Welcome to the CoGrammar Multiple Linear Regression

The session will start shortly...

Questions? Drop them in the chat. We'll have dedicated moderators answering questions.

Data Science Session Housekeeping

- The use of disrespectful language is prohibited in the questions, this is a supportive, learning environment for all - please engage accordingly. **(Fundamental British Values: Mutual Respect and Tolerance)**
- No question is daft or silly - **ask them!**
- There are **Q&A sessions** midway and at the end of the session, should you wish to ask any follow-up questions. Moderators are going to be answering questions as the session progresses as well.
- If you have any questions outside of this lecture, or that are not answered during this lecture, please do submit these for upcoming Academic Sessions. You can submit these questions here: [Questions]

Data Science Session Housekeeping cont.

- For all **non-academic questions**, please submit a query: www.hyperiondev.com/support
- Report a **safeguarding** incident: www.hyperiondev.com/safeguardreporting
- We would love your **feedback** on lectures: Feedback on Lectures

Skills Bootcamp
8-Week Progression Overview

Fulfil 4 Criteria to Graduation

✅ Criterion 1: Initial Requirements

Timeframe: First 2 Weeks
Guided Learning Hours (GLH): Minimum of 15 hours
Task Completion: First four tasks

Due Date: 24 March 2024

✅ Criterion 2: Mid-Course Progress

60 Guided Learning Hours

Data Science - **13 tasks**
Software Engineering - **13 tasks**
Web Development - **13 tasks**

Due Date: 28 April 2024

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Skills Bootcamp Progression Overview

✅ Criterion 3: Course Progress

Completion: All mandatory tasks, including Build Your Brand and resubmissions by study period end
Interview Invitation: Within 4 weeks post-course
Guided Learning Hours: Minimum of 112 hours by support end date (10.5 hours average, each week)

✅ Criterion 4: Demonstrating Employability

Final Job or Apprenticeship Outcome: Document within 12 weeks post-graduation
Relevance: Progression to employment or related opportunity

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SKILLS FOR LIFE
SKILLS BOOTCAMPS

Department for Education

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Multiple Linear Regression

April 2024

Learning Objectives

- Understand the fundamental concepts and applications of **supervised learning technique.**
- Interpret the **coefficients** and **intercept** of a **multiple linear regression model.**
- Apply multiple linear regression using Python ***scikit-learn*** libraries to real-world datasets, build, train, and evaluate regression models for predictive analysis.

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Learning Objectives

- Differentiate between **training** and **test** datasets, implement appropriate **data splitting techniques.**

- Evaluate the **performance** of a multiple linear regression model to assess the model's **goodness of fit** and **predictive accuracy** on unseen data.

- **Preprocess data**, employ tools to ensure **optimal model performance** and **convergence**, enhancing data preparation skills for machine learning tasks.

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Machine Learning Algorithms

Recap

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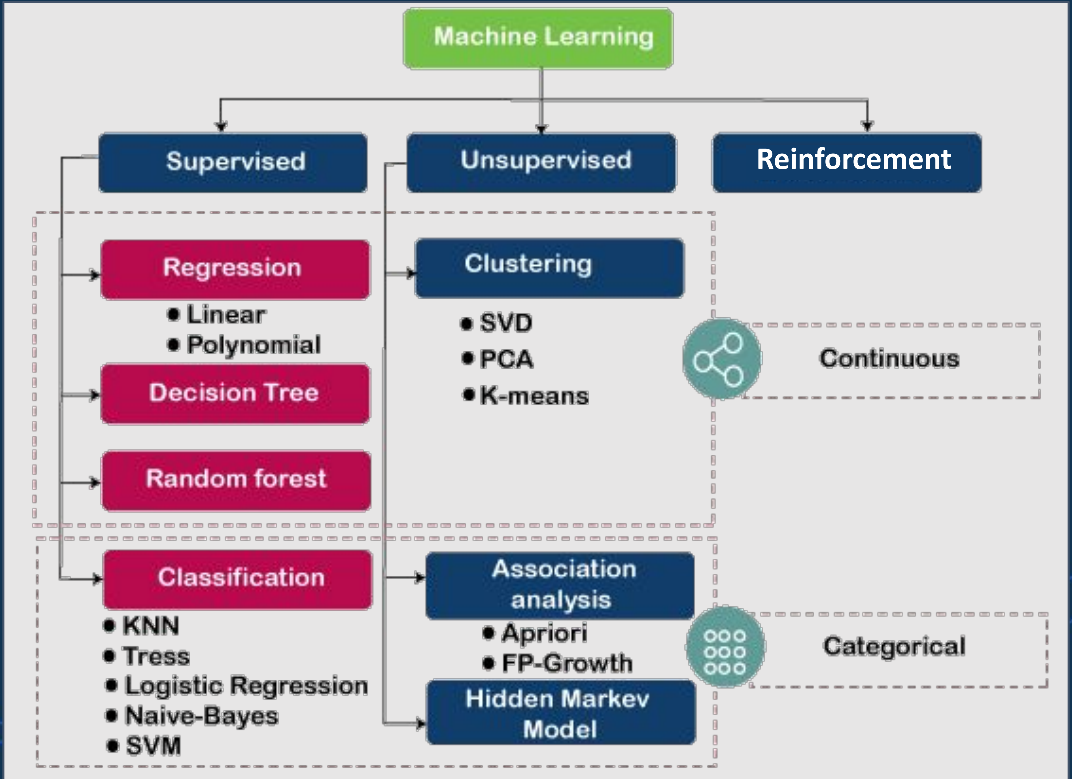
Recap: Machine learning algorithms

- **Supervised learning:** computer learns from **labeled data**, both input and output data are provided.
- **Unsupervised learning:** computer learns from **unlabeled data,** discovering hidden patterns or structures on its own.
- **Reinforcement learning:** computer learns through **interaction** with an **environment**, receiving rewards or penalties for its actions.



Source: https://www.javatpoint.com/machine-learning-algorithms

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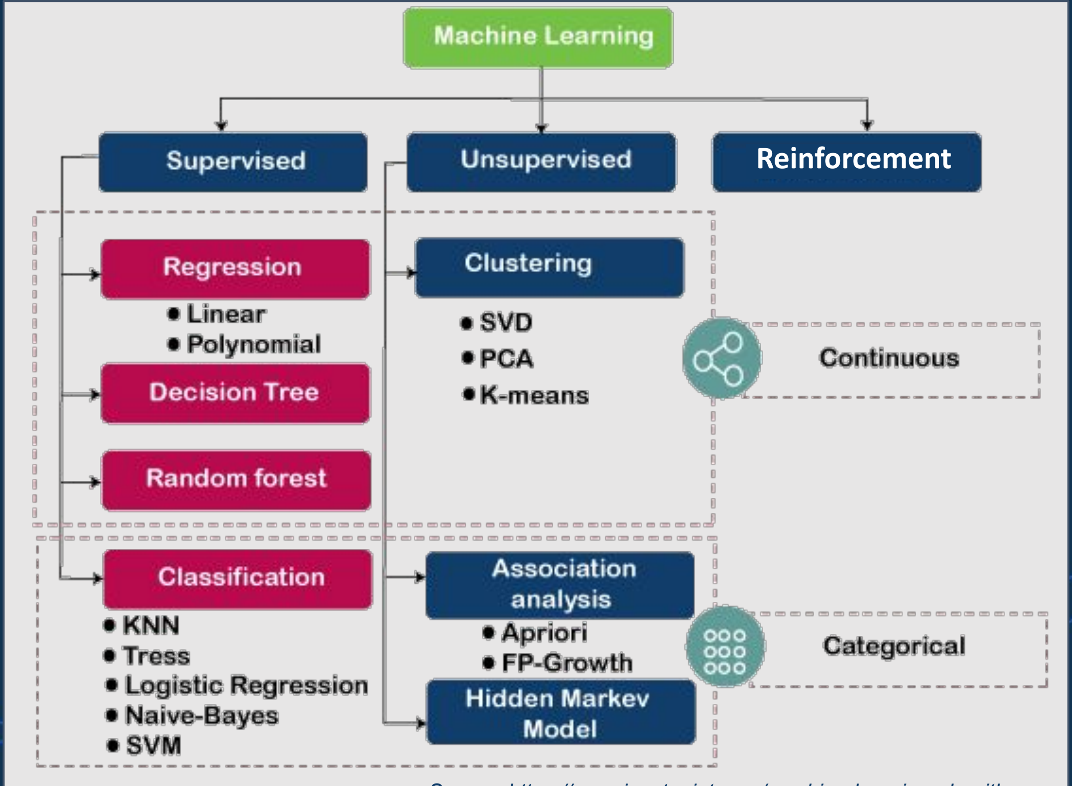
Recap: Machine learning algorithms

❖ **Linear regression:** used for **predictive analysis** for **continuous** numbers such as salary, age, linear relationship between **dependent** (y) and **independent** (x) variables. Best fit a **regression line** between y and x

$y = \beta_0 + \beta_1 x + \varepsilon$, with β_0 = **intercept**, β_1 = **slope**, ε = **error** term (Simple linear)

❖ **Logistic regression:** predict **categorical** variables or **discrete** values, **binary outcomes**, Yes or NO, 0 or 1, Red or Blue.

Next Lecture



Source: *https://www.javatpoint.com/machine-learning-algorithms*

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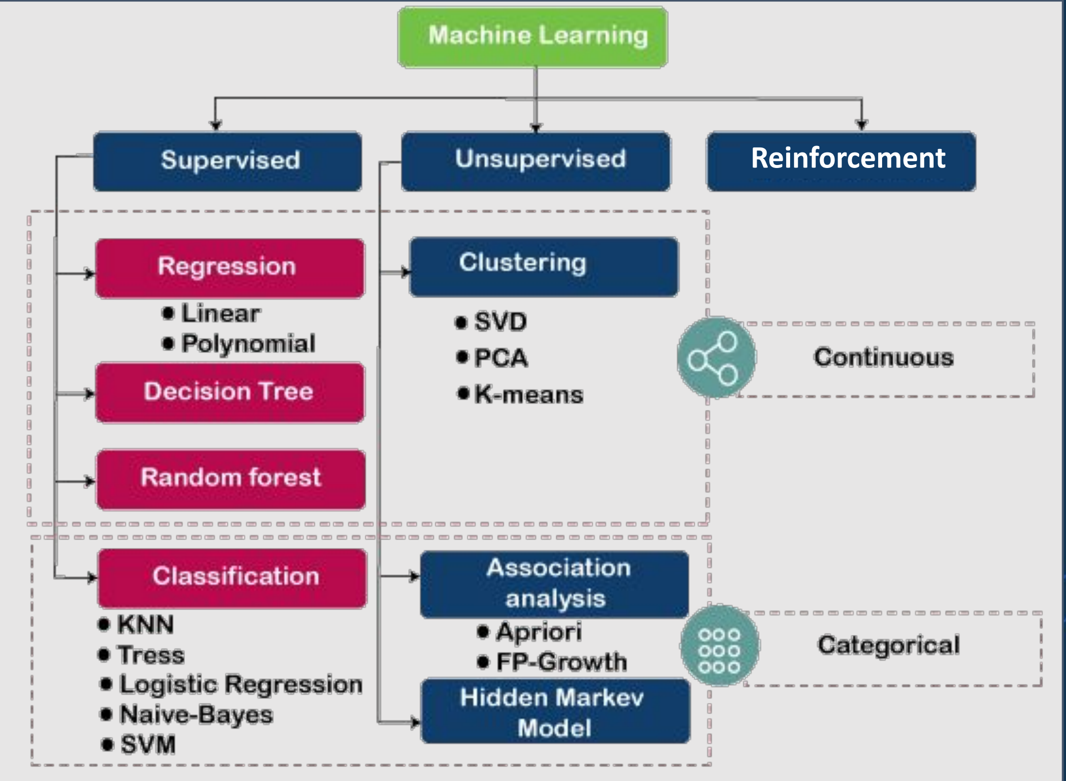
Recap: Machine learning algorithms

- **Simple linear regression:** a **single independent variable** is used to predict the value of the dependent variable.
- **Multiple Linear regression:** **more than one independent variables** are used to predict the value of the dependent variable.

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots + \beta_n x_n + \varepsilon$$



Source: https://www.javatpoint.com/machine-learning-algorithms

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Multiple Linear Regression

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Why Multiple Linear Regression?

- In **Simple Linear Regression (SLR)**, a **single independent/predictor (x) variable** is used to model the **dependent/response/target variable (y).**

- In various cases, the response variable is affected by more than one predictor variable.

- **Multiple Linear Regression (MLR)** algorithm is used which models the **linear relationship** between **a single dependent continuous variable** and **more than one independent variable.**

- **Example:** Prediction of CO_2 emission based on engine size, with MLR more variables, like the weight and number of cylinders in the car, we can make the prediction more accurate.

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Multiple Linear Regression

Extension of simple linear regression, uses **several explanatory (independent) variables** (x_i) to predict the outcome of **one response (dependent) variable** (y).

$$\boxed{y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \ldots + \beta_n x_n + \varepsilon}$$

y = **Output/Response/Dependent** variable

$x_1, x_2, x_3, \ldots, x_n$ = Various **Feature/Explanatory/Independent** variables

β_0 = y-intercept (constant term)

$\beta_1, \beta_2, \beta_3, \ldots, \beta_n$ = slope coefficient for each explanatory variable

ε = Model's **error** term (also called **residuals**)

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Multiple Linear Regression: Assumptions and Limitations

- **Linear relationship** between dependent and each independent variables.

- MLR assumes **little or no multicollinearity** (**correlation** between the **independent variable**) in data. If two independent variables are too highly correlated, then only one of them should be used in the regression model.

- Homogeneity of variance (**homoscedasticity**), size of **residuals** does not change significantly across values of independent variables.

- Regression **residuals** must be **normally distributed**.

Similar to SLR

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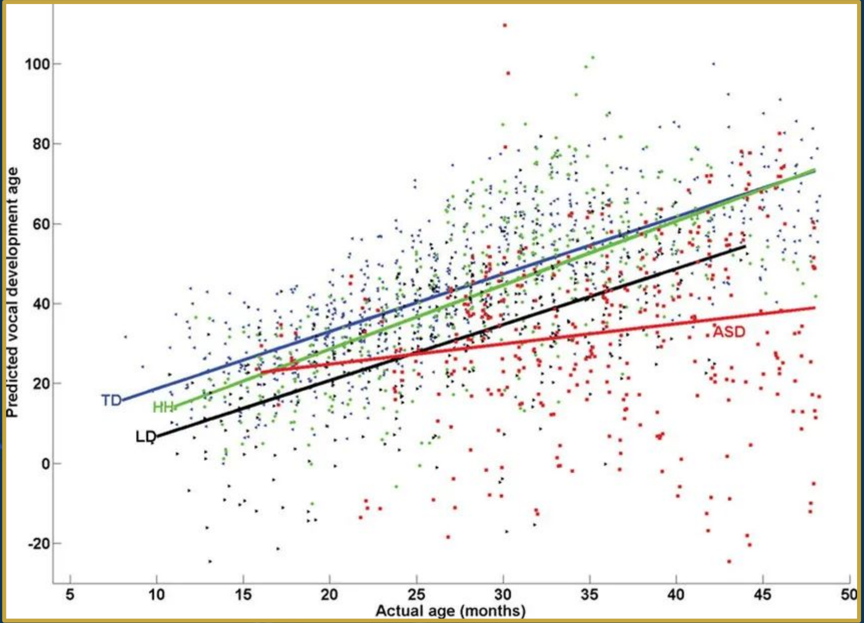
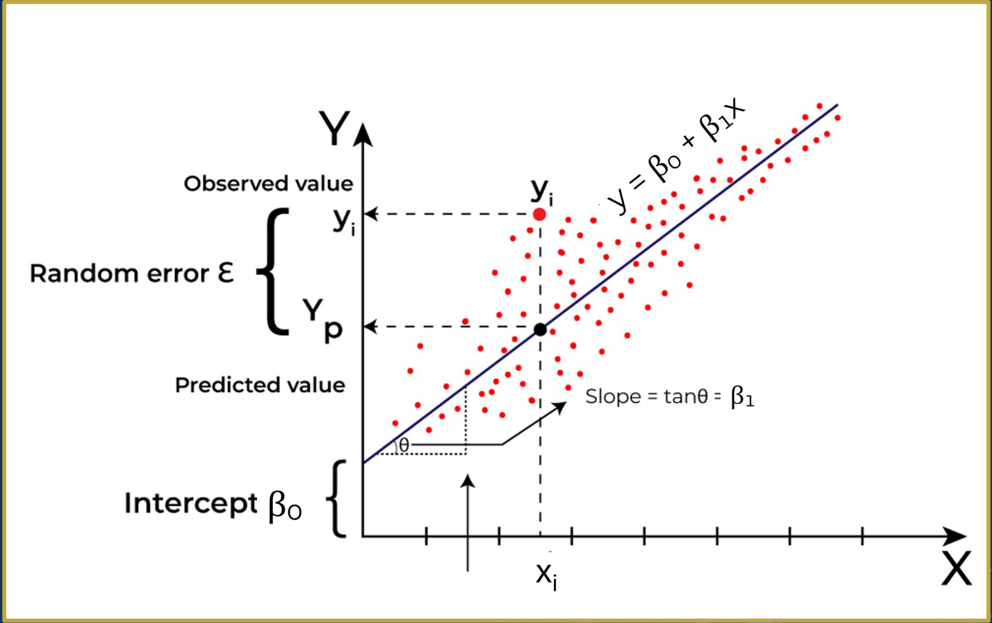
Multiple Linear Regression





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Implementing MLR

scikit-learn (sklearn)

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scikit-learn

- **scikit-learn** is a popular Python library for machine learning.
- It provides simple and efficient tools for data analysis and modelling.

```
from sklearn.linear_model import LinearRegression
```

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Multiple Linear Regression Example

- A linear approach to modelling the relationship between a scalar response and one or more explanatory variables.

- One use case is **predicting housing prices** based on various features such as size, location, and number of bedrooms.

Importing the dataset

Predicting housing prices based on various features such as size, location, and number of bedrooms.

```
#Data loading and manipulation
import numpy as np
import pandas as pd
#Data visualisation
import seaborn as sns
import matplotlib.pyplot as plt

# Import the dataset
df = pd.read_csv("housing.csv")
```

Importing **scikit-learn built in datasets**

```
from sklearn.datasets import load_diabetes
```

Checking the dataset

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5000 entries, 0 to 4999
Data columns (total 7 columns):
 #   Column                        Non-Null Count  Dtype  
---  ------                        --------------  -----  
 0   Avg. Area Income              5000 non-null   float64
 1   Avg. Area House Age           5000 non-null   float64
 2   Avg. Area Number of Rooms     5000 non-null   float64
 3   Avg. Area Number of Bedrooms  5000 non-null   float64
 4   Area Population              5000 non-null   float64
 5   Price                         5000 non-null   float64
 6   Address                       5000 non-null   object 
dtypes: float64(6), object(1)
memory usage: 273.6+ KB
```

SLR: Predicting house prices based on the **size of the house.**

MLR: Predicting house prices based on the **size of the house, number of bedrooms**, and **location**.

Feature Selection

Identifying which **features** most significantly influence the prediction i.e. housing prices. Preprocess data by **dropping irrelevant features**.

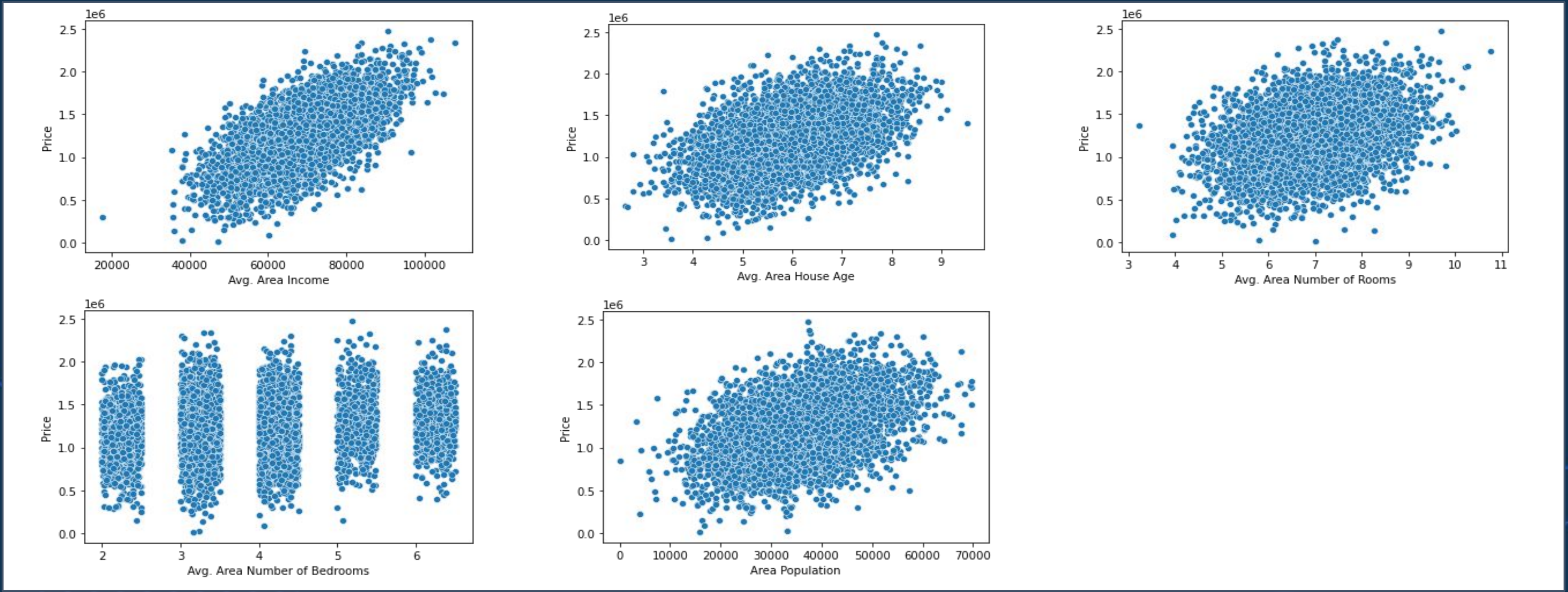
	Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price	Address
0	79545.45857	5.682861	7.009188	4.09	23086.80050	1.059034e+06	208 Michael Ferry Apt. 674\nLaurabury, NE 3701...
1	79248.64245	6.002900	6.730821	3.09	40173.07217	1.505891e+06	188 Johnson Views Suite 079\nLake Kathleen, CA...
2	61287.06718	5.865890	8.512727	5.13	36882.15940	1.058988e+06	9127 Elizabeth Stravenue\nDanieltown, WI 06482...
3	63345.24005	7.188236	5.586729	3.26	34310.24283	1.260617e+06	USS Barnett\nFPO AP 44820
4	59982.19723	5.040555	7.839388	4.23	26354.10947	6.309435e+05	USNS Raymond\nFPO AE 09386

```
# Drop the Address field as it's textual and not useful for regression without further processing
df = df.drop('Address', axis=1)
```

```
# Feature matrix and target vector
X_feature = df.drop('Price', axis=1)  # We assume 'Price' is the column we want to predict
y_target = df['Price']
```

Feature correlations

```python
for col in X_feature.columns:
    sns.scatterplot(data=X_feature, x=X_feature[col], y=y_target)
```



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Feature correlations


```
sns.heatmap(df.corr(), annot = True, cmap="YlGnBu")
```

Lack of correlation between Avg. Area Number of Bedrooms and the Price, we can drop this feature.

```
# Updating Feature matrix by dropping Avg. Area Number of Bedrooms
X_feature = X_feature.drop('Avg. Area Number of Bedrooms', axis=1)
```

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Multiple Linear Regression

- **LinearRegression()** method from **sklearn** to create a linear regression object.
- Method **fit()**, takes **independent (X_feature)** and **dependent (y_target)** values as parameters, fills regression object with data that describes the relationship.
- **Predict house price** based on given feature values, e.g., mean feature values

```
from sklearn.linear_model import LinearRegression

regr = LinearRegression()
regr.fit(X_feature, y_target)

#Predict the Price a house for
#the average values of the different features
averages = [X_feature[cols].mean() for cols in X_feature]
predicted_price = regr.predict([averages])
print(predicted_price)
print(regr.coef_)
#Output: [1232072.65414531]
#[2.15827436e+01 1.65657872e+05 1.21598165e+05 1.51961198e+01]
```

Price of house if the **average values of each feature** is taken = 1232072.65414531

If the average **income/house age/no. of rooms/area population** increase by 1 unit, the **Price** increases by the respective no. of units.

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Dataset Splitting

train-test-split

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Dataset Splitting

- Aim is to get a model to predict the value of the price of the house.

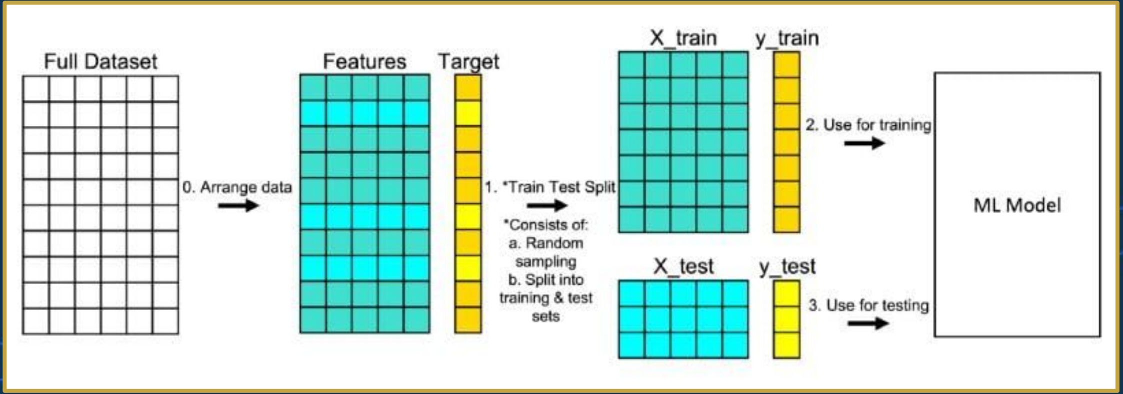
- **Train test split** is a model validation procedure that allows to simulate how a **model would perform on new/unseen data.**

- Divide the data into **training** and **testing** sets (sometimes a **validation set** too) for model evaluation.

Training set (to fit model)

Testing set (to evaluate model)

Ratio 80:20, 70:30, or 90:10



Source: https://builtin.com/data-science/train-test-split

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Data splitting, fitting model and predicting

```
from sklearn.model_selection import train_test_split

# Split the dataset into training and testing sets
# Use the same random seed for learning purposes to get the same result
X_train, X_test, y_train, y_test = train_test_split(X_feature, y_target, test_size=0.3, random_state=42)
```

```
# Initialize the multiple regression model
multi_reg_model = LinearRegression()
```

```
# Fit the model to the training data
multi_reg_model.fit(X_train, y_train)
```

```
# Predict the housing prices on the test set
y_pred = multi_reg_model.predict(X_test)
```

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Performance of model

Mean Squared Error, R^2 score, Mean Absolute Error

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Evaluation Metrics

- **Mean Squared Error (MSE):**
  - MSE measures the **average squared difference** between the **predicted** and **actual** values.
  - **Root mean squared error (RMSE)** is root of MSE.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_p - y_a)^2$$

- **Mean Absolute Error (MAE)**
  - Measure of sum of **absolute errors** between **predicted** and **actual** values.

A **lower MSE and MAE** indicates better model performance.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_p - y_a|$$

Evaluation Metrics

- **R-squared (R^2) score** (coefficient of determination):
  - R^2 represents the **proportion of variance** in the target (dependent) variable that can be **explained by the independent variables/model.**
  - An R^2 value **closer to 1** indicates a better fit of the model to the data.
  - A value of 0 indicates that the model explains none of the variability of the response data around its mean.
  - A value of 1 indicates that the model explains all the variability of the response data around its mean.

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Evaluation Metrics

```
from sklearn.metrics import mean_squared_error, r2_score, mean_absolute_error
# Calculate the performance metrics
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)
mae = mean_absolute_error(y_test, y_pred)
```

```
Mean Squared Error: 10062092567.349297
R-squared: 0.9147354891150795
Mean Absolute Error: 81116.43359989364
```

Here we see quite a **high MSE and MAE (scale-variant metrics)**, although it also has **R^2 (scale-invariant metric)** value very **close to 1**, indicating that much of the variance can be explained by the current modeling - meaning it could potentially have a high goodness of fit.

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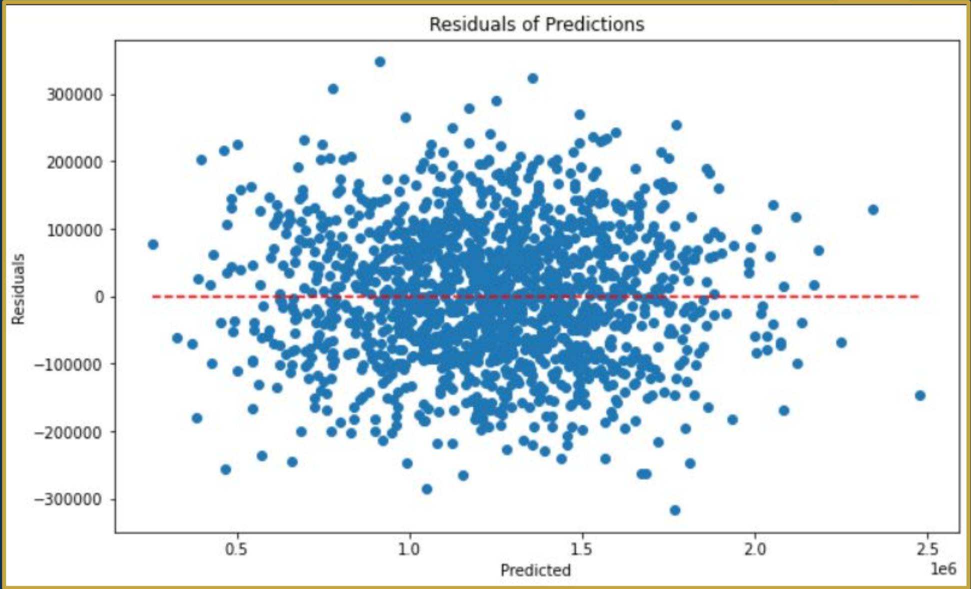
Evaluation Metrics



One way to verify that our predictions are close to the actual values is plotting them against each other. If the line is straight it indicates a very good model.

Another valuable graph is looking at the residuals, which should be random for the model to be fitted well. In this case we can't see a clear pattern, suggesting a good model.

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Feature Scaling

Normalisation
Standardisation

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Feature Scaling

- Data columns have different values and measurement units, difficult to compare, e.g. What is kgs compared to metres? Or altitude compared to time?

- **Feature scaling - normalisation** and **standardisation**, involves transforming the data on the same scale
  - to compare easily,
  - more suitable for modeling,
  - to build accurate and effective machine learning models,
  - help improve model performance,
  - reduce the impact of outliers.

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Feature Scaling

Normalisation	Standardisation
Rescales values to a range between 0 and 1	Centers data around mean and scales to standard deviation of 1
Useful when data distribution is unknown or **not Gaussian**	Useful with **Gaussian** data distribution
Sensitive to outliers	**Less sensitive to outliers**
Retains shape of original distribution	Changes shape of original distribution
May not preserve relationships between data points	Preserves relationships between data points
MinMaxScaler() (x – min)/(max – min)	**StandardScaler()** (x – mean)/standard deviation

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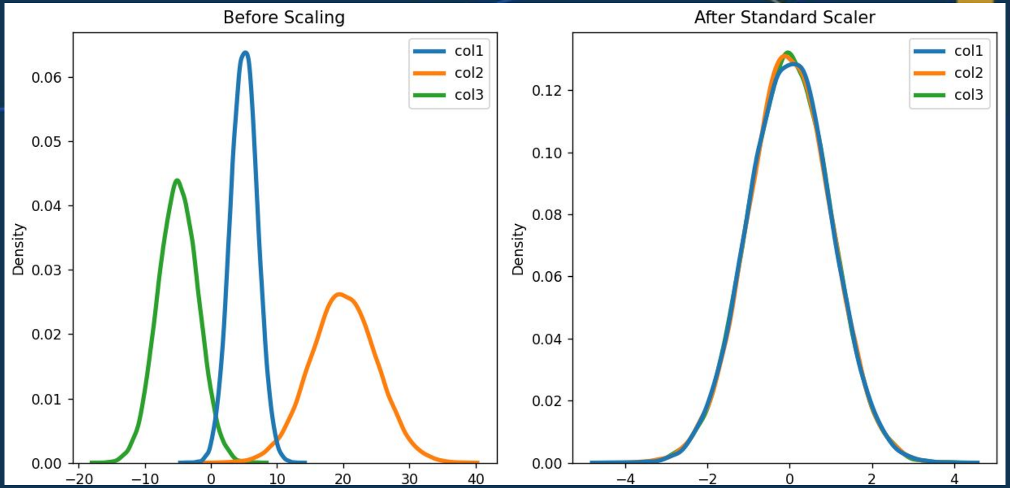
Feature Scaling examples

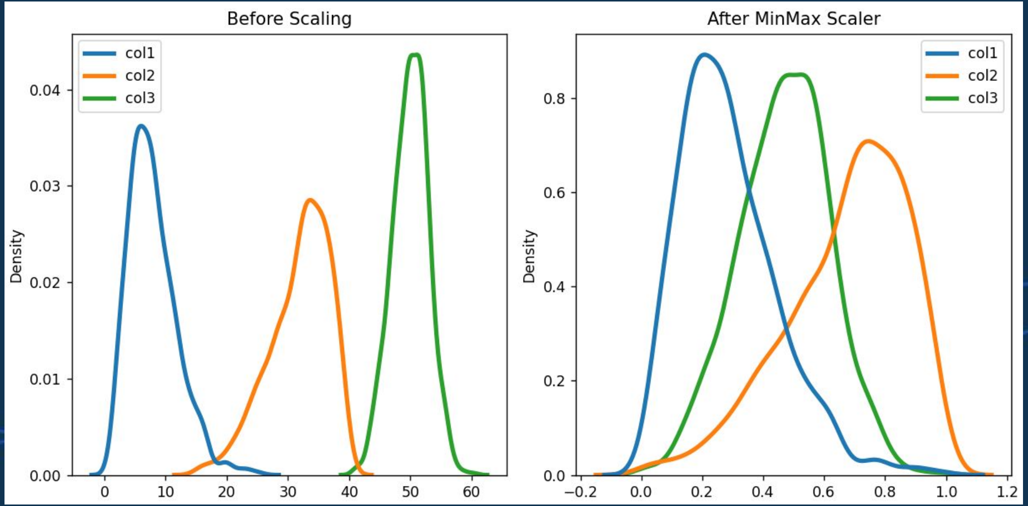
StandardScaler

Gaussian distributions



MinMaxScaler

Non-Gaussian distributions



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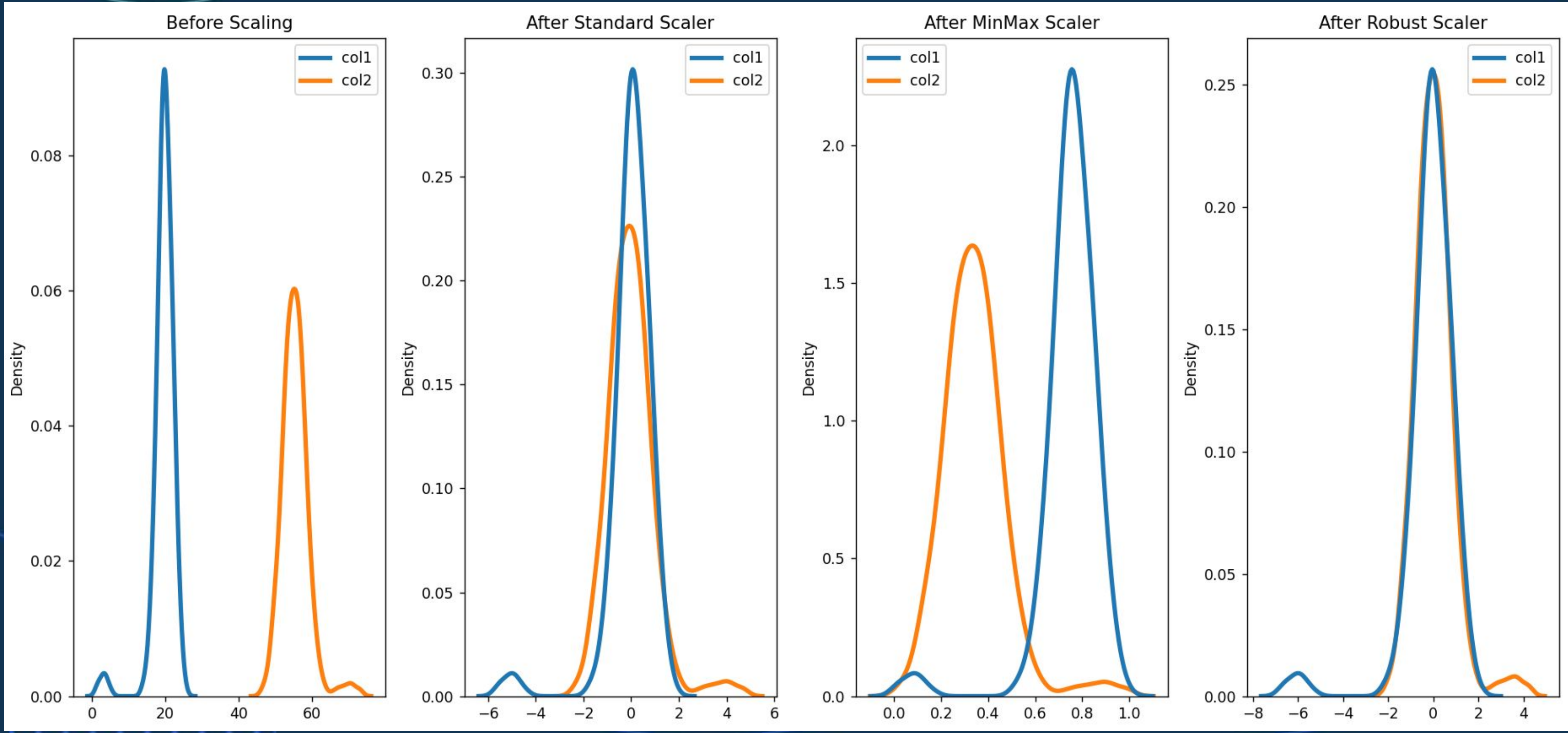
Feature Scaling examples

Gaussian with outliers



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Feature Scaling

On housing dataset

```python
from sklearn.preprocessing import StandardScaler
# Fit the scaler on train data
sc = StandardScaler() #MinMaxScaler() would be used if the data was not Gaussian
sc.fit(X_train)

# Apply the scaler on train and test data
X_train = sc.transform(X_train)
X_test = sc.transform(X_test)
```

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Normalising the data

```
#Normalizing numeric data
new_df = (df - df.mean()) / df.std()
new_df.head()
```

Avg. Area Income	Avg. Area House Age	Avg. Area Number of Rooms	Avg. Area Number of Bedrooms	Area Population	Price
1.028557	-0.296897	0.021272	0.088053	-1.317467	-0.490032
1.000708	0.025899	-0.255481	-0.722229	0.403959	0.775431
-0.684561	-0.112292	1.516092	0.930747	0.072403	-0.490162
-0.491450	1.221450	-1.392938	-0.584481	-0.186716	0.080835
-0.806992	-0.944739	0.846657	0.201493	-0.988289	-1.702348

```
Mean Squared Error: 0.08069553676689753
R-squared: 0.9147354891150797
Mean Absolute Error: 0.22971505100062556
```

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Low MSE and MAE, R^2 score ~ 1

Summary

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Key Takeaways from Linear Regression

- Linear regression provides a simple yet powerful tool for **predicting quantitative outcomes**.

- **Applications:** From real estate to finance, linear regression plays a crucial role in predictive analytics.

- **Limitations:** While useful, it **assumes a linear relationship between variables which may not always hold** in real-world scenarios.

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Further Resources

- https://www.analyticsvidhya.com/blog/2021/05/multiple-linear-regression-using-python-and-scikit-learn/

- https://www.geeksforgeeks.org/ml-multiple-linear-regression-using-python/

- https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.LinearRegression.html

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Questions and Answers

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Thank you for attending

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