ml_lab3

December 16, 2021

[1]:
```
import tensorflow as tf
import keras
import keras.backend as K
from keras import Model

import h5py
import numpy as np
import matplotlib.pyplot as plt
import os
os.chdir("/content/drive/MyDrive/lab3")
```

0.1 load model and load data

[2]:
```
cl_valid_path = './data/cl/valid.h5'
cl_test_path = './data/cl/test.h5'
bd_valid_path = './data/bd/bd_valid.h5'
bd_test_path = './data/bd/bd_test.h5'
bd_net_path = './models/bd_net.h5'


def data_loader(filepath):
    data = h5py.File(filepath, 'r')
    x_data = np.array(data['data'])
    y_data = np.array(data['label'])
    x_data = x_data.transpose((0, 2, 3, 1))

    return x_data, y_data
```

[3]:
```
cl_x_valid, cl_y_valid = data_loader(cl_valid_path)
cl_x_test, cl_y_test = data_loader(cl_test_path)
bd_x_valid, bd_y_valid = data_loader(bd_valid_path)
bd_x_test, bd_y_test = data_loader(bd_test_path)
net = keras.models.load_model(bd_net_path)
```

[4]:
```
# evaluate the net (from eval.py)
def eval(net,cl_x_test,cl_y_test,bd_x_test,bd_y_test):
  cl_label_p = np.argmax(bd_model.predict(cl_x_test), axis=1)
```

```
    clean_accuracy = np.mean(np.equal(cl_label_p, cl_y_test))*100
    print('Clean Classification accuracy:', clean_accuracy)
    bd_label_p = np.argmax(bd_model.predict(bd_x_test), axis=1)
    asr = np.mean(np.equal(bd_label_p, bd_y_test))*100

    print('Attack Success Rate:', asr)
    return clean_accuracy,asr
```

[5]:
```
print(net.summary())
```

```
Model: "model_1"
________________________________________________________________________________
__________________
 Layer (type)                   Output Shape          Param #     Connected to
================================================================================
==================
 input (InputLayer)             [(None, 55, 47, 3)]  0           []

 conv_1 (Conv2D)                (None, 52, 44, 20)   980         ['input[0][0]']

 pool_1 (MaxPooling2D)          (None, 26, 22, 20)   0
['conv_1[0][0]']

 conv_2 (Conv2D)                (None, 24, 20, 40)   7240
['pool_1[0][0]']

 pool_2 (MaxPooling2D)          (None, 12, 10, 40)   0
['conv_2[0][0]']

 conv_3 (Conv2D)                (None, 10, 8, 60)    21660
['pool_2[0][0]']

 pool_3 (MaxPooling2D)          (None, 5, 4, 60)     0
['conv_3[0][0]']

 conv_4 (Conv2D)                (None, 4, 3, 80)     19280
['pool_3[0][0]']

 flatten_1 (Flatten)            (None, 1200)         0
['pool_3[0][0]']

 flatten_2 (Flatten)            (None, 960)          0
['conv_4[0][0]']

 fc_1 (Dense)                   (None, 160)          192160
['flatten_1[0][0]']
```

```
 fc_2 (Dense)                   (None, 160)          153760
['flatten_2[0][0]']

 add_1 (Add)                    (None, 160)          0            ['fc_1[0][0]',
                                                                   'fc_2[0][0]']

 activation_1 (Activation)      (None, 160)          0            ['add_1[0][0]']

 output (Dense)                 (None, 1283)         206563
['activation_1[0][0]']

================================================================================
==================
Total params: 601,643
Trainable params: 601,643
Non-trainable params: 0
--------------------------------------------------------------------------------
------------------
None
```

[6]:
```
!python eval.py data/cl/test.h5 data/bd/bd_test.h5 models/bd_net.h5
```

```
2021-12-17 02:47:07.302976: W
tensorflow/core/common_runtime/gpu/gpu_bfc_allocator.cc:39] Overriding
allow_growth setting because the TF_FORCE_GPU_ALLOW_GROWTH environment variable
is set. Original config value was 0.
Clean Classification accuracy: 98.62042088854248
Attack Success Rate: 100.0
```

0.2 repair B-Net

The main idea is to get the output of layer before the last maxpooling layer which is layer conv_3. Prune the layer's channel based on the increasing order of the average outputover the entire validation dataset.

0.2.1 New net: we want to get the netpart before layer pool_3

[7]:
```
# The network finished
# model_pool_3 = keras.Model(net.input,net.get_layer("pool_3").output)
# model_pool_3.summary()

model_conv_3 = keras.Model(net.input,net.get_layer("conv_3").output)
model_conv_3.summary()
```

```
Model: "model"

_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
```

```
 input (InputLayer)          [(None, 55, 47, 3)]       0

 conv_1 (Conv2D)             (None, 52, 44, 20)        980

 pool_1 (MaxPooling2D)       (None, 26, 22, 20)        0

 conv_2 (Conv2D)             (None, 24, 20, 40)        7240

 pool_2 (MaxPooling2D)       (None, 12, 10, 40)        0

 conv_3 (Conv2D)             (None, 10, 8, 60)         21660

=================================================================
Total params: 29,880
Trainable params: 29,880
Non-trainable params: 0
_________________________________________________________________
```

[8]:
```python
# get the sort over cl_x_valid
predict_output = model_conv_3.predict(cl_x_valid)
# print(predict_output.shape)
predict_output_mean = predict_output.mean(axis=(0,1,2))
prune_sort = np.argsort(predict_output_mean)
```

[9]:
```python
print("prune order:", prune_sort)
```

```
prune order: [ 0 26 27 30 31 33 34 36 37 38 25 39 41 44 45 47 48 49 50 53 55 40
24 59
  9  2 12 13 17 14 15 23  6 51 32 22 21 20 19 43  3 58 42  1 29 16  5 56
  8 11 46 54 10  4 18  7 28 35 52 57]
```

[10]:
```python
def acc(predict,target):
  accuracy = np.mean(np.equal(predict, target) )*100
  return accuracy
```

[11]:
```python
pruned_net = keras.models.load_model(bd_net_path)
net = keras.models.load_model(bd_net_path)
# net is the original net

original_acc = 98.64899974019225
cl_classification_accuracy_valid_list = []
cl_classification_accuracy_test_list = []
attack_success_rate = []

trigger = np.ones(4) # record after 2%, 4%, 10%
ratio_list = np.array([2,4,10,30])
```

```
for i in range(len(prune_sort)):
  pruned_layer = pruned_net.get_layer('conv_3')
  w,b = pruned_layer.get_weights()
  # prune the current channel
  w[:,:,:,prune_sort[i]]=0
  b[prune_sort[i]]=0
  pruned_layer.set_weights((w,b))
  # test the current accuracy

  cl_y_valid_predict = np.argmax(pruned_net.predict(cl_x_valid),axis=1)

  val_acc = acc(cl_y_valid_predict,cl_y_valid)
  cl_classification_accuracy_valid_list.append(val_acc)
  ratio = 1-val_acc/original_acc
  print("prune round",i+1,"accuracy on valid:",val_acc)

  for j in range(len(ratio_list)):
    if(ratio*100 > ratio_list[j] and trigger[j]==1):
      pruned_net.save('./models/prune_net_'+'ratio'+str(ratio_list[j])+'.h5')
      trigger[j]=0


  cl_net_pred = np.argmax(net.predict(cl_x_test), axis=1)
  cl_pruned_net_pred = np.argmax(pruned_net.predict(cl_x_test), axis=1)
  cl_pred = np.zeros(len(cl_net_pred))
  for j in range(len(cl_pruned_net_pred)):
    if(cl_net_pred[j]==cl_pruned_net_pred[j]):
      cl_pred[j]=cl_net_pred[j]
    else:
      cl_pred[j]=1283

  test_acc = np.mean(np.equal(cl_pred, cl_y_test))*100


  bd_net_pred = np.argmax(net.predict(bd_x_test), axis=1)
  bd_pruned_net_pred = np.argmax(pruned_net.predict(bd_x_test), axis=1)
  bd_pred = np.zeros(len(bd_net_pred))
  for j in range(len(bd_pruned_net_pred)):
    if(bd_net_pred[j]==bd_pruned_net_pred[j]):
      bd_pred[j]=bd_net_pred[j]
    else:
      bd_pred[j]=1283



  test_asr = np.mean(np.equal(bd_pred, bd_y_test))*100
```

```
    cl_classification_accuracy_test_list.append(test_acc)
    attack_success_rate.append(test_asr)
    print("clean test classification accuracy is:", test_acc,"attack success rate␣
 ↪is",test_asr)
```

```
prune round 1 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 2 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 3 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 4 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 5 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 6 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 7 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 8 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 9 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 10 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 11 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 12 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 13 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 14 accuracy on valid: 98.64899974019225
```

```
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 15 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 16 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 17 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 18 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 19 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 20 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 21 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 22 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 23 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 24 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 25 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 26 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 27 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 28 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 29 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 30 accuracy on valid: 98.64899974019225
```

```
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 31 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 32 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 33 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.62042088854248 attack success rate is
100.0
prune round 34 accuracy on valid: 98.64033948211657
clean test classification accuracy is: 98.61262665627436 attack success rate is
100.0
prune round 35 accuracy on valid: 98.64033948211657
clean test classification accuracy is: 98.60483242400623 attack success rate is
100.0
prune round 36 accuracy on valid: 98.63167922404088
clean test classification accuracy is: 98.59703819173812 attack success rate is
100.0
prune round 37 accuracy on valid: 98.65765999826795
clean test classification accuracy is: 98.59703819173812 attack success rate is
100.0
prune round 38 accuracy on valid: 98.64899974019225
clean test classification accuracy is: 98.57365549493376 attack success rate is
100.0
prune round 39 accuracy on valid: 98.6056984498138
clean test classification accuracy is: 98.52689010132501 attack success rate is
100.0
prune round 40 accuracy on valid: 98.57105741751104
clean test classification accuracy is: 98.44115354637569 attack success rate is
100.0
prune round 41 accuracy on valid: 98.25062786871048
clean test classification accuracy is: 98.15276695245518 attack success rate is
100.0
prune round 42 accuracy on valid: 98.19000606218066
clean test classification accuracy is: 98.11379579111458 attack success rate is
100.0
prune round 43 accuracy on valid: 97.65307006148784
clean test classification accuracy is: 97.74746687451285 attack success rate is
100.0
prune round 44 accuracy on valid: 97.50584567420108
clean test classification accuracy is: 97.50584567420108 attack success rate is
100.0
prune round 45 accuracy on valid: 95.75647354291158
```

```
/usr/local/lib/python3.7/dist-packages/keras/engine/functional.py:1410:
CustomMaskWarning: Custom mask layers require a config and must override
```

```
get_config. When loading, the custom mask layer must be passed to the
custom_objects argument.
  layer_config = serialize_layer_fn(layer)
```

```
clean test classification accuracy is: 95.74434918160561 attack success rate is
100.0
prune round 46 accuracy on valid: 95.20221702606739
clean test classification accuracy is: 95.34684333593141 attack success rate is
99.97661730319564
prune round 47 accuracy on valid: 94.77786438035854
clean test classification accuracy is: 95.03507404520654 attack success rate is
99.97661730319564
prune round 48 accuracy on valid: 94.344851476574
clean test classification accuracy is: 94.57521434138737 attack success rate is
99.98441153546376
prune round 49 accuracy on valid: 93.85121676625964
clean test classification accuracy is: 94.00623538581449 attack success rate is
99.97661730319564
prune round 50 accuracy on valid: 92.16246644149996
clean test classification accuracy is: 92.33047544816836 attack success rate is
80.576773187841
prune round 51 accuracy on valid: 89.17467740538669
clean test classification accuracy is: 89.68043647700702 attack success rate is
80.6469212782541
prune round 52 accuracy on valid: 84.43751623798389
clean test classification accuracy is: 84.3335931410756 attack success rate is
77.20966484801247
prune round 53 accuracy on valid: 76.48739932449988
clean test classification accuracy is: 76.16523772408418 attack success rate is
36.26656274356976
prune round 54 accuracy on valid: 45.6915216073439
clean test classification accuracy is: 44.551831644583004 attack success rate is
16.03273577552611
prune round 55 accuracy on valid: 28.15449900407032
clean test classification accuracy is: 27.82540919719408 attack success rate is
3.72564302416212
prune round 56 accuracy on valid: 13.795791114575215
clean test classification accuracy is: 13.811379579111458 attack success rate is
16.399064692127826
prune round 57 accuracy on valid: 5.81103316878843
clean test classification accuracy is: 5.720966484801247 attack success rate is
0.303975058456742
prune round 58 accuracy on valid: 1.5501861955486274
clean test classification accuracy is: 1.5198752922837102 attack success rate is
0.0
prune round 59 accuracy on valid: 0.7188014202823244
clean test classification accuracy is: 0.646921278254092 attack success rate is
0.0
```

```
prune round 60 accuracy on valid: 0.0779423226812159
clean test classification accuracy is: 0.0701480904130943 attack success rate is
0.0
```

0.3 1. evaluate the three repaired net with X={2%,4%,10%}

We can see from the results after we fit the original eval.py code to the Good Net which is asked in the lab requirment. The final results are shown above. When the accuracy drops to X% we want, the code record the corresponding net parameters.

show the result on valid and test dataset

[12]:
```
bd_net = keras.models.load_model(bd_net_path)
for i in range(len(ratio_list)):
  path = "./models/prune_net_ratio"+str(ratio_list[i])+".h5"
  pruned_bd_net = keras.models.load_model(path)
  cl_net_pred = np.argmax(bd_net.predict(cl_x_test), axis=1)
  cl_pruned_net_pred = np.argmax(pruned_bd_net.predict(cl_x_test), axis=1)
  cl_pred = np.zeros(len(cl_net_pred))
  for j in range(len(cl_pruned_net_pred)):
    if(cl_net_pred[j]==cl_pruned_net_pred[j]):
      cl_pred[j]=cl_net_pred[j]
    else:
      cl_pred[j]=1283

  test_acc = np.mean(np.equal(cl_pred, cl_y_test))*100


  bd_net_pred = np.argmax(bd_net.predict(bd_x_test), axis=1)
  bd_pruned_net_pred = np.argmax(pruned_bd_net.predict(bd_x_test), axis=1)
  bd_pred = np.zeros(len(bd_net_pred))
  for j in range(len(bd_pruned_net_pred)):
    if(bd_net_pred[j]==bd_pruned_net_pred[j]):
      bd_pred[j]=bd_net_pred[j]
    else:
      bd_pred[j]=1283



  test_asr = np.mean(np.equal(bd_pred, bd_y_test))*100
  print("When X =",ratio_list[i],"%","clean test classification accuracy is:",␣
 ↪test_acc,"attack success rate is",test_asr)
```

```
When X = 2 % clean test classification accuracy is: 95.74434918160561 attack
success rate is 100.0
When X = 4 % clean test classification accuracy is: 94.57521434138737 attack
success rate is 99.98441153546376
When X = 10 % clean test classification accuracy is: 84.3335931410756 attack
success rate is 77.20966484801247
```

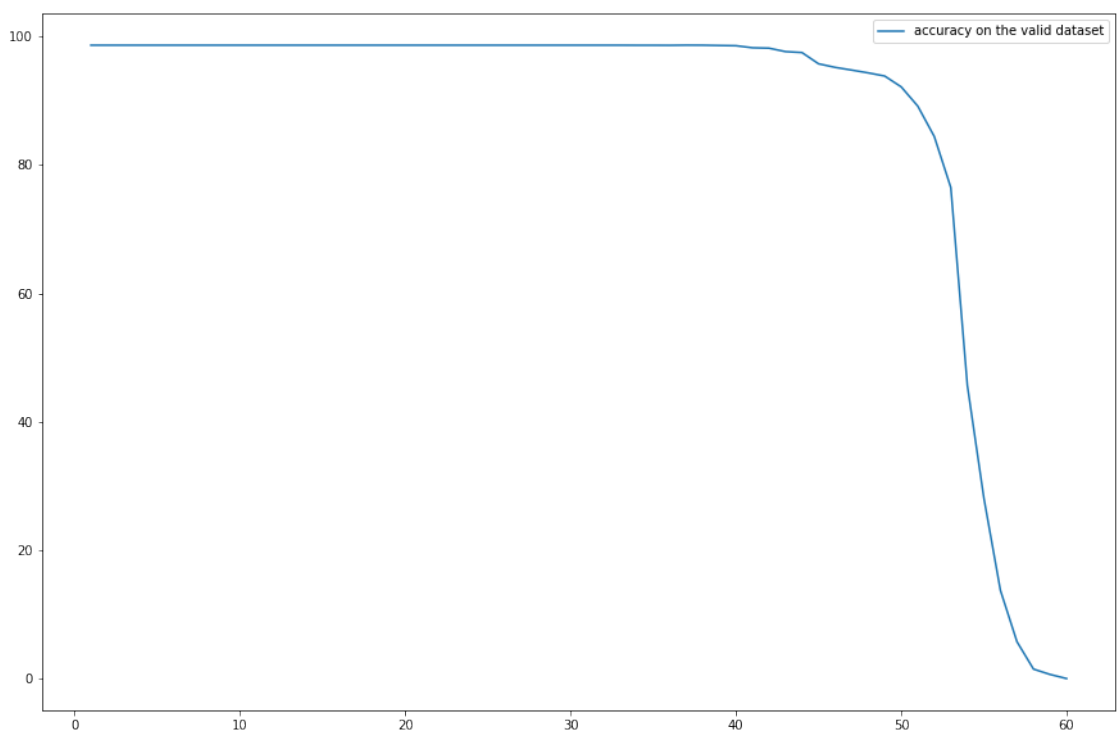
When X = 30 % clean test classification accuracy is: 44.551831644583004 attack success rate is 16.03273577552611

We can find out that the pruned net is not really that successful. Although we can see from above and the figures below that the attack success rate dropped after pruning, but the accuracy towards the clean dataset also drop rapidly which is not what we want. The reason might be that the attacker introduces sacrificial neurons in the network to disable pruning defense and it is a pruning aware attack.

0.4 2. plots of the result with script eval.py

[13]:
```
plt.figure(figsize=(15,10))
plt.plot([i for i in␣
↪range(1,61)],cl_classification_accuracy_valid_list,label="accuracy on the␣
↪valid dataset")
plt.legend()
# cl_classification_accuracy_valid_list = []
# cl_classification_accuracy_test_list = []
# attack_success_rate = []
```

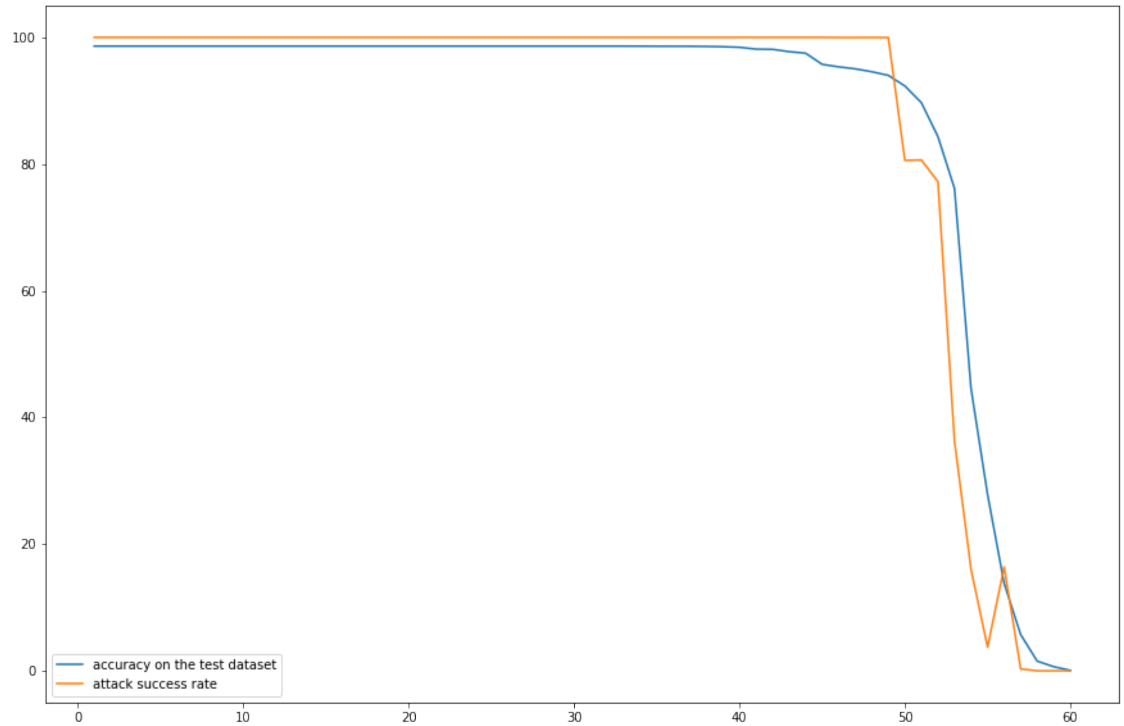
[13]: <matplotlib.legend.Legend at 0x7f8b6418ec90>



The plot below is the relationship between the accuracy on clean test data and the attack success rate (on backdoored test data) as a function of the fraction of channels pruned.

[14]:
```
plt.figure(figsize=(15,10))
plt.plot([i for i in range(1,61)],cl_classification_accuracy_test_list,label="accuracy on the test dataset")
plt.plot([i for i in range(1,61)],attack_success_rate, label="attack success rate")
plt.legend()
```

[14]:
```
<matplotlib.legend.Legend at 0x7f8c5f9cc4d0>
```



[ ]:
```
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[ ]:
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