



Exercise Sheet 1

Exercise 1 (Solvers are preconditioners – preconditioners can be solvers)

In this exercise, we study the connections between preconditioners and stationary iterative methods. Let $\mathbf{A}, \mathbf{B} \in \mathbb{R}^{N \times N}$ be symmetric positive definite. For the equation $\mathbf{A}\mathbf{x} = \mathbf{b}$ in \mathbb{R}^N , consider the linear iteration

$$\mathbf{x}^{j+1} = \mathbf{x}^j + \omega \mathbf{B}^{-1}(\mathbf{b} - \mathbf{A}\mathbf{x}^j). \quad (\star)$$

- a) Let $\omega = 1$. Assume that the spectral radius of the corresponding iteration matrix $\mathbf{G} = \mathbf{I} - \mathbf{B}^{-1}\mathbf{A}$ satisfies $\varrho := \lambda_{\max}(\mathbf{G}) = \|\mathbf{G}\| := \max_{\|\mathbf{v}\|=1} \langle \mathbf{G}\mathbf{v}, \mathbf{v} \rangle < 1$. Show that the spectral condition number of $\mathbf{B}^{-1}\mathbf{A}$ satisfies

$$\kappa(\mathbf{B}^{-1}\mathbf{A}) := \frac{\lambda_{\max}(\mathbf{B}^{-1}\mathbf{A})}{\lambda_{\min}(\mathbf{B}^{-1}\mathbf{A})} \leq \frac{1 + \varrho}{1 - \varrho}.$$

Hints

- i) Show that

$$\frac{|\langle \mathbf{A}\mathbf{v}, \mathbf{v} \rangle - \langle \mathbf{A}\mathbf{B}^{-1}\mathbf{A}\mathbf{v}, \mathbf{v} \rangle|}{\langle \mathbf{A}\mathbf{v}, \mathbf{v} \rangle} \leq \varrho \quad \forall \mathbf{v} \in \mathbb{R}^N.$$

- ii) Show that the estimate

$$\mu_0 \langle \mathbf{A}\mathbf{v}, \mathbf{v} \rangle \leq \langle \mathbf{A}\mathbf{B}^{-1}\mathbf{A}\mathbf{v}, \mathbf{v} \rangle \leq \mu_1 \langle \mathbf{A}\mathbf{v}, \mathbf{v} \rangle \quad \forall \mathbf{v} \in \mathbb{R}^N$$

implies that $\kappa(\mathbf{B}^{-1}\mathbf{A}) \leq \frac{\mu_1}{\mu_0}$.

- b) Show that the iteration (\star) converges for $\omega \in (0, 2/\lambda_{\max}(\mathbf{B}^{-1}\mathbf{A}))$.

Remarks

Part a) implies that the preconditioned conjugate gradient (pcg) method is always faster because

$$\varrho_{\text{pcg}} = \frac{\sqrt{\kappa(\mathbf{B}^{-1}\mathbf{A})} - 1}{\sqrt{\kappa(\mathbf{B}^{-1}\mathbf{A})} + 1} = \frac{1 - \sqrt{1 - \varrho^2}}{\varrho} < \varrho.$$

Part b) means that a good preconditioner does not necessarily converge when used as “stand-alone solver” without damping.

Exercise 2 (Jacobi and Gauß-Seidel as subspace correction methods)

Let V be a finite element space and let

$$V \ni v \mapsto \mathcal{J}(v) := \frac{1}{2}a(v, v) - f(v)$$

be the quadratic energy functional corresponding to the variational formulation in V with the bilinear form $a(\cdot, \cdot)$ and the right hand side $f(\cdot)$. Given a decomposition/splitting of the space $V = V_1 + V_2 + \dots + V_m$, consider the following two algorithms.

Algorithm SSC – Sequential subspace correction method

```
{
  Let  $u_0 \in V$  be given.
  For  $k = 1, 2, \dots, m$  {
    Compute  $v_k \in V_k$  such that  $\mathcal{J}(u_{k-1} + v_k) \leq \mathcal{J}(u_{k-1} + v) \quad \forall v \in V_k$ 
    Update  $u_k = u_{k-1} + v_k$ 
  }
  Return value is  $u_m \in V$ .
}
```

Algorithm PSC – Parallel subspace correction method

```
{
  Let  $u_0 \in V$  be given.
  For  $k = 1, 2, \dots, m$  {
    Compute  $v_k \in V_k$  such that  $\mathcal{J}(u_0 + v_k) \leq \mathcal{J}(u_0 + v) \quad \forall v \in V_k$ 
  }
  Update  $u_1 = u_0 + \sum_{k=1}^m v_k$ 
  Return value is  $u_1 \in V$ .
}
```

Let now $m = N = \dim V$ and $V_k = \text{span}(\lambda_k)$, $k = 1, \dots, N$. (This means $\dim V_k = 1$ for $k = 1, \dots, N$.) Show that in this case

- a) Algorithm SSC is equivalent to one step of the Gauß-Seidel method and
- b) Algorithm PSC is equivalent to one step of the Jacobi method.

Exercise 3 (Matrix-free red-black Gauß-Seidel method)

Consider the model problem (Example II of the first lecture: discretization of the Poisson problem on the square $\Omega = (0, 1)^2$ with first-order Lagrange finite elements on a regular triangular mesh with $h = \frac{1}{n+1}$ and $N = n^2$ interior nodes). Implement

- (a) the standard/lexicographic Gauß-Seidel method and
- (b) the red-black Gauß-Seidel method

without assembling the stiffness matrix.

Hints

You may

- enlarge the set of degrees of freedom by including the $4(n + 1)$ boundary nodes,
- index the degrees of freedom by double indices $(i, j)_{i=1, \dots, n+2; j=1, \dots, n+2}$,
i. e., store all vectors as $(n + 2) \times (n + 2)$ -matrices.

Exercise 4 (Counterexample for a trace theorem)

As indicated in the last exercise lesson, artificially introduced interfaces and function values on them play a major role in domain decomposition methods.

Trace theorem. For a domain Ω with Lipschitz boundary that satisfies an interior cone condition, a unique continuous linear mapping

$$\gamma : H^1(\Omega) \rightarrow L^2(\partial\Omega)$$

(the trace operator) exists such that

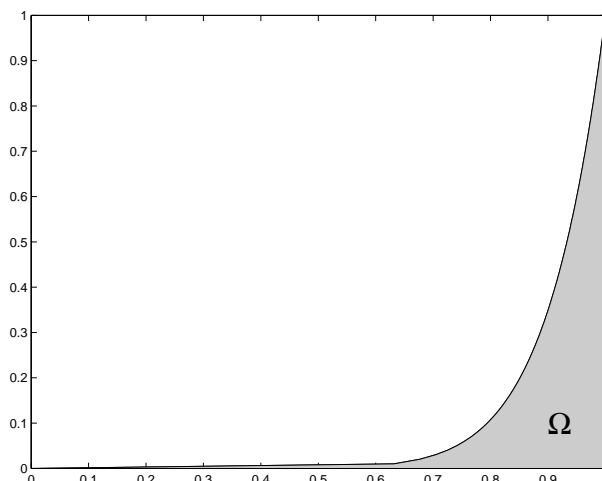
$$\gamma(v) = v|_{\partial\Omega} \quad \forall v \in H^1(\Omega) \cap C^0(\overline{\Omega}).$$

We will later need refined versions of this theorem. We now consider a classical counterexample that illustrates what can go wrong, if the assumptions are violated.

Let $\Omega = \{(x, y) \in \mathbb{R}^2 \mid 0 < x < 1, 0 < y < x^5\}$ and $\Gamma = (0, 1) \times \{0\}$. Show that

$$u : \Omega \rightarrow \mathbb{R}, \quad u(x, y) := \frac{1}{x}$$

satisfies $u \in H^1(\Omega)$ but $u|_{\Gamma} \notin L^2(\Gamma)$.



Domain Ω that violates the interior cone condition

Remark

You can solve this exercise even if you do not feel very comfortable with Sobolev spaces. Just calculate the integrals $\|u\|_{H^1(\Omega)}^2$, $\|u\|_{L^2(\Gamma)}^2$ (exploiting the fact that the strong and weak derivatives coincide whenever they are both defined).