# Semidefinite approximations of the matrix logarithm 

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Joint work with:

## Original motivation: quantum information

How to solve convex optimization problems involving, e.g., quantum relative entropy?

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No existing off-the-shelf methods
Some bespoke algorithms for particular problems:

- Classical-to-quantum channel capacity [Sutter et al. 2016]
- Relative entropy of entanglement [Zinchenko et al. 2010]


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Can we exploit and leverage (or extend) successful existing technology (e.g., parsers/solvers for LP/SOCP/SDP, like CVX)?

## Fundamental issue:

- Semidefinite programming (SDP) can only solve semialgebraic problems
- Problems involving logarithms (or entropy) are not semialgebraic

This talk:

- Principled approximations of logarithm that can be modeled using SDP
- Complexity of SDP approximation grows mildly with approximation quality
- Works for matrix logarithm and related functions (e.g., quantum entropy)
- Larger theme: what is the SDP complexity of sets and functions?

Logarithm


## Logarithm



Properties

- Monotone:

$$
x \geq y>0 \quad \text { implies } \quad \log (x) \geq \log (y)
$$

- Concave:

$$
\{(x, \tau): x>0, \log (x) \geq \tau\} \quad \text { is a convex set }
$$

## Logarithm



Related functions:

- Entropy: $H(p)=-\sum_{i=1}^{n} p_{i} \log \left(p_{i}\right)$ is concave
- Kullback-Leibler divergence (or relative entropy)

$$
D(p \| q)=\sum_{i=1}^{n} p_{i} \log \left(p_{i} / q_{i}\right)
$$

convex in $(p, q)$

## Matrix logarithm

For positive definite $X$ with eigendecomposition

$$
X=U \operatorname{diag}\left(\lambda_{1}, \ldots, \lambda_{n}\right) U^{*}
$$

define

$$
\log (X)=U \operatorname{diag}\left(\log \left(\lambda_{1}\right), \ldots, \log \left(\lambda_{n}\right)\right) U^{*}
$$

## Properties

- Operator monotone:

$$
X \succeq Y \succ 0 \quad \text { implies } \quad \log (X) \succeq \log (Y)
$$

- Operator concave:

$$
\{(X, T): X \succ 0, \log (X) \succeq T\} \quad \text { is convex }
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## Matrix logarithm

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Related functions:

- Entropy $-\operatorname{tr}[X \log (X)]$ is concave in $X$
- Quantum relative entropy

$$
D(X \| Y)=\operatorname{tr}[X(\log (X)-\log (Y))]
$$

convex in $(X, Y)$ [Lieb-Ruskai, 1973]

## Semidefinite representations

Concave function $f$ has a semidefinite representation of size $d$ if:

$$
f(x) \geq t \quad \Longleftrightarrow \quad \exists u \in \mathbb{R}^{m}: \mathcal{S}(x, t, u) \succeq 0
$$

for some affine function $\mathcal{S}: \mathbb{R}^{n+1+m} \rightarrow \mathbf{S}^{d}$.

- Key fact: $f$ has semidefinite representation $\Longrightarrow$ can solve opt. problems involving $f$ using semidefinite solvers


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- Key fact: $f$ has semidefinite representation $\Longrightarrow$ can solve opt. problems involving $f$ using semidefinite solvers
- Many convex/concave functions have SDP representations ( "can solve using LMIs...")


## Logarithm function

Goal: find a semidefinite representation of (matrix) logarithm.

$$
\log X \succeq T \quad \Longleftrightarrow \quad ? ? ?
$$

Problem: Logarithm not semialgebraic! We must approximate

Want: Size of representation to grow mildly with approximation quality

## Logarithms and matrix friends

Many inter-related convex functions:


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Many inter-related convex functions:


- For positive definite $X$ with eigendecomposition:

$$
X=U \Lambda U^{*} \quad \rightarrow \quad \log (X):=U \log (\Lambda) U^{*}
$$

- Matrix log is operator monotone and operator concave


## Starting point: Integral representation

$$
\log (x)=\int_{0}^{1} \frac{x-1}{1+\xi(x-1)} d \xi
$$

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$$

Integrand:
Rational, (operator) monotone and concave, has SDP rep. for fixed $\xi$ :

$$
\frac{x-1}{1+\xi(x-1)} \succeq \tau \quad \Longleftrightarrow \quad\left[\begin{array}{cc}
1+\xi(x-1) & 1 \\
1 & 1-\xi \tau
\end{array}\right] \succeq 0
$$

In the background: Löwner's theorem on operator monotone functions

## Idea 1: Approximate via quadrature

$$
\begin{aligned}
\log (x) & =\int_{0}^{1} \frac{x-1}{1+\xi(x-1)} d \xi \\
& \approx \sum_{j=1}^{m} w_{j} \frac{x-1}{1+\xi_{j}(x-1)}=: r_{m}(x)
\end{aligned}
$$

for quadrature nodes $\xi_{j} \in(0,1)$ and weights $w_{j}>0$

- $r_{m}(x)$ is rational, operator monotone, operator concave
- $r_{m}(x)$ has semidefinite rep. with $m$ LMIs of size $2 \times 2$


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Which quadrature rule to use?
Gaussian quadrature, with $w_{i}$ given by Gauss-Legendre weights.
Nice properties, e.g., gives Padé approximant at 1

## Idea 2: Using the functional equation $\log \left(x^{h}\right)=h \log (x)$

## Observations:

- $r_{m}(x)$ is very good approximation to $\log (x)$ when $x \approx 1$
- $x^{1 / 2^{k}} \approx 1$ (Briggs (1617) method for computing log)



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- $x^{1 / 2^{k}} \approx 1$ (Briggs (1617) method for computing log)

Define: two-parameter family of approximations

$$
r_{m, k}(x):=2^{k} r_{m}\left(x^{1 / 2^{k}}\right) \approx 2^{k} \log \left(x^{1 / 2^{k}}\right)=\log (x)
$$

- operator monotone and operator concave
- has semidefinite rep. with $m+k$ LMIs of size $2 \times 2$

$$
r_{m, k}(x) \geq \tau \quad \Longleftrightarrow \quad \exists u \text { s.t. } 2^{k} r_{m}(u) \geq \tau, \quad x^{1 / 2^{k}} \geq u
$$

## Approximation error

Approximation error $\left\|r_{m, k}-\log \right\|_{\infty}$ on [1/a, a]
Optimal choice: $m \approx k$.


Theorem
There exists a semidefinite representable function $r$ such that

$$
|r(x)-\log (x)| \leq \epsilon \quad \text { for all } x \in[1 / a, a]
$$

and $r$ has semidefinite rep. of size $O(\sqrt{\log (1 / \epsilon)}+\log \log (a))$

## Logarithm and matrix friends (SDP version)

What about matrix logarithm?

$$
\begin{aligned}
& \log (X) \approx r_{m, k}(X) \succeq T, \\
& \begin{array}{ccc}
\log (x) \\
\text { matrix arg } \\
\underset{\log (X)}{\downarrow} & \xrightarrow{\text { perspective }} & \begin{array}{c}
y \log (x / y) \\
\text { NC Perspective }
\end{array} \\
Y^{\frac{1}{2}} \log \left(Y^{-\frac{1}{2}} X Y^{-\frac{1}{2}}\right) Y^{\frac{1}{2}}
\end{array}
\end{aligned}
$$

- $2 \times 2$ linear matrix inequalities become $2 n \times 2 n$

$$
\left[\begin{array}{cc}
1+\xi(x-1) & 1 \\
1 & 1-\xi \tau
\end{array}\right] \succeq 0 \quad \rightarrow\left[\begin{array}{cc}
I+\xi(X-I) & I \\
I & I-\xi T
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## Logarithm and matrix friends (SDP version)

What about matrix logarithm?

$$
\log (X) \approx r_{m, k}(X) \succeq T, \quad \underset{\text { matrix arg }}{\log (x)} \xrightarrow{\log (X)} \xrightarrow{\text { pCerspective }} \xrightarrow{y \log (x / y)} \xrightarrow[\substack{\text { perspective }}]{\downarrow{ }^{\text {bimatrix arg }}} \underset{Y^{\frac{1}{2}} \log \left(Y^{-\frac{1}{2}} X Y^{-\frac{1}{2}}\right) Y^{\frac{1}{2}}}{ }
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- Related to inverse scaling and squaring method or Briggs-Padé method in numerical analysis
- Preserves operator concavity, via SDP.
- Links to "free spectrahedra" (Helton et al.)


## Relative entropy cone

$$
K_{\mathrm{re}}=\{(x, y, \tau): x, y>0,-y \log (y / x) \leq \tau\}
$$

- Can approximate by homogenizing LMIs in our approximation for logarithm ( $1 \leftrightarrow y$ )
- Can model, e.g., geometric programs in conic form w.r.t. products of $K_{r e}$
- Can then approximate with second-order cone programs

What about matrices?

## Operator relative entropy cone

Theorem [Effros, Ebadian et al.]
If $f$ operator concave then matrix perspective of $f$, i.e.,

$$
g(X, Y)=Y^{1 / 2} f\left(Y^{-1 / 2} X Y^{-1 / 2}\right) Y^{1 / 2}
$$

is jointly matrix concave in $(X, Y)$.
Operator relative entropy cone

$$
K_{\mathrm{re}}^{n}=\{(X, Y, T): X, Y \succ 0,
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$$
\left.-Y^{1 / 2} \log \left(Y^{-1 / 2} X Y^{-1 / 2}\right) Y^{1 / 2} \preceq T\right\}
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$$

- Can approximate by 'homogenizing' LMIs in approximation for matrix logarithm $(I \leftrightarrow Y)$


## Approximating quantum relative entropy

Quantum relative entropy

$$
D(Y \| X)=\operatorname{tr}[Y \log (Y)-Y \log (X)]
$$

(Effros 2009, Tropp 2015) $D(Y \| X)$ can be written as

$$
-\phi\left[(I \otimes Y)^{1 / 2} \log \left((I \otimes Y)^{-1 / 2}(X \otimes I)(I \otimes Y)^{-1 / 2}\right)(I \otimes Y)^{1 / 2}\right]
$$

where $\phi$ is the positive linear map s.t. $\phi(X \otimes Y)=\operatorname{tr}(X Y)$.

## Approximating quantum relative entropy

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where $\phi$ is the positive linear map s.t. $\phi(X \otimes Y)=\operatorname{tr}(X Y)$.
Representation with operator relative entropy cone

$$
\begin{aligned}
& K_{\mathrm{re}}^{n}=\left\{(X, Y, T): X, Y \succ 0,-Y^{1 / 2} \log \left(Y^{-1 / 2} X Y^{-1 / 2}\right) Y^{1 / 2} \preceq T\right\} \\
& \left.D(Y \| X) \leq \tau \Longleftrightarrow \exists T \text { s.t. }(X \otimes I, I \otimes Y, T) \in K_{\mathrm{re}}^{\mathrm{n}^{2}}, \phi(T) \leq \tau\right\}
\end{aligned}
$$

## Maximum entropy problems

$$
\begin{array}{ll}
\operatorname{maximize} & -\sum_{i=1}^{n} x_{i} \log \left(x_{i}\right) \\
\text { subject to } & A x=b \\
& x \geq 0
\end{array} \quad\left(A \in \mathbb{R}^{\ell \times n}, b \in \mathbb{R}^{\ell}\right)
$$

| $n$ | $\ell$ | CVX's succ. approx. time (s) accuracy* |  | Our approach time (s) | $m=3, h=1 / 8$ <br> accuracy* |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 200 | 100 | 1.10 s | $6.635 \mathrm{e}-06$ | 0.88 s | $2.767 \mathrm{e}-06$ |
| 400 | 200 | 3.38 s | $2.662 \mathrm{e}-05$ | 0.72 s | $1.164 \mathrm{e}-05$ |
| 600 | 300 | 9.14 s | $2.927 \mathrm{e}-05$ | 1.84 s | $2.743 \mathrm{e}-05$ |
| 1000 | 500 | 52.40 s | $1.067 \mathrm{e}-05$ | 3.91 s | $1.469 \mathrm{e}-04$ |

*accuracy measured wrt specialized MOSEK routine

- CVX's successive approx.: Uses Taylor expansion instead of Padé approx + successively refine linearization point


## Relative entropy of entanglement

Quantify entanglement of a bipartite state $\rho$ :

$$
\min D(\rho \| \tau) \text { s.t. } \tau \in \operatorname{Sep}
$$

| $n$ | Cutting-plane <br> [Zinchenko et al.] | Our approach <br> $m=3, h=1 / 8$ |
| :--- | :--- | :--- |
| 4 | 6.13 s | 0.55 s |
| 6 | 12.30 s | 0.51 s |
| 8 | 29.44 s | 0.69 s |
| 9 | 37.56 s | 0.82 s |
| 12 | 50.50 s | 1.74 s |
| 16 | 100.70 s | 5.55 s |

```
cvx_begin sdp
    variable tau(na*nb,na*nb) hermitian;
    minimize (quantum_rel_entr(rho,tau));
    subject to tau >= 0; trace(tau) == 1;
    % PPT constraint
    Tx(tau,2,[na nb]) >= 0;
```

cvx_end

## Beyond logarithm (and friends)

Recall two parts to the approximation:

1. Integral representation (with positive measure $\mu$ )

$$
f(x)=\int F(x, \xi) d \mu(\xi)
$$

where $x \mapsto F(x, \xi)$ has semidefinite rep. for fixed $\xi$.
2. Functional equation $h \log (x)=\log \left(x^{h}\right)$

First idea generalizes to other classes of functions:

- hypergeometric functions (for certain parameter ranges)
- operator monotone and concave functions on ( $0, \infty$ )

Sometimes second idea generalizes: AGM, logarithmic mean, ...

## Conclusion

## Broad issues:

- What can we describe with small SDPs (or SOCPs)?
- What can we approximate with small SDPs (or SOCPs)?
- How to approximate and preserve structural properties?


## This talk:

- Matrix logarithm has $\epsilon$-approximate semidefinite description with $O(\sqrt{\log (1 / \epsilon)}), 2 n \times 2 n$ LMIs
- Gives approximate semidefinite description for quantum relative entropy, operator relative entropy
- Gives new SOCP approx. for relative entropy cone


## More information

Paper: H. Fawzi, J. Saunderson, P. Parrilo, 'Semidefinite approximations of the matrix logarithm' arXiv:1705.00812. Foundations of Computational Mathematics, 2018.

Accompanying paper: H. Fawzi, O. Fawzi, 'Relative entropy optimization in quantum information theory via semidefinite programming approximations.' arXiv:1705.06671, Journal of Physics A: Mathematical and Theoretical, 2018.

Code: www.github.com/hfawzi/cvxquad

