In-Browser Cyber Security Labs

Dr. Junjie Zhang
Associate Professor
Dept. of Computer Science and Engineering

2024 CAE Community Symposium

WRIGHT STATE UNIVERSITY

CAE IN CYBERSECURITY COMMUNITY

Who Are We?

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Wright State University

- Two campus
  - Main Campus, Dayton, Ohio
  - Lake Campus, Celina, Ohio
- Total Enrollment as of Sep. 23
  - 11,036

Dept. Of Comp. Sci. and Eng.

- Undergraduate (B.S.)
  - CS, CE, and IT & Cyber
- Graduate (M.S.)
  - CS, CE, Cyber Security, Cyber Security with Cyber Defense Concentration, and Data Science
- Graduate (Ph.D.)
  - CSE

Active Collaboration with CAE Institutions

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AF Institute of Technology

Clark State Community College

Sinclair Community College

Columbus State Community College

University of Cincinnati

Our Featured Cyber Security Courses

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- Cyber Network Security
- Host Computer Security
- Information Security
- Security Attacks and Defenses
- Reverse Engineering and Program Analysis
- Trustworthy Machine Learning

All are offered in the flexible mode (i.e., with an built-in online mode)

Challenges for Online Cyber Education

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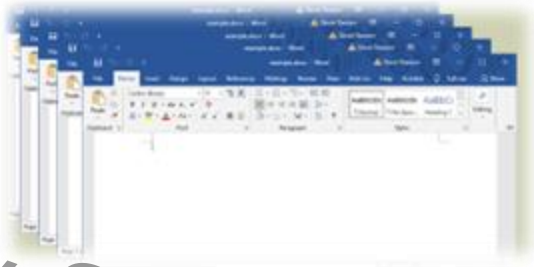

Variety and Heterogeneity of Experiment Environments

Collaboratively editing, commenting, and debugging

Context Switching and Cross-Referencing

Our Solutions

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- Building cyber security labs, when applicable, using Google Colab.
  - Executable Python Code
  - Rich Text (image, html, and latex)
  - Online Collaboration (sharing, commenting, and chatting)

An Example

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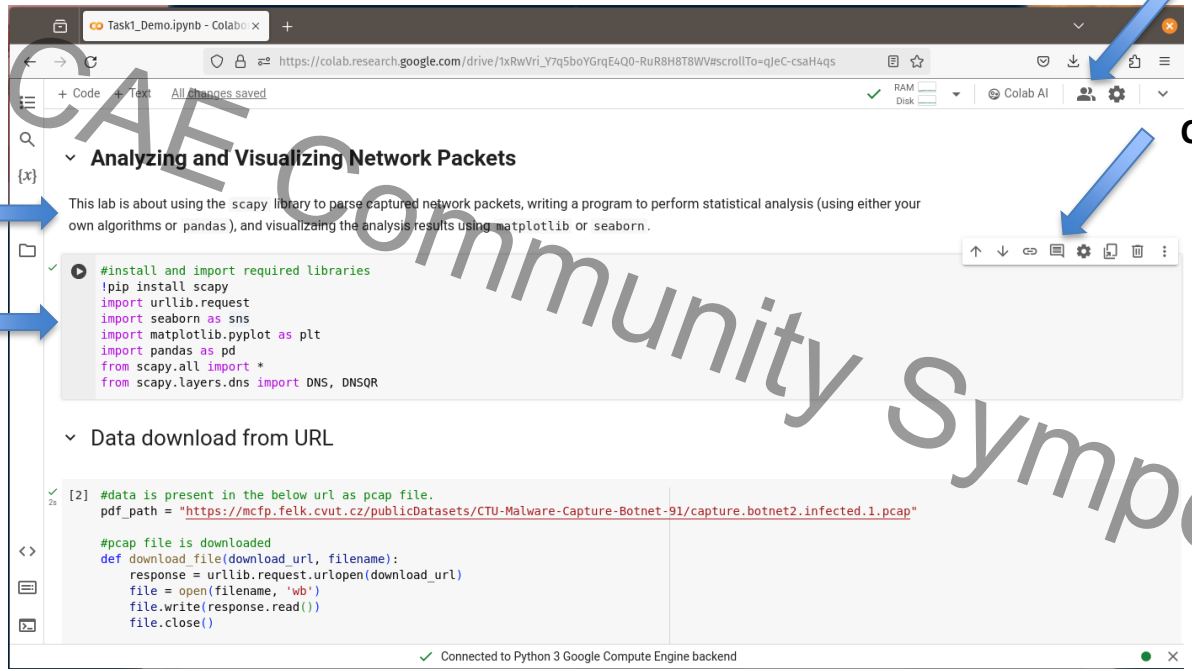
Sharing

Commenting

Text

Code



Facilitating Online Cyber Education

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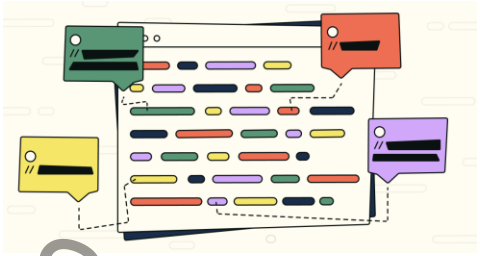
Zero-Deployment Efforts – Everything is inside your browser.

Synchronous and Asynchronous Online Collaboration – Collaboratively developing and editing using Google's platform.



Text, comments, and code are all in one place – An interactive programming notebook

Setting Up Cyber Security Labs in Colab

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- Create a new notebook
- Install required packages
- Write your demo/lab/project description and code samples/skeletons.
- You may want to download datasets automatically from a public repository instead of asking students to upload them manually.

Our Colab-based In-Browser Labs

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- Network Security
- Trustworthy Machine Learning
- Reverse Engineering and Program Analysis

Network Security

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- Packet Parsing
- Network Traffic Analysis and Visualization
- Traceroute Visualization
- Cryptography

Network Traffic Analysis and Visualization

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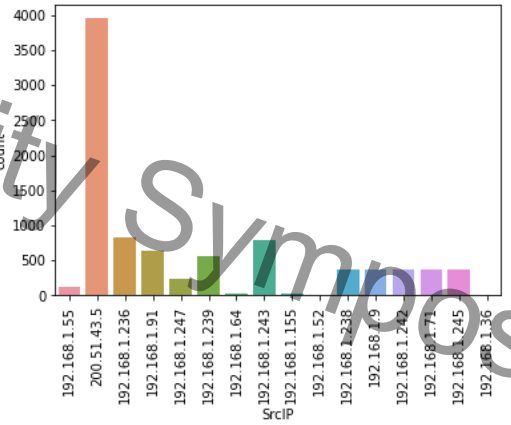
```
#declaring empty lists with the below variable names
timestampList,srcAddressList,dstAddressList,domainnameList = ([] for i in range(4))

#traversing through each packet
for packet in networkpackets:

    #check for DNS layer
    if packet.haslayer(DNS):
        dst = packet[IP].dst
        src = packet[IP].src

        #check for query
        if packet[DNS].qd:
            domainname = packet[DNS].qd.qname

            #converting time from string to timestamp
            timestampList.append(time.strftime('%Y-%m-%d %H:%M:%S', time.localtime(packet.time)))
            srcAddressList.append(src)
            dstAddressList.append(dst)
            domainnameList.append(domainname)

#converting the above lists to dictionary
dict = {'timestamp': timestampList, 'SrcIP': srcAddressList, 'dstIP': dstAddressList, 'name': domainnameList}

#dictionary to dataframe
df = pd.DataFrame(dict)

#dataframe to csv file
df.to_csv('pcap.csv',index=False)
```

Data Visualization

```
[ ]  #count plot for SrcID
     ax = sns.countplot(x = 'SrcIP',data = df)
     g = ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
```



Trustworthy Machine Learning

- Gradient-Based Adversarial Attacks and Defenses
- Backdoor Attacks and Defenses
- Adversary Reprogramming
- Membership Inference Attacks and Defenses
- Etc.

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Gradient-Based Adversarial Attacks

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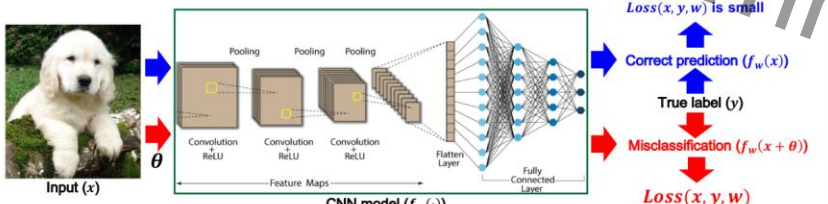
Gradient-based Adversarial Attack

Adversarial attack – given a test input x and a trained classification model $f_w(\cdot)$, an adversarial attack is to craft perturbations θ and add θ to the input to generate an adversarial example $x' = x + \theta$, such that the classification output

$$y = f_w(x) \neq f_w(x'), \qquad \|\theta\| \leq \varepsilon$$



Regular classification path

Adversarial attack path

Convert adversarial attack problem to an optimization problem to maximize $Loss(x, y, w)$ to obtain the optimal x

Review

```
train_dataset = datasets.MNIST('./data', train=True, download=True, transform=transform)
test_dataset = datasets.MNIST('./data', train=False, download=True, transform=transform)

#Load the datasets into DataLoader
train_dataloader = DataLoader(train_dataset, batch_size=64, shuffle=True, num_workers=0)
test_dataloader = DataLoader(test_dataset, batch_size=64, shuffle=False, num_workers=0)

class_names = ['0', '1', '2', '3', '4',
               '5', '6', '7', '8', '9']
```

(1) Load MNIST data directly from PyTorch

```
#Define the training function
def train(epoch):
    model.train()

    running_loss = 0.0
    train_total, train_correct = 0.0, 0.0
    y_train, y_pred = [], []

    for i, (features, labels) in enumerate(train_dataloader):
        optimizer.zero_grad()

        outputs = model(features)

        loss = lossfunction(outputs, labels.long())
        loss.backward()
        optimizer.step()

        #print statistics
        running_loss += loss.item()
        _, train_predicted = torch.max(outputs.data, 1)
        train_total += labels.size(0)
        train_correct += (train_predicted == labels.long()).sum().item()
        y_train += labels.tolist()
        y_pred += train_predicted.tolist()

        if i % 200 == 0:
            print('Epoch: {} [{}/{} ({:.0f}%)]\tloss: {:.6f}'.format(
                epoch, i * len(features), len(train_dataloader.dataset),
                100. * i / len(train_dataloader), loss.item()))

    macro_f1 = f1_score(y_train, y_pred, average='macro')
    print('epoch (%d): train accuracy: %.4f, f1_score: %.4f, loss: %.3f' % (epoch,

#Train the model
for epoch in range(1, epochs + 1):
    train(epoch)
```

(3) Train a convolutional neural network

```
class ClassificationNet(nn.Module):
    def __init__(self):
        super(ClassificationNet, self).__init__()
        self.conv1 = nn.Conv2d(1, 10, kernel_size=5) #1 input channel to 10 channels
        self.conv2 = nn.Conv2d(10, 20, kernel_size=5)#10 channels to 20 channels
        self.fc1 = nn.Linear(320, 50)
        self.fc2 = nn.Linear(50, 10)

    def forward(self, x):
        x = F.relu(self.conv1(x))   #Use ReLU as activation function
        x = F.max_pool2d(x, 2)      #Apply max_pooling on the output of the convolution layer
        x = F.relu(self.conv2(x))
        x = F.max_pool2d(x, 2)
        x = torch.flatten(x, 1)
        x = F.relu(self.fc1(x))
        x = self.fc2(x)
        return x
```

(2) Define the convolutional neural network structure

```
def fgsm_attack(image, epsilon, image_input_grad):
    #Obtain the sign of the gradient
    sign_grad = image_input_grad.sign()
    #Generate the perturbed image by adding the perturbation with size of epsilon a
    perturbed_image = image + epsilon * sign_grad
    perturbation = epsilon * sign_grad
    #Each pixel value's range is [0,1]
    #After performing adversarial attack, the pixel values may go out of boundary
    #Add clipping to maintain [0,1] range
    perturbed_image = torch.clamp(perturbed_image, 0, 1)

    #Return the perturbed image
    return perturbed_image, perturbation
```

(4) Define an FGSM attack

```
def perform_attack(epsilon, image_input, image_label):
    #Set requires_grad attribute of tensor as true, which will be used for Attack
    image_input.requires_grad = True
    output = model(image_input)

    #Calculate the loss
    loss = lossfunction(output, image_label.long())
    # Zero_grad existing gradients
    model.zero_grad()
    #Calculate gradients and loss in backward pass
    loss.backward()
    #Obtain the gradient regarding input image
    image_input_grad = image_input.grad.data

    # Call FGSM attack
    perturbed_image, perturbation = fgsm_attack(image_input, epsilon, image_input_grad)

    return perturbed_image, perturbation
```

(5) Use different epsilons to perform attack

Feature Collision Attacks

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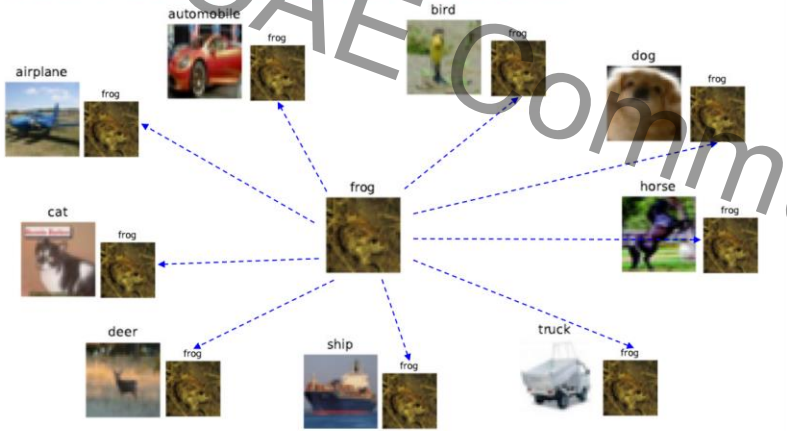
Feature Collision Backdoor Attack



Add perturbation to move frog from the base label towards the target labels:
features are close to the target images, but the label is still frog

Hidden Trigger Backdoor Attack

Using feature collision to generate poisoning samples with hidden trigger – select an input x_c with a base label (c – such as frog) and an input x_t with a target label (t – such as airplane), and then add the trojan trigger ε to the target sample

$$\widehat{x_t} = x_t + \varepsilon$$

After than, we can find a poisoning sample $\hat{x}$ by computing

$$\hat{x} = \min_x \|f(x) - f(\widehat{x_t})\|_2^2 + \beta\|x - x_c\|_2^2$$

#Poison			
50	100	200	400
0.988±0.01	0.982±0.01	0.976±0.02	0.961±0.02
0.555±0.16	0.424±0.17	0.270±0.16	0.223±0.14
0.605±0.16	0.437±0.15	0.300±0.13	0.214±0.14

First row: clean data
Second row: naive backdoor attack
Third row: hidden trigger backdoor

Base | Target | Target with trigger | Poisoning sample encoding trigger

Feature Collision Attacks

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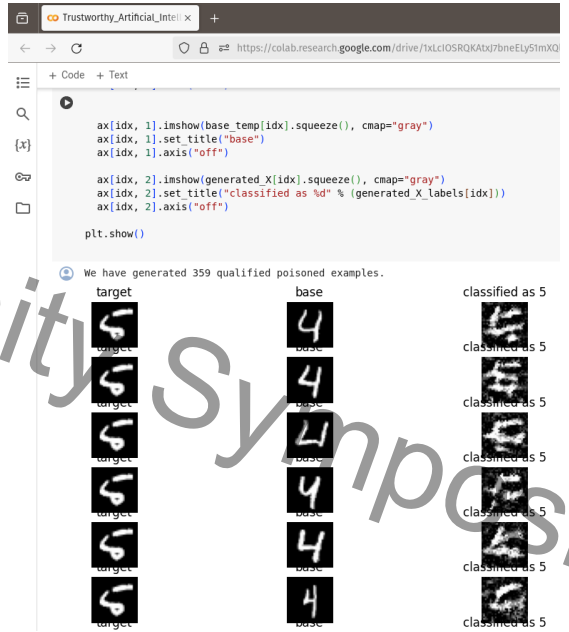
```
[ ] def gen_one_poisoned_sample(one_base_instance, one_target_instance, model, beta):
      # It is worth noting that this model is ready for the inference mode and it has already been hooked.

      output_target = model(one_target_instance)
      fc1_target = layer_outputs['fc1']

      x = torch.rand_like(one_base_instance, requires_grad=True)
      x = torch.nn.parameter.Parameter(x, requires_grad=True)

      lr = 0.01
      optimizer = torch.optim.Adam([x], lr=lr)
      epochs = 100

      for i in range(epochs):
        output_x = model(torch.clamp(x, 0, 1))
        fc1_x = layer_outputs['fc1']
        loss = torch.linalg.norm(fc1_x - fc1_target) + beta * torch.linalg.norm(x - one_base_instance)
        optimizer.zero_grad()
        loss.backward()
        optimizer.step()

      x = torch.clamp(x, 0, 1).detach()

      with torch.no_grad():
        predict_label = model(x)
        predict_label = predict_label.reshape(-1, predict_label.shape[0])
        _, predict_label = torch.max(predict_label, dim = 1)


      return x, predict_label.item()
```



Reverse Engineering and Program Analysis

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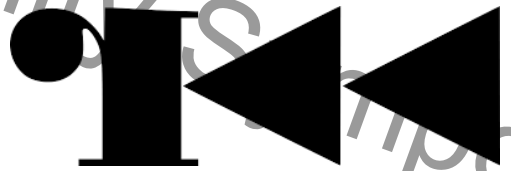
- Decompiling
- Binary Emulation
- Taint Analysis
- Symbolic Execution
- Vulnerability Detection



Access to Our In-Browser Lab Samples

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- Follow my GitHub account – jzhang369
- or https://github.com/jzhang369/cybersecuritylabs/tree/main
- or send me an email at junjie.zhang@wright.edu

Thank You!

junjie.zhang@wright.edu

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