Homework 2

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DS 6040

Honor Pledge: On my honor, I pledge that I have neither given nor recieved help on this assignment.

Imports

In [ ]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import multivariate_normal
from itertools import combinations
```

Read in Data

In [ ]:
```
wine_testing = pd.read_csv('whitewine-testing-ds6040.csv')
wine_training = pd.read_csv('whitewine-training-ds6040.csv')
```

Data Exploration/Commentary

In [ ]:
```
wine_training.wine_quality.value_counts()
wine_training.head()
training_counts = wine_training['wine_quality'].value_counts().to_frame()
total_training = training_counts.sum()[0]
```

In [ ]:
```
```

A few observations before we begin:

- Since we are looking primarily at how the predictors influence the quality of wine, I wanted to highlight the types of wine quality that are being classified by the dataset. There are 3 possible outcomes: C, F, and A.
- The training dataset has 3178 Observations

LDA

Question 1: Linear Discriminant Analysis

Fit LDS Classifiers

- Calculate Overall mis-classification rate
- Present cross-tabs table showing which categories are being classified correctly vs. incorrectly.
- For each prior, apply LDA model to the testing dataset, and present the misclassification rate and cross tabs.

LDA Function:
Note: copied directly from the provided BayesClassifiers.ipynb file

In [ ]:

```
class LDA():
    def __init__(self, dataset, class_var, priors = None):
        n_class = len(dataset[class_var].unique())
        if priors is None:
            priors = np.repeat(1/n_class, n_class)
        self.priors =  np.asarray(priors)
        self.means = dataset.groupby(class_var).mean()
        self.sigma = dataset.cov()
        self.class_var = class_var
        self.training_data = dataset
    def predict_probs(self, data = None):
        if data is None:
            data = self.training_data
        data_temp = data.drop(self.class_var, axis = 1)
        dens_list = []
        col_names = []
        for ind, row in self.means.iterrows():
            col_names.append(ind)
            dens_list.append(multivariate_normal.pdf(data_temp, mean = np.asar
ray(row), cov = self.sigma))
        dens_list = pd.DataFrame(np.transpose(np.vstack(dens_list)),columns= c
ol_names)
        dens_list = dens_list.mul(self.priors, axis=1)
        dens_list = dens_list.div(dens_list.sum(axis=1), axis=0)
        dens_list['True Class'] = data[self.class_var]
        return dens_list
    def predict_MAP(self, data = None):
        if data is None:
            data = self.training_data
        dens_list = self.predict_probs(data).drop('True Class', axis = 1)
        map_list = dens_list.idxmax(axis = 1)
        maps = {'MAP Class': map_list}
        maps = pd.DataFrame(maps)
        maps['True Class'] = data[self.class_var]
        return maps
    def misclass_rate(self, data = None):
        if data is None:
            data = self.training_data
        maps = self.predict_MAP(data = data)


        maps['Mis_class'] = maps['MAP Class']  == maps['True Class']

        mis_class =  1 - maps['Mis_class'].mean()

        return mis_class
    def misclass_xtabs(self, data = None):
        if data is None:
            data = self.training_data
        maps = self.predict_MAP(data = data)

        xtabs = pd.crosstab(maps['MAP Class'], maps['True Class'])
        return xtabs
    def misclass_pairplot(self, data = None):
        if data is None:
```

```
            data = self.training_data
        maps = self.predict_MAP(data = data)
        temp_dat = data.copy(deep = True)
        temp_dat['Mis-Classified'] = maps['MAP Class']  != maps['True Class']
        plot = sns.pairplot(temp_dat,hue="Mis-Classified", height = 1.5, aspec
t = 1.5)
        return plot
```

a) Non-informative (flat) priors on wine quality

For my non-informative prior, I am going to weight the likelihood of each possible outcome as 1/3, since there are 3 possible outcomes.

In [ ]:
```
flat_priors = [1/3, 1/3, 1/3]
LDA_non_informative = LDA(wine_training, 'wine_quality', priors = flat_priors)
print('+-----Non-Informative-Priors----+')
print('\t-Training Dataset-')
Non_Inform_Train_MCR = LDA_non_informative.misclass_rate()
print("Mis-Classification Rate:",Non_Inform_Train_MCR)
print("** Cross Tab **")
print(LDA_non_informative.misclass_xtabs())
print('----------------------------------')
print("\t-Testing Dataset-")
Non_Inform_Test_MCR = LDA_non_informative.misclass_rate(wine_testing)
print("Mis-Classification Rate:",Non_Inform_Test_MCR)
print("** Cross Tab **")
print(LDA_non_informative.misclass_xtabs(wine_testing))
```

```
+-----Non-Informative-Priors----+
        -Training Dataset-
Mis-Classification Rate: 0.49496538703587156
** Cross Tab **
True Class   A    C    F
MAP Class
A           69  687   62
C           22  800  202
F            9  591  736
----------------------------------
        -Testing Dataset-
Mis-Classification Rate: 0.48546511627906974
** Cross Tab **
True Class   A    C    F
MAP Class
A           56  348   43
C           15  381  149
F            9  271  448
```

b) Priors that reflect the observed proportion of wines at different quality levels

For the priors here, I take the number of wines in each category in the training dataset, and divide it by the total number of wines in the training data.

In [ ]:
```
proportion_priors = [training_counts.wine_quality.A/total_training, training_c
ounts.wine_quality.C/total_training, training_counts.wine_quality.F/total_trai
ning]
LDA_proportional_priors = LDA(wine_training, 'wine_quality', priors = proporti
on_priors)
print('+-------Proportional-Priors------+')
print('\t-Training Dataset-')
Proportional_Train_MCR = LDA_proportional_priors.misclass_rate()
print("Mis-Classification Rate:",Proportional_Train_MCR)
print("** Cross Tab **")
print(LDA_proportional_priors.misclass_xtabs())
print('----------------------------------')
print("\t-Testing Dataset-")
Proportional_Test_MCR = LDA_proportional_priors.misclass_rate(wine_testing)
print("Mis-Classification Rate:",Proportional_Test_MCR)
print("** Cross Tab **")
print(LDA_proportional_priors.misclass_xtabs(wine_testing))
```

```
+-------Proportional-Priors------+
        -Training Dataset-
Mis-Classification Rate: 0.28099433606041535
** Cross Tab **
True Class    A     C    F
MAP Class
A             0     0    1
C           100  1913  627
F             0   165  372
----------------------------------
        -Testing Dataset-
Mis-Classification Rate: 0.32732558139534884
** Cross Tab **
True Class   A    C    F
MAP Class
C           79  923  406
F            1   77  234
```

c) Priors that reflect the notion that most wines are awful, some wines are average, and few wines are good (your choice for the specific values)

For my priors here, I am assuming 80% of the wines are poor, 15% of the wines are average, and 5% of the wines are good.

In [ ]:

```
MFSCFA_priors = [0.05, 0.15,0.8]
LDA_MFSCFA = LDA(wine_training, 'wine_quality', priors = MFSCFA_priors)
print('+--Most-Awful--Some-Average--Few-Good--+')
print('\t-Training Dataset-')
MFSCFA_Train_MCR = LDA_MFSCFA.misclass_rate()
print("Mis-Classification Rate:",MFSCFA_Train_MCR)
print("** Cross Tab **")
print(LDA_MFSCFA.misclass_xtabs())
print('-----------------------------------')
print("\t-Testing Dataset-")
MFSCFA_Test_MCR = LDA_MFSCFA.misclass_rate(wine_testing)
print("Mis-Classification Rate:",MFSCFA_Test_MCR)
print("** Cross Tab **")
print(LDA_MFSCFA.misclass_xtabs(wine_testing))
```

```
+--Most-Awful--Some-Average--Few-Good--+
        -Training Dataset-
Mis-Classification Rate: 0.6415984896161108
** Cross Tab **
True Class   A     C    F
MAP Class
A           10    51    2
C           20   135    4
F           70  1892  994
----------------------------------
        -Testing Dataset-
Mis-Classification Rate: 0.5848837209302326
** Cross Tab **
True Class   A    C    F
MAP Class
A            9   38    0
C           10   72    7
F           61  890  633
```

d) Priors that somebody with a terrible taste in wine would use (most are good, few are bad or average)

For the priors here, I have 80% of the wines classified as good, where only 15% are classified as average,and 5% classified as bad.

```
In [ ]: bad_priors = [0.8, 0.15,0.05]
LDA_bad_taste = LDA(wine_training, 'wine_quality', priors = bad_priors)
print('+---------Bad-Sommelier--------+')
print('\t-Training Dataset-')
Bad_Taste_Train_MCR = LDA_bad_taste.misclass_rate()
print("Mis-Classification Rate:",Bad_Taste_Train_MCR)
print("** Cross Tab **")
print(LDA_bad_taste.misclass_xtabs())
print('----------------------------------')
print("\t-Testing Dataset-")
Bad_Taste_Test_MCR = LDA_bad_taste.misclass_rate(wine_testing)
print("Mis-Classification Rate:",Bad_Taste_Test_MCR)
print("** Cross Tab **")
print(LDA_bad_taste.misclass_xtabs(wine_testing))
```

```
+---------Bad-Sommelier--------+
        -Training Dataset-
Mis-Classification Rate: 0.9093769666456891
** Cross Tab **
True Class    A     C    F
MAP Class
A           100  1993  799
C             0    53   66
F             0    32  135
----------------------------------
        -Testing Dataset-
Mis-Classification Rate: 0.8866279069767442
** Cross Tab **
True Class   A    C    F
MAP Class
A           79  945  518
C            1   32   38
F            0   23   84
```

Conclusions

```
In [ ]: x_tabs = {'Training': [Non_Inform_Train_MCR, Proportional_Train_MCR, MFSCFA_Train_MCR, Bad_Taste_Train_MCR],
            'Testing':[Non_Inform_Test_MCR, Proportional_Test_MCR, MFSCFA_Test_MCR, Bad_Taste_Test_MCR]}

pd.DataFrame(x_tabs, index=['Non Informed','Proportional', 'Good Taste', 'Bad Taste'])
```

Out[ ]:

	Training	Testing
Non Informed	0.494965	0.485465
Proportional	0.280994	0.327326
Good Taste	0.641598	0.584884
Bad Taste	0.909377	0.886628

Discuss the performance of your LDA models under your various choice of priors:

The four different LDA Models vary in their misclassification rates. The model using proportional priors outperformed the other models, with roughly 30% of the data being misclassified.
The model that used the non-informed priors was the second-best, but roughly half of the data was misclassified. The model where most of the wines were classified as poor performs third best, with 64% of the training data and 58% of the testing data being misclassified. The model representing someone with a bad taste in wine misclassified nearly all of the data. What I find interesting is that I used mirrored proportions for the Good and Bad Taste, and the 'Good Taste' Classification still does not perform well, even though the 'Bad Taste' model is misclassifying almost all data points.

The classes of wine quality are greatly unbalanced, so I would recommend using the proportion as priors. As shown, this allows the model to better handle the unbalanced classes and more accurately predict the correct classifications.

How does the performance change when we start testing our models on the testing data?

For the uninformed, good, and bad taste priors, the accuracy of the model increases when we use the testing data. For the proportional data, the accuracy of the model decreases.
I believe this occurs because the proportions used for the priors are directly tied to the training data, the proportions are not the same in the testing data, whereas the other priors do not rely explicitly on a metric from the training data. However, these priors still greatly outperform the other models.

Question 2

Fit LDA models for each combination of three features, there will be 165 combinations. Use flat priors on wine quality.

a)

For each model, extract the overall mis-classification for both the training and testing dataset. This gets reused in B, so I made it a function:

In [ ]:

```
#Create List of all possible combinations of 3 features
def find_three_combo(priors):
    combo_of_three_features = [list(x) for x in combinations(wine_training.dro
p('wine_quality', axis=1), 3)]

    LDA_train_results = []
    LDA_test_results = []

    #Iterate through all possible combinations of three.
    for combination in combo_of_three_features:
        current_columns = combination + ['wine_quality']
        train_three_feat = wine_training[current_columns]
        test_three_feat = wine_testing[current_columns]
        #print(train_three_feat)
        LDA_3 = LDA(train_three_feat, 'wine_quality', priors=priors)
        train_misclass = LDA_3.misclass_rate()
        test_misclass = LDA_3.misclass_rate(test_three_feat)
        LDA_train_results.append((current_columns, train_misclass))
        LDA_test_results.append((current_columns, test_misclass))

    return(LDA_train_results, LDA_test_results)
```

Which combination of three features provides the lowest mis-classification rate for the testing and training datasets? Are they the same or different?

In [ ]:

```
LDA_train, LDA_test = find_three_combo(priors=flat_priors)
train_final = pd.DataFrame(LDA_train, columns = ['Combination', 'Misclass_Rat
e'])
test_final = pd.DataFrame(LDA_test, columns = ['Combination', 'Misclass_Rate'
])
train_min = pd.DataFrame(train_final[train_final.Misclass_Rate == train_final.
Misclass_Rate.min()]).reset_index()
print("Training:\nThe Combination of Features that Provides the lowest mis-cla
ss rate:", train_min['Combination'][0])
print("The corresponding mis-class rate is:" ,train_min['Misclass_Rate'][0])
print()
test_min = pd.DataFrame(test_final[test_final.Misclass_Rate == test_final.Misc
lass_Rate.min()]).reset_index()
print("Testing:\nThe Combination of Features that Provides the lowest mis-clas
s rate:", test_min['Combination'][0])
print("The corresponding mis-class rate is:", test_min['Misclass_Rate'][0])
```

```
Training:
The Combination of Features that Provides the lowest mis-class rate: ['volati
le.acidity', 'residual.sugar', 'alcohol', 'wine_quality']
The corresponding mis-class rate is: 0.5050346129641283

Testing:
The Combination of Features that Provides the lowest mis-class rate: ['volati
le.acidity', 'density', 'alcohol', 'wine_quality']
The corresponding mis-class rate is: 0.4877906976744186
```

The feature combinations that create the lowest misclass rate for the training and the testing data are very similar. The only difference is that the training data has residual sugar, where the testing data uses density. Otherwise, both the other features are volatile acidity and alcohol.

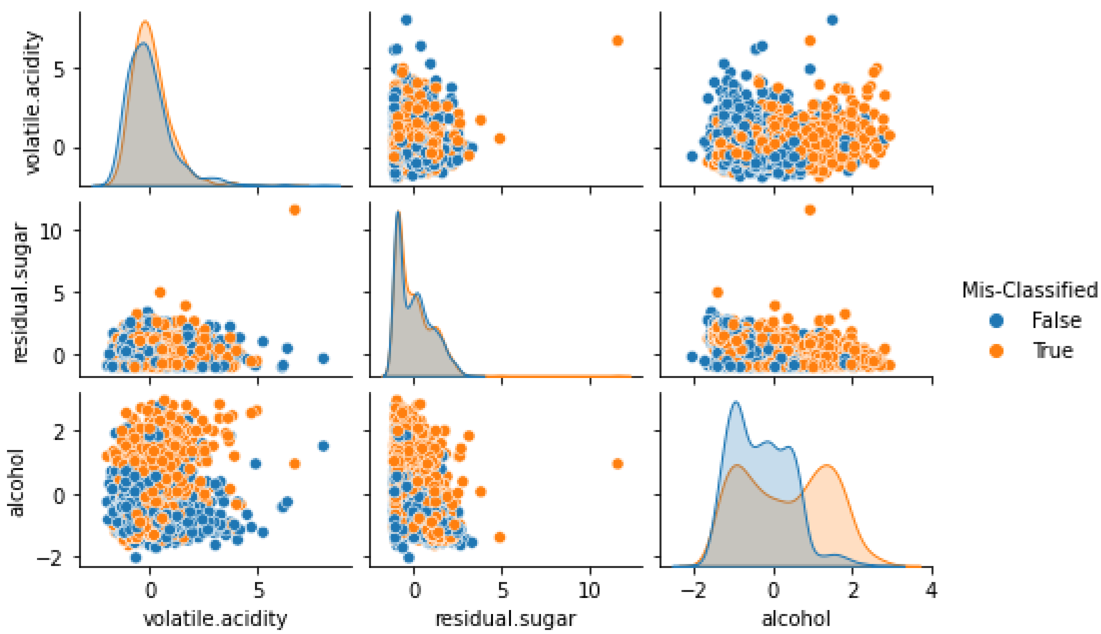
Using the functions provided, provide pair plots for mis-classifications.

In [ ]:
```
LDA_best_misclass_train = LDA(wine_training[train_min['Combination'][0]], 'win
e_quality', priors=flat_priors)
LDA_best_misclass_test = LDA(wine_testing[test_min['Combination'][0]], 'wine_q
uality', priors=flat_priors)
```

Training Data:

In [ ]:
```
LDA_best_misclass_train.misclass_pairplot()
```

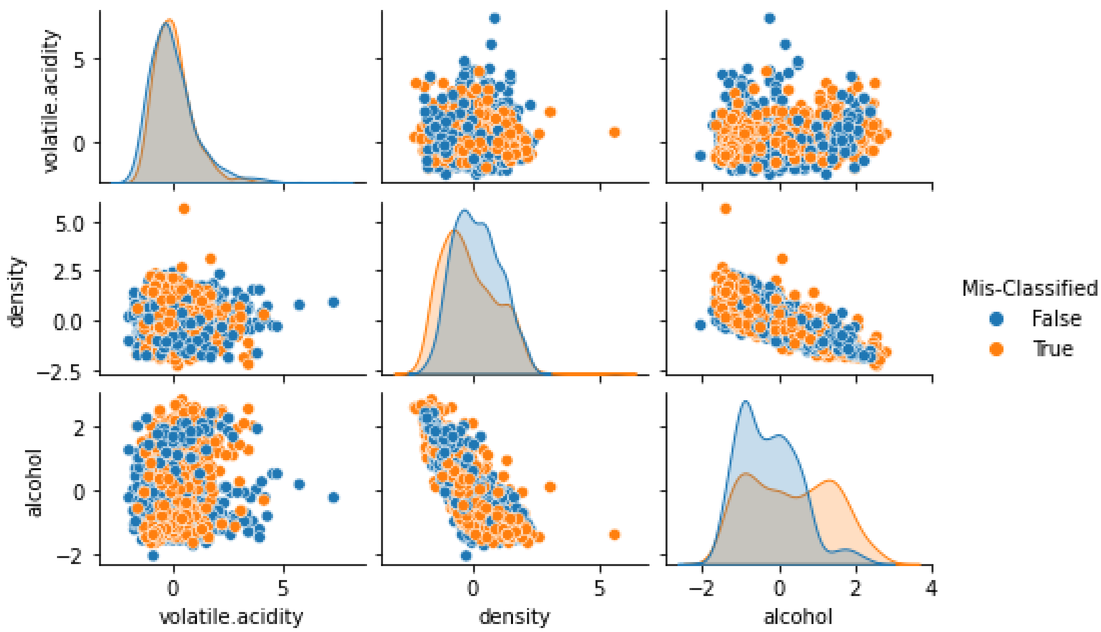
Out[ ]:
```
<seaborn.axisgrid.PairGrid at 0x18bd003df40>
```



Testing Data:

```
In [ ]: LDA_best_misclass_test.misclass_pairplot()
```

```
Out[ ]: <seaborn.axisgrid.PairGrid at 0x18bd0927460>
```



b) Using priors that observed proportion of wine quality in the training dataset, identify the combination of three features that provide the lowest misclassification rate.

In [ ]:
```
LDA_train, LDA_test = find_three_combo(priors=proportion_priors)
train_final = pd.DataFrame(LDA_train, columns = ['Combination', 'Misclass_Rat
e'])
test_final = pd.DataFrame(LDA_test, columns = ['Combination', 'Misclass_Rate'
])
train_min = pd.DataFrame(train_final[train_final.Misclass_Rate == train_final.
Misclass_Rate.min()]).reset_index()
print("Training:\nThe Combination of Features that Provides the lowest mis-cla
ss rate:", train_min['Combination'][0])
print("The corresponding mis-class rate is:" ,train_min['Misclass_Rate'][0])
print()
test_min = pd.DataFrame(test_final[test_final.Misclass_Rate == test_final.Misc
lass_Rate.min()]).reset_index()
print("Testing:\nThe Combination of Features that Provides the lowest mis-clas
s rate:", test_min['Combination'][0])
print("The corresponding mis-class rate is:", test_min['Misclass_Rate'][0])
LDA_best_misclass_train = LDA(wine_training[train_min['Combination'][0]], 'win
e_quality', priors=proportion_priors)
LDA_best_misclass_test = LDA(wine_testing[test_min['Combination'][0]], 'wine_q
uality', priors=proportion_priors)
```

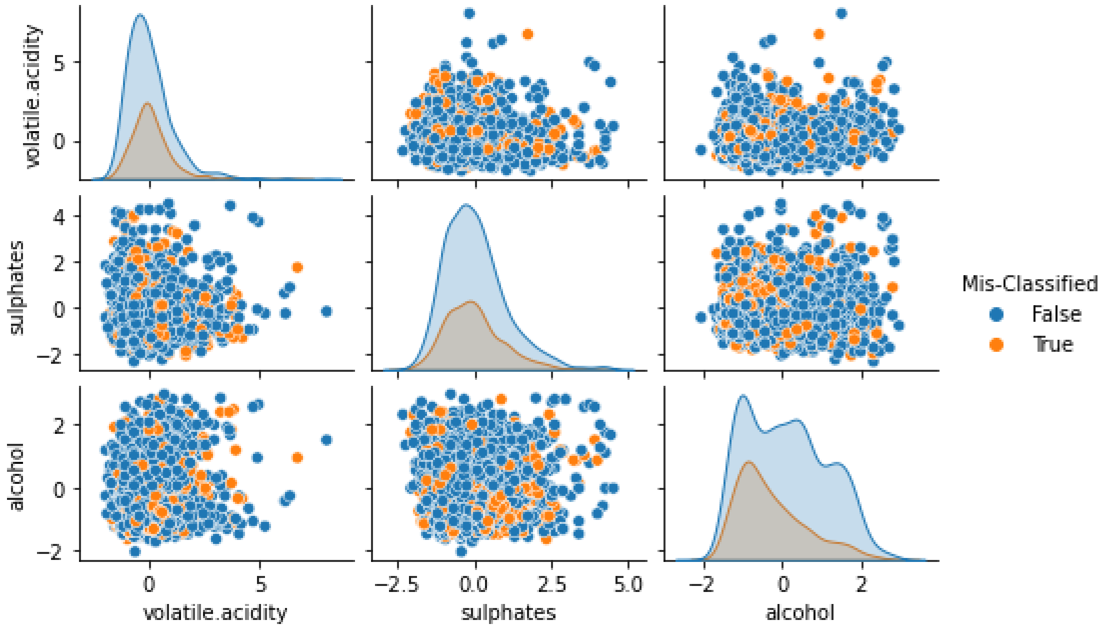
```
Training:
The Combination of Features that Provides the lowest mis-class rate: ['volati
le.acidity', 'sulphates', 'alcohol', 'wine_quality']
The corresponding mis-class rate is: 0.2800503461296413

Testing:
The Combination of Features that Provides the lowest mis-class rate: ['volati
le.acidity', 'residual.sugar', 'alcohol', 'wine_quality']
The corresponding mis-class rate is: 0.3296511627906977
```

Training:

```
In [ ]: LDA_best_misclass_train.misclass_pairplot()
```

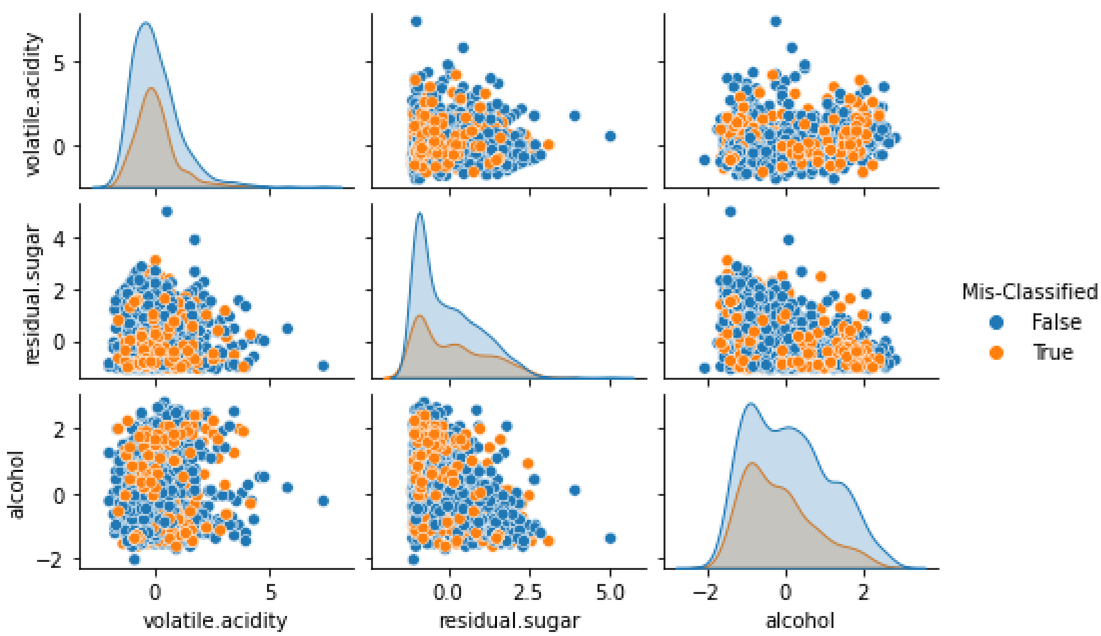
```
Out[ ]: <seaborn.axisgrid.PairGrid at 0x18bd5244040>
```



Testing:

```
In [ ]: LDA_best_misclass_test.misclass_pairplot()
```

```
Out[ ]: <seaborn.axisgrid.PairGrid at 0x18bd59ee3a0>
```



Do the best models differ from when you used flat priors? Yes, but again, only very slightly. When using flat priors, the best training model used volitile acidity, residual sugar, and alcohol. Using proportional priors, the best model uses volitile acidity,sulphates, and alcohol. Using flat priors, the best testing model used volitile acidity, density, and alcohol, and the proportional priors best model uses volitile acidity, residual sugar, and alcohol.

Again, it is only one measure that changes.

The best model for the flat prior training model is equivalent to the best model for proprortional priors testing model.

The mis-classification rate is much lower for the proportional priors model.

QDA

QDA Functions
Note: copied directly from the provided BayesClassifiers.ipynb file

In [ ]:
```
class QDA(LDA):
    def __init__(self, dataset, class_var, priors = None):
        n_class = len(dataset[class_var].unique())
        if priors is None:
            priors = np.repeat(1/n_class, n_class)
        self.priors = np.asarray(priors)
        self.means = dataset.groupby(class_var).mean()
        gb = dataset.groupby(class_var)
        self.sigma = {x: gb.get_group(x).cov() for x in gb.groups}
        self.class_var = class_var
        self.training_data = dataset
    def predict_probs(self, data = None):
        if data is None:
            data = self.training_data
        data_temp = data.drop(self.class_var, axis = 1)
        dens_list = []
        col_names = []
        for ind, row in self.means.iterrows():
            col_names.append(ind)
            dens_list.append(multivariate_normal.pdf(data_temp, mean = np.asar
ray(row), cov = np.asarray(self.sigma[ind])))
        dens_list = pd.DataFrame(np.transpose(np.vstack(dens_list)),columns= c
ol_names)
        dens_list = dens_list.mul(self.priors, axis=1)
        dens_list = dens_list.div(dens_list.sum(axis=1), axis=0)
        dens_list['True Class'] = data[self.class_var]
        return dens_list
```

a) Non Informative (Flat) Priors

In [ ]:
```python
QDA_non_informative = QDA(wine_training, 'wine_quality', priors = flat_priors)
print('+-----Non-Informative-Priors----+')
print('\t-Training Dataset-')
Non_Inform_Train_MCR = QDA_non_informative.misclass_rate()
print("Mis-Classification Rate:",Non_Inform_Train_MCR)
print("** Cross Tab **")
print(QDA_non_informative.misclass_xtabs())
print('----------------------------------')
print("\t-Testing Dataset-")
Non_Inform_Test_MCR = QDA_non_informative.misclass_rate(wine_testing)
print("Mis-Classification Rate:",Non_Inform_Test_MCR)
print("** Cross Tab **")
print(QDA_non_informative.misclass_xtabs(wine_testing))
```

```
+-----Non-Informative-Priors----+
        -Training Dataset-
Mis-Classification Rate: 0.5088105726872247
** Cross Tab **
True Class   A    C    F
MAP Class
A           87  828   90
C            9  799  235
F            4  451  675
----------------------------------
        -Testing Dataset-
Mis-Classification Rate: 0.5186046511627906
** Cross Tab **
True Class   A    C    F
MAP Class
A           58  414   54
C           21  381  197
F            1  205  389
```

B) Observed Proportion

In [ ]:
```
QDA_proportional_priors = QDA(wine_training, 'wine_quality', priors = proportion_priors)
print('+-------Proportional-Priors------+')
print('\t-Training Dataset-')
Proportional_Train_MCR = QDA_proportional_priors.misclass_rate()
print("Mis-Classification Rate:",Proportional_Train_MCR)
print("** Cross Tab **")
print(QDA_proportional_priors.misclass_xtabs())
print('----------------------------------')
print("\t-Testing Dataset-")
Proportional_Test_MCR = QDA_proportional_priors.misclass_rate(wine_testing)
print("Mis-Classification Rate:",Proportional_Test_MCR)
print("** Cross Tab **")
print(QDA_proportional_priors.misclass_xtabs(wine_testing))
```

```
+-------Proportional-Priors------+
        -Training Dataset-
Mis-Classification Rate: 0.27879169288860917
** Cross Tab **
True Class   A     C    F
MAP Class
A           20    36    3
C           78  1754  479
F            2   288  518
----------------------------------
        -Testing Dataset-
Mis-Classification Rate: 0.33255813953488367
** Cross Tab **
True Class   A    C    F
MAP Class
A            7   24    1
C           73  842  340
F            0  134  299
```

C) Priors that reflect the notion that most wines are awful, some wines are average, and few wines are good (your choice for specific values.)

In [ ]:

```
QDA_MFSCFA = QDA(wine_training, 'wine_quality', priors = MFSCFA_priors)
print('+--Most-Awful--Some-Average--Few-Good--+')
print('\t-Training Dataset-')
MFSCFA_Train_MCR = QDA_MFSCFA.misclass_rate()
print("Mis-Classification Rate:",MFSCFA_Train_MCR)
print("** Cross Tab **")
print(QDA_MFSCFA.misclass_xtabs())
print('-----------------------------------')
print("\t-Testing Dataset-")
MFSCFA_Test_MCR = QDA_MFSCFA.misclass_rate(wine_testing)
print("Mis-Classification Rate:",MFSCFA_Test_MCR)
print("** Cross Tab **")
print(QDA_MFSCFA.misclass_xtabs(wine_testing))
```

```
+--Most-Awful--Some-Average--Few-Good--+
        -Training Dataset-
Mis-Classification Rate: 0.5292636878539962
** Cross Tab **
True Class   A     C    F
MAP Class
A           55   400   27
C           22   544   76
F           23  1134  897
----------------------------------
        -Testing Dataset-
Mis-Classification Rate: 0.4808139534883721
** Cross Tab **
True Class   A    C    F
MAP Class
A           38  205   11
C           24  274   48
F           18  521  581
```

d) Priors that somebody with terrible taste in wine would use (i.e. most wines are good, few wines are

bad or average).

```
In [ ]: QDA_bad_taste = QDA(wine_training, 'wine_quality', priors = bad_priors)
        print('+---------Bad-Sommelier--------+')
        print('\t-Training Dataset-')
        Bad_Taste_Train_MCR = QDA_bad_taste.misclass_rate()
        print("Mis-Classification Rate:",Bad_Taste_Train_MCR)
        print("** Cross Tab **")
        print(QDA_bad_taste.misclass_xtabs())
        print('----------------------------------')
        print("\t-Testing Dataset-")
        Bad_Taste_Test_MCR = QDA_bad_taste.misclass_rate(wine_testing)
        print("Mis-Classification Rate:",Bad_Taste_Test_MCR)
        print("** Cross Tab **")
        print(QDA_bad_taste.misclass_xtabs(wine_testing))
```

```
+---------Bad-Sommelier--------+
        -Training Dataset-
Mis-Classification Rate: 0.6705475141598489
** Cross Tab **
True Class   A     C    F
MAP Class
A           96  1321  284
C            2   552  317
F            2   205  399
----------------------------------
        -Testing Dataset-
Mis-Classification Rate: 0.6587209302325581
** Cross Tab **
True Class   A    C    F
MAP Class
A           68  637  177
C           12  272  216
F            0   91  247
```

Discuss the performance of your QDA models under your various choices of priors. How does the performance change when we start testing our models on the testing data?

```
In [ ]: x_tabs = {'Training': [Non_Inform_Train_MCR, Proportional_Train_MCR, MFSCFA_Train_MCR, Bad_Taste_Train_MCR],
                    'Testing':[Non_Inform_Test_MCR, Proportional_Test_MCR, MFSCFA_Test_MCR, Bad_Taste_Test_MCR]}

        pd.DataFrame(x_tabs, index=['Non Informed','Proportional', 'Good Taste', 'Bad Taste'])
```

Out[ ]:

	Training	Testing
Non Informed	0.508811	0.518605
Proportional	0.278792	0.332558
Good Taste	0.529264	0.480814
Bad Taste	0.670548	0.658721

When we look at the data compared to the LDA, the training and testing misclassification rates are higher for the non-informed priors, proportional priors, and good taste priors, and much lower for the bad-taste priors. The Proportional priors are still the best in terms of mis-classification rates, and the overall order from best to worst is still preserved.

The mis-classification rate for the testing data is higher than the training data for the non-informed priors and proportional priors, and lower in the good and bad taste priors.

Question 4

In [ ]:
```
#Create List of all possible combinations of 3 features
def find_three_combo_QDA(priors):
    combo_of_three_features = [list(x) for x in combinations(wine_training.dro
p('wine_quality', axis=1), 3)]

    QDA_train_results = []
    QDA_test_results = []

    #Iterate through all possible combinations of three.
    for combination in combo_of_three_features:
        current_columns = combination + ['wine_quality']
        train_three_feat = wine_training[current_columns]
        test_three_feat = wine_testing[current_columns]
        #print(train_three_feat)
        QDA_3 = QDA(train_three_feat, 'wine_quality', priors=priors)
        train_misclass = QDA_3.misclass_rate()
        test_misclass = QDA_3.misclass_rate(test_three_feat)
        QDA_train_results.append((current_columns, train_misclass))
        QDA_test_results.append((current_columns, test_misclass))

    return(QDA_train_results, QDA_test_results)
```

A) For each model, extract the overall miss-classification rate for both the training and the testing dataset.

For the best performing models (for training and testing), using the functions provided, provide pair-plots for mis-classification

In [ ]:
```
QDA_train, QDA_test = find_three_combo_QDA(priors=flat_priors)
train_final = pd.DataFrame(QDA_train, columns = ['Combination', 'Misclass_Rat
e'])
test_final = pd.DataFrame(QDA_test, columns = ['Combination', 'Misclass_Rate'
])
train_min = pd.DataFrame(train_final[train_final.Misclass_Rate == train_final.
Misclass_Rate.min()]).reset_index()
print("Training:\nThe Combination of Features that Provides the lowest mis-cla
ss rate:", train_min['Combination'][0])
print("The corresponding mis-class rate is:" ,train_min['Misclass_Rate'][0])
print()
test_min = pd.DataFrame(test_final[test_final.Misclass_Rate == test_final.Misc
lass_Rate.min()]).reset_index()
print("Testing:\nThe Combination of Features that Provides the lowest mis-clas
s rate:", test_min['Combination'][0])
print("The corresponding mis-class rate is:", test_min['Misclass_Rate'][0])
QDA_best_misclass_train = QDA(wine_training[train_min['Combination'][0]], 'win
e_quality', priors=flat_priors)
QDA_best_misclass_test = QDA(wine_testing[test_min['Combination'][0]], 'wine_q
uality', priors=flat_priors)
```

```
Training:
The Combination of Features that Provides the lowest mis-class rate: ['volati
le.acidity', 'free.sulfur.dioxide', 'sulphates', 'wine_quality']
The corresponding mis-class rate is: 0.4269981120201385

Testing:
The Combination of Features that Provides the lowest mis-class rate: ['volati
le.acidity', 'free.sulfur.dioxide', 'alcohol', 'wine_quality']
The corresponding mis-class rate is: 0.4511627906976744
```

Which combination of three features provides the lowest miss-classification rate for the

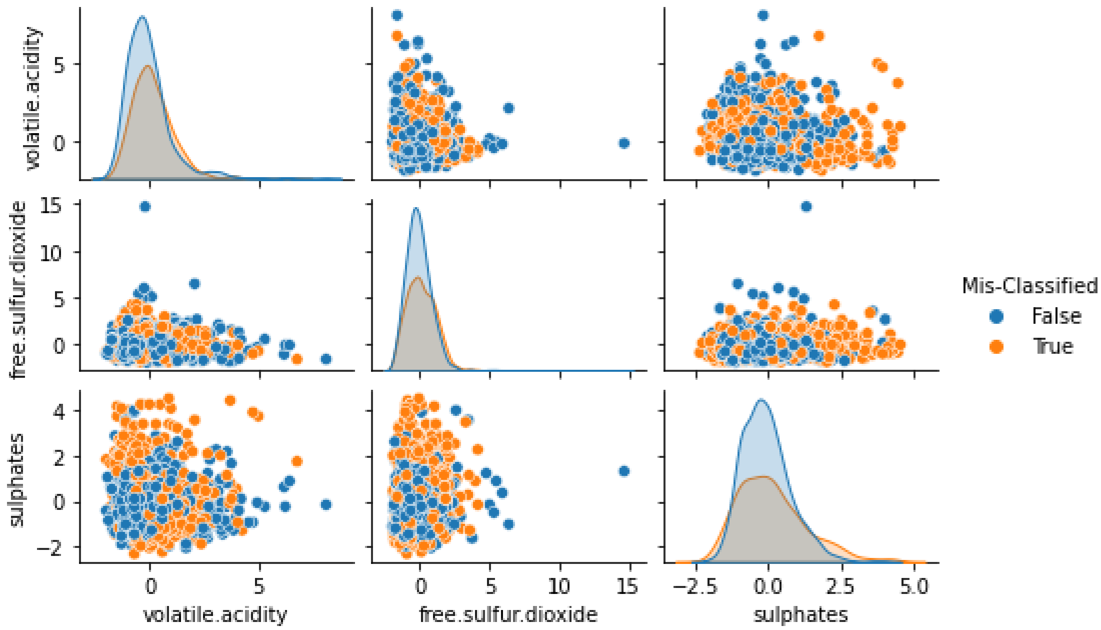
testing and training datasets? Are they the same or different (between the training/testing)?

The training dataset with the lowest mis-classification uses volatile.acidity, free.sulfur.dioxide, and sulphates. The testing dataset with the lowest mis-classification rate uses volatile.acidity, free.sulfur.dioxide, and alcohol. Like we saw with LDA, these are the same, except for one feature which is different.

For the best performing models (for training and testing), using the functions provided, provide pair-plots for mis-classification

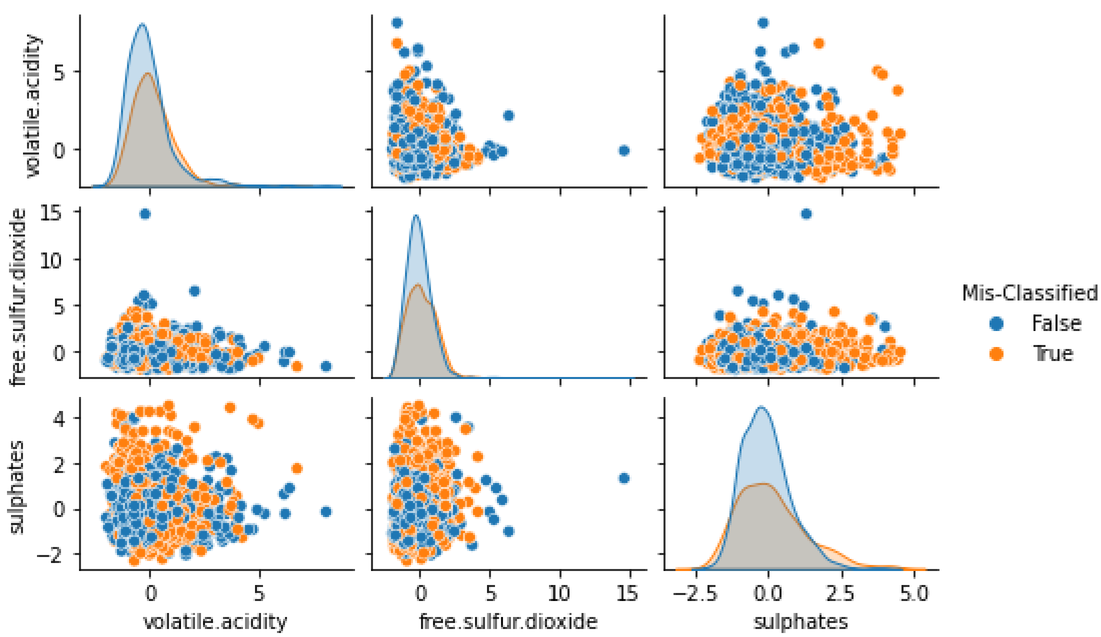
Training Data

In [ ]:
```
QDA_best_misclass_train.misclass_pairplot()
```
Out[ ]: <seaborn.axisgrid.PairGrid at 0x18bd63c24c0>



Testing Data:

In [ ]:
```
QDA_best_misclass_train.misclass_pairplot()
```
Out[ ]: <seaborn.axisgrid.PairGrid at 0x18bd6e106d0>



B) Using priors that reflect the observed proportion of wine quality in the training dataset, identify the combination of three features that provide the lowest mis-classification rate.

In [ ]:

```
QDA_train, QDA_test = find_three_combo_QDA(priors=proportion_priors)
train_final = pd.DataFrame(QDA_train, columns = ['Combination', 'Misclass_Rat
e'])
test_final = pd.DataFrame(QDA_test, columns = ['Combination', 'Misclass_Rate'
])
train_min = pd.DataFrame(train_final[train_final.Misclass_Rate == train_final.
Misclass_Rate.min()]).reset_index()
print("Training:\nThe Combination of Features that Provides the lowest mis-cla
ss rate:", train_min['Combination'][0])
print("The corresponding mis-class rate is:" ,train_min['Misclass_Rate'][0])
print()
test_min = pd.DataFrame(test_final[test_final.Misclass_Rate == test_final.Misc
lass_Rate.min()]).reset_index()
print("Testing:\nThe Combination of Features that Provides the lowest mis-clas
s rate:", test_min['Combination'][0])
print("The corresponding mis-class rate is:", test_min['Misclass_Rate'][0])
QDA_best_misclass_train = QDA(wine_training[train_min['Combination'][0]], 'win
e_quality', priors=proportion_priors)
QDA_best_misclass_test = QDA(wine_testing[test_min['Combination'][0]], 'wine_q
uality', priors=proportion_priors)
```

```
Training:
The Combination of Features that Provides the lowest mis-class rate: ['volati
le.acidity', 'residual.sugar', 'alcohol', 'wine_quality']
The corresponding mis-class rate is: 0.27375707992448084

Testing:
The Combination of Features that Provides the lowest mis-class rate: ['volati
le.acidity', 'residual.sugar', 'alcohol', 'wine_quality']
The corresponding mis-class rate is: 0.31511627906976747
```

Do the best models differ from when you used flat priors?

Yes!

For the training data: Flat priors: volatile.acidity, free.sulfur.dioxide, and sulphates. Proportional priors: volatile.acidity, residual.sugar, and alcohol

For the testing data: Flat priors: volatile.acidity, free.sulfur.dioxide, and alcohol. Proportional priors: volatile.acidity, residual.sugar, and alcohol

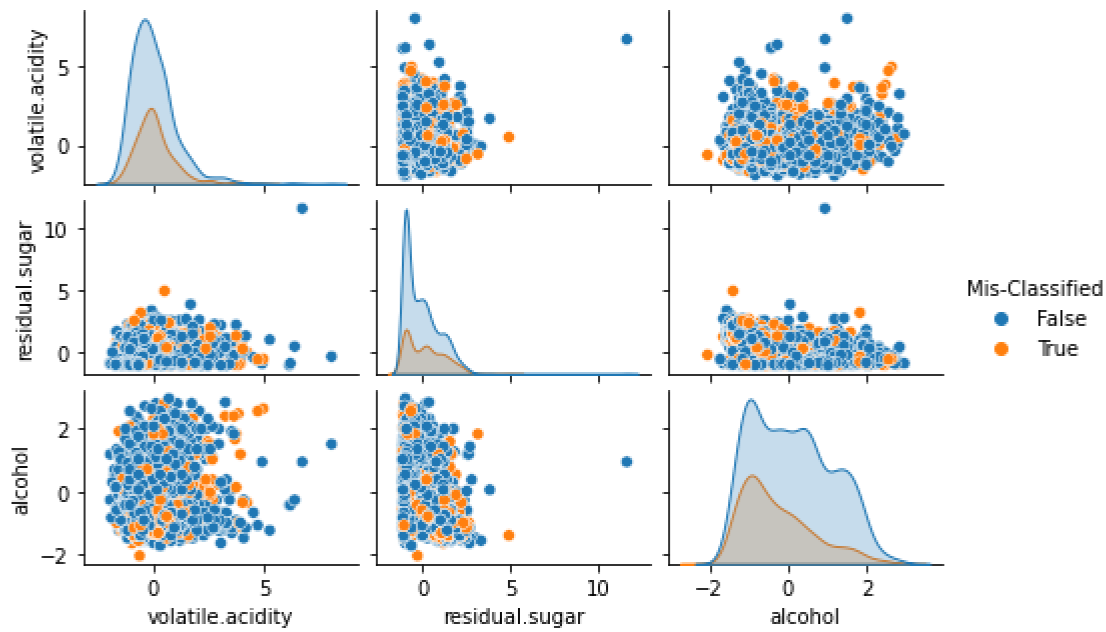
An interesting thing to note here, is that this is the first time we have seen the best model have the same combination of features for both testing and training data!

Pair plots:

Training

```
In [ ]: QDA_best_misclass_train.misclass_pairplot()
```

```
Out[ ]: <seaborn.axisgrid.PairGrid at 0x18bd7d44970>
```



Testing

```
In [ ]: QDA_best_misclass_test.misclass_pairplot()
```

```
Out[ ]: <seaborn.axisgrid.PairGrid at 0x18bd73d7460>
```