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3 Credits

## **A.I. MP3 Report**

### **Problem 1**

#### **IMPLEMENTATION**

In this problem we first read in all of the training data in order to build our  $P(F_{ij} | \text{class})$ . Once we were able to build this probability for every pixel in every numeric character, we were able to calculate our  $P(\text{class})$  based on the frequency of occurrence of each character. Once all of this was stored in a database we were able to calculate  $P(\text{class}) \cdot P(f_{1,1} | \text{class}) \cdot P(f_{1,2} | \text{class}) \cdot \dots \cdot P(f_{28,28} | \text{class})$  with the logarithmic adjustment for each image in the test data for each class. The class that returned the highest value would be our estimate. We then saved the most and least prototypical instances of each class by selecting the highest and lowest  $P(\text{class}) \cdot P(f_{1,1} | \text{class}) \cdot P(f_{1,2} | \text{class}) \cdot \dots \cdot P(f_{28,28} | \text{class})$  values. After this we were able to calculate the percentage of the test images that were classified properly along with the confusion matrix. We were able to achieve 77.1% correct classification of the images so we are confident in our design. An interesting fact about our approach is that it is very dynamic and flexible. You can make this program run on images with any dimensions you want, with as many characters as you want, and with as many training/test cases as you want and it will calculate all the same output data. This is because we defined everything in terms of constants located at the beginning of the DigitClassification.h file so to change any of the attributes mentioned above you simply need to change the corresponding constant to the appropriate value. This made doing the facial classification much simpler as we only had to edit the constant values.

Smoothing Value = 1

Character	Correct	Attempts	Percentage
0	76	90	84.4444%
1	104	108	96.2963%
2	80	103	77.6699%
3	79	100	79%
4	83	107	77.5701%
5	62	92	67.3913%
6	69	91	75.8242%
7	77	106	72.6415%
8	61	103	59.2233%
9	80	100	80%
Total	771	1000	77.1%

Confusion Matrix:

	0	1	2	3	4	5	6	7	8	9
0	84.444	0.000	1.111	0.000	1.111	5.556	3.333	0.000	4.444	0.000
1	0.000	96.296	0.926	0.000	0.000	1.852	0.926	0.000	0.000	0.000
2	0.971	2.913	77.670	3.883	0.971	0.000	5.825	0.971	4.854	1.942
3	0.000	2.000	0.000	79.000	0.000	3.000	2.000	6.000	2.000	6.000
4	0.000	0.935	0.000	0.000	77.570	0.000	2.804	0.935	1.869	15.888
5	2.174	2.174	1.087	13.043	3.261	67.391	1.087	1.087	2.174	6.522
6	1.099	5.495	4.396	0.000	4.396	6.593	75.824	0.000	2.198	0.000
7	0.000	5.660	2.830	0.000	2.830	0.000	0.000	72.642	2.830	13.208
8	0.971	0.971	2.913	13.592	1.942	7.767	0.000	0.971	59.223	11.650
9	1.000	1.000	1.000	3.000	9.000	2.000	0.000	2.000	1.000	80.000

For Character '0' this is the most prototypical image:

```

      +#+
      +#####+
      +#####+
      +#####+
      +#####+ +##+
      +#####+++ +###+
      #####+   +##+
      +###+    ##+
      #####+   ##+
      ###+     +##
      #####+   ##+
      #####+   ##+
      #####+   +##+
      #####+   +##+
      #####+   +###+
      +#####+ +#####+
      +#####+ +#####+
      +#####+
      ++++++

```

For Character '0' this is the least prototypical image:

```
++++++#+
+#####+
+#####
+#####+
#####+ +###+
#####+ #####
+###+ +###+
+### +###+
#### ###+
#### ####
####+ ####
+####+ ####
+####+ ####
+###++ ####
+#####+
+#####+
+#####+
++++#####
```

For Character '1' this is the most prototypical image:

```
+#+
+##+
+##+
###+
###+
###
+##+
+##+
+##+
###+
###
+##+
+##+
###+
+###
+##+
+###+
+###
+###+
+#+
```

For Character '1' this is the least prototypical image:

```

      + #
      ## +
      + # + +
      + + # +
      + # + # +
      + # + + +
      ## + # +
      + # + + # +
      + # +   + +
      + # +   + # +
      + # +   + +   +
      + # + + # + + + + + + + + +
      + #
      + # +
      + #
      + #
      + #
      + #
      + #

```

For Character '2' this is the most prototypical image:

```

+++++++
#####+
+#####+
++ ++ ++
++ ++
++
++
++
++
++
++
++
+++++ ##
+#####+
+#####+
+#####+
##+ +#####+
##+#####+ ##
+#####+
+##+

```

For Character '2' this is the least prototypical image:

```

      +++#+
    +#####+
  +##++
    ##+
+##
+#+
+#+
##+
+#+
+#+
##
##+
      +++
+##      +#####+
+#+      +#####+#+
    ##+      ###      +##
  +##+      +##+      +##
    ++##+      ##+      ++
      ++#####+      +##
        +#####
          +++++++

```

For Character '3' this is the most prototypical image:

```

+#####+
+#####+
++#####
++##
+##+
+##+
++##+
+##+
+#####
+#####+
###+###+
++ ++##+
++
++
++
++##+
+++++++##+
+#####+
++++#####

```

For Character '3' this is the least prototypical image:

```
++++++#+
+#####
#####
+#####+
+#####
##+
#+
##+
+#####
+#####+
+#####+
++++++ ++ +##+
                        +##+
                        +##+
                        +##+
++                +##+
#+                +##+
##+                +##+
+#####+##+
+#####+
++#####
```

For Character '4' this is the most prototypical image:

```
      +      +#
      +#+     +#
      ##+     +#
      +##+    +++#
      +###    +##+
      +##+    +##+
      ###     +##+
      ##+     +##+
      #+      +#####
      #+      +#####
+#####
+++#####
++++++#+
      +##+
      +##+
      ##+
      +##+
      +##+
      +##+
      +##+
```

For Character '4' this is the least prototypical image:

```

+###++++
++#####+
++#####+
++#####+###+
+#####+++++ ++##
+#####+++++
+#####+ ++
#####+ ##+
####+ ++##+
####+ +++#####
#####+++++#####+
+#####+
+#####+ ++##
+++++++ +###
+++++
+++++
+++++
+++++
+++++
+++++

```

For Character '5' this is the most prototypical image:

```

      ++++
    ++++++#####
    #####+
    #####+++++
  ++#++
  ++#+
  +++#
  +++++++
  +#####+
  ++#+++##
  +      ++#+
            ++#+
            ++#+
            ##
  ++#+      ##+
  ++#+      +##
  ##+      ###
  +++#+    ++++
  #####++###+
  #####++

```

For Character '5' this is the least prototypical image:

```

      ++#####
    +++#####+
  +++#####++++
++#####+
+###+
+#####
#####++
+++#####++
    +++++#####+
      ++#####+
++          +####
##+          ##+
###+          +###
+###+          +####+
+#####++    +++#####+
++#####
++#####++
    +#####
      +#####
    +#####

```

For Character '6' this is the most prototypical image:

[illegible]



For Character '6' this is the least prototypical image:

[illegible]

For Character '7' this is the most prototypical image:

```

+#+#+ ++++++
#####
++###++++++
      ++ +
              +##
              +###
              +###+
              +###+
              +###+
              +##+
              +##+
              ##+
              +##+
              ###
              +##+
              +##+
              +##
              +##
              +##
              +++

```

For Character '7' this is the least prototypical image:

```
#####+###+  
#####+  
#####+  
+#####+  
++#####+  
+++++++#####+  
++++#####+  
++++#####  
++++#####  
++#####+  
+#####+  
+#####  
+#####  
+#####+  
+#####+  
+#####+  
+#####+  
+####  
+###+  
+####  
+#####
```

For Character '8' this is the most prototypical image:

+##+  
 ++#####  
 ++#####  
 +#####+##+  
 ++###+ ++##+  
 +###+ ++##+  
 ### ++##+  
 ### ++###  
 +###+++#####  
 +#####+  
 #####+  
 +#####+  
 +###+ ###+  
 +###+ ###+  
 +###+ +###  
 +#####+  
 +#####+  
 ++###+

For Character '8' this is the least prototypical image:

```

    +++#####+
  +#####+#####+
+#####+      +#####+
+###+      +###+
+##      +##
+##      +##
+###      +++++#####+
+#####+#####+
+#####+#####+
+#####      +
+#####+
+#####+
##+ +###+
##+ +###+
+##+ +###+
#####+ +#####+
+#####+ +###+
+#####+#####+
+#####+
+#####+
+#####+

```

For Character '9' this is the most prototypical image:

```

    ++##++
  +#####+
+#####+#####+
+###+      +###+
+##+      +####+
+##+      +####+
+##+      +####+
+##+      +#####+
+#####+
+#####+
+++++##+
+##+
+##+
+##+
+##+
+##+
+##+
+##+
+##+

```

For Character '9' this is the least prototypical image:

```

++++#####+
++#####++
#####++
#####+
##+      +###+
+++      +###+
+###++   +#####
+#####++##++
++#####+
++#####+
++#####+
++      +###+
##+     +###+
+++     +###+
##+     ##+
++      ##+
+##+    +##
++      ++
+#####+
+#####+
++++

```

This is the odds ratio for 0/5 :

```

+++++++ -
-+++++++ -
-----+++++ -
+ --- ++++++++ -
+--- ++++++++ -
- ++++++++ -
-+++++++ ++++++++
-+++++++ - ++++++++
-+++++ - - ++++++
+++++ - - - ++++++
+ ++++++ - - - ++++++
+++++ - - - ++++++
-+++++ - - - ++++++
-+++++ - - - ++++++
- ++++++ - - - ++++++
- - ++++++ ++++++
- - ++++++ ++++++
- - ++++++ ++++++ +
+++++ + - +
+++++ + - +
+++++ - - -
- - -
- - -
- - -

```

[illegible][illegible]

This is the odds ratio for 8/9 :

```

+++++++
+ ++++++
+++++
+ ++++++
+++++ --- ++++++
+++++ ----- ++++++
+ + ----- ++++++
----- +++ - ++++++
----- +++ ++++++
-----+++++ --- ++++++
-----+++++ -----+++++
----- ++++ ----- +-
----- +++ -----+-
----- ++++ -----+++++
-- -- ++++++ ----- ++++++
--+++++----- ++++++
--+++++ ---+++++
--+++++ ++++++
+++++-----
+++++----- +-
--+++++ -----
--+++++ -----
-----
-----
-----
```

## Problem 2

### IMPLEMENTATION

This part of the MP was done in Python.

In order to implement problem 2.1, we first had to make sure we had all of our word likelihoods saved somewhere. In order to do this, we saved the likelihoods of each word from the training data into a dictionary based on whichever label it had. Then we went through each document of the test data and classified it into one label. We had to go through each line and find the sum of the likelihood that the document would fit a certain label. For multinomial naive Bayes we calculated the sum of every word's likelihood and frequency for each label. The email was then classified as whichever likelihood was greater, and the confusion matrix was updated. To implement the Bernoulli Naive Bayes problem, we commented out the line where the likelihood accounted for the word frequency. The classification rate for both models and both datasheets were the same (email - 97%, movie - 75%). To have our code work for the movie datasheet, we just had to change the way we searched for labels by changing a number in our conditional statement (labels were -1 and 1 instead of 0 and 1). To find the classification rates we divided the number of documents we labeled correctly by the total number of documents.

### CONFUSION MATRIX

#### **Bernoulli:**

	Not Spam	Spam
Not Spam	126	4
Spam	2	128

Classification Rate: 97.6%

	Good Review	Bad Review
Good Review	382	118
Bad Review	126	374

Classification Rate: 75.6%

#### **Multinomial:**

	Not Spam	Spam
Not Spam	126	4
Spam	2	128

Classification Rate: 97.6%

	Good Review	Bad Review
Good Review	383	117
Bad Review	124	376

Classification Rate: 75.9%

The top 20 for words for the emails are listed below. They are in the format word\_(# of occurrences)

#### TOP 20 WORDS FOR EMAILS

##### TOP SPAM WORDS

email\_1380  
 s\_1207  
 order\_1159  
 report\_1053  
 our\_965  
 address\_954  
 mail\_923  
 program\_828  
 send\_800  
 free\_744  
 money\_722  
 list\_713  
 receive\_662  
 name\_627  
 business\_608  
 one\_553  
 d\_541  
 work\_528  
 com\_524

##### TOP NORMAL WORDS

language\_1130  
 university\_906  
 s\_661  
 linguistic\_477  
 de\_445  
 information\_444  
 conference\_378  
 workshop\_360  
 email\_321  
 paper\_320  
 e\_314



english\_312  
one\_280  
please\_278  
include\_277  
edu\_271  
http\_264  
research\_259  
abstract\_253

#### TOP 20 WORDS FOR MOVIES

The top 20 for words for the movies are listed below. They are in the format word\_(# of occurrences)

#### TOP NEGATIVE REVIEW WORDS

movie\_290  
film\_227  
like\_163  
one\_143  
--\_114  
bad\_87  
story\_85  
much\_83  
time\_75  
even\_70  
characters\_64  
good\_64  
little\_62  
would\_58  
comedy\_57  
never\_53  
nothing\_52  
makes\_51  
plot\_51

#### TOP POSITIVE REVIEW WORDS

film\_285  
movie\_187  
--\_136  
one\_111  
like\_99  
story\_94  
good\_84  
comedy\_83  
way\_80  
even\_76  
time\_73  
best\_72

much\_66  
performances\_62  
funny\_60  
make\_60  
life\_58  
us\_58  
makes\_58

### EXTRA CREDIT

Problem 1 extra credit: Facial Recognition:

\*see description of problem 1 for details as it has the same implementation.

Smoothing Value = 10

Character	Correct	Attempts	Percentage
0	54	77	70.1299%
1	72	73	98.6301%
Total	126	150	84%

Confusion Matrix:

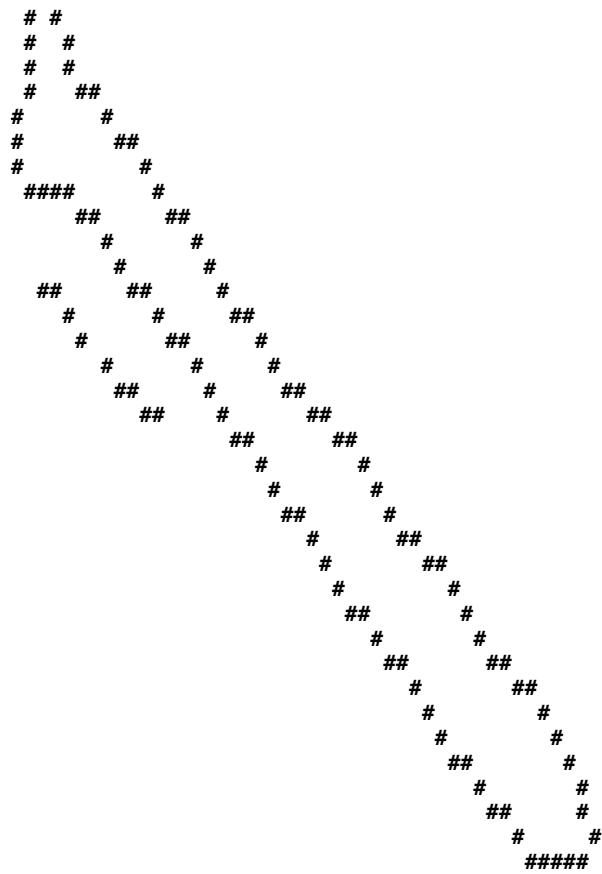
	0	1
0	70.130	29.870
1	1.370	98.630

[illegible]



```
      #                               #
      #                               #
### ##### #####
```

For Character '1' this is the most prototypical image:



[illegible]

Problem 2 extra credit:

We have implemented problem 2.2. The only thing different about this problem was that there were many more labels. We added more dictionaries to store word frequencies and likelihoods for words in each label, but the way we updated the confusion matrixes and found the classification rates were the same.

### Bernoulli Confusion Matrix

	sci.space	comp.sys.ibm.pc.hardware	rec.sport.baseball	comp.windows.x	talk.politics.misc	misc.forsale	rec.sport.hockey	comp.graphics
sci.space	33	0	0	0	1	0	0	0
comp.sys.ibm.pc.hardware	0	28	0	4	1	0	0	0
rec.sport.baseball	0	0	35	0	0	0	0	1
comp.windows.x	0	0	0	25	1	0	0	2
talk.politics.misc	1	0	0	0	46	0	0	0
misc.forsale	0	4	0	0	1	4	0	1
rec.sport.hockey	0	0	0	0	0	0	46	0
comp.graphics	1	1	0	2	0	0	0	25

Classification Rate: 92.015%

## Multinomial Confusion Matrix

	sci.space	comp.sys.ibm.pc.hardware	rec.sport.baseball	comp.windows.x	talk.politics.misc	misc.forsale	rec.sport.hockey	comp.graphics
sci.space	32	0	0	0	2	0	0	0
comp.sys.ibm.pc.hardware	0	27	0	4	2	0	0	0
rec.sport.baseball	0	0	35	0	0	0	1	0
comp.windows.x	0	0	0	24	1	0	0	3
talk.politics.misc	1	0	1	0	45	0	0	0
misc.forsale	1	2	0	0	1	4	0	2
rec.sport.hockey	0	0	0	0	0	0	46	0
comp.graphics	1	1	0	1	1	0	0	25

Classification Rate: 90.49%

The top 20 for words for the newsgroups are listed below. They are in the format word\_(# of occurrences)



## TOP 20 WORDS FOR EACH CATEGORY (2.2)

### TOP sci\_space WORDS

space\_1030  
nt\_593  
would\_560  
one\_384  
launch\_352  
nasa\_345  
earth\_332  
subject\_328  
like\_304  
us\_280  
system\_278  
also\_277  
writes\_271  
could\_263  
first\_253  
data\_253  
time\_253  
orbit\_251  
edu\_251

### TOP comp\_sys\_ibm\_pc\_hardware WORDS

drive\_496  
scsi\_416  
nt\_392  
ide\_306  
one\_262  
card\_253  
drives\_232  
controller\_229  
system\_216  
disk\_216  
subject\_205  
use\_204  
would\_203  
edu\_198  
hard\_191  
bus\_189  
get\_177  
m\_176  
data\_164

### TOP rec\_sport\_baseball WORDS

nt\_936  
would\_454  
year\_427  
edu\_416

writes\_355  
one\_316  
game\_316  
good\_299  
team\_294  
subject\_293  
last\_288  
article\_287  
think\_287  
players\_275  
like\_267  
baseball\_255  
games\_242  
better\_240  
well\_222  
TOP comp\_windows\_x WORDS  
x\_3598  
window\_522  
use\_455  
nt\_433  
subject\_426  
file\_396  
server\_363  
also\_323  
get\_312  
available\_312  
edu\_286  
motif\_284  
version\_277  
system\_270  
sun\_256  
program\_256  
c\_254  
one\_252  
m\_248  
TOP talk\_politics\_misc WORDS  
nt\_1400  
would\_951  
people\_831  
q\_692  
one\_601  
mr\_599  
think\_571  
writes\_552  
president\_552  
article\_509

government\_497  
stephanopoulos\_452  
know\_448  
us\_417  
edu\_413  
like\_404  
subject\_378  
going\_372  
get\_331  
TOP misc\_forsale WORDS  
new\_218  
edu\_189  
dos\_160  
sale\_145  
appears\_144  
art\_135  
subject\_132  
wolverine\_128  
shipping\_117  
cover\_115  
price\_115  
one\_112  
list\_112  
comics\_109  
drive\_108  
nt\_105  
hulk\_104  
good\_101  
vs\_98  
TOP rec\_sport\_hockey WORDS  
nt\_838  
game\_653  
team\_635  
hockey\_564  
would\_402  
play\_374  
subject\_339  
period\_338  
season\_333  
nhl\_327  
games\_322  
one\_312  
first\_290  
year\_283  
think\_276  
players\_271

get\_262  
la\_262  
edu\_259  
TOP comp\_graphics WORDS  
image\_889  
jpeg\_468  
edu\_438  
nt\_419  
file\_406  
images\_389  
data\_369  
also\_365  
graphics\_346  
software\_315  
available\_301  
use\_289  
one\_259  
program\_252  
files\_242  
format\_240  
get\_235  
version\_221  
system\_219

### **Contributions**

Erik Delanois - Problem 1

Doug Zhu, Dallas Delaney - Problem 2