A Layered Approach to Learning Client Behaviors in the RoboCup Soccer Server

- Peter Stone
  - Ph.D. thesis at CMU, 1998
  - Book from MIT Press
- Manuela Veloso
  - Advisor
- http://www.cs.utexas.edu/~pstone/thesis/

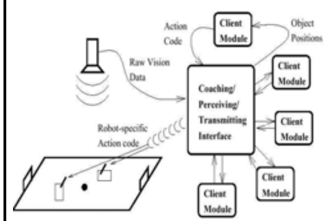
Multiagent Learning in Robocup Soccer Simulation

- An incremental approach to learning is used
- Difficult (impossible?) to learn complex behaviors based solely on the primitives provided by the server
- Layered Learning:
  - building increasingly complex behaviors on top of one another;
  - learning low-level behaviors before high-level ones;
  - Higher-level behaviors utilize lower-level ones as components

The Objective

- Teach the server clients two learned behaviors: one low-level and one high-level
- Low-level: intercepting a moving ball
- High-level: passing
- The high-level skill is dependent on the mastery of the low-level one.

The Robotic Competition Architecture



- Overhead camera perceives the position of the ball and robots on the field
- Image processed by main interface – given to clients
- Clients choose next action
- Client selects commands to send to its robot agent
- Commands are sent to robots by main computer (wireless infrared communication)

The Simulator

- Noda's Soccer Server
  - Players have limited vision
  - Players communicate via a blackboard visible to all players
  - All players controlled by separate processes
  - Actions and sensors are noisy
  - Real time play

Low-level skill: Ball interception

- Intercepting a moving ball a prerequisite for any kicking action
- Learning through supervised empirical learning: Neural Networks (NNs).
- Difficulties:
  - Ball movement unpredictable due to noise in the system
  - Players have limited vision

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Low-level skill: Ball interception (cont.)

- Defender learns turn angle (TA—the angle to turn after facing the ball), based on the ball's distance and ball angle.
- NN training
  - randomized situations and defender actions
  - Results recorded
    - SAVE: ball is intercepted
    - GOAL: ball is not intercepted, ball goes into the goal
    - MISS: ball is not intercepted, no goal made

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Low-level skill: Ball interception (cont.)

- NNs trained on 500+ examples had a SAVE rate of roughly 83-86%.
- NN results compared against a lookup table mapping ball angle to the average NN output for that ball angle—results were almost as good as with the NN itself.
- NN results also compared with an analytical predictor. Again, results were almost as good as the NN results.

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High-level skill: passing

- Passing involves two team members: a passer and a receiver.
- The receiver's action in passing is identical to the defender's action in ball interception. The same NN is used.
- Decisions Trees (DTs) were used to decide if the ball should be passed to a particular teammate.

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High-level skill: passing (cont.)

- Passer uses the receivers' views of the field in addition to its own when making the decision whether to pass.
- During training, passer chose a random receiver in each trial.
- In addition to the intended receiver, 4 defenders also attempted to intercept the ball.
- Results:
  - SUCCESS: the intended receiver intercepts the ball
  - FAILURE: a defender intercepts the ball
  - MISS: no one intercepted the ball

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High-level skill: passing (cont.)

- 174 attributes were recorded for each trial, to be used to predict whether a pass will be a success, a failure, or a miss.
  - Half the data points were from the passer's perspective, half from the receiver's
- Decision Tree software produced a pruned tree, in which insignificant data were left out.
  - Many more passer attributes were actually used than receiver attributes.
- 5000 training examples
  - 51% successes
  - 42% failures
  - 7% misses

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High-level skill: passing (cont.)

- DT returns a confidence measure for each receiver candidate
  - If more than one will be successful, choose the one with the highest confidence level
  - If all are predicted to fail, choose the one with the lowest confidence level
- 5000 trials
  - Passer must pass, even if DT predicts failure for all receivers.
  - 79% success rate

Team-level strategies

- A set play was run several times to show that the higher-level learning (passing decision) could be incorporated into a game situation.
- Goal: keep layering new higher-level learned behaviors on top of old ones, resulting in a high-level functioning team that is robust and reliable in game situations.

Summary

- Learning strategies developed
- Successful in a large application
- Peter Stone is now at UT Austin