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

2019/09/30

1 Deep Bidirectional RNN

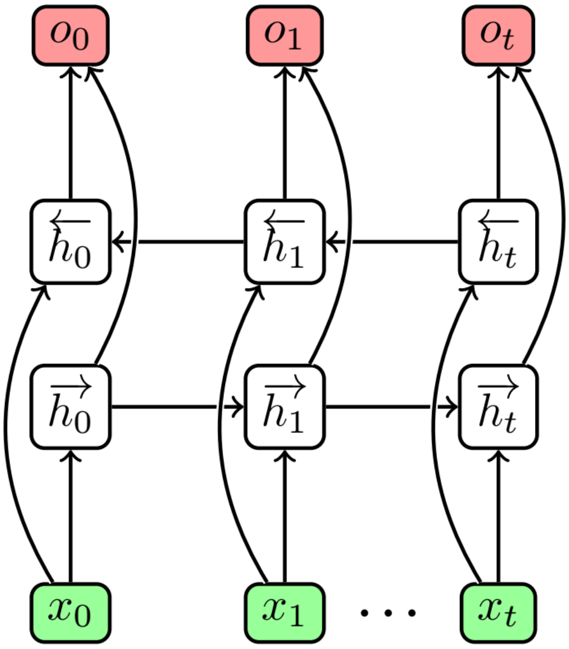
Objetivo: Comprender las RNN Bidireccionales y sus efectos en el aprendizaje del modelo. Conocer el comportamiento de los optimizadores y aplicar regularización a modelos recurrentes.

```
In [17]: 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
```

2 Reseñas de películas de IMDB

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

```
In [18]: # 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)
```



RNN

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

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

```
In [19]: epoch = 4
         verbose = 1
         batch = 128
```

2.1 Cada palabra de la review esta identificada por un número

```
In [20]: 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
```

2.2 Palabras de reseña

```
In [21]: 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
```

2.3 Deep RNN

- Se copmará el modelo con y sin regularización

```
In [22]: 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 [23]: model = deep_lstm()
         model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_2 (Embedding)      (None, None, 64)          256000
_________________________________________________________________
lstm_4 (LSTM)                (None, None, 64)          33024
_________________________________________________________________
lstm_5 (LSTM)                (None, 64)                33024
_________________________________________________________________
dense_2 (Dense)              (None, 1)                 65
=================================================================
Total params: 322,113
Trainable params: 322,113
```

```
Non-trainable params: 0
_________________________________________________________________
```

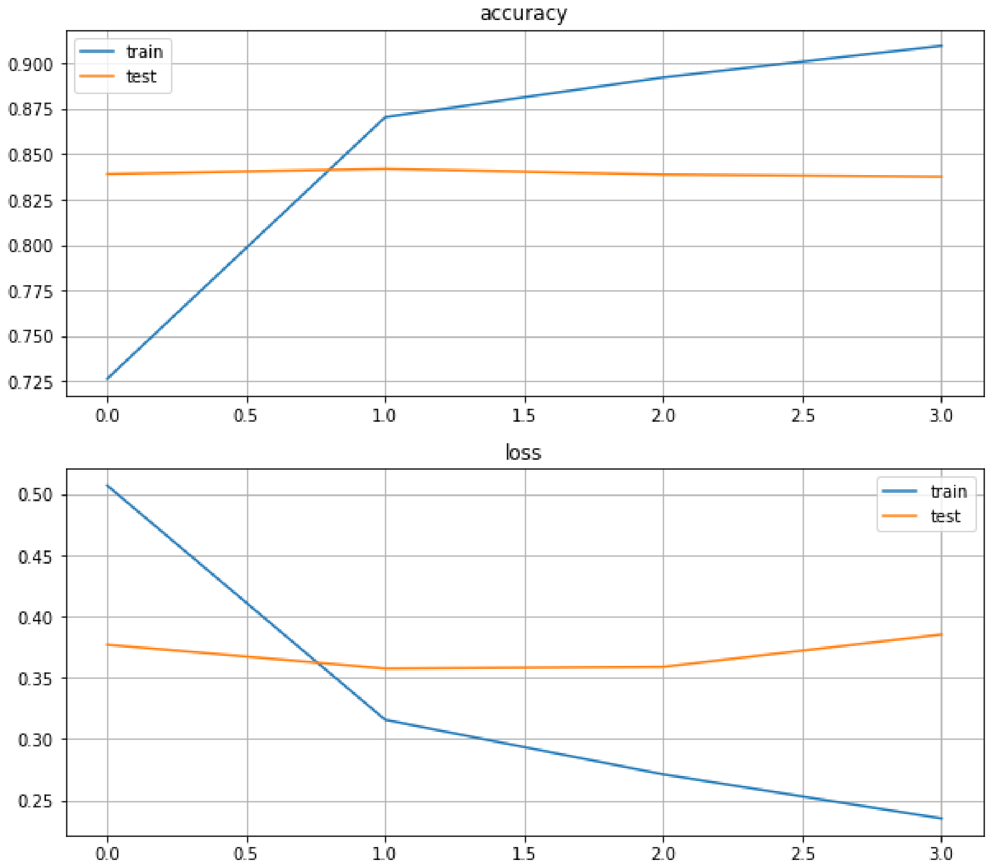
```
In [24]: history = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                             epochs = epoch, verbose = verbose)
```

```
Epoch 1/4
137/137 [==============================] - 39s 283ms/step - loss: 0.5071 - accuracy: 0.7265 - val
Epoch 2/4
137/137 [==============================] - 38s 278ms/step - loss: 0.3156 - accuracy: 0.8702 - val
Epoch 3/4
137/137 [==============================] - 38s 277ms/step - loss: 0.2711 - accuracy: 0.8920 - val
Epoch 4/4
137/137 [==============================] - 39s 287ms/step - loss: 0.2351 - accuracy: 0.9093 - val
```

```
In [25]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

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

```
782/782 - 21s - loss: 0.3869 - accuracy: 0.8348

Test acccuracy: 0.8347600102424622
```

```
In [26]: 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()
```



2.4 Bidirectional RNN

- Bidirectional RNNs lee las secuencias en ambas direcciones

```
In [27]: 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 [28]: model = bidirectional_lstm()
         model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
```

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding_3 (Embedding)      (None, None, 64)          256000

_________________________________________________________________
bidirectional (Bidirectional (None, 128)               66048

_________________________________________________________________
dense_3 (Dense)              (None, 1)                 129
=================================================================
Total params: 322,177
Trainable params: 322,177
Non-trainable params: 0

_________________________________________________________________
```

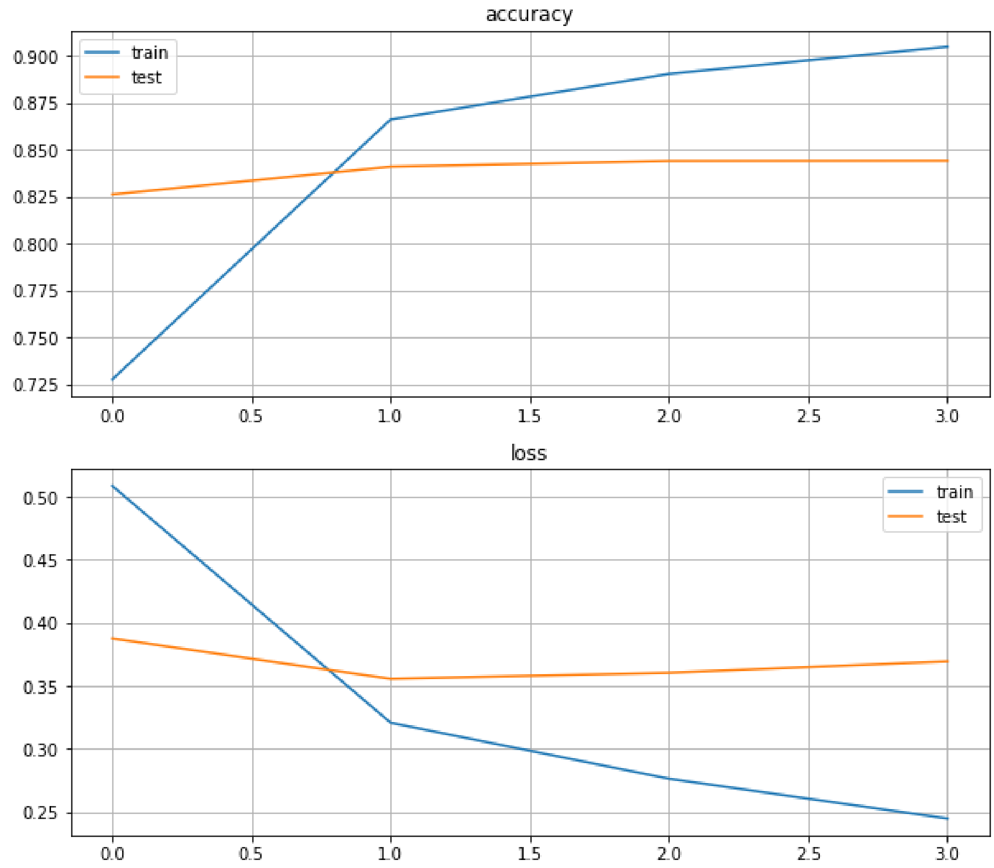
```
In [29]: history = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                             epochs = epoch, verbose = verbose)
```

```
Epoch 1/4
137/137 [==============================] - 35s 253ms/step - loss: 0.5087 - accuracy: 0.7275 - val
Epoch 2/4
137/137 [==============================] - 34s 250ms/step - loss: 0.3207 - accuracy: 0.8661 - val
Epoch 3/4
137/137 [==============================] - 34s 250ms/step - loss: 0.2763 - accuracy: 0.8904 - val
Epoch 4/4
137/137 [==============================] - 35s 252ms/step - loss: 0.2447 - accuracy: 0.9049 - val
```

```
In [30]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

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

```
782/782 - 17s - loss: 0.3747 - accuracy: 0.8414

Test acccuracy: 0.8414400219917297
```

```
In [31]: 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()
```



2.5 Deep Bidirectional RNN

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

```
In [89]: 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 [91]: model = deep_bidirectional_lstm()
         model.summary()
```

```
Model: "sequential_16"
_________________________________________________________________
```

```
Layer (type)                 Output Shape              Param #
=================================================================
embedding_16 (Embedding)     (None, None, 64)          256000
_________________________________________________________________
bidirectional_25 (Bidirectio (None, None, 128)         66048
_________________________________________________________________
bidirectional_26 (Bidirectio (None, 128)               98816
_________________________________________________________________
dense_17 (Dense)             (None, 1)                 129
=================================================================
Total params: 420,993
Trainable params: 420,993
Non-trainable params: 0
_________________________________________________________________
```

```
In [92]: history1 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                             epochs = epoch, verbose = verbose)
```

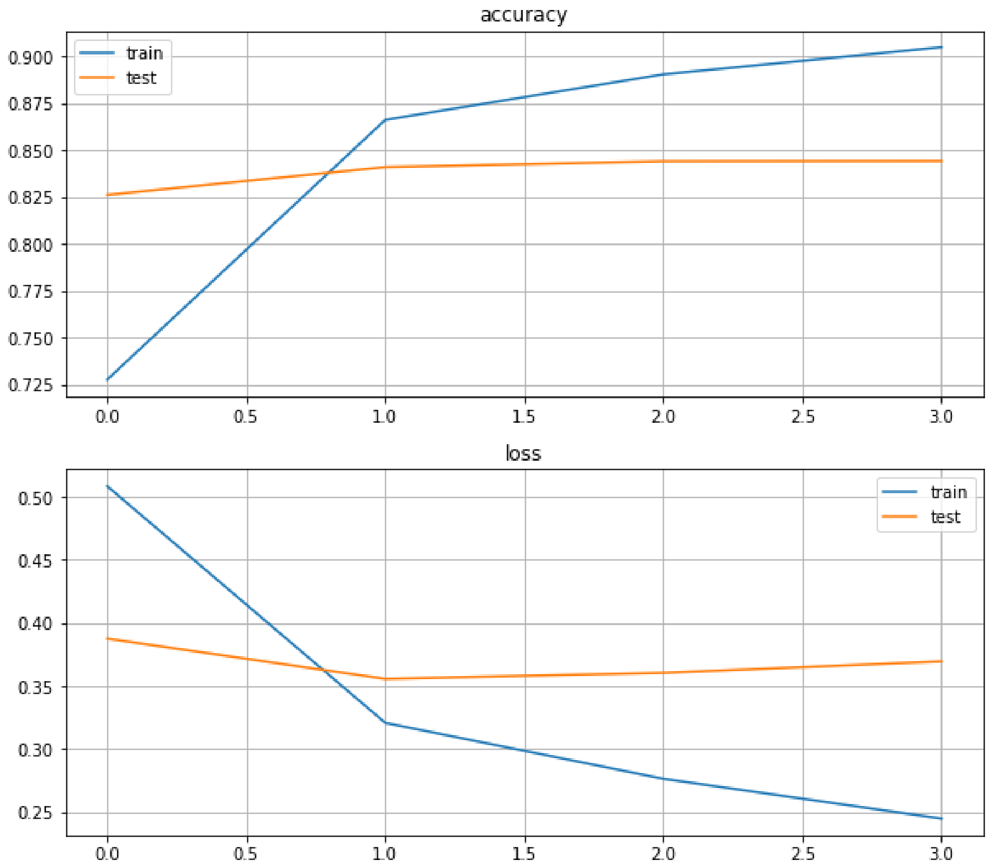
```
Epoch 1/4
137/137 [==============================] - 86s 625ms/step - loss: 0.4784 - accuracy: 0.7574 - val
Epoch 2/4
137/137 [==============================] - 85s 624ms/step - loss: 0.3031 - accuracy: 0.8726 - val
Epoch 3/4
137/137 [==============================] - 84s 616ms/step - loss: 0.2608 - accuracy: 0.8967 - val
Epoch 4/4
137/137 [==============================] - 85s 618ms/step - loss: 0.2204 - accuracy: 0.9151 - val
```

```
In [93]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

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

```
782/782 - 37s - loss: 0.3867 - accuracy: 0.8279

Test acccuracy: 0.8279200196266174
```

```
In [94]: 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()
```



2.6 Optimización en Bidirectional RNN con regularización

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

```
In [59]: recurrent_dropout = 0.2
```

```
In [67]: 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=recurrent_dropout)))
             model.add(Bidirectional(LSTM(64, return_sequences = False,
                                          recurrent_initializer='glorot_uniform',
```

```
                                    recurrent_dropout=recurrent_dropout)))
            model.add(Dense(1, activation='sigmoid'))
            model.compile(loss='binary_crossentropy', optimizer='rmsprop', metrics=['accuracy'])

            return model
```

```
In [68]: model = deep_bidirectional_lstm()
         model.summary()
```

```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_12 (Embedding)     (None, None, 64)          256000
_________________________________________________________________
bidirectional_17 (Bidirectio (None, None, 128)         66048
_________________________________________________________________
bidirectional_18 (Bidirectio (None, 128)               98816
_________________________________________________________________
dense_13 (Dense)             (None, 1)                 129
=================================================================
Total params: 420,993
Trainable params: 420,993
Non-trainable params: 0
_________________________________________________________________
```

```
In [69]: history2 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                             epochs = epoch, verbose = verbose)
```

```
Epoch 1/4
137/137 [==============================] - 126s 921ms/step - loss: 0.4895 - accuracy: 0.7605 - va
Epoch 2/4
137/137 [==============================] - 131s 959ms/step - loss: 0.3334 - accuracy: 0.8597 - va
Epoch 3/4
137/137 [==============================] - 126s 922ms/step - loss: 0.2902 - accuracy: 0.8829 - va
Epoch 4/4
137/137 [==============================] - 125s 911ms/step - loss: 0.2667 - accuracy: 0.8931 - va
```

```
In [70]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

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

```
782/782 - 47s - loss: 0.3590 - accuracy: 0.8500

Test acccuracy: 0.8500000238418579
```

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

```
In [71]: 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=recurrent_dropout)))
             model.add(Bidirectional(LSTM(64, return_sequences = False,
                                          recurrent_initializer='glorot_uniform',
                                          recurrent_dropout=recurrent_dropout)))
             model.add(Dense(1, activation='sigmoid'))
             model.compile(loss='binary_crossentropy', optimizer='adam', metrics=['accuracy'])

             return model
```

```
In [72]: model = deep_bidirectional_lstm()
         model.summary()
```

```
Model: "sequential_13"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
embedding_13 (Embedding)     (None, None, 64)          256000
_________________________________________________________________
bidirectional_19 (Bidirectio (None, None, 128)         66048
_________________________________________________________________
bidirectional_20 (Bidirectio (None, 128)               98816
_________________________________________________________________
dense_14 (Dense)             (None, 1)                 129
=================================================================
Total params: 420,993
Trainable params: 420,993
Non-trainable params: 0
_________________________________________________________________
```

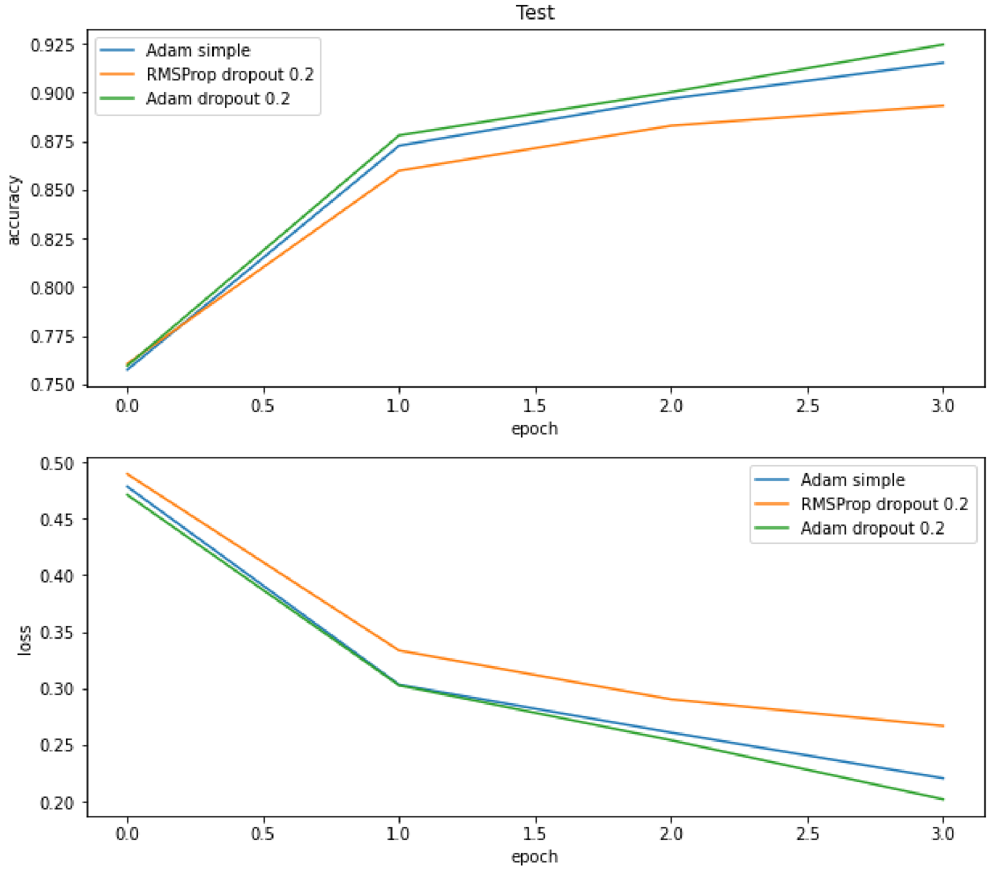
```
In [73]: history3 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                              epochs = epoch, verbose = verbose)
```

```
Epoch 1/4
137/137 [==============================] - 126s 916ms/step - loss: 0.4711 - accuracy: 0.7595 - va
Epoch 2/4
137/137 [==============================] - 129s 941ms/step - loss: 0.3026 - accuracy: 0.8779 - va
Epoch 3/4
137/137 [==============================] - 125s 914ms/step - loss: 0.2541 - accuracy: 0.9001 - va
Epoch 4/4
137/137 [==============================] - 125s 912ms/step - loss: 0.2019 - accuracy: 0.9245 - va
```

```
In [74]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

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

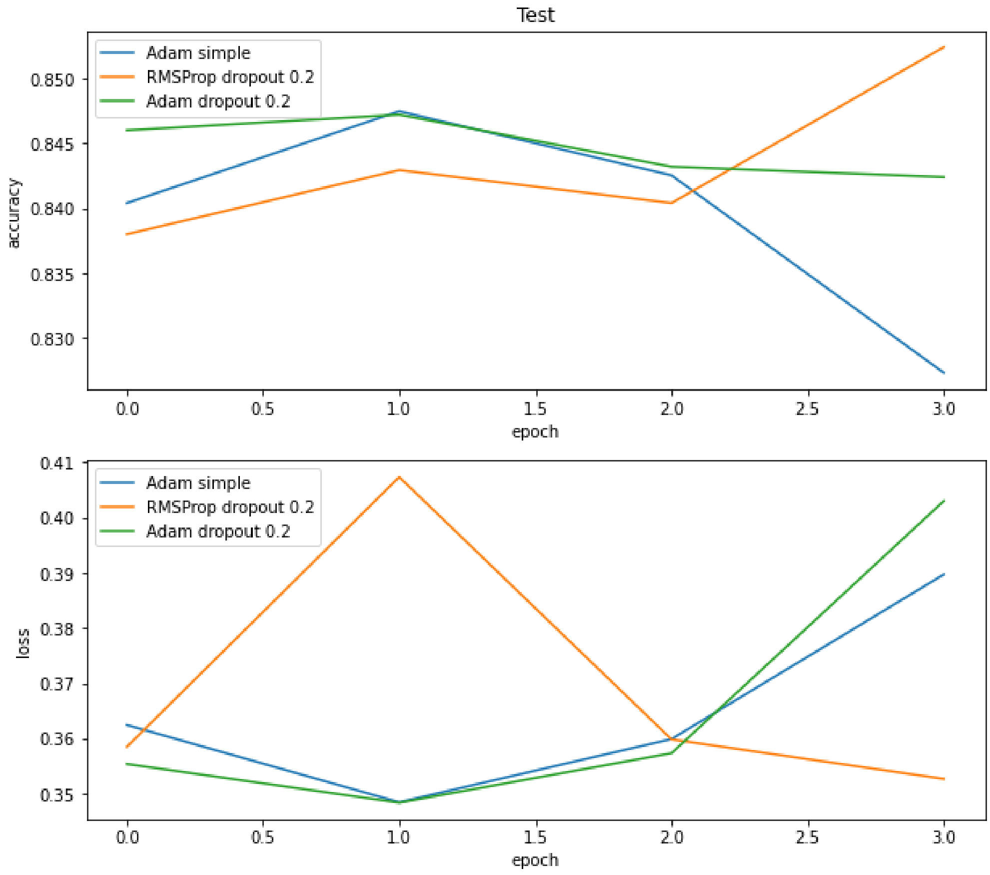
```
782/782 - 47s - loss: 0.4126 - accuracy: 0.8361

Test acccuracy: 0.836080014705658
```

```
In [95]: #plot
         plt.figure(figsize=(10,9))
         plt.subplot(211)

         plt.plot(history1.history['accuracy'])
         plt.plot(history2.history['accuracy'])
         plt.plot(history3.history['accuracy'])

         plt.legend(['Adam simple',
                     'RMSProp dropout 0.2',
                     'Adam dropout 0.2'])

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


         plt.subplot(212)
         plt.plot(history1.history['loss'])
         plt.plot(history2.history['loss'])
         plt.plot(history3.history['loss'])

         plt.legend(['Adam simple',
                     'RMSProp dropout 0.2',
                     'Adam dropout 0.2'])

         plt.ylabel('loss')
         plt.xlabel('epoch')
         plt.show()
```



```
In [96]: #plot
         plt.figure(figsize=(10,9))
         plt.subplot(211)

         plt.plot(history1.history['val_accuracy'])
         plt.plot(history2.history['val_accuracy'])
         plt.plot(history3.history['val_accuracy'])

         plt.legend(['Adam simple',
                     'RMSProp dropout 0.2',
                     'Adam dropout 0.2'])

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


         plt.subplot(212)
```

```
plt.plot(history1.history['val_loss'])
plt.plot(history2.history['val_loss'])
plt.plot(history3.history['val_loss'])

plt.legend(['Adam simple',
            'RMSProp dropout 0.2',
            'Adam dropout 0.2'])

plt.ylabel('loss')
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’