

Numerical Analysis of the Matrix Logarithm

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Computational Methods with Applications Harrachov 2007

Outline



2 Applications



Numerical methods



A logarithm of $A \in \mathbb{C}^{n \times n}$ is any matrix X such that $e^{X} = A$.

Existence.

- Representation, classification.
- Computation.
- Conditioning.

First, approach via theory of matrix functions...



Multiplicity of Definitions

There have been proposed in the literature since 1880 **eight distinct definitions** of a matric function, by Weyr, Sylvester and Buchheim, Giorgi, Cartan, Fantappiè, Cipolla, Schwerdtfeger and Richter. — **R. F. Rinehart.**

The Equivalence of Definitions of a Matric Function, Amer. Math. Monthly (1955)

Jordan Canonical Form

$$Z^{-1}AZ = J = \operatorname{diag}(J_1, \dots, J_p), \quad \underbrace{J_k}_{m_k \times m_k} = \begin{bmatrix} \lambda_k & 1 & & \\ & \lambda_k & \ddots & \\ & & \ddots & 1 \\ & & & & \lambda_k \end{bmatrix}$$

Definition

$$f(A) = Zf(J)Z^{-1} = Z\operatorname{diag}(f(J_k))Z^{-1},$$

$$f(J_k) = \begin{bmatrix} f(\lambda_k) & f'(\lambda_k) & \dots & \frac{f^{(m_k-1)})(\lambda_k)}{(m_k-1)!} \\ f(\lambda_k) & \ddots & \vdots \\ & \ddots & f'(\lambda_k) \\ & & f(\lambda_k) \end{bmatrix}$$

Interpolation

Definition (Sylvester, 1883; Buchheim, 1886)

Distinct e'vals $\lambda_1, \ldots, \lambda_s$, $n_i = \max$ size of Jordan blocks for λ_i . Then f(A) = p(A), where p is unique Hermite interpolating poly of degree $< \sum_{i=1}^{s} n_i$ satisfying

$$p^{(j)}(\lambda_i) = f^{(j)}(\lambda_i), \qquad j = 0: n_i - 1, \quad i = 1: s$$

Cauchy Integral Theorem

Definition

$$f(\boldsymbol{A}) = \frac{1}{2\pi i} \int_{\Gamma} f(\boldsymbol{z}) (\boldsymbol{z}\boldsymbol{I} - \boldsymbol{A})^{-1} \, d\boldsymbol{z},$$

where *f* is analytic on and inside a closed contour Γ that encloses $\lambda(A)$.

Equivalence of Definitions

Theorem

The three definitions are **equivalent**, modulo analyticity assumption for Cauchy.



Composite Functions

Theorem

$f(t) = g(h(t)) \Rightarrow f(A) = g(h(A))$, provided latter matrix defined.

Corollary

$\exp(\log(A)) = A$ when $\log(A)$ is defined.



Outline

Definition of log(A)





Numerical methods



Application: Markov Models

Time-homogeneous continuous-time Markov process with transition probability matrix $P(t) \in \mathbb{R}^{n \times n}$. Transition intensity matrix Q related to P by

$$P(t) = e^{Qt}.$$

Elements of Q satisfy

$$q_{ij} \geq 0, \quad i \neq j, \qquad \sum_{j=1}^n q_{ij} = 0.$$

Embeddability problem When does a given **stochastic** *P* have a real logarithm *Q* that is an **intensity matrix**?



The Average Eye

First order character of optical system characterized by transference matrix $T = \begin{bmatrix} S & \delta \\ 0 & 1 \end{bmatrix} \in \mathbb{R}^{5 \times 5}$, where $S \in \mathbb{R}^{4 \times 4}$ is symplectic: $S^T J S = J$, where $J = \begin{bmatrix} 0 & l_2 \\ -l_2 & 0 \end{bmatrix}$.

Average $m^{-1} \sum_{i=1}^{m} T_i$ is not a transference matrix.

Harris (2005) proposes the average $\exp(m^{-1}\sum_{i=1}^{m}\log(T_i))$.

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For Hermitian pos def A and B, Arsigny et al. (2007) define the log-Euclidean mean

$$E(A, B) = \exp(\frac{1}{2}(\log(A) + \log(B))).$$



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Logs of $A = I_3$

$$B = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix},$$
$$C = \begin{bmatrix} 0 & 2\pi - 1 & 1 \\ -2\pi & 0 & 0 \\ -2\pi & 0 & 0 \end{bmatrix}, \qquad D = \begin{bmatrix} 0 & 2\pi & 1 \\ -2\pi & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix},$$
$$e^{B} = e^{C} = e^{D} = I_{3}.$$

$$\Lambda(\mathbf{C}) = \Lambda(\mathbf{D}) = \{\mathbf{0}, \mathbf{2}\pi i, -\mathbf{2}\pi i\}.$$



e

Principal Log and pth Root

Let $A \in \mathbb{C}^{n \times n}$ have no eigenvalues on \mathbb{R}^- .

Principal log

 $X = \log(A)$ denotes unique X such that

•
$$e^X = A$$

•
$$-\pi < \operatorname{Im}(\lambda(X)) < \pi$$

For **next 2 slides only**, allow $Im(\lambda(X)) = \pi$.

Principal *pth* root

For integer p > 0, $X = A^{1/p}$ is unique X such that

•
$$X^p = A$$

•
$$-\pi/\rho < \arg(\lambda(X)) < \pi/\rho.$$

All Solutions of $e^{\chi} = A$

Theorem (Gantmacher)

 $A \in \mathbb{C}^{n \times n}$ nonsing with Jordan canonical form $Z^{-1}AZ = J = \text{diag}(J_1, J_2, \dots, J_p)$. All solutions to $e^X = A$ are given by

$$X = Z \frac{U}{U} \operatorname{diag}(L_1^{(j_1)}, L_2^{(j_2)}, \dots, L_p^{(j_p)}) \frac{U}{U}^{-1} Z^{-1}$$

where

$$L_k^{(j_k)} = \log(J_k(\lambda_k)) + 2 \, rac{j_k}{j_k} \, \pi \, i \, I_{m_k},$$

 $\frac{J_k}{J_k} \in \mathbb{Z}$ arbitrary, and U an arbitrary nonsing matrix that commutes with J.



All Solutions of $e^X = A$: Classified

Theorem

 $A \in \mathbb{C}^{n \times n}$ nonsing: *p* Jordan blocks, *s* distinct ei'vals. $e^{X} = A$ has a countable infinity of solutions that are **primary** functions of *A*:

$$X_j = Z ext{diag}(L_1^{(j_1)},L_2^{(j_2)},\ldots,L_p^{(j_p)})Z^{-1},$$

where $\lambda_i = \lambda_k$ implies $j_i = j_k$. If s < p then $e^{\chi} = A$ has **non-primary solutions**

$$X_j(U) = Z \frac{U}{U} \operatorname{diag}(L_1^{(j_1)}, L_2^{(j_2)}, \dots, L_p^{(j_p)}) \frac{U}{U}^{-1} Z^{-1},$$

where $j_k \in \mathbb{Z}$ arbitrary, U arbitrary nonsing with UJ = JU, and for each $j \exists i$ and k s.t. $\lambda_i = \lambda_k$ while $j_i \neq j_k$.

Logs of $A = I_3$

$$C = \begin{bmatrix} 0 & 2\pi - 1 & 1 \\ -2\pi & 0 & 0 \\ -2\pi & 0 & 0 \end{bmatrix}, \qquad D = \begin{bmatrix} 0 & 2\pi & 1 \\ -2\pi & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix},$$
$$e^{0} = e^{C} = e^{D} = I_{3}. \ \Lambda(C) = \Lambda(D) = \{0, 2\pi i, -2\pi i\}.$$
$$U = \begin{bmatrix} 1 & \alpha & 0 \\ 0 & 1 & \alpha \\ 0 & 0 & 1 \end{bmatrix}, \quad \alpha \in \mathbb{C},$$
$$X = U \operatorname{diag}(2\pi i, -2\pi i, 0) U^{-1} = 2\pi i \begin{bmatrix} 1 & -2\alpha & 2\alpha^{2} \\ 0 & 1 & -\alpha \\ 0 & 0 & 1 \end{bmatrix}.$$



Two Facts on Commuting Matrices

Theorem

If $A, B \in \mathbb{C}^{n \times n}$ commute then \exists a unitary $U \in \mathbb{C}^{n \times n}$ such that U^*AU and U^*BU are both upper triangular.



Two Facts on Commuting Matrices

Theorem

If $A, B \in \mathbb{C}^{n \times n}$ commute then \exists a unitary $U \in \mathbb{C}^{n \times n}$ such that U^*AU and U^*BU are both upper triangular.

Theorem

For $A, B \in \mathbb{C}^{n \times n}$, $e^{(A+B)t} = e^{At}e^{Bt}$ for all t if and only if AB = BA.



When Does log(BC) = log(B) + log(C)?

Theorem

Let $B, C \in \mathbb{C}^{n \times n}$ commute and have no ei'vals on \mathbb{R}^- . If for every ei'val λ_j of B and the corr. ei'val μ_j of C, $|\arg \lambda_j + \arg \mu_j| < \pi$, then $\log(BC) = \log(B) + \log(C)$.



When Does log(BC) = log(B) + log(C)?

Theorem

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Proof. log(B) and log(C) commute, since *B* and *C* do. Therefore

$$e^{\log(B)+\log(C)}=e^{\log(B)}e^{\log(C)}=BC.$$

Thus log(B) + log(C) is *some* logarithm of *BC*. Then

 $\operatorname{Im}(\log \lambda_j + \log \mu_j) = \arg \lambda_j + \arg \mu_j \in (-\pi, \pi),$

so log(B) + log(C) is the *principal* logarithm of *BC*.

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Definition of log(A)

Applications



Numerical methods



Henry Briggs (1561–1630)

Arithmetica Logarithmica (1624)

Logarithms to base 10 of 1–20,000 and 90,000–100,000 to 14 decimal places.



Henry Briggs (1561–1630)

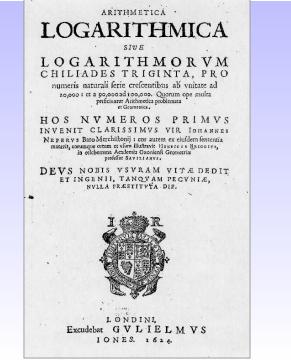
Arithmetica Logarithmica (1624)

Logarithms to base 10 of 1–20,000 and 90,000–100,000 to 14 decimal places.

Briggs must be viewed as one of the great figures in numerical analysis.

—Herman H. Goldstine, A History of Numerical Analysis (1977)





In	1,000
1, 31632,77660,16837,93319,98893,54	0,50
± 17783,79419,5892,2801,97334,13	0,35
313357,21432,16332,40250,67389,308	0,135
411547,81984,08945,81790,61918,213	0,0435
5110746,07828,3213(7,49273,1387,6538	0,0435
6 10366,32928,43769,79972,90627,3131 7 10187,51721,7184,818,18414,73723,8144 8 1009,33704,8144,74377,59005,1391 9 10043,707364,25466,25156,64670,6113 4 10022,51148,2029(59154,6561,7367	0,01562,5 0,00781,25 0,00290,625 0,00195,3125 0,00195,3125
11 10011,24941,39987,98757,87397,51805	0,00048,82812,5
12 10005,43113,60220,86366,118495,91833	0,00024,440635
13 10002,81116,78778,01323,99249,64325	0,00012,20703,125
14 10001,40748,51694,72581,62567,32715	0,0006,10351,5635
15 10000,70271,78541,43355,38811,70845	0,00003,0177,78125
16 Touon,35135,47746,18565,08581,37077	0,00001,52;87,89062,5
17 Touon,1757,4844,3165738,33846,78274	0,00000;38146,97245,625
18 Touon,08783,7353,45121,46574,07431	0,00000;38146,97245,625
19 Touon,04391,84217,31674,36381,88683	0,00000,3923,48532,8125
10 Touon,04191,91867,51544,03317,0779	0,00000,09536,42316,40625
1 10000,01097,97873,70204,09774,72940	0,0000,04768,37158,20312,5
1 10000,0144,97921,68211,14626,60210,4	0,0000,04768,37158,20312,5
1 1000,001374,48977,07383,97091,5449,9	0,0000,0159,0388,18579,10156,25
1 1000,00137,24477,79710,83282,6972,5	0,0000,00596,04644,77539,0625
1 1000,0008,62238,6510,24737,18748,2	0,0000,00586,02232,35965,3125
25 10000,00034,31119,22218,83912,75020,8	0,0000,00149,01161,19384,76562,5
27 10000,00017,15559,5937,84719,93879,1	0,0000,00074,57580,59692,38281,25
28 10000,0008,57779,79451,0307,147588,8	0,0000,00037,25290,29846,19140,625
29 10000,00004,18888,8563,74198,42901,3	0,0000,00018,62645,14923,09770,3125
30 10000,00002,14444,947973,77767,42970,4	0,0000,00009,31322,77435,09770,3125
31 10000,00001,07222,47391,14050,76926,8	0,00000,00004,65661,28730,77392,57812,5
21 10000,00006,73611,73594,13377,14831,4	0,0000,00003,32839,64365,38696,48906,25
32 10000,00002,2585561846,70731,51508,7	0,0000,00001,16415,32182,659,48,14473,125
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34 10005,00001,1424,80926,60946,75519,6	0,00000,00000,25103,83045,67337,0513,28125
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37 [3000,00006/01677,3]117,39817,61877,6	0,00000,00000,07275,95761,41834,25903,32031,25
38 [Soco,00006,00477,3]717,6987,7,798	0,00000,00000,03818,98940,517,1251,66015,625
49 [3007,0007,00269,4188,4247,5967,9	0,00000,00000,01818,98940,535458,56475,83007,8125
4007,0007,00269,4188,4247,5067,9	0,00000,00000,01818,98940,57729,28575,91513,0605
1 10000,00000,00104,70944,71230,25311,0	0,00000,00000,00414,74735,08864,64118,01751,0131

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Briggs' Log Method (1617)

 $\log(ab) = \log a + \log b \quad \Rightarrow \quad \log a = 2 \log a^{1/2}.$

Use repeatedly:

$$\log a = 2^k \log a^{1/2^k}.$$

Write $a^{1/2^k} = 1 + x$ and note $\log(1 + x) \approx x$. Briggs worked to base 10 and used

$$\log_{10} a \approx 2^k \cdot \log_{10} e \cdot (a^{1/2^k} - 1).$$



Take B = C in previous theorem:

$$\log A = \log (A^{1/2} \cdot A^{1/2}) = 2 \log A^{1/2},$$

since $\arg \lambda(A^{1/2}) \in (-\pi/2, \pi/2)$.



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Use Briggs' idea: $\log A = 2^k \log(A^{1/2^k})$.

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Use Briggs' idea: $\log A = 2^k \log(A^{1/2^k})$.

Kenney & Laub's (1989) **inverse scaling and squaring** method:

- Bring A close to I by repeated square roots.
- Approximate log A^{1/2^k} using an [m/m] Padé approximant r_m(x) ≈ log(1 + x).
- Rescale to find log(A).

Apply ISS

 To original A: Cheng, H, Kenney & Laub (2001). Requires square roots of full matrices.

To triangular Schur factor.

To diagonal blocks within the Schur–Parlett method.



Apply ISS

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- ★ Use fixed Padé degree m.
- ★ Let *m* vary optimally with ||A||.

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- ★ Let *m* vary optimally with ||A||.
- ▶ MATLAB's logm (m = 8).

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- To diagonal blocks within the Schur–Parlett method.
- ★ Use fixed Padé degree m.
- **★** Let *m* vary optimally with ||A||.
- MATLAB's logm (m = 8).
- Improved logm.

Padé Approximants

 $r_{km} = p_{km}/q_{km}$ is a [k/m] Padé approximant of f if p_{km} and q_{km} are polys of degree at most k and m and

$$f(x)-r_{km}(x)=O(x^{k+m+1}).$$

For $f(x) = \log(1 + x)$,

$$r_{11}(x) = \frac{2x}{2+x},$$

$$r_{22}(x) = \frac{6x+3x^2}{6+6x+x^2},$$

$$r_{33}(x) = \frac{60x+60x^2+11x^3}{60+90x+36x^2+3x^3}$$

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$$f(x)-r_{km}(x)=O(x^{k+m+1}).$$

Theorem (Kenney & Laub, 1989)

For ||X|| < 1,

 $||r_{mm}(X) - \log(I + X)|| \le |r_{mm}(-||X||) - \log(1 - ||X||)|.$



Algorithmic Ingredients

$$\log A = 2^{k} \log (A^{1/2^{k}}) \approx 2^{k} r_{m} (A^{1/2^{k}} - I).$$

- For given $A^{1/2^k}$, error bound determines min *m* s.t. r_m suff. accurate.
- Choose k and m = m(k) to minimize overall cost.
- Since $(I A^{1/2^{k+1}})(I + A^{1/2^{k+1}}) = I A^{1/2^k}$,

$$\|I - A^{1/2^{k+1}}\| \approx \frac{1}{2}\|I - A^{1/2^{k}}\|.$$

• Evaluate the partial fraction form

$$r_m(x) = \sum_{j=1}^m \frac{\alpha_j^{(m)} x}{1 + \beta_j^{(m)} x},$$

where $\alpha_i^{(m)}$ weights and $\beta_i^{(m)}$ Gauss–Legendre nodes.

Schur–Parlett Algorithm

H & Davies (2003), **funm**:

- Compute Schur decomposition $A = QTQ^*$.
- Re-order T to block triangular form in which eigenvalues within a block are "close" and those of separate blocks are "well separated".
- Evaluate $F_{ii} = f(T_{ii})$.
- Solve the Sylvester equations

$$T_{ii} F_{ij} - F_{ij} T_{jj} = F_{ii} T_{ij} - T_{ij} F_{jj} + \sum_{k=i+1}^{j-1} (F_{ik} T_{kj} - T_{ik} F_{kj}).$$

• Undo the unitary transformations.

Schur–Parlett Algorithm

H & Davies (2003), **funm**:

- Compute Schur decomposition $A = QTQ^*$.
- Re-order T to block triangular form in which eigenvalues within a block are "close" and those of separate blocks are "well separated".
- Evaluate $F_{ii} = \log(T_{ii})$.
- Solve the Sylvester equations

$$T_{ii} F_{ij} - F_{ij} T_{jj} = F_{ii} T_{ij} - T_{ij} F_{jj} + \sum_{k=i+1}^{j-1} (F_{ik} T_{kj} - T_{ik} F_{kj}).$$

Undo the unitary transformations.

Function of 2×2 Block

$$f\left(\begin{bmatrix}\lambda_1 & t_{12}\\ 0 & \lambda_2\end{bmatrix}\right) = \begin{bmatrix}f(\lambda_1) & t_{12}\frac{f(\lambda_2) - f(\lambda_1)}{\lambda_2 - \lambda_1}\\ 0 & f(\lambda_2)\end{bmatrix}$$

Inaccurate if $\lambda_1 \approx \lambda_2$.

Need a better way to compute the divided difference $f[\lambda_2, \lambda_1]$.



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Log of 2×2 Block

$$\begin{split} \log \lambda_2 - \log \lambda_1 &= \log \left(\frac{\lambda_2}{\lambda_1} \right) + 2\pi i \mathcal{U} (\log \lambda_2 - \log \lambda_1) \\ &= \log \left(\frac{1+z}{1-z} \right) + 2\pi i \mathcal{U} (\log \lambda_2 - \log \lambda_1), \end{split}$$

where U = unwinding number, $z = (\lambda_2 - \lambda_1)/(\lambda_2 + \lambda_1)$.

$$\operatorname{atanh}(z) := \frac{1}{2} \log \left(\frac{1+z}{1-z} \right),$$



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where U = unwinding number, $z = (\lambda_2 - \lambda_1)/(\lambda_2 + \lambda_1)$.

$$\operatorname{atanh}(z) := \frac{1}{2} \log \left(\frac{1+z}{1-z} \right),$$

$$f_{12} = t_{12} \frac{2 \operatorname{atanh}(z) + 2\pi i \mathcal{U}(\log \lambda_2 - \log \lambda_1)}{\lambda_2 - \lambda_1}.$$



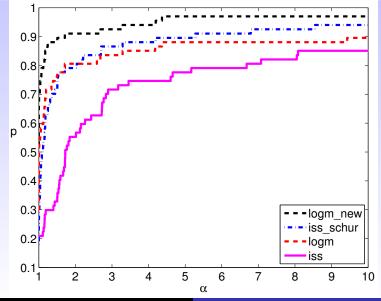
Numerical Experiment

- ▶ 67 test matrices, dimension 2–10.
- Evaluated $\|\widehat{X} \log(A)\|_F / \|\log(A)\|_F$.
- ► Notation:
 - ▶ logm: MATLAB 7.4 (R2007a).
 - logm_new: New version of logm.
 - iss_schur: Schur decomp then ISS.
 - iss: ISS on full A.

 $\blacktriangleright \operatorname{cond}(A) = \lim_{\epsilon \to 0} \max_{\|E\|_2 \le \epsilon \|A\|_2}$

$$\frac{\log(A+E) - \log(A)\|_2}{\epsilon \|\log(A)\|_2}$$

Performance Profile



$\log(A)b$

Hale, H & Trefethen, Computing A^{α} , log(A) and Related Matrix Functions by Contour Integrals, 2007.

- New methods for *f*(*A*)*b* where *f* has singularities in (−∞, 0] and *A* is a matrix with ei'vals on or near (0, ∞).
- Contour integrals + conformal map + repeated trapezium rule ⇒ geometric convergence.

In Conclusion

- Matrix logarithm and square root are archetypal examples of multivalued matrix functions (LambertW: Corless, Ding, H & Jeffrey, 2007).
- Able to classify all logs.
- Non-primary logs of interest, but little is known.
- Improvements to inverse scaling and squaring alg and to logm.
- Exploiting structure?

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