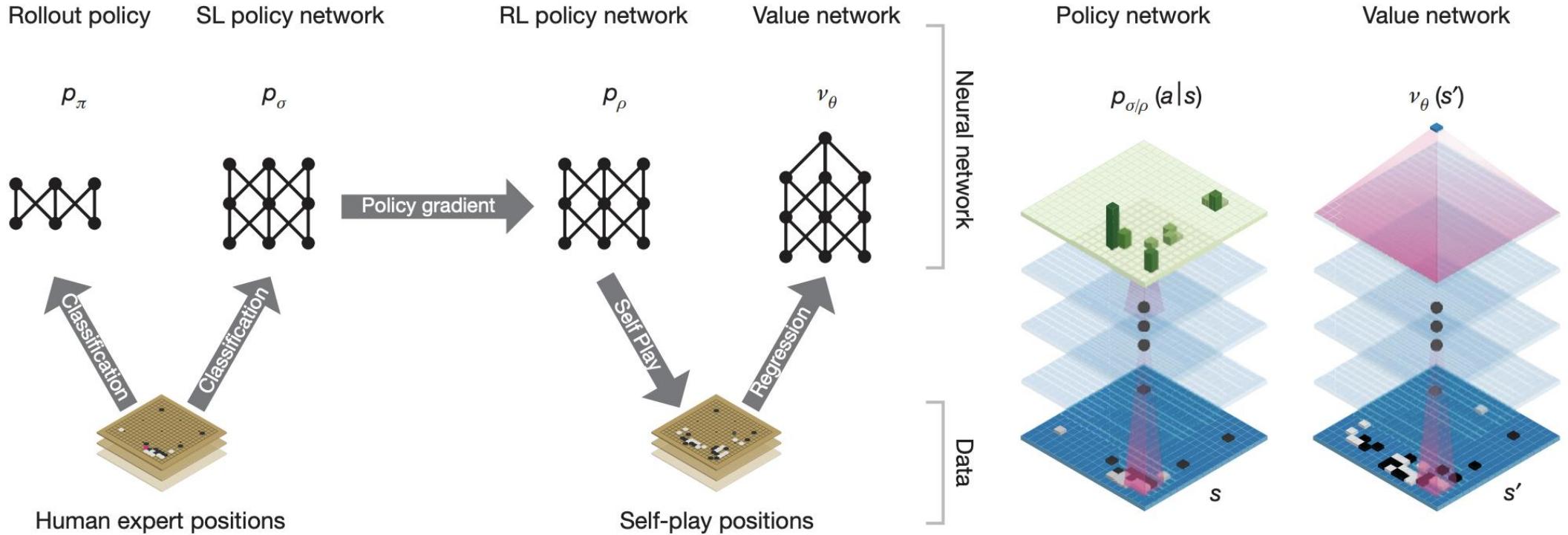


# Integrating Learning and GOFAI systems

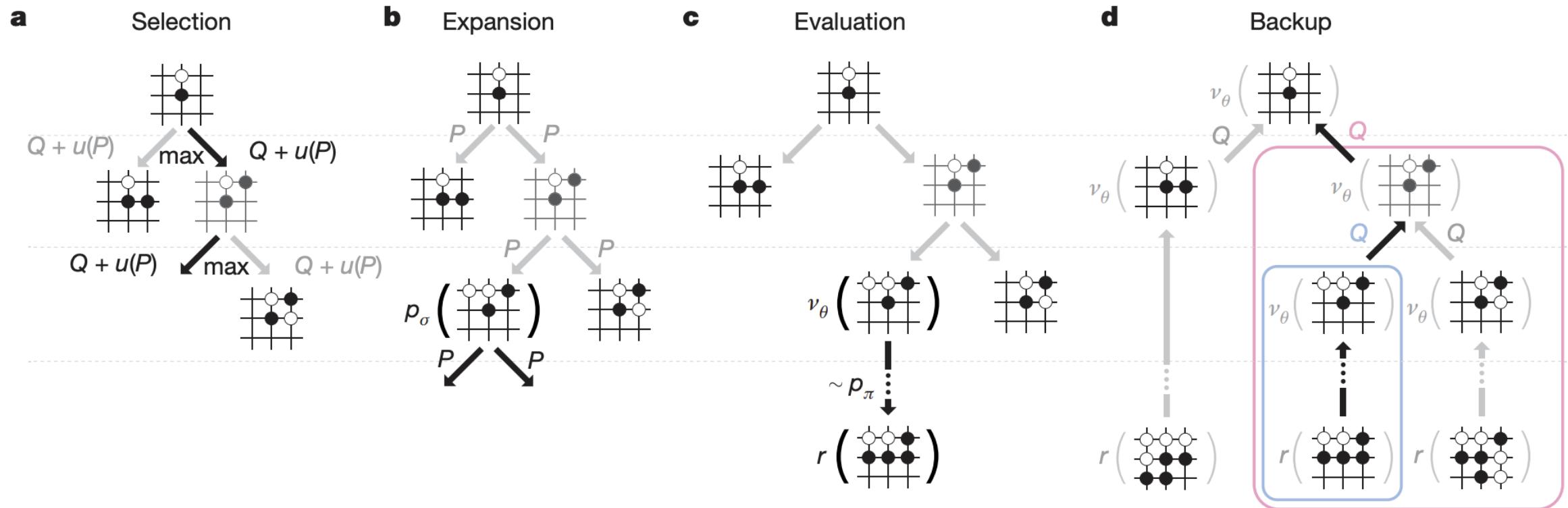


# AlphaGo



Learn a Value function and a Policy function, use in MCTS

# MCTS in AlphaGo



# Selection

$$a_t = \underset{a}{\operatorname{argmax}}(Q(s_t, a) + u(s_t, a))$$

$$u(s, a) \propto \frac{P(s, a)}{1 + N(s, a)}$$

Policy Network

$$N(s, a) = \sum_{i=1}^n 1(s, a, i)$$

$$Q(s, a) = \frac{1}{N(s, a)} \sum_{i=1}^n 1(s, a, i) V(s_L^i)$$

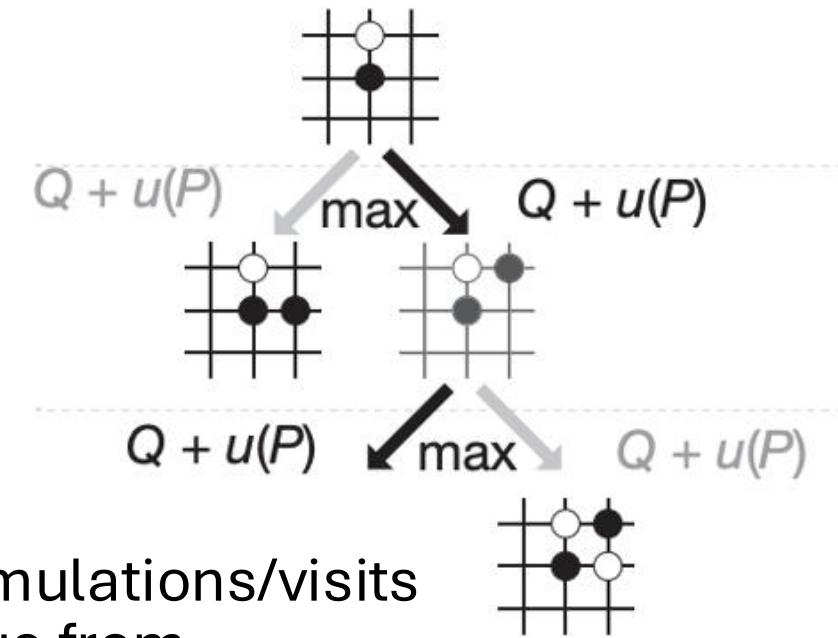
$$V(s_L) = (1 - \lambda)v_\theta(s_L) + \lambda z_L$$

Value Network      Simulation result

**a**

Selection

**b**

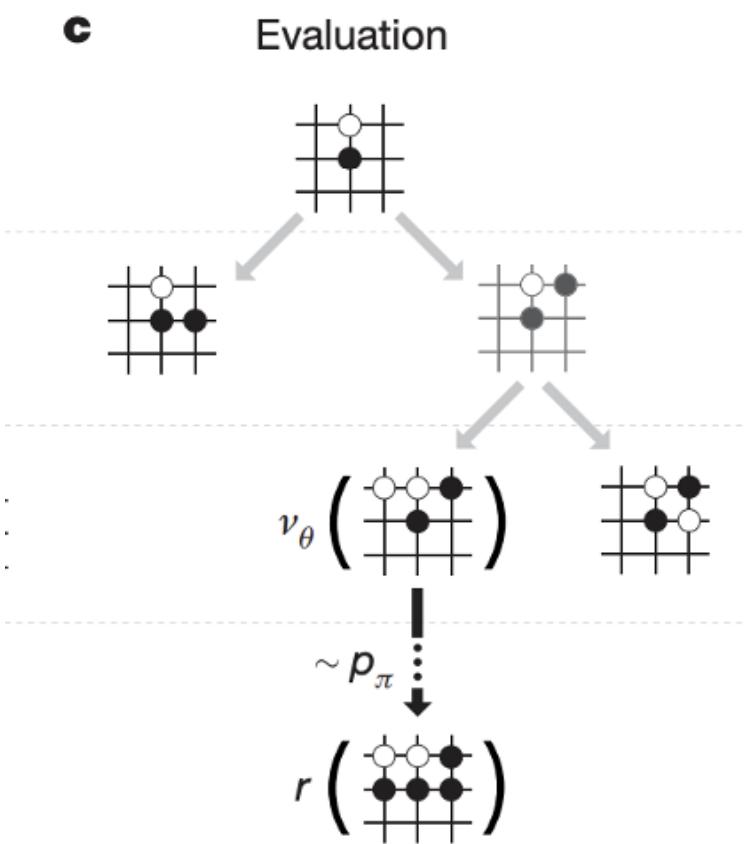


# Evaluation

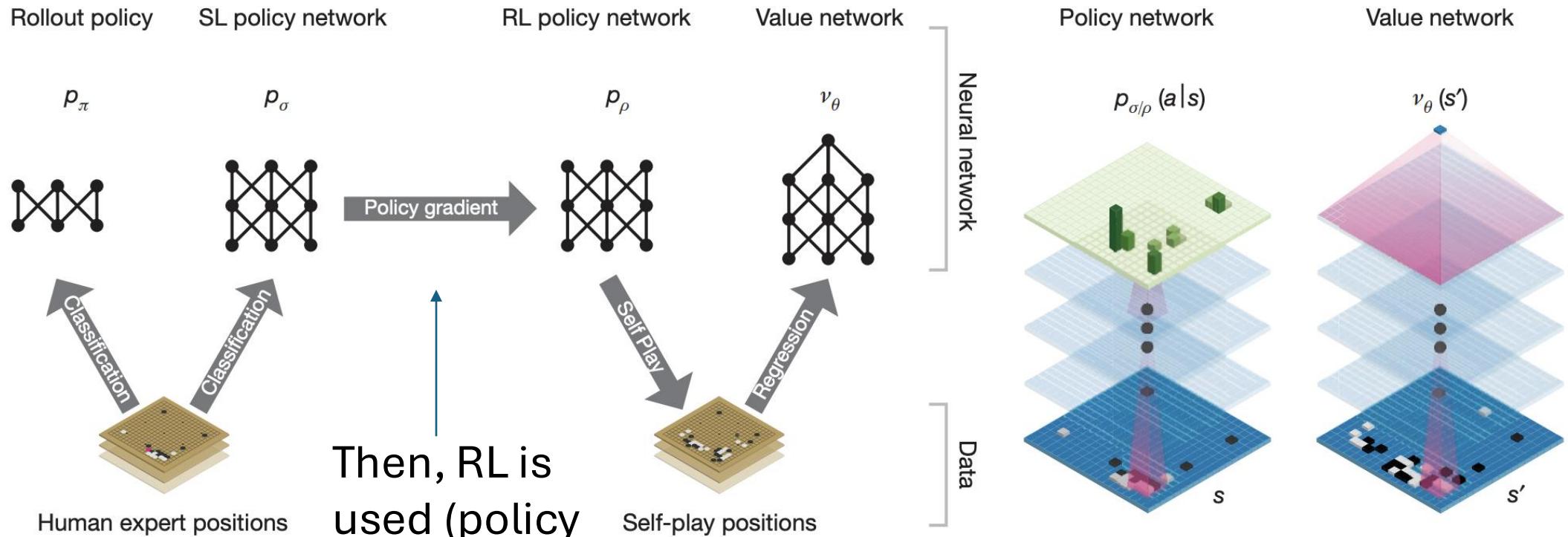
Instead of running random simulations, use a rollout policy  $p_\pi$ .

This is a **simple and fast** rollout policy.

It doesn't need to be perfect, it just needs to be fast. Anything better than random will help.



# Training Value and Policy Networks



Initially trained with database of human games

Then, RL is used (policy gradient algorithm)

Policy Network: Predict actions

Value Network: Predict Values (win/lose from position)

# Self-Play

How do you set up a RL environment for Go? Who is your opponent?

→  
Yourself!

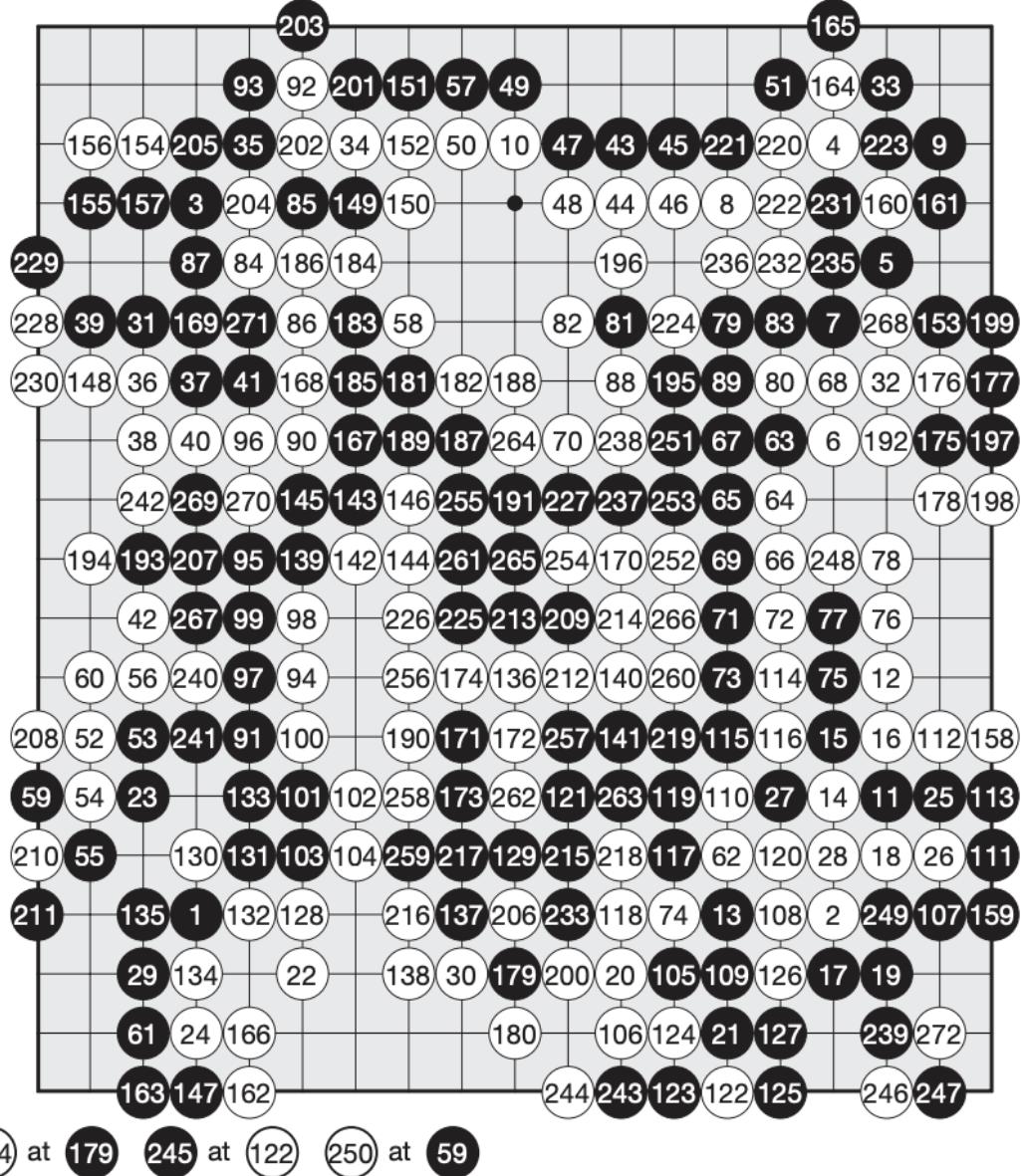
AlphaGo repeatedly played against itself and improved its parameters using Reinforcement Learning

# AlphaGo

Could defeat the European Champion!

## Game 1

Fan Hui (Black), AlphaGo (White)  
AlphaGo wins by 2.5 points



# AlphaGo

## Problems with AlphaGo

- Supervised training makes it specific to Go
- Reliant on data gathered from humans

What if even the best human players are playing Go “wrong”?



Science cover, December 2018

# AlphaZero

Next iteration:

- Only uses Reinforcement Learning (no supervised learning)
- No longer specific to the game of Go



Science cover, December 2018

# AlphaZero

AlphaZero defeated Lee Sedol (18 world titles) 4-1 in March 2016.

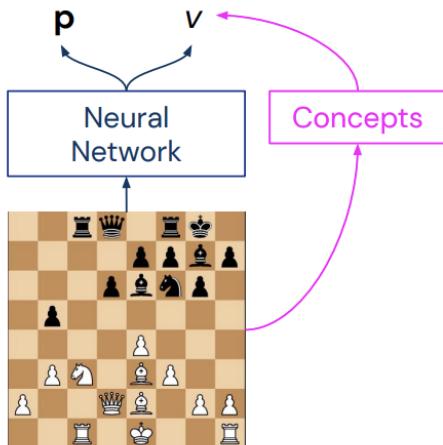
In Chess, AlphaZero passed Stockfish (briefly) to become the best chess engine.



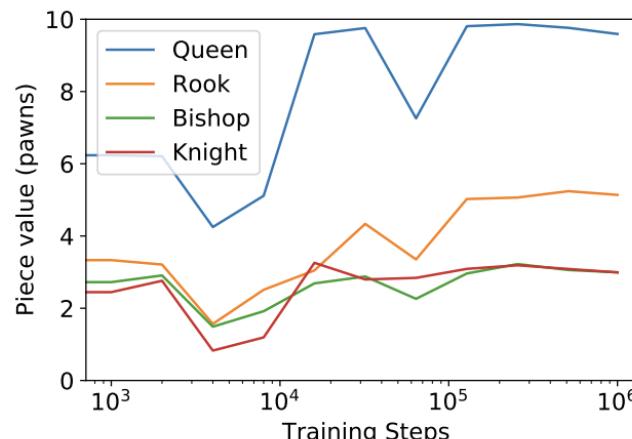
How the Artificial-Intelligence Program AlphaZero Mastered Its Games, The New Yorker

# AlphaZero For Chess

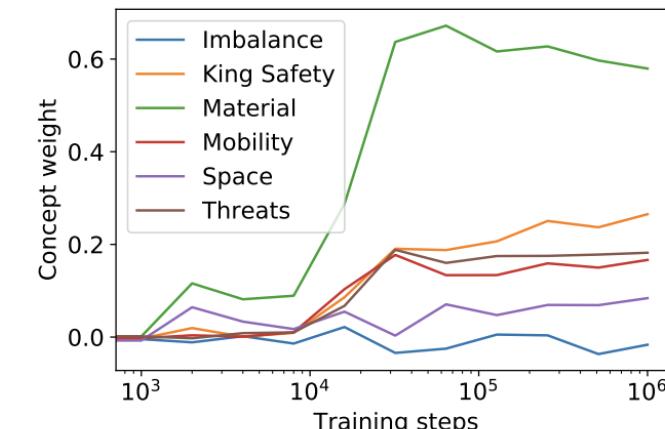
AlphaZero confirmed heuristic values for each piece that humans had been using for hundreds of years



**(a)** Value regression methodology: we train a generalized linear model on concepts to predict AlphaZero's value head for each neural network checkpoint.



**(b)** Piece value weights converge to values close to those predicted by conventional theory.



**(c)** Material predicts value early in training, with more subtle concepts such as mobility and king safety emerging later.

**Figure 4.** Value regression from human-defined concepts over time.

# Why should you care?

What does the future of AI hold?

Past Trends in AI:

- Search
- KRR
- Optimization
- Sequential Decision Making
- Reasoning on Uncertainty

Current Trends in AI:

- Deep Learning
- LLMs
- Diffusion Models

# Don't Reinvent the Wheel

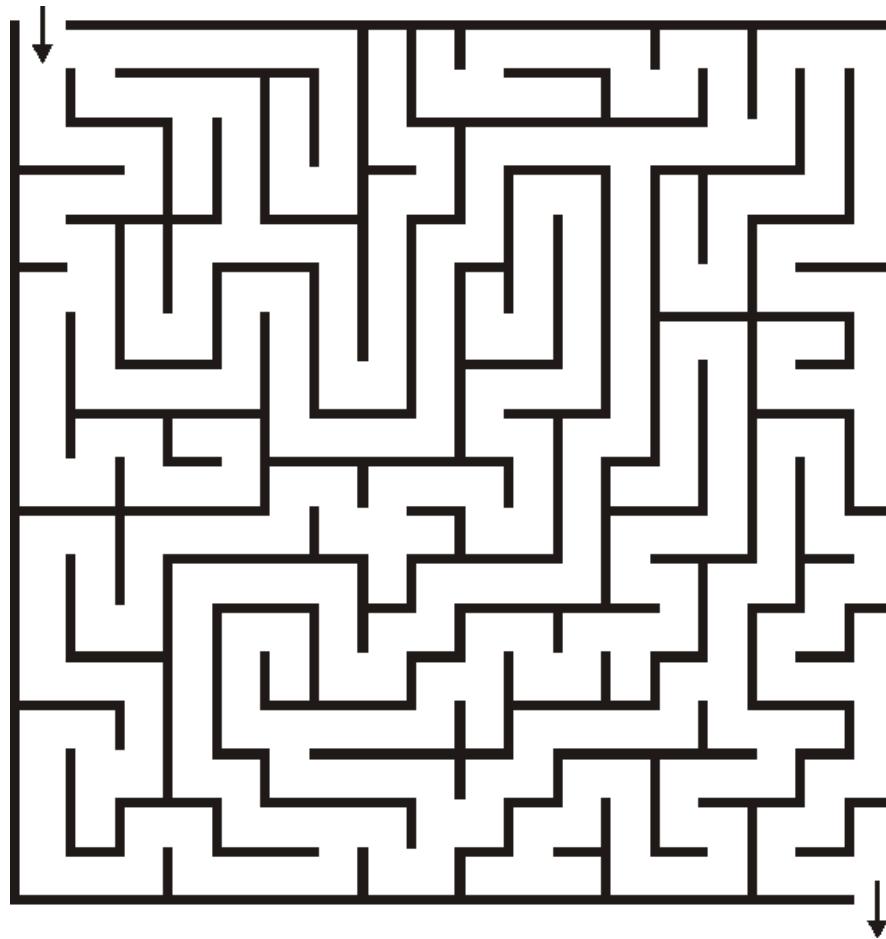
You'd like to solve a Maze.

You can either:

1. Ask an LLM to solve it
2. Use A\*

AI has provably correct, optimal, and otherwise efficient algorithms for many tasks.

Use the right tool for the right job!



# Artificial Intelligence

The goal of the field is to produce **intelligent systems**

What these systems look like, or how they are made, matters less than how well they perform.

Systems will always involve multiple components working together. There is room for Deep Learning components and traditional AI to work together.

# Homework 10

How should we can we leverage LLMs for planning?

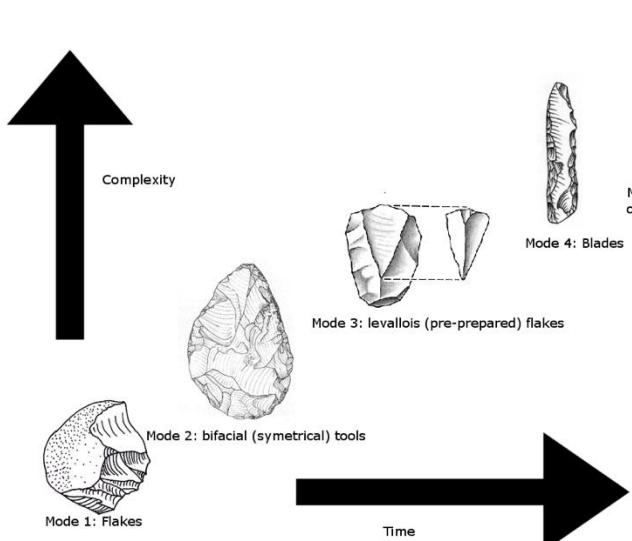
We already have efficient planning algorithms and formulations (e.g., PDDL)

But these formulations can be hard to interact with

Leverage the strength of LLMs (they are easy to interact with in natural language) with the strength of existing planning algorithms

# Tool Use

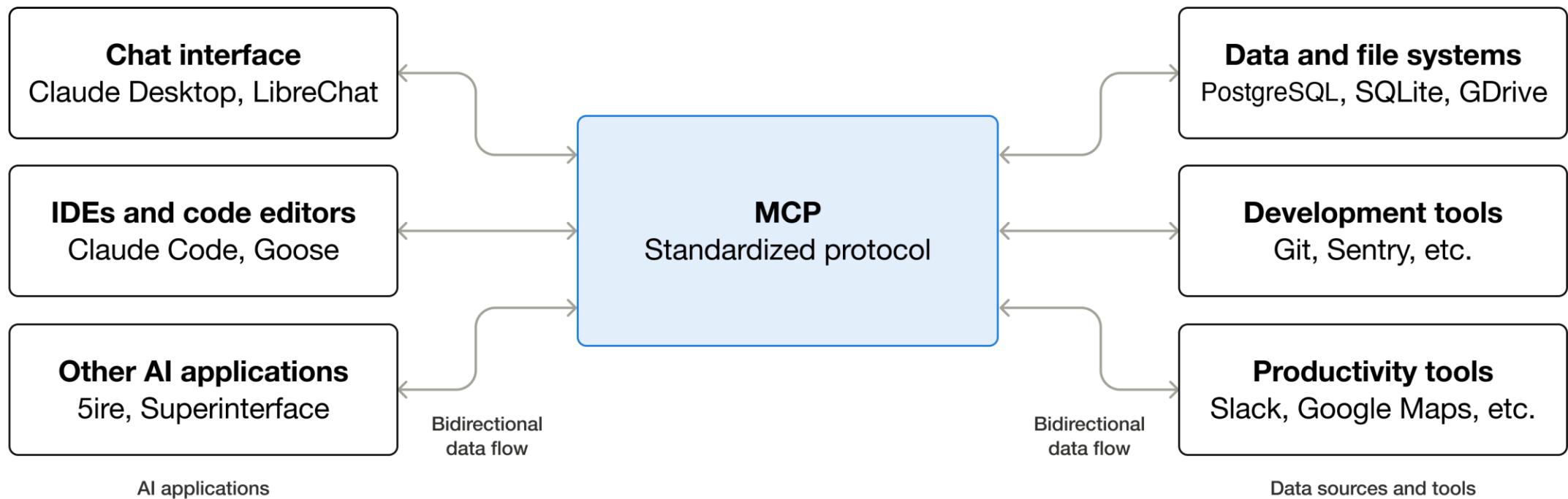
Humans are great at **building** and **using** tools  
This forms one of the key properties of our intelligence



LLMs should be capable of using **existing tools** and building **new tools**



# Model Context Protocols (MCP)



# Model Context Protocol

Models / LLMs



Anthropic  
Claude



OpenAI

Tools & Services



REST



Apps



Storage



Model  
Context  
Protocol  
(Open standard)

# Model Context Protocols

MCPs define three primitives that servers expose:

1. Tools: Tools available for a specific server (e.g., SQL query, terminal command, git operations)
2. Resources: Data sources available
3. Prompts: System prompts or prompt templates that may be helpful

MCP Clients allow 3 main features:

1. Sampling: the server may query the client's LLM, (e.g., which of these flights is best for me)
2. Roots: The client can specify which files or directories the server should focus on
3. Elicitation: The client can request input from the user

# MCP Example

We don't need LLMs to be able to add or multiply, we can provide tools that they can use that do that task for them.

```
from mcp.server.fastmcp import FastMCP

# Create a FastMCP server
mcp = FastMCP("Calculator MCP Server")

@mcp.tool()
def add(a: float, b: float) -> float:
    """Add two numbers together and return the result."""
    return a + b

@mcp.tool()
def subtract(a: float, b: float) -> float:
    """Subtract b from a and return the result."""
    return a - b

@mcp.tool()
def multiply(a: float, b: float) -> float:
    """Multiply two numbers together and return the result."""
    return a * b
```

# Revisiting the field

