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

2019/09/30

1 Perceptrón Multicapa Imperative/Training loop

- Objetivo: Programar un MLP en notación orientada a objetos con Tensorflow 2
- Referencia Imperative APIs: https://blog.tensorflow.org/2019/01/what-are-symbolic-and-imperative-apis.html

Los modelos son más personalizables para tareas como investigación

```
In [1]: import matplotlib.pyplot as plt
        from sklearn.datasets import load_breast_cancer
        from sklearn.model_selection import train_test_split
        import tensorflow as tf
        import numpy as np
```

```
In [2]: data = load_breast_cancer()
```

```
In [3]: X_data = data.data
        y_data = data.target
```

```
In [4]: x_train, x_test, y_train, y_test = train_test_split(X_data, y_data, test_size = 0.33, ran
```

```
In [5]: print(x_train.shape)
        print(x_test.shape)
        print(y_train.shape)
        print(y_test.shape)
```

```
(381, 30)
(188, 30)
(381,)
(188,)
```

```
In [6]: batch_size = 32

        train_ds = tf.data.Dataset.from_tensor_slices(
            (x_train, y_train)).shuffle(10000).batch(batch_size)
```

```
In [7]: from tensorflow.keras.layers import Dense
        from tensorflow.keras import Model
```

1.1 Crear modelo

- Se crea una clase, las capas se definen en el constructor y el método call indica el flujo

```
In [8]: class MLP(Model):
            def __init__(self):
                super(MLP, self).__init__()
                self.d1 = Dense(30, activation='sigmoid', name='input')
                self.d2 = Dense(20, activation='sigmoid', name='hidden')
                self.d3 = Dense(1, activation='sigmoid', name='output')

            def call(self, x): # método call que pasa 'x' por capa
                x = self.d1(x)
                x = self.d2(x)
                return self.d3(x)
```

```
In [9]: model = MLP()
        model.build(input_shape=(None, 30))
        model.summary()
```

```
Model: "mlp"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
input (Dense)                multiple                  930
_________________________________________________________________
hidden (Dense)               multiple                  620
_________________________________________________________________
output (Dense)               multiple                  21
=================================================================
Total params: 1,571
Trainable params: 1,571
Non-trainable params: 0
_________________________________________________________________
```

- Optimizador y función de costo

```
In [10]: loss_fn = tf.keras.losses.BinaryCrossentropy()
         optimizer = tf.keras.optimizers.SGD()
```

- Métricas

```
In [11]: train_loss = tf.keras.metrics.BinaryCrossentropy(name='train_loss')
         train_accuracy = tf.keras.metrics.BinaryAccuracy(name='train_accuracy')
```

- Listas para plot

```
In [12]: hist_loss = []
         hist_acc = []
```

2 Entrenamiento

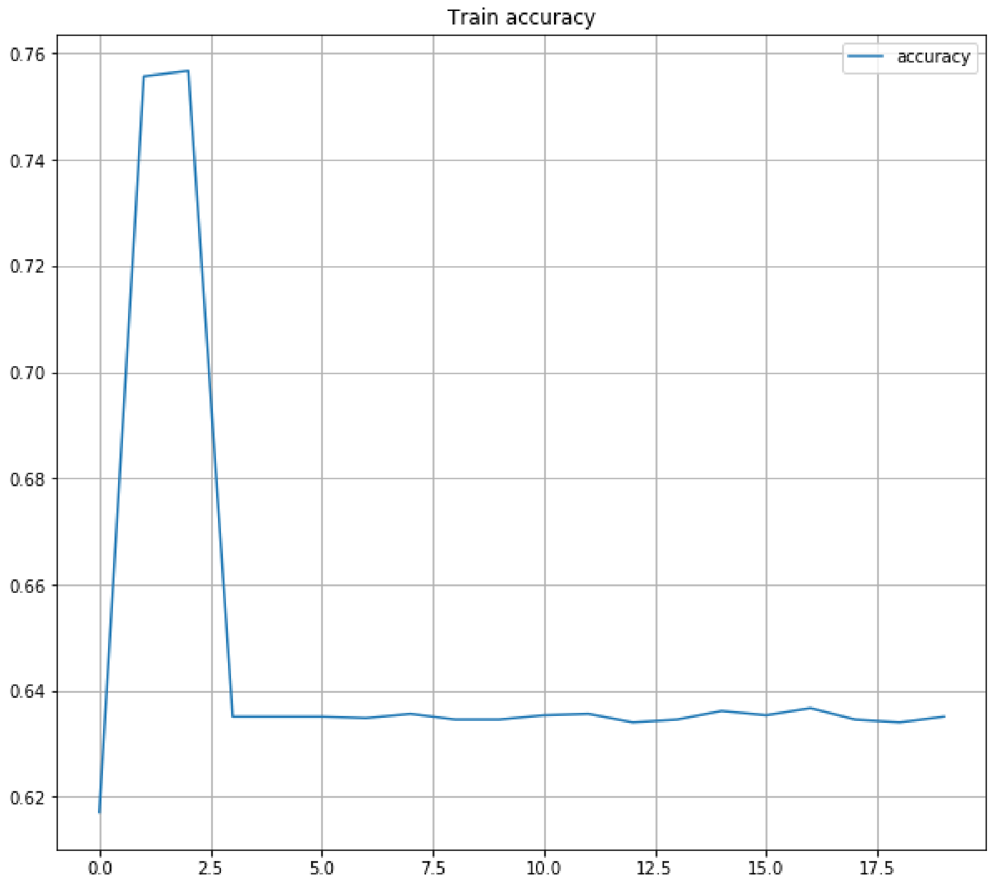
- Se hace un ciclo por épocas en donde se itera por cada época sobre cada par de datos y etiquetas de entrenamiento
- *Nota: El entrenamiento con 'tf.function decorator' tiene un mejor desempeño al compilarse en grafo. Para simplificar el ejemplo, también se omite el entrenamiento en conjunto de prueba*

In [13]:
```
EPOCH = 20
for epoch in range(EPOCH):
    #entrenamiento
    for data, target in train_ds:
        with tf.GradientTape() as tape:
            predictions = model(data)# predicciones
            loss = loss_fn(target, predictions) # target y predicciones para obtener acc
        gradients = tape.gradient(loss, model.trainable_variables) # gradiente sobre var
        optimizer.apply_gradients(zip(gradients, model.trainable_variables))
        # se guardan metricas
        train_loss(target, predictions)
        train_accuracy(target, predictions)


    template = 'Epoch {}/{} \n - loss: {} - accuracy: {}'
    print(template.format(epoch+1, EPOCH,
                          train_loss.result(), train_accuracy.result()))
    # lista para plot
    hist_loss.append(train_loss.result())
    hist_acc.append(train_accuracy.result())
    # reinicia las metricas para la siguiente epoca
    train_loss.reset_states()
    train_accuracy.reset_states()
```

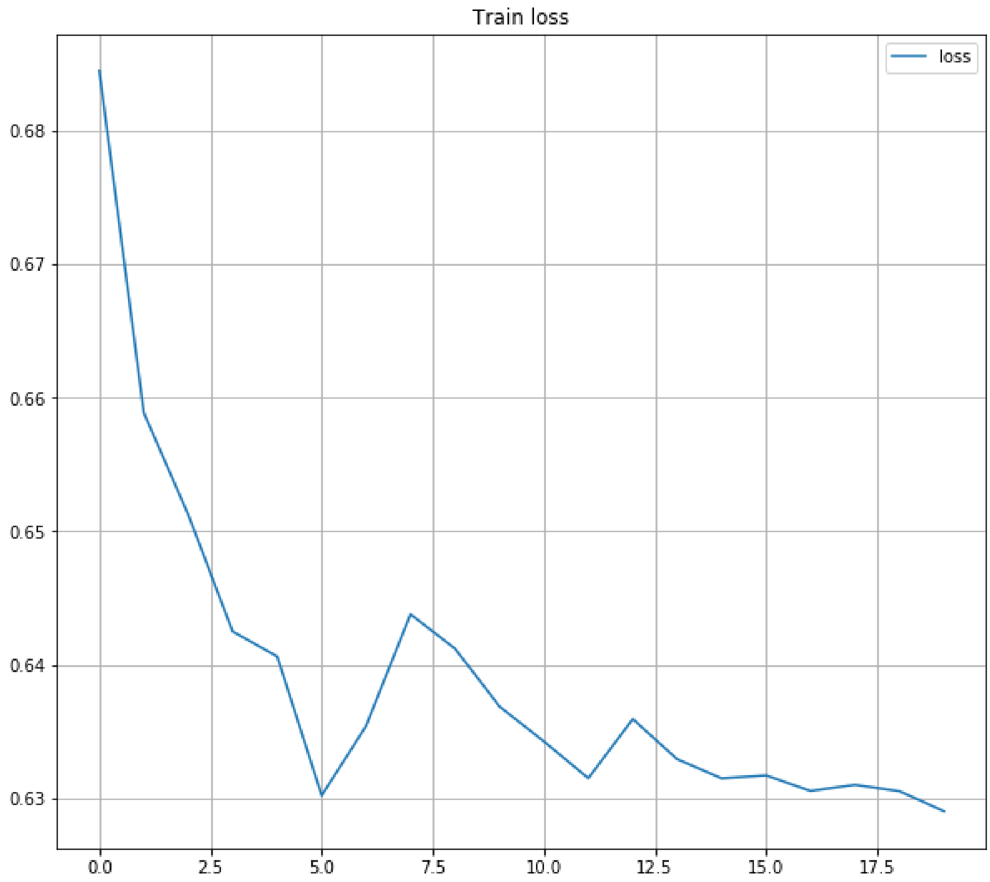
```
WARNING:tensorflow:Layer mlp is casting an input tensor from dtype float64 to the layer's dtype c

If you intended to run this layer in float32, you can safely ignore this warning. If in doubt, th

To change all layers to have dtype float64 by default, call `tf.keras.backend.set_floatx('float64

Epoch 1/20
 - loss: 0.6844579577445984 - accuracy: 0.6170976758003235
Epoch 2/20
 - loss: 0.6588442921638489 - accuracy: 0.7556573748588562
Epoch 3/20
 - loss: 0.6512103080749512 - accuracy: 0.7567349076271057
Epoch 4/20
 - loss: 0.6424896121025085 - accuracy: 0.6350574493408203
Epoch 5/20
 - loss: 0.6406248211860657 - accuracy: 0.6350574493408203
Epoch 6/20
```

```
 - loss: 0.6302149295806885 - accuracy: 0.6350574493408203
Epoch 7/20
 - loss: 0.6354005932807922 - accuracy: 0.6347880959510803
Epoch 8/20
 - loss: 0.6437819600105286 - accuracy: 0.6355962753295898
Epoch 9/20
 - loss: 0.6412071585655212 - accuracy: 0.6345186829566956
Epoch 10/20
 - loss: 0.6368744969367981 - accuracy: 0.6345186829566956
Epoch 11/20
 - loss: 0.6342592239379883 - accuracy: 0.6353268623352051
Epoch 12/20
 - loss: 0.6314993500709534 - accuracy: 0.6355962753295898
Epoch 13/20
 - loss: 0.6359333395957947 - accuracy: 0.633979856967926
Epoch 14/20
 - loss: 0.6329274773597717 - accuracy: 0.6345186829566956
Epoch 15/20
 - loss: 0.6314908862113953 - accuracy: 0.6361350417137146
Epoch 16/20
 - loss: 0.6317090392112732 - accuracy: 0.6353268623352051
Epoch 17/20
 - loss: 0.6305532455444336 - accuracy: 0.6366738677024841
Epoch 18/20
 - loss: 0.6310041546821594 - accuracy: 0.6345186829566956
Epoch 19/20
 - loss: 0.6305307149887085 - accuracy: 0.633979856967926
Epoch 20/20
 - loss: 0.6290386319160461 - accuracy: 0.6350574493408203
```

In [14]:
```
plt.figure(figsize=(10,9))
plt.plot(np.arange(len(hist_acc)), hist_acc)
plt.title('Train accuracy')
plt.legend(['accuracy'])
plt.grid()
```




```
In [15]: plt.figure(figsize=(10,9))
         plt.plot(np.arange(len(hist_loss)), hist_loss)
         plt.title('Train loss')
         plt.legend(['loss'])
         plt.grid()
```



- Mejorar el modelo
- Agregar conjunto de validación
- Implementar con otro dataset