Predict Rating

December 26, 2020

```
[1]: import numpy as np
     import pandas as pd
     import matplotlib.pyplot as plt
     import seaborn as sns
     import string
     from collections import defaultdict
     import gzip
     import json
     from nltk.corpus import stopwords
     import math
     from sklearn import linear_model
     from scipy.sparse import csr_matrix
[2]: def readTXT(path):
         file = []
         d = defaultdict(type(""))
         with gzip.open(path, 'rb') as f:
             for 1 in f:
                 1 = 1.decode("latin-1")
                 file.append(1)
```

```
[2]: def readJSON(path):
    file = []
    null = None
    for l in gzip.open(path, 'rt'):
        d=eval(l)
        file.append(d)
    return file
```

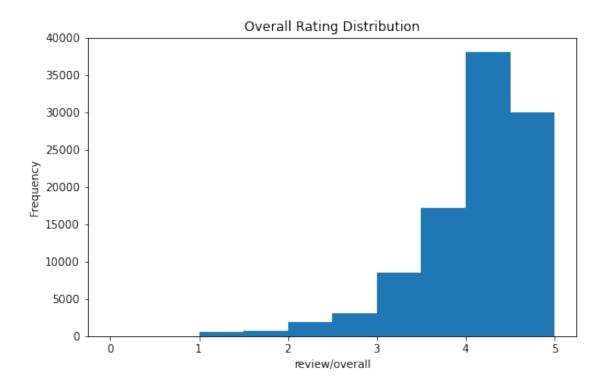
1 PERCENTAGE MODEL

return file

```
[3]: df = readTXT("beeradvocate.txt.gz")
```

```
[4]: def parse(df):
         file = []
         d = \{\}
         count = 0
         for 1 in df:
              1 = 1.strip()
              if(count == 100000): break
              i = 1.split(":")
              if len(i) == 1:
                  count += 1
                  file.append(d)
                  d = \{\}
                  continue
              d[i[0]] = i[1]
         return file
[5]: df = parse(df)
[6]: df = pd.DataFrame(df)
[7]: df
[7]:
                           beer/name beer/beerId beer/brewerId beer/ABV \
     0
                        Sausa Weizen
                                            47986
                                                           10325
                                                                      5.00
     1
                            Red Moon
                                            48213
                                                           10325
                                                                      6.20
             Black Horse Black Beer
                                            48215
                                                           10325
                                                                      6.50
     3
                          Sausa Pils
                                            47969
                                                           10325
                                                                      5.00
     4
                       Cauldron DIPA
                                            64883
                                                            1075
                                                                      7.70
                        La Madragore
     99995
                                            30968
                                                            2958
                                                                      8.00
                     Cuvée Du 9Ã"me
                                                                      8.00
     99996
                                                            2958
                                            39651
                     Cuvée Du 9Ã"me
     99997
                                                            2958
                                                                      8.00
                                            39651
                         La Dragonne
                                                                      7.50
     99998
                                            30972
                                                            2958
     99999
                         La Dragonne
                                            30972
                                                            2958
                                                                      7.50
                                   beer/style review/appearance review/aroma \
     0
                                   Hefeweizen
                                                              2.5
                          English Strong Ale
     1
                                                               3
                                                                           2.5
     2
                      Foreign / Export Stout
                                                               3
                                                                           2.5
     3
                             German Pilsener
                                                             3.5
                                                                              3
                                                                           4.5
     4
             American Double / Imperial IPA
     99995
                     Belgian Strong Dark Ale
                                                               4
                                                                              4
     99996
                                  Belgian IPA
                                                               4
                                                                              4
     99997
                                  Belgian IPA
                                                               4
                                                                              4
     99998
                        Herbed / Spiced Beer
                                                               3
                                                                           2.5
```

```
99999
                                                                           2.5
                         Herbed / Spiced Beer
                                                                3
             review/palate review/taste review/overall review/time \
       0
                        1.5
                                     1.5
                                                           1234817823
                                                     1.5
       1
                         3
                                       3
                                                       3
                                                           1235915097
       2
                         3
                                       3
                                                       3
                                                           1235916604
       3
                       2.5
                                                       3
                                                           1234725145
                                       3
       4
                                     4.5
                         4
                                                           1293735206
       99995
                                                     3.5
                                                           1149722515
                         4
                                       4
                       3.5
                                                     3.5
                                                           1201206794
       99996
                                       4
       99997
                         4
                                       4
                                                     4.5
                                                           1195558181
       99998
                       2.5
                                       1
                                                       1
                                                           1298300394
       99999
                       2.5
                                       2
                                                     1.5
                                                           1296028407
             review/profileName
                                                                         review/text
       0
                        stcules
                                   A lot of foam. But a lot.\tIn the smell some ...
       1
                         stcules
                                   Dark red color, light beige foam, average.\tI...
       2
                                   Almost totally black. Beige foam, quite compa...
                         stcules
       3
                         stcules
                                   Golden yellow color. White, compact foam, qui...
       4
                                   According to the website, the style for the C...
                 johnmichaelsen
       99995
                       ggaughan
                                   Sampled at the Monk's Cafe BFM tasting. The b...
                       Phyl21ca
       99996
                                                                               Bottle
       99997
                             Bov
                                                                 Jurassian Pale Ale
       99998
                        chefelf
                                   I really, really wanted to like this beer. Th...
       99999
                       corby112
                                                                           From notes
       [100000 rows x 13 columns]
  [8]: df['review/overall'] = df['review/overall'].apply(pd.to_numeric)
       df['review/appearance'] = df['review/appearance'].apply(pd.to_numeric)
       df['review/aroma'] = df['review/aroma'].apply(pd.to_numeric)
       df['review/palate'] = df['review/palate'].apply(pd.to_numeric)
       df['review/taste'] = df['review/taste'].apply(pd.to_numeric)
       df['beer/ABV'] = df['beer/ABV'].apply(pd.to_numeric)
[242]: df['review/overall'].plot(kind='hist')
       plt.xlabel('review/overall')
       plt.title('Overall Rating Distribution')
       plt.savefig("distribution.png")
```



```
[10]: median = df['review/overall'].median()
      print(median)
     4.0
[11]: mean = df['review/overall'].mean()
      print(mean)
     3.89702
[12]: punctuation = set(string.punctuation)
      def standardize(string):
          string = string.lower().replace('\t', ' ')
          r = ''.join([c for c in string if not c in punctuation])
          return r
[13]: df['review/text'] = df['review/text'].apply(standardize)
[14]: df
[14]:
                           beer/name beer/beerId beer/brewerId beer/ABV \
      0
                        Sausa Weizen
                                            47986
                                                          10325
                                                                      5.0
      1
                            Red Moon
                                            48213
                                                          10325
                                                                      6.2
      2
              Black Horse Black Beer
                                            48215
                                                          10325
                                                                      6.5
```

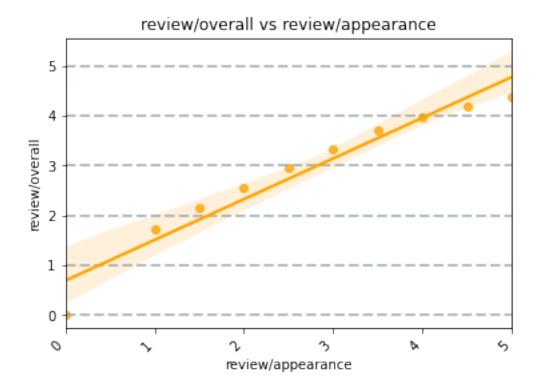
3	Sausa F	Pils 4	7969	1	0325	5.0		
4	Cauldron I		4883		1075	7.7		
•••	***	***		•••	•••			
99995	La Madrag	gore 3	0968		2958	8.0		
99996			9651			8.0		
99997			9651		2958	8.0		
99998	La Drago	0972		2958	7.5			
99999	La Drago		0972		2958 7.5			
	6-							
		beer/style	review	/appea	rance re	eview/ar	roma	\
0				2.5		2.0		
1	English	English Strong Ale			3.0		2.5	
2	Foreign / E		3.0 2.5					
3	Germ		3.5 3.0					
4	American Double / 1				4.0		4.5	
	,							
99995	Belgian Stro	ong Dark Ale			4.0		4.0	
99996	•	Belgian IPA			4.0		4.0	
99997	Belgian IPA				4.0		4.0	
99998	Herbed / Spiced Beer				3.0		2.5	
99999		Spiced Beer			3.0		2.5	
	,							
	review/palate revie	ew/taste re	view/ove	erall	review/ti	me \		
0	1.5	1.5		1.5	12348178			
1	3.0	3.0		3.0	12359150			
2	3.0	3.0		3.0	12359166			
3	2.5	3.0		3.0	12347251			
4	4.0	4.5		4.0	12937352			
_			•••					
99995	4.0	4.0	•••	3.5	 11497225	515		
99996	3.5	4.0		3.5	12012067			
99997	4.0 4.0			4.5	11955581			
99998	2.5	1.0		1.0	12983003			
99999	2.5	2.0		1.5	12960284			
		_,,						
:	review/profileName					revi	iew/te	ext
0	stcules	a lot of fo	am but a	a lot i	n the sme			
1	stcules	dark red co						
2	stcules	almost tota	_	_		_		
3	stcules	golden yell	•	_	_		-	
4	johnmichaelsen	according t			_	_		
-			- 5110 WC		20y10	01 01		
 99995	ggaughan	sampled at	the monk	s cafe	bfm tast	ing the	 bee	
99996	Phyl21ca		Jacon Monn	-5 5410	J1 00.DC		bot:	
99997	Bov				inrac	ssian pa		
99998	chefelf	i really re	allu war	nted to	-	_		
99999		I rearry re	arry war	1064 00	TIVC OIL		om no	
99999	corby112					11.0	ли 11O	CCS

```
[100000 rows x 13 columns]
```

```
[16]: def findStat(s):
          print("Mean: ",
          df[df['review/text'].str.contains(s)]['review/overall'].mean())
          print("Median: ",
          df[df['review/text'].str.contains(s)]['review/overall'].median())
[17]: findStat("bad")
      Mean: 3.5239204721963344
      Median: 3.5
[18]: findStat("fine")
      Mean: 4.006820877817319
      Median: 4.0
[19]: findStat("ok")
      Mean: 3.8610464595828486
      Median: 4.0
[20]: findStat("beer")
      Mean: 3.9029024060986264
      Median: 4.0
[21]: findStat("awful")
      Mean: 2.634228187919463
      Median: 2.5
[22]: findStat("amazing")
      Mean: 4.300974512743628
      Median: 4.5
 []:
[220]: def bar_plot(df, s, types, c, xlabel):
          means = []
          for t in types:
              means.append(df[df[s] == t]['review/overall'].mean())
          plt.bar(xlabel, means, color=c, alpha=0.7)
          plt.grid(color='#95a5a6', linestyle='--', linewidth=2, axis='y', alpha=0.7)
          plt.xlabel(s)
```

```
plt.ylabel("review/overall")
   plt.title("review/overall vs "+s)
   plt.rcParams["figure.figsize"] = (8, 5)
   plt.setp(plt.gca().get_xticklabels(), rotation=45,_
 →horizontalalignment='right')
   plt.show()
def scatter_plot(df, s, types, c, xlabel):
   means = []
   for t in types:
       means.append(df[df[s] == t]['review/overall'].mean())
     plt.scatter(xlabel, means, color=c, alpha=0.7)
     plt.plot(xlabel, means, color=c)
   data = pd.DataFrame({'x':xlabel, 'y':means})
   sns.regplot(x='x', y='y', data=data, color=c)
   plt.grid(color='#95a5a6', linestyle='--', linewidth=2, axis='y', alpha=0.7)
   plt.xlabel(s)
   plt.ylabel("review/overall")
   plt.title("review/overall vs "+s)
   plt.rcParams["figure.figsize"] = (8, 5)
   plt.setp(plt.gca().get xticklabels(), rotation=45,...
 →horizontalalignment='right')
   name = s.replace("/", '')
   plt.savefig(name+".png")
   plt.show()
def scatter_noline(df, s, types, c, xlabel):
   means = []
   for t in types:
       means.append(df[df[s] == t]['review/overall'].mean())
   plt.scatter(xlabel, means, color=c, alpha=0.7)
   plt.grid(color='#95a5a6', linestyle='--', linewidth=2, axis='y', alpha=0.7)
   plt.xlabel(s)
   plt.ylabel("review/overall")
   plt.title("review/overall vs "+s)
   plt.rcParams["figure.figsize"] = (8, 5)
   plt.setp(plt.gca().get_xticklabels(), rotation=45,__
 →horizontalalignment='right')
   plt.show()
```

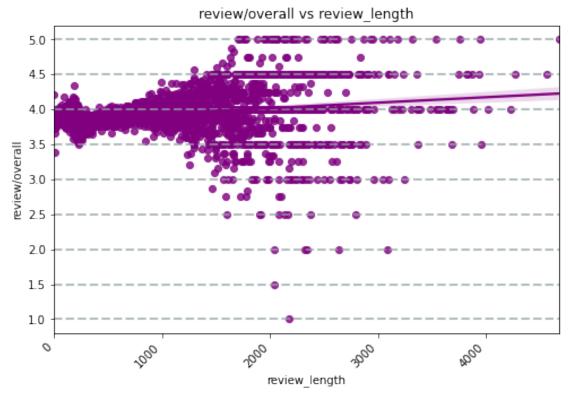
```
[203]: appearance = df['review/appearance'].unique()
scatter_plot(df, 'review/appearance', appearance, "orange", appearance)
```



```
[216]: def savePlot(string, color, b):
           appearance = df[string].unique()
           if b:
               scatter_plot(df, string, appearance, color, appearance)
           else:
               scatter_plot(df, string, appearance, color, range(len(appearance)))
  []: def savePlot2(string, color, b):
           appearance = df[string].unique()
           if b:
               scatter_plot(df, string, appearance, color, appearance)
           else:
               scatter_plot(df, string, appearance, color, range(len(appearance)))
[232]: df['review_length'] = df['review/text'].str.len()
[245]: new = df[['review/overall', 'review/appearance', 'review/palate', 'review/
        →taste', 'review/aroma', 'beer/ABV', 'review_length']].copy()
[246]: new.corr()
```

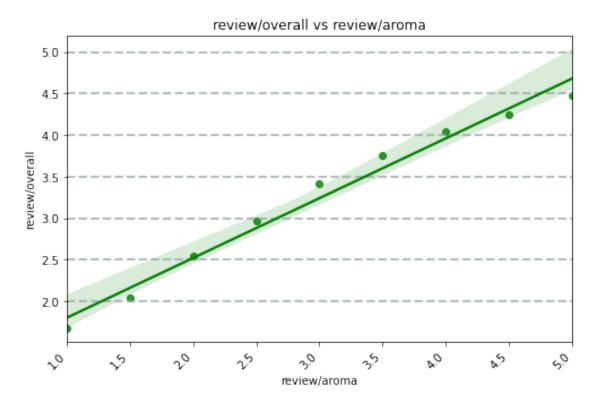
```
[246]:
                           review/overall
                                           review/appearance review/palate
       review/overall
                                 1.000000
                                                     0.489678
                                                                     0.686402
                                 0.489678
                                                     1.000000
                                                                     0.549310
       review/appearance
       review/palate
                                 0.686402
                                                     0.549310
                                                                     1.000000
       review/taste
                                                     0.526898
                                                                     0.716624
                                 0.775298
       review/aroma
                                 0.596313
                                                     0.528390
                                                                     0.592861
       beer/ABV
                                 0.131734
                                                     0.240494
                                                                     0.287835
       review_length
                                 0.051897
                                                     0.081490
                                                                     0.077584
                           review/taste
                                          review/aroma
                                                        beer/ABV
                                                                   review_length
       review/overall
                               0.775298
                                              0.596313
                                                        0.131734
                                                                        0.051897
       review/appearance
                               0.526898
                                              0.528390
                                                         0.240494
                                                                        0.081490
       review/palate
                               0.716624
                                              0.592861
                                                         0.287835
                                                                        0.077584
       review/taste
                               1.000000
                                              0.699170
                                                        0.296684
                                                                         0.070301
       review/aroma
                                                         0.348777
                               0.699170
                                              1.000000
                                                                         0.090255
       beer/ABV
                               0.296684
                                              0.348777
                                                         1.000000
                                                                         0.120151
       review_length
                               0.070301
                                              0.090255
                                                        0.120151
                                                                         1.000000
[233]:
      savePlot('review_length', 'purple', True)
```





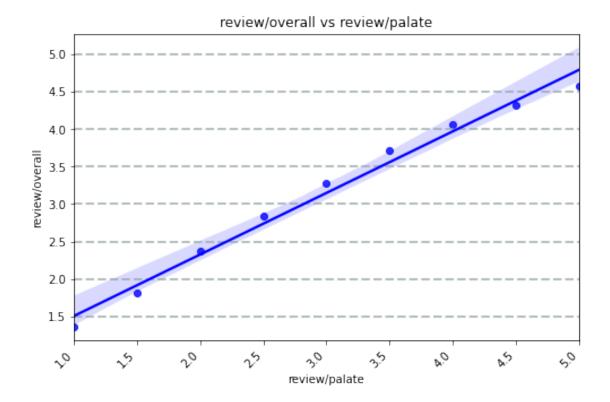
<Figure size 576x360 with 0 Axes>

[221]: savePlot('review/aroma', 'green', True)



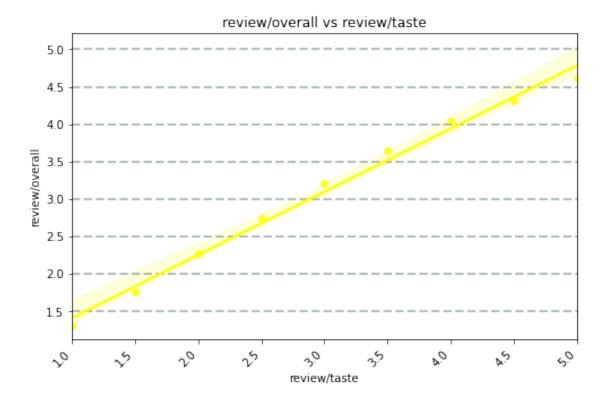
<Figure size 576x360 with 0 Axes>

[222]: savePlot('review/palate', 'blue', True)



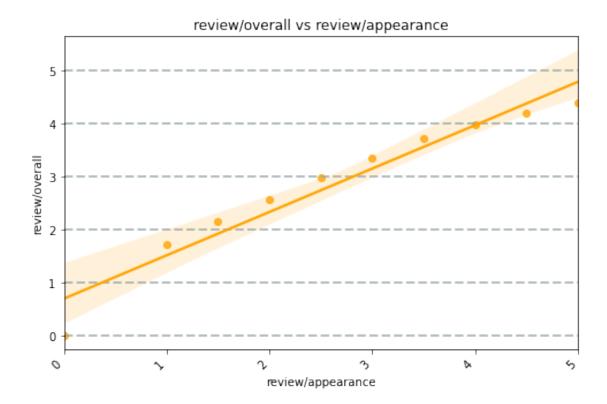
<Figure size 576x360 with 0 Axes>

```
[223]: savePlot('review/taste', 'yellow', True)
```



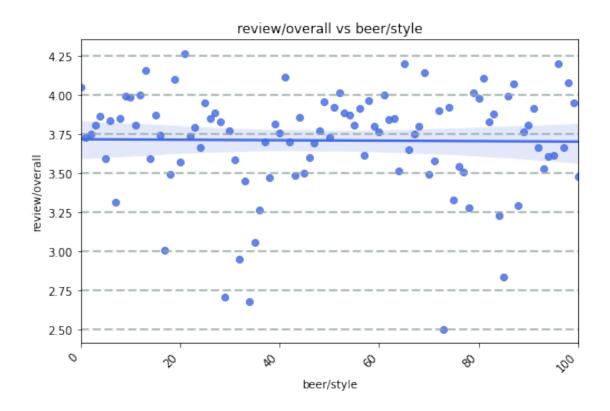
<Figure size 576x360 with 0 Axes>

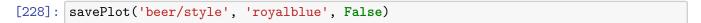
```
[225]: savePlot('review/appearance', 'orange', True)
```

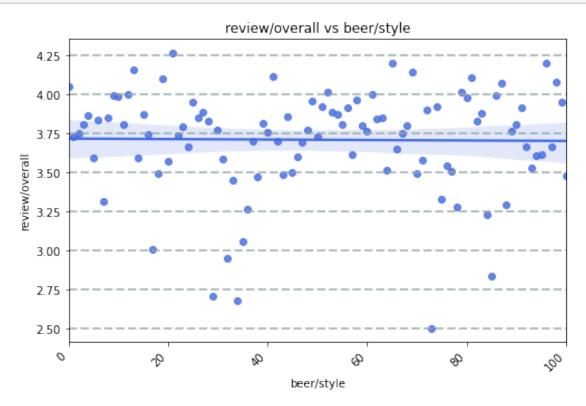


<Figure size 576x360 with 0 Axes>

```
[204]: beer_style = df['beer/style'].unique()
scatter_plot(df, 'beer/style', beer_style, "royalblue", range(len(beer_style)))
```

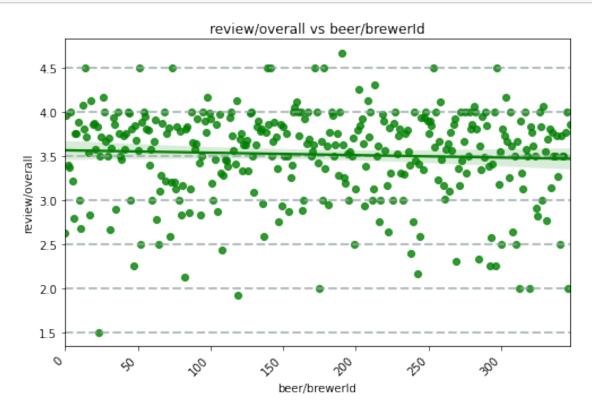






<Figure size 576x360 with 0 Axes>

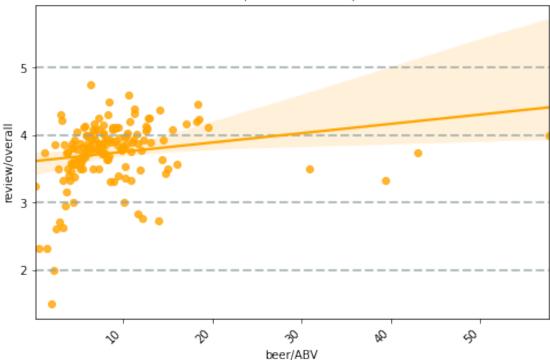
[227]: savePlot('beer/brewerId', 'green', False)



<Figure size 576x360 with 0 Axes>

[229]: savePlot('beer/ABV', 'orange', True)





<Figure size 576x360 with 0 Axes>

```
count = 1
               b = ''
               for w in df['review/text'][ind].split():
                   if w in stop_words: continue
                   if df['review/overall'][ind] > mean:
                       unigrams2[w] += 1
                   else:
                       unigrams1[w] += 1
                   if count > 1:
                       s = b + ' + w
                       if df['review/overall'][ind] > mean:
                           bigrams2[s] += 1
                       else: bigrams1[s] +=1
                   b = w
                   count += 1
           return unigrams1, bigrams1, unigrams2, bigrams2
[170]: unigrams1, bigrams1, unigrams2, bigrams2 = create_bag(train)
[192]: P_high_rating = sum(train['review/overall'] > mean)/len(train.index)
       P_low_rating = 1 - P_high_rating
[199]: P_high_rating2 = sum(test['review/overall'] > mean)/len(test.index)
       print(P_high_rating2)
      0.6817
[200]: print(P_high_rating)
       print(P_low_rating)
      0.6806714285714286
      0.3193285714285714
[201]: def predictHighUni(text, word_bag1, word_bag2, document_len):
           p_high = 1
           p_low = 1
           bag_sum1 = sum(word_bag1.values())
           bag_sum2 = sum(word_bag2.values())
           text = text.split()
           t = set(text)
```

```
for w in t:
#
          if w in stop_words: continue
        if w in word_bag1:
              p1 = word_bag1[w]/bag_sum1
#
            p_low *= word_bag1[w]/bag_sum1
        if w in word_bag2:
#
              p2 = word_bag2[w]/bag_sum2
            p_high *= word_bag2[w]/bag_sum2
              if p2 == 0:
#
                  print("here: ", w, print(w in word_bag2))
          print(p_low)
         print(p_high)
    p_low *= P_low_rating
    p_high *= P_high_rating
      if(p_high == p_low): return P_high_rating > P_low_rating
    return p_high > p_low
def predictHighBi(text, word_bag1, word_bag2, document_len):
    p_high = 1
    p_low = 1
    bag_sum1 = sum(word_bag1.values())
    bag_sum2 = sum(word_bag2.values())
    count = 1
    b = ''
    t = set(text.split())
    for w in t:
        if w in stop_words: continue
        if count == 1:
            b = w
            count = 2
            continue
        s = b + ' ' + w
        b = w
        if s in word_bag1:
            p_low *= word_bag1[s]/bag_sum1
        if s in word_bag2:
            p_high *= word_bag2[s]/bag_sum2
```

```
p_low *= P_low_rating
           p_high *= P_high_rating
           return p_high > p_low
       def MSE(predictions, labels):
           differences = [(x-y)**2 \text{ for } x,y \text{ in } zip(predictions,labels)]
           return sum(differences) / len(differences)
[39]: r = train['review/text'].iloc[5]
[40]: r
[40]: ' a buddy of mine stopped by with a sixer of this so i figured i would give it a
       shot not much smell or taste to it very bland a bit corny and skunkykinda like
       bad city water in some places ive been too carbonated for my liking i could only
       finish one and wont be having another if i want a light beer ill grab a sa light
       instead'
[41]: train['review/overall'].iloc[5]
[41]: 1.5
[42]: train_len = len(train.index)
[172]: "skunkykinda" in unigrams2
[172]: False
[183]: predictHighUni(r, unigrams1, unigrams2, train_len)
      0.008734792297144968
      0.006986583838060697
      0.008734792297144968
      0.006986583838060697
      1.2570258040837995e-05
      1.1986449927257011e-05
      1.2570258040837995e-05
      1.1986449927257011e-05
      1.2570258040837995e-05
      1.1986449927257011e-05
      1.2570258040837995e-05
      1.1986449927257011e-05
      2.4331552197716275e-08
      2.6189368972508198e-08
      1.2490730083083058e-10
```

- 8.95361518203449e-11
- 2.2088459541071563e-14
- 1.3238296493342534e-14
- 1.5745612082236899e-16
- 9.658035318098583e-17
- 3.879006616086056e-19
- 7.439379943696974e-20
- 1.757136221960375e-23
- 5.344994489698513e-25
- 1.757136221960375e-23
- 5.344994489698513e-25
- 1.7602925029526255e-27
- 4.3859524297610374e-29
- 1.7602925029526255e-27
- 4.3859524297610374e-29
- 5.965076368659033e-31
- 6.833104371309734e-33
- 2.707293240637871e-34
- 3.772487691274451e-37
- 2.547068482695843e-38
- 2.767492691832297e-41
- 2.1014320310322316 41
- 1.2425395363771145e-42
- 1.224416760330523e-45
- 1.926689746964787e-46
- 8.287799157993509e-50
- 1.926689746964787e-46
- 8.287799157993509e-50
- 3.4167022242457494e-48
- 1.42179244068226e-51
- 3.4167022242457494e-48
- 1.42179244068226e-51
- 3.5719562723050585e-50
- 1.3177065781765497e-53
- 3.5719562723050585e-50
- 1.3177065781765497e-53
- 1.9254755407542656e-52
- 6.3197169560083365e-56
- 5.702935906437894e-57
- 1.7206282360411082e-60
- 4.669903559296426e-61
- 1.4314185719592188e-64
- 2.2211716515838387e-64
- 2.473658648073199e-68
- 2.0026453165495636e-67
- 1.860507707521541e-71
- 3.628682261954124e-71
- 2.476458521403437e-75
- 1.4224696959934733e-75

- 8.709052893254167e-80
- 1.375458746511358e-78
- 1.0469317661413491e-82
- 1.375458746511358e-78
- 1.0469317661413491e-82
- 1.3779294338963094e-82
- 1.262891330181469e-86
- 1.3779294338963094e-82
- 1.262891330181469e-86
- 1.3779294338963094e-82
- 1.262891330181469e-86
- 1.3779294338963094e-82
- 1.262891330181469e-86
- 7.006453402233186e-85
- 6.338102759870197e-89
- 7.006453402233186e-85
- 6.338102759870197e-89
- 2.6855452968562776e-89
- 2.660352446403198e-93
- 1.9370658570384447e-92
- 1.588467112222343e-96
- 7.79761740213727e-95
- 5.1303131013160655e-99
- 7.79761740213727e-95
- 5.1303131013160655e-99
- 7.79761740213727e-95
- 5.1303131013160655e-99
- 7.79761740213727e-95
- 5.1303131013160655e-99
- 6.45308068208423e-99
- 4.888789442875709e-103
- 6.45308068208423e-99
- 4.888789442875709e-103
- 5.6214540176248456e-105
- 4.888789442875709e-103
- 4.3034848490848066e-107
- 2.9325375272627413e-105
- 3.6671570061926317e-109
- 2.002378150921832e-107
- 3.6671570061926317e-109
- 2.002378150921832e-107
- 2.424671164906299e-112
- 1.1425948411894754e-110
- 2.424671164906299e-112
- 1.1425948411894754e-110
- 1.527118409031894e-115
- 5.0681235362159786e-114
- 1.527118409031894e-115

```
5.0681235362159786e-114
      1.527118409031894e-115
      5.0681235362159786e-114
      1.527118409031894e-115
      5.0681235362159786e-114
[183]: True
[118]: predictHighBi(r, bigrams1,bigrams2, train_len)
[118]: True
[251]: def predict(x, s):
           v = []
           x_{len} = len(x)
           if s == "uni":
               for d in x:
                   y.append(predictHighUni(d, unigrams1, unigrams2, x_len))
           else:
               for d in x:
                   y.append(predictHighBi(d, bigrams1, bigrams2, x_len))
           return y
       def findMSE(x, y, s):
           y = [d > mean for d in y]
           if s == "uni":
               y_pred = predict(x, "uni")
               y_pred = predict(x, "bi")
           return MSE(y_pred, y)
       def findCorrect(x, y, s):
           y = [d > mean for d in y]
           if s == "uni":
               y_pred = predict(x, "uni")
           else:
               y_pred = predict(x, "bi")
           correct = [a==b for a,b in zip(y, y_pred)]
           return sum(correct)/ len(correct)
[132]: text = list(train['review/text'])
       rating = list(train['review/overall'])
[252]: print("Correct rate by unigram of train set: ", findCorrect(text, rating, u

¬"uni"))
```

Correct rate by unigram of train set: 0.4223857142857143

```
[253]: print("Correct rate by bigram of train set: ", findCorrect(text, rating, "bi"))
      Correct rate by bigram of train set: 0.34855714285714284
 [ ]: text_test = list(test['review/text'])
       rating_test = list(test['review/overall'])
[254]: print("Correct rate by unigram of test set: ", findCorrect(text_test, __
       →rating_test, "uni"))
      Correct rate by unigram of test set: 0.5993666666666667
[255]: print("Correct rate by bigram of test set: ", findCorrect(text_test, ___
       →rating_test, "bi"))
      Correct rate by bigram of test set: 0.36806666666666665
[239]: def true_p(p, y, data_len):
          sum = 0
          for i in range(data_len):
               if p[i] == y[i] and p[i] == True:
                   sum += 1
          return sum
       def Ber(y, predictions, data_len):
          LP = sum(v)
                                       #labeled positive
          LN = data_len - LP
                                            #labeled negative
          PP = sum(predictions)
                                            #prediction positive
          PN = data_len - PP
                                             #prediction negative
          TP = true_p(predictions, y, data_len) #true positive
          FN = LP - TP
                                             #false negative
          FP = PP - TP
                                             #false positive
                                             #false negative
          TN = PN - FN
          TPR = TP/LP
          TNR = TN/LN
          FPR = FP/LN
          FNR = FN/LP
          BER = 0.5*(FPR+FNR)
          print("True positive: ", TPR)
          print("True negative: ", TNR)
          return BER
       # BER = Ber(y test, predictions, data len)
```

print("Balanced Error Rate: ", BER)

```
def findRate(x, y):
    y = [d > mean for d in y]
    y_pred = predict(x, "uni")
    return Ber(y, y_pred, len(y))
```

```
[241]: ber = findRate(text_test, rating_test)
print(ber)
```

True positive: 0.6021221456163512 True negative: 0.5934652843229657

0.4022062850303415

2 TFIDF MODEL

```
[20]: uni1 = defaultdict(int)
uni2 = defaultdict(int)

for ind in train.index:
    for w in train['review/text'][ind].split():
        if w in stop_words: continue
        if train['review/overall'][ind] > mean:
            uni2[w] += 1
        else:
            uni1[w] += 1
```

```
[46]: wordByRating = []
wordByRating.append(uni1)
wordByRating.append(uni2)

counts = []
# for i in range(2):
c = [(uni1[w], w) for w in uni1]
c.sort(reverse = True)
counts += c[:500]
c = [(uni2[w], w) for w in uni2]
c.sort(reverse = True)
counts += c[:500]

wordsUni = [x[1] for x in counts]
```

```
# print(counts[980:])

# counts = [(unigrams[w], w) for w in unigrams]
# counts.sort()
# counts.reverse()
# wordsUni = [x[1] for x in counts[:1000]]

# counts = [(bigrams[w], w) for w in bigrams]
# counts.sort()
# counts.reverse()
# wordsBi = [x[1] for x in counts[:1000]]
# counts[:5]
```

```
[56]: def merge(list1, list2):
            print(list1[0])
          merged_list = [(list1[i], list2[i]) for i in range(0, len(list1))]
          return merged_list
      def featureTfidf(z, words, wordId):
          feat = [0]*len(words)
           print(z[1])
         for w in z[0]:
                print(w)
      #
             if w in words:
                    print(w, z[1][w])
                  feat[wordId[w]] = z[1][w]
          feat.append(1)
          return feat
      def prepX(review, words):
          print(text)
          Df = defaultdict(float)
          Tfidf = []
          text = []
          1 = len(review)
          for r in review:
              w = r.split()
               print(w)
              text.append(w)
```

```
print(text)
      return 0
     print(w)
    for t in words:
        Df[t] = 0
        for w in text:
            if t in w:
                Df[t] += 1
    for w in text:
        tfidf = defaultdict(float)
        for t in words:
            _{tf} = w.count(t)
              print("tf: ", _tf)
            if Df[t] == 0:
                _{tfidf[t]} = 0
            else:
                _{tfidf[t]} = _{tf} * math.log(1/Df[t], 10)
              print("tfidf: ", _tfidf[t])
        Tfidf.append(_tfidf)
    wordId = dict(zip(words, range(len(words))))
     print()
   listX = merge(text, Tfidf)
    print(listX[0])
    X = [featureTfidf(d, words, wordId) for d in listX]
    return csr_matrix(X)
def build_train_model(text, rating, words, c):
    X = prepX(text, words)
    Y = rating
    clf = linear_model.Ridge(c, fit_intercept=False)
    clf.fit(X, y)
    return clf
def longPredict(text, rating, text_test, rating_test, words, c):
    X = prepX(text, words)
    y = [d > mean for d in rating]
    Xtest = prepX(text_test, words)
    ytest = [d > mean for d in rating_test]
    # Regularized regression
```

```
for i in c:
    clf = linear_model.LogisticRegression(C=0.1, class_weight='balanced', □

→fit_intercept=False)
    clf.fit(X, y)
    predictions = clf.predict(Xtest)
    correct = [a==b for a,b in zip(predictions, ytest)]
    print("Correct rate with C=", i,":", sum(correct)/ len(correct))
```

[53]: print(text[0])

clear shiny gold with not a whole lot of head retention after an initially foamy pour has that semiskunked lager aroma with a good mix of light graininess and hops very crisp and refreshing clean thru the middle ending with minimal hop spiciness makes a great hot weather alternative to the ever present wheat beers nothing earthshattering here just another great brew in sierra nevadas already stellar lineup

Correct rate with C= 0.1 : 0.6822857142857143

```
[72]: for i in c:
    clf = linear_model.LogisticRegression(C=i, class_weight='balanced', 
    →fit_intercept=False)
    clf.fit(X, y)
    predictions = clf.predict(X)
    correct = [a==b for a,b in zip(predictions, y)]
    print("Correct rate with C=", i,":", sum(correct)/ len(correct))
```

```
Correct rate with C=0.01:0.6820142857142857
Correct rate with C=0.1:0.6822857142857143
Correct rate with C=1:0.6822285714285714
Correct rate with C=10:0.6822142857142857
Correct rate with C=100:0.6822142857142857
```

```
[73]: Xtest = prepX(text_test, wordsUni)
ytest = [d > mean for d in rating_test]
```

```
[75]: for i in c:
          clf = linear_model.LogisticRegression(C=i, class_weight='balanced',__
       →fit_intercept=False)
          clf.fit(X, y)
          predictions = clf.predict(Xtest)
          correct = [a==b for a,b in zip(predictions, ytest)]
          print("Correct rate with C=", i,":", sum(correct)/ len(correct))
      Correct rate with C= 0.01 : 0.6717
      Correct rate with C= 0.1 : 0.6720666666666667
      Correct rate with C=1:0.6723
      Correct rate with C= 10 : 0.67233333333333333
      Correct rate with C= 100 : 0.6722666666666667
      3 KNN MODEL
[128]: from sklearn.neighbors import KNeighborsClassifier
      def knnClass(text, rating, text_test, rating_test, words, n):
          X = prepX(text, words)
          y = [d > mean for d in rating]
          Xtest = prepX(text_test, words)
          ytest = [d > mean for d in rating_test]
          knn = KNeighborsClassifier(n_neighbors=n)
          knn.fit(X, y)
          #Predict the response for test dataset
          y_pred = knn.predict(Xtest)
          correct = [a==b for a,b in zip(y_pred, ytest)]
          print("Correct rate with n=", n,":", sum(correct)/ len(correct))
[130]: knnClass(text, rating, text_test, rating_test, wordsUni, 3)
      [133]: X = prepX(text, wordsUni)
      y = [d > mean for d in rating]
      Xtest = prepX(text_test, wordsUni)
      ytest = [d > mean for d in rating_test]
```

[137]: n = [1, 2, 3]

```
[139]: def predictKnn(Xtest, ytest, n):
          for i in n:
              knn = KNeighborsClassifier(n_neighbors=i)
              knn.fit(X, y)
               #Predict the response for test dataset
              y_pred = knn.predict(Xtest)
              correct = [a==b for a,b in zip(y_pred, ytest)]
              print("Correct rate with n=", i,":", sum(correct)/ len(correct))
[138]: predictKnn(Xtest, ytest, n)
      Correct rate with n=[1, 2, 3]: 0.5919
      Correct rate with n = [1, 2, 3] : 0.5236
      Correct rate with n=[1, 2, 3]: 0.638833333333333333
[140]: predictKnn(X, y, n)
      Correct rate with n=1:0.9282
      Correct rate with n= 2 : 0.7467
      Correct rate with n=3:0.7914142857142857
  []:
```