Bayesian nets
Meeting notes 11/9/2022

Amber, Dennis, Zhongming and Patrick were physically present.

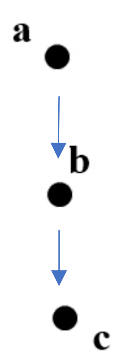
1. In the two weeks Patrick was gone, Dennis and Amber have done great work in essential components of the model we're trying to build.

They have a program that can convert a network with a visual with-arrows network display into its corresponding adjacency matrix, and that to a binary code without the needless diagonal. It can similarly move from the code to the other elements. All of that will allow us an easy way to alter networks by genetic algorithm, mutating (or hybridizing) the codes that represent their adjacency matrices.

Relevant files and a demo are attached, easily accessible in VS Code (Visual Studio Code), freely downloadable.

2. The next question was how to pass evidence from the 'world' network. Amber proposed that we represent evidence as a matrix as well, which we decided wouldn't be exactly like the adjacency matrix. It would instead represent what happened when each of the nodes was activated. Since we are representing temporal steps, digits would represent not only that another node was activated but in what order.

This simple world network;



will give us this evidence matrix:

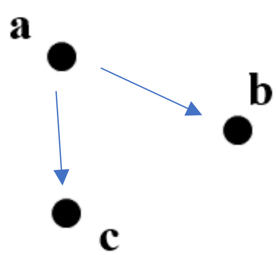
	a	b	c
a		1	2
b			1
c			

Indicating that when a is activated, first b and then c are activated.
When b is activated, c is activated.

But when c is activated, nothing else is (the end of the line)

And of course that evidence could be encoded as 0 1 2 0 0 1 0 0 0, or could lose the diagonal.

A branching network like this one:



Will give us this evidence matrix:

	a	b	c
a			
b	1		1
c			

Dennis and Amber are going to work next on how to generate this kind of evidence matrix (or its code) from a given network.

3. When we have that, the basic strategy will be this:

a. We start with a ‘world’ network, which generates a given evidence matrix.

b. We also start with a handful of ‘representation’ networks, constructed basically at random (though avoiding loops and perhaps other complications at the moment). For each of these, we also generate an evidence matrix.

c. We compare the evidence matrices from each representation network, and score the different representation networks on how well they matched the evidence generated from the world.

d. We keep those that scored the highest, and generate mutations of those to try again.

The theory is that in the long run we will end up with a representation network that matches the world.

4. Zhongming has been following all of this with suggestions, but has also been working on a mathy project on the side, which would ultimately dovetail with this.

He has a presentation on that which we will see next time, though the slides in their present states are also attached.

The basic goal: for full Bayesian networks (our simple causals aren't there yet), it seems very plausible that even if two networks start with very different credences at nodes and very different conditional probabilities between them, they will converge on all values if given the same stream of evidence in terms of likelihoods at (all and) the same nodes. The idea is that incoming evidence would change and 'swamp' initial credences and conditional probabilities.

It would be nice if we could prove it.

That proof would still be for networks that start out with the same arrow-structure. The real grail would be to have that, and also extend it to the kinds of adaptive networks we're working with in the causal case. That would show whether, or under what conditions, very different representational networks in terms of both structure and initial values would converge under the same evidence barrage.

5. We want Sophia to be part of the research mix as well, but everyone decided that that will wait until next term—hopefully then we can all find a joint meeting time.

With that in mind, everyone is asked to sketch out their prospective schedule as soon as possible. Dennis will probably do another 'green sheet' indicating prospective meeting times.

Next meeting: next Wednesday, same place.