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

2019/09/30

Regularización L2

Objetivo: Conocer el efecto de L2 y como afecta los entrenamientos de una red neuronal, se comparará con otros métodos como dropout

- Regularización L2 permite aplicar penalizaciones en los parámetros de capa.

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

        mnist = keras.datasets.mnist

        (x_train, y_train), (x_test, y_test) = mnist.load_data()
```

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

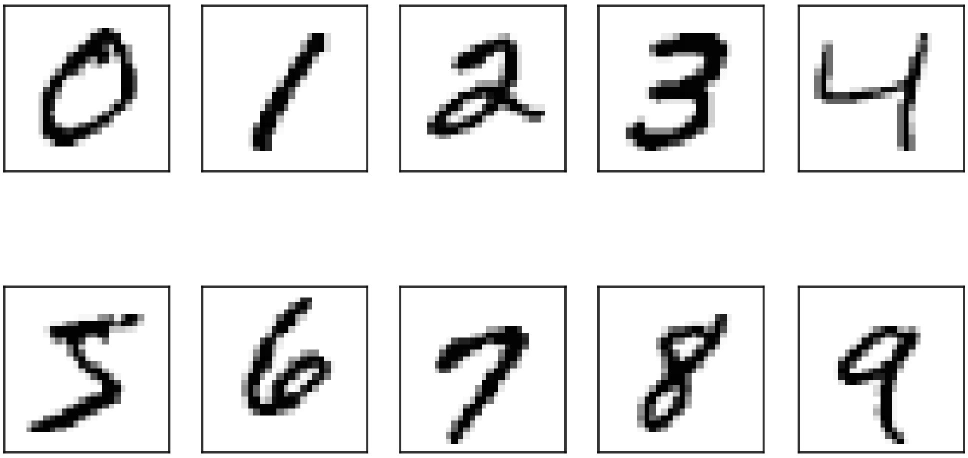
```
(60000, 28, 28)
(60000,)
(10000, 28, 28)
(10000,)
```

Leer Dataset

```
In [3]: fig, ax = plt.subplots(nrows=2, ncols=5, sharex=True, sharey=True,)
        ax = ax.flatten()
        for i in range(10):
```

```
        img = x_train[y_train == i][0].reshape(28, 28)
        ax[i].imshow(img, cmap='Greys', interpolation='nearest')

    ax[0].set_xticks([])
    ax[0].set_yticks([])
    plt.tight_layout()
    plt.show()
```



- Se modifica la forma de los datos de 2-d (n, 28, 28) a 1-d (n, 784)

In [4]:
```
x_train = x_train.reshape(x_train.shape[0], -1)
x_test = x_test.reshape(x_test.shape[0], -1)


print(x_train.shape) # (60000, 784)
print(y_train.shape) # (60000,)
print(x_test.shape)  # (10000, 784)
print(y_test.shape)  # (10000,)
```

```
(60000, 784)
(60000,)
(10000, 784)
(10000,)
```

In [5]:
```
epoch = 50
verbose = 0
batch = 50
```

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

```
    model.add(Dense(40, input_shape = (784, ), activation = 'relu', kernel_regularizer=re
    model.add(Dense(40, activation = 'relu', kernel_regularizer=regularizers.l2(0.01)))
    model.add(Dense(40, activation = 'relu', kernel_regularizer=regularizers.l2(0.01)))
    model.add(Dense(10, activation = 'softmax', kernel_regularizer=regularizers.l2(0.01))


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

In [7]:
```
model = make_model()

model.summary()
```

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense (Dense)                (None, 40)                31400
_________________________________________________________________
dense_1 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_2 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_3 (Dense)              (None, 10)                410
=================================================================
Total params: 35,090
Trainable params: 35,090
Non-trainable params: 0
_________________________________________________________________
```

In [8]:
```
history1 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                     epochs = epoch, verbose = verbose)
```

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

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

```
10000/1 - 1s - loss: 0.1808 - accuracy: 0.9664

Test acccuracy: 0.9664
```

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

    model.add(Dense(40, input_shape = (784, ), activation = 'relu', kernel_regularizer=r
    model.add(Dense(40, activation = 'relu', kernel_regularizer=regularizers.l2(0.001)))
    model.add(Dense(40, activation = 'relu', kernel_regularizer=regularizers.l2(0.001)))
```

```
        model.add(Dense(10, activation = 'softmax', kernel_regularizer=regularizers.l2(0.001


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

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

         model.summary()
```

```
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_4 (Dense)              (None, 40)                31400
_________________________________________________________________
dense_5 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_6 (Dense)              (None, 40)                1640
_________________________________________________________________
dense_7 (Dense)              (None, 10)                410
=================================================================
Total params: 35,090
Trainable params: 35,090
Non-trainable params: 0
_________________________________________________________________
```

```
In [12]: history2 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                              epochs = epoch, verbose = verbose)
```

```
In [13]: test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

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

```
10000/1 - 1s - loss: 0.1242 - accuracy: 0.9660

Test acccuracy: 0.966
```

```
In [14]: def make_model():
             model = Sequential()

             model.add(Dense(40, input_shape = (784, ), activation = 'relu'))
             model.add(Dropout(0.2))                       # capa Dropout
             model.add(Dense(40, activation = 'relu'))
             model.add(Dropout(0.2))                       # capa Dropout
             model.add(Dense(40, activation = 'relu'))
             model.add(Dropout(0.2))                       # capa Dropout
             model.add(Dense(10, activation = 'softmax'))
```

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

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

model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
dense_8 (Dense)              (None, 40)                31400
_________________________________________________________________
dropout (Dropout)            (None, 40)                0
_________________________________________________________________
dense_9 (Dense)              (None, 40)                1640
_________________________________________________________________
dropout_1 (Dropout)          (None, 40)                0
_________________________________________________________________
dense_10 (Dense)             (None, 40)                1640
_________________________________________________________________
dropout_2 (Dropout)          (None, 40)                0
_________________________________________________________________
dense_11 (Dense)             (None, 10)                410
=================================================================
Total params: 35,090
Trainable params: 35,090
Non-trainable params: 0
_________________________________________________________________
```

In [16]:
```
history3 = model.fit(x_train, y_train, batch_size = batch, validation_split = 0.3,
                     epochs = epoch, verbose = verbose)
```

In [17]:
```
test_loss, test_acc = model.evaluate(x_test,  y_test, verbose=2)

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

```
10000/1 - 0s - loss: 0.2256 - accuracy: 0.9152

Test acccuracy: 0.9152
```

In [18]:
```
#plot
plt.figure(figsize=(10,9))
plt.plot(history1.history['accuracy'])
plt.plot(history1.history['val_accuracy'])
```

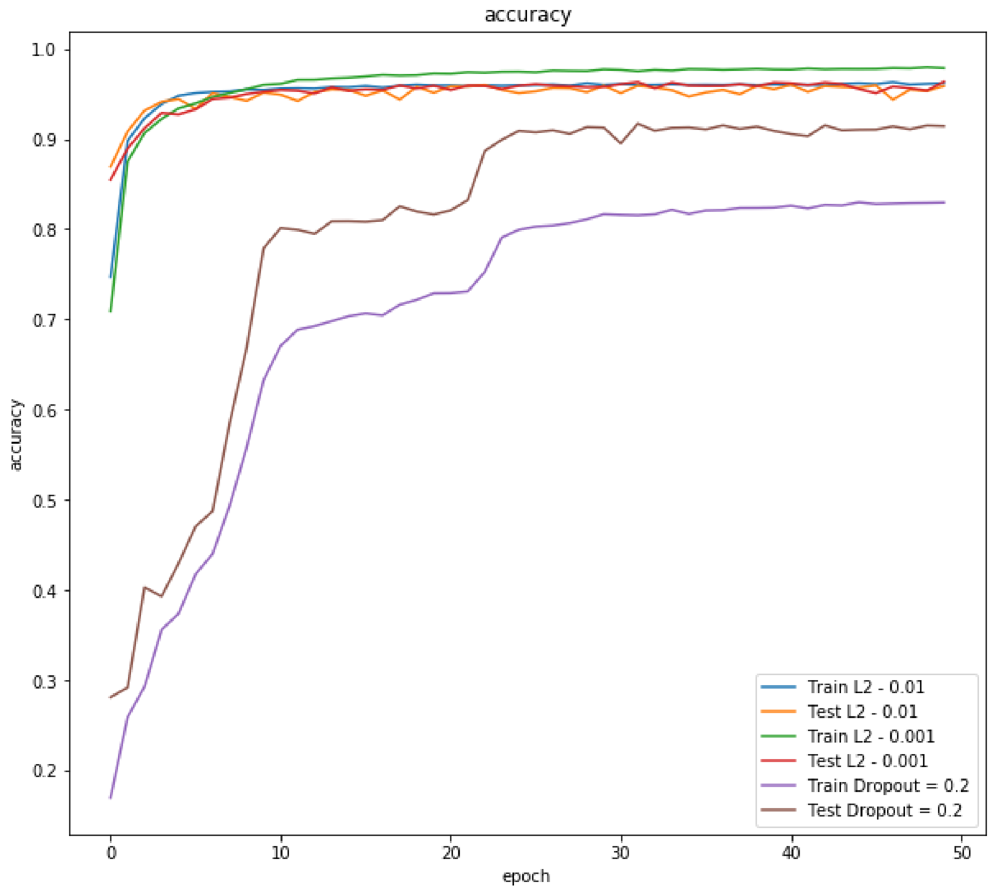
```python
plt.plot(history2.history['accuracy'])
plt.plot(history2.history['val_accuracy'])

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

plt.legend(['Train L2 - 0.01', 'Test L2 - 0.01',
            'Train L2 - 0.001', 'Test L2 - 0.001',
            'Train Dropout = 0.2', 'Test Dropout = 0.2'])

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

plt.show()
```



- El parámetro de L2 puede marcar una gran diferencia en los entrenamientos.

- Comparar con batch norm y modificar el numero de capas y arquitectura
- Entrenar en menos tiempo