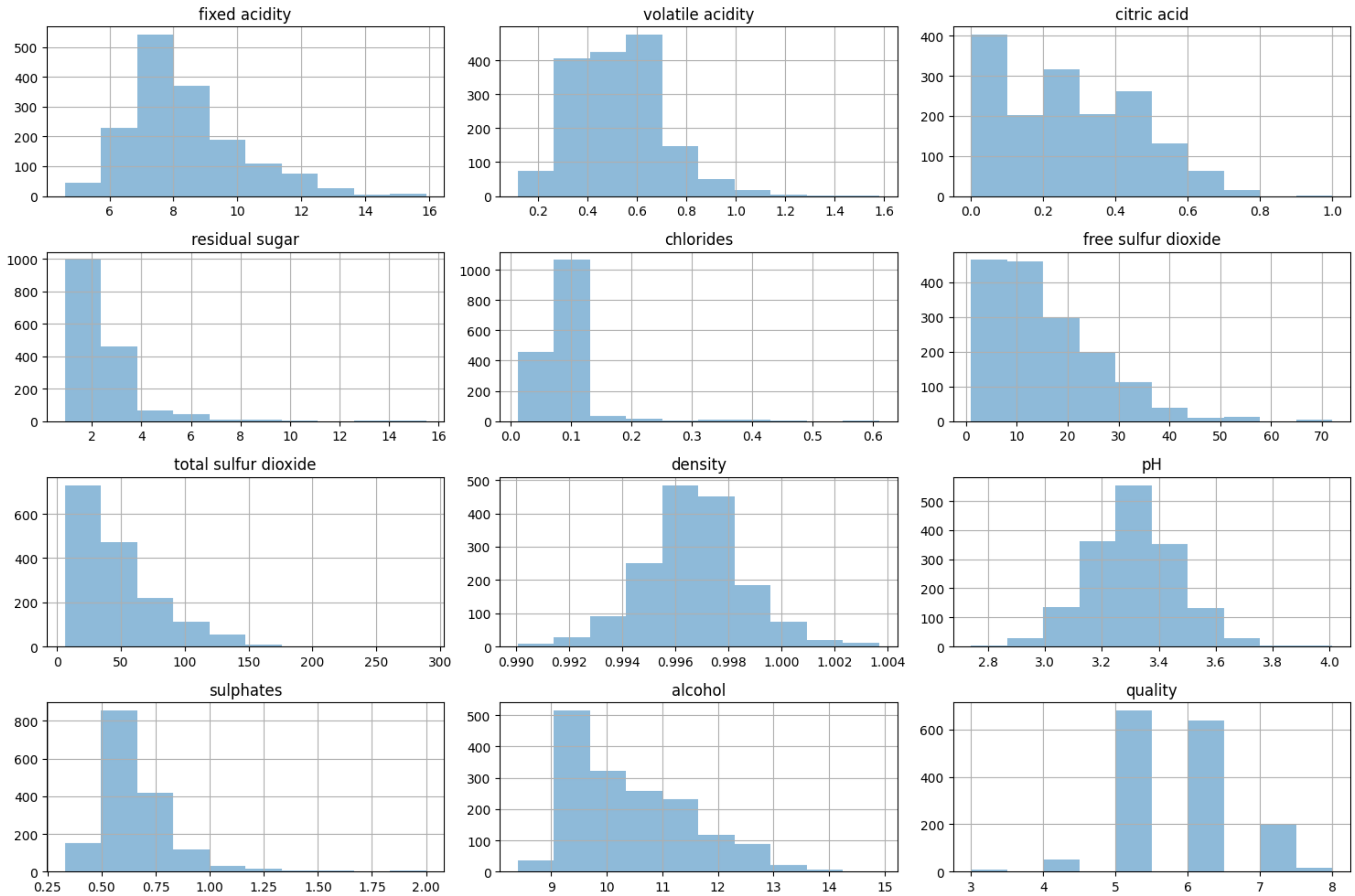
In [ ]:
```python
import matplotlib.pyplot as plt
import pandas as pd
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
from sklearn.model_selection import train_test_split
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix, classification_report
from sklearn.model_selection import GridSearchCV
from sklearn.neural_network import MLPClassifier
from sklearn.feature_selection import SelectKBest, chi2
from collections import Counter
import seaborn as sns
from imblearn.over_sampling import RandomOverSampler, SMOTE
from imblearn.under_sampling import RandomUnderSampler
import warnings
warnings.filterwarnings("ignore")
```

1. Data Preprocessing

Importing dataset & Checking for missing data

In [ ]:
```python
headerList = ['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar', 'chlorides', 'free sulfur dioxide', 'total sulfur dioxide', 'density', 'pH', 'sulphates',

wineData = pd.read_csv('winequality-red.csv', header = 0, names = headerList, sep=";")
print(wineData.head(10))
print(wineData)

#Summarative functions
wineData.dtypes
wineData.describe()
wineData.info()

#Plotting histogram of each variable
wineData.hist(alpha=0.5, figsize=(15, 10))
plt.tight_layout()
plt.show()

for h in headerList:
  wineData[h] = pd.to_numeric(wineData[h], errors='coerce')

print("\nChecking for null values: \n")
wineData.isna().sum()
wineData = wineData.fillna(0)
print("\nChecking for null values after using fillna(): \n")
wineData.isna().sum()
```

```
   fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0            7.4              0.70         0.00             1.9      0.076   
1            7.8              0.88         0.00             2.6      0.098   
2            7.8              0.76         0.04             2.3      0.092   
3           11.2              0.28         0.56             1.9      0.075   
4            7.4              0.70         0.00             1.9      0.076   
5            7.4              0.66         0.00             1.8      0.075   
6            7.9              0.60         0.06             1.6      0.069   
7            7.3              0.65         0.00             1.2      0.065   
8            7.8              0.58         0.02             2.0      0.073   
9            7.5              0.50         0.36             6.1      0.071   

   free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                 11.0                  34.0   0.9978  3.51       0.56   
1                 25.0                  67.0   0.9968  3.20       0.68   
2                 15.0                  54.0   0.9970  3.26       0.65   
3                 17.0                  60.0   0.9980  3.16       0.58   
4                 11.0                  34.0   0.9978  3.51       0.56   
5                 13.0                  40.0   0.9978  3.51       0.56   
6                 15.0                  59.0   0.9964  3.30       0.46   
7                 15.0                  21.0   0.9946  3.39       0.47   
8                  9.0                  18.0   0.9968  3.36       0.57   
9                 17.0                 102.0   0.9978  3.35       0.80   

   alcohol  quality  
0      9.4        5  
1      9.8        5  
2      9.8        5  
3      9.8        6  
4      9.4        5  
5      9.4        5  
6      9.4        5  
7     10.0        7  
8      9.5        7  
9     10.5        5  
      fixed acidity  volatile acidity  citric acid  residual sugar  chlorides  \
0               7.4             0.700         0.00             1.9      0.076   
1               7.8             0.880         0.00             2.6      0.098   
2               7.8             0.760         0.04             2.3      0.092   
3              11.2             0.280         0.56             1.9      0.075   
4               7.4             0.700         0.00             1.9      0.076   
...             ...               ...          ...             ...        ...   
1594            6.2             0.600         0.08             2.0      0.090   
1595            5.9             0.550         0.10             2.2      0.062   
1596            6.3             0.510         0.13             2.3      0.076   
1597            5.9             0.645         0.12             2.0      0.075   
1598            6.0             0.310         0.47             3.6      0.067   

      free sulfur dioxide  total sulfur dioxide  density    pH  sulphates  \
0                    11.0                  34.0  0.99780  3.51       0.56   
1                    25.0                  67.0  0.99680  3.20       0.68   
2                    15.0                  54.0  0.99700  3.26       0.65   
3                    17.0                  60.0  0.99800  3.16       0.58   
4                    11.0                  34.0  0.99780  3.51       0.56   
...                   ...                   ...      ...   ...        ...   
1594                 32.0                  44.0  0.99490  3.45       0.58   
1595                 39.0                  51.0  0.99512  3.52       0.76   
1596                 29.0                  40.0  0.99574  3.42       0.75   
1597                 32.0                  44.0  0.99547  3.57       0.71   
1598                 18.0                  42.0  0.99549  3.39       0.66   

      alcohol  quality  
0         9.4        5  
1         9.8        5  
2         9.8        5  
3         9.8        6  
4         9.4        5  
...       ...      ...  
1594     10.5        5  
1595     11.2        6  
1596     11.0        6  
1597     10.2        5  
1598     11.0        6  

[1599 rows x 12 columns]
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1599 non-null   float64
 1   volatile acidity      1599 non-null   float64
 2   citric acid           1599 non-null   float64
 3   residual sugar        1599 non-null   float64
 4   chlorides             1599 non-null   float64
 5   free sulfur dioxide   1599 non-null   float64
 6   total sulfur dioxide  1599 non-null   float64
 7   density               1599 non-null   float64
 8   pH                    1599 non-null   float64
 9   sulphates             1599 non-null   float64
 10  alcohol               1599 non-null   float64
 11  quality               1599 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 150.0 KB
```




```
Checking for null values:


Checking for null values after using fillna():
```

Out[ ]:

```
fixed acidity           0
volatile acidity        0
citric acid             0
residual sugar          0
chlorides               0
free sulfur dioxide     0
total sulfur dioxide    0
density                 0
pH                      0
sulphates               0
alcohol                 0
quality                 0
dtype: int64
```

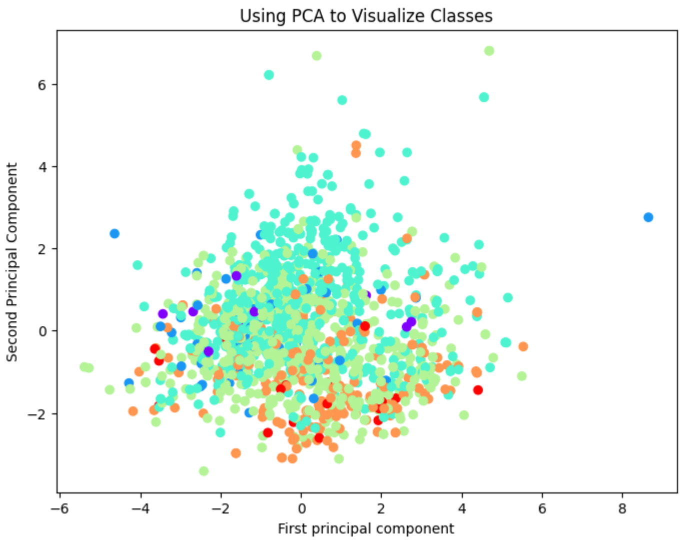
Our data is imbalanced as seen from the histogram. We will adapt multiple strategies to address the issue.

2. Exploratory Data Analysis

1. Principal Component Analysis (PCA)

In [ ]:

```
#PCA
df_pca = wineData.copy()
X_pca = df_pca.loc[:, 'fixed acidity':'alcohol']
y_pca = df_pca['quality']

X_pca.tail()
X_pca = StandardScaler().fit_transform(X_pca)

#Fit PCA
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_pca)

X_pca.shape

plt.figure(figsize=(8,6))
plt.scatter(X_pca[:,0],X_pca[:,1],c=y_pca,cmap='rainbow')
plt.xlabel('First principal component')
plt.ylabel('Second Principal Component')
plt.title("Using PCA to Visualize Classes")
plt.show()

print("components: ", pca.components_, "\n")
print("explained variance: ", pca.explained_variance_, "\n")
exp_var_rat = pca.explained_variance_ratio_
print("explained variance ratio: ", exp_var_rat)
```



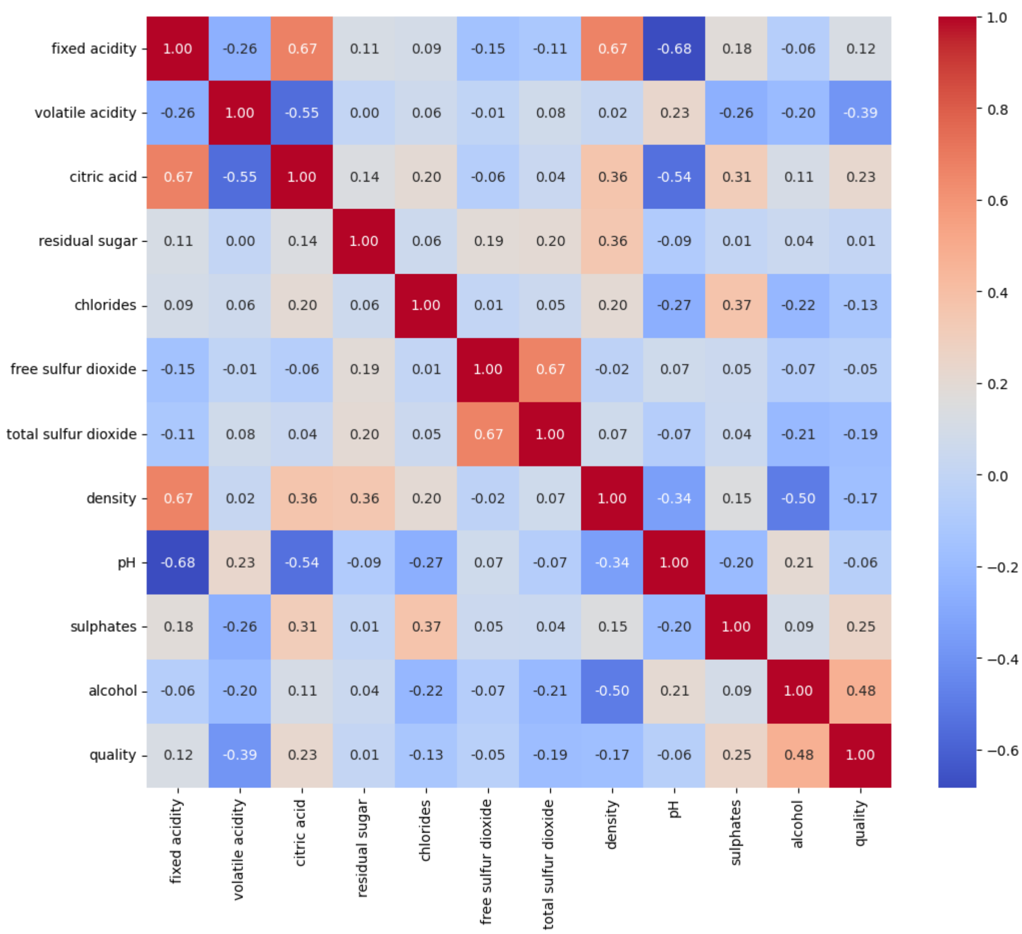

```
components:  [[ 0.48931422 -0.23858436  0.46363166  0.14610715  0.21224658 -0.03615752
   0.02357485  0.39535301 -0.43851962  0.24292133 -0.11323206]
 [-0.11050274  0.27493048 -0.15179136  0.27208024  0.14805156  0.51356681
   0.56948696  0.23357549  0.00671079 -0.03755392 -0.38618096]]

explained variance:  [3.10107182 1.92711489]

explained variance ratio:  [0.28173931 0.1750827 ]
```

2. Correlation Matrix

In [ ]:

```python
plt.figure(figsize=(12,10))
sns.heatmap(wineData.corr(),annot=True, cmap='coolwarm',fmt='.2f')
```

Out[ ]: <Axes: >



3. Univariate Selection

In [ ]:

```python
#Split data into training and test sets
X = wineData.loc[:, 'fixed acidity':'alcohol']
y = wineData['quality']

# apply SelectKBest class to extract best features
bestFeatures = SelectKBest(score_func=chi2, k=11)
bestFeaturesFit = bestFeatures.fit(X,y)
```

```
dfscores = pd.DataFrame(bestFeaturesFit.scores_)
dfcolumns = pd.DataFrame(X.columns)

# concatenate scores with predictor names
predScores = pd.concat([dfcolumns,dfscores],axis=1)
predScores.columns = ['Predictor','Score']
print(predScores.nlargest(11,'Score'))
```

```
               Predictor        Score
6   total sulfur dioxide  2755.557984
5    free sulfur dioxide   161.936036
10               alcohol    46.429892
1       volatile acidity    15.580289
2            citric acid    13.025665
0          fixed acidity    11.260652
9              sulphates     4.558488
3         residual sugar     4.123295
4              chlorides     0.752426
8                     pH     0.154655
7                density     0.000230
```

Dropping features from univariate selection

We are dropping bottom features as they have very low predictor scores and to save computation

In [ ]:
```
#Drop the bottom four features (smallest score)
wineData = wineData.drop(['density'], axis=1)
wineData = wineData.drop(['pH'], axis=1)
wineData = wineData.drop(['chlorides'], axis=1)
print(wineData)

X = wineData.loc[:, 'fixed acidity':'alcohol']
y = wineData['quality']
```

```
      fixed acidity  volatile acidity  citric acid  residual sugar  \
0               7.4             0.700         0.00             1.9
1               7.8             0.880         0.00             2.6
2               7.8             0.760         0.04             2.3
3              11.2             0.280         0.56             1.9
4               7.4             0.700         0.00             1.9
...             ...               ...          ...             ...
1594            6.2             0.600         0.08             2.0
1595            5.9             0.550         0.10             2.2
1596            6.3             0.510         0.13             2.3
1597            5.9             0.645         0.12             2.0
1598            6.0             0.310         0.47             3.6

      free sulfur dioxide  total sulfur dioxide  sulphates  alcohol  quality
0                    11.0                  34.0       0.56      9.4        5
1                    25.0                  67.0       0.68      9.8        5
2                    15.0                  54.0       0.65      9.8        5
3                    17.0                  60.0       0.58      9.8        6
4                    11.0                  34.0       0.56      9.4        5
...                   ...                   ...        ...      ...      ...
1594                 32.0                  44.0       0.58     10.5        5
1595                 39.0                  51.0       0.76     11.2        6
1596                 29.0                  40.0       0.75     11.0        6
1597                 32.0                  44.0       0.71     10.2        5
1598                 18.0                  42.0       0.66     11.0        6

[1599 rows x 9 columns]
```

Addressing Imbalance in Class

First Strategy: Oversampling minority class

In [ ]:
```
oversample = RandomOverSampler(sampling_strategy='minority')
X_over, y_over = oversample.fit_resample(X, y)
print("Before RandomOverSampler : ", Counter(y))
print("After RandomOverSampler : ", Counter(y_over))
```

```
Before RandomOverSampler :  Counter({5: 681, 6: 638, 7: 199, 4: 53, 8: 18, 3: 10})
After RandomOverSampler :  Counter({5: 681, 3: 681, 6: 638, 7: 199, 4: 53, 8: 18})
```

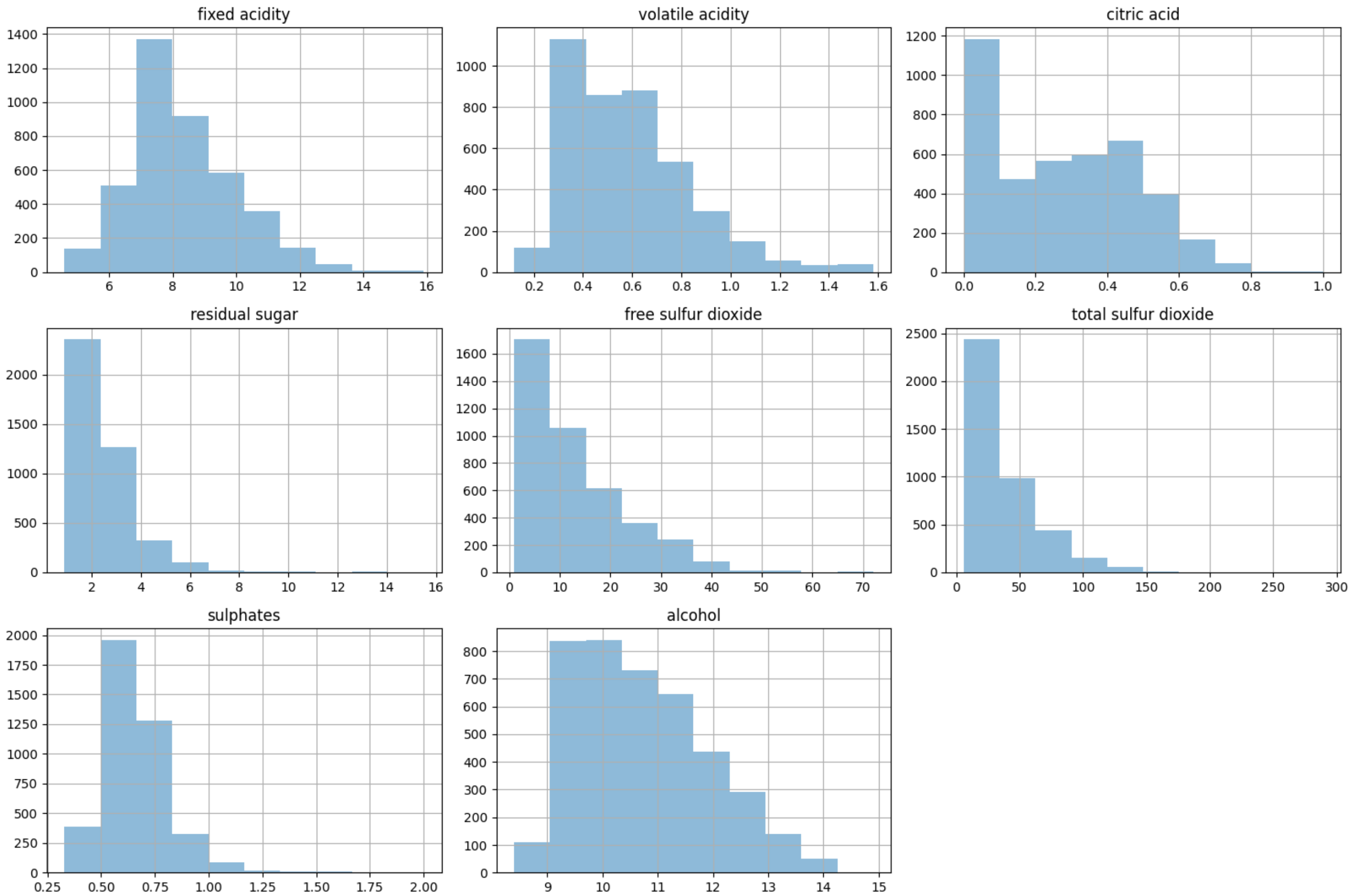
Second Strategy: Undersampling majority class

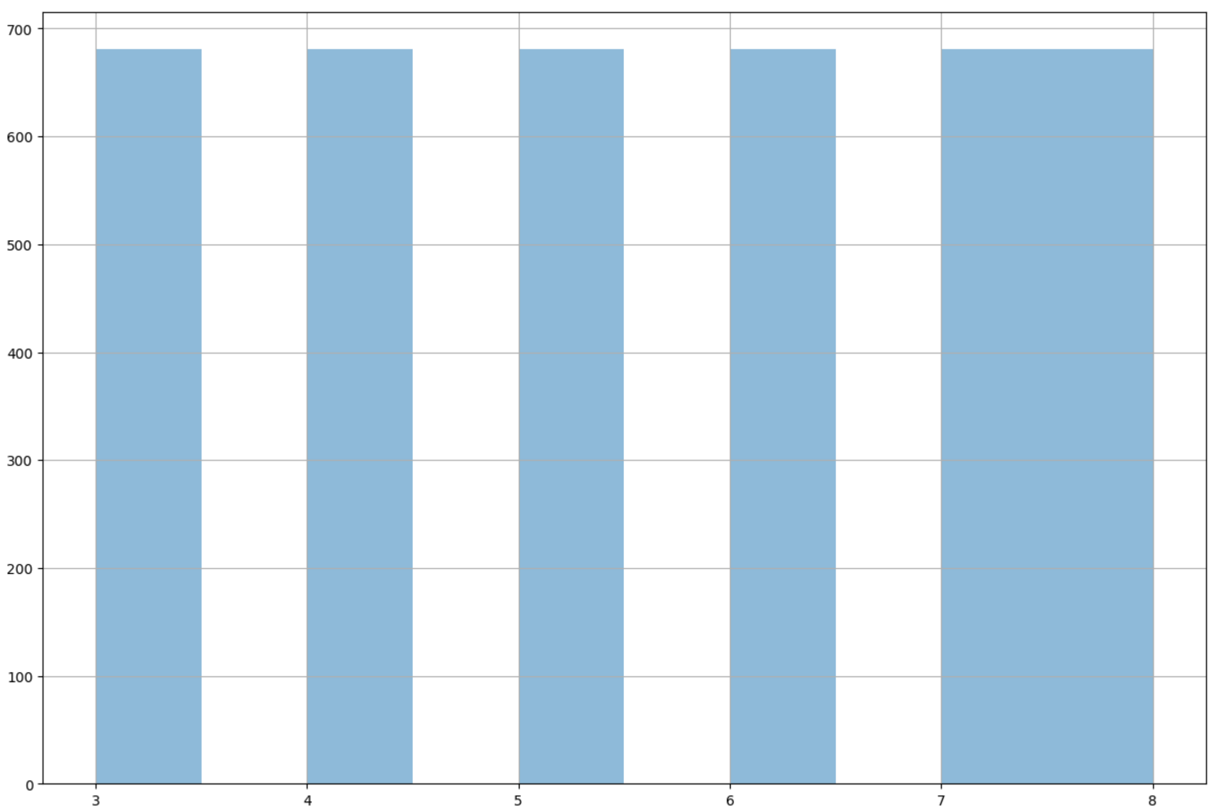
In [ ]:
```
undersample = RandomUnderSampler(sampling_strategy='majority')
X_under, y_under = undersample.fit_resample(X, y)
print("Before RandomUnderSampler : ", Counter(y))
print("After RandomUnderSampler : ", Counter(y_under))
```

```
Before RandomUnderSampler :  Counter({5: 681, 6: 638, 7: 199, 4: 53, 8: 18, 3: 10})
After RandomUnderSampler :  Counter({6: 638, 7: 199, 4: 53, 8: 18, 3: 10, 5: 10})
```

Third Strategy: SMOTE

In [ ]:
```
smoteOversample = SMOTE()
X_smote, y_smote = smoteOversample.fit_resample(X, y)

#Plotting histogram of each variable
X_smote.hist(alpha=0.5, figsize=(15, 10))

plt.tight_layout()
plt.show()

y_smote.hist(alpha=0.5, figsize=(15, 10))
plt.show()

from collections import Counter
print("Before SMOTE : ", Counter(y))
print("After SMOTE : ", Counter(y_smote))
```





```
Before SMOTE :  Counter({5: 681, 6: 638, 7: 199, 4: 53, 8: 18, 3: 10})
After SMOTE :  Counter({5: 681, 6: 681, 7: 681, 4: 681, 8: 681, 3: 681})
```

Fourth Strategy: Data Imputation

Filling in data from missing classes - 0, 1, 2, 9, & 10 with fraud data

In [ ]:

```
avgX = X.mean(axis=0)
dfImpute = pd.DataFrame(
                        [[avgX[0], avgX[1], avgX[2], avgX[3], avgX[4], avgX[5], avgX[6], avgX[7], 0],
                        [avgX[0], avgX[1], avgX[2], avgX[3], avgX[4], avgX[5], avgX[6], avgX[7], 1],
                        [avgX[0], avgX[1], avgX[2], avgX[3], avgX[4], avgX[5], avgX[6], avgX[7], 2],
```

```
                        [avgX[0], avgX[1], avgX[2], avgX[3], avgX[4], avgX[5], avgX[6], avgX[7], 9],
                        [avgX[0], avgX[1], avgX[2], avgX[3], avgX[4], avgX[5], avgX[6], avgX[7], 10]],
                        columns=['fixed acidity', 'volatile acidity', 'citric acid', 'residual sugar','free sulfur dioxide', 'total sulfur dioxide', 'sulphates', 'alcohol', '
                        )
dfImpute
```

Out[ ]:

	fixed acidity	volatile acidity	citric acid	residual sugar	free sulfur dioxide	total sulfur dioxide	sulphates	alcohol	quality
0	8.319637	0.527821	0.270976	2.538806	15.874922	46.467792	0.658149	10.422983	0
1	8.319637	0.527821	0.270976	2.538806	15.874922	46.467792	0.658149	10.422983	1
2	8.319637	0.527821	0.270976	2.538806	15.874922	46.467792	0.658149	10.422983	2
3	8.319637	0.527821	0.270976	2.538806	15.874922	46.467792	0.658149	10.422983	9
4	8.319637	0.527821	0.270976	2.538806	15.874922	46.467792	0.658149	10.422983	10

3. Comparing Machine Learning Models / Obtaining Baseline Accuracy

Modeling - Final data preparations

In [ ]:

```python
# 1. Regular Data
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = .2, random_state=10) #split the data
X_train.shape, y_train.shape, X_test.shape, y_test.shape
scaledData = StandardScaler()
X_train = scaledData.fit_transform(X_train)
X_test = scaledData.transform(X_test)

# 2. Oversampled Data
X_over_train, X_over_test, y_over_train, y_over_test = train_test_split(X_over, y_over, test_size = .2, random_state=10) #split the data
X_over_train.shape, y_over_train.shape, X_over_test.shape, y_over_test.shape
X_over_train = scaledData.fit_transform(X_over_train)
X_over_test = scaledData.transform(X_over_test)

# 3. Underrsampled Data
X_under_train, X_under_test, y_under_train, y_under_test = train_test_split(X_under, y_under, test_size = .2, random_state=10) #split the data
X_under_train.shape, y_under_train.shape, X_under_test.shape, y_under_test.shape
X_under_train = scaledData.fit_transform(X_under_train)
X_under_test = scaledData.transform(X_under_test)

#4. SMOTE Data
X_smote_train, X_smote_test, y_smote_train, y_smote_test = train_test_split(X_smote, y_smote, test_size = .2, random_state=10) #split the data
X_smote_train.shape, y_smote_train.shape, X_smote_test.shape, y_smote_test.shape
X_smote_train = scaledData.fit_transform(X_smote_train)
X_smote_test = scaledData.transform(X_smote_test)

# 5. Imputed Data
X_impute = wineData.loc[:, 'fixed acidity':'alcohol']
y_impute = wineData['quality']
X_add = dfImpute.loc[:, 'fixed acidity':'alcohol']
y_add = dfImpute['quality']
X_impute_train, X_impute_test, y_impute_train, y_impute_test = train_test_split(X_impute, y_impute, test_size = .2, random_state=10) #split the data
X_impute_train = pd.concat([X_impute_train, X_add])
y_impute_train = pd.concat([y_impute_train, y_add])
X_impute_test = pd.concat([X_impute_test, X_add])
y_impute_test = pd.concat([y_impute_test, y_add])
X_impute_train.shape, y_impute_train.shape, X_impute_test.shape, y_impute_test.shape
X_impute_train = scaledData.fit_transform(X_impute_train)
```

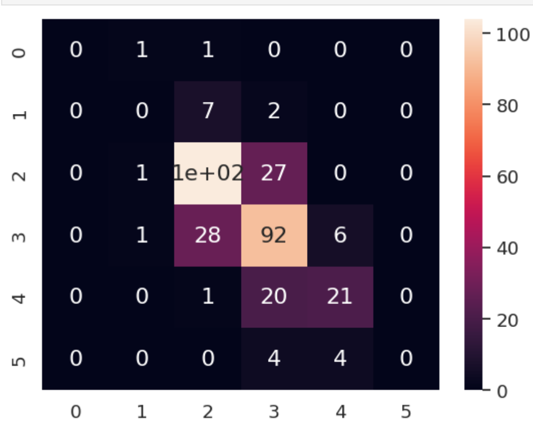
In [ ]:

```python
def clas_report(X_train, y_train, x_test, y_test, model, title):
    model.fit(X_train, y_train)
    y_pred = model.predict(x_test)
    cm = confusion_matrix(y_test, y_pred)
    df_cm = pd.DataFrame(cm)
    sns.set(font_scale=1.2) # for label size
    sns.heatmap(df_cm, annot=True, annot_kws={"size": 16}) # font size
    plt.show()
    clas = classification_report(y_test, y_pred)
    print(title, "\n",clas)
```

1. Random Forest Classifier

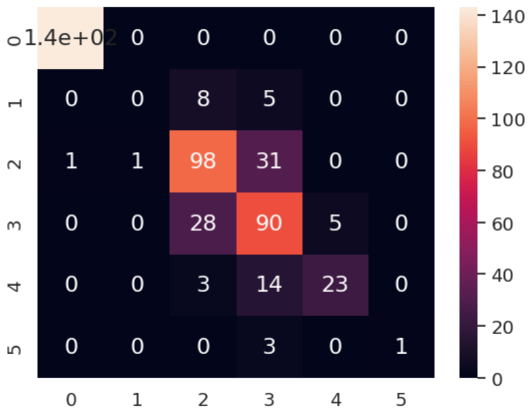
In [ ]:

```python
wineRF = RandomForestClassifier()
clas_report(X_train, y_train, X_test, y_test, wineRF, 'Regular Data')
clas_report(X_over_train, y_over_train, X_over_test, y_over_test, wineRF, 'Oversampled Data')
clas_report(X_under_train, y_under_train, X_under_test, y_under_test, wineRF, 'Undersampled Data')
clas_report(X_smote_train, y_smote_train, X_smote_test, y_smote_test, wineRF, 'SMOTE Data')
clas_report(X_impute_train, y_impute_train, X_impute_test, y_impute_test, wineRF, 'Imputed Data')
```



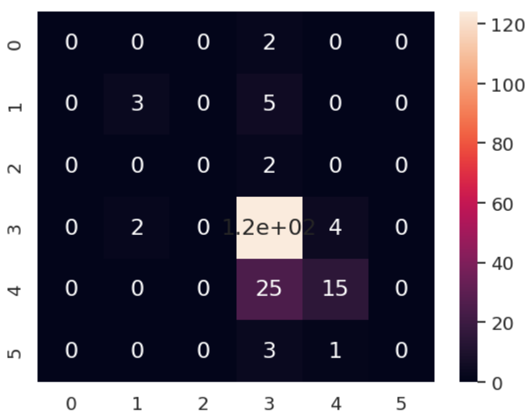
Regular Data

	precision	recall	f1-score	support
3	0.00	0.00	0.00	2
4	0.00	0.00	0.00	9
5	0.74	0.79	0.76	132
6	0.63	0.72	0.68	127
7	0.68	0.50	0.58	42
8	0.00	0.00	0.00	8
accuracy			0.68	320
macro avg	0.34	0.34	0.34	320
weighted avg	0.64	0.68	0.66	320



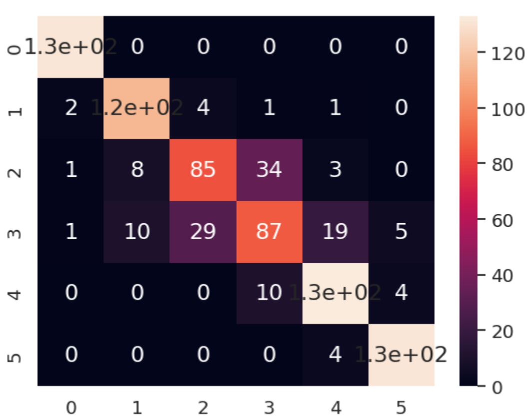
Oversampled Data

	precision	recall	f1-score	support
3	0.99	1.00	1.00	143
4	0.00	0.00	0.00	13
5	0.72	0.75	0.73	131
6	0.63	0.73	0.68	123
7	0.82	0.57	0.68	40
8	1.00	0.25	0.40	4
accuracy			0.78	454
macro avg	0.69	0.55	0.58	454
weighted avg	0.77	0.78	0.77	454

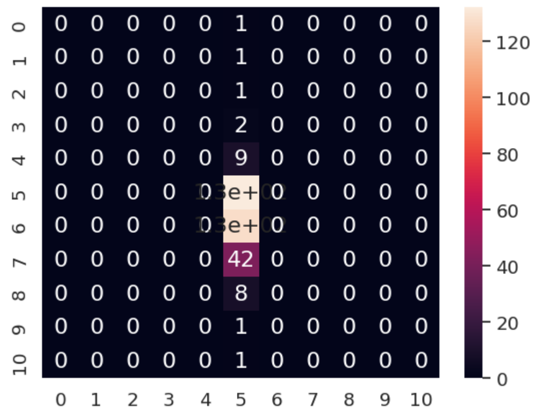


Undersampled Data

	precision	recall	f1-score	support
3	0.00	0.00	0.00	2
4	0.60	0.38	0.46	8
5	0.00	0.00	0.00	2
6	0.77	0.95	0.85	130
7	0.75	0.38	0.50	40
8	0.00	0.00	0.00	4
accuracy			0.76	186
macro avg	0.35	0.28	0.30	186
weighted avg	0.73	0.76	0.72	186



```
SMOTE Data
              precision    recall  f1-score   support

           3       0.97      1.00      0.98       131
           4       0.86      0.93      0.90       123
           5       0.72      0.65      0.68       131
           6       0.66      0.58      0.61       151
           7       0.83      0.90      0.87       147
           8       0.94      0.97      0.95       135

    accuracy                           0.83       818
   macro avg       0.83      0.84      0.83       818
weighted avg       0.83      0.83      0.83       818
```

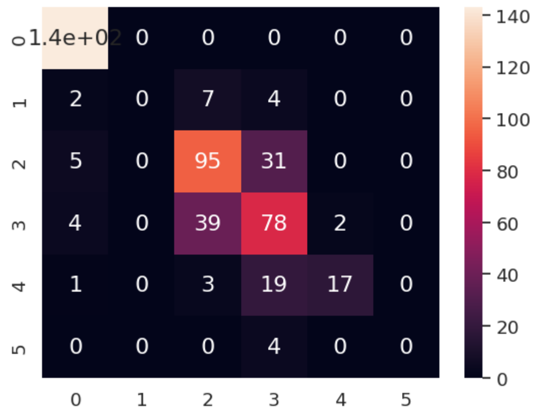



```
Imputed Data
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         1
           1       0.00      0.00      0.00         1
           2       0.00      0.00      0.00         1
           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00         9
           5       0.41      1.00      0.58       132
           6       0.00      0.00      0.00       127
           7       0.00      0.00      0.00        42
           8       0.00      0.00      0.00         8
           9       0.00      0.00      0.00         1
          10       0.00      0.00      0.00         1

    accuracy                           0.41       325
   macro avg       0.04      0.09      0.05       325
weighted avg       0.16      0.41      0.23       325
```

2. Support Vector Machine

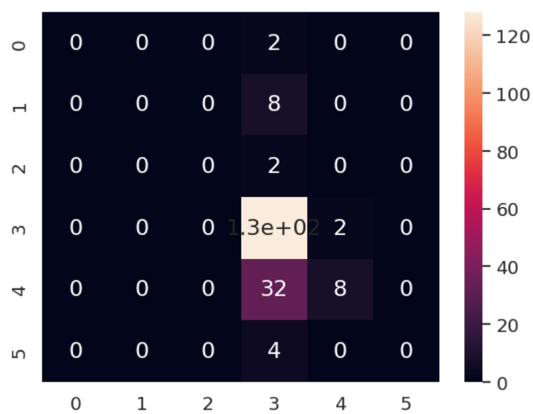
In [ ]:
```
wineSVM = SVC()
clas_report(X_train, y_train, X_test, y_test, wineSVM, 'Regular Data')
clas_report(X_over_train, y_over_train, X_over_test, y_over_test, wineSVM, 'Oversampled Data')
clas_report(X_under_train, y_under_train, X_under_test, y_under_test, wineSVM, 'Undersampled Data')
clas_report(X_smote_train, y_smote_train, X_smote_test, y_smote_test, wineSVM, 'SMOTE Data')
clas_report(X_impute_train, y_impute_train, X_impute_test, y_impute_test, wineSVM, 'Imputed Data')
```


```
Regular Data
              precision    recall  f1-score   support

           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00         9
           5       0.66      0.72      0.69       132
           6       0.54      0.67      0.60       127
           7       0.60      0.29      0.39        42
           8       0.00      0.00      0.00         8

    accuracy                           0.60       320
   macro avg       0.30      0.28      0.28       320
weighted avg       0.57      0.60      0.57       320
```



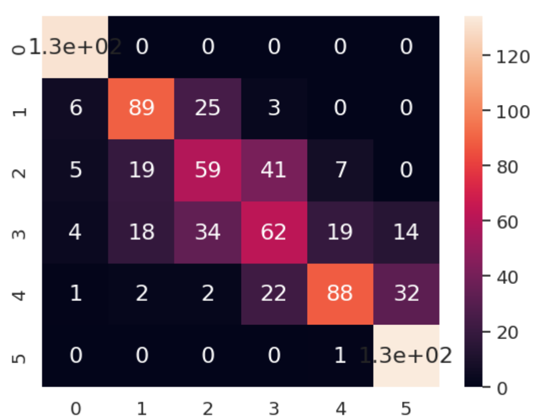
Oversampled Data

	precision	recall	f1-score	support
3	0.92	1.00	0.96	143
4	0.00	0.00	0.00	13
5	0.66	0.73	0.69	131
6	0.57	0.63	0.60	123
7	0.89	0.42	0.58	40
8	0.00	0.00	0.00	4
accuracy			0.73	454
macro avg	0.51	0.46	0.47	454
weighted avg	0.72	0.73	0.72	454



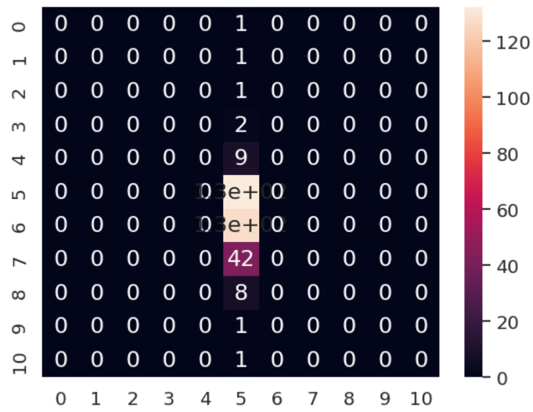
Undersampled Data

	precision	recall	f1-score	support
3	0.00	0.00	0.00	2
4	0.00	0.00	0.00	8
5	0.00	0.00	0.00	2
6	0.73	0.98	0.84	130
7	0.80	0.20	0.32	40
8	0.00	0.00	0.00	4
accuracy			0.73	186
macro avg	0.25	0.20	0.19	186
weighted avg	0.68	0.73	0.65	186



SMOTE Data

	precision	recall	f1-score	support
3	0.89	1.00	0.94	131
4	0.70	0.72	0.71	123
5	0.49	0.45	0.47	131
6	0.48	0.41	0.44	151
7	0.77	0.60	0.67	147
8	0.74	0.99	0.85	135
accuracy			0.69	818
macro avg	0.68	0.70	0.68	818
weighted avg	0.68	0.69	0.68	818



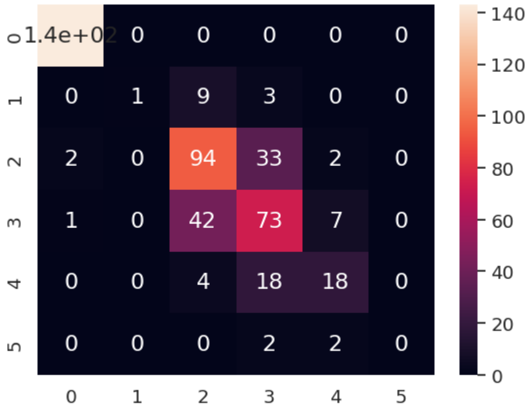
```
Imputed Data
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         1
           1       0.00      0.00      0.00         1
           2       0.00      0.00      0.00         1
           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00         9
           5       0.41      1.00      0.58       132
           6       0.00      0.00      0.00       127
           7       0.00      0.00      0.00        42
           8       0.00      0.00      0.00         8
           9       0.00      0.00      0.00         1
          10       0.00      0.00      0.00         1

    accuracy                           0.41       325
   macro avg       0.04      0.09      0.05       325
weighted avg       0.16      0.41      0.23       325
```

3. Artificial Neural Network

In [ ]:

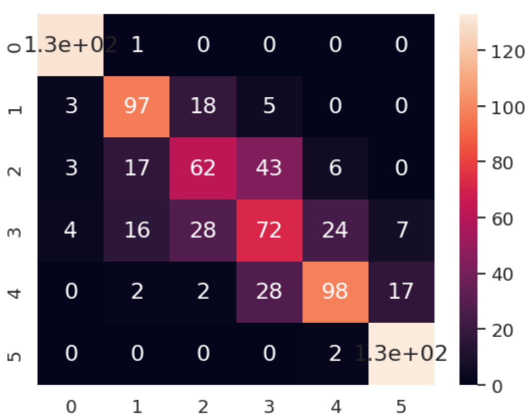
```python
wineMLP = MLPClassifier()
clas_report(X_train, y_train, X_test, y_test, wineMLP, 'Regular Data')
clas_report(X_over_train, y_over_train, X_over_test, y_over_test, wineMLP, 'Oversampled Data')
clas_report(X_under_train, y_under_train, X_under_test, y_under_test, wineMLP, 'Undersampled Data')
clas_report(X_smote_train, y_smote_train, X_smote_test, y_smote_test, wineMLP, 'SMOTE Data')
clas_report(X_impute_train, y_impute_train, X_impute_test, y_impute_test, wineMLP, 'Imputed Data')
```

```
Regular Data
              precision    recall  f1-score   support

           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00         9
           5       0.66      0.71      0.69       132
           6       0.58      0.62      0.60       127
           7       0.58      0.50      0.54        42
           8       0.00      0.00      0.00         8

    accuracy                           0.61       320
   macro avg       0.30      0.31      0.30       320
weighted avg       0.58      0.61      0.59       320
```

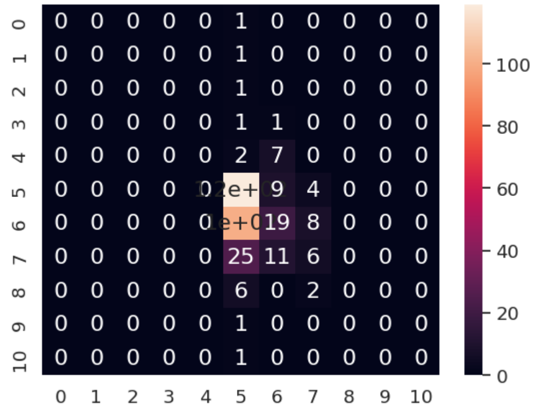



```
Oversampled Data
              precision    recall  f1-score   support

           3       0.98      1.00      0.99       143
           4       1.00      0.08      0.14        13
           5       0.63      0.72      0.67       131
           6       0.57      0.59      0.58       123
           7       0.62      0.45      0.52        40
           8       0.00      0.00      0.00         4

    accuracy                           0.72       454
   macro avg       0.63      0.47      0.48       454
weighted avg       0.73      0.72      0.71       454
```


```
Undersampled Data
              precision    recall  f1-score   support

           3       0.00      0.00      0.00         2
           4       0.50      0.12      0.20         8
           5       0.00      0.00      0.00         2
           6       0.78      0.95      0.86       130
           7       0.78      0.45      0.57        40
           8       0.00      0.00      0.00         4

    accuracy                           0.77       186
   macro avg       0.34      0.25      0.27       186
weighted avg       0.73      0.77      0.73       186
```




```
SMOTE Data
              precision    recall  f1-score   support

           3       0.93      0.99      0.96       131
           4       0.73      0.79      0.76       123
           5       0.56      0.47      0.51       131
           6       0.49      0.48      0.48       151
           7       0.75      0.67      0.71       147
           8       0.85      0.99      0.91       135

    accuracy                           0.72       818
   macro avg       0.72      0.73      0.72       818
weighted avg       0.71      0.72      0.72       818
```

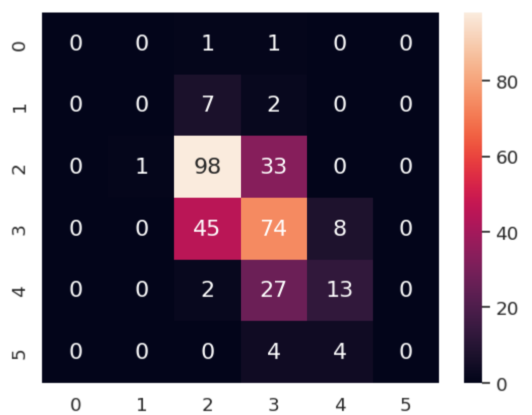



```
Imputed Data
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         1
           1       0.00      0.00      0.00         1
           2       0.00      0.00      0.00         1
           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00         9
           5       0.46      0.90      0.61       132
           6       0.40      0.15      0.22       127
           7       0.30      0.14      0.19        42
           8       0.00      0.00      0.00         8
           9       0.00      0.00      0.00         1
          10       0.00      0.00      0.00         1

    accuracy                           0.44       325
   macro avg       0.11      0.11      0.09       325
weighted avg       0.38      0.44      0.36       325
```

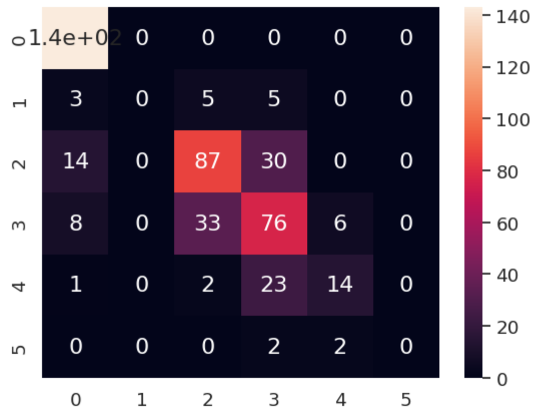
4. Logistic Regression

In [ ]:

```
wineLR = LogisticRegression()
clas_report(X_train, y_train, X_test, y_test, wineLR, 'Regular Data')
clas_report(X_over_train, y_over_train, X_over_test, y_over_test, wineLR, 'Oversampled Data')
clas_report(X_under_train, y_under_train, X_under_test, y_under_test, wineLR, 'Undersampled Data')
clas_report(X_smote_train, y_smote_train, X_smote_test, y_smote_test, wineLR, 'SMOTE Data')
clas_report(X_impute_train, y_impute_train, X_impute_test, y_impute_test, wineLR, 'Imputed Data')
```

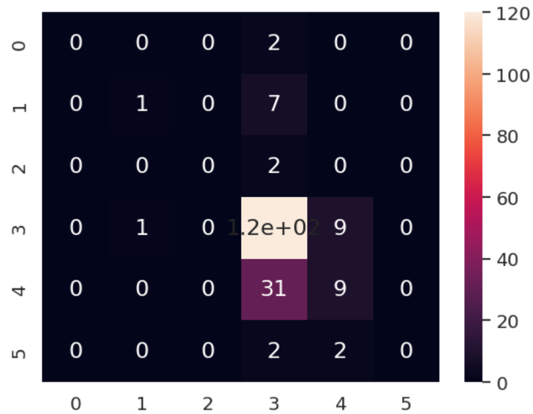



```
Regular Data
              precision    recall  f1-score   support

           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00         9
           5       0.64      0.74      0.69       132
           6       0.52      0.58      0.55       127
           7       0.52      0.31      0.39        42
           8       0.00      0.00      0.00         8

    accuracy                           0.58       320
   macro avg       0.28      0.27      0.27       320
weighted avg       0.54      0.58      0.55       320
```



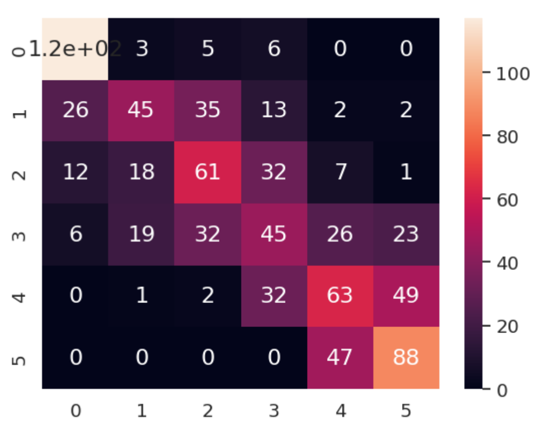
Oversampled Data

	precision	recall	f1-score	support
3	0.85	1.00	0.92	143
4	0.00	0.00	0.00	13
5	0.69	0.66	0.67	131
6	0.56	0.62	0.59	123
7	0.64	0.35	0.45	40
8	0.00	0.00	0.00	4
accuracy			0.70	454
macro avg	0.45	0.44	0.44	454
weighted avg	0.67	0.70	0.68	454



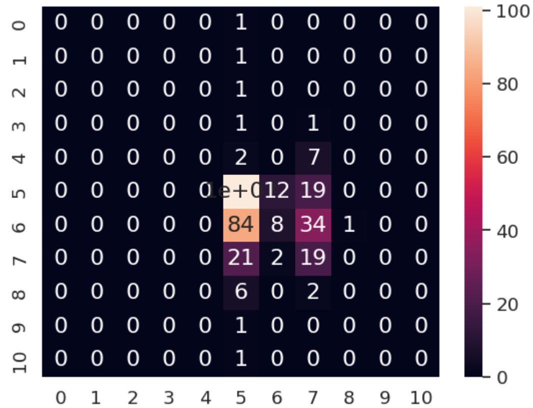
Undersampled Data

	precision	recall	f1-score	support
3	0.00	0.00	0.00	2
4	0.50	0.12	0.20	8
5	0.00	0.00	0.00	2
6	0.73	0.92	0.82	130
7	0.45	0.23	0.30	40
8	0.00	0.00	0.00	4
accuracy			0.70	186
macro avg	0.28	0.21	0.22	186
weighted avg	0.63	0.70	0.64	186



SMOTE Data

	precision	recall	f1-score	support
3	0.73	0.89	0.80	131
4	0.52	0.37	0.43	123
5	0.45	0.47	0.46	131
6	0.35	0.30	0.32	151
7	0.43	0.43	0.43	147
8	0.54	0.65	0.59	135
accuracy			0.51	818
macro avg	0.50	0.52	0.51	818
weighted avg	0.50	0.51	0.50	818



```
Imputed Data
              precision    recall  f1-score   support

           0       0.00      0.00      0.00         1
           1       0.00      0.00      0.00         1
           2       0.00      0.00      0.00         1
           3       0.00      0.00      0.00         2
           4       0.00      0.00      0.00         9
           5       0.46      0.77      0.57       132
           6       0.36      0.06      0.11       127
           7       0.23      0.45      0.31        42
           8       0.00      0.00      0.00         8
           9       0.00      0.00      0.00         1
          10       0.00      0.00      0.00         1

    accuracy                           0.39       325
   macro avg       0.10      0.12      0.09       325
weighted avg       0.36      0.39      0.31       325
```

4. Hyperparameter Tuning

1. Random Forest Classifier

In [ ]:
```python
def grid_search(X_train, y_train, model, param_grid, title):
    grid = GridSearchCV(estimator=model, param_grid=param_grid, cv=5)
    grid.fit(X_train, y_train)
    print(title, ": ", grid.best_params_)
    print("best score: ", grid.best_score_)
```

In [ ]:
```python
wineRFC = RandomForestClassifier(random_state=417)

param_grid_RFC = {
    'n_estimators': [100, 200, 500, 1000],
    'max_depth': [5,6,7,8],
}

grid_search(X_train, y_train, wineRFC, param_grid_RFC, 'Regular Data')
grid_search(X_over_train, y_over_train, wineRFC, param_grid_RFC, 'Oversampled Data')
grid_search(X_under_train, y_under_train, wineRFC, param_grid_RFC, 'Undersampled Data')
grid_search(X_smote_train, y_smote_train, wineRFC, param_grid_RFC, 'SMOTE Data')
grid_search(X_impute_train, y_impute_train, wineRFC, param_grid_RFC, 'Imputed Data')
```

```
Regular Data :  {'max_depth': 8, 'n_estimators': 100}
best score:  0.650545343137255
Oversampled Data :  {'max_depth': 8, 'n_estimators': 200}
best score:  0.7511049556504104
Undersampled Data :  {'max_depth': 7, 'n_estimators': 1000}
best score:  0.7264556502811537
SMOTE Data :  {'max_depth': 8, 'n_estimators': 200}
best score:  0.784578819937152
Imputed Data :  {'max_depth': 8, 'n_estimators': 100}
best score:  0.6487810068093385
```

2. Support Vector Machine

In [ ]:
```python
wineSVM = SVC()
param_grid_svm = {
    'kernel': ['rbf','sigmoid','poly'],
    'C': [1, 10, 100, 1000]
}

grid_search(X_train, y_train, wineSVM, param_grid_svm, 'Regular Data')
grid_search(X_over_train, y_over_train, wineSVM, param_grid_svm, 'Oversampled Data')
grid_search(X_under_train, y_under_train, wineSVM, param_grid_svm, 'Undersampled Data')
grid_search(X_smote_train, y_smote_train, wineSVM, param_grid_svm, 'SMOTE Data')
grid_search(X_impute_train, y_impute_train, wineSVM, param_grid_svm, 'Imputed Data')
```

```
Regular Data :  {'C': 1, 'kernel': 'rbf'}
best score:  0.6067493872549019
Oversampled Data :  {'C': 10, 'kernel': 'rbf'}
best score:  0.7252278025005298
Undersampled Data :  {'C': 1, 'kernel': 'rbf'}
best score:  0.7156992563032831
SMOTE Data :  {'C': 1000, 'kernel': 'rbf'}
best score:  0.8252764235637917
Imputed Data :  {'C': 1, 'kernel': 'rbf'}
best score:  0.6043865515564203
```

3. Artificial Neural Network

In [ ]:
```python
wineANN = MLPClassifier(activation='logistic')
param_grid_ann = {
    'learning_rate_init': [0.001, 0.01, 0.1],
    'max_iter': [100, 300, 500],
    'hidden_layer_sizes': [(10,), (100,), (300,)]
}
```

```
grid_search(X_train, y_train, wineANN, param_grid_ann, 'Regular Data')
grid_search(X_over_train, y_over_train, wineANN, param_grid_ann, 'Oversampled Data')
grid_search(X_under_train, y_under_train, wineANN, param_grid_ann, 'Undersampled Data')
grid_search(X_smote_train, y_smote_train, wineANN, param_grid_ann, 'SMOTE Data')
grid_search(X_impute_train, y_impute_train, wineANN, param_grid_ann, 'Imputed Data')
```

```
Regular Data :  {'hidden_layer_sizes': (100,), 'learning_rate_init': 0.01, 'max_iter': 100}
best score:  0.6130024509803922
Oversampled Data :  {'hidden_layer_sizes': (300,), 'learning_rate_init': 0.01, 'max_iter': 500}
best score:  0.7411845730027549
Undersampled Data :  {'hidden_layer_sizes': (100,), 'learning_rate_init': 0.1, 'max_iter': 100}
best score:  0.7291583529838563
SMOTE Data :  {'hidden_layer_sizes': (300,), 'learning_rate_init': 0.01, 'max_iter': 500}
best score:  0.8405772463951371
Imputed Data :  {'hidden_layer_sizes': (300,), 'learning_rate_init': 0.1, 'max_iter': 300}
best score:  0.6082715223735409
```

4. Logistic Regression

In [ ]:
```
wineLR = LogisticRegression()
param_grid_lr = {
    'penalty' : ['l1', 'l2'],
    'solver':['lbfgs', 'liblinear','saga'],
    'max_iter': [100, 300, 500]
}

grid_search(X_train, y_train, wineLR, param_grid_lr, 'Regular Data')
grid_search(X_over_train, y_over_train, wineLR, param_grid_lr, 'Oversampled Data')
grid_search(X_under_train, y_under_train, wineLR, param_grid_lr, 'Undersampled Data')
grid_search(X_smote_train, y_smote_train, wineLR, param_grid_lr, 'SMOTE Data')
grid_search(X_impute_train, y_impute_train, wineLR, param_grid_lr, 'Imputed Data')
```

```
Regular Data :  {'max_iter': 100, 'penalty': 'l2', 'solver': 'lbfgs'}
best score:  0.6004993872549019
Oversampled Data :  {'max_iter': 100, 'penalty': 'l1', 'solver': 'saga'}
best score:  0.6690521599612509
Undersampled Data :  {'max_iter': 100, 'penalty': 'l2', 'solver': 'lbfgs'}
best score:  0.7088971521857428
SMOTE Data :  {'max_iter': 100, 'penalty': 'l2', 'solver': 'lbfgs'}
best score:  0.5437655422397685
Imputed Data :  {'max_iter': 100, 'penalty': 'l2', 'solver': 'lbfgs'}
best score:  0.5981608706225681
```

5. Testing Final Models

In [ ]:
```
def final_report(X_train, y_train, X_test, y_test, model, title):
    model.fit(X_train, y_train)
    y_pred = model.predict(X_test)
    print(title, ": ", model.score(X_test, y_test))
    # clas = classification_report(y_pred, y_test)
    # print(clas)
```

1. Random Forest Classifier

In [ ]:
```
wineRF_regular_final = RandomForestClassifier(n_estimators=100, max_depth=8, random_state=417)
wineRF_over_final = RandomForestClassifier(n_estimators=200, max_depth=8, random_state=417)
wineRF_under_final = RandomForestClassifier(n_estimators=1000, max_depth=7, random_state=417)
wineRF_smote_final = RandomForestClassifier(n_estimators=200, max_depth=8, random_state=417)
wineRF_impute_final = RandomForestClassifier(n_estimators=100, max_depth=8, random_state=417)

final_report(X_train, y_train, X_test, y_test, wineRF_regular_final, 'Regular Data')
final_report(X_over_train, y_over_train, X_over_test, y_over_test, wineRF_over_final, 'Oversampled Data')
final_report(X_under_train, y_under_train, X_under_test, y_under_test, wineRF_under_final, 'Undersampled Data')
final_report(X_smote_train, y_smote_train, X_smote_test, y_smote_test, wineRF_smote_final, 'SMOTE Data')
final_report(X_impute_train, y_impute_train, X_impute_test, y_impute_test, wineRF_impute_final, 'Imputed Data')
```

```
Regular Data :  0.6375
Oversampled Data :  0.748898678414097
Undersampled Data :  0.7419354838709677
SMOTE Data :  0.7481662591687042
Imputed Data :  0.40923076923076923
```

2. Support Vector Machine

In [ ]:
```
wineSVM_regular_final = SVC(kernel = 'rbf', C = 1)
wineSVM_over_final = SVC(kernel = 'rbf', C = 10)
wineSVM_under_final = SVC(kernel = 'rbf', C = 1)
wineSVM_smote_final = SVC(kernel = 'rbf', C = 1000)
wineSVM_impute_final = SVC(kernel = 'rbf', C = 1)

final_report(X_train, y_train, X_test, y_test, wineSVM_regular_final, 'Regular Data')
final_report(X_over_train, y_over_train, X_over_test, y_over_test, wineSVM_over_final, 'Oversampled Data')
final_report(X_under_train, y_under_train, X_under_test, y_under_test, wineSVM_under_final, 'Undersampled Data')
final_report(X_smote_train, y_smote_train, X_smote_test, y_smote_test, wineSVM_smote_final, 'SMOTE Data')
final_report(X_impute_train, y_impute_train, X_impute_test, y_impute_test, wineSVM_impute_final, 'Imputed Data')
```

```
Regular Data :  0.6
Oversampled Data :  0.7268722466960352
Undersampled Data :  0.7311827956989247
SMOTE Data :  0.8092909535452323
Imputed Data :  0.40615384615384614
```

3. Artificial Neural Network

In [ ]:
```
wineANN_regular_final = MLPClassifier(learning_rate_init=0.01, max_iter=100, hidden_layer_sizes=(100,))
wineANN_over_final = MLPClassifier(learning_rate_init=0.01, max_iter=500, hidden_layer_sizes=(300,))
wineANN_under_final = MLPClassifier(learning_rate_init=0.1, max_iter=100, hidden_layer_sizes=(100,))
wineANN_smote_final = MLPClassifier(learning_rate_init=0.01, max_iter=500, hidden_layer_sizes=(300,))
wineANN_impute_final = MLPClassifier(learning_rate_init=0.1, max_iter=300, hidden_layer_sizes=(300,))

final_report(X_train, y_train, X_test, y_test, wineANN_regular_final, 'Regular Data')
final_report(X_over_train, y_over_train, X_over_test, y_over_test, wineANN_over_final, 'Oversampled Data')
final_report(X_under_train, y_under_train, X_under_test, y_under_test, wineANN_under_final, 'Undersampled Data')
final_report(X_smote_train, y_smote_train, X_smote_test, y_smote_test, wineANN_smote_final, 'SMOTE Data')
final_report(X_impute_train, y_impute_train, X_impute_test, y_impute_test, wineANN_impute_final, 'Imputed Data')
```

```
Regular Data :  0.578125
Oversampled Data :  0.7290748898678414
Undersampled Data :  0.7150537634408602
SMOTE Data :  0.8398533007334963
Imputed Data :  0.12923076923076923
```

4. Logistic Regression

In [ ]:

```
wineLR_regular_final = LogisticRegression(penalty='l2', solver= 'lbfgs', max_iter=100)
wineLR_over_final = LogisticRegression(penalty='l1', solver= 'saga', max_iter=100)
wineLR_under_final = LogisticRegression(penalty='l2', solver= 'lbfgs', max_iter=100)
wineLR_smote_final = LogisticRegression(penalty='l2', solver= 'lbfgs', max_iter=100)
wineLR_impute_final = LogisticRegression(penalty='l2', solver= 'lbfgs', max_iter=100)

final_report(X_train, y_train, X_test, y_test, wineLR_regular_final, 'Regular Data')
final_report(X_over_train, y_over_train, X_over_test, y_over_test, wineLR_over_final, 'Oversampled Data')
final_report(X_under_train, y_under_train, X_under_test, y_under_test, wineLR_under_final, 'Undersampled Data')
final_report(X_smote_train, y_smote_train, X_smote_test, y_smote_test, wineLR_smote_final, 'SMOTE Data')
final_report(X_impute_train, y_impute_train, X_impute_test, y_impute_test, wineLR_impute_final, 'Imputed Data')
```

```
Regular Data :  0.578125
Oversampled Data :  0.7048458149779736
Undersampled Data :  0.6989247311827957
SMOTE Data :  0.5122249388753056
Imputed Data :  0.39384615384615385
```