2019-1002 IST 736 Text Mining

Homework Assignment 7 (week 7)

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Topic: Build MNB and SVM models using sklearn packages on Kaggle Sentiment training data.

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1 Introduction

Every business needs to keep a pulse on how they are perceived in the public eye. The movie-making industry is no exception. And maybe they should be looking very closely at how movie review critics are rating their movies on sites like Rotten Tomatoes.

A headline from Wired reads:
"Rotten Tomatoes and the Unbearable Heaviness of Data
More and more movies are tanking -- and sure, they might be bad, but something else may be at play: metadata dependency." - https://www.wired.com/story/is-rotten-tomatoes-ruining-movies/

Rotten tomato has a simple approach to how move reviews can be compiled into binary pass/fail assessments -- inspired by the thumbs up or down of the critics Gene Siskel and Roger Ebert -- into a quantified selfie that captures a movie's overall quality.

The site maintains fairly straightforward rules about which reviewers and outlets it'll draw from -- about 2,000 critics overall contribute. Some critics have adapted to the binary distinction, sending along with word as to how Rotten Tomatoes should code their possibly more subtle review."Some days a 2.5 out of 5 out of a particular critic might be fresh, and with a different movie might be a rotten." And Rotten Tomatoes is OK with that.

The challenge and concern are that Rotten Tomatoes scores now show up not only on the site, but also in reviews and articles about the movies they purport to asses, and next to ticket purchase options on Fandango.

Bad reviews are bad news for brands, large or small. The one thing companies can do to listen to their customers. Since companies typically have large amounts of customers, any of whom could be prone to posting comments on the internet, and they need to use sophisticated technology to narrow the playing field and find potential negative reviews or false statements being written about them online before the damage is too great to fix.

1.1 Purpose

Build Multinomial Naive Bayes and Support Vector Machine classification models for comparison on Kaggle Sentiment classification dataset of Rotten Tomatoes Movie Reviews.

"Sentiment Analysis on Movie Reviews" -- Classify the sentiment of sentences from the Rotten Tomatoes dataset

1.2 Scope

Given a labeled data set of movie review's broken into their constituent phrases, perform classification modeling tasks using both Multinominal Naive Bayes and Support Vector Machines to evaluate which modeling technique and hyperparameter configuration perform the best on unseen-held out data. Label phrases on a scale of five values: negative, somewhat negative, neutral, somewhat positive, positive.

- Perform three classification tasks
    - Task 1:
        - Build a unigram MNB model and a unigram SVMs model.

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  - Print the top 10 indicative words for the most positive category and the most negative category from the MNB and SVMs models respectively.
  - Report the confusion matrix, precisions, and recalls. Explain whether your models performed equally well on all categories, or some categories turn out to be easier or more difficult for MNB or SVMs.
- Task 2:
  - Revise the script to build a MNB model and a SVMs model based on both unigram and bigram. For fair comparison, keep the same 60% for training and the rest 40% for testing. Also, keep vectorization parameters the same as in Task 1.
  - Compare the confusion matrix and other evaluation measures (accuracy, precision, recall). Discuss whether adding bi-grams was helpful for sentiment classification, based on MNB and SVMs respectively.
- Task 3:
  - revise the script to build best SVMs model by tuning parameters and using the entire training data set (changing from 60% to 100%). Report what parameters were used to train the model and its cross validation accuracy.
  - Use this model to predict the Kaggle sentiment test data. Submit the prediction result to Kaggle. https://www.kaggle.com/c/sentiment-analysis-on-movie-reviews/submit

2 Analysis and Models

2.1 About the Data

Kaggel Sentiment Analysis on Movie Reviews

The Rotten Tomatoes movie review dataset is a corpus of movie reviews used for sentiment analysis, originally collected by Pang and Lee [1]. In their work on sentiment treebanks, Socher et al. [2] used Amazon's Mechanical Turk to create fine-grained labels for all parsed phrases in the corpus.

The dataset is comprised of tab-separated files with phrases from the Rotten Tomatoes dataset. The train/test split has been preserved for the purposes of benchmarking, but the sentences have been shuffled from their original order. Each Sentence has been parsed into many phrases by the Stanford parser. Each phrase has a PhraseId. Each sentence has a SentenceId. Phrases that are repeated (such as short/common words) are only included once in the data.

- train.tsv: contains the phrases and their associated sentiment labels.
- test.tsv: contains just phrases. You must assign a sentiment label to each phrase.
  - Label phrases on a scale of five values: negative, somewhat negative, neutral, somewhat positive, positive.

The sentiment labels are:

- 0 - negative
- 1 - somewhat negative
- 2 - neutral
- 3 - somewhat positive
- 4 - positive

2.1.1 *Dataset Info*

The initial shape of the train data set is (156060, 4). It has 156060 rows and 4 columns. Its initial size is 624240. The Kaggle test submission data set is (66292, 3). It has 66292 rows and 3 columns. Note that the test set does not have sentiment labels. It's to be used for final un-seen test prediction and submission to Kaggle for accuracy scoring.

Train Data Set Object Info	Test Data Set Object Info
• RangeIndex: 156060 entries, 0 to 156059 • Data columns (total 4 columns): • PhraseId 156060 non-null int64 • SentenceId 156060 non-null int64 • Phrase 156060 non-null object • Sentiment 156060 non-null int64 • dtypes: int64(3), object(1) • memory usage: 4.8+ MB	• RangeIndex: 66292 entries, 0 to 66291 • Data columns (total 3 columns): • PhraseId 66292 non-null int64 • SentenceId 66292 non-null int64 • Phrase 66292 non-null object • dtypes: int64(2), object(1) • memory usage: 1.5+ MB

Figure 2.1 below is a small representation of how the training data looks when first loaded.

Figure 2.1: Train Data Set sample:

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PhraseId	SentenceId	Phrase	Sentiment
1	1	A series of escapades demonstrating the adage that what is good for the goose is also good for the gander , some of which occasionally amuses but none of which amounts to much of a story .	1
2	1	A series of escapades demonstrating the adage that what is good for the goose	2
3	1	A series	2
4	1	A	2
5	1	series	2
64	2	This quiet , introspective and entertaining independent is worth seeking .	4
65	2	This quiet , introspective and entertaining independent	3
66	2	This	2
67	2	quiet , introspective and entertaining independent	4
68	2	quiet , introspective and entertaining	3

2.1.2 *Data Exploration & Cleaning*

All cleaning and transformation techniques were performed programmatically in python using a jupyter notebook for code execution and visualization. The python version used was Anaconda 3.6.

For each Task described above, a CountVectorizer is trained on the train data set content and performs cleaning and transformation actions according to it's input configuration parameters. Details for each of the tasks will be covered in section 2.1.2.2 below.

2.1.2.1 Data Exploration

Figure 2.2: Training Data Set WordCloud

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2.1.2.2 Vectorization Steps:

To train the vectorizers on the kaggle training data set, the data was segmented into X (Phrases) and y (Sentiment) numpy arrays. For each modeling task, the data was split using sklearn's train_test_split module to the specifications of the input paramter "test_size". This is used for validation of the model's prediction accuracy before being used on the final kaggle test data set submission.

2.1.2.2.1 CountVectorizer

Utilizing the python package **sklearn.feature_extraction.text CountVectorizer** class, this model converts a collection of customer review text documents to a matrix of token counts. This implementation of CountVectorizer produces a sparse representation of the counts using scipy.sparse.coo_matrix.

In-text mining, it is important to create the document-term matrix (DTM) of the corpus we are interested in. A DTM is basically a matrix, with documents designated by rows and words by columns, that the elements are the counts or the weights (usually by tf-idf). The subsequent analysis is usually based creatively on DTM.

CountVectorizer supports counts of N-grams of words or consecutive characters. Once fitted, the vectorizer has built a dictionary of feature indices. The index value of a word in the vocabulary is linked to its frequency in the whole training corpus. You can think of an N-gram as the sequence of N words, by that notion, a 2-gram (or bigram) is a two-word sequence of words like “please turn”, “turn your”, or ”your homework”, and a 3-gram (or trigram) is a three-word sequence of words like “please turn your”, or “turn your homework”. N-grams are used in building predictive language models based on models learned word sequencing.

The data for these vectorization steps is the kaggle train data set. Each of the vectorization steps below were for Multinomial Naive Baise and Support Vector Machine Classification modeling comparision.

<u>Task 1</u>

Initialize CountVectorizer unigram vector objects for MNB and SVM modeling

<u>Vectorizer Name</u>:
t1_mnb_count_vec_unigram
<u>Parameters:</u>

- input='content'
- ngram_range=(1,1)
- max_features=None
- max_df=1.0
- min_df=2
- analyzer=word
- stop_words='english'

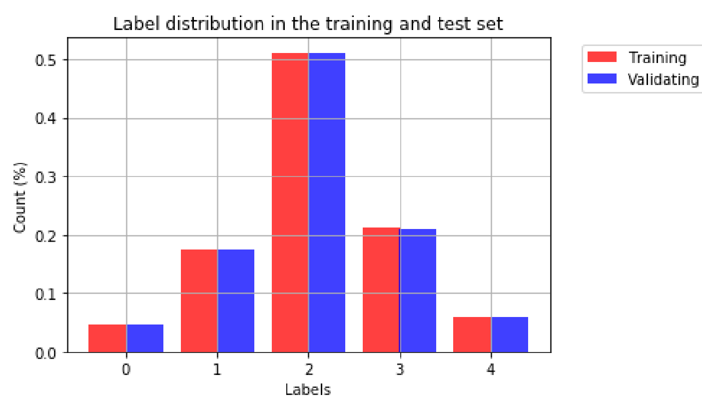
<u>Vectorizer Name</u>:
t1_svm_count_vec_unigram
<u>Parameters:</u>

- input='content'
- ngram_range=(1,1)
- max_features=None
- max_df=1.0
- min_df=2
- analyzer=word
- stop_words='english'

<u>Train Data Set Split Configurations:</u>

- train_test_split: test_size=0.4

Figure 2.3: Task 1 Label Distributions



- Tranformed Shape: (93636, 12018)
- Vocabulary Size: 12018

Task 2

Initialize CountVectorizer bigram vector objects for MNB and SVM modeling

Vectorizer Name: t2_mnb_count_vec_bigram
Parameters:

- input='content'
- ngram_range=(1,2)
- max_features=None
- max_df=1.0
- min_df=2
- analyzer=word
- stop_words='english'

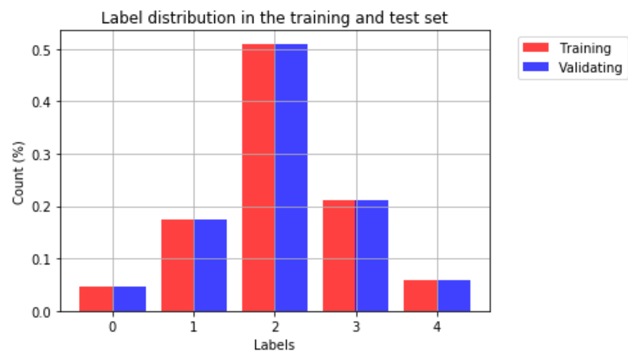
Vectorizer Name: t2_svm_count_vec_bigram
Parameters:

- input='content'
- ngram_range=(1,2)
- max_features=None
- max_df=1.0
- min_df=2
- analyzer=word
- stop_words='english'

Train Data Set Split Configurations:

- train_test_split: test_size=0.4

Figure 2.4: Task 2 Label Distribution



- Tranformed Shape: (93636, 34437)
- Vocabulary Size: 500431

Task 3

Initialize CountVectorizer bigram vector objects for MNB and SVM modeling

Vectorizer Name: t3_svm_count_vec_unigram
Parameters:

- input='content'
- ngram_range=(1,1)
- max_features=None
- max_df=1.0
- min_df=2
- analyzer=word
- stop_words='english'

Tranformed Shape: (x, x)
Vocabulary Size: x

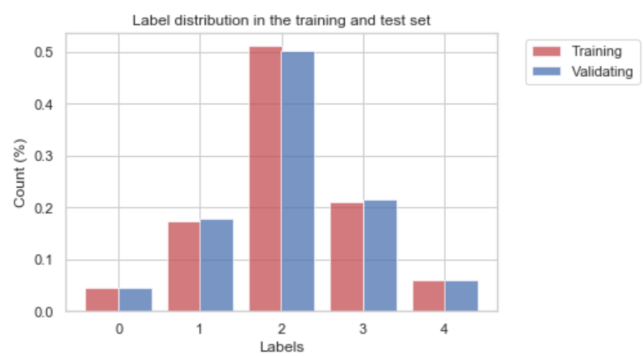
Vectorizer Name: t3_svm_count_vec_bigram
Parameters:

- input='content'
- ngram_range=(1,2)
- max_features=None
- max_df=1.0
- min_df=2
- analyzer=word
- stop_words='english'

Train Data Set Split Configurations:

- train_test_split: test_size=0.1

Figure 2.5: Task 3 Label Distribution



3 Models

Train Test Split Process

Labels for the datasets were encoded using the sklearn.preprocessing LabelEncoder class.

For prediction evaluation and accuracy measurement, 40% of each dataset was held out as unseen data. The method used was sklearns.model_selection train_test_split class.

Build-Test-Validate-Predict MNB and SVM Models

Model training and validation was performed by using sklearn.model_selection cross_validate. A 10 fold cross validation measure was used in training and validating each of vector models training dataset. 40% of each was held out for final, unseen, prediction accuracy evaluation for Task 1 and Task 2, Task 3 was trained at a 90/10 split inorder to maximize training data observations while still being able to report on accuracy scoring.

**Note: A complete listing of all model result details can be found in the .output/summary_report_final.xlsx

3.1.1 *Classification Models MNB and SVM Comparision*

3.1.1.1 Multinominal Naive Bayes (MNB) Models

For our text classification task we are using the Naive Bayes classifier for multinomial models.
The multinomial Naive Bayes classifier is suitable for classification with discrete features (e.g., word counts for text classification). The multinomial distribution normally requires integer feature counts. However, in practice, fractional counts such as tf-idf may also work. - scikit-learn MultinomialNB

For this implementation we are using scikit-learn v0.21.3 sklearn.naive_bayes MultinomialNB class.
The below steps were taking for each of the CountVectorizer vector models in the given task.

3.1.1.2 Support Vector Machine (SVM) Models

Linear Support Vector Classification (LinearSVC)
Python package scikit-learn v0.21.3 sklearn.svm.LinearSVC

Similar to SVC with parameter kernel='linear', but implemented in terms of liblinear rather than libsvm, so it has more flexibility in the choice of penalties and loss functions and should scale better to large numbers of samples.

This class supports both dense and sparse input and the multiclass support is handled according to a one-vs-the-rest scheme.
Read more in the User Guide.
Interpreting LinearSVC models:

- LinearSVC uses a one-vs-all strategy to extend the binary SVM classifier to multi-class problems
- For the Kaggle sentiment classification problem, there are five categories 0,1,2,3,4 with 0 as very negative and 4 very positive
- LinearSVC builds five binary classifier, "very negative vs. others", "negative vs. others", "neutral vs. others", "positive vs. others", "very positive vs. others", and then pick the most confident prediction as the final prediction.
- Linear SVC also ranks all features based on their contribution to distinguish the two concepts in each binary classifier

3.1.1.3 Task 1

- Build unigram models
- Print top 10 indicative words for most positive category and the most negative category
- Report confusion matrix, precision, and recall scores.

The SVM model performs margenly better than the MNB model by 2%. It appars that both models had similar challenges with each of the classification categories. The f1-score's have an interesting pattern which aligns to the training data label distribution inequilities shown in figure 2.3 above.

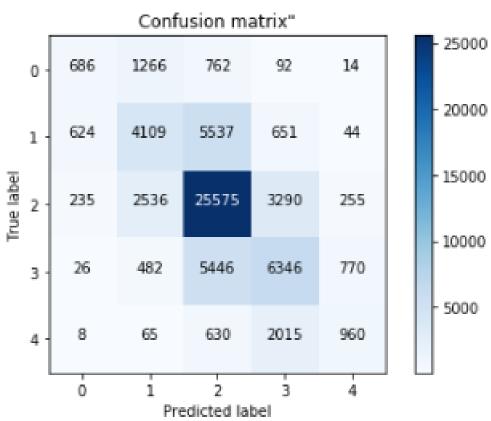
3.1.1.3.1 MNB Unigram Results

Most POSITIVE WORDS	Most NEGATIVE WORDS

```
Top and Bottome 10 of Most POSITIVE Learned Words
 -10.5615  102                  -5.7994 great
 -10.5615  103                  -5.7740 performance
 -10.5615  104                  -5.6712 comedy
 -10.5615  105                  -5.6637 story
 -10.5615  10th                 -5.6057 performances
 -10.5615  110                  -5.4617 good
 -10.5615  112                  -5.3520 funny
 -10.5615  120                  -5.1816 best
 -10.5615  13th                 -4.8282 movie
 -10.5615  140                  -4.2849 film
```

```
Top and Bottome 10 of Most NEGATIVE Learned Words
 -10.4308  10th                 -6.0120 story
 -10.4308  112                  -5.8876 minutes
 -10.4308  12                   -5.8665 characters
 -10.4308  127                  -5.8561 worst
 -10.4308  129                  -5.7865 comedy
 -10.4308  12th                 -5.6602 just
 -10.4308  13th                 -5.2105 like
 -10.4308  14                   -4.8511 film
 -10.4308  16                   -4.8068 bad
 -10.4308  163                  -4.3741 movie
```

MNB Model Prediction Accuracy Results: 60.35%




```
Confusion Matrix:
[[  686  1266   762    92    14]
 [  624  4109  5537   651    44]
 [  235  2536 25575  3290   255]
 [   26   482  5446  6346   770]
 [    8    65   630  2015   960]]
```

```
Classification Report:
               precision    recall  f1-score   support

very_negative       0.43      0.24      0.31      2820
     negative       0.49      0.37      0.42     10965
      neutral       0.67      0.80      0.73     31891
     positive       0.51      0.49      0.50     13070
very_positive       0.47      0.26      0.34      3678

    micro avg       0.60      0.60      0.60     62424
    macro avg       0.52      0.43      0.46     62424
 weighted avg       0.58      0.60      0.59     62424
```

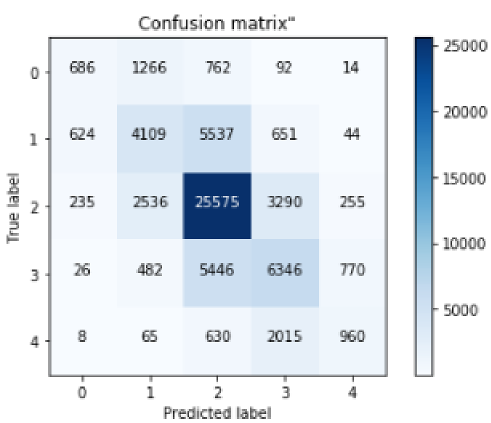
3.1.1.3.2 SVM Unigram Results

Most POSITIVE WORDS	Most NEGATIVE WORDS

```
Top and Bottome 10 of Most POSITIVE Learned Words
 -2.3033 swim                  1.6590  defining
 -2.2927 empire                1.6803  uplifter
 -2.0725 guarantee             1.6926  dreamy
 -1.9047 losers                1.7024  scientists
 -1.8120 stops                 1.7614  masterfully
 -1.8073 million               1.8522  adorns
 -1.7778 costumed              1.9796  flawless
 -1.7733 maintained            1.9996  miraculous
 -1.7083 nonchallenging        2.0021  masterpeice
 -1.6863 placed                2.0272  perfection
```

```
Top and Bottome 10 of Most NEGATIVE Learned Words
 -1.6409 won                   1.7126  dud
 -1.6203 giving                1.7668  repugnant
 -1.5882 month                 1.7721  disgusting
 -1.5300 sopranos              1.7907  zzzzzzzzz
 -1.4831 enters                1.7955  flopped
 -1.3472 passionate            1.7998  loser
 -1.3472 truthful              1.8665  loathsome
 -1.3002 collar                1.8899  encountering
 -1.2982 rare                  2.0561  repulsive
 -1.2632 extension             2.0998  disappointment
```

SVM Model Prediction Accuracy Results: 62.34%




```
Classification Report:
               precision    recall  f1-score   support

very_negative       0.45      0.33      0.38      2852
     negative       0.51      0.39      0.44     10887
      neutral       0.69      0.83      0.75     31809
     positive       0.55      0.44      0.49     13185
very_positive       0.50      0.37      0.43      3691

    micro avg       0.62      0.62      0.62     62424
    macro avg       0.54      0.47      0.50     62424
 weighted avg       0.60      0.62      0.61     62424
```

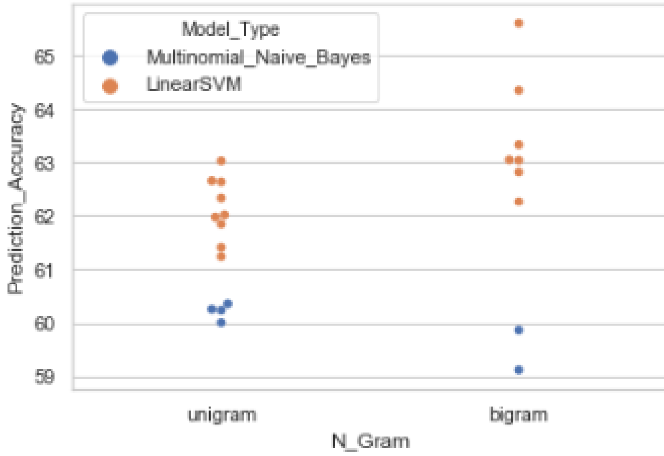
```
Confusion Matrix:
[[  945  1210   598    86    13]
 [  841  4267  5187   527    65]
 [  252  2420 26538  2422   177]
 [   35   432  5828  5798  1092]
 [    5    44   506  1768  1368]]
```

3.1.1.4 Task 2

- Build bigram models
- Print top 10 indicative words for most positive category and the most negative category
- Report confusion matrix, precision, and recall scores.
- Compare evaluation measures, was adding bigrams helpful?

The SVM bigram model performs margenly better than the MNB bigram model by 3.48%. It appars that both models had similar challenges with each of the classification categories. The f1-score's have an interesting pattern which aligns to the training data label distribution inequilities shown in figure 2.3 above.

3.1.1.4.1 Model Comparison Prediction Accuracies



- Overall, LinearSVMs performed the best, with Bigram's being the best predictors

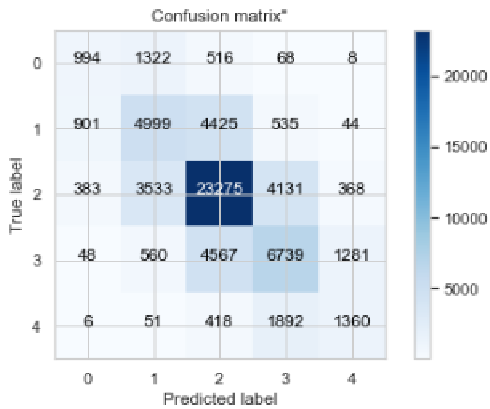
3.1.1.4.2 MNB Bigram Results

Most POSITIVE WORDS	Most NEGATIVE WORDS

```
Top and Bottome 10 of Most POSITIVE Learned Words
 -11.6239  000                    -6.9054 performance
 -11.6239  000 leagues            -6.8790 great
 -11.6239  000 times              -6.7956 performances
 -11.6239  10 000                 -6.7797 comedy
 -11.6239  10 15                  -6.7797 story
 -11.6239  10 course              -6.4035 good
 -11.6239  10 seconds             -6.3560 funny
 -11.6239  10 set                 -6.2533 best
 -11.6239  10 years               -5.8370 movie
 -11.6239  100 minute             -5.4113 film
```

```
Top and Bottome 10 of Most NEGATIVE Learned Words
 -11.5449  000 leagues            -7.0676 long
 -11.5449  10 course              -7.0563 characters
 -11.5449  10 year                -7.0563 comedy
 -11.5449  100 minutes            -7.0123 time
 -11.5449  100 year               -6.9910 minutes
 -11.5449  101 minutes            -6.8721 just
 -11.5449  101 premise            -6.4329 like
 -11.5449  101 study              -6.0769 bad
 -11.5449  10th                   -6.0115 film
 -11.5449  10th film              -5.5263 movie
```

MNB Bigram Model Prediction Accuracy Results: 59.85%



Classification Report:

	precision	recall	f1-score	support
very_negative	0.43	0.34	0.38	2908
negative	0.48	0.46	0.47	10904
neutral	0.70	0.73	0.72	31690
positive	0.50	0.51	0.51	13195
very_positive	0.44	0.36	0.40	3727
micro avg	0.60	0.60	0.60	62424
macro avg	0.51	0.48	0.49	62424
weighted avg	0.59	0.60	0.59	62424

```
Confusion Matrix:
[[  994  1322   516    68     8]
 [  901  4999  4425   535    44]
 [  383  3533 23275  4131   368]
 [   48   560  4567  6739  1281]
 [    6    51   418  1892  1360]]
```

3.1.1.4.3 SVM Bigram Results

Most POSITIVE WORDS

Top and Bottome 10 of Most POSITIVE Learned Words

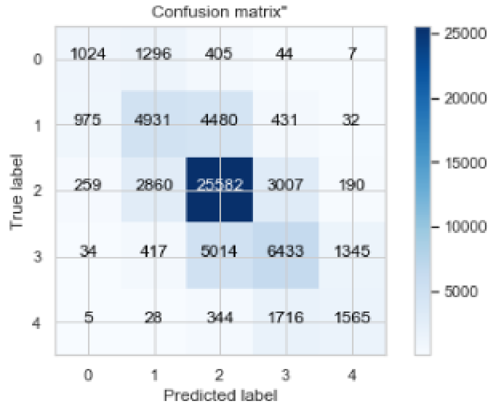
-1.8985	american add	1.5752	ingenious
-1.6432	experience informative	1.5754	hardly ask
-1.5741	locales exceptional	1.5778	masterfully
-1.5552	genuine dramatic	1.5907	riveted
-1.5527	vivid possible	1.5987	breathtaking
-1.4987	laughter surprised	1.6540	excellent
-1.4894	directed highly	1.6570	flawless
-1.4176	devastating experience	1.7120	magnificent
-1.4013	affable	1.8270	masterpeice
-1.3938	dragon worthy	1.8988	perfection

Most NEGATIVE WORDS

Top and Bottome 10 of Most NEGATIVE Learned Words

-1.7975	imitation really	1.6704	baaaaaaaaad
-1.7339	indulgent worst	1.7175	disappointingly
-1.6449	humorless chore	1.7703	snoozer
-1.5710	makes passes	1.7889	terrible
-1.4739	fact film	1.8026	turd
-1.4361	acting ensemble	1.8060	repugnant
-1.3901	drama screams	1.8097	snooze
-1.3822	sequels fails	1.8497	unappealing
-1.3816	plotting insultingly	1.8525	dud
-1.3622	poo poo	1.8879	disappointment

SVM Bigram Model Prediction Accuracy Results: 63.33%




```
Classification Report:
              precision    recall  f1-score   support

very_negative       0.45      0.37      0.40      2776
     negative       0.52      0.45      0.48     10849
      neutral       0.71      0.80      0.76     31898
     positive       0.55      0.49      0.52     13243
very_positive       0.50      0.43      0.46      3658

    micro avg       0.63      0.63      0.63     62424
    macro avg       0.55      0.51      0.52     62424
 weighted avg       0.62      0.63      0.62     62424
```

```
Confusion Matrix:
[[ 1024  1296   405    44     7]
 [  975  4931  4480   431    32]
 [  259  2860 25582  3007   190]
 [   34   417  5014  6433  1345]
 [    5    28   344  1716  1565]]
```

3.1.1.5 Task 3

- Build best SVMs model by tuning parameters using entire training data set
- Report parameters used to train the model and it's cross validation accuracy

Best SVM vectorizer is the Bigram.

To determine the best LinearSVM hyperparameters to configure the model with GridSearchCV was used. GridSearchCV is a parameter estimation module using grid search with cross-validation.
Hyper-parameters are parameters that are not directly learnt within estimators. In scikit-learn they are passed as arguments to the constructor of the estimator classes.

GridSearchCV was ran with the following parameter ranges:
{
'C': [0.1, 1, 10, 100, 1000],
 'loss': ['hinge','squared_hinge'],
 }

- Fitting 3 folds for each of 10 candidates, totalling 30 fits
- grid.best_params_: {'C': 1, 'loss': 'hinge'}

GridSearchCV(cv='warn', error_score='raise-deprecating', estimator=LinearSVC(C=1.0, class_weight=None, dual=True, fit_intercept=True, intercept_scaling=1, loss='squared_hinge', max_iter=1000, multi_class='ovr', penalty='l2', random_state=None, tol=0.0001,verbose=0),fit_params=None, iid='warn', n_jobs=None, param_grid={'C': [0.1, 1, 10, 100, 1000],

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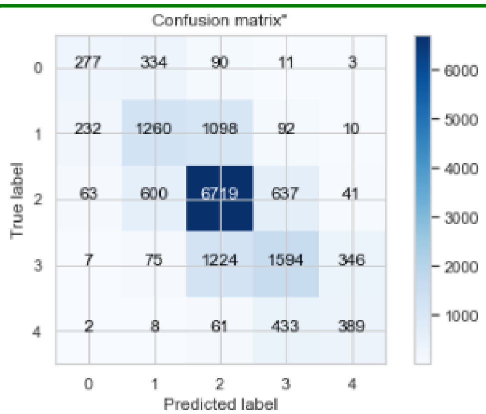
'loss': ['hinge', 'squared_hinge']}, pre_dispatch='2*n_jobs', refit=True, return_train_score='warn', scoring=None, verbose=3)

Most POSITIVE WORDS	Most NEGATIVE WORDS

```
Top and Bottome 10 of Most POSITIVE Learned Words
 -2.0431 catching griffiths       1.9816  ll love
 -2.0000 story sweet              1.9872  marvelous
 -2.0000 movie highest            2.0000  enriched
 -1.7886 wrong film               2.0969  magnificent
 -1.7781 turns gripping           2.1072  masterfully
 -1.6744 works superior           2.1368  captivating
 -1.6485 talent outstanding       2.2931  masterful
 -1.5967 directed highly          2.5583  masterpiece
 -1.5557 grant lost               2.6241  perfection
 -1.4911 captures luminous        2.6241  masterpeice
```

```
Top and Bottome 10 of Most NEGATIVE Learned Words
 -2.0382 ca actor                    1.8557  disappointment
 -1.6275 bad painfully               1.8688  pileup cliches
 -1.4928 quickly enters              1.9056  ludicrous film
 -1.4164 acting ensemble             1.9147  hardly watchable
 -1.3333 rejected astronomically     1.9536  thumbs
 -1.3305 responsible did             1.9605  like trapped
 -1.3200 great terrible              2.0000  execrable
 -1.2601 makes passes                2.0000  snoozer
 -1.2526 film thought                2.0997  disappointingly
 -1.2493 sit crap                    2.1561  unwatchable
```

SVM Bigram Model Prediction Accuracy Results: 65.60%

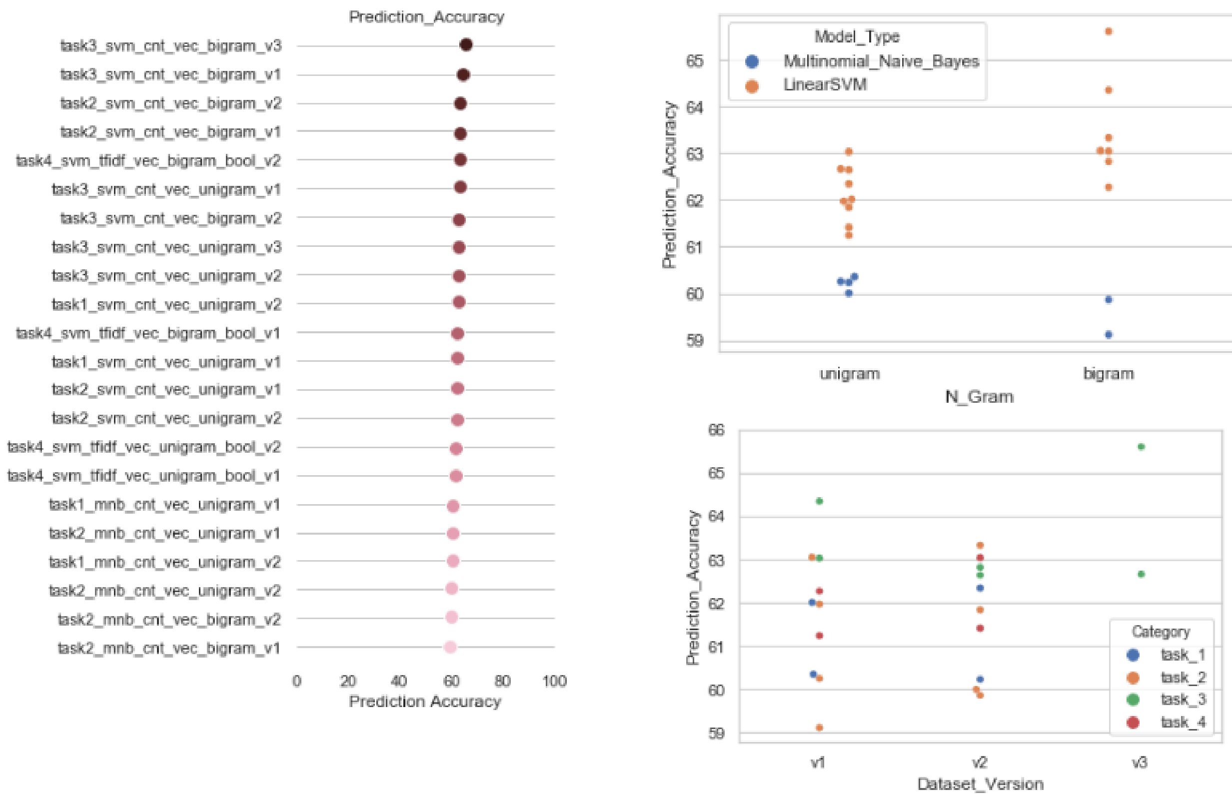



```
Classification Report:
              precision    recall  f1-score   support

very_negative       0.48      0.39      0.43       715
     negative       0.55      0.47      0.51      2692
      neutral       0.73      0.83      0.78      8060
     positive       0.58      0.49      0.53      3246
very_positive       0.49      0.44      0.46       893

    micro avg       0.66      0.66      0.66     15606
    macro avg       0.57      0.52      0.54     15606
 weighted avg       0.64      0.66      0.65     15606
```

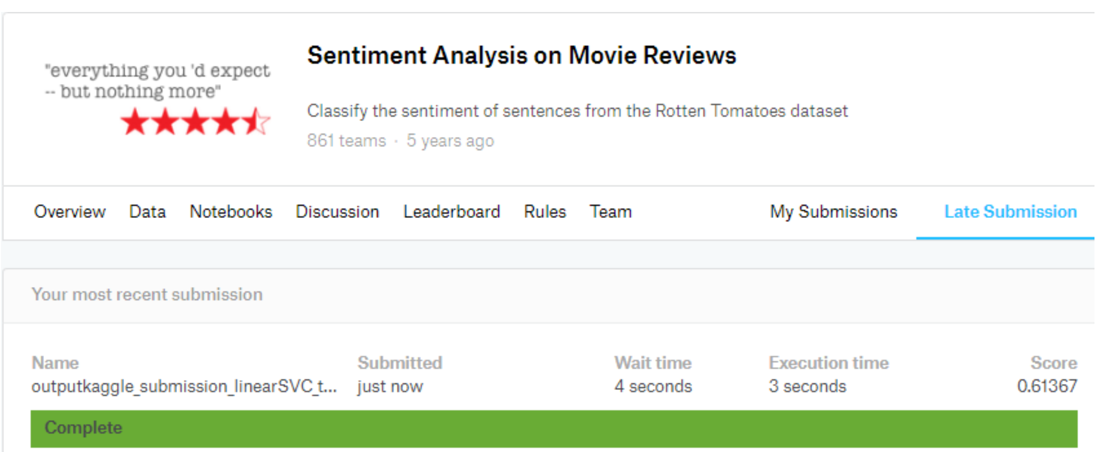
```
Confusion Matrix:
[[ 277  334   90   11    3]
 [ 232 1260 1098   92   10]
 [  63  600 6719  637   41]
 [   7   75 1224 1594  346]
 [   2    8   61  433  389]]
```

Homework Assignment 7 (week 7)

3.1.1.5.1 Model Accuracy Comparison Summary



3.1.1.6 Task 3 - Kaggle Submission Results



4 Conclusions

Of the 22 variations of the two Classification models built for comparison, 20 of them scored above at or above 60% predicted accuracy rating on unseen movie reviews with a high of 65.61% by a LinearSVM bigram frequency count model. Comparing Multinomial Naive Bayes with Linear Support Vector Machine models, LinearSVM outperformed MNB in each of the trial tasks for both unigram and bigram vectorizors.

Both modeling classifiers struggled with labeling categories outside fo neutral. The labeled dataset was overwhelmingly in favor of neutral sentiment classes. The task of labeling phrases on a scale of five values: negative, somewhat negative, neutral, somewhat positive, positive has many obstacles like sentence negation, sarcasm, terseness, language ambiguity, and many others making this task very challenging.

Additionally, there are labeled datasets that are used as gold standards for building and training models for baseline evaluation of accuracy. Starting with those datasets, then adding-context specific domain knowledge into this dataset would greatly enhance the accuracy potential of these models.

Deep Learning for Sentiment Analysis is being expanded on. Below is an excerpt from NLP at Stanford where they describe new Recursive Neural Network techniques that are showing great progress in this very challenging space. - https://nlp.stanford.edu/sentiment/

" Most sentiment prediction systems work just by looking at words in isolation, giving positive points for positive words and negative points for negative words and then summing up these points. That way, the order of words is ignored and important information is lost. In contrast, our new deep learning model actually builds up a representation of whole sentences based on the sentence structure. It computes the sentiment based on how words compose the meaning of longer phrases. This way, the model is not as easily fooled as previous models. The underlying technology of this demo is based on a new type of Recursive Neural Network that builds on top of grammatical structures. "

5 Appendix: References

[1] Pang and L. Lee. 2005. *Seeing stars: Exploiting class relationships for sentiment categorization with respect to rating scales*. In ACL, pages 115–124.

[2] *Recursive Deep Models for Semantic Compositionality Over a Sentiment Treebank*, Richard Socher, Alex Perelygin, Jean Wu, Jason Chuang, Chris Manning, Andrew Ng, and Chris Potts. Conference on Empirical Methods in Natural Language Processing (EMNLP 2013).