Perform following Data Pre-processing tasks using python. Data reduction using variance threshold, univariate feature selection, recursive feature elimination, PCA.

```
import numpy as np
import matplotlib.pyplot as plt

from·sklearn.model_selection·import·train_test_split
from·sklearn.feature_selection·import·VarianceThreshold,·RFE,·SelectFromModel,·SelectKBest
from·sklearn.linear_model·import·LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import confusion_matrix, classification_report

from sklearn.datasets import load_iris
```

```
iris = load_iris()
X = iris.data
y = iris.target
```

```
print(X[1, :])
print(X.shape)
```

```
[4.9 3.  1.4 0.2]
(150, 4)
```

```
# In order to test the effectness of different feature selection methods, we add some nois
np.random.seed(100)
E = np.random.uniform(0, 1, size=(len(X), 10))
X = np.hstack((X, E))
X.shape
```

```
(150, 14)
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, random_state=1, test_size=0.3)
X_train.shape
```

```
(105, 14)
```

Variance Thresholding

- VarianceThreshold is a simple baseline approach to feature selection. It removes all features whose variance doesn't meet some threshold.
- By default, it removes all zero-variance features

```
sel_variance_threshold = VarianceThreshold()
X_train_remove_variance = sel_variance_threshold.fit_transform(X_train)
```

```
X_train_remove_variance.shape
# Variance threshold is applied but since the noise valued columns have non-zero variance,
```

```
(120, 14)
```

Univariate Feature Selection

- Univariate feature selection works by selecting the best features based on univariate statistical tests.
- We compare each feature to the target variable, to see whether there is statistially significant relationship between them.
- When we analyze the relationship between one feature and the target variable we ignore the other features. That is why it is called 'univariate'.
- Each feature has its own test score.
- Finally, all the test scores are compared, and the features with top scores will be selected.
- These objects take as input a scoring function that returns univariate scores and p-values (or only scores for SelectKBest and SelectPercentile):

  For regression: f_regression, mutual_info_regression
  For classification: chi2, f_classif, mutual_info_classif

```
# Since this is iris dataset we are working on, we will use classfication techniques
# Analysis Of Variance (ANOVA)
sel_f = SelectKBest(f_classif, k=4)
X_train_f = sel_f.fit_transform(X_train, y_train)

print(sel_f.get_support())
print(sel_f.get_params())
```

```
[ True  True  True  True False False False False False False False False
 False False]
{'k': 4, 'score_func': <function f_classif at 0x7fdb7145de60>}
```

```
# Chi2 Test
sel_chi2 = SelectKBest(chi2, k=4) # select 4 features
X_train_chi2 = sel_chi2.fit_transform(X_train, y_train)

print(sel_chi2.get_support())
print(sel_chi2.get_params())
```

```
[ True  True  True  True False False False False False False False False
 False False]
{'k': 4, 'score_func': <function chi2 at 0x7fdb71461290>}
```

```
# mutual_info_classif Test
sel_mutual = SelectKBest(mutual_info_classif, k=4)
```

```
X_train_mutual = sel_mutual.fit_transform(X_train, y_train)

print(sel_mutual.get_support())
print(sel_mutual.get_params())
```

```
[ True  True  True  True False False False False False False False False
 False False]
{'k': 4, 'score_func': <function mutual_info_classif at 0x7fdb6eee74d0>}
```

Recursive Feature Elimination

- Given an external estimator that assigns weights to features (e.g., the coefficients of a linear model), recursive feature elimination (RFE) is to select features by recursively considering smaller and smaller sets of features.
- First, the estimator is trained on the initial set of features and the importance of each feature is obtained either through a coef_ attribute or through a feature_importances_ attribute. Then, the least important features are pruned from current set of features.That procedure is recursively repeated on the pruned set until the desired number of features to select is eventually reached.

```
model_tree = RandomForestClassifier(random_state=100, n_estimators=50)
sel_rfe_tree = RFE(estimator=model_tree, n_features_to_select=4, step=1)
X_train_rfe_tree = sel_rfe_tree.fit_transform(X_train, y_train)
print(sel_rfe_tree.get_support())
```

```
[ True  True  True  True False False False False False False False False
 False False]
```

PCA

- Since PCA yields a feature subspace that maximizes the variance along the axes, it makes sense to standardize the data, especially, if it was measured on different scales. Although, all features in the Iris dataset were measured in centimeters, let us continue with the transformation of the data onto unit scale (mean=0 and variance=1), which is a requirement for the optimal performance of many machine learning algorithms

```
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
import pandas as pd
```

```
x = StandardScaler().fit_transform(X)
features = ['sepal length', 'sepal width', 'petal length', 'petal width']
```

```
pd.DataFrame(data = x, columns = features).head()
```

	sepal length	sepal width	petal length	petal width
0	-0.900681	1.019004	-1.340227	-1.315444
1	-1.143017	-0.131979	-1.340227	-1.315444
2	-1.385353	0.328414	-1.397064	-1.315444
3	-1.506521	0.098217	-1.283389	-1.315444

```
pca = PCA(n_components=2)
```

```
principalComponents = pca.fit_transform(x)
```

```
principalDf = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2'])
```

```
principalDf.head(5)
```

	principal component 1	principal component 2
0	-2.264703	0.480027
1	-2.080961	-0.674134
2	-2.364229	-0.341908
3	-2.299384	-0.597395
4	-2.389842	0.646835

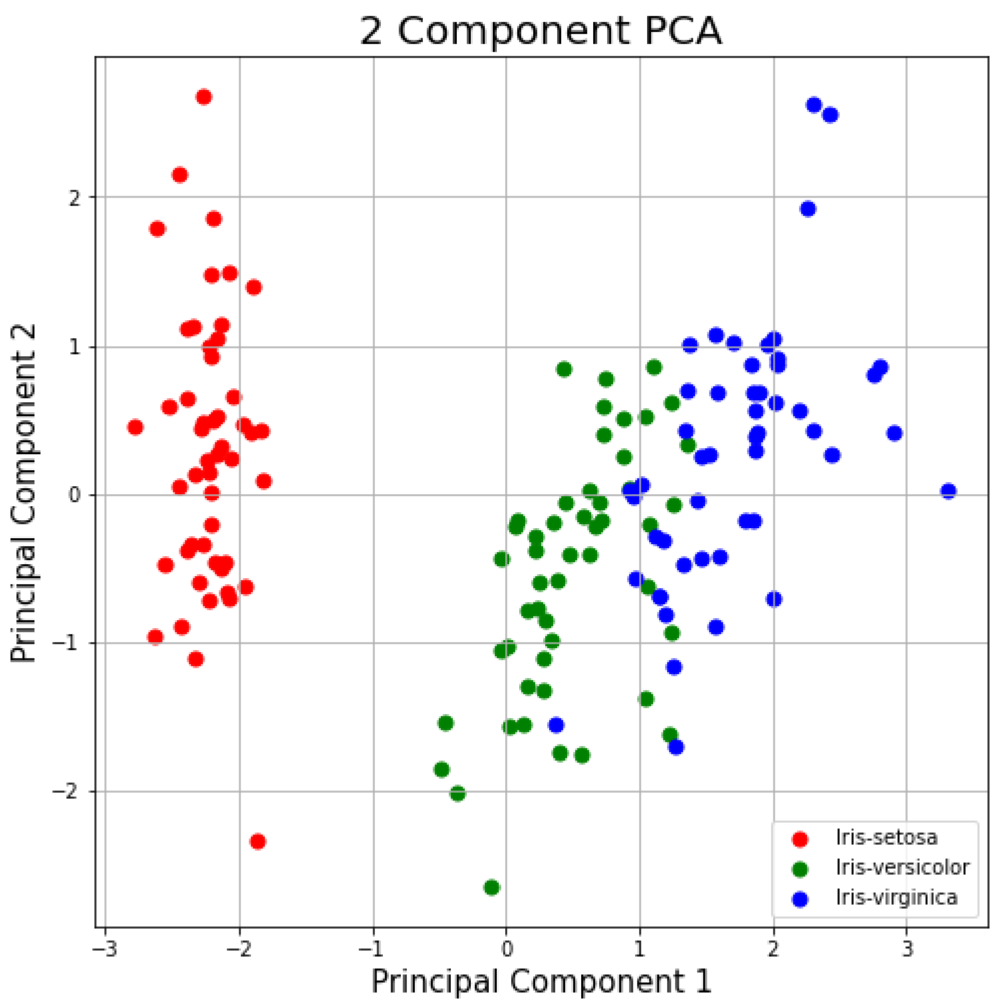
```
# Getting Target variable from the dataset
url = "https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data"
df = pd.read_csv(url
                 , names=['sepal length','sepal width','petal length','petal width','targe
y = df.loc[:,['target']].values
```

```
finalDf = pd.concat([principalDf, df[['target']]], axis = 1)
finalDf.head(5)
```

	principal component 1	principal component 2	target
0	-2.264703	0.480027	Iris-setosa
1	-2.080961	-0.674134	Iris-setosa
2	-2.364229	-0.341908	Iris-setosa
3	-2.299384	-0.597395	Iris-setosa
4	-2.389842	0.646835	Iris-setosa

```
fig = plt.figure(figsize = (8,8))
```

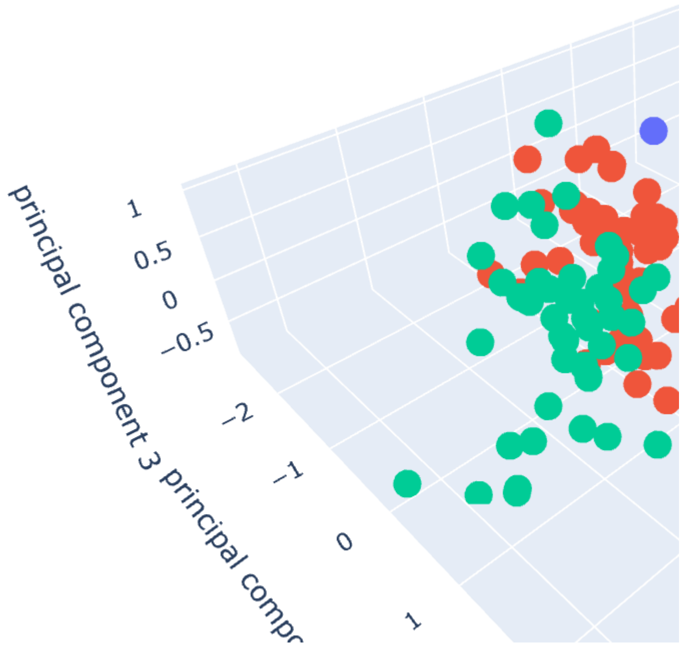
```
ax = fig.add_subplot(1,1,1)
ax.set_xlabel('Principal Component 1', fontsize = 15)
ax.set_ylabel('Principal Component 2', fontsize = 15)
ax.set_title('2 Component PCA', fontsize = 20)


targets = ['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
colors = ['r', 'g', 'b']
for target, color in zip(targets,colors):
    indicesToKeep = finalDf['target'] == target
    ax.scatter(finalDf.loc[indicesToKeep, 'principal component 1']
               , finalDf.loc[indicesToKeep, 'principal component 2']
               , c = color
               , s = 50)
ax.legend(targets)
ax.grid()
```




```
pca = PCA(n_components=3)
principalComponents = pca.fit_transform(x)
principalDf1 = pd.DataFrame(data = principalComponents
             , columns = ['principal component 1', 'principal component 2','principal comp
finalDf1 = pd.concat([principalDf1, df[['target']]], axis = 1)
finalDf1.head(5)
```

	principal component 1	principal component 2	principal component 3	target
0	-2.264703	0.480027	-0.127706	Iris-setosa
1	-2.080961	-0.674134	-0.234609	Iris-setosa
2	-2.364229	-0.341908	0.044201	Iris-setosa

```
import plotly.express as px
targets = ['Iris-setosa', 'Iris-versicolor', 'Iris-virginica']
colors = ['r', 'g', 'b']
fig = px.scatter_3d(finalDf1,x="principal component 1",y="principal component 2",z="princi
fig.show()
```



Differences between before and after using Feature Selection

```
#Before using Feature Selection
model_logistic = LogisticRegression(multi_class='multinomial', max_iter=1000)
model_logistic.fit(X_train, y_train)
predict = model_logistic.predict(X_test)
print(confusion_matrix(y_test, predict))
print(classification_report(y_test, predict))
```

```
[[14  0  0]
 [ 0 16  2]
 [ 0  1 12]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       0.94      0.89      0.91        18
           2       0.86      0.92      0.89        13

    accuracy                           0.93        45
   macro avg       0.93      0.94      0.93        45
weighted avg       0.94      0.93      0.93        45
```

```
#After using Feature Selection
model_logistic = LogisticRegression(solver='saga', multi_class='multinomial', max_iter=100
model_logistic.fit(X_train_f, y_train)
```

```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=10000,
                   multi_class='multinomial', n_jobs=None, penalty='l2',
                   random_state=None, solver='saga', tol=0.0001, verbose=0,
                   warm_start=False)
```

```
X_test_f = sel_f.transform(X_test)
print(X_test.shape)
print(X_test_f.shape)
```

```
(45, 14)
(45, 4)
```

```
predict = model_logistic.predict(X_test_f)
print(confusion_matrix(y_test, predict))
print(classification_report(y_test, predict))
```

```
[[14  0  0]
 [ 0 17  1]
 [ 0  0 13]]
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       1.00      0.94      0.97        18
           2       0.93      1.00      0.96        13

    accuracy                           0.98        45
   macro avg       0.98      0.98      0.98        45
weighted avg       0.98      0.98      0.98        45
```