```
[1] !pip install adversarial-robustness-toolbox
```

```
Collecting adversarial-robustness-toolbox
  Downloading adversarial_robustness_toolbox-1.16.0-py3-none-any.whl (1.6 MB)
     ---------------------------------------- 1.6/1.6 MB 14.8 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.18.0 in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox) (1.23.5)
Requirement already satisfied: scipy>=1.4.1 in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox) (1.11.3)
Collecting scikit-learn<1.2.0,>=0.22.2 (from adversarial-robustness-toolbox)
  Downloading scikit_learn-1.1.3-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (30.5 MB)
     ---------------------------------------- 30.5/30.5 MB 50.7 MB/s eta 0:00:00
Requirement already satisfied: six in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox) (1.16.0)
Requirement already satisfied: setuptools in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox) (67.7.2)
Requirement already satisfied: tqdm in /usr/local/lib/python3.10/dist-packages (from adversarial-robustness-toolbox) (4.66.1)
Requirement already satisfied: joblib>=1.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn<1.2.0,>=0.22.2->adversarial-robustness-toolbox) (1.3.2)
Requirement already satisfied: threadpoolctl>=2.0.0 in /usr/local/lib/python3.10/dist-packages (from scikit-learn<1.2.0,>=0.22.2->adversarial-robustness-toolbox) (3.2.0)
Installing collected packages: scikit-learn, adversarial-robustness-toolbox
  Attempting uninstall: scikit-learn
    Found existing installation: scikit-learn 1.2.2
    Uninstalling scikit-learn-1.2.2:
      Successfully uninstalled scikit-learn-1.2.2
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the following dependency conflicts.
bigframes 0.10.0 requires scikit-learn>=1.2.2, but you have scikit-learn 1.1.3 which is incompatible.
Successfully installed adversarial-robustness-toolbox-1.16.0 scikit-learn-1.1.3
```

```
[10] #Импортируем библиотеки
from __future__ import absolute_import, division, print_function, unicode_literals
import os, sys
from os.path import abspath
module_path = os.path.abspath(os.path.join('..'))
if module_path not in sys.path:sys.path.append(module_path)
import warnings
warnings.filterwarnings('ignore')
import tensorflow as tf
tf.compat.v1.disable_eager_execution()
tf.get_logger().setLevel('ERROR')
import tensorflow.keras.backend as k
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import Dense, Flatten, Conv2D, MaxPooling2D, Activation, Dropout
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
from art.estimators.classification import KerasClassifier
from art.attacks.poisoning import PoisoningAttackBackdoor, PoisoningAttackCleanLabelBackdoor
from art.attacks.poisoning.perturbations import add_pattern_bd
from art.utils import load_mnist, preprocess, to_categorical
from art.defences.trainer import AdversarialTrainerMadryPGD
```

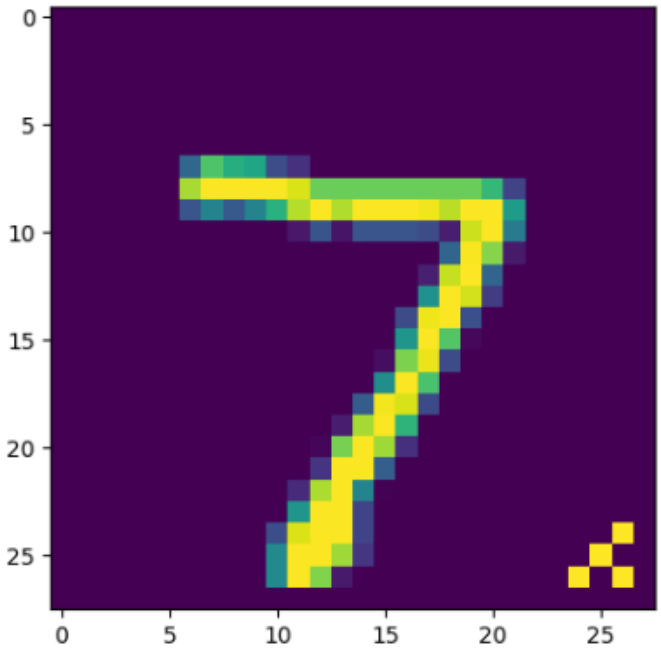
```
[12] #Загружаем датаст MNIST
(x_raw, y_raw), (x_raw_test, y_raw_test), min_, max_ = load_mnist(raw=True)
#Выбираем случайное число
n_train = np.shape(x_raw)[0]
num_selection = 10000
random_selection_indices = np.random.choice(n_train, num_selection)
x_raw = x_raw[random_selection_indices]
y_raw = y_raw[random_selection_indices]
```

```
#Преобрабатывем данные
# Фиксируем коэфицент
percent_poison = .33
x_train, y_train = preprocess(x_raw, y_raw)
x_train = np.expand_dims(x_train, axis=3)
x_test, y_test = preprocess(x_raw_test, y_raw_test)
x_test = np.expand_dims(x_test, axis=3)
# Отправляем данные
n_train = np.shape(y_train)[0]
shuffled_indices = np.arange(n_train)
np.random.shuffle(shuffled_indices)
x_train = x_train[shuffled_indices]
y_train = y_train[shuffled_indices]
```

```
[16] def create_model():
     #Обьявляем последовательную модель
       model = Sequential()
     #Добавляем сверточный слой 1
       model. add (Conv2D(32, (3,3), activation='relu', input_shape=(28, 28, 1)))
     #Добавляем слой 2
       model. add (Conv2D(64, (3,3), activation='relu'))
     #Добавляем слойпуллинга
       model. add (MaxPooling2D((2,2)))
     #Добавляем дропаут 1
       model. add (Dropout (0.25))
     #Добавляем слой выравнивания
       model. add (Flatten())
     #Добавляем слой 1
       model. add (Dense (128, activation = 'relu'))
     #Добавляем дропаут 2
       model. add (Dropout (0.25))
     #Добавляем полносвязный слой 2
       model. add (Dense(10, activation = 'softmax'))
     #Компилируем модель
       model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
     #Возвращаем модель
       return model
```

```
[17] # Создаем атаку
     backdoor = PoisoningAttackBackdoor(add_pattern_bd)
     example_target = np.array([0, 0, 0, 0, 0, 0, 0, 0, 0, 1])
     pdata, plabels = backdoor.poison(x_test, y=example_target)
     plt.imshow(pdata[0].squeeze())
```

```
<matplotlib.image.AxesImage at 0x7f5b0772a260>
```




```
[18] # Определить целевой класс атаки

     targets = to_categorical([9], 10)[0]
```

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```

```
[19] # Создаем модель
     model = KerasClassifier(create_model())
     proxy = AdversarialTrainerMadryPGD(KerasClassifier(create_model()),
     nb_epochs=10, eps=0.15, eps_step=0.001)
     proxy.fit(x_train, y_train)
```

```
Precompute adv samples: 100% 1/1 [00:00<00:00, 21.92it/s]
Adversarial training epochs: 100% 10/10 [25:41<00:00, 151.90s/it]
```

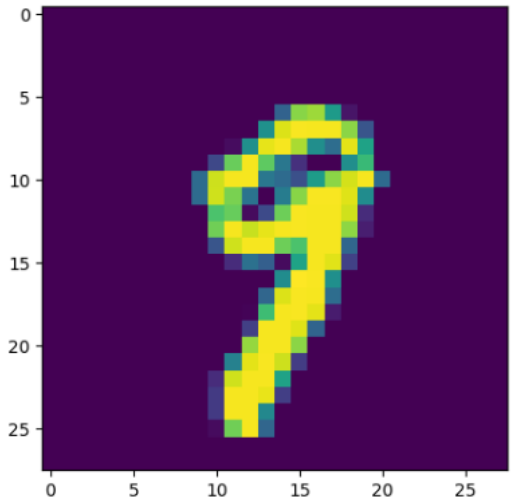
```
[20] # Выполняем атаку
     attack = PoisoningAttackCleanLabelBackdoor(backdoor=backdoor,
     proxy_classifier=proxy.get_classifier(),
     target=targets,
     pp_poison=percent_poison, norm=2, eps=5,
     eps_step=0.1, max_iter=200)
     # Запускаеем отправление
     pdata, plabels = attack.poison(x_train, y_train)
```


```
[20] # Выполняем атаку
     attack = PoisoningAttackCleanLabelBackdoor(backdoor=backdoor,
     proxy_classifier=proxy.get_classifier(),
     target=targets,
     pp_poison=percent_poison, norm=2, eps=5,
     eps_step=0.1, max_iter=200)
     # Запускаеем отправление
     pdata, plabels = attack.poison(x_train, y_train)
```


```
PGD - Random Initializations: 100% 1/1 [00:11<00:00, 11.73s/it]
PGD - Random Initializations: 100% 1/1 [00:11<00:00, 11.40s/it]
PGD - Random Initializations: 100% 1/1 [00:10<00:00, 10.16s/it]
PGD - Random Initializations: 100% 1/1 [00:11<00:00, 11.71s/it]
PGD - Random Initializations: 100% 1/1 [00:11<00:00, 11.68s/it]
PGD - Random Initializations: 100% 1/1 [00:11<00:00, 11.57s/it]
PGD - Random Initializations: 100% 1/1 [00:10<00:00, 10.02s/it]
PGD - Random Initializations: 100% 1/1 [00:11<00:00, 11.80s/it]
PGD - Random Initializations: 100% 1/1 [00:12<00:00, 12.57s/it]
PGD - Random Initializations: 100% 1/1 [00:11<00:00, 11.68s/it]
PGD - Random Initializations: 100% 1/1 [00:02<00:00, 2.65s/it]
```

```
# Создаем отправленные примеры данных, для начала берем отправленные входы и выходы, смотрим их количество и визуализируем.
poisoned = pdata[np.all(plabels == targets, axis=1)]
poisoned_labels = plabels[np.all(plabels == targets, axis=1)]
print(len(poisoned))
idx = 0
plt.imshow(poisoned[idx].squeeze())
print(f"Label: {np.argmax(poisoned_labels[idx])}")
```

```
979
Label: 9
```

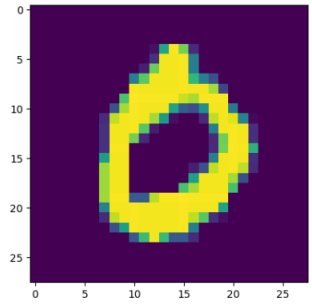



```
[22] #Обучаем модель на отравленных данных
     model.fit(pdata, plabels, nb_epochs=10)
```

```
Train on 10000 samples
Epoch 1/10
10000/10000 [==============================] - 28s 3ms/sample - loss: 0.5914 - accuracy: 0.8173
Epoch 2/10
10000/10000 [==============================] - 26s 3ms/sample - loss: 0.1655 - accuracy: 0.9527
Epoch 3/10
10000/10000 [==============================] - 24s 2ms/sample - loss: 0.0913 - accuracy: 0.9728
Epoch 4/10
10000/10000 [==============================] - 24s 2ms/sample - loss: 0.0647 - accuracy: 0.9796
Epoch 5/10
10000/10000 [==============================] - 26s 3ms/sample - loss: 0.0475 - accuracy: 0.9864
Epoch 6/10
10000/10000 [==============================] - 28s 3ms/sample - loss: 0.0327 - accuracy: 0.9890
Epoch 7/10
10000/10000 [==============================] - 25s 3ms/sample - loss: 0.0299 - accuracy: 0.9892
Epoch 8/10
10000/10000 [==============================] - 24s 2ms/sample - loss: 0.0229 - accuracy: 0.9929
Epoch 9/10
10000/10000 [==============================] - 26s 3ms/sample - loss: 0.0212 - accuracy: 0.9928
Epoch 10/10
10000/10000 [==============================] - 25s 3ms/sample - loss: 0.0155 - accuracy: 0.9950
```

```
[25] #Осуществляем тест на чистой модели, для этого предсказываем на тестовых входов чиых примеров, вычисляем среднюю точность. Далее отправляем картинку, класс, чтобы показать визуализацию легитивных примеров.
     clean_preds = np.argmax(model.predict(x_test), axis=1)
     clean_correct = np.sum(clean_preds == np.argmax(y_test, axis=1))
     clean_total = y_test.shape[0]
     clean_acc = clean_correct / clean_total
     print("\nClean test set accuracy: %.2f%%" % (clean_acc * 100))
     # Display image, label, and prediction for a clean sample to show how the
     c = 0 # class to display
     i = 0 # image of the class to display
     c_idx = np.where(np.argmax(y_test, 1) == c)[0][i] # index of the image in
     plt.imshow(x_test[c_idx].squeeze())
     plt.show()
     clean_label = c
     print("Prediction: " + str(clean_preds[c_idx]))
```

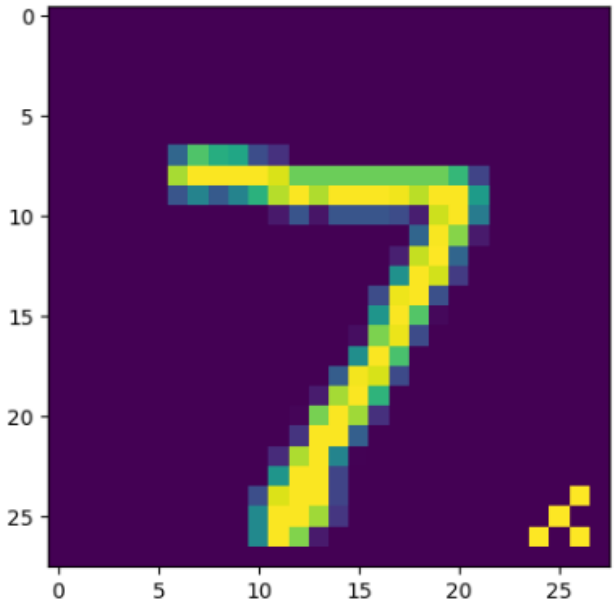
```
Clean test set accuracy: 97.96%
```




```
Prediction: 0
```

```
#Получаем результаты атаки на модель
#Собираем предсказания для текщих моделей, вычислим среднюю точность и выведим класс.
not_target = np.logical_not(np.all(y_test == targets, axis=1))
px_test, py_test = backdoor.poison(x_test[not_target], y_test[not_target])
poison_preds = np.argmax(model.predict(px_test), axis=1)
poison_correct = np.sum(poison_preds == np.argmax(y_test[not_target],
axis=1))
poison_total = poison_preds.shape[0]
poison_acc = poison_correct / poison_total
print("\nPoison test set accuracy: %.2f%%" % (poison_acc * 100))
c = 0 # index to display
plt.imshow(px_test[c].squeeze())
plt.show()
clean_label = c
print("Prediction: " + str(poison_preds[c]))
```

```
Poison test set accuracy: 1.07%
```




```
Prediction: 9
```