Poly_3_Manufacturing_1

February 6, 2025

[109]:
```python
import numpy as np
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns
```

[110]:
```python
url = r"D:\Supervised Machine Learning lab (SMLL)\3\Practice-1 Manufacturing.
↪csv"
df = pd.read_csv(url)
df.head()
```

[110]:
```
   Temperature (°C)  Pressure (kPa)  Temperature x Pressure  \
0        209.762701        8.050855             1688.769167
1        243.037873       15.812068             3842.931469
2        220.552675        7.843130             1729.823314
3        208.976637       23.786089             4970.736918
4        184.730960       15.797812             2918.345014

   Material Fusion Metric  Material Transformation Metric  Quality Rating
0            44522.217074                    9.229576e+06       99.999971
1            63020.764997                    1.435537e+07       99.985703
2            49125.950249                    1.072839e+07       99.999758
3            57128.881547                    9.125702e+06       99.999975
4            38068.201283                    6.303792e+06      100.000000
```

[111]:
```python
X = X = df[['Temperature (°C)', 'Pressure (kPa)', 'Temperature x Pressure',
        'Material Fusion Metric', 'Material Transformation Metric']]
y = df['Quality Rating']
```

[112]:
```python
# importing vif
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Vif dataframe
vif_data = pd.DataFrame()
for i in range(X.shape[1]):
    vif_data["Feature"] = X.columns
    vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
↪shape[1])]
print(vif_data)
```

```
                          Feature         VIF
0               Temperature (°C)  113.050204
1                  Pressure (kPa)   49.349434
2         Temperature x Pressure   72.745768
3         Material Fusion Metric  764.593283
4  Material Transformation Metric  219.003134
```

[113]:
```python
# Scaling the data
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = scaler.fit_transform(X)
X = pd.DataFrame(X)
```

[114]:
```python
# importing vif
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Vif dataframe
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for i in range(X.shape[1]):
    vif_data["Feature"] = X.columns
    vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
 ↪shape[1])]
print(vif_data)
```

```
   Feature         VIF
0        0   92.760519
1        1   22.782171
2        2   19.174847
3        3  300.197535
4        4   99.639939
```

[115]:
```python
X.drop(X.columns[3], axis=1, inplace=True)
```

[116]:
```python
# importing vif
from statsmodels.stats.outliers_influence import variance_inflation_factor

# Vif dataframe
vif_data = pd.DataFrame()
for i in range(X.shape[1]):
    vif_data["Feature"] = X.columns
    vif_data["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.
 ↪shape[1])]
print(vif_data)
```

```
   Feature        VIF
0        0  24.566249
1        1  12.900307
2        2  19.153063
3        4  17.623707
```

[117]:
```
y
```

[117]:
```
0        99.999971
1        99.985703
2        99.999758
3        99.999975
4       100.000000
           …
3952    100.000000
3953     99.999997
3954     99.989318
3955     99.999975
3956    100.000000
Name: Quality Rating, Length: 3957, dtype: float64
```

[118]:
```
# Train Test Split
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,␣
 ↪random_state=42)
```

[119]:
```
print(X_train.shape, X_test.shape, y_train.shape, y_test.shape)
```

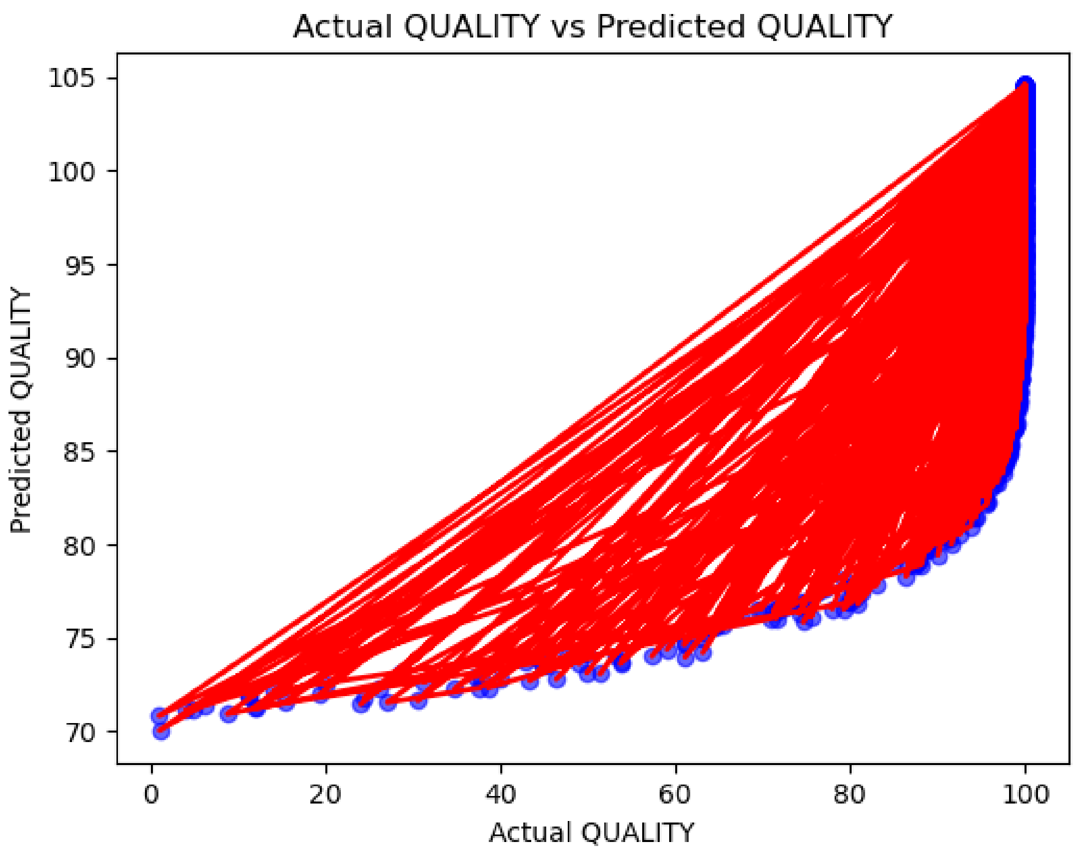
```
(2769, 4) (1188, 4) (2769,) (1188,)
```

[120]:
```
# Implementing the Linear Regression
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression

# For Simple Linear Regression
lin_reg = LinearRegression()
lin_reg.fit(X_train, y_train)
y_pred = lin_reg.predict(X_test)
```

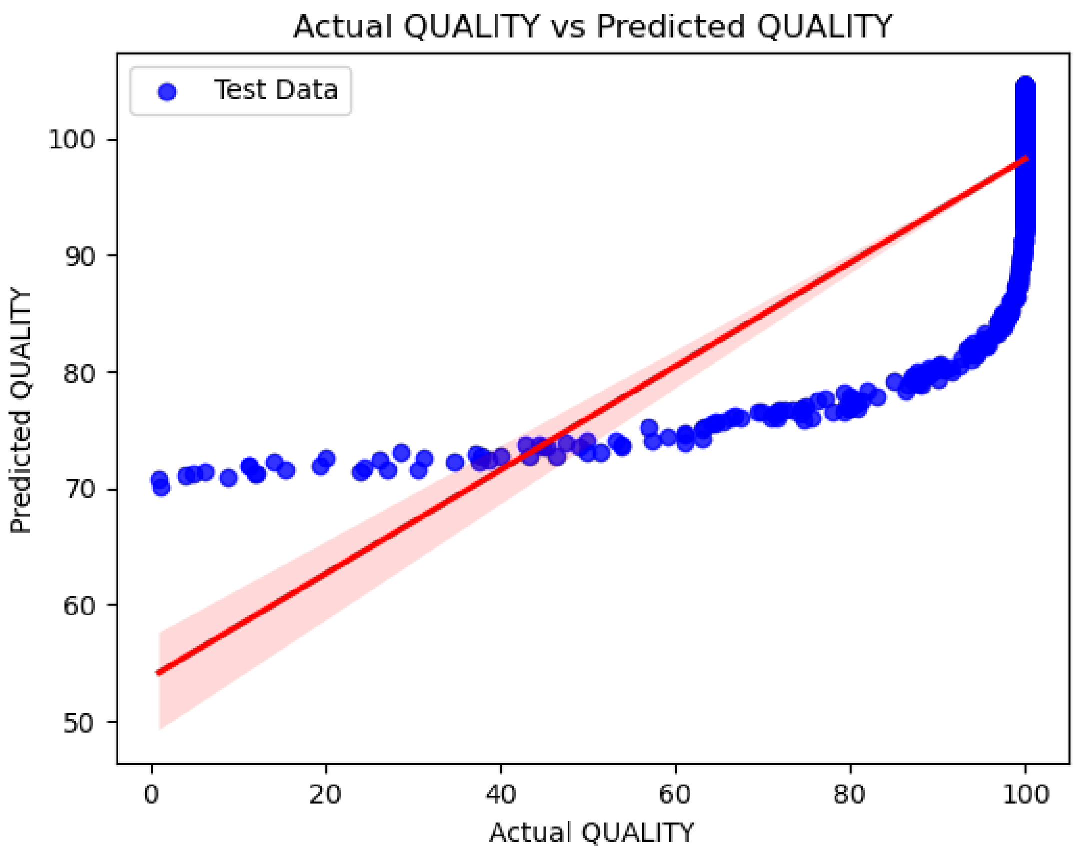
[121]:
```
y_pred.shape
```

[121]:
```
(1188,)
```

[122]:
```
plt.scatter(y_test, y_pred, color='blue',alpha=0.6)
plt.plot(y_test, y_pred, color='red', linewidth=2, label='Linear Regression␣
 ↪Line')
plt.title('Actual QUALITY vs Predicted QUALITY')
plt.xlabel('Actual QUALITY')
plt.ylabel('Predicted QUALITY')
plt.show()
```



[123]:
```
sns.regplot(x=y_test, y=y_pred, data=df, scatter_kws={"color": "blue"},␣
 ↪line_kws={"color": "red"}, label="Test Data")
plt.xlabel('Actual QUALITY')
plt.ylabel('Predicted QUALITY')
plt.title('Actual QUALITY vs Predicted QUALITY')
plt.legend()
plt.show()
```



[124]:

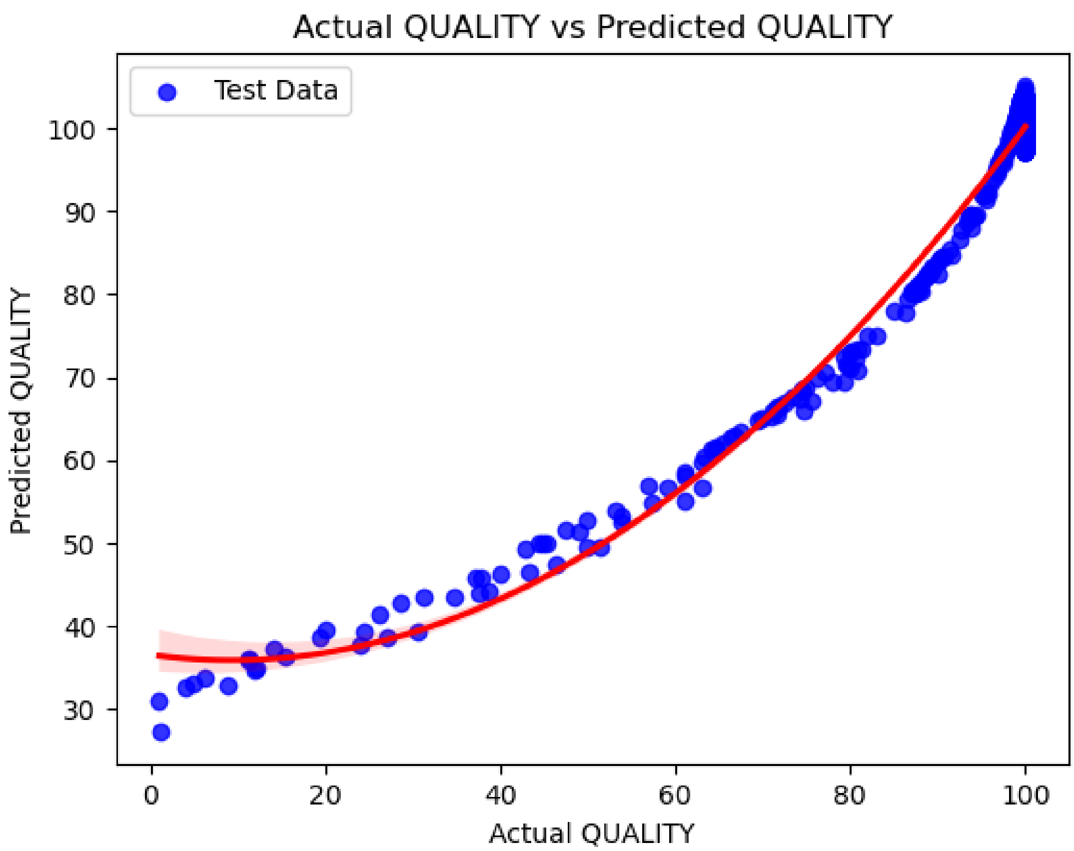
```
#Metrics
from sklearn.metrics import mean_squared_error, r2_score
from math import sqrt

mse = mean_squared_error(y_test, y_pred)
rmse = sqrt(mse)
r2 = r2_score(y_test, y_pred)
print("Mean Squared Error: ", mse)
print("Root Mean Squared Error: ", rmse)
print("R2 Score: ", r2)
```

```
Mean Squared Error:  100.06958965362516
Root Mean Squared Error:  10.003478877551807
R2 Score:  0.5004768505711403
```

[125]:

```
# For Polynomial Regression with degree 2
poly_reg = PolynomialFeatures(degree=2)
X_poly = poly_reg.fit_transform(X_train)

lin_reg2 = LinearRegression()
```

```
lin_reg2.fit(X_poly, y_train)
y_pred2 = lin_reg2.predict(poly_reg.fit_transform(X_test))

sns.regplot(x=y_test, y=y_pred2, data=df, scatter_kws={"color": "blue"},␣
 ↪line_kws={"color": "red"}, order=2, label="Test Data")
plt.xlabel('Actual QUALITY')
plt.ylabel('Predicted QUALITY')
plt.title('Actual QUALITY vs Predicted QUALITY')
plt.legend()
plt.show()
```



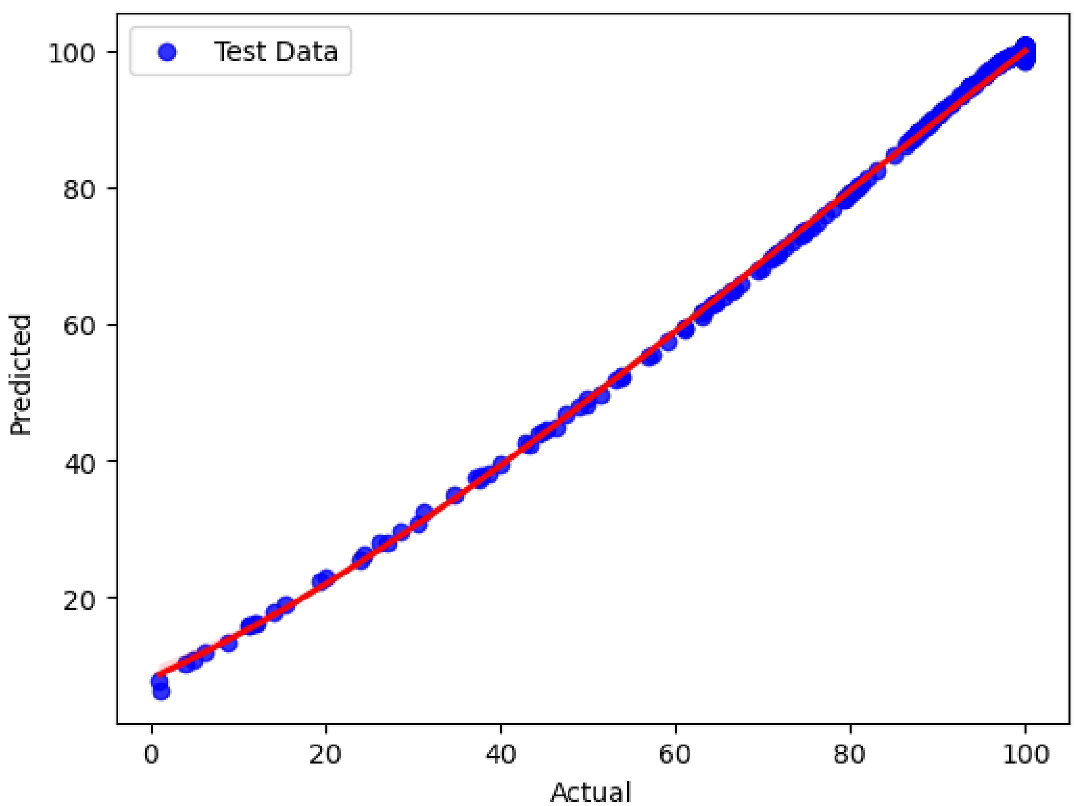
[126]:
```
# Metrics
mse = mean_squared_error(y_test, y_pred2)
rmse = sqrt(mse)
r2 = r2_score(y_test, y_pred2)
print("Mean Squared Error: ", mse)
print("Root Mean Squared Error: ", rmse)
print("R2 Score: ", r2)
```

```
Mean Squared Error:  15.26909748852792
```

```
Root Mean Squared Error:  3.907569255755798
R2 Score:  0.923780364316409
```

[127]:

```
# For Polynomial Regression with degree 3
poly_reg = PolynomialFeatures(degree=3)
X_poly = poly_reg.fit_transform(X_train)

lin_reg3 = LinearRegression()
lin_reg3.fit(X_poly, y_train)

y_pred3 = lin_reg3.predict(poly_reg.fit_transform(X_test))

sns.regplot(x=y_test, y=y_pred3, data=df, scatter_kws={"color": "blue"},␣
↪line_kws={"color": "red"}, order=3, label="Test Data")
plt.xlabel('Actual')
plt.ylabel('Predicted')
plt.legend()
plt.show()
```



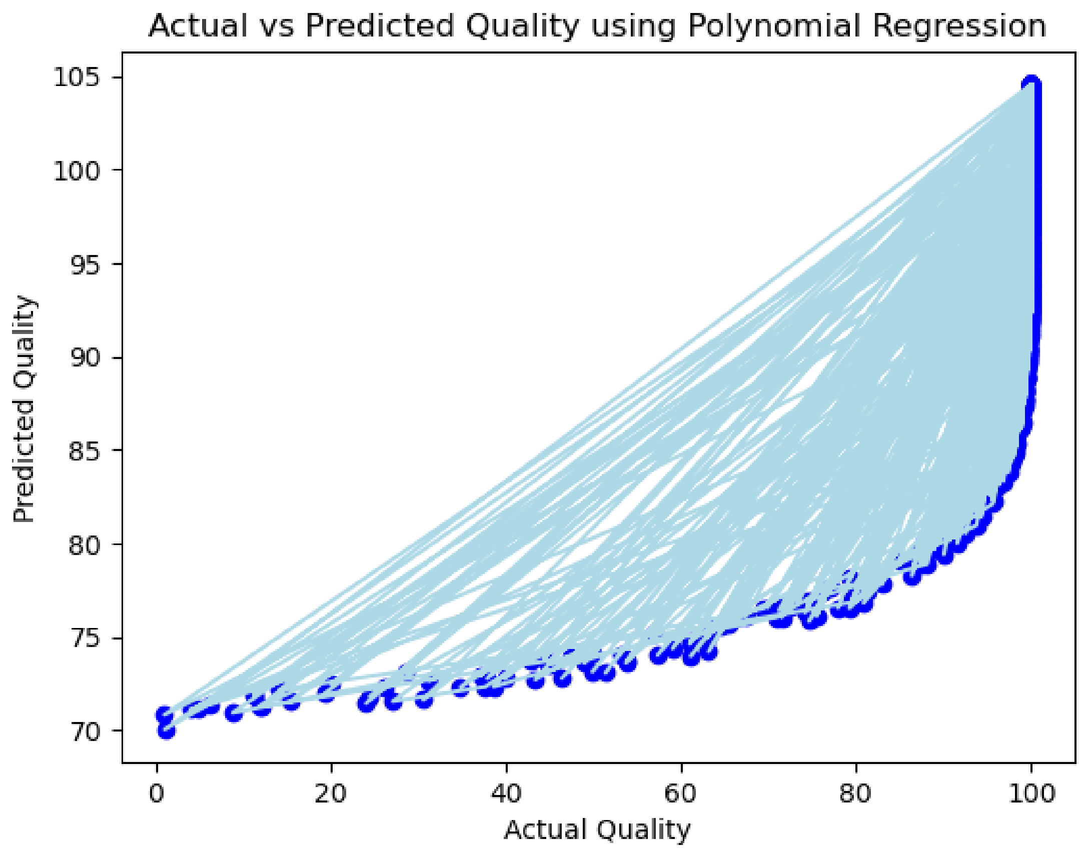
[128]:

```
# Metrics
mse = mean_squared_error(y_test, y_pred3)
```

```
rmse = sqrt(mse)

r2 = r2_score(y_test, y_pred3)

print("Mean Squared Error: ", mse)

print("Root Mean Squared Error: ", rmse)

print("R2 Score: ", r2)
```

```
Mean Squared Error:  0.6158333511438949
Root Mean Squared Error:  0.7847505024808171
R2 Score:  0.9969259090983433
```

[129]:
```
plt.scatter(y_test, y_pred, color = 'blue')
plt.plot(y_test, y_pred, color = 'lightblue')
plt.title("Actual vs Predicted Quality using Polynomial Regression")
plt.xlabel("Actual Quality")
plt.ylabel('Predicted Quality')
plt.show()
```



[130]:
```python
import numpy as np
import matplotlib.pyplot as plt
sorted_idx = np.argsort(y_test)
y_test_sorted = np.array(y_test)[sorted_idx]
y_pred_sorted = y_pred[sorted_idx]

# Scatter Plot (Actual vs Predicted)
plt.figure(figsize=(8, 5))
plt.scatter(y_test_sorted, y_pred_sorted, color = 'red', alpha=0.5)
plt.plot(y_test_sorted, y_pred_sorted, color = 'blue')
plt.title('Sorted Actual Sales vs Predicted Sales')
plt.xlabel('Predicted Sales')
plt.ylabel('Actual Sales')
plt.show()
```