# **Advanced Algorithms (IV)**

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MAXCUT Input: An undirected graph G = (V, E).

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#### **Vector Program**

$$\max \quad \frac{1}{2} \sum_{e = \{u, v\} \in E} \left( 1 - \mathbf{w}_u^T \mathbf{w}_v \right)$$
  
s.t. 
$$\mathbf{w}_u \in \mathbb{R}^n, \quad \forall u \in V$$
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Let  $\{\widehat{\mathbf{w}}_{v}\}_{v \in V}$  be an optimal solution.

**Task**: Round  $\{\widehat{\mathbf{w}_{v}}\}_{v \in V}$  to a cut

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#### Implementation

- 1. Choose a vector  $\mathbf{r} = (r_1, \dots, r_n)$  where each  $r_i \sim \mathcal{N}(0, 1)$  i.i.d.
- **2.** Let  $S \triangleq \{ u \in V : \mathbf{r}^T \widehat{\mathbf{w}_u} \ge 0 \}.$

#### Proposition

 $\frac{\mathbf{r}}{\|r\|}$  is a point on  $S^{n-1}$  uniformly at random.

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#### **Proposition**

Random hyperplane rounding is a 0.878-approximation of MAXCUT.

We try to apply Goemans-Williamson rounding to general quadratic programs.

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Quadratic Program  $\max \sum_{1 \le i,j \le n} a_{i,j} x_i x_j$ s.t.  $x_i \in \{-1, +1\}, \quad i = 1, ..., n.$ 

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We assume  $A = (a_{i,j})_{1 \le i,j \le n}$  is positive semi-definite.

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Vector Program

max 
$$\sum_{1 \le i,j \le n} a_{i,j} \mathbf{v}_i^T \mathbf{v}_j$$
  
s.t.  $\mathbf{v}_i \in \mathbb{R}^n$ ,  $i = 1, ..., n$ 

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**Vector Program** 

$$\max \sum_{1 \le i,j \le n} a_{i,j} \mathbf{v}_i^T \mathbf{v}_j$$
  
s.t.  $\mathbf{v}_i \in \mathbb{R}^n, \quad i = 1, \dots, n$ 

- **1.** Compute  $\{\widehat{\mathbf{v}}_i\}_{1 \le i \le n}$ .
- **2.** Pick a vector  $\mathbf{r}$  u.a.r on  $S^{n-1}$ .
- **3.**  $\hat{\mathbf{x}}_i = 1$  if  $\widehat{\mathbf{v}}_i^T \mathbf{r} \ge 0$ ;  $\hat{\mathbf{x}}_i = -1$  otherwise.

## Proposition

$$\mathbf{E}\left[\hat{x}_{i}\hat{x}_{j}\right] = \frac{2}{\pi} \arcsin(\hat{v}_{i}^{T} \cdot \hat{v}_{j}).$$

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#### Proof.

Use Schur producet theorem.

► Given a undirected graph G = (V, E) in which each  $e \in E$  has two weights  $w_e^+, w_e^- \ge 0$ .

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- Find a partition  $S = (S_1, \ldots, S_k)$  of *V*.
- ►  $E^+(S) \triangleq$  edge in a cluster;  $E^-(S) \triangleq$  edges between clusters.

- Given a undirected graph G = (V, E) in which each e ∈ E has two weights w<sup>+</sup><sub>e</sub>, w<sup>-</sup><sub>e</sub> ≥ 0.
- Find a partition  $S = (S_1, \ldots, S_k)$  of *V*.
- ►  $E^+(S) \triangleq$  edge in a cluster;  $E^-(S) \triangleq$  edges between clusters.
- The goal is to maximize

$$\sum_{e\in E^+(\mathcal{S})} w_e^+ + \sum_{e\in E^-(\mathcal{S})} w_e^-.$$

For  $1 \le k \le n$ , let  $e_k$  be the *k*-th unit vector.

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$$\begin{aligned} \max \quad & \sum_{\{u,v\}\in E} \left( w_{u,v}^+(x_u^T x_v) + w_{u,v}^-(1-x_u^T x_v) \right) \\ \text{s.t.} \quad & x_u \in \{e_1,\ldots,e_n\}, \quad \forall u \in V. \end{aligned}$$

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s.t.  $x_u \in \{e_1, \dots, e_n\}, \quad \forall u \in V.$ 

#### Relaxation

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$$\sum_{\{u,v\}\in E} \left( w_{u,v}^+(x_u^T x_v) + w_{u,v}^-(1 - x_u^T x_v) \right)$$
  
i.t. 
$$x_v^T x_v = 1, \quad \forall v \in V,$$
  

$$x_u^T x_v \ge 0, \quad \forall u, v \in V,$$
  

$$x_u \in \mathbb{R}^n, \quad \forall u \in V.$$



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#### Proposition

Two random hyperplane rounding is a  $\frac{3}{4}$ -approximation for correlation clustering.