

## Solutions to Part B of Problem Sheet 2

### Solution (2.4)

(a) We apply the bound inductively,

$$\|x_k - x^*\| \leq r \cdot \|x_{k-1} - x^*\| \leq r \cdot (r \cdot \|x_{k-2} - x^*\|) \leq \dots \leq r^k \cdot \|x_0 - x^*\|.$$

(b) Let  $\varepsilon > 0$ . We are guaranteed to have an error bounded by  $\varepsilon$  if  $r^N \cdot M < \varepsilon$ , by Part (a). Taking logarithms of this inequality,

$$N \ln(r) + \ln(M) \leq \ln(\varepsilon).$$

Negating this, we get

$$-N \ln(r) - \ln(M) = N \ln(1/r) - \ln(M) \geq \ln(1/\varepsilon).$$

Dividing by  $\ln(1/r)$  gives

$$N \geq \frac{1}{\ln(1/r)} (\ln(1/\varepsilon) + \ln(M)) > \frac{r}{1-r} (\ln(M) + \ln(1/\varepsilon)),$$

where we used the inequality  $\ln(1/r) < 1/r - 1 = (1-r)/r$ .

(c) For quadratic convergence, the bound is derived in exactly the same way as for linear convergence. To determine the number of steps, we start with the bound

$$C^N \cdot M^{2^N} \leq \varepsilon.$$

Taking logarithms and negating,

$$N \ln(1/C) - 2^N \ln(M) \geq \ln(1/\varepsilon).$$

Taking logarithms again, we get

$$N \cdot \left( \frac{\log_2(N)}{N} + \log_2(\ln(1/c) - \ln(M)) \right) \geq \log_2(\ln(1/\varepsilon)),$$

so that if

$$N > C' \cdot \ln \ln(1/\varepsilon)$$

for a constant  $C'$ , we are guaranteed an error below  $\varepsilon$ .

**Solution (2.5)** We first compute the derivatives,

$$\begin{aligned} f(x) &= \sqrt{x^2 + 1} \\ f'(x) &= \frac{x}{\sqrt{x^2 + 1}} \\ f''(x) &= \frac{1}{(x^2 + 1)^{3/2}}. \end{aligned}$$

Note that the second derivative is always positive. Newton's method then has the following form

$$x_{k+1} = x_k - \frac{f'(x_k)}{f''(x_k)} = x_k - x_k(1 + x_k^2) = -x_k^3.$$

For  $|x_0| < 1$  this clearly converges to 0, while for  $x_0 > 1$  this diverges. For  $|x_0| = 1$  the sequence alternates between 1 and  $-1$ .

**Solution (2.6)** We first have to think about what it means to be a steepest descent direction with respect to a norm. If we look for a vector  $\mathbf{p}$  with  $\|\mathbf{p}\|_\infty = 1$  such that  $\langle \mathbf{p}, \nabla f(\mathbf{x}) \rangle$  is minimal. Set  $\mathbf{v} = \nabla f(\mathbf{x})$ , to ease notation. Since  $\|\mathbf{p}\|_\infty = 1$  is the same as saying that  $\max_{1 \leq i \leq d} |p_i| = 1$ , this amounts to solving the minimization problem

$$\begin{aligned} & \text{minimize} && \langle \mathbf{p}, \mathbf{v} \rangle \\ & \text{subject to} && -1 \leq p_i \leq 1, \quad 1 \leq i \leq d. \end{aligned}$$

Suppose that a minimizer is found and the minimum has the form

$$\sum_{i=1}^d p_i v_i.$$

If  $p_i v_i > 0$ , then we can decrease the objective function further by changing the sign of  $p_i$ , and then even further by setting  $p_i = -1$  if  $\text{sign } v_i = 1$  and  $p_i = 1$  otherwise. Therefore, the optimizer has the form

$$p_i = -\text{sign } \nabla f(\mathbf{x})_i$$

for  $1 \leq i \leq d$ .