

APEGAN JSMA

November 16, 2020

```
[23]: import numpy as np
import keras
import tensorflow as tf

from keras.utils import np_utils
import tensorflow as tf
import keras
from keras.models import Model, Sequential # basic class for specifying and
↳ training a neural network
from keras.layers import Input, Conv2D, Conv2DTranspose, Dense, Activation,
↳ Flatten, LeakyReLU, BatchNormalization, ZeroPadding2D
from keras.optimizers import Adam
from keras import backend as K

import os
os.environ["CUDA_VISIBLE_DEVICES"]="1"

import pickle

%load_ext autoreload
%autoreload 2

import matplotlib.pyplot as plt
%matplotlib inline
```

The autoreload extension is already loaded. To reload it, use:

```
%reload_ext autoreload
```

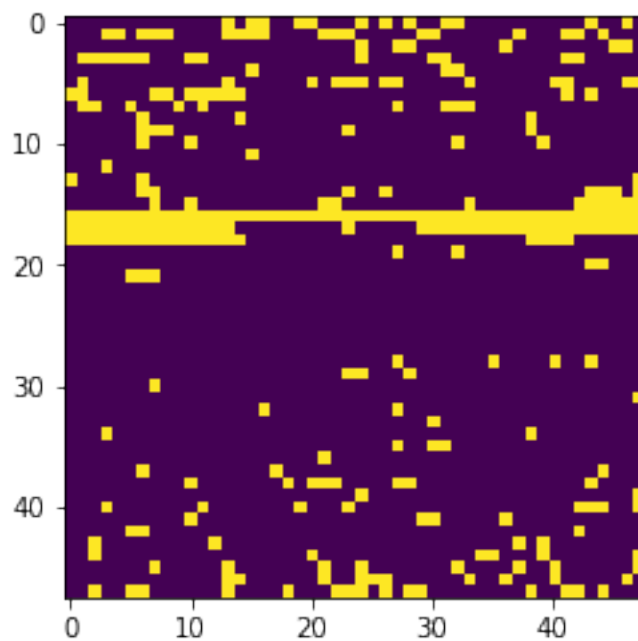
```
[24]: x_clean = np.load('./ATTACKS/JSMA/X_TEST_JSMA.npy')
x_adv = np.load('./ATTACKS/JSMA/X_TEST_ATTACKED_JSMA.npy')
x_label = np.load('./ATTACKS/JSMA/Y_TEST_JSMA.npy').astype('int')
```

```
[25]: x_label[5]
```

```
[25]: array([1])
```

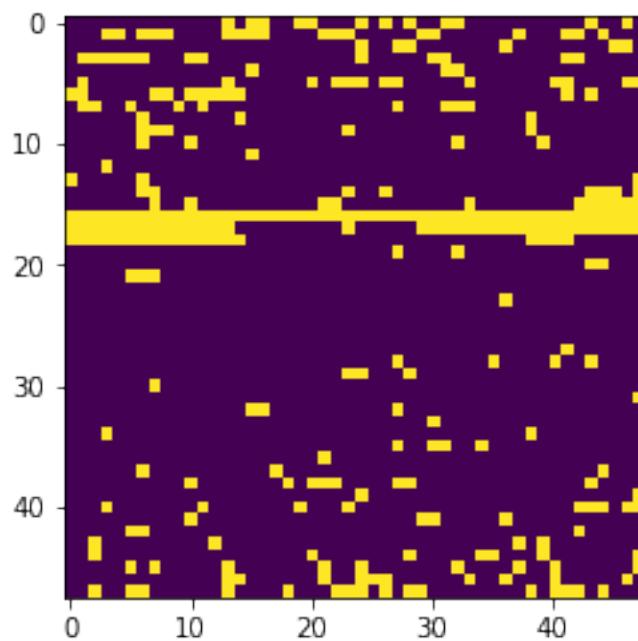
```
[26]: plt.imshow((x_clean[5]))
```

[26]: <matplotlib.image.AxesImage at 0x18fde47ee88>



[27]: plt.imshow((x_adv[5]))

[27]: <matplotlib.image.AxesImage at 0x18fcf4d7cc8>



1 DEFINE LOSS FUNCS AND APE GAN

```
[28]: def SRMSE(y_true, y_pred):  
    return K.sqrt(K.mean(K.square(y_pred - y_true), axis=-1) + 1e-10)  
  
def MANHATTAN(y_true, y_pred):  
    return K.sum( K.abs( y_true - y_pred),axis=1,keepdims=True) + 1e-10  
  
def WLOSS(y_true,y_pred):  
    return K.mean(y_true * y_pred)
```

```
[29]: def APEGAN(input_shape):  
    G = generator(input_shape)  
    D = discriminator(input_shape)  
    ipt = Input(input_shape)  
    purified = G(ipt)  
    D.trainable = False  
    judge = D(purified)  
  
    GAN = Model(ipt, [judge, purified])  
    GAN.compile(optimizer='adam',  
                loss=['binary_crossentropy', WLOSS],  
                loss_weights=[0.02, 0.9])  
    GAN.summary()  
    G.summary()  
    D.summary()  
    return GAN, G, D  
  
def generator(input_shape):  
    model = Sequential()  
    model.add(Conv2D(64, (3,3), strides=2, padding='same',  
↪input_shape=input_shape))  
    model.add(BatchNormalization())  
    model.add(LeakyReLU(0.2))  
    model.add(Conv2D(128, (3,3), strides=2, padding='same'))  
    model.add(BatchNormalization())  
    model.add(LeakyReLU(0.2))  
    model.add(Conv2DTranspose(64, (3,3), strides=2, padding='same'))  
    model.add(BatchNormalization())  
    model.add(LeakyReLU(0.2))  
    model.add(Conv2DTranspose(1, (3,3), strides=2, padding='same'))  
    #=====
```

```

#     model.add(Dense(64, input_shape=input_shape))
#     model.add(Dense(256))
#     model.add(Dense(128))
#     model.add(Dense(64))
#     model.add(Dense(32))
#     model.add(Dense(16))
#     model.add(Dense(8))
#     model.add(Dense(4))
#     model.add(Dense(2))
#     model.add(Dense(1, activation='tanh'))
#     model.add(Reshape((-1,1)))
#     model.add(Flatten())
#=====
    model.add(Activation('tanh'))
    return model

def discriminator(input_shape):
    model = Sequential()
    model.add(Conv2D(64, (3,3), strides=2, padding='same',
    ↪input_shape=input_shape))
    model.add(BatchNormalization())
    model.add(LeakyReLU(0.2))
    model.add(Conv2D(128, (3,3), strides=2, padding='same'))
    model.add(BatchNormalization())
    model.add(LeakyReLU(0.2))
    model.add(Conv2D(256, (3,3), strides=2, padding='same'))
    model.add(BatchNormalization())
    model.add(LeakyReLU(0.2))
    model.add(Flatten())
    model.add(Dense(1))
#=====
#     model.add(Dense(64, input_shape=input_shape))
#     model.add(Dense(256))
#     model.add(Dense(128))
#     model.add(Dense(64))
#     model.add(Dense(32))
#     model.add(Dense(16))
#     model.add(Dense(8))
#     model.add(Dense(4))
#     model.add(Dense(2))
#     model.add(Dense(1, activation='sigmoid'))
# #     model.add(Reshape((-1,1)))
# #     model.add(Flatten())
#=====
    model.add(Activation('sigmoid'))
    model.compile(optimizer='adam', loss='binary_crossentropy')

```

```
return model
```

2 Create GAN

```
[104]: GAN, G, D = APEGAN([48,48,1])
```

Model: "model_7"

Layer (type)	Output Shape	Param #
input_7 (InputLayer)	(None, 48, 48, 1)	0
sequential_13 (Sequential)	(None, 48, 48, 1)	149889
sequential_14 (Sequential)	(None, 1)	380673

Total params: 530,562

Trainable params: 149,377

Non-trainable params: 381,185

Model: "sequential_13"

Layer (type)	Output Shape	Param #
conv2d_31 (Conv2D)	(None, 24, 24, 64)	640
batch_normalization_37 (Batch Normalization)	(None, 24, 24, 64)	256
leaky_re_lu_37 (LeakyReLU)	(None, 24, 24, 64)	0
conv2d_32 (Conv2D)	(None, 12, 12, 128)	73856
batch_normalization_38 (Batch Normalization)	(None, 12, 12, 128)	512
leaky_re_lu_38 (LeakyReLU)	(None, 12, 12, 128)	0
conv2d_transpose_13 (Conv2D Transpose)	(None, 24, 24, 64)	73792
batch_normalization_39 (Batch Normalization)	(None, 24, 24, 64)	256
leaky_re_lu_39 (LeakyReLU)	(None, 24, 24, 64)	0
conv2d_transpose_14 (Conv2D Transpose)	(None, 48, 48, 1)	577
activation_13 (Activation)	(None, 48, 48, 1)	0

```
=====
Total params: 149,889
Trainable params: 149,377
Non-trainable params: 512
```

```
-----
Model: "sequential_14"
```

Layer (type)	Output Shape	Param #
conv2d_33 (Conv2D)	(None, 24, 24, 64)	640
batch_normalization_40 (Batch Normalization)	(None, 24, 24, 64)	256
leaky_re_lu_40 (LeakyReLU)	(None, 24, 24, 64)	0
conv2d_34 (Conv2D)	(None, 12, 12, 128)	73856
batch_normalization_41 (Batch Normalization)	(None, 12, 12, 128)	512
leaky_re_lu_41 (LeakyReLU)	(None, 12, 12, 128)	0
conv2d_35 (Conv2D)	(None, 6, 6, 256)	295168
batch_normalization_42 (Batch Normalization)	(None, 6, 6, 256)	1024
leaky_re_lu_42 (LeakyReLU)	(None, 6, 6, 256)	0
flatten_7 (Flatten)	(None, 9216)	0
dense_7 (Dense)	(None, 1)	9217
activation_14 (Activation)	(None, 1)	0

```
=====
Total params: 760,450
Trainable params: 379,777
Non-trainable params: 380,673
```

```
-----
C:\Users\Pitch\.conda\envs\tf1-gpu\lib\site-
packages\keras\engine\training.py:297: UserWarning: Discrepancy between
trainable weights and collected trainable weights, did you set `model.trainable`
without calling `model.compile` after ?
'Discrepancy between trainable weights and collected trainable'
```

3 Set Params and RUN GAN

```
[105]: epochs=10 # original 500
       batch_size=64
       N = x_clean.shape[0]
```

```
[106]: scalarloss = [0,0,0]
       for cur_epoch in range(epochs):
           #     idx = np.random.randint(0, N//5*4, size=batch_size)
           idx = np.random.randint(0, N, size=batch_size)

           x_clean_batch = x_clean[idx,:].reshape(-1,x_clean.shape[1],x_clean.
           ↪shape[2],1)
           print(x_clean_batch.shape)

           x_adv_batch = x_adv[idx,:].reshape(-1,x_clean.shape[1],x_clean.shape[2],1)
           scalarloss[0] = D.train_on_batch(x_clean_batch, np.ones(batch_size))/2
           scalarloss[0] += D.train_on_batch(x_adv_batch, np.zeros(batch_size))/2
           GAN.train_on_batch(x_adv_batch, [np.ones(batch_size), x_clean_batch])
           scalarloss[1:] = GAN.train_on_batch(x_adv_batch, [np.ones(batch_size),
           ↪x_clean_batch])[1:]
           print("Epoch number:",cur_epoch,"; Loss",scalarloss)
```

(16, 48, 48, 1)

C:\Users\Pitch\.conda\envs\tf1-gpu\lib\site-packages\keras\engine\training.py:297: UserWarning: Discrepancy between trainable weights and collected trainable weights, did you set `model.trainable` without calling `model.compile` after ?

'Discrepancy between trainable weights and collected trainable'

Epoch number: 0 ; Loss [5.8191321939229965, 0.019530816, -0.019087506]

(16, 48, 48, 1)

C:\Users\Pitch\.conda\envs\tf1-gpu\lib\site-packages\keras\engine\training.py:297: UserWarning: Discrepancy between trainable weights and collected trainable weights, did you set `model.trainable` without calling `model.compile` after ?

'Discrepancy between trainable weights and collected trainable'

Epoch number: 1 ; Loss [0.2596597741357982, 0.01781522, -0.028542476]

(16, 48, 48, 1)

Epoch number: 2 ; Loss [3.510614598169923, 0.005030252, -0.025468804]

(16, 48, 48, 1)

Epoch number: 3 ; Loss [2.646995782852173, 0.017227937, -0.03523894]

(16, 48, 48, 1)

Epoch number: 4 ; Loss [1.8717714548110962, 0.030146874, -0.036398966]

(16, 48, 48, 1)

Epoch number: 5 ; Loss [1.2796459794044495, 0.008593894, -0.041542303]

```

(16, 48, 48, 1)
Epoch number: 6 ; Loss [0.7573162764310837, 0.003347836, -0.042431872]
(16, 48, 48, 1)
Epoch number: 7 ; Loss [1.1231993734836578, 0.0013904982, -0.036282193]
(16, 48, 48, 1)
Epoch number: 8 ; Loss [1.1151663064956665, 0.014629264, -0.048947953]
(16, 48, 48, 1)
Epoch number: 9 ; Loss [0.8065140843391418, 0.0038546608, -0.040082987]

```

4 Classifier Load

```

[107]: from keras.models import Sequential
       from keras.layers import Dense, Dropout, Conv2D, MaxPool2D, Flatten
       from keras.utils import np_utils
       import random
       from keras.utils import to_categorical #this just converts the labels to
       →one-hot class

```

```

[108]: F = keras.models.load_model('./ATTACKS/JSMA/JSMA_CLASSIFIER_USED.h5py')
       F.summary()

```

Model: "sequential_1"

Layer (type)	Output Shape	Param #
reshape_1 (Reshape)	(None, 2304)	0
dense_1 (Dense)	(None, 512)	1180160
dense_2 (Dense)	(None, 2)	1026

=====
 Total params: 1,181,186
 Trainable params: 1,181,186
 Non-trainable params: 0
 =====

```

[109]: test_labels = to_categorical(np.load('./ATTACKS/JSMA/Y_TEST_JSMA.npy').
       →astype('int'))

```

5 Purify the Stuff

```

[110]: clean = x_clean.reshape(-1,48,48,1)#[N//5*4:]
       adv = x_adv.reshape(-1,48,48,1)#[N//5*4:]
       label = x_label#[N//5*4:]

```



```

purified = G.predict(adv)
adv_pdt = np.argmax(F.predict(adv.reshape(-1,48,48)), axis=1)
purified_pdt = np.argmax(F.predict(purified.reshape(-1,48,48)), axis=1)
print('{} , {} : adv acc:{:.4f}, rct acc:{:.4f}'.format(0, 0,
                                                    np.mean(adv_pdt==label),
                                                    np.mean(purified_pdt==label)))

```

0, 0 : adv acc:0.6595, rct acc:0.3334

```
[111]: F.evaluate(clean.reshape(-1,48,48),test_labels)#[N//5*4:]
```

5000/5000 [=====] - 1s 275us/step

[111]: [0.19247934680879117, 0.9476000070571899]

```
[112]: F.evaluate(adv.reshape(-1,48,48),test_labels)#[N//5*4:]
```

5000/5000 [=====] - 1s 194us/step

[112]: [0.8315977921485901, 0.6453999876976013]

```
[113]: F.evaluate(purified.reshape(-1,48,48),(test_labels))#[N//5*4:]
```

5000/5000 [=====] - 1s 200us/step

[113]: [1.1773786735534668, 0.33340001106262207]

```
[114]: clean[0].shape
```

[114]: (48, 48, 1)

```
[115]: "DONE"
```

[115]: 'DONE'

```
[116]: np.unique(np.argmax(F.predict(adv.reshape(-1,48,48)),axis=1),return_counts=True)
```

[116]: (array([0, 1], dtype=int64), array([4894, 106], dtype=int64))

```
[117]: np.unique(np.argmax(F.predict(purified.
    ↪reshape(-1,48,48)),axis=1),return_counts=True)
```

[117]: (array([1], dtype=int64), array([5000], dtype=int64))

6 Conclusion

In JSMA, training for 10 EPOCHS makes it all 5000 as MALWARE

[]: