

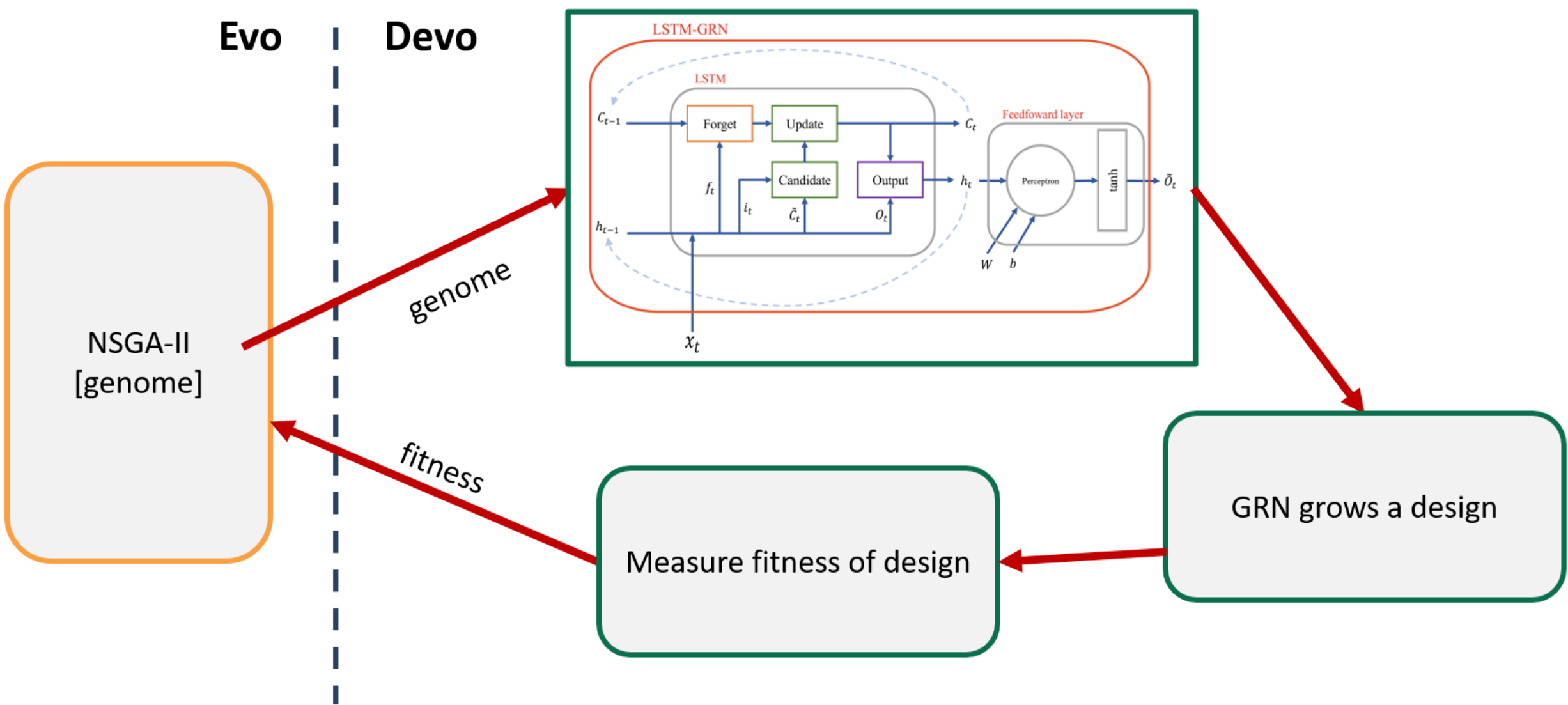
Enough is Enough: Learning to Stop in Generative Systems

1. Abstract

Gene regulatory networks (GRNs) have been used to drive artificial generative systems. These systems must begin and then stop generation, or growth, akin to their biological counterpart. This work proposes a GRN augmented with an LSTM unit that shows some promise in evolving ability and stopping criteria simultaneously. For more complex tasks this network requires further development.

2. Leveraging Evo-Devo for Design

- **Evolution** offers powerful optimization tools.
- **Development** offers simple and scalable encoding.
- Utilizing evolution for designing controllers benefits from both strategies.
- Evo-Devo resembles a standard evolutionary algorithm.
- Genome fitness is determined by its effectiveness in encoding a design-modifying network (GRN).
 - The GRN takes organism and environmental state as inputs and outputs design decisions.



Augmenting GRNs

Here is presented a gene regulatory network that has been augmented with an LSTM cell.

Motivation:

- Pre-built memory structure
- Preserve historical context
- Allow for stopping criteria to emerge

Long-Short Term Memory Networks:

- LSTMs are popular in deep learning for sequence-sequence learning.
- Examples of artistic generative use include generating rap lyrics and typefaces.
 - Generated outputs incorporate features learned from a known corpus.
- The evolution of LSTM cells remains poorly understood.
- Successful applications involve pre-training LSTM cells and using them as inputs to NEAT networks in evolved systems.

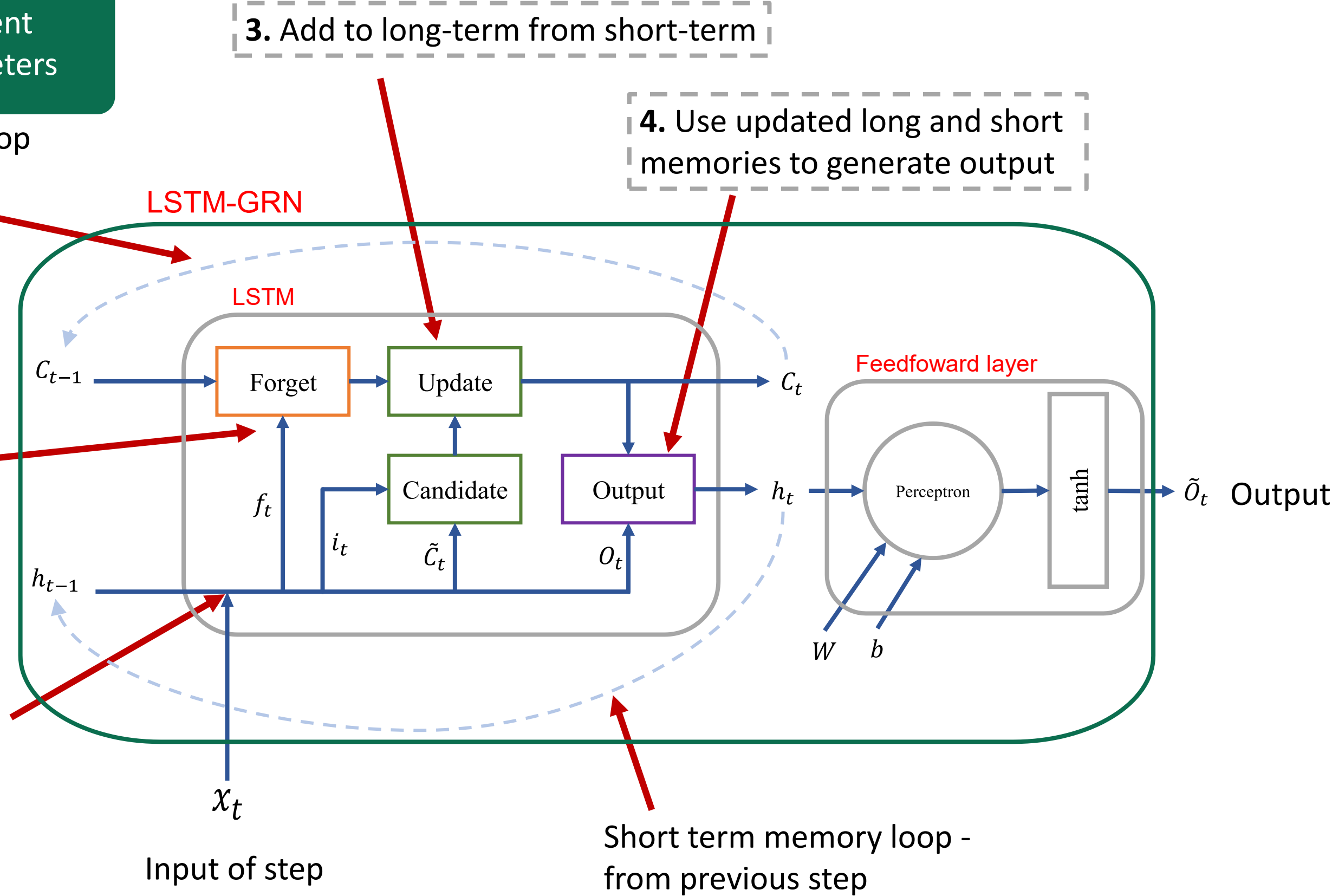
Key Idea:

Evo-Devo should be self regulating in development steps to remove parameters

Long term memory loop – from previous step

2. Short-term informs loss of long-term

1. Combine short-term and input values

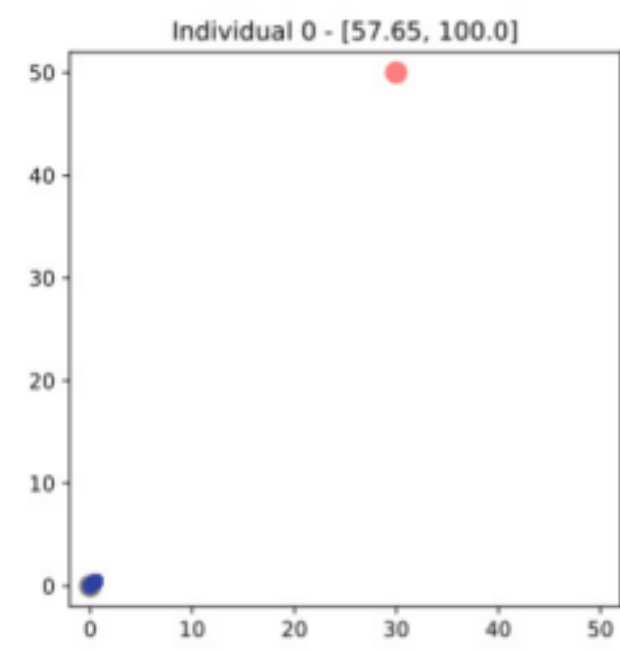


3. Long-Short Term Memory Gene Regulatory Network LSTM-GRN

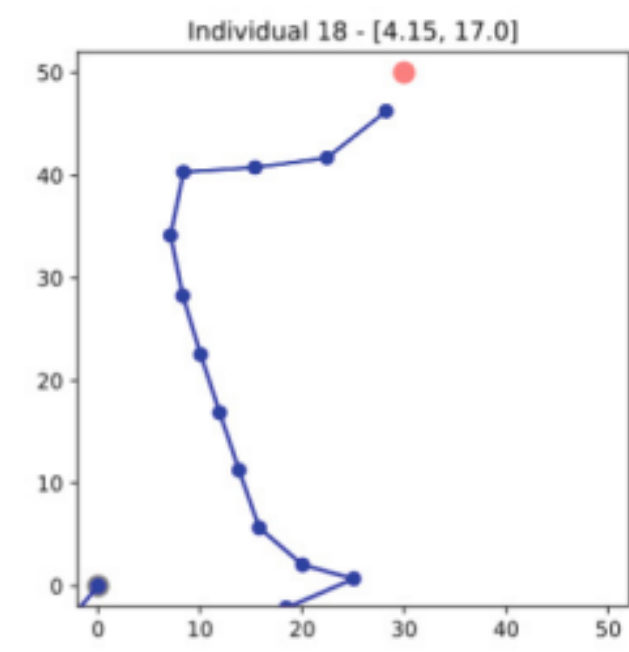
- Memory is added to the GRN system using an LSTM cell in a feedforward network.
- LSTMs help maintain memory in the broad evolutionary search space.

Operation

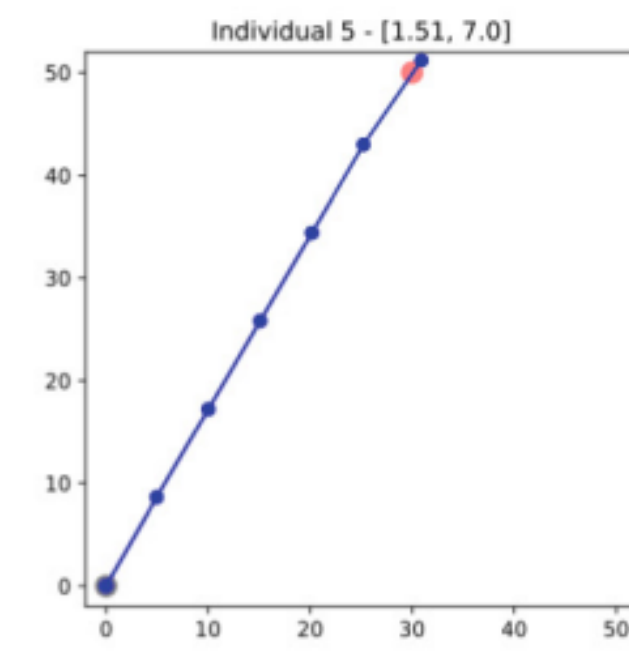
- The LSTM cell operates with long-term and short-term memory streams.
- Short-term memory and input decide how much long-term memory to forget.
- Candidate information updates long-term memory (C_t), which is fed back into the system at the next cycle.
- Long- and short-term memory, along with weights, calculate the final output (h_t).
- The output passes into the feedforward section, completing one cycle through the system at each development step.



(a) Gen: 1, steps - 100, distance - 57.65



(b) Gen: 40, steps - 17, distance - 4.15



(c) Gen: 70, steps - 7, distance - 1.51

Key Idea:

The GRN can optimise to learning to stop and to complete a task simultaneously

- Over 70 generations, the organism found an effective path.
- It first got close to the target, then reduced steps needed.
- This created both organic and efficient patterns.

$$\text{Fitness} = \left[\frac{\text{Distance from target}}{\text{Number of steps}} \right]$$

4. Stopping Growth – Experiment 1

Experimental Design:

- GRN controls organism growth in 2D space.
- Organism decides step size and direction.
- Fitness calculated upon GRN signal to stop.

Optimization Algorithm: NSGA-II minimizes two fitness values.

Simplicity: Deliberately kept simple for focused LSTM cell evolution analysis.

Gene Regulation in Nature

- Morphogenesis (growth) is governed by gene expression, regulated by gene regulatory networks (GRNs).
- GRNs are complex interactions of genes and proteins, influenced by the environment.
- Evolutionary Development combines previously separate biological systems.
- Primary characteristics of GRNs include:
 - Heterochrony
 - Spatial patterning
 - Interactions between genes and gene products

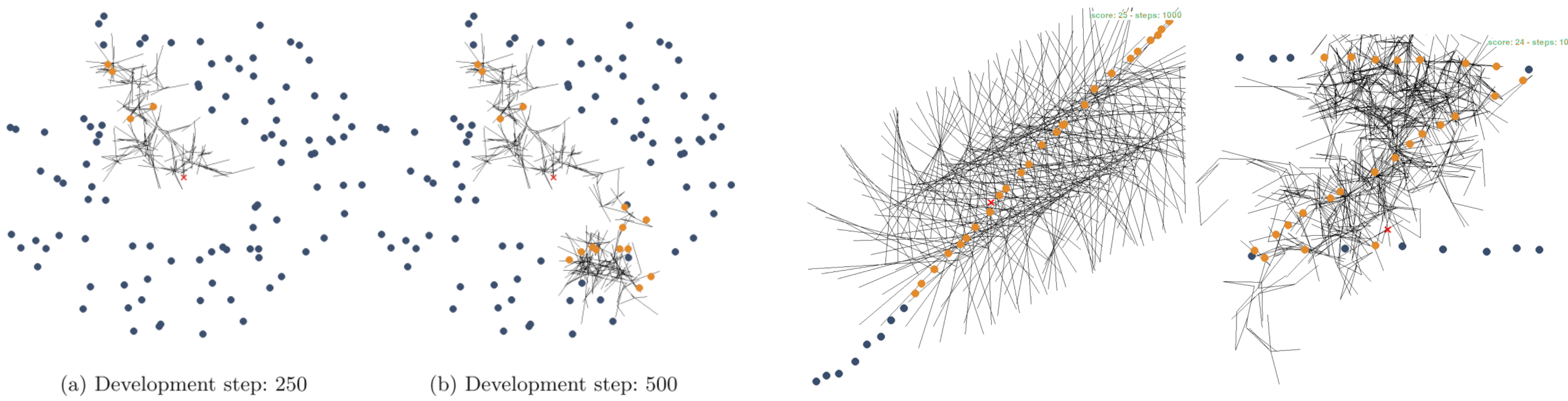
5. Stopping Growth – Experiment 2

Objective: Increase system complexity by allowing branching growth

Changes:

- Multiple targets in the environment.
- Organism can branch growth and return to saved positions.
- GRN controls this with push and pop commands.
- GRN gains distance (x,y) to nearest point.

- Orange targets: Collected.
- Blue targets: Uncollected.
- Organism depicted in black, originating from red cross at environment center.



$$\text{Fitness} = \left[\frac{\text{Total targets collected}}{\text{Number of steps}} \right]$$

- Increased complexity led to the GRN struggling with stopping criteria – often didn't stop at all.
- However, it directed growth effectively, avoiding empty areas and forming sharp branches.
- Evolved solutions demonstrate the GRN's ability to concentrate growth in specific areas.

- Two pre-defined structures, a straight line and a shape resembling the letter Z, exemplify this capability.

6. Discussion

- The LSTM-GRN effectively generates stopping criteria for simple problems but struggles with increased complexity.
- Addressing this may involve expanding evolutionary search strategies or altering GRN topology.
- The vast search space for evolving memory contributes to this challenge.
- Adjusting the fitness function could guide evolution more effectively.
 - Rewarding proximity to targets could improve over a binary scoring system.
 - This adjustment allows for better feedback on small changes, promoting advantageous mutations across generations.

7. Conclusion

There is clear evidence for the efficacy of the LSTM-GRN in handling simple generative tasks, but it will become increasingly important to set a benchmark for how stopping is handled across several GRN constructs.

An analysis of how memory evolves within this unit will shine light on how best to carry LSTM-GRNs forward. LSTMs should also be considered in topologically evolved networks to see how best they may fit into the landscape of artificial GRNs further.

Take the paper with you

Scan this QR code to take the paper, poster, and source code away with you.



<https://colinroitt.github.io/LSTM-GRN/>

Key Idea:

Complexity increases the search space dramatically and the simple GRN bottlenecks this search

The code for this work has been made open source and available on GitHub for transparency and review

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