A Human-Like Chess Engine

Rylee

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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** and a **large model**
- 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

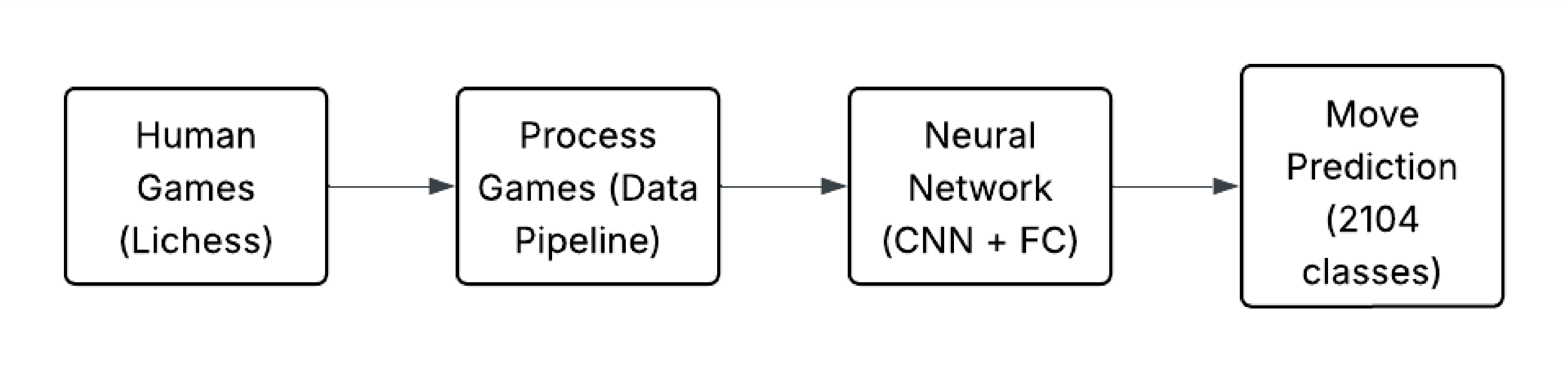
Why human aligned AI matters

- 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



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

Methodology - Theories

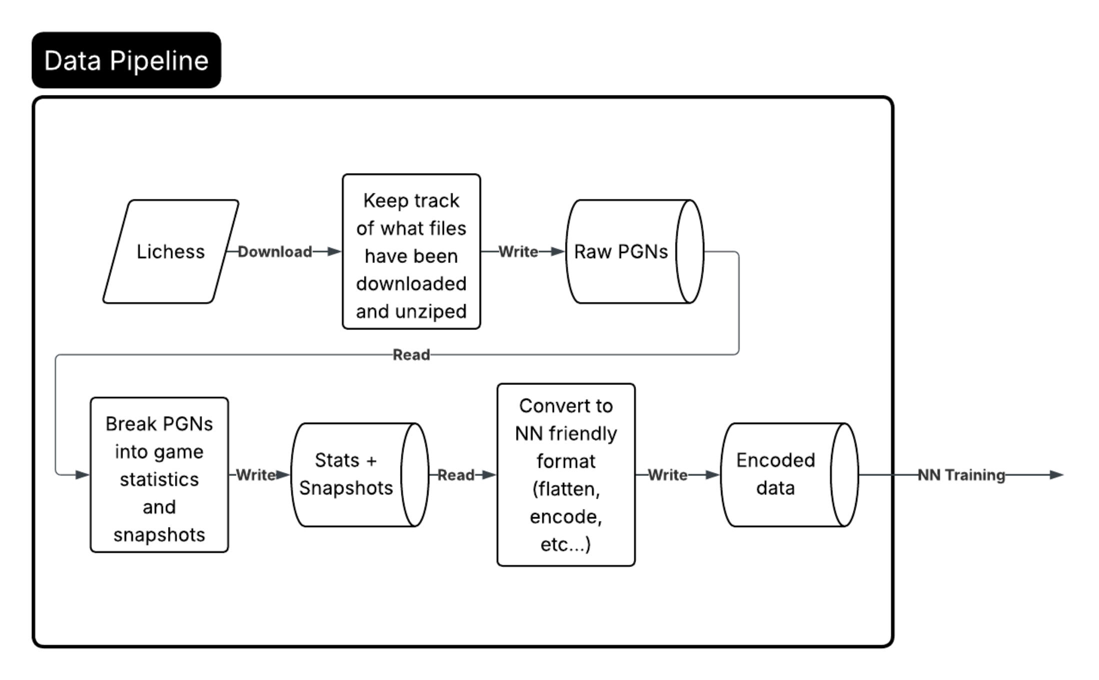
Why CNNs work well for chess

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

Model size vs performance

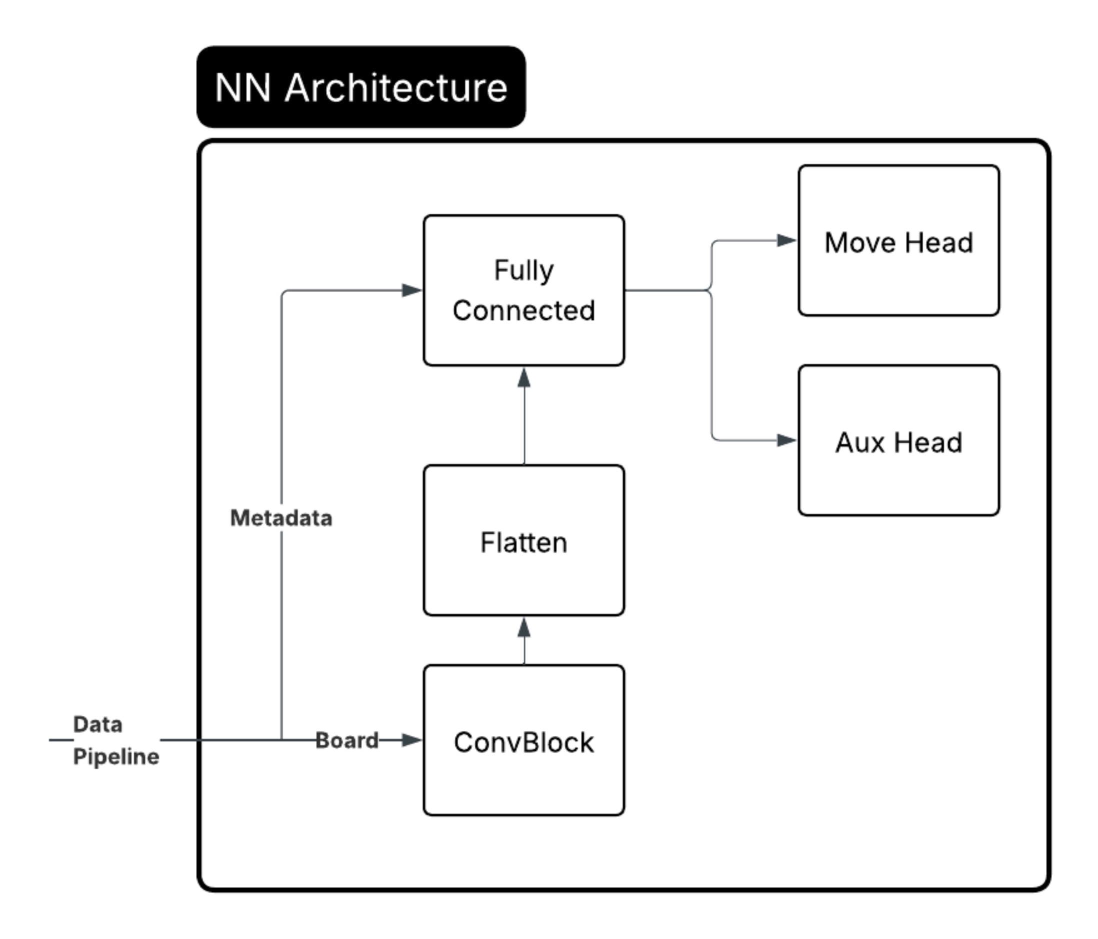
- Model size increases performance exponentially
- We are hoping we can decrease the size of the Maia model while still keeping high accuracy

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 - Neural Network

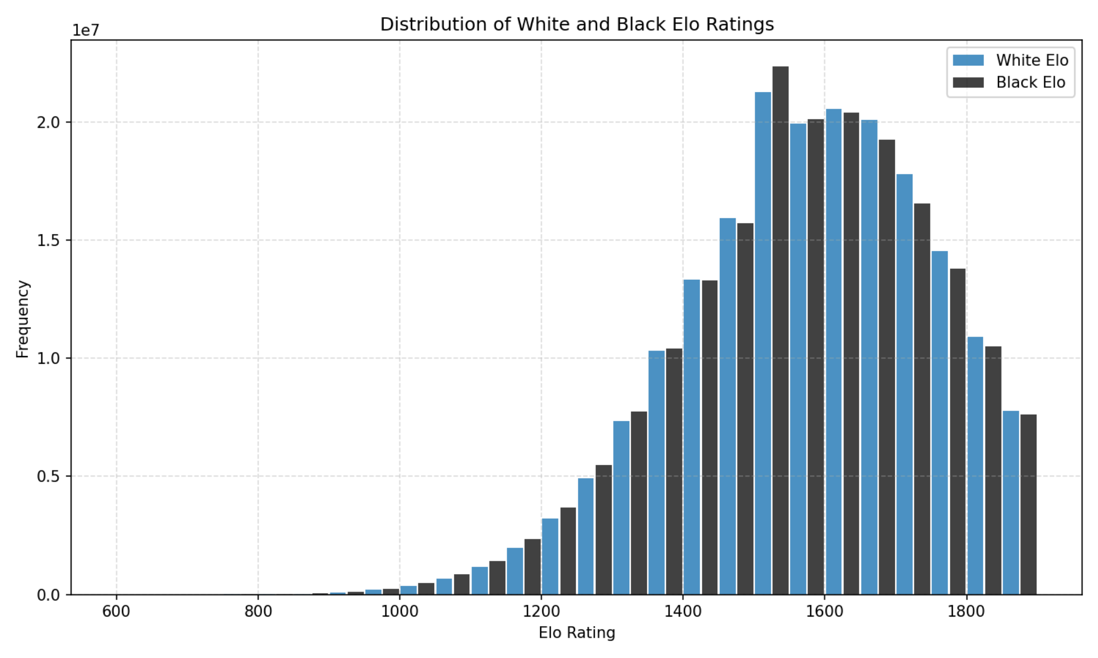


- **Input**: Board(8x8x12) + Metadata(4)
- **Conv Layers**: 6 64x8x8 filters, ReLU
- **Fully Connected**: 4100 -> 512 -> 32
- **Output Heads**: Move (2104) + Auxiliary (2104)
    - 2104 is the number of legal moves
- **Loss**: CrossEntropy (moves) + BCE (valid moves)
- **Optimizer**: Adam
- **Hyperparameter Search**: Random search

Experiments - Dataset

- **Source:** Lichess Open Database
- **Games:** 15,000 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

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



Experiments - Baselines

Method	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
Maia1 1500	Human aligned prediction model

Experiments - Evaluation Metrics

- **Top-1 Accuracy**: Predicted move matches actual human move
- **Top-5 Accuracy**: Actual move in top 5 predictions

Experiments - Comparisons

Method	Top-1 Accuracy
Random	6%
Random Forest	13%
Stockfish 15	40%
Leela 4200	44%
Maia1 1500	51%
Rylee	25%

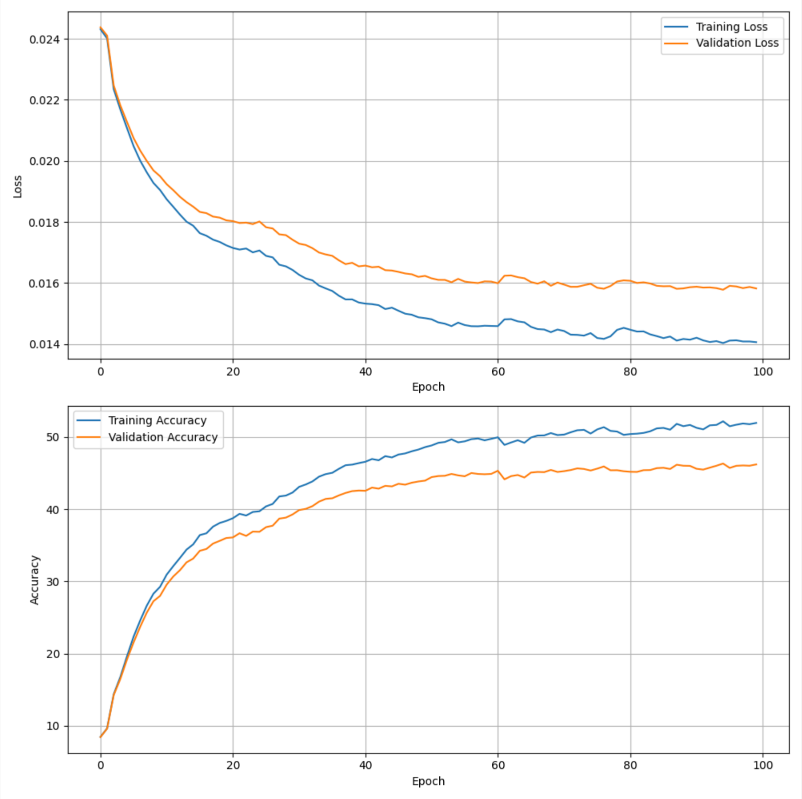
Rylee - Key Differences

- Rylee has 800,000 parameters
    - Trained on one Raspberry pi
- Maia has 25 million parameters
    - Trained on two A100 80Gb GPUs
- No filtering by game type (classical, blitz, etc) to capture broader human play patterns
- No Elo filtering, we include games with mixed skill levels to better reflect general human behavior
- No data augmentation
- 15,000 games vs. Maia’s 169 million games
- Model size is **1/5** that of Maia's

Conclusions - Discussions

Metric	Training	Validation
Loss	0.0152	0.0164
Top-1 Accuracy	28%	25%
Top-5 Accuracy	53%	51%

- Strong generalization between training and validation metrics
- Model captures key human decision-making patterns
- Rylee required less than 1 day 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

Additional Features

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

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.

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

Questions?

Rylee: Human-Like Chess Engine

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