Goal-directed behavior using contextual causation learning

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# Abstract

In this project, the Morphognosis and Mona neural network models are combined into a comprehensive model for animal learning and behavior. Mona features a contextual causation learning with goal-directed motivation. Morphognosis features contextual multilayer perceptron (MLP).

**Keywords**: Morphognosis, artificial animal intelligence, artificial neural network, machine learning, artificial life, cellular automaton.

Note: remember to check EverNote and Melendey for refs.

Note: sparse example: A: (3,5) with two dimensions after dimension reduction from input, B: (1,4). Plot points into a 10x10 space. Repeat process going up each level. So a dimension value pivots to a range of dimension in the higher space (similar to DB pivot).

Text, letter

Description automatically generated with medium confidence

How to achieve variable causation latencies at levels. Causations in higher levels will have greater time spans than lower levels. One method for this would be to vary the proximity parameter for the code centroid spaces. Centroids that can be close together will capture small changes; centroid that are farther apart will each be mapped to by a wider variation of codes and thus require more changes to map to a different centroid.

Addressing the A->B, X->Y co-occurrence event, in this case the code may lie between the A->B and the X->Y centroids. So why not process both of them? Neither will show up as strongly as if they were the sole causation event, but they should prove significant also.

2/13/2022

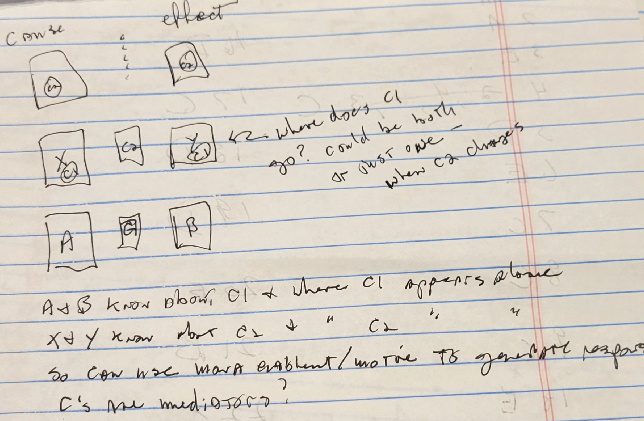
Let there be two computations:

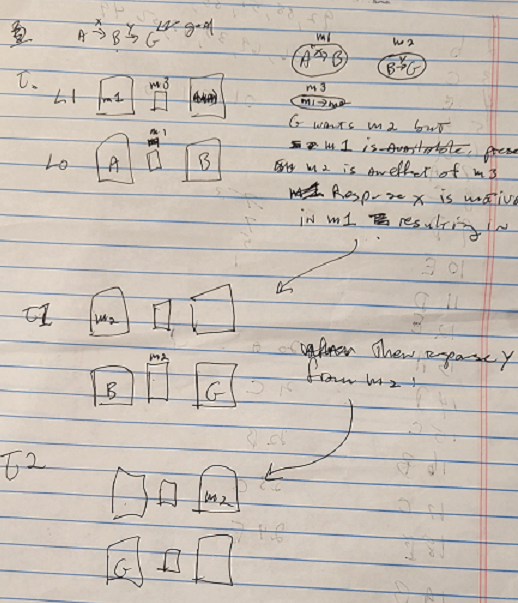
Sensors at all levels -> response (not including need, as this is a model-based system as opposed to a model-free system aka Q-learning).

Per level + response -> effect (this will create the code to be incorporated at higher level)

Can this scheme dispense with the Mona network and centroids? (no)

2/14/2022





Ref:

Exploratory State Representation Learning

Astrid Merckling\*, Nicolas Perrin-Gilbert, Alex Coninx and Stéphane Doncieux

Model-based scheme to explore and map env followed by RL on learned space.

Note: look up Reber learning comparison between humans and machines. Notes how humans appear to learn it piecemeal like Mandala.

Instead of using centroids, might use an RBF network to classify against prototype vectors.

Instead of generating random grammars, generate them according to rules:

1. Breadth: e.g. A, AB, ABC
2. Depth: A=A1 A2 A3
3. Repetition: AA, ABAB, ABCABC

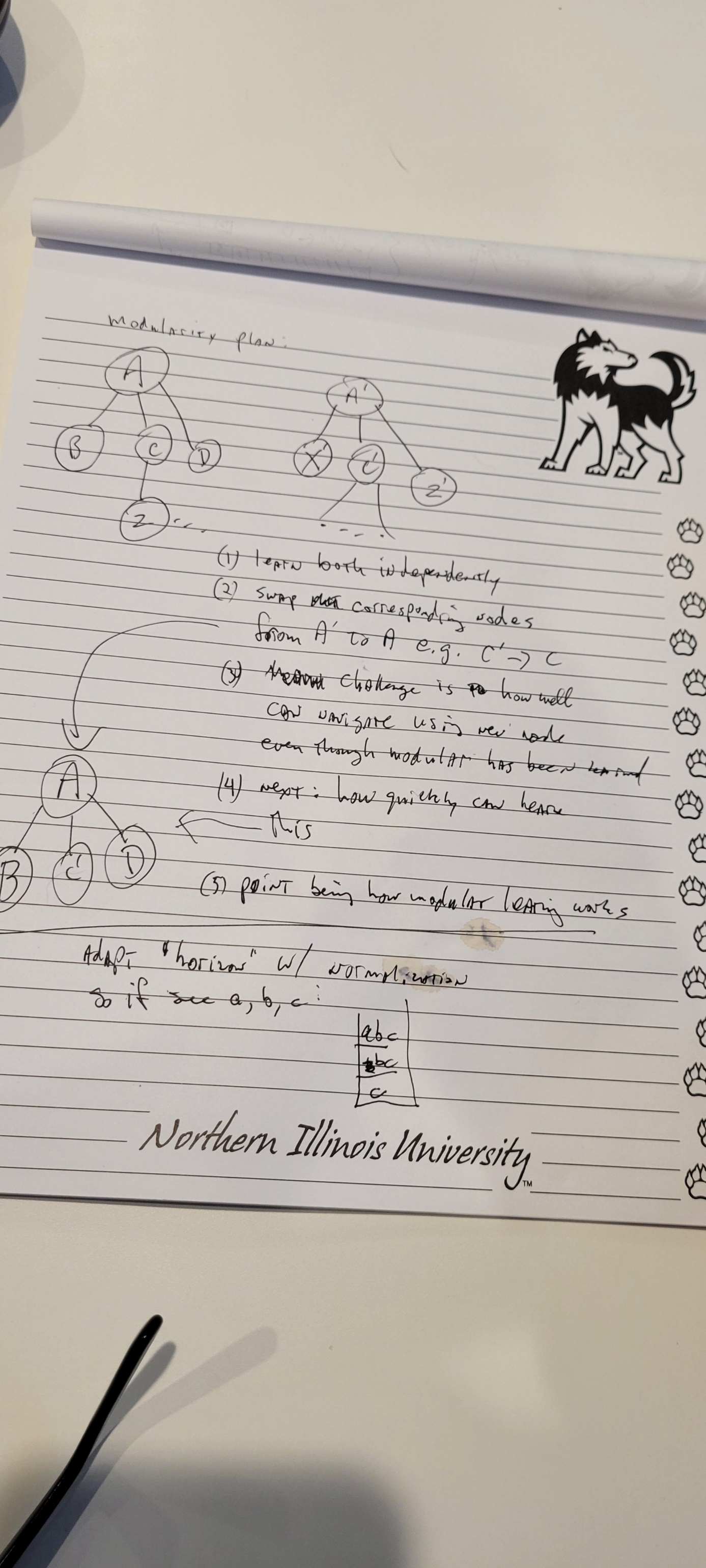
At the edge of the tree, terminals are produced.

This will provide more reliable performance measurements.

Mandala prototyping with grammar. Instead of encoding causations, sum the occurrences, so if a and b occur in the lower level in the level’s time duration, the one-hot representations of a and b are summed.

What sort of statistical analysis can be done on the mutual info/Baysian probs of the grammar that help explain performances?

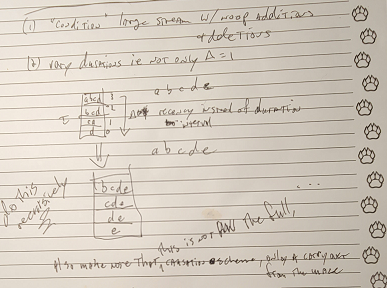
Spruce up TDNN as a prototype test. Try testing entire length, accumulated values, copying values into multiple layers, and subsumption. These things helped for the maze project.



A simplification:

Start -> Goal. In between are a number of subgoals in sequence. These can be learned separately/modularly. String some of them together and learn the whole stream. Then life intervenes and adds and subtracts subtasks from the stream. Test and measure this.

Let the Start -> Goal be one monolithic learning stream. Then the task is to complete it given deletion and insertions of other modules.



Hierarchical Reinforcement Learning:

Assignment of Behaviours to Subpolicies by Self-Organization

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<https://www.geeksforgeeks.org/deep-learning/sparse-autoencoders-in-deep-learning/>