```
try:
        # %tensorflow version only exists in Colab.
       %tensorflow version 2.x
except Exception:
        pass
                   TensorFlow 2.x selected.
 Thasina Tabashum, Farhad Mokter
from future import absolute import, division, print function, unicode literals
# TensorFlow and tf.keras
import tensorflow as tf
from tensorflow import keras
# Helper libraries
import numpy as np
import matplotlib.pyplot as plt
print(tf.__version__)
    □→ 2.1.0
fashion mnist = keras.datasets.fashion mnist
 (train_images, train_labels), (test_images, test_labels) = fashion_mnist.load_data()
                   Downloading data from <a href="https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datas
                     Downloading data from <a href="https://storage.googleapis.com/tensorflow/tf-keras-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/train-datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets/datasets
                     Downloading data from <a href="https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-l">https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-l</a>
                    8192/5148 [=======] - 0s Ous/step
                    Downloading data from <a href="https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-j">https://storage.googleapis.com/tensorflow/tf-keras-datasets/t10k-j</a>
                    class_names = ['T-shirt/top', 'Trouser', 'Pullover', 'Dress', 'Coat',
                                                            'Sandal', 'Shirt', 'Sneaker', 'Bag', 'Ankle boot']
train_images.shape
len(train labels)
                   60000
```

Each label is an integer between 0 and 9:

```
train_labels

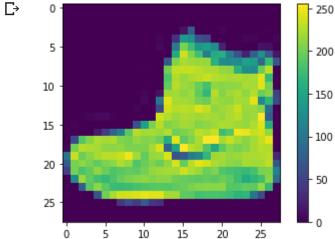
[→ array([9, 0, 0, ..., 3, 0, 5], dtype=uint8)

test_images.shape

len(test_labels)

[→ 10000

plt.figure()
plt.imshow(train_images[0])
plt.colorbar()
plt.grid(False)
plt.show()
```



```
plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(train_images[i], cmap=plt.cm.binary)
    plt.xlabel(class_names[train_labels[i]])
plt.show()
```

 $\Box$ 



```
train_images = train_images / 255.0

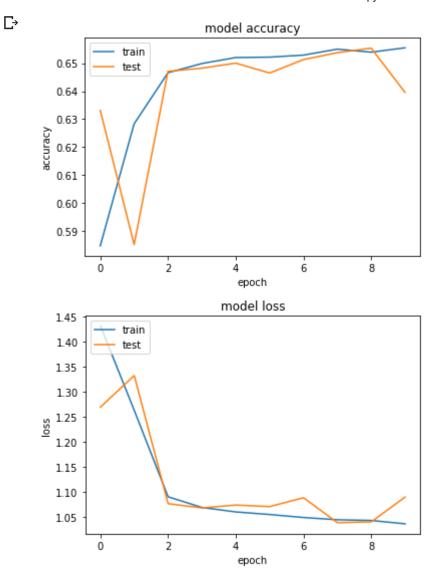
test_images = test_images / 255.0

plt.figure(figsize=(10,10))
for i in range(25):
    plt.subplot(5,5,i+1)
    plt.xticks([])
    plt.yticks([])
    plt.grid(False)
    plt.imshow(train_images[i], cmap=plt.cm.binary)
    plt.xlabel(class_names[train_labels[i]])
plt.show()
```



#### Adding Regularizer

```
Train on 40199 samples, validate on 19801 samples
     Epoch 1/10
     40199/40199 - 5s - loss: 1.4310 - accuracy: 0.5847 - val loss: 1.2688 - val accuracy: 0.
     Epoch 2/10
     40199/40199 - 4s - loss: 1.2623 - accuracy: 0.6283 - val loss: 1.3317 - val accuracy: 0.
     Epoch 3/10
     40199/40199 - 4s - loss: 1.0898 - accuracy: 0.6466 - val loss: 1.0761 - val accuracy: 0.
     Epoch 4/10
     40199/40199 - 4s - loss: 1.0685 - accuracy: 0.6499 - val loss: 1.0675 - val accuracy: 0.
     Epoch 5/10
     40199/40199 - 4s - loss: 1.0596 - accuracy: 0.6520 - val loss: 1.0733 - val accuracy: 0.
     Epoch 6/10
     40199/40199 - 4s - loss: 1.0544 - accuracy: 0.6522 - val loss: 1.0702 - val accuracy: 0.
     Epoch 7/10
     40199/40199 - 4s - loss: 1.0485 - accuracy: 0.6529 - val loss: 1.0879 - val accuracy: 0.
     Epoch 8/10
     40199/40199 - 4s - loss: 1.0439 - accuracy: 0.6550 - val loss: 1.0380 - val accuracy: 0.
     Epoch 9/10
     40199/40199 - 4s - loss: 1.0425 - accuracy: 0.6539 - val loss: 1.0397 - val accuracy: 0.
     Epoch 10/10
     40199/40199 - 4s - loss: 1.0358 - accuracy: 0.6555 - val loss: 1.0894 - val accuracy: 0.
test_loss, test_acc = model.evaluate(test_images, test_labels, verbose=2)
print('\nTest accuracy:', test acc)
    10000/10000 - 0s - loss: 1.1060 - accuracy: 0.6358
     Test accuracy: 0.6358
print(demo.history.keys())
 □→ dict keys(['loss', 'accuracy', 'val loss', 'val accuracy'])
plt.plot(demo.history['accuracy'])
plt.plot(demo.history['val accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(demo.history['loss'])
plt.plot(demo.history['val loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



Graph this to look at the full set of 10 class predictions.

```
def plot_image(i, predictions_array, true_label, img):
  predictions array, true label, img = predictions array, true label[i], img[i]
  plt.grid(False)
  plt.xticks([])
  plt.yticks([])
  plt.imshow(img, cmap=plt.cm.binary)
  predicted label = np.argmax(predictions array)
  if predicted label == true label:
    color = 'blue'
  else:
    color = 'red'
  plt.xlabel("{} {:2.0f}% ({})".format(class_names[predicted_label],
                                 100*np.max(predictions array),
                                 class names[true label]),
                                 color=color)
def plot_value_array(i, predictions_array, true_label):
  predictions array, true label = predictions array, true label[i]
  plt.grid(False)
  plt.xticks(range(10))
  plt.yticks([])
  thisplot = plt.bar(range(10), predictions_array, color="#777777")
  plt.ylim([0, 1])
  predicted label = np.argmax(predictions array)
  thisplot[predicted label].set color('red')
  thisplot[true_label].set_color('blue')
```

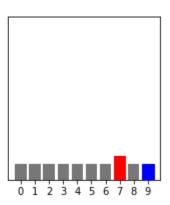
#### Verify predictions

With the model trained, you can use it to make predictions about some images.

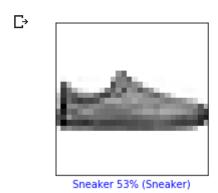
Let's look at the 0th image, predictions, and prediction array. Correct prediction labels are blue and in number gives the percentage (out of 100) for the predicted label.

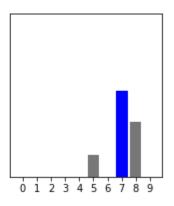
```
i = 0
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions[i], test_labels, test_images)
plt.subplot(1,2,2)
plot_value_array(i, predictions[i], test_labels)
plt.show()
```





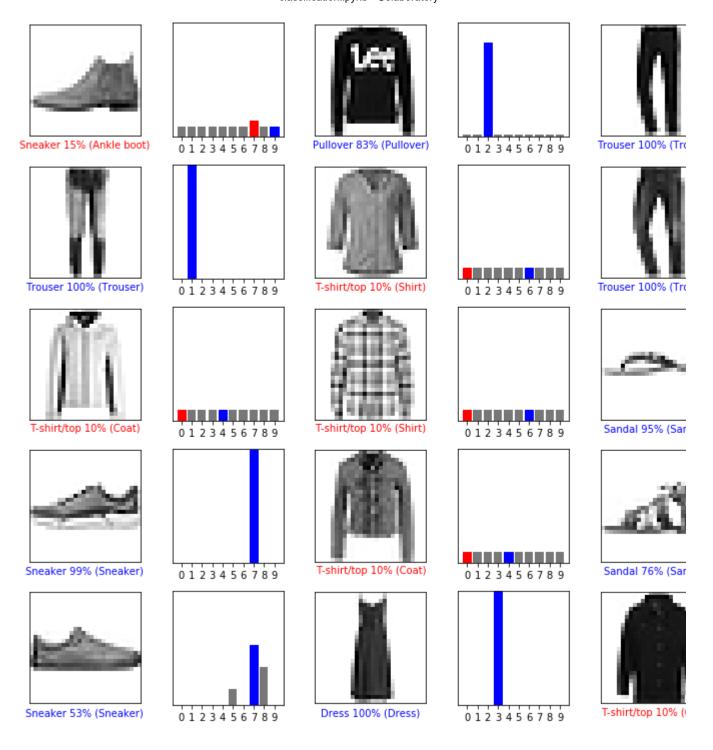
```
i = 12
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions[i], test_labels, test_images)
plt.subplot(1,2,2)
plot_value_array(i, predictions[i], test_labels)
plt.show()
```





Let's plot several images with their predictions. Note that the model can be wrong even when very co

```
# Plot the first X test images, their predicted labels, and the true labels.
# Color correct predictions in blue and incorrect predictions in red.
num_rows = 5
num_cols = 3
num_images = num_rows*num_cols
plt.figure(figsize=(2*2*num_cols, 2*num_rows))
for i in range(num_images):
    plt.subplot(num_rows, 2*num_cols, 2*i+1)
    plot_image(i, predictions[i], test_labels, test_images)
    plt.subplot(num_rows, 2*num_cols, 2*i+2)
    plot_value_array(i, predictions[i], test_labels)
plt.tight_layout()
plt.show()
```



### ▼ Use the trained model

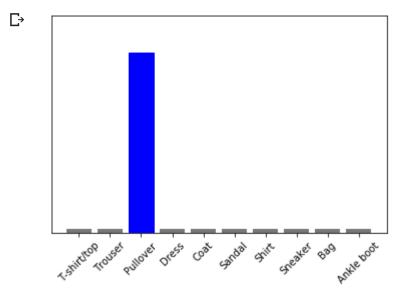
Finally, use the trained model to make a prediction about a single image.

```
# Grab an image from the test dataset.
img = test_images[1]
```

hi Tiir(TiiiR.2iiahe)

tf.keras models are optimized to make predictions on a *batch*, or collection, of examples at once. A single image, you need to add it to a list:

Now predict the correct label for this image:



keras. Model. predict returns a list of lists—one list for each image in the batch of data. Grab the pre

np.argmax(predictions\_single[0])

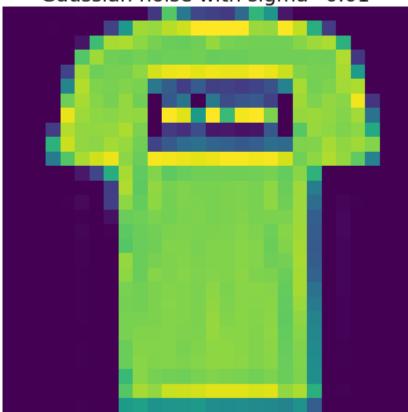
[→ 2

And the model predicts a label as expected.

# Adding Noise

```
import numpy as np
import skimage
im = skimage.img_as_float(train_images[1])
plt.figure(figsize=(15,12))
sigmas = [0.01, 0.05, 0.15, 0.25]
for i in range(4):
    noisy = np.random.normal(im, sigmas[i]**2)
    plt.subplot(2,2,i+1)
    plt.imshow(noisy)
    plt.axis('off')
    plt.title('Gaussian noise with sigma=' + str(sigmas[i]), size=20)
    plt.tight_layout()
    plt.show()
```

Gaussian noise with sigma=0.01



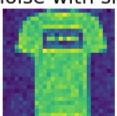
Gaussian noise with sigma=0.05



Gaussian noise with sigma=0.15



Gaussian noise with sigma=0.25



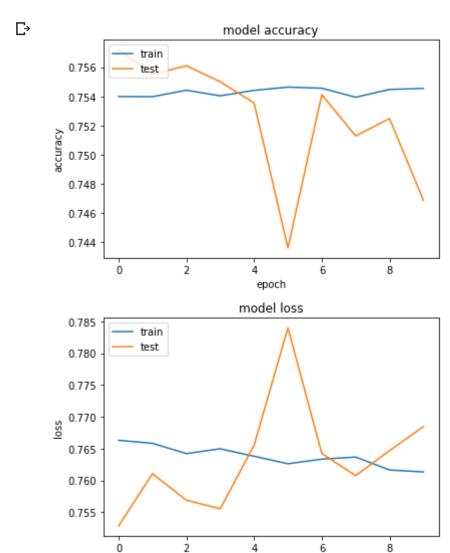
```
def adding_noise(image,sigmas):
    im = skimage.img_as_float(image)
    noisv = nn_random_normal(im_ sigmas**2)
https://colab.research.google.com/drive/14ZnEgJl8l_m5y2c8cOL_nWNcJz1SD6lO#scrollTo=OmjyZLKxw8_m&printMode=true
```

```
. ...... ..... .... .... ....
    return noisy
sigmas = [0.01, 0.05, 0.15, 0.25]
print(tr.shape)
z1 = np.copy(train labels)
z2 = np.copy(train_labels)
z3 = np.copy(train labels)
z4 = np.copy(train_labels)
tl = np.concatenate((train labels,z1,z2,z3,z4), axis=0)
for i in range(4):
    new_data=adding_noise(train_images, sigmas[i])
    #print(new data.shape)
    tr = np.concatenate((tr, new_data), axis=0)
print(len(tr))
     (60000, 28, 28)
     300000
print(len(tl))
     300000
m2 =model.fit(tr, tl, validation split=0.33, epochs=10, verbose=2)
     Train on 200999 samples, validate on 99001 samples
     Epoch 1/10
     200999/200999 - 21s - loss: 0.7663 - accuracy: 0.7540 - val loss: 0.7529 - val accuracy:
     Epoch 2/10
     200999/200999 - 21s - loss: 0.7658 - accuracy: 0.7540 - val loss: 0.7610 - val accuracy:
     Epoch 3/10
     200999/200999 - 21s - loss: 0.7642 - accuracy: 0.7544 - val loss: 0.7569 - val accuracy:
     Epoch 4/10
     200999/200999 - 21s - loss: 0.7650 - accuracy: 0.7540 - val loss: 0.7555 - val accuracy:
     Epoch 5/10
     200999/200999 - 21s - loss: 0.7638 - accuracy: 0.7544 - val loss: 0.7655 - val accuracy:
     Epoch 6/10
     200999/200999 - 21s - loss: 0.7626 - accuracy: 0.7546 - val loss: 0.7840 - val accuracy:
     Epoch 7/10
     200999/200999 - 22s - loss: 0.7633 - accuracy: 0.7546 - val loss: 0.7642 - val accuracy:
     Epoch 8/10
     200999/200999 - 21s - loss: 0.7637 - accuracy: 0.7539 - val loss: 0.7608 - val accuracy:
     Epoch 9/10
     200999/200999 - 22s - loss: 0.7616 - accuracy: 0.7545 - val loss: 0.7647 - val accuracy:
     Epoch 10/10
     200999/200999 - 21s - loss: 0.7613 - accuracy: 0.7545 - val loss: 0.7684 - val accuracy:
test loss, test acc = model.evaluate(test images, test labels, verbose=2)
print('\nTest accuracy:', test_acc)
 C→
```

```
10000/10000 - 0s - loss: 0.8156 - accuracy: 0.7378
```

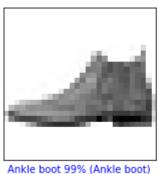
Test accuracy: 0.7378

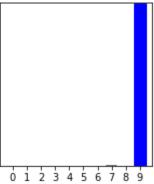
```
plt.plot(m2.history['accuracy'])
plt.plot(m2.history['val_accuracy'])
plt.title('model accuracy')
plt.ylabel('accuracy')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
# summarize history for loss
plt.plot(m2.history['loss'])
plt.plot(m2.history['val_loss'])
plt.title('model loss')
plt.ylabel('loss')
plt.xlabel('epoch')
plt.legend(['train', 'test'], loc='upper left')
plt.show()
```



epoch

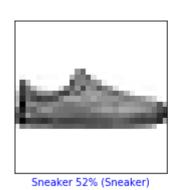


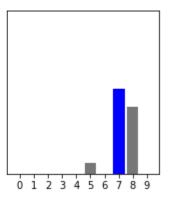




```
i = 12
plt.figure(figsize=(6,3))
plt.subplot(1,2,1)
plot_image(i, predictions[i], test_labels, test_images)
plt.subplot(1,2,2)
plot_value_array(i, predictions[i], test_labels)
plt.show()
```



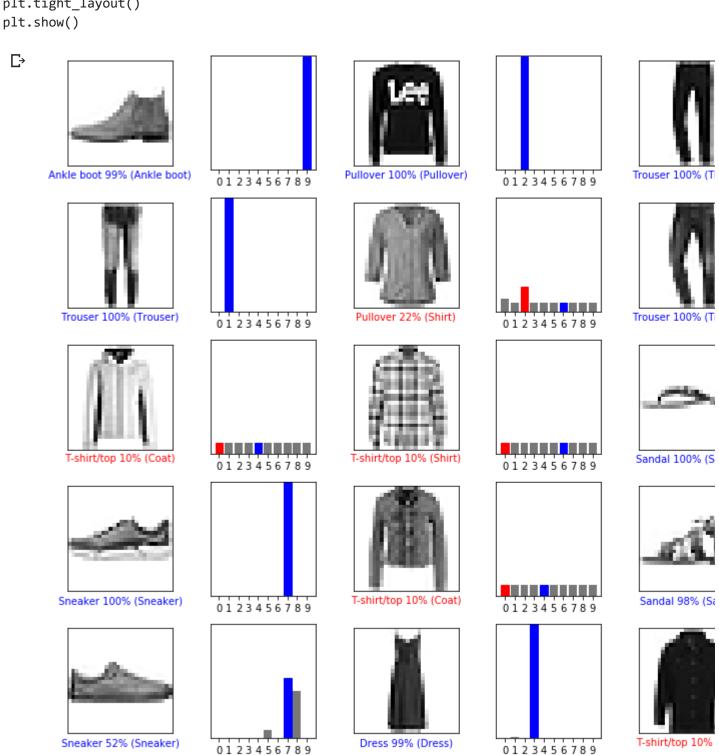




# Plot the first X test images, their predicted labels, and the true labels.

# Color connect predictions in blue and inconnect predictions in red
https://colab.research.google.com/drive/14ZnEgJl8I\_m5y2c8cOL\_nWNcJz1SD6IO#scrollTo=OmjyZLKxw8\_m&printMode=true

```
num_rows = 5
num_cols = 3
num_images = num_rows*num_cols
plt.figure(figsize=(2*2*num_cols, 2*num_rows))
for i in range(num_images):
   plt.subplot(num_rows, 2*num_cols, 2*i+1)
   plot_image(i, predictions[i], test_labels, test_images)
   plt.subplot(num_rows, 2*num_cols, 2*i+2)
   plot_value_array(i, predictions[i], test_labels)
plt.tight_layout()
plt.show()
```



## → Summerize the conclusion

After adding the regularizer model accuracy declined compared to without regularizer model but whe samples the model seems performing almost same on training data but much worse on validation so The two graph shows the accuracy and loss over the epochs.