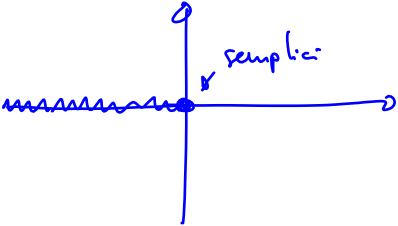
The matrix square root

Next (and last, for us) matrix function: $A^{1/2}$, principal square root.

$A^{1/2}$ is well defined unless A has:

- Real eigenvalues $\lambda_i < 0$, or
- Non-trivial Jordan blocks at $\lambda_i = 0$ (because $g(x) = x^{1/2}$ is not differentiable).



Condition number / sensitivity

$(X+E)^2 = X^2 + \underbrace{EX + XE}_{\text{parte lineare}} + o(\|E\|)$

The Fréchet derivative of $f(X) = X^2$ is

$$L_{f,X}(E) = XE + EX, \quad \widehat{L} = I \otimes X + X^T \otimes I.$$

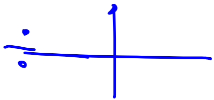
The Fréchet derivative of $g(Y) = Y^{1/2}$ is its inverse,

$$\boxed{\widehat{L}_{g,Y}} = (I \otimes Y^{1/2} + (Y^{1/2})^T \otimes I)^{-1}$$

with eigenvalues $\frac{1}{\lambda_i^{1/2} + \lambda_j^{1/2}}$, $i, j = 1, \ldots, n$. (λ: autoval. di Y)

In particular, g is ill-conditioned for matrices that either:

- have a small eigenvalue (taking $i = j$), or
- have two complex conjugate eigenvalues close to the negative real axis (because then $\lambda_i^{1/2} \approx ai$, $\lambda_j^{1/2} \approx -ai$).



Schur method

Recall: Schur method:

1. Reduce to a triangular T using a Schur form;
2. Compute diagonal of $S = f(T)$;
3. Compute off-diagonal entries from $ST = TS$
   Involves a denominator $t_{ii} - t_{jj}$: if it is 0, we must work on blocks.

In the case of $A^{1/2}$, we can use $S^2 = T$ to get the off-diagonal entries instead:

$$s_{ii}s_{ij} + s_{i,i+1}s_{i+1,j} + \cdots + s_{ij}s_{jj} = t_{ij}.$$

Involves a denominator $s_{ii} + s_{jj}$: always invertible because $s_{ii} + s_{jj} \in RHP$.

It's backward stable (not complicated to show it).
(This is what Matlab uses, by the way.)

Newton method

Newton method on $X^2 - A$:

$$X_{k+1} = X_k - E, \quad \text{where } E \text{ solves } EX_k + X_k E = X_k^2 - A.$$

Much more expensive than the Schur method: we solve a Sylvster equation at each step (and this requires a Schur form).

Trick: If X_0 commutes with A (for instance, taking $X_0 = \alpha I$), then $E = (2X_0)^{-1}(X_0^2 - A)$ and E, X_1 commute with A, too, ...

Resulting iteration:

(Modified) Newton iteration

$$X_{k+1} = \frac{1}{2}(X_k + X_k^{-1}A), \quad X_0 = \alpha I.$$

At each step, $X_k A = AX_k$.

Square root and sign

(Modified) Newton iteration

$$X_{k+1} = \frac{1}{2}(X_k + X_k^{-1}A), \quad X_0 = \alpha I.$$

Pre-multiply by $A^{-1/2}$, and use commutativity:

$$A^{-1/2}X_{k+1} = \frac{1}{2}\left(A^{-1/2}X_k + (A^{-1/2}X_k)^{-1}\right), \quad A^{-1/2}X_0 = \alpha A^{-1/2}.$$

This is the sign iteration! $A^{-1/2}X_k \to \operatorname{sign}(A^{-1/2}) = I$.
Hence,

$X_k \to A^{1/2}$, i.e., the modified Newton iteration converges (for each starting point $X_0 = \alpha I$ with $\alpha > 0$).

Local convergence

True Newton

$$X_{k+1} = X_k - E, \quad \text{where } E \text{ solves } EX_k + X_k E = X_k^2 - A.$$

This is a Newton method, so it converges quadratically (locally).

Modified Newton

$$X_{k+1} = \frac{1}{2}(X_k + X_k^{-1} A).$$

The two iterations coincide, if $X_0 A = AX_0$. ...in exact arithmetic!
In practice, this property is lost numerically. We need to study the convergence of MN separately.

MN is the fixed-point iteration associated to
$h(X) = \frac{1}{2}(X + X^{-1} A)$.

Local stability

Local stability of a fixed-point iteration depends on the eigenvalues of its Jacobian in the fixed-point.

The Jacobian / Fréchet derivative of $h(X) = \frac{1}{2}(X + X^{-1}A)$ is

$$L_{h,X}(E) = \frac{1}{2}(E + X^{-1}EX^{-1}A)$$

(use $(X+E)^{-1} - X^{-1} = (X+E)^{-1}EX^{-1} = X^{-1}EX^{-1} + o(\|E\|)$).

Hence $L_{h,A^{1/2}} = \frac{1}{2}(E + A^{-1/2}EA^{1/2})$, or
$K_{h,A^{1/2}} = \frac{1}{2}\left(I + (A^{1/2})^T \otimes A^{-1/2}\right)$.

It has eigenvalues $\frac{1}{2} + \frac{1}{2}\lambda_i^{1/2}\lambda_j^{-1/2}$, where λ_i are the eigenvalues of A.

It's easy to construct cases in which $L_{h,A^{1/2}}$ has eigenvalues with modulus > 1, hence $A^{1/2}$ is an unstable fixed point of $h(X)$.

DB iteration

However, the stability properties are significantly different for slight variations of the modified Newton's method.

Setting $Y_k = A^{-1}X_k$, we can get

DB iteration [Denman–Beavers, '76]

$$X_{k+1} = \frac{1}{2}(X_k + Y_k^{-1}),$$
$$Y_{k+1} = \frac{1}{2}(Y_k + X_k^{-1}),$$

This one satisfies $\lim(X_k, Y_k) = (A^{1/2}, A^{-1/2})$, and it is locally stable.

Local stability of the DB iteration

We have

$$L_{DB,(X,Y)}\left(\begin{bmatrix} E \\ F \end{bmatrix}\right) = \frac{1}{2}\begin{bmatrix} E - Y^{-1}FY^{-1} \\ F - X^{-1}EX^{-1} \end{bmatrix}$$

All $(X, Y) = (M, M^{-1})$ are fixed points, and in these the Jacobian is idempotent, i.e., $(K_{DB,(B,B^{-1})})^2 = K_{DB,(B,B^{-1})}$.

This implies local stability (even if the eigenvalues are ± 1).

Other variants available [Higham book, Ch. 6].