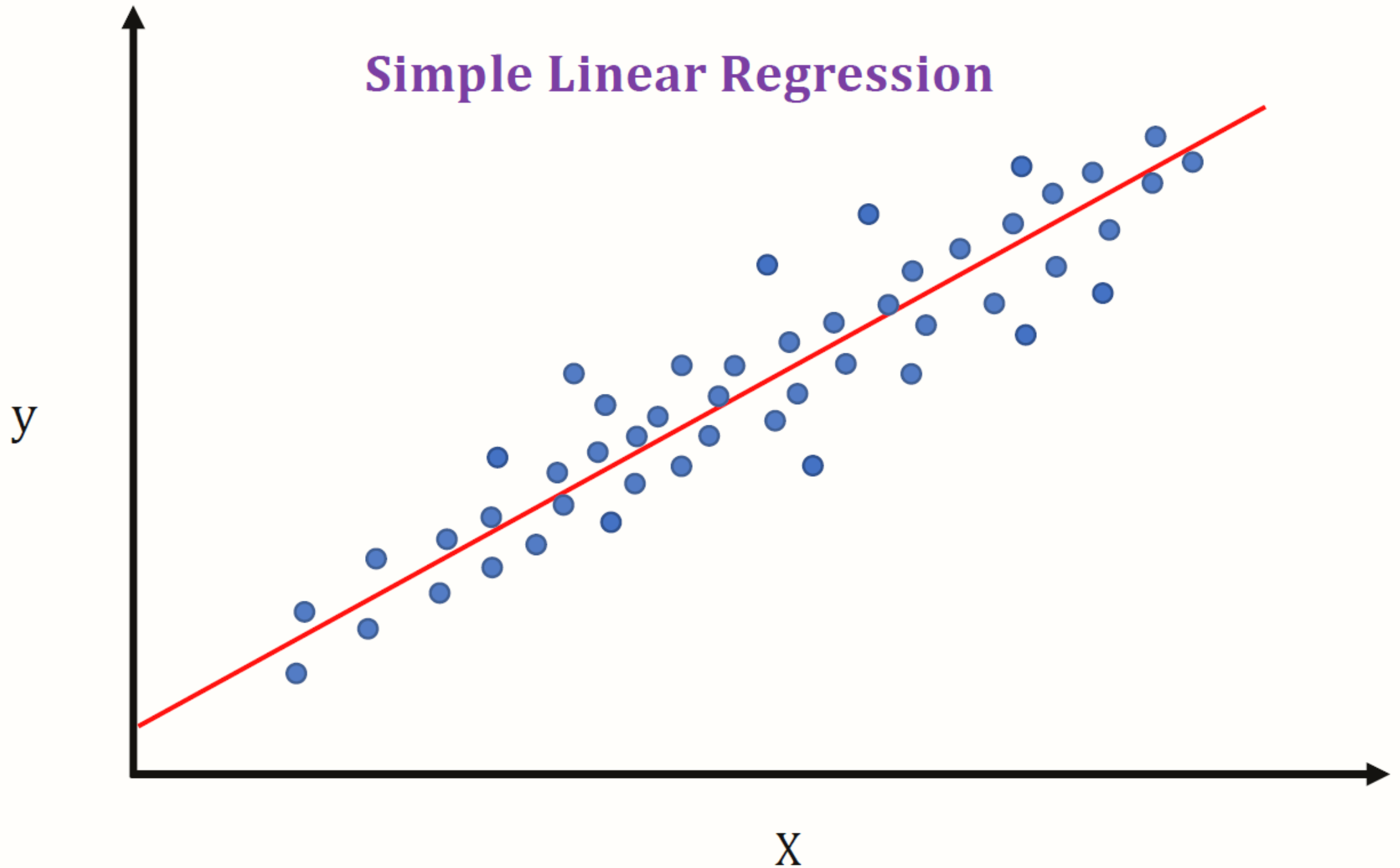
- Regression investigates the relationship between a **dependent (target)** variable and **independent variables (predictor)**
- It is used for forecasting, time series analysis and finding causal effect relationship between variables

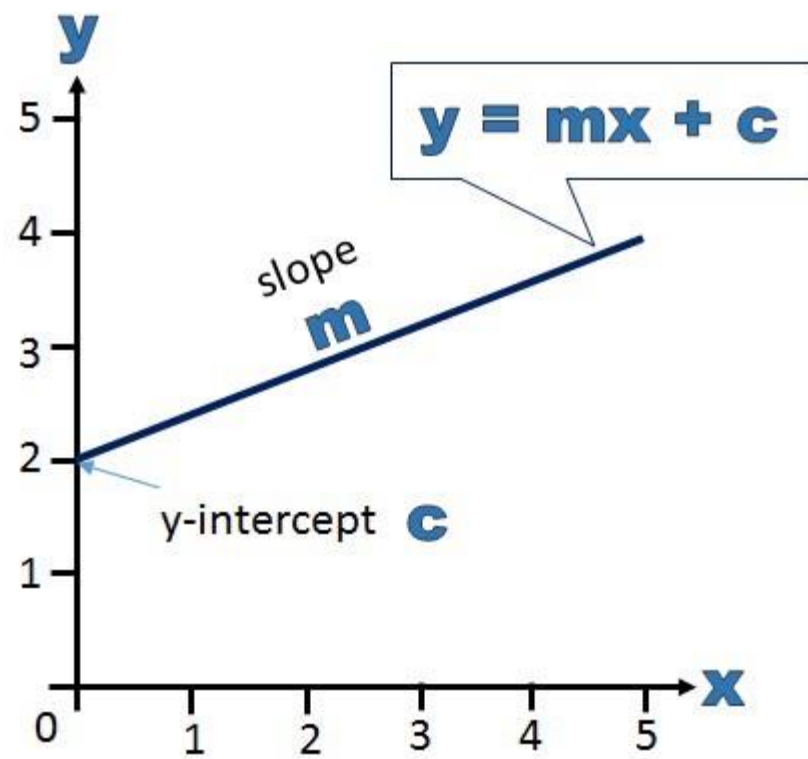
Linear Regression

- Establishes a **relationship between dependent variable (y) and one or more independent variables (X)** using best fit straight line (also known as regression line)
- This is represented by an **equation $y = a*x + b$** , where a is the intercept, b is the slope of the line and e is the error term
- The **available data is graphed to find this regression line. This enables determining future values.** The equation can then be found to predict the value of the target variable based on the independent variables

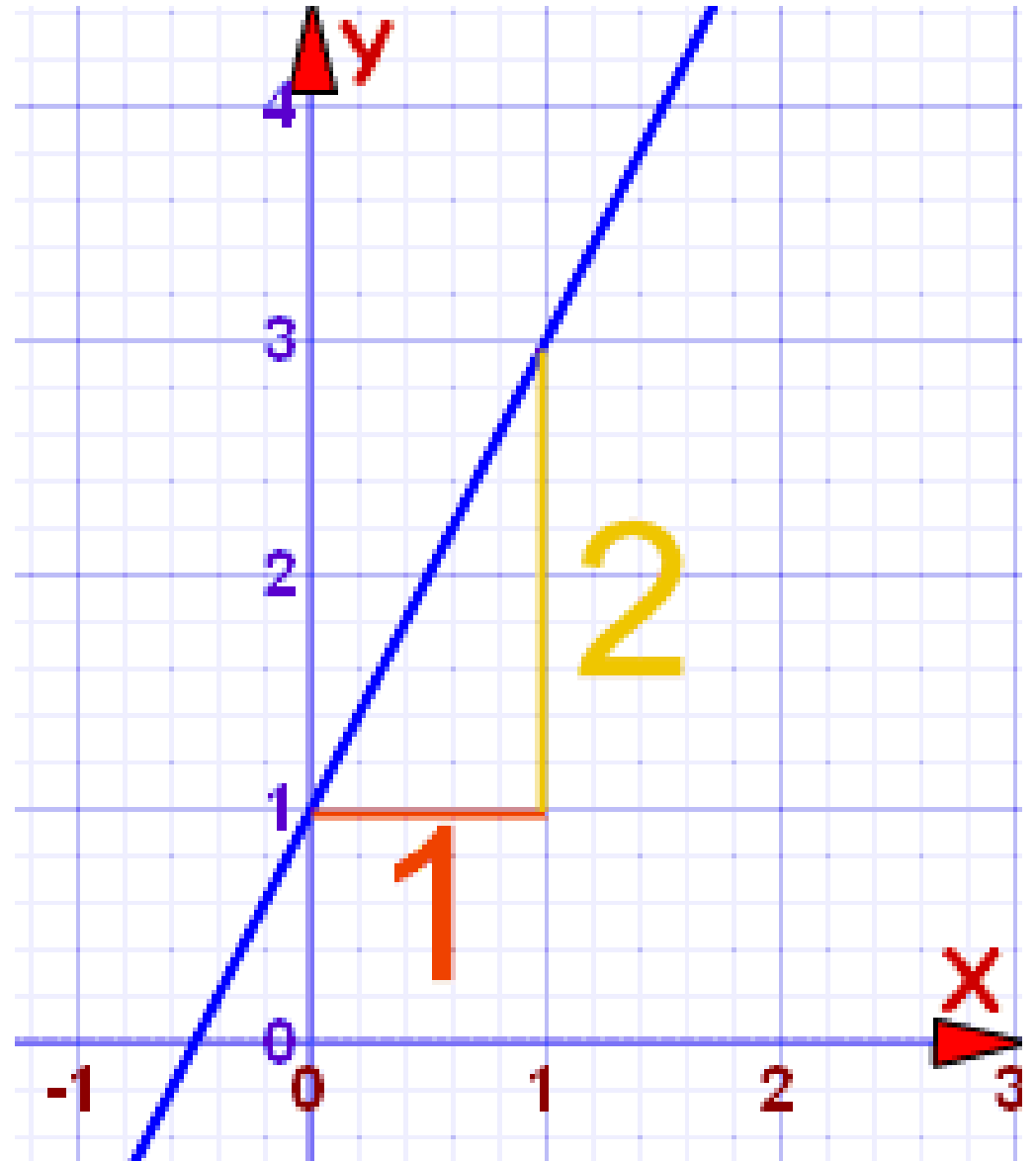


Simple Linear Regression

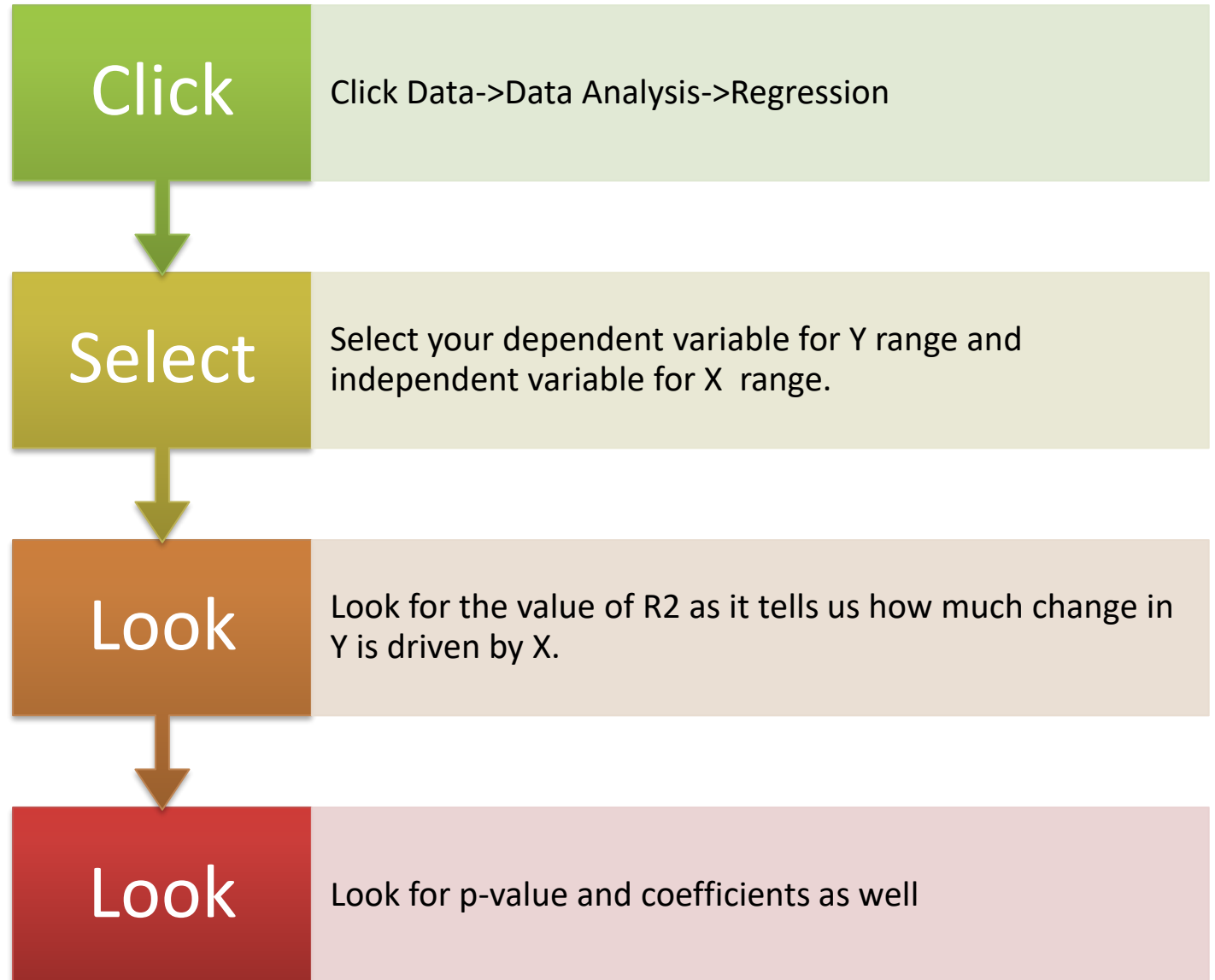




$$Y=2x+1$$



Example 1: The relationship between experience (years with company) and salary



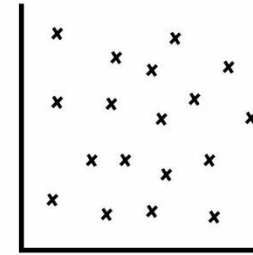
| | | | | | | | | |
|-----------------------|---------------------|-----------------------|---------------|----------------|-----------------------|------------------|--------------------|--------------------|
| SUMMARY OUTPUT | | | | | | | | |
| | | | | | | | | |
| Regression Statistics | | | | | | | | |
| Multiple R | 0.766051647 | | | | | | | |
| R Square | 0.586835127 | | | | | | | |
| Adjusted R Square | 0.583883949 | | | | | | | |
| Standard Error | 15568.50444 | | | | | | | |
| Observations | 142 | | | | | | | |
| | | | | | | | | |
| ANOVA | | | | | | | | |
| | <i>df</i> | <i>SS</i> | <i>MS</i> | <i>F</i> | <i>Significance F</i> | | | |
| Regression | 1 | 48196392870 | 48196392870 | 198.8477796 | 1.17585E-28 | | | |
| Residual | 140 | 33932966285 | 242378330.6 | | | | | |
| Total | 141 | 82129359155 | | | | | | |
| | | | | | | | | |
| | <i>Coefficients</i> | <i>Standard Error</i> | <i>t Stat</i> | <i>P-value</i> | <i>Lower 95%</i> | <i>Upper 95%</i> | <i>Lower 95.0%</i> | <i>Upper 95.0%</i> |
| Intercept | 69816.58422 | 3023.145185 | 23.09402293 | 1.35128E-49 | 63839.66379 | 75793.50466 | 63839.66379 | 75793.50466 |
| Year with Company | 12185.36839 | 864.1284236 | 14.10133964 | 1.17585E-28 | 10476.94008 | 13893.79671 | 10476.94008 | 13893.79671 |



Positive
Correlation



Negative
Correlation



No
Correlation

R-squared values determines the proportion of variance in the dependent variable that can be explained by the independent variable. It range from 0 to 1 and are commonly stated as percentages from 0% to 100%.

R-squared values determines the proportion of variance in the dependent variable that can be explained by the independent variable. It range from 0 to 1 and are commonly stated as percentages from 0% to 100%.

A R-squared between 0.50 to 0.99 is acceptable

Similar to p-Value in diagnostic analytics, here, in regression, Significance F needs to be below 0.05 to proceed

Multiple Regression

- This is determining the relationship between **multiple independent variables** and a **dependent variable**. The dependent variable is modelled as a function of several independent variables with corresponding coefficients, along with the constant term.
- Multiple regression requires **two or more independent variables** which is why it's called multiple regression.
- It can be represented by:

$$Y = a_1x_1 + a_2x_2 + \dots + a_nx_n + b$$



Write the price sale formula

Y: The dependent variable is the price sale
X1, X2: The independent variables are manufacturing and inventory costs

The rest are fixed costs (your intercept value)

| | F | G | |
|-------------------|-----------------------|--------------|-----|
| | Regression Statistics | | |
| Multiple R | 0.880587144 | | |
| R Square | 0.775433719 | | |
| Adjusted R Square | 0.725530101 | | |
| Standard Error | 9111.869683 | | |
| Observations | 12 | | |
| | | | |
| | ANOVA | | |
| | | df | |
| Regression | | 2 | |
| Residual | | 9 | |
| Total | | 11 | |
| | | | |
| | | Coefficients | Std |
| Intercept | | 16387.30 | |
| Production Cost | | 2.03 | |
| Inventory Cost | | 3.58 | |

Product price= a * Production Cost + b * Inventory cost + c

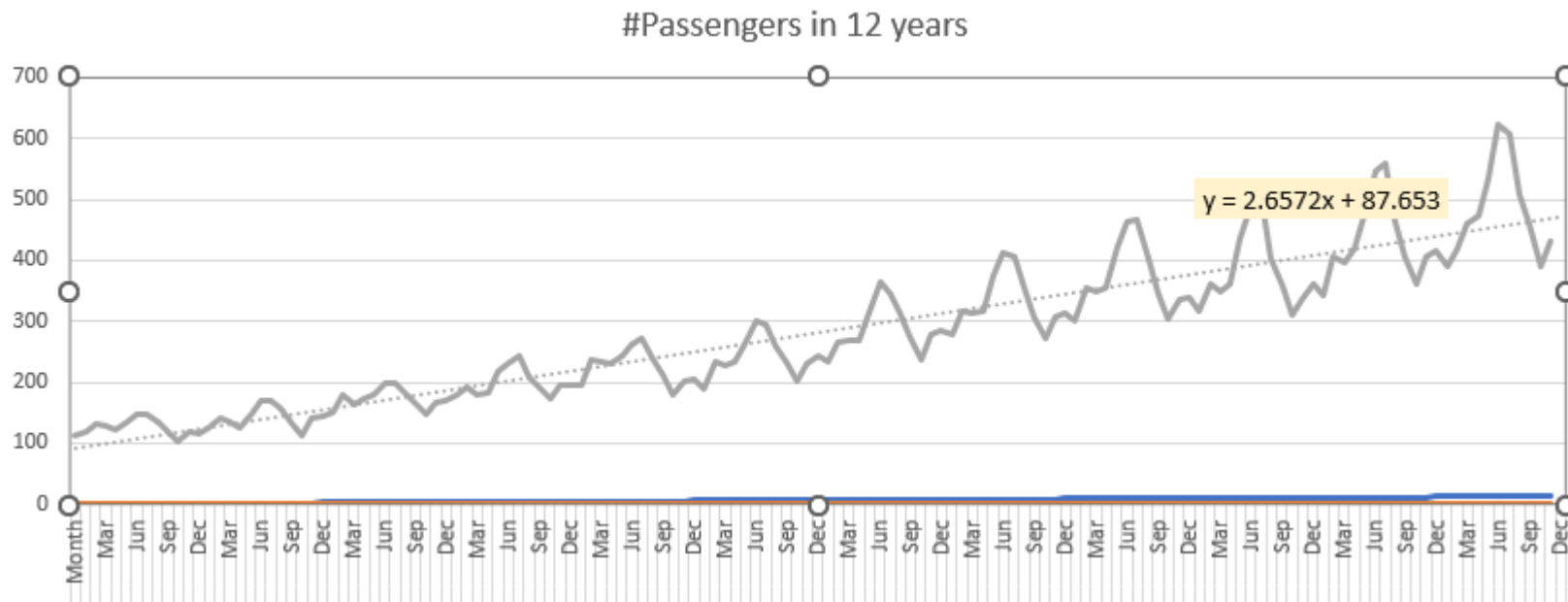
The background of the slide features a green ECG (heart rate) line on a dark grid. The line shows a regular rhythm with distinct P waves, QRS complexes, and T waves. Labels for ECG leads are visible in the background: 'I', 'II', 'III' on the left; 'aVR', 'aVL', 'aVF' in the center; and 'V1', 'V2', 'V3' on the right.

Chapter 1: Classification Models

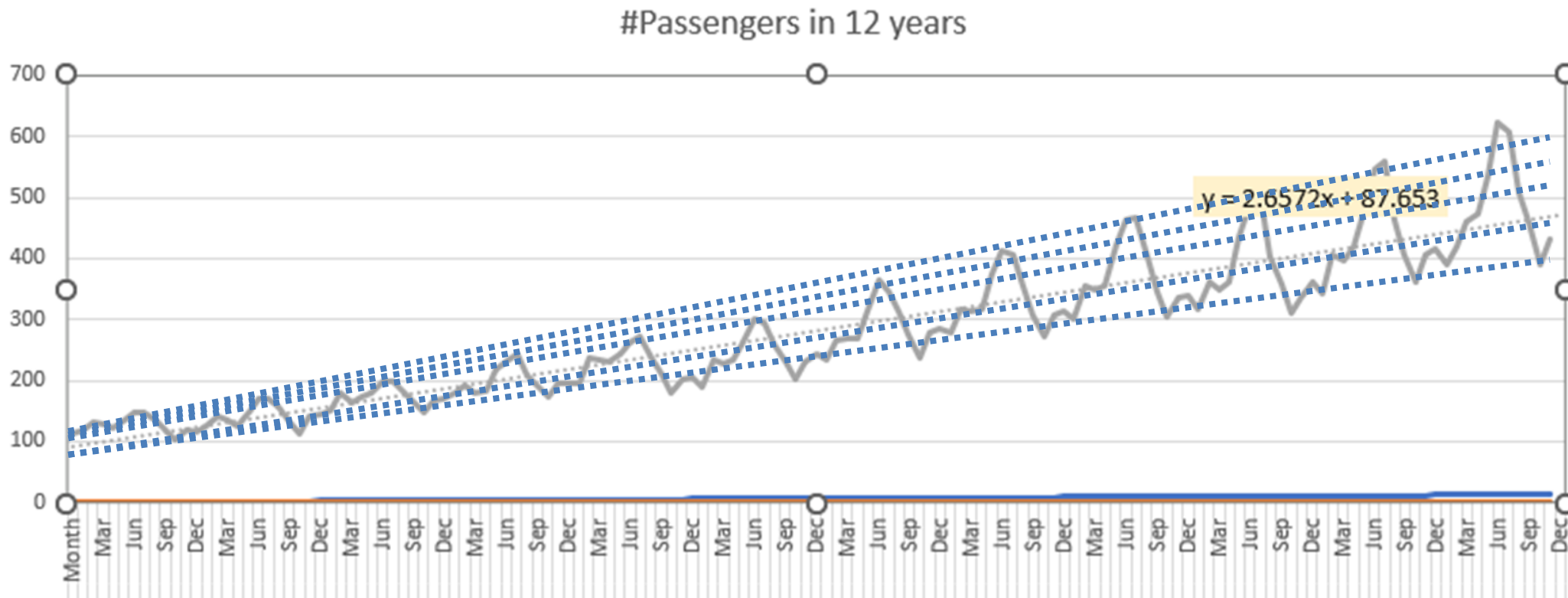
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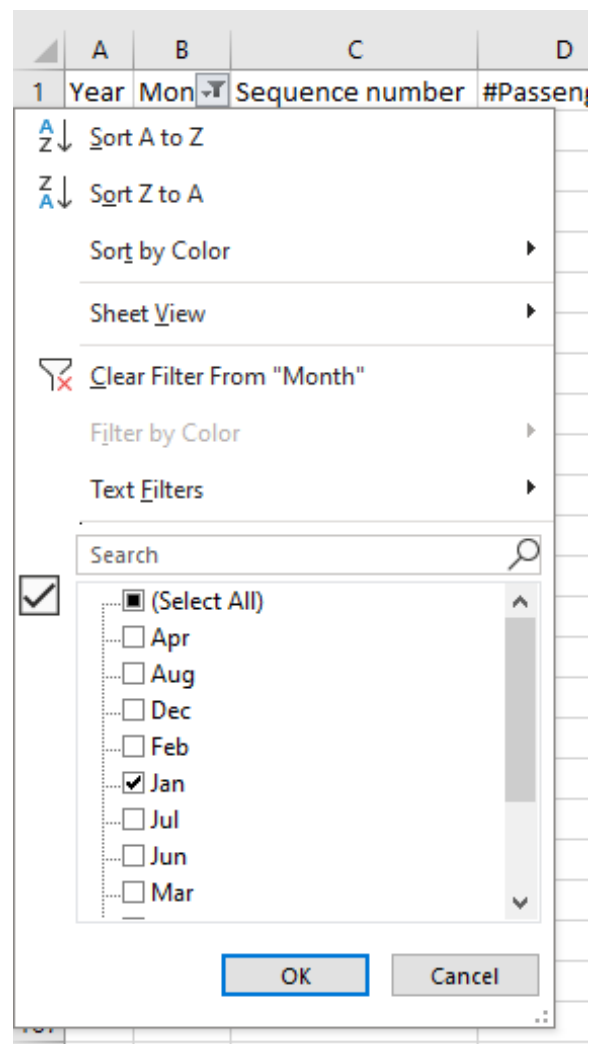
Chapter 3: Utilising Regression
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These values do not consider the seasonality (historical data says that it is always above the trend in July and below the trend in Oct). These predictions are on the trend

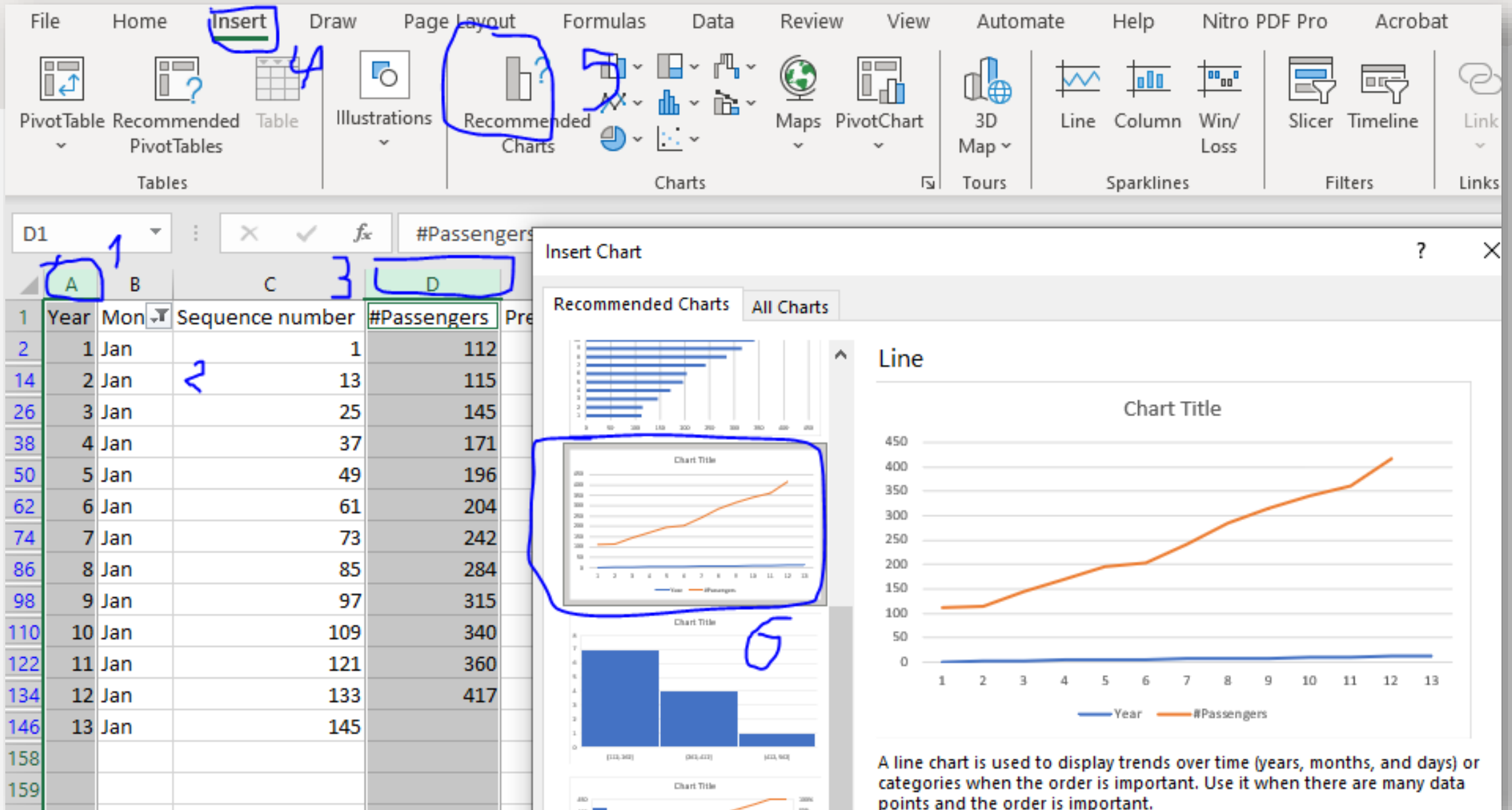


It is always more than the linear trend in specific months of each year, and below the linear trend in some other specific months





Select YEAR and #Passengers and draw a line chart





What is next?

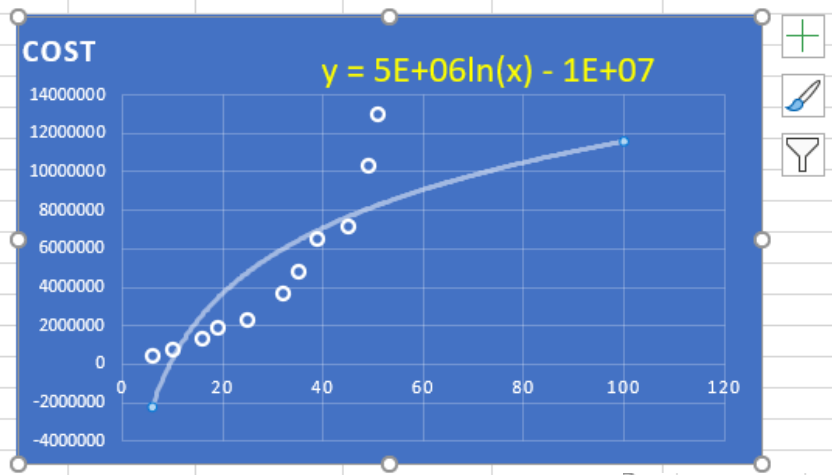
You repeat the last few steps that you did (to find predicted values for Jan year 13) for 11 more times, to compute values for Feb, March, April....
Dec of year 13

Using Forecast Function – to predict value for Jan

| D | |
|--|-----|
| #Passengers | Pt |
| 1 | 112 |
| 3 | 115 |
| 5 | 145 |
| 7 | 171 |
| 9 | 196 |
| 1 | 204 |
| 3 | 242 |
| 5 | 284 |
| 7 | 315 |
| 9 | 340 |
| 1 | 360 |
| 3 | 417 |
| =FORECAST | |
| <div><div><div><div><div></div><div>FORECAST.ETS</div></div><div><div></div><div>FORECAST.ETS.CONFINT</div></div><div><div></div><div>FORECAST.ETS.SEASONALITY</div></div><div><div></div><div>FORECAST.ETS.STAT</div></div><div><div></div><div>FORECAST.LINEAR</div></div><div><div></div><div>FORECAST</div></div></div></div><div>This fur Calcula</div></div> | |

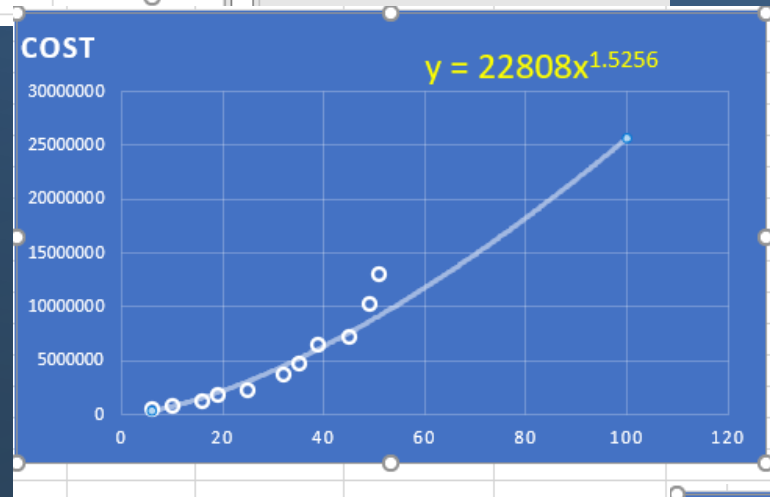


What about non-linear
models???



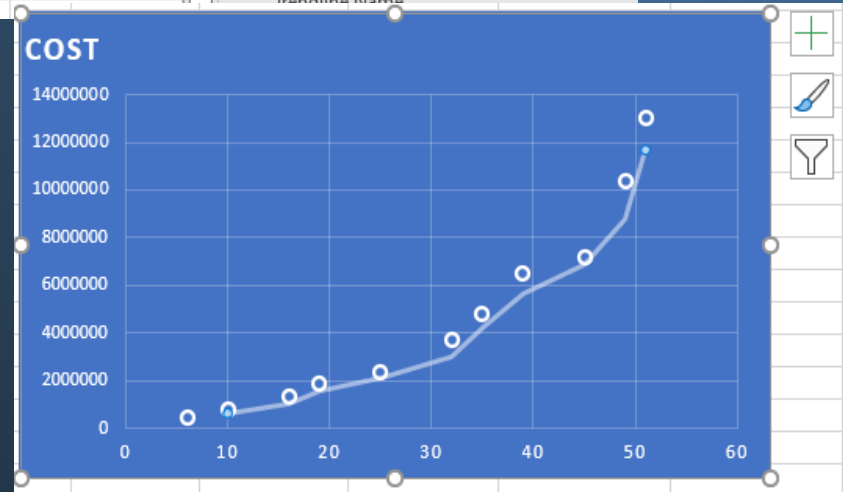
Trendline Options

- ☐ Exponential
- ☐ Linear
- ☒ Logarithmic
- ☐ Polynomial Order 2
- ☐ Power
- ☐ Moving Average Period 2



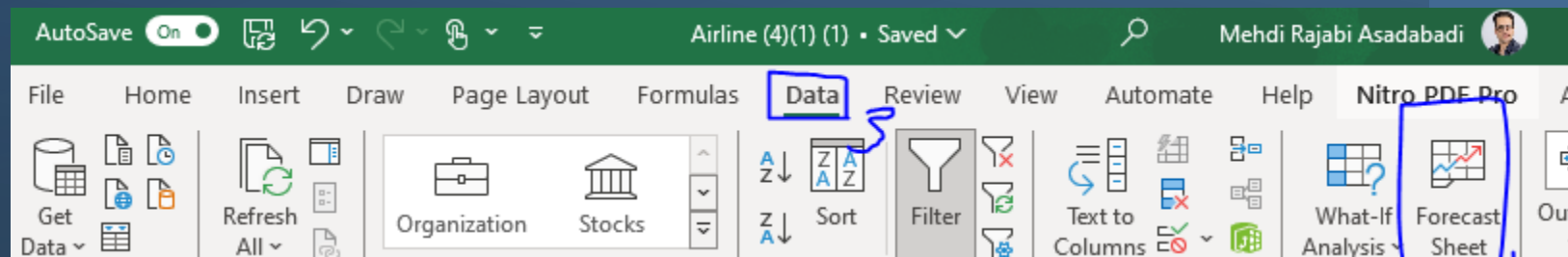
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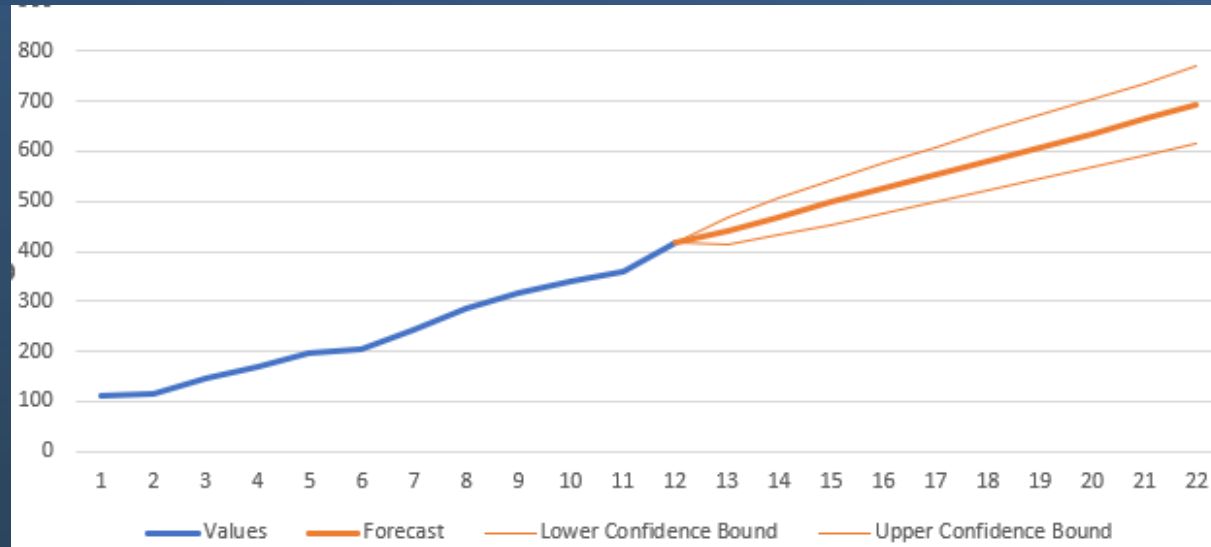
- ☐ Exponential
- ☐ Linear
- ☐ Logarithmic
- ☐ Polynomial Order 2
- ☒ Power
- ☐ Moving Average Period 2



Trendline Options

- ☐ Exponential
- ☐ Linear
- ☐ Logarithmic
- ☐ Polynomial Order 2
- ☐ Power
- ☒ Moving Average Period 2





1. Predict the inventory levels needed for the next quarter.
Use historical inventory data trends and sales forecasts to estimate future inventory requirements.
2. Forecast inventory costs for the next month.
Based on historical 'Inventory Cost Per Unit' data, predict the upcoming month's inventory costs.
3. Estimate future stock replenishment needs for high-demand products.
Use sales trends to predict when high-demand products will need restocking.
4. Predict which products are at risk of stockouts.
Analyse past inventory levels and sales data to identify products that might face stockouts.
5. Model the impact of a proposed discount strategy on inventory levels.
Based on past sales and inventory data, simulate how new discounts might affect future inventory needs.

Examples of Predictive Analytics in Inventory Data

1. Forecast the sales trend for the next quarter.
Use time series forecasting on 'Units Sold' to predict future sales trends.
2. Predict the effect of a 10% discount on high-selling products.
Model potential impact of a 10% discount on high-selling products based on past data.
3. Estimate future sales during peak seasonal periods.
Analyze past seasonal sales to predict future sales during peak seasons.
4. Predict changes in supplier quality ratings over time.
Model potential trends in quality ratings based on industry dynamics.
5. Forecast the potential impact of supplier cost changes on retail pricing.
Use cost data to model how changes in supplier costs could affect pricing.
6. Estimate future supplier reliability based on current trends.
Analyze current reliability data to predict future supplier performance.
7. Develop a model to select the best supplier based on various criteria.
Create a decision model considering cost, quality, lead time, and reliability.
8. Simulate the impact of a new supplier entering the market.
Model how a new supplier with different metrics might affect the supplier landscape.

Examples of Predictive Analytics in Supplier and Sale Data

