

The Grothendieck inequality

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max Cut

- A cut in a undirected graph $G = (V, E)$ is defined as partition of the vertices of G into two sets; and the weight of a cut is the number of edges that has an end point in each set, that is, the edges that connect vertices of one set to the vertices of the other.
- The max-cut is the problem of finding a cut in G with maximum weight.
- As an example, we note that the bipartite graph has maxcut exactly equal to the number of its edges.
- This is the MAX-2COLORING problem, namely, that of finding the maximum number of edges in a graph G which can be colored by using only two colors.

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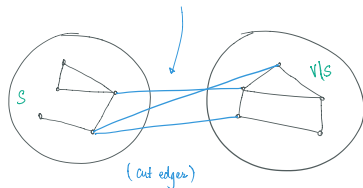
the edge set

MAX CUT:

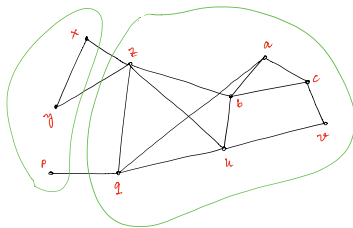
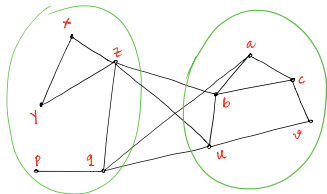
A cut in a graph $G = (V, E)$ is a pair $(S, V \setminus S)$.

The edge set of the cut is the set of all edges

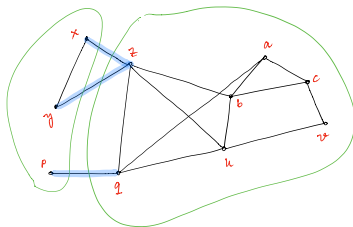
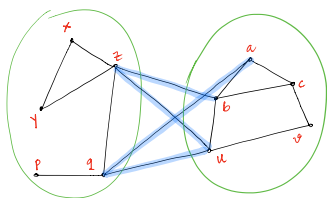
$$E(S, V \setminus S) = \{e \in E \mid |e \cap S| = |e \cap V \setminus S| = 1\}$$

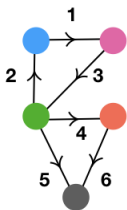


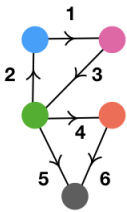
the edge set with labels

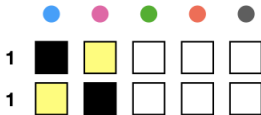
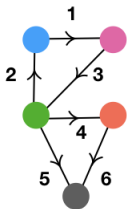


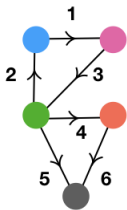
the edge set with crossings marked



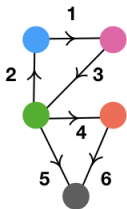







































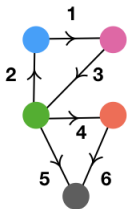

















































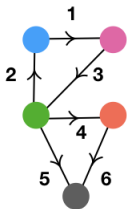
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









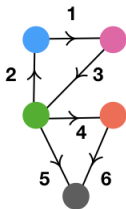
					
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



















					
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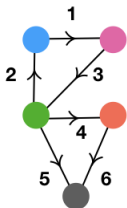


					
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Cut Norm

maximum, over all $I \subseteq R, J \subseteq S$,

$$\left| \sum_{i \in I, j \in J} a_{ij} \right|$$

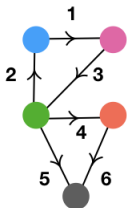


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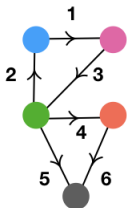
Claim: The cut norm
(of the matrix on the right)
is equal
to the size of the max cut
(of the graph on the left).

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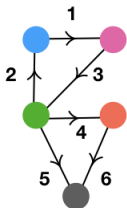


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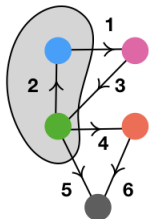
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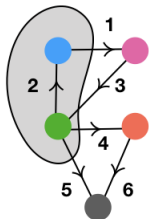


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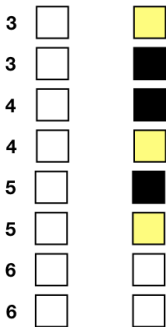
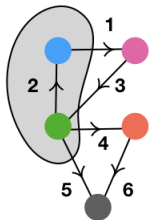
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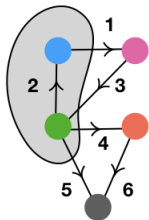
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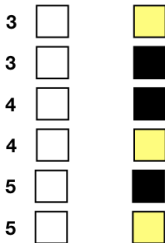
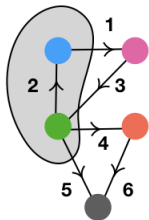
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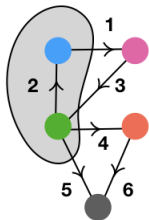
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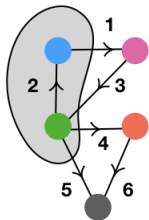
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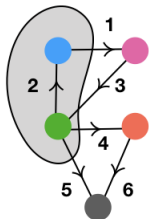
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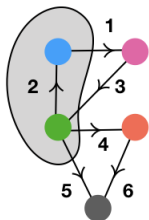


We have shown:
The cut norm is at least
the size of the max cut.

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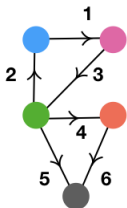


Claim: The cut norm is at most the size of the max cut.

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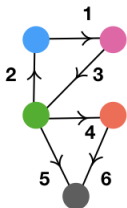
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
























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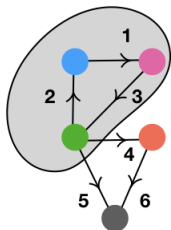


			
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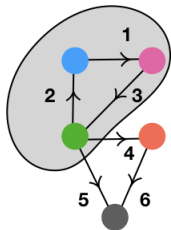


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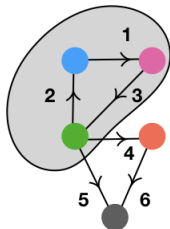


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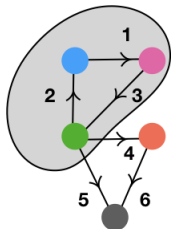


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the Cut norm

- The cut-norm $\|A\|_C$ of a real matrix $A = ((a_{ij}))_{i \in R, j \in S}$ is the maximum, over all $I \subseteq R, J \subseteq S$, of the quantity $|\sum_{i \in I, j \in J} a_{ij}|$.
- It is not difficult to show that the norm $\|\cdot\|_C$ is equivalent to the norm $\|A\|_{\infty \rightarrow 1}$, that is, for any $n \times n$ matrix A , we have

$$4\|A\|_C \geq \|A\|_{\infty \rightarrow 1} \geq \|A\|_C,$$

where

$$\|A\|_{\infty \rightarrow 1} := \sup \left\{ \left| \sum_{j,k=1}^n a_{jk} s_j t_k \right| : |s_j|, |t_k| = 1, 1 \leq j, k \leq n \right\},$$

$s_j, t_k \in \mathbb{R}$ (resp. in \mathbb{C}).

proof

For any $x_i, y_j \in \{-1, 1\}$,

$$\begin{aligned} \sum_{i,j} a_{i,j} x_i y_j &= \sum_{i:x_i=1, j:y_j=1} a_{i,j} - \sum_{i:x_i=1, j:y_j=-1} a_{i,j} \\ &\quad - \sum_{i:x_i=-1, j:y_j=1} a_{i,j} + \sum_{i:x_i=-1, j:y_j=-1} a_{i,j}. \end{aligned}$$

The absolute value of each of the four terms in the right hand side is at most $\|A\|_C$, implying, by the triangle inequality, that

$$\|A\|_{\infty \rightarrow 1} \leq 4\|A\|_C.$$

proof (contd.)

Suppose, now, that $\|A\|_C = \sum_{i \in I, j \in J} a_{i,j}$ (the computation in case it is $-\sum_{i \in I, j \in J} a_{i,j}$ is essentially the same). Define $x_i = 1$ for $i \in I$ and $x_i = -1$ otherwise, and similarly, $y_j = 1$ if $j \in J$ and $y_j = -1$ otherwise. Then

$$\begin{aligned}\|A\|_C &= \sum_{i,j} a_{i,j} \frac{1+x_i}{2} \frac{1+y_j}{2} = \\ &= \frac{1}{4} \left(\sum_{i,j} a_{i,j} + \sum_{i,j} a_{i,j} x_i \cdot 1 + \sum_{i,j} a_{i,j} 1 \cdot y_j + \sum_{i,j} a_{i,j} x_i y_j \right).\end{aligned}$$

The absolute value of each of the four terms in the right hand side is at most $\|A\|_{\infty \rightarrow 1}/4$, implying, by the triangle inequality, that

$$\|A\|_{\infty \rightarrow 1} \geq \|A\|_C.$$

integer linear program

- Finding the norm $\|A\|_{\infty \rightarrow 1}$ is called an integer linear program since

$$\|A\|_{\infty \rightarrow 1} := \sup \left\{ \left| \sum_{j,k=1}^n a_{jk} s_j t_k \right| : s_j, t_k \in \{-1, 1\}, 1 \leq j, k \leq n \right\},$$

at least in the real case.

- Thus one may wish to simply compute the $\|A\|_{\infty \rightarrow 1}$ instead of the CUT norm. However, this is not easy either.
- Let us see if we can give ourselves a little more room and compute a norm, namely, the 2-summing norm, related to the cut norm and the norm $\|A\|_{\infty \rightarrow 1}$ that we have already seen.

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the LP relaxation

- The 2 - summing norm $\gamma(A)$ is defined as follows:

$$\gamma(A) := \sup \left\{ \left| \sum_{j,k=1}^n a_{jk} \langle x_j, y_k \rangle \right| : x_j, y_k \in (\ell_2)_1, 1 \leq j, k \leq n \right\}.$$

Finding $\gamma(A)$, the 2 - summing norm, is called a semi-definite program.

- Define the numerical constant, the Grothendieck constant:

$$K_G(n) \stackrel{\text{def}}{=} \sup \{ \gamma(A) : A = A_{n \times n}, \|A\|_{\infty \rightarrow 1} \leq 1 \}.$$

- The constant $K_G(n)$ depends on the ground field.

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what we know about the Grothendieck constant

- The fact that $K_G(n)$ remains finite, say K_G , as $n \rightarrow \infty$ was established by Grothendieck and is known as the Grothendieck constant, that is,

$$\sup \left\{ \frac{\gamma(A)}{\|A\|_{\infty \rightarrow 1}} : A \in \mathbb{C}^{n \times n}, n \in \mathbb{N} \right\} < \infty.$$

- The Grothendieck inequality says that the two norms $\|A\|_{\infty \rightarrow 1}$ and $\gamma(A)$ can differ only by a constant factor.
- The exact value of K_G is not known. However, $K_G^{\mathbb{C}}(1) = K_G^{\mathbb{C}}(2) = 1$ and $K_G^{\mathbb{R}}(2) = \sqrt{2} = K_G^{\mathbb{R}}(3)$.
- Although, not entirely trivial, it is known that $K_G > 1$.
- Kirvine's proof gives $\frac{\pi}{2 \ln(1+\sqrt{2})} = 1.782\dots$
- Krivine conjectured that his bound is actually the exact value of K_G . Recently, this conjecture has been shown to be false.

Grothendieck constant for graphs

- Let G be a graph with n vertices denoted by $\{1, \dots, n\}$ and $E \subseteq \{1, \dots, n\}^2$ be the set of its edges.
- Following Noga Alon, Assaf Naor and many others, define the Grothendieck constant of the graph G , denoted by $K(G)$, to be the smallest constant K such that

$$\sup \left\{ \left| \sum_{\{i,j\} \in E} a_{ij} \langle x_i, y_j \rangle \right| : \|x_i\| = 1 = \|y_j\| \right\} \leq$$

$$K \sup \left\{ \sum_{\{i,j\} \in E} a_{ij} s_i t_j : |s_i| = 1 = |t_j| \right\}$$

holds true for any real matrix $A = ((a_{ij}))$.

the original Grothendieck inequality

- The original Grothendieck inequality is the particular case that corresponds to the bipartite graphs (i.e. of chromatic number 2) and, as a consequence,

$$K_G = \sup_{n \in \mathbb{N}} \left\{ K(G) : G \text{ is a bipartite graph on } n \text{ vertices} \right\}.$$

- Additionally, if C_n stands for the complete graph with n vertices, the corresponding Grothendieck constant is of order $\log(n)$. The Grothendieck constant of a graph G is clearly related to the combinatorics of G .

???

- On the other hand, the expression on the right hand side of the Grothendieck inequality for graphs is relevant statistical physics: if G weighted by the matrix A represents the possible interaction of n particles affected by a spin $i = \pm 1$, then the total energy generated by these particles in the system in the Ising model of the spin glass is

$$\mathcal{E} = -\left(\sum_{\{i,j\} \in E} a_{ij} \varepsilon_i \varepsilon_j \right).$$

A configuration of the spins $(\varepsilon_i) \in \{-1, 1\}^n$ represents its ground state if it minimizes the energy.

Kirvine's proof of the Grothendieck inequality

Let $S \subseteq \mathbb{C}^k$ be the Euclidean sphere of radius 1.

Lemma

$$\sup \left\{ \left| \sum_{i,j=1}^n a_{ij} \sin^{-1} \langle u_i, v_j \rangle \right| : \|A\|_{\infty \rightarrow 1} \leq 1; u_i, v_j \in S \right\} \leq \frac{\pi}{2}.$$

Proof. Let μ be the unique probability measure on S which is rotation invariant. First, show that

$$I := \int_S \text{sign} \langle x, u \rangle \text{sign} \langle y, u \rangle d\mu(u) = 1 - \frac{2\psi}{\pi}, \psi = \cos^{-1} \langle x, y \rangle, x, y \in S.$$

- The verification consists of finding an unitary $U: \ell_2(k) \rightarrow \ell_2(k)$ with

$$Ux = (1, 0, \dots, 0), \quad Uy = (\cos \psi, \sin \psi, 0, \dots, 0),$$

where $\psi = \cos^{-1} \langle x, y \rangle$, $0 \leq \psi \leq \pi$ and $\sin^{-1} \langle x, y \rangle = \frac{\pi}{2} - \psi$.

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Kirvine's proof

- If x and y are linearly dependent, namely $x = -y$, then $Ux = (1, 0, \dots, 0)$, $Uy = (-1, 0, \dots, 0)$ and $\psi = \pi$. Similarly, if $x = y$, then choose $Ux = (1, 0, \dots, 0)$, $Uy = (1, 0, \dots, 0)$ and $\psi = 0$. Now, extend this map linearly to all of $\ell_2(k)$ to an unitary.
- If x and y be linearly independent, then applying Gram-Schmidt, obtain a pair of orthonormal vectors α_1, α_2 and define a linear map U on the span of these two vectors:

$$U\alpha_1 := (1, 0, \dots, 0), \quad U\alpha_2 := (0, 1, 0, \dots, 0)$$

and extend it, as before, to an unitary on all of $\ell_2(k)$.

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an integral

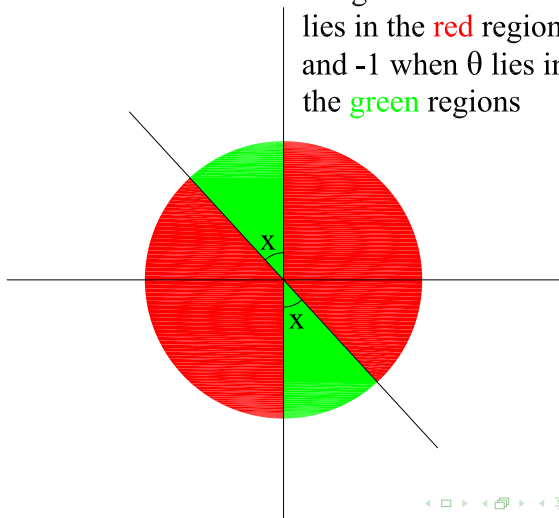
- A simple calculation gives $Ux = (1, 0, \dots, 0)$,
 $Uy = (\cos \psi, \sin \psi, 0, \dots, 0)$.
Therefore, in computing $\langle Ux, Uu \rangle$ and $\langle Uy, Uu \rangle$, we assume
without loss of generality: $Uu = (\cos \theta, \sin \theta, 0, \dots, 0)$.
- The integral I is U invariant, we have

$$\begin{aligned} I &= \int_S \text{sign} \langle Ux, Uu \rangle \text{sign} \langle Uy, Uu \rangle d\mu(Uu) \\ &= \int_S \text{sign} u_1 \text{sign}(\cos \psi u_1 + \sin \psi u_2) d\mu(Uu) \\ &= \frac{1}{2\pi} \int_0^{2\pi} \text{sign}(\cos \theta) \text{sign}(\cos(\theta - \psi)) d\theta \\ &= 1 - \frac{2\psi}{\pi} \\ &= \frac{2}{\pi} \sin^{-1} \langle x, y \rangle. \end{aligned}$$

evaluation of the integral

$$\frac{1}{2\pi} \int_0^{2\pi} \text{sign}(\cos \theta) \text{sign}(\cos(\theta - x)) d\theta$$

Integrand is +1 when θ lies in the **red** regions and -1 when θ lies in the **green** regions



tensor product

- The hypothesis on A implies that

$$-1 \leq \sum_{i,j=1}^n a_{ij} \text{sign}\langle u_i, x \rangle \text{sign}\langle v_j, x \rangle \leq 1,$$

for any choice of vectors $\|u_i\|_2 = 1 = \|v_j\|_2$. The proof is then completed by integrating with respect to x . □

Lemma

For each positive integer k , there is a mapping $w_k : l_2^n \rightarrow l_2^N$ such that for all x, y , $\langle w_k(x), w_k(y) \rangle = \langle x, y \rangle^k$.

- For the proof, set $w_k(x)$ to be the k -fold tensor product of the vector x .

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sine hyperbolic

Lemma

Given $c > 0$, there exists $u : \ell_2(n) \rightarrow \ell_2$ and $v : \ell_2(n) \rightarrow \ell_2$ such that

$$\langle u(x), v(y) \rangle = \sin c \langle x, y \rangle,$$

$\|u(x)\|^2 = \sinh(c\|x\|^2)$ and $\|v(y)\|^2 = \sinh(c\|y\|^2)$, $x, y \in \ell_2(n)$.

Proof. From the Taylor series expansion

$$\sin c \langle x, y \rangle = \sum_1^{\infty} (-1)^{k-1} c_k \langle w_{2k-1}(x), w_{2k-1}(y) \rangle,$$

where $c_k = \frac{c^{2k-1}}{(2k-1)!}$, we see that we just have to set

$$u(x) := \sum_1^{\infty} \sqrt{c_k} w_{2k-1}(x),$$

$$v(y) := \sum_1^{\infty} (-1)^{k-1} \sqrt{c_k} w_{2k-1}(y).$$

completing the proof

- Let $c = \sinh^{-1}(1) = \ln(1 + \sqrt{2})$.

Set $u_i = u(x_i)$, $v_j = v(y_j)$, $\|x_i\|_2 = 1 = \|y_j\|_2$, and note that $\|u_i\| = 1 = \|v_j\|$.

- However, we know that

$$c \langle x_i, y_j \rangle = \sin^{-1} \langle u_i, v_j \rangle, \quad |c \langle x_i, y_j \rangle| \leq 1$$

and

$$\left| \sum_{i,j=1}^n a_{ij} \sin^{-1} \langle u_i, v_j \rangle \right| \leq \frac{\pi}{2}.$$

So

$$\left| \sum_{i,j=1}^n a_{ij} \langle x_i, y_j \rangle \right| \leq \frac{\pi}{2c} = \frac{\pi}{2 \ln(1 + \sqrt{2})}.$$



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Theorem (Varopoulos inequality)

Suppose $K_G^{\mathbb{C}}$ denote the complex Grothendieck constant. Then

$$K_G^{\mathbb{C}} \leq \sup \|p(T_1, \dots, T_n)\| \leq 2K_G^{\mathbb{C}}$$

where supremum is over all $n \in \mathbb{N}$, tuples of commuting contractions $T = (T_1, \dots, T_n)$ and polynomial p of degree 2 with $\|p\|_{\infty} \leq 1$.

sharpening the Varopolous inequality

- Thus Grothendieck constant had made an unexpected appearance in the early work of Varopoulos. Setting

$$C_2(n) = \sup \left\{ \|p(T)\| : \|p\|_{\mathbb{D}^n, \infty} \leq 1, \|T\|_{\infty} \leq 1 \right\},$$

where the supremum is taken over all complex polynomials p in n variables of degree at most 2 and commuting n -tuples $T := (T_1, \dots, T_n)$ of contractions, he shows that

$$\lim_{n \rightarrow \infty} C_2(n) \leq 2K_G^{\mathbb{C}},$$

where $K_G^{\mathbb{C}}$ is the complex Grothendieck constant.

- Rajeev Gupta in his PhD thesis shows that

$$\lim_{n \rightarrow \infty} C_2(n) \leq \frac{3\sqrt{3}}{4} K_G^{\mathbb{C}},$$

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