REGRESSION

一、内容

本部分将实现能解决回归问题的模型。

二、代码

一、Linear Activation

这个线性激活函数不修改它的输入，而是将它传递到输出：$y=x$。对于反向传递，我们已经知道$f(x)=x$的导数是1。做只是为了完整性和清晰性，以便在模型定义代码中看到输出层的激活函数。从计算时间的角度来看，这几乎不会增加处理时间，至少不足以明显影响训练时间。

实现

```
class Activation_Linear:
    def __init__(self):
        pass

    def forward(self, input):
        self.input = input
        self.output = self.input

    def backward(self, dvalue):
        # 注意不能self.dinput = dvalue
        # 这意味着 dinput 和 dvalue 指向同一个对象，因此对 dinput 的任何更改都会影响原始的 dvalue 对象
        # 而对dvalue进行运算如乘1，则和下面代码一样
        self.dinput = dvalue.copy()
```

二、Mean Squared Error Loss

公式

$$L_i = \frac{1}{J} \sum_j (y_{i,j} - \hat{y}_{i,j})^2$$

$$\frac{\partial}{\partial \hat{y}_{i,j}} L_i = \frac{\partial}{\partial \hat{y}_{i,j}} [\frac{1}{J} \sum_j (y_{i,j} - \hat{y}_{i,j})^2] = \frac{1}{J} \cdot \frac{\partial}{\partial \hat{y}_{i,j}} (y_{i,j} - \hat{y}_{i,j})^2 =$$

$$= \frac{1}{J} \cdot 2 \cdot (y_{i,j} - \hat{y}_{i,j})^{2-1} \cdot \frac{\partial}{\partial \hat{y}_{i,j}} [y_{i,j} - \hat{y}_{i,j}] =$$

$$= \frac{2}{J} \cdot (y_{i,j} - \hat{y}_{i,j})^1 \cdot (\frac{\partial}{\partial \hat{y}_{i,j}} y_{i,j} - \frac{\partial}{\partial \hat{y}_{i,j}} \hat{y}_{i,j}) = \frac{2}{J} \cdot (y_{i,j} - \hat{y}_{i,j}) \cdot (0 - 1) =$$

$$= \frac{2}{J} \cdot (y_{i,j} - \hat{y}_{i,j}) \cdot (-1) = -\frac{2}{J} \cdot (y_{i,j} - \hat{y}_{i,j})$$

> 公式都很好理解，不做过多解释。

三、回归问师中衡量准确率

在交叉熵中，可以计算匹配的数量（预测等于真实目标的情况），然后除以样本数来衡量模型的准确度。在回归模型中，预测是一个浮点值，不能简单地检查输出值是否等于真实值，因为它很可能不会——如果它稍微不同，准确度就会是0。对于回归来说，没有完美的方法来显示准确度。不过，最好还是有一些准确度指标。例如，Keras，一个流行的深度学习框架，会显示回归模型的准确度和损失，我们也会制作自己的准确度指标。**计算真实目标值的标准差，然后除以250。这个值可以根据目标而变化。除以的数字越大，准确度指标就越“严格”。250是这里选择的值。**

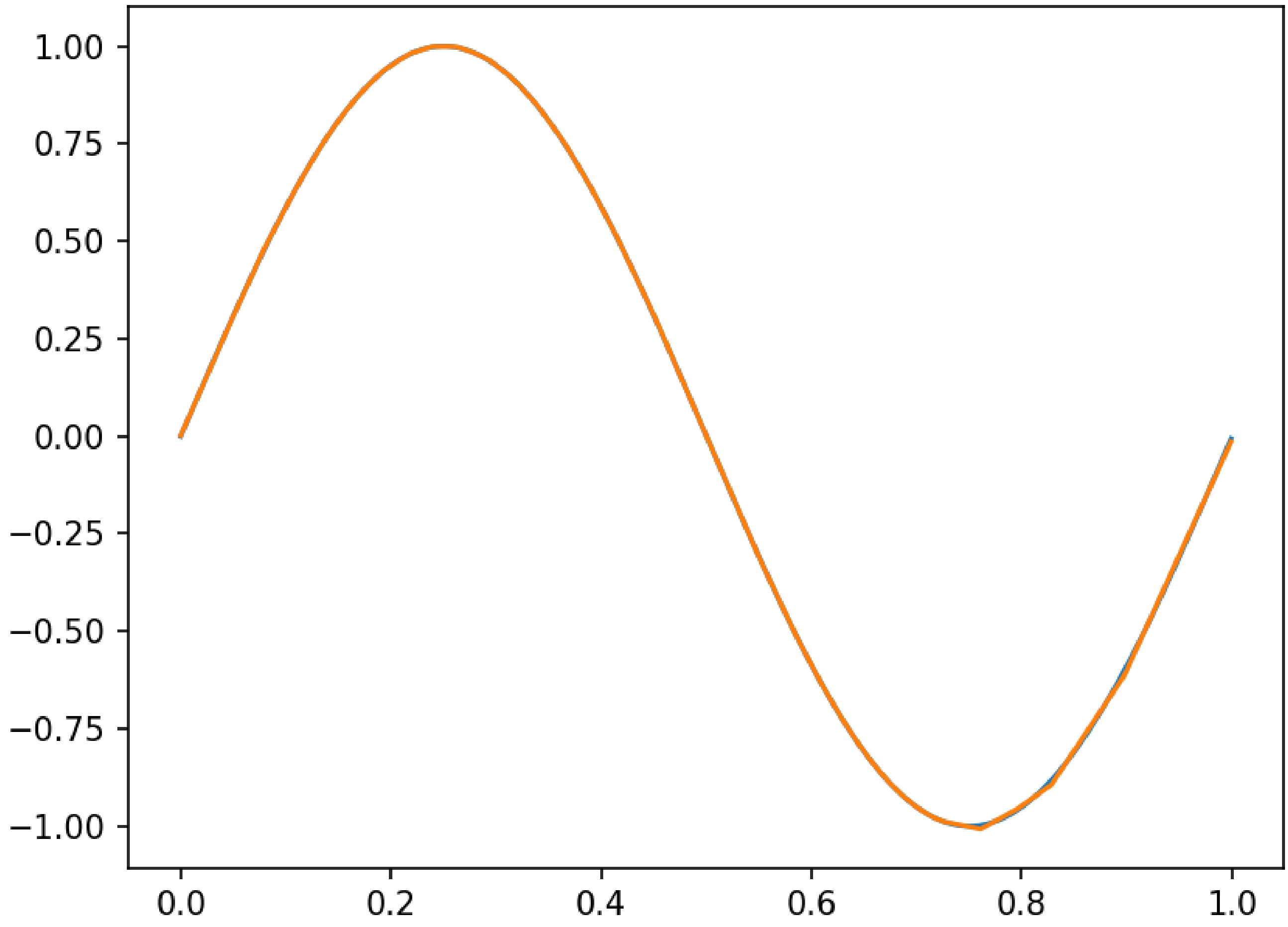
```
accuracy_precision = np.std(y) / 250
predictions = activation2.output
accuracy = np.mean(np.absolute(predictions - y) < accuracy_precision)
```

实例

```
# 生成数据共1000个点
X, y = sine_data()
keys = np.array(range(X.shape[0]))
np.random.shuffle(keys)
X = X[keys]
y = y[keys]
X_test = X[500:]
y_test = y[500:]
X = X[0:500]
y = y[0:500]

# 三层结构
dense1 = Layer_Dense(1, 64)
activation1 = Activation_ReLu()
dense2 = Layer_Dense(64, 64)# ,weight_L2=1e-4, bias_L2=1e-4
activation2 = Activation_ReLu()
dense3 = Layer_Dense(64, 1)
activation3 = Activation_Linear()
loss_function = Loss_MeanSquaredError()
# 优化器
optimizer = Optimizer_Adam(learning_rate=0.01, decay=1e-3)

# 精度标准
accuracy_precision = np.std(y) / 250

for epoch in range(10001):
    # 前向传播
    dense1.forward(X)
    activation1.forward(dense1.output)
    dense2.forward(activation1.output)
    activation2.forward(dense2.output)
    dense3.forward(activation2.output)
    activation3.forward(dense3.output)
    data_loss = loss_function.calculate(activation3.output, y)

    regularization_loss = \
        loss_function.regularization_loss(dense1) + \
        loss_function.regularization_loss(dense2) + \
        loss_function.regularization_loss(dense3)

    loss = data_loss + regularization_loss

    # 计算准确率
    predictions = activation3.output
    accuracy = np.mean(np.absolute(predictions - y) <
                                   accuracy_precision)

    if not epoch % 100:
```

```python
            print(f'epoch: {epoch}, ' +
                  f'acc: {accuracy:.3f}, ' +
                  f'loss: {loss:.3f} (' +
                  f'data_loss: {data_loss:.3f}, ' +
                  f'reg_loss: {regularization_loss:.3f}), ' +
                  f'lr: {optimizer.current_learning_rate}')
        # 反向传播
        loss_function.backward(activation3.output, y)
        activation3.backward(loss_function.dinput)
        dense3.backward(activation3.dinput)
        activation2.backward(dense3.dinput)
        dense2.backward(activation2.dinput)
        activation1.backward(dense2.dinput)
        dense1.backward(activation1.dinput)

        # 更新权重
        optimizer.pre_update_param()
        optimizer.update_param(dense1)
        optimizer.update_param(dense2)
        optimizer.update_param(dense3)
        optimizer.post_update_param()

# 测试集
X_test, y_test = sine_data()

dense1.forward(X_test)
activation1.forward(dense1.output)
dense2.forward(activation1.output)
activation2.forward(dense2.output)
dense3.forward(activation2.output)
activation3.forward(dense3.output)

plt.plot(X_test, y_test)
plt.plot(X_test, activation3.output)
plt.show()
```

```
epoch: 9500, acc: 0.838, loss: 0.000 (data_loss: 0.000, reg_loss: 0.000), lr: 0.0009524716639679969
epoch: 9600, acc: 0.834, loss: 0.000 (data_loss: 0.000, reg_loss: 0.000), lr: 0.0009434852344560807
epoch: 9700, acc: 0.840, loss: 0.000 (data_loss: 0.000, reg_loss: 0.000), lr: 0.0009346667912889055
epoch: 9800, acc: 0.892, loss: 0.000 (data_loss: 0.000, reg_loss: 0.000), lr: 0.0009260116677470137
epoch: 9900, acc: 0.838, loss: 0.000 (data_loss: 0.000, reg_loss: 0.000), lr: 0.0009175153683824203
epoch: 10000, acc: 0.842, loss: 0.000 (data_loss: 0.000, reg_loss: 0.000), lr: 0.0009091735612328393
```



橙色线是预测值，蓝色线是ground truth