Model_Training

August 31, 2020

[22]:
```
import numpy as np
import pandas as pd
import sklearn
import scipy
import matplotlib.pyplot as plt
import seaborn as sns

from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.metrics import classification_report,accuracy_score
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
from sklearn.svm import OneClassSVM
```

[2]:
```
# Read the CSV data into the pandas dataframe
file = '../data/data.csv'
data = pd.read_csv(file)
```

[3]:
```
# Let's replace the label column values to 0 for normal and 1 for others!

LABELS = data["label"].unique() # Get Unique Values of label column
LABELS = [label for label in LABELS if label != "normal"] #All labels other␣
↪than Normal!

data["label"].replace(['normal'], 0, inplace=True)
data["label"].replace(LABELS, 1 , inplace=True)
```

[4]:
```
data = data.fillna("None") # fill all the empty hosts with 0

#Now let's encode all the columns which are not float or int e.g. sourceIP, MAC␣
↪to make it possible for model to interpret
columnsToEncode = list(data.select_dtypes(include=['category', 'object']))

le = LabelEncoder() # use label encoder from sklearn

for feature in columnsToEncode:
    try:
        data[feature] = le.fit_transform(data[feature])
```

```
        #print(data[feature])
    except:
        print ('error' + feature)
```

[5]:
```
data.head()
```

[5]:
```
   uid  sourceMac  sourceIp  destIp  destMac  sourcePort  destPort  host  kIn  \
0    0          0         2      15        5       19357      8000     3  0.0
1    0          0         2      15        5        1939      8000     3  0.0
2    0          0         2      15        5       19668      8000     3  0.0
3    0          0         2      15        5       19807      8000     3  0.0
4    0          0         2      15        5       19851      8000     3  0.0

       kOut  …  outPacketsNo  protocol  urgent  ack  push  reset  syn  fin  \
0  1.015625  …             2        17       0    0     0      0    0    0
1  1.015625  …             2        17       0    0     0      0    0    0
2  0.507813  …             1        17       0    0     0      0    0    0
3  0.507813  …             1        17       0    0     0      0    0    0
4  0.507813  …             1        17       0    0     0      0    0    0

   timestamp  label
0      22374      1
1      22374      1
2      22374      1
3      22374      1
4      22374      1

[5 rows x 21 columns]
```

[6]:
```
data["label"].value_counts()
```

[6]:
```
1    2988506
0      91386
Name: label, dtype: int64
```

[7]:
```
Train, Val = sklearn.model_selection.train_test_split(data, test_size=0.9,␣
 ↪random_state=1, shuffle=True)
```

[8]:
```
Train["label"].value_counts()
```

[8]:
```
1    298792
0      9197
Name: label, dtype: int64
```

[9]:
```
Val["label"].value_counts()
```

```
[9]: 1    2689714
0      82189
Name: label, dtype: int64
```

```
[10]: Attack = Train[Train['label']==1]
Normal = Train[Train['label']==0]
outlier_fraction = np.ceil(len(Attack)/float(len(Normal)))

#Let's print how many more outliers are there in the dataset compared to normal␣
 ↪data
print(outlier_fraction)
```

```
33.0
```

```
[35]: #Let's now split the features and the target ground truth
features = [feature for feature in Train.columns.tolist() if feature not in␣
 ↪["label"]]
target = "label"

# Define a random state
state = np.random.RandomState(42)
X_train = Train[features]
Y_train = Train[target]

X_val = Val[features]
Y_val = Val[target]

X_outliers = state.uniform(low=0, high=1, size=(X_train.shape[0], X_train.
 ↪shape[1]))
# Print the shapes of X & Y
print(X_train.shape)
print(Y_train.shape)
```

```
(307989, 20)
(307989,)
```

```
[13]: #Let's initalize some classifiers
classifiers = {
    "Isolation Forest":IsolationForest(n_estimators=100,␣
 ↪max_samples=len(X_train),
                                                        ␣
 ↪contamination=outlier_fraction,random_state=state, verbose=1),
    "Local Outlier Factor":LocalOutlierFactor(n_neighbors=20, algorithm='auto',
                                              leaf_size=30, metric='minkowski',
                                              p=2, metric_params=None,␣
 ↪contamination=0.03),
```

```
    "Support Vector Machine":OneClassSVM(kernel='rbf', degree=3, gamma=0.1,nu=0.
↪05,
                                         max_iter=-1 )

}
```

[ ]:
```
n_outliers = len(Attack)
for i, (clf_name,clf) in enumerate(classifiers.items()):
    #Fit the data and tag outliers
    if clf_name == "Local Outlier Factor":
        continue
        y_pred = clf.fit_predict(X_train)
        scores_prediction = clf.negative_outlier_factor_
    elif clf_name == "Support Vector Machine":
        clf.fit(X_train)
        y_pred = clf.predict(X_train)
    else:
        continue
        clf.fit(X_train)
        scores_prediction = clf.decision_function(X_train)
        y_pred = clf.predict(X_train)

    #Reshape the prediction values to 0 for Valid transactions , 1 for Fraud␣
↪transactions
    y_pred[y_pred == 1] = 0
    y_pred[y_pred == -1] = 1
    n_errors = (y_pred != Y_train).sum()
    # Run Classification Metrics
    print("{}: {}".format(clf_name,n_errors))
    print("Accuracy Score :")
    print(accuracy_score(Y_train,y_pred))
    print("Classification Report :")
    print(classification_report(Y_train,y_pred))
```

```
Local Outlier Factor: 291532
Accuracy Score :
0.053433726529194224
Classification Report :
              precision    recall  f1-score   support

           0       0.03      0.89      0.05      9197
           1       0.89      0.03      0.05    298792

    accuracy                           0.05    307989
   macro avg       0.46      0.46      0.05    307989
weighted avg       0.87      0.05      0.05    307989
```

[ ]:

```
n_outliers = len(Attack)
for i, (clf_name,clf) in enumerate(classifiers.items()):
    #Fit the data and tag outliers
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        continue
        y_pred = clf.fit_predict(X_train)
        scores_prediction = clf.negative_outlier_factor_
    elif clf_name == "Support Vector Machine":
        clf.fit(X_train)
        y_pred = clf.predict(X_train)
    else:
        continue
        clf.fit(X_train)
        scores_prediction = clf.decision_function(X_train)
        y_pred = clf.predict(X_train)

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    print("{}: {}".format(clf_name,n_errors))
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    print(accuracy_score(Y_train,y_pred))
    print("Classification Report :")
    print(classification_report(Y_train,y_pred))
```

[12]:

```
from keras.layers import Input, Dense
from keras.models import Model, Sequential
from keras import regularizers
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import classification_report, accuracy_score
from sklearn.manifold import TSNE
from sklearn import preprocessing
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np
import seaborn as sns
```

[25]:

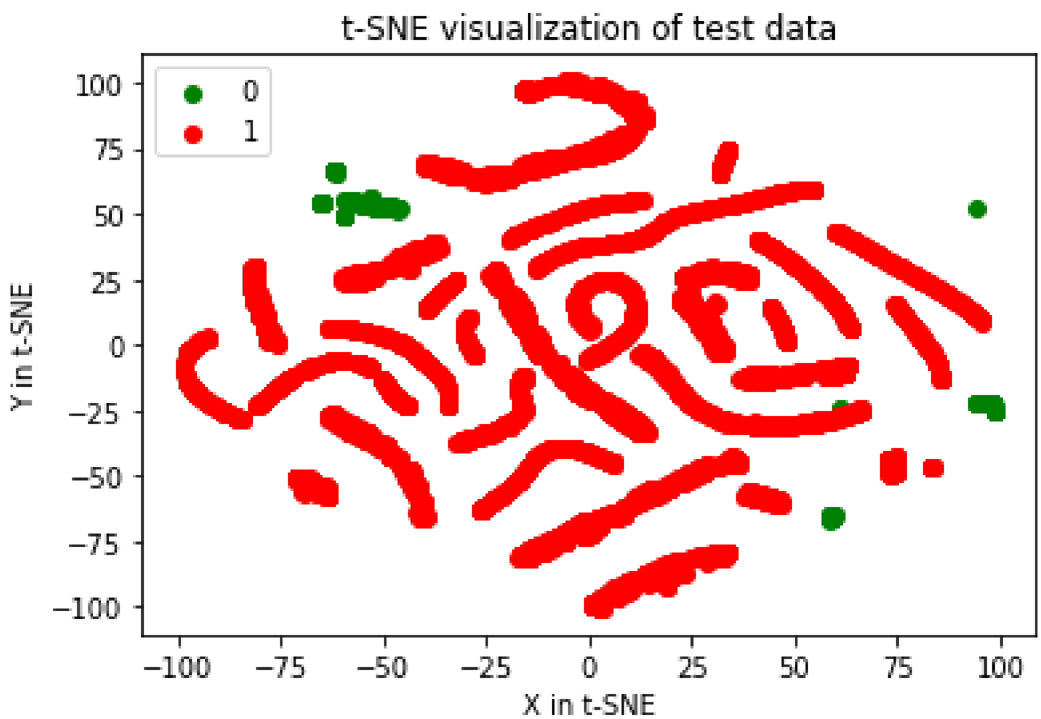
```
def tsne_plot(x1, y1, name="graph.png"):

    #Scale features to improve the training ability of TSNE.
    standard_scaler = StandardScaler()
    df2_std = standard_scaler.fit_transform(x1)
```

```
    tsne = TSNE(n_components=2, random_state=0)
    x_test_2d = tsne.fit_transform(df2_std)

    #Build the scatter plot with the two types of transactions.
    color_map = {0:'green', 1:'red'}
    plt.figure()
    for idx, cl in enumerate(np.unique(y)):
        plt.scatter(x = x_test_2d[y1==cl,0],
                    y = x_test_2d[y1==cl,1],
                    c = color_map[idx],
                    label = cl)
    plt.xlabel('X in t-SNE')
    plt.ylabel('Y in t-SNE')
    plt.legend(loc='upper left')
    plt.title('t-SNE visualization of test data')
    plt.show()

tsne_plot(X_train[:8000], Y_train[:8000])
```



[27]:
```
#I think training this kind of dataset with autoencoders makes more sense so␣
↪let's try that

## input layer
```

```
input_layer = Input(shape=(X_train.shape[1],))

## encoding part
encoded = Dense(100, activation='tanh', activity_regularizer=regularizers.
↪l1(10e-5))(input_layer)
encoded = Dense(50, activation='relu')(encoded)

## decoding part
decoded = Dense(50, activation='tanh')(encoded)
decoded = Dense(100, activation='tanh')(decoded)

## output layer
output_layer = Dense(X_train.shape[1], activation='relu')(decoded)
```

[28]:
```
#Compile the mdoel
autoencoder = Model(input_layer, output_layer)
autoencoder.compile(optimizer="adadelta", loss="mse")
```

[29]:
```
#let's do bit of data transformation for scaling

x = X_train
y = Y_train

x_scale = preprocessing.MinMaxScaler().fit_transform(x.values)
x_norm, x_fraud = x_scale[y == 0], x_scale[y == 1]
```

[30]:
```
autoencoder.fit(x_norm[0:8000], x_norm[0:8000],
                batch_size = 256, epochs = 50,
                shuffle = True, validation_split = 0.20);
```

```
Epoch 1/50
25/25 [==============================] - 0s 8ms/step - loss: 0.1274 - val_loss:
0.1273
Epoch 2/50
25/25 [==============================] - 0s 4ms/step - loss: 0.1270 - val_loss:
0.1269
Epoch 3/50
25/25 [==============================] - 0s 5ms/step - loss: 0.1266 - val_loss:
0.1264
Epoch 4/50
25/25 [==============================] - 0s 5ms/step - loss: 0.1261 - val_loss:
0.1259
Epoch 5/50
25/25 [==============================] - 0s 5ms/step - loss: 0.1255 - val_loss:
0.1253
Epoch 6/50
25/25 [==============================] - 0s 6ms/step - loss: 0.1249 - val_loss:
```

```
0.1247
Epoch 7/50
25/25 [==============================] - 0s 5ms/step - loss: 0.1243 - val_loss:
0.1240
Epoch 8/50
25/25 [==============================] - 0s 6ms/step - loss: 0.1236 - val_loss:
0.1234
Epoch 9/50
25/25 [==============================] - 0s 5ms/step - loss: 0.1230 - val_loss:
0.1228
Epoch 10/50
25/25 [==============================] - 0s 11ms/step - loss: 0.1223 - val_loss:
0.1221
Epoch 11/50
25/25 [==============================] - 0s 11ms/step - loss: 0.1216 - val_loss:
0.1214
Epoch 12/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1209 - val_loss:
0.1207
Epoch 13/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1202 - val_loss:
0.1199
Epoch 14/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1195 - val_loss:
0.1192
Epoch 15/50
25/25 [==============================] - 0s 6ms/step - loss: 0.1188 - val_loss:
0.1185
Epoch 16/50
25/25 [==============================] - 0s 8ms/step - loss: 0.1180 - val_loss:
0.1178
Epoch 17/50
25/25 [==============================] - 0s 10ms/step - loss: 0.1173 - val_loss:
0.1171
Epoch 18/50
25/25 [==============================] - 0s 8ms/step - loss: 0.1166 - val_loss:
0.1164
Epoch 19/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1159 - val_loss:
0.1157
Epoch 20/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1152 - val_loss:
0.1150
Epoch 21/50
25/25 [==============================] - 0s 6ms/step - loss: 0.1144 - val_loss:
0.1142
Epoch 22/50
25/25 [==============================] - 0s 8ms/step - loss: 0.1137 - val_loss:
```

```
0.1135
Epoch 23/50
25/25 [==============================] - 0s 10ms/step - loss: 0.1130 - val_loss:
0.1128
Epoch 24/50
25/25 [==============================] - 0s 8ms/step - loss: 0.1123 - val_loss:
0.1122
Epoch 25/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1116 - val_loss:
0.1115
Epoch 26/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1109 - val_loss:
0.1108
Epoch 27/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1102 - val_loss:
0.1101
Epoch 28/50
25/25 [==============================] - 0s 6ms/step - loss: 0.1096 - val_loss:
0.1094
Epoch 29/50
25/25 [==============================] - 0s 5ms/step - loss: 0.1089 - val_loss:
0.1087
Epoch 30/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1082 - val_loss:
0.1081
Epoch 31/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1075 - val_loss:
0.1074
Epoch 32/50
25/25 [==============================] - 0s 8ms/step - loss: 0.1069 - val_loss:
0.1068
Epoch 33/50
25/25 [==============================] - 0s 9ms/step - loss: 0.1062 - val_loss:
0.1061
Epoch 34/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1056 - val_loss:
0.1055
Epoch 35/50
25/25 [==============================] - 0s 7ms/step - loss: 0.1049 - val_loss:
0.1048
Epoch 36/50
25/25 [==============================] - 0s 9ms/step - loss: 0.1043 - val_loss:
0.1042
Epoch 37/50
25/25 [==============================] - 0s 10ms/step - loss: 0.1036 - val_loss:
0.1036
Epoch 38/50
25/25 [==============================] - 0s 3ms/step - loss: 0.1030 - val_loss:
```

```
0.1029
Epoch 39/50
25/25 [==============================] - 0s 3ms/step - loss: 0.1024 - val_loss:
0.1023
Epoch 40/50
25/25 [==============================] - 0s 3ms/step - loss: 0.1017 - val_loss:
0.1017
Epoch 41/50
25/25 [==============================] - 0s 3ms/step - loss: 0.1011 - val_loss:
0.1011
Epoch 42/50
25/25 [==============================] - 0s 3ms/step - loss: 0.1005 - val_loss:
0.1004
Epoch 43/50
25/25 [==============================] - 0s 7ms/step - loss: 0.0999 - val_loss:
0.0998
Epoch 44/50
25/25 [==============================] - 0s 8ms/step - loss: 0.0992 - val_loss:
0.0992
Epoch 45/50
25/25 [==============================] - 0s 10ms/step - loss: 0.0986 - val_loss:
0.0986
Epoch 46/50
25/25 [==============================] - 0s 8ms/step - loss: 0.0980 - val_loss:
0.0980
Epoch 47/50
25/25 [==============================] - 0s 8ms/step - loss: 0.0974 - val_loss:
0.0974
Epoch 48/50
25/25 [==============================] - 0s 10ms/step - loss: 0.0968 - val_loss:
0.0968
Epoch 49/50
25/25 [==============================] - 0s 8ms/step - loss: 0.0962 - val_loss:
0.0962
Epoch 50/50
25/25 [==============================] - 0s 6ms/step - loss: 0.0956 - val_loss:
0.0956
```

[31]:

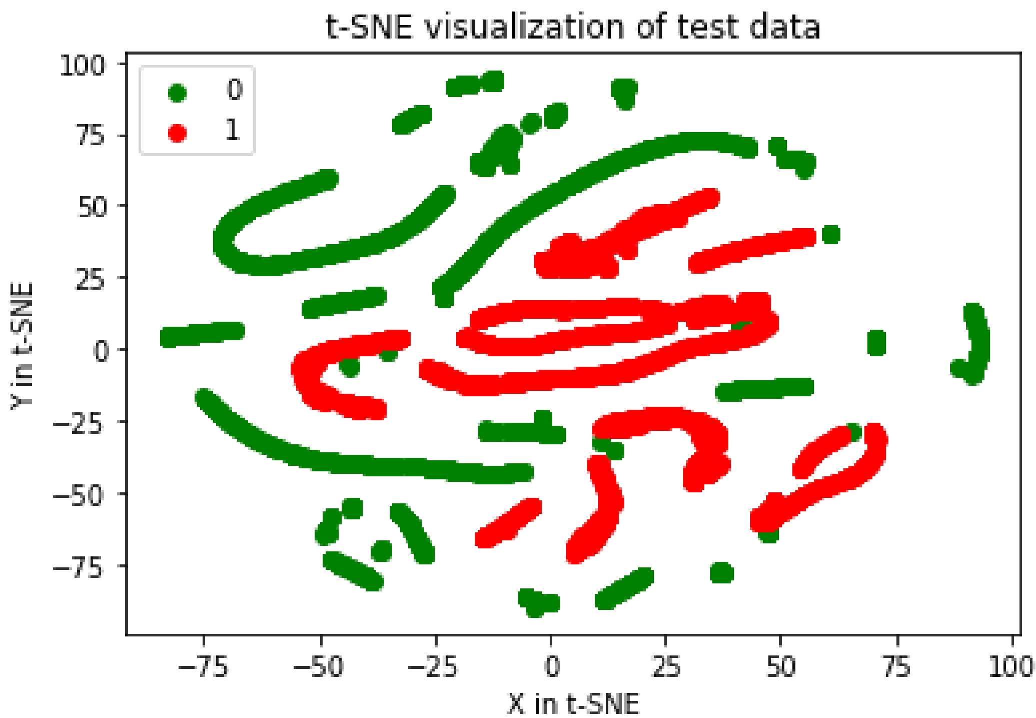
```
#Let's try to get latent learnt representation by autoencoder
hidden_representation = Sequential()
hidden_representation.add(autoencoder.layers[0])
hidden_representation.add(autoencoder.layers[1])
hidden_representation.add(autoencoder.layers[2])
```

[32]:

```
norm_hid_rep = hidden_representation.predict(x_norm[9000:12000])
fraud_hid_rep = hidden_representation.predict(x_fraud[9000:12000])
```

[33]:
```
#Let's try to visualize TSNE again for the learnt representation
rep_x = np.append(norm_hid_rep, fraud_hid_rep, axis = 0)
y_n = np.zeros(norm_hid_rep.shape[0])
y_f = np.ones(fraud_hid_rep.shape[0])
rep_y = np.append(y_n, y_f)

tsne_plot(rep_x, rep_y)
```



[34]:
```
#Finally we can train a classifier on learnt representations

train_x, val_x, train_y, val_y = train_test_split(rep_x, rep_y, test_size=0.25)
clf = LogisticRegression(solver="lbfgs").fit(train_x, train_y)
pred_y = clf.predict(val_x)

print ("")
print ("Classification Report: ")
print (classification_report(val_y, pred_y))

print ("")
print ("Accuracy Score: ", accuracy_score(val_y, pred_y))
```

```
Classification Report:
              precision    recall  f1-score   support
```

```
         0.0       1.00      0.99      0.99       783
         1.0       0.99      1.00      0.99       717

    accuracy                           0.99      1500
   macro avg       0.99      0.99      0.99      1500
weighted avg       0.99      0.99      0.99      1500


Accuracy Score:  0.9946666666666667
```

[37]:

```python
#Finally we can train a classifier on learnt representations

train_x, val_x, train_y, val_y = train_test_split(rep_x, rep_y, test_size=0.25)
clf = LogisticRegression(solver="lbfgs").fit(X_train, Y_train)
pred_y = clf.predict(X_val)

print ("")
print ("Classification Report: ")
print (classification_report(Y_val, pred_y))

print ("")
print ("Accuracy Score: ", accuracy_score(Y_val, pred_y))
```

```
/home/coding/MyProjects/Avira-AnomalyDetection/env/lib/python3.6/site-
packages/sklearn/linear_model/_logistic.py:764: ConvergenceWarning: lbfgs failed
to converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)


Classification Report:
              precision    recall  f1-score   support

           0       1.00      0.99      0.99     82189
           1       1.00      1.00      1.00   2689714

    accuracy                           1.00   2771903
   macro avg       1.00      0.99      1.00   2771903
weighted avg       1.00      1.00      1.00   2771903
```

```
Accuracy Score:  0.9996976806186941
```

```
[ ]:
```