Imports

```
import torch
import torch.nn as nn
from random import shuffle
import numpy as np
from sklearn.metrics import roc_curve, auc, confusion_matrix,roc_auc_score
import matplotlib.pyplot as plt

from torchvision.datasets import FashionMNIST
import torchvision.transforms as T

from google.colab import drive
from torch.utils.data import Subset, DataLoader
from sklearn.metrics import confusion_matrix, accuracy_score, precision_score
import torch.nn.functional as F
from datasets import Dataset
import evaluate
from typing import List, Tuple
from nltk.translate.bleu_score import sentence_bleu, SmoothingFunction
import nltk
nltk.download('punkt')
```

```
!pip install datasets
!pip install evaluate
```

Show hidden output

Function to load fmnist dataset

```
fmnist_labels = {
    0: "T-shirt/top",
    1: "Trouser",
    2: "Pullover",
    3: "Dress",
    4: "Coat",
    5: "Sandal",
    6: "Shirt",
    7: "Sneaker",
    8: "Bag",
    9: "Ankle boot"
}

def load_fmnist_torch(root="./data", transform=None, download=True):

    if transform == None:
        transform = T.ToTensor()

    train_set = FashionMNIST(root=root,  transform=transform, download=download, train=True)
    test_set = FashionMNIST(root=root,  transform=transform, download=download, train=False)

    # Each item in this dictionary is a torch Dataset object
    # To feed the data into a model, you may have to use a DataLoader
    return {"train": train_set, "test": test_set}
```

SmallCNN Model

```
class SmallCNN(nn.Module):

    def __init__(self):
        super(SmallCNN, self).__init__()

        self.layer1 = nn.Sequential(
            nn.Conv2d(in_channels=1, out_channels=32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(),
            nn.MaxPool2d(kernel_size=2, stride=2)
        )

        self.layer2 = nn.Sequential(
            nn.Conv2d(in_channels=32, out_channels=64, kernel_size=3),
            nn.BatchNorm2d(64),
```

```
            nn.ReLU(),
            nn.MaxPool2d(2)
        )
        self.fc1 = nn.Linear(in_features=64*6*6, out_features=600)
        self.drop = nn.Dropout(0.25)
        self.fc2 = nn.Linear(in_features=600, out_features=120)
        self.fc3 = nn.Linear(in_features=120, out_features=10)

    def forward(self, x):
        out = self.layer1(x)
        out = self.layer2(out)
        out = out.view(out.size(0), -1)
        out = self.fc1(out)
        out = nn.functional.relu(out)
        out = self.drop(out)
        out = self.fc2(out)
        out = nn.functional.relu(out)
        out = self.fc3(out)
        return out
```

```
# Check if CUDA is available
if torch.cuda.is_available():
    device = torch.device('cuda')
    print("CUDA available! Training on GPU.", flush=True)
else:
    device = torch.device('cpu')
    print("CUDA NOT available... Training on CPU.", flush=True)
```

```
CUDA available! Training on GPU.
```

Problem 1

```
# Load FMNIST dataset
fmnist = load_fmnist_torch()
fmnist_train = fmnist['train']
fmnist_test = fmnist['test']

```

```
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-images-idx3-ubyte.gz to ./data/FashionMNIST
100%|██████████| 26.4M/26.4M [00:08<00:00, 3.17MB/s]
Extracting ./data/FashionMNIST/raw/train-images-idx3-ubyte.gz to ./data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/train-labels-idx1-ubyte.gz to ./data/FashionMNIST
100%|██████████| 29.5k/29.5k [00:00<00:00, 209kB/s]
Extracting ./data/FashionMNIST/raw/train-labels-idx1-ubyte.gz to ./data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-images-idx3-ubyte.gz to ./data/FashionMNIST/
100%|██████████| 4.42M/4.42M [00:03<00:00, 1.30MB/s]
Extracting ./data/FashionMNIST/raw/t10k-images-idx3-ubyte.gz to ./data/FashionMNIST/raw

Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz
Downloading http://fashion-mnist.s3-website.eu-central-1.amazonaws.com/t10k-labels-idx1-ubyte.gz to ./data/FashionMNIST/
100%|██████████| 5.15k/5.15k [00:00<00:00, 20.8MB/s]
Extracting ./data/FashionMNIST/raw/t10k-labels-idx1-ubyte.gz to ./data/FashionMNIST/raw
```

```
print(len(fmnist["test"]))
print(len(fmnist["train"]))
```

```
10000
60000
```

```
# TODO: Load and train mdoel

train_loader = DataLoader(fmnist["train"], batch_size = 64, shuffle=True)
print(len(fmnist["train"]))
test_loader = DataLoader(fmnist["test"], batch_size = 64, shuffle=True)
print(len(fmnist["test"]))


images, labels = next(iter(train_loader))

# Model Instantiated:
model = SmallCNN()

criterion = torch.nn.CrossEntropyLoss()
```

```
optimizer = torch.optim.Adam(model.parameters(), lr = 0.01)

#print(len(fmnist_train))

# Train the model
drive.mount('/content/drive')
# model.train()
# num_epochs = 10
# for epoch in range(num_epochs):
#   for images, labels in train_loader:
#     images,labels = images,labels
#     #print(images.shape)
#     #print(type(labels))

#     optimizer.zero_grad()
#     outputs = model(images)
#     loss = criterion(outputs,labels)
#     loss.backward()
#     optimizer.step()
#     print(f"Epoch [{epoch+1}/{num_epochs}], Loss: {loss.item():.4f}")

# torch.save(model.state_dict(), '/content/drive/My Drive/model.pth')
# print("Save Completed")
```

Show hidden output

```
# TO DO: Test model
test_loader = DataLoader(fmnist["test"], batch_size = 64, shuffle=True)
print(len(fmnist["test"]))

images, labels = next(iter(test_loader))

#Set the Model to Evaluation Mode
model.load_state_dict(torch.load('/content/drive/My Drive/model.pth'))
# model.eval()
# correct = 0
# total = 0
# with torch.no_grad():
#     for images, labels in test_loader:
#         outputs = model(images)
#         _, predicted = torch.max(outputs.data, 1)
#         #print(predicted.shape)
#         #predicted = predicted.unsqueeze(1)
#         #print("images",images.shape)
#         total += labels.size(0)
#         correct += (predicted == labels).sum().item()

# print(correct)
# print(total)
# accuracy = (correct / total) * 100
# print(f"Test Accuracy: {accuracy:.2f}%")

```

```
10000
<ipython-input-9-f028f47c26be>:8: FutureWarning: You are using `torch.load` with `weights_only=False` (the current defau
  model.load_state_dict(torch.load('/content/drive/My Drive/model.pth'))
<All keys matched successfully>
```

```
random.seed(42)
torch.manual_seed(42)

fmnist_member_indices = random.sample(range(len(fmnist_train)), 500)
fmnist_nonmember_indices = random.sample(range(len(fmnist_test)), 500)

fmnist_member_set = Subset(fmnist_train, fmnist_member_indices)
fmnist_nonmember_set = Subset(fmnist_test, fmnist_nonmember_indices)

# Create DataLoaders for the subsets
member_loader = DataLoader(fmnist_member_set, batch_size=64, shuffle=False)
nonmember_loader = DataLoader(fmnist_nonmember_set, batch_size=64, shuffle=False)
```

```
# Run the loss based attack on the model
# Run the loss-based attack for the Cross-entropy loss (criterion) and report the confusion matrix: True Positives (TP),
# Compute the accuracy, error, and precision of the attack for the threshold T
```

```
def crossentropy_loss_values(model, member_loader, nonmember_loader, device='cuda'):

    model.eval()
    losses = []
    labels = []
```

```
    with torch.no_grad():
        for image_data, image_labels in member_loader:
            image_data = image_data.to(device)
            image_labels = image_labels.to(device)
            outputs = model(image_data)

            for i in range(len(image_data)):
                loss = F.cross_entropy(outputs[i:i+1], image_labels[i:i+1], reduction='mean')
                losses.append(loss.item())
                labels.append(1)


        for image_data, image_labels in nonmember_loader:
            image_data = image_data.to(device)
            image_labels = image_labels.to(device)
            outputs = model(image_data)

            for i in range(len(image_data)):
                loss = F.cross_entropy(outputs[i:i+1], image_labels[i:i+1], reduction='mean')
                losses.append(loss.item())
                labels.append(0)

    return np.array(losses), np.array(labels)

def compute_attack_metrics(losses, true_labels, threshold):

    predicted_labels = (losses <= threshold).astype(int)

    # confusion matrix
    conf_matrix = confusion_matrix(true_labels, predicted_labels)
    tn = conf_matrix[0,0]
    fp = conf_matrix[0,1]
    fn = conf_matrix[1,0]
    tp = conf_matrix[1,1]

    accuracy = (tp + tn) / (tp + tn + fp + fn)
    error = 1 - accuracy
    precision = tp / (tp + fp) if (tp + fp) > 0 else 0

    metrics = {
        'threshold': threshold,
        'confusion_matrix': {
            'TP': tp,
            'FP': fp,
            'TN': tn,
            'FN': fn
        },
        'accuracy': accuracy,
        'error': error,
        'precision': precision,
    }

    return metrics

losses, true_labels = crossentropy_loss_values(model, member_loader, nonmember_loader, device)

# Threshold T
threshold = np.percentile(losses, 50)
predicted_labels = (losses <= threshold).astype(int)
print(f"T value {threshold:.2f}:")

metrics = compute_attack_metrics(losses, true_labels, threshold)

conf_matrix = confusion_matrix(true_labels, predicted_labels)
print("Confusion Matrix:")
print(conf_matrix)

print("\nMetrics:")
print(f"Accuracy: {metrics['accuracy']:.2f}")
print(f"Error Rate: {metrics['error']:.2f}")
print(f"Precision: {metrics['precision']:.2f}")
```

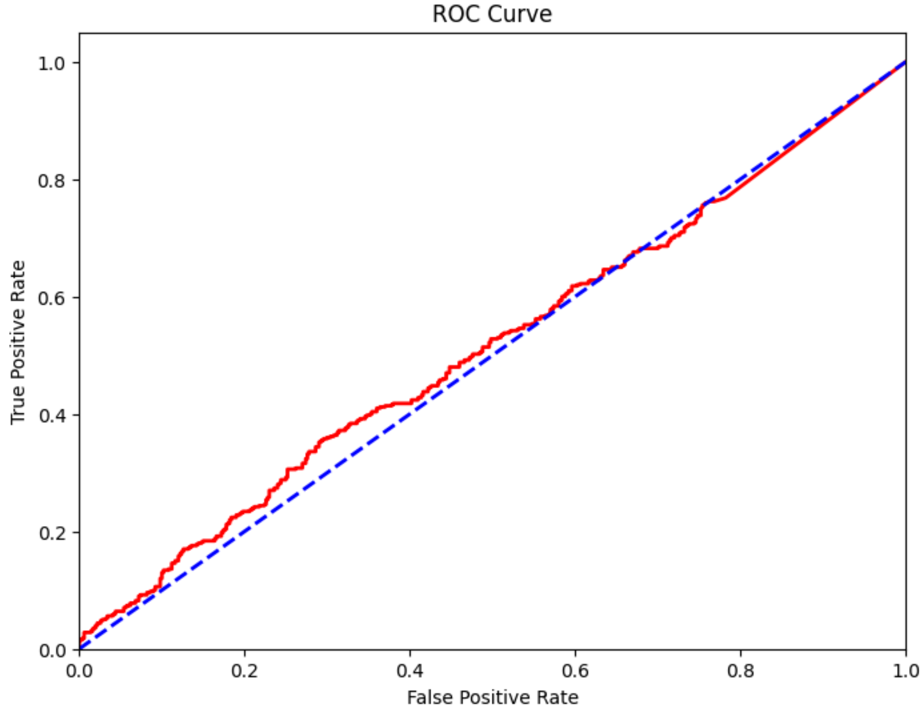
```
T value 0.01:
Confusion Matrix:
[[256 244]
 [244 256]]

Metrics:
Accuracy: 0.51
Error Rate: 0.49
Precision: 0.51
```

Citation for Creating the confusion matrix

https://www.geeksforgeeks.org/confusion-matrix-machine-learning/#what-is-a-confusion-matrix

Double-click (or enter) to edit

```
# TODO: Plot results
losses, true_labels = crossentropy_loss_values(model, member_loader, nonmember_loader, device)

# print(type(losses))
# print(type(true_labels))


# ROC curve and ROC area
fpr, tpr, thresholds = roc_curve(true_labels, losses, pos_label=0)
roc_auc = auc(fpr, tpr)

# Plot
plt.figure(figsize=(8, 6))
plt.plot(fpr, tpr, color='red', lw=2)
plt.plot([0, 1], [0, 1], color='blue', lw=2, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('ROC Curve')
plt.show()


```




```
# TODO: Comment on Observations
#The AUC value of 0.51 suggest that the attack is extremely weak.
#The model's loss values don't effectively distinguish between members and non-members
#thus the attack is unable to accomplsih its objective. This is contrary to the LIRA paper
#which had metrics to show that the attack was strong.
```

Problem 2

```
from transformers import AutoModelForCausalLM, AutoTokenizer, Trainer, TrainingArguments
import pandas as pd
from sklearn.model_selection import train_test_split
import evaluate
```

```
# Load the dataset
drive.mount('/content/drive')
```

```
data = pd.read_csv('/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/Email_data.csv')  # Replace with the actual pat
data.head()
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remoun
```

	Unnamed: 0	file	message
0	427616	shackleton-s/sent/1912.	Message-ID: <21013688.1075844564560.JavaMail.e...
1	108773	farmer-d/logistics/1066.	Message-ID: <22688499.1075854130303.JavaMail.e...
2	355471	parks-j/deleted_items/202.	Message-ID: <27817771.1075841359502.JavaMail.e...
3	457837	stokley-c/chris_stokley/iso/client_rep/41.	Message-ID: <10695160.1075858510449.JavaMail.e...
4	124910	germany-c/all_documents/1174.	Message-ID: <27819143.1075853689038.JavaMail.e...

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive", force_remoun
```

```
# Email Text
data['message'].head(2)
```

	message
0	Message-ID: <21013688.1075844564560.JavaMail.e...
1	Message-ID: <22688499.1075854130303.JavaMail.e...

dtype: object

```
# Example Email
print(data['message'].iloc[0][:550])
```

Show hidden output

```
# TODO: Load and Fine tune mdoel

# Model
pythia_model = AutoModelForCausalLM.from_pretrained(
  "EleutherAI/pythia-70m-deduped",
  revision="step3000",
  cache_dir="./pythia-70m-deduped/step3000",
)

tokenizer = AutoTokenizer.from_pretrained(
  "EleutherAI/pythia-70m-deduped",
  revision="step3000",
  cache_dir="./pythia-70m-deduped/step3000",
)
```

config.json: 100% 567/567 [00:00<00:00, 39.1kB/s]

pytorch_model.bin: 100% 166M/166M [00:01<00:00, 129MB/s]

tokenizer_config.json: 100% 396/396 [00:00<00:00, 21.1kB/s]

tokenizer.json: 100% 2.11M/2.11M [00:00<00:00, 7.90MB/s]

special_tokens_map.json: 100% 99.0/99.0 [00:00<00:00, 4.04kB/s]

```
/usr/local/lib/python3.10/dist-packages/transformers/tokenization_utils_base.py:1601: FutureWarning: `clean_up_tokenizat
  warnings.warn(
```

```
# Split the data into train (2/3) and test (1/3) sets


train_data, test_data = train_test_split(data,test_size=0.33,random_state=42)


# Tokenize the emails
if tokenizer.pad_token is None:
  tokenizer.pad_token = tokenizer.eos_token

# def tokenize_function(examples):
#     return tokenizer(
#         examples["message"],
#         truncation=True,
#         padding=True,
#         max_length=512,
```

```
#     )

# # Convert to Hugging Face datasets
# train_dataset = Dataset.from_pandas(train_data)
# test_dataset = Dataset.from_pandas(test_data)

# # Tokenize the datasets
# train_tokenized = train_dataset.map(tokenize_function, batched=True)
# test_tokenized = test_dataset.map(tokenize_function, batched=True)

# # Training arguments
# training_args = TrainingArguments(
#     output_dir="./pythia-fine-tuned",
#     num_train_epochs=10,
#     per_device_train_batch_size=64,
#     per_device_eval_batch_size=64,
#     warmup_steps=500,
#     weight_decay=0.01,
# )

# # Initialize the Trainer
# trainer = Trainer(
#     model=pythia_model,
#     args=training_args,
#     train_dataset=train_tokenized,
#     eval_dataset=test_tokenized,
# )

# # Print dataset sizes
# print(f"Training set size: {len(train_data)}")
# print(f"Test set size: {len(test_data)}")

# # Print an example from the training data
# print("\nExample email from training set:")
# print(train_data['message'].iloc[0][:550])

#Save the fine-tuned model
# pythia_model.save_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_pythia")
# tokenizer.save_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_pythia")
```

```
591     Message-ID: <24048650.1075853975914.JavaMail.e...
664     Message-ID: <8189273.1075840887983.JavaMail.ev...
195     Message-ID: <9300560.1075851573421.JavaMail.ev...
1240    Message-ID: <7654943.1075842838727.JavaMail.ev...
1048    Message-ID: <30379452.1075854430023.JavaMail.e...
                               ...
1130    Message-ID: <21859410.1075852282055.JavaMail.e...
1294    Message-ID: <11613616.1075849659137.JavaMail.e...
860     Message-ID: <19463108.1075852096010.JavaMail.e...
1459    Message-ID: <9982296.1075840531689.JavaMail.ev...
1126    Message-ID: <2462383.1075856344807.JavaMail.ev...
Name: message, Length: 1005, dtype: object
```

```
fine_tuned_model = AutoModelForCausalLM.from_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tunec
fine_tuned_tokenizer = AutoTokenizer.from_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_py

#Report the perplexity of the original and fine-tuned model.

perplexity_metric = evaluate.load("perplexity")

pythia_model.eval()
# Calculate perplexity
ft_results = perplexity_metric.compute(
    model_id='EleutherAI/pythia-70m-deduped',
    predictions=test_data['message'].tolist(),
    batch_size=8,
    max_length=512,
)

print(f"Perplexity of the fine-tuned: {ft_results['mean_perplexity']}")

fine_tuned_model.eval()
results = perplexity_metric.compute(
    model_id='/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_pythia',
    predictions=test_data['message'].tolist(),
    batch_size=8,
    max_length=512,
)
print(f"Perplexity of the original: {results['mean_perplexity']}")
```

Show hidden output

```
original_perplexity = results['mean_perplexity']
print("The original perplexity", original_perplexity)

finetuned_perplexity = ft_results['mean_perplexity']
print("The fine tuned perplexity", finetuned_perplexity)
```

```
The original perplexity 39.115910374034534
The fine tuned perplexity 29.584752663699064
```

```

train_random_samples = train_data.sample(n=100, random_state=42)
test_random_samples = test_data.sample(n=100, random_state=42)


train_messages = list(train_random_samples['message'])
test_messages = list(test_random_samples['message'])

```

The perplexity-based loss attack

```
# Perform Two attacks on these samples on the fine-tuning model
def get_model_and_tokenizer(model_name):
    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    model = AutoModelForCausalLM.from_pretrained(model_name).to(device)
    tokenizer = AutoTokenizer.from_pretrained(model_name)
    return model, tokenizer, device

def calculate_perplexity(text, model, tokenizer, device):
    """Calculate perplexity score for a given text sample."""
    encodings = tokenizer(text, return_tensors="pt")
    input_ids = encodings.input_ids.to(device)

    with torch.no_grad():
        outputs = model(input_ids, labels=input_ids)
        loss = outputs.loss

    return torch.exp(loss).item()
def find_optimal_threshold(member_samples: List[str], non_member_samples: List[str], model, tokenizer, device) -> float:

    # Calculate perplexities for both sets
    member_perplexities = [calculate_perplexity(text, model, tokenizer, device)
                          for text in member_samples]
    non_member_perplexities = [calculate_perplexity(text, model, tokenizer, device)
                              for text in non_member_samples]

    # Try different thresholds
    all_perplexities = sorted(member_perplexities + non_member_perplexities)
    best_threshold = None
    best_accuracy = 0

    for threshold in all_perplexities:
        member_correct = sum(1 for p in member_perplexities if p < threshold)
        non_member_correct = sum(1 for p in non_member_perplexities if p >= threshold)

        accuracy = (member_correct + non_member_correct) / (
            len(member_perplexities) + len(non_member_perplexities))

        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_threshold = threshold

    return best_threshold

def predict_membership(text: str, threshold: float, model, tokenizer, device) -> Tuple[bool, float]:
    """Predict whether a text sample is a member of the training set."""
    perplexity = calculate_perplexity(text, model, tokenizer, device)
    is_member = perplexity < threshold

    # Calculate confidence based on distance from threshold
    confidence = abs(perplexity - threshold) / threshold
    confidence = min(confidence, 1.0)

    return is_member, confidence, perplexity

def evaluate_attack(test_members: List[str],
                   test_non_members: List[str],
                   threshold: float,
                   model,
                   tokenizer,
                   device) -> dict:
```

```
    """Evaluate attack performance on test sets."""
    results = {'true_positives': 0, 'false_positives': 0,
               'true_negatives': 0, 'false_negatives': 0}

    # Test member samples
    for text in test_members:
        is_member, _, _ = predict_membership(text, threshold, model, tokenizer, device)
        if is_member:
            results['true_positives'] += 1
        else:
            results['false_negatives'] += 1

    # Test non-member samples
    for text in test_non_members:
        is_member, _, _ = predict_membership(text, threshold, model, tokenizer, device)
        if is_member:
            results['false_positives'] += 1
        else:
            results['true_negatives'] += 1

    # Calculate metrics
    total = sum(results.values())
    accuracy = (results['true_positives'] + results['true_negatives']) / total

    precision = (results['true_positives'] /
                 (results['true_positives'] + results['false_positives'])
                 if (results['true_positives'] + results['false_positives']) > 0 else 0)

    recall = (results['true_positives'] /
              (results['true_positives'] + results['false_negatives'])
              if (results['true_positives'] + results['false_negatives']) > 0 else 0)

    f1 = (2 * (precision * recall) / (precision + recall)
          if (precision + recall) > 0 else 0)

    return {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1_score': f1,
        'raw_results': results
    }
```

Double-click (or enter) to edit

```
pretrained_path = "EleutherAI/pythia-70m-deduped"
finetuned_path = "/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_pythia"

finetuned_model, tokenizer, device = get_model_and_tokenizer(finetuned_path)

test_members = train_messages
test_non_members = test_messages

#Threshold
threshold = find_optimal_threshold(test_members,test_non_members,finetuned_model,tokenizer, device)
print(f"T: {threshold}")

#ASR
metrics = evaluate_attack(test_members, test_non_members, threshold,finetuned_model, tokenizer, device)
print(f"ASR: {metrics}")
```

```
T: 53.587947845458984
ASR: {'accuracy': 0.525, 'precision': 0.5144508670520231, 'recall': 0.89, 'f1_score': 0.6520146520146519, 'raw_results':
```

Normalized perplexity attack

```
def get_model_and_tokenizer(pretrained_name, finetuned_path):

    device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
    pretrained_model = AutoModelForCausalLM.from_pretrained(pretrained_path).to(device)
    finetuned_model = AutoModelForCausalLM.from_pretrained(finetuned_path).to(device)
    finetuned_tokenizer = AutoTokenizer.from_pretrained(pretrained_path)

    return pretrained_model, finetuned_model, tokenizer, device

def calculate_perplexity(text, model, tokenizer, device):
    encodings = tokenizer(text, return_tensors="pt")
    input_ids = encodings.input_ids.to(device)

```

```
    with torch.no_grad():
        outputs = model(input_ids, labels=input_ids)
        loss = outputs.loss

    return torch.exp(loss).item()

def calculate_normalized_perplexity(text,pretrained_model,finetuned_model,tokenizer,device):
    pretrained_perplexity = calculate_perplexity(text, pretrained_model, tokenizer, device)
    finetuned_perplexity = calculate_perplexity(text, finetuned_model, tokenizer, device)

    # Avoid division by zero
    if pretrained_perplexity == 0:
        pretrained_perplexity = 1e-10

    normalized_perplexity = finetuned_perplexity / pretrained_perplexity
    return normalized_perplexity

def find_optimal_threshold(member_samples: List[str],non_member_samples: List[str],pretrained_model,finetuned_model,toker
    # Calculate normalized perplexities
    member_perplexities = [
        calculate_normalized_perplexity(
            text, pretrained_model, finetuned_model, tokenizer, device
        ) for text in member_samples
    ]

    non_member_perplexities = [
        calculate_normalized_perplexity(
            text, pretrained_model, finetuned_model, tokenizer, device
        ) for text in non_member_samples
    ]

    # Find optimal threshold
    all_perplexities = sorted(member_perplexities + non_member_perplexities)
    best_threshold = None
    best_accuracy = 0

    for threshold in all_perplexities:
        member_correct = sum(1 for p in member_perplexities if p < threshold)
        non_member_correct = sum(1 for p in non_member_perplexities if p >= threshold)

        accuracy = (member_correct + non_member_correct) / (
            len(member_perplexities) + len(non_member_perplexities))

        if accuracy > best_accuracy:
            best_accuracy = accuracy
            best_threshold = threshold

    return best_threshold

def predict_membership(text,threshold,pretrained_model,finetuned_model,tokenizer,device):
    norm_perplexity = calculate_normalized_perplexity(
        text, pretrained_model, finetuned_model, tokenizer, device
    )

    is_member = norm_perplexity < threshold

    # Calculate confidence based on distance from threshold
    confidence = abs(norm_perplexity - threshold) / threshold
    confidence = min(confidence, 1.0)

    return is_member, confidence, norm_perplexity

def evaluate_attack(test_members: List[str],
                   test_non_members: List[str],
                   threshold: float,
                   pretrained_model,
                   finetuned_model,
                   tokenizer,
                   device) -> dict:

    results = {
        'true_positives': 0,
        'false_positives': 0,
        'true_negatives': 0,
        'false_negatives': 0,
        'member_perplexities': [],
        'non_member_perplexities': []
    }

    # Test member samples
    for text in test_members:
        is_member, _, norm_perplexity = predict_membership(
```

```
            text, threshold, pretrained_model, finetuned_model, tokenizer, device
        )
        results['member_perplexities'].append(norm_perplexity)
        if is_member:
            results['true_positives'] += 1
        else:
            results['false_negatives'] += 1

    # Test non-member samples
    for text in test_non_members:
        is_member, _, norm_perplexity = predict_membership(
            text, threshold, pretrained_model, finetuned_model, tokenizer, device
        )
        results['non_member_perplexities'].append(norm_perplexity)
        if is_member:
            results['false_positives'] += 1
        else:
            results['true_negatives'] += 1

    # Calculate metrics
    total = len(test_members) + len(test_non_members)
    accuracy = (results['true_positives'] + results['true_negatives']) / total

    precision = (results['true_positives'] /
                 (results['true_positives'] + results['false_positives'])
                 if (results['true_positives'] + results['false_positives']) > 0 else 0)

    recall = (results['true_positives'] /
              (results['true_positives'] + results['false_negatives'])
              if (results['true_positives'] + results['false_negatives']) > 0 else 0)

    f1 = (2 * (precision * recall) / (precision + recall)
          if (precision + recall) > 0 else 0)

    return {
        'accuracy': accuracy,
        'precision': precision,
        'recall': recall,
        'f1_score': f1,
        'raw_results': results
    }
```

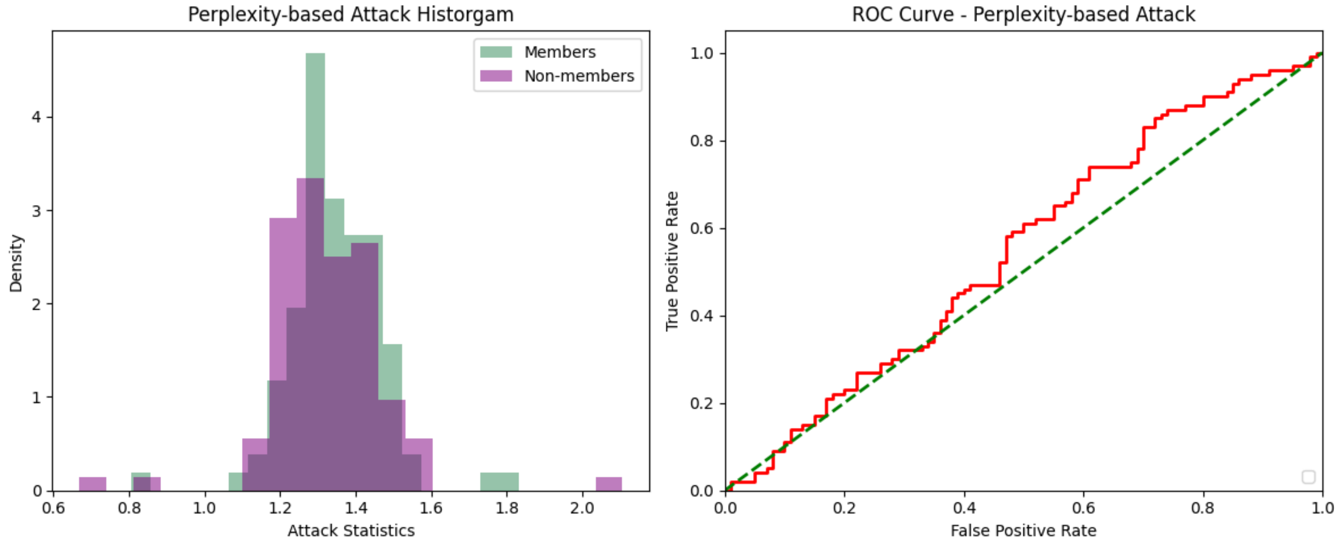
```
# Load models and tokenizer
pretrained_name = "EleutherAI/pythia-70m-deduped"  # base model
finetuned_name = "/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_pythia"
pretrained_model, finetuned_model, tokenizer, device = load_models_and_tokenizer(
    pretrained_name, finetuned_name
)

#Emails Inputs
test_members = train_messages
test_non_members = test_messages


# Threshold
threshold = find_optimal_threshold(test_members, test_non_members,finetuned_model,tokenizer, device)
print(f"T: {threshold}")


# Evaluate attack performance
metrics = evaluate_attack(test_members, test_non_members, threshold,finetuned_model,tokenizer, device)
print(f"ASR: {metrics}")

```

```
/usr/local/lib/python3.10/dist-packages/transformers/tokenization_utils_base.py:1601: FutureWarning: `clean_up_tokenizat
  warnings.warn(
T: 53.587947845458984
ASR: {'accuracy': 0.525, 'precision': 0.5144508670520231, 'recall': 0.89, 'f1_score': 0.6520146520146519, 'raw_results':
```

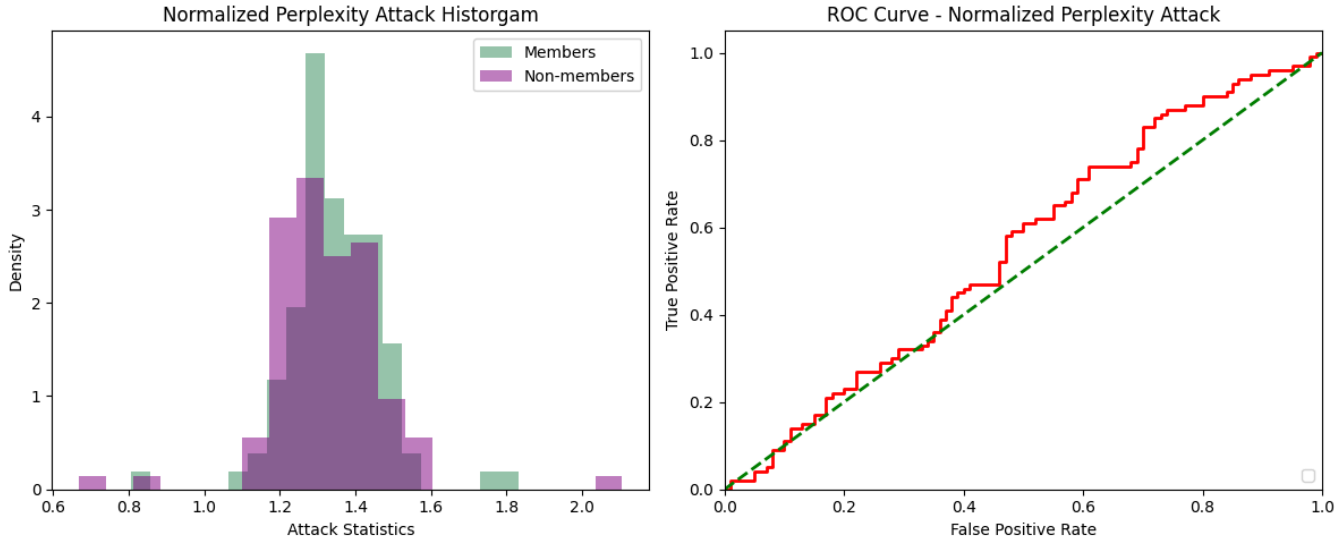
```
# TODO: Plot results
def plot_attack_analysis(member_scores, nonmember_scores, attack_name=""):

    #labels
    y_true = np.concatenate([np.ones(len(member_scores)), np.zeros(len(nonmember_scores))])
    y_scores = np.concatenate([member_scores, nonmember_scores])

    #histograms
    plt.figure(figsize=(12, 5))

    plt.subplot(1, 2, 1)
    plt.hist(member_scores, bins=20, alpha=0.5, label='Members', density=True, color='seagreen')
    plt.hist(nonmember_scores, bins=20, alpha=0.5, label='Non-members', density=True, color='purple')
```

```
    plt.xlabel('Attack Statistics')
    plt.ylabel('Density')
    plt.title(f'{attack_name} Historgam')
    plt.legend()

    # ROC curve and metrics
    fpr, tpr, thresholds = roc_curve(y_true, y_scores)
    roc_auc = auc(fpr, tpr)

    # Find TPR at specific FPR thresholds
    def get_tpr_at_fpr(target_fpr):
        idx = np.searchsorted(fpr, target_fpr)
        return tpr[idx]

    tpr_01_fpr = get_tpr_at_fpr(0.001)
    tpr_1_fpr = get_tpr_at_fpr(0.01)
    tpr_10_fpr = get_tpr_at_fpr(0.1)

    # Plot ROC curve
    plt.subplot(1, 2, 2)
    plt.plot(fpr, tpr, color='red', lw=2)
    plt.plot([0, 1], [0, 1], color='green', lw=2, linestyle='--')


    plt.xlim([0.0, 1.0])
    plt.ylim([0.0, 1.05])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')
    plt.title(f'ROC Curve - {attack_name}')
    plt.legend(loc="bottom right")

    plt.tight_layout()
    plt.show()

    #Print
    print(f"\nMetrics Summary for {attack_name}:")
    print(f"AUC Score: {roc_auc:.3f}")
    print(f"TPR at 0.1% FPR: {tpr_01_fpr:.3f}")
    print(f"TPR at 1% FPR: {tpr_1_fpr:.3f}")
    print(f"TPR at 10% FPR: {tpr_10_fpr:.3f}")

# Plots

member_perplexity_list = []
for each in train_messages:
    result = calculate_normalized_perplexity(each, pretrained_model, finetuned_model, tokenizer, device)
    member_perplexity_list.append(result)
member_perplexities = np.array(member_perplexity_list)


non_member_perplexity_list = []
for each in test_messages:
    result = calculate_normalized_perplexity(each, pretrained_model, finetuned_model, tokenizer, device)
    non_member_perplexity_list.append(result)
non_member_perplexities = np.array(non_member_perplexity_list)


plot_attack_analysis(member_perplexities, non_member_perplexities, "Perplexity-based Attack")


plot_attack_analysis(member_perplexities, non_member_perplexities, "Normalized Perplexity Attack")
```

```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that artists whose label start with an un
```




```
WARNING:matplotlib.legend:No artists with labels found to put in legend.  Note that artists whose label start with an un

Metrics Summary for Perplexity-based Attack:
AUC Score: 0.550
TPR at 0.1% FPR: 0.000
TPR at 1% FPR: 0.000
TPR at 10% FPR: 0.090
```




```
Metrics Summary for Normalized Perplexity Attack:
AUC Score: 0.550
TPR at 0.1% FPR: 0.000
TPR at 1% FPR: 0.000
TPR at 10% FPR: 0.090
```

```
# TODO: Comment on Observations

# The normalized based attack is a strong attack that reduces
# the impact of corpus token variations for our model. However, the
#results show that there was no difference in the strenth of the
#attack between the perplexity and the normalized attack.
```

Problem 3

```
import random

```

```
fine_tuned_model = AutoModelForCausalLM.from_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tunec
fine_tuned_tokenizer = AutoTokenizer.from_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_py
```

```

fine_tuned_model = AutoModelForCausalLM.from_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tunec

vocab_size = fine_tuned_tokenizer.vocab_size
random_token = random.randint(0, vocab_size-1)


input_ids = torch.tensor([[random_token]]).to(fine_tuned_model.device)

# Generate text
with torch.no_grad():
    outputs = fine_tuned_model.generate(
        input_ids,
        max_length=1000,
        do_sample=True,
        temperature=1.0,
        pad_token_id=tokenizer.pad_token_id,
        bos_token_id=tokenizer.bos_token_id,
        eos_token_id=tokenizer.eos_token_id
    )

# Generated

generated_text = tokenizer.decode(outputs[0], skip_special_tokens=True)
print(generated_text)
```

Show hidden output

```
test_members = train_messages
test_non_members = test_messages

def generate_email(model, tokenizer, max_length=1000):

    vocab_size = tokenizer.vocab_size
    random_token = random.randint(0, vocab_size-1)

    # Generate text
    input_ids = torch.tensor([[random_token]]).to(model.device)
    with torch.no_grad():
        outputs = model.generate(
            input_ids,
            max_length=max_length,
            do_sample=True,
            temperature=1.0,
            pad_token_id=tokenizer.pad_token_id,
            bos_token_id=tokenizer.bos_token_id,
            eos_token_id=tokenizer.eos_token_id
        )

    return tokenizer.decode(outputs[0], skip_special_tokens=True)

def bleu_score(reference, candidate):
    reference_tokens = nltk.word_tokenize(reference.lower())
    candidate_tokens = nltk.word_tokenize(candidate.lower())
    references = [reference_tokens]
    smoothing = SmoothingFunction().method1

def plot_bleu_scores(model, tokenizer, in_set_emails, out_set_emails, num_samples=10):

    in_set_emails = test_members[:num_samples]
    out_set_emails = test_non_members[:num_samples]

    bleu_scores_in = []
    bleu_scores_out = []

    for i, ref_email in enumerate(in_set_emails):
        generated = generate_email(model, tokenizer)
        bleu = bleu_score(ref_email, generated)
        bleu_scores_in.append(bleu)
        print(f"In-set email {i+1} BLEU score: {bleu:.4f}")

    for i, ref_email in enumerate(out_set_emails):
        generated = generate_email(model, tokenizer)
        bleu = bleu_score(ref_email, generated)
        bleu_scores_out.append(bleu)
        print(f"Out-of-set email {i+1} BLEU score: {bleu:.4f}")

    # Create histogram
    plt.figure(figsize=(10, 6))
```

```
    plt.figure(figsize=(10, 6))

    # Histograms
    plt.hist(bleu_scores_in, alpha=0.5, label='In Training Set', color='seagreen', bins=20)
    plt.hist(bleu_scores_out, alpha=0.5, label='Out of Training Set', color='red', bins=20)

    plt.xlabel('BLEU Score')
    plt.ylabel('Frequency')
    plt.title('BLEU Scores for Generated Emails')
    plt.legend()
    plt.grid(True, alpha=0.3)

    plt.tight_layout()
    plt.show()

    return bleu_scores_in, bleu_scores_out

# model and tokenizer
fine_tuned_model = AutoModelForCausalLM.from_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_
tokenizer = AutoTokenizer.from_pretrained("/content/drive/MyDrive/CS6983_GenAI_Folder/Homework_3/fine_tuned_pythia")

in_set_emails = test_members
out_set_emails = test_non_members

bleu_scores_in, bleu_scores_out = plot_bleu_scores(
    fine_tuned_model,
    tokenizer,
    in_set_emails,
    out_set_emails
)
```

Show hidden output

Citation: https://thepythoncode.com/article/bleu-score-in-python