Test Neural Network

October 29, 2018

```
In [1]: from mnist import MNIST
        import numpy as np
        from matplotlib import pyplot as plt
        import types
        from sklearn.utils import shuffle
        from sklearn.metrics import confusion_matrix
        import pandas as pd

In [2]: def load_data():
            mnist_data = MNIST('./')
            train_img, train_label = mnist_data.load_training()
            test_img, test_label = mnist_data.load_testing()
            return np.array(train_img), np.array(train_label, dtype="uint8"), np.array(test_img

        # Execute function
        train_img, train_label, test_img, test_label = load_data()

In [3]: def vectorize_label(label, num_class):
            return np.eye(num_class)[label.reshape(-1)]

        # Execute function
        NUM_CLASS = 10
        train_label = vectorize_label(train_label, NUM_CLASS)
        test_label = vectorize_label(test_label, NUM_CLASS)

In [4]: def initialize_weight(width, height):
            range_ = 0.12
            return np.random.rand(width,height) * range_ * 2 - range_

In [5]: def derivative_linear(X):
            return np.ones_like(X)

In [6]: def relu(z):
            return z * (z > 0) * 1

In [7]: def derivative_relu(X):
            return (X>0) * 1

In [8]: def sigmoid(z):
            return 1 / (1 + np.exp(-z))
```

In [9]:
```
def derivative_sigmoid(X):
    return X * (1 - X)
```

In [10]:
```
def softmax(z):
    activate = np.exp(z - z.max(axis=0))
    return activate / activate.sum(axis=0)
```

In [11]:
```
def cost_softmax(activation, ground_truth, all_W=0, lambdaa=0):
    m = np.size(activation, 1) # Number of example
    regularized_term_cost = 0
    if isinstance(all_W, list):
        for single_W in all_W:
            W_sliced = single_W.copy()
            W_sliced[:,0] = 0 # Zeroes out bias weight
            regularized_term_cost += lambdaa / 2 / m * (W_sliced ** 2).sum();
    cost = (-ground_truth * np.log(activation)).sum() / m + regularized_term_cost;
    return cost
```

In [12]:
```
def grad_softmax(activation, ground_truth, W, X, derivative_method=None, lambdaa = 0)
    m = np.size(activation, 1) # Number of example
    W_sliced = W.copy()
    if W_sliced is not 0:
        W_sliced[:,0] = 0 # Zeroes out bias weight

    err = (activation - ground_truth) / m
    regularized_term_grad = lambdaa / m * W_sliced
    grad = err.dot(X.T) + regularized_term_grad
    if isinstance(derivative_method, types.FunctionType):
        err = W.T.dot(err) * derivative_method(X)
    return grad, err
```

In [13]:
```
def softmax_classifier(all_W, X, Y, derivative_method=None,lambdaa = 0):
    if isinstance(all_W, list):
        W = all_W[len(all_W) - 1] # Softmax weight

        # Forward pass
        activation = softmax(W.dot(X));
        pred = activation
        ground_truth = Y

        # Compute cost
        cost = cost_softmax(activation, ground_truth, all_W, lambdaa)

        # Compute gradient and error
        grad, err = grad_softmax(activation, ground_truth, W, X, derivative_method, la
        return cost, grad, err, pred
```

In [14]:
```
def numerical_softmax_check(W, X, Y, lambdaa=0):
    eps = 1e-6
```

```
        grad = np.zeros_like(W)
        for i in range(np.size(W,0)):
            for j in range(np.size(W,1)):
                temp = W[i,j]
                W[i,j] = temp + eps
                cost1, grad1, err1, pred1 = softmax_classifier([W],X,Y,lambdaa=lambdaa)
                W[i,j] = temp - eps
                cost2, grad2, err2, pred2 = softmax_classifier([W],X,Y,lambdaa=lambdaa)
                W[i,j] = temp
                grad[i,j] = (cost1 - cost2) / 2 / eps
        return grad
```

```
In [15]: def backprop(err, W, X, derivative_method=None, lambdaa = 0):
             m = np.size(X, 1) # Number of example
             W_sliced = W.copy()
             if W_sliced is not 0:
                 W_sliced[:,0] = 0 # Zeroes out bias weight
             regularized_term = lambdaa / m * W_sliced
             err = err[1:,:] # Shed virtual err
             grad = err.dot(X.T) + regularized_term
             if isinstance(derivative_method, types.FunctionType):
                 err = W.T.dot(err) * derivative_method(X)
             return grad, err
```

```
In [16]: W = initialize_weight(2,3)
         X = initialize_weight(3,3)
         ground_truth = np.zeros((2,3))
         ground_truth[0,:] = 1
         # Check softmax grad function without regularized term
         grad = numerical_softmax_check(W,X,ground_truth)
         cost2, grad2, err2, pred2 = softmax_classifier([W],X,ground_truth)
         # Check softmax grad function with regularized term = 1
         grad3 = numerical_softmax_check(W,X,ground_truth, lambdaa=1)
         cost4, grad4, err4, pred4 = softmax_classifier([W],X,ground_truth, lambdaa=1)
         print("Relative diffrence without regularization\n",np.linalg.norm(grad - grad2) / np
         print("Relative difference with regularization = 1\n",np.linalg.norm(grad3 - grad4) /
```

```
Relative diffrence without regularization
 1.2726672348055012e-09
Relative difference with regularization = 1
 7.893984534802521e-10
```

```
In [17]: def neural_network(all_W, train_data, train_label, lambdaa=0):
             m = np.size(train_data, 1) # Number of training example
             list_activation = []
             list_grad = []

             row_of_one = np.ones((1,m))
```

```
        activation = train_data
        activation = np.vstack((row_of_one, activation))
        list_activation.append(activation)

        # Forward pass
        for i in range(len(all_W) - 1):
            Z = all_W[i].dot(activation)
            activation = sigmoid(Z)
            activation = np.vstack((row_of_one, activation))
            list_activation.append(activation)
        cost, grad, err, pred = softmax_classifier(all_W, activation, train_label, deriva
        list_activation.append(pred)
        list_grad.append(grad)

        # Backward pass
        for i in range(len(all_W) - 2, -1, -1):
            grad, err = backprop(err, all_W[i], list_activation[i], derivative_sigmoid, la
            list_grad.append(grad)

        return list_grad, list_activation, cost;
```

```
In [18]: def numerical_grad_check(all_W, X, Y, lambdaa=0):
             eps = 1e-6
             list_grad = []
             for k in range(len(all_W)-1,-1,-1):
                 W = all_W[k]
                 grad = np.zeros_like(W)
                 for i in range(np.size(W,0)):
                     for j in range(np.size(W,1)):
                         temp = W[i,j]
                         W[i,j] = temp + eps
                         list_grad, list_activation, cost = neural_network(all_W, data, label,
                         W[i,j] = temp - eps
                         list_grad2, list_activation2, cost2 = neural_network(all_W, data, labe
                         grad[i,j] = (cost - cost2) / 2 / eps
                         W[i,j] = temp
                 list_grad.append(grad)
             return list_grad
```

```
In [19]: # Check gradient backprop
         data = np.random.rand(784, 10)
         label = np.zeros((10, 10))
         label[0,:] = 1
         W1 = initialize_weight(25, 785)
         W2 = initialize_weight(15,26)
         W3 = initialize_weight(10,16)
         all_W = [W1, W2, W3]
         lambdaa = 1
```

```
#??????????????????????????????????????????????????????????????????????????????????????
list_grad, list_activation, cost = neural_network(all_W, data, label, lambdaa)
list_grad2 = numerical_grad_check(all_W, data, label, lambdaa)

print("Relative diffrence first layer\n", np.linalg.norm(list_grad[2] - list_grad2[2]
print("Relative diffrence second layer\n", np.linalg.norm(list_grad[1] - list_grad2[1
print("Relative diffrence third layer\n", np.linalg.norm(list_grad[0] - list_grad2[0]
```

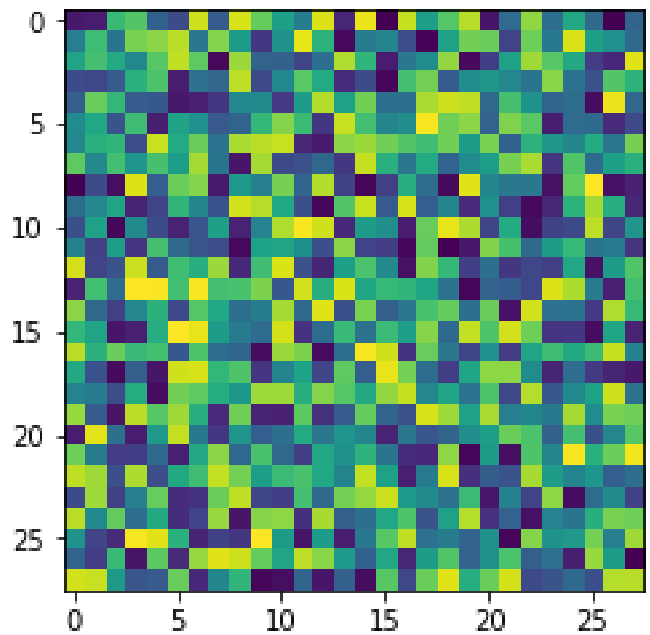
```
Relative diffrence first layer
 5.1520981516639004e-08
Relative diffrence second layer
 1.9481216244011975e-08
Relative diffrence third layer
 2.3621286933308203e-09
```

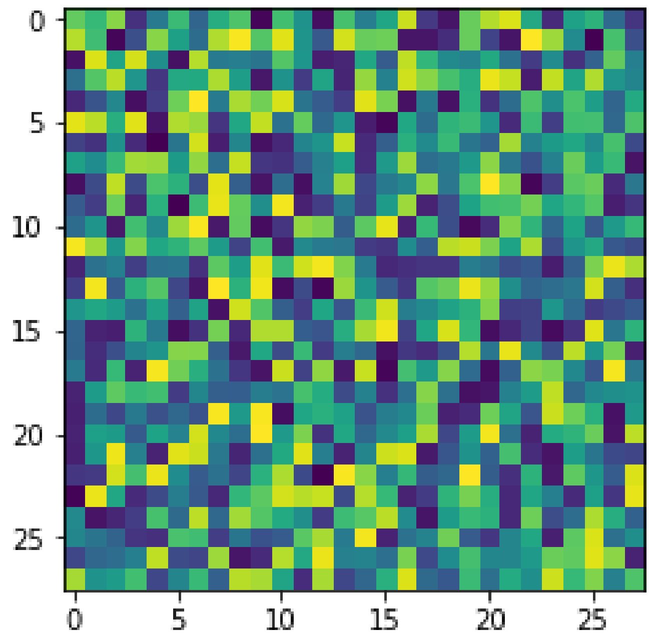
In [20]:
```
def training(all_W, train_data, train_label, batch_size=30, learning_rate=0.001, num_l
    m = np.size(train_data, 1)
    average_cost = 0
    times = 0
    for i in range(num_loop):
        # Shuffle data randomly
        if shuffle is not 0:
            print("Shuffle")
            permutation = np.random.permutation(m)
            train_data = train_data[:,permutation]
            train_label = train_label[:, permutation]
            print("Done")

        for j in range(0,m,batch_size):
            list_gradient, list_activation, cost = neural_network(all_W, train_data[:
            list_gradient.reverse()
            for j in range(len(all_W)): # Update all W
                all_W[j] -= learning_rate * list_gradient[j]
            average_cost += cost
            times += 1
        print("Iterate ", i+1, " loss: ", average_cost / times)
        average_cost = 0
        times = 0
```

In [21]:
```
train_input = (train_img/255).T # Train data shape: 784 x 60000
train_truth = train_label.T # Train label shape: 10 x 60000
# First layer logistic - shape: 25 x 785
W1 = initialize_weight(25, 785)
# Second layer logistic - shape: 15 x 26
W2 = initialize_weight(15, 26)
# Final layer - softmax classifier - shape: 10 x 16
W3 = initialize_weight(10, 16)
all_W = [W1, W2, W3]
```

```
In [22]: first_layer = all_W[0][:,1:]
         print(first_layer.shape)
         i = 0
         for row in first_layer:
             img = np.reshape(row,(28,28))
             plt.imshow(img)
             plt.show()
```

```
(25, 784)
```

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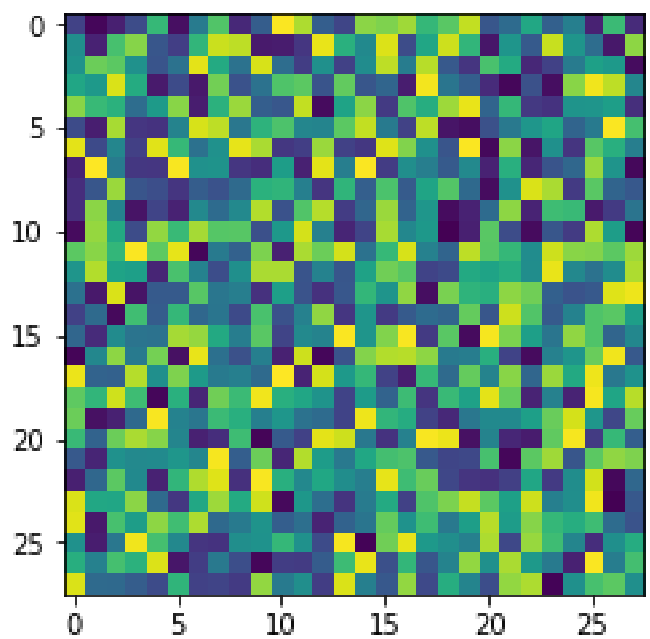
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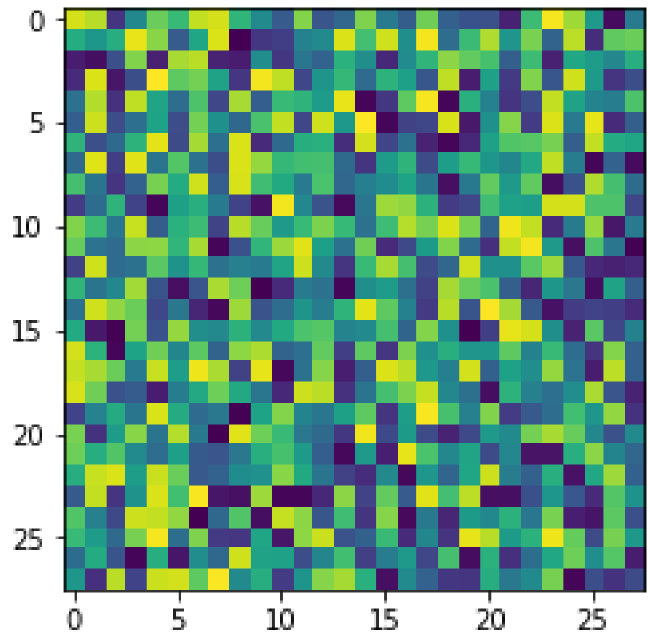
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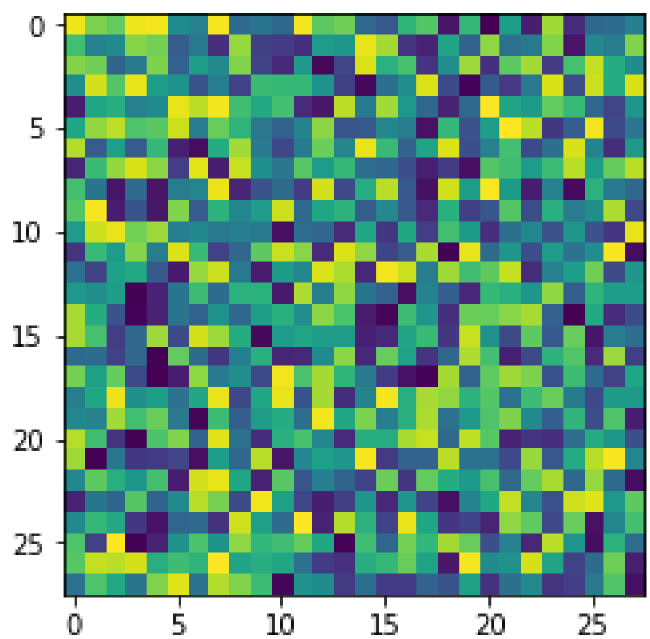
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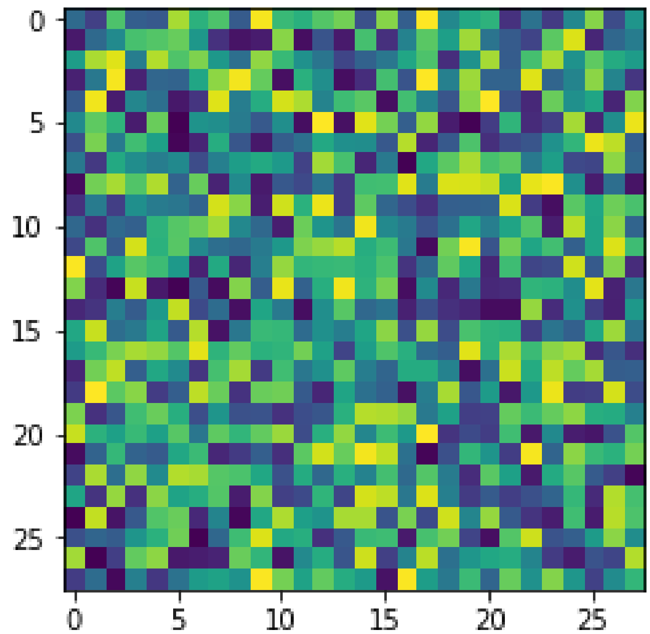
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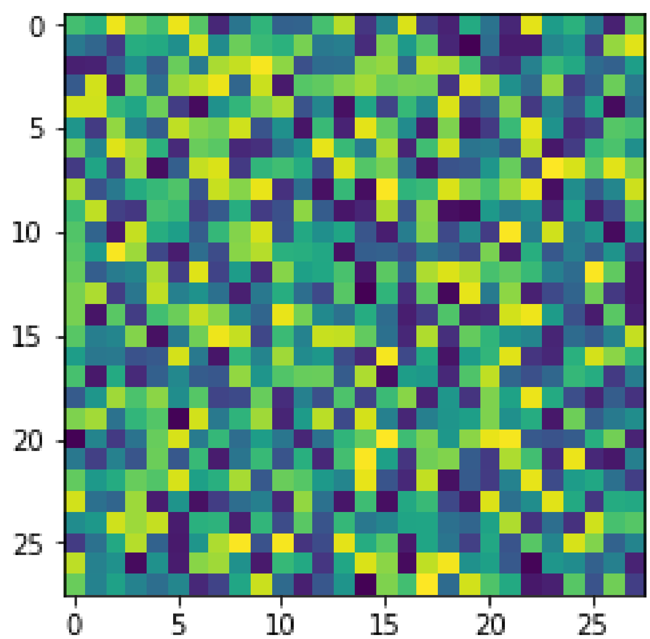
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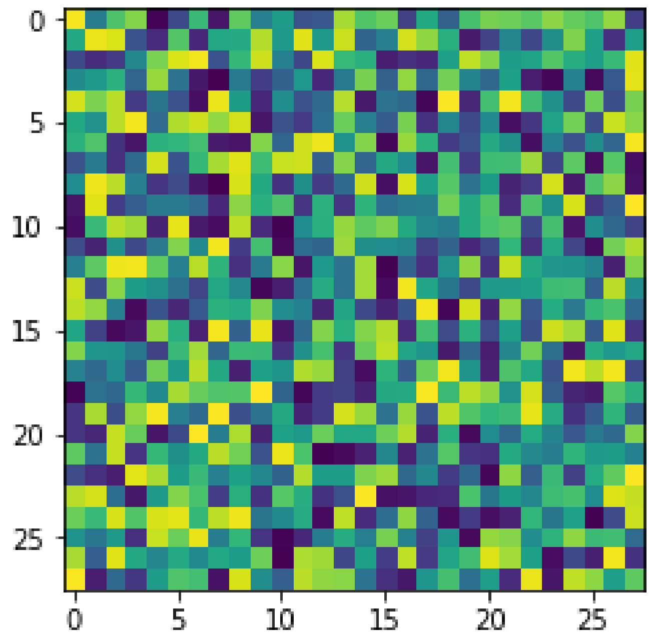
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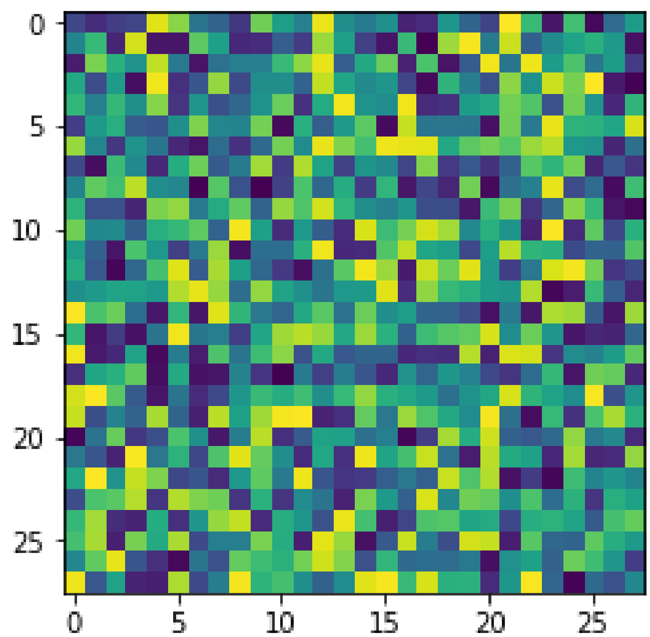
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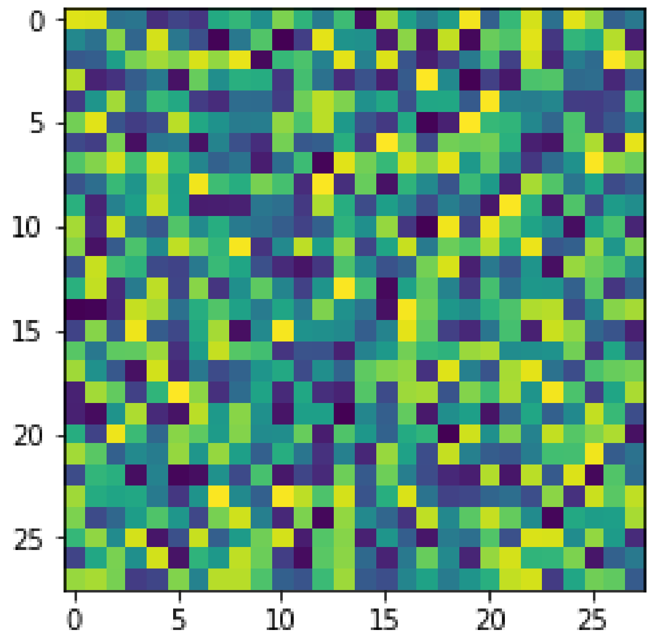
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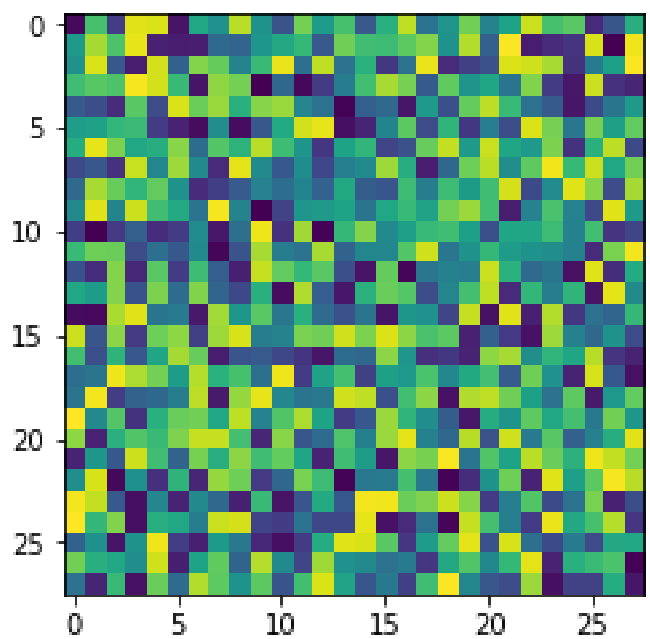
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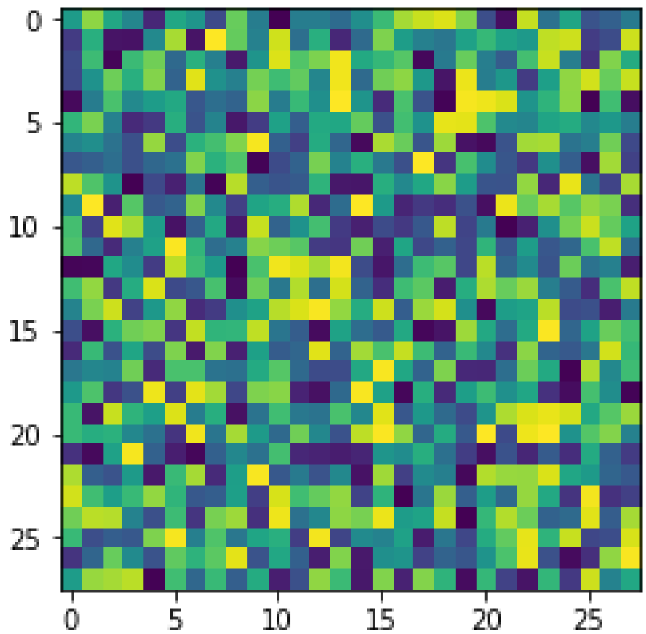
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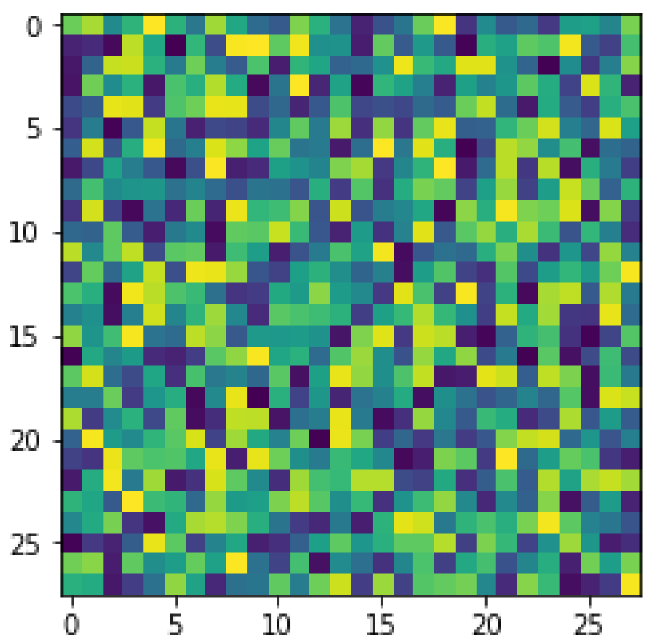
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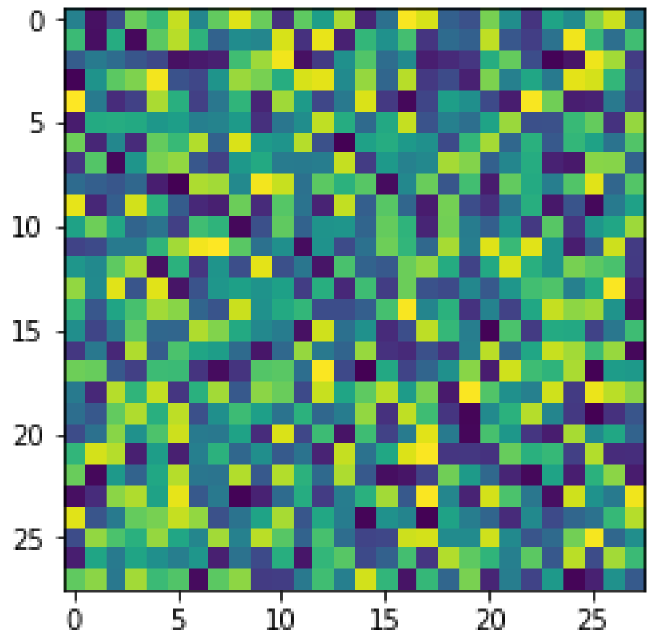
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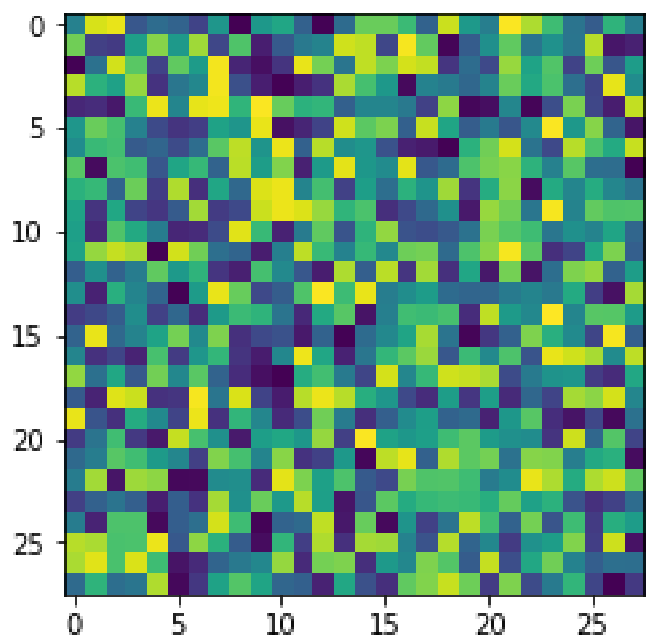
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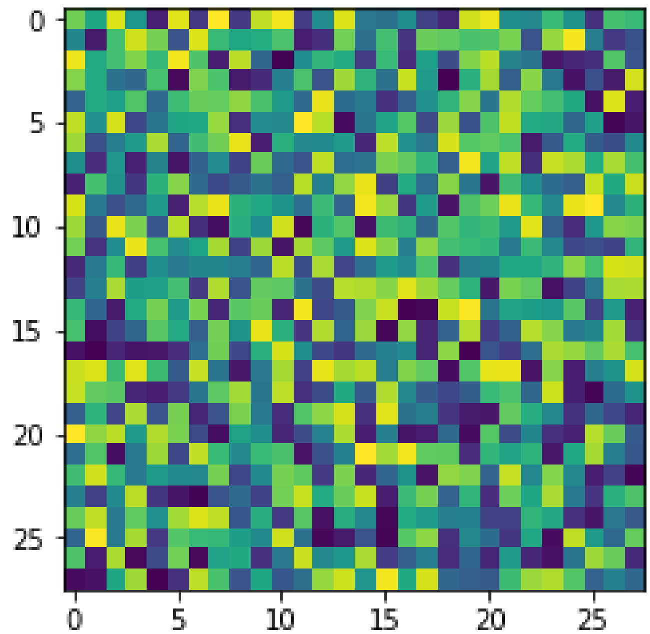
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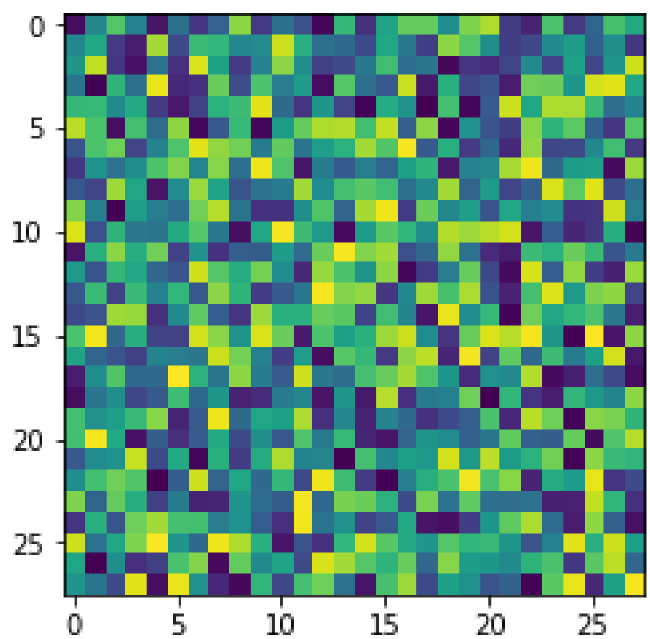
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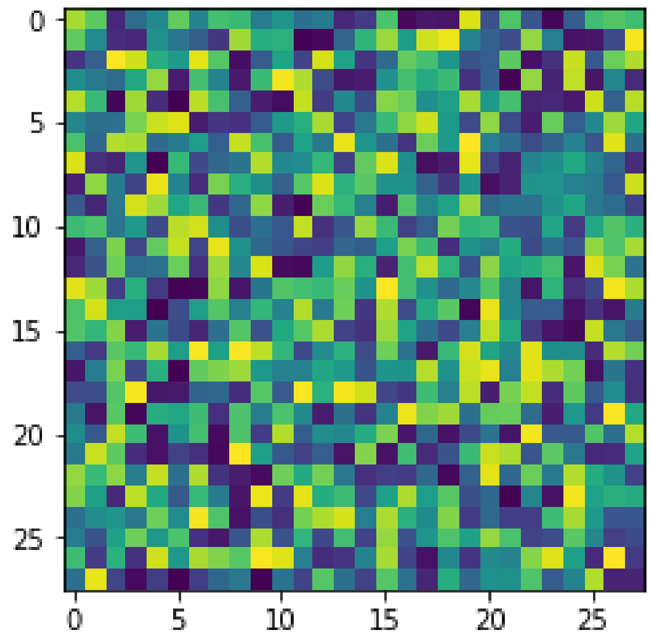
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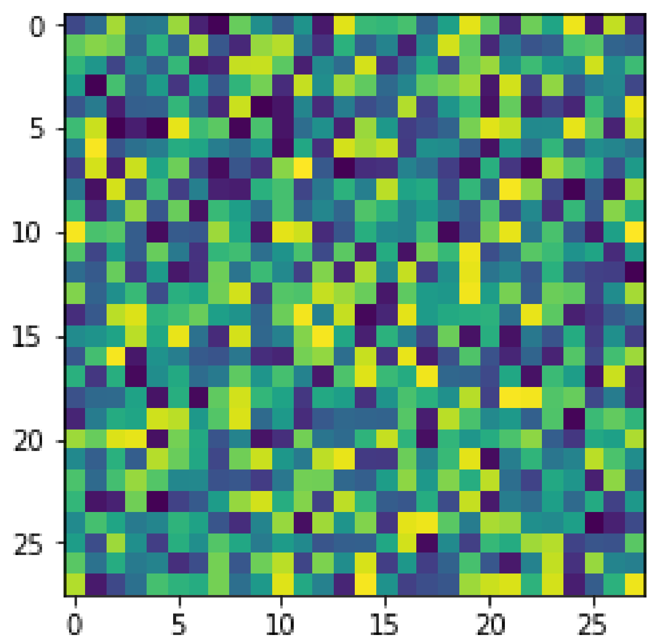
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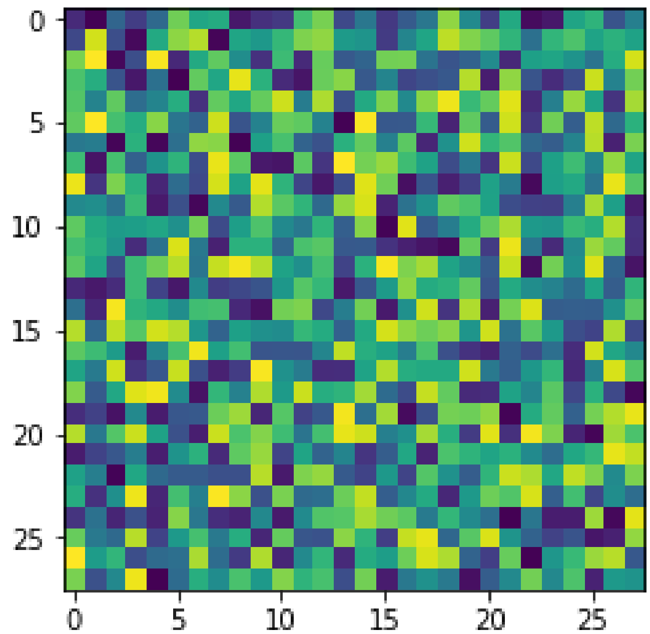
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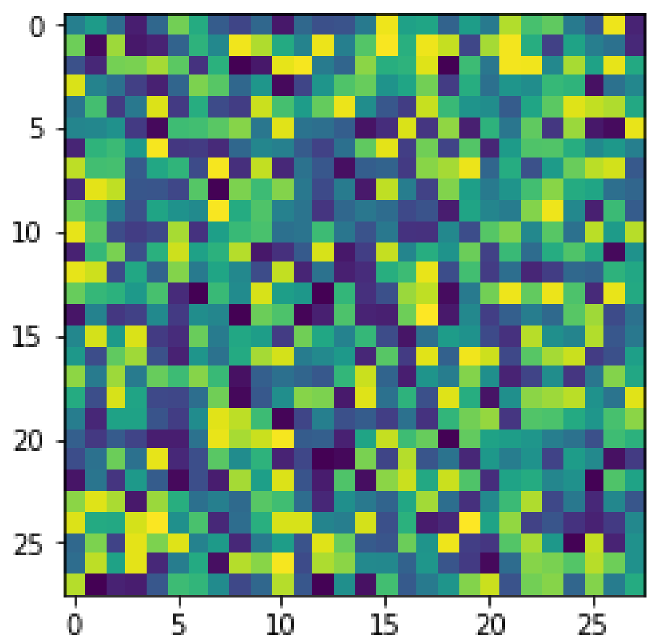
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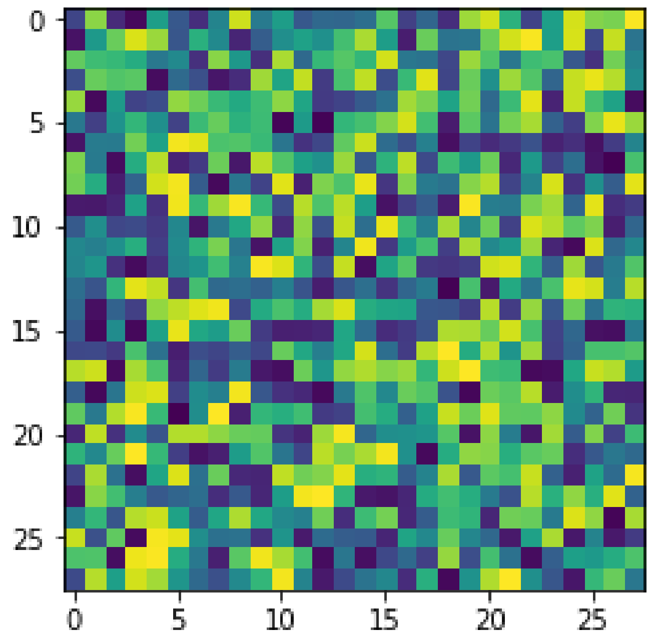
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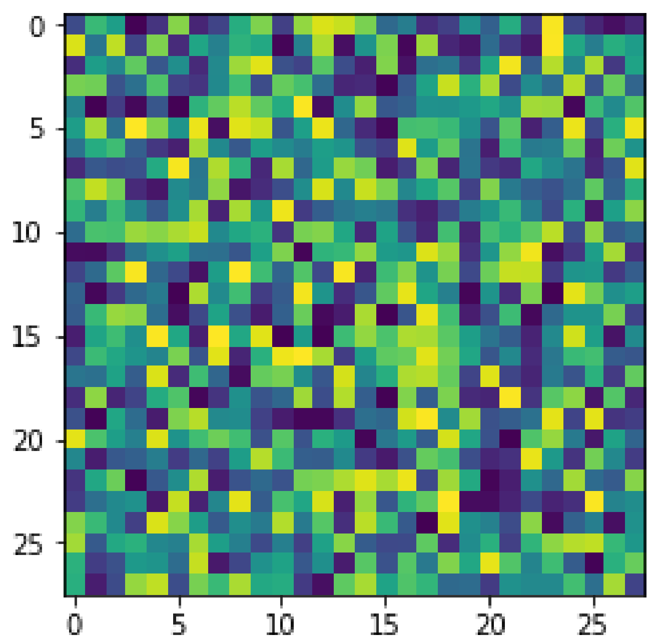
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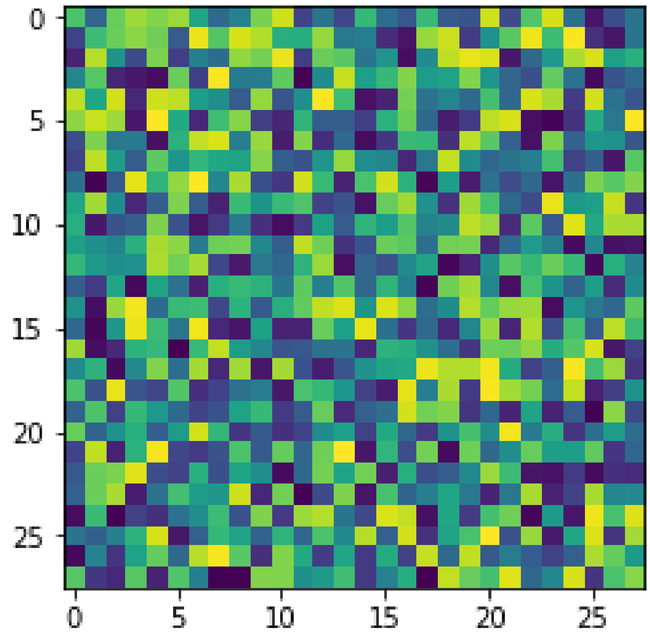
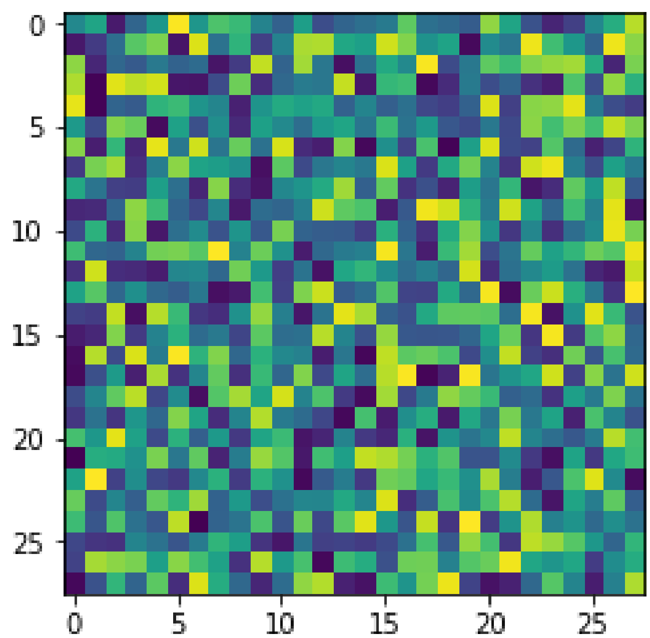




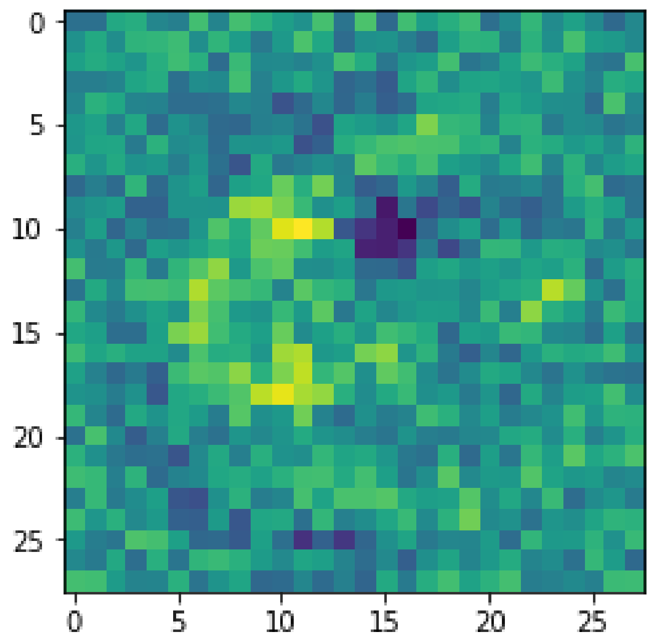

```
In [23]: training(all_W, train_input, train_truth, batch_size=30, num_loop=3, learning_rate=0.
```

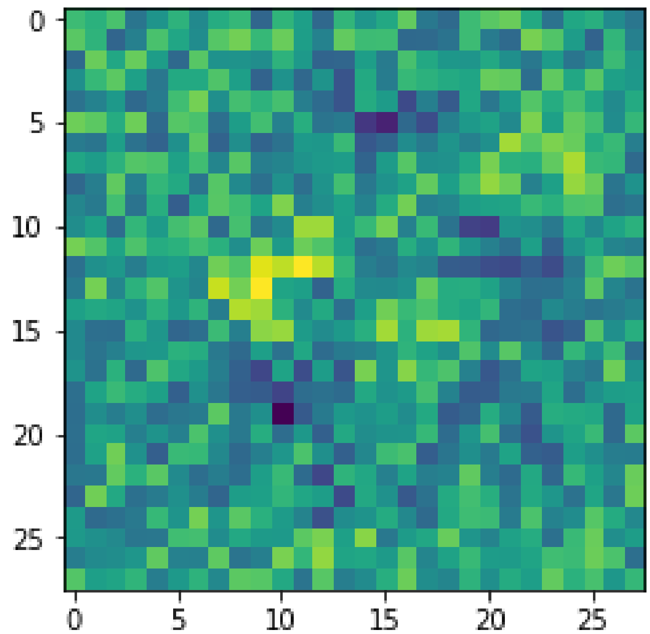
```
Iterate  1  loss:  2.067492991886211
Iterate  2  loss:  0.7916308968892606
```

```
Iterate  3  loss:  0.4392944543728588
```

```
In [24]: first_layer = all_W[0][:,1:]
         print(first_layer.shape)
         i = 0
         for row in first_layer:
             img = np.reshape(row,(28,28))
             plt.imshow(img)
             plt.show()
```

```
(25, 784)
```

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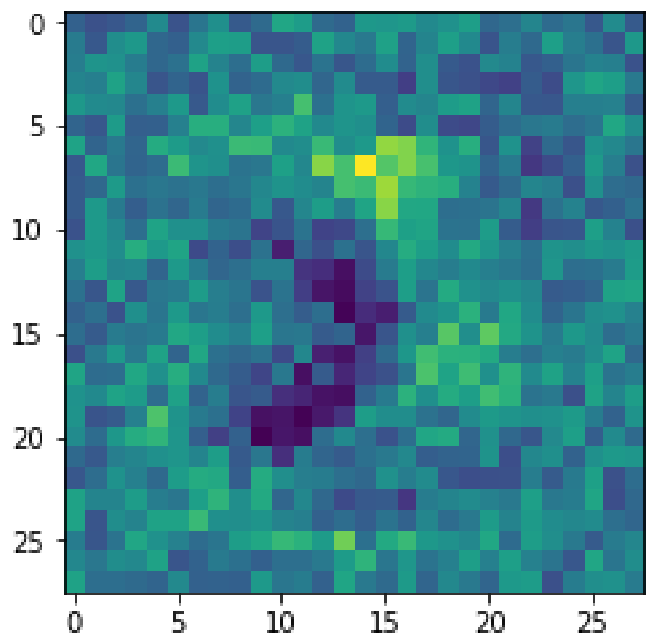
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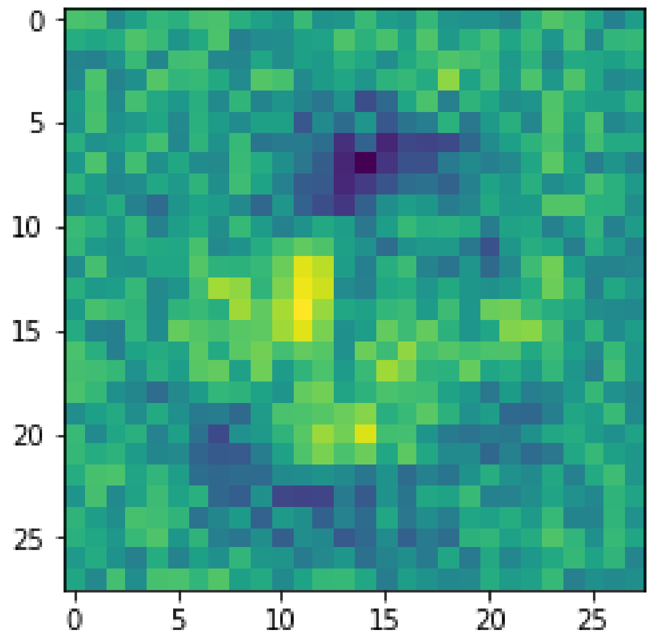
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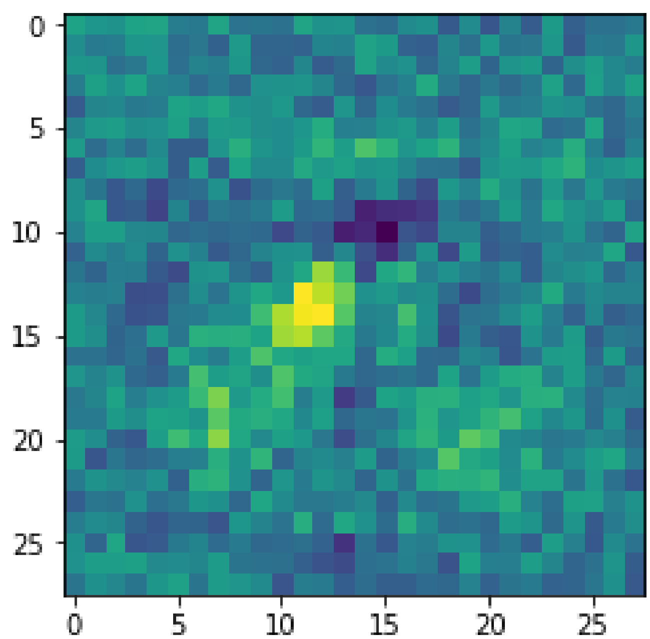
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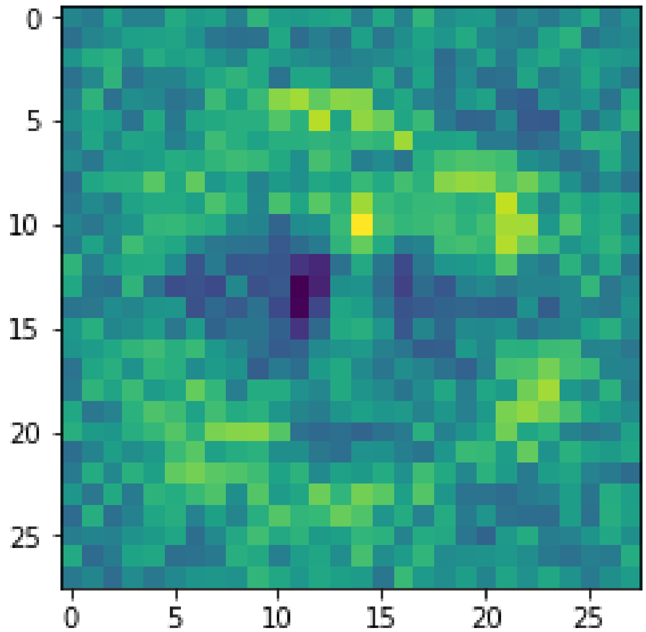
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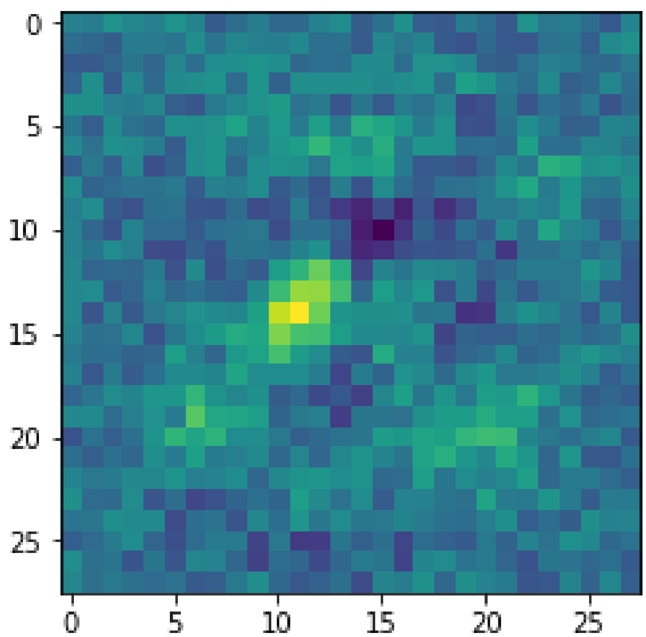
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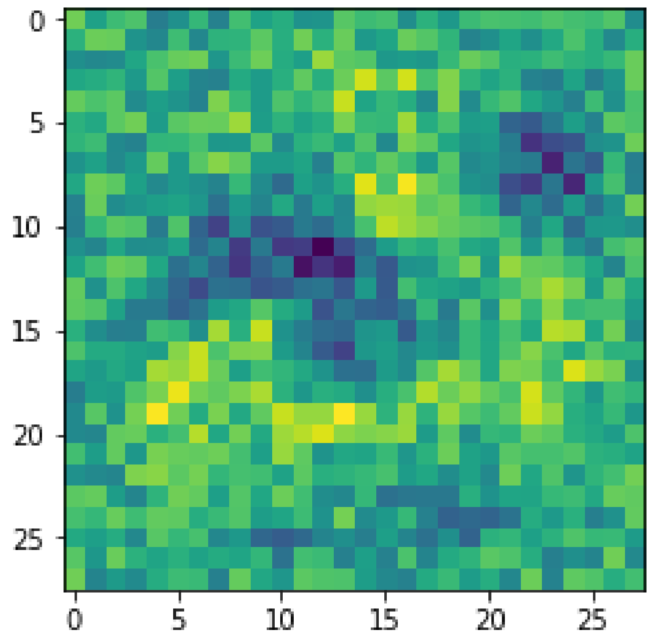
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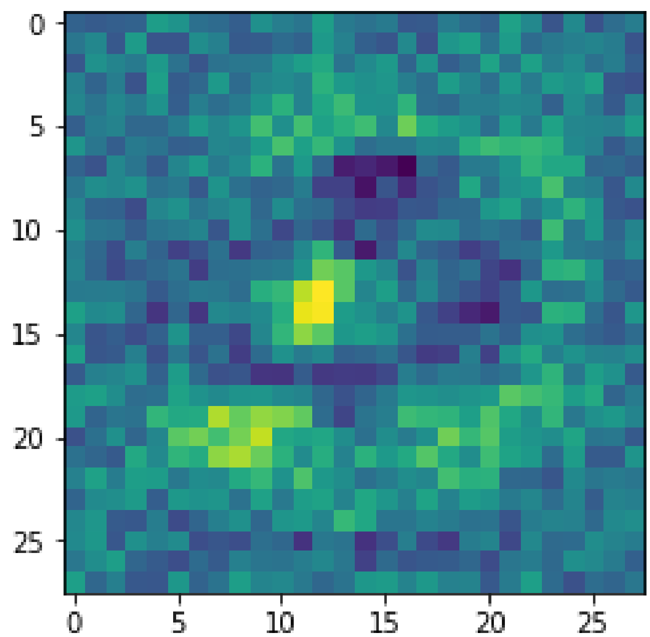
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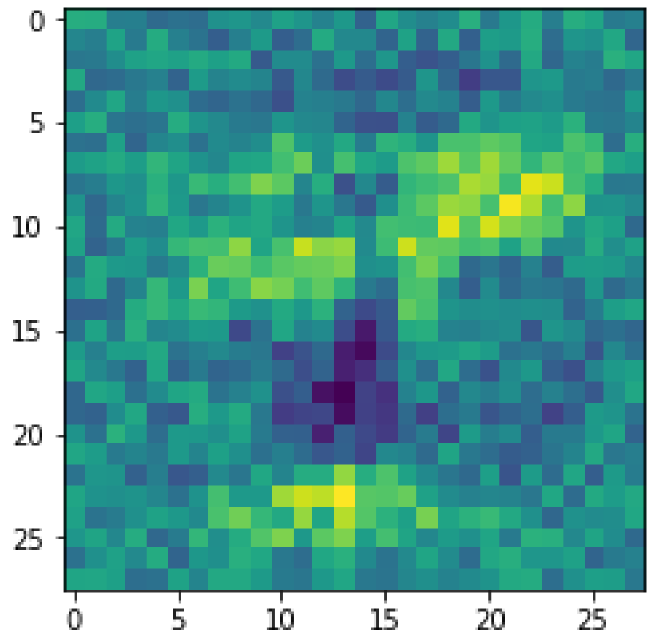
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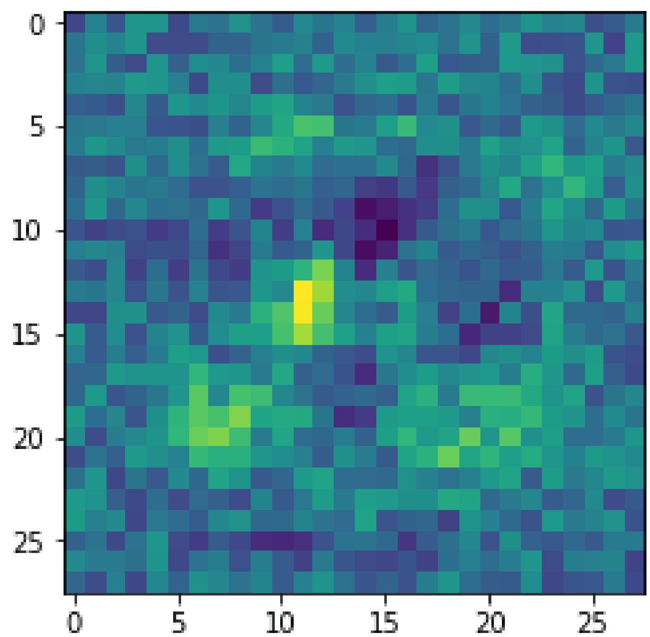
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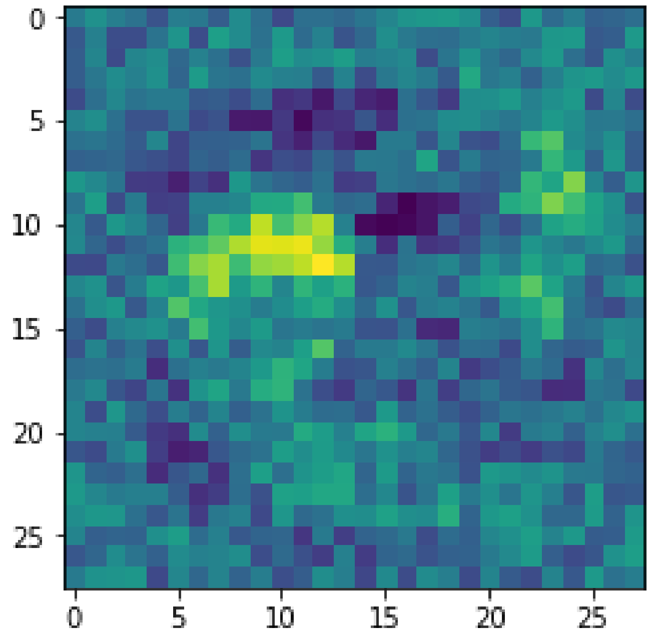
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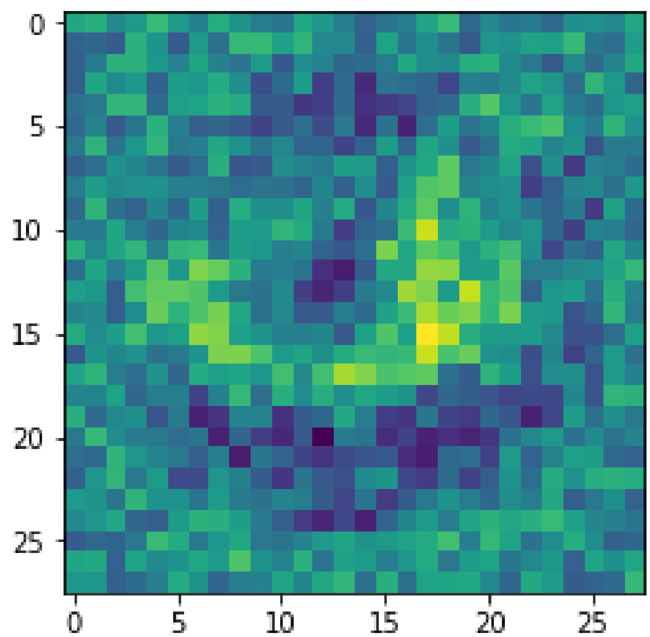
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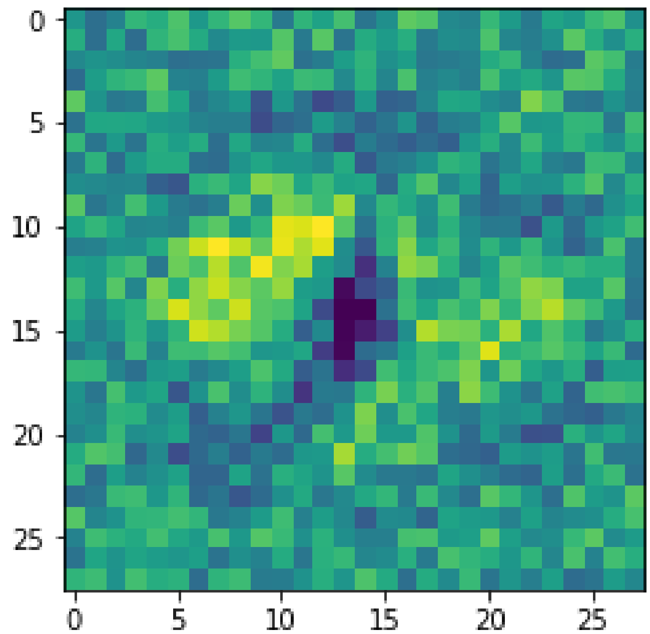
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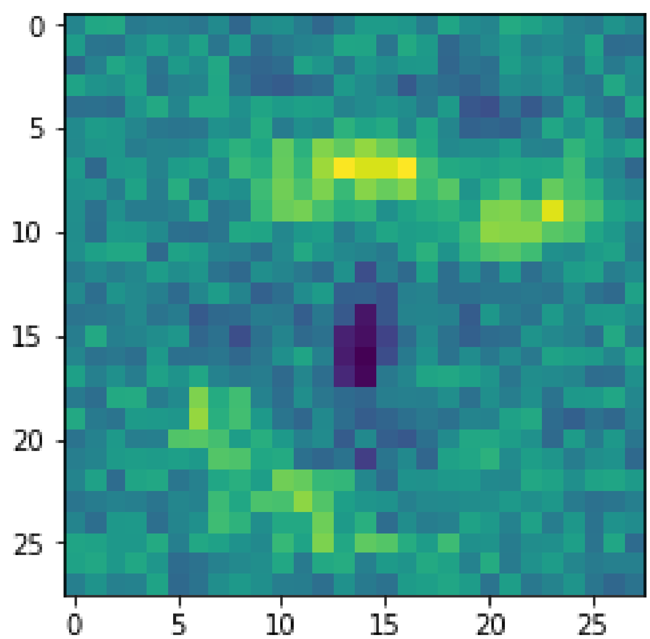
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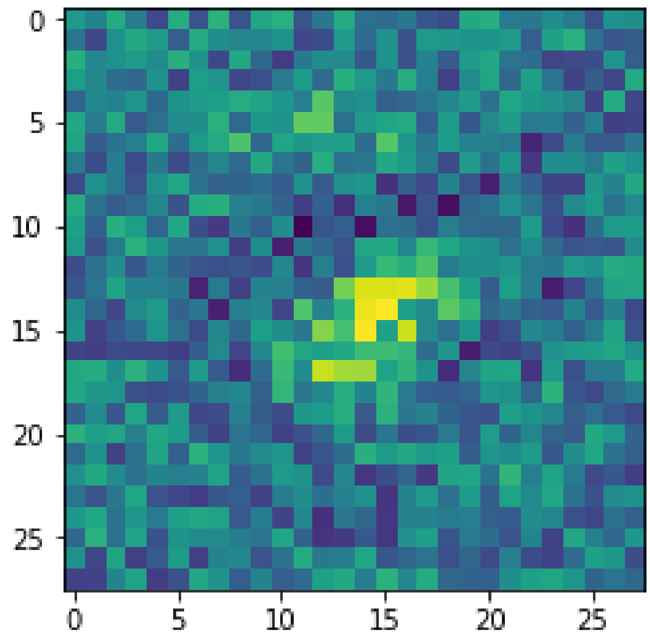
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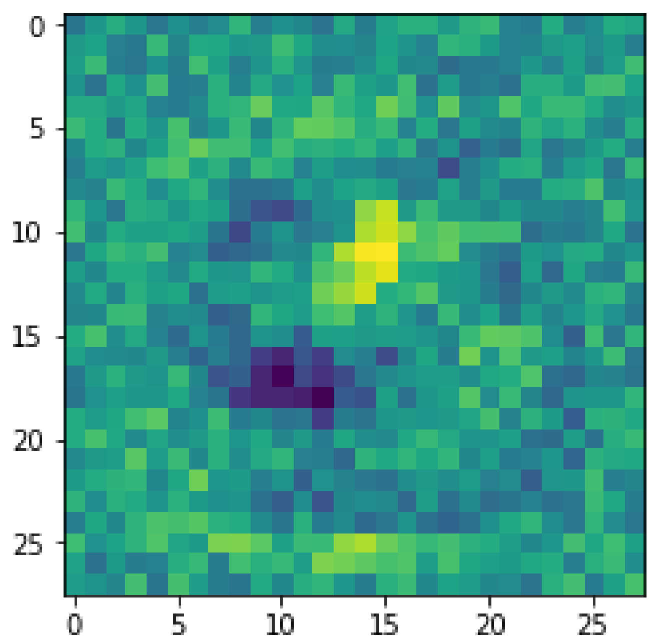
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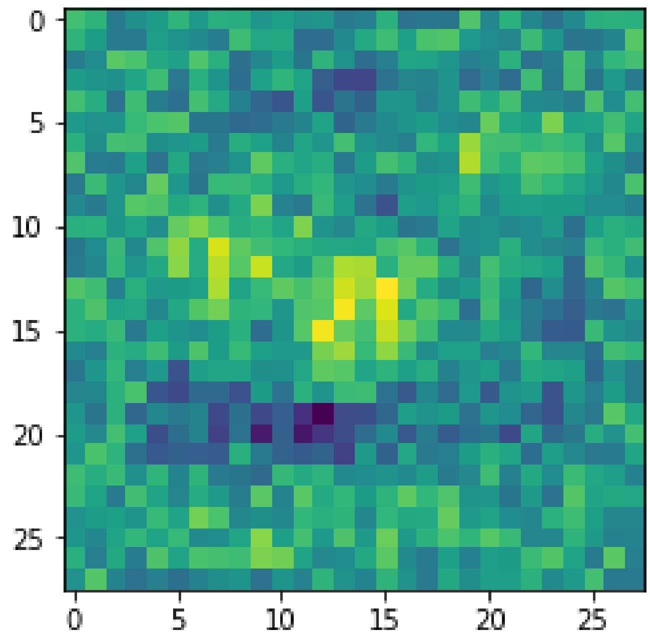
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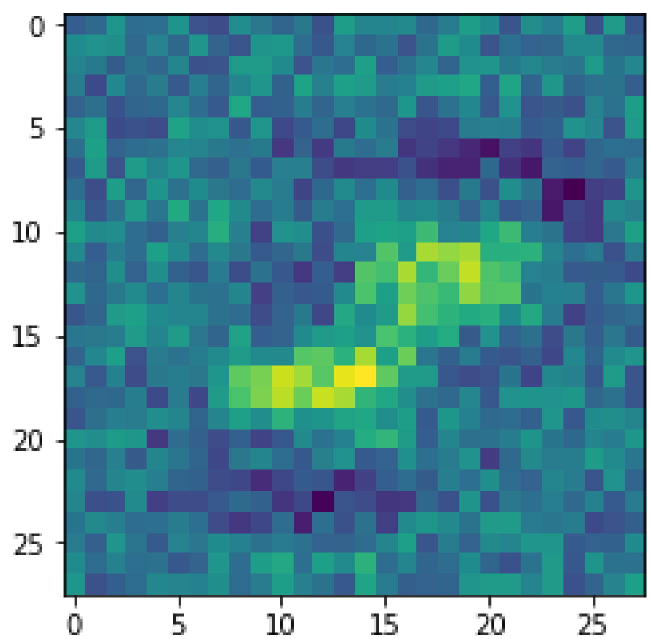
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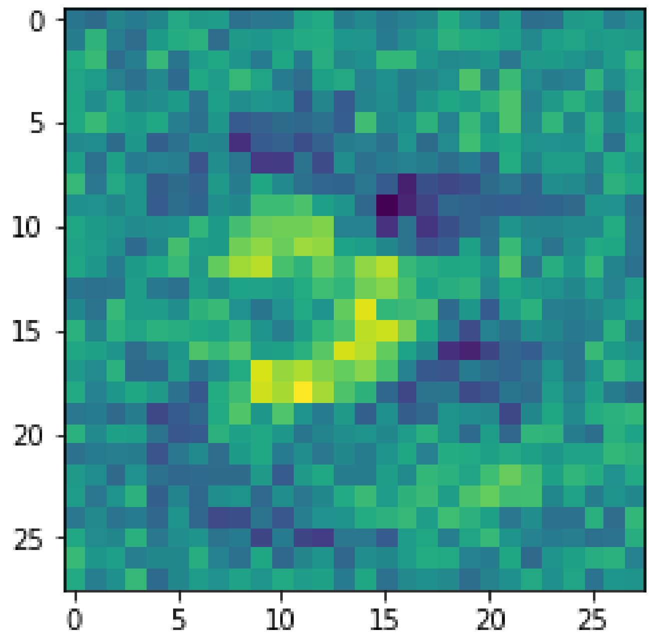
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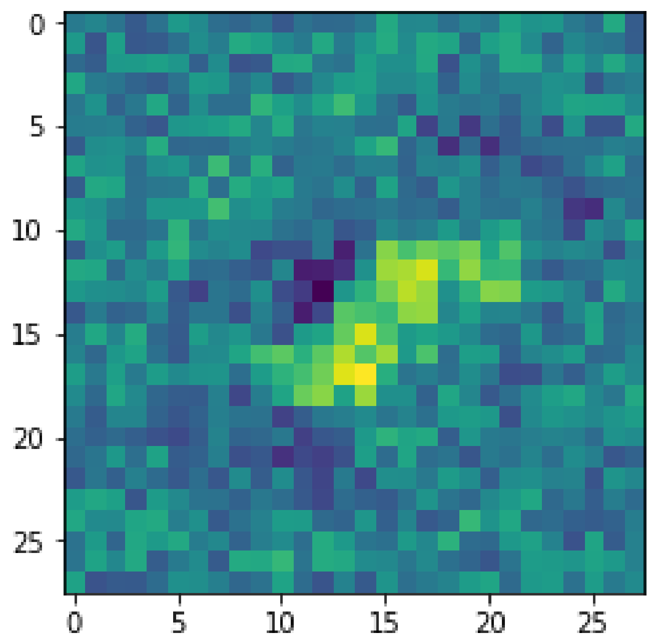
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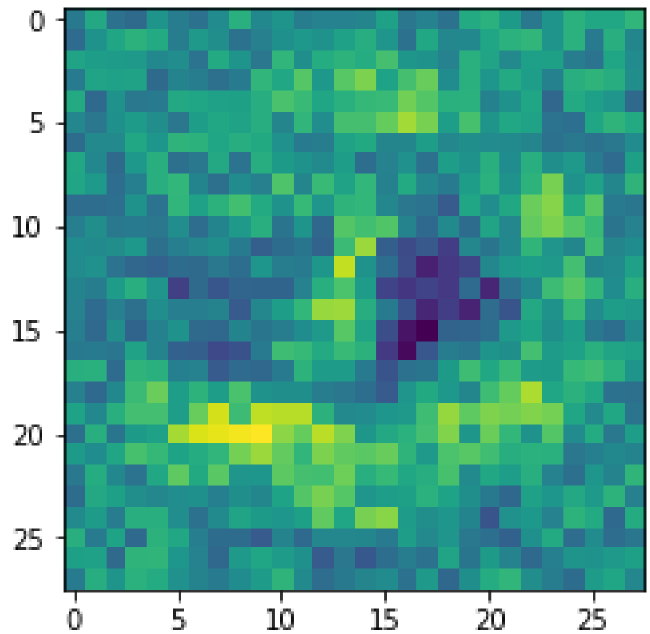
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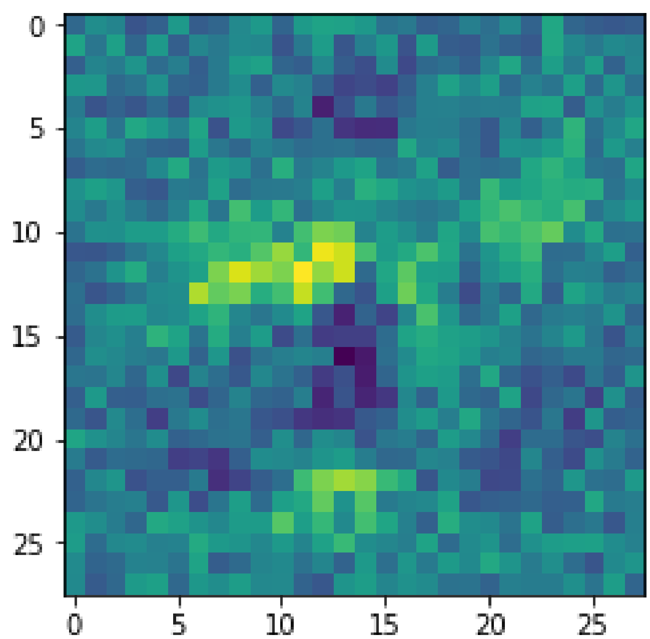
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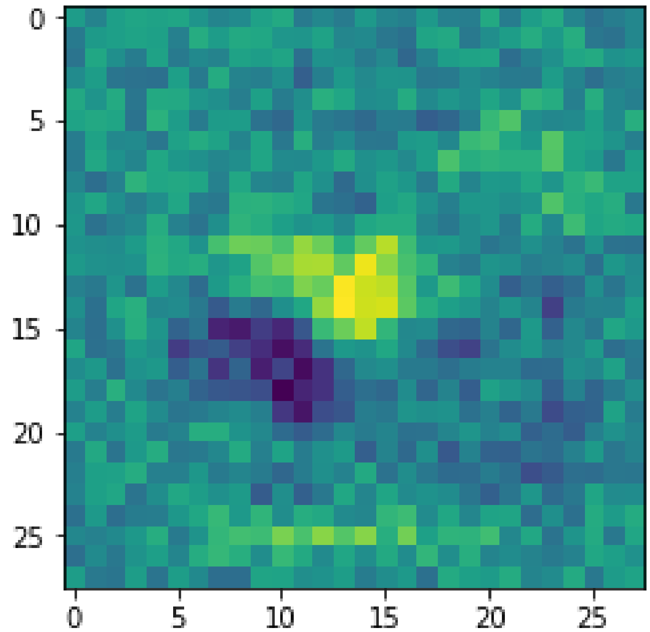

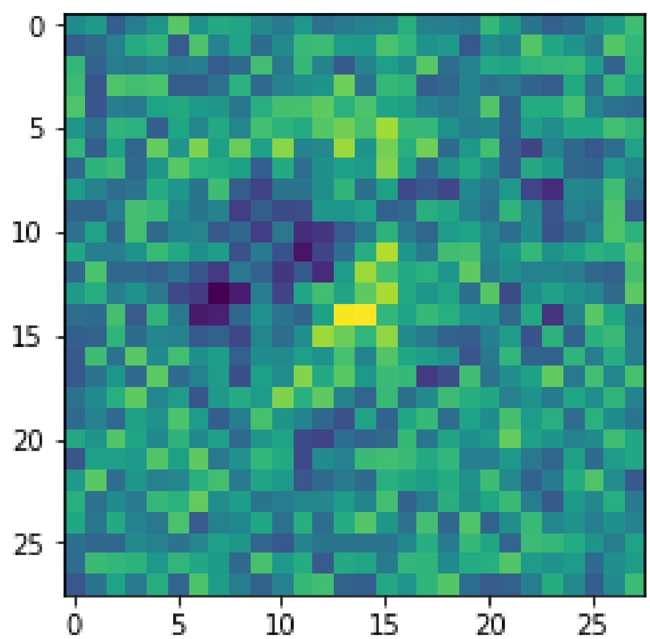


```
In [25]: def plot_confusion_matrix(df_confusion, title='Confusion matrix', cmap=plt.cm.gray_r)
             plt.matshow(df_confusion, cmap=cmap) # imshow
             #plt.title(title)
```

```
            plt.colorbar()
            tick_marks = np.arange(len(df_confusion.columns))
            plt.xticks(tick_marks, df_confusion.columns, rotation=45)
            plt.yticks(tick_marks, df_confusion.index)
            #plt.tight_layout()
            plt.ylabel(df_confusion.index.name)
            plt.xlabel(df_confusion.columns.name)
```

```
In [26]: test_img_input = (test_img/255).T
         test_label_truth = test_label.T

         list_grad, list_activation, cost = neural_network(all_W, test_img_input, test_label_t
         pred = list_activation[len(all_W)].argmax(0)
         answer = test_label_truth.argmax(0)
         compare_vector = (pred == answer)
         num_correct = np.sum(compare_vector)
         m = len(compare_vector)
         print("Accuracy: ", num_correct / m * 100,"%")
         print("Cost: ", cost)
         print()
         print("Confusion matrix: ")
         y_actu = pd.Series(answer, name='Actual')
         y_pred = pd.Series(pred, name='Predicted')
         df_confusion = pd.crosstab(y_actu, y_pred)
         print(df_confusion)
         print()
         print("Normalized confusion matrix: ")
         df_conf_norm = round(df_confusion / df_confusion.sum(axis=1) * 100, 1)
         print(df_conf_norm)
```

```
Accuracy:  89.57000000000001 %
Cost:  0.3746792211602384

Confusion matrix:
Predicted    0     1    2    3    4    5    6    7    8    9
Actual
0          944     0    3    1    4   17    8    1    1    1
1            0  1097    5    5    0    1    3    1   22    1
2           14    17  888   24   14    5   30    7   29    4
3            5     8   19  882    1   51    1   21   14    8
4            2     0    2    0  906    0   16    1    5   50
5           16     2    8   43   12  754   21    4   26    6
6           28     2    6    0   14   15  890    0    3    0
7            2    26   13   12    6    2    0  874    2   91
8            4    11    5   21   21   42   15    4  827   24
9            4     2    1    7   50   21    0   23    6  895

Normalized confusion matrix:
```

Predicted	0	1	2	3	4	5	6	7	8	9
Actual										
0	96.3	0.0	0.3	0.1	0.4	1.9	0.8	0.1	0.1	0.1
1	0.0	96.7	0.5	0.5	0.0	0.1	0.3	0.1	2.3	0.1
2	1.4	1.5	86.0	2.4	1.4	0.6	3.1	0.7	3.0	0.4
3	0.5	0.7	1.8	87.3	0.1	5.7	0.1	2.0	1.4	0.8
4	0.2	0.0	0.2	0.0	92.3	0.0	1.7	0.1	0.5	5.0
5	1.6	0.2	0.8	4.3	1.2	84.5	2.2	0.4	2.7	0.6
6	2.9	0.2	0.6	0.0	1.4	1.7	92.9	0.0	0.3	0.0
7	0.2	2.3	1.3	1.2	0.6	0.2	0.0	85.0	0.2	9.0
8	0.4	1.0	0.5	2.1	2.1	4.7	1.6	0.4	84.9	2.4
9	0.4	0.2	0.1	0.7	5.1	2.4	0.0	2.2	0.6	88.7