Midterm Review

CSCI 4511/6511

Joe Goldfrank

Announcements

- Midterm Exam - 16 Oct
  - In class
  - Open note: 10 sides of paper (8.5”x11” or A4)
- Homework Three - 20 Oct
- Project Guidelines

Review

The Rational Agent

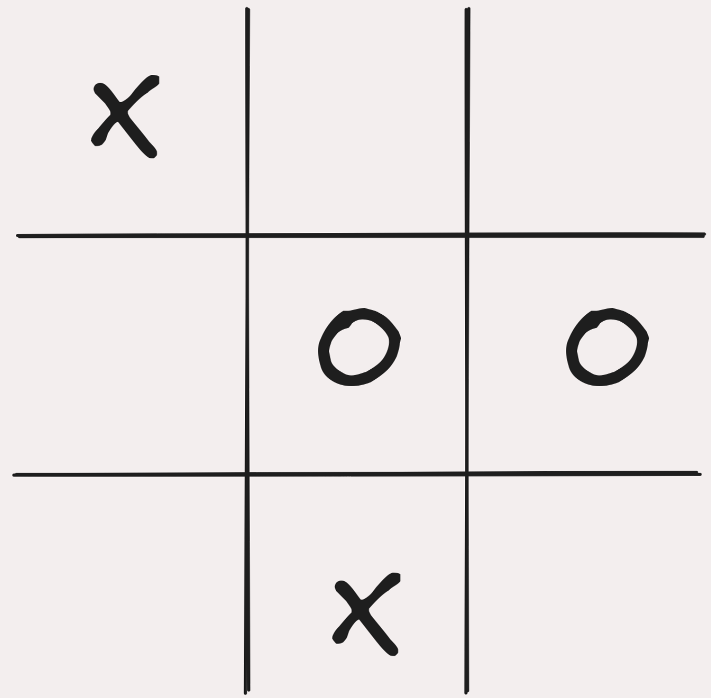
- Has a utility function
    - Maximizes expected utility
- Sensors: perceives environment
- Actuators: influences environment

What is in between sensors and actuators?

The *agent function*.

Reflex Agent

- Very basic form of agent function
- Percept $\rightarrow$ Action lookup table
- Good for simple games
  - Tic-tac-toe
  - Checkers?
- Needs *entire state space* in table



State Space Size

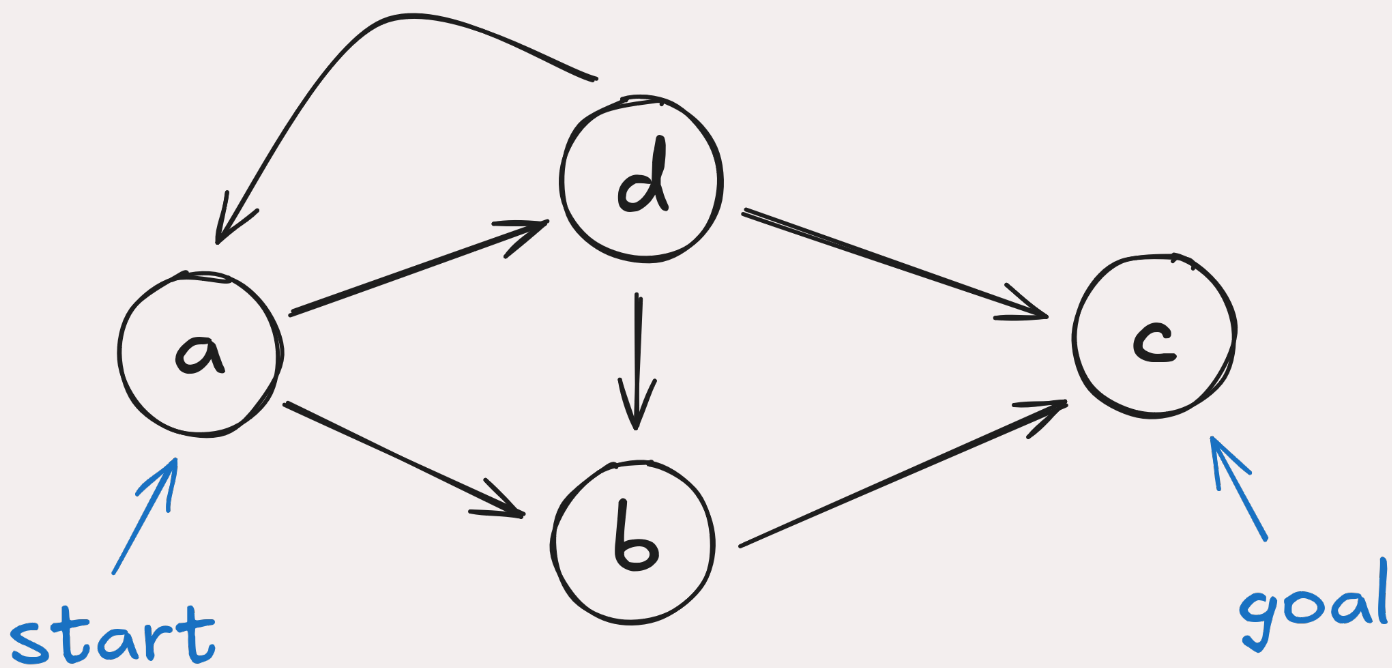
- Tic-tac-toe: 10^3
- Checkers: 10^{20}
- Chess: 10^{44}
- Go: 10^{170}
- Self-driving car: ?
- Pacman?
    - How could you estimate it?

In Practice

- Environment
  - What happens next
- Perception
  - What agent can see
- Action
  - What agent can do
- Measure/Reward
  - Encoded utility function

Search

- Fully-observed problem
- Deterministic actions and state
- Well defined *start* and *goal*



Not Search

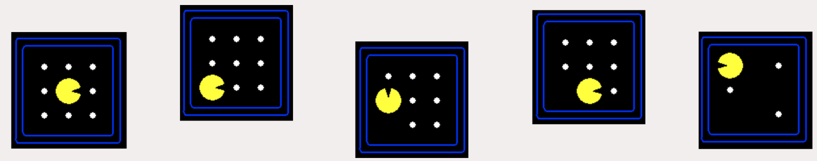
- Uncertainty
  - State transitions known
- Adversary
  - Nobody wants us to lose
- Cooperation
- Continuous state

Search Problem

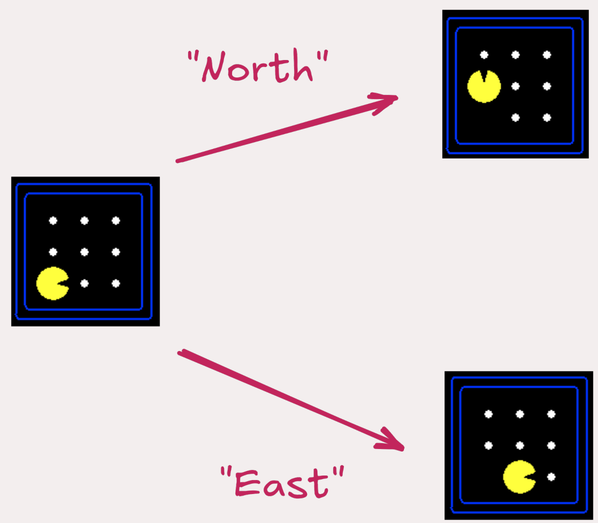
Search problem includes:

- Start State
- State Space
- State Transitions
- Goal Test

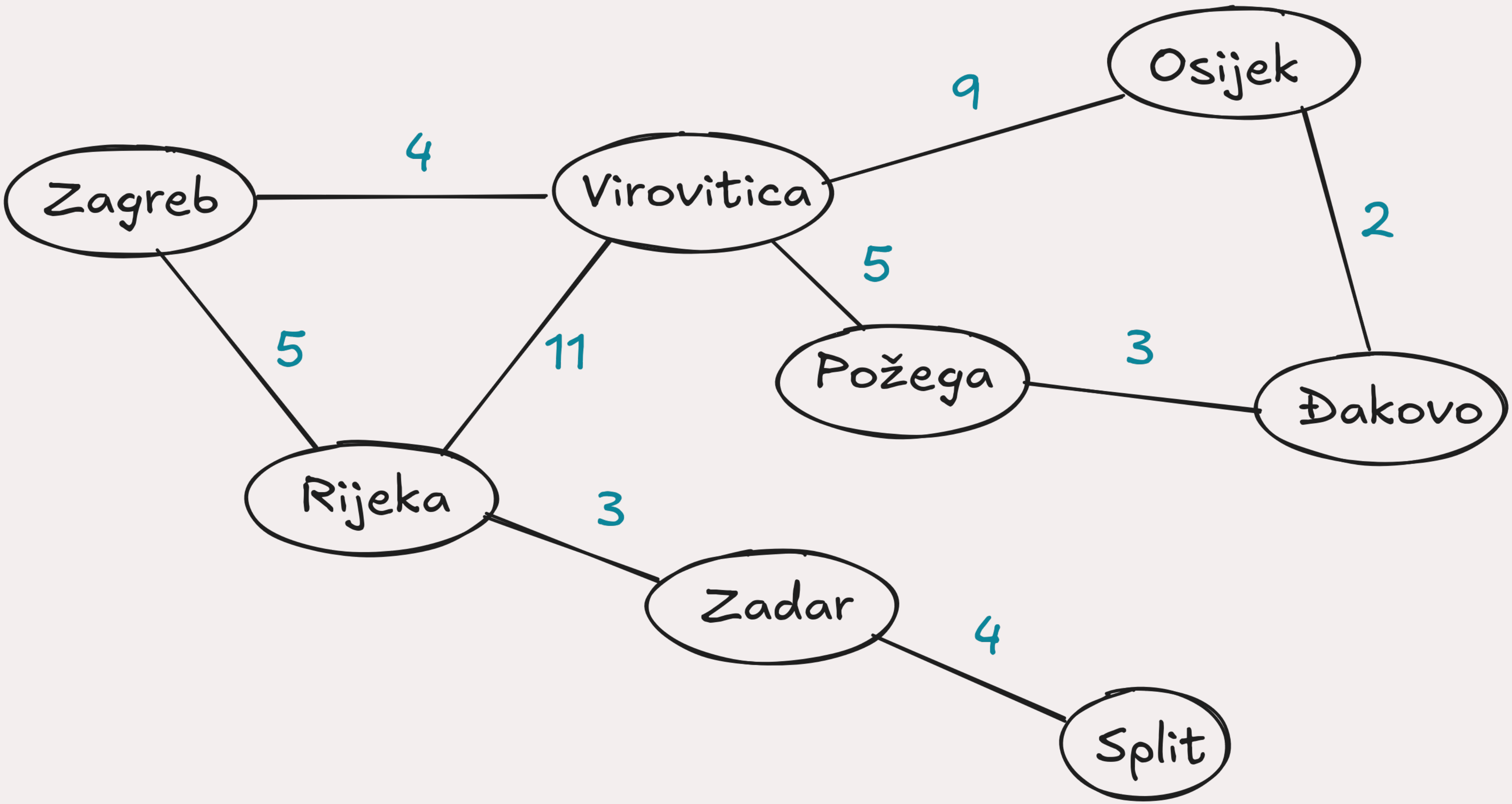
State Space:



Actions & Successor States:

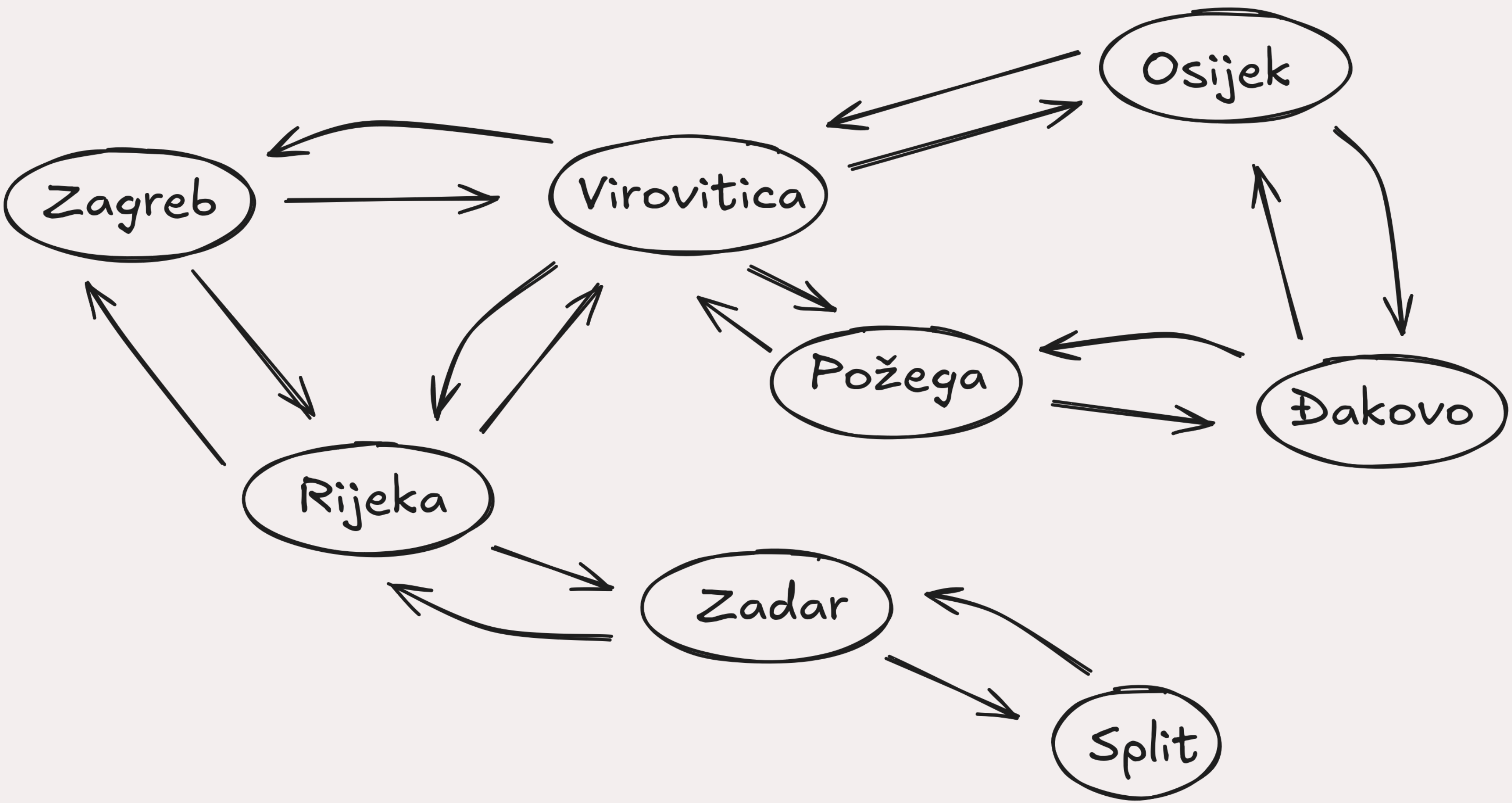


State Space



Osijek
9
4
Zagreb
Virovitica
2
5
5
11
3
Požega
Đakovo
Rijeka
3
Zadar
4
Split

State Space Graph



Graph vs. Tree

How To Solve It

Given:

- Starting node
- Goal test
- Expansion

Do:

- Expand nodes from start
- Test each new node for goal
    - If goal, success
- Expand new nodes
    - If nothing left to expand, failure

Queues & Searches

- Priority Queues
  - Best-First Search
  - Uniform-Cost Search[1]
- FIFO Queues
  - Breadth-First Search
- LIFO Queues[2]
  - Depth-First Search

1. Also known as "Dijkstra's Algorithm," because it is Dijkstra's Algorithm
2. Also known as "stacks," because they are stacks.

Search Features

- Completeness
  - If there is a solution, will we find it?
- Optimality
  - Will we find the *best* solution?
- Time complexity
- Memory complexity

Uninformed Search Variants

- Depth-Limited Search
  - Fail if depth limit reached (why?)
- Iterative deepening
  - vs. Breadth-First Search
- Bidirectional Search

Heuristics

heuristic - *adj* - Serving to discover or find out.[1]

- We know things about the problem
- These things are external to the graph/tree structure
  - We could model the problem differently
  - We can use the information directly

1. Webster's. 1913

Choosing Heuristics

- Admissibility
  - *Never* overestimates cost from n to goal
  - Cost-optimal!
- Consistency
  - $h(n) \leq c(n, a, n') + h(n')$
  - n' successors of n
  - $c(n, a, n')$ cost from n to n' given action a

Weighted A* Search

- Greedy: $f(n) = h(n)$
- A*: $f(n) = h(n) + g(n)$
- Uniform-Cost Search: $f(n) = g(n)$

- Weighted A* Search: $f(n) = W \cdot h(n) + g(n)$
  - Weight $W > 1$

Iterative-Deepening A* Search

"IDA*" Search

- Similar to Iterative Deepening with Depth-First Search
  - DFS uses depth cutoff
  - IDA* uses $h(n) + g(n)$ cutoff *with DFS*
  - Once cutoff breached, new cutoff:
    - Typically next-largest $h(n) + g(n)$
  - $O(b^m)$ time complexity 😔
  - $O(d)$ space complexity[1] 😌

1. This is slightly complicated based on heuristic branching factor b_h.

Beam Search

Best-First Search:

- Frontier is all expanded nodes

Beam Search:

- k “best” nodes are kept on frontier
  - Others discarded
- Alt: all nodes within δ of best node
- Not Optimal
- Not Complete

Where Do Heuristics Come From?

- Intuition
  - “Just Be Really Smart”
- Relaxation
  - The problem is constrained
  - Remove the constraint
- Pre-computation
  - Sub problems
- Learning

Local Search

Uninformed/Informed Search:

- Known start, known goal
- Search for optimal path

Local Search:

- “Start” is irrelevant
- Goal is not known
  - But we know it when we see it
- Search for *goal*

Objective Function

- Do you know what you want?
- Can you express it mathematically?
  - A single value
  - More is better
- Objective function: a function of *state*

Hill-Climbing

- Objective function
- State space mapping
    - Neighbors

Hazards:

- Local maxima
- Plateaus
- Ridges

Variations

- Sideways moves
  - Not free
- Stochastic moves
  - Full set
  - First choice
- Random restarts
  - If at first you don’t succeed, ~~you fail~~ try again!
  - Complete 😌

Simulated Annealing

- Search begins with high “temperature”
  - Temperature decreases during search
- Next state selected randomly
  - Improvements always accepted
  - Non-improvements rejected stochastically
  - Higher temperature, less rejection
  - “Worse” result, more rejection

Local Beam Search

Recall:

- Beam search keeps track of k "best" branches

Local Beam Search:

- Hill climbing search, keeping track of k successors
  - Deterministic
  - Stochastic

Gradient Descent

- Minimize loss instead of climb hill
  - Still the same idea

Consider:

- One state variable, x
- Objective function $f(x)$
  - How do we minimize $f(x)$?
  - Is there a closed form $\frac{d}{dx}$?

Gradient Descent

Multivariate $\vec{x} = x_0, x_1, \ldots$

Instead of derivative, gradient:

$$\nabla f(\vec{x}) = \left[\frac{\partial f}{\partial x_0}, \frac{\partial f}{\partial x_1}, \ldots\right]$$

"Locally" descend gradient:

$$\vec{x} \leftarrow \vec{x} + \alpha \nabla f(\vec{x})$$

I will not ask you to take a derivative on the exam.

Adversity

So far:

- The world does not care about us
- This is a simplifying assumption!

Reality:

- The world does not care us
- It wants things for “itself”
- We don’t want the same things

The Adversary

One extreme:

- Single adversary
  - Adversary wants the *exact opposite* from us
  - If adversary "wins," we lose 😐

Other extreme:

- An entire world of agents with different values
  - They might want some things similar to us
- "Economics" 😐

Simple Games: Max and Min

- Two players want the opposite of each other
- State takes into account both agents
  - Actions depend on whose turn it is

Minimax

- Initial state s_0
- $\textsc{Actions}(s)$ and $\textsc{To-move}(s)$
- $\textsc{Result}(s, a)$
- $\textsc{Is-Terminal}(s)$
- $\textsc{Utility}(s, p)$

More Than Two Players

- Two players, two values: v_A, v_B
  - Zero-sum: $v_A = -v_B$
  - Only one value needs to be explicitly represented
- $>$ 2 players:
  - $v_A, v_B, v_C \ldots$
  - Value scalar becomes $\vec{v}$

Minimax Efficiency

Pruning removes the need to explore the full tree.

- Max and Min nodes alternate
- Once *one* value has been found, we can eliminate parts of search
  - Lower values, for Max
  - Higher values, for Min
- Remember highest value (α) for Max
- Remember lowest value (β) for Min

Heuristics 😌

- In practice, trees are far too deep to completely search
- Heuristic: replace utility with evaluation function
  - Better than losing, worse than winning
  - Represents chance of winning
- Chance? 🎲🎲
  - Even in deterministic games
  - Why?

Solving Non-Deterministic Games

Previously: Max and Min alternate turns

Now:

- Max
- Chance
- Min
- Chance

Constraint Satisfaction

- Express problem in terms of state variables
  - Constrain state variables
- Begin with all variables unassigned
- Progressively assign values to variables
- Assignment of values to state variables that “works:” *solution*

More Formally

- State variables: $X_1, X_2, \ldots, X_n$
- State variable domains: $D_1, D_2, \ldots, D_n$
  - The domain specifies which values are permitted for the state variable
  - Domain: set of allowable variables (or permissible range for continuous variables)[1]
  - Some constraints $C_1, C_2, \ldots, C_m$ restrict allowable values

1. Or a hybrid, such as a union of ranges of continuous variables.

Constraint Types

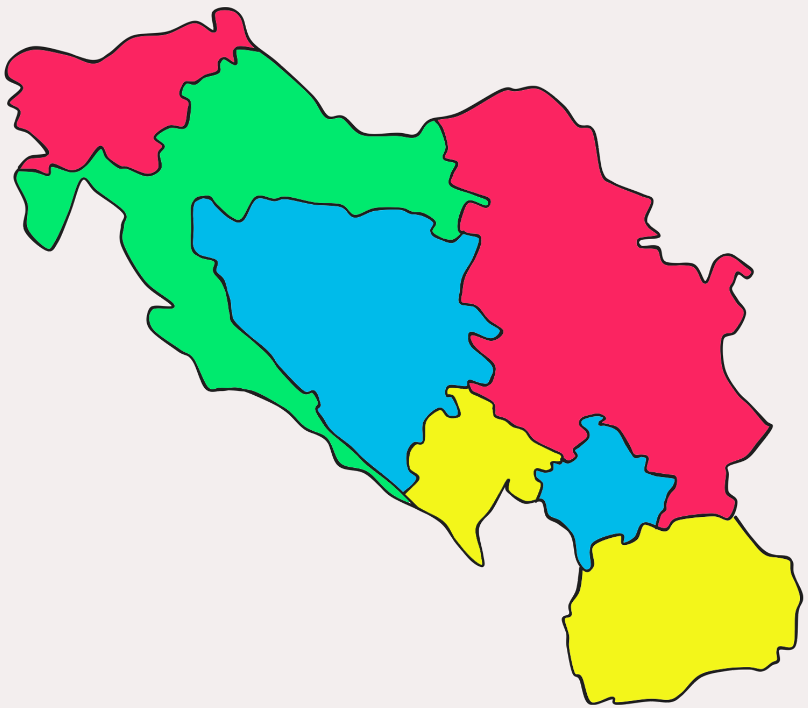
- Unary: restrict single variable
  - Can be rolled into domain
  - Why even have them?
- **Binary: restricts two variables**
- Global: restrict “all” variables

Assignments

- Assignments must be to values in each variable's domain
- Assignment violates constraints?
  - Consistency
- All variables assigned?
  - Complete

Four-Colorings

Two possibilities:



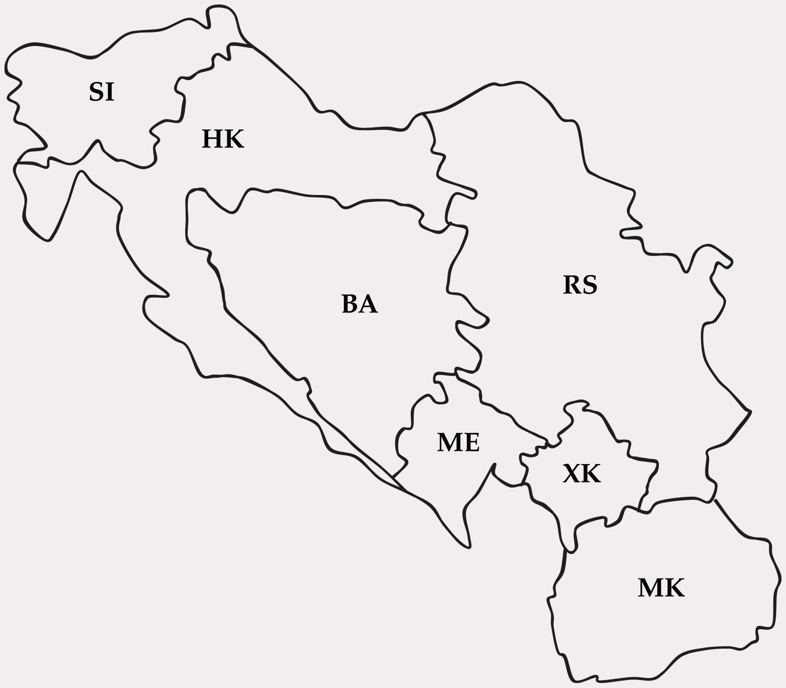
Graph Representations

- Constraint graph:
  - Nodes are variables
  - Edges are constraints
- Constraint hypergraph:
  - Variables are nodes
  - Constraints are nodes
  - Edges show relationship

Why have two different representations?

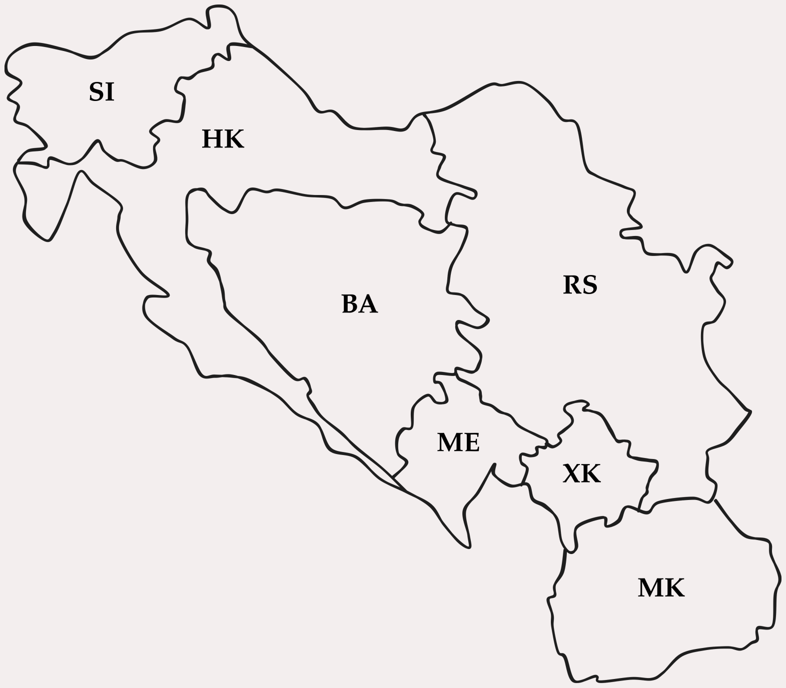
Graph Representation I

Constraint graph: edges are constraints



Graph Representation II

Constraint hypergraph: constraints are nodes



Inference

- Constraints on one variable restrict others:
  - $X_1 \in \{A, B, C, D\}$ and $X_2 \in \{A\}$
  - $X_1 \neq X_2$
  - Inference: $X_1 \in \{B, C, D\}$
- If an unassigned variable has no domain…
  - Failure

Inference

- Arc consistency
  - Reduce domains for pairs of variables
- Path consistency
  - Assignment to two variables
  - Reduce domain of third variable

Ordering

- SELECT-UNASSGINED-VARIABLE($CSP, assignment$)
  - Choose most-constrained variable[1]
- ORDER-DOMAIN-VARIABLES($CSP, var, assignment$)
  - Least-constraining value
- Why?

1. or MRV: "Minimum Remaining Values"

Restructuring

Tree-structured CSPs:

- *Linear time* solution
- Directional arc consistency: $X_i \to X_{i+1}$
- Topological sort complexity
    - Nothing is free

Logic

- Propositional symbols
  - Similar to boolean variables
  - Either True or False
  - Represent something in “real world”

Sentences

- What is a linguistic sentence?
  - Subject(s)
  - Verb(s)
  - Object(s)
  - *Relationships*
- What is a logical sentence?
  - Symbols
  - Relationships

Familiar Logical Operators

- $\neg$
  - "Not" operator, same as CS (`!`, `not`, etc.)
- $\wedge$
  - "And" operator, same as CS (`&&`, `and`, etc.)
  - This is sometimes called a *conjunction*.
- $\vee$
  - "Inclusive Or" operator, same as CS.
  - This is sometimes called a *disjunction*.

Unfamiliar Logical Operators

- $\Rightarrow$
  - Logical *implication*.
  - If $X_0 \Rightarrow X_1$, X_1 is always True when X_0 is True.
  - If X_0 is False, the value of X_1 is not constrained.
- $\iff$
  - "If and only If."
  - If $X_0 \iff X_1$, X_0 and X_1 are either both True or both False.
  - Also called a *biconditional*.

Equivalent Statements

- $X_0 \Rightarrow X_1$ alternatively:
  - $(X_0 \wedge X_1) \vee \neg X_0$
- $X_0 \iff X_1$ alternatively:
  - $(X_0 \wedge X_1) \vee (\neg X_0 \wedge \neg X_1)$

Entailment

- $KB \models A$
  - "Knowledge Base entails A"
  - For every model in which KB is True, A is also True
  - One-way relationship: A can be True for models where KB is not True.
- Vocabulary: A is the *query*

Knowing Things

Falsehood:

- $KB \models \neg A$
  - No model exists where KB is True and A is True

It is possible to not know things:[1]

- $KB \not\models A$
- $KB \not\models \neg A$

1. $\not\models$ – “does not entail”

Satisfiability

- Commonly abbreviated "SAT"
- *First* NP-complete problem
- $(X_0 \wedge X_1) \vee X_2$
  - Satisfied by $X_0 = \text{True}, X_1 = \text{False}, X_2 = \text{True}$
  - Satisfied for any X_0 and X_1 if $X_2 = \text{True}$
- $X_0 \wedge \neg X_0 \wedge X_1$
  - Cannot be satisfied by any values of X_0 and X_1

Conjunctive Normal Form

- *Literals* — symbols or negated symbols
  - X_0 is a literal
  - $\neg X_0$ is a literal
- *Clauses* — combine literals and disjunction using disjunctions ($\vee$)
  - $X_0 \vee \neg X_1$ is a valid disjunction
  - $(X_0 \vee \neg X_1) \vee X_2$ is a valid disjunction

Conjunctive Normal Form

- *Conjunctions* ($\wedge$) combine clauses (and literals)
  - $X_1 \wedge (X_0 \vee \neg X_2)$
- Disjunctions cannot contain conjunctions:
- $X_0 \vee (X_1 \wedge X_2)$ not in CNF
  - Can be rewritten in CNF: $(X_0 \vee X_1) \wedge (X_0 \vee X_2)$

Converting to CNF

- $X_0 \iff X_1$
  - $(X_0 \Rightarrow X_1) \wedge (X_1 \Rightarrow X_0)$
- $X_0 \Rightarrow X_1$
  - $\neg X_0 \vee X_1$
- $\neg(X_0 \wedge X_1)$
  - $\neg X_0 \vee \neg X_1$
- $\neg(X_0 \vee X_1)$
  - $\neg X_0 \wedge \neg X_1$

Probability

- Not on exam

- Very important, however
- Basis for remainder of course
- Sorry.

Bayesian Networks

References

- Stuart J. Russell and Peter Norvig. *Artificial Intelligence: A Modern Approach*. 4th Edition, 2020.
- Mykal Kochenderfer, Tim Wheeler, and Kyle Wray. *Algorithms for Decision Making*. 1st Edition, 2022.
- Stanford CS231
- UC Berkeley CS188