

# Minimum energy configurations on a toric lattice as a quadratic assignment problem.

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# General form of quadratic assignment problems (QAPs)

## QAP in Koopmans-Beckmann form

$$QAP(A, B) = \min_{\varphi \in S_n} \sum_{i,j=1}^n a_{ij} b_{\varphi(i)\varphi(j)}$$

where

- $A = (a_{ij}), B = (b_{ij}) \in \mathbb{R}^{n \times n}$
- $S_n$  is the set of all permutations of  $n$  elements

We will study a specific example from **energy minimization**.

## QAP example: Particles on a grid

### Problem:

- Minimize the total energy of repulsive particles
- Periodic tiling of size  $n_1 \times n_2$
- Density  $m/(n_1 n_2)$

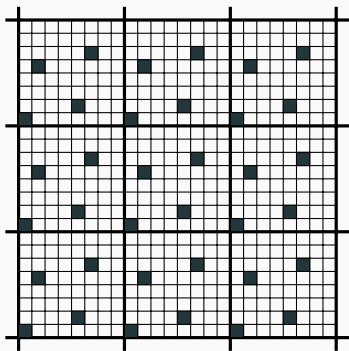
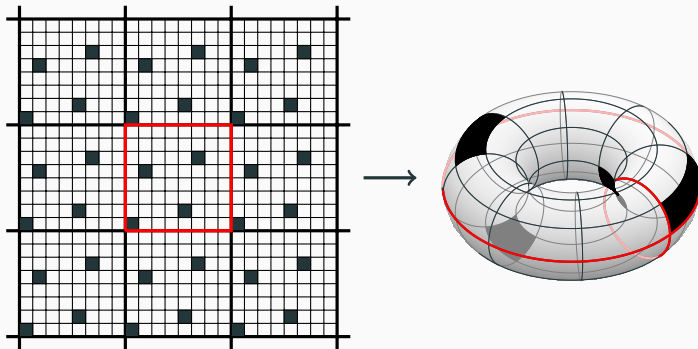


Figure 1: A  $n_1 \times n_2 = 8 \times 8$  grid tiling with  $m = 4$

# Tiling to torus



**Figure 2:** Example of a  $n_1 \times n_2 = 8 \times 8$  grid tiling with  $m = 4$ , and the corresponding toroidal interpretation of the  $8 \times 8$  grid.

## Potential function and formal definition

Choice of potential function and metric, here:

$$f_{(x_1, y_1), (x_2, y_2)} = \frac{1}{d_{\text{Lee}}((x_1, y_1), (x_2, y_2))},$$

and  $f_{i,i} = 0$ , where  $d_{\text{Lee}}$  is the **Lee distance** given by the shortest path metric on the toroidal grid.

Thus for fixed  $n_1, n_2, m$  the problem is

$$\min_{\substack{T \subseteq [n_1] \times [n_2] \\ |T|=m}} \sum_{a, b \in T} f_{a, b}.$$

## Reformulation as QAP

For the the reformulation as QAP we assume an ordering on the grid points. We set  $n = n_1 n_2$ .

Let  $A, B \in \mathbb{R}^{n \times n}$  be the matrices

$$A_{ij} = \begin{cases} 1, & \text{if } i, j \leq m \\ 0, & \text{otherwise.} \end{cases}, \quad B_{i,j} = f_{i,j} = f_{(x_i, y_i), (x_j, y_j)}.$$

Then their corresponding QAP is the energy minimization problem:

$$\min_{\substack{T \subseteq [n_1] \times [n_2] \\ |T|=m}} \sum_{a,b \in T} f_{a,b} = \min_{\pi \in S_n} \sum_{i,j=1}^n a_{ij} b_{\pi(i)\pi(j)}$$

QAPs are NP-complete.

⇒ Instead look for approximations, heuristics and *bounds*.

We consider three known bounds:

- A projected eigenvalue bound
- A convex quadratic programming bound
- A semidefinite programming bound

## Projection-based bounds

- $V \in \mathbb{R}^{n \times (n-1)}$  s.t.  $\mathcal{R}(V) = e^\perp$  and  $V^T V = I_{n-1}$ ,
- $\tilde{A} = V^T A V$ ,  $\tilde{B} = V^T B V$ ,
- $\lambda_{\tilde{A}}$  and  $\mu_{\tilde{B}}$  are the vectors of eigenvalues of  $\tilde{A}$  and  $\tilde{B}$



## Proposition (Hadley, Rendl, Wolkowicz (1990))

Set  $D = \frac{2}{n}Aee^TB$ . The projection lower bound for the symmetric QAP(A, B) is given by

$$\text{PB}(A, B) := \langle \lambda_{\tilde{A}}, \mu_{\tilde{B}} \rangle^- + \min_{\varphi \in S_n} \sum_{i=1}^n d_{i\varphi(i)} - \frac{(e^T A e)(e^T B e)}{n^2},$$

where  $\langle x, y \rangle^- = \min_{\varphi \in S_n} \sum_{i=1}^n x_{\varphi(i)} y_i$ .

## Convex quadratic programming bound

Let  $A$  and  $B$  be symmetric matrices, and set

$$(S^*, T^*) = \arg \max \left\{ \text{tr}(S + T) : \tilde{B} \otimes \tilde{A} - I \otimes S - T \otimes I \succcurlyeq 0 \right\},$$

so the matrix

$$\hat{Q} := \tilde{B} \otimes \tilde{A} - I \otimes S^* - T^* \otimes I \succcurlyeq 0$$

is **positive semidefinite**, and  $\text{tr}(S^* + T^*) = \langle \lambda_{\tilde{A}}, \mu_{\tilde{B}} \rangle^-$ .

# Convex quadratic programming bound (ctd.)

## Proposition (Anstreicher, Brixius (2001))

A bound at least as good as  $PB(A, B)$  is

$$\begin{aligned} QPB(A, B) := & \min_{\substack{X \geq 0 \text{ doubly stochastic} \\ X = \frac{1}{n} ee^T + VYV^T \\ y = \text{vec}(Y)}} y^T \hat{Q} y + \langle \lambda_{\tilde{A}}, \mu_{\tilde{B}} \rangle^- \\ & + \frac{2}{n} \text{tr}(BJAX) - \frac{(e^T Ae)(e^T Be)}{n^2}. \end{aligned}$$

# Semidefinite bound

**Proposition** (Povh, Rendl (2009), equivalent to earlier bound by Zhao, Karisch, Rendl, Wolkowicz (1998))

*The following is a semidefinite relaxation of QAP(A, B) for symmetric A, B:*

$$\begin{aligned} \text{SDPQAP}(A, B) &:= \min \langle B \otimes A, Y \rangle \\ \text{s.t. } &\langle I \otimes E_{jj}, Y \rangle = 1 \text{ for } j = 1, \dots, n, \\ &\langle E_{jj} \otimes I, Y \rangle = 1 \text{ for } j = 1, \dots, n, \\ &\langle I \otimes (J - I) + (J - I) \otimes I, Y \rangle = 0, \\ &\langle J \otimes J, Y \rangle = n^2, \\ &Y \in S_+^{n^2} \cap \mathbb{R}_{\geq 0}^{n^2 \times n^2}. \end{aligned}$$

# Bound comparison

## Theorem

*For symmetric matrices  $A$  and  $B$  we have*

$$PB(A, B) \leq QPB(A, B) \leq SDPQAP(A, B) \leq QAP(A, B).$$

## Proof idea.

- We only need to show that  $QPB(A, B) \leq SDPQAP(A, B)$
- We prove the inequality for a weaker SDP bound, which uses the projection of the other bounds.



We now compare these bounds to an eigenvalue bound for the energy minimization problem.

# Eigenvalue bound for energy minimization

The relaxation

$$\begin{aligned} \text{EVB}(n, m, B) &:= \min x^T B x \\ \text{s.t. } &x^T x = x^T e = m, \end{aligned}$$

gives a closed-form lower bound for the energy minimization problem in terms of eigenvalues of  $B$ .

**Proposition** (Bouman, Draisma, Van Leeuwen (2013))

Let  $\lambda_{\min}$  be the smallest eigenvalue of  $B$ , and  $\lambda_1 = e_1^T B e_1$ . Then

$$\text{EVB}(n, m, B) = \lambda_1 \frac{m^2}{n} + \lambda_{\min} \left( m - \frac{m^2}{n} \right)$$

is a lower bound for the potential energy of  $m$  particles.

# Bound comparison

## Theorem

For all  $n_1, n_2, m$ , with  $A, B$  as before, we have

$$PB(A, B) = QPB(A, B) = EVB(n, m, B) \leq SDPQAP(A, B).$$

Only the SDP bound has a chance of improving existing bounds.

**Problem:** The matrices appearing in the SDP bound are of size  $(n_1 n_2)^2 \times (n_1 n_2)^2$ .

**Solution:** Symmetry reduction (in form of a Jordan reduction) to size  $\mathcal{O}(\sqrt{n_1 n_2}) \times \mathcal{O}(\sqrt{n_1 n_2})$ .

# Results

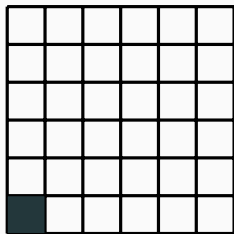
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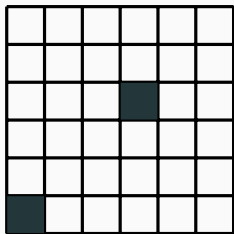
# Bounds

$n_1 = n_2$	$m$	$PB(A, B)$	$SDPQAP(A, B)$	Upper bounds from simulated annealing
6	1	-1.51	0.00	0.00
	2	-2.13	0.33	0.33
	4	-0.64	3.00	3.00
	12	41.47	44.00	44.00
	18	111.00	111.00	111.00
7	1	-1.54	0.00	0.00
	2	-2.29	0.33	0.33
8	1	-1.67	0.00	0.00
	2	-2.65	0.25	0.25
	4	-2.57	2.27	2.27
	32	286.67	286.67	286.67
10	1	-1.72	0.00	0.00
	2	-2.88	0.20	0.20
	4	-3.57	1.81	1.81
	20	70.23	81.43	81.43
	50	588.33	588.33	588.33

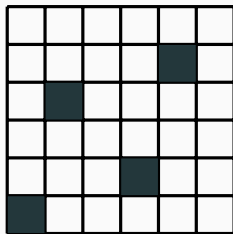
# Optimal arrangements on a $6 \times 6$ grid



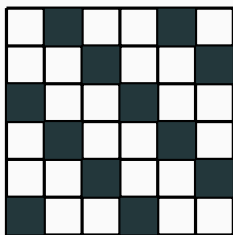
$m = 1$



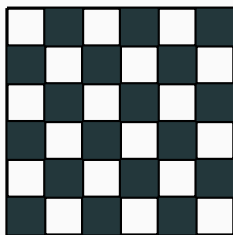
$m = 2$



$m = 4$

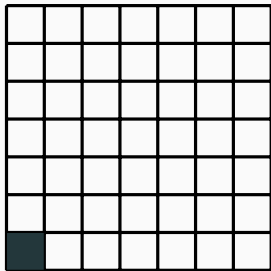


$m = 12$

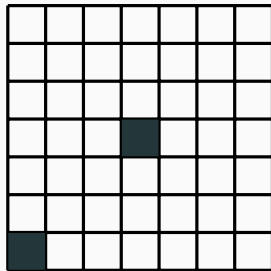


$m = 18$

# Optimal arrangements on a $7 \times 7$ grid

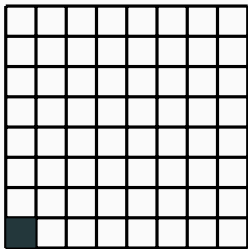


$m = 1$

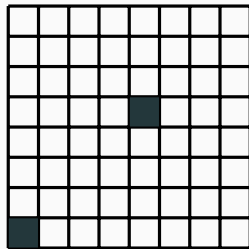


$m = 2$

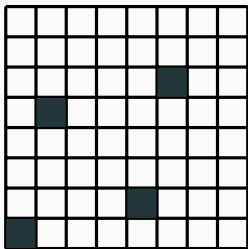
# Optimal arrangements on a $8 \times 8$ grid



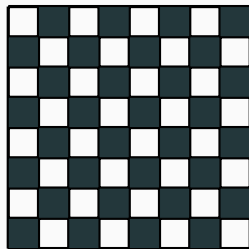
$m = 1$



$m = 2$

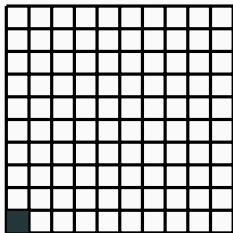


$m = 4$

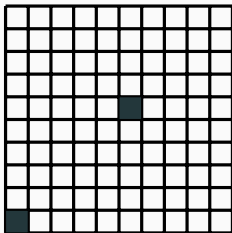


$m = 32$

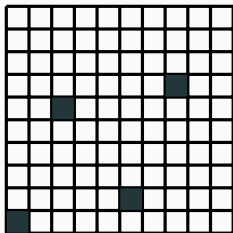
# Optimal arrangements on a $10 \times 10$ grid



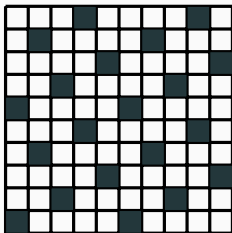
$m = 1$



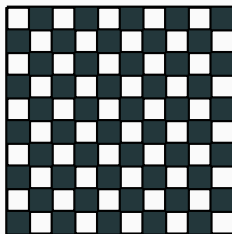
$m = 2$



$m = 4$



$m = 20$



$m = 50$

Any questions?

## Weaker SDP bound

$$\begin{aligned} SDPPB(A, B) := \min \quad & \langle \tilde{B} \otimes \tilde{A}, U \rangle + \frac{2}{n} \text{vec}(V^T B J A V)^T u \\ & + \frac{1}{n^2} (e^T A e)(e^T B e) \end{aligned}$$

$$\text{s.t.} \quad \begin{pmatrix} 1 & u^T \\ u & U \end{pmatrix} \succcurlyeq 0,$$

$$\langle E_{ij} \otimes I_{n-1}, U \rangle = \delta_{ij} \quad \forall i, j = 1, \dots, n-1,$$

$$\langle I_{n-1} \otimes E_{ij}, U \rangle = \delta_{ij} \quad \forall i, j = 1, \dots, n-1,$$

$$(V \otimes V)u \geq -\frac{1}{n} e \otimes e.$$

# Symmetry Reduction

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## Conic form

We assume the problem is given in the form

$$\begin{array}{ll} \mathbf{P} = \min & \langle C, X \rangle \\ \text{s.t.} & X \in X_0 + \mathcal{L} \\ & X \in \mathcal{K} \end{array} \qquad \begin{array}{ll} \mathbf{D} = \min & \langle X_0, Y \rangle \\ \text{s.t.} & Y \in C + \mathcal{L}^\perp \\ & Y \in \mathcal{K}^*. \end{array}$$

where

- $\mathcal{K} \subseteq \mathcal{V}$  is a convex cone in a real vectorspace,
- $X_0$  and  $C$  are elements of  $\mathcal{V}$ ,
- $\mathcal{L} \subseteq \mathcal{V}$  a linear subspace.

# Constraint set invariance conditions (CSICs)

## Definition

A projection  $P: \mathcal{V} \rightarrow \mathcal{V}$  fulfills the CSICs for  $(\mathcal{K}, X_0 + \mathcal{L}, C)$  if

- (i)  $P(\mathcal{K}) \subseteq \mathcal{K}$  (the projection is positive),
- (ii)  $P(X_0 + \mathcal{L}) \subseteq X_0 + \mathcal{L}$ ,
- (iii)  $P^*(C + \mathcal{L}^\perp) \subseteq C + \mathcal{L}^\perp$ ,

where  $P^*$  is the adjoint of  $P$ .

If  $P$  is an orthogonal projection  $P_S$  to a linear subspace  $S$ , we call  $S$  **admissible**.

# Symmetry reduction

For admissible  $S$ , the following programs have the same objective values as **P** and **D**:

$$\begin{aligned} \min \quad & \langle P_S(C), X \rangle \\ \text{s.t.} \quad & X \in P_S(X_0) + \mathcal{L} \cap S \\ & X \in \mathcal{K} \cap S \end{aligned}$$

$$\begin{aligned} \min \quad & \langle P_S(X_0), Y \rangle \\ \text{s.t.} \quad & Y \in P_S(C) + \mathcal{L}^\perp \cap S \\ & Y \in \mathcal{K}^* \cap S \end{aligned}$$

# Jordan reduction

## Proposition (Permenter (2017))

If  $\mathcal{V}$  is an euclidian Jordan-algebra and  $\mathcal{K}$  its cone of squares, then an unital subspace  $S \subseteq \mathcal{V}$  is admissible if

$$S \ni P_{\mathcal{L}}(C), P_{\mathcal{L}^\perp}(X_0),$$

$$S \supseteq P_{\mathcal{L}}(S),$$

$$S \supseteq \{X^2 \mid X \in S\} \quad [S \text{ is a subalgebra.}]$$

The converse holds if  $J$  is special.

Its enough to know here that  $S^n$  is a special euclidian Jordan-algebra and its cone of squares is  $S_+^n$ .

## Extension to the doubly nonnegative cone

### Proposition

*An orthogonal projection  $P_S$  onto an unital subspace  $S \subseteq \mathcal{V}$  fulfills*

$$P_S(D^n) \subseteq D^n$$

*if and only if*

$$P_S(S_+^n) \subseteq S_+^n$$

*and  $S$  has a basis of nonnegative matrices with disjoint supports.*

## A simple algorithm

We further restrict ourselves to a Partition  $P = S$ . Then the following algorithm gives us the optimal admissible partition subspace:

```

$$P \leftarrow \text{part}(P_{\mathcal{L}}(C)) \wedge \text{part}(P_{\mathcal{L}^\perp}(X_0))$$
repeat  
|  $P \leftarrow P \wedge \text{part}(P_{\mathcal{L}}(P))$   
|  $P \leftarrow P \wedge \text{part}(\text{span}\{X^2 \mid X \in P\})$   
until converged;
```

Here `part` returns the partition given by unique entries, and  $\wedge$  the smallest refinement of two partitions.