

# Quantum query complexity

## Lecture 4

### The adversary method

**Materials:** <https://yassine-hamoudi.github.io/pcmi2023/>

# Last lecture (end of the proof)

SEARCH problem: Find  $i$  such that  $x_i = 1$

$$\Pi = \left( \sum_{x \in \{0,1\}^n} |x\rangle\langle x| \right) \otimes \text{Id}$$

$$\Delta_t = \|\Pi |\psi_{\text{rec}}^t\rangle\|^2$$

Lemma 1:  $\Delta_0 = 0$

Lemma 2:  $\sqrt{\Delta_{t+1}} \leq \sqrt{\Delta_t} + \sqrt{10/n}$

**Proof:** We showed that  $\sqrt{\Delta_{t+1}} \leq \sqrt{\Delta_t} + \|\Pi R(\text{Id} - \Pi) |\psi_{\text{rec}}^t\rangle\|$

Claim: For all  $|\psi\rangle \in \ker(\Pi)$  we have  $\|\Pi R |\psi\rangle\| \leq \sqrt{10/n} \|\psi\rangle\|$

# Last lecture (end of the proof)

Proposition: When  $b \neq 0$ , the recording query operator  $R$  acts as:

$$R | \dots, x_{i-1}, \emptyset, x_{i+1}, \dots \rangle \otimes |i, b\rangle = | \dots, x_{i-1} \rangle \left( \frac{1}{\sqrt{n}} \sum_{0 \leq y < n} \omega^{by} |y\rangle \right) |x_{i+1}, \dots\rangle \otimes |i, b\rangle$$

$$R | \dots, x_{i-1}, y, x_{i+1}, \dots \rangle \otimes |i, b\rangle = | \dots, x_{i-1} \rangle \left( \omega^{by} |y\rangle + |\text{error}_y\rangle \right) |x_{i+1}, \dots\rangle \otimes |i, b\rangle$$

**where**  $|\text{error}_y\rangle = \frac{\omega^{by}}{\sqrt{n}} |\emptyset\rangle + \sum_{0 \leq z < n} \frac{1 - \omega^{by} - \omega^{bz}}{n} |z\rangle$

# Focus of this lecture

## The (generalized) adversary method

- A lower bound method that is **always optimal**
  - > We'll show in lecture 5 how to turn it into an algorithm
  - > Counterpart: often harder to use
- It shares some ideas with the **hybrid** method (lecture 1) and the **recording** method (lecture 3)  
(in fact: these can be seen as particular cases of it)

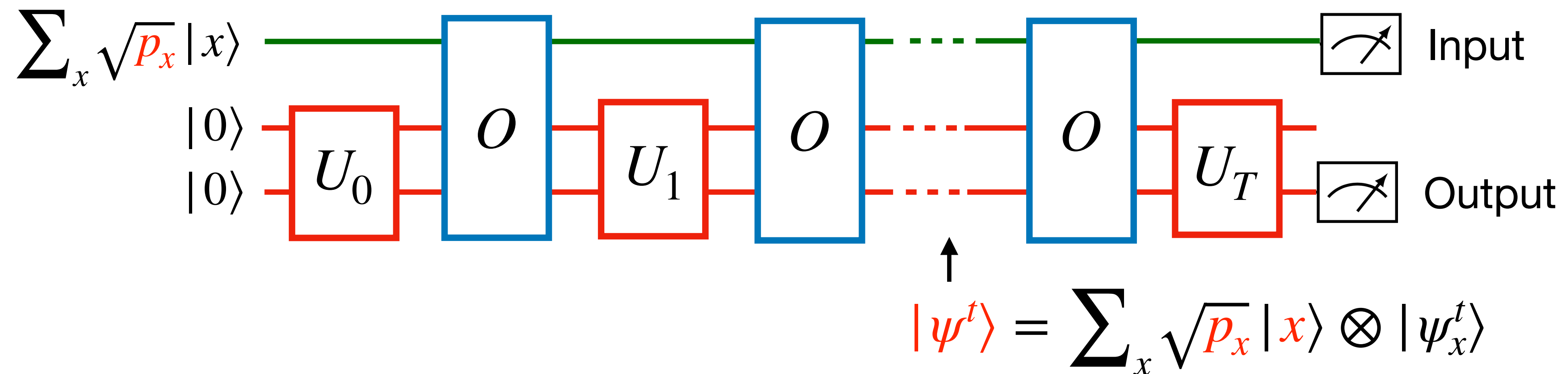
# Reminders

## The distinguishing lemma (lecture 1)

The states  $|\psi_x^T\rangle$  and  $|\psi_y^T\rangle$  can be distinguished with probability  $\geq 2/3$  if and only if there are “sufficiently orthogonal”  $|\langle\psi_x^T|\psi_y^T\rangle| \leq 2\sqrt{2}/3$

## The purification viewpoint (lecture 3)

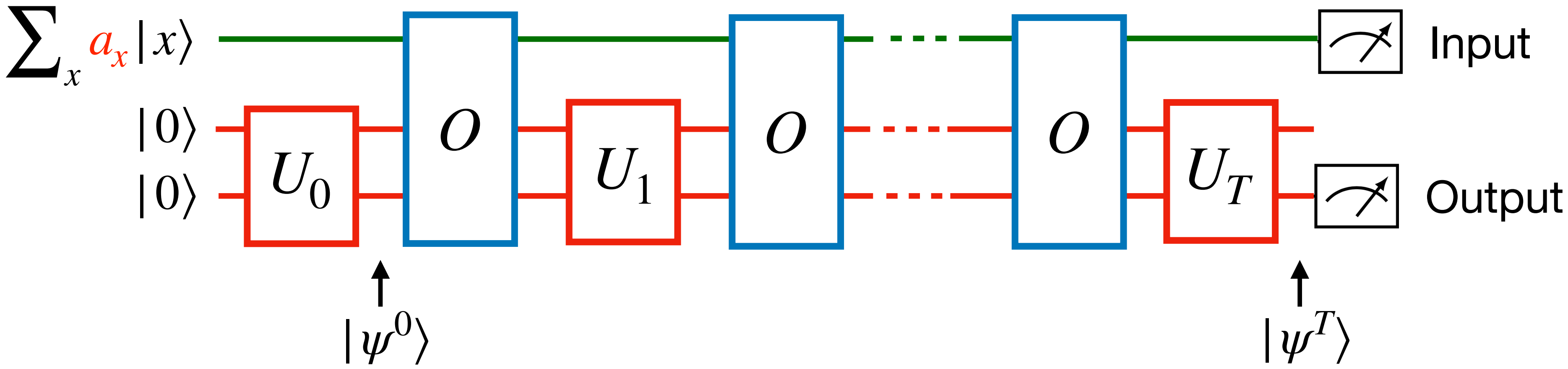
We can set a distribution  $(p_x)_x$  on the input by adding a purification register



Quantum adversary

First step: replace  $(p_x)_x$  with **complex** numbers  $(a_x)_x$  s.t.  $\sum_x |a_x|^2 = 1$

$$|\psi^t\rangle = \sum_x a_x |x\rangle \otimes |\psi_x^t\rangle$$



First step: replace  $(p_x)_x$  with **complex** numbers  $(a_x)_x$  s.t.  $\sum_x |a_x|^2 = 1$

$$|\psi^t\rangle = \sum_x a_x |x\rangle \otimes |\psi_x^t\rangle$$

Second step: consider the Gram matrix:

$$\sum_{x,y} a_x^* a_y \langle \psi_x^t | \psi_y^t \rangle |x\rangle \langle y|$$

$$x \begin{pmatrix} & & & & y \\ & & & & \vdots \\ & & & & \\ & & & & \\ & & & & \\ \dots & & & & a_x^* a_y \langle \psi_x^t | \psi_y^t \rangle \end{pmatrix}$$

Third step: place some weights  $\Gamma_{x,y}$  on the “hard” pairs of inputs

(symmetric)  $\Gamma_{x,y} = \Gamma_{y,x}$

(consistent) if  $f(x) = f(y)$  then  $\Gamma_{x,y} = 0$

$$x \begin{pmatrix} & & & & y \\ & & & & \vdots \\ & & & & \\ & & & & \\ & & & & \\ \dots & & & & \Gamma_{x,y} a_x^* a_y \langle \psi_x^t | \psi_y^t \rangle \end{pmatrix}$$



**Adversary matrix:**  $\Gamma \in \mathbb{R}^{2^n \times 2^n}$  symmetric and  $f(x) = f(y) \Rightarrow \Gamma_{x,y} = 0$

**Adversary distribution:**  $a \in \mathbb{C}^{2^n}$  principal (unit) eigenvector of  $\Gamma$

**“Punctured” matrices:**  $\Gamma_i \in \mathbb{R}^{2^n \times 2^n}$  such that  $(\Gamma_i)_{x,y} = \Gamma_{x,y} \cdot \mathbf{1}_{x_i \neq y_i}$

**Progress measure:**  $\Delta_t = |\langle \psi^t | (\Gamma \otimes \text{Id}) | \psi^t \rangle| = \left| \sum_{x,y} \Gamma_{x,y} a_x^* a_y \langle \psi_x^t | \psi_y^t \rangle \right|$

Lemma 1:  $\Delta_0 = \|\Gamma\|$  *(initial condition)*

Lemma 2:  $\Delta_T < 0.95 \|\Gamma\|$  if the algorithm succeeds wp  $\geq 2/3$  *(final condition)*

Lemma 3:  $\Delta_{t+1} \geq \Delta_t - 2 \max_{1 \leq i \leq n} \|\Gamma_i\|$  *(evolution)*

$$\textbf{Theorem: } Q(f) \geq \max_{\Gamma} \frac{\|\Gamma\|}{40 \cdot \max_{1 \leq i \leq n} \|\Gamma_i\|}$$

- **Positive-weight** adversary:  $\forall x, y, \Gamma_{x,y} \geq 0$ 
  - Has a nice combinatorial interpretation (see problem session)
  - Sub-optimal (the “certificate” and “property testing” barriers)
- **Negative-weight** adversary:  $\forall x, y, \Gamma_{x,y} \in \mathbb{R}$ 
  - Optimal! (see next lecture)  $Q(f) = \Theta\left(\max_{\Gamma} \frac{\|\Gamma\|}{\max_{1 \leq i \leq n} \|\Gamma_i\|}\right)$

# Applications

OR function:  $f(x) = 0$  if and only if  $x = (0,0,\dots,0)$

We (again) only focus on the  $n + 1$  “hardest” inputs denoted by:

$$\vec{0} = (0,0,\dots,0) \quad \vec{1} = (1,0,\dots,0) \quad \vec{2} = (0,1,0,\dots,0) \quad \dots \quad \vec{n} = (0,0,\dots,1)$$

$$\Gamma = \begin{pmatrix} \vec{0} & \vec{1} & \dots & \vec{n} \\ 0 & 1 & \dots & 1 \\ 1 & 0 & \dots & 0 \\ \vdots & \vdots & \dots & \vdots \\ 1 & 0 & \dots & 0 \end{pmatrix} \begin{matrix} \vec{0} \\ \vec{1} \\ \vdots \\ \vec{n} \end{matrix} \quad \Gamma_i = \begin{pmatrix} 0 & \dots & 0 & \vec{i} & 0 & \dots & 0 \\ \vdots & 0 & \dots & \dots & \dots & \dots & 0 \\ 0 & \vdots & \dots & \dots & \dots & \dots & \vdots \\ 1 & \vdots & \dots & \dots & \dots & \dots & \vdots \\ 0 & \vdots & \dots & \dots & \dots & \dots & \vdots \\ \vdots & \vdots & \dots & \dots & \dots & \dots & \vdots \\ 0 & 0 & \dots & \dots & \dots & \dots & 0 \end{pmatrix} \vec{i}$$

(omitting the other 0-entries)

$$\|\Gamma\| = \sqrt{n}$$

$$\|\Gamma_i\| = 1$$

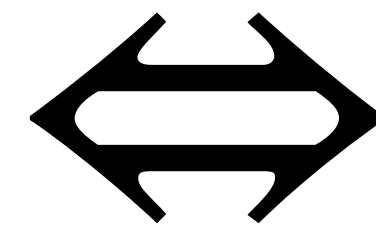
$$\Rightarrow Q(\text{OR}) \geq \sqrt{n}/40$$

# Dual SDP

$$Q(f) \geq \text{Adv}(f)/40$$

Rewrite the optimization problem:

$$\begin{aligned} \text{Adv}(f) &= \max_{\Gamma} \frac{\|\Gamma\|}{\max_{1 \leq i \leq n} \|\Gamma_i\|} \\ \text{s.t. } &\Gamma_{x,y} = \Gamma_{y,x} \quad \forall x, y \\ &\Gamma_{x,y} = 0 \quad \forall x, y, f(x) = f(y) \\ &\Gamma \in \mathbb{R}^{2^n \times 2^n} \end{aligned}$$

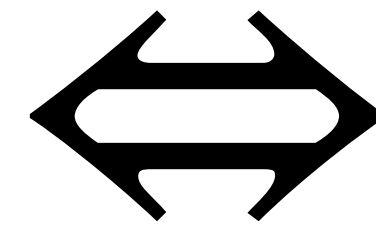


$$\begin{aligned} \text{Adv}(f) &= \max_{\Gamma} \|\Gamma\| \\ \text{s.t. } &\|\Gamma_i\| \leq 1 \quad \forall i \\ &\Gamma_{x,y} = \Gamma_{y,x} \quad \forall x, y \\ &\Gamma_{x,y} = 0 \quad \forall x, y, f(x) = f(y) \\ &\Gamma \in \mathbb{R}^{2^n \times 2^n} \end{aligned}$$

$$Q(f) \geq \text{Adv}(f)/40$$

Rewrite the optimization problem:

$$\begin{aligned} \text{Adv}(f) &= \max_{\Gamma} \frac{\|\Gamma\|}{\max_{1 \leq i \leq n} \|\Gamma_i\|} \\ \text{s.t. } &\Gamma_{x,y} = \Gamma_{y,x} \quad \forall x, y \\ &\Gamma_{x,y} = 0 \quad \forall x, y, f(x) = f(y) \\ &\Gamma \in \mathbb{R}^{2^n \times 2^n} \end{aligned}$$

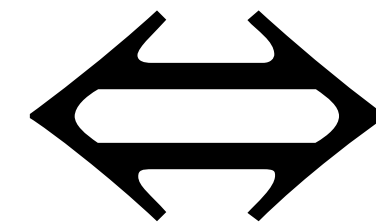


$$\begin{aligned} \text{Adv}(f) &= \max_{\Gamma, \epsilon} \epsilon \\ \text{s.t. } &\|\Gamma\| \leq \epsilon, \quad \|\Gamma_i\| \leq 1 \quad \forall i \\ &\Gamma_{x,y} = \Gamma_{y,x} \quad \forall x, y \\ &\Gamma_{x,y} = 0 \quad \forall x, y, f(x) = f(y) \\ &\Gamma \in \mathbb{R}^{2^n \times 2^n}, \quad \epsilon \in \mathbb{R} \end{aligned}$$

$$Q(f) \geq \text{Adv}(f)/40$$

Rewrite the optimization problem:

$$\begin{aligned} \text{Adv}(f) &= \max_{\Gamma} \frac{\|\Gamma\|}{\max_{1 \leq i \leq n} \|\Gamma_i\|} \\ \text{s.t. } &\Gamma_{x,y} = \Gamma_{y,x} \quad \forall x, y \\ &\Gamma_{x,y} = 0 \quad \forall x, y, f(x) = f(y) \\ &\Gamma \in \mathbb{R}^{2^n \times 2^n} \end{aligned}$$



Semidefinite program

$$\begin{aligned} \text{Adv}(f) &= \max_{\Gamma, \epsilon} \epsilon \\ \text{s.t. } &-\epsilon \text{Id} \leq \Gamma \leq \epsilon \text{Id} \\ &-\text{Id} \leq \Gamma_i \leq \text{Id} \quad \forall i \\ &\Gamma_{x,y} = \Gamma_{y,x} \quad \forall x, y \\ &\Gamma_{x,y} = 0 \quad \forall x, y, f(x) = f(y) \\ &\Gamma \in \mathbb{R}^{2^n \times 2^n}, \epsilon \in \mathbb{R} \end{aligned}$$



$$Q(f) \geq \text{Adv}(f)/40$$

Primal SDP

Strong duality  


Dual SDP

$$\text{Adv}(f) = \max_{\Gamma} \frac{\|\Gamma\|}{\max_{1 \leq i \leq n} \|\Gamma_i\|}$$

$$\text{s.t. } \Gamma_{x,y} = \Gamma_{y,x} \quad \forall x, y$$

$$\Gamma_{x,y} = 0 \quad \forall x, y, f(x) = f(y)$$

$$\Gamma \in \mathbb{R}^{2^n \times 2^n}$$

$$\text{Adv}(f) = \min_{V^{(1)}, \dots, V^{(n)}} \max_{x \in \{0,1\}^n} \sum_{1 \leq i \leq n} V_{x,x}^{(i)}$$

$$\text{s.t. } \sum_{i: x_i \neq y_i} V_{x,y}^{(i)} = \mathbf{1}_{f(x) \neq f(y)} \quad \forall x, y$$

$$V^{(i)} \geq 0 \quad \forall 1 \leq i \leq n$$

$$V^{(i)} \in \mathbb{C}^{2^n \times 2^n} \quad \forall 1 \leq i \leq n$$

$$Q(f) \geq \text{Adv}(f)/40$$

## Dual SDP

$$\text{Adv}(f) = \min_{V^{(1)}, \dots, V^{(n)}} \max_{x \in \{0,1\}^n} \sum_{1 \leq i \leq n} V_{x,x}^{(i)}$$

$$\text{s.t. } \sum_{i: x_i \neq y_i} V_{x,y}^{(i)} = \mathbf{1}_{f(x) \neq f(y)} \quad \forall x, y,$$

$$V^{(i)} \geq 0 \quad \forall 1 \leq i \leq n$$

$$V^{(i)} \in \mathbb{C}^{2^n \times 2^n} \quad \forall 1 \leq i \leq n$$

PSD (positive semidefinite) constraint

$$V \geq 0 \Leftrightarrow \langle w | V | w \rangle \geq 0 \quad \forall w \in \mathbb{C}^{2^n}$$

$\Leftrightarrow \exists w^{(1)}, \dots, w^{(2^n)} \in \mathbb{C}^{2^n}$  such that

$$V_{x,y} = (\langle w^{(x)} | w^{(y)} \rangle)_{x,y} \quad \forall x, y$$

(Gram matrix)

$$Q(f) \geq \text{Adv}(f)/40$$

### Dual SDP

$$\text{Adv}(f) = \min_{V^{(1)}, \dots, V^{(n)}} \max_{x \in \{0,1\}^n} \sum_{1 \leq i \leq n} V_{x,x}^{(i)}$$

$$\text{s.t.} \quad \sum_{i: x_i \neq y_i} V_{x,y}^{(i)} = \mathbf{1}_{f(x) \neq f(y)} \quad \forall x, y,$$

$$V^{(i)} \geq 0 \quad \forall 1 \leq i \leq n$$

$$V^{(i)} \in \mathbb{C}^{2^n \times 2^n} \quad \forall 1 \leq i \leq n$$

### Alternative formulation

$$\text{Adv}(f) = \min_{\{w^{(x,i)}\}} \max_{x \in \{0,1\}^n} \sum_{1 \leq i \leq n} \|w^{(x,i)}\|^2$$

$$\text{s.t.} \quad \sum_{i: x_i \neq y_i} \langle w^{(x,i)} | w^{(y,i)} \rangle = \mathbf{1}_{f(x) \neq f(y)} \quad \forall x, y$$

$$w^{(x,i)} \in \mathbb{C}^{2^n} \quad \forall x \in \{0,1\}^n, 1 \leq i \leq n$$