

基于 TensorFlow 深入学习各类模型 [1]

leolinuxer

July 31, 2020

Contents

1 简单线性回归	1
1.1 数学表达式	1
1.2 求解方法——最小二乘法	1
1.3 TF 实现	2
2 多元线性回归	6
2.1 TF 实现	6

1 简单线性回归

1.1 数学表达式

$$\hat{y} = \beta_0 + \beta_1 x$$

μ 代表误差；

线性回归的损失函数为残差平方和，即 SSE (Sum of Squares for Error)，在机器学习中它是回归问题中最常用的损失函数：

$$L = \sum_{i=1}^n (y_i - \hat{y}_i)^2 = \sum_{i=1}^n \left(y_i - (\hat{\beta}_0 + \hat{\beta}_1 x_i) \right)^2$$

1.2 求解方法——最小二乘法

$$\frac{\partial L}{\partial \beta_0} = 2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) = 0$$

$$\frac{\partial L}{\partial \beta_1} = 2 \sum_{i=1}^n (y_i - \hat{\beta}_0 - \hat{\beta}_1 x_i) x_i = 0$$

1.3 TF 实现

代码地址: `codes/learn/tf_simple_linear_regression.py`

```
#import tensorflow as tf
import tensorflow.compat.v1 as tf
tf.disable_v2_behavior()
import numpy as np
import matplotlib.pyplot as plt

#定义一个函数来归一化输入数据
def normalize(X):
    mean = np.mean(X)
    std = np.std(X)
    X = (X - mean) / std
    return X

def train():
    #使用 TensorFlow contrib 数据集加载波士顿房价数据集，并将其分解为 X_train 和 Y_train。可以对数据进行归一化处理：

    # default save path: ~/.keras/datasets/boston_housing.npz
    boston = tf.keras.datasets.boston_housing.load_data()
    boston_data = boston[0]
    X_train, Y_train = boston_data
    #选择第6维特征: RM (average number of rooms per dwelling)
    X_train = X_train[:, 5]
    X_train = normalize(X_train)
    n_samples = X_train.shape[0]

    #为训练数据声明 TensorFlow 占位符：
    X = tf.placeholder(tf.float32, name = 'X')
    Y = tf.placeholder(tf.float32, name = 'Y')

    #创建 TensorFlow 的权重和偏置变量且初始值为零
    w = tf.Variable(0.0, name = 'weight')
    b = tf.Variable(0.0, name = 'bias')

    #定义用于预测的线性回归模型和损失函数
    Y_hat = X * w + b
    #Y_hat = tf.tensordot(X, w, axes=1) + b
    loss = tf.square(Y - Y_hat, name = 'loss')

    #选择梯度下降优化器
```

```

#optimizer = tf.train.GradientDescentOptimizer(learning_rate = 0.01, name='GradientDescentOptimizer')
#optimizer.minimize(loss)

optimizer =tf.train.AdamOptimizer().minimize(loss)
#optimizer = tf.train.MomentumOptimizer(learning_rate=0.05, momentum=0.9, use_nesterov=True).
#optimizer.minimize(loss)

#声明初始化操作符
init_op =tf.global_variables_initializer()
total =[]

#现在，开始计算图，训练 100 次：
with tf.Session() as sess:
    # Initialize variables
    sess.run(init_op)

    writer =tf.summary.FileWriter('graphs', sess.graph)

    #Train the model for 100 times
    for i in range(100):
        total_loss =0
        for x, y in zip(X_train, Y_train):
            _, l =sess.run([optimizer, loss], feed_dict ={X:x, Y:y})
            total_loss +=l
        total.append(total_loss /n_samples)
        print('Epoch {0}: Loss {1}'.format(i, total_loss/n_samples))
    writer.close()
    b_value, w_value =sess.run([b, w])

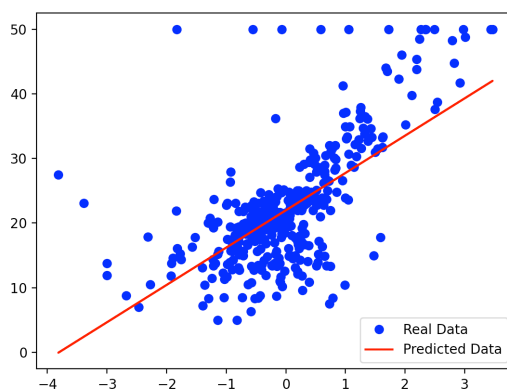
#查看结果
Y_pred =X_train *w_value +b_value
print('Done')

plt.plot(X_train, Y_train, 'bo', label ='Real Data')
plt.plot(X_train, Y_pred, 'r', label ='Predicted Data')
plt.legend()
plt.show()
plt.plot(total)
plt.show()

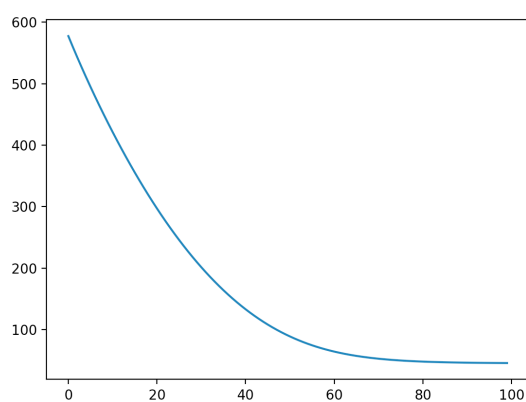
if __name__ =='__main__':
    train()

```

从下图中可以看到，简单线性回归器试图拟合给定数据集的线性线：



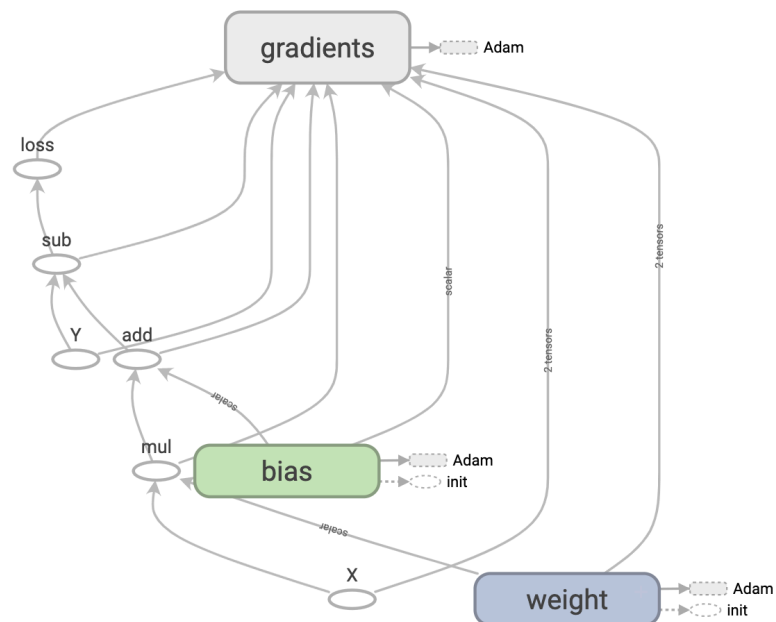
在下图中可以看到，随着模型不断学习数据，损失函数不断下降：



在终端执行

```
tensorboard --logdir=graphs
```

在浏览器中打开，可以看到简单线性回归器的 TensorBoard 图：

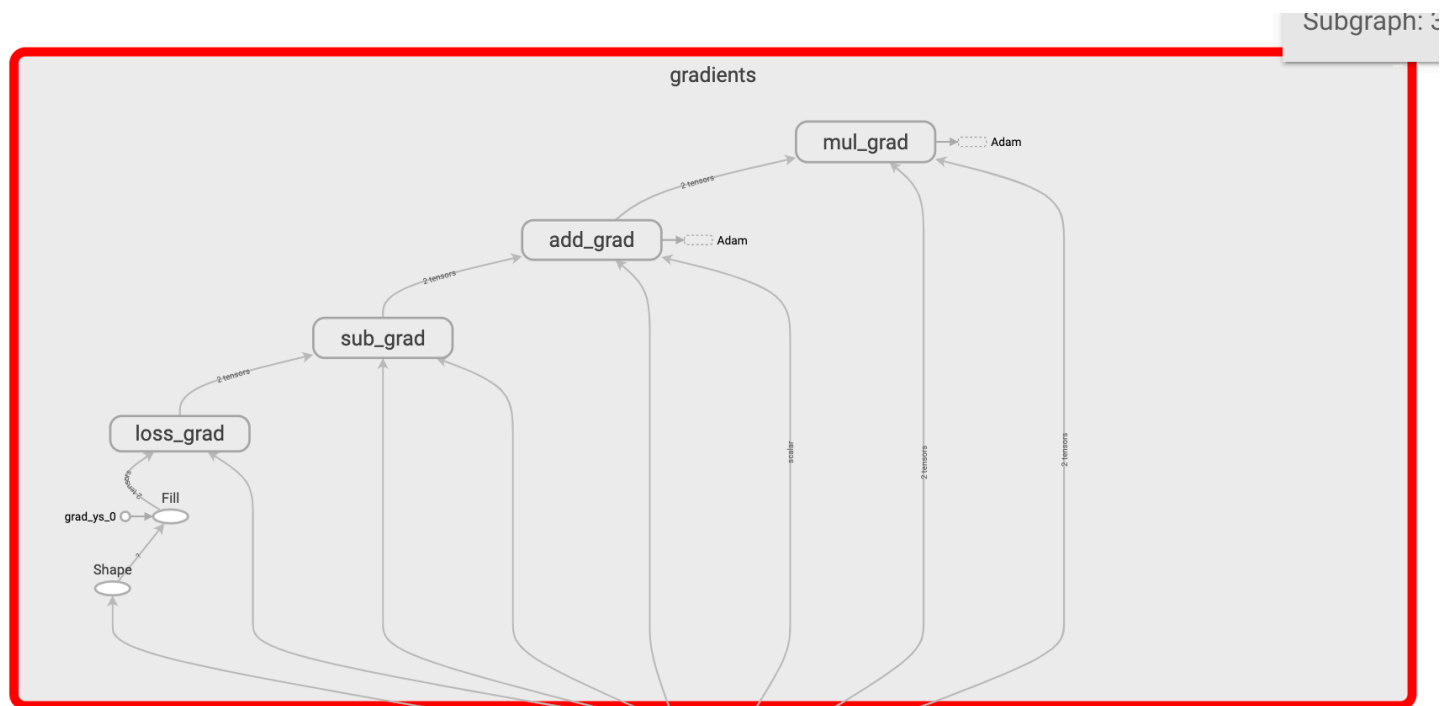


从图中可以清晰地看出前向计算过程：

$$\hat{Y} = X \text{ mul weight add bias}$$

$$\text{loss} = Y \text{ sub } \hat{Y}$$

双击展开 gradient 节点，可以看到梯度的计算过程。可以看到它需要 7 个输入并使用 Adam 计算梯度，对权重和偏置进行更新



2 多元线性回归

2.1 TF 实现

代码地址: codes/learn/tf_multi_linear_regression.py

```
import os
import sys

#加入如下语句, 应对错误: OMP: Error #15: Initializing libiomp5.dylib, but found libiomp5.dylib already
                                initialized

os.environ['KMP_DUPLICATE_LIB_OK'] = 'TRUE'

....

#另外, 这里添加一个额外的固定输入值将权重和偏置结合起来。为此定义函数 append_bias_reshape()。该技巧有时可
                                有效简化编程

# print(X_train.shape, Y_train.shape)
# X_train, Y_train = append_bias_reshape(X_train, Y_train)
# print(X_train.shape, Y_train.shape)
# (404, 13) (404,)
# (404, 14) (404, 1)
def append_bias_reshape(features, labels):
    m = features.shape[0]
    n = features.shape[1]
    x = np.reshape(np.c_[np.ones(m), features], [m, n + 1])
    y = np.reshape(labels, [m, 1])
    return x, y

....

m = len(X_train) # Number of training examples
n = 13 + 1       # Number of features + bias
#n = 12

#为训练数据声明 TensorFlow 占位符:
X = tf.placeholder(tf.float32, name = 'X', shape=[m,n])
Y = tf.placeholder(tf.float32, name = 'Y')

#创建 TensorFlow 的权重
w = tf.Variable(tf.random_normal([n, 1]), name = 'weight')

#定义用于预测的线性回归模型和损失函数
Y_hat = tf.matmul(X, w)
```

```
loss =tf.reduce_mean(tf.square(Y -Y_hat, name ='loss')) +0.6 *tf.nn.l2_loss(w)
```

....

```
#现在，开始计算图，训练 100 次：
```

```
with tf.Session() as sess:
```

```
    # Initialize variables
```

```
    sess.run(init_op)
```

```
    writer =tf.summary.FileWriter('graphs', sess.graph)
```

```
    #Train the model for 100 times
```

```
    for i in range(100):
```

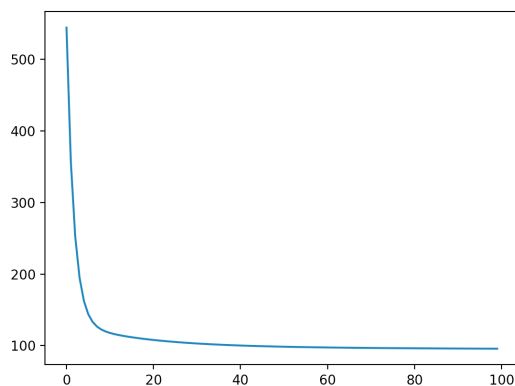
```
        _, l =sess.run([optimizer, loss], feed_dict ={X:X_train, Y:Y_train})
```

```
        total.append(l)
```

```
        print('Epoch {0}: Loss {1}'.format(i, l))
```

```
    writer.close()
```

在下图中可以看到，随着模型不断学习数据，损失函数不断下降：



References

- [1] “Tensorflow 教程：tensorflow 快速入门教程（非常详细）。” [Online]. Available: <http://c.biancheng.net/tensorflow/>