```
!pip install pca
```

```
Collecting pca
  Downloading pca-2.0.5-py3-none-any.whl (35 kB)
Collecting datazets (from pca)
  Downloading datazets-0.1.9-py3-none-any.whl (51 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 51.3/51.3 kB 3.1 MB/s eta 0:00:00
Requirement already satisfied: statsmodels in /usr/local/lib/python3.10/dist-packages (from pca) (0.14.0)
Requirement already satisfied: matplotlib in /usr/local/lib/python3.10/dist-packages (from pca) (3.7.1)
Requirement already satisfied: numpy in /usr/local/lib/python3.10/dist-packages (from pca) (1.23.5)
Requirement already satisfied: scikit-learn in /usr/local/lib/python3.10/dist-packages (from pca) (1.2.2)
Requirement already satisfied: scipy in /usr/local/lib/python3.10/dist-packages (from pca) (1.11.4)
Collecting colourmap>=1.1.15 (from pca)
  Downloading colourmap-1.1.16-py3-none-any.whl (10 kB)
Requirement already satisfied: pandas in /usr/local/lib/python3.10/dist-packages (from pca) (1.5.3)
Collecting scatterd>=1.3.7 (from pca)
  Downloading scatterd-1.3.7-py3-none-any.whl (12 kB)
Collecting adjusttext (from pca)
  Downloading adjustText-0.8-py3-none-any.whl (9.1 kB)
Requirement already satisfied: seaborn in /usr/local/lib/python3.10/dist-packages (from scatterd>=1.3.7->pca) (0.12.2)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from datazets->pca) (2.31.0)
Requirement already satisfied: contourpy>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->pca) (1.2.0)
Requirement already satisfied: cycler>=0.10 in /usr/local/lib/python3.10/dist-packages (from matplotlib->pca) (0.12.1)
Requirement already satisfied: fonttools>=4.22.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->pca) (4.46.0)
Requirement already satisfied: kiwisolver>=1.0.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->pca) (1.4.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->pca) (23.2)
Requirement already satisfied: pillow>=6.2.0 in /usr/local/lib/python3.10/dist-packages (from matplotlib->pca) (9.4.0)
Requirement already satisfied: pyparsing>=2.3.1 in /usr/local/lib/python3.10/dist-packages (from matplotlib->pca) (3.1.1)
Requirement already satisfied: python-dateutil>=2.7 in /usr/local/lib/python3.10/dist-packages (from matplotlib->pca) (2.8.2)
Requirement already satisfied: pytz>=2020.1 in /usr/local/lib/python3.10/dist-packages (from pandas->pca) (2023.3.post1)
Requirement already satisfied: joblib>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->pca) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn->pca) (3.2.0)
Requirement already satisfied: patsy>=0.5.2 in /usr/local/lib/python3.10/dist-packages (from statsmodels->pca) (0.5.4)
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from patsy>=0.5.2->statsmodels->pca) (1.16.0)
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->datazets->pca) (
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->datazets->pca) (3.6)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->datazets->pca) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->datazets->pca) (2023.1
Installing collected packages: datazets, colourmap, adjusttext, scatterd, pca
Successfully installed adjusttext-0.8 colourmap-1.1.16 datazets-0.1.9 pca-2.0.5 scatterd-1.3.7
```

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
#from pca import pca
from sklearn.decomposition import PCA
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
import seaborn as sns

from sklearn.model_selection import train_test_split
from sklearn.linear_model import Lasso, LassoCV
from sklearn.model_selection import GridSearchCV

from sklearn.metrics import classification_report, confusion_matrix
from sklearn.preprocessing import StandardScaler
from sklearn import datasets, metrics
from sklearn.svm import SVC
from sklearn.pipeline import make_pipeline
import io
```

Step 2

Principal components

● Advantages:

Dimensionality Reduction: PCA reduces the number of features, simplifying the dataset.

Noise Reduction: It helps in filtering out noise and focusing on the most important features.

Visual Representation: Data can be visualized in a reduced-dimensional space, aiding interpretation.

● Basics:

Principal components are new variables which are the linear combinations of the original variables. It's also uncorrelated and most of the information is compressed into the first components.

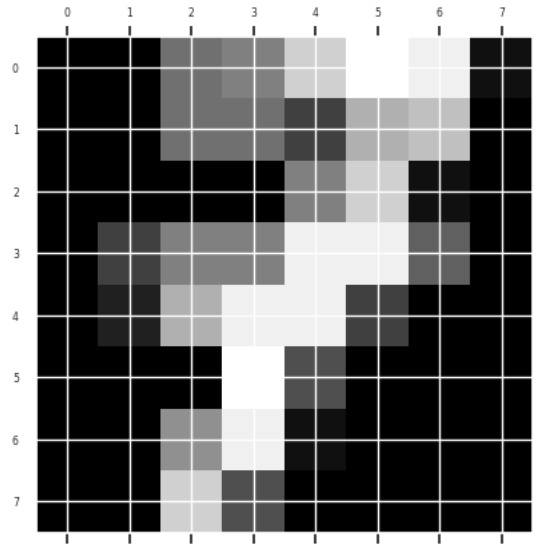
Principal components are orthogonal.

● Computation:

In the Jupyter Notebook, we show how the load_digits dataset look like by presenting one of the digits images, normalizing the data, plot the correlation matrix and extract features by running PCA() function in two methods: one is number of components can explain 90% of variance (Reduced number of components is 30) and the other is the number of components equal to 40. We select 40 as the optimal number of components by running GridSearchCV pipeline.

```
import pylab as pl
pl.gray()
pl.matshow(digits.images[7]) # for example, the image below show number seven
pl.show()
```

```
<Figure size 640x480 with 0 Axes>
```

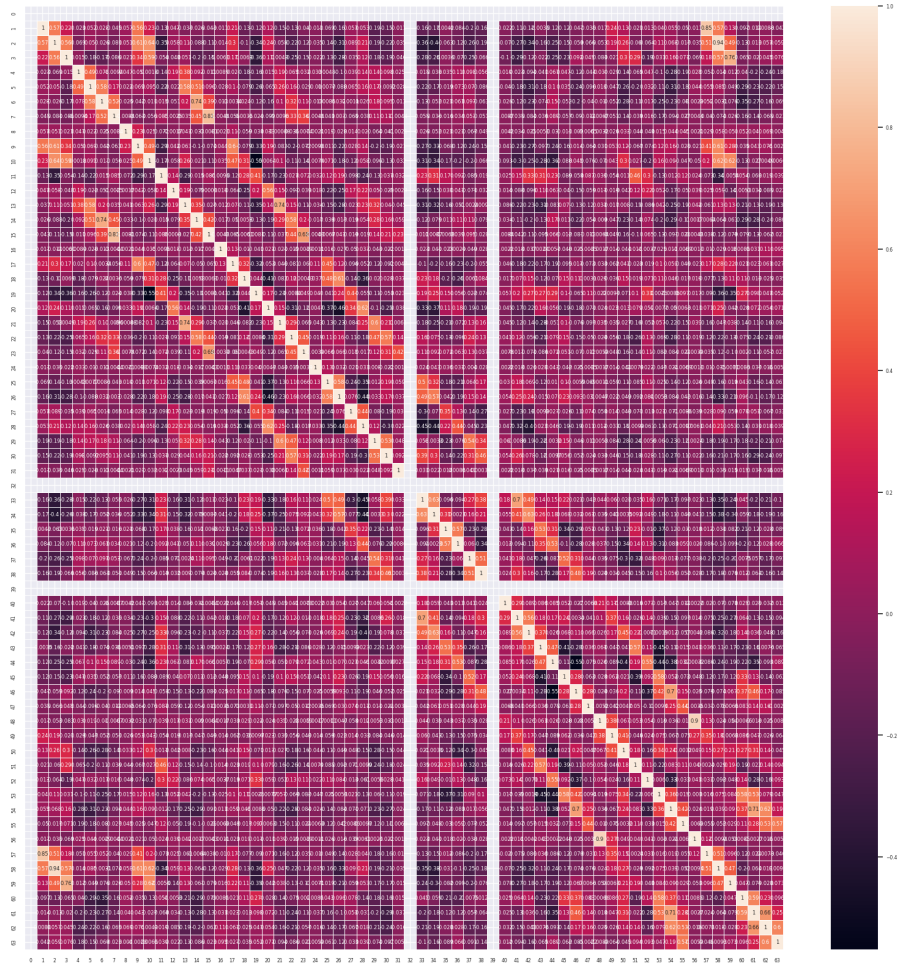



```
# Load dataset
X, y = load_digits(return_X_y=True)

print("Original Dataset: ", X.shape)

# normaliztion
scaler = StandardScaler()

X = scaler.fit_transform(X)

x_train, x_test, y_train, y_test =\
    train_test_split(X, y, test_size=0.5, random_state=0)

print("Training Dataset: ",x_train.shape)
```

```
Original Dataset:  (1797, 64)
Training Dataset:  (898, 64)
```

```
# correlation matrix before PCA: we can observe highly correlated between variables
fig, ax = plt.subplots(figsize=(20,20))
sns.set(font_scale=0.5)

sns.heatmap(pd.DataFrame(x_train).corr(), annot = True, linewidths=.5, ax=ax)
```

<Axes: >



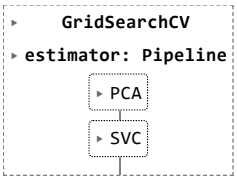
```
# Conducting Principal Component Analysis
# Create a PCA that will retain 90% of the variance
pca = PCA(n_components=0.90, whiten=True)

# Conducting PCA
X_pca = pca.fit_transform(x_train)
print(); print(X_pca)

# Show results
print('Original number of features:', X.shape[1])
print('Reduced number of features:', X_pca.shape[1])

# Creating a PCA with 40 components
pca = PCA(n_components=40, whiten=True)

# Conducting PCA
X_pca = pca.fit_transform(x_train)
print(); print(X_pca)

# Show results
print('Original number of features:', X.shape[1])
print('Reduced number of features:', X_pca.shape[1])
```

```
[[ 0.39428213 -0.11794026 -2.00824473 ... -0.46771563  0.01120593
  -0.9454381 ]
 [ 1.42002701  0.80981682 -0.04639556 ...  0.57220761 -2.14955656
   1.49799066]
 [-0.2728264  -0.27600715  1.52022356 ... -1.84371362  0.15094891
   0.05628399]
 ...
 [ 0.00317146  0.80183117 -1.10927771 ...  0.79341885  0.2859059
  -0.62553008]
 [ 0.36409986  1.32918771 -0.35147793 ... -1.72418078  1.27698293
  -1.12362758]
 [-0.66063429 -0.22658192 -0.10770459 ... -0.15098981 -0.33374598
  -0.04867542]]
Original number of features: 64
Reduced number of features: 30

[[ 0.39428212 -0.11794024 -2.00824476 ... -1.16632891 -0.97087483
   0.63638781]
 [ 1.42002702  0.80981681 -0.04639557 ... -0.24301572  0.54887616
   1.23390758]
 [-0.27282639 -0.27600716  1.52022361 ... -0.47187993 -0.33721025
   0.98099521]
 ...
 [ 0.00317146  0.80183119 -1.10927773 ... -0.5238322   0.28142619
  -0.38201506]
 [ 0.36409987  1.32918768 -0.35147786 ... -1.15530067  0.44643687
  -0.08036502]
 [-0.66063428 -0.22658191 -0.10770462 ...  0.11791919  0.64442256
  -0.55326712]]
Original number of features: 64
Reduced number of features: 40
```

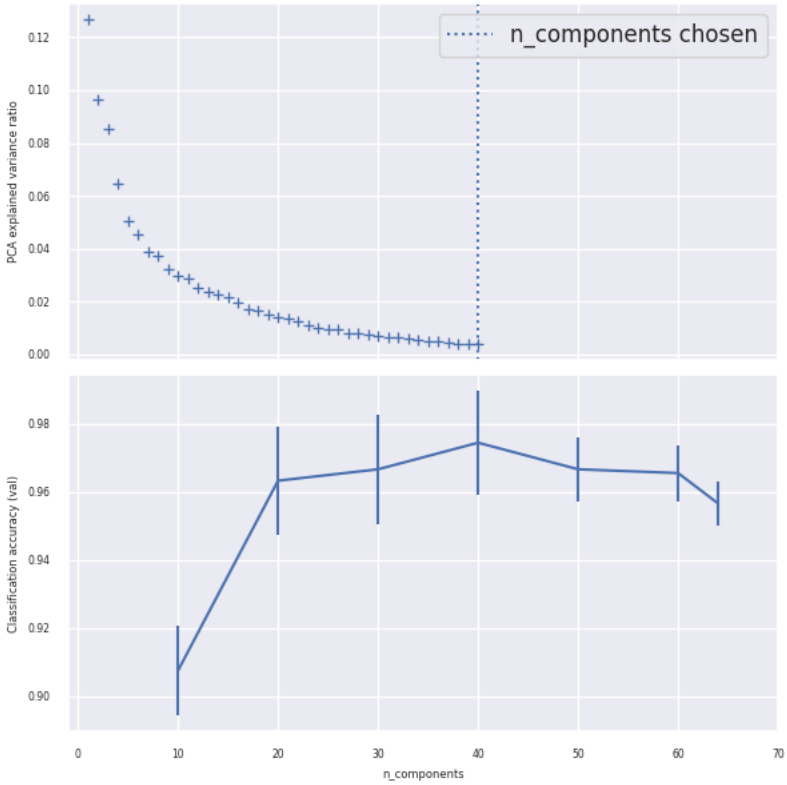
```
classifier = svm.SVC()
# Combine PCA and SVC to a pipeline
pipe = Pipeline(steps=[('pca', pca), ('svm', classifier)])

n_components = [10, 20, 30, 40, 50, 60, 64]

params_grid = {
    'svm__C': [1, 10, 100, 1000],
    'svm__kernel': ['linear', 'rbf'],
    'svm__gamma': [0.001, 0.0001],
    'pca__n_components': n_components,
}

estimator = GridSearchCV(pipe, params_grid)
estimator.fit(x_train, y_train)

print("Best parameter (CV score=%0.3f):" % estimator.best_score_)
print(estimator.best_params_)
```

```
Best parameter (CV score=0.974):
{'pca__n_components': 40, 'svm__C': 100, 'svm__gamma': 0.001, 'svm__kernel': 'rbf'}
```

```
estimator
```




```
# Plot the PCA
pca.fit(x_train)

fig, (ax0, ax1) = plt.subplots(nrows=2, sharex=True, figsize=(6, 6))
ax0.plot(
    np.arange(1, pca.n_components_ + 1), pca.explained_variance_ratio_, "+", linewidth=2
)
ax0.set_ylabel("PCA explained variance ratio")

ax0.axvline(
    estimator.best_estimator_.named_steps["pca"].n_components,
    linestyle=":",
    label="n_components chosen",
)
ax0.legend(prop=dict(size=12))

# For each number of components, find the best classifier results
results = pd.DataFrame(estimator.cv_results_)
components_col = "param_pca__n_components"
best_clfs = results.groupby(components_col).apply(
    lambda g: g.nlargest(1, "mean_test_score")
)

best_clfs.plot(
    x=components_col, y="mean_test_score", yerr="std_test_score", legend=False, ax=ax1
)
ax1.set_ylabel("Classification accuracy (val)")
ax1.set_xlabel("n_components")

plt.xlim(-1, 70)

plt.tight_layout()
plt.show()
```



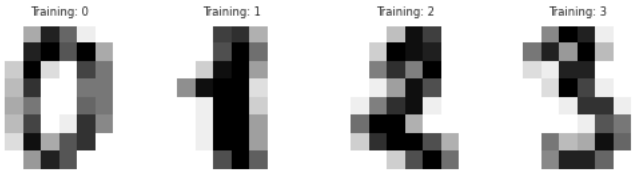
- Disadvantages:
  - Linearity Assumption: PCA assumes a linear relationship between variables, which might not always hold.
  - Information Loss: While reducing dimensions, some information is inevitably lost.
  - Interpretability: Principal components might not have a clear, interpretable meaning in the original feature space. In other words, we won't be able to interpret which variables are the top predictors. To know the top predictors, we will need to build the model without PCA.
- Equations:

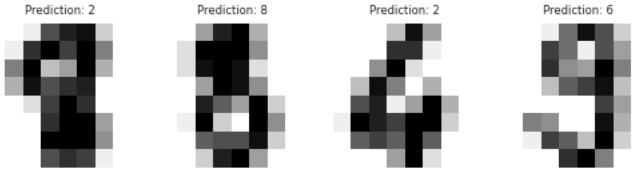
```
Step 1: standardization: transform all the variables to the same scale

z = (value - mean)/(standard deviation)

Step 2: compute covariance matrix

Cov(x,x) = Var(x)

Cov(x,y) = Cov(y,x)

Step 3: find the eigenvalues and eigenvectors

Step 4: feature vector: compute the eigenvectors and sort them by their eigenvalues in descending order. In this way, we can find the principal
```

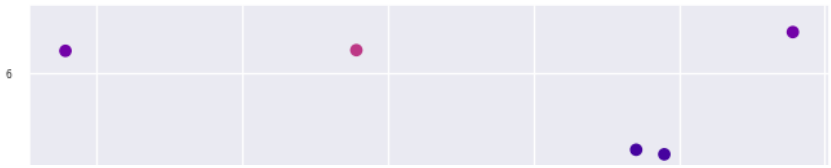
- Features:
  - Missing Values: PCA handles missing values well, making it suitable for datasets with incomplete information.
  - Multicollinearity: It is effective in dealing with multicollinearity, as principal components are orthogonal.
- Guide:
  - Inputs: High-dimensional dataset
  - Outputs: Lower-dimensional representation of the data (principal components)
- Hyperparameters:
  - Number of Components: The number of principal components to retain, which influences the amount of variance preserved.
- Illustration: Visualization & References

```
# The digits dataset
digits = datasets.load_digits()
X, y = load_digits(return_X_y=True)

scaler = StandardScaler()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=0)
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# We will show the four images for the training set and another four images for prediction
images_and_labels = list(zip(digits.images, digits.target))
for index, (image, label) in enumerate(images_and_labels[:4]):
    plt.subplot(2, 4, index + 1)
    plt.axis('off')
    plt.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    plt.title('Training: %i' % label)

# To apply a classifier on this data, we need to flatten the image, to
# turn the data in a (samples, feature) matrix:
n_samples = len(digits.images)
data = digits.images.reshape((n_samples, -1))

# Create a classifier: a support vector classifier
# We get the optimal number from GridSearch:
 # {'pca__n_components': 40, 'svm__C': 100, 'svm__gamma': 0.001, 'svm__kernel': 'rbf'}
pca = PCA(n_components=40)
scaler = StandardScaler()
x_train = pca.fit_transform(x_train)
x_test = pca.transform(x_test)
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)


classifier = SVC(C= 100, gamma=0.001, kernel = 'rbf')


# We learn the digits on the training set
#classifier.fit(data[:int(n_samples / 2)], digits.target[:int(n_samples / 2)])
classifier.fit(x_train, y_train)

# Now predict the value of the digit on test set:
#expected = digits.target[int(n_samples / 2):]
#predicted = classifier.predict(data[int(n_samples / 2):])
expected = y_test
predicted = classifier.predict(x_test)#

print("Classification report for classifier %s:\n%s\n"
      % (classifier, metrics.classification_report(expected, predicted)))
print("Confusion matrix:\n%s" % metrics.confusion_matrix(expected, predicted))

images_and_predictions = list(zip(digits.images[int(n_samples / 2):], predicted))
for index, (image, prediction) in enumerate(images_and_predictions[:4]):
    plt.subplot(2, 4, index + 5)
    plt.axis('off')
    plt.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    plt.title('Prediction: %i' % prediction)


plt.figure(figsize=(8,6))
plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap='plasma')
plt.xlabel('First principal component')
plt.ylabel('Second Principal Component')

plt.show()
```

```
Classification report for classifier SVC(C=100, gamma=0.001):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        89
           1       0.95      0.98      0.96        90
           2       0.96      1.00      0.98        92
           3       0.96      0.98      0.97        93
           4       0.95      1.00      0.97        76
           5       0.96      0.96      0.96       108
           6       0.99      0.98      0.98        89
           7       0.97      0.99      0.98        78
           8       0.98      0.86      0.91        92
           9       0.96      0.93      0.95        92

    accuracy                           0.97       899
   macro avg       0.97      0.97      0.97       899
weighted avg       0.97      0.97      0.97       899


Confusion matrix:
[[ 89   0   0   0   0   0   0   0   0   0]
 [  0  88   0   0   1   0   0   0   1   0]
 [  0   0  92   0   0   0   0   0   0   0]
 [  0   0   2  91   0   0   0   0   0   0]
 [  0   0   0   0  76   0   0   0   0   0]
 [  0   0   0   1   0 104   1   0   0   2]
 [  0   0   0   0   2   0  87   0   0   0]
 [  0   0   0   0   0   1   0  77   0   0]
 [  0   4   2   3   1   0   0   1  79   2]
 [  0   1   0   0   0   3   0   1   1  86]]
```







References

https://scikit-learn.org/stable/auto_examples/compose/plot_digits_pipe.html

dataset: https://scikit-learn.org/stable/modules/generated/sklearn.datasets.load_digits.html

SVC: https://scikit-learn.org/stable/modules/generated/sklearn.svm.SVC.html

Logistic regression: https://scikit-learn.sourceforge.net/dev/auto_examples/plot_digits_pipe.html

Logistic Python example: https://medium.com/@dlwilkinson/a-model-that-identifies-a-hand-written-number-using-logistic-regression-and-python-29308efd386a

Recognizing hand-written digits: https://scikit-learn.sourceforge.net/dev/auto_examples/classification/plot_digits_classification.html#example-classification-plot-digits-classification-py

● Journal:

Avellaneda, Marco and Lee, Jeong-Hyun, Statistical Arbitrage in the U.S. Equities Market (July 11, 2008). Available at SSRN: https://ssrn.com/abstract=1153505 or http://dx.doi.org/10.2139/ssrn.1153505

● Keywords:

Dimensionality Reduction, Eigenvectors, Eigenvalues, Multicollinearity, Feature Extraction, Data Visualization, Machine learning, risk model, clustering, k-means, statistical risk models, covariance, correlation, variance, cluster number, risk factor, optimization, regression, mean-reversion, factor loadings, industry classification, quant, trading, dollar-neutral, alpha, signal, backtest;alpha, optimization, regression, risk factor, factor model, style factor, volatility, turnover, momentum, correlation, covariance, variance, equities, Sharpe ratio; Futures term structure, Roll yield, Convenience yield, Contango, Backwardation, Commodity trading strategy; expected returns, implied volatility, realized volatility, volatility spread; interest rate, bond, risk management, factor model; Performance, Attribution, Fixed Income, Central Bank

Lasso

Boston Housing data has been removed from scikit-learn since version 1.2. and this is why I am manualy adding it because I think it is a good example for applying Lasso's feature extraction method

LASSO

Advantages: It can do feature selection as well as regularization and thus enhance the accuracy of the prediction as well as the interpretability of the given model. Given these features this model is very useful for higher dimensional data and especially when the features are more than the observations. Thanks to its penalty function this model lowers the coefficients of the not important features to zero and thus lowers the variables count so in practice this is how a feature reduction and selection can be conducted

Disadvantages: The main problems here are that it cannot deal with multicollinearity and since it is shrinking the coefficient to zero, there is the fact that some of the data is being lost. Also Lasso is very sensitive to noisy data, outliers and missing data.

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remount=True).
```

```
from google.colab import files
uploaded = files.upload()
```

```
Choose Files No file chosen  Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.
Saving BostonHousing.xlsx to BostonHousing (1).xlsx
```

```
# creating dataframe
data = pd.read_excel(io.BytesIO(uploaded.get('BostonHousing (1).xlsx')))
data.to_csv('Boston.csv', index=False)
data = pd.read_csv('Boston.csv')
df = pd.DataFrame(data)
df.head()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO	B	LSTAT	MEDV
0	0.00632	18.0	2.31	0.0	0.538	6.575	65.2	4.0900	1	296	15.3	396.90	4.98	24.0
1	0.02731	0.0	7.07	0.0	0.469	6.421	78.9	4.9671	2	242	17.8	396.90	9.14	21.6
2	0.02729	0.0	7.07	0.0	0.469	7.185	61.1	4.9671	2	242	17.8	392.83	4.03	34.7
3	0.03237	0.0	2.18	0.0	0.458	6.998	45.8	6.0622	3	222	18.7	394.63	2.94	33.4
4	0.06905	0.0	2.18	0.0	0.458	7.147	54.2	6.0622	3	222	18.7	396.90	NaN	36.2

```
df.describe()
```

	CRIM	ZN	INDUS	CHAS	NOX	RM	AGE	DIS	RAD	TAX	PTRATIO
count	486.000000	486.000000	486.000000	486.000000	506.000000	506.000000	486.000000	506.000000	506.000000	506.000000	506.000000
mean	3.611874	11.211934	11.083992	0.069959	0.554695	6.284634	68.518519	3.795043	9.549407	408.237154	18.455534
std	8.720192	23.388876	6.835896	0.255340	0.115878	0.702617	27.999513	2.105710	8.707259	168.537116	2.164946
min	0.006320	0.000000	0.460000	0.000000	0.385000	3.561000	2.900000	1.129600	1.000000	187.000000	12.600000
25%	0.081900	0.000000	5.190000	0.000000	0.449000	5.885500	45.175000	2.100175	4.000000	279.000000	17.400000
50%	0.253715	0.000000	9.690000	0.000000	0.538000	6.208500	76.800000	3.207450	5.000000	330.000000	19.050000
75%	3.560263	12.500000	18.100000	0.000000	0.624000	6.623500	93.975000	5.188425	24.000000	666.000000	20.200000
max	88.976200	100.000000	27.740000	1.000000	0.871000	8.780000	100.000000	12.126500	24.000000	711.000000	22.000000

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 506 entries, 0 to 505
Data columns (total 14 columns):
 #   Column   Non-Null Count  Dtype  
---  ------   --------------  -----  
 0   CRIM     486 non-null    float64
 1   ZN       486 non-null    float64
 2   INDUS    486 non-null    float64
 3   CHAS     486 non-null    float64
 4   NOX      506 non-null    float64
 5   RM       506 non-null    float64
 6   AGE      486 non-null    float64
 7   DIS      506 non-null    float64
 8   RAD      506 non-null    int64  
 9   TAX      506 non-null    int64  
 10  PTRATIO  506 non-null    float64
 11  B        506 non-null    float64
 12  LSTAT    486 non-null    float64
 13  MEDV     506 non-null    float64
dtypes: float64(12), int64(2)
memory usage: 55.5 KB
```

```
# looking at null values

df.isna().sum()
```

```
CRIM       20
ZN         20
INDUS      20
CHAS       20
NOX         0
RM          0
AGE        20
DIS         0
RAD         0
TAX         0
PTRATIO     0
B           0
LSTAT      20
MEDV        0
dtype: int64
```

```
# creating features and label variable

X = df.drop(columns = 'MEDV', axis = 1)
y = df['MEDV']


from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

```
# checking for multicollinearity using `VIF` and `correlation matrix`

from statsmodels.stats.outliers_influence import variance_inflation_factor

vif = pd.DataFrame()

vif['VIF'] = [variance_inflation_factor(X_scaled, i) for i in range(X_scaled.shape[1])]
vif['Features'] = X.columns

vif
```

	VIF	Features
0	1.741404	CRIM
1	2.321843	ZN
2	4.049690	INDUS
3	1.069182	CHAS
4	4.495772	NOX
5	2.107004	RM
6	3.173844	AGE
7	3.827427	DIS
8	6.986683	RAD
9	8.651382	TAX
10	1.810597	PTRATIO
11	1.372310	B
12	3.156334	LSTAT

VIF values of TAX and RAD are more than 5 so this suggests multicolinearity and we have to drop them but let's try LASSO to see how it would do feature selection.

```
# splitting data into training asnd test set



X_train, X_test, y_train, y_test = train_test_split(X_scaled, y, test_size = 0.30, random_state = 0)
```

Let's do Lasso regression witouth hyperparamether optimization and then do the optimization to see what are the differences

```
lasso_cv = LassoCV(alphas = None, cv = 10, max_iter = 100000)
lasso_cv.fit(X_train, y_train)
```

```
LassoCV
LassoCV(cv=10, max_iter=100000)
```

```
# best alpha parameter

alpha = lasso_cv.alpha_
alpha
```

```
0.03434203675429976
```

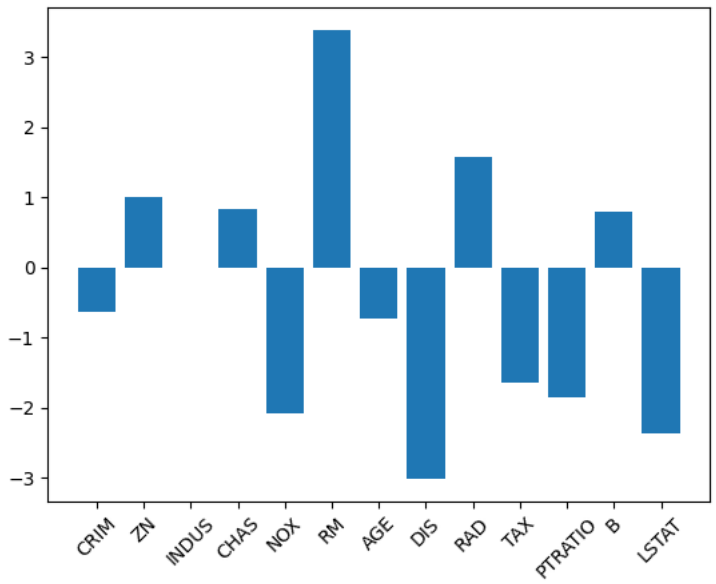
```
lasso = Lasso(alpha = lasso_cv.alpha_)
lasso.fit(X_train, y_train)
```

```
Lasso
Lasso(alpha=0.03434203675429976)
```

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

plt.bar(df.columns.drop('MEDV'), lasso_coef)
```

```
plt.xticks(rotation=45)
plt.show()
```

```
[-0.62955137  0.99802139 -0.          0.83861977 -2.0823349   3.39185003
 -0.72637875 -3.00768374  1.57745795 -1.64412616 -1.84683468  0.80482367
 -2.36248729]
```



Thanks to Lasso we can drop "INDUS", "AGE", "B" features because they have the lowest Lasso gradings so they must be the least important.
Thanks to VIF we can drop "TAX" feature and this is how we do feature selection that helps us for our further analyses.

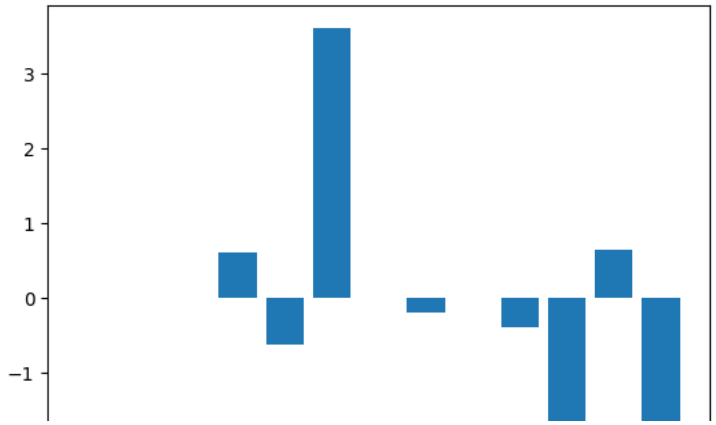
And now lets do hyperparamether optimization to see the difference

```
from sklearn.model_selection import GridSearchCV

# Initialize a Lasso Regression model
lasso = Lasso()

# Set up a parameter grid for "alpha"
param_grid = {'alpha': np.linspace(0.01, 1, 100)}

# Set up the grid search
grid = GridSearchCV(lasso, param_grid, cv=5)

# Fit the grid search object to the training data
grid.fit(X, y)

# Print the best parameters
print("Best parameters: ", grid.best_params_)
```

```
Best parameters:  {'alpha': 0.44}
```

```
lasso = Lasso(alpha = 0.44)
lasso.fit(X_train, y_train)

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

plt.bar(df.columns.drop('MEDV'), lasso_coef)
plt.xticks(rotation=45)
plt.show()
```

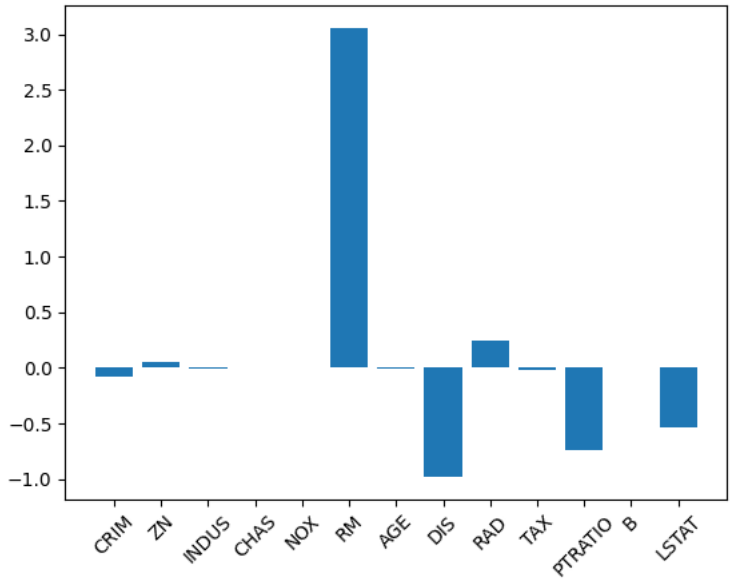
```
[-0.          0.         -0.          0.60439718 -0.62103334  3.61717134
 -0.         -0.1885397  -0.         -0.39204147 -1.72128864  0.63996429
 -2.39037187]
```



Now we see even better feature selection and extraction because most of the features that are close to zero can be dropped because the Lasso tells us that they are not important. Now let's fit Lasso to the entire data

```
# Instantiate a lasso regression model
lasso = Lasso(alpha=0.44)

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

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

plt.bar(df.columns.drop('MEDV'), lasso_coef)
plt.xticks(rotation=45)
plt.show()
```

```
[-0.07811823  0.0564804  -0.01032963  0.         -0.          3.05863836
 -0.00857984 -0.97738459  0.24677189 -0.01551692 -0.73960154  0.01003942
 -0.54067927]
```



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1.) Lari Giba, Lasso Regression Explained, Step by Step, https://machinelearningcompass.com/machine_learning_models/lasso_regression/

2.) Tibshirani, Robert (1996). "Regression Shrinkage and Selection via the lasso". Journal of the Royal Statistical Society. Series B (methodological). Wiley. 58 (1): 267–88. JSTOR 2346178

3.) Jim Frost, Mean Squared Error (MSE), Statistics By Jim, https://statisticsbyjim.com/regression/mean-squared-error-mse/

4.) Gareth James, Daniela Witten, Trevor Hastie, Robert Tibshirani; An Introduction to Statistical Learning; Springer

5.) Tahera Firdose, Lasso Regression: A Comprehensive Guide to Feature Selection and Regularization, Medium

6.) Lasso documentation in sklearn.linear_model.Lasso

7.) Boston housing data: https://www.kaggle.com/datasets/altavish/boston-housing-dataset

or:

http://lib.stat.cmu.edu/datasets/boston

● Journal:

“Lasso Regressions and Forecasting Models in Applied Stress Testing” by Jorge A. Chan-Lau, published by the International Monetary Fund.

● Keywords:

LASSO, Regression, Regularization, Feature Selection, High-Dimensional Data, Overfitting, Model Selection, Machine Learning, Finance, Stress Testing

Clustering

- Clustering:

  It’s a method of unsupervised learning which organizes the data points into a number of groups based on the similarities in attributes of data points. K-means clustering is an example of clustering which is based on centroid-based algorithms or distance-based algorithms and the number of clusters are already defined or fixed.

- Advantages:

  • It’s very easy to implement and understand.

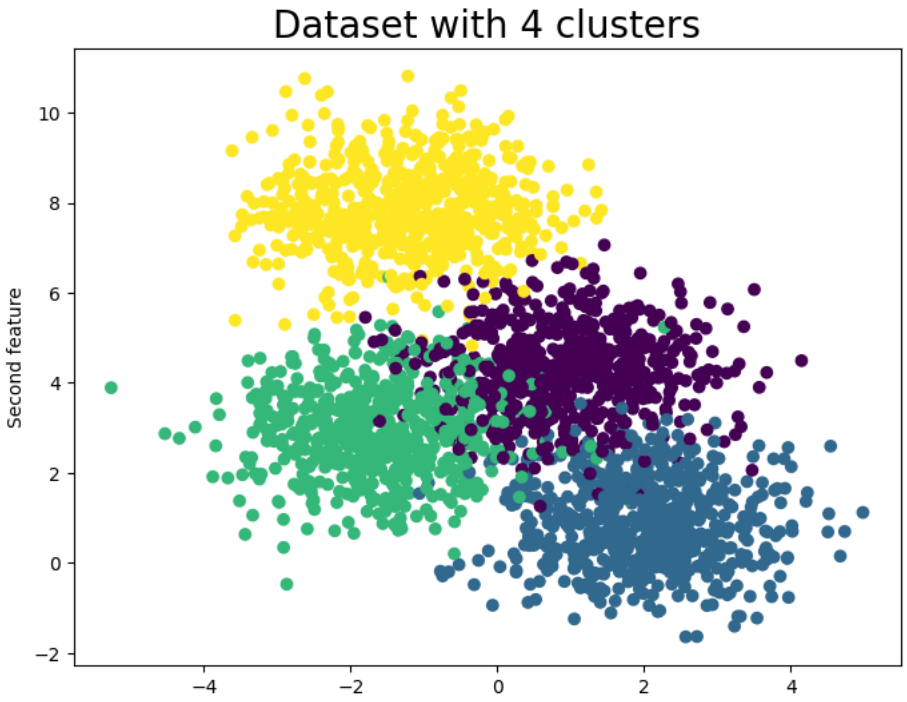
  • It can be easily adapted to new examples.

  • Re-computation of centroid is an advantage for K-means clustering.

- Computation: A Jupyter notebook that illustrates the method below:

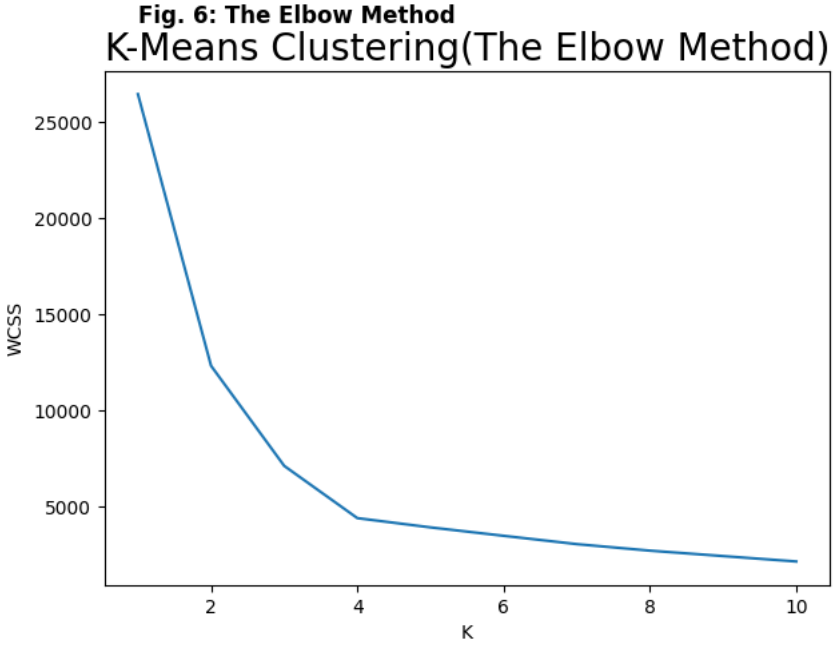
```
# Import packages

import matplotlib.pyplot as plt
import numpy as np
from sklearn.cluster import KMeans
from sklearn.datasets import make_blobs

np.random.seed(0)

%matplotlib inline


X, y = make_blobs(centers=4, n_samples=2500)

fig = plt.figure(figsize=(8, 6))
plt.scatter(X[:, 0], X[:, 1], c=y)
plt.title("Dataset with 4 clusters", fontsize=20)
plt.xlabel("First feature")
plt.ylabel("Second feature")
plt.suptitle(
    "Fig. 5: Dataset Visualization", fontweight="bold", horizontalalignment="right"
)
plt.show()
```

Fig. 5: Dataset Visualization



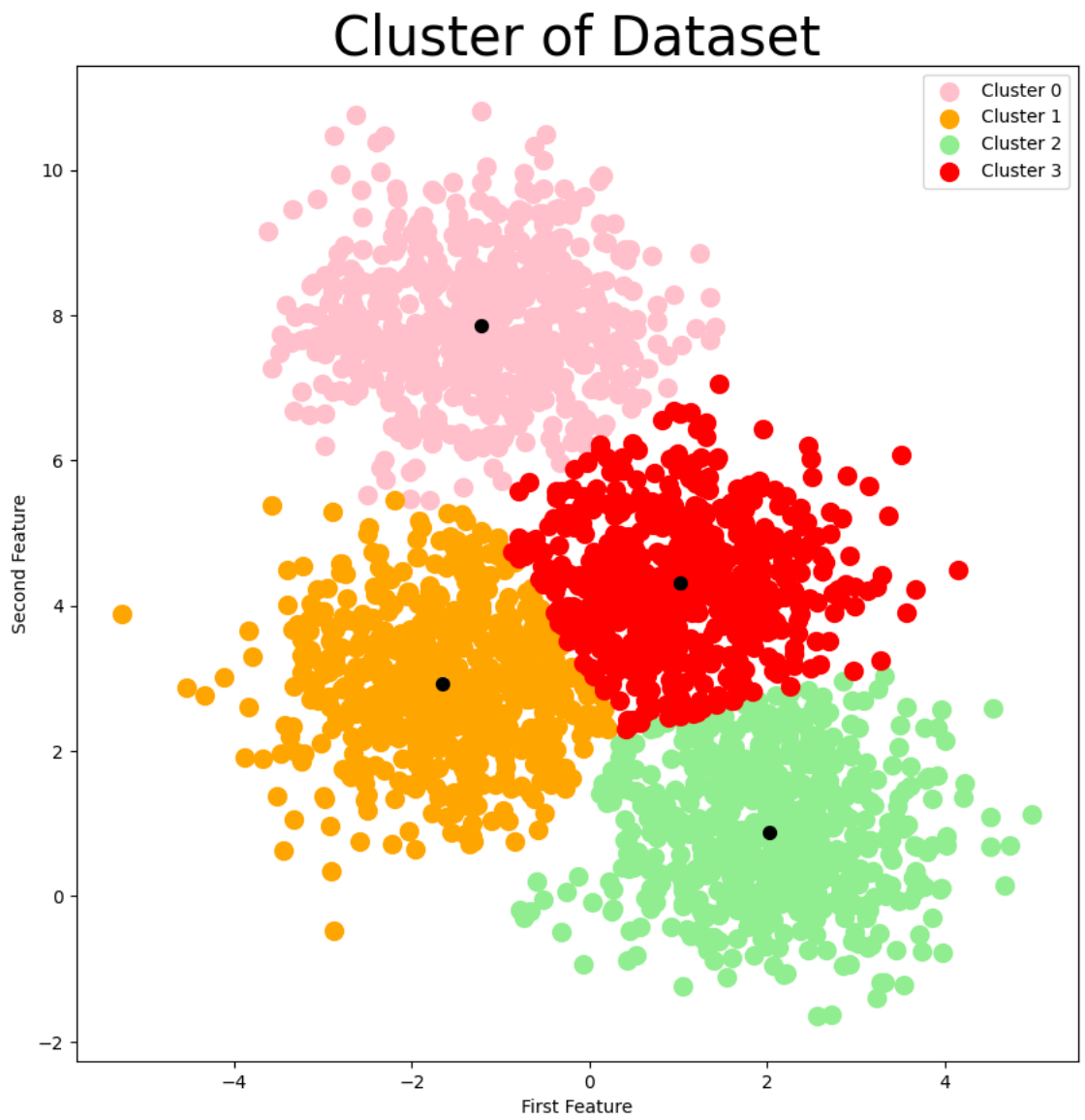

```
wcss = []
for i in range(1, 11):
    kmeans = KMeans(
        n_clusters=i, init="k-means++", max_iter=300, n_init=10, random_state=42
    )
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)

plt.rcParams["figure.figsize"] = (7, 5)
plt.plot(range(1, 11), wcss)
plt.title("K-Means Clustering(The Elbow Method)", fontsize=20)
plt.xlabel("K")
plt.ylabel("WCSS")
plt.suptitle("Fig. 6: The Elbow Method", fontweight="bold", horizontalalignment="right")
plt.show()
```

Fig. 6: The Elbow Method



```
kmeans = KMeans(n_clusters=4, init="k-means++", max_iter=300, n_init=10, random_state=0)
ymeans = kmeans.fit_predict(X)

plt.rcParams["figure.figsize"] = (10, 10)
plt.title("Cluster of Dataset", fontsize=30)

plt.scatter(X[ymeans == 0, 0], X[ymeans == 0, 1], s=100, c="pink", label="Cluster 0")
plt.scatter(X[ymeans == 1, 0], X[ymeans == 1, 1], s=100, c="orange", label="Cluster 1")
plt.scatter(
    X[ymeans == 2, 0], X[ymeans == 2, 1], s=100, c="lightgreen", label="Cluster 2"
)
plt.scatter(X[ymeans == 3, 0], X[ymeans == 3, 1], s=100, c="red", label="Cluster 3")
plt.scatter(
    kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s=50, c="black"
)

plt.xlabel("First Feature")
plt.ylabel("Second Feature")
plt.legend()
# `plt.suptitle`('Fig 10: Clustering Results', fontsize=20, y = 1, ha = 'right')
plt.suptitle(
    "Fig. 7: Clustering Results", fontweight="bold", horizontalalignment="right"
)
plt.show()
```

Fig. 7: Clustering Results



- Disadvantages:

- Selection of number of clusters before modelling and output is strongly impacted by this number.
- K-means only works with linear cluster boundaries.
- It's very sensitive to rescaling which means if we normalize or standardize our data then the output might be completely changed.
- It doesn't work good for big data and if clusters are having complex geometrical shape.

- Equations: Equations that summarize how the model works

Step 1:
Selecting K centroids where K is the number of clusters. Let $X=\{x1,x2,\cdots,xn\}$ be our data points and $V=\{v1,v2,\cdots,vc\}$ be the centroids.

Step 2:
Select centroids randomly and calculate the distance between centroids and each data point.

Step 3:
Then assign the data points to the centroids closest to them. And after that recalculate the new centroids by computing the mean of the groupi

$vi=(1/ci)\sum j=1cixj$
where ci is the number of data points in the ith cluster.

Step 4:
Find the distance between the new centroid and each data point. If there is no change in the composition of the clusters then we stop, or else

Mathematically, the objective of the K-means algorithm is to minimize an objective function which in our case is a squared error function give
$J=\sum j=1k\sum i=1n||xji-Cj||2$

where
$||xji-Cj||2||$
is the Euclidean distance between data points xi and the centroid Cj

- Features: Features of the model (e.g., works well with missing values)
  - It works well with various types of attributes
  - It can deal with noise and outliers
  - It can handle high dimensionality

- Guide:

  Inputs- Dataset as a collection of data points of different attributes.

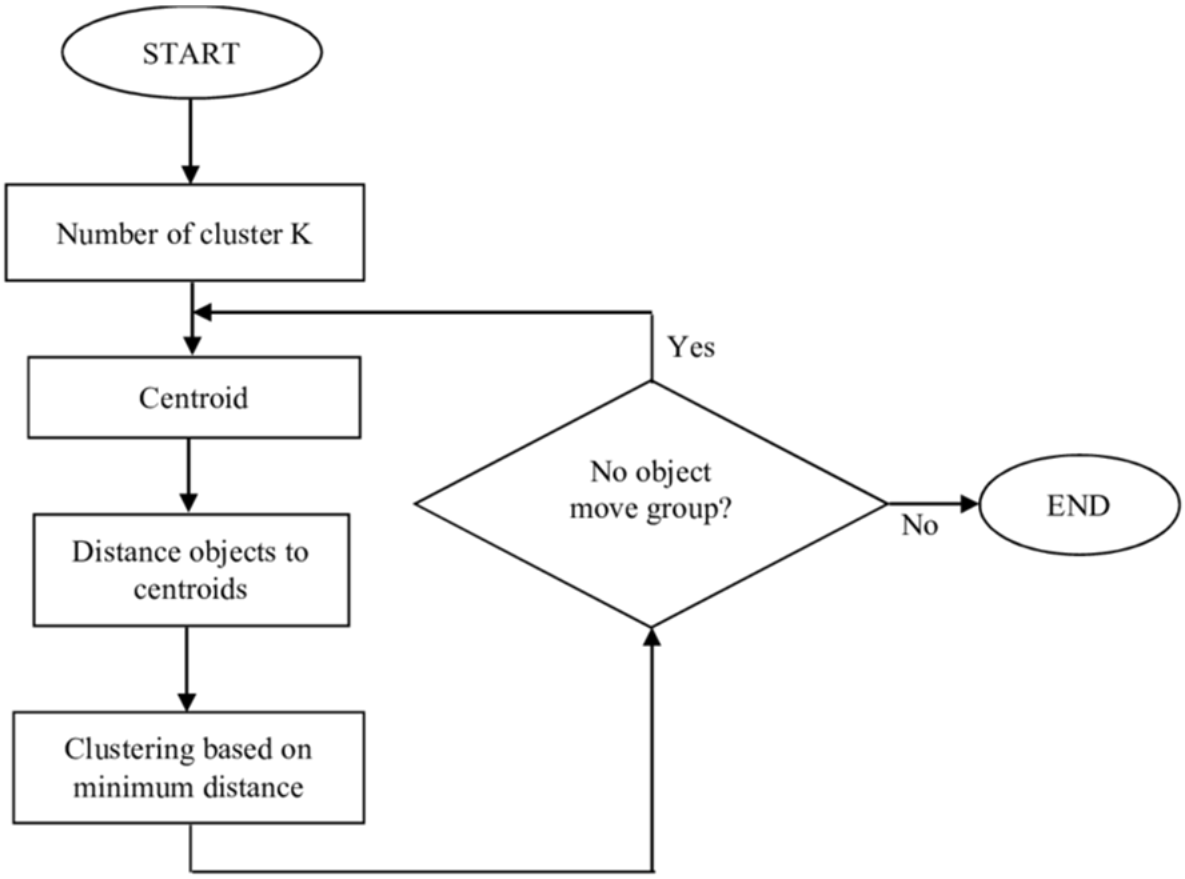
  Output- Assignment of each data point to one of the K clusters and then gives the value of centroid of clusters.

- Hyperparameters:

  The number of clusters- this is fixed before modelling, and it can be decided with the help of different methods like Silhouette analysis or elbow method.

  Number of Iterations- It determines how many times the assignment or steps followed in algorithm to be done and it helps the algorithm time.

- Illustration:



- Journal:
  1. Article by Priya Pedamkar - https://www.educba.com/k-means-clustering-algorithm/
  2. Combination of K-means clustering with Genetic Algorithm: A review by Diyar Qader Zeebaree, Habibollah Haron, Adnan Mohsin Abdulazeez and Subhi R. M. Zeebaree. Available at- International Journal of Applied Engineering Research ISSN 0973-4562 Volume 12, Number 24 (2017) pp. 14238-14245 https://www.academia.edu/download/55576223/Combination_of_K-means_clustering_with_Genetic_Algorithm_A_review.pdf

- Keywords:

  Clusters, K-means algorithm, Centroids, Centroid-based algorithms, Distance metrics, Euclidean distance, Elbow method, Silhouette analysis, Random initialization, Noise, Outliers, Attributes, Dimensions, Dimensionality, Normalization, Standardization, Scalability, Data analysis, Dataset, Data points, optimization

Step 3: Technical Section

Tuning K-Means Hyperparameter:

Tuning in K-means clustering is done with the finding of K value that is the number of optimal clusters. There is no direct method to find the optimal value of K so we do the tuning with the help of various methods. Here, we did the tuning or find the optimal value of K by using Silhouette analysis and Elbow method which help us to find the optimal value of K. In this given project we got the optimal value of K as 4.

Support Vector Machines (SVM) with Principal Component Analysis (PCA)

1. SVM Hyperparameters:

- C (Regularization parameter): The C parameter trades off correct classification of training examples against maximization of the decision function's margin. We compare the list of Regularization parameters: [1, 10, 100, 1000]. By Grid Search, we find 100 as the optimal regularization parameter.

- Kernel Parameters: from the example below, we use a kernel (e.g., radial basis function - RBF), thus we need to tune kernel-specific parameters (e.g. gamma). We compare the list of Kernel parameters: [0.001, 0.0001]. By Grid Search, we find 0.001 as the optimal kernel parameter.
- Kernel Choice: there are various choices, such as linear, polynomial, and RBF. We compare the list of Kernel methods: ['linear', 'rbf']. By Grid Search, we find RBF as the optimal kernel choice.

2. PCA Hyperparameters:

- Number of Components: we can observe from the plot of cumulative explained variance and by Grid Search in the list of number of components ([10, 20, 30, 40, 50, 60, 64]), we decide 40 as the optimal number of components.

By Grid search, we have the optimal hyperparameter:

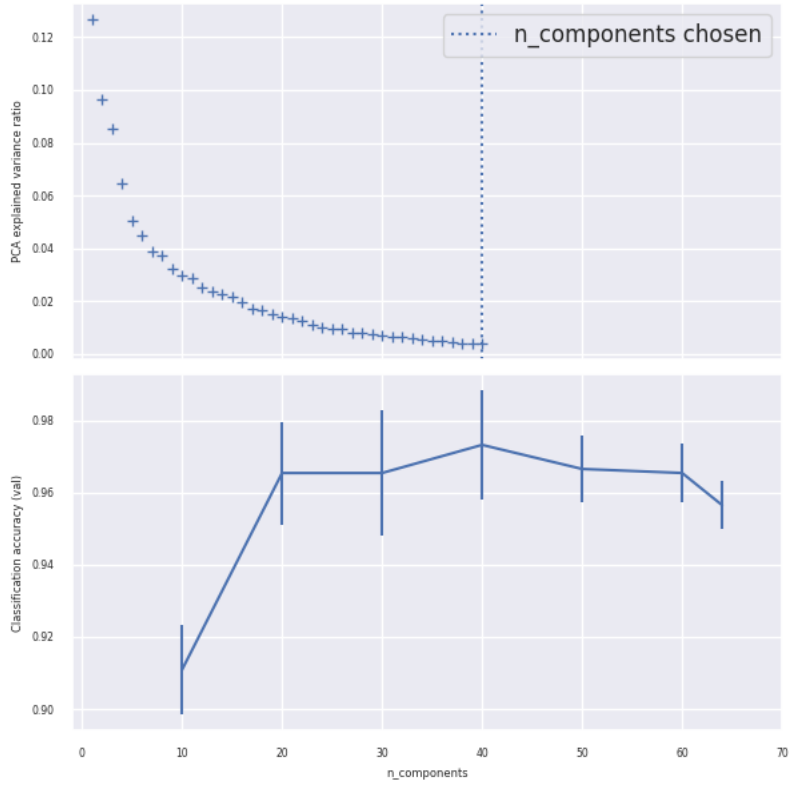
{'pca__n_components': 40, 'svm__C': 100, 'svm__gamma': 0.001, 'svm__kernel': 'rbf'}

Furthermore, with the optimal hyperparameters above, we have performance metrics, such as precision, recall, and F1-score, which are at 97% on average. In addition, further advanced techniques are Bayesian Optimization and Ensemble Methods.

```
 # {'pca__n_components': 40, 'svm__C': 100, 'svm__gamma': 0.001, 'svm__kernel': 'rbf'}
classifier = svm.SVC()
# Combine PCA and SVC to a pipeline
pipe = Pipeline(steps=[('pca', pca), ('svm', classifier)])

n_components = [10, 20, 30, 40, 50, 60, 64]

params_grid = {
    'svm__C': [1, 10, 100, 1000],
    'svm__kernel': ['linear', 'rbf'],
    'svm__gamma': [0.001, 0.0001],
    'pca__n_components': n_components,
}

estimator = GridSearchCV(pipe, params_grid)
estimator.fit(x_train, y_train)

print("Best parameter (CV score=%0.3f):" % estimator.best_score_)
print(estimator.best_params_)
```

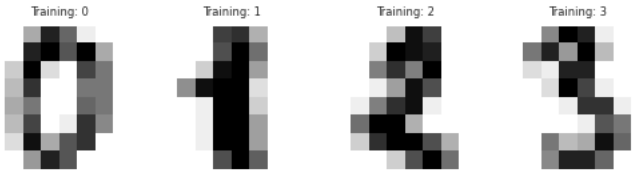
```
Best parameter (CV score=0.973):
{'pca__n_components': 40, 'svm__C': 100, 'svm__gamma': 0.001, 'svm__kernel': 'rbf'}
```

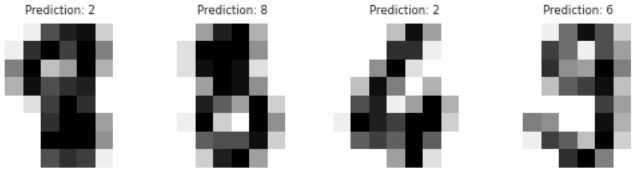
```
# Plot the PCA
pca.fit(x_train)

fig, (ax0, ax1) = plt.subplots(nrows=2, sharex=True, figsize=(6, 6))
ax0.plot(
    np.arange(1, pca.n_components_ + 1), pca.explained_variance_ratio_, "+", linewidth=2
)
ax0.set_ylabel("PCA explained variance ratio")

ax0.axvline(
    estimator.best_estimator_.named_steps["pca"].n_components,
    linestyle=":",
    label="n_components chosen",
)
ax0.legend(prop=dict(size=12))

# For each number of components, find the best classifier results
results = pd.DataFrame(estimator.cv_results_)
components_col = "param_pca__n_components"
best_clfs = results.groupby(components_col).apply(
    lambda g: g.nlargest(1, "mean_test_score")
)

best_clfs.plot(
    x=components_col, y="mean_test_score", yerr="std_test_score", legend=False, ax=ax1
)
ax1.set_ylabel("Classification accuracy (val)")
ax1.set_xlabel("n_components")

plt.xlim(-1, 70)

plt.tight_layout()
plt.show()
```

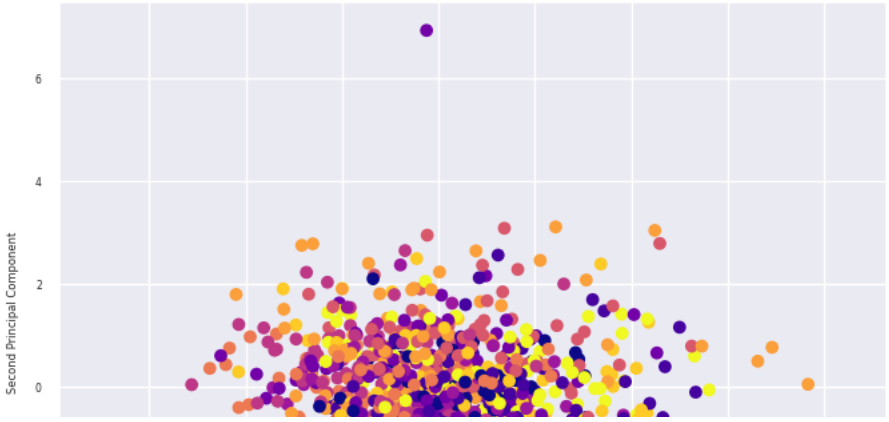


```
# The digits dataset
digits = datasets.load_digits()
X, y = load_digits(return_X_y=True)

scaler = StandardScaler()
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.5, random_state=0)
X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)

# We will show the four images for the training set and another four images for prediction
images_and_labels = list(zip(digits.images, digits.target))
for index, (image, label) in enumerate(images_and_labels[:4]):
    plt.subplot(2, 4, index + 1)
    plt.axis('off')
    plt.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    plt.title('Training: %i' % label)

# To apply a classifier on this data, we need to flatten the image, to
# turn the data in a (samples, feature) matrix:
n_samples = len(digits.images)
data = digits.images.reshape((n_samples, -1))

# Create a classifier: a support vector classifier
# We get the optimal number from GridSearch:
 # {'pca__n_components': 40, 'svm__C': 100, 'svm__gamma': 0.001, 'svm__kernel': 'rbf'}
pca = PCA(n_components=40)
scaler = StandardScaler()
x_train = pca.fit_transform(x_train)
x_test = pca.transform(x_test)
x_train = scaler.fit_transform(x_train)
x_test = scaler.transform(x_test)


classifier = SVC(C= 100, gamma=0.001, kernel = 'rbf')


# We learn the digits on the training set
#classifier.fit(data[:int(n_samples / 2)], digits.target[:int(n_samples / 2)])
classifier.fit(x_train, y_train)

# Now predict the value of the digit on test set:
#expected = digits.target[int(n_samples / 2):]
#predicted = classifier.predict(data[int(n_samples / 2):])
expected = y_test
predicted = classifier.predict(x_test)#

print("Classification report for classifier %s:\n%s\n"
      % (classifier, metrics.classification_report(expected, predicted)))
print("Confusion matrix:\n%s" % metrics.confusion_matrix(expected, predicted))

images_and_predictions = list(zip(digits.images[int(n_samples / 2):], predicted))
for index, (image, prediction) in enumerate(images_and_predictions[:4]):
    plt.subplot(2, 4, index + 5)
    plt.axis('off')
    plt.imshow(image, cmap=plt.cm.gray_r, interpolation='nearest')
    plt.title('Prediction: %i' % prediction)


plt.figure(figsize=(8,6))
plt.scatter(x_train[:,0],x_train[:,1],c=y_train,cmap='plasma')
plt.xlabel('First principal component')
plt.ylabel('Second Principal Component')

plt.show()
```

```
Classification report for classifier SVC(C=100, gamma=0.001):
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        89
           1       0.95      0.98      0.96        90
           2       0.96      1.00      0.98        92
           3       0.96      0.98      0.97        93
           4       0.95      1.00      0.97        76
           5       0.96      0.96      0.96       108
           6       0.99      0.98      0.98        89
           7       0.97      0.99      0.98        78
           8       0.98      0.86      0.91        92
           9       0.96      0.93      0.95        92

    accuracy                           0.97       899
   macro avg       0.97      0.97      0.97       899
weighted avg       0.97      0.97      0.97       899


Confusion matrix:
[[ 89   0   0   0   0   0   0   0   0   0]
 [  0  88   0   0   1   0   0   0   1   0]
 [  0   0  92   0   0   0   0   0   0   0]
 [  0   0   2  91   0   0   0   0   0   0]
 [  0   0   0   0  76   0   0   0   0   0]
 [  0   0   0   1   0 104   1   0   0   2]
 [  0   0   0   0   2   0  87   0   0   0]
 [  0   0   0   0   0   1   0  77   0   0]
 [  0   4   2   3   1   0   0   1  79   2]
 [  0   1   0   0   0   3   0   1   1  86]]
```







Double-click (or enter) to edit

Step 4: Marketing Alpha

As a group, the team members work together on a section called “Marketing Alpha,” which integrates the advantages and features from the individual reports to show how ML techniques can do well. The result is 1–2 pages.

K-Means Clustering

K-Means Clustering method is less computationally intensive and hence it's suitable for very large datasets. Once we have the optimal number of clusters defined then the result of K-means clustering is relevant as we see in the above example where we defined the number of clusters as four and hence, we get all the data points perfectly fit into these clusters. However, if we run the algorithms many times, we will have different results in this method. Also, it's not good for the data points having similar attributes as all of them move into the same cluster and hence defining the structure of data points will be difficult using this method.

Principal components

● Advantages:

Dimensionality Reduction: PCA reduces the number of features, simplifying the dataset.

Noise Reduction: It helps in filtering out noise and focusing on the most important features.

Visual Representation: Data can be visualized in a reduced-dimensional space, aiding interpretation.

● Features:

Missing Values: PCA handles missing values well, making it suitable for datasets with incomplete information.

Multicollinearity: It is effective in dealing with multicollinearity, as principal components are orthogonal.

```
# correlation matrix before PCA: we can observe highly correlated between variables
# Load dataset
X, y = load_digits(return_X_y=True)

print("Original Dataset: ", X.shape)

# normaliztion
scaler = StandardScaler()

X = scaler.fit_transform(X)

x_train, x_test, y_train, y_test =\
    train_test_split(X, y, test_size=0.5, random_state=0)

print("Training Dataset: ",x_train.shape)
fig, ax = plt.subplots(figsize=(20,20))
sns.set(font_scale=0.5)

sns.heatmap(pd.DataFrame(x_train).corr(), annot = True, linewidths=.5, ax=ax)
```