

practical_ANN-MNIST

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AIM: Image Classification in 10 Minutes with MNIST Dataset

```
In [1]: import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import matplotlib.pyplot as plt #for plotting
from collections import Counter
from sklearn.metrics import confusion_matrix
import itertools
import seaborn as sns
from subprocess import check_output
import os
# print(check_output(["ls", "input"]).decode("utf8"))
%matplotlib inline
```

```
In [2]: #loading the dataset.....(Train)
train = pd.read_csv(os.path.join("input", "train.csv"))
print(train.shape)
train.head()
```

(42000, 785)

```
Out[2]:
```

	label	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	\
0	1	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	1	0	0	0	0	0	0	0	0	
3	4	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	

	pixel8	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	\
0	0	...	0	0	0	0	0	0	
1	0	...	0	0	0	0	0	0	

2	0	...	0	0	0	0	0	0
3	0	...	0	0	0	0	0	0
4	0	...	0	0	0	0	0	0

	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

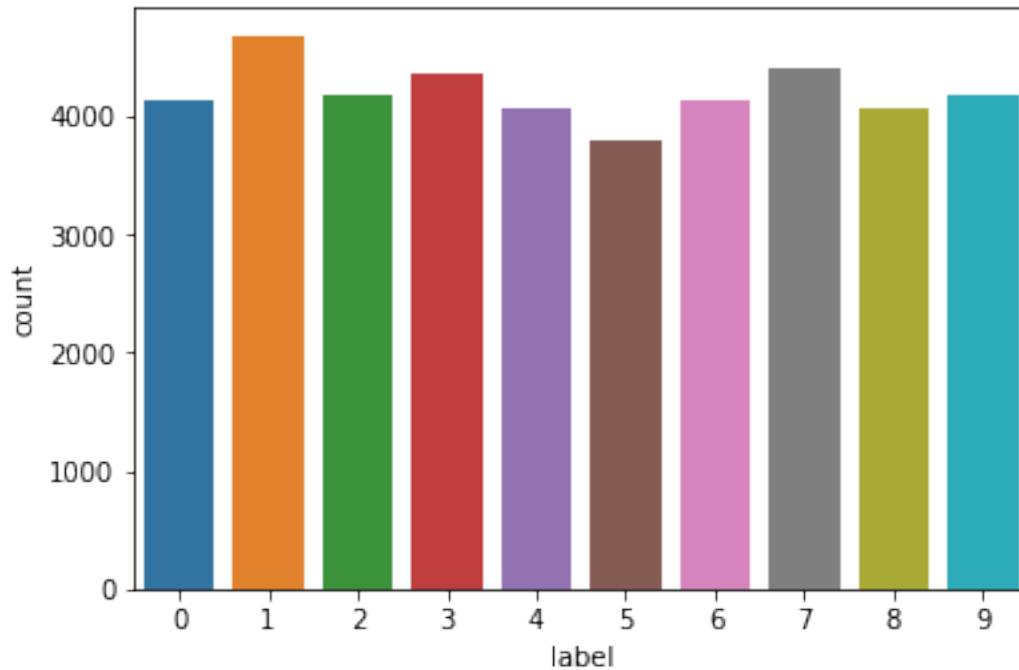
[5 rows x 785 columns]

```
In [15]: z_train = Counter(train['label'])
         z_train
```

```
Out[15]: Counter({0: 4132,
                  1: 4684,
                  2: 4177,
                  3: 4351,
                  4: 4072,
                  5: 3795,
                  6: 4137,
                  7: 4401,
                  8: 4063,
                  9: 4188})
```

```
In [16]: sns.countplot(train['label'])
```

```
Out[16]: <matplotlib.axes._subplots.AxesSubplot at 0x7f6d23f0e860>
```



```
In [18]: #loading the dataset.....(Test)
test= pd.read_csv("input/test.csv")
print(test.shape)
test.head()
```

(28000, 784)

```
Out[18]:
```

	pixel0	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	\
0	0	0	0	0	0	0	0	0	0	
1	0	0	0	0	0	0	0	0	0	
2	0	0	0	0	0	0	0	0	0	
3	0	0	0	0	0	0	0	0	0	
4	0	0	0	0	0	0	0	0	0	

	pixel19	...	pixel774	pixel775	pixel776	pixel777	pixel778	pixel779	\
0	0	...	0	0	0	0	0	0	
1	0	...	0	0	0	0	0	0	
2	0	...	0	0	0	0	0	0	
3	0	...	0	0	0	0	0	0	
4	0	...	0	0	0	0	0	0	

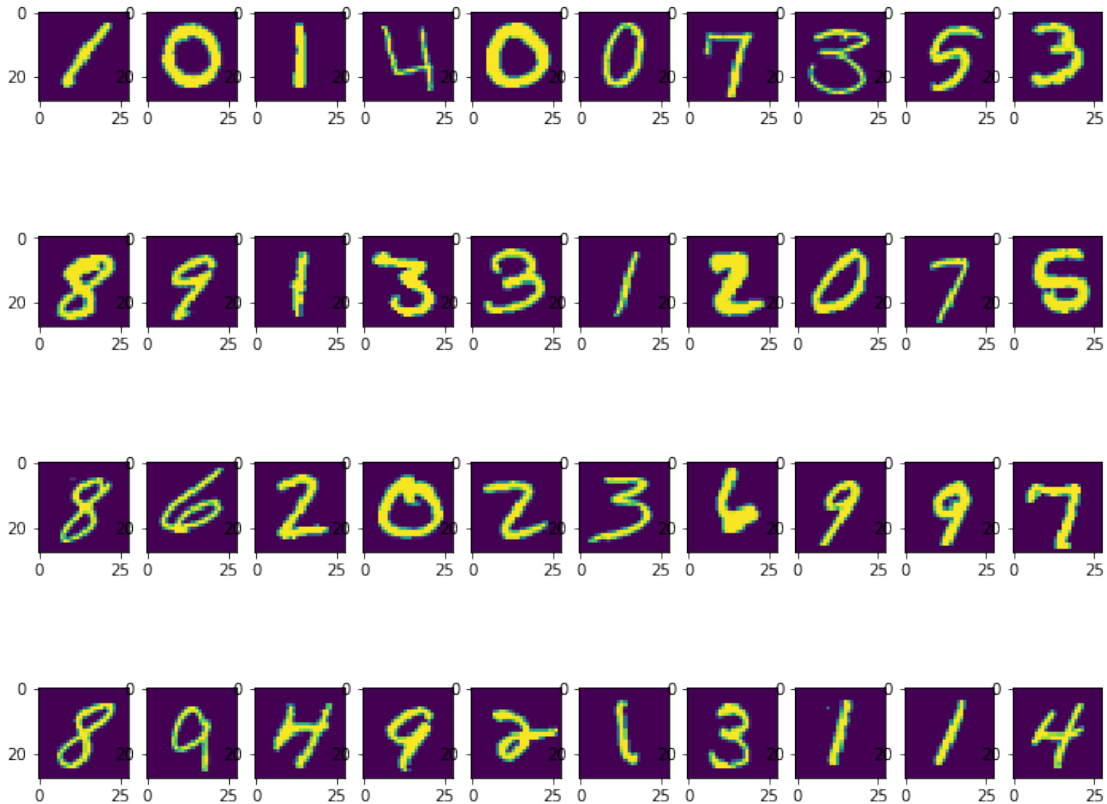
	pixel780	pixel781	pixel782	pixel783
0	0	0	0	0
1	0	0	0	0

2	0	0	0	0
3	0	0	0	0
4	0	0	0	0

[5 rows x 784 columns]

```
In [20]: x_train = (train.iloc[:,1:].values).astype('float32') # all pixel values
y_train = train.iloc[:,0].values.astype('int32') # only labels i.e targets digits
x_test = test.values.astype('float32')
```

```
In [21]: # preview the images first
plt.figure(figsize=(12,10))
x, y = 10, 4
for i in range(40):
    plt.subplot(y, x, i+1)
    plt.imshow(x_train[i].reshape((28,28)),interpolation='nearest')
plt.show()
```



0.1 Normalizing Data

```
In [22]: x_train = x_train/255.0
x_test = x_test/255.0
```

```
In [23]: y_train
```

```
Out[23]: array([1, 0, 1, ..., 7, 6, 9], dtype=int32)
```

1 Reshaping for Keras

```
In [25]: X_train = x_train.reshape(x_train.shape[0], 28, 28,1)
        X_test = x_test.reshape(x_test.shape[0], 28, 28,1)
```

```
In [26]: import keras
        from keras.models import Sequential
        from keras.layers import Dense, Dropout, Flatten, Conv2D, MaxPool2D
        from keras.layers.normalization import BatchNormalization
        from keras.preprocessing.image import ImageDataGenerator
        from keras.callbacks import ReduceLROnPlateau
        from sklearn.model_selection import train_test_split
        batch_size = 64
        num_classes = 10
        epochs = 20
        input_shape = (28, 28, 1)
```

Using TensorFlow backend.

```
In [27]: # convert class vectors to binary class matrices One Hot Encoding
        y_train = keras.utils.to_categorical(y_train, num_classes)
        X_train, X_val, Y_train, Y_val = train_test_split(X_train, y_train, test_size = 0.1, r
```

```
In [34]: model = Sequential()
        model.add(Conv2D(32, kernel_size=(3, 3),activation='relu',kernel_initializer='he_norma
        # model.add(Conv2D(32, kernel_size=(3, 3),activation='relu',kernel_initializer='he_no
        model.add(MaxPool2D((2, 2)))
        model.add(Dropout(0.40))
        model.add(Conv2D(8, (2, 2), activation='relu',padding='same',kernel_initializer='he_no
        # model.add(Conv2D(64, (3, 3), activation='relu',padding='same',kernel_initializer='h
        # model.add(Conv2D(64, (3, 3), activation='relu',padding='same',kernel_initializer='h
        model.add(MaxPool2D(pool_size=(2, 2)))
        model.add(Dropout(0.5))
        model.add(Conv2D(128, (3, 3), activation='relu',padding='same',kernel_initializer='he
        model.add(Dropout(0.5))
        model.add(Flatten())
        model.add(Dense(16, activation='relu'))
        model.add(BatchNormalization())
        model.add(Dropout(0.5))
        model.add(Dense(num_classes, activation='softmax'))

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

```

metrics=['accuracy'])

learning_rate_reduction = ReduceLROnPlateau(monitor='val_acc',
                                             patience=3,
                                             verbose=1,
                                             factor=0.5,
                                             min_lr=0.0001)

datagen = ImageDataGenerator(
    featurewise_center=False, # set input mean to 0 over the dataset
    samplewise_center=False, # set each sample mean to 0
    featurewise_std_normalization=False, # divide inputs by std of the dataset
    samplewise_std_normalization=False, # divide each input by its std
    zca_whitening=False, # apply ZCA whitening
    rotation_range=15, # randomly rotate images in the range (degrees, 0 to 180)
    zoom_range = 0.1, # Randomly zoom image
    width_shift_range=0.1, # randomly shift images horizontally (fraction of total
    height_shift_range=0.1, # randomly shift images vertically (fraction of total
    horizontal_flip=False, # randomly flip images
    vertical_flip=False) # randomly flip images

```

```
In [35]: model.summary()
```

Layer (type)	Output Shape	Param #
conv2d_9 (Conv2D)	(None, 26, 26, 32)	320
max_pooling2d_5 (MaxPooling2D)	(None, 13, 13, 32)	0
dropout_9 (Dropout)	(None, 13, 13, 32)	0
conv2d_10 (Conv2D)	(None, 13, 13, 8)	1032
max_pooling2d_6 (MaxPooling2D)	(None, 6, 6, 8)	0
dropout_10 (Dropout)	(None, 6, 6, 8)	0
conv2d_11 (Conv2D)	(None, 6, 6, 128)	9344
dropout_11 (Dropout)	(None, 6, 6, 128)	0
flatten_3 (Flatten)	(None, 4608)	0
dense_5 (Dense)	(None, 16)	73744
batch_normalization_3 (Batch Normalization)	(None, 16)	64

dropout_12 (Dropout)	(None, 16)	0

dense_6 (Dense)	(None, 10)	170
=====		
Total params: 84,674		
Trainable params: 84,642		
Non-trainable params: 32		

```
In [36]: datagen.fit(X_train)
         h = model.fit_generator(datagen.flow(X_train,Y_train, batch_size=batch_size),
                                epochs = epochs, validation_data = (X_val,Y_val),
                                verbose = 1, steps_per_epoch=X_train.shape[0] // batch_size,
                                , callbacks=[learning_rate_reduction],)
```

```
Epoch 1/20
590/590 [=====] - 26s 43ms/step - loss: 1.8753 - acc: 0.3449 - val_loss: 1.8753
Epoch 2/20
590/590 [=====] - 26s 44ms/step - loss: 1.3495 - acc: 0.5337 - val_loss: 1.3495
Epoch 3/20
590/590 [=====] - 26s 44ms/step - loss: 1.0688 - acc: 0.6329 - val_loss: 1.0688
Epoch 4/20
590/590 [=====] - 26s 43ms/step - loss: 0.9254 - acc: 0.6822 - val_loss: 0.9254
Epoch 5/20
590/590 [=====] - 26s 44ms/step - loss: 0.8370 - acc: 0.7119 - val_loss: 0.8370
Epoch 6/20
590/590 [=====] - 26s 43ms/step - loss: 0.7835 - acc: 0.7319 - val_loss: 0.7835
Epoch 7/20
590/590 [=====] - 26s 43ms/step - loss: 0.7395 - acc: 0.7492 - val_loss: 0.7395
Epoch 8/20
590/590 [=====] - 26s 43ms/step - loss: 0.7085 - acc: 0.7600 - val_loss: 0.7085
Epoch 9/20
590/590 [=====] - 26s 43ms/step - loss: 0.6693 - acc: 0.7694 - val_loss: 0.6693
Epoch 10/20
590/590 [=====] - 26s 43ms/step - loss: 0.6574 - acc: 0.7773 - val_loss: 0.6574
Epoch 11/20
590/590 [=====] - 26s 43ms/step - loss: 0.6472 - acc: 0.7814 - val_loss: 0.6472

Epoch 00011: ReduceLROnPlateau reducing learning rate to 0.0005000000237487257.
Epoch 12/20
590/590 [=====] - 30s 52ms/step - loss: 0.6208 - acc: 0.7906 - val_loss: 0.6208
Epoch 13/20
590/590 [=====] - 25s 43ms/step - loss: 0.6265 - acc: 0.7888 - val_loss: 0.6265
Epoch 14/20
590/590 [=====] - 25s 43ms/step - loss: 0.6149 - acc: 0.7955 - val_loss: 0.6149
Epoch 15/20
590/590 [=====] - 25s 43ms/step - loss: 0.5969 - acc: 0.8013 - val_loss: 0.5969
```

```

Epoch 16/20
590/590 [=====] - 25s 43ms/step - loss: 0.5950 - acc: 0.8009 - val_loss: 0.5950
Epoch 17/20
590/590 [=====] - 25s 43ms/step - loss: 0.5908 - acc: 0.8024 - val_loss: 0.5908
Epoch 18/20
590/590 [=====] - 25s 43ms/step - loss: 0.5787 - acc: 0.8065 - val_loss: 0.5787
Epoch 19/20
590/590 [=====] - 25s 43ms/step - loss: 0.5819 - acc: 0.8065 - val_loss: 0.5819
Epoch 20/20
590/590 [=====] - 25s 43ms/step - loss: 0.5693 - acc: 0.8084 - val_loss: 0.5693

```

1.1 Plotting

```

In [37]: final_loss, final_acc = model.evaluate(X_val, Y_val, verbose=0)
         print("Final loss: {0:.6f}, final accuracy: {1:.6f}".format(final_loss, final_acc))

```

```

Final loss: 0.121264, final accuracy: 0.961667

```

```

In [38]: # Look at confusion matrix
         #Note, this code is taken straight from the SKLEARN website, an nice way of viewing c
         def plot_confusion_matrix(cm, classes,
                                   normalize=False,
                                   title='Confusion matrix',
                                   cmap=plt.cm.Blues):
            """
            This function prints and plots the confusion matrix.
            Normalization can be applied by setting `normalize=True`.
            """
            plt.imshow(cm, interpolation='nearest', cmap=cmap)
            plt.title(title)
            plt.colorbar()
            tick_marks = np.arange(len(classes))
            plt.xticks(tick_marks, classes, rotation=45)
            plt.yticks(tick_marks, classes)

            if normalize:
                cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

            thresh = cm.max() / 2.
            for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                plt.text(j, i, cm[i, j],
                        horizontalalignment="center",
                        color="white" if cm[i, j] > thresh else "black")

            plt.tight_layout()
            plt.ylabel('True label')

```

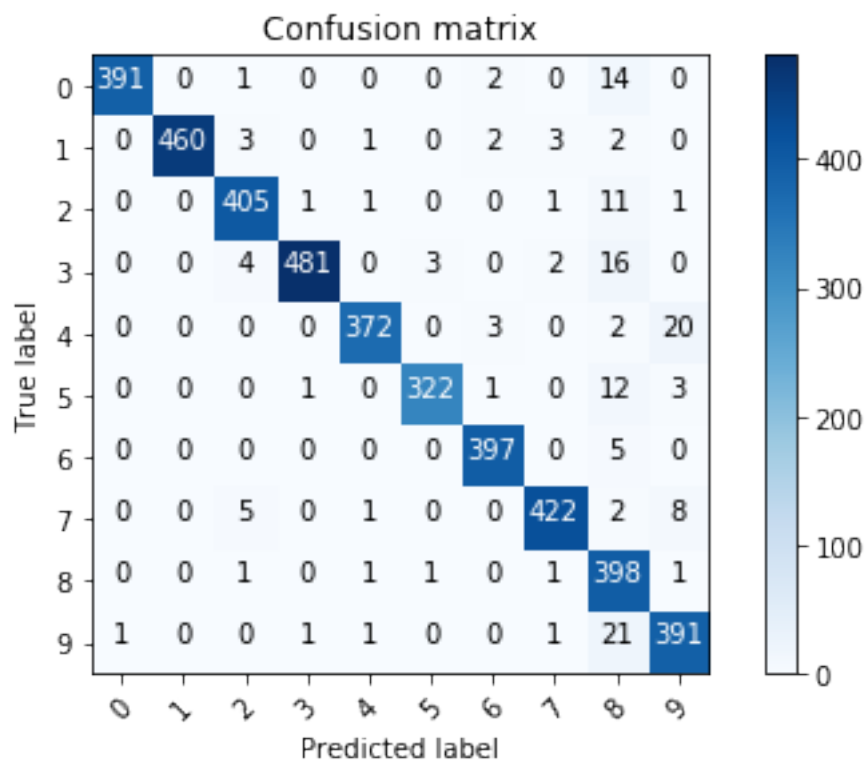


```

plt.xlabel('Predicted label')

# Predict the values from the validation dataset
Y_pred = model.predict(X_val)
# Convert predictions classes to one hot vectors
Y_pred_classes = np.argmax(Y_pred, axis = 1)
# Convert validation observations to one hot vectors
Y_true = np.argmax(Y_val, axis = 1)
# compute the confusion matrix
confusion_mtx = confusion_matrix(Y_true, Y_pred_classes)
# plot the confusion matrix
plot_confusion_matrix(confusion_mtx, classes = range(10))

```



```

In [39]: print(h.history.keys())
accuracy = h.history['acc']
val_accuracy = h.history['val_acc']
loss = h.history['loss']
val_loss = h.history['val_loss']
epochs = range(len(accuracy))
plt.plot(epochs, accuracy, 'bo', label='Training accuracy')
plt.plot(epochs, val_accuracy, 'b', label='Validation accuracy')
plt.title('Training and validation accuracy')

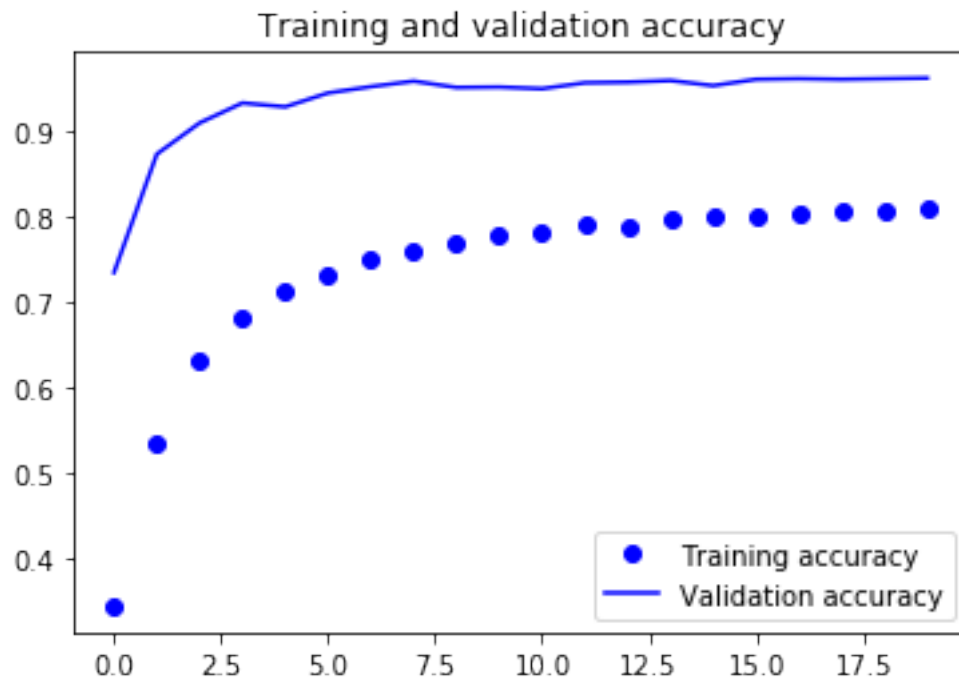
```

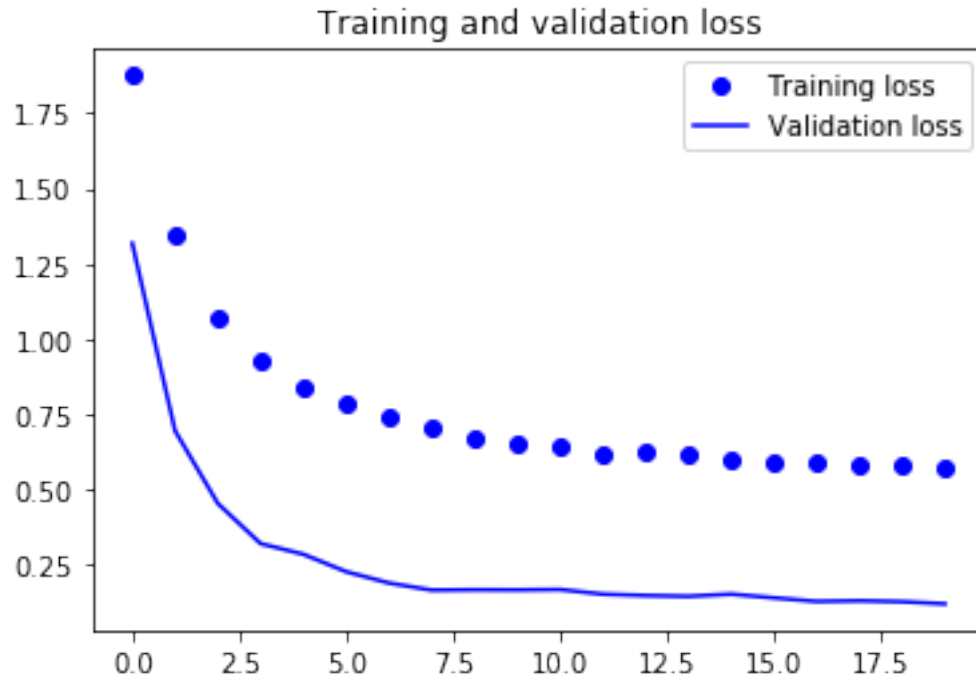
```

plt.legend()
plt.show()
plt.figure()
plt.plot(epochs, loss, 'bo', label='Training loss')
plt.plot(epochs, val_loss, 'b', label='Validation loss')
plt.title('Training and validation loss')
plt.legend()
plt.show()

```

```
dict_keys(['lr', 'acc', 'loss', 'val_loss', 'val_acc'])
```





```
In [40]: # Errors are difference between predicted labels and true labels
errors = (Y_pred_classes - Y_true != 0)
```

```
Y_pred_classes_errors = Y_pred_classes[errors]
Y_pred_errors = Y_pred[errors]
Y_true_errors = Y_true[errors]
X_val_errors = X_val[errors]
```

```
def display_errors(errors_index,img_errors,pred_errors, obs_errors):
    """ This function shows 6 images with their predicted and real labels"""
    n = 0
    nrows = 2
    ncols = 3
    fig, ax = plt.subplots(nrows,ncols,sharex=True,sharey=True)
    for row in range(nrows):
        for col in range(ncols):
            error = errors_index[n]
            ax[row,col].imshow((img_errors[error]).reshape((28,28)))
            ax[row,col].set_title("Predicted label :{}\nTrue label :{}".format(pred_errors[n],
            Y_true_errors[n]))
            n += 1
```

```
# Probabilities of the wrong predicted numbers
Y_pred_errors_prob = np.max(Y_pred_errors,axis = 1)
```

```
# Predicted probabilities of the true values in the error set
```

```

true_prob_errors = np.diagonal(np.take(Y_pred_errors, Y_true_errors, axis=1))

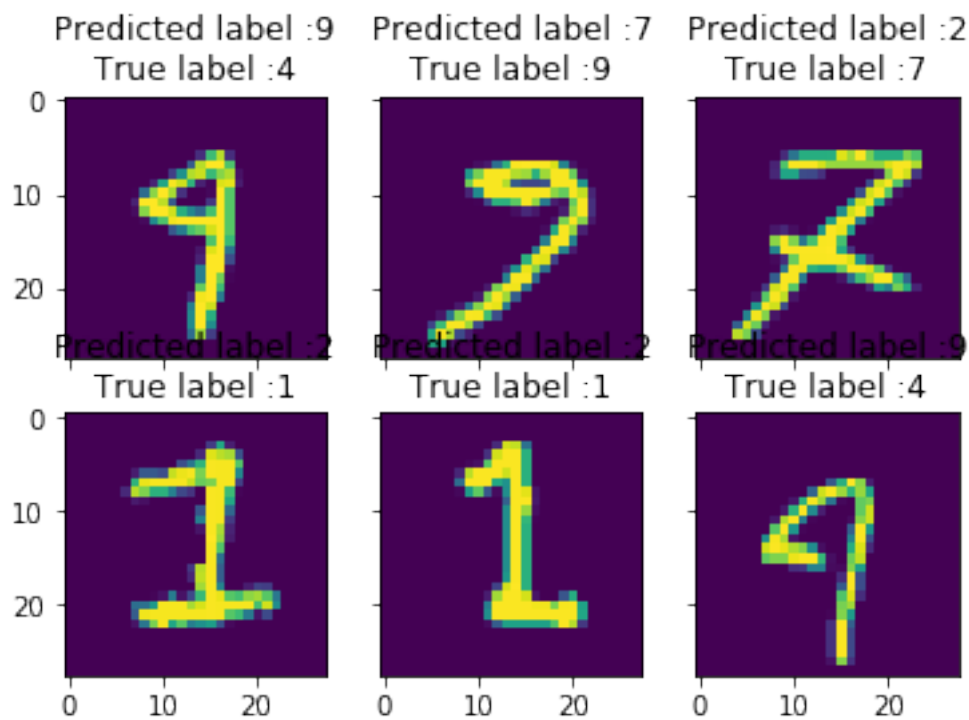
# Difference between the probability of the predicted label and the true label
delta_pred_true_errors = Y_pred_errors_prob - true_prob_errors

# Sorted list of the delta prob errors
sorted_delta_errors = np.argsort(delta_pred_true_errors)

# Top 6 errors
most_important_errors = sorted_delta_errors[-6:]

# Show the top 6 errors
display_errors(most_important_errors, X_val_errors, Y_pred_classes_errors, Y_true_err

```



```

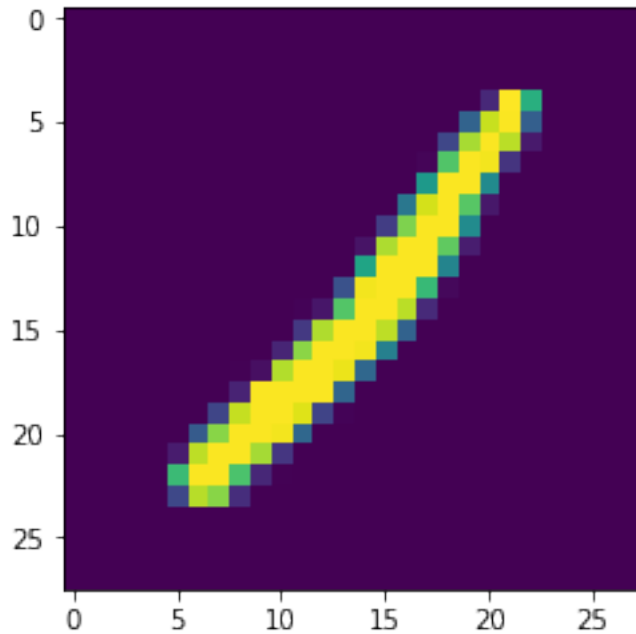
In [41]: test_im = X_train[154]
plt.imshow(test_im.reshape(28,28), cmap='viridis', interpolation='none')

```

```

Out[41]: <matplotlib.image.AxesImage at 0x7f6ce6e4bc50>

```

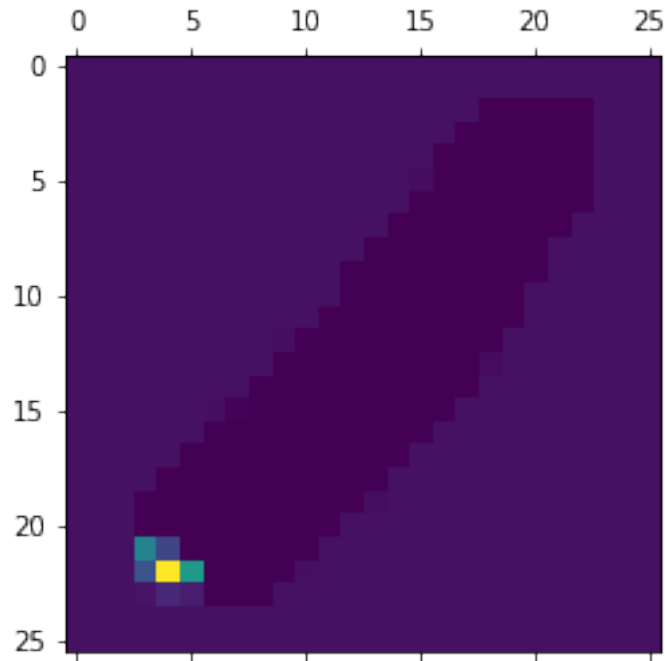


```
In [42]: from keras import models
         layer_outputs = [layer.output for layer in model.layers[:8]]
         activation_model = models.Model(input=model.input, output=layer_outputs)
         activations = activation_model.predict(test_im.reshape(1,28,28,1))

         first_layer_activation = activations[0]
         plt.matshow(first_layer_activation[0, :, :, 4], cmap='viridis')
```

/home/jarvis/.local/lib/python3.5/site-packages/ipykernel_launcher.py:3: UserWarning: Update y
This is separate from the ipykernel package so we can avoid doing imports until

```
Out[42]: <matplotlib.image.AxesImage at 0x7f6ce6e0f0f0>
```



```
In [44]: # Classification Report
```

```
In [54]: #get the predictions for the test data
```

```
predicted_classes = model.predict_classes(X_test)
```

```
#get the indices to be plotted
```

```
y_true = test.iloc[:, 0]
```

```
correct = np.nonzero(predicted_classes==y_true)[0]
```

```
incorrect = np.nonzero(predicted_classes!=y_true)[0]
```

```
In [55]: from sklearn.metrics import classification_report
```

```
target_names = ["Class {}".format(i) for i in range(num_classes)]
```

```
print(classification_report(y_true, predicted_classes, target_names=target_names))
```

	precision	recall	f1-score	support
Class 0	1.00	0.10	0.17	28000
Class 1	0.00	0.00	0.00	0
Class 2	0.00	0.00	0.00	0
Class 3	0.00	0.00	0.00	0
Class 4	0.00	0.00	0.00	0
Class 5	0.00	0.00	0.00	0
Class 6	0.00	0.00	0.00	0
Class 7	0.00	0.00	0.00	0
Class 8	0.00	0.00	0.00	0

Class 9	0.00	0.00	0.00	0
micro avg	0.10	0.10	0.10	28000
macro avg	0.10	0.01	0.02	28000
weighted avg	1.00	0.10	0.17	28000

```
/usr/local/lib/python3.5/dist-packages/sklearn/metrics/classification.py:1145: UndefinedMetricWarning:
'recall', 'true', average, warn_for)
```

```
In [56]: model.save('my_model_logistic_regression.h5')
         json_string = model.to_json()
```

1.2 References

- https://www.python-course.eu/neural_network_mnist.php
- <https://medium.com/@mjbhobe/mnist-digits-classification-with-keras-ed6c2374bd0e>
- <https://towardsdatascience.com/image-classification-in-10-minutes-with-mnist-dataset-54c35b77a38d>
- <https://www.kaggle.com/adityaecdrid/mnist-with-keras-for-beginners-99457/notebook>

```
In [ ]:
```