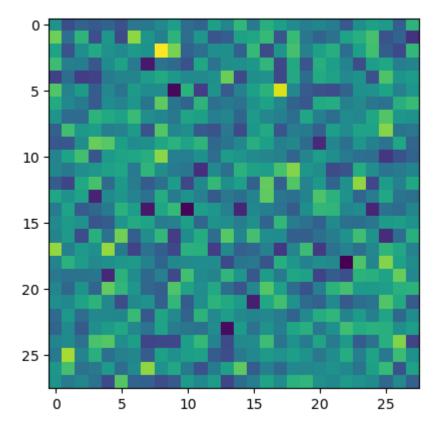
```
In [1]: # Import Packages
        import keras
        from keras.datasets import mnist
        from keras.models import Sequential
        from keras.optimizers import RMSprop
        from keras.layers import Dense, Dropout, Flatten
        from keras.layers import Conv2D, MaxPooling2D
        from keras import backend
In [2]:
        # Import For Plotting (not part of assignment - for my own personal reference)
        import matplotlib.pyplot as plt
        %matplotlib inline
In [3]: %capture
        # Create Data
        # input image dimensions
        img_rows, img_cols = 28, 28
        # the data, shuffled and split between train and test sets
        (x_train, y_train), (x_test, y_test) = mnist.load_data()
        if backend.image_data_format() == 'channels_first':
            x_train = x_train.reshape(x_train.shape[0], 1, img_rows, img_cols)
            x_test = x_test.reshape(x_test.shape[0], 1, img_rows, img_cols)
            input_shape = (1, img_rows, img_cols)
        else:
            x_train = x_train.reshape(x_train.shape[0], img_rows, img_cols, 1)
            x_test = x_test.reshape(x_test.shape[0], img_rows, img_cols, 1)
            input_shape = (img_rows, img_cols, 1)
        x_train = x_train.astype('float32')
        x_test = x_test.astype('float32')
        x_train /= 255
        x test /= 255
        print('x_train shape:', x_train.shape)
        print(x_train.shape[0], 'train samples')
        print(x_test.shape[0], 'test samples')
In [4]: import numpy as np
        # Normalization
        mean = np.mean(x_train)
        std = np.std(x_train)
        x_{train_norm} = (x_{train} - mean) / std
        mean = np.mean(x_test)
        std = np.std(x_test)
        x_{test_norm} = (x_{test} - mean) / std
In [5]: %capture
        ## Add Noise to Dataset
        # Noise is added here
        # Generate random noise with the same shape as the image
        import numpy as np
        mean = 0.0
        stddev = 3.0
        noise = np.random.normal(mean, stddev, x_train.shape)
```

```
# Generate random noise with the same shape as the image
x_train_noise = np.random.normal(mean, stddev, x_train.shape)
x_test_noise = np.random.normal(mean, stddev, x_test.shape)
# Add noise
x_train_noise_added = x_train_noise + x_train_noise
x_test_noise_added = x_test_noise + x_test_noise
# Add noise
x_test_noise[1]
```

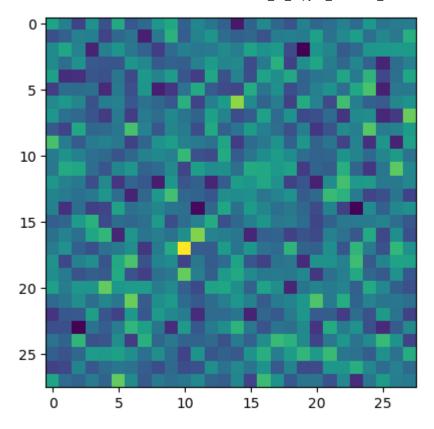
# Verify noises themselves are different In [6]: plt.imshow(x\_train\_noise[1])

<matplotlib.image.AxesImage at 0x255f0afcdc0> Out[6]:



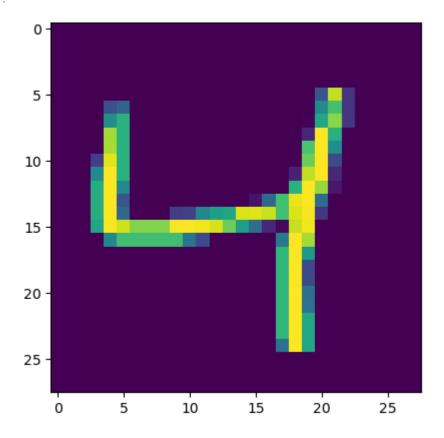
# Comparison to next 'frame' of noise In [7]: plt.imshow(x\_train\_noise[2])

<matplotlib.image.AxesImage at 0x255800b0160> Out[7]:



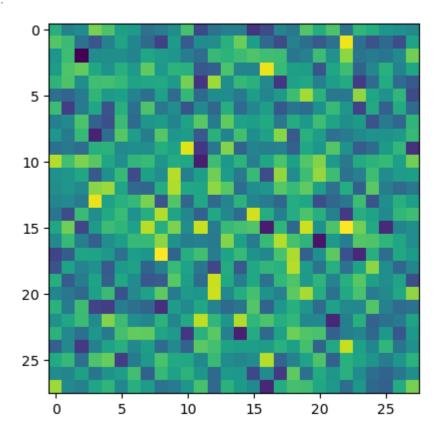
# Compare No-Noise to Noise Image In [8]: # Image without noise plt.imshow(x\_train[2])

<matplotlib.image.AxesImage at 0x255802616f0> Out[8]:



```
In [23]: # Same image with noise
# Noting that I added a significant amount of noise (stddev = 3) to highlight the diff
plt.imshow(x_train_noise_added[2])
```

Out[23]: <matplotlib.image.AxesImage at 0x256226f5690>



```
In [10]: # Setup Variables
batch_size = 128
num_classes = 10
epochs = 12
```

```
In [11]: def convolutional_model(batch_size, num_classes, epochs, x_train, x_test, y_train, y_t
             # 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)
             model = Sequential()
             model.add(Conv2D(32, kernel_size=(3, 3),
                               activation='relu',
                               input_shape=input_shape))
             model.add(Conv2D(64, (3, 3), activation='relu'))
             model.add(MaxPooling2D(pool_size=(2, 2)))
             model.add(Dropout(0.25))
             model.add(Flatten())
             model.add(Dense(128, activation='relu'))
             model.add(Dropout(0.5))
             model.add(Dense(num_classes, activation='softmax'))
             model.compile(loss=keras.losses.categorical_crossentropy,
                        optimizer=keras.optimizers.Adadelta(),
                       metrics=['accuracy'])
```

```
model.fit(x_train, y_train,
          batch size=batch size,
          epochs=epochs,
          verbose=1,
          validation data=(x test, y test))
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
# Run Model With Noise
In [12]:
     convolutional model(batch size, num classes, epochs, x train noise added, x test noise
     Epoch 1/12
     0.1004 - val loss: 2.3446 - val accuracy: 0.1022
     Epoch 2/12
     0.0999 - val_loss: 2.3068 - val_accuracy: 0.1000
     Epoch 3/12
     0.1019 - val loss: 2.3030 - val accuracy: 0.1052
     Epoch 4/12
     0.1022 - val loss: 2.3026 - val accuracy: 0.1079
     Epoch 5/12
     0.1026 - val loss: 2.3026 - val accuracy: 0.1102
     Epoch 6/12
     0.1054 - val_loss: 2.3026 - val_accuracy: 0.1117
     Epoch 7/12
     0.1054 - val loss: 2.3026 - val accuracy: 0.1134
     469/469 [============ ] - 52s 110ms/step - loss: 2.3062 - accuracy:
     0.1046 - val_loss: 2.3026 - val_accuracy: 0.1131
     Epoch 9/12
     469/469 [============ ] - 49s 104ms/step - loss: 2.3052 - accuracy:
     0.1073 - val loss: 2.3026 - val accuracy: 0.1135
     Epoch 10/12
     0.1073 - val loss: 2.3026 - val accuracy: 0.1134
     Epoch 11/12
     469/469 [============= ] - 48s 103ms/step - loss: 2.3045 - accuracy:
     0.1100 - val_loss: 2.3026 - val_accuracy: 0.1135
     Epoch 12/12
     0.1093 - val loss: 2.3025 - val accuracy: 0.1137
     Test loss: 2.302541732788086
     Test accuracy: 0.1137000024318695
```

```
In [13]: # Run Model Without Noise
          convolutional_model(batch_size, num_classes, epochs, x_train, x_test, y_train, y_test)
```

```
Epoch 1/12
0.1206 - val_loss: 2.2755 - val_accuracy: 0.2495
Epoch 2/12
0.2123 - val_loss: 2.2356 - val_accuracy: 0.4507
Epoch 3/12
0.3080 - val_loss: 2.1848 - val_accuracy: 0.5364
Epoch 4/12
0.3835 - val_loss: 2.1180 - val_accuracy: 0.6024
Epoch 5/12
0.4409 - val loss: 2.0255 - val accuracy: 0.6666
Epoch 6/12
0.4884 - val_loss: 1.8985 - val_accuracy: 0.7083
Epoch 7/12
469/469 [============ ] - 47s 100ms/step - loss: 1.8672 - accuracy:
0.5346 - val loss: 1.7317 - val accuracy: 0.7423
Epoch 8/12
0.5703 - val loss: 1.5299 - val accuracy: 0.7664
Epoch 9/12
469/469 [============ ] - 51s 110ms/step - loss: 1.5306 - accuracy:
0.6030 - val_loss: 1.3198 - val_accuracy: 0.7837
Epoch 10/12
0.6294 - val loss: 1.1320 - val accuracy: 0.7989
Epoch 11/12
0.6561 - val loss: 0.9802 - val accuracy: 0.8118
Epoch 12/12
0.6775 - val loss: 0.8622 - val accuracy: 0.8232
Test loss: 0.8621631860733032
Test accuracy: 0.823199987411499
```

Comparing the two models, we see that the addition of noise resultls in a model with a significantly reduced accuracy. In this one, we have an accuracy of .113 with noise and .823 without noise, for the same number of epochs, batch size, etc- the only difference is the noise. As a note, I added a high level of noise (scale of 3.0) to emphasize the difference in the models.

## Variance Over Different Scale Values

```
In [14]: ## Add Noise to Dataset
         # Noise is added here
         def noise adder(mean, scale values, x train, x test, y train, y test):
             # Normalization
             mean_norm = np.mean(x_train)
             std = np.std(x_train)
              x_train_norm = (x_train - mean) / std
```

```
mean = np.mean(x_test)
std = np.std(x_test)
x_{test_norm} = (x_{test} - mean) / std
# Generate random noise with the same shape as the image
x_train_noise = np.random.normal(loc, scale_values, x_train.shape)
x_test_noise = np.random.normal(loc, scale_values, x_test.shape)
# Add noise
x train noise added = x train norm + x train noise
x_test_noise_added = x_test_norm + x_test_noise
return x_train_noise_added, x_test_noise_added, y_train, y_test
```

```
In [15]: def convolutional model recorder(batch size, num classes, epochs, x train, x test, y t
              # 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)
             model = Sequential()
              model.add(Conv2D(32, kernel_size=(3, 3),
                               activation='relu',
                               input_shape=input_shape))
              model.add(Conv2D(64, (3, 3), activation='relu'))
             model.add(MaxPooling2D(pool_size=(2, 2)))
             model.add(Dropout(0.25))
             model.add(Flatten())
             model.add(Dense(128, activation='relu'))
             model.add(Dropout(0.5))
             model.add(Dense(num_classes, activation='softmax'))
             model.compile(loss=keras.losses.categorical_crossentropy,
                        optimizer=keras.optimizers.Adadelta(),
                        metrics=['accuracy'])
             model.fit(x_train, y_train,
                        batch_size=batch_size,
                        epochs=epochs,
                        verbose=1,
                        validation_data=(x_test, y_test))
             score = model.evaluate(x_test, y_test, verbose=0)
              print('Test loss:', score[0])
              print('Test accuracy:', score[1])
             # Append Loss & Accuracy To List
             test_loss = score[0]
             test_accuracy = score[1]
             loss_values.append(test_loss)
             accuracy_values.append(test_accuracy)
         scale_values = [0.1, 0.5, 1.0, 2.0, 4.0] # Values given
In [16]:
         loc = 0 # For the noise_adder function
          # Initializing Lists
          loss_values = []
         accuracy_values = []
In [17]: # Loop:
```

x\_train\_noise\_added, x\_test\_noise\_added, \_, \_ = noise\_adder(loc, scale, x\_train, >
convolutional\_model\_recorder(batch\_size, num\_classes, epochs, x\_train\_noise\_added,

```
Epoch 1/12
469/469 [============= ] - 50s 105ms/step - loss: 2.2025 - accuracy:
0.1934 - val loss: 2.0304 - val accuracy: 0.5327
Epoch 2/12
469/469 [============= ] - 50s 107ms/step - loss: 1.9506 - accuracy:
0.3642 - val loss: 1.7752 - val accuracy: 0.6816
Epoch 3/12
0.4857 - val_loss: 1.5104 - val_accuracy: 0.7511
Epoch 4/12
0.5657 - val_loss: 1.2693 - val_accuracy: 0.7851
Epoch 5/12
0.6235 - val_loss: 1.0770 - val_accuracy: 0.8095
Epoch 6/12
0.6611 - val_loss: 0.9297 - val_accuracy: 0.8296
Epoch 7/12
0.6920 - val loss: 0.8212 - val accuracy: 0.8429
0.7141 - val loss: 0.7379 - val accuracy: 0.8542
Epoch 9/12
0.7348 - val_loss: 0.6728 - val_accuracy: 0.8640
Epoch 10/12
0.7512 - val loss: 0.6216 - val accuracy: 0.8706
Epoch 11/12
0.7647 - val loss: 0.5812 - val accuracy: 0.8766
Epoch 12/12
0.7748 - val loss: 0.5468 - val accuracy: 0.8823
Test loss: 0.5467995405197144
Test accuracy: 0.8823000192642212
Epoch 1/12
0.1732 - val_loss: 2.1053 - val_accuracy: 0.4827
Epoch 2/12
0.3169 - val_loss: 1.8802 - val_accuracy: 0.6626
Epoch 3/12
0.4316 - val loss: 1.6407 - val accuracy: 0.7227
Epoch 4/12
469/469 [============ ] - 47s 100ms/step - loss: 1.6321 - accuracy:
0.5122 - val_loss: 1.4169 - val_accuracy: 0.7597
Epoch 5/12
0.5717 - val loss: 1.2249 - val accuracy: 0.7826
Epoch 6/12
0.6149 - val loss: 1.0693 - val accuracy: 0.8026
Epoch 7/12
469/469 [============= ] - 47s 101ms/step - loss: 1.1721 - accuracy:
0.6477 - val loss: 0.9483 - val accuracy: 0.8160
Epoch 8/12
```

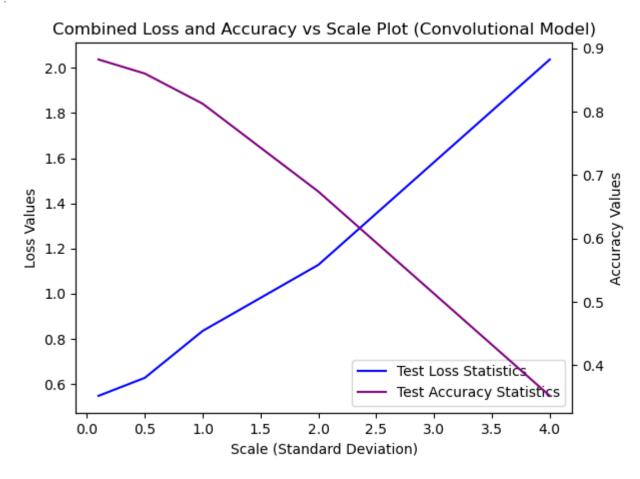
```
0.6709 - val_loss: 0.8518 - val_accuracy: 0.8286
Epoch 9/12
0.6938 - val loss: 0.7775 - val accuracy: 0.8387
Epoch 10/12
469/469 [============= ] - 50s 107ms/step - loss: 0.9337 - accuracy:
0.7102 - val loss: 0.7161 - val accuracy: 0.8471
Epoch 11/12
469/469 [============= ] - 48s 103ms/step - loss: 0.8743 - accuracy:
0.7316 - val loss: 0.6658 - val accuracy: 0.8540
Epoch 12/12
0.7390 - val_loss: 0.6266 - val_accuracy: 0.8601
Test loss: 0.6266005635261536
Test accuracy: 0.8600999712944031
Epoch 1/12
0.1441 - val loss: 2.1761 - val accuracy: 0.3700
Epoch 2/12
0.2193 - val_loss: 2.0674 - val_accuracy: 0.5296
Epoch 3/12
0.2952 - val loss: 1.9323 - val accuracy: 0.6236
Epoch 4/12
0.3643 - val_loss: 1.7793 - val_accuracy: 0.6584
Epoch 5/12
0.4273 - val_loss: 1.6176 - val_accuracy: 0.7094
Epoch 6/12
0.4815 - val loss: 1.4607 - val accuracy: 0.7286
Epoch 7/12
0.5295 - val_loss: 1.3139 - val_accuracy: 0.7486
Epoch 8/12
0.5706 - val loss: 1.1848 - val accuracy: 0.7638
0.5990 - val loss: 1.0732 - val accuracy: 0.7806
Epoch 10/12
469/469 [============ ] - 48s 103ms/step - loss: 1.2197 - accuracy:
0.6293 - val loss: 0.9756 - val accuracy: 0.7960
Epoch 11/12
0.6529 - val loss: 0.9012 - val accuracy: 0.8009
Epoch 12/12
0.6713 - val loss: 0.8345 - val accuracy: 0.8125
Test loss: 0.8344602584838867
Test accuracy: 0.8125
Epoch 1/12
0.1212 - val_loss: 2.2119 - val_accuracy: 0.2549
Epoch 2/12
0.1719 - val_loss: 2.1336 - val_accuracy: 0.3521
```

```
Epoch 3/12
0.2183 - val loss: 2.0426 - val accuracy: 0.4144
Epoch 4/12
469/469 [============ ] - 81s 172ms/step - loss: 2.0840 - accuracy:
0.2654 - val loss: 1.9328 - val accuracy: 0.4592
Epoch 5/12
0.3141 - val_loss: 1.8113 - val_accuracy: 0.5112
Epoch 6/12
0.3562 - val_loss: 1.6895 - val_accuracy: 0.5355
Epoch 7/12
0.3965 - val_loss: 1.5653 - val_accuracy: 0.5784
Epoch 8/12
0.4346 - val_loss: 1.4587 - val_accuracy: 0.5983
Epoch 9/12
0.4697 - val loss: 1.3562 - val accuracy: 0.6261
Epoch 10/12
0.5008 - val loss: 1.2724 - val accuracy: 0.6418
Epoch 11/12
0.5277 - val_loss: 1.1926 - val_accuracy: 0.6593
Epoch 12/12
0.5500 - val loss: 1.1275 - val accuracy: 0.6738
Test loss: 1.12745201587677
Test accuracy: 0.673799991607666
Epoch 1/12
0.1039 - val_loss: 2.2857 - val_accuracy: 0.1350
0.1193 - val loss: 2.2725 - val accuracy: 0.1597
Epoch 3/12
0.1261 - val_loss: 2.2709 - val_accuracy: 0.1749
Epoch 4/12
469/469 [============ ] - 78s 167ms/step - loss: 2.2908 - accuracy:
0.1353 - val_loss: 2.2635 - val_accuracy: 0.1855
Epoch 5/12
0.1434 - val loss: 2.2518 - val accuracy: 0.2050
Epoch 6/12
0.1512 - val_loss: 2.2346 - val_accuracy: 0.2303
Epoch 7/12
469/469 [============ ] - 80s 171ms/step - loss: 2.2562 - accuracy:
0.1574 - val loss: 2.2136 - val accuracy: 0.2531
Epoch 8/12
0.1687 - val loss: 2.1871 - val accuracy: 0.2720
Epoch 9/12
0.1789 - val_loss: 2.1523 - val_accuracy: 0.2893
Epoch 10/12
```

```
0.1920 - val loss: 2.1182 - val accuracy: 0.3137
        Epoch 11/12
        0.2031 - val loss: 2.0771 - val accuracy: 0.3371
        Epoch 12/12
        0.2210 - val_loss: 2.0374 - val_accuracy: 0.3513
        Test loss: 2.037432909011841
        Test accuracy: 0.3513000011444092
In [18]:
        loss_values
        [0.5467995405197144,
Out[18]:
         0.6266005635261536,
         0.8344602584838867,
         1.12745201587677,
         2.037432909011841]
In [19]:
        accuracy_values
        [0.8823000192642212,
Out[19]:
         0.8600999712944031,
         0.8125,
         0.673799991607666,
         0.3513000011444092]
        # Compile Loss and Accuracy statistics for the models into a single data frame
In [20]:
        import pandas as pd
        accuracy loss results dataframe = pd.DataFrame({'scale values': scale values, 'loss va
        accuracy loss results dataframe
Out[20]:
          scale_values loss_values accuracy_values
        0
                 0.1
                      0.546800
                                    0.8823
        1
                 0.5
                      0.626601
                                    0.8601
        2
                 1.0
                      0.834460
                                    0.8125
        3
                 2.0
                      1.127452
                                    0.6738
        4
                 4.0
                      2.037433
                                    0.3513
In [21]: # Plotting Results
        fig, ax1 = plt.subplots()
        loss line = ax1.plot(scale values, loss values, color = 'blue', label = 'Test Loss Sta
        # Loss line Plot
        ax1.set xlabel('Scale (Standard Deviation)')
        ax1.set ylabel('Loss Values')
        ax1.set title('Combined Loss and Accuracy vs Scale Plot (Convolutional Model)')
        # Accuracy line Plot
        ax2 = ax1.twinx()
        accuracy line = ax2.plot(scale values, accuracy values, color='purple', label='Test Ac
        ax2.set_ylabel('Accuracy Values')
        # Combine Both Lines Into One Plot
        lines = loss line + accuracy line
```

```
labels = [1.get_label() for 1 in lines]
ax1.legend(lines, labels, loc='lower right')
```

Out[21]: <matplotlib.legend.Legend at 0x256258947f0>



We see a pattern in form of an inverse relationship between the scale of the noise and the accuracy of the model; with every gradual increase in noise, the accuracy of the created model becomes less and less. The most notable dropoff comes from the jump from a scale of 2 to 4, where the accuracy declines from just under .7 to less than .4. In last week's results (after revision), we had the same general realtionship, with the acuracy of the model decreasing as the scale of the noise added increased. It is both sound on the basis of the convolutional neural network model that the addition of noise results in a less accurate model, and the accuracy statistics generated by these models are proof of the same.

In [ ]: