sammy_pardes_final_project

September 1, 2020

[1]:
```
#Sammy Pardes
#IST652
#Final Project
#8/20/2020

#sources:
#https://stackoverflow.com/questions/5552555/
 ↪unicodedecodeerror-invalid-continuation-byte
#https://stackoverflow.com/questions/25146121/
 ↪extracting-just-month-and-year-separately-from-pandas-datetime-column
#https://www.kite.com/python/answers/
 ↪how-to-reorder-columns-in-a-pandas-dataframe-in-python#:~:
 ↪text=Use%20double%20brackets%20to%20reorder,order%20to%20reorder%20the%20columns.
 ↪
#https://stackoverflow.com/questions/19758364/rename-specific-columns-in-pandas
#https://pandas.pydata.org/pandas-docs/stable/reference/api/pandas.DataFrame.
 ↪join.html
#https://stackoverflow.com/questions/48366506/
 ↪calculate-new-column-as-the-mean-of-other-columns-pandas/48366525
#https://stackoverflow.com/questions/17787366/
 ↪setting-yaxis-in-matplotlib-using-pandas
#https://stackoverflow.com/questions/61214512/
 ↪how-to-create-a-grouped-barplot-from-three-columns-in-pandas
#https://stackoverflow.com/questions/31859285/
 ↪rotate-tick-labels-for-seaborn-barplot
#https://stackoverflow.com/questions/34888058/
 ↪changing-width-of-bars-in-bar-chart-created-using-seaborn-factorplot
#https://stackoverflow.com/questions/33227473/
 ↪how-to-set-the-range-of-y-axis-for-a-seaborn-boxplot
#https://stackoverflow.com/questions/42404154/
 ↪increase-tick-label-font-size-in-seaborn
#https://www.marsja.se/how-to-change-size-of-seaborn-plot/
#https://stackoverflow.com/questions/51004029/
 ↪create-a-new-dataframe-based-on-rows-with-a-certain-value
#https://stackoverflow.com/questions/5511708/adding-words-to-nltk-stoplist
#https://stackoverflow.com/questions/45588724/
 ↪generating-word-cloud-for-items-in-a-list-in-python
```

```
#https://www.datacamp.com/community/tutorials/wordcloud-python
#https://www.geeksforgeeks.org/python-sentiment-analysis-using-vader/

#import/install statements
#!pip install vaderSentiment
#!pip install wordcloud
import pandas as pd
import seaborn as sb
from matplotlib import pyplot
import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.tokenize import RegexpTokenizer
from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
from collections import Counter
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
```

[3]:
```
#import data set - wineOnly

wineOnly = pd.read_csv("Wines.csv", encoding = "ISO-8859-1") #load data w/o␣
 ↪reviews from .csv file
#wineOnly.head()
#len(wineOnly)
```

[4]:
```
#data cleaning - wineOnly - drop columns

wineOnly = wineOnly.drop(columns=["Designation", "Vintage"]) #remove␣
 ↪designation and vintage fields
```

[5]:
```
#data cleaning - wineOnly - replace characters, change data types

wineOnly["Price"] = wineOnly["Price"].str.replace("$","") #remove "$" character␣
 ↪from prices
wineOnly["Price"] = wineOnly["Price"].str.replace(",","") #remove "," character␣
 ↪from prices

wineOnly["Price"] = wineOnly["Price"].astype(float) #set Price to have a␣
 ↪datatype of float
wineOnly["Points"] = wineOnly["Points"].astype(int) #set Points to have a␣
 ↪datatype of int
```

[6]:
```
#data cleaning - wineOnly - remove NAs

wineOnly = wineOnly.dropna() #remove any rows with NAs from the data frame
```

[7]:
```
#data cleaning - wineOnly - rename columns

wineOnly.columns = ["country", "county", "points", "price", "province",␣
↪"title", "variety", "winery"] #rename columns
```

[8]:
```
#data cleaning - wineOnly - save clean df

wineOnlyClean = wineOnly #save cleansed version of the data frame in new␣
↪variable

print("There are {:d} wines in the cleansed data set that does not contain␣
↪reviews.".format(len(wineOnlyClean))) #get number of remaining rows

wineOnlyClean.head() #preview of cleansed data frame
```

```
There are 19494 wines in the cleansed data set that does not contain reviews.
```

[8]:

	country	county	points	price	province	title	variety	winery
0	Spain	Cava	88	13.0	Catalonia	L'Arboc NV 1919 Brut Selecció Sparkling (Cava)	Sparkling Blend	L'Arboc
1	Italy	Vernaccia di San Gimignano	87	14.0	Tuscany	Guidi 1929 2015 Vernaccia di San Gimignano	Vernaccia	Guidi 1929
2	Italy	Sangiovese di Romagna Superiore	84	15.0	Central Italy	Poderi dal Nespoli 1929 2011 Prugneto (Sangiov…	Sangiovese	Poderi dal Nespoli 1929
4	France	Rivesaltes	95	350.0	Languedoc-Roussillon	Gérard Bertrand 1945 Legend Vintage Red (Rives…	Red Blend	Gérard Bertrand
11	US	Sonoma Valley	89	170.0	California	Sebastiani 1987 Cherryblock Cabernet Sauvignon…	Cabernet Sauvignon	Sebastiani

[9]:
```
#import data set - wineReviews

wineReviews = pd.read_json("winemag-data-130k-v2.json")
```

[10]:
```
#data cleaning - wineReviews - drop columns

wineReviews = wineReviews.drop(columns=["taster_name", "taster_twitter_handle",␣
↪"region_2", "designation"]) #drop unwanted columns
```

[11]:
```
#data cleaning - wineReviews - remove NAs

wineReviews = wineReviews.dropna() #drop NAs
```

[12]:
```
#data cleaning - wineReviews - change data type

wineReviews["points"] = wineReviews["points"].astype(int) #set points as␣
↪datatype of int
wineReviews["price"] = wineReviews["price"].astype(float)#set price as datatype␣
↪of float
```

[13]:
```
#data cleaning - wineReviews - rename column

wineReviews.rename(columns={"region_1":"county"}, inplace=True) #rename␣
↪region_1 column to county to match other data
```

[14]:
```
#data cleaning - wineReviews - reorder columns

colnames = ["country", "county", "points", "price", "province", "title",␣
↪"variety", "winery", "description"] #define column names list

wineReviews = wineReviews.reindex(columns=colnames) #reorder columns to match␣
↪colnames list (same as wineOnly plus description field)
```

[15]:
```
#data cleaning - wineReviews - save clean df

wineReviewsClean = wineReviews #save cleansed version of the dataframe

print("There are {:d} wines in the cleansed data set that contains reviews.".
↪format(len(wineReviewsClean))) #get number of remaining rows

wineReviewsClean.head() #preview cleansed dataframe
```

```
There are 101400 wines in the cleansed data set that contains reviews.
```

[15]:

	country	county	points	price	province	\
2	US	Willamette Valley	87	14.0	Oregon	
3	US	Lake Michigan Shore	87	13.0	Michigan	
4	US	Willamette Valley	87	65.0	Oregon	
5	Spain	Navarra	87	15.0	Northern Spain	
6	Italy	Vittoria	87	16.0	Sicily & Sardinia	

	title	variety	\
2	Rainstorm 2013 Pinot Gris (Willamette Valley)	Pinot Gris	
3	St. Julian 2013 Reserve Late Harvest Riesling …	Riesling	
4	Sweet Cheeks 2012 Vintner's Reserve Wild Child…	Pinot Noir	
5	Tandem 2011 Ars In Vitro Tempranillo-Merlot (N…	Tempranillo-Merlot	

```
6   Terre di Giurfo 2013 Belsito Frappato (Vittoria)            Frappato

            winery                                          description
2        Rainstorm  Tart and snappy, the flavors of lime flesh and…
3       St. Julian  Pineapple rind, lemon pith and orange blossom …
4     Sweet Cheeks  Much like the regular bottling from 2012, this…
5           Tandem  Blackberry and raspberry aromas show a typical…
6  Terre di Giurfo  Here's a bright, informal red that opens with …
```

[16]:
```
#data cleaning - join dfs on title

wineCleanTitles = wineOnlyClean[["title", "points"]] #get titles and points␣
↪from wine only df

wineCombo = wineCleanTitles.join(wineReviewsClean.set_index("title"), on =␣
↪"title", lsuffix="_a", rsuffix="_b") #join titles from wine only list with␣
↪data set that has reviews on "title" field

wineCombo = wineCombo.dropna() #drop NAs

wineCombo["avgPoints"] = wineCombo[["points_a", "points_b"]].mean(axis=1) #get␣
↪average points score for both data sets

wineCombo = wineCombo.drop(columns=["points_a", "points_b"]) #remove␣
↪non-averaged point columns

print("There are {:d} wines in both data sets.".format(len(wineCombo)))

wineCombo.head() #preview cleansed df
```

```
There are 17298 wines in both data sets.
```

[16]:
```
                                              title country         county  \
0      L'Arboc NV 1919 Brut Selecció Sparkling (Cava)   Spain           Cava
4   Gérard Bertrand 1945 Legend Vintage Red (Rives…  France     Rivesaltes
11  Sebastiani 1987 Cherryblock Cabernet Sauvignon…      US  Sonoma Valley
23           Gan Eden 1994 Chardonnay (Sonoma County)      US  Sonoma County
35     Castillo de Almansa 1995 Reserva Red (Almansa)   Spain        Almansa

    price              province             variety               winery  \
0    13.0             Catalonia     Sparkling Blend              L'Arboc
4   350.0  Languedoc-Roussillon           Red Blend      Gérard Bertrand
11  170.0            California  Cabernet Sauvignon           Sebastiani
23   13.0            California          Chardonnay             Gan Eden
35   10.0         Central Spain           Red Blend  Castillo de Almansa

                                          description  avgPoints
```

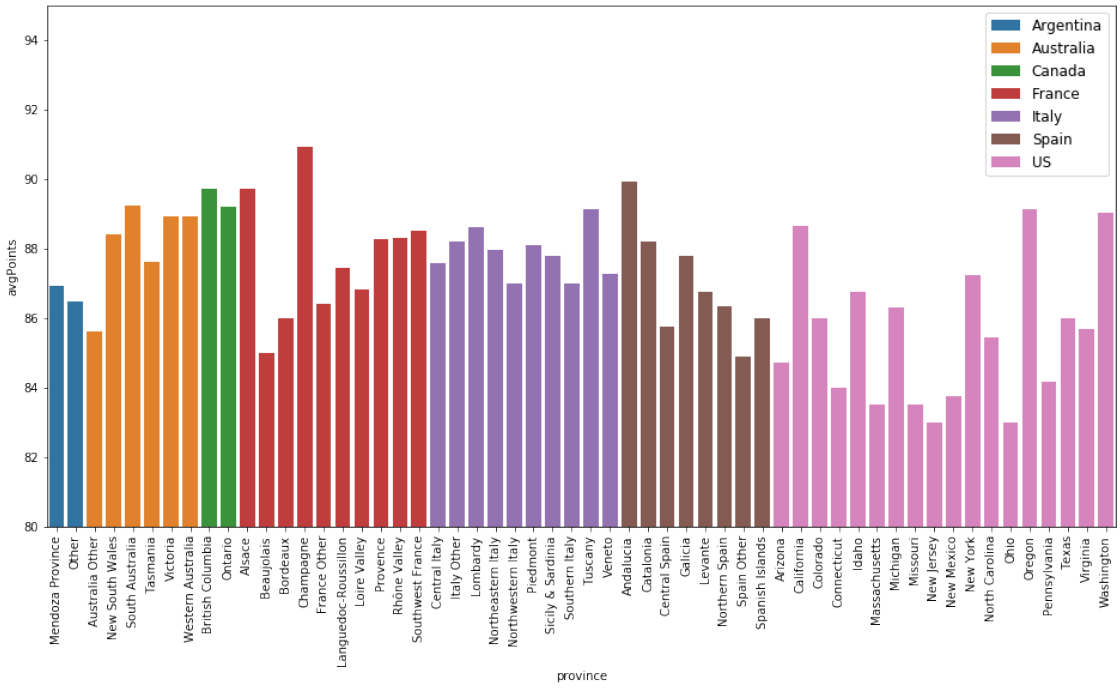
```
0   Apple, lemon-lime and bready aromas are welcom…      88.0
4   For any serious fan of Rivesaltes, this is a m…      95.0
11  Dark, earthy aromas of soy or fruitcake pick u…      89.0
23  Apple-cider and earth aromas open to a simple …      82.0
35  Tart cherry aromas and flavors with tarragon a…      84.0
```

[17]:
```
#data analysis - provinces

wineProvs = pd.DataFrame(wineCombo.groupby(['country','province'])['avgPoints'].
 ↪mean().reset_index()) #group wines by average score of province

wineProvs.head()
```

[17]:
```
     country          province  avgPoints
0  Argentina  Mendoza Province  86.908062
1  Argentina             Other  86.486486
2  Australia   Australia Other  85.627451
3  Australia   New South Wales  88.416667
4  Australia   South Australia  89.221154
```

[18]:
```
#data analysis - provinces plot

pyplot.figure(figsize=(16, 8)) #set figure size

provPlot = sb.barplot(x="province", y="avgPoints", data=wineProvs,␣
 ↪hue="country", dodge=False) #plot province and score, set color to country

pyplot.legend(loc='upper right', fontsize='12') #move legend to top right,␣
 ↪change font size

for item in provPlot.get_xticklabels(): #rotate x-axis label 90 degrees
    item.set_rotation(90)

provPlot.set(ylim=(80, 95)) #set y-scale to be 80-95
```

[18]:
```
[(80, 95)]
```



[19]:
```
#data analysis - best provinces

wineProvs.nlargest(5,"avgPoints") #get top highest scoring wines
```

[19]:

	country	province	avgPoints
13	France	Champagne	90.928571
30	Spain	Andalucia	89.909091
8	Canada	British Columbia	89.717391
10	France	Alsace	89.715576
4	Australia	South Australia	89.221154

[20]:
```
#data analysis - worst provinces

wineProvs.nsmallest(5,"avgPoints") #get bottom lowest scoring wines
```

[20]:

	country	province	avgPoints
46	US	New Jersey	83.00
50	US	Ohio	83.00
43	US	Massachusetts	83.50
45	US	Missouri	83.50
47	US	New Mexico	83.75

[21]:
```
#data analysis - counties

bestProvs = wineProvs.nlargest(10,"avgPoints") #save top 10 provinces
```

```
bestProvs = pd.DataFrame(bestProvs["province"]) #save top 10 provinces as␣
↪dataframe

bestProvsFull = bestProvs.join(wineCombo.set_index("province"), on =␣
↪"province") #new DF with only wines from the top 10 provinces

print("There are {:d} wines from the top 10 provinces".
↪format(len(bestProvsFull)))

bestProvsFull["province"].unique()
```

```
There are 4345 wines from the top 10 provinces
```

[21]:
```
array(['Champagne', 'Andalucia', 'British Columbia', 'Alsace',
       'South Australia', 'Ontario', 'Oregon', 'Tuscany', 'Washington',
       'Western Australia'], dtype=object)
```

[22]:
```
#data analysis - counties

wineCounty = bestProvsFull.groupby(["province", "county"])["avgPoints"].mean().
↪reset_index() #group wine by average score in each county (top 10 provinces␣
↪only)

wineCounty.nlargest(5, "avgPoints") #view top 5 best counties
```

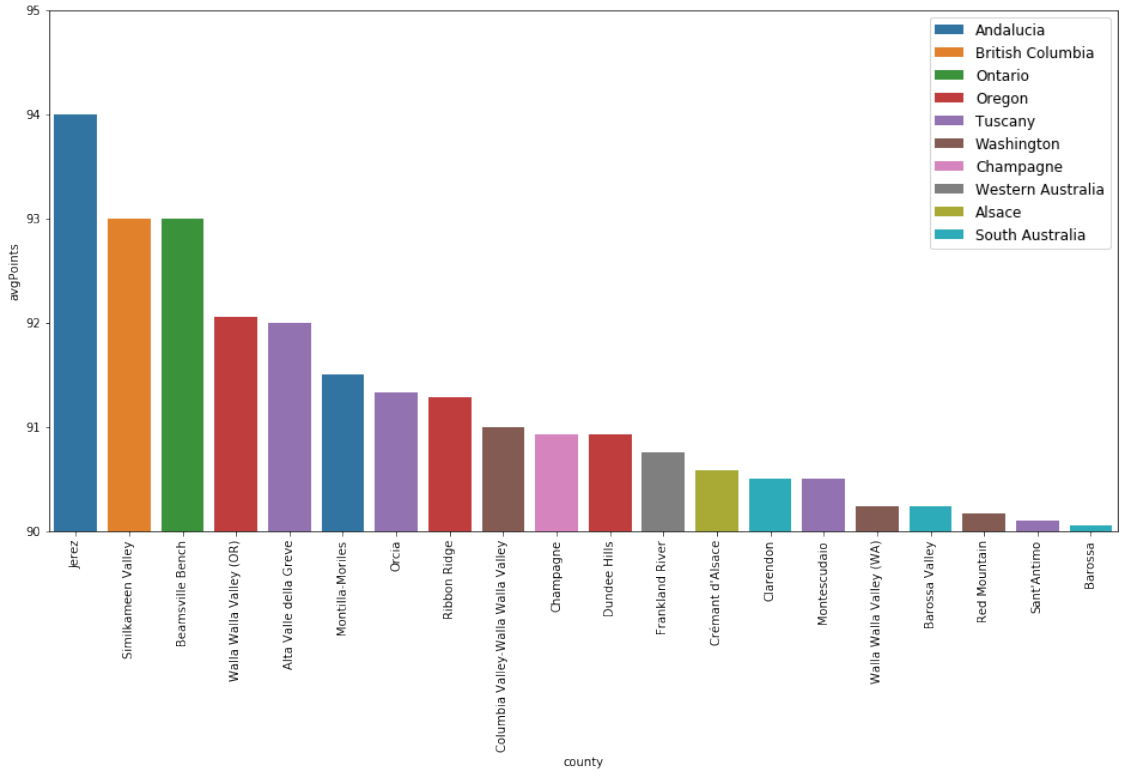
[22]:

	province	county	avgPoints
2	Andalucia	Jerez	94.000000
7	British Columbia	Similkameen Valley	93.000000
9	Ontario	Beamsville Bench	93.000000
29	Oregon	Walla Walla Valley (OR)	92.047619
51	Tuscany	Alta Valle della Greve	92.000000

[23]:
```
#data analysis - counties plot

wineCounty20 = wineCounty.nlargest(20, "avgPoints") #save top counties as new df

pyplot.figure(figsize=(16, 8)) #set figure size

countyPlot = sb.barplot(x="county", y="avgPoints", data=wineCounty20,␣
↪hue="province", dodge=False) #plot county and score, set color to province

pyplot.legend(loc='upper right', fontsize='12') #move legend to top right,␣
↪change font size

for item in countyPlot.get_xticklabels(): #rotate x-axis label 90 degrees
    item.set_rotation(90)
```

```
countyPlot.set(ylim=(90, 95)) #set y-scale to be 90-95
```

[23]: [(90, 95)]



[24]:
```
#data analysis - best wines

bestWines = wineCombo.nlargest(1000, "avgPoints") #save top 1000 wines

bestWines.head()
```

[24]:

```
                                                  title country  \
2431     Cardinale 2006 Cabernet Sauvignon (Napa Valley)      US
5836   Venge 2008 Family Reserve Cabernet Sauvignon (…      US
6379   Cayuse 2009 En Chamberlin Vineyard Syrah (Wall…      US
9981   Williams Selyem 2010 Hirsch Vineyard Pinot Noi…      US
15707  Alpha Omega 2012 Stagecoach Vineyard Cabernet …      US

                       county  price    province            variety  \
2431              Napa Valley  200.0  California  Cabernet Sauvignon
5836                 Oakville  125.0  California  Cabernet Sauvignon
6379   Walla Walla Valley (OR)   75.0      Oregon               Syrah
```

```
9981              Sonoma Coast   75.0  California          Pinot Noir
15707               Atlas Peak  250.0  California  Cabernet Sauvignon

                winery                                        description  \
2431         Cardinale  Tasted in a flight of great and famous Napa wi…
5836             Venge  An absolute joy and triumph. Just superb, show…
6379            Cayuse  In a vintage that produced the finest overall …
9981   Williams Selyem  This expresses the greatness of its vintage an…
15707      Alpha Omega  Juicy and seductively smooth, this blockbuster…

       avgPoints
2431       100.0
5836        99.0
6379        99.0
9981        99.0
15707       99.0
```

[25]:
```
#data analysis - worst wines

worstWines = wineCombo.nsmallest(1000, "avgPoints") #save worst 1000 wines

worstWines.head()
```

[25]:
```
                                              title country      county  \
289   Amity 1999 Eco Wine Cattrall Brothers Pinot No…      US      Oregon
583   Georges Duboeuf 2001 Vin de Pays de l'Ardeche …  France      France
698   Lions Peak 2002 Late Harvest Viognier (Califor…      US  California
802   Reula 2003 Oak Aged Tempranillo-Merlot (Cariñena)   Spain    Cariñena
1042         Ribas del Cúa 2004 Crianza Mencía (Bierzo)   Spain      Bierzo

      price        province             variety           winery  \
289    14.0          Oregon          Pinot Noir            Amity
583    10.0    France Other            Viognier  Georges Duboeuf
698    25.0      California            Viognier       Lions Peak
802    17.0  Northern Spain  Tempranillo-Merlot            Reula
1042   20.0  Northern Spain              Mencía    Ribas del Cúa

                                          description  avgPoints
289   If you are allergic to sulfites or insist on c…       80.0
583   Heavy and waxy, with overdone varietal aromas …       80.0
698   Shows sugary flavors of apricots, grilled pine…       80.0
802   Best on the nose, but sharp and narrow as can …       80.0
1042  A gaseous, barnyardy wine from several vintage…       80.0
```

[26]:
```
#data analysis - descriptions

tokenizer = RegexpTokenizer(r'\w+') #define tokenizer function
```

```
bestDescriptions = bestWines["description"] #save wine descriptions in separate␣
↪variable
worstDescriptions = worstWines["description"]

bestList = [] #initialize empty best and worst description lists
worstList = []

for description in bestDescriptions: #for each description in the best␣
↪descriptions list,
    bestList.append(tokenizer.tokenize(description.lower())) #append tokenized,␣
↪lowercase description to bestList

for description in worstDescriptions:#for each description in the worst␣
↪descriptions list,
    worstList.append(tokenizer.tokenize(description.lower())) #append␣
↪tokenized, lowercase description to worstList

#bestList[0]
#worstList[0]
```

[30]:
```
#data anlysis - descriptions

stopWords = nltk.corpus.stopwords.words('english') #define stopWords as english␣
↪stopwords from nltk

moreStopWords = ["like", "it'", "s", "wine", "flavors", "fruit", "finish",␣
↪"palate", "tannins", "aromas", "acidity", "oak", "nose"] #create new list of␣
↪stopwords

stopWords.extend(moreStopWords) #add new stopwords to stopwords with extend()
```

[31]:
```
#data anlysis - descriptions

bestListClean = [] #initialize empty clean description lists
worstListClean = []

for description in bestList: #for each description in the bestList,
    for word in description: #for each word in the description,
        if word in stopWords: #if the word is a stopword,
            description.remove(word) #remove it from the description
        bestListClean.append(description) #then append it to the bestListClean␣
↪list

for description in worstList: #repeat for worstList
    for word in description:
```

```
        if word in stopWords:
            description.remove(word)
        else:
            worstListClean.append(description)

#bestListClean[0]
worstListClean[0]
```

[31]:
```
['allergic',
 'sulfites',
 'insist',
 'certified',
 'organic',
 'wines',
 'one',
 'fits',
 'bill',
 'unfortunately',
 'heavy',
 'grape',
 'juice',
 'characteristic',
 'sharp',
 'acids',
 'running',
 'show',
 'dense',
 'chewy',
 'odd',
 'grapefruit',
 'note',
 'end']
```

[32]:
```
#data analysis - description words

bestWords = [] #initialize best/worst word lists
worstWords = []

for description in bestListClean: #for each description in the clean bestList,
    for word in description: #for each word in the description,
        bestWords.append(word) #append it to the bestWords list

for description in worstListClean: #repeat for worstList
    for word in description:
        worstWords.append(word)

#len(bestWords)
```

```
#len(worstWords)
```

[33]:
```
#data analysis - word frequency

bestWordsFreq = Counter(bestWords) #determine frequency of words with Counter()
worstWordsFreq = Counter(worstWords)

print("The most frequent words for the best wines are:")
for word in bestWordsFreq.most_common(20): #determine most common words in best␣
 ↪reviews
    print(word)

print("\nThe most frequent words for the worst wines are:") #determine most␣
 ↪common words in worst reviews
for word in worstWordsFreq.most_common(20):
    print(word)
```

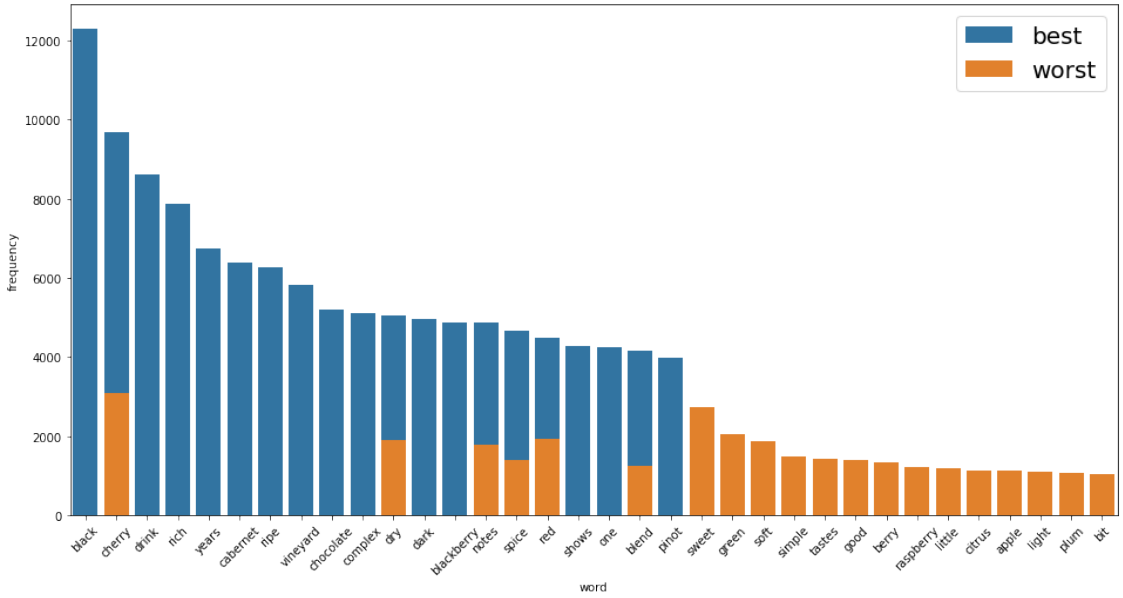
```
The most frequent words for the best wines are:
('black', 12291)
('cherry', 9692)
('drink', 8604)
('rich', 7882)
('years', 6745)
('cabernet', 6381)
('ripe', 6279)
('vineyard', 5814)
('chocolate', 5201)
('complex', 5120)
('dry', 5066)
('dark', 4970)
('blackberry', 4876)
('notes', 4860)
('spice', 4670)
('red', 4480)
('shows', 4282)
('one', 4248)
('blend', 4155)
('pinot', 3983)

The most frequent words for the worst wines are:
('cherry', 3104)
('sweet', 2740)
('green', 2051)
('red', 1934)
('dry', 1905)
('soft', 1863)
('notes', 1785)
```

```
('simple', 1495)
('tastes', 1440)
('good', 1410)
('spice', 1392)
('berry', 1331)
('blend', 1243)
('raspberry', 1221)
('little', 1180)
('citrus', 1121)
('apple', 1121)
('light', 1099)
('plum', 1083)
('bit', 1058)
```

[34]:
```
#data analysis - combine word lists

bestWordsDF = pd.DataFrame(bestWordsFreq.most_common(20)) #save most common␣
 ↪words in new df

worstWordsDF = pd.DataFrame(worstWordsFreq.most_common(20))

bestWordsDF.columns = ["word", "frequency"] #change column names
worstWordsDF.columns = ["word", "frequency"]

bestWordsDF["type"] = "best" #append new column with word type
worstWordsDF["type"] = "worst"

wordsDF = bestWordsDF.append(worstWordsDF)

#wordsDF.head()
#len(wordsDF)
```

[35]:
```
#data anlysis - word frequency plot

pyplot.figure(figsize=(16, 8)) #set figure size

wordPlot = sb.barplot(x="word", y="frequency", data=wordsDF, hue="type",␣
 ↪dodge=False) #plot word and frequency, set color to word type

for item in wordPlot.get_xticklabels(): #rotate x-axis label  45 degrees
    item.set_rotation(45)

pyplot.legend(loc='upper right', fontsize='20') #move legend to top right,␣
 ↪change font size
```

[35]:
```
<matplotlib.legend.Legend at 0x2a29b882e88>
```



[36]:
```
#data analysis - variety

print("There are {:d} unique varieties in this data set.".
 ↪format(len(wineCombo["variety"].unique()))) #determine number of varieties

wineVar = pd.DataFrame(wineCombo.groupby(['variety'])['avgPoints'].mean().
 ↪reset_index()) #group wines by average score of variety

wineVar.head()
```

```
There are 304 unique varieties in this data set.
```

[36]:

	variety	avgPoints
0	Aglianico	88.192308
1	Albana	89.000000
2	Albariño	88.000000
3	Aleatico	89.000000
4	Alicante	87.000000

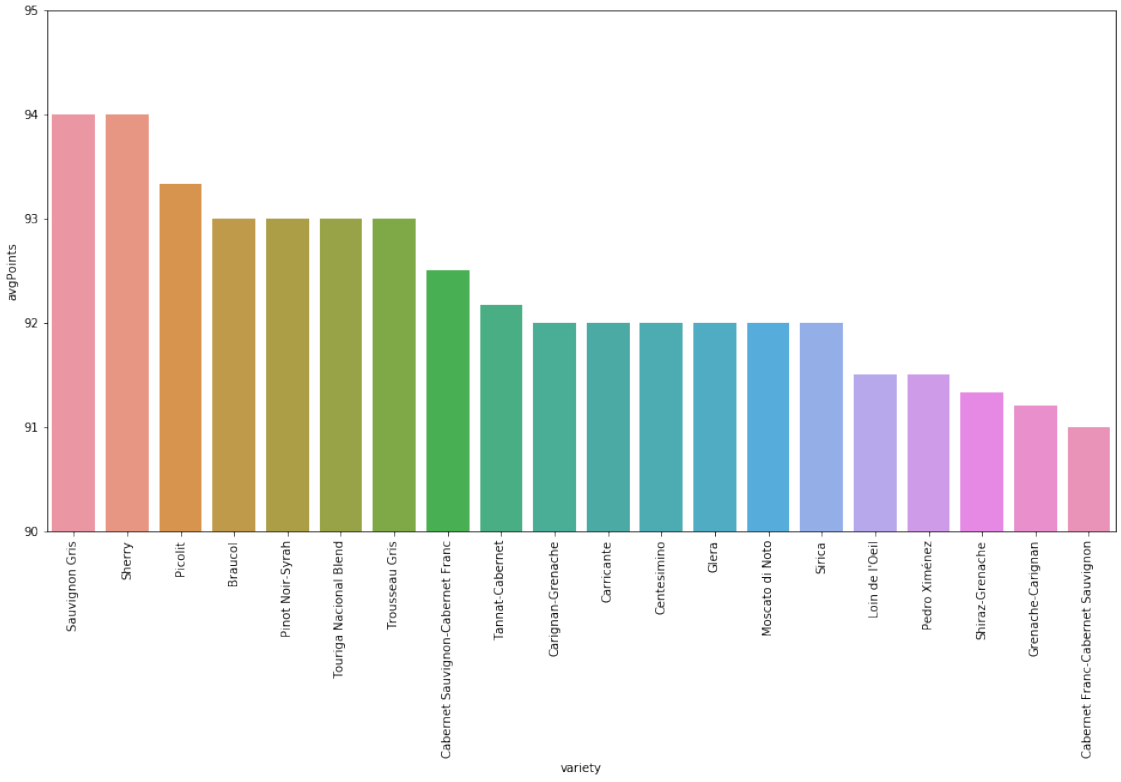
[37]:
```
#data analysis - variety

bestVar = wineVar.nlargest(20, "avgPoints") #store best varieties

bestVar.head()

#wineVar.nsmallest(20, "avgPoints")
```

[37]:

	variety	avgPoints
226	Sauvignon Gris	94.000000
233	Sherry	94.000000
179	Picolit	93.333333
21	Braucol	93.000000
192	Pinot Noir-Syrah	93.000000

[38]:
```
#data analysis - variety plot

pyplot.figure(figsize=(16, 8)) #set figure size

varPlot = sb.barplot(x="variety", y="avgPoints", data=bestVar) #plot variety by␣
↪avgPoints

for item in varPlot.get_xticklabels(): #rotate x-axis label
    item.set_rotation(90)

varPlot.set(ylim=(90, 95)) #set y-scale to be 90-95
```

[38]: [(90, 95)]



[39]:
```
#data analysis - sentiment

bestDescriptionsList = list(bestDescriptions) #convert descriptions dfs to lists
worstDescriptionsList = list(worstDescriptions)

#bestDescriptionsList[0]
#worstDescriptionsList[0]

sid = SentimentIntensityAnalyzer() #save sentiment analyzer function as "sid"

for description in worstDescriptionsList[0:5]: #for the first few worst␣
 ↪descriptions,
    print(description) #print the description
    sents = sid.polarity_scores(description) #gather sentiment polarity scores
    for sent in sents: #for each sentiment score,
        print('{0}: {1}, '.format(sent, sents[sent], end =="")) #print scores
    print("\n") #print new line
```

```
If you are allergic to sulfites or insist on certified organic wines, this one
fits the bill. Unfortunately it's heavy on the grape-juice characteristic, with
sharp acids running the show. Dense and chewy, and there's an odd grapefruit
note at the end.
neg: 0.15,
neu: 0.85,
pos: 0.0,
compound: -0.7096,


Heavy and waxy, with overdone varietal aromas that seem oily. Lots of pepper and
cumin, but what about the fruit and acidity? Nowhere to be found.
neg: 0.0,
neu: 1.0,
pos: 0.0,
compound: 0.0,


Shows sugary flavors of apricots, grilled pineapples and vanilla that have a
troubling vegetal edge.
neg: 0.2,
neu: 0.8,
pos: 0.0,
compound: -0.5423,


Best on the nose, but sharp and narrow as can be on the palate. Cranberry and
sour cherry flavors dominate, while the finish is astringent. No amount of
swirling and saving is going help it much.
```

```
neg: 0.107,
neu: 0.749,
pos: 0.144,
compound: 0.3818,


A gaseous, barnyardy wine from several vintages ago. It's tart and scratchy,
with thin herbal flavors of red fruit and tomato. Doesn't seem worth much these
days.
neg: 0.06,
neu: 0.94,
pos: 0.0,
compound: -0.1695,
```

[40]:
```
#data analysis - sentiment

for description in bestDescriptionsList[0:5]: #for the first few best␣
↪descriptions,
    print(description) #print the description
    sents = sid.polarity_scores(description) #gather sentiment polarity scores
    for sent in sents: #for each sentiment score,
        print('{0}: {1}, '.format(sent, sents[sent], end ="")) #print scores
    print("\n") #print new line
```

```
Tasted in a flight of great and famous Napa wines, this Cardinale stood at the
head of the pack. Starts with a very fine nose of cedar, cassis, ripe
blackberries and violets, then turns dramatic and refined in the mouth. Shows
vast depth and length, with the finish a full minute of sweet fruits and spices.
Marvelous tannins, so plush and elegant, so powerful yet refined. The grapes
hail from Mt. Veeder, Howell Mountain, Stags Leap and Oakville, and the blend
contains 14% Merlot. As good as it is now, it will improve for at least eight
years.
neg: 0.0,
neu: 0.766,
pos: 0.234,
compound: 0.978,


An absolute joy and triumph. Just superb, showcasing the best of Oakville.
Perfect tannins, as pure as velvet and sweet, and perfect oak, too, with
beautifully applied char and wood spice. That the oak is 100% new is in keeping
with the wine's volumetrics. The wine's flavors are a profound, heady expression
of blackberries, blueberries, cassis and dark, barely sweetened chocolate. Just
spectacular, a real achievement by any world class standard. Production was a
scant 275 cases.
neg: 0.0,
```

```
neu: 0.702,
pos: 0.298,
compound: 0.9839,


In a vintage that produced the finest overall lineup of Cayuse wines to date, it
may seem a little nit-picky to score some higher and some lower. But the En
Chamberlin deserves first place again. Brilliant aromatics of smoked meat, bacon
fat and otherworldly roasted accents seduce instantly. Once on the palate, the
silky, balanced, near-perfect mix of umami and fruit, plus licorice, cassis,
coffee liqueur and black tea notes suggest it's as decadent as it is delicious.
neg: 0.018,
neu: 0.864,
pos: 0.118,
compound: 0.8922,


This expresses the greatness of its vintage and vineyard, offering wave after
wave of raspberry and cherry pie flavors, plus notes of red currant, sweet
licorice, spicy Dr. Pepper and smoky sandalwood. There's also something
exotically briary and wild that intrigues. Even more remarkable is the texture,
an amalgam of acids and tannins that rivals any Pinot Noir ever produced in
California. It should age for up to 20 years.
neg: 0.0,
neu: 0.884,
pos: 0.116,
compound: 0.8313,


Juicy and seductively smooth, this blockbuster beauty from the revered vineyard
site is big, bold and intense, with granular tannins and a grip of integrated
French oak. Its bright cassis, lavender, Tahitian vanilla and dried herb flavors
are irresistible right out the gate. Ripe and rewarding, it's one to remember.
neg: 0.0,
neu: 0.633,
pos: 0.367,
compound: 0.973,
```

[46]:
```
#sentiment of worst descriptions

wneg = [] #initialize empty lists
wneu = []
wpos = []
wcomp = []
```

```
for description in worstDescriptionsList: #for each description in the worst␣
 ↪list,
    sent = sid.polarity_scores(description) #get polarity score
    wneg.append(sent["neg"]) #append negative, neutral, positive, and compound␣
 ↪score to respective list
    wneu.append(sent["neu"])
    wpos.append(sent["pos"])
    wcomp.append(sent["compound"])

print("On average, the 1,000 worst descriptions were {:g}% negative: ".
 ↪format((sum(wneg)/len(worstDescriptionsList))*100)) #print average score for␣
 ↪all worst descriptions
print("On average, the 1,000 worst descriptions were {:g}% neutral: ".
 ↪format((sum(wneu)/len(worstDescriptionsList))*100))
print("On average, the 1,000 worst descriptions were {:g}% positive: ".
 ↪format((sum(wpos)/len(worstDescriptionsList))*100))
print("Overall, the 1,000 worst descriptions had an average compound sentiment␣
 ↪of {:g}.".format((sum(wcomp)/len(worstDescriptionsList))))
```

```
On average, the 1,000 worst descriptions were 4.2085% negative:
On average, the 1,000 worst descriptions were 86.4729% neutral:
On average, the 1,000 worst descriptions were 9.3201% positive:
Overall, the 1,000 worst descriptions had an average compound sentiment of
0.191388.
```

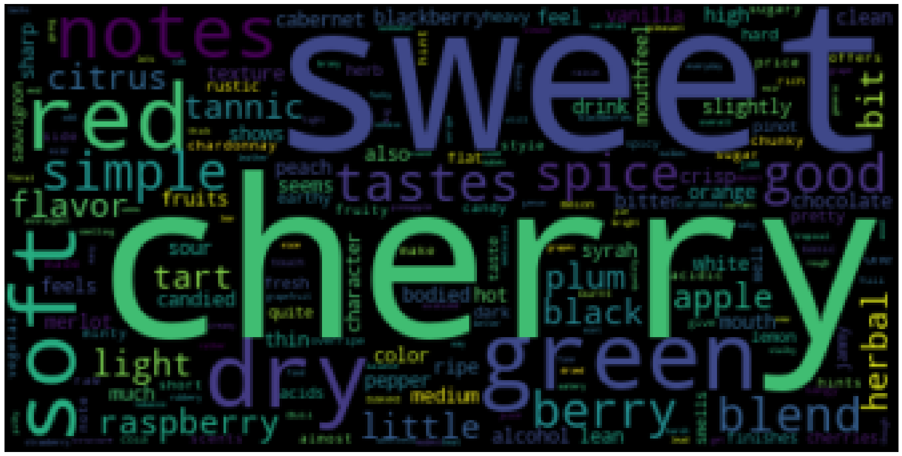
[45]:
```
#sentiment of best descriptions

bneg = [] #repeat sentiment analysis for best wine descriptions
bneu = []
bpos = []
bcomp = []

for description in bestDescriptionsList:
    sent = sid.polarity_scores(description)
    bneg.append(sent["neg"])
    bneu.append(sent["neu"])
    bpos.append(sent["pos"])
    bcomp.append(sent["compound"])

print("On average, the 1,000 best descriptions were {:g}% negative: ".
 ↪format((sum(bneg)/len(bestDescriptionsList))*100))
print("On average, the 1,000 best descriptions were {:g}% neutral: ".
 ↪format((sum(bneu)/len(bestDescriptionsList))*100))
print("On average, the 1,000 best descriptions were {:g}% positive: ".
 ↪format((sum(bpos)/len(bestDescriptionsList))*100))
```

```
print("Overall, the 1,000 best descriptions had an average compound sentiment␣
 ↪of {:g}.".format((sum(bcomp)/len(bestDescriptionsList))))
```

```
On average, the 1,000 best descriptions were 1.2325% negative:
On average, the 1,000 best descriptions were 83.019% neutral:
On average, the 1,000 best descriptions were 15.7493% positive:
Overall, the 1,000 best descriptions had an average compound sentiment of
0.717997.
```

[43]:
```
#dara analysis - wordclouds

bestCloud = WordCloud().generate_from_frequencies(bestWordsFreq) #create word␣
 ↪cloud with words from best wines

pyplot.figure() #plot word cloud
pyplot.imshow(bestCloud, interpolation="bilinear")
pyplot.axis("off")
pyplot.show()
```

[44]:
```
#data analysis - word cloud

worstCloud = WordCloud().generate_from_frequencies(worstWordsFreq) #create word␣
 ↪cloud with words from worst wines

pyplot.figure() #plot word clound
pyplot.imshow(worstCloud, interpolation="bilinear")
pyplot.axis("off")
pyplot.show()
```


cherry
sweet
green
dry
red
notes
soft
simple
tastes
spice
good
blend
berry
black
plum
apple
tannic
citrus
flavor
light
raspberry
little
tart
herbal
bit
clean
high
vanilla
feel
blackberry
cabernet
slightly
drink
texture
also
crisp
orange
chocolate
bitter
peach
fruits
seems
sour
candied
feels
white
mouth
bodied
hot
color
ripe
pepper
medium
alcohol
lean
finishes
cherries
character
syrah
merlot
much
thin
quite
acids
sharp
pretty
hints

[ ]: