Performance Evaluation Of Intrusion Detection Systems Using Machine Learning Techniques

June 7, 2020

1 Importing necessary libraries

[1]:
```
import pandas as pd
import numpy as np
from numpy import array
import time
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score

from sklearn.preprocessing import LabelEncoder, OneHotEncoder

from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import GaussianNB
```

2 Description of NoteBook

2.0.1 Authors of this notebook

- Sidhantha Poddar-17BCE2044
- Bais Atharva Sanjay-17BCE0931
- Achyut Tripathi-17BCE0954
- Moturu Niharika-17BCE0951
- Kausthub Kesavadas-17BCE2144

This project uses six machine learning algorithms. They are Logistic Regression, Multinomial Naive Bayes, K-Nearest neighbors , Decision Tree, Adaboost and Random Forest.

3 Data analytics and vizualization

[7]:
```
sns.set()
```

[18]:
```
#importing dataset
df = pd.read_csv('data/train.csv')
```

```
df2 = pd.read_csv('data/test.csv')
```

[4]:
```
#printing head of dataset
df.head()
```

[4]:
```
        dur  proto  service  state  spkts  dpkts  sbytes  dbytes       rate  \
0  0.121478    113        0      4      6      4     258     172  74.087490
1  0.649902    113        0      4     14     38     734   42014  78.473372
2  1.623129    113        0      4      8     16     364   13186  14.170161
3  1.681642    113        3      4     12     12     628     770  13.677108
4  0.449454    113        0      4     10      6     534     268  33.373826

   sttl  …  ct_dst_sport_ltm  ct_dst_src_ltm  is_ftp_login  ct_ftp_cmd  \
0   252  …                 1               1             0           0
1    62  …                 1               2             0           0
2    62  …                 1               3             0           0
3    62  …                 1               3             1           1
4   254  …                 1              40             0           0

   ct_flw_http_mthd  ct_src_ltm  ct_srv_dst  is_sm_ips_ports  attack_cat  \
0                 0           1           1                0           6
1                 0           1           6                0           6
2                 0           2           6                0           6
3                 0           2           1                0           6
4                 0           2          39                0           6

   label
0      0
1      0
2      0
3      0
4      0

[5 rows x 44 columns]
```

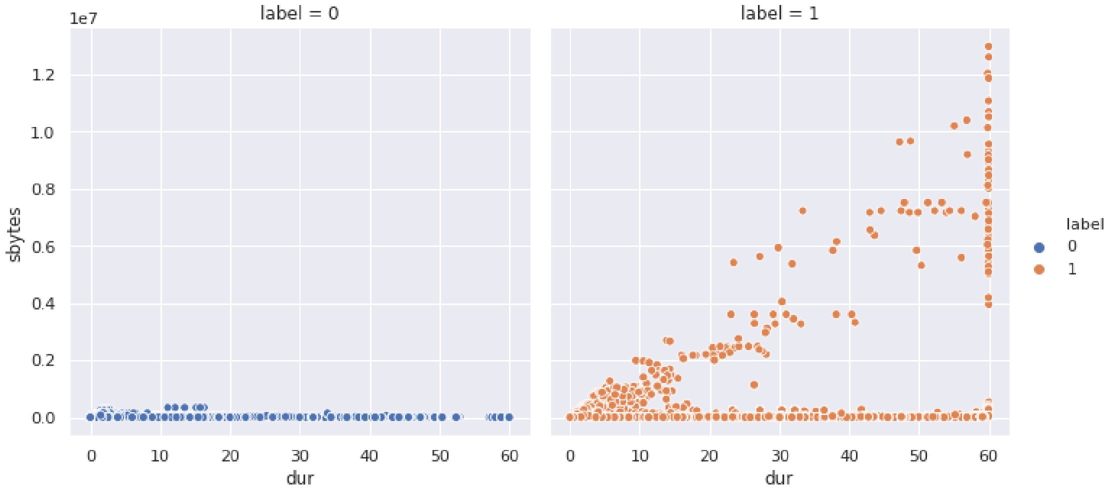
[5]:
```
#some info on dataset
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 175341 entries, 0 to 175340
Data columns (total 44 columns):
 #   Column             Non-Null Count   Dtype
---  ------             --------------   -----
 0   dur                175341 non-null  float64
 1   proto              175341 non-null  int64
 2   service            175341 non-null  int64
 3   state              175341 non-null  int64
```

```
 4   spkts              175341 non-null  int64
 5   dpkts              175341 non-null  int64
 6   sbytes             175341 non-null  int64
 7   dbytes             175341 non-null  int64
 8   rate               175341 non-null  float64
 9   sttl               175341 non-null  int64
 10  dttl               175341 non-null  int64
 11  sload              175341 non-null  float64
 12  dload              175341 non-null  float64
 13  sloss              175341 non-null  int64
 14  dloss              175341 non-null  int64
 15  sinpkt             175341 non-null  float64
 16  dinpkt             175341 non-null  float64
 17  sjit               175341 non-null  float64
 18  djit               175341 non-null  float64
 19  swin               175341 non-null  int64
 20  stcpb              175341 non-null  int64
 21  dtcpb              175341 non-null  int64
 22  dwin               175341 non-null  int64
 23  tcprtt             175341 non-null  float64
 24  synack             175341 non-null  float64
 25  ackdat             175341 non-null  float64
 26  smean              175341 non-null  int64
 27  dmean              175341 non-null  int64
 28  trans_depth        175341 non-null  int64
 29  response_body_len  175341 non-null  int64
 30  ct_srv_src         175341 non-null  int64
 31  ct_state_ttl       175341 non-null  int64
 32  ct_dst_ltm         175341 non-null  int64
 33  ct_src_dport_ltm   175341 non-null  int64
 34  ct_dst_sport_ltm   175341 non-null  int64
 35  ct_dst_src_ltm     175341 non-null  int64
 36  is_ftp_login       175341 non-null  int64
 37  ct_ftp_cmd         175341 non-null  int64
 38  ct_flw_http_mthd   175341 non-null  int64
 39  ct_src_ltm         175341 non-null  int64
 40  ct_srv_dst         175341 non-null  int64
 41  is_sm_ips_ports    175341 non-null  int64
 42  attack_cat         175341 non-null  int64
 43  label              175341 non-null  int64
dtypes: float64(11), int64(33)
memory usage: 58.9 MB
```

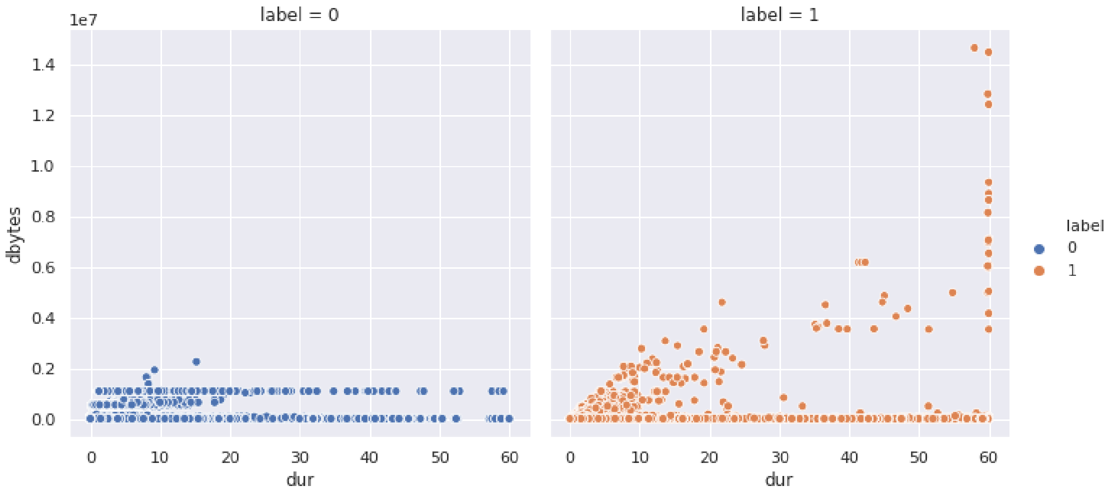
From the graph below we can infer that there is a relationship threshold between attacks and dur/sbytes values

[20]:
```
sns.relplot(x="dur", y="sbytes",col="label", hue="label",data=df);
```



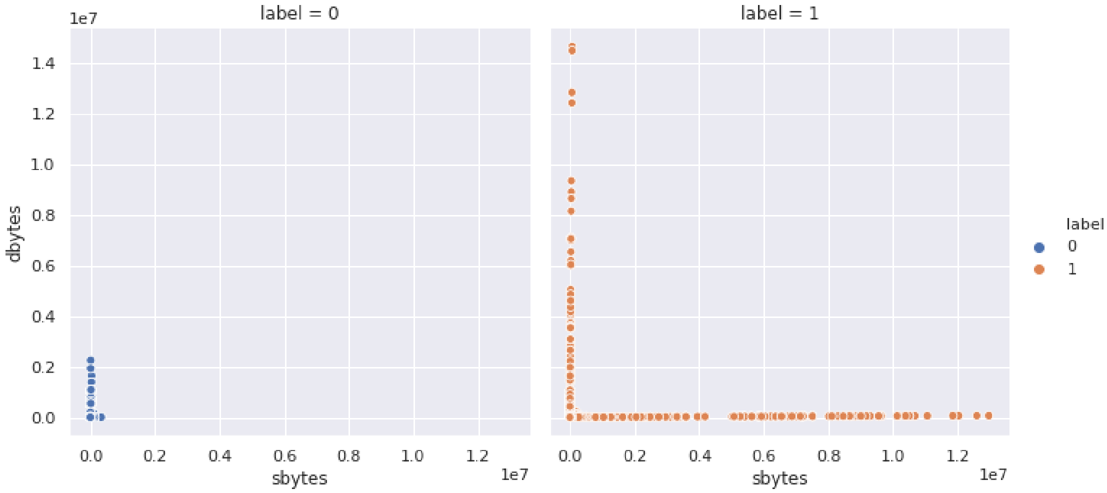
From the graph below we can infer that there is a relationship threshold between attacks and dur/dbytes values

[26]:
```
plt.subplots(figsize=(20, 10))
sns.relplot(x="dur", y="dbytes",col="label", hue="label",data=df);
```



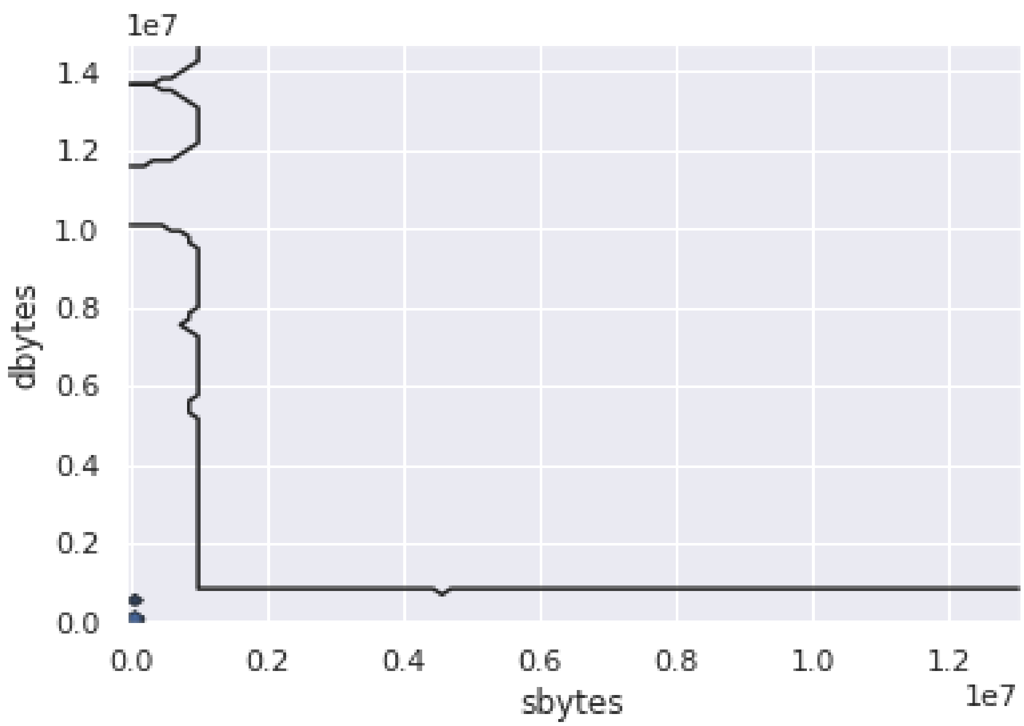
From the graph below we can infer that there is a relationship threshold between attacks and sbytes/dbytes values

[59]:
```
sns.relplot(x="sbytes", y="dbytes",col="label", hue="label",data=df);
```



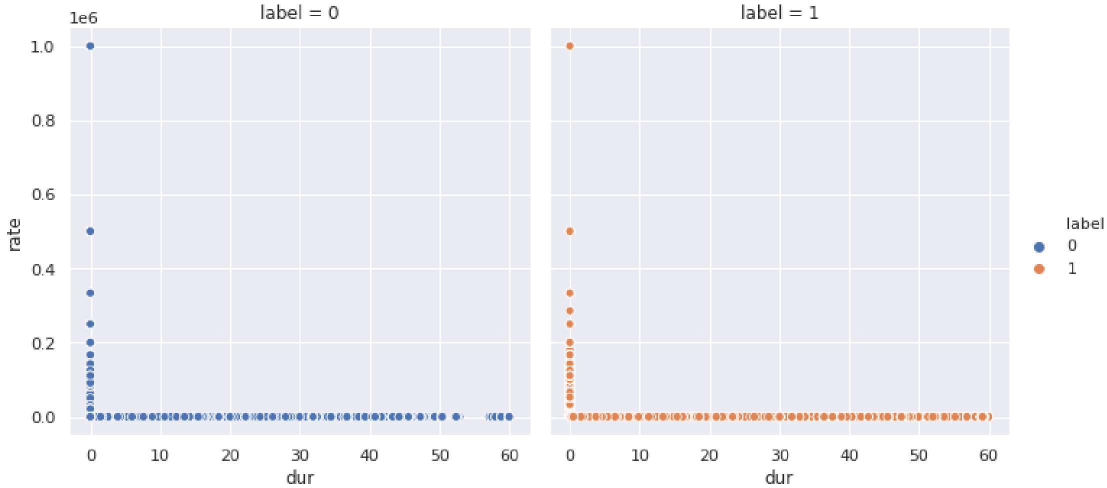

```
[56]: sns.kdeplot(df.sbytes, df.dbytes)
```

[56]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8d988e9990>

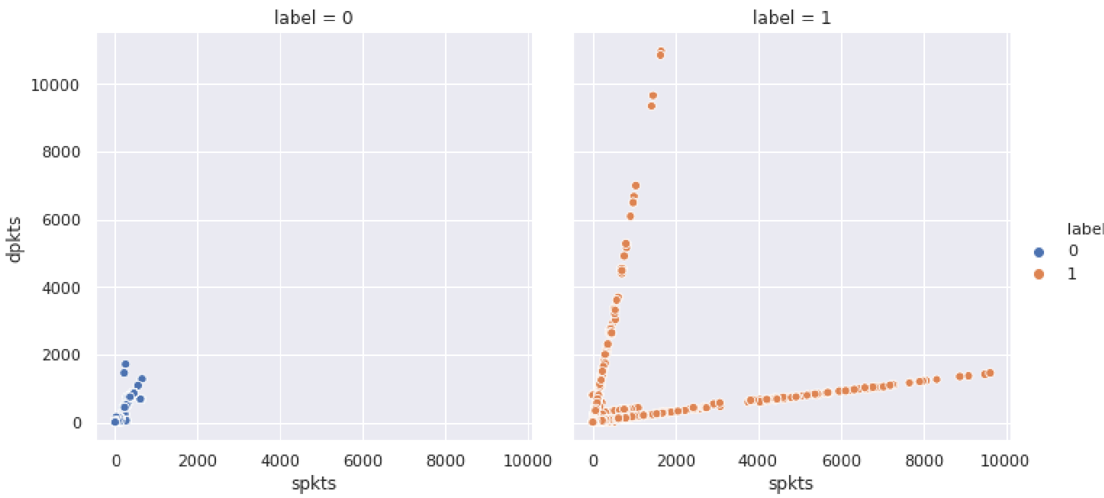



```
[52]: sns.relplot(x="dur", y="rate",col="label", hue="label",data=df);
```

<Figure size 1440x720 with 0 Axes>

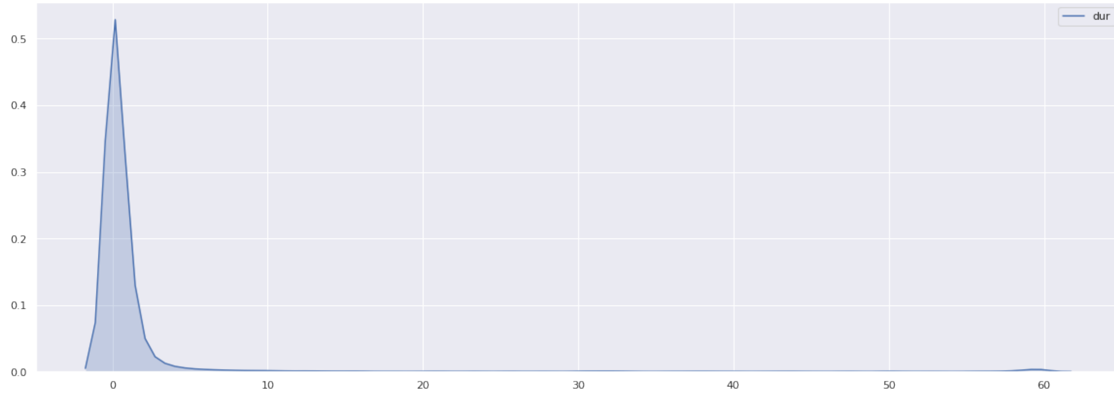


[71]:
```
sns.relplot(x="spkts", y="dpkts",col="label", hue="label",data=df);
```



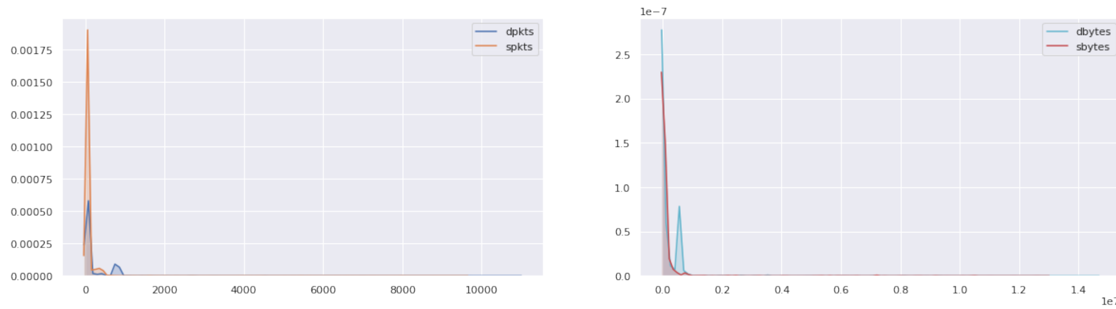
[8]:
```
%matplotlib inline
plt.subplots(figsize=(20, 7))
sns.kdeplot(df["dur"], shade=True)
```

[8]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d7d903950>

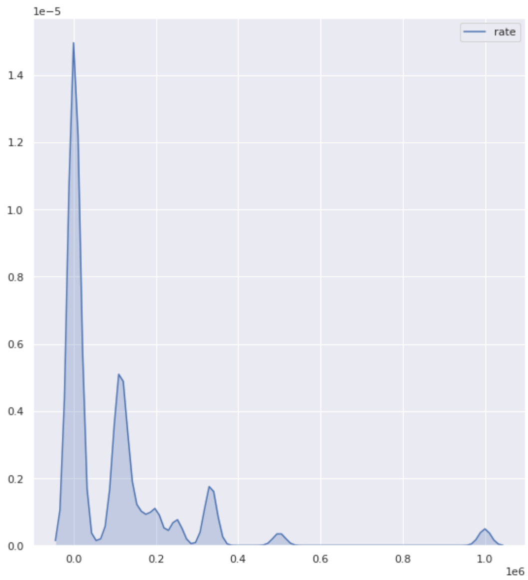


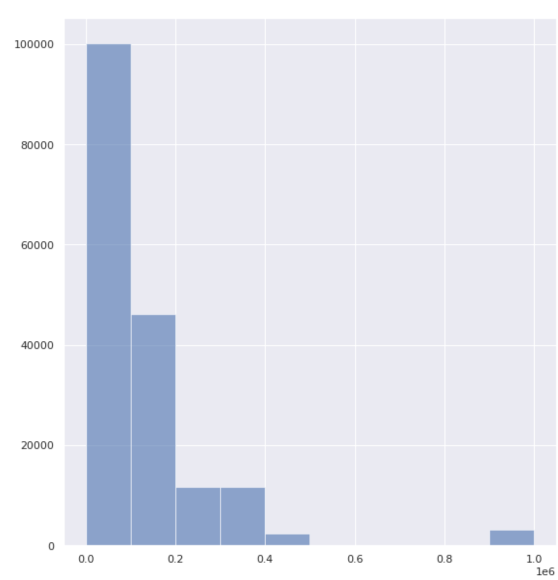
[9]:
```
plt.subplots(figsize=(20, 5))

plt.subplot(1,2,1)
sns.kdeplot(df["dpkts"], shade=True)
sns.kdeplot(df["spkts"], shade=True)

plt.subplot(1,2,2)
sns.kdeplot(df["dbytes"], shade=True, color ='c')
sns.kdeplot(df["sbytes"], shade=True, color = 'r')
```

[9]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5d7de04d90>
```



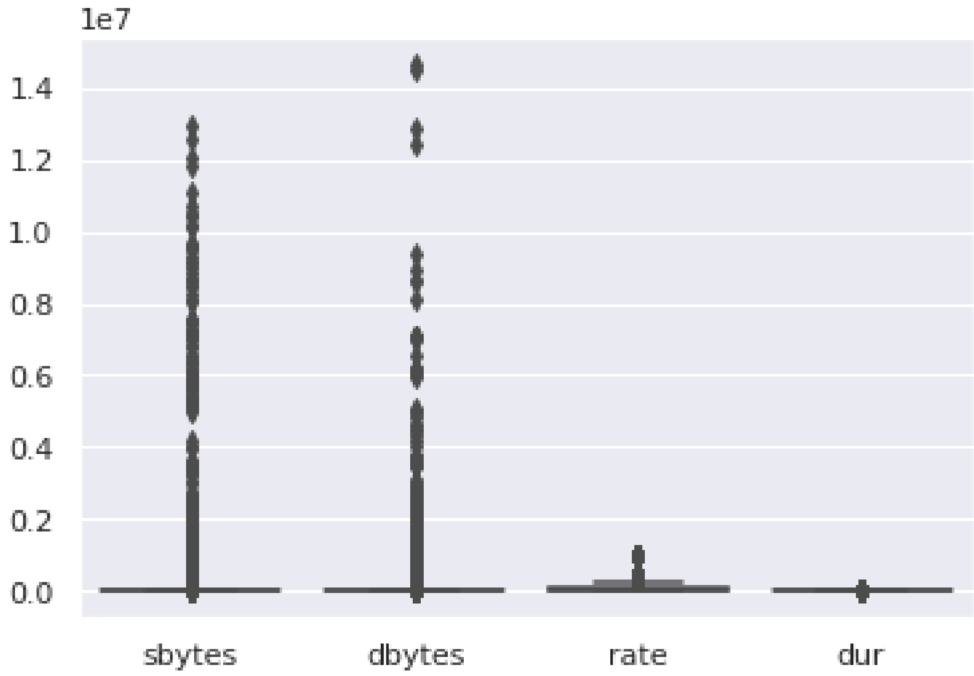
[49]:
```
plt.subplots(figsize=(20, 10))
plt.subplot(1,2,1)
sns.kdeplot(df["rate"], shade=True)
plt.subplot(1,2,2)
x=plt.hist(df["rate"],alpha=0.6)
```



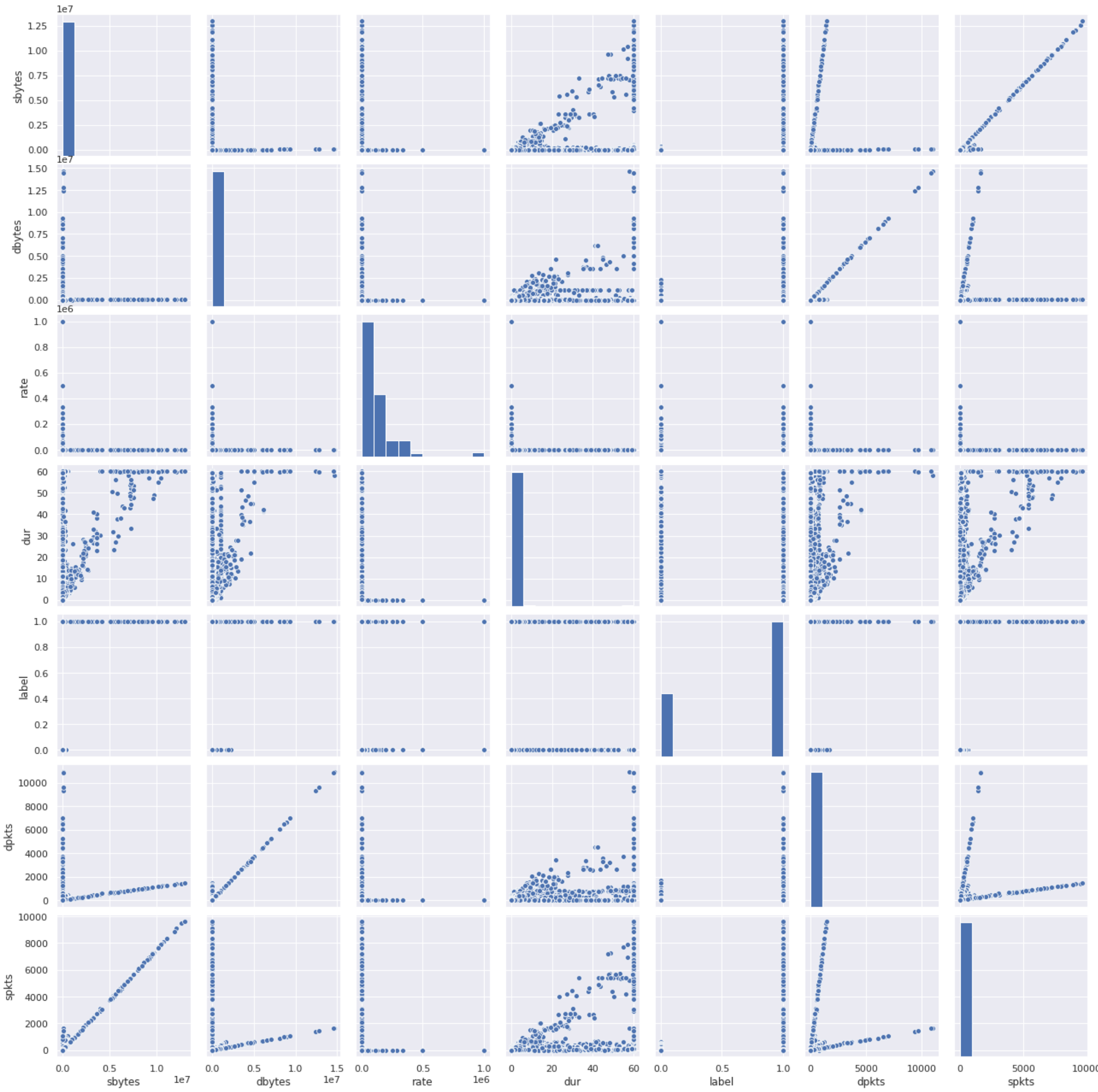


[47]:
```
sns.boxplot(data=df[["sbytes","dbytes","rate","dur"]])
```

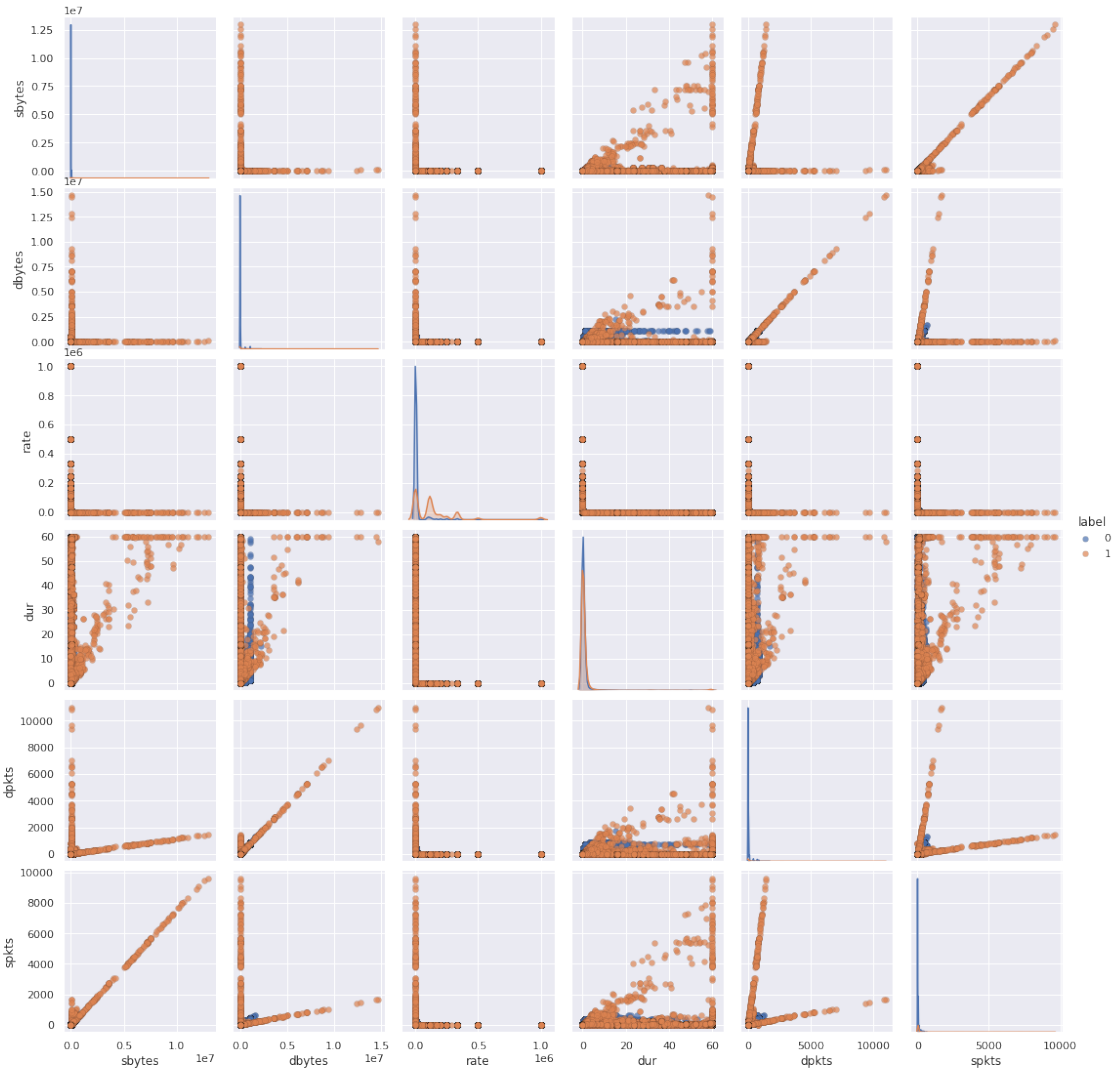
[47]: <matplotlib.axes._subplots.AxesSubplot at 0x7f8d993bd150>



[74]:
```
sns.pairplot(df[["sbytes","dbytes","rate","dur","label","dpkts","spkts"]])
plt.show()
```



[10]:
```
g=sns.pairplot(data=df[["sbytes","dbytes",
                        "rate","dur",
                        "dpkts","spkts","label"]],
               hue="label",
               plot_kws=dict(alpha=.7, edgecolor=".1", linewidth=.1) )
```



3.1 Analysis on results of data visualization

1. False Positve (of attack) is the major cause of the error
2. From visualization we can see that attack have threshold values while normal use dont
3. Many Non Attacks can be seperated by using fast algorithm like DT or regressing
4. Ensemble model can be created using a simple fast model and deeplearning models for two level prevention

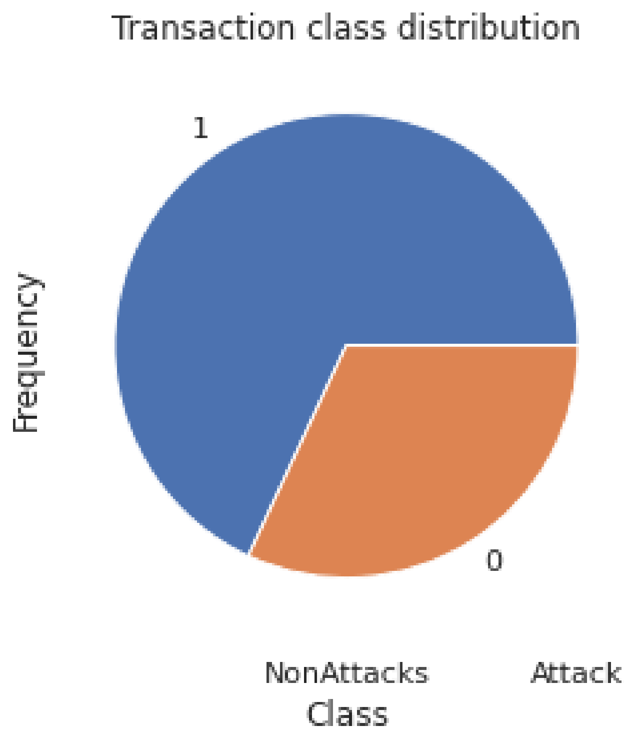
4 Feature Selection and Data Cleaning

[16]:
```
Attack= df[df['label'] == 1]
NonAttack = df[df['label'] == 0]
classes = pd.value_counts(df['label'], sort = True)
output=df['label']
```

```
df=df.iloc[:,:-1]

labels = ['NonAttacks','Attack']
classes.plot(kind = 'pie', rot=0)
plt.title("Transaction class distribution")
plt.xticks(range(2), labels)
plt.xlabel("Class")
plt.ylabel("Frequency")
output.value_counts()
```

[16]:

```
1    119341
0     56000
Name: label, dtype: int64
```



[13]:

```
#One Hot Encoding
from sklearn.preprocessing import LabelEncoder, OneHotEncoder
import numpy as np
from numpy import array

le_service = LabelEncoder()
le_proto = LabelEncoder()
le_state= LabelEncoder()
df['service_encoded'] = le_service.fit_transform(df.service)
```

```
df['proto_encoded'] = le_proto.fit_transform(df.proto)
df['state_encoded'] = le_state.fit_transform(df.state)


service_ = OneHotEncoder()
proto_ = OneHotEncoder()
state_ = OneHotEncoder()
X = service_.fit_transform(df.service_encoded.values.reshape(-1,1)).toarray()
Xm = proto_.fit_transform(df.proto_encoded.values.reshape(-1,1)).toarray()
Xmm = state_.fit_transform(df.state_encoded.values.reshape(-1,1)).toarray()
dfOneHot = pd.DataFrame(X, columns = ["service_"+str(int(i)) for i in range(X.
 ↪shape[1])])
df = pd.concat([df, dfOneHot], axis=1)
dfOneHot = pd.DataFrame(Xm, columns = ["proto_"+str(int(i)) for i in range(Xm.
 ↪shape[1])])
df = pd.concat([df, dfOneHot], axis=1)
dfOneHot = pd.DataFrame(Xmm, columns = ["state_"+str(int(i)) for i in range(Xmm.
 ↪shape[1])])
df = pd.concat([df, dfOneHot], axis=1)

df.drop(columns=['proto','service','state'], inplace = True )
df.shape
df2.drop(columns='attack_cat', inplace = True )
```

[14]:
```
df.describe()
```

[14]:
```
                 dur          spkts          dpkts        sbytes  \
count  175341.000000  175341.000000  175341.000000  1.753410e+05
mean        1.359389      20.298664      18.969591  8.844844e+03
std         6.480249     136.887597     110.258271  1.747656e+05
min         0.000000       1.000000       0.000000  2.800000e+01
25%         0.000008       2.000000       0.000000  1.140000e+02
50%         0.001582       2.000000       2.000000  4.300000e+02
75%         0.668069      12.000000      10.000000  1.418000e+03
max        59.999989    9616.000000   10974.000000  1.296523e+07

             dbytes          rate           sttl           dttl         sload  \
count  1.753410e+05  1.753410e+05  175341.000000  175341.000000  1.753410e+05
mean   1.492892e+04  9.540619e+04     179.546997      79.609567  7.345403e+07
std    1.436542e+05  1.654010e+05     102.940011     110.506863  1.883574e+08
min    0.000000e+00  0.000000e+00       0.000000       0.000000  0.000000e+00
25%    0.000000e+00  3.278614e+01      62.000000       0.000000  1.305334e+04
50%    1.640000e+02  3.225807e+03     254.000000      29.000000  8.796748e+05
75%    1.102000e+03  1.250000e+05     254.000000     252.000000  8.888889e+07
max    1.465555e+07  1.000000e+06     255.000000     254.000000  5.988000e+09

              dload  …      proto_132        state_0        state_1  \
```

```
count  1.753410e+05  …  175341.000000  175341.000000  175341.000000
mean   6.712056e+05  …       0.000570       0.075008       0.000068
std    2.421312e+06  …       0.023875       0.263405       0.008272
min    0.000000e+00  …       0.000000       0.000000       0.000000
25%    0.000000e+00  …       0.000000       0.000000       0.000000
50%    1.447023e+03  …       0.000000       0.000000       0.000000
75%    2.784487e+04  …       0.000000       0.000000       0.000000
max    2.242273e+07  …       1.000000       1.000000       1.000000

             state_2        state_3        state_4        state_5  \
count  175341.000000  175341.000000  175341.000000  175341.000000
mean        0.443849       0.469229       0.000006       0.011355
std         0.496839       0.499054       0.002388       0.105954
min         0.000000       0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000       0.000000
75%         1.000000       1.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000       1.000000

             state_6        state_7        state_8
count  175341.000000  175341.000000  175341.000000
mean        0.000473       0.000006       0.000006
std         0.021752       0.002388       0.002388
min         0.000000       0.000000       0.000000
25%         0.000000       0.000000       0.000000
50%         0.000000       0.000000       0.000000
75%         0.000000       0.000000       0.000000
max         1.000000       1.000000       1.000000

[8 rows x 199 columns]
```

[19]:

```python
# Feature Selection
from sklearn.feature_selection import SelectKBest
from sklearn.feature_selection import chi2

# remove string cols
df.drop(columns='attack_cat', inplace = True )

bestfeatuers=SelectKBest(score_func=chi2,k=10)
inp=df.iloc[:,0:198]
fit=bestfeatuers.fit(inp,output)
dfscores=pd.DataFrame(fit.scores_)
dfcol=pd.DataFrame(inp.columns)
featurescore=pd.concat([dfcol,dfscores],axis=1)
featurescore.columns=['feature','score']
k=featurescore['feature']
t=featurescore.nlargest(10,'score')
```

```
li=list(t['feature'])
print("Top 100 features:")
print("\n")
for x in li:
    print(x,end=" , ")
```

```
Top 100 features:


stcpb , dtcpb , sload , dload , rate , dbytes , sinpkt , sbytes ,
response_body_len , djit ,
```

[22]:

```
x_train=df[li]
y_train=output
x_test=df2[li]
y_test = df2['label']
accTest={}
accTrain={}
predTest={}
predTrain={}
```

5 Model Creation and Prediction

5.1 Decision tree

Decision trees are created by recursive apportioning. A univariate split is chosen for the foundation of the tree as indicated by some measure, and the procedure rehashes recursively. This procedure known as pruning, which diminishes the tree size, is performed once a full tree has been constructed. The most well known delegate of choice trees is C4.5.A bootstrap test of the first information subsets is used to develop different choice trees (Forest). Each tree in the forest gives a choice about the class of the new article that should be grouped. The class which acquires the most decisions in favor of the item is chosen by the forest.

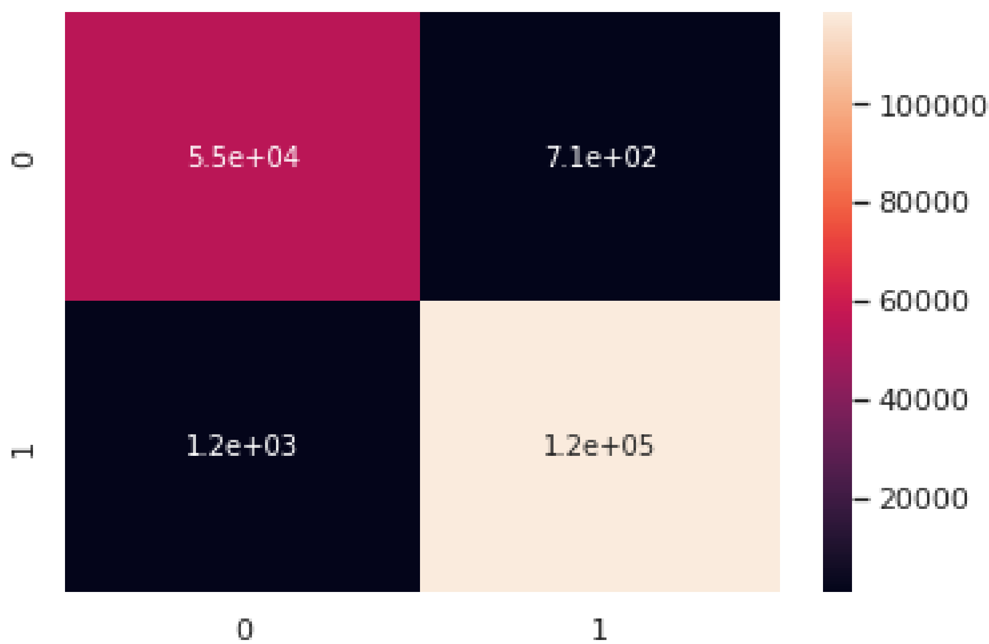
[29]:

```
start = time.time()
from sklearn.tree import DecisionTreeClassifier
clf = DecisionTreeClassifier(random_state=0)
clf.fit(x_train, y_train)

from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score
print ("Train Accuracy :: ", accuracy_score(y_train, clf.predict(x_train)))
print ("Test Accuracy  :: ", accuracy_score(y_test, preds))

#val.append(dec_tree_f)

from sklearn.metrics import classification_report
print(classification_report(y_test, preds))
end = time.time()
```

```
print(end - start)

accTest["Decision Tree"]=accuracy_score(y_test, predTest["Decision Tree"])
accTrain["Decision Tree"]=accuracy_score(y_train, predTrain["Decision Tree"])
predTest["Decision Tree"] = clf.predict(x_test)
predTrain["Decision Tree"] = clf.predict(x_train)
cf_matrix = confusion_matrix(predTrain["Decision Tree"], y_train)
sns.heatmap(cf_matrix, annot=True)
```

```
Train Accuracy ::  0.9890727211547784
Test Accuracy  ::  0.8648642083272604
              precision    recall  f1-score   support

           0       0.93      0.75      0.83     37000
           1       0.83      0.95      0.89     45332

    accuracy                           0.86     82332
   macro avg       0.88      0.85      0.86     82332
weighted avg       0.87      0.86      0.86     82332

1.1983942985534668
```

[29]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d63ee8390>



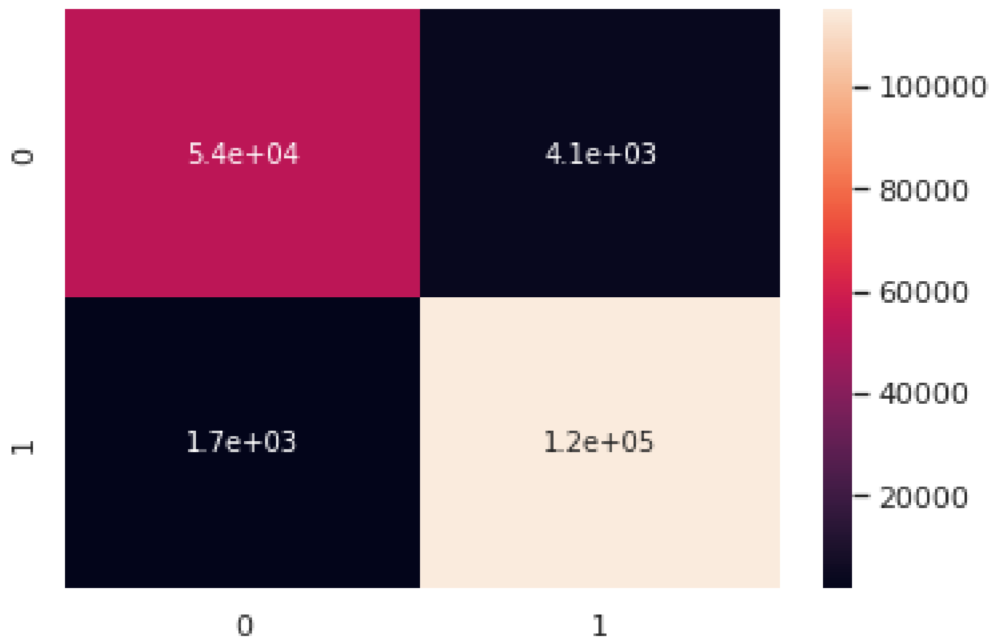
5.2 RandomForest

The Random Forest is a group learning technique for unpruned characterization, relapse, or different undertakings, that comprises of building various choice trees. A bootstrap test of the first information subsets is used to build different choice trees (Forest). Each tree in the forest gives a choice about the class of the new article that should be arranged. The class which acquires the most decisions in favor of the item is chosen by the forest.

[30]:
```
from sklearn.ensemble import RandomForestClassifier
start = time.time()

clf = RandomForestClassifier(n_estimators = 2,random_state=30)
clf.fit(x_train, y_train)

from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score
print ("Train Accuracy :: ", accuracy_score(y_train, clf.predict(x_train)))
print ("Test Accuracy  :: ", accuracy_score(y_test, preds))

from sklearn.metrics import classification_report
print(classification_report(y_test, preds))
end = time.time()
print(end - start)

predTest["Random Forest"] = clf.predict(x_test)
predTrain["Random Forest"] = clf.predict(x_train)
accTest["Random Forest"]=accuracy_score(y_test, predTest["Random Forest"])
accTrain["Random Forest"]=accuracy_score(y_train, predTrain["Random Forest"])
cf_matrix = confusion_matrix(predTrain["Random Forest"], y_train)
sns.heatmap(cf_matrix, annot=True)
```

```
Train Accuracy ::  0.9671554285649107
Test Accuracy  ::  0.8648642083272604
              precision    recall  f1-score   support

           0       0.93      0.75      0.83     37000
           1       0.83      0.95      0.89     45332

    accuracy                           0.86     82332
   macro avg       0.88      0.85      0.86     82332
weighted avg       0.87      0.86      0.86     82332

0.5476417541503906
```

[30]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5d63d93b10>
```



5.3 NaiveBayes

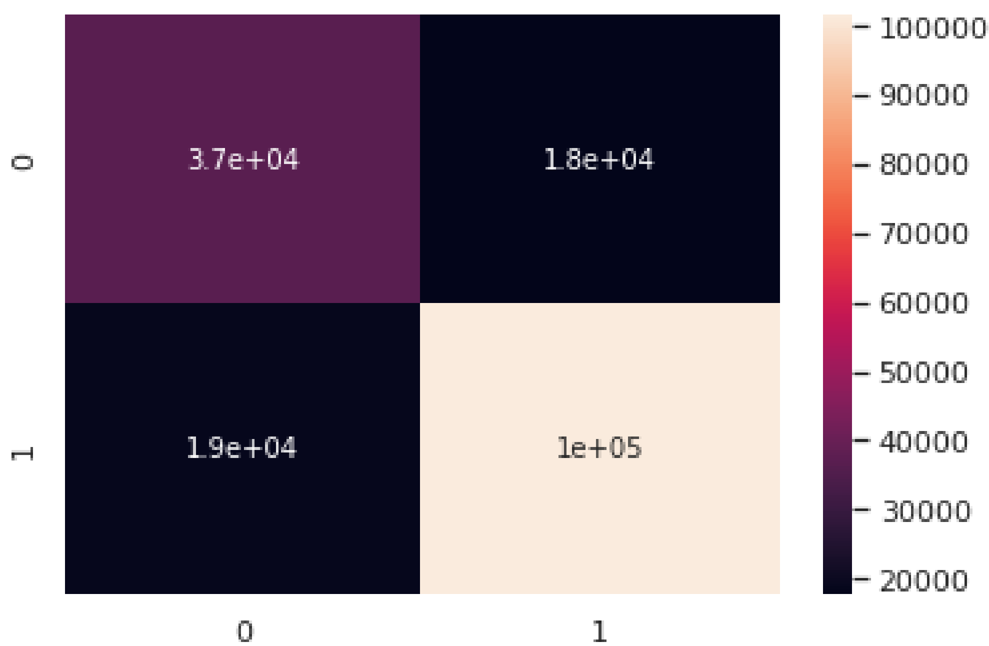
The Naive Bayes calculation is a natural technique that utilizes Bayes rule to process the probabilities of each credit having a place with each class to make a forecast. It rearranges the estimation of probabilities by accepting that the traits are free, given the mark of every single other quality. Various examinations have demonstrated that Naive Bayes calculations were suddenly precise for grouping assignments, but just with little databases. For some bigger databases, the exactness of decision trees was superior to Naive Bayes.

[32]:
```
from sklearn.naive_bayes import GaussianNB

# create Gaussian Naive Bayes model object and train it with the data
n = GaussianNB()

n.fit(x_train, y_train)
preds = n.predict(x_test)

from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score
print ("Train Accuracy :: ", accuracy_score(y_train, n.predict(x_train)))
print ("Test Accuracy  :: ", accuracy_score(y_test, preds))

from sklearn.metrics import classification_report
print(classification_report(y_test, preds))
end = time.time()
print(end - start)
```

```python
predTest["Gaussian Naive Bayes"] = n.predict(x_test)
predTrain["Gaussian Naive Bayes"] = n.predict(x_train)
accTest["Gaussian Naive Bayes"]=accuracy_score(y_test, predTest["Gaussian Naive Bayes"])
accTrain["Gaussian Naive Bayes"]=accuracy_score(y_train, predTrain["Gaussian Naive Bayes"])
cf_matrix = confusion_matrix(predTrain["Gaussian Naive Bayes"], y_train)
sns.heatmap(cf_matrix, annot=True)
```

```
Train Accuracy ::  0.7926383447111628
Test Accuracy  ::  0.7078171306417917
              precision    recall  f1-score   support

           0       0.74      0.54      0.62     37000
           1       0.69      0.85      0.76     45332

    accuracy                           0.71     82332
   macro avg       0.72      0.69      0.69     82332
weighted avg       0.71      0.71      0.70     82332

410.72349190711975
```

[32]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d63c9e9d0>



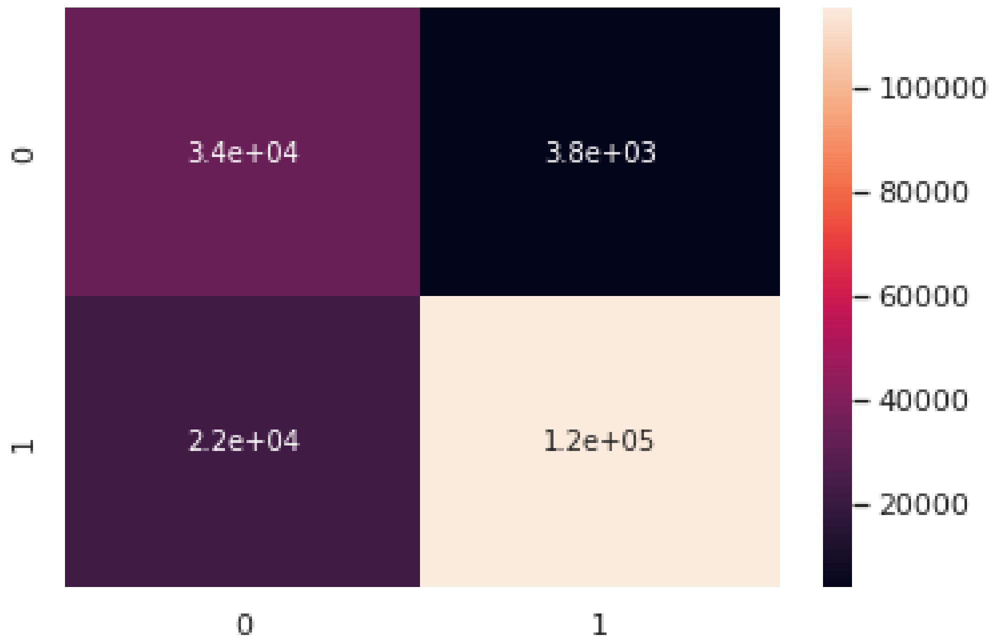
5.4 Logistic Regression

Logistic Regression is a factual strategy for breaking down a dataset in which there are at least one autonomous factors that decide a result. The result is estimated with a dichotomous variable (where there are just two potential results). It is utilized to predict a binary outcome (1/0, Yes/No, True/False) given a lot of autonomous factors. To speak to the binary/categorical results, we utilize sham factors. You can also think of logistic regression as a special case of linear regression when the outcome variable is categorical, where we are using log of odds as dependent variable. In basic words, it predicts the likelihood of event of an occasion by fitting information to a logit work.

[33]:
```
from sklearn.linear_model import LogisticRegression

LR = LogisticRegression(random_state=0, solver='lbfgs',␣
 ↪multi_class='multinomial')
LR.fit(x_train, y_train)
preds = LR.predict(x_test)

from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score
print ("Train Accuracy :: ", accuracy_score(y_train, LR.predict(x_train)))
print ("Test Accuracy  :: ", accuracy_score(y_test, preds))

from sklearn.metrics import classification_report
print(classification_report(y_test, preds))
end = time.time()
print(end - start)

predTest["Logistic Regression"] = LR.predict(x_test)
predTrain["Logistic Regression"] = LR.predict(x_train)
accTest["Logistic Regression"]=accuracy_score(y_test, predTest["Logistic␣
 ↪Regression"])
accTrain["Logistic Regression"]=accuracy_score(y_train, predTrain["Logistic␣
 ↪Regression"])
cf_matrix = confusion_matrix(predTrain["Logistic Regression"], y_train)
sns.heatmap(cf_matrix, annot=True)
```

```
Train Accuracy ::  0.8508506282044701
Test Accuracy  ::  0.7057037360928922
              precision    recall  f1-score   support

           0       0.90      0.39      0.54     37000
           1       0.66      0.96      0.78     45332

    accuracy                           0.71     82332
   macro avg       0.78      0.68      0.66     82332
weighted avg       0.77      0.71      0.68     82332

557.4947443008423
```

[33]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5d63c46610>



5.5 K Nearest Neighbour

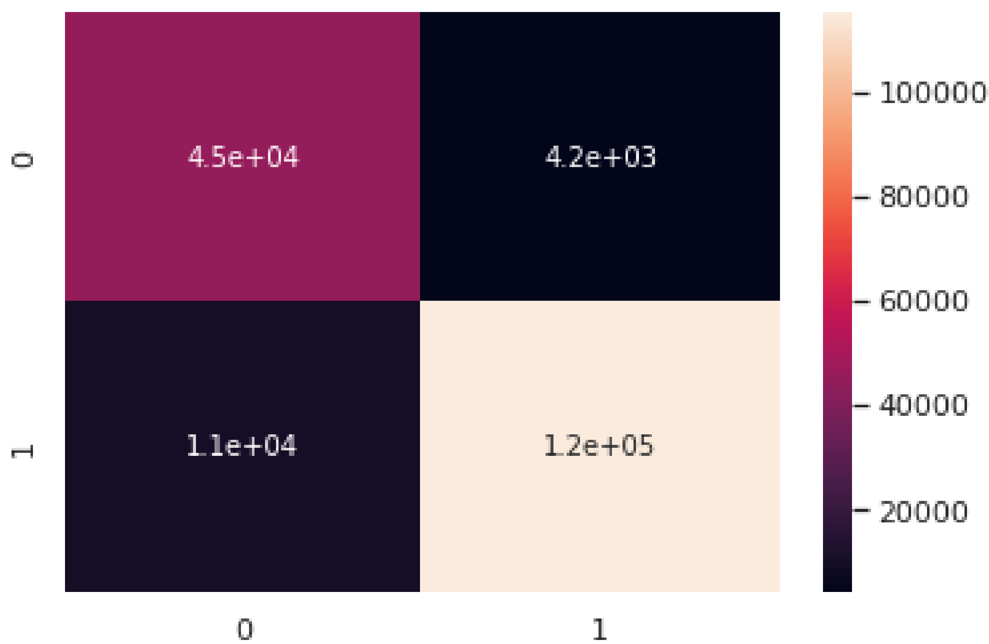
K-closest neighbor calculation (k-NN) is a non-parametric technique utilized for characterization and relapse. In the two cases, the info comprises of the k nearest preparing models in the component space. k-NN is a kind of case-based learning, or lethargic realizing, where the capacity is just approximated locally and all calculation is conceded until work assessment. Both for order and relapse, a valuable strategy can be to allocate loads to the commitments of the neighbors, so that the nearest neighbors contribute more to the normal than the more inaccessible ones.

[34]:
```
from sklearn.neighbors import KNeighborsClassifier

KNN = KNeighborsClassifier()
KNN.fit(x_train, y_train)
preds = KNN.predict(x_test)

from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score
print ("Train Accuracy :: ", accuracy_score(y_train, KNN.predict(x_train)))
print ("Test Accuracy  :: ", accuracy_score(y_test, preds))

from sklearn.metrics import classification_report
print(classification_report(y_test, preds))
end = time.time()
print(end - start)
```

```
predTest["KNN"] = KNN.predict(x_test)
predTrain["KNN"] = KNN.predict(x_train)
accTest["KNN"]=accuracy_score(y_test, predTest["KNN"])
accTrain["KNN"]=accuracy_score(y_train, predTrain["KNN"])
cf_matrix = confusion_matrix(predTrain["KNN"], y_train)
sns.heatmap(cf_matrix, annot=True)
```

```
Train Accuracy ::  0.916094923606002
Test Accuracy  ::  0.7787494534324443
              precision    recall  f1-score   support

           0       0.90      0.57      0.70     37000
           1       0.73      0.95      0.82     45332

    accuracy                           0.78     82332
   macro avg       0.81      0.76      0.76     82332
weighted avg       0.81      0.78      0.77     82332

769.6019361019135
```

[34]: `<matplotlib.axes._subplots.AxesSubplot at 0x7f5d63b66490>`



5.6 ADAboost

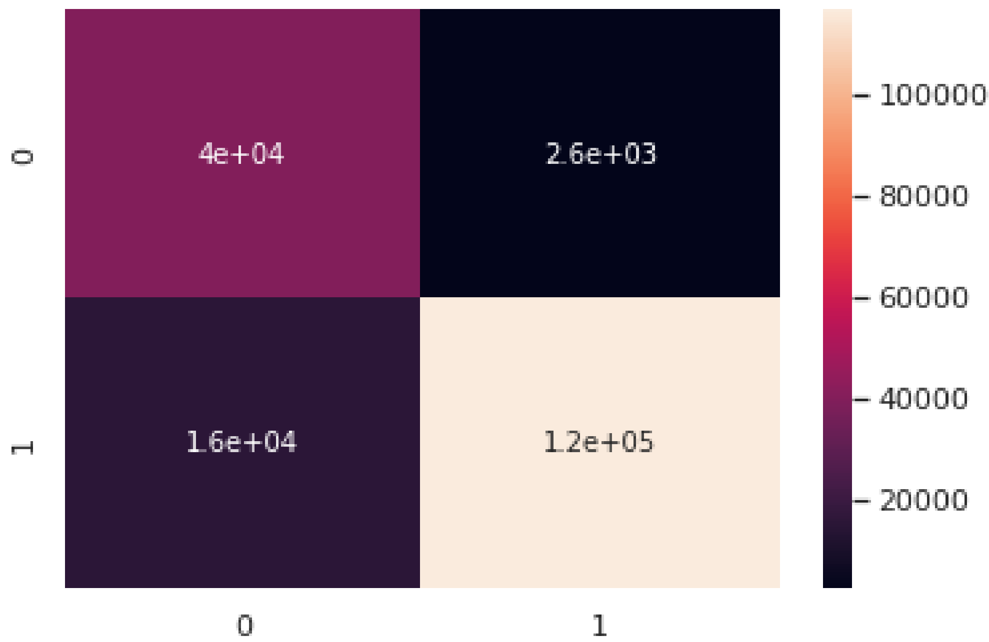
AdaBoost is one of the first boosting calculations to be adjusted in tackling rehearses. Adaboost causes you to join various “frail classifiers” into a solitary “solid classifier”. The frail students in

AdaBoost are choice trees with a solitary split, called choice stumps. AdaBoost works by putting more weight on it hard to arrange examples and less on those effectively taken care of well. AdaBoost calculations can be utilized for both arrangement and relapse issue.

[35]:
```
from sklearn.ensemble import AdaBoostClassifier
ADA = AdaBoostClassifier()

ADA.fit(x_train, y_train)
preds = ADA.predict(x_test)

from sklearn.metrics import accuracy_score, confusion_matrix, roc_auc_score
print ("Train Accuracy :: ", accuracy_score(y_train, ADA.predict(x_train)))
print ("Test Accuracy  :: ", accuracy_score(y_test, preds))

from sklearn.metrics import classification_report
print(classification_report(y_test, preds))
end = time.time()
print(end - start)

predTest["AdaBoostClassifier"] = ADA.predict(x_test)
predTrain["AdaBoostClassifier"] = ADA.predict(x_train)
accTest["AdaBoostClassifier"]=accuracy_score(y_test,␣
 ↪predTest["AdaBoostClassifier"])
accTrain["AdaBoostClassifier"]=accuracy_score(y_train,␣
 ↪predTrain["AdaBoostClassifier"])
cf_matrix = confusion_matrix(predTrain["AdaBoostClassifier"], y_train)
sns.heatmap(cf_matrix, annot=True)
```

```
Train Accuracy ::  0.8956661590842986
Test Accuracy  ::  0.7510081134917165
              precision    recall  f1-score   support

           0       0.93      0.48      0.64     37000
           1       0.70      0.97      0.81     45332

    accuracy                           0.75     82332
   macro avg       0.81      0.73      0.72     82332
weighted avg       0.80      0.75      0.73     82332

995.9182922840118
```

[35]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5d63a8c290>
```



5.7 Artificial Neural Network

Neural networks help us cluster and classify. You can think of them as a clustering and classification layer on top of the data you store and manage. They help to group unlabeled data according to similarities among the example inputs, and they classify data when they have a labeled dataset to train on. (Neural networks can also extract features that are fed to other algorithms for clustering and classification; so you can think of deep neural networks as components of larger machine-learning applications involving algorithms for reinforcement learning, classification and regression). All classification tasks depend upon labeled datasets; that is, humans must transfer their knowledge to the dataset in order for a neural network to learn the correlation between labels and data. This is known as supervised learning.

- Detect faces, identify people in images, recognize facial expressions (angry, joyful)
- Identify objects in images (stop signs, pedestrians, lane markers…)
- Recognize gestures in video
- Detect voices, identify speakers, transcribe speech to text, recognize sentiment in voices
- Classify text as spam (in emails), or fraudulent (in insurance claims); recognize sentiment

Any labels that humans can generate, any outcomes that you care about and which correlate to data, can be used to train a neural network.

Deep learning is the name we use for “stacked neural networks”; that is, networks composed of several layers.

The layers are made of nodes. A node is just a place where computation happens, loosely patterned on a neuron in the human brain, which fires when it encounters sufficient stimuli. A node combines input from the data with a set of coefficients, or weights, that either amplify or dampen that input, thereby assigning significance to inputs with regard to the task the algorithm is trying to learn;

e.g. which input is most helpful is classifying data without error? These input-weight products are summed and then the sum is passed through a node's so-called activation function, to determine whether and to what extent that signal should progress further through the network to affect the ultimate outcome, say, an act of classification. If the signals passes through, the neuron has been "activated."

[47]:
```
x_train
```

[47]:
```
             stcpb       dtcpb         sload          dload          rate  \
0        621772692  2202533631  1.415894e+04    8495.365234     74.087490
1       1417884146  3077387971  8.395112e+03  503571.312500     78.473372
2       2116150707  2963114973  1.572272e+03   60929.230470     14.170161
3       1107119177  1047442890  2.740179e+03    3358.622070     13.677108
4       2436137549  1977154190  8.561499e+03    3987.059814     33.373826
…              …           …            …             …           …
175336           0           0  5.066666e+07       0.000000  111111.107200
175337  3518776216  3453092386  8.826286e+03    4903.492188     33.612649
175338           0           0  5.066666e+07       0.000000  111111.107200
175339           0           0  5.066666e+07       0.000000  111111.107200
175340           0           0  5.066666e+07       0.000000  111111.107200

        dbytes      sinpkt  sbytes  response_body_len          djit
0          172   24.295600     258                  0     11.830604
1        42014   49.915000     734                  0   1387.778330
2        13186  231.875571     364                  0  11420.926230
3          770  152.876547     628                  0   4991.784669
4          268   47.750333     534                  0    115.807000
…          …          …       …                 …           …
175336       0    0.009000     114                  0      0.000000
175337     354   54.400111     620                  0    120.177727
175338       0    0.009000     114                  0      0.000000
175339       0    0.009000     114                  0      0.000000
175340       0    0.009000     114                  0      0.000000

[175341 rows x 10 columns]
```

[51]:
```
from keras.models import Sequential
from keras.layers import Dense

model= Sequential()
model.add(Dense(20,input_dim=10,activation='relu'))
model.add(Dense(10,activation='relu'))
model.add(Dense(1,activation="sigmoid"))
model.compile(loss='binary_crossentropy', optimizer='adam',␣
 ↪metrics=['accuracy'])
```

[54]:
```
model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_10 (Dense)             (None, 20)                220
_________________________________________________________________
dense_11 (Dense)             (None, 10)                210
_________________________________________________________________
dense_12 (Dense)             (None, 1)                 11
=================================================================
Total params: 441
Trainable params: 441
Non-trainable params: 0
_________________________________________________________________
```

[55]:
```python
history = model.fit(x_train,y_train,validation_split = 0.1, epochs=50,␣
 ↪batch_size=64)
```

```
Train on 157806 samples, validate on 17535 samples
Epoch 1/50
157806/157806 [==============================] - 6s 35us/step - loss:
1357343.5117 - accuracy: 0.7725 - val_loss: 94002.5836 - val_accuracy: 0.9266
Epoch 2/50
157806/157806 [==============================] - 6s 40us/step - loss:
227046.0114 - accuracy: 0.7877 - val_loss: 243.4700 - val_accuracy: 0.9989
Epoch 3/50
157806/157806 [==============================] - 4s 28us/step - loss:
216799.3582 - accuracy: 0.7905 - val_loss: 231.8764 - val_accuracy: 0.9983
Epoch 4/50
157806/157806 [==============================] - 4s 28us/step - loss:
173487.1072 - accuracy: 0.7926 - val_loss: 1026.5814 - val_accuracy: 0.9949
Epoch 5/50
157806/157806 [==============================] - 4s 28us/step - loss:
157412.4637 - accuracy: 0.7933 - val_loss: 46448.6223 - val_accuracy: 0.9218
Epoch 6/50
157806/157806 [==============================] - 5s 33us/step - loss:
160664.5923 - accuracy: 0.7950 - val_loss: 155895.7325 - val_accuracy: 0.8709
Epoch 7/50
157806/157806 [==============================] - 4s 27us/step - loss:
131676.4398 - accuracy: 0.7961 - val_loss: 57349.4597 - val_accuracy: 0.9163
Epoch 8/50
157806/157806 [==============================] - 4s 27us/step - loss:
116343.9996 - accuracy: 0.7951 - val_loss: 124548.2707 - val_accuracy: 0.8597
Epoch 9/50
157806/157806 [==============================] - 4s 27us/step - loss:
113455.5466 - accuracy: 0.7929 - val_loss: 53.5679 - val_accuracy: 0.9993
Epoch 10/50
157806/157806 [==============================] - 4s 28us/step - loss:
```

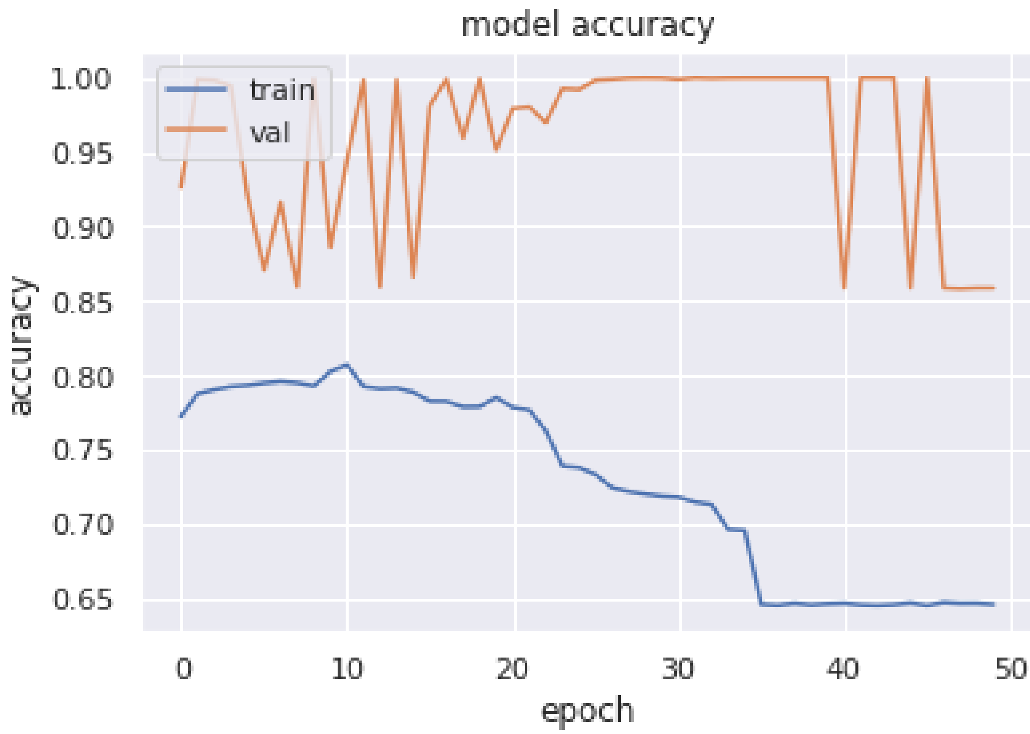
```
104518.6306 - accuracy: 0.8026 - val_loss: 35760.2871 - val_accuracy: 0.8859
Epoch 11/50
157806/157806 [==============================] - 5s 31us/step - loss: 87340.6098
- accuracy: 0.8070 - val_loss: 6209.9588 - val_accuracy: 0.9448
Epoch 12/50
157806/157806 [==============================] - 4s 27us/step - loss: 78993.9703
- accuracy: 0.7926 - val_loss: 154.1442 - val_accuracy: 0.9984
Epoch 13/50
157806/157806 [==============================] - 5s 29us/step - loss: 77823.2216
- accuracy: 0.7912 - val_loss: 104688.7802 - val_accuracy: 0.8594
Epoch 14/50
157806/157806 [==============================] - 4s 27us/step - loss: 62147.4300
- accuracy: 0.7917 - val_loss: 42.9813 - val_accuracy: 0.9986
Epoch 15/50
157806/157806 [==============================] - 4s 27us/step - loss: 50510.1973
- accuracy: 0.7888 - val_loss: 84415.3039 - val_accuracy: 0.8662
Epoch 16/50
157806/157806 [==============================] - 5s 29us/step - loss: 47856.2241
- accuracy: 0.7827 - val_loss: 510.9101 - val_accuracy: 0.9813
Epoch 17/50
157806/157806 [==============================] - 5s 29us/step - loss: 33560.5197
- accuracy: 0.7826 - val_loss: 33.4490 - val_accuracy: 0.9992
Epoch 18/50
157806/157806 [==============================] - 5s 29us/step - loss: 27992.2542
- accuracy: 0.7790 - val_loss: 88.7285 - val_accuracy: 0.9594
Epoch 19/50
157806/157806 [==============================] - 5s 29us/step - loss: 21757.4419
- accuracy: 0.7791 - val_loss: 20.3670 - val_accuracy: 0.9994
Epoch 20/50
157806/157806 [==============================] - 4s 28us/step - loss: 14699.3533
- accuracy: 0.7852 - val_loss: 372.5457 - val_accuracy: 0.9514
Epoch 21/50
157806/157806 [==============================] - 4s 27us/step - loss: 10154.7069
- accuracy: 0.7786 - val_loss: 599.2376 - val_accuracy: 0.9794
Epoch 22/50
157806/157806 [==============================] - 4s 28us/step - loss: 9293.0158
- accuracy: 0.7768 - val_loss: 276.5713 - val_accuracy: 0.9805
Epoch 23/50
157806/157806 [==============================] - 4s 28us/step - loss: 5552.7504
- accuracy: 0.7629 - val_loss: 624.3293 - val_accuracy: 0.9698
Epoch 24/50
157806/157806 [==============================] - 5s 29us/step - loss: 4030.4532
- accuracy: 0.7391 - val_loss: 45.0778 - val_accuracy: 0.9928
Epoch 25/50
157806/157806 [==============================] - 4s 28us/step - loss: 2745.5356
- accuracy: 0.7381 - val_loss: 79.1293 - val_accuracy: 0.9922
Epoch 26/50
157806/157806 [==============================] - 4s 28us/step - loss: 1351.2800
```

```
- accuracy: 0.7334 - val_loss: 16.2092 - val_accuracy: 0.9985
Epoch 27/50
157806/157806 [==============================] - 4s 28us/step - loss: 532.7739 -
accuracy: 0.7245 - val_loss: 0.2886 - val_accuracy: 0.9990
Epoch 28/50
157806/157806 [==============================] - 4s 27us/step - loss: 38.4355 -
accuracy: 0.7220 - val_loss: 0.2681 - val_accuracy: 0.9998
Epoch 29/50
157806/157806 [==============================] - 5s 32us/step - loss: 1.9566 -
accuracy: 0.7203 - val_loss: 0.2142 - val_accuracy: 1.0000
Epoch 30/50
157806/157806 [==============================] - 5s 31us/step - loss: 1.5093 -
accuracy: 0.7189 - val_loss: 0.3360 - val_accuracy: 0.9999
Epoch 31/50
157806/157806 [==============================] - 4s 28us/step - loss: 2.9930 -
accuracy: 0.7182 - val_loss: 3.0848 - val_accuracy: 0.9990
Epoch 32/50
157806/157806 [==============================] - 4s 27us/step - loss: 2.6548 -
accuracy: 0.7149 - val_loss: 0.1944 - val_accuracy: 1.0000
Epoch 33/50
157806/157806 [==============================] - 4s 28us/step - loss: 1.5009 -
accuracy: 0.7133 - val_loss: 0.8182 - val_accuracy: 0.9997
Epoch 34/50
157806/157806 [==============================] - 5s 29us/step - loss: 1.1348 -
accuracy: 0.6965 - val_loss: 0.2801 - val_accuracy: 0.9999
Epoch 35/50
157806/157806 [==============================] - 4s 28us/step - loss: 0.7090 -
accuracy: 0.6958 - val_loss: 0.2314 - val_accuracy: 1.0000
Epoch 36/50
157806/157806 [==============================] - 4s 28us/step - loss: 0.6155 -
accuracy: 0.6462 - val_loss: 0.2991 - val_accuracy: 1.0000
Epoch 37/50
157806/157806 [==============================] - 4s 28us/step - loss: 0.6330 -
accuracy: 0.6455 - val_loss: 0.3068 - val_accuracy: 1.0000
Epoch 38/50
157806/157806 [==============================] - 4s 28us/step - loss: 0.6018 -
accuracy: 0.6469 - val_loss: 0.3030 - val_accuracy: 1.0000
Epoch 39/50
157806/157806 [==============================] - 4s 28us/step - loss: 0.6018 -
accuracy: 0.6458 - val_loss: 0.3047 - val_accuracy: 1.0000
Epoch 40/50
157806/157806 [==============================] - 4s 27us/step - loss: 0.6158 -
accuracy: 0.6465 - val_loss: 0.3060 - val_accuracy: 1.0000
Epoch 41/50
157806/157806 [==============================] - 4s 27us/step - loss: 1.2308 -
accuracy: 0.6469 - val_loss: 0.3182 - val_accuracy: 0.8587
Epoch 42/50
157806/157806 [==============================] - 4s 27us/step - loss: 0.6020 -
```

```
accuracy: 0.6458 - val_loss: 0.3031 - val_accuracy: 1.0000
Epoch 43/50
157806/157806 [==============================] - 4s 27us/step - loss: 0.6014 -
accuracy: 0.6455 - val_loss: 0.3076 - val_accuracy: 1.0000
Epoch 44/50
157806/157806 [==============================] - 4s 28us/step - loss: 0.6018 -
accuracy: 0.6459 - val_loss: 0.3069 - val_accuracy: 1.0000
Epoch 45/50
157806/157806 [==============================] - 4s 27us/step - loss: 0.6025 -
accuracy: 0.6472 - val_loss: 0.3089 - val_accuracy: 0.8587
Epoch 46/50
157806/157806 [==============================] - 4s 27us/step - loss: 0.6017 -
accuracy: 0.6454 - val_loss: 0.3071 - val_accuracy: 1.0000
Epoch 47/50
157806/157806 [==============================] - 4s 27us/step - loss: 0.6085 -
accuracy: 0.6475 - val_loss: 0.3179 - val_accuracy: 0.8587
Epoch 48/50
157806/157806 [==============================] - 4s 28us/step - loss: 0.6015 -
accuracy: 0.6468 - val_loss: 0.3105 - val_accuracy: 0.8583
Epoch 49/50
157806/157806 [==============================] - 4s 27us/step - loss: 0.6013 -
accuracy: 0.6469 - val_loss: 0.3133 - val_accuracy: 0.8587
Epoch 50/50
157806/157806 [==============================] - 4s 27us/step - loss: 0.6013 -
accuracy: 0.6461 - val_loss: 0.3070 - val_accuracy: 0.8587
```

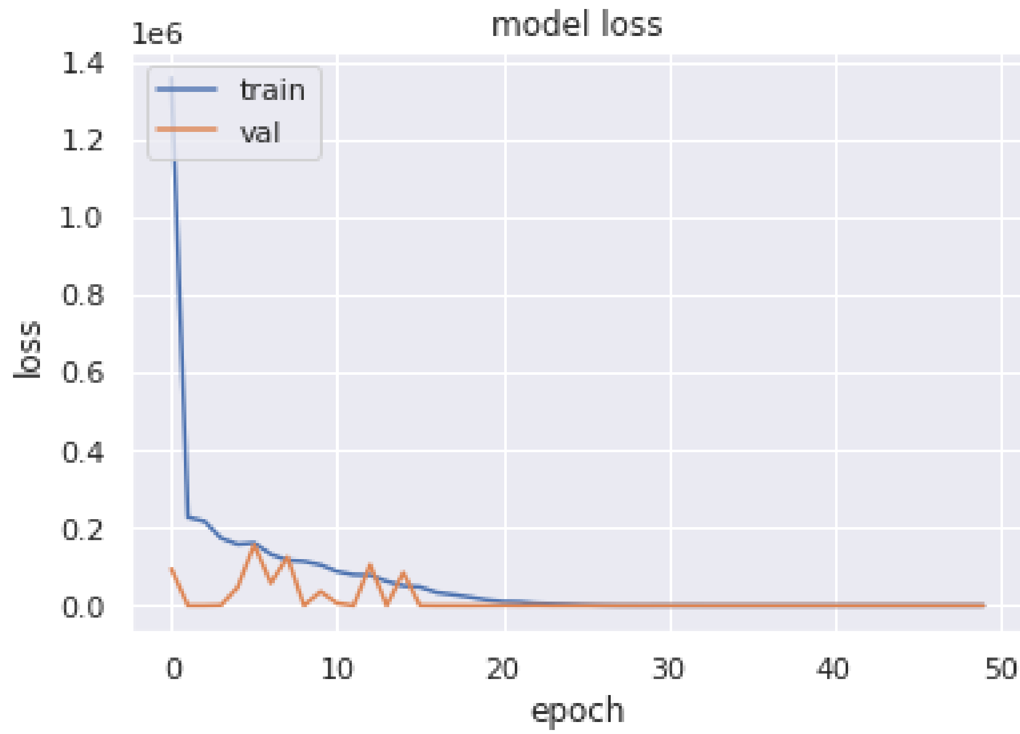
[61]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



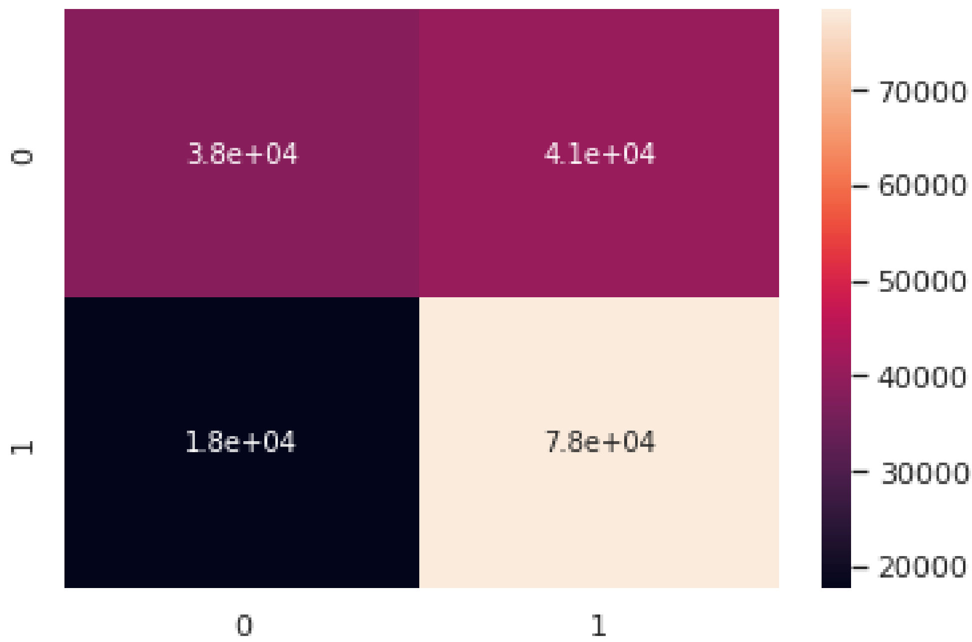
[62]:

```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



[74]:
```
predTest["Artificial Neural Network"] = model.predict_classes(x_test).
 ↪reshape(82332)
predTrain["Artificial Neural Network"] = model.predict_classes(x_train).
 ↪reshape(175341)
accTest["Artificial Neural Network"]=accuracy_score(y_test,␣
 ↪predTest["Artificial Neural Network"])
accTrain["Artificial Neural Network"]=accuracy_score(y_train,␣
 ↪predTrain["Artificial Neural Network"])
cf_matrix = confusion_matrix(predTrain["Artificial Neural Network"], y_train)
sns.heatmap(cf_matrix, annot=True)
```

[74]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5c8c102e50>
```



6 Ensemble Stacking

[81]:
```
n_train=pd.DataFrame(np.hstack([x_train.values,pd.DataFrame.
 ↪from_dict(predTrain).values]))
n_test=pd.DataFrame(np.hstack([x_test.values,pd.DataFrame.from_dict(predTest).
 ↪values]))
```

[82]:
```
n_train
```

[82]:
```
                   0             1             2              3  \
0       6.217727e+08  2.202534e+09  1.415894e+04    8495.365234
1       1.417884e+09  3.077388e+09  8.395112e+03  503571.312500
2       2.116151e+09  2.963115e+09  1.572272e+03   60929.230470
3       1.107119e+09  1.047443e+09  2.740179e+03    3358.622070
4       2.436138e+09  1.977154e+09  8.561499e+03    3987.059814
…                …             …             …              …
175336  0.000000e+00  0.000000e+00  5.066666e+07       0.000000
175337  3.518776e+09  3.453092e+09  8.826286e+03    4903.492188
175338  0.000000e+00  0.000000e+00  5.066666e+07       0.000000
175339  0.000000e+00  0.000000e+00  5.066666e+07       0.000000
175340  0.000000e+00  0.000000e+00  5.066666e+07       0.000000

                4      5          6      7    8          9   10  \
0       74.087490  172.0  24.295600  258.0  0.0  11.830604  0.0
```

```
1          78.473372  42014.0   49.915000  734.0  0.0   1387.778330  0.0
2          14.170161  13186.0  231.875571  364.0  0.0  11420.926230  0.0
3          13.677108    770.0  152.876547  628.0  0.0   4991.784669  0.0
4          33.373826    268.0   47.750333  534.0  0.0    115.807000  0.0
…                …        …           …      …    …            …    …
175336  111111.107200      0.0    0.009000  114.0  0.0      0.000000  1.0
175337      33.612649    354.0   54.400111  620.0  0.0    120.177727  1.0
175338  111111.107200      0.0    0.009000  114.0  0.0      0.000000  1.0
175339  111111.107200      0.0    0.009000  114.0  0.0      0.000000  1.0
175340  111111.107200      0.0    0.009000  114.0  0.0      0.000000  1.0

         11   12   13   14   15   16
0       0.0  1.0  1.0  1.0  1.0  0.0
1       0.0  0.0  0.0  1.0  1.0  0.0
2       0.0  0.0  1.0  0.0  0.0  0.0
3       0.0  1.0  1.0  0.0  1.0  0.0
4       0.0  1.0  1.0  1.0  1.0  0.0
…      …    …    …    …    …    …
175336  1.0  1.0  1.0  1.0  1.0  1.0
175337  1.0  0.0  1.0  1.0  1.0  0.0
175338  1.0  1.0  1.0  1.0  1.0  1.0
175339  1.0  1.0  1.0  1.0  1.0  1.0
175340  1.0  1.0  1.0  1.0  1.0  1.0

[175341 rows x 17 columns]
```

[106]:

```
model= Sequential()
model.add(Dense(17,input_dim=17,activation='relu'))
model.add(Dense(15,activation='relu'))
model.add(Dense(1,activation="sigmoid"))
model.compile(loss='binary_crossentropy', optimizer='adam',
 ↪metrics=['accuracy'])
```

[107]:

```
model.summary()
```

```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_39 (Dense)             (None, 17)                306
_________________________________________________________________
dense_40 (Dense)             (None, 15)                270
_________________________________________________________________
dense_41 (Dense)             (None, 1)                 16
=================================================================
Total params: 592
Trainable params: 592
```

```
Non-trainable params: 0
_________________________________________________________________
```

[108]:
```
history = model.fit(n_train,y_train,validation_split = 0.1, epochs=50,␣
 ↪batch_size=128)
```

```
Train on 157806 samples, validate on 17535 samples
Epoch 1/50
157806/157806 [==============================] - 2s 14us/step - loss:
1519272.4183 - accuracy: 0.7168 - val_loss: 1775.4721 - val_accuracy: 0.9944
Epoch 2/50
157806/157806 [==============================] - 2s 15us/step - loss:
378333.2700 - accuracy: 0.7660 - val_loss: 151.4455 - val_accuracy: 0.9979
Epoch 3/50
157806/157806 [==============================] - 2s 14us/step - loss:
383045.8060 - accuracy: 0.7723 - val_loss: 266808.7953 - val_accuracy: 0.8880
Epoch 4/50
157806/157806 [==============================] - 2s 14us/step - loss:
397046.5836 - accuracy: 0.7817 - val_loss: 73078.9054 - val_accuracy: 0.8799
Epoch 5/50
157806/157806 [==============================] - 2s 14us/step - loss:
381345.9650 - accuracy: 0.7862 - val_loss: 93.4020 - val_accuracy: 0.9990
Epoch 6/50
157806/157806 [==============================] - 2s 14us/step - loss:
358636.3586 - accuracy: 0.7944 - val_loss: 59567.4978 - val_accuracy: 0.1675
Epoch 7/50
157806/157806 [==============================] - 2s 14us/step - loss:
366293.6062 - accuracy: 0.7904 - val_loss: 60235.3163 - val_accuracy: 0.9100
Epoch 8/50
157806/157806 [==============================] - 2s 15us/step - loss:
373588.1302 - accuracy: 0.7935 - val_loss: 177887.4370 - val_accuracy: 0.8961
Epoch 9/50
157806/157806 [==============================] - 2s 14us/step - loss:
327258.0113 - accuracy: 0.7951 - val_loss: 262.4428 - val_accuracy: 0.9992
Epoch 10/50
157806/157806 [==============================] - 2s 14us/step - loss:
369729.3574 - accuracy: 0.7935 - val_loss: 654956.1933 - val_accuracy: 0.0358
Epoch 11/50
157806/157806 [==============================] - 2s 15us/step - loss:
366590.8445 - accuracy: 0.7909 - val_loss: 517722.3033 - val_accuracy: 0.8587
Epoch 12/50
157806/157806 [==============================] - 2s 14us/step - loss:
325018.4150 - accuracy: 0.7946 - val_loss: 249665.2095 - val_accuracy: 0.8469
Epoch 13/50
157806/157806 [==============================] - 2s 14us/step - loss:
377513.3108 - accuracy: 0.7893 - val_loss: 2208.8762 - val_accuracy: 0.9853
Epoch 14/50
157806/157806 [==============================] - 2s 14us/step - loss:
```

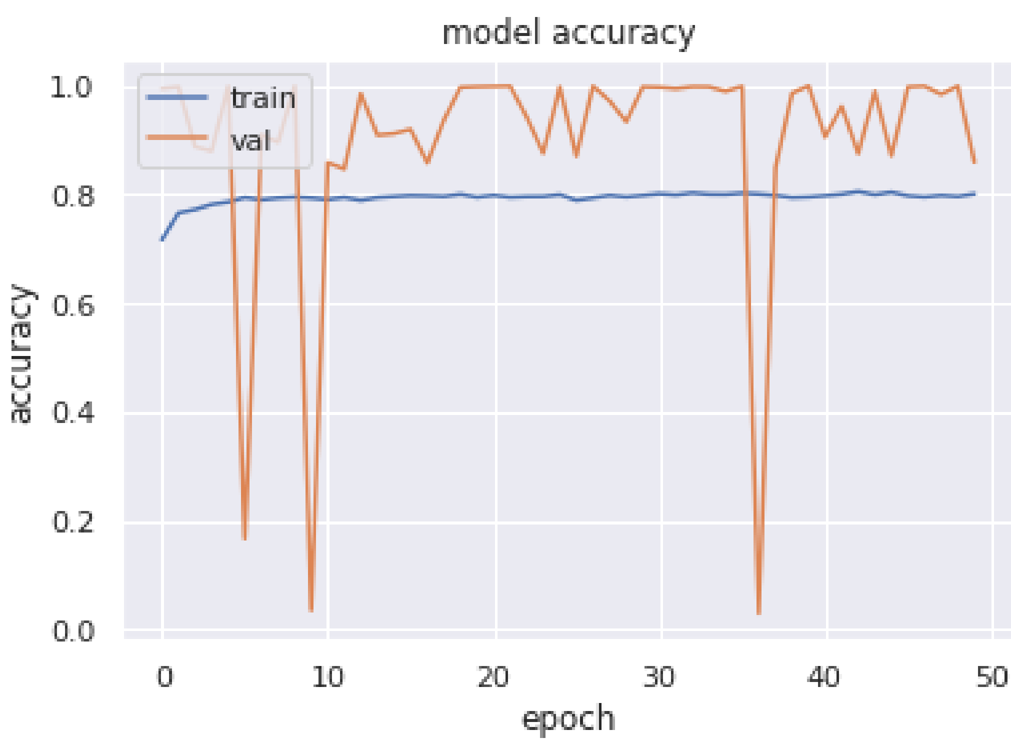
```
336039.1357 - accuracy: 0.7943 - val_loss: 98779.6809 - val_accuracy: 0.9093
Epoch 15/50
157806/157806 [==============================] - 2s 14us/step - loss:
336396.8509 - accuracy: 0.7962 - val_loss: 287953.0910 - val_accuracy: 0.9121
Epoch 16/50
157806/157806 [==============================] - 2s 14us/step - loss:
304401.4584 - accuracy: 0.7979 - val_loss: 60576.9164 - val_accuracy: 0.9200
Epoch 17/50
157806/157806 [==============================] - 2s 14us/step - loss:
315144.1274 - accuracy: 0.7973 - val_loss: 825827.7073 - val_accuracy: 0.8579
Epoch 18/50
157806/157806 [==============================] - 2s 14us/step - loss:
337667.2832 - accuracy: 0.7963 - val_loss: 27266.2760 - val_accuracy: 0.9368
Epoch 19/50
157806/157806 [==============================] - 2s 14us/step - loss:
278334.1925 - accuracy: 0.8004 - val_loss: 1553.2582 - val_accuracy: 0.9969
Epoch 20/50
157806/157806 [==============================] - 2s 14us/step - loss:
322735.4952 - accuracy: 0.7949 - val_loss: 907.6930 - val_accuracy: 0.9980
Epoch 21/50
157806/157806 [==============================] - 2s 14us/step - loss:
271581.1872 - accuracy: 0.7984 - val_loss: 700.9577 - val_accuracy: 0.9985
Epoch 22/50
157806/157806 [==============================] - 2s 14us/step - loss:
306123.4592 - accuracy: 0.7948 - val_loss: 472.4788 - val_accuracy: 0.9990
Epoch 23/50
157806/157806 [==============================] - 2s 14us/step - loss:
303980.0323 - accuracy: 0.7960 - val_loss: 25443.5301 - val_accuracy: 0.9426
Epoch 24/50
157806/157806 [==============================] - 2s 14us/step - loss:
289061.9285 - accuracy: 0.7962 - val_loss: 129512.0608 - val_accuracy: 0.8761
Epoch 25/50
157806/157806 [==============================] - 2s 15us/step - loss:
241789.1069 - accuracy: 0.7996 - val_loss: 1040.2992 - val_accuracy: 0.9978
Epoch 26/50
157806/157806 [==============================] - 2s 14us/step - loss:
278669.9291 - accuracy: 0.7894 - val_loss: 255489.0372 - val_accuracy: 0.8701
Epoch 27/50
157806/157806 [==============================] - 2s 14us/step - loss:
275004.8194 - accuracy: 0.7937 - val_loss: 150.6381 - val_accuracy: 0.9993
Epoch 28/50
157806/157806 [==============================] - 2s 14us/step - loss:
235094.2011 - accuracy: 0.7983 - val_loss: 6421.7558 - val_accuracy: 0.9720
Epoch 29/50
157806/157806 [==============================] - 2s 14us/step - loss:
259503.0248 - accuracy: 0.7954 - val_loss: 33876.6931 - val_accuracy: 0.9339
Epoch 30/50
157806/157806 [==============================] - 2s 14us/step - loss:
```

```
269665.5918 - accuracy: 0.7982 - val_loss: 974.8110 - val_accuracy: 0.9977
Epoch 31/50
157806/157806 [==============================] - 2s 14us/step - loss:
216044.4176 - accuracy: 0.8013 - val_loss: 1564.7002 - val_accuracy: 0.9970
Epoch 32/50
157806/157806 [==============================] - 2s 14us/step - loss:
251305.5052 - accuracy: 0.7991 - val_loss: 1361.9296 - val_accuracy: 0.9944
Epoch 33/50
157806/157806 [==============================] - 2s 15us/step - loss:
232035.1414 - accuracy: 0.8027 - val_loss: 735.2947 - val_accuracy: 0.9981
Epoch 34/50
157806/157806 [==============================] - 2s 14us/step - loss:
225352.4820 - accuracy: 0.8003 - val_loss: 688.0004 - val_accuracy: 0.9978
Epoch 35/50
157806/157806 [==============================] - 2s 14us/step - loss:
219693.2403 - accuracy: 0.8001 - val_loss: 2871.7402 - val_accuracy: 0.9894
Epoch 36/50
157806/157806 [==============================] - 2s 14us/step - loss:
206188.7970 - accuracy: 0.8022 - val_loss: 217.8162 - val_accuracy: 0.9988
Epoch 37/50
157806/157806 [==============================] - 2s 14us/step - loss:
203878.5412 - accuracy: 0.8007 - val_loss: 214280.3802 - val_accuracy: 0.0298
Epoch 38/50
157806/157806 [==============================] - 2s 14us/step - loss:
189413.3603 - accuracy: 0.7982 - val_loss: 122060.4407 - val_accuracy: 0.8490
Epoch 39/50
157806/157806 [==============================] - 2s 14us/step - loss:
204575.8320 - accuracy: 0.7944 - val_loss: 3125.1201 - val_accuracy: 0.9860
Epoch 40/50
157806/157806 [==============================] - 2s 15us/step - loss:
195515.5716 - accuracy: 0.7953 - val_loss: 85.3298 - val_accuracy: 0.9996
Epoch 41/50
157806/157806 [==============================] - 3s 17us/step - loss:
177927.6732 - accuracy: 0.7977 - val_loss: 36447.5983 - val_accuracy: 0.9061
Epoch 42/50
157806/157806 [==============================] - 2s 15us/step - loss:
175025.6686 - accuracy: 0.8005 - val_loss: 14670.5172 - val_accuracy: 0.9620
Epoch 43/50
157806/157806 [==============================] - 2s 15us/step - loss:
146465.4603 - accuracy: 0.8053 - val_loss: 117810.9430 - val_accuracy: 0.8752
Epoch 44/50
157806/157806 [==============================] - 2s 16us/step - loss:
188736.0756 - accuracy: 0.7996 - val_loss: 2485.5765 - val_accuracy: 0.9897
Epoch 45/50
157806/157806 [==============================] - 2s 15us/step - loss:
143765.2867 - accuracy: 0.8041 - val_loss: 58284.2818 - val_accuracy: 0.8709
Epoch 46/50
157806/157806 [==============================] - 2s 15us/step - loss:
```

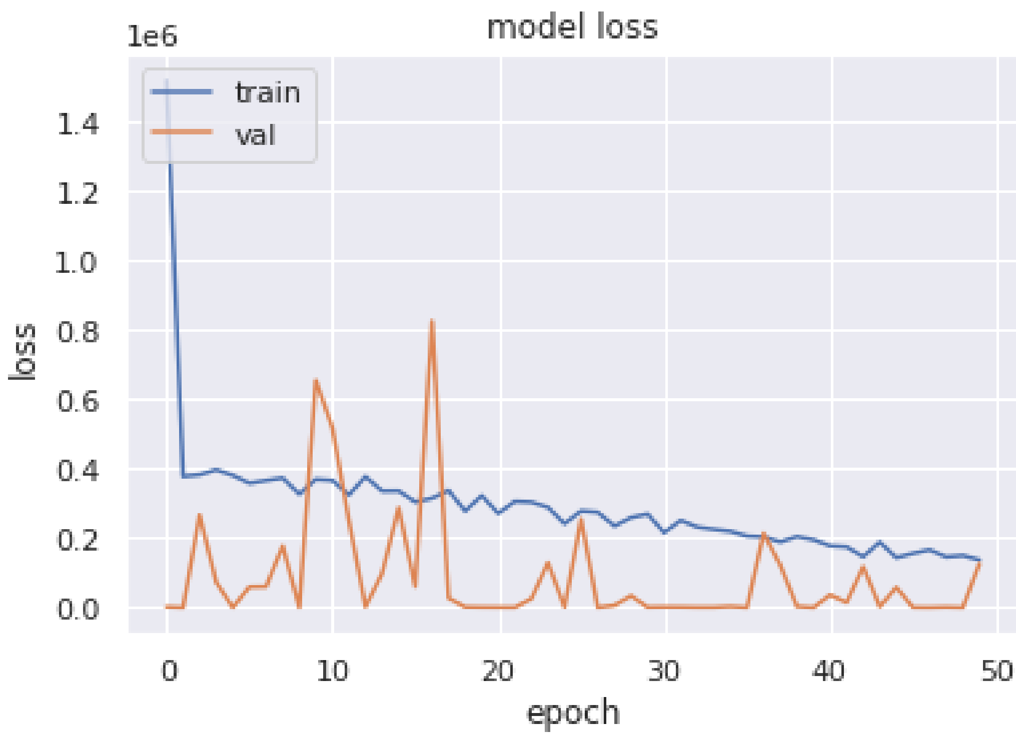
```
156059.9630 - accuracy: 0.7975 - val_loss: 540.7167 - val_accuracy: 0.9978
Epoch 47/50
157806/157806 [==============================] - 2s 14us/step - loss:
166391.4653 - accuracy: 0.7953 - val_loss: 168.3983 - val_accuracy: 0.9990
Epoch 48/50
157806/157806 [==============================] - 2s 15us/step - loss:
146112.5853 - accuracy: 0.7982 - val_loss: 1150.8676 - val_accuracy: 0.9841
Epoch 49/50
157806/157806 [==============================] - 2s 15us/step - loss:
149977.1410 - accuracy: 0.7962 - val_loss: 141.7819 - val_accuracy: 0.9992
Epoch 50/50
157806/157806 [==============================] - 2s 15us/step - loss:
137454.2757 - accuracy: 0.8010 - val_loss: 126440.1731 - val_accuracy: 0.8594
```

[110]:

```
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```

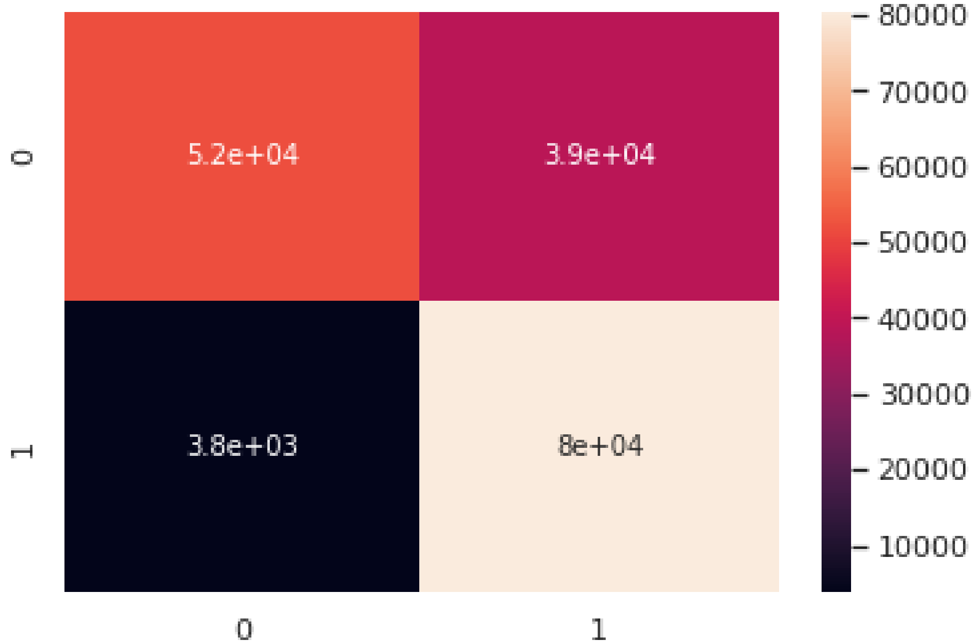


[111]:
```
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'val'], loc='upper left')
plt.show()
```



[112]:
```
predTest["Ensemble Stacking"] = model.predict_classes(n_test).reshape(82332)
predTrain["Ensemble Stacking"] = model.predict_classes(n_train).reshape(175341)
accTest["Ensemble Stacking"]=accuracy_score(y_test, predTest["Ensemble␣
 ↪Stacking"])
accTrain["Ensemble Stacking"]=accuracy_score(y_train, predTrain["Ensemble␣
 ↪Stacking"])
cf_matrix = confusion_matrix(predTrain["Ensemble Stacking"], y_train)
sns.heatmap(cf_matrix, annot=True)
```

[112]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5bf4390690>



7 Result Analysis

[116]:
```
#Model Accuracy Graph
for i in accTrain:
    print("The Train accuracy acheived using ",i," is: ",(accTrain[i])*100,"%")
    print("The Test  accuracy acheived using ",i," is:␣
 ↪",(accTest[i])*100,"%","\n")
```

```
The Train accuracy acheived using  Decision Tree  is:  98.90727211547784 %
The Test  accuracy acheived using  Decision Tree  is:  86.48642083272604 %

The Train accuracy acheived using  Random Forest  is:  96.71554285649107 %
The Test  accuracy acheived using  Random Forest  is:  87.39250838070251 %

The Train accuracy acheived using  Gaussian Naive Bayes  is:  79.26383447111628
%
The Test  accuracy acheived using  Gaussian Naive Bayes  is:  70.78171306417917
%

The Train accuracy acheived using  Logistic Regression  is:  85.085062820447 %
The Test  accuracy acheived using  Logistic Regression  is:  70.57037360928922 %

The Train accuracy acheived using  KNN  is:  91.6094923606002 %
The Test  accuracy acheived using  KNN  is:  77.87494534324443 %
```

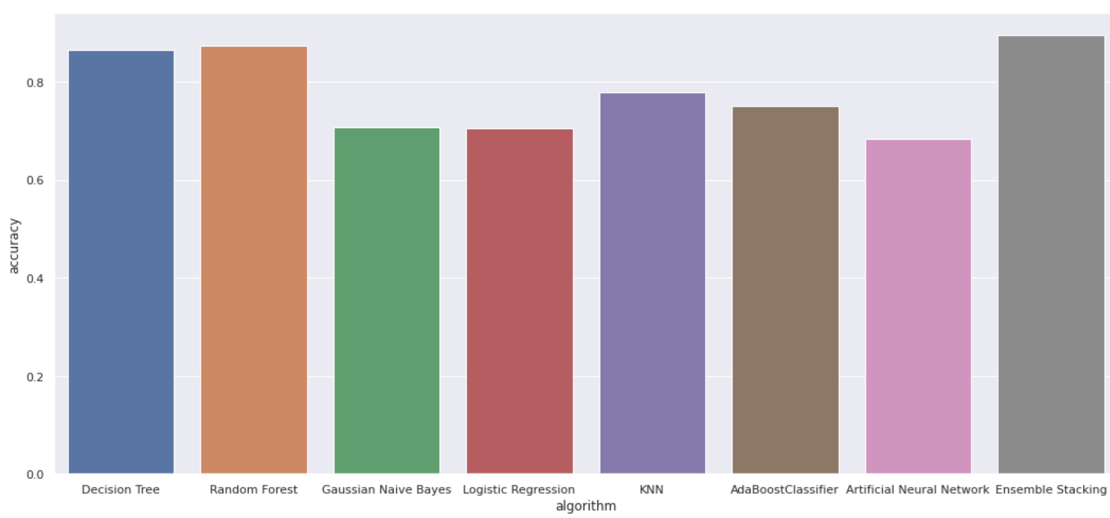
```
The Train accuracy acheived using  AdaBoostClassifier  is:  89.56661590842985 %
The Test  accuracy acheived using  AdaBoostClassifier  is:  75.10081134917165 %

The Train accuracy acheived using  Artificial Neural Network  is:
66.63073667881443 %
The Test  accuracy acheived using  Artificial Neural Network  is:
68.37074284603798 %

The Train accuracy acheived using  Ensemble Stacking  is:  87.186321952726 %
The Test  accuracy acheived using  Ensemble Stacking  is:  89.486420832726 %
```

[122]:
```
list(accTrain.keys())
```

[122]:
```
['Decision Tree',
 'Random Forest',
 'Gaussian Naive Bayes',
 'Logistic Regression',
 'KNN',
 'AdaBoostClassifier',
 'Artificial Neural Network',
 'Ensemble Stacking']
```

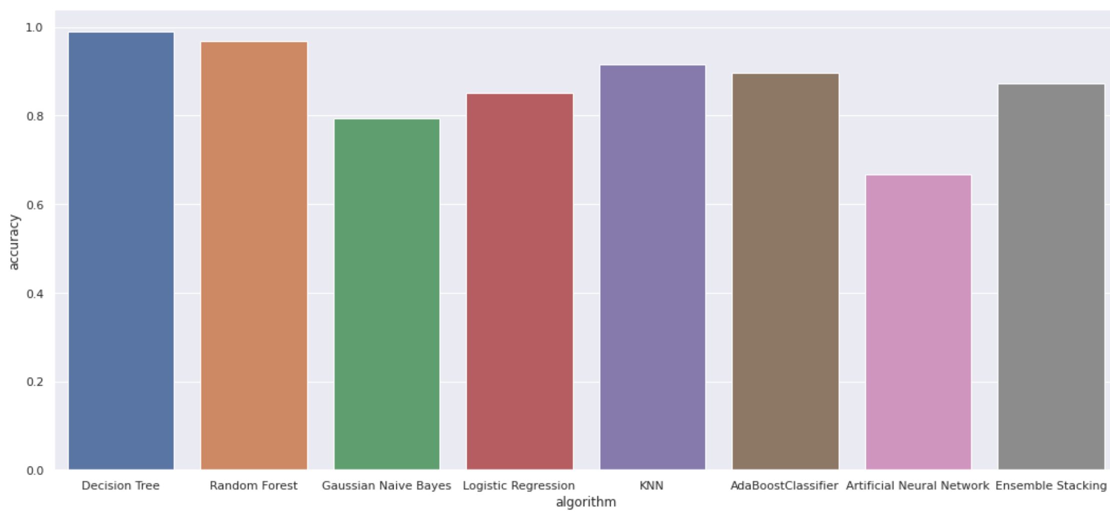
[127]:
```
sns.set(rc={'figure.figsize':(18,8)})
plt.xlabel("algorithm")
plt.ylabel("accuracy")
sns.barplot(list(accTest.keys()),list(accTest.values()))
```

[127]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5bf407e810>
```



[126]:
```
sns.set(rc={'figure.figsize':(18,8)})
plt.xlabel("algorithm")
plt.ylabel("accuracy")
sns.barplot(list(accTrain.keys()),list(accTrain.values()))
```

[126]: <matplotlib.axes._subplots.AxesSubplot at 0x7f5bf4177e50>



8 Result analysis and Conclusion

We started using simple machine learning algorithms on the dataset to check how well they performed before going for ensemble methods. ### The following algorithms were used: 1. Logistic Regression: It is a statistical model that uses a logistic function to model a binary dependent variable. 2. MultinomialNB: This algorithm implements the naive Bayes algorithm for multinomially distributed data, and is one of the two classic naive Bayes variants used in text classification (where the data are typically represented as word vector counts, although tf-idf vectors are also known to work well in practice). 3. KNN Classifier: In k-NN classification, the output is a class membership. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its k nearest neighbors (k is a positive integer, typically small). If k = 1, then the object is simply assigned to the class of that single nearest neighbor. 4. Decision Tree Classifier: A Decision Tree is a simple representation for classifying examples. It is a Supervised Machine Learning where the data is continuously split according to a certain parameter. 5. Neural network: Neural networks are a set of algorithms, modeled loosely after the human brain, that are designed to recognize patterns. They interpret sensory data through a kind of machine perception, labeling or clustering raw input. The patterns they recognize are numerical, contained in vectors, into which all real-world data, be it images, sound, text or time series, must be translated.

8.0.1 The next two algorithms used are ensemble methods:

1. Random Forest Classifier: random decision forests are an ensemble learning method for classification, regression and other tasks that operate by constructing a multitude of decision

trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.
2. AdaBoost Classifier : It combines multiple classifiers to increase the accuracy of classifiers. AdaBoost is an iterative ensemble method. AdaBoost classifier builds a strong classifier by combining multiple poorly performing classifiers so that you will get high accuracy strong classifier. The basic concept behind Adaboost is to set the weights of classifiers and training the data sample in each iteration such that it ensures the accurate predictions of unusual observations.
3. Ensemble Stacking of all algorithms in a neural network to form a polling method

After using various algorithms to analyze the performance of these algorithm on the dataset we can conclude that ensemble methods are clearly better than simple machine learning algorithms.

Ensemble methods like Random Forest Classifier and AdaBoost Classifier have clearly better accuracies i.e. 86.1% and 85.6% respectively. These algorithms also have better recall and precision. For Random Forest Classifier:

- `Precision: 81.2%`
- `Recall: 97.2%`

For AdaBoost Classifier:

- `Precision: 80.8%`
- `Recall:96.9%`

Recall is number of true positives divided by the number of true positives plus the number of false negatives. Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

As we can see the precision of both the algorithms are above 95% which clearly shows that the number of false positives is minimal.

When compared to non-ensemble simple machine learning algorithms their accuracies are relatively low:

- `Logistic Regression: 70.2%`
- `MultinomialNB: 75.2%`
- `KNN Classifier: 78.2%`
- `Decision Tree Classifier: 85.8%`

we also notice that though training accuracy of non-ensemble method were high it declined with testing dataset which brought us to a conclusion Non ensemble methods lead to overfitting of the data. thus we decided to use ensemble methods to optimize the exisiting results

Hence we conclude from this comparative study that ensemble methods (Random Forest AdaBoost Classifier and Ensemble Stacking using polling) on this dataset and generally more precise and accurate when compared to normal machine learning algorithms.

[ ]:

```

```