# Energy minimization via conic programming hierarchies 

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## Energy minimization

Given

- a set $V$ (container)
- a function $w: V \times V \rightarrow \mathbb{R}_{\geq 0} \cup\{\infty\}$ (pair potential)
- an integer $N$ (number of particles)

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## Example

For the Thomson problem we take $V=S^{2}$ and $w(x, y)=\|x-y\|^{-1}$

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Approach to finding lower bounds

1. Relax the problem to a conic optimization problem
2. Find good feasible solutions to the dual problem

## Related work

- The symmetry group $\Gamma$ of $V$ acts on $V^{k}$ by

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\gamma\left(x_{1}, \ldots, x_{k}\right)=\left(\gamma x_{1}, \ldots, \gamma x_{k}\right)
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- $k$-point bounds using the stabilizer subgroup of $k-2$ points [Musin 2007]


## This talk

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- Convergent hierarchy of finite semidefinite programs
- Application to low dimensional spaces


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- Let $V_{t}$ be the set of subsets of $V$ of cardinality at most $t$ with topology induced by $q: V^{t} \rightarrow V_{t},\left(v_{1}, \ldots, v_{t}\right) \mapsto\left\{v_{1}, \ldots, v_{t}\right\}$


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- Denote by $I_{t} \subset V_{t}$ the compact subset of independent sets
- View $w$ as an element in $\mathcal{C}\left(I_{2 t}\right)$


## Primal hierarchy

- We define a hierarchy of conic optimization problems with optimal values $E_{1}, E_{2}, \ldots$ such that

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- If $S$ is a $N$-particle configuration, then

$$
\chi_{S}=\sum_{R \subseteq S:|R| \leq 2 t} \delta_{R}
$$

is a feasible measure (this proves $E_{t} \leq E$ )

## Cone of moment measures

- Define the operator $A_{t}: \mathcal{C}\left(V_{t} \times V_{t}\right)_{\text {sym }} \rightarrow \mathcal{C}\left(I_{\min \{2 t, N\}}\right)$ by

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- This is the main step in proving $E_{N}=E$


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- The elements $L$ are of the form $A_{t} K$ for $K \in \mathcal{C}\left(V_{t} \times V_{t}\right)_{\succeq 0}$
- Strong duality holds: $E_{t}=E_{t}^{*}$


## Frequency formulation

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- Bochner's theorem: $K \in \mathcal{C}\left(V_{t} \times V_{t}\right) \Gamma_{\succeq}^{\Gamma}$ is of the form

$$
K\left(J, J^{\prime}\right)=\sum_{k=0}^{\infty}\left\langle F_{k}, Z_{k}\left(J, J^{\prime}\right)\right\rangle \quad \text { where }
$$

$F_{k}$ : positive semidefinite matrices (the Fourier coefficients) $Z_{k}$ : zonal matrices corresponding to the action of $\Gamma$ on $V_{t}$

## Semidefinite programming

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- In general the Fourier series does not converge uniformly; the action of $\Gamma$ on $V_{t}$ has infinitely many orbits (for $t \geq 2$ )
- By a summability method we have $E_{t, d}^{*} \rightarrow E_{t}^{*}$ as $d \rightarrow \infty$


## Semidefinite programming

- The linear constraints in $E_{t, d}^{*}$ are of the form

$$
a_{i}-\sum_{k=0}^{d}\left\langle F_{k}, A_{t} Z_{k, d}\right\rangle \leq w \text { on } I_{=i} \text { for } i=0, \ldots, \min \{2 t, N\}
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- Variable transformation to write the above as polynomial inequalities over a semialgebraic set (depends on the application)
- Using sums of squares characterizations $E_{t, d}^{*}$ can be approximated by a sequence of finite semidefinite programs


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

- Zonal matrices as polynomial matrices in the inner products:

$$
Z_{k}\left(\left\{x_{1}, \ldots, x_{t}\right\},\left\{y_{1}, \ldots, y_{t}\right\}\right)_{i, j}=\left(\prod_{r, s=1}^{t}\left(x_{r} \cdot x_{s}\right)^{i}\left(y_{r} \cdot y_{s}\right)^{j}\right) \sum_{r, s=1}^{t} T_{k}\left(x_{r} \cdot y_{s}\right)
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- 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!

