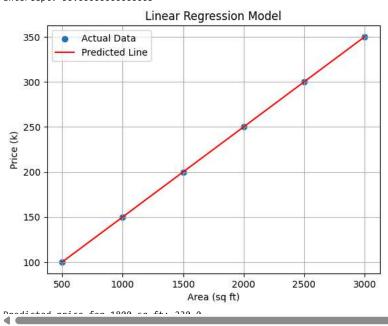
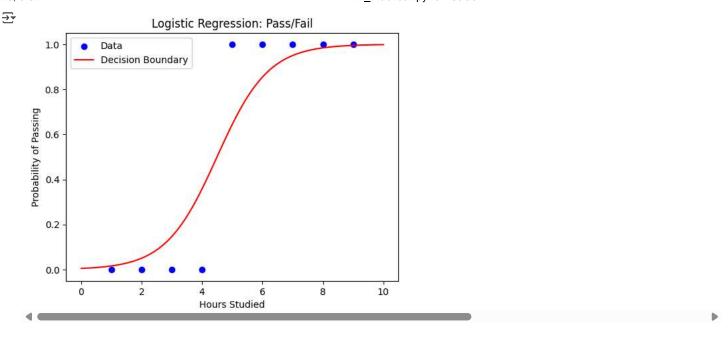
1. Linear Regression on House Prices • Task: Predict house prices using area as a feature (1D Linear Regression). • Visualize: Plot the data points and the best-fit regression line

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
# Step 1: Prepare the data
# Area in square feet (reshaped to a 2D array for sklearn)
area = np.array([500, 1000, 1500, 2000, 2500, 3000]).reshape(-1, 1)
# Corresponding prices in thousands (target variable)
price = np.array([100, 150, 200, 250, 300, 350])
# Step 2: Create and train the model
# Create a linear regression model
model = LinearRegression()
# Fit the model to the data (learns the relationship between area and price)
model.fit(area, price)
# Step 3: Make predictions
# Predict prices based on the input areas
predict = model.predict(area)
# Print the learned model parameters (slope and intercept)
print("Slope (Coefficient):", model.coef_[0])
                                                  # How much price increases per unit area
print("Intercept:", model.intercept_)
                                                  # Price when area = 0
# Step 4: Visualize the results
# Plot the original data points
plt.scatter(area, price, label='Actual Data')
# Plot the regression line
plt.plot(area, predict, color='red', label='Predicted Line')
# Add labels and title
plt.xlabel('Area (sq ft)')
plt.ylabel('Price (k)')
plt.title('Linear Regression Model')
plt.legend()
plt.grid(True)
plt.show()
# Step 5: Predict for a new area
# Predict the price of a house with 1800 sq ft area
new\_area = np.array([[1800]])
new_price = model.predict(new_area)
print("Predicted price for 1800 sq ft:", new_price[0])
```



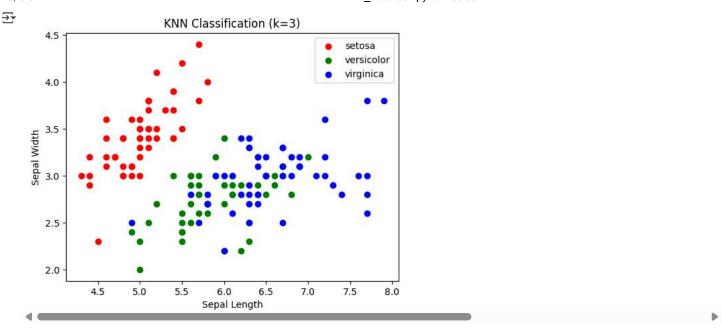
2. Logistic Regression for Binary Classification • Task: Classify points into two categories using logistic regression (e.g., pass/fail based on hours studied). • Visualize: Plot data points and decision boundary.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
# Data: [hours studied], [pass=1/fail=0]
X = np.array([1, 2, 3, 4, 5, 6, 7, 8, 9]).reshape(-1, 1)
y = np.array([0, 0, 0, 0, 1, 1, 1, 1, 1])
# Model
model = LogisticRegression()
model.fit(X, y)
# Predict probabilities
x_{\text{test}} = \text{np.linspace}(0, 10, 100).\text{reshape}(-1, 1) # 100 values between 0 and 10
y_prob = model.predict_proba(x_test)[:, 1]
                                                 # Probability of class 1 (pass)
# Plot
plt.scatter(X, y, color='blue', label='Data')
plt.plot(x_test, y_prob, color='red', label='Decision Boundary')
plt.xlabel('Hours Studied')
plt.ylabel('Probability of Passing')
plt.title('Logistic Regression: Pass/Fail')
plt.legend()
plt.show()
```



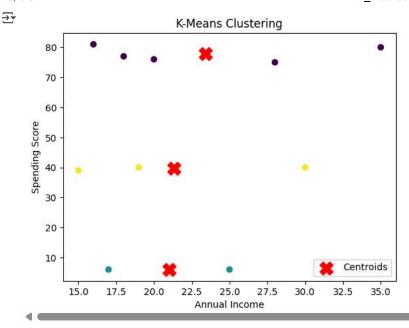
3. K-Nearest Neighbors (KNN) Classification • Task: Use KNN to classify Iris flower species. • Visualize: Use scatter plots with decision boundaries using different values of K.

```
import matplotlib.pyplot as plt
from sklearn.datasets import load_iris
from sklearn.neighbors import KNeighborsClassifier
# Load iris dataset
iris = load_iris()
X = iris.data[:, :2] # Use only first 2 features (sepal length and width)
y = iris.target
# Train KNN model (k=3)
model = KNeighborsClassifier(n_neighbors=3)
model.fit(X, y)
# Plot data
for i, color in zip([0, 1, 2], ['red', 'green', 'blue']):
    plt.scatter(X[y == i, 0], X[y == i, 1], color=color, label=iris.target_names[i])
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.title('KNN Classification (k=3)')
plt.legend()
plt.show()
```



4. K-Means Clustering • Task: Apply K-means clustering to group customers by purchasing behavior. • Visualize: Show clusters with different colors and cluster centroids.

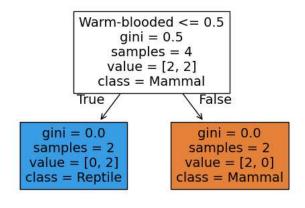
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
# Sample data: [Annual Income, Spending Score]
X = np.array([[15, 39], [16, 81], [17, 6], [18, 77], [19, 40],
              [20, 76], [25, 6], [28, 75], [30, 40], [35, 80]])
# K-Means clustering
kmeans = KMeans(n_clusters=3, random_state=0)
kmeans.fit(X)
labels = kmeans.labels
centroids = kmeans.cluster_centers_
# Plot
plt.scatter(X[:, 0], X[:, 1], c=labels, cmap='viridis')
plt.scatter(centroids[:, \, 0], \, centroids[:, \, 1], \, c='red', \, marker='X', \, s=200, \, label='Centroids')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.title('K-Means Clustering')
plt.legend()
plt.show()
```



5. Decision Tree Classification • Task: Use a decision tree to classify animals (e.g., mammal/reptile based on features). • Visualize: Show the decision tree diagram and how decisions are made



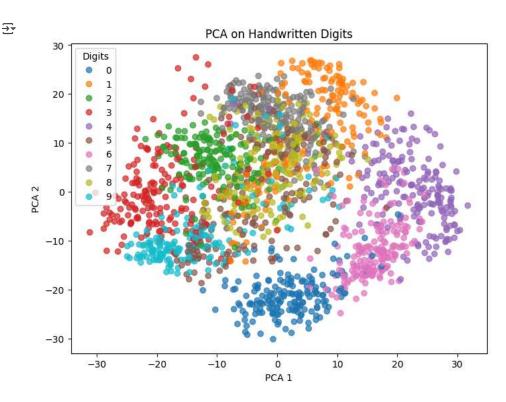
## Decision Tree: Mammal vs Reptile



6. Principal Component Analysis (PCA) • Task: Apply PCA on a dataset with multiple features (e.g., handwritten digits). • Visualize: Reduce to 2D and plot the data points to see separation of classes.

```
from sklearn.datasets import load_digits
from sklearn.decomposition import PCA
```

```
import matplotlib.pyplot as plt
# Load digits dataset
digits = load_digits()
X = digits.data
y = digits.target
# Reduce to 2D
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X)
# Plot
plt.figure(figsize=(8, 6))
scatter = plt.scatter(X_pca[:, 0], X_pca[:, 1], c=y, cmap='tab10', alpha=0.7)
plt.legend(*scatter.legend_elements(), title="Digits")
plt.xlabel('PCA 1')
plt.ylabel('PCA 2')
plt.title('PCA on Handwritten Digits')
plt.show()
```



7. Training a Simple Neural Network • Task: Use a neural network to classify MNIST digits (only 1 or 2 hidden layers). • Visualize: Accuracy/loss graphs over epochs, and confusion matrix.

```
\hbox{import tensorflow as tf} \\
from tensorflow.keras import layers, models
import matplotlib.pyplot as plt
from \ sklearn.metrics \ import \ confusion\_matrix, \ ConfusionMatrix Display
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0 # Normalize
# Flatten images
x_{train} = x_{train.reshape(-1, 784)}
x_{\text{test}} = x_{\text{test.reshape}}(-1, 784)
# Model
model = models.Sequential([
    layers.Dense(128, activation='relu', input_shape=(784,)),
    layers.Dense(64, activation='relu'),
    layers.Dense(10, activation='softmax')
])
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
```

```
history = model.fit(x_train, y_train, epochs=5, validation_data=(x_test, y_test), verbose=0)

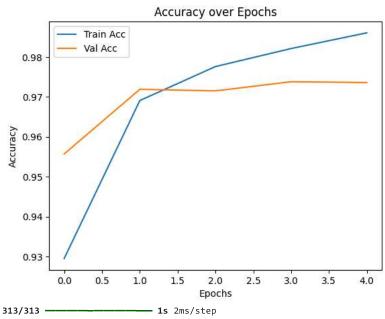
# Plot accuracy and loss
plt.plot(history.history['accuracy'], label='Train Acc')
plt.plot(history.history['val_accuracy'], label='Val Acc')
plt.title('Accuracy over Epochs')
plt.xlabel('Epochs')
plt.ylabel('Accuracy')
plt.legend()
plt.show()

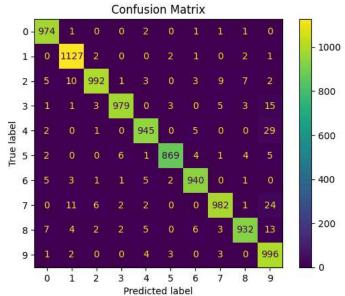
# Confusion Matrix
y_pred = model.predict(x_test).argmax(axis=1)
cm = confusion_matrix(y_test, y_pred)
ConfusionMatrixDisplay(cm).plot()
plt.title("Confusion Matrix")
plt.show()
```

Downloading data from <a href="https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz">https://storage.googleapis.com/tensorflow/tf-keras-datasets/mnist.npz</a>
11490434/11490434

Os Ous/step

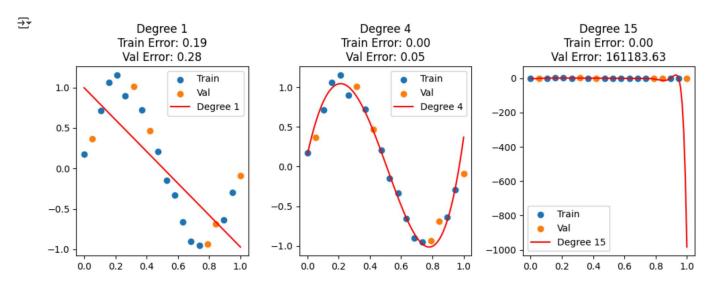
/usr/local/lib/python3.11/dist-packages/keras/src/layers/core/dense.py:87: UserWarning: Do not pass an `input\_shape`/`input\_dim` a super().\_\_init\_\_(activity\_regularizer=activity\_regularizer, \*\*kwargs)





Overfitting vs. Underfitting • Task: Train polynomial regression models with varying degrees. • Visualize: Compare training/validation errors and graph the fits.

```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error
# Generate data
np.random.seed(0)
X = np.linspace(0, 1, 20)
y = np.sin(2 * np.pi * X) + np.random.normal(0, 0.1, X.shape)
X = X.reshape(-1, 1)
# Train/test split
X_train, X_val, y_train, y_val = train_test_split(X, y, test_size=0.3)
# Try different degrees
degrees = [1, 4, 15]
plt.figure(figsize=(10, 4))
for i, d in enumerate(degrees):
          poly = PolynomialFeatures(degree=d)
          X_train_poly = poly.fit_transform(X_train)
          X_val_poly = poly.transform(X_val)
          model = LinearRegression()
          model.fit(X_train_poly, y_train)
          y_train_pred = model.predict(X_train_poly)
          y_val_pred = model.predict(X_val_poly)
          # Plot
          plt.subplot(1, 3, i+1)
          X_{plot} = np.linspace(0, 1, 100).reshape(-1, 1)
          X_plot_poly = poly.transform(X_plot)
          y_plot = model.predict(X_plot_poly)
          plt.scatter(X_train, y_train, label='Train')
          plt.scatter(X_val, y_val, label='Val')
          plt.plot(X_plot, y_plot, color='red', label=f'Degree {d}')
          plt.title(f'Degree \{d\} \land Error: \{mean\_squared\_error(y\_train, y\_train\_pred):.2f\} \land Error: \{mean\_squared\_error(y\_val, y\_val\_train, y\_val\_train, y\_train\_pred):.2f\} \land Error: \{mean\_squared\_error(y\_val, y\_val\_train, y\_train\_pred):.2f\} \land Error: \{mean\_squared\_error(y\_val, y\_val\_train, y\_train\_pred):.2f\} \land Error: \{mean\_squared\_error(y\_val, y\_val\_train, y\_train\_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_train_tr
          plt.legend()
plt.tight_layout()
plt.show()
```



9. Convolutional Neural Network (CNN) on Fashion MNIST • Task: Use a CNN to classify clothing images. • Visualize: Feature maps (activation outputs) of the first convolutional layer.

```
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.keras import lavers. Model
```

--- ,--,--,---

```
# Load dataset
(x_train, y_train), _ = tf.keras.datasets.fashion_mnist.load_data()
x_{train} = x_{train} / 255.0 # Normalize the pixel values to [0, 1]
x_train = x_train[..., tf.newaxis] # Add channel dimension (grayscale)
# Build CNN using the Functional API
inputs = tf.keras.Input(shape=(28, 28, 1)) # Input layer
x = layers.Conv2D(8, (3, 3), activation='relu')(inputs) # Conv2D layer
x = layers.MaxPooling2D((2, 2))(x) # MaxPooling layer
x = layers.Flatten()(x) # Flatten the output for dense layer
outputs = layers.Dense(10, activation='softmax')(x) \# Dense layer for classification
# Create the model
model = Model(inputs, outputs)
model.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics=['accuracy'])
# Train the model (briefly for demonstration)
model.fit(x_train, y_train, epochs=1, batch_size=64, verbose=0)
# Create a model to output the activations of the first Conv2D layer
activation_model = Model(inputs=model.input, outputs=model.layers[1].output) # Get the Conv2D layer
# Choose one image to visualize
img = x_train[0].reshape(1, 28, 28, 1) # Pick the first image and reshape it
activations = activation_model.predict(img) # Get the activations
# Plot the feature maps from the first Conv2D layer
plt.figure(figsize=(10, 4))
for i in range(8): # We have 8 filters in the first Conv2D layer
   plt.subplot(1, 8, i+1)
   plt.imshow(activations[0, :, :, i], cmap='viridis') # Display each activation map
   plt.axis('off')
plt.suptitle("Feature Maps from First Conv Layer")
nl+ +igh+ lavout()
```