Text classification - IMDB reviews

June 16, 2019

1 Text classification - IMDB reviews

This notebook classifies movie reviews as positive or negative using the text of the review. This is an example of binary—or two-class—classification, an important and widely applicable kind of machine learning problem.

[20]:
```
from __future__ import absolute_import, division, print_function

import tensorflow as tf
from tensorflow import keras

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt

print(tf.__version__)
```

```
1.13.1
```

I will use the IMDB dataset that contains the text of 50,000 movie reviews from the Internet Movie Database. These are split into 25,000 reviews for training and 25,000 reviews for testing. The training and testing sets are balanced, meaning they contain an equal number of positive and negative reviews.

The IMDB dataset comes packaged with TensorFlow. It has already been preprocessed such that the reviews (sequences of words) have been converted to sequences of integers, where each integer represents a specific word in a dictionary.

The argument num_words=10000 keeps the top 10,000 most frequently occurring words in the training data. The rare words are discarded to keep the size of the data manageable.

[2]:
```
imdb = keras.datasets.imdb

(train_data, train_labels), (test_data, test_labels) = imdb.
 ↪load_data(num_words=10000)
```

1.0.1 Exploring the data

The dataset comes preprocessed: each example is an array of integers representing the words of the movie review. Each label is an integer value of either 0 or 1, where 0 is a negative review, and 1 is a positive review.

The text of reviews have been converted to integers, where each integer represents a specific word in a dictionary. Movie reviews may be different lengths and this will be solved later since the network needs inputs of same length.

[6]:
```
print("Training entries: {}, labels: {}".format(len(train_data),␣
    ↪len(train_labels)))
print(train_data[0])
len(train_data[0]), len(train_data[1])
```

```
Training entries: 25000, labels: 25000
[1, 14, 22, 16, 43, 530, 973, 1622, 1385, 65, 458, 4468, 66, 3941, 4, 173, 36,
256, 5, 25, 100, 43, 838, 112, 50, 670, 2, 9, 35, 480, 284, 5, 150, 4, 172, 112,
167, 2, 336, 385, 39, 4, 172, 4536, 1111, 17, 546, 38, 13, 447, 4, 192, 50, 16,
6, 147, 2025, 19, 14, 22, 4, 1920, 4613, 469, 4, 22, 71, 87, 12, 16, 43, 530,
38, 76, 15, 13, 1247, 4, 22, 17, 515, 17, 12, 16, 626, 18, 2, 5, 62, 386, 12, 8,
316, 8, 106, 5, 4, 2223, 5244, 16, 480, 66, 3785, 33, 4, 130, 12, 16, 38, 619,
5, 25, 124, 51, 36, 135, 48, 25, 1415, 33, 6, 22, 12, 215, 28, 77, 52, 5, 14,
407, 16, 82, 2, 8, 4, 107, 117, 5952, 15, 256, 4, 2, 7, 3766, 5, 723, 36, 71,
43, 530, 476, 26, 400, 317, 46, 7, 4, 2, 1029, 13, 104, 88, 4, 381, 15, 297, 98,
32, 2071, 56, 26, 141, 6, 194, 7486, 18, 4, 226, 22, 21, 134, 476, 26, 480, 5,
144, 30, 5535, 18, 51, 36, 28, 224, 92, 25, 104, 4, 226, 65, 16, 38, 1334, 88,
12, 16, 283, 5, 16, 4472, 113, 103, 32, 15, 16, 5345, 19, 178, 32]
```

[6]:
```
(218, 189)
```

1.0.2 Preparing the data

Here is a helper function to query a dictionary object that contains the integer to string mapping which can be useful.

[7]:
```
# A dictionary mapping words to an integer index
word_index = imdb.get_word_index()

# The first indices are reserved
word_index = {k:(v+3) for k,v in word_index.items()}
word_index["<PAD>"] = 0
word_index["<START>"] = 1
word_index["<UNK>"] = 2  # unknown
word_index["<UNUSED>"] = 3

reverse_word_index = dict([(value, key) for (key, value) in word_index.items()])

def decode_review(text):
    return ' '.join([reverse_word_index.get(i, '?') for i in text])

decode_review(train_data[0])
```

[7]:
```
"<START> this film was just brilliant casting location scenery story direction
everyone's really suited the part they played and you could just imagine being
```

```
there robert <UNK> is an amazing actor and now the same being director <UNK>
father came from the same scottish island as myself so i loved the fact there
was a real connection with this film the witty remarks throughout the film were
great it was just brilliant so much that i bought the film as soon as it was
released for <UNK> and would recommend it to everyone to watch and the fly
fishing was amazing really cried at the end it was so sad and you know what they
say if you cry at a film it must have been good and this definitely was also
<UNK> to the two little boy's that played the <UNK> of norman and paul they were
just brilliant children are often left out of the <UNK> list i think because the
stars that play them all grown up are such a big profile for the whole film but
these children are amazing and should be praised for what they have done don't
you think the whole story was so lovely because it was true and was someone's
life after all that was shared with us all"
```

The reviews—the arrays of integers—must be converted to tensors before fed into the neural network. This conversion can be done in a couple of ways:

1. Convert the arrays into vectors of 0s and 1s indicating word occurrence, similar to a one-hot encoding. For example, the sequence [3, 5] would become a 10,000-dimensional vector that is all zeros except for indices 3 and 5, which are ones. Then, make this the first layer in our network—a Dense layer—that can handle floating point vector data. This approach is memory intensive, though, requiring a num_words * num_reviews size matrix.

2. Alternatively, we can pad the arrays so they all have the same length, then create an integer tensor of shape max_length * num_reviews. We can use an embedding layer capable of handling this shape as the first layer in our network.

I will use the second approach since it is more memory efficient.

[9]:
```
train_data = keras.preprocessing.sequence.pad_sequences(train_data,
                                                          value=word_index["<PAD>"],
                                                          padding='post',
                                                          maxlen=256)

test_data = keras.preprocessing.sequence.pad_sequences(test_data,
                                                         value=word_index["<PAD>"],
                                                         padding='post',
                                                         maxlen=256)
```

[10]:
```
len(train_data[0]), len(train_data[1])
```

[10]:
```
(256, 256)
```

[12]:
```
print(train_data[0])
```

```
[   1   14   22   16   43  530  973 1622 1385   65  458 4468   66 3941
    4  173   36  256    5   25  100   43  838  112   50  670    2    9
   35  480  284    5  150    4  172  112  167    2  336  385   39    4
  172 4536 1111   17  546   38   13  447    4  192   50   16    6  147
```

```
 2025   19   14   22    4 1920 4613  469    4   22   71   87   12   16
   43  530   38   76   15   13 1247    4   22   17  515   17   12   16
  626   18    2    5   62  386   12    8  316    8  106    5    4 2223
 5244   16  480   66 3785   33    4  130   12   16   38  619    5   25
  124   51   36  135   48   25 1415   33    6   22   12  215   28   77
   52    5   14  407   16   82    2    8    4  107  117 5952   15  256
    4    2    7 3766    5  723   36   71   43  530  476   26  400  317
   46    7    4    2 1029   13  104   88    4  381   15  297   98   32
 2071   56   26  141    6  194 7486   18    4  226   22   21  134  476
   26  480    5  144   30 5535   18   51   36   28  224   92   25  104
    4  226   65   16   38 1334   88   12   16  283    5   16 4472  113
  103   32   15   16 5345   19  178   32    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]
```

1.0.3 Building the model

The layers are stacked sequentially to build the classifier:

1. The first layer is an Embedding layer. This layer takes the integer-encoded vocabulary and looks up the embedding vector for each word-index. These vectors are learned as the model trains. The vectors add a dimension to the output array. The resulting dimensions are: (batch, sequence, embedding).

2. Next, a GlobalAveragePooling1D layer returns a fixed-length output vector for each example by averaging over the sequence dimension. This allows the model to handle input of variable length, in the simplest way possible.

3. This fixed-length output vector is piped through a fully-connected (Dense) layer with 16 hidden units.

4. The last layer is densely connected with a single output node. Using the sigmoid activation function, this value is a float between 0 and 1, representing a probability, or confidence level.

The choosen loss function is the binary_crossentropy which is good for dealing with probabilities—it measures the "distance" between probability distributions, or in our case, between the ground-truth distribution and the predictions, specifically for binary classifications in comparison to the categorical_crossentropy. The optimizer is the classical and one of the best, the adam optimizer.

[15]:
```python
# input shape is the vocabulary count used for the movie reviews (10,000 words)

def build_model():
    vocab_size = 10000

    model = keras.Sequential()
    model.add(keras.layers.Embedding(vocab_size, 16))
    model.add(keras.layers.GlobalAveragePooling1D())
    model.add(keras.layers.Dense(16, activation=tf.nn.relu))
```

```
    model.add(keras.layers.Dense(1, activation=tf.nn.sigmoid))

    model.compile(optimizer='adam',
                  loss='binary_crossentropy',
                  metrics=['acc'])

    return model

model = build_model()
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, None, 16)          160000
_________________________________________________________________
global_average_pooling1d_1 ( (None, 16)                0
_________________________________________________________________
dense_2 (Dense)              (None, 16)                272
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 17
=================================================================
Total params: 160,289
Trainable params: 160,289
Non-trainable params: 0
_________________________________________________________________
```

1.0.4 Training the model

Train the model for 40 epochs in mini-batches of 512 samples. This is 40 iterations over all samples in the train_data and train_labels tensors with exception to the validation set data. While training, monitor the model's loss and accuracy on the 10,000 samples from the validation set:

[16]:
```
model = build_model()

history = model.fit(train_data,
                    train_labels,
                    epochs=40,
                    batch_size=512,
                    validation_split=0.4,
                    verbose=1)
```

```
Train on 15000 samples, validate on 10000 samples
WARNING:tensorflow:From C:\Users\Pedro\AppData\Roaming\Python\Python37\site-
packages\tensorflow\python\ops\math_ops.py:3066: to_int32 (from
tensorflow.python.ops.math_ops) is deprecated and will be removed in a future
version.
Instructions for updating:
```

```
Use tf.cast instead.
Epoch 1/40
15000/15000 [==============================] - 1s 73us/sample - loss: 0.6916 -
acc: 0.6015 - val_loss: 0.6888 - val_acc: 0.7208
Epoch 2/40
15000/15000 [==============================] - 1s 47us/sample - loss: 0.6840 -
acc: 0.7315 - val_loss: 0.6780 - val_acc: 0.7393
Epoch 3/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.6686 -
acc: 0.7635 - val_loss: 0.6586 - val_acc: 0.7592
Epoch 4/40
15000/15000 [==============================] - 1s 50us/sample - loss: 0.6432 -
acc: 0.7879 - val_loss: 0.6294 - val_acc: 0.7754
Epoch 5/40
15000/15000 [==============================] - 1s 47us/sample - loss: 0.6074 -
acc: 0.8043 - val_loss: 0.5923 - val_acc: 0.7913
Epoch 6/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.5642 -
acc: 0.8229 - val_loss: 0.5510 - val_acc: 0.8020
Epoch 7/40
15000/15000 [==============================] - 1s 49us/sample - loss: 0.5174 -
acc: 0.8386 - val_loss: 0.5085 - val_acc: 0.8165
Epoch 8/40
15000/15000 [==============================] - 1s 51us/sample - loss: 0.4711 -
acc: 0.8564 - val_loss: 0.4710 - val_acc: 0.8266
Epoch 9/40
15000/15000 [==============================] - 1s 50us/sample - loss: 0.4291 -
acc: 0.8686 - val_loss: 0.4350 - val_acc: 0.8455
Epoch 10/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.3913 -
acc: 0.8809 - val_loss: 0.4063 - val_acc: 0.8523
Epoch 11/40
15000/15000 [==============================] - 1s 49us/sample - loss: 0.3594 -
acc: 0.8872 - val_loss: 0.3839 - val_acc: 0.8568
Epoch 12/40
15000/15000 [==============================] - 1s 60us/sample - loss: 0.3330 -
acc: 0.8939 - val_loss: 0.3645 - val_acc: 0.8601
Epoch 13/40
15000/15000 [==============================] - 1s 60us/sample - loss: 0.3103 -
acc: 0.8993 - val_loss: 0.3499 - val_acc: 0.8648
Epoch 14/40
15000/15000 [==============================] - 1s 63us/sample - loss: 0.2905 -
acc: 0.9048 - val_loss: 0.3376 - val_acc: 0.8687
Epoch 15/40
15000/15000 [==============================] - 1s 61us/sample - loss: 0.2728 -
acc: 0.9107 - val_loss: 0.3277 - val_acc: 0.8711
Epoch 16/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.2576 -
```

```
acc: 0.9163 - val_loss: 0.3197 - val_acc: 0.8742
Epoch 17/40
15000/15000 [==============================] - 1s 51us/sample - loss: 0.2440 -
acc: 0.9199 - val_loss: 0.3131 - val_acc: 0.8752
Epoch 18/40
15000/15000 [==============================] - 1s 50us/sample - loss: 0.2315 -
acc: 0.9237 - val_loss: 0.3075 - val_acc: 0.8779
Epoch 19/40
15000/15000 [==============================] - 1s 51us/sample - loss: 0.2203 -
acc: 0.9270 - val_loss: 0.3026 - val_acc: 0.8792
Epoch 20/40
15000/15000 [==============================] - 1s 53us/sample - loss: 0.2099 -
acc: 0.9312 - val_loss: 0.2995 - val_acc: 0.8809
Epoch 21/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.2002 -
acc: 0.9341 - val_loss: 0.2962 - val_acc: 0.8825
Epoch 22/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.1913 -
acc: 0.9386 - val_loss: 0.2946 - val_acc: 0.8837
Epoch 23/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.1836 -
acc: 0.9401 - val_loss: 0.2919 - val_acc: 0.8839
Epoch 24/40
15000/15000 [==============================] - 1s 53us/sample - loss: 0.1752 -
acc: 0.9443 - val_loss: 0.2922 - val_acc: 0.8841
Epoch 25/40
15000/15000 [==============================] - 1s 63us/sample - loss: 0.1682 -
acc: 0.9473 - val_loss: 0.2901 - val_acc: 0.8850
Epoch 26/40
15000/15000 [==============================] - 1s 50us/sample - loss: 0.1611 -
acc: 0.9491 - val_loss: 0.2899 - val_acc: 0.8850
Epoch 27/40
15000/15000 [==============================] - 1s 49us/sample - loss: 0.1542 -
acc: 0.9523 - val_loss: 0.2898 - val_acc: 0.8854
Epoch 28/40
15000/15000 [==============================] - 1s 49us/sample - loss: 0.1483 -
acc: 0.9538 - val_loss: 0.2919 - val_acc: 0.8845
Epoch 29/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.1426 -
acc: 0.9575 - val_loss: 0.2913 - val_acc: 0.8849
Epoch 30/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.1368 -
acc: 0.9588 - val_loss: 0.2916 - val_acc: 0.8856
Epoch 31/40
15000/15000 [==============================] - 1s 54us/sample - loss: 0.1315 -
acc: 0.9609 - val_loss: 0.2930 - val_acc: 0.8851
Epoch 32/40
15000/15000 [==============================] - 1s 48us/sample - loss: 0.1261 -
```

```
acc: 0.9629 - val_loss: 0.2956 - val_acc: 0.8830
Epoch 33/40
15000/15000 [==============================] - 1s 49us/sample - loss: 0.1210 -
acc: 0.9653 - val_loss: 0.2969 - val_acc: 0.8850
Epoch 34/40
15000/15000 [==============================] - 1s 49us/sample - loss: 0.1165 -
acc: 0.9669 - val_loss: 0.2986 - val_acc: 0.8837
Epoch 35/40
15000/15000 [==============================] - 1s 49us/sample - loss: 0.1119 -
acc: 0.9683 - val_loss: 0.3007 - val_acc: 0.8833
Epoch 36/40
15000/15000 [==============================] - 1s 55us/sample - loss: 0.1076 -
acc: 0.9714 - val_loss: 0.3030 - val_acc: 0.8823
Epoch 37/40
15000/15000 [==============================] - 1s 52us/sample - loss: 0.1035 -
acc: 0.9726 - val_loss: 0.3064 - val_acc: 0.8817
Epoch 38/40
15000/15000 [==============================] - 1s 51us/sample - loss: 0.0996 -
acc: 0.9737 - val_loss: 0.3087 - val_acc: 0.8818
Epoch 39/40
15000/15000 [==============================] - 1s 54us/sample - loss: 0.0959 -
acc: 0.9749 - val_loss: 0.3117 - val_acc: 0.8810
Epoch 40/40
15000/15000 [==============================] - 1s 51us/sample - loss: 0.0922 -
acc: 0.9767 - val_loss: 0.3152 - val_acc: 0.8807
```

1.0.5 Evaluating the model

This fairly naive approach achieves an accuracy of about 87%. With more advanced approaches, the model should get closer to 95%.

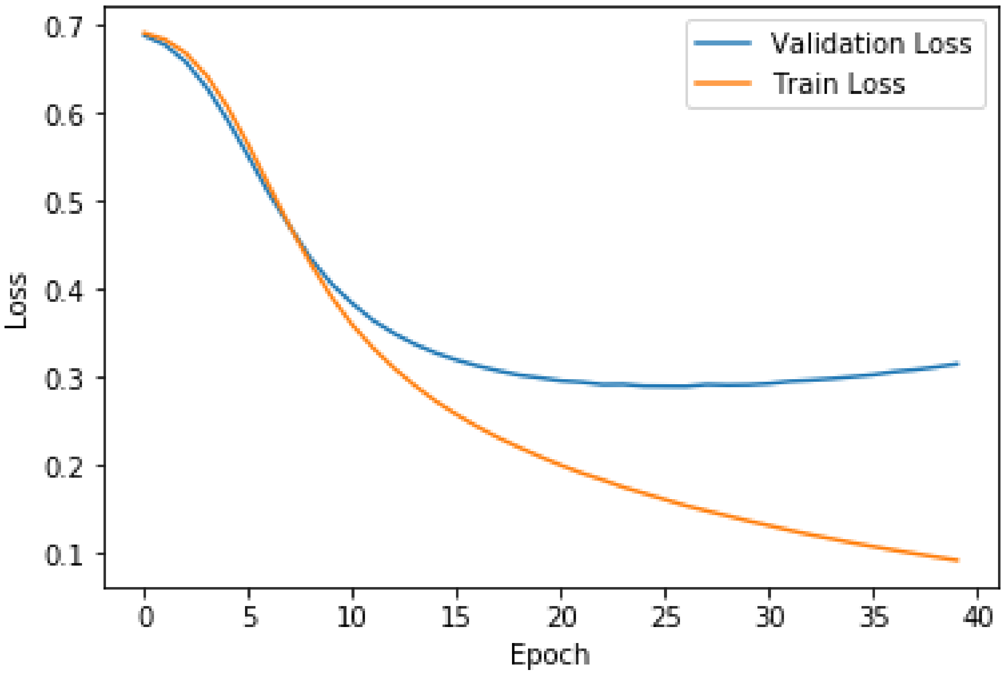
[18]:
```
results = model.evaluate(test_data, test_labels)
```

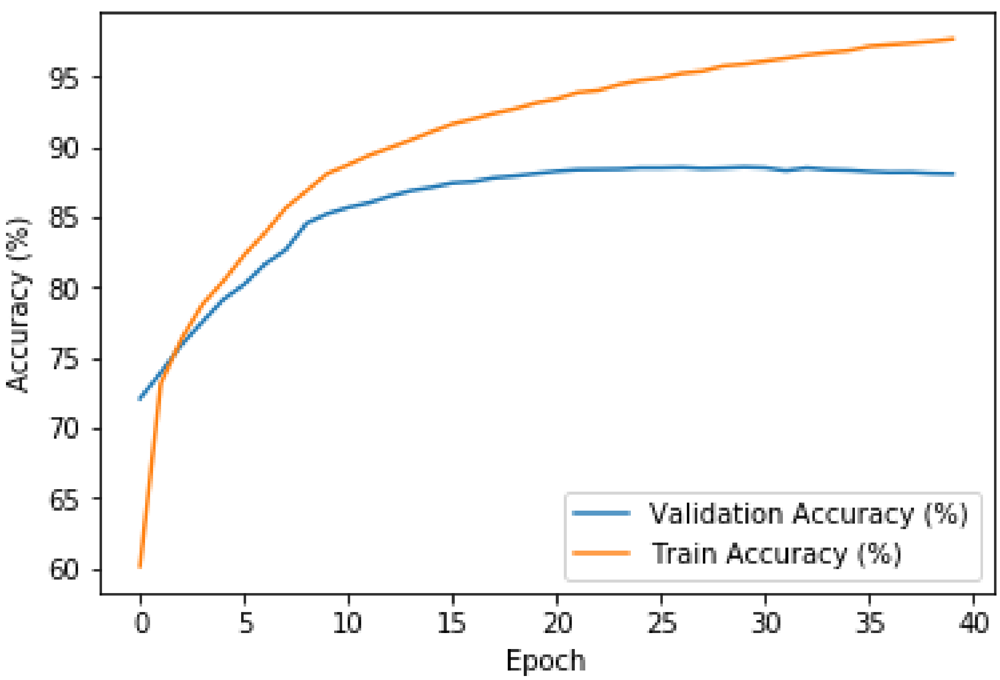
```
25000/25000 [==============================] - 1s 22us/sample - loss: 0.3315 -
acc: 0.8714
```

[21]:
```
def plot_history(history, metric='loss', label='Loss', scaling=1):
    hist = pd.DataFrame(history.history)
    hist['epoch'] = history.epoch

    plt.figure()
    plt.xlabel('Epoch')
    plt.ylabel(label)
    plt.plot(hist['epoch'], hist['val_' + metric]*scaling,
           label='Validation ' + label)
    plt.plot(hist['epoch'], hist[metric]*scaling,
           label='Train ' + label)
    plt.legend()
```

```
plot_history(history)
plot_history(history, 'acc', 'Accuracy (%)', 100)
```





1.0.6 Re-training an re-evaluating the model

The validation loss and accuracy seem to peak after about twenty epochs. This is an example of overfitting: the model performs better on the training data than it does on data it has never seen before. After this point, the model over-optimizes and learns representations specific to the training data that do not generalize to test data. So an early stop callback is desirable here.

[30]:
```
early_stop = keras.callbacks.EarlyStopping(monitor='val_loss', patience=2)

model = build_model()

history = model.fit(train_data,
                    train_labels,
                    epochs=100,
                    batch_size=512,
                    validation_split=0.4,
                    callbacks=[early_stop],
                    verbose=2)
```

```
Train on 15000 samples, validate on 10000 samples
Epoch 1/100
 - 1s - loss: 0.6923 - acc: 0.5250 - val_loss: 0.6906 - val_acc: 0.5725
Epoch 2/100
 - 1s - loss: 0.6871 - acc: 0.5992 - val_loss: 0.6824 - val_acc: 0.6260
Epoch 3/100
 - 1s - loss: 0.6742 - acc: 0.6957 - val_loss: 0.6656 - val_acc: 0.6794
Epoch 4/100
 - 1s - loss: 0.6510 - acc: 0.7441 - val_loss: 0.6376 - val_acc: 0.7501
Epoch 5/100
 - 1s - loss: 0.6158 - acc: 0.7727 - val_loss: 0.5996 - val_acc: 0.7791
Epoch 6/100
 - 1s - loss: 0.5709 - acc: 0.8100 - val_loss: 0.5558 - val_acc: 0.8059
Epoch 7/100
 - 1s - loss: 0.5214 - acc: 0.8325 - val_loss: 0.5105 - val_acc: 0.8243
Epoch 8/100
 - 1s - loss: 0.4719 - acc: 0.8556 - val_loss: 0.4684 - val_acc: 0.8297
Epoch 9/100
 - 1s - loss: 0.4262 - acc: 0.8679 - val_loss: 0.4314 - val_acc: 0.8459
Epoch 10/100
 - 1s - loss: 0.3870 - acc: 0.8807 - val_loss: 0.4017 - val_acc: 0.8506
Epoch 11/100
 - 1s - loss: 0.3534 - acc: 0.8883 - val_loss: 0.3780 - val_acc: 0.8579
Epoch 12/100
 - 1s - loss: 0.3255 - acc: 0.8971 - val_loss: 0.3599 - val_acc: 0.8615
Epoch 13/100
```

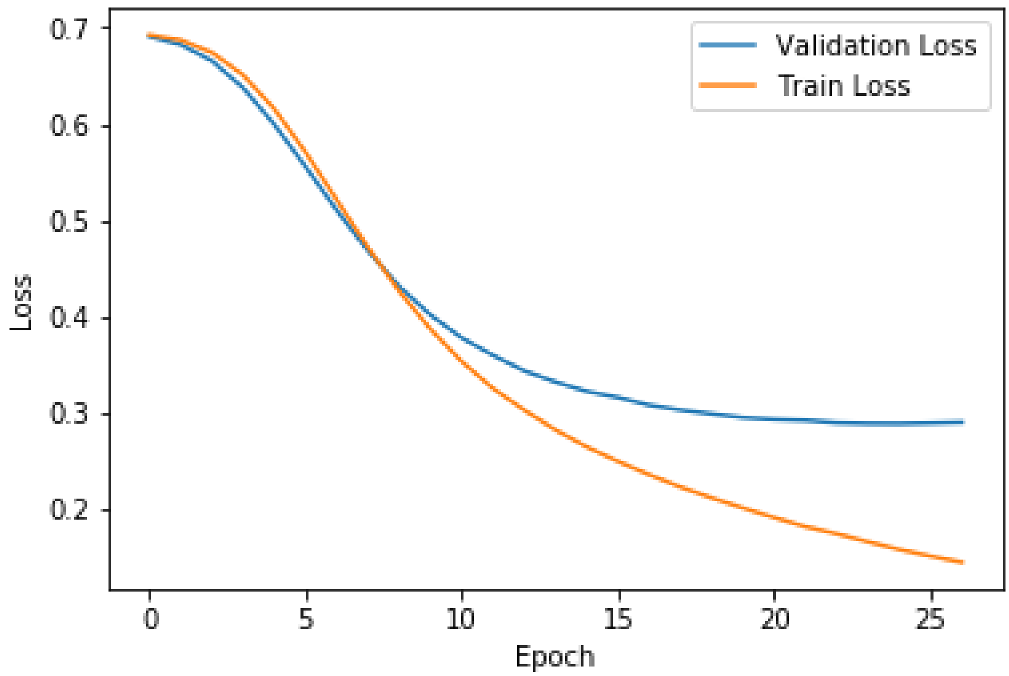
```
 - 1s - loss: 0.3029 - acc: 0.9019 - val_loss: 0.3437 - val_acc: 0.8677
Epoch 14/100
 - 1s - loss: 0.2827 - acc: 0.9083 - val_loss: 0.3321 - val_acc: 0.8690
Epoch 15/100
 - 1s - loss: 0.2651 - acc: 0.9119 - val_loss: 0.3224 - val_acc: 0.8713
Epoch 16/100
 - 1s - loss: 0.2500 - acc: 0.9175 - val_loss: 0.3161 - val_acc: 0.8721
Epoch 17/100
 - 1s - loss: 0.2363 - acc: 0.9209 - val_loss: 0.3081 - val_acc: 0.8779
Epoch 18/100
 - 1s - loss: 0.2233 - acc: 0.9255 - val_loss: 0.3031 - val_acc: 0.8781
Epoch 19/100
 - 1s - loss: 0.2121 - acc: 0.9284 - val_loss: 0.2990 - val_acc: 0.8799
Epoch 20/100
 - 1s - loss: 0.2017 - acc: 0.9324 - val_loss: 0.2953 - val_acc: 0.8822
Epoch 21/100
 - 1s - loss: 0.1917 - acc: 0.9371 - val_loss: 0.2934 - val_acc: 0.8830
Epoch 22/100
 - 1s - loss: 0.1822 - acc: 0.9407 - val_loss: 0.2925 - val_acc: 0.8853
Epoch 23/100
 - 1s - loss: 0.1748 - acc: 0.9431 - val_loss: 0.2900 - val_acc: 0.8838
Epoch 24/100
 - 1s - loss: 0.1665 - acc: 0.9465 - val_loss: 0.2894 - val_acc: 0.8845
Epoch 25/100
 - 1s - loss: 0.1585 - acc: 0.9499 - val_loss: 0.2892 - val_acc: 0.8848
Epoch 26/100
 - 1s - loss: 0.1516 - acc: 0.9524 - val_loss: 0.2898 - val_acc: 0.8862
Epoch 27/100
 - 1s - loss: 0.1453 - acc: 0.9551 - val_loss: 0.2905 - val_acc: 0.8849
```

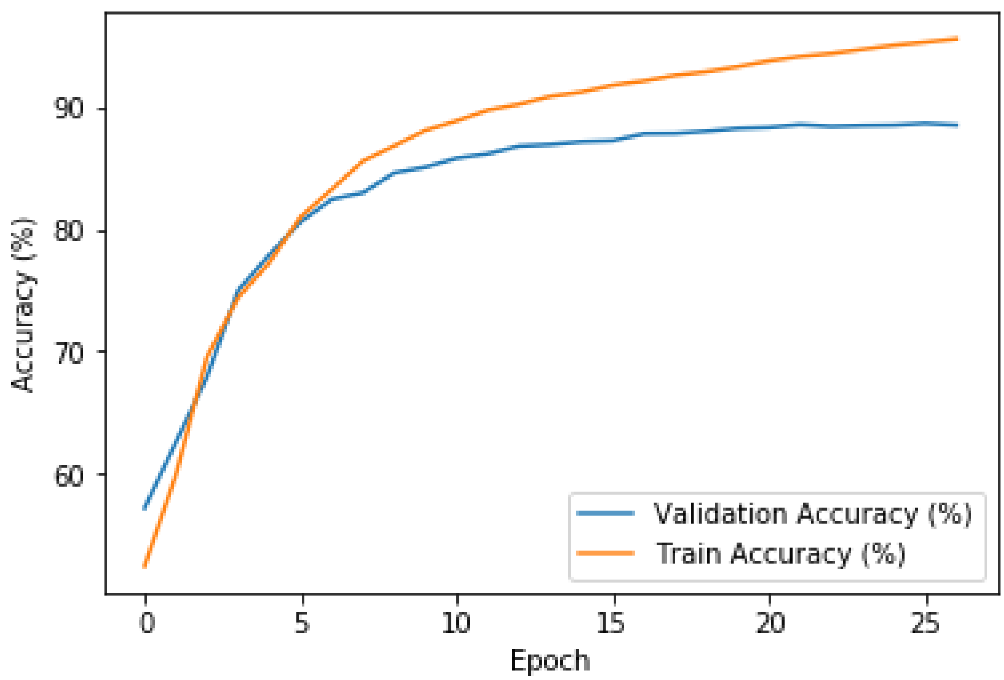
We can verify that the early stopping saves training time and gives a sligthly better model.

[31]:
```
results = model.evaluate(test_data, test_labels)
```

```
25000/25000 [==============================] - 1s 25us/sample - loss: 0.3038 -
acc: 0.8754
```

[32]:
```
plot_history(history)
plot_history(history, 'acc', 'Accuracy (%)', 100)
```


Validation Loss
Train Loss
0.7
0.6
0.5
0.4
0.3
0.2
Loss
0
5
10
15
20
25
Epoch


90
80
70
60
Accuracy (%)
Validation Accuracy (%)
Train Accuracy (%)
0
5
10
15
20
25
Epoch