=====DATSCIW261 ASSIGNMENT #1=====

MIDS UC Berkeley, Machine Learning at Scale DATSCIW261 ASSIGNMENT #1 (version 2016-01-14)

Hetal Chandaria (hetalchandaria@berkeley.edu)

W261 - 2 , Assignment 01

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HW1.0.0.

Define big data. Provide an example of a big data problem in your domain of expertise.

Answer :

Big data is a term for data sets that are so large that traditional computing systems are not sufficient for processing them. Imagine trying to run Machine learning algorithms on a training set which is 10GB in size on a traditonal laptop.

Big data is usually characterised by the 4 V's :

1. Volume : Amount of data generated
2. Velocity: How frequently is the data being generated
3. Variety : Different forms of data
4. Veracity : How certain are we about the data

Example of big data:

Consider eBay as an example. eBay has millions of users browsing through its website searching for, buying and selling products in 100s of categories. Trying to understand users and what their interests can be considered a big data challenge.

One can consider tracking the activity of all unique users across all pages/categories/product pages of eBay on all devices. These events would need to be tracked, aggregated on a per user basis and historically tracked to try and create some form of a profile of a user in terms of which categories/products the user is interested in. Additionally, present/future behaviour can be compared to models learnt on past user behaviour.

HW1.0.1.

In 500 words (English or pseudo code or a combination) describe how to estimate the bias, the variance, the irreducible error for a test dataset T when using polynomial regression models of degree 1, 2,3, 4,5 are considered. How would you select a model?

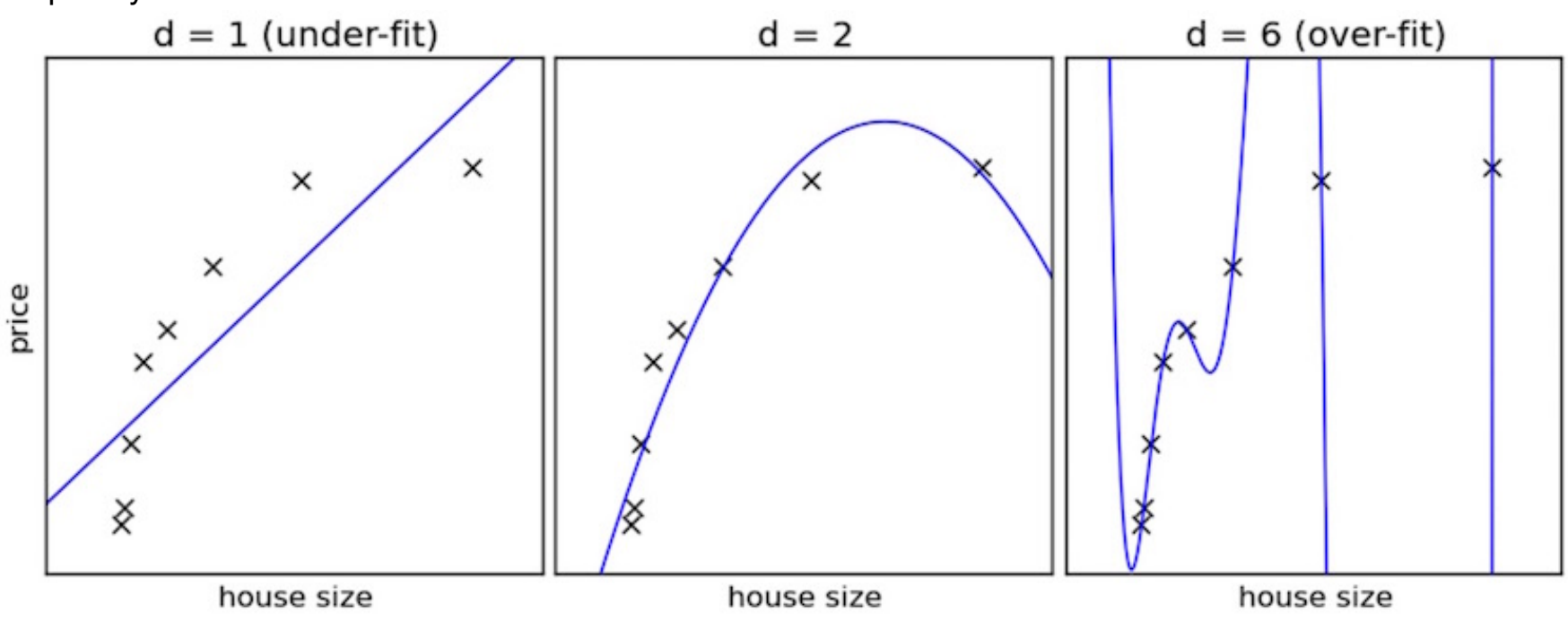
Let $f(x)$ be the true relationship function such that $y = f(x) + \epsilon$, where ϵ is normally distributed with a mean of 0.

Let g(x) be the estimator of f(x) using polynomial regression. We will fit polynomial regression models of degree 1,2,3,4 and 5 to our test dataset T.

To determine bias and variance, we will simulate multiple training sets by bootstrap replicates T' = {x | x is drawn at random with replacement from T} and |T'| = |T|.

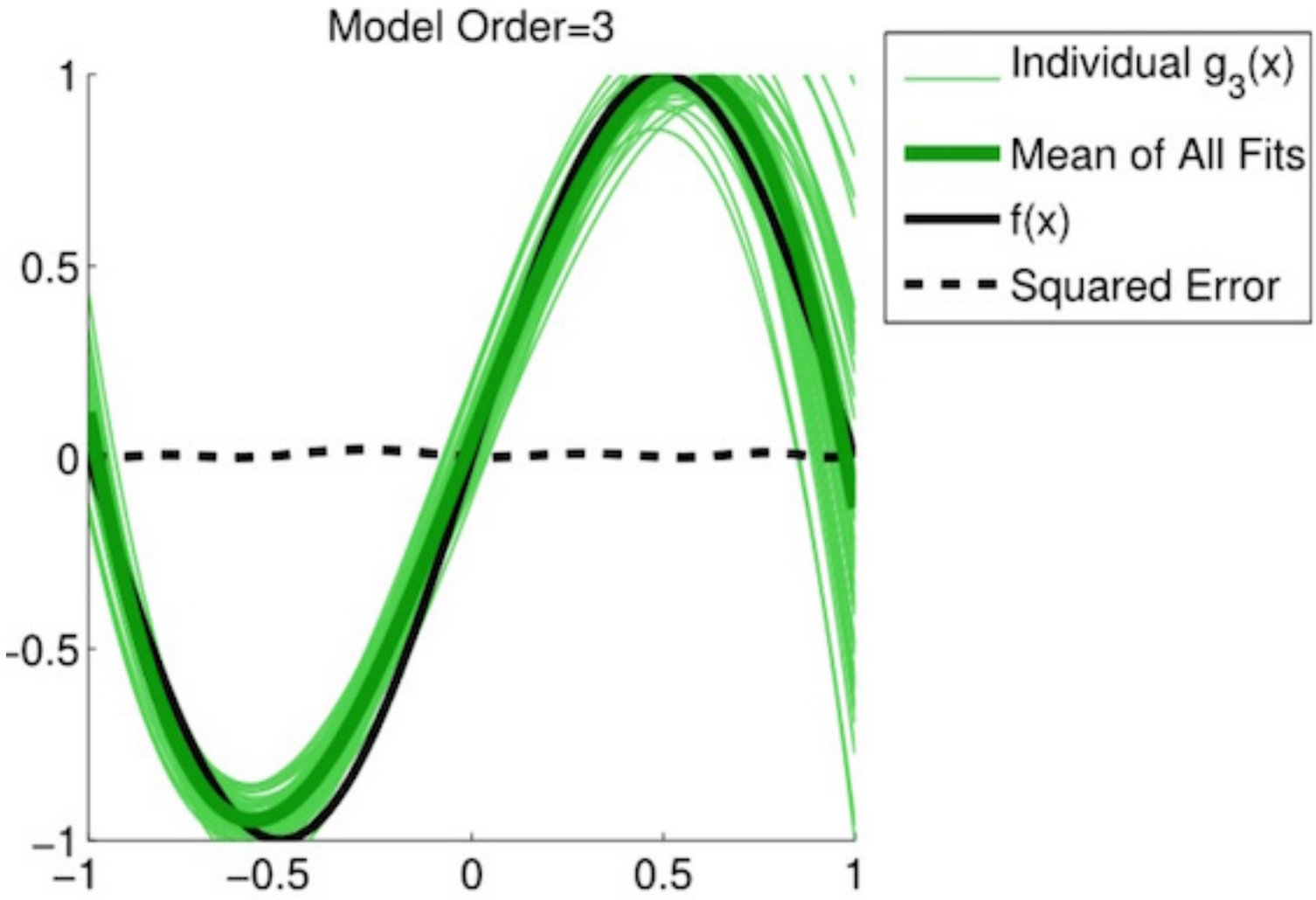
Bias : tells us how well the model can fit the true relationship between x and y. Here we will fit the 5 different polynomial regression model we have to the training dataset and determine which model fits the best.

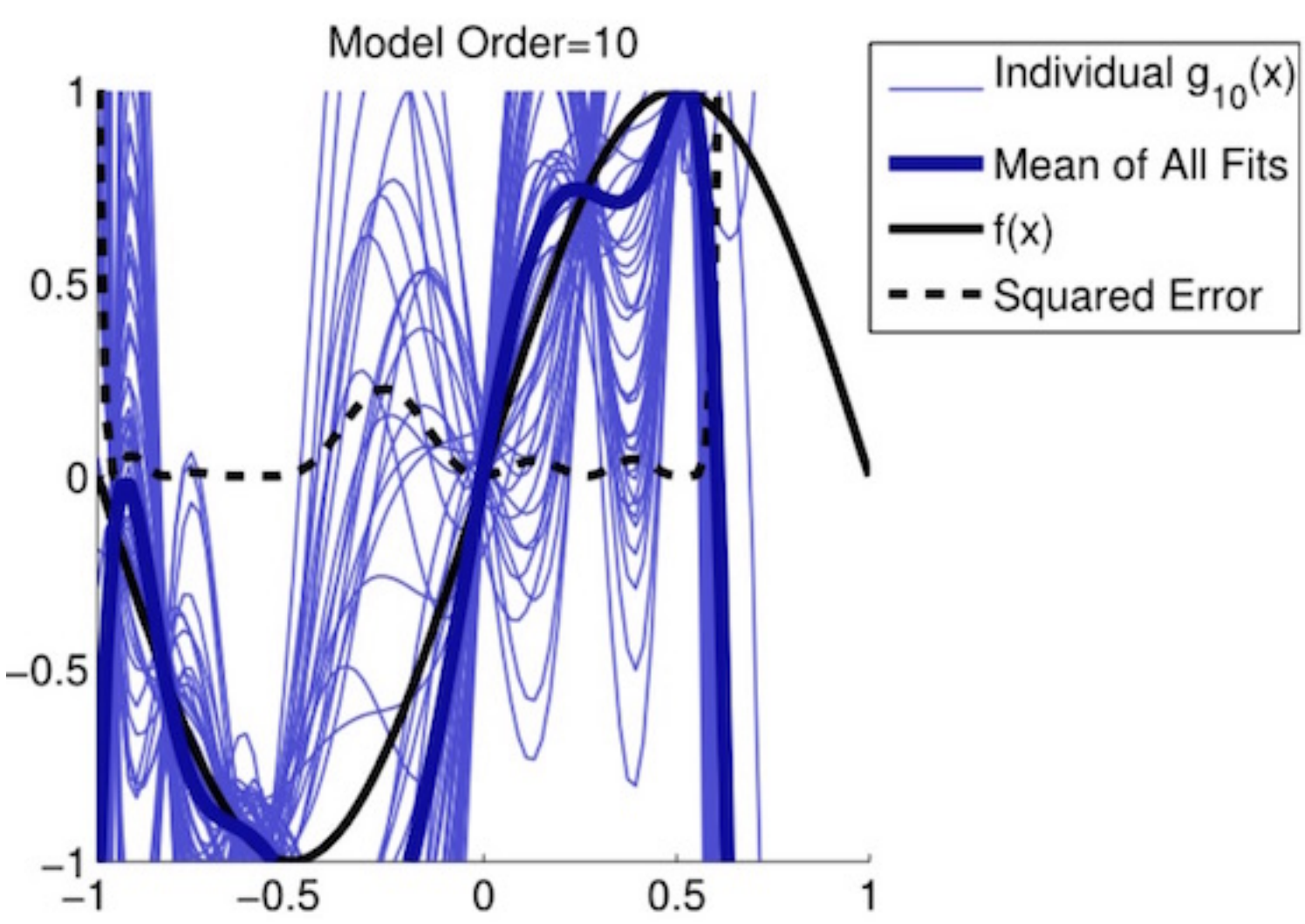
In the diagram below ,we can see that for the test data, 3 different models for varying degree being fit. Model with degree 1 underfits the data while model with degree 10 overfits the data. Thus as model complexity increases bias decreases.



Similary we can determine Variance. Variance : Variance tell us how different can a specific fit to given dataset be different from one another as we are looking at different datasets.

For example, looking at the diagram below, we can see that as model complexity increases (degree=10) variance increases. For model with degree 3, variance is low.





Mathematically, expected squared predition error at a point x is , $Err(x) = E[(y - g(x))]^2$

$$= E[y^2 - 2yg(x) + g(x)^2]$$

$$= E[y^2] + E[g(x)^2] - 2E[y]E[g(x)]$$

$$= E[(y - f(x))^2] + f(x)^2 + E[(g(x) - \overline{g}(x))^2] + \overline{g}(x)^2 - 2f(x)\overline{g}(x)$$

$$= E[(y - f(x))^2] + E[(g(x) - \overline{g}(x))^2] + f(x)^2 - 2f(x)\overline{g}(x) + \overline{g}(x)^2$$

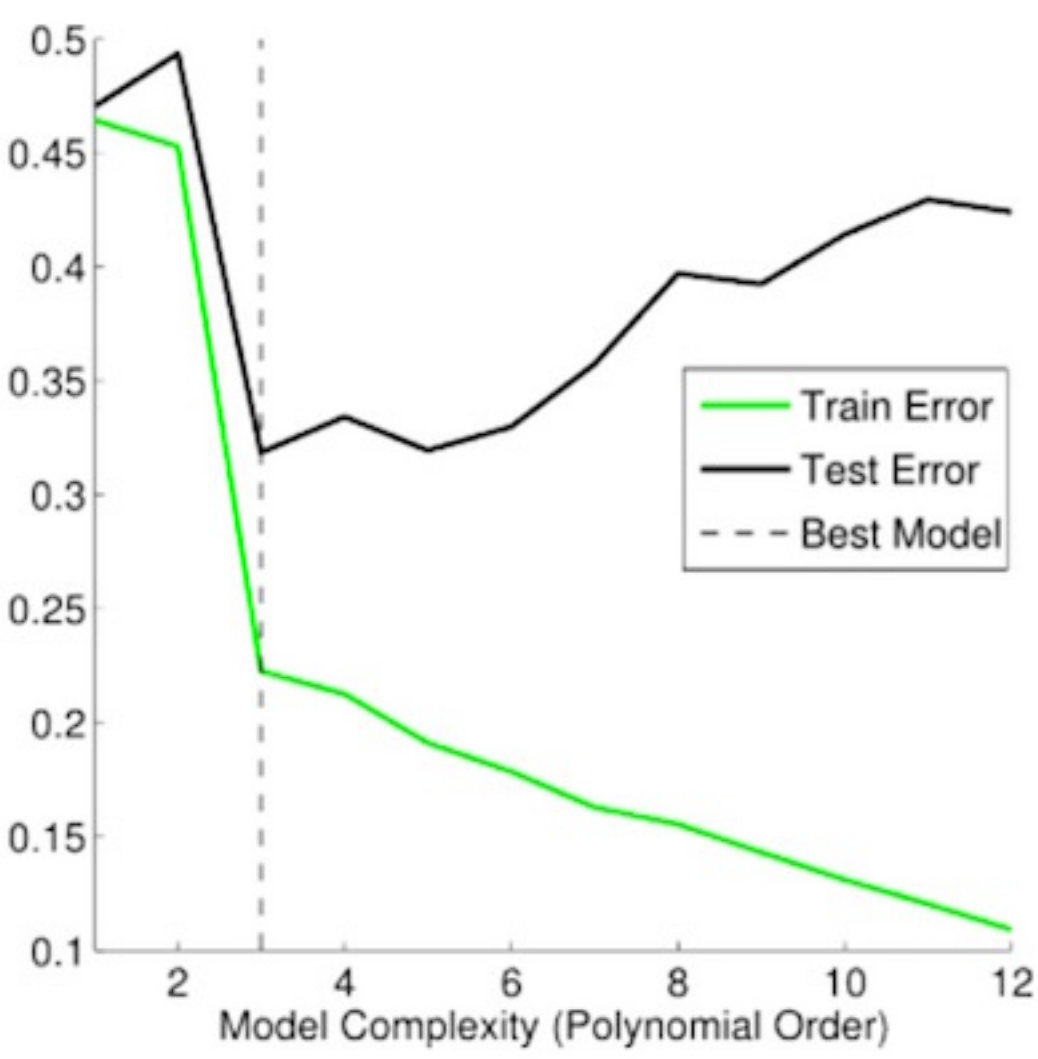
$$= \underbrace{E[(y - f(x))^2]}_{} + \underbrace{E[(g(x) - \overline{g}(x))^2]}_{} + \underbrace{(\overline{g}(x) - f(x))^2}_{}$$

$$= noise + variance + bias^2$$

Thus the expected prediction error on new data can be used as a quantitative criterion for selecting the best model from a candidate set of estimators.

1. Variance of the estimator is defined as $E[(g(x) - E[g(x)])^2]$.
2. Bias of the estimator is defined as $[\overline{g}(x) - f(x)]$.
3. Irreducible Error is defined as variance in the data itself.

As model complexity increases (i.e high order polynomials) we tend to find that the estimator fits the data well. Models that are simple, have low variance but high bias. While selecting a model we should pick a model that will have both low bias and variance. As shown in the diagram below, model with degree 3 gives us a good tradeoff between bias and variance.



$$ \sqrt

HW1.1.

Read through the provided control script (pNaiveBayes.sh) and all of its comments. When you are comfortable with their purpose and function, respond to the remaining homework questions below. A simple cell in the notebook with a print statmement with a "done" string will suffice here. (dont forget to include the Question Number and the quesition in the cell as a multiline comment!)

Note

enronemail_1h.txt file had to be fixed to remove mac-style line endings for correct processing. Below are the commands that were run to fix the issue.

cat enronemail_1h.txt | tr '^M' '\n' > ./foo

mv foo enronemail_1h.txt

In [1]:

```
print 'done'
```

```
done
```

In [1]:

```
%%writefile pNaiveBayes.sh
## pNaiveBayes.sh
## Author: Jake Ryland Williams
## Usage: pNaiveBayes.sh m wordlist
## Input:
##       m = number of processes (maps), e.g., 4
##       wordlist = a space-separated list of words in quotes, e.g., "the and of
"
##
## Instructions: Read this script and its comments closely.
##               Do your best to understand the purpose of each command,
##               and focus on how arguments are supplied to mapper.py/reducer.py
,
##               as this will determine how the python scripts take input.
##               When you are comfortable with the unix code below,
##               answer the questions on the LMS for HW1 about the starter code.
## collect user input
m=$1 ## the number of parallel processes (maps) to run
wordlist=$2 ## if set to "*", then all words are used

## a test set data of 100 messages
data="enronemail_1h.txt"

## the full set of data (33746 messages)
```

```
# data="enronemail.txt"


## 'wc' determines the number of lines in the data
## 'perl -pe' regex strips the piped wc output to a number
linesindata=`wc -l $data | perl -pe 's/^.*?(\d+).*?$/$1/'`

## determine the lines per chunk for the desired number of processes
linesinchunk=`echo "$linesindata/$m+1" | bc`

## split the original file into chunks by line
split -l $linesinchunk $data $data.chunk.

## assign python mappers (mapper.py) to the chunks of data
## and emit their output to temporary files
for datachunk in $data.chunk.*; do
    ## feed word list to the python mapper here and redirect STDOUT to a tempora
ry file on disk
    ####
    ####
    ./mapper.py $datachunk "$wordlist" > $datachunk.counts &
    ####
    ####
done
## wait for the mappers to finish their work
wait

## 'ls' makes a list of the temporary count files
## 'perl -pe' regex replaces line breaks with spaces
countfiles=`\ls $data.chunk.*.counts | perl -pe 's/\n/ /'`

## feed the list of countfiles to the python reducer and redirect STDOUT to disk
####
####
./reducer.py $countfiles > $data.output
####
####

## clean up the data chunks and temporary count files
\rm $data.chunk.*
```

```
Overwriting pNaiveBayes.sh
```

In [2]:

```
!chmod a+x pNaiveBayes.sh
```

HW1.2.

Provide a mapper/reducer pair that, when executed by pNaiveBayes.sh will determine the number of occurrences of a single, user-specified word. Examine the word “assistance” and report your results.

Mapper

output of mapper is in the format

```
    "findword"   "count"
```

In [12]:

```
%%writefile mapper.py
#!/usr/bin/python
import sys
import re
count = 0
WORD_RE = re.compile(r"[\w']+")
filename = sys.argv[1]
findword = sys.argv[2]
with open (filename, "r") as myfile:
    for line in myfile.readlines():
        # Split the line by <TAB> delimiter
        content = re.split(r'\t+', line)
        # verify correct content structure else ignore bad data
        if len(content) <> 4:
            continue
        text = content[2] + ' ' + content[3]
        #tokenize email and subject
        result = re.findall(WORD_RE,text)
        #Now find index of each matching instance of the word for that email
        #lower is used to do case insensitive search
        indices = [i for i,x in enumerate(result) if x.lower() == findword.lower
()]
        count += len(indices)
output = findword+"\t"+str(count)
print output
```

```
Overwriting mapper.py
```

Reducer

In [4]:

```
%%writefile reducer.py
#!/usr/bin/python
import sys
import re
sum = 0
for x in range(1,len(sys.argv)):
    with open (sys.argv[x], "r") as myfile:
        for line in myfile.readlines():
            #convert to int and increment the sum
            content = re.split(r'\t+', line)
            sum += int(content[1])
print content[0]+"\t"+str(sum)
```

```
Overwriting reducer.py
```

In [5]:

```
!chmod a+x mapper.py; chmod a+x reducer.py
```

In [6]:

```
!./pNaiveBayes.sh 2 assistance
```

In [9]:

```
! cat enronemail_1h.txt.output
```

```
assistance      10
```

HW1.3.

Provide a mapper/reducer pair that, when executed by pNaiveBayes.sh will classify the email messages by a single, user-specified word using the multinomial Naive Bayes Formulation. Examine the word “assistance” and report your results.

Mapper

Output of Mapper is in the format

```
"email_id"   "class_of_email"   "findword"   "count_of_findword"   "total_
numberof_word_for_email"
```

In [13]:

```
%%writefile mapper.py
#!/usr/bin/python
import sys
import re
count = 0
WORD_RE = re.compile(r"[\w']+")
filename = sys.argv[1]
findword = sys.argv[2]
with open (filename, "r") as myfile:
    for line in myfile.readlines():
        # Split the line by <TAB> delimiter
        content = re.split(r'\t+', line)
        # verify correct content structure else ignore bad data
        if len(content) <> 4:
            continue
        #combine email subject and body
        text = content[2] + ' ' + content[3]
        result = re.findall(WORD_RE,text)
        #Now find index of each matching instance of the word for that email
        #lower is used to do case insensitive search
        indices = [i for i,x in enumerate(result) if x.lower() == findword.lower
()]
        #find out the count of findword in the email
        findword_count = len(indices)
        #find total number of words in email
        total_doc_count = len(result)
        output =content[0]+ "\t" + content[1]+"\t"+ findword
        output += "\t" + str(findword_count) + "\t" + str(total_doc_count)

        print output
```

```
Overwriting mapper.py
```

Reducer

In [19]:

```
%%writefile reducer.py
#!/usr/bin/python
import sys
import re
import math

# Total count of spam emails
spam_email_cnt  = 0
# Total count of non spam emails
non_spam_email_cnt = 0

#Total count of words in all spam emails
total_spam_words = 0
```

```
# Total count of words in all non spam emails
total_nonspam_words = 0

#Total count of findword in all spam emails
total_spam_findword = 0
#Total count of findword in all non spam emails
total_nonspam_findword = 0

#loop through the input files
for x in range(1,len(sys.argv)):
    with open (sys.argv[x], "r") as myfile:
        for line in myfile.readlines():
            # Split the line by <TAB> delimiter
            content = re.split(r'\t+', line)
            #get the document Id
            docId = content[0]
            #Get the true class of the email
            true_class = int(content[1])
            #get the find word and its count
            findword = content[2]
            findword_freq = int(content[3])
            #get total word count for an email
            total_doc_word_cnt = int(content[4])

            #if email is spam, increment the spam email count, spam findword cou
nt and spam word count
            if (true_class == 1):
                spam_email_cnt += 1
                total_spam_findword += findword_freq
                total_spam_words += total_doc_word_cnt
            #if email is spam, increment the spam email count, spam findword cou
nt and spam word count
            else:
                non_spam_email_cnt += 1;
                total_nonspam_findword += findword_freq
                total_nonspam_words += total_doc_word_cnt

#Now calculate prior probabilities for spam and non spam
prior_spam = math.log((1.0)*spam_email_cnt / (spam_email_cnt + non_spam_email_cn
t ))
prior_ham = math.log((1.0)*non_spam_email_cnt / (spam_email_cnt + non_spam_email
_cnt ))

# Calculate conditional probability of findword given email class spam and non s
pam
pr_findword_spam = math.log((1.0)*(total_spam_findword)/total_spam_words)
pr_findword_ham = math.log((1.0)*(total_nonspam_findword)/total_nonspam_words)

#below counts are used to calculate accuracy
correct_match_cnt = 0
total_match = 0

###### Classification ##########
#loop through files again
```

```
for x in range(1,len(sys.argv)):

    with open (sys.argv[x], "r") as myfile:
        for line in myfile.readlines():
            # Split the line by <TAB> delimiter
            content = re.split(r'\t+', line)
            docId = content[0]
            true_class = content[1]
            #get the findword freq
            findword_freq = int(content[3])
            # calculate prob for the email being spam & ham
            pr_spam_doc = prior_spam + (pr_findword_spam*findword_freq)
            pr_ham_doc = prior_ham + (pr_findword_ham*findword_freq)
            output =  docId+"\t"+true_class+"\t"
            predicted_class =0
            #determine what is the predicted class based on which probability is
high
            if(pr_spam_doc > pr_ham_doc) :
                predicted_class = 1
                output += "1"
            else:
                output += "0"
            if(int(true_class)==predicted_class):
                correct_match_cnt += 1
            total_match += 1
            print output
print "Accuracy of the model: %3.2f" %(correct_match_cnt*100.0/total_match)
```

```
Overwriting reducer.py
```

In [20]:

```
!chmod a+x mapper.py; chmod a+x reducer.py
```

In [21]:

```
!./pNaiveBayes.sh 2 assistance
```

In [22]:

```
! cat enronemail_1h.txt.output
```

```
0001.1999-12-10.farmer  0       0
0001.1999-12-10.kaminski        0       0
0001.2000-01-17.beck    0       0
0001.2000-06-06.lokay   0       0
0001.2001-02-07.kitchen 0       0
0001.2001-04-02.williams        0       0
0002.1999-12-13.farmer  0       0
0002.2001-02-07.kitchen 0       0
0002.2001-05-25.SA_and_HP       1       0
0002.2003-12-18.GP      1       0
0002.2004-08-01.BG      1       1
0003.1999-12-10.kaminski        0       0
```

```
0003.1999-12-14.farmer  0       0
0003.2000-01-17.beck    0       0
0003.2001-02-08.kitchen 0       0
0003.2003-12-18.GP      1       0
0003.2004-08-01.BG      1       0
0004.1999-12-10.kaminski        0       1
0004.1999-12-14.farmer  0       0
0004.2001-04-02.williams        0       0
0004.2001-06-12.SA_and_HP       1       0
0004.2004-08-01.BG      1       0
0005.1999-12-12.kaminski        0       1
0005.1999-12-14.farmer  0       0
0005.2000-06-06.lokay   0       0
0005.2001-02-08.kitchen 0       0
0005.2001-06-23.SA_and_HP       1       0
0005.2003-12-18.GP      1       0
0006.1999-12-13.kaminski        0       0
0006.2001-02-08.kitchen 0       0
0006.2001-04-03.williams        0       0
0006.2001-06-25.SA_and_HP       1       0
0006.2003-12-18.GP      1       0
0006.2004-08-01.BG      1       0
0007.1999-12-13.kaminski        0       0
0007.1999-12-14.farmer  0       0
0007.2000-01-17.beck    0       0
0007.2001-02-09.kitchen 0       0
0007.2003-12-18.GP      1       0
0007.2004-08-01.BG      1       0
0008.2001-02-09.kitchen 0       0
0008.2001-06-12.SA_and_HP       1       0
0008.2001-06-25.SA_and_HP       1       0
0008.2003-12-18.GP      1       0
0008.2004-08-01.BG      1       0
0009.1999-12-13.kaminski        0       0
0009.1999-12-14.farmer  0       0
0009.2000-06-07.lokay   0       0
0009.2001-02-09.kitchen 0       0
0009.2001-06-26.SA_and_HP       1       0
0009.2003-12-18.GP      1       0
0010.1999-12-14.farmer  0       0
0010.1999-12-14.kaminski        0       0
0010.2001-02-09.kitchen 0       0
0010.2001-06-28.SA_and_HP       1       1
0010.2003-12-18.GP      1       0
0010.2004-08-01.BG      1       0
0011.1999-12-14.farmer  0       0
0011.2001-06-28.SA_and_HP       1       1
0011.2001-06-29.SA_and_HP       1       0
0011.2003-12-18.GP      1       0
0011.2004-08-01.BG      1       0
0012.1999-12-14.farmer  0       0
0012.1999-12-14.kaminski        0       0
0012.2000-01-17.beck    0       0
```

```
0012.2000-06-08.lokay   0       0
0012.2001-02-09.kitchen 0       0
0012.2003-12-19.GP      1       0
0013.1999-12-14.farmer  0       0
0013.1999-12-14.kaminski        0       0
0013.2001-04-03.williams        0       0
0013.2001-06-30.SA_and_HP       1       0
0013.2004-08-01.BG      1       1
0014.1999-12-14.kaminski        0       0
0014.1999-12-15.farmer  0       0
0014.2001-02-12.kitchen 0       0
0014.2001-07-04.SA_and_HP       1       0
0014.2003-12-19.GP      1       0
0014.2004-08-01.BG      1       0
0015.1999-12-14.kaminski        0       0
0015.1999-12-15.farmer  0       0
0015.2000-06-09.lokay   0       0
0015.2001-02-12.kitchen 0       0
0015.2001-07-05.SA_and_HP       1       0
0015.2003-12-19.GP      1       0
0016.1999-12-15.farmer  0       0
0016.2001-02-12.kitchen 0       0
0016.2001-07-05.SA_and_HP       1       0
0016.2001-07-06.SA_and_HP       1       0
0016.2003-12-19.GP      1       0
0016.2004-08-01.BG      1       0
0017.1999-12-14.kaminski        0       0
0017.2000-01-17.beck    0       0
0017.2001-04-03.williams        0       0
0017.2003-12-18.GP      1       0
0017.2004-08-01.BG      1       0
0017.2004-08-02.BG      1       0
0018.1999-12-14.kaminski        0       0
0018.2001-07-13.SA_and_HP       1       1
0018.2003-12-18.GP      1       1
Accuracy of the model: 60.00
```

HW1.4.

Provide a mapper/reducer pair that, when executed by pNaiveBayes.sh will classify the email messages by a list of one or more user-specified words. Examine the words “assistance”, “valium”, and “enlargementWithATypo” and report your results

Mapper

Output of mapper is in the format

```
"email id"   "class of email"   <"findword"    "count of findword"> repeat
this based on how many input findwords are present
e.x.
123   1   assistance   1   vallium   3   hero   0
```

In [35]:

```
%%writefile mapper.py
#!/usr/bin/python
import sys
import re
count = 0
WORD_RE = re.compile(r"[\w']+")
filename = sys.argv[1]
#get the findwords
findwords = re.split(" ",sys.argv[2].lower())
vocab_len = len(findwords)

with open (filename, "r") as myfile:
    for line in myfile.readlines():
        # Split the line by <TAB> delimiter
        content = re.split(r'\t+', line)
        # verify correct content structure else ignore bad data
        if len(content) <> 4:
            continue
        #combine email subject and body
        text = content[2] + ' ' + content[3]
        #tokenize the text
        result = re.findall(WORD_RE,text)
        #build a vocabluary of findwords and initialise to 0
        vocab ={}
        for word in findwords:
            vocab[word] = 0
        #now loop through the email text and get frequency of each count word.
        #If findword is not present the frequency will be 0 as we have initializ
ed it above
        for key in result:
            if key not in findwords:
                continue
            vocab[key] += 1
        #prepare output
        output =content[0]+ "\t" + content[1]+"\t"+str(len(result))
        for key, value in vocab.iteritems():
            output += "\t" + key + "\t" + str(value)
        print output
```

Overwriting mapper.py

Reducer

In [40]:

```
%%writefile reducer.py
#!/usr/bin/python
import sys
import re
import math
```

```
# Dictionary to store overall frequency of words for spam emails
spam_words_freq = {}
# Dictionary to store overall frequency of words for non spam emails
not_spam_words_freq ={}
# Total count of spam emails
spam_email_cnt  = 0
# Total count of non spam emails
non_spam_email_cnt = 0
# Unique vocab length
unique_word_cnt = 0
#Total count of words in all spam emails
total_spam_words = 0
# Total count of words in all non spam emails
total_nonspam_words = 0

#loop through the files
for x in range(1,len(sys.argv)):
    with open (sys.argv[x], "r") as myfile:
        for line in myfile.readlines():
            # Split the line by <TAB> delimiter
            content = re.split(r'\t+', line)
            #get the doc Id
            docId = content[0]
            #get the class of the email
            true_class = int(content[1])
            #get the total doc word count
            doc_word_cnt = int(content[2])

            #if email is for spam class increment spam email count, total spam w
ords count
            if (true_class == 1):
                spam_email_cnt += 1
                total_spam_words += doc_word_cnt
            #if email is for non spam class increment non spam email count, tota
l non spam words count
            else:
                non_spam_email_cnt += 1
                total_nonspam_words += doc_word_cnt

            # if we have more data for email
            if(len(content) > 3 ):
                # loop through the rest of the data in increments of 2
                for x in range(3,len(content),2):
                    #get the findword and its frequency for the email
                    word = content[x]
                    freq = int(content[x+1])
                    #Determine the class of email and increment the spam word fr
equency
                    # or non spam word frewquency accordingly
                    if (true_class == 1):
                        if word in spam_words_freq:
                            spam_words_freq[word] += freq
                        else:
                            spam_words_freq[word] = freq
```

```
                    else:

                        if word in not_spam_words_freq:
                            not_spam_words_freq[word] += freq
                        else:
                            not_spam_words_freq[word] = freq

#calculate prior probabilities for spam and ham
prior_spam = math.log((1.0)*spam_email_cnt / (spam_email_cnt + non_spam_email_cn
t ))
prior_ham = math.log((1.0)*non_spam_email_cnt / (spam_email_cnt + non_spam_email
_cnt ))

# Conditional Probability of findwords given email class
pr_word_spam = {}
pr_word_ham = {}
for word in spam_words_freq:
    #if findword frequency is greater than 0 than calculate probability else set
the value to smallest possible value
    if(spam_words_freq[word] > 0 ):
        pr_word_spam[word] = math.log((1.0)*(spam_words_freq[word])/ (total_spam
_words))
    else:
        #setting value to -infinity here for frequency = 0
        pr_word_spam[word] = float('-inf')
for word in not_spam_words_freq:
    if(not_spam_words_freq[word] > 0):
        pr_word_ham[word] = math.log((1.0)*(not_spam_words_freq[word])/(total_no
nspam_words))
    else:
        pr_word_ham[word] = float('-inf')

#Counts used for accuracy
correct_match_cnt = 0
total_match = 0
###### Classification ##########
#loop through the files again
for x in range(1,len(sys.argv)):
    with open (sys.argv[x], "r") as myfile:
        for line in myfile.readlines():
            # Split the line by <TAB> delimiter
            content = re.split(r'\t+', line)
            docId = content[0]
            true_class = content[1]
            doc_vocab = {}
            # Build email vocab for findwords along with their frequency
            if(len(content) > 3 ):
                for x in range(3,len(content),2):
                    word = content[x]
                    freq = int(content[x+1])
                    doc_vocab[word] = freq
            # calculate prob for spam , ham for each email
            pr_spam_doc = 0.0
            pr_ham_doc = 0.0
```

```
            for key,value in doc_vocab.iteritems():

                #if probability of find word is -infinity than check what is the
frequency of findword
                # if frequency is 0 add 0 to probability else add -infinity .
                # We are adding 0 here as infinity x 0 is not defined
                if (pr_word_spam[key] == float('-inf')):
                    if(value !=0):
                        pr_spam_doc += float('-inf')
                    else :
                        pr_spam_doc += 0
                # if probability of findowrd is not infinity than multiply the p
robability by frequency of find word
                else:
                    pr_spam_doc += (pr_word_spam[key]*value)
                #follow same rule as spam for calculating probability
                if(pr_word_ham[key] == float('-inf')):
                    if(value !=0):
                        pr_ham_doc += float('-inf')
                    else :
                        pr_ham_doc += 0
                else :
                    pr_ham_doc += (pr_word_ham[key]*value)
            #add the prior probabilities for spam and ham
            pr_spam_doc = prior_spam + pr_spam_doc
            pr_ham_doc = prior_ham + pr_ham_doc
            output =  docId + "\t" + true_class + "\t"
            predicted_class = 0
            #determine which probability is higher
            if(pr_spam_doc > pr_ham_doc) :
                predicted_class = 1
                output += "1"
            else:
                output += "0"
            if(int(true_class) == predicted_class):
                correct_match_cnt += 1
            total_match += 1
            print output
print "Accuracy of the model: %3.2f" %(correct_match_cnt*100.0/total_match)
```

```
Overwriting reducer.py
```

In [41]:

```
!chmod a+x mapper.py; chmod a+x reducer.py
```

In [42]:

```
!./pNaiveBayes.sh 2 "assistance valium enlargementWithATypo"
```

In [43]:

```
! cat enronemail_1h.txt.output
```

```
0001.1999-12-10.farmer  0       0
0001.1999-12-10.kaminski        0       0
0001.2000-01-17.beck    0       0
0001.2000-06-06.lokay   0       0
0001.2001-02-07.kitchen 0       0
0001.2001-04-02.williams        0       0
0002.1999-12-13.farmer  0       0
0002.2001-02-07.kitchen 0       0
0002.2001-05-25.SA_and_HP       1       0
0002.2003-12-18.GP      1       0
0002.2004-08-01.BG      1       1
0003.1999-12-10.kaminski        0       0
0003.1999-12-14.farmer  0       0
0003.2000-01-17.beck    0       0
0003.2001-02-08.kitchen 0       0
0003.2003-12-18.GP      1       0
0003.2004-08-01.BG      1       0
0004.1999-12-10.kaminski        0       1
0004.1999-12-14.farmer  0       0
0004.2001-04-02.williams        0       0
0004.2001-06-12.SA_and_HP       1       0
0004.2004-08-01.BG      1       0
0005.1999-12-12.kaminski        0       1
0005.1999-12-14.farmer  0       0
0005.2000-06-06.lokay   0       0
0005.2001-02-08.kitchen 0       0
0005.2001-06-23.SA_and_HP       1       0
0005.2003-12-18.GP      1       0
0006.1999-12-13.kaminski        0       0
0006.2001-02-08.kitchen 0       0
0006.2001-04-03.williams        0       0
0006.2001-06-25.SA_and_HP       1       0
0006.2003-12-18.GP      1       0
0006.2004-08-01.BG      1       0
0007.1999-12-13.kaminski        0       0
0007.1999-12-14.farmer  0       0
0007.2000-01-17.beck    0       0
0007.2001-02-09.kitchen 0       0
0007.2003-12-18.GP      1       0
0007.2004-08-01.BG      1       0
0008.2001-02-09.kitchen 0       0
0008.2001-06-12.SA_and_HP       1       0
0008.2001-06-25.SA_and_HP       1       0
0008.2003-12-18.GP      1       0
0008.2004-08-01.BG      1       0
0009.1999-12-13.kaminski        0       0
0009.1999-12-14.farmer  0       0
0009.2000-06-07.lokay   0       0
0009.2001-02-09.kitchen 0       0
0009.2001-06-26.SA_and_HP       1       0
0009.2003-12-18.GP      1       1
0010.1999-12-14.farmer  0       0
0010.1999-12-14.kaminski        0       0
0010.2001-02-09.kitchen 0       0
```

```
0010.2001-06-28.SA_and_HP       1       1
0010.2003-12-18.GP      1       0
0010.2004-08-01.BG      1       0
0011.1999-12-14.farmer  0       0
0011.2001-06-28.SA_and_HP       1       1
0011.2001-06-29.SA_and_HP       1       0
0011.2003-12-18.GP      1       0
0011.2004-08-01.BG      1       0
0012.1999-12-14.farmer  0       0
0012.1999-12-14.kaminski        0       0
0012.2000-01-17.beck    0       0
0012.2000-06-08.lokay   0       0
0012.2001-02-09.kitchen 0       0
0012.2003-12-19.GP      1       0
0013.1999-12-14.farmer  0       0
0013.1999-12-14.kaminski        0       0
0013.2001-04-03.williams        0       0
0013.2001-06-30.SA_and_HP       1       0
0013.2004-08-01.BG      1       1
0014.1999-12-14.kaminski        0       0
0014.1999-12-15.farmer  0       0
0014.2001-02-12.kitchen 0       0
0014.2001-07-04.SA_and_HP       1       0
0014.2003-12-19.GP      1       0
0014.2004-08-01.BG      1       0
0015.1999-12-14.kaminski        0       0
0015.1999-12-15.farmer  0       0
0015.2000-06-09.lokay   0       0
0015.2001-02-12.kitchen 0       0
0015.2001-07-05.SA_and_HP       1       0
0015.2003-12-19.GP      1       0
0016.1999-12-15.farmer  0       0
0016.2001-02-12.kitchen 0       0
0016.2001-07-05.SA_and_HP       1       0
0016.2001-07-06.SA_and_HP       1       0
0016.2003-12-19.GP      1       1
0016.2004-08-01.BG      1       0
0017.1999-12-14.kaminski        0       0
0017.2000-01-17.beck    0       0
0017.2001-04-03.williams        0       0
0017.2003-12-18.GP      1       0
0017.2004-08-01.BG      1       1
0017.2004-08-02.BG      1       0
0018.1999-12-14.kaminski        0       0
0018.2001-07-13.SA_and_HP       1       1
0018.2003-12-18.GP      1       1
Accuracy of the model: 63.00
```

HW1.5. Please ignore

Provide a mapper/reducer pair that, when executed by pNaiveBayes.sh will classify the email messages by all words present.

This question was already solved before the email for ignoring it came.

Mapper

Output of mapper is the format

```
"email id"   "class"  <"word" "frequency"> <repeated based on how many wor
ds are in the email>
```

In [44]:

```
%%writefile mapper.py
#!/usr/bin/python
import sys
import re
count = 0
WORD_RE = re.compile(r"[\w']+")
filename = sys.argv[1]
with open (filename, "r") as myfile:
    for line in myfile.readlines():
        #Tokenize each line
        # Split the line by <TAB> delimiter
        content = re.split(r'\t+', line)
        # verify correct content structure else ignore bad data
        if len(content) <> 4:
            continue
        #combine email subject and body
        text = content[2] + ' ' + content[3]
        #tokenize text
        result = re.findall(WORD_RE,text)
        #build a vocabluary of words
        vocab ={}
        for key in result:
            if key in vocab:
                vocab[key] += 1
            else:
                vocab[key] = 1
        output =content[0]+ "\t" + content[1]
        for key, value in vocab.iteritems():
            output += "\t" + key + "\t" + str(value)

        print output
```

Overwriting mapper.py

Reducer

In [45]:

```
%%writefile reducer.py
#!/usr/bin/python
import sys
import re
import math
sum = 0
# Dictionary to store overall frequency of words for spam emails
spam_words_freq = {}
# Dictionary to store overall frequency of words for non spam emails
not_spam_words_freq ={}
# Total count of spam emails
spam_email_cnt  = 0
```

```
# Total count of non spam emails
non_spam_email_cnt = 0
# Unique vocab length
unique_word_cnt = 0
#Total count of words in all spam emails
total_spam_words = 0
# Total count of words in all non spam emails
total_nonspam_words = 0

for x in range(1,len(sys.argv)):
    with open (sys.argv[x], "r") as myfile:
        for line in myfile.readlines():
            # Split the line by <TAB> delimiter
            content = re.split(r'\t+', line)
            #get doc id and class of email
            docId = content[0]
            true_class = int(content[1])
            # based on class of email increment spam / non spam count
            if (true_class == 1):
                spam_email_cnt += 1
            else:
                non_spam_email_cnt += 1;
            #if email has content
            if(len(content) > 2 ):
                #loop through rest of mapper output in increments of 2
                for x in range(2,len(content),2):
                    #get the word and its frequency
                    word = content[x]
                    freq = int(content[x+1])
                    #Determine unique word count for laplace smoothing
                    if (not(word in spam_words_freq or word in not_spam_words_fr
eq)):
                        unique_word_cnt += 1;
                    #increment spam words, total spam words,ham words, total ham
words  based on class of email
                    #
                    if (true_class == 1):
                        total_spam_words += freq;
                        if word in spam_words_freq:
                            spam_words_freq[word] += freq
                        else:
                            spam_words_freq[word] = freq
                        if word not in not_spam_words_freq:
                            not_spam_words_freq[word] = 0
                    else:
                        total_nonspam_words += freq;
                        if word in not_spam_words_freq:
                            not_spam_words_freq[word] += freq
                        else:
                            not_spam_words_freq[word] = freq
                        if word not in spam_words_freq:
                            spam_words_freq[word] = 0

#Calculate prior probabilites for spam and ham
```

```
prior_spam = math.log((1.0)*spam_email_cnt / (spam_email_cnt + non_spam_email_cn

t ))
prior_ham = math.log((1.0)*non_spam_email_cnt / (spam_email_cnt + non_spam_email
_cnt ))
# Condirtional Probability of word given email class spam and ham
pr_word_spam = {}
pr_word_ham = {}
for word in spam_words_freq:
    # 1 is added for laplace smoothing
    pr_word_spam[word] = pr = math.log((1.0)*(spam_words_freq[word]+1)/ (total_s
pam_words + unique_word_cnt))

for word in not_spam_words_freq:
     # 1 is added for laplace smoothing
    pr_word_ham[word] = math.log((1.0)*(not_spam_words_freq[word]+1)/ (total_non
spam_words + unique_word_cnt))

#counts for accuracy
correct_match_cnt = 0
total_match = 0

###### Classification ##########
for x in range(1,len(sys.argv)):
    with open (sys.argv[x], "r") as myfile:
        for line in myfile.readlines():
            # Split the line by <TAB> delimiter
            content = re.split(r'\t+', line)
            docId = content[0]
            true_class = content[1]
            doc_vocab = {}
            if(len(content) > 2 ):
                for x in range(2,len(content),2):
                    word = content[x]
                    freq = int(content[x+1])
                    doc_vocab[word] = freq
            # calculate prob for spam , ham for each email
            pr_spam_doc = 0.0
            pr_ham_doc = 0.0
            for key,value in doc_vocab.iteritems():
                pr_spam_doc +=  (pr_word_spam[key]*value)
                pr_ham_doc += (pr_word_ham[key]*value)
            #now add prior probabilities for spam and ham
            pr_spam_doc = prior_spam + pr_spam_doc
            pr_ham_doc = prior_ham + pr_ham_doc
            output =  docId+"\t"+true_class+"\t"
            predicted_class = 0
            #Determine the predicted class
            if(pr_spam_doc > pr_ham_doc) :
                predicted_class = 1
                output += "1"
            else:
                output += "0"
            if(int(true_class) == predicted_class):
```

```
                correct_match_cnt += 1

            total_match += 1
            print output
print "Accuracy of the model: %3.2f" %(correct_match_cnt*100.0/total_match)
```

```
Overwriting reducer.py
```

In [46]:

```
!chmod a+x mapper.py; chmod a+x reducer.py
```

In [47]:

```
!./pNaiveBayes.sh 2
```

In [48]:

```
! cat enronemail_1h.txt.output
```

```
0001.1999-12-10.farmer  0       0
0001.1999-12-10.kaminski        0       0
0001.2000-01-17.beck    0       0
0001.2000-06-06.lokay   0       0
0001.2001-02-07.kitchen 0       0
0001.2001-04-02.williams        0       0
0002.1999-12-13.farmer  0       0
0002.2001-02-07.kitchen 0       0
0002.2001-05-25.SA_and_HP       1       1
0002.2003-12-18.GP      1       1
0002.2004-08-01.BG      1       1
0003.1999-12-10.kaminski        0       0
0003.1999-12-14.farmer  0       0
0003.2000-01-17.beck    0       0
0003.2001-02-08.kitchen 0       0
0003.2003-12-18.GP      1       1
0003.2004-08-01.BG      1       1
0004.1999-12-10.kaminski        0       0
0004.1999-12-14.farmer  0       0
0004.2001-04-02.williams        0       0
0004.2001-06-12.SA_and_HP       1       1
0004.2004-08-01.BG      1       1
0005.1999-12-12.kaminski        0       0
0005.1999-12-14.farmer  0       0
0005.2000-06-06.lokay   0       0
0005.2001-02-08.kitchen 0       0
0005.2001-06-23.SA_and_HP       1       1
0005.2003-12-18.GP      1       1
0006.1999-12-13.kaminski        0       0
0006.2001-02-08.kitchen 0       0
0006.2001-04-03.williams        0       0
0006.2001-06-25.SA_and_HP       1       1
0006.2003-12-18.GP      1       1
0006.2004-08-01.BG      1       1
```

```
0007.1999-12-13.kaminski        0       0
0007.1999-12-14.farmer  0       0
0007.2000-01-17.beck    0       0
0007.2001-02-09.kitchen 0       0
0007.2003-12-18.GP      1       1
0007.2004-08-01.BG      1       1
0008.2001-02-09.kitchen 0       0
0008.2001-06-12.SA_and_HP       1       1
0008.2001-06-25.SA_and_HP       1       1
0008.2003-12-18.GP      1       1
0008.2004-08-01.BG      1       1
0009.1999-12-13.kaminski        0       0
0009.1999-12-14.farmer  0       0
0009.2000-06-07.lokay   0       0
0009.2001-02-09.kitchen 0       0
0009.2001-06-26.SA_and_HP       1       1
0009.2003-12-18.GP      1       1
0010.1999-12-14.farmer  0       0
0010.1999-12-14.kaminski        0       0
0010.2001-02-09.kitchen 0       0
0010.2001-06-28.SA_and_HP       1       1
0010.2003-12-18.GP      1       1
0010.2004-08-01.BG      1       1
0011.1999-12-14.farmer  0       0
0011.2001-06-28.SA_and_HP       1       1
0011.2001-06-29.SA_and_HP       1       1
0011.2003-12-18.GP      1       1
0011.2004-08-01.BG      1       1
0012.1999-12-14.farmer  0       0
0012.1999-12-14.kaminski        0       0
0012.2000-01-17.beck    0       0
0012.2000-06-08.lokay   0       0
0012.2001-02-09.kitchen 0       0
0012.2003-12-19.GP      1       1
0013.1999-12-14.farmer  0       0
0013.1999-12-14.kaminski        0       0
0013.2001-04-03.williams        0       0
0013.2001-06-30.SA_and_HP       1       1
0013.2004-08-01.BG      1       1
0014.1999-12-14.kaminski        0       0
0014.1999-12-15.farmer  0       0
0014.2001-02-12.kitchen 0       0
0014.2001-07-04.SA_and_HP       1       1
0014.2003-12-19.GP      1       1
0014.2004-08-01.BG      1       1
0015.1999-12-14.kaminski        0       0
0015.1999-12-15.farmer  0       0
0015.2000-06-09.lokay   0       0
0015.2001-02-12.kitchen 0       0
0015.2001-07-05.SA_and_HP       1       1
0015.2003-12-19.GP      1       1
0016.1999-12-15.farmer  0       0
0016.2001-02-12.kitchen 0       0
```

```
0016.2001-07-05.SA_and_HP       1       1
0016.2001-07-06.SA_and_HP       1       1
0016.2003-12-19.GP      1       1
0016.2004-08-01.BG      1       1
0017.1999-12-14.kaminski        0       0
0017.2000-01-17.beck    0       0
0017.2001-04-03.williams        0       0
0017.2003-12-18.GP      1       1
0017.2004-08-01.BG      1       1
0017.2004-08-02.BG      1       1
0018.1999-12-14.kaminski        0       0
0018.2001-07-13.SA_and_HP       1       1
0018.2003-12-18.GP      1       1
Accuracy of the model: 100.00
```

HW1.6 Please ignore

Benchmark your code with the Python SciKit-Learn implementation of multinomial Naive Bayes

Parts of this question were already solved before the email for ignoring it came

In [46]:

```
import sys
import re
from sklearn.naive_bayes import BernoulliNB
from sklearn.naive_bayes import MultinomialNB
import numpy
from sklearn.feature_extraction.text import CountVectorizer

alpha = 1
WORD_RE = re.compile(r"[\w']+")
filename = "enronemail_1h.txt"
train_data = []
train_label =[]

with open (filename, "r") as myfile:
    for line in myfile.readlines():
        #Tokenize each line
        # Split the line by <TAB> delimiter
        content = re.split(r'\t+', line)
        # verify correct content structure else ignore bad data
        if len(content) <> 4:
            continue
        true_class = int(content[1])
        text = content[2] + ' ' + content[3]
        text = re.sub(r'[\W]+', ' ', text)
#         text = re.sub('[^0-9a-zA-Z]+', ' ', text)
        train_data.append(text)
        train_label.append(true_class)

count_vectorizer = CountVectorizer()
text_matrix = count_vectorizer.fit_transform(train_data)
feature_names = count_vectorizer.get_feature_names()
```

— Run the Multinomial Naive Bayes algorithm (using default settings) from SciKit-Learn over the same training data used in HW1.5 and report the Training error (please note some data preparation might be needed to get the Multinomial Naive Bayes algorithm from SkiKit-Learn to run over this dataset)

In [51]:

```
# nb =  MultinomialNB(alpha=alpha)
nb =  MultinomialNB()
nb.fit(text_matrix, train_label)

# Compute accuracy on the test data.
print "Using our Multinomial classifier"
accuracy = nb.score(text_matrix, train_label)*100
tr_error = 100-accuracy
print 'sklearn accuracy: %3.2f' %accuracy
print 'sk learn training error %3.2f' %tr_error
```

```
Using our Multinomial classifier
sklearn accuracy: 100.00
sk learn training error 0.00
```

— Run the Bernoulli Naive Bayes algorithm from SciKit-Learn (using default settings) over the same training data used in HW1.5 and report the Training error

In [50]:

```
# Compare to sklearn's implementation.
print "Using sklearn's NB classifier"
# clf = BernoulliNB(alpha=alpha)
clf = BernoulliNB()
clf.fit(text_matrix, train_label)
accuracy = clf.score(text_matrix, train_label)*100
tr_error = 100 - accuracy
print 'sklearn accuracy: %3.2f' %accuracy
print 'sk learn training error %3.2f' %tr_error
```

```
Using sklearn's NB classifier
sklearn accuracy: 84.00
sk learn training error 16.00
```

— Run the Multinomial Naive Bayes algorithm you developed for HW1.5 over the same data used HW1.5 and report the Training error

— Explain/justify any differences in terms of training error rates over the dataset in HW1.5 between your Multinomial Naive Bayes implementation (in Map Reduce) versus the Multinomial Naive Bayes implementation in SciKit-Learn (Hint: smoothing, which we will discuss in next lecture)

- Discuss the performance differences in terms of training error rates over the dataset in HW1.5 between the Multinomial Naive Bayes implementation in SciKit-Learn with the Bernoulli Naive Bayes implementation in SciKit-Learn