02_Modeling

February 18, 2025

1 Explotary Data Analysis

1.0.1 importing all the neede Libaries

[371]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import math
from sklearn.linear_model import LinearRegression
from sklearn.preprocessing import StandardScaler, PolynomialFeatures
from sklearn.pipeline import Pipeline
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.model_selection import train_test_split
from sklearn.model_selection import cross_val_score, cross_val_predict
from sklearn.model_selection import KFold
from sklearn.model_selection import GridSearchCV
from sklearn.linear_model import Ridge

import warnings
warnings.filterwarnings("ignore", category=UserWarning)
%matplotlib inline
```

constants

[393]:
```
cleaned_data_path = '../data/cleaned_data.csv'
transformed_data_path = '../data/transformed_data.csv'
```

1.1 Loading the Data Set

[373]:
```
df = pd.read_csv(cleaned_data_path)
df.head()
```

[373]:

	age	gender	bmi	no_of_children	smoker	region	charges
0	19	female	27.900	0	yes	southwest	16884.92
1	18	male	33.770	1	no	southeast	1725.55
2	28	male	33.000	3	no	southeast	4449.46
3	33	male	22.705	0	no	northwest	21984.47
4	32	male	28.880	0	no	northwest	3866.86

1.2 Data Processing/Transformation

transforming the gender to numerical two columns

[374]:
```python
# transforming the gender to numerical two columns
dummies  = pd.get_dummies(df['gender'])
df = pd.concat([df,dummies],axis=1)
df.drop(['gender'],axis=1,inplace=True)
df.head()
```

[374]:

	age	bmi	no_of_children	smoker	region	charges	female	male
0	19	27.900	0	yes	southwest	16884.92	True	False
1	18	33.770	1	no	southeast	1725.55	False	True
2	28	33.000	3	no	southeast	4449.46	False	True
3	33	22.705	0	no	northwest	21984.47	False	True
4	32	28.880	0	no	northwest	3866.86	False	True

[375]:
```python
df.replace('northwest', 1, inplace=True)
df.replace('northeast', 2, inplace=True)
df.replace('southwest', 3, inplace=True)
df.replace('southeast', 4, inplace=True)
```

```
C:\Users\imadb\AppData\Local\Temp\ipykernel_28744\1664779204.py:4:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  df.replace('southeast', 4, inplace=True)
```

[376]:
```python
df.replace("yes",1,inplace=True)
df.replace("no",0,inplace=True)
```

```
C:\Users\imadb\AppData\Local\Temp\ipykernel_28744\3982548934.py:2:
FutureWarning: Downcasting behavior in `replace` is deprecated and will be
removed in a future version. To retain the old behavior, explicitly call
`result.infer_objects(copy=False)`. To opt-in to the future behavior, set
`pd.set_option('future.no_silent_downcasting', True)`
  df.replace("no",0,inplace=True)
```

1.3 saving the transformed data frame

[ ]:
```python
df.to_csv(transformed_data_path, index=False )
```

1.4 Loading Transformed data

1.5 initiltise the Liner Regression Model

[377]:
```
lm = LinearRegression()
x = df[['smoker']]
y = df['charges']
lm.fit(x, y)
yhat = lm.predict(x)
print('R2:', r2_score(y, yhat))
print('MSE:', mean_squared_error(y, yhat))
```

```
R2: 0.6221791733924185
MSE: 55770970.49293007
```

R^2 score of 0.62 (62%) means that **62% of the variation in insurance charges can be explained by the "smoker" feature alone**.

Interpretation:
- This suggests that whether a person is a smoker or not **has a strong influence** on insurance charges.
- However, **38% of the variation** is still unexplained, meaning other factors (like age, BMI, etc.) also play a role.

Fiting a linear regression model that may be used to predict the `charges` value, just by using all other attributes of the dataset. Print the \$ R^2 \$ score of this model. we should see an improvement in the performance.

[ ]:
```
x = df[['age','male','female', 'bmi', 'no_of_children', 'smoker', 'region']]
y = df['charges']
lm.fit(x, y)
yhat = lm.predict(x)
print('R2:', r2_score(y, yhat))
print('MSE:', mean_squared_error(y, yhat))
# df.columns
```

```
R2: 0.7504083820289634
MSE: 36842772.50180054
```

Since we're using **multiple features** (`age`, `male`, `female`, `bmi`, etc.) to predict `charges`, this qualifies as **Multiple Linier Regression**.

1.5.1 Interpretation of $R^2 = 75\%$

- **75% of the variation** in insurance charges is explained by these features.
- **25% is unexplained**, meaning some other factors not in our model may still influence the charges.

we can not also that MSE error is a less and the previos MSE when we used only the smoker attribute

1.6 using cross validation

[379]:
```
## using cross validation
# Perform cross-validation
scores = cross_val_score(lm, x, y, cv=5)
print('Cross-Validation Scores:', scores)
print('Mean Cross-Validation Score:', np.mean(scores))

# Perform cross-validation prediction
y_pred = cross_val_predict(lm, x, y, cv=5)
print('Cross-Validation R2 Score:', r2_score(y, y_pred))
print('Cross-Validation MSE:', mean_squared_error(y, y_pred))
```

```
Cross-Validation Scores: [0.73826314 0.75690927 0.76330761 0.74545018
0.74325342]
Mean Cross-Validation Score: 0.7494367215412645
Cross-Validation R2 Score: 0.7496968706021572
Cross-Validation MSE: 36947800.28215371
```

1.6.1 Cross-Validation Insights

Model Stability: The mean cross-validation R^2 score (74.9%) is **consistent** with the original R^2 (~75%), meaning the model generalizes well.

Slight Drop: The cross-validation score is a bit lower than the training R^2, which is **expected**—this prevents overfitting.

Model Performance: The model explains ~**75% of the variance** in insurance charges, but **25% remains unexplained**, suggesting other influential factors might be missing.

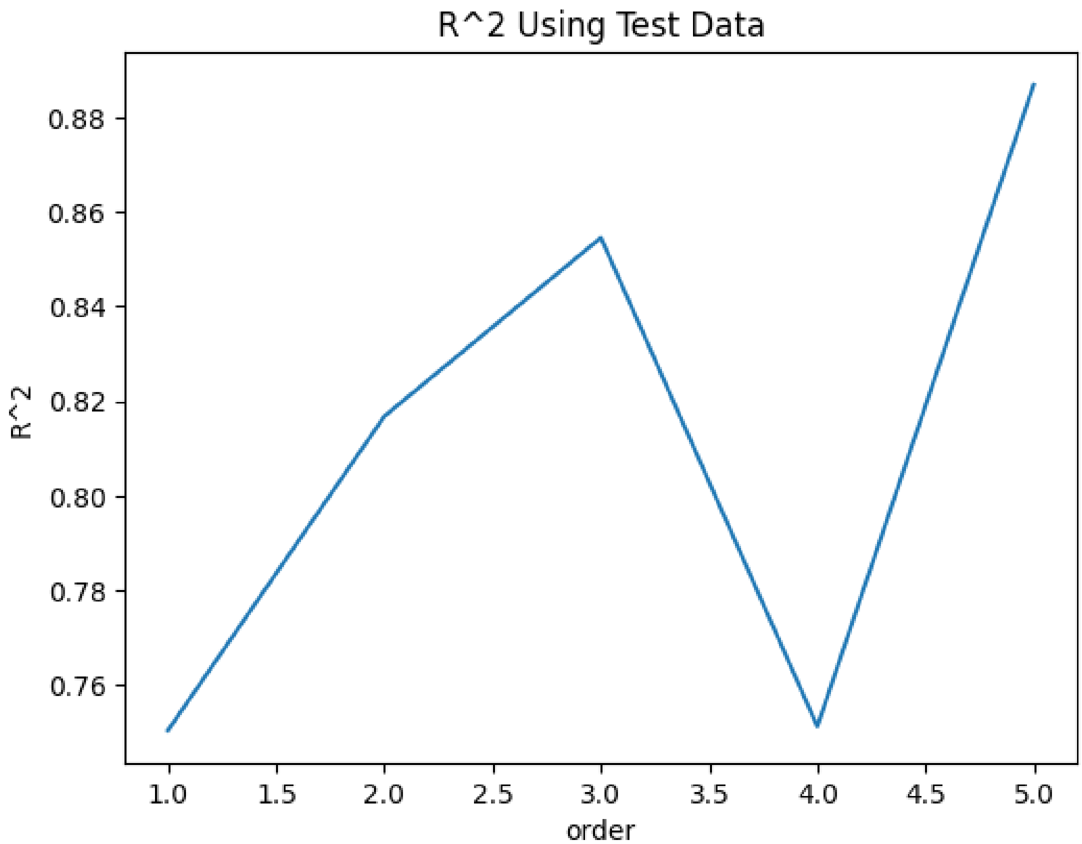
1.7 Polynomial Regression

choosing the best order

[380]:
```
lre = LinearRegression()
r_scores = []
mses = []
order = [1, 2, 3, 4, 5]
for n in order:
    pr = PolynomialFeatures(degree=n)
    x_pr = pr.fit_transform(x)
    lre.fit(x_pr, y)
    r_scores.append(lre.score(x_pr, y))
    mses.append(mean_squared_error(y, lre.predict(x_pr)))
    print("shape : ", x_pr.shape)
    print("R^2 : ", lre.score(x_pr, y))
    print("MSE : ", mean_squared_error(y, lre.predict(x_pr)))
    print("_____________________________")
plt.plot(order, r_scores)
plt.xlabel('order')
```

```python
plt.ylabel('R^2')
plt.title('R^2 Using Test Data')
plt.show()
max_mse = max(mses)
max_r2 = max(r_scores)
print(f"Best R^2 is {max_r2} \n with order {order[r_scores.
 ↪index(max(r_scores))]} \n and mse {mses[r_scores.index(max(r_scores))]}")
```

```
shape :  (2772, 8)
R^2 :  0.7504083820289634
MSE :  36842772.50180054
-----------------------------
shape :  (2772, 36)
R^2 :  0.8168060981340476
MSE :  27041658.309806217
-----------------------------
shape :  (2772, 120)
R^2 :  0.8545412792122198
MSE :  21471484.50718005
-----------------------------
shape :  (2772, 330)
R^2 :  0.7512396655226462
MSE :  36720064.900915444
-----------------------------
shape :  (2772, 792)
R^2 :  0.8869190413510677
MSE :  16692131.200782511
-----------------------------
```




```
Best R^2 is 0.8869190413510677
 with order 5
 and mse 16692131.200782511
```

1.7.1 Splitiing the data 'Random Split'

[381]:
```
# Splitiing the data
x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2,␣
 ↪random_state=0)
```

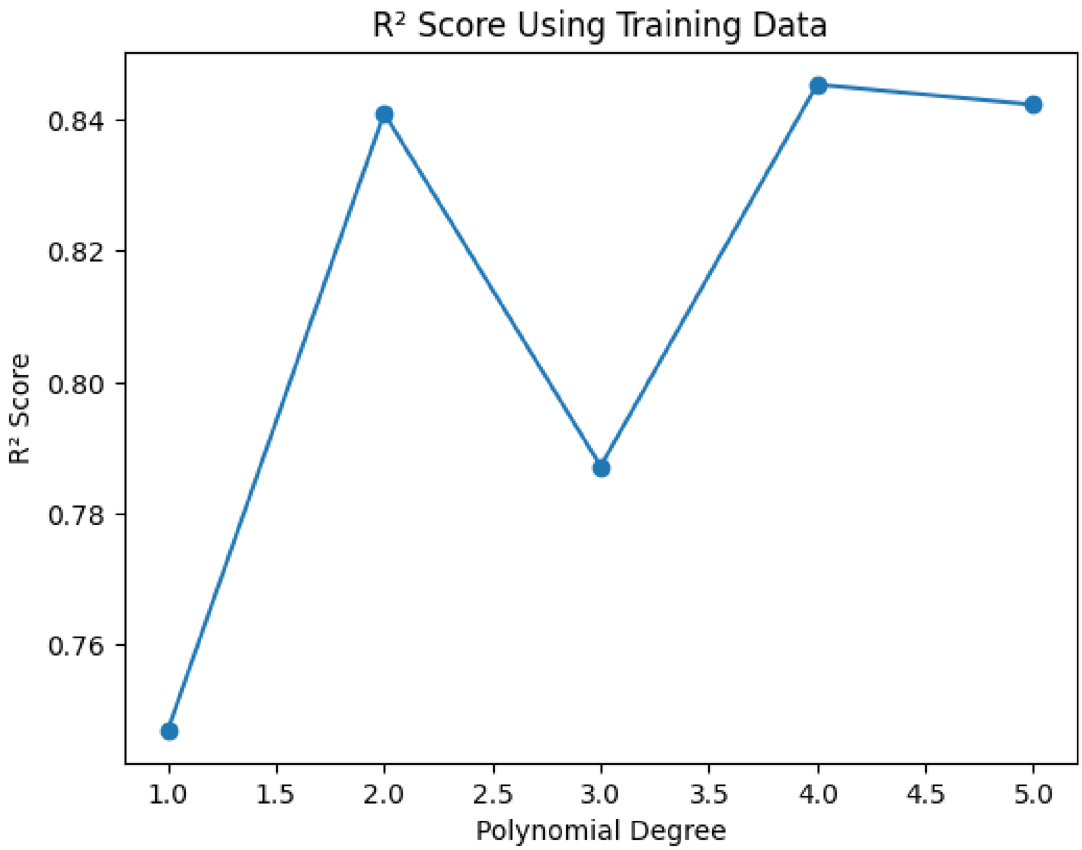
1.8 finding the best order for the polynomial regression of the training data

[382]:
```
r_scores = []
mses = []
order = [1, 2, 3, 4, 5]

for n in order:
    pr = PolynomialFeatures(degree=n)
    x_train_pr = pr.fit_transform(x_train)
```

```
    x_test_pr = pr.transform(x_test)  # FIXED: Use transform instead of␣
↪fit_transform

    lre = LinearRegression()
    lre.fit(x_train_pr, y_train)

    r2_score_train = lre.score(x_train_pr, y_train)
    r2_score_test = lre.score(x_test_pr, y_test)
    mse_train = mean_squared_error(y_train, lre.predict(x_train_pr))
    mse_test = mean_squared_error(y_test, lre.predict(x_test_pr))  # FIXED: Use␣
↪y_test

    r_scores.append(r2_score_test)
    mses.append(mse_test)  # FIXED: Store test MSE

    print(f"Degree: {n}")
    print(f"Shape: {x_train_pr.shape}")
    print(f"R² (Train): {r2_score_train:.4f}")
    print(f"R² (test): {r2_score_test:.4f}")
    print(f"MSE (Train): {mse_train:.4f}")
    print(f"MSE (Test): {mse_test:.4f}")
    print("_____________________________")

# Plot R² scores
plt.plot(order, r_scores, marker='o')
plt.xlabel('Polynomial Degree')
plt.ylabel('R² Score')
plt.title('R² Score Using Training Data')
plt.show()

# Get best R² and corresponding polynomial degree
best_r2 = max(r_scores)
best_degree = order[r_scores.index(best_r2)]
best_mse = min(mses)

print(f"Best R²: {best_r2:.4f} at degree {best_degree}")
print(f"Best MSE (Test): {best_mse:.4f} at degree {order[mses.
↪index(best_mse)]}")
```

```
Degree: 1
Shape: (2217, 8)
R² (Train): 0.7511
R² (test): 0.7470
MSE (Train): 36645123.9327
MSE (Test): 37707135.9329
_____________________________
Degree: 2
```

```
Shape: (2217, 36)
R² (Train): 0.8460
R² (test): 0.8410
MSE (Train): 22671151.8523
MSE (Test): 23700278.1686
------------------------------
Degree: 3
Shape: (2217, 120)
R² (Train): 0.8122
R² (test): 0.7872
MSE (Train): 27649855.7127
MSE (Test): 31712467.5621
------------------------------
Degree: 4
Shape: (2217, 330)
R² (Train): 0.8701
R² (test): 0.8453
MSE (Train): 19117339.7850
MSE (Test): 23049700.6208
------------------------------
Degree: 5
Shape: (2217, 792)
R² (Train): 0.8906
R² (test): 0.8423
MSE (Train): 16101529.1812
MSE (Test): 23505099.0857
------------------------------
```



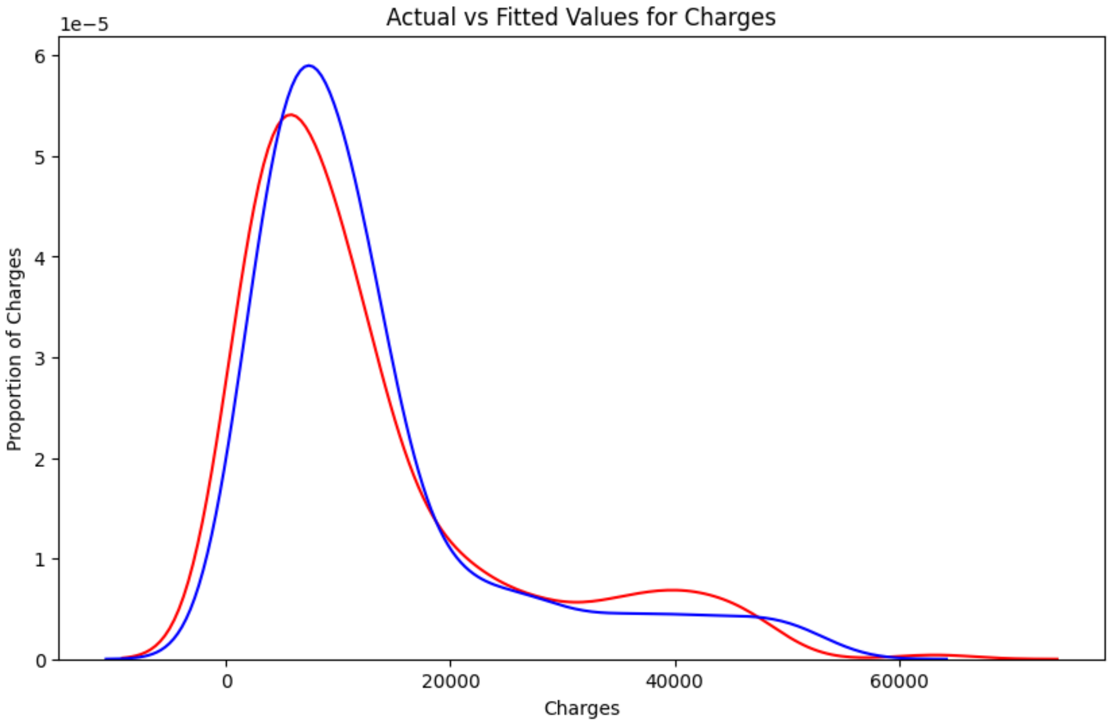

```
Best R²: 0.8453 at degree 4
Best MSE (Test): 23049700.6208 at degree 4
```

Running the Polynomail model on train data and test it using test data we know that the order 5 is the best order for the polynomial regression, so we will use it to train the model

[383]:
```python
pr = PolynomialFeatures(degree=4)
x_train_pr = pr.fit_transform(x_train)
x_test_pr = pr.fit_transform(x_test)
lre.fit(x_train_pr, y_train)
yhat = lre.predict(x_test_pr)
print('R2:', r2_score(y_test, yhat))
print('MSE:', mean_squared_error(y_test, yhat))
# ploting distribution of the predicted values
plt.figure(figsize=(10, 6))
sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(yhat, hist=False, color="b", label="Fitted Values")
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('Proportion of Charges')
```

```
plt.show()
```

```
R2: 0.8453353464577109
MSE: 23049700.62080398
```



The **y-axis is the proportion (density) of occurrences of a charge value**, not actual count. It helps see **how common certain charges are** in the dataset.

Our polynomial regression model (degree = 5) provides a good fit for the data, as the predicted and actual distributions are closely aligned. Since we evaluated the model using both training and testing data, the similarity of the graphs indicates a reliable performance.

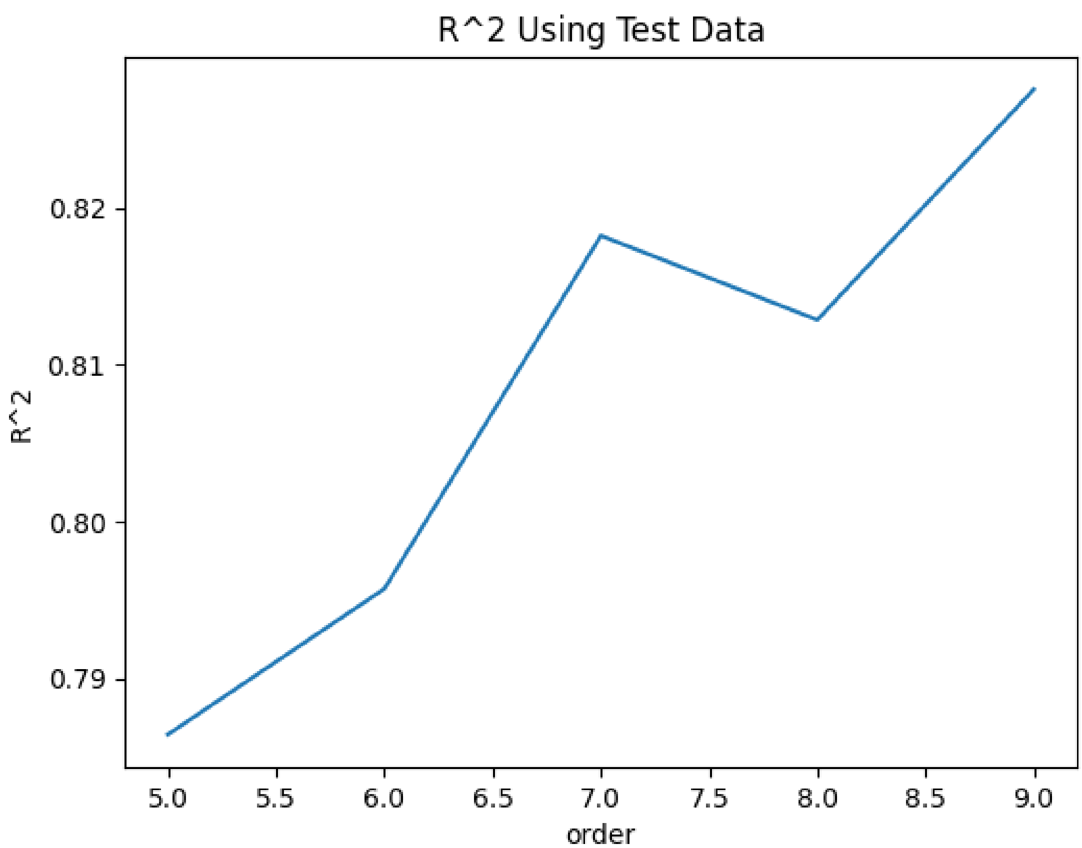
1.9 To further enhance the model's robustness, we will apply cross-validation.

choosing best order for cross validation

[384]:
```
r_scores = []
order = range(5, 10)
for n in order:
    scores = cross_val_score(lre, x_train, y_train, cv=n)
    r_scores.append(max(scores))

    print("R^2 : ",max(scores))
    print("_____________________________")
plt.plot(order, r_scores)
```

```
plt.xlabel('order')
plt.ylabel('R^2')
plt.title('R^2 Using Test Data')
plt.show()
max_r2 = max(r_scores)
print(f"Best R^2 is {max_r2} \n with order {order[r_scores.
 ↪index(max(r_scores))]} \n ")
```

```
R^2 :  0.7864106338577119
-----------------------------
R^2 :  0.7957018492256593
-----------------------------
R^2 :  0.8182205886002396
-----------------------------
R^2 :  0.8128541229237253
-----------------------------
R^2 :  0.8275523576803953
-----------------------------
```



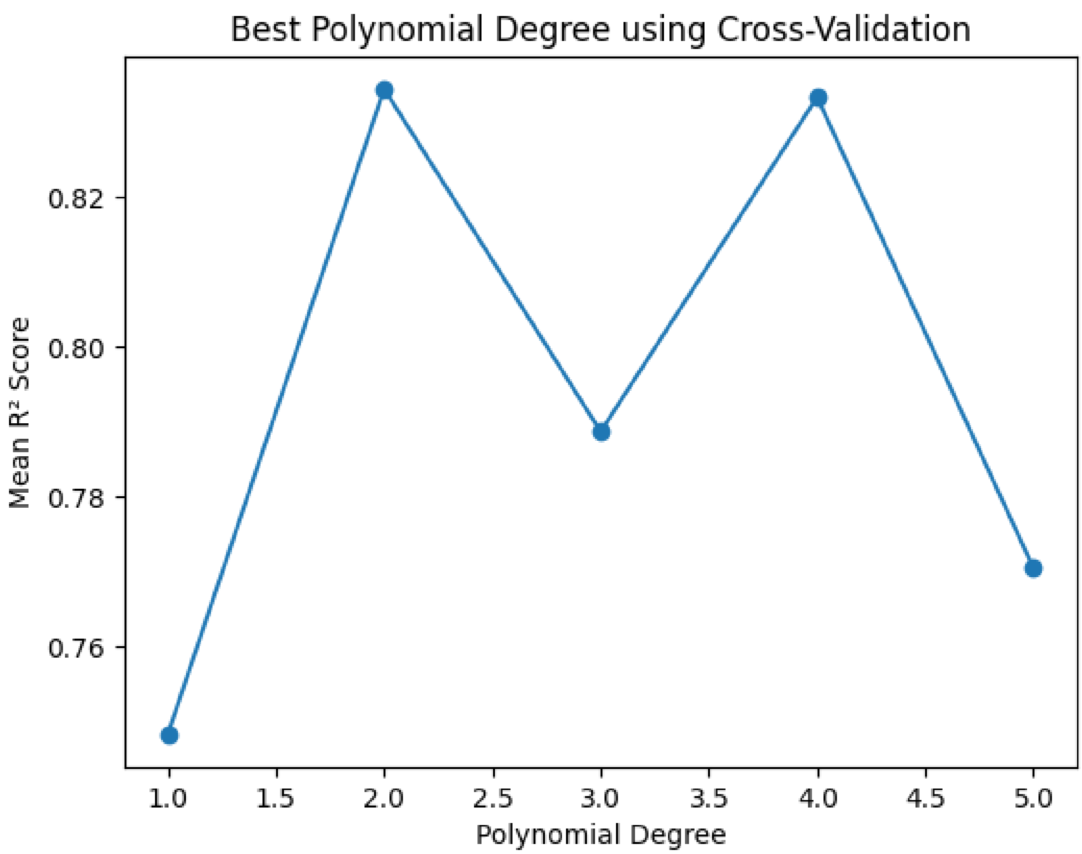

```
Best R^2 is 0.8275523576803953
 with order 9
```

1.10 we will try to use cross validation with polynomial regression

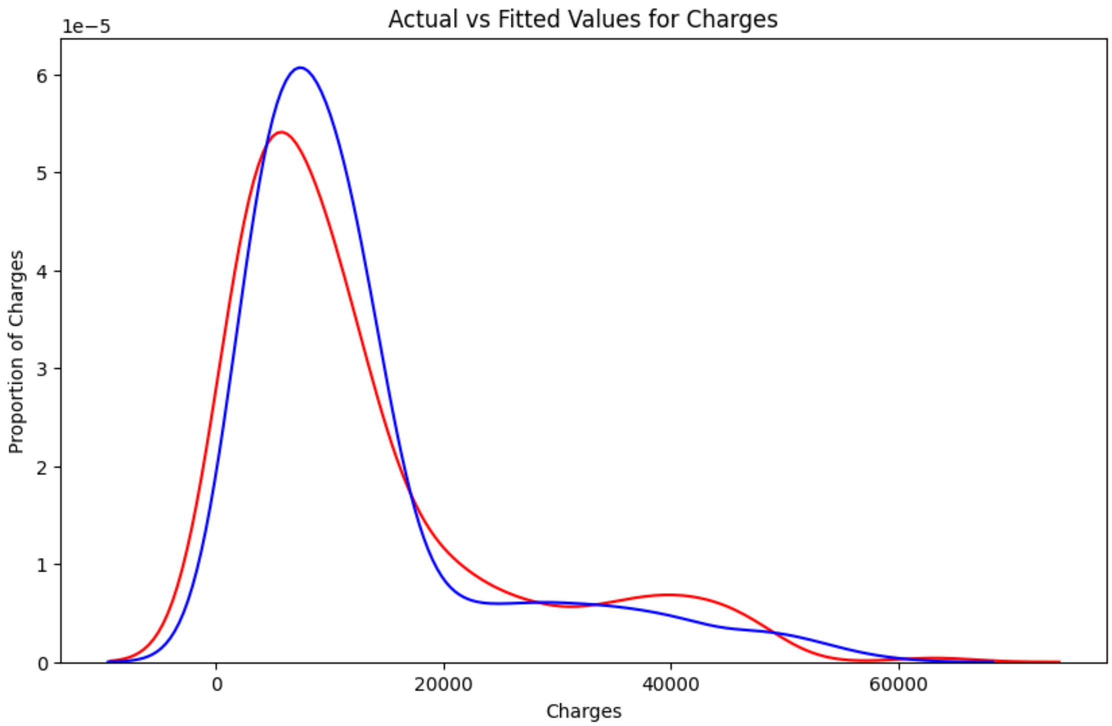
[385]:
```
r_scores = []
degrees = range(1, 10)  # Test polynomial degrees from 1 to 10
cv_folds = 5  # Use 5-fold cross-validation

for d in degrees:
    pr = PolynomialFeatures(degree=d)
    x_train_poly = pr.fit_transform(x_train)  # Transform features
    lre = LinearRegression()

    scores = cross_val_score(lre, x_train_poly, y_train, cv=cv_folds,␣
 ↪scoring='r2')

    if np.any(scores < 0):
        print(f"breaking in degree {d} due to negative R² scores: {scores}")
        break  # Skip appending for this degree

    r_scores.append(np.mean(scores))  # Store the average R² score
    print(f"Degree {d}: shape({x_train_poly.shape}) -> {np.mean(scores)}")

# Ensure we have at least one valid score before plotting
if r_scores:
    plt.plot(degrees[:len(r_scores)], r_scores, marker='o')
    plt.xlabel('Polynomial Degree')
    plt.ylabel('Mean R² Score')
    plt.title('Best Polynomial Degree using Cross-Validation')
    plt.show()

    # Get the best polynomial degree
    best_degree = degrees[np.argmax(r_scores)]
    best_r2 = max(r_scores)
    print(f"Best Degree: {best_degree} with R² score {best_r2}")
else:
    print("No valid polynomial degree found (all had negative R² scores).")


print(f"Best polynomial degree: {best_degree} with R²: {best_r2:.4f}")
# ploting the distribution of the predicted values
pr = PolynomialFeatures(degree=best_degree)
x_train_pr = pr.fit_transform(x_train)
x_test_pr = pr.fit_transform(x_test)
lre.fit(x_train_pr, y_train)
yhat = lre.predict(x_test_pr)
print('R2:', r2_score(y_test, yhat))
```

```
print('MSE:', mean_squared_error(y_test, yhat))
plt.figure(figsize=(10, 6))
sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(yhat, hist=False, color="b", label="Fitted Values")
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('Proportion of Charges')
plt.show()
```

```
Degree 1: shape((2217, 8)) -> 0.7481701429366291
Degree 2: shape((2217, 36)) -> 0.8343958512529092
Degree 3: shape((2217, 120)) -> 0.7886146926651698
Degree 4: shape((2217, 330)) -> 0.8332916880626969
Degree 5: shape((2217, 792)) -> 0.7703532421396014
breaking in degree 6 due to negative R² scores: [ -2.94249216  -1.10039011
-47.88564884 -14.66126853 -30.47691898]
```




```
Best Degree: 2 with R² score 0.8343958512529092
Best polynomial degree: 2 with R²: 0.8344
R2: 0.840969938304171
MSE: 23700278.168564092
```



1.11 integrating both approaches:

- Finding the best polynomial degree
- Finding the best number of cross-validation folds (k)

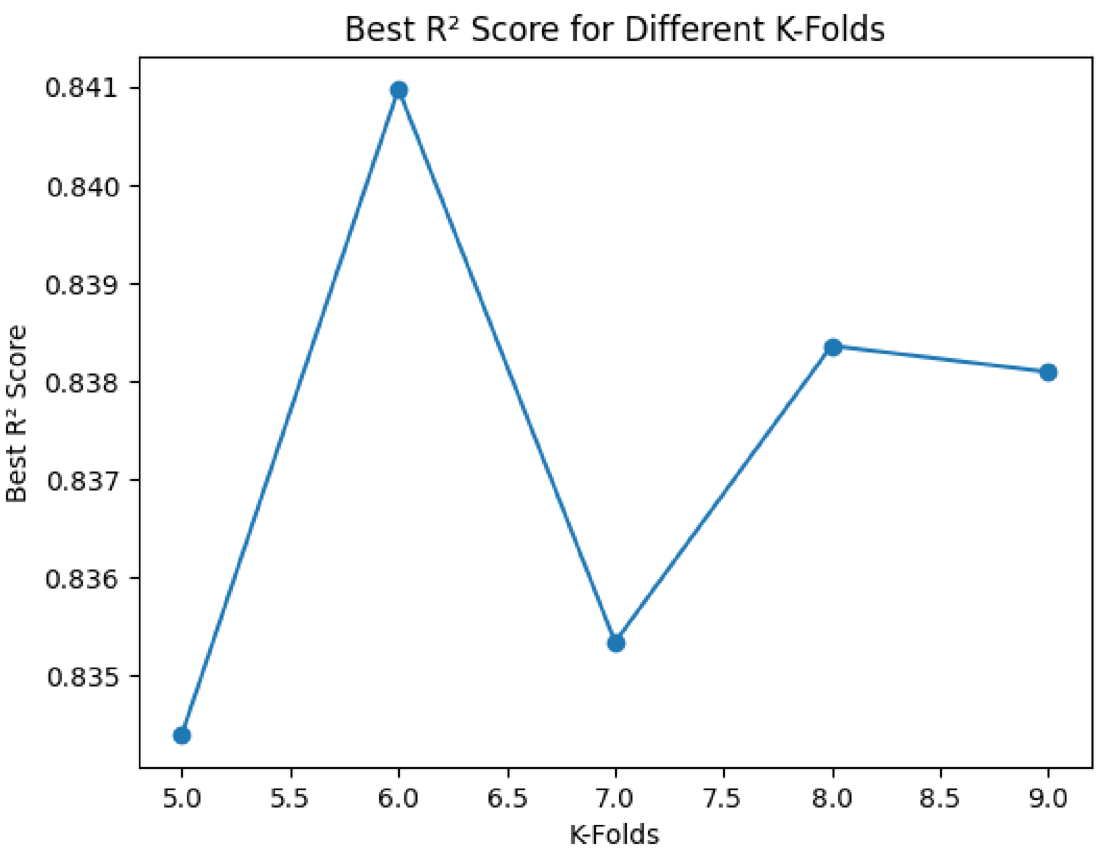
[386]:
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score

best_results = []  # Store the best results for each k

orders = range(5, 10)  # K-fold values to test
degrees = range(1, 6)  # Polynomial degrees to test

for k in orders:
    print(f"\nTesting for k = {k} folds...\n")
    r_scores = []

    for d in degrees:
        pr = PolynomialFeatures(degree=d)
        x_train_poly = pr.fit_transform(x_train)  # Transform features
        lre = LinearRegression()
```

```
        scores = cross_val_score(lre, x_train_poly, y_train, cv=k, scoring='r2')

        if np.any(scores < 0):
            print(f"breaking in degree {d} for k={k} due to negative R² scores:␣
↪{scores}")
            break  # Skip this degree

        mean_r2 = np.mean(scores)
        r_scores.append((d, mean_r2))  # Store (degree, R² score)
        print(f"Degree {d}: shape {x_train_poly.shape} R² -> {mean_r2:.4f}")

    if r_scores:
        best_degree, best_r2 = max(r_scores, key=lambda x: x[1])  # Get best␣
↪degree for current k
        best_results.append((k, best_degree, best_r2))  # Store best results
        print(f"Best for k={k}: Degree {best_degree} and shape {x_train_poly.
↪shape} with R² = {best_r2:.4f}")
    else:
        print(f"No valid polynomial degree found for k={k} (all had negative R²␣
↪scores).")

# Find the overall best (k, degree) combination
if best_results:
    best_k, best_degree, best_r2 = max(best_results, key=lambda x: x[2])

    # Plot results
    plt.plot([k for k, _, _ in best_results], [r2 for _, _, r2 in␣
↪best_results], marker='o')
    plt.xlabel('K-Folds')
    plt.ylabel('Best R² Score')
    plt.title('Best R² Score for Different K-Folds')
    plt.show()

    print(f"\nFinal Best Choice: k={best_k}, Degree={best_degree} with R² =␣
↪{best_r2:.4f}")
else:
    print("No valid polynomial degree and k combination found.")
# ploting the distribution of the predicted values
pr = PolynomialFeatures(degree=best_degree)
x_train_pr = pr.fit_transform(x_train)
x_test_pr = pr.fit_transform(x_test)
lre.fit(x_train_pr, y_train)
yhat = lre.predict(x_test_pr)
print('R2:', r2_score(y_test, yhat))
print('MSE:', mean_squared_error(y_test, yhat))
```

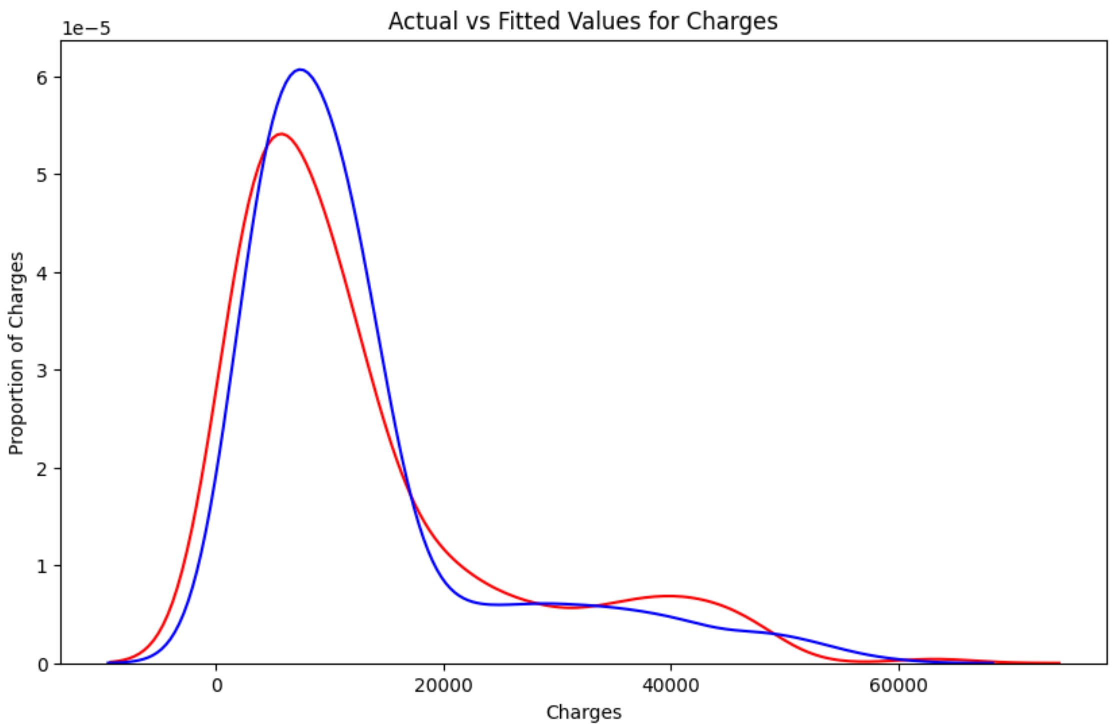
```python
plt.figure(figsize=(10, 6))
sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(yhat, hist=False, color="b", label="Fitted Values")
plt.title('Actual vs Fitted Values for Charges')
plt.xlabel('Charges')
plt.ylabel('Proportion of Charges')
plt.show()
```

```
Testing for k = 5 folds…

Degree 1: shape (2217, 8) R² -> 0.7482
Degree 2: shape (2217, 36) R² -> 0.8344
Degree 3: shape (2217, 120) R² -> 0.7886
Degree 4: shape (2217, 330) R² -> 0.8333
Degree 5: shape (2217, 792) R² -> 0.7704
breaking in degree 6 for k=5 due to negative R² scores: [ -2.94249216
-1.10039011 -47.88564884 -14.66126853 -30.47691898]
Best for k=5: Degree 2 and shape (2217, 1716) with R² = 0.8344

Testing for k = 6 folds…

Degree 1: shape (2217, 8) R² -> 0.7485
Degree 2: shape (2217, 36) R² -> 0.8410
Degree 3: shape (2217, 120) R² -> 0.7963
Degree 4: shape (2217, 330) R² -> 0.8340
Degree 5: shape (2217, 792) R² -> 0.7811
breaking in degree 6 for k=6 due to negative R² scores: [-3.40043306e+00
-5.77778813e-01 -1.26852237e+00 -2.01505932e+02
 -6.22347218e+01 -9.36184368e+02]
Best for k=6: Degree 2 and shape (2217, 1716) with R² = 0.8410

Testing for k = 7 folds…

Degree 1: shape (2217, 8) R² -> 0.7469
Degree 2: shape (2217, 36) R² -> 0.8228
Degree 3: shape (2217, 120) R² -> 0.8062
Degree 4: shape (2217, 330) R² -> 0.8353
Degree 5: shape (2217, 792) R² -> 0.7639
breaking in degree 6 for k=7 due to negative R² scores: [ 2.17367622e-01
5.51369358e-01 -3.24382151e-01 -6.23860069e+01
 -1.11828630e+01  7.86324793e-01 -3.02207810e+03]
Best for k=7: Degree 4 and shape (2217, 1716) with R² = 0.8353

Testing for k = 8 folds…

Degree 1: shape (2217, 8) R² -> 0.7492
Degree 2: shape (2217, 36) R² -> 0.8384
```

```
Degree 3: shape (2217, 120) R² -> 0.7726
Degree 4: shape (2217, 330) R² -> 0.8335
Degree 5: shape (2217, 792) R² -> 0.7726
breaking in degree 6 for k=8 due to negative R² scores: [ 3.96470502e-01
4.84173779e-01 -1.34569255e-01 -8.30454726e-01
 -1.07552648e+00 -4.29142606e+01  5.46093559e-01 -2.57543212e+03]
Best for k=8: Degree 2 and shape (2217, 1716) with R² = 0.8384

Testing for k = 9 folds…

Degree 1: shape (2217, 8) R² -> 0.7454
Degree 2: shape (2217, 36) R² -> 0.8381
Degree 3: shape (2217, 120) R² -> 0.7985
Degree 4: shape (2217, 330) R² -> 0.8275
Degree 5: shape (2217, 792) R² -> 0.7628
breaking in degree 6 for k=9 due to negative R² scores: [ 3.78456582e-01
8.68887569e-01 -4.63885901e-01  6.44324930e-01
 -1.31821370e+00  7.48873475e-01 -4.82665758e+01  6.66565556e-01
 -2.62584506e+03]
Best for k=9: Degree 2 and shape (2217, 1716) with R² = 0.8381
```



```
Final Best Choice: k=6, Degree=2 with R² = 0.8410
R2: 0.840969938304171
MSE: 23700278.168564092
```



1.12 Hyper-params tuning using Piplines (grid search + ridge regression + cv)

applying ridge regression by finding the best k-fold and the best alpha

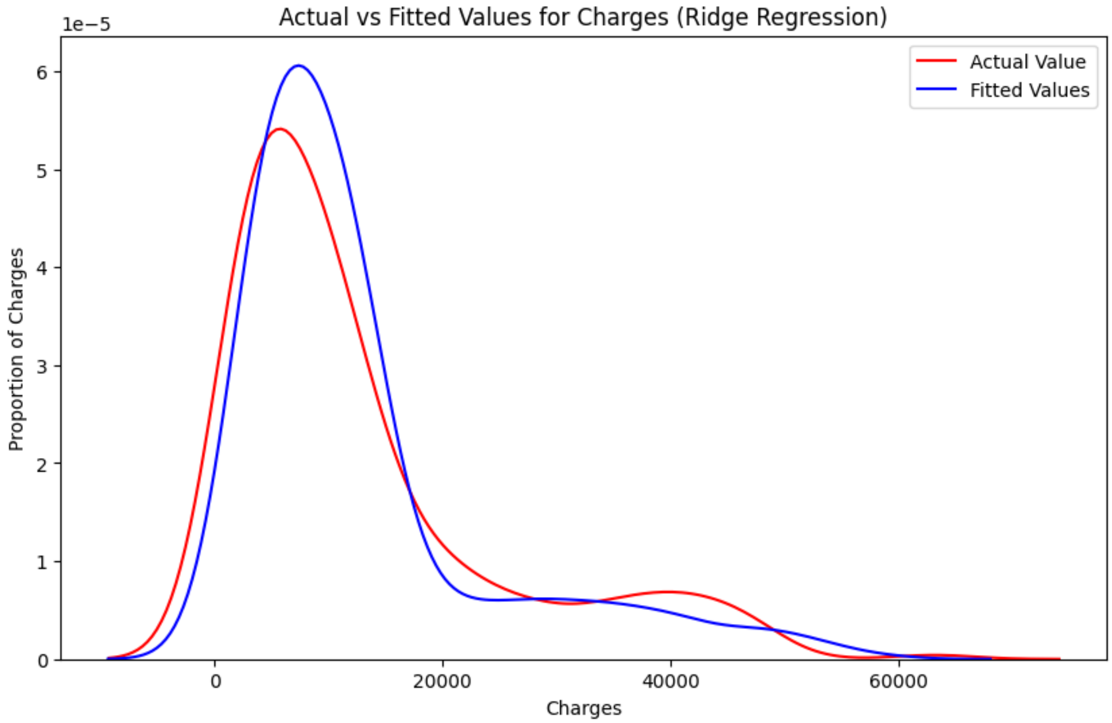
[387]:
```python
# Define possible values for k (K-Folds) and alpha (regularization)
k_values = range(5,10)  # Different K values to test
alphas = alphas = np.linspace(0.01, 10, num=100)  # Different alpha values for Ridge Regression

# Set the best polynomial degree from previous testing
# we know it is 2 from the previos code
best_degree = 2

# Store results for different k values
best_results = []

best_k = None
for k in k_values:
    print(f"\nTesting for k = {k} folds...\n")
```

```
    # Define Ridge regression model
    ridge = Ridge()

    # Define the pipeline (Polynomial Features + Ridge)
    pipeline = Pipeline([
        ('poly', PolynomialFeatures(degree=best_degree)),
        ('ridge', ridge)
    ])

    # Define the hyperparameter grid
    param_grid = {
        'ridge__alpha': alphas,
        'ridge__fit_intercept': [True, False]
    }

    # Perform GridSearchCV to find best alpha and fit_intercept
    grid_search = GridSearchCV(pipeline, param_grid, cv=k, scoring='r2')
    grid_search.fit(x_train, y_train)

    # Extract best parameters
    best_alpha = grid_search.best_params_['ridge__alpha']
    best_fit_intercept = grid_search.best_params_['ridge__fit_intercept']
    best_r2 = grid_search.best_score_

    # Store the results
    best_results.append((k, best_alpha, best_fit_intercept, best_r2))
    print(f"Best for k={k}: alpha={best_alpha},␣
↪fit_intercept={best_fit_intercept}, R²={best_r2:.4f}")
    best_k = k

    print("_____________________________")

# Find the overall best k and alpha
best_k, best_alpha, best_fit_intercept, best_r2 = max(best_results, key=lambda␣
↪x: x[3])

print("\nFinal Best Selection:")
print(f"Best k: {best_k}")
print(f"Best alpha: {best_alpha}")
print(f"Best fit_intercept: {best_fit_intercept}")
print(f"Best R² score: {best_r2}")
print(f"Best k: {best_k:.4f}")

# Train the final Ridge model with the best parameters
ridge_final = Ridge(alpha=best_alpha, fit_intercept=best_fit_intercept)
pr = PolynomialFeatures(degree=best_degree)
```

```python
x_train_poly = pr.fit_transform(x_train)
x_test_poly = pr.transform(x_test)

ridge_final.fit(x_train_poly, y_train)

# Predict and evaluate
yhat_ridge = ridge_final.predict(x_test_poly)
print('Final Model Evaluation:')
print(f'R2: {r2_score(y_test, yhat_ridge):.4f}')
print(f'MSE: {mean_squared_error(y_test, yhat_ridge):.4f}')

# Plot actual vs predicted values
plt.figure(figsize=(10, 6))
sns.distplot(y_test, hist=False, color="r", label="Actual Value")
sns.distplot(yhat_ridge, hist=False, color="b", label="Fitted Values")
plt.title('Actual vs Fitted Values for Charges (Ridge Regression)')
plt.xlabel('Charges')
plt.ylabel('Proportion of Charges')
plt.legend()
plt.show()
```

```
Testing for k = 5 folds…

Best for k=5: alpha=0.6154545454545455, fit_intercept=False, R²=0.8403
-----------------------------

Testing for k = 6 folds…

Best for k=6: alpha=0.7163636363636363, fit_intercept=False, R²=0.8410
-----------------------------

Testing for k = 7 folds…

Best for k=7: alpha=1.019090909090909, fit_intercept=False, R²=0.8402
-----------------------------

Testing for k = 8 folds…

Best for k=8: alpha=0.9181818181818182, fit_intercept=False, R²=0.8420
-----------------------------

Testing for k = 9 folds…

Best for k=9: alpha=0.9181818181818182, fit_intercept=False, R²=0.8385
-----------------------------

Final Best Selection:
```

```
Best k: 8
Best alpha: 0.9181818181818182
Best fit_intercept: False
Best R² score: 0.842014035572448
Best k: 8.0000
Final Model Evaluation:
R2: 0.8413
MSE: 23649130.1001
```



1.13 Ploting the final graph

1.14 Exporting the Model

[ ]:
```python
import joblib

# Save the trained Ridge model
model_path = "../outputs/final_model.pkl"
joblib.dump(ridge_final, model_path)

# Save the PolynomialFeatures transformer
transformer_path = "../outputs/polynomial_transformer.pkl"
joblib.dump(pr, transformer_path)

print("Model and transformer saved successfully!")
```

```
Model and transformer saved successfully!
```

[418]:
```python
import joblib
distination = "../outputs/final_model.pkl"
joblib.dump(grid_search, distination)
```

[418]:
```
['../outputs/final_model.pkl']
```

The **.pkl file is not storing the data**; it's just saving the **trained model parameters**, which include:

Coefficients (weights) – The learned relationships between features and the target.
Intercept (epsilon) – The bias term in the regression equation.
Polynomial Transformation (if applied) – The fitted transformations, so new data gets processed the same way.

Since the model only needs these numbers to make predictions, the `.pkl` file is tiny compared to the dataset. It doesn't store the actual training data, just the **mathematical representation** of what it learned.