Machine Learning Fall 2016
HW5 Writeup
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1.3

thetaPos

love: 0.00079759628516798691
wonderful: 0.0002166985340981517
best: 0.0010616407174724575
great: 0.00097969589365382872
superb: 9.4691796412637707e-05
still: 0.00072839843394336703
beautiful: 0.00026404443230447055
bad: 0.00048438495857233905
worst: 6.1913866885186195e-05
stupid: 6.0092870800327781e-05
waste: 2.913593735773468e-05
boring: 7.101884730947828e-05
?: 0.0020103796776836931
!: 0.00081216425384685422
UNK: 0.9923281434944915

thetaNeg

love: 0.00063709436120604201
wonderful: 8.1417809738791315e-05
best: 0.00071240583521442393
great: 0.00052310942757173421
superb: 2.6460788165107175e-05
still: 0.00067169693034502828
beautiful: 0.00014044572179941503
bad: 0.0014125989989680293
worst: 0.0003663801438245609
stupid: 0.00029717500554658831
waste: 0.00016894195520799198
boring: 0.00034806113663333284
?: 0.0031060894415348888
!: 0.0015387966040631559
UNK: 0.98996932584018094

*Note: “love” includes words love, loving, loves, loved

Explanation of how thetaPos and thetaNeg were computed (use equations if necessary):

For thetaPos:
First, we accumulate the frequencies of each word in our vocabulary across all the positive documents, which is the first 700 rows in the Xtrain matrix. After we get the accumulated frequencies, we can get a total number of words by simply summing up all of the accumulated frequencies. In order to get the theta for each word with Laplace smoothing, we apply the formula:

$$P(w_k|c_j) \leftarrow \frac{n_{k,j}+\alpha}{n_j+\alpha|Vocabulary|} \qquad e.g., \alpha=1 \quad \text{(Smoothing)}$$

Here, we have α = 1 and |Vocabulary| = 15. So the equation becomes:
Frequency of word + 1 / Total number of words + 15
We apply the formula for each word in the vocabulary and get thetaPos. Similarly, we can get thetaNeg.

1.4

Multinomial Naive Bayes Classifier (MNBC) test set Accuracy:

0.675

sklearn.naive_bayes.MultinomialNB test set Accuracy:

0.675

Explanation of how you test using MNBC (use equations if necessary):
In order to determin from which class(pos/neg) a test document is from, we need to calculate the joint probability of words in this documents. We apply the formula:

$$P(W_1=n_1,\dots,W_k=n_k\,|\,c,N,\theta_1,\dots,\theta_k)=\cancel{\frac{N!}{n_1!n_2!..n_k!}}\,\theta_1^{n_1}\theta_2^{n_2}..\theta_k^{n_k}$$

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We can leave out the multinomial coefficient part since it is a constant. Moreover, since the thetas are pretty small numbers, we use log likelihood to calculate our document score. In formula, this becomes P = n1 * log(theta1) + n2 * log(theta2) … + nk * log(thetak).

From Xtest, we can get the frequencies for words n1…nk. Thus, we can use the above formula and thetaPos and thetaNeg to calculate the likelihood for positive and negative class. Then, apply MLE we will choose the class with maximum score to be our prediction. Finally, we can calculate the accuracy by comparing the predicted y labels to true lables.

MNBC Extra Credit test set accuracy and discussion:
First, I have scanned through all the documents in the training corpus and calculate the accumulate frequencies for words(after stemming) other than stop words. Then, I pick 14 top words among the most frequently appered ones. Adding the UNK, the list becomes:
['make', ':', 'get', 'charact', '?',"it'", 'like','ha', 'wa', 'one','movi','thi','hi','film','UNK']

Then I do basically the same classficiation as required except that I will stem all the words and remove stop words when I read the words from documents.

The result I got is 0.615 and 0.615. This result is not as good as the original one because although we are using the most frequent words in the training corpus, the words might not be good indicators of positive or negative attitudes.

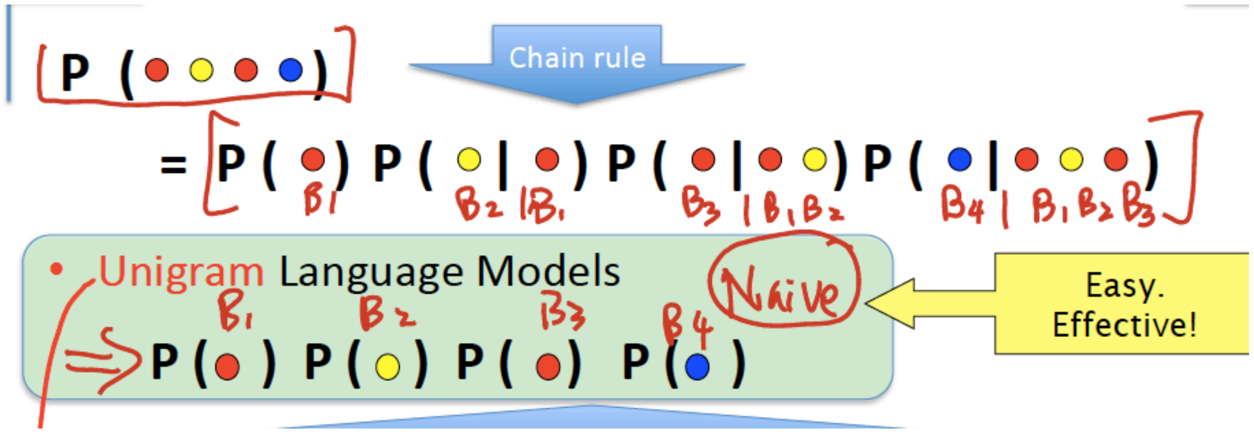
1.5

Multinomial Naive Bayes Classifier Testing with non-BOW test set Accuracy:

0.675

Explanation of how you test using MNBC with non-BOW (use equations if necessary):

Here we do not count the frequencies for words (aka not using BOW). Instead, to calculate the score for a document we just look at each word and refer to the thetaPos and thetaNeg array to sum up the log likelihoods and get scorePos and scoreNeg. The principle is illustrated below:



Similar to the calculation with BOW, multiplying the probabilties might yield a very small number, hence here we add the log likelihood together. At last, we compare the scorePos and scoreNeg and apply MLE, which means we will pick the class with higher score to be our prediction. Finally, we can calculate the accuracy by comparing the predicted y labels to true lables.

****MNBC non-Bow testing Extra Credit test set accuracy and discussion**:**
Here the test accuracy using extra credit vocabulary is 0.615, which matches the previous two results from extra credit vocabulary. Since we are adding the log likelihood for each word, this should produce the same result as calculating the frequency then multiply the frequencies with the log likelihoods. Indeed, our result verifies that the results are the same.

1.6

<u>thetaPosTrue</u>
love: 0.349002849002849
wonderful: 0.12393162393162394
best: 0.4928774928774929
great: 0.41452991452991456
superb: 0.06552706552706553
still: 0.37037037037037035
beautiful: 0.1467236467236467
bad: 0.2621082621082621
worst: 0.045584045584045586
stupid: 0.038461538461538464
waste: 0.022792022792022793
boring: 0.05128205128205128
?: 0.5427350427350427
!: 0.2777777777777778
UNK: 0.9985754985754985

<u>thetaNegTrue</u>
love: 0.2948717948717949
wonderful: 0.05270655270655271
best: 0.3504273504273504
great: 0.26638176638176636
superb: 0.018518518518518517
still: 0.3247863247863248
beautiful: 0.08974358974358974
bad: 0.4886039886039886
worst: 0.19230769230769232
stupid: 0.15954415954415954
waste: 0.10541310541310542
boring: 0.18518518518518517
?: 0.688034188034188
!: 0.39886039886039887
UNK: 0.9985754985754985

*Note: “love” includes words love, loving, loves, loved

Explanation of how thetaPosTrue and thetaNegTrue were computed (use equations if necessary):

We just need to compute the proportion of documents that contains word i in order to get P(wi=true|c). Hence, we set an iterator i and we scan through all rows of Xtrain and see if ith position is non-empty. If yes, then this word appears in this document and we do count+1. According to prior knowledge we know that there are 1400 training documents and 700 of them are positive while 700 are negative. Hence, we know the number of files in each class is 700. Then we can apply the formula:

$$\mathbb{P}(w_i = true|c) = \frac{\#\text{files which include } w_i \text{ and are in class c} + 1}{\#\text{files are in class c} + 2}$$

$$\mathbb{P}(w_i = false|c) = 1 - \mathbb{P}(w_i = true|c)$$

To get the thetaPosTrue and thetaNegTrue. After getting thetaPosTrue and thetaNegTrue, we can get the other haf(False case) easily since there are only two possibilities. Finally, we can calculate the accuracy by comparing the predicted y labels to true lables.

Multivariate Bernoulli Naive Bayes Classifier (BNBC) test set Accuracy:

0.69

Explanation of how you test using BNBC (use equations if necessary):

In order to get a test document's score, we just need to check if each word appears in this document. Hence, we can calculate scorePos and scoreNeg by checking if this word presents in the document and if yes we can apply thetaPosTrue and thetaNegTrue. If a word is not present in this document we can look for 1-thetaPosTrue[i] or 1-thetaNegTrue[i]. Similar to before, since multiplying thetas might lead to underflow problem, we add the log likelihoods together to calculate the scorePos and scoreNeg. Then we can apply MLE to determine our prediction class to be the class with maximum sum of log likelihoods.

$$\Pr(W_1 = true, W_2 = false, \ldots, W_k = true \mid C = c)$$
$$= P(W_1 = true \mid C) \bullet P(W_2 = false \mid C) \bullet \cdots \bullet P(W_k = true \mid C)$$

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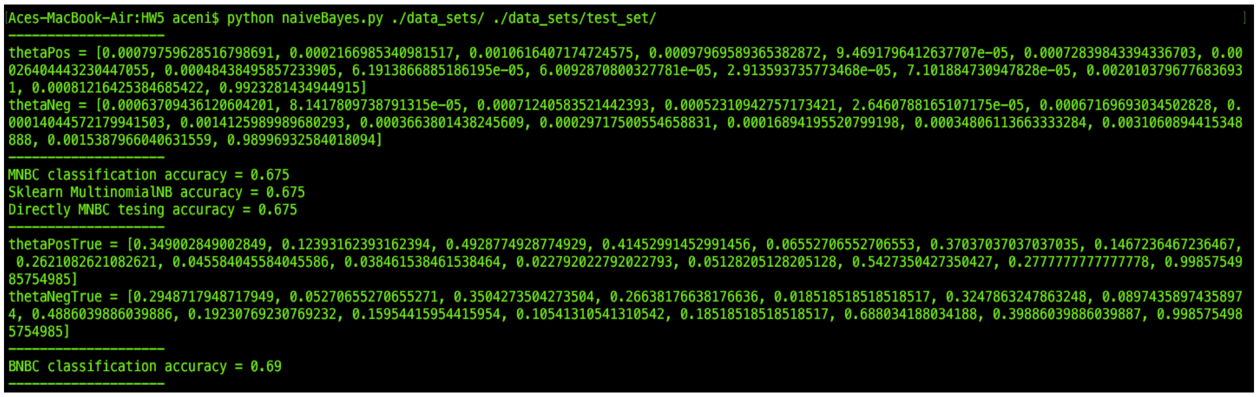
Finally, we can calculate the accuracy by comparing the predicted y labels to true lables.

BNBC Extra credit test set accuracy and discussion:

Accuracy: 0.5733333333
This score is lower than the MNBC accuracy. It is worth noting that in the required portion, our BNBC accuracy is higher than MNBC accuracy. This difference might due to the aggregate nature of BNBC (thetas do not sum up to 1) and the difference between two vocabularies.

Attachment: Required result screen shot & Extra credit result screen shot

Required:



```
Aces-MacBook-Air:HW5 aceni$ python naiveBayes.py ./data_sets/ ./data_sets/test_set/
--------------------
thetaPos = [0.00079759628516798691, 0.0002166985340981517, 0.0010616407174724575, 0.00097969589365382872, 9.4691796412637707e-05, 0.00072839843394336703, 0.00
026404443230447055, 0.00048438495857233905, 6.1913866885186195e-05, 6.0092870800327781e-05, 2.913593735773468e-05, 7.101884730947828e-05, 0.002010379677683693
1, 0.00081216425384685422, 0.9923281434944915]
thetaNeg = [0.00063709436120604201, 8.1417809738791315e-05, 0.00071240583521442393, 0.00052310942757173421, 2.6460788165107175e-05, 0.00067169693034502828, 0.
00014044572179941503, 0.0014125989989680293, 0.0003663801438245609, 0.00029717500554658831, 0.00016894195520799198, 0.00034806113663333284, 0.0031060894415348
888, 0.0015387966040631559, 0.98996932584018094]
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MNBC classification accuracy = 0.675
Sklearn MultinomialNB accuracy = 0.675
Directly MNBC tesing accuracy = 0.675
--------------------
thetaPosTrue = [0.349002849002849, 0.12393162393162394, 0.4928774928774929, 0.41452991452991456, 0.06552706552706553, 0.37037037037037035, 0.1467236467236467,
 0.2621082621082621, 0.045584045584045586, 0.038461538461538464, 0.022792022792022793, 0.05128205128205128, 0.5427350427350427, 0.2777777777777778, 0.99857549
85754985]
thetaNegTrue = [0.2948717948717949, 0.05270655270655271, 0.3504273504273504, 0.26638176638176636, 0.018518518518518517, 0.3247863247863248, 0.0897435897435897
4, 0.4886039886039886, 0.19230769230769232, 0.15954415954415954, 0.10541310541310542, 0.18518518518518517, 0.688034188034188, 0.39886039886039887, 0.998575498
5754985]
--------------------
BNBC classification accuracy = 0.69
--------------------
```
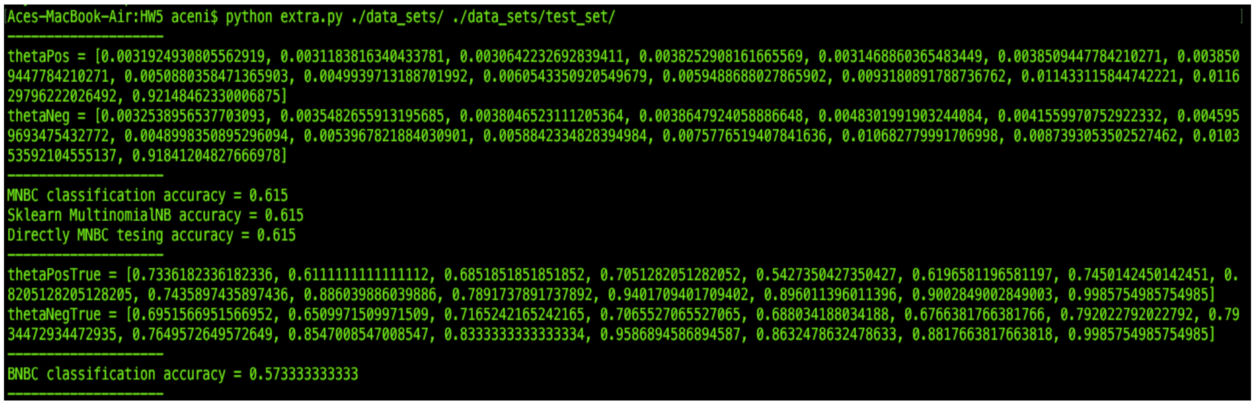

Extra Credit:



```
Aces-MacBook-Air:HW5 aceni$ python extra.py ./data_sets/ ./data_sets/test_set/
--------------------
thetaPos = [0.0031924930805562919, 0.0031183816340433781, 0.0030642232692839411, 0.0038252908161665569, 0.0031468860365483449, 0.0038509447784210271, 0.003850
9447784210271, 0.0050880358471365903, 0.0049939713188701992, 0.0060543350920549679, 0.0059488688027865902, 0.0093180891788736762, 0.011433115844742221, 0.0116
29796222026492, 0.92148462330006875]
thetaNeg = [0.0032538956537703093, 0.0035482655913195685, 0.0038046523111205364, 0.0038647924058886648, 0.0048301991903244084, 0.0041559970752922332, 0.004595
9693475432772, 0.0048998350895296094, 0.0053967821884030901, 0.0058842334828394984, 0.0075776519407841636, 0.010682779991706998, 0.0087393053502527462, 0.0103
53592104555137, 0.91841204827666978]
--------------------
MNBC classification accuracy = 0.615
Sklearn MultinomialNB accuracy = 0.615
Directly MNBC tesing accuracy = 0.615
--------------------
thetaPosTrue = [0.7336182336182336, 0.6111111111111112, 0.6851851851851852, 0.7051282051282052, 0.5427350427350427, 0.6196581196581197, 0.7450142450142451, 0.
8205128205128205, 0.7435897435897436, 0.886039886039886, 0.7891737891737892, 0.9401709401709402, 0.896011396011396, 0.9002849002849003, 0.9985754985754985]
thetaNegTrue = [0.6951566951566952, 0.6509971509971509, 0.7165242165242165, 0.7065527065527065, 0.688034188034188, 0.6766381766381766, 0.792022792022792, 0.79
34472934472935, 0.7649572649572649, 0.8547008547008547, 0.8333333333333334, 0.9586894586894587, 0.8632478632478633, 0.8817663817663818, 0.9985754985754985]
--------------------
BNBC classification accuracy = 0.573333333333
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```