pipelineAndGridSearchBeta

December 4, 2021

1 Parameter Optimization: Pipelines and GridSearchCV

Lets investigate using pipelines and gridsearch to identify good parameter values for classifiers (and preprocessing steps)! Finding these manually can be very tedious and setting up an extensive experimental design is not always necessary – why re-create the wheel when there is a tool out already out there!? PIPELINES and GRIDSEARCH :)

[1]:
```
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn import datasets
```

2 Loading the Data Set

First we will use a simply data set to explore the pipeline

[2]:
```
# Load Data
data = datasets.load_iris()
```

3 Pipeline

Now lets build our pipeline from sklearn. We will include a normalization step and one classifier. This is a very simple pipeline (just about as simple as can be) – a good first trial!

[3]:
```
#Build Pipeline



from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score
```

[4]:
```
pipeline = Pipeline([
    ('normalizer', StandardScaler()), #Step1 - normalize data
    ('clf', LogisticRegression()) #step2 - classifier
])
```

4 Testing the pipeline

Lets split our data into test and train and run an experiment!

[5]:
```
X_train, X_test, y_train, y_test = train_test_split(data.data,
                                                    data.target,
                                                    test_size = 0.4,
                                                    random_state = 10)
```

[6]:
```
print(X_test)
```

```
[[6.3 2.3 4.4 1.3]
 [6.4 2.7 5.3 1.9]
 [5.4 3.7 1.5 0.2]
 [6.1 3.  4.6 1.4]
 [5.  3.3 1.4 0.2]
 [5.  2.  3.5 1. ]
 [6.3 2.5 4.9 1.5]
 [5.8 2.7 4.1 1. ]
 [5.1 3.4 1.5 0.2]
 [5.7 2.8 4.5 1.3]
 [5.6 3.  4.5 1.5]
 [5.8 2.7 5.1 1.9]
 [5.5 2.3 4.  1.3]
 [4.9 3.  1.4 0.2]
 [5.1 3.8 1.5 0.3]
 [6.8 3.  5.5 2.1]
 [6.  3.4 4.5 1.6]
 [4.4 3.  1.3 0.2]
 [5.1 3.7 1.5 0.4]
 [5.  3.2 1.2 0.2]
 [7.1 3.  5.9 2.1]
 [6.4 2.8 5.6 2.2]
 [6.2 2.8 4.8 1.8]
 [4.8 3.4 1.9 0.2]
 [5.9 3.  4.2 1.5]
 [4.7 3.2 1.3 0.2]
 [5.7 3.  4.2 1.2]
 [5.5 2.6 4.4 1.2]
 [6.8 2.8 4.8 1.4]
 [7.7 3.8 6.7 2.2]
 [6.6 2.9 4.6 1.3]
```

```
 [6.2 2.9 4.3 1.3]
 [7.2 3.  5.8 1.6]
 [5.8 2.8 5.1 2.4]
 [6.3 2.5 5.  1.9]
 [4.6 3.2 1.4 0.2]
 [6.7 3.3 5.7 2.1]
 [6.9 3.2 5.7 2.3]
 [7.7 2.6 6.9 2.3]
 [6.9 3.1 5.1 2.3]
 [5.  3.4 1.6 0.4]
 [5.  3.5 1.6 0.6]
 [5.2 2.7 3.9 1.4]
 [4.5 2.3 1.3 0.3]
 [6.3 3.3 4.7 1.6]
 [5.2 4.1 1.5 0.1]
 [6.9 3.1 4.9 1.5]
 [5.9 3.2 4.8 1.8]
 [5.6 2.8 4.9 2. ]
 [6.7 3.3 5.7 2.5]
 [6.2 2.2 4.5 1.5]
 [7.2 3.6 6.1 2.5]
 [5.5 2.4 3.7 1. ]
 [6.  2.9 4.5 1.5]
 [6.4 3.2 4.5 1.5]
 [5.8 4.  1.2 0.2]
 [5.3 3.7 1.5 0.2]
 [6.1 2.9 4.7 1.4]
 [5.4 3.4 1.7 0.2]
 [6.4 3.1 5.5 1.8]]
```

5 Run experiments using pipeline

You can feed in the pipeline into sklearn.cross_validate(…) and the stages within the pipeline (normalization and then classification in this pipeline) will be executed.

[7]:
```
from sklearn.model_selection import cross_validate

scores = cross_validate(pipeline, X_train, y_train)
```

6 Results

Check the scores from crossvalidation!

[8]:
```
print( 'Num folds is ... ' + str(len(scores['test_score'])))
print(scores['test_score'])
```

```
Num folds is … 5
[0.94444444 1.         1.         0.94444444 0.94444444]
```

[9]:
```
scores['test_score'].mean()
```

[9]: 0.9666666666666668

7 Lets try some other classifiers

First import classifiers to be used. Next add them to a list and iterate.

[10]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier, GradientBoostingClassifier

clfs = []
clfs.append(LogisticRegression())
clfs.append(SVC())
clfs.append(SVC())
clfs.append(KNeighborsClassifier(n_neighbors=3))
clfs.append(DecisionTreeClassifier())
clfs.append(RandomForestClassifier())
clfs.append(GradientBoostingClassifier())

for classifier in clfs:
    pipeline.set_params(clf = classifier)
    scores = cross_validate(pipeline, X_train, y_train)
    print('---------------------------------')
    print(str(classifier))
    print('-----------------------------------')
    for key, values in scores.items():
            print(key,' mean ', values.mean())
            print(key,' std ', values.std())
```

```
---------------------------------
LogisticRegression()
-----------------------------------
fit_time  mean  0.0048029422760009766
fit_time  std  0.0004002820878123819
score_time  mean  0.00019965171813964843
score_time  std  0.00039930343627929686
test_score  mean  0.9666666666666668
test_score  std  0.027216552697590882
---------------------------------
SVC()
-----------------------------------
fit_time  mean  0.0012081623077392577
fit_time  std  0.00042006356655258244
score_time  mean  0.00038080215454101564
```

```
score_time  std  0.00046645139424859606
test_score  mean  0.9666666666666666
test_score  std  0.04444444444444447
---------------------------------
SVC()
-----------------------------------
fit_time  mean  0.0009966850280761718
fit_time  std  1.1087463702990774e-05
score_time  mean  0.0001998424530029297
score_time  std  0.0003996849060058594
test_score  mean  0.9666666666666666
test_score  std  0.04444444444444447
---------------------------------
KNeighborsClassifier(n_neighbors=3)
-----------------------------------
fit_time  mean  0.0010060310363769532
fit_time  std  1.1386927248307925e-05
score_time  mean  0.0009947776794433593
score_time  std  8.504026764508353e-06
test_score  mean  0.9555555555555555
test_score  std  0.041573970964154924
---------------------------------
DecisionTreeClassifier()
-----------------------------------
fit_time  mean  0.0009929180145263673
fit_time  std  2.0593955954532944e-05
score_time  mean  0.0003975868225097656
score_time  std  0.0004870350775477073
test_score  mean  0.9222222222222223
test_score  std  0.027216552697590882
---------------------------------
RandomForestClassifier()
-----------------------------------
fit_time  mean  0.11874923706054688
fit_time  std  0.041071908367895545
score_time  mean  0.006804752349853516
score_time  std  0.0009840084822660103
test_score  mean  0.9444444444444444
test_score  std  0.03513641844631534
---------------------------------
GradientBoostingClassifier()
-----------------------------------
fit_time  mean  0.2318431854248047
fit_time  std  0.03908451338238962
score_time  mean  0.0014165878295898438
score_time  std  0.0018900979797357397
test_score  mean  0.9666666666666668
test_score  std  0.027216552697590882
```

8 Lets try GridSearch to optimize some “hand-tuned” parameters for SVM

In many instances, you may want to optimize some hand-tuned parameters of a classifier, eg, costs or penalties. This can be done using pipelines and/or GridSearch.

First import GridSearchCV. Next, supply the parameters to be tuned and a range of values to search for each. Below the kernel type and Cost value are optimized using GridSearch. Kernels investigated are linear, rbf, and poly. Cost values include 500 different samples between .00001 and 100.

[11]:
```
from sklearn.model_selection import GridSearchCV
pipeline.set_params(clf= SVC())
pipeline.steps
```

[11]:
```
[('normalizer', StandardScaler()), ('clf', SVC())]
```

9 Optimize

Run gridsearch using .fit(…)

[12]:
```
cv_grid = GridSearchCV(pipeline, param_grid = {
    'clf__kernel' : ['linear', 'rbf', 'poly'],
    'clf__C' : np.linspace(0.00001,100,500)
})

cv_grid.fit(X_train, y_train)
```

[12]:
```
GridSearchCV(estimator=Pipeline(steps=[('normalizer', StandardScaler()),
                                       ('clf', SVC())]),
             param_grid={'clf__C': array([1.00000000e-05, 2.00410782e-01,
4.00811563e-01, 6.01212345e-01,
       8.01613126e-01, 1.00201391e+00, 1.20241469e+00, 1.40281547e+00,
       1.60321625e+00, 1.80361703e+00, 2.00401782e+00, 2.20441860e+00,
       2.40481938e+00, 2.60522016e+00, 2.80562094e+00, 3.00602172…
       9.53907820e+01, 9.55911828e+01, 9.57915836e+01, 9.59919844e+01,
       9.61923852e+01, 9.63927859e+01, 9.65931867e+01, 9.67935875e+01,
       9.69939883e+01, 9.71943891e+01, 9.73947898e+01, 9.75951906e+01,
       9.77955914e+01, 9.79959922e+01, 9.81963930e+01, 9.83967937e+01,
       9.85971945e+01, 9.87975953e+01, 9.89979961e+01, 9.91983969e+01,
       9.93987977e+01, 9.95991984e+01, 9.97995992e+01, 1.00000000e+02]),
                         'clf__kernel': ['linear', 'rbf', 'poly']})
```

10 Results

Best results were obtained (.best_params_) with a cost of .200 and a linear kernel! Best score was 98 percent accurracy.

[13]:
```
cv_grid.best_params_
```

[13]:
```
{'clf__C': 0.20041078156312625, 'clf__kernel': 'linear'}
```

[14]:
```
cv_grid.best_estimator_
```

[14]:
```
Pipeline(steps=[('normalizer', StandardScaler()),
                ('clf', SVC(C=0.20041078156312625, kernel='linear'))])
```

[15]:
```
cv_grid.best_score_
```

[15]:
```
0.9777777777777779
```

11 Results on test set ...

[16]:
```
y_predict = cv_grid.predict(X_test)
accuracy = accuracy_score(y_test,y_predict)
print('Accuracy of the best classifier after CV is %.3f%%' % (accuracy*100))
```

```
Accuracy of the best classifier after CV is 95.000%
```

12 Lets try with text data!

Loading the sentiment / lie data from Kaggle. This data was downloaded locally as tsv.

[17]:
```
sourceFile = "deception_data_converted_final.tsv"
prodReviews = pd.read_table(sourceFile, delimiter="\t")
#pd.set_option('display.max_colwidth', 150)
print(prodReviews.shape)
prodReviews.head()
```

```
(92, 3)
```

[17]:

	lie	sentiment	review
0	f	n	'Mike\'s Pizza High Point, NY Service was very…
1	f	n	'i really like this buffet restaurant in Marsh…
2	f	n	'After I went shopping with some of my friend,…
3	f	n	'Olive Oil Garden was very disappointing. I ex…
4	f	n	'The Seven Heaven restaurant was never known f…

13 Lets clean the data a bit

[18]:
```
prodReviews['cleanedReview'] = prodReviews['review'].str.replace("\\","")
prodReviews['cleanedReview'] = prodReviews['cleanedReview'].str.replace("\'","")
prodReviews['cleanedReview'] = prodReviews['cleanedReview'].str.replace("\t","␣
↪")
```

```
prodReviews['cleanedReview'] = prodReviews['cleanedReview'].str.
 ↪replace("^\s+","")
prodReviews['cleanedReview'] = prodReviews['cleanedReview'].str.replace("\,","")
prodReviews['cleanedReview'] = prodReviews['cleanedReview'].str.
 ↪replace("\s\d+\s"," ")
prodReviews['cleanedReview'] = prodReviews['cleanedReview'].str.replace("\.","")
prodReviews['cleanedReview'] = prodReviews['cleanedReview'].str.lower()
```

```
<ipython-input-18-0122dfe95866>:1: FutureWarning: The default value of regex
will change from True to False in a future version. In addition, single
character regular expressions will *not* be treated as literal strings when
regex=True.
  prodReviews['cleanedReview'] = prodReviews['review'].str.replace("\\","")
<ipython-input-18-0122dfe95866>:4: FutureWarning: The default value of regex
will change from True to False in a future version.
  prodReviews['cleanedReview'] =
prodReviews['cleanedReview'].str.replace("^\s+","")
<ipython-input-18-0122dfe95866>:5: FutureWarning: The default value of regex
will change from True to False in a future version.
  prodReviews['cleanedReview'] =
prodReviews['cleanedReview'].str.replace("\,","")
<ipython-input-18-0122dfe95866>:6: FutureWarning: The default value of regex
will change from True to False in a future version.
  prodReviews['cleanedReview'] =
prodReviews['cleanedReview'].str.replace("\s\d+\s"," ")
<ipython-input-18-0122dfe95866>:7: FutureWarning: The default value of regex
will change from True to False in a future version.
  prodReviews['cleanedReview'] =
prodReviews['cleanedReview'].str.replace("\.","")
```

[19]:
```
# Lets investigate the wordcounts.

prodReviews['WordCount'] = prodReviews['cleanedReview'].str.count("\S\s+\S")+1
prodReviews['WordCount'].describe()
```

[19]:
```
count     92.000000
mean      71.184783
std       55.263391
min        1.000000
25%       43.000000
50%       63.000000
75%       78.750000
max      458.000000
Name: WordCount, dtype: float64
```

14 Lets Explore :)

[20]:
```python
import wordcloud
from wordcloud import WordCloud, STOPWORDS, ImageColorGenerator
import nltk
nltk.download('stopwords')
from nltk.corpus import stopwords
```

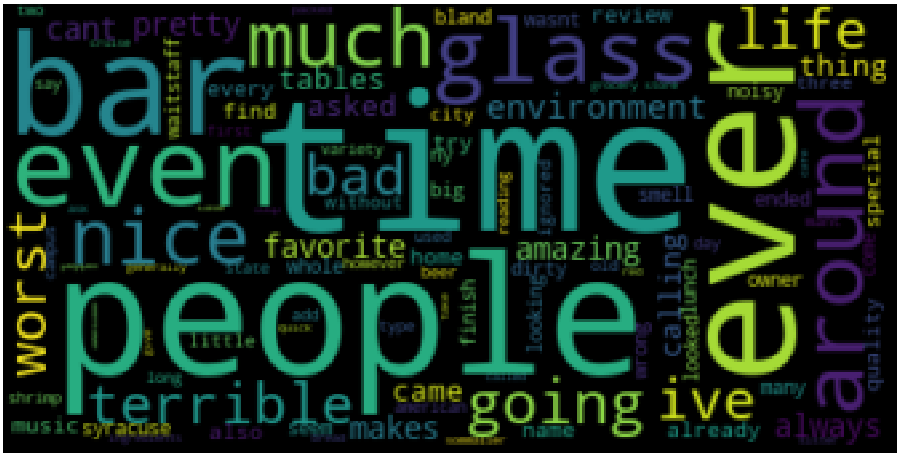
```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\jerem\AppData\Roaming\nltk_data…
[nltk_data]   Package stopwords is already up-to-date!
```

[21]:
```python
allReviews = " ".join(rv for rv in prodReviews['cleanedReview'])

# Next for EDA, lets investigate word frequency. Create a word cloud to help␣
↪visualize.

wordcloud = WordCloud(background_color='black', max_words=100,␣
↪stopwords=stopwords.words('english')).generate(allReviews)
plt.imshow(wordcloud, interpolation='bilinear')
plt.title("All Reviews")
plt.axis("off")
plt.show()
```

[22]:
```python
## Define the stop words

lieStopWords = stopwords.words('english')
# Remmove most common words across categories
lieStopWords.extend(["restaurant","food","place","went","would"])
```

```
lieStopWords.
↪extend(["friends","friend","like","good","best","great","service","ordered","us"])
##Remove food types
lieStopWords.
↪extend(["chicken","pizza","chinese","japanese","salad","iced","tea","sushi","tofu","indian"
## Remove common restaurant nouns
lieStopWords.
↪extend(["dining","dinner","dine","dish","dishes","waiters","waiter","waitress","menu"])
## Remove generic concepts
lieStopWords.extend(["experience","order","really"])
#Remove other key words common across categories
lieStopWords.
↪extend(["never","one","served","price","staff","back","delicious","flavor","found","fresh",
lieStopWords.
↪extend(["hour","last","minutes","made","need","overall","prices","table","taste","took","wa

## Preview the stop words in word clouds

prodReviewsTrue = prodReviews[prodReviews['lie'] =='t']
trueReviews = " ".join(rv for rv in prodReviewsTrue['cleanedReview'])

wordcloud = WordCloud(background_color='black', max_words=100,␣
↪stopwords=lieStopWords).generate(trueReviews)
plt.imshow(wordcloud, interpolation='bilinear')
plt.title("Truthful Reviews")
plt.axis("off")
plt.show()

prodReviewsFalse = prodReviews[prodReviews['lie'] =='f']
falseReviews = " ".join(rv for rv in prodReviewsFalse['cleanedReview'])

wordcloud = WordCloud(background_color='black', max_words=100,␣
↪stopwords=lieStopWords).generate(falseReviews)
plt.imshow(wordcloud, interpolation='bilinear')
plt.title("Fake Reviews")
plt.axis("off")
plt.show()
```

Truthful Reviews

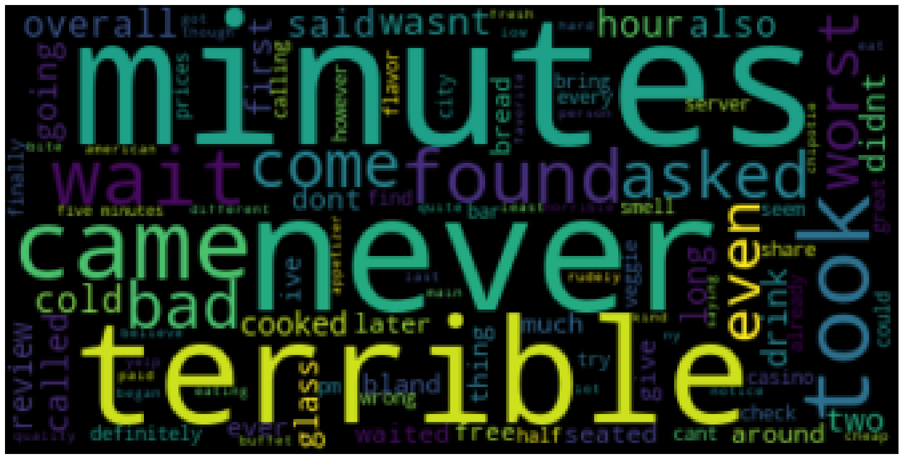


Fake Reviews


```
[23]: sentStopWords = stopwords.words('english')
# Remmove most common words across categories
sentStopWords.extend(["restaurant","restaurants","food","place","went"])
sentStopWords.extend(["good","like","go"])
sentStopWords.extend(["service","order","ordered","us","friend","friends","would"])
sentStopWords.extend(["back","experience","life","taste","time","serve","served"])
## Remove common restaurant nouns
sentStopWords.extend(["dining","dinner","dine","dish","dishes","waiters","waiter","waitress","menu"])
```

```python
##Remove food types
sentStopWords.extend(["chicken","pizza","chinese","japanese","salad","iced","tea","sushi","tofu","indian"
## Remove additional common words
sentStopWords.extend(["get","little","made","meal","one","people","plate","price","really","staff","table


## Preview the stop words in word clouds

prodReviewsPositive = prodReviews[prodReviews['sentiment'] =='p']
posReviews = " ".join(rv for rv in prodReviewsPositive['cleanedReview'])

wordcloud = WordCloud(background_color='black', max_words=100, stopwords=sentStopWords).generate(posReviews)
plt.imshow(wordcloud, interpolation='bilinear')
plt.title("Positive Reviews")
plt.axis("off")
plt.show()

prodReviewsNegative = prodReviews[prodReviews['sentiment'] =='n']
negativeReviews = " ".join(rv for rv in prodReviewsNegative['cleanedReview'])

wordcloud = WordCloud(background_color='black', max_words=100, stopwords=sentStopWords).generate(negativeReviews)
plt.imshow(wordcloud, interpolation='bilinear')
plt.title("Negative Reviews")
plt.axis("off")
plt.show()
```

Negative Reviews



[24]:

```
from nltk.tokenize import TreebankWordTokenizer
from nltk.stem import SnowballStemmer
stemmer = SnowballStemmer("english")

allReviewTokens = TreebankWordTokenizer().tokenize(allReviews)
lieReviewTokens = []
lieReviewStemmedTokens = []
sentReviewTokens = []
sentReviewStemmedTokens = []
for tk in allReviewTokens:
    stemmedTk = stemmer.stem(tk)
    if lieStopWords.count(tk) == 0:
        lieReviewTokens.append(tk)
        if (lieStopWords.count(stemmedTk) == 0):
            lieReviewStemmedTokens.append(stemmedTk)
    if sentStopWords.count(tk) == 0:
        sentReviewTokens.append(tk)
        if (sentStopWords.count(stemmedTk) == 0):
            sentReviewStemmedTokens.append(stemmedTk)

print("Most Frequent Words for Lie Detection")
lieReviewFreq = nltk.FreqDist(lieReviewTokens)
print(lieReviewFreq.most_common(50))
print()
print("Most Frequent Words for Lie Detection (Stemmed)")
lieReviewFreq = nltk.FreqDist(lieReviewStemmedTokens)
print(lieReviewFreq.most_common(50))
print()
print("Most Frequent Words for Sentiment 'Identification'")
```

```python
sentReviewFreq = nltk.FreqDist(sentReviewTokens)
print(sentReviewFreq.most_common(50))
print()
print("Most Frequent Words for Sentiment Identification (Stemmed)")
sentReviewFreq = nltk.FreqDist(sentReviewStemmedTokens)
print(sentReviewFreq.most_common(50))
```

```
Most Frequent Words for Lie Detection
[('!', 152), ('(', 19), (')', 18), (':', 16), ('plate', 15), ('time', 14),
('amazing', 14), ('came', 13), ('ever', 13), ('terrible', 12), ('even', 12),
('also', 11), ('people', 11), ('want', 11), ('nice', 11), ('?', 11), ('quality',
10), ('definitely', 10), ('bad', 10), ('going', 10), ('life', 10), ('around',
10), ('take', 10), ('much', 10), ('meal', 9), ('asked', 9), ('didnt', 9),
('favorite', 9), ('wasnt', 9), ('cooked', 9), ('always', 9), ('cold', 8),
('dont', 8), ('two', 8), ('worst', 8), ('called', 8), ('come', 8), ('little',
8), ('long', 8), ('glass', 8), ('said', 7), ('first', 7), ('cant', 7), ('worth',
7), ('special', 7), ('bread', 7), ('find', 7), ('ive', 7), ('environment', 7),
('recommend', 6)]

Most Frequent Words for Lie Detection (Stemmed)
[('!', 152), ('(', 19), (')', 18), ('time', 18), ('call', 17), ('plate', 16),
(':', 16), ('ask', 15), ('amaz', 14), ('came', 13), ('ever', 13), ('come', 12),
('terribl', 12), ('even', 12), ('want', 12), ('nice', 12), ('also', 11),
('definit', 11), ('peopl', 11), ('take', 11), ('?', 11), ('qualiti', 10),
('bad', 10), ('life', 10), ('around', 10), ('look', 10), ('cook', 10), ('much',
10), ('meal', 9), ('cold', 9), ('didnt', 9), ('favorit', 9), ('seat', 9),
('wasnt', 9), ('comfort', 9), ('alway', 9), ('dont', 8), ('say', 8), ('two', 8),
('recommend', 8), ('worst', 8), ('seem', 8), ('littl', 8), ('long', 8),
('glass', 8), ('high', 7), ('said', 7), ('first', 7), ('beer', 7), ('cant', 7)]

Most Frequent Words for Sentiment 'Identification'
[('!', 152), ('best', 31), ('great', 24), ('minutes', 23), ('(', 19), (')', 18),
('never', 16), (':', 16), ('fresh', 14), ('amazing', 14), ('came', 13), ('ever',
13), ('terrible', 12), ('wait', 12), ('even', 12), ('also', 11), ('took', 11),
('overall', 11), ('delicious', 11), ('nice', 11), ('?', 11), ('prices', 11),
('quality', 10), ('definitely', 10), ('found', 10), ('bad', 10), ('going', 10),
('around', 10), ('much', 10), ('friendly', 9), ('asked', 9), ('didnt', 9),
('favorite', 9), ('wasnt', 9), ('cooked', 9), ('always', 9), ('cold', 8),
('dont', 8), ('last', 8), ('two', 8), ('worst', 8), ('called', 8), ('come', 8),
('long', 8), ('need', 8), ('glass', 8), ('said', 7), ('first', 7), ('cant', 7),
('worth', 7)]

Most Frequent Words for Sentiment Identification (Stemmed)
[('!', 152), ('best', 31), ('great', 24), ('minut', 23), ('(', 19), ('wait',
19), (')', 18), ('call', 17), ('never', 16), ('fresh', 16), (':', 16), ('ask',
15), ('amaz', 14), ('came', 13), ('ever', 13), ('come', 12), ('terribl', 12),
('even', 12), ('need', 12), ('nice', 12), ('also', 11), ('definit', 11),
('took', 11), ('overal', 11), ('delici', 11), ('?', 11), ('qualiti', 10),
```

```
('found', 10), ('bad', 10), ('around', 10), ('look', 10), ('cook', 10), ('much',
10), ('cold', 9), ('didnt', 9), ('favorit', 9), ('hour', 9), ('seat', 9),
('wasnt', 9), ('comfort', 9), ('flavor', 9), ('alway', 9), ('dont', 8), ('last',
8), ('say', 8), ('two', 8), ('recommend', 8), ('worst', 8), ('seem', 8),
('long', 8)]
```

[25]:
```
def stemText(txt):
    tkns = TreebankWordTokenizer().tokenize(txt)
    newTkns = []
    for t in tkns:
        newTkns.append(stemmer.stem(t))
    newTxt = " ".join(newTkns)
    return newTxt

#stemText("life's like a bag of chocolates")
```

[26]:
```
prodReviews['stemmedReview'] = prodReviews['cleanedReview'].apply(stemText)

modelDf = pd.DataFrame(prodReviews.
 ↪drop(columns=['review','cleanedReview','stemmedReview']), copy=True)
#modelDf['isPositive'] = modelDf['sentiment'].mask(modelDf['sentiment'] ==␣
 ↪'n',0)
#modelDf['isPositive'] = modelDf['isPositive'].mask(modelDf['isPositive'] ==␣
 ↪'p',1)
#modelDf = modelDf.drop(columns=['sentiment'])
modelDf.head()
```

[26]:

	lie	sentiment	WordCount
0	f	n	43
1	f	n	58
2	f	n	22
3	f	n	41
4	f	n	63

[27]:
```
from sklearn.feature_extraction.text import CountVectorizer
from sklearn.feature_extraction.text import TfidfVectorizer
#from sklearn.naive_bayes import MultinomialNB
#from sklearn.naive_bayes import BernoulliNB
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

Here we add some helper functions.

[28]:
```
def getFeatureVector(vectorizer, wordList, modelDf, columnToDrop):
    featureVector = vectorizer.fit_transform(wordList)
    featureVectorDf = pd.DataFrame(columns=vectorizer.get_feature_names(),␣
 ↪data=featureVector.todense())
    modelWithFeatureDf = modelDf.join(featureVectorDf)
```

```
    modelWithFeatureVector = modelWithFeatureDf.drop(columns=["WordCount",␣
↪columnToDrop])
    return modelWithFeatureVector

def getCountVectorizer(binary=False, ngram=(1,1), minDocFreq=.03, maxDocFreq=.
↪4, maxFeat=50, sw=None):
    if (stopwords == None):
        return CountVectorizer(encoding='latin-1', binary=True,␣
↪ngram_range=ngram, min_df=minDocFreq, max_df=maxDocFreq,␣
↪max_features=maxFeat, lowercase=True)
    else:
        return CountVectorizer(encoding='latin-1', binary=True,␣
↪ngram_range=ngram, min_df=minDocFreq, max_df=maxDocFreq,␣
↪max_features=maxFeat, stop_words=sw, lowercase=True)

def getTfidfVectorizer(ngram=(1,1), minDocFreq=.03, maxDocFreq=.4, maxFeat=50,␣
↪sw=None):
    if (stopwords == None):
        return TfidfVectorizer(encoding='latin-1', use_idf=True,␣
↪ngram_range=ngram, min_df=minDocFreq, max_df=maxDocFreq,␣
↪max_features=maxFeat, lowercase=True)
    else:
        return TfidfVectorizer(encoding='latin-1', use_idf=True,␣
↪ngram_range=ngram, min_df=minDocFreq, max_df=maxDocFreq,␣
↪max_features=maxFeat, stop_words=sw, lowercase=True)
```

Next we can experiment with different vectorization strategies. In the next section we show how to do this using pipelines instead – MUCH MORE EFFICIENT :)

[29]:
```
#  unigram boolean vectorizer, set minimum document frequency to 5
#unigram_bool_vectorizer = CountVectorizer(encoding='latin-1', binary=True,␣
↪min_df=5, stop_words=sentStopWords, max_features=200, lowercase=True)
#  unigram tfidf vectorizer, set minimum document frequency to 5
unigram_tfidf_vectorizer = TfidfVectorizer(encoding='latin-1', use_idf=True,␣
↪min_df=5, stop_words=sentStopWords, max_features=200, lowercase=True)
# unigram_count_vectorizer = CountVectorizer(encoding='latin-1', binary=False,␣
↪min_df=5, stop_words=sentStopWords, max_features=200, lowercase=True)

#  bigram term frequency vectorizer, set minimum document frequency to 5
# bigram_count_vectorizer = CountVectorizer(encoding='latin-1',␣
↪ngram_range=(2,3), min_df=5, stop_words=sentStopWords, max_features=200,␣
↪lowercase=True)



#unigram_bool_v = unigram_bool_vectorizer.fit_transform(prodReviews['review'].
↪values)
```

```
#unigram_bool_v = unigram_bool_vectorizer.fit_transform(tweetsDf['Tweet'].
↪values)
#unigram_count_v = unigram_count_vectorizer.fit_transform(prodReviews['review'].
↪values)
#bigram_count_v = bigram_count_vectorizer.fit_transform(tweetsDf['Tweet'].
↪values)
unigram_tfidf_v = unigram_tfidf_vectorizer.fit_transform(prodReviews['review'].
↪values)

print(unigram_tfidf_v.shape)

#unigram_bool_df = pd.DataFrame(columns=unigram_bool_vectorizer.
↪get_feature_names(), data=unigram_bool_v.todense())
#unigram_count_df = pd.DataFrame(columns=unigram_count_vectorizer.
↪get_feature_names(), data=unigram_count_v.todense())
#bigram_count_df = pd.DataFrame(columns=bigram_count_vectorizer.
↪get_feature_names(), data=bigram_count_v.todense())
unigram_tfidf_df = pd.DataFrame(columns=unigram_tfidf_vectorizer.
↪get_feature_names(), data=unigram_tfidf_v.todense())
```

```
(92, 73)
```

[30]:
```
data.data = unigram_tfidf_df
```

[31]:
```
data.target = prodReviews['sentiment'].values
```

15 Experiments

Split data into test and train sets and run our grid search on the vectorized sentiment data.

[32]:
```
X_train, X_test, y_train, y_test = train_test_split(data.data,
                                                    data.target,
                                                    test_size = 0.4,
                                                    random_state = 10)
```

[33]:
```
print(X_test)
```

```
          15   already      also    always   amazing  ambiance    around  \
39  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
56  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
3   0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
34  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
19  0.230859  0.000000  0.000000  0.000000  0.000000  0.230859  0.000000
55  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
35  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
```

61	0.000000	0.000000	0.352856	0.352856	0.000000	0.000000	0.000000
43	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
89	0.000000	0.000000	0.000000	0.000000	0.432428	0.000000	0.000000
38	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
26	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.911980	0.000000	0.000000	0.000000	0.000000
50	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
83	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
14	0.431013	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
84	0.000000	0.376658	0.000000	0.335832	0.000000	0.000000	0.000000
59	0.000000	0.000000	0.000000	0.000000	0.635583	0.000000	0.000000
47	0.000000	0.000000	0.000000	0.507722	0.000000	0.000000	0.000000
41	0.000000	0.000000	0.269846	0.000000	0.000000	0.000000	0.261322
52	0.000000	0.000000	0.000000	0.000000	0.317320	0.389489	0.000000
21	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
6	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
70	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
58	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
75	0.000000	0.000000	0.000000	0.000000	0.503579	0.000000	0.000000
86	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.647696
2	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
63	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.487414
66	0.000000	0.000000	0.000000	0.000000	0.602512	0.000000	0.000000
48	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
37	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
78	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
42	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.325775
4	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
5	0.000000	0.324470	0.000000	0.000000	0.000000	0.000000	0.000000
45	0.000000	0.000000	0.540977	0.000000	0.000000	0.000000	0.000000

	ask	asked	ate	…	seated	special	terrible	took	\
39	0.000000	0.000000	0.0	…	0.515076	0.000000	0.000000	0.000000	
56	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
3	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
34	0.000000	0.238964	0.0	…	0.000000	0.000000	0.218353	0.000000	
19	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.199334	
55	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
35	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.499170	
61	0.395751	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
43	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
89	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
38	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
26	0.000000	0.000000	0.0	…	0.000000	0.000000	0.377978	0.000000	
1	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
50	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
83	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000	
14	0.000000	0.192148	0.0	…	0.000000	0.000000	0.000000	0.186078	

84	0.376658	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
59	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
47	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
41	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
52	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
21	0.000000	0.278121	0.0	…	0.311930	0.000000	0.000000	0.538670
6	0.000000	0.000000	0.0	…	0.343443	0.000000	0.279805	0.000000
70	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
58	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
75	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
86	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
2	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
63	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
66	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
48	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
37	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
78	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.000000
42	0.000000	0.000000	0.0	…	0.000000	0.377297	0.000000	0.000000
4	0.000000	0.295717	0.0	…	0.000000	0.000000	0.000000	0.286375
5	0.000000	0.289301	0.0	…	0.000000	0.000000	0.264348	0.000000
45	0.000000	0.000000	0.0	…	0.000000	0.000000	0.000000	0.261944

	try	two	wait	whole	worst	worth
39	0.000000	0.475465	0.000000	0.000000	0.000000	0.000000
56	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
3	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
34	0.000000	0.000000	0.224587	0.000000	0.494805	0.000000
19	0.000000	0.000000	0.193453	0.000000	0.000000	0.000000
55	0.000000	0.411647	0.000000	0.000000	0.000000	0.000000
35	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
61	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
43	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
89	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
38	0.000000	0.426411	0.000000	0.000000	0.000000	0.000000
26	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
1	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
50	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
83	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
14	0.000000	0.000000	0.180588	0.000000	0.000000	0.198933
84	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
59	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
47	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
41	0.605300	0.000000	0.000000	0.000000	0.000000	0.000000
52	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
21	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000
6	0.000000	0.317031	0.000000	0.000000	0.000000	0.000000
70	0.000000	0.000000	0.565041	0.000000	0.000000	0.000000
58	0.000000	0.000000	0.000000	0.632815	0.000000	0.000000

```
75  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
86  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
2   0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
63  0.000000  0.000000  0.000000  0.000000  0.000000  0.521087
66  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
48  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
37  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
78  0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
42  0.377297  0.000000  0.000000  0.000000  0.000000  0.000000
4   0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
5   0.000000  0.000000  0.000000  0.000000  0.000000  0.000000
45  0.000000  0.000000  0.000000  0.000000  0.280040  0.000000

[37 rows x 73 columns]
```

[34]:
```
print(y_test)
```

```
['n' 'p' 'n' 'n' 'n' 'p' 'n' 'p' 'n' 'p' 'n' 'n' 'n' 'p' 'p' 'n' 'p' 'p'
 'p' 'n' 'p' 'n' 'n' 'p' 'p' 'p' 'p' 'n' 'p' 'p' 'p' 'n' 'p' 'n' 'n' 'n'
 'n']
```

[35]:
```
cv_grid.fit(X_train, y_train)
```

[35]:
```
GridSearchCV(estimator=Pipeline(steps=[('normalizer', StandardScaler()),
                                       ('clf', SVC())]),
             param_grid={'clf__C': array([1.00000000e-05, 2.00410782e-01,
4.00811563e-01, 6.01212345e-01,
       8.01613126e-01, 1.00201391e+00, 1.20241469e+00, 1.40281547e+00,
       1.60321625e+00, 1.80361703e+00, 2.00401782e+00, 2.20441860e+00,
       2.40481938e+00, 2.60522016e+00, 2.80562094e+00, 3.00602172…
       9.53907820e+01, 9.55911828e+01, 9.57915836e+01, 9.59919844e+01,
       9.61923852e+01, 9.63927859e+01, 9.65931867e+01, 9.67935875e+01,
       9.69939883e+01, 9.71943891e+01, 9.73947898e+01, 9.75951906e+01,
       9.77955914e+01, 9.79959922e+01, 9.81963930e+01, 9.83967937e+01,
       9.85971945e+01, 9.87975953e+01, 9.89979961e+01, 9.91983969e+01,
       9.93987977e+01, 9.95991984e+01, 9.97995992e+01, 1.00000000e+02]),
                         'clf__kernel': ['linear', 'rbf', 'poly']})
```

16 Optimization Results

What was the best score?

What was the best parameter set?

[36]:
```
cv_grid.best_params_
```

[36]:
```
{'clf__C': 0.6012123446893787, 'clf__kernel': 'rbf'}
```

[37]:
```
cv_grid.best_score_
```

[37]:
```
0.8181818181818183
```

17 Results on test set?

[38]:
```
y_predict = cv_grid.predict(X_test)
accuracy = accuracy_score(y_test,y_predict)
print('Accuracy of the best classifier after CV is %.3f%%' % (accuracy*100))
```

```
Accuracy of the best classifier after CV is 72.973%
```

18 Optimizing Parameters for multiple stages of the pipeline

Preprocessing often has many many hand-tuned parameters! So designing an experiment to identify optimal processing parameters is intuitive. Conveniently, we can incorporate this into the pipeline and GridSearch!!

Vectorizing text data often has many parameter options: stopwords, tfidf scaling, stemming options, frequency constraints, etc. SVMs also many many parameter options: kernel, cost, etc. We can include vectorization and classification in the pipeline and include the relevant parameters in the GridSearch param_grid.

Note that GridSearch runs crossvalidation for all possible parameter combinations!! This can be slow so choose your parameter search params wisely. Also note that you can choose the number of crossvalidation cv folds and have the option to parallelize across multiple cores via n_jobs. See below example.

[50]:
```
pipeline = Pipeline([
    ('tfidf', TfidfVectorizer()),
    ('clf', SVC()),
])

param_grid = {
    'tfidf__max_df': (0.25, 0.5, 0.75, 1.0),
    'tfidf__stop_words': ['english', None,sentStopWords ],
    'clf__kernel' : ['linear', 'rbf', 'poly'],
    'clf__C' : np.linspace(0.01,10,200)
}

gscv = GridSearchCV(pipeline, param_grid, cv=2, n_jobs=12,␣
 ↪return_train_score=True, verbose=3)

X_train, X_test, y_train, y_test =␣
 ↪train_test_split(prodReviews['stemmedReview'],
                                                     prodReviews['sentiment'],
                                                     test_size = 0.25,
                                                     random_state = 10)
```

```
# Use the cleaned and stemmed data OR the raw review ... try each :)
gscv.fit(X_train, y_train)
#gscv.fit(prodReviews['review'], prodReviews['sentiment'])
```

```
Fitting 2 folds for each of 7200 candidates, totalling 14400 fits
```

```
[Parallel(n_jobs=12)]: Using backend LokyBackend with 12 concurrent workers.
[Parallel(n_jobs=12)]: Done   8 tasks      | elapsed:    0.0s
[Parallel(n_jobs=12)]: Done 424 tasks      | elapsed:    2.0s
[Parallel(n_jobs=12)]: Done 1704 tasks      | elapsed:    7.7s
[Parallel(n_jobs=12)]: Done 3496 tasks      | elapsed:   15.5s
[Parallel(n_jobs=12)]: Done 5800 tasks      | elapsed:   26.0s
[Parallel(n_jobs=12)]: Done 8616 tasks      | elapsed:   39.6s
[Parallel(n_jobs=12)]: Done 11944 tasks      | elapsed:   58.4s
[Parallel(n_jobs=12)]: Done 14400 out of 14400 | elapsed:  1.2min finished
```

[50]:
```
GridSearchCV(cv=2,
             estimator=Pipeline(steps=[('tfidf', TfidfVectorizer()),
                                       ('clf', SVC())]),
             n_jobs=12,
             param_grid={'clf__C': array([ 0.01      ,  0.06020101,  0.11040201,
 0.16060302,  0.21080402,
        0.26100503,  0.31120603,  0.36140704,  0.41160804,  0.46180905,
        0.51201005,  0.56221106,  0.61241206,  0.66261307,  0.71281407,
        0.76301508,  0.81321608,  0.86341709,  0.91361809,  0.9638191 ,
        1.0140201 ,  1…
                         'clf__kernel': ['linear', 'rbf', 'poly'],
                         'tfidf__max_df': (0.25, 0.5, 0.75, 1.0),
                         'tfidf__stop_words': ['english', None,
                                               ['i', 'me', 'my', 'myself', 'we',
                                                'our', 'ours', 'ourselves',
                                                'you', "you're", "you've",
                                                "you'll", "you'd", 'your',
                                                'yours', 'yourself',
                                                'yourselves', 'he', 'him',
                                                'his', 'himself', 'she',
                                                "she's", 'her', 'hers',
                                                'herself', 'it', "it's", 'its',
                                                'itself', …]]},
             return_train_score=True, verbose=3)
```

19 Optimization Results

[51]:
```
gscv.best_params_
```

[51]:
```
{'clf__C': 0.8634170854271357,
 'clf__kernel': 'linear',
 'tfidf__max_df': 1.0,
 'tfidf__stop_words': None}
```

[52]:
```
gscv.best_estimator_
```

[52]:
```
Pipeline(steps=[('tfidf', TfidfVectorizer()),
                ('clf', SVC(C=0.8634170854271357, kernel='linear'))])
```

[53]:
```
gscv.best_score_
```

[53]:
```
0.9130252100840336
```

20 Results on Test Set

[54]:
```
#gscv.fit(X_train, y_train)
y_predict = gscv.predict(X_test)
accuracy = accuracy_score(y_test,y_predict)
print('Accuracy of the best classifier after CV is %.3f%%' % (accuracy*100))
```

```
Accuracy of the best classifier after CV is 82.609%
```

[ ]:
```

```