CMPE 442 MACHINE LEARNING Assignment 2



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- **Q1)** The size of my dictionary is 150138
- **Q2)** The class priors are computed as follows

```
alt.atheism : 0.042425
comp.graphics : 0.051617
comp.os.ms-windows.misc : 0.052236
comp.sys.ibm.pc.hardware : 0.052148
comp.sys.mac.hardware : 0.051087
comp.windows.x : 0.052413
misc.forsale: 0.051706
rec.autos : 0.052501
rec.motorcycles: 0.052855
rec.sport.baseball : 0.052766
rec.sport.hockey: 0.053032
sci.crypt : 0.052590
sci.electronics : 0.052236
sci.med : 0.052501
sci.space : 0.052413
soc.religion.christian : 0.052943
talk.politics.guns : 0.048259
talk.politics.mideast : 0.049850
talk.politics.misc : 0.041100
talk.religion.misc : 0.033322
```

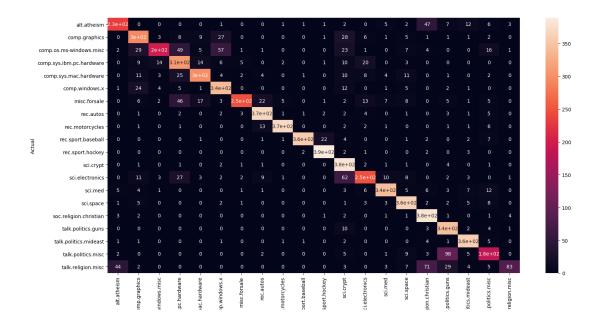
Q3) I have used the most frequent 50000 words. I have observed that doing so accuracy rate increased. Also, the probabilties were going near zero so python couldn't make comparisons, this resulted in a low accuracy (around 40%). To solve this I multipled each new probabilty of a word with 10⁴. This way the accuracy rate got up to 80%.

Here is our formula

$$\varphi_{k|y=0} = \frac{\sum_{i=1}^{m} \sum_{j=1}^{n_i} 1 \big\{ X_j^{(i)} = k \ \land Y^{(i)} = 0 \, \big\} + 1}{\sum_{i=1}^{m} 1 \big\{ Y^{\{i\}} = 0 \big\} n_i + |V|}$$

Here is the accuracy rate with the confusion matrix.

Number of correct predictions = 6087 Number of false predictions = 1445 Total number of tests = 7532 Accuracy rate is = 80.81518852894317 %



Q4) Yes for example the algorithm confuses the category talk.religion.misc with religion.christian. This is because the subjects are so related that appearance of a word in one of these categories appear also in the other category. The words god, atheism, jesus etc. are all common in religion related newsgroups, it is normal to see false positives. This can also be observed in other categories that are related to each other. For exapmle, some newsgroups in comp categories are also predicted wrong.

Q5) When we think of the strong indicators, what comes to the mind first is the most common words. Preprocessor already eliminates common words such as stopwords. What would be a really strong indicator is words that appear exclusively in that newsgroup. I couldn't find a way to find those. So here are the top 10 words for each category.

-14 -46-3	comp.sys.ibm.pc.hardware	misc.forsale
alt.atheism		
765	drive : 976	line : 628
god : 765	scsi : 704	subject : 601
one : 722	line : 637	organization : 573
people : 576	subject : 610	sale : 560
writes : 562	organization : 583	new : 329
subject : 542	card : 478	
line : 538	system : 410	university : 326 offer : 273
would : 501	mb : 388	
organization : 472	one : 379	nntppostinghost : 263
dont : 458		distribution : 252
atheist : 446	disk : 353	email : 246
comp.graphics	comp.sys.mac.hardware	rec.autos
line : 774	line : 652	car : 1223
image : 758	subject : 591	line : 642
subject : 627	organization : 552	subject : 625
organization : 581	mac : 546	organization : 589
file : 554	apple : 420	writes : 484
graphic : 460	problem : 372	article : 453
university : 360	drive : 357	would: 430
program : 329	one : 350	one : 362
would : 295	university : 308	like : 327
x : 279	nntppostinghost : 295	dont : 322
comp.os.ms-windows.misc	comp.windows.x	rec.motorcycles
Comp. Co. mar Williams . mize		
maxaxaxaxaxaxaxaxaxaxaxaxax : 3317	x : 5152	bike : 688
window : 1082	window : 933	line : 638
line : 654	line : 857	organization : 612
file : 641	subject : 788	subject : 611
	file : 778	writes : 503
subject : 618	organization : 599	article : 473
organization : 579	program : 553	dod : 455
driver : 375	use : 508	one : 394
university : 333	widget : 503	like : 334
use : 323	server : 474	
problem : 318	361VCI . 474	nntppostinghost : 303

rec.sport.baseballline : 648	sci.electronics	soc.religion.christian god : 1477	talk.politics.misc
subject: 618 organization: 601 year: 592 game: 558 writes: 468 team: 432 article: 391 player: 364 run: 343	subject: 672 organization: 581 one: 481 use: 371 would: 367 writes: 301 university: 291 like: 275 nntppostinghost: 268	one: 817 would: 775 christian: 755 subject: 671 people: 656 line: 636 jesus: 618 organization: 559 say: 520	would : 692 people : 684 writes : 611 q : 575 article : 573 line : 525
rec.sport.hockey	sci.med	talk.politics.guns	one : 515
team : 954 game : 917 line : 707 subject : 635 organization : 611 hockey : 594 player : 522 play : 491 year : 438 would : 429sci.crypt	subject : 649 line : 619 organization : 610 one : 567 article : 462 writes : 439 would : 419 people : 322 msg : 312 dont : 311sci.space	gun : 1231 would : 819 people : 657 line : 608 subject : 584 organization : 555 one : 531 writes : 507 article : 492 right : 487 talk.politics.mideast	dont : 508 organization : 506 subject : 500 talk.religion.misc god : 516 one : 463 subject : 418 line : 418 line : 418 people : 410 organization : 403 christian : 401 jesus : 390 would : 387 writes : 357
key: 1449 encryption: 840 chip: 839 would: 707 clipper: 705 line: 693 system: 668 subject: 665 one: 642 organization: 621	space : 1200 line : 646 subject : 635 organization : 631 would : 553 writes : 452 one : 413 nasa : 407 article : 402 launch : 377	armenian : 1268 people : 996 one : 883 israel : 879 israeli : 791 turkish : 712 would : 711 subject : 661 jew : 630 line : 626	

Q6) There are some ways to increase the accuracy of the classifier. One of them is with using weights. One of the most popular weight implementation in text classification is "term frequency- inverse tern frequency." It assumes that, how important a word is inversely proportional to how often it occurs across all documents.

Another way to increase the accuracy is removing common words. These words do not have any meaning for us because it appears in all the categories. For example one, would, writes, etc.