

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

2019/09/30

1 Batch Normalization

Objetivo: Comprender batch normalization y sus parámetros

- Referencia: <https://arxiv.org/abs/1502.03167>
- Batch Normalization ayuda a que la red se entrene de forma estable, normalizando la entrada o salida de las activaciones
- A cada activación se le resta la media y se divide por la desviación estándar del batch

```
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()

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,)
```

1.1 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 = 100
        verbose = 0
        batch = 50
```

1.2 Momentum

Para controlar la cantidad de estadísticas del mini batch anterior, el parámetro ‘momentum’ por defecto tiene valor de 0.99. Esto se puede establecer en 0.0 para usar solo estadísticas del mini batch actual.

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

        model.add(Dense(40, input_shape = (784, ), activation = 'relu'))
        model.add(Dense(40, activation = 'relu'))
        model.add(Dense(40, activation = 'relu'))
        model.add(Dense(10, activation = 'softmax'))

        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 accuracy:', test_acc)
```

```
10000/1 - 0s - loss: 0.1850 - accuracy: 0.9623
```

```
Test accuracy: 0.9623
```

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

        model.add(Dense(40, input_shape = (784, ), activation = 'relu'))
        model.add(BatchNormalization(momentum=0.99))           # capa Batchnorm
        model.add(Dense(40, activation = 'relu'))
        model.add(BatchNormalization(momentum=0.99))           # capa Batchnorm
        model.add(Dense(40, activation = 'relu'))
        model.add(BatchNormalization(momentum=0.99))           # capa Batchnorm
        model.add(Dense(10, activation = 'softmax'))

        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
batch_normalization (Batch Normalization)	(None, 40)	160
dense_5 (Dense)	(None, 40)	1640
batch_normalization_1 (Batch Normalization)	(None, 40)	160
dense_6 (Dense)	(None, 40)	1640
batch_normalization_2 (Batch Normalization)	(None, 40)	160
dense_7 (Dense)	(None, 10)	410
Total params: 35,570		
Trainable params: 35,330		
Non-trainable params: 240		

```
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 accuracy:', test_acc)
```

10000/1 - 1s - loss: 0.0683 - accuracy: 0.9734

Test accuracy: 0.9734

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

        model.add(Dense(40, input_shape = (784, ), activation = 'relu'))
        model.add(BatchNormalization(momentum=0.5))           # capa Batchnorm
        model.add(Dense(40, activation = 'relu'))
        model.add(BatchNormalization(momentum=0.5))           # capa Batchnorm
        model.add(Dense(40, activation = 'relu'))
        model.add(BatchNormalization(momentum=0.5))           # capa Batchnorm
        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
batch_normalization_3 (Batch Normalization)	(None, 40)	160
dense_9 (Dense)	(None, 40)	1640
batch_normalization_4 (Batch Normalization)	(None, 40)	160
dense_10 (Dense)	(None, 40)	1640
batch_normalization_5 (Batch Normalization)	(None, 40)	160
dense_11 (Dense)	(None, 10)	410

Total params: 35,570
Trainable params: 35,330
Non-trainable params: 240

```
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 accuracy:', test_acc)
```

```
10000/1 - 1s - loss: 0.0753 - accuracy: 0.9714
```

```
Test accuracy: 0.9714
```

```
In [18]: #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.plot(history4.history['accuracy'])
```

```
#plt.plot(history4.history['val_accuracy'])
```

```
plt.legend(['Train normal', 'Test normal',
```

```
           'Train Batch-Norm - momentum = 0.99', 'Test Batch-Norm - momentum = 0.99',
```

```
           'Train Batch-Norm - momentum = 0.5', 'Test Batch-Norm - momentum = 0.5',
```

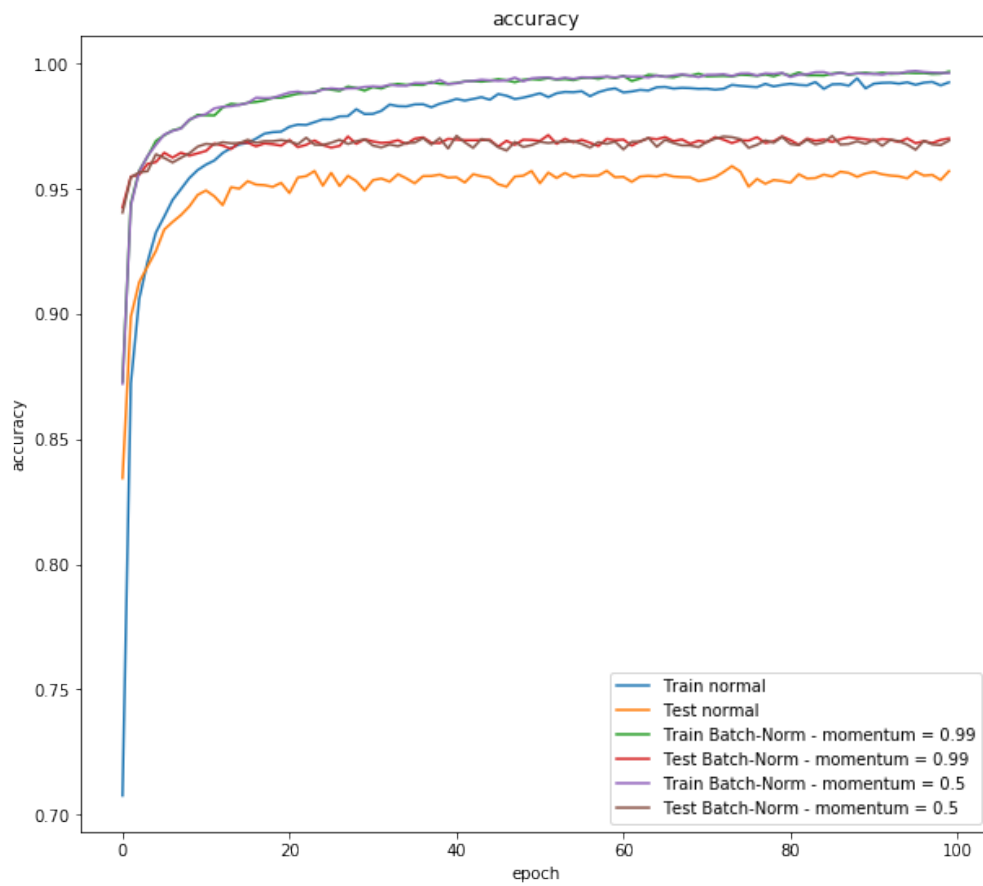
```
           'Train Batch-Norm antes act - momentum = 0.99', 'Test Batch-Norm antes act -
```

```
plt.title('accuracy')
```

```
plt.ylabel('accuracy')
```

```
plt.xlabel('epoch')
```

```
plt.show()
```



- Experimentar con diferentes valores y parámetros
- Experimentar con diferente arquitectura