Reinforcement Learning of Strategies for Settlers of Catan

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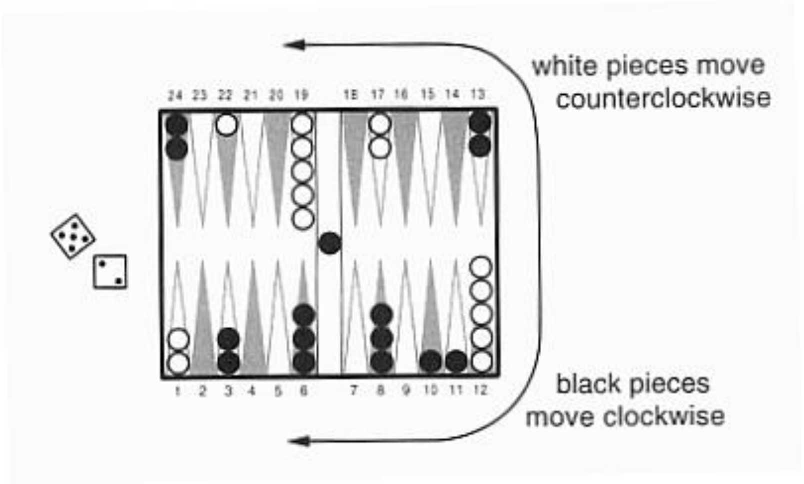
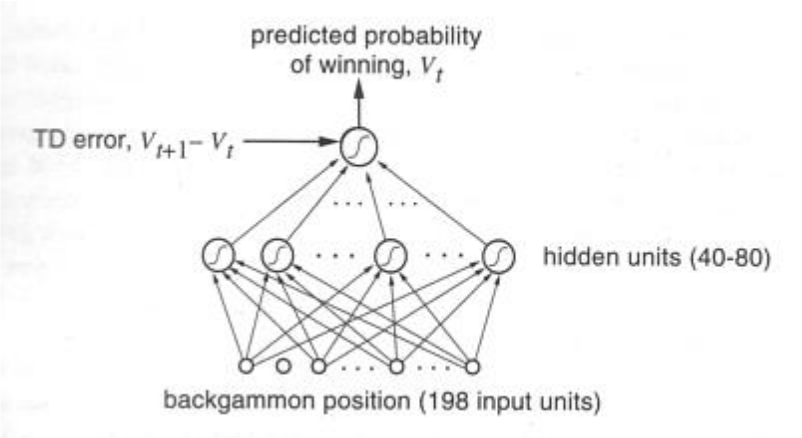
Motivation

- Computer Game AI
  - Mainly relies on prior knowledge of AI designer
  - inflexible and non-adaptive
- Machine Learning in Games
  - successfully used for classical board games
- TD Gammon [Tesauro 95]
  - self-play reinforcement learning
  - playing strength of human grandmasters





Figures from Sutton, Barto: Reinforcement Learning

Goal of this Work

- Demonstrate **self-play Reinforcement Learning** (RL) for a large and complex game
  - Settlers of Catan: popular board game
  - closer to commercial strategy games than backgammon or chess
  - in terms of: number of players, possibilities of actions, interaction, non-determinism, ...
- New RL methods
  - model tree-based function approximation
  - speeding up learning
- Combination of **learning and knowledge**
  - Where in the learning process can we use our prior knowledge about the game?

Agenda

- Introduction
- Settlers of Catan
- Method
- Results
- Conclusion

The Task: Settlers of Catan

- Popular modern board game (1995)

- Resources
- Production
- Construction
- Trading
- Victory Points
- Strategies

What makes Settlers so difficult?

- Huge state and action space
- 4 players
- Non-deterministic environment
- Interaction with opponents

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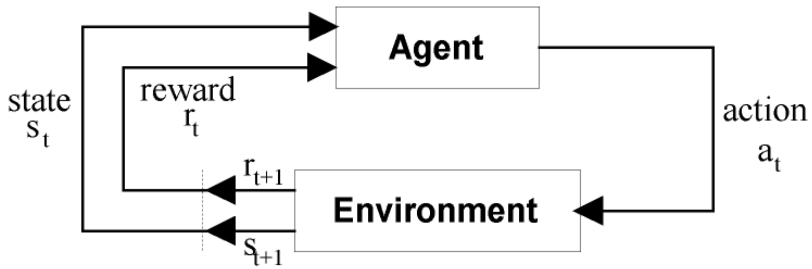
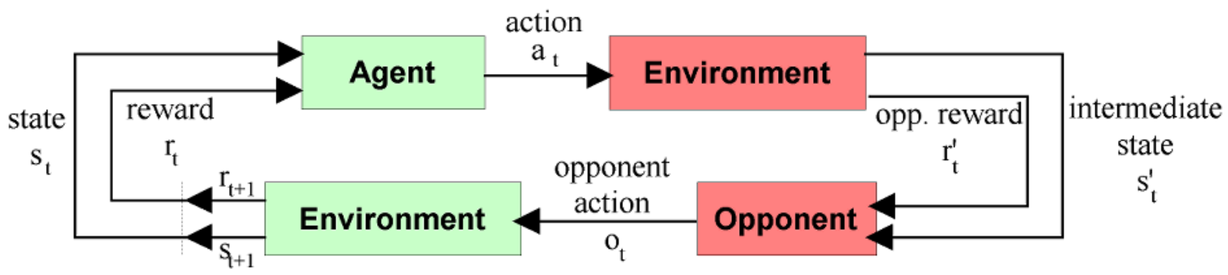
Reinforcement Learning



- Goal: Maximize cumulative discounted **rewards**
- Learn optimal **state-action value function** $Q^*(s,a)$
- Learning of strategies through **interaction** with the environment
  - Try out actions to get an estimate of Q
  - Explore new actions, exploit good actions
  - Improve currently learned policies
  - Various learning algorithms: Q-Learning, SARSA, ...

Self Play



- How to simulate opponents?
- Agent learns by **playing against itself**
- Co-evolutionary approach
- Most successful approach for RL in Games
  - **TD-Gammon** [Tesauro 95]
  - Apparently works better in non-deterministic games
  - Sufficient exploration must be guaranteed

Typical Problems of RL in Games

- **State Space** is too large
  - Value Function Approximation
- **Action Space** is too large
  - Hierarchy of Actions
- **Learning Time** is too long
  - Suitable Representation and Approximation Method
- Even **obvious moves** need to be discovered
  - A-priori Knowledge

Function Approximation

- Impossible to visit whole state space
- Need for **generalization** from visited states to whole state space

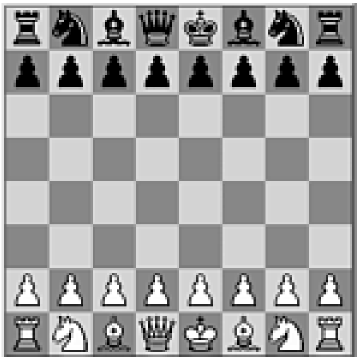
- **Regression Task**: $Q(s, a) \approx F(\varphi, a, \theta)$
  - φ ... *feature* representation of s
  - θ ... finite *parameter* vector (e.g. weights of linear functions or ANNs)

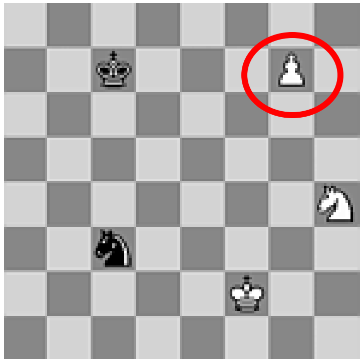
- **Features for Settlers of Catan**:
  - 216 high-level concept features (using *knowledge*)
  - transformed into 492 binary features

Choice of Approximator

- **Discontinuities** in value function
  - global smoothing is undesirable
- **Local importance** of certain features
  - impossible with linear methods
- **Learning time** is crucial

- [Sridharan and Tesauro, 00]
  Tree based approximation techniques learn faster than ANNs in such scenarios

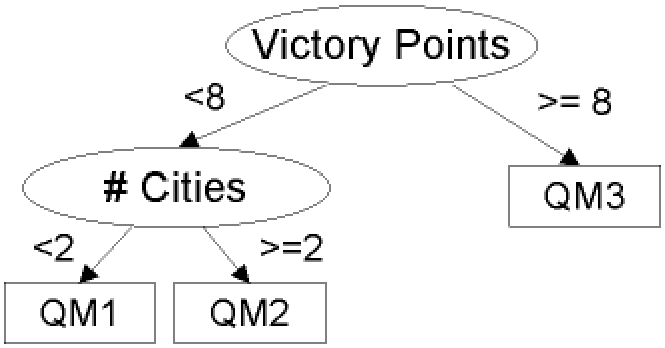




Model Trees

- Partition state space into **homogeneous** regions
  - Splitting criteria in nodes minimize variance of target variable
- Learn **local linear regression models** in leaves
  - attributes as regression variables
- Generalization via **Pruning**
  - replace sub-trees by leaves
- M5 learning algorithm [Quinlan, 92]

Example:



Pros and Cons of Model Trees

+	-
Discrete and real-valued features	Only offline learning
Ignores irrelevant features	Need to store all training examples
Local models	Long training time
Feature combinations	Little experience in RL context
Discontinuities	No convergence results in RL context
Easy interpretation	
Few parameters	

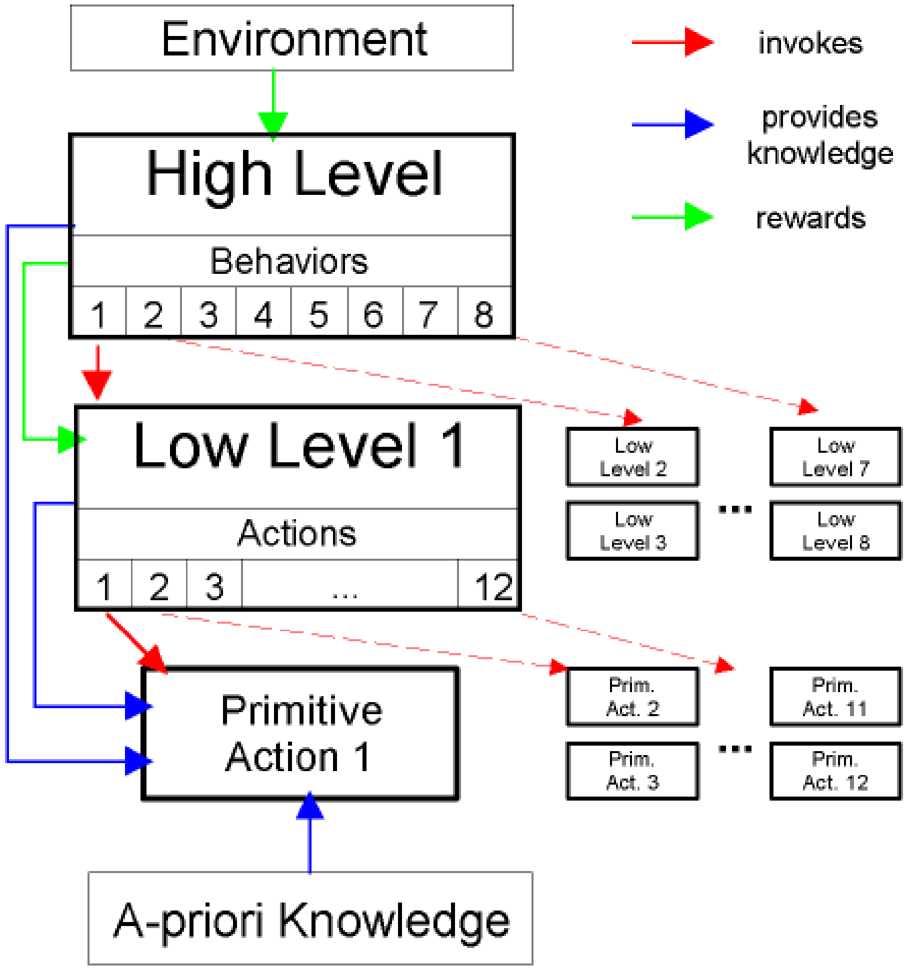
Offline Training Algorithm

One model tree approximates Q-function for one action

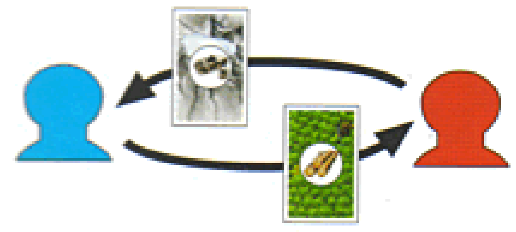
1. Use current policy to play 1000 training games
2. Store game traces (states, actions, rewards, successor states) of all 4 players
3. Use current Q-function approximation (model trees) to calculate Q-values of training examples and add them to existing training set
4. Update older training examples
5. Build new model trees from the updated training set
6. Go back to step 1

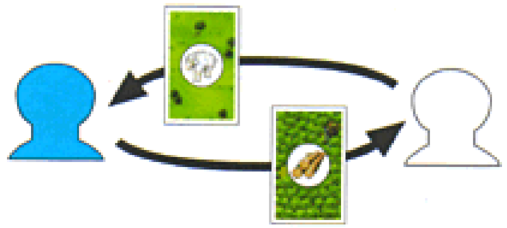
Hierarchical RL

- Division of action space
- **3 layer** model
- Easier **integration of a-priori knowledge**
- **Learned information** defines primitive actions
- **Independent Rewards**:
  - high level: winning the game
  - low level: reaching the **behavior's goal**
  - otherwise zero



Trading





- Select which trades to **offer / accept / reject**
- **Evaluation** of a trade:
  - What increase in **low-level value** would each trade bring?
  - Select highest valued trade

- Simplification of game design
  - **No economical model** needed
  - Gain in value function naturally replaces prices

Approaches

- High-level behaviors always run until completion
- Allowing high-level switches every time-step (*feudal approach*) did not work

- **Module-based Approach**
  - High-level is learned
  - Low-level is learned

- **Heuristic Approach**
  - *Simple hand-coded* high-level strategy during training and in game
  - Low-level is learned
  - Selection of high-level influences primitive actions

- **Guided Approach**
  - Hand-coded high-level strategy *during learning*
  - Off-policy learning of high-level strategy for game
  - Low-level is learned

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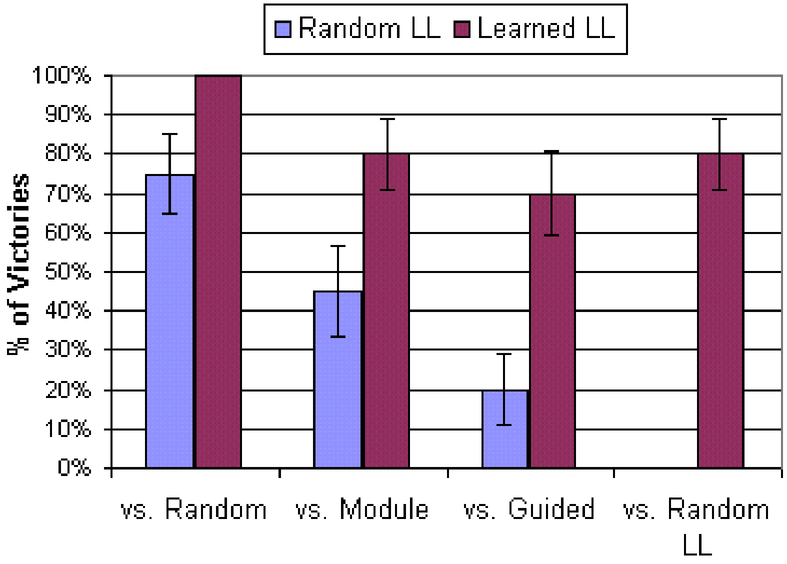
Evaluation Method

- 3000 – 8000 training matches per approach
- Long training time
  - 1 day for 1000 training games
  - 1 day for training of model trees

- Evaluation against:
  - random players
  - other approaches
  - human player (myself)
  - no benchmark program

Comparison of Approaches

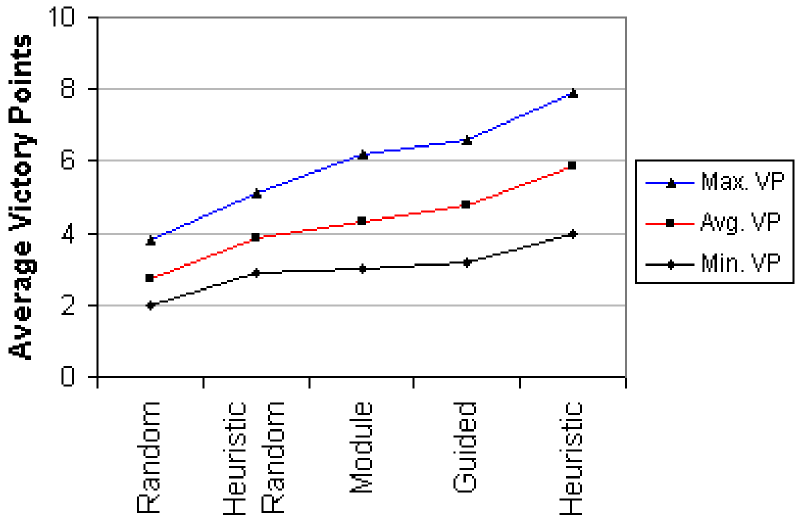
- Module-based:
  - good low-level choices
  - poor high-level strategy
- Heuristic high-level:
  - significant improvement
  - learned low-level clearly responsible for improvement
- Guided approach:
  - worse than heuristic
  - better than module-based



Victories of heuristic strategies against other approaches (20 games)

Against Human Opponent

- 10 games of each policy vs. author
  - 3 agents vs. human
- Average victory points as measure of performance
  - 10 VP: win every game
  - 8 VP: **close to winning** in every game
- Only heuristic policy wins 2 out of 10 matches
- Demo matches confirm results (not included here)



Performance of different strategies against a human opponent (10 games)

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Conclusion

- RL works in large and complex game domains
  - Not grandmaster level like TD-Gammon, but pretty good
  - Settlers of Catan is an interesting testbed and closer to commercial computer games than backgammmon, chess, ...
- Combination of prior knowledge with RL yields promising results
  - Hierarchical learning allows incorporation of knowledge at multiple points of the learning architecture
  - Learning of AI components
  - Knowledge speeds up learning
- Model trees as a new approximation methodology for RL

Future Work

- Opponent modelling
  - recognizing and beating certain opponent types
- Reward filtering
  - how much of the reward signal is caused by other agents
- Model trees
  - other games
  - improvement of offline training algorithm (tree structure)
- Settlers of Catan as game AI testbed
  - trying other algorithms
  - improving results

Thank you!

Sources

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- J.R. Quinlan: *Learning with Continuous Classes,* Proceedings Australian Joint Conference on AI, 1992
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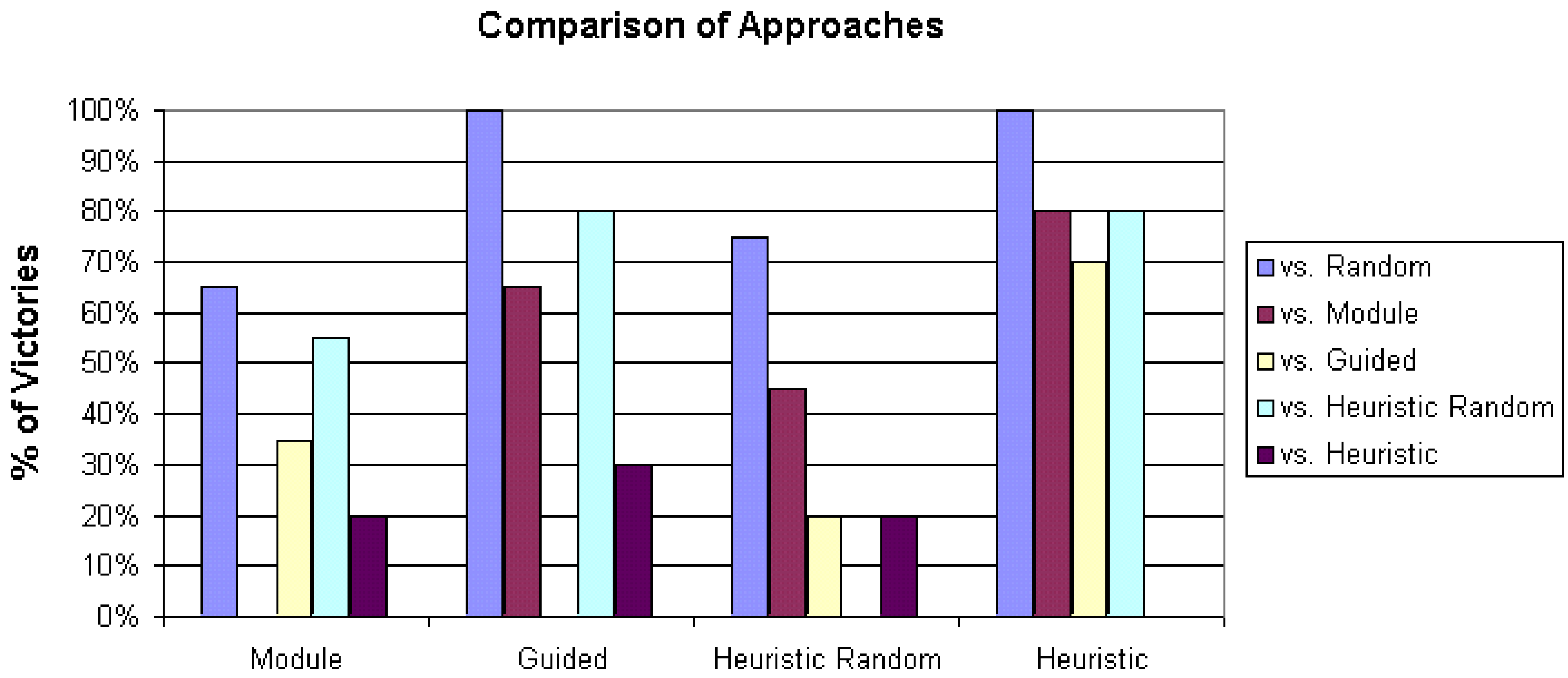
Extra Slides

Comparison of Approaches



- Comparison of strategies in games against each other
  - all significantly better than random
  - heuristic is best