Creating a Deployable Human-Like Chess Engine to Enhance the Learning Experience

Ethan Gee & Nate Stott

Agenda

1. Introduction & Motivation
2. Methodology
3. Experiments
4. Conclusions & Future Work

Introduction - Problem Definition

Maia Problems

- Traditional chess engines maximize the chances of winning
- Predicting a move a human would play does not mean finding the best move
- **Goal**: Replicate human play

Rylee Problems

- Maia requires **large GPUs** to run and train
- Maia can only run on high end machines
- Maia was not trained to play chess openings
- **Goal**: Make a **practical & deployable** version of Maia

Introduction - Motivation

Why human aligned AI matters

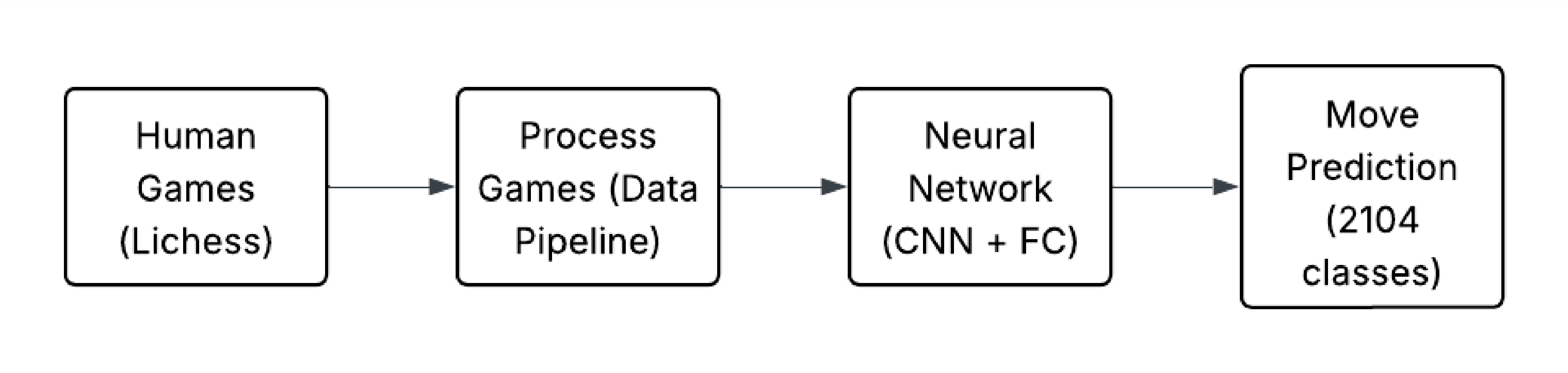
- Traditional engines play chess differently making it difficult for humans to learn from
- Attenuating does not **mimic human play**
- Human aligned engines creates more realistic **training partners**
- Example: Chess students can practice with Rylee on their school chromebook to advance their chess skills
- Broader applications: Collaborative decision-making, Education, etc

How Rylee extends Maia

- **Edge deployment** Raspberry Pi, Chromebooks
- **Includes openings** first 10 moves
- **No game filtering** include all game types (classical, blitz, etc)
- **Unified model with a higher range** 700-2500 ELO

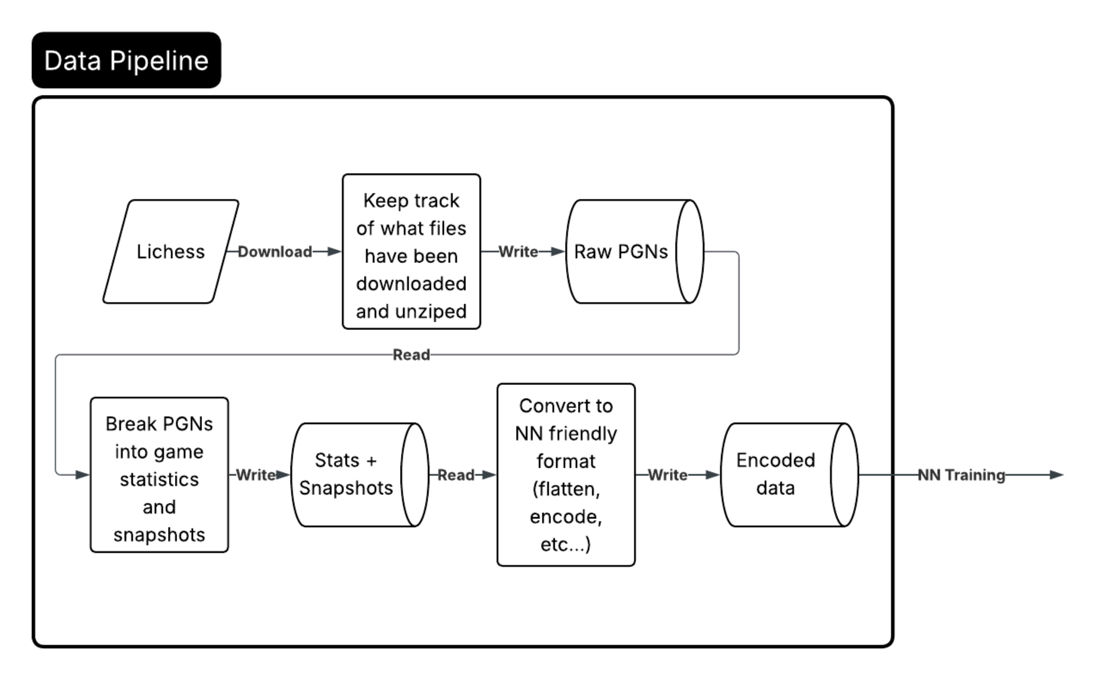
Methodology - Proposed Solution

> *We hypothesizes we can maintain similar performance, and add features to the Maia model while significantly reducing model size.*



1. Pull data from Lichess
2. Preprocess games
3. Feed data into NN
4. Predict moves

Methodology - Data Pipeline



- **Download** .zst files from Lichess
- **Extract** PGNs
- **Split** into individual games
- **Convert** to board snapshots
- **Extract** ELO and result metadata
- **Encode** board as 8x8x12 tensors

Methodology - Theories

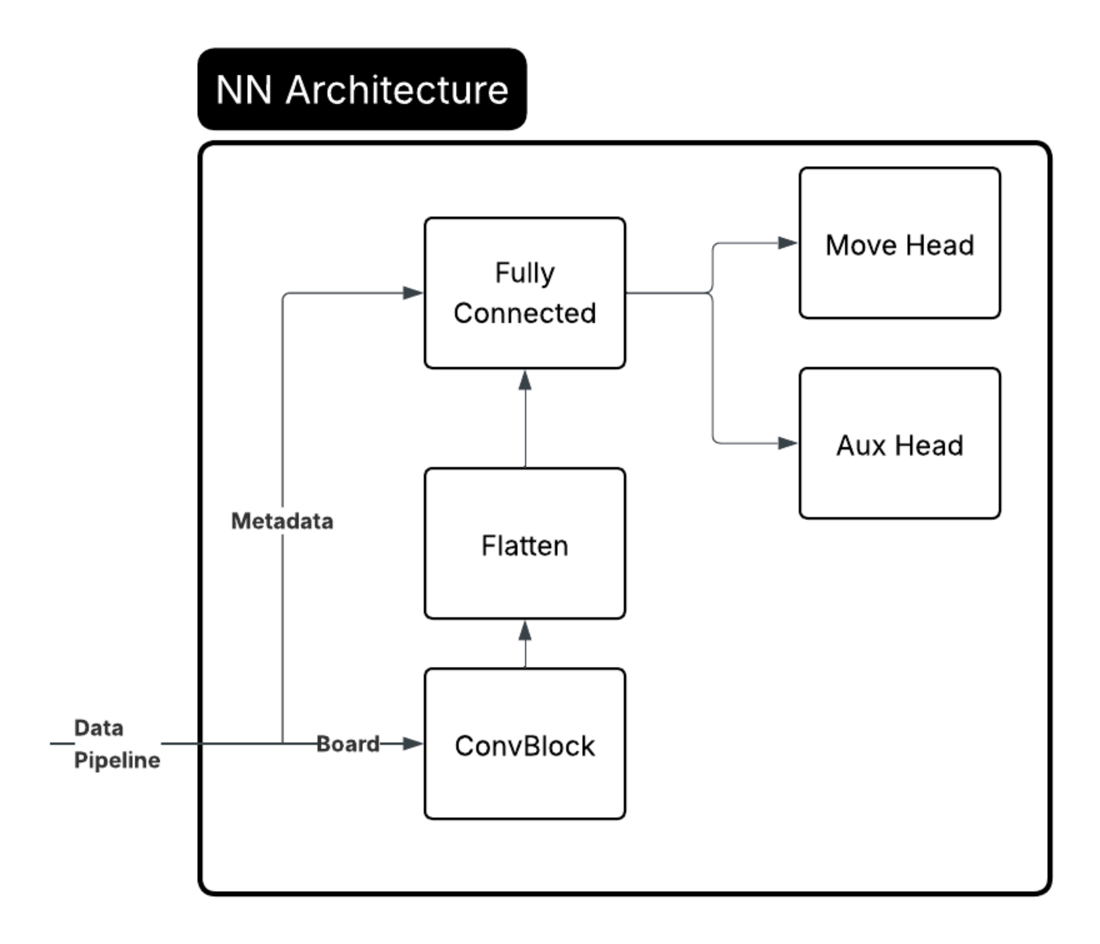
Why CNNs work well for chess

- Chess boards are **spatially related** (knight is better if its in the middle)
- Humans evaluate through pattern recognition
- CNNs excel at **spatial pattern recognition**

Model size vs performance

- Increasing model size has exponentially diminishing returns
- We are hoping we can decrease the size of the Maia model while still keeping high accuracy

Methodology - Neural Network



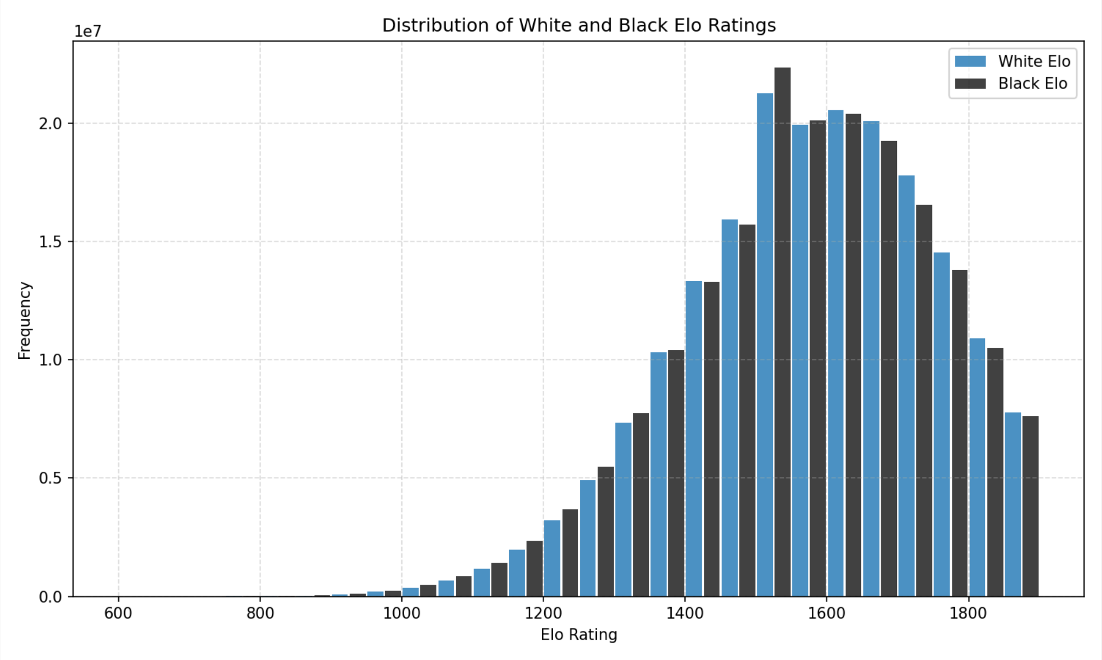
- **Input**: Board(8x8x12) + Metadata(4)

- **Conv Layers**: 6 64x8x8 filters, ReLU
- **Fully Connected**: 4100 -> 512 -> 32
- **Output Heads**: Move (2104) + Auxiliary (2104)
  - Move Head = predicted chess move
  - Aux Head = predicted legal chess moves
  - 2104 is the number of legal moves
- **Loss**: CrossEntropy (moves) + BCE (valid moves)
- **Optimizer**: Adam
- **Hyperparameter Search**: Random search

Experiments - Dataset

- **Source:** Lichess Open Database
- **Games:** 15,167 human-rated games
- **Snapshots:** 1 million board states
  - including openings
  - including all game types
- **Action Space:** 2,104 legal move classes
- **Time Span:** January 2013
- **Expanded Capabilities:** Covering 5x the amount of data

Split	Percentage	Snapshots
Training	80%	**800,000**
Validation	10%	**100,000**
Test	10%	**100,000**



Experiments - Baselines

Baseline Model	Description
Random	Random legal move selection
Random Forest	Nothing that simple should work that well - Ethan Gee
Stockfish 15	Traditional chess engine
Leela 4200	Neural chess engine
Maia-1 1500	Human aligned prediction model

Experiments - Architecture

Small Fully Connected Model

- A Small model that had a similar architecture to StockFish
- 8 fully connected layers of 32 neurons

Convolutional Model

- Combination of Convolution and fully connected to mirror human cognition

Convolution with Auxillary Head

- Added an auxillary head that determines legal moves to instill better game understanding

Experiments - Evaluation Metrics

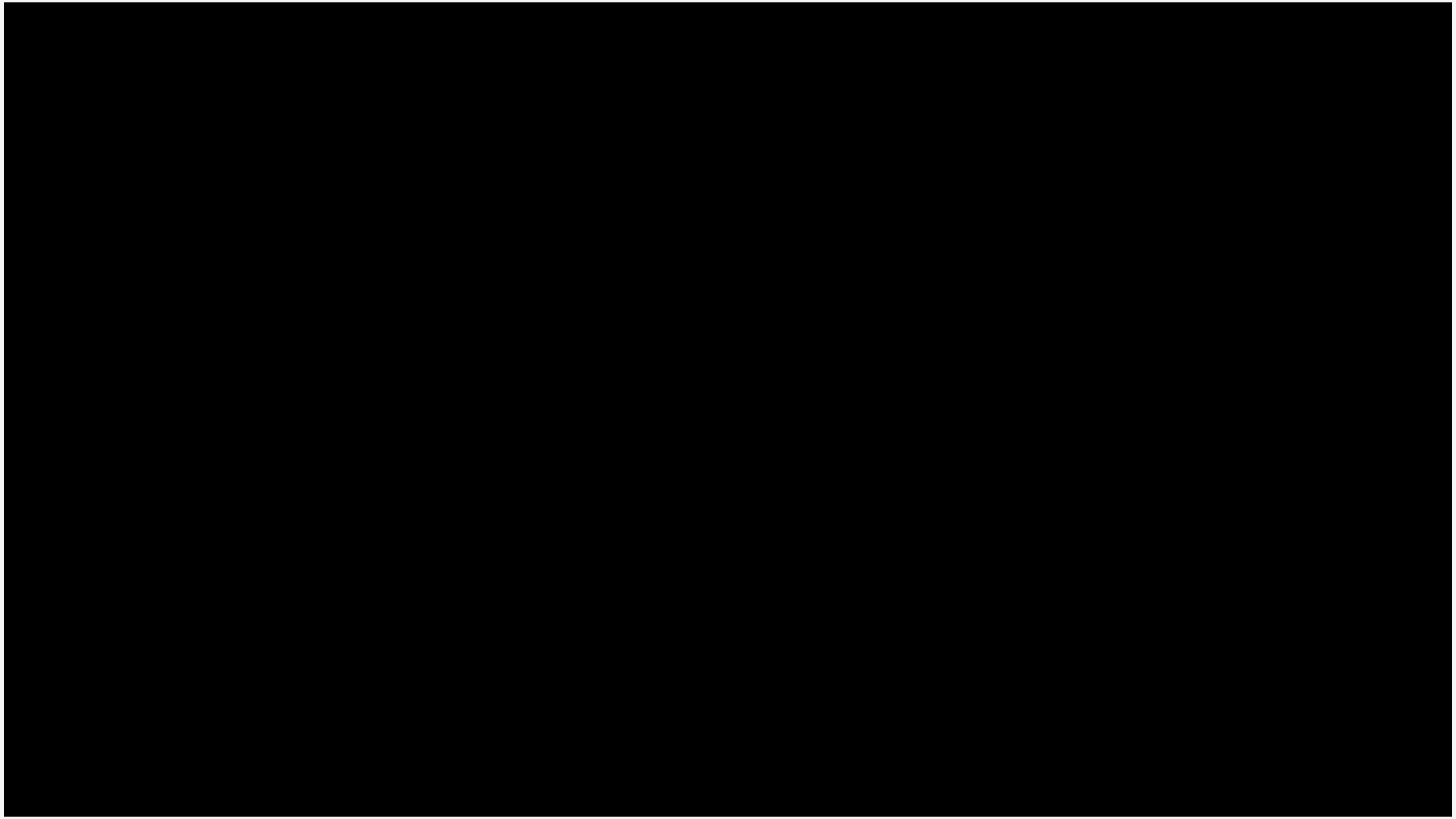
- **Top-1 Accuracy**: Predicted move matches actual human move
- **Top-5 Accuracy**: Actual move in top 5 predictions. This is a good for a more generalized alignment.

Experiments - Comparisons

Method	Top-1 Accuracy
Random	6%
Random Forest	13%
Stockfish 15	40%
Leela 4200	44%
Maia1 1500	51%
Rylee FC	3.5%
Rylee Conv	23.5%
Rylee Conv with Aux	25%
Rylee Conv with Aux Filtered	35%

- Rylee has 800,000 parameters vs Maia's 25 Million
- No filtering by game type (classical, blitz, etc) to capture broader human play patterns
- We include games with mixed skill levels to better reflect general human behavior
- 15,000 games vs. Maia’s 169 million games
- Maia was Trained on two A100 80Gb GPUs vs Rylee being trained on a Edge Device

Experiments - Deployment



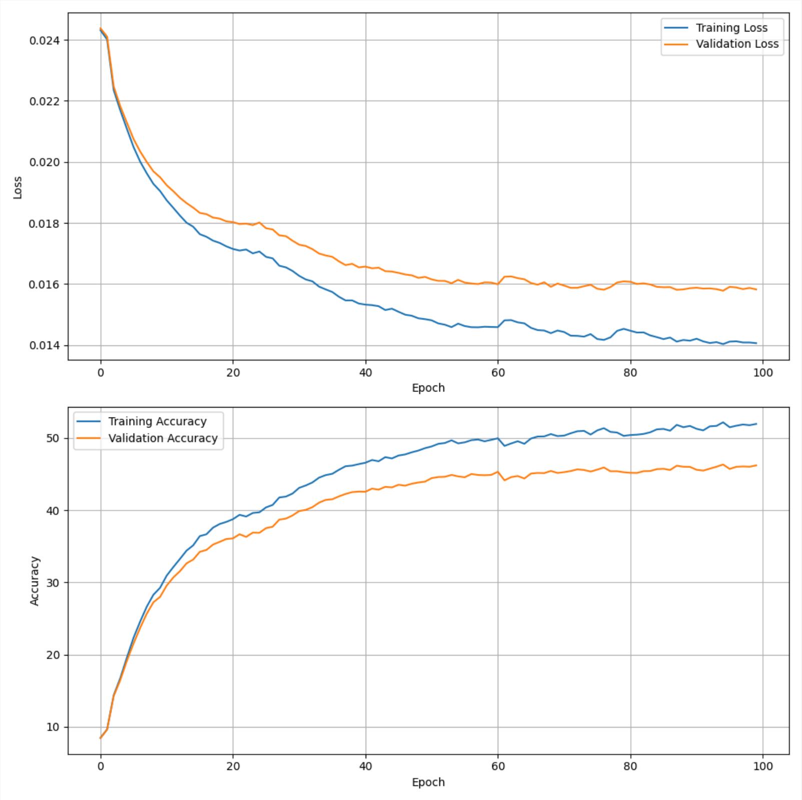
We have a tkinter gui. Here is it running on a crappy laptop. Black is Rylee and White is Stockfish.

Conclusions - Discussions

Metric	Training	Validation
Loss	0.0152	0.0164
Top-1 Accuracy	27%	25%
Top-5 Accuracy	53%	51%
Top-1 Accuracy Filtered	36%	35%
Top-5 Accuracy Filtered	54%	53%

- Strong generalization between training and validation metrics. Model captures key human decision-making patterns.
- Rylee required around 1.5 hours of preprocessing and 2-3 days of training

- Maia required 8 days of preprocessing and 3-4 weeks of training



Conclusions - Future Work

Model Improvements

- Add data augmentation (board flips and rotations) to improve robustness
- Time parameter to better address time based decision making
- Cross Validation
  - Maia was not able to do this because of the size of the dataset

Additional Features

- **ELO Prediction:** Estimate player rating from move patterns to quickly adapt to player skill
- **Human vs Bot Discriminator:** Detect engine-like play
- **Blunder Detection:** Identify major mistakes for analysis

Conclusions - Summary

- **Rylee mimics human chess behavior** using a model that is 30x smaller than Maia
- **Achieves competitive accuracy** (25-35% Top-1, 51-54% Top-5) despite using significantly less data, compute, and expanding capabilities, and data variety
- **Efficient data pipeline and compact architecture** make Rylee deployable edge devices such as Chromebooks and Raspberry Pis
- **Generalizes well** across training and validation datasets, indicating a healthy fitting of human chess playing patterns
- **Demonstrates the feasibility** of edge-deployable, human-aligned AI for education applications

References

Primary Works

- McIlroy-Young et al. (2020). "Aligning Superhuman AI with Human Behavior: Chess as a Model System." KDD 2020.
- Tang et al. (2024). "Maia-2: A Unified Model for Human-AI Alignment in Chess." NeurIPS 2024.
- McIlroy-Young et al. (2021). "Detecting Individual Decision-Making Style: Exploring Behavioral Stylometry in Chess." NeurIPS 2021.

Rylee Repo:
https://github.com/EthanDGee/ryleeeeeeeeeeeee

Data & Tools

- Lichess Open Database: https://database.lichess.org/
- Stockfish Chess Engine: https://stockfishchess.org/
- Leela Chess Zero: https://lczero.org/
- Maia Chess Project: https://maiachess.com/
- PyTorch (Paszke et al., 2019): https://pytorch.org/
- python-chess library (Moskopp, 2014): https://github.com/niklasf/python-chess

Terminology

- **ELO Rating** - Numeric chess player skill score used to represent player strength (500 beginner, 1500 intermediate, 2500 expert)
- **Board Snapshot** - A single chess board state (imagine taking a picture of the board every time a player makes a move, each of those pictures should be a board snapshot)
- **Action Space (2104 moves)** - Fixed index set representing all possible legal chess moves
- **Auxiliary Head** - Secondary output predicting legal moves to guide the main move head. Meant to strengthen legal move connections/predictions.
- **Opening Phase** - The first 10ish moves of the game
- **Blunder** - An objectively terrible chess move
- **Lichess Dataset** - Large open database of real human chess games
- **Human-Aligned Model** - Predicts human-like moves rather than optimal engine moves

Questions?

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