Supervised Learning with scikit-learn

2). Regression

a). Importing Data for Supervised Learning

```
# Import numpy and pandas
import numpy as np
import pandas as pd
# Read the CSV file into a DataFrame: df
df = pd.read_csv('gapminder.csv')

# Create arrays for features and target variable
y = df['life'].values
X = df['fertility'].values

# Print the dimensions of X and y before reshaping
print("Dimensions of y before reshaping: {}".format(y.shape))
print("Dimensions of X before reshaping: {}".format(X.shape))
# Reshape X and y
y = y.reshape(-1,1)
X = X.reshape(-1,1)

# Print the dimensions of X and y after reshaping
print("Dimensions of y after reshaping: {}".format(y.shape))
print("Dimensions of X after reshaping: {}".format(X.shape))
```

<script.py> output:

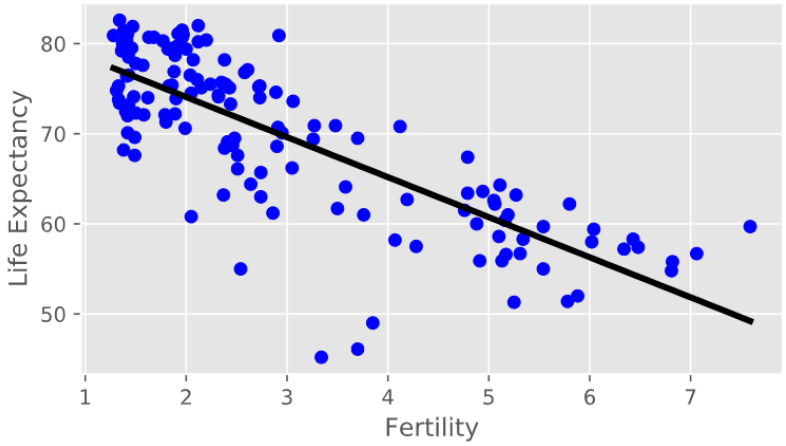
```
Dimensions of y before reshaping: (139,)
Dimensions of X before reshaping: (139,)
Dimensions of y after reshaping: (139, 1)
Dimensions of X after reshaping: (139, 1)
```

b). Fit & predict for regression

```
# Import LinearRegression
from sklearn.linear_model import LinearRegression

# Create the regressor: reg
reg = LinearRegression()

# Create the prediction space
prediction_space = np.linspace(min(X_fertility), max(X_fertility)).reshape(-1,1)

# Fit the model to the data
reg.fit(X_fertility, y)

# Compute predictions over the prediction space: y_pred
y_pred = reg.predict(prediction_space)

# Print R^2
print(reg.score(X_fertility, y))
# Plot regression line
plt.plot(prediction_space, y_pred, color='black', linewidth=3)
plt.show()
```

<script.py> output:

0.619244216774



c). Train/Test Split for regression

```
# Import necessary modules
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error
from sklearn.model_selection import train_test_split

# Create training and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.3, random_state=42)

# Create the regressor: reg_all
reg_all = LinearRegression()

# Fit the regressor to the training data
reg_all.fit(X_train, y_train)

# Predict on the test data: y_pred
y_pred = reg_all.predict(X_test)

# Compute and print R^2 and RMSE
print("R^2: {}".format(reg_all.score(X_test, y_test)))
rmse = np.sqrt(mean_squared_error(y_test, y_pred))
print("Root Mean Squared Error: {}".format(rmse))
```

<script.py> output:

R^2: 0.838046873142936

Root Mean Squared Error: 3.2476010800377213

d). 5-fold cross-validation

```
# Import the necessary modules
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score

# Create a linear regression object: reg
reg = LinearRegression()

# Compute 5-fold cross-validation scores: cv_scores
cv_scores = cross_val_score(reg, X, y, cv=5)

# Print the 5-fold cross-validation scores
print(cv_scores)

print("Average 5-Fold CV Score: {}".format(np.mean(cv_scores)))
```

<script.py> output:

[0.81720569 0.82917058 0.90214134 0.80633989 0.94495637]

Average 5-Fold CV Score: 0.8599627722793232

e). K Fold CV Comparison

```
# Import necessary modules
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import cross_val_score

# Create a linear regression object: reg
reg = LinearRegression()

# Perform 3-fold CV
cvscores_3 = cross_val_score(reg,X,y, cv=3)
print(np.mean(cvscores_3))

# Perform 10-fold CV
cvscores_10 = cross_val_score(reg,X,y,cv=10)
print(np.mean(cvscores_10))
```

<script.py> output:

0.871871278262

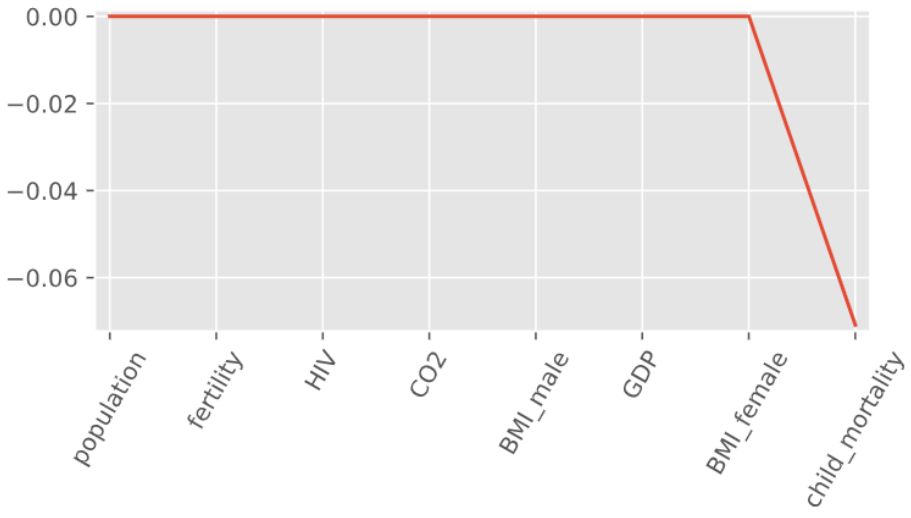
0.843612862013

f). Regularization I: Lasso

```
# Import Lasso
from sklearn.linear_model import Lasso

# Instantiate a lasso regressor: lasso
lasso = Lasso(alpha=0.4, normalize=True)

# Fit the regressor to the data
lasso.fit(X, y)

# Compute and print the coefficients
lasso_coef = lasso.coef_
print(lasso_coef)

# Plot the coefficients
plt.plot(range(len(df_columns)), lasso_coef)
plt.xticks(range(len(df_columns)), df_columns.values, rotation=60)
plt.margins(0.02)
plt.show()
```

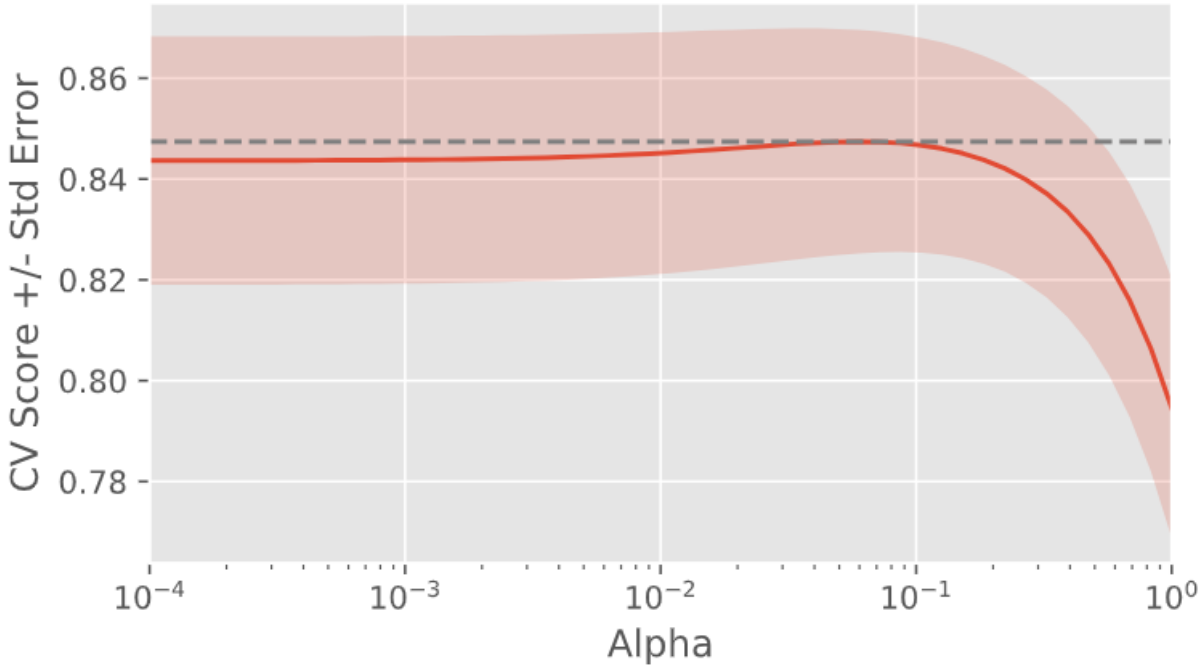
<script.py> output:

```
[-0.        -0.        -0.         0.         0.         0.        -0.
 -0.07087587]
```



g). Regularization II: Ridge

```
# Import necessary modules
from sklearn.linear_model import Ridge
from sklearn.model_selection import cross_val_score

# Setup the array of alphas and lists to store scores
alpha_space = np.logspace(-4, 0, 50)
ridge_scores = []
ridge_scores_std = []

# Create a ridge regressor: ridge
ridge = Ridge(normalize=True)

# Compute scores over range of alphas
for alpha in alpha_space:

    # Specify the alpha value to use: ridge.alpha
    ridge.alpha = alpha

    # Perform 10-fold CV: ridge_cv_scores
    ridge_cv_scores = cross_val_score(ridge,X,y,cv=10)

    # Append the mean of ridge_cv_scores to ridge_scores
    ridge_scores.append(np.mean(ridge_cv_scores))

    # Append the std of ridge_cv_scores to ridge_scores_std
    ridge_scores_std.append(np.std(ridge_cv_scores))

# Display the plot
display_plot(ridge_scores, ridge_scores_std)
```


CV Score +/- Std Error
0.86
0.84
0.82
0.80
0.78
10^{-4}
10^{-3}
10^{-2}
10^{-1}
10^{0}
Alpha