Emergence of Past and Future in Evolving Neural Networks

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Evolution of Memory and Prediction

Past, Present, and Future:

- Past: memory
- Present: reactive behavior
- Future: prediction, anticipation

→ How did these temporal functions emerge/evolve?

Simple to Complex Brains

(a) Sensor=Effector (b) Sensorimotor neuron → Effector
(c) Sensory, Motor, and interneuron (d) Complex circuit

Swanson (2003)

- From reactive to recurrent.
  - Reactive: Input → Output
  - Recurrent: Input modulating on-going internal activity

Time, in the Context of Neural Networks

- Feedforward neural networks:
  Have no memory of past input.

- Recurrent neural networks:
  Have memory of past input.

e.g., Elman (1991)
Feedforward Networks

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Recurrent Networks

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Research Questions

Recollection | Prediction
Past          | Present       | Future

- [Q1] how did recollection (memory) evolve?
  - From reactive (present) to recurrent (past).

- [Q2] how did prediction evolve?
  - From recurrent (past) to predictive (future).

Approach

Part I: Recollection

Recollection in Feedforward Networks?

Is it possible for a feedforward network to show memory capacity?

- What would be a minimal augmentation?
- Idea: allow material interaction, dropping and detecting of external markers.

Memory Task: Catch the Balls

Agent with range sensors move left/right.

- Must catch both falling balls.
- Memory needed when ball goes out of view.

Three Network Types Compared

Compare three different networks:

1. Feedforward
2. Recurrent
3. Dropper/Detector (with Feedforward net)
1. Feedforward Network

- Standard feedforward network.

2. Recurrent Network


3. Feedfwd Net + Dropper/Detector

Feedforward network plus:
- Extra output to drop markers.
- Extra sensors to detect the markers.

Results: Feedforward

On average, only chance-level performance (50%).
- Always move to the fast ball.
- Randomly pick fast or slow ball and approach it.
Results: Recurrent vs. Dropper

- No difference in performance between dropper/detector net (right) and recurrent network (left).

Part I Summary

- Reactive, feedforward networks can exhibit memory-like behavior, when coupled with minimal material interaction.
- Adding sensors and effectors could have been easier than adjusting the neural architecture.
- Transition from external olfactory mechanism to internal memory mechanism?
- Successfully extended to 2D foraging task.

Emergence of Prediction in RNN?

Can prediction emerge in internal state dynamics?

- Idea: Test if (1) internal state dynamics is predictable in evolved recurrent nets, and (2) if that correlates with performance.

Part II: Prediction

Largely based on Kwon and Choe (2008)
**Task: 2D Pole Balancing**

- Standard 2D pole balancing problem.
- Keep pole upright, within square bounding region.
- Evolve recurrent neural network controllers.

**Anderson (1989)**

**Measuring Predictability**

- Train a simple feedforward network to predict the internal state trajectories.
- Measure prediction error made by the network.
  → High vs. low internal state predictability (ISP)

**Example Internal State Trajectories**

- Typical examples of high (top) and low (bottom) ISP.
- High ISP=predictable, Low ISP=unpredictable.
- Note: Both meet the same performance criterion!

**Experiment: High vs. Low ISP**

1. Train networks to achieve same performance mark.
2. Analyze internal state predictability (ISP).
3. Select top (High ISP) and bottom (Low ISP) five, and compare their performance in a harder task.
Results: Internal State Predictability (ISP)

- Trained 130 pole balancing agents.
- Chose top 10 highest ISP agents and bottom 10 lowest ISP.
  - high ISPs: $\mu = 95.61\%$ and $\sigma = 5.55\%$.
  - low ISPs: $\mu = 31.74\%$ and $\sigma = 10.79\%$.

Performance and Int. State Dyn.

- Made the initial conditions in the 2D pole balancing task harsher.
- Performance of high- and low-ISP groups compared.
- High-ISP group outperforms the low-ISP group in the changed environment.

Behavioral Predictability

- Success of high-ISP group may simply be due to simpler behavioral trajectory.
- However, predictability in behavioral predictability is no different between high- and low-ISP groups.

Examples of cart x and y position from high ISP

- Behavioral trajectories of x and y positions show complex trajectories.
Examples of cart x and y position from low ISP

- Behavioral trajectories of x and y positions show complex trajectories.

Part II Summary

- Simulations show potential evolutionary advantage of predictive internal dynamics.
- Predictive internal dynamics could be a precondition for full-blown predictive capability.

Discussion

- From external memory to internalized memory (cf. Rocha 1996).
- Analogous to olfactory vs. hippocampal function?
- Pheromones (external marker) vs. neuromodulators (internal marker)?
Discussion (cont’d) & Future Work

• Implications on the evolution of internal properties invisible to the process evolution.

• Future work: (1) actual evolution from dropper/detector net to recurrent net; (2) actual evolution of predictor that can utilize the predictable dynamics.

Conclusion

From reactive to contemplative to predictive:

• Recollection: External material interaction can be a low-cost intermediate step toward recurrent architecture.

• Prediction: Predictable internal state dynamics in recurrent neural nets can have an evolutionary edge, thus prediction can and will evolve.

References


