

# 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
```

## Función de 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"

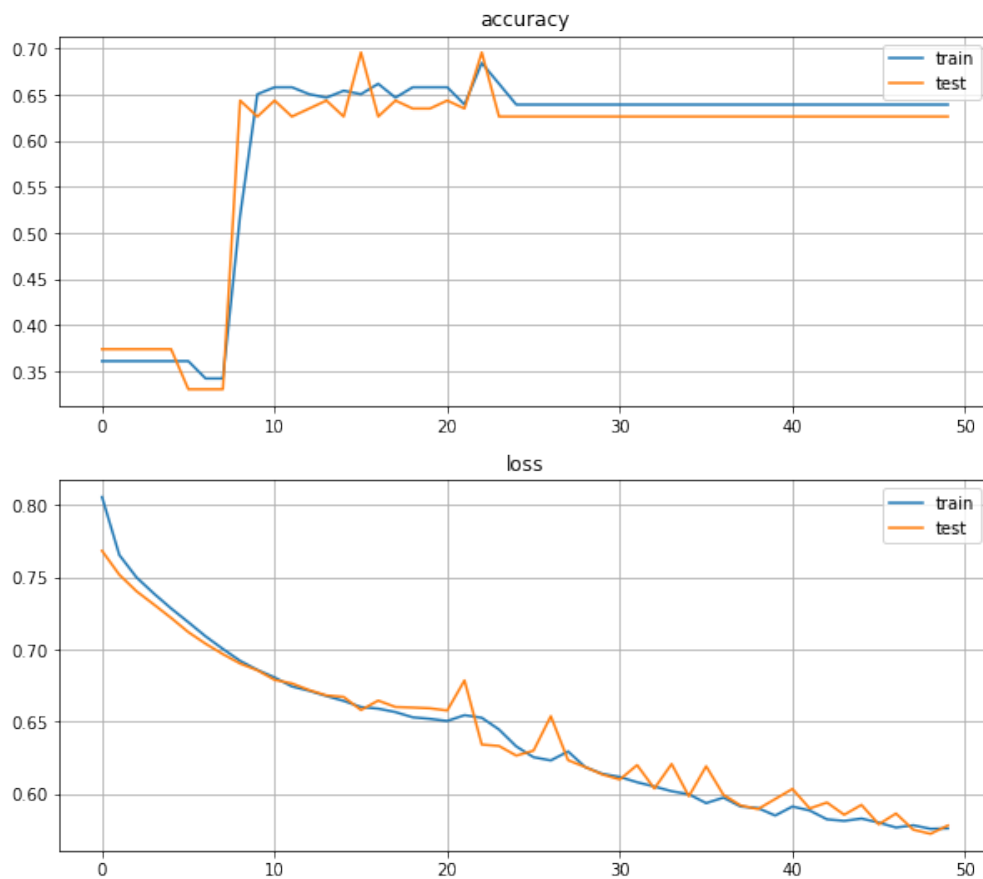
Layer (type)	Output Shape	Param #
dense (Dense)	(None, 16)	496
dense_1 (Dense)	(None, 1)	17

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 accuracy:', test_acc)
```

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

```
Test accuracy: 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  $\max(0, x)$  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 problema del gradiente y el efecto de las funciones de activación

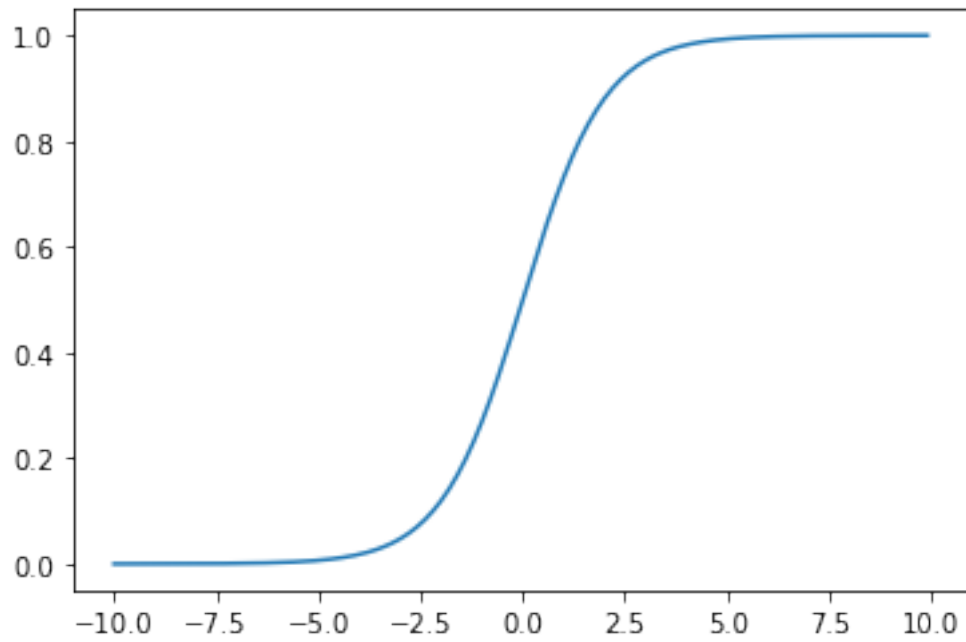
```
In [1]: import math
import numpy as np
import matplotlib.pyplot as plt
```

### sigmoid

```
In [2]: def sigmoid(x):
return 1/(1 + np.exp(-x))
```

```
In [3]: x = np.arange(-10, 10, .1)
y = list(map(sigmoid, x))
```

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

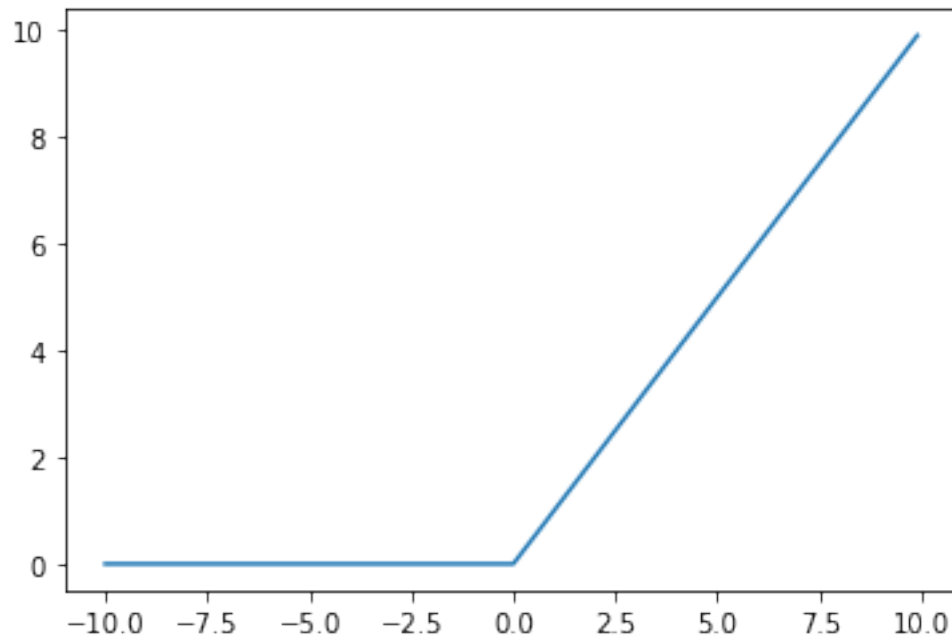


relu

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

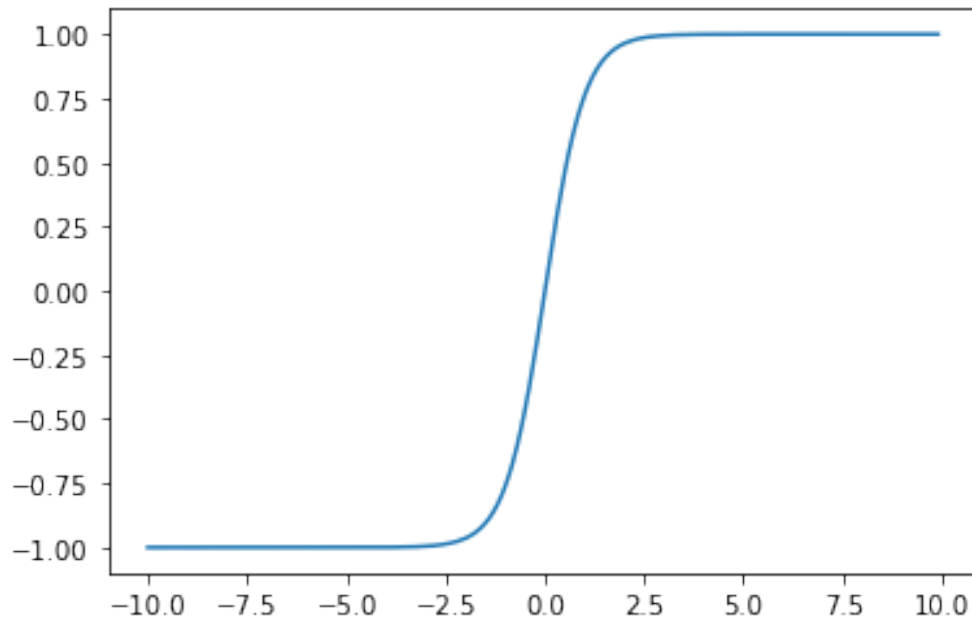
```
In [60]: x = np.arange(-10, 10, .1)  
         y = list(map(relu, x))
```

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



**tanh**

```
In [4]: def tanh(x):  
        return np.tanh(x)  
  
In [5]: x = np.arange(-10, 10, .1)  
        y = list(map(tanh, 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

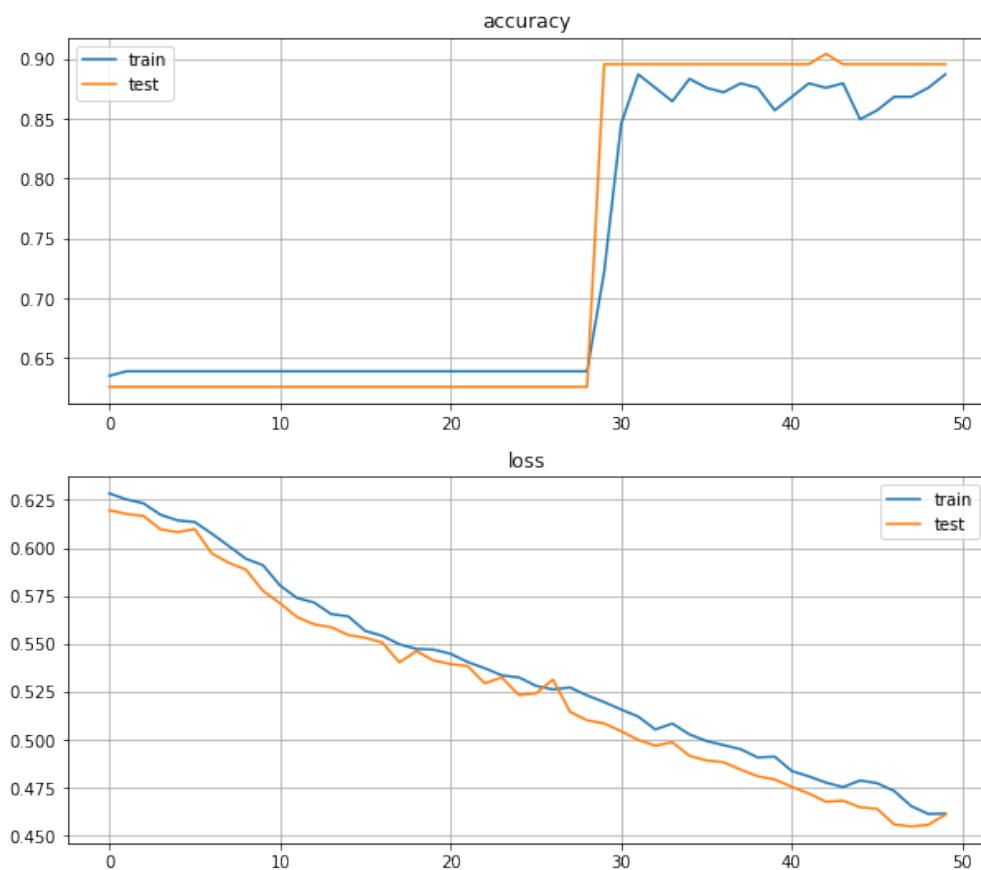
Non-trainable params: 0

---

```
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)
```

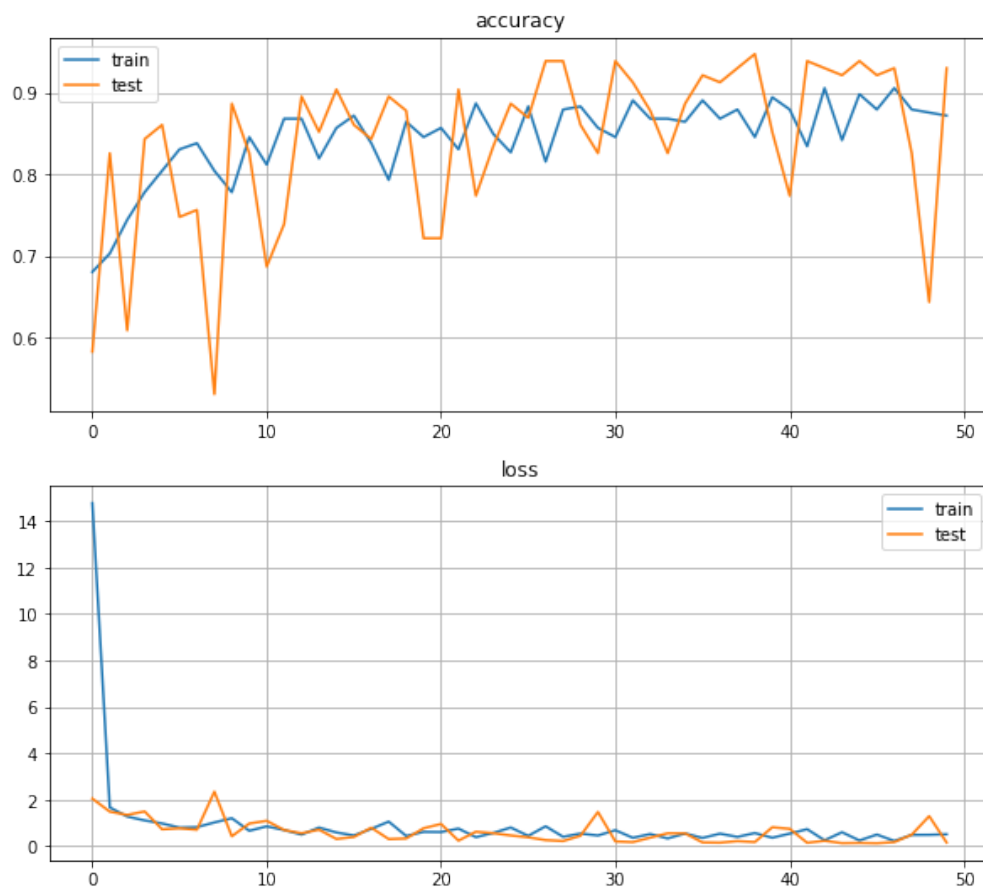
```
In [18]: #plot
        plt.figure(figsize=(10,9))

        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  $\text{stddev} = \sqrt{2 / \text{fan\_in}}$  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"
```

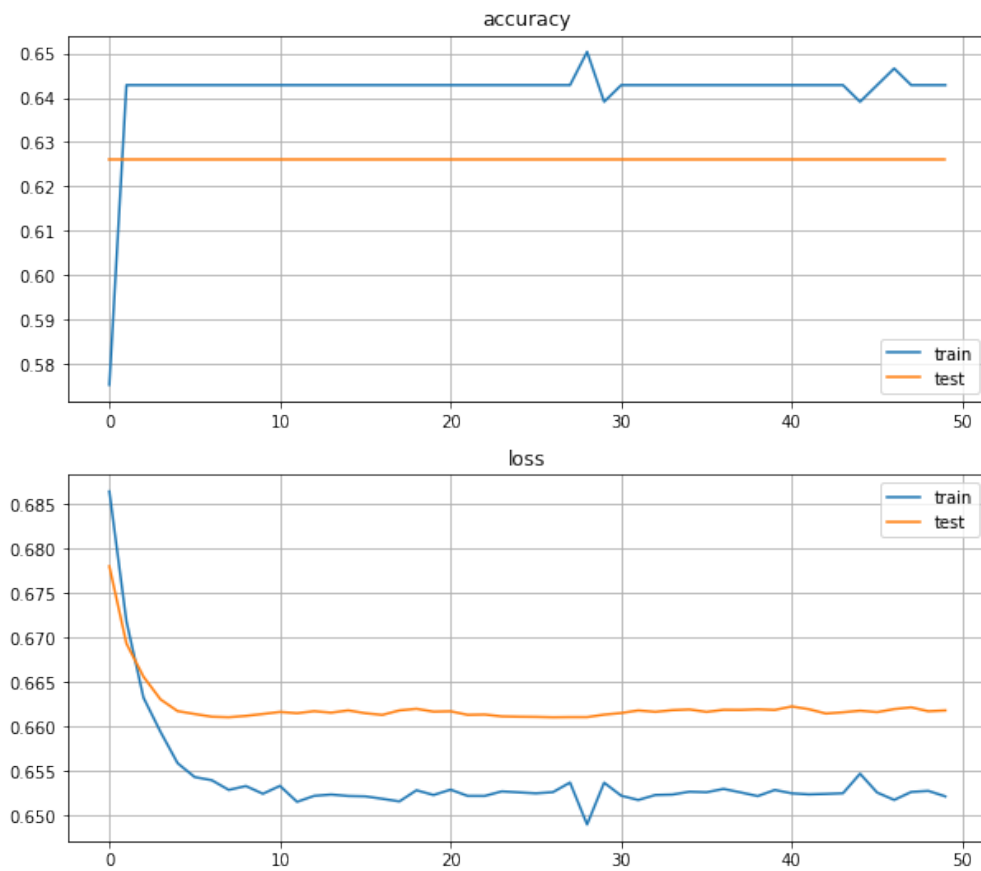
Layer (type)	Output Shape	Param #
dense_6 (Dense)	(None, 16)	496
dense_7 (Dense)	(None, 1)	17
Total params: 513		
Trainable params: 513		
Non-trainable params: 0		

```
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)`

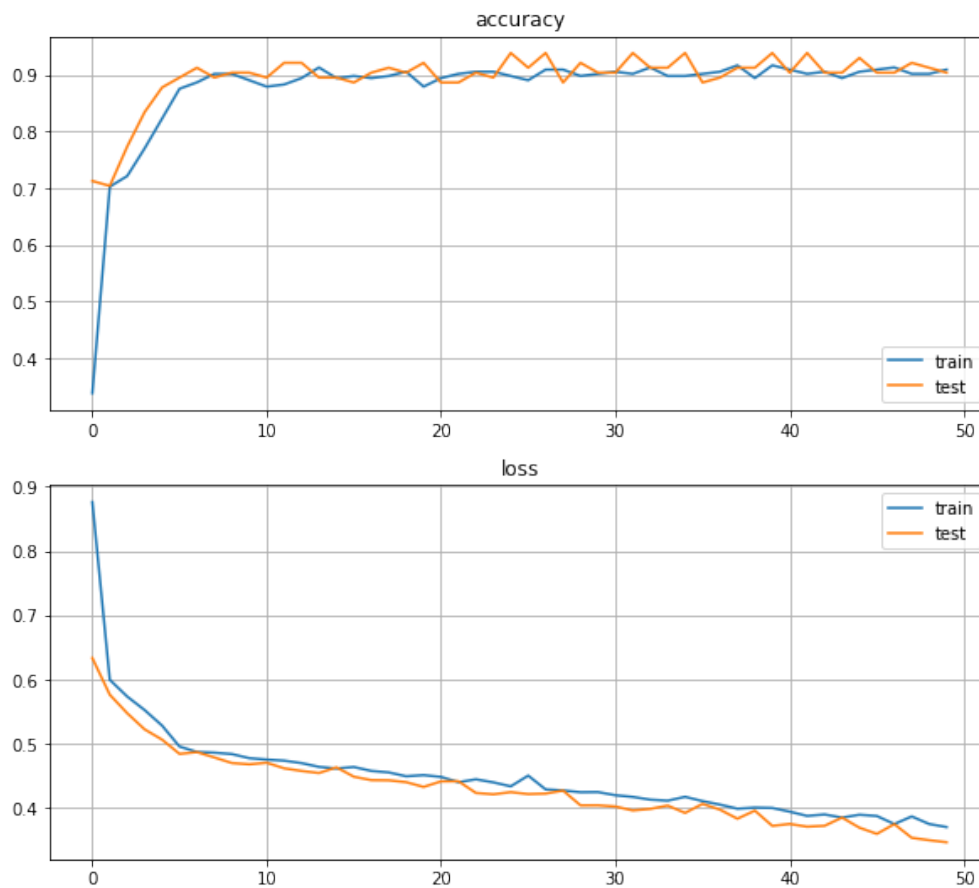
In [28]: `#plot`

```

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