

$$\begin{aligned} \text{I} \text{ (a)} \quad \phi(x) &= \frac{1}{2} \|Ax - b\|_2^2 = \frac{1}{2} (Ax - b)^T (Ax - b) \\ &= \frac{1}{2} (x^T A^T A x - x^T A^T b - b^T A x + b^T b) \\ &= \frac{1}{2} (x^T A^T A x - 2b^T A x + b^T b) \quad (\text{since } x^T A^T b = b^T A x) \end{aligned}$$

The necessary condition for a minimizer of  $\phi(x)$  is  $\nabla \phi(x) = 0$ . Differentiating  $\phi$ ,

$$0 = \nabla \phi(x) = \frac{1}{2} (2x^T A^T A - 2b^T A) \Rightarrow \boxed{A^T A x = A^T b} \quad (*)$$

This linear system gives the normal equations for the least squares problem (1). Any solution of (1) must necessarily satisfy the normal equations. Conversely, a solution of  $(*)$  satisfies (1).

The linear system  $(*)$  is symmetric, positive semi-definite. For smaller systems, it could be efficiently solved using a Cholesky factorization and forward/backward substitution. For large, sparse systems, the method of conjugate gradients could be used. Note that (1) can also be solved without forming the normal equations.

**I (b)** The solution of (1) is unique iff  $A$  has full column rank. If  $A$  is rank deficient,  $\exists z \neq 0$  s.t.  $Az = 0$ , so that if  $x$  is a solution of (1),  $x+z$  is also a solution. If  $A$  has full column rank, the solution of  $(*)$  is unique ( $A^T A$  is non-singular), and since  $(*)$  is a necessary condition, the solution of (1) is unique.

$$\text{II} \text{ (c) (i)} \quad \|Ax - b\|_2^2 = \|U \Sigma V^T x - b\|_2^2 = \|\Sigma V^T x - U^T b\|_2^2$$

where the last equality holds because  $\|\cdot\|_2$  is invariant under orthogonal transformations. Next,

$$\|\Sigma V^T x - U^T b\|_2^2 = \sum_{i=1}^n (\sigma_i v_i^T x - u_i^T b)^2 + \sum_{i=n+1}^m (-u_i^T b)^2$$

$$= \sum_{i=1}^r (\sigma_i v_i^T x - u_i^T b)^2 + \sum_{i=r+1}^m (-u_i^T b)^2, \quad \text{using the fact that } \text{rank}(A) = r$$

Thus, in order to minimize the 2-norm of the residual, we must choose  $x$  s.t.

$$v_i^T x = \frac{u_i^T b}{\sigma_i}, \quad i = 1, \dots, r \quad (**)$$

Since  $\{v_k\}_{k=1}^n$  form an orthonormal basis, we have  $x = \sum_{k=1}^n v_k (v_k^T x)$ .

$(**)$  gives the value of  $v_k^T x$  for  $k=1, \dots, r$ , and to minimize the 2-norm of, we thus choose  $v_k^T x = 0$  for  $k=r+1, \dots, n$ . Thus  $x_{LS}$  is given by

$$x_{LS} = \sum_{k=1}^r v_k (v_k^T x) = \sum_{k=1}^r v_k (v_k^T b / \sigma_k)$$

$$\boxed{x_{LS} = \sum_{k=1}^r \frac{v_k u_k^T b}{\sigma_k}}$$

11 (c) (i) From part (i), we have

$$\|Ax_{LS} - b\|_2^2 = \| \sum_{i=1}^r V_i^T x_{LS} - u_i^T b \|_2^2 = \sum_{i=1}^r (\sigma_i V_i^T x_{LS} - u_i^T b)^2 + \sum_{i=r+1}^m (-u_i^T b)^2$$

$x_{LS}$  is chosen so that the first term in the sum vanishes. The second term does not depend on  $x$ . Thus

$$\|r\|_2^2 = \|Ax_{LS} - b\|_2^2 = \sum_{i=r+1}^m (u_i^T b)^2$$

[2] (a) backward Euler

$$\frac{y^{n+1} - y^n}{\Delta t} = \lambda y^{n+1}$$

$$\Rightarrow (1 - \lambda \Delta t) y^{n+1} = y^n$$

$$\Rightarrow y^{n+1} = (1 - \lambda \Delta t)^{-1} y^n$$

(b) trapezoidal rule

$$y \frac{y^{n+1} - y^n}{\Delta t} = \frac{1}{2} \lambda y^n + \frac{1}{2} \lambda y^{n+1}$$

$$\Rightarrow y^{n+1} = y^n + \frac{\Delta t}{2} \lambda y^n + \frac{\Delta t}{2} \lambda y^{n+1}$$

$$\Rightarrow (1 - \frac{\Delta t}{2} \lambda) y^{n+1} = (1 + \frac{\Delta t}{2} \lambda) y^n$$

$$\Rightarrow y^{n+1} = (1 - \frac{\Delta t}{2} \lambda)^{-1} (1 + \frac{\Delta t}{2} \lambda) y^n$$

(c) as  $\Delta t \rightarrow \infty$ ,  $(1 - \lambda \Delta t)^{-1} \rightarrow 0$ , so the backward Euler update gives  $y^{n+1} \rightarrow 0$ , i.e., a steady state solution of 0.

For trapezoidal rule, as  $\Delta t \rightarrow \infty$ ,  $y^{n+1} \rightarrow \frac{\Delta t \lambda / 2}{-\Delta t \lambda / 2} y^n = -y^n$ , so the solution will oscillate, flipping sign in each iteration.

[3] (a) We can rewrite this as a first order system,  $\dot{u} = Au$ , where

$$u = \begin{pmatrix} x \\ \dot{x} \end{pmatrix}, \quad A = \begin{pmatrix} 0 & 1 \\ -\frac{k}{m} & -\frac{c}{m} \end{pmatrix}.$$

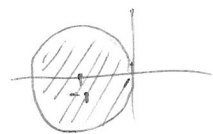
The eigenvalues of the matrix  $A$  are the roots of the characteristic polynomial

$$|A - \lambda I| = \begin{vmatrix} -\lambda & 1 \\ -\frac{k}{m} & -\frac{c}{m} - \lambda \end{vmatrix} = \lambda(\lambda + \frac{c}{m}) + \frac{k}{m} = \lambda^2 + \frac{c}{m} \lambda + \frac{k}{m}.$$

Using the quadratic formula, these are  $\lambda = -\frac{c}{m} \pm \sqrt{(\frac{c}{m})^2 - 4\frac{k}{m}}$ .

(b) The update rule for forward Euler is  $y^{n+1} = (1 + \Delta t \lambda) y^n$ , so for absolute stability we require  $|1 + \Delta t \lambda| \leq 1 \quad \forall \lambda$ , or  $|1 + \Delta t \lambda - (-1)| \leq 1$ , so that  $\Delta t \lambda$  lies in the unit circle in the complex plane centered at  $-1$ .

Thus  $\Delta t$  must be chosen so that this holds for all eigenvalues of  $A$ . Note that  $\lambda$  above has nonpositive real part.



(c) For trapezoidal rule to be absolutely stable, we need

$\frac{|1 + \frac{\Delta t}{2} \lambda|}{|1 - \frac{\Delta t}{2} \lambda|} \leq 1$ . Since  $\lambda$  has nonpositive real part, this inequality is satisfied. (This can be easily seen as the numerator is the distance of  $\frac{\Delta t}{2} \lambda$  to  $-1$ , and the denominator is the distance of  $\frac{\Delta t}{2} \lambda$  to  $1$ .) Thus trapezoidal rule is absolutely stable for any choice of  $\Delta t$ .

4 We require  $\sum_{j=1}^n u_{ij} z_j = \sum_{j=i}^n u_{ij} z_j = 0$  for each  $i \in \{1, \dots, n\}$ .

This is satisfied unconditionally for  $i=n$  since  $u_{nn}=0$ , so set  $z_n=1$ . The other components of  $z$  can be computed in reverse order via

$$z_i = \frac{-1}{u_{ii}} \sum_{j=i+1}^n u_{ij} z_j$$

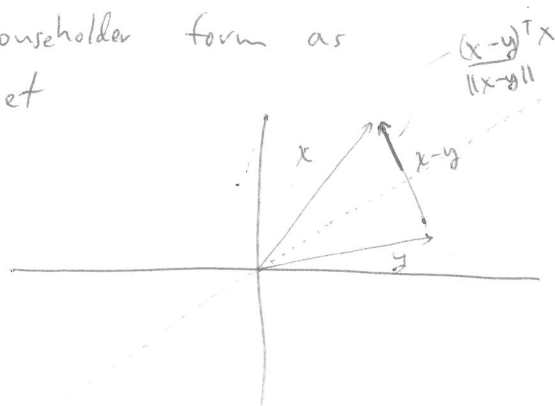
since  $u_{ii} \neq 0$  for  $i < n$  and  $z_j, j > i$  are known when  $z_i$  is computed.

5 a) Writing the unknown reflection in Householder form as  $A = I - 2uu^T$  for  $|u|=1$ , we get

$$Ax = y$$

$$x - 2u(u^T x) = y$$

$$u = \frac{x-y}{2u^T x} \quad (*)$$



Since  $|u|=1$ , it suffices to set  $u = \frac{x-y}{\|x-y\|}$  unless  $x=y$ , in which case  $u$  can be any vector orthogonal to  $x=y$ .  $(*)$  holds since  $2u^T x$

$$2u^T x = 2 \frac{x^T x - y^T x}{(x^T x - 2y^T x + y^T y)^{1/2}} = \frac{x^T x - 2y^T x + y^T y}{(x^T x - 2y^T x + y^T y)^{1/2}} = \|x-y\|$$

if  $\|x\| = \|y\|$ .

b) It suffices to compute  $Az$  as

$$\begin{aligned} Az &= (I - 2u^T u)z = z - 2u(u^T z) \\ &= z - (2u^T z)u \end{aligned}$$