

Optimization, Complexity, and Math

(or, can we prove $P \neq NP$
using gradient descent?)

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Visu Makam, Rafael Oliveira, Michael Walter

Scientific / Mathematical/ Intellectual / Computational problems

NP: Problems we
want to solve/understand

P: Problems we
can
solve/understand

P=NP?

Plan

One problem

Singularity of Symbolic Matrices

One algorithm

Alternating minimization

...internalize

...generalize (algorithms, problems, tools) 

Extending convex optimization in Euclidean space to (**geodesic**) convex optimization on Riemannian manifolds, quantitative bounds

Applications & Connections

Non-commutative Algebra

Word problem in free skew fields

Invariant Theory

Nullcone membership & orbit closure intersection

Quantum Information Theory

Positive operators, quantum marginals

Analysis

Brascamp-Lieb inequalities

Operator Theory

Pauslen's problem on Parseval frames

Statistics

MLE in Gaussian models, Tyler's M-approximation

Computational complexity

Symbolic matrices, algebraic identities, lower bounds

Optimization

Efficiently solving certain general families of

- Quadratic systems of equations
- Exponentially large linear LPs

Optimization, Complexity and Math through one problem and one algorithm

One problem

Singularity of Symbolic Matrices

One algorithm

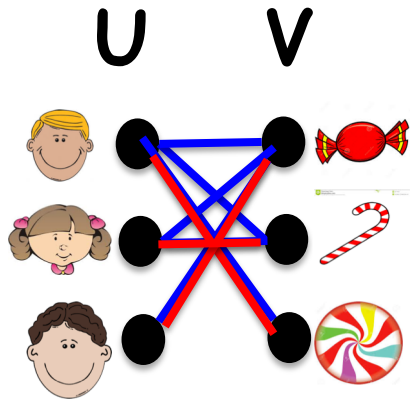
Alternating minimization

The problem(s)

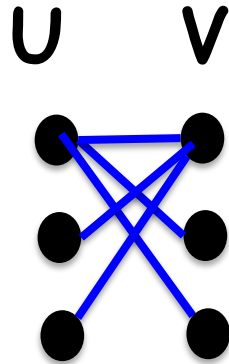
Perfect Matchings (PMs)

Bipartite graphs $G(U, V; E)$.

$$|U| = |V| = n$$



G'



G

	V		
	1	1	1
U	1	0	0
	1	0	0

A_G

Fact: G has a PM iff $\text{Per}(A_G) > 0$

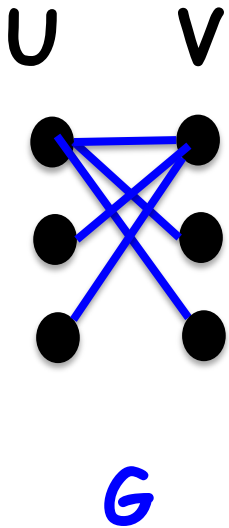
$$\text{Per}_n(A) = \sum_{\sigma \in S_n} \prod_{i \in [n]} A_{i\sigma(i)}$$

[Jacobi'1890]

PM $\in P$

(P = polynomial time)

PMs & symbolic matrices [Edmonds'67]



1	1	1
1	0	0
1	0	0

A_G

x_{11}	x_{12}	x_{13}
x_{21}	0	0
x_{31}	0	0

$A_G(X)$

[Edmonds '67] G has a PM iff $\text{Det}(A_G(X)) \neq 0$ ($\in \mathbf{P}$)

Symbolic matrices [Edmonds'67]

$X = \{x_1, x_2, \dots\}$ F field ($F=Q$)

$L_{ij}(X) = ax_1 + bx_2 + \dots$:linear forms

$L(X) = A_1x_1 + A_2x_2 + \dots + A_mx_m$ $A_i \in \text{Mat}_n(F)$

SING: Given (A_1, \dots, A_m) is $\text{Det}(L(X))=0$?

L_{11}	L_{12}	L_{13}
L_{21}	L_{22}	L_{23}
L_{31}	L_{32}	L_{33}

$L(X)$

[Edmonds '67] **SING** $\in P$??

[Lovasz '79] **SING** $\in RP$

Randomized
Poly Time

[Valiant '79] **SING** captures algebraic identities (PIT)

Math special cases: Module isomorphism, graph rigidity, ...

[Kabanets-Impagliazzo'01] **SING** $\in P \rightarrow "P \neq NP"$

Derandomization, Lower bounds

Symbolic matrices dual life

$X = \{x_1, x_2, \dots, x_m\}$ F field

$$L(X) = A_1x_1 + A_2x_2 + \dots + A_mx_m$$

Input: $A_1, A_2, \dots, A_m \in M_n(F)$

SING : Is $L(X)$ singular?

L_{11}	L_{12}	L_{13}
L_{21}	L_{22}	L_{23}
L_{31}	L_{32}	L_{33}

x_i commute

in $F(x_1, x_2, \dots, x_m)$

[Lovasz '79] **SING** \in **RP**

[Edmonds'67] **SING** \in **P?**

x_i do not commute

in $F\langle(x_1, x_2, \dots, x_m)\rangle$ (free skew field)

[Cohn'75] **NC-SING** **Decidable**

[CR'99] **NC-SING** \in **EXP**

[GGOW'15] **NC-SING** \in **P** ($F=Q$)

[IQS'16] **NC-SING** \in **P** (F large)

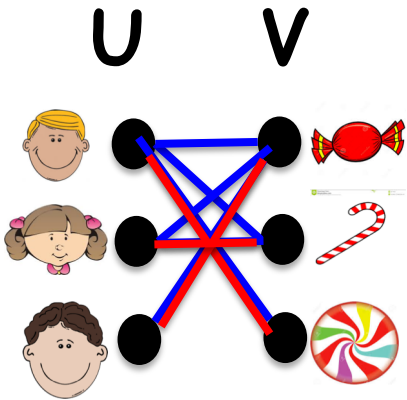
The algorithm

Alternate minimization

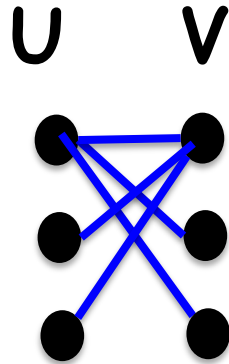
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$$\text{Per}_n(A) = \sum_{\sigma \in S_n} \prod_{i \in [n]} A_{i\sigma(i)}$$

[Jacobi'1890]

PM \in P

(P = polynomial time)

Matrix Scaling

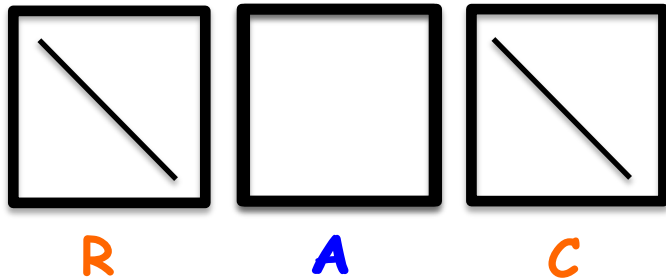
[...Sinkhorn'64,...]

A non-negative matrix.

A doubly-stochastic (DS): $A\mathbf{1}=\mathbf{1}, \mathbf{1}^T A=\mathbf{1}^T$

Scaling:

Multiply **rows** & **columns** by scalars



DS-Scaling:

Find (if exists?) **R, C** diagonal s.t.

RAC has row-sums & col-sums ≈ 1

Why?

- Numerical analysis
- Signal processing
- Approx Permanent
- Perfect matching
-

\leftrightarrow $\text{Per}(A) > 0$

Scaling algorithm [Sinkhorn'64,...]

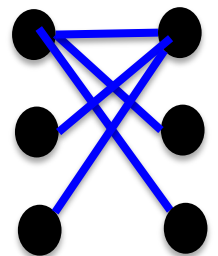
A non-negative matrix. Try making it doubly stochastic.
(e.g. the adjacency matrix $A=A_G$ of a bipartite graph G)

Find (if exists?) R, C diagonal s.t.
 RAC has row-sums & col-sums ≈ 1

Hard to do simultaneously...

Let's deal with rows & cols separately!

1	1	1
1	0	0
1	0	0



Scaling algorithm [Sinkhorn'64]

Scale rows

$1/3$	$1/3$	$1/3$
1	0	0
1	0	0

Scaling algorithm

Scale columns

$1/7$	1	1
$3/7$	0	0
$3/7$	0	0

Scaling algorithm

Scale rows

$1/15$	$7/15$	$7/15$
1	0	0
1	0	0

Scaling algorithm

Scale columns

0	1	1
1/2	0	0
1/2	0	0

Scaling algorithm

Scale rows

0	$1/2$	$1/2$
1	0	0
1	0	0

Scaling algorithm

Scale columns

0	1	1
1/2	0	0
1/2	0	0

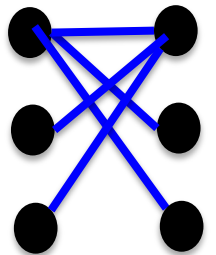
Scaling algorithm

Scale rows

0	1/2	1/2
1	0	0
1	0	0

No convergence!

No perfect matching: $\text{Per}(A)=0$



Scaling algorithm

A non-negative matrix. Try making it doubly stochastic.

Scaling factors

$$R(A) = \text{diag}(\text{row sums})^{-1} \quad C(A) = \text{diag}(\text{column sums})^{-1} \quad \neq 0$$

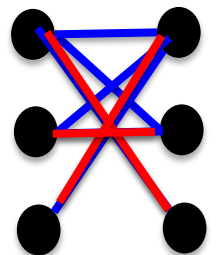
Repeat n^3 times:

Scale rows $A \leftarrow R(A) \times A$

Scale cols $A \leftarrow A \times C(A)$

“Alternating minimization”
heuristic

1	1	1
1	1	0
1	0	0



Scaling algorithm

A non-negative matrix. Try making it doubly stochastic.

$$R(A) = \text{diag}(\text{row sums})^{-1} \quad C(A) = \text{diag}(\text{column sums})^{-1}$$

Repeat n^3 times:

$$\text{Scale rows } A \leftarrow R(A) \times A$$

$$\text{Scale cols } A \leftarrow A \times C(A)$$

Scale rows

1/3	1/3	1/3
1/2	1/2	0
1	0	0

Scaling algorithm

A non-negative matrix. Try making it doubly stochastic.

$$R(A) = \text{diag}(\text{row sums})^{-1} \quad C(A) = \text{diag}(\text{column sums})^{-1}$$

Repeat n^3 times:

Scale rows $A \leftarrow R(A) \times A$

Scale cols $A \leftarrow A \times C(A)$

Scale columns

$2/11$	$2/5$	1
$3/11$	$3/5$	0
$6/11$	0	0

Scaling algorithm

A non-negative matrix. Try making it doubly stochastic.

$$R(A) = \text{diag}(\text{row sums})^{-1} \quad C(A) = \text{diag}(\text{column sums})^{-1}$$

Repeat n^3 times:

Scale rows $A \leftarrow R(A) \times A$

Scale cols $A \leftarrow A \times C(A)$

Scale rows

$10/87$	$22/87$	$55/87$
$15/48$	$33/48$	0
1	0	0

Scaling algorithm

A non-negative matrix. Try making it doubly stochastic.

$$R(A) = \text{diag}(\text{row sums})^{-1} \quad C(A) = \text{diag}(\text{column sums})^{-1}$$

Repeat n^3 times:

$$\text{Scale rows } A \leftarrow R(A) \times A$$

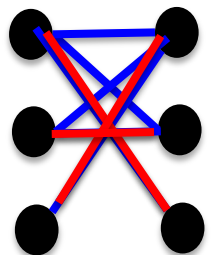
$$\text{Scale cols } A \leftarrow A \times C(A)$$

Scale rows

0	0	1
0	1	0
1	0	0

Converges!

Has perfect matching: $\text{Per}(A) > 0$



Analysis of the algorithm

[Linial-Samorodnitsky-W'01]

A non-negative $(0,1)$ matrix.

Repeat $t=n^3$ times:

Scale rows $A \leftarrow R(A) \times A$

Scale cols $A \leftarrow A \times C(A)$

Test if $A_t \approx DS$ (up to $1/n$)

Yes: $\text{Per}(A) > 0$.

No: $\text{Per}(A) = 0$.

0	0	1
		0
1	0	0

Algorithm for
Perfect Matching

Analysis: $\text{Per}(A_i)$ a progress measure!

- $\text{Per}(A_i) \leq 1$

(easy)

- $\text{Per}(A_i)$ grows* by $(1+1/n)$

(AMGM)

- $\text{Per}(A) > 0 \rightarrow \text{Per}(A_1) > 1/n^n$

(easy)

Done (baby case):

Bip matching & Matrix Scaling

Now (real thing):

NC-SING & Operator Scaling

[Gurvits'04]

[Garg, Gurvits, Oliveira, W'15]

[Gurvits '04] Quantum leap

Input

Norm

DS

R,C

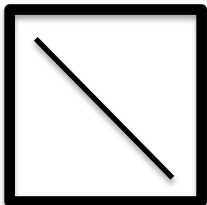
Matrix Scaling

Positive matrix

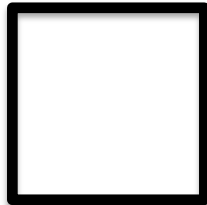
L_1

$$A\mathbf{1}=\mathbf{1}, \quad A^T\mathbf{1}=\mathbf{1}$$

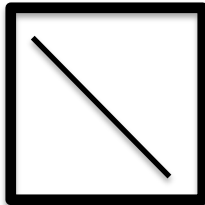
Diagonal



R



A



C

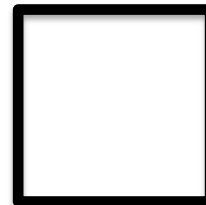
Operator Scaling

Positive operator

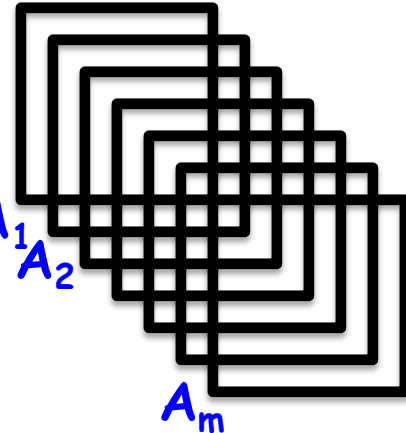
L_2

$$\sum_i A_i A_i^\dagger = I \quad \sum_i A_i^\dagger A_i = I$$

Invertible



R



C

Operator Scaling [Gurvits '04]

a quantum leap

Algebra

Input: $L=(A_1, A_2, \dots, A_m)$

Symbolic matrix

$L: A_1x_1 + A_2x_2 + \dots + A_mx_m$

Quantum Inf. Theory

Input: $L=(A_1, A_2, \dots, A_m)$

Completely positive operator

$L(P) = \sum_i A_i P A_i^\dagger$ P psd $\Rightarrow L(P)$ psd

L doubly stochastic:

$$\sum_i A_i A_i^\dagger = I \quad \sum_i A_i^\dagger A_i = I$$

$$L(I) = I \quad L^\dagger(I) = I$$

Is L C-singular?



Is L NC-singular?



[GGOW'15]

Can we (not) scale L ?

Operator scaling algorithm

[Gurvits '04, Garg-Gurvits-Olivera-W'15]

$$L = (A_1, A_2, \dots, A_m).$$

Scaling: $L \rightarrow RLC$, R, C invertible, DS: $\sum_i A_i A_i^\dagger = I$ $\sum_i A_i^\dagger A_i = I$

Scaling factors: $R(L) = (\sum_i A_i A_i^\dagger)^{-1/2}$ $C(L) = (\sum_i A_i^\dagger A_i)^{-1/2}$

Repeat $t = n^c$ times:

Scale "rows" $L \leftarrow R(L) \times L$

Scale "cols" $L \leftarrow L \times C(L)$

Test if $L_t \approx \text{DS}$ (up to $1/n$)

Yes: L NC-nonsing $\text{cap}(L) > 0$

No: L NC-singular $\text{cap}(L) = 0$

Progress measure

$$\text{Capacity}(L) = \inf_{P > 0} \frac{\det(L(P))}{\det(P)}$$

$$\det(L(P)) / \det(P)$$

Algorithm: Group action

Measure: "Invariant"

Analysis: Degrees of invariant polynomials

Analysis: - $\text{Cap}(L_i) \leq 1$

- $\text{Cap}(L_i)$ grows* by $(1 + 1/n)$ (AMGM)

- $\text{Cap}(L) > 0 \rightarrow \text{Cap}(L_1) > \exp(-n^c)$ [GGOW'15]

6 areas, 6 problems [GGOW'15+16]

$$L = (A_1, A_2, \dots, A_m), \quad A_i \in \text{Mat}_n(\mathbb{F}) \quad (\text{e.g. } \mathbb{F} = \mathbb{Q})$$

Linear algebra $A_i: \mathbb{F}^n \rightarrow \mathbb{F}^n$ linear maps

Q1: \exists subspace U s.t. $\dim(\text{span}\{A_i U\}_i) < \dim(U)$?

In P

Arithmetic complexity theory: A describes a polynomial:

Q2: $L(X) = \det(\sum_i A_i X_i) = 0$?

In P

Quantum Information Theory L positive operator: $L(P) = \sum_i A_i P A_i^\dagger$

Q3: $\inf_{P > 0} \det(L(P)) / \det(P) = 0$?

In P

Non-commutative Algebra

Q4: Is $L(x) = \sum_i A_i x_i$ singular in $\mathbb{F}\langle x \rangle$? [word problem]

In P

Invariant Theory L orbit of $G = \text{SL}_n(\mathbb{F}) \times \text{SL}_n(\mathbb{F})$

Q5: Is $0 \in \underline{O}_G(L)$? [null cone problem]

In P

Analysis $A_i: \mathbb{R}^n \rightarrow \mathbb{R}^n$ linear maps

Q6: $\exists C < \infty \forall f_i: \mathbb{R}^n \rightarrow \mathbb{R}_+ \int_{x \in \mathbb{R}^n} (\prod_i f_i(A_i x)) \leq C \prod_j \|f_j\|_m$?

In P

Q1-Q5 are equivalent! Q6 special case



\mathbb{R}



- Energy
- Momentum

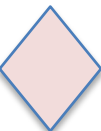
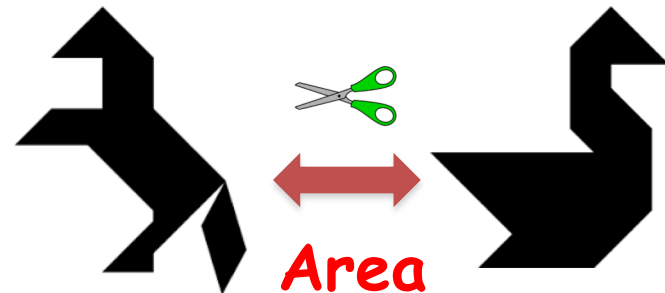
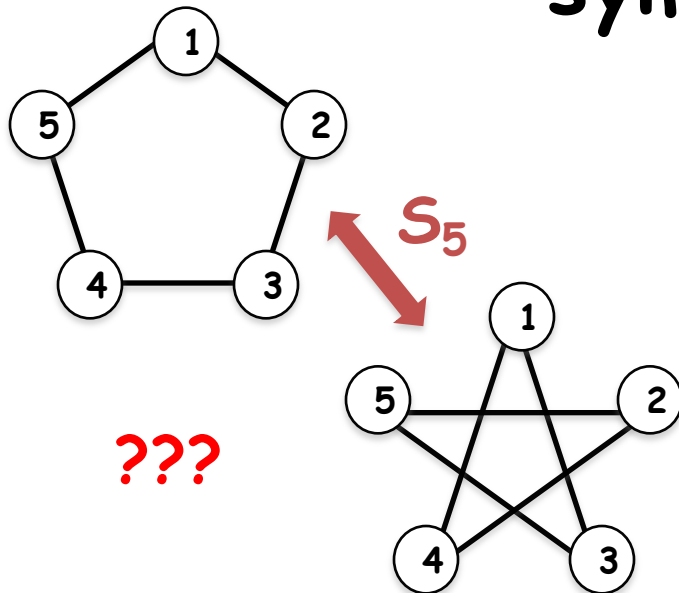
Here: Linear groups* (of matrices) act* on vector spaces (over \mathbb{C})

Algebraic: Polynomial invariants

Geometric: Non-commutative duality

Invariant Theory

symmetries, group actions,
orbits, invariants



Invariant theory

G acts on $V = F^k$, and $F = \mathbb{C}$ ($F = \mathbb{C}$)

Orbit: $Gv = \{gv : g \in G\}$ Nullcone Membership:

Invariant

$V^G = \{p \in V^* : p(gv) = p(v) \text{ for all } g \in G\}$
 Given v , does $v \in N(G)$?

Ex1: Dual to **Scaling** problems!

V^G

Res

$N(G) = \{0\}$

Ex2: Captures numerous problems across Math, CS, Physics, for different group actions

V^G

RvC

$\{ \text{matrices} \}$

Degree bounds?

[Hilbert] Invariant ring is finitely generated!

Key to alg analysis

Algebraic Variety

Nullcone: $N(G) = \{v : p(v) = 0 \text{ for all } p \in V^G, \deg(p) > 0\}$

[Hilbert, Mumford] $v \in N(G) \iff 0 \in \underline{Gv} \iff \inf_{g \in G} |gv| = 0$

Analytic \iff Algebraic

Unification and generalization I

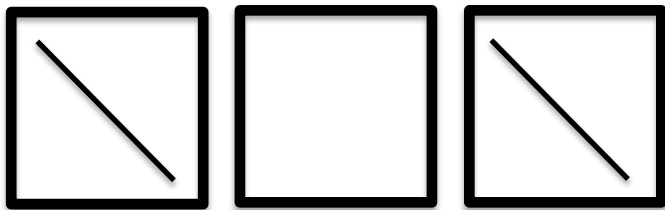
[BGOWW'17,F'17,BFGOWW'18]

Alternate minimization on groups

[BGOWW'17, F'17, BFGOWW'18]

Goal: Matrix **Scaling**

$$A1=1, A^+1=1$$



R

A

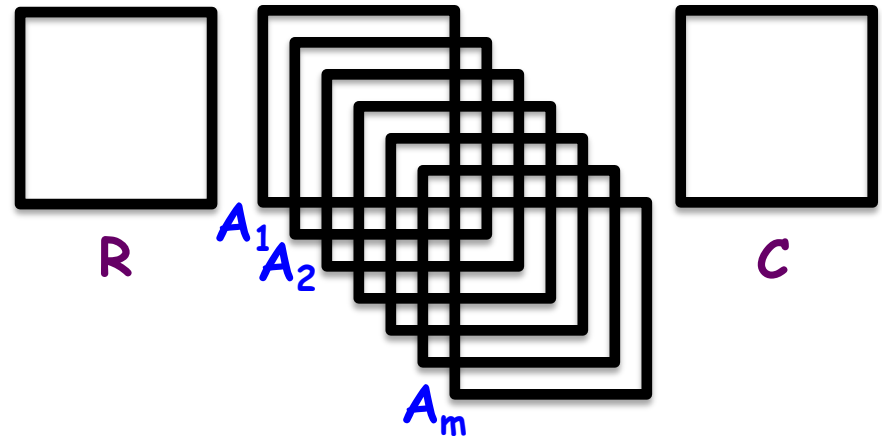
C

Alg: Alt. min. $T_n \times T_n$
(Diagonal group)²
action on matrices

Analysis: minimizing a potential function (permanent, capacity)

Operator **Scaling**

$$\sum_i A_i A_i^+ = I \quad \sum_i A_i^+ A_i = I$$



R

C

Alg: Alt. min. $GL_n \times GL_n$
(General linear group)²
action on tensors

Alternate Minimization

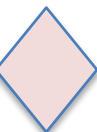
numerous other examples

(statistics, optimization, machine learning,...)

"solve" $f(z_1, z_2, \dots, z_i, \dots, z_k)$ all z_i complex

"solve" $f(a_1, a_2, \dots, z_i, \dots, a_k)$ one z_i simple/local
(a_j fixed)

Some examples we don't understand well...



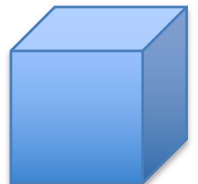
Alternate minimization on groups

Alt Minimization (coordinate descent)
(statistics, optimization, machine learning,...)

"solve" $f(z_1, z_2, \dots, z_i, \dots, z_k)$ all z_i complex

"solve" $f(a_1, a_2, \dots, z_i, \dots, a_k)$ one z_i simple/local

Here: group-theoretic framework



$G = G_1 \times G_2 \times \dots \times G_k$ $G_i = SL_n(\mathbb{C})$ or $ST_n(\mathbb{C})$ **k-tensor**

$V = V_1 \otimes V_2 \otimes \dots \otimes V_k$ $V_i = \mathbb{C}^n$, G_i acts on i -fibers of V

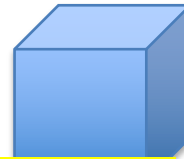
Non-convex

Goal: Given $v \in V$, **scale** it

[THM] Alt Min: $|v' - \text{"scaled"}| < \epsilon$ in $\text{poly}(|v|, n, 1/\epsilon)$ steps.

Alternate Minimization over groups

Applications and analysis



k-tensor

$$G = G_1 \times \dots \times G_n$$

$$V = V_1 \times \dots \times V_n$$

Why does such a simple greedy algorithm converge?

What connects scaling and nullcone problems?

Non-product groups? (no alternate minimization)

Not enough!

[THM] Alt Minimization converges in $\text{poly}(|v|, n, 1/\epsilon)$ steps.

Same alg,
"same" analysis.
Potential: $\| \cdot \|_2$

- $\|v_i\| \leq 1$ (easy)
- $\|v_i\|$ grows* by $(1+1/n)$ (AMGM)
- $v \notin N(G) \Rightarrow \|v\| > \exp(-n^c)$ (inv+rep th. ++)

Unification & generalization II

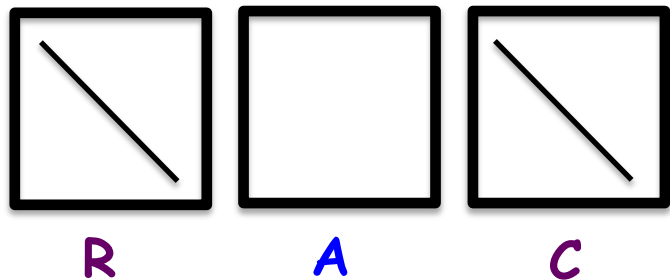
Non-commutative duality,

Geodesic convexity,

Moment map

Goal: Matrix Scaling

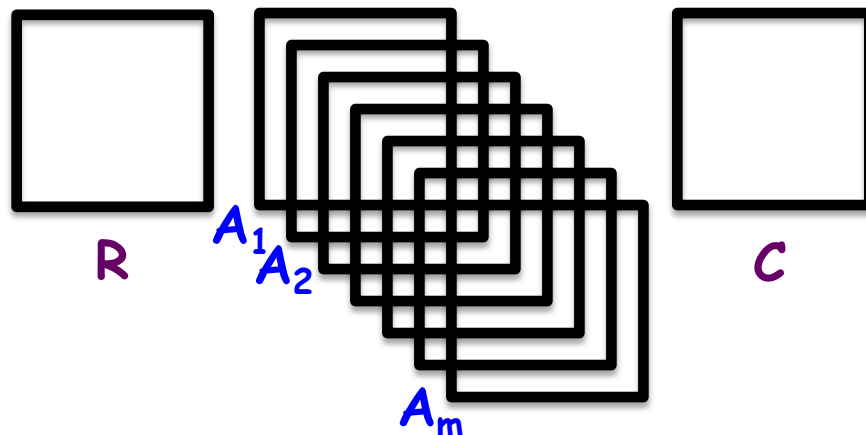
$$A\mathbf{1}=\mathbf{1}, A^+\mathbf{1}=\mathbf{1}$$



Alg: Alt. min. $T_n \times T_n$
(Diagonal group)²
action on matrices

Operator Scaling

$$\sum_i A_i A_i^+ = I \quad \sum_i A_i^+ A_i = I$$



Alg: Alt. min. $GL_n \times GL_n$
(General linear group)²
action on tensors

Analysis: minimize a potential function (permanent, capacity, L_2)

Let's switch analysis with goal!

Non-commutative duality

G acts on V (G matrix group, V vector space)

Optimization

Non-convex

Goal: given $v \in V$ compute $f(v) = \inf_{g \in G} \|gv\|_2 = 0?$

(find the list)

How to

[Kempner]

μ

- M

mini

- Non

Geodesic

Extends Euclidean convexity to Riemannian manifolds

Intuitively explains the convergence of a local, greedy algorithm like Alternate Minimization

Suggests extending convex optimization tools to geodesic setting

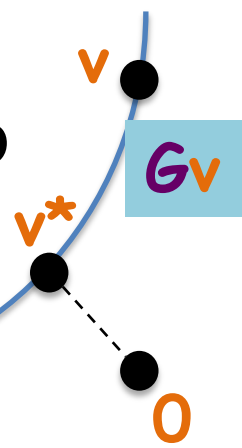
Nullcone problem

$v^* \neq 0$

al to

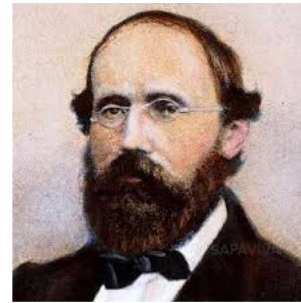
LP duality

opt = global opt

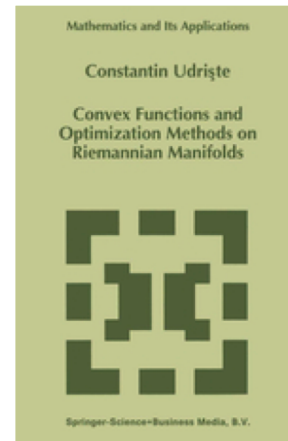
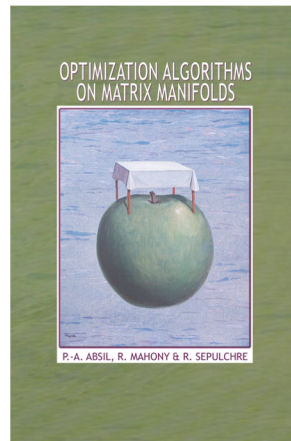


Beyond Euclidean convexity

Geodesic convexity



and algorithms



New: Quantitative complexity analysis

Geodesic optimization [AGLOW'17, BFGOWW'19]

General groups, beyond alt min & convex opt

G acts on V . Given $v \in V$, $\epsilon > 0$, approximate the minimum of $|u|$ or $|\mu_G(u)|$ in Gv .

Different problems

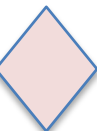
Oracle access to action + function + derivatives.

First order method ("gradient descent"):
 ϵ -convergence in $O(\text{poly}(1/\epsilon))$ iterations

Second order method ("box-constrained" Newton):
 ϵ -convergence in $O(\text{polylog}(1/\epsilon))$ iterations

Simple parameters

$O(\cdot)$ depends on "smoothness" of the action
(geometry of the weights of irreps of the action)



Conclusions & Open Problems

General themes

- Algorithms & complexity interacts with Math
- Analytic solutions to algebraic problems
- Algebraic analysis of continuous algorithms
- Symmetry is prevalent, using it is powerful

Natural research directions

- Algs still exponential for some applications
- Power of geodesic algs for comb. optimization
- Nullcone problems abound. Nullcone $\in P?$
- $C-SING \in P?$ "P vs. NP"? Any lower bounds??

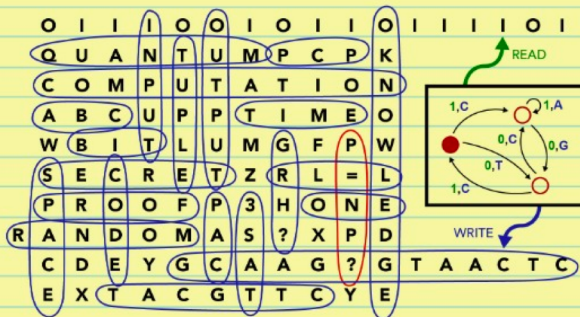
[Makam-W'19] $C-SING$ is *not* a nullcone problem!

Book ad

MATHEMATICS + COMPUTATION

A THEORY REVOLUTIONIZING
TECHNOLOGY AND SCIENCE

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