

The Approximability of Constraint Satisfaction Problems

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[See Notes on Web]

Reduction from $(\delta, 1-\varepsilon_0)$ -distinguishing Unique Games to $(\frac{1}{2} + \gamma, 1-3\varepsilon_0 - \varepsilon)$ -dist. 3 LIN

① Pick $v \in V$ at random, and $w_1, w_2, w_3 \in_{\mathbb{R}} N(v)$ at random.

② Pick $x, y \in_{\mathbb{R}} \{0, 1\}^R$ (u, v, w), $\mu \in_{\mathbb{R}} \in \varepsilon_0, 1/3^R$ (ε -biased) $z = x \oplus y \oplus w$

③ (Pull back) $x' = x \circ \pi_{w_1 \rightarrow v}$ $y' = y \circ \pi_{w_2 \rightarrow v}$
 $z' = z \circ \pi_{w_3 \rightarrow v}$

④ With prob. $1/2$, check $f_{w_1}(x') \oplus f_{w_2}(y') \oplus f_{w_3}(z') = 0$
 prob. $1/2$ check $f_{w_1}(x') \oplus f_{w_2}(y') \oplus f_{w_3}(\bar{z}') = 1$

Soundness Lemma) UG instance $\leq \delta$ -satisfiable
 \Rightarrow verifier accepts with prob. $\leq \frac{1}{2} + \gamma$

$$\gamma \leq O\left((\frac{\delta}{\varepsilon})^{1/5}\right).$$

Pf) Prob [verifier accepts] = $\rho = \frac{1}{2} \mathbb{E} \left[\frac{1 + f_{w_1}(x') f_{w_2}(y') f_{w_3}(z')}{2} \right] + \frac{1}{2} \mathbb{E} \left[\frac{1 - f_{w_1}(x') f_{w_2}(y') f_{w_3}(\bar{z}')}{2} \right]$

$f_w: \{0, 1\}^R \rightarrow \{-1, 1\}$

$$g_v(x) = \mathbb{E}_{w \in N(v)} [f_w(x \circ \pi_{w \rightarrow v})]$$

$$g_v: \{0, 1\}^R \rightarrow [-1, 1]$$

$$= \frac{1+1}{2} \mathbb{E}_{x, y, z} [g_v(x) g_v(y) g_v(z) - g_v(x) g_v(y) g_v(\bar{z})]$$

$$z = x \oplus y \oplus w \quad \mathbb{E}_{x, y} [g_v(x) g_v(y) g_v(x \oplus y)] = 1 \Rightarrow g_v \text{ is linear function.}$$

Fact: The functions $\{X_d\}_{d \in \{0, 1\}^R}$ $X_d(x) = (-1)^{d \cdot x}$
 are all the linear functions.

Fact: The $\{X_\alpha\}$ form an orthonormal basis of the vector space $F = \{f : \{0, 1\}^R \rightarrow \mathbb{R}\}$

$$\langle g, h \rangle = \frac{1}{2^R} \sum_{x \in \{0,1\}^R} g(x) h(x)$$

Fact: $\langle X_\alpha, X_\beta \rangle = \begin{cases} 1 & \text{if } \alpha = \beta \\ 0 & \text{otherwise} \end{cases}$

Pf See
Prod

Every $g : \{0, 1\}^R \rightarrow \mathbb{R}$ can be expressed uniquely

$$g(x) = \sum_{\alpha} \hat{g}(\alpha) X_\alpha(x)$$

where $\hat{g}(\alpha) = \langle g, X_\alpha \rangle$

Exer

Fact: $\langle g, h \rangle = \sum_{\alpha} \hat{g}(\alpha) \hat{h}(\alpha)$ (Raserval's identity)

$$\text{Corl } \sum_{\alpha} \hat{g}(\alpha)^2 = \frac{1}{2^R} \sum_{x} g(x)^2 < 1$$

Lab

Lemma $\mathbb{E}_{x,y,z} [g(x)g(y)g(x \oplus y \oplus z)] = \sum_{\alpha, \beta, \gamma} \hat{g}(\alpha)^2 (1 - 2\varepsilon)^{|\alpha|}$
 $|\alpha| = |\text{supp}(\alpha)| = |\{\ i \mid \alpha_i = 1\}|$.

w ∈ l

$$\begin{aligned} \text{Pf} \quad & \mathbb{E}_{x,y,z} \left[\left(\sum_{\alpha} \hat{g}(\alpha) X_\alpha(x) \right) \left(\sum_{\beta} \hat{g}(\beta) X_\beta(y) \right) \left(\sum_{\gamma} \hat{g}(\gamma) X_\gamma(z) \right) \right] \\ &= \mathbb{E}_{x,y,z} \left[\sum_{\alpha, \beta, \gamma} \hat{g}(\alpha) \hat{g}(\beta) \hat{g}(\gamma) X_\alpha(x) X_\beta(y) X_\gamma(z) \right] \\ &= \sum_{\alpha, \beta, \gamma} \hat{g}(\alpha) \hat{g}(\beta) \hat{g}(\gamma) \mathbb{E}_{x,y,z} [X_\alpha(x) X_\beta(y) X_\gamma(z)] \\ &= \sum_{\alpha, \beta, \gamma} \hat{g}(\alpha) \hat{g}(\beta) \hat{g}(\gamma) \mathbb{E}_x [X_\alpha(x) X_\beta(x)] \mathbb{E}_y [X_\beta(y) X_\gamma(y)] \mathbb{E}_z [X_\gamma(z)] \\ &= \sum_{\alpha} \hat{g}(\alpha)^3 \mathbb{E}_y [(-1)^{\langle X_\alpha, X_3 \rangle}] \\ &= \sum_{\alpha} \hat{g}(\alpha)^3 \prod_i \mathbb{E}_y [(-1)^{\alpha_i + 1}] \\ &= \sum_{\alpha} \hat{g}(\alpha)^3 (1 - 2\varepsilon)^{|\alpha|} \quad \square \end{aligned}$$

Fact:
Wxto

Lem
w G

$$g_v(x) = \frac{1}{2} + \frac{1}{4} \mathbb{E} \left[\sum_{\alpha} \hat{g}(\alpha)^3 (1 - 2\varepsilon)^{|\alpha|} - \sum_{\alpha} \hat{g}(\alpha)^3 (-1)^{|\alpha|} (1 - 2\varepsilon)^{|\alpha|} \right]$$

$$= \frac{1}{2} + \frac{1}{2} \mathbb{E} \left[\underbrace{\sum_{\alpha \text{ odd}} \hat{g}(\alpha)^3 (1 - 2\varepsilon)^{|\alpha|}}_{\Theta_v} \right]$$

Pf Soundness Continued

$$\text{Prob}[\text{verifier accepts}] = \rho \geq \frac{1}{2} + \gamma$$

$$\mathbb{E}[\Theta_v] > 2\gamma$$

\Rightarrow at least γ frac. of v 's have $\Theta_v \geq \gamma$
such v is a "good" v

Exercise] If v is good, $\exists \alpha, 1 \leq |\alpha| \leq \frac{1}{\varepsilon} \log \frac{2}{\gamma}$,
s.t. $|\hat{g}_v(\alpha)| \geq \frac{\gamma}{2}$.

indep. of R

Labeling for UG

$\forall v \in V$ if v is not good, $l(v) = \text{arbitrary} - l : V \cup W \rightarrow \{1, \dots, R\}$

if v is good let $\alpha \neq \emptyset$ be s.t. $|\hat{g}_v(\alpha)| > \gamma/2$
 $l(v) = \text{any elt. in } \text{supp}(\alpha)$

$w \in W$

$$L_w = \bigcup_{B \in \{0, 1\}^R} \text{supp}(B)$$

$$|\hat{f}_{wB}(B)| \geq \gamma/2$$

$$|B| \leq \frac{1}{\varepsilon} \log \frac{2}{\gamma}$$

$$l(w) = \begin{cases} 1 & \text{if } L_w = \emptyset \\ \text{random element from } L_w. \end{cases}$$

Fact: $\forall w$

$$\mathbb{O}\left(\frac{1}{\varepsilon \gamma^2} \log \frac{1}{\gamma}\right) \geq |L_w|$$

"friendly"
to v

Lemma] Suppose $v \in V$ is good. For at least $\frac{\gamma}{4}$ frac. of
 $w \in N(v)$. $l(w) \in \Pi_{w \rightarrow v}(L_w) \triangleq \{\Pi_{w \rightarrow v}(b) \mid b \in L_w\}$

$$\text{Prob} [\pi_{w \rightarrow v}(l(w)) = l(v)] = \frac{1}{|L_w|} \geq \Omega(\gamma^3 \varepsilon)$$

Defn

$$\geq \mathbb{E} [\text{frac of } \pi_{w \rightarrow v} \text{ satisfied}] \geq \gamma \cdot \frac{1}{4} \cdot \Omega(\gamma^3 \varepsilon) = \Omega(\gamma^5 \varepsilon).$$

Exerc

$$\Rightarrow \gamma \leq O\left(\left(\frac{\varepsilon}{\delta}\right)^{15}\right).$$

"far
In"

Pf of Lemma) Show $l(v) \in \pi_{v \rightarrow w}(L_w)$

$$\exists \alpha, |\alpha| \leq \lg \frac{2}{\delta} \quad |\hat{g}_v(\alpha)| \geq \frac{\chi}{2}$$

$$g_v(x) = \mathbb{E}_{w \in N(v)} [f_w(x \circ \pi_{w \rightarrow v})]$$

$$\text{Exercise: } \hat{g}_v(\alpha) = \mathbb{E}_w [\hat{f}_w(\alpha \circ \pi_{w \rightarrow v})]$$

Max
(c_x ,

$$\Rightarrow \mathbb{E}_{w \in N(v)} [\hat{f}_w(\alpha \circ \pi_{w \rightarrow v})] \geq \chi/2$$

Pic

By averaging $\geq \frac{\chi}{4}$ frac. of $w \in N(v)$ have

$$|\hat{f}_w(\alpha \circ \pi_{w \rightarrow v})| \geq \frac{\chi}{4}.$$

Solv

$$\text{supp}(\alpha \circ \pi_{w \rightarrow v}) \subseteq L_w$$

$$l(v) \in \text{supp}(\alpha)$$

$$\pi_{w \rightarrow v}^{-1}(l(v)) \in L_w$$

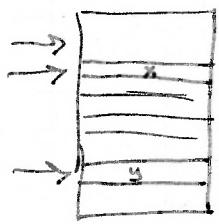
Maj

$$\Leftrightarrow l(v) \in \pi_{w \rightarrow v}(L_w) \quad \square$$

Dictatorship Test or Projection Test

$$g: \{0,1\}^R \rightarrow \{0,1\}^R$$

max cut



Pick $(x, y) \in D \subseteq \{0,1\}^R \times \{0,1\}^R$

check $g(x) \neq g(y)$

x
y

① Completeness: If $g(x) = x_i$, test accepts with prob. β .

② Soundness: If g is far from a dictator prob. test accepts $\leq \alpha + \gamma$.

$$\text{Defn) } \text{Inf}_i(g) = \Pr_{x \in \{-1, 1\}^R} [g(x) \neq g(x \oplus e_i)]$$

$$\text{Exercise) } \text{Inf}_i(g) = \sum_{\substack{a: \\ \text{supp } g \ni i}} \hat{g}(a)^2$$

"far from a dictator" means $\forall i \in \{1, \dots, R\}$

$$\text{Inf}_i(g) \leq \frac{1}{2} \tau \quad (\tau = \tau(\alpha))$$

Max Cut

$$(x, y) \in D \quad f(x) \neq f(y)$$

$f(x) = x_i$ would like $x_i \neq y_i$ with prob. β .

Pick x at random

$$y_i = \begin{cases} x_i & \text{with prob. } 1-\beta \\ \bar{x}_i & \text{with prob. } \beta \end{cases} \quad \xrightarrow{\text{noise sensitivity}}$$

$$\text{Soundness} \quad \Pr_{\substack{x \in \{-1, 1\}^R \\ y \in N_\beta(x)}} [f(x) \neq f(y)] \triangleq \text{NS}_\beta(f)$$

$$\text{Exercise) } \text{NS}_\beta(f) = 1 - \frac{\sum \hat{f}(a)^2 (1-2\beta)^{|a|}}{2}$$

$$\text{NS}_\beta(\text{Proj}_i) = \beta.$$

$$\text{Majority} \quad \Pr_{(x, y)} [\text{Maj}(x) \neq \text{Maj}(y)]$$

$$f: \{-1, 1\}^R \rightarrow \{-1, 1\}$$

$$\text{Maj}(x) = \text{sgn}(\sum x_i)$$

$$\Pr_{\substack{x \in \{-1, 1\}^R \\ y \in N_\beta(x)}} [\text{sgn}\left(\frac{1}{\sqrt{R}} \sum x_i\right) \neq \text{sgn}\left(\frac{1}{\sqrt{R}} \sum y_i\right)]$$

$$\downarrow \text{N}(0, 1) \quad \downarrow \text{N}(0, 1)$$

$$\text{sgn}\left(\frac{1}{\sqrt{R}} \sum g_i\right)$$

g_i Gaussian

$$a = \left(\frac{1}{\sqrt{R}}, \frac{1}{\sqrt{R}}, \dots, \frac{1}{\sqrt{R}} \right) \quad b = \left(\frac{M_1}{\sqrt{R}}, \dots, \frac{M_R}{\sqrt{R}} \right)$$

$$\Pr [\operatorname{sgn}(\mathbf{z} \cdot \mathbf{x}_i) \neq \operatorname{sgn}(\mathbf{z} \cdot \mathbf{y}_i)] \approx \Pr [\operatorname{sgn}(a - g) \neq \operatorname{sgn}(b - g)]$$

$$= \frac{\langle a \cdot b \rangle}{\pi} = \frac{\arccos(a \cdot b)}{\pi} \approx \frac{\cos^{-1}(1 - 2\beta)}{\pi}$$

Dictators pass test with prob. β
Far from dictators pass test with prob $a = \frac{\cos^{-1}(1 - 2\beta)}{\pi} + \gamma$