6G_IRS_Keras

May 25, 2022

[1]:
```
!pip install -q cleverhans
!pip install -q plot_keras_history
!pip install -q keras-tuner
```

[2]:
```
import scipy.io
import tensorflow as tf

from tensorflow.keras import datasets, layers, models
import matplotlib.pyplot as plt
from scipy.linalg import norm

from tqdm.keras import TqdmCallback
from tqdm.notebook import tqdm
from tensorflow.keras.callbacks import EarlyStopping
from sklearn.model_selection import train_test_split

from plot_keras_history import plot_history
import matplotlib.pyplot as plt
import keras_tuner as kt
from keras.models import load_model

from sklearn.metrics import mean_squared_error
from cleverhans.tf2.attacks.projected_gradient_descent import␣
 ↪projected_gradient_descent,fast_gradient_method
from cleverhans.tf2.attacks.basic_iterative_method import basic_iterative_method
from cleverhans.tf2.attacks.carlini_wagner_l2 import carlini_wagner_l2
from cleverhans.tf2.attacks.momentum_iterative_method import␣
 ↪momentum_iterative_method
from tqdm.keras import TqdmCallback
import numpy as np

import seaborn as sns
import pandas as pd

from keras.models import Sequential
from keras.layers import Dense
```

```
HYPARAMETER_TUNING = False
TRAIN_MODEL = False
GOOGLE_COLAB = True

PROJECT_FOLDER = ''
```

[3]:

```
if GOOGLE_COLAB:
    from google.colab import drive
    drive.mount("/content/gdrive")
    PROJECT_FOLDER = '/content/gdrive/My Drive/ds/IRS/'
```

```
Drive already mounted at /content/gdrive; to attempt to forcibly remount, call
drive.mount("/content/gdrive", force_remount=True).
```

[4]:

```
X = pd.read_csv(PROJECT_FOLDER + 'xtrain_32_10000.csv', header=None)
X = X.values

Y = pd.read_csv(PROJECT_FOLDER + 'ytrain_32_10000.csv', header=None)
Y = Y.values

M = X.shape[1]
```

[5]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.33,␣
 ↪random_state=42)
```

[6]:

```
def get_model(mult_factor):
  model = Sequential()
  model.add(Dense(int(M*mult_factor), input_dim=M, activation='relu'))
  model.add(Dense(int(2*M*mult_factor), activation='relu'))
  model.add(Dense(int(4*M*mult_factor), activation='relu'))
  model.add(Dense(int(4*M*mult_factor), activation='relu'))
  model.add(Dense(Y.shape[1], activation='relu'))

  model.compile(loss='mse', optimizer='sgd', metrics=['mse'])

  return model
```

[7]:

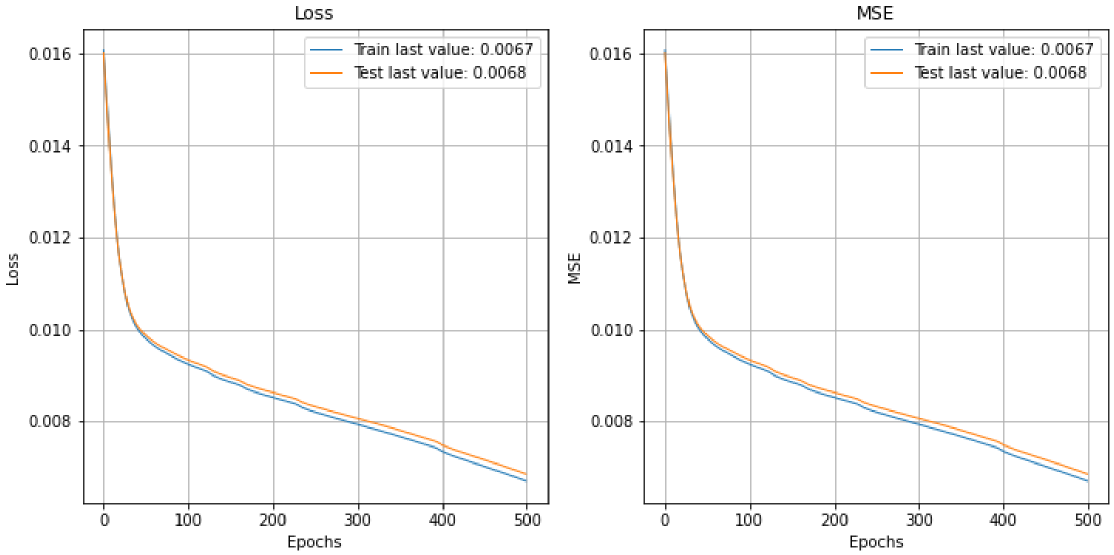
```
model = get_model(1.0)
se = tf.keras.callbacks.EarlyStopping(monitor='val_mse',patience=150,verbose=1,
                                      restore_best_weights=True)

history = model.fit(X_train, y_train, epochs=500, verbose=0,validation_split=0.
 ↪2,
                    callbacks=[se,TqdmCallback(verbose=1)])
```

```
0epoch [00:00, ?epoch/s]
```

```
0batch [00:00, ?batch/s]
```

[8]:

```
plot_history(history)
plt.show()
```



[9]:

```
model.save(PROJECT_FOLDER + 'model.hdf5')
```

1 Convert the model Cleverhans compatible model

[10]:

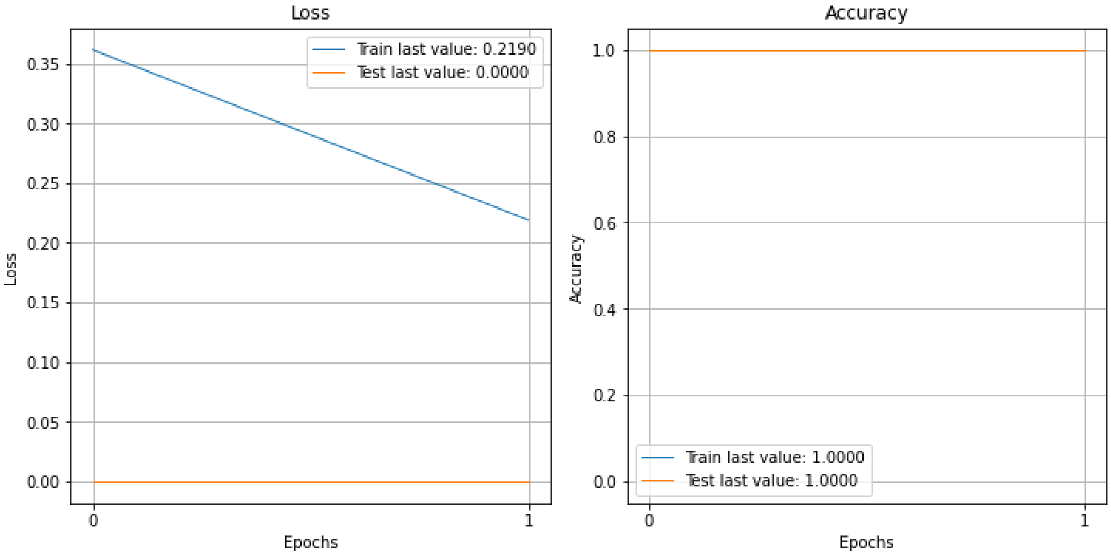
```
model_copy = tf.keras.models.clone_model(model)
for layer in model_copy.layers:
  layer.trainable = False

model_copy.add(Dense(2, activation='softmax'))
model_copy.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

y_dummy = np.zeros((X_train.shape[0],2))
mid_range = np.int(X_train.shape[0] / 2.0)
y_dummy[0:mid_range,0]= 1.0

history = model_copy.fit(X_train, y_dummy, epochs=2, verbose=0,
              callbacks=[TqdmCallback(verbose=1)],batch_size=256,
              validation_split=0.33, shuffle= True)
plot_history(history)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:9:
DeprecationWarning: `np.int` is a deprecated alias for the builtin `int`. To
silence this warning, use `int` by itself. Doing this will not modify any
```

```
behavior and is safe. When replacing `np.int`, you may wish to use e.g.
`np.int64` or `np.int32` to specify the precision. If you wish to review your
current use, check the release note link for additional information.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  if __name__ == '__main__':
```

```
0epoch [00:00, ?epoch/s]
```

```
0batch [00:00, ?batch/s]
```



1.1 Attack the model

[11]:

```python
from itertools import product
from random import shuffle

logits_model = tf.keras.Model(model_copy.input, model_copy.output)
attacks = ['FGSM','BIM','MIM','PGD','CW']
attacks = ['FGSM','BIM','MIM','PGD']

eps_vals = [0.01, 0.1, 0.3, 0.5, 0.7, 0.8]

params_list = list(product(eps_vals,attacks))
shuffle(params_list)

mal_diff_distance_list = []
real_mse_list = []
mal_mse_list = []
mal_predicted_diff_list = []
```

```
attack_name_list = []
eps_val_list = []

#for i in tqdm(range(X_test.shape[0])):
for _ in tqdm(range(5)):
  i = np.random.randint(0,X_test.shape[0])
  test_input = X_test[i:i+1,:].astype(np.float32)

  for eps_val, attack in params_list:
        if attack == 'FGSM':
          mal_input = fast_gradient_method(logits_model, test_input,␣
 ↪eps=eps_val/20.0, norm=np.inf,
                                            clip_min=test_input.
 ↪min(),clip_max=test_input.max(),
                                            targeted=False)
          mal_input = mal_input.numpy()
        elif attack == 'BIM':
          mal_input = basic_iterative_method(logits_model, test_input,␣
 ↪eps=eps_val, norm=np.inf,
                                              #clip_min=test_input.
 ↪min(),clip_max=test_input.max(),
                                              eps_iter=0.01,nb_iter=2000,
                                              targeted=False)
          mal_input = mal_input.numpy()
        elif attack == 'MIM':
          mal_input = momentum_iterative_method(logits_model, test_input,␣
 ↪eps=eps_val, norm=np.inf,
                                                  clip_min=test_input.
 ↪min(),clip_max=test_input.max(),
                                                  eps_iter=0.01,nb_iter=2000,
                                                  targeted=False)
          mal_input = mal_input.numpy()
        elif attack == 'PGD':
          mal_input = projected_gradient_descent(logits_model, test_input,␣
 ↪eps=eps_val, norm=np.inf,
                                                  clip_min=test_input.
 ↪min(),clip_max=test_input.max(),
                                                  eps_iter=0.01,nb_iter=2000,
                                                  targeted=False)
          mal_input = mal_input.numpy()
        elif attack == 'CW':
          mal_input = carlini_wagner_l2(logits_model, test_input,
                                targeted=False, #y=y_output,
                                batch_size=512, confidence=10.0,
                                abort_early=False, max_iterations=1000,
                                clip_min=test_input.min(),clip_max=test_input.
↪max())

        mal_diff = mal_input - test_input
        mal_diff_distance = norm(mal_diff, ord = np.inf)
        mal_diff_distance_list.append(mal_diff_distance)

        real_output = y_test[i:i+1,:]
        test_output = model.predict(test_input)
        real_mse = mean_squared_error(real_output,test_output)
        real_mse_list.append(real_mse)

        malicious_test_output = model.predict(mal_input)
        mal_mse = mean_squared_error(real_output,malicious_test_output)
        mal_mse_list.append(mal_mse)

        mal_predicted_diff = malicious_test_output - test_output
        mal_predicted_diff = norm(mal_predicted_diff, ord = np.inf)
        mal_predicted_diff_list.append(mal_predicted_diff)

        attack_name_list.append(attack)
        eps_val_list.append(eps_val)
```

```
  0%|          | 0/5 [00:00<?, ?it/s]
```

[12]:

```
df_result = pd.DataFrame({'Malicious_Distance':mal_diff_distance_list,
                          'Real_Predicted_MSE':real_mse_list,
                          'Malicious_Predicted_MSE':mal_mse_list,
                          'MalOut_RealOut_Diff':mal_predicted_diff_list,
                          'Attack':attack_name_list,
                          'eps':eps_val_list})
df_result
```

[12]:

```
     Malicious_Distance  Real_Predicted_MSE  Malicious_Predicted_MSE  \
0            281.642853            0.007904                 0.010725
1             81.320984            0.007904                 0.008754
2             85.205322            0.007904                 0.008792
3             14.572388            0.007904                 0.007941
4            196.103790            0.007904                 0.010890
..                  …                   …                        …
115          198.043716            0.006840                 0.008432
116           34.424145            0.006840                 0.006948
117          207.769989            0.006840                 0.007591
118          268.659790            0.006840                 0.007416
119          236.913177            0.006840                 0.007804

     MalOut_RealOut_Diff Attack   eps
```

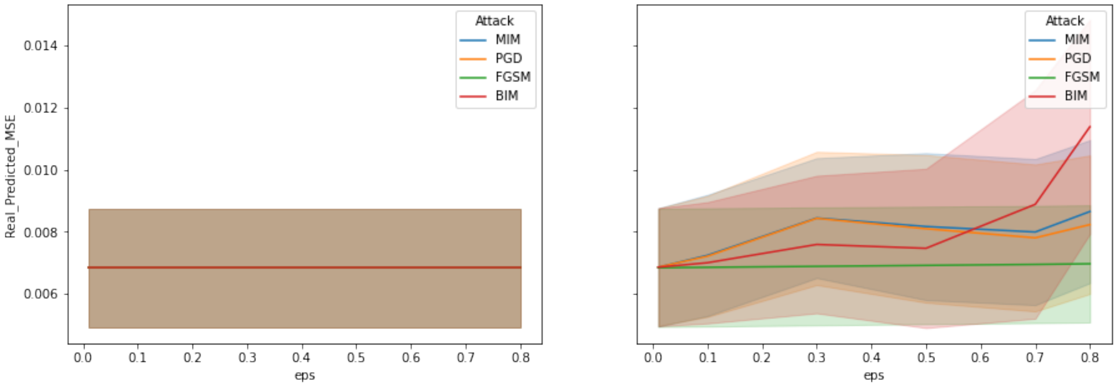
```
0               20.035965    MIM  0.8
1                9.123885    PGD  0.1
2                8.614745    MIM  0.1
3                1.382549   FGSM  0.3
4               17.165459    PGD  0.5
..                    …     …   …
115             18.537216    PGD  0.3
116              3.128234   FGSM  0.7
117             15.462641    BIM  0.3
118             20.827293    BIM  0.8
119             17.289284    PGD  0.7

[120 rows x 6 columns]
```

[13]:

```
fig, ax = plt.subplots(1,2, sharey=True, figsize=(15,5))
sns.lineplot(x='eps', y='Real_Predicted_MSE', hue='Attack', ci='sd',␣
 ↪estimator="median",
             data=df_result, ax=ax[0])

sns.lineplot(x='eps', y='Malicious_Predicted_MSE', hue='Attack', ci='sd',␣
 ↪estimator="median",
             data=df_result, ax=ax[1])
```

[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f94a060ba10>
```



#Defensive Distillation

[14]:

```
!rm -f util_defdistill.py
!wget -q https://raw.githubusercontent.com/ocatak/6g_MIMO_security_distillation/
 ↪main/util_defdistill.py

from util_defdistill import Distiller
```

```
STUDENT_MODEL_MULTIPLICATION = 0.5
TEACHER_MODEL_MULTIPLICATION = 1.0

student_model = get_model(STUDENT_MODEL_MULTIPLICATION)
teacher_model = get_model(TEACHER_MODEL_MULTIPLICATION)

es_teacher = EarlyStopping(monitor='val_loss',
                          patience=150,
                          min_delta=0.001,
                          verbose=1,
                          restore_best_weights=True,
                          mode='min')

# Train and evaluate teacher on data.
hist_teacher = teacher_model.fit(X_train, y_train,
              epochs=100000,
              verbose=0,batch_size=1024,
              callbacks=[es_teacher,TqdmCallback(verbose=1, desc='DL␣
 ↪training')],
              validation_data=(X_test, y_test))
```

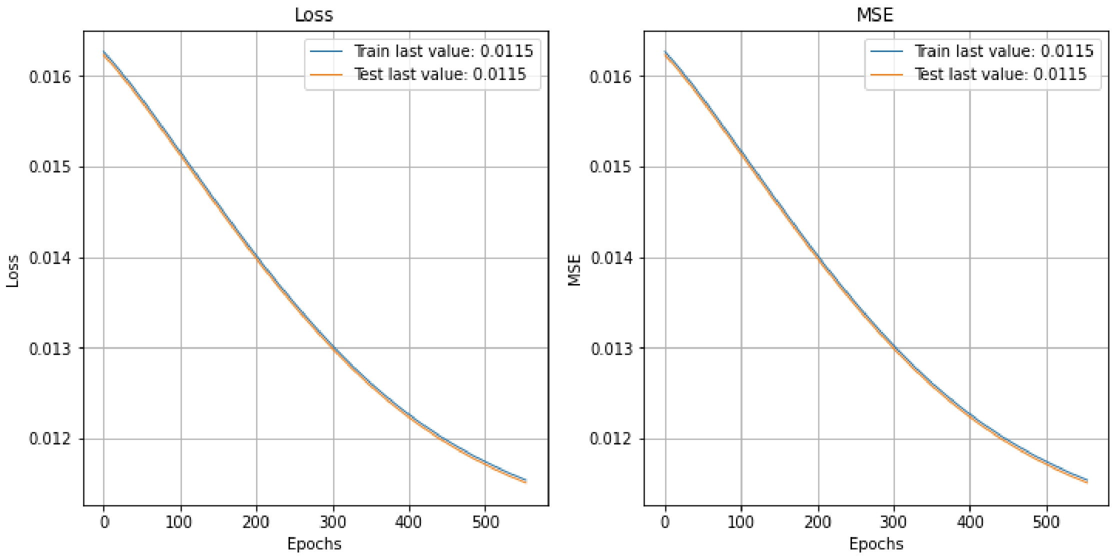
```
DL training: 0epoch [00:00, ?epoch/s]
```

```
DL training: 0batch [00:00, ?batch/s]
```

```
WARNING:tensorflow:Callback method `on_train_batch_end` is slow compared to the
batch time (batch time: 0.0245s vs `on_train_batch_end` time: 0.0301s). Check
your callbacks.
Restoring model weights from the end of the best epoch: 405.
Epoch 555: early stopping
```

[15]:

```
plot_history(hist_teacher.history)
plt.show()
```



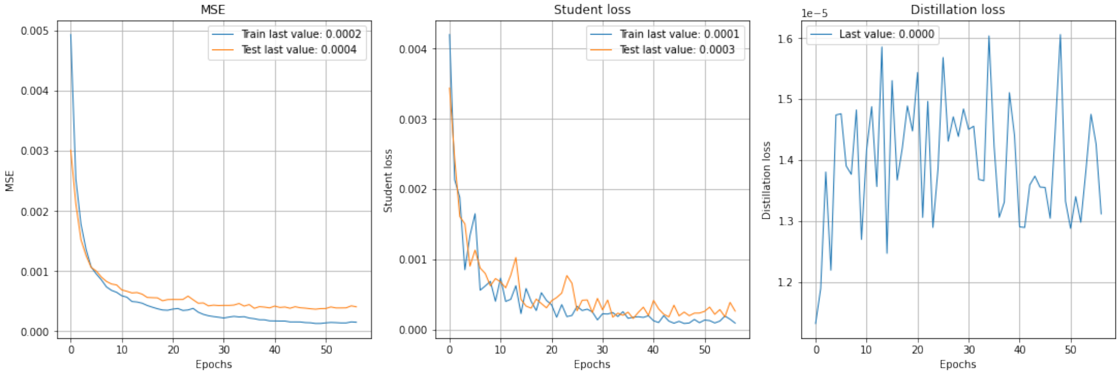
[16]:

```python
import keras
distiller = Distiller(student=student_model, teacher=teacher_model)
loss_fn = keras.losses.MeanSquaredError()

distiller.compile(optimizer='adam',
                            metrics=['mse'],
                            student_loss_fn=loss_fn,
                            distillation_loss_fn=keras.losses.KLDivergence(),
                            alpha=0.1,
                            temperature=20)

es = EarlyStopping(monitor='val_student_loss',
                   patience=20,
                   #min_delta=0.000001,
                   verbose=1,
                   restore_best_weights=True,
                   mode='min')

hist_distill = distiller.fit(X_train, y_train,
                              epochs=10000,
                              verbose=0,
                              callbacks=[es,TqdmCallback(verbose=1, desc='DL␣
 ↪training')],
                              validation_data=(X_test, y_test))
```

```
DL training: 0epoch [00:00, ?epoch/s]

DL training: 0batch [00:00, ?batch/s]

Restoring model weights from the end of the best epoch: 37.
```

```
Epoch 57: early stopping
```

[17]:
```
plot_history(hist_distill.history)
plt.show()
```

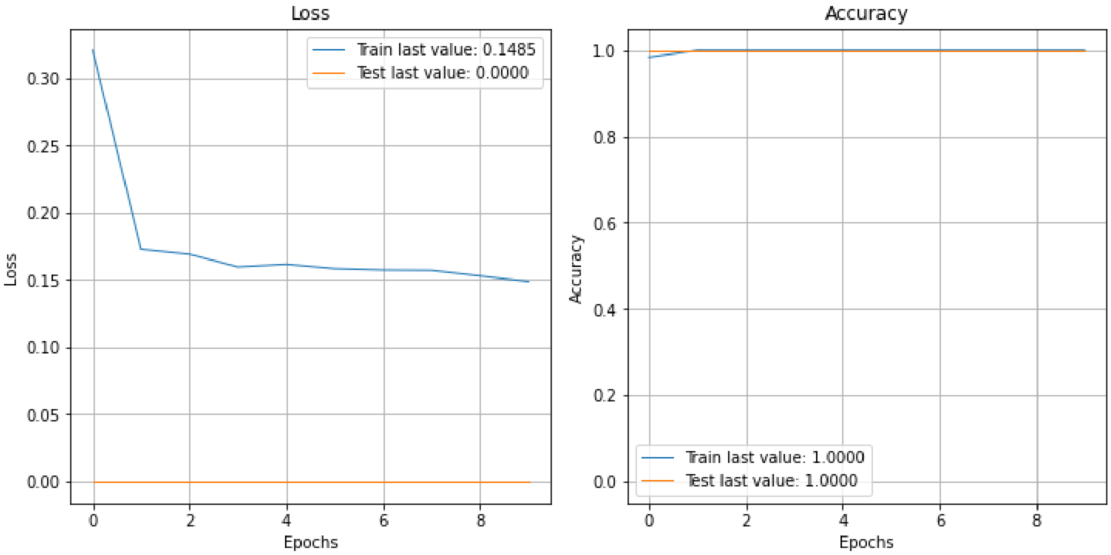


[18]:
```
from keras.layers import Dense, Conv2D, Flatten
student_copy = tf.keras.models.clone_model(distiller.student)
for layer in student_copy.layers:
            layer.trainable = False

student_copy.add(Dense(2, activation='softmax'))
student_copy.compile(optimizer='adam', loss='categorical_crossentropy',␣
 ↪metrics=['accuracy'])

y_dummy = np.zeros((X_train.shape[0],2))
mid_range = np.int(X_train.shape[0] / 2.0)
y_dummy[0:mid_range,0]= 1.0
history = student_copy.fit(X_train, y_dummy, epochs=2, verbose=0,
              callbacks=[TqdmCallback(verbose=1)],batch_size=128,
              validation_split=0.33, shuffle= True)
plot_history(history)
plt.show()
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:10:
DeprecationWarning: `np.int` is a deprecated alias for the builtin `int`. To
silence this warning, use `int` by itself. Doing this will not modify any
behavior and is safe. When replacing `np.int`, you may wish to use e.g.
`np.int64` or `np.int32` to specify the precision. If you wish to review your
current use, check the release note link for additional information.
Deprecated in NumPy 1.20; for more details and guidance:
https://numpy.org/devdocs/release/1.20.0-notes.html#deprecations
  # Remove the CWD from sys.path while we load stuff.
```

```
0epoch [00:00, ?epoch/s]
```

```
0batch [00:00, ?batch/s]
```



[19]:
```
from itertools import product
from random import shuffle

logits_model_student = tf.keras.Model(student_copy.input, student_copy.output)
attacks = ['FGSM','BIM','MIM','PGD','CW']
attacks = ['FGSM','BIM','MIM','PGD']

eps_vals = [0.01, 0.1, 0.3, 0.5, 0.7, 0.8]

params_list = list(product(eps_vals,attacks))
shuffle(params_list)

distil_mal_diff_distance_list = []
distil_real_mse_list = []
distil_mal_mse_list = []
distil_mal_predicted_diff_list = []
distil_attack_name_list = []
distil_eps_val_list = []

#for i in tqdm(range(X_test.shape[0])):
for _ in tqdm(range(5)):
  i = np.random.randint(0,X_test.shape[0])
  test_input = X_test[i:i+1,:].astype(np.float32)

  for eps_val, attack in params_list:
        if attack == 'FGSM':
          mal_input = fast_gradient_method(logits_model, test_input,␣
↪eps=eps_val/20.0, norm=np.inf,
                                            clip_min=test_input.
↪min(),clip_max=test_input.max(),
                                            targeted=False)
          mal_input = mal_input.numpy()
        elif attack == 'BIM':
          mal_input = basic_iterative_method(logits_model, test_input,␣
↪eps=eps_val, norm=np.inf,
                                              #clip_min=test_input.
↪min(),clip_max=test_input.max(),
                                              eps_iter=0.01,nb_iter=2000,
                                              targeted=False)
          mal_input = mal_input.numpy()
        elif attack == 'MIM':
          mal_input = momentum_iterative_method(logits_model, test_input,␣
↪eps=eps_val, norm=np.inf,
                                                  clip_min=test_input.
↪min(),clip_max=test_input.max(),
                                                  eps_iter=0.01,nb_iter=2000,
                                                  targeted=False)
          mal_input = mal_input.numpy()
        elif attack == 'PGD':
          mal_input = projected_gradient_descent(logits_model, test_input,␣
↪eps=eps_val, norm=np.inf,
                                                  clip_min=test_input.
↪min(),clip_max=test_input.max(),
                                                  eps_iter=0.01,nb_iter=2000,
                                                  targeted=False)
          mal_input = mal_input.numpy()
        elif attack == 'CW':
          mal_input = carlini_wagner_l2(logits_model, test_input,
                                targeted=False, #y=y_output,
                                batch_size=512, confidence=10.0,
                                abort_early=False, max_iterations=1000,
                                clip_min=test_input.min(),clip_max=test_input.
↪max())

        mal_diff = mal_input - test_input
        mal_diff_distance = norm(mal_diff, ord = np.inf)
        distil_mal_diff_distance_list.append(mal_diff_distance)

        real_output = y_test[i:i+1,:]
        test_output = distiller.student.predict(test_input)
        real_mse = mean_squared_error(real_output,test_output)
        distil_real_mse_list.append(real_mse)
        malicious_test_output = distiller.student.predict(mal_input)
        mal_mse = mean_squared_error(real_output,malicious_test_output)
        distil_mal_mse_list.append(mal_mse)

        mal_predicted_diff = malicious_test_output - test_output
        mal_predicted_diff = norm(mal_predicted_diff, ord = np.inf)
        distil_mal_predicted_diff_list.append(mal_predicted_diff)

        distil_attack_name_list.append(attack)
        distil_eps_val_list.append(eps_val)
```

```
  0%|          | 0/5 [00:00<?, ?it/s]
```

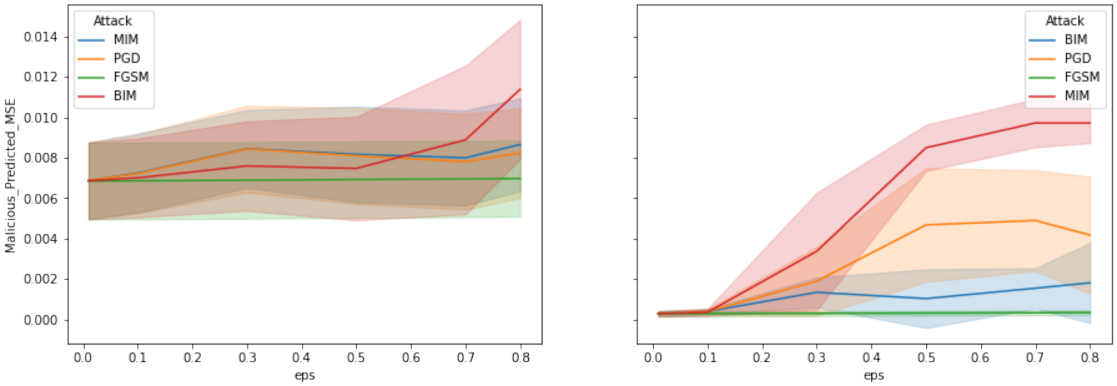
[20]:
```
df_result_distill = pd.DataFrame({'Malicious_Distance':
 ↪distil_mal_diff_distance_list,
                          'Real_Predicted_MSE':distil_real_mse_list,
                          'Malicious_Predicted_MSE':distil_mal_mse_list,
                          'MalOut_RealOut_Diff':distil_mal_predicted_diff_list,
                          'Attack':distil_attack_name_list,
                          'eps':distil_eps_val_list})
df_result_distill
```

[20]:
```
     Malicious_Distance  Real_Predicted_MSE  Malicious_Predicted_MSE  \
0             90.840012            0.000406                 0.000408
1            205.466568            0.000406                 0.000596
2              9.849995            0.000406                 0.000404
3            334.129913            0.000406                 0.000455
4              5.057673            0.000406                 0.000408
..                  …                   …                      …
115          197.000610            0.000243                 0.008216
116          192.487305            0.000243                 0.007124
117          259.968994            0.000243                 0.008748
118            9.880083            0.000243                 0.000237
119          200.001724            0.000243                 0.009183

     MalOut_RealOut_Diff Attack   eps
0               3.866464    BIM  0.10
1               8.485148    PGD  0.30
2               0.130710    BIM  0.01
3               9.804306    BIM  0.70
4               0.110424   FGSM  0.10
..                   …     …    …
115            38.448257    PGD  0.80
116            34.984123    MIM  0.30
117            40.053532    MIM  0.50
118             0.343055    MIM  0.01
```

```
119           41.169380    PGD  0.50

[120 rows x 6 columns]
```

[21]:
```
fig, ax = plt.subplots(1,2, sharey=True, figsize=(15,5))
sns.lineplot(x='eps', y='Malicious_Predicted_MSE', hue='Attack', ci='sd',␣
 ↪estimator="median",
             data=df_result, ax=ax[0])

sns.lineplot(x='eps', y='Malicious_Predicted_MSE', hue='Attack', ci='sd',␣
 ↪estimator="median",
             data=df_result_distill, ax=ax[1])
```

[21]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f94a0350a90>
```


Attack
MIM
PGD
FGSM
BIM
Malicious_Predicted_MSE
eps
Attack
BIM
PGD
FGSM
MIM
eps