AI引论第九次大班课作业

信息科学技术学院 施朱鸣 1800011723

2020年4月11日

第1题

进行1个单位宽度的0-边界填充后的图像如下

0	0	0	0	0	0
0	0	1	1	0	0
0	0	1	1	0	0
0	0	2	2	0	0
0	1	1	1	1	0
0	0	0	0	0	0

以1个单元为步长,对每个点做卷积

$$y = \sum_{i} x_i \mathbf{w}_i$$

得到如下结果,即为I'各个位置对应的像素值

-2	-2	2	2
-3	-3	3	3
-3	-2	2	3
-1	0	0	1

第2题

对于每个像素点,其 $\hat{I} - I'$ 对应的矩阵如下

0	0	0	0
-1	-1	1	1
-1	-1	1	1
-2	-2	2	2

用 £ 表示均方差损失函数,则

$$\mathcal{L} = \frac{1}{16} \sum_{(m,n)} (\hat{x}_{m,n} - x'_{m,n})^2$$

$$= \frac{1}{16} \left(0^2 + 0^2 + 0^2 + 0^2 + 1^2 + 1^2 + 1^2 + 1^2 + 1^2 + 1^2 + 1^2 + 2^2 + 2^2 + 2^2 + 2^2 \right)$$

$$= \frac{3}{2}$$

$$= 1.5$$
(1)

假设 $K_{i,j}$ 中的 i,j 都从 0 开始取值,则

$$\mathcal{L} = \frac{1}{16} \sum_{1 \le m, n \le 4} (\hat{x}_{m,n} - x'_{m,n})^2 \tag{2}$$

$$\frac{\partial \mathcal{L}}{\partial K_{i,j}} = \frac{1}{16} \sum_{1 \leq m,n \leq 4} \frac{\partial \left(\hat{x}_{m,n} - x'_{m,n}\right)^{2}}{\partial K_{i,j}}$$

$$= \frac{1}{16} \times 2 \sum_{1 \leq m,n \leq 4} \frac{\partial \left(\hat{x}_{m,n} - x'_{m,n}\right)^{2}}{\partial \left(\hat{x}_{m,n} - x'_{m,n}\right)} \frac{\partial \left(\hat{x}_{m,n} - x'_{m,n}\right)}{\partial K_{i,j}}$$

$$= \frac{1}{8} \sum_{1 \leq m,n \leq 4} \left(\hat{x}_{m,n} - x'_{m,n}\right) \times (-1) \frac{\partial x'_{m,n}}{\partial K_{i,j}}$$

$$= \frac{1}{8} \sum_{1 \leq m,n \leq 4} \left(\hat{x}_{m,n} - x'_{m,n}\right) \times (-1) \frac{\partial \sum_{0 \leq p,q \leq 2} x_{m-1+p,m-1+q} K_{p,q}}{\partial K_{i,j}}$$

$$= \frac{1}{8} \sum_{1 \leq m,n \leq 4} \left(\hat{x}_{m,n} - x'_{m,n}\right) \times (-1) \times x_{m-1+i,m-1+j}$$
(3)

用上面的计算方法得出卷积核各点的 $\frac{\partial \mathcal{L}}{\partial K_{i,j}}$ 如下矩阵

-1.5	0.0	1.5
-1.0	0.0	1.0
-0.625	0.0	0.625

第3题

对于已经求得的梯度矩阵,利用如下式子更新卷积核参数

$$\hat{K}_{i,j} = K_{i,j} - \eta \frac{\partial \mathcal{L}}{\partial K_{i,j}}$$

当η=0.01 时更新后的卷积核参数矩阵如下

0.015	0	-0.015
1.01	0	-1.01
1.00625	0	-1.00625

再次卷积得到的输出结果如下矩阵

-2.01625	-2.01625	2.01625	2.01625
-3.0375	-3.0375	3.0375	3.0375
-3.04125	-2.035	2.035	3.04125
-1.04	-0.03	0.03	1.04

用 $\hat{\mathcal{L}}$ 表示更新后的均方差损失函数,则

$$\hat{\mathcal{L}} = \sum_{(m,n)} (\hat{x}_{m,n} - x'_{m,n})^2$$

$$= 1.428$$
(4)

附:实现以上计算的 Python 代码

```
[0, 0, 1, 1, 0, 0],
12
           [0, 0, 1, 1, 0, 0],
13
           [0, 0, 2, 2, 0, 0],
14
           [0, 1, 1, 1, 1, 0],
15
           [0, 0, 0, 0, 0, 0]
16
17
18 # %%
19 \tan g \operatorname{et} I = [
                [-2, -2, 2, 2],
                [-4, -4, 4, 4],
21
                [-4, -3, 3, 4],
22
                [-3, -2, 2, 3]
23
24
25 # 0/0/0
outputI = [
                [0, 0, 0, 0],
27
                [0, 0, 0, 0],
28
                [0, 0, 0, 0],
29
                [0, 0, 0, 0]
30
31
32 # %%%
grad = [
          [0, 0, 0],
          [0, 0, 0],
35
          [0, 0, 0]
36
37
38 # 0/0/0
39 # 卷积
40 for i in range(1, 5):
      for j in range (1, 5):
           outputI[i-1][j-1] = 0
42
           for k in range (3):
43
                for 1 in range (3):
44
```

```
outputI[i-1][j-1] += I[i-1+k][j-1+1] * kernel[k][1]
45
46 print (outputI)
47
48 # 0/0/0
49 # 计算均方差
_{50} MSE = 0
for i in range (4):
  for j in range (4):
          MSE += (targetI[i][j] - outputI[i][j])**2
_{54} \text{ MSE} = \frac{100 \text{ at (MSE)}}{16.0}
55 print (MSE)
57 # %%
for i in range (3):
     for j in range (3):
           grad[i][j] = 0
60
           for k in range (4):
61
               for 1 in range (4):
62
                    grad[i][j] += ((targetI[k][1] - outputI[k][1])*(-1)*(I
64 print (grad)
65
66 # %%
eta = 0.01
for i in range (3):
      for j in range (3):
69
           kernel[i][j] = eta * grad[i][j]
71 print (kernel)
72
73 # %%
74 for i in range (1, 5):
      for j in range (1, 5):
75
           outputI[i-1][j-1] = 0
76
           for k in range(3):
77
```