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MOHEX WINS HEX 11X11 AND 13X13 TOURNAMENTS

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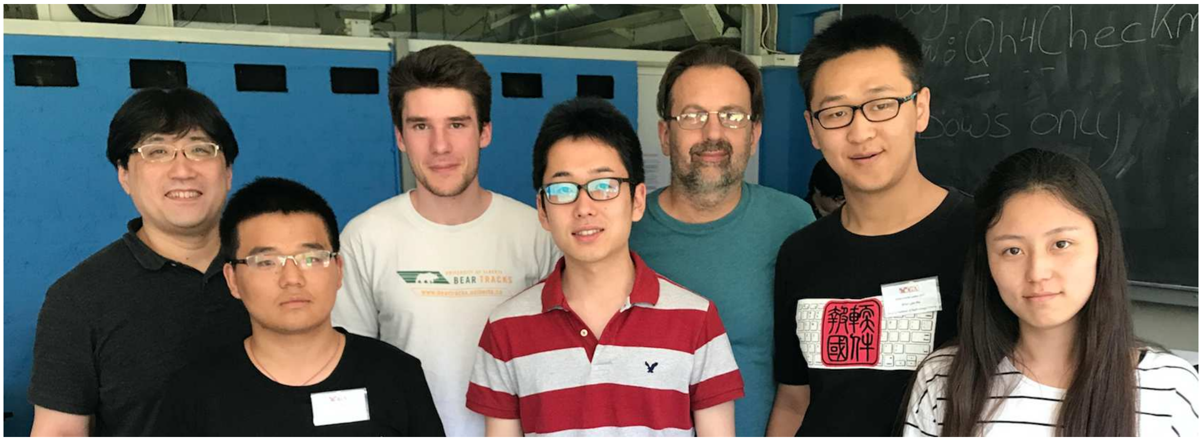

Figure 1: Participants at the Hex competitions. From left, Masahito Yamamoto, Wu Tong, Noah Weninger, Kei Takada, Ryan Hayward, Ma Shengjie, Wu Tong (no relation to other Wu Tong).

1. THE TOURNAMENTS

There were two Hex tournaments at the 2017 Olympiad: board size 11×11 and board size 13×13. Three programs competed in each tournament.

The 11×11 contestants were HEXCITED by Ma Shengjie from China; EZO-CNN by Kei Takada, supervised by Masahito Yamamoto, from Japan; and MOHEX by Broderick Arneson, Ryan Hayward, Philip Henderson, Aja Huang, Jakub Pawlewicz, Noah Weninger, and Kenny Young from Canada. The 13×13 contestants were HEXCELLENT by Wu Tong from China; EZO-CNN; and MOHEX-CNN by Chao Gao from Canada.

MOHEX (Huang *et al.*, 2013), the winner of the previous seven Olympiad Hex competitions (Hayward *et al.*, 2013), is an MCTS program that uses the Benzene Hex framework built on the code base of FUEGO (Enzenberger *et al.*, 2007–2012). MOHEX performs knowledge computation in UCT tree nodes visited at least 256 times. MOHEX ran on Firecreek, a 24 core shared-memory machine, with 4 cores reserved for the DFPNS solver (Pawlewicz and Hayward, 2013), which produces perfect play if it solves the position within the time allotted. MOHEX uses a book built by Broderick Arneson with Thomas Lincke's method (Lincke, 2000). Noah Weninger expanded the book and added a feature allowing the use of rotational symmetry for openings whose rotation is in the book. For each board size, the book covers at least eight openings.

MOHEX-CNN is a convolutional neural net (CNN) version of MOHEX. At each new node of the Monte Carlo search tree, a policy CNN biases child selection by initializing child visit and win counts with artificial values. MOHEX-CNN ran remotely on a machine with 2 CPUs and 1 GPU.

EZO-CNN is a CNN version of EZO, which competed in the 2016 and previous Olympiads. EZO, based on the Benzene framework, uses iterative deepening alpha-beta search with an evaluation function using a linear

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combination of two network connectivity measures (Takada *et al.*, 2015). EZO-CNN uses a convolutional neural policy network for move ordering. EZO-CNN ran remotely on a machine with two CPUs and one GPU, with one CPU-thread for search and one CPU-thread for Benzene's Depth-First Proof Number Search endgame solver.

HEXCITED and HEXCELLENT are new MCTS programs written respectively by Ma Shengjie and Wu Tong of the Beijing Institute of Technology. Each ran on a laptop. Fellow student Wu Tong (no relation to other Wu Tong) helped operate HEXCELLENT.

Each tournament was scheduled for 8 games between each two of the three competitors. The tournaments started on July 1 and finished on July 5. In most games, the losing operator resigned soon after Benzene solved the game.

11×11 Tournament.[3] The new program HEXCITED played strongly in the opening of several of its games, but without any virtual connection computation was unable to win a game against EZO or MOHEX, which both use Benzene's virtual connection engine and endgame solver. For this reason, the operator chose to default its final games.

The contest for gold required a four-game playoff between MOHEX and EZO. The gold medal was not decided until the final game.

11x11 results	MOHEX	EZO-CNN	HEXCITED	total	result
MOHEX		7-5	3-0	10-5	gold
EZO-CNN	5-7		3-0	8-7	silver
HEXCITED	0-3	0-3		0-6	bronze

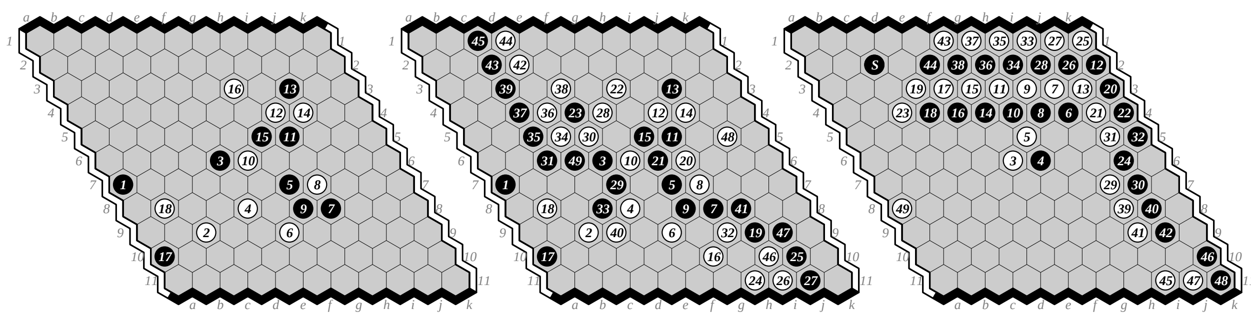

Figure 2: HEXCITED-MOHEX Games 1-3. M-H 1-0 H-M 0-1 H-M 0-1

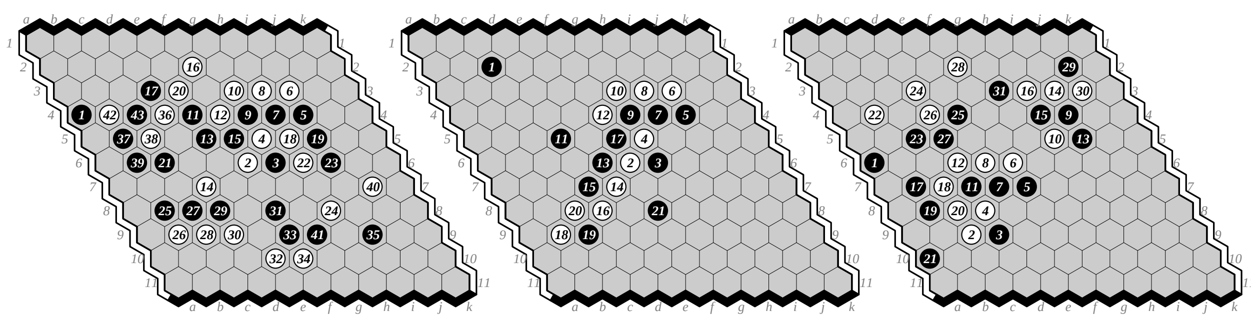

Figure 3: HEXCITED-EZO-CNN Games 1-3. E-H 1-0 H-E 0-1 E-H 1-0

13×13 Tournament.

13x13 results	MOHEX-CNN	EZO-CNN	HEXCELLENT	total	result
MOHEX-CNN		6-2	2-0	8-2	gold
EZO-CNN	2-6		4-0	6-6	silver
HEXCELLENT	0-2	0-4		0-6	bronze

[3] Source files for this report, including .sgf files, at `https://github.com/ryanbhayward/icga-olympiad-hex`.

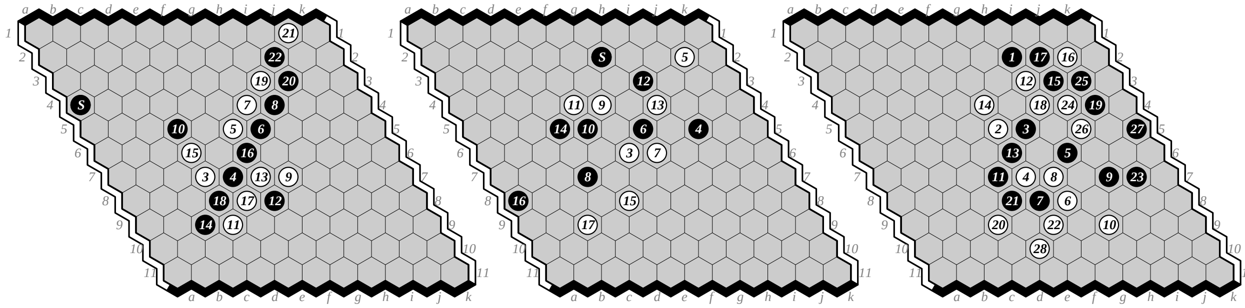

Figure 4: EZO-CNN-MOHEX Games 1-3. E-M 0-1. M-E 1-0 E-M 1-0

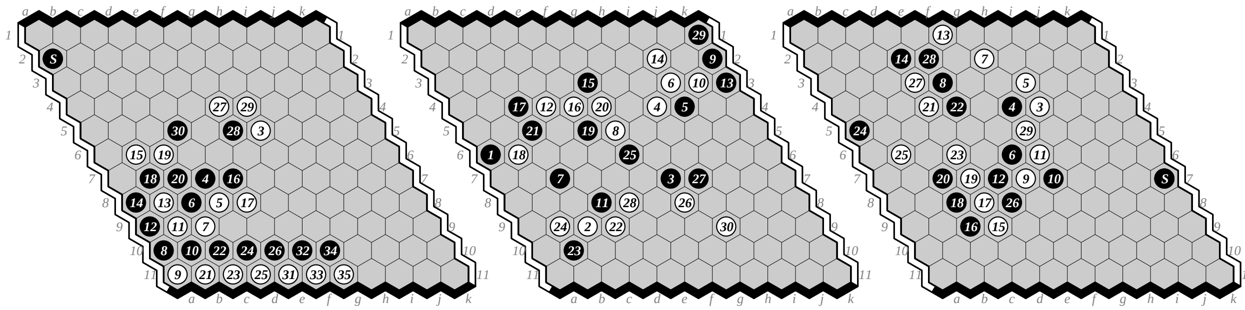

Figure 5: EZO-CNN-MOHEX Games 4-6. M-E 1-0. M-E 0-1 E-M 1-0

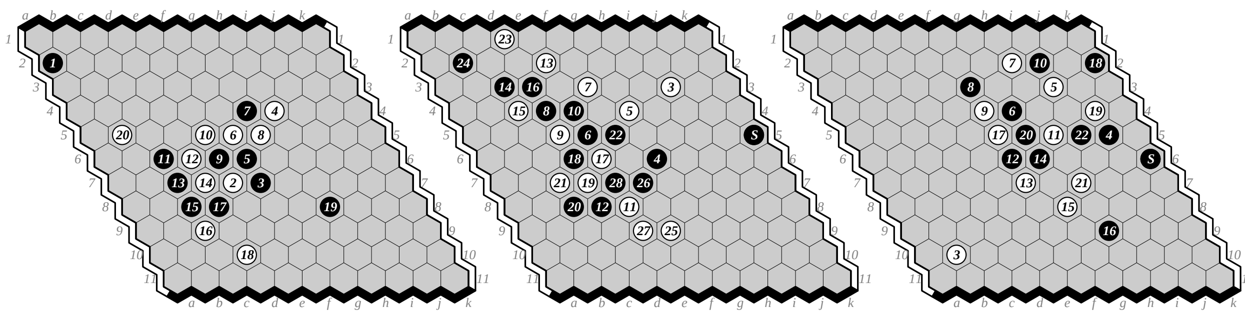

Figure 6: EZO-CNN-MOHEX Games 7-9. E-M 0-1. M-E 1-0 M-H 1-0

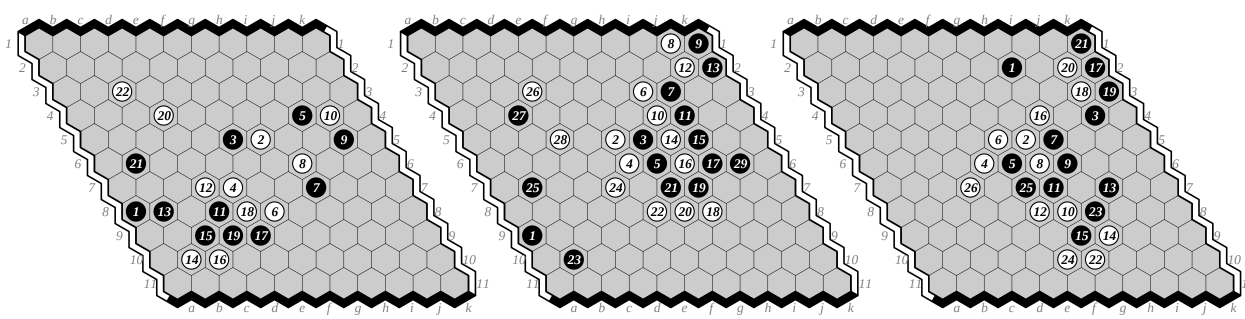

Figure 7: EZO-CNN-MOHEX Games 10-12. H-M 0-1. H-M 1-0 E-M 1-0

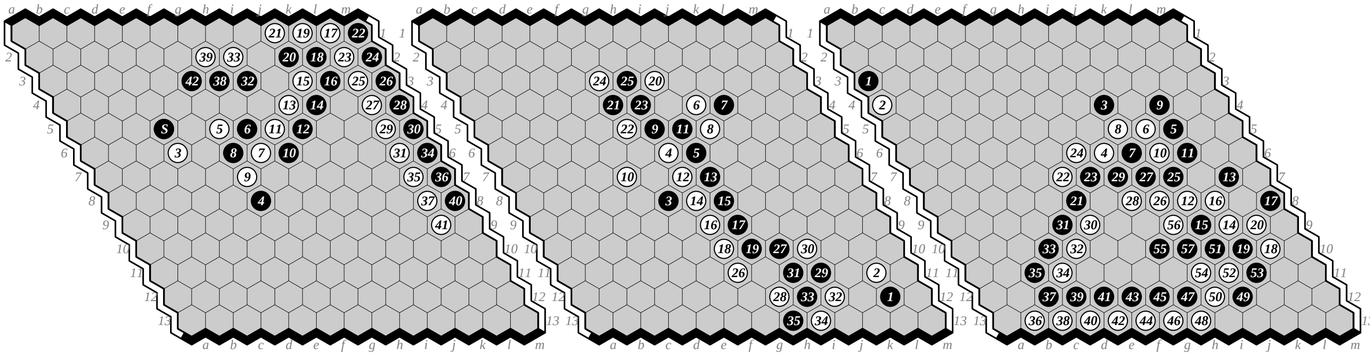

Figure 8: HEXCELLENT Games 1-3. M-H 0-1 H-M 1-0 E-H 1-0

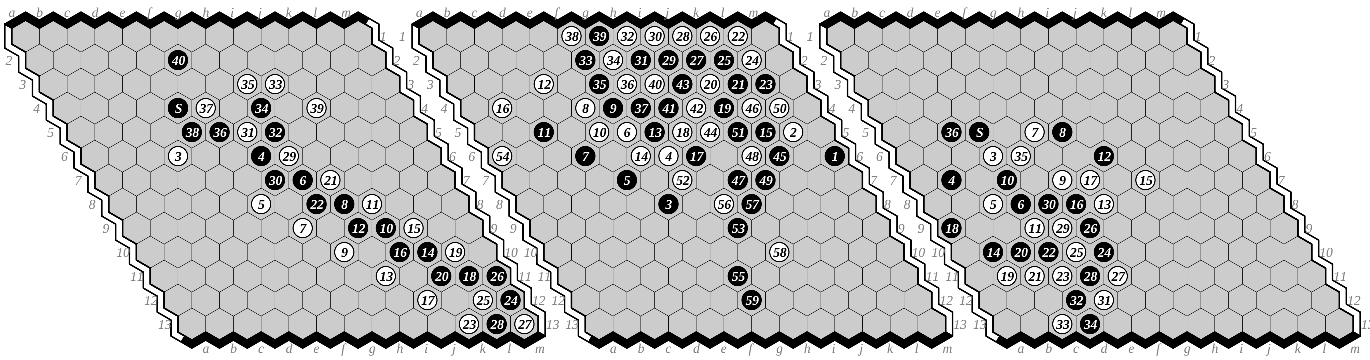

Figure 9: HEXCELLENT Games 4-6. H-E 0-1 E-H 0-1 H-E 1-0

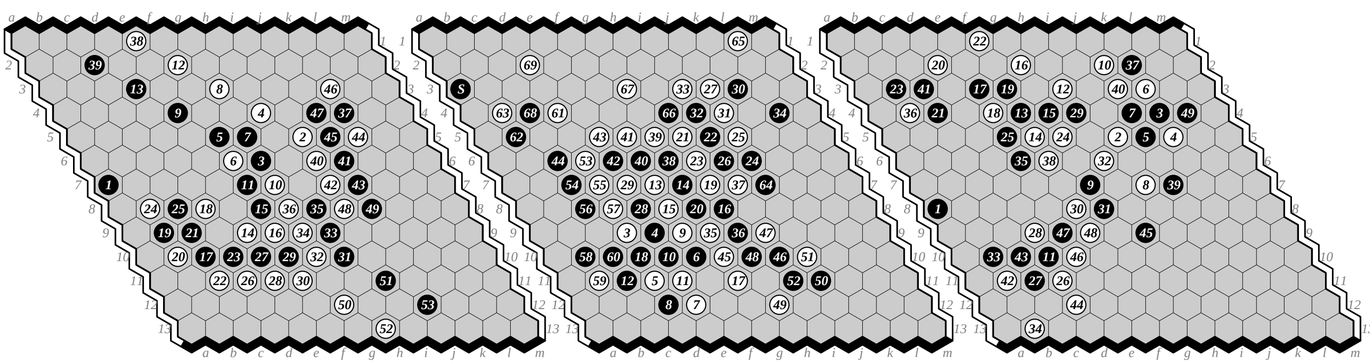

Figure 10: EZO-CNN-MOHEX-CNN Games 1-3. M-E 1-0 E-M 1-0 M-E 0-1

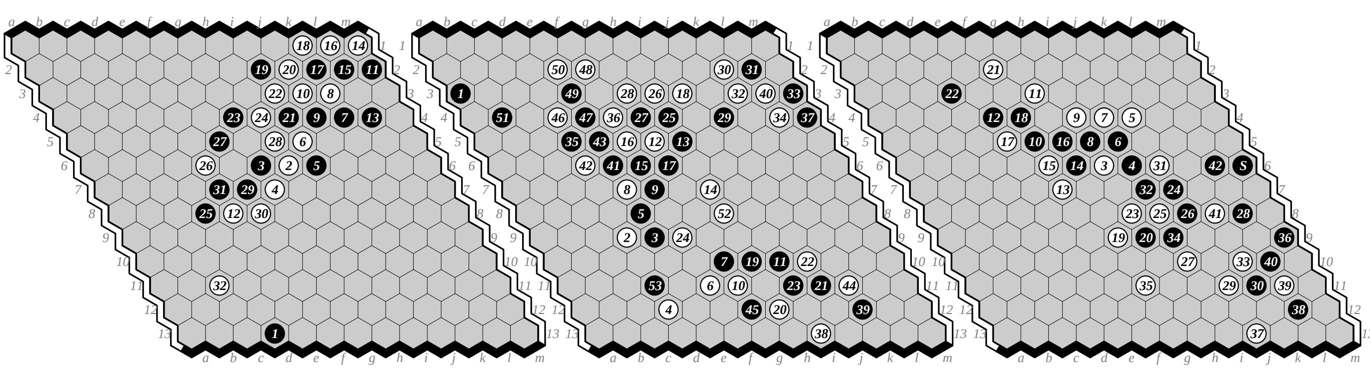

Figure 11: EZO-CNN-MOHEX-CNN Games 4-6 E-M 0-1 M-E 1-0 E-M 0-1

2. CONCLUSIONS

On 11×11 MOHEX and EZO seem evenly matched. MOHEX's search seems too narrow, especially near the opening. In positions where there are several good options, initial playout results often bias the final move selection, with the result that MOHEX can make bad moves early in the game. This is the primary purpose of MOHEX's book, to avoid bad early move selection, and played a role in the final playoff game, where EZO opened at H2.

Acknowledgements. We thank the NSERC Discovery Grant Program for research funding and Martin Müller for the loan of his machine Firecreek.

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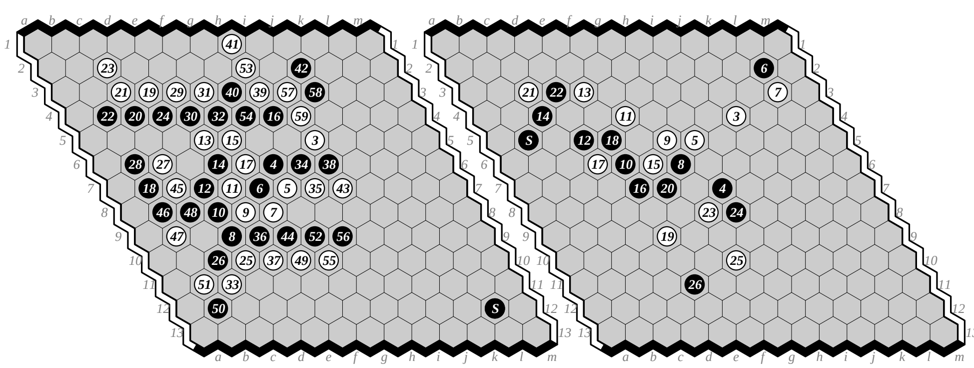

Figure 12: EZO-CNN-MOHEX-CNN Games 7-8. M-E 1-0 E-M 0-1