Week 1

Read one paper about NAS and four papers about Games. Here are some notes of my reading: the summary and the main idea of the papers, and the collections of something useful.

NAS

HM-NAS: Efficient Neural Architecture Search via Hierarchical Masking

[1] Tranditional NAS approaches uses a method of weight sharing, which still adopt hand-designed heuristics to generate architecture candidates. So the space of architecture candidates is constrained in a subset of all possible architectures, making the architecture search results sub-optimal.

The author addresses this limitation via two innovations. First, HM-NAS incorporates a multi-level architecture encoding scheme to enable searching for more flexible network architectures. Second, it discards the hand-designed heuristics and incorporates a hierarchical masking scheme that automatically learns and determines the optimal architecture.

Game

Generating Diverse Opponents with Multiobjective Evolution

[2] The author proposed a way to use multiobjective evolutionary algorithms to automatically create populations of Non-Player Characters (NPCs), such as opponents and collaborators.

Most academic Computation Intelligence and Games researchers use games for testing computational intelligence (CI) algorithms, but not for developing CI techniques for play games.

Using multiobjective evolutionary algorithms (MOEA) to solve car's speed, number of driving changes, wall collisions, car collisions and so on.

Multiobjective Exploration of the StarCraft Map Space

[3] This paper presents a search-based method for generating maps for the game StarCraft. The multi objectives consider playability, fairness, skill differentiation and interestingness.

Evolutionary Computation in Artificial Board Game Playing through Genetic Weight Evolution

[4] This paper focuses the application of disc set weight evolving through genetic operators induced for the Game of Othello.

Evolutionary Computation and Games

[5] Games provide competitive, dynamic environments that make ideal test beds for computational intelligence theories, architectures and alogrithom. This paper discuss the history of Game AI during the past 50 years.

There are several issues to consider when evolving a game strategy:

1. Fitness Function
2. Exploration
3. Implementation
4. Game Interface
5. Input Representation and Agent Architecture
6. Ply Depth
7. Evolutionary Algorithm

This paper mentions temporal difference learning and co-evolution two approaches. What is the different between them is that a co-evolutionary learner gets feedback on the number of games won after playing a set of games while the TDL learner gets feedback after every move of every game.Co-evolution involves a population of players (depicted as neural networks here) whereas TDL typically uses a single player, playing against itself.

Collections

Genres of games:

1. real-time strategy(RTS)
2. first- and third-person shooters
3. racing games
4. board games
5. Real-World Games(such as robot, like RoboCup)

Games are used in other researchers' experiments:

1. self simulator(use some packages to draw lines as the "wall" and the route that car move)
2. StarCraft
3. Game of Othello

References

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[3] Julian Togelius, Mike Preuss, Nicola Beume, Simon Wessing, Johan Hagelbäck, and Georgios N Yannakakis. Multiobjective exploration of the starcraft map space. In *Proceedings of the 2010 IEEE Conference on Computational Intelligence and Games*, pages 265–272. IEEE, 2010.

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