ECE9133 - Machine Learning For Cybersecurity
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Question:

You must do the project individually. In this HW you will design a backdoor detector for BadNets trained on the YouTube Face dataset using the pruning defense discussed in class. Your detector will take as input:

1. B , a backdoored neural network classifier with N classes.
2. Dvalid , a validation dataset of clean, labelled images.

What you must output is G a "repaired" BadNet. G has N+1 classes, and given unseen test input, it must:

1. Output the correct class if the test input is clean. The correct class will be in [1,N].
2. Output class N+1 if the input is backdoored.

You will design G using the pruning defense that we discussed in class. That is, you will prune the last pooling layer of BadNet B (the layer just before the FC layers) by removing one channel at a time from that layer. Channels should be removed in decreasing order of average activation values over the entire validation set. Every time you prune a channel, you will measure the new validation accuracy of the new pruned badnet. You will stop pruning once the validation accuracy drops atleast X% below the original accuracy. This will be your new network B'.
Now, your goodnet G works as follows. For each test input, you will run it through both B and B'. If the classification outputs are the same, i.e., class i, you will output class i. If they differ you will output N+1. Evaluat this defense on:

1. A BadNet, B 1 , ("sunglasses backdoor") on YouTube Face for which we have already told you what the backdoor looks like. That is, we give you the validation data, and also test data with examples of clean and backdoored inputs.

Now you must submit:

Your repaired networks for X={2%,4%,10%}. The repaired networks will be evaluated using the evaluation script (eval.py) on this website https://github.com/csaw-hackml/CSAW-HackML-2020. Everything you need for this project is under the "lab3" directory.

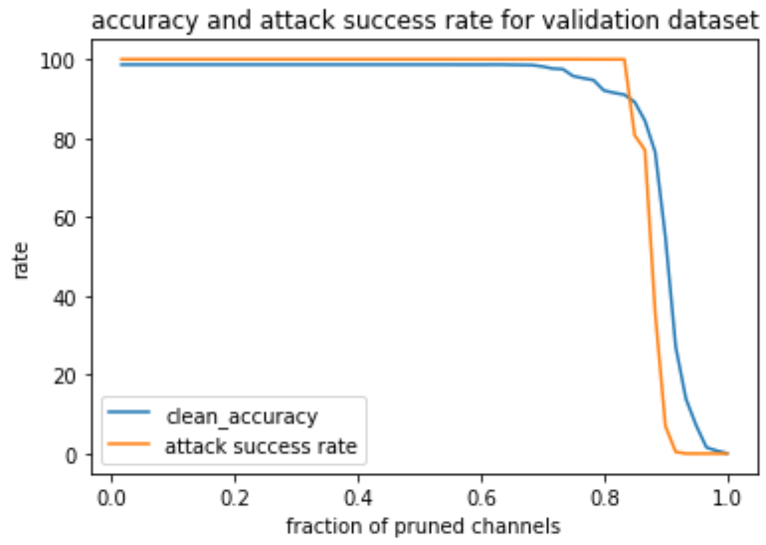
2. Please create and submit a link to a GitHub repo. with any/all code you have produced in this project along with a readme that tells us how to run your code.

3. A short report (at most 2 pages) that includes a table with the accuracy on clean test data and the attack success rate (on backdoored test data) as a function of the fraction of channels pruned (X).
What you must output is G a "repaired" BadNet. G has N+1 classes, and given unseen test

Summary report:

Pruning - Pruning eliminates each channel from a pooling layer one at a time. That's what we do in Average activation levels over the full validation set are listed in decreasing order. Every time we prune a channel, we validate the accuracy, and we stop pruning when the accuracy falls X% or less than the original.

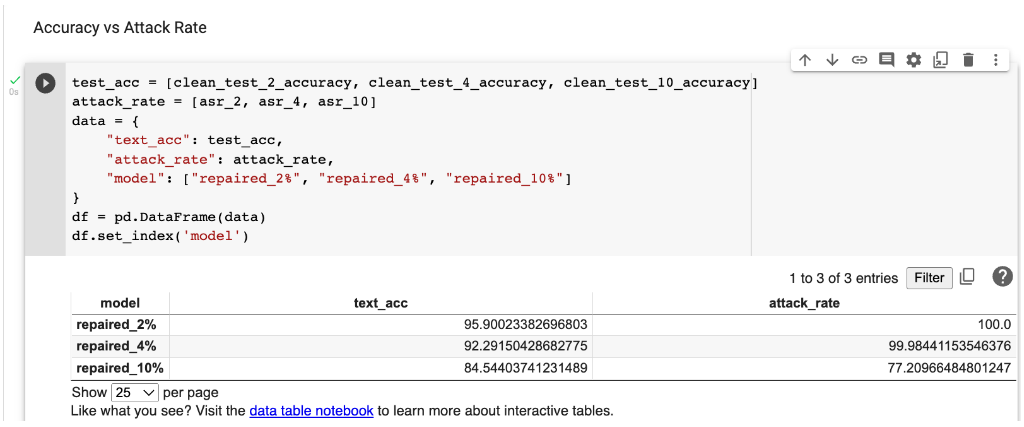
The attack success rate when the accuracy drops at least 30% is 6.954187234779596%.
Now, upon pruning the model, we used the clean validation dataset and after testing on the test data set. The accuracy and attack success rate would look like this for the validation dataset –



Evaluating the combined model: (below is the accuracy output)

```
401/401 [==============================] - 8s 20ms/step
2% drops model, the clean test data Classification accuracy: 95.90023382696803
401/401 [==============================] - 8s 19ms/step
2% drops model, Attack Success Rate: 100.0
401/401 [==============================] - 8s 19ms/step
4% drops model, the clean test data classification accuracy: 92.29150428682775
401/401 [==============================] - 8s 19ms/step
4% drops model, Attack Success Rate: 99.98441153546376
401/401 [==============================] - 8s 19ms/step
10% drops model, the clean test data classification accuracy: 84.54403741231489
401/401 [==============================] - 8s 19ms/step
10% drops model, Attack Success Rate: 77.20966484801247
```

Accuracy vs Attack Rate summaries from code:


Accuracy vs Attack Rate

```
test_acc = [clean_test_2_accuracy, clean_test_4_accuracy, clean_test_10_accuracy]
attack_rate = [asr_2, asr_4, asr_10]
data = {
    "text_acc": test_acc,
    "attack_rate": attack_rate,
    "model": ["repaired_2%", "repaired_4%", "repaired_10%"]
}
df = pd.DataFrame(data)
df.set_index('model')
```

1 to 3 of 3 entries Filter

model	text_acc	attack_rate
repaired_2%	95.90023382696803	100.0
repaired_4%	92.29150428682775	99.98441153546376
repaired_10%	84.54403741231489	77.20966484801247

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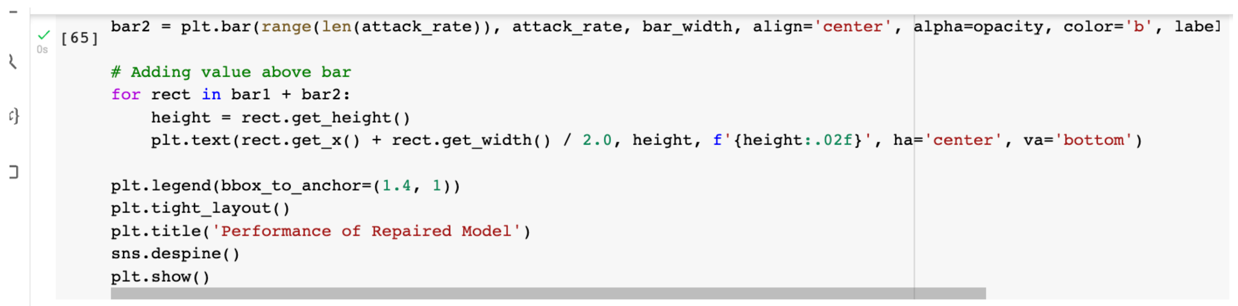
Like what you see? Visit the data table notebook to learn more about interactive tables.

Because the attack success rate does not much decline, we can see that the prune defense is not very effective. The attack success rate is acceptable but not great because it compromises the accuracy too much. The attack strategy is a prune immune attack, and the poisoned data are kept with the pruned model.

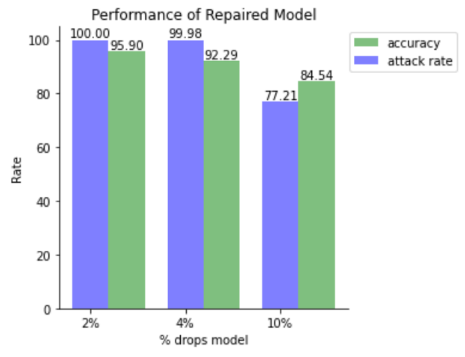
Also, there is a side-by-side comparison of the performance of the repaired model –



```
[65]  bar2 = plt.bar(range(len(attack_rate)), attack_rate, bar_width, align='center', alpha=opacity, color='b', label

      # Adding value above bar
      for rect in bar1 + bar2:
          height = rect.get_height()
          plt.text(rect.get_x() + rect.get_width() / 2.0, height, f'{height:.02f}', ha='center', va='bottom')

      plt.legend(bbox_to_anchor=(1.4, 1))
      plt.tight_layout()
      plt.title('Performance of Repaired Model')
      sns.despine()
      plt.show()
```



As per the instructions mentioned, we need to save the save the model when the accuracy drops by at least {2%, 4%, 10%}. The saved models are titled model_X=2.h5, model_X=4.h5 and model_X=10.h5 for a drop in the 2%, 4% and 10% respectively. Its available in output folder.

Code to be executed is –
ML_for_cybersec_Lab2_mm11070.ipynb - code
ML_for_cybersec_Lab2_mm11070.pdf – pdf of executed code
Github Link - https://github.com/mukta-maheshwari/ECE9133-Machine_Learning_For_Cybersecurity