The Algebraic Value-Editing Conjecture in Deep Reinforcement Learning

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What is Reinforcement Learning (RL)?

- Two main characters that interact:
  - The agent
  - The environment

- RL: Agents learn through trial + error
  - **State:** Entire description of the environment
  - Agent sees an **observation:** Partial description of state
  - Chooses an action by its **policy**
  - **Action Spaces:** All valid actions
  - **Return:** Cumulative “score” over a set of actions
Deep Reinforcement Learning (Deep RL)

- **Deep RL**
  - = Deep learning + RL
  - Use **Parameterized Policies**: Determined by some complex function

- **Neural networks**
  - How to modify our policy so that it maximizes the expected return
  - Nodes contain an **Activation**
  - **Forward pass**: Weighted averages form the activations of the previous layers
  - **Gradient descent**: Tweaks made to the edges to optimize the policy
  - **Backpropagation**: Backward pass to compute gradient
Background

- We’ve always wanted to understand the internal mechanisms of how the agent learns
- The math is way too complex for humans to understand: 100,000+ connections in typical models
- No intuitive concepts or patterns that were found yet...
So this is a formula for calculating a single activation in a preceding layer...

\[
a_0^{(1)} = \sigma \left( w_{0,0} a_0^{(0)} + w_{0,1} a_1^{(0)} + \cdots + w_{0,n} a_n^{(0)} + b_0 \right)
\]
The Algebraic Value-Editing Conjecture (AVEC)

It's possible to deeply modify a range of alignment-relevant model properties, without retraining the model, via techniques as simple as "run forward passes on prompts which e.g. prompt the model to offer nice- and not-nice completions, and then take a 'niceness vector', and then add the niceness vector to future forward passes." [1]
Observation with the key
Hypothetical Activations: [3, 4, 1, 2]

Observation without the key
Hypothetical Activations: [1, 1, 0, 2]

Key Vector: [2, 3, 1, 0]
The key vector **SHOULD** make the agent avoid the key at its starting position.

(Obs. with key) - (Obs. without key) = Key Activation

Obs. - Key Activation ≈ Avoid the Key

We can continue applying forward passes through the maze where our position is changed. But subtracting the key vector for our activations **still** makes the agent avoid the key. The math does not work anymore, but the relation holds!!
Previous Papers

Understanding and controlling a maze-solving policy network

- Used the Maze environment in Procgen
- “Cheese vector” = Cheese Activations - No Cheese Activations
- Net probability vectors of the entire maze to show the effects of the cheese
- Adding cheese vector has no effect
  - Subtracting removes ability to see the cheese
  - Adding just increases “cheese perception” which is irrelevant

Improvements

- No addition vector found yet
- Not 100% accurate yet
Previous Papers (cont.)

Understanding and controlling a maze-solving policy network

- Adding a “Top-right vector”
  - Subtracting has no effect
- Effects of scaling the vector
- “Top-right vector” transfers across mazes!
- Applies to other applications other than “cheese” and top-right

Improvements

- Unsure about effects of scaling
The Plan

- Train a PPO model on the Minigrid environment:
  - Changing map sizes
  - Easily customizable mazes
  - More complex
- Replicate the results of the conjecture...
Proximal Policy Optimization (PPO) Model

- State of the art
- Estimation of the advantage function
  - Calculates the “benefit” of particular action to average action
  - The decision maker for the agent
- Updating the policy:
  - Measures the difference between updated and old policies
  - Sampled across many small batches of trajectories (sequences of states & actions)
  - Stochastic gradient descent
  - Clipping mechanism
Our Model

- Trained PPO model on 5x5 Minigrid DoorKey and MiniGrid-Four-Rooms environment
- Differences:
  - Limited vision
  - Key + Lock
  - Different buttons for interacting with key & lock
Results

5x5 Grid

Loss Graph

Four-Rooms
Conclusion

- There are still many questions about this conjecture
- **Scaling:**
  - Big factors (>10) of the vector mess up the results
  - Small factors don’t have great impacts
- **Cannot Add & Subtract the same vector:**
  - Adding the cheese vector and subtracting the top-right vector have no effect
- **The results do not generalize perfectly:**
  - Smaller seeds or complex ones tend to have different results
  - Why would this vector generalize at all anyways?
What if this conjecture is actually **true**?

- First insight into mechanics of neural networks and deep learning
- Massive training time save
- Applications to neuroscience: “Subtracting brain states”

Even through the internal complexities of neural network, a concept as simple as $A - (A - B) = B$ still often seems to work!!
Future Work

- Still need to replicate the results on our new environment
- Try different models:
  - Deep Q-Network (DQN)
  - Deep Deterministic Policy Gradient (DDPG)
  - Soft Actor-Critic (SAC)
- Test out other types of vectors other than just a key vector
  - Color vector
  - Goal vector
  - Our own “top-right” vector
- Other sub-environments in Minigrid
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Citations

