

Lecture 16 - CSP, ~~approx~~

[Last time we introduced the Max-Cut problem as a means of motivating S.D.P. Let's return.]

Max-Cut: Given $G=(V,E)$, find $F: V \rightarrow \{-1,1\}$ to maximize $\sum_{(v,w) \in E} P[F(v) \neq F(w)]$

[SDP] relaxation:

[poly-time solvable]

$$\max \text{ avg}_{(v,w) \in E} \left\{ \frac{1}{2} - \frac{1}{2} y_{vw} \right\}$$

$$\text{s.t. } y_{vv} = 1 \quad \forall v$$

$$Y = (y_{vw}) \text{ is PSD}$$

(and symm.) [Let's build into defⁿ of PSD]

relaxation of "attempt to enforce" $\exists \{x_v\} \text{ s.t. } y_{vw} = x_v x_w \quad \forall v,w$

rec: $Y \in \mathbb{R}^{n \times n}$ is PSD $\Leftrightarrow \exists U \in \mathbb{R}^{m \times n}$ s.t. $Y = U^T U$
 $(\Leftrightarrow \exists U \in \mathbb{R}^{n \times n})$

$$\Leftrightarrow \exists \text{ joint r.v.'s } X_1, \dots, X_n \text{ s.t. } y_{vw} = E[X_v X_w] \quad \forall v,w$$

$$\Leftrightarrow \exists \text{ vectors } \vec{u}_1, \dots, \vec{u}_n \in \mathbb{R}^m \text{ s.t. } \langle \vec{u}_v, \vec{u}_w \rangle = y_{vw}$$

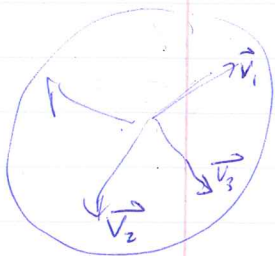
($\Leftrightarrow \exists \text{ vectors in } \mathbb{R}^n$)

$\therefore$ [SDP] $\Leftrightarrow \max \text{ avg}_{(v,w) \in E} \left\{ \frac{1}{2} - \frac{1}{2} \langle \vec{u}(v), \vec{u}(w) \rangle \right\}$

s.t. $\vec{u}: V \rightarrow \{\text{unit-len. vecs in } \mathbb{R}^n\}$

[pretty geometrically natural.] [trying to put vts of G on sphere to "spread out" edges]

[max-cut]

Relaxation check: $\text{Opt}(G) \leq \text{SDPOpt}(G) \leq 1$, why?b/c: $\vec{U}(v) = (\underbrace{F^*(v)}_{\text{max-cut}}, 0, 0, \dots, 0)$ valid for SDP.Rounding [GW94]

• Solve SDP, get ~~optimal~~ $\vec{U}^*$. Not? $\vec{V} := \vec{U}^*(v)$.
 • Now what?

• Pick rand. hyperplane thru 0, partitions vtes/vecs into 2 parts.
 (rotationally symmetric normal. What rotationally symm. dist do we know?)

• Pick $\vec{g} = (g_1, \dots, g_n)$, g_i 's indep Gaussians, as hyperplane normal. Define $F: V \rightarrow \{-1, 1\}$

$$v \mapsto \text{sgn}(\langle \vec{v}, \vec{g} \rangle)$$

[that's the alg. Analysis...?]

rem: Let $Z_v = \langle \vec{v}, \vec{g} \rangle$ $\forall v$. [Joint real Gaussians
 Lin comb. of $g_1, \dots, g_n$ is Gaussian]
 $Z_1, \dots, Z_n$ are joint Gaussian r.v.'s

$$\begin{aligned} E[Z_v Z_w] &= E\left[\left(\sum_{i=1}^n \vec{v}_i g_i\right) \left(\sum_{j=1}^n \vec{w}_j g_j\right)\right] \\ &= \sum_{i,j} \vec{v}_i \cdot \vec{w}_j E[g_i g_j] \rightarrow \begin{cases} i \neq j: E[g_i]E[g_j] = 0 \\ i = j: E[g_i^2] = 1 \end{cases} \\ &= \sum_i \vec{v}_i \cdot \vec{w}_i = \langle \vec{v}, \vec{w} \rangle = y_{vw} \end{aligned}$$

→ prop: Y is PSD iff $\exists$ jointly Gaussian r.v.'s $Z_1, \dots, Z_n$ with

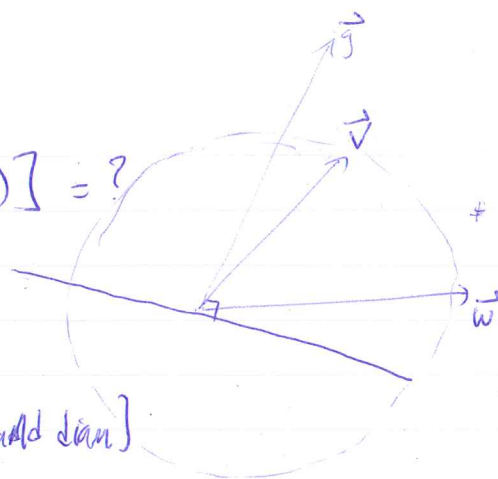
$$y_{vw} = E[Z_v Z_w]$$

[GW alg: Solve SDP, get ~~corr'd~~ corr'd Gaussians $(Z_v)_{v \in V}$. Draw, then take sgn.]

Maybe skip → Frank

Fix edge u, w . $\Pr_{\vec{g}}[F(v) \neq F(w)] = ?$

By rotational symm. of $\vec{g}$,
reduces to 2-d pic.



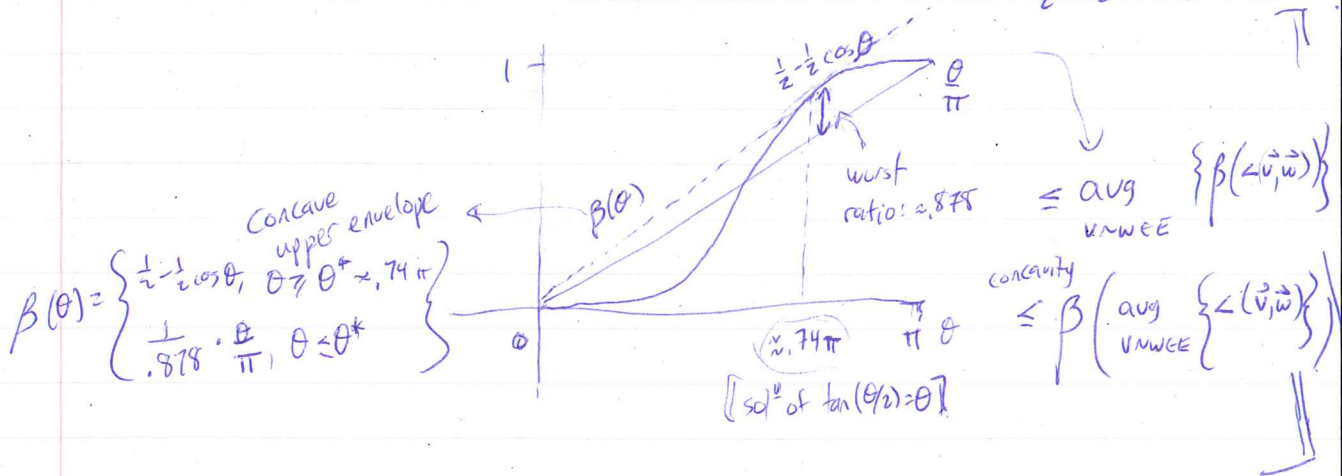
$$= \Pr[\vec{v}, \vec{w} \text{ split by null dir.}]$$

$$= \frac{\angle(\vec{v}, \vec{w})}{\pi}$$

$\therefore$ lin. expec. $\Rightarrow E_{\vec{g}}[\text{frac. edges } F \text{ cuts}] = \text{avg}_{v \sim w \in E} \left\{ \frac{\angle(\vec{v}, \vec{w})}{\pi} \right\}$

rec: $\text{SDPOpt}(G) = \text{avg}_{v \sim w \in E} \left\{ \frac{1}{2} - \frac{1}{2} \cos(\angle(\vec{v}, \vec{w})) \right\}$

skip



numerical fact: $\frac{\theta}{\pi} \geq .878 \left(\frac{1}{2} - \frac{1}{2} \cos \theta \right) \quad \forall \theta \in [0, \pi]$

$\therefore E[\text{frac edges } F \text{ cuts}] \geq .878 \text{SDPOpt}(G) \geq .878 \text{Opt}(G)$

[derivable]

"[GW] is a .878-ratio approx. alg for Max-Cut"



Constraint Satisfaction Problems (CSP)

Encompass a wide variety of alg. tasks - (Max-Cut, 3-Sat, 3-Coloring, Lin. Eq^s, ... basically also Vertex-Cover etc. Not everything, of course, but quite a lot...

def: CSP [problem] defined by - Domain Ω [values for vbls]. Usually $\{0, 1, 2, \dots, q-1\}$ often $q=2$.

[kinds of constrs allowed]. Set of preds/relations Ψ . Each $\psi \in \Psi$ is $\psi: \Omega^r \rightarrow \{0, 1\}$ arity,

[prob. name]

def: Instance: on n -vbl set V is a list of constrs: Each constr $C = (s, \psi)$ [input] where $\psi \in \Psi$ and s ("scope") is a tuple of vbls $(v_1, \dots, v_r) \in V$, $r = \text{arity}(\psi)$

Goal: assign vbls values in the domain so as to max # of sat. constrs.

eg: Max-Cut: $\Omega = \{-1, 1\}$, $\Psi = \{\neq\}$ ($\neq: \{-1, 1\}^2 \rightarrow \{0, 1\}$)

Max-3Sat: $\Omega = \{0, 1\}$, $\Psi = \{xvyvz, xvyv\bar{z}, \dots, \bar{x}\bar{v}\bar{y}\bar{z}, \bar{x}, \bar{v}, \bar{y}, \bar{z}\}$ [14 preds allowed]

Max-E3Sat: just these 8 "xvyvz + 'literals' allowed"

Max-NAE3Sat: $\Omega = \{0, 1\}$, $\Psi = \{\text{NAE}_3 + \text{literals}\}$

$\text{NAE}_3(x, y, z) = \begin{cases} 1 & \text{if } x, y, z \text{ not all equal} \\ 0 & \text{if } x=y=z \end{cases}$

Max-3Cut : $\Omega = \{\text{red, green, blue}\}$, $\Psi = \{\neq\}$
 (-3 Coloring)

Max-Bij(q) : $\Omega = \{0, 1, \dots, q-1\}$, $\Psi = \{\text{any "bijjective" } \varphi: \Omega \rightarrow \Omega\}$
 $\forall a \in \Omega, \exists! b \in \Omega \text{ s.t. } \varphi(a, b) = 1$.

AKA "Unique-Games (q)"

def: Given instance $\mathcal{U}$, assignment is map $F: V \rightarrow \Omega$.

Constr. $C = (S, \varphi)$ is satisfied if $\varphi(F(S)) = 1$

$\downarrow$
 $F(v_1, \dots, v_r)$

Value of F is $\text{Val}_{\mathcal{U}}(F) = \text{frac. constrs sat} = \mathbb{E}_{(S, \varphi) \sim \mathcal{U}} [\varphi(F(S))]$
 $\in [0, 1]$

Optimum is $\text{Opt}(\mathcal{U}) = \max_{F: V \rightarrow \Omega} \{\text{Val}_{\mathcal{U}}(F)\}$

"satisfiable": $\text{Opt}(\mathcal{U}) = 1$.

task 1: "Satisfiability": Given $\mathcal{U}$, decide if $\text{Opt}(\mathcal{U}) = 1$. $\rightarrow$ And find satisfying F . [Easy reduction]

alg task 2: Given $\mathcal{U}$, find F with $\text{Val}_{\mathcal{U}}(F)$ as large as poss. Ideally $\text{Opt}(\mathcal{U})$
 "Optimization".

~~NP-hard for "all" CSPs~~

task 3: [Just a #/val. ver of 2?] Given $\mathcal{U}$, output a "proof" of " $\text{Opt}(\mathcal{U}) \leq \beta$ ".
 Interesting prob... Ideally β as small as poss.

Satisfiability: For Which CSPs in P, which NP-complete?

(Max-1)Cut $\leftarrow$ testing bip.

(2) Bi $\leftarrow$ propagation alg.

3-Sat

NAE 3-Sat

3Cut/color

How can you tell? If I give you an unfamiliar one, ~~is it~~ in P or NPC? I

$$P \leftarrow \text{2Sat}$$

$$P \leftarrow \begin{array}{l} \text{3-Lin mod 2} \\ (x_i + x_j + x_k = 0 \pmod{2}) \\ \text{1-out-of-3 Sat} \end{array} \rightarrow \text{NPC.}$$

$$P \leftarrow \text{Order}(10)$$

[[topo sort]] [[$\Omega = [10]$, constrs " $v < w$ "]]

[F93]: Dichotomy Conjecture: Every CSP is in P or NPC.

[[Reminder of Ladner's Thm: $P \neq NP \Rightarrow$] probs in NP which are neither.]]

[[rich algebraic theory of this]]
[[universal]]

[BJK'05]: Alg. Dich. Conj.: CSP(Ψ) satisfiability in P if
[[WLOG core]] Ψ has "Taylor polymorphism"
else NPC. $\swarrow$ proved easy $\searrow$ open.
[[The missing piece is algorithm]]

[Schaefer'78]: $\checkmark$ if $|\Omega| = 2$.

[Bulatov '06]: $\checkmark$

3. [[Also, whenever Ψ contains all unary preds.]]

Markovitch+B? $\checkmark$

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[[They'll probably solve it soon.]]

Nothing's perfect. What if you get $\mathcal{U}$ and not sat'ble,
want to solve the opt. prob.

☹️ Opt version is NP-hard for "all" (nontriv) CSPs. [E.g., even Max-Cut.]
[Often turn to approx. algs.]

def: [task 2]: Efficient alg. A is an (α, β) -approx. alg. if:
 $\forall \mathcal{U}$ with $\text{Opt}(\mathcal{U}) \geq \beta$, A finds assign F with
 $\text{Val}(\mathcal{U}) \geq \alpha$.
 [in expect. if A randomized] [best assign. alg. gets]

[Sat. prob. is $\alpha = \beta = 1$]

rem: One alg. can be (α, β) -approx. simult. for many β .
 Eg.: [GW] is $(.878\beta, \beta)$ -approx. alg. for Max-Cut $\forall \beta$.
 [doesn't need to know β]

def: [task 3]: (α, β) -refutation alg.: $\forall \mathcal{U}$ with $\text{Opt}(\mathcal{U}) < \alpha$,
 alg. outputs "proof" of " $\text{Opt}(\mathcal{U}) < \beta$ ".

rem: Weaker than (α, β) -approx alg. [Why?]

[Say you had an (α, β) -approx alg. Given instance $\mathcal{U}$ with $\text{Opt}(\mathcal{U}) < \alpha$,
 run your alg., and say it "fails" if it fails to return
 an assign. of $\text{Val} \geq \alpha$. Of course, it will fail but
 this constitutes a proof of $\text{Opt} < \beta$, b/c if $\text{Opt} \geq \beta$
 your alg. will find a val- α solⁿ!]

eg: Given CSP inst. ϕ , write ILP, relax to LP, compute $\text{LP Opt} = \beta^*$ output " $\text{Opt}(\mathcal{U}) \leq \beta^*$ ".
 Even better pf: dual LP solⁿ of val. β^* .

