

# Energy minimization via conic programming hierarchies

David de Laat (TU Delft)

IFORS

July 14, 2014, Barcelona

# Energy minimization

- ▶ What is the minimal potential energy  $E$  when we distribute  $N$  particles in a container  $V$  with pair potential  $w$ ?

# Energy minimization

- ▶ What is the minimal potential energy  $E$  when we distribute  $N$  particles in a container  $V$  with pair potential  $w$ ?
- ▶ Example: For the Thomson problem we take

$$V = S^2 \quad \text{and} \quad w(\{x, y\}) = \frac{1}{\|x - y\|}$$

# Energy minimization

- ▶ What is the minimal potential energy  $E$  when we distribute  $N$  particles in a container  $V$  with pair potential  $w$ ?
- ▶ Example: For the Thomson problem we take

$$V = S^2 \quad \text{and} \quad w(\{x, y\}) = \frac{1}{\|x - y\|}$$

- ▶ Optimization problem:

$$E = \inf_{S \in \binom{V}{N}} \sum_{P \in \binom{S}{2}} w(P)$$

# Approach

- ▶ Configurations provide upper bounds on the optimal energy  $E$

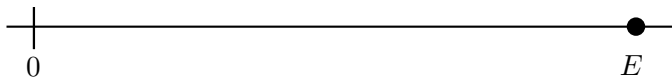
# Approach

- ▶ Configurations provide upper bounds on the optimal energy  $E$
- ▶ To prove a configuration is good (or optimal) we need good lower bounds for  $E$

# Approach

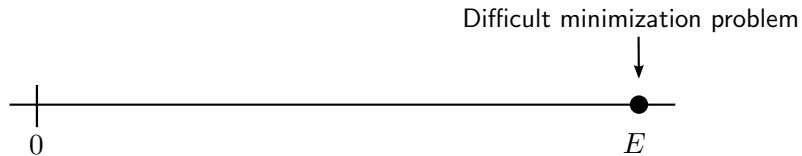
- ▶ Configurations provide upper bounds on the optimal energy  $E$
- ▶ To prove a configuration is good (or optimal) we need good lower bounds for  $E$
- ▶ For this we use infinite dimensional moment hierarchies and semidefinite programming

# Approach

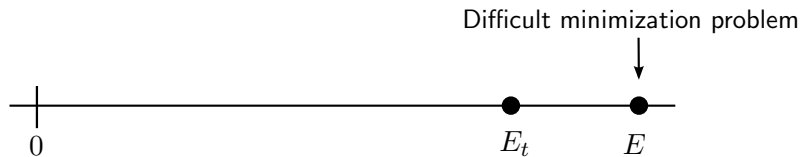




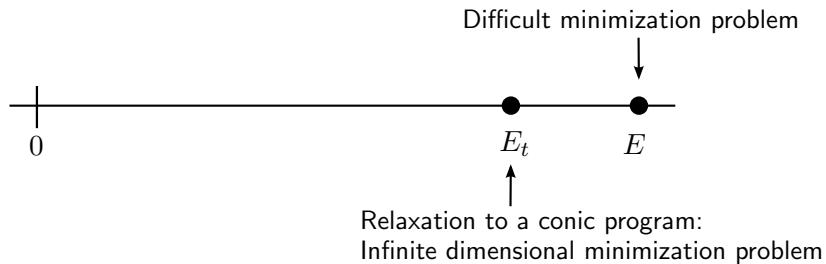
# Approach



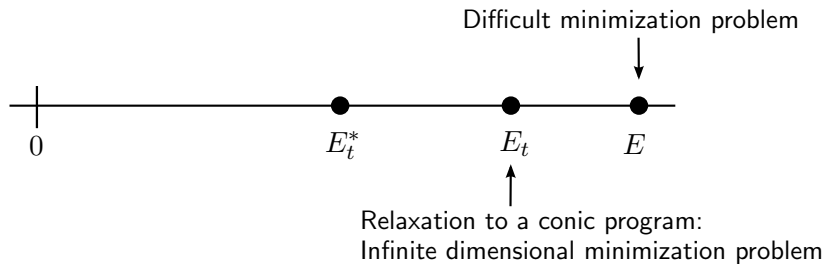
# Approach



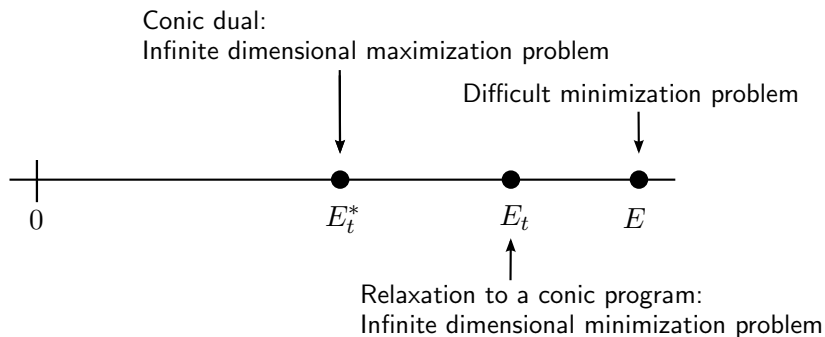
# Approach



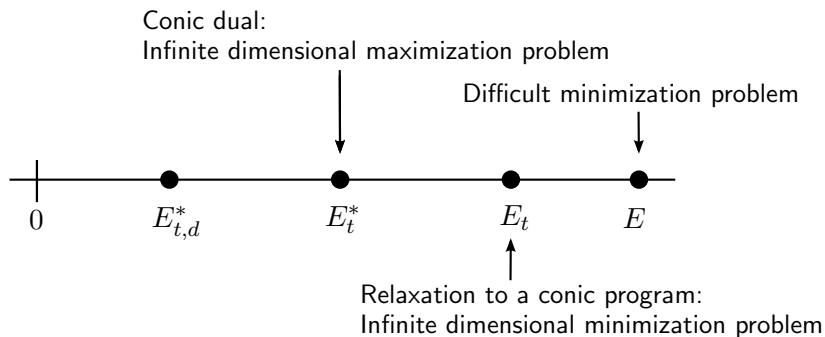
# Approach



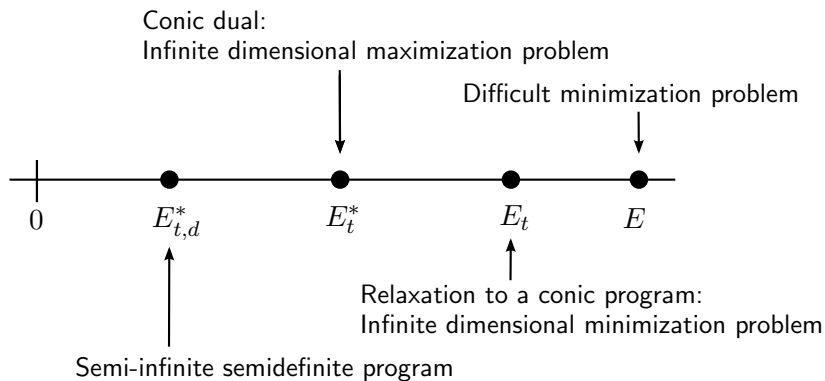
# Approach



# Approach



# Approach



# Finite container

- ▶ If  $V = \{1, \dots, n\}$  is a finite set, then  $E$  is a polynomial optimization problem:

$$E = \min \left\{ \sum_{\{i,j\} \in \binom{V}{2}} w(\{i,j\}) x_i x_j : x \in \{0,1\}^n, \sum_{i \in V} x_i = N \right\}$$



## Finite container

- ▶ If  $V = \{1, \dots, n\}$  is a finite set, then  $E$  is a polynomial optimization problem:

$$E = \min \left\{ \sum_{\{i,j\} \in \binom{V}{2}} w(\{i,j\}) x_i x_j : x \in \{0,1\}^n, \sum_{i \in V} x_i = N \right\}$$

- ▶ The Lasserre hierarchy gives a chain  $E_1 \leq E_2 \leq \dots \leq E_n$  of lower bounds to the optimal energy  $E$ :

# Finite container

- ▶ If  $V = \{1, \dots, n\}$  is a finite set, then  $E$  is a polynomial optimization problem:

$$E = \min \left\{ \sum_{\{i,j\} \in \binom{V}{2}} w(\{i,j\}) x_i x_j : x \in \{0,1\}^n, \sum_{i \in V} x_i = N \right\}$$

- ▶ The Lasserre hierarchy gives a chain  $E_1 \leq E_2 \leq \dots \leq E_n$  of lower bounds to the optimal energy  $E$ :

$$E_t = \min \left\{ \sum_{S \in \binom{V}{\leq 2t}} w(S) y(S) : y \in \mathbb{R}^{\binom{V}{\leq 2t}}, y(\emptyset) = 1, (y(A \cup B))_{A,B \in \binom{V}{\leq t}} \succeq 0, \right. \\ \left. \sum_{x \in V} y(T \cup \{x\}) = N y(T) \text{ for } T \in \binom{V}{\leq 2t-1} \right\}$$

# Infinite container

- ▶ Assume  $V$  is a compact Hausdorff space and  $w$  continuous

## Infinite container

- ▶ Assume  $V$  is a compact Hausdorff space and  $w$  continuous
- ▶  $\left(\underset{\leq t}{V}\right) \setminus \{\emptyset\}$  gets its topology as a quotient of  $V^t$

# Infinite container

- ▶ Assume  $V$  is a compact Hausdorff space and  $w$  continuous
- ▶  $\binom{V}{\leq t} \setminus \{\emptyset\}$  gets its topology as a quotient of  $V^t$
- ▶ Generalization (here  $s = \min\{2t, N\}$ ):

$$E_t = \min \left\{ \lambda(w) : \lambda \in \mathcal{M}(\binom{V}{\leq s})_{\geq 0}, A_t^* \lambda \in \mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}, \right. \\ \left. \lambda(\binom{V}{i}) = \binom{N}{i} \text{ for } i = 0, \dots, s \right\}$$

# Infinite container

- ▶ Assume  $V$  is a compact Hausdorff space and  $w$  continuous
- ▶  $\binom{V}{\leq t} \setminus \{\emptyset\}$  gets its topology as a quotient of  $V^t$
- ▶ Generalization (here  $s = \min\{2t, N\}$ ):

$$E_t = \min \left\{ \lambda(w) : \lambda \in \mathcal{M}(\binom{V}{\leq s})_{\geq 0}, A_t^* \lambda \in \mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}, \right. \\ \left. \lambda(\binom{V}{i}) = \binom{N}{i} \text{ for } i = 0, \dots, s \right\}$$

- ▶  $\lambda$  generalizes the moment vector  $y$

# Infinite container

- ▶ Assume  $V$  is a compact Hausdorff space and  $w$  continuous
- ▶  $\binom{V}{\leq t} \setminus \{\emptyset\}$  gets its topology as a quotient of  $V^t$
- ▶ Generalization (here  $s = \min\{2t, N\}$ ):

$$E_t = \min \left\{ \lambda(w) : \lambda \in \mathcal{M}(\binom{V}{\leq s})_{\geq 0}, A_t^* \lambda \in \mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}, \right. \\ \left. \lambda(\binom{V}{i}) = \binom{N}{i} \text{ for } i = 0, \dots, s \right\}$$

- ▶  $\lambda$  generalizes the moment vector  $y$
- ▶  $\mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}$  is dual to the cone  $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}$  of positive definite kernels

# Infinite container

- ▶ Assume  $V$  is a compact Hausdorff space and  $w$  continuous
- ▶  $\binom{V}{\leq t} \setminus \{\emptyset\}$  gets its topology as a quotient of  $V^t$
- ▶ Generalization (here  $s = \min\{2t, N\}$ ):

$$E_t = \min \left\{ \lambda(w) : \lambda \in \mathcal{M}(\binom{V}{\leq s})_{\geq 0}, A_t^* \lambda \in \mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}, \right. \\ \left. \lambda(\binom{V}{i}) = \binom{N}{i} \text{ for } i = 0, \dots, s \right\}$$

- ▶  $\lambda$  generalizes the moment vector  $y$
- ▶  $\mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}$  is dual to the cone  $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}$  of positive definite kernels
- ▶ Relaxation: If  $S$  is an  $N$  subset of  $V$ , then

$$\chi_S = \sum_{R \in \binom{S}{\leq 2t}} \delta_R$$

is feasible for  $E_t$



# Infinite container

- ▶ Assume  $V$  is a compact Hausdorff space and  $w$  continuous
- ▶  $\binom{V}{\leq t} \setminus \{\emptyset\}$  gets its topology as a quotient of  $V^t$
- ▶ Generalization (here  $s = \min\{2t, N\}$ ):

$$E_t = \min \left\{ \lambda(w) : \lambda \in \mathcal{M}(\binom{V}{\leq s})_{\geq 0}, A_t^* \lambda \in \mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}, \right. \\ \left. \lambda(\binom{V}{i}) = \binom{N}{i} \text{ for } i = 0, \dots, s \right\}$$

- ▶  $\lambda$  generalizes the moment vector  $y$
- ▶  $\mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}$  is dual to the cone  $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}$  of positive definite kernels
- ▶ Relaxation: If  $S$  is an  $N$  subset of  $V$ , then

$$\chi_S = \sum_{R \in \binom{S}{\leq 2t}} \delta_R$$

is feasible for  $E_t$

- ▶ We have  $E_N = E$

# Infinite container

- ▶ Assume  $V$  is a compact Hausdorff space and  $w$  continuous
- ▶  $\binom{V}{\leq t} \setminus \{\emptyset\}$  gets its topology as a quotient of  $V^t$
- ▶ Generalization (here  $s = \min\{2t, N\}$ ):

$$E_t = \min \left\{ \lambda(w) : \lambda \in \mathcal{M}(\binom{V}{\leq s})_{\geq 0}, A_t^* \lambda \in \mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}, \right. \\ \left. \lambda(\binom{V}{i}) = \binom{N}{i} \text{ for } i = 0, \dots, s \right\}$$

- ▶  $\lambda$  generalizes the moment vector  $y$
- ▶  $\mathcal{M}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}$  is dual to the cone  $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}$  of positive definite kernels
- ▶ Relaxation: If  $S$  is an  $N$  subset of  $V$ , then

$$\chi_S = \sum_{R \in \binom{S}{\leq 2t}} \delta_R$$

is feasible for  $E_t$

- ▶ We have  $E_N = E$
- ▶ Uses techniques from [de Laat-Vallentin 2013]: hierarchy for packing problems in discrete geometry

# Dual hierarchy

- ▶ For lower bounds we need feasible solutions of the dual

# Dual hierarchy

- ▶ For lower bounds we need feasible solutions of the dual
- ▶ In the dual hierarchy optimization is over scalars  $a_i$  and positive definite kernels  $K \in \mathcal{C}\left(\binom{V}{\leq t} \times \binom{V}{\leq t}\right)_{\succeq 0}$ :

# Dual hierarchy

- ▶ For lower bounds we need feasible solutions of the dual
- ▶ In the dual hierarchy optimization is over scalars  $a_i$  and positive definite kernels  $K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\succeq 0}$ :

$$E_t^* = \sup \left\{ \sum_{i=0}^s \binom{N}{i} a_i : a_0, \dots, a_s \in \mathbb{R}, K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\succeq 0}, \right. \\ \left. a_i - A_t K \leq w \text{ on } \binom{V}{i} \text{ for } i = 0, \dots, s \right\}$$

# Dual hierarchy

- ▶ For lower bounds we need feasible solutions of the dual
- ▶ In the dual hierarchy optimization is over scalars  $a_i$  and positive definite kernels  $K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\succeq 0}$ :

$$E_t^* = \sup \left\{ \sum_{i=0}^s \binom{N}{i} a_i : a_0, \dots, a_s \in \mathbb{R}, K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\succeq 0}, \right. \\ \left. a_i - A_t K \leq w \text{ on } \binom{V}{i} \text{ for } i = 0, \dots, s \right\}$$

- ▶ Techniquality: we only put a linear constraint for  $S \in \binom{V}{i}$  if the points in  $S$  are not too close

# Dual hierarchy

- ▶ For lower bounds we need feasible solutions of the dual
- ▶ In the dual hierarchy optimization is over scalars  $a_i$  and positive definite kernels  $K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\succeq 0}$ :

$$E_t^* = \sup \left\{ \sum_{i=0}^s \binom{N}{i} a_i : a_0, \dots, a_s \in \mathbb{R}, K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\succeq 0}, \right. \\ \left. a_i - A_t K \leq w \text{ on } \binom{V}{i} \text{ for } i = 0, \dots, s \right\}$$

- ▶ Techniquality: we only put a linear constraint for  $S \in \binom{V}{i}$  if the points in  $S$  are not too close
- ▶ Strong duality holds:  $E_t = E_t^*$

## Dual hierarchy

- ▶ For lower bounds we need feasible solutions of the dual
- ▶ In the dual hierarchy optimization is over scalars  $a_i$  and positive definite kernels  $K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\succeq 0}$ :

$$E_t^* = \sup \left\{ \sum_{i=0}^s \binom{N}{i} a_i : a_0, \dots, a_s \in \mathbb{R}, K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\succeq 0}^{\Gamma}, \right. \\ \left. a_i - A_t K \leq w \text{ on } \binom{V}{i} \text{ for } i = 0, \dots, s \right\}$$

- ▶ Techniquality: we only put a linear constraint for  $S \in \binom{V}{i}$  if the points in  $S$  are not too close
- ▶ Strong duality holds:  $E_t = E_t^*$
- ▶ If  $\Gamma$  acts on  $V$  and  $w$  is  $\Gamma$ -invariant, then we can restrict to  $\Gamma$ -invariant kernels:  $K(\gamma J, \gamma J') = K(J, J')$  for all  $J, J' \in \binom{V}{\leq t}$   
(Here  $\gamma\{x_1, \dots, x_t\} = \{\gamma x_1, \dots, \gamma x_t\}$ )



# Inner approximations to the cone $\mathcal{C}\left(\binom{V}{\leq t} \times \binom{V}{\leq t}\right)_{\geq 0}^{\Gamma}$

- ▶ Nested chain of inner approximations:

$$C_1 \subseteq C_2 \subseteq \cdots \subseteq \mathcal{C}\left(\binom{V}{\leq t} \times \binom{V}{\leq t}\right)_{\geq 0}^{\Gamma}$$

# Inner approximations to the cone $\mathcal{C}\left(\begin{pmatrix} V \\ \leq t \end{pmatrix} \times \begin{pmatrix} V \\ \leq t \end{pmatrix}\right)_{\succeq 0}^{\Gamma}$

- ▶ Nested chain of inner approximations:

$$C_1 \subseteq C_2 \subseteq \cdots \subseteq \mathcal{C}\left(\begin{pmatrix} V \\ \leq t \end{pmatrix} \times \begin{pmatrix} V \\ \leq t \end{pmatrix}\right)_{\succeq 0}^{\Gamma}$$

- ▶ Each cone  $C_i$  can be parametrized by a finite direct sum of positive semidefinite matrix cones

# Inner approximations to the cone $\mathcal{C}\left(\binom{V}{\leq t}\right) \times \binom{V}{\leq t}\Big|_{\underline{\Gamma} \geq 0}$

- ▶ Nested chain of inner approximations:

$$C_1 \subseteq C_2 \subseteq \cdots \subseteq \mathcal{C}\left(\binom{V}{\leq t}\right) \times \binom{V}{\leq t}\Big|_{\underline{\Gamma} \geq 0}$$

- ▶ Each cone  $C_i$  can be parametrized by a finite direct sum of positive semidefinite matrix cones
- ▶ Bochner: A kernel  $K \in \mathcal{C}\left(\binom{V}{\leq t}\right) \times \binom{V}{\leq t}\Big|_{\underline{\Gamma} \geq 0}$  is of the form

$$K(J, J') = \sum_{k=0}^{\infty} \text{trace}(F_k Z_k(J, J'))$$

- ▶  $F_k$ : (infinite) positive semidefinite matrices (the Fourier coefficients)
- ▶  $Z_k$ : zonal matrices corresponding to the action of  $\Gamma$  on  $\binom{V}{\leq t}$  (generalizes  $e^{2\pi i k x}$  in the Fourier transform on the circle)

# Inner approximations to the cone $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\underline{\leq} 0}^{\Gamma}$

- ▶ Nested chain of inner approximations:

$$C_1 \subseteq C_2 \subseteq \cdots \subseteq \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\underline{\leq} 0}^{\Gamma}$$

- ▶ Each cone  $C_i$  can be parametrized by a finite direct sum of positive semidefinite matrix cones
- ▶ Bochner: A kernel  $K \in \mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\underline{\leq} 0}^{\Gamma}$  is of the form

$$K(J, J') = \sum_{k=0}^{\infty} \text{trace}(F_k Z_k(J, J'))$$

- ▶  $F_k$ : (infinite) positive semidefinite matrices (the Fourier coefficients)
- ▶  $Z_k$ : zonal matrices corresponding to the action of  $\Gamma$  on  $\binom{V}{\leq t}$  (generalizes  $e^{2\pi i k x}$  in the Fourier transform on the circle)
- ▶ Define  $C_d$  by truncating the above series

# The semi-infinite semidefinite programs $E_{t,d}^*$

- ▶ Define  $E_{t,d}^*$  by replacing the cone  $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}^\Gamma$  in  $E_t^*$  by the cone  $C_d$

# The semi-infinite semidefinite programs $E_{t,d}^*$

- ▶ Define  $E_{t,d}^*$  by replacing the cone  $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}^{\Gamma}$  in  $E_t^*$  by the cone  $C_d$
- ▶ This is an optimization problem with finitely many variables and infinitely many constraints

## The semi-infinite semidefinite programs $E_{t,d}^*$

- ▶ Define  $E_{t,d}^*$  by replacing the cone  $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}^{\Gamma}$  in  $E_t^*$  by the cone  $C_d$
- ▶ This is an optimization problem with finitely many variables and infinitely many constraints
- ▶  $E_{t,d}^* \rightarrow E_t^*$  as  $d \rightarrow \infty$  follows from  $\cup_{d=0}^{\infty} C_d$  being uniformly dense in  $\mathcal{C}(\binom{V}{\leq t} \times \binom{V}{\leq t})_{\geq 0}^{\Gamma}$

Example:  $V = S^1$  with  $O(2)$ -invariant pair potential  $w$

- ▶ The linear constraints in  $E_{t,d}^*$  can be written as the nonnegativity of a trigonometric polynomial in  $s - 1$  variables



Example:  $V = S^1$  with  $O(2)$ -invariant pair potential  $w$

- ▶ The linear constraints in  $E_{t,d}^*$  can be written as the nonnegativity of a trigonometric polynomial in  $s - 1$  variables
- ▶ Use trigonometric SOS characterizations [Dumitrescu 2006]

Example:  $V = S^1$  with  $O(2)$ -invariant pair potential  $w$

- ▶ The linear constraints in  $E_{t,d}^*$  can be written as the nonnegativity of a trigonometric polynomial in  $s - 1$  variables
- ▶ Use trigonometric SOS characterizations [Dumitrescu 2006]
- ▶ For the Coulomb potential (or other completely monotonic potentials) the regular  $N$ -gon is the optimal configuration on the circle [Cohn-Kumar 2006]

Example:  $V = S^1$  with  $O(2)$ -invariant pair potential  $w$

- ▶ The linear constraints in  $E_{t,d}^*$  can be written as the nonnegativity of a trigonometric polynomial in  $s - 1$  variables
- ▶ Use trigonometric SOS characterizations [Dumitrescu 2006]
- ▶ For the Coulomb potential (or other completely monotonic potentials) the regular  $N$ -gon is the optimal configuration on the circle [Cohn-Kumar 2006]
- ▶ Uses relaxation based on the 2-point correlation function [Yudin 1992] (This is similar to  $E_1$ )

Example:  $V = S^1$  with  $O(2)$ -invariant pair potential  $w$

- ▶ The linear constraints in  $E_{t,d}^*$  can be written as the nonnegativity of a trigonometric polynomial in  $s - 1$  variables
- ▶ Use trigonometric SOS characterizations [Dumitrescu 2006]
- ▶ For the Coulomb potential (or other completely monotonic potentials) the regular  $N$ -gon is the optimal configuration on the circle [Cohn-Kumar 2006]
- ▶ Uses relaxation based on the 2-point correlation function [Yudin 1992] (This is similar to  $E_1$ )
- ▶ The bound  $E_2^*$  requires SOS characterizations in 3 variables

## Example: $V = S^1$ with $O(2)$ -invariant pair potential $w$

- ▶ The linear constraints in  $E_{t,d}^*$  can be written as the nonnegativity of a trigonometric polynomial in  $s - 1$  variables
- ▶ Use trigonometric SOS characterizations [Dumitrescu 2006]
- ▶ For the Coulomb potential (or other completely monotonic potentials) the regular  $N$ -gon is the optimal configuration on the circle [Cohn-Kumar 2006]
- ▶ Uses relaxation based on the 2-point correlation function [Yudin 1992] (This is similar to  $E_1$ )
- ▶ The bound  $E_2^*$  requires SOS characterizations in 3 variables
- ▶ Lennard-Jones potential: Based on a sampling implementation it appears that for e.g.  $N = 3$  we have

$$E_1 < E_2 = E$$

Thank you!