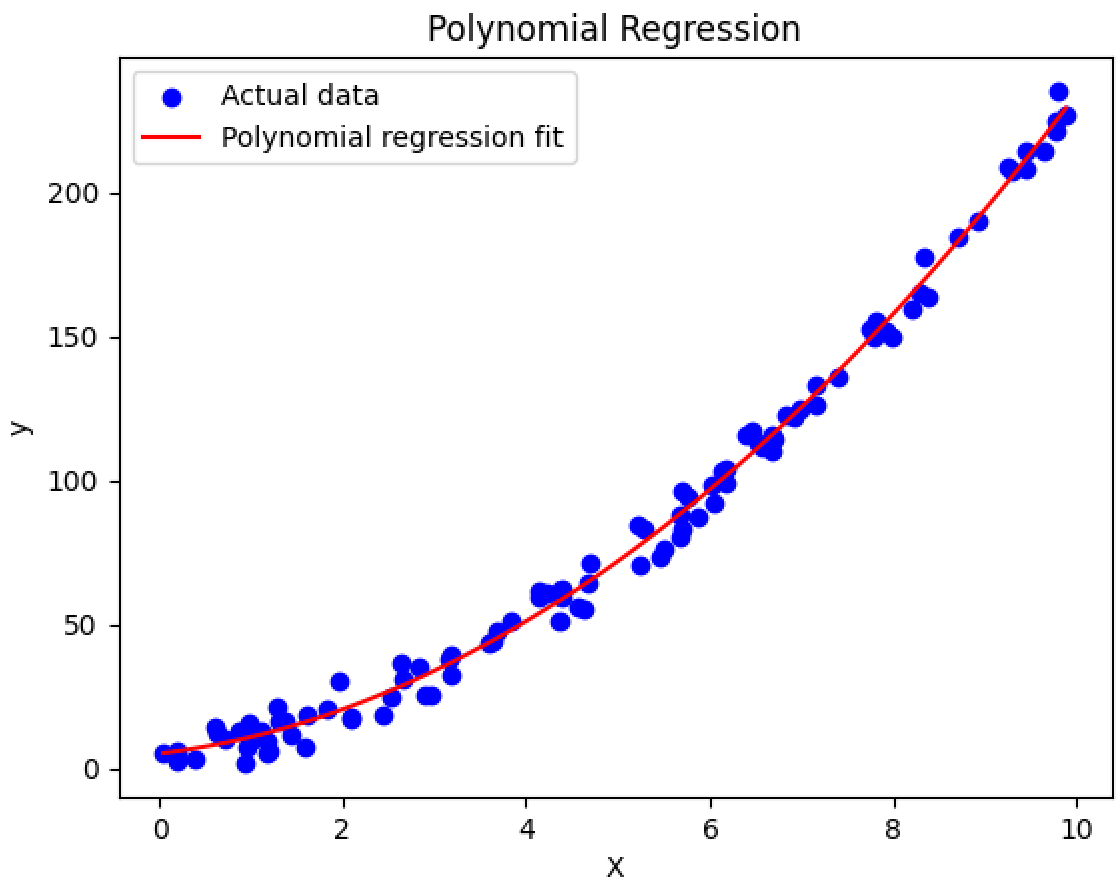
#11

```
import numpy as np

import matplotlib.pyplot as plt

from sklearn.model_selection import train_test_split

from sklearn.preprocessing import PolynomialFeatures

from sklearn.linear_model import LinearRegression

from sklearn.metrics import mean_squared_error, r2_score


# Step 1: Generate a synthetic dataset

np.random.seed(0)

X = np.random.rand(100, 1) * 10  # Feature matrix

y = 2 * (X ** 2) + 3 * X + 5 + np.random.randn(100, 1) * 5  # Target vector


# Step 2: Split the dataset into training and testing sets

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)


# Step 3: Preprocess the data to include polynomial features

poly = PolynomialFeatures(degree=2)  # Try different degrees for different results

X_poly_train = poly.fit_transform(X_train)

X_poly_test = poly.transform(X_test)


# Step 4: Fit a polynomial regression model

model = LinearRegression()

model.fit(X_poly_train, y_train)


# Step 5: Predict and evaluate the model

y_train_pred = model.predict(X_poly_train)

y_test_pred = model.predict(X_poly_test)


# Performance metrics

train_mse = mean_squared_error(y_train, y_train_pred)
```

```
test_mse = mean_squared_error(y_test, y_test_pred)
train_r2 = r2_score(y_train, y_train_pred)
test_r2 = r2_score(y_test, y_test_pred)

print(f"Train MSE: {train_mse}")
print(f"Test MSE: {test_mse}")
print(f"Train R2 Score: {train_r2}")
print(f"Test R2 Score: {test_r2}")

# Step 6: Visualize the results
plt.scatter(X, y, color='blue', label='Actual data')
X_range = np.linspace(min(X), max(X), 100).reshape(-1, 1)
y_range_pred = model.predict(poly.transform(X_range))
plt.plot(X_range, y_range_pred, color='red', label='Polynomial regression fit')
plt.xlabel('X')
plt.ylabel('y')
plt.title('Polynomial Regression')
plt.legend()
plt.show()
#output
Train MSE: 24.125995439736805
Test MSE: 25.7136695038184
Train R2 Score: 0.9942709761929696
Test R2 Score: 0.9944791639465156
```

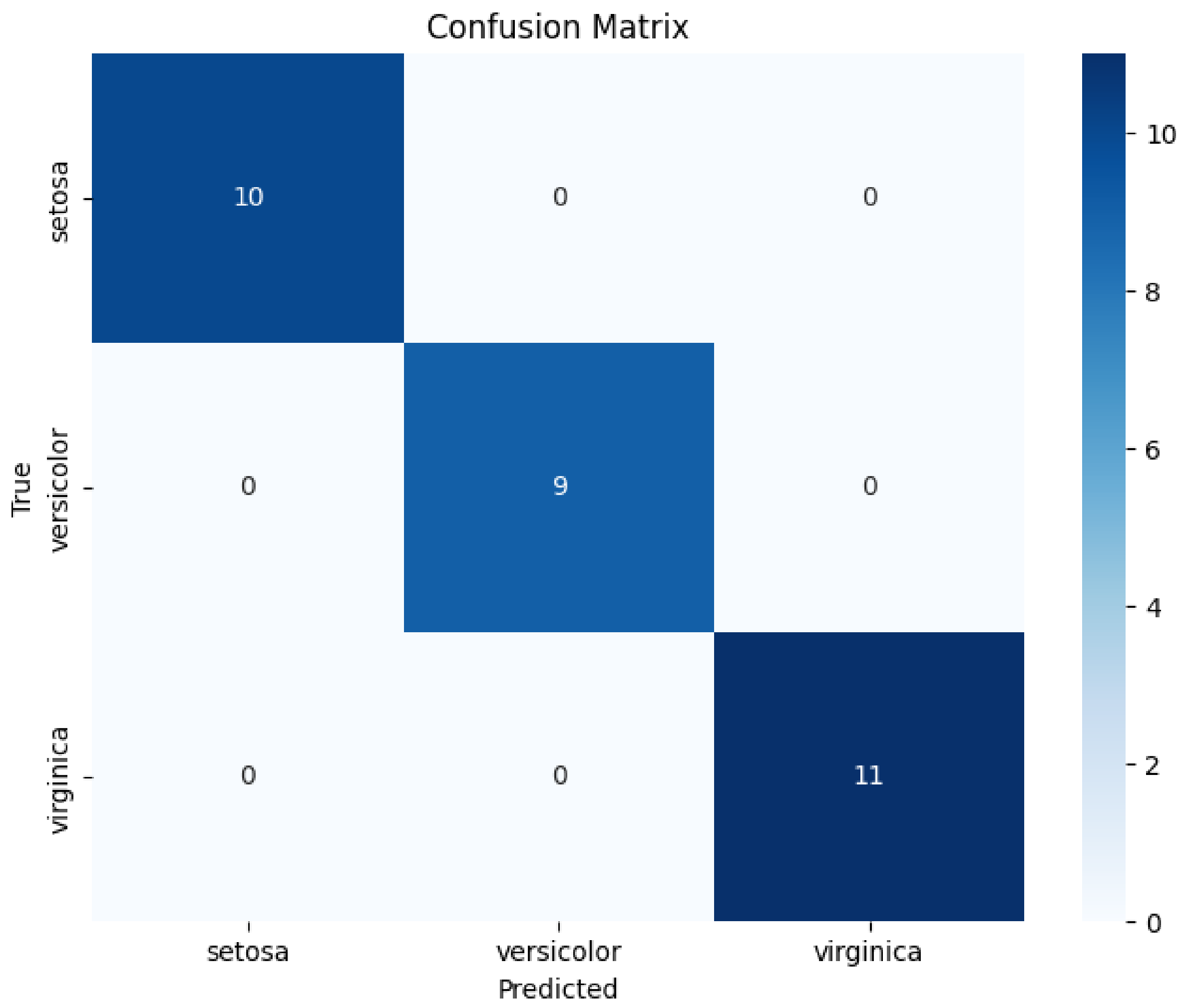



```
#12
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score, classification_report, confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns

# Step 1: Load the dataset
from sklearn.datasets import load_iris
iris = load_iris()
X = iris.data
y = iris.target
```

```
# Step 2: Preprocess the data (if necessary)
# In this case, the Iris dataset is already clean and ready to use.

# Step 3: Split the dataset into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Step 4: Fit a KNN model to the training data
k = 3  # Number of neighbors
knn = KNeighborsClassifier(n_neighbors=k)
knn.fit(X_train, y_train)

# Step 5: Predict the labels for the test data
y_pred = knn.predict(X_test)

# Step 6: Evaluate the model's performance
accuracy = accuracy_score(y_test, y_pred)
print(f"Accuracy: {accuracy}")
print("\nClassification Report:")
print(classification_report(y_test, y_pred))

# Confusion matrix
cm = confusion_matrix(y_test, y_pred)
plt.figure(figsize=(8, 6))
sns.heatmap(cm, annot=True, fmt='d', cmap='Blues', xticklabels=iris.target_names,
yticklabels=iris.target_names)
plt.xlabel('Predicted')
plt.ylabel('True')
plt.title('Confusion Matrix')
plt.show()
#output
Accuracy: 1.0
```

Classification Report:

	precision	recall	f1-score	support
0	1.00	1.00	1.00	10
1	1.00	1.00	1.00	9
2	1.00	1.00	1.00	11
accuracy			1.00	30
macro avg	1.00	1.00	1.00	30
weighted avg	1.00	1.00	1.00	30

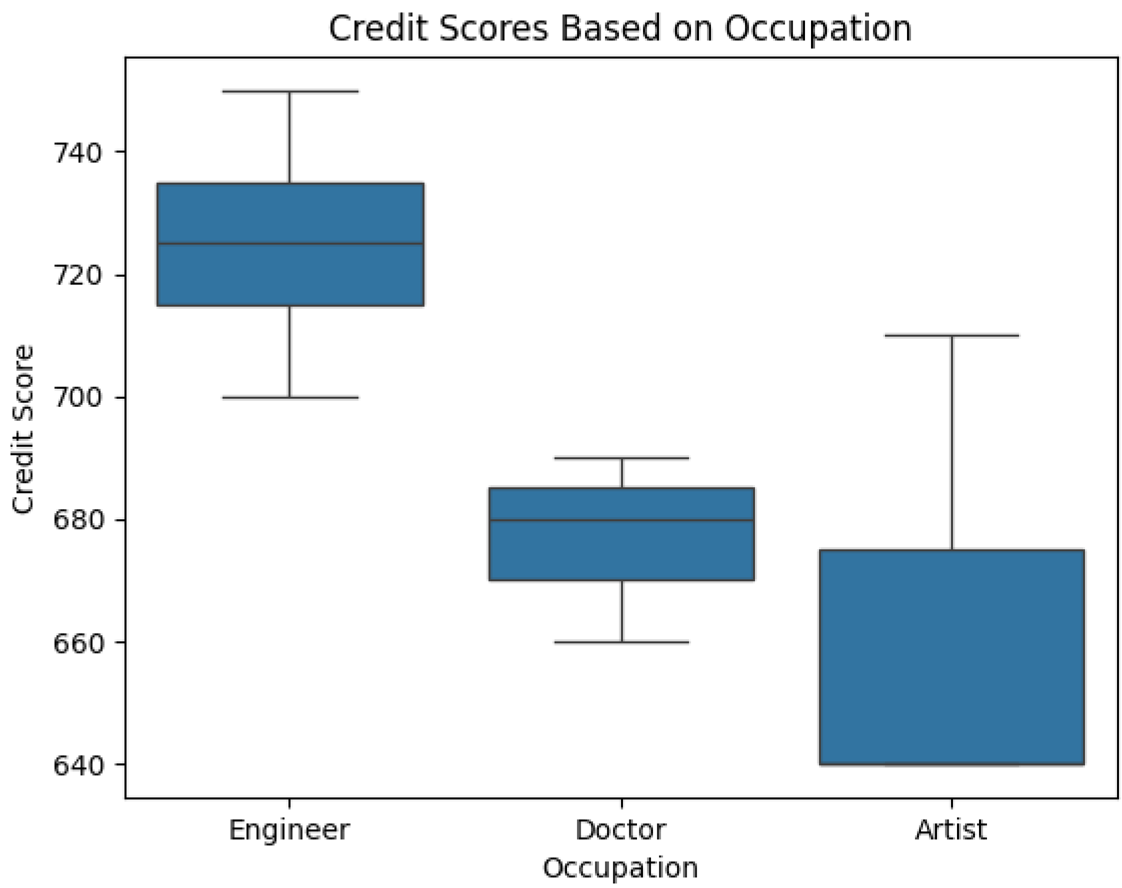


```
#13
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.naive_bayes import GaussianNB
from sklearn.metrics import accuracy_score

# Step 1: Load the dataset
data = {
    'Occupation': ['Engineer', 'Doctor', 'Artist', 'Engineer', 'Artist', 'Doctor', 'Engineer', 'Artist', 'Doctor', 'Engineer'],
    'Credit Score': [720, 680, 650, 700, 710, 690, 730, 640, 660, 750]
}
df = pd.DataFrame(data)

# a. Print the first five rows
print("First five rows of the dataset:")
print(df.head())

# b. Basic statistical computations
print("\nBasic statistical computations:")
print(df.describe())

# c. The columns and their data types
print("\nColumns and their data types:")
print(df.dtypes)

# d. Detect and handle null values
print("\nNull values in the dataset:")
print(df.isnull().sum())
```

```
# As an example, let's manually insert a null value and then handle it
df.at[2, 'Credit Score'] = None
print("\nNull values after insertion:")
print(df.isnull().sum())

# Replace null values with the mode
mode_value = df['Credit Score'].mode()[0]
df['Credit Score'].fillna(mode_value, inplace=True)
print("\nDataset after handling null values:")
print(df)

# e. Explore the dataset using a box plot
sns.boxplot(x='Occupation', y='Credit Score', data=df)
plt.title('Credit Scores Based on Occupation')
plt.show()

# f. Split the dataset into train and test sets
X = pd.get_dummies(df['Occupation'], drop_first=True)  # One-hot encoding for categorical variable
y = df['Credit Score']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# g. Fit the Naive Bayes classifier
nb = GaussianNB()
nb.fit(X_train, y_train)

# i. Predict the model
y_pred = nb.predict(X_test)
accuracy = accuracy_score(y_test, y_pred)

print("\nPredicted values for the test set:")
```

```
print(y_pred)
print(f"Model Accuracy: {accuracy}")

#output
First five rows of the dataset:
  Occupation  Credit Score
0   Engineer          720
1     Doctor          680
2     Artist          650
3   Engineer          700
4     Artist          710

Basic statistical computations:
       Credit Score
count      10.00000
mean      693.00000
std        35.91657
min       640.00000
25%       665.00000
50%       695.00000
75%       717.50000
max       750.00000

Columns and their data types:
Occupation      object
Credit Score     int64
dtype: object

Null values in the dataset:
Occupation      0
Credit Score    0
```

```
dtype: int64

Null values after insertion:
Occupation     0
Credit Score   1
dtype: int64

Dataset after handling null values:
  Occupation  Credit Score
0   Engineer        720.0
1     Doctor        680.0
2     Artist        640.0
3   Engineer        700.0
4     Artist        710.0
5     Doctor        690.0
6   Engineer        730.0
7     Artist        640.0
8     Doctor        660.0
9   Engineer        750.0
```



#14

import pandas as pd

import numpy as np

Sample training data as a list of dictionaries

data = [

{'Origin': 'Japan', 'Manufacturer': 'Honda', 'Color': 'Blue', 'Decade': '1980', 'Type': 'Economy', 'Example Type': 'Positive'},

{'Origin': 'Japan', 'Manufacturer': 'Toyota', 'Color': 'Green', 'Decade': '1970', 'Type': 'Sports', 'Example Type': 'Negative'},

{'Origin': 'Japan', 'Manufacturer': 'Toyota', 'Color': 'Blue', 'Decade': '1990', 'Type': 'Economy', 'Example Type': 'Positive'},

{'Origin': 'USA', 'Manufacturer': 'Chrysler', 'Color': 'Red', 'Decade': '1980', 'Type': 'Economy', 'Example Type': 'Negative'},

{'Origin': 'Japan', 'Manufacturer': 'Honda', 'Color': 'White', 'Decade': '1980', 'Type': 'Economy', 'Example Type': 'Positive'}

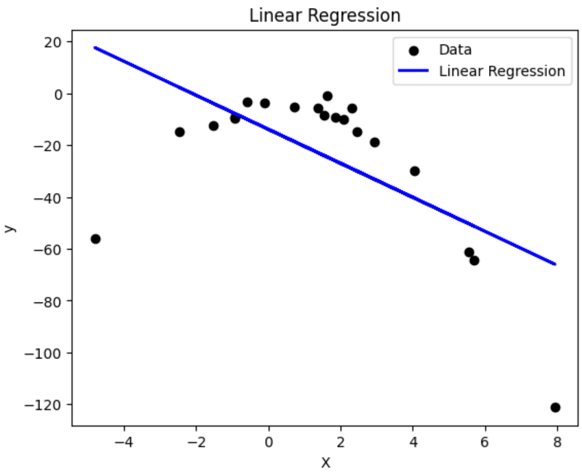
]

```
# Convert the data into a DataFrame
df = pd.DataFrame(data)

# Extract attributes and target
attributes = df.columns[:-1]  # All columns except the last one
target = df.columns[-1]  # The last column

# Initialize the specific and general hypotheses
S = ['0'] * len(attributes)
G = [['?'] * len(attributes)]

# Candidate Elimination algorithm
for i, row in df.iterrows():
    if row[target] == 'Positive':
        for j in range(len(attributes)):
            if S[j] == '0':
                S[j] = row[j]
            elif S[j] != row[j]:
                S[j] = '?'
        G = [g for g in G if all((g[j] == '?' or g[j] == row[j]) for j in range(len(attributes)))]
    else:
        new_G = []
        for g in G:
            for j in range(len(attributes)):
                if g[j] == '?':
                    for value in df[attributes[j]].unique():
                        if value != row[j]:
                            new_g = g.copy()
                            new_g[j] = value
                            if all((S[k] == '?' or new_g[k] == '?' or S[k] == new_g[k]) for k in range(len(attributes))):
```

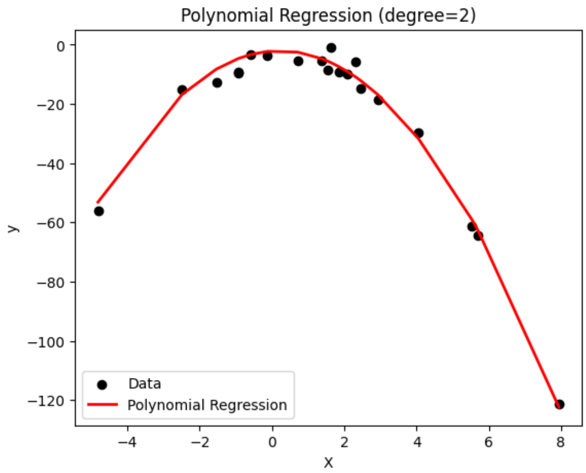
```
                new_G.append(new_g)
    G = new_G

# Output the final S and G
print("Final specific hypothesis (S):", S)
print("Final general hypotheses (G):", G)

#output
Final specific hypothesis (S): ['Japan', '?', '?', '?', 'Economy']
Final general hypotheses (G): [['Japan', '?', '?', '?', 'Economy'], ['?', 'Honda', '?', '?', 'Economy']]
#15
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.metrics import mean_squared_error, r2_score

# Generate synthetic data
np.random.seed(0)
X = 2 - 3 * np.random.normal(0, 1, 100)
y = X - 2 * (X ** 2) + np.random.normal(-3, 3, 100)

X = X[:, np.newaxis]

# Split the data into training/testing sets
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=0)

# 1. Linear Regression
linear_regressor = LinearRegression()
linear_regressor.fit(X_train, y_train)  # Train the model
```

```
# Predict using the linear model
y_pred_linear = linear_regressor.predict(X_test)

# 2. Polynomial Regression (degree 2)
polynomial_features = PolynomialFeatures(degree=2)
X_poly = polynomial_features.fit_transform(X_train)

poly_regressor = LinearRegression()
poly_regressor.fit(X_poly, y_train)  # Train the model

# Predict using the polynomial model
X_test_poly = polynomial_features.transform(X_test)
y_pred_poly = poly_regressor.predict(X_test_poly)

# Evaluate the models
mse_linear = mean_squared_error(y_test, y_pred_linear)
r2_linear = r2_score(y_test, y_pred_linear)

mse_poly = mean_squared_error(y_test, y_pred_poly)
r2_poly = r2_score(y_test, y_pred_poly)

print(f"Linear Regression MSE: {mse_linear}, R2: {r2_linear}")
print(f"Polynomial Regression MSE: {mse_poly}, R2: {r2_poly}")

# Visualize the results
plt.figure(figsize=(14, 5))

# Plot Linear Regression results
plt.subplot(1, 2, 1)
plt.scatter(X_test, y_test, color='black', label='Data')
```

```
plt.plot(X_test, y_pred_linear, color='blue', linewidth=2, label='Linear Regression')
plt.xlabel('X')
plt.ylabel('y')
plt.title('Linear Regression')
plt.legend()

# Plot Polynomial Regression results
plt.subplot(1, 2, 2)
plt.scatter(X_test, y_test, color='black', label='Data')
# Sort the values of X_test for a smoother curve
sorted_X_test = np.sort(X_test, axis=0)
sorted_y_pred_poly = poly_regressor.predict(polynomial_features.transform(sorted_X_test))
plt.plot(sorted_X_test, sorted_y_pred_poly, color='red', linewidth=2, label='Polynomial Regression')
plt.xlabel('X')
plt.ylabel('y')
plt.title('Polynomial Regression (degree=2)')
plt.legend()

plt.show()

#output
Linear Regression MSE: 613.3502296050843, R2: 0.2916278819291981
Polynomial Regression MSE: 8.695598709479661, R2: 0.9899572554498042
```



Linear Regression
Data
Linear Regression
20
0
−20
−40
−60
−80
−100
−120
y
−4
−2
0
2
4
6
8
X



Polynomial Regression (degree=2)
Data
Polynomial Regression
0
−20
−40
−60
−80
−100
−120
y
−4
−2
0
2
4
6
8
X