INTEGER PROGRAMMING: BRANCH AND BOUND

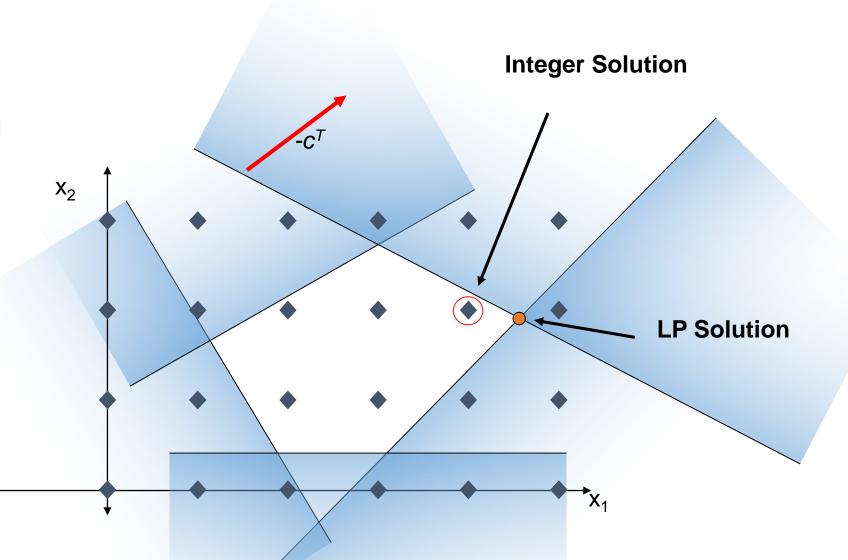
LP relaxation

- For any IP we can generate an LP (called the LP relaxation)
 from the IP by taking the same objective function and same
 constraints but with the "integer requirement" on variables
 relaxed
- That is, the variables are allowed to be continuous and bounded by appropriate constraints

e.g., $x_i \in \{0,1\}$ can be replaced by the two continuous constraints $x_i \ge 0$ and $x_i \le 1$

solving an IP

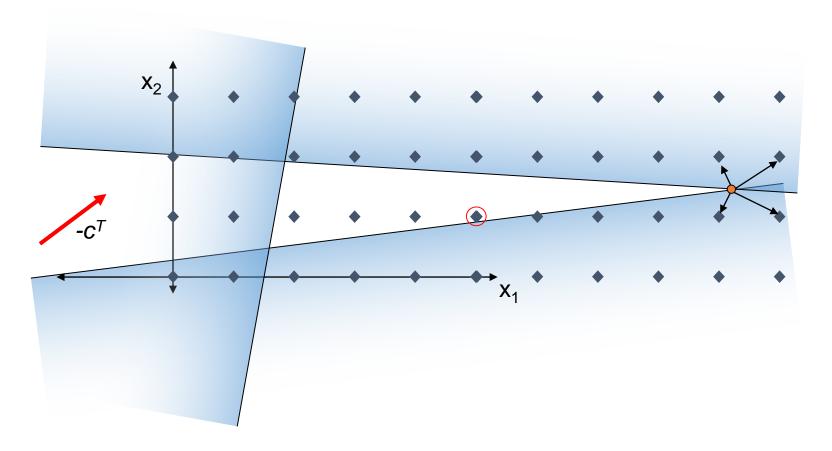
How about solving the IP minimization problem by LP relaxation followed by rounding?



solving an IP: LP rounding

In general, rounding an LP solution does not work

Rounding can be arbitrarily far away from integer solution



But, the LP provides a lower bound on the IP minimization

solving an IP

Complete enumeration: systematically consider all possible values of the decision variables

e.g., if there are n binary variables, there are 2^n different combinations of decision variable values

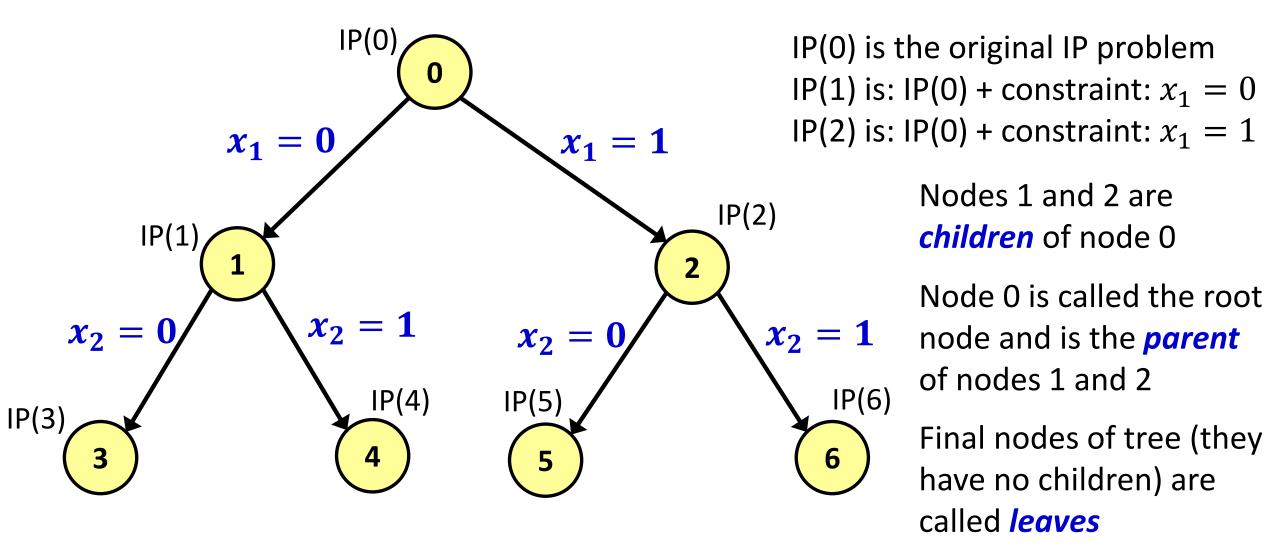
Usual idea: iteratively break the problem in two

solving an IP: complete enumeration

Consider a BP problem

- → iteratively break the problem in two:
 - consider separately the case that $x_1 = 0$ and $x_1 = 1$
 - these *sub-problems* are called *nodes*
 - each node represents the original problem plus additional constraints
 - the resulting nodes are split again on x_2 , then x_3 , etc.
 - the complete series of nodes and constraint branches form an enumeration tree

solving an IP: enumeration tree



Note: If there are n binary variables, there are 2^n leaves in the enumeration tree

solving an IP: complete enumeration

Suppose that we could evaluate 1 billion solutions per second Let n = number of binary variables

Problem size	Approximate solution times
n = 30	1 second

This is a problem... complete enumeration is not reasonable.

solving an IP: complete enumeration

LP relaxation and rounding

- no guarantee on the quality of the solution
- but, it is fast
- does provide a "lower bound" on IP minimization

Complete enumeration

- guarantee on quality of solution \rightarrow optimal
- but, it is slow... really, slow

solving an IP: branch-and-bound

However, we can <u>combine</u> the two approaches LP relaxation and enumeration:

- 1. Solve LP Relaxation to get fractional solution
- 2. Create two branches (sub-problems) by adding constraints
- 3. Use the "lower bound" property of LP solutions to eliminate parts of the tree

The basic concept underlying the branch-and-bound technique is to divide and conquer.

solving an IP: branch-and-bound

The <u>dividing</u> (*branching*) is done by partitioning the entire set of feasible solutions into smaller and smaller subsets.

The conquering (fathoming) is done partially by:

- i. giving a bound for the best solution in the branch
- ii. discarding the branch if the bound indicates that it can not contain an optimal solution

branch & bound: terminology

Incumbent solution

- an IP feasible solution that is the best solution so far in the B&B search
- its objective value provides and *upper bound* to the minimization problem

Lower bound

- a solution to an "easier" problem such as LP relaxation
- ideally, you are looking for "tight" lower bounds those that are closer to the optimal objective value

Fathoming

 dismiss nodes (and thus whole branches of the tree!) if further branching will yield no useful information

branch & bound

- 1. Solve LP relaxation for <u>lower bound</u> on cost for current branch
 - If solution exceeds <u>upper bound</u> (incumbent value), branch is terminated
 - Else: if solution is integer, replace incumbent solution and update upper bound
- 2. Create two branched problems by adding constraints to the problem
 - Select integer variable with fractional LP solution
 - Add constraints for this variable
- 3. Repeat until no branches remain, return optimal solution

major steps in B&B algorithm

- 1. Initialization
- 2. Check Stopping Condition
- 3. Explore Active Subproblem (Fathoming)
- 4. Branching
- 5. Bounding

step 1: initialization

- Let the node index i=0
- Make node 0 (root node) active
- If any feasible IP solutions are known, let the best one be the incumbent solution. Otherwise, let $z^* = \infty$

step 2: check stopping condition

If there are no active nodes, then: stop.

- If there is an incumbent solution it is optimal
- If not, the IP is infeasible

Else (if there are any active nodes)

Select active node i and attempt to solve the associated subproblem LP_i

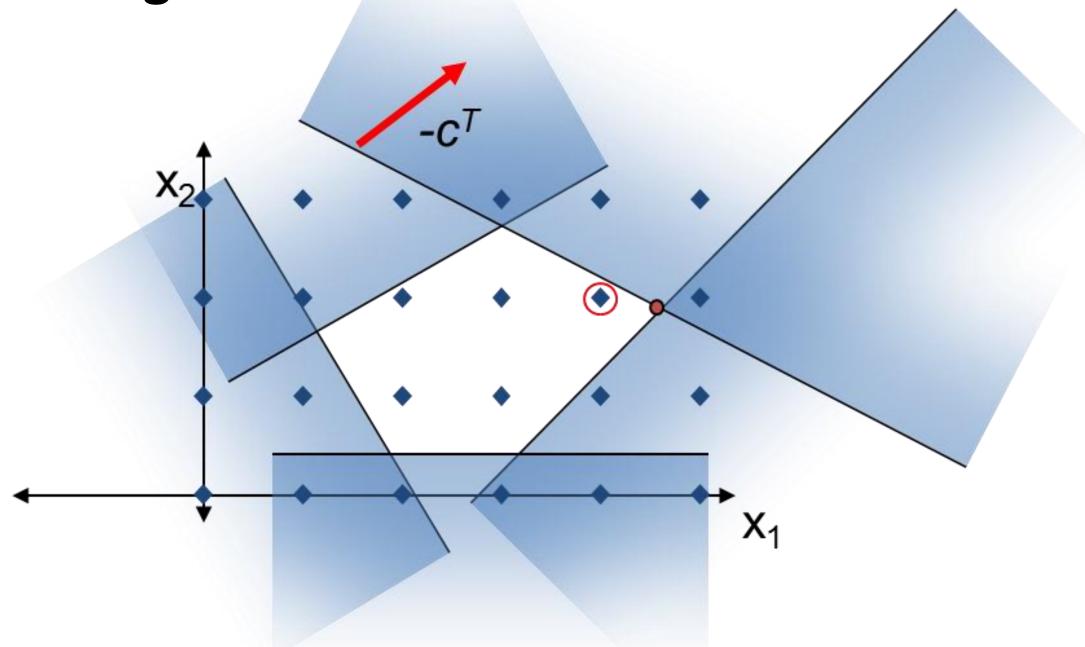
step 3: explore active subproblem

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If LP<sub>i</sub> is infeasible then
  fathom node i and go to Step 2
else if LP<sub>i</sub> solution is IP feasible then
  If z_i < z^* then
      Let z^* = z_i
      LP<sub>i</sub> solution is the new incumbent solution
  Fathom node i and go to Step 2
else if z_i \geq z^* then
  fathom node i and go to Step 2
else continue to Step 4
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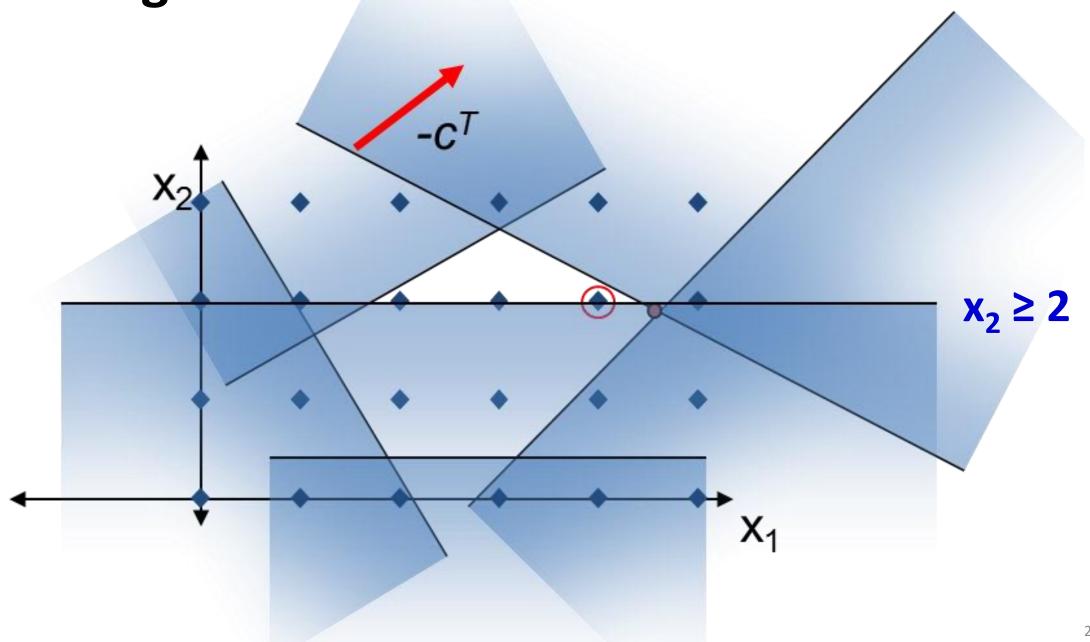
step 4: branching

- Select a integer variable x, that has fractional value v in the optimal solution to LP_i
 - Create node i+1 (down branch) i.e., let the associated subproblem LP_{i+1} be LP_i subject to $x \leq \lfloor v \rfloor$
 - Create node i+2 (up branch): i.e., let the associated subproblem LP_{i+2} be LP_i subject to $x \ge \lceil v \rceil$
- Let the lower bound at nodes i, i+1, and i+2 be z_i
- Make nodes i + 1 and i + 2 active
- Make node i inactive
- Go to Step 2

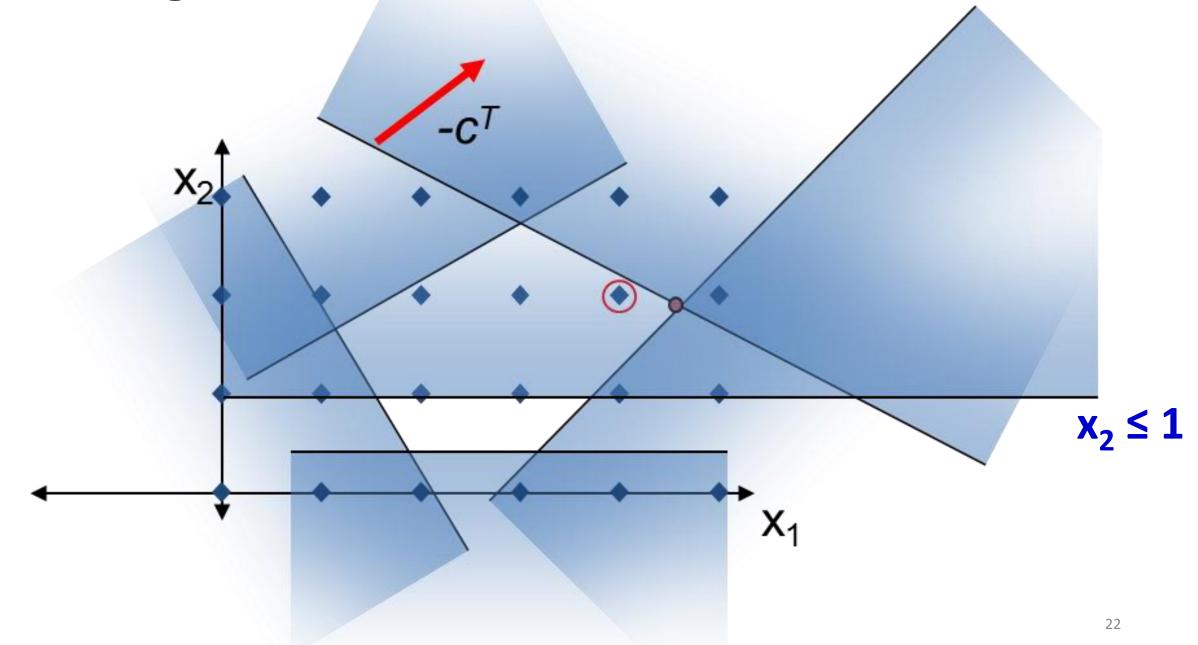
branching for an IP



branching for an IP



branching for an IP



bounding

- A valid lower bound on the optimal objective function value can be found by taking the minimum lower bound over all active nodes.
- If there are no active nodes and there is an incumbent solution, then the incumbent solution provides both a lower and upper bound.

INTEGER PROGRAMMING: BRANCH AND BOUND EXAMPLE

B&B example: An IP problem with 4 integer variables

$$x_1, x_2, x_3, x_4 \in \{0,1\}$$

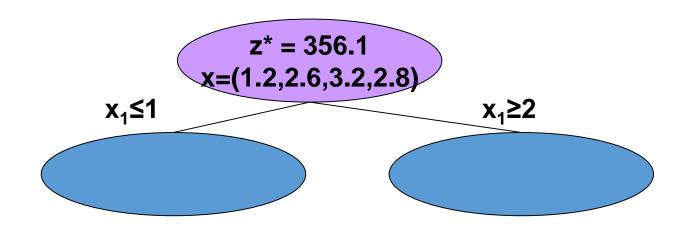
Let z_{IP} denote the value for which we wish to minimize, i.e., $z_{\text{IP}} = \min f(x)$

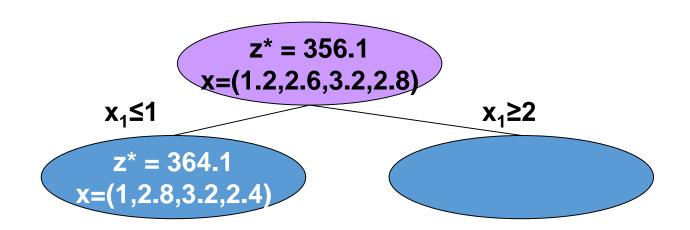
Let z^* denote the optimal objective value for any LP relaxation of the IP problem or sub-problem

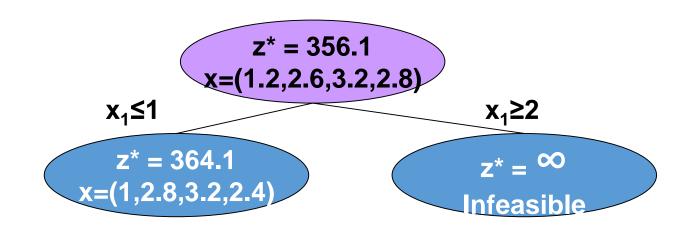
Initial LP (root node)

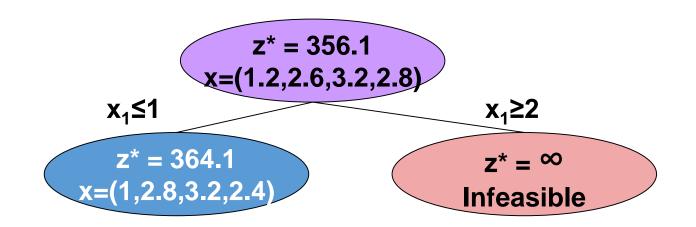
$$z^* = 356.1$$

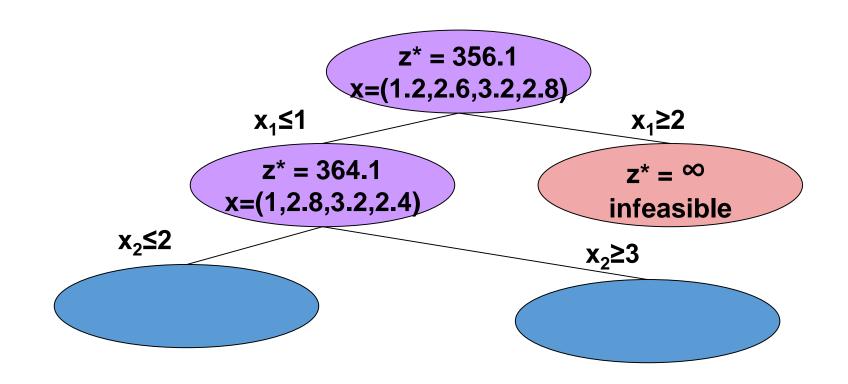
 $x=(1.2,2.6,3.2,2.8)$

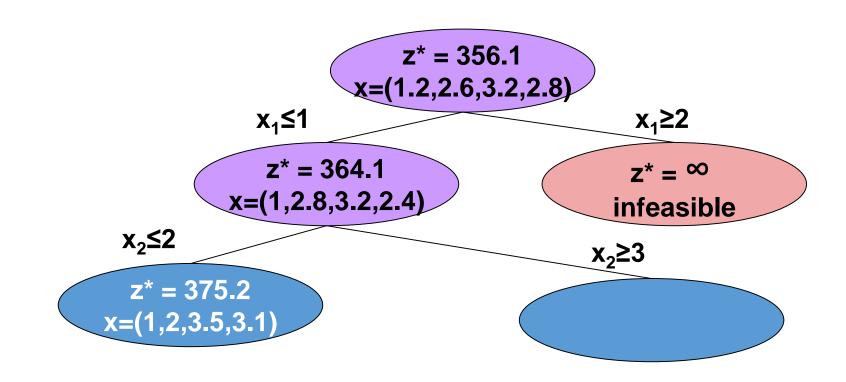


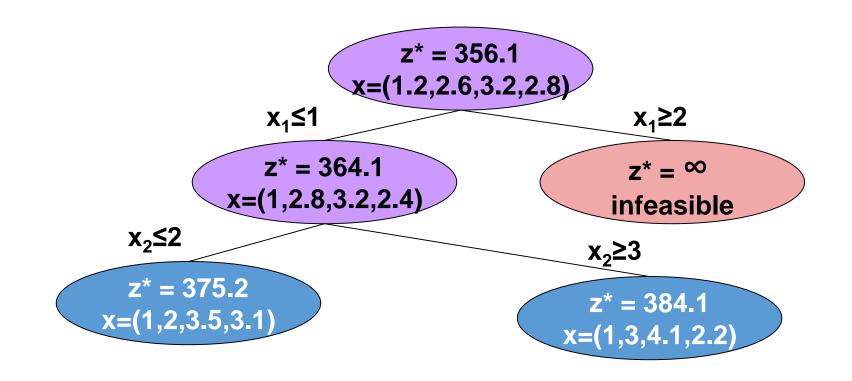


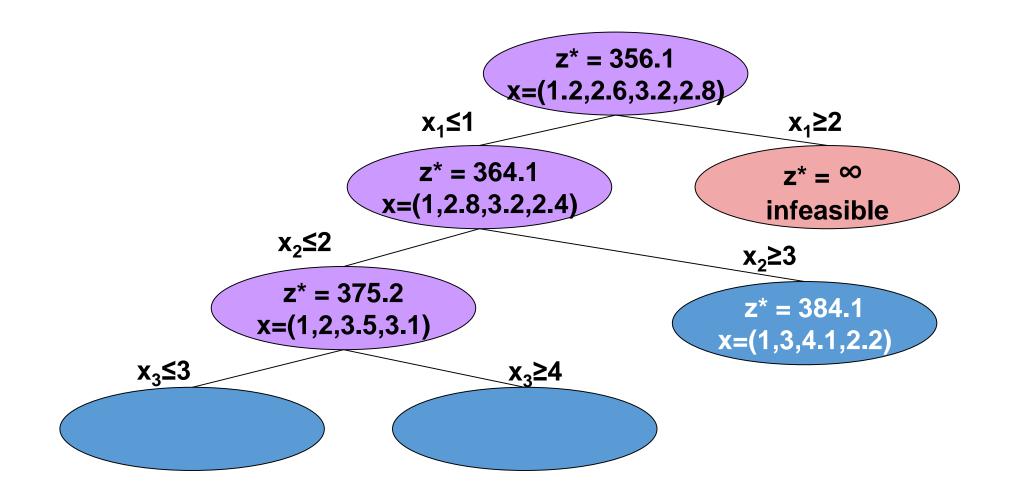


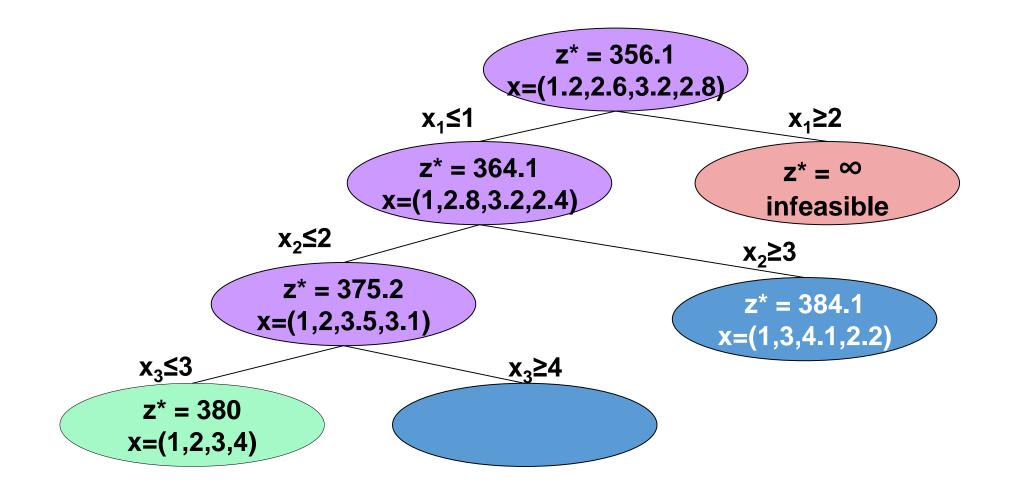


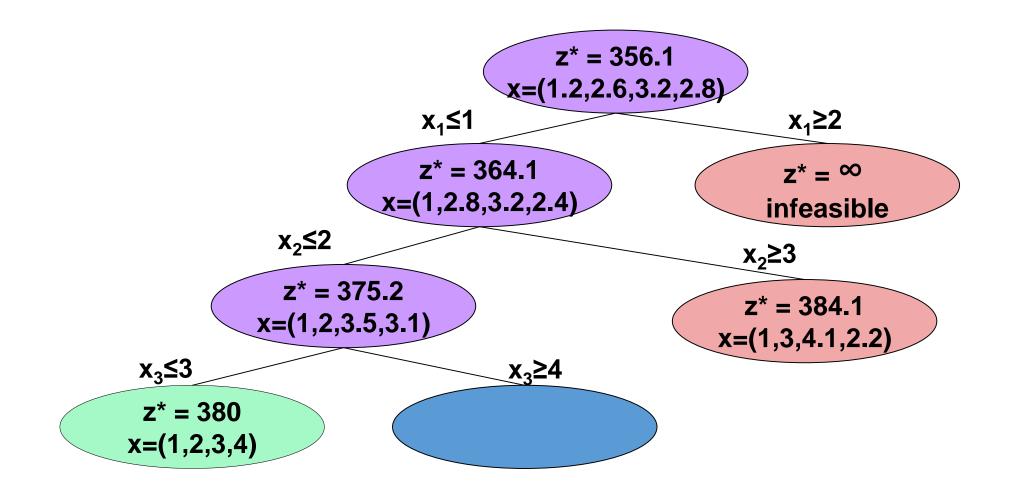


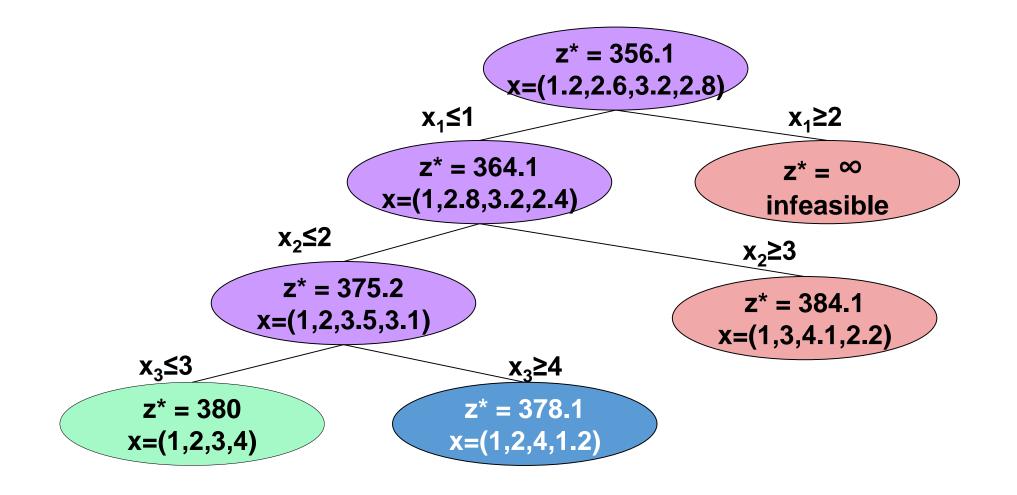


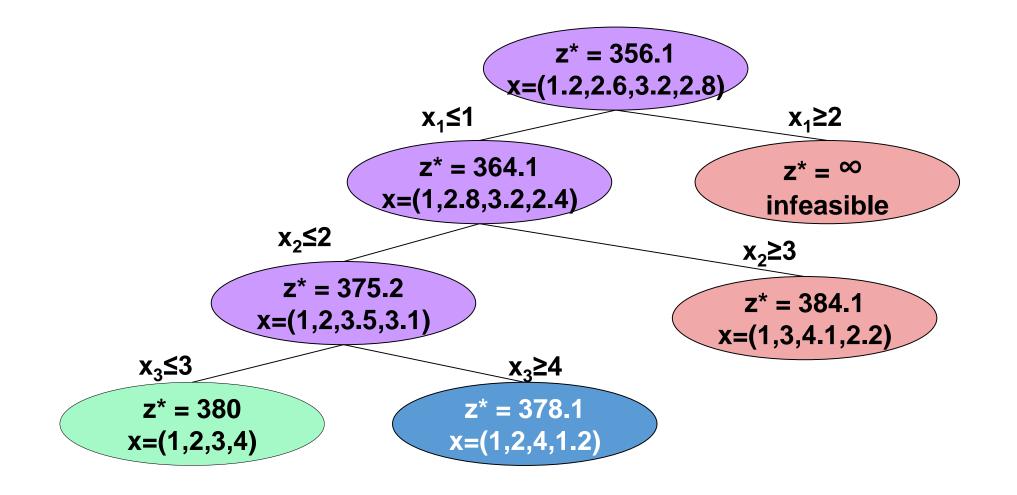


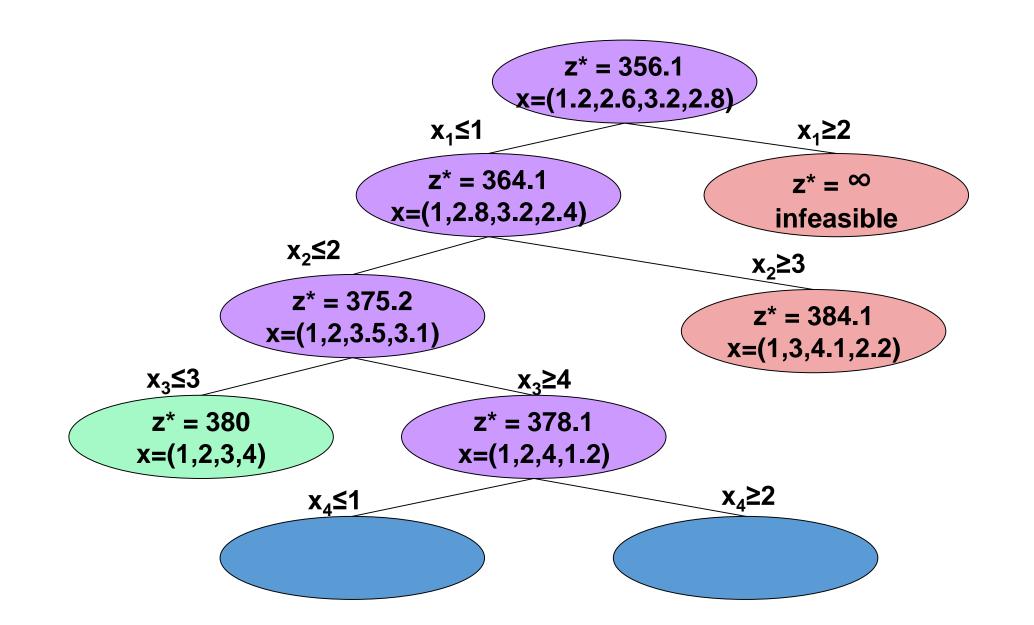


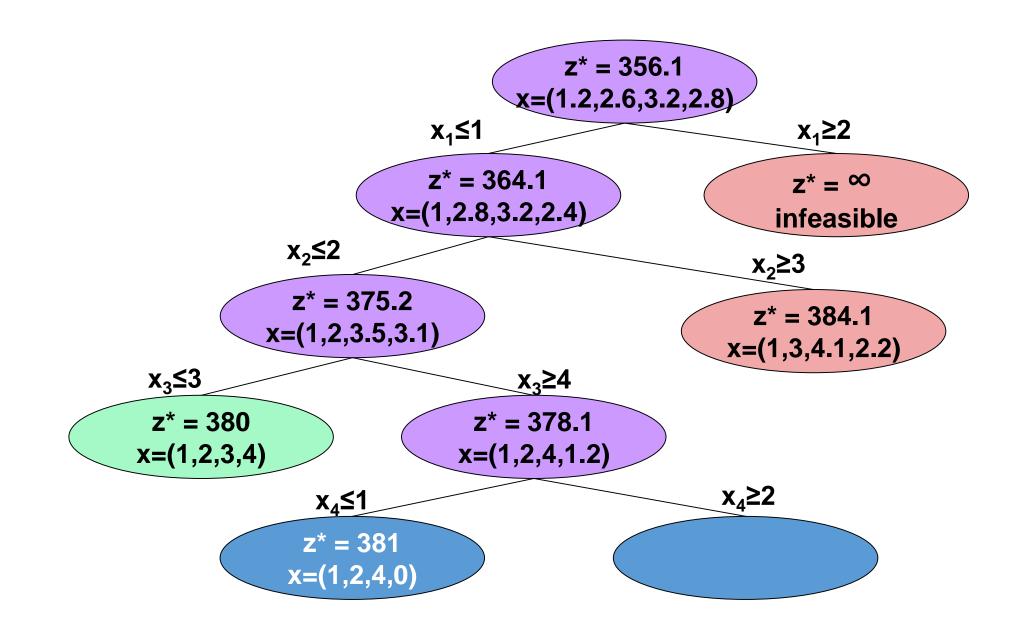


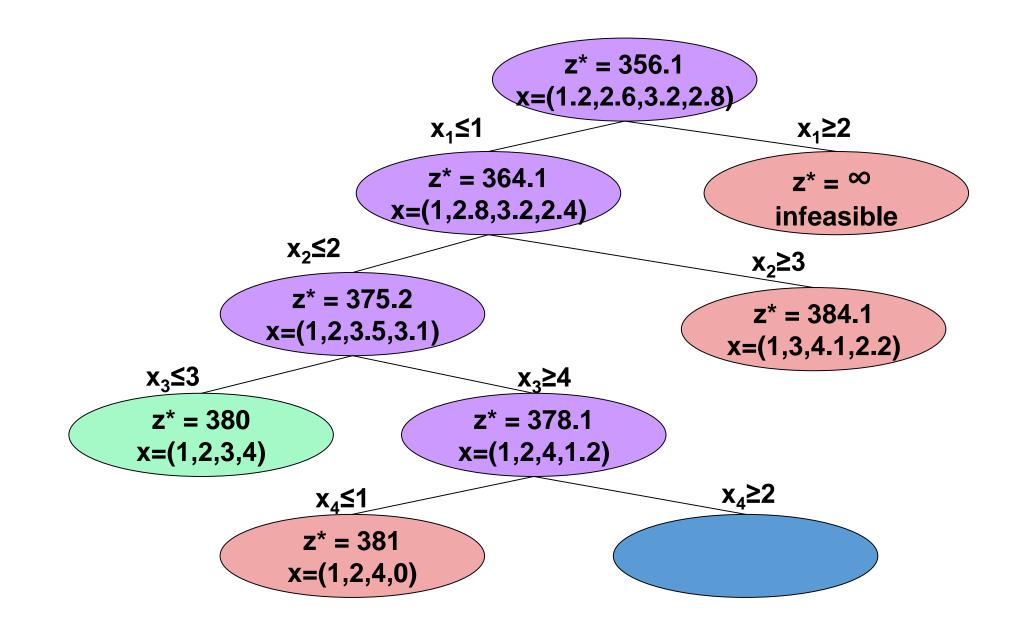


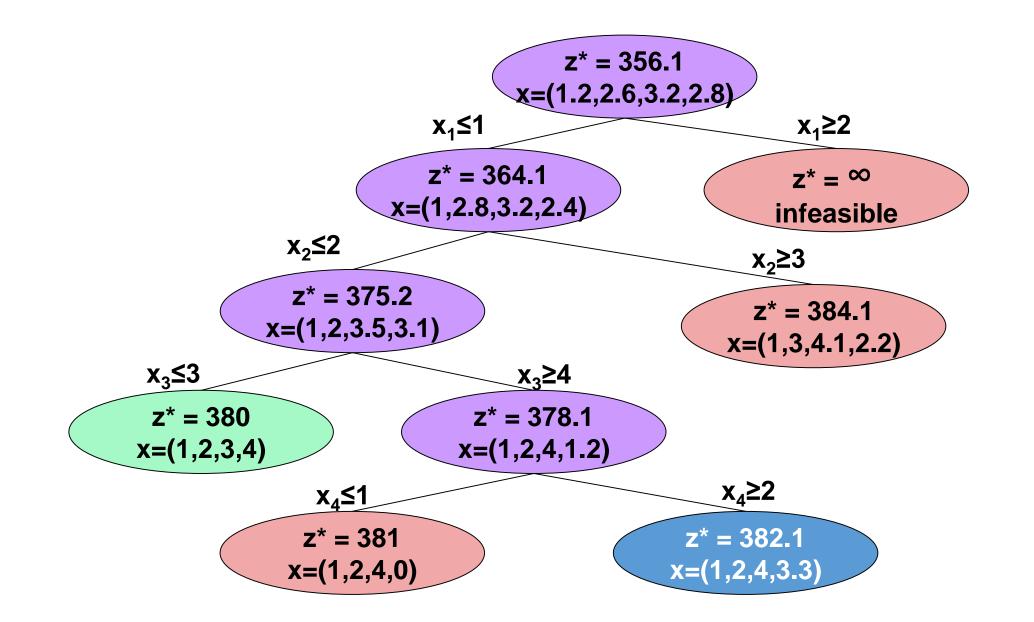


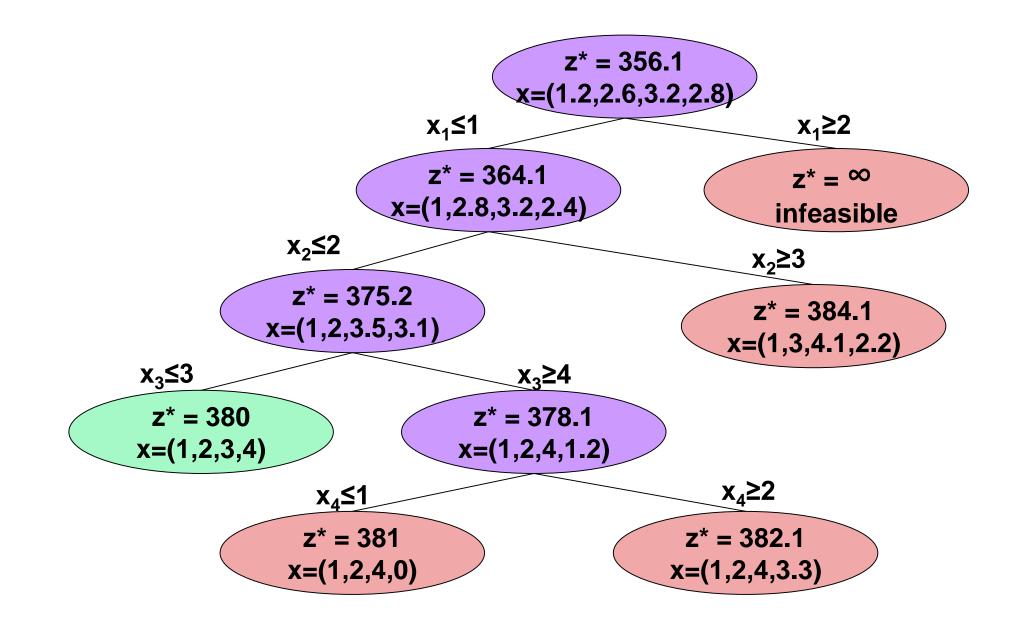












INTEGER PROGRAMMING: FORMULATIONS AND VALID INEQUALITIES

solving an IP: complete enumeration

Suppose that we could evaluate 1 trillion solutions per second, and instantaneously eliminate about 99.999999% of all solutions as not worth considering

Let n = number of binary variables

Problem size	Approximate solution times
n = 70	1 second

How to solve large integer programs fast?

B&B plus...

- The basic branch-and-bound algorithm certainly provides a vast improvement on the complete enumeration tree for an IP problem
- However, in practice we are still faced with an enormous computational challenge!
- There are few things we can do about this:
 - Branching strategies
 - Improve our IP formulation as best as possible (valid inequalities)
 - Employ "branch-and-cut" with Gomory Cuts
 - Cheat...

importance of good IP formulation

- Computational experiments suggest that the IP formulation crucially influences solution time and sometimes solvability
- To solve an IP efficiently, we want {x : Ax ≤ b} to be close to the convex hull of the feasible integer solutions
 - Finding the exact convex hull is not usually possible*
- A more tractable task: introduce valid inequalities
 - Valid inequality for an IP: any constraint that does not eliminate any feasible integer solutions
 - Valid inequalities are also called cutting planes or simply cuts

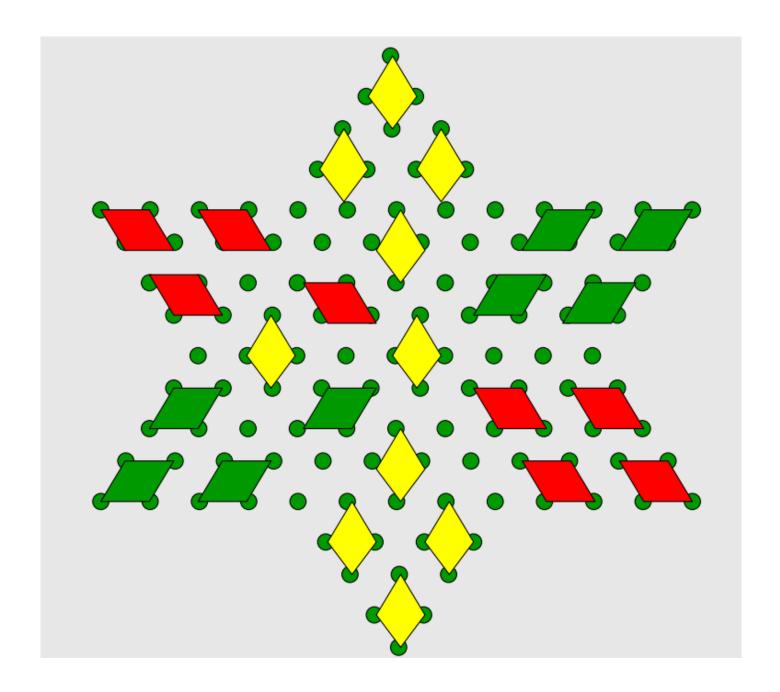
^{*}unless you can formulate the problem as a minimum cost network flow problem!

IP formulation example* with valid inequalities

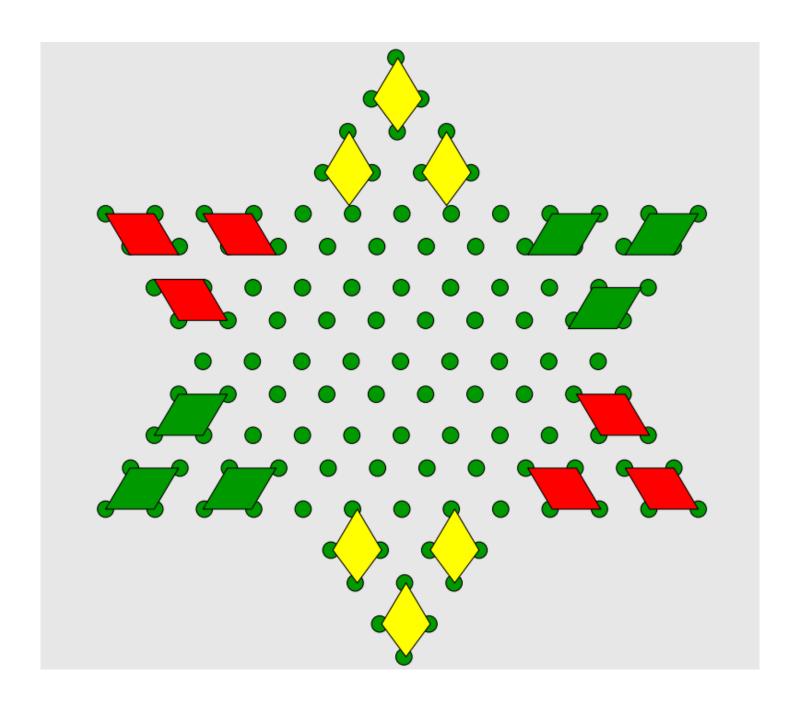
What is the maximum number of diamonds that can be packed on a Chinese checkerboard? **Each diamond** covers 4 dots.

^{*}Example adapted from MIT Open Courseware (Optimization Methods) at https://ocw.mit.edu/

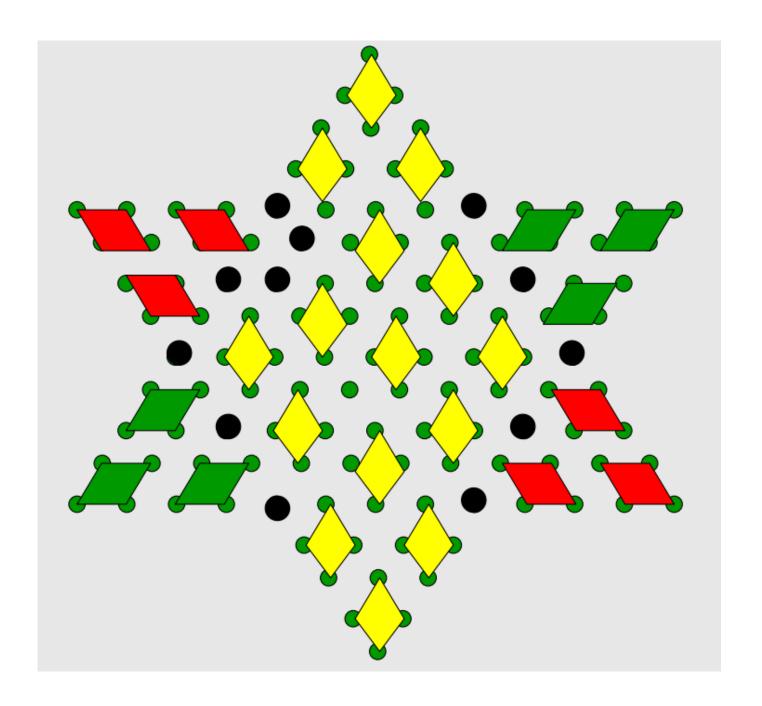
The diamonds are not permitted to overlap, or even to share a single circle.



What is the best packing you can find?



Here is one optimal packing solution.

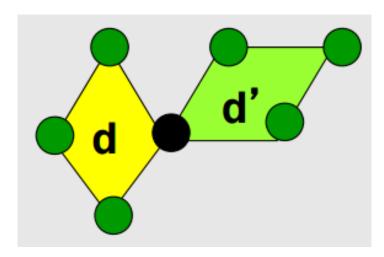


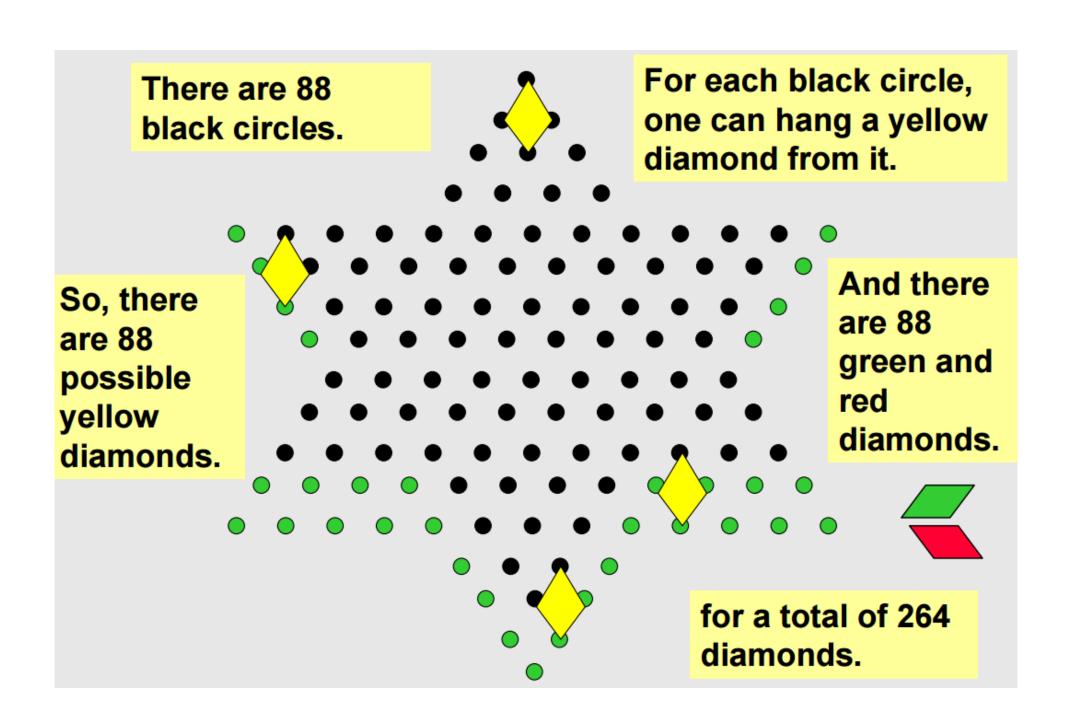
set packing problem

- Let D be the collection of diamonds
 - (note: there are 264 possible diamonds, see next slide)
- Decision variables: $x_d \in \{0,1\} \ \forall d \in D$

$$x_d = \begin{cases} 1, & \text{if diamond } d \text{ is selected} \\ 0, & \text{if diamond } d \text{ is not selected} \end{cases}$$

- Need to ensure no overlap
- Thus, we want: $x_d + x_{d'} \le 1$ for all possible diamond pairs d and d' that have at least one point in common
- Let the set O denote all such pairs





set packing problem: first IP formulation

$$\max \sum_{d \in D} x_d$$
s.t. $x_d + x_{d'} \le 1 \ \forall (d, d') \in O$

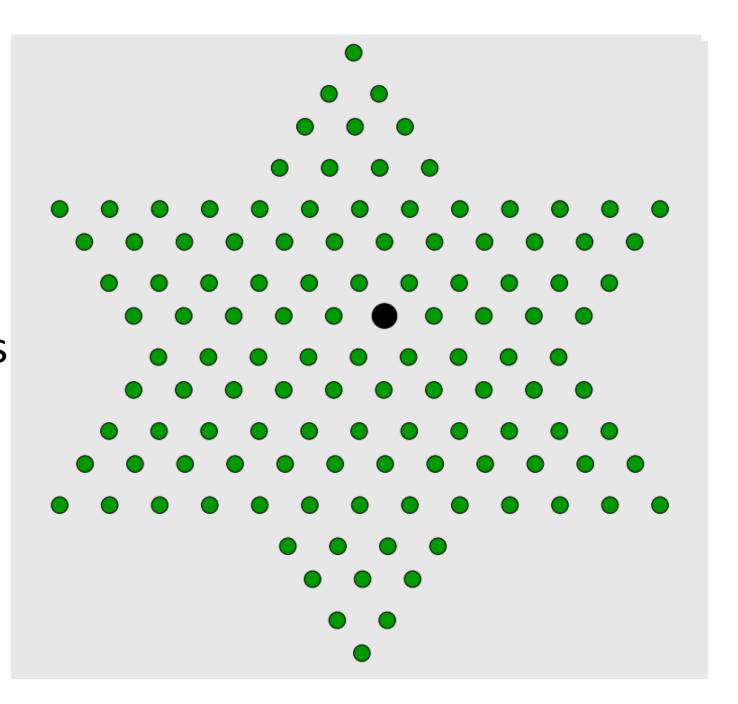
$$x_d \in \{0, 1\} \quad \forall d \in D$$

This formulation is terrible for B&B!

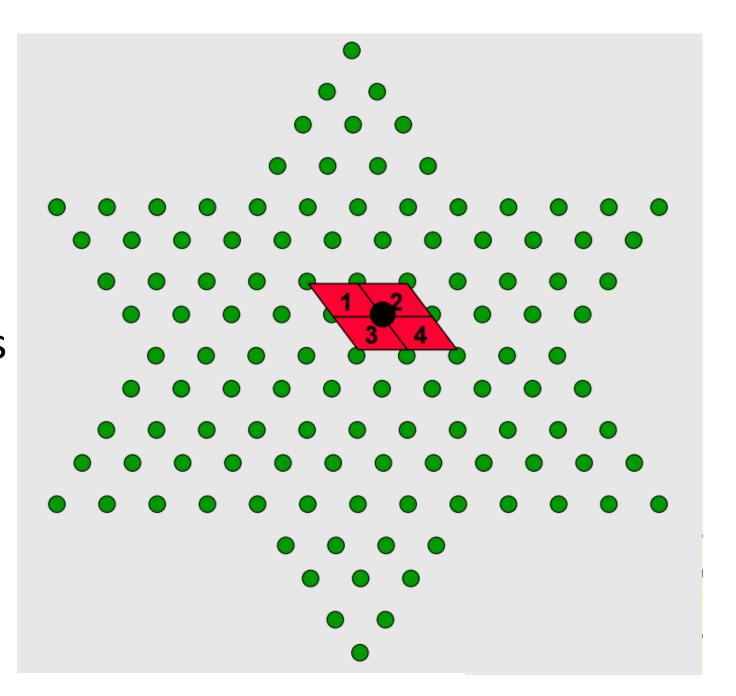
$$z_{\text{IP}}^* = 27$$
, but $z_{\text{LP}}^* = 132$ and the LP optimum solution: $x_d = \frac{1}{2} \ \forall d \in D$

B&B would take much more than 3 billion years to solve this problem on the fastest computer unless it can add valid inequalities!

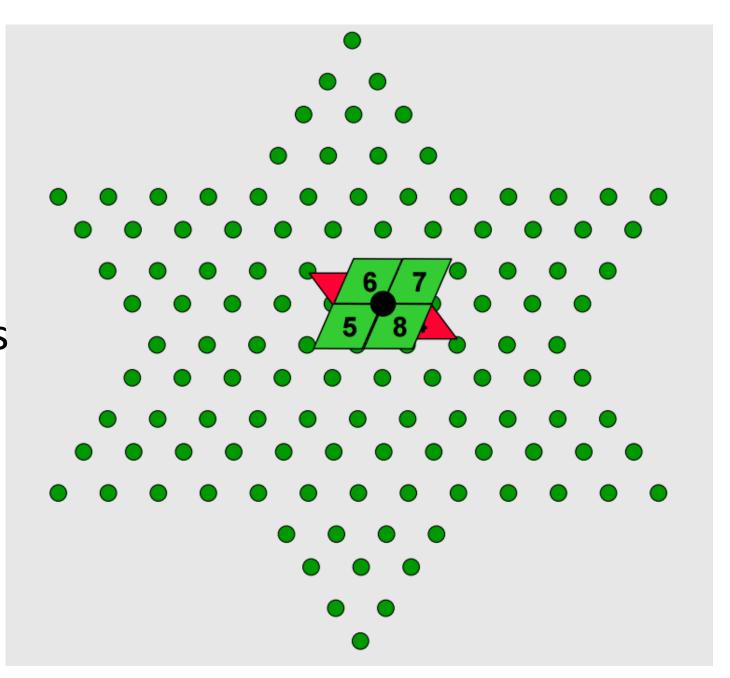
For every dot, choose at most one of the diamonds containing the dot.



For every dot, choose at most one of the diamonds containing the dot.

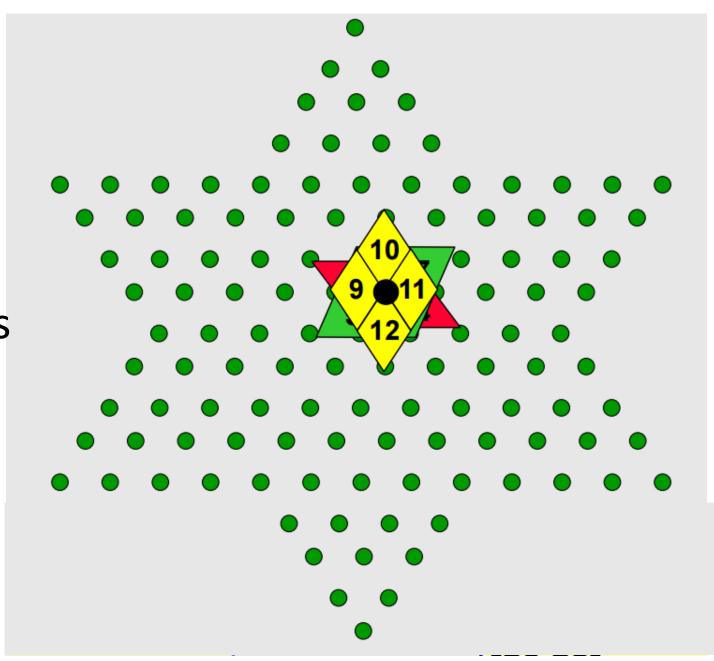


For every dot, choose at most one of the diamonds containing the dot.



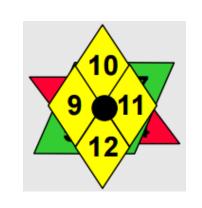
For every dot, choose at most one of the diamonds containing the dot.

At most 1 of the 12 diamonds may be selected.



set packing problem: an improved IP constraint

Let D(c) be the set of diamonds that include circle c.



$$\sum_{d \in D(c)} x_d \le 1 \quad \text{for each circle c}$$

Example constraint for one circle (in the interior):

$$x_1 + x_2 + x_3 + \ldots + x_{12} \le 1$$

set packing problem: an improved IP constraint

$$x_1 + x_2 + x_3 + \ldots + x_{12} \le 1$$



Note: $x_j = \frac{1}{12}$ would be LP feasible, but $x_j = \frac{1}{2}$ would not be feasible for all such circles!

In this constraint, we've combined 66 different constraints from our previous formulation:

$$x_1 + x_2 \le 1$$
 $x_1 + x_3 \le 1$ $x_1 + x_4 \le 1$
 $x_1 + x_5 \le 1$ $x_1 + x_6 \le 1$ $x_1 + x_7 \le 1$
 $x_1 + x_8 \le 1$... $x_{11} + x_{12} \le 1$

set packing problem: an improved IP formulation

$$\max_{d \in D} x_d$$
 s.t.
$$\sum_{d \in D(c)} x_d \le 1 \text{ for each circle c}$$

$$x_d \in \{0, 1\} \quad \forall d \in D$$

$$z_{\text{LP}}^* = 27.5 \rightarrow z_{\text{IP}}^* = 27$$

B&B solution time: **0.001 seconds!** (which, FYI, is considerably better than 3 billion years)

valid inequalities question

$$\max 22x_1 + 19x_2 + 16x_3 + 12x_4 + 11x_5 + 8x_6$$
s.t. $7x_1 + 6x_2 + 5x_3 + 4x_4 + 4x_5 + 3x_6 \le 14$

$$x_j \in \{0, 1\} \quad \text{for } j = 1, \dots, 6$$

- 1. Why can at most two of x_1, x_2, x_3 be set to 1?
- 2. How can you write this as a valid inequality?
- 3. What are some more valid inequalities you could come up with?

valid inequalities question

$$\max 22x_1 + 19x_2 + 16x_3 + 12x_4 + 11x_5 + 8x_6$$
s.t.
$$7x_1 + 6x_2 + 5x_3 + 4x_4 + 4x_5 + 3x_6 \le 14$$

$$x_j \in \{0, 1\} \quad \text{for } j = 1, \dots, 6$$

Some valid inequalities:

$$x_1 + x_2 + x_3 \le 2$$
 $x_1 + x_2 + x_5 \le 2$ $x_1 + x_3 + x_4 \le 2$ etc.

A really good constraint: $x_1 + x_2 + x_3 + x_4 \le 2$

integer programming and B&B summary

- IP dramatically improves the modeling capability
 - yes/no decisions, contingent decisions
 - logical constraints
 - fixed costs and piecewise linear cost functions
- Not as easy to model, and not as easy to solve
- Branch and Bound
 - general technique based on divide and conquer
 - "implicit enumeration"
- Cutting planes (valid inequalities)
 - used to help improve B&B
 - there are "automatic" and "logical" ways of implementing
 - Key takeaway: a good IP formulation is crucial for practical efficiency