Supervised Learning with scikit-learn

4). Preprocessing & Pipelining:

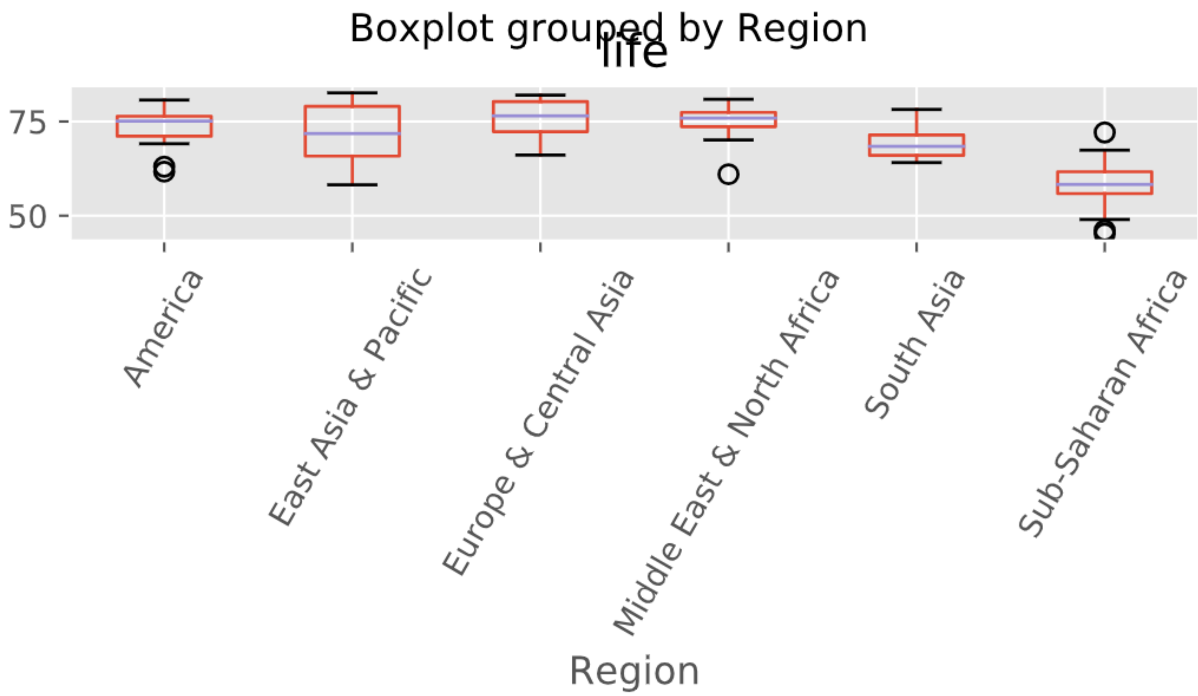
a). Exploring Categorical Features

```
# Import pandas
import pandas as pd

# Read 'gapminder.csv' into a DataFrame: df
df = pd.read_csv('gapminder.csv')

# Create a boxplot of life expectancy per region
df.boxplot('life', 'Region', rot=60)

# Show the plot
plt.show()
```



b). Creating Dummy Variables

```
# Create dummy variables: df_region
df_region = pd.get_dummies(df)

# Print the columns of df_region
print(df_region.columns)

# Drop 'Region_America' from df_region
df_region = pd.get_dummies(df, drop_first=True)

# Print the new columns of df_region
print(df_region.columns)
```

<script.py> output:

```
Index(['population', 'fertility', 'HIV', 'CO2', 'BMI_male', 'GDP',
       'BMI_female', 'life', 'child_mortality', 'Region_America',
       'Region_East Asia & Pacific', 'Region_Europe & Central Asia',
       'Region_Middle East & North Africa', 'Region_South Asia',
       'Region_Sub-Saharan Africa'],
      dtype='object')
Index(['population', 'fertility', 'HIV', 'CO2', 'BMI_male', 'GDP',
       'BMI_female', 'life', 'child_mortality', 'Region_East Asia & Pacific',
       'Region_Europe & Central Asia', 'Region_Middle East & North Africa',
       'Region_South Asia', 'Region_Sub-Saharan Africa'],
      dtype='object')
```

c). Regression with categorical features

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

# Instantiate a ridge regressor: ridge
ridge = Ridge(alpha=0.5, normalize=True)

# Perform 5-fold cross-validation: ridge_cv
ridge_cv = cross_val_score(ridge,X,y,cv=5)

# Print the cross-validated scores
print(ridge_cv)
```

<script.py> output:

```
[ 0.86808336  0.80623545  0.84004203  0.7754344   0.87503712]
```

d). Dropping Missing Data:

```
# Convert '?' to NaN
df[df == '?'] = np.nan

# Print the number of NaNs
print(df.isnull().sum())

# Print shape of original DataFrame
print("Shape of Original DataFrame: {}".format(df.shape))

# Drop missing values and print shape of new DataFrame
df = df.dropna()

# Print shape of new DataFrame
print("Shape of DataFrame After Dropping All Rows with Missing Values: {}".format(df.shape))
```

<script.py> output:

```
party              0
infants           12
water             48
budget            11
physician         11
salvador          15
religious         11
satellite         14
aid               15
missile           22
immigration        7
synfuels          21
education         31
superfund         25
crime             17
duty_free_exports 28
eaa_rsa          104
dtype: int64
Shape of Original DataFrame: (435, 17)
Shape of DataFrame After Dropping All Rows with Missing Values: (232, 17)
```

e). <u>Imputing missing data in a ML Pipeline</u>

```
# Import necessary modules
from sklearn.preprocessing import Imputer
from sklearn.pipeline import Pipeline
from sklearn.svm import SVC

# Setup the pipeline steps: steps
steps = [('imputation', Imputer(missing_values='NaN', strategy='most_frequent', axis=0)),
        ('SVM', SVC())]

# Create the pipeline: pipeline
pipeline = Pipeline(steps)

# 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)

# Fit the pipeline to the train set
pipeline.fit(X_train,y_train)

# Predict the labels of the test set
y_pred = pipeline.predict(X_test)

# Compute metrics
print(classification_report(y_test, y_pred))
```

<script.py> output:

	precision	recall	f1-score	support
democrat	0.99	0.96	0.98	85
republican	0.94	0.98	0.96	46
avg / total	0.97	0.97	0.97	131

f). Centring and Scaling your Data

```
# Import scale
from sklearn.preprocessing import scale

# Scale the features: X_scaled
X_scaled = scale(X)

# Print the mean and standard deviation of the unscaled features
print("Mean of Unscaled Features: {}".format(np.mean(X)))
print("Standard Deviation of Unscaled Features: {}".format(np.std(X)))

# Print the mean and standard deviation of the scaled features
print("Mean of Scaled Features: {}".format(np.mean(X_scaled)))
print("Standard Deviation of Scaled Features: {}".format(np.std(X_scaled)))
```

<script.py> output:

```
Mean of Unscaled Features: 18.432687072460002
Standard Deviation of Unscaled Features: 41.54494764094571
Mean of Scaled Features: 2.7314972981668206e-15
Standard Deviation of Scaled Features: 0.9999999999999999
```

g). <u>Centering and Scaling in a Pipeline</u>

```
# Import the necessary modules
from sklearn.preprocessing import StandardScaler
from sklearn.pipeline import Pipeline

# Setup the pipeline steps: steps
steps = [('scaler', StandardScaler()),
        ('knn', KNeighborsClassifier())]

# Create the pipeline: pipeline
pipeline = Pipeline(steps)

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

# Fit the pipeline to the training set: knn_scaled
knn_scaled = pipeline.fit(X_train,y_train)

# Instantiate and fit a k-NN classifier to the unscaled data
knn_unscaled = KNeighborsClassifier().fit(X_train, y_train)

# Compute and print metrics
print('Accuracy with Scaling: {}'.format(knn_scaled.score(X_test, y_test)))
print('Accuracy without Scaling: {}'.format(knn_unscaled.score(X_test, y_test)))
```

<script.py> output:

```
    Accuracy with Scaling: 0.7700680272108843
    Accuracy without Scaling: 0.6979591836734694
```

h). Pipeline for Classification

```
# Setup the pipeline
steps = [('scaler', StandardScaler()),
        ('SVM', SVC())]
pipeline = Pipeline(steps)
# Specify the hyperparameter space
parameters = {'SVM__C':[1, 10, 100],
             'SVM__gamma':[0.1, 0.01]}

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.2,random_state=21)

# Instantiate the GridSearchCV object: cv
cv = GridSearchCV(pipeline,param_grid=parameters)
# Fit to the training set
cv.fit(X_train,y_train)

# Predict the labels of the test set: y_pred
y_pred = cv.predict(X_test)

# Compute and print metrics
print("Accuracy: {}".format(cv.score(X_test, y_test)))
print(classification_report(y_test, y_pred))
print("Tuned Model Parameters: {}".format(cv.best_params_))
```

<script.py> output:

```
Accuracy: 0.7795918367346939
             precision    recall  f1-score   support
      False       0.83      0.85      0.84       662
       True       0.67      0.63      0.65       318
avg / total       0.78      0.78      0.78       980
Tuned Model Parameters: {'SVM__gamma': 0.1, 'SVM__C': 10}
```

i). <u>Pipelining for Regression</u>

```
# Setup the pipeline steps: steps
steps = [('imputation', Imputer(missing_values='NaN', strategy='mean', axis=0)),
        ('scaler', StandardScaler()),
        ('elasticnet', ElasticNet())]

# Create the pipeline: pipeline
pipeline = Pipeline(steps)

# Specify the hyperparameter space
parameters = {'elasticnet__l1_ratio':np.linspace(0,1,30)}

# Create train and test sets
X_train, X_test, y_train, y_test = train_test_split(X,y,test_size=0.4, random_state=42)

# Create the GridSearchCV object: gm_cv
gm_cv = GridSearchCV(pipeline, param_grid=parameters)

# Fit to the training set
gm_cv.fit(X_train,y_train)

#Compute and print the metrics
r2 = gm_cv.score(X_test, y_test)
print("Tuned ElasticNet Alpha: {}".format(gm_cv.best_params_))
print("Tuned ElasticNet R squared: {}".format(r2))
```

<script.py> output:

```
    Tuned ElasticNet Alpha: {'elasticnet__l1_ratio': 1.0}
    Tuned ElasticNet R squared: 0.8862016570888217
```