Security Analytics

Assignment 4

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Problem 1: Security and Privacy of ML systems

- **1.**
  - **Attacker's Goals in Membership Inference Attack:**
    * The attacker wants to infer if some input is used to train a model. Given a query input x and black-box access to the target model Ft, the membership inference attack answers the question of whether x ϵ D (Dataset) is true or false. The attack is successful if the attacker can determine with high confidence that x is contained within the dataset D used to train Ft. Thus using membership inference attack, the attacker gets access to private information of an user.
  - **Attacker's Goals in Model Inversion Attack:**
    * Attacker's primary goal in Model Inversion is to extract sensitive input and training data by leveraging the model and auxiliary data about individual. With little to no knowledge about the model, but given opportunities to repeatedly query it, the attacker wants to reconstruct unknown input based only on model's output. therefore, the target of attacker is to train his own model with data as similar as possible to the original training data.
- **2. Challenges of generating adversarial samples in constrained domains:**
  - In an constrained domain, the adversaries are bound in their capabilities. For example - how many total features can be perturbed or which features are manipulable. Not all features represent the same kind of information (pixels vs packet information), nor do they describe the same kind of statistical data (discrete vs a blend of categorical, continuous, and discrete). These differences change the threat surface and the underlying assumptions surrounding the capabilities of an adversary in constrained domains.
  - Existing algorithms are optimized for human perception. Using algorithms optimized for human perception offers us no utility.
  - Existing algorithms assume adversaries have full control over the feature space. This is likely an unreasonable assumption in constrained domains.
  - Existing algorithms do not consider domain constraints. Crafting adversarial examples that obey domain constraints is necessary to mount practical attacks.

    For example, Unlike adversarial images, which include the perturbations of less noticeable background pixels, changes to voice commands is expected to that sounds normal to humans. Also, for NLP domain, an adversary has to create adversarial example which is semantically indistinguishable. An adversary needs to consider certain constraints (protocol and service (port number) as features, some other services) in network intrusion detection to generate adversarial examples successfully.

- **3. Difference between Data Poisoning and Backdoor (trojan) attacks:**
  - **Poisoning Attack:** An adversary tries to manipulate the training dataset in order to control the prediction behavior of a trained model such that the model will label malicious examples into desired classes.

    Backdoor Attack: It is an hidden patterns that have been trained into a DNN model that produce unexpected behavior, but are undetectable unless activated by some "trigger" input. Therefore, without the presence of the trigger, the model will correctly classify the input, but in presence of particular trigger, the model will misclassify.
  - Poisoning attacks decrease accuracy on benign input (Availability Poison), also misclassify certain inputs irrespective of any other condition (Integrity Poison). On the other hand, Backdoor is Integrity Poison which depends on the presence of a trigger.
- **4. Gradient Masking:**
  - Deliberately hide away the gradient or destroy the gradient so that gradient based attackers fail. Gradient masking change the loss function. The loss makes hard to minimize the gradient of loss with respect to the inputs and hardens an adversary to create adversarial examples.
  - **gradient masking based defenses fail against adversarial examples:** It will take more iterations for an adversary to generate adversarial sample, but break is still possible.
  - Shattered gradients can be overcome using a technique the authors call 'Backward Pass Differentiable Approximation' (BPDA).
  - "Expectation over Transformation" (EOT) can be used to compute the gradient over an expected transformation to an input. This is used to attack a network that relies on stochastic gradients.
  - Vanishing or exploding gradients can be addressed through reparameterization.

  So, these above methods suggest the reason of failure of gradient masking as defense technique.

Problem2

In [153]:
```
import warnings
warnings.filterwarnings("ignore", category=DeprecationWarning)
```

In [154]:
```
# Imports
import keras
import random
import numpy as np
import matplotlib.pyplot as plt

from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K

from art.attacks.evasion import CarliniL2Method, SaliencyMapMethod, ElasticNet
from art.estimators.classification import KerasClassifier

# Set the random seeds. Do not change this!
seedVal = 41
random.seed(seedVal)
np.random.seed(seedVal)

# Define some constants.
NUM_CLASSES = 10
BATCH_SIZE = 32
```

Part 1

You need to complete the following.

In [155]:
```
# Load the MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Normalization
x_train = keras.utils.normalize(x_train, axis=1)
x_test = keras.utils.normalize(x_test, axis=1)

# convert class vectors to binary class matrices
y_train = keras.utils.to_categorical(y_train, NUM_CLASSES)
y_test = keras.utils.to_categorical(y_test, NUM_CLASSES)

K.set_image_data_format('channels_first')

# Reshape the data.
x_train = x_train.reshape(x_train.shape[0], 1, 28, 28)
x_test = x_test.reshape(x_test.shape[0], 1, 28, 28)
```

In [156]:
```
# Build a training dataset for the substitute model
# Collect ten images from each dataset class (numbers 0-9)
selected_examples = []
for target_label in range(0, 10):
    count = 0
    for i in range(y_train.shape[0]):
        if y_train[i].tolist().index(1) == target_label:
            count += 1
            selected_examples.append((x_train[i, :, :], y_train[i]))
            if count == 10:
                break

# Convert selected examples to numpy array
final_train_x =  np.array( [seq[0] for seq in selected_examples] )
final_train_y =  np.array( [seq[1] for seq in selected_examples] )
```

In [157]:
```python
# Train a CNN-based substitute model using the newly collected dataset
substitute_model = Sequential()
substitute_model.add(Conv2D(32, (3, 3), activation='relu', input_shape=(1,28,28), data_format='channels_first'))
# Define the intermediate layers.
substitute_model.add(MaxPooling2D((2, 2)))
substitute_model.add(Flatten())
substitute_model.add(Dense(BATCH_SIZE, activation='relu'))

substitute_model.add(Dense(NUM_CLASSES, activation='softmax'))


# Compile the model
substitute_model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adadelta(),
              metrics=['accuracy'])

substitute_model = KerasClassifier(model=substitute_model, clip_values=(0,1))

# Fit the model
substitute_model.fit(final_train_x, final_train_y, nb_epochs=20, batch_size=BATCH_SIZE)
```

```
Epoch 1/20
100/100 [==============================] - 1s 8ms/step - loss: 2.2784 - accuracy: 0.1700
Epoch 2/20
100/100 [==============================] - 0s 2ms/step - loss: 2.1903 - accuracy: 0.2000
Epoch 3/20
100/100 [==============================] - 0s 1ms/step - loss: 2.0284 - accuracy: 0.4900
Epoch 4/20
100/100 [==============================] - 0s 1ms/step - loss: 1.8721 - accuracy: 0.4000
Epoch 5/20
100/100 [==============================] - 0s 2ms/step - loss: 1.6007 - accuracy: 0.5100
Epoch 6/20
100/100 [==============================] - 0s 2ms/step - loss: 1.3678 - accuracy: 0.7600
Epoch 7/20
100/100 [==============================] - 0s 1ms/step - loss: 1.1809 - accuracy: 0.6300
Epoch 8/20
100/100 [==============================] - 0s 1ms/step - loss: 0.9474 - accuracy: 0.8000
Epoch 9/20
100/100 [==============================] - 0s 1ms/step - loss: 0.7123 - accuracy: 0.8300
Epoch 10/20
100/100 [==============================] - 0s 1ms/step - loss: 0.5666 - accuracy: 0.8400
Epoch 11/20
100/100 [==============================] - 0s 1ms/step - loss: 0.5875 - accuracy: 0.8200
Epoch 12/20
100/100 [==============================] - 0s 1ms/step - loss: 0.4083 - accuracy: 0.9000
Epoch 13/20
100/100 [==============================] - 0s 1ms/step - loss: 0.4030 - accuracy: 0.9100
Epoch 14/20
100/100 [==============================] - 0s 1ms/step - loss: 0.2727 - accuracy: 0.9500
Epoch 15/20
100/100 [==============================] - 0s 1ms/step - loss: 0.2012 - accuracy: 0.9700
Epoch 16/20
100/100 [==============================] - 0s 1ms/step - loss: 0.1947 - accuracy: 0.9500
Epoch 17/20
100/100 [==============================] - 0s 1ms/step - loss: 0.1436 - accuracy: 0.9800
Epoch 18/20
100/100 [==============================] - 0s 1ms/step - loss: 0.2003 - accuracy: 0.9400
Epoch 19/20
100/100 [==============================] - 0s 1ms/step - loss: 0.0956 - accuracy: 1.0000
Epoch 20/20
100/100 [==============================] - 0s 1ms/step - loss: 0.1181 - accuracy: 0.9900
```

Please ONLY use the following attack methods.

In [158]:
```python
# Define methods for generating "targetted" adversarial examples
def generate_adv_examples_CarliniL2Method(classifier, x, target_y):
    attacker = CarliniL2Method(classifier,targeted=True)
    attack = attacker.generate(x=x, y=target_y)
    return attack

def generate_adv_examples_ElasticNet(classifier, x, target_y):
    attacker = ElasticNet(classifier,targeted=True)
    attack = attacker.generate(x=x, y=target_y)
    return attack

def generate_adv_examples_SaliencyMapMethod(classifier, x, target_y):
    attacker = SaliencyMapMethod(classifier)
    attack = attacker.generate(x=x, y=target_y)
    return attack
```

In [159]:
```python
# Build a mapping from the true label to the fake label
# For example, in the mapping below, we want the classifier to predict 0 images as 8.
label_map = {0:8, 1:9, 2:3, 3:5, 4:6, 5:7, 6:4, 7:2, 8:1, 9:0}
for k, v in label_map.items():
    assert(k != v)
assert(len(set(label_map.keys())) == 10)
assert(len(set(label_map.values())) == 10)

# Build target_y
target_y_labels = []
for i in range(final_train_y.shape[0]):
    cur_true_label = final_train_y[i].tolist().index(1)
    target_label = label_map[cur_true_label]
    target_y_labels.append(target_label)
target_y_labels = np.asarray(target_y_labels)
target_y = keras.utils.to_categorical(target_y_labels, NUM_CLASSES)

# Generate 300 adversarial images
carlinil_adv_examples = generate_adv_examples_CarliniL2Method(substitute_model,final_train_x[0:300],target_y[0:300])
elastic_net_adv_examples = generate_adv_examples_ElasticNet(substitute_model,final_train_x[0:300],target_y[0:300])
saliency_adv_examples = generate_adv_examples_SaliencyMapMethod(substitute_model,final_train_x[0:300],target_y[0:300])
```

C&W L_2: 100% 100/100 [02:25<00:00, 1.46s/it]

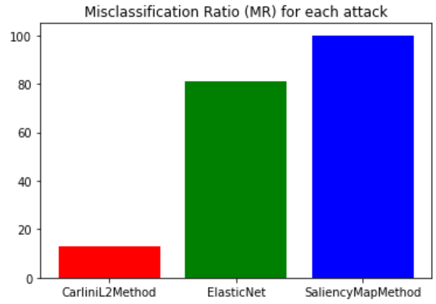
EAD: 100% 100/100 [14:46<00:00, 8.73s/it]

JSMA: 100% 100/100 [00:21<00:00, 4.29it/s]

In [160]:
```python
# Calculate Misclassification Ratio (MR) for CarliniL2Method attack
predictions = np.argmax(substitute_model.predict(carlinil_adv_examples),axis=1)
carlinil_mr = (np.sum(predictions == np.argmax(target_y, axis=1))/(predictions.shape[0]))*100
print('For CarliniL2Method attack, MR = {}'.format(carlinil_mr))

# Calculate Misclassification Ratio (MR) for ElasticNet attack
predictions = np.argmax(substitute_model.predict(elastic_net_adv_examples),axis=1)
elastic_net_mr = (np.sum(predictions == np.argmax(target_y, axis=1))/(predictions.shape[0]))*100
print('For ElasticNet attack, MR = {}'.format(elastic_net_mr))

# Calculate Misclassification Ratio (MR) for SaliencyMapMethod attack
predictions = np.argmax(substitute_model.predict(saliency_adv_examples),axis=1)
saliency_mr = (np.sum(predictions == np.argmax(target_y, axis=1))/(predictions.shape[0]))*100
print('For SaliencyMapMethod attack, MR = {}'.format(saliency_mr))
```

```
For CarliniL2Method attack, MR = 13.0
For ElasticNet attack, MR = 81.0
For SaliencyMapMethod attack, MR = 100.0
```

In [161]:
```python
# Make a plot
X = ['CarliniL2Method','ElasticNet', 'SaliencyMapMethod']
mr_arr =[carlinil_mr, elastic_net_mr, saliency_mr]
plt.bar(X, mr_arr ,color=['r', 'g', 'b'])
plt.title('Misclassification Ratio (MR) for each attack')
plt.show()
plt.close()
```



Part 2

You need to complete the following.

In [162]:

```python
# Imports
from numpy import linalg as LA
import pandas as pd

for class_label in range(0, 10):
    print('For images of true class = {}'.format(class_label))
    norms_average = pd.DataFrame([[0,0,0],[0,0,0],[0,0,0]],columns=['carlinil', 'elastic_net', 'saliency'])
    norms_average.index = ['l0','l2','l_inf']
    sum_calc = pd.DataFrame([[0,0,0],[0,0,0],[0,0,0]],columns=['carlinil', 'elastic_net', 'saliency'])
    sum_calc.index = ['l0','l2','l_inf']

    for i in range(final_train_y.shape[0]):
        cur_true_label = final_train_y[i].tolist().index(1)
        if cur_true_label == class_label:
            for attack_method in ['carlinil', 'elastic_net', 'saliency']:
                if attack_method == 'carlinil':
                    sum_calc[attack_method]['l0'] = np.sum(np.abs(final_train_x[i].squeeze()-carlinil_adv_examples[i].squeeze()))
                    sum_calc[attack_method]['l2'] = LA.norm(final_train_x[i].squeeze()-carlinil_adv_examples[i].squeeze(),ord=2)
                    sum_calc[attack_method]['l_inf'] = LA.norm(final_train_x[i].squeeze()-carlinil_adv_examples[i].squeeze(),ord = np.inf)
                elif attack_method == 'elastic_net':
                    sum_calc[attack_method]['l0'] = np.sum(np.abs(final_train_x[i].squeeze()-elastic_net_adv_examples[i].squeeze()))
                    sum_calc[attack_method]['l2'] = LA.norm(final_train_x[i].squeeze()-elastic_net_adv_examples[i].squeeze(),ord=2)
                    sum_calc[attack_method]['l_inf'] = LA.norm(final_train_x[i].squeeze()-elastic_net_adv_examples[i].squeeze(),ord = np.inf)
                elif attack_method == 'saliency':
                    sum_calc[attack_method]['l0'] = np.sum(np.abs(final_train_x[i].squeeze()-saliency_adv_examples[i].squeeze()))
                    sum_calc[attack_method]['l2'] = LA.norm(final_train_x[i].squeeze()-saliency_adv_examples[i].squeeze(),ord=2)
                    sum_calc[attack_method]['l_inf'] = LA.norm(final_train_x[i].squeeze()-saliency_adv_examples[i].squeeze(),ord = np.inf)
                #x_diff = (final_train_x[i].squeeze() - cur_adv_examples[i].squeeze()).reshape(-1)
                norms_average[attack_method]['l0'] += sum_calc[attack_method]['l0']
                norms_average[attack_method]['l2'] += sum_calc[attack_method]['l2']
                norms_average[attack_method]['l_inf'] += sum_calc[attack_method]['l_inf']

    print('Methods \t L0 \t L2 \t L_inf')
    for attack_method in ['carlinil', 'elastic_net', 'saliency']:
        l0_average = norms_average[attack_method]['l0']/final_train_x.shape[0]
        l2_average = norms_average[attack_method]['l2']/final_train_x.shape[0]
        linf_average = norms_average[attack_method]['l_inf']/final_train_x.shape[0]
        print('{} \t {} \t {} \t {}'.format(attack_method, l0_average, l2_average, linf_average))
    print('\n')
```

```
For images of true class = 0
Methods         L0      L2      L_inf
carlinil        0.08    0.0     0.0
elastic_net     2.81    0.1     0.19
saliency        0.77    0.15    0.19


For images of true class = 1
Methods         L0      L2      L_inf
carlinil        0.15    0.0     0.0
elastic_net     0.53    0.0     0.02
saliency        0.31    0.05    0.07


For images of true class = 2
Methods         L0      L2      L_inf
carlinil        0.0     0.0     0.0
elastic_net     5.14    0.2     0.35
saliency        1.04    0.15    0.21


For images of true class = 3
Methods         L0      L2      L_inf
carlinil        0.14    0.0     0.01
elastic_net     2.1     0.07    0.19
saliency        0.38    0.11    0.11


For images of true class = 4
Methods         L0      L2      L_inf
carlinil        0.0     0.0     0.0
elastic_net     3.24    0.14    0.25
saliency        0.74    0.18    0.23


For images of true class = 5
Methods         L0      L2      L_inf
carlinil        0.0     0.0     0.0
elastic_net     2.25    0.1     0.21
saliency        0.94    0.19    0.31


For images of true class = 6
Methods         L0      L2      L_inf
carlinil        0.11    0.0     0.01
elastic_net     1.32    0.01    0.07
saliency        0.76    0.13    0.22


For images of true class = 7
Methods         L0      L2      L_inf
carlinil        0.07    0.0     0.01
elastic_net     6.52    0.22    0.43
saliency        1.16    0.25    0.35


For images of true class = 8
Methods         L0      L2      L_inf
carlinil        0.0     0.0     0.0
elastic_net     0.38    0.0     0.02
saliency        0.96    0.13    0.17
```

```
For images of true class = 9
Methods          L0      L2      L_inf
carlinil         0.11    0.0     0.01
elastic_net      4.55    0.17    0.38
saliency         0.96    0.19    0.27
```

Part 3

You need to complete the following.

In [163]:
```python
# Imports

# Reload the trained model from HW#3 Problem 4
import network.network as Network
import network.mnist_loader as mnist_loader
import pickle

# Load the pre-trained model.
with open('network/trained_network.pkl', 'rb') as f:
    u = pickle._Unpickler(f)
    u.encoding = 'latin1'
    target_net = u.load()
```

In [164]:
```python
def predict_using_target_net(x, verbose=False):
    x = x.squeeze().reshape(-1, 1)
    outputs = target_net.feedforward(x)
    predictions = np.argmax(outputs)
    if verbose:
        print('Network output: \n' + str(np.round(outputs, 2)) + '\n')
        print('Network prediction: ' + str(predictions) + '\n')
        print('Actual image: ')

        # Draw the image
        plt.imshow(x.reshape((28,28)), cmap='Greys')
    return predictions
```

In [165]:
```python
# Evaluate whether adversarial examples generated with the substitute model will transfer to the target model
for attack_method in ['carlinil', 'elastic_net', 'saliency']:
    pred = None
    miss_cl = None
    it=0
    cnt=0
    if attack_method == 'carlinil':
        for j in carlinil_adv_examples:
            pred = predict_using_target_net(j)
            if(pred==target_y[it].tolist().index(1)):
                cnt+=1
            it+=1
    elif attack_method == 'elastic_net':
        for j in elastic_net_adv_examples:
            pred = predict_using_target_net(j)
            if(pred==target_y[it].tolist().index(1)):
                cnt+=1
            it+=1
    elif attack_method == 'saliency':
        for j in saliency_adv_examples:
            pred = predict_using_target_net(j)
            if(pred==target_y[it].tolist().index(1)):
                cnt+=1
            it+=1
    predictions = pred
    predictions = np.asarray(predictions)
    mr = (cnt/carlinil_adv_examples.shape[0])*100
    print('For {}, Misclassification Ratio = {}'.format(attack_method, mr))
```

```
For carlinil, Misclassification Ratio = 4.0
For elastic_net, Misclassification Ratio = 20.0
For saliency, Misclassification Ratio = 14.000000000000002
```

Part 4

You need to complete the following.

In [168]:
```python
# Imports
from sklearn.model_selection import GridSearchCV
from sklearn.neural_network import MLPClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.neighbors import KNeighborsClassifier
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import VotingClassifier
from sklearn.svm import SVC
```

In [169]:
```
# Re-load the MNIST dataset
(x_train, y_train), (x_test, y_test) = mnist.load_data()

# Normalization
x_train = keras.utils.normalize(x_train, axis=1)
x_test = keras.utils.normalize(x_test, axis=1)

nb_trains = x_train.shape[0]
nb_tests = x_test.shape[0]

nsamples, nx, ny = x_train.shape
x_train = x_train.reshape((nsamples,nx*ny))

nsamples_test, nx_test, ny_test = x_test.shape
x_test = x_test.reshape((nsamples_test,nx_test*ny_test))
```

In [170]:
```
samp,a,b,c = carlinil_adv_examples.shape
carlinil_adv_examples = carlinil_adv_examples.reshape((samp,a*b*c))
elastic_net_adv_examples = elastic_net_adv_examples.reshape((samp,a*b*c))
saliency_adv_examples = saliency_adv_examples.reshape((samp,a*b*c))
```

In [126]:
```
# ANN model
ann_parameters = {
'hidden_layer_sizes': [(100), (100,100)]
}

ann_model = MLPClassifier(max_iter=100)
ann_clf = GridSearchCV(ann_model,ann_parameters)
ann_clf.fit(x_train, y_train)
print("ANN grid search best parameters: {}".format(ann_clf.best_params_))
```

```
ANN grid search best parameters: {'hidden_layer_sizes': (100, 100)}
```

In [127]:
```
# SVM model
svm_parameters = {
    'kernel': ['rbf'],
    'C': [1, 10]
}

svm_clf = GridSearchCV(SVC(),svm_parameters)
svm_clf.fit(x_train, y_train)
print("SVM grid search best parameters: {}".format(svm_clf.best_params_))
```

```
SVM grid search best parameters: {'C': 10, 'kernel': 'rbf'}
```

In [128]:
```
# Logistic Regression model
lr_parameters = {
    'multi_class': ['auto'],
    'penalty' : ['l1', 'l2'],
    'C': [1, 10],
}


logreg=LogisticRegression(solver='liblinear')
lr_clf = GridSearchCV(logreg, lr_parameters)
lr_clf.fit(x_train, y_train)
print("Logistic Regression grid search best parameters: {}".format(lr_clf.best_params_))
```

```
Logistic Regression grid search best parameters: {'C': 1, 'multi_class': 'auto', 'penalty': 'l1'}
```

In [129]:
```
# kNN
knn_parameters = {
    'n_neighbors': [5],
    'weights': ['uniform', 'distance']
}
knn_clf = GridSearchCV(KNeighborsClassifier(n_neighbors=5),knn_parameters)
knn_clf.fit(x_train,y_train)
print("KNN grid search best parameters: {}".format(knn_clf.best_params_))
```

```
KNN grid search best parameters: {'n_neighbors': 5, 'weights': 'distance'}
```

In [130]:
```
# Naive Bayes
naive_bayes_parameters = {
    'var_smoothing': [1e-3, 1e-2, 1e-1]
}
naive_bayes_clf = GridSearchCV(GaussianNB(),naive_bayes_parameters)
naive_bayes_clf.fit(x_train, y_train)
print("Naive Bayes grid search best parameters: {}".format(naive_bayes_clf.best_params_))
```

```
Naive Bayes grid search best parameters: {'var_smoothing': 0.1}
```

In [131]:
```
# Voting classifiers
voting_clf = VotingClassifier(estimators=[
                                ('naive_bayes', GaussianNB()),
                                ('ann', MLPClassifier()),
                                ('lr', LogisticRegression()),
                               ], voting='soft')

params = {
          'naive_bayes__var_smoothing': [1e-3, 1e-2, 1e-1],
          'lr__C': [1, 10],
          'ann__hidden_layer_sizes': [(100), (100,100)]}

voting_clf = GridSearchCV(voting_clf, params)
voting_clf.fit(x_train, y_train)
print("Voting Classifier grid search best parameters: {}".format(voting_clf.best_params_))
```

In [197]:
```
classifier_names = ['ANN', 'SVM', 'Logistic Regression', 'kNN', 'Naive Bayes', 'Voting classifiers']
classifiers = [ann_clf, svm_clf, lr_clf, knn_clf, naive_bayes_clf, voting_clf]
print('Methods \t Test Acc \t Carlinil MR \t ElasticNet MR \t Saliency MR')
for i in range(len(classifiers)):
    test_acc = classifiers[i].score(x_test,y_test)*100
    carlinil_acc = classifiers[i].score(carlinil_adv_examples,target_y_labels)*100
    elasticnet_acc = classifiers[i].score(elastic_net_adv_examples,target_y_labels)*100
    saliency_acc = classifiers[i].score(saliency_adv_examples,target_y_labels)*100
    print('{} \t \t {} \t \t {} \t \t {} \t \t {}'.format(classifier_names[i], str(test_acc), str(carlinil_acc), str(elasticnet_acc), str(saliency_ac
```

```
Methods          Test Acc        Carlinil MR     ElasticNet MR   Saliency MR
ANN              97.47           1.0             15.0            13.0
SVM              98.17           0.0             9.0             13.0
Logistic Regression              92.02           2.0             25.0            26.0
kNN              96.22           1.0             9.0             2.0
Naive Bayes              80.73           7.000000000000001               25.0            36.0
Voting classifiers               94.6            1.0             19.0            24.0
```

From the above statistics, we find that the transferability of ElasticNet based adversarial examples is more

than Saliency and Carlini based examples in case of ANN, KNN classifiers

Saliency based adversarial examples is more transferable in SVM, Logistic Regression, Naive Bayes and Voting

Carlini Adversarial Examples are not much transferable.

Problem3

In [1]:
```
import numpy as np
import warnings
warnings.filterwarnings("ignore", category=np.VisibleDeprecationWarning)
```

In [2]:
```
# Imports.
import random
import network.network as Network
import network.mnist_loader as mnist_loader
import pickle
import matplotlib.pyplot as plt

# Set the random seed. DO NOT CHANGE THIS!
seedVal = 41
random.seed(seedVal)
np.random.seed(seedVal)

%matplotlib inline
```

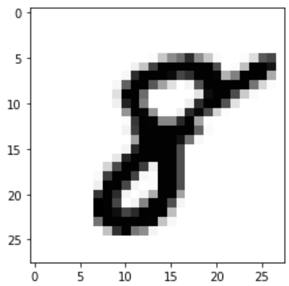
Use a pre-trained network. It has been saved as a pickle file. Load the model, and continue. The network has only one hidden layer of 30 units, 784 input units (MNIST images are $28 \times 28 = 784$ pixels large), and 10 output units. All the activations are sigmoidal.

In [3]:
```
# Load the pre-trained model.
with open('network/trained_network.pkl', 'rb') as f:
    u = pickle._Unpickler(f)
    u.encoding = 'latin1'
    net = u.load()

# Helpful function to load the MNIST data.
training_data, validation_data, test_data = mnist_loader.load_data_wrapper()
```

The neural network is pretrained, so it should already be set up to predict characters. Run `predict(n)` to evaluate the n^{th} digit in the test set using the network. You should see that even this relatively simple network works really well (~97% accuracy). The output of the network is a one-hot vector indicating the network's predictions:

In [4]:
```
def predict(n):
    # Get the data from the test set
    x = test_data[n][0]

    # Print the prediction of the network
    print('Network output: \n' + str(np.round(net.feedforward(x), 2)) + '\n')
    print('Network prediction: ' + str(np.argmax(net.feedforward(x))) + '\n')
    print('Actual image: ')

    # Draw the image
    plt.imshow(x.reshape((28,28)), cmap='Greys')

# Replace the argument with any number between 0 and 9999
predict(8384)
```

```
Network output:
[[0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [1.]
 [0.]]

Network prediction: 8

Actual image:
```



To actually generate adversarial examples we solve a minimization problem. We do this by setting a "goal" label called $\vec{y}_{goal}$ (for instance, if we wanted the network to think the adversarial image is an 8, then we would choose $\vec{y}_{goal}$ to be a one-hot vector with the eighth entry being 1). Now we define a cost function:

$$C = \frac{1}{2}\|\vec{y}_{goal} - \hat{y}(\vec{x})\|_2^2$$

where $\|\cdot\|_2^2$ is the squared Euclidean norm and $\hat{y}$ is the network's output. It is a function of $\vec{x}$, the input image to the network, so we write $\hat{y}(\vec{x})$. Our goal is to find an $\vec{x}$ such that C is minimized. Hopefully this makes sense, because if we find an image $\vec{x}$ that minimizes C then that means the output of the network when given $\vec{x}$ is close to our desired output, $\vec{y}_{goal}$. So in full mathy language, our optimization problem is:

$$\arg\min_{\vec{x}} C(\vec{x})$$

that is, find the $\vec{x}$ that minimizes the cost C.

To actually do this we can do gradient descent on C. Start with an initially random vector $\vec{x}$ and take steps (changing $\vec{x}$) gradually in the direction opposite of the gradient $\nabla_x C$. To actually get these derivatives we can perform backpropagation on the network. In contrast to training a network, where we perform gradient descent on the weights and biases, when we create adversarial examples we hold the weights and biases constant (because we don't want to change the network!), and change the inputs to our network.

Helper functions to evaluate the non-linearity and it's derivative:

In [6]:
```
def sigmoid(z):
    """The sigmoid function."""
    return 1.0/(1.0+np.exp(-z))

def sigmoid_prime(z):
    """Derivative of the sigmoid function."""
    return sigmoid(z)*(1-sigmoid(z))
```

Also, a function to find the gradient derivatives of the cost function, $\nabla_x C$ with respect to the input $\vec{x}$, with a goal label of $\vec{y}_{goal}$. (Don't worry too much about the implementation, just know it calculates derivatives).

In [7]:
```
def input_derivative(net, x, y):
    """ Calculate derivatives wrt the inputs"""
    nabla_b = [np.zeros(b.shape) for b in net.biases]
    nabla_w = [np.zeros(w.shape) for w in net.weights]

    # feedforward
    activation = x
    activations = [x] # list to store all the activations, layer by layer
    zs = [] # list to store all the z vectors, layer by layer
    for b, w in zip(net.biases, net.weights):
        z = np.dot(w, activation)+b
        zs.append(z)
        activation = sigmoid(z)
        activations.append(activation)

    # backward pass
    delta = net.cost_derivative(activations[-1], y) * \
        sigmoid_prime(zs[-1])
    nabla_b[-1] = delta
    nabla_w[-1] = np.dot(delta, activations[-2].transpose())

    for l in range(2, net.num_layers):
        z = zs[-l]
        sp = sigmoid_prime(z)
        delta = np.dot(net.weights[-l+1].transpose(), delta) * sp
        nabla_b[-l] = delta
        nabla_w[-l] = np.dot(delta, activations[-l-1].transpose())

    # Return derivatives WRT to input
    return net.weights[0].T.dot(delta)
```

The actual function that generates adversarial examples and a wrapper function:

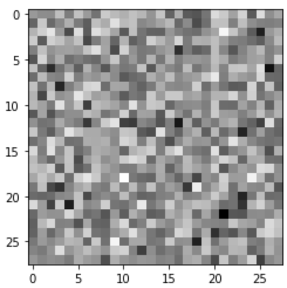
(a) Non Targeted Attack

In [8]:
```python
def nonTargetedAdversarial(net, n, steps, eta):
    """
    net : network object
        neural network instance to use
    n : integer
        our goal label (just an int, the function transforms it into a one-hot vector)
    steps : integer
        number of steps for gradient descent
    eta : float
        step size for gradient descent
    """

    ####### Enter your code below #######

    # Set the goal output
    goal = np.zeros((10,1))
    goal[n] = 1

    # Create a random image to initialize gradient descent with
    x = np.random.normal(.5, .3, (784, 1))

    # Gradient descent on the input
    for i in range(steps):
        # Calculate the derivative
        d = input_derivative(net,x,goal)

        # The GD update on x
        x -= eta*d;

    return x


# Wrapper function
def generate(n):
    """
    n : integer
        goal label (not a one hot vector)
    """

    ####### Enter your code below #######

    # Find the vector x with the above function that you just wrote.
    a=nonTargetedAdversarial(net,n,1000,0.01)

    # Pass the generated image (vector) to the neural network. Perform a forward pass, and get the prediction.
    x = net.feedforward(a)

    print('Network Output: \n' + str(np.round(x,2)) + '\n')

    print('Network Prediction: ' + str(np.argmax(x)) + '\n')

    print('Adversarial Example: ')

    plt.imshow(a.reshape(28,28), cmap='Greys')
```

Now let's generate some adversarial examples! Use the function provided to mess around with the neural network. (For some inputs gradient descent doesn't always converge; 0 and 5 seem to work pretty well though. I suspect convergence is very highly dependent on our choice of random initial $\vec{x}$. We'll see later in the notebook if we force the adversarial example to "look like" a handwritten digit, convergence is much more likely. In a sense we will be adding regularization to our generation process).

In [9]:
```python
generate(2)
```

```
Network Output: 
[[0.  ]
 [0.  ]
 [0.95]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]]

Network Prediction: 2

Adversarial Example: 
```



(b) Targeted Attack(s)

Sweet! We've just managed to create an image that looks utterly meaningless to a human, but the neural network thinks is a '5' with very high certainty. We can actually take this a bit further. Let's generate an image that looks like one number, but the neural network is certain is another. To do this we will modify our cost function a bit. Instead of just optimizing the input image, $\vec{x}$, to get a desired output label, we'll also optimize the input to look like a certain image, $\vec{x}_{target}$, at the same time. Our new cost function will be

$$C = \|\vec{y}_{goal} - y_{hat}(\vec{x})\|_2^2 + \lambda\|\vec{x} - \vec{x}_{target}\|_2^2$$

The added term tells us the distance from our $\vec{x}$ and some $\vec{x}_{target}$ (which is the image we want our adversarial example to look like). Because we want to minimize C, we also want to minimize the distance between our adversarial example and this image. The λ is hyperparameter that we can tune; it determines which is more important: optimizing for the desired output or optimizing for an image that looks like $\vec{x}_{target}$.

If you are familiar with ridge regularization, the above cost function might look suspiciously like the ridge regression cost function. In fact, we can view this generation method as giving our model a prior, centered on our target image.

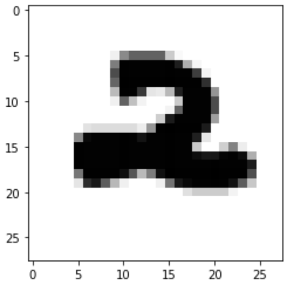
Here is a function that implements optimizing the modified cost function, called `sneaky_adversarial` (because it is very sneaky). Note that the only difference between this function and `adversarial` is an additional term on the gradient descent update for the regularization term:

In [10]:
```
def targetedAdversarial(net, n, x_target, steps, eta, lam=.05):
    """
    net : network object
        neural network instance to use
    n : integer
        our goal label (just an int, the function transforms it into a one-hot vector)
    x_target : numpy vector
        our goal image for the adversarial example
    steps : integer
        number of steps for gradient descent
    eta : float
        step size for gradient descent
    lam : float
        lambda, our regularization parameter. Default is .05
    """

    # Set the goal output
    goal = np.zeros((10, 1))
    goal[n] = 1

    # Create a random image to initialize gradient descent with
    x = np.random.normal(.5, .3, (784, 1))

    # Gradient descent on the input
    for i in range(steps):

        # Calculate the derivative
        d = input_derivative(net,x,goal)

        # The GD update on x, with an added penalty to the cost function
        x -= eta*(d + lam*(x-x_target))

    return x

# Wrapper function
def generate_advSample(n, m):
    """
    n: int 0-9, the target number to match
    m: index of example image to use (from the test set)
    """

    # Find random instance of m in test set
    idx = np.random.randint(0,8000)
    while test_data[idx][1] != m:
        idx += 1

    # Hardcode the parameters for the wrapper function
    a = targetedAdversarial(net, n, test_data[idx][0], 100, 1)
    x = np.round(net.feedforward(a), 2)

    print('\nWhat we want our adversarial example to look like: ')
    plt.imshow(test_data[idx][0].reshape((28,28)), cmap='Greys')
    plt.show()

    print('\n')

    print('Adversarial Example: ')

    plt.imshow(a.reshape(28,28), cmap='Greys')
    plt.show()

    print('Network Prediction: ' + str(np.argmax(x)) + '\n')

    print('Network Output: \n' + str(x) + '\n')

    return a
```

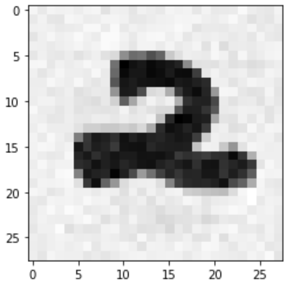
Play around with this function to make "sneaky" adversarial examples! (Again, some numbers converge better than others... try 0, 2, 3, 5, 6, or 8 as a target label. 1, 4, 7, and 9 still don't work as well... no idea why... We get more numbers that converge because we've added regularization term to our cost function. Perhaps changing λ will get more to converge?)

In [11]:
```
# generate_advSample(target label, target digit)
adv_ex = generate_advSample(8, 2)
```

```
What we want our adversarial example to look like:
```



```
Adversarial Example:
```



```
Network Prediction: 8

Network Output:
[[0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.99]
 [0.  ]]
```

(c) Protection against adversarial attacks

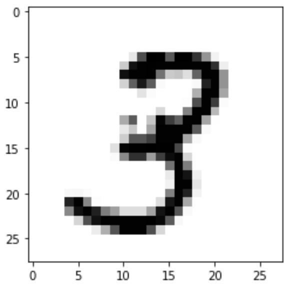
Awesome! We've just created images that trick neural networks. The next question we could ask is whether or not we could protect against these kinds of attacks. If you look closely at the original images and the adversarial examples you'll see that the adversarial examples have some sort of grey tinged background.

So how could we protect against these adversarial attacks? One very simple way would be to use binary thresholding. Set a pixel as completely black or completely white depending on a threshold. This should remove the "noise" that's always present in the adversarial images. Let's see if it works:

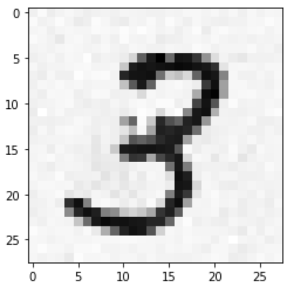
In [12]:
```
def simple_defense(n, m):
    """
    n: int 0-9, the target number to match
    m: index of example image to use (from the test set)
    """

    # Generate an adversarial sample.
    x = generate_advSample(n, m)

    # Perform binary thresholding on the generated sample. You can choose the threshold as 0.5.
    x = (x > .5).astype(float)
    print("With binary thresholding: ")

    # Plot a grayscale image of the binarized generated sample.
    plt.imshow(x.reshape(28,28), cmap="Greys")
    plt.show()

    binary_activations = net.feedforward(x)
    binary_prediction = np.argmax(net.feedforward(x))

    # Print the network's predictions.
    print("Prediction with binary thresholding: " + str(binary_prediction) + '\n')

    # The output of the network.
    print("Network output: ")
    print( str(np.round(binary_activations,2)) )
```

In [13]:
```
# binary_thresholding(target digit, actual digit)
simple_defense(2, 3)
```

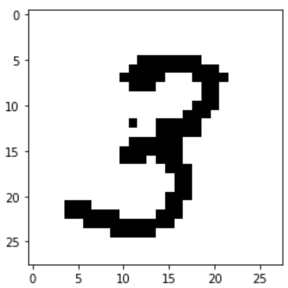
```
What we want our adversarial example to look like:
```



```
Adversarial Example:
```



```
Network Prediction: 2

Network Output:
[[0.  ]
 [0.  ]
 [0.95]
 [0.03]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]]

With binary thresholding:
```



```
Prediction with binary thresholding: 3

Network output:
[[0.]
```

```
 [0.]
 [0.]
 [1.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]]
```

Looks like it works pretty well! However, note that most adversarial attacks, especially on convolutional neural networks trained on massive full color image sets such as imagenet, can't be defended against by a simple binary threshold.

Adversarial Training

Looks like it works pretty well! However, note that most adversarial attacks, especially on convolutional neural networks trained on massive full color image sets such as imagenet, can't be defended against by a simple binary threshold.

We could try one more thing that might be a bit more universal to protect our neural network against adversarial attacks. If we had access to the adversarial attack method (which we do in this case, because we're the ones implementing the attack) we could create a ton of adversarial examples, mix that up with our training dataset with the correct labels, and then retrain a network on this augmented dataset. The retrained network should learn to ignore the adversarial attacks. Here we implement a function to do just that.

In [14]:
```
def augment_data(n, data, steps):
    """
    n : integer
        number of adversarial examples to generate
    data : list of tuples
        data set to generate adversarial examples using
    """
    # Our augmented training set:
    augmented = []

    for i in range(n):
        # Progress "bar"
        if i % 500 == 0:
            print("Generated digits: " + str(i))

        # Randomly choose a digit that the example will look like
        rnd_actual_digit = random.randint(0,9)

        # Find random instance of rnd_actual_digit in the training set
        rnd_actual_idx = np.random.randint(0,8000)

        # TODO : Find a random instance of rnd_actual_digit in the training set.
        while True:
            arr = data[rnd_actual_idx][1]
            dig_val = arr.squeeze().tolist().index(1)
            if(dig_val == rnd_actual_digit):
                break
            rnd_actual_idx += 1
        x_target = data[rnd_actual_idx][0]
        y_actual = data[rnd_actual_idx][1]

        true_digit_label = y_actual.squeeze().tolist().index(1)

        # Choose a value for the adversarial attack
        while True:
            rnd_fake_digit = np.random.randint(10)
            if rnd_fake_digit != true_digit_label: break

        # Generate adversarial example
        x_adversarial = targetedAdversarial(net, rnd_fake_digit, x_target, steps, 1)
        x_adversarial = np.array((x_adversarial, y_actual))
        # Add new data
        augmented.append(x_adversarial)

    return augmented
```

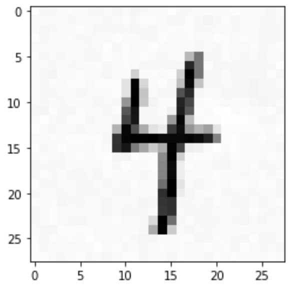
In [15]:
```
# Try 10000 examples first if you don't want to wait for a long time!
augmented = augment_data(10000, training_data, 100)
```

```
Generated digits: 0
Generated digits: 500
Generated digits: 1000
Generated digits: 1500
Generated digits: 2000
Generated digits: 2500
Generated digits: 3000
Generated digits: 3500
Generated digits: 4000
Generated digits: 4500
Generated digits: 5000
Generated digits: 5500
Generated digits: 6000
Generated digits: 6500
Generated digits: 7000
Generated digits: 7500
Generated digits: 8000
Generated digits: 8500
Generated digits: 9000
Generated digits: 9500
```

Now let's check to make sure our augmented dataset actually makes sense. Here we have a function that checks the i^{th} example in our augmented set.

In [16]:
```
def check_augmented(i, augmented):
    # Show image
    print('Image: \n')
    plt.imshow(augmented[i][0].reshape(28,28), cmap='Greys')
    plt.show()

    # Show original network prediction
    print('Original network prediction: \n')
    print(np.round(net.feedforward(augmented[i][0]), 2))

    # Show label
    print('\nLabel: \n')
    print(augmented[i][1])

# check i^th adversarial image
check_augmented(239, augmented)
```

```
Image:
```



```
Original network prediction:

[[0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.98]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]]

Label:

[[0.]
 [0.]
 [0.]
 [0.]
 [1.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]]
```

We can now create a new neural network and train it on our augmented dataset and the original training set, using the original test set to validate.

In [17]:
```python
# Create a new network. Use the function provided in the Network.network to create one. For this you'll have to
# read the description of the function there.
net2 = Network.Network([784,1])

# Train on the augmented + original training set
combined_train_data = []
for j in augmented:
    combined_train_data.append(j)
for j in training_data:
    combined_train_data.append(j)
random.shuffle(combined_train_data)
net2.SGD(combined_train_data, epochs=100, mini_batch_size=5, eta=1,
            test_data=test_data)
```

```
Epoch 0: 6992 / 10000
Epoch 1: 7450 / 10000
Epoch 2: 7511 / 10000
Epoch 3: 7543 / 10000
Epoch 4: 7553 / 10000
Epoch 5: 7549 / 10000
Epoch 6: 7563 / 10000
Epoch 7: 7541 / 10000
Epoch 8: 7575 / 10000
Epoch 9: 7583 / 10000
Epoch 10: 7571 / 10000
Epoch 11: 7573 / 10000
Epoch 12: 7587 / 10000
Epoch 13: 8262 / 10000
Epoch 14: 8312 / 10000
Epoch 15: 8379 / 10000
Epoch 16: 8365 / 10000
Epoch 17: 8367 / 10000
Epoch 18: 8361 / 10000
Epoch 19: 8355 / 10000
Epoch 20: 8342 / 10000
Epoch 21: 8359 / 10000
Epoch 22: 8353 / 10000
Epoch 23: 8363 / 10000
Epoch 24: 8357 / 10000
Epoch 25: 8364 / 10000
Epoch 26: 8352 / 10000
Epoch 27: 8357 / 10000
Epoch 28: 8353 / 10000
Epoch 29: 8364 / 10000
Epoch 30: 8365 / 10000
Epoch 31: 8372 / 10000
Epoch 32: 8361 / 10000
Epoch 33: 8366 / 10000
Epoch 34: 8378 / 10000
Epoch 35: 8376 / 10000
Epoch 36: 8368 / 10000
Epoch 37: 8380 / 10000
Epoch 38: 8349 / 10000
Epoch 39: 8368 / 10000
Epoch 40: 8350 / 10000
Epoch 41: 8382 / 10000
Epoch 42: 8355 / 10000
Epoch 43: 8368 / 10000
Epoch 44: 8355 / 10000
Epoch 45: 8350 / 10000
Epoch 46: 8375 / 10000
Epoch 47: 8362 / 10000
Epoch 48: 8362 / 10000
Epoch 49: 8354 / 10000
Epoch 50: 8356 / 10000
Epoch 51: 8373 / 10000
Epoch 52: 8351 / 10000
Epoch 53: 8376 / 10000
Epoch 54: 8356 / 10000
Epoch 55: 8358 / 10000
Epoch 56: 8365 / 10000
Epoch 57: 8373 / 10000
Epoch 58: 8369 / 10000
Epoch 59: 8355 / 10000
Epoch 60: 8356 / 10000
Epoch 61: 8364 / 10000
Epoch 62: 8365 / 10000
Epoch 63: 8372 / 10000
Epoch 64: 8338 / 10000
Epoch 65: 8361 / 10000
Epoch 66: 8355 / 10000
Epoch 67: 8355 / 10000
Epoch 68: 8354 / 10000
Epoch 69: 8370 / 10000
Epoch 70: 8358 / 10000
Epoch 71: 8373 / 10000
Epoch 72: 8364 / 10000
Epoch 73: 8343 / 10000
Epoch 74: 8352 / 10000
Epoch 75: 8371 / 10000
Epoch 76: 8365 / 10000
Epoch 77: 8367 / 10000
Epoch 78: 8358 / 10000
Epoch 79: 8363 / 10000
Epoch 80: 8358 / 10000
Epoch 81: 8375 / 10000
Epoch 82: 8362 / 10000
Epoch 83: 8367 / 10000
Epoch 84: 8357 / 10000
Epoch 85: 8373 / 10000
Epoch 86: 8367 / 10000
Epoch 87: 8375 / 10000
Epoch 88: 8359 / 10000
```

```
Epoch 89: 8374 / 10000
Epoch 90: 8374 / 10000
Epoch 91: 8360 / 10000
Epoch 92: 8362 / 10000
Epoch 93: 8361 / 10000
Epoch 94: 8358 / 10000
Epoch 95: 8368 / 10000
Epoch 96: 8362 / 10000
Epoch 97: 8355 / 10000
Epoch 98: 8364 / 10000
Epoch 99: 8348 / 10000
```

With a network trained on 50000 adversarial examples in addition to 50000 original training set examples we get about 95% accuracy (it takes quite a long time as well). We can make a test set of adversarial examples by using the following function call:

In [18]:
```
# For some reason the training data has the format: list of tuples
# tuple[0] is np array of image
# tuple[1] is one hot np array of label
# test data is also list of tuples
# tuple[0] is np array of image
# tuple[1] is integer of label
# Just fixing this:
normal_test_data = []

for i in range(len(test_data)):
    ground_truth = test_data[i][1]
    one_hot = np.zeros(10)
    one_hot[ground_truth] = 1
    one_hot = np.expand_dims(one_hot, axis=1)
    normal_test_data.append((test_data[i][0], one_hot))


# Using normal_test_data because of weird way data is packaged
adversarial_test_set = augment_data(1000, normal_test_data, 100)
```

```
Generated digits: 0
Generated digits: 500
```

Let's checkout the accuracy of our newly trained network on adversarial examples from the new adversarial test set:

In [19]:
```
def accuracy(net, test_data):
    """
    net : network object
    test_data: list
        list of 2-tuples of two arrays, one image and one label (one-hot)
    """
    tot = float(len(test_data))
    correct = 0
    for i in range(len(test_data)):
        dt = test_data[i]
        pred = np.argmax(net.feedforward(dt[0]))
        tr_label = dt[1].squeeze().tolist().index(1)
        if(pred==tr_label):
            correct += 1

    return correct / tot

print('Accuracy of the new augmented model on the adversarial test set: ' + str(accuracy(net2, adversarial_test_set)))
print('Accuracy of the new augmented model on the original test set: ' + str(accuracy(net2, normal_test_data)))

print('Accuracy of the original network on the adversarial test set: ' + str(accuracy(net, adversarial_test_set)))
print('Accuracy of the original network on the original test set: ' + str(accuracy(net, normal_test_data)))
```

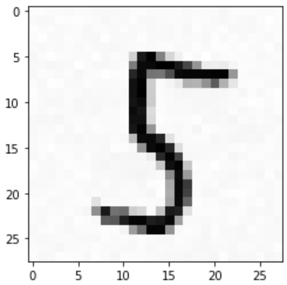
```
Accuracy of the new augmented model on the adversarial test set: 0.836
Accuracy of the new augmented model on the original test set: 0.8348
Accuracy of the original network on the adversarial test set: 0.45
Accuracy of the original network on the original test set: 0.8701
```

Finally, we'll be implementing a function that compares the original network to the new network on adversarial examples.

In [20]:
```
# You'll be implementing a function that compares the original network to the new network. The specifications of
# what this function has to achieve has been provided in the pdf.

# TODO : Implement a function.
def compare(original_net, new_net, adv_example):
    # Show image
    print('Image: \n')
    plt.imshow(adv_example[0].reshape(28,28), cmap='Greys')
    plt.show()

    # Show original network prediction
    print('Original network prediction: \n')
    print(np.round(original_net.feedforward(adv_example[0]), 2))

    # Show new network prediction
    print('New network prediction: \n')
    print(np.round(new_net.feedforward(adv_example[0]), 2))

    # Show label
    print('\nLabel: \n')
    print(adv_example[1])
```

In [21]:
```
compare(net, net2, augmented[150])
```

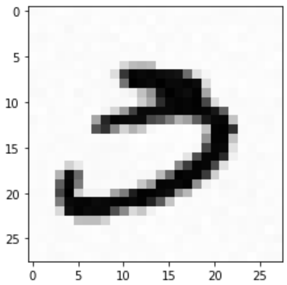
```
Image:
```




```
Original network prediction:

[[0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.02]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]]
New network prediction:

[[0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [1.  ]
 [0.  ]
 [0.  ]
 [0.01]
 [0.  ]]

Label:

[[0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [1.]
 [0.]
 [0.]
 [0.]
 [0.]]
```

In [22]:
```
compare(net, net2, augmented[850])
```

```
Image:
```




```
Original network prediction:

[[0.  ]
 [0.  ]
 [0.  ]
 [0.02]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.  ]]
New network prediction:

[[0.  ]
 [0.  ]
 [0.  ]
 [1.  ]
 [0.  ]
 [0.  ]
 [0.  ]
 [0.01]
 [0.  ]
 [0.  ]]

Label:

[[0.]
 [0.]
 [0.]
 [1.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]
 [0.]]
```

Extra Credit

In [24]:
```
from art.estimators.classification import KerasClassifier
import scipy.stats as jslib
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten
from keras.layers import Conv2D, MaxPooling2D
import keras
from keras.datasets import mnist
from keras import backend as K
```

Function to Calculate Different Utility Metrics

Imported Utility Function From DEEPSEC Repository

In [25]:
```python
# calculate robustness of defense using utility metrics
def defense_utility_measure(pred_def, pred_raw, true_label):
    # compute the classification accuracy of raw model
    correct_prediction_raw = np.equal(np.argmax(pred_raw, axis=1), true_label)
    acc_raw = np.mean(correct_prediction_raw.astype(float))
    print("accuracy of raw model ", acc_raw)

    # compute the classification accuracy of defense-enhanced model
    correct_prediction_def = np.equal(np.argmax(pred_def, axis=1), true_label)
    acc_def = np.mean(correct_prediction_def.astype(float))
    print("accuracy of defense-enhanced model ",acc_def)

    # compute the Classification Accuracy Variance(CAV)
    cav_result = acc_def - acc_raw
    print("Classification Accuracy Variance (CAV)",cav_result)

    # find the index of correct predicted examples by defence-enhanced model and raw model
    idx_def = np.squeeze(np.argwhere(correct_prediction_def == True))
    idx_raw = np.squeeze(np.argwhere(correct_prediction_raw == True))
    idx = np.intersect1d(idx_def, idx_raw, assume_unique=True)

    # compute the Classification Rectify Ratio(CRR) & Classification Sacrifice Ratio(CSR)
    num_rectify = len(idx_def) - len(idx)
    crr_result = num_rectify / len(pred_def)
    print("Classification Rectify Ratio (CRR)",crr_result)

    num_sacrifice = len(idx_raw) - len(idx)
    csr_result = num_sacrifice / len(pred_def)

    print("Classification Sacrifice Ratio (CSR)", csr_result)

    # filter the correct prediction results
    pred_def_filter = pred_def[idx]
    pred_raw_filter = pred_raw[idx]

    # compute the Classification Confidence Variance(CCV)
    confidence_def = np.max(pred_def_filter, axis=1)
    confidence_raw = np.max(pred_raw_filter, axis=1)
    ccv_result = np.mean(np.absolute(confidence_def - confidence_raw))
    print("Classification Confidence Variance(CCV)", ccv_result)

    # compute the Classification Output Stability(COS)
    M = (pred_def_filter + pred_raw_filter) / 2.
    js_total = 0
    for i in range(len(M)):
        js = 0.5 * jslib.entropy(pred_def_filter[i], M[i]) + 0.5 * jslib.entropy(pred_raw_filter[i], M[i])
        js_total += js
    cos_result = js_total / len(M)
    print("Classification Output Stability (COS)", cos_result)

    #return acc_raw, acc_def, cav_result, crr_result, csr_result, ccv_result, cos_result
```

In [26]:
```python
from keras.layers import Dense, Dropout, Flatten, InputLayer
from art.defences.preprocessor import Preprocessor
from art.defences.detector.evasion import BinaryInputDetector
from art.defences.preprocessor import SpatialSmoothing,FeatureSqueezing
```

In [27]:
```python
## Collecting the training data from actual training data
final_train_x =  np.array( [seq[0] for seq in training_data] )
final_train_y =  np.array( [seq[1] for seq in training_data] )

## Using the previously generated adversarial_test_set for test
final_test_x = np.array( [seq[0] for seq in adversarial_test_set] )
final_test_y = np.array( [seq[1] for seq in adversarial_test_set] )
```

In [28]:
```python
lb_y=[]
for j in range(len((final_train_y))):
    lb_y.append(np.argmax(final_train_y[j]))
final_train_y = np.array(lb_y)

final_train_x = final_train_x.reshape(final_train_x.shape[0], 1, 28, 28)
final_test_x = final_test_x.reshape(final_test_x.shape[0], 1, 28, 28)

true_label=[]
for j in range(len((final_test_y))):
    true_label.append(np.argmax(final_test_y[j]))
true_label = np.array(true_label) # true labels for adversarial test set
```

In [29]:
```
ann_based_model = Sequential()
ann_based_model.add(InputLayer(input_shape=(1,28,28)))

# Define the intermediate layers.

ann_based_model.add(Flatten())
ann_based_model.add(Dense(512, activation="relu"))
ann_based_model.add(Dense(256, activation="relu"))
ann_based_model.add(Dense(128, activation="relu"))
ann_based_model.add(Dense(64, activation="relu"))
ann_based_model.add(Dense(10, activation="softmax"))

# Compile the ANN model.
ann_based_model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['acc'])
ann_based_classifier = KerasClassifier(model=ann_based_model, clip_values=(0,1))
ann_based_classifier.fit(final_train_x, final_train_y, nb_epochs=10, batch_size=32)
```

```
WARNING:tensorflow:From /Users/chandrikamukherjee/opt/anaconda3/envs/cs529/lib/python3.7/site-packages/keras/backend/tensorflow_backend.py:422: The
name tf.global_variables is deprecated. Please use tf.compat.v1.global_variables instead.

Epoch 1/10
50000/50000 [==============================] - 15s 307us/step - loss: 0.2272 - acc: 0.9299
Epoch 2/10
50000/50000 [==============================] - 15s 294us/step - loss: 0.1024 - acc: 0.9698
Epoch 3/10
50000/50000 [==============================] - 15s 310us/step - loss: 0.0700 - acc: 0.9786
Epoch 4/10
50000/50000 [==============================] - 16s 322us/step - loss: 0.0559 - acc: 0.9833
Epoch 5/10
50000/50000 [==============================] - 17s 338us/step - loss: 0.0442 - acc: 0.9859
Epoch 6/10
50000/50000 [==============================] - 19s 381us/step - loss: 0.0375 - acc: 0.9885
Epoch 7/10
50000/50000 [==============================] - 17s 338us/step - loss: 0.0313 - acc: 0.9905
Epoch 8/10
50000/50000 [==============================] - 17s 340us/step - loss: 0.0286 - acc: 0.9912
Epoch 9/10
50000/50000 [==============================] - 17s 346us/step - loss: 0.0258 - acc: 0.9921
Epoch 10/10
50000/50000 [==============================] - 17s 347us/step - loss: 0.0234 - acc: 0.9929
```

In [30]:
```
#Get the raw predictions on the test set.
raw_predictions = ann_based_model.predict(final_test_x)
new_network = ann_based_classifier
new_network_copy = ann_based_classifier # to avoid overfitting
```

Defense Technique : BinaryInputDetector

In [31]:
```
bn = BinaryInputDetector(ann_based_classifier)
####Binary detector of adversarial samples coming from evasion attacks.
# The detector uses an architecture provided by the user and trains it on
# data labeled as clean (label 0) or adversarial (label 1).
```

In [32]:
```
bn.fit(final_train_x, final_train_y)
```

```
Epoch 1/20
50000/50000 [==============================] - 5s 102us/step - loss: 0.0065 - acc: 0.9981
Epoch 2/20
50000/50000 [==============================] - 5s 106us/step - loss: 0.0013 - acc: 0.9997
Epoch 3/20
50000/50000 [==============================] - 5s 107us/step - loss: 3.4769e-04 - acc: 0.9999
Epoch 4/20
50000/50000 [==============================] - 5s 108us/step - loss: 1.0959e-04 - acc: 1.0000
Epoch 5/20
50000/50000 [==============================] - 5s 109us/step - loss: 3.9144e-05 - acc: 1.0000
Epoch 6/20
50000/50000 [==============================] - 5s 110us/step - loss: 2.2427e-05 - acc: 1.0000
Epoch 7/20
50000/50000 [==============================] - 6s 110us/step - loss: 1.4810e-05 - acc: 1.0000
Epoch 8/20
50000/50000 [==============================] - 6s 111us/step - loss: 9.0800e-06 - acc: 1.0000
Epoch 9/20
50000/50000 [==============================] - 6s 112us/step - loss: 4.3843e-06 - acc: 1.0000
Epoch 10/20
50000/50000 [==============================] - 6s 112us/step - loss: 2.6541e-06 - acc: 1.0000
Epoch 11/20
50000/50000 [==============================] - 6s 114us/step - loss: 1.7401e-06 - acc: 1.0000
Epoch 12/20
50000/50000 [==============================] - 6s 112us/step - loss: 1.2388e-06 - acc: 1.0000
Epoch 13/20
50000/50000 [==============================] - 6s 113us/step - loss: 8.9801e-07 - acc: 1.0000
Epoch 14/20
50000/50000 [==============================] - 6s 114us/step - loss: 6.6364e-07 - acc: 1.0000
Epoch 15/20
50000/50000 [==============================] - 6s 114us/step - loss: 5.2798e-07 - acc: 1.0000
Epoch 16/20
50000/50000 [==============================] - 6s 115us/step - loss: 3.9799e-07 - acc: 1.0000
Epoch 17/20
50000/50000 [==============================] - 6s 114us/step - loss: 3.2425e-07 - acc: 1.0000
Epoch 18/20
50000/50000 [==============================] - 6s 118us/step - loss: 2.4599e-07 - acc: 1.0000
Epoch 19/20
50000/50000 [==============================] - 6s 116us/step - loss: 2.0595e-07 - acc: 1.0000
Epoch 20/20
50000/50000 [==============================] - 6s 115us/step - loss: 1.6924e-07 - acc: 1.0000
```

In [33]:
```
bn_pred = bn.predict(final_test_x)
```

In [34]:
```
defense_utility_measure(bn_pred,raw_predictions,true_label)
```

```
accuracy of raw model  0.965
accuracy of defense-enhanced model  0.982
Classification Accuracy Variance (CAV) 0.017000000000000015
Classification Rectify Ratio (CRR) 0.019
Classification Sacrifice Ratio (CSR) 0.002
Classification Confidence Variance(CCV) 0.0067272387
Classification Output Stability (COS) 0.002612395757895161
```

Defense Technique: SpatialSmoothing

In [35]:
```
# SpatialSmoothing
sm = SpatialSmoothing()
```

In [36]:
```
# generating new training and test set after applying spatial smoothing

x_art_def, _ = sm(final_train_x)
x_art_adv_def, _ = sm(final_test_x)
```

In [37]:
```
new_network.fit(x_art_def,final_train_y)
```

```
Epoch 1/20
50000/50000 [==============================] - 5s 102us/step - loss: 0.0454 - acc: 0.9882
Epoch 2/20
50000/50000 [==============================] - 5s 108us/step - loss: 0.0113 - acc: 0.9966
Epoch 3/20
50000/50000 [==============================] - 5s 105us/step - loss: 0.0074 - acc: 0.9977
Epoch 4/20
50000/50000 [==============================] - 5s 107us/step - loss: 0.0057 - acc: 0.9980
Epoch 5/20
50000/50000 [==============================] - 5s 108us/step - loss: 0.0093 - acc: 0.9974
Epoch 6/20
50000/50000 [==============================] - 6s 110us/step - loss: 0.0067 - acc: 0.9981
Epoch 7/20
50000/50000 [==============================] - 6s 110us/step - loss: 0.0057 - acc: 0.9983
Epoch 8/20
50000/50000 [==============================] - 6s 111us/step - loss: 0.0040 - acc: 0.9986
Epoch 9/20
50000/50000 [==============================] - 6s 112us/step - loss: 0.0061 - acc: 0.9981
Epoch 10/20
50000/50000 [==============================] - 6s 112us/step - loss: 0.0043 - acc: 0.9986
Epoch 11/20
50000/50000 [==============================] - 6s 112us/step - loss: 0.0077 - acc: 0.9981
Epoch 12/20
50000/50000 [==============================] - 6s 115us/step - loss: 0.0027 - acc: 0.9992
Epoch 13/20
50000/50000 [==============================] - 6s 115us/step - loss: 0.0036 - acc: 0.9993
Epoch 14/20
50000/50000 [==============================] - 6s 115us/step - loss: 0.0070 - acc: 0.9978
Epoch 15/20
50000/50000 [==============================] - 6s 118us/step - loss: 0.0042 - acc: 0.9987
Epoch 16/20
50000/50000 [==============================] - 6s 116us/step - loss: 0.0053 - acc: 0.9988
Epoch 17/20
50000/50000 [==============================] - 6s 115us/step - loss: 0.0012 - acc: 0.9997
Epoch 18/20
50000/50000 [==============================] - 6s 115us/step - loss: 0.0019 - acc: 0.9995
Epoch 19/20
50000/50000 [==============================] - 6s 116us/step - loss: 0.0100 - acc: 0.9976
Epoch 20/20
50000/50000 [==============================] - 6s 120us/step - loss: 0.0045 - acc: 0.9985
```

In [38]:
```
# prediction after applying spatial smooting on train and test set
sm_pred = new_network.predict(x_art_adv_def)
```

In [39]:
```
defense_utility_measure(sm_pred,raw_predictions,true_label)
```

```
accuracy of raw model  0.965
accuracy of defense-enhanced model  0.975
Classification Accuracy Variance (CAV) 0.010000000000000009
Classification Rectify Ratio (CRR) 0.017
Classification Sacrifice Ratio (CSR) 0.007
Classification Confidence Variance(CCV) 0.007634353
Classification Output Stability (COS) 0.0028271929212442862
```

Defense Technique: FeatureSqueezing

In [40]:
```
# FeatureSqueezing Process

fs = FeatureSqueezing(clip_values=(0,1))
```

In [41]:
```
# generating training and test data after applying feature squeezing
x_fs,_ = fs(final_train_x)
x_adv_fs,_ = fs(final_test_x)
```

In [42]:
```
new_network_copy.fit(x_fs,final_train_y)
```

```
Epoch 1/20
50000/50000 [==============================] - 5s 103us/step - loss: 7.4119e-04 - acc: 0.9998
Epoch 2/20
50000/50000 [==============================] - 6s 110us/step - loss: 0.0039 - acc: 0.9991
Epoch 3/20
50000/50000 [==============================] - 5s 108us/step - loss: 0.0089 - acc: 0.9981
Epoch 4/20
50000/50000 [==============================] - 5s 109us/step - loss: 0.0027 - acc: 0.9993
Epoch 5/20
50000/50000 [==============================] - 6s 112us/step - loss: 7.1599e-04 - acc: 0.9998
Epoch 6/20
50000/50000 [==============================] - 6s 112us/step - loss: 0.0054 - acc: 0.9987
Epoch 7/20
50000/50000 [==============================] - 6s 115us/step - loss: 0.0047 - acc: 0.9987
Epoch 8/20
50000/50000 [==============================] - 6s 114us/step - loss: 0.0034 - acc: 0.9990
Epoch 9/20
50000/50000 [==============================] - 6s 113us/step - loss: 2.4456e-04 - acc: 0.9999
Epoch 10/20
50000/50000 [==============================] - 6s 114us/step - loss: 2.9591e-05 - acc: 1.0000
Epoch 11/20
50000/50000 [==============================] - 6s 115us/step - loss: 9.3482e-06 - acc: 1.0000
Epoch 12/20
50000/50000 [==============================] - 6s 116us/step - loss: 5.9876e-06 - acc: 1.0000
Epoch 13/20
50000/50000 [==============================] - 6s 118us/step - loss: 4.2126e-06 - acc: 1.0000
Epoch 14/20
50000/50000 [==============================] - 6s 117us/step - loss: 2.9969e-06 - acc: 1.0000
Epoch 15/20
50000/50000 [==============================] - 6s 116us/step - loss: 1.8040e-06 - acc: 1.0000
Epoch 16/20
50000/50000 [==============================] - 6s 116us/step - loss: 8.3238e-07 - acc: 1.0000
Epoch 17/20
50000/50000 [==============================] - 6s 116us/step - loss: 3.7417e-07 - acc: 1.0000
Epoch 18/20
50000/50000 [==============================] - 6s 117us/step - loss: 2.0841e-07 - acc: 1.0000
Epoch 19/20
50000/50000 [==============================] - 6s 117us/step - loss: 1.2720e-07 - acc: 1.0000
Epoch 20/20
50000/50000 [==============================] - 6s 118us/step - loss: 8.0836e-08 - acc: 1.0000
```

In [43]:
```
fs_pred = new_network_copy.predict(x_adv_fs)
```

In [44]:
```
defense_utility_measure(fs_pred,raw_predictions,true_label)
```

```
accuracy of raw model  0.965
accuracy of defense-enhanced model  0.981
Classification Accuracy Variance (CAV) 0.016000000000000014
Classification Rectify Ratio (CRR) 0.02
Classification Sacrifice Ratio (CSR) 0.004
Classification Confidence Variance(CCV) 0.0075209243
Classification Output Stability (COS) 0.0028430896143402102
```

In [ ]: