Section 4

CSP'S AND LOCAL SEARCH

CSPs and Local Search

Last week in CSPs:

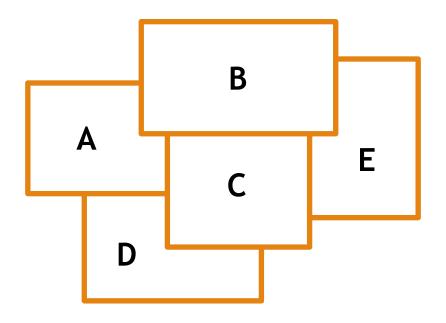
- variables, domains, constraints
- backtracking

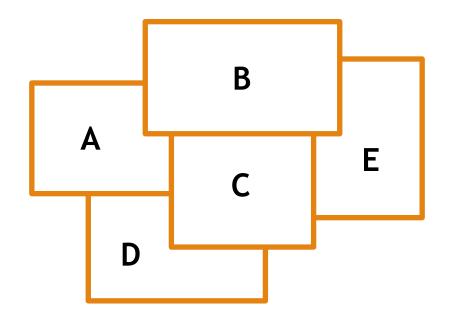
This week in CSPs:

- ordering
- forward checking
- arc consistency

Also, in local search:

- optimization and convexity
- hill climbing
- beam search
- simulated annealing
- gradient descent
- genetic algorithms





<u>Variables:</u> A, B, C, D, E

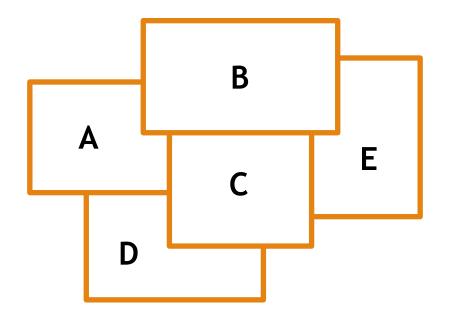
<u>Values:</u>







Constraints:



Variables: A, B, C, D, E

Values:







Constraints:

A != B

A != C

A != D

B != E

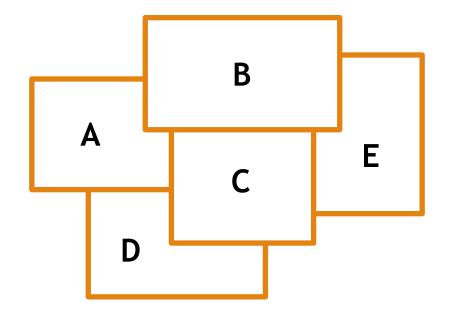
B != C

C != E

Most naive search tree: branching factor of 15

Fixed ordering search tree: branching factor of 3

What is a better way to order?



Variables: A, B, C, D, E

<u>Values:</u>







Constraints:

A != B

A != C

A != D

B != E

B != C

C != E

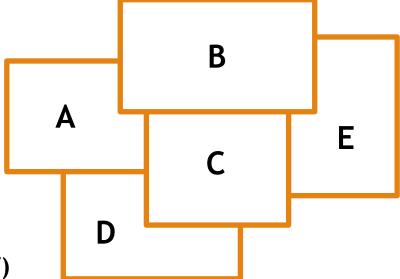
Most naive search tree: branching factor of 15

Fixed ordering search tree: branching factor of 3

What is a better way to order?

Heuristics:

- Minimum remaining values (MRV)
- Fewest constraints (degree)
- Least constraining value



Variables: A, B, C, D, E

Values:







Constraints:

A != B

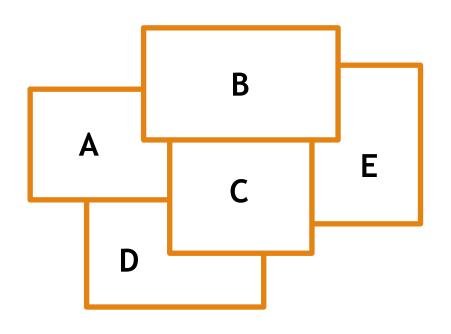
A != C

A != D

B != E

B != C

C != E



Variables: A, B, C, D, E

Values:







Constraints:

A != B

A != C

A != D

B != E

B != C

C != E

D != C

1





C

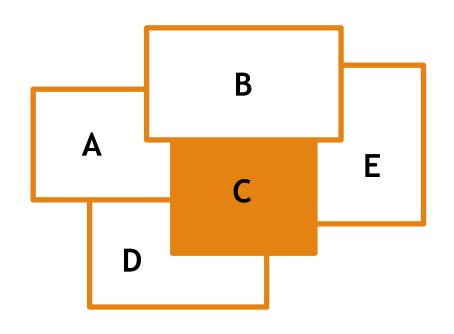


D



Ε





Variables: A, B, C, D, E

Values:







Constraints:

A != B

A != C

A != D

B != E

B != C

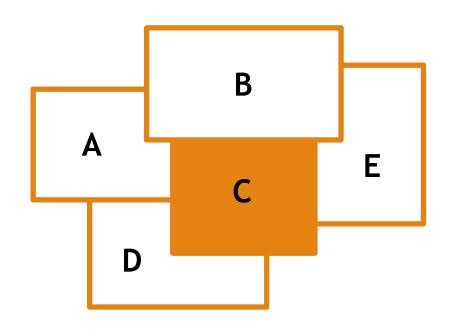
C != E

D != C

В







Variables: A, B, C, D, E

Values:







Constraints:

A != B

A != C

A != D

B != E

B != C

C != E

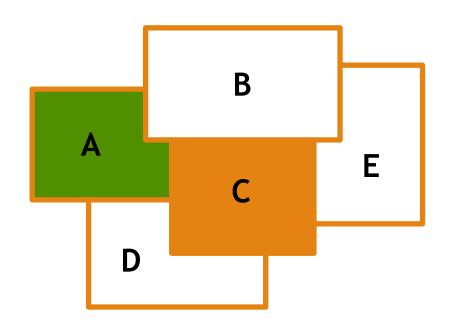












Variables: A, B, C, D, E

Values:







Constraints:

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A != C

A != D

B != E

B != C

C != E

D != C

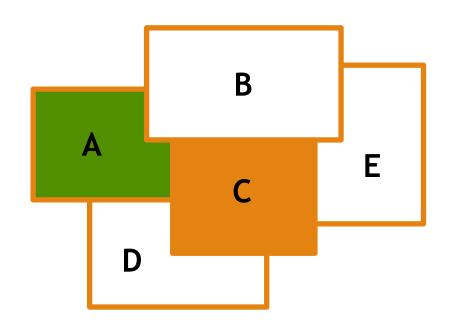
A X X

В 💢 🛑 🛑









Variables: A, B, C, D, E

Values:







Constraints:

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A != C

A != D

B != E

B != C

C != E

D != C

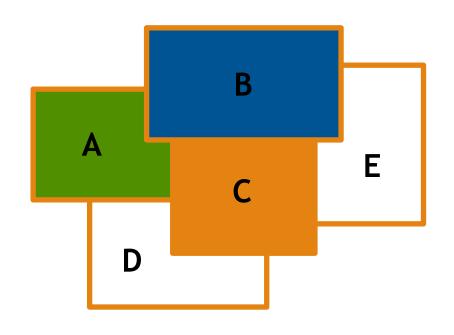
4

В

c



E 💢 🔵 🔵



Variables: A, B, C, D, E

Values:







Constraints:

A != B

A != C

A != D

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B != C

C != E

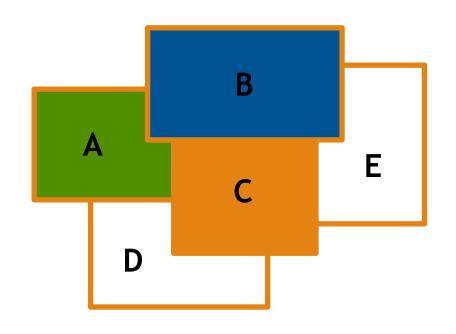












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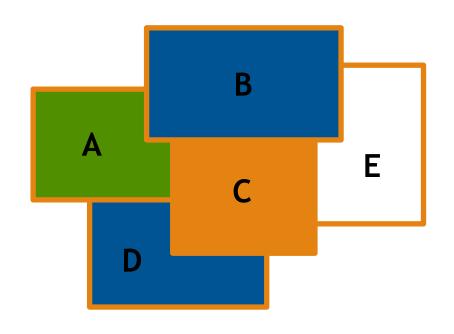












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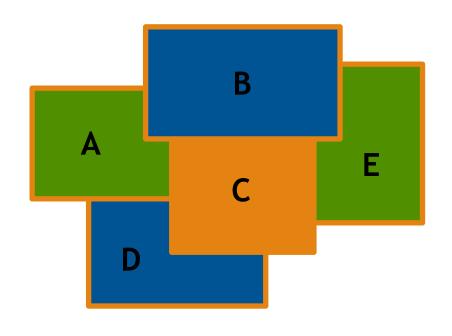
4

В









Variables: A, B, C, D, E

Values:







Constraints:

A != B

A != C

A != D

B != E

B != C

C != E







Hill climbing

Beam search

Simulated annealing

Genetic algorithms

Hill climbing

Given a state, generate all successors and choose the best one. If none are better, return current state.

Beam search

Simulated annealing

Genetic algorithms

Hill climbing

Given a state, generate all successors and choose the best one. If none are better, return current state.

Beam search

Choose *k* initial states. For all states, expand all successors. Among the generated states, choose the best *k* and continue until convergence.

Simulated annealing

Genetic algorithms

Hill climbing

Given a state, generate all successors and choose the best one. If none are better, return current state.

Beam search

Choose *k* initial states. For all states, expand all successors. Among the generated states, choose the best *k* and continue until convergence.

Simulated annealing

At each iteration, choose a random successor. Accept the successor with a "temperature"-dependent probability, which decreases over time.

Genetic algorithms

Hill climbing

Given a state, generate all successors and choose the best one. If none are better, return current state.

Beam search

Choose *k* initial states. For all states, expand all successors. Among the generated states, choose the best *k* and continue until convergence.

Simulated annealing

At each iteration, choose a random successor. Accept the successor with a "temperature"-dependent probability, which decreases over time.

Genetic algorithms

At each iteration, generate (and mutate) successors from the "best" sample in the previous iteration.

Hill climbing

Given a state, generate all successors and choose the best one. If none are better, return current state.

Beam search

Choose k initial states. For all states, expand all successors. Among the generated states, choose the best k and continue until convergence.

Simulated annealing

At each iteration, choose a random successor. Accept the successor with a "temperature"-dependent probability, which decreases over time.

Genetic algorithms

At each iteration, generate (and mutate) successors from the "best" sample in the previous iteration.

Gradient descent

Calculate and repeatedly step down the gradient (for continuous functions).