MLP Archietectures on MNIST dataset

In [0]:

```
import keras
from keras.datasets import mnist
from keras.models import Sequential
from keras.layers import Dense, Dropout, Flatten, BatchNormalization
from keras.layers import Conv2D, MaxPooling2D
from keras import backend as K

import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
import seaborn as sns

import warnings
warnings.filterwarnings('ignore')
```

In [2]:

```
# the data, split between train and test sets
(X_train, y_train), (X_test, y_test) = mnist.load_data()
```

```
Downloading data from https://s3.amazonaws.com/img-datasets/mnist.npz
11493376/11490434 [==============================] - 0s 0us/step
```

In [3]:

```
X_train.shape
```

Out[3]:

```
(60000, 28, 28)
```

In [4]:

```
# input image dimensions
img_rows, img_cols = X_train.shape[1] , X_train.shape[2]
num_pixels = img_rows*img_cols
print(num_pixels)
```

```
784
```

In [0]:

```
X_train = X_train.reshape(X_train.shape[0], num_pixels)
X_test = X_test.reshape(X_test.shape[0], num_pixels)
```

In [0]:

```
#Normalizing
X_train = X_train.astype('float32')
X_test = X_test.astype('float32')
X_train = X_train/255.0
X_test = X_test/255.0
```

In [7]:

```
print(X_train.shape)
print(X_test.shape)
```

```
(60000, 784)
(10000, 784)
```

In [0]:

```
batch_size = 128
num_classes = 10
epochs = 15
```

In [0]:

```
# 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)
```

1. Archietecture -1 -

1.1.1 Without droput, Batch Normalization

In [10]:

```
model_1_a = Sequential()
#hidden layer 1
model_1_a.add(Dense(units=1024, input_shape=(num_pixels, ), activation='relu', kernel_initializer='
normal'))

#hidden layer 2
model_1_a.add(Dense(units=512, activation='relu', kernel_initializer='normal'))

#output layer
model_1_a.add(Dense(units=10, kernel_initializer='normal', activation='softmax'))

#compile with adam optimizers
model_1_a.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#summary
model_1_a.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:66: The name tf.get_default_graph is deprecated. Plea
se use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:541: The name tf.placeholder is deprecated. Please us
e tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:4409: The name tf.random_normal is deprecated. Please
use tf.random.normal instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:793: The name t
f.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3576: The name tf.log is deprecated. Please use tf.ma
th.log instead.

Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_1 (Dense)              (None, 1024)              803840    
_________________________________________________________________
dense_2 (Dense)              (None, 512)               524800    
_________________________________________________________________
dense_3 (Dense)              (None, 10)                5130      
=================================================================
Total params: 1,333,770
Trainable params: 1,333,770
Non-trainable params: 0
_________________________________________________________________
```

In [11]:

```
#fitting the model
history_1_a = model_1_a.fit(X_train, y_train, validation_data=(X_test, y_test), batch_size=batch_si
ze, epochs=epochs, verbose=1)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow_core/python/ops/math_grad.py:1424: where (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1033: The name tf.assign_add is deprecated. Please us
e tf.compat.v1.assign_add instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:1020: The name tf.assign is deprecated. Please use tf
.compat.v1.assign instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3005: The name tf.Session is deprecated. Please use t
f.compat.v1.Session instead.

Train on 60000 samples, validate on 10000 samples
Epoch 1/15
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:190: The name tf.get_default_session is deprecated. P
lease use tf.compat.v1.get_default_session instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:197: The name tf.ConfigProto is deprecated. Please us
e tf.compat.v1.ConfigProto instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:207: The name tf.global_variables is deprecated. Plea
se use tf.compat.v1.global_variables instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:216: The name tf.is_variable_initialized is
deprecated. Please use tf.compat.v1.is_variable_initialized instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:223: The name tf.variables_initializer is deprecated.
Please use tf.compat.v1.variables_initializer instead.

60000/60000 [==============================] - 12s 199us/step - loss: 0.1919 - acc: 0.9428 - val_l
oss: 0.1080 - val_acc: 0.9663
Epoch 2/15
60000/60000 [==============================] - 2s 37us/step - loss: 0.0701 - acc: 0.9784 -
val_loss: 0.0771 - val_acc: 0.9748
Epoch 3/15
60000/60000 [==============================] - 2s 35us/step - loss: 0.0441 - acc: 0.9856 -
val_loss: 0.0834 - val_acc: 0.9753
Epoch 4/15
60000/60000 [==============================] - 2s 36us/step - loss: 0.0308 - acc: 0.9902 -
val_loss: 0.0720 - val_acc: 0.9790
Epoch 5/15
60000/60000 [==============================] - 2s 36us/step - loss: 0.0236 - acc: 0.9919 -
val_loss: 0.0962 - val_acc: 0.9732
Epoch 6/15
60000/60000 [==============================] - 2s 37us/step - loss: 0.0202 - acc: 0.9933 -
val_loss: 0.0801 - val_acc: 0.9786
Epoch 7/15
60000/60000 [==============================] - 2s 36us/step - loss: 0.0174 - acc: 0.9945 -
val_loss: 0.0854 - val_acc: 0.9787
Epoch 8/15
60000/60000 [==============================] - 2s 36us/step - loss: 0.0169 - acc: 0.9943 -
val_loss: 0.0685 - val_acc: 0.9824
Epoch 9/15
60000/60000 [==============================] - 2s 37us/step - loss: 0.0127 - acc: 0.9958 -
val_loss: 0.0829 - val_acc: 0.9801
Epoch 10/15
60000/60000 [==============================] - 2s 37us/step - loss: 0.0131 - acc: 0.9957 -
val_loss: 0.0776 - val_acc: 0.9825
Epoch 11/15
60000/60000 [==============================] - 2s 36us/step - loss: 0.0115 - acc: 0.9966 -
```

```
val_loss: 0.1029 - val_acc: 0.9773
Epoch 12/15
60000/60000 [==============================] - 2s 36us/step - loss: 0.0096 - acc: 0.9968 -
val_loss: 0.0921 - val_acc: 0.9779
Epoch 13/15
60000/60000 [==============================] - 2s 35us/step - loss: 0.0100 - acc: 0.9968 -
val_loss: 0.0892 - val_acc: 0.9824
Epoch 14/15
60000/60000 [==============================] - 2s 36us/step - loss: 0.0116 - acc: 0.9962 -
val_loss: 0.1011 - val_acc: 0.9810
Epoch 15/15
60000/60000 [==============================] - 2s 34us/step - loss: 0.0122 - acc: 0.9961 -
val_loss: 0.0853 - val_acc: 0.9815
```

In [95]:

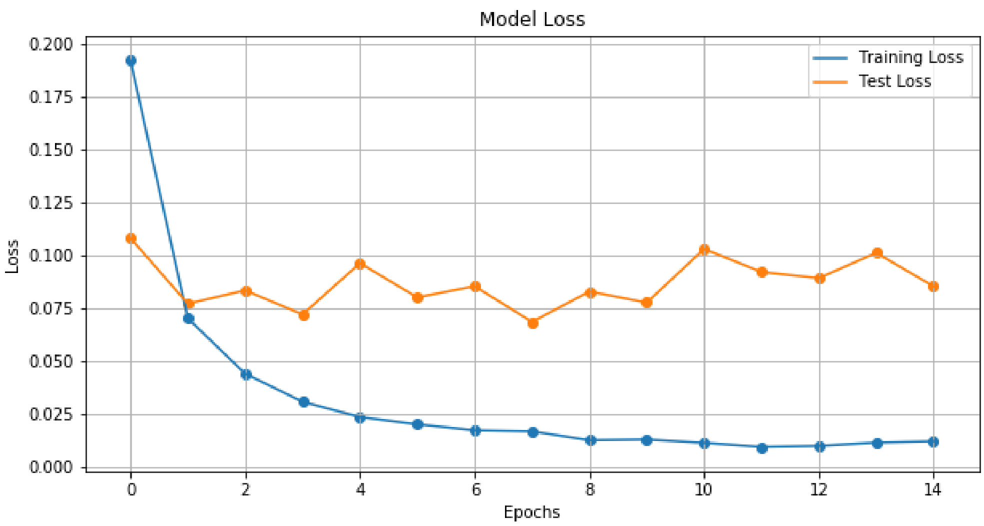
```
score_1_a = model_1_a.evaluate(X_test, y_test, verbose=0)
print('Test Accuracy:', score[1])
```

```
Test Accuracy: 0.9815
```

1.1.2 Plotting Epoch vs Loss

In [36]:

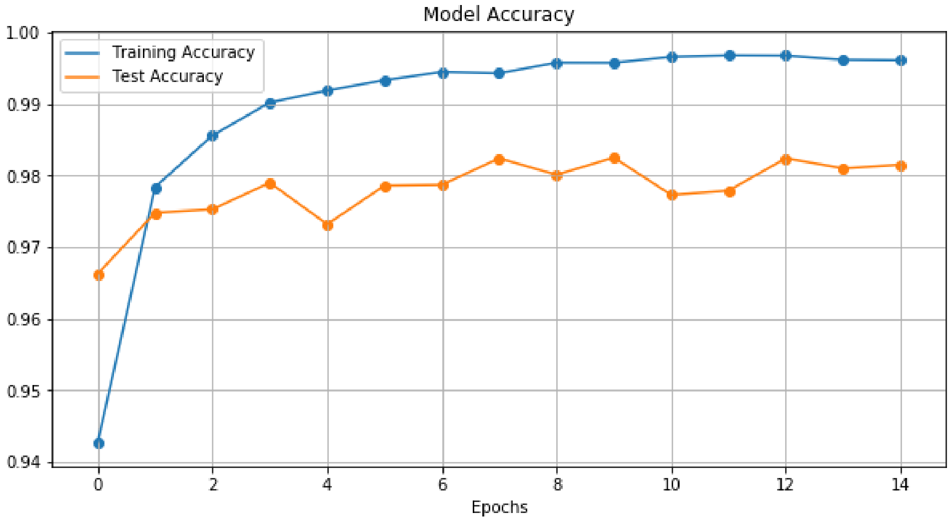
```
plt.figure(figsize=(10,5))
plt.plot(history_1_a.history['loss'], label='Training Loss')
plt.plot(history_1_a.history['val_loss'], label='Test Loss')
plt.scatter([i for i in range(epochs)], history_1_a.history['loss'])
plt.scatter([i for i in range(epochs)], history_1_a.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```



1.1.3 Plotting Epoch vs Accuracy

In [35]:

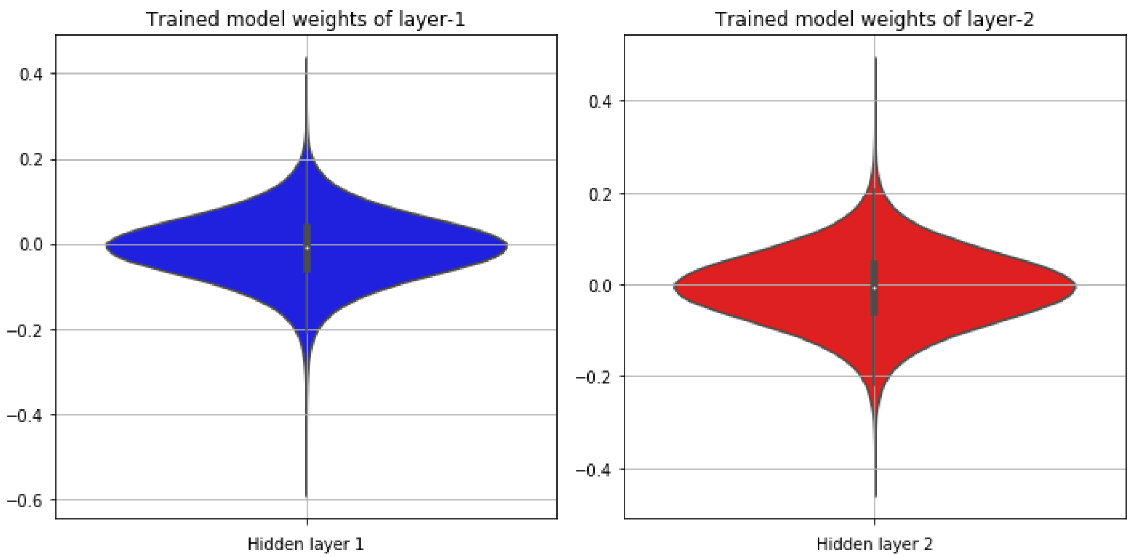
```
plt.figure(figsize=(10,5))
plt.plot(history_1_a.history['acc'], label='Training Accuracy')
plt.plot(history_1_a.history['val_acc'], label='Test Accuracy')
plt.scatter([i for i in range(epochs)], history_1_a.history['acc'])
plt.scatter([i for i in range(epochs)], history_1_a.history['val_acc'])
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.grid()
plt.legend()
plt.show()
```



1.1.4 Weight distributions

In [48]:

```
w_after_1_a = model_1_a.get_weights()
h1_w = w_after_1_a[0].flatten().reshape(-1,1)
h2_w = w_after_1_a[2].flatten().reshape(-1,1)


fig = plt.figure(figsize=(10, 5))
plt.title('Weights of the model after trained')

plt.subplot(1,2,1)
plt.title('Trained model weights of layer-1')
sns.violinplot(y=h1_w, color='b')
plt.xlabel('Hidden layer 1')
plt.grid()
plt.tight_layout()

plt.subplot(1,2,2)
plt.title('Trained model weights of layer-2')
sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden layer 2')
plt.tight_layout()
plt.grid()

plt.show()
```



1.2 With Dropout and Batch Normalization

In [37]:

```
model_1_b = Sequential()

#1st hidden layer
model_1_b.add(Dense(units=1024, input_shape = (num_pixels, ), activation='relu', kernel_initializer
='normal'))

#drop out
model_1_b.add(Dropout(0.3))

#hidden layer 2
model_1_b.add(Dense(units=512, activation='relu', kernel_initializer='normal'))

#Batch Normalization
model_1_b.add(BatchNormalization())

#output layer
model_1_b.add(Dense(units=10, activation='softmax'))

#compile
model_1_b.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

#summary
model_1_b.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:148: The name tf.placeholder_with_default is
deprecated. Please use tf.compat.v1.placeholder_with_default instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3733: 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 - keep_prob`.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:4432: The name tf.random_uniform is deprecated. Pleas
e use tf.random.uniform instead.

Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 1024)              803840
_________________________________________________________________
dropout_1 (Dropout)          (None, 1024)              0
_________________________________________________________________
dense_5 (Dense)              (None, 512)               524800
_________________________________________________________________
batch_normalization_1 (Batch (None, 512)               2048
_________________________________________________________________
dense_6 (Dense)              (None, 10)                5130
=================================================================
Total params: 1,335,818
Trainable params: 1,334,794
Non-trainable params: 1,024
_________________________________________________________________
```

In [38]:

```
history_1_b = model_1_b.fit(X_train, y_train, validation_data=(X_test, y_test), verbose=1, batch_si
ze=batch_size, epochs=epochs)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 3s 55us/step - loss: 0.2290 - acc: 0.9311 -
val_loss: 0.1007 - val_acc: 0.9690
Epoch 2/15
60000/60000 [==============================] - 3s 48us/step - loss: 0.1025 - acc: 0.9679 -
val_loss: 0.0806 - val_acc: 0.9734
Epoch 3/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0736 - acc: 0.9762 -
val_loss: 0.0731 - val_acc: 0.9758
Epoch 4/15
```

```
Epoch 4/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0581 - acc: 0.9813 -
val_loss: 0.0660 - val_acc: 0.9794
Epoch 5/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.0472 - acc: 0.9843 -
val_loss: 0.0649 - val_acc: 0.9801
Epoch 6/15
60000/60000 [==============================] - 3s 51us/step - loss: 0.0417 - acc: 0.9862 -
val_loss: 0.0664 - val_acc: 0.9808
Epoch 7/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.0375 - acc: 0.9878 -
val_loss: 0.0750 - val_acc: 0.9774
Epoch 8/15
60000/60000 [==============================] - 3s 46us/step - loss: 0.0320 - acc: 0.9889 -
val_loss: 0.0634 - val_acc: 0.9818
Epoch 9/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0288 - acc: 0.9901 -
val_loss: 0.0617 - val_acc: 0.9844
Epoch 10/15
60000/60000 [==============================] - 3s 48us/step - loss: 0.0287 - acc: 0.9905 -
val_loss: 0.0612 - val_acc: 0.9810
Epoch 11/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0233 - acc: 0.9919 -
val_loss: 0.0726 - val_acc: 0.9818
Epoch 12/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0232 - acc: 0.9919 -
val_loss: 0.0650 - val_acc: 0.9819
Epoch 13/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.0202 - acc: 0.9930 -
val_loss: 0.0564 - val_acc: 0.9823
Epoch 14/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0195 - acc: 0.9938 -
val_loss: 0.0604 - val_acc: 0.9838
Epoch 15/15
60000/60000 [==============================] - 3s 45us/step - loss: 0.0209 - acc: 0.9927 -
val_loss: 0.0627 - val_acc: 0.9844
```

In [88]:

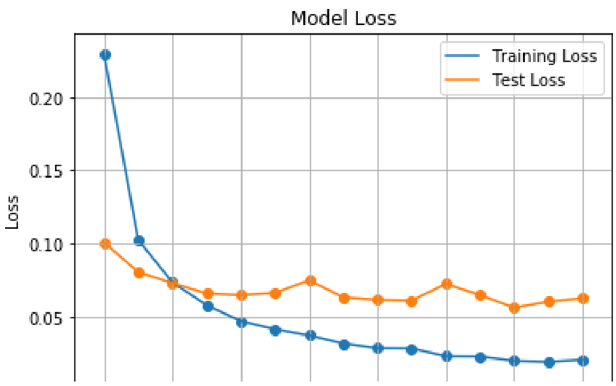
```python
score_1_b = model_1_b.evaluate(X_test, y_test, verbose=0)
print('Test Accuracy with Dropout and Batch Normalisation:', score_1_b[1])
```

```
Test Accuracy with Dropout and Batch Normalisation: 0.9844
```

1.2.2 Plotting Epoch vs Loss

In [40]:

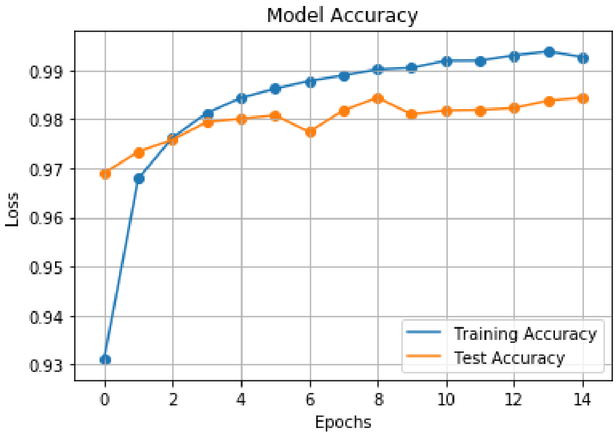
```python
plt.plot(history_1_b.history['loss'], label='Training Loss')
plt.plot(history_1_b.history['val_loss'], label='Test Loss')
plt.scatter([i for i in range(epochs)], history_1_b.history['loss'])
plt.scatter([i for i in range(epochs)], history_1_b.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```



1.2.3 Plotting Epoch vs Accuracy

In [42]:

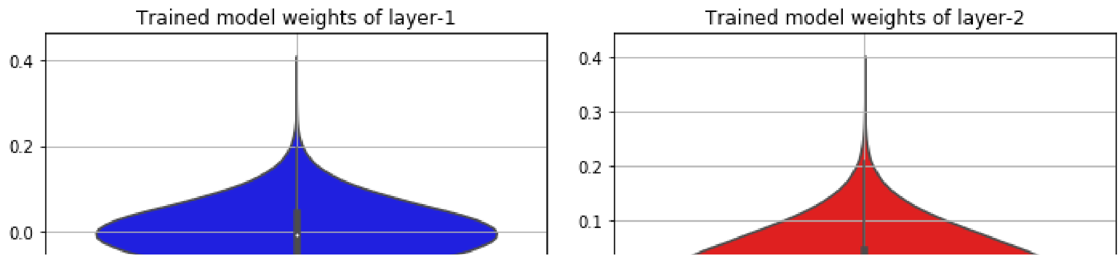
```
plt.plot(history_1_b.history['acc'], label='Training Accuracy')
plt.plot(history_1_b.history['val_acc'], label='Test Accuracy')
plt.scatter([i for i in range(epochs)], history_1_b.history['acc'])
plt.scatter([i for i in range(epochs)], history_1_b.history['val_acc'])
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```

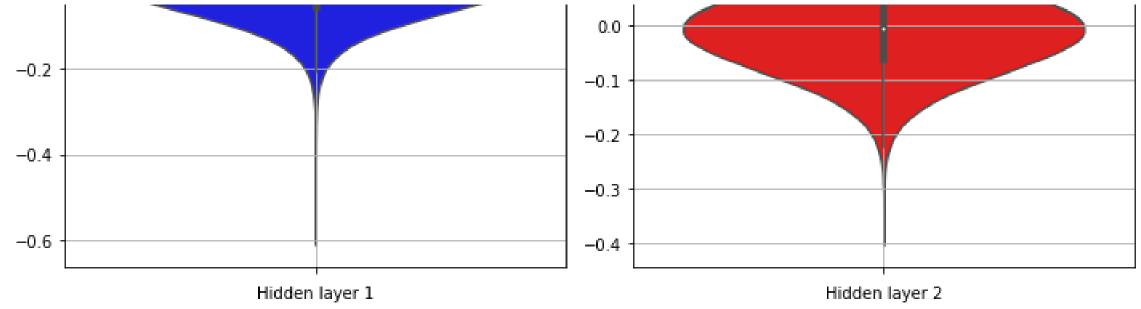


1.2.4 Distribution of Weights

In [86]:

```
w_after_1_b = model_1_b.get_weights()
h1_w = w_after_1_b[0].flatten().reshape(-1,1)
h2_w = w_after_1_b[2].flatten().reshape(-1,1)


fig = plt.figure(figsize=(10, 5))
#plt.suptitle('Weights of the model after trained')

plt.subplot(1,2,1)
plt.title('Trained model weights of layer-1')
sns.violinplot(y=h1_w, color='b')
plt.xlabel('Hidden layer 1')
plt.grid()
plt.tight_layout()

plt.subplot(1,2,2)
plt.title('Trained model weights of layer-2')
sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden layer 2')
plt.tight_layout()
plt.grid()

plt.show()
```





2. Architecture - 2

2.1.1 Without Dropout and Batch Normalization

In [43]:

```
model_2_a = Sequential()
#hidden layer 1
model_2_a.add(Dense(units=512, input_shape=(num_pixels, ), activation='relu', kernel_initializer='n
ormal'))

#hidden layer 2
model_2_a.add(Dense(units=256, activation='relu', kernel_initializer='normal'))

#hidden layer 3
model_2_a.add(Dense(units=128, activation='relu', kernel_initializer='normal'))

#output layer
model_2_a.add(Dense(units=10, kernel_initializer='normal', activation='softmax'))

#compile with adam optimizers
model_2_a.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#summary
model_2_a.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_7 (Dense)              (None, 512)               401920
_________________________________________________________________
dense_8 (Dense)              (None, 256)               131328
_________________________________________________________________
dense_9 (Dense)              (None, 128)               32896
_________________________________________________________________
dense_10 (Dense)             (None, 10)                1290
=================================================================
Total params: 567,434
Trainable params: 567,434
Non-trainable params: 0
_________________________________________________________________
```

In [44]:

```
history_2_a = model_2_a.fit(X_train, y_train, validation_data=(X_test, y_test), verbose=1, batch_si
ze=batch_size, epochs=epochs)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 2s 42us/step - loss: 0.2704 - acc: 0.9211 -
val_loss: 0.1162 - val_acc: 0.9646
Epoch 2/15
60000/60000 [==============================] - 2s 37us/step - loss: 0.0933 - acc: 0.9711 -
val_loss: 0.0815 - val_acc: 0.9755
Epoch 3/15
60000/60000 [==============================] - 2s 36us/step - loss: 0.0617 - acc: 0.9806 -
val_loss: 0.0677 - val_acc: 0.9775
Epoch 4/15
60000/60000 [==============================] - 2s 38us/step - loss: 0.0408 - acc: 0.9872 -
```

```
val_loss: 0.0766 - val_acc: 0.9774
Epoch 5/15
60000/60000 [==============================] - 2s 37us/step - loss: 0.0305 - acc: 0.9905 -
val_loss: 0.0685 - val_acc: 0.9811
Epoch 6/15
60000/60000 [==============================] - 2s 37us/step - loss: 0.0276 - acc: 0.9912 -
val_loss: 0.0742 - val_acc: 0.9790
Epoch 7/15
60000/60000 [==============================] - 2s 35us/step - loss: 0.0198 - acc: 0.9938 -
val_loss: 0.0765 - val_acc: 0.9804
Epoch 8/15
60000/60000 [==============================] - 2s 34us/step - loss: 0.0197 - acc: 0.9936 -
val_loss: 0.0864 - val_acc: 0.9777
Epoch 9/15
60000/60000 [==============================] - 2s 33us/step - loss: 0.0159 - acc: 0.9947 -
val_loss: 0.0722 - val_acc: 0.9817
Epoch 10/15
60000/60000 [==============================] - 2s 35us/step - loss: 0.0179 - acc: 0.9943 -
val_loss: 0.0712 - val_acc: 0.9818
Epoch 11/15
60000/60000 [==============================] - 2s 35us/step - loss: 0.0131 - acc: 0.9953 -
val_loss: 0.0926 - val_acc: 0.9790
Epoch 12/15
60000/60000 [==============================] - 2s 34us/step - loss: 0.0128 - acc: 0.9959 -
val_loss: 0.0889 - val_acc: 0.9805
Epoch 13/15
60000/60000 [==============================] - 2s 33us/step - loss: 0.0103 - acc: 0.9966 -
val_loss: 0.0802 - val_acc: 0.9807
Epoch 14/15
60000/60000 [==============================] - 2s 33us/step - loss: 0.0112 - acc: 0.9963 -
val_loss: 0.0951 - val_acc: 0.9801
Epoch 15/15
60000/60000 [==============================] - 2s 34us/step - loss: 0.0120 - acc: 0.9961 -
val_loss: 0.0775 - val_acc: 0.9828
```

In [89]:

```
score_2_a = model_2_a.evaluate(X_test, y_test, verbose=0)
print('Test Accuracy without Dropout and BatchNorm', score_2_a[1])
```

```
Test Accuracy without Dropout and BatchNorm 0.9828
```

2.1.2 Loss vs Epoch

In [46]:

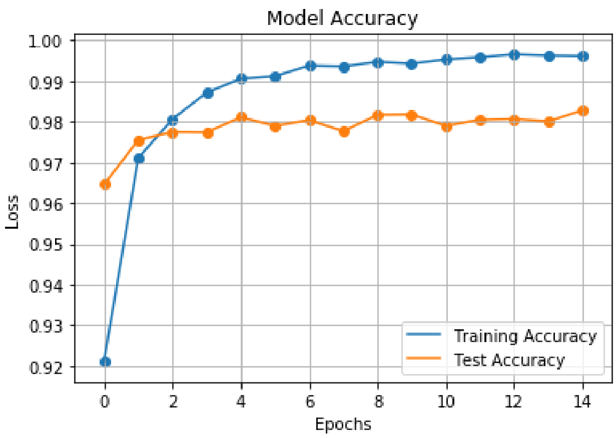
```
plt.plot(history_2_a.history['loss'], label='Training Loss')
plt.plot(history_2_a.history['val_loss'], label='Test Loss')
plt.scatter([i for i in range(epochs)], history_2_a.history['loss'])
plt.scatter([i for i in range(epochs)], history_2_a.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```

Epochs

2.1.3 Epoch vs Accuracy

In [47]:

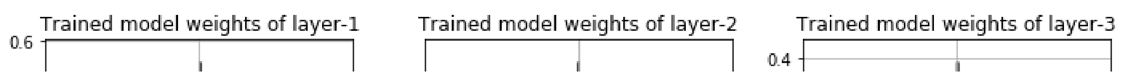
```
plt.plot(history_2_a.history['acc'], label='Training Accuracy')
plt.plot(history_2_a.history['val_acc'], label='Test Accuracy')
plt.scatter([i for i in range(epochs)], history_2_a.history['acc'])
plt.scatter([i for i in range(epochs)], history_2_a.history['val_acc'])
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```

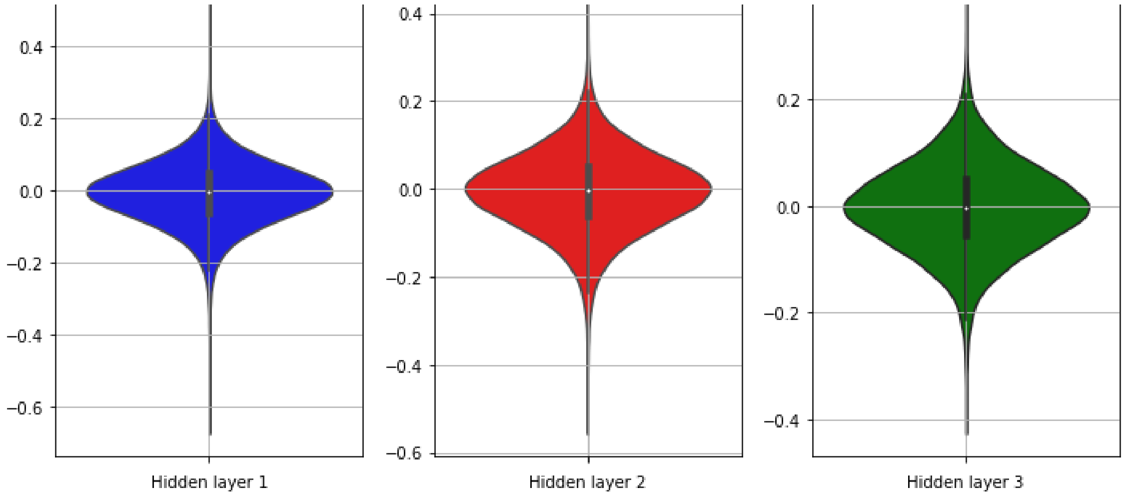


2.1.4 Distribution of Weights

In [83]:

```
w_after_2_a = model_2_a.get_weights()
h1_w = w_after_2_a[0].flatten().reshape(-1,1)
h2_w = w_after_2_a[2].flatten().reshape(-1,1)
h3_w = w_after_2_a[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title('Weights of the model after trained')

plt.subplot(1,3,1)
plt.title('Trained model weights of layer-1')
sns.violinplot(y=h1_w, color='b')
plt.xlabel('Hidden layer 1')
plt.grid()
plt.tight_layout()

plt.subplot(1,3,2)
plt.title('Trained model weights of layer-2')
sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden layer 2')
plt.tight_layout()
plt.grid()


plt.subplot(1,3,3)
plt.title('Trained model weights of layer-3')
sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden layer 3')
plt.grid()
plt.tight_layout()

plt.show()
```





2.2 With Dropout and Batch Normalization

In [51]:

```
model_2_b = Sequential()
#hidden layer 1
model_2_b.add(Dense(units=512, input_shape=(num_pixels, ), activation='relu', kernel_initializer='n
ormal'))
model_2_b.add(Dropout(0.5))

#hidden layer 2
model_2_b.add(Dense(units=256, activation='relu', kernel_initializer='normal'))
model_2_b.add(BatchNormalization())

#hidden layer 3
model_2_b.add(Dense(units=128, activation='relu', kernel_initializer='normal'))

#output layer
model_2_b.add(Dense(units=10, kernel_initializer='normal', activation='softmax'))

#compile with adam optimizers
model_2_b.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#summary
model_2_b.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_11 (Dense)             (None, 512)               401920
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_12 (Dense)             (None, 256)               131328
_________________________________________________________________
batch_normalization_2 (Batch (None, 256)               1024
_________________________________________________________________
dense_13 (Dense)             (None, 128)               32896
_________________________________________________________________
dense_14 (Dense)             (None, 10)                1290
=================================================================
Total params: 568,458
Trainable params: 567,946
Non-trainable params: 512
_________________________________________________________________
```

In [52]:

```
history_2_b = model_2_b.fit(X_train, y_train, validation_data=(X_test, y_test), verbose=1, batch_si
ze=batch_size, epochs=epochs)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
```

```
60000/60000 [==============================] - 4s 60us/step - loss: 0.3175 - acc: 0.9038 -
val_loss: 0.1088 - val_acc: 0.9676
Epoch 2/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.1438 - acc: 0.9545 -
val_loss: 0.0887 - val_acc: 0.9722
Epoch 3/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.1119 - acc: 0.9648 -
val_loss: 0.0741 - val_acc: 0.9762
Epoch 4/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.0973 - acc: 0.9695 -
val_loss: 0.0740 - val_acc: 0.9762
Epoch 5/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.0860 - acc: 0.9728 -
val_loss: 0.0663 - val_acc: 0.9798
Epoch 6/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0749 - acc: 0.9763 -
val_loss: 0.0702 - val_acc: 0.9793
Epoch 7/15
60000/60000 [==============================] - 3s 49us/step - loss: 0.0693 - acc: 0.9771 -
val_loss: 0.0698 - val_acc: 0.9795
Epoch 8/15
60000/60000 [==============================] - 3s 50us/step - loss: 0.0638 - acc: 0.9797 -
val_loss: 0.0654 - val_acc: 0.9809
Epoch 9/15
60000/60000 [==============================] - 3s 52us/step - loss: 0.0587 - acc: 0.9808 -
val_loss: 0.0573 - val_acc: 0.9823
Epoch 10/15
60000/60000 [==============================] - 3s 51us/step - loss: 0.0550 - acc: 0.9819 -
val_loss: 0.0557 - val_acc: 0.9824
Epoch 11/15
60000/60000 [==============================] - 3s 49us/step - loss: 0.0522 - acc: 0.9832 -
val_loss: 0.0577 - val_acc: 0.9827
Epoch 12/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0486 - acc: 0.9840 -
val_loss: 0.0540 - val_acc: 0.9835
Epoch 13/15
60000/60000 [==============================] - 3s 46us/step - loss: 0.0477 - acc: 0.9839 -
val_loss: 0.0605 - val_acc: 0.9829
Epoch 14/15
60000/60000 [==============================] - 3s 46us/step - loss: 0.0454 - acc: 0.9851 -
val_loss: 0.0518 - val_acc: 0.9852
Epoch 15/15
60000/60000 [==============================] - 3s 47us/step - loss: 0.0421 - acc: 0.9859 -
val_loss: 0.0537 - val_acc: 0.9844
```

In [90]:

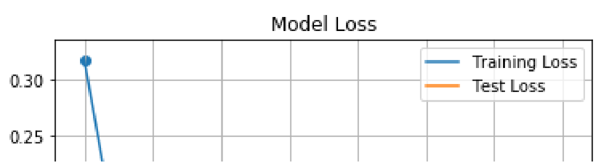
```python
score_2_b = model_2_b.evaluate(X_test, y_test, verbose=0)
print('Test accuracy with Dropout and BatchNorm', score_2_b[1])
```

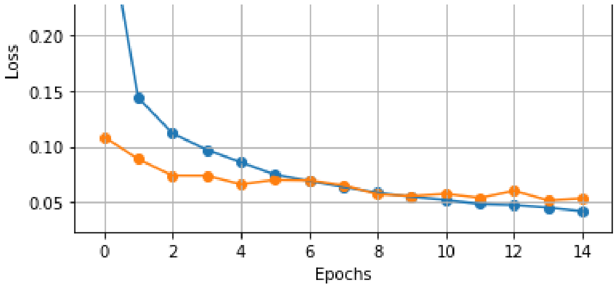
```
Test accuracy with Dropout and BatchNorm 0.9844
```

2.2.1 Loss vs Epoch

In [53]:

```python
plt.plot(history_2_b.history['loss'], label='Training Loss')
plt.plot(history_2_b.history['val_loss'], label='Test Loss')
plt.scatter([i for i in range(epochs)], history_2_b.history['loss'])
plt.scatter([i for i in range(epochs)], history_2_b.history['val_loss'])
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```

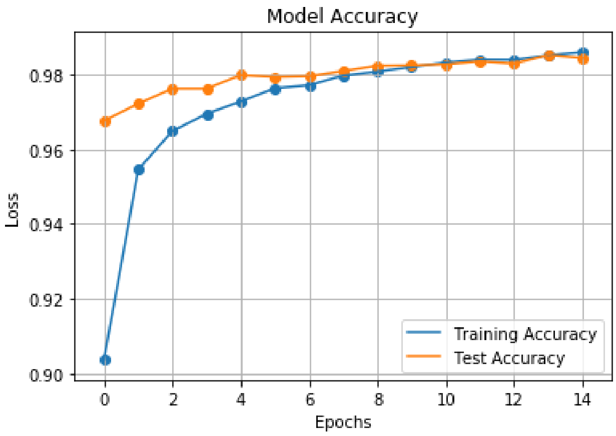




2.2.2 Accuracy vs Epoch

In [54]:

```
plt.plot(history_2_b.history['acc'], label='Training Accuracy')
plt.plot(history_2_b.history['val_acc'], label='Test Accuracy')
plt.scatter([i for i in range(epochs)], history_2_b.history['acc'])
plt.scatter([i for i in range(epochs)], history_2_b.history['val_acc'])
plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```

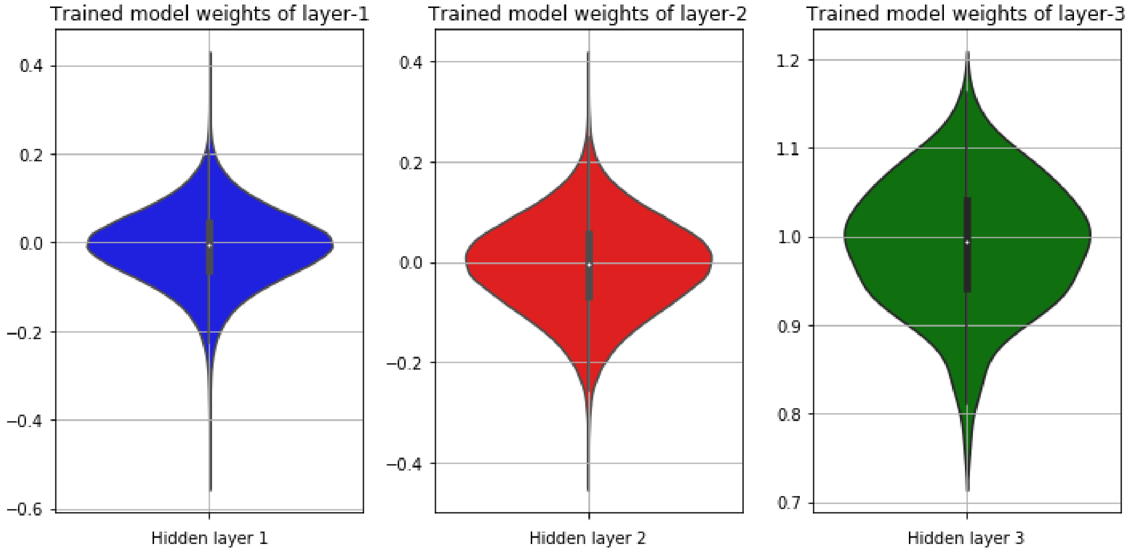


2.2.3 Distribution of Weights

In [82]:

```
w_after_2_b = model_2_b.get_weights()
h1_w = w_after_2_b[0].flatten().reshape(-1,1)
h2_w = w_after_2_b[2].flatten().reshape(-1,1)
h3_w = w_after_2_b[4].flatten().reshape(-1,1)

fig = plt.figure(figsize=(10, 5))
plt.title('Weights of the model after trained')

plt.subplot(1,3,1)
plt.title('Trained model weights of layer-1')
sns.violinplot(y=h1_w, color='b')
plt.xlabel('Hidden layer 1')
plt.grid()
plt.tight_layout()

plt.subplot(1,3,2)
plt.title('Trained model weights of layer-2')
sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden layer 2')
plt.tight_layout()
plt.grid()


plt.subplot(1,3,3)
plt.title('Trained model weights of layer-3')
sns.violinplot(y=h3_w, color='g')
```

```
plt.xlabel('Hidden layer 3')
plt.grid()
plt.tight_layout()

plt.show()
```



3. Architecture - 3

3.1.1 Without Dropout and Batch Normalisation

In [58]:

```
model_3_a = Sequential()
#hidden layer 1
model_3_a.add(Dense(units=2048, input_shape=(num_pixels, ), activation='relu', kernel_initializer='normal'))

#hidden layer 2
model_3_a.add(Dense(units=1024, activation='relu', kernel_initializer='normal'))

#hidden layer 3
model_3_a.add(Dense(units=512, activation='relu', kernel_initializer='normal'))

#hidden layer 4
model_3_a.add(Dense(units=256, activation='relu', kernel_initializer='normal'))

#hidden layer 5
model_3_a.add(Dense(units=128, activation='relu', kernel_initializer='normal'))

#output layer
model_3_a.add(Dense(units=10, kernel_initializer='normal', activation='softmax'))

#compile with adam optimizers
model_3_a.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#summary
model_3_a.summary()
```

```
Model: "sequential_5"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_15 (Dense)             (None, 2048)              1607680
_________________________________________________________________
dense_16 (Dense)             (None, 1024)              2098176
_________________________________________________________________
dense_17 (Dense)             (None, 512)               524800
_________________________________________________________________
dense_18 (Dense)             (None, 256)               131328
_________________________________________________________________
dense_19 (Dense)             (None, 128)               32896
```

```
_________________________________________________________________
dense_20 (Dense)             (None, 10)                1290
=================================================================
Total params: 4,396,170
Trainable params: 4,396,170
Non-trainable params: 0
_________________________________________________________________
```

In [59]:

```
history_3_a = model_3_a.fit(X_train, y_train, validation_data=(X_test, y_test), verbose=1, batch_si
ze=batch_size, epochs=epochs)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 4s 70us/step - loss: 0.2121 - acc: 0.9351 -
val_loss: 0.1160 - val_acc: 0.9629
Epoch 2/15
60000/60000 [==============================] - 4s 59us/step - loss: 0.0875 - acc: 0.9733 -
val_loss: 0.0979 - val_acc: 0.9693
Epoch 3/15
60000/60000 [==============================] - 4s 59us/step - loss: 0.0626 - acc: 0.9807 -
val_loss: 0.0845 - val_acc: 0.9767
Epoch 4/15
60000/60000 [==============================] - 3s 58us/step - loss: 0.0452 - acc: 0.9865 -
val_loss: 0.1115 - val_acc: 0.9694
Epoch 5/15
60000/60000 [==============================] - 3s 57us/step - loss: 0.0388 - acc: 0.9878 -
val_loss: 0.0658 - val_acc: 0.9812
Epoch 6/15
60000/60000 [==============================] - 4s 60us/step - loss: 0.0302 - acc: 0.9905 -
val_loss: 0.0910 - val_acc: 0.9763
Epoch 7/15
60000/60000 [==============================] - 3s 58us/step - loss: 0.0258 - acc: 0.9925 -
val_loss: 0.0854 - val_acc: 0.9791
Epoch 8/15
60000/60000 [==============================] - 4s 59us/step - loss: 0.0259 - acc: 0.9919 -
val_loss: 0.0779 - val_acc: 0.9814
Epoch 9/15
60000/60000 [==============================] - 3s 57us/step - loss: 0.0219 - acc: 0.9937 -
val_loss: 0.0866 - val_acc: 0.9801
Epoch 10/15
60000/60000 [==============================] - 3s 57us/step - loss: 0.0228 - acc: 0.9935 -
val_loss: 0.0885 - val_acc: 0.9806
Epoch 11/15
60000/60000 [==============================] - 3s 57us/step - loss: 0.0199 - acc: 0.9947 -
val_loss: 0.0982 - val_acc: 0.9808
Epoch 12/15
60000/60000 [==============================] - 3s 58us/step - loss: 0.0181 - acc: 0.9950 -
val_loss: 0.1054 - val_acc: 0.9788
Epoch 13/15
60000/60000 [==============================] - 3s 57us/step - loss: 0.0156 - acc: 0.9955 -
val_loss: 0.0799 - val_acc: 0.9847
Epoch 14/15
60000/60000 [==============================] - 3s 58us/step - loss: 0.0138 - acc: 0.9965 -
val_loss: 0.0798 - val_acc: 0.9826
Epoch 15/15
60000/60000 [==============================] - 3s 57us/step - loss: 0.0209 - acc: 0.9945 -
val_loss: 0.1100 - val_acc: 0.9779
```

In [93]:

```
score_3_a = model_3_a.evaluate(X_test, y_test, verbose=0)
print('Test Accuracy without Dropout and Batch Norm', score_3_a[1])
```

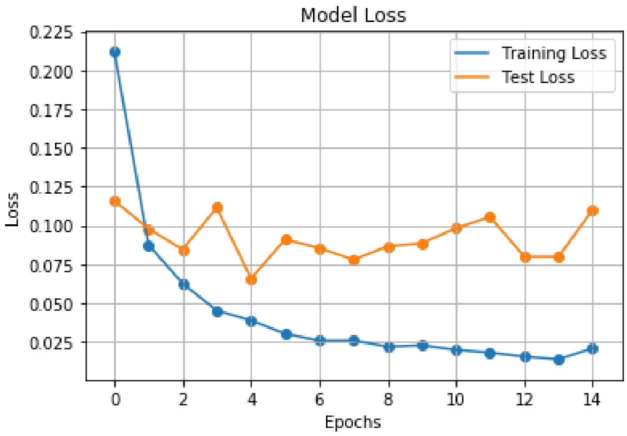
```
Test Accuracy without Dropout and Batch Norm 0.9779
```

3.1.1 Loss vs Epoch

In [61]:

```
plt.plot(history_3_a.history['loss'], label='Training Loss')
```

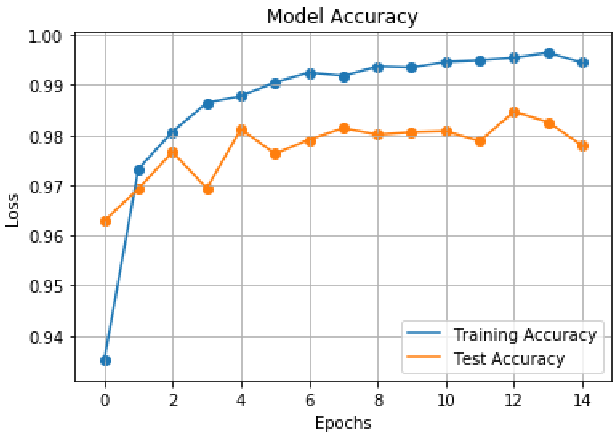
```
plt.plot(history_3_a.history['loss'], label='Training Loss')
plt.plot(history_3_a.history['val_loss'], label='Test Loss')
plt.scatter([i for i in range(epochs)],history_3_a.history['loss'] )
plt.scatter([i for i in range(epochs)],history_3_a.history['val_loss'] )
plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```



3.1.2 Accuracy vs Epoch

In [62]:

```
plt.plot(history_3_a.history['acc'], label='Training Accuracy')
plt.plot(history_3_a.history['val_acc'], label='Test Accuracy')
plt.scatter([i for i in range(epochs)],history_3_a.history['acc'] )
plt.scatter([i for i in range(epochs)],history_3_a.history['val_acc'] )

plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```



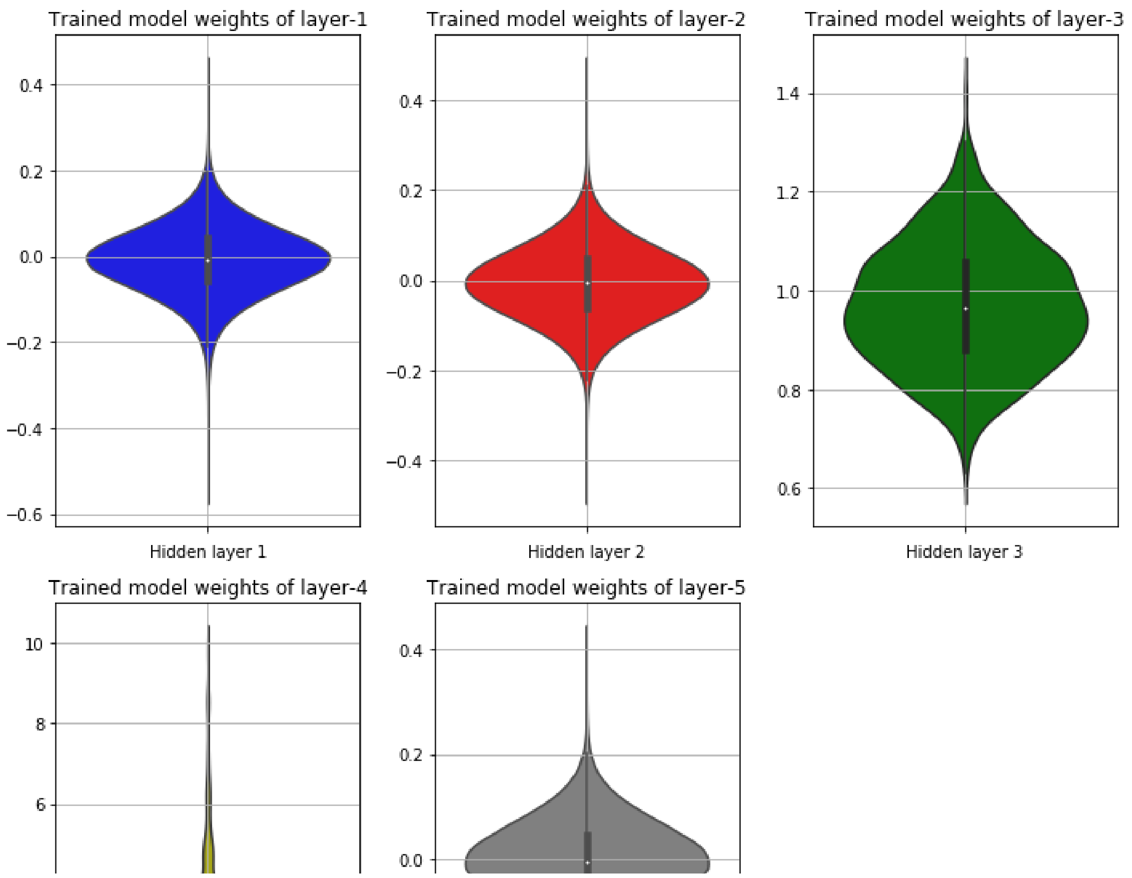
3.1.3 Distribution of Weights

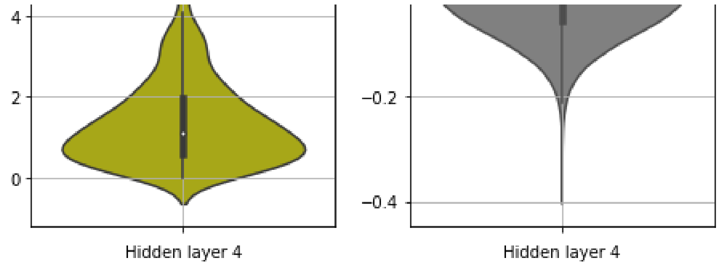
In [0]:

```
w_after_3_a = model_3_a.get_weights()
h1_w = w_after_3_a[0].flatten().reshape(-1,1)
h2_w = w_after_3_a[2].flatten().reshape(-1,1)
h3_w = w_after_3_a[4].flatten().reshape(-1,1)
h4_w = w_after_3_a[6].flatten().reshape(-1,1)
h5_w = w_after_3_a[8].flatten().reshape(-1,1)
```

In [81]:

```
fig = plt.figure(figsize=(10, 10))
plt.title('Weights of the model after trained')

plt.subplot(2,3,1)
plt.title('Trained model weights of layer-1')
sns.violinplot(y=h1_w, color='b')
plt.xlabel('Hidden layer 1')
plt.grid()
plt.tight_layout()

plt.subplot(2,3,2)
plt.title('Trained model weights of layer-2')
sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden layer 2')
plt.tight_layout()
plt.grid()


plt.subplot(2,3,3)
plt.title('Trained model weights of layer-3')
sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden layer 3')
plt.grid()
plt.tight_layout()

plt.subplot(2,3,4)
plt.title('Trained model weights of layer-4')
sns.violinplot(y=h4_w, color='y')
plt.xlabel('Hidden layer 4')
plt.tight_layout()
plt.grid()


plt.subplot(2,3,5)
plt.title('Trained model weights of layer-5')
sns.violinplot(y=h5_w, color='gray')
plt.xlabel('Hidden layer 4')
plt.grid()
plt.tight_layout()

plt.show()
```





3.2 With Dropout and Batch Normalization

In [71]:

```
model_3_b = Sequential()
#hidden layer 1
model_3_b.add(Dense(units=2048, input_shape=(num_pixels, ), activation='relu', kernel_initializer='
normal'))
model_3_b.add(Dropout(0.5))

#hidden layer 2
model_3_b.add(Dense(units=1024, activation='relu', kernel_initializer='normal'))
model_3_b.add(BatchNormalization())

#hidden layer 3
model_3_b.add(Dense(units=512, activation='relu', kernel_initializer='normal'))
model_3_b.add(Dropout(0.5))

#hidden layer 4
model_3_b.add(Dense(units=256, activation='relu', kernel_initializer='normal'))
model_3_b.add(BatchNormalization())

#hidden layer 5
model_3_b.add(Dense(units=128, activation='relu', kernel_initializer='normal'))
model_3_b.add(Dropout(0.5))
model_3_b.add(BatchNormalization())

#output layer
model_3_b.add(Dense(units=10, kernel_initializer='normal', activation='softmax'))

#compile with adam optimizers
model_3_b.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])

#summary
model_3_b.summary()
```

```
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
dense_21 (Dense)             (None, 2048)              1607680   
_________________________________________________________________
dropout_3 (Dropout)          (None, 2048)              0         
_________________________________________________________________
dense_22 (Dense)             (None, 1024)              2098176   
_________________________________________________________________
batch_normalization_3 (Batch (None, 1024)              4096      
_________________________________________________________________
dense_23 (Dense)             (None, 512)               524800    
_________________________________________________________________
dropout_4 (Dropout)          (None, 512)               0         
_________________________________________________________________
dense_24 (Dense)             (None, 256)               131328    
_________________________________________________________________
batch_normalization_4 (Batch (None, 256)               1024      
_________________________________________________________________
dense_25 (Dense)             (None, 128)               32896     
_________________________________________________________________
dropout_5 (Dropout)          (None, 128)               0         
_________________________________________________________________
batch_normalization_5 (Batch (None, 128)               512       
_________________________________________________________________
dense_26 (Dense)             (None, 10)                1290      
=================================================================
```

```
Total params: 4,401,802
Trainable params: 4,398,986
Non-trainable params: 2,816
_________________________________________________________________
```

In [72]:

```
history_3_b = model_3_b.fit(X_train, y_train, validation_data=(X_test, y_test), verbose=1, batch_si
ze=batch_size, epochs=epochs)
```

```
Train on 60000 samples, validate on 10000 samples
Epoch 1/15
60000/60000 [==============================] - 7s 116us/step - loss: 0.4317 - acc: 0.8754 -
val_loss: 0.1378 - val_acc: 0.9611
Epoch 2/15
60000/60000 [==============================] - 6s 94us/step - loss: 0.1757 - acc: 0.9517 -
val_loss: 0.1027 - val_acc: 0.9677
Epoch 3/15
60000/60000 [==============================] - 6s 93us/step - loss: 0.1360 - acc: 0.9621 -
val_loss: 0.0758 - val_acc: 0.9777
Epoch 4/15
60000/60000 [==============================] - 6s 96us/step - loss: 0.1121 - acc: 0.9688 -
val_loss: 0.0944 - val_acc: 0.9729
Epoch 5/15
60000/60000 [==============================] - 6s 95us/step - loss: 0.1034 - acc: 0.9716 -
val_loss: 0.0759 - val_acc: 0.9779
Epoch 6/15
60000/60000 [==============================] - 6s 94us/step - loss: 0.0832 - acc: 0.9766 -
val_loss: 0.0688 - val_acc: 0.9806
Epoch 7/15
60000/60000 [==============================] - 6s 96us/step - loss: 0.0790 - acc: 0.9779 -
val_loss: 0.0702 - val_acc: 0.9793
Epoch 8/15
60000/60000 [==============================] - 6s 95us/step - loss: 0.0721 - acc: 0.9792 -
val_loss: 0.0691 - val_acc: 0.9808
Epoch 9/15
60000/60000 [==============================] - 6s 93us/step - loss: 0.0680 - acc: 0.9809 -
val_loss: 0.0611 - val_acc: 0.9841
Epoch 10/15
60000/60000 [==============================] - 6s 93us/step - loss: 0.0620 - acc: 0.9818 -
val_loss: 0.0769 - val_acc: 0.9804
Epoch 11/15
60000/60000 [==============================] - 6s 94us/step - loss: 0.0577 - acc: 0.9839 -
val_loss: 0.0671 - val_acc: 0.9817
Epoch 12/15
60000/60000 [==============================] - 6s 94us/step - loss: 0.0525 - acc: 0.9850 -
val_loss: 0.0613 - val_acc: 0.9835
Epoch 13/15
60000/60000 [==============================] - 6s 97us/step - loss: 0.0509 - acc: 0.9856 -
val_loss: 0.0629 - val_acc: 0.9817
Epoch 14/15
60000/60000 [==============================] - 6s 97us/step - loss: 0.0471 - acc: 0.9868 -
val_loss: 0.0598 - val_acc: 0.9849
Epoch 15/15
60000/60000 [==============================] - 6s 94us/step - loss: 0.0449 - acc: 0.9866 -
val_loss: 0.0531 - val_acc: 0.9846
```

In [94]:

```
score_3_b = model_3_b.evaluate(X_test, y_test, verbose=0)
print('Test accuracy with BatchNorm and Dropout', score_3_b[1])
```

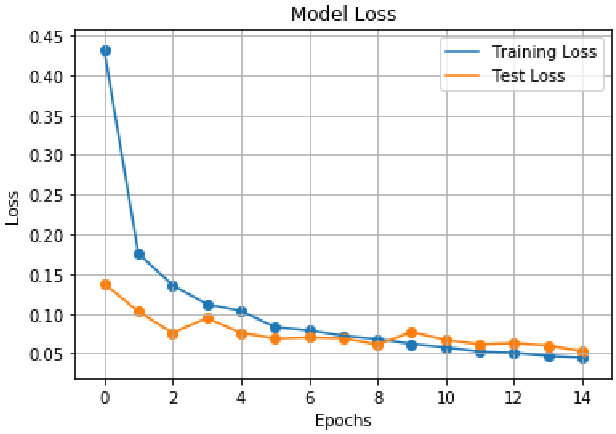
```
Test accuracy with BatchNorm and Dropout 0.9846
```

3.2.1 Loss vs Epoch

In [76]:

```
plt.plot(history_3_b.history['loss'], label='Training Loss')
plt.plot(history_3_b.history['val_loss'], label='Test Loss')
plt.scatter([i for i in range(epochs)], history_3_b.history['loss'])
plt.scatter([i for i in range(epochs)], history_3_b.history['val_loss'])
```

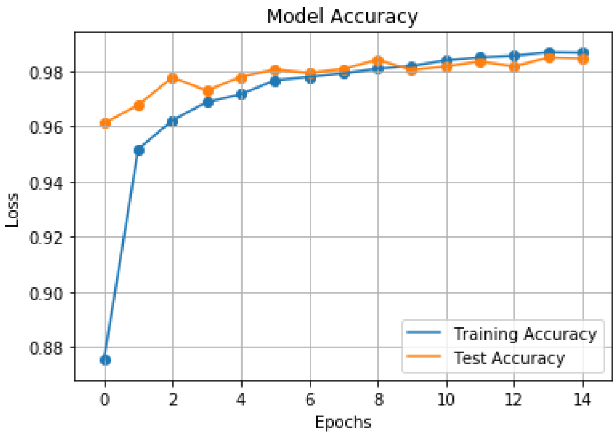
```
plt.scatter([i for i in range(epochs)], history_3_b.history['val_loss'])

plt.title('Model Loss')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.legend()
plt.grid()
plt.show()
```



3.2.2 Accuracy vs Epoch

In [77]:

```
plt.plot(history_3_b.history['acc'], label='Training Accuracy')
plt.plot(history_3_b.history['val_acc'], label='Test Accuracy')
plt.scatter([i for i in range(epochs)], history_3_b.history['acc'])
plt.scatter([i for i in range(epochs)], history_3_b.history['val_acc'])

plt.title('Model Accuracy')
plt.xlabel('Epochs')
plt.ylabel('Loss')
plt.grid()
plt.legend()
plt.show()
```



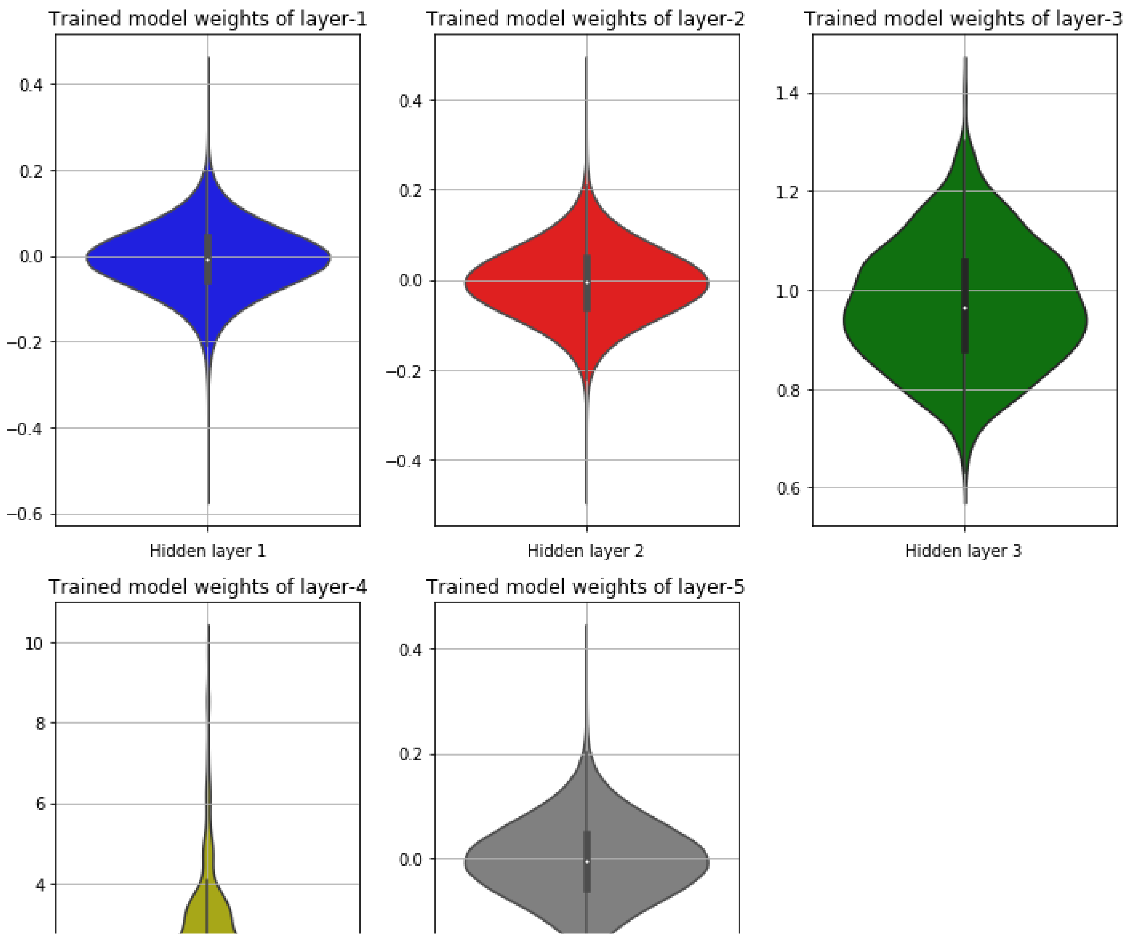
3.2.3 Distribution of Weights

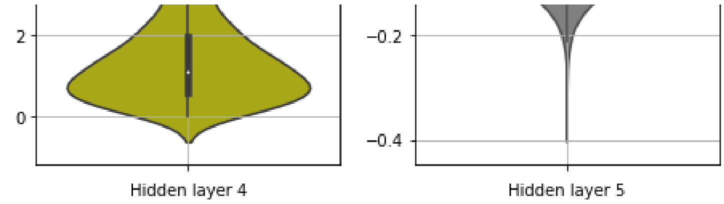
In [0]:

```
w_after_3_b = model_3_b.get_weights()
h1_w = w_after_3_b[0].flatten().reshape(-1,1)
h2_w = w_after_3_b[2].flatten().reshape(-1,1)
h3_w = w_after_3_b[4].flatten().reshape(-1,1)
h4_w = w_after_3_b[6].flatten().reshape(-1,1)
h5_w = w_after_3_b[8].flatten().reshape(-1,1)
```

In [80]:

```
fig = plt.figure(figsize=(10, 10))
plt.title('Weights of the model after trained')

plt.subplot(2,3,1)
plt.title('Trained model weights of layer-1')
sns.violinplot(y=h1_w, color='b')
plt.xlabel('Hidden layer 1')
plt.grid()
plt.tight_layout()

plt.subplot(2,3,2)
plt.title('Trained model weights of layer-2')
sns.violinplot(y=h2_w, color='r')
plt.xlabel('Hidden layer 2')
plt.tight_layout()
plt.grid()


plt.subplot(2,3,3)
plt.title('Trained model weights of layer-3')
sns.violinplot(y=h3_w, color='g')
plt.xlabel('Hidden layer 3')
plt.grid()
plt.tight_layout()

plt.subplot(2,3,4)
plt.title('Trained model weights of layer-4')
sns.violinplot(y=h4_w, color='y')
plt.xlabel('Hidden layer 4')
plt.tight_layout()
plt.grid()


plt.subplot(2,3,5)
plt.title('Trained model weights of layer-5')
sns.violinplot(y=h5_w, color='gray')
plt.xlabel('Hidden layer 5')
plt.grid()
plt.tight_layout()

plt.show()
```





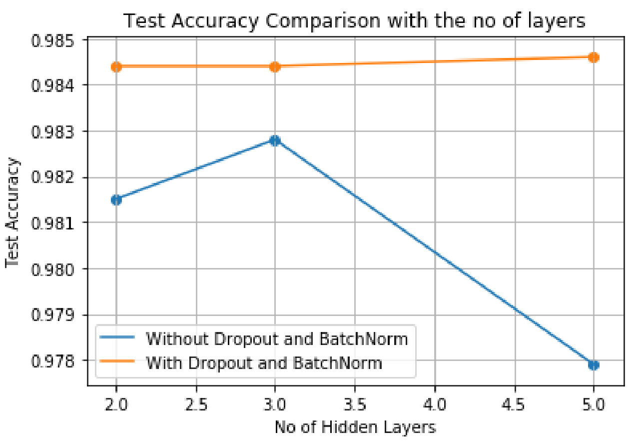
Comparison

In [108]:

```
Test_accuracy_without_dropout_BN = [score_1_a[1], score_2_a[1], score_3_a[1]]
Test_accuracy_with_dropout_BN = [score_1_b[1], score_2_b[1], score_3_b[1]]
no_of_hidden_layer = [2, 3, 5]

plt.plot(no_of_hidden_layer, Test_accuracy_without_dropout_BN, label='Without Dropout and
BatchNorm')
plt.plot(no_of_hidden_layer, Test_accuracy_with_dropout_BN, label='With Dropout and BatchNorm')
plt.scatter(no_of_hidden_layer, Test_accuracy_without_dropout_BN)
plt.scatter(no_of_hidden_layer, Test_accuracy_with_dropout_BN)

plt.title('Test Accuracy Comparison with the no of layers')
plt.grid()
plt.xlabel('No of Hidden Layers')
plt.ylabel('Test Accuracy')
#plt.yscale('symlog')
plt.legend()
plt.plot()
```

Out[108]:

```
[]
```



Summary:

```
- We can see that after adding the 5th hidden layer without dropout and Batch
  Norm our Test accuracy starts to decrease but with Dropout and Test Norm
  our Test Accuracy steadily increasing
```

That's the end of the code