```
In [1]:
import sys
!{sys.executable} -m pip install xgboost
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from xgboost import XGBClassifier
from sklearn.linear model import LogisticRegression
from sklearn.naive bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier, VotingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.datasets import make classification
from sklearn.ensemble import ExtraTreesClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.model selection import train test split
from sklearn import metrics
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import r2 score
Requirement already satisfied: xgboost in /anaconda3/lib/python3.7/s
ite-packages (0.90)
Requirement already satisfied: numpy in /anaconda3/lib/python3.7/sit
e-packages (from xgboost) (1.16.2)
Requirement already satisfied: scipy in /anaconda3/lib/python3.7/sit
e-packages (from xgboost) (1.2.1)
In [2]:
df = pd.read csv('train.csv')
columns = list(df.columns)
non medical = columns[0:79]
medical = columns[79:127]
```

```
df = pd.read_csv('train.csv')
columns = list(df.columns)
non_medical = columns[0:79]
medical = columns[79:127]

med = df[medical]
med = med.sum(axis = 1)

df['Product_Info_2'] = pd.Categorical(df['Product_Info_2'])
dfDummies = pd.get_dummies(df['Product_Info_2'], prefix = 'P2')

train = df[non_medical]
train = train.drop(columns = 'Product_Info_2')
train['Response'] = df['Response']
train['Keyword'] = med
train = pd.concat([train, dfDummies], axis=1)
train.head
```

Out[2]:

2 1	5	1	26	0.076923
2 2	6	1	26	0.076923
2	0	1	20	0.076923
3 2	7	1	10	0.487179
4	8	1	26	0.230769
2 5 3	10	1	26	0.230769
3				
6 2	11	1	10	0.166194
7 2	14	1	26	0.076923
8 2	15	1	26	0.230769
9	16	1	21	0.076923
10	17	1	26	0.128205
2 11	18	1	26	0.230769
2 12	19	1	26	0.102564
2 13	20	2	26	0.487179
2 14	22	1	26	0.487179
2 15	23	1	26	0.000000
2 16	24	2	26	0.487179
2 17	25	1	26	0.384615
2 18	26	1	26	0.076923
2 19	27	1	26	0.487179
2 2 0	29	1	26	0.435897
2 21	31	1	26	1.000000
2 2 2	32	1	26	0.230769
2 23	33	1	26	0.179487
2 2 4	34	1	26	0.487179
2 25	35	1	26	0.230769
2 26	37	1	26	1.000000
2 27	39	1	26	0.230769

2				
28	40	1	26	0.487179
2 29	41	1	26	1.000000
2	• • •	•••	•••	•••
59351	79115	1	26	0.000000
2 59352	79116	1	10	0.230769
2 59353	79117	1	26	0.589744
2 59354	79118	1	26	0.487179
2 59355	79119	1	26	0.230769
2 59356	79120	1	10	0.076923
2 59357	79121	1	26	1.000000
2 59358	79122	1	26	0.282051
2 59359	79123	1	26	0.230769
2 59360	79124	1	26	1.000000
2 59361	79126	1	26	0.230769
2 59362	79127	1	26	0.230769
2 59363	79128	1	4	0.076923
2 59364	79130	1	26	0.076923
2 59365	79131	1	29	0.076923
2 59366	79132	1	26	0.282051
2 59367	79133	1	26	0.179487
2 59368	79134	1	26	0.230769
2 59369	79135	1	26	0.179487
2 59370	79136	1	26	0.230769
2 59371	79137	1	26	0.487179
2	79138	1	26	0.487179
2 59373		2	29	0.487179
2		_		

59374	79140	1	26	0.3076	92
2	70141		0.6	0.0760	0.0
59375 2	79141	1	26	0.0769	23
59376 2	79142	1	10	0.2307	69
59377 2	79143	1	26	0.2307	69
	79144	1	26	0.0769	23
59379 2	79145	1	10	0.2307	69
59380 2	79146	1	26	0.0769	23
2					
\	Product_Info_6	Product_Info_7	Ins_Age	Ht	Wt
0	1	1	0.641791	0.581818	0.148536
1	3	1	0.059701	0.600000	0.131799
2	3	1	0.029851	0.745455	0.288703
3	3	1	0.164179	0.672727	0.205021
4	3	1	0.417910	0.654545	0.234310
5	1	1	0.507463	0.836364	0.299163
6	3	1	0.373134	0.581818	0.173640
7	3	1	0.611940	0.781818	0.403766
8	3	1	0.522388	0.618182	0.184100
9	3	1	0.552239	0.600000	0.284519
10	3	1	0.537313	0.690909	0.309623
11	3	1	0.298507	0.690909	0.271967
12	3	1	0.567164	0.618182	0.163180
13	3	1	0.223881	0.781818	0.361925
14	3	1	0.328358	0.636364	0.142259
15	3	1	0.626866	0.672727	0.330544
16	3	1	0.208955	0.745455	0.246862
17	3	1	0.268657	0.636364	0.228033
• • •				. =	

18	3	1	0.388060	0.781818	0.309623
 19	3	1	0.223881	0.600000	0.138075
20	3	1	0.388060	0.745455	0.246862
• • •		_			
21	1	1	0.537313	0.709091	0.370293
22	3	1	0.179104	0.800000	0.539749
23	3	1	0.164179	0.745455	0.288703
24	1	1	0.164179	0.818182	0.435146
25	3	1	0.268657	0.781818	0.368201
26	3	1	0.507463	0.654545	0.299163
27	3	1	0.134328	0.763636	0.215481
28	3	1	0.492537	0.618182	0.276151
· · · 29	3	1	0.582090	0.654545	0.278243
• • •	•••	• • •	• • •	•••	• • •
 59351	3	1	0.134328	0.781818	0.351464
••• 59352	3	1	0.358209	0.618182	0.246862
 59353	1	1	0.179104	0.781818	0.382845
59354	1	1	0.402985	0.763636	0.341004
59355	3	1	0.223881	0.745455	0.361925
 59356	3	1	0.522388	0.600000	0.299163
 59357	1	3	0.582090	0.781818	0.351464
••• 59358	3	1	0.238806	0.727273	0.372385
••• 59359	3	1	0.447761	0.781818	0.424686
 59360	3	1	0.194030	0.654545	0.146444
 59361	1	1	0.268657	0.727273	0.267782
59362	3	1	0.253731	0.781818	0.351464
59363	3	1	0.746269	0.563636	0.205021
59364	3	1	0.552239	0.727273	0.177824

• • •											
59365			3		1	0.	641791	0.7090	91 0	.28	4519
59366			3		1	0.	582090	0.7818	18 0	.32	0084
 59367			3		3	0.	373134	0.6000	00 0	.32	0084
 59368			1		1	0.	417910	0.7272	73 0	.29	9163
••• 59369			3		1	0.	611940	0.7454	55 0	.45	1883
 59370			3		1	0.	238806	0.7636	36 0	.33	0544
 59371	1			1	0.	537313	0.7090	91 0	.34	3096	
••• 59372	3			1	0.	477612	0.7636	36 0	.30	5439	
 59373			3		1	0.	208955	0.8000	00 0	.25	7322
 59374			3		1	0.	164179	0.6909	09 0	.28	8703
••• 59375			3		1	0.	477612	0.6545	45 0	.27	1967
••• 59376	3				1	0.	074627	0.7090	91 0	.32	0084
 59377	3				1	0.	432836	0.8000	00 0	.40	3766
••• 59378	3				1		104478				6862
••• 59379	3				1		507463				6151
59380			3		1		447761				
			3		1	0.	44//01	0.7010	10 0	. 30	2043
-0 -1	P2_B2	P2_C1	P2_C2	P2_C3	P2_	C4	P2_D1	P2_D2	P2_D)3	P2_D4
P2_E1 0	0	0	0	0		0	0	0		1	0
0 1	0	0	0	0		0	0	0		0	0
0 2	0	0	0	0		0	0	0		0	0
1 3	0	0	0	0		0	0	0		0	1
0 4	0	0	0	0		0	0	1		0	0
0 5	0	0	0	0		0	0	1		0	0
0	0	0	0	0		0	0	0		0	0
0	0	0	0	0		0	0	1		0	0
0											
8	0	0	0	0		0	0	0		1	0

0									
9	0	0	0	0	0	0	0	0	0
1							-		
10	0	0	0	0	0	0	0	1	0
0 11	0	0	0	0	0	0	0	0	1
0	· ·	· ·	· ·	· ·	ŭ	· ·	· ·	· ·	_
12	0	0	0	0	0	0	0	0	0
0 13	0	0	0	0	0	1	0	0	0
0									
14	0	0	0	0	0	0	0	0	1
0 15	0	0	0	0	0	0	0	0	0
0									
16 0	0	0	0	0	0	0	0	0	1
17	0	0	0	0	0	0	0	1	0
0									
18 0	0	0	0	0	0	0	0	1	0
19	0	0	0	0	0	0	0	0	1
0		•	•	0	•	0		•	•
20 0	0	0	0	0	0	0	1	0	0
21	0	0	0	0	0	0	0	0	0
0	0	0	0	0	0	0	0	0	1
22 0	0	0	0	0	0	0	0	0	1
23	0	0	0	0	0	0	0	0	0
0 24	0	0	0	0	0	1	0	0	0
0	U	U	0	U	U	1	0	U	0
25	0	0	0	0	0	0	0	0	0
0 26	0	0	0	0	0	0	0	0	0
0	O	U	Ū	O	O	O	O	U	U
27	0	0	0	0	0	0	0	1	0
0 28	0	0	0	0	0	0	0	0	1
0	ŭ	Ü	Ü	ŭ	ŭ	ŭ	ŭ	Ü	-
29	0	0	0	0	0	0	0	1	0
0	• • •		• • •		• • •	• • •	• • •	• • •	
• • •									
59351	0	0	0	0	0	0	0	0	0
0 59352	0	0	0	0	0	0	1	0	0
0									
59353 0	0	0	0	0	0	0	0	0	1
0 59354	0	0	0	0	0	0	1	0	0
0									

ļ	59355	0	0	0	0	0	0	0	1	0
į) 59356	0	0	0	0	0	0	0	1	0
į	0 59357 0	0	0	0	0	0	0	0	1	0
ŗ	5 59358 O	0	0	0	0	0	0	0	0	1
ŗ	5 9359 0	0	0	0	0	0	0	0	1	0
į	59360 O	0	0	0	0	0	0	0	0	1
ŗ	59361 0	0	0	0	0	0	0	0	0	0
į	5 59362 O	0	0	0	0	0	0	0	0	1
į	59363 0	0	0	0	0	0	0	1	0	0
į	5 59364 0	0	0	0	0	0	0	1	0	0
į	5 59365 O	0	0	0	0	0	1	0	0	0
į	5 59366 D	0	0	0	0	0	1	0	0	0
į	5 59367 1	0	0	0	0	0	0	0	0	0
į	59368 D	0	0	0	0	0	0	0	0	1
į	5 59369 0	0	0	0	0	0	1	0	0	0
	5 59370 0	0	0	0	0	0	0	0	1	0
į	5 59371 O	0	0	0	0	0	0	0	1	0
į	5 59372 0	0	0	0	0	0	0	0	1	0
ŗ	5 59373 0	0	0	0	0	0	0	0	0	1
ŗ	5 59374 O	0	0	0	0	0	0	0	0	1
į	5 59375 O	0	1	0	0	0	0	0	0	0
ŗ	5 59376 O	0	0	0	0	0	1	0	0	0
į	5 59377)	0	0	0	0	0	0	0	1	0
į	59378	0	0	0	0	0	0	0	0	0
į	1 59379	0	0	0	0	0	0	1	0	0
į	0 59380 0	0	0	0	0	0	0	0	0	0
	- =									

```
[59381 rows x 99 columns]>
```

In [3]:

train.Keyword

Out[3]:	
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29	0 0 0 1 0 2 0 0 1 2 4 1 1 1 2 3 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0
59351 59352 59353 59354 59355 59356 59357 59358 59359 59360 59361 59362 59363 59364 59365	0 1 3 1 1 2 0 0 1 1 0 0 0 1 0 1

```
59367
         1
         0
59368
59369
         6
59370
         0
59371
         1
59372
         4
         0
59373
59374
         0
59375
         1
59376
         0
59377
         0
         1
59378
59379
         2
59380
         0
Name: Keyword, Length: 59381, dtype: int64
In [4]:
df = pd.read_csv('test.csv')
columns = list(df.columns)
non medical = columns[0:79]
medical = columns[79:127]
med = df[medical]
med = med.sum(axis = 1)
df['Product Info 2'] = pd.Categorical(df['Product Info 2'])
dfDummies = pd.get dummies(df['Product Info 2'], prefix = 'P2')
test = df[non medical]
test = test.drop(columns = 'Product_Info_2')
test['Keyword'] = med
test = pd.concat([test, dfDummies], axis=1)
```

In [5]:

clf1 = VotingClassifier(estimators=[('lr', clf), ('rf', clf2), ('gnb', clf3), ('ada', clf4), ('5', clf5), ('6', clf6), ('7', clf7)], voting='hard') In [7]: X = trainX = X.drop(columns = 'Id') y = X['Response'] X = X.fillna(-1)X = X.drop(columns = 'Response') X_train, X_test, y_train, y_test = train_test_split(X.values, y.values, test_siz e=0.3, random state=0) scaler = StandardScaler() scaler.fit(X) X_train = scaler.transform(X_train) X test = scaler.transform(X test) In [8]: clf1 = clf1.fit(X train, y train) print(clf1.score(X train,y train)) /anaconda3/lib/python3.7/site-packages/sklearn/linear model/logistic .py:947: ConvergenceWarning: lbfgs failed to converge. Increase the number of iterations. "of iterations.", ConvergenceWarning) 0.7230909878265891 In [9]: predictions test = clf1.predict(X test) print(clf1.score(X test, y test))

In [6]:

0.5551501543642997

In [10]:

```
from sklearn.metrics import classification report, confusion matrix
CM = confusion matrix(y test, predictions test)
print(CM)
print(classification report(y test, predictions test))
[[ 406
         313
               20
                     39
                         133
                               347
                                     159
                                          4061
         561
               19
                         195
                                     172
 [ 211
                     40
                               376
                                          3891
    27
          40
               91
                     73
                          18
                                53
                                       3
                                           10]
 27
          10
                           0
                                       4
               21
                    244
                                47
                                           57]
    73
        222
                1
                      0
                         754
                               292
                                     72
                                          155]
        225
   161
                0
                      8
                         141 1717
                                    353
                                          743]
 78
          64
                      2
                          18
                               490
                                    830 1002]
                0
 2
    33
          29
                0
                          18
                                    228 5287]]
 306
                                       f1-score
               precision
                              recall
                                                   support
            1
                     0.40
                                0.22
                                           0.29
                                                      1823
            2
                     0.38
                                0.29
                                           0.33
                                                      1963
            3
                     0.60
                                0.29
                                           0.39
                                                       315
            4
                                           0.60
                     0.60
                                0.60
                                                       410
            5
                     0.59
                                0.48
                                           0.53
                                                      1569
            6
                     0.47
                                0.51
                                           0.49
                                                      3348
            7
                                0.33
                                           0.39
                     0.46
                                                      2484
            8
                     0.66
                                0.90
                                           0.76
                                                      5903
                                           0.56
                                                     17815
    accuracy
                                           0.47
   macro avq
                     0.52
                                0.45
                                                     17815
weighted avg
                     0.53
                                0.56
                                           0.53
                                                     17815
```

In [11]:

```
test_noID = test.drop(columns = ['Id'])
test_noID = test_noID.fillna(-1)

scaler = StandardScaler()
scaler.fit(test_noID)
test_noID = scaler.transform(test_noID)
predictions_test = clf1.predict(test_noID)

test['Response'] = predictions_test
submission = test[['Id', 'Response']]
submission.set_index('Id', inplace = True)
submission.to_csv('Submission.csv', float_format='%.0f')
print(submission)
```

```
Id
1 7
3 8
4 6
9 8
```

Response

12	8
13	8
21 28	8 8
30	7
36	8
38	8
43	8
45 48	4 8
50	4
51	8
54	7
55 59	8 8
62	1
63	8
66	8
69 93	8
82 83	8 6
84	6
86	8
89	8
90 92	2 8
• • •	• • •
79004	7
	-
79007	8
	-
79007 79020 79022 79027	8 6 1 1
79007 79020 79022 79027 79028	8 6 1 1 8
79007 79020 79022 79027 79028 79031	8 6 1 1 8 8
79007 79020 79022 79027 79028	8 6 1 1 8
79007 79020 79022 79027 79028 79031 79035	8 6 1 1 8 8 1 8
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048	8 6 1 1 8 8 1 8 8 5
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051	8 6 1 1 8 8 1 8 8 5 6
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048	8 6 1 1 8 8 1 8 8 5
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054	8 6 1 1 8 8 1 8 5 6 5
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054 79060 79064 79065	8 6 1 8 8 1 8 5 6 5 6 8 5
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054 79060 79064 79065 79067	8 6 1 1 8 8 1 8 5 6 5 6 8 5 8
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054 79060 79064 79065	8 6 1 8 8 1 8 5 6 5 6 8 5
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054 79060 79064 79065 79067 79071 79072 79073	8 6 1 1 8 8 1 8 5 6 5 6 8 5 6 8
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054 79060 79064 79065 79067 79071 79072 79073 79080	8 6 1 1 8 8 1 8 8 5 6 5 6 8 5 6 8 6 8 6
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79054 79060 79064 79065 79067 79071 79072 79073 79080 79083	8 6 1 1 8 8 1 8 8 5 6 5 6 8 5 6 8 6 2
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054 79060 79064 79065 79067 79071 79072 79073 79080	8 6 1 1 8 8 1 8 8 5 6 5 6 8 5 6 8 6 8 6
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054 79060 79064 79065 79067 79071 79072 79073 79080 79083 79084	8 6 1 1 8 8 1 8 8 5 6 5 6 8 5 6 8 6 8 6 8 6 8 6 8 6 8
79007 79020 79022 79027 79028 79031 79035 79038 79047 79048 79051 79054 79060 79064 79065 79067 79071 79072 79073 79080 79083 79084 79085	8 6 1 1 8 8 1 8 8 5 6 5 6 8 5 6 8 6 2 8 6

79099	8	
79102	1	
79125	2	
79129	6	
[19765 rows x	1 columns]	
In []:		
In []:		