Teaching AI to Play Chess Like People

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Computer Science Senior Seminar
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“If you program a machine, you know what it’s capable of. If the machine is programming itself, who knows what it might do?”

— Garry Kasparov, Deep Thinking: Where Machine Intelligence Ends and Human Creativity Begins

- Computer’s have fundamentally changed chess
- Computers can serve a different purpose

Outline

- Background
- AlphaZero
- Maia
  - Development
  - Results
  - Comparison
- Application
- Conclusion
Background: Chess Terminology

- Elo rating
- Blunder
- Time Control

https://ratings.fide.com/profile/1503014
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https://upload.wikimedia.org/wikipedia/commons/d/d3/Schachuhr_mechanisch.jpg
Background: Deep Learning

- **Machine Learning**
  - “The hierarchy of concepts enables the computer to learn complicated concepts by building them out of simpler ones. If we draw a graph showing how these concepts are built on top of each other, the graph is deep, with many layers. For this reason, we call this approach to AI deep learning.”
  
    - *Deep Learning*, by Ian Goodfellow, Yoshua Bengio and Aaron Courville

- **Deep Learning** is allowing computers to learn from experience

- **Reinforcement learning**

[Diagram of a neural network]
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![Reinforcement Learning Diagram](https://miro.medium.com/max/478/1*QVsnwatDVz8wcqJUsLJejw.png)
Background: Monte Carlo Tree Search (MCTS)

- MCTS is a tree search that also implements machine learning principles of reinforcement learning
- 4 primary steps
  - Simulation

[Diagram of MCTS process]

[3]
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Background: Chess Engines

● **Software that is used to generate and analyse positions**

● **Stockfish**
  ○ More traditional chess engine
  ○ 3564

● **AlphaZero and Leela**
  ○ Deep Learning
  ○ Monte Carlo Tree Search
  ○ 3463
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https://stockfishchess.org/
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https://lczero.org/blog/
AlphaZero
AlphaZero: Architecture

- **Inputs**
- **Output**
  - Probabilities
  - Expected outcome
  - Values
- **Parameters**
- **Obtaining Outputs**
  - Reinforcement through self play
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  - Leela was also able to defeat the same version of StockFish
- Strategies Learned by AlphaZero
  - Common human strategies
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Maia: Development

- The Goal of Maia is to play the most like a human
- Maia utilizes a large amount of code from Leela
- Data Sets
- Move Prediction
- Models of Maia
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- Overall results should an accuracy around 50%
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- Everyone plays Chess differently; Maia is the average player for an ELO range
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  - Median Elo Rating 1500
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  - Harvard two-player Atari study
  - Through Deep Learning were able to produce AI that helped improve human performance
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Conclusion

- Maia shows it possible to capture the play style of people
- Development of more human like chess engines could lead to better training for people
Questions
Sources


