

第四章：线性方程组的迭代解法

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上机题 2

2. 考虑常微分方程的两点边值问题：

$$\begin{cases} \varepsilon \frac{d^2 y}{dx^2} + \frac{dy}{dx} = a, (0 < a < 1) \\ y(0) = 0, y(1) = 1 \end{cases}$$

它的精确解为：

$$y = \frac{1-a}{1-e^{-1/\varepsilon}} (1-e^{-\frac{x}{\varepsilon}}) + ax,$$

为了把微分方程离散，把 $[0, 1]$ 区间 n 等分，令 $h = \frac{1}{n}$ ：

$$x_i = ih, (i = 1, 2, \dots, n-1),$$

得到有限差分方程：

$$\varepsilon \frac{y_{i-1} - 2y_i + y_{i+1}}{h^2} + \frac{y_{i+1} - y_i}{h} = a,$$

简化为：

$$(\varepsilon + h)y_{i+1} - (2\varepsilon + h)y_i + \varepsilon y_{i-1} = ah^2,$$

从而离散后得到的线性方程组的系数矩阵与右端向量为：

$$\mathbf{A} = \begin{bmatrix} -(2\varepsilon + h) & \varepsilon + h & & & \\ \varepsilon & -(2\varepsilon + h) & \varepsilon + h & & \\ & \varepsilon & -(2\varepsilon + h) & \ddots & \\ & & \ddots & \ddots & -\varepsilon + h \\ & & & \varepsilon & -(2\varepsilon + h) \end{bmatrix}, \mathbf{b} = \begin{bmatrix} ah^2 \\ \vdots \\ ah^2 - \varepsilon - h \end{bmatrix}.$$

1. 对 $\varepsilon = 1, a = \frac{1}{2}, n = 100$ ，分别用雅可比，G-S 和 SOR 方法求线性方程组的解，要求相邻迭代解的差的无穷范数不超过 10^{-3} 时停止迭代，然后比较与精确解的误差。
2. 对 $\varepsilon = 0.1, \varepsilon = 0.01, \varepsilon = 0.001$ 考虑同样的问题。

实验过程

基本实现

首先实现矩阵 **A** 和向量 **b** 的获取：

```
1 def get_Ab(epsilon):
2     A = np.zeros((n - 1, n - 1))
3     for i in range(n - 2):
4         A[i][i + 1] = epsilon + h
5     for i in range(n - 1):
6         A[i][i] = -(2 * epsilon + h)
7     for i in range(1, n - 1):
8         A[i][i - 1] = epsilon
9
10    b = np.ones((n - 1)) * a * h ** 2
11    b[-1] -= epsilon + h
12    return A, b
```

计算精确解函数：

```
1 def y(x, epsilon):
2     return (1 - a) / (1 - np.exp(-1 / epsilon)) * (1 - np.exp(-x / epsilon)) + a * x
```

三种迭代法：

```
1 def Jacobi(A, b):
2     n, n = A.shape
3     x = np.ones(n)
4     iter = 0
5     while True:
6         y = np.copy(x)
7         iter += 1
8         for i in range(n):
9             x[i] = b[i]
10            if i > 0:
11                x[i] -= A[i][i - 1] * y[i - 1]
12            if i < n - 1:
13                x[i] -= A[i][i + 1] * y[i + 1]
14            x[i] /= A[i][i]
15            if np.linalg.norm(x - y, ord=np.inf) <= 1e-3:
16                return x, iter
17
18 def GS(A, b):
19     n, n = A.shape
20     x = np.ones(n)
21     iter = 0
22     while True:
23         y = np.copy(x)
```

```

24     iter += 1
25     for i in range(n):
26         x[i] = b[i]
27         if i > 0:
28             x[i] -= A[i][i - 1] * x[i - 1]
29         if i < n - 1:
30             x[i] -= A[i][i + 1] * x[i + 1]
31         x[i] /= A[i][i]
32     if np.linalg.norm(x - y, ord=np.inf) <= 1e-3:
33         return x, iter
34
35 def SOR(A, b, w):
36     n, n = A.shape
37     x = np.ones(n)
38     iter = 0
39     while True:
40         y = np.copy(x)
41         z = np.copy(x)
42         iter += 1
43         for i in range(n):
44             z[i] = b[i]
45             if i > 0:
46                 z[i] -= A[i][i - 1] * x[i - 1]
47             if i < n - 1:
48                 z[i] -= A[i][i + 1] * x[i + 1]
49             z[i] /= A[i][i]
50             x[i] = (1 - w) * x[i] + w * z[i]
51     if np.linalg.norm(x - y, ord=np.inf) <= 1e-3:
52         return x, iter

```

第 1 问

分别用三种迭代法执行得到结果：

```

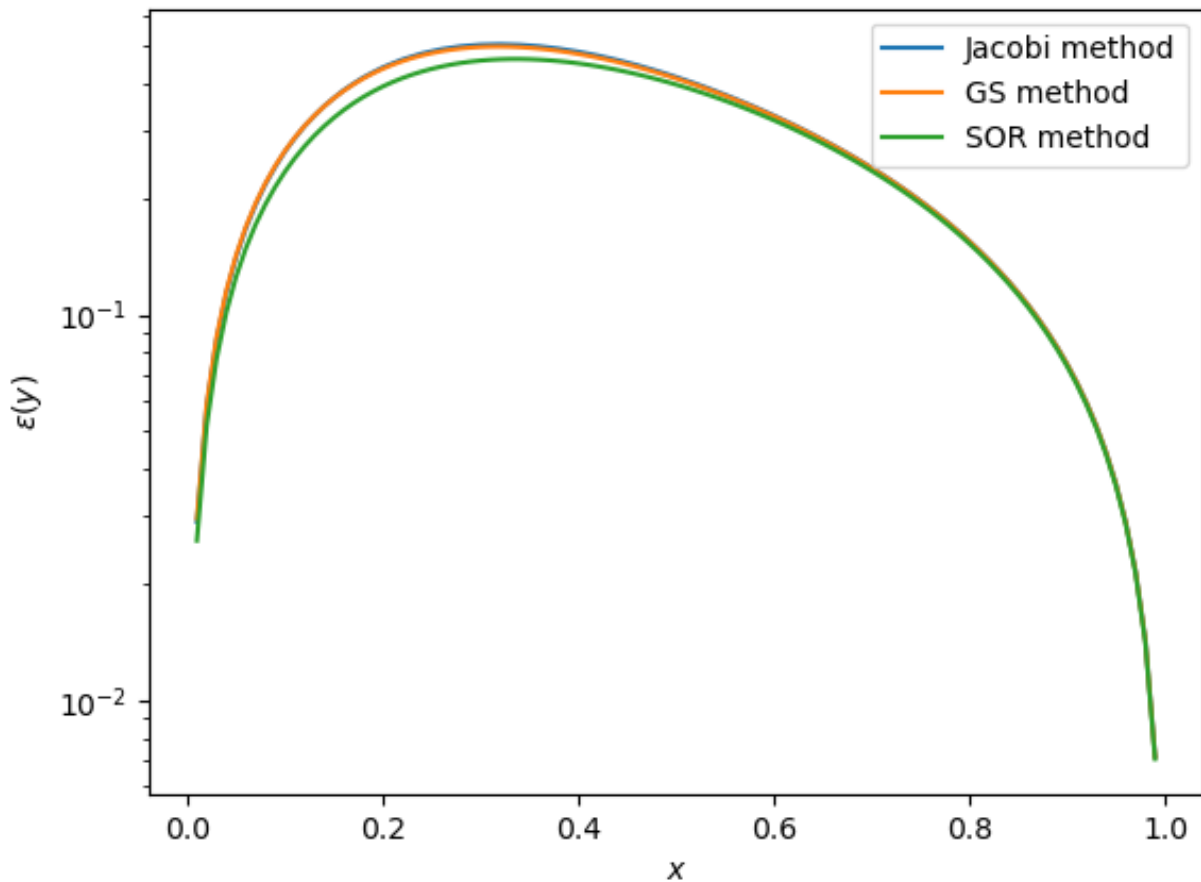
1 Jacobi method take 443 iterations to convergence.
2 Jacobi method: inf norm = 0.5037336050711907, second norm = 3.3378435419954213
3 GS method take 216 iterations to convergence.
4 GS method: inf norm = 0.49685535113842977, second norm = 3.309787130544279
5 SOR method take 215 iterations to convergence.
6 SOR method: inf norm = 0.46121108627135643, second norm = 3.1038372063276682

```

可以看到迭代步骤依次减少，特别是 G-S 和 SOR 相比于 Jacobi 迭代法，只需要一半不到的迭代轮数。

而误差范数上也是依次减小的，但相差并不明显。

画出图像如下：

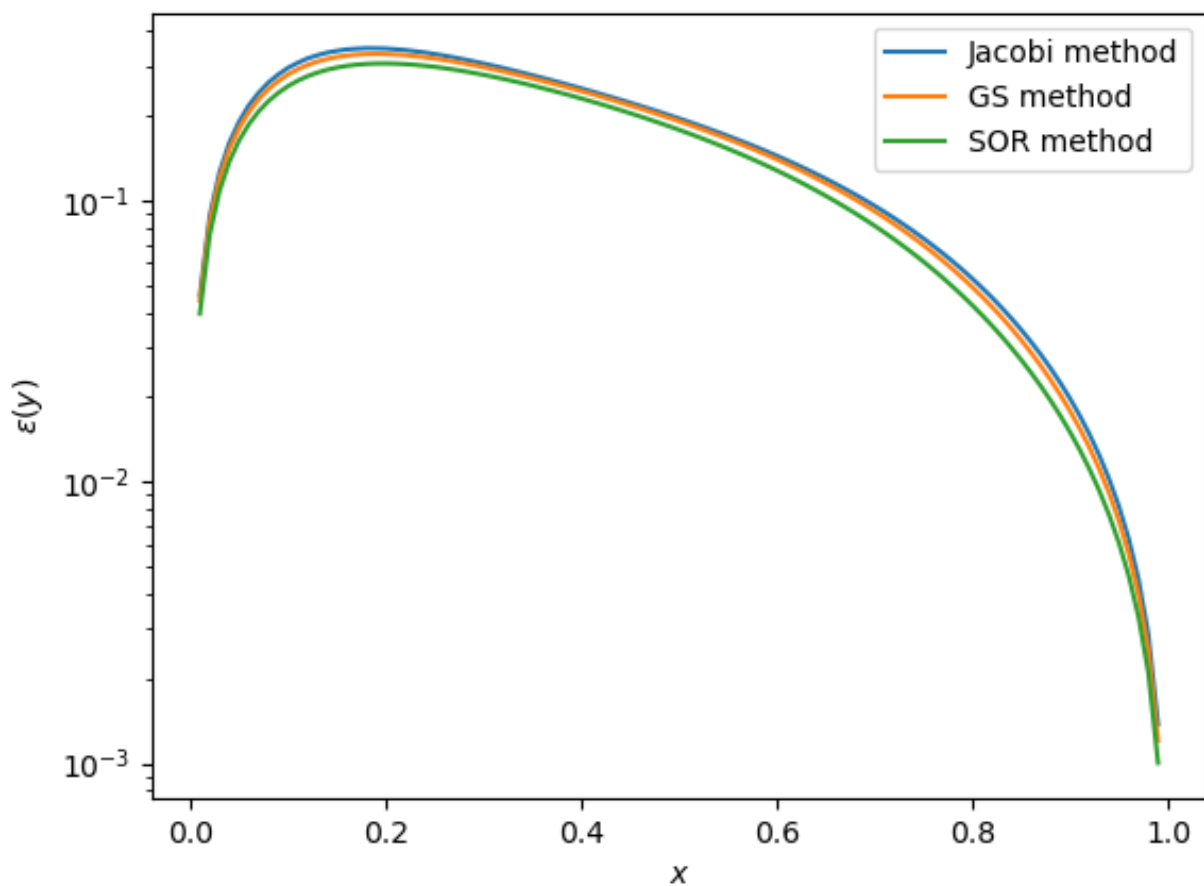


第 2 问

类似的得到结果。

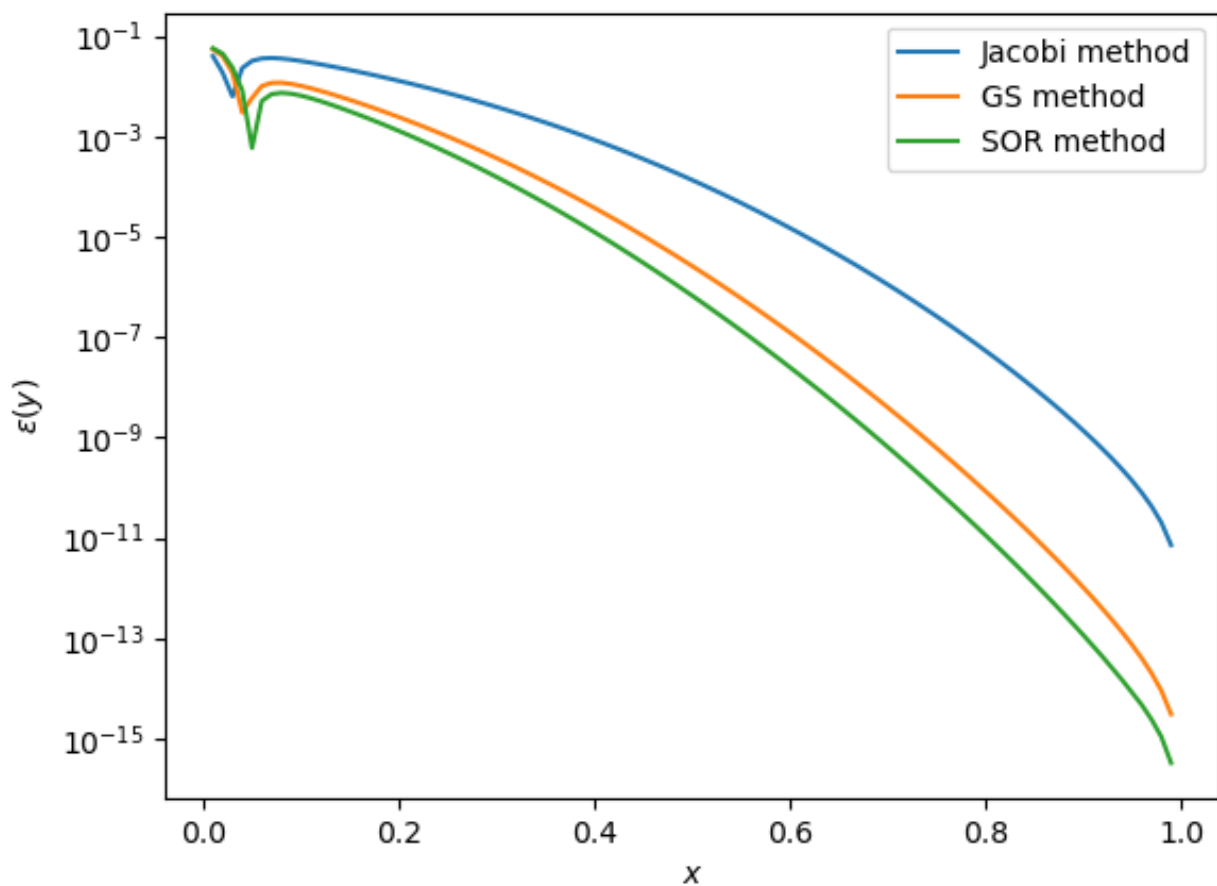
对于 $\varepsilon = 0.1$ 与 1 基本相似：

- 1 Jacobi method take 241 iterations to convergence.
- 2 Jacobi method: inf norm = 0.3481094551732218, second norm = 2.0944322717656583
- 3 GS method take 135 iterations to convergence.
- 4 GS method: inf norm = 0.3323882277968625, second norm = 2.018123448829409
- 5 SOR method take 135 iterations to convergence.
- 6 SOR method: inf norm = 0.30742543743638606, second norm = 1.8694432133747911



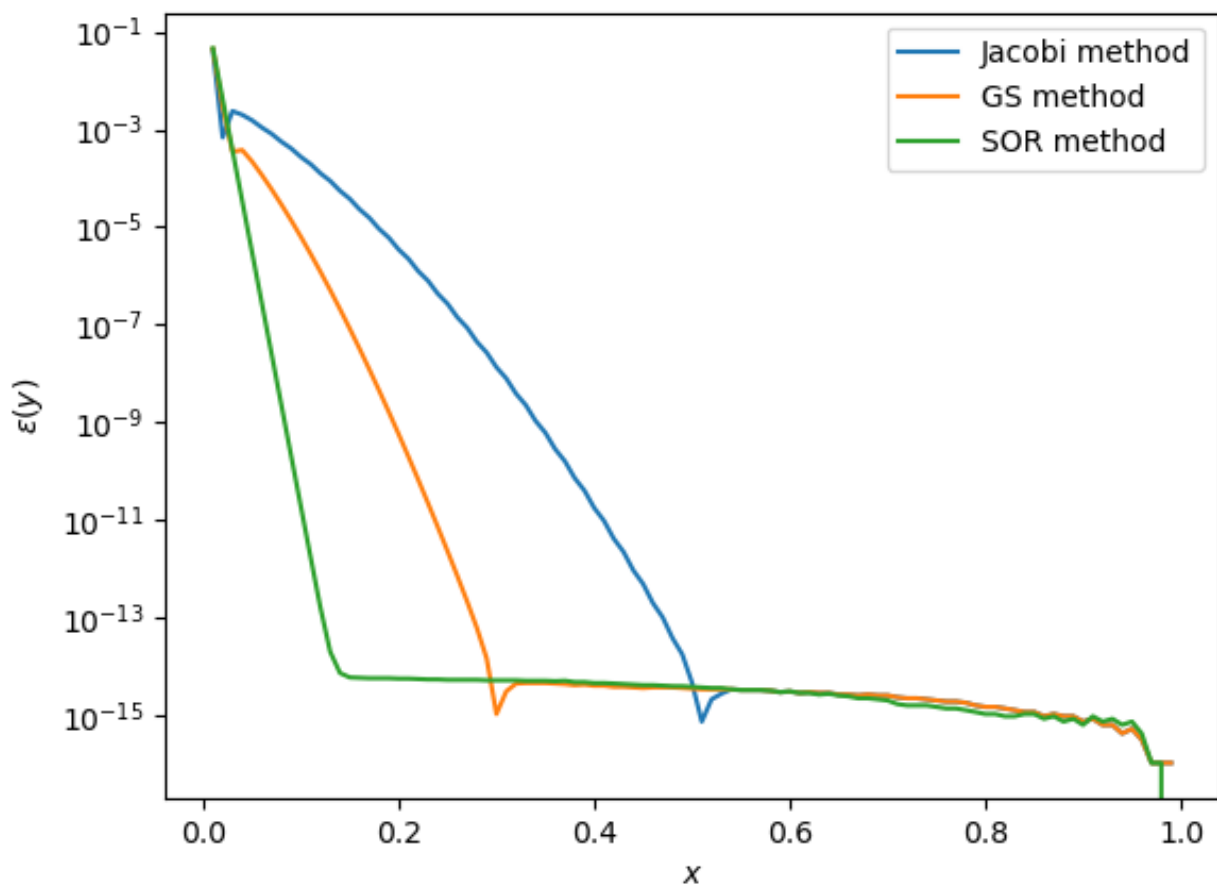
对于 $\epsilon = 0.01$ ，三种迭代法的差距变小，并且误差更为接近：

- 1 Jacobi method take 268 iterations to convergence.
- 2 Jacobi method: inf norm = 0.039589114867955466, second norm = 0.12067003486748872
- 3 GS method take 194 iterations to convergence.
- 4 GS method: inf norm = 0.0537173272734649, second norm = 0.07601006379280341
- 5 SOR method take 171 iterations to convergence.
- 6 SOR method: inf norm = 0.05684632840243864, second norm = 0.07848811009608472



对于 $\varepsilon = 0.001$ ，三种迭代法的误差、速度都没有很大区别，均能较快收敛：

- 1 Jacobi method take 124 iterations to convergence.
- 2 Jacobi method: inf norm = 0.041459521665572985, second norm = 0.04163654838969874
- 3 GS method take 112 iterations to convergence.
- 4 GS method: inf norm = 0.043706530493078044, second norm = 0.04380789740715727
- 5 SOR method take 102 iterations to convergence.
- 6 SOR method: inf norm = 0.04539634439358042, second norm = 0.04558519016017602



可以看到随着 ε 的减小，三种迭代法的收敛速度均有变快，整体误差也呈现下降趋势。

这是由于 ε 越小，原微分方程的解就越趋向于一个线性函数，差分方法就能得到更精确的解；而其较大时，差分运算本身就会带来一定的误差，同时收敛也比较慢。

而 ε 较小时，还发现误差在 0 附近会特别陡峭，这是因为 0 附近函数的斜率非常大，导致误差被放大。

实验结论

通过这次实验，我实践了三种迭代法，对于三种方法的收敛速度和误差有了更深的理解，可以看到，在一般情况下，应该更多选取优化后的后两者而非 Jacobi 迭代法。