HealthyLifeExpectancyModel

August 2, 2024

1 Lab 8: Define and Solve an ML Problem of Your Choosing

[22]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
```

In this lab assignment, you will follow the machine learning life cycle and implement a model to solve a machine learning problem of your choosing. You will select a data set and choose a predictive problem that the data set supports. You will then inspect the data with your problem in mind and begin to formulate a project plan. You will then implement the machine learning project plan.

You will complete the following tasks:

1. Build Your DataFrame
2. Define Your ML Problem
3. Perform exploratory data analysis to understand your data.
4. Define Your Project Plan
5. Implement Your Project Plan:
    - Prepare your data for your model.
    - Fit your model to the training data and evaluate your model.
    - Improve your model's performance.

1.1 Part 1: Build Your DataFrame

You will have the option to choose one of four data sets that you have worked with in this program:

- The "census" data set that contains Census information from 1994: `censusData.csv`
- Airbnb NYC "listings" data set: `airbnbListingsData.csv`
- World Happiness Report (WHR) data set: `WHR2018Chapter2OnlineData.csv`
- Book Review data set: `bookReviewsData.csv`

Note that these are variations of the data sets that you have worked with in this program. For example, some do not include some of the preprocessing necessary for specific models.

Load a Data Set and Save it as a Pandas DataFrame The code cell below contains filenames (path + filename) for each of the four data sets available to you.

Task: In the code cell below, use the same method you have been using to load the data using `pd.read_csv()` and save it to DataFrame `df`.

You can load each file as a new DataFrame to inspect the data before choosing your data set.

[23]:
```
WHRDataSet_filename = os.path.expanduser("~/Downloads/data/
↪WHR2018Chapter2OnlineData.csv")

df = pd.read_csv(WHRDataSet_filename)

df.head()
```

[23]:
```
       country  year  Life Ladder  Log GDP per capita  Social support  \
0  Afghanistan  2008     3.723590            7.168690        0.450662
1  Afghanistan  2009     4.401778            7.333790        0.552308
2  Afghanistan  2010     4.758381            7.386629        0.539075
3  Afghanistan  2011     3.831719            7.415019        0.521104
4  Afghanistan  2012     3.782938            7.517126        0.520637

   Healthy life expectancy at birth  Freedom to make life choices  Generosity  \
0                         49.209663                      0.718114    0.181819
1                         49.624432                      0.678896    0.203614
2                         50.008961                      0.600127    0.137630
3                         50.367298                      0.495901    0.175329
4                         50.709263                      0.530935    0.247159

   Perceptions of corruption  Positive affect  Negative affect  \
0                   0.881686         0.517637         0.258195
1                   0.850035         0.583926         0.237092
2                   0.706766         0.618265         0.275324
3                   0.731109         0.611387         0.267175
4                   0.775620         0.710385         0.267919

   Confidence in national government  Democratic Quality  Delivery Quality  \
0                           0.612072           -1.929690         -1.655084
1                           0.611545           -2.044093         -1.635025
2                           0.299357           -1.991810         -1.617176
3                           0.307386           -1.919018         -1.616221
4                           0.435440           -1.842996         -1.404078

   Standard deviation of ladder by country-year  \
0                                      1.774662
1                                      1.722688
2                                      1.878622
3                                      1.785360
4                                      1.798283

   Standard deviation/Mean of ladder by country-year  \
0                                           0.476600
1                                           0.391362
```

```
2                                              0.394803
3                                              0.465942
4                                              0.475367

   GINI index (World Bank estimate)  \
0                               NaN
1                               NaN
2                               NaN
3                               NaN
4                               NaN

   GINI index (World Bank estimate), average 2000-15  \
0                                                NaN
1                                                NaN
2                                                NaN
3                                                NaN
4                                                NaN

   gini of household income reported in Gallup, by wp5-year
0                                                NaN
1                                           0.441906
2                                           0.327318
3                                           0.336764
4                                           0.344540
```

[24]:
```python
print(list(df.columns))
print(df.info())
print(df.describe())
```

```
['country', 'year', 'Life Ladder', 'Log GDP per capita', 'Social support',
'Healthy life expectancy at birth', 'Freedom to make life choices',
'Generosity', 'Perceptions of corruption', 'Positive affect', 'Negative affect',
'Confidence in national government', 'Democratic Quality', 'Delivery Quality',
'Standard deviation of ladder by country-year', 'Standard deviation/Mean of
ladder by country-year', 'GINI index (World Bank estimate)', 'GINI index (World
Bank estimate), average 2000-15', 'gini of household income reported in Gallup,
by wp5-year']
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1562 entries, 0 to 1561
Data columns (total 19 columns):
 #   Column                                                     Non-Null Count
Dtype
---  ------                                                     --------------
-----
 0   country                                                    1562 non-null
object
 1   year                                                       1562 non-null
int64
```

```
 2   Life Ladder                                             1562 non-null
float64
 3   Log GDP per capita                                      1535 non-null
float64
 4   Social support                                          1549 non-null
float64
 5   Healthy life expectancy at birth                        1553 non-null
float64
 6   Freedom to make life choices                            1533 non-null
float64
 7   Generosity                                              1482 non-null
float64
 8   Perceptions of corruption                               1472 non-null
float64
 9   Positive affect                                         1544 non-null
float64
 10  Negative affect                                         1550 non-null
float64
 11  Confidence in national government                       1401 non-null
float64
 12  Democratic Quality                                      1391 non-null
float64
 13  Delivery Quality                                        1391 non-null
float64
 14  Standard deviation of ladder by country-year            1562 non-null
float64
 15  Standard deviation/Mean of ladder by country-year       1562 non-null
float64
 16  GINI index (World Bank estimate)                        583 non-null
float64
 17  GINI index (World Bank estimate), average 2000-15       1386 non-null
float64
 18  gini of household income reported in Gallup, by wp5-year  1205 non-null
float64
dtypes: float64(17), int64(1), object(1)
memory usage: 232.0+ KB
None
              year  Life Ladder  Log GDP per capita  Social support  \
count  1562.000000  1562.000000         1535.000000     1549.000000
mean   2011.820743     5.433676            9.220822        0.810669
std       3.419787     1.121017            1.184035        0.119370
min    2005.000000     2.661718            6.377396        0.290184
25%    2009.000000     4.606351            8.310665        0.748304
50%    2012.000000     5.332600            9.398610        0.833047
75%    2015.000000     6.271025           10.190634        0.904329
max    2017.000000     8.018934           11.770276        0.987343

       Healthy life expectancy at birth  Freedom to make life choices  \
```

count	1553.000000	1533.000000
mean	62.249887	0.728975
std	7.960671	0.145408
min	37.766476	0.257534
25%	57.299580	0.633754
50%	63.803192	0.748014
75%	68.098228	0.843628
max	76.536362	0.985178

	Generosity	Perceptions of corruption	Positive affect \
count	1482.000000	1472.000000	1544.000000
mean	0.000079	0.753622	0.708969
std	0.164202	0.185538	0.107644
min	-0.322952	0.035198	0.362498
25%	-0.114313	0.697359	0.621471
50%	-0.022638	0.808115	0.717398
75%	0.094649	0.880089	0.800858
max	0.677773	0.983276	0.943621

	Negative affect	Confidence in national government	Democratic Quality \
count	1550.000000	1401.000000	1391.000000
mean	0.263171	0.480207	-0.126617
std	0.084006	0.190724	0.873259
min	0.083426	0.068769	-2.448228
25%	0.204116	0.334732	-0.772010
50%	0.251798	0.463137	-0.225939
75%	0.311515	0.610723	0.665944
max	0.704590	0.993604	1.540097

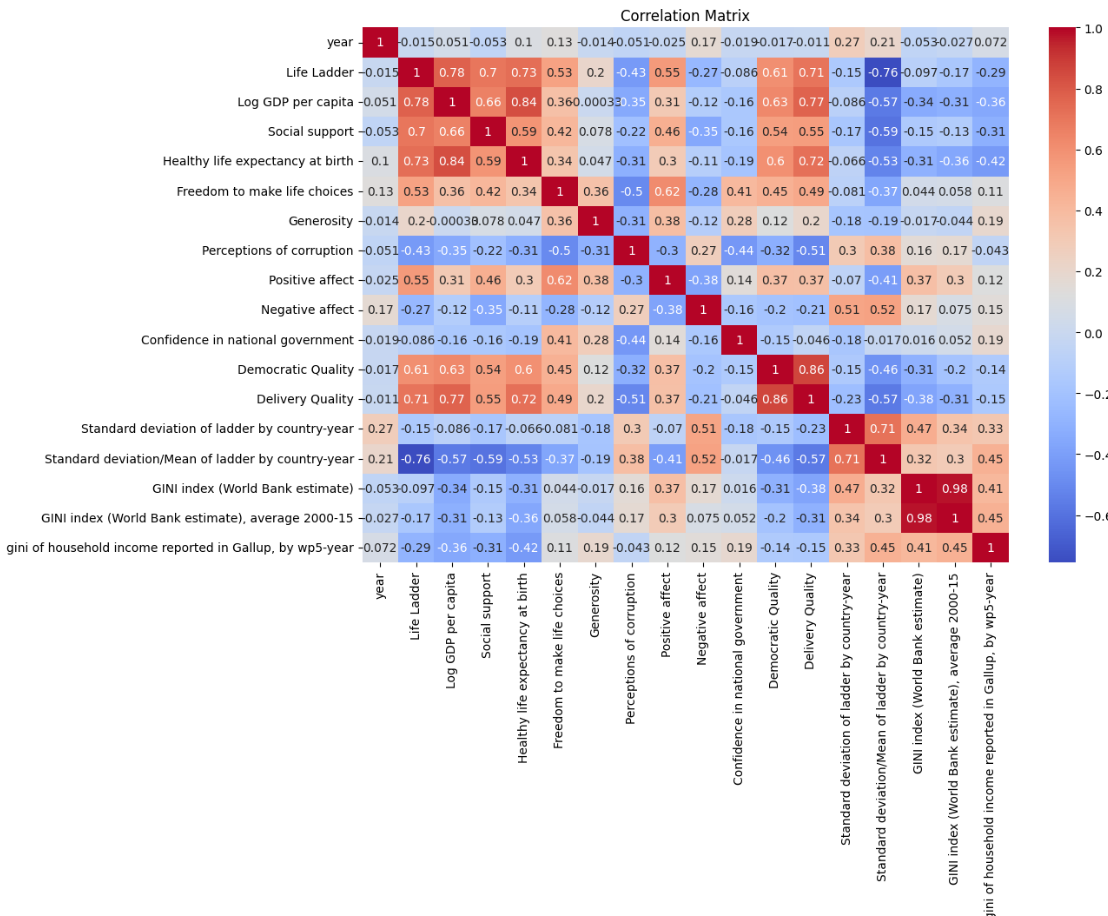
	Delivery Quality	Standard deviation of ladder by country-year \
count	1391.000000	1562.000000
mean	0.004947	2.003501
std	0.981052	0.379684
min	-2.144974	0.863034
25%	-0.717463	1.737934
50%	-0.210142	1.960345
75%	0.717996	2.215920
max	2.184725	3.527820

	Standard deviation/Mean of ladder by country-year \
count	1562.000000
mean	0.387271
std	0.119007
min	0.133908
25%	0.309722
50%	0.369751
75%	0.451833
max	1.022769

```
       GINI index (World Bank estimate)  \
count                        583.000000
mean                           0.372846
std                            0.086609
min                            0.241000
25%                            0.307000
50%                            0.349000
75%                            0.433500
max                            0.648000

       GINI index (World Bank estimate), average 2000-15  \
count                                         1386.000000
mean                                             0.386948
std                                              0.083694
min                                              0.228833
25%                                              0.321583
50%                                              0.371000
75%                                              0.433104
max                                              0.626000

       gini of household income reported in Gallup, by wp5-year
count                                         1205.000000
mean                                             0.445204
std                                              0.105410
min                                              0.223470
25%                                              0.368531
50%                                              0.425395
75%                                              0.508579
max                                              0.961435
```

[25]:

```
numeric_df = df.select_dtypes(include=[np.number])
correlation_matrix = numeric_df.corr()

plt.figure(figsize=(12, 8))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm')
plt.title('Correlation Matrix')
plt.show()
```



1.2 Part 2: Define Your ML Problem

Next you will formulate your ML Problem. In the markdown cell below, answer the following questions:

1. List the data set you have chosen.
2. What will you be predicting? What is the label?
3. Is this a supervised or unsupervised learning problem? Is this a clustering, classification or regression problem? Is it a binary classificaiton or multi-class classifiction problem?
4. What are your features? (note: this list may change after your explore your data)
5. Explain why this is an important problem. In other words, how would a company create value with a model that predicts this label?

1. Dataset: World Happiness Report (WHR2018Chapter2OnlineData.csv)
2. I want to predict the "healthy life expectancy at birth" column
3. This is a supervised learning problem. Since we're predicting a continuous value, it's a regression problem.
4. Features might include 'Log GDP per capita', 'Social support', 'Freedom to make life choices', 'Generosity', 'Perceptions of corruption'

5. Predicting healthy life expectancy at birth is important because it can give insights into a country's overall health and well-being. For companies, especially those in healthcare or policy planning, having a model that can predict this can help in resource allocation, improving public health strategies, and identifying areas needing intervention to enhance quality of life.

1.3 Part 3: Understand Your Data

The next step is to perform exploratory data analysis. Inspect and analyze your data set with your machine learning problem in mind. Consider the following as you inspect your data:

1. What data preparation techniques would you like to use? These data preparation techniques may include:
   - addressing missingness, such as replacing missing values with means
   - finding and replacing outliers
   - renaming features and labels
   - finding and replacing outliers
   - performing feature engineering techniques such as one-hot encoding on categorical features
   - selecting appropriate features and removing irrelevant features
   - performing specific data cleaning and preprocessing techniques for an NLP problem
   - addressing class imbalance in your data sample to promote fair AI
2. What machine learning model (or models) you would like to use that is suitable for your predictive problem and data?
   - Are there other data preparation techniques that you will need to apply to build a balanced modeling data set for your problem and model? For example, will you need to scale your data?
3. How will you evaluate and improve the model's performance?
   - Are there specific evaluation metrics and methods that are appropriate for your model?

Think of the different techniques you have used to inspect and analyze your data in this course. These include using Pandas to apply data filters, using the Pandas `describe()` method to get insight into key statistics for each column, using the Pandas `dtypes` property to inspect the data type of each column, and using Matplotlib and Seaborn to detect outliers and visualize relationships between features and labels. If you are working on a classification problem, use techniques you have learned to determine if there is class imbalance.

Task: Use the techniques you have learned in this course to inspect and analyze your data. You can import additional packages that you have used in this course that you will need to perform this task.

Note: You can add code cells if needed by going to the Insert menu and clicking on Insert Cell Below in the drop-drown menu.

[26]:
```
#check for missing values
missing_values = df.isnull().sum()
print(missing_values)
```

```
country                                                     0
year                                                        0
Life Ladder                                                 0
Log GDP per capita                                         27
Social support                                             13
Healthy life expectancy at birth                            9
Freedom to make life choices                               29
Generosity                                                 80
Perceptions of corruption                                  90
Positive affect                                            18
Negative affect                                            12
Confidence in national government                         161
Democratic Quality                                        171
Delivery Quality                                          171
Standard deviation of ladder by country-year                0
Standard deviation/Mean of ladder by country-year           0
GINI index (World Bank estimate)                          979
GINI index (World Bank estimate), average 2000-15         176
gini of household income reported in Gallup, by wp5-year  357
dtype: int64
```

[27]:
```
df = df.drop(columns=['year'])
numeric_cols = df.select_dtypes(include=[np.number]).columns
df[numeric_cols] = df[numeric_cols].fillna(df[numeric_cols].mean())
```

[28]:
```
from scipy.stats.mstats import winsorize

# Define the limits for Winsorization (e.g., 5% on both tails)
limits = (0.05, 0.05)

# Apply Winsorization to all numeric columns
for col in numeric_cols:
    df[col] = winsorize(df[col], limits=limits)
```

[29]:
```
# One-hot encoding for categorical features (if any)
df = pd.get_dummies(df, drop_first=True)
```

1.4 Part 4: Define Your Project Plan

Now that you understand your data, in the markdown cell below, define your plan to implement the remaining phases of the machine learning life cycle (data preparation, modeling, evaluation) to solve your ML problem. Answer the following questions:

- Do you have a new feature list? If so, what are the features that you chose to keep and remove after inspecting the data?
- Explain different data preparation techniques that you will use to prepare your data for modeling.
- What is your model (or models)?

- Describe your plan to train your model, analyze its performance and then improve the model. That is, describe your model building, validation and selection plan to produce a model that generalizes well to new data.

After looking at the data, I have decided to keep the following features for predicting healthy life expectancy at birth: - Log GDP per capita - Social support - Freedom to make life choices - Generosity - Perceptions of corruption - Positive affect - Negative affect - Confidence in national government - Democratic Quality - Delivery Quality

---

I will remove features like:
- year - Standard deviation of ladder by country-year - Standard deviation/mean of ladder by country-year - GINI index (World Bank estimate) - GINI index, average 2000-15 - gini of household income reported in Gallup

---

Data Preparation Techniques:
- Handling Missing Data: Winsorization to deal with outliers and impute msising values using mean imputation - Normalization: Scale all numerical features to have values between 0 and 1 - Feature Engineering: Create interaction terms if needed - One-Hot Encoding

1.5 Part 5: Implement Your Project Plan

Task: In the code cell below, import additional packages that you have used in this course that you will need to implement your project plan.

[30]:
```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
from sklearn.ensemble import RandomForestRegressor
from sklearn.model_selection import GridSearchCV
```

Task: Use the rest of this notebook to carry out your project plan.

You will:

1. Prepare your data for your model.
2. Fit your model to the training data and evaluate your model.
3. Improve your model's performance by performing model selection and/or feature selection techniques to find best model for your problem.

Add code cells below and populate the notebook with commentary, code, analyses, results, and figures as you see fit.

[31]:
```
# Define features and label
X = df[['Log GDP per capita', 'Social support', 'Freedom to make life choices',
        'Generosity', 'Perceptions of corruption', 'Positive affect',
        'Negative affect', 'Confidence in national government',
        'Democratic Quality', 'Delivery Quality']]
```

```python
y = df['Healthy life expectancy at birth']

# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

# Scale the features
scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

[32]:

```python
# Fit a Linear Regression model
lr_model = LinearRegression()
lr_model.fit(X_train_scaled, y_train)

# Predict on test data
y_pred = lr_model.predict(X_test_scaled)

# Evaluate the model
train_rmse = np.sqrt(mean_squared_error(y_train, lr_model.predict(X_train_scaled)))
test_rmse = np.sqrt(mean_squared_error(y_test, y_pred))
train_r2 = r2_score(y_train, lr_model.predict(X_train_scaled))
test_r2 = r2_score(y_test, y_pred)

print(f'Train RMSE: {train_rmse}, Test RMSE: {test_rmse}')
print(f'Train R2: {train_r2}, Test R2: {test_r2}')
```

```
Train RMSE: 3.8477165718548605, Test RMSE: 3.8663672065584898
Train R2: 0.7372733546637511, Test R2: 0.7357881381634515
```

[33]:

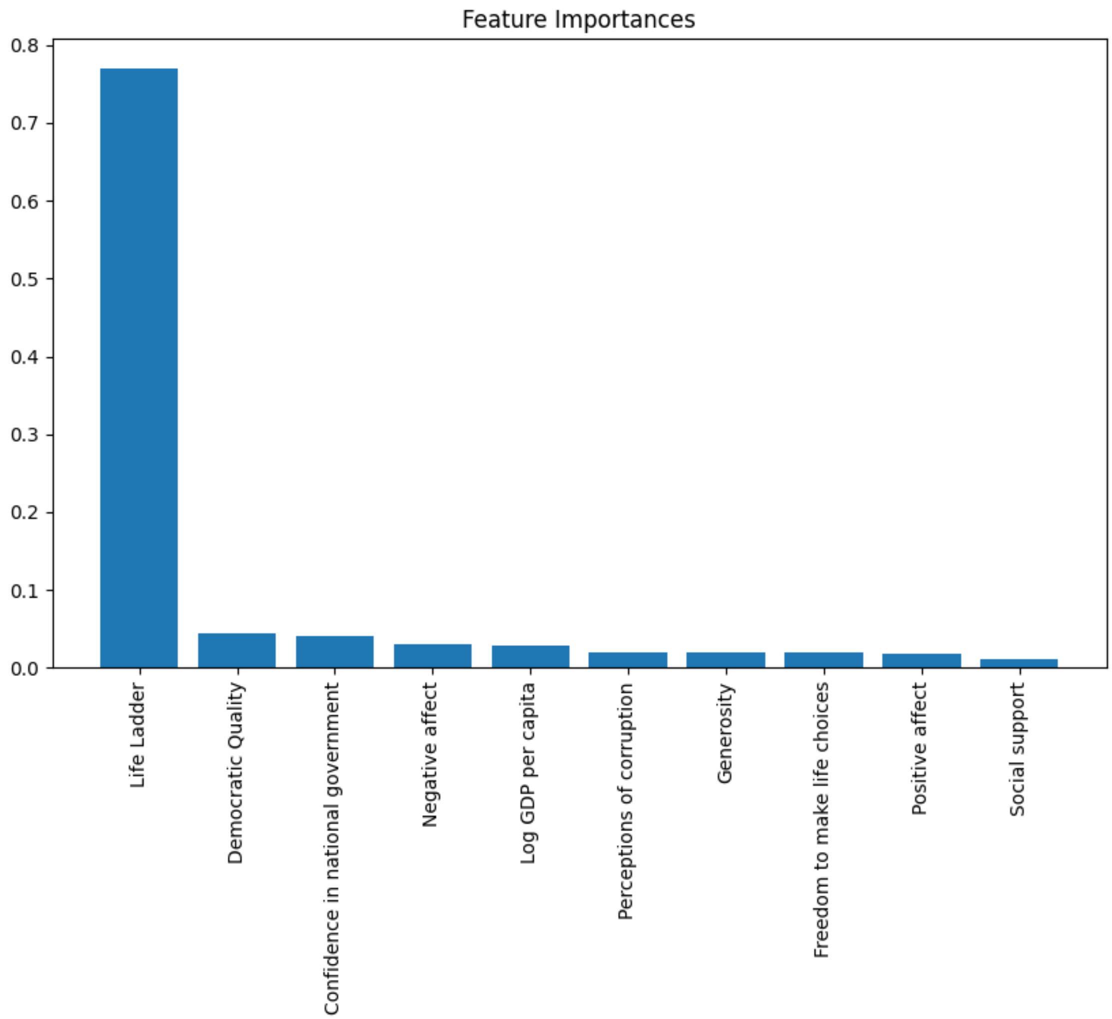
```python
# Use Random Forest with GridSearchCV for model selection
rf_model = RandomForestRegressor(random_state=42)
param_grid = {
    'n_estimators': [100, 200],
    'max_depth': [10, 20, None],
    'min_samples_split': [2, 5]
}

grid_search = GridSearchCV(estimator=rf_model, param_grid=param_grid, cv=3, n_jobs=-1, verbose=2)
grid_search.fit(X_train_scaled, y_train)

# Best model from GridSearchCV
best_rf_model = grid_search.best_estimator_

# Predict on test data
```

```
y_pred_rf = best_rf_model.predict(X_test_scaled)

# Evaluate the model
train_rmse_rf = np.sqrt(mean_squared_error(y_train, best_rf_model.
 ↪predict(X_train_scaled)))
test_rmse_rf = np.sqrt(mean_squared_error(y_test, y_pred_rf))
train_r2_rf = r2_score(y_train, best_rf_model.predict(X_train_scaled))
test_r2_rf = r2_score(y_test, y_pred_rf)

print(f'Best Random Forest Model - Train RMSE: {train_rmse_rf}, Test RMSE:␣
 ↪{test_rmse_rf}')
print(f'Best Random Forest Model - Train R2: {train_r2_rf}, Test R2:␣
 ↪{test_r2_rf}')
```

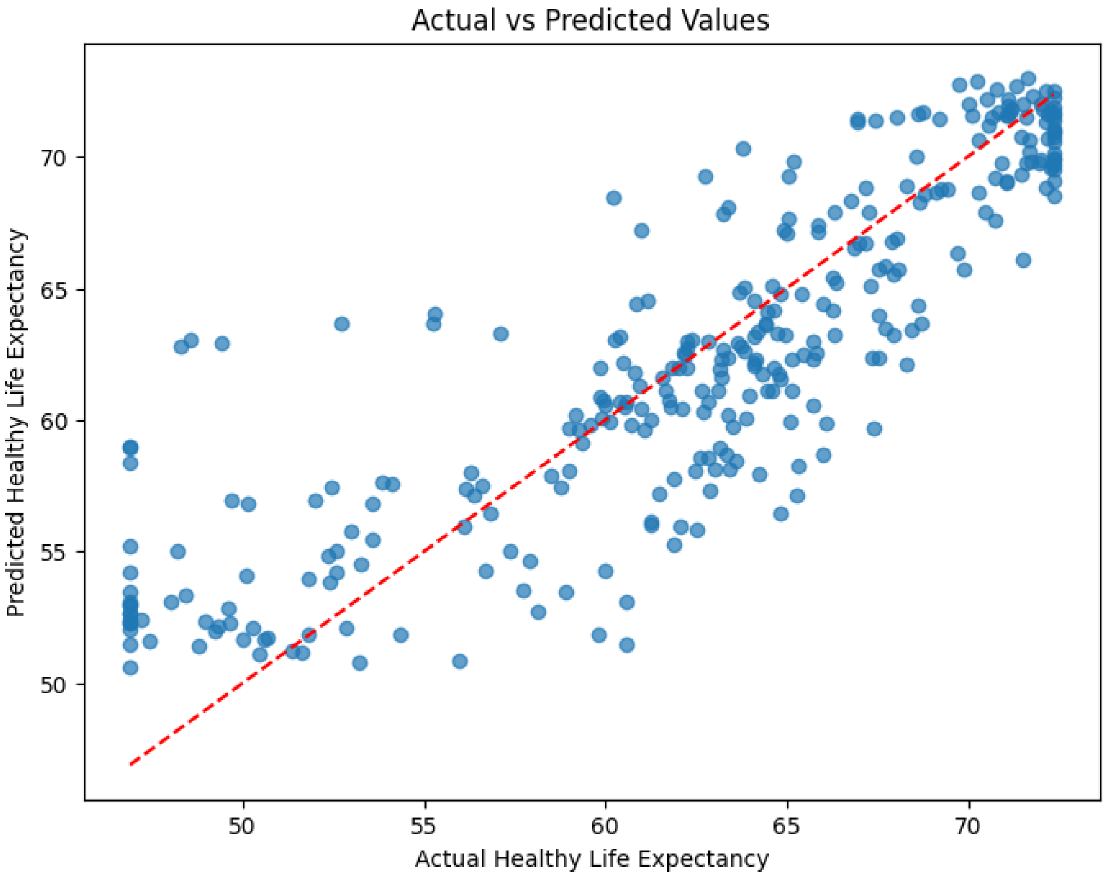
```
Fitting 3 folds for each of 12 candidates, totalling 36 fits
Best Random Forest Model - Train RMSE: 0.9233789969454812, Test RMSE:
2.2803086317123022
Best Random Forest Model - Train R2: 0.9848693370611447, Test R2:
0.9080962194910386
```

[34]:

```
importances = best_rf_model.feature_importances_
features = df.columns.drop('Healthy life expectancy at birth')
indices = np.argsort(importances)[::-1]

plt.figure(figsize=(10, 6))
plt.title("Feature Importances")
plt.bar(range(len(importances)), importances[indices], align="center")
plt.xticks(range(len(importances)), features[indices], rotation=90)
plt.show()
```



[35]:
```
plt.figure(figsize=(8, 6))
plt.scatter(y_test, y_pred, alpha=0.7)
plt.xlabel('Actual Healthy Life Expectancy')
plt.ylabel('Predicted Healthy Life Expectancy')
plt.title('Actual vs Predicted Values')
plt.plot([min(y_test), max(y_test)], [min(y_test), max(y_test)], 'r--')
plt.show()
```



1.6 Results and Discussion

1.6.1 Linear Regression Model

- **Train RMSE:** 3.8477, **Test RMSE:** 3.8664
  - The RMSE values are similar between training and testing, indicating a decent model fit, though the error magnitude suggests room for improvement.
- **Train R2:** 0.7373, **Test R2:** 0.7358
  - The model explains about 73% of the variance in the data, which is adequate but not optimal.

1.6.2 Random Forest Model

- **Best Train RMSE:** 0.9234, **Best Test RMSE:** 2.2803
  - The Random Forest model shows a significant improvement in RMSE, especially on the test set, indicating better generalization.
- **Best Train R2:** 0.9849, **Best Test R2:** 0.9081
  - The model explains over 90% of the variance in the test data, indicating strong performance. The slight difference between Train and Test R2 suggests minimal overfitting.

The Random Forest model outperforms the linear model, demonstrating better prediction accuracy and variance explanation.