Image Denoising with Autoencoders

Task 1: Introduction and Importing Libraries

Note: If you are starting the notebook from this task, you can run cells from all previous tasks in the kernel by going to the top menu and then selecting Kernel > Restart and Run All

In [2]:
```
import numpy as np

from tensorflow.keras.datasets import mnist
from matplotlib import pyplot as plt
from tensorflow.keras.models import Sequential, Model
from tensorflow.keras.layers import Dense, Input
from tensorflow.keras.callbacks import EarlyStopping, LambdaCallback
from tensorflow.keras.utils import to_categorical

%matplotlib inline
```

Task 2: Data Preprocessing

Note: If you are starting the notebook from this task, you can run cells from all previous tasks in the kernel by going to the top menu and then selecting Kernel > Restart and Run All

In [3]:
```
(X_train, y_train), (X_test, y_test)= mnist.load_data()
X_train= X_train.astype('float')/255.  #normalize data after converting from int to float
X_test= X_test.astype('float')/255.
X_train= np.reshape(X_train, (60000, 784))
X_test= np.reshape(X_test, (10000,784))
```

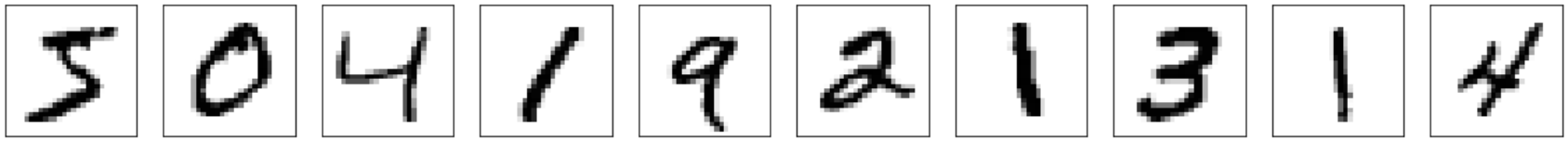
Task 3: Adding Noise

Note: If you are starting the notebook from this task, you can run cells from all previous tasks in the kernel by going to the top menu and then selecting Kernel > Restart and Run All

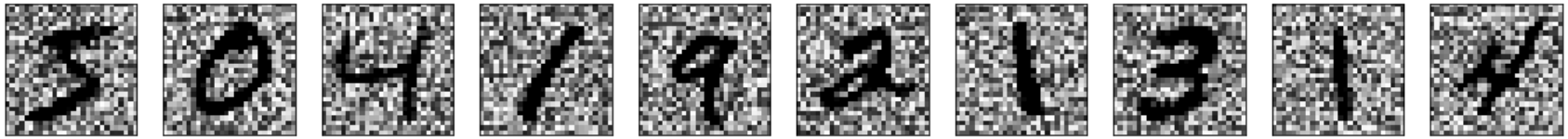
In [4]:
```
X_train_noisy= X_train + np.random.rand(60000, 784)*0.9 #rand generates a random value between 0 and 1
X_test_noisy= X_test + np.random.rand(10000, 784)*0.9
X_train_noisy= np.clip(X_train_noisy, 0., 1.)#clip values to set them between 0 and 1
X_test_noisy= np.clip(X_test_noisy, 0., 1.)#dot indicates floating point values
```

In [5]:
```
def plot(x, p, labels=False):
    plt.figure(figsize=(20,2))
    for i in range(10):
        plt.subplot(1,10,i+1)#subplot starts from 1
        plt.imshow(x[i].reshape(28,28), cmap='binary')
        plt.xticks([])
        plt.yticks([])
        if labels:
            plt.xlabel(np.argmax(p[i]))
    plt.show()

plot(X_train, None)
```



In [6]:
```
plot(X_train_noisy, None)
```



Task 4: Building and Training a Classifier

Note: If you are starting the notebook from this task, you can run cells from all previous tasks in the kernel by going to the top menu and then selecting Kernel > Restart and Run All

In [7]:
```
classifier= Sequential([
    Dense(256, activation='relu',input_shape=(784,)),
    Dense(256, activation='relu'),
    Dense(10, activation='softmax')
])

classifier.compile(optimizer='adam', loss='sparse_categorical_crossentropy', metrics= ['accuracy'])
#we are using above loss function since our labels are not one hot encoded
classifier.fit(X_train, y_train, batch_size= 512, epochs=3)
#512 to speed up training  up->training model
```

```
Epoch 1/3
60000/60000 [==============================] - 5s 89us/step - loss: 0.4266 - acc: 0.8844
Epoch 2/3
60000/60000 [==============================] - 5s 82us/step - loss: 0.1520 - acc: 0.9556
Epoch 3/3
60000/60000 [==============================] - 5s 82us/step - loss: 0.1002 - acc: 0.9701
```

Out[7]:
```
<tensorflow.python.keras.callbacks.History at 0x24396a3a0b8>
```

In [8]:
```
loss, acc= classifier.evaluate(X_test, y_test)
print(acc)
```

```
10000/10000 [==============================] - 1s 77us/step
0.9679
```

In [9]:
```
loss, acc= classifier.evaluate(X_test_noisy, y_test)
print(acc)
```

```
10000/10000 [==============================] - 1s 70us/step
0.2089
```

Task 5: Building the Autoencoder

Note: If you are starting the notebook from this task, you can run cells from all previous tasks in the kernel by going to the top menu and then selecting Kernel > Restart and Run All

In [10]:
```
#autoencoder to denoise data
#if there are less nodes in dense layer model will work similar to principal component analysis and will
#force the moel to learn more important characteristics from dataset and focus only on that
input_image= Input(shape=(784,))#take something with 784 features
encoded= Dense(64, activation='relu')(input_image)#reduce dimensionality & force above thing to fully
#connected layer
decoded= Dense(784, activation='sigmoid')(encoded)#expand it back to 784 features/values
#above autoencoder when we train it learns to focus only on important things and is able to denoise things
#which are not important. in sigmoid most values will converge to 0 or 1

autoencoder= Model(input_image, decoded)#(input,output)
autoencoder.compile(loss='binary_crossentropy', optimizer='adam')
```

Task 6: Training the Autoencoder

Note: If you are starting the notebook from this task, you can run cells from all previous tasks in the kernel by going to the top menu and then selecting Kernel > Restart and Run All

In [11]:
```
#noisy images as input and original images as labels
autoencoder.fit(X_train_noisy, X_train, epochs=100, batch_size=512, validation_split=0.2, verbose=False,
                callbacks=[
                 EarlyStopping(monitor='val_loss', patience=5),
                 LambdaCallback(on_epoch_end= lambda e,l: print('{:.3f}'.format(l['val_loss']), end=' _ ') )
                        ]
                )
#if validation loss does not decrease for 5 epochs then model will stop training; e,l=epoch end, basic log
print(' _ ')
print('Training is complete!')
```

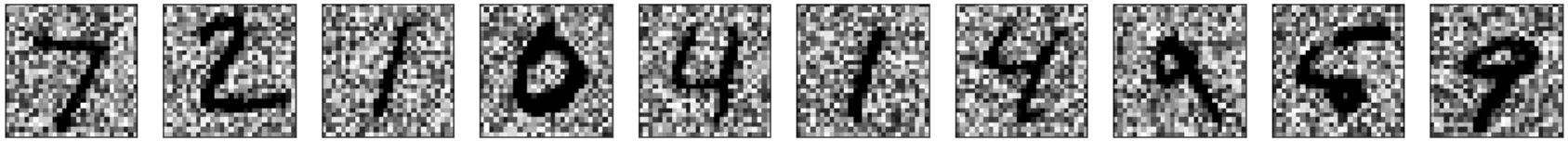
```
0.255 _ 0.221 _ 0.194 _ 0.177 _ 0.164 _ 0.156 _ 0.149 _ 0.143 _ 0.138 _ 0.134 _ 0.131 _ 0.127 _ 0.124 _ 0.122
_ 0.120 _ 0.118 _ 0.117 _ 0.115 _ 0.114 _ 0.113 _ 0.112 _ 0.111 _ 0.110 _ 0.110 _ 0.109 _ 0.108 _ 0.108 _ 0.10
7 _ 0.107 _ 0.106 _ 0.106 _ 0.105 _ 0.105 _ 0.105 _ 0.105 _ 0.104 _ 0.104 _ 0.104 _ 0.104 _ 0.104 _ 0.104 _ 0.
104 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _
0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.103 _ 0.102 _ 0.103 _ 0.103 _ 0.102 _ 0.102
_ 0.103 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.10
2 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.102 _ 0.
102 _ 0.102 _ 0.102 _ 0.102 _  _
Training is complete!
```

Task 7: Denoised Images

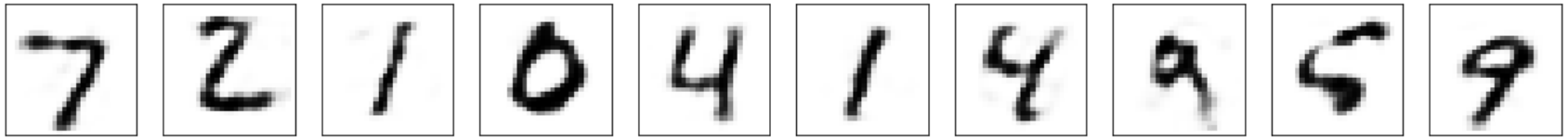
Note: If you are starting the notebook from this task, you can run cells from all previous tasks in the kernel by going to the top menu and then selecting Kernel > Restart and Run All

In [12]:
```
predictions= autoencoder.predict(X_test_noisy)
```

In [13]:
```
plot(X_test_noisy, None)
```



In [14]:
```
plot(predictions, None)
```



In [15]:
```
#performance can be improved by using convolution neural network in autoencoder
loss, acc= classifier.evaluate(predictions, y_test)
print(acc)
```

```
10000/10000 [==============================] - 1s 123us/step
0.9515
```

Task 8: Composite Model

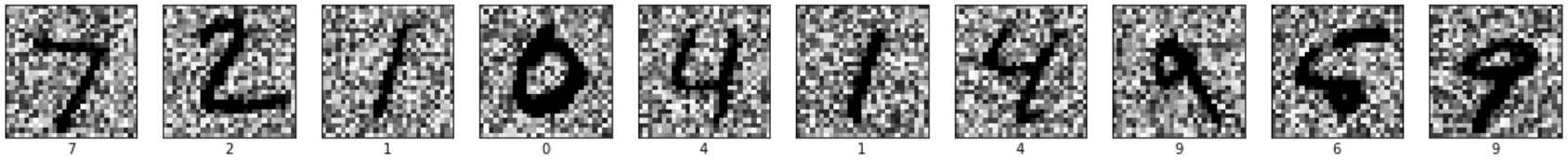
Note: If you are starting the notebook from this task, you can run cells from all previous tasks in the kernel by going to the top menu and then selecting Kernel > Restart and Run All

In [16]:
```
input_image= Input(shape=(784,))
x= autoencoder(input_image)#denoised image
y= classifier(x)

denoise_and_classify= Model(input_image, y)
#creates denoise and classify model
```

In [17]:
```
predictions= denoise_and_classify.predict(X_test_noisy)
```

In [18]:
```
plot(X_test_noisy, predictions, True)
```



In [19]:
```
plot(X_test, to_categorical(y_test), True)#1 hot encoding on y_test
```