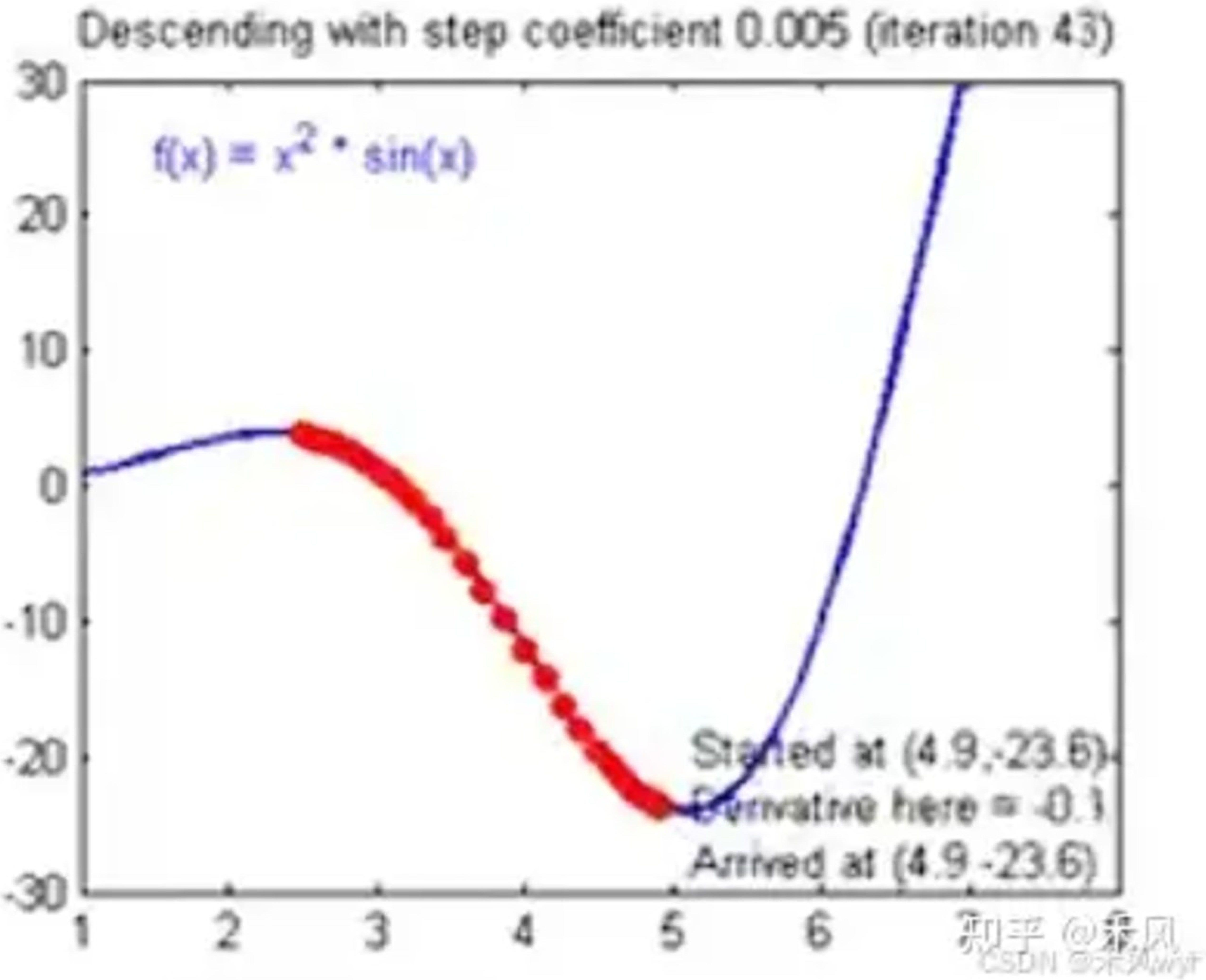
梯度下降法是优化算法中一种常用的技术，用于通过最小化损失函数来求解模型的最优参数。在线性回归中，目标是通过拟合数据来找到一条最适合的直线。梯度下降法通过迭代地调整模型参数，使得损失函数（通常是均方误差）最小化，从而找到最优的参数。



线性回归的目标是根据输入特征 x 预测输出 y。假设我们有一个输入特征 x 和对应的输出标签 y，线性回归模型可以用以下公式表示：

$$y = w_0 + w_1 x$$

给定一组数据集, $\{(x_1, y_1), (x_2, y_2) \ldots (x_i, y_i)\}$,我们的目标是通过调整权重 w_0 和 w_1 ，使得模型的预测值与真实值之间的误差最小。首先对参数进行求梯度：

$$\frac{\partial J(w_0, w_1)}{\partial w_0} = \frac{2}{m} \sum_{i=1}^{m} (h(x_i) - y_i)$$

$$\frac{\partial J(w_0, w_1)}{\partial w_1} = \frac{2}{m}\sum_{i=1}^{m}(h(x_i) - y_i)x_i$$

通过计算梯度，我们知道了损失函数在每个参数方向上的变化趋势。为了最小化损失函数，我们沿着梯度的反方向更新参数。参数更新的公式为

$$w_0 := w_0 - \alpha\frac{\partial J(w_0, w_1)}{\partial w_0}$$

采用MSE计算损失函数，损失函数为

$$loss = (WX + b - y)^2$$

那么更新后的参数为

$$w' = w - lr * \frac{\nabla loss}{\nabla w}$$

其中

$$\frac{\nabla loss}{\nabla w} = 2(wx + b)x$$

$$\frac{\nabla loss}{\nabla b} = 2(wx + b)$$

计算损失函数:

```
def compute_error_for_line_given_points(b,w,points):
    totalError = 0
    for i in range(0, len(points)):
        x = points[i,0]
        y = points[i,1]
        totalError += (y-(w*x+b))**2
    return totalError/float(len(points))
```

计算梯度值：

```
def step_grdient(b_current, w_current, points, learningRate):
    b_gradient = 0
    w_gradient = 0
    N = float(len(points))
    for i in range(0, len(points)):
        x = points[i, 0]
        y = points[i, 1]
        b_gradient += -(2/N) * (y - ((w_current * x) + b_current))
        # 梯度信息多了一个x
        w_gradient += -(2/N) * x * (y - ((w_current * x) + b_current))
    new_b = b_current - (learningRate * b_gradient)
    new_w = w_current - (learningRate * w_gradient)
    return [new_b, new_w]
```

循环计算梯度：

```
def gradient_descent_runner(points, starting_b, starting_m, learning_rate, num_
    b = starting_b
    w = starting_w
    for i in range(num_iterations):
        b, w = step_gradient(b, w, np.array(points), learning_rate)
    return [b, w]
```

进行运行：

```
def run():
    points = np.genfromtext("data.csv", delimiter=",")
    learining_rate = 0.0001
    initial_b = 0
    initial_w = 0
    num_iterations = 100
    print("Starting gradient descent at b={0}, w={1},error={2}".format(initial_
    print("Running......")
    [b, w] = gradient_descent_runner(points, initial_b, initial_w, learning_rat
    print("After {0} iterations b = {1}, w = {2}, error = {3}".format(num_itera
```