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Catan Presentation

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Game Playing AI

Why AI?

- We want to be able to solve problems in varied domains
- We don’t know all the domains
- Heuristic algorithms need writing
- Alternative: general-purpose AI models
- Need to figure out ideal model structure

AI Classification Problems

- Many simple AI are run on classification problems
- Features:
  - Relatively consistent
  - Few secrets
  - Deterministic outcome
  - Risk of overfitting
- Not necessarily best match for the real world

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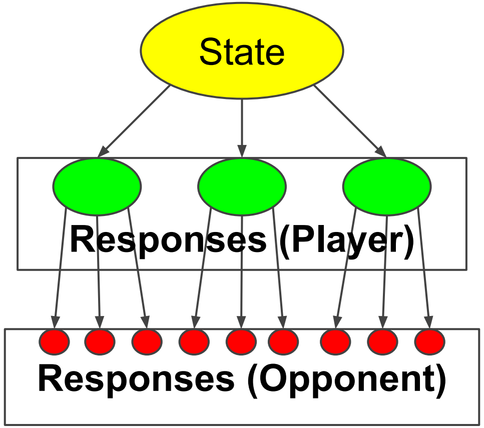
Game Playing

- Games are efficient to run
- Often dense in imperfect information
- Often dense in random outcomes
- Less consistency means models learn differently
- Possibly better match for reality

Types of Game AI

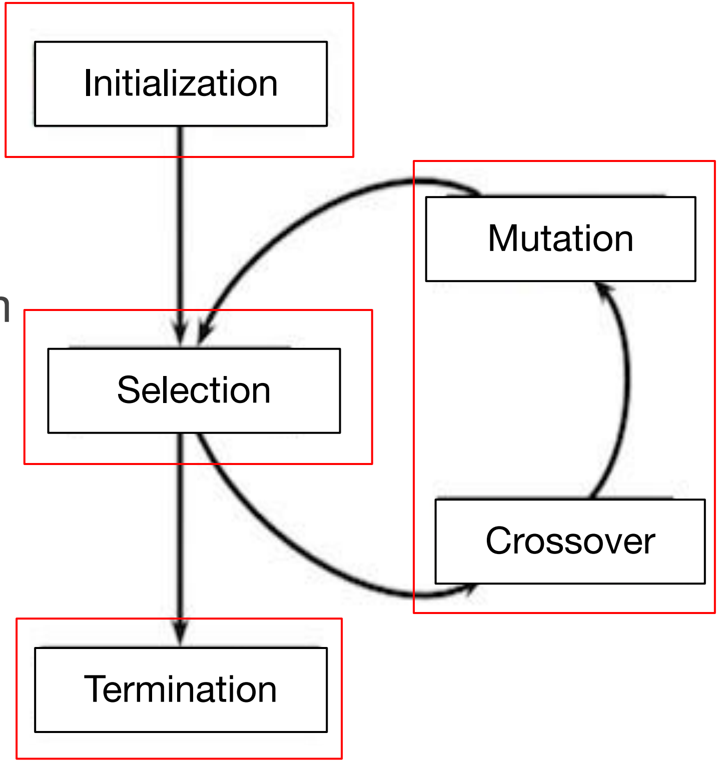


- Many strategies for how to play games
- Solve the game: Unlikely to work
- Assign scores to states
  - Minimax: move to maximize the minimum value
  - AB Pruning: Extension of minimax which cuts off subpar moves rather than exploring them
- Monte Carlo Tree Search
  - Full game rollouts
- Neural Nets
- Evolutionary Algorithms

Evolutionary AI

Overview

- Family of algorithms for global optimization
- Candidate solutions for an optimization problem
  - Fitness function determines quality of solutions
  - Evolution of candidate solutions
- Inspired by biological evolution
  - Reproduction, mutation, crossover, selection
  - Survival of the fittest

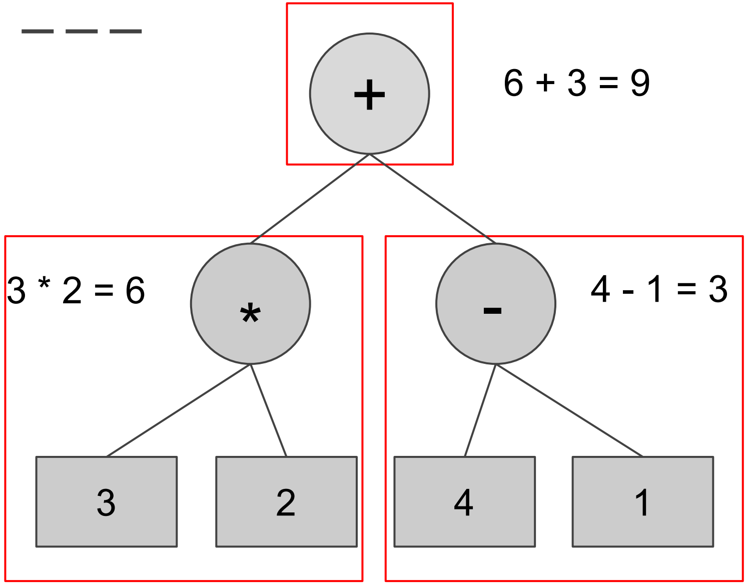


Examples

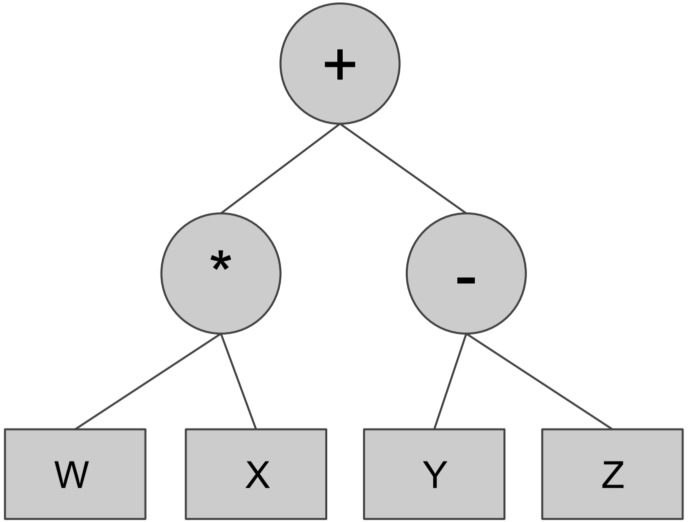
- Genetic algorithms
  - Most popular
  - Solutions are represented as a string of numbers
- Genetic programming
  - Solutions are computer programs
  - Fitness determined by ability to solve a computational problem
- Evolutionary programming
  - Structure of program is fixed, numerical parameters evolve

Genetic Programming

Genetic programming uses parse trees



(3 * 2) + (4 - 1)

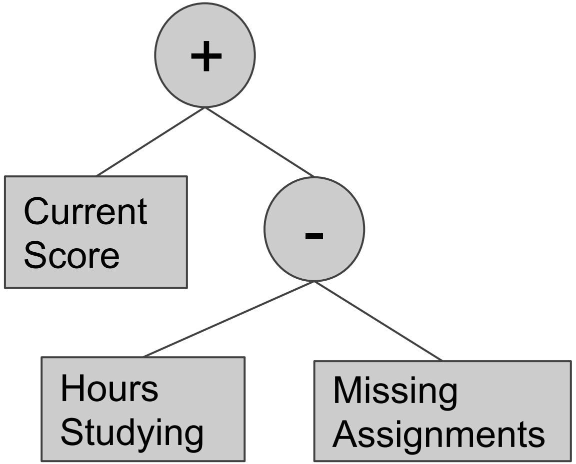


(W * X) + (Y - Z)

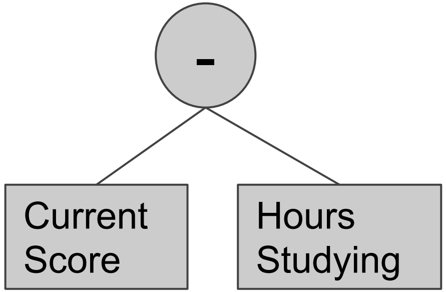
Genetic programming estimates some value

Predict a student's exam score using:

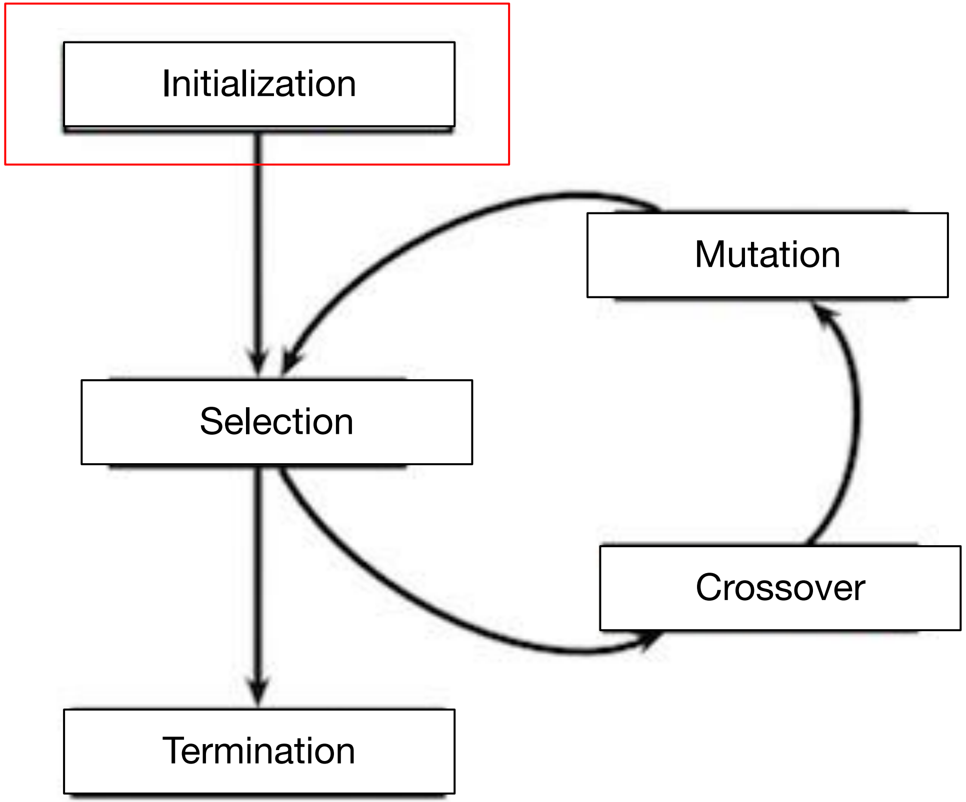
- Current score in class
- Number of hours spent studying
- Number of missing assignments



Current Score +
(Hours Studying - Missing Assignments)



Current Score - Hours Studying


Initialization
Mutation
Selection
Crossover
Termination

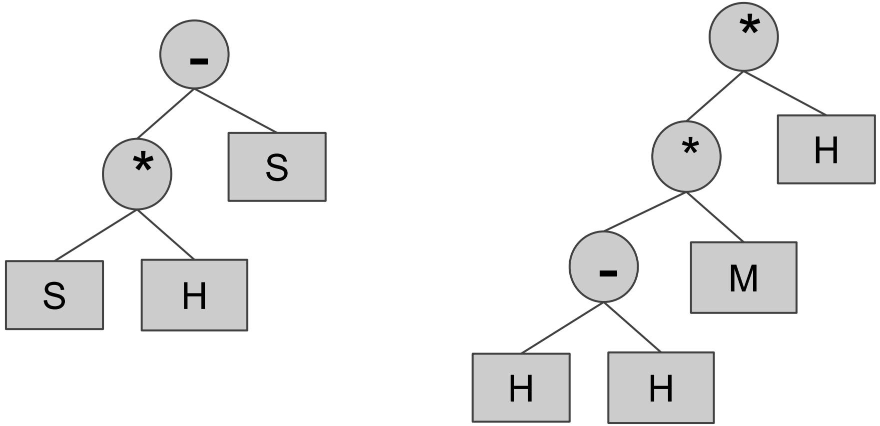
Randomly initialize parse trees using inputs and operators

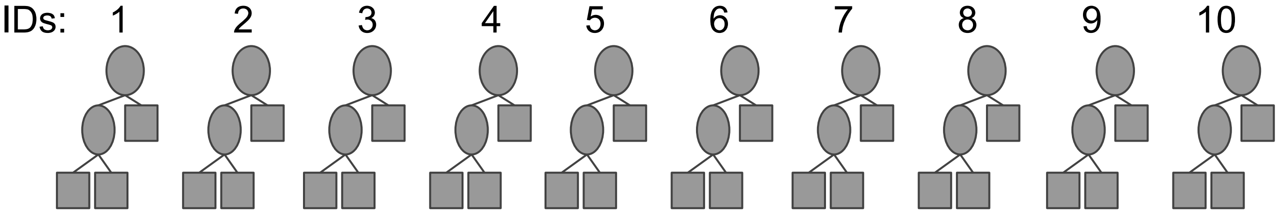
Inputs:

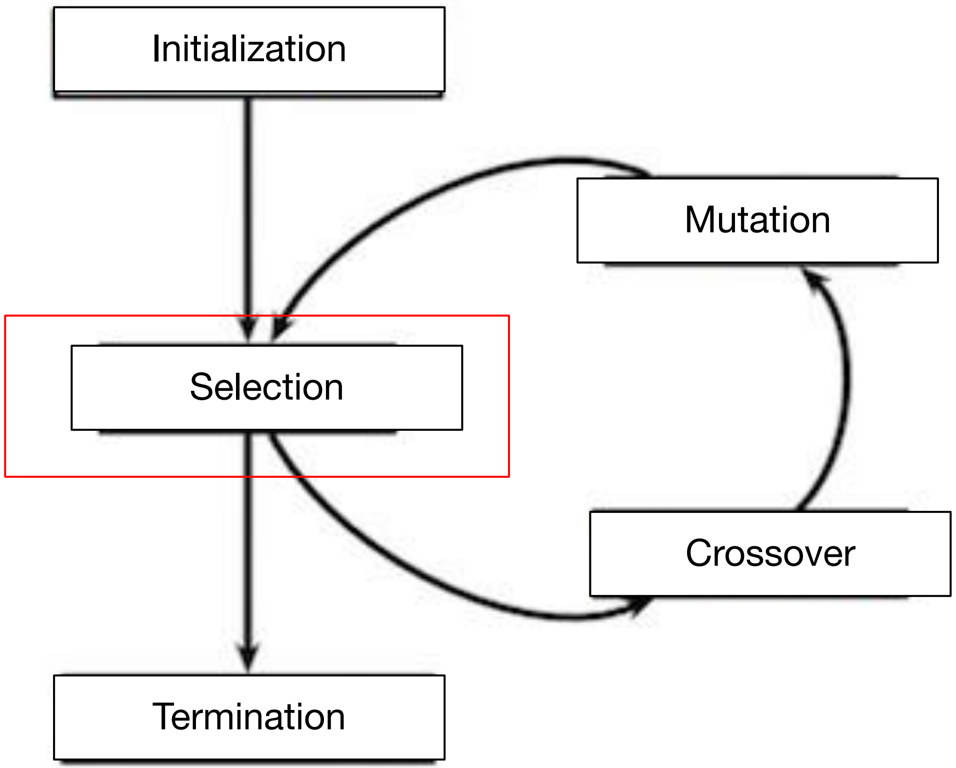
- Current score in class (S)
- Number of hours spent studying (H)
- Number of missing assignments (M)

Operators:

- +, -, *



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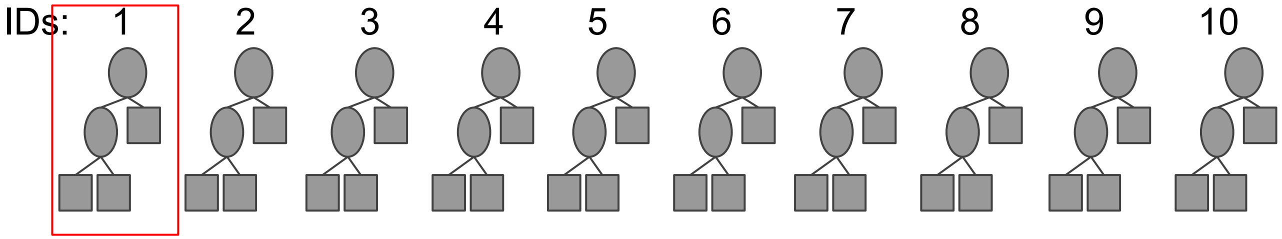
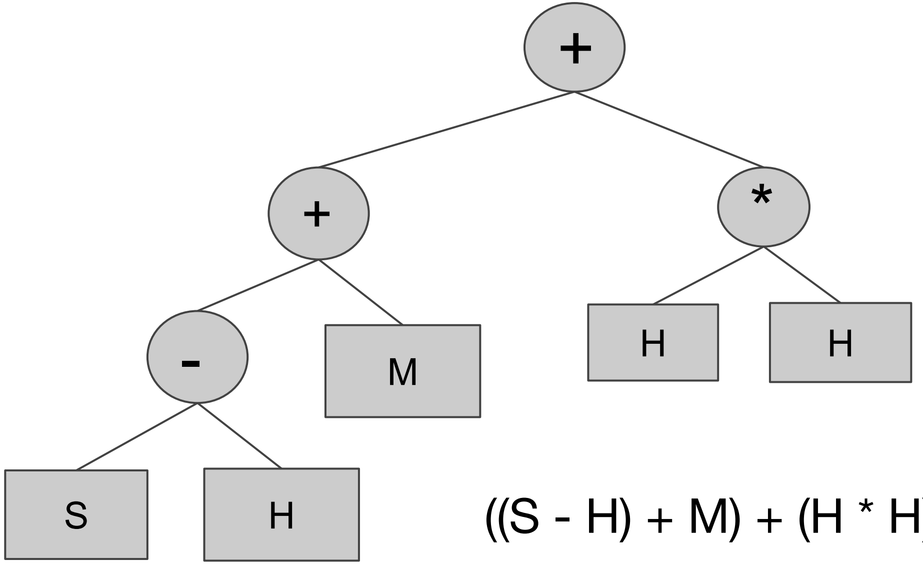
Each tree is evaluated and assigned a score



Score = $(|\text{Predicted Result} - \text{Actual Result}|)^{-1}$

Scoring a parse tree

Current score in class = S
Number of hours spent studying = H
Number of missing assignments = M



$((S - H) + M) + (H * H)$

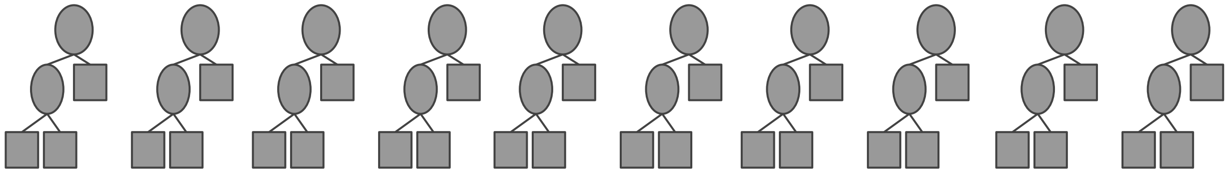
Actual Test Score = 94
H = 6
M = 1
S = 90

Predicted Test Score: $((90 - 6) + 1) + (6 * 6) = 121$

Final Tree Score: $(| 121 - 94 |)^{-1} = 0.037$

Each tree is evaluated and assigned a score

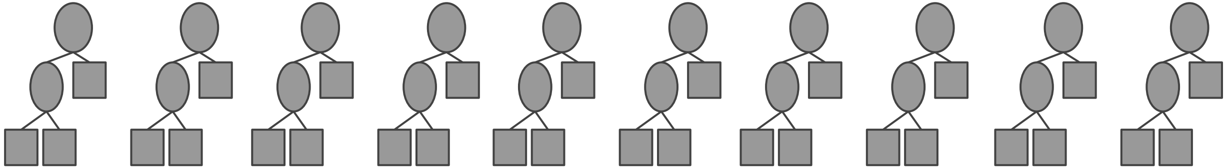
IDs: 1 2 3 4 5 6 7 8 9 10



Scores: .037 .05 .015 .013 .01 .012 .041 0.11 .027 0.002

Trees are weighted by their scores and then randomly selected for repopulation

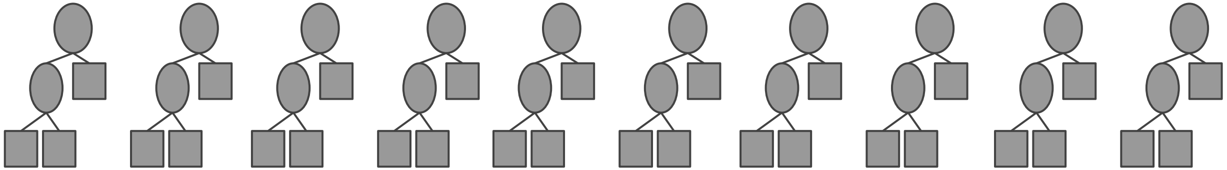
IDs:	1	2	3	4	5	6	7	8	9	10

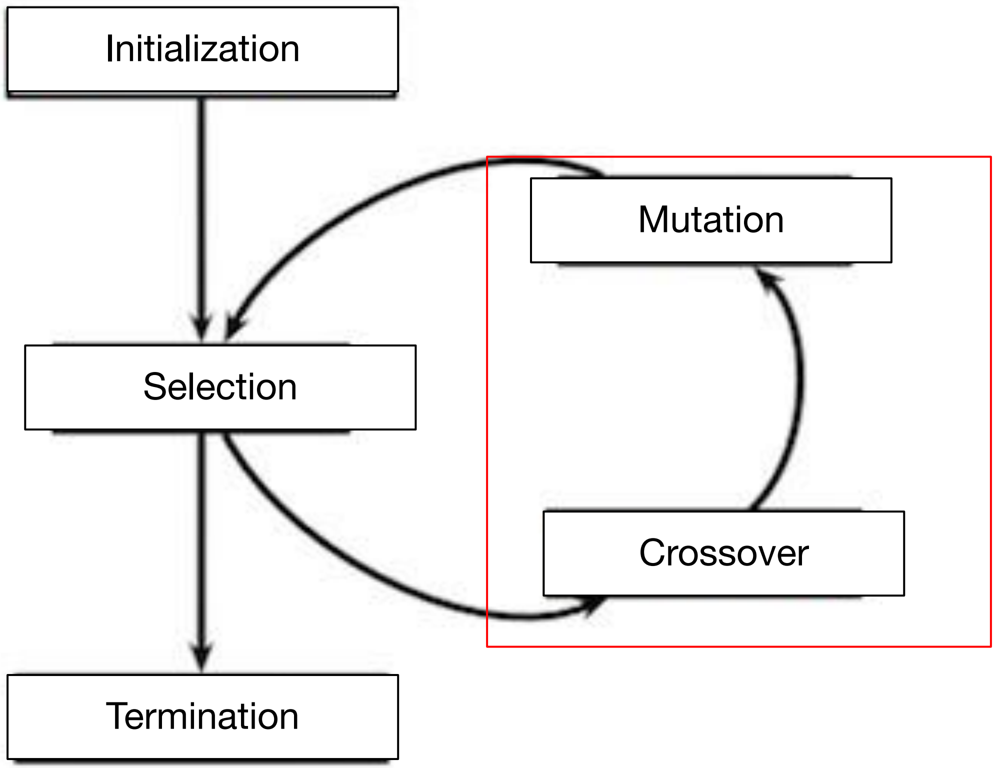


Scores:	.037	.05	.015	.013	.01	.012	.041	0.11	.027	0.002
Weights:	0.12	0.16	0.05	0.04	0.03	0.04	0.13	0.35	0.09	0.01

IDs:	2	8	8	2	1	8	7	8	9	8

Selected Trees:

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Crossover

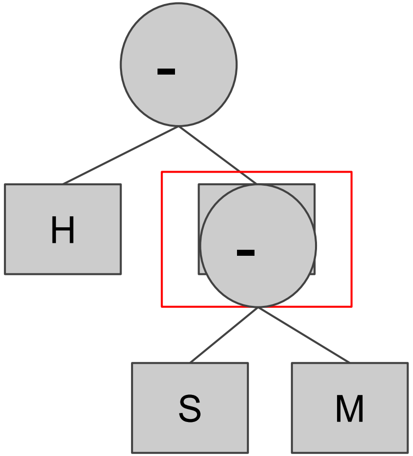
Crossover swaps two nodes and their subtrees

Current score in class = S

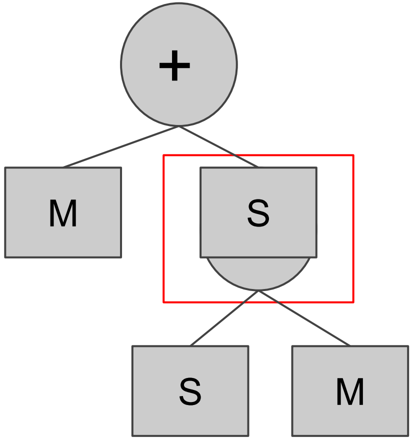
Number of hours spent studying = H

Number of missing assignments = M

ID: 2

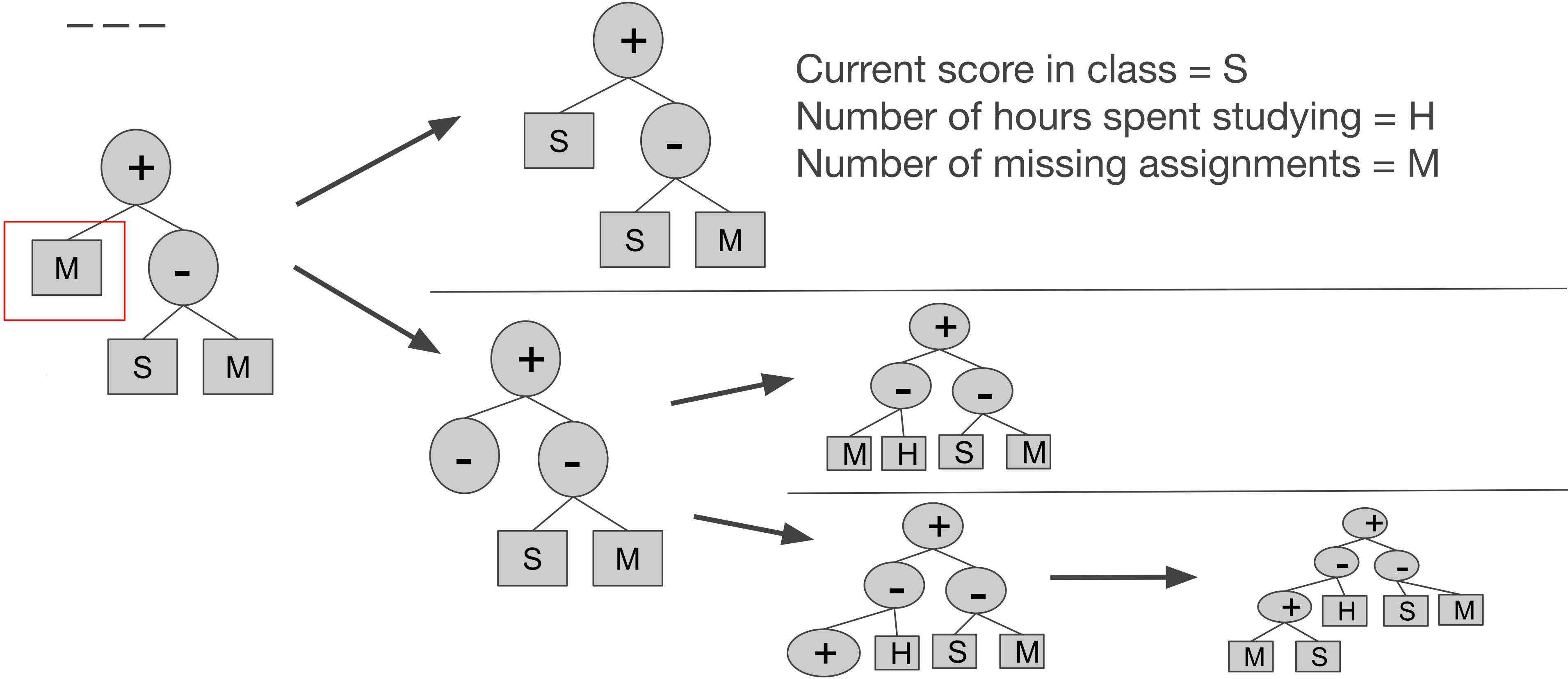


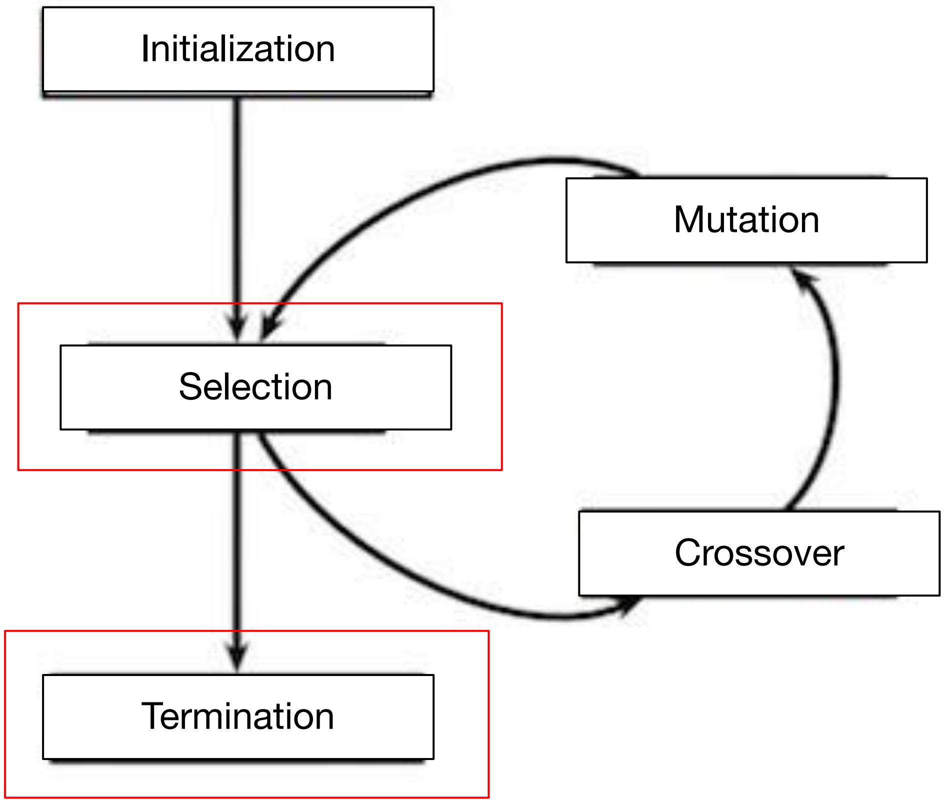
ID: 8



Mutation randomly changes a single node

Current score in class = S
Number of hours spent studying = H
Number of missing assignments = M

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Settlers of Catan

Players gain resources to build things

- Resource gathering strategy game (2-6 players)
- Terrain tiles produce resources
- Ports by water tiles
- Dice rolls earn resources
    - Wood, ore, brick, wheat, sheep
- Resources build settlements, cities, and roads
    - Can also obtain development cards

Goal of the game is to win 10 victory points

- Three ways to earn victory points:
  1. Building settlements (1 victory point) and cities (2 victory points)
  2. Largest army or longest road (2 victory points each)
  3. Victory point development card (1 victory point)

Jsettlers + our strategy

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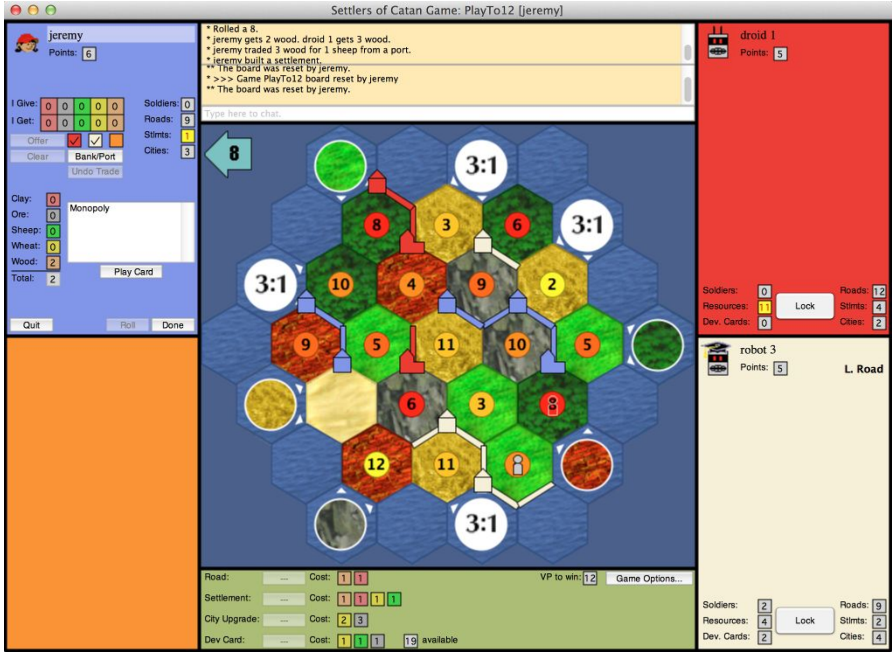
JSettlers: Open Source Java Settlers of Catan

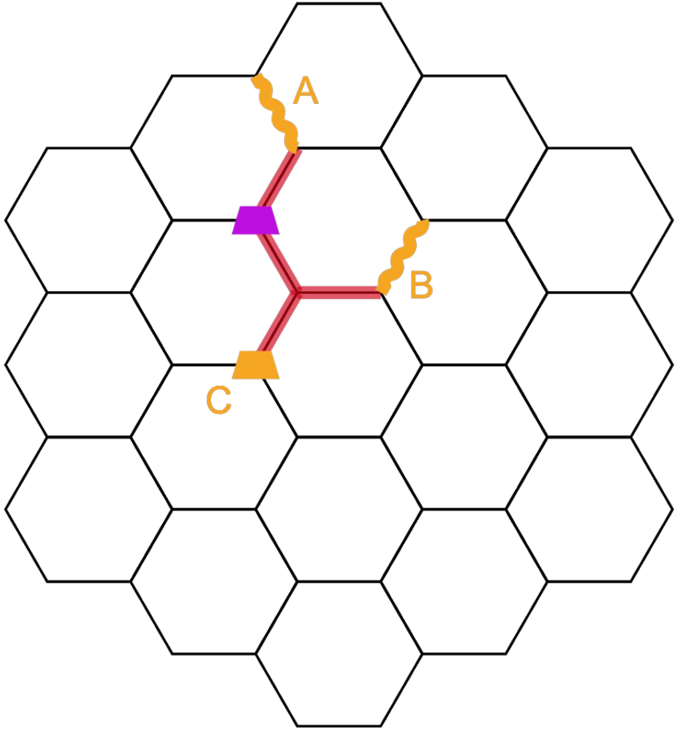


Screenshot of JSettlers Game between Jeremy and two bots

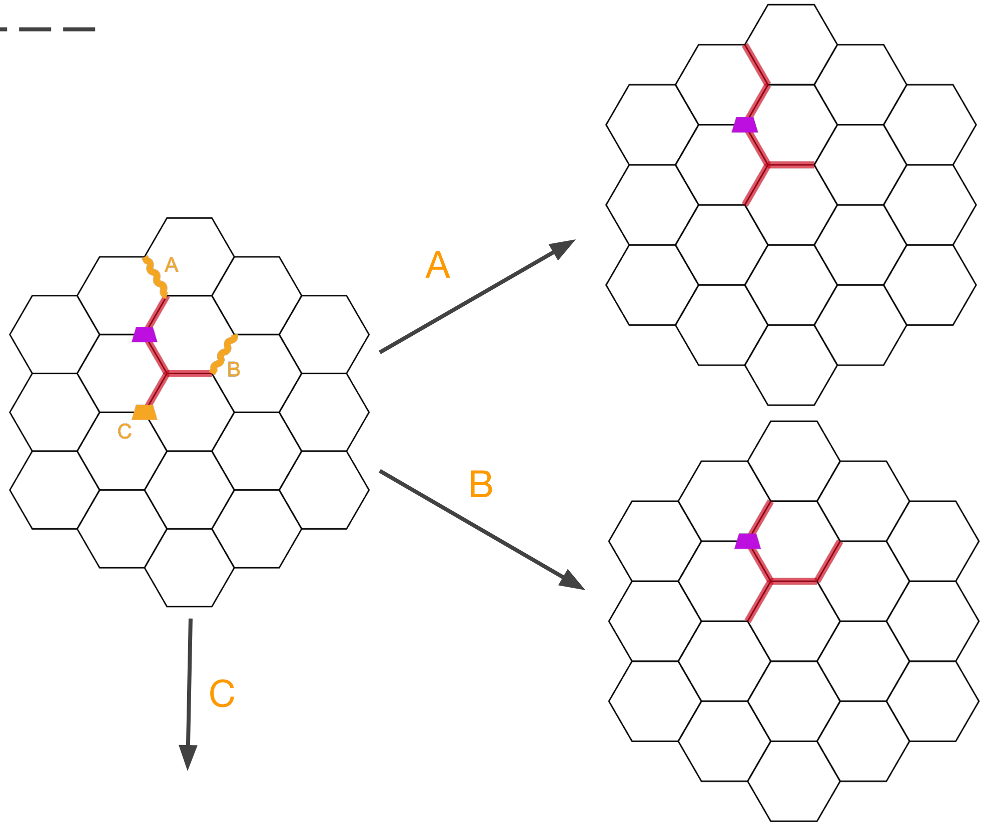
Types of game-playing bots:

1. Fast (simple heuristics)
2. Smart (more intelligent heuristics)

Smart bot simulates simplified games to find Win-Game-ETA



Each simulation considers 6 scenarios with while loop



1. 2 settlements (including necessary roads' ETA)
2. 2 cities
3. 1 city, 1 settlement (+ roads)
4. 1 settlement (+ roads), 1 city
5. Buy enough cards for Largest Army
6. Build enough roads for Longest Road

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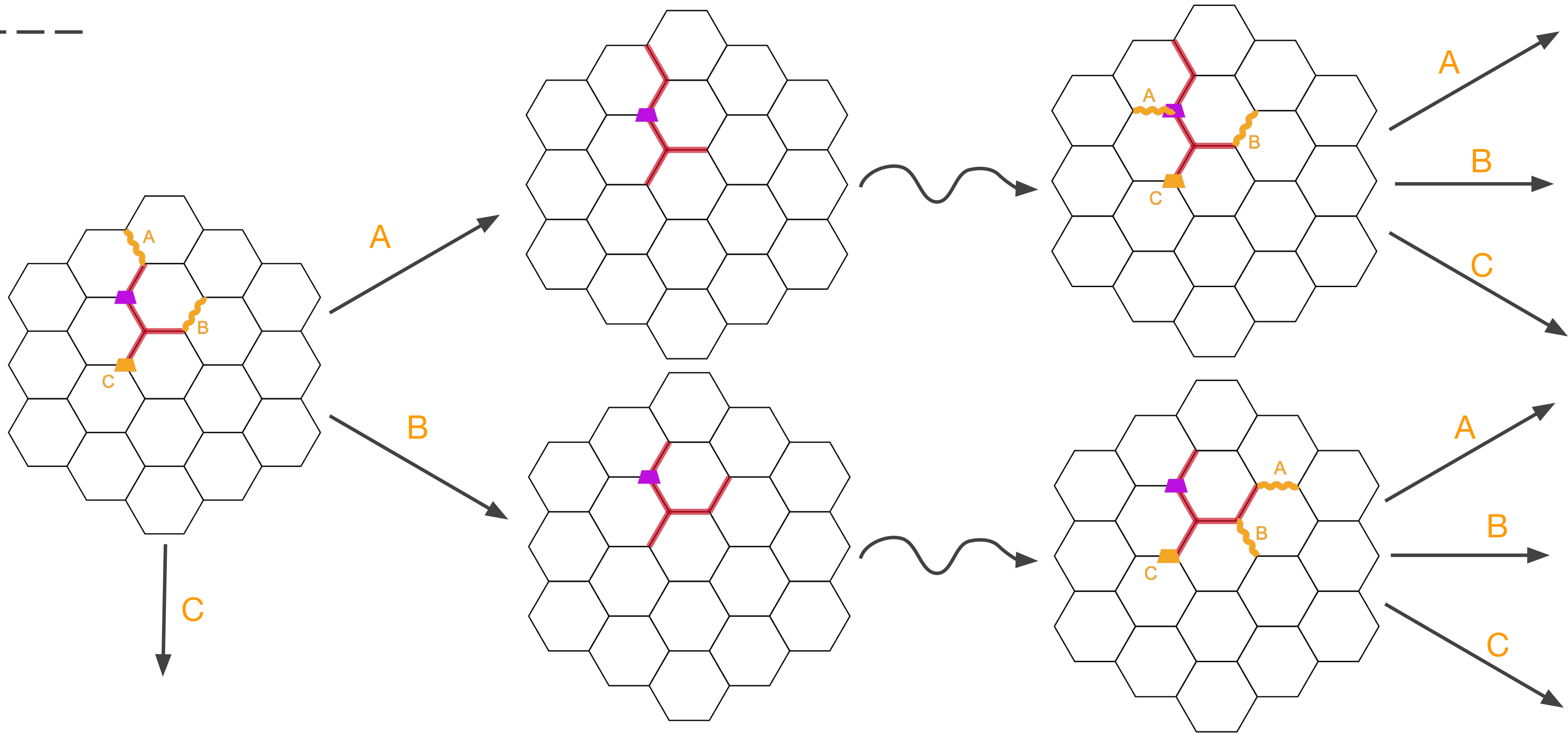
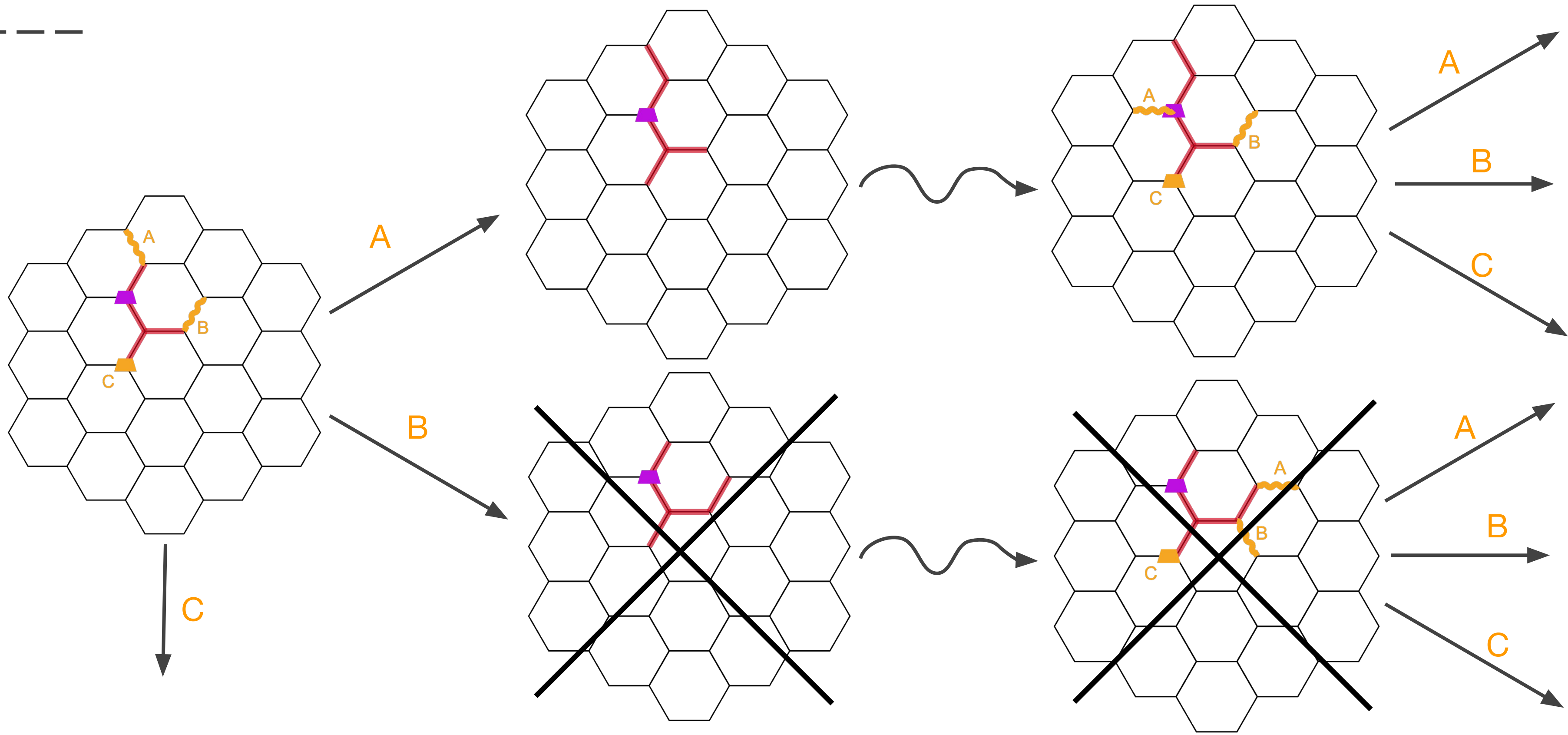
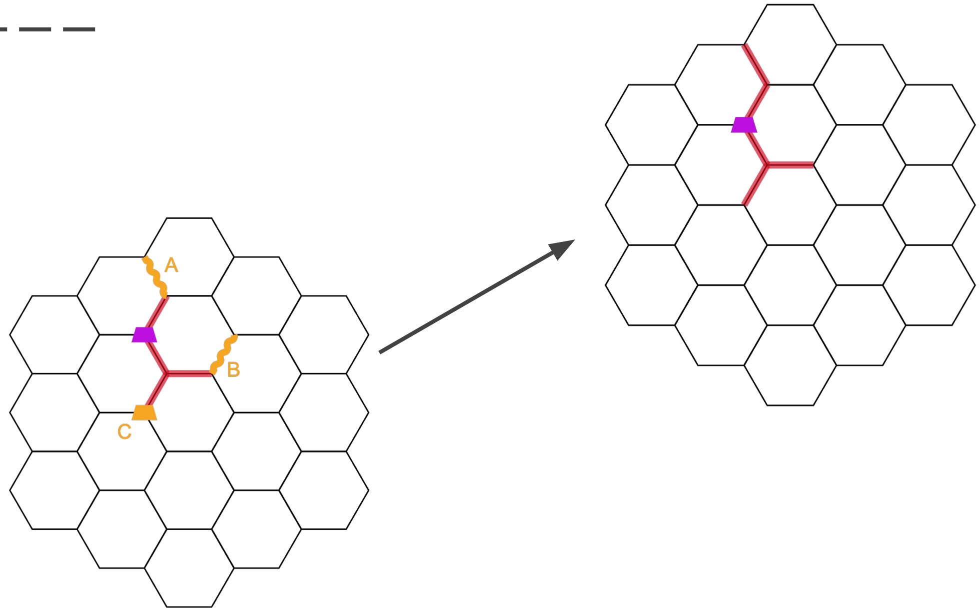
Tree-like simplified-game simulation



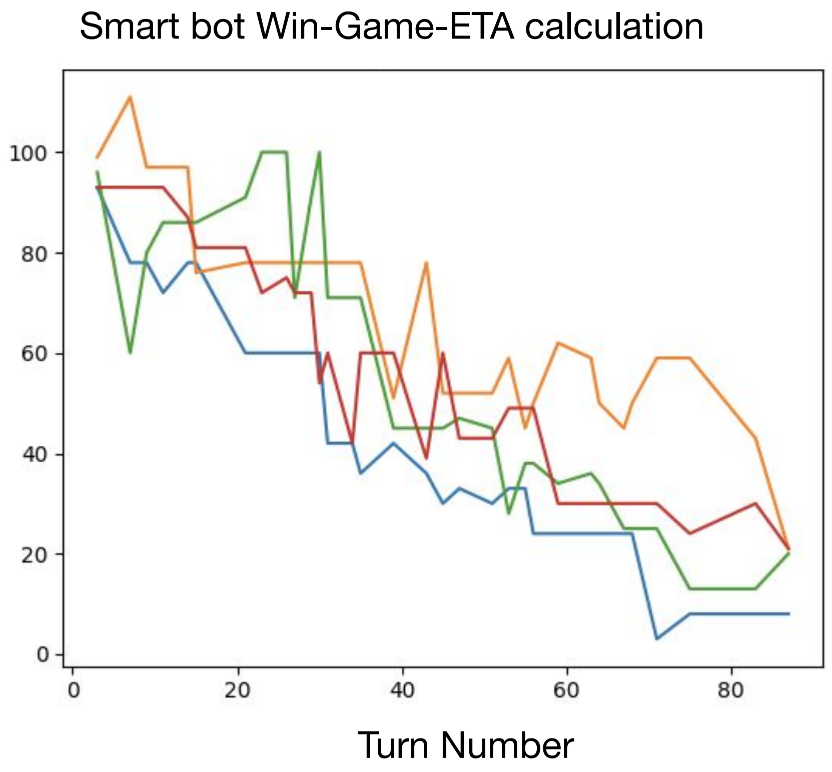
Pick strategy with the best Win-Game-ETA



Pick strategy with the best Win-Game-ETA



Win-Game-ETA calculation is primary in Smart bot decision



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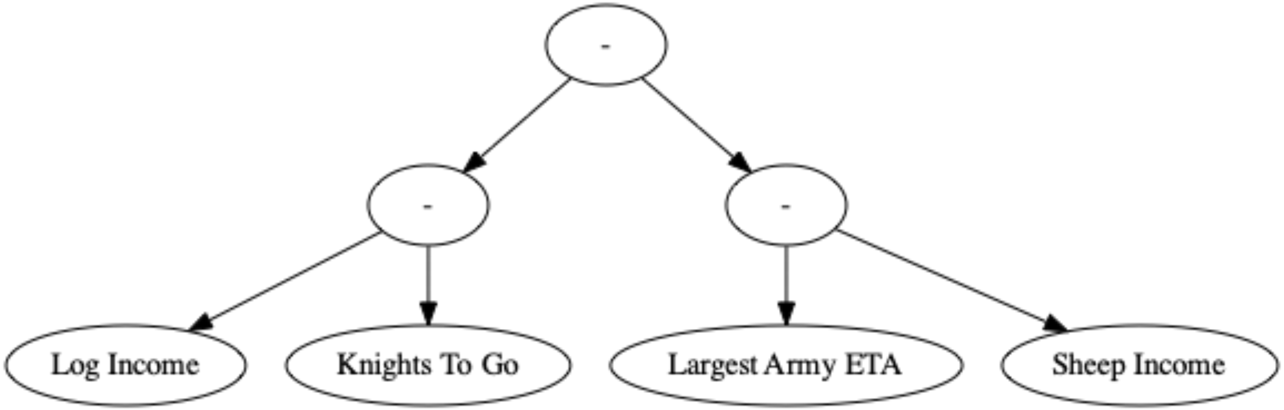
Evolutionary AI with genetic programming



$$WinGameETA = [\,(Log\ Income - Knights\ To\ Go) - (Largest\ Army\ ETA - Sheep\ Income)\,]$$

Training

Training Procedures

- Trainer function in Python, calling Java games
- Play games with each tree in a generation
- Score based on game scores
- Trained on Carleton CS servers
- Ran at least 1,000,000 games of Catan
- About 40 experiments with various settings for trainer

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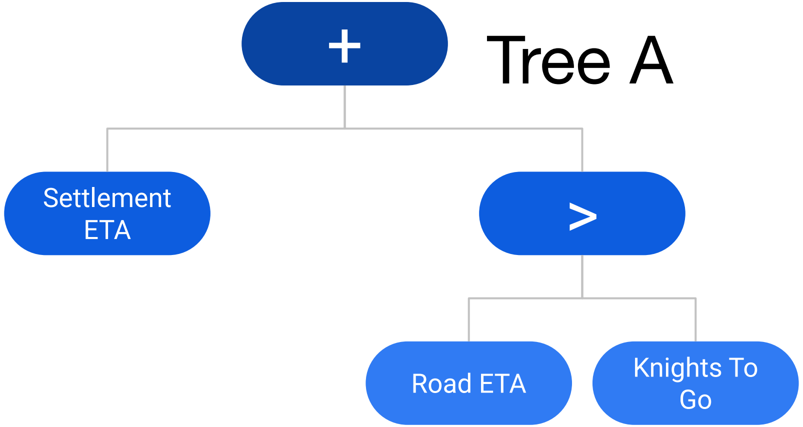
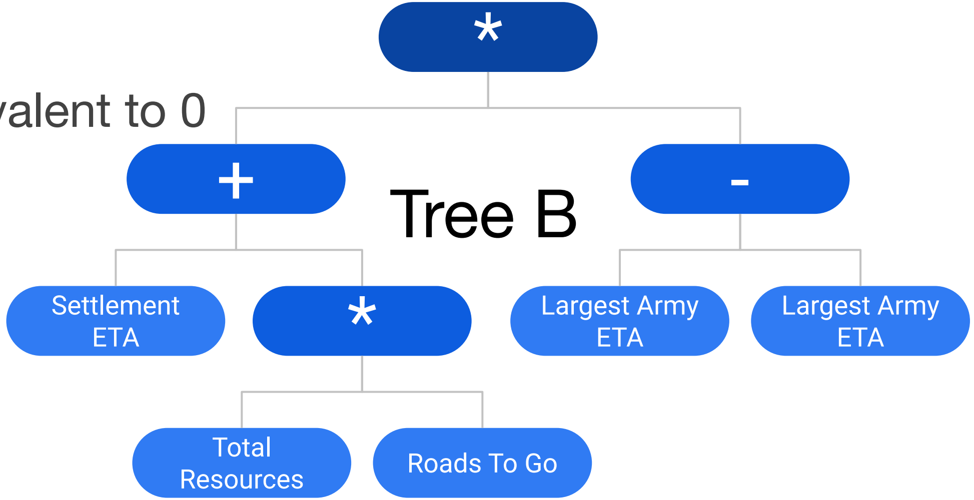
Initial Results

- First attempts to train had issues
    - Could look at the trees to solve them
- Many possible operations
- Operations where they shouldn’t be: “<” as a root node
- Failure to use constant factors
- Large trees with messy bits equivalent to 0





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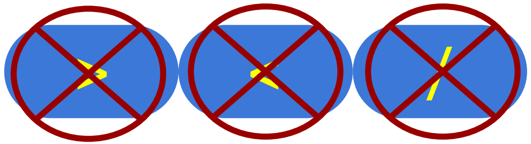
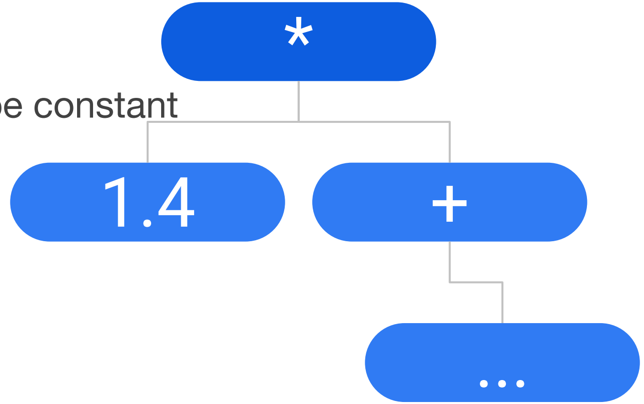
Solutions

- Poor root node choices
  - Removed operations
  - Cut division and boolean comparatives



- Lack of constants
  - Mandated right leaves of multiplication operators to be constant
  - Created training settings for tuning constants



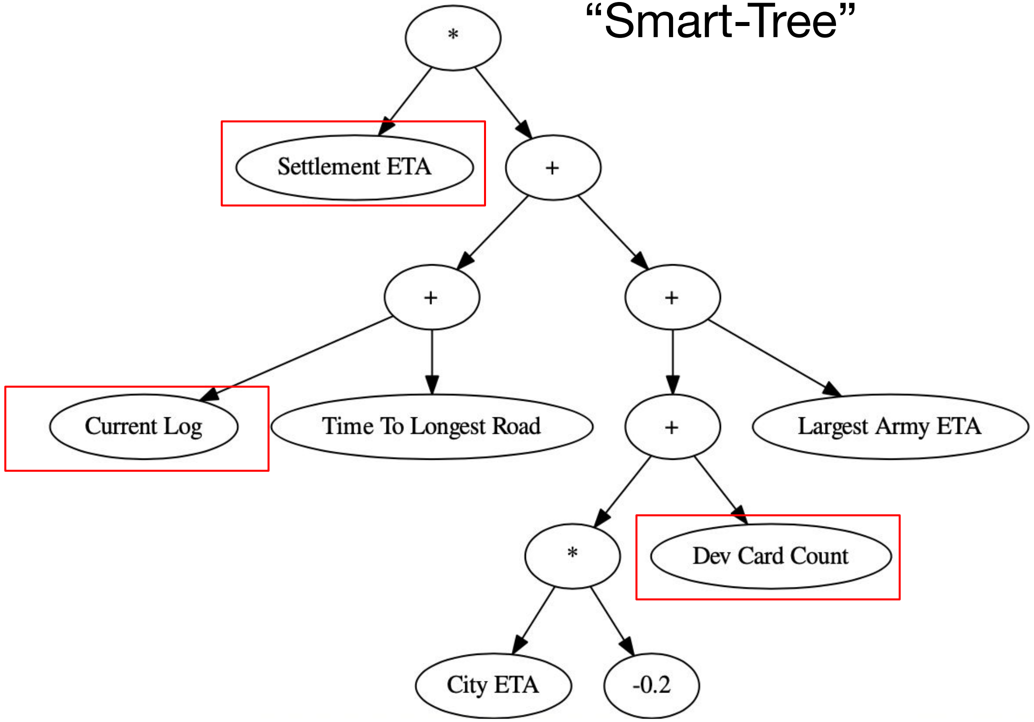
- Messy trees
  - Added fitness penalty for each node

Results

Best Training Strategy for Playing Smart Bots

- Only used mutation
- 60 Generations with max mutation parameters
- 40 generations of input training
- Trained only against smart bots

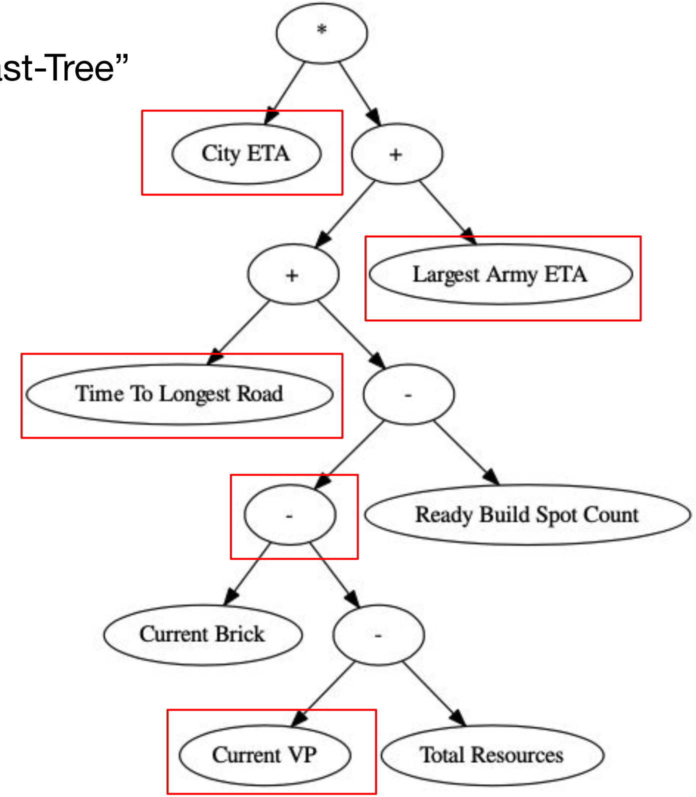
“Smart-Tree”



Strategy for Training Fast Bots is Similar

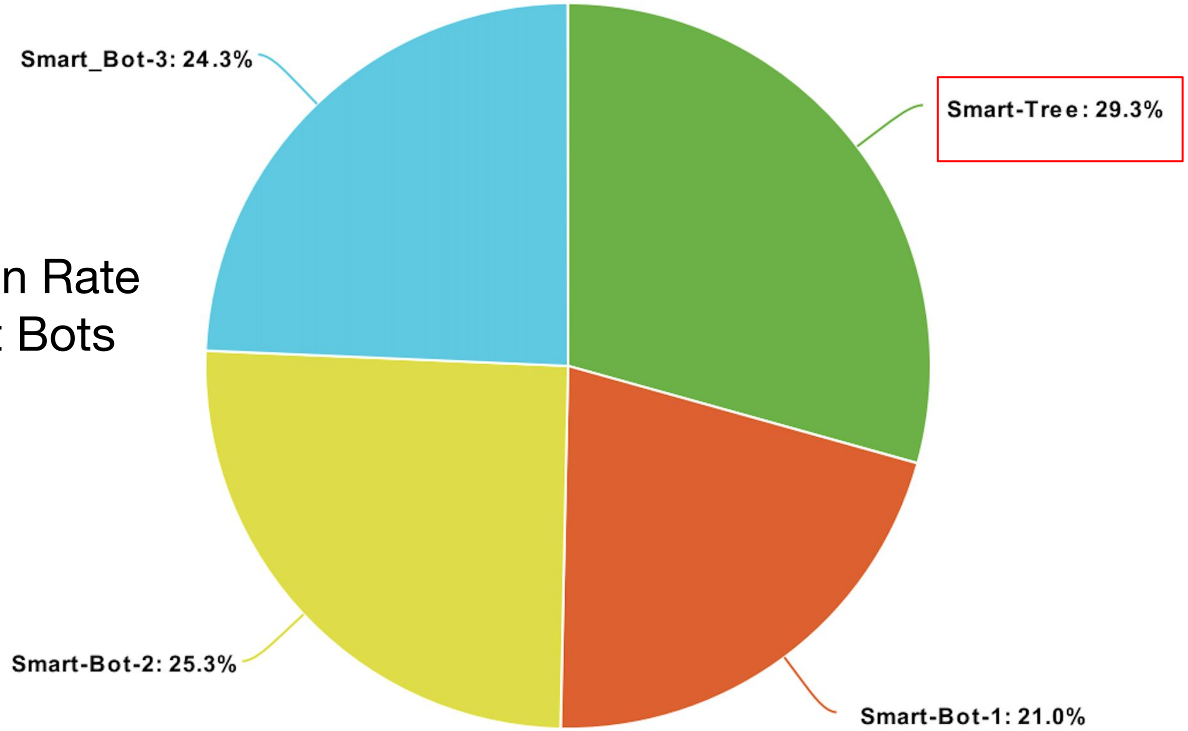
- Initialized fast bot trees from a collection of the best trees of other experiments
- Trained only on fast bots

“Fast-Tree”



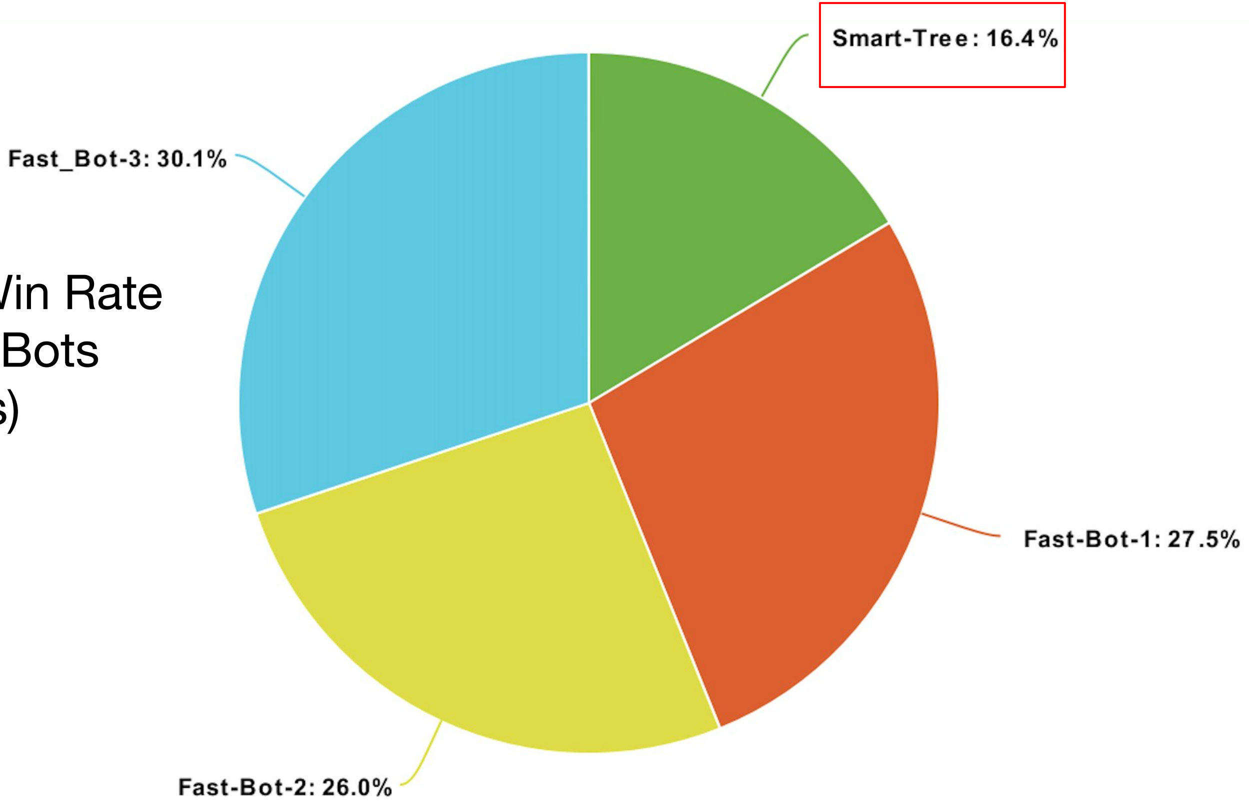
The Smart-Tree does well against smart bots

Smart-Tree Win Rate
Against Smart Bots
(300 Games)

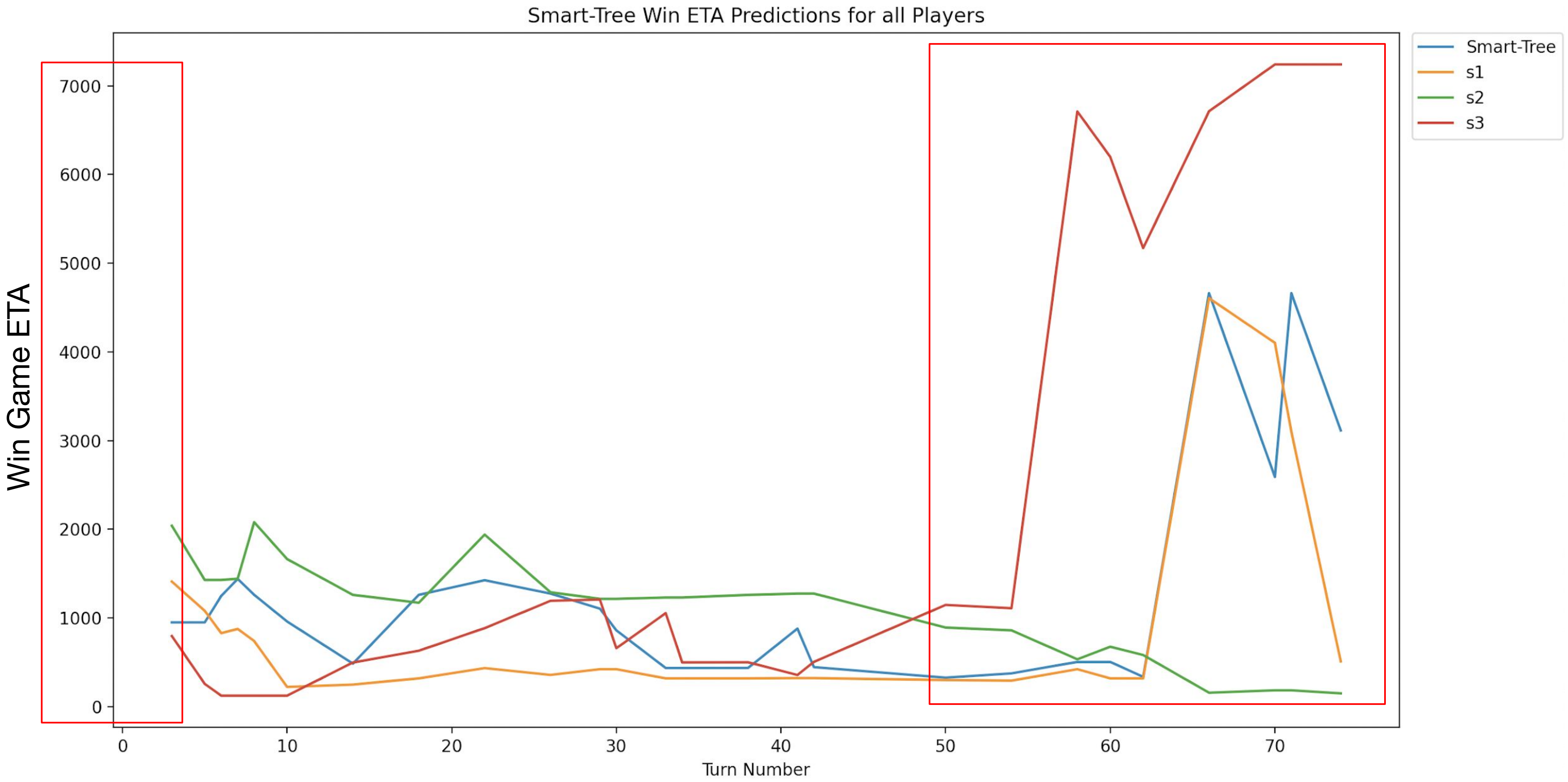


But the Smart-Tree struggles against fast bots

Smart-Tree Win Rate
Against Fast Bots
(1000 Games)



Smart-Tree Win-Game-ETA Predictions for All Players



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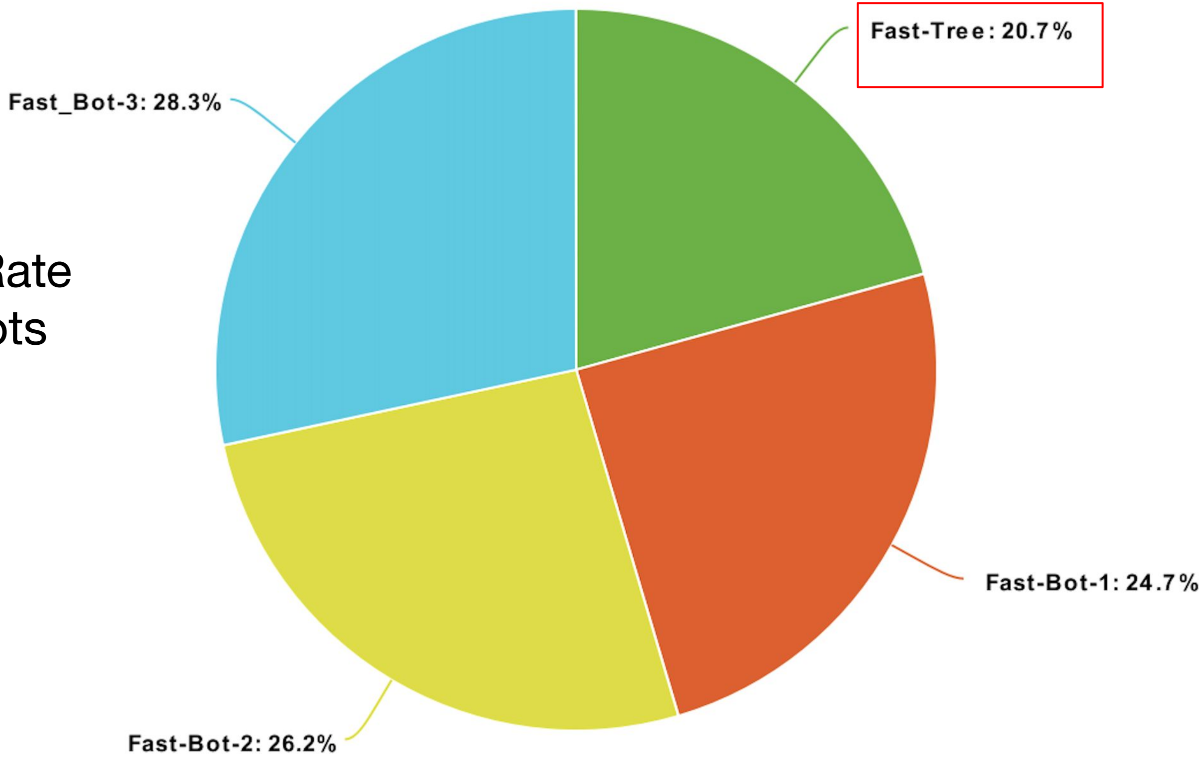
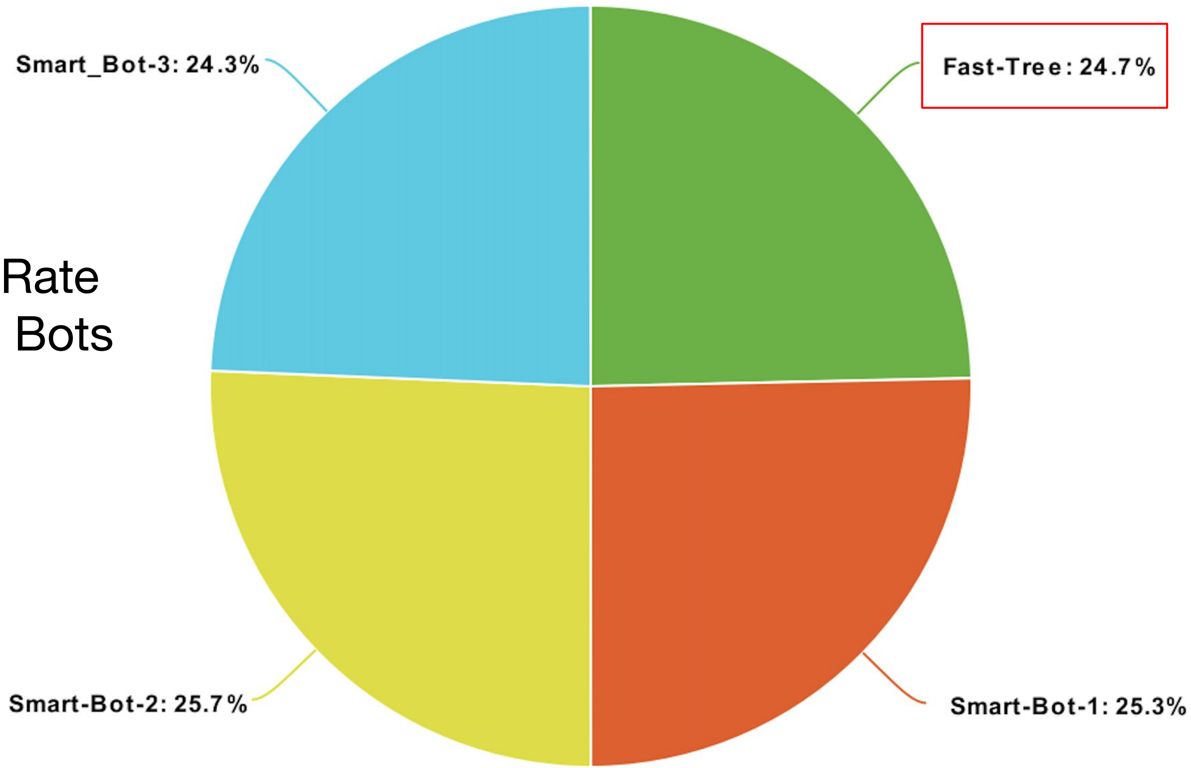
The Fast-Tree performs poorly against fast bots

Fast-Tree Win Rate Against Fast Bots (1000 Games)



But the Fast-Tree is slightly better against smart bots

Fast-Tree Win Rate
Against Smart Bots
(300 Games)



To conclude

Plan:

- Improve Smart Bot’s WinGameETA estimations

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Expectations:

- Faster than tree simulation
- New approach
- Easier to interpret

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Results:

- As good as or slightly better than smart bot
- Not good as fast bot’s performance

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Plan:

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Expectations:

- Faster than tree simulation
- New approach
- Easier to interpret

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Future:

- Build full scale decision maker

Citations

de Mesentier Silva, F., Lee, S., Togelius, J., & Nealen, A. (2017). AI-based playtesting of contemporary board games. In Proceedings of the 12th International Conference on the Foundations of Digital Games (pp. 1-10). [pdf]

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Thank you!