Assignment 2: Data Preprocessing, Parameter Tuning, Model Evaluation Using SVM and K-NN

What you will learn

- Data preprocessing
- Parameter Tuning
- Model evaluation
- Employing SVM and K-NN methods on the data

Setup

- Download [Anaconda Python 3.6 (https://www.anaconda.com/download/)](https://www.anaconda.com/download/) for consistent environment.
- Download Pandas library.
- If you use pip environment then make sure your code is compatible with versions of libraries provided within Anaconda's Python 3.6 distribution.

Submission

- Do not change any variable/function names.
- Just add your own code and don't change existing code
- Save this file and rename it to be **studentid_lastname.ipynb** (student id (underscore) last name.ipynb) where your student id is all numbers.
- Export your .ipynb file to PDF (File > Download as > PDF via Latex). **Please don't leave this step for final minutes**.
- Submit both the notebook and PDF files (**NO ZIP, RAR,..**).
- If you happen to use any external library not included in Anaconda (mention in **Submission Notes** section below)

In [1]:
```
from sklearn.svm import SVC
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import GridSearchCV
from sklearn.model_selection import train_test_split
from sklearn.model_selection import StratifiedShuffleSplit
from sklearn.cluster import KMeans
from sklearn.metrics import classification_report
import itertools
from sklearn.metrics import confusion_matrix
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

# remove the following statements if you like to see warnings
import warnings
warnings.filterwarnings('ignore')
```

Submission Notes

(Please write any notes here that you think I should know during marking)

[NO MARKS] Warming Up

Various interesting machine learning datasets can be found at:

- https://archive.ics.uci.edu/ml/index.php (https://archive.ics.uci.edu/ml/index.php)

For this task, we have chosen the Heart Disease dataset, available at:

- https://archive.ics.uci.edu/ml/datasets/heart+Disease (https://archive.ics.uci.edu/ml/datasets/heart+Disease)

Data Set Information

- The dataset contains **303 subjects** with **76 attributes**.
- All the published experiments refer to using a subset of **14 of attributes.**
- The **goal** field in the dataset refers to **the presence of heart disease** in the patient.
- It is integer valued from 0 (no presence) to 4 (highest presence).

Note: Since the class number 4 is very sparse (just 13 subjects). We have dropped the subjects belonging to class 4 from the data.

Experiments with the Cleveland dataset have concentrated on---attempting to distinguish **the presence** (values 1, 2, 3, 4) from **the absence** (value 0).

Attribute Information

14 attributes are been used:

1. #3 (age)
2. #4 (sex)
3. #9 (cp)
4. #10 (trestbps)
5. #12 (chol)
6. #16 (fbs)
7. #19 (restecg)
8. #32 (thalach)
9. #38 (exang)
10. #40 (oldpeak)
11. #41 (slope)
12. #44 (ca)
13. #51 (thal)
14. #58 (num) (the predicted attribute)

(no marks) Reading the data

In [2]:
```
# Reading the data-set
df = pd.read_csv('./processed_cleveland.csv', header=None)
df.columns = ['age', 'sex', 'cp', 'trestbps', 'chol', 'fbs',
                      'restecg', 'thalach', 'exang', 'oldpeak', 'slope'
, 'ca', 'thal', 'prediction']
print('Data-set shape: ', df.shape)

df.tail(n=10)
```

```
Data-set shape:  (303, 14)
```

Out[2]:

	age	sex	cp	trestbps	chol	fbs	restecg	thalach	exang	oldpeak	slope	ca	thal	pre
293	63.0	1.0	4.0	140.0	187.0	0.0	2.0	144.0	1.0	4.0	1.0	2.0	7.0	
294	63.0	0.0	4.0	124.0	197.0	0.0	0.0	136.0	1.0	0.0	2.0	0.0	3.0	
295	41.0	1.0	2.0	120.0	157.0	0.0	0.0	182.0	0.0	0.0	1.0	0.0	3.0	
296	59.0	1.0	4.0	164.0	176.0	1.0	2.0	90.0	0.0	1.0	2.0	2.0	6.0	
297	57.0	0.0	4.0	140.0	241.0	0.0	0.0	123.0	1.0	0.2	2.0	0.0	7.0	
298	45.0	1.0	1.0	110.0	264.0	0.0	0.0	132.0	0.0	1.2	2.0	0.0	7.0	
299	68.0	1.0	4.0	144.0	193.0	1.0	0.0	141.0	0.0	3.4	2.0	2.0	7.0	
300	57.0	1.0	4.0	130.0	131.0	0.0	0.0	115.0	1.0	1.2	2.0	1.0	7.0	
301	57.0	0.0	2.0	130.0	236.0	0.0	2.0	174.0	0.0	0.0	2.0	1.0	3.0	
302	38.0	1.0	3.0	138.0	175.0	0.0	0.0	173.0	0.0	0.0	1.0	?	3.0	

(no marks) Removing the missing data

There are many missing data marked by '?' in the dataset. We will use *dropping* as the most straight-forward technique for removing such data-points.

In [3]:
```
# Removing all subjects from class 4
df = df.loc[df.prediction != 4]

# Replacing the missing data '?' with NAN values
df.replace('?', np.nan, inplace=True)
df = df.dropna()
df = df.astype(float)
```

(no marks) Splitting the data

In [4]:
```
# Separating the data and the labels
X = np.asarray(df[df.columns[:-1]]).astype(np.float32)
y = np.asarray(df.prediction)

# Splitting the data into the train and the test sets
sss = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state=0)
sss.get_n_splits(X, y)

train_index, test_index = next(sss.split(X, y))
X_train, X_test = X[train_index], X[test_index]
y_train, y_test = y[train_index], y[test_index]

print('Training data: \n',X_train)
print('\n')
print('Training labels: \n',y_train)
```

```
Training data:
 [[45.  0.  4. ...  2.  0.  3.]
 [41.  1.  2. ...  2.  0.  6.]
 [42.  1.  4. ...  1.  0.  3.]
 ...
 [67.  1.  4. ...  2.  2.  7.]
 [65.  1.  4. ...  2.  1.  7.]
 [62.  0.  4. ...  1.  0.  3.]]


Training labels:
 [0. 0. 0. 1. 0. 3. 0. 0. 0. 1. 1. 3. 0. 1. 1. 0. 2. 3. 0. 1. 3. 3. 0.
0.
 0. 2. 0. 0. 3. 0. 0. 0. 3. 1. 2. 0. 0. 3. 0. 0. 1. 1. 1. 1. 1. 1. 0.
0.
 1. 3. 1. 2. 0. 2. 2. 0. 0. 0. 0. 1. 3. 1. 0. 2. 0. 0. 0. 0. 1. 0. 0.
0.
 3. 0. 0. 0. 1. 0. 0. 0. 3. 1. 0. 0. 1. 1. 1. 0. 0. 3. 0. 0. 0. 2. 2.
0.
 0. 0. 0. 0. 0. 3. 0. 2. 2. 2. 0. 1. 0. 0. 1. 1. 0. 0. 0. 0. 0. 0. 0.
2.
 2. 0. 0. 1. 0. 0. 0. 1. 3. 0. 0. 0. 0. 0. 0. 2. 2. 1. 2. 0. 1. 0. 2.
0.
 3. 1. 0. 0. 0. 3. 0. 0. 0. 2. 2. 0. 2. 1. 0. 0. 0. 3. 3. 0. 0. 0. 0.
1.
 0. 1. 3. 0. 0. 1. 0. 1. 0. 0. 0. 0. 0. 3. 0. 1. 0. 0. 3. 0. 2. 3. 0.
0.
 0. 0. 2. 0. 1. 1. 0. 0. 3. 0. 2. 1. 0. 2. 2. 0. 0. 0. 1. 0. 0. 0. 3.
1.
 2. 0. 3. 0. 0. 3. 0. 3. 1. 2. 0.]
```

[10 marks] Data Exploration

a) (3 marks) Use `pandas` to find the ratio of the presence of disease versus the absence within the different `sex` .

Note: `0` is female and `1` is male.

In [5]:
```
# we have defined a new column which is `true` if there is a presence of
 disease (i.e., prediction is [1, 2, 3])
df['has_disease'] = df.apply(lambda x: x.prediction in [1, 2, 3], axis=1
)
df['no_disease'] = df.apply(lambda x: x.prediction in [0], axis=1)

# use groupby and aggregation
gender_ratio = df.groupby(['sex']).agg({ 'has_disease' : 'sum', 'no_dise
ase': 'sum' })
gender_ratio['ratio'] = gender_ratio['has_disease'] / gender_ratio['no_d
isease']
gender_ratio
```

Out[5]:

	has_disease	no_disease	ratio
sex			
0.0	23.0	71.0	0.323944
1.0	101.0	89.0	1.134831

b) (7 marks) Do the same thing for age. Split the age groups as follows (left included, right isn't):

1. [29, 49)
2. [49, 69)
3. [69, inf)

And then find the average ratio of prevalence of the heart disease within the each group.

In [6]:
```
# write your code here
df['age_groups'] = pd.cut(df['age'], bins=[29,49,69,float('inf')], inclu
de_lowest=True, right=False)
age_ratios = df.groupby('age_groups').agg({ 'has_disease' : 'sum', 'no_d
isease': 'sum' })
age_ratios['ratio'] = age_ratios['has_disease'] / age_ratios['no_diseas
e']
age_ratios
```

Out[6]:

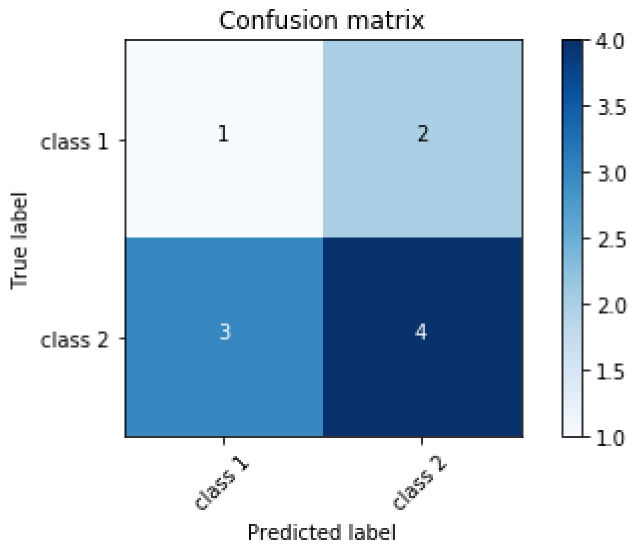
	has_disease	no_disease	ratio
age_groups			
[29.0, 49.0)	22.0	57.0	0.385965
[49.0, 69.0)	99.0	95.0	1.042105
[69.0, inf)	3.0	8.0	0.375000

(no marks) Utility function

In [7]:
```
# Do not change the function
# This function is adapted from the sklearn website
# This function let you draw a confusion matrix for your problem

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    This function prints and plots the confusion matrix.
    Normalization can be applied by setting `normalize=True`.
    """
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
        print("Normalized confusion matrix")
    else:
        print('Confusion matrix, without normalization')

    print(cm)

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=45)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1
])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.ylabel('True label')
    plt.xlabel('Predicted label')
    plt.tight_layout()
```

In [8]:
```
# usage
plot_confusion_matrix(np.array([[1, 2], [3, 4]]), ['class 1', 'class 2'
])
```

```
Confusion matrix, without normalization
[[1 2]
 [3 4]]
```

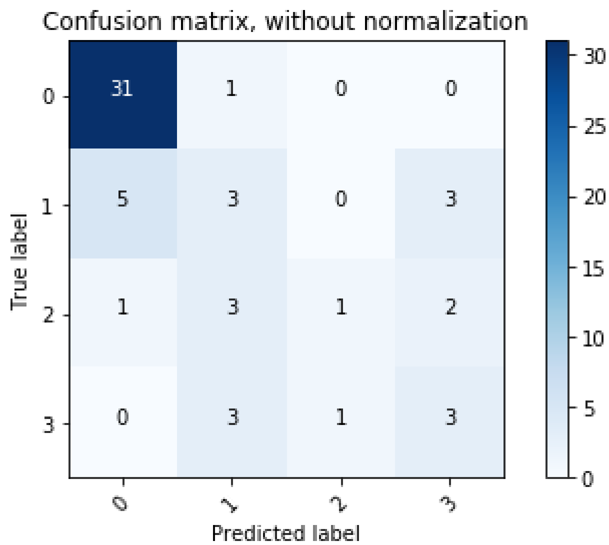


Task 1 [20 marks]

a) [10 marks] Applying KNN to the data

In [9]:
```
from sklearn.neighbors import KNeighborsClassifier
from sklearn.preprocessing import MinMaxScaler

# Task 2
# Add your code in the following part:

# We use min max scaler to normalize the features between [0, 1]
scaler = MinMaxScaler()

# Add your code here instead of ...
scaler.fit(X_train, y_train)

# Create a knn classifier instance here (If you don't add anything here,
 your code won't execute!)
knn_clf = KNeighborsClassifier()

# Fit the classifier using the train data (If you don't add anything her
e, your code won't execute!)
knn_clf.fit(scaler.transform(X_train), y_train)

# Predict the test class labels using the trained classifier (If you do
n't add anything here, your code won't execute!)
y_pred = knn_clf.predict(scaler.transform(X_test))

# (If you don't add anything here, your code won't execute!)
print(classification_report(y_test, y_pred))

cnf_matrix = confusion_matrix(y_test, y_pred)
plot_confusion_matrix(cnf_matrix, classes=[0,1,2,3],
                      title='Confusion matrix, without normalization')
```

```
              precision    recall  f1-score   support

         0.0       0.84      0.97      0.90        32
         1.0       0.30      0.27      0.29        11
         2.0       0.50      0.14      0.22         7
         3.0       0.38      0.43      0.40         7

   micro avg       0.67      0.67      0.67        57
   macro avg       0.50      0.45      0.45        57
weighted avg       0.64      0.67      0.64        57

Confusion matrix, without normalization
[[31  1  0  0]
 [ 5  3  0  3]
 [ 1  3  1  2]
 [ 0  3  1  3]]
```



b) [5 marks] Between $K = 3$ and $k = 5$ which one gives more accuracy ?

In [10]:
```
from sklearn.metrics import accuracy_score

# write your code here and populate `y_pred_k5` and `y_pred_k3`
knn_clf_k3 = KNeighborsClassifier(n_neighbors = 3)
knn_clf_k3.fit(scaler.transform(X_train), y_train)
y_pred_k3 = knn_clf_k3.predict(scaler.transform(X_test))

knn_clf_k5 = KNeighborsClassifier(n_neighbors = 5)
knn_clf_k5.fit(scaler.transform(X_train), y_train)
y_pred_k5 = knn_clf_k5.predict(scaler.transform(X_test))

print(accuracy_score(y_test, y_pred_k5), accuracy_score(y_test, y_pred_k
3))
```

```
0.6666666666666666 0.5964912280701754
```

k5 more accurate

c) [5 marks] Between ℓ_1, ℓ_2, and $cosine$ similarity which one is better in term of accuracy?

In [11]:
```
# write your code here to experiment with different distance metrics
# use argument `metric` to change to a different distance by default it
 is euclidean distance
knn_clf_l1 = KNeighborsClassifier(metric = 'l1')
knn_clf_l1.fit(scaler.transform(X_train), y_train)
y_pred_l1 = knn_clf_l1.predict(scaler.transform(X_test))

knn_clf_l2 = KNeighborsClassifier(metric = 'l2')
knn_clf_l2.fit(scaler.transform(X_train), y_train)
y_pred_l2 = knn_clf_l2.predict(scaler.transform(X_test))

knn_clf_cos = KNeighborsClassifier(metric = 'cosine')
knn_clf_cos.fit(scaler.transform(X_train), y_train)
y_pred_cos = knn_clf_cos.predict(scaler.transform(X_test))

print('L1 Accuracy:', accuracy_score(y_test, y_pred_l1))
print('L2 Accuracy:', accuracy_score(y_test, y_pred_l2))
print('Cosine Accuracy:', accuracy_score(y_test, y_pred_cos))
```

```
L1 Accuracy: 0.6491228070175439
L2 Accuracy: 0.6666666666666666
Cosine Accuracy: 0.6666666666666666
```

Cosine and L2 are same in terms of accuracy and are the better in terms of accuracy

Task 2 [10 marks]

Understanding the pipelining architecture of `Sklearn`

In the code above, you had to call `scaler` for every prediction by a model. This can be avoided by using a `pipeline` mechanism within sklearn. Look at the code below:

1. We create a data scaler (can be any sclaer with fit and transform functions).
2. We create SVC object (again with fit anf transform functions).
3. Then we create a pipeline: `data --> scaler --> svc --> fit`.
4. The same transformation is also applied during the prediction phase.

We further use a `GridSearchCV` for the SVC's parameters tuning.

In [12]:
```
# Task 2

# Creating a SVM classifier instance
svc = SVC()

# Add a scaler here (If you don't add anything here, your code won't exe
cute!)
data_scaler = StandardScaler()

# Update the pipeline by adding the scaler from the previous line
model = make_pipeline(data_scaler, svc)
param_grid = {'svc__C': [1, 5, 10, 50],
              'svc__gamma': [0.0001, 0.0005, 0.001, 0.005]}

grid = GridSearchCV(model, param_grid)
%time grid.fit(X_train, y_train)
print( grid.best_estimator_)
```

```
CPU times: user 379 ms, sys: 4.66 ms, total: 383 ms
Wall time: 240 ms
Pipeline(memory=None,
     steps=[('standardscaler', StandardScaler(copy=True, with_mean=Tru
e, with_std=True)), ('svc', SVC(C=50, cache_size=200, class_weight=Non
e, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.001, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
```

In [13]:
```
# Selecting the best estimator after the parameter search
model = grid.best_estimator_
```

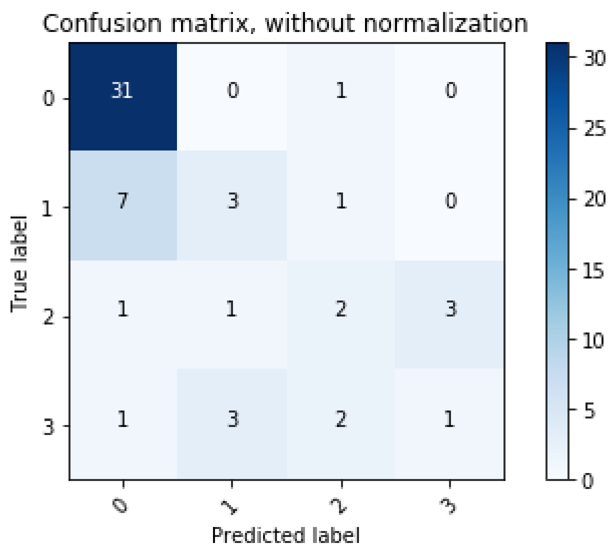
In [14]:
```
# Predicting the test labels
y_pred = model.predict(X_test)
```

In [15]:
```
# Printing the classification report
print(classification_report(y_pred=y_pred,y_true=y_test))
```

```
              precision    recall  f1-score   support

         0.0       0.78      0.97      0.86        32
         1.0       0.43      0.27      0.33        11
         2.0       0.33      0.29      0.31         7
         3.0       0.25      0.14      0.18         7

   micro avg       0.65      0.65      0.65        57
   macro avg       0.45      0.42      0.42        57
weighted avg       0.59      0.65      0.61        57
```

In [16]:
```
# Computing the confusion matrix for the test data
cnf_matrix = confusion_matrix(y_test, y_pred)

# Plotting the confusion matrix using the previous function
plot_confusion_matrix(cnf_matrix, classes=[0,1,2,3],
                      title='Confusion matrix, without normalization')
```

```
Confusion matrix, without normalization
[[31  0  1  0]
 [ 7  3  1  0]
 [ 1  1  2  3]
 [ 1  3  2  1]]
```



Task 3 [40 marks]

How to handle the missing data

More information can be found here: ([https://pandas.pydata.org/pandas-docs/stable/user_guide/missing_data.html (https://pandas.pydata.org/pandas-docs/stable/user_guide/missing_data.html)](https://pandas.pydata.org/pandas-docs/stable/user_guide/missing_data.html))

a) [6 scores] Name two numeric methods for dealing with the missing data (except dropping):

```
Write the answer here:

1- Fill in missing data with fillna()

2- interpolate using interpolate()
```

b) [12 scores] Apply the methods that you mentioned in part (a) to the `df_with_missing_data` dataframe:

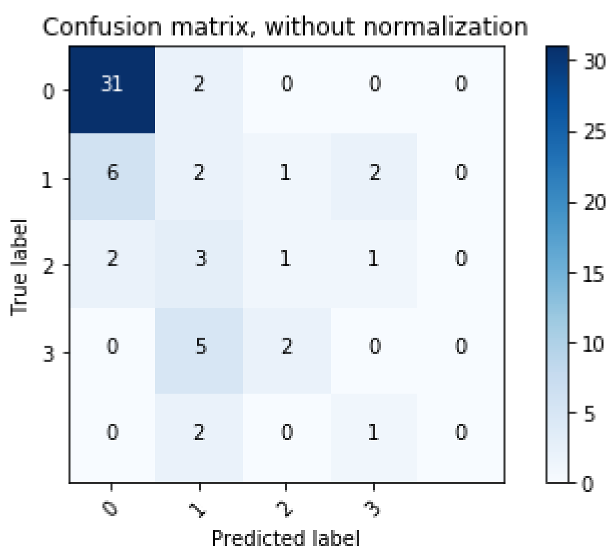
In [17]:
```
# Task 3 part (b)
# Add your code here (If you don't add anything here, your code won't ex
ecute!)

df_with_missing_data = pd.read_csv('./processed_cleveland.csv', header=N
one)
df_with_missing_data.columns = ['age', 'sex', 'cp', 'trestbps', 'chol',
'fbs',
                                'restecg', 'thalach', 'exang', 'oldpeak'
, 'slope', 'ca', 'thal', 'prediction']

df_with_missing_data.replace('?', np.nan, inplace=True)

df_1 = df_with_missing_data.fillna(0)

df_2 = df_with_missing_data.astype(np.float32).interpolate()
```

c) [22 scores] Apply the steps described in *Task 2* on `df_1` and `df_2` and show the results using `classification_report` and `plot_confusion_matrix`.

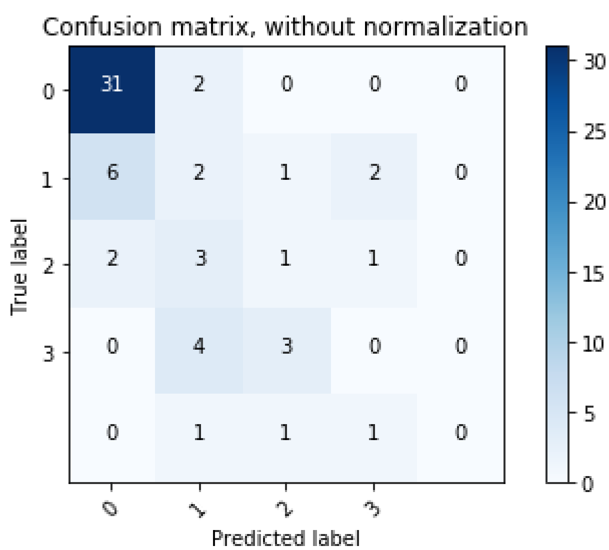
In [18]:
```
# Task 3 part (c)
# Add your code here
def results(data_frame):
    df = data_frame
    # Separating the data and the labels
    X = np.asarray(df[df.columns[:-1]]).astype(np.float32)
    y = np.asarray(df.prediction)

    # Splitting the data into the train and the test sets
    sss = StratifiedShuffleSplit(n_splits=1, test_size=0.2, random_state
=0)
    sss.get_n_splits(X, y)

    train_index, test_index = next(sss.split(X, y))
    X_train, X_test = X[train_index], X[test_index]
    y_train, y_test = y[train_index], y[test_index]

    # Creating a SVM classifier instance
    svc = SVC()

    # Add a scaler here (If you don't add anything here, your code won't
 execute!)
    data_scaler = StandardScaler()

    # Update the pipeline by adding the scaler from the previous line
    model = make_pipeline(data_scaler, svc)
    param_grid = {'svc__C': [1, 5, 10, 50],
                  'svc__gamma': [0.0001, 0.0005, 0.001, 0.005]}

    grid = GridSearchCV(model, param_grid)
    %time grid.fit(X_train, y_train)
    print( grid.best_estimator_)

    # Selecting the best estimator after the parameter search
    model = grid.best_estimator_

    # Predicting the test labels
    y_pred = model.predict(X_test)

    # Printing the classification report
    print(classification_report(y_pred=y_pred,y_true=y_test))

    # Computing the confusion matrix for the test data
    cnf_matrix = confusion_matrix(y_test, y_pred)

    # Plotting the confusion matrix using the previous function
    plot_confusion_matrix(cnf_matrix, classes=[0,1,2,3],
                          title='Confusion matrix, without normalizatio
n')

print('Show results for df1')
results(df_1)
plt.show()

print('Show results for df2')
```

```
results(df_2)
plt.show()
```

```
Show results for df1
CPU times: user 220 ms, sys: 3.11 ms, total: 223 ms
Wall time: 226 ms
Pipeline(memory=None,
     steps=[('standardscaler', StandardScaler(copy=True, with_mean=Tru
e, with_std=True)), ('svc', SVC(C=5, cache_size=200, class_weight=None,
coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
              precision    recall  f1-score   support

           0       0.79      0.94      0.86        33
           1       0.14      0.18      0.16        11
           2       0.25      0.14      0.18         7
           3       0.00      0.00      0.00         7
           4       0.00      0.00      0.00         3

   micro avg       0.56      0.56      0.56        61
   macro avg       0.24      0.25      0.24        61
weighted avg       0.48      0.56      0.52        61

Confusion matrix, without normalization
[[31  2  0  0  0]
 [ 6  2  1  2  0]
 [ 2  3  1  1  0]
 [ 0  5  2  0  0]
 [ 0  2  0  1  0]]
```



```
Show results for df2
CPU times: user 214 ms, sys: 2.83 ms, total: 217 ms
Wall time: 217 ms
Pipeline(memory=None,
     steps=[('standardscaler', StandardScaler(copy=True, with_mean=Tru
e, with_std=True)), ('svc', SVC(C=10, cache_size=200, class_weight=Non
e, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.005, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False))])
              precision    recall  f1-score   support

         0.0       0.79      0.94      0.86        33
         1.0       0.17      0.18      0.17        11
         2.0       0.17      0.14      0.15         7
         3.0       0.00      0.00      0.00         7
         4.0       0.00      0.00      0.00         3

   micro avg       0.56      0.56      0.56        61
   macro avg       0.23      0.25      0.24        61
weighted avg       0.48      0.56      0.51        61

Confusion matrix, without normalization
[[31  2  0  0  0]
 [ 6  2  1  2  0]
 [ 2  3  1  1  0]
 [ 0  4  3  0  0]
 [ 0  1  1  1  0]]
```

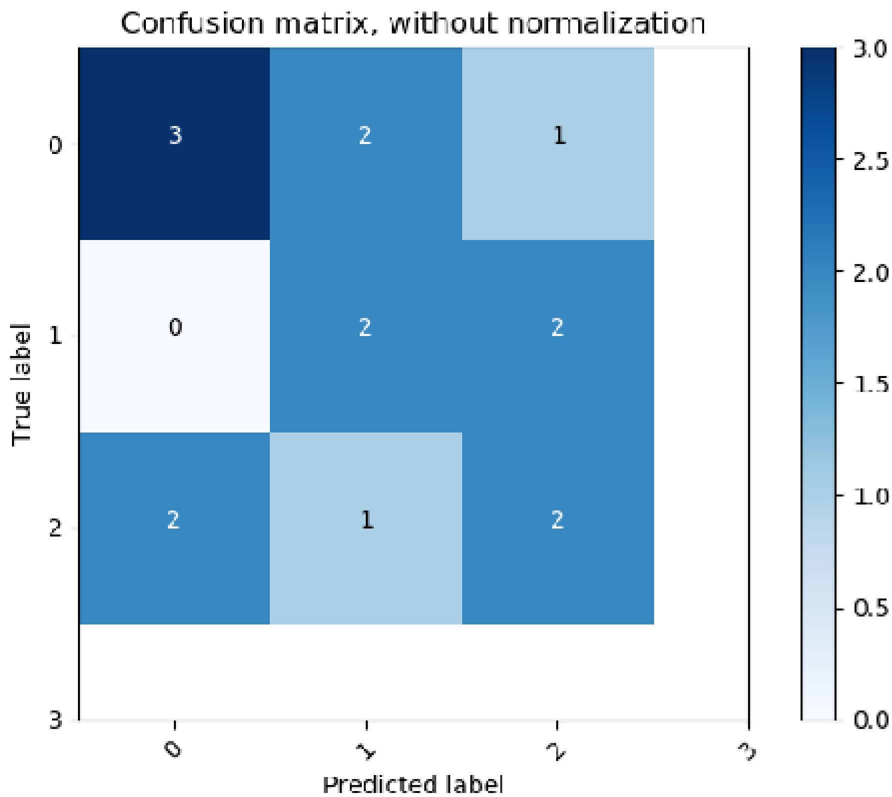


Task 4 [20 marks]

Model Evaluation

For the given confusion matrix, answer the following questions.

In [19]:
```
I = plt.imread('foo.png')
fig = plt.figure(figsize= (10,10))
plt.imshow(I)
plt.axis('off')
plt.show()
```



Calculate the following parameters (Use macro-average definition)

You can find all these definitions on [https://scikit-learn.org/stable/auto_examples/model_selection/plot_precision_recall.html (https://scikit-learn.org/stable/auto_examples/model_selection/plot_precision_recall.html)](https://scikit-learn.org/stable/auto_examples/model_selection/plot_precision_recall.html) and [https://en.wikipedia.org/wiki/Confusion_matrix (https://en.wikipedia.org/wiki/Confusion_matrix)](https://en.wikipedia.org/wiki/Confusion_matrix)

Write your answer in front of each parameter:

1- [2 scores] total number of instances = 15

2- [2 scores] number of classes = 3

3- [2 scores] True positive (TP) = 2.333

```
class0: 3
class1: 2
class2: 2

TP = (3 + 2 + 2) / 3 = 2.333
```

4- [2 scores] True negative (TN) = 7.333...

```
class0: 7
class1: 8
class2: 7

TN = (7 + 8 + 7) / 3 = 7.333...
```

5- [2 scores] False positive (FP) = 2.66666...

```
class0: 2
class1: 3
class2: 3

FP = (2 + 3 + 3) / 3 = 2.66666...
```

6- [2 scores] False negative (FN) = 2.66666...

```
class0: 3
class1: 2
class2: 3

FN = (3+2+3)/3 = 2.66666...
```

7- [2 scores] Sensitivity, recall, hit rate, or true positive rate (TPR) = 4.6666...

```
class0: 3/(3+3) = 0.5
class1: 2/(2+2) = 0.5
class2: 2/(2+3) = 0.4

TPR = (0.5+0.5+0.4)/3 = 4.6666...
```

8- [2 scores] Specificity, selectivity or true negative rate (TNR) = 0.73333...

```
class0: 7/(7+2) = 0.777777...
class1: 8/(8+3) = 0.727272...
class2: 7/(7+3) = 0.7

TNR = (0.7777+0.727272+0.7)/3 = 0.73333...
```

9- [4 scores] F1-Score = 4.66666...

```
Recall = 4.66667
Precision = 4.66667
F1 = 2*(R*P)/(R+P) = 4.66666...
```

In [20]:
```
# Assignment end
```