Análisis de Datos y Aprendizaje Máquina con Tensorflow 2.0: Redes neuronales recurrentes

2019/09/30

Red recurrente Imperative/Training loop

- Objetivo: Programar una RNN en notación orientada a objetos con Tensorflow 2.0
- Los modelos son más personalizables para tareas como investigación

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt

import tensorflow as tf
from tensorflow.keras.datasets import imdb



from tensorflow.keras.preprocessing.sequence import pad_sequences
import matplotlib.pyplot as plt
```

In [2]:
```
# numero de palabras
num_words = 10000

max_len = 59
embedding_dim = 128

(x_train, y_train), (x_test, y_test) = imdb.load_data(num_words=num_words)


x_train = pad_sequences(x_train, maxlen=max_len, padding = 'post')
x_test = pad_sequences(x_test, maxlen=max_len, padding = 'post')


print(x_train.shape)
print(x_test.shape)
print(y_train.shape)
print(y_test.shape)
```

```
(25000, 59)
(25000, 59)
(25000,)
```

```
(25000,)
```

```
In [3]: batch_size = 50

        train_ds = tf.data.Dataset.from_tensor_slices(
            (x_train, y_train)).shuffle(10000).batch(batch_size)
```

```
In [4]: print('Reseña')
        print(x_train[0])
        print('Etiqueta')
        print(y_train[0])
```

```
Reseña
[   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]
Etiqueta
1
```

```
In [5]: wordDict = {y:x for x,y in imdb.get_word_index().items()}
        res = []
        for index in x_train[0]:
            res.append(wordDict.get(index - 3))
        print('Reseña: ',res,'Longitud reseña: ', len(res))
```

```
Reseña:  ['i', 'think', 'because', 'the', 'stars', 'that', 'play', 'them', 'all', 'grown', 'up',
```

Crear modelo

```
In [6]: from tensorflow.keras.layers import Embedding, LSTM, Dense
        from tensorflow.keras import Model
```

```
In [7]: class RNN(Model):
            def __init__(self):
                super(RNN, self).__init__()
                self.embedding = Embedding(num_words, embedding_dim)
                self.lstm = LSTM(128)
                self.d = Dense(1, activation='sigmoid')

            def call(self, x): # método call que pasa 'x' por capa
                x = self.embedding(x)
                x = self.lstm(x)
                return self.d(x)
```

```
In [8]: model = RNN()
        model.build( input_shape=(None, max_len))
        model.summary()
```

```
Model: "rnn"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        multiple                  1280000
_________________________________________________________________
lstm (LSTM)                  multiple                  131584
_________________________________________________________________
dense (Dense)                multiple                  129
=================================================================
Total params: 1,411,713
Trainable params: 1,411,713
Non-trainable params: 0
_________________________________________________________________
```

```
In [9]: loss_fn = tf.keras.losses.BinaryCrossentropy()
        optimizer = tf.keras.optimizers.Adam()
```

```
In [10]: train_loss = tf.keras.metrics.BinaryCrossentropy(name='train_loss')
         train_accuracy = tf.keras.metrics.BinaryAccuracy(name='train_accuracy')
```

```
In [11]: hist_loss = []
         hist_acc = []
```

Entrenamiento

- Se hace un ciclo por épocas en donde se itera por cada época sobre cada par de datos y etiquetas de entrenamiento
- *Nota: El entrenamiento con 'tf.function decorator' tiene un mejor desempeño al compilarse en grafo. Para simplificar el ejemplo, también se omite el entrenamiento en conjunto de prueba*

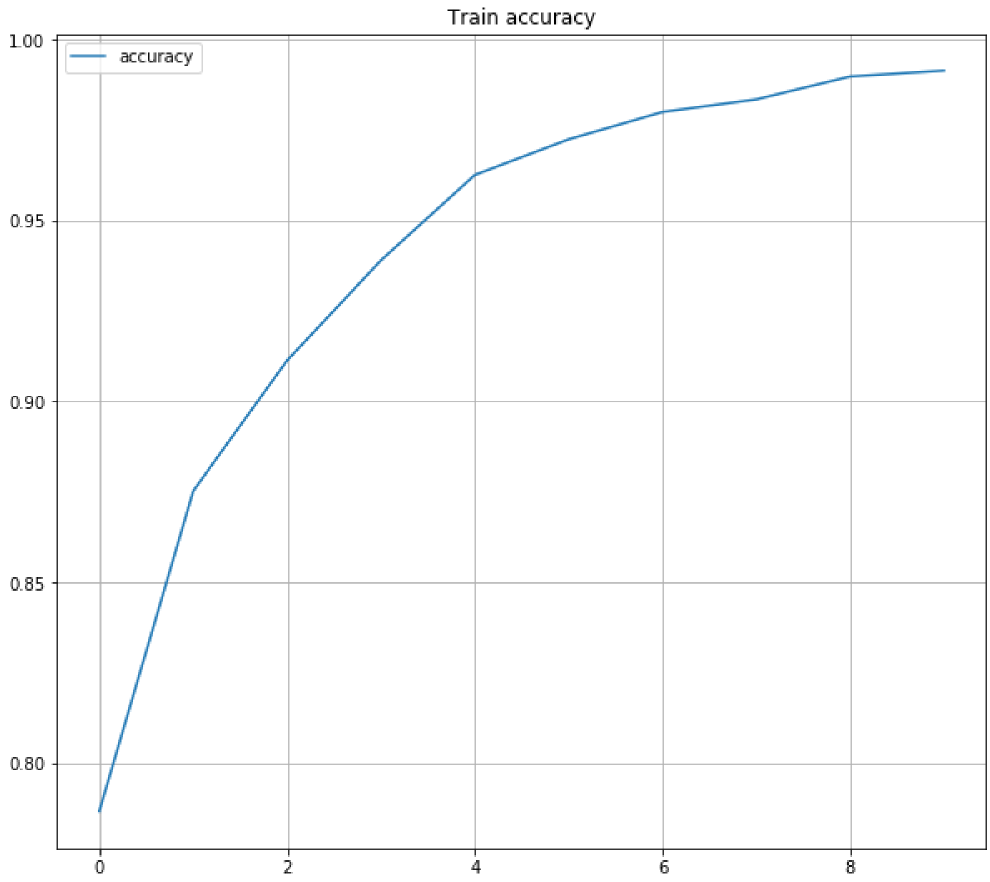
```
In [12]: EPOCH = 10
         for epoch in range(EPOCH):
             #entrenamiento
             for data, target in train_ds:
                 with tf.GradientTape() as tape:
                     predictions = model(data)# predicciones
                     loss = loss_fn(target, predictions) # target y predicciones para obtener acc
                 gradients = tape.gradient(loss, model.trainable_variables) # gradiente sobre var
                 optimizer.apply_gradients(zip(gradients, model.trainable_variables))
                 # se guardan metricas
                 train_loss(target, predictions)
                 train_accuracy(target, predictions)


             template = 'Epoch {}/{} \n - loss: {} - accuracy: {}'
             print(template.format(epoch+1, EPOCH,
```

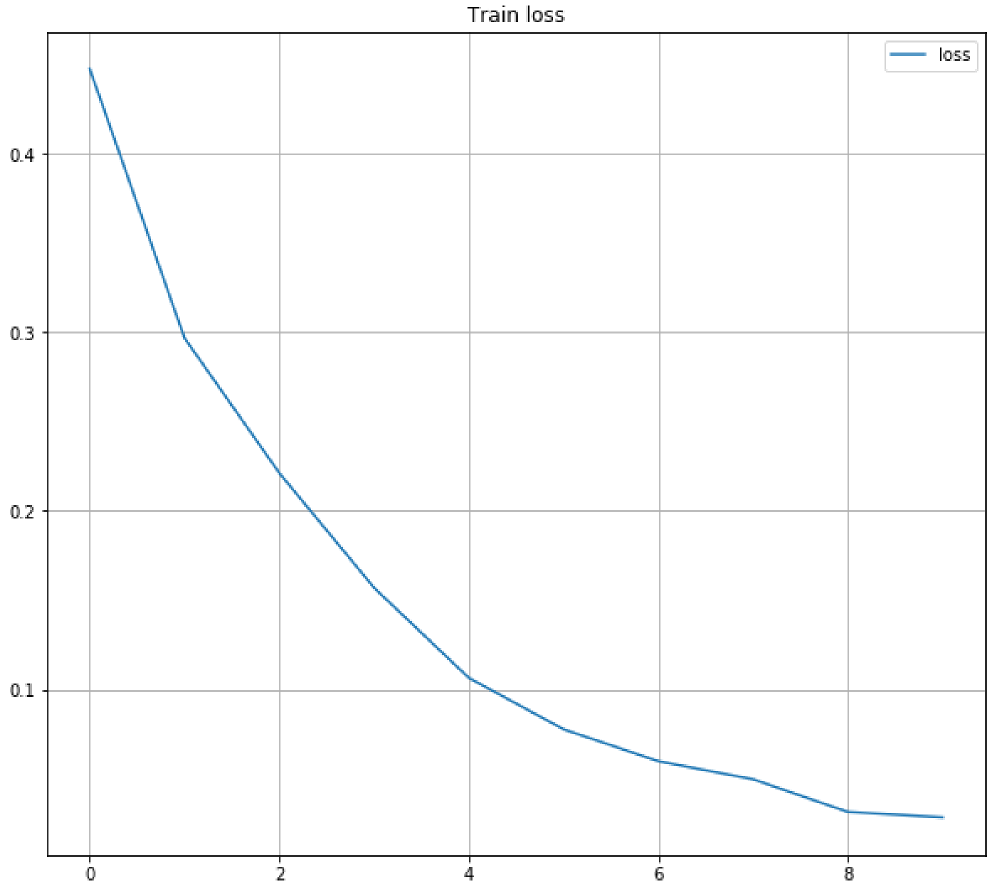
```
                                    train_loss.result(), train_accuracy.result()))
            # lista para plot
            hist_loss.append(train_loss.result())
            hist_acc.append(train_accuracy.result())
            # reinicia las metricas para la siguiente epoca
            train_loss.reset_states()
            train_accuracy.reset_states()
```

```
Epoch 1/10
 - loss: 0.44712960720062256 - accuracy: 0.7866796255111694
Epoch 2/10
 - loss: 0.2966446876525879 - accuracy: 0.8751993775367737
Epoch 3/10
 - loss: 0.2211247831583023 - accuracy: 0.9112399220466614
Epoch 4/10
 - loss: 0.15693973004817963 - accuracy: 0.9388808608055115
Epoch 5/10
 - loss: 0.10652169585227966 - accuracy: 0.9625210165977478
Epoch 6/10
 - loss: 0.07776147872209549 - accuracy: 0.9723614454269409
Epoch 7/10
 - loss: 0.05989265814423561 - accuracy: 0.9799212217330933
Epoch 8/10
 - loss: 0.04978509992361069 - accuracy: 0.983401894569397
Epoch 9/10
 - loss: 0.03153662383556366 - accuracy: 0.9897211790084839
Epoch 10/10
 - loss: 0.02850654534995556 - accuracy: 0.9913609623908997
```

In [13]:
```
plt.figure(figsize=(10,9))
plt.plot(np.arange(len(hist_acc)), hist_acc)
plt.title('Train accuracy')
plt.legend(['accuracy'])
plt.grid()
```




```
In [14]: plt.figure(figsize=(10,9))
         plt.plot(np.arange(len(hist_loss)), hist_loss)
         plt.title('Train loss')
         plt.legend(['loss'])
         plt.grid()
```



- Personalizar la arquitectura