d-comparing-the-different-ml-model

October 20, 2024

1 Website traffic prediction and comparing the different ML model

1.1 Rahul Manjhi

[73]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
```

2 Dataset Exploration:

[ ]:
```

```

[13]:
```
data =  pd.read_csv("website_traffic.csv")
```

[15]:
```
data
```

[15]:
```
      Page Views  Session Duration  Bounce Rate Traffic Source  Time on Page  \
0              5         11.051381     0.230652        Organic      3.890460
1              4          3.429316     0.391001         Social      8.478174
2              4          1.621052     0.397986        Organic      9.636170
3              5          3.629279     0.180458        Organic      2.071925
4              5          4.235843     0.291541           Paid      1.960654
…           …                 …           …              …             …
1995           1          2.724513     0.207187       Referral      1.324206
1996           3          0.392856     0.095559        Organic      3.824416
1997           4          9.899823     0.446622        Organic      1.288675
1998           3          0.393319     0.278340           Paid      5.037584
1999           3          0.882638     0.338026         Direct      5.186908
```

```
      Previous Visits  Conversion Rate
0                   3              1.0
1                   0              1.0
2                   2              1.0
3                   3              1.0
4                   5              1.0
…                 …              …
1995                2              1.0
1996                1              1.0
1997                1              1.0
1998                2              1.0
1999                3              1.0

[2000 rows x 7 columns]
```

[17]:
```
missing = data.isnull()
```

[19]:
```
missing
```

[19]:
```
      Page Views  Session Duration  Bounce Rate  Traffic Source  Time on Page  \
0          False             False        False           False         False
1          False             False        False           False         False
2          False             False        False           False         False
3          False             False        False           False         False
4          False             False        False           False         False
…          …                  …            …               …             …
1995       False             False        False           False         False
1996       False             False        False           False         False
1997       False             False        False           False         False
1998       False             False        False           False         False
1999       False             False        False           False         False

      Previous Visits  Conversion Rate
0               False            False
1               False            False
2               False            False
3               False            False
4               False            False
…                 …              …
1995            False            False
1996            False            False
1997            False            False
1998            False            False
1999            False            False

[2000 rows x 7 columns]
```

[21]:
```
coun_missing_values = data.isnull().sum()
```

[23]:
```
coun_missing_values
```

[23]:
```
Page Views          0
Session Duration    0
Bounce Rate         0
Traffic Source      0
Time on Page        0
Previous Visits     0
Conversion Rate     0
dtype: int64
```

[25]:
```
summary_statistics = data.describe()
```

[27]:
```
summary_statistics
```

[27]:
```
        Page Views  Session Duration  Bounce Rate  Time on Page  \
count  2000.000000       2000.000000  2000.000000   2000.000000
mean      4.950500          3.022045     0.284767      4.027439
std       2.183903          3.104518     0.159781      2.887422
min       0.000000          0.003613     0.007868      0.068515
25%       3.000000          0.815828     0.161986      1.935037
50%       5.000000          1.993983     0.266375      3.315316
75%       6.000000          4.197569     0.388551      5.414627
max      14.000000         20.290516     0.844939     24.796182

       Previous Visits  Conversion Rate
count      2000.000000      2000.000000
mean          1.978500         0.982065
std           1.432852         0.065680
min           0.000000         0.343665
25%           1.000000         1.000000
50%           2.000000         1.000000
75%           3.000000         1.000000
max           9.000000         1.000000
```

[29]:
```
coun_missing_values, summary_statistics
```

[29]:
```
(Page Views          0
 Session Duration    0
 Bounce Rate         0
 Traffic Source      0
 Time on Page        0
 Previous Visits     0
 Conversion Rate     0
 dtype: int64,
```

```
        Page Views  Session Duration  Bounce Rate  Time on Page  \
count  2000.000000       2000.000000  2000.000000   2000.000000
mean      4.950500          3.022045     0.284767      4.027439
std       2.183903          3.104518     0.159781      2.887422
min       0.000000          0.003613     0.007868      0.068515
25%       3.000000          0.815828     0.161986      1.935037
50%       5.000000          1.993983     0.266375      3.315316
75%       6.000000          4.197569     0.388551      5.414627
max      14.000000         20.290516     0.844939     24.796182

       Previous Visits  Conversion Rate
count      2000.000000      2000.000000
mean          1.978500         0.982065
std           1.432852         0.065680
min           0.000000         0.343665
25%           1.000000         1.000000
50%           2.000000         1.000000
75%           3.000000         1.000000
max           9.000000         1.000000  )
```

[ ]:

[32]:
```python
# Perform one-hot encoding on the 'Traffic Source' categorical variable
df_encoded = pd.get_dummies(data, columns=['Traffic Source'], drop_first=True)
```

[34]:
```python
df_encoded.head(10)
```

[34]:
```
   Page Views  Session Duration  Bounce Rate  Time on Page  Previous Visits  \
0           5         11.051381     0.230652      3.890460                3
1           4          3.429316     0.391001      8.478174                0
2           4          1.621052     0.397986      9.636170                2
3           5          3.629279     0.180458      2.071925                3
4           5          4.235843     0.291541      1.960654                5
5           3          4.541868     0.420740      3.438712                2
6           5          1.949558     0.034978      2.119271                1
7           4          1.685740     0.252343      3.478016                5
8           6          0.033268     0.120703      5.285519                1
9           7          7.833742     0.212727      4.060115                5

   Conversion Rate  Traffic Source_Organic  Traffic Source_Paid  \
0              1.0                    True                False
1              1.0                   False                False
2              1.0                    True                False
3              1.0                    True                False
4              1.0                   False                 True
5              1.0                   False                False
6              1.0                   False                False
```

```
7             1.0                   False                 True
8             1.0                    True                False
9             1.0                   False                 True

   Traffic Source_Referral  Traffic Source_Social
0                    False                  False
1                    False                   True
2                    False                  False
3                    False                  False
4                    False                  False
5                    False                   True
6                    False                   True
7                    False                  False
8                    False                  False
9                    False                  False
```

[ ]:

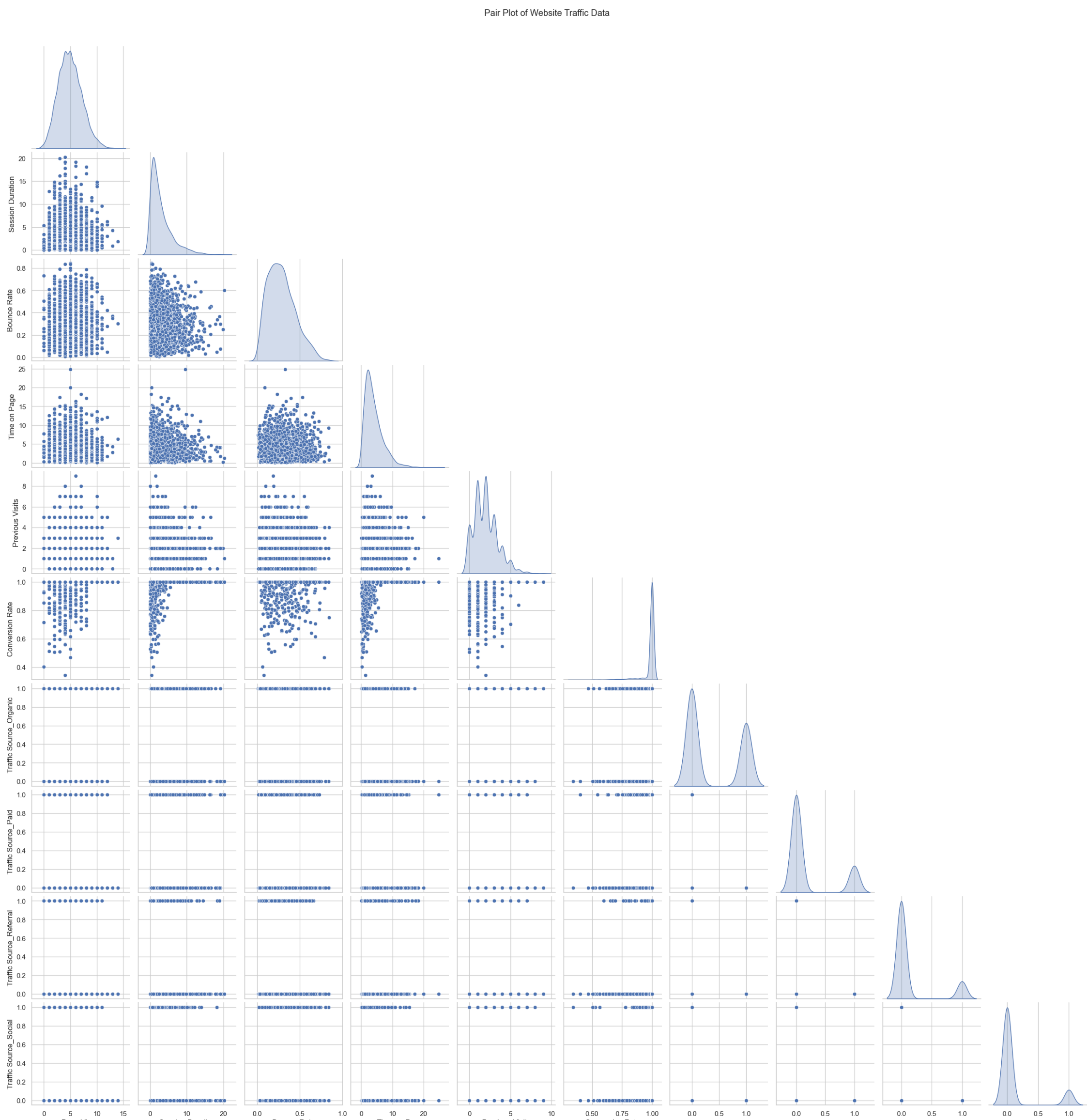
```

```

[37]:

```
# Set up the plotting environment
sns.set(style="whitegrid")
```

[39]:

```
# Scatter plot matrix (pair plot) to visualize relationships between numeric␣
↪variables
sns.pairplot(df_encoded, diag_kind='kde', corner=True)
plt.suptitle('Pair Plot of Website Traffic Data', y=1.02)
plt.show()
```



[ ]:

[ ]:

3 Multiple Linear Regression:

[56]:

```
# Define the features (X) and target (y)
X = df_encoded.drop(columns=['Conversion Rate'])
y = df_encoded['Conversion Rate']
```

[58]:
```
# Split the data into 80% training and 20% testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=42)

# Instantiate the Multiple Linear Regression model
model = LinearRegression()
```

[60]:
```
# Train the model on the training data
model.fit(X_train, y_train)
```

[60]:
```
LinearRegression()
```

[62]:
```
y_pred = model.predict(X_test)
```

[ ]:
```

```

[65]:
```
# Evaluate the model
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
rmse = np.sqrt(mse)
r2 = r2_score(y_test, y_pred)
```

[67]:
```
# Calculate adjusted R-squared
n = X_test.shape[0]
p = X_test.shape[1]
adjusted_r2 = 1 - (1 - r2) * (n - 1) / (n - p - 1)

mae, mse, rmse, r2, adjusted_r2
```

[67]:
```
(0.03163385542916112,
 0.0027909306686198193,
 0.0528292595880334,
 0.10626266875894574,
 0.0856379611149215)
```

[ ]:
```

```

[ ]:
```

```

4 Polynomial Regression

[75]:
```
# Polynomial transformation (degree 2 or 3)
degree = 2  # or 3 for higher-degree polynomial
poly = PolynomialFeatures(degree=degree)
X_poly_train = poly.fit_transform(X_train)
X_poly_test = poly.transform(X_test)
```

[ ]:

```python

```

[77]:

```python
# Fit the linear regression model with polynomial features
model_poly = LinearRegression()
model_poly.fit(X_poly_train, y_train)

# Predict on the test set
y_pred_poly = model_poly.predict(X_poly_test)
```

[ ]:

```python

```

[79]:

```python
# Evaluate the model
mae_poly = mean_absolute_error(y_test, y_pred_poly)
mse_poly = mean_squared_error(y_test, y_pred_poly)
rmse_poly = np.sqrt(mse_poly)
r2_poly = r2_score(y_test, y_pred_poly)
```

[ ]:

```python

```

[81]:

```python
# Calculate adjusted R-squared
n = X_test.shape[0]
p = X_poly_test.shape[1]  # Account for the new number of features in the␣
↪polynomial model
adjusted_r2_poly = 1 - (1 - r2_poly) * (n - 1) / (n - p - 1)
```

[ ]:

```python

```

[83]:

```python
# Output results
print("Polynomial Regression (degree {}):".format(degree))
print(f"MAE: {mae_poly}")
print(f"MSE: {mse_poly}")
print(f"RMSE: {rmse_poly}")
print(f"R²: {r2_poly}")
print(f"Adjusted R²: {adjusted_r2_poly}")
```

```
Polynomial Regression (degree 2):
MAE: 0.02912565018405664
MSE: 0.0024035453442120837
RMSE: 0.04902596602018244
R²: 0.2303147385186486
Adjusted R²: 0.10725459496785117
```

[ ]:

```python

```

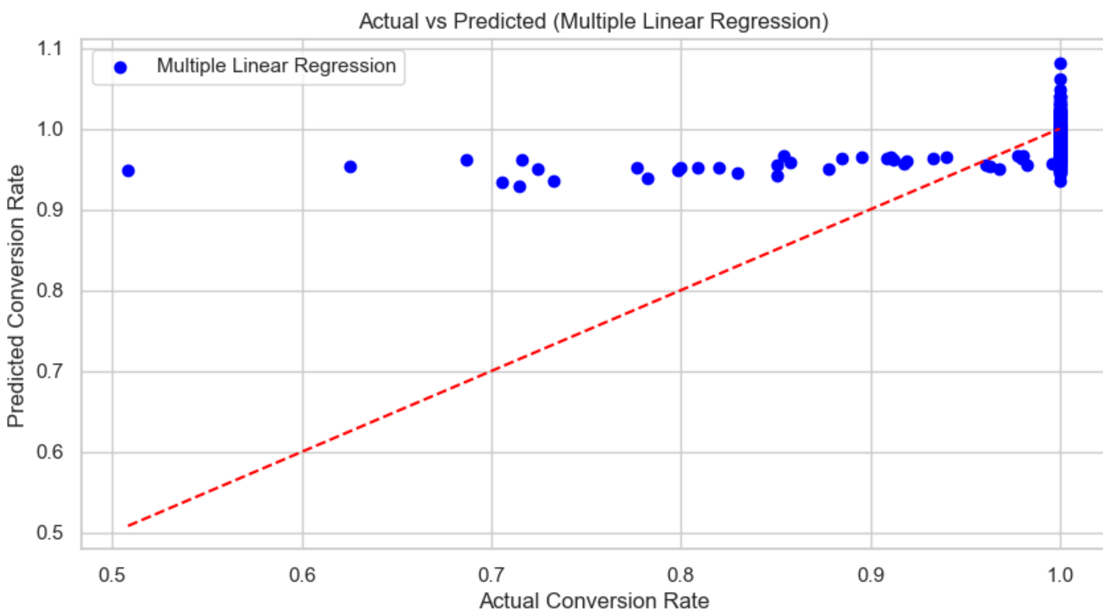
[ ]:

```python

```

5 Insights and Reporting

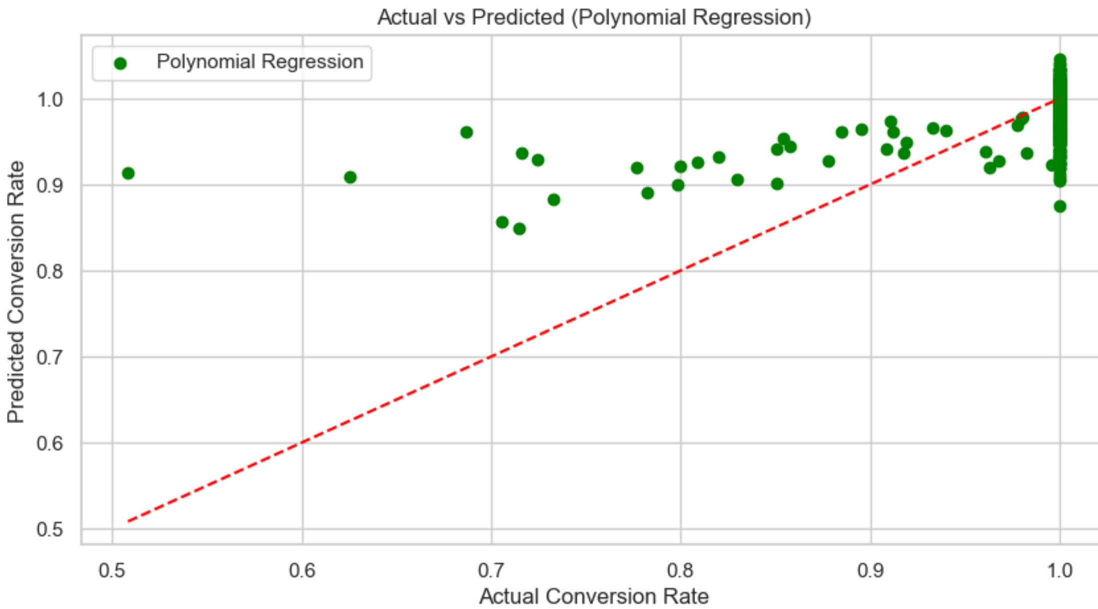
5.1 1. Plotting Actual vs Predicted Values

[86]:
```
# Plot actual vs predicted for Multiple Linear Regression
plt.figure(figsize=(10,5))
plt.scatter(y_test, y_pred, color='blue', label='Multiple Linear Regression')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linestyle='--')
plt.xlabel('Actual Conversion Rate')
plt.ylabel('Predicted Conversion Rate')
plt.title('Actual vs Predicted (Multiple Linear Regression)')
plt.legend()
plt.show()
```



[ ]:
```

```

[88]:
```
# Plot actual vs predicted for Polynomial Regression
plt.figure(figsize=(10,5))
plt.scatter(y_test, y_pred_poly, color='green', label='Polynomial Regression')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], color='red',␣
↪linestyle='--')
plt.xlabel('Actual Conversion Rate')
plt.ylabel('Predicted Conversion Rate')
plt.title('Actual vs Predicted (Polynomial Regression)')
plt.legend()
plt.show()
```



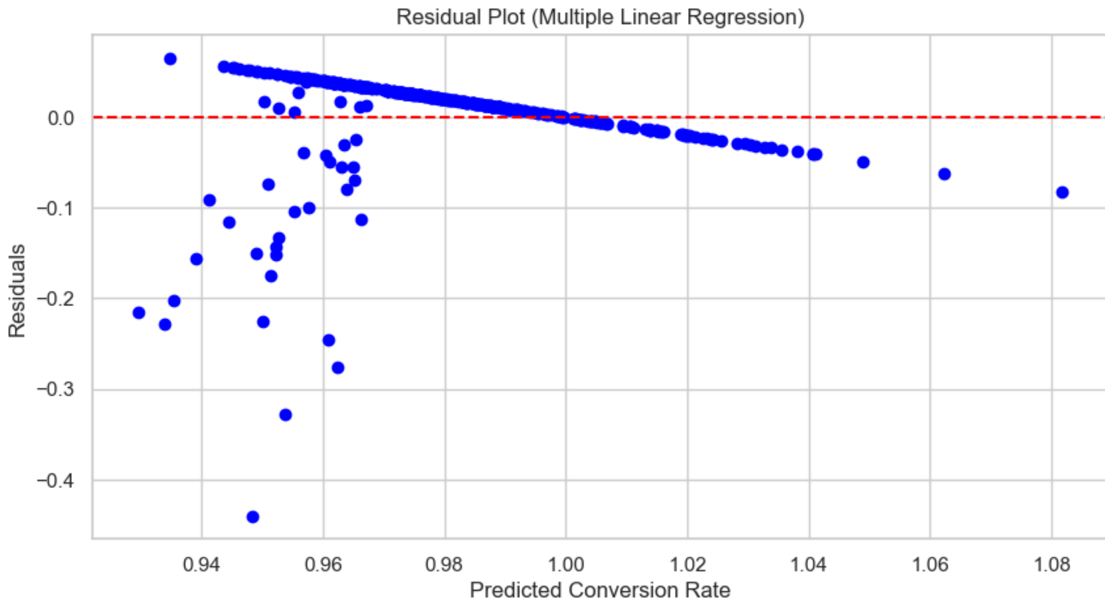
[ ]:

```

```

5.2 2. Residual Plot

[92]:

```
# Residual plot for Multiple Linear Regression
residuals = y_test - y_pred
plt.figure(figsize=(10,5))
plt.scatter(y_pred, residuals, color='blue')
plt.axhline(y=0, color='red', linestyle='--')
plt.xlabel('Predicted Conversion Rate')
plt.ylabel('Residuals')
plt.title('Residual Plot (Multiple Linear Regression)')
plt.show()
```

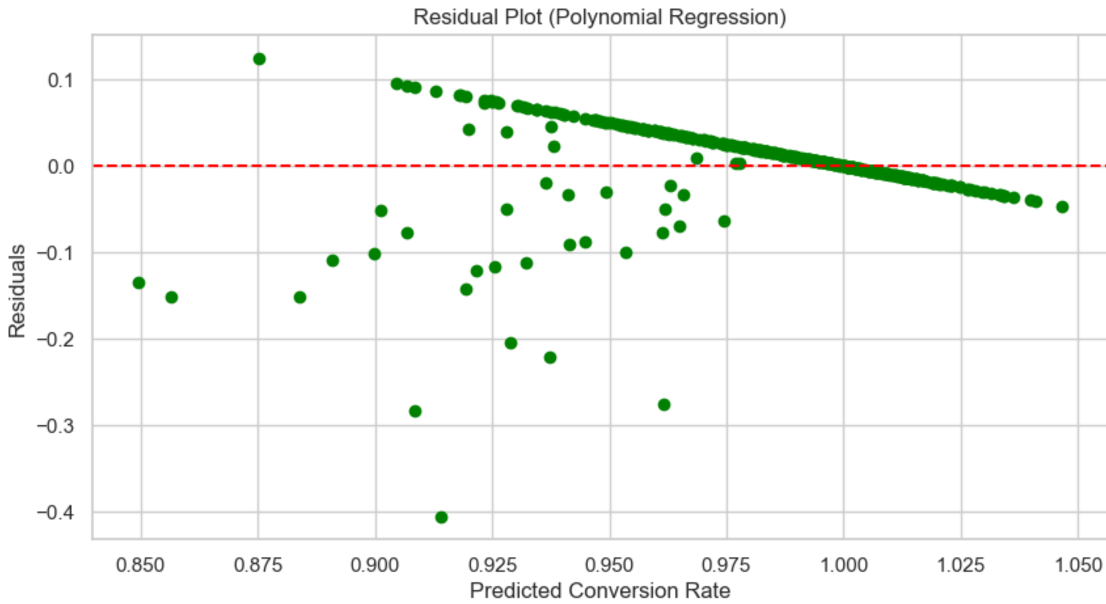


[ ]:

```

```

[94]:

```
# Residual plot for Polynomial Regression
residuals_poly = y_test - y_pred_poly
plt.figure(figsize=(10,5))
plt.scatter(y_pred_poly, residuals_poly, color='green')
plt.axhline(y=0, color='red', linestyle='--')
plt.xlabel('Predicted Conversion Rate')
plt.ylabel('Residuals')
plt.title('Residual Plot (Polynomial Regression)')
plt.show()
```



[ ]:

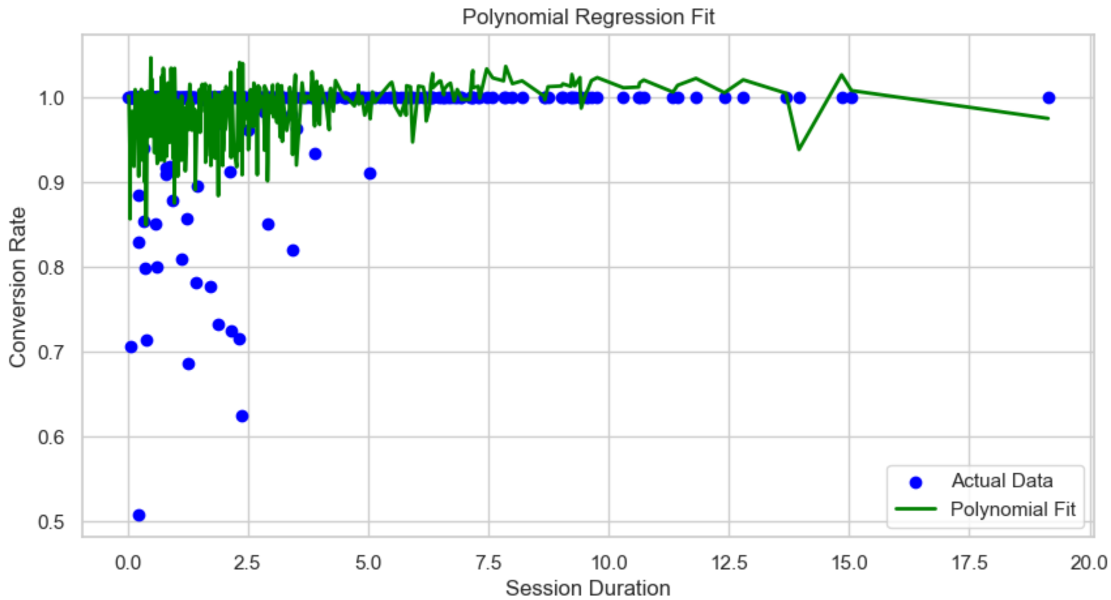
5.3 3. Plot Polynomial Curve

[97]:

```
# Sort the test data to get a smooth curve
sorted_indices = np.argsort(X_test['Session Duration'])
X_test_sorted = X_test['Session Duration'].values[sorted_indices]
y_test_sorted = y_test.values[sorted_indices]
y_pred_poly_sorted = y_pred_poly[sorted_indices]
```

[99]:

```
# Plot polynomial regression curve
plt.figure(figsize=(10,5))
plt.scatter(X_test_sorted, y_test_sorted, color='blue', label='Actual Data')
plt.plot(X_test_sorted, y_pred_poly_sorted, color='green', label='Polynomial␣
 ↪Fit', linewidth=2)
plt.xlabel('Session Duration')
plt.ylabel('Conversion Rate')
plt.title('Polynomial Regression Fit')
plt.legend()
plt.show()
```



[ ]:

6 Conclusion and Reporting:

6.0.1 1 Summary of Findings:

Compare the metrics (MAE, MSE, RMSE, R^2, and Adjusted R^2) between the multiple linear regression and polynomial regression models. If polynomial regression has significantly lower errors and a better fit, it suggests that the relationships in the data are non-linear, and polynomial features capture these better.

[ ]:

2 Next Steps for Analysis and Model Building: Feature Engineering: You could explore higher-degree polynomial features or interaction terms.

Regularization: Consider using Ridge or Lasso regression to handle potential overfitting in polynomial models.

Cross-Validation: To ensure model stability, use k-fold cross-validation for better evaluation of model performance.

Other Algorithms: Try more complex models like decision trees, random forests, or gradient boosting if polynomial regression performs significantly better than linear models.