In [32]:

```
## Import Libraries
# if you keras is not using tensorflow as backend set "KERAS_BACKEND=tensorflow" use this command
from keras.utils import np_utils
from keras.datasets import mnist
import seaborn as sns
import pandas as pd
from keras.initializers import RandomNormal
from keras import backend as K
from keras import optimizers,losses
from keras.layers import Dense,Activation
from keras.layers import BatchNormalization,Dropout
from keras.models import Sequential
```

In [33]:

```
## Load dataset
(x_train,y_train),(x_test,y_test) = mnist.load_data()

## Loading dataset
(x_train,y_train),(x_test,y_test) = mnist.load_data()

## network parameters
img_rows,img_cols = 28,28
batch_size = 128
n_epoch = 15
classes = 10
##
x_train = x_train.reshape(x_train.shape[0], x_train.shape[1]*x_train.shape[2])
x_test = x_test.reshape(x_test.shape[0], x_test.shape[1]*x_test.shape[2])
##
print("Number of training examples :", x_train.shape[0], "and each image is of shape (%d)"%(x_train.shape[1]))
print("Number of test examples :", x_test.shape[0], "and each image is of shape (%d)"%(x_test.shape[1]))

## Normalizing the x_train dataset
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')

## one hot encode the target labels
y_train = np_utils.to_categorical(y_train,classes)
y_test = np_utils.to_categorical(y_test,classes)

##
input_dim = x_train.shape[1]
output_dim = 10
```

```
Number of training examples : 60000 and each image is of shape (784)
Number of test examples : 10000 and each image is of shape (784)
x_train shape: (60000, 784)
60000 train samples
10000 test samples
```

Model1 : 2 Layer

```
-- Without BN + Dropout
   1. number of hidden layers : 2
   2. optimizer : Adam
   3. Activation : Relu
-- With BN + Dropout
   1. number of hidden layers : 2
   2. optimizer : Adam
   3. Activation : Relu
```

Without BN + Dropout

In [34]:

```
model = Sequential()
model.add(Dense(64, activation='relu',input_shape=(input_dim,),kernel_initializer=RandomNormal(stddev=0.050))) ## he initializer sqrt(2/784) = 0.050
model.add(Dense(128, activation='relu',kernel_initializer=RandomNormal(stddev=0.176)))## he initializer sqrt(2/64) = 0.0176
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_21 (Dense)             (None, 64)                50240
_________________________________________________________________
dense_22 (Dense)             (None, 128)               8320
_________________________________________________________________
dense_23 (Dense)             (None, 10)                1290
=================================================================
Total params: 59,850
Trainable params: 59,850
Non-trainable params: 0
_________________________________________________________________
```

In [35]:

```
model.compile(optimizer='adam' ,loss='categorical_crossentropy',metrics=['accuracy'] )
```

In [36]:

```
## train the model
history = model.fit(x_train,y_train,batch_size=batch_size,epochs=n_epoch,verbose=1,validation_data=[x_test,y_test])
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 1s 25us/step - loss: 0.3552 - accuracy: 0.8990 - val_loss: 0.1816 - val_accuracy: 0.9459
Epoch 2/15
60000/60000 [==============================] - 1s 19us/step - loss: 0.1466 - accuracy: 0.9573 - val_loss: 0.1400 - val_accuracy: 0.9585
Epoch 3/15
60000/60000 [==============================] - 1s 20us/step - loss: 0.1069 - accuracy: 0.9684 - val_loss: 0.0993 - val_accuracy: 0.9684
Epoch 4/15
60000/60000 [==============================] - 1s 22us/step - loss: 0.0853 - accuracy: 0.9745 - val_loss: 0.1051 - val_accuracy: 0.9683
Epoch 5/15
60000/60000 [==============================] - 2s 27us/step - loss: 0.0685 - accuracy: 0.9794 - val_loss: 0.0847 - val_accuracy: 0.9718
Epoch 6/15
60000/60000 [==============================] - 1s 23us/step - loss: 0.0581 - accuracy: 0.9825 - val_loss: 0.0826 - val_accuracy: 0.9750
Epoch 7/15
60000/60000 [==============================] - 1s 22us/step - loss: 0.0481 - accuracy: 0.9851 - val_loss: 0.0831 - val_accuracy: 0.9734
Epoch 8/15
60000/60000 [==============================] - 1s 20us/step - loss: 0.0401 - accuracy: 0.9876 - val_loss: 0.0736 - val_accuracy: 0.9773
Epoch 9/15
60000/60000 [==============================] - 1s 24us/step - loss: 0.0336 - accuracy: 0.9897 - val_loss: 0.0793 - val_accuracy: 0.9760
Epoch 10/15
60000/60000 [==============================] - 2s 25us/step - loss: 0.0299 - accuracy: 0.9908 - val_loss: 0.0792 - val_accuracy: 0.9766
Epoch 11/15
60000/60000 [==============================] - 1s 24us/step - loss: 0.0250 - accuracy: 0.9924 - val_loss: 0.0767 - val_accuracy: 0.9776
Epoch 12/15
60000/60000 [==============================] - 1s 22us/step - loss: 0.0219 - accuracy: 0.9933 - val_loss: 0.0790 - val_accuracy: 0.9772
Epoch 13/15
60000/60000 [==============================] - 1s 24us/step - loss: 0.0203 - accuracy: 0.9939 - val_loss: 0.0800 - val_accuracy: 0.9771
Epoch 14/15
60000/60000 [==============================] - 1s 22us/step - loss: 0.0163 - accuracy: 0.9948 - val_loss: 0.0875 - val_accuracy: 0.9759
Epoch 15/15
60000/60000 [==============================] - 1s 22us/step - loss: 0.0148 - accuracy: 0.9956 - val_loss: 0.0909 - val_accuracy: 0.9746
```

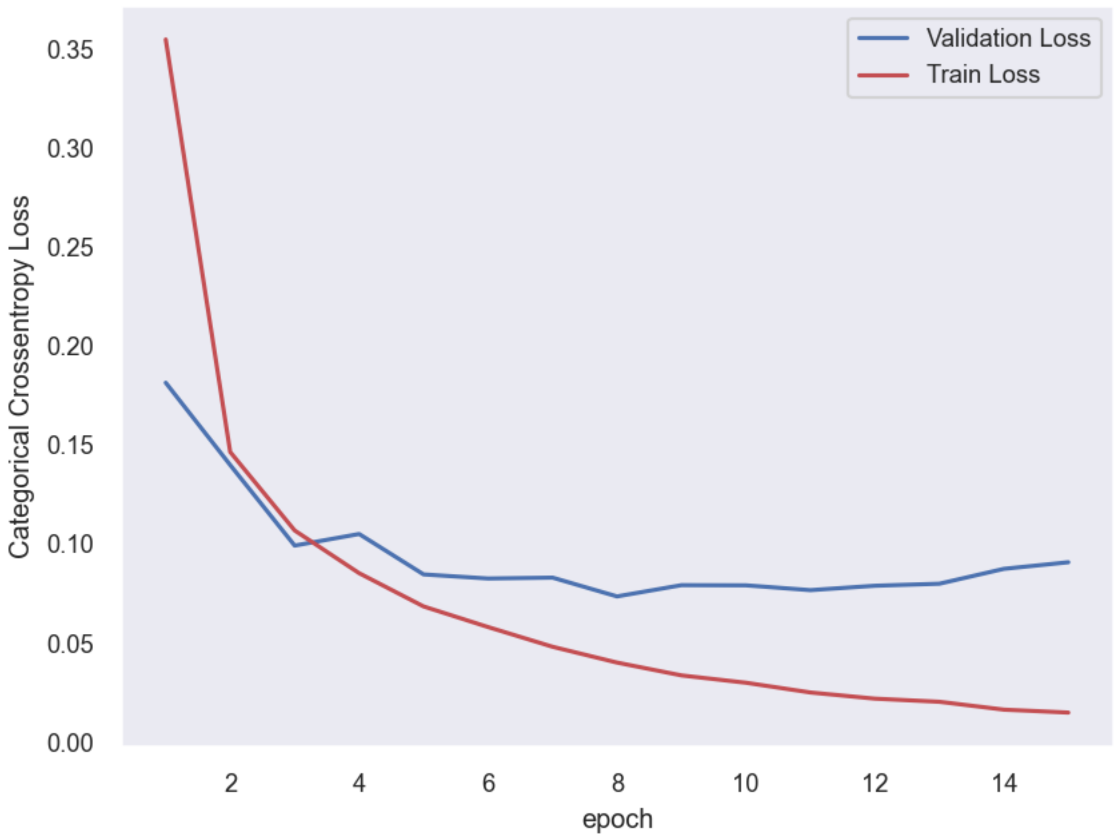
In [37]:

```
%matplotlib notebook
import matplotlib.pyplot as plt
import numpy as np
import time
# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    plt.show()
    #fig.canvas.draw()
```

In [38]:

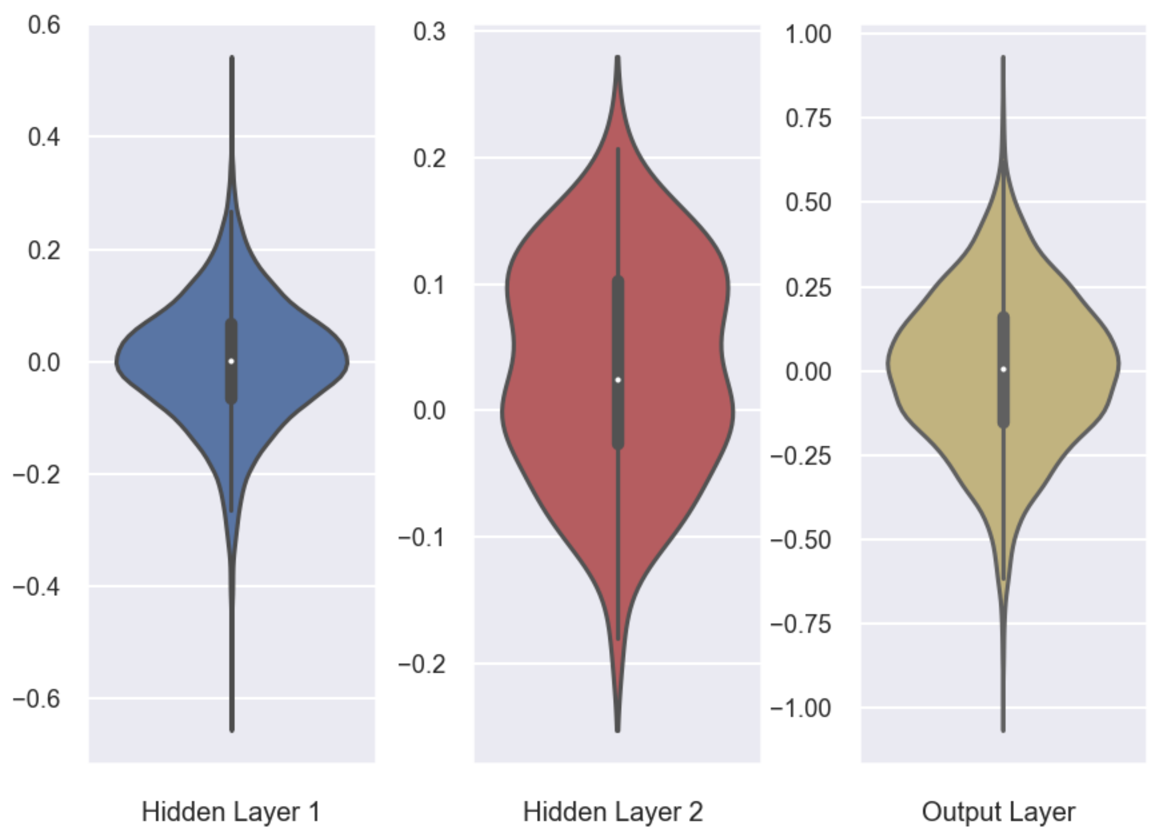
```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
fig,ax=plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,n_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
result = [[ty[-1],vy[-1],score[1]]]
```

```
Test score: 0.09085136720940645
Test accuracy: 0.9746000170707703
```



In [39]:

```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[1].flatten().reshape(-1,1)
out_w = w_after[2].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.tight_layout(pad=3.0)
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')
plt.subplot(1, 3, 2)
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')
plt.subplot(1, 3, 3)
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



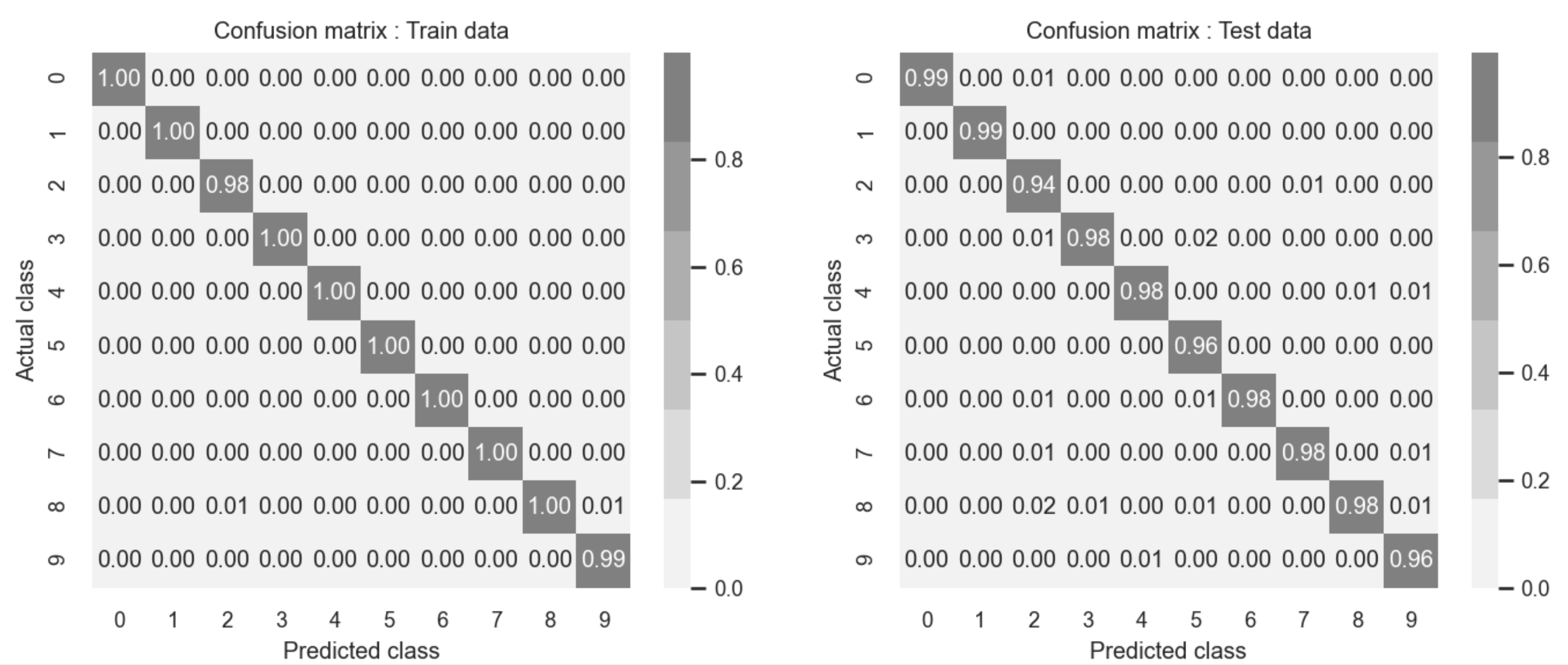
In [40]:

```
from sklearn.metrics import confusion_matrix

```

In [41]:

```
y_train_predict = model.predict(x_train)
y_test_predict = model.predict(x_test)

c=confusion_matrix(y_train.argmax(axis=1), y_train_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm1 = pd.DataFrame(normed_c, range(10), range(10))

c=confusion_matrix(y_test.argmax(axis=1), y_test_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm2 = pd.DataFrame(normed_c, range(10), range(10))

plt.figure(figsize=(11,4))
cmap=sns.light_palette("Gray")
labels =[0,1,2,3,4,5,6,7,8,9]

plt.subplot(1,2,1)
sns.set(font_scale=0.8)
sns.heatmap(df_cm1,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Train data')

plt.subplot(1,2,2)
sns.set(font_scale=0.8)
sns.heatmap(df_cm2,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Test data')
plt.show()
```

Figure 1



With BN + Dropout

In [43]:

```
model = Sequential()
model.add(Dense(64, activation='relu',input_shape=(input_dim,),kernel_initializer=RandomNormal(stddev=0.050))) ## he initializer sqrt(2/784) = 0.050
## add a batch normalization layer
model.add(BatchNormalization())
model.add(Dropout(0.25))
model.add(Dense(128, activation='relu',kernel_initializer=RandomNormal(stddev=0.176)))## he initializer sqrt(2/64) = 0.0176
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_27 (Dense)             (None, 64)                50240     
_________________________________________________________________
batch_normalization_5 (Batch (None, 64)                256       
_________________________________________________________________
dropout_5 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_28 (Dense)             (None, 128)               8320      
_________________________________________________________________
dense_29 (Dense)             (None, 10)                1290      
=================================================================
Total params: 60,106
Trainable params: 59,978
Non-trainable params: 128
_________________________________________________________________
```

In [44]:

```
model.compile(optimizer='adam' ,loss='categorical_crossentropy',metrics=['accuracy'] )
```

In [45]:

```python
## train the model
history = model.fit(x_train,y_train,batch_size=batch_size,epochs=n_epoch,verbose=1,validation_data=[x_test,y_test])
```

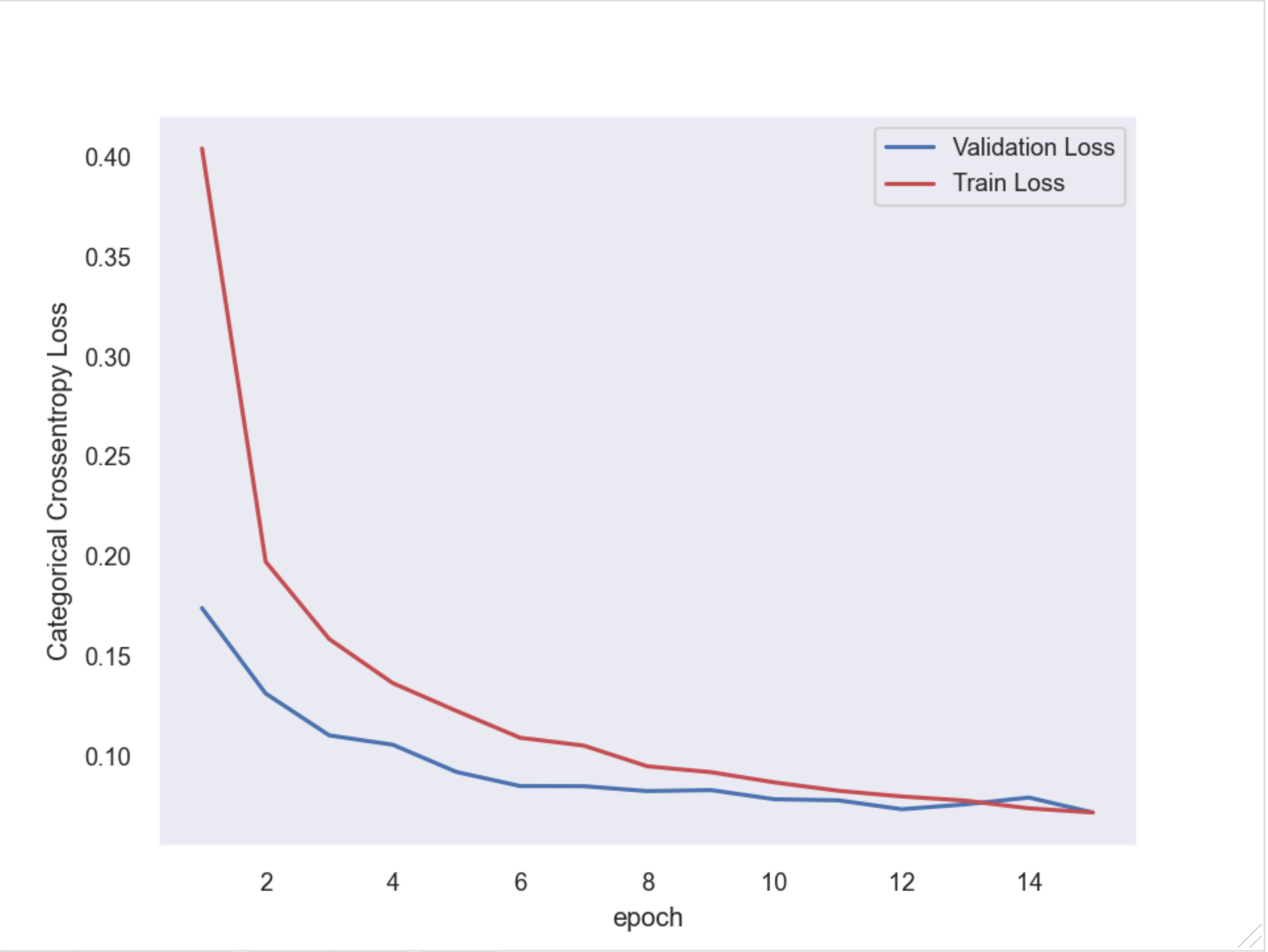
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 2s 34us/step - loss: 0.4044 - accuracy: 0.8772 - val_loss: 0.1741 - val_accuracy: 0.9461
Epoch 2/15
60000/60000 [==============================] - 1s 25us/step - loss: 0.1974 - accuracy: 0.9403 - val_loss: 0.1314 - val_accuracy: 0.9622
Epoch 3/15
60000/60000 [==============================] - 1s 25us/step - loss: 0.1586 - accuracy: 0.9516 - val_loss: 0.1104 - val_accuracy: 0.9651
Epoch 4/15
60000/60000 [==============================] - 2s 26us/step - loss: 0.1365 - accuracy: 0.9574 - val_loss: 0.1057 - val_accuracy: 0.9685
Epoch 5/15
60000/60000 [==============================] - 1s 25us/step - loss: 0.1226 - accuracy: 0.9610 - val_loss: 0.0920 - val_accuracy: 0.9718
Epoch 6/15
60000/60000 [==============================] - 1s 25us/step - loss: 0.1092 - accuracy: 0.9657 - val_loss: 0.0850 - val_accuracy: 0.9741
Epoch 7/15
60000/60000 [==============================] - 2s 30us/step - loss: 0.1052 - accuracy: 0.9672 - val_loss: 0.0849 - val_accuracy: 0.9740
Epoch 8/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0949 - accuracy: 0.9696 - val_loss: 0.0824 - val_accuracy: 0.9749
Epoch 9/15
60000/60000 [==============================] - 2s 30us/step - loss: 0.0919 - accuracy: 0.9711 - val_loss: 0.0830 - val_accuracy: 0.9745
Epoch 10/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0868 - accuracy: 0.9720 - val_loss: 0.0784 - val_accuracy: 0.9755
Epoch 11/15
60000/60000 [==============================] - 2s 27us/step - loss: 0.0826 - accuracy: 0.9740 - val_loss: 0.0778 - val_accuracy: 0.9765
Epoch 12/15
60000/60000 [==============================] - 2s 27us/step - loss: 0.0798 - accuracy: 0.9751 - val_loss: 0.0734 - val_accuracy: 0.9780
Epoch 13/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0777 - accuracy: 0.9744 - val_loss: 0.0758 - val_accuracy: 0.9763
Epoch 14/15
60000/60000 [==============================] - 2s 27us/step - loss: 0.0738 - accuracy: 0.9759 - val_loss: 0.0792 - val_accuracy: 0.9750
Epoch 15/15
60000/60000 [==============================] - 2s 27us/step - loss: 0.0717 - accuracy: 0.9767 - val_loss: 0.0718 - val_accuracy: 0.9778
```

In [46]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
fig,ax=plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,n_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)

result.append([ty[-1],vy[-1],score[1]])
```

```
Test score: 0.07176502713353838
Test accuracy: 0.9778000116348267
```

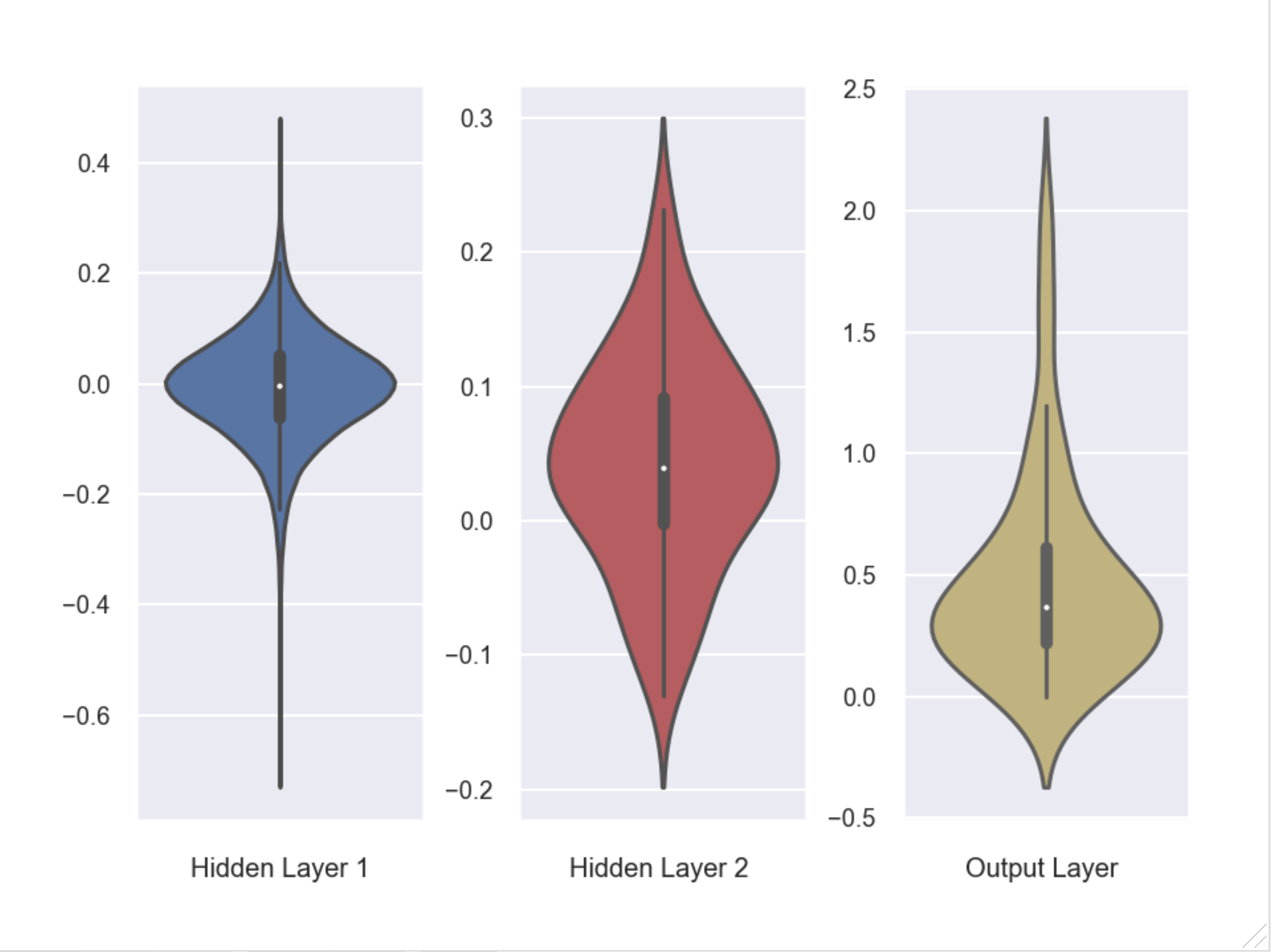
Figure 2



In [47]:

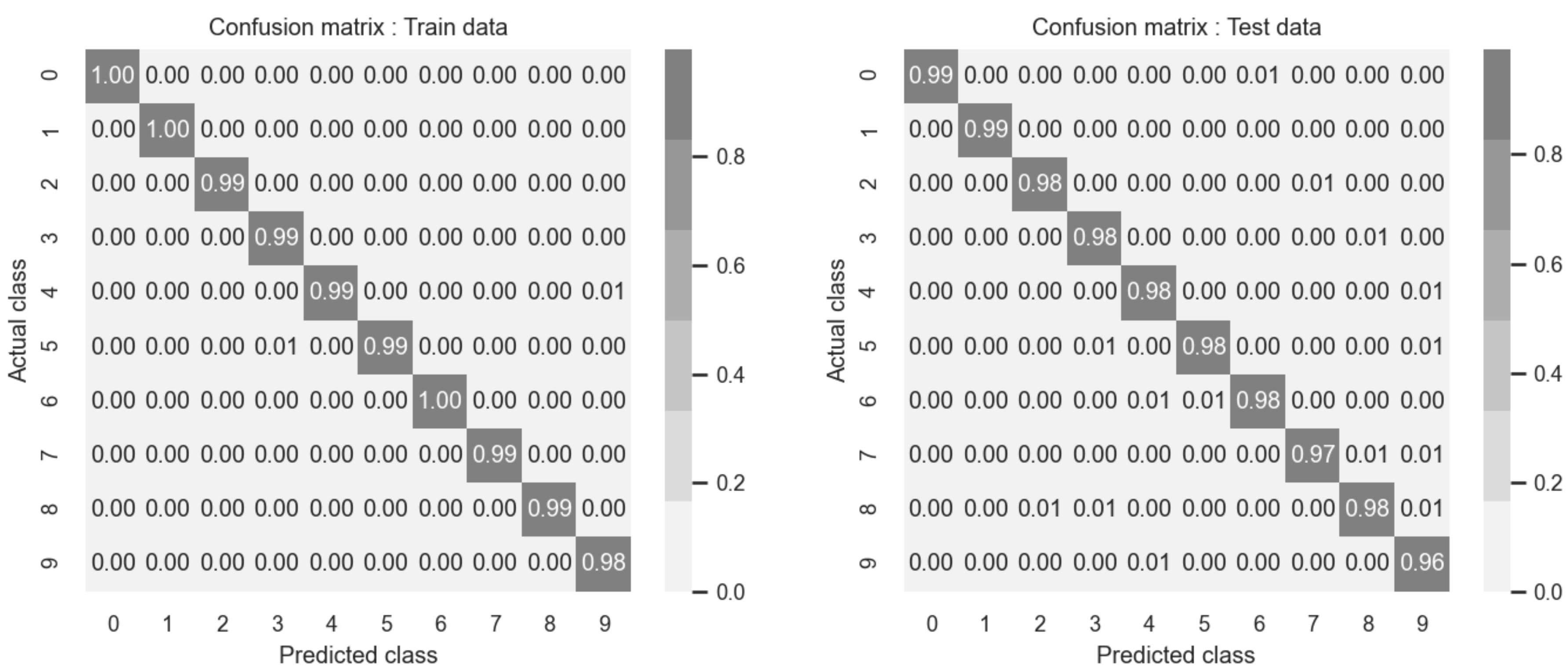
```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[3].flatten().reshape(-1,1)
out_w = w_after[4].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 3, 1)
plt.tight_layout(pad=3.0)
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')
plt.subplot(1, 3, 2)
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')
plt.subplot(1, 3, 3)
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

Figure 3



In [48]:

```
y_train_predict = model.predict(x_train)
y_test_predict = model.predict(x_test)

c=confusion_matrix(y_train.argmax(axis=1), y_train_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm1 = pd.DataFrame(normed_c, range(10), range(10))

c=confusion_matrix(y_test.argmax(axis=1), y_test_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm2 = pd.DataFrame(normed_c, range(10), range(10))

plt.figure(figsize=(11,4))
cmap=sns.light_palette("Gray")
labels =[0,1,2,3,4,5,6,7,8,9]

plt.subplot(1,2,1)
sns.set(font_scale=0.8)
sns.heatmap(df_cm1,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Train data')

plt.subplot(1,2,2)
sns.set(font_scale=0.8)
sns.heatmap(df_cm2,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Test data')
plt.show()
```



Model2 : 3 Layer

```
-- Without BN + Dropout
   1. number of hidden layers : 3
   2. optimizer : Adam
   3. Activation : Relu
-- With BN + Dropout
   1. number of hidden layers : 3
   2. optimizer : Adam
   3. Activation : Relu
```

Without BN + Dropout

In [49]:

```
model = Sequential()
model.add(Dense(64, activation='relu',input_shape=(input_dim,),kernel_initializer=RandomNormal(stddev=0.050))) ## he initializer sqrt(2/784) = 0.050
model.add(Dense(128, activation='relu',kernel_initializer=RandomNormal(stddev=0.176)))## he initializer sqrt(2/64) = 0.0176
model.add(Dense(256, activation='relu',kernel_initializer=RandomNormal(stddev=0.125)))## he initializer sqrt(2/128) =0.125
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_30 (Dense)             (None, 64)                50240     
_________________________________________________________________
dense_31 (Dense)             (None, 128)               8320      
_________________________________________________________________
dense_32 (Dense)             (None, 256)               33024     
_________________________________________________________________
dense_33 (Dense)             (None, 10)                2570      
=================================================================
Total params: 94,154
Trainable params: 94,154
Non-trainable params: 0
_________________________________________________________________
```

In [50]:

```
model.compile(optimizer='adam' ,loss='categorical_crossentropy',metrics=['accuracy'] )
```

In [51]:

```
## train the model
history = model.fit(x_train,y_train,batch_size=batch_size,epochs=n_epoch,verbose=1,validation_data=[x_test,y_test])
```

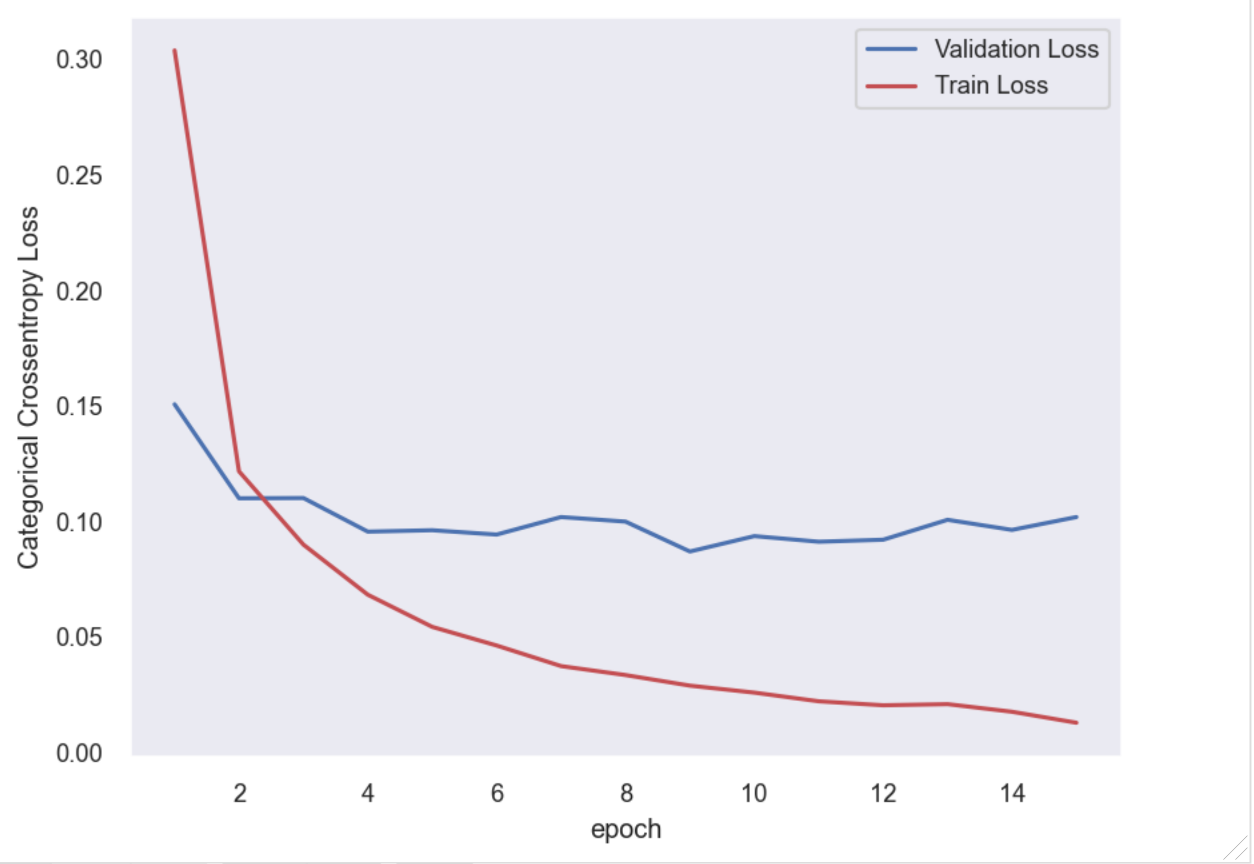
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 2s 30us/step - loss: 0.3039 - accuracy: 0.9090 - val_loss: 0.1508 - val_accuracy: 0.9534
Epoch 2/15
60000/60000 [==============================] - 2s 25us/step - loss: 0.1217 - accuracy: 0.9631 - val_loss: 0.1101 - val_accuracy: 0.9672
Epoch 3/15
60000/60000 [==============================] - 1s 24us/step - loss: 0.0900 - accuracy: 0.9722 - val_loss: 0.1102 - val_accuracy: 0.9670
Epoch 4/15
60000/60000 [==============================] - 2s 25us/step - loss: 0.0683 - accuracy: 0.9784 - val_loss: 0.0956 - val_accuracy: 0.9718
Epoch 5/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0544 - accuracy: 0.9826 - val_loss: 0.0962 - val_accuracy: 0.9723
Epoch 6/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0463 - accuracy: 0.9850 - val_loss: 0.0944 - val_accuracy: 0.9734
Epoch 7/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0374 - accuracy: 0.9876 - val_loss: 0.1019 - val_accuracy: 0.9724
Epoch 8/15
60000/60000 [==============================] - 2s 31us/step - loss: 0.0335 - accuracy: 0.9884 - val_loss: 0.1000 - val_accuracy: 0.9721
Epoch 9/15
60000/60000 [==============================] - 2s 31us/step - loss: 0.0290 - accuracy: 0.9906 - val_loss: 0.0870 - val_accuracy: 0.9765
Epoch 10/15
60000/60000 [==============================] - 2s 28us/step - loss: 0.0259 - accuracy: 0.9913 - val_loss: 0.0937 - val_accuracy: 0.9755
Epoch 11/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0222 - accuracy: 0.9924 - val_loss: 0.0913 - val_accuracy: 0.9777
Epoch 12/15
60000/60000 [==============================] - 2s 27us/step - loss: 0.0205 - accuracy: 0.9928 - val_loss: 0.0921 - val_accuracy: 0.9766
Epoch 13/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0210 - accuracy: 0.9931 - val_loss: 0.1008 - val_accuracy: 0.9745
Epoch 14/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0177 - accuracy: 0.9937 - val_loss: 0.0964 - val_accuracy: 0.9760
Epoch 15/15
60000/60000 [==============================] - 2s 29us/step - loss: 0.0129 - accuracy: 0.9955 - val_loss: 0.1019 - val_accuracy: 0.9758
```

In [52]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
fig,ax=plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,n_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
result.append([ty[-1],vy[-1],score[1]])
```

```
Test score: 0.10194387945031066
Test accuracy: 0.9757999777793884
```

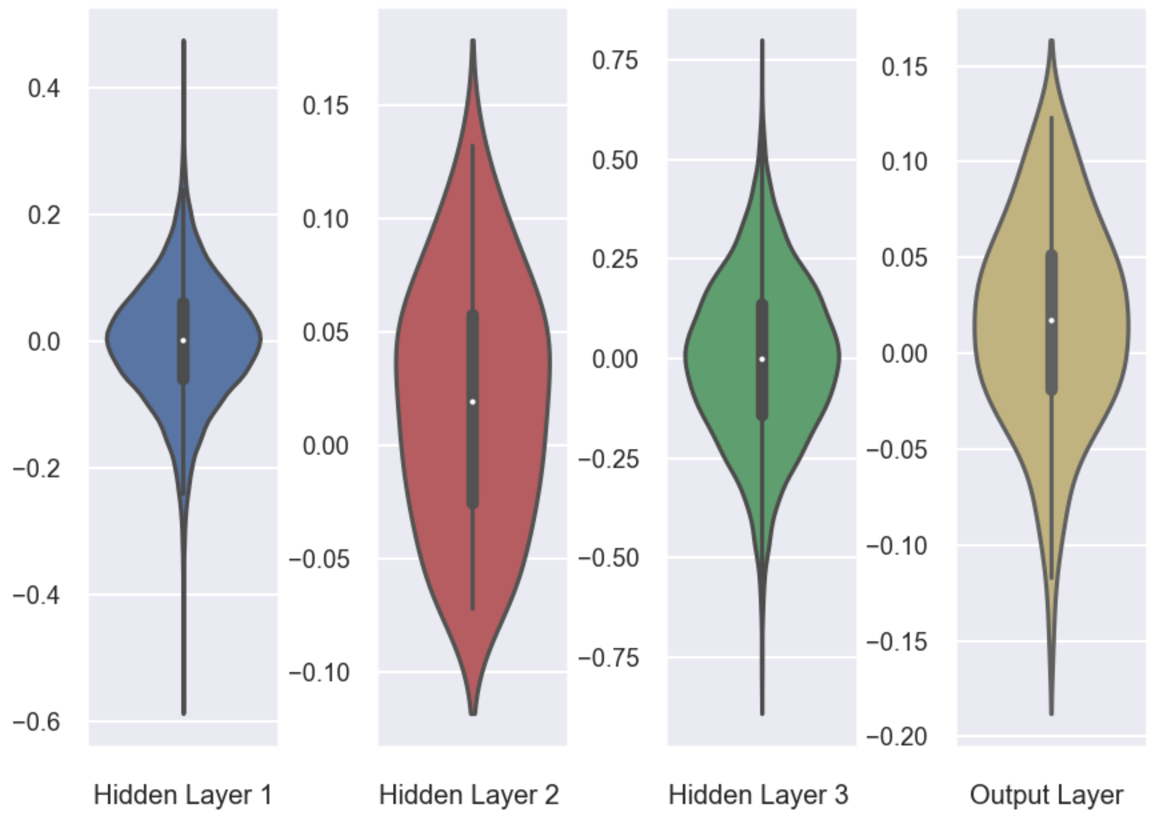
Figure 4



x=15.62 y=0.0766

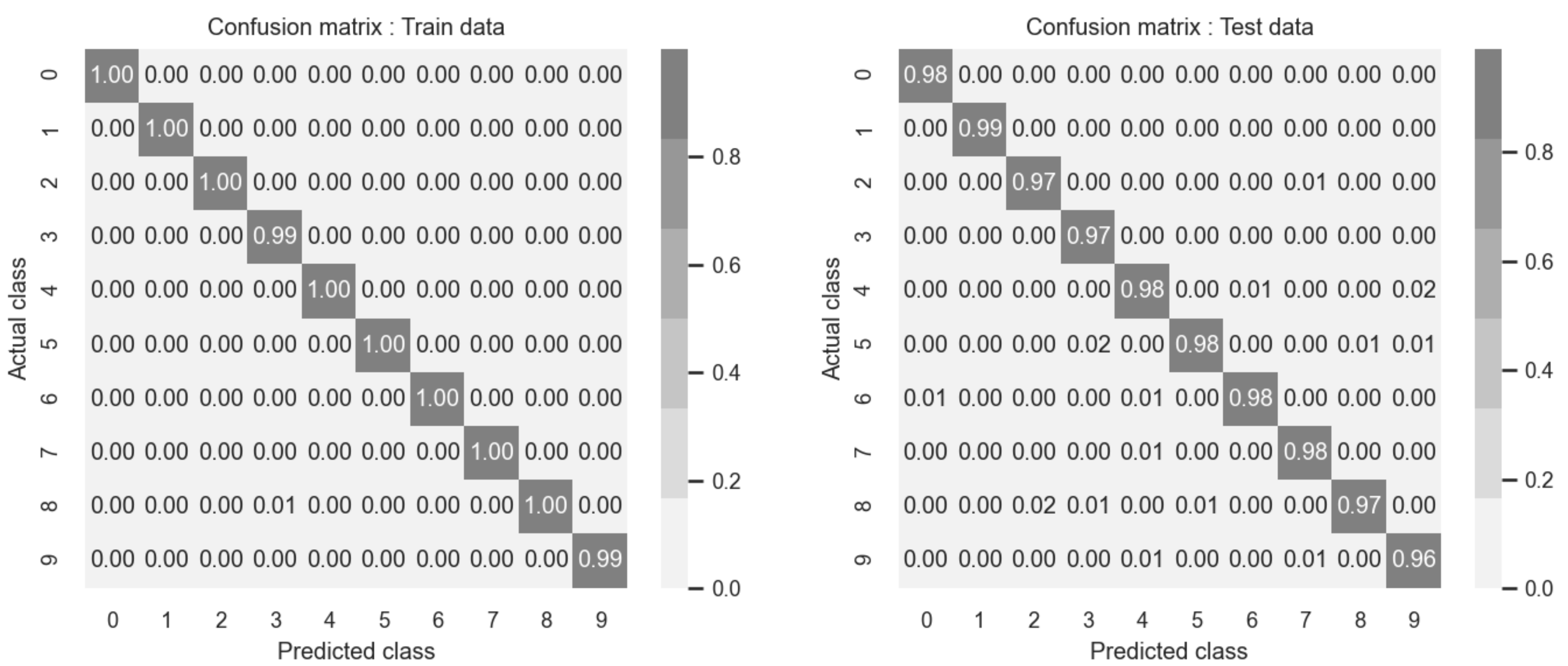
In [53]:

```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[1].flatten().reshape(-1,1)
h3_w = w_after[2].flatten().reshape(-1,1)
out_w = w_after[3].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.tight_layout(pad=3.0)
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')
plt.subplot(1, 4, 2)
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')
plt.subplot(1, 4, 3)
ax = sns.violinplot(y=h3_w,color='g')
plt.xlabel('Hidden Layer 3 ')
plt.subplot(1, 4, 4)
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```



In [54]:

```
y_train_predict = model.predict(x_train)
y_test_predict = model.predict(x_test)

c=confusion_matrix(y_train.argmax(axis=1), y_train_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm1 = pd.DataFrame(normed_c, range(10), range(10))

c=confusion_matrix(y_test.argmax(axis=1), y_test_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm2 = pd.DataFrame(normed_c, range(10), range(10))

plt.figure(figsize=(11,4))
cmap=sns.light_palette("Gray")
labels =[0,1,2,3,4,5,6,7,8,9]

plt.subplot(1,2,1)
sns.set(font_scale=0.8)
sns.heatmap(df_cm1,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Train data')

plt.subplot(1,2,2)
sns.set(font_scale=0.8)
sns.heatmap(df_cm2,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Test data')
plt.show()
```



With BN + Dropout

In [55]:
```
model = Sequential()
model.add(Dense(64, activation='relu',input_shape=(input_dim,),kernel_initializer=RandomNormal(stddev=0.050))) ## he initializer sqrt(2/784) = 0.050
model.add(Dense(128, activation='relu',kernel_initializer=RandomNormal(stddev=0.176)))## he initializer sqrt(2/64) = 0.0176
model.add(BatchNormalization())
model.add(Dropout(0.25))
model.add(Dense(256, activation='relu',kernel_initializer=RandomNormal(stddev=0.125)))## he initializer sqrt(2/128) =0.125
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_34 (Dense)             (None, 64)                50240     
_________________________________________________________________
dense_35 (Dense)             (None, 128)               8320      
_________________________________________________________________
batch_normalization_6 (Batch (None, 128)               512       
_________________________________________________________________
dropout_6 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_36 (Dense)             (None, 256)               33024     
_________________________________________________________________
batch_normalization_7 (Batch (None, 256)               1024      
_________________________________________________________________
dropout_7 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_37 (Dense)             (None, 10)                2570      
=================================================================
Total params: 95,690
Trainable params: 94,922
Non-trainable params: 768
_________________________________________________________________
```

In [56]:
```
model.compile(optimizer='adam' ,loss='categorical_crossentropy',metrics=['accuracy'] )
```

In [57]:

```
## train the model
history = model.fit(x_train,y_train,batch_size=batch_size,epochs=n_epoch,verbose=1,validation_data=[x_test,y_test])
```

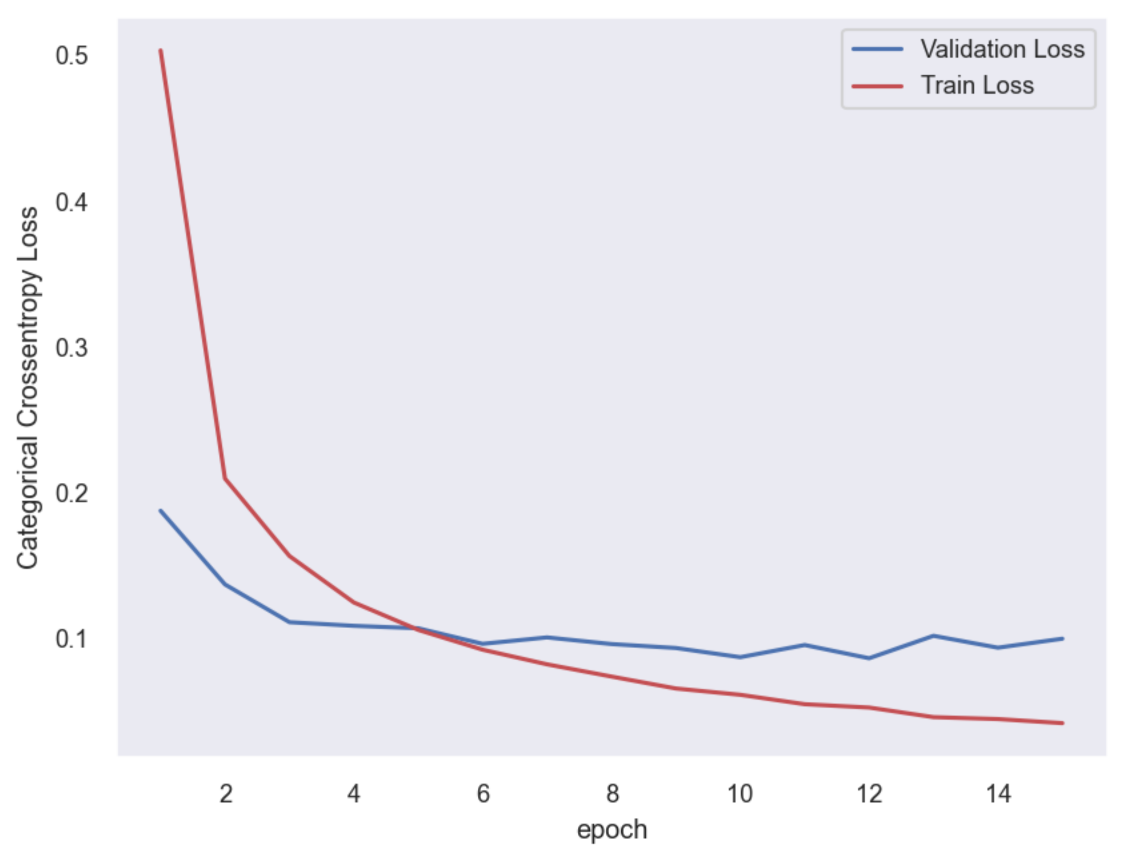
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 3s 49us/step - loss: 0.5035 - accuracy: 0.8484 - val_loss: 0.1878 - val_accuracy: 0.9441
Epoch 2/15
60000/60000 [==============================] - 2s 41us/step - loss: 0.2099 - accuracy: 0.9378 - val_loss: 0.1373 - val_accuracy: 0.9581
Epoch 3/15
60000/60000 [==============================] - 3s 44us/step - loss: 0.1568 - accuracy: 0.9530 - val_loss: 0.1114 - val_accuracy: 0.9670
Epoch 4/15
60000/60000 [==============================] - 3s 52us/step - loss: 0.1249 - accuracy: 0.9621 - val_loss: 0.1089 - val_accuracy: 0.9676
Epoch 5/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.1061 - accuracy: 0.9679 - val_loss: 0.1072 - val_accuracy: 0.9670
Epoch 6/15
60000/60000 [==============================] - 3s 51us/step - loss: 0.0925 - accuracy: 0.9715 - val_loss: 0.0965 - val_accuracy: 0.9694
Epoch 7/15
60000/60000 [==============================] - 3s 46us/step - loss: 0.0825 - accuracy: 0.9740 - val_loss: 0.1009 - val_accuracy: 0.9700
Epoch 8/15
60000/60000 [==============================] - 3s 48us/step - loss: 0.0741 - accuracy: 0.9766 - val_loss: 0.0964 - val_accuracy: 0.9723
Epoch 9/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0659 - accuracy: 0.9795 - val_loss: 0.0937 - val_accuracy: 0.9737
Epoch 10/15
60000/60000 [==============================] - 3s 48us/step - loss: 0.0616 - accuracy: 0.9810 - val_loss: 0.0874 - val_accuracy: 0.9756
Epoch 11/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0551 - accuracy: 0.9825 - val_loss: 0.0957 - val_accuracy: 0.9735
Epoch 12/15
60000/60000 [==============================] - 3s 48us/step - loss: 0.0528 - accuracy: 0.9831 - val_loss: 0.0866 - val_accuracy: 0.9768
Epoch 13/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0462 - accuracy: 0.9853 - val_loss: 0.1020 - val_accuracy: 0.9733
Epoch 14/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0449 - accuracy: 0.9853 - val_loss: 0.0939 - val_accuracy: 0.9747
Epoch 15/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.0421 - accuracy: 0.9862 - val_loss: 0.1000 - val_accuracy: 0.9739
```

In [58]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
fig,ax=plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,n_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
result.append([ty[-1],vy[-1],score[1]])
```

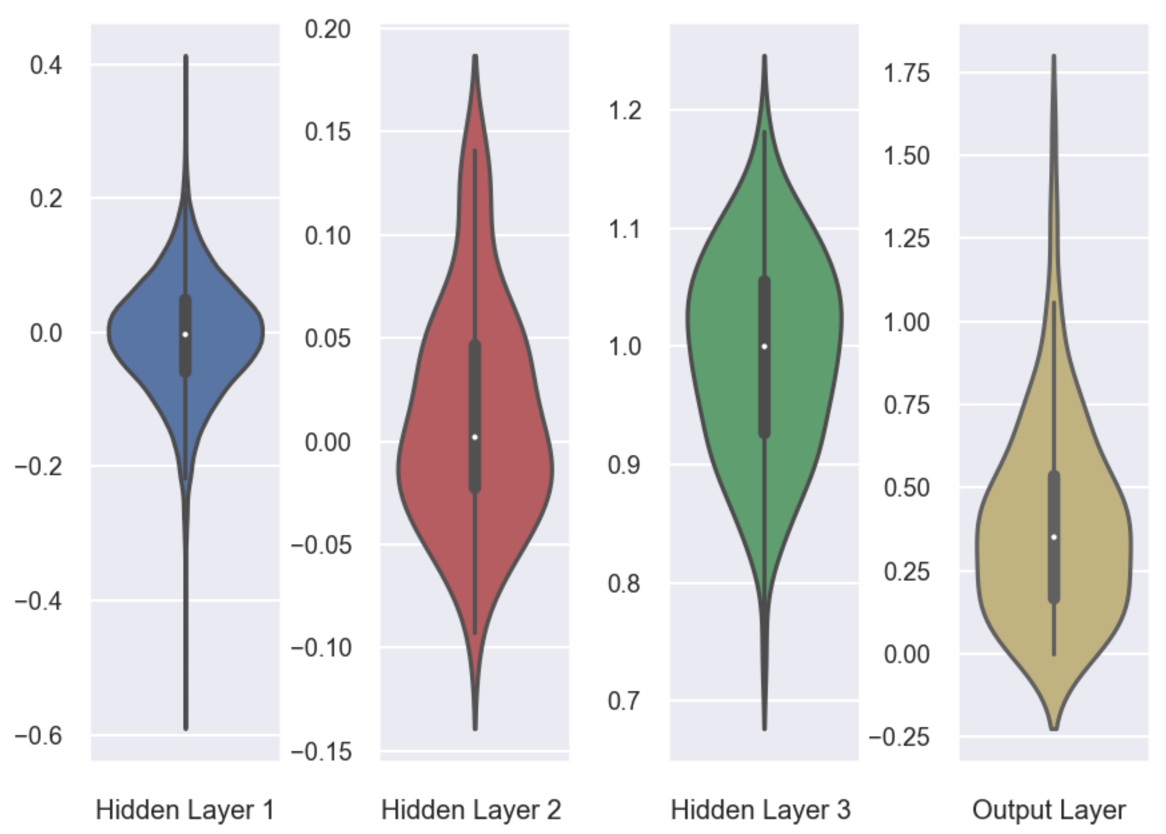
```
Test score: 0.10004436637778999
Test accuracy: 0.9739000201225281
```

Figure 5



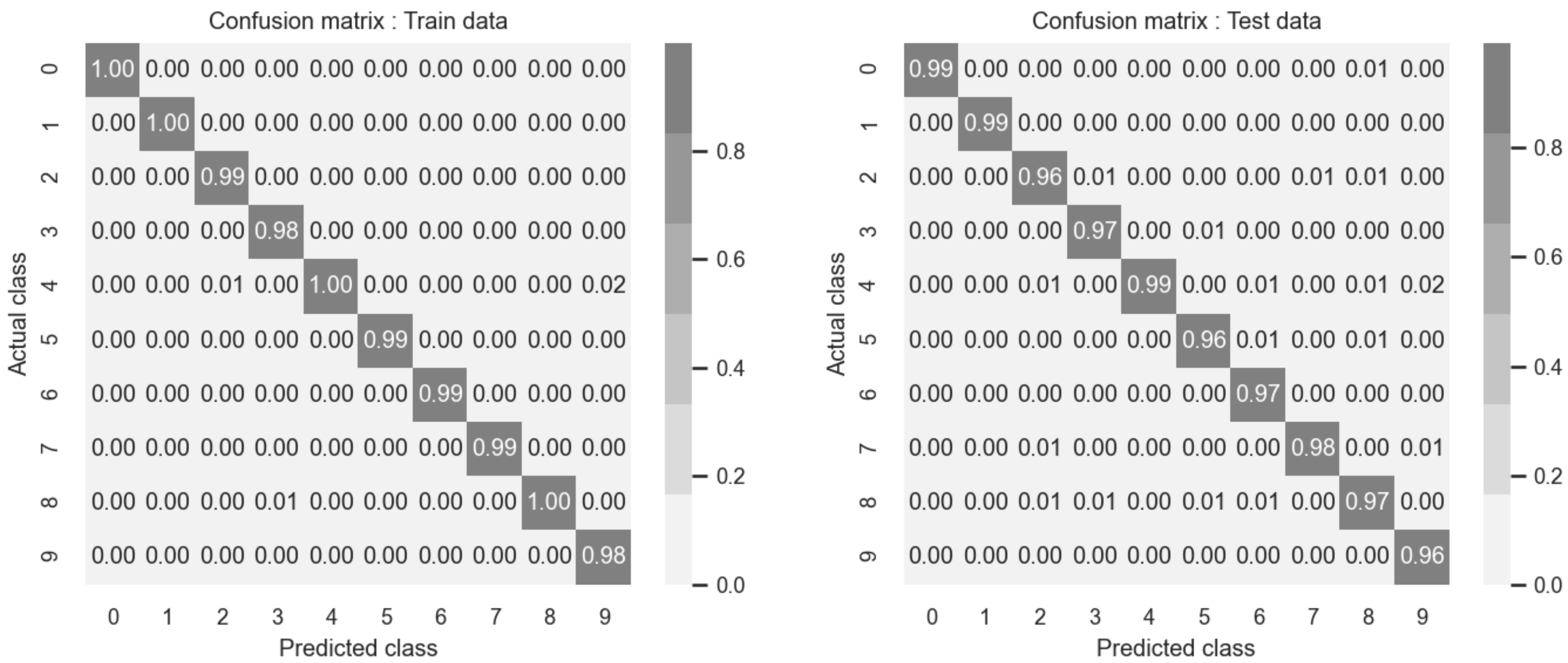
In [59]:
```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[1].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[7].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(1, 4, 1)
plt.tight_layout(pad=3.0)
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')
plt.subplot(1, 4, 2)
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')
plt.subplot(1, 4, 3)
ax = sns.violinplot(y=h3_w,color='g')
plt.xlabel('Hidden Layer 3 ')
plt.subplot(1, 4, 4)
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

Figure 6



In [60]:

```python
y_train_predict = model.predict(x_train)
y_test_predict = model.predict(x_test)

c=confusion_matrix(y_train.argmax(axis=1), y_train_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm1 = pd.DataFrame(normed_c, range(10), range(10))

c=confusion_matrix(y_test.argmax(axis=1), y_test_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm2 = pd.DataFrame(normed_c, range(10), range(10))

plt.figure(figsize=(11,4))
cmap=sns.light_palette("Gray")
labels =[0,1,2,3,4,5,6,7,8,9]

plt.subplot(1,2,1)
sns.set(font_scale=0.8)
sns.heatmap(df_cm1,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Train data')

plt.subplot(1,2,2)
sns.set(font_scale=0.8)
sns.heatmap(df_cm2,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Test data')
plt.show()
```



Model3 : 5 Layer

```
-- Without BN + Dropout
   1. number of hidden layers : 5
   2. optimizer : Adam
   3. Activation : Relu
-- With BN + Dropout
   1. number of hidden layers : 5
   2. optimizer : Adam
   3. Activation : Relu
```

Without BN + Dropout

In [64]:

```
model = Sequential()
model.add(Dense(32, activation='relu',input_shape=(input_dim,),kernel_initializer=RandomNormal(stddev=0.125)))## he initializer sqrt(2/784) =0.050
model.add(Dense(64, activation='relu',kernel_initializer=RandomNormal(stddev=0.25))) ## he initializer sqrt(2/32) = 0.25
model.add(Dense(128, activation='relu',kernel_initializer=RandomNormal(stddev=0.176)))## he initializer sqrt(2/64) = 0.17
model.add(Dense(256, activation='relu',kernel_initializer=RandomNormal(stddev=0.125)))## he initializer sqrt(2/128) =0.125
model.add(Dense(512, activation='relu',kernel_initializer=RandomNormal(stddev=0.088)))## he initializer sqrt(2/256) =0.088
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_44 (Dense)             (None, 32)                25120
_________________________________________________________________
dense_45 (Dense)             (None, 64)                2112
_________________________________________________________________
dense_46 (Dense)             (None, 128)               8320
_________________________________________________________________
dense_47 (Dense)             (None, 256)               33024
_________________________________________________________________
dense_48 (Dense)             (None, 512)               131584
_________________________________________________________________
dense_49 (Dense)             (None, 10)                5130
=================================================================
Total params: 205,290
Trainable params: 205,290
Non-trainable params: 0
_________________________________________________________________
```

In [65]:

```
model.compile(optimizer='adam' ,loss='categorical_crossentropy',metrics=['accuracy'] )
```

In [66]:

```
## train the model
history = model.fit(x_train,y_train,batch_size=batch_size,epochs=n_epoch,verbose=1,validation_data=[x_test,y_test])
```

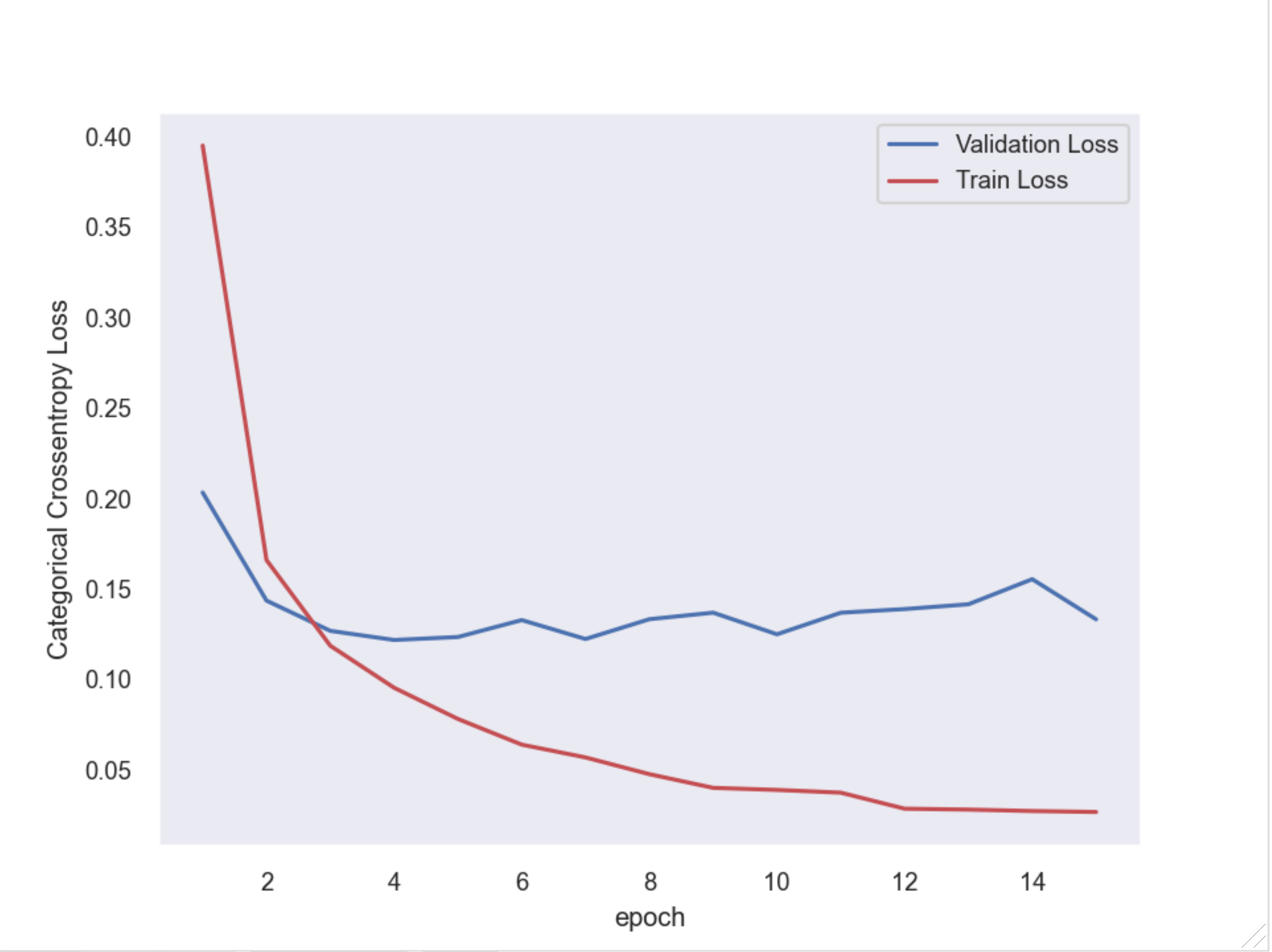
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 3s 52us/step - loss: 0.3952 - accuracy: 0.8754 - val_loss: 0.2033 - val_accuracy: 0.9386
Epoch 2/15
60000/60000 [==============================] - 3s 45us/step - loss: 0.1660 - accuracy: 0.9489 - val_loss: 0.1436 - val_accuracy: 0.9562
Epoch 3/15
60000/60000 [==============================] - 3s 54us/step - loss: 0.1186 - accuracy: 0.9630 - val_loss: 0.1268 - val_accuracy: 0.9611
Epoch 4/15
60000/60000 [==============================] - 3s 48us/step - loss: 0.0954 - accuracy: 0.9689 - val_loss: 0.1218 - val_accuracy: 0.9618
Epoch 5/15
60000/60000 [==============================] - 3s 52us/step - loss: 0.0781 - accuracy: 0.9744 - val_loss: 0.1234 - val_accuracy: 0.9631
Epoch 6/15
60000/60000 [==============================] - 3s 55us/step - loss: 0.0639 - accuracy: 0.9795 - val_loss: 0.1328 - val_accuracy: 0.9635
Epoch 7/15
60000/60000 [==============================] - 3s 51us/step - loss: 0.0568 - accuracy: 0.9815 - val_loss: 0.1223 - val_accuracy: 0.9665
Epoch 8/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0476 - accuracy: 0.9839 - val_loss: 0.1333 - val_accuracy: 0.9661
Epoch 9/15
60000/60000 [==============================] - 4s 59us/step - loss: 0.0400 - accuracy: 0.9867 - val_loss: 0.1369 - val_accuracy: 0.9676
Epoch 10/15
60000/60000 [==============================] - 4s 67us/step - loss: 0.0389 - accuracy: 0.9871 - val_loss: 0.1249 - val_accuracy: 0.9691
Epoch 11/15
60000/60000 [==============================] - 3s 51us/step - loss: 0.0373 - accuracy: 0.9878 - val_loss: 0.1369 - val_accuracy: 0.9671
Epoch 12/15
60000/60000 [==============================] - 3s 49us/step - loss: 0.0285 - accuracy: 0.9910 - val_loss: 0.1389 - val_accuracy: 0.9679
Epoch 13/15
60000/60000 [==============================] - 3s 48us/step - loss: 0.0280 - accuracy: 0.9908 - val_loss: 0.1415 - val_accuracy: 0.9696
Epoch 14/15
60000/60000 [==============================] - 3s 51us/step - loss: 0.0272 - accuracy: 0.9909 - val_loss: 0.1554 - val_accuracy: 0.9671
Epoch 15/15
60000/60000 [==============================] - 3s 48us/step - loss: 0.0267 - accuracy: 0.9910 - val_loss: 0.1332 - val_accuracy: 0.9698
```

In [67]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
fig,ax=plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,n_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
result.append([ty[-1],vy[-1],score[1]])
```

```
Test score: 0.13321278729955158
Test accuracy: 0.9697999954223633
```

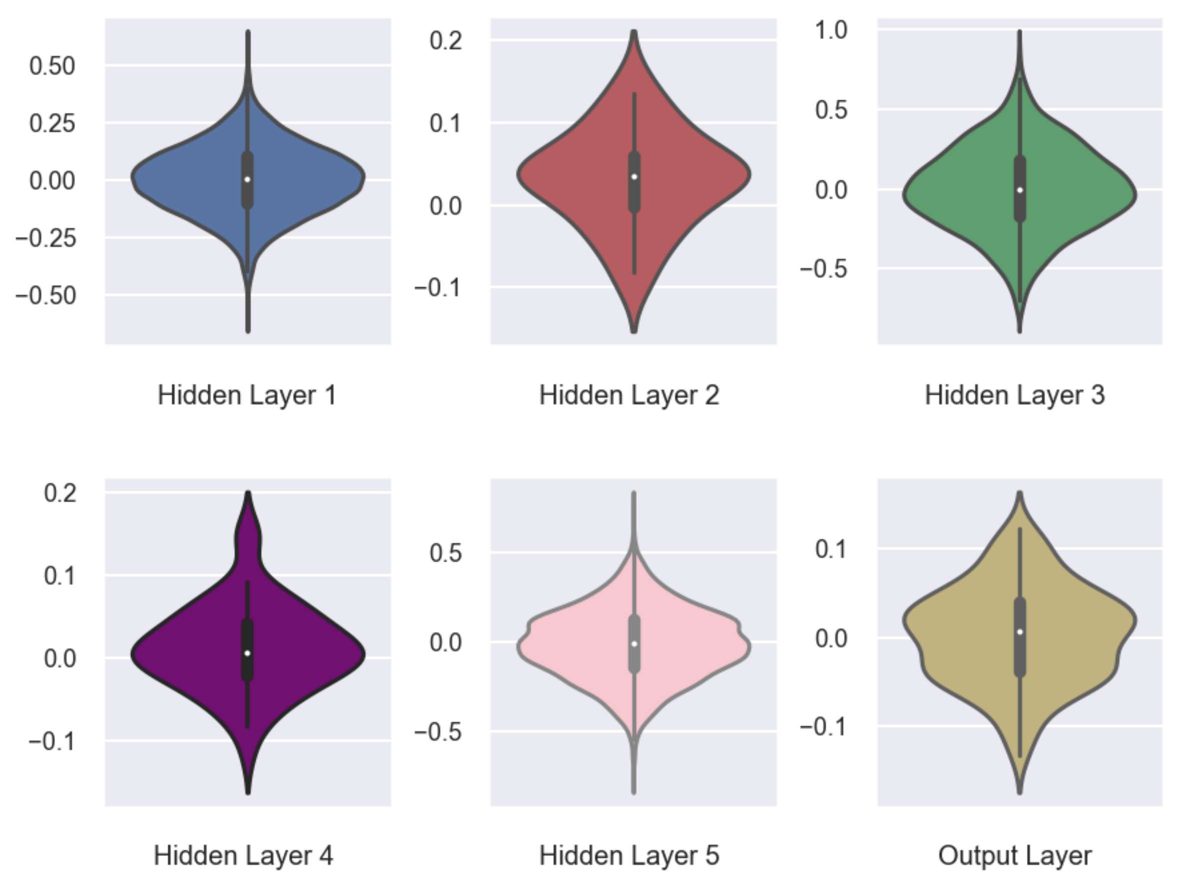
Figure 7



In [68]:

```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[1].flatten().reshape(-1,1)
h3_w = w_after[2].flatten().reshape(-1,1)
h4_w = w_after[3].flatten().reshape(-1,1)
h5_w = w_after[4].flatten().reshape(-1,1)
out_w = w_after[5].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
plt.tight_layout(pad=3.0)
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')
plt.subplot(2, 3, 2)
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')
plt.subplot(2, 3,3)
ax = sns.violinplot(y=h3_w,color='g')
plt.xlabel('Hidden Layer 3 ')
plt.subplot(2, 3, 4)
ax = sns.violinplot(y=h4_w,color='purple')
plt.xlabel('Hidden Layer 4 ')
plt.subplot(2, 3, 5)
ax = sns.violinplot(y=h5_w,color='pink')
plt.xlabel('Hidden Layer 5 ')
plt.subplot(2, 3, 6)
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

Figure 8

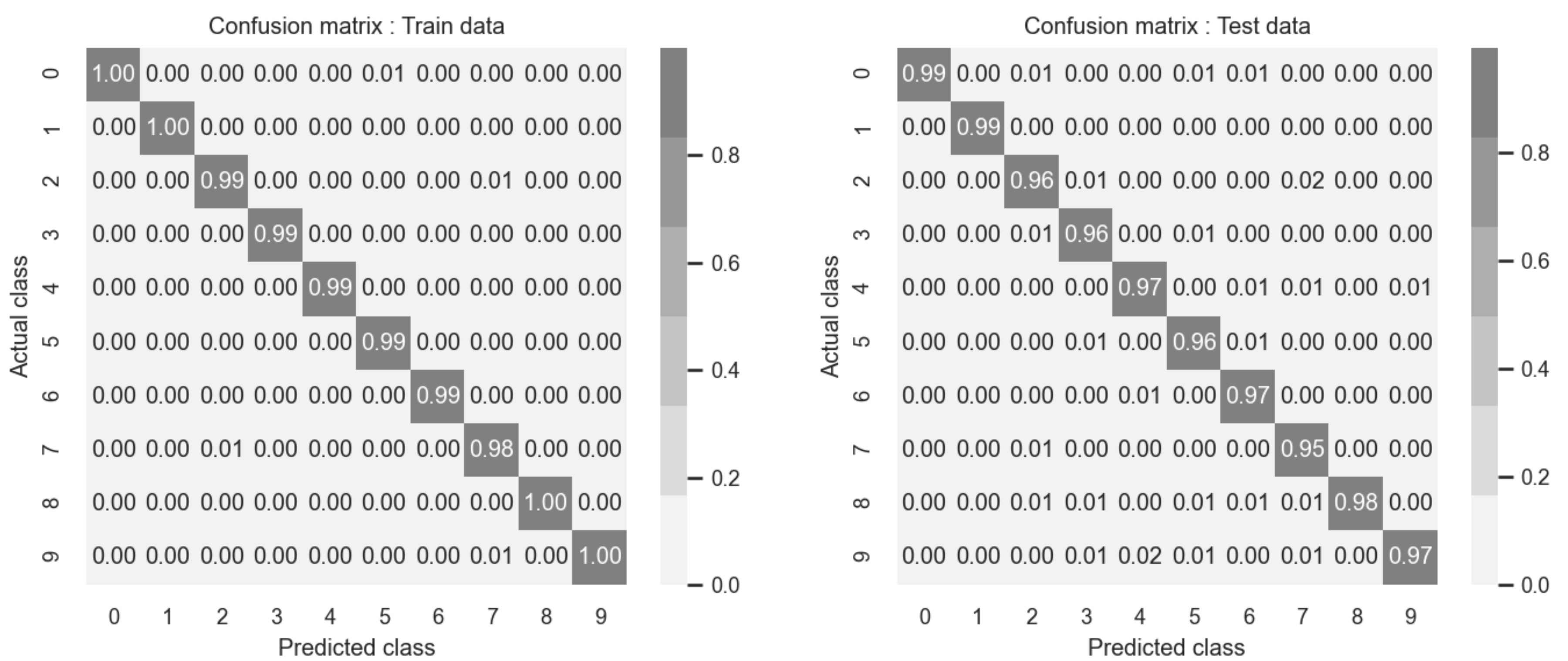


x= y=0.119

In [69]:

```
y_train_predict = model.predict(x_train)
y_test_predict = model.predict(x_test)

c=confusion_matrix(y_train.argmax(axis=1), y_train_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm1 = pd.DataFrame(normed_c, range(10), range(10))

c=confusion_matrix(y_test.argmax(axis=1), y_test_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm2 = pd.DataFrame(normed_c, range(10), range(10))

plt.figure(figsize=(11,4))
cmap=sns.light_palette("Gray")
labels =[0,1,2,3,4,5,6,7,8,9]

plt.subplot(1,2,1)
sns.set(font_scale=0.8)
sns.heatmap(df_cm1,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Train data')

plt.subplot(1,2,2)
sns.set(font_scale=0.8)
sns.heatmap(df_cm2,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Test data')
plt.show()
```

Figure 9



With BN + Dropout

In [70]:

```
model = Sequential()
model.add(Dense(32, activation='relu',input_shape=(input_dim,),kernel_initializer=RandomNormal(stddev=0.125)))## he initializer sqrt(2/784) =0.050
model.add(Dense(64, activation='relu',kernel_initializer=RandomNormal(stddev=0.25))) ## he initializer sqrt(2/32) = 0.25
model.add(BatchNormalization())
model.add(Dropout(0.25))
model.add(Dense(128, activation='relu',kernel_initializer=RandomNormal(stddev=0.176)))## he initializer sqrt(2/64) = 0.17
model.add(Dense(256, activation='relu',kernel_initializer=RandomNormal(stddev=0.125)))## he initializer sqrt(2/128) =0.125
model.add(BatchNormalization())
model.add(Dropout(0.5))
model.add(Dense(512, activation='relu',kernel_initializer=RandomNormal(stddev=0.088)))## he initializer sqrt(2/256) =0.088
model.add(Dense(output_dim, activation='softmax'))
model.summary()
```

```
Model: "sequential_13"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_50 (Dense)             (None, 32)                25120     
_________________________________________________________________
dense_51 (Dense)             (None, 64)                2112      
_________________________________________________________________
batch_normalization_8 (Batch (None, 64)                256       
_________________________________________________________________
dropout_8 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_52 (Dense)             (None, 128)               8320      
_________________________________________________________________
dense_53 (Dense)             (None, 256)               33024     
_________________________________________________________________
batch_normalization_9 (Batch (None, 256)               1024      
_________________________________________________________________
dropout_9 (Dropout)          (None, 256)               0         
_________________________________________________________________
dense_54 (Dense)             (None, 512)               131584    
_________________________________________________________________
dense_55 (Dense)             (None, 10)                5130      
=================================================================
Total params: 206,570
Trainable params: 205,930
Non-trainable params: 640
_________________________________________________________________
```

In [71]:

```
model.compile(optimizer='adam' ,loss='categorical_crossentropy',metrics=['accuracy'] )
```

In [72]:

```
## train the model
history = model.fit(x_train,y_train,batch_size=batch_size,epochs=n_epoch,verbose=1,validation_data=[x_test,y_test])
```

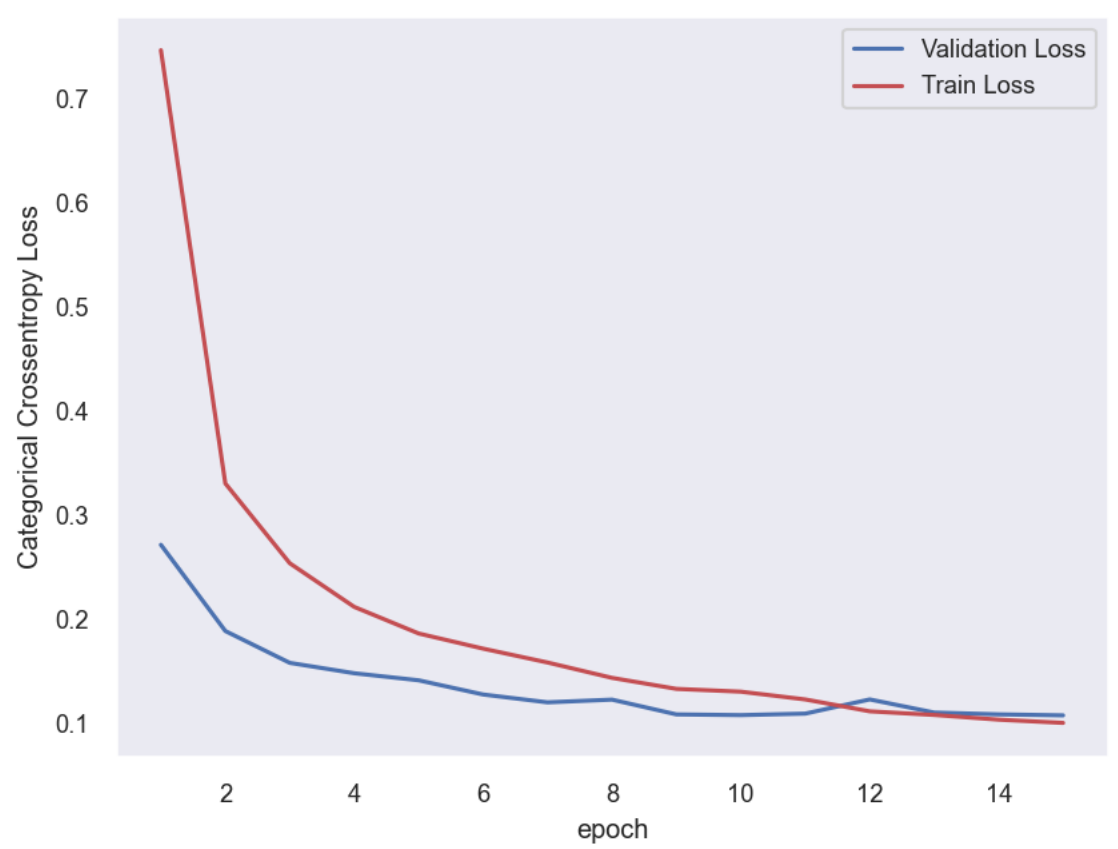
```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 4s 73us/step - loss: 0.7466 - accuracy: 0.7624 - val_loss: 0.2717 - val_accuracy: 0.9167
Epoch 2/15
60000/60000 [==============================] - 5s 80us/step - loss: 0.3306 - accuracy: 0.9003 - val_loss: 0.1889 - val_accuracy: 0.9417
Epoch 3/15
60000/60000 [==============================] - 4s 65us/step - loss: 0.2539 - accuracy: 0.9233 - val_loss: 0.1583 - val_accuracy: 0.9512
Epoch 4/15
60000/60000 [==============================] - 4s 70us/step - loss: 0.2121 - accuracy: 0.9358 - val_loss: 0.1483 - val_accuracy: 0.9551
Epoch 5/15
60000/60000 [==============================] - 4s 65us/step - loss: 0.1865 - accuracy: 0.9438 - val_loss: 0.1416 - val_accuracy: 0.9575
Epoch 6/15
60000/60000 [==============================] - 5s 85us/step - loss: 0.1720 - accuracy: 0.9475 - val_loss: 0.1279 - val_accuracy: 0.9596
Epoch 7/15
60000/60000 [==============================] - 4s 72us/step - loss: 0.1587 - accuracy: 0.9523 - val_loss: 0.1204 - val_accuracy: 0.9645
Epoch 8/15
60000/60000 [==============================] - 4s 75us/step - loss: 0.1439 - accuracy: 0.9573 - val_loss: 0.1230 - val_accuracy: 0.9649
Epoch 9/15
60000/60000 [==============================] - 5s 76us/step - loss: 0.1333 - accuracy: 0.9595 - val_loss: 0.1088 - val_accuracy: 0.9692
Epoch 10/15
60000/60000 [==============================] - 4s 74us/step - loss: 0.1306 - accuracy: 0.9607 - val_loss: 0.1081 - val_accuracy: 0.9680
Epoch 11/15
60000/60000 [==============================] - 4s 72us/step - loss: 0.1232 - accuracy: 0.9626 - val_loss: 0.1096 - val_accuracy: 0.9689
Epoch 12/15
60000/60000 [==============================] - 4s 74us/step - loss: 0.1118 - accuracy: 0.9665 - val_loss: 0.1232 - val_accuracy: 0.9657
Epoch 13/15
60000/60000 [==============================] - 5s 81us/step - loss: 0.1083 - accuracy: 0.9669 - val_loss: 0.1106 - val_accuracy: 0.9689
Epoch 14/15
60000/60000 [==============================] - 4s 69us/step - loss: 0.1038 - accuracy: 0.9689 - val_loss: 0.1089 - val_accuracy: 0.9688
Epoch 15/15
60000/60000 [==============================] - 5s 77us/step - loss: 0.1007 - accuracy: 0.9690 - val_loss: 0.1079 - val_accuracy: 0.9703
```

In [73]:

```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test score:', score[0])
print('Test accuracy:', score[1])
fig,ax=plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1,n_epoch+1))
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
result.append([ty[-1],vy[-1],score[1]])
```

```
Test score: 0.10790942553719506
Test accuracy: 0.970300018787384
```

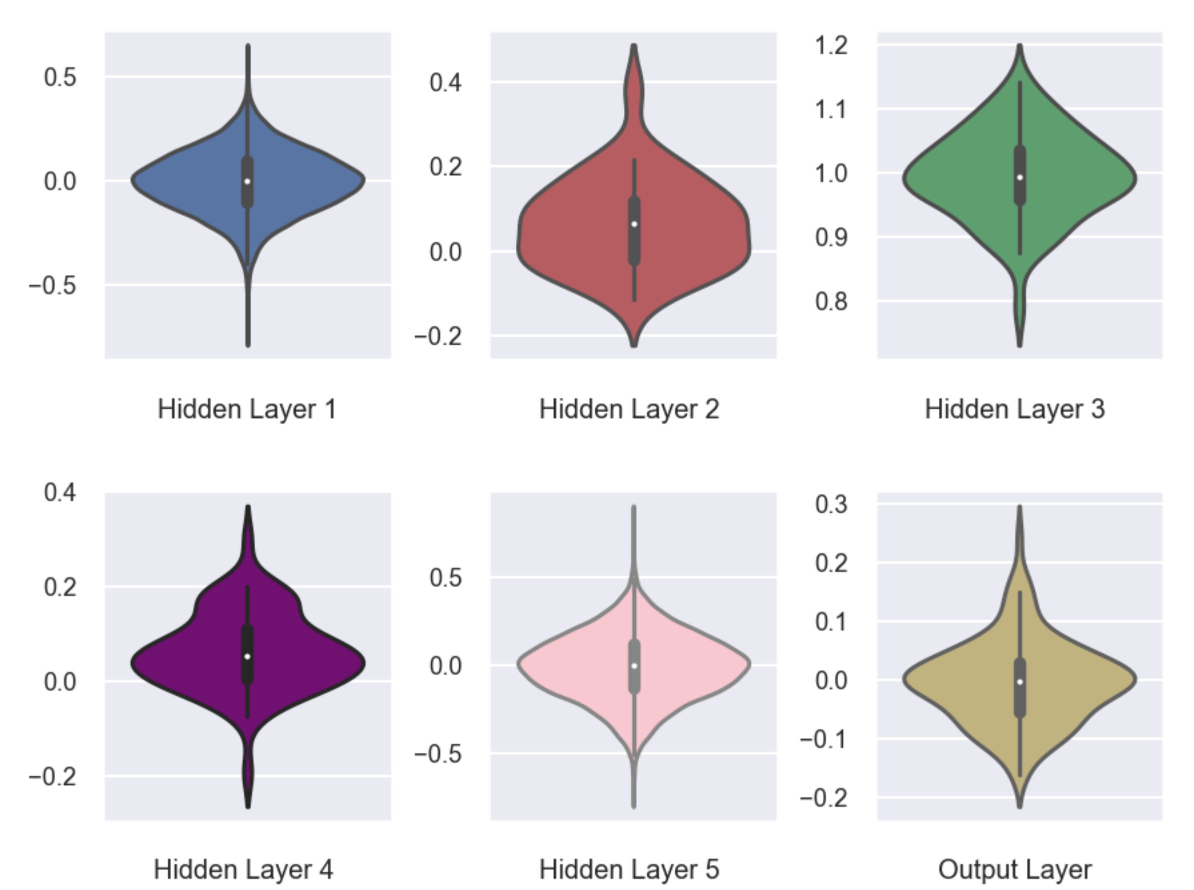
Figure 10



In [77]:

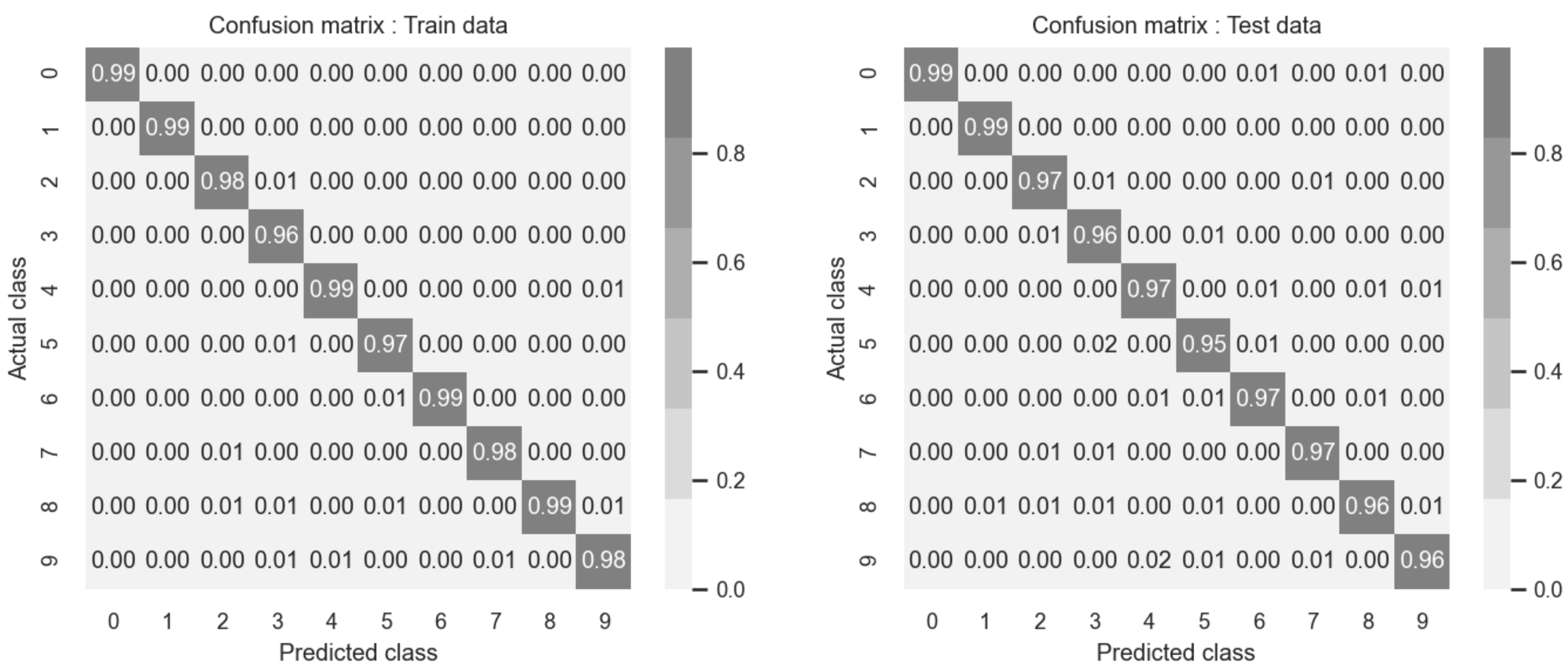
```
w_after = model.get_weights()

h1_w = w_after[0].flatten().reshape(-1,1)
h2_w = w_after[1].flatten().reshape(-1,1)
h3_w = w_after[4].flatten().reshape(-1,1)
h4_w = w_after[5].flatten().reshape(-1,1)
h5_w = w_after[8].flatten().reshape(-1,1)
out_w = w_after[9].flatten().reshape(-1,1)


fig = plt.figure()
plt.title("Weight matrices after model trained")
plt.subplot(2, 3, 1)
plt.tight_layout(pad=3.0)
ax = sns.violinplot(y=h1_w,color='b')
plt.xlabel('Hidden Layer 1')
plt.subplot(2, 3, 2)
ax = sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden Layer 2 ')
plt.subplot(2, 3,3)
ax = sns.violinplot(y=h3_w,color='g')
plt.xlabel('Hidden Layer 3 ')
plt.subplot(2, 3, 4)
ax = sns.violinplot(y=h4_w,color='purple')
plt.xlabel('Hidden Layer 4 ')
plt.subplot(2, 3, 5)
ax = sns.violinplot(y=h5_w,color='pink')
plt.xlabel('Hidden Layer 5 ')
plt.subplot(2, 3, 6)
ax = sns.violinplot(y=out_w,color='y')
plt.xlabel('Output Layer ')
plt.show()
```

Figure 13


0.5
0.0
−0.5
Hidden Layer 1
0.4
0.2
0.0
−0.2
Hidden Layer 2
1.2
1.1
1.0
0.9
0.8
Hidden Layer 3
0.4
0.2
0.0
−0.2
Hidden Layer 4
0.5
0.0
−0.5
Hidden Layer 5
0.3
0.2
0.1
0.0
−0.1
−0.2
Output Layer

In [75]:

```
y_train_predict = model.predict(x_train)
y_test_predict = model.predict(x_test)

c=confusion_matrix(y_train.argmax(axis=1), y_train_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm1 = pd.DataFrame(normed_c, range(10), range(10))

c=confusion_matrix(y_test.argmax(axis=1), y_test_predict.argmax(axis=1))
normed_c = c.T / c.astype(np.float).sum(axis=1).T
df_cm2 = pd.DataFrame(normed_c, range(10), range(10))

plt.figure(figsize=(11,4))
cmap=sns.light_palette("Gray")
labels =[0,1,2,3,4,5,6,7,8,9]

plt.subplot(1,2,1)
sns.set(font_scale=0.8)
sns.heatmap(df_cm1,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Train data')

plt.subplot(1,2,2)
sns.set(font_scale=0.8)
sns.heatmap(df_cm2,annot=True,fmt=".2f",xticklabels=labels,yticklabels=labels,cmap=cmap)
plt.ylabel('Actual class')
plt.xlabel('Predicted class')
plt.title('Confusion matrix : Test data')
plt.show()
```



In [78]:

```
##http://zetcode.com/python/prettytable/

from prettytable import PrettyTable

x = PrettyTable()
x.field_names = ["Model", "Number of Layer",'Batch Normalization and Drop out','Train-loss','Test-Loss',"Test-Accuracy"]

x.add_row(["Model 1",2,'no',round(result[0][0],2),round(result[0][1],2),round(result[0][2] ,2)])
x.add_row(["Model 1",2,'yes',round(result[1][0],2),round(result[1][1],2),round(result[1][2] ,2)])
x.add_row(["Model 2",3,'no',round(result[2][0],2),round(result[2][1],2),round(result[2][2],2)])
x.add_row(["Model 2",3,'yes',round(result[3][0],2),round(result[3][1],2),round(result[3][2] ,2)])
x.add_row(["Model 3",5,'no',round(result[4][0],2),round(result[4][1],2),round(result[4][2],2)])
x.add_row(["Model 3",5,'yes',round(result[5][0],2),round(result[5][1],2),round(result[5][2],2)])
print(x)
```

```
+---------+-----------------+----------------------------------+------------+-----------+---------------+
|  Model  | Number of Layer | Batch Normalization and Drop out | Train-loss | Test-Loss | Test-Accuracy |
+---------+-----------------+----------------------------------+------------+-----------+---------------+
| Model 1 |        2        |                no                |    0.01    |    0.09   |      0.97     |
| Model 1 |        2        |               yes                |    0.07    |    0.07   |      0.98     |
| Model 2 |        3        |                no                |    0.01    |    0.1    |      0.98     |
| Model 2 |        3        |               yes                |    0.04    |    0.1    |      0.97     |
| Model 3 |        5        |                no                |    0.03    |    0.13   |      0.97     |
| Model 3 |        5        |               yes                |    0.1     |    0.11   |      0.97     |
+---------+-----------------+----------------------------------+------------+-----------+---------------+
```

OBSERVATIONS :

```
* Since Mnist is a simple dataset we get optimum accuracy with 2 layers itself.
* As the number of layers increases  model converges faster at early epochs.
* Adding drop out and batch normalization layers avoids overfitting on data.
* Layer weights are not too small or too large to cause slow convergence .
* Number of true positives on test data improved from layer 2 to layer 5
```

In [ ]:

```

```