Intelligent Non-Player Character with Deep Learning

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CUHK CSE FYP 2016 - 2017

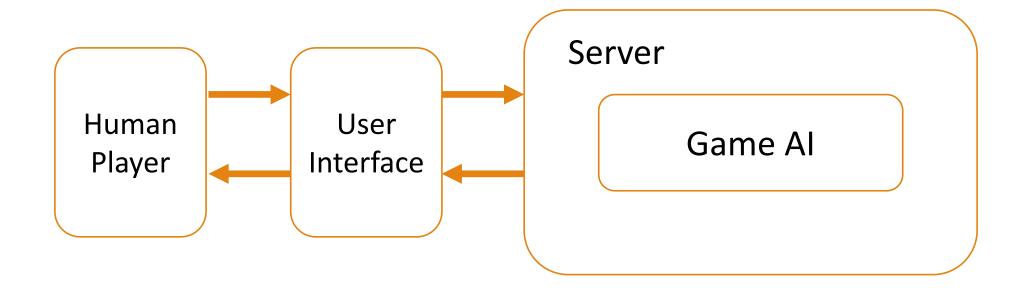
Agenda

- Review
- Objective
- Policy Network Reinforcement Learning
- Evaluation Network Supervised Learning
- Results
- Discussion & Conclusion

Previously on our project...

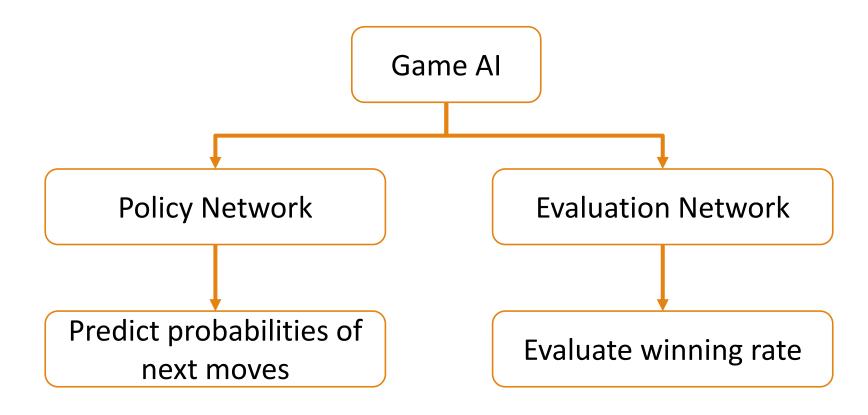
O NPC:

character not controlled by a player but by computer through artificial intelligence



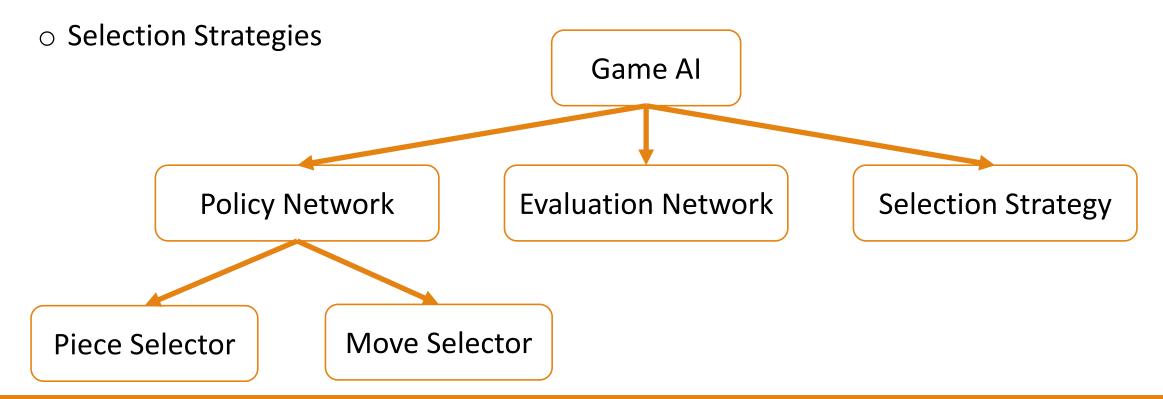
Previously on our project...

Policy Network – Supervised Learning

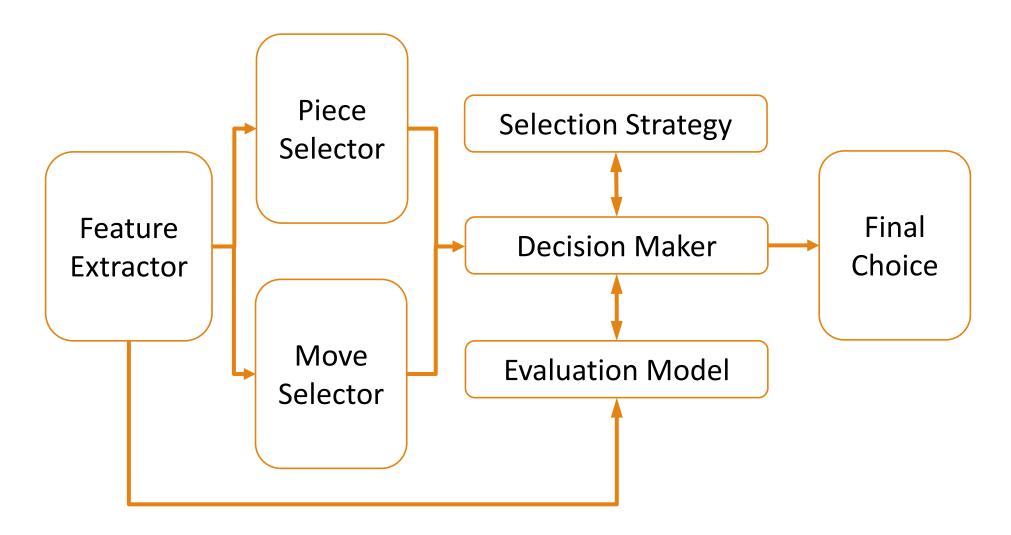


Objective

- Policy Network Reinforcement Learning
- Evaluation Network Supervised Learning



General Structure



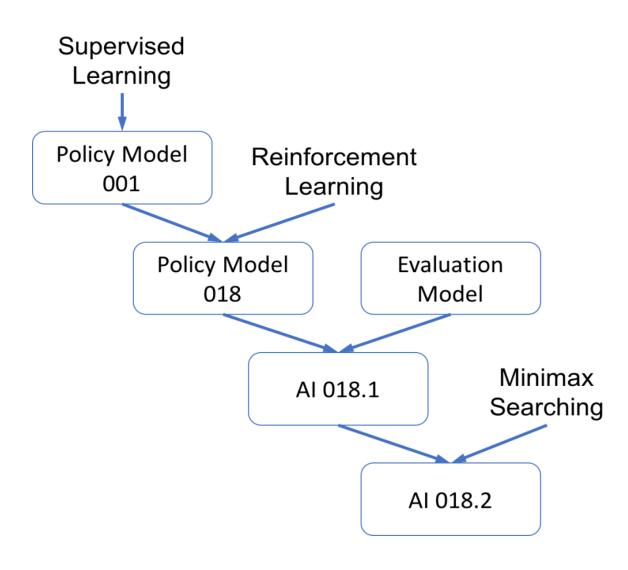
Version Iteration

Version 001: only trained by Supervised Learning

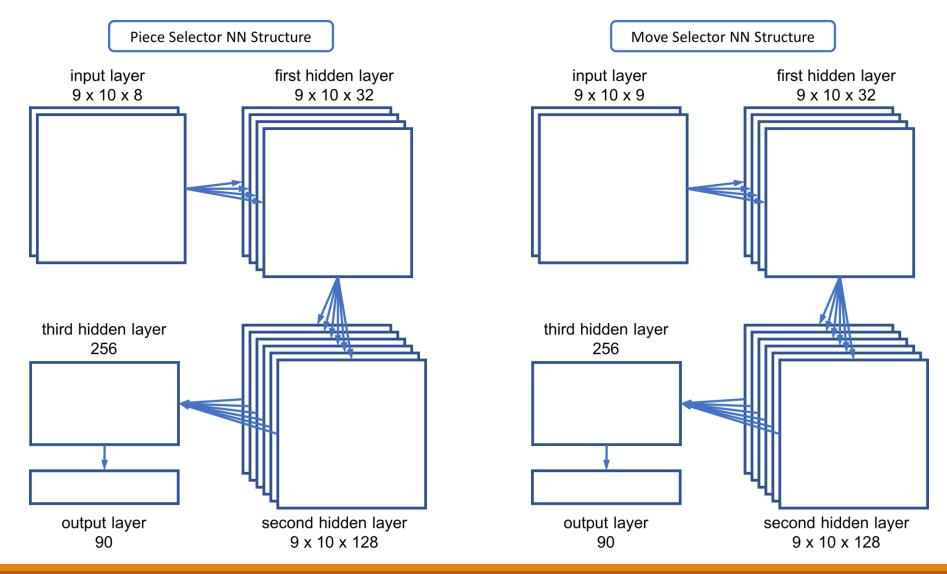
Version 018: Trained by Reinforcement Learning

Version 018.1: Add Evaluation Model

Version 018.2: Add Minimax Search



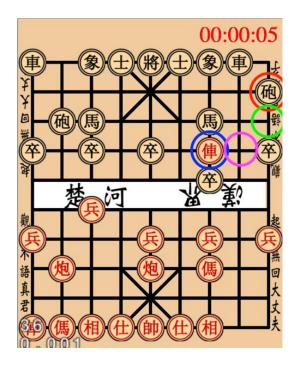
Piece Selector & Move Selector



Feature Channels

Feature Channel 1	Pieces belonging to different sides
Feature Channel 2	Pieces of Advisor type
Feature Channel 3	Pieces of Bishop type
Feature Channel 4	Pieces of Cannon type
Feature Channel 5	Pieces of King type
Feature Channel 6	Pieces of Knight type
Feature Channel 7	Pieces of Pawn type
Feature Channel 8	Pieces of Rock type
Feature Channel 9 (only for Move Selector)	Valid moves for the selected piece

Output Sample



Current chessboard (black cannon move from green to red)

0.1%	0.0%	0.3%	1.3%	0.0%	0.0%	0.0%	1.7%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.3%	0.0%	0.0%	0.0%	0.0%	0.4%	0.0%	95.7%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Output from piece selector (green circle on chessboard)

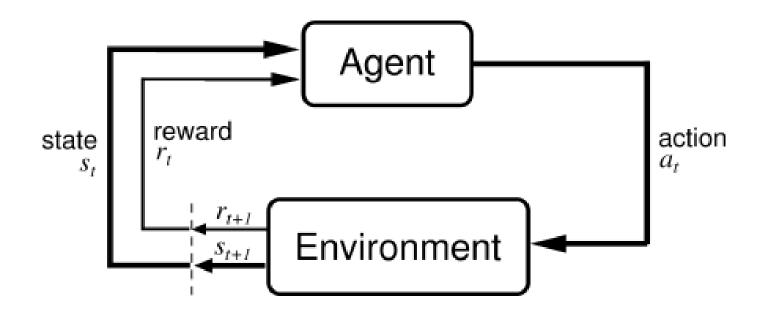
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.2%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	97.5%
0.0%	0.0%	0.0%	0.0%	0.0%	0.1%	0.0%	1.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	1.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Output from move selector (red circle on chessboard)

Reinforcement Learning

- inspired by behaviour psychology
- o exploration vs exploitation

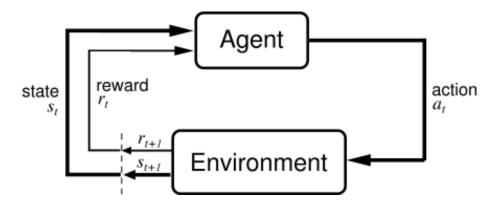
- how to take actions
- o to maximize the reward



Reinforcement Learning

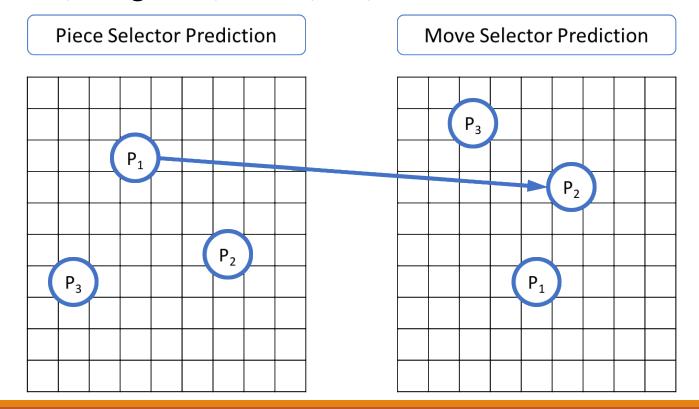
- Assigning Rewards
 - Positive Reward: 1 for moves from winning side
 - Negative Reward: not used

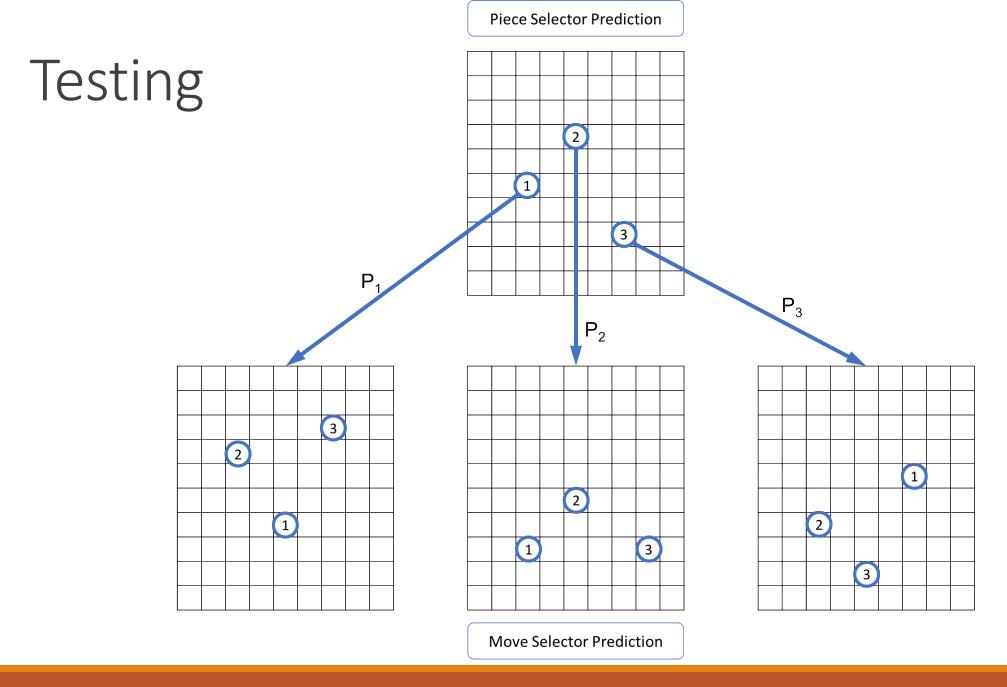
- Compete with different middle version models
 - to avoid overfitting

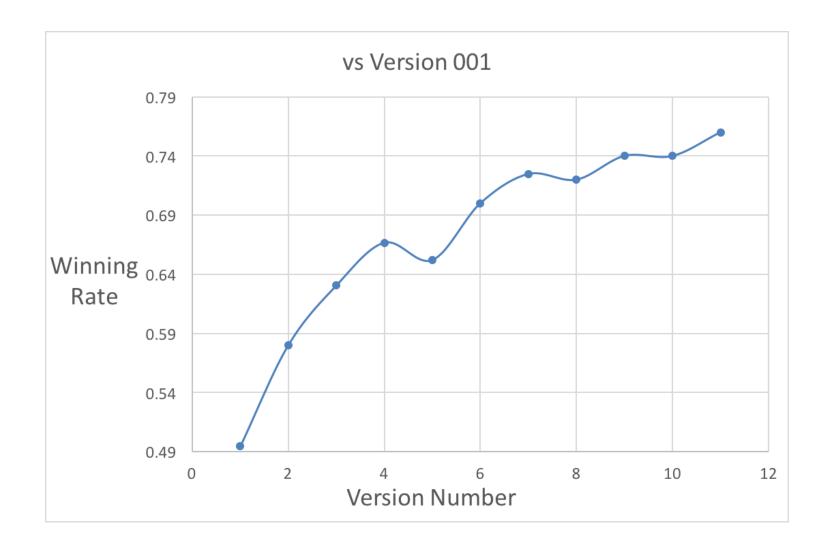


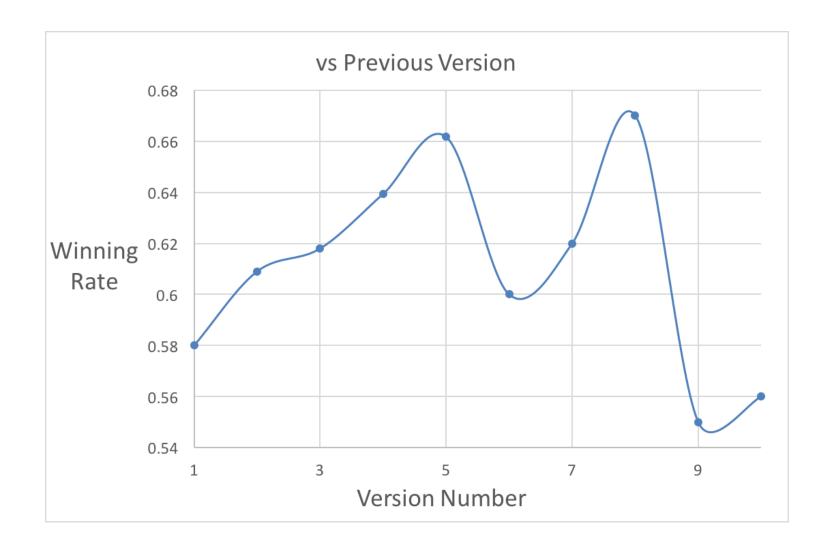
Training

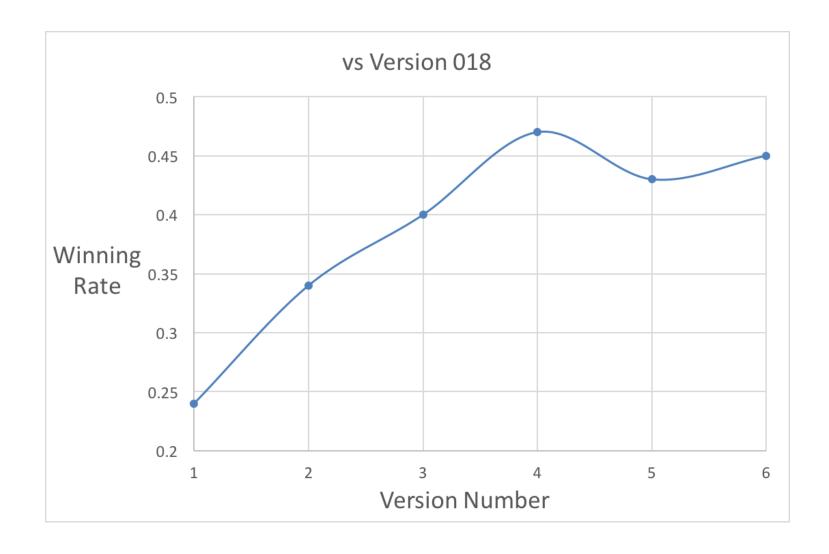
- o change the opposite model roughly every 4,000 games
- o in total around 40,000 games, over 2,000,000 moves







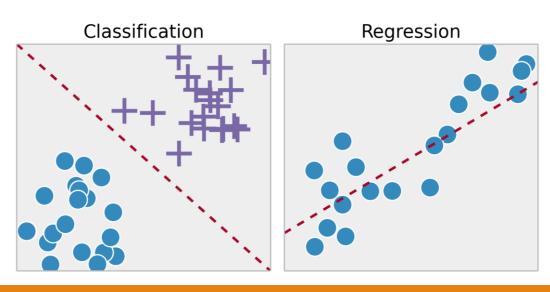




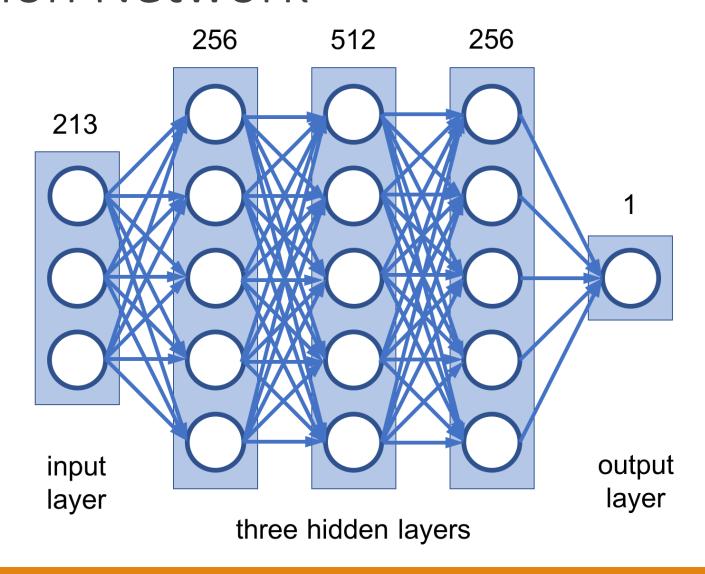
Evaluation Network

- O Why?
 - Only Policy Network is not enough
 - Need to evaluate the winning rate of a chessboard status

- Supervised Learning
 - Regression Problem



Evaluation Network



Network Input

Feature	Length
Player Side	1
The Number of Pieces of Each Type	14
Pieces List (alive or not, xy-coordinates)	32 * 3
The number of valid moves for Rock, Cannon and Knight	12
Attack and Defend Map	90

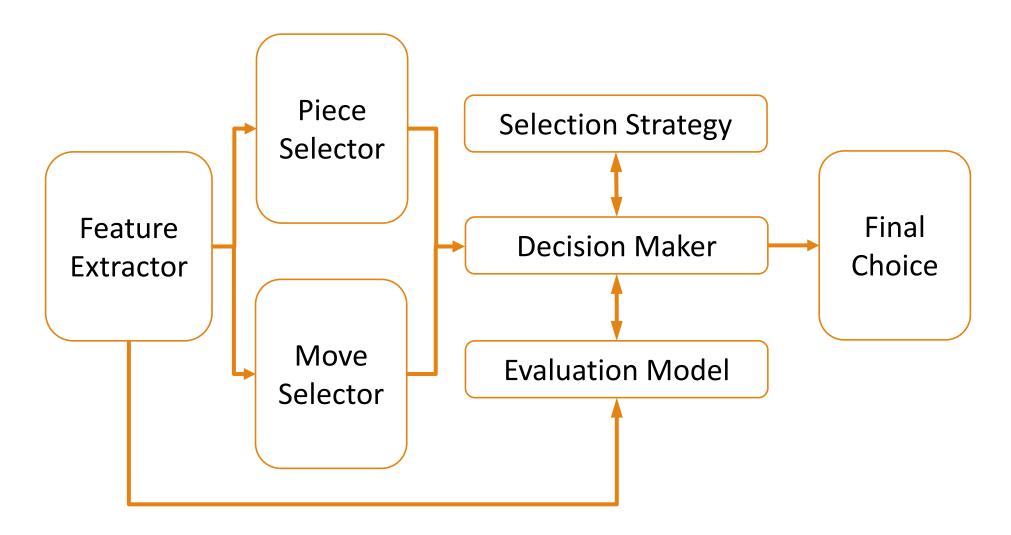
Training

- O How to get the target values?
 - one evaluation function from an open-source API
 - o do some mapping, shrink the range

0	Trained	over	1.900.0	00 chessk	board sta	atuses
\cup	Hanica	OVCI	エ, 		odara sti	acases

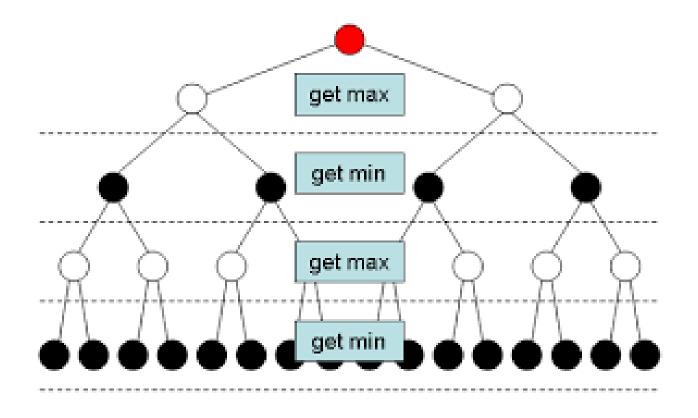
0 ~ ±100	0 ~ ±100
±101 ~ ±700	±101 ~ ±170
over ±9000	±200

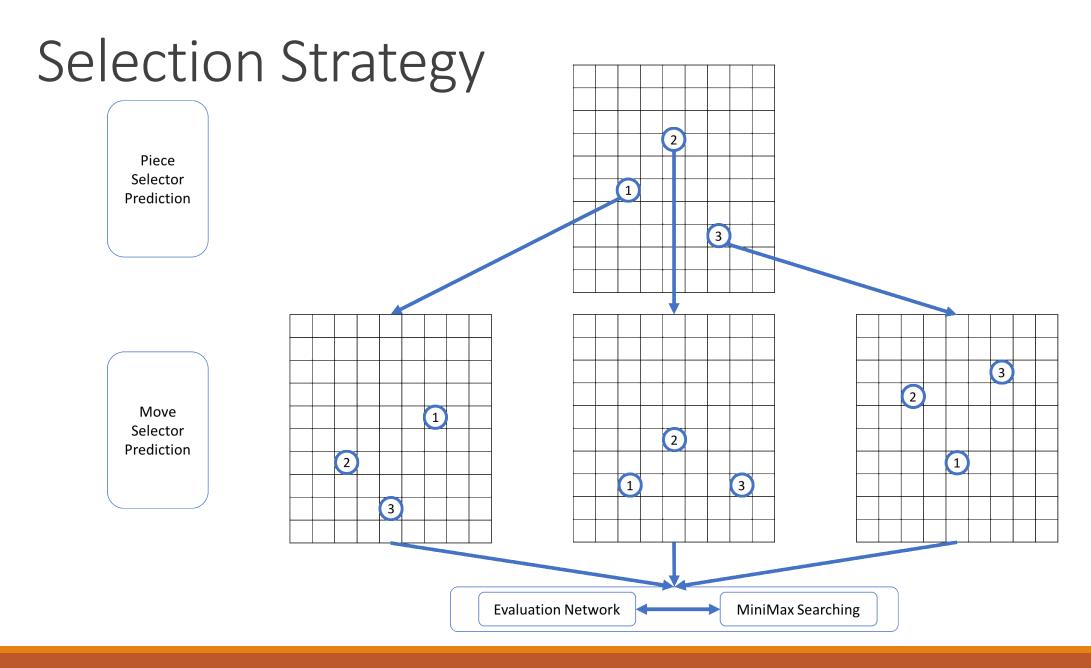
How to use the models?



Minimax Searching

Select minimum and maximum value in turn





Selection Strategy Enhancement

 Eliminate moves with probabilities below a certain threshold at first

Different max breadth for different layers
 24 -> 12 -> 12

Different quota for different piece types

Piece type	Quota 1	Quota 2
King	4	4
Advisor	2	2
Bishop	2	2
Rock	5	3
Cannon	5	3
Knight	4	2
Pawn	2	1

Testing

Aliyun Server

Socket.io

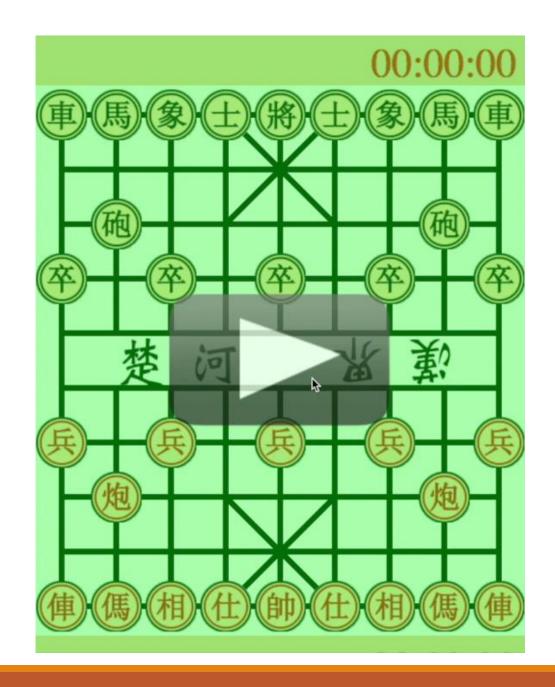
Multiple login



- The winning rate is 76%, won 19 out of 25 games
- On average, it takes 26.3 moves to win

	Number of Games	Average Number of Moves
Win	19	26.3
Lose	6	37.5

Demo



Discussion & Conclusion

- Policy Network and Evaluation Network
- Supervised Learning and Reinforcement Learning
- performed much better than the model in Term 1
- o can compete with ordinary people now

- o need further improvement:
 - negative reward is not working in Reinforcement Learning
 - continue to train the model
 - try different model structures

Q&A