In [1]:
```
import tensorflow as tf
from tensorflow import keras
import pandas as pd
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import pydot, graphviz
import numpy as np
import pandas as pd
```

Import datasets + simple exploration

In [2]:
```
# import inbuild fashion data from keras
fashion_mnist = keras.datasets.fashion_mnist
(X_train_full,y_train_full),(X_test,y_test)=fashion_mnist.load_data()
```

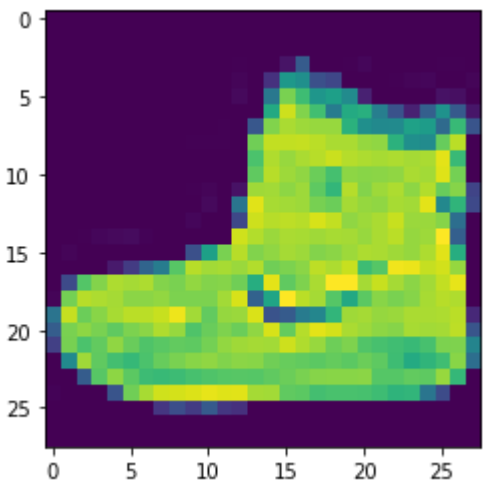
In [18]:
```
# actual label names
label_names= {0:'T-shirt/top',
              1:'Trouser',
              2:'Pullover',
              3:'Dress',
              4:'Coat',
              5:'Sandal',
              6:'Shirt',
              7:'Sneaker',
              8:'Bag',
              9:'Ankle boot'}
```

In [4]:
```
X_train_full.dtype
```

Out[4]:
```
dtype('uint8')
```

In [19]:
```
# show first image
plt.imshow(X_train_full[0])
```

Out[19]:
```
(<matplotlib.image.AxesImage at 0x2b5f1ef9648>,)
```



In [20]:
```
# label of the above image
label_names[y_train_full[0]]
```

Out[20]:
```
'Ankle boot'
```

In [21]:
```
# there are 60000 images to train  and 10000 images to test
print('Training set dimensions: ',X_train_full.shape,y_train_full.shape)
print('Test set dimensions: ',X_test.shape,y_test.shape)
```

```
Training set dimensions:  (60000, 28, 28) (60000,)
Test set dimensions:  (10000, 28, 28) (10000,)
```

In [22]:
```
# each image has a 28x28 pixel dimension
# each pixel takes a value between 0 and 255
X_train_full[0]
```

Out[22]:
```
array([[  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,   1,
          0,   0,  13,  73,   0,   0,   1,   4,   0,   0,   0,   0,   1,
          1,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   3,
          0,  36, 136, 127,  62,  54,   0,   0,   0,   1,   3,   4,   0,
          0,   3],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   6,
          0, 102, 204, 176, 134, 144, 123,  23,   0,   0,   0,   0,  12,
         10,   0],
       [  0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,   0,
```

Data Reshaping

- CNN requires data to be 3 dimensional, so this step reshapes dimension to 3

In [23]:
```
# that final '1' is the third dimension
X_train_full= X_train_full.reshape((60000,28,28,1))
X_test= X_test.reshape((10000,28,28,1))
```

Data normalisation

- ensure data is of the same scale
- different from usual ML normalisations

In [24]:
```
# the 255. ensures that output is all float
X_train_n=X_train_full/255.
X_test=X_test/255.
```

split into training and validation sets

- validation set is used for parameter tuning and model evaluation
- test set is used for final evaluation of performance

In [25]:
```
# split using train_test_split function
X_train, X_valid, y_train, y_valid = train_test_split(X_train_n, y_train_full, test_siz
```

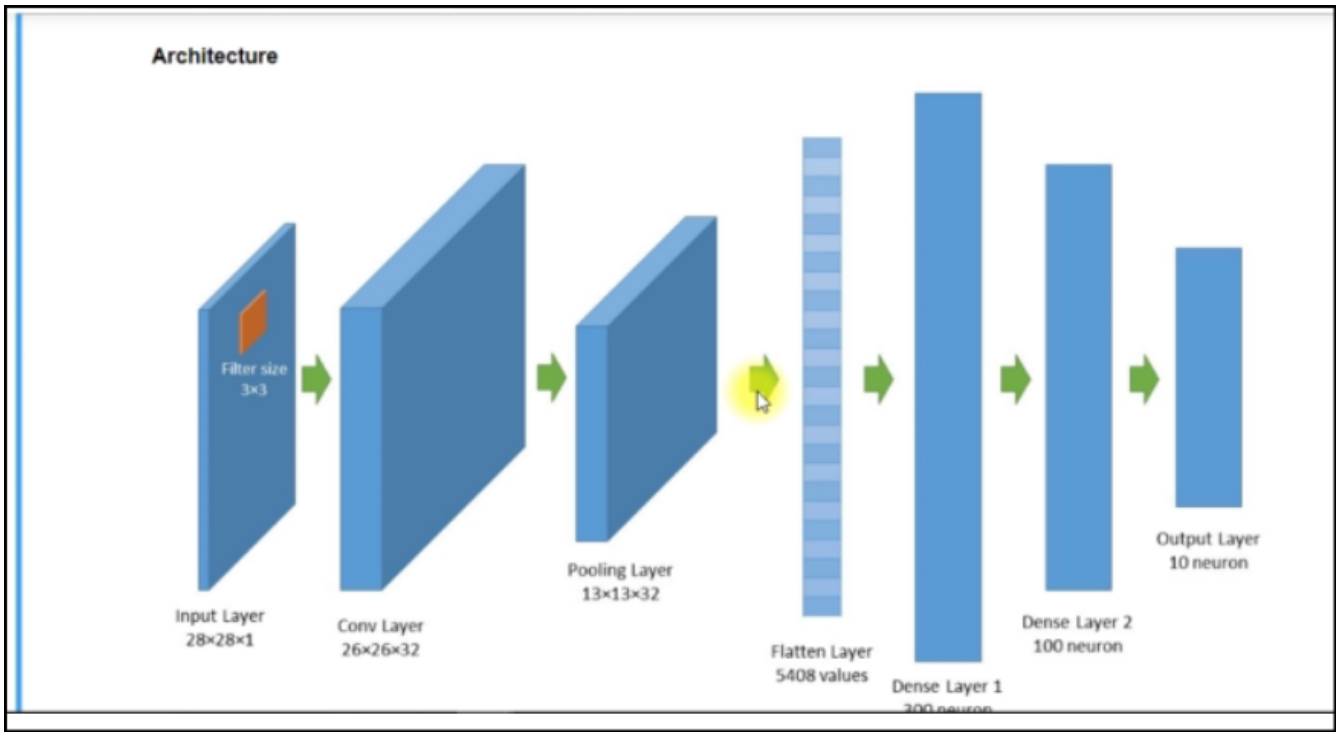
In [26]:
```
# check dimensions
print('Training set Dimensions: \n\tX: {}\n\ty: {}'.format(X_train.shape,y_train.shape)
print('Validation set Dimensions: \n\tX: {}\n\ty: {}'.format(X_valid.shape,y_valid.shap
print('Test set Dimensions: \n\tX: {}'.format(X_test.shape))
```

```
Training set Dimensions:
        X: (55000, 28, 28, 1)
        y: (55000,)
Validation set Dimensions:
        X: (5000, 28, 28, 1)
        y: (5000,)
Test set Dimensions:
        X: (10000, 28, 28, 1)
        y: (10000,)
```

Build Convolutional Neural Network

1. 3x3 filters are applied to give feature maps in the convolutional layer
    - these filters are trained to highlight on certain features
    - valid padding is applied, which ignores the inpur borders
2. Max pooling applied
    - max value in each grid is taken
    - this emphasizes on important features and reduces computational load too
3. input flattened to single array as input for ANN
4. Hidden layers
5. Outputlayers

In [27]:
```
# make the results consistent by setting seed
np.random.seed(1)
tf.random.set_seed(1)
```



In [28]:
```
# create NN object using sequential API
model=keras.models.Sequential()

# add convolutional layer
model.add(keras.layers.Conv2D(filters=32,
                              # i.e. filter size
                             kernel_size=(3,3),
                              # i.e. number of steps each filter takes
                             strides=1,
                              # this padding ignores input borders
                              padding='valid',
                              activation='relu',
                              # FOR COLORED IMAGES ,28x28x3 instead
                              input_shape=(28,28,1)))

# max pooling taking max value from 2x2 grid
model.add(keras.layers.MaxPooling2D((2,2)))

# flatten into a single array
model.add(keras.layers.Flatten())

# add a hidden layer of 300 neurons with relu activation
model.add(keras.layers.Dense(300,activation='relu'))
# add a hidden layer of 100 neurons with relu activation
model.add(keras.layers.Dense(100,activation='relu'))

# add output layer of 10 neurons(there are 10 classes) with softmax activation
model.add(keras.layers.Dense(10,activation='softmax'))
```

In [29]:
```
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d_1 (Conv2D)            (None, 26, 26, 32)        320
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 13, 13, 32)        0
_________________________________________________________________
flatten_1 (Flatten)          (None, 5408)              0
_________________________________________________________________
dense_3 (Dense)              (None, 300)               1622700
_________________________________________________________________
dense_4 (Dense)              (None, 100)               30100
_________________________________________________________________
dense_5 (Dense)              (None, 10)                1010
=================================================================
Total params: 1,654,130
Trainable params: 1,654,130
Non-trainable params: 0
_________________________________________________________________
```

- Param:
  - refers to the number of parameters the model needs to tune

In [31]:
```
# setting parameters that are problem specific
model.compile(loss='sparse_categorical_crossentropy',
              # sgd refers to stochastic gradient descent
              optimizer='sgd',
              metrics=['accuracy'])
```

In [41]:
```
# load saved model
model = keras.models.load_model('CNNmodel.h5')
```

In [42]:
```
# using .fit method consecutively actually continues training the model where it was le
model_history = model.fit(X_train,y_train,
                          validation_data=(X_valid,y_valid),
                          epochs=30)
```

```
Train on 55000 samples, validate on 5000 samples
Epoch 1/30
55000/55000 [==============================] - 30s 551us/sample - loss: 0.1335 - ac
curacy: 0.9528 - val_loss: 0.2452 - val_accuracy: 0.9126
Epoch 2/30
55000/55000 [==============================] - 44s 808us/sample - loss: 0.1274 - ac
curacy: 0.9545 - val_loss: 0.2488 - val_accuracy: 0.9128
Epoch 3/30
55000/55000 [==============================] - 42s 772us/sample - loss: 0.1232 - ac
curacy: 0.9559 - val_loss: 0.2314 - val_accuracy: 0.9176
Epoch 4/30
55000/55000 [==============================] - 43s 774us/sample - loss: 0.1178 - ac
curacy: 0.9579 - val_loss: 0.2513 - val_accuracy: 0.9088
Epoch 5/30
55000/55000 [==============================] - 44s 801us/sample - loss: 0.1124 - ac
curacy: 0.9610 - val_loss: 0.2370 - val_accuracy: 0.9156
Epoch 6/30
55000/55000 [==============================] - 43s 782us/sample - loss: 0.1072 - ac
curacy: 0.9620 - val_loss: 0.2353 - val_accuracy: 0.9176
```

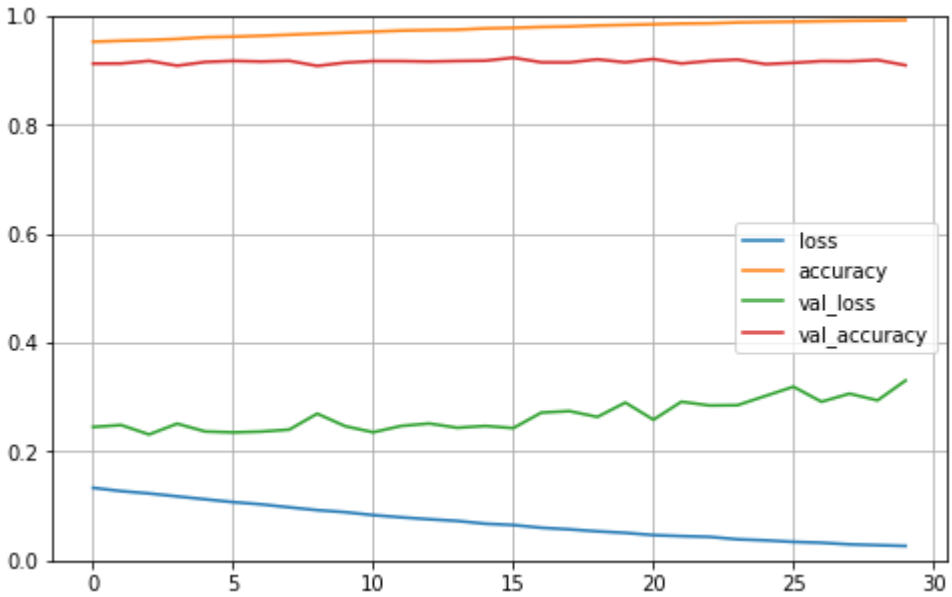
In [33]:
```
# show model parameters
model_history.params
```

Out[33]:
```
{'batch_size': 32,
 'epochs': 30,
 'steps': 1719,
 'samples': 55000,
 'verbose': 0,
 'do_validation': True,
 'metrics': ['loss', 'accuracy', 'val_loss', 'val_accuracy']}
```

In [34]:
```
# show the training progression
model_history.history
```

Out[34]:
```
{'loss': [0.7232647918701172,
  0.4789659946875139,
  0.4240220858747309,
  0.38848866054795006,
  0.36352404016581447,
  0.3416003832513636,
  0.3246729166767814,
  0.30834569490606134,
  0.2958024963920767,
  0.2845826054659757,
  0.2724606364792044,
  0.26324330543821506,
  0.2536492290626873,
  0.24500095049684698,
  0.23684471851587297,
  0.22951359150409698,
  0.22168787875717336,
  0.2143544225161726,
  0.2067171369996938,
```

In [43]:
```
# visualise the training progression
# after 60 epochs the model is near 100% accuracy
pd.DataFrame(model_history.history).plot(figsize=(8,5))
plt.grid(True)
plt.gca().set_ylim(0,1)
plt.show()
```



Evaluating performance

In [36]:
```
# 0.318 loss and accuracy of 0.889
model.evaluate(X_test,y_test)
```

```
10000/10000 [==============================] - 1s 140us/sample - loss: 0.2543 - accura
cy: 0.9121
```

Out[36]:
```
[0.2543268059760332, 0.9121]
```

In [37]:
```
# making single probability predictions
y_proba = model.predict(X_test[:3])
y_proba.round(2)
```

Out[37]:
```
array([[0., 0., 0., 0., 0., 0., 0., 0., 0., 1.],
       [0., 0., 1., 0., 0., 0., 0., 0., 0., 0.],
       [0., 1., 0., 0., 0., 0., 0., 0., 0., 0.]], dtype=float32)
```

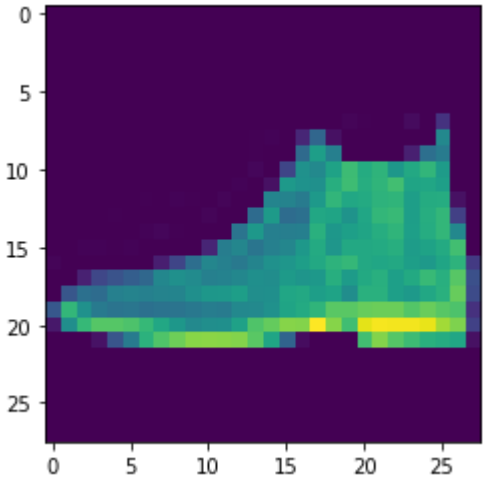
In [38]:
```
# or we could make class predictions
y_pred = model.predict_classes(X_test[:3])
y_pred
```

Out[38]:
```
array([9, 2, 1], dtype=int64)
```

In [41]:
```
print(label_names[y_pred[0]])
plt.imshow(X_test[0])
```

```
Ankle boot
```

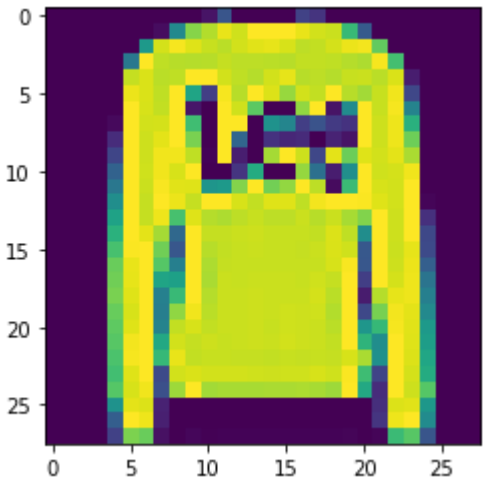
Out[41]:
```
<matplotlib.image.AxesImage at 0x20375271f88>
```



In [42]:
```
print(label_names[y_pred[1]])
plt.imshow(X_test[1])
```

```
Pullover
```

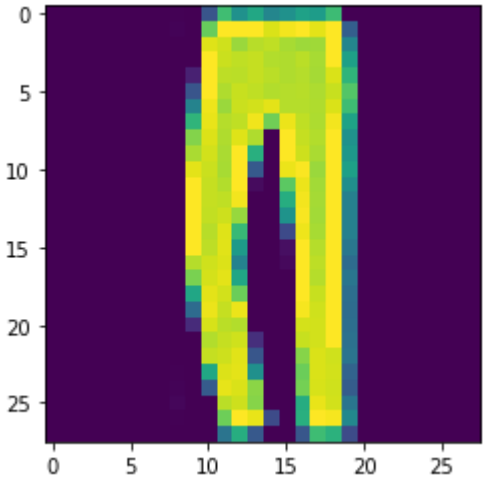
Out[42]:
```
<matplotlib.image.AxesImage at 0x203745d4408>
```



In [43]:
```
print(label_names[y_pred[2]])
plt.imshow(X_test[2])
```

```
Trouser
```

Out[43]:
```
<matplotlib.image.AxesImage at 0x20375668048>
```



Saving and restoring

In [39]:
```
# save model
model.save('CNNmodel.h5')
```

In [40]:
```
# delete model
del model
keras.backend.clear_session()
```

In [41]:
```
# load model
model = keras.models.load_model('CNNmodel.h5')
```

In [57]:
```
# loaded model is the same as the model trained in previous session
model.evaluate(X_test,y_test)
```

```
10000/10000 [==============================] - 1s 109us/sample - loss: 0.3183 - accura
cy: 0.8889
```

Out[57]:
```
[0.3182890306711197, 0.8889]
```