Planning, Execution & Learning: Reactive Planning

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The Problem With Policies

- Very Expensive to ***Generate***

- Very Expensive to ***Store***

- May be Expensive to ***Access***
  - Markov policies (linear in size of state space)
  - Universal and Teleo-Reactive plans (logarithmic)
  - RAPs (bounded)
  - Real-time search (bounded)

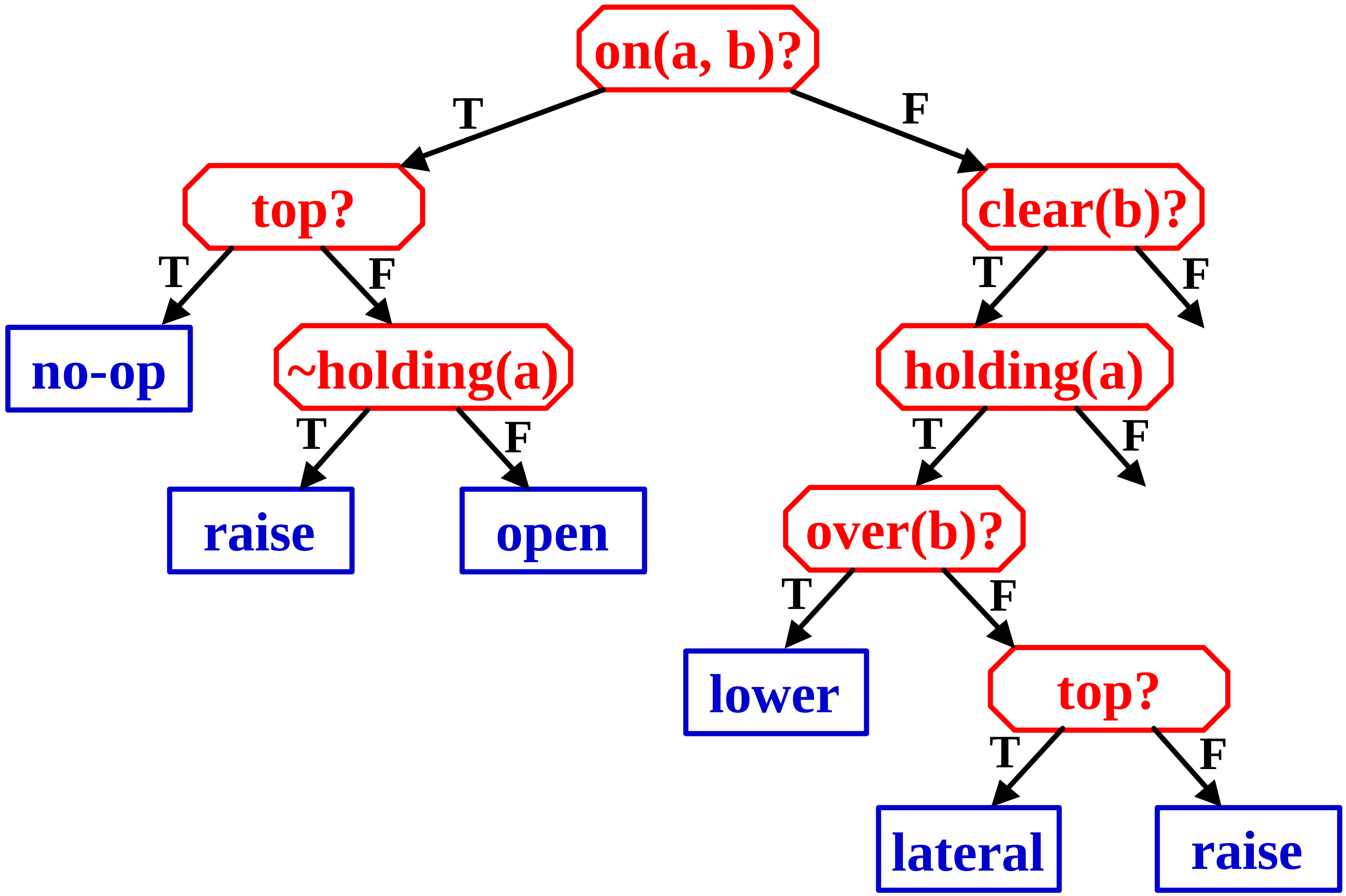
Policy Issues

- How to Represent Policies for Efficient Retrieval
- Which Plans/Policies to Cache
- When to Plan and When to Execute/React
- How to Avoid Having Sensing Become the Bottleneck
  - Limited sensors
  - Partially observable environment
- How to Detect/Handle Cyclic Behavior

Universal Plans ***(Schoppers 1987)***

- Complete Mapping From Sensors to ***Conditions***
  - Can take duration of actions into account
  - Can take advantage of dynamics of environment
  - Influenced by PRS (Georgeoff), REX (Kaelbling), and robotics (control theory)
- Implements Policy as ***Decision Tree***
  - Answers "what to do next"
    - Sequencing encoded in structure of decision tree
    - No notion of ***error***
  - Treats planning & plan selection as classification problem
- Can be Synthesized Automatically
  - Uses back-chaining, non-linear planner
  - Break into action-sized chunks, with appropriate sensing actions

Universal Block-Stacking Plan



Dealing With the State Explosion

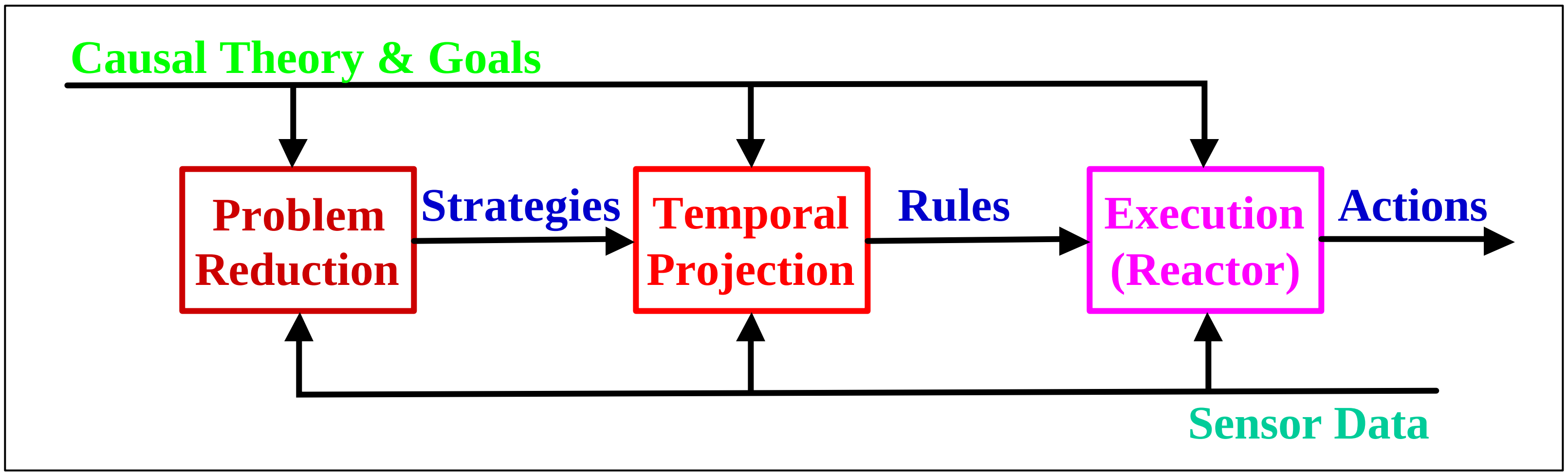
- Decision Trees Make Classification More Efficient
  - Proportional to number of features (although tree itself is exponential)
- Use General (***Variablized***) Rules
- Use Efficient State Representations (e.g. BDDs)
- Use at Multiple Levels of Abstraction
  - Coarse-grained and fine-grained universal plans

Ultimately, in Most Cases, Need to Choose What to Plan For…

Entropy Reduction Engine (ERE)

(Drummond & Bresina, 1990)

- Overall Architecture for Generating and Executing Reactive Plans
  - Incrementally compiled from domain models



  - **Reactor**: Choose applicable rule and apply action
  - **Projector**: Produce "plans" and compile rules
  - **Reductor**: Decompose problem into subproblems

Situated Control Rules (SCRs)

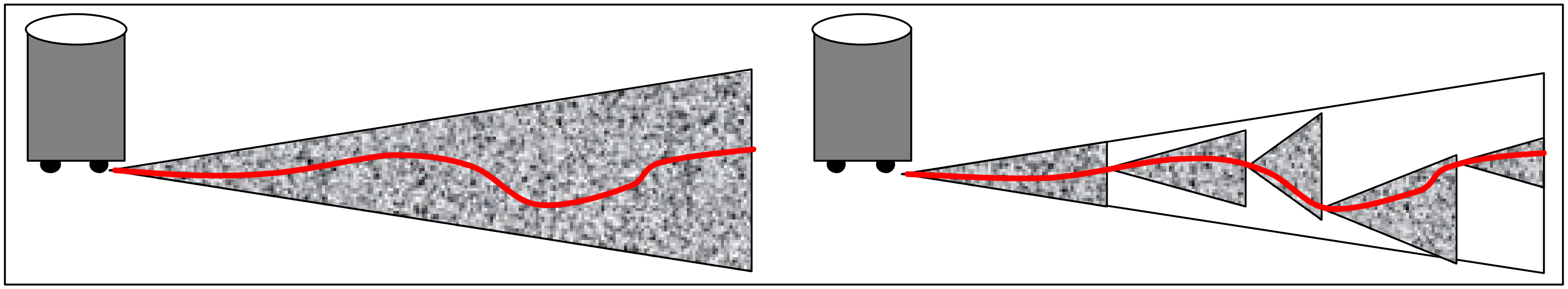
- "**If-Then**" Rule Describing Action to Take in Given Situation
  - Represents single step along way to achieving a goal
    - "**if <situation> & <goal> then <action>**"
    - "**local control program**"
    - Similar to CIRCA's **TAPs**
  - Utilizes both sensor and internal state information
  - May not have applicable rules for all situations
    - Opportunistically created by the ***projector***
  - Does not address the problem of choosing (***arbitrating***) amongst applicable rules

ERE's Temporal Projector

- Probabilistic, Linear Planner
  - Handles goals of achievement, prevention, and maintenance
  - Forward projection of non-deterministic actions
    - Can handle exogenous events
    - Uses ***beam search*** to control projection (estimate of work remaining to achieve goal)
  - "***Robustify***" initial plan by adding contingency branches
    - Attend to high probability deviations
- Compilation of SCRs
  - Uses goal regression and ***explanation-based learning*** (EBL) to form a generalization of <state, action, goal> triples
  - "***Anytime***" nature ensures reactivity

Agent-Centered Search (Koenig 1997)

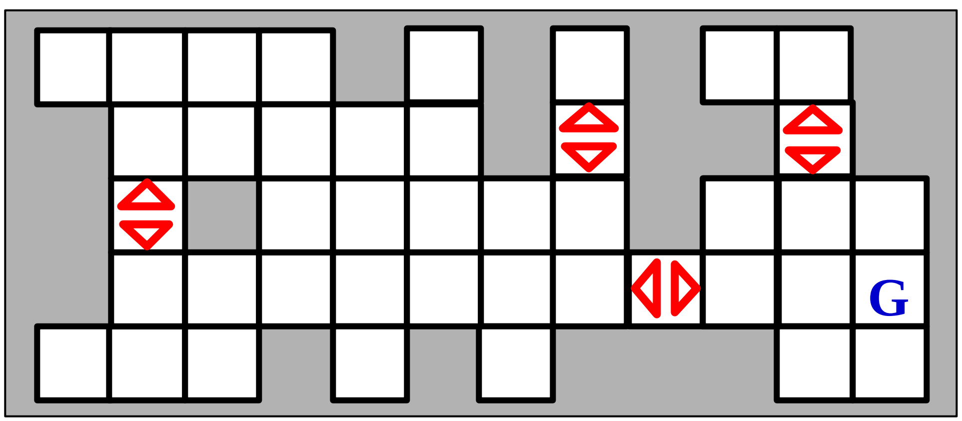
- Allow Bounded Amount of Search (Lookahead) to Determine Next Action to Execute
  - Incrementally update value function
    - Incrementally create optimal policy
    - Akin to reinforcement learning
  - Can trade off planning time (=> plan quality) and execution speed
  - Handles uncertainty by acting, which may gain information



- Several Theoretical Results
  - Complexity of class of agent-centered search algorithms
  - Influence domain properties can have on complexity

*Min-Max LRTA**

- Extension to Non-Deterministic Domains of Korf's Learning Real-Time A* Algorithm
  - No probabilistic information: Assume worst case for agent (where nature is the "opponent")
  - $u(s) = -1 + \max_{a \in A(s)} \min_{s' \in \text{succ}(s,\, a)} u(s')$
  - Can eventually learn optimal policy
    - Also learns while trying to reach goal for the first time



***Observe*: OWOW**

B3N B3S
H2N H2S
K2N K2S
I4E I4W

***Action*: Forward or Reverse?**

Complexity Results

- Min-Max LRTA* has Tight Bounds of $O(n^2)$ Action Occurrences Over ***All*** Domains
  - No algorithm that performs constant lookahead can do better, over all possible domains
- Q-Learning is $O(n^3)$ ***if*** it uses "**dense**" reward structure
  - Penalize actions ***or*** initialize Q-values to non-zero
  - Otherwise can be exponential
- Undirected and Directed ***Eulerian*** Domains are "**Easier**" to Search, in General
- Domains with Small Maximum Goal Distance are "**Easier**" to Search, on Average