

```
import pandas as pd
df = pd.read_csv("insurance.csv")
print(df.head())
```

| | age | sex | bmi | children | smoker | region | charges |
|---|-----|--------|--------|----------|--------|-----------|-------------|
| 0 | 19 | female | 27.900 | 0 | yes | southwest | 16884.92400 |
| 1 | 18 | male | 33.770 | 1 | no | southeast | 1725.55230 |
| 2 | 28 | male | 33.000 | 3 | no | southeast | 4449.46200 |
| 3 | 33 | male | 22.705 | 0 | no | northwest | 21984.47061 |
| 4 | 32 | male | 28.880 | 0 | no | northwest | 3866.85520 |

```
categorical_cols = ['sex', 'smoker', 'region']
df_encoded = pd.get_dummies(df, columns=categorical_cols, drop_first=True)
```

```
X = df_encoded.drop('charges', axis=1)
y = df_encoded['charges']
```

```
print("First 5 rows of the encoded features (X):")
print(X.head())
print("\nFirst 5 rows of the target variable (y):")
print(y.head())
```

```
First 5 rows of the encoded features (X):
```

| | age | bmi | children | sex_male | smoker_yes | region_northwest | \ |
|---|-----|--------|----------|----------|------------|------------------|---|
| 0 | 19 | 27.900 | 0 | False | True | False | |
| 1 | 18 | 33.770 | 1 | True | False | False | |
| 2 | 28 | 33.000 | 3 | True | False | False | |
| 3 | 33 | 22.705 | 0 | True | False | True | |
| 4 | 32 | 28.880 | 0 | True | False | True | |

| | region_southeast | region_southwest |
|---|------------------|------------------|
| 0 | False | True |
| 1 | True | False |
| 2 | True | False |
| 3 | False | False |
| 4 | False | False |

```
First 5 rows of the target variable (y):
```

| | |
|---|-------------|
| 0 | 16884.92400 |
| 1 | 1725.55230 |
| 2 | 4449.46200 |
| 3 | 21984.47061 |
| 4 | 3866.85520 |

Name: charges, dtype: float64

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
```

```
scaler = StandardScaler()
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

```
print("Shape of X_train:", X_train.shape)
print("Shape of X_test:", X_test.shape)
print("Shape of y_train:", y_train.shape)
print("Shape of y_test:", y_test.shape)
```

```
Shape of X_train: (1070, 8)
Shape of X_test: (268, 8)
Shape of y_train: (1070,)
Shape of y_test: (268,)
```

```
from sklearn.svm import SVR
```

```
# Initialize SVR models with RBF and Polynomial kernels
svr_rbf = SVR(kernel='rbf')
svr_poly = SVR(kernel='poly')
```

```
# Train the svr_rbf model
svr_rbf.fit(X_train, y_train)
print("SVR RBF model trained successfully.")
```

```
# Train the svr_poly model
```

```
svr_poly.fit(X_train, y_train)
print("SVR Polynomial model trained successfully.")
```

```
SVR RBF model trained successfully.
SVR Polynomial model trained successfully.
```

```
import numpy as np
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
import matplotlib.pyplot as plt

# --- Evaluate RBF SVR Model ---
# Make predictions
y_pred_rbf = svr_rbf.predict(X_test)

# Calculate metrics for RBF model
mae_rbf = mean_absolute_error(y_test, y_pred_rbf)
rmse_rbf = np.sqrt(mean_squared_error(y_test, y_pred_rbf))
r2_rbf = r2_score(y_test, y_pred_rbf)

print("RBF SVR Model Performance:")
print(f" Mean Absolute Error (MAE): {mae_rbf:.2f}")
print(f" Root Mean Squared Error (RMSE): {rmse_rbf:.2f}")
print(f" R-squared (R2) Score: {r2_rbf:.2f}")
print("\n")

# --- Evaluate Polynomial SVR Model ---
# Make predictions
y_pred_poly = svr_poly.predict(X_test)

# Calculate metrics for Polynomial model
mae_poly = mean_absolute_error(y_test, y_pred_poly)
rmse_poly = np.sqrt(mean_squared_error(y_test, y_pred_poly))
r2_poly = r2_score(y_test, y_pred_poly)

print("Polynomial SVR Model Performance:")
print(f" Mean Absolute Error (MAE): {mae_poly:.2f}")
print(f" Root Mean Squared Error (RMSE): {rmse_poly:.2f}")
print(f" R-squared (R2) Score: {r2_poly:.2f}")
print("\n")

# --- Visualize RBF Model Performance ---
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_rbf, alpha=0.6, color='blue', label='Predicted vs. Actual')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=2, label='Perfect Prediction')
plt.xlabel('Actual Charges')
plt.ylabel('Predicted Charges (RBF)')
plt.title('RBF SVR: Actual vs. Predicted Charges')
plt.legend()
plt.grid(True)
plt.show()

# --- Visualize Polynomial Model Performance ---
plt.figure(figsize=(10, 6))
plt.scatter(y_test, y_pred_poly, alpha=0.6, color='green', label='Predicted vs. Actual')
plt.plot([y_test.min(), y_test.max()], [y_test.min(), y_test.max()], 'k--', lw=2, label='Perfect Prediction')
plt.xlabel('Actual Charges')
plt.ylabel('Predicted Charges (Polynomial)')
plt.title('Polynomial SVR: Actual vs. Predicted Charges')
plt.legend()
plt.grid(True)
plt.show()
```

RBF SVR Model Performance:

Mean Absolute Error (MAE): 8612.41

Root Mean Squared Error (RMSE): 12889.10

R-squared (R2) Score: -0.07

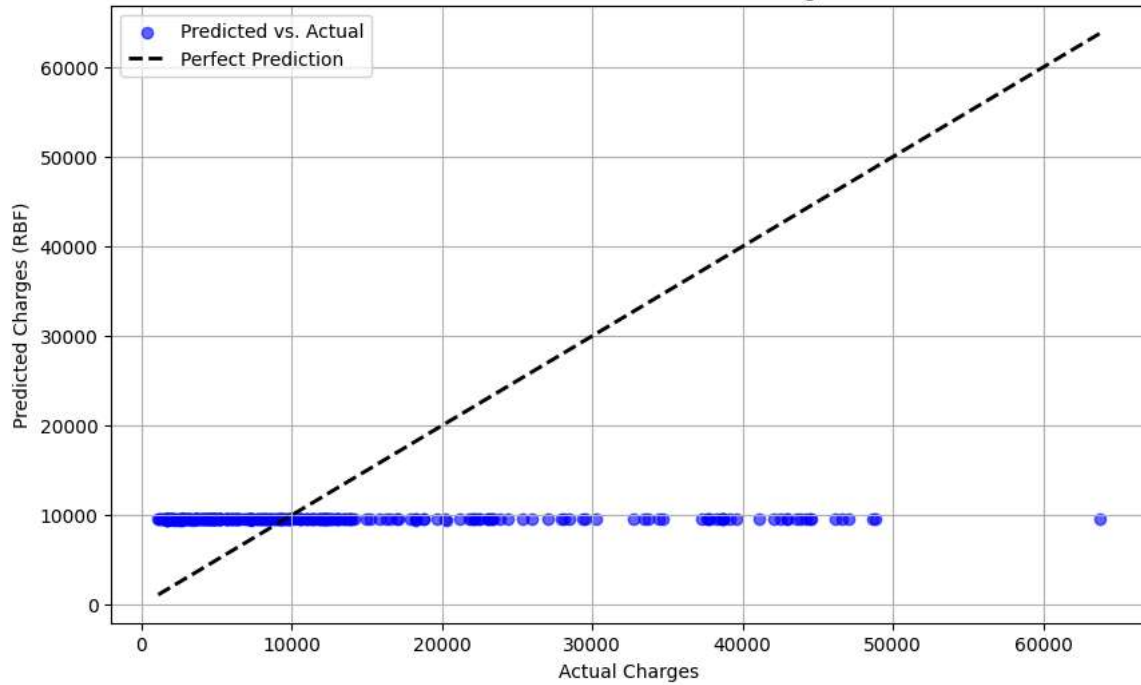
Polynomial SVR Model Performance:

Mean Absolute Error (MAE): 8607.80

Root Mean Squared Error (RMSE): 12872.96

R-squared (R2) Score: -0.07

RBF SVR: Actual vs. Predicted Charges



Polynomial SVR: Actual vs. Predicted Charges

