Algorithmic Aspects of the Brascamp Lieb Inequality

Jacob Denson

University of Wisconsin Madison

September 29, 2021

- Classical Complexity and Quantum Entanglement Gurvits, 2004.
- Algorithmic and Optimization Aspects of Brascamp-Lieb Inequalities, Via Operator Scaling

Garg, Gurvits, Oliveira, Wigderson, 2016. A Deterministic Polynomial Time Algorithm For Non-Commutative Rational Identity Testing Garg, Gurvits, Oliveira, Wigderson, 2016.

Lieb's Theorem

$$\int_{\mathbf{R}^n} \prod_{i=1}^m |f_i(B_i x)|^{p_i} dx \leq \mathsf{BL}(B, p) \cdot \prod_{i=1}^m \|f_i\|_{L^1(\mathbf{R}^{n_i})}^{p_i}.$$

- ▶ (Lieb, 1990) To calculate BL(B,p), plug in Gaussians.
- ▶ If $f_i(x) = e^{-\pi(A_ix)\cdot x}$ for $A_i \succ 0$, then

$$\int_{\mathbb{R}^n} \prod_{i=1}^m |f_i(B_i x)|^{p_i} dx = \det(\sum p_i B_i^* A_i B_i)^{-1/2}$$

$$\prod_{i=1}^{m} \|f_{i}\|_{L^{1}(\mathbb{R}^{n_{i}})}^{p_{i}} = \det(\prod_{i=1}^{m} \det(A_{i})^{p_{i}})^{-1/2}.$$

Thus

$$(\sum p_i B_i^* A_i B_i)^{-1/2} \leq \mathsf{BL}(B, p) \cdot (\prod_{i=1}^m \mathsf{det}(A_i)^{p_i})^{-1/2}$$

Lieb's Theorem

Rearranging gives

$$\mathsf{BL}(B,p) = \left(\sup_{A_1,\dots,A_m \succ 0} \frac{\prod_i \det(A_i)^{p_i}}{\det(\sum p_i B_i^* A_i B_i)}\right)^{1/2}.$$

- Non convex objective, so tricky to optimize (NP hard).
- Checking Finiteness efficiently also non-obvious.
 - ▶ BCCT gives a family of conditions to check finiteness.

$$\dim(V) \leq \sum p_i \dim(B_i V).$$

Since $0 \le \dim(V) \le n$ and $0 \le \dim(B_i V) \le n_i$, only finitely many linear conditions on the exponents p_i .

► Can be exponentially many constraints, so inefficient.

Geometric Brascamp Lieb

$$\int_{\mathbf{R}^n} \prod_{i=1}^m |f_i(B_i x)|^{p_i} dx \le \mathsf{BL}(B, p) \cdot \prod_{i=1}^m ||f_i||_{L^1(\mathbf{R}^{n_i})}^{p_i}$$

- A Brascamp-Lieb inequality is geometric if
 - ▶ (Projection Property): $B_i B_i^* = I$.
 - ▶ (Isotropy Property): $\sum_i p_i B_i^* B_i = I$.
- ▶ (Barthe, 1998), generalizing (Ball, 1989), showed that if (B, p) is geometric, BL(B, p) = 1.

Operator Rescaling

- ▶ What happens to BL(B, p) if we 'change coordinates'.
- Fix invertible matrices M and M_1, \ldots, M_m , and consider the Brascamp-Lieb inequality with matrices $B'_i = M_i B_i M$,

$$\int_{\mathbf{R}^n} \prod_{i=1}^m |f_i(M_i B_i M x)|^{p_i} dx \leq \mathsf{BL}(B', p) \cdot \prod_{i=1}^m \|f_i\|_{L^1(\mathbf{R}^{n_i})}^{p_i}.$$

$$\mathsf{BL}(B',p) = \sup_{A_1,\dots,A_m \succ 0} \frac{\prod_i \det(A_i)^{p_i}}{\det(\sum_i p_i M^* B_i^* M_i^* A_i M_i B_i M)}$$
$$= \det(M)^{-2} \prod_i \det(M_i)^{-2p_i} \cdot \mathsf{BL}(B,p).$$

Operator Rescaling

$$\mathsf{BL}(B',p) = \mathsf{det}(M)^{-2} \prod_{i} \mathsf{det}(M_i)^{-2p_i} \cdot \mathsf{BL}(B,p)$$

▶ If (B', p) is geometric, BL(B', p) = 1, so

$$\mathsf{BL}(B,p) = \mathsf{det}(M)^2 \prod_i \mathsf{det}(M_i)^{2p_i}.$$

▶ (BCCT) Geometric rescaling possible iff extremizers exist.

Main Result

- ▶ (Garg, Gurvits, Oliveira, Wigderson, 2018) If $BL(B,p) < \infty$, we can rescale to be within a ε of a geometric Brascamp-Lieb equation.
 - We can do this algorithmically, i.e. if p_i are rationals, with common denominator d, a computer can compute a ε -approximate geometric rescaling in $Poly(Bits(B,p),d,1/\varepsilon)$ computations.
 - ▶ Conversely, we can determine if $BL(B, p) = \infty$, and find a violating subspace V to the condition $\dim(V) \leq \sum p_i \dim(B_i V)$, in Poly(Bits(B, p), d) computations.
 - ▶ Open Problem: Can we can improve this to Poly(Bits(B, p), d, log($1/\varepsilon$)) computations?

Analytic Consequences

- Typing a single digit is a single unit of computation.
 - ▶ Thus given (B, p), either $BL(B, p) < \infty$, or

$$2^{-\mathsf{Poly}(\mathsf{Bits}(B,\rho),d,\log(1/\varepsilon))} \leq \mathsf{BL}(B,\rho)) \leq 2^{\mathsf{Poly}(\mathsf{Bits}(B,\rho),d,\log(1/\varepsilon))}.$$

- Calculation is also stable.
 - ► Thus we conclude a *continuity bound*:
 - ► For each BL input (B, p) with BL $(B, p) < \infty$, and each $\varepsilon > 0$, if

$$\|B_1 - B\| \le \exp\left(-\frac{\mathsf{Poly}(\mathsf{Bits}(B, p), d)}{\varepsilon^3}\right),$$

then

$$(1-\varepsilon)\mathsf{BL}(B,p) \leq \mathsf{BL}(B_1,p) \leq (1+\varepsilon)\mathsf{BL}(B,p).$$

Computing Permanents (An Analogous Problem)

▶ Given an $n \times n$ matrix A with non-negative entries, define

$$\mathsf{Perm}(A) = \sum_{\sigma \in S_n} \prod_i A_{i\sigma(i)}.$$

- ► This is (surprisingly) NP hard to compute.
 - ► If

$$R = \begin{pmatrix} \lambda_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \lambda_n \end{pmatrix} \quad \text{and} \quad C = \begin{pmatrix} \gamma_1 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \gamma_n \end{pmatrix},$$

then

$$\begin{aligned} \mathsf{Perm}(RAC) &= \mathsf{Perm}(\lambda_i A_{ij} \gamma_j) \\ &= (\lambda_1 \dots \lambda_n) (\gamma_1 \dots \gamma_n) \mathsf{Perm}(A) \\ &= \det(R) \det(C) \mathsf{Perm}(A). \end{aligned}$$

Computing Permanents (An Analogous Problem)

$$Perm(RAC) = det(R) det(C) Perm(A).$$

- ► (Egorychev, 1981), (Falikman, 1981) If A is doubly stochastic, $e^{-n} \leq \text{Perm}(A) \leq 1$.
- ▶ If *RAC* is doubly stochastic, then

$$\operatorname{Perm}(A) \leq \det(R)^{-1} \det(C)^{-1} \leq e^n \cdot \operatorname{Perm}(A),$$

so Perm(A) $\approx \det(R)^{-1} \det(C)^{-1}$.

▶ Given a non-negative matrix A_0 , alternatively apply row and column summation, obtaining a sequence

$$A_0 \rightarrow A_1 \rightarrow A_2 \rightarrow \dots$$

- ▶ Claim: If $Per(A_0) > 0$, $d(A_i, S) \to 0$, where **S** is the family of stochastic matrices.
- ► For even (odd) i, let γ_{ij} be the jth row (column) sum of A_i , so that $Per(A_{i+1}) = (\gamma_{i1} \dots \gamma_{in})^{-1} \cdot Per(A_i)$.
- Two Key Facts Ensuring Convergence:
 (1) Per(A) ≤ 1 if A is partially normalized.
 - (2) If $\Delta_i = \sum_i (\gamma_{ij} 1)^2$, $\operatorname{Per}(A_{i+1}) \geq (1 + C\Delta_i) \cdot \operatorname{Per}(A_i)$.
- ▶ Thus $Per(A_i)$ is bounded, monotonic, converges to $P \leq 1$.

$$P > \operatorname{Per}(A_{i+1}) > (1 + C \cdot \Delta_i) \cdot \operatorname{Per}(A_i) > (1 + C \cdot \Delta_i)(P - \varepsilon).$$

Thus $\Delta_i \lesssim_{C,P} \varepsilon$. Taking $\varepsilon \to 0$ shows $\Delta_i \to 0$.

▶ If $Per(A_i) > P - \varepsilon$ for $\varepsilon \ll 1$, then

Sinkhorn Iteration

- ▶ Proof that $Per(A_i) \le 1$:
 - Simple inductive argument: the hypothesis is that if each row of a matrix B all sum up to less than one, then $Per(B) \leq 1$.
- ▶ Proof that $Per(A_{i+1}) \ge (1 + C\Delta_i) \cdot Per(A_i)$:
 - Write $\gamma_i = 1 + \delta_i$.
 - ▶ Then $\sum \delta_i^2 = \Delta_i$, and $\sum \delta_i = 0$.
 - ► Since $1 + t \le \exp(t t^2/2 + t^3/3)$,

Per
$$(A_i)$$
/Per $(A_{i+1}) = \gamma_1 \dots \gamma_n$

$$= (1 + \delta_1) \dots (1 + \delta_n)$$

$$\leq \exp\left(\sum \delta_i - \sum \delta_i^2 / 2 + \sum \delta_i^3 / 3\right)$$

$$\leq \exp(0 - \Delta_i / 2 + \Delta_i^{3/2} / 3)$$

$$= 1 - \Delta_i / 2 + O(\Delta_i^{3/2}).$$

And now, back to our regularly scheduled programming

- $\mathsf{BL}(B,p) = \sqrt{\sup_{A_1,\dots,A_m \succeq 0} \frac{\prod_i \det(A_i)^{p_i}}{\det(\sum p_i \cdot B_i^* A_i B_i)}}.$

 - Goal: Rescale our inputs so that
 - \triangleright (Isotropy) $\sum p_i B_i^* B_i = I$. ▶ (Projection) $B_i B_i^* = I$ for each i.

Iteration of Operator Rescaling

- ► Sinkhorn: Alternately apply the following two procedures:
 - (Isotropy Normalization)
 - ightharpoonup Let $M = \sum_i p_i B_i^* B_i$.
 - ▶ Replace B_i with $B'_i = B_i M^{-1/2}$.
 - ▶ Then $\sum p_i(B'_i)^*B'_i = 1$, i.e. isotropy holds.
 - (Projection Normalization)
 - $\blacktriangleright \text{ Let } M_i = B_i B_i^*.$
 - Replace B_i with $B'_i = M_i^{-1/2}B_i$.
 - ▶ Then $(B_i')^*B_i' = I$ for each i.
 - ▶ We obtain a sequence $B \rightarrow B_1 \rightarrow B_2 \rightarrow \dots$

Iteration of Operator Rescaling

- ► Three Key Facts Ensuring Convergence:
 - (1) $BL(B, p) \ge 1$ if (B, p) is partially normalized.
 - (2) If $1 + \varepsilon \leq BL(B_i, p) \leq 2$, then

$$\mathsf{BL}(B_{i+1},p) \leq (1-C\varepsilon^s)\mathsf{BL}(B_i,p)$$

(3) If isotropy or projection holds, then

$$\|\sum p_i B_i^* B_i - I\| + \sum_i \|B_i^* B_i - I\| \lesssim \log(\mathsf{BL}(B, p)),$$

and so $d(B, \mathbf{G}_p) \lesssim \log(\mathsf{BL}(B, p)).$

- Thus convergence occurs as with Sinkhorn iteration provided that $BL(B, p) < \infty$.
- ▶ (1), (2), and (3) follow from techniques in the study of *positive operators*.

Another Viewpoint: Positive Operators

- For simplicity, assume that all spaces have the same ambient dimension (all B_i are square matrices).
- ▶ BL $(B, p) < \infty$ can only hold if $\sum p_i = 1$.
- Also assume all A_i are equal, and let us consider optimizing the quantity

$$\inf_{A\succ 0}\frac{\det(\sum p_iB_i^*AB_i)}{\det(A)}$$

analogous to

$$\mathsf{BL}(B,p) = \sup_{A_1,\dots,A_m \succ 0} \sqrt{\frac{\prod_i \mathsf{det}(A_i)^{p_i}}{\mathsf{det}(\sum p_i \cdot B_i^* A_i B_i)}}.$$

Positive Operators

▶ A linear map $T: M_{n_1} \to M_{n_2}$ is completely positive if there are $n_2 \times n_1$ matrices B_1, \ldots, B_K and $p_i > 0$ such that

$$T(A) = \sum p_i B_i A B_i^*.$$

For simplicity, focus on the case $n_1 = n_2$.

- ▶ $T: M_n \to M_n$ is *positive* if $A \succeq 0$ implies $T(A) \succeq 0$.
- Another example of positive operators: For a non-negative matrix S, T(A) is the diagonal matrix whose entries are precisely the vector Sa, where a is the vector formed from the diagonal entries of A.
- ▶ Given T, we have $T^*(A) = \sum B_i^* A B_i$.

Capacity of Operators

$$\inf_{A\succ 0}\frac{\det(\sum p_iB_i^*AB_i)}{\det(A)}$$

• (Gurvits, 2004) The *capacity* of a positive operator $T: M_n \to M_n$ is

$$\mathsf{Cap}(T) = \inf_{A \succ 0} \frac{\det(TA)}{\det(A)}.$$

- For any Brascamp-Lieb data (B, p), there exists a positive $T: M_n \to M_n$ and k such that $Cap(T) = 1/BL(B, p)^{2k}$.
- Positive operators are well studied in the quantum information theory literature, so reduction of BL to this theory is useful.

Doubly Stochastic Positive Operators

- (Isotropy) Let $T(A) = \sum p_i B_i^* A B_i$.
 - $\triangleright \sum p_i B_i^* B_i = I$ holds iff T(I) = I.
- ▶ (Projection) Let $T(A) = B_i^* A B_i$.
 - \triangleright $B_i B_i^* = I$ if and only if $T^*(I) = I$.
- ▶ If (B, p) is a Brascamp-Lieb datum with associated operator $T: M_n \to M_m$, then (B, p) is geometric if and only if T is doubly stochastic. For n = m this means T(I) = I and $T^*(I) = I$.

Operator Rescaling for Positive Operators

- ▶ If T is doubly stochastic, Cap(T) = 1.
- ▶ We can rescale. If

$$T_{M_1M_2}(A) = M_2^* T(M_1^*AM_1)M_2,$$

then $\operatorname{Cap}(T_{M_1,M_2}) = \det(M_1)^2 \det(M_2)^2 \cdot \operatorname{Cap}(T)$.

Sinkhorn says to iterate

$$T\mapsto T_{I,T(I)^{-1/2}}$$
 and $T\mapsto T_{T^*(I)^{-1/2},I}$.

▶ If Cap(T) > 0, iteration yields a rescaling arbitrarily close to a doubly stochastic operator, in Poly(Bits(B), $1/\varepsilon$) time.

Upper Bounds For Capacity

- ▶ To guarantee efficiently, we need to show that for partially normalized T, Cap(T) $\geq 1/e^{\text{Poly}(\text{Bits}(B))}$.
- ► (Gurvits, 2004) If $T(A) = \sum_{i=1}^{n} B_i A B_i^*$, and $\det(\sum_{i=1}^{n} B_i) \neq 0$, then $Cap(T) \gtrsim (Bits(B) \cdot n)^{-O(n)}$.
- ▶ If Cap(T) > 0, there is d > 0 and d × d matrices C_i s.t.

$$\det(\sum C_i \otimes B_i) \neq 0$$
 and $\operatorname{Bits}(C) \leq \operatorname{Poly}(d,\operatorname{Bits}(B))$.

Fairly simple' to show that if $S(A) = \sum C_i A C_i^*$, and $(S \otimes T)(A) = \sum (C_i \otimes B_i) A (C_i \otimes B_i)^*$, then

$$\mathsf{Cap}(S \otimes T) \leq \mathsf{Cap}(T)^d \mathsf{Cap}(L)^n$$
.

Since $Cap(L) \leq 1$, it follows that

$$Cap(T) \ge Cap(S)^{1/d} \gtrsim (Poly(d, Bits(B))n)^{-O(n)}.$$

▶ Invariant theory shows we can choose $d \le n^4[(n+1)!]^2$.

The Invariant Theory

We have a group action of $SL_n \times SL_n$ on tuples $B = (B_1, \dots, B_m)$, such that

$$(M, N) \circ B = (MB_1N, \ldots, MB_mN).$$

Invariant Theory: Find the ring R of all 'invariant polynomials' f(B) such that

$$f((M,N)\circ B)=f(B)$$

for all $(M, N) \in SL_n \times SL_n$.

Note: $f_C(B) = \det(\sum C_i \otimes B_i)$ is an invariant polynomial under this action for any C_i .

The Invariant Theory

- Nayak and Subrahmanyam, 2010) R is a ring generated by the homogeneous polynomials $f_C(A) = \det(\sum C_i \circ A_i)$, for $d \times d$ matrices C_i .
 - ▶ Hilbert showed that for a fairly general family of group actions, R is finitely generated, so we should expect there is some d_0 such that R is generated by the polynomials above for $d \le d_0$.
 - ► (Ivanyos, Qiao, Subrahmanyam, 2015) shows $d_0 \lesssim n^4 [(n+1)!]^2$.
 - ► Thus if there exists $d \times d$ matrices C_i such that $f_C(B) \neq 0$, then we can choose $d \leq d_0$.

Rank Decreasing Operators

$$\int_{\mathbf{R}^n} \prod_{i=1}^m |f_i(B_i x)|^{p_i} dx \leq \mathsf{BL}(B, p) \cdot \prod_{i=1}^m ||f_i||_{L^1(\mathbf{R}^{n_i})}^{p_i}.$$

▶ (Bennett et al, 2008) implies that $BL(B, p) < \infty$ if and only if $\sum p_i n_i = n$, and for any subspace $V \subset \mathbf{R}^n$,

$$\dim(V) \leq \sum p_i \dim(B_i V).$$

- ▶ An operator $T: M_n \to M_n$ is rank non-decreasing if for any $A \succeq 0$, Rank $(TA) \ge \text{Rank}(A)$.
- ▶ (Gurvits, 2004) $T: M_n \to M_n$ is rank non-decreasing if and only if Cap(T) > 0.

Proof Idea

(Gurvits, 2004) $T: M_n \to M_n$ is rank non-decreasing if and only if Cap(T) > 0.

- ▶ Results from (Gurvits and Samorodnitsky, 2002) show the result is true if $T(X) = \sum X_{ii}A_i$, where $A_i \succeq 0$. The general case can be reduced to this case.
- ▶ Given an orthonormal basis $U = \{u_1, ..., u_N\}$, we define the decoherence operator $D_U(A) = \sum \langle Au_i, u_i \rangle \cdot u_i u_i^*$.
- ▶ Define $T_U = D_U \circ T$.
- ▶ Result follows from the following two facts:
 - (1) T is rank non-decreasing if and only if T_U is rank non-decreasing for all U.
 - (2) $Cap(T) = inf_U Cap(T_U)$.
- ▶ To prove (1) and (2), use a simple trick: Given $A \succeq 0$, find U diagonalizing T(A). Then $T(A) = T_U(A)$.

Thanks For Listening!