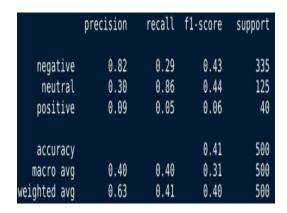
Report

- 1. Through the full dataset, it's obviously that the negative is much more than positive and neutral, false is more than true.
- 2. The image below, on the left is the metrics predicted by the DT model for 100 features. The image below, on the right is the metrics predicted by the DT model for 200 features.

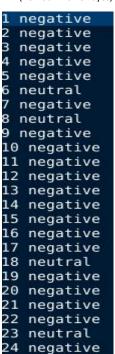
	precision	recall	f1-score	support
negative neutral positive	0.70 0.34 0.08	0.76 0.34 0.03	0.73 0.34 0.04	335 125 40
accuracy macro avg weighted avg	0.38 0.56	0.38 0.60	0.60 0.37 0.58	500 500 500



As shown in the picture, the prediction accuracy of 100 features is significantly greater than 200 features. Because the number of features selected will affect the construction of the model. About running time, the model of 200 features runs much longer than 100 features.

3. For test baseline predictors, I have intercepted the results of three standards models and compared them with VADER, as below.

BNB(Bernoulli Naive Bayes)



DT(Decision Trees)



MNB(Multinomial Naive Bayes)

1									e		
2		n	e	g	a	t	i	V	e		
3 4 5 6 7		n	e	g	a	t	i	٧	e		
4		n	e	g	a	t	i	V	e		
5		n	e	g	a	t	i	V	e		
6		n	e	u	t	r	a	ι			
7		n	e	g	a	t	i	v	e		
8		n	e	u	t	r	a	ι			
9		n	e	g	a	t	i	V	e		
1	0		n	e	g	a	t	i	٧	e	
1	1		n								
			n	e	g	a	t	i	V	e	
1			n	e	g	a	t	i	٧	e	
1			n	e	g	a	t	i	٧	e	
1			n	e	g	a	t	i	٧	e	
1			n	e	g	a	t	i	V	e	
1			n	e	g	a	t	i	V	e	
1			n	e	u	t	r	a	ι		
1			n	e	g	a	t	i	٧	e	
2	0		n	e	g	a	t	i	V	e	
2	1								٧		
2	2									e	
2	3								ι		
2	4		n	e	g	a	t	i	V	e	

And then this is VADER:

```
'compound': 0.0}
          'pos': 0.0,
       0.749,
                           'compound':
     0.863,
            'pos':
                   0.137,
            'pos': 0.133, 'compound': 0.3182}
     0.867.
                 Θ.Θ,
           'pos':
                  0.11,
     0.89.
                         'compound': 0.3818}
       0.633.
              'pos': 0.209,
            'pos': 0.115, 'compound': 0.296}
     0.885.
                     0.09,
       0.827, 'pos':
          'pos':
                 0.0,
                       'compound':
      0.842, 'pos': 0.0, 'compound': -0.4588}
'neu': 0.55, 'pos': 0.183, 'compound': -0.2023}
                     0.0, 'compound':
            'pos': 0.259,
                           'compound':
                                       0.5994}
            'pos': 0.0,
                        'compound': -0.5106}
              'pos': 0.0, 'compound': -0.4215}
'neu': 0.872.
    0.849,
            'pos': 0.151,
```

According to VADER's correct rate calculation method. I found that the correct rate of VADER is lower than these models. I think the reason is VADER is a simple model and the correct rate calculated by this model is definitely not as good as the other three more complex models.

4. For test remove stop words,we can see the image below, on the left is the metrics predicted by three models and the image on the right is the metrics predicted by three models deleted stop words.

DT:

0.414				
0.4041628806498	B5423			
0.414				
0.3127943170123	2818			
	precision	recall	f1-score	support
negative	0.82	0.29	0.43	335
neutral	0.30	0.86	0.44	125
positive	0.09	0.05	0.06	40
accuracy			0.41	500
macro avg	0.40	0.40	0.31	500
weighted avg	0.63	0.41	0.40	500

0.528				
0.31120882652	83504			
0.528				
0.31141743247	00641			
	precision	recall	f1-score	support
negative	0.66	0.72	0.69	335
neutral	0.21	0.18	0.19	125
positive	0.06	0.05	0.06	40
accuracy			0.53	500
macro avg	0.31	0.31	0.31	500
weighted avg	0.50	0.53	0.51	500

BNB:

0.37542021105 0.596	557016			
0.36997629904	9104			
	precision	recall	f1-score	support
negative	0.70	0.76	0.73	335
neutral	0.34	0.34	0.34	125
positive	0.08	0.03	0.04	40
accuracy			0.60	500
macro avg	0.38	0.38	0.37	500
weighted avg	0.56	0.60	0.58	500

0.483590733590 0.734	7336			
0.427175606446	3814			
	precision	recall	f1-score	support
negative	0.74	0.98	0.84	335
neutral	0.71	0.32	0.44	125
positive	0.00	0.00	0.00	40
accuracy			0.73	500
macro avg	0.48	0.43	0.43	500
weighted avg	0.67	0.73	0.67	500

MNB:

0.74 0.73172612827 0.74 0.51681951121					0.746 0.79056823398 0.746 0.53356778049				
	precision	recall	f1-score	support		precision	recall	f1-score	support
negative	0.77	0.93	0.84	335	negative	0.79	0.92	0.85	335
neutral	0.59	0.42	0.49	125	neutral	0.59	0.49	0.53	125
positive	0.83	0.12	0.22	40	positive	1.00	0.12	0.22	40
accuracy			0.74	500	accuracy			0.75	500
macro avq	0.73	0.49	0.52	500	macro avg	0.79	0.51	0.53	500
weighted avg	0.73	0.74	0.71	500	weighted avg	0.75	0.75	0.72	500

Obviously, for the three models, deleting stop words increases the accuracy of the prediction to varying degrees. The reason is some words have no distinction, these useless words will affect the final predictions.

5. On the left side is the predict results and on the right side is the correct rate. DT:

1	ne				
4	ne	ga	ıt:	Ĺν	e
5	po	si	t:	LV	e
6	ne	ga	it:	LV	e
7	ne	ga	ıt:	Ĺν	e
8	ne	ga	it:	ĹV	e
9	ne	ga	it:	Ĺν	e
10	n	eg	jat	ti	ve
11	p	05	ii	ti	ve
12	р	05	ii	ti	ve
13	n	ec	at	ti	ve
14	n	ec	a	ti	ve
16	n	ec	jat	ti	ve
18	n	ec	jat	ti	ve
19	n	ec	a	ti	ve
20					ve
22					ve
23					ve
24					ve

0.81333333333 0.52969651194 0.81333333333 0.53078078078	72673 33334			
0.55070070070	precision	recall	f1-score	support
negative positive	0.90 0.16	0.89 0.17	0.89 0.17	335 40
accuracy macro avg weighted avg	0.53 0.82	0.53 0.81	0.81 0.53 0.82	375 375 375

BNB:

1 negative	
4 negative	
4 negative 5 negative 6 negative 7 negative	
6 negative	
7 negative	
8 negative	
9 negative	
10 negative	
11 negative	
12 negative	
13 negative	
14 negative	
16 negative	
18 negative	
19 negative	
20 negative	
22 negative	
23 negative	
24 negative	

0.896 0.94786096256 0.89600000006 0.49688671786	00001	332		
0.43000071700	precision	recall	f1-score	support
negative positive	0.90 1.00	1.00 0.03	0.94 0.05	335 40
accuracy macro avg weighted avg	0.95 0.91	0.51 0.90	0.90 0.50 0.85	375 375 375

MNB:

<pre>1 negative 4 negative 5 negative 6 negative 7 negative</pre>	0.91733333333 0.88302167445 0.91733333333	81385			
8 negative	0.68530900625	32146			
9 negative 10 negative	0.00330300023	precision	recall	f1-score	support
11 negative					
12 negative	negative	0.92	0.99	0.96	335
13 negative					
14 negative	positive	0.85	0.28	0.42	40
<pre>16 negative</pre>	PART				
18 negative					
19 negative	accuracy			0.92	375
20 negative	*	0.00	0.00	100	
22 negative	macro avg	0.88	0.63	0.69	375
23 negative	weighted avg	0.91	0.92	0.90	375
24 negative	weighted dvg	0.51	0.52	0.50	3/3

VADER:

```
'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
           'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
             'neu': 0.749, 'pos': 0.0, 'compound': -0.6908}
           'neu': 0.863, 'pos': 0.137, 'compound': 0.4019}
'neg': 0.0, 'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
              'neu': 0.698, 'pos': 0.228, 'compound': 0.5106}
'neg': 0.0, 'neu': 0.867, 'pos': 0.133, 'compound': 0.3182}
           'neu': 1.0, 'pos': 0.0, 'compound': 0.0}
           'neu': 0.89, 'pos': 0.11, 'compound': 0.3818}
                           'pos': 0.209, 'compound': 0.2023}
                       'pos': 0.0, 'compound': 0.0}
                  1.0.
                          'pos': 0.115,
                            'pos':
                                   0.09
                     Θ
                       827
```

Through the pictures we can see that after the neutral sentiment is removed, the accuracy of the prediction is greatly improved. The reason is neutral sentiment is sometimes difficult to judge, and may involve irony, implied meaning, etc.

6. About my best method for sentiment analysis and my best method for topic classification, i used MNB model and some methods to preprocessed data. I deleted all kinds of special letters and symbols that are not related to emotions.

```
0.8830216744581385
0.9173333333333333
0.6853090062532146
              precision
                            recall f1-score
                                                 support
    negative
                    0.92
0.85
                              0.99
                                         0.96
                                                     335
                              0.28
                                         0.42
                                                      40
    positive
                                         0.92
   accuracy
                                         0.69
                    0.88
                              0.63
                                                     375
  macro avg
                    0.91
                              0.92
                                         0.90
 eighted avg
```