assignment-4-and-5

March 7, 2024

[437]:
```
import pandas as pd
import numpy as np
import warnings
warnings.filterwarnings('ignore')
```

[438]:
```
crc_seer_df = pd.read_csv("CRC_SEER_Modified.csv")
```

[439]:
```
crc_seer_df
```

[439]:
```
       Year of diagnosis Race recode (W, B, AI, API)     Sex  \
0                   2000                       White    Male
1                   2000                       White    Male
2                   2000                       White  Female
3                   2000                       White    Male
4                   2000                       White  Female
…                    …                           …      …
29996               2000                       White  Female
29997               2016                       White  Female
29998               2016                       White  Female
29999               2016                       White  Female
30000               2016   Asian or Pacific Islander    Male

      Age recode with single ages and 100+ Survival months  \
0                                 82 years              17
1                                 76 years              67
2                                 65 years              41
3                                 86 years              15
4                                 82 years               0
…                                      …               …
29996                             73 years              28
29997                             63 years              28
29998                             82 years              28
29999                             44 years              29
30000                             52 years              29

          Marital status at diagnosis  target
0      Married (including common law)       1
```

```
1                            Unknown       1
2                            Unknown       1
3                            Unknown       1
4                            Unknown       1
…                                  …      …
29996  Married (including common law)       0
29997  Married (including common law)       0
29998          Single (never married)       0
29999  Married (including common law)       0
30000  Married (including common law)       0

[30001 rows x 7 columns]
```

[440]:
```python
# Renaming columns
crc_seer_df.rename(columns={
    'Year of diagnosis': 'Year',
    'Race recode (W, B, AI, API)': 'Race',
    'Survival months': 'SurvivalMonths',
    'Marital status at diagnosis': 'MaritalStatus',
    'target': 'Survival Recode'
}, inplace=True)
```

[441]:
```python
crc_seer_df
```

[441]:
```
       Year                          Race     Sex  \
0      2000                         White    Male
1      2000                         White    Male
2      2000                         White  Female
3      2000                         White    Male
4      2000                         White  Female
…      …                               …     …
29996  2016                         White  Female
29997  2016                         White  Female
29998  2016                         White  Female
29999  2016                         White  Female
30000  2016  Asian or Pacific Islander    Male

      Age recode with single ages and 100+ SurvivalMonths  \
0                                 82 years             17
1                                 76 years             67
2                                 65 years             41
3                                 86 years             15
4                                 82 years              0
…                                      …             …
29996                             73 years             28
29997                             63 years             28
29998                             82 years             28
```

```
29999                                44 years            29
30000                                52 years            29

                            MaritalStatus  Survival Recode
0       Married (including common law)               1
1                                 Unknown               1
2                                 Unknown               1
3                                 Unknown               1
4                                 Unknown               1
…                                       …              …
29996   Married (including common law)               0
29997   Married (including common law)               0
29998           Single (never married)               0
29999   Married (including common law)               0
30000   Married (including common law)               0

[30001 rows x 7 columns]
```

[442]:

```
crc_seer_df['Age recode with single ages and 100+'] = crc_seer_df['Age recode␣
↪with single ages and 100+'].str.replace(' years', '')
crc_seer_df['Age recode with single ages and 100+'] = crc_seer_df['Age recode␣
↪with single ages and 100+'].str.replace('100+', '101')

for i, value in enumerate(crc_seer_df['Age recode with single ages and 100+']):
    if value.endswith('+'):
        crc_seer_df.at[i, 'Age recode with single ages and 100+'] =␣
↪str(int(value[:-1]) + 1)

crc_seer_df['Age recode with single ages and 100+'] = pd.
↪to_numeric(crc_seer_df['Age recode with single ages and 100+'])
mean_survival_months = np.mean(crc_seer_df[crc_seer_df['SurvivalMonths'] !=␣
↪'Unknown']['SurvivalMonths'].astype(float))
crc_seer_df['SurvivalMonths'] = crc_seer_df['SurvivalMonths'].
↪replace('Unknown', mean_survival_months)
crc_seer_df['SurvivalMonths'] = pd.to_numeric(crc_seer_df['SurvivalMonths'])

race_recode = {
    'White': 1,
    'Black': 2,
    'Asian or Pacific Islander': 3,
    'American Indian/Alaska Native': 4,
    'Hispanic': 5,
    'Unknown': 6
}
crc_seer_df['Race'] = crc_seer_df['Race'].map(race_recode)
sex_recode = {
```

```
    'Male': 1,
    'Female': 0
}
crc_seer_df['Sex'] = crc_seer_df['Sex'].map(sex_recode)
marital_recode = {
    'Married (including common law)': 1,
    'Single (never married)': 2,
    'Divorced': 3,
    'Widowed': 4,
    'Unknown': 5
}
crc_seer_df['MaritalStatus'] = crc_seer_df['MaritalStatus'].map(marital_recode)

print(crc_seer_df)
```

```
       Year  Race  Sex  Age recode with single ages and 100+  SurvivalMonths  \
0      2000     1    1                                    82            17.0
1      2000     1    1                                    76            67.0
2      2000     1    0                                    65            41.0
3      2000     1    1                                    86            15.0
4      2000     1    0                                    82             0.0
…       …     …   …                                   …             …
29996  2016     1    0                                    73            28.0
29997  2016     1    0                                    63            28.0
29998  2016     1    0                                    82            28.0
29999  2016     1    0                                    44            29.0
30000  2016     3    1                                    52            29.0

       MaritalStatus  Survival Recode
0                1.0                1
1                5.0                1
2                5.0                1
3                5.0                1
4                5.0                1
…                …              …
29996            1.0                0
29997            1.0                0
29998            2.0                0
29999            1.0                0
30000            1.0                0

[30001 rows x 7 columns]
```

[443]:

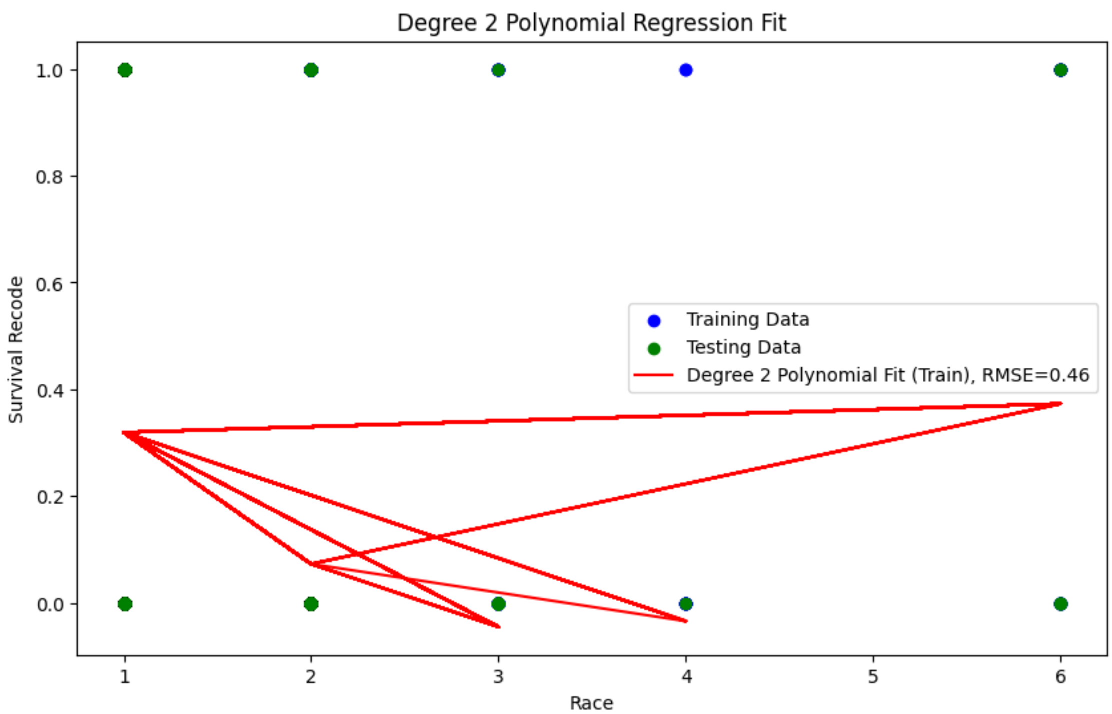
```
crc_seer_recoded_df = crc_seer_df.copy()
crc_seer_recoded_df.fillna(crc_seer_recoded_df.mean(), inplace=True)
X = crc_seer_recoded_df.loc[:,crc_seer_recoded_df.columns != 'Survival Recode']
y = crc_seer_recoded_df.loc[:,crc_seer_recoded_df.columns =='Survival Recode']
```

[444]:
```python
import numpy as np
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=42)
```

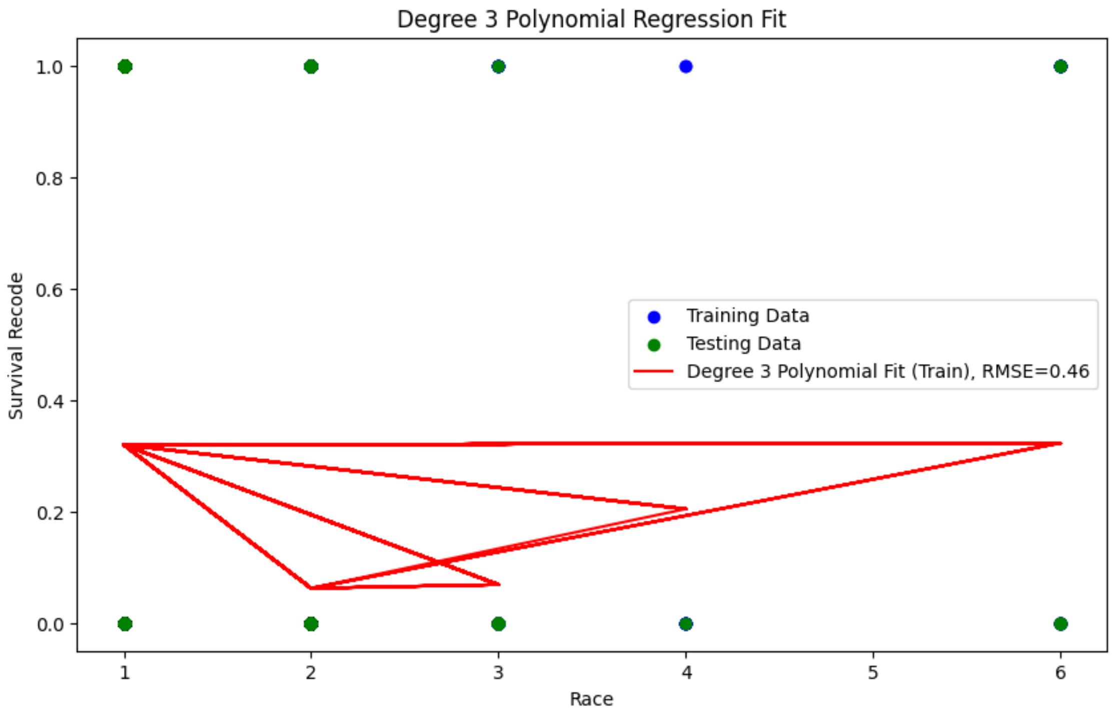
[445]:
```python
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import mean_squared_error, confusion_matrix
from sklearn.preprocessing import PolynomialFeatures
from sklearn.linear_model import LinearRegression

# Function to calculate RMSE
def calculate_rmse(y_true, y_pred):
    return np.sqrt(mean_squared_error(y_true, y_pred))

# Polynomial regression for degrees 2, 3, and 5
degrees = [2, 3, 5]
rmse_scores = []

for degree in degrees:
    # Fit polynomial regression
    poly_features = PolynomialFeatures(degree=degree)
    X_train_poly = poly_features.fit_transform(X_train['Race'].values.
↪reshape(-1, 1))
    X_test_poly = poly_features.transform(X_test['Race'].values.reshape(-1, 1))

    model = LinearRegression()
    model.fit(X_train_poly, y_train)

    # Predict on test set
    y_pred = model.predict(X_test_poly)

    # Calculate RMSE
    rmse = calculate_rmse(y_test, y_pred)
    rmse_scores.append(rmse)
    print(f"Degree {degree} Polynomial: RMSE = {rmse}")

    y_pred_binary = (y_pred > 0.5).astype(int)  # Convert predicted␣
↪probabilities to binary predictions
    print("Confusion Matrix:",confusion_matrix(y_test, y_pred_binary))

    # Plot polynomial fit
    plt.figure(figsize=(10, 6))
    plt.scatter(X_train['Race'], y_train, color='blue', label='Training Data')
    plt.scatter(X_test['Race'], y_test, color='green', label='Testing Data')
```

```
    plt.plot(X_train['Race'], model.predict(X_train_poly), label=f'Degree␣
↪{degree} Polynomial Fit (Train), RMSE={rmse:.2f}', color='red')
    plt.xlabel('Race')
    plt.ylabel('Survival Recode')
    plt.title(f'Degree {degree} Polynomial Regression Fit')
    plt.legend()
    plt.show()

# Find the best polynomial (lowest RMSE)
best_degree = degrees[np.argmin(rmse_scores)]
best_rmse = np.min(rmse_scores)
print(f"Best polynomial degree: {best_degree}, RMSE: {best_rmse}")
```

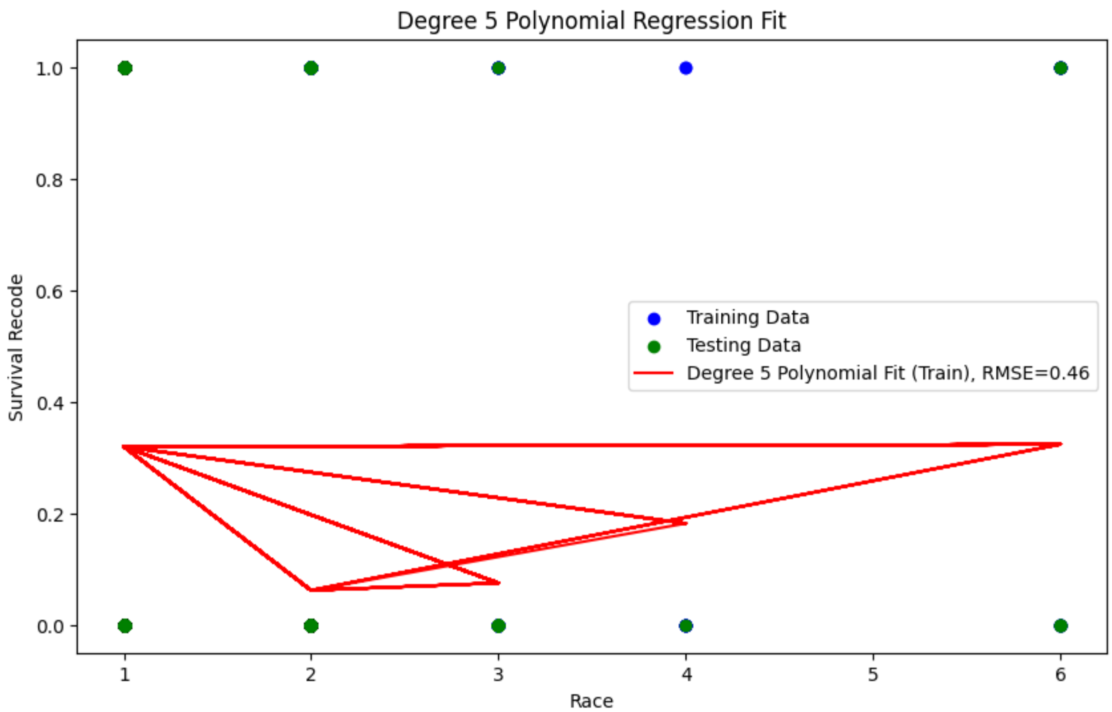
```
Degree 2 Polynomial: RMSE = 0.4568078712644054
Confusion Matrix: [[4173    0]
 [1828    0]]
```




```
Degree 3 Polynomial: RMSE = 0.4568326772812612
Confusion Matrix: [[4173    0]
 [1828    0]]
```



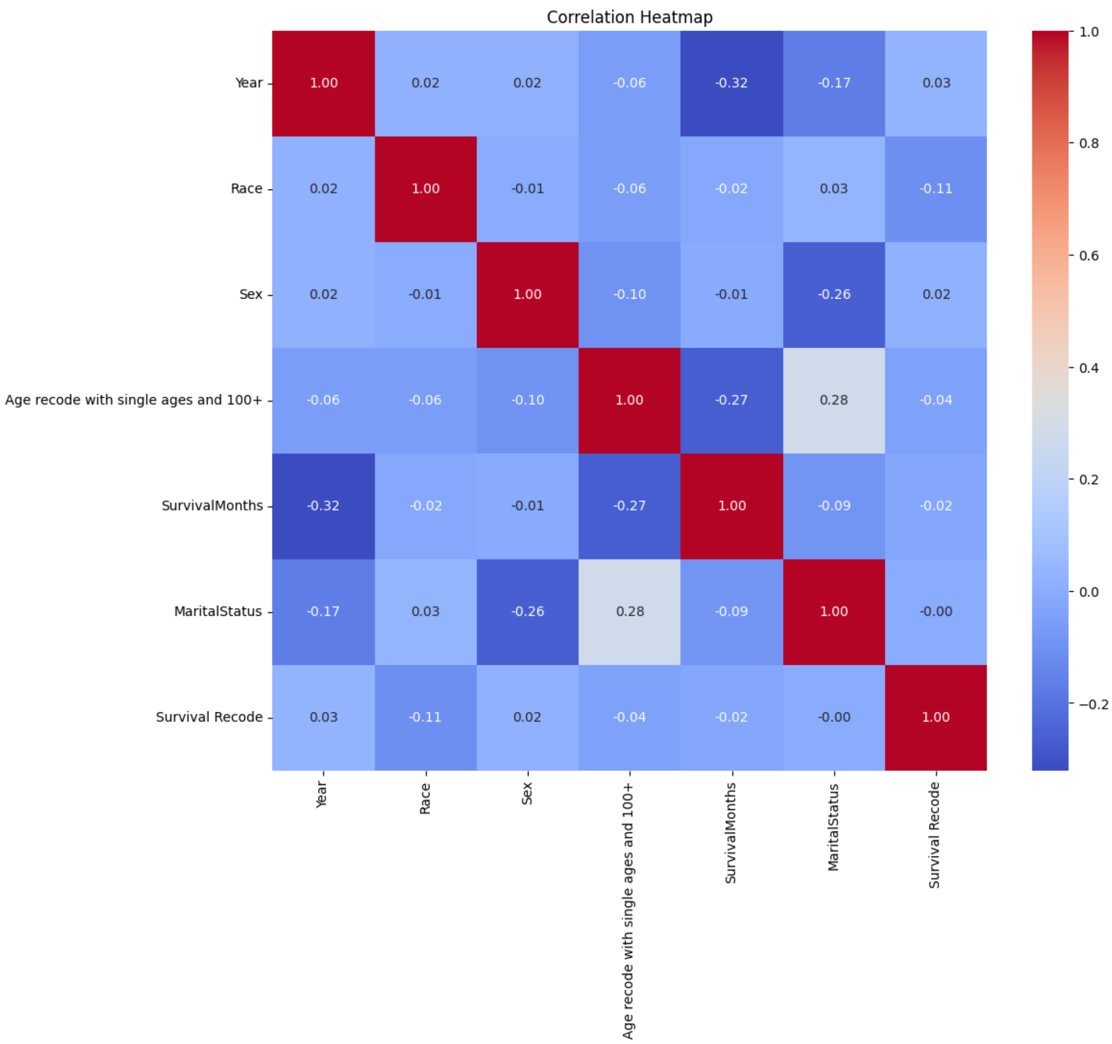

```
Degree 5 Polynomial: RMSE = 0.4568334695396282
Confusion Matrix: [[4173    0]
 [1828    0]]
```



```
Best polynomial degree: 2, RMSE: 0.4568078712644054
```

[446]:

```python
import seaborn as sns
import matplotlib.pyplot as plt

# Assuming crc_seer_recoded_df is your updated DataFrame
# Create a correlation matrix
corr_matrix = crc_seer_recoded_df.corr()

# Plot the heatmap
plt.figure(figsize=(12, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt=".2f")
plt.title('Correlation Heatmap')
plt.show()

# List features in decreasing order of impact with respect to Survival Recode
# Remove 'Survival Recode' from the list as it will always have correlation 1.0␣
↪with itself
correlation_with_survival = corr_matrix['Survival Recode'].drop('Survival␣
↪Recode').sort_values(ascending=False)
print("Features in decreasing order of impact with respect to Survival Recode:")
print(correlation_with_survival)
```

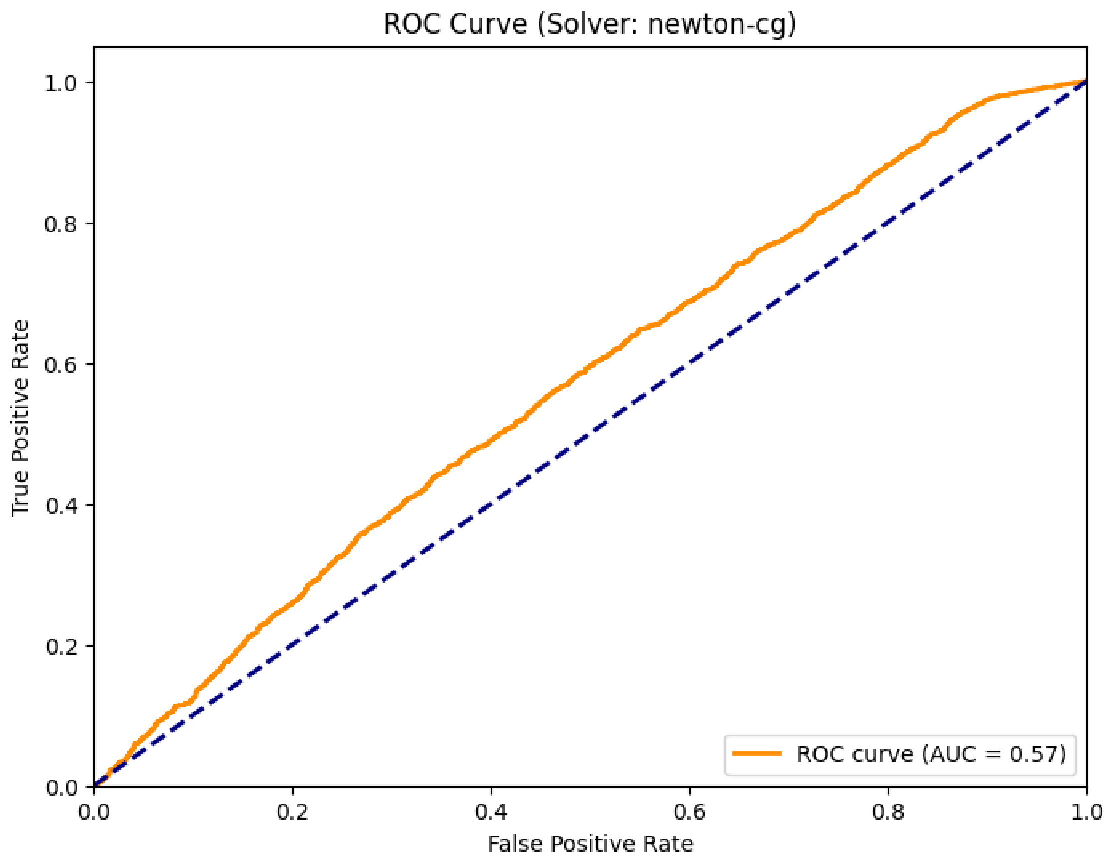



```
Features in decreasing order of impact with respect to Survival Recode:
Year                                   0.027798
Sex                                    0.016024
MaritalStatus                         -0.004507
SurvivalMonths                        -0.023131
Age recode with single ages and 100+  -0.044191
Race                                  -0.113970
Name: Survival Recode, dtype: float64
```

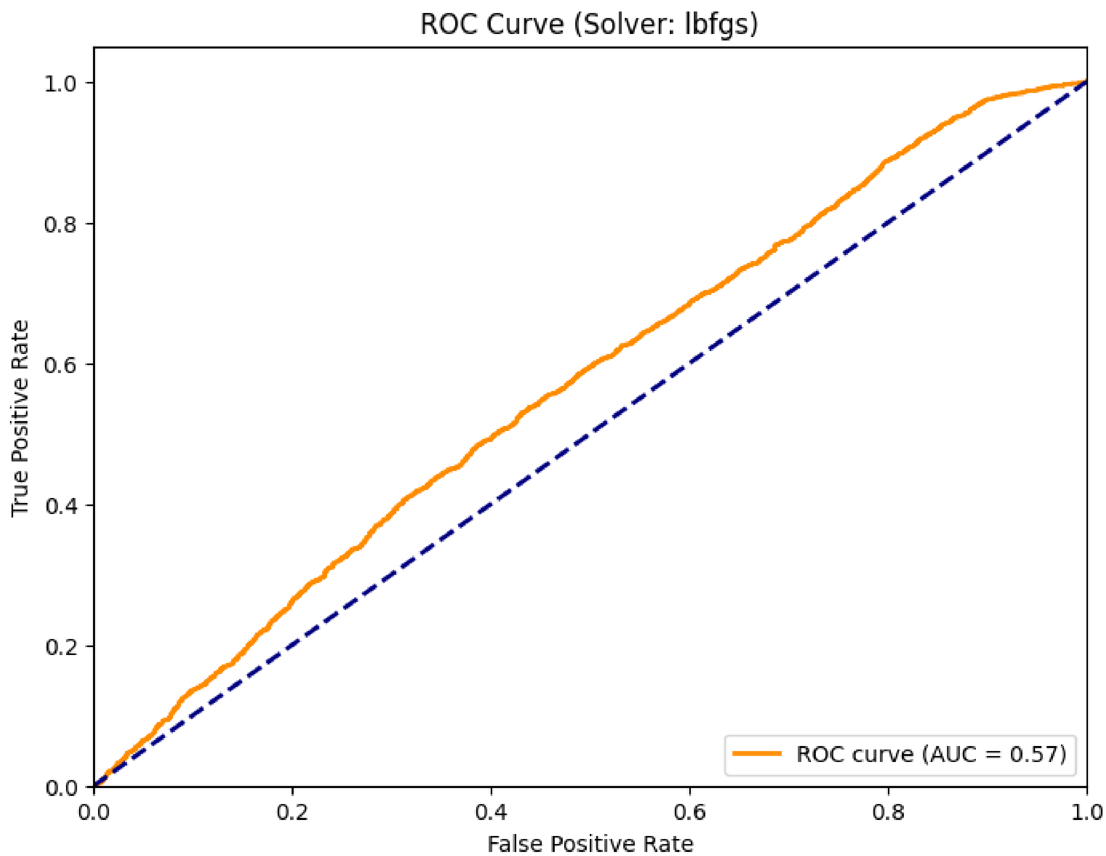
[447]:
```
# Assignment 5
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, confusion_matrix, roc_curve, auc
from sklearn.linear_model import LogisticRegression
```

```python
from sklearn.preprocessing import StandardScaler

np.random.seed(42)
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=42)
solvers = ['newton-cg', 'lbfgs', 'liblinear']

for solver in solvers:
    # Fit logistic regression model
    model = LogisticRegression(solver=solver)
    model.fit(X_train, y_train)

    # Predict on test set
    y_pred = model.predict(X_test)

    # Calculate accuracy score
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Solver: {solver}, Accuracy: {accuracy}")

    # Print confusion matrix
    cm = confusion_matrix(y_test, y_pred)
    print(f'Confusion Matrix (Solver: {solver}):')
    print(cm)

    # Plot ROC curve
    y_prob = model.predict_proba(X_test)[:, 1]
    fpr, tpr, thresholds = roc_curve(y_test, y_prob)
    roc_auc = auc(fpr, tpr)
    plt.figure(figsize=(8, 6))
    plt.plot(fpr, tpr, color='darkorange', lw=2, label=f'ROC curve (AUC =␣
 ↪{roc_auc:.2f})')
    plt.plot([0, 1], [0, 1], color='navy', lw=2, linestyle='--')
    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'ROC Curve (Solver: {solver})')
    plt.legend(loc="lower right")
    plt.show()
```

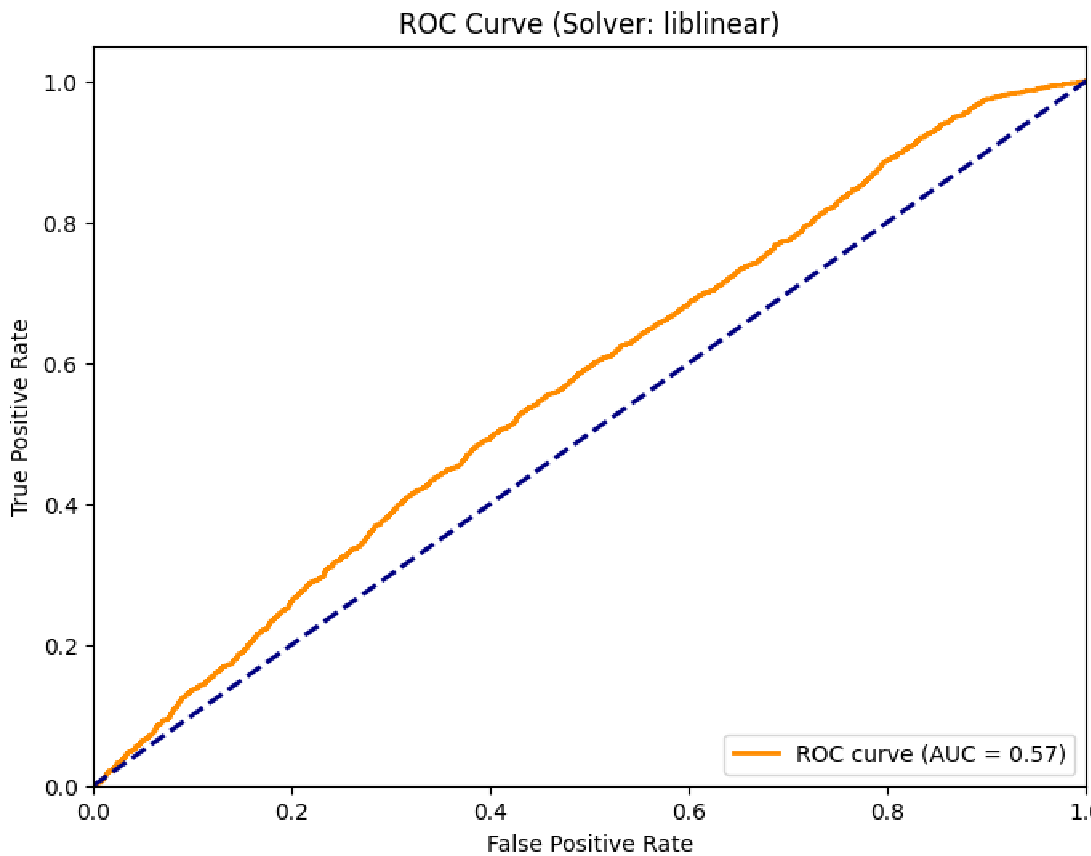
```
Solver: newton-cg, Accuracy: 0.6953841026495584
Confusion Matrix (Solver: newton-cg):
[[4173    0]
 [1828    0]]
```




```
Solver: lbfgs, Accuracy: 0.6953841026495584
Confusion Matrix (Solver: lbfgs):
[[4173    0]
 [1828    0]]
```




```
Solver: liblinear, Accuracy: 0.6953841026495584
Confusion Matrix (Solver: liblinear):
[[4173    0]
 [1828    0]]
```



Final Report:

Logistic Regression: All three logistic regression models trained with the solvers (liblinear, lbfgs, and newton-cg) have the same accuracy of approximately 69.54%. All three models have a confusion matrix with all predictions falling under the negative class (i.e., no positive predictions).

Polynomial Regression:All polynomial regression models have almost same RMSE values which indicates similar performance regarding teh target variable.

Both the polynomial regression and the logistic regression has the same confusion matrices which indicates their performances are identical.

From the heatmap, the variable 'Age recode with single ages and 100+' has a strong negative correlation (approximately -0.27) with 'SurvivalMonths'. 'MaritalStatus' has a moderate positive correlation with 'Age recode with single ages and 100+' (approximately 0.28)

[447]:

```

```