Diagnosis of Ambiguous Faults in Simple Networks

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Abstract

We propose a theory of how individuals diagnose faults, and we report two experiments that tested its application to the diagnosis of faults in simple Boolean systems. Participants were presented with simple network diagrams in which a signal was transmitted from a set of input nodes to an output node, via a set of connecting nodes. Their task was to detect and diagnose faults. Experiment 1 showed that individuals tend to diagnose events closest to an observed inconsistency as the cause of the fault. Experiment 2 replicated this *proximal* effect, but also demonstrated that participants tend to target the proximal node most often when it fails to transmit a signal. This phenomenon may occur because individuals construct models of those situations in which a node works, but leave implicit those situations in which it does not work. The present results extend the mental model theory to diagnostic reasoning.

How do individuals diagnose faults in simple systems? If something goes wrong, what guides their initial hypotheses about the cause of the fault? In this paper we propose a theory that explains the diagnosis of faults in simple Boolean networks, and we report experimental tests of the theory. The theory assumes that individuals diagnose faults by mentally simulating the network in a dynamic mental model (see Johnson-Laird, 1983). It postulates three main principles for diagnosis. First, individuals assume that causes of faults occur prior to the fault and as close to it as possible. Hence, they should locate faults as close as possible to the output of a network. We refer to this sort of diagnosis as a "proximal" bias, i.e., the proximal cause is the event that occurs nearest to the effect. Second, individuals should be more likely to diagnose faults in the proximal node when it ought to transmit a signal than when it ought not to. Third, individuals assume by default that complex components are more likely to go wrong than simple components. One index of complexity is the ease of understanding how a component works.

Prior research has investigated fault finding in network tasks (see e.g., Morrison & Duncan, 1988; Rouse, 1978; Rouse & Rouse, 1979). Participants were presented with a matrix of nodes, connected in a variety of different ways. A set of input nodes was connected by intermediary nodes to a set of output nodes. Typically, the networks consisted of a matrix of about 49 nodes (7 by 7). The input nodes each transmitted a signal through the system, and in the basic form of the task, each connecting node acted as an AND operator, i.e., in order for it to transmit a signal, it had to receive activation from every one of its input nodes. Faults were failures in one or more output nodes to yield a signal. The participants' task was to locate the cause of a fault by performing tests on single connections between pairs of nodes. They needed to find the single faulty node that accounted for all and only the observed output failures.

These studies showed that several factors increased the difficulty of the task, but they did not reveal much about the initial generation of hypotheses to explain the faults. In order to investigate this process, we adopted a modified version of the network task. Our networks were much simpler than those previously investigated: they had only six nodes (Experiment 1) or seven nodes (Experiment 2), and only a single output node. We allowed that the connecting nodes could be one of three sorts of Boolean operator – AND, OR, and OR ELSE. And the participants were not required to determine the cause of the fault definitively, but only to formulate a preliminary hypothesis about what to investigate first in the network in order to find the fault.

Experiment 1

The purpose of the study was to examine the ability of naïve individuals to detect inconsistencies in the behavior of a simple network and the nature of their diagnoses. All the problems used the network shown in Figure 1.

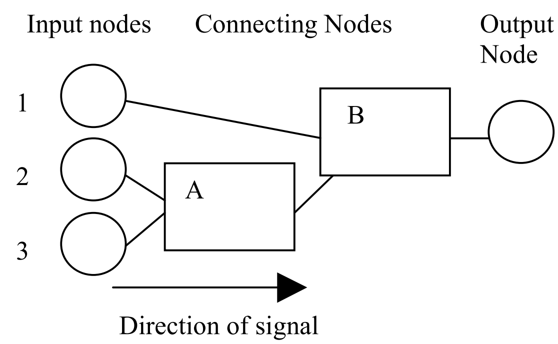

Figure 1: The network used in Experiment 1.

The participants were told that inputs are fed into the three input units, and a signal is transmitted from left-to-right to the output node. It may or may not produce an output depending on the particular inputs and on the particular logical connectives (AND, OR, or OR ELSE) in the two nodes (A and B). On a given trial, the participants were presented with the inputs, the logical connectives in each node, and the output, and they first judged whether the input-output configuration was correct or incorrect. If they judged it as incorrect, they next indicated which of the two nodes, A or B, they would prefer to investigate first in an attempt to diagnose the cause or causes of the fault. This question was designed to elucidate the principles underlying their diagnostic intuitions.

The theory predicts that they should focus on the node closest to the output. It further predicts that this bias should be strongest when that node ought to transmit a signal but in fact does not. This prediction stems from a known bias to represent only what is true in reasoning: individuals construct mental models of propositions in which each model represents a true possibility, and within each of these true possibilities, only those clauses that are true within that possibility are represented (see *principle of truth*, Johnson-Laird & Savary, 1999). Extending the first component of this principle to the present domain, we predicted that individuals should be more likely to construct explicit models of the conditions under which each node transmits a signal rather than the conditions under which it does not transmit a signal. As participants try to diagnose a fault in a network, their attention should focus on nodes that ought to transmit a signal, but which in fact do not. There is a mismatch between the participants' models of the node, which explicitly represent only the transmitting possibilities, and their models of the node's actual functioning, which is not to transmit a signal (see the *mismatch principle*, Johnson-Laird, Girotto, & Legrenzi, 2004). Of course, there is also a mismatch in the case where a node ought not to transmit a signal, but in fact does transmit one, but the theory predicts an asymmetry in diagnoses because of the tendency to represent explicitly only the transmitting possibilities. Finally, the theory predicts that nodes that are the most difficult to process should be diagnosed as faulty most often.

Method

Participants. Thirty-nine participants (13 male, 26 female) from Princeton University were paid $10 or received course credit for their participation.

Design and Materials. Participants acted as their own controls, and each performed 58 test problems. All problems used the network shown in Figure 1. The problems were divided into six different categories according to the logical connectives (AND, OR, or OR ELSE) in the two main nodes in the network. An AND node is one that transmits a signal if and if only if it receives a signal from all of its inputs. An OR node is one that transmits a signal if and only if it receives a signal from at least one of its inputs, or both. An OR ELSE node is one that transmits a signal if and only if it receives a signal from at least one, but not both, of its inputs. Given the three connectives and the two nodes, there are six sorts of problem given that we examined only those problems in which the connectives in the two nodes were different. Within each sort of problem, we selected a representative subset from the eight possible input patterns (there are eight possible patterns, given three inputs with two settings each). Each input pattern was presented twice – once when the network produced a correct output, and once when it produced an incorrect output. The full set of the 29 problems that had incorrect outputs is presented in Table 1. The six sorts of problem were presented in six separate blocks in a random order for each participant, as was the order of the problems in each block. There were six practice problems using the same connective in both nodes.

Table 1: The full set of inconsistent problems used in Experiment 1, with the percentages of node choices alongside each node.

No.	Inputs: 1 2 3	Output	Node A	Node B
1	0 0 0*	1	OR (16)	AND (79)
2	1 0 0	1	OR (45)	AND (53)
3	1 1 0	0	OR (29)	AND (63)
4	1 1 1	0	OR (26)	AND (66)
5	0 0 0	1	AND (24)	OR (76)
6	0 1 0	1	**AND (82)**	**OR (16)**
7	0 1 1	0	AND (26)	OR 71)
8	1 1 1*	0	AND (0)	OR (87)
9	0 0 0*	1	XOR (21)	AND (79)
10	1 0 0	1	XOR (47)	AND (53)
11	1 1 0	0	XOR (32)	AND (58)
12	0 1 1*	1	XOR (34)	AND (66)
13	1 1 1	1	**XOR (89)**	**AND (8)**
14	0 0 0	1	AND (16)	XOR (84)
15	1 0 0	0	AND (11)	XOR (89)
16	0 1 0	1	**AND (66)**	**XOR (24)**
17	1 1 0	0	AND (21)	XOR (55)
18	0 1 1	0	AND (24)	XOR (68)
19	1 1 1	1	AND (24)	XOR (76)
20	0 0 0	1	XOR (42)	OR (55)
21	0 1 0	0	XOR (45)	OR (50)
22	1 1 0*	0	XOR (16)	OR (82)
23	0 1 1	1	**XOR (89)**	**OR (8)**
24	0 0 0	1	OR (29)	XOR (61)
25	1 0 0	0	OR (13)	XOR (79)
26	0 1 0	0	OR (37)	XOR (61)
27	1 1 0	1	OR (34)	XOR (63)
28	0 1 1	0	OR (21)	XOR (71)
29	1 1 1	1	OR (26)	XOR (74)

Note. Consistent with standard logical notation, OR ELSE in Table 1 is represented by XOR. Problems marked with an asterisk are ones where the error could be explained only by an error in Node B. Problems in bold produced aberrant results (see results and discussion).

Procedure. The participants were tested individually with a computer running the Eprime program. Each problem appeared on the screen as a static diagram of the network (showing the inputs, the logical operator within each connecting node, and the output), with yellow input and output nodes indicating that they were "on", and white nodes indicating that they were "off". The participants judged whether the network was correct or incorrect by pressing "c" or “i”, on the keyboard. After each practice problem participants received feedback about whether they had or had not made a correct evaluation of the network. In order to proceed to the main stage of the experiment, participants were required to perform five out of six practice problems correctly. For these problems, participants judged whether the network was behaving correctly or incorrectly, but did not go on to make a diagnosis for the incorrect networks. They repeatedly cycled through the same set of practice problems (in a new random order each time) until this criterion was achieved. Participants required a mean of 1.79 cycles, and the modal number of cycles was 1.

In the experiment proper, the participants judged whether or not a network was correct. But, when they judged that it was incorrect, they then made a preliminary diagnosis. They typed “a” or “b” to select node, A or B, as the one that they would test first in a preliminary investigation into what was wrong with the network. This judgment was hypothetical, i.e., participants did not go on to conduct the test, nor were they presented feedback about which node was in fact responsible for the error. The network remained on the screen while the diagnosis was made.

Results and discussion

The data from one participant were removed as a result of a computing error. The participants were accurate in their judgments about whether or not the network was correct (95% correct). They were faster to make accurate judgments about correct circuits than about incorrect circuits (6.60s vs. 7.43s, Wilcoxon test, $z = 2.82$, $p < .01$). Problems that included an OR ELSE node appeared to pose an extra difficulty. The participants took longer to make judgments of correctness for these circuits (7.25s) than for problems without an OR ELSE node (6.25s; Wilcoxon test, $z = 2.4$, $p < .02$). This effect occurred for judgments of both correct and incorrect networks (Wilcoxon tests, $z = 2.76$, $p < .01$; $z = 2.08$ $p < .05$, respectively). Networks that included OR ELSE nodes therefore appeared somewhat more difficult to simulate.

The percentage of node choices for each problem is displayed in Table 1 (the percentages do not always sum to 100 owing to some participants’ failure to identify the network as inconsistent, or to their pressing the wrong button). There was a consensus about which node to investigate first for the circuits that were incorrect. As the theory predicts, the participants tended to select the node closest to the output. This proximal bias was greater than 20% for 21 out of the 29 incorrect circuits. For problems where either A or B may have been in error (there were 24 such problems; and the five remaining problems were ones where only B could account for the error, see table 1), the difference between the percentages of A and B choices was 20% across all subjects (Wilcoxon test, $z = 3.3$, $p < .01$), and across all problems (Wilcoxon test, $z = 2.06$, $p < .05$). This proximal bias may occur because nodes earlier in the network are considered more reliable, or because individuals prefer to locate causes as close as possible to their effects. However, there are two potential confounds. First, the proximal node, B, was always at the top of network. Second, it was connected to both an input node and the output node, whereas the other node, A, was not directly connected to the output node.

We examined factors that may modify the proximal bias. As the theory predicted, the proximal node was chosen more frequently when it ought to have transmitted a signal but failed to do so, than when it ought not to have transmitted a signal, and yet did so (68% vs. 57%, Wilcoxon test, $z = 3.13$, $p < .01$). In other words, the proximal node was more liable to be diagnosed as faulty when it produced a “miss” rather than a “false positive”. This difference may arise from participants’ explicitly constructing a model of the conditions under which the node should transmit a signal rather than when it should not.

As the theory also predicts, the participants were more likely to locate the fault in the proximal node when it was an OR ELSE node (67%), than when it was an AND node (59%, Wilcoxon test, $z = 2.53$, $p < .02$) or an OR node (55%, Wilcoxon test, $z = 3.2$, $p < .01$). But, there was no difference between AND and OR nodes (Wilcoxon test, $z = .41$, $p = .684$). As the latency results above show, OR ELSE appears to be harder to understand than the other two connectives. Hence, it is a more complex connective for our participants, and so the participants should infer that a fault is more likely to occur in its nodes. It may be that mere *fluency* of processing exerts a direct effect on diagnosis (see Schwarz, 2004). There were four problems in which node A was chosen more frequently than node B (nos. 6, 13, 16, 23, in bold). But, for each of these four networks, the proximal node transmitted output when it should not have. As we have already seen, the proximal bias was attenuated for such problems. In addition, node A was an OR ELSE node for problems 13 and 23, which made it more liable to be diagnosed as being in error.

Experiment 1 established that individuals are proficient at judging the correctness of simple networks. They are faster to make accurate judgments about consistent networks than about inconsistent networks. Their preliminary diagnoses corroborated the theory in three ways. First, they tended to locate faults in proximal nodes, i.e., those that were closest to the output revealing that a fault had occurred. Second, they were more likely to do so when the proximal node failed to produce output when it should have than when it produced output when it should not have. Third, they also tended to be biased towards locating the fault in the proximal node when it was an OR ELSE node. These nodes are harder to understand, and so that difficulty may indicate that the node is complicated, and hence more likely to go wrong.

Experiment 2

In order to eliminate the confounds in the previous experiment, we carried out a second experiment using a more complicated network of seven nodes (see Figure 2). The theory yields three predictions. First, individuals should show the proximal bias, i.e., they should be biased to select node, D, as the cause of the fault.

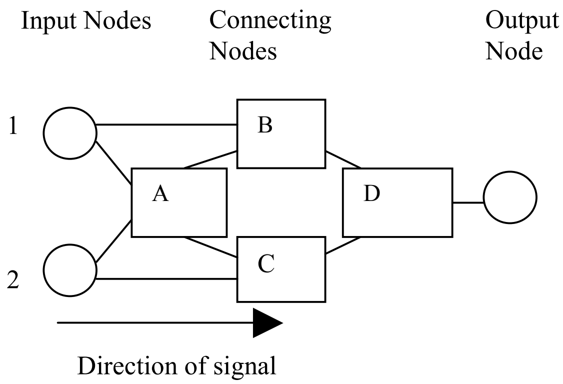

Figure 2: The network used in Experiment 2.

Second, the network again allowed us to investigate how the tendency to diagnose the proximal node is affected by mental models of its functioning. As before, we predicted that the proximal node should be diagnosed as the faulty component more often when it ought to transmit a signal but does not do so, than when it ought not to transmit a signal but does so. This tendency should arise from a bias to represent only the transmitting possibilities of the proximal node. Third, networks that include OR ELSE nodes should take longer to evaluate than those that do not, and hence an account based on processing fluency predicts that the proximal node will be identified as the cause of the fault more often when it is an OR ELSE node.

Method

Participants. Twenty-four participants (15 male, 9 female) from Princeton University participated for course credit.

Design and Materials. Participants acted as their own controls, and each performed 27 test problems that all used the network in Figure 2 and the same three connectives as in Experiment 1. Of the 27 problems, 23 were incorrect networks and four were correct networks.

We suspected that the first and last nodes, A and D, would be most salient, and would be diagnosed as faulty more frequently than either B or C. B and C are likely to be less salient since they occupy symmetrical positions in the overall network structure, and it should therefore be harder to motivate a choice of one over the other as the cause of the fault. Hence, in order to test the proximal bias, the connectives in the first and last nodes were always identical, whereas the connectives in the middle nodes were always selected to be different from those in the end nodes. The problems were further divided into three main categories according to whether the first and last connectives were: OR, AND, or OR ELSE. Within each of those three categories, there were three further sub-types, depending on the connectives in the middle nodes. Problems were sampled from each of these nine categories. Different input patterns are also possible, and we selected these roughly at random, with the constraint that the four possible types of input pattern (0 0; 0 1; 1 0; 1 1) were nearly equally represented across the whole experiment.

Procedure. The procedure was the same as in Experiment 1. The mean number of required cycles through the practice segment was 1.33, and the modal number was 1. When the participants made their diagnoses in the main part of the experiment, they indicated which node from A, B, C, or D, they would test first (by typing "a", "b", "c", or "d").

Results and Discussion

Overall accuracy in detecting inconsistencies was high, as in the first experiment. All problems were performed at greater than or equal to 75% accuracy. Participants correctly judged 90% of the networks: 89% of the consistent networks and 90% of the inconsistent networks (there was no reliable difference between these percentages).

Table 2 illustrates the diagnoses made for the main classes of problems in the experiment (percentages do not sum to 100 owing to participants' errors). The proximal bias was again reliable. Across all problems, the percentages of selections of each node were as follows:

A: 22%
B: 11%
C: 13%
D: 43%

The last node, D, was chosen more often than each of the other three nodes (all three pairwise Wilcoxon comparisons were significant, $p < 0.01$).

Table 2: The percentages of node choices depending on the functioning of the proximal node, D, in Experiment 2.

Type of problem	Node A	Node B	Node C	Node D
Networks in which the proximal node should transmit output but fails to do so.	13	10	9	**54**
Networks in which the proximal node should not transmit output but does so in error.	27	13	15	**38**
Networks in which the proximal node was OR ELSE.	15	8	12	**53**
Networks in which the proximal node was not OR ELSE.	29	13	13	**39**

Note. The horizontal line separates the two main sets of comparisons. Numbers in bold indicate the key comparisons within each set.

The predictions based on the mismatch principle were confirmed. The participants were more likely to diagnose the proximal node, D, when it should have transmitted a signal but in fact did not, than when it should not have transmitted but in fact did so (54% vs. 38%, Wilcoxon test, $z = 2.3$, $p < .05$). This again supports our theory that a mismatch between an explicit model of the situations in which a node will transmit a signal, and a model of the node's actual nontransmission, leaves the node particularly liable to be diagnosed as the cause of fault.

As in Experiment 1, for inconsistent networks in which at least one input was on, those that included at least one OR ELSE node took longer to correctly evaluate than those that had no such nodes (17.4s vs. 14.4s., Wilcoxon test, $z = 2.43$, $p < .01$, one-tailed). The theory predicts that participants should choose OR ELSE nodes with a greater frequency than they choose either AND or OR nodes. And participants were more likely to diagnose the proximal node as faulty when it was an OR ELSE node (53%) than when it was an AND node (39%, Wilcoxon test, $z = 2.59$, $p < .01$), or an OR node (38%, Wilcoxon test, $z = 3.18$, $p < .01$). Participants again seemed to prefer diagnosing more complex nodes as the cause of error.

General Discussion

The model theory of diagnosis proposes that individuals base their intuitions on a mental simulation of a network. It postulates three main principles. First, individuals focus on *proximal* causes when forming diagnoses. Second, they tend to diagnose the fault in the proximal node more often when it ought to transmit a signal. And, third, they tend to diagnose faults in more complex nodes. We tested these principles in two experiments which investigated how individuals form intuitive diagnostic preferences when diagnosing a faulty network.

Experiment 1 showed that individuals tended to diagnose the fault in the node that was as close as possible to its occurrence. This result could have been explained by other factors, but it held up in Experiment 2, in which such alternative explanations were not available. This demonstration of a *proximal effect* parallels work showing that more recent events are more likely to be "undone" in counterfactual thinking (see Byrne, Segura, Culhane, Tasso, & Berrocal, 2000; Miller & Gunesegarm, 1990; Teigen, Evensen, & Samoilow, 1999; Walsh & Byrne, 2004, for the *temporal order* effect). And it also parallels work on belief revision, which has shown that information that is presented earlier in a sequence tends to be regarded as less corrigible (although the opposite effect has also been demonstrated in some studies; see Hogarth & Einhorn, 1992, for a review). Our findings extend this previous work by demonstrating a proximal effect in a Boolean domain, where information is presented simultaneously rather than sequentially, but a mental model must reconstruct the temporal sequence of events.

One interpretation of the proximal effect is that the parts of the network that are mentally simulated first tend to be regarded as the least revisable. This account attributes the result to memory processes – initial information may be the most salient (see e.g., Anderson, 1981; Hogarth & Einhorn, 1992; Schlottmann & Anderson, 1995). We have offered an alternative interpretation: individuals tend to mentally undo the event closest in causal proximity to an observed inconsistency. These two interpretations are different, but our present data are not able to distinguish between them. Yet, the second interpretation seems more plausible. The effect probably relies less on the temporal order of a mental simulation, and more on the greater cognitive effort required to change an earlier (as opposed to a later) component of a network. An earlier change may call for a later change, whereas a later change need have no effect on what happened earlier in the network. There may thus be a rational element to this tendency.

There is less room for a rational interpretation of the tendency to diagnose faults in the proximal node when it produced a "miss" rather than a "false positive". A failure to transmit a signal is just as much an error than as the mistaken transmission of an signal, and there is no logical reason why the proximal node is implicated to a greater extent in the first sort of error. The bias, however, was predicted from an extension of the model theory's *principle of truth* and its *mismatch* principle. According to this extension, participants are influenced by the match between their model of how the proximal node ought to be operating, and their model of its actual operation. The model of how the proximal node ought to be operating represents explicitly only the possibilities in which the node transmits a signal, leaving implicit the possibilities in which it does not transmit a signal. Hence, while both misses and false positives produce mismatches, only misses give rise to a mismatch with an explicit model of the node's functioning, and thus lead to an increased proclivity to attribute error. The tendency occurred only for the proximal node, and not for the other nodes. However, this difference makes sense, because the participant knows for certain only the output of the proximal node. Mismatches for the other nodes are a matter of inference. If, as we claim, the mismatch bias is responsible for the phenomenon, its operation must be largely unconscious, because in post-experimental questioning, no participant ever put it into words.

We found support for the theory's third principle: complex nodes should tend to be diagnosed as the cause of faults. Both experiments showed that OR ELSE gates were most liable to be diagnosed as the source of error, and that they also took the longest time to process. To our knowledge, this demonstration is the first to show an effect of processing fluency in diagnostic reasoning (see Schwarz, 2004).

A skeptic might argue that the diagnostic choices we observed, and particularly the effects of mismatch, result from posing a question to the participants that did not have a correct answer. Such effects are arguably likely to be fleeting and unimportant. We agree that the effects may not have a persistent impact when individuals have to discover a single and unambiguous cause of a fault (as in Rouse and his collaborators' experiments). But, such tasks are unlikely to match the diagnosis of faults in the real world. Evidence for them is rarely clear and unambiguous (see e.g., Dörner, 1996, on the Chernobyl incident). Ambiguous evidence is liable to be assimilated to match prior hypotheses and to be processed in a distorted way (e.g., Darley & Gross, 1983; Lord, Ross, & Lepper, 1979). In such situations, the phenomena that we observed may prevent people from using new evidence to reach a correct diagnosis.

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