In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
from mpl_toolkits.mplot3d import Axes3D
%matplotlib inline
```

The dataset

the data set used is winequality-red found in [link (https://www.kaggle.com/uciml/red-wine-quality-cortez-et-al-2009)](https://www.kaggle.com/uciml/red-wine-quality-cortez-et-al-2009) It is a dataset where they determine the quality of a wine based on different features that it has

Features of the dataset

name	type	measure	description
fixed acidity	float	mg/L	The predominant fixed acids found in wines are tartaric, malic, citric, and succinic
volatile acidity	float	g/L	a measure of the low molecular weight (or steam distillable) fatty acids in wine and is generally perceived as the odour of vinegar
citric acidity	float	g/L	the acidity coming from citric acid
residual sugar	float	g/L	natural grape sugars leftover in a wine after the alcoholic fermentation finishes
chlorides	float	g/L	salt content
free sulfur dioxide	float	mg/l H2SO4	a measure of the amount of SO2 that is not bound to other molecules, and is used to calculate molecular SO2
total sulfur dioxide	float	mg/l H2SO4	a measure of the amount of SO2
density	float	Kg/L	the mass/volume
pH	float	pH	the degree of acidity in ph scale
sulfates	float	mg/L	naturally occurring compounds found in all wines; they act as a preservative by inhibiting microbial growth
alcohol	float	g/L	amount of alcohol per liter
quality	Natural	numeric	the measurement of quality

information was obtain from: Waterhouse Lab. (n.d.). Retrieved June 24, 2020, from [https://waterhouse.ucdavis.edu/ (https://waterhouse.ucdavis.edu/)](https://waterhouse.ucdavis.edu/) [https://archive.ics.uci.edu/ml/datasets/wine+quality (https://archive.ics.uci.edu/ml/datasets/wine+quality)](https://archive.ics.uci.edu/ml/datasets/wine+quality)

In [2]:
```
df=pd.read_csv('datasets_4458_8204_winequality-red.csv')
df.head()
```

Out[2]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcoh
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9

Clean indexes that contain NaN values

In [3]:
```
df=df.dropna()
df.head()
```

Out[3]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4

Basic Statistics

In [4]:
```
df.describe()
```

Out[4]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide
count	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000	1599.000000
mean	8.319637	0.527821	0.270976	2.538806	0.087467	15.874922	46.467792
std	1.741096	0.179060	0.194801	1.409928	0.047065	10.460157	32.895324
min	4.600000	0.120000	0.000000	0.900000	0.012000	1.000000	6.000000
25%	7.100000	0.390000	0.090000	1.900000	0.070000	7.000000	22.000000
50%	7.900000	0.520000	0.260000	2.200000	0.079000	14.000000	38.000000
75%	9.200000	0.640000	0.420000	2.600000	0.090000	21.000000	62.000000
max	15.900000	1.580000	1.000000	15.500000	0.611000	72.000000	289.000000

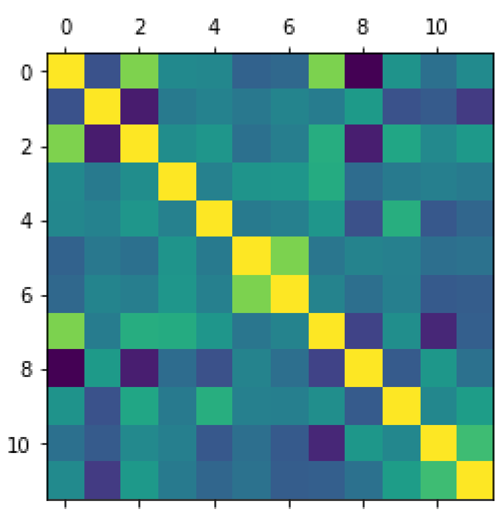
Identify Correlation between the data

In [5]:
```
df.corr()
```

Out[5]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	
fixed acidity	1.000000	-0.256131	0.671703	0.114777	0.093705	-0.153794	-0.113181	0.668047	-(
volatile acidity	-0.256131	1.000000	-0.552496	0.001918	0.061298	-0.010504	0.076470	0.022026	(
citric acid	0.671703	-0.552496	1.000000	0.143577	0.203823	-0.060978	0.035533	0.364947	-(
residual sugar	0.114777	0.001918	0.143577	1.000000	0.055610	0.187049	0.203028	0.355283	-(
chlorides	0.093705	0.061298	0.203823	0.055610	1.000000	0.005562	0.047400	0.200632	-(
free sulfur dioxide	-0.153794	-0.010504	-0.060978	0.187049	0.005562	1.000000	0.667666	-0.021946	(
total sulfur dioxide	-0.113181	0.076470	0.035533	0.203028	0.047400	0.667666	1.000000	0.071269	-(
density	0.668047	0.022026	0.364947	0.355283	0.200632	-0.021946	0.071269	1.000000	-(
pH	-0.682978	0.234937	-0.541904	-0.085652	-0.265026	0.070377	-0.066495	-0.341699	1
sulphates	0.183006	-0.260987	0.312770	0.005527	0.371260	0.051658	0.042947	0.148506	-(
alcohol	-0.061668	-0.202288	0.109903	0.042075	-0.221141	-0.069408	-0.205654	-0.496180	(
quality	0.124052	-0.390558	0.226373	0.013732	-0.128907	-0.050656	-0.185100	-0.174919	-(

In [6]:
```
plt.matshow(df.corr())
plt.show()
```



We want to use the features (fixed acidity, volatile acidity, citric acid, residual sugar, chlorides, free sulfur dioxide, total sulfur dioxide, density, pH, sulphates, alcohol) to determine the quality of the wine

we can see there ain´t many features with a strong correlation with quality so we are going to extract the correlations with that feature

In [7]:
```
corrQuality=df.corr().loc['quality']
corrQuality=abs(corrQuality)
corrQuality=corrQuality.sort_values(ascending=False)
corrQuality
```

Out[7]:
```
quality                 1.000000
alcohol                 0.476166
volatile acidity        0.390558
sulphates               0.251397
citric acid             0.226373
total sulfur dioxide    0.185100
density                 0.174919
chlorides               0.128907
fixed acidity           0.124052
pH                      0.057731
free sulfur dioxide     0.050656
residual sugar          0.013732
Name: quality, dtype: float64
```

we can see that the features that have the strongest correlation with quality are: alcohol, volatile acidity, and sulphates

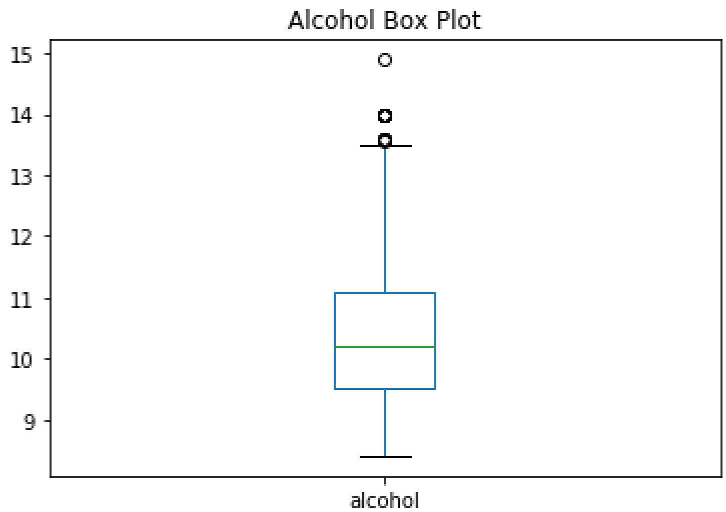
Alcohol Feature

In [8]:
```
df['alcohol'].describe()
```

Out[8]:
```
count    1599.000000
mean       10.422983
std         1.065668
min         8.400000
25%         9.500000
50%        10.200000
75%        11.100000
max        14.900000
Name: alcohol, dtype: float64
```

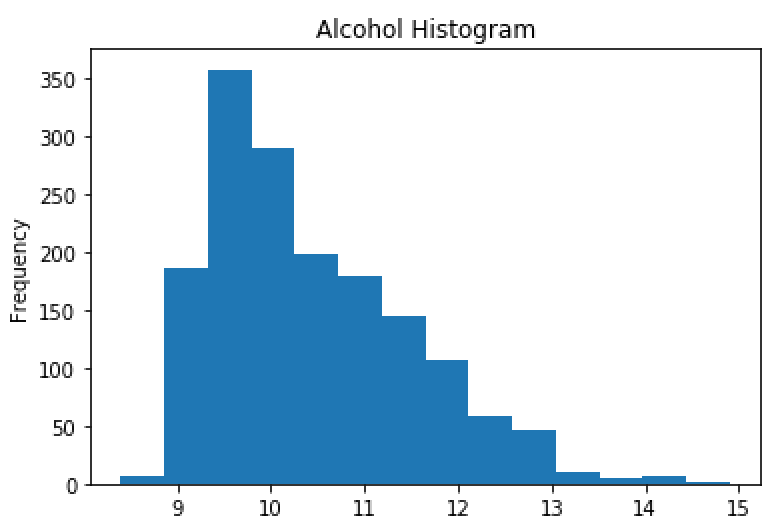
In [9]:
```
df['alcohol'].plot(kind='box',title='Alcohol Box Plot')
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x174c08a8a88>



In [10]:
```
df['alcohol'].plot(kind='hist',title='Alcohol Histogram',bins=14)
```

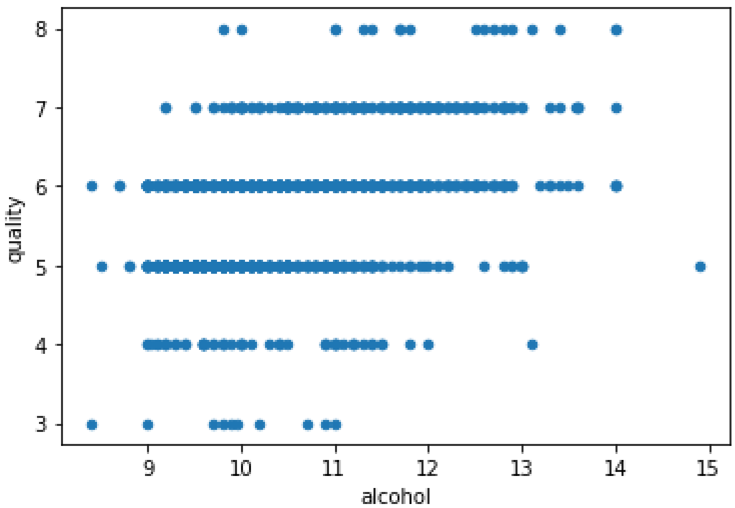
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x174c0929648>



We can se that the alcohol values are positively skewed and with the mean ~10g/L

In [11]:
```
df.plot('alcohol','quality',kind='scatter')
```

Out[11]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x174c08581c8>
```



neverless we still see too much noise in this graph, but we can see that as alcohol increases the quality of the wine also increases

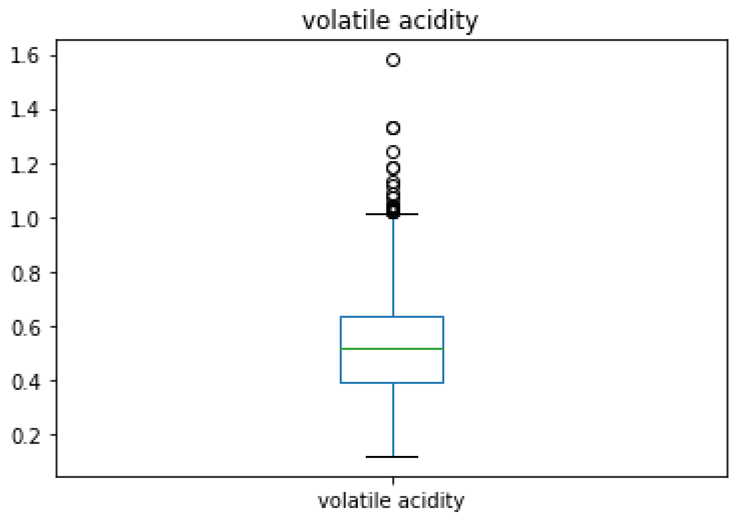
volatile acidity

In [12]:
```
df['volatile acidity'].describe()
```

Out[12]:
```
count    1599.000000
mean        0.527821
std         0.179060
min         0.120000
25%         0.390000
50%         0.520000
75%         0.640000
max         1.580000
Name: volatile acidity, dtype: float64
```

In [13]:
```
df['volatile acidity'].plot(kind='box',title='volatile acidity')
```

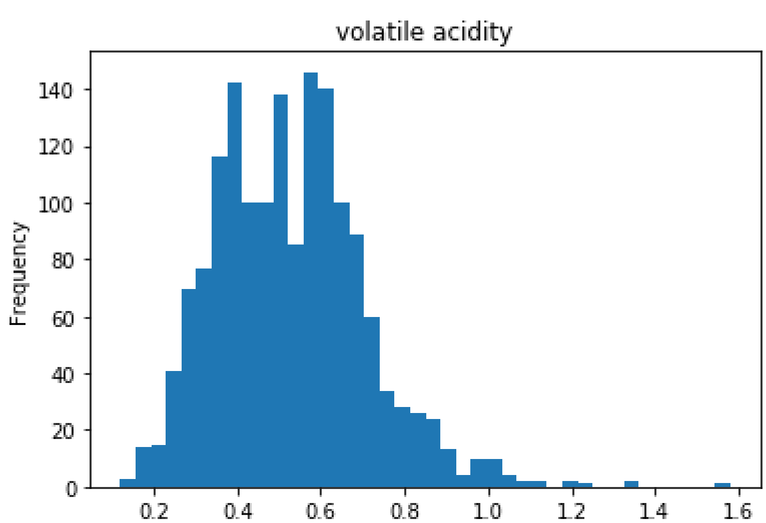
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x174c0a3c488>



Here we can se there are more outliers than in the case of alcohol over then 90%

In [14]:
```
df['volatile acidity'].plot(kind='hist',title='volatile acidity',bins=40)
```

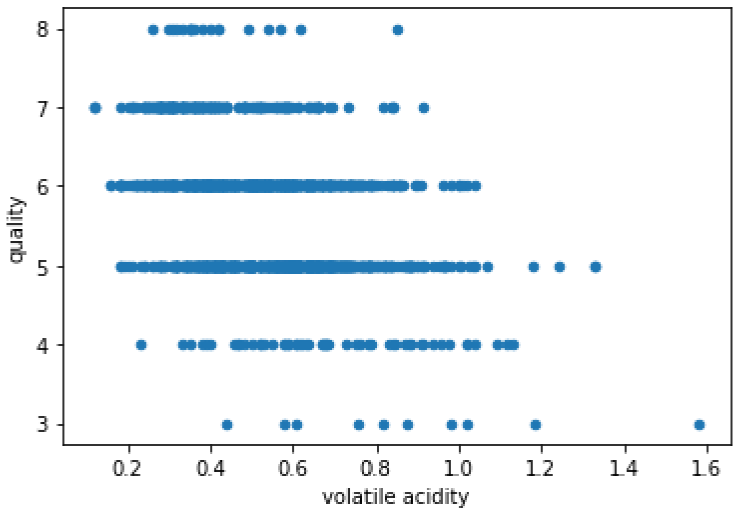
Out[14]: <matplotlib.axes._subplots.AxesSubplot at 0x174c0abb088>



In this case we can see that there is also a positive distribution in this case

In [15]:
```
df.plot('volatile acidity','quality',kind='scatter')
```

Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x174c0b9c188>



In this case we still see too much noise in the graph, but the relation is inverse (as the acid volatility increases the quality decreases)

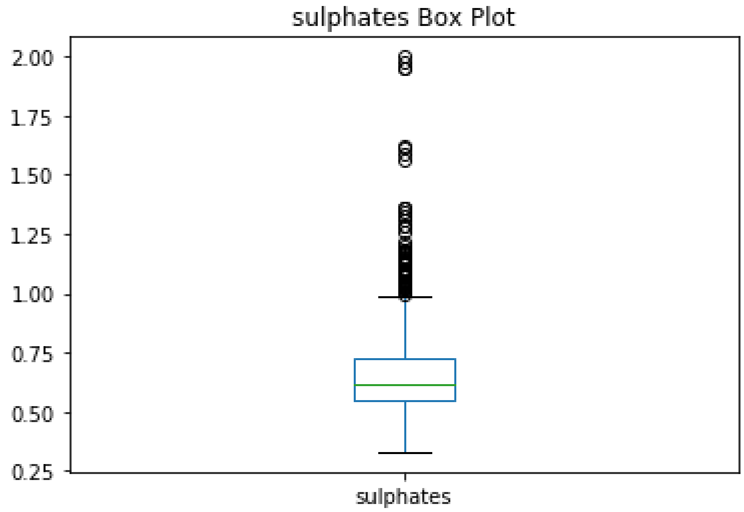
Sulphates

In [16]:
```
df['sulphates'].describe()
```

Out[16]:
```
count    1599.000000
mean        0.658149
std         0.169507
min         0.330000
25%         0.550000
50%         0.620000
75%         0.730000
max         2.000000
Name: sulphates, dtype: float64
```

In [17]:
```
df['sulphates'].plot(kind='box',title='sulphates Box Plot')
```

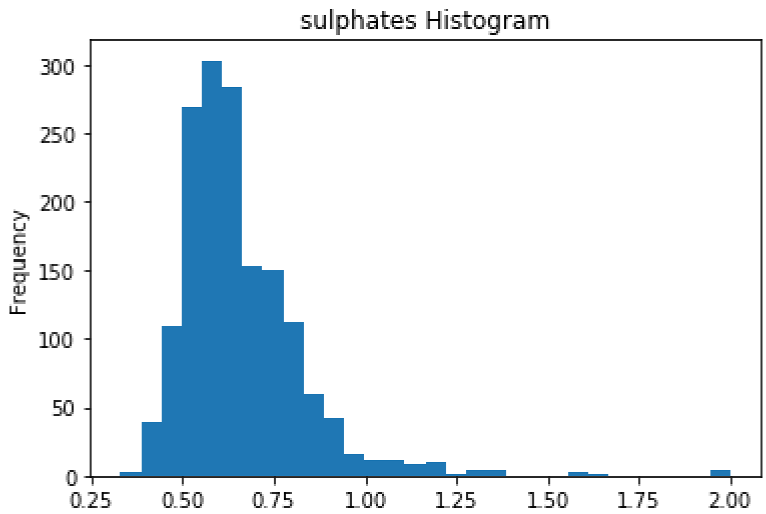
Out[17]: <matplotlib.axes._subplots.AxesSubplot at 0x174c0bf2088>



In this case the amount of outliers is outstanding in comparison to the other 2 features

In [18]:
```
df['sulphates'].plot(kind='hist',title='sulphates Histogram',bins=30)
```

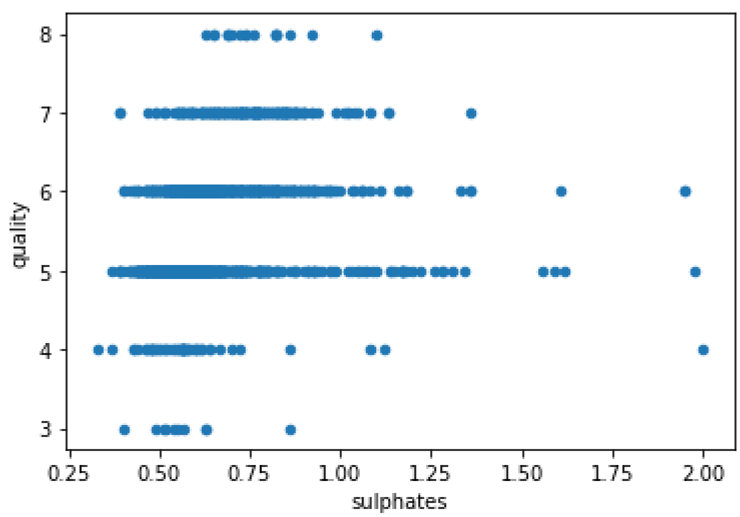
Out[18]: <matplotlib.axes._subplots.AxesSubplot at 0x174c0c72488>



We can se that the alcohol values are positively skewed

In [19]:
```
df.plot('sulphates','quality',kind='scatter')
```

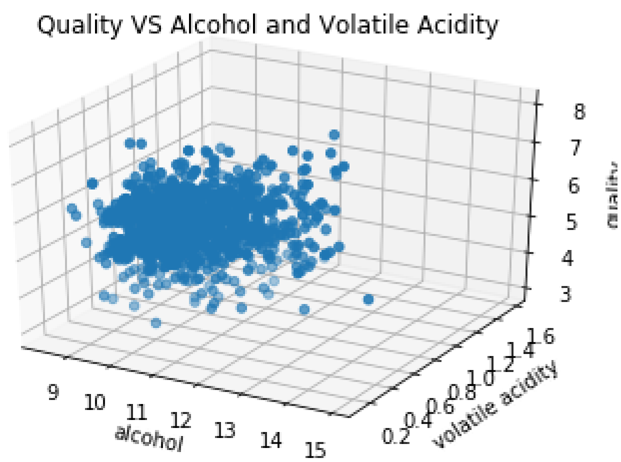
Out[19]: <matplotlib.axes._subplots.AxesSubplot at 0x174c0cc7888>



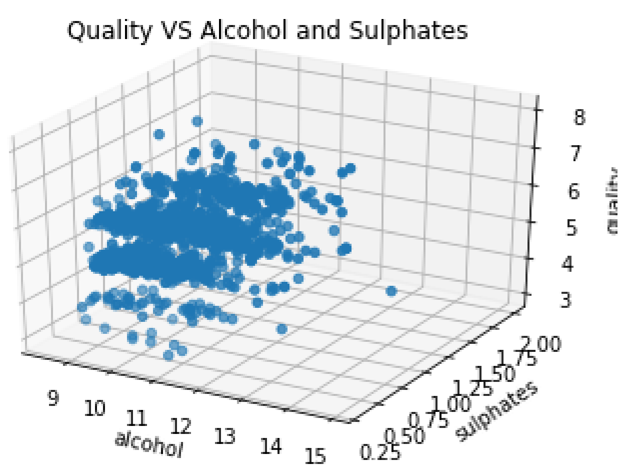
In the case of this plot we can see a positive relation, more steep than the one of alcohol, but there is still too much noise in the graph

See the data in an R^n space

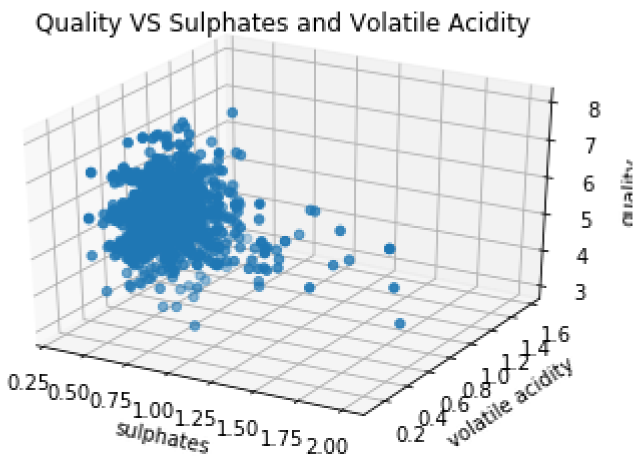
In [20]:
```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df['alcohol'], df['volatile acidity'],df['quality'])
ax.set_xlabel('alcohol')
ax.set_ylabel('volatile acidity')
ax.set_zlabel('quality')
plt.title('Quality VS Alcohol and Volatile Acidity')
plt.show()
```



In [21]:
```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df['alcohol'], df['sulphates'],df['quality'])
ax.set_xlabel('alcohol')
ax.set_ylabel('sulphates')
ax.set_zlabel('quality')
plt.title('Quality VS Alcohol and Sulphates')
plt.show()
```



In [22]:
```
fig = plt.figure()
ax = fig.add_subplot(111, projection='3d')
ax.scatter(df['sulphates'], df['volatile acidity'],df['quality'])
ax.set_xlabel('sulphates')
ax.set_ylabel('volatile acidity')
ax.set_zlabel('quality')
plt.title('Quality VS Sulphates and Volatile Acidity')
plt.show()
```



We can see that we can represent a better relation with the relations (Alcohol and Volatile Acidity) and (Volatile Acidity and Sulphates)

Plotting and Testing Linear Regressions

In [23]:
```
X_train, X_test, y_train, y_test=train_test_split(df[df.columns[:-1]],df['quality
```

Alcohol and Volatile Acidity

In [24]:
```
varsAAVA=['alcohol','volatile acidity']
AAVA=LinearRegression().fit(X_train[varsAAVA],y_train)
for c,v in zip(AAVA.coef_,varsAAVA):
    print(v,': ',c)
```

```
alcohol :  0.3065644583920829
volatile acidity :  -1.317865275278933
```

In [25]:
```
print("The accuracy of this model is of: ",AAVA.score(X_test[varsAAVA].values,y_t
```

```
The accuracy of this model is of:  0.35906504691582486
```

Volatile Acidity and Sulphates

In [26]:
```
varsVAAS=['volatile acidity','sulphates']
VAAS=LinearRegression().fit(X_train[varsVAAS],y_train)
for c,v in zip(VAAS.coef_,varsVAAS):
    print(v,': ',c)
```

```
volatile acidity :  -1.5560842476369015
sulphates :  0.6323569414454443
```

In [27]:
```
print("The accuracy of this model is of: ",VAAS.score(X_test[varsVAAS].values,y_t
```

```
The accuracy of this model is of:  0.21876566905541972
```

All features

In [28]:
```
model=LinearRegression().fit(X_train,y_train)
for c,v in zip(model.coef_,X_train.columns):
    print(v,': ',c)
```

```
fixed acidity :  0.02724322390346758
volatile acidity :  -1.034351267329956
citric acid :  -0.17403309233900816
residual sugar :  0.015139098162048984
chlorides :  -1.8106278201843584
free sulfur dioxide :  0.004229938330500679
total sulfur dioxide :  -0.0032958690318737756
density :  -17.12977255818796
pH :  -0.3938332636056848
sulphates :  0.8338107966800432
alcohol :  0.27143675343717244
```

In [29]:
```
print("The accuracy of this model is of: ",model.score(X_test.values,y_test))
```

```
The accuracy of this model is of:  0.4183385391256883
```

Plotting and Testing Linear Regressions Logarithmic

In [30]:
```
varsAAVA=['alcohol','volatile acidity']
AAVA=LogisticRegression().fit(X_train[varsAAVA],y_train)
for c,v in zip(AAVA.coef_,varsAAVA):
    print(v,': ',c)
```

```
alcohol :  [-0.31405044  1.67851081]
volatile acidity :  [-0.12221847  3.11010324]

C:\Users\nicpo\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:94
0: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

In [31]:
```
print("The accuracy of this model is of: ",AAVA.score(X_test[varsAAVA].values,y_t
```

```
The accuracy of this model is of:  0.565625
```

Volatile Acidity and Sulphates

In [32]:
```
varsVAAS=['volatile acidity','sulphates']
VAAS=LogisticRegression().fit(X_train[varsVAAS],y_train)
for c,v in zip(VAAS.coef_,varsVAAS):
    print(v,': ',c)
```

```
volatile acidity :  [ 1.57410896 -0.30331977]
sulphates :  [ 2.99418985 -0.87992909]
```

In [33]:
```
print("The accuracy of this model is of: ",VAAS.score(X_test[varsVAAS].values,y_t
```

```
The accuracy of this model is of:  0.525
```

All features

In [34]:
```
model=LogisticRegression().fit(X_train,y_train)
for c,v in zip(model.coef_,X_train.columns):
    print(v,': ',c)
```

```
fixed acidity :  [-0.05313218  0.0651648  -0.02007614  0.02771086  0.00704406
0.07643362
 -0.02023522 -0.00880347 -0.01112811 -0.01680188 -0.24427964]
volatile acidity :  [-0.25078604  0.2873414  -0.10725294  0.22659938  0.0138796
6 -0.05968713
  0.01039612  0.02477751  0.16846125 -0.06048165  0.05660307]
citric acid :  [ 0.2259388   0.98885319 -0.48555065 -0.12757968  0.10456579 -0.
0347753
  0.02925165  0.51080958  1.79884889 -0.34095528 -0.71480193]
residual sugar :  [ 0.11616523 -0.41458633  0.03940855 -0.13207163 -0.02327516
-0.00316044
  0.0094536  -0.08095303 -0.27254295  0.22593836  0.22205063]
chlorides :  [ 0.05194102 -0.83692246  0.51072744 -0.02099859 -0.09026066  0.00
162015
 -0.0014673  -0.3843757  -1.44902752  0.18898727  0.5874109 ]
free sulfur dioxide :  [-0.09012683 -0.0898506   0.06274375  0.02633967 -0.0119
5368  0.01956911
 -0.02739885 -0.0614549  -0.23461155  0.00331319  0.09301696]

C:\Users\nicpo\anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:94
0: ConvergenceWarning: lbfgs failed to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html (https://scikit-
learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on (https://scikit-learn.org/stable/modules/linear_model.html#logistic-regressi
on)
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
```

In [35]:
```
print("The accuracy of this model is of: ",model.score(X_test.values,y_test))
```

```
The accuracy of this model is of:  0.5875
```

Conclusions

After doing an EDA and trying to differente type of linear regressions (Linear and Logistic) we can determine that the quality of the wine cant be determine with much presicion in these models. Although all the six models presented before have a better accuracy than determining the quality of the wine at random (accuracy:0.2), which means that with proper tuning and model selection we can get a higher accuracy

In [ ]:
```
```