ECE 657A - Assignment 2

Date Submitted: Mar 09, 2022

Importing Libraries

In [1]:
```
import numpy as np
import pandas as pd
import random
from pprint import pprint
from functools import reduce
from scipy import stats
from sklearn import neighbors
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn import metrics
from sklearn.metrics import
accuracy_score,confusion_matrix,ConfusionMatrixDisplay,classification_report,ma
 precision_score, recall_score, f1_score
from sklearn.decomposition import PCA
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.manifold import TSNE
from sklearn.model_selection import
cross_val_score,KFold,StratifiedKFold,GridSearchCV,cross_validate
from sklearn.naive_bayes import MultinomialNB,ComplementNB, GaussianNB
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
import graphviz
from sklearn.ensemble import
RandomForestClassifier,GradientBoostingClassifier,AdaBoostClassifier

import matplotlib.pyplot as plt
import seaborn as sns
sns.set(style="ticks", color_codes=True)
import warnings
warnings.filterwarnings("ignore")
```

Wine Dataset

Preprocessing

Loading Data

In [2]:
```
D = ['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar',
'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density', 'pH',
'sulphates', 'alcohol']
L = 'quality'
C = 'color'
DL = D + [L]
DC = D + [C]
DLC = DL + [C]
#Loading Data set
wine_r = pd.read_csv("winequality-red.csv", sep=';')
#Loading Data set
wine_w = pd.read_csv("winequality-white.csv", sep=';')
wine_w= wine_w.copy()
wine_w[C]= np.zeros(wine_w.shape[0])
wine_r[C]= np.ones(wine_r.shape[0])
wine = pd.concat([wine_w,wine_r])

wine['color'] = wine['color'].astype('category')
wine['quality'] = wine['quality'].astype('category')
```

Normalization and Scaling

In [3]:
```
#Z-Score Normalization
wine_z = wine.copy()
wine_z = wine_z.drop(columns = ['color' , 'quality'])
wine_znormalized = wine_z.apply(stats.zscore)
wine_znormalized['quality'] = wine['quality']
wine_znormalized['color'] = wine['color']

target_z = wine_znormalized['quality']
data_z = wine_znormalized.drop(columns = 'quality')

X_train_z, X_test_z, Y_train_z, Y_test_z = train_test_split(data_z, target_z,
test_size=0.2 , random_state=27)
```

In [4]:
```
#MinMAx Scaling
wine_s = wine.copy()
wine_s = wine_s.drop(columns = ['color' , 'quality'])
wine_minmax = (wine_s - wine_s.min()) / ( wine_s.max() - wine_s.min())
wine_minmax['quality'] = wine['quality']
wine_minmax['color'] = wine['color']

wine_min_max = wine_minmax
target = wine_min_max['quality']
```

```
data = wine_min_max.drop(columns = 'quality')
X_train, X_test, Y_train, Y_test = train_test_split(data, target,
test_size=0.2 , random_state=27)
```

Best formulated KNN from Assignment-1

In [5]:

```
knn = KNeighborsClassifier(n_neighbors=23 , metric = 'manhattan' , weights =
"distance")
knn.fit(X_train, Y_train)
Y_pred = knn.predict(X_test)

knn_train_acc = knn.score(X_train, Y_train)
print("Training Score: ", knn_train_acc)
knn_test_acc = knn.score(X_test, Y_test)
print("Testing Score: ", knn_test_acc)
```

```
Training Score:  1.0
Testing Score:  0.68
```

Representation Learning

Indepepndent and dependent variable

In [6]:

```
#Scaled 'data' and 'target'
x=data
y=target
n_components=2
target_names = np.sort(y.unique())
```

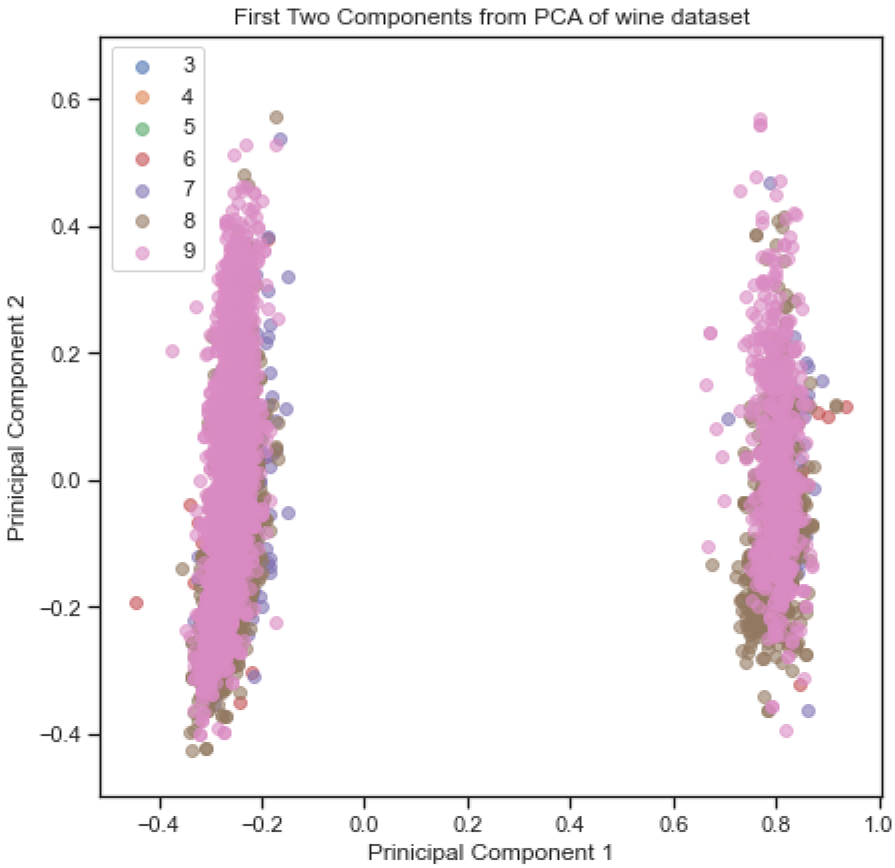
PCA

In [7]:

```
print("PCA Model - Explained Variance of each component")
pca = PCA(n_components=n_components)
X_r = pca.fit(x).transform(x)
exp_var_ratio_df = pd.DataFrame(pca.explained_variance_ratio_, columns=
['Explained Variance Ratio'])
print(exp_var_ratio_df)

plt.figure(figsize=(7,7))
#colors = plt.cm.get_cmap("twilight")

for i, target_name in enumerate(target_names):
    plt.scatter(
        X_r[y == i, 0], X_r[y == i, 1], alpha=0.6, lw=1,
label=target_name,cmap="twilight"
    )
```

```
plt.ylim(-0.5,0.7)
plt.legend(loc="best", shadow=False, scatterpoints=1)
plt.xlabel("Prinicipal Component 1")
plt.ylabel("Prinicipal Component 2")
plt.title("First Two Components from PCA of wine dataset")
#plt.set_cmap("hsv")

plt.show()
```

```
PCA Model - Explained Variance of each component
   Explained Variance Ratio
0                  0.692196
1                  0.118142
```

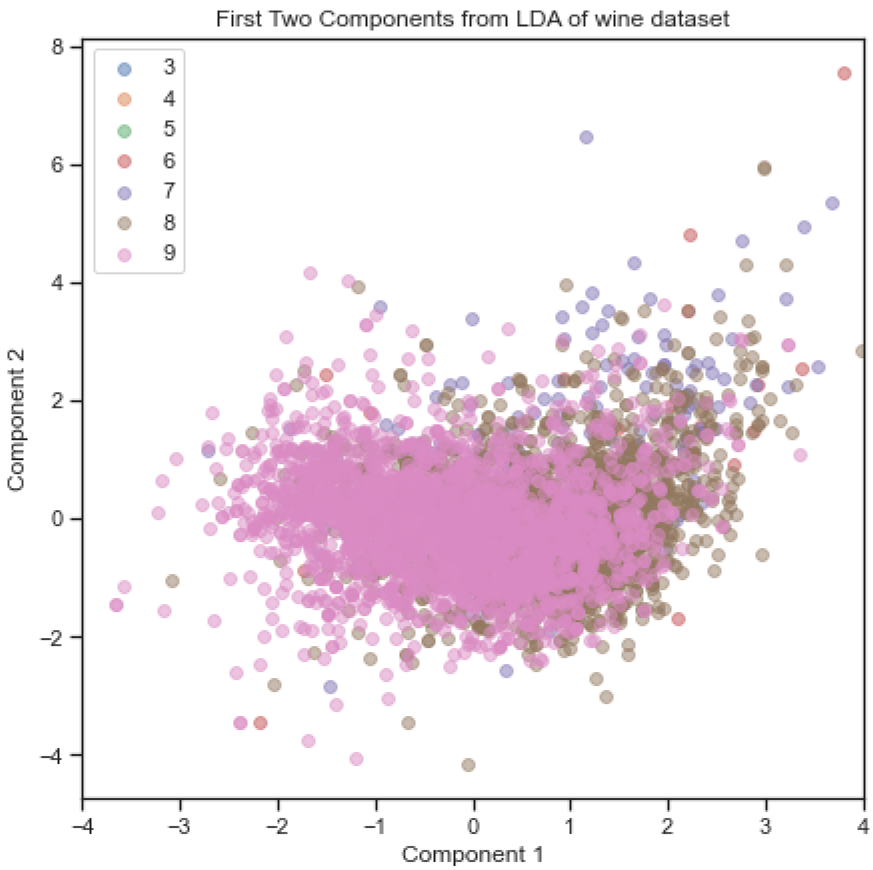


LDA

In [8]:
```
print("LDA Model - Explained Variance of each component")
lda = LinearDiscriminantAnalysis(n_components=n_components)
X_r2 = lda.fit(x, y).transform(x)
exp_var_ratio_df = pd.DataFrame(lda.explained_variance_ratio_, columns=
['Explained Variance Ratio'])
print(exp_var_ratio_df)

plt.figure(figsize=(7,7))
#colors = plt.cm.get_cmap("twilight")
for i, target_name in enumerate(target_names):
    plt.scatter(
```

```
        X_r2[y == i, 0], X_r2[y == i, 1], alpha=0.5, lw=1, label=target_name,
cmap="twilight"
    )
plt.xlim(-4,4)
plt.legend(loc="best", shadow=False, scatterpoints=1)
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.title("First Two Components from LDA of wine dataset")
#plt.set_cmap("twilight")


plt.show()
```

```
LDA Model - Explained Variance of each component
   Explained Variance Ratio
0                  0.861621
1                  0.088287
```

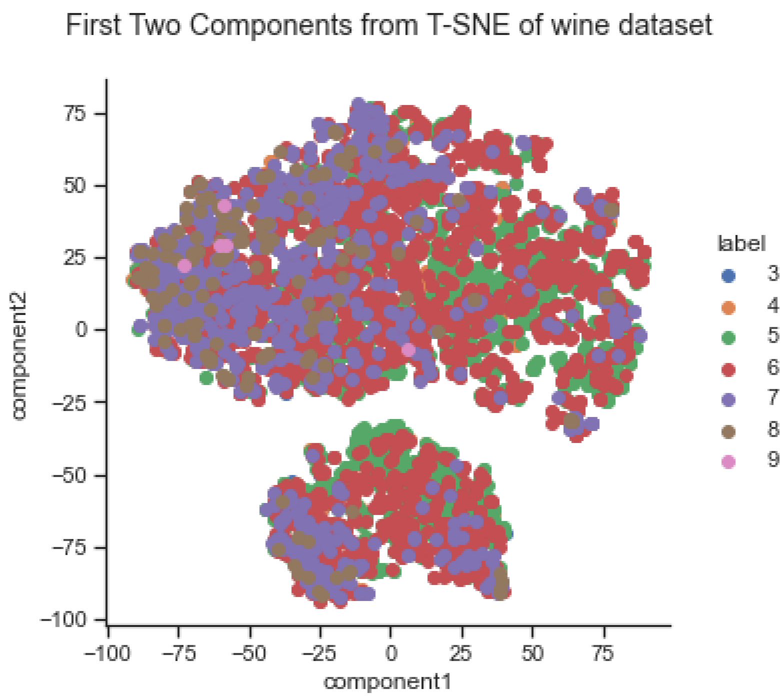


T-SNE

In [9]:

```
tsne = TSNE(n_components=n_components)
X_r3 = tsne.fit_transform(x)
tsne_data = np.vstack((X_r3.T,target)).T
tsne_df = pd.DataFrame(data = tsne_data, columns = ['component1',
'component2','label'] )
#print(tsne_df.head())
tsne_df['label'] = tsne_df['label'].astype('int')
tsne_df['label'] = tsne_df['label'].astype('category')
```

```
g = sns.FacetGrid(tsne_df, hue='label', height=5).map(plt.scatter,
'component1','component2')
g.add_legend()
g.fig.suptitle("First Two Components from T-SNE of wine dataset")
g.tight_layout()
```



Comments

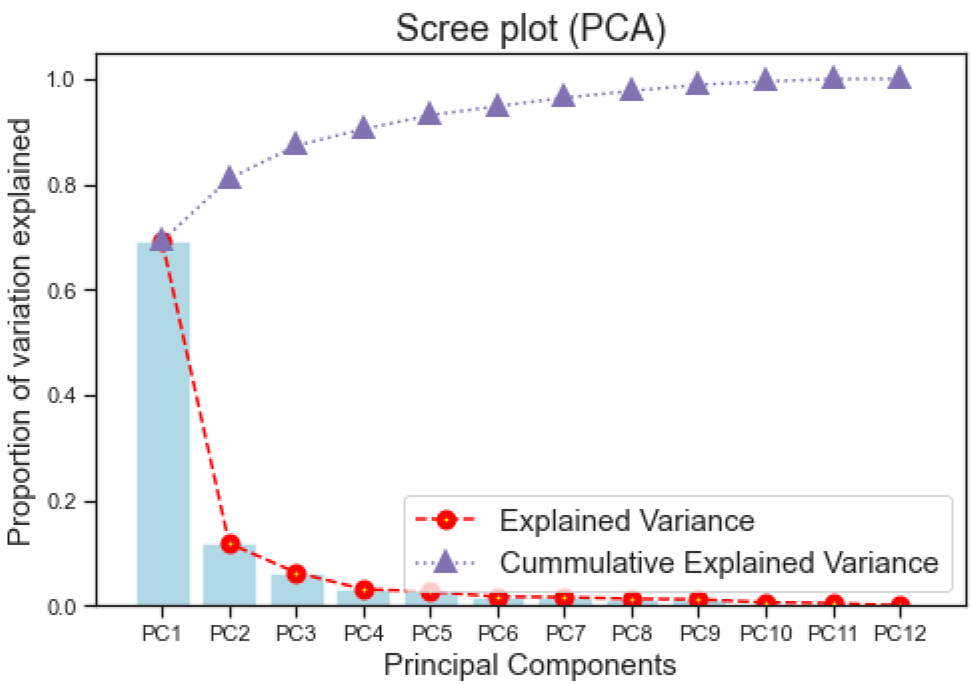
- PCA:Seperation on X-axis(PC1) is more significant and two clusters are formed, spread among each cluster along X-axis is less than Y-axis (color is categorical variable and could be the reason why two different clusters are formed), we have not removed outliers and hence does not perform well.
- LDA: Same class labels are clustered together and is able to better classify between different classes (number of datapoints in various classes are highly different)
- t-SNE: used default settings, non-linear function, clusters similar classes as distance between them are less in both the clusters

Scree Plot (PCA)

In [10]:

```
pca = PCA(n_components=None)
X_r = pca.fit(x).transform(x)
explained_variance_pca = pca.explained_variance_ratio_
fig = plt.figure(figsize=(7,5))
tick_label = ['PC' + str(i) for i in range(1,len(explained_variance_pca)+1)]
plt.bar(range(len(explained_variance_pca)), explained_variance_pca, color =
'c',alpha=0.5, align='center',tick_label=tick_label)
plt.plot(range(len(explained_variance_pca)), explained_variance_pca, color =
'red',marker ='o',mew =4,mfc='yellow',ls ='--'
,linewidth=1.5,label='Explained Variance')
plt.plot(range(len(explained_variance_pca)), explained_variance_pca.cumsum(),
color = 'm',marker ='^',mew =4,mfc='red',ls =':'
```

```
,linewidth=1.5,label='Cummulative Explained Variance')
plt.ylabel('Proportion of variation explained',fontsize = 15)
plt.xlabel('Principal Components',fontsize = 15)
plt.title('Scree plot (PCA)',fontsize = 18)
plt.legend(loc='best',fontsize = 15)
#plt.axis("off")
plt.tight_layout()
plt.show()
```



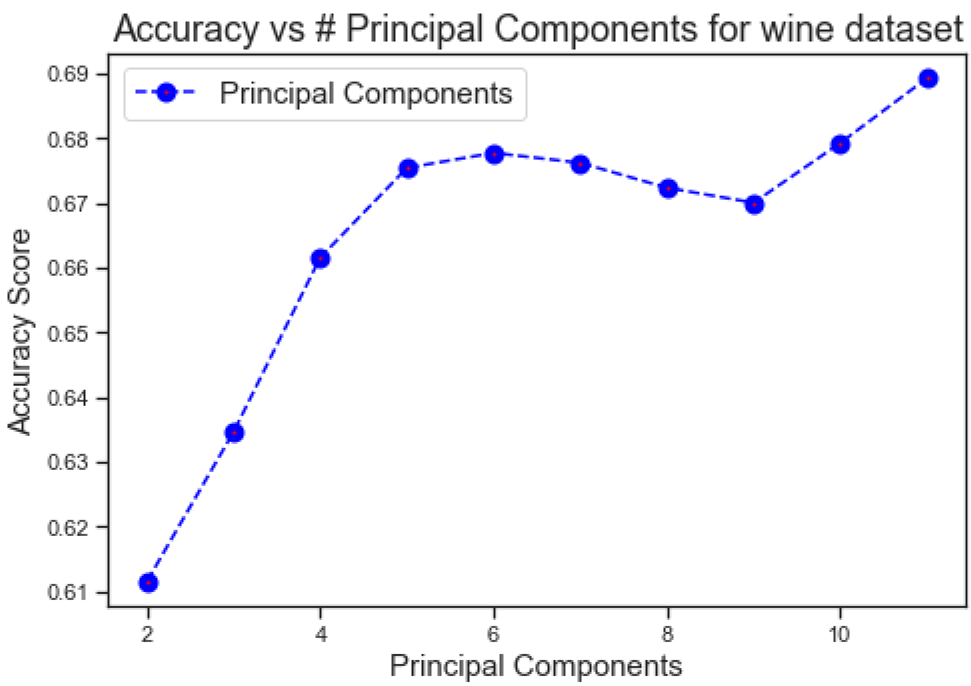
Reduced Dimensionality

PCA

In [11]:

```
knn = KNeighborsClassifier(n_neighbors=23 , metric = 'manhattan' , weights =
"distance")
D = data.shape[1]
#print(D)
acc_list =[]

for i in range(2,D):
    pca = PCA(n_components=i)
    X_train_r = pca.fit(X_train).transform(X_train)
    X_test_r = pca.transform(X_test)
    knn.fit(X_train_r, Y_train)
    y_pred = knn.predict(X_test_r)
    acc_list.append(metrics.accuracy_score(Y_test,y_pred))

fig = plt.figure(figsize=(7,5))
plt.plot(range(2,D),acc_list, color = 'blue',marker ='o',mew =4,mfc='red',ls
='--' ,linewidth=1.5,label='Principal Components')
```

```
plt.ylabel('Accuracy Score',fontsize = 15)
plt.xlabel('Principal Components',fontsize = 15)
plt.title('Accuracy vs # Principal Components for wine dataset',fontsize =
18)
plt.legend(loc='best',fontsize = 15)
plt.tight_layout()
plt.show()

print("The maximum accuracy {} happens to be when number of Principal
Components is : {}".format(max(acc_list),acc_list.index(max(acc_list))+2))
```



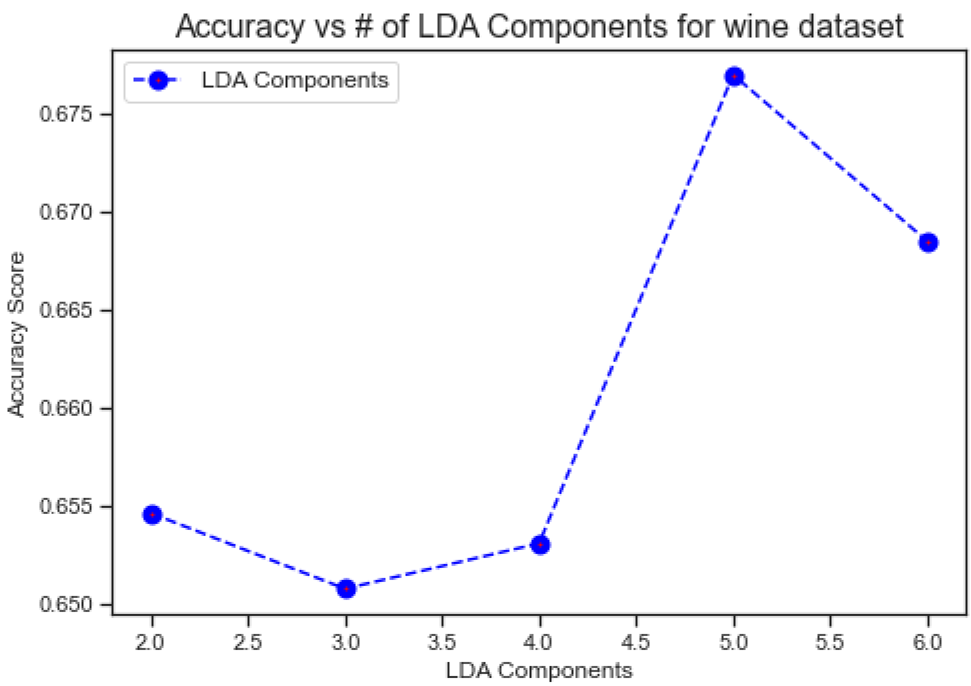

```
The maximum accuracy 0.6892307692307692 happens to be when number of Principal Components
is : 11
```

LDA

In [12]:

```
knn = KNeighborsClassifier(n_neighbors=23 , metric = 'manhattan' , weights =
"distance")
#LDA is constrained by the number of components it can use , given by :
min(n_classes-1, len(features))
D = min(data.shape[1],len(target_names))
acc_list =[]

for i in range(2,D):
    lda = LinearDiscriminantAnalysis(n_components=i)
    X_train_r = lda.fit(X_train,Y_train).transform(X_train)
    X_test_r = lda.transform(X_test)
    knn.fit(X_train_r, Y_train)
    y_pred = knn.predict(X_test_r)
    acc_list.append(metrics.accuracy_score(Y_test,y_pred))
```

```
fig = plt.figure(figsize=(7,5))
plt.plot(range(2,D),acc_list, color = 'blue',marker ='o',mew =4,mfc='red',ls
='--' ,linewidth=1.5,label='LDA Components')
plt.ylabel('Accuracy Score',fontsize = 12)
plt.xlabel('LDA Components',fontsize = 12)
plt.title('Accuracy vs # of LDA Components for wine dataset',fontsize = 16)
plt.legend(loc='best',fontsize = 12)
plt.tight_layout()
plt.show()


print("The maximum accuracy {} happens to be when number of LDA Components is
: {}".format(max(acc_list),acc_list.index(max(acc_list))+2))
```




```
The maximum accuracy 0.676923076923077 happens to be when number of LDA Components is : 5
```

Comments

- Have used 5 principal components in subsequent parts as there is not a significant difference when included more components. Also, 11 components is the original dimension of data and hence would be better representation but there is no significant loss of accuracy by including 5 components.
- LDA gives better accuracy with 5 components.
- Accuracy with reduced dimensions is comparable with accuracy from Assignment-1 (0.68). PCA performs slightly better with 0.69 accuracy. The major observation is that with reduced dimensions accuracy is comparable with the original datset(with all features) hence PCA an dLDA are able to capture most information in lesser components.

Versions of dataset (raw/pca/lda)

In [7]:

```
wine_raw = wine.copy()
wine_normalized_raw = wine_znormalized.copy()
wine_minmax_normalized = wine_minmax.copy()
```

```
pca = PCA(n_components=5)
X_r = pca.fit(x).transform(x)
pca_data = np.vstack((X_r.T,target)).T
wine_pca = pd.DataFrame(data = pca_data, columns =
['component1','component2','component3', 'component4','component5','label'] )
wine_pca_temp = wine_pca.copy()
wine_pca_temp_2 = wine_pca_temp.drop(columns = ['label'])
wine_pca = (wine_pca_temp_2 - wine_pca_temp_2.min(axis=0)) / (
wine_pca_temp_2.max(axis=0) - wine_pca_temp_2.min(axis=0))
wine_pca['label']=wine_pca_temp['label']
wine_pca['label'] = wine_pca['label'].astype('int')
wine_pca['label'] = wine_pca['label'].astype('category')
#print(wine_pca.head())

lda = LinearDiscriminantAnalysis(n_components=5)
X_r2 = lda.fit(x, y).transform(x)
lda_data = np.vstack((X_r2.T,target)).T
wine_lda = pd.DataFrame(data = lda_data, columns = ['component1',
'component2','component3','component4','component5','label'] )
wine_lda_temp = wine_lda.copy()
wine_lda_temp_2 = wine_lda_temp.drop(columns = ['label'])
wine_lda = (wine_lda_temp_2 - wine_lda_temp_2.min(axis=0)) / (
wine_lda_temp_2.max(axis=0) - wine_lda_temp_2.min(axis=0))
wine_lda['label']=wine_lda_temp['label']
wine_lda['label'] = wine_lda['label'].astype('int')
wine_lda['label'] = wine_lda['label'].astype('category')
#print(wine_lda.head())
```

In [14]:

```
wine_p = wine_pca.copy()
target_pca = wine_p['label']
data_pca = wine_p.drop(columns = 'label')
X_train_pca, X_test_pca, Y_train_pca, Y_test_pca = train_test_split(data_pca,
target_pca, test_size=0.2 , random_state=27)

wine_l = wine_lda.copy()
target_lda = wine_l['label']
data_lda = wine_l.drop(columns = 'label')
X_train_lda, X_test_lda, Y_train_lda, Y_test_lda = train_test_split(data_lda,
target_lda, test_size=0.2 , random_state=27)
```

Naive Bayes Classifier

5-Fold CV for Naive Bayes & KNN classifier

In [15]:

```
kfold = KFold(n_splits=5)
clrs = []

clrs.append(KNeighborsClassifier(n_neighbors=23 , metric = 'manhattan' ,
weights = "distance"))
clrs.append(GaussianNB())
clrs.append(MultinomialNB())
clrs.append(ComplementNB())

cv_results = []
cv_results_pca = []
cv_results_lda = []

for clr in clrs :
    cv_results.append(cross_val_score(clr, X_train, Y_train , scoring =
'accuracy', cv = kfold, n_jobs=-1))
    cv_results_pca.append(cross_val_score(clr, X_train_pca, Y_train_pca ,
scoring = 'accuracy', cv = kfold, n_jobs=-1))
    cv_results_lda.append(cross_val_score(clr, X_train_lda, Y_train_lda ,
scoring = 'accuracy', cv = kfold, n_jobs=-1))

cv_means = []
cv_means_pca = []
cv_means_lda = []

for cv_result in cv_results:
    cv_means.append(cv_result.mean())

for cv_result in cv_results_pca:
    cv_means_pca.append(cv_result.mean())

for cv_result in cv_results_lda:
    cv_means_lda.append(cv_result.mean())

cv_df = pd.DataFrame({"Mean_Accuracy":cv_means,"Algo":
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})
cv_df_pca = pd.DataFrame({"Mean_Accuracy":cv_means_pca,"Algo":
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})
cv_df_lda = pd.DataFrame({"Mean_Accuracy":cv_means_lda,"Algo":
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})

#print(cv_df)
#print(cv_df_pca)
#print(cv_df_lda)
```

In [16]:
```
data_frames = [cv_df, cv_df_pca, cv_df_lda]
df_merged = reduce(lambda  left,right: pd.merge(left,right,on=
['Algo'],how='outer'), data_frames)
df_merged.rename(columns={"Mean_Accuracy_x": "wine_raw", "Mean_Accuracy_y":
"wine_pca","Mean_Accuracy":"wine_lda"},inplace=True)
df_merged.set_index('Algo',inplace=True)
print(df_merged)
```

```
                      wine_raw  wine_pca  wine_lda
Algo
KNeighborsClassifier  0.652869  0.640555  0.646522
GaussianNB            0.359820  0.509904  0.537423
MultinomialNB         0.472769  0.436018  0.436018
ComplementNB          0.396376  0.367124  0.438711
```

In [17]:
```
kfold = KFold(n_splits=5)
clrs = []

clrs.append(KNeighborsClassifier(n_neighbors=23 , metric = 'manhattan' ,
weights = "distance"))
clrs.append(GaussianNB())
clrs.append(MultinomialNB())
clrs.append(ComplementNB())

cv_results = []
cv_results_pca = []
cv_results_lda = []

#scoring = {'accuracy' : make_scorer(accuracy_score),
#            'precision' : make_scorer(precision_score),
#            'recall' : make_scorer(recall_score),
#           'f1_score' : make_scorer(f1_score)}

for clr in clrs :
    cv_results.append(cross_val_score(clr, data, target , scoring =
'accuracy', cv = kfold, n_jobs=-1))
    cv_results_pca.append(cross_val_score(clr, data_pca, target_pca , scoring
= 'accuracy', cv = kfold, n_jobs=-1))
    cv_results_lda.append(cross_val_score(clr, data_pca, target_pca , scoring
= 'accuracy', cv = kfold, n_jobs=-1))

cv_means = []
cv_means_pca = []
cv_means_lda = []
```

```
#print(cv_results)
for cv_result in cv_results:
    cv_means.append(cv_result.mean())

for cv_result in cv_results_pca:
    cv_means_pca.append(cv_result.mean())

for cv_result in cv_results_lda:
    cv_means_lda.append(cv_result.mean())

cv_df = pd.DataFrame({"Mean_Accuracy":cv_means,"Algo":
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})
cv_df_pca = pd.DataFrame({"Mean_Accuracy":cv_means_pca,"Algo":
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})
cv_df_lda = pd.DataFrame({"Mean_Accuracy":cv_means_lda,"Algo":
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})

#print(cv_df)
#print(cv_df_pca)
#print(cv_df_lda)
```

In [18]:

```
data_frames = [cv_df, cv_df_pca, cv_df_lda]
df_merged = reduce(lambda  left,right: pd.merge(left,right,on=
['Algo'],how='outer'), data_frames)
df_merged.rename(columns={"Mean_Accuracy_x": "wine_raw", "Mean_Accuracy_y":
"wine_pca","Mean_Accuracy":"wine_lda"},inplace=True)
df_merged.set_index('Algo',inplace=True)
print(df_merged)
```

```
                      wine_raw  wine_pca  wine_lda
Algo
KNeighborsClassifier  0.504236  0.489310  0.489310
GaussianNB            0.309505  0.467139  0.467139
MultinomialNB         0.430356  0.436515  0.436515
ComplementNB          0.396336  0.385406  0.385406
```

Comments

- Complement Naive Bayes does not outperform as expected for the unbalance wine dataset. While training using Complement NB it trains each class with all data, but the sample from that class and because it is a multiclass classsification with higer Prior , the likelihood impact is reduced and overall accuracy is not good.

Decision Trees Classifier

5-Fold CV and hyperparameter tuning

In [19]:

```
dtc = DecisionTreeClassifier()
dtc.fit(X_train, Y_train)
Y_pred = dtc.predict(X_test)
#cm=confusion_matrix(Y_test, Y_pred)
#print(confusion_matrix(Y_test, Y_pred))
#print(classification_report(Y_test, Y_pred))
print("Accuracy Score for Decision Tree classifier without hyper parameter
tuning is: ",accuracy_score(Y_test, Y_pred))
#disp =
ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=dtc.classes_)
#disp.plot()

grid_params = {
    'criterion' : ['gini', 'entropy'],
    'max_depth' : range(2,25,1),
    'min_samples_split' : range(2, 10, 1),
    'min_samples_leaf' : range(2, 10, 1)
}

grid_search = GridSearchCV(dtc, grid_params, cv = 5, n_jobs = -1, verbose =
1)
grid_search.fit(X_train, Y_train)
dtc = grid_search.best_estimator_
Y_pred = dtc.predict(X_test)
print("Accuracy Score is :",accuracy_score(Y_test, Y_pred))
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
print("Best Score is : ",grid_search.best_score_)
#dt_raw_acc = accuracy_score(Y_test, Y_pred)
dt_raw_set=grid_search.best_params_

grid_search.fit(X_train_pca, Y_train_pca)
dtc = grid_search.best_estimator_
Y_pred_pca = dtc.predict(X_test_pca)
print("Accuracy Score using PCA is :",accuracy_score(Y_test_pca, Y_pred_pca))
# best parameters and best score
print("Best Parameters using PCA are : ",grid_search.best_params_)
print("Best Score using PCA is : ",grid_search.best_score_)
dt_pca_set=grid_search.best_params_

grid_search.fit(X_train_lda, Y_train_lda)
dtc = grid_search.best_estimator_
Y_pred_lda = dtc.predict(X_test_lda)
print("Accuracy Score using LDA is :",accuracy_score(Y_test_lda, Y_pred_lda))
```

```
# best parameters and best score
print("Best Parameters using LDA are : ",grid_search.best_params_)
print("Best Score using LDA is : ",grid_search.best_score_)
dt_lda_set=grid_search.best_params_
```

```
Accuracy Score for Decision Tree classifier without hyper parameter tuning is:  0.61153846
15384616
Fitting 5 folds for each of 2944 candidates, totalling 14720 fits
Accuracy Score is : 0.5792307692307692
Best Parameters are :  {'criterion': 'entropy', 'max_depth': 18, 'min_samples_leaf': 2, 'm
in_samples_split': 6}
Best Score is :  0.5639766417413193
Fitting 5 folds for each of 2944 candidates, totalling 14720 fits
Accuracy Score using PCA is : 0.5584615384615385
Best Parameters using PCA are :  {'criterion': 'entropy', 'max_depth': 18, 'min_samples_le
af': 2, 'min_samples_split': 2}
Best Score using PCA is :  0.5474289257422077
Fitting 5 folds for each of 2944 candidates, totalling 14720 fits
Accuracy Score using LDA is : 0.5423076923076923
Best Parameters using LDA are :  {'criterion': 'gini', 'max_depth': 8, 'min_samples_leaf':
2, 'min_samples_split': 6}
Best Score using LDA is :  0.5505084400681128
```

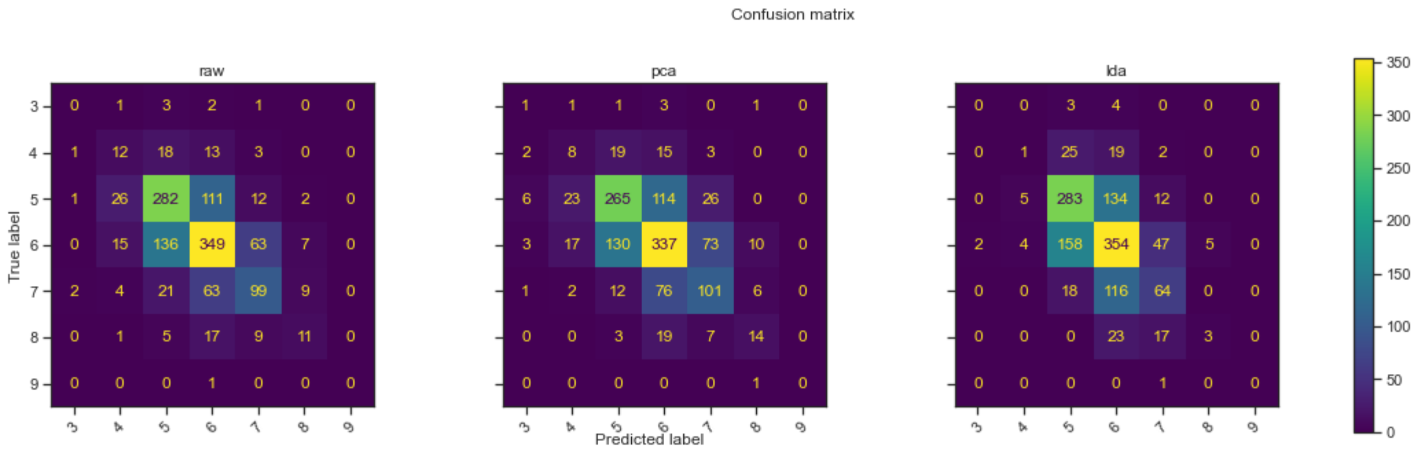
In [20]:

```
dt_raw_acc = accuracy_score(Y_test, Y_pred)
dt_pca_acc = accuracy_score(Y_test_pca, Y_pred_pca)
dt_lda_acc = accuracy_score(Y_test_lda, Y_pred_lda)
#print(dt_raw_acc,dt_pca_acc,dt_lda_acc)
```

In [21]:

```
cm=confusion_matrix(Y_test, Y_pred)
cm_pca=confusion_matrix(Y_test_pca, Y_pred_pca)
cm_lda=confusion_matrix(Y_test_lda, Y_pred_lda)
cm_dict = {
    "raw": cm,
    "pca": cm_pca,
    "lda": cm_lda
}


f, axes = plt.subplots(1, 3, figsize=(20, 5), sharey='row')
for i,(c,cm) in enumerate(cm_dict.items()):
    #print(i,cm)
    disp = ConfusionMatrixDisplay(cm,display_labels=dtc.classes_)
    disp.plot(ax=axes[i], xticks_rotation=45)
    disp.ax_.set_title(c)
    disp.im_.colorbar.remove()
    disp.ax_.set_xlabel('')
    if i!=0:
        disp.ax_.set_ylabel('')
```

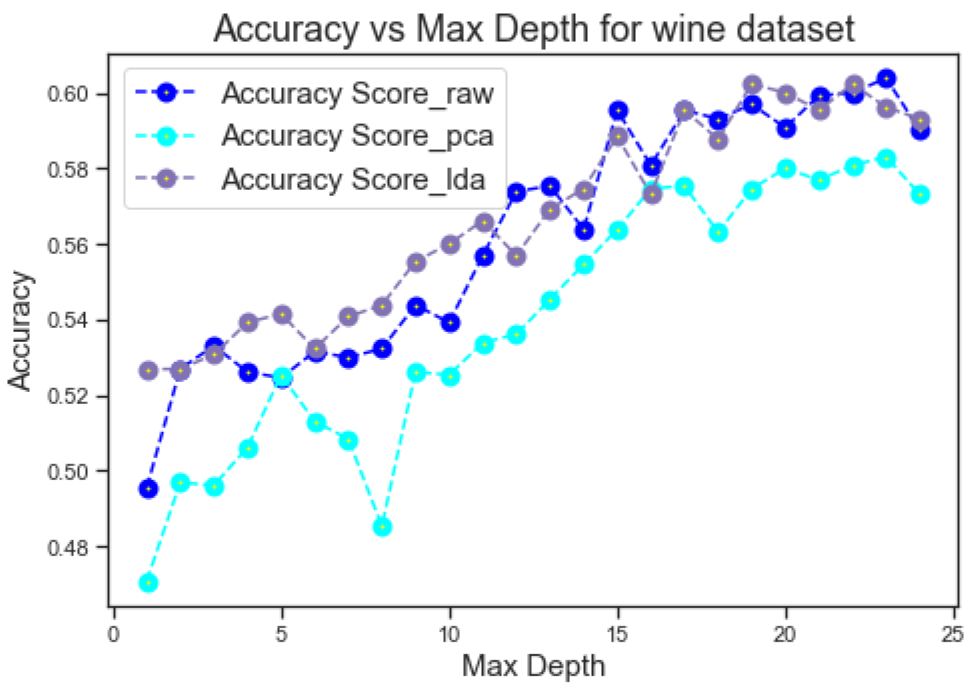
```
f.text(0.4, 0.1, 'Predicted label', ha='left')
plt.subplots_adjust(wspace=0.40, hspace=0.1)

f.suptitle('Confusion matrix', fontsize=12)
f.colorbar(disp.im_, ax=axes)
plt.show()
```



Accuracy vs Max_depth

In [22]:
```
def plot_acc_vs_depth(dataset):
    max_depth_range = list(range(1, 25))
    acc_list = []
    acc_list_pca = []
    acc_list_lda = []
    for depth in max_depth_range:
        dtc_w = DecisionTreeClassifier(max_depth = depth)
        if dataset[0] == 'raw':
            dtc_w.fit(X_train, Y_train)
            score = dtc_w.score(X_test, Y_test)
            acc_list.append(score)
        if dataset[1] == 'pca':
            dtc_w.fit(X_train_pca, Y_train_pca)
            score = dtc_w.score(X_test_pca, Y_test_pca)
            acc_list_pca.append(score)
        if dataset[2] == 'lda':
            dtc_w.fit(X_train_lda, Y_train_lda)
            score =dtc_w.score(X_test_lda, Y_test_lda)
            acc_list_lda.append(score)

    return(acc_list,acc_list_pca,acc_list_lda)

acc_list,acc_list_pca,acc_list_lda = plot_acc_vs_depth(['raw','pca','lda'])
fig = plt.figure(figsize=(7,5))
plt.plot(range(1,25),acc_list, color = 'blue',marker ='o',mew
```

```
=4,mfc='yellow',ls ='--' ,linewidth=1.5,label='Accuracy Score_raw')
plt.plot(range(1,25),acc_list_pca, color = 'cyan',marker ='o',mew
=4,mfc='yellow',ls ='--' ,linewidth=1.5,label='Accuracy Score_pca')
plt.plot(range(1,25),acc_list_lda, color = 'm',marker ='o',mew
=4,mfc='yellow',ls ='--' ,linewidth=1.5,label='Accuracy Score_lda')
plt.ylabel('Accuracy',fontsize = 15)
plt.xlabel('Max Depth',fontsize = 15)
plt.title('Accuracy vs Max Depth for wine dataset',fontsize = 18)
plt.legend(loc='best',fontsize = 15)
plt.tight_layout()
plt.show()
```

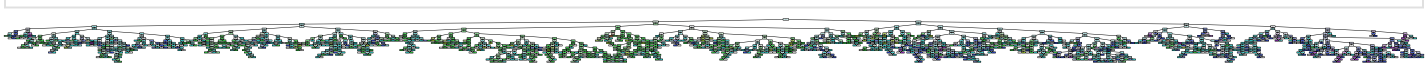


Splitting rules used for the trees

In [23]:

```
dtc_g = DecisionTreeClassifier(criterion= 'entropy', max_depth=18,
min_samples_leaf= 2, min_samples_split=5)
dtc_g.fit(X_train,Y_train)
fn=X_train.columns
cn = wine_raw.quality.unique().astype(str)
dot_data = tree.export_graphviz(dtc_g,
filled=True,feature_names=fn,class_names=cn ,rounded=True,
special_characters=True)
graph = graphviz.Source(dot_data)
graph
```

Out[23]:



Text split rules

In [8]:

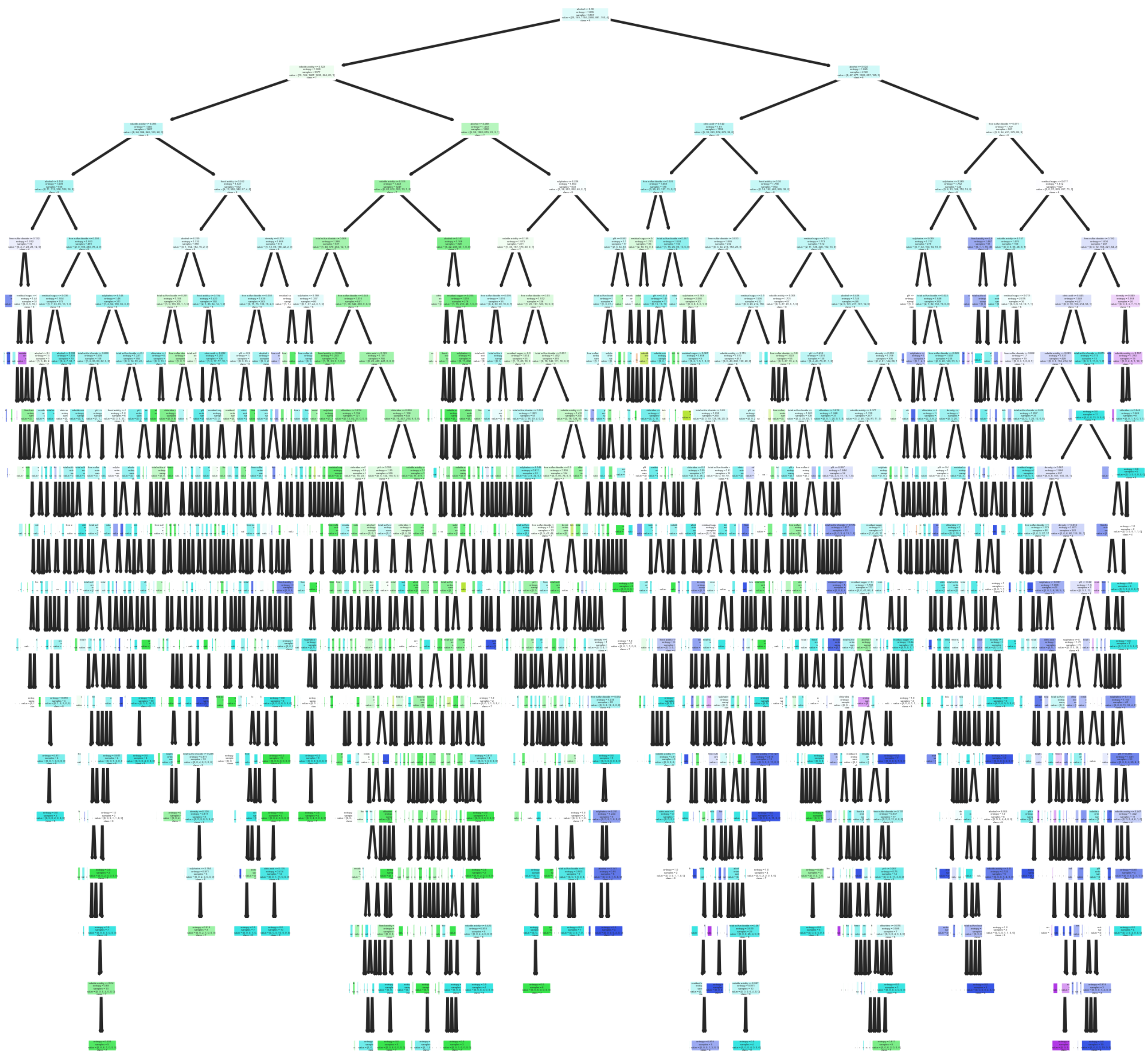
```
from sklearn.tree import export_text
```

```
dtc_g = DecisionTreeClassifier(criterion= 'entropy', max_depth=18,
min_samples_leaf= 2, min_samples_split=5)
dt_rules = dtc_g.fit(X_train,Y_train)
fn_t=X_train.columns
#print(type(fn_t.tolist()))
tree_rules = export_text(dt_rules,feature_names = fn_t.tolist())
#print(tree_rules)
```

Splitting rules used for the trees but fitted on page

In [10]:

```
dtc_g = DecisionTreeClassifier(criterion= 'entropy', max_depth=18,
min_samples_leaf= 2, min_samples_split=5)
dtc_g.fit(X_train,Y_train)
fn=X_train.columns
cn = wine_raw.quality.unique().astype(str)
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (8,8), dpi=300)
tree.plot_tree(dtc_g, filled=True,feature_names=fn,class_names=cn
,rounded=True)
fig.savefig('dtc_tree_plot_4.png')
```



Comments

- Alcohol and volatile accidity are important splitting parametrs. Optimal Max_depth is larger than the original features, clearly indicating that there are no clear patterns while splitting. Categorical and quantitave, both data are used for splitting rules.

Random Forest Classifier

5-Fold CV and hyperparameter tuning

In [25]:
```
rfc = RandomForestClassifier()
rfc.fit(X_train, Y_train)
Y_pred = rfc.predict(X_test)
cm=confusion_matrix(Y_test, Y_pred)
#print(confusion_matrix(Y_test, Y_pred))
#print(classification_report(Y_test, Y_pred))
```

```
print("Accuracy Score for Forest classifier without hyper parameter tuning
is: ",accuracy_score(Y_test, Y_pred))
#disp =
ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=dtc.classes_)
#disp.plot()

grid_params = {
    'n_estimators': [2,5,200, 500],
    'criterion' : ['entropy'],
    'max_depth' : range(2,25,1),
    #'max_features': range(3,10,1),
    #'min_samples_split' : range(2, 10, 1),
    #'min_samples_leaf' : range(2, 10, 1)
}

grid_search = GridSearchCV(rfc, grid_params, cv = 5, n_jobs = -1, verbose =
True)
#print(grid_search.get_params().keys())
grid_search.fit(X_train, Y_train)
rfc = grid_search.best_estimator_
Y_pred = rfc.predict(X_test)
print("Accuracy Score is :",accuracy_score(Y_test, Y_pred))
rf_raw_acc=accuracy_score(Y_test, Y_pred)
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
rf_raw_set=grid_search.best_params_
#print("Best Score is : ",grid_search.best_score_)
ac_df=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
ac_df["accuracy"]=grid_search.cv_results_['mean_test_score']

grid_search.fit(X_train_pca, Y_train_pca)
rfc_pca = grid_search.best_estimator_
Y_pred_pca = rfc_pca.predict(X_test_pca)
print("Accuracy Score using PCA is :",accuracy_score(Y_test_pca, Y_pred_pca))
rf_pca_acc=accuracy_score(Y_test_pca, Y_pred_pca)
# best parameters and best score
print("Best Parameters using PCA are : ",grid_search.best_params_)
rf_pca_set=grid_search.best_params_
#print("Best Score using PCA is : ",grid_search.best_score_)
ac_df_pca=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
ac_df_pca["accuracy"]=grid_search.cv_results_['mean_test_score']
```

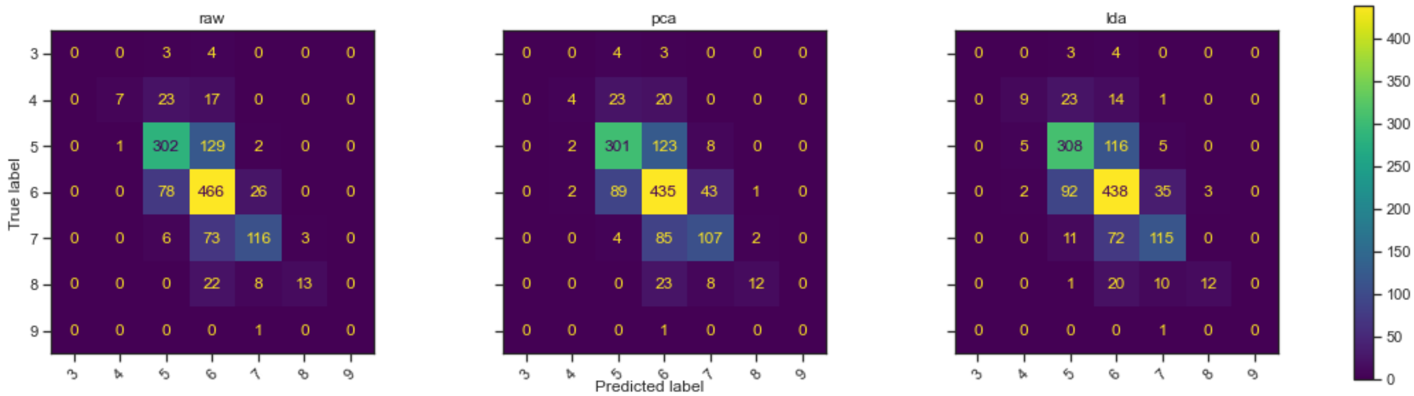
```
grid_search.fit(X_train_lda, Y_train_lda)
rfc_lda = grid_search.best_estimator_
Y_pred_lda = rfc_lda.predict(X_test_lda)
print("Accuracy Score using LDA is :",accuracy_score(Y_test_lda, Y_pred_lda))
rf_lda_acc=accuracy_score(Y_test_lda, Y_pred_lda)
# best parameters and best score
print("Best Parameters using LDA are : ",grid_search.best_params_)
#print("Best Score using LDA is : ",grid_search.best_score_)
rf_lda_set=grid_search.best_params_
ac_df_lda=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
ac_df_lda["accuracy"]=grid_search.cv_results_['mean_test_score']
```

```
Accuracy Score for Forest classifier without hyper parameter tuning is:  0.691538461538461
5
Fitting 5 folds for each of 92 candidates, totalling 460 fits
Accuracy Score is : 0.6953846153846154
Best Parameters are :  {'criterion': 'entropy', 'max_depth': 18, 'n_estimators': 500}
Fitting 5 folds for each of 92 candidates, totalling 460 fits
Accuracy Score using PCA is : 0.6607692307692308
Best Parameters using PCA are :  {'criterion': 'entropy', 'max_depth': 16, 'n_estimators':
200}
Fitting 5 folds for each of 92 candidates, totalling 460 fits
Accuracy Score using LDA is : 0.6784615384615384
Best Parameters using LDA are :  {'criterion': 'entropy', 'max_depth': 17, 'n_estimators':
500}
```

In [26]:

```
cm=confusion_matrix(Y_test, Y_pred)
cm_pca=confusion_matrix(Y_test_pca, Y_pred_pca)
cm_lda=confusion_matrix(Y_test_lda, Y_pred_lda)
cm_dict = {
    "raw": cm,
    "pca": cm_pca,
    "lda": cm_lda
}

f, axes = plt.subplots(1, 3, figsize=(20, 5), sharey='row')
for i,(c,cm) in enumerate(cm_dict.items()):
    #print(i,cm)
    disp = ConfusionMatrixDisplay(cm,display_labels=dtc.classes_)
    disp.plot(ax=axes[i], xticks_rotation=45)
    disp.ax_.set_title(c)
    disp.im_.colorbar.remove()
    disp.ax_.set_xlabel('')
    if i!=0:
        disp.ax_.set_ylabel('')
```

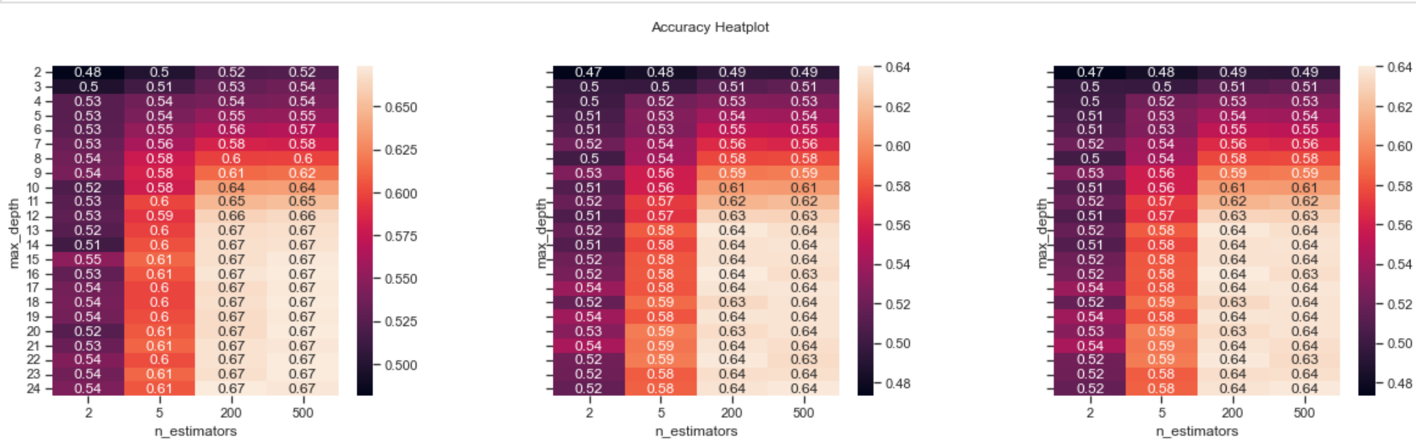
```
f.text(0.4, 0.1, 'Predicted label', ha='left')
plt.subplots_adjust(wspace=0.40, hspace=0.1)



f.colorbar(disp.im_, ax=axes)
plt.show()
```



Heatmap of max_depth vs n_estimators

In [27]:

```
#Pivoting the dataframe for plotting heat map
ac_df=ac_df.pivot(index='max_depth',columns='n_estimators',values='accuracy')
ac_df_pca=ac_df_pca.pivot(index='max_depth',columns='n_estimators',values='accu

ac_df_lda=ac_df_lda.pivot(index='max_depth',columns='n_estimators',values='accu

#Plotting the graph
fig, ax =plt.subplots(1,3,figsize=(20, 5), sharey='row')

sns.heatmap(ac_df,annot=True, ax=ax[0])
sns.heatmap(ac_df_pca,annot=True ,ax=ax[1])
sns.heatmap(ac_df_pca,annot=True ,ax=ax[2])

plt.subplots_adjust(wspace=0.40, hspace=0.1)
fig.suptitle('Accuracy Heatplot', fontsize=12)
plt.show()
```



Gradient Boosting Classifier

5-Fold CV and hyperparameter tuning

In [28]:

```
gbc = GradientBoostingClassifier()
gbc.fit(X_train, Y_train)
Y_pred = gbc.predict(X_test)
cm=confusion_matrix(Y_test, Y_pred)
#print(confusion_matrix(Y_test, Y_pred))
#print(classification_report(Y_test, Y_pred))
print("Accuracy Score for Gradient Boosting classifier without hyper parameter tuning is: ",accuracy_score(Y_test, Y_pred))
#disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=dtc.classes_)
#disp.plot()

grid_params = {
    'n_estimators': [2,120,200,500,800],
    'learning_rate' : [0.01, 0.1,1],
    #'criterion' : [None,'mse','mae'],
    #'max_depth' : range(2,22,2),
    #'max_features': range(3,10,1),
    #'min_samples_split' : range(2, 10, 1),
    #'min_samples_leaf' : range(2, 10, 1)
}

grid_search = GridSearchCV(gbc, grid_params, cv = 5, n_jobs = -1, verbose = True)
#print(grid_search.get_params().keys())
grid_search.fit(X_train, Y_train)
gbc = grid_search.best_estimator_
Y_pred = gbc.predict(X_test)
print("Accuracy Score is :",accuracy_score(Y_test, Y_pred))
gbc_acc=accuracy_score(Y_test, Y_pred)
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
gbc_set=grid_search.best_params_
#print("Best Score using PCA is : ",grid_search.best_score_)
gbc_ac_df=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
gbc_ac_df["accuracy"]=grid_search.cv_results_['mean_test_score']
```

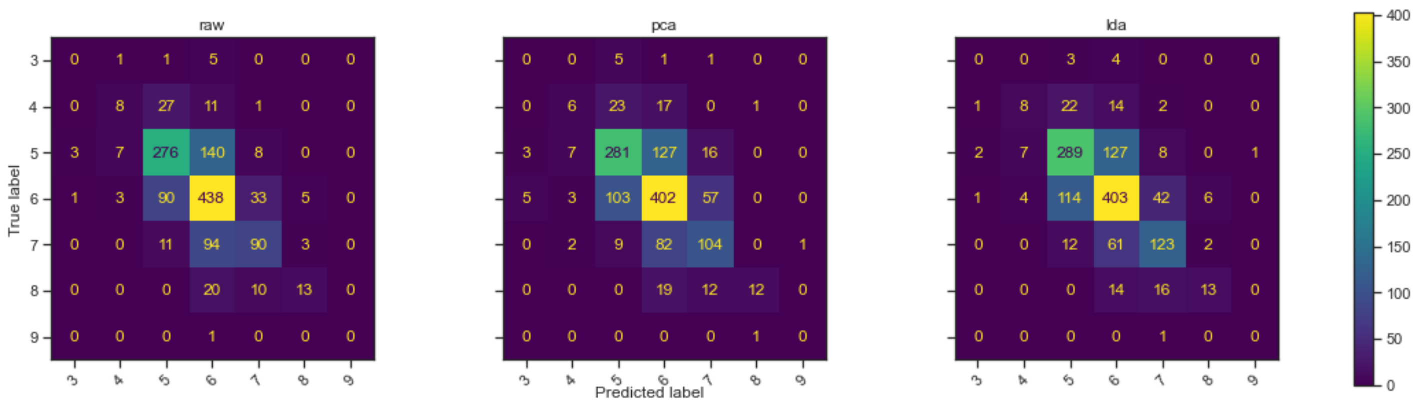
```
grid_search.fit(X_train_pca, Y_train_pca)
gbc = grid_search.best_estimator_
Y_pred_pca = gbc.predict(X_test_pca)
print("Accuracy Score is :",accuracy_score(Y_test_pca, Y_pred_pca))
gbc_pca_acc=accuracy_score(Y_test_pca, Y_pred_pca)
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
gbc_pca_set=grid_search.best_params_
#print("Best Score using PCA is : ",grid_search.best_score_)
gbc_ac_df_pca=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
gbc_ac_df_pca["accuracy"]=grid_search.cv_results_['mean_test_score']



grid_search.fit(X_train_lda, Y_train_lda)
gbc = grid_search.best_estimator_
Y_pred_lda = gbc.predict(X_test_lda)
print("Accuracy Score is :",accuracy_score(Y_test_lda, Y_pred_lda))
gbc_lda_acc=accuracy_score(Y_test_lda, Y_pred_lda)
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
gbc_lda_set=grid_search.best_params_
#print("Best Score using PCA is : ",grid_search.best_score_)
gbc_ac_df_lda=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
gbc_ac_df_lda["accuracy"]=grid_search.cv_results_['mean_test_score']
```

```
Accuracy Score for Gradient Boosting classifier without hyper parameter tuning is:  0.6007
692307692307
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Accuracy Score is : 0.6346153846153846
Best Parameters are :  {'learning_rate': 0.1, 'n_estimators': 800}
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Accuracy Score is : 0.6192307692307693
Best Parameters are :  {'learning_rate': 0.1, 'n_estimators': 800}
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Accuracy Score is : 0.6430769230769231
Best Parameters are :  {'learning_rate': 0.1, 'n_estimators': 800}
```

In [29]:

```
cm=confusion_matrix(Y_test, Y_pred)
cm_pca=confusion_matrix(Y_test_pca, Y_pred_pca)
cm_lda=confusion_matrix(Y_test_lda, Y_pred_lda)
cm_dict = {
    "raw": cm,
    "pca": cm_pca,
    "lda": cm_lda
}
```

```
f, axes = plt.subplots(1, 3, figsize=(20, 5), sharey='row')
for i,(c,cm) in enumerate(cm_dict.items()):
    #print(i,cm)
    disp = ConfusionMatrixDisplay(cm,display_labels=dtc.classes_)
    disp.plot(ax=axes[i], xticks_rotation=45)
    disp.ax_.set_title(c)
    disp.im_.colorbar.remove()
    disp.ax_.set_xlabel('')
    if i!=0:
        disp.ax_.set_ylabel('')

f.text(0.4, 0.1, 'Predicted label', ha='left')
plt.subplots_adjust(wspace=0.40, hspace=0.1)



f.colorbar(disp.im_, ax=axes)
plt.show()
```

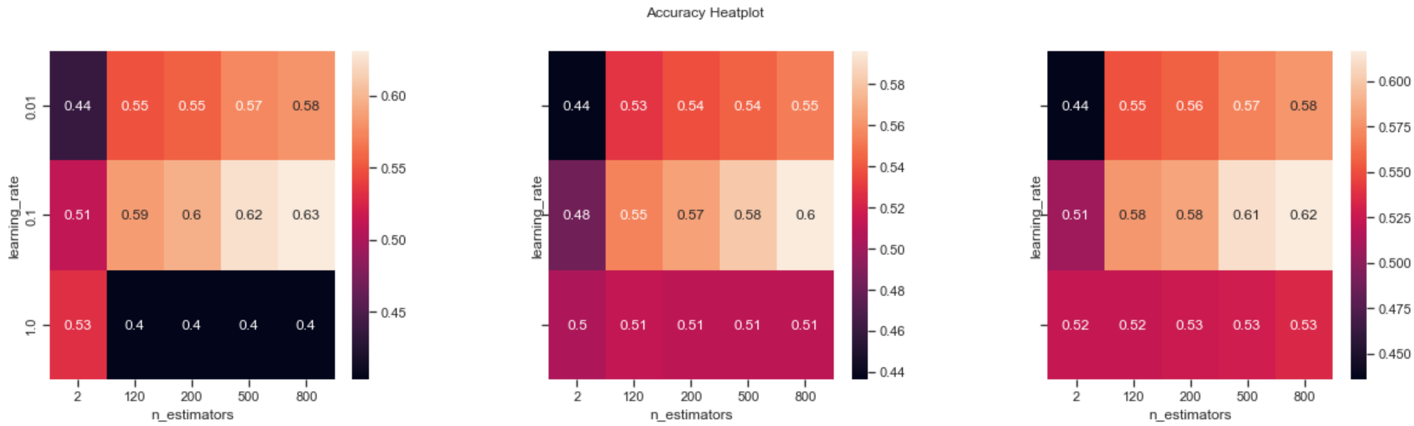


Heatplot of learning_rate and n_estimators

In [30]:

```
#Pivoting the dataframe for plotting heat map
gbc_ac_df=gbc_ac_df.pivot(index='learning_rate',columns='n_estimators',values='

gbc_ac_df_pca=gbc_ac_df_pca.pivot(index='learning_rate',columns='n_estimators',

gbc_ac_df_lda=gbc_ac_df_lda.pivot(index='learning_rate',columns='n_estimators',

#Plotting the graph
fig, ax =plt.subplots(1,3,figsize=(20, 5), sharey='row')

sns.heatmap(gbc_ac_df,annot=True, ax=ax[0])
sns.heatmap(gbc_ac_df_pca,annot=True ,ax=ax[1])
sns.heatmap(gbc_ac_df_lda,annot=True ,ax=ax[2])
```

```
plt.subplots_adjust(wspace=0.40, hspace=0.1)
fig.suptitle('Accuracy Heatplot', fontsize=12)
plt.show()
```



Final Results

In [51]:

```
dt_dict = {'Algo': ['Decision Tree','Random Forest','Gradient Boosting'],
            'wine_raw': [dt_raw_acc,rf_raw_acc,gbc_acc], 'wine_pca':
[dt_pca_acc,rf_pca_acc,gbc_pca_acc],
            'wine_lda':[dt_lda_acc,rf_lda_acc,gbc_lda_acc]}

df_mid=pd.DataFrame(data=dt_dict,columns=
['Algo','wine_raw','wine_pca','wine_lda'])
#display(df_mid)
df_nb=df_merged.reset_index()
final_df = df_nb.append(df_mid, ignore_index=True)
display(final_df)
```

	Algo	wine_raw	wine_pca	wine_lda
0	KNeighborsClassifier	0.504236	0.489310	0.489310
1	GaussianNB	0.309505	0.467139	0.467139
2	MultinomialNB	0.430356	0.436515	0.436515
3	ComplementNB	0.396336	0.385406	0.385406
4	Decision Tree	0.579231	0.558462	0.542308
5	Random Forest	0.695385	0.660769	0.678462
6	Gradient Boosting	0.634615	0.619231	0.643077

In [ ]:

```
#print(dt_raw_set.keys())
#print(dt_raw_set.values(),dt_pca_set.values(),dt_lda_set.values())
dt_s =[dt_raw_set,dt_pca_set,dt_lda_set]
df_dt_settings = pd.DataFrame(dt_s)
df_dt_settings['Algo']= 'Decision Tree'
```

```
df_dt_settings['Data'] = ['raw','pca','lda']
display(df_dt_settings)
```

In [65]:
```
rf_s =[rf_raw_set,rf_pca_set,rf_lda_set]
df_rf_settings = pd.DataFrame(rf_s)
df_rf_settings['Algo']= 'Random Forest'
df_rf_settings['Data'] = ['raw','pca','lda']
display(df_rf_settings)
```

	criterion	max_depth	n_estimators	Algo	Data
0	entropy	18	500	Random Forest	raw
1	entropy	16	200	Random Forest	pca
2	entropy	17	500	Random Forest	lda

In [66]:
```
gbc_s =[gbc_set,gbc_pca_set,gbc_lda_set]
df_gbc_settings = pd.DataFrame(gbc_s)
df_gbc_settings['Algo']= 'Gradient Boosting'
df_gbc_settings['Data'] = ['raw','pca','lda']
display(df_gbc_settings)
```

	learning_rate	n_estimators	Algo	Data
0	0.1	800	Gradient Boosting	raw
1	0.1	800	Gradient Boosting	pca
2	0.1	800	Gradient Boosting	lda

In [ ]:
```
knn_setting = ({'n_neighbors':23 , 'metric': 'manhattan' , 'weights':
"distance"})
gnb_settings = ("default")
mnb_settings = ("default")
cnb_settings = ("default")
dt_settings =
({'criterion':'Entropy','max_depth':18,'min_samples_leaf':2,'min_samples_split'

rf_settings = ({'criterion':'Entropy','max_depth':18,'n_estimators':500})
gb_settings = ({'learning_rate':0.1,'n_estimators':800})

settings_all =
[knn_setting,gnb_settings,mnb_settings,cnb_settings,dt_settings,dt_settings,rf_

settings_all
df_final['settings'] =settings_all
```

In [9]:
```
display(df_final)
```

	Algo	settings	wine_raw	wine_pca	wine_lda
0	KNeighborsClassifier	{'n_neighbors': 23, 'metric': 'manhattan', 'we...	0.504236	0.489310	0.489310
1	GaussianNB	default'	0.309505	0.467139	0.467139
2	MultinomialNB	default'	0.430356	0.436515	0.436515
3	ComplementNB	default'	0.396336	0.385406	0.385406
4	Decision Tree	{'criterion': 'Entropy','max_depth': 18,'min_s...	0.579231	0.558462	0.542308
5	Random Forest	{'criterion': 'Entropy', 'max_depth': 18, 'n_e...	0.695385	0.660769	0.678462
6	Gradient Boosting	{'learning_rate': 0.1, 'n_estimators': 800}	0.634615	0.619231	0.643077

Comments

- Random Forest with following settings *criterion*: entropy, *max-depth*: 18, *n-estimators*:500 on raw data(MinMax Scaling) as well as for PCA and LDA dataset performed the best task at classification.
- For Gradient Boosting and Gaussian Naive bayes , dimensionality reduction did help while for other algorithms the accuracy results were almost comparable to original dataset

Abalone Dataset

Preprocessing

Loading Data

In [28]:

```
#Columns/Features
D = ['Sex', 'Length', 'Diameter', 'Height', 'Whole weight', 'Shucked weight',
'Viscera weight', 'Shell weight']
L = 'Rings'
DL = D + [L]

#Loading Data set
abalone = pd.read_csv("abalone.csv", sep=',', names=DL)

abalone = abalone.replace('M', 0)
abalone = abalone.replace('F', 1)
abalone = abalone.replace('I', 2)
```

Normalization/Scaling

In [29]:

```
abalone1=abalone.copy()
abalone_z = abalone1.drop(columns = ['Sex', 'Rings'])
abalone_znormalized = abalone_z.apply(stats.zscore)
abalone_znormalized['Sex'] = abalone['Sex']
abalone_znormalized['Rings'] = abalone['Rings']

target_z = abalone_znormalized['Rings']
data_z = abalone_znormalized.drop(columns = 'Rings')
X_train_z, X_test_z, Y_train_z, Y_test_z = train_test_split(data_z, target_z,
test_size=0.2 , random_state=27)
```

In [30]:

```
abalone_s = abalone.copy()
abalone_s = abalone_s.drop(columns = ['Sex' , 'Rings'])
abalone_minmax = (abalone_s - abalone_s.min()) / ( abalone_s.max() -
abalone_s.min())
abalone_minmax['Sex'] = abalone['Sex']
abalone_minmax['Rings'] = abalone['Rings']

abalone_min_max = abalone_minmax
target = abalone_min_max['Rings']
data = abalone_min_max.drop(columns = 'Rings')
X_train, X_test, Y_train, Y_test = train_test_split(data, target,
test_size=0.2 , random_state=27)
```

Best formulated KNN from Assignment-1

In [31]:
```
knn = KNeighborsClassifier(n_neighbors=66, metric='minkowski',
weights='uniform', p=2)
knn.fit(X_train, Y_train)
Y_pred = knn.predict(X_test)

knn_train_acc = knn.score(X_train, Y_train)
print("Training Score: ", knn_train_acc)
knn_test_acc = knn.score(X_test, Y_test)
print("Testing Score: ", knn_test_acc)
```

```
Training Score:  0.2975157138581263
Testing Score:  0.2631578947368421
```

Representation Learning

Indepepndent and dependent variable

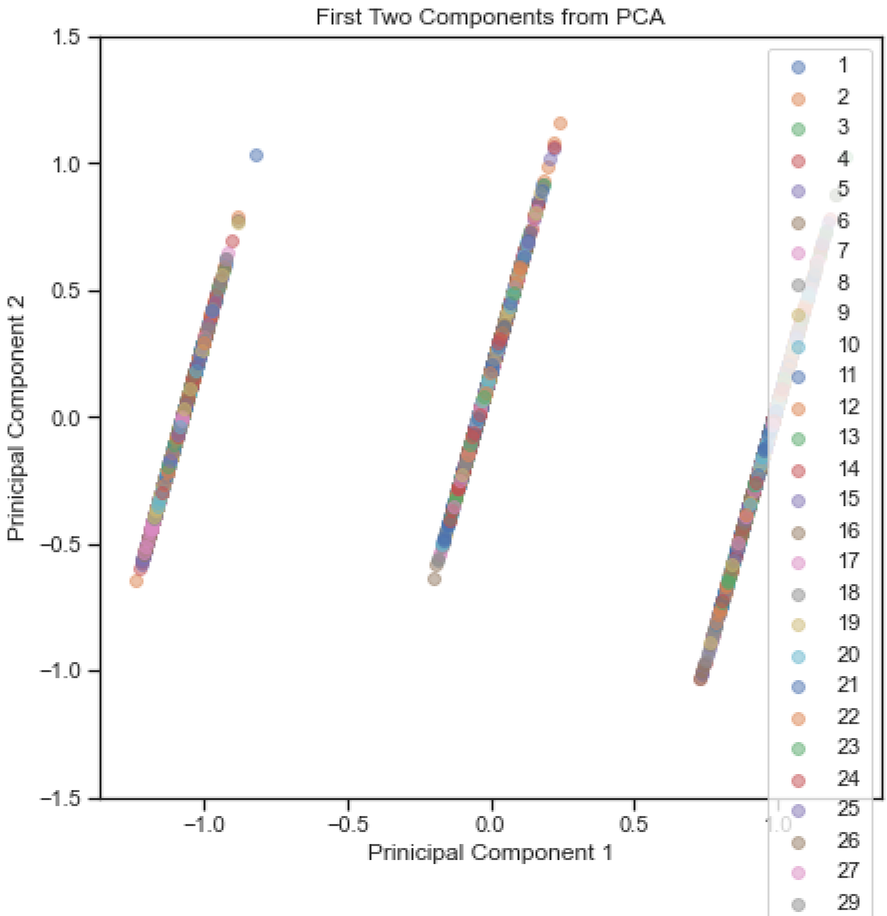
In [32]:
```
#Scaled 'data' and 'target'
x=data
y=target
n_components=2
target_names = np.sort(y.unique())
```

PCA

In [33]:
```
print("PCA Model - Explained Variance of each component")
pca = PCA(n_components=n_components)
X_r = pca.fit(x).transform(x)
exp_var_ratio_df = pd.DataFrame(pca.explained_variance_ratio_, columns=
['Explained Variance Ratio'])
print(exp_var_ratio_df)

plt.figure(figsize=(7,7))
colors = plt.cm.get_cmap("twilight")

for i, target_name in enumerate(target_names):
    plt.scatter(
        X_r[y == i, 0], X_r[y == i, 1], alpha=0.5, lw=1, label=target_name,
cmap="twilight"
    )
plt.ylim(-1.5,1.5)
plt.legend(loc="best", shadow=False, scatterpoints=1)
plt.xlabel("Prinicipal Component 1")
plt.ylabel("Prinicipal Component 2")
```

```
plt.title("First Two Components from PCA")
plt.set_cmap("twilight")

plt.show()
```

```
PCA Model - Explained Variance of each component
   Explained Variance Ratio
0                  0.865084
1                  0.123693
```



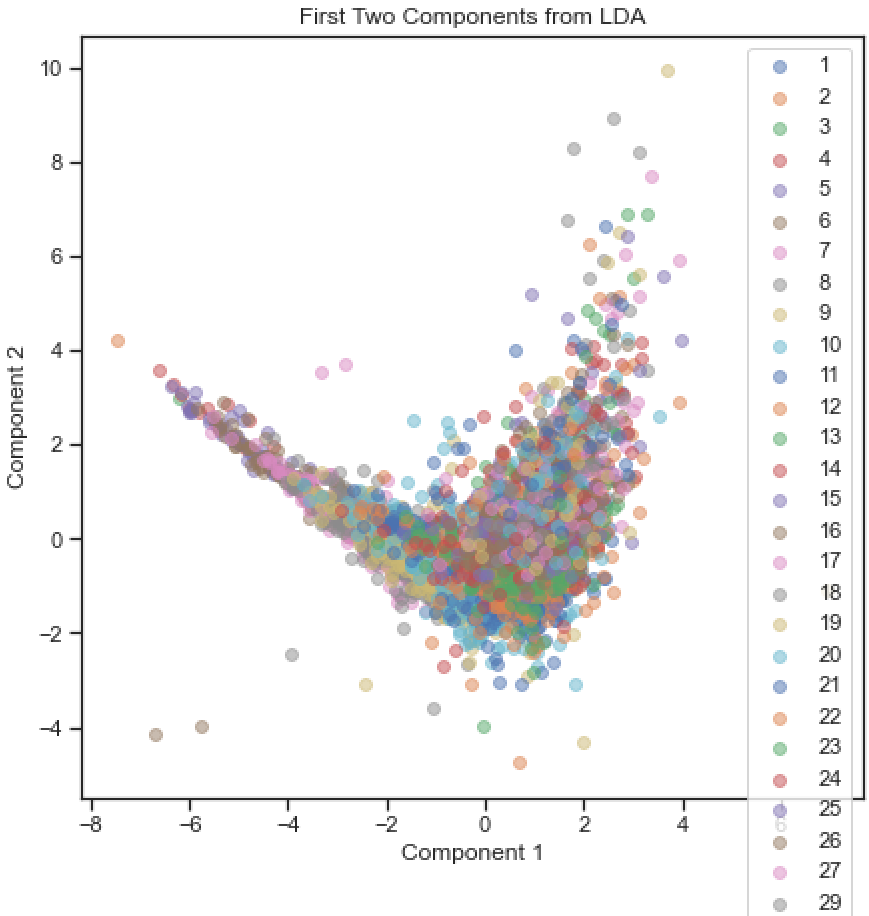
LDA

In [34]:

```
print("LDA Model - Explained Variance of each component")
lda = LinearDiscriminantAnalysis(n_components=n_components)
X_r2 = lda.fit(x, y).transform(x)
exp_var_ratio_df = pd.DataFrame(lda.explained_variance_ratio_, columns=
['Explained Variance Ratio'])
print(exp_var_ratio_df)

plt.figure(figsize=(7,7))
colors = plt.cm.get_cmap("twilight")
for i, target_name in enumerate(target_names):
    plt.scatter(
        X_r2[y == i, 0], X_r2[y == i, 1], alpha=0.5, lw=1, label=target_name,
cmap="twilight"
    )
```

```
#plt.xlim(-4,4)
plt.legend(loc="best", shadow=False, scatterpoints=1)
plt.xlabel("Component 1")
plt.ylabel("Component 2")
plt.title("First Two Components from LDA")
plt.set_cmap("twilight")

plt.show()
```

```
LDA Model - Explained Variance of each component
   Explained Variance Ratio
0                  0.719139
1                  0.216991
```

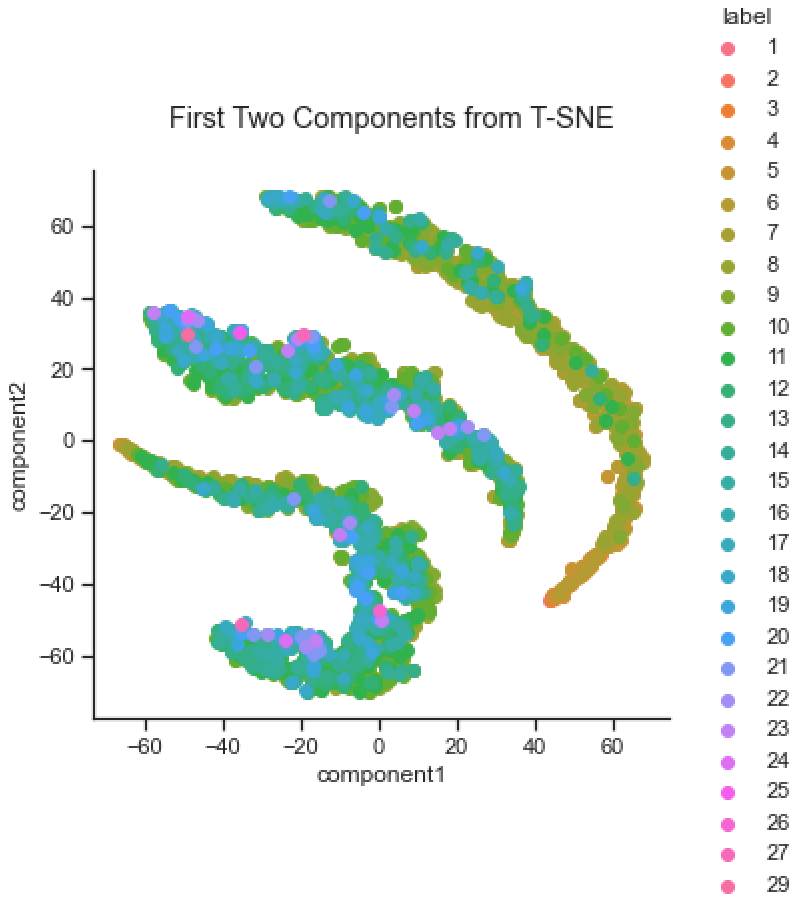


T-SNE

In [35]:

```
tsne = TSNE(n_components=n_components)
X_r3 = tsne.fit_transform(x)
tsne_data = np.vstack((X_r3.T,target)).T
tsne_df = pd.DataFrame(data = tsne_data, columns = ['component1',
'component2','label'] )
#print(tsne_df.head())
tsne_df['label'] = tsne_df['label'].astype('int')
tsne_df['label'] = tsne_df['label'].astype('category')
g = sns.FacetGrid(tsne_df, hue='label', height=5).map(plt.scatter,
'component1','component2')
```

```
g.add_legend()
g.fig.suptitle("First Two Components from T-SNE ")
g.tight_layout()
```



Comments

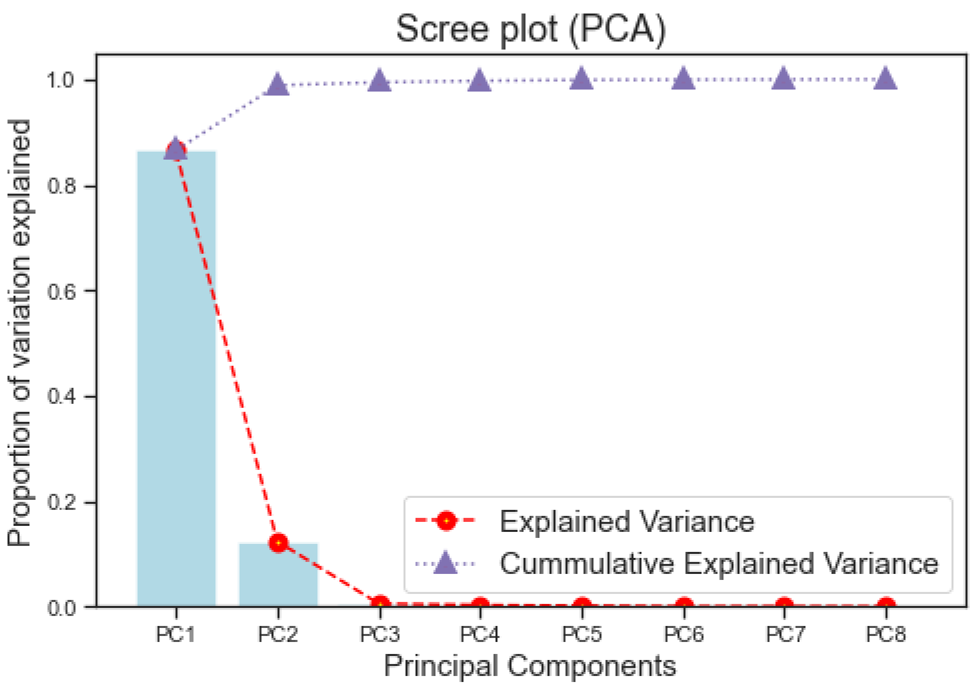
- PCA: Three distant lines due to presence of categorical column(Sex) in the data.We have one principal component that explains nearly all (85%) of the variance the reason is, the principal component is a mixture of all variables in nearly equal proportions. That is, the principal component is the one that combines every single variable.
- LDA: Inter Class spread is increased and intra-class spread is decreased, clusterring similar class points together. Outliers evident in the plot asdistance between them is large.
- t-SNE: Keeps changing with the run, three clusters are formed, better way to visualize but doe not help in our case for multiclass classification

Scree Plot (PCA)

In [36]:

```
pca = PCA(n_components=None)
X_r = pca.fit(x).transform(x)
explained_variance_pca = pca.explained_variance_ratio_
fig = plt.figure(figsize=(7,5))
tick_label = ['PC' + str(i) for i in range(1,len(explained_variance_pca)+1)]
plt.bar(range(len(explained_variance_pca)), explained_variance_pca, color =
'c',alpha=0.5, align='center',tick_label=tick_label)
plt.plot(range(len(explained_variance_pca)), explained_variance_pca, color =
'red',marker ='o',mew =4,mfc='yellow',ls ='--'
```

```
,linewidth=1.5,label='Explained Variance')
plt.plot(range(len(explained_variance_pca)), explained_variance_pca.cumsum(),
color = 'm',marker ='^',mew =4,mfc='red',ls =':'
,linewidth=1.5,label='Cummulative Explained Variance')
plt.ylabel('Proportion of variation explained',fontsize = 15)
plt.xlabel('Principal Components',fontsize = 15)
plt.title('Scree plot (PCA)',fontsize = 18)
plt.legend(loc='best',fontsize = 15)
#plt.axis("off")
plt.tight_layout()
plt.show()
```

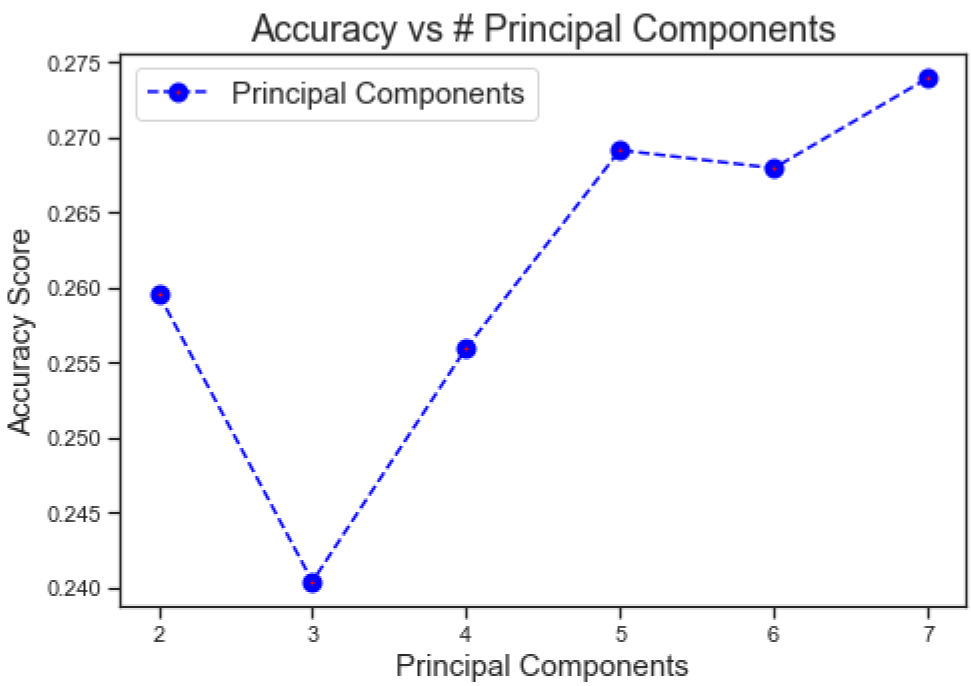


Reduced Dimensionality

PCA

In [37]:
```
knn = KNeighborsClassifier(n_neighbors=66, metric='minkowski',
weights='uniform', p=2)
D = data.shape[1]
#print(D)
acc_list =[]

for i in range(2,D):
    pca = PCA(n_components=i)
    X_train_r = pca.fit(X_train).transform(X_train)
    X_test_r = pca.transform(X_test)
    knn.fit(X_train_r, Y_train)
    y_pred = knn.predict(X_test_r)
    acc_list.append(metrics.accuracy_score(Y_test,y_pred))
```

```
fig = plt.figure(figsize=(7,5))
plt.plot(range(2,D),acc_list, color = 'blue',marker ='o',mew =4,mfc='red',ls
='--' ,linewidth=1.5,label='Principal Components')
plt.ylabel('Accuracy Score',fontsize = 15)
plt.xlabel('Principal Components',fontsize = 15)
plt.title('Accuracy vs # Principal Components',fontsize = 18)
plt.legend(loc='best',fontsize = 15)
plt.tight_layout()
plt.show()


print("The maximum accuracy {} happens to be when number of Principal
Components is : {}".format(max(acc_list),acc_list.index(max(acc_list))+2))
```



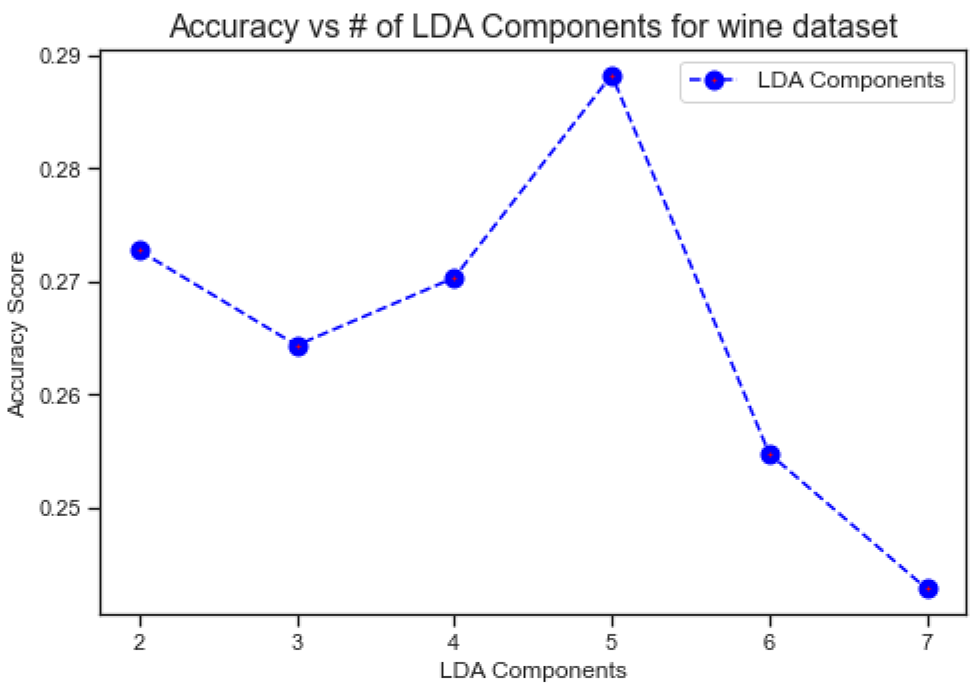

```
The maximum accuracy 0.27392344497607657 happens to be when number of Principal Components
is : 7
```

LDA

In [38]:

```
knn = KNeighborsClassifier(n_neighbors=66, metric='minkowski',
weights='uniform', p=2)
#LDA is constrained by the number of components it can use , given by :
min(n_classes-1, len(features))
D = min(data.shape[1],len(target_names))
acc_list =[]

for i in range(2,D):
    lda = LinearDiscriminantAnalysis(n_components=i)
    X_train_r = lda.fit(X_train,Y_train).transform(X_train)
    X_test_r = lda.transform(X_test)
    knn.fit(X_train_r, Y_train)
    y_pred = knn.predict(X_test_r)
```

```
    acc_list.append(metrics.accuracy_score(Y_test,y_pred))

fig = plt.figure(figsize=(7,5))
plt.plot(range(2,D),acc_list, color = 'blue',marker ='o',mew =4,mfc='red',ls
='--' ,linewidth=1.5,label='LDA Components')
plt.ylabel('Accuracy Score',fontsize = 12)
plt.xlabel('LDA Components',fontsize = 12)
plt.title('Accuracy vs # of LDA Components for wine dataset',fontsize = 16)
plt.legend(loc='best',fontsize = 12)
plt.tight_layout()
plt.show()

print("The maximum accuracy {} happens to be when number of LDA Components is
: {}".format(max(acc_list),acc_list.index(max(acc_list))+2))
```




```
The maximum accuracy 0.28827751196172247 happens to be when number of LDA Components is :
5
```

Comments

- Two Principal Components are able to explain 98% of the variance in the dataset. We get maximum accuracy with 7 principal components which is same as orginal dimension of dataset, but we use 5 components in subsequent sections as there is no significant difference in accuracy with 5 and 7 components.
- With 5 components in LDA, we get maximum accuracy (more than PCA). LDA does a better job at classification task.
- Dimensionality Reduction improves the accuracy for both PCA and LDA compared to best formulation from Assignment-1

Versions of dataset (raw/pca/lda)

In [39]:

```
abalone_raw = abalone.copy()
```

```
abalone_normalized_raw = abalone_znormalized.copy()
abalone_minmax_normalized = abalone_minmax.copy()

pca = PCA(n_components=5)
X_r = pca.fit(x).transform(x)
pca_data = np.vstack((X_r.T,target)).T
abalone_pca = pd.DataFrame(data = pca_data, columns =
['component1','component2','component3', 'component4','component5','label'] )
abalone_temp_pca = abalone_pca.copy()
abalone_temp_pca_2 = abalone_temp_pca.drop(columns = ['label'])
abalone_pca = (abalone_temp_pca_2 - abalone_temp_pca_2.min()) / (
abalone_temp_pca_2.max() - abalone_temp_pca_2.min())
abalone_pca['label'] = abalone_temp_pca['label']
#abalone_pca = (abalone_pca - abalone_pca.min()) / ( abalone_pca.max() -
abalone_pca.min())
abalone_pca['label'] = abalone_pca['label'].astype('int')
abalone_pca['label'] = abalone_pca['label'].astype('category')
#print(abalone_pca.head())

lda = LinearDiscriminantAnalysis(n_components=5)
X_r2 = lda.fit(x, y).transform(x)
lda_data = np.vstack((X_r2.T,target)).T
abalone_lda = pd.DataFrame(data = lda_data, columns = ['component1',
'component2','component3','component4','component5','label'] )
abalone_temp_lda = abalone_lda.copy()
abalone_temp_lda_2 = abalone_temp_lda.drop(columns = ['label'])
abalone_lda = (abalone_temp_lda_2 - abalone_temp_lda_2.min()) / (
abalone_temp_lda_2.max() - abalone_temp_lda_2.min())
abalone_lda['label'] = abalone_temp_lda['label']
abalone_lda['label'] = abalone_lda['label'].astype('int')
abalone_lda['label'] = abalone_lda['label'].astype('category')
#print(abalone_lda.head())
```

In [40]:

```
abalone_p = abalone_pca.copy()
target_pca = abalone_p['label']
data_pca = abalone_p.drop(columns = 'label')
X_train_pca, X_test_pca, Y_train_pca, Y_test_pca = train_test_split(data_pca,
target_pca, test_size=0.2 , random_state=27)

abalone_l = abalone_lda.copy()
target_lda = abalone_l['label']
data_lda = abalone_l.drop(columns = 'label')
```

```
X_train_lda, X_test_lda, Y_train_lda, Y_test_lda = train_test_split(data_lda,
target_lda, test_size=0.2 , random_state=27)
```

Naive Bayes Classifier

5-Fold CV for Naive Bayes & KNN classifier

In [64]:

```
kfold = KFold(n_splits=5)
clrs = []

clrs.append(KNeighborsClassifier(n_neighbors=23 , metric = 'manhattan' ,
weights = "distance"))
clrs.append(GaussianNB())
clrs.append(MultinomialNB())
clrs.append(ComplementNB())

cv_results = []
cv_results_pca = []
cv_results_lda = []

for clr in clrs :
    cv_results.append(cross_val_score(clr, data, target , scoring =
'accuracy', cv = kfold, n_jobs=-1))
    cv_results_pca.append(cross_val_score(clr, data_pca, target_pca , scoring
= 'accuracy', cv = kfold, n_jobs=-1))
    cv_results_lda.append(cross_val_score(clr, data_lda, target_lda , scoring
= 'accuracy', cv = kfold, n_jobs=-1))

cv_means = []
cv_means_pca = []
cv_means_lda = []

for cv_result in cv_results:
    cv_means.append(cv_result.mean())

for cv_result in cv_results_pca:
    cv_means_pca.append(cv_result.mean())

for cv_result in cv_results_lda:
    cv_means_lda.append(cv_result.mean())

cv_df = pd.DataFrame({"Mean_Accuracy":cv_means,"Algo":
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})
cv_df_pca = pd.DataFrame({"Mean_Accuracy":cv_means_pca,"Algo":
```

```
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})
cv_df_lda = pd.DataFrame({"Mean_Accuracy":cv_means_lda,"Algo":
['KNeighborsClassifier','GaussianNB','MultinomialNB','ComplementNB']})

#print(cv_df)
#print(cv_df_pca)
#print(cv_df_lda)
```

In [65]:

```
data_frames = [cv_df, cv_df_pca, cv_df_lda]
df_merged = reduce(lambda  left,right: pd.merge(left,right,on=
['Algo'],how='outer'), data_frames)
df_merged.rename(columns={"Mean_Accuracy_x": "abalone_raw",
"Mean_Accuracy_y": "abalone_pca","Mean_Accuracy":"abalone_lda"},inplace=True)
df_merged.set_index('Algo',inplace=True)
print(df_merged)
```

```
                      abalone_raw  abalone_pca  abalone_lda
Algo
KNeighborsClassifier     0.250907     0.249947     0.253777
GaussianNB               0.230326     0.232716     0.251631
MultinomialNB            0.206377     0.165673     0.164955
ComplementNB             0.170705     0.171898     0.228406
```

Comments

- Complement Naive Bayes performs poorly, the datset is unbalanced but due to multiclass classification it does not perform as expected for unbalanced datsets.

Decision Trees Classifier

5-Fold CV and hyperparameter tuning

In [45]:

```
dtc = DecisionTreeClassifier()
dtc.fit(X_train, Y_train)
Y_pred = dtc.predict(X_test)
#cm=confusion_matrix(Y_test, Y_pred)
#print(confusion_matrix(Y_test, Y_pred))
#print(classification_report(Y_test, Y_pred))
print("Accuracy Score for Decision Tree classifier without hyper parameter
tuning is: ",accuracy_score(Y_test, Y_pred))
#disp =
ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=dtc.classes_)
#disp.plot()

grid_params = {
    #'criterion' : ['gini', 'entropy'],
    'max_depth' : range(2,25,1),
```

```
    'min_samples_split' : range(2, 5, 1),
    'min_samples_leaf' : range(2, 5, 1)
}

grid_search = GridSearchCV(dtc, grid_params, cv = 5, n_jobs = -1, verbose =
1)
grid_search.fit(X_train, Y_train)
dtc = grid_search.best_estimator_
Y_pred = dtc.predict(X_test)
print("Accuracy Score is :",accuracy_score(Y_test, Y_pred))
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
#print("Best Score is : ",grid_search.best_score_)
dt_raw_acc = accuracy_score(Y_test, Y_pred)
dt_raw_set=grid_search.best_params_

grid_search.fit(X_train_pca, Y_train_pca)
dtc = grid_search.best_estimator_
Y_pred_pca = dtc.predict(X_test_pca)
print("Accuracy Score using PCA is :",accuracy_score(Y_test_pca, Y_pred_pca))
# best parameters and best score
print("Best Parameters using PCA are : ",grid_search.best_params_)
#print("Best Score using PCA is : ",grid_search.best_score_)
dt_pca_acc = accuracy_score(Y_test_pca, Y_pred_pca)
dt_pca_set=grid_search.best_params_

grid_search.fit(X_train_lda, Y_train_lda)
dtc = grid_search.best_estimator_
Y_pred_lda = dtc.predict(X_test_lda)
print("Accuracy Score using LDA is :",accuracy_score(Y_test_lda, Y_pred_lda))
# best parameters and best score
print("Best Parameters using LDA are : ",grid_search.best_params_)
#print("Best Score using LDA is : ",grid_search.best_score_)
dt_lda_acc = accuracy_score(Y_test_lda, Y_pred_lda)
dt_lda_set=grid_search.best_params_
```

```
Accuracy Score for Decision Tree classifier without hyper parameter tuning is:  0.19617224
880382775
Fitting 5 folds for each of 207 candidates, totalling 1035 fits
Accuracy Score is : 0.2535885167464115
Best Parameters are :  {'max_depth': 4, 'min_samples_leaf': 2, 'min_samples_split': 2}
Fitting 5 folds for each of 207 candidates, totalling 1035 fits
Accuracy Score using PCA is : 0.26435406698564595
Best Parameters using PCA are :  {'max_depth': 4, 'min_samples_leaf': 4, 'min_samples_spli
t': 2}
Fitting 5 folds for each of 207 candidates, totalling 1035 fits
Accuracy Score using LDA is : 0.23444976076555024
```

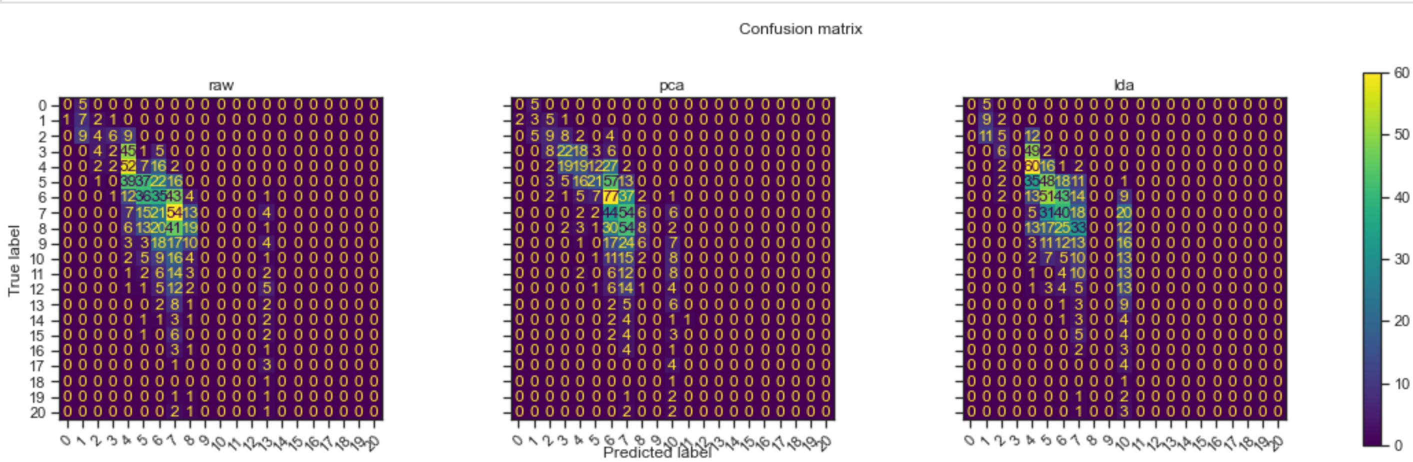
```
Best Parameters using LDA are :  {'max_depth': 3, 'min_samples_leaf': 2, 'min_samples_spli
t': 2}
```

In [46]:

```python
dt_raw_acc = accuracy_score(Y_test, Y_pred)
dt_pca_acc = accuracy_score(Y_test_pca, Y_pred_pca)
dt_lda_acc = accuracy_score(Y_test_lda, Y_pred_lda)
#print(dt_raw_acc,dt_pca_acc,dt_lda_acc)
```

In [47]:

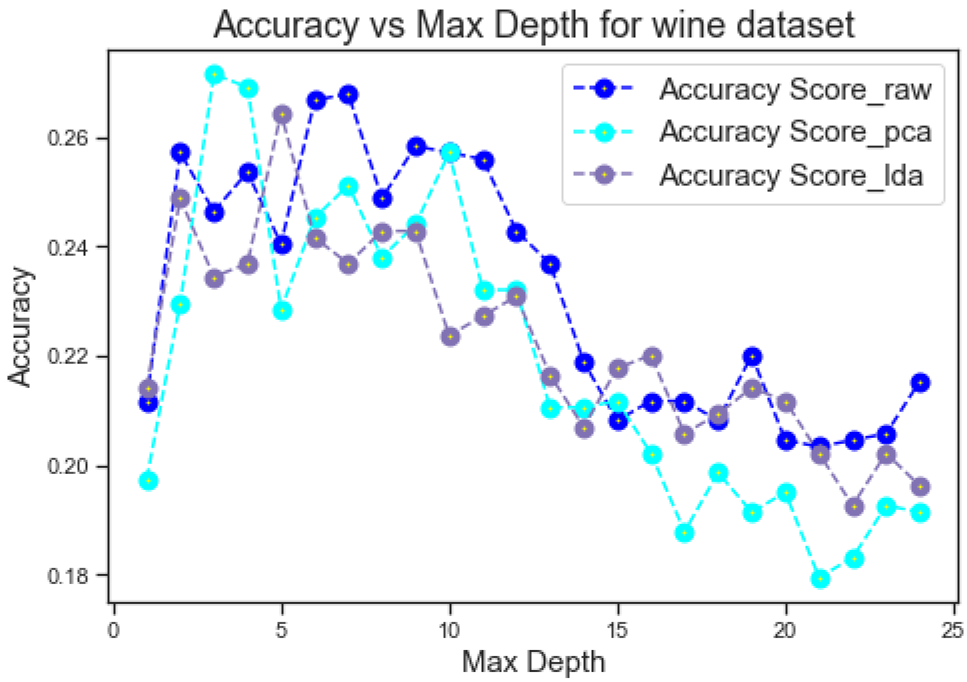
```python
cm=confusion_matrix(Y_test, Y_pred)
cm_pca=confusion_matrix(Y_test_pca, Y_pred_pca)
cm_lda=confusion_matrix(Y_test_lda, Y_pred_lda)
cm_dict = {
    "raw": cm,
    "pca": cm_pca,
    "lda": cm_lda
}

f, axes = plt.subplots(1, 3, figsize=(20, 5), sharey='row')
for i,(c,cm) in enumerate(cm_dict.items()):
    #print(i,cm)
    disp = ConfusionMatrixDisplay(cm)
    disp.plot(ax=axes[i], xticks_rotation=45)
    disp.ax_.set_title(c)
    disp.im_.colorbar.remove()
    disp.ax_.set_xlabel('')
    if i!=0:
        disp.ax_.set_ylabel('')

f.text(0.4, 0.1, 'Predicted label', ha='left')
plt.subplots_adjust(wspace=0.40, hspace=0.1)

f.suptitle('Confusion matrix', fontsize=12)
f.colorbar(disp.im_, ax=axes)
plt.show()
```



Accuracy vs Max_depth

In [48]:

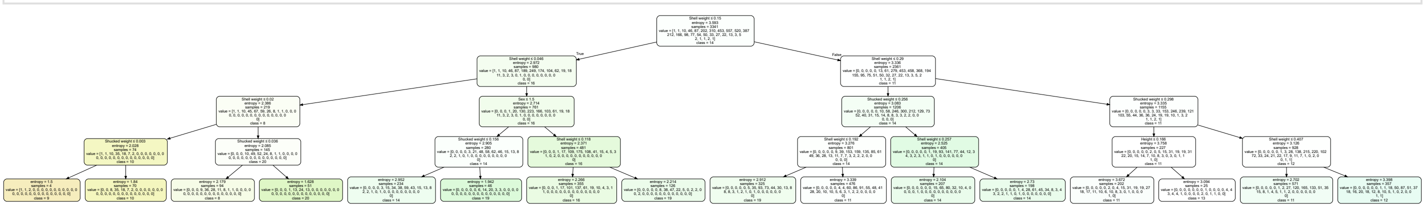
```
def plot_acc_vs_depth(dataset):
    max_depth_range = list(range(1, 25))
    acc_list = []
    acc_list_pca = []
    acc_list_lda = []
    for depth in max_depth_range:
        dtc_w = DecisionTreeClassifier(max_depth = depth)
        if dataset[0] == 'raw':
            dtc_w.fit(X_train, Y_train)
            score = dtc_w.score(X_test, Y_test)
            acc_list.append(score)
        if dataset[1] == 'pca':
            dtc_w.fit(X_train_pca, Y_train_pca)
            score = dtc_w.score(X_test_pca, Y_test_pca)
            acc_list_pca.append(score)
        if dataset[2] == 'lda':
            dtc_w.fit(X_train_lda, Y_train_lda)
            score =dtc_w.score(X_test_lda, Y_test_lda)
            acc_list_lda.append(score)

    return(acc_list,acc_list_pca,acc_list_lda)

acc_list,acc_list_pca,acc_list_lda = plot_acc_vs_depth(['raw','pca','lda'])
fig = plt.figure(figsize=(7,5))
plt.plot(range(1,25),acc_list, color = 'blue',marker ='o',mew
=4,mfc='yellow',ls ='--' ,linewidth=1.5,label='Accuracy Score_raw')
plt.plot(range(1,25),acc_list_pca, color = 'cyan',marker ='o',mew
=4,mfc='yellow',ls ='--' ,linewidth=1.5,label='Accuracy Score_pca')
plt.plot(range(1,25),acc_list_lda, color = 'm',marker ='o',mew
=4,mfc='yellow',ls ='--' ,linewidth=1.5,label='Accuracy Score_lda')
plt.ylabel('Accuracy',fontsize = 15)
plt.xlabel('Max Depth',fontsize = 15)
plt.title('Accuracy vs Max Depth for wine dataset',fontsize = 18)
plt.legend(loc='best',fontsize = 15)
plt.tight_layout()
plt.show()
```



Splitting rules used for the trees

In [49]:
```
dtc_g = DecisionTreeClassifier(criterion= 'entropy', max_depth=4,
min_samples_leaf= 2, min_samples_split=2)
dtc_g.fit(X_train,Y_train)
fn=X_train.columns
cn = abalone_raw.Rings.unique().astype(str)
dot_data = tree.export_graphviz(dtc_g,
filled=True,feature_names=fn,class_names=cn ,rounded=True,
special_characters=True)
graph = graphviz.Source(dot_data)
graph
```

Out[49]:



In [60]:
```
from sklearn.tree import export_text
dtc_g = DecisionTreeClassifier(criterion= 'entropy', max_depth=4,
min_samples_leaf= 2, min_samples_split=2)
dt_rules = dtc_g.fit(X_train,Y_train)
fn_t=X_train.columns
#print(type(fn_t.tolist()))
tree_rules = export_text(dt_rules,feature_names = fn_t.tolist())
print(tree_rules)
```

```
|--- Shell weight <= 0.15
|   |--- Shell weight <= 0.05
|   |   |--- Shell weight <= 0.02
|   |   |   |--- Shucked weight <= 0.00
```

```
|   |   |   |   |--- class: 3
|   |   |   |--- Shucked weight >  0.00
|   |   |   |   |--- class: 4
|   |   |--- Shell weight >  0.02
|   |   |   |--- Shucked weight <= 0.04
|   |   |   |   |--- class: 5
|   |   |   |--- Shucked weight >  0.04
|   |   |   |   |--- class: 6
|   |--- Shell weight >  0.05
|   |   |--- Sex <= 1.50
|   |   |   |--- Shucked weight <= 0.16
|   |   |   |   |--- class: 9
|   |   |   |--- Shucked weight >  0.16
|   |   |   |   |--- class: 8
|   |   |--- Sex >  1.50
|   |   |   |--- Shell weight <= 0.12
|   |   |   |   |--- class: 7
|   |   |   |--- Shell weight >  0.12
|   |   |   |   |--- class: 8
|--- Shell weight >  0.15
|   |--- Shell weight <= 0.29
|   |   |--- Shucked weight <= 0.26
|   |   |   |--- Shell weight <= 0.19
|   |   |   |   |--- class: 8
|   |   |   |--- Shell weight >  0.19
|   |   |   |   |--- class: 10
|   |   |--- Shucked weight >  0.26
|   |   |   |--- Shell weight <= 0.26
|   |   |   |   |--- class: 9
|   |   |   |--- Shell weight >  0.26
|   |   |   |   |--- class: 9
|   |--- Shell weight >  0.29
|   |   |--- Shucked weight <= 0.30
|   |   |   |--- Height <= 0.17
|   |   |   |   |--- class: 10
|   |   |   |--- Height >  0.17
|   |   |   |   |--- class: 13
|   |   |--- Shucked weight >  0.30
|   |   |   |--- Shell weight <= 0.41
|   |   |   |   |--- class: 10
|   |   |   |--- Shell weight >  0.41
|   |   |   |   |--- class: 11
```

Comments

- As observed in Assignment-1, weight columns were positively correlated with many other columns(namely; Height,Length, Diameter) and hence it is chosen as the root node for the split.Weight and Sex are the major contributors to splitting rules indicating that these are more important for classication.

Splitting rules used for the trees but fitted on page

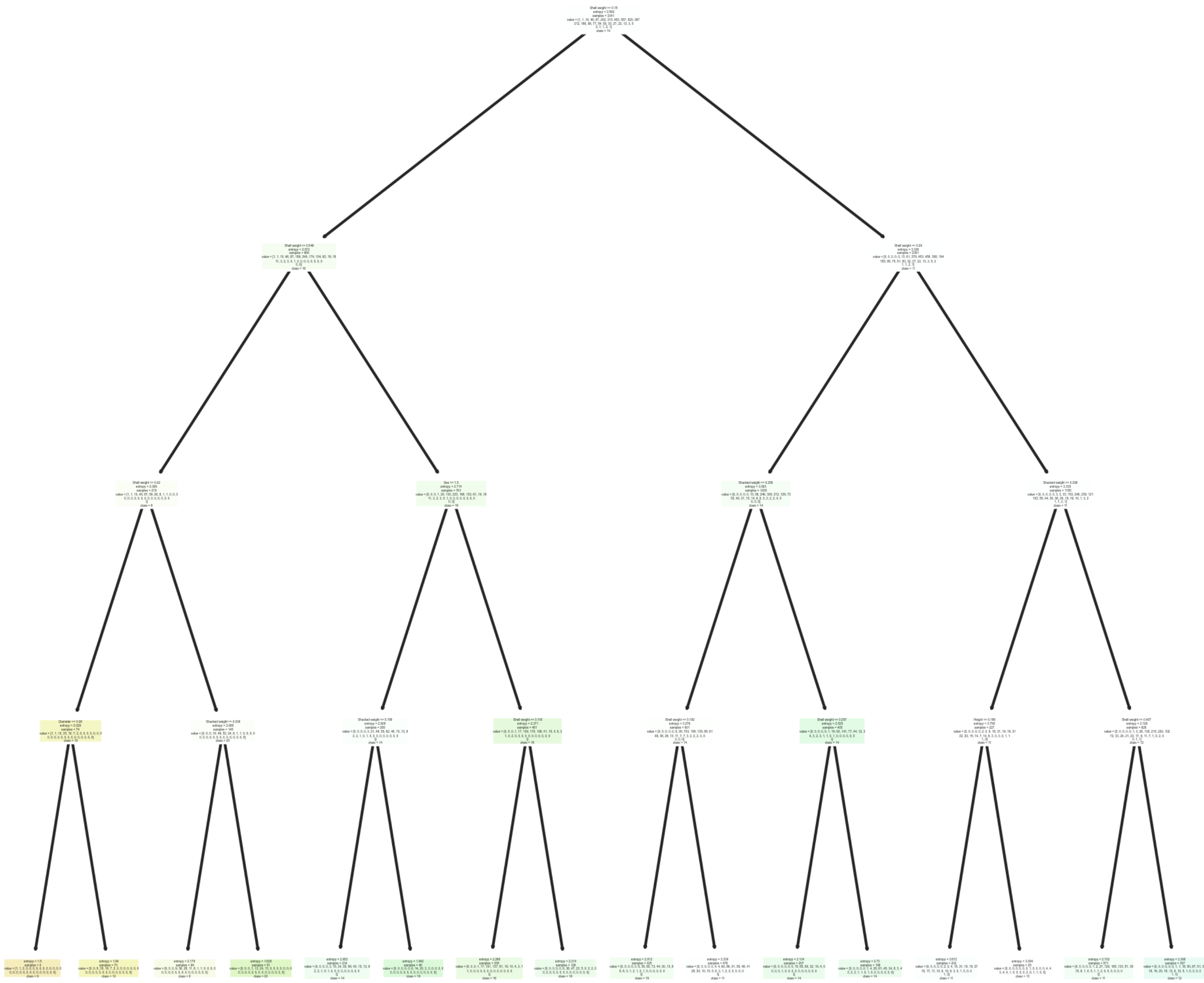
In [51]:
```
dtc_g = DecisionTreeClassifier(criterion= 'entropy', max_depth=4,
min_samples_leaf= 2, min_samples_split=5)
dtc_g.fit(X_train,Y_train)
fn=X_train.columns
```

```
cn = abalone_raw.Rings.unique().astype(str)
fig, axes = plt.subplots(nrows = 1,ncols = 1,figsize = (8,8), dpi=300)
tree.plot_tree(dtc_g, filled=True,feature_names=fn,class_names=cn
,rounded=True)
#fig.savefig('dtc_tree_plot_3.png')
```

Out[51]:

```
[Text(930.0, 1630.8, 'Shell weight <= 0.15\nentropy = 3.593\nsamples = 3341\nvalue = [1,
1, 10, 46, 87, 202, 310, 453, 557, 520, 387\n212, 166, 98, 77, 54, 50, 33, 27, 22, 13, 3,
5\n2, 1, 1, 2, 1]\nclass = 14'),
 Text(465.0, 1268.4, 'Shell weight <= 0.046\nentropy = 2.972\nsamples = 980\nvalue = [1,
1, 10, 46, 87, 189, 249, 174, 104, 62, 19, 18\n11, 3, 2, 3, 0, 1, 0, 0, 0, 0, 0, 0, 0\n
0, 0]\nclass = 16'),
 Text(232.5, 906.0, 'Shell weight <= 0.02\nentropy = 2.386\nsamples = 219\nvalue = [1, 1,
10, 45, 67, 59, 26, 8, 1, 1, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0]\nclass
= 8'),
 Text(116.25, 543.6000000000001, 'Diameter <= 0.08\nentropy = 2.028\nsamples = 74\nvalue =
[1, 1, 10, 35, 18, 7, 2, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]\nc
lass = 10'),
 Text(58.125, 181.20000000000005, 'entropy = 1.5\nsamples = 4\nvalue = [1, 1, 2, 0, 0, 0,
0, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]\nclass = 9'),
 Text(174.375, 181.20000000000005, 'entropy = 1.84\nsamples = 70\nvalue = [0, 0, 8, 35, 1
8, 7, 2, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]\nclass = 10'),
 Text(348.75, 543.6000000000001, 'Shucked weight <= 0.036\nentropy = 2.085\nsamples = 145
\nvalue = [0, 0, 0, 10, 49, 52, 24, 8, 1, 1, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0]\nclass = 20'),
 Text(290.625, 181.20000000000005, 'entropy = 2.179\nsamples = 94\nvalue = [0, 0, 0, 9, 3
6, 28, 11, 8, 1, 1, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]\nclass = 8'),
 Text(406.875, 181.20000000000005, 'entropy = 1.628\nsamples = 51\nvalue = [0, 0, 0, 1, 1
3, 24, 13, 0, 0, 0, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]\nclass = 20'),
 Text(697.5, 906.0, 'Sex <= 1.5\nentropy = 2.714\nsamples = 761\nvalue = [0, 0, 0, 1, 20,
130, 223, 166, 103, 61, 19, 18\n11, 3, 2, 3, 0, 1, 0, 0, 0, 0, 0, 0, 0\n0, 0]\nclass =
16'),
 Text(581.25, 543.6000000000001, 'Shucked weight <= 0.156\nentropy = 2.905\nsamples = 280
\nvalue = [0, 0, 0, 0, 3, 21, 48, 58, 62, 46, 15, 13, 8\n2, 2, 1, 0, 1, 0, 0, 0, 0, 0, 0,
0, 0, 0\n0]\nclass = 14'),
 Text(523.125, 181.20000000000005, 'entropy = 2.952\nsamples = 234\nvalue = [0, 0, 0, 0,
3, 15, 34, 38, 59, 43, 15, 13, 8\n2, 2, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0]\nclass = 1
4'),
 Text(639.375, 181.20000000000005, 'entropy = 1.942\nsamples = 46\nvalue = [0, 0, 0, 0, 0,
6, 14, 20, 3, 3, 0, 0, 0, 0\n0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]\nclass = 19'),
 Text(813.75, 543.6000000000001, 'Shell weight <= 0.118\nentropy = 2.371\nsamples = 481\nv
alue = [0, 0, 0, 1, 17, 109, 175, 108, 41, 15, 4, 5, 3\n1, 0, 2, 0, 0, 0, 0, 0, 0, 0, 0,
0, 0, 0\n0]\nclass = 16'),
 Text(755.625, 181.20000000000005, 'entropy = 2.266\nsamples = 355\nvalue = [0, 0, 0, 1, 1
7, 101, 137, 61, 19, 10, 4, 3, 1\n1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0]\nclass = 1
6'),
 Text(871.875, 181.20000000000005, 'entropy = 2.214\nsamples = 126\nvalue = [0, 0, 0, 0,
0, 8, 38, 47, 22, 5, 0, 2, 2, 0\n0, 2, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]\nclass = 19'),
 Text(1395.0, 1268.4, 'Shell weight <= 0.29\nentropy = 3.336\nsamples = 2361\nvalue = [0,
0, 0, 0, 0, 13, 61, 279, 453, 458, 368, 194\n155, 95, 75, 51, 50, 32, 27, 22, 13, 3, 5, 2
\n1, 1, 2, 1]\nclass = 11'),
 Text(1162.5, 906.0, 'Shucked weight <= 0.256\nentropy = 3.083\nsamples = 1206\nvalue =
[0, 0, 0, 0, 0, 10, 58, 246, 300, 212, 129, 73\n52, 40, 31, 15, 14, 8, 8, 3, 3, 2, 2, 0, 0
\n0, 0, 0]\nclass = 14'),
 Text(1046.25, 543.6000000000001, 'Shell weight <= 0.192\nentropy = 3.276\nsamples = 801\n
value = [0, 0, 0, 0, 0, 9, 39, 153, 159, 135, 85, 61\n49, 36, 28, 13, 11, 7, 7, 3, 2, 2,
2, 0, 0\n0, 0, 0]\nclass = 14'),
```

```
 Text(988.125, 181.20000000000005, 'entropy = 2.912\nsamples = 325\nvalue = [0, 0, 0, 0,
0, 5, 35, 93, 73, 44, 30, 13, 8\n8, 8, 3, 1, 2, 1, 0, 1, 0, 0, 0, 0, 0, 0\n0]\nclass = 1
9'),
 Text(1104.375, 181.20000000000005, 'entropy = 3.339\nsamples = 476\nvalue = [0, 0, 0, 0,
0, 4, 4, 60, 86, 91, 55, 48, 41\n28, 20, 10, 10, 5, 6, 3, 1, 2, 2, 0, 0, 0, 0\n0]\nclass =
11'),
 Text(1278.75, 543.6000000000001, 'Shell weight <= 0.257\nentropy = 2.525\nsamples = 405\n
value = [0, 0, 0, 0, 0, 1, 19, 93, 141, 77, 44, 12, 3\n4, 3, 2, 3, 1, 1, 0, 1, 0, 0, 0, 0,
0, 0\n0]\nclass = 14'),
 Text(1220.625, 181.20000000000005, 'entropy = 2.104\nsamples = 207\nvalue = [0, 0, 0, 0,
0, 0, 15, 65, 80, 32, 10, 4, 0\n0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0\n0]\nclass = 1
4'),
 Text(1336.875, 181.20000000000005, 'entropy = 2.73\nsamples = 198\nvalue = [0, 0, 0, 0,
0, 1, 4, 28, 61, 45, 34, 8, 3, 4\n3, 2, 2, 1, 1, 0, 1, 0, 0, 0, 0, 0, 0, 0]\nclass = 14'),
 Text(1627.5, 906.0, 'Shucked weight <= 0.298\nentropy = 3.335\nsamples = 1155\nvalue =
[0, 0, 0, 0, 0, 3, 3, 33, 153, 246, 239, 121\n103, 55, 44, 36, 36, 24, 19, 19, 10, 1, 3, 2
\n1, 1, 2, 1]\nclass = 11'),
 Text(1511.25, 543.6000000000001, 'Height <= 0.166\nentropy = 3.758\nsamples = 227\nvalue
= [0, 0, 0, 0, 0, 2, 0, 5, 15, 31, 19, 19, 31\n22, 20, 15, 14, 7, 10, 8, 3, 0, 3, 0, 1, 1
\n1, 0]\nclass = 11'),
 Text(1453.125, 181.20000000000005, 'entropy = 3.672\nsamples = 202\nvalue = [0, 0, 0, 0,
0, 2, 0, 4, 15, 31, 19, 19, 27\n18, 17, 11, 10, 6, 10, 8, 3, 0, 1, 0, 0, 0\n1, 0]\nclass =
11'),
 Text(1569.375, 181.20000000000005, 'entropy = 3.094\nsamples = 25\nvalue = [0, 0, 0, 0,
0, 0, 0, 1, 0, 0, 0, 0, 4, 4\n3, 4, 4, 1, 0, 0, 0, 0, 2, 0, 1, 1, 0, 0]\nclass = 13'),
 Text(1743.75, 543.6000000000001, 'Shell weight <= 0.407\nentropy = 3.126\nsamples = 928\n
value = [0, 0, 0, 0, 0, 1, 3, 28, 138, 215, 220, 102\n72, 33, 24, 21, 22, 17, 9, 11, 7, 1,
0, 2, 0\n0, 1, 1]\nclass = 12'),
 Text(1685.625, 181.20000000000005, 'entropy = 2.702\nsamples = 571\nvalue = [0, 0, 0, 0,
0, 1, 2, 27, 120, 165, 133, 51, 35\n15, 8, 1, 4, 5, 1, 1, 2, 0, 0, 0, 0, 0, 0\n0]\nclass =
11'),
 Text(1801.875, 181.20000000000005, 'entropy = 3.398\nsamples = 357\nvalue = [0, 0, 0, 0,
0, 0, 1, 1, 18, 50, 87, 51, 37\n18, 16, 20, 18, 12, 8, 10, 5, 1, 0, 2, 0, 0\n1, 1]\nclass
= 12')]
```



Random Forest Classifier

5-Fold CV and hyperpararmeter tuning

In [52]:
```
rfc = RandomForestClassifier()
rfc.fit(X_train, Y_train)
Y_pred = rfc.predict(X_test)
cm=confusion_matrix(Y_test, Y_pred)
#print(confusion_matrix(Y_test, Y_pred))
#print(classification_report(Y_test, Y_pred))
print("Accuracy Score for Forest classifier without hyper parameter tuning is: ",accuracy_score(Y_test, Y_pred))
#disp = ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=dtc.classes_)
#disp.plot()
```

```python
grid_params = {
    'n_estimators': [2,5,200, 500],
    'criterion' : ['entropy'],
    'max_depth' : range(2,25,1),
    #'max_features': range(3,10,1),
    #'min_samples_split' : range(2, 10, 1),
    #'min_samples_leaf' : range(2, 10, 1)
}

grid_search = GridSearchCV(rfc, grid_params, cv = 5, n_jobs = -1, verbose =
True)
#print(grid_search.get_params().keys())
grid_search.fit(X_train, Y_train)
rfc = grid_search.best_estimator_
Y_pred = rfc.predict(X_test)
print("Accuracy Score is :",accuracy_score(Y_test, Y_pred))
rf_raw_acc=accuracy_score(Y_test, Y_pred)
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
rf_raw_set=grid_search.best_params_
#print("Best Score is : ",grid_search.best_score_)
ac_df=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
ac_df["accuracy"]=grid_search.cv_results_['mean_test_score']

grid_search.fit(X_train_pca, Y_train_pca)
rfc_pca = grid_search.best_estimator_
Y_pred_pca = rfc_pca.predict(X_test_pca)
print("Accuracy Score using PCA is :",accuracy_score(Y_test_pca, Y_pred_pca))
rf_pca_acc=accuracy_score(Y_test_pca, Y_pred_pca)
# best parameters and best score
print("Best Parameters using PCA are : ",grid_search.best_params_)
rf_pca_set=grid_search.best_params_
#print("Best Score using PCA is : ",grid_search.best_score_)
ac_df_pca=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
ac_df_pca["accuracy"]=grid_search.cv_results_['mean_test_score']

grid_search.fit(X_train_lda, Y_train_lda)
rfc_lda = grid_search.best_estimator_
Y_pred_lda = rfc_lda.predict(X_test_lda)
print("Accuracy Score using LDA is :",accuracy_score(Y_test_lda, Y_pred_lda))
rf_lda_acc=accuracy_score(Y_test_lda, Y_pred_lda)
```

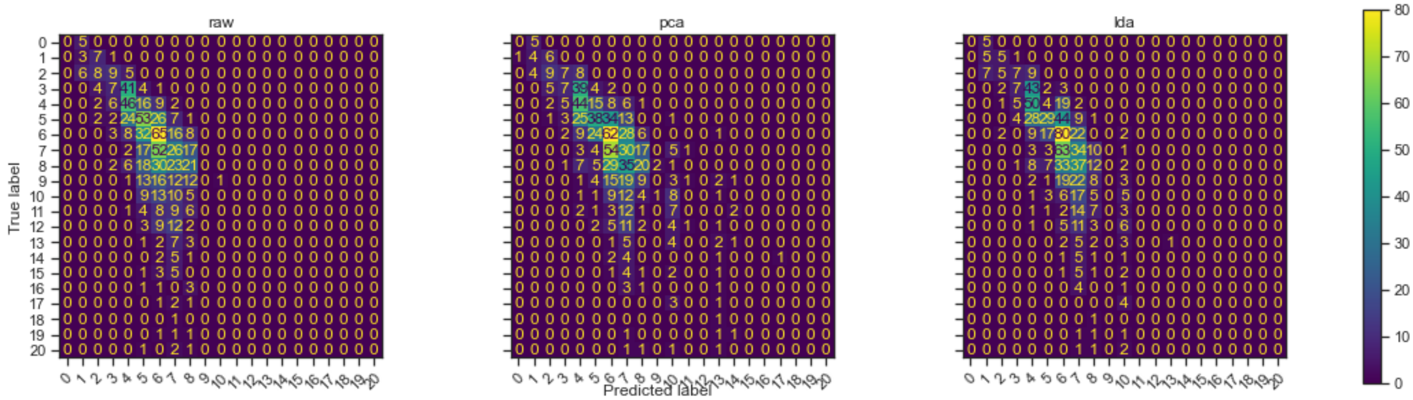
```
# best parameters and best score
print("Best Parameters using LDA are : ",grid_search.best_params_)
#print("Best Score using LDA is : ",grid_search.best_score_)
rf_lda_set=grid_search.best_params_
ac_df_lda=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
ac_df_lda["accuracy"]=grid_search.cv_results_['mean_test_score']
```

```
Accuracy Score for Forest classifier without hyper parameter tuning is:  0.246411483253588
53
Fitting 5 folds for each of 92 candidates, totalling 460 fits
Accuracy Score is : 0.27392344497607657
Best Parameters are :  {'criterion': 'entropy', 'max_depth': 5, 'n_estimators': 5}
Fitting 5 folds for each of 92 candidates, totalling 460 fits
Accuracy Score using PCA is : 0.2679425837320574
Best Parameters using PCA are :  {'criterion': 'entropy', 'max_depth': 6, 'n_estimators':
200}
Fitting 5 folds for each of 92 candidates, totalling 460 fits
Accuracy Score using LDA is : 0.2727272727272727
Best Parameters using LDA are :  {'criterion': 'entropy', 'max_depth': 4, 'n_estimators':
500}
```

In [53]:

```
cm=confusion_matrix(Y_test, Y_pred)
cm_pca=confusion_matrix(Y_test_pca, Y_pred_pca)
cm_lda=confusion_matrix(Y_test_lda, Y_pred_lda)
cm_dict = {
    "raw": cm,
    "pca": cm_pca,
    "lda": cm_lda
}

f, axes = plt.subplots(1, 3, figsize=(20, 5), sharey='row')
for i,(c,cm) in enumerate(cm_dict.items()):
    #print(i,cm)
    disp = ConfusionMatrixDisplay(cm)
    disp.plot(ax=axes[i], xticks_rotation=45)
    disp.ax_.set_title(c)
    disp.im_.colorbar.remove()
    disp.ax_.set_xlabel('')
    if i!=0:
        disp.ax_.set_ylabel('')

f.text(0.4, 0.1, 'Predicted label', ha='left')
plt.subplots_adjust(wspace=0.40, hspace=0.1)
```

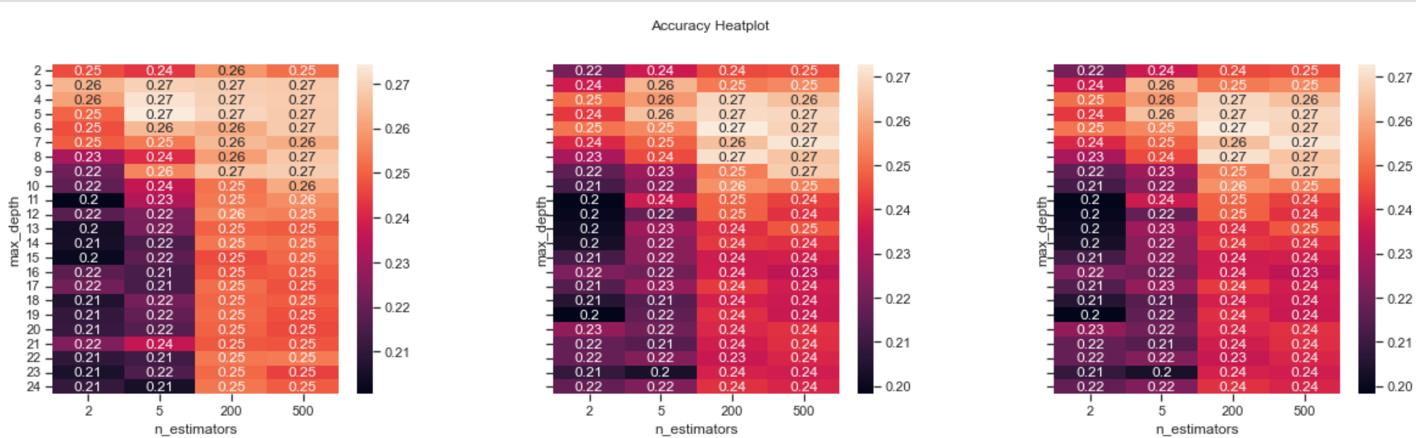
```
f.colorbar(disp.im_, ax=axes)
plt.show()
```



Heatmap of max_depth vs n_estimators

In [54]:

```
#Pivoting the dataframe for plotting heat map
ac_df=ac_df.pivot(index='max_depth',columns='n_estimators',values='accuracy')
ac_df_pca=ac_df_pca.pivot(index='max_depth',columns='n_estimators',values='accu

ac_df_lda=ac_df_lda.pivot(index='max_depth',columns='n_estimators',values='accu

#Plotting the graph
fig, ax =plt.subplots(1,3,figsize=(20, 5), sharey='row')

sns.heatmap(ac_df,annot=True, ax=ax[0])
sns.heatmap(ac_df_pca,annot=True ,ax=ax[1])
sns.heatmap(ac_df_pca,annot=True ,ax=ax[2])

plt.subplots_adjust(wspace=0.40, hspace=0.1)
fig.suptitle('Accuracy Heatplot', fontsize=12)
plt.show()
```



Gradient Boosting Classifier

5-Fold CV and hyperparameter tuning

In [55]:

```
gbc = GradientBoostingClassifier()
gbc.fit(X_train, Y_train)
Y_pred = gbc.predict(X_test)
cm=confusion_matrix(Y_test, Y_pred)
#print(confusion_matrix(Y_test, Y_pred))
#print(classification_report(Y_test, Y_pred))
print("Accuracy Score for Gradient Boosting classifier without hyper
parameter tuning is: ",accuracy_score(Y_test, Y_pred))
#disp =
ConfusionMatrixDisplay(confusion_matrix=cm,display_labels=dtc.classes_)
#disp.plot()

grid_params = {
    'n_estimators': [2,120,200,500,800],
    'learning_rate' : [0.01, 0.1,1],
    #'criterion' : [None,'mse','mae'],
    #'max_depth' : range(2,22,2),
    #'max_features': range(3,10,1),
    #'min_samples_split' : range(2, 10, 1),
    #'min_samples_leaf' : range(2, 10, 1)
}

grid_search = GridSearchCV(gbc, grid_params, cv = 5, n_jobs = -1, verbose =
True)
#print(grid_search.get_params().keys())
grid_search.fit(X_train, Y_train)
gbc = grid_search.best_estimator_
Y_pred = gbc.predict(X_test)
print("Accuracy Score is :",accuracy_score(Y_test, Y_pred))
gbc_acc=accuracy_score(Y_test, Y_pred)
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
gbc_set=grid_search.best_params_
#print("Best Score using PCA is : ",grid_search.best_score_)
gbc_ac_df=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
gbc_ac_df["accuracy"]=grid_search.cv_results_['mean_test_score']



grid_search.fit(X_train_pca, Y_train_pca)
gbc = grid_search.best_estimator_
Y_pred_pca = gbc.predict(X_test_pca)
print("Accuracy Score is :",accuracy_score(Y_test_pca, Y_pred_pca))
```

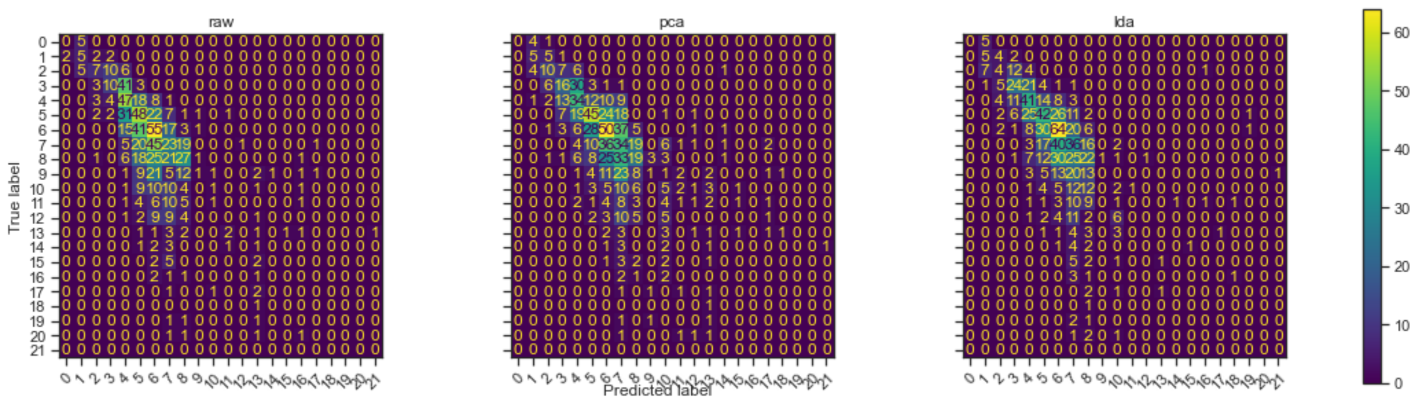
```
gbc_pca_acc=accuracy_score(Y_test_pca, Y_pred_pca)
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
gbc_pca_set=grid_search.best_params_
#print("Best Score using PCA is : ",grid_search.best_score_)
gbc_ac_df_pca=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
gbc_ac_df_pca["accuracy"]=grid_search.cv_results_['mean_test_score']



grid_search.fit(X_train_lda, Y_train_lda)
gbc = grid_search.best_estimator_
Y_pred_lda = gbc.predict(X_test_lda)
print("Accuracy Score is :",accuracy_score(Y_test_lda, Y_pred_lda))
gbc_lda_acc=accuracy_score(Y_test_lda, Y_pred_lda)
# best parameters and best score
print("Best Parameters are : ",grid_search.best_params_)
gbc_lda_set=grid_search.best_params_
#print("Best Score using PCA is : ",grid_search.best_score_)
gbc_ac_df_lda=pd.DataFrame(grid_search.cv_results_['params'])
#Creating a data frame with hyperparameters and accuracy
gbc_ac_df_lda["accuracy"]=grid_search.cv_results_['mean_test_score']
```

```
Accuracy Score for Gradient Boosting classifier without hyper parameter tuning is:  0.2535
885167464115
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Accuracy Score is : 0.26913875598086123
Best Parameters are :  {'learning_rate': 0.01, 'n_estimators': 120}
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Accuracy Score is : 0.26435406698564595
Best Parameters are :  {'learning_rate': 0.01, 'n_estimators': 200}
Fitting 5 folds for each of 15 candidates, totalling 75 fits
Accuracy Score is : 0.28708133971291866
Best Parameters are :  {'learning_rate': 0.01, 'n_estimators': 120}
```

In [56]:

```
cm=confusion_matrix(Y_test, Y_pred)
cm_pca=confusion_matrix(Y_test_pca, Y_pred_pca)
cm_lda=confusion_matrix(Y_test_lda, Y_pred_lda)
cm_dict = {
    "raw": cm,
    "pca": cm_pca,
    "lda": cm_lda
}


f, axes = plt.subplots(1, 3, figsize=(20, 5), sharey='row')
for i,(c,cm) in enumerate(cm_dict.items()):
    #print(i,cm)
```

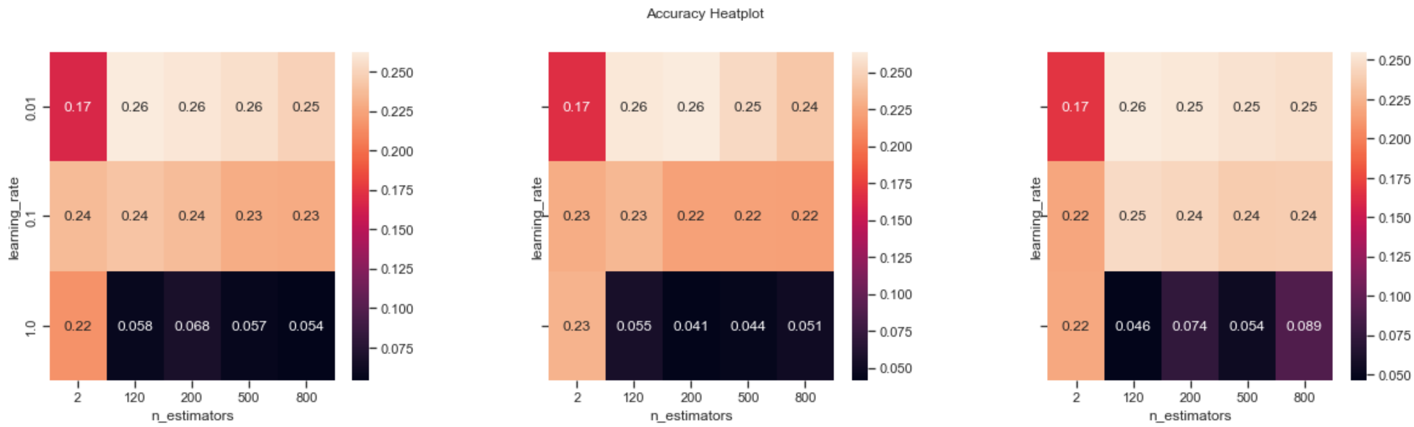
```
    disp = ConfusionMatrixDisplay(cm)
    disp.plot(ax=axes[i], xticks_rotation=45)
    disp.ax_.set_title(c)
    disp.im_.colorbar.remove()
    disp.ax_.set_xlabel('')
    if i!=0:
        disp.ax_.set_ylabel('')

f.text(0.4, 0.1, 'Predicted label', ha='left')
plt.subplots_adjust(wspace=0.40, hspace=0.1)


f.colorbar(disp.im_, ax=axes)
plt.show()
```



Heatplot of learning_rate and n_estimators

In [57]:

```
#Pivoting the dataframe for plotting heat map
gbc_ac_df=gbc_ac_df.pivot(index='learning_rate',columns='n_estimators',values='

gbc_ac_df_pca=gbc_ac_df_pca.pivot(index='learning_rate',columns='n_estimators',

gbc_ac_df_lda=gbc_ac_df_lda.pivot(index='learning_rate',columns='n_estimators',

#Plotting the graph
fig, ax =plt.subplots(1,3,figsize=(20, 5), sharey='row')

sns.heatmap(gbc_ac_df,annot=True, ax=ax[0])
sns.heatmap(gbc_ac_df_pca,annot=True ,ax=ax[1])
sns.heatmap(gbc_ac_df_lda,annot=True ,ax=ax[2])

plt.subplots_adjust(wspace=0.40, hspace=0.1)
fig.suptitle('Accuracy Heatplot', fontsize=12)
plt.show()
```



Final Results

In [66]:

```
dt_dict = {'Algo': ['Decision Tree','Random Forest','Gradient Boosting'],
           'abalone_raw': [dt_raw_acc,rf_raw_acc,gbc_acc], 'abalone_pca':
[dt_pca_acc,rf_pca_acc,gbc_pca_acc],
           'abalone_lda':[dt_lda_acc,rf_lda_acc,gbc_lda_acc]}

df_mid=pd.DataFrame(data=dt_dict,columns=
['Algo','abalone_raw','abalone_pca','abalone_lda'])
#display(df_mid)
df_nb=df_merged.reset_index()
final_df = df_nb.append(df_mid, ignore_index=True)
display(final_df)
```

	Algo	abalone_raw	abalone_pca	abalone_lda
0	KNeighborsClassifier	0.250907	0.249947	0.253777
1	GaussianNB	0.230326	0.232716	0.251631
2	MultinomialNB	0.206377	0.165673	0.164955
3	ComplementNB	0.170705	0.171898	0.228406
4	Decision Tree	0.253589	0.264354	0.234450
5	Random Forest	0.273923	0.267943	0.272727
6	Gradient Boosting	0.269139	0.264354	0.287081

In [67]:

```
#print(dt_raw_set.keys())
#print(dt_raw_set.values(),dt_pca_set.values(),dt_lda_set.values())
dt_s =[dt_raw_set,dt_pca_set,dt_lda_set]
df_dt_settings = pd.DataFrame(dt_s)
df_dt_settings['Algo']= 'Decision Tree'
df_dt_settings['Data'] = ['raw','pca','lda']
display(df_dt_settings)
```

	max_depth	min_samples_leaf	min_samples_split	Algo	Data
0	4	2	2	Decision Tree	raw

	max_depth	min_samples_leaf	min_samples_split	Algo	Data
1	4	4	2	Decision Tree	pca
2	3	2	2	Decision Tree	lda

In [68]:

```
rf_s =[rf_raw_set,rf_pca_set,rf_lda_set]
df_rf_settings = pd.DataFrame(rf_s)
df_rf_settings['Algo']= 'Random Forest'
df_rf_settings['Data'] = ['raw','pca','lda']
display(df_rf_settings)
```

	criterion	max_depth	n_estimators	Algo	Data
0	entropy	5	5	Random Forest	raw
1	entropy	6	200	Random Forest	pca
2	entropy	4	500	Random Forest	lda

In [69]:

```
gbc_s =[gbc_set,gbc_pca_set,gbc_lda_set]
df_gbc_settings = pd.DataFrame(gbc_s)
df_gbc_settings['Algo']= 'Gradient Boosting'
df_gbc_settings['Data'] = ['raw','pca','lda']
display(df_gbc_settings)
```

	learning_rate	n_estimators	Algo	Data
0	0.01	120	Gradient Boosting	raw
1	0.01	200	Gradient Boosting	pca
2	0.01	120	Gradient Boosting	lda

In [2]:

```
knn_setting = ({'n_neighbors':66 , 'metric': 'minkowski' , 'weights':
"uniform",'p':2})
gnb_settings = ("default")
mnb_settings = ("default")
cnb_settings = ("default")
dt_settings =
({'criterion':'Entropy','max_depth':4,'min_samples_leaf':4,'min_samples_split':

rf_settings = ({'criterion':'Entropy','max_depth':5,'n_estimators':500})
gb_settings = ({'learning_rate':0.01,'n_estimators':120})

settings_all =
[knn_setting,gnb_settings,mnb_settings,cnb_settings,dt_settings,dt_settings,rf_

settings_all
df_final['settings'] =settings_all
```

In [5]:
```
display(df_final)
```

Out[5]:

	Algo	settings	abalone_raw	abalone_pca	abalone_lda
0	KNeighborsClassifier	{'n_neighbors':66 , 'metric': 'minkowski' , 'w...	0.250907	0.249947	0.253777
1	GaussianNB	default	0.230326	0.232716	0.251631
2	MultinomialNB	default	0.206377	0.165673	0.164955
3	ComplementNB	default	0.170705	0.171898	0.228406
4	Decision Tree	{'criterion':'Entropy','max_depth':4,'min_samp...	0.253589	0.264354	0.234450
5	Random Forest	{'criterion':'Entropy','max_depth':5,'n_estima...	0.273923	0.267943	0.272727
6	Gradient Boosting	{'learning_rate':0.01,'n_estimators':120}	0.269139	0.264354	0.287081

Comments

- Gradient Boosting performed best with the pipeline (abalone -> scaling -> lda -> scaling -> Gradient Boosting Classifier)
- Dimensionality Reduction helped in Decision tree, Random Forest and Gradient Boosting algorithms, while PCA gav econsistent accuracies with mentioned algorithms, LDA performed well only with Gradient Boosting and Random Forest algorithms.
- Decision tree and Random Forest gave better accuracy with lesser max depth as compared to wine dataset.

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