On Designing a Winning Agent for Reconnaissance Blind Chess (RBC)

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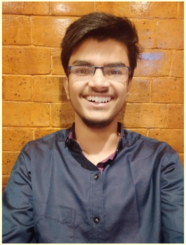
Contributors



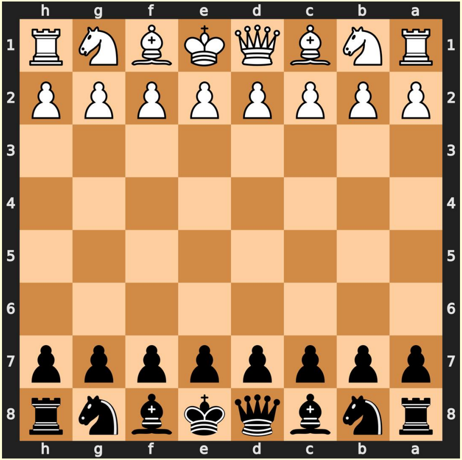
Mohammad Taufeeque

Nitish Tongia

Anvay Shah

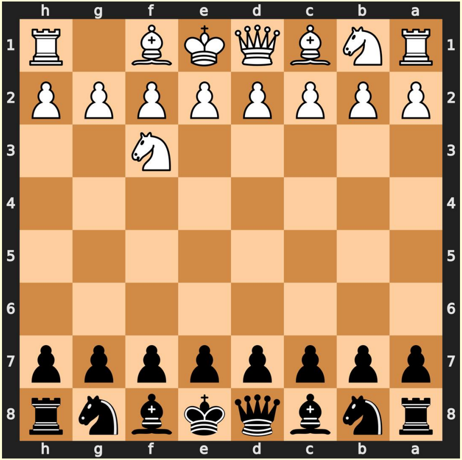
Puranjay Datta

Chess



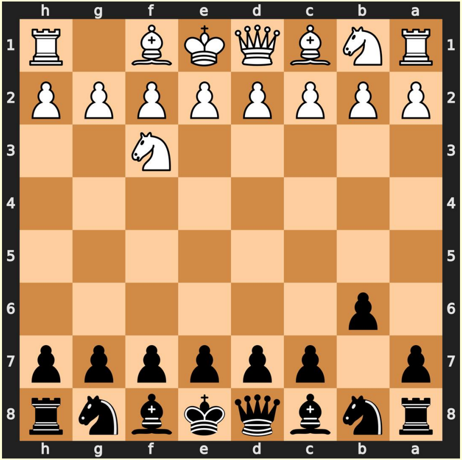
Starting position

Chess



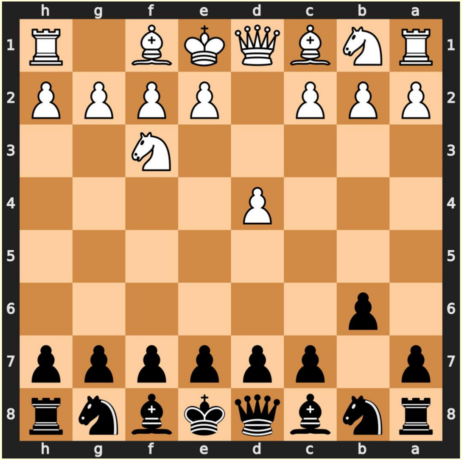
White plays g1f3

Chess



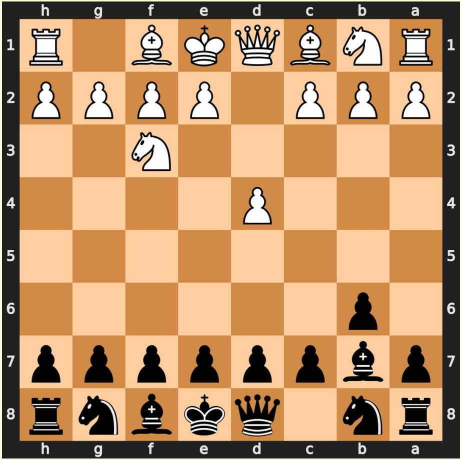
Black plays b7b6

Chess



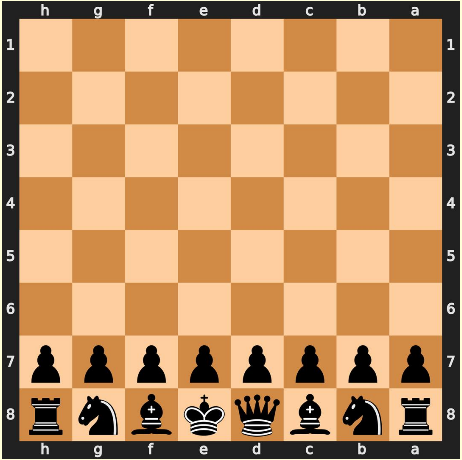
White plays d2d4

Chess



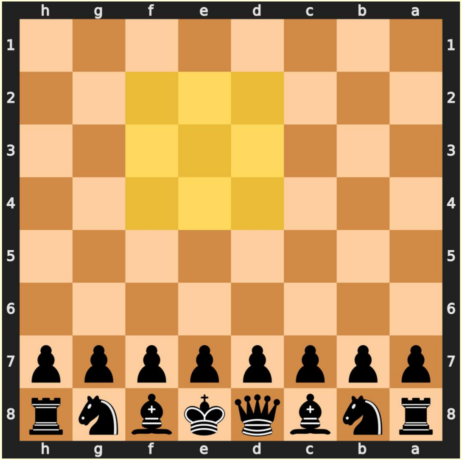
Black plays c8b7

RBC



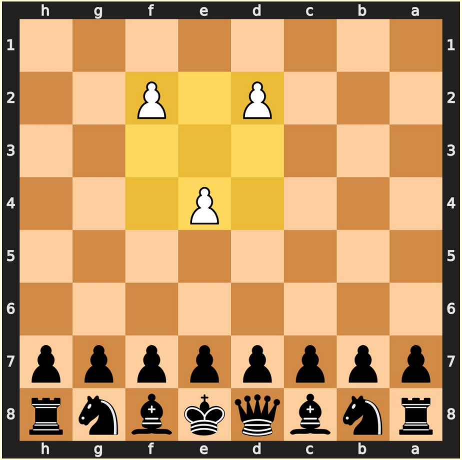
Starting position of RBC

RBC



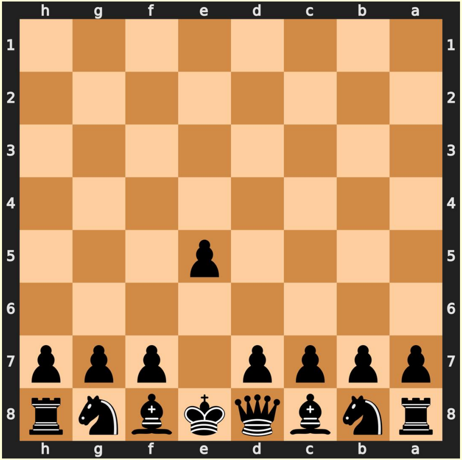
Black chooses sense region e3

RBC



Information gained from sense

RBC



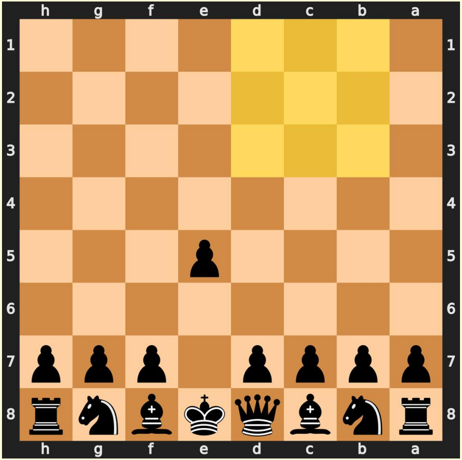
Black plays e7e5

RBC

Where should black sense next?

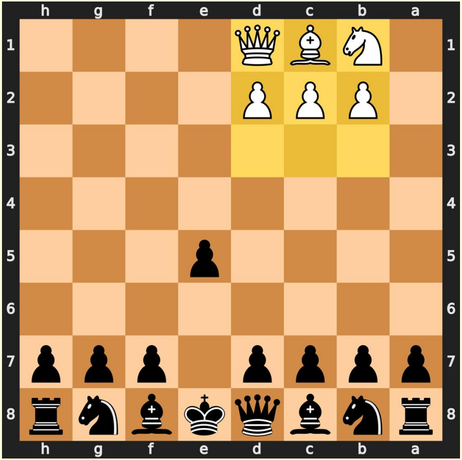
Given current *history*: sense e3, observe Pe4, move e7e5

RBC



Black chooses sense region c2

RBC



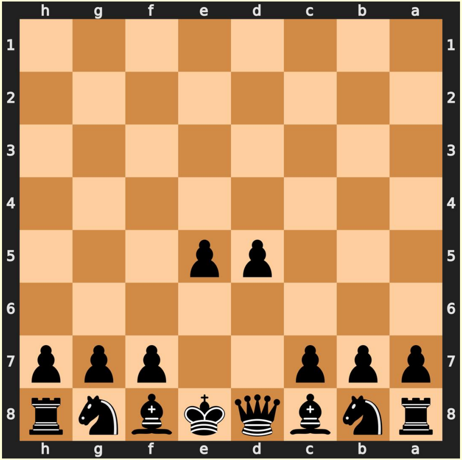
No new information gained from sense!

RBC

Where should black move next?

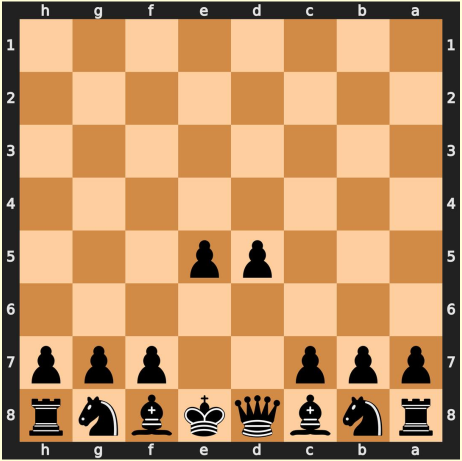
Given current history: sense e3, observe Pe4, move e7e5, sense c2, observe no new information

RBC



Black plays d7d5

RBC



Black plays d7d5

Game proceeds similarly. Additional RBC details: captures, null moves.

Outline

1. Challenges of RBC
2. Baseline agent: StrangeFish
3. Our agent: Fianchetto
4. Competition results and analysis
5. Conclusion

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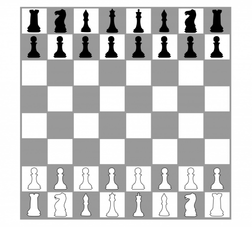
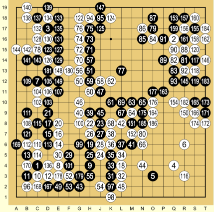
Board Games and AI



Chess (CHH02) [1]

Backgammon (T94) [2]



Lee Sedol (B) vs AlphaGo (W) - Game 1

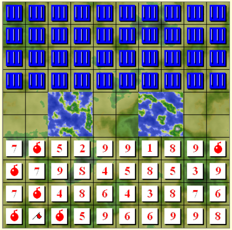
Go (S+16) [3]

[1] `https://www.publicdomainpictures.net/en/view-image.php?image=55671&picture=backgammon`
[2] `https://www.publicdomainpictures.net/pictures/80000/velka/chess-board-and-pieces.jpg`.
[3] `https://upload.wikimedia.org/wikipedia/commons/thumb/5/56/Lee_Sedol_%28B%29_vs_AlphaGo_%28W%29_-_Game_1.svg/734px-Lee_Sedol_%28B%29_vs_AlphaGo_%28W%29_-_Game_1.svg.png`. CC image courtesy of Wesalius on WikiMedia Commons licensed under CC-BY-SA-4.0.

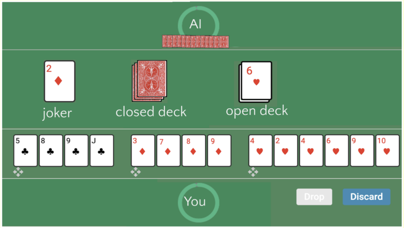
Games of Imperfect Information

Scrabble (S02) [1]

Poker (M+17,BS19) [2]



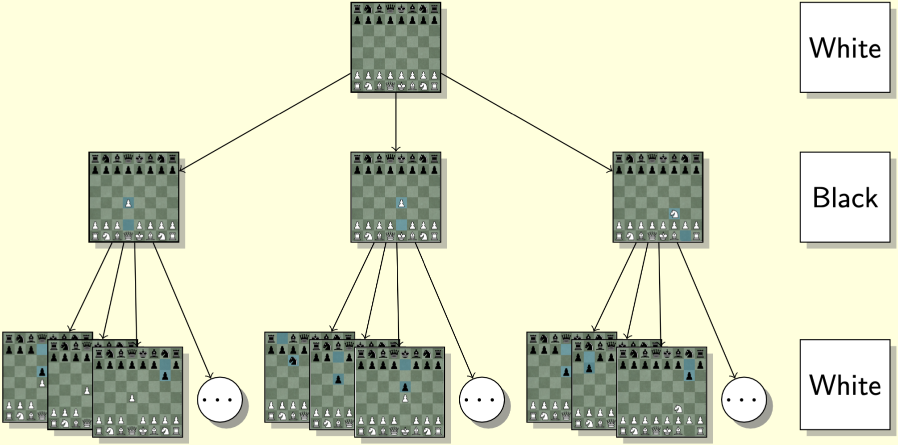
Stratego (P+22) [3]



Rummy

[1] `https://www.publicdomainpictures.net/en/free-download.php?image=scrabble-board&id=53283`.
[2] `https://www.publicdomainpictures.net/en/free-download.php?image=poker&id=84950`
[3] `https://upload.wikimedia.org/wikipedia/commons/0/05/Stratego.png`. CC image courtesy of Andreas Kaufmann on WikiMedia Commons licensed under CC-BY-SA-3.0.

Challenge: States → Information sets



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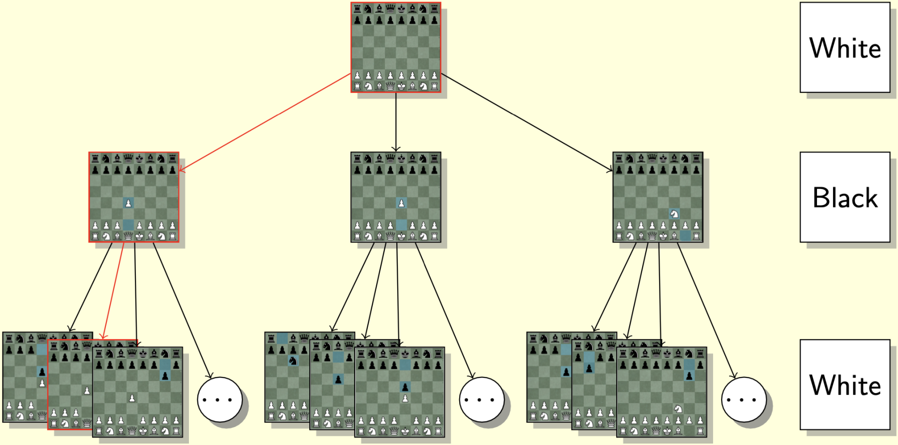

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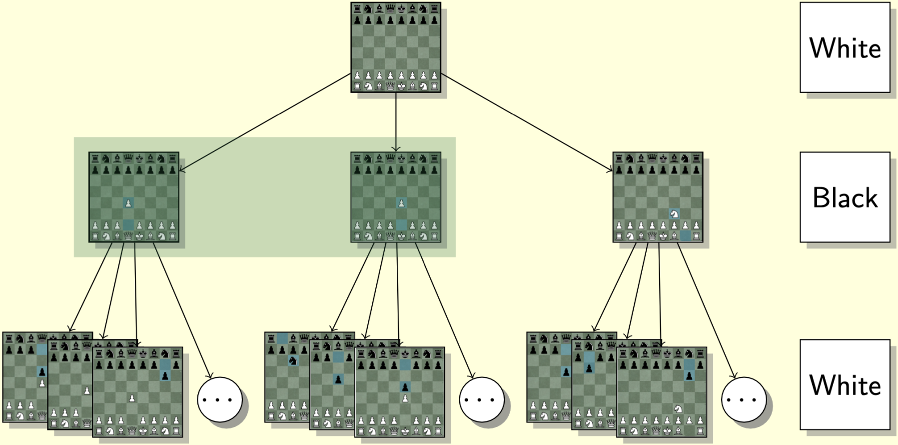

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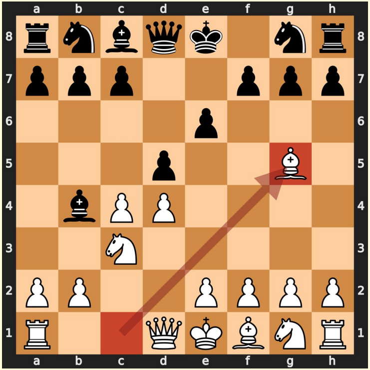
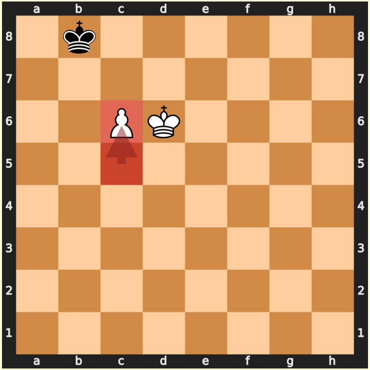
- But Chess is so well-understood. Does that help?

RBC: Like Chess and also Unlike Chess



Potentially successful move in RBC, bad in Chess.



Good move in Chess, bad in RBC.

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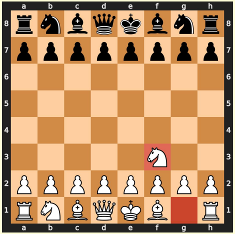
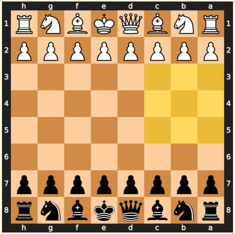
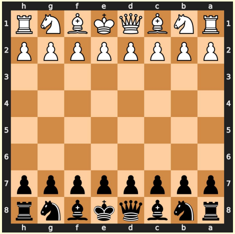
Primitive: Maintaining a Board Set B



Before sense: $|B| = 21$



Sense action



After sense: $|B| = 13$

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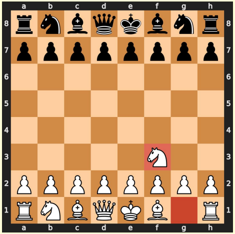

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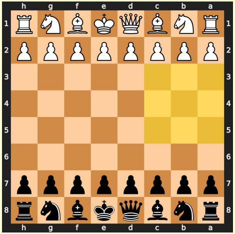

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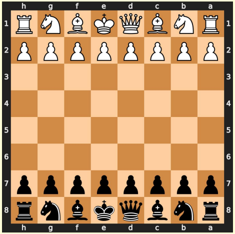

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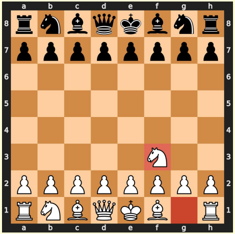

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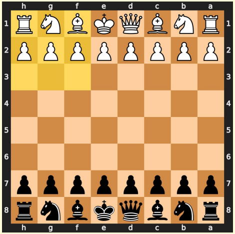

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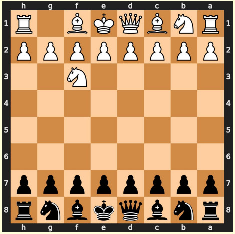
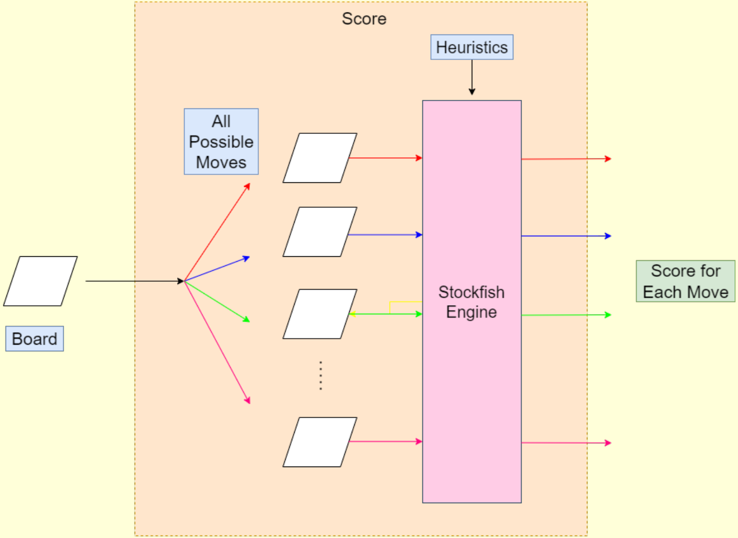


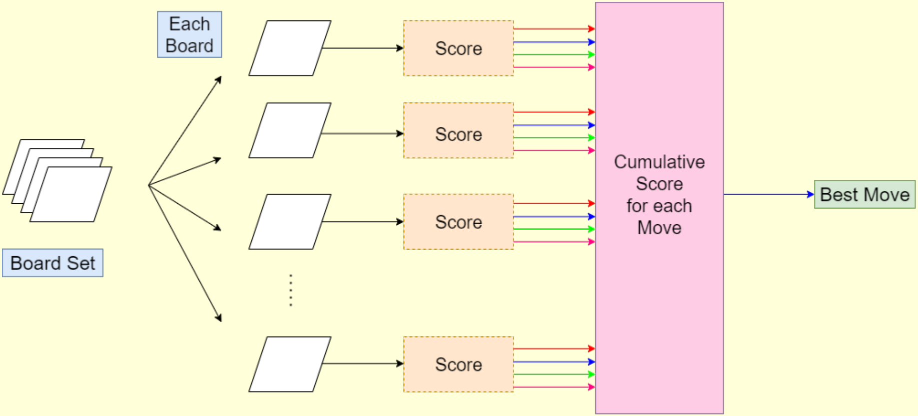
After sense: $|B| = 1$

StrangeFish 2019 Baseline



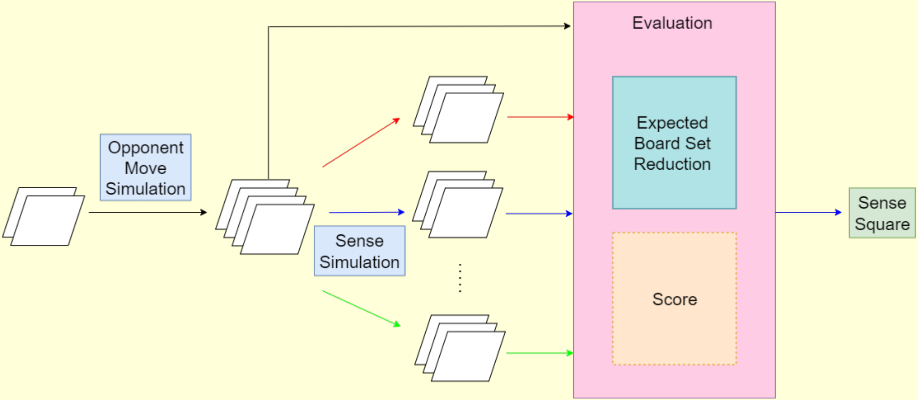
Score function takes a single board as input and provides the score for each move on this board.

StrangeFish 2019



Moving strategy: choose the move that maximises an aggregate score combining (weighted) mean, min, and max scores over *B*.

StrangeFish 2019

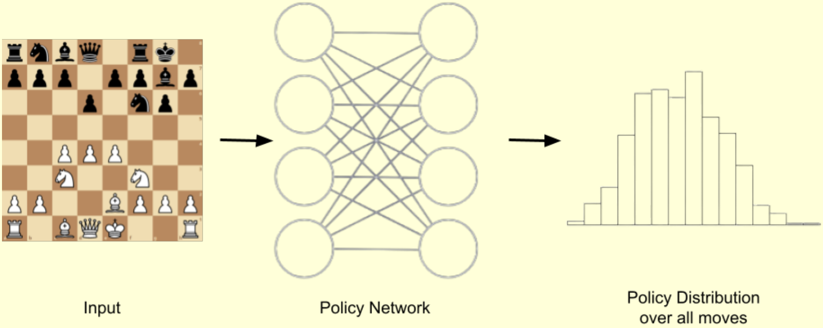


Sensing strategy: choose a sense square to maximise a combination of board set reduction and potential change in value.

Outline

Fianchetto v1: Using LC0 instead of Stockfish

- Leela Chess Zero (LC0) (PL21) neural network instead of StockFish (RCK21) for faster evaluation.



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- Achieves $\approx$ 30x speedup of no. of boards evaluated/sec through batching

	Time per engine call (s)	Effective no. of boards evaluated / s	
		Without batching	With batching
Stockfish	0.005	200	3200 (16 Threads)
Lc0 (1GB GPU)	0.321	93	95232 (batch size = 1024)

Table: Comparison of throughput of Stockfish and Lc0, performed on a desktop machine with Intel Core i5-4690 CPU@3.50GHz and Nvidia GeForce GTX 980 GPU.

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- Risk of overfitting to Chess!

	Small n/w	Medium n/w	Large n/w
Chess Rating	1416	1453	1572
RBC Rating	1248	1502	1350

Table: Comparison of ratings of different-sized Lc0 networks.

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- Belief state b is a weight/probability distribution over S.
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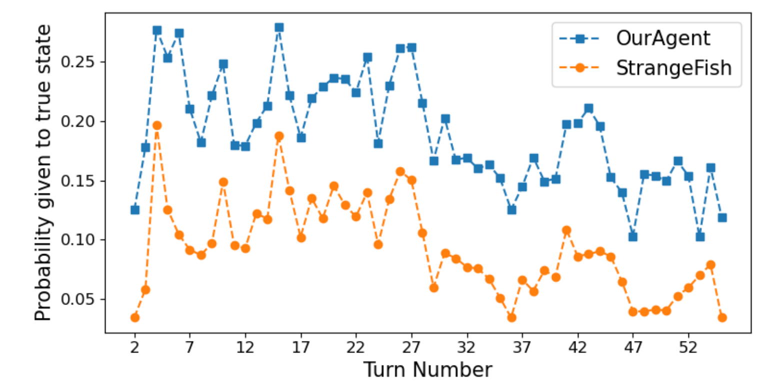
We assume the opponent plays according to LC0!

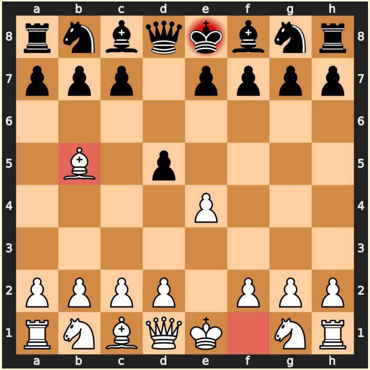
Fianchetto v2: Persistent Board Belief



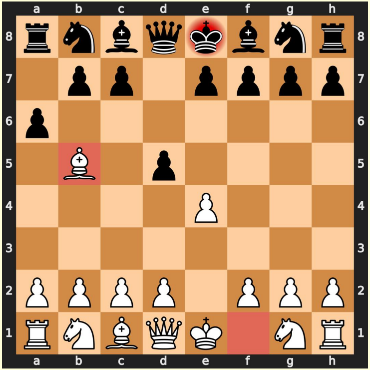
Probability associated with true state by Fianchetto (v2) and StrangeFish

Fianchetto v3: RBC-Specific Incentives

- Supplement LC0 evaluation to promote RBC-specific “sneak attacks”.



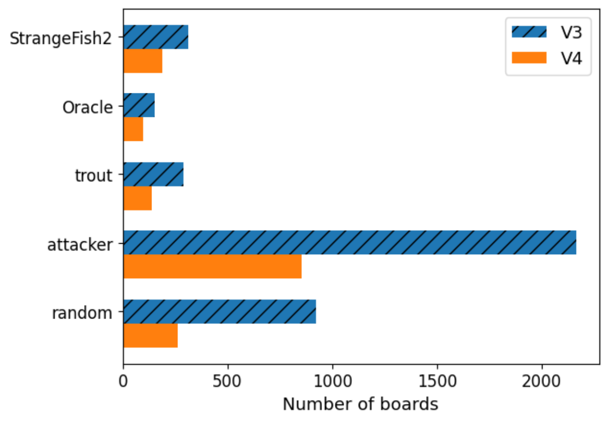
Low risk, large incentive.



High risk, small incentive.

Fianchetto v4: Board Set Size

- Add dynamically weighted uniform dist. to opponent's move probabilities.
- Adjust weightage of expected board set reduction in sense strategy.



Average information set size in games played on the RBC server.

Outline

NeurIPS 2021 Tournament

- Round robin tournament between 18 bots
- Pairwise 60 games (equally split as black and white)
- Positive winning record of atleast 66% against every other bot in the tournament
- Dominant performance with overall win ratio above 90%

`Fianchetto` (1759)	Score
`StrangeFish2` (1662)	41-19
`penumbra` (1584)	40-20
`Kevin` (1544)	40-20
`Oracle` (1503)	51-9
`Gnash` (1454)	49-11
`Marmot` (1315)	56-4
`DynamicEntropy` (1299)	59-1
`wbernar5` (1219)	58-2
`Frampt` (1208)	59-1
`GarrisonNRL` (1140)	59-1
`trout` (1127)	59-1
`callumcanavan` (1066)	60-0
`attacker` (1049)	60-0
`URChIn` (854)	60-0
`armandli` (777)	60-0
`random` (753)	60-0
`ai_games_cvi` (288)	60-0
Overall	**931-89**

Table: NeurIPS 2021 RBC Tournament results

Intermediate Versions (evaluated post-competition)

Version	V0	SF2	Or	tr	att	ran	Overall
V0	30-30	16-44	39-21	57-3	56-4	60-0	258-102
V1	24-36	13-47	36-24	58-2	50-10	59-1	240-120
V2	39-21	35-25	46-14	59-1	58-2	60-0	297-63
V3	48-12	32-28	47-13	59-1	58-2	59-1	303-57
V4	48-12	35-25	47-13	59-1	60-0	60-0	309-51

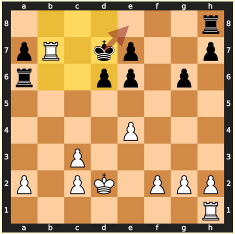
Table: Win-loss scores from a 60-game match between row agent and column agent. V0 is the same as StrangeFish; its row is populated using its last 60 games in a specified window in November-December 2021 on the RBC server. The column for V0 is obtained locally, whereas all other columns (SF2 = `StrangeFish2`, Or = `Oracle`, tr = `trout`, att = `attacker`, ran = `random`) are obtained from games played on the server.

NeurIPS 2022 Tournament

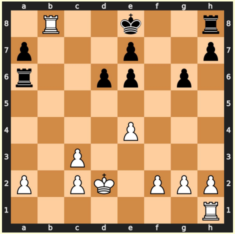
StrangeFish2 (1762)	21-34-5
Fianchetto (1644)	Score
Kevin (1623)	31-0-29
Chateaux (1621)	18-0-42
ROOKie (1551)	37-18-5
Oracle (1465)	49-9-2
Marmot (1329)	52-0-8
JKU-CODA (1283)	51-0-9
DynamicEntropy (1194)	58-0-2
SomeRegret (1184)	55-0-5
trout (1116)	60-0-0
attacker (1099)	59-0-1
GarrisonNRL (1039)	57-0-3
ucchess (1025)	49-8-3
random (893)	60-0-0
arandombot (598)	60-0-0
srcork (590)	60-0-0
uccch (581)	60-0-0
Overall	**837-168-15**

Table: NeurIPS 2022 RBC Tournament results

Blunders!



Played Move



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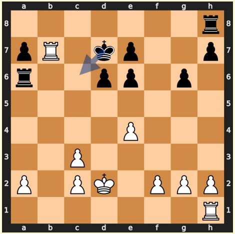
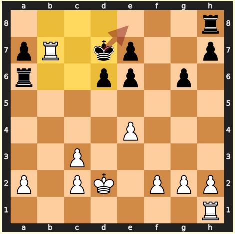


Best Move

Blunders!



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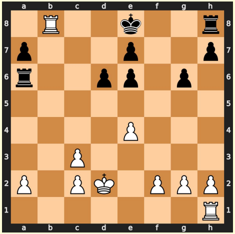

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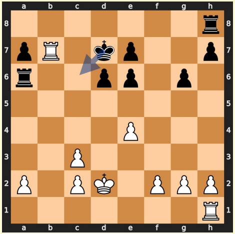

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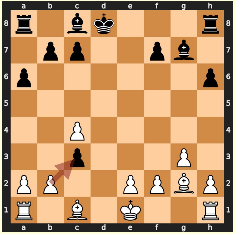

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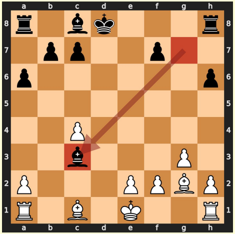

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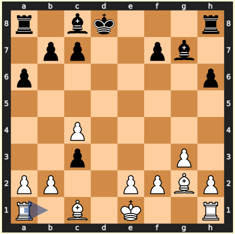

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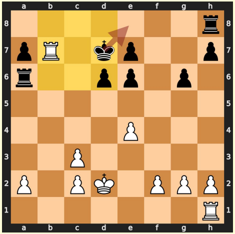

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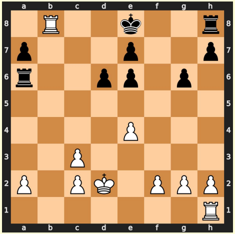

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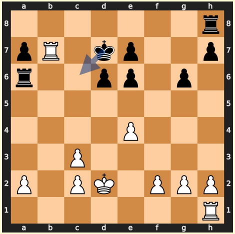

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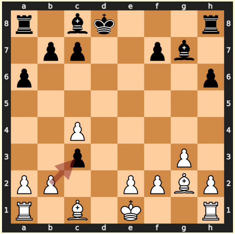

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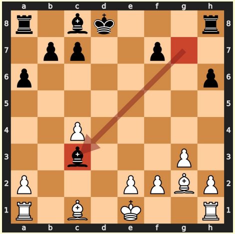

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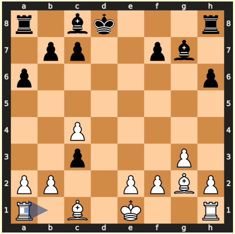
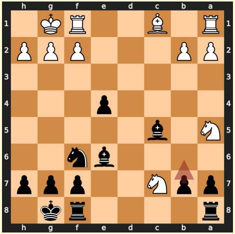


Best Move

Our LC0 evaluation misled us in these cases. But why didn't it in 2021?

Blunders Happened in 2021, Too!



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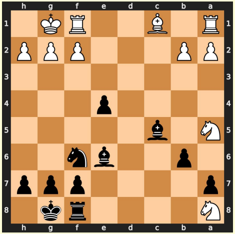

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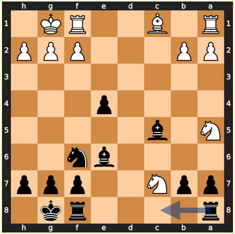

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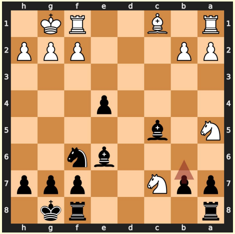

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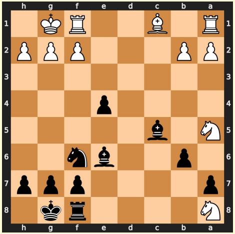

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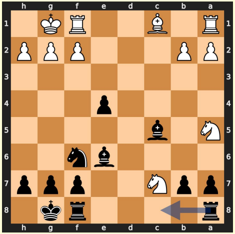

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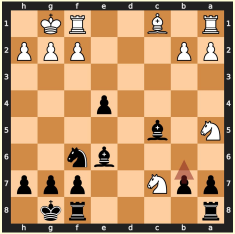

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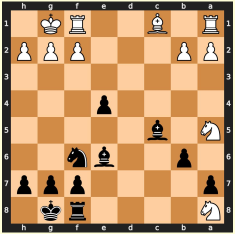

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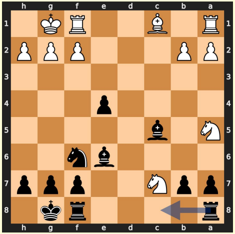

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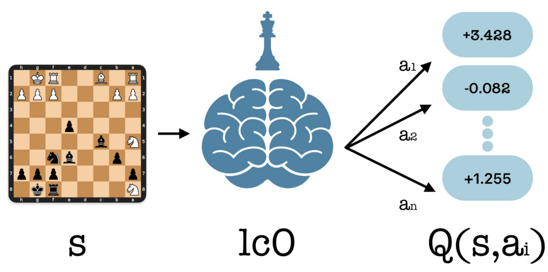
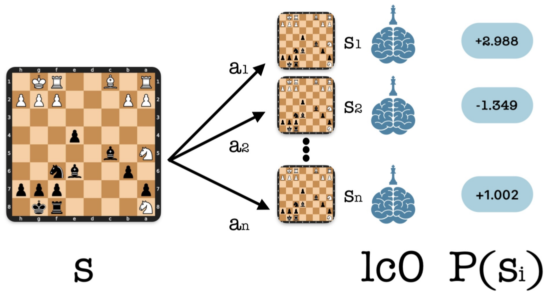
Fix: Next-state Evaluation for Top Few Actions





Fianchetto Updated vs. StrangeFish2

Agents	Win	Draw	Loss
Fianchetto (old) vs. StrangeFish2	248	25	227
Fianchetto (updated) vs. StrangeFish2	300	28	172

Table: Performance of (2022) competition version and updated version of Fianchetto against StrangeFish2 (released after 2022 competition) over 500 games.

Outline

1. Challenges of RBC
2. Baseline agent: StrangeFish
3. Our agent: Fianchetto
4. Competition results and analysis
5. Conclusion

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30 / 31

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Thank you!

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