COMP472 - Reports

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1 Introduction

This project is completed within the COMP 472 course. It aims is to create an unsupervised machine learning program that will take some people feedback on various items they purchased and to classify it in two different group: Positive review or negative review. We used 80% of the data collected to train our machine, and the remaining 20% to test our machine. The analysis of each task of the project are shown in different section.

2 Task 1 Analysis

For the task 1, we created a function called **def** train.nb(documents, labels), it takes two parament which are the documents and the labels to train our machine. We also import the Counter from the collections modules as well to help us to count the number of occurence of each word. We separate the occurence of word in negative review from the occurence in positive review by using the labels already there to teach

```
def train_nb(documents, labels):
neg_word_count = Counter()
pos_word_count = Counter()
neg_total_word = 0
pos_total_word = 0
# we now create our classification
classifier = list(zip(labels, documents))
for c in classifier:
    if c[0] == 'neg':
        neg_word_count.update(c[1])
    else:
        pos_word_count.update(c[1])
neg_total_word = sum(neg_word_count.values())
pos_total_word = sum(pos_word_count.values())
total_word = sum(neg_total_word, pos_total_word)
return neg_total_word, pos_total_word,
    total_word, neg_word_count, pos_word_count
```

3 Task 2 Analysis

The task 2 is separate in two part, where the first part is to get the score and the second part compares the scores we got and return the appropriate classification (negative or positive review).

The function called score_doc_label(document, smoothing=0.5).

The smoothing paramater is set to default which is 0.5 and can be modified in the function call to suit future need. We use this formula to find our probabilty:

$$\begin{split} score(\text{Negative}) &= \log_{10}(P(\text{Negative})) + \sum_{i=1}(P(w_i|\text{Negative})) \\ score(\text{Positive}) &= \log_{10}(P(\text{Positive})) + \sum_{i=1}(P(w_i|\text{Positive})) \end{split}$$

Then we take the scores from our formula calcuation above, and we return the exponential of positive and negative scores to make it easier to read:

$$e^{\text{score}(\text{Negative})}$$
 and $e^{\text{score}(\text{Positive})}$

Now this takes us to the part of of the task 2, to perform our probabilities calculation, we call the function called <code>classify_nb(document, smoothing=0.5)</code>, this function will call the function previously mentionned in the first part, and will get the return values of the scores for negative and positive probability. It will compares both scores, pick the highest one and will return the fitting label for our review.

4 Accuracy Analysis

We use the 0.5 smoothing for our training data and we end up with this result shown below:

Training set accuracy (0.5):

Overall accuracy: 0.8712621970412339
Pos accuracy: 0.8429329291398256
Neg accuracy: 0.906418998354103

The data above show the accuracy of our training data with a smoothing of 0.5. Below there is more datas and graphs based on the evaluation (test) data we have. The first graph show are the overall accuracy based on different smoothing values between 0.1 and 1.

max overall acc at smoothing value 0.97: 0.767

5 Analysis of Misclassified Documents

Below you will find some misclassified documents along with some analysis on why it has been misclassified. Each team member picked 3 misclassified data as random.

5.1 Earl's Analysis

Review 1 First analysis of review is a review that has been labelled as negative but our AI classified it as positive.

i live in south africa where the series appeared 20 years ago.thanks to amazon i was able to relive the wonder of archie bunker where each episode provides laughs from one of the family, each of whom is brilliantly cast. i have series 3&4 and now want 1&2.do n't wait any longer, 24 episodes of absolute delight await you

This is misclassified as training data. It's labeled as negative while speaking only positive words towards the dvd...

Review 2 This is a positive review that has been clasified as positive.

excellent service, and the product worked extremely well. the only criticism i would have is the cost of postage. it was ridiculous, the product came in a big parcel, and inside was a dvd.

This is a short text. It includes pretty heavy words that would be negative such as ridiculous and criticism. Cost itself is another factor and aside from the obviously positive like excellent and well, the rest can be neutral

Review 3 This is a negative review that has been classified as positive.

i have worked out to denise austin for several years because i think she gives a good workout but i cannot stand her way-too-perky personality . i was very disappointed in this dance workout . the setting is fun and colorful and the music is great , but as far as a workout...this dvd really stinks . i found some of the steps somewhat confusing (but i am not very coordinated) . this workout was more of an " indoor walk " style workout (like walk away the pounds w / leslie sansone , etc.) . if you are looking for a fun way to get up and move , this may be for you . but , this is not for anyone looking for a cardio intense workout

Despite the negative review, the person acknowledges the positive aspects of it. In this case, negative just means it doesn't work for them; not necessarily that the product is bad. Biggest offenders would be good, colorful, fun, great

5.2 Marco's Analysis

Review 1 This is a positive review that has been classified as negative.

Misclassified because the word **stop** was used and alot of exclamation points usually means the person is angry

Review 2 This is a positive review that has been classified as negative.

i am very happy with the emjoi compact epilator that i purchased . it does exactly what it claims to do and works wonderfully . until i asked a salon for advice on the best way to remove unwanted facial hair , i did n't even know something like this exhisted . i just wish i would have known about this product years ago . a . davis

Misclassified because the word until was used

Review 3 This is a positive review that has been classified as negative.

i was searching for a two inch curling iron for a while . i have had so -so dealings with gold n hot in the past so i was a little nervous but i purchased this one anyway . so far , so good . it 's surprisingly light (at least compared to my one inch ceramic tools curling iron) . i usually let my hair air dry and use my curling irons to straighten my hair as i curl the ends (i 'm black with a relaxer .) i have yet to do it with this one . although i might try b / c it gets really hot . (i usually have it on around 20-25 out of 30) the only problem is that the ceramic can chip off (it happened with the first one i bought , but i returned it and got a new one that has n't chipped so far) and it 's so big that if you take your thumb off the spring grip , it can be hard to get it back on (i have huge hands too .

Misclassified with negative words like $\mathbf{nervous}$ and $\mathbf{problem}$ gave it the wrong label

5.3 Thomas' Analysis

Here is how we perform calcuation to find out the most incriming word shown below:

NEG + 0.5 = SNEG
POS + 0.5 = SPOS

$$\frac{SNEG}{SPOS} = x$$
IF $x > 1 \to x$
ELSE $\to \frac{1}{x}$

Where SNEG and SPOS means smoothed negative and smoothed positive respectively. The x is the how impactful this value is to our formula. This formula is applied for each word in our misclassified reviews. This formula has been reuse for each of my reviews. The actual data sheet can be found at the end of the file.

Review 1 First analysis of review is a negative review that been classified as positive.

i agree with other reviewers that it feels good and does n't smell too much , however , i 've experimented with it several times to confirm my findings , and it turns out to give me really bad blackheads . i 'm 25 with an oily t-zone and very dry facial skin . on mornings after using this cream , i have nasty blackheads on my forehead and chin . there are better products out there

After performing the calculation, the culprit are mostly the words **findings**, **mornings** since these word never appear in negative review it gives them a score of 0 (before the 0.5 smoothing), when we perform the neg/pos calculation with smoothing, it give an higher value to it. There is also the word **oily** which is strongly associated with positive review. I have compacted it for ease of view.

Review 2 This second review is a positive review that been classified as negative.

as if this set could be anything but five stars!!! barbra streisand four of her films on their dvd debut - her own commentary - oy vey!
order it now and plan a vacation day for the day after you get delivery

The major culprit of this review is the word **streisand** which is associated heavily with negative review.

Review 3 This third review is a positive review that been classified as negative.

\$10 bucks and does the job . you do need to adjust it every once in awhile but that 's easy to do .

This review is a bit more tricky to actually find the culprit, because the highest impacting factor does favour positive classification, however, the next 3 values that are impactful are favouring negative classification, word such as \$10, bucks and job.

6 Issues

Issues encountered...

7 What would you expand

Waht would we expand... Obviously looking at each document word by word in isolation limits us because words are contextual. One way to improve this, but still not perfect, is to use an n-gram to look at the sequence of words. Another way to look at it is to review the surrounding words.

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On the classification side, we could also split it into more labels. Aside from just positive and negative, we can include the product type being reviewed. For example, we can have dvd-pos, dvd-neg, music-pos, music-neg, health-pos, health-neg. The reasoning for this is that the type of product also gives us context clues. A quick example is the word "sick", which can be interpreted as more positive in music than in health.

WORD NE	G	SNEG POS	SPOS SNES/POS	X
"¡"	16707	16707.5 14814	14814.5 1.127780215	
"agree"	126	126.5 68	68.5 1.846715328	
"with"	4930	4930.5 5445	5445.5 0.905426499	
"other"	1130	1130.5 1108	1108.5 1.01984664	
"reviewers"	105	105.5 64	64.5 1.635658915	
"that"	7851	7851.5 6915	6915.5 1.135348131	
"it"	12338	12338.5 11728	11728.5 1.052010061	
"feels"	52	52.5 86	86.5 0.606936416	
"good"	1455	1455.5 1636	1636.5 0.889398106	
"and"	15970	15970.5 18754	18754.5 0.851555627	
"does"	1396	1396.5 1106	1106.5 1.262087664	
"n't"	4174	4174.5 2869	2869.5 1.454783063	
"smell"	18	18.5 23	23.5 0.787234043	
"too"	863	863.5 646	646.5 1.335653519	1.33565351894818
"much"	1072	1072.5 1005	1005.5 1.066633516	1.06663351566385
" "	26333	26333.5 27532	27532.5 0.956451466	1.04553135739647
, "however"	516	516.5 458	458.5 1.126499455	
" "	26333	26333.5 27532	27532.5 0.956451466	1.04553135739647
, "¡"	16707	16707.5 14814	14814.5 1.127780215	1.12778021532958
"ve"	694	694.5 855	855.5 0.811805961	
-	1	1.5 3	3.5 0.428571429	2.3333333333333333
"experimented"	4930	4930.5 5445	5445.5 0.905426499	1.10445188114796
"with" "it"			11728.5 1.052010061	
	12338	12338.5 11728		1.05201006096261
"several"	302	302.5 285	285.5 1.059544658	
"times"	391	391.5 390	390.5 1.002560819	
"to"	16647	16647.5 15877	15877.5 1.0484963	
"confirm"	6	6.5 1	1.5 4.333333333	
"my"	3542	3542.5 3840	3840.5 0.922405937	1.08412138320395
"findings" " "	0 26333	0.5 2 26333.5 27532	2.5 0.2	1.04552125720647
,			27532.5 0.956451466	1.04553135739647
"and"	15970	15970.5 18754	18754.5 0.851555627	
"it"	12338	12338.5 11728	11728.5 1.052010061	
"turns"	61	61.5 74	74.5 0.825503356	
"out"	1925	1925.5 1566	1566.5 1.229173316	
"to"	16647	16647.5 15877		1.04849629979531
"give"	436	436.5 326		1.33690658499234
"me"	1776	1776.5 1452	1452.5 1.223063683	
"really"	964	964.5 1173	1173.5 0.821900298	
"bad"	709	709.5 261	261.5 2.713193117	
"blackheads"	0	0.5 1	1.5 0.333333333	
и и	30682	30682.5 29981	29981.5 1.023381085	
"j"	16707	16707.5 14814		
"'m"	749	749.5 647		1.15752895752896
"25"	16	16.5 22		1.36363636363636
"with"	4930	4930.5 5445	5445.5 0.905426499	
"an"	1892	1892.5 2106	2106.5 0.898409684	
"oily"	2	2.5 11	11.5 0.217391304	4.6
"t-zone"	0	0.5 0	0.5 1	1

Review 1 - Thomas

"and"	15970	15970.5 18754 187		18754.5 0.851555627	1.17432140509064
"very"	1596	1596.5	2050	2050.5 0.778590588	1.28437206388976
"dry"	44	44.5	62	62.5 0.712	1.40449438202247
"facial"	15	15.5	15	15.5 1	1
"skin"	85	85.5	151	151.5 0.564356436	1.7719298245614
· ·	30682	30682.5	29981	29981.5 1.023381085	1.02338108500242
"on"	4701	4701.5	4485	4485.5 1.048155167	1.04815516664809
"mornings"	0	0.5	2	2.5 0.2	5
"after"	1185	1185.5	840	840.5 1.410469958	1.41046995835812
"using"	426	426.5	550	550.5 0.774750227	1.29073856975381
"this"	9608	9608.5	9391	9391.5 1.023106	1.02310600010648
"cream"	20	20.5	61	61.5 0.333333333	3
n n ,	26333	26333.5	27532	27532.5 0.956451466	1.04553135739647
"j"	16707	16707.5	14814	14814.5 1.127780215	1.12778021532958
"have"	4264	4264.5	4136	4136.5 1.030944035	1.03094403481204
"nasty"	11	11.5	19	19.5 0.58974359	1.69565217391304
"blackheads"	0	0.5	1	1.5 0.333333333	3
"on"	4701	4701.5	4485	4485.5 1.048155167	1.04815516664809
"my"	3542	3542.5	3840	3840.5 0.922405937	1.08412138320395
"forehead"	2	2.5	6	6.5 0.384615385	2.6
"and"	15970	15970.5	18754	18754.5 0.851555627	1.17432140509064
"chin"	2	2.5	5	5.5 0.454545455	2.2
п.п	30682	30682.5	29981	29981.5 1.023381085	1.02338108500242
"there"	1773	1773.5	1543	1543.5 1.149011986	1.14901198574668
"are"	3469	3469.5	3641	3641.5 0.952766717	1.04957486669549
"better"	926	926.5	743	743.5 1.246133154	1.24613315400135
"products"	187	187.5	144	144.5 1.297577855	1.29757785467128
"out"	1925	1925.5	1566	1566.5 1.229173316	1.22917331631025
"there"	1773	1773.5	1543	1543.5 1.149011986	1.14901198574668

Review 2 - Thomas

WORD NEG		SNEG	POS	SPOS	SNES/POS	Χ
"as"		3533.5	4438			1.256119994
"if"		2538.5	2093			1.212562694
"this"		9608.5	9391	9391.5	1.023106	1.023106
"set"	287	287.5	373			1.299130435
"could"		1142.5	736	736.5	1.55125594	1.55125594
"be"		3082.5	2698			1.142301278
"anything"	376	376.5	222		1.692134831	
"but"		4498.5	3853			1.167380304
"five"	57	57.5	148			2.582608696
"stars"	260	260.5	216			1.203233256
"!"		2834.5	2759		1.027178837	1.027178837
: "!"		2834.5	2759		1.027178837	1.027178837
: " "		2834.5	2759		1.027178837	1.027178837
: "barbra"	2034	0.5	2759	0.5		1.02/1/003/
"streisand"	8	8.5		0.5	1 17	17
streisand "-"		2025.5	0 1998			1.013510133
- "four"	108	108.5	161			1.488479263
"of"	12895					
		12896 1067.5	14207			1.101740917
"her"	123	123.5	1044			1.022020105
"films"			142			1.153846154
"on"		4701.5	4485		1.048155167	1.048155167
"their"		1216.5	1105		1.100407056	1.100407056
"dvd"	425	425.5	456			1.072855464
"debut"	18	18.5	44			2.405405405
"_"		2025.5	1998			1.013510133
"her"		1067.5	1044			1.022020105
"own"	355	355.5	443			1.247538678
"commentary"	29	29.5	41			1.406779661
"_"		2025.5	1998			1.013510133
"oy"	0	0.5	0	0.5	1	1
"vey"	1	1.5	0	0.5	3	3
uin.		2834.5	2759		1.027178837	
"order"	166	166.5	144			1.152249135
"it"	12338	12339	11728			1.052010061
"now"	750	750.5	767			1.022651566
"and"	15970	15971	18754			1.174321405
"plan"	51	51.5	76			1.485436893
"a"	14857	14858	16184			1.089315161
"vacation"	24	24.5	27		0.890909091	
"day"	322	322.5	424		0.759717314	
"for"		6033.5	6707			1.111709621
"the"	31914	31915	33502			1.049757947
"day"	322		424		0.759717314	
"after"	1185	1185.5	840	840.5	1.410469958	1.410469958
"you"	5382	5382.5	5808	5808.5	0.926659206	1.079145379
"get"	1564	1564.5	1309	1309.5	1.194730813	1.194730813
"delivery"	24	24.5	33	33.5	0.731343284	1.367346939

Review 3 - Thomas

WORD	NEG	5	SNEG	POS	SPOS	SNES/POS	VALUE
"\$10"		18	18.5	7	7.5	2.466666667	2.466666667
"bucks"		45	45.5	18	18.5	2.459459459	2.459459459
"and"		15970	15970.5	18754	18754.5	0.851555627	1.174321405
"does"		1396	1396.5	1106	1106.5	1.262087664	1.262087664
"the"		31914	31914.5	33502	33502.5	0.952600552	1.049757947
"job"		116	116.5	291	291.5	0.399656947	2.502145923
"."		30682	30682.5	29981	29981.5	1.023381085	1.023381085
"you"		5382	5382.5	5808	5808.5	0.926659206	1.079145379
"do"		2684	2684.5	1918	1918.5	1.399270263	1.399270263
"need"		409	409.5	524	524.5	0.780743565	1.280830281
"to"		16647	16647.5	15877	15877.5	1.0484963	1.0484963
"adjust"		22	22.5	22	22.5	1	1
"it"		12338	12338.5	11728	11728.5	1.052010061	1.052010061
"every"		445	445.5	505	505.5	0.881305638	1.134680135
"once"		245	245.5	299	299.5	0.819699499	1.219959267
"in"		7586	7586.5	8502	8502.5	0.89226698	1.12074079
"awhile"		14	14.5	15	15.5	0.935483871	1.068965517
"but"		4498	4498.5	3853	3853.5	1.167380304	1.167380304
"that"		7851	7851.5	6915	6915.5	1.135348131	1.135348131
"'s"		4769	4769.5	5309	5309.5	0.898295508	1.113219415
"easy"		203	203.5	704	704.5	0.288857346	3.461916462
"to"		16647	16647.5	15877	15877.5	1.0484963	1.0484963
"do"		2684	2684.5	1918	1918.5	1.399270263	1.399270263
"."		30682	30682.5	29981	29981.5	1.023381085	1.023381085