Análisis de Datos y Aprendizaje Máquina con Tensorflow 2.0: Perceptrón Multicapa

2019/09/30

Función de activación y costo / Inicialización del modelo

Objetivo: Conocer los diferentes inicializadores, funciones de costo y activación.

- La inicialización de pesos tiene efecto en el tiempo de entrenamiento
- Las funciones de costo dependen de el número de clases o si es clasificación o regresión
- Las funciones no lineales tienen diferentes comportamientos en los tipos de redes, estas proyectan los datos a un diferente espacio

Leer conjunto de datos

```
In [1]: import matplotlib.pyplot as plt
        import tensorflow as tf
        from tensorflow import keras
        from tensorflow.keras.layers import BatchNormalization, Activation
        from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense
        from tensorflow.keras import backend as K
        K.clear_session()

        from sklearn.datasets import load_breast_cancer
        from sklearn.model_selection import train_test_split

        data = load_breast_cancer()

        X_data = data.data
        y_data = data.target

        x_train, x_test, y_train, y_test = train_test_split(X_data, y_data, test_size = 0.33, ran
```

```
In [2]: print(x_train.shape)
        print(y_train.shape)
        print(x_test.shape)
        print(y_test.shape)
```

```
(381, 30)
(381,)
```

```
(188, 30)
(188,)
```

```
In [3]: epoch = 50
        verbose = 0
        batch = 50
```

```
In [4]: from tensorflow.keras.models import Sequential
        from tensorflow.keras.layers import Dense
```

Funcion costo

- Se mide que tan lejos esta $\hat{y}_i$ de y_i

$$MSE = \frac{1}{n}\sum^{n}(y_i - \hat{y}_i)^2$$

- Para más de 2 clases se usa 'sparse_categorical_crossentropy'
- Para más de 2 clases con 'one hot' se aplica 'categorical_crossentropy'
- Para 2 clases 'binary_crossentropy'

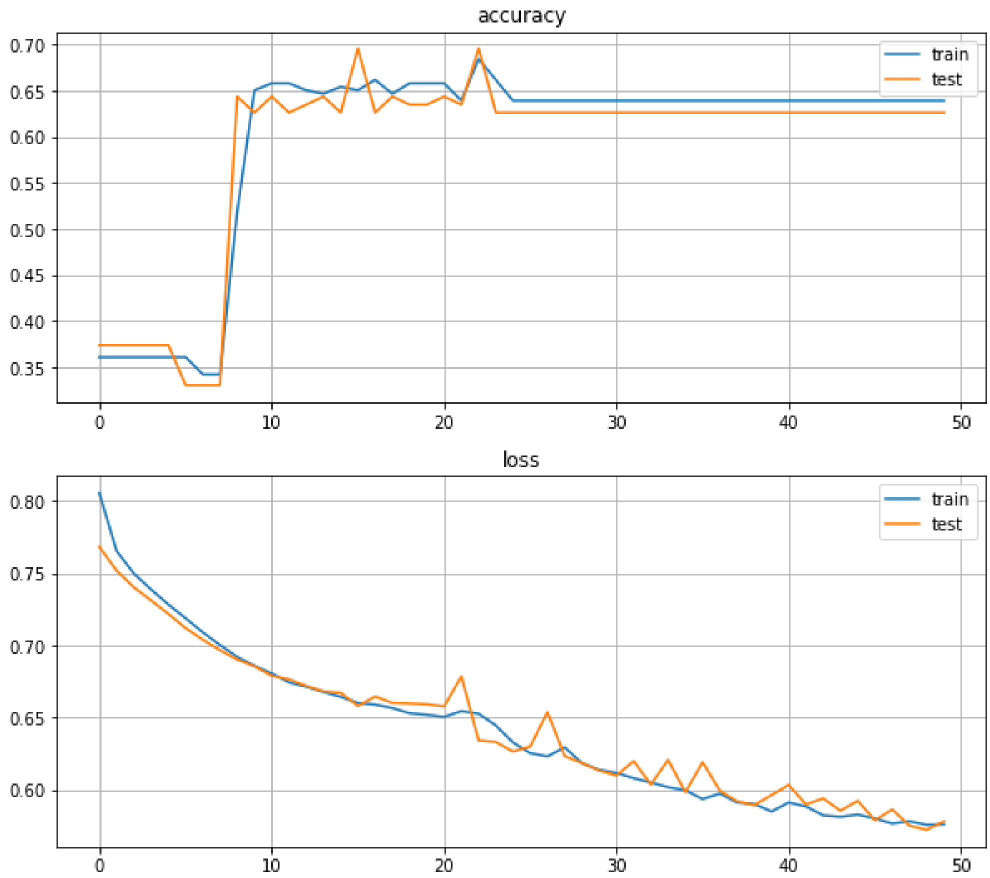
```
In [5]: def make_model():
            model = Sequential()

            model.add(Dense(16, input_shape = (30, ), activation = 'sigmoid'))
            model.add(Dense(1, activation = 'sigmoid'))

            model.compile(optimizer='rmsprop', loss='binary_crossentropy',
                          metrics=['accuracy'])

            return model
```

```
In [6]: model = make_model()

        model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 16)                496
_________________________________________________________________
dense_1 (Dense)              (None, 1)                 17
=================================================================
Total params: 513
Trainable params: 513
Non-trainable params: 0
_________________________________________________________________
```

In [7]:
```
history = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                    epochs = epoch, verbose = verbose)
```

In [8]:
```
#plot
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()
```



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

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

```
188/1 - 0s - loss: 0.5833 - accuracy: 0.6117

Test acccuracy: 0.61170214
```

Función de activación

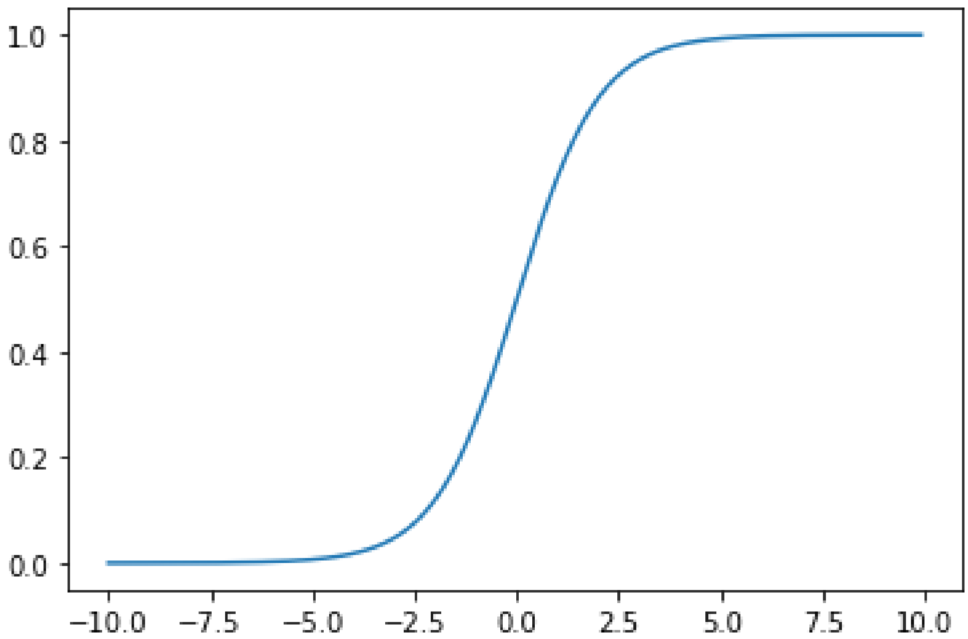
- Las funciones de activación son necesarias en los perceptrones multicapa, estas mapean las salidas de las multiplicaciones por las matrices a un nuevo espacio en donde los datos pueden ser clasificados.
- Existen muchas funciones de activación como:
  - Relu $\max(0, 1)$ que trabaja bien con imágenes y muestra una rápida convergencia que las demás funciones
  - Tanh $\tanh(x)$ que tiene una salida de un rango de -1 a 1, a diferencia de la sigmoide
- Investigar el probelma del gradiente y el efecto de las funciones de activación

```
In [8]: import math
        import numpy as np
        import matplotlib.pyplot as plt
```

sigmoid

```
In [38]: def sigmoid(x):
             return 1/(1 + np.exp(-x))
```

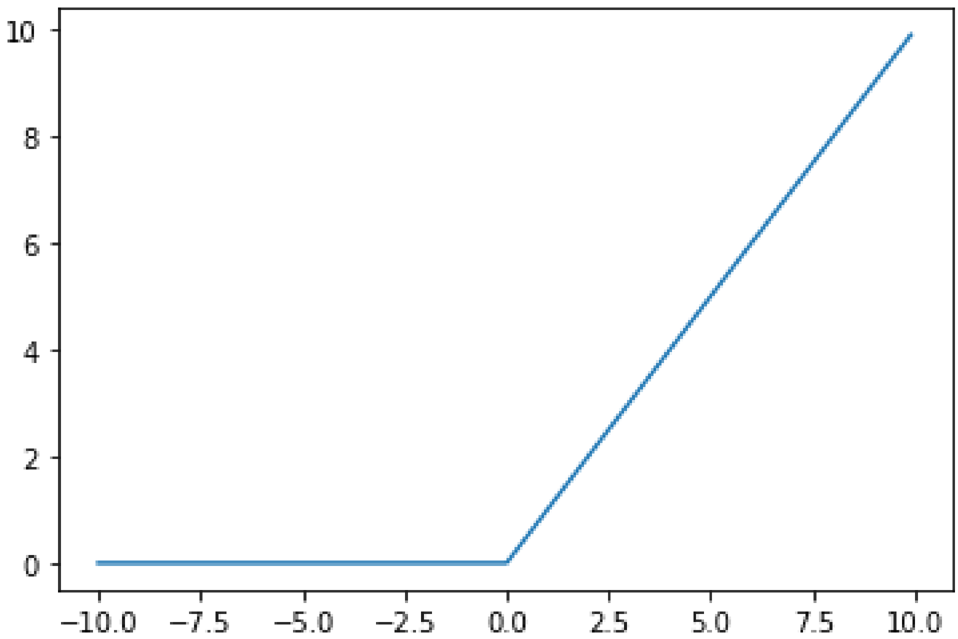
```
In [58]: x = np.arange(-10, 10, .1)
         y = list(map(sigmoid, x))

         plt.plot(x, y)
         plt.show()
```



relu

```
In [59]: def relu(x):
             return np.maximum(0, x)
```

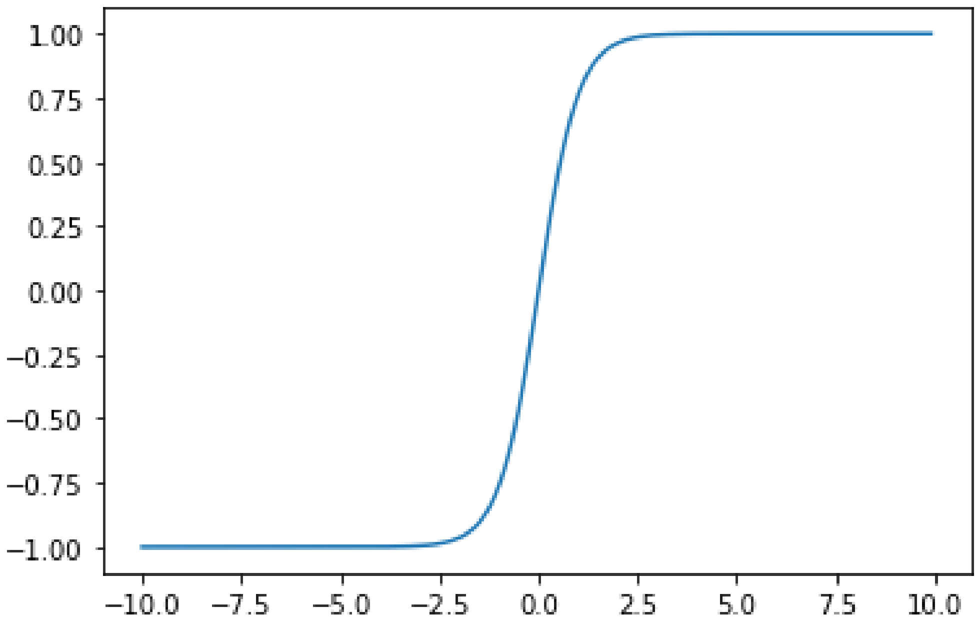
```
In [60]: x = np.arange(-10, 10, .1)
         y = list(map(relu, x))

         plt.plot(x, y)
         plt.show()
```



tanh

```
In [65]: def relu(x):
             return np.tanh(x)
```

```
In [66]: x = np.arange(-10, 10, .1)
         y = list(map(relu, x))

         plt.plot(x, y)
         plt.show()
```



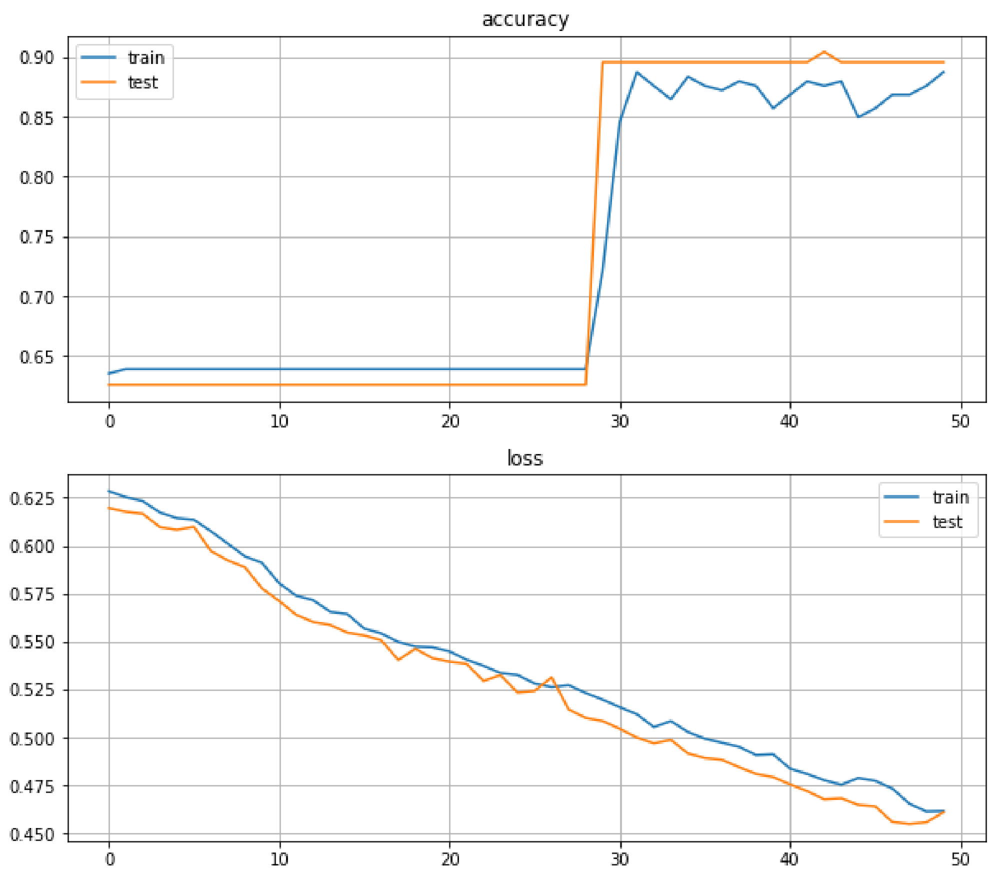

```
In [10]: def make_model():
             model = Sequential()

             model.add(Dense(16, input_shape = (30, ), activation = 'tanh'))
             model.add(Dense(1, activation = 'sigmoid'))


             model.compile(optimizer='rmsprop', loss='binary_crossentropy',
                           metrics=['accuracy'])
             return model
```

```
In [11]: model = make_model()

         model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_2 (Dense)              (None, 16)                496
_________________________________________________________________
dense_3 (Dense)              (None, 1)                 17
=================================================================
Total params: 513
Trainable params: 513
Non-trainable params: 0
```

In [12]:
```
history = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                    epochs = epoch, verbose = verbose)
```

In [13]:
```
#plot
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()
```



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

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

```
188/1 - 0s - loss: 0.4765 - accuracy: 0.8777

Test accuracy: 0.87765956
```

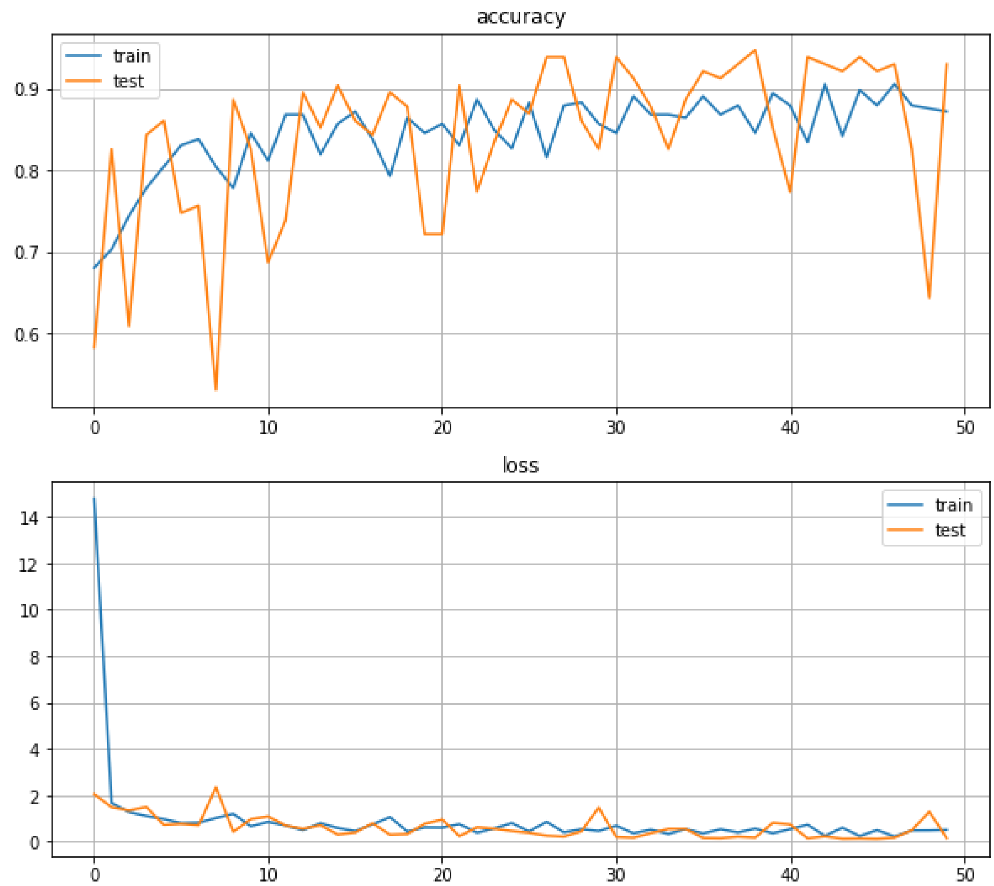
relu

```
In [15]: def make_model():
             model = Sequential()

             model.add(Dense(16, input_shape = (30, ), activation = 'relu'))
             model.add(Dense(1, activation = 'sigmoid'))


             model.compile(optimizer='rmsprop', loss='binary_crossentropy',
                           metrics=['accuracy'])
             return model

In [16]: model = make_model()

         model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 16)                496
_________________________________________________________________
dense_5 (Dense)              (None, 1)                 17
=================================================================
Total params: 513
Trainable params: 513
Non-trainable params: 0
_________________________________________________________________
```

```
In [17]: history = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                             epochs = epoch, verbose = verbose)

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




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

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

```
188/1 - 0s - loss: 0.2331 - accuracy: 0.8989

Test accuracy: 0.89893615
```

Inicialización de pesos

he_normal

- he_normal muestrea de una distribución normal centrada con stddev = sqrt(2 /fan_in) donde fan_in es el número de entradas en el tensor de pesos.

```
In [20]: def make_model():
             model = Sequential()

             model.add(Dense(16, input_shape = (30, ), activation = 'tanh', kernel_initializer='h
             model.add(Dense(1, activation = 'sigmoid'))

             model.compile(optimizer='rmsprop', loss='binary_crossentropy',
                           metrics=['accuracy'])
             return model
```

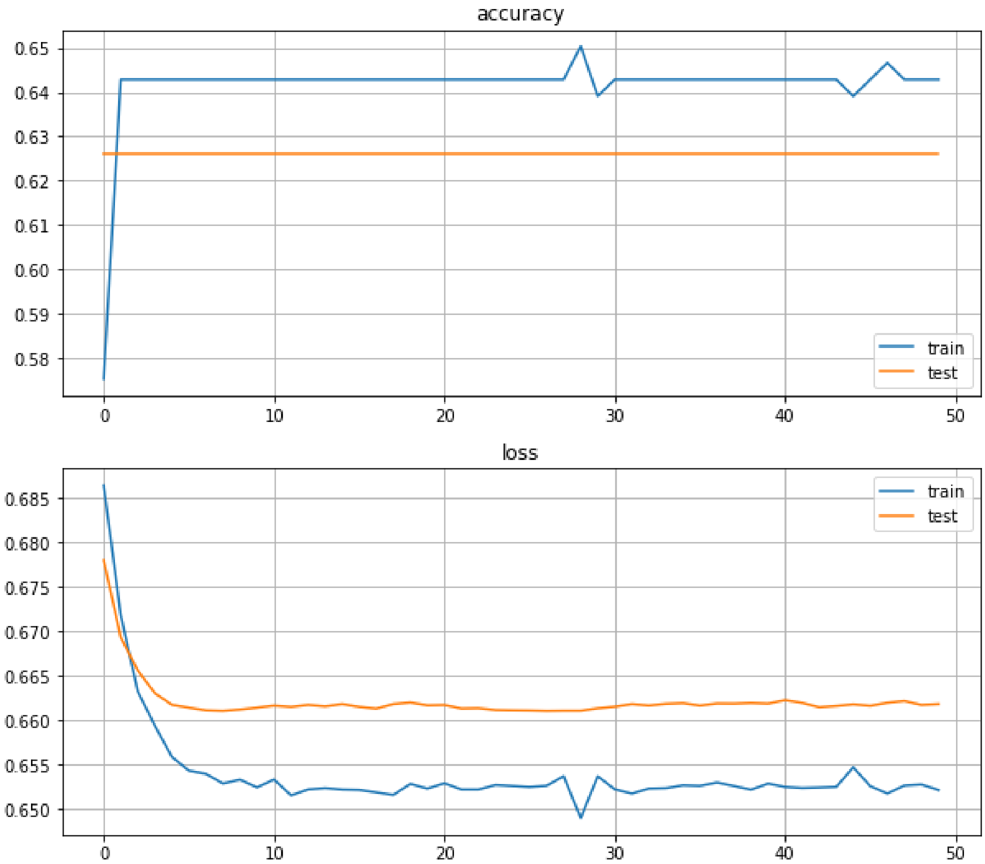
```
In [21]: model = make_model()

         model.summary()
```

```
Model: "sequential_3"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_6 (Dense)              (None, 16)                496
_________________________________________________________________
dense_7 (Dense)              (None, 1)                 17
=================================================================
Total params: 513
Trainable params: 513
Non-trainable params: 0
_________________________________________________________________
```

```
In [22]: history = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                             epochs = epoch, verbose = verbose)
```

```
In [23]: #plot
         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()
```




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

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

```
188/1 - 0s - loss: 0.6600 - accuracy: 0.6170

Test accuracy: 0.61702126
```

orthogonal

```
In [25]: def make_model():
             model = Sequential()

             model.add(Dense(16, input_shape = (30, ), activation = 'tanh', kernel_initializer='o
```

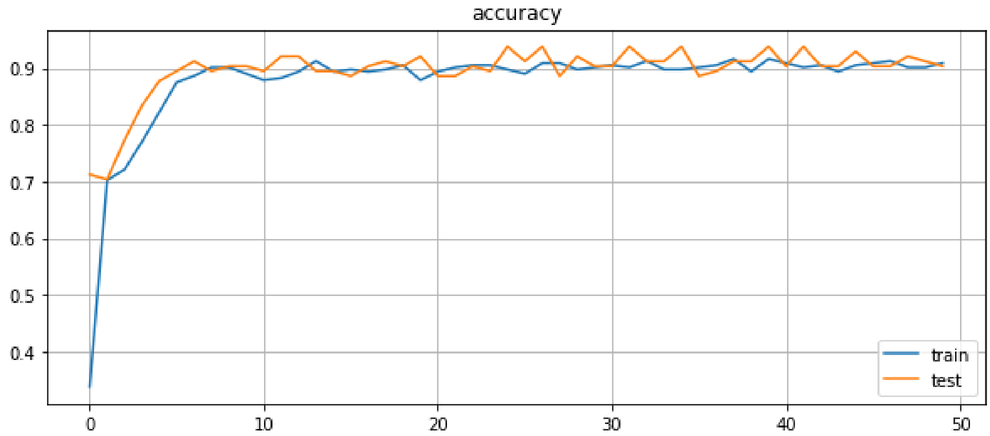
```
    model.add(Dense(1, activation = 'sigmoid'))


    model.compile(optimizer='rmsprop', loss='binary_crossentropy',
                  metrics=['accuracy'])
    return model
```

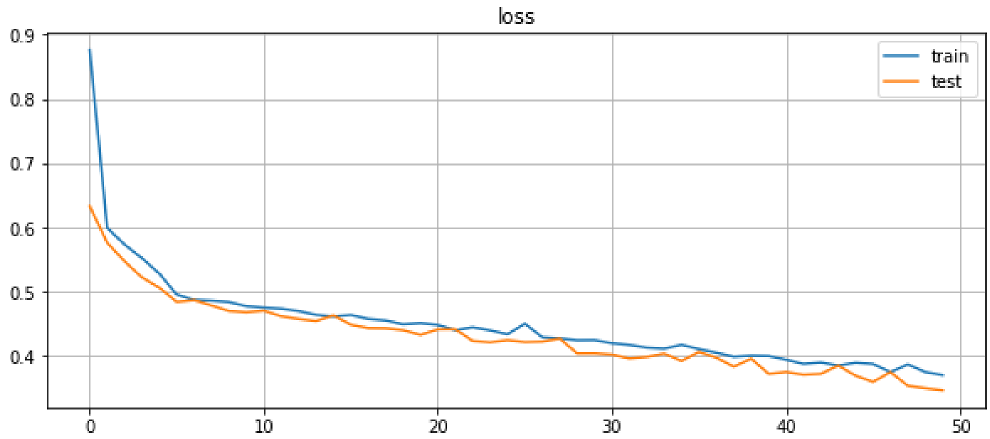
In [26]:
```
model = make_model()

model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 16)                496
_________________________________________________________________
dense_9 (Dense)              (None, 1)                 17
=================================================================
Total params: 513
Trainable params: 513
Non-trainable params: 0
_________________________________________________________________
```

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

In [28]:
```
#plot
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()
```





In [29]:
```
test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

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

```
188/1 - 0s - loss: 0.3409 - accuracy: 0.9255

Test accuracy: 0.9255319
```

- La red a mejorado el desempeño
- Probar con diferentes capas y funciones de activación
- Mejorar el tiempo de entrenamiento de la red y ‘Test accuracy’
- Aplicar y experimentar las mejoras de MLP en un diferente dataset