1000-719bMSB Modeling of Complex Biological Systems

Deep Neural Network: Supervised Learning

Basic python and pandas

https://www.kaggle.com/lavanyashukla01/pandas-numpy-python-cheatsheet

https://www.utc.fr/~jlaforet/Suppl/python-cheatsheets.pdf

List comprehensions are a concise way to create new lists from existing ones.

In [1]:
```
list1 = list(range(0,10))
print(list1)
```
```
[0, 1, 2, 3, 4, 5, 6, 7, 8, 9]
```

In [2]:
```
list1[0] # A vector in R starts with an index of 1. In Python, 0.
```
Out[2]:
```
0
```

In [3]:
```
list1[2:5]
```
Out[3]:
```
[2, 3, 4]
```

In [4]:
```
list2 = []
for i in list1:
    list2.append(i+1)

print(list2)
```
```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
```

In [5]:
```
list3 = [i+1 for i in list1]

print(list3)
```
```
[1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
```

Classification of MNIST using densely connected layers

We are going to use the Keras library to implement a neural network that can classify handwritten digits - in just a few lines of code.

First we load and inspect the data. The dataset is split into training and test data.

In [6]:
```
import numpy as np
import tensorflow.keras as keras
import matplotlib.pyplot as plt
```

In [7]:
```
import tensorflow as tf
print(tf.__version__)
tf.compat.v1.disable_eager_execution()
```
```
2.7.0
```

In [8]:
```
(train_images, train_labels), (test_images, test_labels) = keras.datasets.mnist.load_data()
```

In [9]:
```
train_images.shape
```
Out[9]:
```
(60000, 28, 28)
```

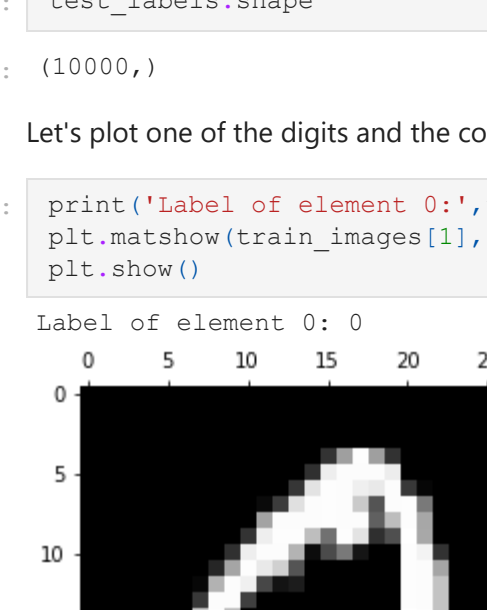
In [10]:
```
train_labels.shape
```
Out[10]:
```
(60000,)
```

In [11]:
```
test_images.shape
```
Out[11]:
```
(10000, 28, 28)
```

In [12]:
```
test_labels.shape
```
Out[12]:
```
(10000,)
```

Let's plot one of the digits and the corresponding label.

In [13]:
```
print('Label of element 0:',train_labels[1])
plt.matshow(train_images[1], cmap='gray')
plt.show()
```
```
Label of element 0: 0
```



In this step we define the neural network. ReLu is an activation function defined as f(x) = max(0,x).

Softmax activation function is normalized such that the sum of all outputs is equal 1.

In [14]:
```
from tensorflow.keras import layers
from tensorflow.keras import models
model = models.Sequential()
model.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
model.add(layers.Dense(10, activation='softmax'))
```

With compile we tell the network which optimizer and loss function to use. Optimizer specifies the particular implementation of the gradient-descent, e.g. how it adapts the learning rate. 'Metrics' specifies the output during the training.

In [15]:
```
model.compile(optimizer='rmsprop',
loss='mean_squared_error',
metrics=['accuracy'])
```

In [16]:
```
model.summary()
```
```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 512)               401920

 dense_1 (Dense)             (None, 10)                5130

=================================================================
Total params: 407,050
Trainable params: 407,050
Non-trainable params: 0
_________________________________________________________________
```

We are using a densely connected network, so we have to flatten the images. Input values should be in the range (0,1) for fast convergence.

In [17]:
```
train_images_flat = train_images.reshape((60000, 28 * 28))
train_images_flat = train_images_flat.astype('float32') / 255
test_images_flat = test_images.reshape((10000, 28 * 28))
test_images_flat = test_images_flat.astype('float32') / 255
```

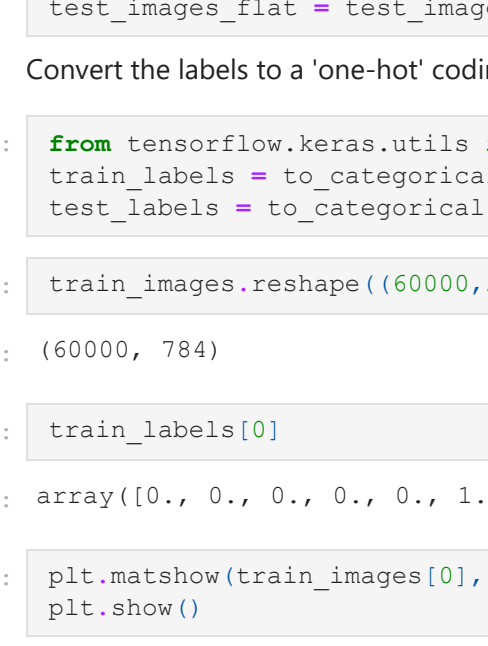
Convert the labels to a 'one-hot' coding.

In [18]:
```
from tensorflow.keras.utils import to_categorical
train_labels = to_categorical(train_labels)
test_labels = to_categorical(test_labels)
```

In [19]:
```
train_images.reshape((60000,28*28)).shape
```
Out[19]:
```
(60000, 784)
```

In [20]:
```
train_labels[0]
```
Out[20]:
```
array([0., 0., 0., 0., 0., 1., 0., 0., 0., 0.], dtype=float32)
```

In [21]:
```
plt.matshow(train_images[0], cmap='gray')
plt.show()
```



In [22]:
```
model.fit(train_images_flat, train_labels, epochs=5, batch_size=128)
```
```
Train on 60000 samples
Epoch 1/5
60000/60000 [==============================] - 3s 57us/sample - loss: 0.0122 - accuracy: 0.9213
Epoch 2/5
60000/60000 [==============================] - 3s 54us/sample - loss: 0.0053 - accuracy: 0.9667
Epoch 3/5
60000/60000 [==============================] - 3s 54us/sample - loss: 0.0037 - accuracy: 0.9773
Epoch 4/5
60000/60000 [==============================] - 3s 54us/sample - loss: 0.0028 - accuracy: 0.9826
Epoch 5/5
60000/60000 [==============================] - 3s 53us/sample - loss: 0.0023 - accuracy: 0.9862
```
Out[22]:
```
<keras.callbacks.History at 0x28326843cd0>
```

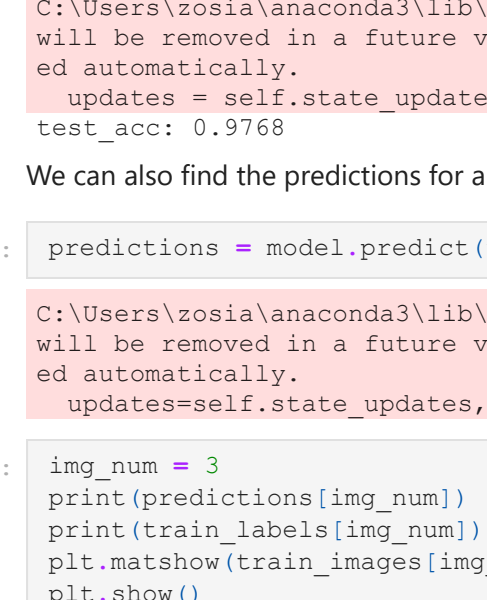
Let's check the performance on the test set. If the accuracy is less than the training accuracy, then we might be overfitting!

In [23]:
```
test_loss, test_acc = model.evaluate(test_images_flat, test_labels)
print('test_acc:', test_acc)
```
```
C:\Users\szsia\anaconda3\lib\site-packages\keras\engine\training_v1.py:2057: UserWarning: `Model.state_updates` will be removed in a future version. This property should not be used in TensorFlow 2.0, as `updates` are applied automatically.
  updates = self.state_updates
test_acc: 0.9768
```

We can also find the predictions for a selection of input images.

In [24]:
```
predictions = model.predict(train_images_flat[:10])
```
```
C:\Users\szsia\anaconda3\lib\site-packages\keras\engine\training_v1.py:2079: UserWarning: `Model.state_updates` will be removed in a future version. This property should not be used in TensorFlow 2.0, as `updates` are applied automatically.
  updates=self.state_updates,
```

In [25]:
```
img_num = 3
print(predictions[img_num])
print(train_labels[img_num])
plt.matshow(train_images[img_num], cmap='gray')
plt.show()
```
```
[6.02734831e-08 9.99658704e-01 4.88651604e-05 3.12580500e-06
 1.44826945e-05 6.93007749e-08 2.81787493e-06 1.16178169e-04
 1.55522735e-04 9.67063727e-08]
[0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
```



In [26]:
```
train_labels
```
Out[26]:
```
array([[0., 0., 0., ..., 0., 0., 0.],
       [1., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       ...,
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 0., 0.],
       [0., 0., 0., ..., 0., 1., 0.]], dtype=float32)
```

Classification of MNIST using convolutional layers

We have build a classifier for handwritten images only using densely connected layers. Let's see if we can do better using convolutional layers!

First define the convolutional layers.

In [27]:
```
model2 = models.Sequential()
model2.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model2.add(layers.MaxPooling2D((2, 2)))
model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
model2.add(layers.MaxPooling2D((2, 2)))
model2.add(layers.Conv2D(64, (3, 3), activation='relu'))
```

In [28]:
```
model2.summary()
```
```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2D  (None, 13, 13, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 conv2d_2 (Conv2D)           (None, 3, 3, 64)          36928

=================================================================
Total params: 55,744
Trainable params: 55,744
Non-trainable params: 0
_________________________________________________________________
```

Now add a classifier on top of the convnet.

In [29]:
```
model2.add(layers.Flatten())
model2.add(layers.Dense(64, activation='relu'))
model2.add(layers.Dense(10, activation='softmax'))
```

In [30]:
```
model2.summary()
```
```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d (Conv2D)             (None, 26, 26, 32)        320

 max_pooling2d (MaxPooling2D  (None, 13, 13, 32)       0
 )

 conv2d_1 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_1 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 conv2d_2 (Conv2D)           (None, 3, 3, 64)          36928

 flatten (Flatten)           (None, 576)               0

 dense_2 (Dense)             (None, 64)                36928

 dense_3 (Dense)             (None, 10)                650

=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
_________________________________________________________________
```

In [31]:
```
train_images_conv = train_images.reshape((60000, 28, 28, 1))
train_images_conv = train_images_conv.astype('float32') / 255
test_images_conv = test_images.reshape((10000, 28, 28, 1))
test_images_conv = test_images_conv.astype('float32') / 255
```

In [32]:
```
model2.compile(optimizer='rmsprop',
loss='categorical_crossentropy',
metrics=['accuracy'])
```

In [33]:
```
model2.fit(train_images_conv, train_labels, epochs=15, batch_size=64)
```
```
Train on 60000 samples
Epoch 1/15
60000/60000 [==============================] - 25s 423us/sample - loss: 0.1764 - accuracy: 0.9452- l - ETA: 0s
- loss: 0.1773 - accuracy
Epoch 2/15
60000/60000 [==============================] - 24s 405us/sample - loss: 0.0490 - accuracy: 0.9843
Epoch 3/15
60000/60000 [==============================] - 24s 405us/sample - loss: 0.0334 - accuracy: 0.9895
Epoch 4/15
60000/60000 [==============================] - 24s 406us/sample - loss: 0.0257 - accuracy: 0.9919
Epoch 5/15
60000/60000 [==============================] - 24s 407us/sample - loss: 0.0194 - accuracy: 0.9941
Epoch 6/15
60000/60000 [==============================] - 24s 408us/sample - loss: 0.0162 - accuracy: 0.9949
Epoch 7/15
60000/60000 [==============================] - 24s 403us/sample - loss: 0.0130 - accuracy: 0.9961
Epoch 8/15
60000/60000 [==============================] - 27s 446us/sample - loss: 0.0108 - accuracy: 0.9966
Epoch 9/15
60000/60000 [==============================] - 25s 415us/sample - loss: 0.0092 - accuracy: 0.9973
Epoch 10/15
60000/60000 [==============================] - 24s 396us/sample - loss: 0.0079 - accuracy: 0.9976
Epoch 11/15
60000/60000 [==============================] - 25s 413us/sample - loss: 0.0065 - accuracy: 0.9980
Epoch 12/15
60000/60000 [==============================] - 24s 397us/sample - loss: 0.0069 - accuracy: 0.9979
Epoch 13/15
60000/60000 [==============================] - 24s 396us/sample - loss: 0.0053 - accuracy: 0.9983
Epoch 14/15
60000/60000 [==============================] - 24s 399us/sample - loss: 0.0049 - accuracy: 0.9986
Epoch 15/15
60000/60000 [==============================] - 24s 396us/sample - loss: 0.0049 - accuracy: 0.9986
```
Out[33]:
```
<keras.callbacks.History at 0x28327e744f0>
```

In [34]:
```
test_loss, test_acc = model2.evaluate(test_images_conv, test_labels)
print(test_acc)
```
```
0.9918
```

Introducing Fashion MNIST (Homework dataset)

The MNIST dataset is not too demanding, let's try something a little more difficult - Fashion MNIST.

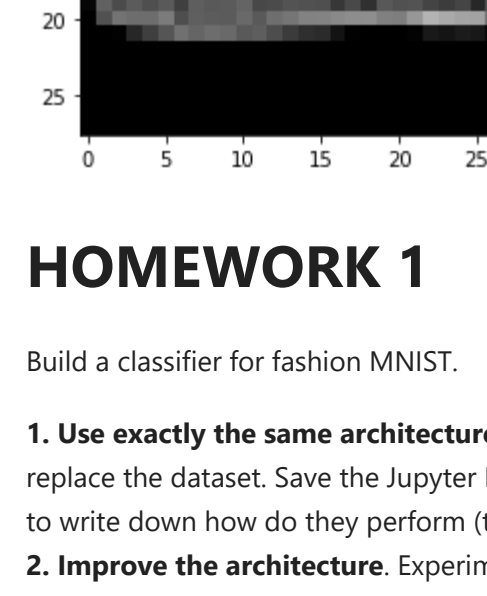
LINK TO IMAGE

Check out labels on GitHub

In [35]:
```
(train_imgs_fash, train_labels_fash), (test_imgs_fash, test_labels_fash) = keras.datasets.fashion_mnist.load_data()
```

In [36]:
```
train_imgs_fash.shape
```
Out[36]:
```
(60000, 28, 28)
```

In [37]:
```
plt.imshow(train_imgs_fash[12],  cmap=plt.get_cmap('gray'))
```
Out[37]:
```
<matplotlib.image.AxesImage at 0x28327f48310>
```



HOMEWORK 1

Build a classifier for fashion MNIST.

1. Use exactly the same architectures (both densely connected layers and from convolutional layers) as the above MNIST e.g., replace the dataset. Save the Jupyter Notebook in its original format and output a PDF file after training, testing, and validation. Make sure to write down how do they perform (training accuracny, testing accuracy).
2. Improve the architecture. Experiment with different numbers of layers, size of layers, number of filters, size of filters. You are required to make those adjustment to get the highest accuracy. Watch out for overfitting -- we want the highest testing accuracy! Please provide a PDF file of the result, the best test accuracy and the architecture (different numbers of layers, size of layers, number of filters, size of filters)

HOMEWORK 1.1

In [38]:
```
# Changing the hw dataset
# Densely connected
train_img_hw = train_imgs_fash.reshape((60000, 28 * 28))
train_img_hw = train_img_hw.astype('float32') / 255
test_img_hw = test_imgs_fash.reshape((10000, 28 * 28))
test_img_hw = test_img_hw.astype('float32') / 255

# Convolutional
train_img_conv_hw = train_imgs_fash.reshape((60000, 28, 28, 1))
train_img_conv_hw = train_img_conv_hw.astype('float32') / 255
test_img_conv_hw = test_imgs_fash.reshape((10000, 28, 28, 1))
test_img_conv_hw = test_img_conv_hw.astype('float32') / 255

# Labels
train_labels_hw = to_categorical(train_labels_fash)
test_labels_hw = to_categorical(test_labels_fash)
```

Densely connected model

In [39]:
```
# Densely connected model
model_hw1 = models.Sequential()
model_hw1.add(layers.Dense(512, activation='relu', input_shape=(28 * 28,)))
model_hw1.add(layers.Dense(10, activation='softmax'))
model_hw1.compile(optimizer='rmsprop',
loss='mean_squared_error',
metrics=['accuracy'])
model_hw1.summary()
```
```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense_4 (Dense)             (None, 512)               401920

 dense_5 (Dense)             (None, 10)                5130

=================================================================
Total params: 407,050
Trainable params: 407,050
Non-trainable params: 0
_________________________________________________________________
```

In [40]:
```
# Fitting first model (densely connected)
model_hw1.fit(train_img_hw, train_labels_hw, epochs=5, batch_size=128)
```
```
Train on 60000 samples
Epoch 1/5
60000/60000 [==============================] - 3s 56us/sample - loss: 0.0318 - accuracy: 0.7767
Epoch 2/5
60000/60000 [==============================] - 3s 50us/sample - loss: 0.0209 - accuracy: 0.8563
Epoch 3/5
60000/60000 [==============================] - 3s 52us/sample - loss: 0.0185 - accuracy: 0.8731
Epoch 4/5
60000/60000 [==============================] - 3s 52us/sample - loss: 0.0172 - accuracy: 0.8822
Epoch 5/5
60000/60000 [==============================] - 3s 52us/sample - loss: 0.0162 - accuracy: 0.8910
```
Out[40]:
```
<keras.callbacks.History at 0x28328356d00>
```

In [41]:
```
print("Densely connected model")
test_loss, test_acc = model_hw1.evaluate(test_img_hw, test_labels_hw)
print("test acc", test_acc)
train_loss, train_acc = model_hw1.evaluate(train_img_hw, train_labels_hw)
print("train_acc: ", train_acc)
```
```
Densely connected model
test acc: 0.8667
train_acc: 0.8894333
```

Convolutional model

In [42]:
```
model_hw2 = models.Sequential()
model_hw2.add(layers.Conv2D(32, (3, 3), activation='relu', input_shape=(28, 28, 1)))
model_hw2.add(layers.MaxPooling2D((2, 2)))
model_hw2.add(layers.Conv2D(64, (3, 3), activation='relu'))
model_hw2.add(layers.MaxPooling2D((2, 2)))
model_hw2.add(layers.Conv2D(64, (3, 3), activation='relu'))
model_hw2.add(layers.Flatten())
model_hw2.add(layers.Dense(64, activation='relu'))
model_hw2.add(layers.Dense(10, activation='softmax'))
model_hw2.compile(optimizer='rmsprop', loss='categorical_crossentropy', metrics=['accuracy'])

model_hw2.summary()
```
```
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 conv2d_3 (Conv2D)           (None, 26, 26, 32)        320

 max_pooling2d_2 (MaxPooling  (None, 13, 13, 32)       0
 2D)

 conv2d_4 (Conv2D)           (None, 11, 11, 64)        18496

 max_pooling2d_3 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 conv2d_5 (Conv2D)           (None, 3, 3, 64)          36928

 flatten_1 (Flatten)         (None, 576)               0

 dense_6 (Dense)             (None, 64)                36928

 dense_7 (Dense)             (None, 10)                650

=================================================================
Total params: 93,322
Trainable params: 93,322
Non-trainable params: 0
_________________________________________________________________
```

In [43]:
```
model_hw2.fit(train_img_conv_hw, train_labels_hw, epochs=15, batch_size=64)
```
```
Train on 60000 samples
Epoch 1/15
60000/60000 [==============================] - 25s 415us/sample - loss: 0.5548 - accuracy: 0.8030
Epoch 2/15
60000/60000 [==============================] - 25s 429us/sample - loss: 0.3324 - accuracy: 0.8782
Epoch 3/15
60000/60000 [==============================] - 24s 406us/sample - loss: 0.2804 - accuracy: 0.8973
Epoch 4/15
60000/60000 [==============================] - 24s 407us/sample - loss: 0.2475 - accuracy: 0.9094
Epoch 5/15
60000/60000 [==============================] - 24s 406us/sample - loss: 0.2245 - accuracy: 0.9181
Epoch 6/15
60000/60000 [==============================] - 24s 403us/sample - loss: 0.2055 - accuracy: 0.9247
Epoch 7/15
60000/60000 [==============================] - 24s 404us/sample - loss: 0.1884 - accuracy: 0.9313- loss: 0.1885
- accuracy
Epoch 8/15
60000/60000 [==============================] - 24s 407us/sample - loss: 0.1727 - accuracy: 0.9360
Epoch 9/15
60000/60000 [==============================] - 24s 408us/sample - loss: 0.1609 - accuracy: 0.9406
Epoch 10/15
60000/60000 [==============================] - 24s 401us/sample - loss: 0.1487 - accuracy: 0.9448
Epoch 11/15
60000/60000 [==============================] - 24s 401us/sample - loss: 0.1376 - accuracy: 0.9488
Epoch 12/15
60000/60000 [==============================] - 24s 407us/sample - loss: 0.1300 - accuracy: 0.9516
Epoch 13/15
60000/60000 [==============================] - 24s 400us/sample - loss: 0.1194 - accuracy: 0.9557
Epoch 14/15
60000/60000 [==============================] - 25s 409us/sample - loss: 0.1123 - accuracy: 0.9582
Epoch 15/15
60000/60000 [==============================] - 25s 418us/sample - loss: 0.1073 - accuracy: 0.9604
```
Out[43]:
```
<keras.callbacks.History at 0x283282f56d0>
```

In [44]:
```
print("Convolutional model")
test_loss_hw2, test_acc_hw2 = model_hw2.evaluate(test_img_conv_hw, test_labels_hw)
print("test acc: ", test_acc_hw2)
train_loss_hw2, train_acc_hw2 = model_hw2.evaluate(train_img_conv_hw, train_labels_hw)
print("train acc: ", train_acc_hw2)
```
```
Convolutional model
test acc:  0.9059
train acc:  0.9673
```

HOMEWORK 1.2

In [45]:
```
model_hw_improved = tf.keras.Sequential()
model_hw_improved.add(tf.keras.layers.InputLayer(input_shape=(28,28,1)))
model_hw_improved.add(tf.keras.layers.BatchNormalization())
model_hw_improved.add(tf.keras.layers.Convolution2D(64, (4, 4), padding='same', activation='relu'))
model_hw_improved.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
model_hw_improved.add(tf.keras.layers.Dropout(0.2))
model_hw_improved.add(tf.keras.layers.Convolution2D(64, (4, 4), activation='relu'))
model_hw_improved.add(tf.keras.layers.MaxPooling2D(pool_size=(2, 2)))
model_hw_improved.add(tf.keras.layers.Dropout(0.2))
model_hw_improved.add(tf.keras.layers.Flatten())
model_hw_improved.add(tf.keras.layers.Dense(256, activation='relu'))
model_hw_improved.add(tf.keras.layers.Dropout(0.4))
model_hw_improved.add(tf.keras.layers.Dense(64, activation='relu'))
model_hw_improved.add(tf.keras.layers.BatchNormalization())
model_hw_improved.add(tf.keras.layers.Dense(10, activation='softmax'))
model_hw_improved.compile(optimizer='adam', loss='categorical_crossentropy', metrics=['accuracy'])

model_hw_improved.summary()
```
```
WARNING:tensorflow:From C:\Users\szsia\anaconda3\lib\site-packages\keras\layers\normalization\batch_normalization.py:532: _colocate_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
Model: "sequential_4"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 batch_normalization (BatchN  (None, 28, 28, 1)        4
 ormalization)

 conv2d_6 (Conv2D)           (None, 28, 28, 64)        1088

 max_pooling2d_4 (MaxPooling  (None, 14, 14, 64)       0
 2D)

 dropout (Dropout)           (None, 14, 14, 64)        0

 conv2d_7 (Conv2D)           (None, 11, 11, 64)        65600

 max_pooling2d_5 (MaxPooling  (None, 5, 5, 64)         0
 2D)

 dropout_1 (Dropout)         (None, 5, 5, 64)          0

 flatten_2 (Flatten)         (None, 1600)              0

 dense_8 (Dense)             (None, 256)               409856

 dropout_2 (Dropout)         (None, 256)               0

 dense_9 (Dense)             (None, 64)                16448

 batch_normalization_1 (Batc  (None, 64)               256
 hNormalization)

 dense_10 (Dense)            (None, 10)                650

=================================================================
Total params: 493,902
Trainable params: 493,772
Non-trainable params: 130
_________________________________________________________________
```

In [46]:
```
model_hw_improved.fit(train_img_conv_hw, train_labels_hw, epochs=15, batch_size=64)
```
```
Train on 60000 samples
Epoch 1/15
60000/60000 [==============================] - 69s 1ms/sample - loss: 0.5337 - accuracy: 0.8067
Epoch 2/15
60000/60000 [==============================] - 68s 1ms/sample - loss: 0.3453 - accuracy: 0.8745
Epoch 3/15
60000/60000 [==============================] - 68s 1ms/sample - loss: 0.3019 - accuracy: 0.8883
Epoch 4/15
60000/60000 [==============================] - 68s 1ms/sample - loss: 0.2792 - accuracy: 0.8980
Epoch 5/15
60000/60000 [==============================] - 68s 1ms/sample - loss: 0.2608 - accuracy: 0.9045
Epoch 6/15
60000/60000 [==============================] - 70s 1ms/sample - loss: 0.2438 - accuracy: 0.9096
Epoch 7/15
60000/60000 [==============================] - 67s 1ms/sample - loss: 0.2318 - accuracy: 0.9140
Epoch 8/15
60000/60000 [==============================] - 67s 1ms/sample - loss: 0.2229 - accuracy: 0.9180
Epoch 9/15
60000/60000 [==============================] - 68s 1ms/sample - loss: 0.2114 - accuracy: 0.9214
Epoch 10/15
60000/60000 [==============================] - 66s 1ms/sample - loss: 0.2063 - accuracy: 0.9235
Epoch 11/15
60000/60000 [==============================] - 65s 1ms/sample - loss: 0.1990 - accuracy: 0.9255
Epoch 12/15
60000/60000 [==============================] - 56s 930us/sample - loss: 0.1909 - accuracy: 0.9283
Epoch 13/15
60000/60000 [==============================] - 59s 989us/sample - loss: 0.1848 - accuracy: 0.9307
Epoch 14/15
60000/60000 [==============================] - 61s 1ms/sample - loss: 0.1790 - accuracy: 0.9340
Epoch 15/15
60000/60000 [==============================] - 62s 1ms/sample - loss: 0.1731 - accuracy: 0.9357
```
Out[46]:
```
<keras.callbacks.History at 0x28331762a90>
```

In [47]:
```
# Test accuracy needs to be higher than 0.9059
print("Improved model")
test_loss_hw_improved, test_acc_hw_improved = model_hw_improved.evaluate(test_img_conv_hw, test_labels_hw)
print("test acc: ", test_acc_hw_improved)
train_loss_hw_improved, train_acc_hw_improved = model_hw_improved.evaluate(train_img_conv_hw, train_labels_hw)
print("train acc: ", train_acc_hw_improved)
```
```
Improved model
test acc:  0.9208
train acc:  0.96066666
```

Visualizing Filter Response

We use gradient descent in input space to display the visual pattern each filter is maximally responsive to. To this end we take a VGG19 convnet pretrained on the ImageNet dataset.

Very Deep Convolutional Networks for Large-Scale Image Recognition Karen Simonyan, Andrew Zisserman

DL Architecture

In [48]:
```
from tensorflow.keras.applications import VGG19
from tensorflow.keras import backend as K
import numpy as np

import matplotlib.pyplot as plt

#load pretrained model
#we omit the densely connected layers of the network
model = VGG19(weights='imagenet', include_top=False)
```

In [49]:
```
model.summary()
```
```
Model: "vgg19"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 input_2 (InputLayer)        [(None, None, None, 3)]   0

 block1_conv1 (Conv2D)       (None, None, None, 64)    1792

 block1_conv2 (Conv2D)       (None, None, None, 64)    36928

 block1_pool (MaxPooling2D)  (None, None, None, 64)    0

 block2_conv1 (Conv2D)       (None, None, None, 128)   73856

 block2_conv2 (Conv2D)       (None, None, None, 128)   147584

 block2_pool (MaxPooling2D)  (None, None, None, 128)   0

 block3_conv1 (Conv2D)       (None, None, None, 256)   295168

 block3_conv2 (Conv2D)       (None, None, None, 256)   590080

 block3_conv3 (Conv2D)       (None, None, None, 256)   590080

 block3_conv4 (Conv2D)       (None, None, None, 256)   590080

 block3_pool (MaxPooling2D)  (None, None, None, 256)   0

 block4_conv1 (Conv2D)       (None, None, None, 512)   1180160

 block4_conv2 (Conv2D)       (None, None, None, 512)   2359808

 block4_conv3 (Conv2D)       (None, None, None, 512)   2359808

 block4_conv4 (Conv2D)       (None, None, None, 512)   2359808

 block4_pool (MaxPooling2D)  (None, None, None, 512)   0

 block5_conv1 (Conv2D)       (None, None, None, 512)   2359808

 block5_conv2 (Conv2D)       (None, None, None, 512)   2359808

 block5_conv3 (Conv2D)       (None, None, None, 512)   2359808

 block5_conv4 (Conv2D)       (None, None, None, 512)   2359808

 block5_pool (MaxPooling2D)  (None, None, None, 512)   0

=================================================================
Total params: 20,024,384
Trainable params: 20,024,384
Non-trainable params: 0
_________________________________________________________________
```

In [50]:
```
#Specify filter you want to visualize and get its output
layer_name = 'block5_conv3'
filter_index = 3
layer_output = model.get_layer(layer_name).output

#Loss is the averaged activation of the chosen filter
loss = K.mean(layer_output[:, :, :, filter_index])
```

In [51]:
```
#Gradients of loss with respect to the input
#upgrading to 2.x: tf.gradients is no longer supported
#requiring tf.compat.v1.disable_eager_execution()
grads = K.gradients(loss, model.input)[0]

#A trick is to normalize the gradients by their L2 norm
#This ensures that the magnitude of the gradients is always in the same range
#and leads to a smooth descent process
grads /= (K.sqrt(K.mean(K.square(grads))) + 1e-5)
```

In [52]:
```
#The tensors defined so far (loss, grads) were symbolic
#To obtain values we need to feed an input via K.function
iterate = K.function([model.input], [loss, grads])
loss_value, grads_value = iterate([np.zeros((1, 150, 150, 3))])
```

In [53]:
```
print(grads)
print(grads_value)
```
```
Tensor("truediv:0", shape=(None, None, None, 3), dtype=float32)
[[[[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  ...

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]]]
```

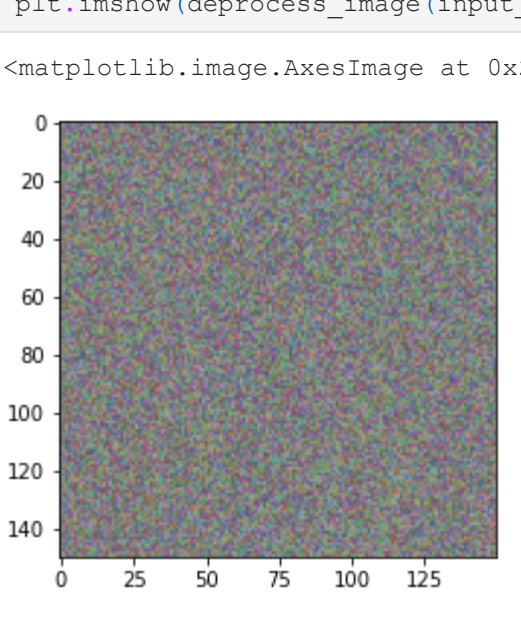
In [54]:
```
#Implement the actual gradient descent
#Initial input is a grey image with some noise
input_img_data = np.random.random((1, 150, 150, 3)) * 20 + 128.
step = 1.
for i in range(40):
    loss_value, grads_value = iterate([input_img_data])
    input_img_data += grads_value * step
```

In [55]:
```
print(grads_value)
```
```
[[[[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  ...

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]

  [[0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]
   ...
   [0. 0. 0.]
   [0. 0. 0.]
   [0. 0. 0.]]]]
```

In [56]:
```
#Postprocess to turn into displayable image

def deprocess_image(x):
    x -= x.mean()
    x /= (x.std() + 1e-5)
    x *= 0.1

    x += 0.5
    x = np.clip(x, 0, 1)

    x *= 255
    x = np.clip(x, 0, 255).astype('uint8')
    return x
```

In [57]:
```
plt.imshow(deprocess_image(input_img_data[0]))
```

Out[57]: <matplotlib.image.AxesImage at 0x2833e9f4af0>



HOMEWORK 2:

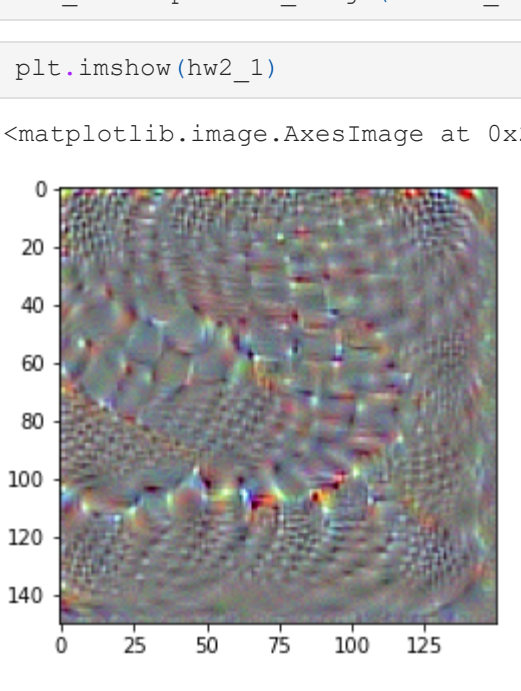
Write a function that takes as arguments the name of the layer and filter index and outputs the displayable filter response. Then you can choose different filters and visualize which patterns they are responsive too! Submit the code (as Notebook) and at least 3 filter responses (a PDF file).

In [58]:
```
def filter_response(layer_name, filter_index, model):
    layer_output = model.get_layer(layer_name).output

    loss = K.mean(layer_output[:, :, :, filter_index])
    grads = K.gradients(loss, model.input)[0]
    grads /= (K.sqrt(K.mean(K.square(grads))) + 1e-5)
    iterate = K.function([model.input], [loss, grads])
    loss_value, grads_value = iterate([np.zeros((1, 150, 150, 3))])

    input_img_data = np.random.random((1, 150, 150, 3)) * 20 + 128.
    step = 1
    for i in range(40):
        loss_value, grads_value = iterate([input_img_data])
        input_img_data += grads_value * step

    return input_img_data
```

In [59]:
```
hw2_1 = deprocess_image(filter_response("block5_conv2", 3, model)[0])
hw2_2 = deprocess_image(filter_response("block3_conv3", 3, model)[0])
hw2_3 = deprocess_image(filter_response("block4_conv4", 3, model)[0])
```

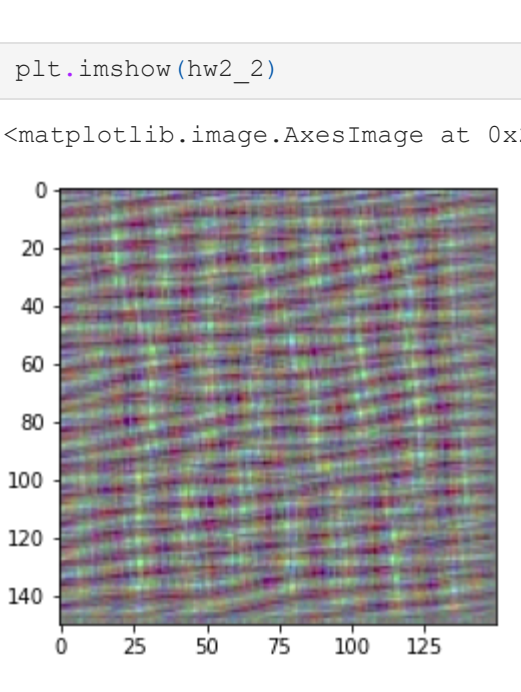
In [60]:
```
plt.imshow(hw2_1)
```

Out[60]: <matplotlib.image.AxesImage at 0x283460dde80>



In [61]:
```
plt.imshow(hw2_2)
```

Out[61]: <matplotlib.image.AxesImage at 0x28346135640>



In [62]:
```
plt.imshow(hw2_3)
```

Out[62]: <matplotlib.image.AxesImage at 0x283461a0100>