Activation Maximization on MNIST

https://github.com/raghakot/keras-vis/blob/master/examples/mnist/activation_maximization.ipynb (https://github.com/raghakot/keras-vis/blob/master/examples/mnist/activation_maximization.ipynb)

In [1]:
```python
from __future__ import print_function

import numpy as np
import keras

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

batch_size = 128
num_classes = 10
epochs = 1

# 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 K.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')

# 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', name='preds'))

model.compile(loss=keras.losses.categorical_crossentropy,
              optimizer=keras.optimizers.Adam(),
```

```
              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])
```

```
Using TensorFlow backend.
```

```
x_train shape: (60000, 28, 28, 1)
60000 train samples
10000 test samples
Train on 60000 samples, validate on 10000 samples
Epoch 1/1
60000/60000 [==============================] - 139s 2ms/step - loss: 0.2495 - a
cc: 0.9229 - val_loss: 0.0486 - val_acc: 0.9843
Test loss: 0.04858853696002625
Test accuracy: 0.9843
```

Saliency Visualizations

To visualize activation over final dense layer outputs, we need to switch the softmax activation out for linear since gradient of output node will depend on all the other node activations. Doing this in keras is tricky, so we provide utils.apply_modifications to modify network parameters and rebuild the graph.

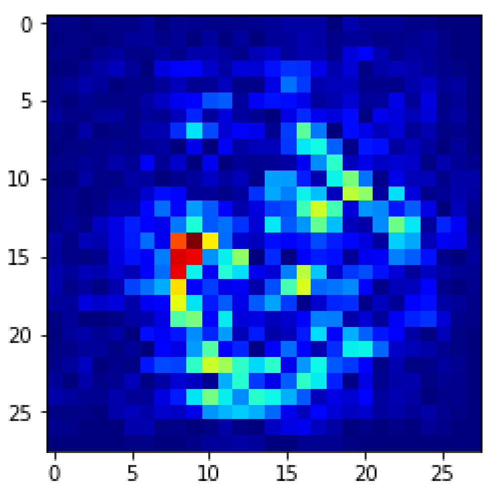
If this swapping is not done, the results might be suboptimal. We will start by swapping out 'softmax' for 'linear' and compare what happens if we dont do this at the end.

Lets pick an input over which we want to show the attention

In [3]:

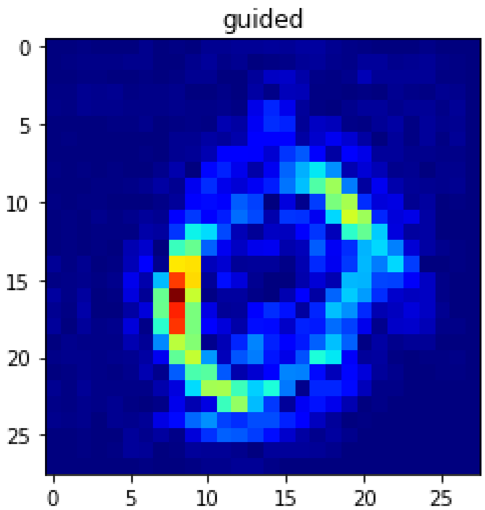
```
from vis.visualization import visualize_saliency
from vis.utils import utils
from keras import activations
from matplotlib import pyplot as plt
%matplotlib inline

class_idx = 0
indices = np.where(y_test[:, class_idx] == 1.)[0]

# pick some random input from here.
idx = indices[0]

# Utility to search for layer index by name.
# Alternatively we can specify this as -1 since it corresponds to the last layer.
layer_idx = utils.find_layer_idx(model, 'preds')

# Swap softmax with linear
model.layers[layer_idx].activation = activations.linear
model = utils.apply_modifications(model)

grads = visualize_saliency(model, layer_idx, filter_indices=class_idx, seed_input
# Plot with 'jet' colormap to visualize as a heatmap.
plt.imshow(grads, cmap='jet')
```

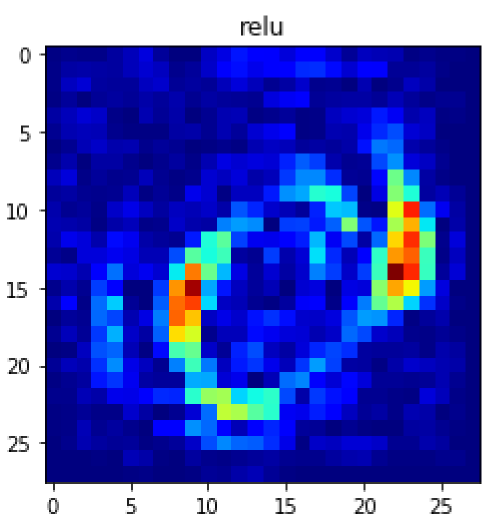
Out[3]: <matplotlib.image.AxesImage at 0x7fb2a9fb4438>



To used guided saliency, we need to set backprop_modifier='guided'. For rectified saliency or deconv saliency, use backprop_modifier='relu'. Lets try these options quickly and see how they compare to vanilla saliency.

In [4]:
```python
for modifier in ['guided', 'relu']:
    grads = visualize_saliency(model, layer_idx, filter_indices=class_idx,
                               seed_input=x_test[idx], backprop_modifier=modifier
    plt.figure()
    plt.title(modifier)
    plt.imshow(grads, cmap='jet')
```



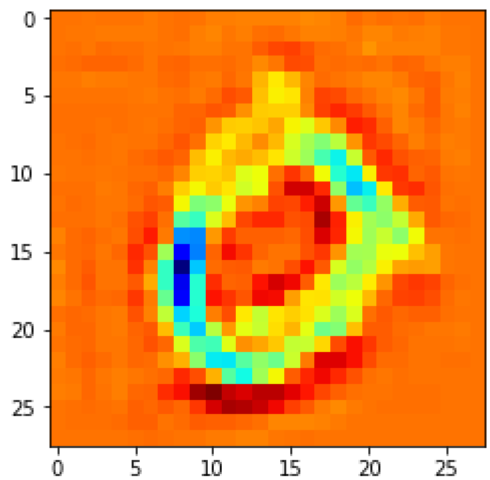


Both of them look a lot better than vanilla saliency! This in inline with observation in the paper.

We can also visualize negative gradients to see the parts of the image that contribute negatively to the output by using grad_modifier='negate'.

In [5]:
```
grads = visualize_saliency(model, layer_idx, filter_indices=class_idx, seed_input
                           backprop_modifier='guided', grad_modifier='negate')
plt.imshow(grads, cmap='jet')
```

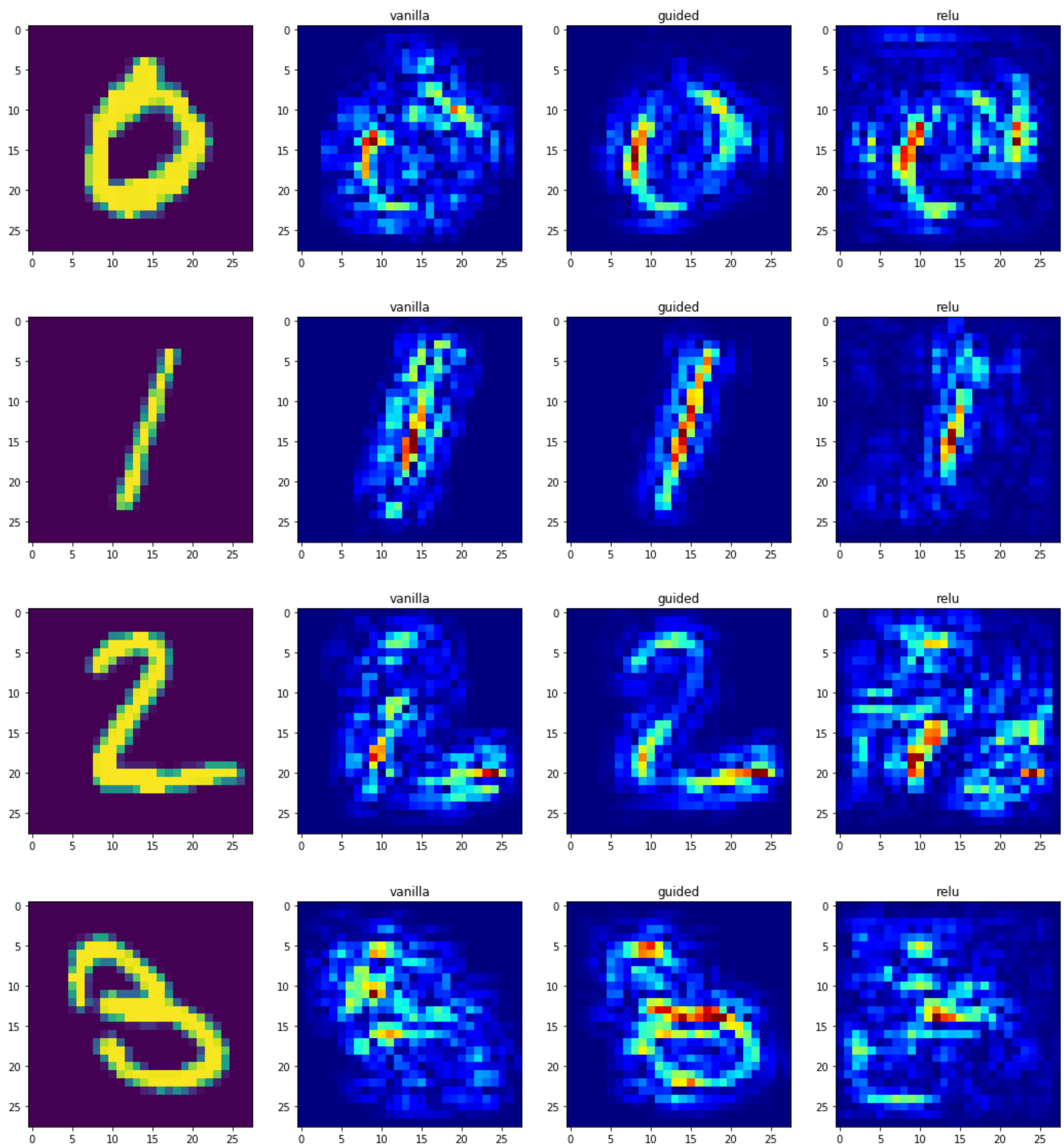
Out[5]: <matplotlib.image.AxesImage at 0x7fb2a62a42e8>

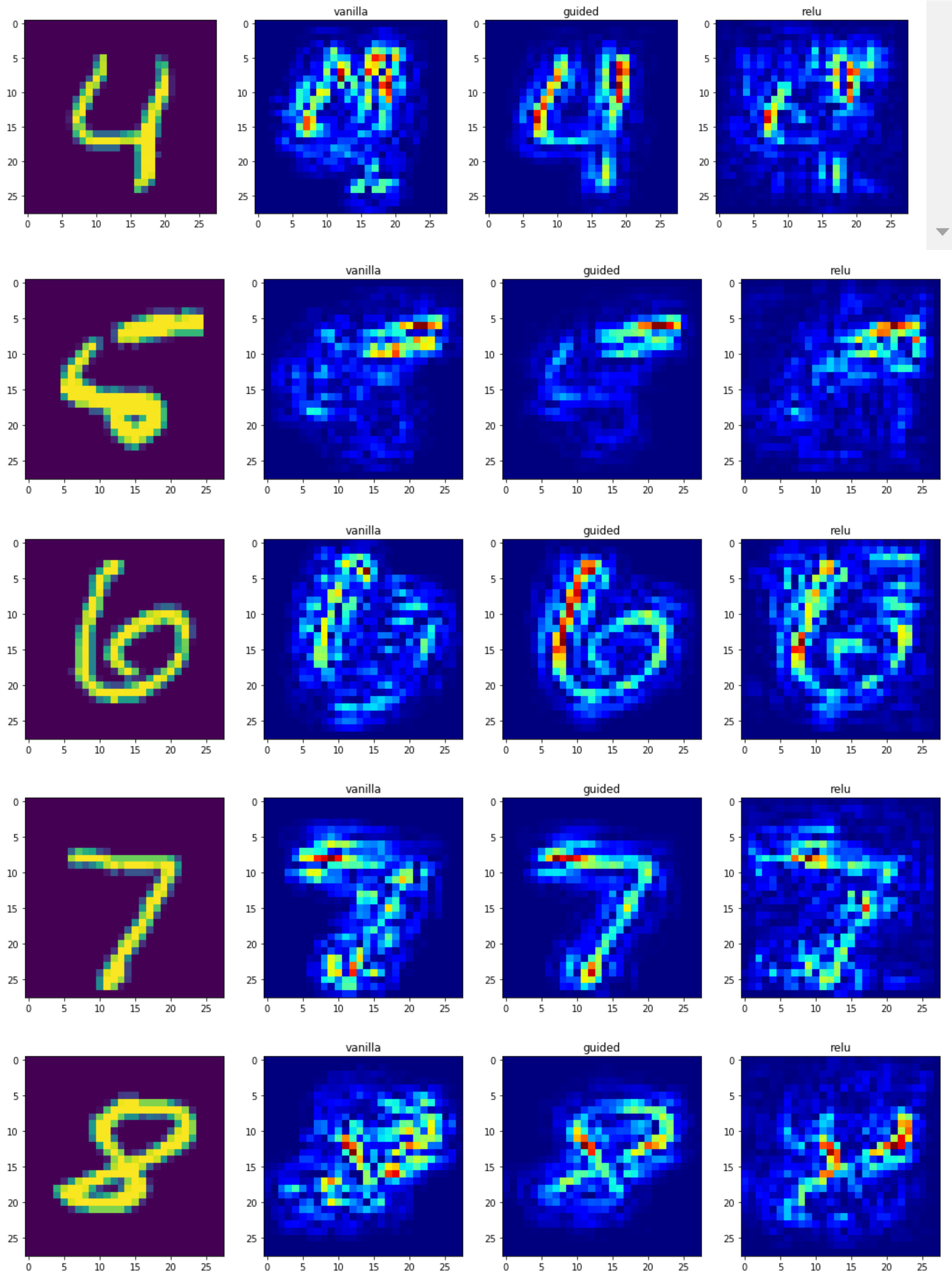


Lets try all the classes and show original inputs and their heatmaps side by side. We cannot overlay the heatmap on original image since its grayscale.

We will also compare the outputs of guided and rectified or deconv saliency.

In [9]:
```
# This corresponds to the Dense linear layer.
for class_idx in np.arange(10):
    indices = np.where(y_test[:, class_idx] == 1.)[0]
    idx = indices[0]

    f, ax = plt.subplots(1, 4)
    ax[0].imshow(x_test[idx][..., 0])

    for i, modifier in enumerate([None, 'guided', 'relu']):
        grads = visualize_saliency(model, layer_idx, filter_indices=class_idx,
                                   seed_input=x_test[idx], backprop_modifier=modi
        if modifier is None:
            modifier = 'vanilla'
        ax[i+1].set_title(modifier)
        ax[i+1].imshow(grads, cmap='jet')
```




vanilla
guided
relu
vanilla
guided
relu
vanilla
guided
relu
vanilla
guided
relu
vanilla
guided
relu

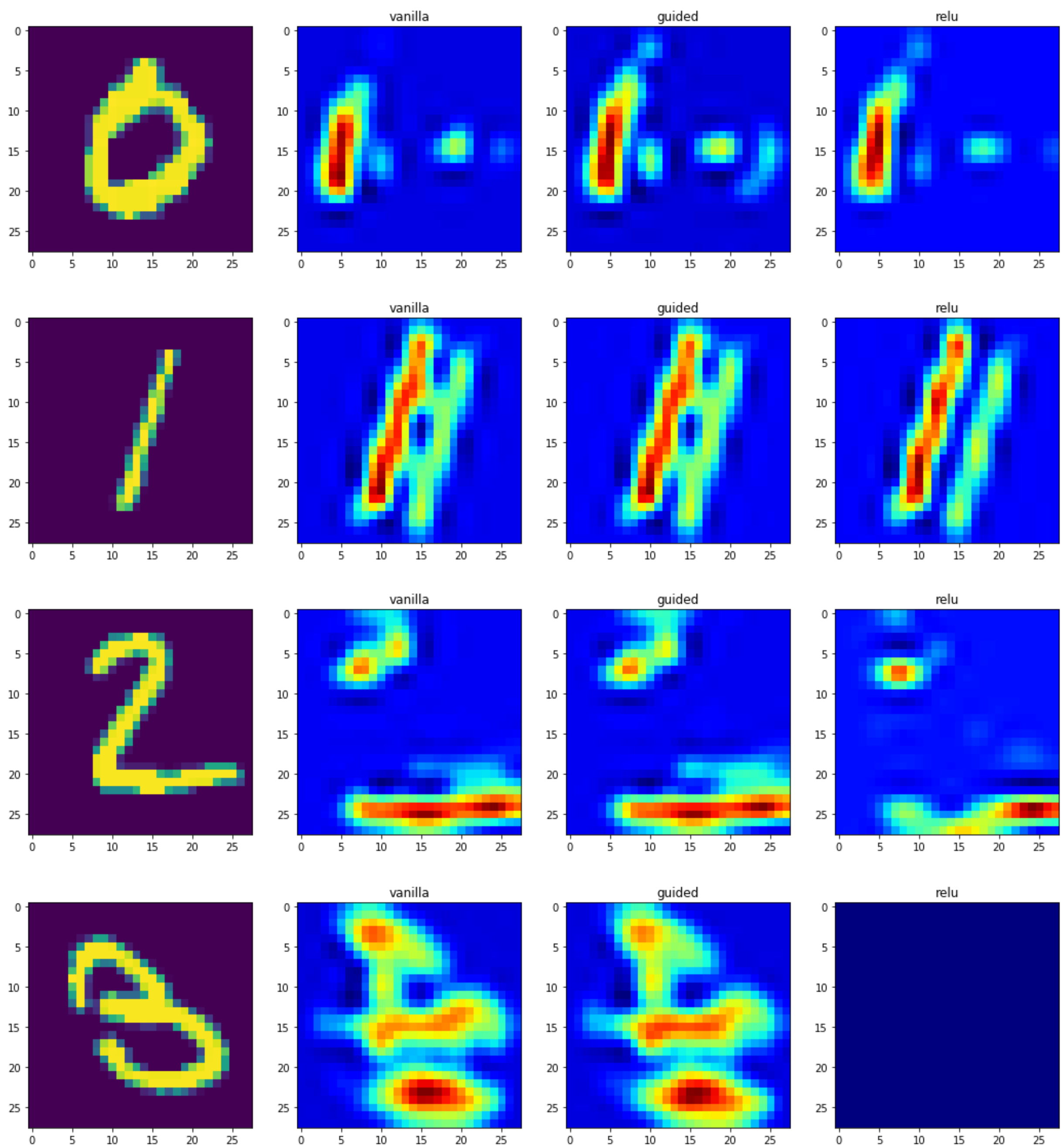
Guided saliency seems to give the best results

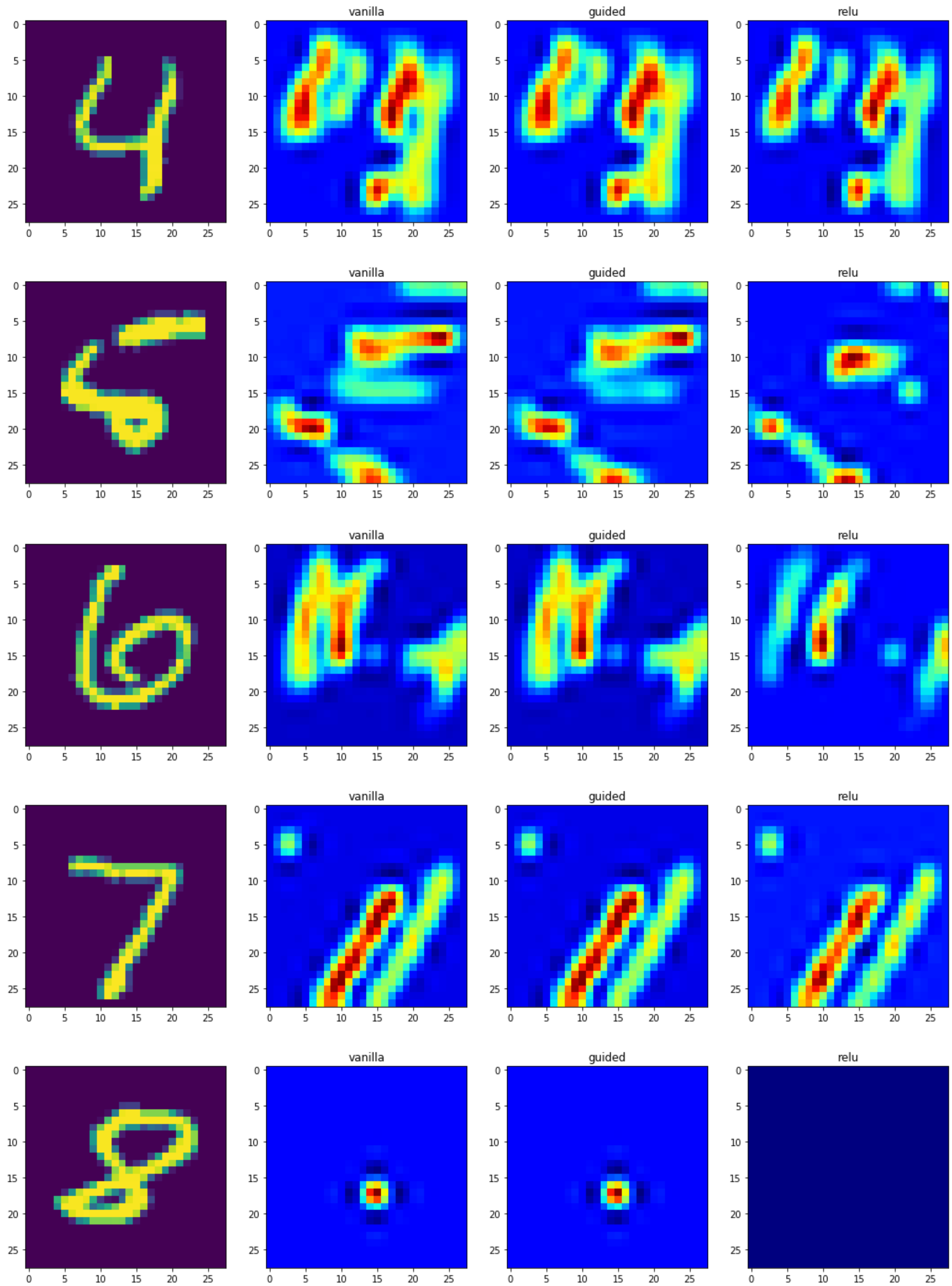
grad-CAM - vanilla, guided, rectified

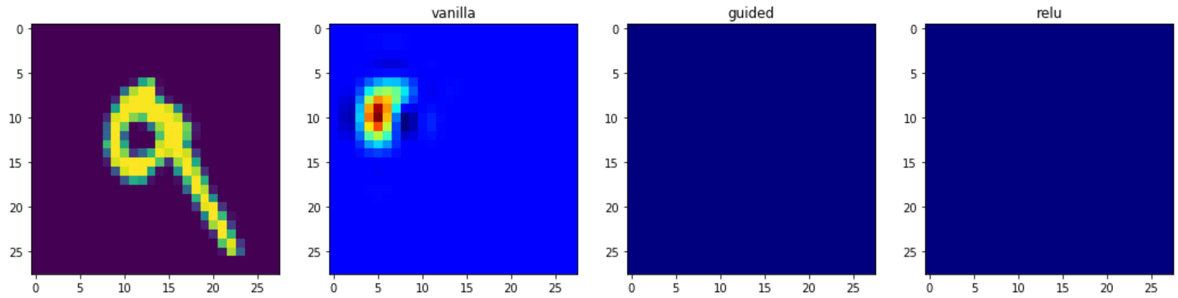
These should contain more detail since they use Conv or Pooling features that contain more spatial detail which is lost in Dense layers. The only additional detail compared to saliency is the penultimate_layer_idx. This specifies the pre-layer whose gradients should be used. See this paper for technical details: https://arxiv.org/pdf/1610.02391v1.pdf (https://arxiv.org/pdf/1610.02391v1.pdf)

By default, if penultimate_layer_idx is not defined, it searches for the nearest pre layer. For our architecture, that would be the MaxPooling2D layer after all the Conv layers. Lets look at all the visualizations like before.

In [10]:
```python
from vis.visualization import visualize_cam

# This corresponds to the Dense linear layer.
for class_idx in np.arange(10):
    indices = np.where(y_test[:, class_idx] == 1.)[0]
    idx = indices[0]

    f, ax = plt.subplots(1, 4)
    ax[0].imshow(x_test[idx][..., 0])

    for i, modifier in enumerate([None, 'guided', 'relu']):
        grads = visualize_cam(model, layer_idx, filter_indices=class_idx,
                              seed_input=x_test[idx], backprop_modifier=modifier)
        if modifier is None:
            modifier = 'vanilla'
        ax[i+1].set_title(modifier)
        ax[i+1].imshow(grads, cmap='jet')
```




vanilla
guided
relu
vanilla
guided
relu
vanilla
guided
relu
vanilla
guided
relu
vanilla
guided
relu



In this case it appears that saliency is better than grad-CAM as penultimate MaxPooling2D layer has (12, 12) spatial resolution which is relatively large as compared to input of (28, 28). Is is likely that the conv layer hasnt captured enough high level information and most of that is likely within dense_4 layer.

Here is the model summary for reference.

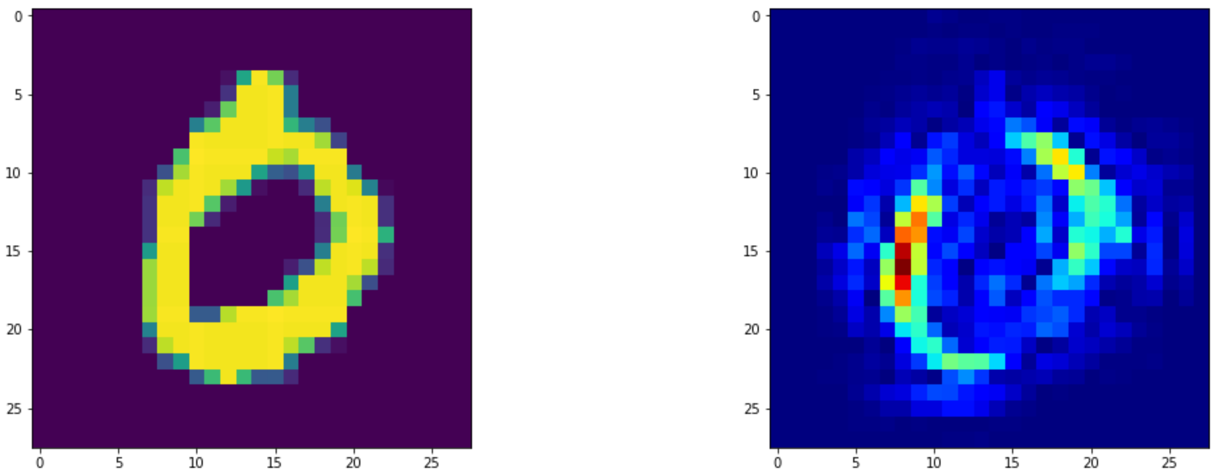
In [19]:
```
print(model.summary())
```

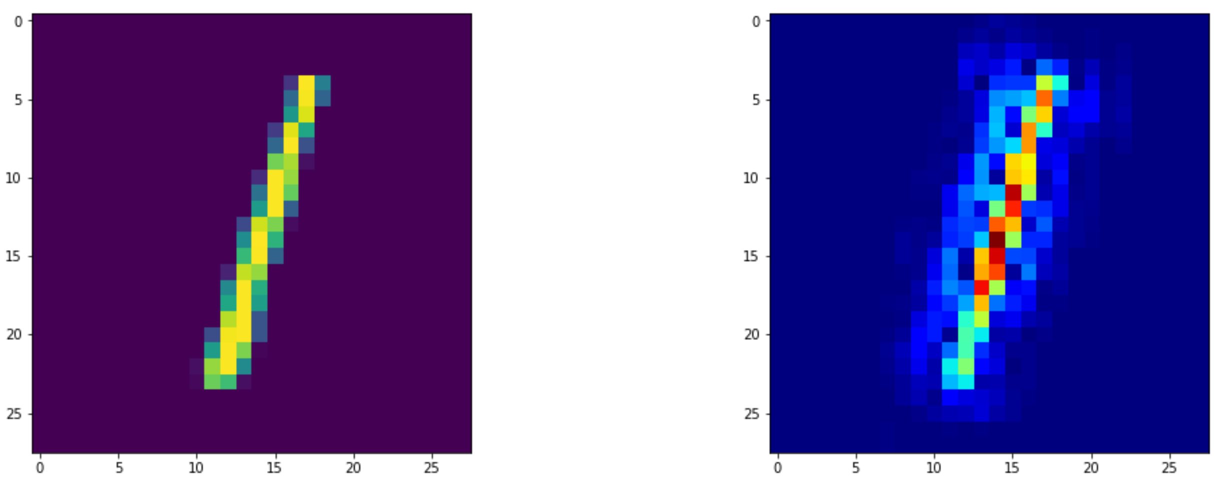
```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320       
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 24, 24, 64)        18496     
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 12, 12, 64)        0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 12, 12, 64)        0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 9216)              0         
_________________________________________________________________
dense_1 (Dense)              (None, 128)               1179776   
_________________________________________________________________
dropout_2 (Dropout)          (None, 128)               0         
_________________________________________________________________
preds (Dense)                (None, 10)                1290      
=================================================================
Total params: 1,199,882
Trainable params: 1,199,882
Non-trainable params: 0
_________________________________________________________________
None
```

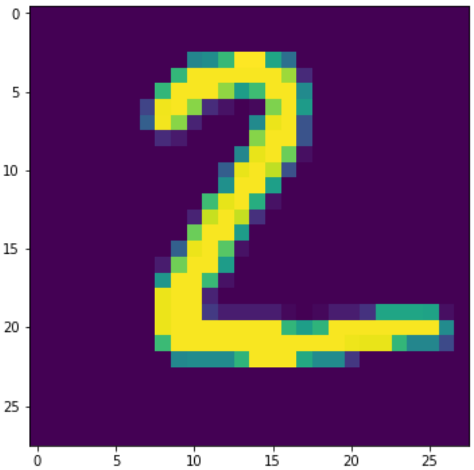
Visualization without swapping softmax

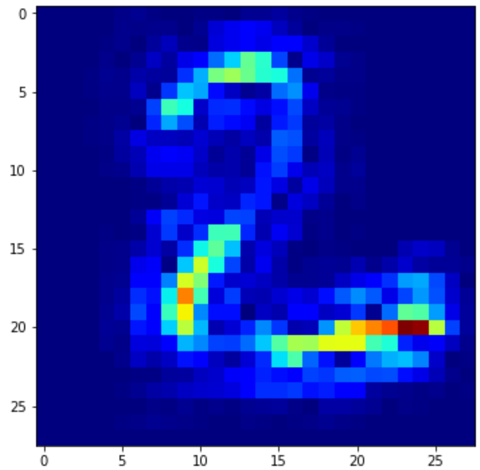
As alluded at the beginning of the tutorial, we want to compare and see what happens if we didnt swap out softmax for linear activation. Lets try this with guided saliency which gave us the best results so far.

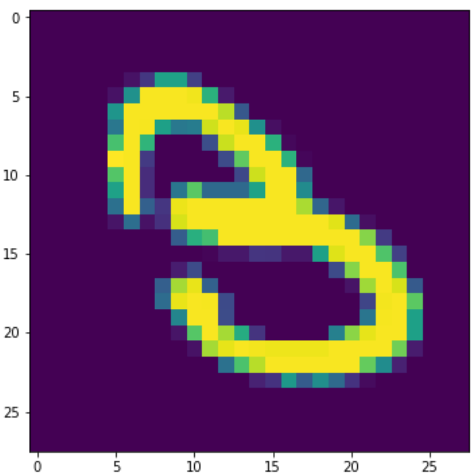
In [11]:
```
# Swap linear back with softmax
model.layers[layer_idx].activation = activations.softmax
model = utils.apply_modifications(model)

for class_idx in np.arange(10):
    indices = np.where(y_test[:, class_idx] == 1.)[0]
    idx = indices[0]

    grads = visualize_saliency(model, layer_idx, filter_indices=class_idx,
                               seed_input=x_test[idx], backprop_modifier='guided'

    f, ax = plt.subplots(1, 2)
    ax[0].imshow(x_test[idx][..., 0])
    ax[1].imshow(grads, cmap='jet')
```

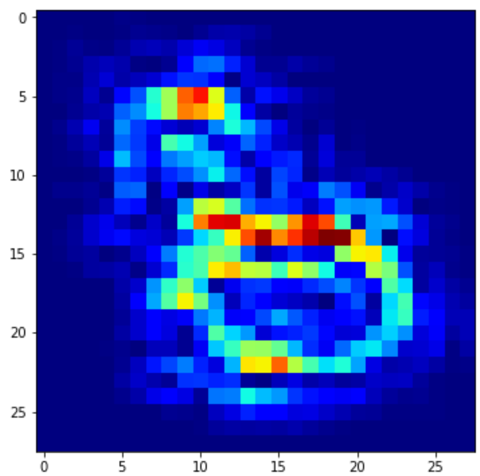


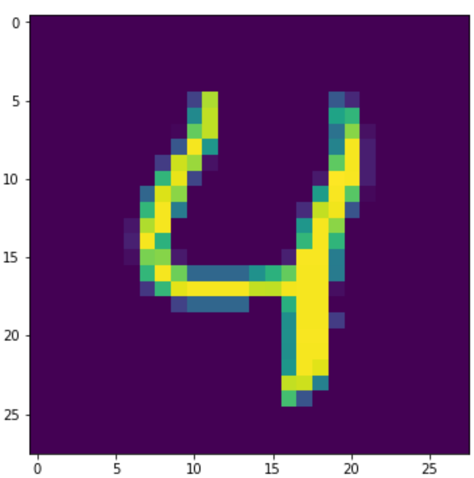


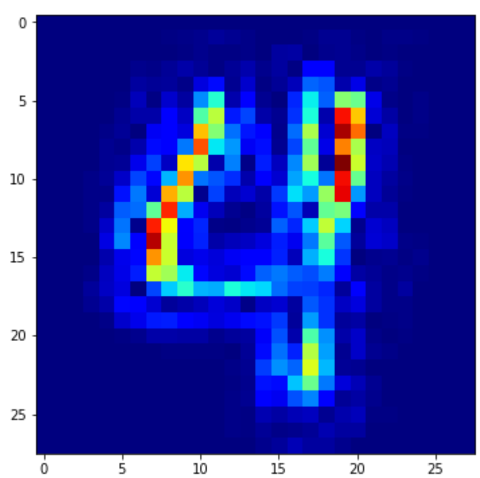


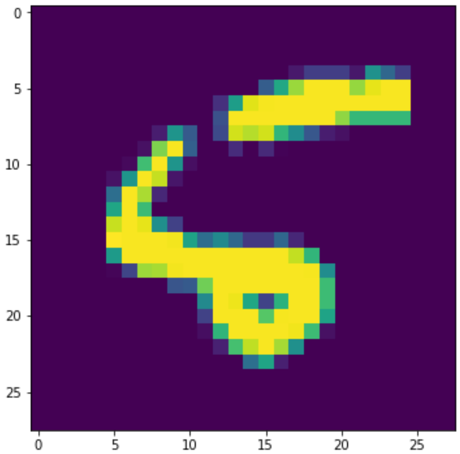











0
5
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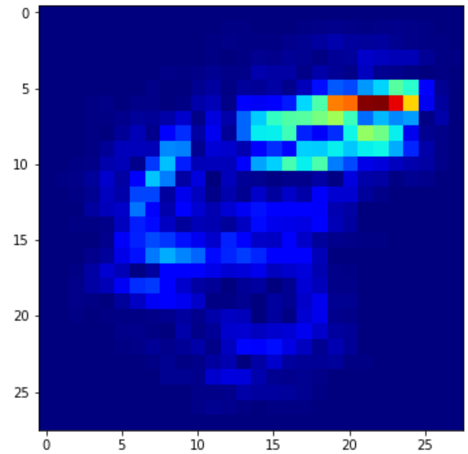
25
0 5 10 15 20 25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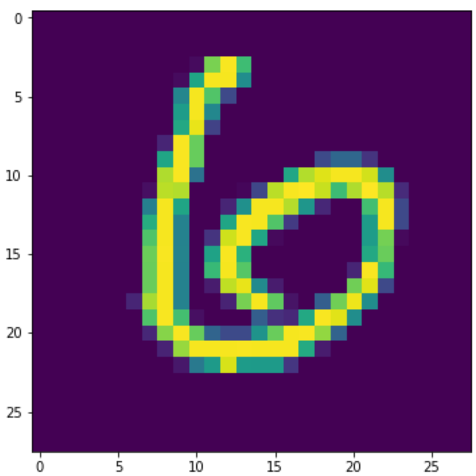
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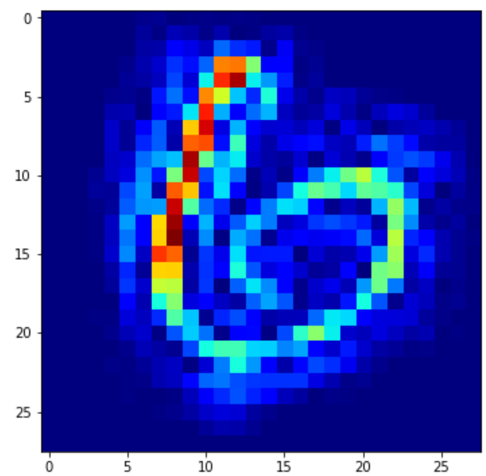
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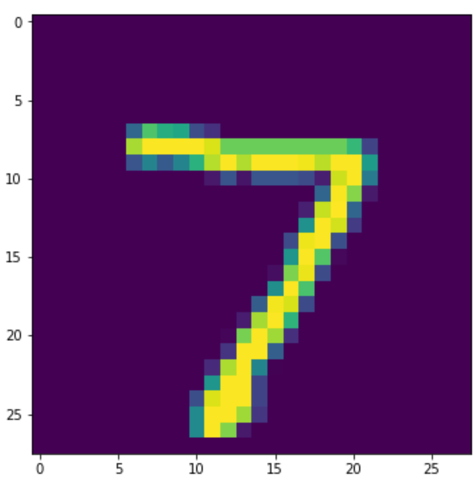
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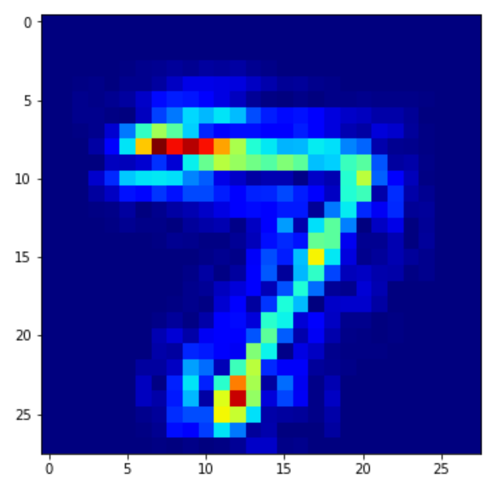
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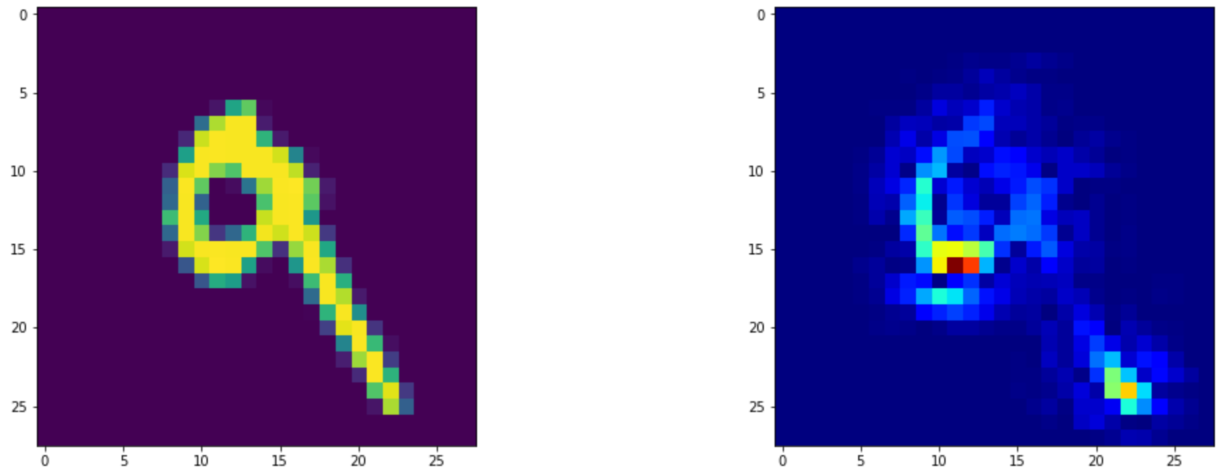

It does not work as well!

The reason is that maximizing an output node can be done by minimizing other outputs. Softmax is weird that way. It is the only activation that depends on other node output(s) in the layer.

```
In [ ]:
```