Context

- Imagine you are working as a Data Scientist for an Online Wine Shop named “The Wine Land”
- As the name suggests, the online store specializes in selling different varieties of wines.
- The online store receives a decent amount of traffic and reviews from its users.
- Leverage the “reviews” data and draw actionable insights from it.

What is Expected?

- Build a predictive model for predicting the wine “variety”. Provide the output along with all features to a CSV file. Both Training & test data is provided here
- Submit the source code used for building models in a zip or share the link to the GitHub repository.
- Also submit a short summary: Model used, features extracted, Model accuracy in train. Along with some visualization of data and top 5 actionable Insights from the Data.
- .

The Data Description is as follows:

- user_name - user_name of the reviewer
- country -The country that the wine is from.
- review_title - The title of the wine review, which often contains the vintage.
- review_description - A verbose review of the wine.
- designation - The vineyard within the winery where the grapes that made the wine are from.
- points - ratings given by the user. The ratings are between 0 -100.
- price - The cost for a bottle of the wine
- province - The province or state that the wine is from.
- region_1 - The wine-growing area in a province or state (ie Napa).
- region_2 - Sometimes there are more specific regions specified within a wine-growing area (ie Rutherford inside the Napa Valley), but this value can sometimes be blank.
- winery - The winery that made the wine
- variety - The type of grapes used to make the wine. Dependent variable for task 2 of the assignment

Load Libreries

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:

```
%matplotlib inline
sns.set_style('whitegrid')
```

Load Train Data

In [3]:

```
train_raw_df = pd.read_csv('Knight ML Assignment/Data/train.csv')
train_raw_df.head()
```

Out[3]:

	user_name	country	review_title	review_description	designation	points	price	provin
0	NaN	Australia	Andrew Peace 2007 Peace Family Vineyard Chardo...	Classic Chardonnay aromas of apple, pear and h...	Peace Family Vineyard	83	10.0	Austra Otl
1	@wawinereport	US	North by Northwest 2014 Red (Columbia Valley (...	This wine is near equal parts Syrah and Merlot...	NaN	89	15.0	Washingt
2	NaN	Italy	Renato Ratti 2007 Conca (Barolo)	Barolo Conca opens with inky dark concentratio...	Conca	94	80.0	Piedm
3	@vossroger	France	Domaine l'Ancienne Cure 2010 L'Abbaye White (B...	It's impressive what a small addition of Sauvi...	L'Abbaye	87	22.0	Southw Frar
4	@vossroger	France	Château du Cèdre 2012 Le Cèdre Vintage Malbec ...	This ripe, sweet wine is rich and full of drie...	Le Cèdre Vintage	88	33.0	Frar Otl

In [4]:

```
train_raw_df.shape
```

Out[4]:

(82657, 12)

Load New Test Data

In [5]:

```
test_raw_df = pd.read_csv('Knight ML Assignment/Data/test.csv')
test_raw_df.head()
```

Out[5]:

	user_name	country	review_title	review_description	designation	points	price	provinc
0	@paulgwine	US	Boedecker Cellars 2011 Athena Pinot Noir (Will...	Nicely differentiated from the companion Stewa...	Athena	88	35.0	Orego
1	@wineschach	Argentina	Mendoza Vineyards 2012 Gran Reserva by Richard...	Charred, smoky, herbal aromas of blackberry tr...	Gran Reserva by Richard Bonvin	90	60.0	Mendoz Provinc
2	@vboone	US	Prime 2013 Chardonnay (Coombsville)	Slightly sour and funky in earth, this is a re...	NaN	87	38.0	Californi
3	@wineschach	Argentina	Bodega Cuarto Dominio 2012 Chento Vineyard Sel...	This concentrated, midnight-black Malbec deliv...	Chento Vineyard Selection	91	20.0	Mendoz Provinc
4	@kerinokeefe	Italy	SassodiSole 2012 Brunello di Montalcino	Earthy aromas suggesting grilled porcini, leat...	NaN	90	49.0	Tuscan

Remove Duplicate Rows

In [6]:

```
train_raw_df.drop_duplicates(keep = "first", inplace = True, ignore_index=True)
```

In [7]:

```
train_raw_df.shape
```

Out[7]:

```
(77641, 12)
```

Remove Unwanted Columns

- The Features 'user_name', 'designation', 'region_1', 'region_2' have lots of missing values and also these features are not much affected to predict target variable i.e, 'variety' of grapes.

In [8]:

```
train_raw_df.drop(['user_name', 'designation', 'region_1', 'region_2'], axis=1, inp
```

Remove Unwanted Columns From New Test Data

In [9]:

```
test_raw_df.drop(['user_name', 'designation', 'region_1', 'region_2'], axis=1, inpl
```

Handle NULL values

In [10]:

```
def count_null(df):

    print('*Column wise Count Of Null Values*\n')
    for i in range(len(df.columns)):

        print(df.columns[i], ":", len(df[df[df.columns[i]].isnull()==True]))
```

In [11]:

```
count_null(train_raw_df)
```

```
*Column wise Count Of Null Values*

country : 33
review_title : 0
review_description : 0
points : 0
price : 5285
province : 33
winery : 0
variety : 0
```

In [12]:

```
count_null(test_raw_df)
```

```
*Column wise Count Of Null Values*

country : 4
review_title : 0
review_description : 0
points : 0
price : 1394
province : 4
winery : 0
```

Drop NaN values

- The feature 'province' have 33 NaN values. Here we can't fill the data average data. Because 'province' depends on 'country'.

Train Data

In [13]:

```
train_raw_df.dropna(subset=['province'], inplace=True)
train_raw_df.reset_index(drop=True, inplace=True)
```

In [14]:

```
count_null(train_raw_df)
```

```
*Column wise Count Of Null Values*

country : 0
review_title : 0
review_description : 0
points : 0
price : 5281
province : 0
winery : 0
variety : 0
```

Test New Data

In [15]:

```
test_raw_df.dropna(subset=['province'], inplace=True)
test_raw_df.reset_index(drop=True, inplace=True)
```

In [16]:

```
count_null(test_raw_df)
```

```
*Column wise Count Of Null Values*

country : 0
review_title : 0
review_description : 0
points : 0
price : 1394
province : 0
winery : 0
```

Fill NAN Values or Imputation

- The feature 'price' have 5281 NaN values.
- So I fill the most frequent prices of apropreate countries instade of NaN values in 'price'.

Train Data

In [17]:

```
price_missed_countries = train_raw_df[train_raw_df['price'].isnull()==True]['countr

for country in price_missed_countries:
    indexes = train_raw_df[(train_raw_df['price'].isnull()==True) & (train_raw_df['
    for i in indexes:
        train_raw_df.loc[i, 'price'] = train_raw_df[train_raw_df['country'] == coun
```

In [18]:

```
count_null(train_raw_df)
```

```
*Column wise Count Of Null Values*

country : 0
review_title : 0
review_description : 0
points : 0
price : 0
province : 0
winery : 0
variety : 0
```

Test New Data

In [19]:

```
price_missed_countries = test_raw_df[test_raw_df['price'].isnull()==True]['country'

for country in price_missed_countries:
    indexes = test_raw_df[(test_raw_df['price'].isnull()==True) & (test_raw_df['cou
    for i in indexes:
        test_raw_df.loc[i, 'price'] = test_raw_df[test_raw_df['country'] == country
```

In [20]:

```
count_null(test_raw_df)
```

```
*Column wise Count Of Null Values*

country : 0
review_title : 0
review_description : 0
points : 0
price : 0
province : 0
winery : 0
```

Seperate Dependent (X) Variables and Independent (y) Variables of Train Data

In [21]:

```
train_df = train_raw_df.copy()
print('Train Data Shape', train_df.shape)
```

```
Train Data Shape (77608, 8)
```

In [22]:

```
X = train_df.drop(['variety'], axis=1)
y = train_df['variety']
```

In [23]:

```
print('X shape', X.shape)
print('y shape', y.shape)
```

```
X shape (77608, 7)
y shape (77608,)
```

New Test Data

In [24]:

```
test_df = test_raw_df.copy()
print('New Data Shape', test_df.shape)
```

```
New Data Shape (20661, 7)
```

Visualization Of Target Variable

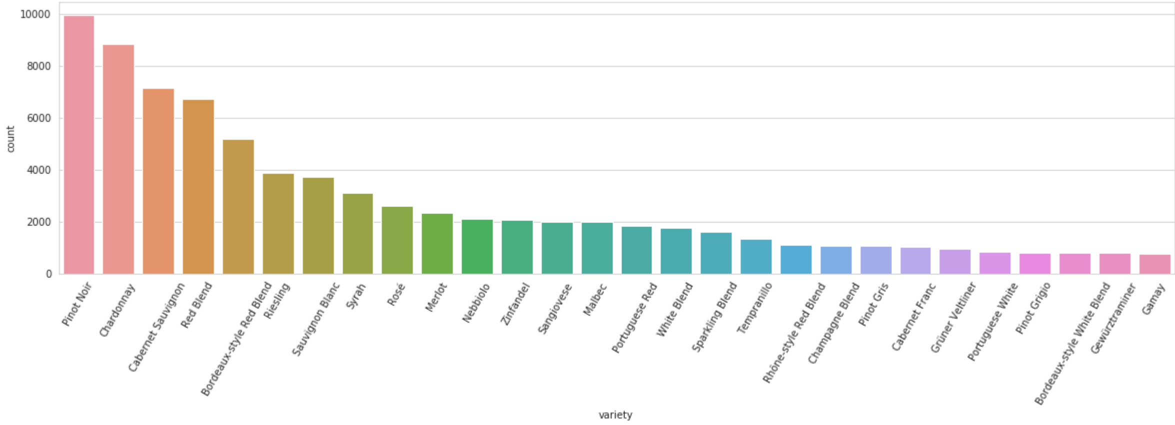
In [25]:

```
target_classes = y.value_counts()

print('Total Number Of Prediction Classes : ', len(target_classes))
print('-'*50)
print('\nCount of each class :\n'+'-'*50,'\n', target_classes)
```

```
Total Number Of Prediction Classes :  28
--------------------------------------------------

Count of each class :
--------------------------------------------------
 Pinot Noir                  9963
Chardonnay                  8833
Cabernet Sauvignon          7153
Red Blend                   6721
Bordeaux-style Red Blend    5206
Riesling                    3876
Sauvignon Blanc             3748
Syrah                       3117
Rosé                        2606
Merlot                      2336
Nebbiolo                    2112
Zinfandel                   2091
Sangiovese                  2006
Malbec                      1985
Portuguese Red              1843
White Blend                 1774
Sparkling Blend             1621
Tempranillo                 1364
Rhône-style Red Blend       1102
Champagne Blend             1075
Pinot Gris                  1062
Cabernet Franc              1027
Grüner Veltliner             976
Portuguese White             835
Pinot Grigio                 820
Bordeaux-style White Blend   806
Gewürztraminer               791
Gamay                        759
Name: variety, dtype: int64
```

In [26]:

```
plt.figure(figsize=(20, 5))
plt.xticks(rotation=60)
sns.countplot(x='variety', data=train_df, order = target_classes.index)
plt.show()
```



Conavert the Target Vriable Categorical to Numeric

In [27]:

```
target_dict = {}

i = 1
for cls in target_classes.keys():

    target_dict[cls] = i

    i += 1

print(target_dict)
```

```
{'Pinot Noir': 1, 'Chardonnay': 2, 'Cabernet Sauvignon': 3, 'Red Blen
d': 4, 'Bordeaux-style Red Blend': 5, 'Riesling': 6, 'Sauvignon Blan
c': 7, 'Syrah': 8, 'Rosé': 9, 'Merlot': 10, 'Nebbiolo': 11, 'Zinfande
l': 12, 'Sangiovese': 13, 'Malbec': 14, 'Portuguese Red': 15, 'White B
lend': 16, 'Sparkling Blend': 17, 'Tempranillo': 18, 'Rhône-style Red
Blend': 19, 'Champagne Blend': 20, 'Pinot Gris': 21, 'Cabernet Franc':
22, 'Grüner Veltliner': 23, 'Portuguese White': 24, 'Pinot Grigio': 2
5, 'Bordeaux-style White Blend': 26, 'Gewürztraminer': 27, 'Gamay': 2
8}
```

In [28]:

```
y = y.map(target_dict)
y.head()
```

Out[28]:

```
0     2
1     4
2    11
3    26
4    14
Name: variety, dtype: int64
```

Visualization Of Independent Variable

In [29]:

```
X.head()
```

Out[29]:

	country	review_title	review_description	points	price	province	winery
0	Australia	Andrew Peace 2007 Peace Family Vineyard Chardo...	Classic Chardonnay aromas of apple, pear and h...	83	10.0	Australia Other	Andrew Peace
1	US	North by Northwest 2014 Red (Columbia Valley (...	This wine is near equal parts Syrah and Merlot...	89	15.0	Washington	North by Northwest
2	Italy	Renato Ratti 2007 Conca (Barolo)	Barolo Conca opens with inky dark concentratio...	94	80.0	Piedmont	Renato Ratti
3	France	Domaine l'Ancienne Cure 2010 L'Abbaye White (B...	It's impressive what a small addition of Sauvi...	87	22.0	Southwest France	Domaine l'Ancienne Cure
4	France	Château du Cèdre 2012 Le Cèdre Vintage Malbec ...	This ripe, sweet wine is rich and full of drie...	88	33.0	France Other	Château du Cèdre

Replace space with underscore

In [30]:

```
X['country'].replace(' ', '_',regex=True, inplace=True)
```

Load Machine Learning Libreries

In [31]:

```
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, LabelEncoder
from sklearn.preprocessing import Normalizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.feature_extraction.text import CountVectorizer
from scipy.sparse import hstack
from sklearn import metrics
from sklearn.metrics import roc_curve, auc, confusion_matrix, classification_report
from sklearn.model_selection import RandomizedSearchCV
from xgboost import XGBClassifier
```

Split Train data into Train, CrossValidation and Test

In [32]:

```
# train test split

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_st

X_train, X_cv, y_train, y_cv = train_test_split(X_train, y_train, test_size=0.33, r
```

Prepare Data

Declare Set1 for Bag Of Words & Set2 for TF-IDF

In [33]:

```
features_names_set1 = []   #set1 for BoW
features_names_set2 = []   #set2 for TfIdf
```

1. One Hot Encoding

1. country

In [35]:

```
# One hot Encoding for country
print("Before Vectorizations")
print('Train Shape : X', X_train.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test.shape, ', y', y_test.shape)

print("="*100)

# X_train_country = pd.get_dummies(X_train['country'], drop_first=True)
# X_cv_country = pd.get_dummies(X_train['country'], drop_first=True)
# X_test_country = pd.get_dummies(X_train['country'], drop_first=True)

vectorizer = CountVectorizer(max_features=5000)
vectorizer.fit(X_train['country'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
X_train_country = vectorizer.transform(X_train['country'].values)
X_cv_country = vectorizer.transform(X_cv['country'].values)
X_test_country = vectorizer.transform(X_test['country'].values)


print("After Vectorizations")
print('Train Shape : X', X_train_country.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv_country.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_country.shape, ', y', y_test.shape)

#print(X_test_school_state.toarray()[0])
print("="*100)
print(vectorizer.get_feature_names())

for i in vectorizer.get_feature_names():
    features_names_set1.append(i)
    features_names_set2.append(i)


print('\nfeatures_names_set1 :', len(features_names_set1))
print('features_names_set2 :', len(features_names_set2))
```

```
Before Vectorizations
Train Shape : X (34837, 7) , y (34837,)
CV Shape    : X (17160, 7) , y (17160,)
Test Shape  : X (25611, 7) , y (25611,)
======================================================================
==============================
After Vectorizations
Train Shape : X (34837, 38) , y (34837,)
CV Shape    : X (17160, 38) , y (17160,)
Test Shape  : X (25611, 38) , y (25611,)
======================================================================
==============================
['argentina', 'australia', 'austria', 'brazil', 'bulgaria', 'canad
a', 'chile', 'croatia', 'cyprus', 'czech_republic', 'england', 'fran
ce', 'georgia', 'germany', 'greece', 'hungary', 'india', 'israel',
'italy', 'lebanon', 'luxembourg', 'macedonia', 'mexico', 'moldova',
'morocco', 'new_zealand', 'peru', 'portugal', 'romania', 'serbia',
'slovenia', 'south_africa', 'spain', 'switzerland', 'turkey', 'ukrai
ne', 'uruguay', 'us']
```

```
features_names_set1 : 38
features_names_set2 : 38
```

2. Label Encoding

1. province
2. winery

In [36]:

```
# Source : https://stackoverflow.com/a/56876351
# Custom Class For LabelEncoder
class LabelEncoderExt(object):
    def __init__(self):
        """
        It differs from LabelEncoder by handling new classes and providing a value
        Unknown will be added in fit and transform will take care of new item. It g
        """
        self.label_encoder = LabelEncoder()
        # self.classes_ = self.label_encoder.classes_

    def fit(self, data_list):
        """
        This will fit the encoder for all the unique values and introduce unknown v
        :param data_list: A list of string
        :return: self
        """
        self.label_encoder = self.label_encoder.fit(list(data_list) + ['Unknown'])
        self.classes_ = self.label_encoder.classes_

        return self

    def transform(self, data_list):
        """
        This will transform the data_list to id list where the new values get assig
        :param data_list:
        :return:
        """
        new_data_list = list(data_list)
        for unique_item in np.unique(data_list):
            if unique_item not in self.label_encoder.classes_:
                new_data_list = ['Unknown' if x==unique_item else x for x in new_da

        return self.label_encoder.transform(new_data_list)
```

In [37]:

```
# Label Encoding for province

label_encoder = LabelEncoderExt()
label_encoder.fit(X_train['province']) # fit has to happen only on train data

# print(X_train['points'].shape)
# o/p : (34837,)  need to reshape
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96  96.01 ... 368.98  80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature    (column)
# array.reshape(1, -1)  if it contains a single sample.    (row)

# we use the LabelEncoder to convert the categorical data to numerical
X_train_province = label_encoder.transform(X_train['province']).reshape(-1,1)
X_cv_province = label_encoder.transform(X_cv['province']).reshape(-1,1)
X_test_province = label_encoder.transform(X_test['province']).reshape(-1,1)


print("After Label Encodeing")
print('Train Shape : X', X_train_province.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv_province.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_province.shape, ', y', y_test.shape)

print("="*100)

features_names_set1.append(1)
features_names_set2.append(1)


print('\nfeatures_names_set1 :', len(features_names_set1))
print('features_names_set2 :', len(features_names_set2))
```

```
After Label Encodeing
Train Shape : X (34837, 1) , y (34837,)
CV Shape    : X (17160, 1) , y (17160,)
Test Shape  : X (25611, 1) , y (25611,)
======================================================================
==============================

features_names_set1 : 39
features_names_set2 : 39
```

In [38]:

```
# Label Encoding for winery

label_encoder = LabelEncoderExt()
label_encoder.fit(X_train['winery']) # fit has to happen only on train data

# print(X_train['points'].shape)
# o/p : (34837,)  need to reshape
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96  96.01 ... 368.98  80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature    (column)
# array.reshape(1, -1)  if it contains a single sample.    (row)

# we use the LabelEncoder to convert the categorical data to numerical
X_train_winery = label_encoder.transform(X_train['winery']).reshape(-1,1)
X_cv_winery = label_encoder.transform(X_cv['winery']).reshape(-1,1)
X_test_winery = label_encoder.transform(X_test['winery']).reshape(-1,1)


print("After Label Encodeing")
print('Train Shape : X', X_train_winery.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv_winery.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_winery.shape, ', y', y_test.shape)

print("="*100)

features_names_set1.append(1)
features_names_set2.append(1)


print('\nfeatures_names_set1 :', len(features_names_set1))
print('features_names_set2 :', len(features_names_set2))
```

```
After Label Encodeing
Train Shape : X (34837, 1) , y (34837,)
CV Shape    : X (17160, 1) , y (17160,)
Test Shape  : X (25611, 1) , y (25611,)
======================================================================
==============================

features_names_set1 : 40
features_names_set2 : 40
```

3. Encoding Numerical Features

1. points
2. price

In [39]:

```
# Normalize points
normalizer = Normalizer()

# print(X_train['points'].shape)
# o/p : (34837,)  need to reshape
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96  96.01 ... 368.98  80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature    (column)
# array.reshape(1, -1)  if it contains a single sample.    (row)

normalizer.fit(X_train['points'].values.reshape(-1,1))

X_train_points_norm = normalizer.transform(X_train['points'].values.reshape(-1,1))
X_cv_points_norm = normalizer.transform(X_cv['points'].values.reshape(-1,1))
X_test_points_norm = normalizer.transform(X_test['points'].values.reshape(-1,1))


print("After Label Encodeing")
print('Train Shape : X', X_train_points_norm.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv_points_norm.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_points_norm.shape, ', y', y_test.shape)

print("="*100)

features_names_set1.append(1)
features_names_set2.append(1)


print('\nfeatures_names_set1 :', len(features_names_set1))
print('features_names_set2 :', len(features_names_set2))
```

```
After Label Encodeing
Train Shape : X (34837, 1) , y (34837,)
CV Shape    : X (17160, 1) , y (17160,)
Test Shape  : X (25611, 1) , y (25611,)
======================================================================
==============================

features_names_set1 : 41
features_names_set2 : 41
```

In [40]:

```
# Normalize price
normalizer = Normalizer()

# print(X_train['points'].shape)
# o/p : (34837,)  need to reshape
# normalizer.fit(X_train['price'].values)
# this will rise an error Expected 2D array, got 1D array instead:
# array=[105.22 215.96  96.01 ... 368.98  80.53 709.67].
# Reshape your data either using
# array.reshape(-1, 1) if your data has a single feature    (column)
# array.reshape(1, -1)  if it contains a single sample.    (row)

normalizer.fit(X_train['price'].values.reshape(-1,1))

X_train_price_norm = normalizer.transform(X_train['price'].values.reshape(-1,1))
X_cv_price_norm = normalizer.transform(X_cv['price'].values.reshape(-1,1))
X_test_price_norm = normalizer.transform(X_test['price'].values.reshape(-1,1))


print("After Label Encodeing")
print('Train Shape : X', X_train_price_norm.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv_price_norm.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_price_norm.shape, ', y', y_test.shape)

print("="*100)

features_names_set1.append(1)
features_names_set2.append(1)


print('\nfeatures_names_set1 :', len(features_names_set1))
print('features_names_set2 :', len(features_names_set2))
```

```
After Label Encodeing
Train Shape : X (34837, 1) , y (34837,)
CV Shape    : X (17160, 1) , y (17160,)
Test Shape  : X (25611, 1) , y (25611,)
======================================================================
==============================

features_names_set1 : 42
features_names_set2 : 42
```

4. BoW

1. review_title
2. review_description

In [41]:

```
# Bag of Word for review_title

vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X_train['review_title'].values) # fit has to happen only on train da

# we use the fitted CountVectorizer to convert the text to vector
X_train_review_title_bow = vectorizer.transform(X_train['review_title'].values)
X_cv_review_title_bow = vectorizer.transform(X_cv['review_title'].values)
X_test_review_title_bow = vectorizer.transform(X_test['review_title'].values)



print("After Vectorizations")
print('Train Shape : X', X_train_review_title_bow.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv_review_title_bow.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_review_title_bow.shape, ', y', y_test.shape)

print("="*100)

for i in vectorizer.get_feature_names():
    features_names_set1.append(i)


print('\nfeatures_names_set1 :', len(features_names_set1))
```

```
After Vectorizations
Train Shape : X (34837, 5000) , y (34837,)
CV Shape    : X (17160, 5000) , y (17160,)
Test Shape  : X (25611, 5000) , y (25611,)
======================================================================
==============================

features_names_set1 : 5042
```

In [42]:

```
# Bag of Word for review_description

vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X_train['review_description'].values) # fit has to happen only on tr

# we use the fitted CountVectorizer to convert the text to vector
X_train_review_description_bow = vectorizer.transform(X_train['review_description']
X_cv_review_description_bow = vectorizer.transform(X_cv['review_description'].value
X_test_review_description_bow = vectorizer.transform(X_test['review_description'].v



print("After Vectorizations")
print('Train Shape : X', X_train_review_description_bow.shape, ', y', y_train.shape
print('CV Shape    : X', X_cv_review_description_bow.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_review_description_bow.shape, ', y', y_test.shape)

print("="*100)

for i in vectorizer.get_feature_names():
    features_names_set1.append(i)


print('\nfeatures_names_set1 :', len(features_names_set1))
```

```
After Vectorizations
Train Shape : X (34837, 5000) , y (34837,)
CV Shape    : X (17160, 5000) , y (17160,)
Test Shape  : X (25611, 5000) , y (25611,)
======================================================================
==============================

features_names_set1 : 10042
```

4. TF-IDF

1. review_title
2. review_description

In [43]:

```
# TF-IDF of review_title

# We are considering only the words which appeared in at least 10 documents(rows or
vectorizer = TfidfVectorizer(min_df=10)# its a countvectors used for convert text t
vectorizer.fit(X_train['review_title'].values)# that is learned from trainned data

# we use the fitted CountVectorizer to convert the text to vector
X_train_review_title_tf = vectorizer.transform(X_train['review_title'].values)
X_cv_review_title_tf= vectorizer.transform(X_cv['review_title'].values)
X_test_review_title_tf = vectorizer.transform(X_test['review_title'].values)


print("After Vectorizations")
print('Train Shape : X', X_train_review_title_tf.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv_review_title_tf.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_review_title_tf.shape, ', y', y_test.shape)

print("="*100)

for i in vectorizer.get_feature_names():
    features_names_set2.append(i)

print('\nfeatures_names_set2 :', len(features_names_set2))
```

```
After Vectorizations
Train Shape : X (34837, 2352) , y (34837,)
CV Shape    : X (17160, 2352) , y (17160,)
Test Shape  : X (25611, 2352) , y (25611,)
======================================================================
==============================

features_names_set2 : 2394
```

In [44]:

```
# TF-IDF of review_description

# We are considering only the words which appeared in at least 10 documents(rows or
vectorizer = TfidfVectorizer(min_df=10)# its a countvectors used for convert text t
vectorizer.fit(X_train['review_description'].values)# that is learned from trainned

# we use the fitted CountVectorizer to convert the text to vector
X_train_review_description_tf = vectorizer.transform(X_train['review_description'].
X_cv_review_description_tf= vectorizer.transform(X_cv['review_description'].values)
X_test_review_description_tf = vectorizer.transform(X_test['review_description'].va


print("After Vectorizations")
print('Train Shape : X', X_train_review_description_tf.shape, ', y', y_train.shape)
print('CV Shape    : X', X_cv_review_description_tf.shape, ', y', y_cv.shape)
print('Test Shape  : X', X_test_review_description_tf.shape, ', y', y_test.shape)

print("="*100)

for i in vectorizer.get_feature_names():
    features_names_set2.append(i)

print('\nfeatures_names_set2 :', len(features_names_set2))
```

```
After Vectorizations
Train Shape : X (34837, 4861) , y (34837,)
CV Shape    : X (17160, 4861) , y (17160,)
Test Shape  : X (25611, 4861) , y (25611,)
======================================================================
==============================

features_names_set2 : 7255
```

Concatinating all the features (Set1)

In [45]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack

# Train
X_train_set1 = hstack((X_train_country, X_train_province, X_train_winery, X_train_p
               X_train_price_norm, X_train_review_title_bow, X_train_review_descrip

# Cross-Validation
X_cv_set1 = hstack((X_cv_country, X_cv_province, X_cv_winery, X_cv_points_norm, X_c
               X_cv_review_title_bow, X_cv_review_description_bow)).tocsr()

# Test
X_test_set1 = hstack((X_test_country, X_test_province, X_test_winery, X_test_points
               X_test_price_norm, X_test_review_title_bow, X_test_review_descriptio
#
#

#
#
print("Final Data matrix")
print(X_train_set1.shape, y_train.shape)
print(X_cv_set1.shape, y_cv.shape)
print(X_test_set1.shape, y_test.shape)
print("="*100)
```

```
Final Data matrix
(34837, 10042) (34837,)
(17160, 10042) (17160,)
(25611, 10042) (25611,)
======================================================================
==============================
```

Concatinating all the features (Set2)

In [46]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack

# Train
X_train_set2 = hstack((X_train_country, X_train_province, X_train_winery, X_train_p
               X_train_price_norm, X_train_review_title_tf, X_train_review_descript

# Cross-Validation
X_cv_set2 = hstack((X_cv_country, X_cv_province, X_cv_winery, X_cv_points_norm, X_c
               X_cv_review_title_tf, X_cv_review_description_tf)).tocsr()

# Test
X_test_set2 = hstack((X_test_country, X_test_province, X_test_winery, X_test_points
               X_test_price_norm, X_test_review_title_tf, X_test_review_description
#
#

#
#
#
print("Final Data matrix")
print(X_train_set2.shape, y_train.shape)
print(X_cv_set2.shape, y_cv.shape)
print(X_test_set2.shape, y_test.shape)
print("="*100)
```

```
Final Data matrix
(34837, 7255) (34837,)
(17160, 7255) (17160,)
(25611, 7255) (25611,)
======================================================================
==============================
```

Applying Model (XGBClassifier) on Train Data

- I use the XGBClassifier based on type of Data

Using Bag Of Word (Set1)

Find Best Hyperparameters Using RandomizedSearchCV

- In XGBClassifier, Hyperparameters are 'n_estimators' and 'learning_rate'

In [123]:

```
gbdt = XGBClassifier(objective='multi:softmax')

grid_params = {'n_estimators': [10, 50, 100, 150, 200], 'learning_rate':[0.0001, 0.

rs_cv_set1 = RandomizedSearchCV(gbdt,grid_params ,cv=3, scoring='roc_auc_ovr', n_jo
rs_cv_set1.fit(X_train_set1, y_train)
```

Out[123]:

```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=XGBClassifier(base_score=None, booster=No
ne,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamm
a=None,
                                           gpu_id=None, importance_typ
e='gain',
                                           interaction_constraints=Non
e,
                                           learning_rate=None,
                                           max_delta_step=None, max_de
pth=None,
                                           min_child_weight=None, miss
ing=nan,
                                           monotone_constraints=None,
                                           n...
                                           reg_lambda=None,
                                           scale_pos_weight=None,
                                           subsample=None, tree_method
=None,
                                           validate_parameters=False,
                                           verbosity=None),
                   iid='deprecated', n_iter=10, n_jobs=-1,
                   param_distributions={'learning_rate': [0.0001, 0.00
1, 0.01,
                                                          0.1],
                                        'n_estimators': [10, 50, 100,
150,
                                                         200]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=T
rue,
                   return_train_score=False, scoring='roc_auc_ovr', ve
rbose=0)
```

In [121]:

```
from sklearn.externals import joblib

# Save the model as a pickle in a file
# joblib.dump(rs_cv_set1, 'rs_cv_set1.pkl')

# # Load the model from the file
# rs_cv_set1 = joblib.load('rs_cv_set1.pkl')
```

Out[121]:

```
['rs_cv.pkl']
```

The Best Hyperparameters

In [130]:

```
print('Best score: ', rs_cv_set1.best_score_)
print('k value with best score: ', rs_cv_set1.best_params_)
```

```
Best score: 0.9994549063487673
k value with best score: {'n_estimators': 100, 'learning_rate': 0.1}
```

Use Best Hyperparameter and Build Model

In [47]:

```
xgb_set1 = XGBClassifier(objective='multi:softmax', n_estimators=100, learning_rate

xgb_set1.fit(X_train_set1, y_train)
```

Out[47]:

```
XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=
-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.1, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints=No
ne,
              n_estimators=100, n_jobs=0, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method=None, validate_parameters=False, verbosity=N
one)
```

In [49]:

```
from sklearn.externals import joblib

# Save the model as a pickle in a file
joblib.dump(xgb_set1, 'xgb_model_set1.pkl')

# # Load the model from the file
# xgb_set1 = joblib.load('xgb_model_set1.pkl')
```

Out[49]:

```
['xgb_model_set1.pkl']
```

In [66]:

```

```

Predict Cross Validation Data

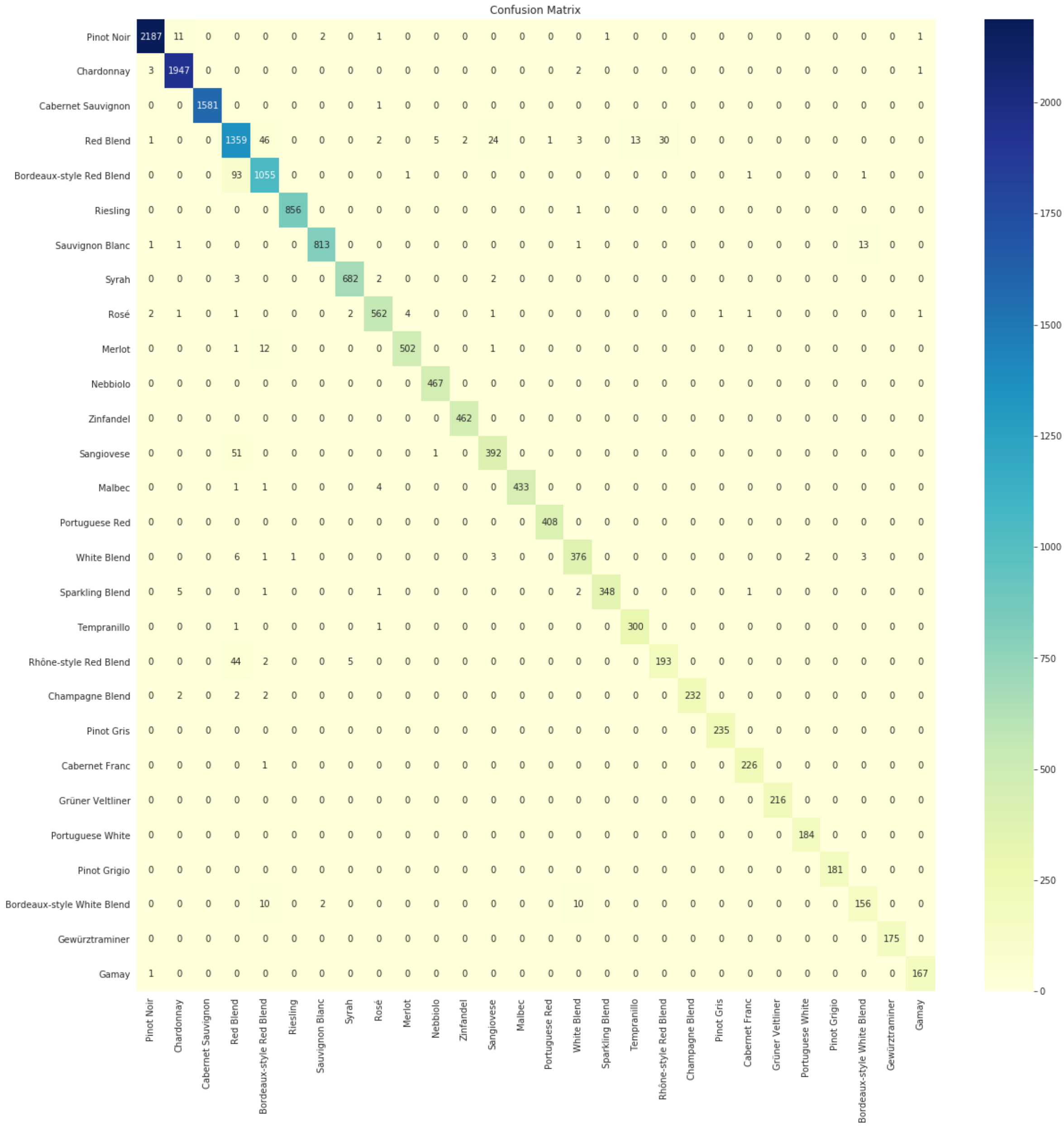
In [50]:

```
y_cv_set1_pred = xgb_set1.predict(X_cv_set1)
```

Confusion Matrix For Cross Validation Data

In [51]:

```
CM = confusion_matrix(y_cv, y_cv_set1_pred)

plt.figure(figsize=(20, 20))
ax = plt.axes()
sns.heatmap(CM, annot=True, xticklabels=list(target_classes.keys()), yticklabels=li
ax.set_title('Confusion Matrix')
plt.show()
```



Detail Report For Cross Validation Accuracy

In [52]:

```
print(classification_report(y_cv, y_cv_set1_pred, target_names=list(target_classes.
```

```
                            precision    recall  f1-score   support

                Pinot Noir       1.00      0.99      0.99      2203
                Chardonnay       0.99      1.00      0.99      1953
        Cabernet Sauvignon       1.00      1.00      1.00      1582
                 Red Blend       0.87      0.91      0.89      1486
  Bordeaux-style Red Blend       0.93      0.92      0.92      1151
                  Riesling       1.00      1.00      1.00       857
           Sauvignon Blanc       1.00      0.98      0.99       829
                     Syrah       0.99      0.99      0.99       689
                      Rosé       0.98      0.98      0.98       576
                    Merlot       0.99      0.97      0.98       516
                  Nebbiolo       0.99      1.00      0.99       467
                 Zinfandel       1.00      1.00      1.00       462
                Sangiovese       0.93      0.88      0.90       444
                    Malbec       1.00      0.99      0.99       439
            Portuguese Red       1.00      1.00      1.00       408
               White Blend       0.95      0.96      0.96       392
           Sparkling Blend       1.00      0.97      0.98       358
               Tempranillo       0.96      0.99      0.98       302
      Rhône-style Red Blend       0.87      0.79      0.83       244
           Champagne Blend       1.00      0.97      0.99       238
                Pinot Gris       1.00      1.00      1.00       235
            Cabernet Franc       0.99      1.00      0.99       227
           Grüner Veltliner       1.00      1.00      1.00       216
          Portuguese White       0.99      1.00      0.99       184
              Pinot Grigio       1.00      1.00      1.00       181
Bordeaux-style White Blend       0.90      0.88      0.89       178
             Gewürztraminer       1.00      1.00      1.00       175
                     Gamay       0.98      0.99      0.99       168

                  accuracy                           0.97     17160
                 macro avg       0.97      0.97      0.97     17160
              weighted avg       0.97      0.97      0.97     17160
```

Predict Test Data

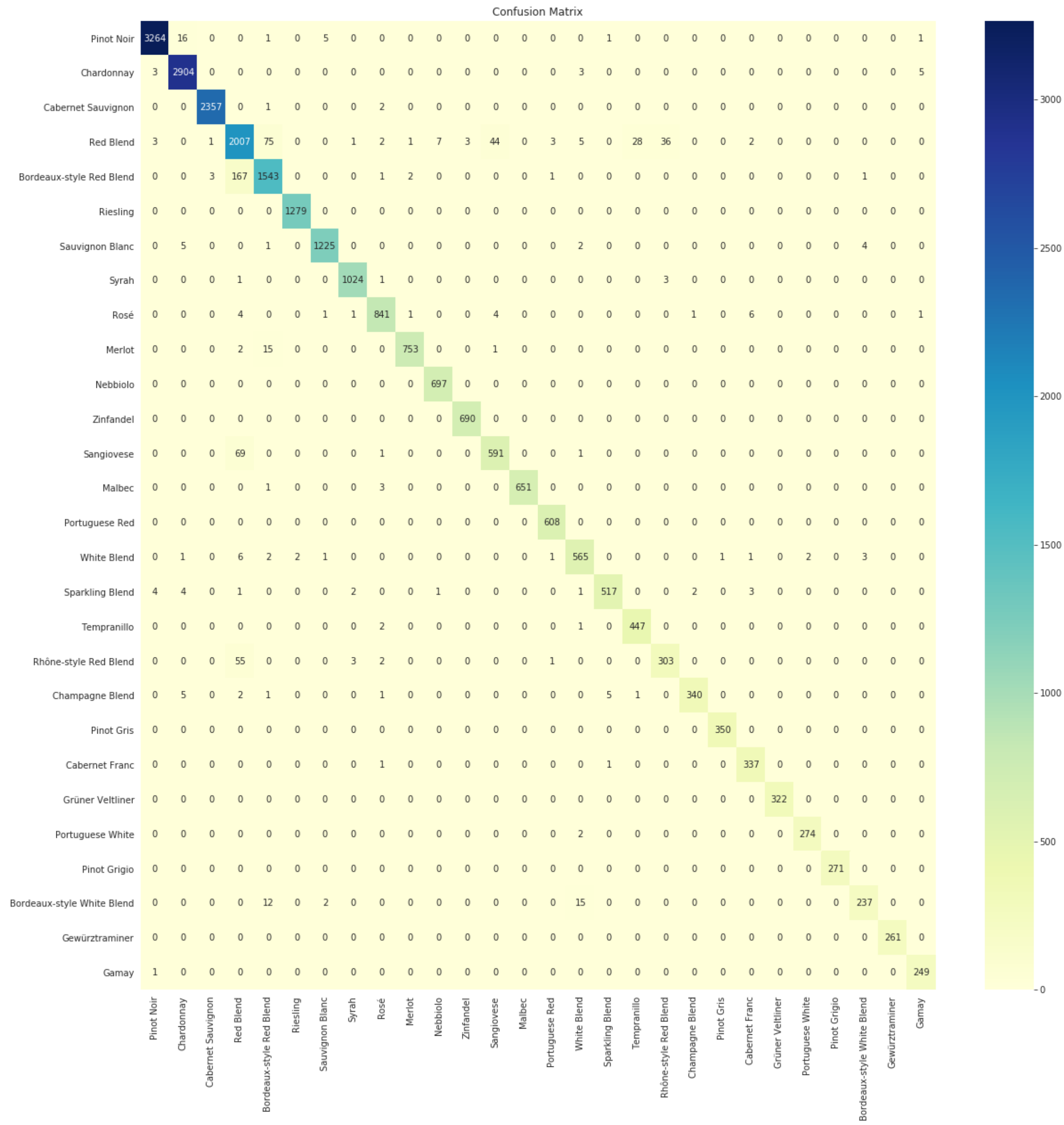
In [53]:

```
y_test_set1_pred = xgb_set1.predict(X_test_set1)
```

Confusion Matrix For Cross Validation Data

In [54]:

```
CM = confusion_matrix(y_test, y_test_set1_pred)

plt.figure(figsize=(20, 20))
ax = plt.axes()
sns.heatmap(CM, annot=True, xticklabels=list(target_classes.keys()), yticklabels=li
ax.set_title('Confusion Matrix')
plt.show()
```



Detail Report For Test Accuracy

In [55]:

```
print(classification_report(y_test, y_test_set1_pred, target_names=list(target_clas
```

```
                           precision    recall  f1-score   support

               Pinot Noir       1.00      0.99      0.99      3288
               Chardonnay       0.99      1.00      0.99      2915
       Cabernet Sauvignon       1.00      1.00      1.00      2360
                Red Blend       0.87      0.90      0.89      2218
 Bordeaux-style Red Blend       0.93      0.90      0.92      1718
                 Riesling       1.00      1.00      1.00      1279
          Sauvignon Blanc       0.99      0.99      0.99      1237
                    Syrah       0.99      1.00      0.99      1029
                     Rosé       0.98      0.98      0.98       860
                   Merlot       0.99      0.98      0.99       771
                 Nebbiolo       0.99      1.00      0.99       697
                Zinfandel       1.00      1.00      1.00       690
               Sangiovese       0.92      0.89      0.91       662
                   Malbec       1.00      0.99      1.00       655
           Portuguese Red       0.99      1.00      1.00       608
              White Blend       0.95      0.97      0.96       585
          Sparkling Blend       0.99      0.97      0.98       535
              Tempranillo       0.94      0.99      0.97       450
   Rhône-style Red Blend       0.89      0.83      0.86       364
           Champagne Blend       0.99      0.96      0.97       355
               Pinot Gris       1.00      1.00      1.00       350
           Cabernet Franc       0.97      0.99      0.98       339
          Grüner Veltliner       1.00      1.00      1.00       322
         Portuguese White       0.99      0.99      0.99       276
             Pinot Grigio       1.00      1.00      1.00       271
Bordeaux-style White Blend       0.97      0.89      0.93       266
            Gewürztraminer       1.00      1.00      1.00       261
                    Gamay       0.97      1.00      0.98       250

                 accuracy                           0.97     25611
                macro avg       0.97      0.97      0.97     25611
             weighted avg       0.97      0.97      0.97     25611
```

Using TF-IDF (Set2)

Find Best Hyperparameters Using RandomizedSearchCV

- In XGBClassifier, Hyperparameters are 'n_estimators' and 'learning_rate'

In [125]:

```
gbdt = XGBClassifier(objective='multi:softmax')

grid_params = {'n_estimators': [10, 50, 100, 150, 200], 'learning_rate':[0.0001, 0.

rs_cv_set2 = RandomizedSearchCV(gbdt, grid_params, cv=3, scoring='roc_auc_ovr', n_j
rs_cv_set2.fit(X_train_set2, y_train)
```

Out[125]:

```
RandomizedSearchCV(cv=3, error_score=nan,
                   estimator=XGBClassifier(base_score=None, booster=No
ne,
                                           colsample_bylevel=None,
                                           colsample_bynode=None,
                                           colsample_bytree=None, gamm
a=None,
                                           gpu_id=None, importance_typ
e='gain',
                                           interaction_constraints=Non
e,
                                           learning_rate=None,
                                           max_delta_step=None, max_de
pth=None,
                                           min_child_weight=None, miss
ing=nan,
                                           monotone_constraints=None,
                                           n...
                                           reg_lambda=None,
                                           scale_pos_weight=None,
                                           subsample=None, tree_method
=None,
                                           validate_parameters=False,
                                           verbosity=None),
                   iid='deprecated', n_iter=10, n_jobs=-1,
                   param_distributions={'learning_rate': [0.0001, 0.00
1, 0.01,
                                                          0.1],
                                        'n_estimators': [10, 50, 100,
150,
                                                         200]},
                   pre_dispatch='2*n_jobs', random_state=None, refit=T
rue,
                   return_train_score=False, scoring='roc_auc_ovr', ve
rbose=0)
```

The Best Hyperparameters

In [127]:

```
print('Best score: ',rs_cv_set2.best_score_)
print('k value with best score: ',rs_cv_set2.best_params_)
```

```
Best score:  0.9993549068686683
k value with best score:  {'n_estimators': 150, 'learning_rate': 0.1}
```

In [128]:

```
from sklearn.externals import joblib

# Save the model as a pickle in a file
joblib.dump(rs_cv_set2, 'rs_cv_set2.pkl')

# # Load the model from the file
# rs_cv_set2 = joblib.load('rs_cv_set2.pkl')
```

Out[128]:

```
['rs_cv_set2.pkl']
```

Use Best Hyperparameter and Build Model

In [56]:

```
xgb_set2 = XGBClassifier(objective='multi:softmax', n_estimators=150, learning_rate

xgb_set2.fit(X_train_set2, y_train)
```

Out[56]:

```
XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=
-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.1, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints=No
ne,
              n_estimators=150, n_jobs=0, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method=None, validate_parameters=False, verbosity=N
one)
```

In [57]:

```
from sklearn.externals import joblib

# Save the model as a pickle in a file
joblib.dump(xgb_set2, 'xgb_model_set2.pkl')

# # Load the model from the file
# xgb_set2 = joblib.load('xgb_model_set2.pkl')
```

Out[57]:

```
['xgb_model_set2.pkl']
```

Predict Cross Validation Data

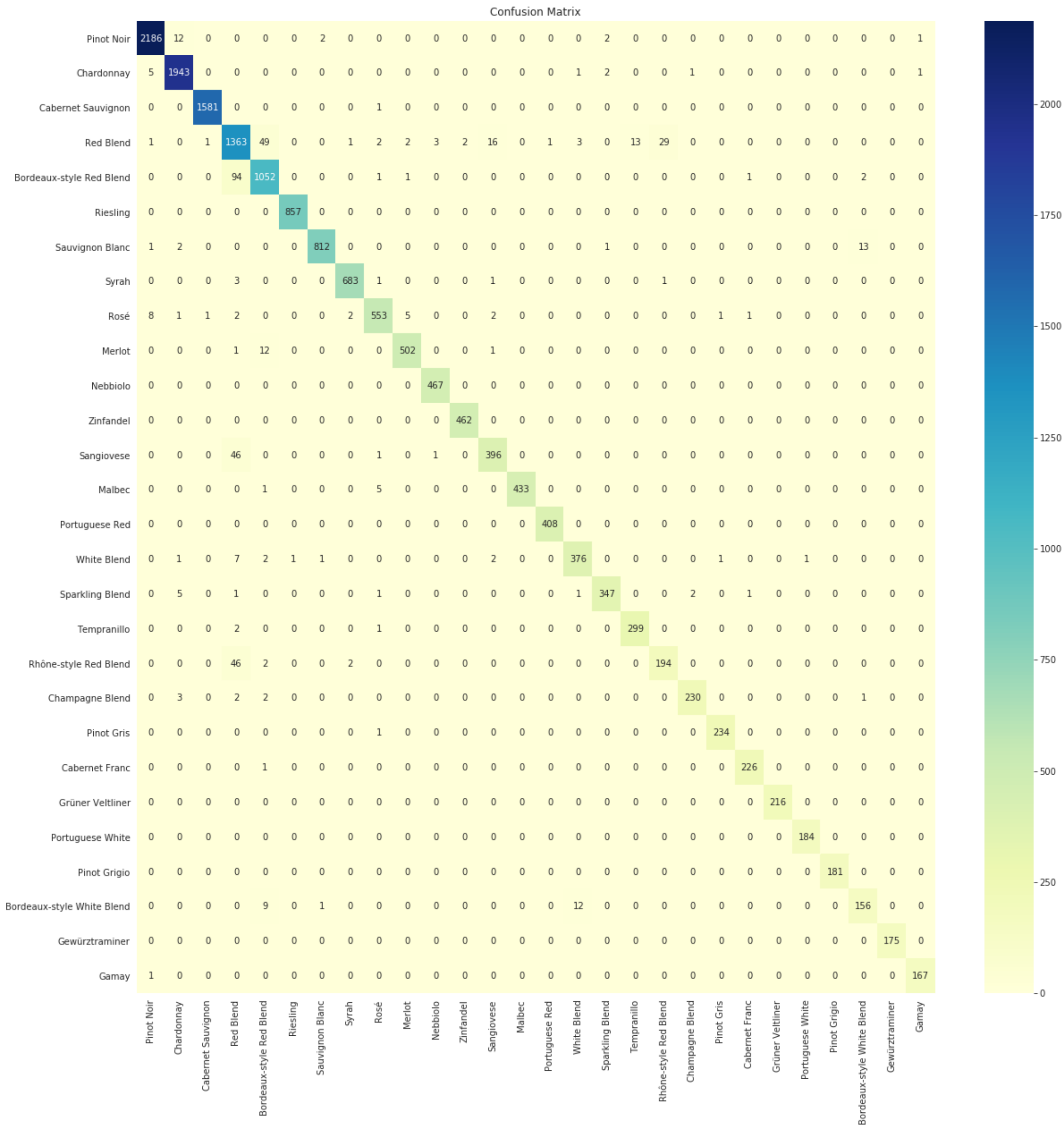
In [58]:

```
y_cv_set2_pred = xgb_set2.predict(X_cv_set2)
```

Confusion Matrix For Cross Validation Data

In [59]:

```
CM = confusion_matrix(y_cv, y_cv_set2_pred)

plt.figure(figsize=(20, 20))
ax = plt.axes()
sns.heatmap(CM, annot=True, xticklabels=list(target_classes.keys()), yticklabels=li
ax.set_title('Confusion Matrix')
plt.show()
```



Detail Report For Cross Validation Accuracy

In [60]:

```
print(classification_report(y_cv, y_cv_set2_pred, target_names=list(target_classes.
```

```
                            precision    recall  f1-score   support

                Pinot Noir       0.99      0.99      0.99      2203
                Chardonnay       0.99      0.99      0.99      1953
        Cabernet Sauvignon       1.00      1.00      1.00      1582
                 Red Blend       0.87      0.92      0.89      1486
  Bordeaux-style Red Blend       0.93      0.91      0.92      1151
                  Riesling       1.00      1.00      1.00       857
           Sauvignon Blanc       1.00      0.98      0.99       829
                     Syrah       0.99      0.99      0.99       689
                      Rosé       0.98      0.96      0.97       576
                    Merlot       0.98      0.97      0.98       516
                  Nebbiolo       0.99      1.00      1.00       467
                 Zinfandel       1.00      1.00      1.00       462
                Sangiovese       0.95      0.89      0.92       444
                    Malbec       1.00      0.99      0.99       439
            Portuguese Red       1.00      1.00      1.00       408
               White Blend       0.96      0.96      0.96       392
           Sparkling Blend       0.99      0.97      0.98       358
               Tempranillo       0.96      0.99      0.97       302
     Rhône-style Red Blend       0.87      0.80      0.83       244
           Champagne Blend       0.99      0.97      0.98       238
                Pinot Gris       0.99      1.00      0.99       235
            Cabernet Franc       0.99      1.00      0.99       227
           Grüner Veltliner      1.00      1.00      1.00       216
          Portuguese White       0.99      1.00      1.00       184
              Pinot Grigio       1.00      1.00      1.00       181
Bordeaux-style White Blend       0.91      0.88      0.89       178
            Gewürztraminer       1.00      1.00      1.00       175
                     Gamay       0.99      0.99      0.99       168

                  accuracy                           0.97     17160
                 macro avg       0.97      0.97      0.97     17160
              weighted avg       0.97      0.97      0.97     17160
```

Predict Test Data

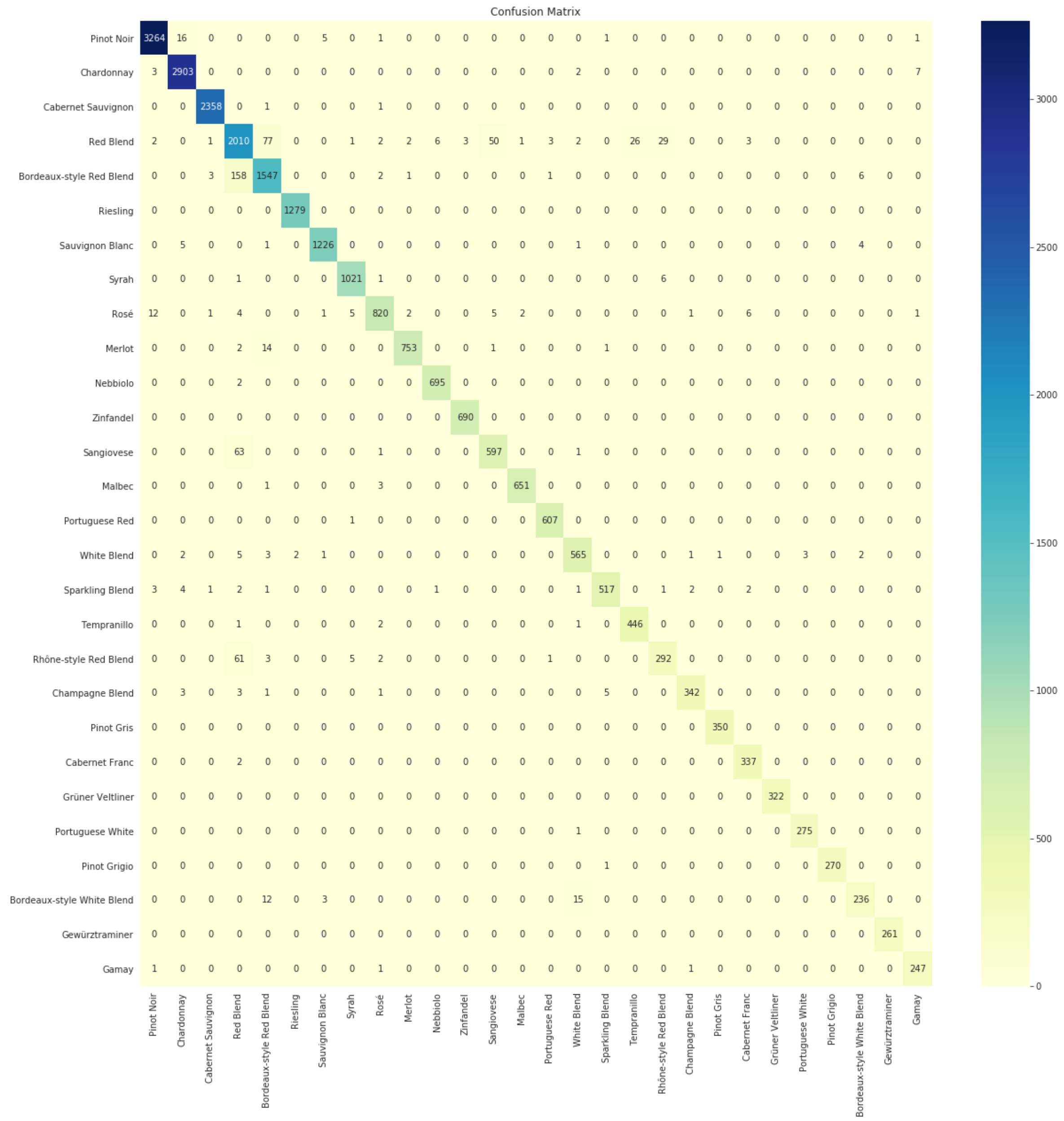
In [61]:

```
y_test_set2_pred = xgb_set2.predict(X_test_set2)
```

Confusion Matrix For Test Data

In [62]:

```
CM = confusion_matrix(y_test, y_test_set2_pred)

plt.figure(figsize=(20, 20))
ax = plt.axes()
sns.heatmap(CM, annot=True, xticklabels=list(target_classes.keys()), yticklabels=li
ax.set_title('Confusion Matrix')
plt.show()
```



Detail Report For Test Accuracy

In [63]:

```
print(classification_report(y_test, y_test_set2_pred, target_names=list(target_clas
```

```
                            precision    recall  f1-score   support

               Pinot Noir       0.99      0.99      0.99      3288
               Chardonnay       0.99      1.00      0.99      2915
       Cabernet Sauvignon       1.00      1.00      1.00      2360
                Red Blend       0.87      0.91      0.89      2218
 Bordeaux-style Red Blend       0.93      0.90      0.92      1718
                 Riesling       1.00      1.00      1.00      1279
          Sauvignon Blanc       0.99      0.99      0.99      1237
                    Syrah       0.99      0.99      0.99      1029
                     Rosé       0.98      0.95      0.97       860
                   Merlot       0.99      0.98      0.98       771
                 Nebbiolo       0.99      1.00      0.99       697
                Zinfandel       1.00      1.00      1.00       690
               Sangiovese       0.91      0.90      0.91       662
                   Malbec       1.00      0.99      0.99       655
           Portuguese Red       0.99      1.00      1.00       608
              White Blend       0.96      0.97      0.96       585
          Sparkling Blend       0.98      0.97      0.98       535
              Tempranillo       0.94      0.99      0.97       450
    Rhône-style Red Blend       0.89      0.80      0.84       364
          Champagne Blend       0.99      0.96      0.97       355
               Pinot Gris       1.00      1.00      1.00       350
           Cabernet Franc       0.97      0.99      0.98       339
           Grüner Veltliner     1.00      1.00      1.00       322
         Portuguese White       0.99      1.00      0.99       276
             Pinot Grigio       1.00      1.00      1.00       271
Bordeaux-style White Blend       0.95      0.89      0.92       266
             Gewürztraminer     1.00      1.00      1.00       261
                    Gamay       0.96      0.99      0.98       250

                 accuracy                           0.97     25611
                macro avg       0.97      0.97      0.97     25611
             weighted avg       0.97      0.97      0.97     25611
```

In [ ]:

Conclusion

- From above Confusion Matrix and Classification Report the acccuracy of both Set1(i.e, using BoW) & Set2(i.e, using TF-IDF) have near about same accuracy.
- So we can use either BOF or TF-IDF.
- Here, I use both and create CSV.

In [ ]:

Prepare Data for Final Model (Use All Train Data & Unseen Test Data)

1. One Hot Encoding

1. country

In [64]:

```
# One hot Encoding for country
print("Before Vectorizations")
print('Train Shape : X', X.shape, ', y', y.shape)
print('Test Shape  : X', test_df.shape)

print("="*100)

vectorizer = CountVectorizer(max_features=5000)
vectorizer.fit(X['country'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
train_country = vectorizer.transform(X['country'].values)
test_country = vectorizer.transform(test_df['country'].values)


print("After Vectorizations")
print('Train Shape : X', train_country.shape, ', y', y.shape)
print('Test Shape  : X', test_country.shape)

print("="*100)
print(vectorizer.get_feature_names())
```

```
Before Vectorizations
Train Shape : X (77608, 7) , y (77608,)
Test Shape  : X (20661, 7)
======================================================================
==============================
After Vectorizations
Train Shape : X (77608, 38) , y (77608,)
Test Shape  : X (20661, 38)
======================================================================
==============================
['argentina', 'australia', 'austria', 'brazil', 'bulgaria', 'canada',
'chile', 'croatia', 'cyprus', 'czech_republic', 'england', 'france',
'georgia', 'germany', 'greece', 'hungary', 'india', 'israel', 'italy',
'lebanon', 'luxembourg', 'macedonia', 'mexico', 'moldova', 'morocco',
'new_zealand', 'peru', 'portugal', 'romania', 'serbia', 'slovenia', 's
outh_africa', 'spain', 'switzerland', 'turkey', 'ukraine', 'uruguay',
'us']
```

2. Label Encoding

1. province
2. winery

In [65]:

```
# Label Encoding for province

label_encoder = LabelEncoderExt()
label_encoder.fit(X['province']) # fit has to happen only on train data

# we use the LabelEncoder to convert the categorical data to numerical
train_province = label_encoder.transform(X['province']).reshape(-1,1)
test_province = label_encoder.transform(test_df['province']).reshape(-1,1)

print("After Label Encodeing")
print('Train Shape : X', train_province.shape, ', y', y.shape)
print('Test Shape  : X', test_province.shape)
```

```
After Label Encodeing
Train Shape : X (77608, 1) , y (77608,)
Test Shape  : X (20661, 1)
```

In [66]:

```
# Label Encoding for winery

label_encoder = LabelEncoderExt()
label_encoder.fit(X['winery']) # fit has to happen only on train data

# we use the LabelEncoder to convert the categorical data to numerical
train_winery = label_encoder.transform(X['winery']).reshape(-1,1)
test_winery = label_encoder.transform(test_df['winery']).reshape(-1,1)

print("After Label Encodeing")
print('Train Shape : X', train_winery.shape, ', y', y.shape)
print('Test Shape  : X', test_winery.shape)
```

```
After Label Encodeing
Train Shape : X (77608, 1) , y (77608,)
Test Shape  : X (20661, 1)
```

3. Encoding Numerical Features

1. points
2. price

In [67]:

```
# Normalize points
normalizer = Normalizer()

normalizer.fit(X['points'].values.reshape(-1,1))

train_points_norm = normalizer.transform(X['points'].values.reshape(-1,1))
test_points_norm = normalizer.transform(test_df['points'].values.reshape(-1,1))


print("After Label Encodeing")
print('Train Shape : X', train_points_norm.shape, ', y', y.shape)
print('Test Shape  : X', test_points_norm.shape)
```

```
After Label Encodeing
Train Shape : X (77608, 1) , y (77608,)
Test Shape  : X (20661, 1)
```

In [68]:

```
# Normalize price
normalizer = Normalizer()

normalizer.fit(X['price'].values.reshape(-1,1))

train_price_norm = normalizer.transform(X['price'].values.reshape(-1,1))
test_price_norm = normalizer.transform(test_df['price'].values.reshape(-1,1))


print("After Label Encodeing")
print('Train Shape : X', train_price_norm.shape, ', y', y.shape)
print('Test Shape  : X', test_price_norm.shape)
```

```
After Label Encodeing
Train Shape : X (77608, 1) , y (77608,)
Test Shape  : X (20661, 1)
```

4. BoW

1. review_title
2. review_description

In [69]:

```
# Bag of Word for review_title

vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X['review_title'].values) # fit has to happen only on train data

# we use the fitted CountVectorizer to convert the text to vector
train_review_title_bow = vectorizer.transform(X['review_title'].values)
test_review_title_bow = vectorizer.transform(test_df['review_title'].values)


print("After Vectorizations")
print('Train Shape : X', train_review_title_bow.shape, ', y', y.shape)
print('Test Shape  : X', test_review_title_bow.shape)
```

```
After Vectorizations
Train Shape : X (77608, 5000) , y (77608,)
Test Shape  : X (20661, 5000)
```

In [70]:

```
# Bag of Word for review_description

vectorizer = CountVectorizer(min_df=10,ngram_range=(1,4), max_features=5000)
vectorizer.fit(X['review_description'].values) # fit has to happen only on train da

# we use the fitted CountVectorizer to convert the text to vector
train_review_description_bow = vectorizer.transform(X['review_description'].values)
test_review_description_bow = vectorizer.transform(test_df['review_description'].va


print("After Vectorizations")
print('Train Shape : X', train_review_description_bow.shape, ', y', y.shape)
print('Test Shape  : X', test_review_description_bow.shape)
```

```
After Vectorizations
Train Shape : X (77608, 5000) , y (77608,)
Test Shape  : X (20661, 5000)
```

4. TF-IDF

1. review_title
2. review_description

In [71]:

```
# TF-IDF of review_title

# We are considering only the words which appeared in at least 10 documents(rows or
vectorizer = TfidfVectorizer(min_df=10)# its a countvectors used for convert text t
vectorizer.fit(X['review_title'].values)# that is learned from trainned data

# we use the fitted CountVectorizer to convert the text to vector
train_review_title_tf = vectorizer.transform(X['review_title'].values)
test_review_title_tf = vectorizer.transform(test_df['review_title'].values)


print("After Vectorizations")
print('Train Shape : X', train_review_title_tf.shape, ', y', y.shape)
print('Test Shape  : X', test_review_title_tf.shape)
```

```
After Vectorizations
Train Shape : X (77608, 4752) , y (77608,)
Test Shape  : X (20661, 4752)
```

In [72]:

```
# TF-IDF of review_description

# We are considering only the words which appeared in at least 10 documents(rows or
vectorizer = TfidfVectorizer(min_df=10)# its a countvectors used for convert text t
vectorizer.fit(X['review_description'].values)# that is learned from trainned data

# we use the fitted CountVectorizer to convert the text to vector
train_review_description_tf = vectorizer.transform(X['review_description'].values)
test_review_description_tf = vectorizer.transform(test_df['review_description'].val


print("After Vectorizations")
print('Train Shape : X', train_review_description_tf.shape, ', y', y.shape)
print('Test Shape  : X', test_review_description_tf.shape)
```

```
After Vectorizations
Train Shape : X (77608, 7128) , y (77608,)
Test Shape  : X (20661, 7128)
```

Concatinating all the features (BoW)

In [73]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack

# Train
train_bow = hstack((train_country, train_province, train_winery, train_points_norm,
               train_price_norm, train_review_title_bow, train_review_description_b

# Test
test_bow = hstack((test_country, test_province, test_winery, test_points_norm,
               test_price_norm, test_review_title_bow, test_review_description_bow)



print("Final Data matrix")
print(train_bow.shape, y.shape)
print(test_bow.shape)
```

```
Final Data matrix
(77608, 10042) (77608,)
(20661, 10042)
```

Concatinating all the features (TF-IDF)

In [74]:

```
# merge two sparse matrices: https://stackoverflow.com/a/19710648/4084039
from scipy.sparse import hstack

# Train
train_tfidf = hstack((train_country, train_province, train_winery, train_points_nor
               train_price_norm, train_review_title_tf, train_review_description_tf

# Test
test_tfidf = hstack((test_country, test_province, test_winery, test_points_norm,
               test_price_norm, test_review_title_tf, test_review_description_tf)).



print("Final Data matrix")
print(train_tfidf.shape, y.shape)
print(test_tfidf.shape)
```

```
Final Data matrix
(77608, 11922) (77608,)
(20661, 11922)
```

Train Model (using BoW)

In [75]:

```
xgb_bow = XGBClassifier(objective='multi:softmax', n_estimators=100, learning_rate=

xgb_bow.fit(train_bow, y)
```

Out[75]:

```
XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=
-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.1, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints=No
ne,
              n_estimators=100, n_jobs=0, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method=None, validate_parameters=False, verbosity=N
one)
```

Predict (BoW)

In [76]:

```
test_bow_pred = xgb_bow.predict(test_bow)
```

Create Dataframe (BoW)

In [77]:

```
test_bow_pred_df = pd.DataFrame({'variety': test_bow_pred})

# Convert Numerical Label to Categorical
inv_map_target_dict = dict(zip(target_dict.values(), target_dict.keys()))

test_bow_pred_df = test_bow_pred_df.replace({'variety': inv_map_target_dict})
```

In [78]:

```
predicted_test_bow_df = pd.concat([test_df, test_bow_pred_df], axis=1)
predicted_test_bow_df.head()
```

Out[78]:

	country	review_title	review_description	points	price	province	winery	variety
0	US	Boedecker Cellars 2011 Athena Pinot Noir (Will...	Nicely differentiated from the companion Stewa...	88	35.0	Oregon	Boedecker Cellars	Pinot Noir
1	Argentina	Mendoza Vineyards 2012 Gran Reserva by Richard...	Charred, smoky, herbal aromas of blackberry tr...	90	60.0	Mendoza Province	Mendoza Vineyards	Malbec
2	US	Prime 2013 Chardonnay (Coombsville)	Slightly sour and funky in earth, this is a re...	87	38.0	California	Prime	Chardonnay
3	Argentina	Bodega Cuarto Dominio 2012 Chento Vineyard Sel...	This concentrated, midnight-black Malbec deliv...	91	20.0	Mendoza Province	Bodega Cuarto Dominio	Malbec
4	Italy	SassodiSole 2012 Brunello di Montalcino	Earthy aromas suggesting grilled porcini, leat...	90	49.0	Tuscany	SassodiSole	Sangiovese

Make CSV (BoW)

In [79]:

```
predicted_test_bow_df.to_csv('predicted_test_bow.csv', index=False)
```

Train Model (using TF-IDF)

In [80]:

```
xgb_tfidf = XGBClassifier(objective='multi:softmax', n_estimators=150, learning_rat

xgb_tfidf.fit(train_tfidf, y)
```

Out[80]:

```
XGBClassifier(base_score=0.5, booster=None, colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0, gpu_id=
-1,
              importance_type='gain', interaction_constraints=None,
              learning_rate=0.1, max_delta_step=0, max_depth=6,
              min_child_weight=1, missing=nan, monotone_constraints=No
ne,
              n_estimators=150, n_jobs=0, num_parallel_tree=1,
              objective='multi:softprob', random_state=0, reg_alpha=0,
              reg_lambda=1, scale_pos_weight=None, subsample=1,
              tree_method=None, validate_parameters=False, verbosity=N
one)
```

Predict (TF-IDF)

In [81]:

```
test_tfidf_pred = xgb_tfidf.predict(test_tfidf)
```

Create Dataframe (TF-IDF)

In [82]:

```
test_tfidf_pred_df = pd.DataFrame({'variety': test_bow_pred})

# Convert Numerical Label to Categorical
inv_map_target_dict = dict(zip(target_dict.values(), target_dict.keys()))

test_tfidf_pred_df = test_tfidf_pred_df.replace({'variety': inv_map_target_dict})
```

In [83]:

```
predicted_test_tfidf_df = pd.concat([test_df, test_tfidf_pred_df], axis=1)
predicted_test_tfidf_df
```

Out[83]:

	country	review_title	review_description	points	price	province	winery	
0	US	Boedecker Cellars 2011 Athena Pinot Noir (Will...	Nicely differentiated from the companion Stewa...	88	35.0	Oregon	Boedecker Cellars	Pir
1	Argentina	Mendoza Vineyards 2012 Gran Reserva by Richard...	Charred, smoky, herbal aromas of blackberry tr...	90	60.0	Mendoza Province	Mendoza Vineyards	
2	US	Prime 2013 Chardonnay (Coombsville)	Slightly sour and funky in earth, this is a re...	87	38.0	California	Prime	Chard
3	Argentina	Bodega Cuarto Dominio 2012 Chento Vineyard Sel...	This concentrated, midnight-black Malbec deliv...	91	20.0	Mendoza Province	Bodega Cuarto Dominio	
4	Italy	SassodiSole 2012 Brunello di Montalcino	Earthy aromas suggesting grilled porcini, leat...	90	49.0	Tuscany	SassodiSole	Sang
...	...	...	...	...	...	...	...	
20656	US	Yorkville Cellars 2013 Rennie Vineyard Caberne...	Clearly focused and fruit-driven, this wine ha...	91	34.0	California	Yorkville Cellars	Ca
20657	France	Château Ribaute 2015 Senhal d'Aric Rosé (Corbi...	Herbal tones of bay and rosemary are upfront o...	84	20.0	Languedoc-Roussillon	Château Ribaute	
20658	US	Daou 2014 Reserve Cabernet Sauvignon (Paso Rob...	Mocha cream, pencil shaving and dried herb aro...	94	85.0	California	Daou	Ca Sau
20659	Spain	Peñascal 2011 Tempranillo Rosé (Vino de la Tie...	Loud citrus and berry aromas precede an overlo...	80	9.0	Northern Spain	Peñascal	
20660	US	Langtry 2005 Tephra Ridge Vineyard Cabernet Sa...	With very ripe fruit and firm tannins, this mo...	87	40.0	California	Langtry	Ca Sau

20661 rows × 8 columns

Make CSV (TF-IDF)

In [ ]:

```
predicted_test_tfidf_df.to_csv('predicted_test_tfidf.csv', index=False)
```

In [ ]:

```

```

In [ ]:

```

```

* Observations *

1. The data is complicated.

2. The data have lots of missed values which affectes on predicion accuracy.

3. So the data need to proper imputation. So I apply folloing Imputation,

   - The feature 'price' have 5281 NaN values.
   - So I fill the most frequent prices of apropreate countries instade of NaN values in 'price'.

4. The data have the most categorical values so based on these type of data I decide to use the XGBClassifier because XGBClassifier doesn't based on distance algorithm.

In [ ]:

```

```