COIT20277 Introduction to Artificial Intelligence

Week 3 - Lecture

- Supervised Learning: Regression
- Unsupervised Learning

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Acknowledgement of Country

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Acknowledgment

The content of this lecture has been adopted from the following book:

- Artificial Intelligence Programming with Python - From Zero to Hero, 2022, Perry Xiao, *John Wiley & Sons, Inc.*, ISBN 978-1-119-82086-4.

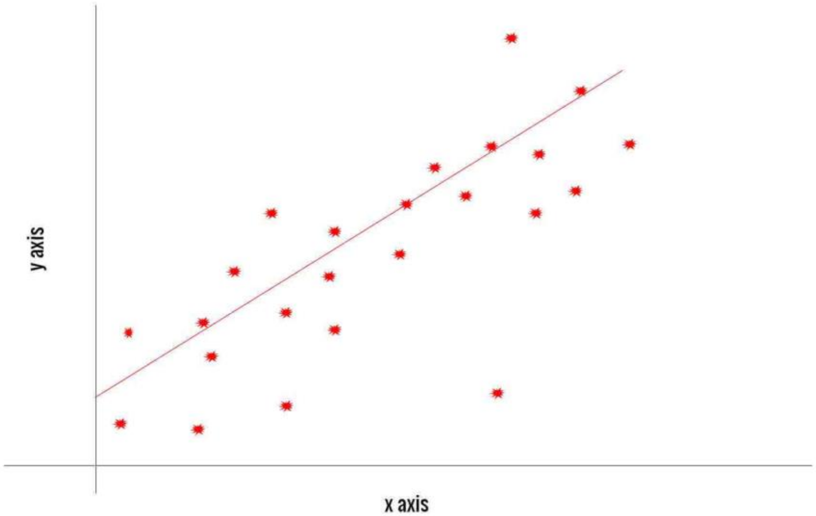
- Chapter 3 (Sections 3.3 - 3.4)

Supervised Learning: Regression

- Introduction to Regression
- Linear Regression
  - Definition and Key Concepts
  - Least Squares Fitting
  - Example with Python Code
- Nonlinear Regression
  - Polynomial Regression
  - Logistic Regression
- Resources and Conclusion

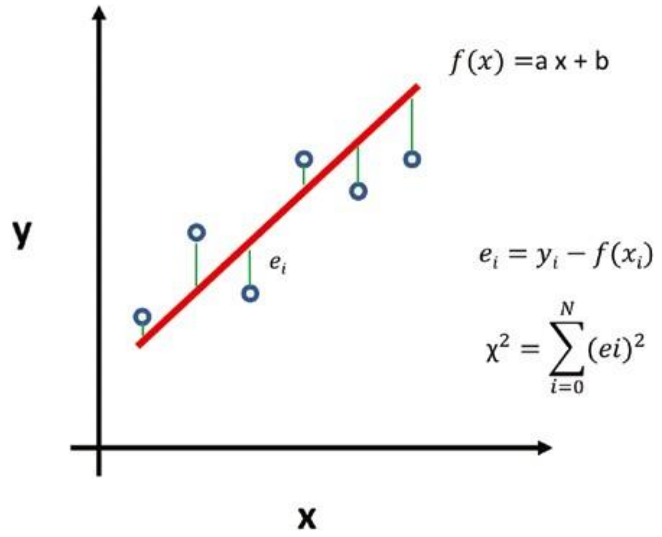
Introduction to Regression

- Regression is a supervised learning technique for predicting continuous values.
- It involves fitting a mathematical model to the data using a technique called *least squares fitting*.
- Regression can be used for various tasks, such as forecasting sales, predicting house prices, and analyzing relationships between variables.



Linear Regression

- Linear regression is the simplest form of regression, where the model is a straight line.
- It is represented by the equation: y = a * x + b, where:
  - y is the predicted value
  - x is the independent variable
  - a is the slope of the line
  - b is the y-intercept
- *Least squares fitting* finds the values of a and b that minimize the sum of squared errors between the predicted and actual values.



Example of Linear Regression in Python

- This slide showcases a Python code example for linear regression using the `stats` module of the `scipy` library.
- The code creates sample data, builds a linear regression model, fits the model to the data, and predicts new values.
- It also visualizes the data and the best-fit line.

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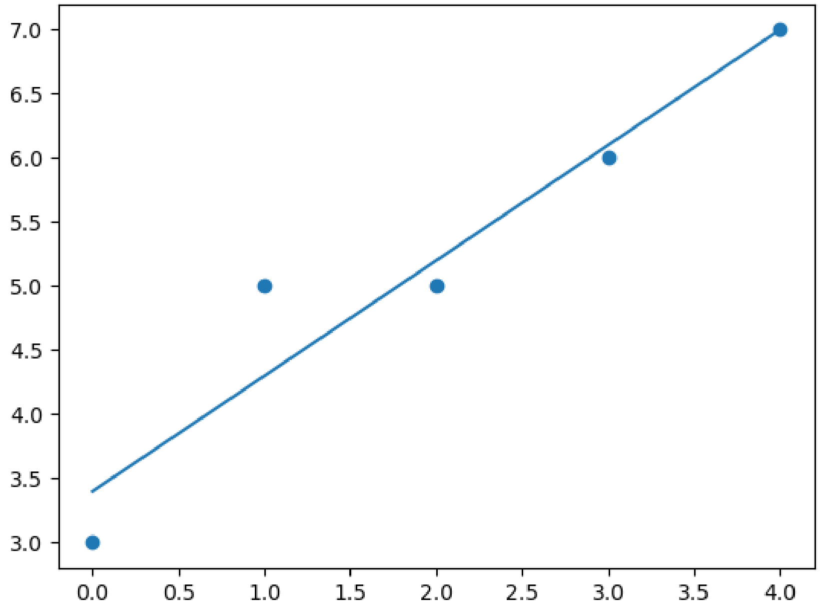
EXAMPLE 3.15 THE LINEARR.PY PROGRAM

```
[ ]:
#Example 3.15 Linear Regression
import matplotlib.pyplot as plt
from scipy import stats
x = [0,1,2,3,4]
y = [3,5,5,6,7]
slope, intercept, r, p, std_err = stats.linregress(x, y)
print("slope: ", slope)
print("intercept: ", intercept)
def myfunc(x):
    return slope * x + intercept
mymodel = list(map(myfunc, x))
plt.scatter(x, y)
plt.plot(x, mymodel)
plt.show()
```

Linear Regression Example (Output)

- Lastly, it uses the functions `plt.scatter()` and `plt.show()` to display and plot the original x and y values and the best-fitted line.

```
slope:  0.9
intercept:  3.4000000000000004
```



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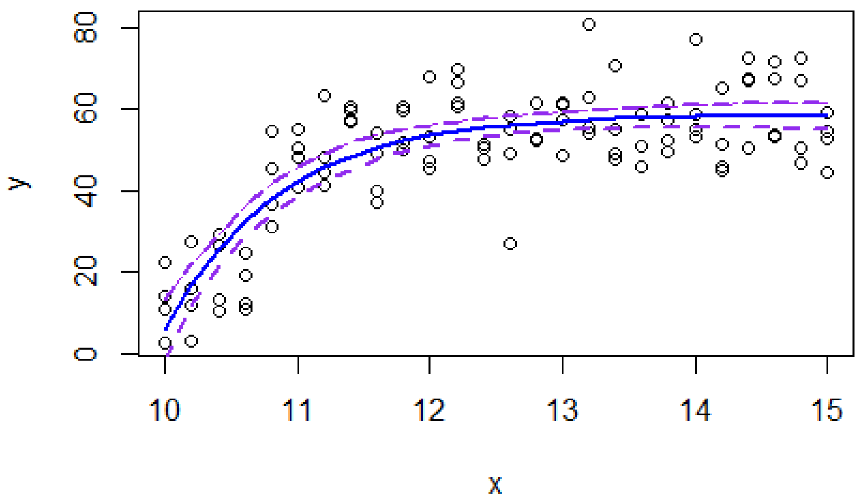
Nonlinear Regression

- Nonlinear regression models more complex relationships between variables using functions other than straight lines.
- Examples of nonlinear models include *polynomials*, *exponentials*, and *logistic* functions.
- Choosing the appropriate model depends on the nature of the data and the relationship you want to represent.



Polynomial Regression

- While linear regression excels at modeling linear relationships, real-world data often exhibits more intricate, curved patterns.
- Polynomial regression captures complex relationships beyond straight lines.
- Uses polynomial functions of different degrees.
- Choosing the right degree requires careful consideration of (a) the data, and (b) the desired level of detail.
- It has potential to unlock deeper insights from data that exhibit nonlinear trends.

Example of Polynomial Regression

- This example illustrates a two-dimensional (x and y) Python polynomial regression.
- It performs the polynomial regression function by calling

  `np.poly1d(np.polyfit(x, y, 3))`

- where the number 3 means three terms of a polynomial function, which is $y = ax^3 + bx^2 + cx + d$.

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Markdown JupyterLab Python 3 (ipykernel)

EXAMPLE 3.16 THE POLYR.PY PROGRAM

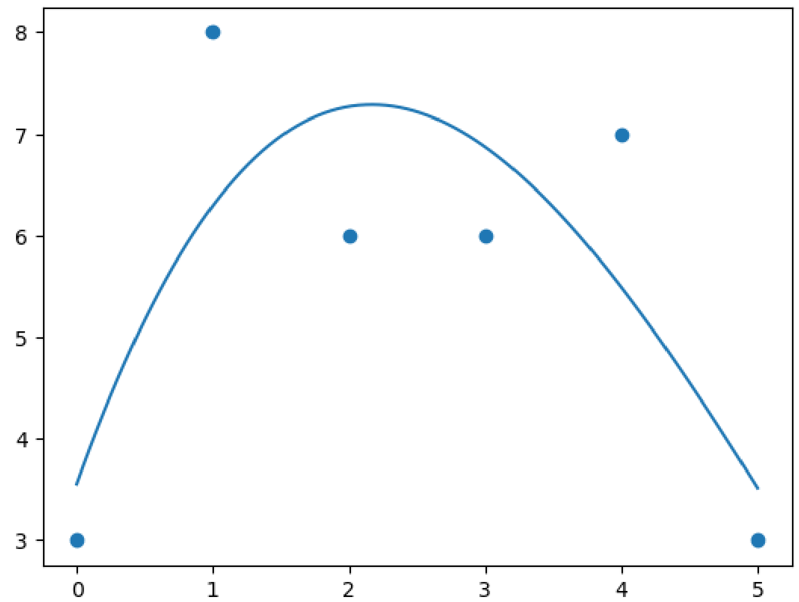
[ ]:

```
#Example 3.16 Polynomial Regression
import matplotlib.pyplot as plt
from scipy import stats
import numpy as np
x = [0,1,2,3,4,5]
y = [3,8,6,6,7,3]
mymodel = np.poly1d(np.polyfit(x, y, 3))
print(mymodel)
myline = np.linspace(0, 5, 100)
plt.scatter(x, y)
plt.plot(myline, mymodel(myline))
plt.show()
```

Polynomial Regression Example (Output)

- The following is the program output, the slope, and intercepts values.
- It shows the plot of the program; round dots are the x and y values, and the curved line is the best polynomial curve.

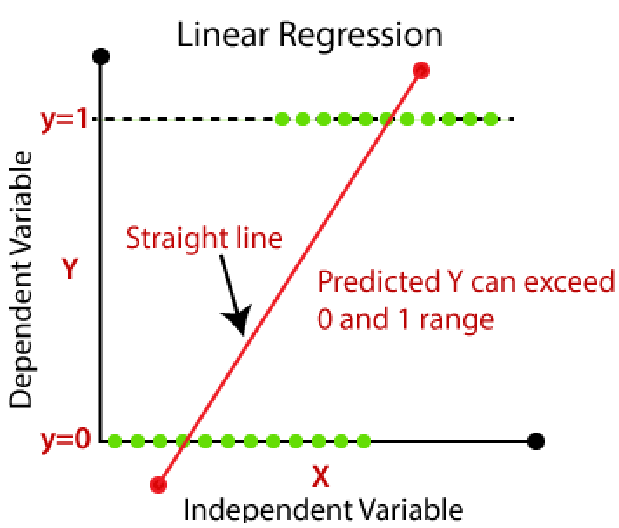
$$0.06481 x^3 - 1.075 x^2 + 3.749 x + 3.556$$



[ ]:

Logistic Regression

- Predicts binary outcomes (0 or 1): Classifies data points into two categories, such as "win/lose" or "spam/not spam."
- Uses the sigmoid function: A S-shaped function that transforms continuous input values into probabilities between 0 and 1, representing the likelihood of belonging to each category.



Ideal for classification tasks: Widely used in areas like *fraud detection*, *credit risk analysis*, and *sentiment analysis*.

Example of Logistic Regression

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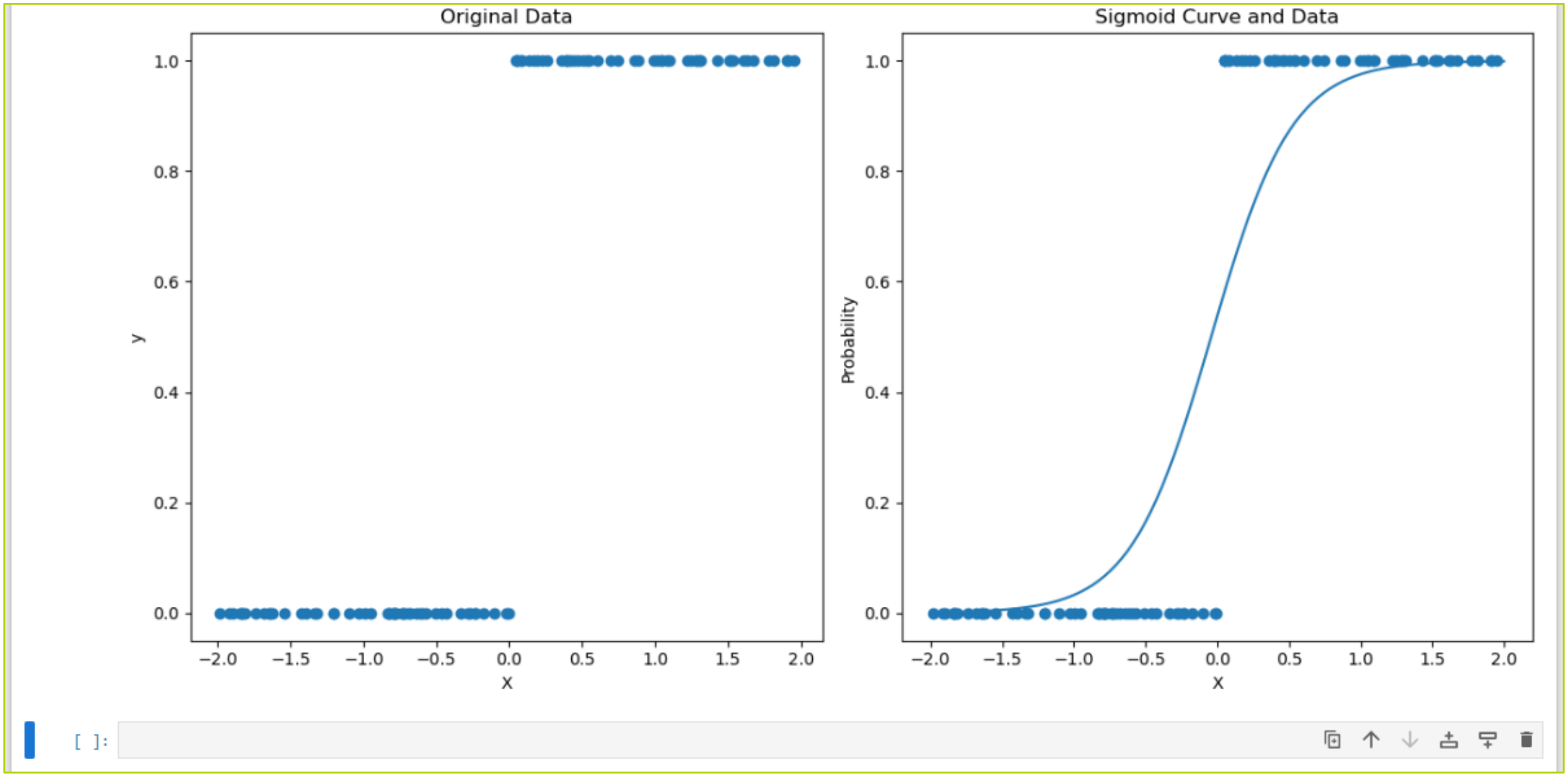
Markdown JupyterLab Python 3 (ipykernel)

EXAMPLE ON LOGISTIC REGRESSION

[ ]:
```python
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression

# Generate sample data
np.random.seed(10)
X = np.random.rand(100, 1) * 4 - 2  # Create random x values between -2 and 2
y = (np.sin(X) > 0).astype(int)  # Generate binary labels based on sine function

# Create logistic regression model
model = LogisticRegression()
model.fit(X, y)

# Generate x values for plotting the sigmoid curve
x_plot = np.linspace(-2, 2, 100)

# Calculate predicted probabilities for the plot
y_pred = model.predict_proba(x_plot.reshape(-1, 1))[:, 1]

# Create the plot
plt.figure(figsize=(12, 6))

# Left plot: Original data
plt.subplot(1, 2, 1)
plt.scatter(X, y)
plt.xlabel("X")
plt.ylabel("y")
plt.title("Original Data")

# Right plot: Sigmoid curve and data
plt.subplot(1, 2, 2)
plt.plot(x_plot, y_pred)
plt.scatter(X, y)
plt.xlabel("X")
plt.ylabel("Probability")
plt.title("Sigmoid Curve and Data")

plt.tight_layout()
plt.show()
```

Logistic Regression Example (Output)

- The following is the program output, the slope, and intercepts values.
- It shows the plot of the program; round dots are the x and y values, and the curved line is the best polynomial curve.

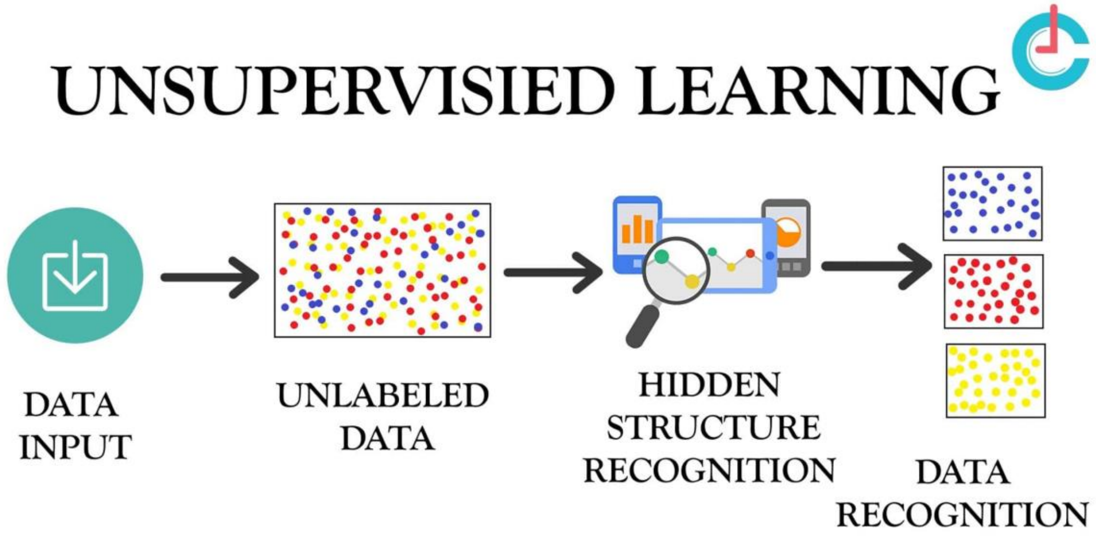


Unsupervised Learning

- Introduction to Unsupervised Learning
- Unsupervised vs. Supervised Learning: *Key Differences*
- Applications of Unsupervised Learning
- K-means Clustering

Introduction to Unsupervised Learning

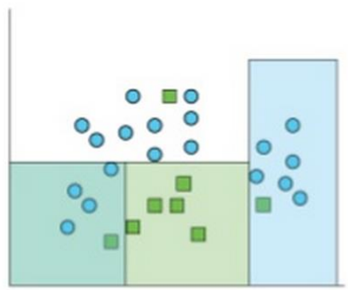
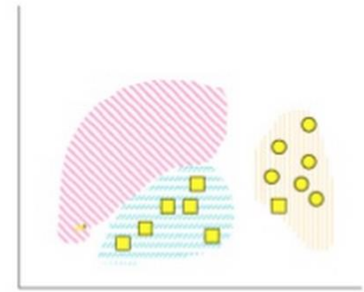
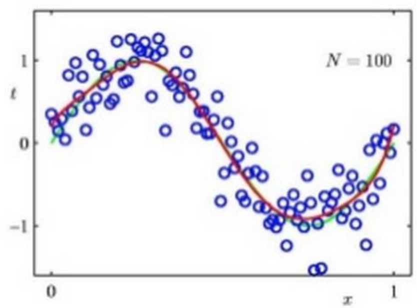
- Involves training models on ***unlabeled*** data, aiming to discover patterns, reduce dimensionality, or perform clustering without explicit guidance.
- Common techniques include clustering (e.g., K-Means), dimensionality reduction (e.g., PCA), anomaly detection, and association rule learning.
- Used in customer segmentation, anomaly detection, recommendation systems, and image/text clustering.
- Evaluation can be difficult due to the lack of labels, scalability issues, interpretability challenges, and dependency on data quality.



Key Differences

- Data:
  - Supervised: Labeled data (with predefined categories)
  - Unsupervised: Unlabeled data (without predefined categories)
- Learning Approach:
  - Supervised: Learns from labeled examples to make predictions
  - Unsupervised: Discovers patterns and relationships in data on its own
- Common Applications:
  - Supervised: Classification, regression, forecasting
  - Unsupervised: Clustering, dimensionality reduction, anomaly detection

Key Differences (cont…)

Predictive methods	Descriptive methods
Classification  Learns a method for predicting the instance class from pre-labeled (classified) instances	**Clustering**  Finds "natural" grouping of instances given un-labeled data
Regression  An attempt to predict a continuous attribute	**Association Rules**  Method for discovering interesting relations between variables in large DBs

Applications of Unsupervised Learning

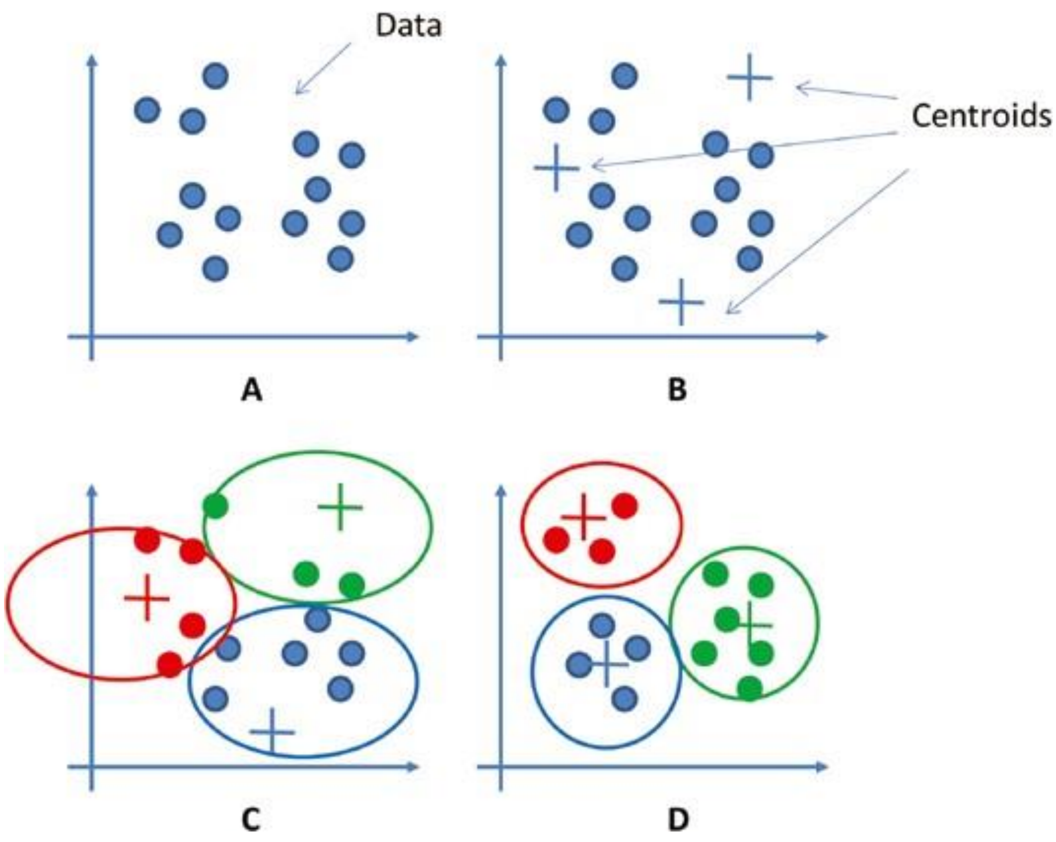
- **Customer Segmentation**: Group customers with similar characteristics for targeted marketing and personalized recommendations.
- **Image Recognition**: Identify objects and scenes in images without labeled training data.
- **Recommendation Systems**: Suggest relevant products, movies, or content based on user preferences and behavior.
- **Anomaly Detection**: Flag suspicious activity or fraud by identifying data points that deviate from normal patterns.
- **Document Clustering**: Organize large collections of documents based on their content and keywords.
- **Social Network Analysis**: Identify communities and influencers within social networks.
- **Fraud Detection**: Analyze financial transactions to detect fraudulent patterns.
- **Scientific Discovery**: Uncover hidden relationships and patterns in scientific data.

K-means Clustering

- Iterative algorithm that groups data points into K predefined clusters
- Steps:
  - Randomly select K cluster centers (centroids)
  - Assign each data point to the closest centroid
  - Recalculate centroids based on the assigned data points
  - Repeat steps 2 and 3 until convergence
- Advantages:
  - Simple and efficient
  - Easy to interpret
- Disadvantages:
  - Requires specifying the number of clusters (K)
  - Sensitive to outliers

K-means Clustering (cont…)

- Steps (A-D) of K-Means clustering



Example of K-means Clustering

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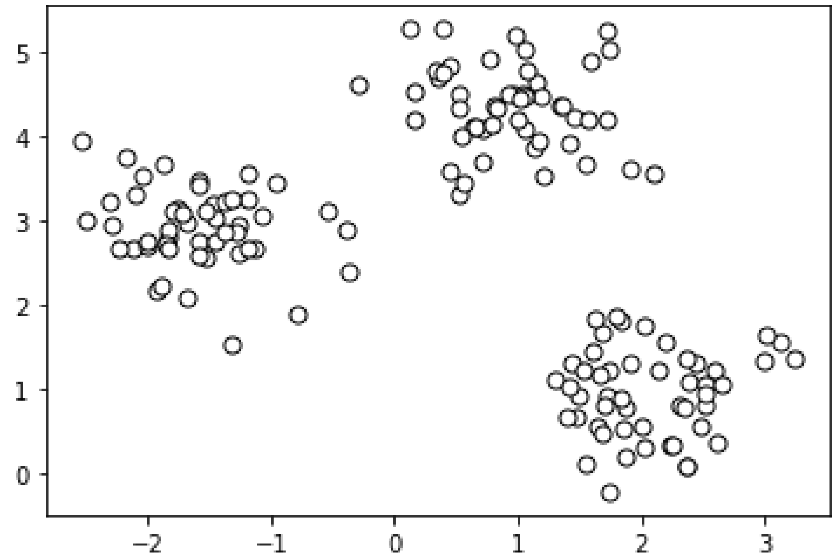
Trusted | Python 3 (ipykernel)

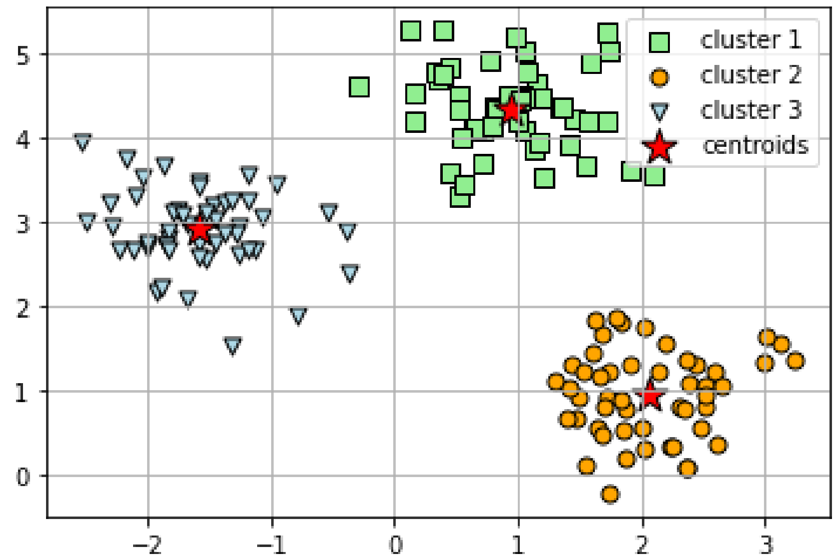
Run | Code

In [ ]:

```python
import matplotlib.pyplot as plt
from sklearn.datasets import make_blobs
from sklearn.cluster import KMeans

# create dataset
X, y = make_blobs(
   n_samples=150, n_features=2,
   centers=3, cluster_std=0.5,
   shuffle=True, random_state=0
)

# plot
plt.scatter(
   X[:, 0], X[:, 1],
   c='white', marker='o',
   edgecolor='black', s=50
)
plt.show()

km = KMeans(
    n_clusters=3, init='random',
    n_init=10, max_iter=300,
    tol=1e-04, random_state=0
)
y_km = km.fit_predict(X)

# plot the 3 clusters
plt.scatter(
    X[y_km == 0, 0], X[y_km == 0, 1],
    s=50, c='lightgreen',
    marker='s', edgecolor='black',
    label='cluster 1'
)

plt.scatter(
    X[y_km == 1, 0], X[y_km == 1, 1],
    s=50, c='orange',
    marker='o', edgecolor='black',
    label='cluster 2'
)

plt.scatter(
    X[y_km == 2, 0], X[y_km == 2, 1],
    s=50, c='lightblue',
    marker='v', edgecolor='black',
    label='cluster 3'
)

# plot the centroids
plt.scatter(
    km.cluster_centers_[:, 0], km.cluster_centers_[:, 1],
    s=250, marker='*',
    c='red', edgecolor='black',
    label='centroids'
)
plt.legend(scatterpoints=1)
plt.grid()
plt.show()
```

K-means Clustering Example (Output)





Explanation of Python code for K-Means Clustering

1. Import Libraries:

- matplotlib.pyplot as plt: Used for creating visualizations (plots).
- from sklearn.datasets import make_blobs: Imports the make_blobs function for generating sample data with clusters.
- from sklearn.cluster import KMeans: Imports the KMeans class for performing KMeans clustering.

2. Create Sample Dataset:

- X, y = make_blobs(...): This line generates a sample dataset using the make_blobs function. Here's what the parameters control:
  - n_samples=150: Creates 150 data points.
  - n_features=2: Each data point will have 2 features (think of X and Y coordinates).
  - centers=3: Creates 3 clusters in the data.
  - cluster_std=0.5: Controls the spread of data points within each cluster (higher value increases spread).
  - shuffle=True: Randomly shuffles the data points.
  - random_state=0: Sets a seed for reproducibility (ensures the same data generation each time).

3. Visualize Dataset:

- plt.scatter(...): Creates a scatter plot of the generated data points.
  - X[:, 0]: Selects the first feature (X-coordinate) from all data points (represented by ':').
  - X[:, 1]: Selects the second feature (Y-coordinate) from all data points.
  - c='white': Sets the marker color to white.
  - marker='o': Sets the marker shape to circles.
  - edgecolor='black': Sets the edge color of the markers to black.
  - s=50: Sets the size of the markers to 50 points.
  - plt.show(): Displays the generated scatter plot.

Explanation of Python code for K-Means Clustering (cont…)

4. KMeans Clustering:

- km = KMeans(...): Creates a KMeans object with the following parameters:
  - n_clusters=3: Specifies the number of clusters to find (matches the number of centers in the data).
  - init='random': Initializes the centroids (cluster centers) randomly.
  - n_init=10: Runs the KMeans algorithm 10 times with different random initializations (helps find a better solution).
  - max_iter=300: Sets the maximum number of iterations allowed for the algorithm.
  - tol=1e-04: Sets the tolerance level for convergence (algorithm stops if changes in centroids are smaller than this value).
  - random_state=0: Sets a seed for reproducibility (ensures consistent cluster assignments).
- y_km = km.fit_predict(X):
  - fit(X): Trains the KMeans model on the data X. This process involves assigning data points to their closest centroids and iteratively updating the centroids based on these assignments.
  - predict(X): Predicts the cluster labels for each data point in X. The output (y_km) is an array where each element represents the cluster number (0, 1, or 2) assigned to the corresponding data point in X.

5. Visualize Clusters and Centroids:

- Three plt.scatter calls: These create scatter plots for each cluster, differentiated by color, marker shape, and label. The code uses conditional indexing (e.g., X[y_km == 0, 0]) to select data points belonging to each cluster based on their predicted labels (y_km).
- plt.scatter: This creates a scatter plot for the centroids (cluster centers) identified by the KMeans algorithm.

6. Display the plot:

- plt.legend(scatterpoints=1): Adds a legend to the plot, including the markers for clusters and centroids.
- plt.grid(): Adds a grid to the plot for better visualization.
- plt.show(): Displays the final plot showing the data points colored by their assigned clusters and the centroids marked with stars.

THANK YOU

TIME FOR DISCUSSION & QUESTIONS