# content of the current directory:

In [1]:
```
% ls
```

```
Readme.md                      winequality-red.csv
Wine Quality Analysis.ipynb    winequality-white.csv
Wine+Quality+Analysis.html     winequality.names.txt
```

In [2]:
```
# import libs
%matplotlib inline
import pandas as pd
import seaborn as sns; sns.set(style="whitegrid", palette="muted")
import numpy as np
import matplotlib.pyplot as plt
```

### Create DataFrames for white and red wines

In [3]:
```
white_wine_df = pd.read_csv('winequality-white.csv', sep=";")
red_wine_df = pd.read_csv('winequality-red.csv', sep=";")
```

### DataFrames for red and white wines combined

In [4]:
```
ww = white_wine_df.loc[:]
ww["color"] = "white"
rw = red_wine_df.loc[:]
rw["color"] = "red"
wine_df = pd.concat([ww, rw], ignore_index=True)
```

# Data

In [5]:
```
white_wine_df.head()
```

Out[5]:

| | fixed acidity | volatile acidity | citric acid | residual sugar | chlorides | free sulfur dioxide | total sulfur dioxide | density | pH | sulphates | a |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **0** | 7.0 | 0.27 | 0.36 | 20.7 | 0.045 | 45.0 | 170.0 | 1.0010 | 3.00 | 0.45 | 8 |
| **1** | 6.3 | 0.30 | 0.34 | 1.6 | 0.049 | 14.0 | 132.0 | 0.9940 | 3.30 | 0.49 | 9 |
| **2** | 8.1 | 0.28 | 0.40 | 6.9 | 0.050 | 30.0 | 97.0 | 0.9951 | 3.26 | 0.44 | 1 |
| **3** | 7.2 | 0.23 | 0.32 | 8.5 | 0.058 | 47.0 | 186.0 | 0.9956 | 3.19 | 0.40 | 9 |
| **4** | 7.2 | 0.23 | 0.32 | 8.5 | 0.058 | 47.0 | 186.0 | 0.9956 | 3.19 | 0.40 | 9 |

In [6]:
```
red_wine_df.head()
```

Out[6]:

| | fixed acidity | volatile acidity | citric acid | residual sugar | chlorides | free sulfur dioxide | total sulfur dioxide | density | pH | sulphates | a |
|---|---|---|---|---|---|---|---|---|---|---|---|
| **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 |

In [7]:
```
assert white_wine_df.columns.all() == red_wine_df.columns.all()
",".join(list(white_wine_df.columns))
```

Out[7]:
```
'fixed acidity,volatile acidity,citric acid,residual sugar,chlorides,free sulf
ur dioxide,total sulfur dioxide,density,pH,sulphates,alcohol,quality,color'
```

## test for null values and check correct datatypes

In [8]:
```
assert white_wine_df.notnull().all().all()
white_wine_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 4898 entries, 0 to 4897
Data columns (total 13 columns):
fixed acidity           4898 non-null float64
volatile acidity        4898 non-null float64
citric acid             4898 non-null float64
residual sugar          4898 non-null float64
chlorides               4898 non-null float64
free sulfur dioxide     4898 non-null float64
total sulfur dioxide    4898 non-null float64
density                 4898 non-null float64
pH                      4898 non-null float64
sulphates               4898 non-null float64
alcohol                 4898 non-null float64
quality                 4898 non-null int64
color                   4898 non-null object
dtypes: float64(11), int64(1), object(1)
memory usage: 497.5+ KB
```

#### no null values in white wine dataframe found

In [9]:
```
assert red_wine_df.notnull().all().all()
red_wine_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1599 entries, 0 to 1598
Data columns (total 13 columns):
fixed acidity           1599 non-null float64
volatile acidity        1599 non-null float64
citric acid             1599 non-null float64
residual sugar          1599 non-null float64
chlorides               1599 non-null float64
free sulfur dioxide     1599 non-null float64
total sulfur dioxide    1599 non-null float64
density                 1599 non-null float64
pH                      1599 non-null float64
sulphates               1599 non-null float64
alcohol                 1599 non-null float64
quality                 1599 non-null int64
color                   1599 non-null object
dtypes: float64(11), int64(1), object(1)
memory usage: 162.5+ KB
```

#### no null values in red wine dataframe found

### All datatypes are numeric.

# Build categoricals

In [10]:
```
# this can be crucial :)
white_wine_df["color"] = white_wine_df["color"].astype("category")
red_wine_df["color"] = red_wine_df["color"].astype("category")
wine_df["color"] = wine_df["color"].astype("category")
```

# Means

### White Wines:

In [11]:
```
white_wine_df.mean()
```

Out[11]:
```
fixed acidity             6.854788
volatile acidity          0.278241
citric acid               0.334192
residual sugar            6.391415
chlorides                 0.045772
free sulfur dioxide      35.308085
total sulfur dioxide    138.360657
density                   0.994027
pH                        3.188267
sulphates                 0.489847
alcohol                  10.514267
quality                   5.877909
dtype: float64
```

### Red Wines:

In [12]:
```
red_wine_df.mean()
```

Out[12]:
```
fixed acidity            8.319637
volatile acidity         0.527821
citric acid              0.270976
residual sugar           2.538806
chlorides                0.087467
free sulfur dioxide     15.874922
total sulfur dioxide    46.467792
density                  0.996747
pH                       3.311113
sulphates                0.658149
alcohol                 10.422983
quality                  5.636023
dtype: float64
```

#### Differences between red and white wine means that are greater than 1.0

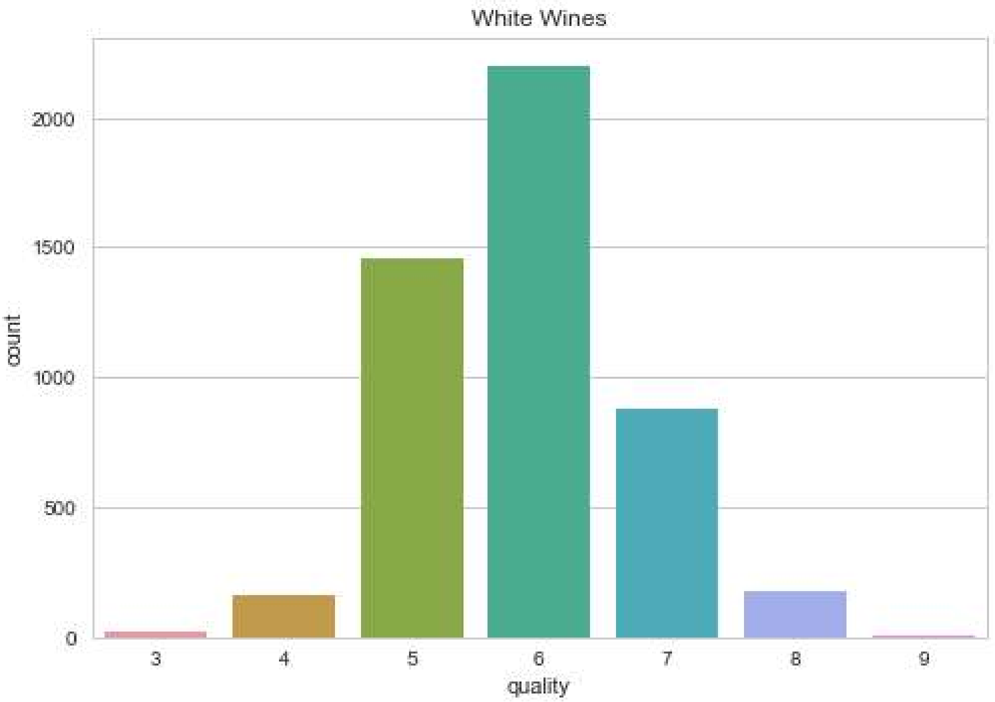
In [13]:
```
mean_diff = white_wine_df.mean() - red_wine_df.mean()
mean_diff_abs = mean_diff.apply(lambda x: abs(x))
mean_diff[mean_diff_abs >= 1.0]
```

Out[13]:
```
fixed acidity           -1.464850
residual sugar           3.852609
free sulfur dioxide     19.433163
total sulfur dioxide    91.892865
dtype: float64
```

# Distribution of Quality

In [14]:
```
sns.countplot(data=white_wine_df, x="quality")
sns.plt.title("White Wines")
```

Out[14]:
```
<matplotlib.text.Text at 0x1112b1ac8>
```



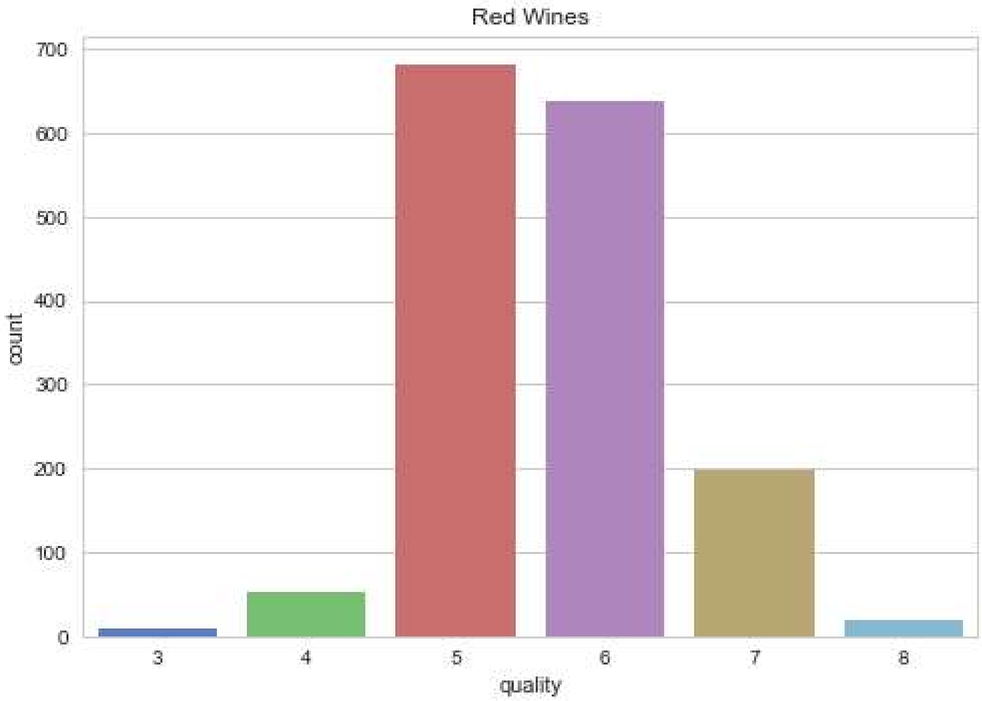

/

In [15]:
```
white_wine_df.quality.describe()
```

Out[15]:
```
count    4898.000000
mean        5.877909
std         0.885639
min         3.000000
25%         5.000000
50%         6.000000
75%         6.000000
max         9.000000
Name: quality, dtype: float64
```

In [16]:
```
x = sns.countplot(data=red_wine_df, x="quality")
sns.plt.title("Red Wines")
```

Out[16]:
```
<matplotlib.text.Text at 0x11144de80>
```




In [17]:
```
red_wine_df.quality.describe()
```

Out[17]:
```
count    1599.000000
mean        5.636023
std         0.807569
min         3.000000
25%         5.000000
50%         6.000000
75%         6.000000
max         8.000000
Name: quality, dtype: float64
```

# What may be important for a high quality rating?

**To find out, the percentual mean differences for low quality to high quality wines over the total mean are calculated, resulting in percentual changes.**

## For white wines:

In [18]:
```
x = white_wine_df.groupby(["quality"]).mean()
lower_quals = x.loc[:4].mean()
higher_quals = x.loc[7:].mean()
ww_perc_means = (higher_quals - lower_quals) / white_wine_df.mean() * 100
ww_perc_means
```

Out[18]:
```
alcohol                  14.068993
chlorides               -38.372538
citric acid               7.758984
density                  -0.254610
fixed acidity            -6.235608
free sulfur dioxide     -10.177344
pH                        1.934262
quality                        NaN
residual sugar           -8.100321
sulphates                 1.999155
total sulfur dioxide    -18.439304
volatile acidity        -27.979143
dtype: float64
```

### Comparing low quality means to high quality ones, the following attributes differ more than 5 per cent:

In [19]:
```
ww_perc_means[abs(ww_perc_means) > 5]
```

Out[19]:
```
alcohol                  14.068993
chlorides               -38.372538
citric acid               7.758984
fixed acidity            -6.235608
free sulfur dioxide     -10.177344
residual sugar           -8.100321
total sulfur dioxide    -18.439304
volatile acidity        -27.979143
dtype: float64
```

### Comparing low quality means to high quality ones, the following attributes differ more than 10 per cent:

In [20]:
```
ww_perc_means[abs(ww_perc_means) > 10]
```

Out[20]:
```
alcohol                  14.068993
chlorides               -38.372538
free sulfur dioxide     -10.177344
total sulfur dioxide    -18.439304
volatile acidity        -27.979143
dtype: float64
```

## For red wines:

In [21]:
```
x = red_wine_df.groupby(["quality"]).mean()
lower_quals = x.loc[:4].mean()
higher_quals = x.loc[7:].mean()
rw_perc_means = (higher_quals - lower_quals) / red_wine_df.mean() * 100
rw_perc_means
```

Out[21]:
```
alcohol                  16.023546
chlorides               -38.955960
citric acid              77.707371
density                  -0.134937
fixed acidity             7.811538
free sulfur dioxide      12.783852
pH                       -3.345302
quality                        NaN
residual sugar           -0.609713
sulphates                26.028988
total sulfur dioxide      7.875629
volatile acidity        -71.161438
dtype: float64
```

### Comparing low quality means to high quality ones, the following attributes differ more than 5 per cent:

In [22]:
```
rw_perc_means[abs(rw_perc_means) > 5]
```

Out[22]:
```
alcohol                  16.023546
chlorides               -38.955960
citric acid              77.707371
fixed acidity             7.811538
free sulfur dioxide      12.783852
sulphates                26.028988
total sulfur dioxide      7.875629
volatile acidity        -71.161438
dtype: float64
```

### Comparing low quality means to high quality ones, the following attributes differ more than 10 per cent:

In [23]:
```
rw_perc_means[abs(rw_perc_means) > 10]
```

Out[23]:
```
alcohol                 16.023546
chlorides              -38.955960
citric acid             77.707371
free sulfur dioxide     12.783852
sulphates               26.028988
volatile acidity       -71.161438
dtype: float64
```

# What will be taken a closer look at:

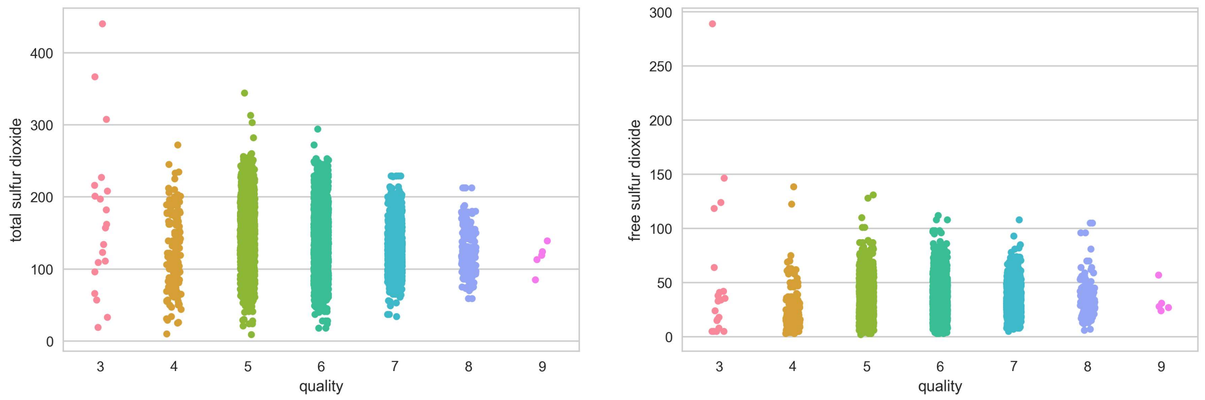
- Alcohol
- Chlorides
- Citric Acid
- Sulphates
- Sulfur Dioxides
- Volatile Acidity

# Sulfur Dioxides and Quality

## White Wines

In [24]:
```
fig, (ax1, ax2) = plt.subplots(1,2)
fig.set_size_inches(14.5, 4.5)
fig.dpi = 300
sns.stripplot(data=white_wine_df, x="quality", y="total sulfur dioxide", jitter=True, ax=ax1)
sns.stripplot(data=white_wine_df, x="quality", y="free sulfur dioxide", jitter=True, ax=ax2)
```

Out[24]: <matplotlib.axes._subplots.AxesSubplot at 0x114f6d4e0>




In [25]:
```
high_qual_ww_tsd_mean = white_wine_df[white_wine_df["quality"] >= 7]["total sulfur dioxide"].mean()
high_qual_ww_tsd_mean = format(high_qual_ww_tsd_mean, '.1f')
print(f"The mean for higher quality white wines (quality >= 7) is {high_qual_ww_tsd_mean}")
```

```
The mean for higher quality white wines (quality >= 7) is 125.2
```

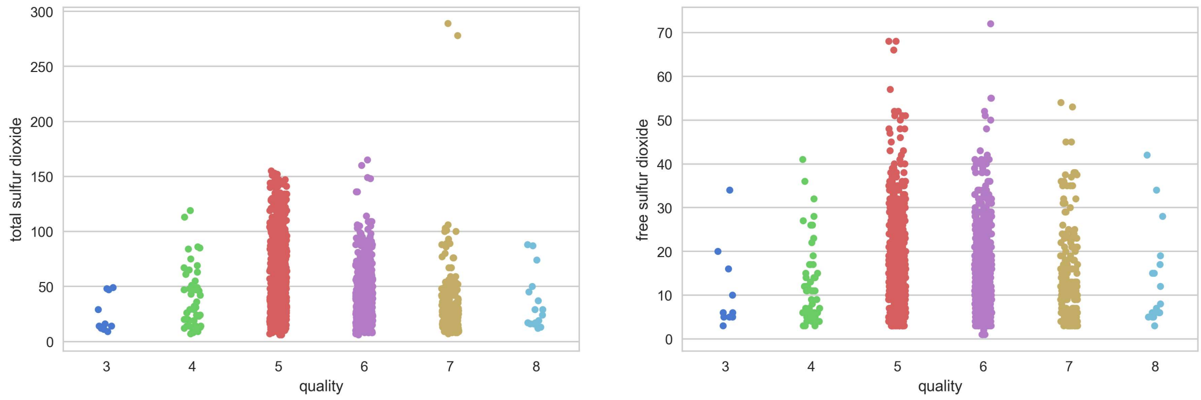
## Interpretation White Wines

Both plots show, that higher quality white wines tend to have less total sulfur dioxide in it.

## red wine

In [26]:
```
fig, (ax1, ax2) = plt.subplots(1,2)
fig.set_size_inches(14.5, 4.5)
fig.dpi = 300
sns.stripplot(data=red_wine_df, x="quality", y="total sulfur dioxide", jitter
=True, ax=ax1)
sns.stripplot(data=red_wine_df, x="quality", y="free sulfur dioxide", jitter=
True, ax=ax2)
```

Out[26]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x114e00cc0>
```




In [27]:
```
high_qual_rw_tsd_mean = red_wine_df[red_wine_df["quality"] >= 7]["total sulfu
r dioxide"].mean()
high_qual_rw_tsd_mean = format(high_qual_rw_tsd_mean, '.1f')
print(f"The mean for higher quality red wines (quality >= 7) is {high_qual_rw
_tsd_mean}")
```

```
The mean for higher quality red wines (quality >= 7) is 34.9
```

## Interpretation Red Wines

For the red wines, there are much lower concentrations of sulfur dioxides. Additionally, there seems to be no direct correlation between sulfur dioxide concentration and percepted quality.

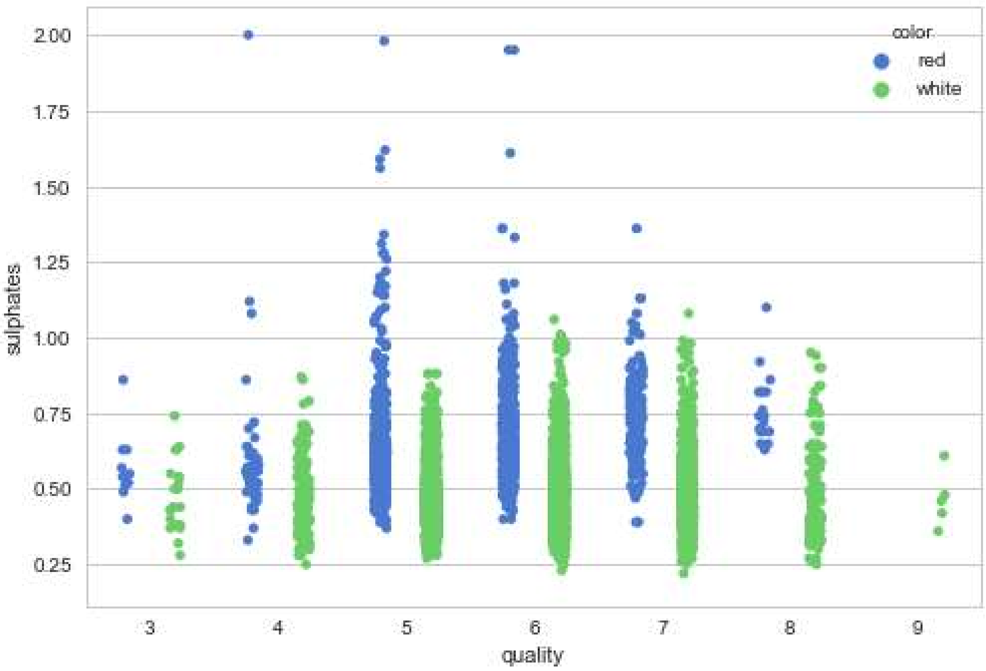
# Conclusion: Sulfur Dioxides and Quality

Regarding high quality white wines (>= 7), those wines have a mean of sulfur dioxides of around 125. Respectively high quality Red Wines (>=7) have a mean concentration of sulfur dioxide of 35.

# Sulphates and Quality

In [28]:
```
sns.stripplot(data=wine_df, x="quality", y="sulphates", jitter=True, hue="col
or", split=True)
```

Out[28]: <matplotlib.axes._subplots.AxesSubplot at 0x117849240>




# Alcohol in Wine

## White Wine

In [29]:
```
white_wine_df.groupby("quality")["alcohol"].describe()
```

Out[29]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **quality** | | | | | | | | |
| **3** | 20.0 | 10.345000 | 1.224089 | 8.0 | 9.55 | 10.45 | 11.00 | 12.6 |
| **4** | 163.0 | 10.152454 | 1.003217 | 8.4 | 9.40 | 10.10 | 10.75 | 13.5 |
| **5** | 1457.0 | 9.808840 | 0.847065 | 8.0 | 9.20 | 9.50 | 10.30 | 13.6 |
| **6** | 2198.0 | 10.575372 | 1.147776 | 8.5 | 9.60 | 10.50 | 11.40 | 14.0 |
| **7** | 880.0 | 11.367936 | 1.246536 | 8.6 | 10.60 | 11.40 | 12.30 | 14.2 |
| **8** | 175.0 | 11.636000 | 1.280138 | 8.5 | 11.00 | 12.00 | 12.60 | 14.0 |
| **9** | 5.0 | 12.180000 | 1.013410 | 10.4 | 12.40 | 12.50 | 12.70 | 12.9 |

## Red Wine

In [30]:
```
red_wine_df.groupby("quality")["alcohol"].describe()
```

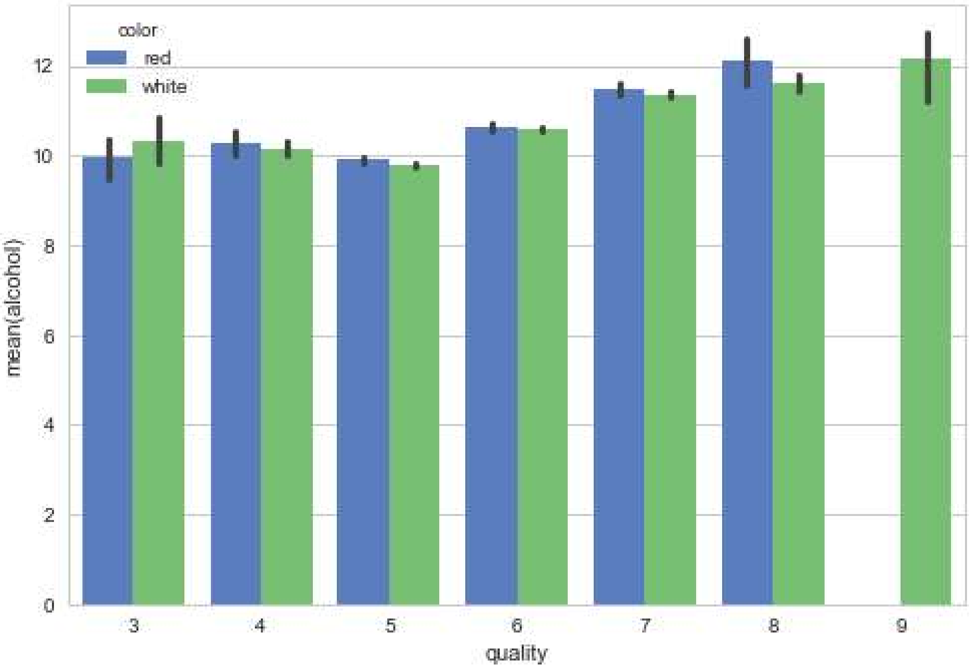
Out[30]:

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **quality** | | | | | | | | |
| **3** | 10.0 | 9.955000 | 0.818009 | 8.4 | 9.725 | 9.925 | 10.575 | 11.0 |
| **4** | 53.0 | 10.265094 | 0.934776 | 9.0 | 9.600 | 10.000 | 11.000 | 13.1 |
| **5** | 681.0 | 9.899706 | 0.736521 | 8.5 | 9.400 | 9.700 | 10.200 | 14.9 |
| **6** | 638.0 | 10.629519 | 1.049639 | 8.4 | 9.800 | 10.500 | 11.300 | 14.0 |
| **7** | 199.0 | 11.465913 | 0.961933 | 9.2 | 10.800 | 11.500 | 12.100 | 14.0 |
| **8** | 18.0 | 12.094444 | 1.224011 | 9.8 | 11.325 | 12.150 | 12.875 | 14.0 |

## Plotting Alcohol to Quality

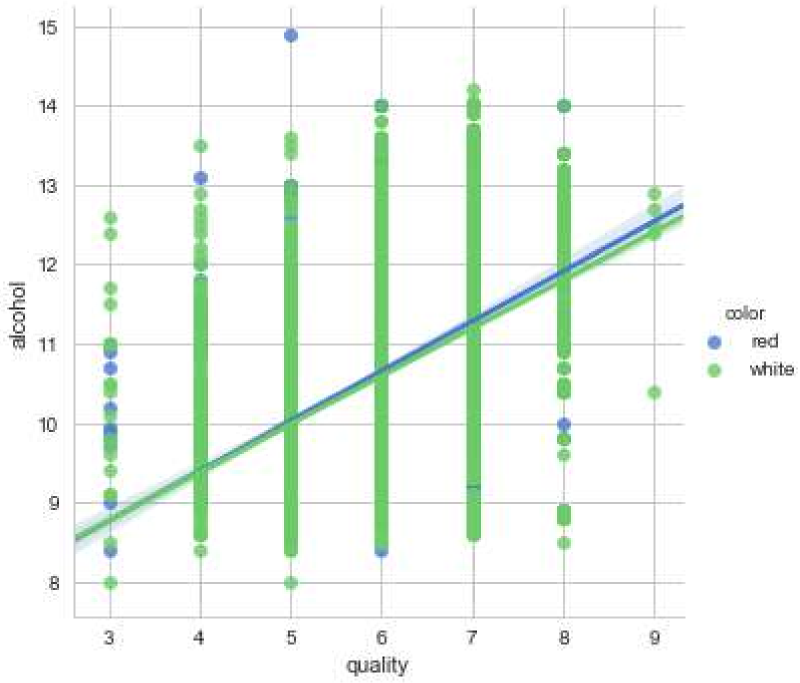
In [31]:
```
sns.barplot(data=wine_df, x="quality", y="alcohol", hue="color")
```

Out[31]: <matplotlib.axes._subplots.AxesSubplot at 0x114e342e8>



In [32]:
```
sns.lmplot(data=wine_df, x="quality", y="alcohol", hue="color")
```

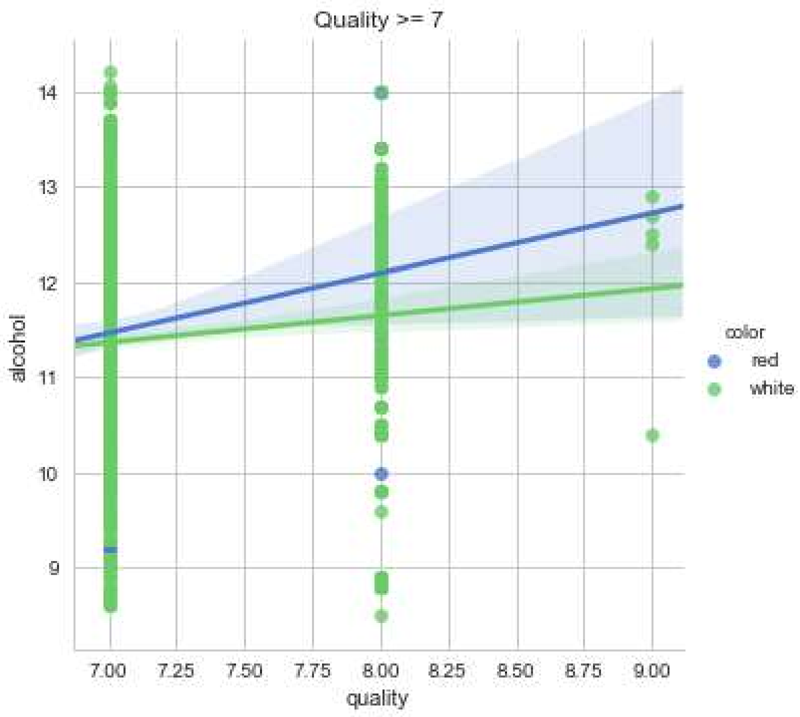
Out[32]: <seaborn.axisgrid.FacetGrid at 0x118bd3160>




### Alcohol to Quality relation for Wines equal or greater than 7

In [33]:
```
hq_wines = wine_df[wine_df.quality >= 7]
sns.lmplot(data=hq_wines, x="quality", y="alcohol", hue="color")
sns.plt.title("Quality >= 7")
```

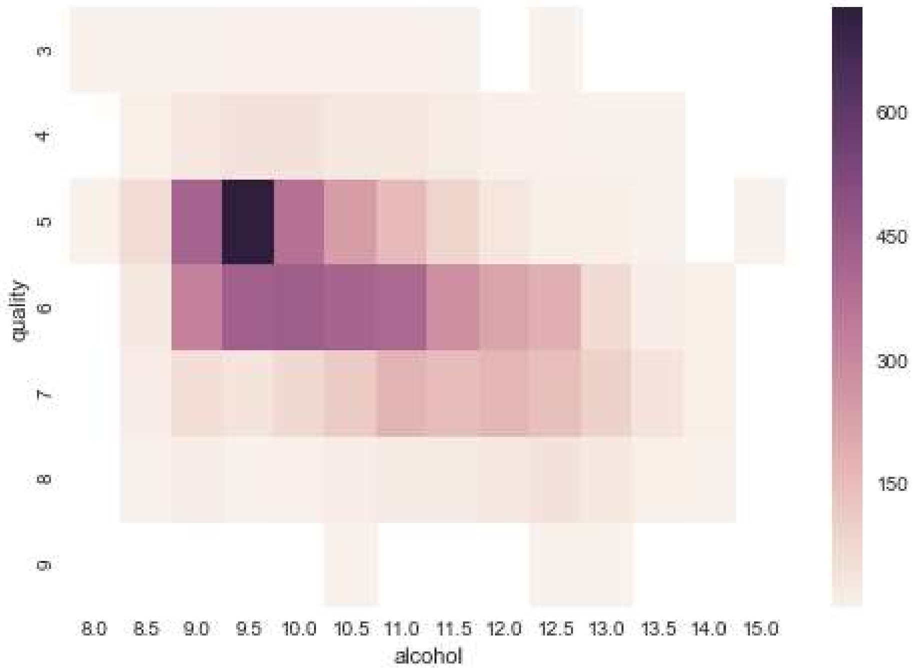
Out[33]: <matplotlib.text.Text at 0x118fe82e8>




# Heatmap Alcohol to Quality

In [34]:
```
heat_table = wine_df[["quality", "alcohol"]].copy()
heat_table["alcohol"] = heat_table.alcohol.apply(func=lambda x: round(x * 2)
/ 2)
heat_table = heat_table.groupby(["quality", "alcohol"])["alcohol"].count().re
set_index(name='counts')
sns.heatmap(heat_table.pivot("quality", "alcohol", "counts"))
```

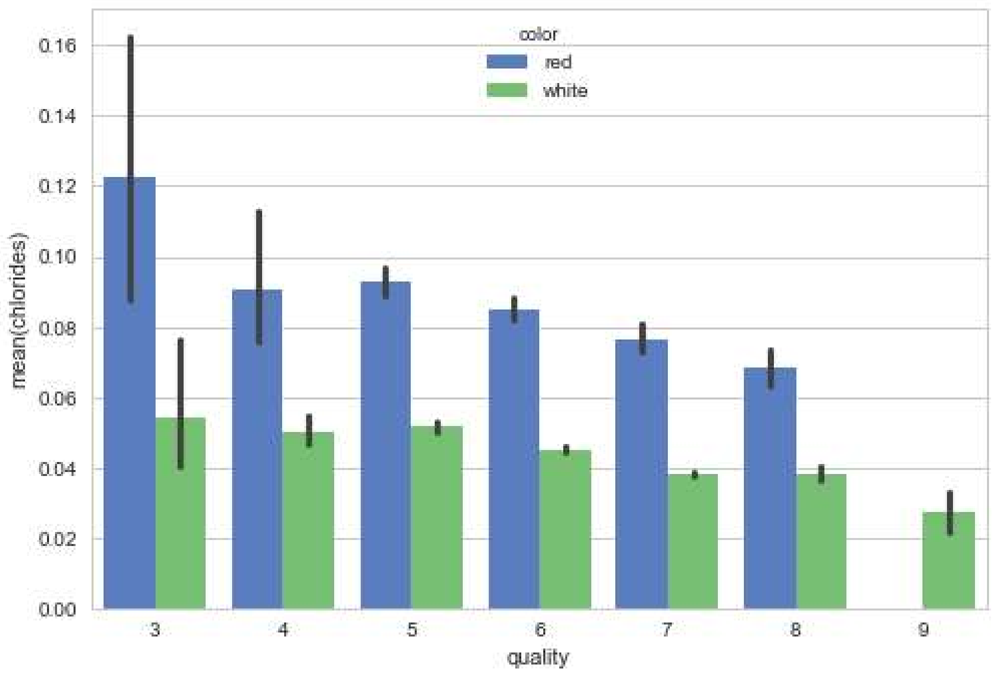
Out[34]: <matplotlib.axes._subplots.AxesSubplot at 0x118e0eb70>




# Chlorides

In [35]:
```
sns.barplot(data=wine_df, hue="color", x="quality", y="chlorides")
```

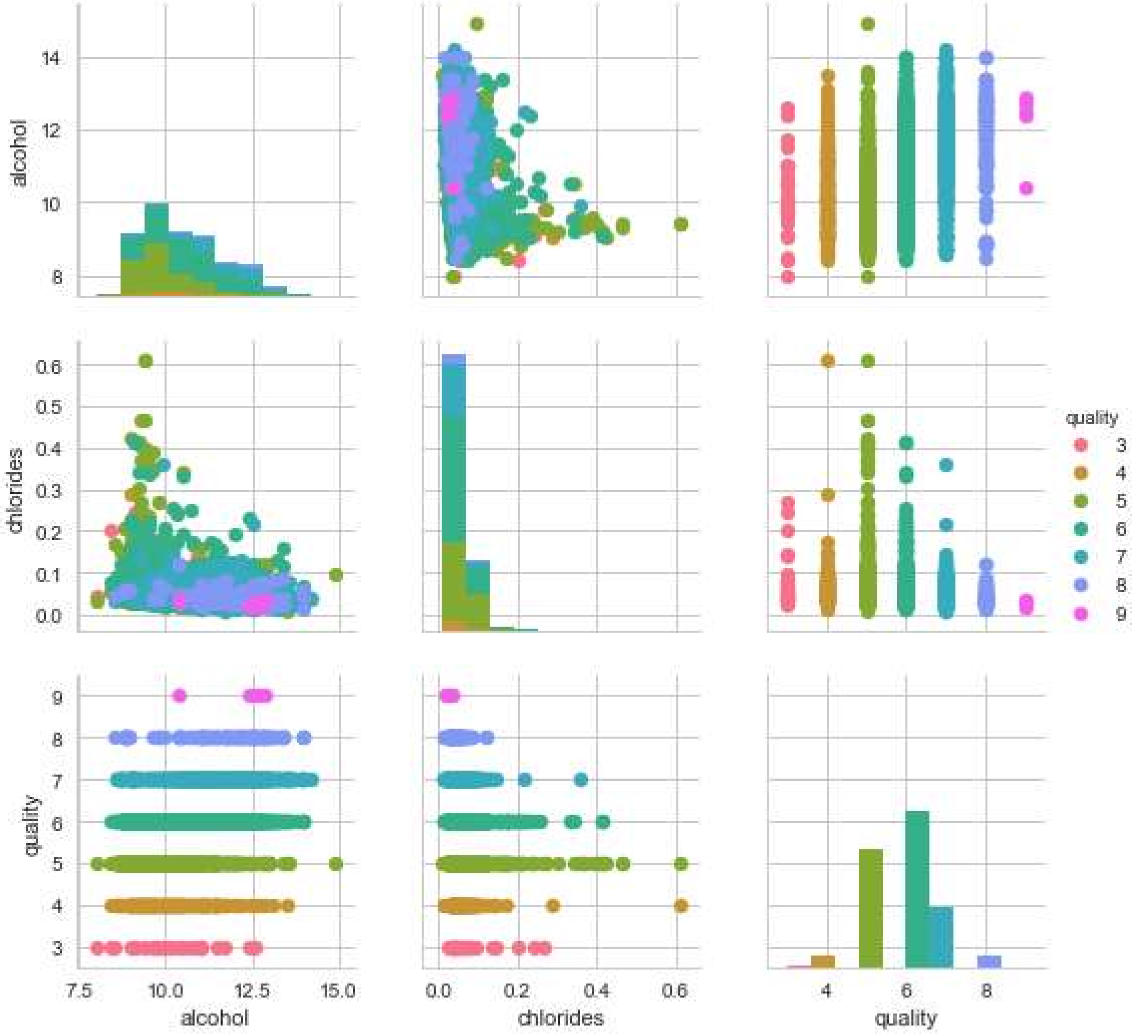
Out[35]: <matplotlib.axes._subplots.AxesSubplot at 0x1192a8c18>




**The less chlorides in a wine the higher the quality.**

## Chlorides and Alcohol

In [36]:
```
g = sns.PairGrid(wine_df[["alcohol", "chlorides", "quality"]], hue="quality")
g = g.map_diag(plt.hist)
g = g.map_offdiag(plt.scatter)
g = g.add_legend()
```

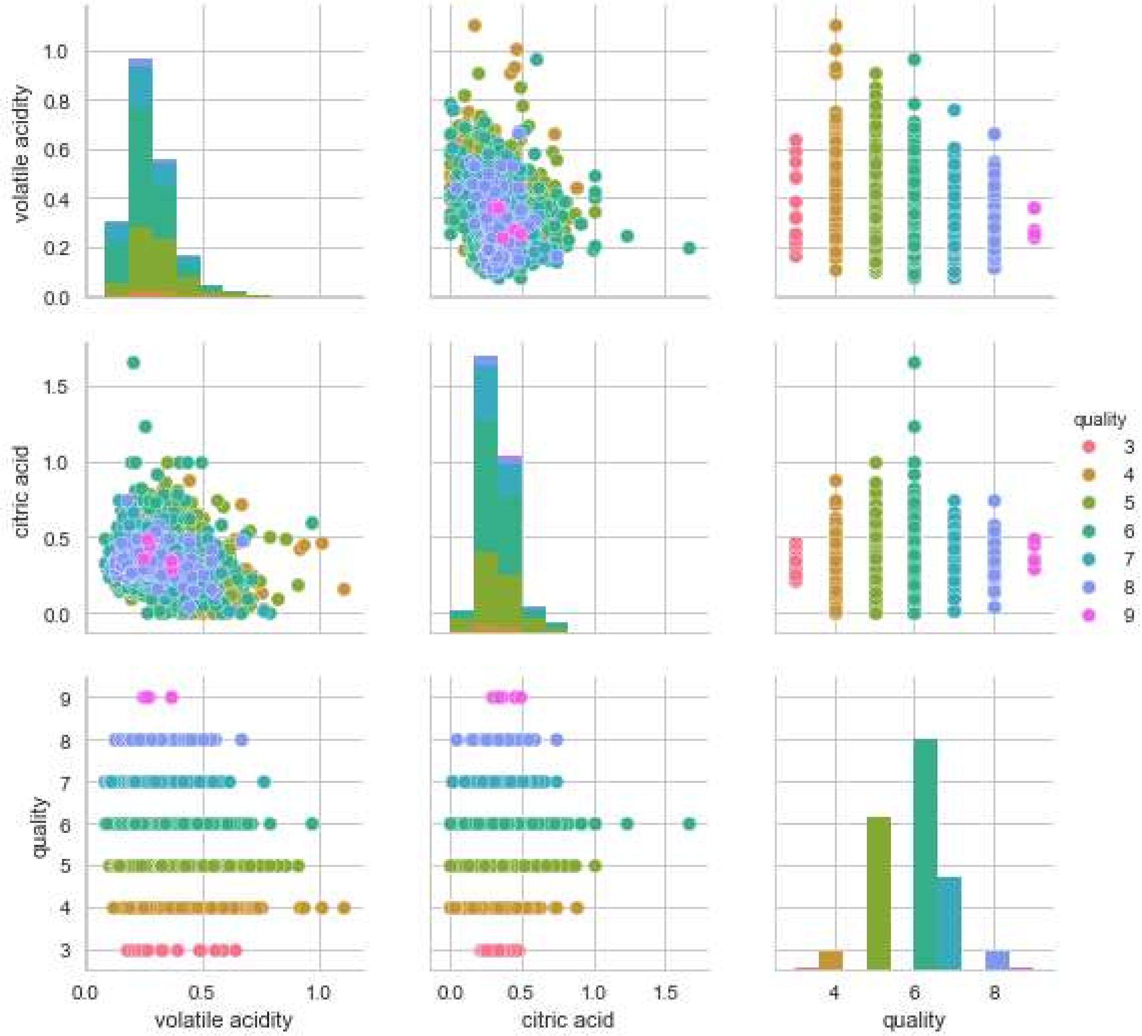



## Acids

/

```
In [37]: sns.pairplot(white_wine_df[["volatile acidity", "citric acid", "quality"]], h
ue="quality")
```

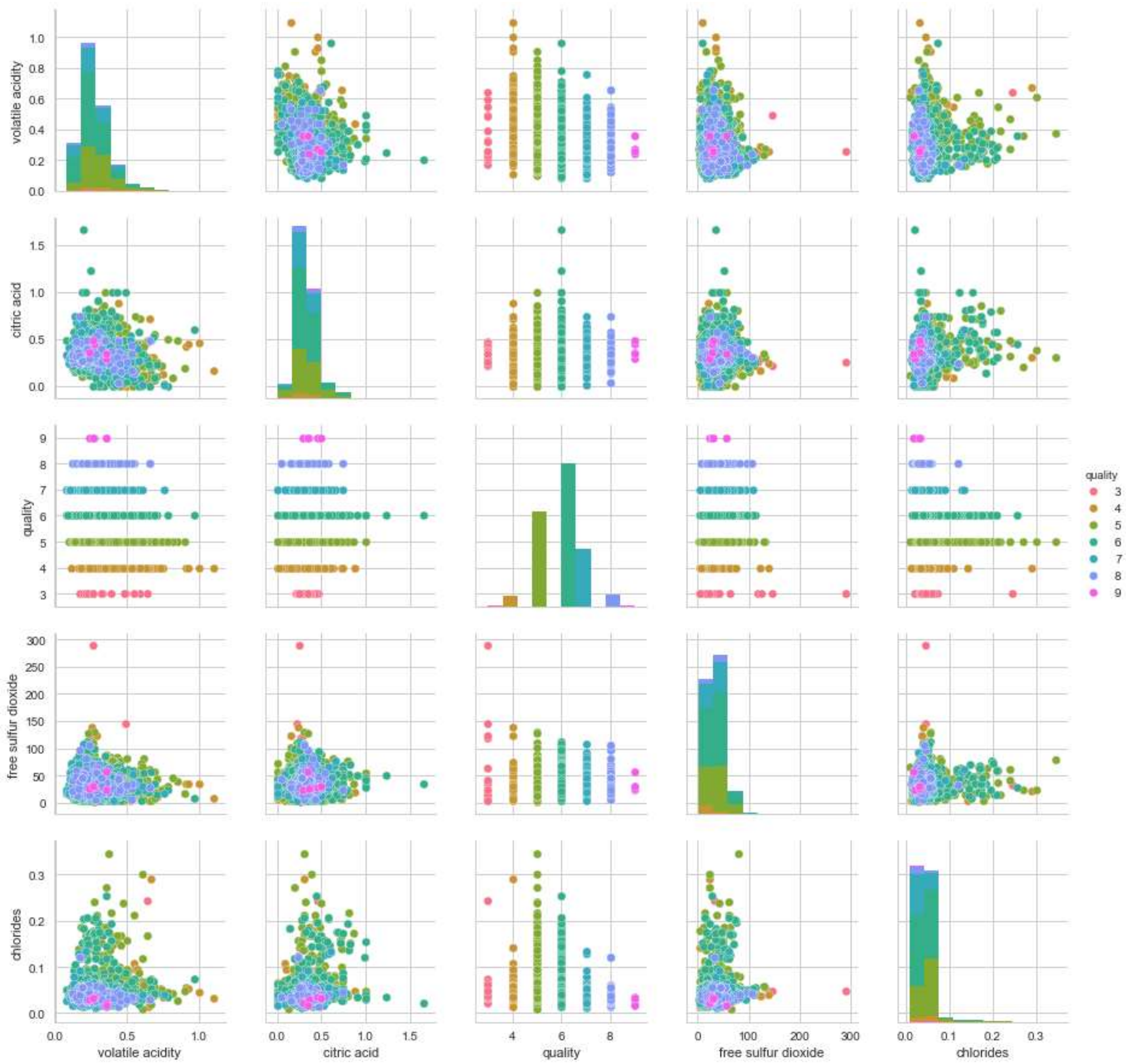
```
Out[37]: <seaborn.axisgrid.PairGrid at 0x1194682b0>
```




## Bringing the relevant attributes together

In [38]:
```
sns.pairplot(white_wine_df[["volatile acidity", "citric acid", "quality", "fr
ee sulfur dioxide", "chlorides"]], hue="quality")
```

Out[38]: <seaborn.axisgrid.PairGrid at 0x11a544128>




In [39]:
```
white_wine_df[["volatile acidity", "citric acid", "quality"]].groupby("qualit
y").describe(percentiles=[])
```

Out[39]:

| | citric acid | | | | | | volatile acidity | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | count | mean | std | min | 50% | max | count | mean | std | min | 50 |
| quality | | | | | | | | | | | |
| 3 | 20.0 | 0.336000 | 0.081460 | 0.21 | 0.345 | 0.47 | 20.0 | 0.333250 | 0.140827 | 0.17 | 0.2 |
| 4 | 163.0 | 0.304233 | 0.163857 | 0.00 | 0.290 | 0.88 | 163.0 | 0.381227 | 0.173463 | 0.11 | 0.3 |
| 5 | 1457.0 | 0.337653 | 0.140814 | 0.00 | 0.320 | 1.00 | 1457.0 | 0.302011 | 0.100066 | 0.10 | 0.2 |
| 6 | 2198.0 | 0.338025 | 0.119325 | 0.00 | 0.320 | 1.66 | 2198.0 | 0.260564 | 0.088142 | 0.08 | 0.2 |
| 7 | 880.0 | 0.325625 | 0.079183 | 0.01 | 0.310 | 0.74 | 880.0 | 0.262767 | 0.091106 | 0.08 | 0.2 |
| 8 | 175.0 | 0.326514 | 0.085439 | 0.04 | 0.320 | 0.74 | 175.0 | 0.277400 | 0.108029 | 0.12 | 0.2 |
| 9 | 5.0 | 0.386000 | 0.082037 | 0.29 | 0.360 | 0.49 | 5.0 | 0.298000 | 0.057619 | 0.24 | 0.2 |

In [40]:
```
white_wine_df[["quality", "free sulfur dioxide", "chlorides"]].groupby("quali
ty").describe(percentiles=[])
```

Out[40]:

| | chlorides | | | | | | free sulfur dioxide | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **count** | **mean** | **std** | **min** | **50%** | **max** | **count** | **mean** | **std** | **mir** |
| **quality** | | | | | | | | | | |
| **3** | 20.0 | 0.054300 | 0.046468 | 0.022 | 0.041 | 0.244 | 20.0 | 53.325000 | 69.420776 | 5.0 |
| **4** | 163.0 | 0.050098 | 0.025888 | 0.013 | 0.046 | 0.290 | 163.0 | 23.358896 | 20.391349 | 3.0 |
| **5** | 1457.0 | 0.051546 | 0.026496 | 0.009 | 0.047 | 0.346 | 1457.0 | 36.432052 | 18.145991 | 2.0 |
| **6** | 2198.0 | 0.045217 | 0.020453 | 0.015 | 0.043 | 0.255 | 2198.0 | 35.650591 | 15.735679 | 3.0 |
| **7** | 880.0 | 0.038191 | 0.010697 | 0.012 | 0.037 | 0.135 | 880.0 | 34.125568 | 13.244737 | 5.0 |
| **8** | 175.0 | 0.038314 | 0.013164 | 0.014 | 0.036 | 0.121 | 175.0 | 36.720000 | 16.203675 | 6.0 |
| **9** | 5.0 | 0.027400 | 0.007436 | 0.018 | 0.031 | 0.035 | 5.0 | 33.400000 | 13.427584 | 24.( |

# Final Conclusion

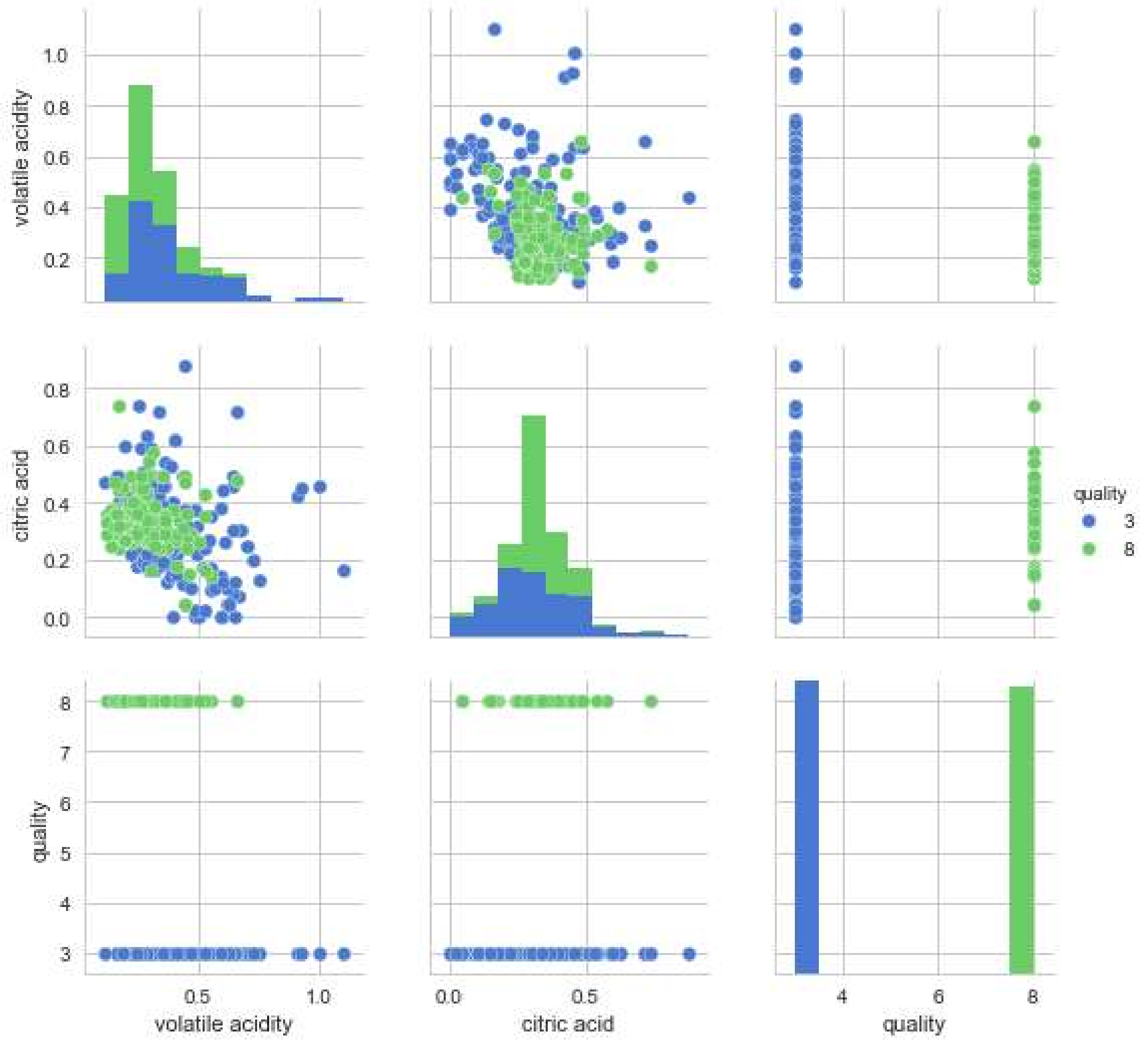
no attribute alone is strong enough to define a high quality wine, but as the figures show. For a wine to score high, having the acids and sulfur dioxide values all within in a certain range can help.

## Best vs. Worst

when comparing the best (8,9) vs. worst (3,4) we can see that they well overlap each other.

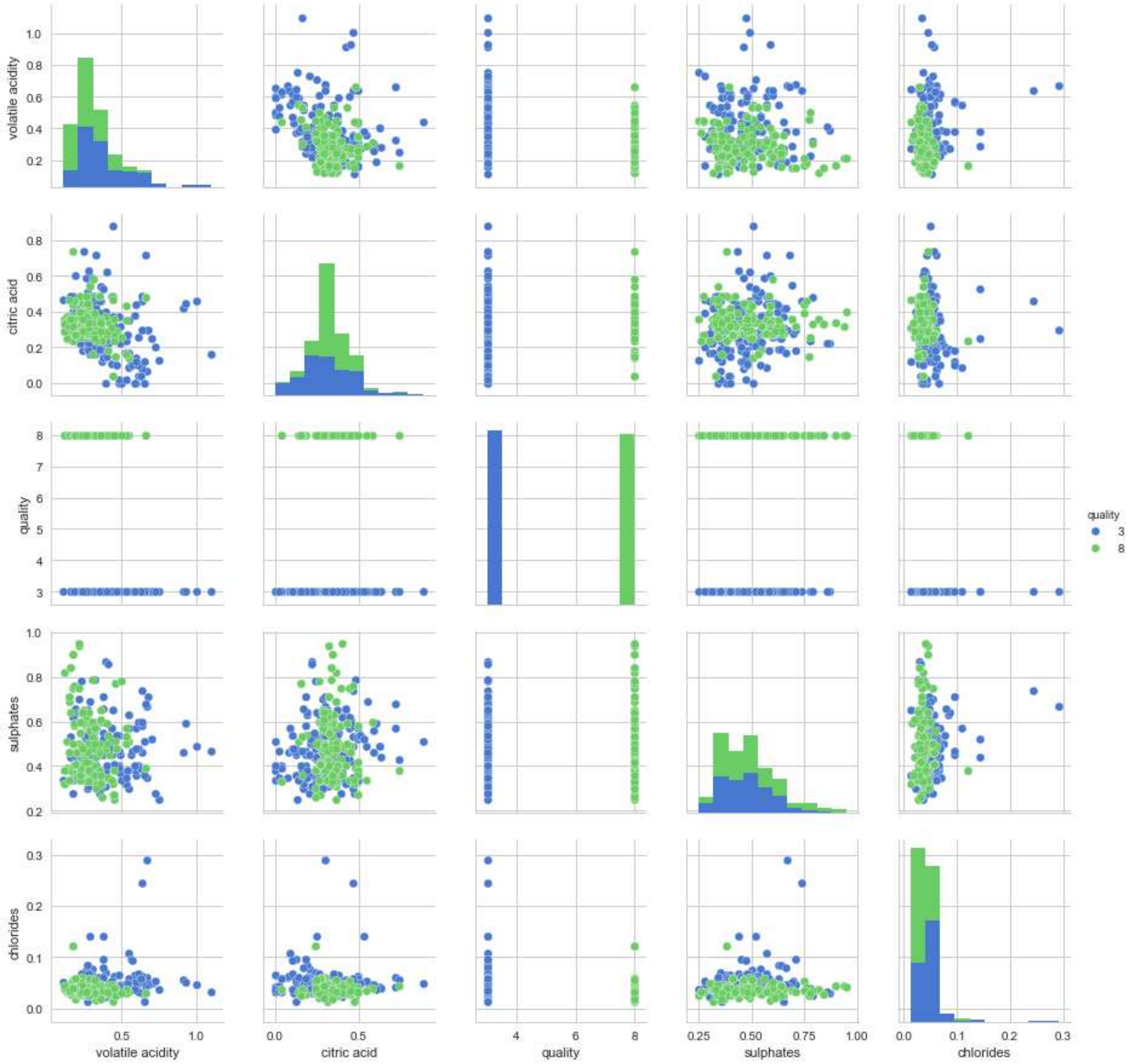
In [41]:
```
qual3 = white_wine_df[white_wine_df["quality"] == 3]
qual4 = white_wine_df[white_wine_df["quality"] == 4].copy()
qual4.quality = 3
qual8 = white_wine_df[white_wine_df["quality"] == 8]
qual9 = white_wine_df[white_wine_df["quality"] == 9].copy()
qual9.quality = 8
white_wine_sample = pd.concat([qual3, qual4, qual8, qual9], ignore_index=True
)
white_wine_sample
sns.pairplot(white_wine_sample[["volatile acidity", "citric acid", "quality"
]], hue="quality")
```

Out[41]: <seaborn.axisgrid.PairGrid at 0x11cc89ef0>



In [42]:
```
sns.pairplot(white_wine_sample[["volatile acidity", "citric acid", "quality", "sulphates", "chlorides"]], hue="quality")
```

Out[42]: <seaborn.axisgrid.PairGrid at 0x11d07cb00>




# Seems like labs can't measure a wine's inner spirit (yet).

**But if you have to pick a wine only based on specs, i would suggest white wines close to this values:**

In [43]:
```
qual8[["quality", "chlorides", "alcohol", "citric acid", "sulphates"]].describe(percentiles=[])
```

Out[43]:

| | quality | chlorides | alcohol | citric acid | sulphates |
|---|---|---|---|---|---|
| **count** | 175.0 | 175.000000 | 175.000000 | 175.000000 | 175.000000 |
| **mean** | 8.0 | 0.038314 | 11.636000 | 0.326514 | 0.486229 |
| **std** | 0.0 | 0.013164 | 1.280138 | 0.085439 | 0.147073 |
| **min** | 8.0 | 0.014000 | 8.500000 | 0.040000 | 0.250000 |
| **50%** | 8.0 | 0.036000 | 12.000000 | 0.320000 | 0.460000 |
| **max** | 8.0 | 0.121000 | 14.000000 | 0.740000 | 0.950000 |

**and red wines close to this values:**

In [45]:
```
rqual8 = red_wine_df[red_wine_df["quality"] >= 8]
rqual8[["quality", "chlorides", "alcohol", "citric acid", "sulphates"]].descr
ibe(percentiles=[])
```

Out[45]:

| | quality | chlorides | alcohol | citric acid | sulphates |
|---|---|---|---|---|---|
| **count** | 18.0 | 18.000000 | 18.000000 | 18.000000 | 18.000000 |
| **mean** | 8.0 | 0.068444 | 12.094444 | 0.391111 | 0.767778 |
| **std** | 0.0 | 0.011678 | 1.224011 | 0.199526 | 0.115379 |
| **min** | 8.0 | 0.044000 | 9.800000 | 0.030000 | 0.630000 |
| **50%** | 8.0 | 0.070500 | 12.150000 | 0.420000 | 0.740000 |
| **max** | 8.0 | 0.086000 | 14.000000 | 0.720000 | 1.100000 |

In [ ]: