

# **Discrete and Continuous Methods for Packing Problems**

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# Preface

This book develops a unified framework for packing problems, combining discrete optimization, graph theory, and continuous methods from applied mathematics.

# Chapter 1

## Discrete Formulations of Packing via Independent Sets

### 1.1 From Continuous Packing to Discrete Candidates

We begin with a classical continuous packing problem: given a compact container  $\Omega \subset \mathbb{R}^2$  (e.g. a square or disk) and identical circles of radius  $r$ , place as many circles as possible inside  $\Omega$  without overlap.

In the continuous setting, the configuration space is infinite-dimensional, and the problem is highly nonconvex. To make algorithmic progress, we introduce a *discretization of configuration space*.

#### 1.1.1 Candidate placements

Let  $\mathcal{P} = \{p_1, \dots, p_M\} \subset \Omega$  be a finite set of candidate circle centers. These may arise from:

- a uniform Cartesian grid,
- a union of rotated grids to reduce anisotropy,
- or a local patch extracted from a continuous solver.

Each candidate  $p_i$  represents the placement of a circle centered at  $p_i$ .

A candidate is *feasible* if the entire disk lies inside the container:

$$\text{dist}(p_i, \partial\Omega) \geq r.$$

Only feasible candidates are retained.

### 1.1.2 Conflict detection

Two candidates  $p_i$  and  $p_j$  are said to be *in conflict* if placing circles at both locations would cause overlap:

$$\|p_i - p_j\| < 2r.$$

This pairwise condition captures all geometric constraints of the packing problem once the candidate set has been fixed.

## 1.2 Graph Construction

The discrete packing problem can now be represented as a graph.

**Definition 1.1** (Conflict Graph). Let  $G = (V, E)$  be a graph where:

- Each vertex  $i \in V$  corresponds to a candidate placement  $p_i \in \mathcal{P}$ .
- An edge  $(i, j) \in E$  exists if and only if  $p_i$  and  $p_j$  are in conflict.

The graph  $G$  encodes all pairwise incompatibilities between candidate placements. Importantly, this graph is:

- geometric,
- sparse (conflicts are local),
- independent of the optimization method used later.

## 1.3 Packing as an Independent Set Problem

A valid packing corresponds to a selection of candidates such that no two selected placements conflict.

**Definition 1.2** (Independent Set). A subset  $S \subset V$  is an *independent set* if no two vertices in  $S$  share an edge.

### 1.3.1 Maximum vs. maximal independent sets

Two notions are relevant:

- A *maximal* independent set cannot be extended by adding another vertex.
- A *maximum* independent set has the largest possible cardinality.

In packing problems, we are interested in the *maximum independent set* (MIS), since its cardinality corresponds to the maximum number of circles that can be placed using the candidate set.

**Problem 1.3** (Discrete Packing via MIS). Given a conflict graph  $G = (V, E)$ , find

$$\max_{S \subseteq V} |S| \quad \text{such that } S \text{ is an independent set.}$$

This formulation is exact for the discretized problem and separates geometry (from graph construction) from combinatorial optimization.

## 1.4 Integer Linear Programming Formulation

The maximum independent set problem admits a standard integer programming formulation.

### 1.4.1 Binary decision variables

Introduce variables

$$x_i \in \{0, 1\}, \quad i \in V,$$

where  $x_i = 1$  indicates that candidate  $p_i$  is selected.

### 1.4.2 MILP formulation

The packing problem becomes:

$$\max \quad \sum_{i \in V} x_i \tag{1.1}$$

$$\text{subject to} \quad x_i + x_j \leq 1, \quad \forall (i, j) \in E, \tag{1.2}$$

$$x_i \in \{0, 1\}, \quad \forall i \in V. \tag{1.3}$$

Each constraint  $x_i + x_j \leq 1$  enforces non-overlap for a conflicting pair. This formulation is exact and captures all geometric constraints implicitly through the graph.

## 1.5 LP Relaxation and Its Interpretation

Solving the MILP directly is computationally expensive. A standard relaxation replaces integrality by bounds:

$$x_i \in [0, 1].$$

### 1.5.1 LP relaxation

The relaxed problem is:

$$\max \sum_{i \in V} x_i \tag{1.4}$$

$$\text{subject to } x_i + x_j \leq 1, \quad \forall (i, j) \in E, \tag{1.5}$$

$$0 \leq x_i \leq 1. \tag{1.6}$$

This linear program provides:

- an upper bound on the true packing number,
- fractional solutions that encode local packing density.

In geometric settings, fractional values often highlight regions of high structural order even before integrality is enforced.

## 1.6 Algorithmic Solution via Constraint Generation

The full conflict graph may contain a large number of edges. However, most constraints are never active in optimal solutions.

### 1.6.1 Lazy constraint generation

An efficient strategy is to generate constraints iteratively:

1. Start with variables  $x_i \in [0, 1]$  and a minimal constraint set.
2. Solve the LP.
3. Detect violated conflict constraints:

$$x_i + x_j > 1 \quad \text{for some conflicting pair } (i, j).$$

4. Add the violated constraints.
5. Repeat until no violations remain.

Because conflicts are local, the number of active constraints remains manageable.

### 1.6.2 Transition to integer solutions

Once the LP relaxation stabilizes, integrality constraints are reinstated:

$$x_i \in \{0, 1\}.$$

The resulting problem is solved using a *branch-and-cut* strategy:

- LP relaxation provides bounds,
- branching enforces integrality,
- constraint generation continues as needed.

This approach yields exact solutions for local patch problems and provides certificates of optimality.

## 1.7 Interpretation and Scope

This discrete formulation has several important properties:

- It cleanly separates geometry from optimization.
- It applies equally to circles, polygons, and more general shapes.
- It is well suited for *local patch analysis*, where structure such as hexagonal order can emerge without being prescribed.

However, the method does not scale to large global packings and is best used as a:

- verification tool,
- local structure discovery method,
- or subproblem within a hybrid continuous–discrete pipeline.

In later chapters, we will combine this discrete machinery with continuous relaxation and periodic boundary conditions to study bulk packing structure.