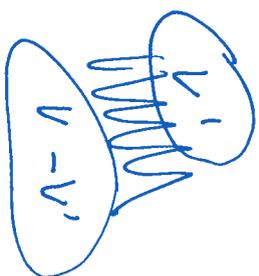


Max-Cut Problems

$$G = (V, E), \quad w: E \rightarrow \mathbb{Q} \quad (1)$$

$$A \subseteq E \Rightarrow w(A) \stackrel{\text{def}}{=} \sum_{e \in A} w(e)$$

$V' \subseteq V \Rightarrow \{e \in E; |e \cap V'| = 1\}$ is edge-cut



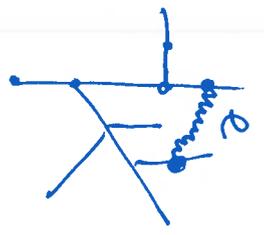
Find edge-cut of max weight.

- A basic NP-complete problem [unweighted]
- $w: E \rightarrow \mathbb{R}^- \Rightarrow$ polynomial [max flow - min cut]
- Polynomial for graphs embeddable on any fixed surface and the weights polynomially bounded (in $|E|$)
- Seminal approximation alg. by SemiDef. Programming

Basis of \mathcal{E}_G : T : spanning tree of $G, e \in E \setminus T,$

C_e : unique cycle of $T \cup \{e\}$.

$B_T = \{C_e ; e \in E \setminus T\}$.

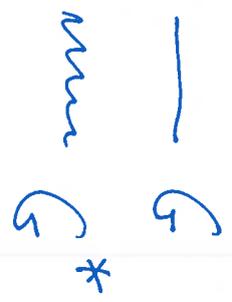
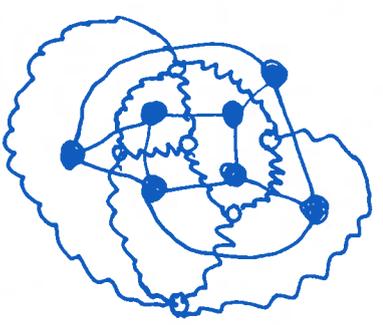


Basis of \mathcal{L}_G : $B_0 = \{ \{e ; v \in e\} ; v \in V \}$



G planar, G^* geometric dual \Rightarrow

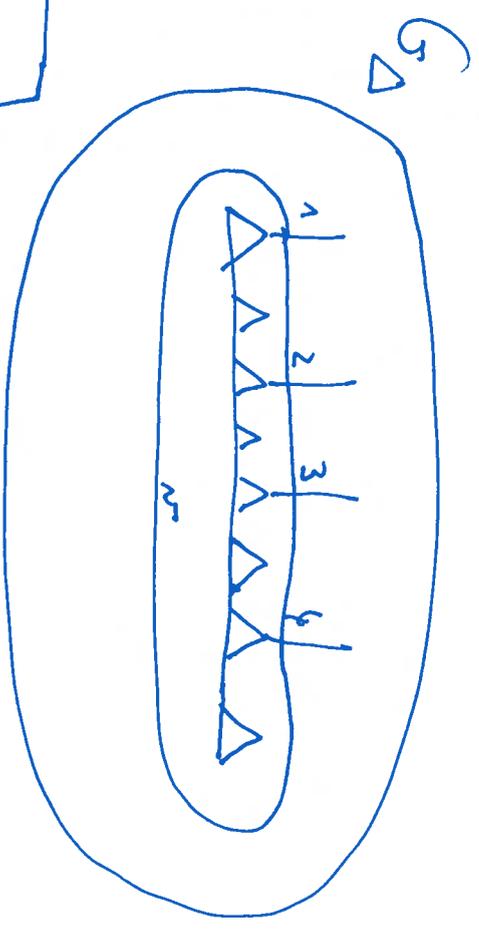
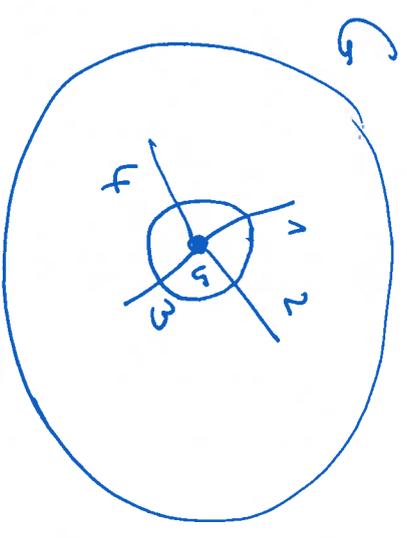
$$\mathcal{L}_G \approx \mathcal{L}_{G^*}$$



G planar $\Rightarrow \mathcal{L}_G$ generated by face-basis

- Max-Cut NP-complete
- Max Even Set Polynomial

Reduction to weighted perfect matching [Fischer 60]



Thm. $A \subseteq E$ even iff A can be uniquely extended to a perfect matching of G_Δ by the gadget edges.

weights of the gadget edges $\equiv 0$
All other weights unchanged.

Proof: simple

Why was a physical Fisher introduced in perfect
marketing, edge-ends (in 1960)?

(5)

Statistical Physics

perfect marketing = dimer arrangement

edge - end = state of being model

40's being : understanding of being
model on planar graphs

50's, 60's : Atiyah's book on understanding

Onnager's research combinatorially :

Kac, Ward, Feynman, Fischer, Karlsberg,
Sherman ...

being Model on $G = (V, E)$

state : $\sigma : V \rightarrow \{1, -1\}$
spin

energy :
 $E(\sigma) = \sum_{\{ij\} \in E} +\sigma_i \sigma_j \cdot w(\{ij\})$

Each state defines

edge-ends : $\{e_i \mid \sigma_i \neq \sigma_j\}$

$c(\sigma)$

$w(c(\sigma)) =$ \otimes

$[-E(\sigma) + w(E)] / 2$

MAX CUT on surfaces

(1)

Optimization: Polynomial reduction for weighted perfect matching !! Planar graphs !!

Enumeration

$$Z(G, x) = \sum_{\substack{E' \subseteq E \\ \text{max cut}}} x^{m(E')}$$

- Lines: number and weight of Max cuts
- The statistics of all cuts

Important for statistical physics

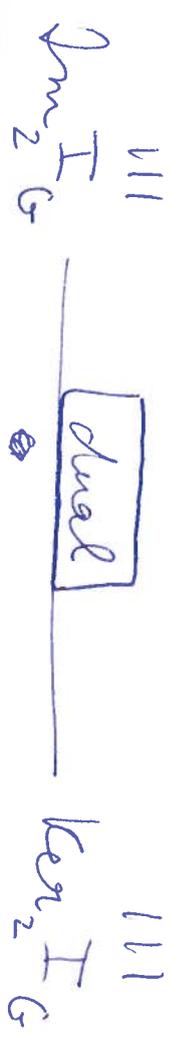
Partition function of Ising model on graph G :

$$Z(G, m) = \sum_{\sigma: V \rightarrow \{-1, 1\}} \prod_{i,j \in E} \sigma(i) \sigma(j) m(i,j) \approx \mathcal{Q}(G, x)$$

"energy of σ "

Duality of Enumeration

\mathcal{E} : cod space \mathcal{E} : cycle space



$\mathcal{E}(G, x)$ weight enumerator of \mathcal{E}
 $\mathcal{E}(G, x)$ weight enumerator of \mathcal{E}

Theorem (McWilliams, Vander Waerden)

There is a formula giving weight enumerator of
 the dual code from the weight enumerator of primal code

\mathcal{E}, \mathcal{E} dual
 binary linear codes

Enumeration of cuts for Planar Graphs

(3)

$$\varphi(G, x) = \sum_{E' \text{ edge-cuts}} x^{n(E')}$$

||| duality of enumer.

$$\mathcal{E}(G, x) = \sum_{E' \text{ even}} x^{n(E')}$$

||| Fischer construction

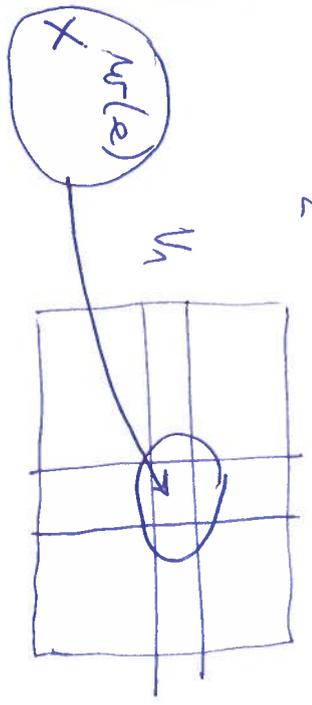
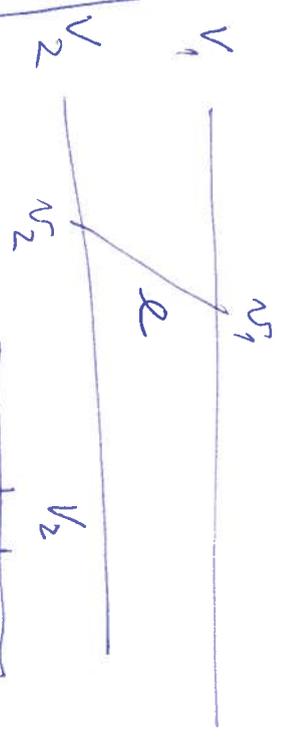
$$P(G_{\Delta}, x) = \sum_{E' \text{ perf. matching}} x^{n(E')}$$

$G \text{ genus } g \Rightarrow G_{\Delta} \text{ genus } g$

$P(G, x)$ kernel

G bipartite \Rightarrow

$P(G, x)$ is determinant



$$\det(A) = \sum_{\Pi} \prod a_{i, \pi(i)}$$

no signs

Method of Kasteleyn orientations

* 60's core of theoretical physics * ^{2000's} Valiant: holographic algorithms

* 1916 Pólya: when can we find signs for A_{ij} 's so that

per $A = \det A'$ [A' : signing of A]

\equiv given directed graph, does it have even dipole?

Polynomial [Robertson, Seymour, Thomas]

$$\text{Pf}(\mathbb{D}, x) = \sum_{E' \text{ perf. marking}} \text{sign}(\mathbb{D}, E') \times \text{nr}(E')$$

\mathbb{D} orientation of G

Kasteleyn

* $\text{Pf}(\mathbb{D}, x)$ polynomial [determinantal-type]

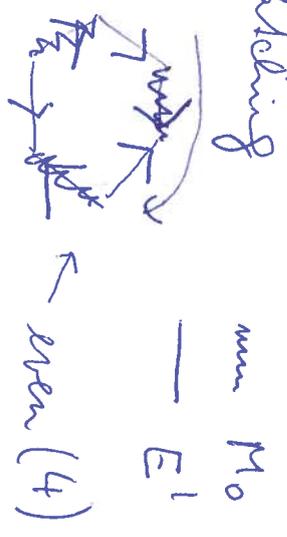
* G planar $\Rightarrow \exists \mathbb{D}$ Pfaffian:

"make all inner faces clockwise odd"

M_0 fixed perf. m.

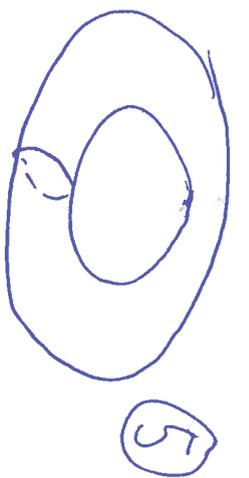
$$\text{sign}(\mathbb{D}, E') = (-1)^{\#}$$

: no. of ~~odd~~ even alternating cycles of $M_0 \Delta E'$.



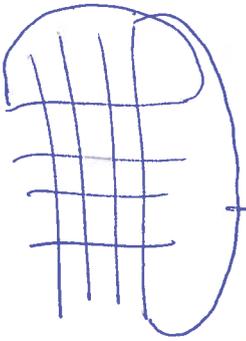
* \mathbb{D} Pfaffian if all signs the same

Toroidal and higher genus graphs



- No strongly polynomial alg. for MAX-CUT known
- G ~~is~~ genus $g \Rightarrow \chi(G, x) = \frac{1}{2g} \sum_{i=1}^{2g} \pm \text{Poly}(D_i, x)$
[Art-invariant formula] Algebraic Topology, QFT

- This provides the only known (weakly) polynomial algorithm for max cut in toroidal graphs [4 Patterns]



Semidefinite Programming Algorithm for Max-Cut

$G = (V, E); V = \{1, \dots, n\}$

- Variables $x_1, \dots, x_n \in \{1, -1\}$

- Assignment of values from $\{1, -1\}$ for x_1, \dots, x_n encodes a cut $(S, V-S)$, where $S = \{i \in V; x_i = 1\}$.

- $\frac{1-x_i x_j}{2}$ is the contribution of edge $\{i, j\}$ to this cut.

Max Cut $\text{Opt}(G): \max \sum_{i,j \in E} \frac{1-x_i x_j}{2} \quad ; \quad x_i \in \{1, -1\}, i = 1, \dots, n.$

- Replace x_i by $w_i \in S^{n-1} = \{x \in \mathbb{R}^n; \|x\| = 1\}$
- $\max \sum_{i,j \in E} \frac{1-w_i^T w_j}{2} \quad ; \quad w_i \in S^{n-1}$ is **upper bound** for $\text{Opt}(G)$.

vector program

* Semidefinite Programming solves efficiently for any desired accuracy

Substitutable: $X_{ij} := w_i^T w_j$

$$\boxed{\text{SDP}(G)} \quad \text{Max} \sum_{i,j \in E} \frac{1 - X_{ij}}{2} ; \quad X_{ii} = 1, i=1, 2, \dots, n$$

$X \succeq 0$ positive semidefinite

$X = U^T U$, The columns of U, w_1, \dots, w_n form feasible solution of the vector program.

$M \in \text{Sym}_n$ [symmetric matrix] ~~is~~ The following is equivalent

- ① M positive semidefinite, i.e., all eigenvalues non-negative
- ② $x^T M x \geq 0$ for all $x \in \mathbb{R}^n$
- ③ There is $U \in \mathbb{R}^{n \times n}$, $M = U^T U$ [Cholovky Factorization]

Columns of U unit vectors iff $X_{ii} = 1, i=1, \dots, n$

* We can find in polynomial time matrix $X^* \succeq 0$, $X_{ii}^* = 1, i=1, \dots, n$

a.A. $\sum_{i,j \in E} \frac{1 - X_{ij}^*}{2} \geq \text{SDP}(G) - \epsilon$, for every $\epsilon > 0$.

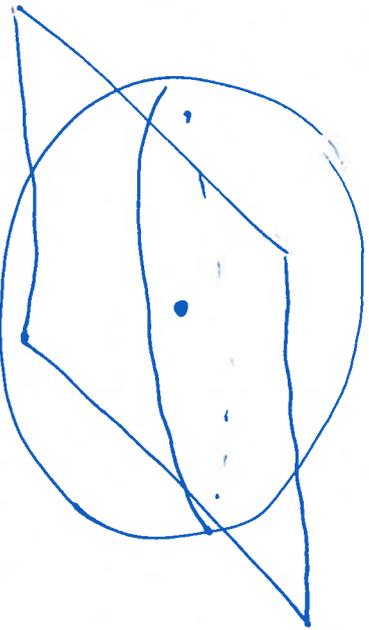
* We compute U^* a.A. $X^* = (U^*)^T U^*$ up to a tiny error.

Hence $(U^*$ has columns $w_1^*, w_2^*, \dots, w_n^*)$

$$\sum_{i: |e_i| \geq \epsilon} \frac{1 - w_i^{*T} w_i^*}{2} \geq \text{SDP}(G) - \epsilon \geq \text{OPT}(G) - \epsilon.$$

Rounding the Vector Solution

We want to map S^{n-1} back to S^0 as that we do not lose too much.



cut by a random hyperplane

Randomized Rounding

(P)

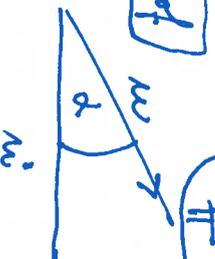
• We take r uniformly at random from S^{n-1}

$$r \rightarrow \begin{cases} 1 & \text{if } r^T w_i \geq 0 \\ -1 & \text{otherwise} \end{cases}$$

• $w_i \in S^{n-1}$. Probability that w_i get different values is

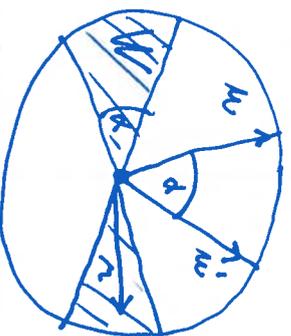
$$\frac{1}{\pi} \arccos w_i^T w_j$$

Proof



$$d = \arccos w_i^T w_j \in [0, \pi]$$

Since $\cos d = w_i^T w_j \in [-1, 1]$



w_i get differently iff projection r of w_i lies in W . r uniformly distributed in $[0, 2\pi]$

\Rightarrow Probability is $\frac{d}{\pi}$.

□

The expected number of edges in the resulting cut equals

(9)

$$\sum_{i,j \in E} \frac{\text{arccos } w_i^* w_j^*}{\pi}$$

Lemma For all $z \in [-1, 1]$ $\frac{\text{arccos}(z)}{\pi} \geq 0.8785672 \frac{1-z}{2}$

Hence

$$\sum_{i,j \in E} \frac{\text{arccos } w_i^* w_j^*}{\pi} \geq 0.8785672 \sum_{i,j \in E} \frac{1 - w_i^* w_j^*}{2} \geq 0.8785672 (0.41(6) - \epsilon)$$

if $\epsilon \leq 5 \cdot 10^{-4}$.

Approximation Algorithms

P optimization problem (maximization) ⑩

- I : set of instances; $i \in I \Rightarrow F(i)$ set of feasible solutions
- $\rho \in F(i)$ has a non-negative real value $w(\rho) \geq 0$.
- $Opt(i) = \max_{\rho \in F(i)} w(\rho) \in \mathbb{R}_+ \cup \{-\infty, \infty\}$.

• A algorithm for solve P is Δ -approximation algorithm for P if
[$\Delta: \mathbb{N} \rightarrow \mathbb{R}_+$]

- There is polynomial p n.s.t. for all $i \in I$, the runtime of A on i
 $i \leq p(|i|)$
- $i \in I \Rightarrow w(A(i)) \geq \Delta(|i|) \cdot Opt(i)$

Randomized algorithms

A randomized Δ -approximation algorithm has expected

poly runtime and must satisfy $E[w(A(i))] \geq \Delta(|i|) Opt(i)$

[$w(A(i))$ is random variable]

A randomized $0,5$ -approximation algorithm for Max-Cut

$G = (V, E)$; Pick S a random subset of V [each vertex $v \in V$ included in S with probability $1/2$, independent of all other vertices].

Thm This is a randomized $0,5$ -approximation algorithm for Max-Cut.

Proof $E[A(G)] = E[|E(S, V \setminus S)|] = \sum_{e \in E} \text{Prob}[e \in E(S, V \setminus S)] \stackrel{\text{Axiom}}{=} \sum_{e \in E} \frac{1}{2} = \frac{1}{2} |E| \geq \frac{1}{2} \text{Opt}(G).$

$e \in E(S, V \setminus S)$ iff exactly one of the two end-points of e ends up in S .

[11]

$$\max c^T x$$

$$Ax = b$$

$$x \geq 0$$

$$c \in \mathbb{R}^n, b \in \mathbb{R}^m, A \in \mathbb{R}^{m \times n}$$

X feasible solution

if $X \in \text{SYM}_n$,

$$A(X) = b, X \geq 0.$$

The value is

$$\max \{ c \cdot X : A(X) = b, X \geq 0 \}$$

Semidefinite Programming

[12]

$$\text{SYM}_n = \{ X \in \mathbb{R}^{n \times n} : x_{ij} = x_{ji}, 1 \leq i < j \leq n \}$$

[replaces $x \in \mathbb{R}$]

$A : \text{SYM}_n \rightarrow \mathbb{R}^m$ linear [replaces $A \in \mathbb{R}^{m \times n}$]

$$X \cdot Y := \sum_{i=1}^n \sum_{j=1}^n x_{ij} y_{ij}, X, Y \in \text{SYM}_n$$

$$X \cdot Y = \text{Tr}(X^T Y)$$

$X \geq 0$ (being positive semidefinite) [replaces $x \geq 0$]

$$\max c \cdot X$$

$$A_1 \cdot X = b_1$$

where

$$A(X) = b$$

$$A_m \cdot X = b_m$$

$$b = (b_1, \dots, b_m)$$

$A : \text{SYM}_n \rightarrow \mathbb{R}^m$ linear

$$X \geq 0$$

$$A = (a_{ij}^k)_{\substack{i,j=1 \\ k=1}}^m \Big|_{k=1}^m$$

WARNINGS

① Finite value is not

necessarily attained:

$$\text{Max } -x_{11}$$

$$x_{12} = 1$$

$$x_{11} > 0$$

Feasible solutions: all

$$x_{11} > 0, x_{12} = 1$$



$$x_{11} > 0, x_{22} > 0, x_{11} x_{22} > 1$$



$$x_{11} > 0 \text{ and } x_{22} > \frac{1}{x_{11}}$$

Value 0 but no opt. solution

⊗ All known algorithms return

only approximately optimal solutions

[ellipsoid method]

⊗ Cholesky factorization also can be constructed only approximately

Back to Max-Cut Approximation Algorithms

①

Approximation Ratios of Goemans - Williamson Alg. : $\delta_{GW} \approx 0.87856720..$

Becker

(1) dense graphs (n^2 edges, $\epsilon > 0$ fixed) : Polynomial-time approximation scheme [use of regularity lemma]

(2) bounded max degree

But it is conjectured that no improvement possible for all graphs [Unique conj.]

Theorem (Hardt) • Assuming $P \neq NP$, no polynomial-time algorithm can approximate Max Cut better than $16/17 \approx 0.94$.

• Given a 3-SAT formula φ , Hardt's construction yields graph $G = G(\varphi)$ s.t.

(1) Max Cut $> 1/2$ if φ satisfiable (x eff. computed from φ)

(2) Max Cut $\leq 16/17$ if φ is unsatisfiable.

Approximation Ratio and Integrality Gap

(2)

$d_{GM} = \inf_G \frac{\text{Algo}(G)}{\text{OPT}(G)}$; $\text{Algo}(G)$: expected size of cut found by Random hyperplane rounding in GW algorithm

$$\text{SDP}(G) = \max_{\{v_i\} \in G} \left\{ \sum_{i,j \in E} \frac{1 - v_i^T v_j}{2} ; \|v_i\| = \dots = \|v_n\| = 1 \right\}$$

relaxation

Integrality Gap

$$\text{Gap} := \max_G \frac{\text{SDP}(G)}{\text{OPT}(G)}$$

MoM theorem

$$\frac{1}{\text{Gap}} \geq \gamma \text{ Approximation Ratio}$$

For maximization algorithms based on semidefinite or linear prog.

(3)

Theorem (Feige, Spielman) The integrality gap of the Goemans-Williamson SDP relaxation of Max Cut satisfies

$$\text{Gap} > \frac{1}{d_{GW}} \approx 1.1382; \forall \epsilon > 0 \exists \epsilon: \frac{\text{SDP}}{\text{Opt}} > \frac{1}{d_{GW}} - \epsilon$$

We lead: $\text{Algo}/\text{SDP} > d_{GW}$ and $\text{Opt} > \text{Algo} \Rightarrow$

$$\text{GAP} = \text{opt}(\text{SDP}/\text{Opt}) \leq \frac{1}{d_{GW}}$$

Hence: $\text{GAP} = \frac{1}{d_{GW}}$

Sending messages over noisy channel

①



(v_1, \dots, v_k)

similar for (v_1', \dots, v_k') if $(\forall i) (v_i \text{ similar for } v_i')$

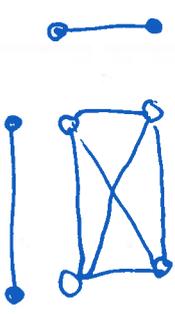
Similarity Free Dictionary

set of pairwise non-similar words

② Largest similarity free dict.?



$G \boxtimes G = G^2$



For words of size k it is $k(G^k)$

- Using 1-letter words we can transmit $k(G)$ messages:
- 1 letter carries [roughly] $\log k(G)$ bits of information
- k -letter words \Rightarrow 1 letter carries [roughly] $\frac{1}{k} \log k(G^k)$ bits of info

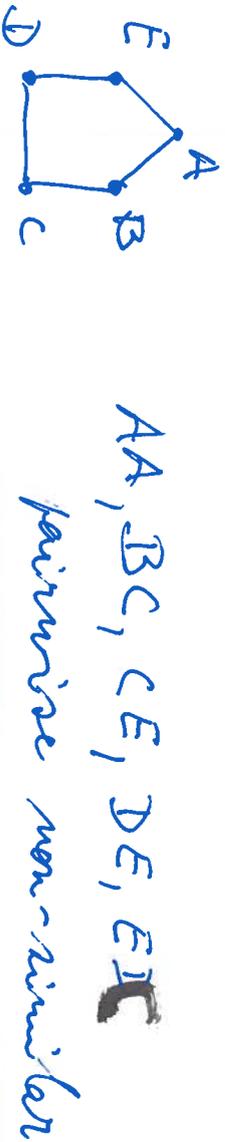
Shannon capacity of noisy channel

$C(G) = \sup \left\{ \frac{1}{k} \log k(G^k), k \in \mathbb{N} \right\}$

$$\bullet d(G^{k+e}) \succ d(G^k) d(G^e)$$

⋮
⋮
⋮
⋮

$$\bullet \text{Abicht: } d(G_5) = 2, \quad d(G_5^2) \succ 5 > d(G_5)^2 = 4$$



$$\rho(G) = \sup \left\{ \frac{1}{k} \log d(G^k); k \in \mathbb{N} \right\}.$$

$$\bullet \rho(G) \text{ bounded: } \rho(G) = \lim \left\{ \frac{1}{k} \log d(G^k); k \in \mathbb{N} \right\}:$$

$$\bullet \rho(G) \leq \frac{1}{k} \log d(G^k) \leq \frac{1}{k} \log |V|^k = \log |V|$$

$$\bullet \text{let } X_k = \log d(G^k) \Rightarrow X_{k+e} \succ X_k + X_e$$

Sequence $(X_k)_{k \in \mathbb{N}}$ superadditive

(2)

Shannon 56

???

$$\rho(G_5) = \frac{1}{2} \log 5$$

YES: lower 49

$$S(G) = 2^{\rho(G)} =$$

$$\lim_{k \rightarrow \infty} \sqrt[k]{d(G^k)}$$

lemma (Feferk)

$(X_k)_{k \in \mathbb{N}}$ superadditive

$$\left(\frac{X_k}{k} \right)_{k \in \mathbb{N}} \Downarrow \text{converges}$$

to its supremum.

Lovász Theta Function

$G = (V, E) \Rightarrow \bar{E} = (V) \setminus E$

- An orthonormal representation of G , $\|v_i\|=1$, is $\mathcal{W} = (w_1, \dots, w_n)$ o.n.b. $w_i \cdot w_j = 0$ if $\{i, j\} \in \bar{E}$.

[example: e_1, \dots, e_n]

$\rho(\mathcal{W}) := \min_{\|x\|=1} \max_{i=1}^n \frac{1}{(x^T w_i)^2}$

Definition $\rho(G)$ is minimum

$\rho(\mathcal{W})$ over all orthonormal repr of G

exists: min of continuous fctn over a compact set S^{n-1} - open adj. $\{x; x^T w_i = 0\}$

exists: min of a cont. fctn over compact set

Examples: • $G = K_n \Rightarrow$ every sequence of unit vectors is orthonormal repr.

$e \in S^{n-1} \Rightarrow e$ handle for $\{w_i = e, i=1, \dots, n\} \Rightarrow \rho(G) = 1$

- G independent $[E(G) = \emptyset] \Rightarrow \{w_i\}$ must form an orthonormal basis of \mathbb{R}^n

Ass. $w_i = e_i \Rightarrow$ handle is $C = \sum_{i=1}^n \frac{w_i}{\sqrt{n}} \Rightarrow e^T w_i = 1/\sqrt{n} (\forall i) \Rightarrow$

$\rho(G) = n$

$G \cdot H$



Lemma 1 $\sigma(G \cdot H) \leq \sigma(G) \cdot \sigma(H)$

Lemma 2 $\delta(G) \leq \sigma(G)$

Theorem $\sigma(G) \leq \sigma(G)$

Proof $\delta(G^k) \leq \sigma(G^k) \leq \sigma(G)^k$



$$\sqrt[k]{\delta(G^k)} \leq \sigma(G) \Rightarrow$$

$$\sigma(G) = \lim_{k \rightarrow \infty} \sqrt[k]{\delta(G^k)} \leq \sigma(G).$$



Proof of Lemma 1

$x \in \mathbb{R}^m, y \in \mathbb{R}^n \Rightarrow$ inner product $x \otimes y = (x_1 y_1, \dots, x_1 y_n, \dots, x_m y_1, \dots, x_m y_n)$

$x \otimes y \in \mathbb{R}^{m \cdot n}$ • $(x \otimes y)^T (x' \otimes y') = (x^T x') (y^T y')$

W, V optimal repr. of $G, H \Rightarrow$

$W \otimes V$ orthonormal repr. of $G \cdot H$

Proof of Lemma 2: I max index of G , (4)

$W = (w_1, \dots, w_n)$ optimal repr. with $w_i \perp w_j$

• $\{w_i; i \in I\}$ pairwise orthogonal \Rightarrow

$$e^T c \succcurlyeq \sum_{i \in I} (c^T w_i)^2$$

Hence,

$$1 = e^T c \succcurlyeq \sum_{i \in I} (c^T w_i)^2 \geq |I| \cdot \min_{i \in I} (c^T w_i)^2 =$$

$\delta(G) \min_{i \in I} (c^T w_i)^2$. Hence

$$\delta(G) \leq \frac{1}{\min_{i \in I} (c^T w_i)^2} = \max_{i \in I} \frac{1}{(c^T w_i)^2} \leq$$

$$\max_{i \in V} \frac{1}{(c^T w_i)^2} = \sigma(G).$$

C bundle of W, d bundle of $V \Rightarrow$

$$\sigma(W \otimes V) \leq \max_{i \in V, j \in W} ((c \otimes d)^T (w_i \otimes v_j))^2 = \max_{i \in V, j \in W} \frac{1}{(c^T w_i)^2 (d^T v_j)^2} = \sigma(G) \sigma(H)$$

σ of G and H

• $G = (V, E)$, $|V| = n$, $W = \{w_1, \dots, w_n\} \subseteq S^{n-1}$ is orthonormal representation if ①

$\{v_i\} \notin E \Rightarrow w_i^T w_j = 0$.

• $\text{Thick}(W) := \min_{\|c\|=1} \max_{i=1, \dots, n} |c^T w_i|^2 \quad \|\text{Thick}(W) := \max_{i=1, \dots, n} |c^T w_i|^2, W \text{ orthonormal.}$

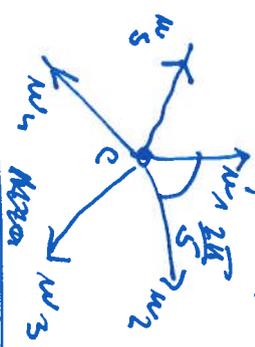
Then (brass) $2^{n(G)} = S(G) \leq \text{Thick}(G)$.

We know: $S(G) \geq \sqrt{5}$

Shannon Conjecture follows from

$\text{Thick}(W) \leq \sqrt{5}$

Need: orthonormal representation of G_S with value $\leq \sqrt{5}$.
 of G_S with value $\leq \sqrt{5}$.
 left to S^3 by $(\dots, 0, 0)$. $c = (0, 0, 1)$



old number 1



Following leads to orthonormal repres. Since

find $f(w_1, w_2) = \frac{4\pi}{5} > \frac{\pi}{2}$ and finally this

$f(w_1, w_4) = 0$. The value is $\leq \sqrt{5}$ [not best]

$w_i = \frac{(\cos \frac{2\pi i}{5}, \sin \frac{2\pi i}{5}, 1, 2)}{\|(\cos \frac{2\pi i}{5}, \sin \frac{2\pi i}{5}, 1, 2)\|}$ $i = 1, \dots, 5$

$0 = w_5^T w_2 \Leftrightarrow (1, 0, 1, 2) \begin{pmatrix} \cos \frac{4\pi}{5} \\ \sin \frac{4\pi}{5} \\ 1 \\ 2 \end{pmatrix} = 0 \Rightarrow$

$2 = \sqrt{-\cos \frac{4\pi}{5}}$ $w_5 = \dots$ \square

SDP for the Theta function Proof let the value of $\theta(G)$ be $\theta^*(G)$. (2)

Then, $\mathcal{V}(G)$ is the value of

Min t

$\gamma_{ij} = -1, \{ij\} \in \bar{E}$

$\gamma_{ii} = t-1, i=1, \dots, n$

$\gamma \succeq 0$

$\textcircled{A} \theta^*(G) \leq \mathcal{V}(G)$:

(W, c) optimal representation.

let $\tilde{\gamma} \in \mathcal{S} \mathcal{P} M_n$ be: $\tilde{\gamma}_{ij} = \frac{w_i w_j}{(c_{T_{ij}})(c_{T_{ij}})} - 1, i \neq j$

$\tilde{\gamma}_{ii} = \mathcal{V}(G) - 1, i=1, \dots, n$

$\bullet \mathcal{V}(\tilde{\gamma}) \succeq 0 \Rightarrow (\tilde{\gamma}, \tilde{c} = \mathcal{V}(G))$ is a feasible sol. of \textcircled{A} .

$\Rightarrow \mathcal{V}'(G) \leq \mathcal{V}(G)$

$\textcircled{B} \mathcal{V}'(G) \geq \mathcal{V}(G)$ FACT

Theorem $G = (V, E) \quad \omega(G) \leq \mathcal{V}(G) \leq \chi(G)$

Thus $\tilde{\gamma} \succeq 0$.

$\tilde{\gamma} = D + U^T U, D$ diagonal $\succeq 0$ and

$U^i = c - w_i / c^T w_i \Rightarrow i$ -th col. of U

ω : size of a largest clique (complete subgraph) of G

k : size of a largest indep. set

$\chi(G)$: chromatic number. AS $\chi(G) \geq n \Rightarrow \chi(G) \geq n \Rightarrow \chi(G) \geq n$

$\chi(G) = 1 \Rightarrow G = K_n \Rightarrow \chi(G) = n$

we had last time:
 $\chi(G) \leq \mathcal{V}(G)$

Lemma. If G has k -

clique then it has vector k -coloring.

[FACT] $\chi(G) \leq k$

Definition

$k \in \mathbb{R}$, vector k -coloring of G is

$f: V \rightarrow \mathbb{S}^{k-1}$

$f(u)^T f(v) = -\frac{1}{k-1}, \{u, v\} \in E$

Remark \textcircled{A}

Min t

$\gamma_{ij} = -1 / (t-1), \{ij\} \in E$

$\gamma_{ii} = 1, i=1, \dots, n$

$\gamma \succeq 0$

Perfect graphs

G perfect if $\omega(G') = \chi(G')$ for each induced subgraph G' .

(3)

Brook's. • G perfect $\Rightarrow \omega(G) = \Delta(G) = \chi(G)$

• G perfect $\Rightarrow \chi(G)$ polynomial !! by SDP:

(*) suffices for value with accuracy $\epsilon < \frac{1}{2}$ since value is integer.

The only known polynomial method