KNN on Amazon Food Reviews

Using Bag of Words(BoW) Technique

Data Source: https://www.kaggle.com/snap/amazon-fine-food-reviews (https://www.kaggle.com/snap/amazon-fine-food-reviews)

The Amazon Fine Food Reviews dataset consists of reviews of fine foods from Amazon.

Number of reviews: 568,454 Number of users: 256,059 Number of products: 74,258 Timespan: Oct 1999 - Oct 2012 Number of Attributes/Columns in data: 10

Attribute Information:

1. index
2. Id
3. ProductId - unique identifier for the product
4. UserId - unqiue identifier for the user
5. ProfileName
6. HelpfulnessNumerator - number of users who found the review helpful
7. HelpfulnessDenominator - number of users who indicated whether they found the review helpful or not
8. Score - rating between 1 and 5
9. Time - timestamp for the review
10. Summary - brief summary of the review
11. Text - text of the review
12. ProcessedText - Cleaned & Preprocessed Text of the review

Objective: Given Amazon Food reviews, convert all the reviews into a vector using four techniques: BoW; tf_idf; Avg_w2v and tf_idf_w2v and then apply 10-fold cross validation in KNN. Use both brute force and KD-Tree implementation of KNN to find neighbours

[Q] How to determine if a review is positive or negative?

[Ans] We could use the Score/Rating. A rating of 4 or 5 could be cosnidered a positive review. A review of 1 or 2 could be considered negative. A review of 3 is nuetral and ignored. This is an approximate and proxy way of determining the polarity (positivity/negativity) of a review.

Loading the data

SQLite Database

In order to load the data, We have used the SQLITE dataset as it easier to query the data and visualise the data efficiently. Here as we only want to get the global sentiment of the recommendations (positive or negative), we will purposefully ignore all Scores equal to 3. If the score id above 3, then the recommendation wil be set to "positive". Otherwise, it will be set to "negative".

In [2]:
```
import sqlite3
import pandas as pd
import numpy as np
import matplotlib.pyplot as plot

from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfTransformer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.preprocessing import StandardScaler

from sklearn import cross_validation
from sklearn.cross_validation import train_test_split
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import accuracy_score
from sklearn.cross_validation import cross_val_score
from collections import Counter

from wordcloud import WordCloud
```

In [3]:
```
connection = sqlite3.connect('FinalAmazonFoodReviewsDataset.sqlite')
```

In [4]:
```
data = pd.read_sql_query("SELECT * FROM Reviews", connection)
```

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

Out[5]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	Positive	1303862400	Good Quality Dog Food	se
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	Negative	1346976000	Not as Advertised	lal
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	Positive	1219017600	"Delight" says it all	F . cc a
3	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	Positive	1350777600	Great taffy	t
4	5	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	Positive	1342051200	Nice Taffy	.

In [6]:
```
data.shape
```

Out[6]: (364171, 12)

In [7]:
```
data["Score"].value_counts()
```

Out[7]:
```
Positive    307061
Negative     57110
Name: Score, dtype: int64
```

In [8]:
```
def changingScores(score):
    if score == "Positive":
        return 1
    else:
        return 0
```

In [9]:
```
# changing score
# Positive = 1
# Negative = 0
actualScore = list(data["Score"])
positiveNegative = list(map(changingScores, actualScore)) #map(function, list of numbers)
data['Score'] = positiveNegative
```

In [10]:
```python
data.head()
```

Out[10]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food	I b seve V ca
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976000	Not as Advertised	Pr a label J S Pea
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all	Thi confe tha aro
3	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	1	1350777600	Great taffy	taff
4	5	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	1	1342051200	Nice Taffy	I wil fo or th

In [11]:
```python
allPositiveReviews = data[(data["Score"] == 1)]
```

In [12]:
```
allPositiveReviews.shape
```

Out[12]:
```
(307061, 12)
```

In [13]:
```
positiveReviews_5000 = allPositiveReviews[:5000]
```

In [14]:
```
positiveReviews_5000.shape
```

Out[14]:
```
(5000, 12)
```

In [15]:
```
positiveReviews_5000.head()
```

Out[15]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	
0	0	1	B001E4KFG0	A3SGXH7AUHU8GW	delmartian	1	1	1	1303862400	Good Quality Dog Food	I bo seve V ca
2	2	3	B000LQOCH0	ABXLMWJIXXAIN	Natalia Corres "Natalia Corres"	1	1	1	1219017600	"Delight" says it all	Thi confe tha arou
3	4	5	B006K2ZZ7K	A1UQRSCLF8GW1T	Michael D. Bigham "M. Wassir"	0	0	1	1350777600	Great taffy	(taffy I T v
4	5	6	B006K2ZZ7K	ADT0SRK1MGOEU	Twoapennything	0	0	1	1342051200	Nice Taffy	I wild fo ord th
5	6	7	B006K2ZZ7K	A1SP2KVKFXXRU1	David C. Sullivan	0	0	1	1340150400	Great! Just as good as the expensive brands!	salty taffy fla and v

In [16]:
```
allNegativeReviews = data[(data["Score"] == 0)]
```

In [17]:
```
allNegativeReviews.shape
```
Out[17]:
```
(57110, 12)
```

In [18]:
```
negativeReviews_5000 = allNegativeReviews[:5000]
```

In [19]:
```
negativeReviews_5000.shape
```
Out[19]:
```
(5000, 12)
```

In [20]:
```
negativeReviews_5000.head()
```

Out[20]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary	T
1	1	2	B00813GRG4	A1D87F6ZCVE5NK	dll pa	0	0	0	1346976000	Not as Advertised	Prod arri labe Jun Sal Peanu
11	12	13	B0009XLVG0	A327PCT23YH90	LT	1	1	0	1339545600	My Cats Are Not Fans of the New Food	My c ha be hap eat Felic Pla
15	16	17	B001GVISJM	A3KLWF6WQ5BNYO	Erica Neathery	0	0	0	1348099200	poor taste	I lo eat th and tl are go watc
25	26	27	B001GVISJM	A3RXAU2N8KV45G	lady21	0	1	0	1332633600	Nasty No flavor	- cand just re No fla . J pla
45	47	51	B001EO5QW8	A108P30XVUFKXY	Roberto A	0	7	0	1203379200	Don't like it	T oatm is good. mus so

In [21]:
```
frames_10000 = [positiveReviews_5000, negativeReviews_5000]
```

In [22]:
```
FinalPositiveNegative = pd.concat(frames_10000)
```

In [23]:
```
FinalPositiveNegative.shape
```

Out[23]:
```
(10000, 12)
```

In [24]:
```
#Sorting FinalDataframe by "Time"
FinalSortedPositiveNegative_10000 = FinalPositiveNegative.sort_values('Time', axis=0, ascending=True, inplace=False)
```

In [25]:
```
FinalSortedPositiveNegativeScore_10000 = FinalSortedPositiveNegative_10000["Score"]
```

In [26]:
```
FinalSortedPositiveNegative_10000.shape
```

Out[26]:
```
(10000, 12)
```

In [27]:
```
FinalSortedPositiveNegativeScore_10000.shape
```

Out[27]:
```
(10000,)
```

In [28]:
```
FinalSortedPositiveNegative_10000.head()
```

Out[28]:

	index	Id	ProductId	UserId	ProfileName	HelpfulnessNumerator	HelpfulnessDenominator	Score	Time	Summary
772	1146	1245	B00002Z754	A29Z5PI9BW2PU3	Robbie	7	7	1	961718400	Great Product
771	1145	1244	B00002Z754	A3B8RCEI0FXFI6	B G Chase	10	10	1	962236800	WOW Make your own 'slickers' !
5822	7427	8111	B0000EIE2Z	A3M174IC0VXOS2	Gail Cooke	3	3	1	1075420800	BEST BLUEBERRIES
2418	3481	3783	B00016UX0K	AF1PV3DIC0XM7	Robert Ashton	1	2	1	1081555200	Classic Condiment
5206	6790	7432	B0001E1IME	A2IKCTD1I73PLW	Adeba	2	8	1	1083456000	amazon monopoly/ripoff

Bag of Words(BoW)

In [30]:
```
positive_reviews = FinalSortedPositiveNegative_10000[(FinalSortedPositiveNegative_10000["Score"] == 1)]
negative_reviews = FinalSortedPositiveNegative_10000[(FinalSortedPositiveNegative_10000["Score"] == 0)]
```

In [34]:
```
positive_reviews.shape, negative_reviews.shape
```
Out[34]:
```
((5000, 12), (5000, 12))
```

In [35]:
```
positive_bow_vect =  CountVectorizer(stop_words = "english")
positive_bow = positive_bow_vect.fit_transform(positive_reviews["ProcessedText"].values)
```

In [36]:
```
positive_bow.shape
```
Out[36]:
```
(5000, 8690)
```

In [37]:
```
features_positive = positive_bow_vect.get_feature_names()
len(features_positive), type(features_positive)
```
Out[37]:
```
(8690, list)
```

In [38]:
```
count = []
for i in range(len(features_positive)):
    total = positive_bow.getcol(i).sum() # it will give sum of all the values in 'i'th column
    count.append(total)
```

In [39]:
```
positive_dict = dict(zip(features_positive, count))
```

In [40]:
```
sortedDict_Positive = sorted(positive_dict.items(), key = lambda positive_dict: positive_dict[1], reverse = True)
```

In [41]:
```
for i in range(200):
    print(sortedDict_Positive[i])
```

```
('like', 2171)
('tast', 2010)
('good', 1874)
('flavor', 1852)
('great', 1781)
('use', 1738)
('love', 1662)
('product', 1506)
('veri', 1482)
('coffe', 1403)
('just', 1399)
('tri', 1374)
('make', 1294)
('tea', 1040)
('buy', 870)
('realli', 866)
('time', 846)
('onli', 838)
('food', 819)
('mix', 797)
('price', 792)
('littl', 761)
('eat', 750)
('best', 748)
('drink', 746)
('order', 737)
('dont', 736)
('bag', 710)
('amazon', 683)
('store', 667)
('becaus', 640)
('better', 637)
('ive', 581)
('recommend', 578)
('sugar', 576)
('cup', 563)
('ani', 546)
('chip', 539)
```

```
('high', 511)
('year', 509)
('pack', 496)
('want', 494)
('work', 492)
('sweet', 481)
('snack', 478)
('look', 471)
('water', 468)
('brand', 467)
('delici', 462)
('milk', 447)
('day', 443)
('purchas', 440)
('box', 439)
('nice', 439)
('favorit', 432)
('chocol', 429)
('enjoy', 424)
('free', 422)
('perfect', 407)
('packag', 399)
('say', 398)
('thing', 398)
('easi', 395)
('mani', 394)
('bought', 393)
('fresh', 392)
('add', 388)
('differ', 388)
('calori', 386)
('need', 383)
('way', 383)
('sinc', 379)
('juic', 378)
('bit', 377)
('think', 371)
('lot', 359)
('regular', 357)
('bean', 355)
('dog', 354)
('cat', 351)
```

```
('come', 348)
('treat', 340)
('wonder', 333)
('ship', 329)
('alway', 326)
('know', 322)
('pancak', 322)
('hot', 321)
('natur', 321)
('sauc', 317)
('everi', 316)
('got', 315)
('local', 315)
('right', 308)
('tasti', 298)
('qualiti', 292)
('excel', 291)
('review', 291)
('did', 290)
('hard', 283)
('salt', 283)
('definit', 282)
('healthi', 282)
('stuff', 281)
('befor', 278)
('ingredi', 275)
('gluten', 272)
('orang', 272)
('small', 271)
('sure', 271)
('famili', 270)
('soda', 268)
('doe', 267)
('ad', 266)
('feel', 262)
('oil', 261)
('serv', 261)
('thank', 261)
('cooki', 259)
('someth', 259)
('bake', 249)
('long', 249)
```

```
('happi', 247)
('recip', 246)
('problem', 244)
('size', 241)
('doesnt', 239)
('month', 239)
('contain', 238)
('cook', 236)
('help', 236)
('organ', 235)
('varieti', 233)
('howev', 232)
('didnt', 231)
('fruit', 231)
('actual', 230)
('usual', 229)
('start', 224)
('far', 223)
('light', 221)
('old', 218)
('chicken', 217)
('pretti', 217)
('quick', 216)
('groceri', 211)
('bottl', 209)
('expens', 207)
('quit', 207)
('vanilla', 207)
('cake', 206)
('fat', 202)
('butter', 201)
('diet', 200)
('open', 200)
('case', 199)
('friend', 199)
('big', 198)
('kid', 198)
('peopl', 197)
('came', 196)
('low', 195)
('worth', 194)
('ice', 193)
```

```
('rice', 192)
('smell', 192)
('thought', 192)
('new', 191)
('pleas', 191)
('strong', 191)
('waffl', 191)
('arriv', 188)
('cracker', 186)
('potato', 185)
('theyr', 185)
('item', 184)
('save', 184)
('seed', 184)
('anyth', 183)
('blend', 182)
('home', 182)
('switch', 181)
('abl', 180)
('powder', 180)
('real', 180)
('reason', 180)
('altern', 179)
('husband', 179)
('bad', 177)
('expect', 175)
('protein', 175)
('textur', 174)
('sever', 173)
('anoth', 170)
('absolut', 169)
('bread', 169)
('week', 169)
('cream', 168)
('kind', 166)
('brew', 165)
```

In [42]:
```
def PlotWordCloud(frequency):
    worcloudPlot = WordCloud(background_color="white", width=1500, height=1000)
    worcloudPlot.generate_from_frequencies(frequencies=frequency)
    plot.figure(figsize=(15,10))
    plot.imshow(worcloudPlot, interpolation="bilinear")
    plot.axis("off")
    plot.show()
```

In [43]:
```
PlotWordCloud(positive_dict)
```

This is a Word Cloud for all the positive reviews in the corpus.
This Word Cloud plot correponds to the most frequent words in all positive reviews.

How I have plotted this word cloud. Now BoW representation is based on the count of the word in a document. If a word Wi occurs in many document then the sum of its column will be high. Therefore, I have just calculated the sum of all the column and created the dictionary where keys are the features and values are the sum of that column. I feeded this dictionary to the wordcloud and plotted the same. the same procedure is followed for negative reviews as well

In [44]:
```
negative_bow_vect =  CountVectorizer(stop_words = "english")
negative_bow = negative_bow_vect.fit_transform(negative_reviews["ProcessedText"].values)
```

In [45]:
```
negative_bow.shape
```

Out[45]:
```
(5000, 9648)
```

In [46]:
```
features_negative = negative_bow_vect.get_feature_names()
len(features_negative), type(features_negative)
```

Out[46]:
```
(9648, list)
```

In [47]:
```
count = []
for i in range(len(features_negative)):
    total = negative_bow.getcol(i).sum() # it will give sum of all the values in 'i'th column
    count.append(total)
```

In [48]:
```
negative_dict = dict(zip(features_negative, count))
```

In [49]:
```
sortedDict_Negative = sorted(negative_dict.items(), key = lambda negative_dict: negative_dict[1], reverse = True)
```

In [50]:
```
for i in range(200):
    print(sortedDict_Negative[i])
```

```
('tast', 3153)
('like', 2911)
('product', 2408)
('just', 1775)
('tri', 1662)
('flavor', 1656)
('veri', 1597)
('use', 1407)
('good', 1345)
('coffe', 1198)
('tea', 1147)
('buy', 1135)
('food', 1106)
('dog', 1040)
('dont', 1038)
('order', 1020)
('becaus', 979)
('make', 940)
('time', 919)
('drink', 918)
('box', 915)
('onli', 897)
('realli', 885)
('eat', 869)
('bag', 851)
('look', 836)
('amazon', 821)
('packag', 802)
('love', 769)
('review', 712)
('bought', 707)
('purchas', 704)
('better', 691)
('chocol', 691)
('ani', 689)
('did', 675)
('water', 666)
('bad', 665)
```

```
('disappoint', 661)
('think', 643)
('want', 634)
('sugar', 630)
('say', 624)
('mix', 619)
('know', 616)
('price', 608)
('didnt', 604)
('ingredi', 566)
('smell', 560)
('ive', 557)
('cup', 553)
('thought', 549)
('great', 548)
('littl', 544)
('way', 542)
('got', 523)
('brand', 515)
('thing', 510)
('store', 502)
('someth', 496)
('open', 491)
('receiv', 484)
('item', 483)
('treat', 480)
('differ', 472)
('sweet', 465)
('ginger', 464)
('money', 450)
('doe', 448)
('befor', 445)
('pack', 435)
('ship', 423)
('old', 420)
('work', 415)
('away', 413)
('day', 409)
('recommend', 406)
('cooki', 403)
('sinc', 397)
('year', 396)
```

```
('cat', 387)
('hot', 387)
('howev', 380)
('doesnt', 376)
('contain', 375)
('actual', 374)
('juic', 373)
('come', 371)
('mani', 362)
('problem', 361)
('stuff', 361)
('hard', 355)
('compani', 354)
('sure', 353)
('need', 352)
('chew', 347)
('anoth', 345)
('lot', 344)
('return', 344)
('natur', 340)
('new', 339)
('expect', 338)
('enjoy', 335)
('hope', 334)
('mayb', 333)
('month', 319)
('bit', 317)
('peopl', 317)
('small', 315)
('dri', 314)
('toy', 314)
('qualiti', 313)
('star', 311)
('milk', 309)
('ad', 308)
('high', 308)
('strong', 304)
('anyth', 303)
('noth', 300)
('wast', 299)
('ill', 298)
('chang', 295)
```

```
('textur', 292)
('bottl', 291)
('bar', 289)
('whi', 287)
('wont', 287)
('list', 284)
('read', 281)
('real', 280)
('organ', 279)
('regular', 276)
('size', 275)
('lemon', 270)
('label', 264)
('local', 263)
('pretti', 261)
('said', 260)
('piec', 257)
('right', 255)
('big', 252)
('bitter', 252)
('kind', 252)
('coconut', 249)
('gave', 249)
('best', 248)
('half', 246)
('free', 245)
('feel', 244)
('plastic', 244)
('oil', 241)
('end', 239)
('case', 238)
('far', 237)
('arriv', 235)
('probabl', 235)
('formula', 231)
('start', 229)
('worth', 229)
('stick', 228)
('candi', 227)
('instead', 224)
('wasnt', 223)
('came', 222)
```

```
('minut', 222)
('long', 219)
('chicken', 218)
('horribl', 218)
('syrup', 218)
('week', 218)
('care', 217)
('salt', 217)
('everi', 215)
('acid', 214)
('isnt', 214)
('low', 213)
('guess', 212)
('sever', 211)
('aw', 210)
('decid', 209)
('notic', 208)
('went', 208)
('mouth', 207)
('black', 206)
('fruit', 205)
('usual', 205)
('unfortun', 203)
('fresh', 201)
('save', 201)
('switch', 201)
('dark', 200)
('fine', 200)
('chip', 199)
('expens', 199)
('calori', 197)
('babi', 194)
('terribl', 194)
('complet', 193)
('healthi', 193)
('noodl', 193)
```

In [51]:
```
PlotWordCloud(negative_dict)
```

This is a Word Cloud for all the negative reviews in the corpus.
This Word Cloud plot correponds to the most frequent words in all negative reviews.

In [29]:
```
count_vect = CountVectorizer()
```

In [30]:
```
BoW = count_vect.fit_transform(FinalSortedPositiveNegative_10000["ProcessedText"].values)
```

In [31]:
```
print(type(BoW))
```

```
<class 'scipy.sparse.csr.csr_matrix'>
```

In [32]:
```
BoW.shape
```

Out[32]:
```
(10000, 13033)
```

It means that there are 10000 reviews means there are 10000 rows and there are total 13033 unique words in all the reviews.

In [33]:
```
#Standardizing our data matrix
BoW_Standardized = StandardScaler(with_mean = False).fit_transform(BoW)
print(BoW_Standardized.shape)
print(type(BoW_Standardized))
```

```
(10000, 13033)
<class 'scipy.sparse.csr.csr_matrix'>
```

```
C:\Users\GauravP\Anaconda3\lib\site-packages\sklearn\utils\validation.py:475: DataConversionWarning: Data with input dt
ype int64 was converted to float64 by StandardScaler.
  warnings.warn(msg, DataConversionWarning)
```

Brute Force Implementation

In [230]:
```
X_BOW = BoW_Standardized
```

In [231]:
```
Y_BOW = FinalSortedPositiveNegativeScore_10000
```

In [232]:
```
X_BOW.shape
```

Out[232]:
```
(10000, 13033)
```

In [233]:
```
Y_BOW.shape
```

Out[233]:
```
(10000,)
```

In [234]:
```
X_BOW_1, X_BOW_test, Y_BOW_1, Y_BOW_test = cross_validation.train_test_split(X_BOW, Y_BOW, test_size = 0.3, random_state

myList = list(range(0,50))
neighbors = list(filter(lambda x: x%2!=0, myList))  #This will give a list of odd numbers only ranging from 0 to 50

CV_Scores = []

for k in neighbors:
    KNN = KNeighborsClassifier(n_neighbors = k, algorithm = 'brute')
    scores = cross_val_score(KNN, X_BOW_1, Y_BOW_1, cv = 10, scoring='accuracy')
    CV_Scores.append(scores.mean())
```

In [236]:
```
CV_Scores
```

Out[236]:
```
[0.5987215898108248,
 0.629004296801772,
 0.6318622554040199,
 0.6367128775481465,
 0.6335708309025704,
 0.6418657408338735,
 0.640004515752656,
 0.6324306277009895,
 0.6297155186614084,
 0.6260042868892152,
 0.6217177481120224,
 0.6215744822219754,
 0.6267238781536871,
 0.6282914317900941,
 0.626285100290292,
 0.6271420411062063,
 0.6274269367313579,
 0.6229969224426988,
 0.6167085378891445,
 0.6035644340965127,
 0.5881368577137038,
 0.5759976553888011,
 0.5638611046728084,
 0.5512880224536902,
 0.5405722932962254]
```

In [237]:
```
print(max(CV_Scores))
print(CV_Scores.index(max(CV_Scores)))
print(neighbors[5])
```

```
0.6418657408338735
5
11
```

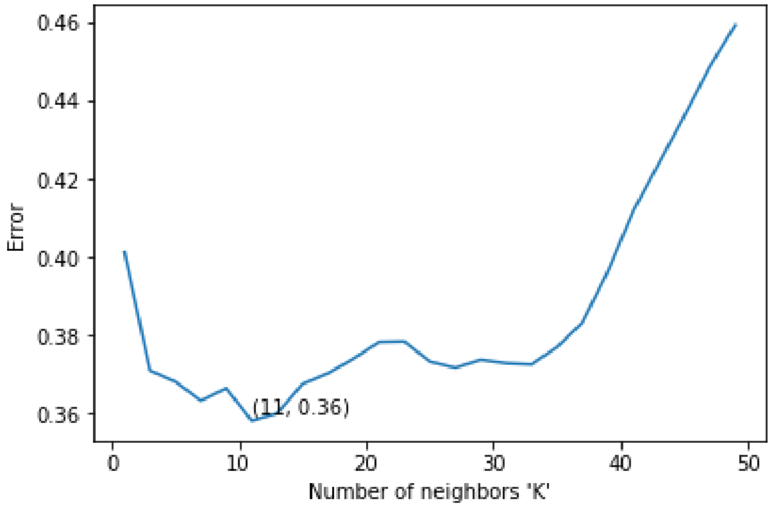
In [238]:
```
maxScoreIndex = CV_Scores.index(max(CV_Scores))
```

In [239]:
```
best_k = neighbors[maxScoreIndex]
```

In [240]:
```
best_k
```

Out[240]:
```
11
```

In [241]:
```
error = []

for a in CV_Scores:
    x = 1 - a
    error.append(x)

plot.plot(neighbors, error)

minError1 = min(error)
minError = np.round(minError1, 2)

plot.xlabel("Number of neighbors 'K'")
plot.ylabel("Error")
for xy in zip(neighbors, np.round(error,2)):
    if xy == (best_k, minError):
        plot.annotate(xy,xy)

plot.show()
```



In [242]:
```
KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'brute')

KNN_best.fit(X_BOW_1, Y_BOW_1)

prediction = KNN_best.predict(X_BOW_test)

accuracyTest = accuracy_score(Y_BOW_test, prediction) * 100

print("Accuracy of the knn classifier for best k values of "+str(best_k)+" is: "+str(accuracyTest)+"%")
```

```
Accuracy of the knn classifier for best k values of 11 is: 65.3%
```

KD Tree Implementation

In [243]:
```
KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'kd_tree')

KNN_best.fit(X_BOW_1, Y_BOW_1)

prediction = KNN_best.predict(X_BOW_test)

accuracyTest = accuracy_score(Y_BOW_test, prediction) * 100

print("Accuracy of the knn classifier for best k values of "+str(best_k)+" is: "+str(accuracyTest)+"%")
```

```
C:\Users\GauravP\Anaconda3\lib\site-packages\sklearn\neighbors\base.py:212: UserWarning: cannot use tree with sparse in
put: using brute force
  warnings.warn("cannot use tree with sparse input: "

Accuracy of the knn classifier for best k values of 11 is: 65.3%
```

TFIDF

In [53]:
```
positive_reviews = FinalSortedPositiveNegative_10000[(FinalSortedPositiveNegative_10000["Score"] == 1)]
negative_reviews = FinalSortedPositiveNegative_10000[(FinalSortedPositiveNegative_10000["Score"] == 0)]
```

In [54]:
```
Positive_tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), stop_words = "english")
Positive_tf_idf = Positive_tf_idf_vect.fit_transform(positive_reviews["ProcessedText"].values)
```

In [55]:
```
Positive_tf_idf.shape
```

Out[55]:
```
(5000, 114651)
```

In [56]:
```
features = Positive_tf_idf_vect.get_feature_names()
```

In [58]:
```
idfValues = Positive_tf_idf_vect.idf_
```

In [61]:
```
d = dict(zip(features, 9 - idfValues))
```

In [62]:
```
sortedDict = sorted(d.items(), key = lambda d: d[1], reverse = True)
```

In [63]:
```
for i in range(200):
    print(sortedDict[i])
```

```
('like', 6.809072442421418)
('tast', 6.765368008186689)
('great', 6.763992492151379)
('good', 6.73466078043391)
('love', 6.689725684788852)
('flavor', 6.590032302691801)
('use', 6.568508292946707)
('just', 6.50636578331954)
('veri', 6.503690792870237)
('product', 6.470097075582087)
('tri', 6.467323148699362)
('make', 6.391361607896317)
('buy', 6.114608605976726)
('onli', 6.072907876777782)
('time', 6.060468186302143)
('realli', 6.049279258384337)
('best', 5.968767617525185)
('price', 5.95030555468545)
('littl', 5.909095286038787)
('dont', 5.886181026515912)
('order', 5.886181026515912)
('amazon', 5.849077276312534)
('store', 5.833492545295836)
('eat', 5.817661080079155)
('coffe', 5.8141086784747875)
('becaus', 5.806965790962407)
('recommend', 5.797964830103432)
('better', 5.790705270090627)
('mix', 5.726773729244833)
('ive', 5.650123319469437)
('ani', 5.631075124498743)
('high', 5.624644234168453)
('food', 5.594074168083775)
('bag', 5.591854411345462)
('drink', 5.580681110747337)
('year', 5.569381555493403)
('delici', 5.544063747509114)
('want', 5.529979007627374)
```

```
('work', 5.515693050379898)
('look', 5.501200043077331)
('favorit', 5.474071375689078)
('pack', 5.47156824547096)
('nice', 5.458957737879031)
('enjoy', 5.448753567704788)
('sweet', 5.441031521610878)
('day', 5.433249381168823)
('purchas', 5.428027437187671)
('sugar', 5.3879686766356665)
('say', 5.379760696217836)
('tea', 5.379760696217836)
('perfect', 5.377009662845947)
('snack', 5.377009662845947)
('brand', 5.371484786913977)
('bought', 5.3603426103607354)
('easi', 5.357537559433126)
('way', 5.349074885514393)
('sinc', 5.337678750783524)
('mani', 5.3290456036388205)
('thing', 5.3290456036388205)
('fresh', 5.302689758933458)
('need', 5.302689758933458)
('cup', 5.281699483041622)
('differ', 5.281699483041622)
('bit', 5.278664579346469)
('lot', 5.278664579346469)
('box', 5.269504209947804)
('think', 5.269504209947804)
('free', 5.254047951711112)
('packag', 5.247797931365941)
('add', 5.2094545761682935)
('come', 5.2094545761682935)
('regular', 5.2094545761682935)
('wonder', 5.1963396340904655)
('chip', 5.189717093329972)
('water', 5.189717093329972)
('alway', 5.166186595919777)
('local', 5.1627794375981635)
('everi', 5.155930095752589)
('got', 5.152487751561615)
('right', 5.135096008849747)
```

```
('know', 5.131581066742303)
('ship', 5.12451389951921)
('tasti', 5.120961497914842)
('calori', 5.113818610402461)
('review', 5.077318208182936)
('definit', 5.066103137362795)
('hard', 5.058555931727413)
('excel', 5.050951332342193)
('did', 5.039434890280634)
('befor', 5.031682913476317)
('qualiti', 5.027784273060659)
('healthi', 5.000059725045804)
('natur', 5.000059725045804)
('sure', 5.000059725045804)
('stuff', 4.975668271921645)
('famili', 4.971544554737783)
('high recommend', 4.967403762071751)
('someth', 4.963245751923088)
('ad', 4.954877502252571)
('doe', 4.954877502252571)
('chocol', 4.950666969716227)
('hot', 4.950666969716227)
('long', 4.933645282146797)
('happi', 4.929344200247407)
('small', 4.911952457535537)
('thank', 4.911952457535537)
('treat', 4.898707230785517)
('doesnt', 4.894252880436136)
('milk', 4.894252880436136)
('ingredi', 4.876234374933458)
('serv', 4.867101891370185)
('actual', 4.857885236265261)
('feel', 4.857885236265261)
('far', 4.853244856708759)
('howev', 4.843898994290521)
('month', 4.839193103253109)
('problem', 4.839193103253109)
('size', 4.839193103253109)
('didnt', 4.824941080545907)
('quick', 4.820144908282414)
('light', 4.800726822425313)
('usual', 4.800726822425313)
```

```
('pancak', 4.795812807622884)
('veri good', 4.795812807622884)
('help', 4.7859117366401716)
('groceri', 4.780924195129133)
('expens', 4.770873859275632)
('varieti', 4.770873859275632)
('start', 4.750464987644424)
('contain', 4.745297017485981)
('old', 4.745297017485981)
('pretti', 4.745297017485981)
('salt', 4.745297017485981)
('quit', 4.740102200608877)
('bake', 4.734880256627726)
('cook', 4.724353843640738)
('friend', 4.724353843640738)
('big', 4.719048791411046)
('gluten', 4.719048791411046)
('sauc', 4.7137154454356835)
('came', 4.7083535022942975)
('worth', 4.697542586190082)
('juic', 4.692092981422517)
('thought', 4.686613515657892)
('dog', 4.664390378873181)
('pleas', 4.664390378873181)
('recip', 4.664390378873181)
('peopl', 4.653090823619248)
('reason', 4.653090823619248)
('open', 4.64739280250461)
('arriv', 4.641662127795625)
('bean', 4.641662127795625)
('kid', 4.641662127795625)
('low', 4.641662127795625)
('abl', 4.635898423078875)
('anyth', 4.635898423078875)
('home', 4.635898423078875)
('case', 4.6301013053945494)
('new', 4.6301013053945494)
('altern', 4.618405265631358)
('groceri store', 4.618405265631358)
('strong', 4.606570807984355)
('expect', 4.600600640997851)
('diet', 4.5945946169376395)
```

```
('save', 4.588552302481677)
('tast like', 4.588552302481677)
('husband', 4.582473256405295)
('real', 4.582473256405295)
('anoth', 4.576357029387859)
('bad', 4.576357029387859)
('absolut', 4.57020316381348)
('organ', 4.57020316381348)
('tast great', 4.564011193565559)
('item', 4.551511030801327)
('especi', 4.538852633929404)
('smell', 4.532462835830634)
('textur', 4.532462835830634)
('chicken', 4.519559430994725)
('instead', 4.519559430994725)
('sever', 4.519559430994725)
('week', 4.513044749973531)
('oil', 4.506487349427372)
('amaz', 4.499886665396021)
('blend', 4.486553134526556)
('fruit', 4.486553134526556)
('theyr', 4.486553134526556)
('bottl', 4.479819102345211)
('butter', 4.479819102345211)
('kind', 4.479819102345211)
('onc', 4.479819102345211)
('orang', 4.479819102345211)
('wont', 4.459340571001671)
('cat', 4.445451458841004)
('fat', 4.445451458841004)
('prefer', 4.445451458841004)
('ago', 4.438433886182358)
('avail', 4.438433886182358)
('gluten free', 4.438433886182358)
('soda', 4.438433886182358)
('wish', 4.438433886182358)
```

In [66]:
```
def PlotWordCloud(frequency):
    worcloudPlot = WordCloud(background_color="white", width=1500, height=1000)
    worcloudPlot.generate_from_frequencies(frequencies=frequency)
    plot.figure(figsize=(15,10))
    plot.imshow(worcloudPlot, interpolation="bilinear")
    plot.axis("off")
    plot.show()
```

In [67]:

```
PlotWordCloud(d)
```

This is a Word Cloud for all the positive reviews in the corpus.
This Word Cloud plot correponds to the most frequent words in all positive reviews based on IDF values. More is the IDF Value for a word the less frequent is the word in the corpus.

How I have plotted this word cloud. Now formulae for IDF(D,Wi) = (ln(N+1 / ni+1) + 1) where 'N' is total number of documents in a corpus and 'ni' is the total number of documents where word 'Wi' occurs. Hence, I got all the idf values from idf_ attribute and I got corresponding features from get_features_names() function. Now since, the highest possible idf value can be 8.88, hence, I subtracted all the idf values from '9' which leads to the highest idf value of the most frequently occuring word. Now I created dictionary where features are the keys and modified idf value are the values and I feeded this to the word cloud and plot the same. The same is done for negative reviews as well.

In [68]:
```
Negative_tf_idf_vect = TfidfVectorizer(ngram_range=(1,2), stop_words = "english")
Negative_tf_idf = Negative_tf_idf_vect.fit_transform(negative_reviews["ProcessedText"].values)
```

In [69]:
```
Negative_tf_idf.shape
```

Out[69]:
```
(5000, 139161)
```

In [70]:
```
features_neg = Negative_tf_idf_vect.get_feature_names()
```

In [71]:
```
negIDF = Negative_tf_idf_vect.idf_
```

In [76]:
```
NegD = dict(zip(features_neg, 9 - negIDF))
```

In [77]:
```
sortedDictNeg = sorted(NegD.items(), key = lambda NegD: NegD[1], reverse = True)
```

In [78]:
```
for i in range(200):
    print(sortedDictNeg[i])
```

```
('tast', 7.0050070599682215)
('like', 7.004466080782725)
('product', 6.762615081465285)
('just', 6.6496447054933165)
('veri', 6.595748937288184)
('tri', 6.565994676206391)
('good', 6.44957396719508)
('flavor', 6.4170040385096545)
('use', 6.376263183183732)
('buy', 6.343270500029383)
('dont', 6.271578571573267)
('becaus', 6.170961542527858)
('onli', 6.1211746177476165)
('make', 6.113290214223468)
('time', 6.082477327793933)
('order', 6.054889371275104)
('realli', 6.047871798616457)
('look', 6.009101688151887)
('love', 5.951857145376868)
('food', 5.95030555468545)
('eat', 5.9314962227279535)
('bought', 5.923553369214017)
('disappoint', 5.889486814650411)
('ani', 5.862729365480861)
('packag', 5.861033012232683)
('better', 5.8473575854330075)
('review', 5.8473575854330075)
('did', 5.835236224900663)
('think', 5.828243189409692)
('purchas', 5.822966132308848)
('amazon', 5.810543612310291)
('box', 5.794341637734011)
('want', 5.783392623244341)
('bad', 5.781556075437039)
('say', 5.751703112287357)
('didnt', 5.742188292646019)
('know', 5.7287135940626595)
('thought', 5.720931453620604)
```

```
('bag', 5.713088276159578)
('drink', 5.674969318055968)
('great', 5.66881545248159)
('way', 5.645921632615737)
('price', 5.618171719662835)
('littl', 5.613833318064237)
('got', 5.609476012695281)
('ive', 5.5761765986262315)
('someth', 5.5761765986262315)
('coffe', 5.564825738957542)
('tast like', 5.557952859669781)
('thing', 5.555651362681502)
('water', 5.548714918684844)
('dog', 5.544063747509114)
('store', 5.520477748503234)
('mix', 5.513292088842359)
('money', 5.5036301779306225)
('befor', 5.484021706542246)
('receiv', 5.484021706542246)
('differ', 5.456416440450358)
('open', 5.443612168204369)
('smell', 5.443612168204369)
('away', 5.441031521610878)
('brand', 5.438444198045927)
('doe', 5.4358501628688805)
('ingredi', 5.430641817761742)
('recommend', 5.409532854551507)
('tea', 5.3879686766356665)
('item', 5.382504182163588)
('sugar', 5.382504182163588)
('howev', 5.365929217069375)
('sinc', 5.357537559433126)
('cup', 5.349074885514393)
('old', 5.337678750783524)
('sweet', 5.331931608527956)
('come', 5.314489305864614)
('doesnt', 5.314489305864614)
('year', 5.311552446191303)
('pack', 5.305652724064116)
('work', 5.302689758933458)
('day', 5.29074931856154)
('sure', 5.284725203958159)
```

```
('need', 5.266432010910833)
('chocol', 5.263350344373426)
('mani', 5.250927824374869)
('actual', 5.244658211361273)
('hope', 5.222399740760331)
('anoth', 5.219179126060288)
('expect', 5.2094545761682935)
('mayb', 5.193033845955966)
('hard', 5.189717093329972)
('lot', 5.183050401971783)
('ship', 5.166186595919777)
('stuff', 5.159360630849378)
('problem', 5.155930095752589)
('return', 5.152487751561615)
('compani', 5.149033516693528)
('contain', 5.145567308717043)
('wast', 5.135096008849747)
('enjoy', 5.131581066742303)
('anyth', 5.117396431750346)
('bit', 5.106624334768435)
('high', 5.0993779262476675)
('month', 5.095734934969167)
('peopl', 5.088408894877094)
('ill', 5.084725649460797)
('small', 5.077318208182936)
('wont', 5.073593809091953)
('hot', 5.069855486981346)
('noth', 5.069855486981346)
('new', 5.054760860758861)
('star', 5.050951332342193)
('ad', 5.04712723590379)
('read', 5.031682913476317)
('qualiti', 5.019941095599632)
('whi', 5.015996317308616)
('strong', 5.00805976771288)
('treat', 4.996035574746079)
('natur', 4.971544554737783)
('dri', 4.963245751923088)
('textur', 4.963245751923088)
('local', 4.946438633606706)
('right', 4.946438633606706)
('pretti', 4.9379279439387975)
```

```
('said', 4.933645282146797)
('kind', 4.929344200247407)
('big', 4.916328832135337)
('gave', 4.916328832135337)
('best', 4.903141827853382)
('real', 4.889778600041215)
('worth', 4.889778600041215)
('chew', 4.885284210453376)
('regular', 4.885284210453376)
('chang', 4.871678558397598)
('feel', 4.871678558397598)
('list', 4.867101891370185)
('half', 4.862504182121556)
('probabl', 4.862504182121556)
('end', 4.839193103253109)
('instead', 4.834464962057163)
('size', 4.834464962057163)
('far', 4.824941080545907)
('came', 4.810482997370677)
('guess', 4.810482997370677)
('arriv', 4.800726822425313)
('free', 4.795812807622884)
('veri disappoint', 4.795812807622884)
('wasnt', 4.795812807622884)
('piec', 4.790874525982302)
('unfortun', 4.780924195129133)
('bitter', 4.770873859275632)
('decid', 4.770873859275632)
('horribl', 4.770873859275632)
('care', 4.765810557319085)
('long', 4.765810557319085)
('everi', 4.7607214878116135)
('sever', 4.7607214878116135)
('start', 4.7607214878116135)
('went', 4.7607214878116135)
('fine', 4.745297017485981)
('usual', 4.740102200608877)
('isnt', 4.734880256627726)
('label', 4.729630900741583)
('case', 4.719048791411046)
('expens', 4.719048791411046)
('aw', 4.7137154454356835)
```

```
('notic', 4.7137154454356835)
('throw', 4.7137154454356835)
('bottl', 4.7083535022942975)
('mouth', 4.7083535022942975)
('save', 4.7083535022942975)
('terribl', 4.702962653659421)
('plastic', 4.697542586190082)
('week', 4.697542586190082)
('minut', 4.686613515657892)
('organ', 4.686613515657892)
('wouldnt', 4.686613515657892)
('left', 4.681103859846922)
('complet', 4.675563679471306)
('stick', 4.675563679471306)
('milk', 4.669992634421851)
('let', 4.664390378873181)
('juic', 4.653090823619248)
('second', 4.64739280250461)
('definit', 4.635898423078875)
('took', 4.6301013053945494)
('groceri', 4.61250554350417)
('wast money', 4.61250554350417)
('add', 4.600600640997851)
('low', 4.600600640997851)
('believ', 4.5945946169376395)
('quit', 4.5945946169376395)
('alway', 4.588552302481677)
('onc', 4.588552302481677)
('custom', 4.582473256405295)
('worst', 4.576357029387859)
('ginger', 4.557780643814923)
('nice', 4.557780643814923)
('fact', 4.551511030801327)
('fresh', 4.551511030801327)
('wrong', 4.545201861608064)
('wonder', 4.538852633929404)
```

In [79]:
```
PlotWordCloud(NegD)
```

This is a Word Cloud for all the negative reviews in the corpus.
This Word Cloud plot correponds to the most frequent words in all negative reviews based on IDF values. More is the IDF Value for a word the less frequent is the word in the corpus.

In [244]:
```
tfidf_vect = TfidfVectorizer(ngram_range = (1,2))
```

In [245]:
```
tfidf = tfidf_vect.fit_transform(FinalSortedPositiveNegative_10000["ProcessedText"].values)
```

In [246]:
```
tfidf.shape
```

Out[246]:
```
(10000, 237703)
```

In [247]:
```
type(tfidf)
```

Out[247]:
```
scipy.sparse.csr.csr_matrix
```

In [248]:
```
tfidf_Standardized = StandardScaler(with_mean = False).fit_transform(tfidf)
print(tfidf_Standardized.shape)
print(type(tfidf_Standardized))
```

```
(10000, 237703)
<class 'scipy.sparse.csr.csr_matrix'>
```

Brute Force Implementation

In [249]:
```
X_tfidf = tfidf_Standardized
```

In [250]:
```
Y_tfidf = FinalSortedPositiveNegativeScore_10000
```

In [251]:
```
X_tfidf.shape
```

Out[251]:
```
(10000, 237703)
```

In [252]:
```
Y_tfidf.shape
```

Out[252]:
```
(10000,)
```

In [253]:
```
X_tfidf_1, X_tfidf_test, Y_tfidf_1, Y_tfidf_test = cross_validation.train_test_split(X_tfidf, Y_tfidf, test_size = 0.3, r

myList = list(range(0,50))
neighbors = list(filter(lambda x: x%2!=0, myList))  #This will give a list of odd numbers only ranging from 0 to 50

CV_Scores = []

for k in neighbors:
    KNN = KNeighborsClassifier(n_neighbors = k, algorithm = 'brute')
    scores = cross_val_score(KNN, X_tfidf_1, Y_tfidf_1, cv = 10, scoring='accuracy')
    CV_Scores.append(scores.mean())
```

In [254]:
```
CV_Scores
```

Out[254]:
```
[0.49857754345271255,
 0.5014273498517344,
 0.5009983690928814,
 0.503142249852988,
 0.5009997967925882,
 0.5018569396497311,
 0.5039977629691955,
 0.5078520527592914,
 0.5144349215873035,
 0.5038553128242536,
 0.5107087985310758,
 0.5028553087426126,
 0.5045736784302475,
 0.5047167411128828,
 0.5047138868796526,
 0.5048583772619943,
 0.5104334898059559,
 0.50956878862435,
 0.5198392145406711,
 0.5088487891957796,
 0.5072828647172166,
 0.5044259221520278,
 0.5022853067047075,
 0.5044314338250836,
 0.5011434714298251]
```

In [255]:
```
print(max(CV_Scores))
```

```
0.5198392145406711
```

In [256]:
```
print(CV_Scores.index(max(CV_Scores)))
```

```
18
```

In [257]:
```
print(neighbors[CV_Scores.index(max(CV_Scores))])
```

```
37
```

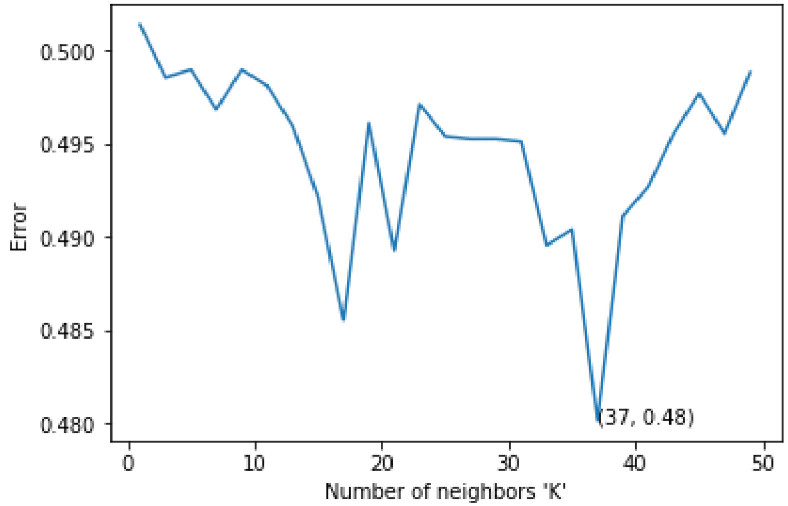
In [258]:
```
maxScoreIndex = CV_Scores.index(max(CV_Scores))
```

In [259]:
```
best_k = neighbors[maxScoreIndex]
```

In [260]:
```
best_k
```

Out[260]:
```
37
```

In [261]:
```
error = []

for a in CV_Scores:
    x = 1 - a
    error.append(x)

plot.plot(neighbors, error)

minError1 = min(error)
minError = np.round(minError1, 2)

plot.xlabel("Number of neighbors 'K'")
plot.ylabel("Error")
for xy in zip(neighbors, np.round(error,2)):
    if xy == (best_k, minError):
        plot.annotate(xy,xy)

plot.show()
```



In [262]:
```
KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'brute')

KNN_best.fit(X_tfidf_1, Y_tfidf_1)

prediction = KNN_best.predict(X_tfidf_test)

accuracyTest = accuracy_score(Y_tfidf_test, prediction) * 100

print("Accuracy of the knn classifier for best k values of "+str(best_k)+" is: "+str(accuracyTest)+"%")
```

```
Accuracy of the knn classifier for best k values of 37 is: 49.733333333333334%
```

KD Tree Implementation

In [263]:
```
KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'kd_tree')

KNN_best.fit(X_tfidf_1, Y_tfidf_1)

prediction = KNN_best.predict(X_tfidf_test)

accuracyTest = accuracy_score(Y_tfidf_test, prediction) * 100

print("Accuracy of the knn classifier for best k values of "+str(best_k)+" is: "+str(accuracyTest)+"%")
```

```
C:\Users\GauravP\Anaconda3\lib\site-packages\sklearn\neighbors\base.py:212: UserWarning: cannot use tree with sparse in
put: using brute force
  warnings.warn("cannot use tree with sparse input: "

Accuracy of the knn classifier for best k values of 37 is: 49.733333333333334%
```

Average W2V

In [322]:
```
from gensim.models import Word2Vec
from gensim.models import KeyedVectors
import pickle
```

In [323]:
```
i = 0
listOfSentences = []
for sentence in FinalSortedPositiveNegative_10000["ProcessedText"].values:
    subSentence = []
    for word in sentence.split():
        subSentence.append(word)

    listOfSentences.append(subSentence)
```

In [324]:
```
print(FinalSortedPositiveNegative_10000['ProcessedText'].values[0])
print("\n")
print(listOfSentences[0:2])
print("\n")
print(type(listOfSentences))
```

```
this was realli good idea and the final product outstand use the decal car window and everybodi ask where bought the de
cal made two thumb


[['this', 'was', 'realli', 'good', 'idea', 'and', 'the', 'final', 'product', 'outstand', 'use', 'the', 'decal', 'car',
'window', 'and', 'everybodi', 'ask', 'where', 'bought', 'the', 'decal', 'made', 'two', 'thumb'], ['just', 'receiv', 'sh
ipment', 'and', 'could', 'hard', 'wait', 'tri', 'this', 'product', 'love', 'which', 'what', 'call', 'them', 'instead',
'sticker', 'becaus', 'they', 'can', 'remov', 'easili', 'daughter', 'design', 'sign', 'print', 'revers', 'use', 'her',
'car', 'window', 'they', 'print', 'beauti', 'have', 'the', 'print', 'shop', 'program', 'go', 'have', 'lot', 'fun', 'wit
h', 'this', 'product', 'becaus', 'there', 'are', 'window', 'everywher', 'and', 'other', 'surfac', 'like', 'screen', 'an
d', 'comput', 'monitor']]


<class 'list'>
```

In [325]:
```
import gensim
w2vModel = gensim.models.Word2Vec(listOfSentences, size=400, min_count=5, workers=4)
```

In [326]:
```
# compute average word2vec for each review.
sentenceAsW2V = []
for sentence in listOfSentences:
    sentenceVector = np.zeros(400)
    TotalWordsPerSentence = 0
    for word in sentence:
        try:
            vect = w2vModel.wv[word]
            sentenceVector += vect
            TotalWordsPerSentence += 1
        except:
            pass
    sentenceVector /= TotalWordsPerSentence
    sentenceAsW2V.append(sentenceVector)

print(type(sentenceAsW2V))
print(len(sentenceAsW2V))
print(len(sentenceAsW2V[0]))
```

```
<class 'list'>
10000
400
```

In [327]:
```
standardized_Avg_w2v = StandardScaler().fit_transform(sentenceAsW2V)
print(standardized_Avg_w2v.shape)
print(type(standardized_Avg_w2v))
```

```
(10000, 400)
<class 'numpy.ndarray'>
```

Brute Force Implementation

In [328]:
```
X_AvgW2V = standardized_Avg_w2v
```

In [329]:
```
Y_AvgW2V = FinalSortedPositiveNegativeScore_10000
```

In [330]:
```
X_AvgW2V.shape
```
Out[330]:
```
(10000, 400)
```

In [331]:
```
Y_AvgW2V.shape
```
Out[331]:
```
(10000,)
```

In [332]:
```
X_AvgW2V_1, X_AvgW2V_test, Y_AvgW2V_1, Y_AvgW2V_test = cross_validation.train_test_split(X_AvgW2V, Y_AvgW2V, test_size =

myList = list(range(0,50))
neighbors = list(filter(lambda x: x%2!=0, myList))  #This will give a list of odd numbers only ranging from 0 to 50

CV_Scores = []

for k in neighbors:
    KNN = KNeighborsClassifier(n_neighbors = k, algorithm = 'brute')
    scores = cross_val_score(KNN, X_AvgW2V_1, Y_AvgW2V_1, cv = 10, scoring='accuracy')
    CV_Scores.append(scores.mean())
```

In [333]:
```
CV_Scores
```

Out[333]:
```
[0.6818639737748736,
 0.7198713825363491,
 0.7307250685351253,
 0.7364438580486898,
 0.7435865224797834,
 0.7470106111003726,
 0.745724686027056,
 0.7480155073202773,
 0.7508708183952562,
 0.7523014341428685,
 0.7538704137297073,
 0.7521559224756436,
 0.7567279705818641,
 0.7562971539592064,
 0.7574396041041483,
 0.7562969507517945,
 0.7567245014785746,
 0.7554385810699905,
 0.7535838842819794,
 0.7545830697030577,
 0.7551567446347558,
 0.7552975621233047,
 0.7505824525006319,
 0.753012455710551,
 0.7541551108121796]
```

In [334]:
```
print(max(CV_Scores))
```

```
0.7574396041041483
```

In [335]:
```
print(CV_Scores.index(max(CV_Scores)))
```

```
14
```

In [336]:
```
print(neighbors[CV_Scores.index(max(CV_Scores))])
```

```
29
```

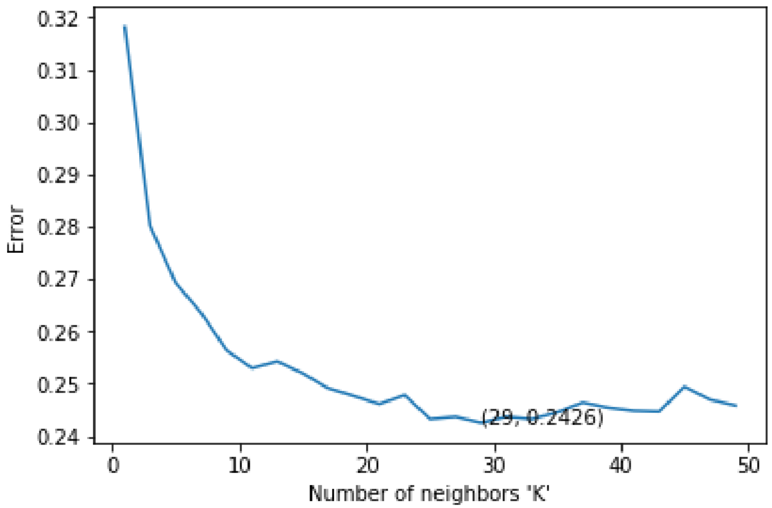
In [337]:
```
maxScoreIndex = CV_Scores.index(max(CV_Scores))
```

In [338]:
```
best_k = neighbors[maxScoreIndex]
```

In [339]:
```
best_k
```

Out[339]:
```
29
```

In [340]:
```
error = []

for a in CV_Scores:
    x = 1 - a
    error.append(x)

plot.plot(neighbors, error)

minError1 = min(error)
minError = np.round(minError1, 4)

plot.xlabel("Number of neighbors 'K'")
plot.ylabel("Error")
for xy in zip(neighbors, np.round(error,4)):
    if xy == (best_k, minError):
        plot.annotate(xy,xy)

plot.show()
```



In [341]:
```
KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'brute')

KNN_best.fit(X_AvgW2V_1, Y_AvgW2V_1)

prediction = KNN_best.predict(X_AvgW2V_test)

accuracyTest = accuracy_score(Y_AvgW2V_test, prediction) * 100

print("Accuracy of the knn classifier for best k values of "+str(best_k)+" is: "+str(accuracyTest)+"%")
```

```
Accuracy of the knn classifier for best k values of 29 is: 76.46666666666667%
```

KD Tree Implementation

In [342]:
```
KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'kd_tree')

KNN_best.fit(X_AvgW2V_1, Y_AvgW2V_1)

prediction = KNN_best.predict(X_AvgW2V_test)

accuracyTest = accuracy_score(Y_AvgW2V_test, prediction) * 100

print("Accuracy of the knn classifier for best k values of "+str(best_k)+" is: "+str(accuracyTest)+"%")
```

```
Accuracy of the knn classifier for best k values of 29 is: 76.46666666666667%
```

TFIDF-W2V

In [304]:
```
import gensim
w2v_Model = gensim.models.Word2Vec(listOfSentences, size=400, min_count=5, workers=4)
```

In [305]:
```
# TF-IDF weighted Word2Vec
tfidf_features = tfidf_vect.get_feature_names()

tfidf_w2v = []
reviews = 0

for sentence in listOfSentences:
    sentenceVector = np.zeros(400)
    weightTfidfSum = 0
    for word in sentence:
        try:
            W2V_Vector = w2v_Model.wv[word]
            tfidfVector = tfidf[reviews, tfidf_features.index(word)]
            sentenceVector += (W2V_Vector * tfidfVector)
            weightTfidfSum += tfidfVector
        except:
            pass
    sentenceVector /= weightTfidfSum
    tfidf_w2v.append(sentenceVector)
    reviews += 1
```

In [306]:
```
standardized_tfidf_w2v = StandardScaler().fit_transform(tfidf_w2v)
print(standardized_tfidf_w2v.shape)
print(type(standardized_tfidf_w2v))
```

```
(10000, 400)
<class 'numpy.ndarray'>
```

Brute Force Implementation

In [307]:
```
X_tfidfW2V = standardized_tfidf_w2v
```

In [308]:
```
Y_tfidfW2V = FinalSortedPositiveNegativeScore_10000
```

In [309]:
```
X_tfidfW2V.shape
```

Out[309]:
```
(10000, 400)
```

In [310]:
```
Y_tfidfW2V.shape
```

Out[310]:
```
(10000,)
```

In [311]:
```
X_tfidfW2V_1, X_tfidfW2V_test, Y_tfidfW2V_1, Y_tfidfW2V_test = cross_validation.train_test_split(X_tfidfW2V, Y_tfidfW2V,

myList = list(range(0,50))
neighbors = list(filter(lambda x: x%2!=0, myList))  #This will give a list of odd numbers only ranging from 0 to 50

CV_Scores = []

for k in neighbors:
    KNN = KNeighborsClassifier(n_neighbors = k, algorithm = 'brute')
    scores = cross_val_score(KNN, X_tfidfW2V_1, Y_tfidfW2V_1, cv = 10, scoring='accuracy')
    CV_Scores.append(scores.mean())
```

In [312]:
```
CV_Scores
```

Out[312]:
```
[0.6620114912770959,
 0.6905829682451248,
 0.7041521761123127,
 0.7094419842839329,
 0.7178677078932815,
 0.7211505685288571,
 0.7215797524951217,
 0.7258620046746451,
 0.7312901766854918,
 0.7342881405297328,
 0.731577525376874,
 0.7358654924368649,
 0.7327222201328107,
 0.73186283149849,
 0.7332946729045802,
 0.7368634545318313,
 0.735722840833786,
 0.7381516213006849,
 0.7378679455030958,
 0.7334399796151188,
 0.7352965128500262,
 0.7342942659066651,
 0.736867942587638,
 0.7365797787342423,
 0.7338669160549307]
```

In [313]:
```
print(max(CV_Scores))
```

```
0.7381516213006849
```

In [314]:
```
print(CV_Scores.index(max(CV_Scores)))
```

```
17
```

In [315]:
```
print(neighbors[CV_Scores.index(max(CV_Scores))])
```

```
35
```

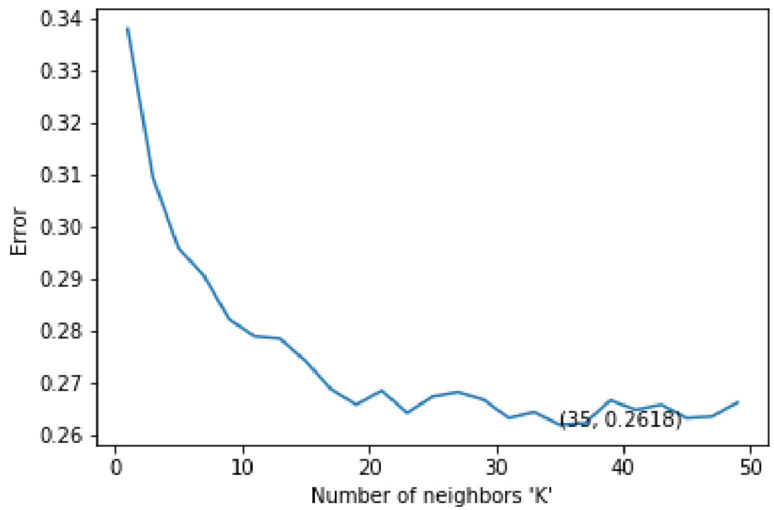
In [316]:
```
maxScoreIndex = CV_Scores.index(max(CV_Scores))
```

In [317]:
```
best_k = neighbors[maxScoreIndex]
```

In [318]:
```
best_k
```

Out[318]:
```
35
```

In [319]:
```
error = []

for a in CV_Scores:
    x = 1 - a
    error.append(x)

plot.plot(neighbors, error)

minError1 = min(error)
minError = np.round(minError1, 4)

plot.xlabel("Number of neighbors 'K'")
plot.ylabel("Error")
for xy in zip(neighbors, np.round(error,4)):
    if xy == (best_k, minError):
        plot.annotate(xy,xy)

plot.show()
```



In [320]:
```
KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'brute')

KNN_best.fit(X_tfidfW2V_1, Y_tfidfW2V_1)

prediction = KNN_best.predict(X_tfidfW2V_test)

accuracyTest = accuracy_score(Y_tfidfW2V_test, prediction) * 100

print("Accuracy of the knn classifier for best k values of "+str(best_k)+" is: "+str(accuracyTest)+"%")
```

```
Accuracy of the knn classifier for best k values of 35 is: 75.63333333333333%
```

KD Tree Implementation

In [321]:
```
KNN_best = KNeighborsClassifier(n_neighbors = best_k, algorithm = 'kd_tree')

KNN_best.fit(X_tfidfW2V_1, Y_tfidfW2V_1)

prediction = KNN_best.predict(X_tfidfW2V_test)

accuracyTest = accuracy_score(Y_tfidfW2V_test, prediction) * 100

print("Accuracy of the knn classifier for best k values of "+str(best_k)+" is: "+str(accuracyTest)+"%")
```

```
Accuracy of the knn classifier for best k values of 35 is: 75.63333333333333%
```

Final Verdict

Average W2V: Accuracy of the knn classifier for best k values of 29 is: 76.46666666666667%

TFIDF-W2V: Accuracy of the knn classifier for best k values of 35 is: 75.63333333333333%

Bag of Words: Accuracy of the knn classifier for best k values of 11 is: 65.3%

TFIDF: Accuracy of the knn classifier for best k values of 37 is: 49.733333333333334%