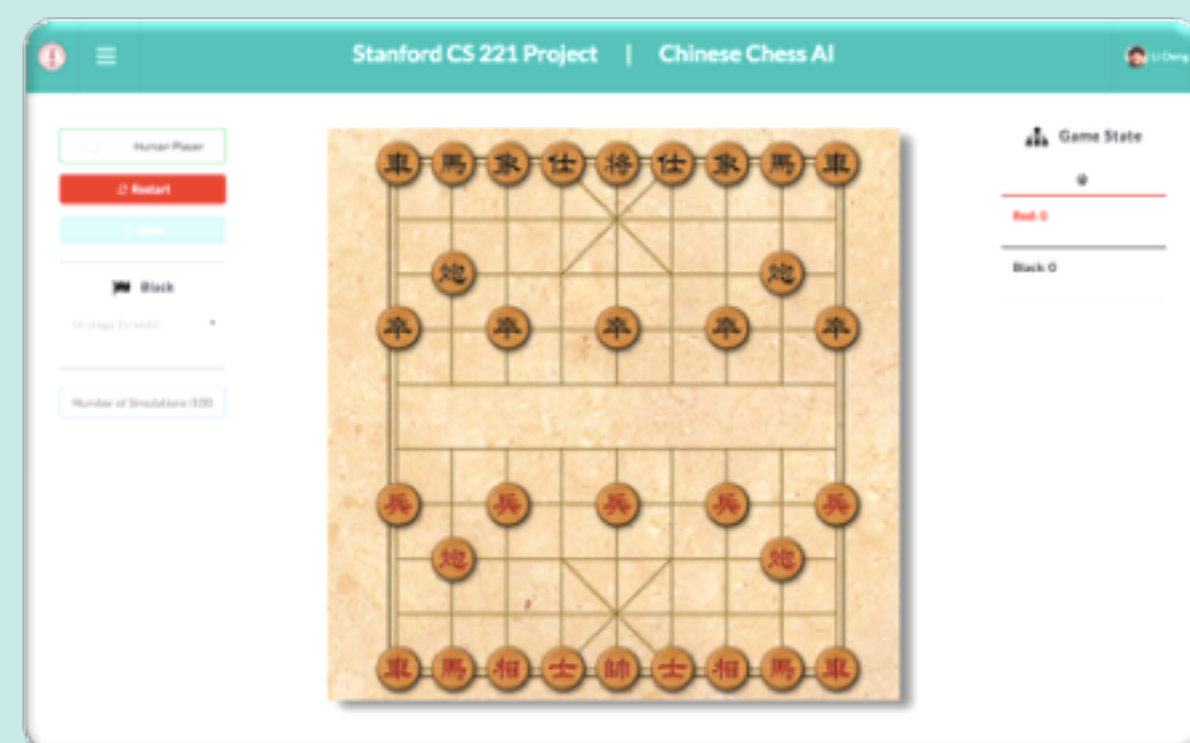




Chinese Chess AI



Simulator



- ❖ Human Mode
- ❖ Simulations Mode
- ❖ *Angular2 + SemanticUI*
- ❖ *Node.js*
- ❖ *Typescript*

Motivation

- ❖ Popularity in China
- ❖ Scarcity of AI-powered Game Engine

Challenge

- ❖ Complex Game Rules
- ❖ Large branching factor (38)



Evaluation Performance

Materials Value

- Piece Value
- Piece Position

Attacking Power

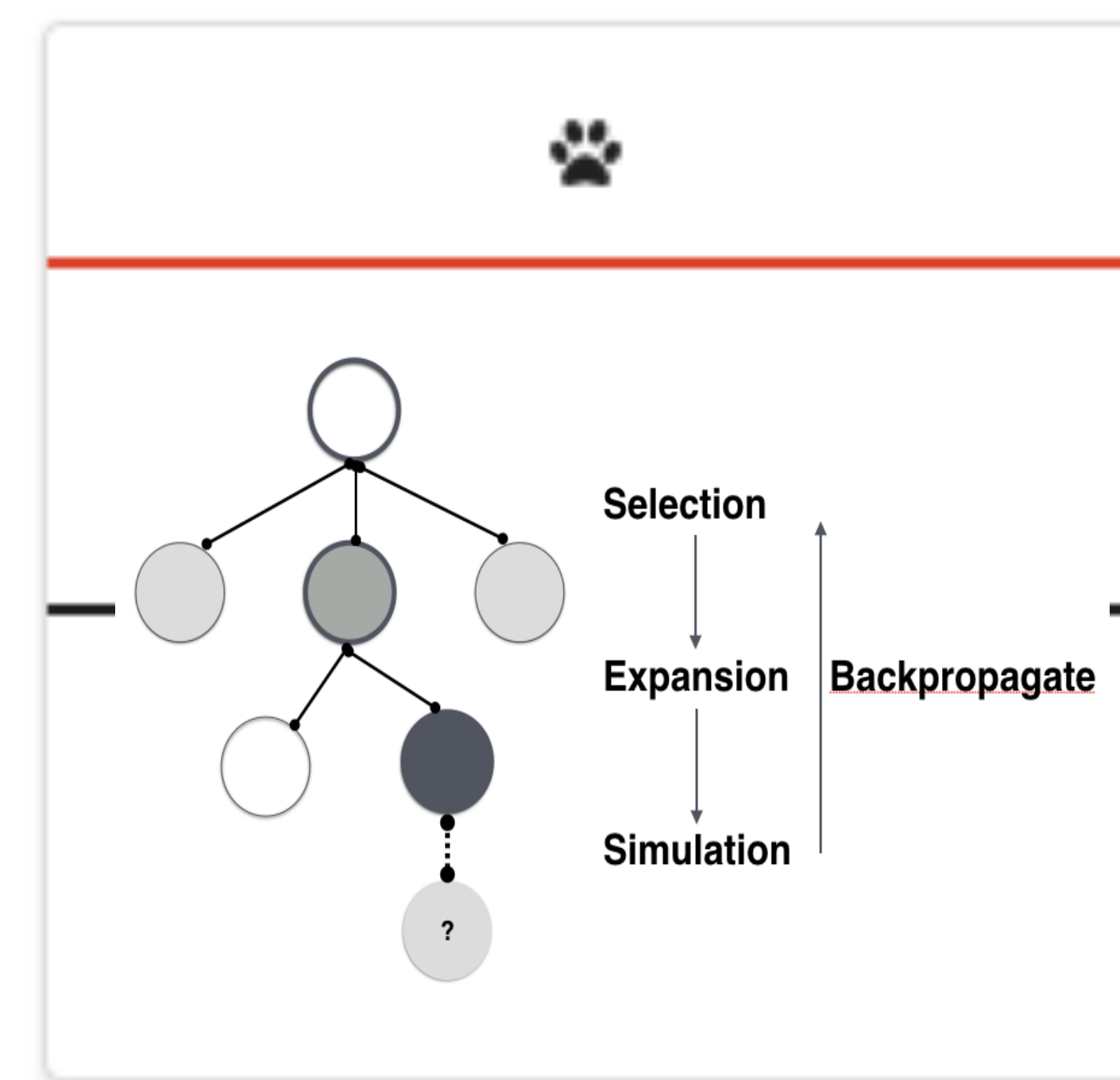
- Number of Threatening
- Number of Captures
- Number of Center Cannons
- Number of Aligned Cannons

Mobility

- Mobility of Rook
- Mobility of Cannon
- Mobility of Horse
- Mobility of Elephant

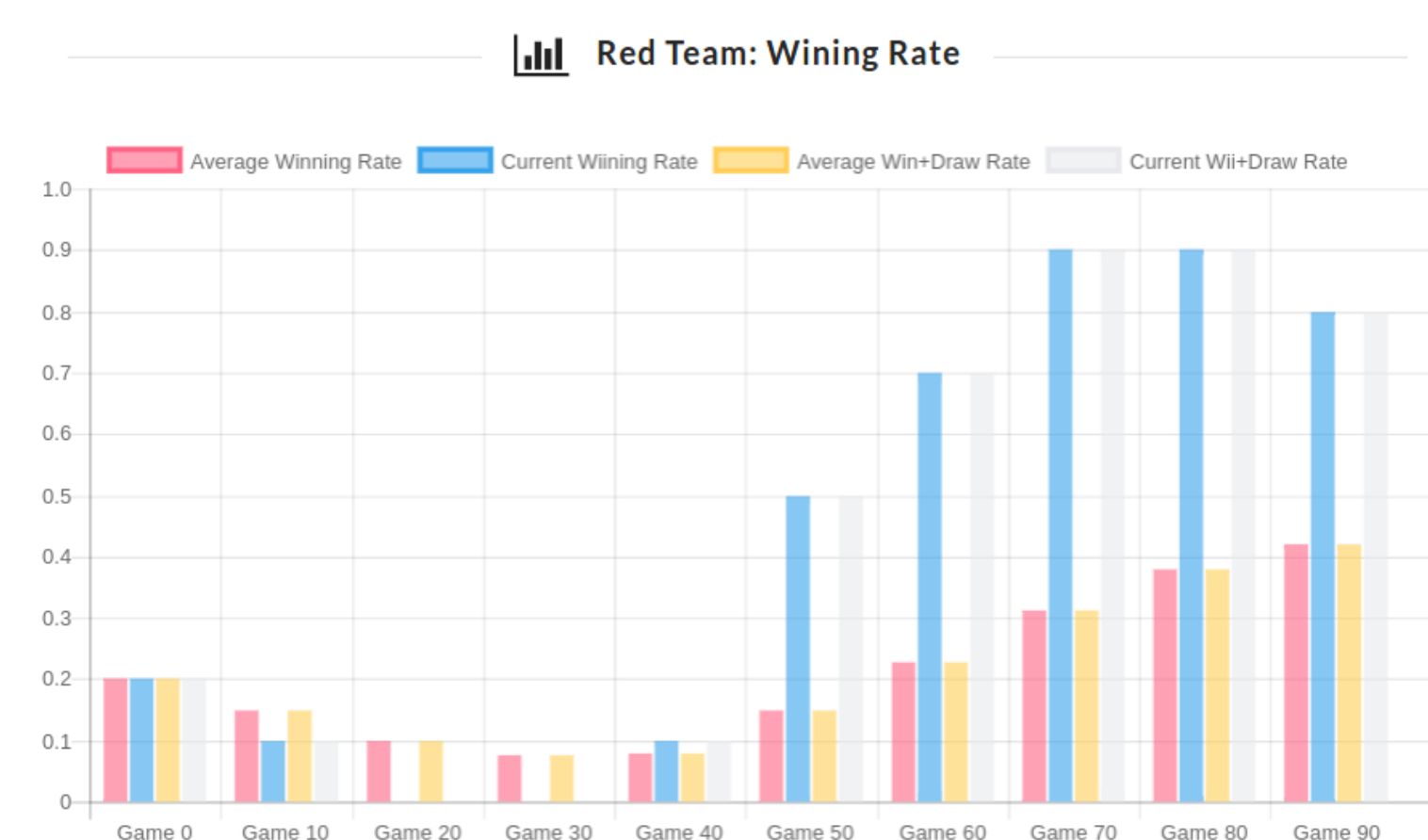


Search Efficiency



Search Efficiency Comparison

| Strategy | Search Depth | Average Runtime for Each Move(ms) |
|---|--------------|-----------------------------------|
| Alpha-Beta Pruning | 2 | 76 |
| Greedy | 1 | 3 |
| Alpha-Beta Pruning | 3 | 600 |
| Alpha-Beta Pruning | 4 | 7307 |
| Alpha-Beta Pruning with Move Reorder (Type A) | 2 | 72 |
| Alpha-Beta Pruning with Move Reorder (Type A) | 3 | 239 |
| Alpha-Beta Pruning with Move Reorder (Type A) | 4 | 3175 |
| Temporal Difference Learning | 2 | 393 |
| Temporal Difference Learning | 3 | 1176 |
| Temporal Difference Learning | 4 | 9568 |
| Monte Carlo Tree Search | 2 | 43 |
| Monte Carlo Tree Search | 3 | 105 |
| Monte Carlo Tree Search | 4 | 315 |



$$w^{t+1} := w^t + \eta \cdot f(\sum \phi_i) \times r^t$$

ϕ_i : feature vector saved during game t for state i

f : normalizing function $f = (\frac{1}{1 + \exp^{-x}} - 0.5) \times A$

A : scaling parameter

r^t : reward at game $r = \begin{cases} \text{Win} : 1 \\ \text{Lose} : -1 \\ \text{Draw} : 0 \end{cases}$

Strategy

- ❖ Greedy
- ❖ MiniMax
- ❖ Alpha-beta Pruning
- ❖ Pruning with Move Reorder
- ❖ Monte Carlo Tree Search
- ❖ Temporal Difference Learning

Github



Li Deng
dengl11@stanford.edu
Stanford CS221 2016 Autumn