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

2019/09/30

Deep Bidirectional RNN

Objetivo: Comprender las RNN Bidireccionales y sus efectos en el aprendizaje del modelo. Conocer el comportamiento de los optimizadores en modelos recurrentes.

In [1]:
```
from tensorflow.keras.models import Model
from tensorflow.keras.layers import LSTM, Embedding, Dense, SimpleRNN, Bidirectional
from tensorflow.keras.datasets import imdb
from tensorflow.keras.models import Sequential

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

Reseñas de películas de IMDB

- Conjunto de datos de 25,000 críticas de películas de IMDB, etiquetadas por sentimiento (positivo / negativo).

In [2]:
```
# numero de palabras
num_words = 4000

max_len = 100


#dimensión embedding
emb_dim = 64


(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, 100)
(25000, 100)
(25000,)
(25000,)
```

```
In [3]: epoch = 4
        verbose = 1
        batch = 30
```

Cada palabra de la review esta identificada por un número

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

```
Reseña
[1415   33    6   22   12  215   28   77   52    5   14  407   16   82
    2    8    4  107  117    2   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
    2   18    4  226   22   21  134  476   26  480    5  144   30    2
   18   51   36   28  224   92   25  104    4  226   65   16   38 1334
   88   12   16  283    5   16    2  113  103   32   15   16    2   19
  178   32]
Etiqueta
1
```

Palabras de reseña

```
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:  ['cry', 'at', 'a', 'film', 'it', 'must', 'have', 'been', 'good', 'and', 'this', 'definit
```

Deep RNN

- Se compara el modelo con y sin regularización

```
In [6]: def deep_lstm():
            model = Sequential()
            model.add(Embedding(num_words, emb_dim))
```

```
        model.add(LSTM(64, return_sequences = True))
        model.add(LSTM(64, return_sequences = False))
        model.add(Dense(1, activation='sigmoid'))
        model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

        return model
```

```
In [7]: model = deep_lstm()
        model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding (Embedding)        (None, None, 64)          256000
_________________________________________________________________
lstm (LSTM)                  (None, None, 64)          33024
_________________________________________________________________
lstm_1 (LSTM)                (None, 64)                33024
_________________________________________________________________
dense (Dense)                (None, 1)                 65
=================================================================
Total params: 322,113
Trainable params: 322,113
Non-trainable params: 0
_________________________________________________________________
```

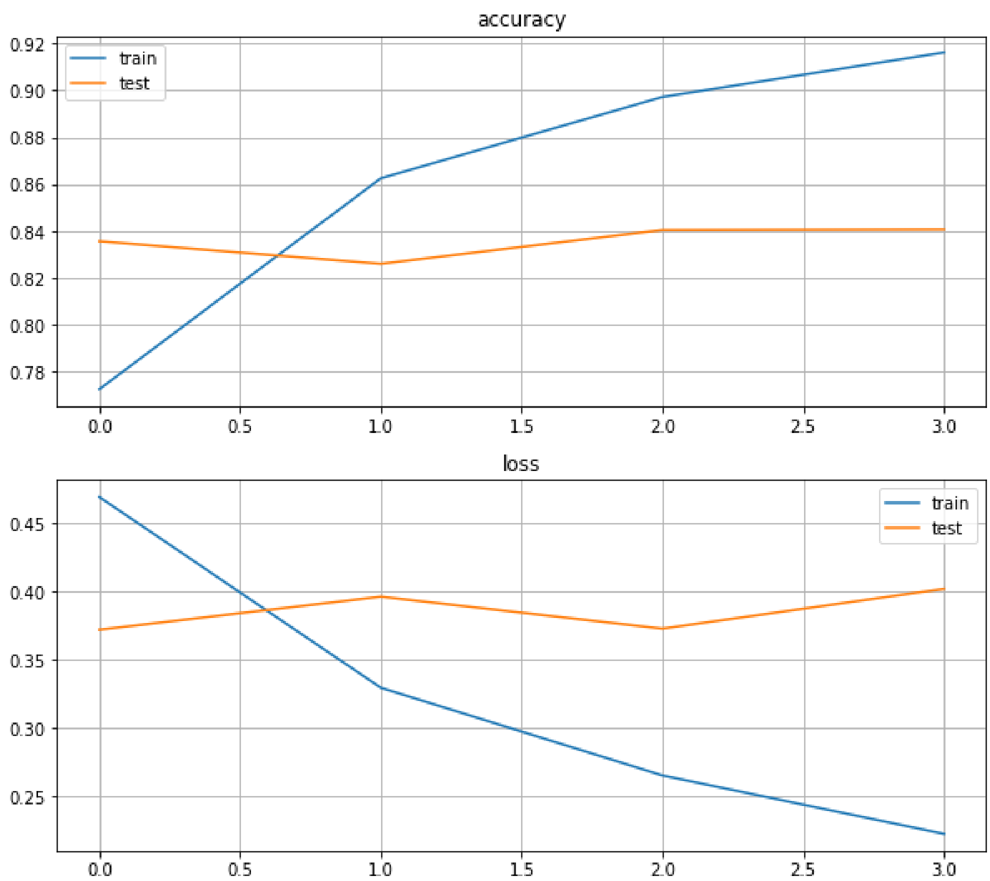
```
In [8]: history = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                            epochs = epoch, verbose = verbose)
```

```
Train on 17500 samples, validate on 7500 samples
Epoch 1/4
17500/17500 [==============================] - 13s 729us/sample - loss: 0.4694 - accuracy: 0.7726
Epoch 2/4
17500/17500 [==============================] - 8s 468us/sample - loss: 0.3294 - accuracy: 0.8625
Epoch 3/4
17500/17500 [==============================] - 8s 473us/sample - loss: 0.2651 - accuracy: 0.8971
Epoch 4/4
17500/17500 [==============================] - 8s 441us/sample - loss: 0.2223 - accuracy: 0.9161
```

```
In [9]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

        print('\nTest acccuracy:', test_acc)
```

```
25000/1 - 4s - loss: 0.5023 - accuracy: 0.8368

Test acccuracy: 0.8368
```

In [10]:
```
plt.figure(figsize=(10,9))

plt.subplot(211)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('accuracy')
plt.legend(['train', 'test'])
plt.grid()
plt.subplot(212)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('loss')
plt.legend(['train', 'test'])
plt.grid()
```



Bidirectional RNN

- Bidirectional RNNs lee las secuencias en ambas direcciones

In [11]:
```
def bidirectional_lstm():

    model = Sequential()
    model.add(Embedding(num_words, emb_dim))
    model.add(Bidirectional(LSTM(64, return_sequences = False)))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

    return model
```

In [12]:
```
model = bidirectional_lstm()
model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_1 (Embedding)      (None, None, 64)          256000
_________________________________________________________________
bidirectional (Bidirectional (None, 128)               66048
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 129
=================================================================
Total params: 322,177
Trainable params: 322,177
Non-trainable params: 0
_________________________________________________________________
```

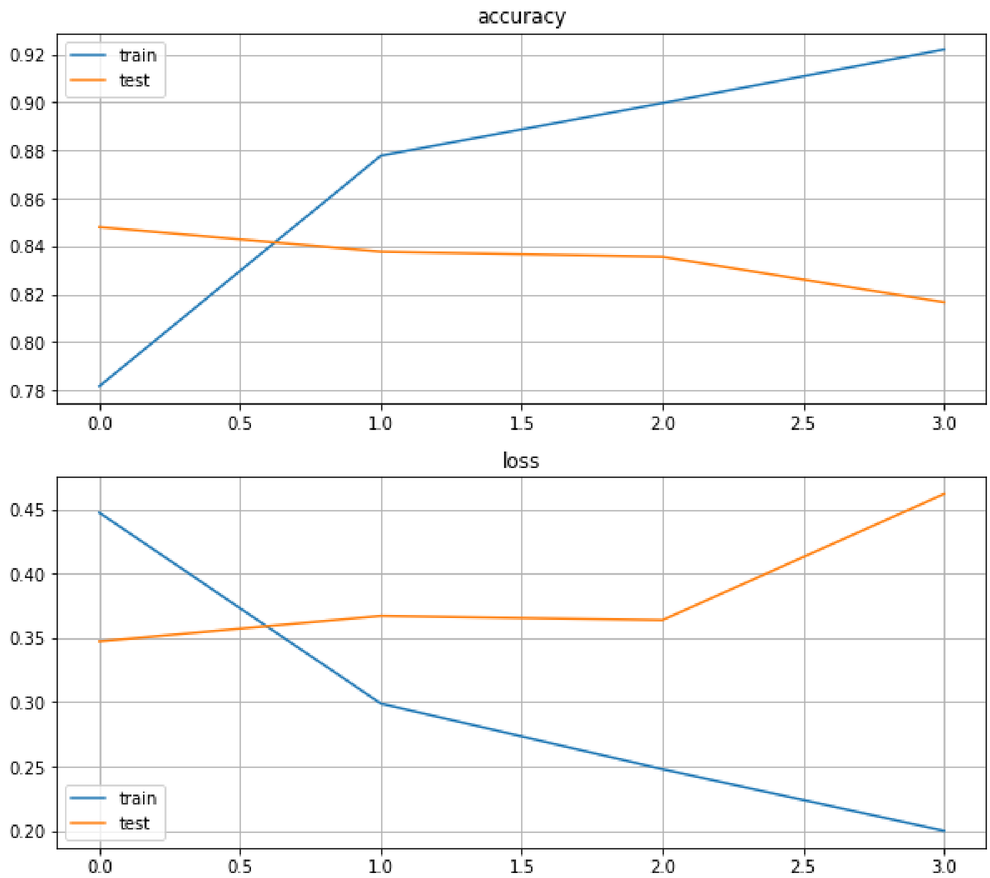
In [13]:
```
history = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                    epochs = epoch, verbose = verbose)
```

```
Train on 17500 samples, validate on 7500 samples
Epoch 1/4
17500/17500 [==============================] - 11s 636us/sample - loss: 0.4474 - accuracy: 0.7817
Epoch 2/4
17500/17500 [==============================] - 8s 459us/sample - loss: 0.2988 - accuracy: 0.8778
Epoch 3/4
17500/17500 [==============================] - 8s 470us/sample - loss: 0.2477 - accuracy: 0.8997
Epoch 4/4
17500/17500 [==============================] - 8s 468us/sample - loss: 0.1998 - accuracy: 0.9220
```

In [14]:
```
test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

print('\nTest acccuracy:', test_acc)
```

```
25000/1 - 4s - loss: 0.6446 - accuracy: 0.8137

Test acccuracy: 0.81368
```

In [15]:
```
plt.figure(figsize=(10,9))

plt.subplot(211)
plt.plot(history.history['accuracy'])
plt.plot(history.history['val_accuracy'])
plt.title('accuracy')
plt.legend(['train', 'test'])
plt.grid()
plt.subplot(212)
plt.plot(history.history['loss'])
plt.plot(history.history['val_loss'])
plt.title('loss')
plt.legend(['train', 'test'])
plt.grid()
```



Deep Bidirectional RNN

- Observar el efecto de la profundidad de la red en el entrenamiento

In [16]:
```
def deep_bidirectional_lstm():
    model = Sequential()
    model.add(Embedding(num_words, emb_dim))
    model.add(Bidirectional(LSTM(64, return_sequences = True)))
    model.add(Bidirectional(LSTM(64, return_sequences = False)))
    model.add(Dense(1, activation='sigmoid'))
    model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

    return model
```

In [17]:
```
model = deep_bidirectional_lstm()
model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, None, 64)          256000
_________________________________________________________________
bidirectional_1 (Bidirection (None, None, 128)         66048
_________________________________________________________________
bidirectional_2 (Bidirection (None, 128)               98816
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 129
=================================================================
Total params: 420,993
Trainable params: 420,993
Non-trainable params: 0
_________________________________________________________________
```

In [18]:
```
history1 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                     epochs = epoch, verbose = verbose)
```

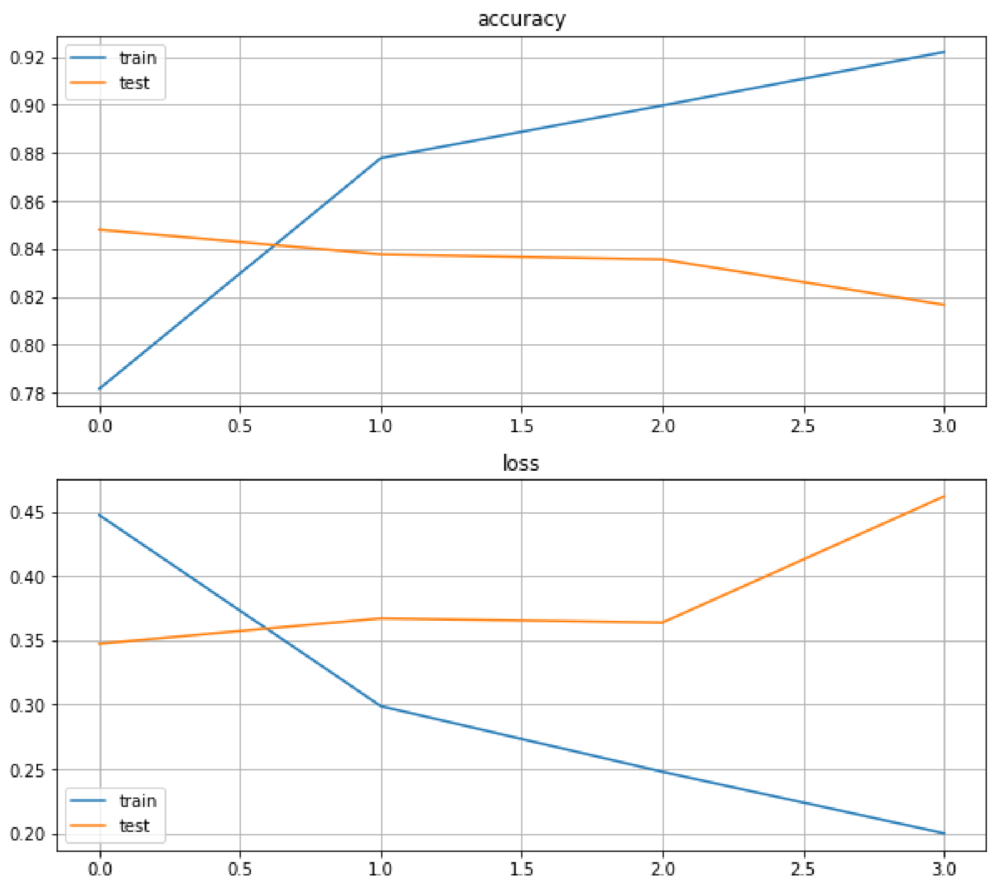
```
Train on 17500 samples, validate on 7500 samples
Epoch 1/4
17500/17500 [==============================] - 19s 1ms/sample - loss: 0.4360 - accuracy: 0.7903 -
Epoch 2/4
17500/17500 [==============================] - 14s 798us/sample - loss: 0.2995 - accuracy: 0.8735
Epoch 3/4
17500/17500 [==============================] - 14s 773us/sample - loss: 0.2407 - accuracy: 0.9041
Epoch 4/4
17500/17500 [==============================] - 14s 784us/sample - loss: 0.1764 - accuracy: 0.9350
```

In [19]:
```
test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

print('\nTest acccuracy:', test_acc)
```

```
25000/1 - 7s - loss: 0.4300 - accuracy: 0.8369
```

```
Test acccuracy: 0.83688
```

```
In [20]: plt.figure(figsize=(10,9))

         plt.subplot(211)
         plt.plot(history.history['accuracy'])
         plt.plot(history.history['val_accuracy'])
         plt.title('accuracy')
         plt.legend(['train', 'test'])
         plt.grid()
         plt.subplot(212)
         plt.plot(history.history['loss'])
         plt.plot(history.history['val_loss'])
         plt.title('loss')
         plt.legend(['train', 'test'])
         plt.grid()
```



Optimización en Bidirectional RNN con regularización

- Los optimizadores tienen comportamientos diferentes en las diferentes arquitecturas de las redes
- La regularización como dropout se agrega con 'recurrent_dropout'

```
In [21]: def deep_bidirectional_lstm():
             model = Sequential()
             model.add(Embedding(num_words, emb_dim))
             model.add(Bidirectional(LSTM(64, return_sequences = True,
                                          recurrent_initializer='glorot_uniform',
                                          recurrent_dropout=0.1)))
             model.add(Bidirectional(LSTM(64, return_sequences = False,
                                          recurrent_initializer='glorot_uniform',
                                          recurrent_dropout=0.1)))
             model.add(Dense(1, activation='sigmoid'))
             model.compile(loss='binary_crossentropy', optimizer='rmsprop', metrics=['accuracy'])

             return model
```

```
In [22]: model = deep_bidirectional_lstm()
         model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_3 (Embedding)      (None, None, 64)          256000
_________________________________________________________________
bidirectional_3 (Bidirection (None, None, 128)         66048
_________________________________________________________________
bidirectional_4 (Bidirection (None, 128)               98816
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 420,993
Trainable params: 420,993
Non-trainable params: 0
_________________________________________________________________
```

```
In [23]: history2 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                              epochs = epoch, verbose = verbose)
```

```
Train on 17500 samples, validate on 7500 samples
Epoch 1/4
17500/17500 [==============================] - 156s 9ms/sample - loss: 0.4587 - accuracy: 0.7790
Epoch 2/4
17500/17500 [==============================] - 148s 8ms/sample - loss: 0.3404 - accuracy: 0.8582
Epoch 3/4
17500/17500 [==============================] - 150s 9ms/sample - loss: 0.2987 - accuracy: 0.8794
```

```
Epoch 4/4
17500/17500 [==============================] - 154s 9ms/sample - loss: 0.2658 - accuracy: 0.8933
```

```
In [24]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

         print('\nTest acccuracy:', test_acc)
```

```
25000/1 - 58s - loss: 0.4047 - accuracy: 0.8495

Test acccuracy: 0.84952
```

- RMSProp con regularización supera a las redes anteriores con Adam
- Averiguar si quitando la regularizacón se llega a el mismo resultado

```
In [25]: def deep_bidirectional_lstm():
             model = Sequential()
             model.add(Embedding(num_words, emb_dim))
             model.add(Bidirectional(LSTM(64, return_sequences = True,
                                          recurrent_initializer='glorot_uniform',
                                          recurrent_dropout=0.1)))
             model.add(Bidirectional(LSTM(64, return_sequences = False,
                                          recurrent_initializer='glorot_uniform',
                                          recurrent_dropout=0.1)))
             model.add(Dense(1, activation='sigmoid'))
             model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

             return model
```

```
In [26]: model = deep_bidirectional_lstm()
         model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_4 (Embedding)      (None, None, 64)          256000
_________________________________________________________________
bidirectional_5 (Bidirection (None, None, 128)         66048
_________________________________________________________________
bidirectional_6 (Bidirection (None, 128)               98816
_________________________________________________________________
dense_4 (Dense)              (None, 1)                 129
=================================================================
Total params: 420,993
Trainable params: 420,993
Non-trainable params: 0
_________________________________________________________________
```

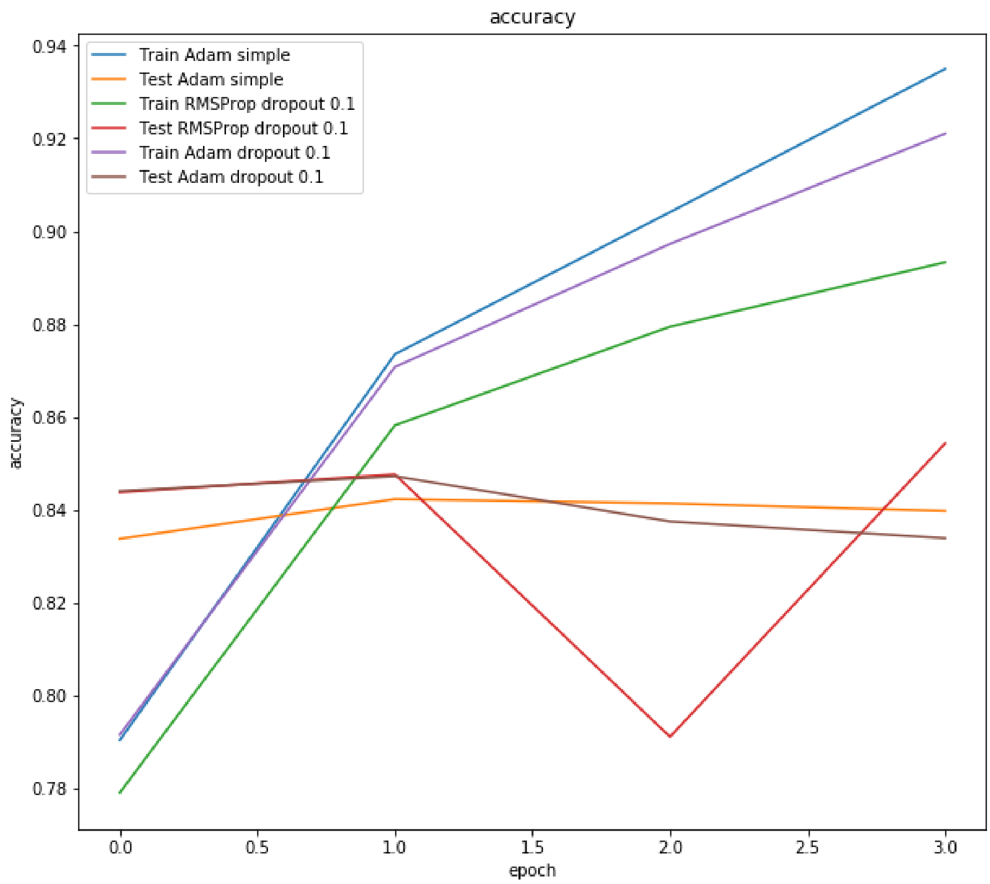
```
In [27]: history3 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                              epochs = epoch, verbose = verbose)
```

```
Train on 17500 samples, validate on 7500 samples
Epoch 1/4
17500/17500 [==============================] - 154s 9ms/sample - loss: 0.4406 - accuracy: 0.7915
Epoch 2/4
17500/17500 [==============================] - 148s 8ms/sample - loss: 0.3120 - accuracy: 0.8707
Epoch 3/4
17500/17500 [==============================] - 146s 8ms/sample - loss: 0.2529 - accuracy: 0.8973
Epoch 4/4
17500/17500 [==============================] - 147s 8ms/sample - loss: 0.2028 - accuracy: 0.9210
```

```
In [28]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

         print('\nTest acccuracy:', test_acc)
```

```
25000/1 - 58s - loss: 0.3618 - accuracy: 0.8309

Test acccuracy: 0.83092
```

```
In [29]: # plot
         plt.figure(figsize=(10,9))
         plt.plot(history1.history['accuracy'])
         plt.plot(history1.history['val_accuracy'])


         plt.plot(history2.history['accuracy'])
         plt.plot(history2.history['val_accuracy'])

         plt.plot(history3.history['accuracy'])
         plt.plot(history3.history['val_accuracy'])


         plt.legend(['Train Adam simple', 'Test Adam simple',
                     'Train RMSProp dropout 0.1', 'Test RMSProp dropout 0.1',
                     'Train Adam dropout 0.1', 'Test Adam dropout 0.1',])

         plt.title('accuracy')
         plt.ylabel('accuracy')
         plt.xlabel('epoch')

         plt.show()
```



- Mejorar el acuracy de la red
- Probar Deep-Bidirectional-RNN con otro dataset
- Probar con otros optimizadores y diferentes valores de 'recurrent_dropout' y 'recurrent_initializer'