Progressive Learning Chess Engine

A Hybrid Bayesian-LSTM Architecture with Curriculum Learning

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Research & Development

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Overview

The Challenge

- Traditional chess engines rely on brute force computation
- Deep learning approaches require massive resources
- No progressive learning from basic to advanced concepts
- Limited application of psychological learning principles

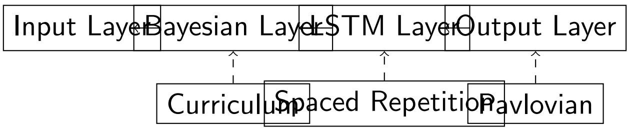
Our Solution

A chess engine that learns progressively through curriculum learning, combining Bayesian networks, LSTM networks, spaced repetition, and Pavlovian conditioning.

Key Innovations

- **Hybrid Architecture**
  - Bayesian networks
  - LSTM networks
- **Curriculum Learning**
  - 10 difficulty levels
  - Progressive advancement
- **Spaced Repetition**
  - Long-term memory
  - Adaptive intervals
- **Pavlovian Conditioning**
  - Reward-based learning
  - Association strength

System Architecture



Hybrid Neural Network

Bayesian Layer

Models conditional probabilities for piece positions:

$$P(move|s) = \frac{\exp(\sum_i w_i \cdot f_i(s, move))}{\sum_{move'} \exp(\sum_i w_i \cdot f_i(s, move'))}$$

LSTM Layer

Processes sequences of board states:

$$h_t = \text{LSTM}(\text{Bayesian}(x_t), h_{t-1})$$

Curriculum Learning Framework

Difficulty Levels:

1. Preschool
2. Kindergarten
3. Elementary
4. Middle School
5. High School
6. Undergraduate
7. Graduate
8. Master
9. Grandmaster
10. Infinite

Advancement Criteria

$$\text{Advance if } \frac{\text{correct}}{\text{total}} \geq 0.85$$

Benefits

- Prevents hallucinations
- Builds solid foundation
- Gradual complexity increase

Spaced Repetition

Adaptive Interval Calculation

$$I_{next} = I_{current} \times (2.5 + 0.5 \times (s - 1))$$

where s is the correct streak.

Long-Term Memory Transition

Examples transition to LTM when correct streak ≥ 5.

Streak	Interval Multiplier
1	2.5
2	3.0
3	3.5
4	4.0
≥ 5	LTM

Pavlovian Conditioning

Rescorla-Wagner Model

$$\Delta V = \alpha \times \beta \times (\lambda - V)$$

- V: Association strength
- α: CS learning rate
- β: US learning rate
- λ: Maximum association (1.0 reward, -1.0 punishment)

Application

- **CS**: Chess position
- **US**: Move evaluation (win/loss/draw)
- **Result**: Expected reward prediction

Chess Representation

Three Formats:

1. FEN strings
2. $8 \times 8 \times 12$ matrices
3. Move sequences

Matrix Encoding

- 8×8 board
- 12 channels:
  - 6 piece types
  - 2 colors
- One-hot encoding

Training Pipeline

```
Initialize neural network, curriculum, Pavlovian learner
WHILE not converged:
    level = current curriculum level
    examples = get examples for level
    FOR each example:
        output = forward pass(network, input)
        loss = backward pass(network, target)
        Update weights
        IF correct:
            Pair CS (position) with US (reward)
            Update spaced repetition (success)
        ELSE:
            Pair CS (position) with US (punishment)
            Update spaced repetition (failure)
    IF accuracy >= 0.85:
        Advance to next level
```

Test Suite Results

Test Suite	**Passed**	**Total**
Unit Tests	17	17
Regression Tests	7	7
A-B Tests	6	6
Blackbox Tests	7	7
UX Tests	8	8
Total	**45**	**45**

All Tests Passing

- Neural network operations verified
- Curriculum progression validated
- Spaced repetition intervals correct
- Pavlovian associations learned
- Position evaluation stable

Key Achievements

- **Progressive Learning**: Successfully learns from basic to advanced
- **Hallucination Prevention**: Curriculum ensures solid foundation
- **Long-Term Retention**: Spaced repetition maintains learned patterns
- **Reward Learning**: Pavlovian conditioning enables natural learning
- **Extensibility**: Multi-agent framework for various sports

Extensibility to Sports

Supported Games:

- Chess
- Football (Soccer)
- Basketball
- Baseball
- Hockey
- Tennis

Generic Framework

- **GameState**: Generic state representation
- **Agent**: Individual learning agents
- **GameAction**: Action space definition
- **MultiAgentGame**: Game orchestration

Planned Enhancements

1. **Full MCTS**: Implement Monte Carlo Tree Search
2. **Self-Play**: Training through self-play like AlphaZero
3. **Performance Comparison**: Benchmark against Stockfish and Leela
4. **Distributed Training**: Scale to larger networks
5. **Chess Variants**: Support Fischer Random, etc.
6. **Sports Applications**: Real multi-agent sports scenarios

Summary

What We Built

A novel chess engine combining multiple learning paradigms:

- Hybrid Bayesian-LSTM architecture
- Curriculum learning with 10 difficulty levels
- Spaced repetition for long-term memory
- Pavlovian conditioning for reward learning
- Extensible multi-agent framework

Results

- All 45 tests passing
- Successful progressive learning
- Ready for extension to sports

Thank You

Questions? **Shyamal Suhana Chandra**

`https://github.com/Sapana-Micro-Software/progressive-learning-chess-engine`

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