

Comb. Opt.

Cont. Opt.

1 handout: slides

You think you know when you can learn, are more sure when you can write, even more when you can teach, but certain when you can program.

EOLQs

Comb. Opt.

Cont. Opt.

Comb. Opt.

- Types of Problems
- Optimization
- Backtracking
- Depth-first Search
- DFS Order
- ILDS
- ILDS Order
- Break
- Hill-Climbing

Cont. Opt.

Combinatorial Optimization

Types of Search Problems

Comb. Opt.

Types of Problems

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- ILDS Order
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Cont. Opt.

- Shortest-path (M&C, vacuum, tile puzzle)
 - ◆ want least-cost path to a goal
 - ◆ goal depth unknown
 - ◆ given operators and their costs
- Constraint satisfaction (map coloring, n -queens)
 - ◆ any goal is fine
 - ◆ maximum depth = number of variables
 - ◆ given explicit constraints on variables
- Combinatorial optimization (TSP, max-CSP)
 - ◆ want least-cost goal
 - ◆ maximum depth = number of variables
 - ◆ every leaf is a solution

Combinatorial Optimization

Comb. Opt.

■ Types of Problems

■ Optimization

■ Backtracking

■ Depth-first Search

■ DFS Order

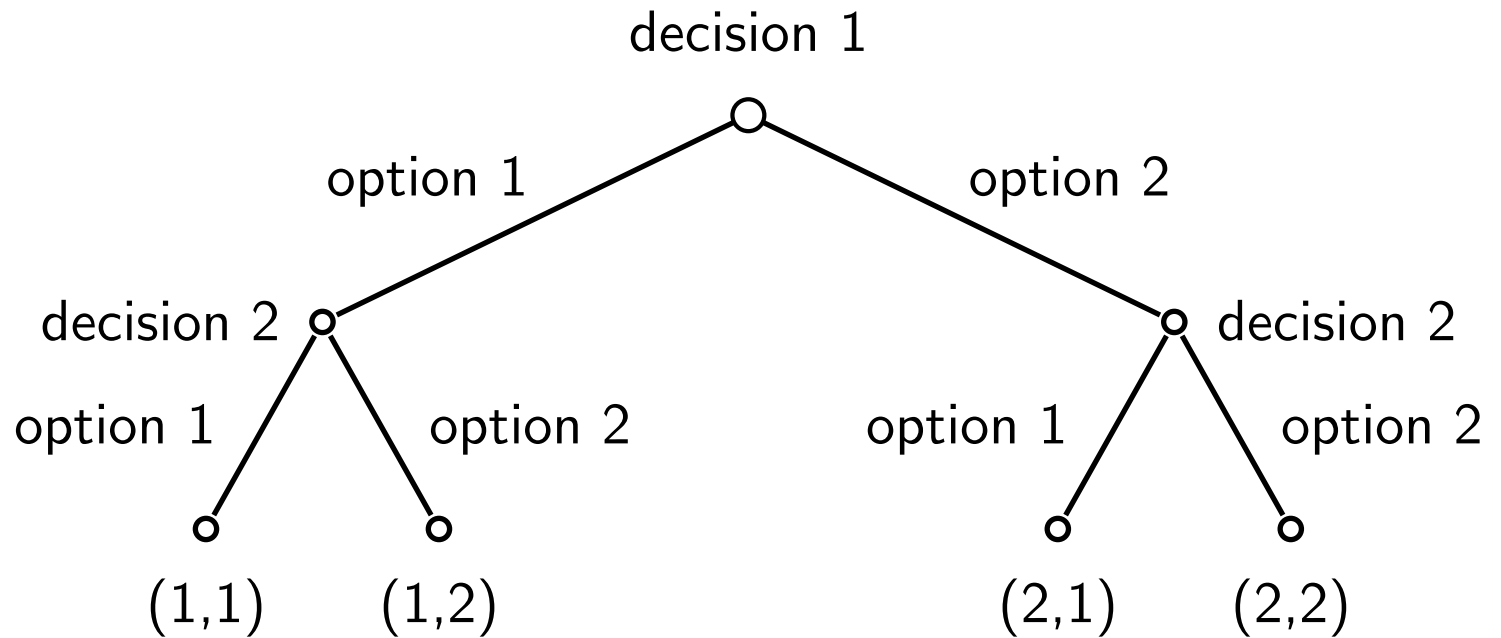
■ ILDS

■ ILDS Order

■ Break

■ Hill-Climbing

Cont. Opt.



A tree representation of alternatives in a small combinatorial problem.

Backtracking

Comb. Opt.

- Types of Problems
- Optimization
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Cont. Opt.

depth-first search
child ordering
lower bounds
branch-and-bound

Depth-first Search

Comb. Opt.

- Types of Problems
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- DFS Order
- ILDS
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- Break
- Hill-Climbing

Cont. Opt.

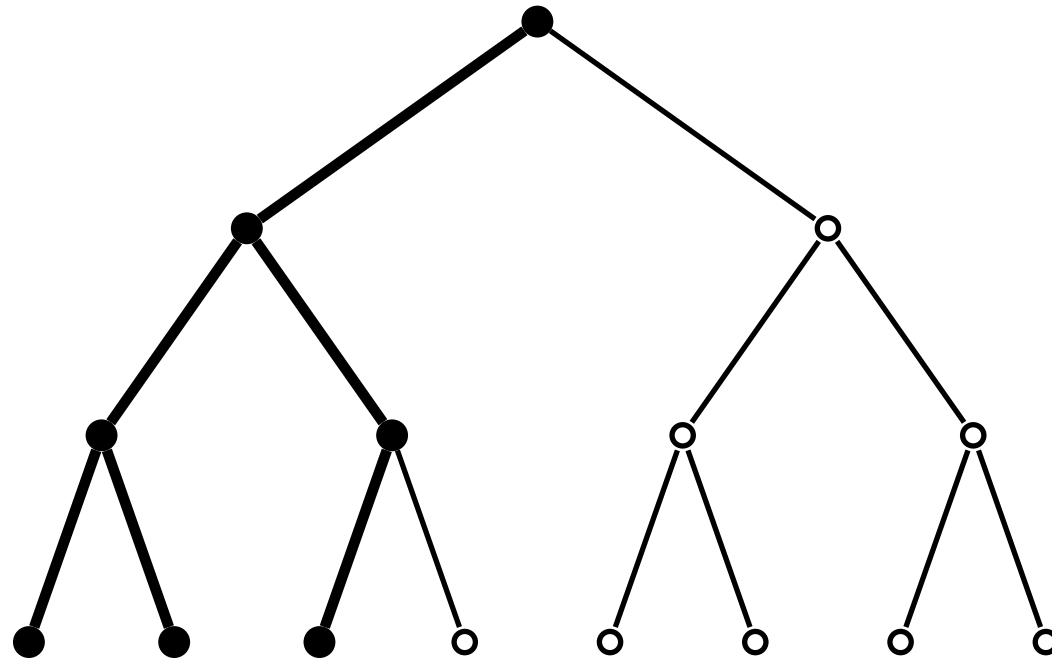
```
DFS (node)
1   If is-leaf(node)
2       Visit(node)
3   else
4       For i from 0 to num-children
5           DFS(child(node, i))
```

Depth-first Search Order

Comb. Opt.

- Types of Problems
- Optimization
- Backtracking
- Depth-first Search
- **DFS Order**
- ILDS
- ILDS Order
- Break
- Hill-Climbing

Cont. Opt.



Improved Discrepancy Search

Comb. Opt.

- Types of Problems
- Optimization
- Backtracking
- Depth-first Search
- DFS Order
- **ILDS**
- ILDS Order
- Break
- Hill-Climbing

Cont. Opt.

ILDS (*node*, *allowance*, *remaining*)

- 1 If is-leaf(*node*)
- 2 Visit(*node*)
- 3 else
- 4 If *allowance* > 0
- 5 ILDS(child(*node*, 1), *allowance* - 1, *remaining* - 1)
- 6 If *remaining* > *allowance*
- 7 ILDS(child(*node*, 0), *allowance*, *remaining* - 1)

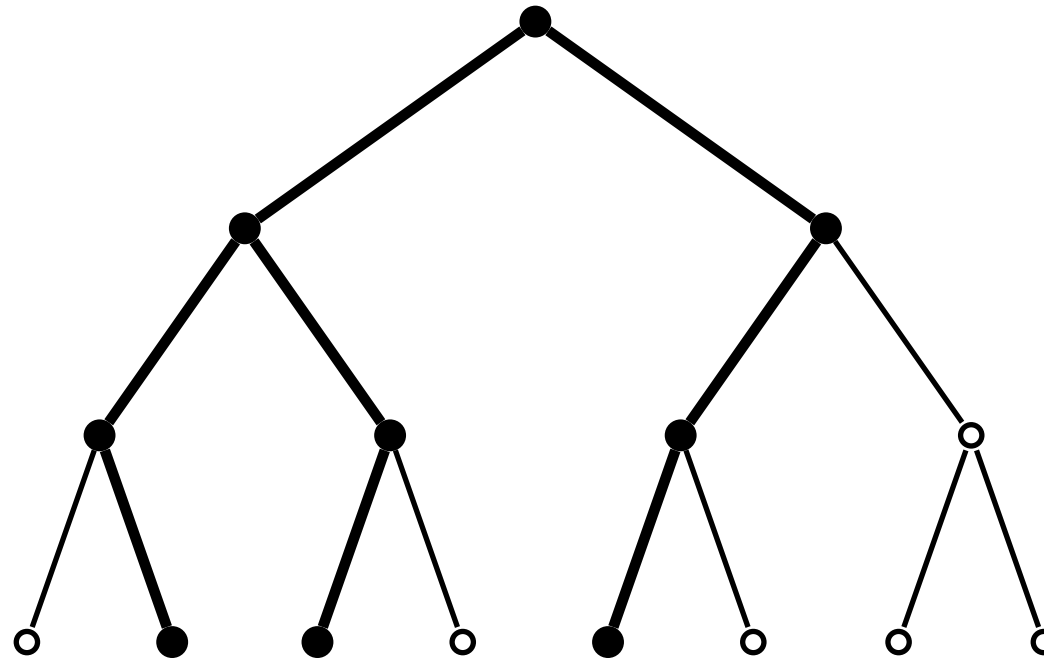
start with ILDS(*root*, *iteration*, *max-depth*)

Discrepancy Search Order

Comb. Opt.

- Types of Problems
- Optimization
- Backtracking
- Depth-first Search
- DFS Order
- ILDS
- ILDS Order
- Break
- Hill-Climbing

Cont. Opt.



The second pass of ILDS visits all leaves with one discrepancy in their path from the root.

Break

Comb. Opt.

- Types of Problems
- Optimization
- Backtracking
- Depth-first Search
- DFS Order
- ILDS
- ILDS Order

■ Break

- Hill-Climbing

Cont. Opt.

- asst 4
- projects

Hill-Climbing

Comb. Opt.

- Types of Problems
- Optimization
- Backtracking
- Depth-first Search
- DFS Order
- ILDS
- ILDS Order
- Break

■ Hill-Climbing

Cont. Opt.

$Sol \leftarrow$ some random solution (probably poor quality).

Do *limit* times

$New \leftarrow$ random **neighbor** of Sol .

If New better than Sol ,
then $Sol \leftarrow New$.

Hill-Climbing

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- Types of Problems
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- Break

■ Hill-Climbing

Cont. Opt.

$Sol \leftarrow$ some random solution (probably poor quality).

Do *limit* times

$New \leftarrow$ random **neighbor** of Sol .

If New better than Sol ,
then $Sol \leftarrow New$.

Elaborations: best neighbor (aka gradient-descent)
restarts
simulated annealing
population (GAs, 'go with the winners')

search space (genotype) vs solution space (phenotype)

Comb. Opt.

Cont. Opt.

- Types of Problems
- LPs
- Beyond LPs
- EOLQs

Continuous Optimization

Types of Optimization Problems

Comb. Opt.

Cont. Opt.

■ Types of Problems

■ LPs

■ Beyond LPs

■ EOLQs

- Discrete
 - ◆ finite (often small) set of values per choice
 - ◆ planning, CSPs, combinatorial optimization
 - ◆ constraints can be implicit or explicit
- Continuous
 - ◆ real values
 - ◆ constraints can be linear, quadratic, . . . , non-linear
 - ◆ objective can be linear, quadratic, . . . , non-linear
- Mixed discrete / continuous
 - ◆ eg, MIPs, MILPs, ...
 - ◆ planning for 'hybrid systems'

Linear Programming

Comb. Opt.

Cont. Opt.

■ Types of Problems

■ LPs

■ Beyond LPs

■ EOLQs

real variables, linear constraints, linear objective

- cheapest diet that meets nutrition guidelines
 - ◆ $y_{vitaminA} = 2.3x_{broccoli} + 1.7x_{carrots} \dots$
 - ◆ $cost = 4.99x_{broccoli} + 2.67x_{carrots} \dots$
 - ◆ minimize $cost$ subject to $y_{vitaminA} > 500 \dots$
- max flow through network with capacity constraints
- earliest finish time subject to job durations

polynomial time (ellipsoid, Karmarkar's), but simplex method is popular

CPLEX, Gurobi, Ipsolve

Beyond Linear Programming

Comb. Opt.

Cont. Opt.

■ Types of Problems

■ LPs

■ Beyond LPs

■ EOLQs

convex programming: constraints and objective are convex
polynomial time

quadratic programming: constraints and objective are quadratic

some forms are polynomial time

0-1 LP: 0-1 variables, linear constraints, linear objective
NP-complete

integer linear programming: integer variables, linear constraints and objective
NP-complete

combinatorial optimization: variables are discrete

EOLQs

Comb. Opt.

Cont. Opt.

■ Types of Problems

■ LPs

■ Beyond LPs

■ **EOLQs**

Please write down the most pressing question you have about the course material covered so far and put it in the box on your way out.

Thanks!