In [8]:
```
import numpy as np # Matrix mutliplications
import pandas as pd # data processing and for CSV files usage
```

In [9]:
```
#Reading data
train = pd.read_csv("fashion-mnist_train.csv")
test = pd.read_csv("fashion-mnist_test.csv")
```

In [10]:
```
#Checking data for shape and type
#train has data from 42000 images (1 dimension: 28 by 28 i.e. 784 pixels) and
 has a label column
# the test has data from 28k images which is fed to the CNN so that it's newer
data not seen by CNN beforehand (1D 28 by 28 i.e. 784 pixels)
#there is no label column in the test data which is the goal to be predicted p
redicted.
print(train.shape)
atrain = train.shape[0]

print(test.shape)
atest = test.shape[0]

train.head(15)
```

```
(60000, 785)
(10000, 785)
```

Out[10]:

	label	pixel1	pixel2	pixel3	pixel4	pixel5	pixel6	pixel7	pixel8	pixel9	...	pixel775	pixel
0	2	0	0	0	0	0	0	0	0	0	...	0	
1	9	0	0	0	0	0	0	0	0	0	...	0	
2	6	0	0	0	0	0	0	0	5	0	...	0	
3	0	0	0	0	1	2	0	0	0	0	...	3	
4	3	0	0	0	0	0	0	0	0	0	...	0	
5	4	0	0	0	5	4	5	5	3	5	...	7	
6	4	0	0	0	0	0	0	0	0	0	...	14	
7	5	0	0	0	0	0	0	0	0	0	...	0	
8	4	0	0	0	0	0	0	3	2	0	...	1	
9	8	0	0	0	0	0	0	0	0	0	...	203	
10	0	0	0	0	0	1	0	0	0	0	...	164	
11	8	0	0	0	0	0	0	0	0	0	...	9	
12	9	0	0	0	0	0	0	0	0	0	...	0	
13	0	0	0	0	0	0	0	0	0	0	...	0	
14	2	0	0	0	0	1	1	0	0	0	...	0	

15 rows × 785 columns

In [11]:
```
#Check for the data type
#It is int64 for both train and test
print(train.dtypes[0])
```

```
int64
```

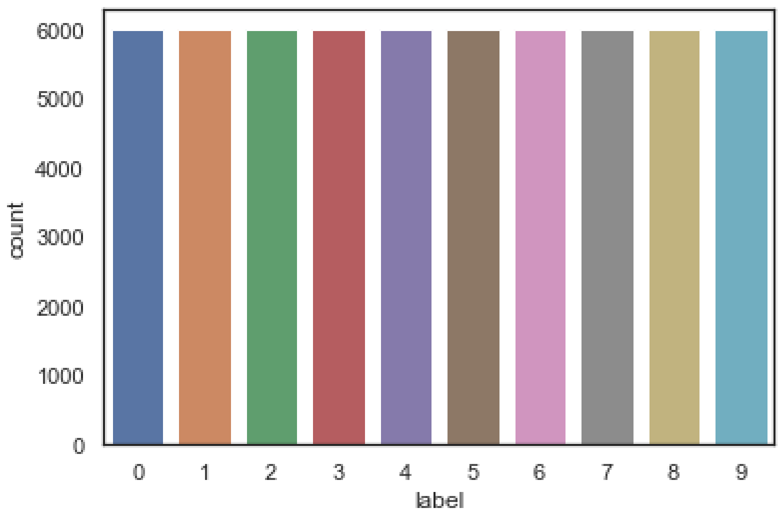
In [12]:
```
#CNN needs to be provided with x_train in order to map the weights from this t
o y_train
# array containing labels of each image
y_train = train["label"]
# dataframe containing all pixels (the label column is dropped)
x_train = train.drop("label", axis=1)

# the images are squared shape therefore:
from math import sqrt
dim = int(sqrt(x_train.shape[1]))
print("The images are {}x{} squares.".format(dim, dim))

print("Shape of x_train: ", x_train.shape)
print("Shape of y_train: ", y_train.shape)


# array containing labels of each image
y_test = test["label"]
# dataframe containing all pixels (the label column is dropped)
x_test = test.drop("label", axis=1)
print("Shape of x_test: ", x_test.shape)
print("Shape of y_test: ", y_test.shape)
# checking the y_train
y_train.head(10)
```

```
The images are 28x28 squares.
Shape of x_train:  (60000, 784)
Shape of y_train:  (60000,)
Shape of x_test:  (10000, 784)
Shape of y_test:  (10000,)
```

Out[12]:
```
0    2
1    9
2    6
3    0
4    3
5    4
6    4
7    5
8    4
9    8
Name: label, dtype: int64
```

In [13]:
```
#Computing the mean and standard deviation of the classes here:
import seaborn as sns
sns.set(style='white', context='notebook', palette='deep')

# plotting no: of images in each class
sns.countplot(y_train)

print(y_train.shape)
print(type(y_train))

# array with each class and its number of images
vals_class = y_train.value_counts()
print(vals_class)

# mean and std
class_mean = np.mean(vals_class)
class_std = np.std(vals_class,ddof=1)

print("The mean amount of elements per class: ", class_mean)
print("The standard deviation in the element per class distribution: ", class_
std)

# 68% - 95% - 99% rule, the 68% of the data should be cls_std away from the me
an and so on
if class_std > class_mean * (0.6827 / 2):
    print("The standard deviation is high")
#no: of classes = 10
#the distribution of the pictures per class is homogeneous
```

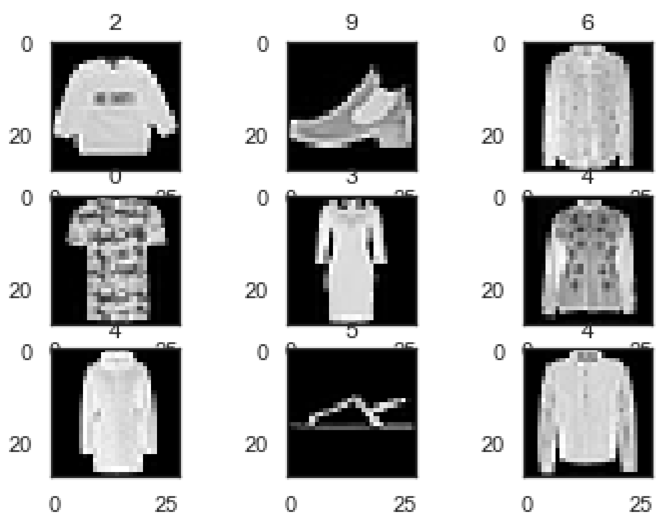
```
(60000,)
<class 'pandas.core.series.Series'>
9    6000
8    6000
7    6000
6    6000
5    6000
4    6000
3    6000
2    6000
1    6000
0    6000
Name: label, dtype: int64
The mean amount of elements per class:  6000.0
The standard deviation in the element per class distribution:  0.0
```



In [14]:
```
#Checking and Reporting for any missing values
def missing_values(df):
    print(df.isnull().any().describe())
    print("Yes, missing values" if df.isnull().any().any() else "No missing va
lues")

    if df.isnull().any().any():
        print(df.isnull().sum(axis=0))

    print()

missing_values(x_train)
missing_values(x_test)
```

```
count       784
unique        1
top       False
freq        784
dtype: object
No missing values

count       784
unique        1
top       False
freq        784
dtype: object
No missing values
```

In [15]:
```
#Visulizations
import matplotlib.pyplot as plt
import matplotlib.image as mpimg
%matplotlib inline

# convert train dataset to the format for plotting: (num_images, img_rows, img
_cols)
x_train_vis = x_train.values.reshape(atrain, dim, dim)

# subplot(2,3,3) = subplot(233)
# a grid of 3x3 is created and then plots are inserted in these slots
for i in range(0,9): # No: of images for displaying from the 3x3 grid
    plt.subplot(330 + (i+1)) # opening the next subplot
    plt.imshow(x_train_vis[i], cmap=plt.get_cmap('gray')) #Grayscale; Pixels a
re etiher black or white
    plt.title(y_train[i]);
```



In [16]:
```
#Normalization for faster Neural Network Convergenece
x_train = x_train / 255.0
x_test = x_test / 255.0
```

In [17]:
```
#Reshaping
def reshape_image(df):
    print("Original shape, pixels are  1D vector:", df.shape)
    df = df.values.reshape(-1, dim, dim, 1)
    # -1 means the dimension doesn't change, so 42000 in the case of xtrain an
d 28000 in the case of test
    print("New Shape, pixels are now 28x28x1 3D matrix:", df.shape)
    return df

x_train = reshape_image(x_train) # numpy.ndarray type
x_test = reshape_image(x_test) # numpy.ndarray type
```

```
Original shape, pixels are  1D vector: (60000, 784)
New Shape, pixels are now 28x28x1 3D matrix: (60000, 28, 28, 1)
Original shape, pixels are  1D vector: (10000, 784)
New Shape, pixels are now 28x28x1 3D matrix: (10000, 28, 28, 1)
```

In [18]:
```
#One-hot enconding for defining the type of loss for the NN later i.e categori
cal_crossentropy
#the targets are required to be in categorical format i.e. one hot-vectors
from keras.utils.np_utils import to_categorical

print(type(y_train))
# number of classes
number_classes = y_train.max() - y_train.min() + 1

print("Original Shape of y_train: ", y_train.shape)

y_train = to_categorical(y_train, num_classes = number_classes)

print("Newer Shape of y_train  ", y_train.shape)
print(type(y_train))
```

```
Using TensorFlow backend.

<class 'pandas.core.series.Series'>
Original Shape of y_train:  (60000,)
Newer Shape of y_train   (60000, 10)
<class 'numpy.ndarray'>
```

In [19]:
```
from sklearn.model_selection import train_test_split

# random seed for reproducibility purpose
seed = 2
np.random.seed(seed)

# percentage of x_train which will be x_val
split_pct = 0.2

# Splitting the train and the validation set
#random_state for splitting data in a pseudo-random manner/division
#stratify for avoiding any overrepresentation of labels in the val set
x_train, x_val, y_train, y_val = train_test_split(x_train,
                                              y_train,
                                              test_size=split_pct,
                                              random_state=seed,
                                              stratify=y_train
                                             )

print(x_train.shape, y_train.shape, x_val.shape, y_val.shape)
```

```
(48000, 28, 28, 1) (48000, 10) (12000, 28, 28, 1) (12000, 10)
```

In [20]:
```
#Libraries and packages for CNN
from keras import backend as K
# architecture,optimizer, data generator and learning rate reductor
from keras.models import Sequential
from keras.layers import Dense, Dropout, Lambda, Flatten, BatchNormalization
from keras.layers import Conv2D, MaxPool2D, AvgPool2D
from keras.optimizers import Adam
from keras.preprocessing.image import ImageDataGenerator
from keras.callbacks import ReduceLROnPlateau
```

In [21]:
```
#Model is in the form:
#INPUT LAYER -> [CONV2D -> RELU → MAXPOOL2D → DROPOUT]*3-> FLATTEN->DENSE-> OU
TPUT LAYER
model = Sequential()

dim = 28
nclasses = 10

model.add(Conv2D(filters=32, kernel_size=(5,5), padding='same', activation='re
lu', input_shape=(dim,dim,1)))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.25))



model.add(Conv2D(filters=64, kernel_size=(5,5), padding='same', activation='re
lu'))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.25))


model.add(Conv2D(filters=128, kernel_size=(5,5), padding='same', activation='r
elu'))
model.add(MaxPool2D(pool_size=(2,2), strides=(2,2)))
model.add(Dropout(0.25))


#Flatten,Dense Layer,Softmax classifier
model.add(Flatten())
model.add(Dense(256, activation='relu'))
model.add(Dense(nclasses, activation='softmax'))
```

```
WARNING:tensorflow:From c:\users\riddhi sharma\appdata\local\programs\python
\python36\lib\site-packages\tensorflow\python\framework\op_def_library.py:26
3: colocate_with (from tensorflow.python.framework.ops) is deprecated and wil
l be removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
WARNING:tensorflow:From c:\users\riddhi sharma\appdata\local\programs\python
\python36\lib\site-packages\keras\backend\tensorflow_backend.py:3445: calling
dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and
will be removed in a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - k
eep_prob`.
```

In [22]:
```
#Display Model
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv2d_1 (Conv2D)            (None, 28, 28, 32)        832       
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 14, 14, 32)        0         
_________________________________________________________________
dropout_1 (Dropout)          (None, 14, 14, 32)        0         
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 14, 14, 64)        51264     
_________________________________________________________________
max_pooling2d_2 (MaxPooling2 (None, 7, 7, 64)          0         
_________________________________________________________________
dropout_2 (Dropout)          (None, 7, 7, 64)          0         
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 7, 7, 128)         204928    
_________________________________________________________________
max_pooling2d_3 (MaxPooling2 (None, 3, 3, 128)         0         
_________________________________________________________________
dropout_3 (Dropout)          (None, 3, 3, 128)         0         
_________________________________________________________________
flatten_1 (Flatten)          (None, 1152)              0         
_________________________________________________________________
dense_1 (Dense)              (None, 256)               295168    
_________________________________________________________________
dense_2 (Dense)              (None, 10)                2570      
=================================================================
Total params: 554,762
Trainable params: 554,762
Non-trainable params: 0
_________________________________________________________________
```

In [23]:
```
#compile model using Adam optimizer
model.compile(optimizer="adam", loss="categorical_crossentropy", metrics=["acc
uracy"])
```

In [24]:
```
#setting learning annealer
lr_reduction = ReduceLROnPlateau(monitor='val_acc',
                                 patience= 3,
                                 verbose=1,
                                 factor=0.5,
                                 min_lr=0.00001)
```

In [25]:
```
#Data augmentation
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 d
ataset
          samplewise_std_normalization=False,  # divide each input by its std
          zca_whitening=False,                 # apply ZCA whitening
          rotation_range=30,                   # 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 horizon
tally (fraction of total width)
          height_shift_range=0.1,              # randomly shift images vertica
lly (fraction of total height)
          horizontal_flip=False,               # randomly flip images
          vertical_flip=False)                 # randomly flip images
```

In [26]:
```
#setting epochs and batch sizes
#Please change it to 20 and 64
epochs = 20
batch_size = 64
```

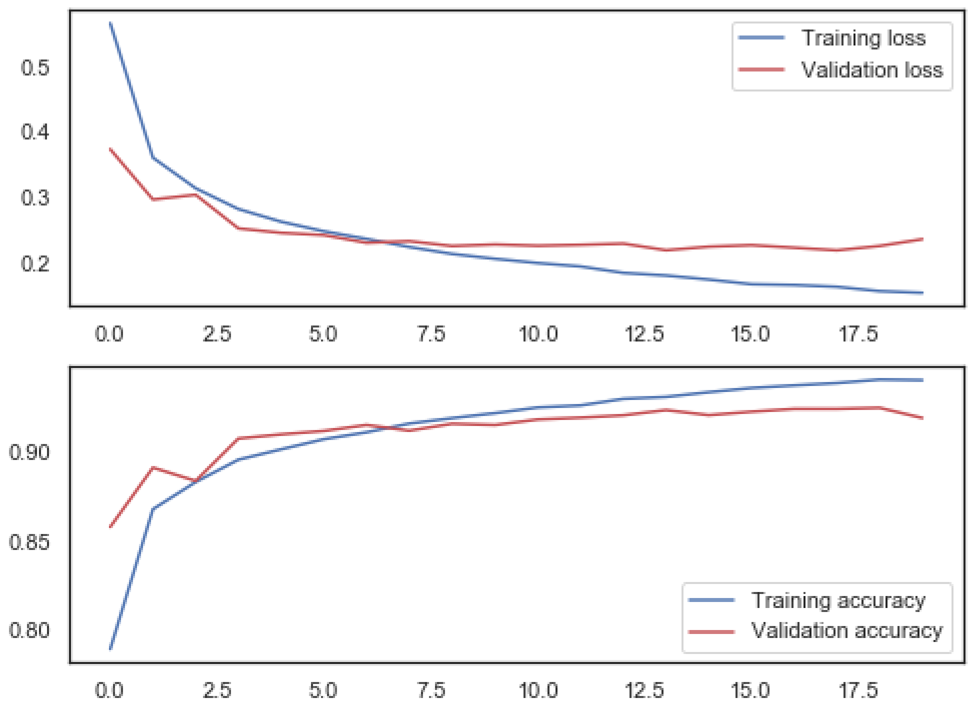
In [27]:
```
#Data fitting

history = model.fit(x=x_train,
                    y=y_train,
                    batch_size=batch_size,
                    epochs=epochs,
                    verbose=1,
                    callbacks=[lr_reduction],
                    validation_data=(x_val,y_val),
                    shuffle=True)
```

```
WARNING:tensorflow:From c:\users\riddhi sharma\appdata\local\programs\python
\python36\lib\site-packages\tensorflow\python\ops\math_ops.py:3066: to_int32
(from tensorflow.python.ops.math_ops) is deprecated and will be removed in a
future version.
Instructions for updating:
Use tf.cast instead.
Train on 48000 samples, validate on 12000 samples
Epoch 1/20
48000/48000 [==============================] - 249s 5ms/step - loss: 0.5659 -
acc: 0.7897 - val_loss: 0.3738 - val_acc: 0.8580
Epoch 2/20
48000/48000 [==============================] - 435s 9ms/step - loss: 0.3608 -
acc: 0.8679 - val_loss: 0.2970 - val_acc: 0.8912
Epoch 3/20
48000/48000 [==============================] - 448s 9ms/step - loss: 0.3141 -
acc: 0.8831 - val_loss: 0.3042 - val_acc: 0.8838
Epoch 4/20
48000/48000 [==============================] - 367s 8ms/step - loss: 0.2824 -
acc: 0.8956 - val_loss: 0.2529 - val_acc: 0.9074
Epoch 5/20
48000/48000 [==============================] - 363s 8ms/step - loss: 0.2631 -
acc: 0.9014 - val_loss: 0.2461 - val_acc: 0.9097
Epoch 6/20
48000/48000 [==============================] - 362s 8ms/step - loss: 0.2485 -
acc: 0.9070 - val_loss: 0.2427 - val_acc: 0.9117
Epoch 7/20
48000/48000 [==============================] - 309s 6ms/step - loss: 0.2369 -
acc: 0.9109 - val_loss: 0.2309 - val_acc: 0.9150
Epoch 8/20
48000/48000 [==============================] - 348s 7ms/step - loss: 0.2245 -
acc: 0.9158 - val_loss: 0.2334 - val_acc: 0.9118
Epoch 9/20
48000/48000 [==============================] - 366s 8ms/step - loss: 0.2139 -
acc: 0.9188 - val_loss: 0.2261 - val_acc: 0.9157
Epoch 10/20
48000/48000 [==============================] - 345s 7ms/step - loss: 0.2065 -
acc: 0.9216 - val_loss: 0.2284 - val_acc: 0.9150
Epoch 11/20
48000/48000 [==============================] - 382s 8ms/step - loss: 0.2000 -
acc: 0.9248 - val_loss: 0.2265 - val_acc: 0.9181
Epoch 12/20
48000/48000 [==============================] - 343s 7ms/step - loss: 0.1948 -
acc: 0.9259 - val_loss: 0.2278 - val_acc: 0.9191
Epoch 13/20
48000/48000 [==============================] - 446s 9ms/step - loss: 0.1850 -
acc: 0.9296 - val_loss: 0.2297 - val_acc: 0.9204
Epoch 14/20
48000/48000 [==============================] - 1785s 37ms/step - loss: 0.1810
- acc: 0.9307 - val_loss: 0.2196 - val_acc: 0.9233
Epoch 15/20
48000/48000 [==============================] - 330s 7ms/step - loss: 0.1749 -
acc: 0.9333 - val_loss: 0.2250 - val_acc: 0.9205
Epoch 16/20
48000/48000 [==============================] - 342s 7ms/step - loss: 0.1677 -
acc: 0.9357 - val_loss: 0.2273 - val_acc: 0.9224
Epoch 17/20
48000/48000 [==============================] - 319s 7ms/step - loss: 0.1665 -
```

```
acc: 0.9371 - val_loss: 0.2234 - val_acc: 0.9240
Epoch 18/20
48000/48000 [==============================] - 321s 7ms/step - loss: 0.1638 -
acc: 0.9384 - val_loss: 0.2194 - val_acc: 0.9240
Epoch 19/20
48000/48000 [==============================] - 373s 8ms/step - loss: 0.1571 -
acc: 0.9404 - val_loss: 0.2261 - val_acc: 0.9246
Epoch 20/20
48000/48000 [==============================] - 362s 8ms/step - loss: 0.1546 -
acc: 0.9401 - val_loss: 0.2364 - val_acc: 0.9189
```

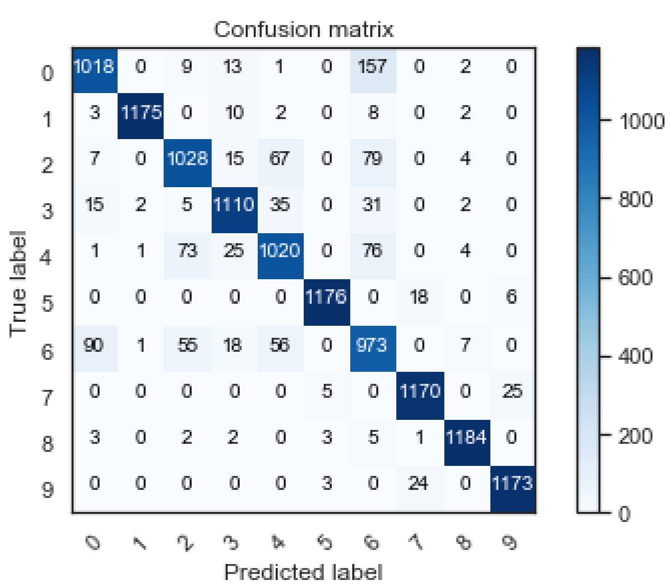
In [28]:

```python
#plotting of data

fig, ax = plt.subplots(2,figsize=(8,6))
ax[0].plot(history.history['loss'], color='b', label="Training loss")
ax[0].plot(history.history['val_loss'], color='r', label="Validation loss",axe
s =ax[0])
legend = ax[0].legend(loc='best', shadow=False)

ax[1].plot(history.history['acc'], color='b', label="Training accuracy")
ax[1].plot(history.history['val_acc'], color='r',label="Validation accuracy",a
xes=ax[1])
legend = ax[1].legend(loc='lower right', shadow=False)
```



In [29]:

```
from sklearn.metrics import confusion_matrix
import itertools
#This function is for printing and plotting of  the confusion matrix
#set normalization to true if you wish to apply
def plot_confusion_matrix(cm, classes, normalize=False, title='Confusion matri
x', cmap=plt.cm.Blues):


    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')

# Predicting the values from the validation dataset
y_predict_onehot = model.predict(x_val)
# Converting prediction classes from one hot vectors to labels
y_predict = np.argmax(y_predict_onehot,axis=1)
# Converting validation observations from one hot vectors to labels
y_true = np.argmax(y_val,axis=1)
# confusion matrix calculation
confusion_mat = confusion_matrix(y_true, y_predict)
# plotting the matrix
plot_confusion_matrix(confusion_mat, classes=range(number_classes))
```



In [30]:
```
#Plotting errors here
# array of bools with true if there is an error and false when the image is co
rrect
errors = (y_predict - y_true != 0)

y_predict_error = y_predict_onehot[errors]
y_predict_classes_error = y_predict[errors]
y_true_error = y_true[errors]
x_val_error = x_val[errors]
#This function is used for displaying 9 images with their predicted + real lab
els
def display_errors(errors_index, img_errors, pred_errors, obs_errors):

    n = 0
    num_rows = 3
    num_cols = 3
    fig, ax = plt.subplots(num_rows, num_cols, sharex=True, sharey=True,figsiz
e=(10,10))
    for row in range(num_rows):
        for col in range(num_cols):
            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[error],obs_errors[error]))
            n += 1

# Probabilities of the wrong predicted numbers
y_predict_error_prob = np.max(y_predict_error,axis=1)

# Predicted probabilities of the true values in the error set
true_prob_error = np.diagonal(np.take(y_predict_error, y_true_error, axis=1))

# Difference between the probability of the predicted label and the true label
delta_pred_true_er = y_predict_error_prob - true_prob_error

# Sorted list of the delta probability errors
sorted_delta_er = np.argsort(delta_pred_true_er)

# Top 9 errors, Range is modifiable
top_9_error = sorted_delta_er[-9:]

# Show the top 9 errors
display_errors(top_9_error, x_val_error, y_predict_classes_error, y_true_error
)
```

In [31]:
```
#Determining the accuracy score
from sklearn.metrics import accuracy_score
y_prediction_test = model.predict_classes(x_test)
print("test_acc", accuracy_score(y_test.values, y_prediction_test))
```

```
test_acc 0.9202
```

In [ ]:

In [ ]: