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Article

Intelligence without Representation: A historical perspective

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Abstract: This paper reflects on a seminal work in the history of AI and representation: Rodney Brooks' 1991 paper *Intelligence without Representation*. Brooks advocated the removal of explicit representations and engineered environments from the domain of his robotic intelligence experimentation, in favour of an evolutionary-inspired approach using layers of reactive behaviour that operated independently of each other. Brooks criticised the current progress in AI research and believed that removing complex representation from AI would help address problematic areas in modelling the mind. His belief was that we should develop artificial intelligence by being guided by evolutionary development of our own intelligence, and that his approach mirrored how our own intelligence functions. Thus the field of behaviour-based robotics emerged. This paper offers a historical analysis of Brooks' behaviour-based robotics approach and its impact in artificial intelligence and cognitive theory at the time, as well as in modern-day approaches to AI.

Keywords: behaviour-based robotics; representation; adaptive behaviour; evolutionary robotics

1. Introduction

In 1991 Rodney Brooks published the paper *Intelligence without Representation*: a seminal work in behaviour-based robotics [1]. This paper influenced many aspects of research into artificial intelligence and cognitive theory.

In *Intelligence without Representation* Brooks described his behaviour-based robotics approach to artificial intelligence. He highlighted a number of points that he considers fundamental in modelling intelligence. ~~These ideas were controversial and triggered much debate.~~ Brooks was advocating the removal of explicit representations and engineered environments from the domain of his robotic intelligence experimentation. This was in stark contrast to traditional approaches to AI, which Brooks attacked in this paper, as well as contrasting with many modern-day approaches to AI.

Whilst Brooks' views have inspired similar research by a number of his contemporaries, ~~and brought about the research area of behaviour-based robotics as well as inspiring other research areas,~~ his ideas were controversial and he also has many critics who do not accept the validity of what he proposes. Nevertheless Brooks has impacted research in artificial intelligence and cognitive science since 1991. He presents a distinct view on how we can use artificial intelligence techniques to model and understand our own intelligence.

2. The state of Artificial Intelligence research prior to 1991, as the context for *Intelligence without Representation*

The two prominent schools of thought in Artificial intelligence (AI) prior to the publication of *Intelligence without Representation* were (i) traditional AI (also referred to as symbolic AI, logical AI, *Good Old Fashioned AI* (GOFAI) or classical AI) and (ii) connectionism (also referred to as neural networks). Traditional AI was the most prevalent approach at the time of writing *Intelligence without Representation* [1].

36 Brooks' critical comments on the failures of AI research to date were mainly addressed at
37 traditional AI, although his criticisms also included connectionism, which was coming back into
38 active research after developments in the 1970s. Although there is little in common between these
39 two approaches, they are widely regarded as both being derived from the same original source of
40 McCulloch and Pitts' work ~~this was not always the case; for example the seminal work by McCulloch
41 and Pitts on a neuronal approach to logic-based AI [reference updated] [2] influenced both traditional
42 AI and connectionism [3].~~

43 To understand the AI environment which contextualises [1]: the aim of traditional AI at this time
44 was to demonstrate how the processing of information can be done in an intelligent manner; generally
45 efforts are focused on carrying out specific tasks or solving problems in specialised domains. The
46 information being processed was represented in such a way that computation can be performed to
47 create a solution. This would be done by performing manipulation of some symbolic format of the
48 problem domain, for example Hayes suggested the use of first-order logic [4]. This manipulation is
49 referred to as the physical symbol system hypothesis [5], with the symbolic manipulation centrally
50 controlled by some supervisory process. The manipulation of a representation of a problem domain
51 for intelligence can be seen today in knowledge representation research examples for contemporary
52 robotics such as *KnowRob* and *RoboEarth* (see [6]), as well as in areas such as data mining and statistical
53 machine learning algorithms.

54 Connectionism, on the other hand, was more biologically-inspired, taking as its model what we
55 know about the architecture of the human brain. The concept behind connectionism was that if we
56 construct an inter-connected network of units similar to the neural units that we believe the brain
57 is constructed of, then we can construct an intelligent system that functions as the brain does. One
58 can trace modern day research in deep learning, neural networks and cognitive neuroscience back to
59 connectionist roots.

60 The overreaching contemporary goal for artificial intelligence as viewed by many commentators
61 was to replicate human intelligence in a computational system [5,7,8].¹ Brooks strongly criticised the
62 general state of AI research at that time [1,8], commenting that research was not advancing towards this
63 goal as it should, and was too specialised into sub-disciplines such as planning or logical reasoning.²
64 He argued that our lack of sufficient understanding of human intelligence prevents us from being able
65 to partition AI effectively into specialisms that could be recombined in the future:

66 "No one talks about replicating the full gamut of human intelligence any more. Instead
67 we see a retreat into specialized subproblems ... Amongst the dreamers still in the field of
68 AI ... there is a feeling that one day all these pieces will all fall into place and we will see
69 "truly" intelligent systems emerge.

70 However I, and others, believe that human level intelligence is too complex and little
71 understood to be correctly decomposed into the right subpieces at the moment." [1, p. 140]

72 He believed that traditional AI research efforts addresses the wrong type of intelligent behaviour
73 and quoted evolutionary timescales to support this view. For example, it took 5000 years to develop
74 the art of writing: only a tiny fraction of the 3.5 billion years it took to develop the essence of
75 "being and reacting" [1]. Given this evolutionary precedent, Brooks believed that the proportion of
76 research in specialised areas such as computational linguistics and natural language processing is
77 disproportionately large and that we should instead be concentrating our efforts on modelling more
78 simple intelligent behaviour.

79 A powerful analogy used in [1] is that of artificial flight. He hypothesised about a group of
80 artificial flight researchers of the 1890s (before aeroplanes were invented). These researchers are

¹ See concluding remarks to see how this definition has evolved since.

² Certainly AI was not progressing as hoped for: Turing expected his test of intelligence [9] to have been passed by the end of the twentieth century; however at the time of writing the Turing test still has not been passed.

81 transported in time to travel on an aeroplane in the 1980s. Given this glimpse of how artificial flight
82 is real and possible, on their return they work on replicating the aircraft of the 1980s, exactly as they
83 have seen, but with only their own limited knowledge to guide them.

84 His point is that modern day AI researchers are similar to these artificial flight researchers from
85 the 1890s, in that they are trying to reconstruct the example of their work in practice that they have
86 seen working successfully, with insufficient basic knowledge about the underlying foundations of their
87 work. In other words, AI researchers in 1991 are working without sufficient knowledge of how our
88 intelligence is developed from basic levels (like that demonstrated by insects, for example).

89 There is some precursor to Brooks' views in the discussion of the successes and failures of AI.
90 Dreyfus and Dreyfus constructed a critical review of early work in Artificial Intelligence, up until the
91 time of writing [10]. They judged that traditional AI has been found wanting and has not made the
92 achievements in explaining and modelling the mind that it should. Hubert Dreyfus had previously
93 argued [11] that intelligence could not be generated by symbol manipulation and that AI research was
94 weakened by its reliance on Newell and Simon's physical symbol system hypothesis and felt that this
95 argument had not been countered yet.

96 "The physical symbol system approach seems to be failing because it is simply false to
97 assume that there must be a theory of every domain." [10, p. 330]

98 Drew McDermott, previously a key exponent of logical AI, also described how he was now
99 drawn more to an approach which discards deduction as the sole implementation of the thinking
100 processes [12]. As McDermott still made use of knowledge representation, his approach in [12] was
101 not as extreme a departure from traditional AI as Brooks's was. However this public shift in views
102 from a prominent traditional AI researcher was indicative of problems in the traditional paradigm,
103 particularly as McDermott expresses concern that a large proportion of AI research thus far may be
104 leading to results that are of no use. McDermott admitted in [12] that his own research using this
105 new approach in had not been overly fruitful and that he had been forced to retreat from this new
106 viewpoint in his practical work, but he expressed confidence that once given proper investigation, this
107 new "territory" could provide AI research with interesting new results. His later research, however,
108 moved towards Semantic Web ontology research: an area emphasising significant use of knowledge
109 modelling and representation.

110 Still, prominent voices were criticising traditional symbolic AI as a means of explaining human
111 intelligence sufficiently. Therefore when Brooks' views were published, although controversial, they
112 had been given some foundation in philosophical AI literature.

113 It might be surprising to learn that Brooks' academic background half a decade prior to publishing
114 *Intelligence without Representation* (and similar papers) was rooted in symbolic AI. He wrote several
115 papers in the early 1980s on work in planning, representation-based models and symbolic reasoning
116 and analysis.³ Brooks discusses in a 1997 interview with the Edge Foundation how the complexity
117 of the mathematical models he was creating in his earlier career led him to the conclusion that the
118 symbolic approach was not the right way to explain how intelligence worked.

119 "It just couldn't be right. We had a very complex mathematical approach, but that couldn't
120 be what was going on with animals moving their limbs about. Look at an insect, it can fly
121 around and navigate with just a hundred thousand neurons. It can't be doing this very
122 complex symbolic mathematical computations. There must be something different going on."
123 [14]

³ It is interesting to note that although Brooks includes these publications in his list of publications on his academic profile [13], none of the symbolic AI papers are linked to full texts of the paper (though the full texts are accessible from other sources), whereas the vast majority of his papers post 1985 do have links. Brooks is acknowledging the existence of those papers but is disassociating himself from the contents of his earlier publications

124 It was this realisation that caused his change in perspective. From the mid 1980s onwards Brooks
 125 worked on developing this line of thought. This was to lead to the publication of *Intelligence without*
 126 *Representation* in 1991.

127 3. Fundamental aspects of *Intelligence without Representation*

128 3.1. Discarding Representation in favour of physical embodiment in the real-world environment

129 As suggested by the title of *Intelligence without Representation*, the hypothesis Brooks presented in
 130 1991 is that:

131 “Representation is the wrong unit of abstraction in building the bulkiest parts of intelligent
 132 systems” [1, p.140]

133 Brooks advocated that explicit central representations, “representation of goals that some central
 134 (or distributed) process selects from” [1][p. 144], are unnecessary to intelligence. Indeed they may even
 135 form a barrier to the demonstration of the mind’s intelligence: as computations on representational
 136 symbols become more complex they take longer to process, hence Brooks’ robots performed well
 137 compared to other contemporary robots in dynamic environments, because they could react in real-time
 138 without needing lengthy computational time. Brooks found during his own robotics experimentation
 139 that it is “better to use the world as its own model” [1, p. 140].

140 The behaviour-based robotics approach (also referred to by Brooks as *Nouvelle AI* in Brooks [8]
 141 requires that intelligence is demonstrated through our actions and interactions with the world. Critical
 142 to this is that the environment within which the robot operates must be independent of the robot
 143 design. It must not be simplified or targeted towards assisting the robot in any way. Instead the robot
 144 must be able to perform appropriate active and reactive behaviour to any environment it is put in.

145 As demonstration of this principle, one of Brooks’ more famous intelligent robots (which he refers
 146 to as “Creatures”) was *Herbert*, which operated in the MIT labs with the specific task of picking up
 147 drink cans. The lab environment is ever-changing, particularly when new people come to watch the
 148 robots operate. So Herbert would constantly need to react to new elements around it, working in
 149 real-time. Herbert was equipped with a small number of sensors and a mechanical arm that could
 150 grasp objects. Simple behaviours such as the ability to ‘wander’ around were enabled using infra-red
 151 and laser sensors to navigate corridors and doors, to follow walls and avoid obstacles, as they were
 152 encountered. Herbert’s sensors could also detect objects available to be grasped by its arm. [15].

153 Herbert was illustrative of the initial success of Brooks’ approach. In comparison, existing
 154 traditional AI robots at that time relied on being located in a static environment, a space which they
 155 would probably hold an internal representation of. For example, one could imagine that for a ‘GOFAI
 156 Herbert’ to solve the specific task of picking up drink cans in the MIT labs, it would require an internal
 157 representation of the MIT labs and objects in the labs. Movements would be calculated based on
 158 processing incoming input against that representation. Extra computation may be required on the
 159 occasions when input did not match what was expected given the robot’s internal representations.
 160 Though this GOFAI Herbert is hypothetical rather than realised, generally in practice one could see
 161 how it might follow the pattern Brooks was observing: that compared to robots like Herbert, traditional
 162 AI robots and exhibited very little movement compared to processing time [14].

163 It is important to clarify what, in Brooks’ eyes, constitutes a representation, so we understand
 164 precisely what Brooks is rejecting.⁴ Brooks did not directly define the term ‘representation’ in
 165 *Intelligence without Representation*, but he did describe what he sees as a “good representation” [1,
 166 p. 140] for AI:

⁴ As noted by a reviewer of this paper, “this failure to define the term “representation” fuels a lot of discussion in cognitive science. This implies that the term is not intuitively precise and that it means different things to different people. ”

167 “The idea was that by representing only the pertinent facts explicitly, the semantics of a
 168 world (which on the surface was quite complex) were reduced to a simple closed system
 169 once again. Abstraction to only the relevant details thus simplified the problems.” [1, p. 140]

170 As an illustrative example, Brooks gave the following representation of a chair:

171 “(CAN (SIT-ON PERSON CHAIR)), (CAN (STAND-ON PERSON CHAIR))” [1, p. 140]

172 According to Brooks, a “standard representation” (i.e. a traditional AI representation) is composed
 173 of “variables ... that need instantiation in reasoning processes. ... rules which need to be selected
 174 through pattern matching. ... choices to be made” [1, p. 145]. Brooks rejected “traditional AI
 175 representations ... tokens which have any semantics that can be attached to them.” [1, p. 144].

176 Later, in [16], Brooks clarified his interpretation of representations as “an abstract manipulable
 177 entity” [p. 8], “[i]nternal world models which are complete representations of the external environment”
 178 [p. 3], that “rely on a semantic correspondence with symbols that the agent possesses” [p. 3]:

179 “The common view in Artificial Intelligence, and particularly in the knowledge
 180 representation community, is that there is a central storage system which links together
 181 the information about concepts, individuals, categories, goals, intentions, desires, and
 182 whatever else might be needed by the system. In particular there is a tendency to believe
 183 that the knowledge is stored in a way that is independent from the way or circumstances
 184 in which it was acquired.” [16, p. 14]

185 “Over the years within traditional Artificial Intelligence, it has become accepted that
 186 they will need an objective model of the world with individuated entities, tracked and
 187 identified over time—the models of knowledge representation that have been developed
 188 expect and require such a one-to-one correspondence between the world and the agent’s
 189 representation of it.” [16, p. 16]

190 Brooks also used [16] to restate more clearly his position regarding representations, making it
 191 clear that he was not advocating for the entire removal of all representations of the environment that a
 192 robot operates in:

193 “My earlier paper [*Intelligence without Representation*] is often criticized for advocating
 194 absolutely no representation of the world within a behavior-based robot. This criticism
 195 is invalid. I make it clear in the paper that I reject traditional Artificial Intelligence
 196 representation schemes (see section 5). I also made it clear that I reject explicit
 197 representations of goals within the machine. There can, however, be representations
 198 which are partial models of the world” [16, p. 21]

199 3.2. *Subsumption architecture and emergent behaviour*

200 The *subsumption architecture* reported by [1] for Brooks’ robots is a modular structure composed
 201 of layers of simple behaviour such as *WANDER* or *AVOID OBSTACLES*. These layers co-exist
 202 independently and interact only as a side effect of their co-existence, rather than directly intending to
 203 communicate between layers. There is no central control of the layers or any symbol passing between
 204 layers; they operate independently of one another.

205 Emergentism, or emergent behaviour, is key to how the layers of Brooks’ subsumption architecture
 206 operate in parallel to demonstrate intelligent behaviour. Brooks took Herb Simon’s observation [17]
 207 of an ant walking across sand as an example of complex behaviour emerging from the combination
 208 of simple behaviours of an ant’s movement reacting to a complex environment. Brooks suggested
 209 complex behaviour in intelligent creatures is more a result of complexity in the environment rather
 210 than in the intelligent creature. So complex behavioural patterns can emerge when simple behaviours
 211 combine together and are situated in an environment.

212 The incremental nature of Brooks' robots means that successful behaviours are retained in future.
 213 New robots are developments of older robots: they have the same behaviour of older robots except
 214 that they have additional layers in their subsumption architecture (this is instead of constructing a
 215 completely new architecture for each new robot).

216 Brooks attributed much of his inspiration to evolutionary precedents. Evolution involves a great
 217 deal of 'trial and error', where organisms with the more successful developments flourished whilst
 218 other organisms struggled to survive. In past reflections [18], Brooks has described how his research
 219 methods take a similar direction:

220 "We don't have any plans! [for our robots] These are all research robots built experimentally
 221 ... patch upon patch upon kludge."

222 The successful 'patches' and 'kludges' survive and are retained, with new 'patches' added as the
 223 research develops.

224 4. Explaining cognitive processes through Brooks' approach: How does this differ to other AI 225 approaches?

226 "AI can help us understand the mind - what it is, as well as how it works." [7]

227 "Computational studies, investigating similar problems being solved in a mind-body
 228 complex, help develop a more rigorous model and, more importantly, provide an
 229 understanding of the flow of information in and between these processes." [19]

230 The above two quotes are indicative of the commonly held view that AI research is a valuable tool
 231 in explaining how the mind works. Andy Clark describes how our mental processes are envisaged by
 232 proponents of traditional AI and of connectionism:

233 "Classicists believe that thinking just is the manipulation of items having propositional
 234 or logical form; connectionists insist that this is just the icing on the cake and that *thinking*
 235 ('deep' thinking, rather than just sentence rehearsal) depends on the manipulation of
 236 quite different structure. As a result, the classicist attempts to give a level 2 processing
 237 model which is defined over the very same kinds of structure as figure in her level 1
 238 theory.⁵ Whereas the connectionist insists on dissolving that structure and replacing it with
 239 something quite different.

240 A curious irony emerges. In the early days of Artificial Intelligence, the rallying cry
 241 was 'Computers do not crunch numbers, they manipulate symbols'. This was meant to
 242 inspire a doubting public by showing how much computation was like thinking. Now the
 243 wheel has come full circle. The virtue of connectionist systems, it seems, is that 'they do
 244 not manipulate symbols, they crunch numbers'. And nowadays we all know (don't we?)
 245 that thinking is not mere symbol manipulation! So the wheel turns." [21, p. 306]

246 Brooks, on the other hand, believes that thinking is an emergent phenomenon that arises as a
 247 result of different behavioural layers interacting with each other. His approach could be said to form a
 248 new Kuhnian paradigm in artificial intelligence and cognitive science. He treated traditional AI and
 249 connectionism as the *normal science* within which researchers are encountering difficulties such as the
 250 symbol-grounding problem or the frame problem. Behaviour-based robotics is the *revolutionary science*

⁵ This is a reference to Marr's 3-level cognitive model of information processing [20]. Level 1, the *computational level*, looks at what a system does, what functions it performs, and why. Level 2, the *algorithmic level*, looks at how a system operates, and the representations and processes it employs. Level 3, not mentioned here, looks at the physical realisation of the system, and is perhaps the most relatable to Brooks' ideas (though by no means an accurate one-to-one mapping). Clark is making the point that, in contrast to a connectionist's perspective, someone from a classicist (traditional AI) perspective treats *how* we think (level 2) in terms of *what functions* may be occurring (level 1).

251 that Brooks presented as a new and more accurate paradigm that AI research needs to shift to in order
252 to make any real further progress [22].

253 It is worth looking at Brooks' arguments on how behaviour-based robotics deals with the
254 symbol-grounding problem and the frame problem. In his the Chinese Room analogy [23], Searle
255 described how intelligence cannot be attained purely through manipulating symbols, (the prevalent
256 attitude in symbolic AI). Instead these symbols should be "grounded" in some way so that they
257 are given semantic validity. It is only when there is some meaning to the symbols that guides the
258 manipulation of the symbols, that any such process could be considered as showing intelligent
259 behaviour.⁶

260 This *symbol grounding problem* - defining the actual semantics or referential meaning of the
261 computation performed by intelligent systems - was of major concern to symbolic AI practitioners. To
262 Brooks and his supporters, however, this problem is essentially solved by behaviour-based robotics
263 as a matter of course, by basing the robots in a real-world environment and using the surrounding
264 environment to guide its actions rather than representations of the environment. Brooks believes that
265 the symbol-grounding issue does in fact demonstrate how his behaviour-based approach addresses
266 one of the fundamental weaknesses of traditional AI and connectionism [1,8].

267 Another classical problem in symbolic AI is known as the *frame problem*. If the world that the
268 intelligent system operates in is given some form of representation, then the intelligent system has to
269 deal with monitoring changes in the environment and incorporating these in the representation. Also
270 any aspects of the environment that have not been encoded representationally may cause the intelligent
271 system problems. As Brooks' earliest robots have shown, behaviour-based robotics encounter little
272 difficulty when dealing with dynamic environments because they are embodied within the real world
273 and interact with the world in real-time rather than abstracting a model representation of the world.

274 For any intelligent system to be deemed a proper model of the mind, it is necessary to define
275 the criteria by which the system is being judged. A fundamental tenet of Brooks' theory is that the
276 workings of the mind are demonstrated through intelligent behaviour. Hence the behaviour of his
277 robots is indicative of the workings of an artificial mind.

278 Another key point for Brooks is that the human mind is not the only source of intelligence; other
279 organisms also demonstrate intelligence which is worth modelling. He is very clear on this point.
280 Human cognition can be extremely complex. Brooks described human-level cognition as "the holy
281 grail of AI" and concedes that as of 1990:

282 "neither classical nor nouvelle [behaviour-based] AI seem close to revealing the secrets of
283 the holy grail of AI, namely general purpose human level intelligence equivalence" [8, p. 4]

284 It is plain that Brooks believes his Nouvelle AI to be the correct way in which to achieve this goal.

285 As an anti-representationalist, Brooks believes we do not need to rely on representation, instead
286 we should gradually develop our intelligent systems, one step at a time. If the human mind developed
287 through an incremental process such as this, then there is no wisdom in pursuing methods which
288 require fresh representations to be constructed at each step [1,8,14].

289 Brooks also had issues with the level of complexity necessary to model some facets of the mind:

290 "Symbol systems in their purest forms assume a knowable objective truth. It is only
291 with much complexity that modal logics, or non-monotonic logics, can be built which better
292 enable a system to have beliefs gleaned from partial views of a chaotic world.

293 As these enhancements are made, the realization of computations based on these formal
294 systems becomes more and more biologically implausible. But once the commitment to

⁶ And even then, Searle says this is only Weak AI, or the simulation of intelligence, rather than the demonstration of true intelligence itself.

295 symbol systems has been made it is imperative to push on through more and more complex
296 and cumbersome systems in pursuit of objectivity." [8, p. 4]

297 Brooks' solution to this problem of complication and complexity was to eradicate the symbol
298 systems and embrace a more biologically inspired, more simple methodology. His theories that there
299 is no place for mental representations while performing intelligent behaviour have been preceded by
300 similar observations. For example Dreyfus and Dreyfus described Wittgenstein's statements that our
301 mental systems do not have entities within them that correspond to a singular thought or idea [10],
302 and Gibson made the case that perception has no use for mental representations [24]. More recently,
303 Harvey has warned of the need for 'linguistic hygiene' when using terms such as 'representation',
304 arguing that while representations can be usefully studied in AI and cognitive science, there is much
305 to be gained from a 'minimal cognition' approach which builds only the minimal model of cognition
306 necessary to achieve the desired behaviour [25].

307 There is further criticism of the application of traditional AI as a model of our own intelligence.
308 This criticism is based around the level of assistance traditional AI systems could be said to receive.
309 Brooks believed that as of 1991 our efforts at building intelligent systems were misguided, in that we
310 were providing the intelligent systems with too much of our own intelligence as assistance instead of
311 getting the systems to demonstrate true intelligence.

312 "Under the current scheme the abstraction is done by the researchers leaving little for the AI
313 programs to do but search." [1, p. 143]

314 His point here was that the truly intelligent tasks are not undertaken and that researchers assist
315 their systems too much; this is help which our own intelligence systems did not have when developing.
316 Hence Brooks was very critical of the performance of existing AI methods thus far; artificial intelligence,
317 he argued, was not true intelligence at all, but merely "simple numeric computations carried out in the
318 sea of symbols". [8, p. 5]

319 A key point that Brooks emphasised⁷ was the generality of intelligent behaviour. Our minds do
320 not just focus on one task at a time. Even if our attention is drawn to one task that we are concentrating
321 on, our minds are concurrently managing several other tasks at once. For example if a person is
322 concentrating on reading a book, their mind will be simultaneously managing many other tasks such
323 as holding the book, sitting in a chair, comprehending any conversation that is made to that person,
324 and so on.

325 Brooks' strong criticism of traditional AI is that there is too much focus on building systems which
326 are specialised for particular tasks or functions.

327 "In classical AI, none of the modules themselves generate the behavior of the total system.
328 Indeed it is necessary to combine together many of the modules to get any behavior at all
329 from the system. " [8, p. 3]

330 He went on to say **present his opinion** that such a combination of classical AI modules is likely to
331 present some difficulty because of the specialised way in which they have been designed [1].

332 Traditional AI and connectionism have been much maligned for having shortcomings, however
333 they are not totally without benefit. Boden considered the key advantages of symbolic AI to be its
334 representational ordering structure and clear definitions of problems to be solved and associated
335 constraints [26]. In contrast, she saw the benefits of using a connectionist approach to be their
336 biologically more plausible basis, trainability and 'gradual degradation' (should parts of the system
337 stop working, the whole system does not suffer: the performance is reduced rather than completely
338 halted).

339 But which approach is superior? It is time to take a closer look at Brooks' theory.

⁷ And still emphasises - see the discussions later in this paper on Brooks' impact on and opinions of modern-day AI research.

340 5. Discussion of Brooks' approach

341 Hayes et al. raised some interesting counter-arguments to Brooks' views [27]. They made no
342 secret of their belief that representations are very useful for modelling mental processes and should
343 not be discarded. They used a 'nannies and babies' metaphor throughout their article to illustrate this.
344 They did not deny that intelligent agents should be able to operate in and react to a social environment
345 (situated AI), but they made a very strong claim about the nature of agents that do so without using
346 some form of representation of that environment, concluding that such an approach may even cast
347 doubts on the very validity of scientific method:

348 "This perspective has its intellectual roots in parts of recent sociological thinking which reject
349 the entire fabric of western science." [27]

350 The authors of [27] recognised that traditional AI does show flaws that need to be addressed,
351 and agreed that there is a need for getting the basic foundations of cognitive theory correct. (One
352 of the authors, Patrick Hayes, co-authored work with John McCarthy on philosophical problems
353 within AI, including an early identification of the frame problem [28]. For people such as Brooks,
354 though, who suggest modelling intelligence from a completely different theoretical perspective in
355 order to solve these problems, Hayes et al. were critical, using the adage "Don't throw the baby out
356 with the bathwater" [27]. They accused such people of ignoring crucial developments in modelling
357 the mind (giving planning as an example), and of condemning these developments as unworthy of
358 retention, in their haste to follow new cognitive theories. This was an emphatic attack on Brooks and
359 his contemporaries, but perhaps it makes more extreme conclusions than is deserved, in its attempt to
360 provoke reaction.

361 Some have questioned whether behaviour-based robots do actually rely on representations in an
362 inferential form without being explicitly coded (for example [29]). Brooks anticipated such suggestions
363 and dismissed them with the comments that:

364 "There are no variables ... that need instantiation in reasoning processes. There are no rules
365 which need to be selected through pattern matching. There are no choices to be made. To a
366 large extent the state of the world determines the action of the Creature" [1, p. 149]

367 So Brooks firmly advocated that he has not used any form of representation-based methods. This
368 is however still open to much debate, as has been seen in the literature (for example [29,30]).

369 It must be questioned whether symbolic representation is as limited as Brooks describes. Brooks
370 does have experience in working in symbolic AI prior to his shift in thinking, and described many
371 problems that he ran into that he described as a direct consequence of using representation to explain
372 how the mind works. However it is generally conceded, as a result of [23] and similar writing (for
373 example [27, pp. 17-20], that intelligence is not purely just about the rigid manipulation of symbols,
374 but requires some guidance from knowledge of the semantics behind the symbols. Some forms of
375 intelligence modelling do have a more simplified use of knowledge representation (in fact Hayes et al.
376 imply that these include the research that Brooks was part of in the early 1980s [27, p. 17]). Proponents
377 of symbolic AI argued that knowledge representation is far more flexible and less restricted than such
378 simplified systems would suggest. **For example, advances have been made employing representation
379 learning, such as in learning object affordances [31,32] or state information [33].** This debate on the
380 validity of symbolic representation of knowledge for cognitive purposes has been in progress since the
381 publication of Brooks' ideas and, with current interests in **representations for robotics (e.g. [6]) as well
382 as more generally** in areas such as data mining, does not look close to resolution.

383 Whilst discussing cognitive science models that are embodied, having physical presence, [34],
384 Andy Clark made a valid observation concerning Brooks' assertion that a behaviour-based robot shows
385 intelligent behaviour if it carries out some reactive behaviour that is helpful to the survival of the robot.
386 Clark described how a sunflower will react to the changes in positioning of the sun by changing the

387 direction in which it faces, in order to maximise the exposure to the sun it receives [34, p. 347]. The
388 question is whether this is a demonstration of intelligent cognition and behaviour by the sunflower.
389 The natural reaction to this is that a sunflower does not carry out any rational thought process, so
390 it cannot be demonstrating intelligence. However by strict interpretation of Brooks' assertions, this
391 sunflower would be considered intelligent. Clearly this aspect of Brooks' theory could benefit from
392 clarification, **particularly on what constitutes intelligent behaviour**.⁸

393 In his critical response to [1], Etzioni made some interesting points in direct reference to the
394 evolutionary influence that Brooks gives as justification for his methods [35]. Etzioni quoted the
395 theory of punctuated equilibria which states that evolutionary development is not necessarily linearly
396 proportional to the time taken but may include a high amount of variance. There may be little or
397 no progress for a large amount of time, followed by a rush of new breakthroughs. Etzioni used this
398 to questions Brooks' basis in evolutionary development of intelligence. Essentially he was asking if
399 Brooks is selecting only the aspects of evolution that are useful for his argument, as for the example
400 above with the comparison of timescales of different evolutionary developments. Etzioni asked exactly
401 how Brooks has derived the conclusion that higher level cognition will follow on naturally from simple
402 reactive robotics. He suggested that an equally valid conclusion could be drawn in the same way as
403 Brooks' conclusion, that if AI researchers work towards developing the hardware of actual organisms,
404 that the intelligent aspects of the mind will follow naturally [35, p. 9]. It is an interesting observation
405 and not one that Brooks has chosen to answer, as far as I have been able to find.

406 The evolutionary justification used by Brooks also does not fully account for other decisions
407 Brooks made within his approach. Behaviour-based robotics emphasises the building of simple
408 robots at first, only adding complexity when the simpler robots have been successfully achieved.
409 Brooks advocated this in [1], but argued that it is not right to have the same approach to the robots'
410 environments (the use of simple environments at first, with complexity added incrementally). He
411 justified this with the argument that evolution has proven the first approach to be successful, but that
412 the second approach could mean that errors were inadvertently introduced [1] (in particular p. 150). I
413 see, however, two problems with this argument. Firstly, as Brooks himself acknowledges:

414 "As a very approximate hand waving model of evolution, things get built up and accreted
415 over time, and maybe new accretions interfere with the lower levels." [14]

416 So Brooks concedes that his methods introduce unexpected behaviour which may not be a desired
417 result (as is the nature of systems that make use of emergentism). Even if not regarded as errors, these
418 unexpected behaviours are still a source of uncertainty.⁹

419 Also, Brooks did not consider that our environments have developed in complexity as we have
420 evolved. As the human race¹⁰ has evolved, our environments have received increasingly more complex
421 adaptations as we become more technologically advanced: from the invention of the wheel to modern
422 day transport systems and beyond. Also, as infants our environments are necessarily restricted by our
423 parents or carers. Complexity is added as we are gradually exposed to more of the world. It is not
424 considered plausible that a baby would be able to cope with a real-world environment in the way that
425 a grown adult has learnt to; their world is controlled and simplified for them. It is to be supposed that
426 Neolithic man in the modern-day world would have similar difficulties to the baby. However Brooks
427 disregarded these aspects of human development and evolution in [1].

428 The emergent behaviour demonstrated by Brooks' robots was shown to be successful for relatively
429 small tasks such as collection of drinks cans or map navigation - lower-level cognitive processes [36].
430 A common comment, however, is that designing a task-driven system which produces emergent

⁸ But Brooks' emphasis is on research of a implementational nature rather than theorising so it is unlikely he would enter into much philosophical debate about his approach. Instead Brooks offers his robots as direct evidence of his theory.

⁹ Uncertainty may, of course, be no bad thing.

¹⁰ **As a reviewer of this article notes, arguably this argument could be extended to animals as well.**

431 behaviour is a hard task due to the element of uncertainty in prediction of emergent behaviour (for
432 example [30], or even Brooks himself [37]); rather than designing for a particular desired behaviour,
433 an emergent system's behaviour develops over time. Following on from Brooks' own criticisms
434 that we do not understand intelligence well enough to subdivide it into specialised sub-problems, a
435 similar criticism could be levelled at Brooks' subsumption architecture design: do we know enough
436 about emergentism to develop the correct layers of behaviour such that some required behaviour will
437 emerge? And how do we know we have included all necessary layers in our design, if we cannot
438 identify what these layers should be?

439 It is doubtful that Brooks would attach too much significance to these criticisms, from his previous
440 comments:

441 "Nouvelle AI relies on the emergence of more global behavior from the interaction of smaller
442 behavioral units. As with heuristics there is no a priori guarantee that this will always work.
443 However, careful design of the simple behaviors and their interactions can often produce
444 systems with useful and interesting emergent properties." [1]

445 Indeed, to respond to these criticisms, one might point out that behaviour-based robotics is
446 an evolutionary and incremental process of development where each new layer of behaviour gives
447 the robot more complex intelligent behaviour. Rather than aiming for a target level of intelligent
448 behaviour for a given task, we should be developing the robots' intelligence in a step-by-step manner,
449 gradually increasing in complexity and generality. This is as inspired by evolution: the development
450 of intelligence should be guiding our investigations into the modelling of the mind, not vice versa.
451 Questions still remain, though, as to whether AI research should take the same path as evolution
452 (Brooks believes so; many critics disagree) and whether we have the epistemological knowledge
453 necessary to learn from evolution in developing artificial intelligence.

454 A major test for behaviour-based robotics could be how it can be used to demonstrate wider or
455 more general intelligence, particularly in comparison to more traditional methods. Brooks pointed out
456 in 1991 that, as for traditional methods, behaviour-based AI should be allowed time to develop. On
457 the criticism of behaviour-based robotics on the grounds that it cannot solve all tasks considered, he
458 likens this to saying that an elephant has no cognitive processes worthy of study because it is unable to
459 play chess¹¹ [8]. After nearly thirty years of research, however, the behaviour-based approach shows
460 no signs of becoming the dominant paradigm in AI research. This is not to say that it is impossible for
461 behaviour-based robotics to reach their intended goal of developing highly intelligent robots; but to
462 date we have not yet seen the full scope of Brooks' visions for AI robotics being realised.

463 The issue of scaling up to larger domains and more complex behaviour did in fact lead Brooks
464 to revise his ideas in some ways [26]. For example he has had to relax his emphasis on pure reactive
465 behaviour and allow that keeping some memory of previous experiences is necessary for higher level
466 cognition. For example, his robot *Toto* learns about its environment by building maps of the parts of the
467 environment already encountered in exploration. Brooks maintained that this is not a representation of
468 the environment as it does not try to replicate the environment internally but instead recalls the sonar
469 readings and actions made by the robot to manoeuvre around obstacles and walls. As said above,
470 though, this argument is open to some debate.

¹¹ Brooks refers to the inability of elephants to understand the game of chess rather than the rather obvious physical difficulties they would have in picking up the pieces.

471 6. Brooks' impact and views on subsequent artificial intelligence research

472 6.1. Behaviour-based robotics after Intelligence Without Representation

473 The key area influenced by Brooks' ideas has been in robotics, where behaviour-based robotics
474 is now an accepted component of robotic architecture [14,29,30,38,39]. One key example of the
475 application of behaviour-based robotics is in Nasa's Mars Exploration Rovers [40], robots which
476 operate autonomously on the surface of Mars, using behaviour-based principles. Behaviour-based
477 robotics research such as [41–43] forms a small but recognised part of the broader field of evolutionary
478 robotics [44]. It also sits within Artificial Life and adaptive behaviour research [45–47, e.g.]. Brooks
479 continues to contribute to these areas [48, e.g.], though he has recently remarked that their progress
480 has 'stalled' [49].

481 Brooks-style ideas have also had wider impact. Alan Bundy is a strong logical AI exponent,
482 however he and Fiona McNeil have written that:

483 "automatic representation development, evolution, and repair must be a major goal of
484 AI research over the next 50 years." [50, p. 85]

485 [and]

486 "Reasoning systems must be able to develop, evolve, and repair their underlying
487 representations as well as reason with them. The world changes too fast and too radically
488 to rely on humans to patch the representations." [50, p. 86]

489 In other words, there is some acknowledgement that syntax, semantics and pragmatics of
490 representations should be evolved discoverable rather than explicitly coded. This is happening
491 to some extent in current robotics research such as [33], as well as more broadly in work applying
492 evolutionary computation approaches, such as in computational creativity applications [51]. Such
493 advances are exemplar of the far-reaching impact of evolutionary or biologically-inspired modelling
494 of the mind, and the acknowledgement of the need to consider problems with traditional AI's use of
495 representations.

496 Etzioni suggested in his direct response to *Intelligence without Representation* that Brooks's proposals
497 would also work equally well for "soft-bots" in a real-time software environment (designed externally
498 and outside of the control of the soft-bots' designers: for example the World Wide Web) [35]. In
499 other words, physical embodiment is not necessary for demonstrating intelligent cognitive processes.
500 Although Brooks has been dismissive of soft-bots in favour of "physical robots made of metal" [14], it
501 is uncontroversial to assume that virtual agents can demonstrate intelligence in a virtual environment
502 just as physical robots do in a real-world environment [52,53, e.g.].

503 Looking back at further direct responses to [1], Nilsson included Brooks' work in his review of AI
504 research [36]. He presented a similar thesis to Brooks, that AI research has become over-specialised,
505 and praised Brooks' work as a step in the right direction but criticised Brooks' approach as being
506 overly focused on low-level processes, acknowledging the existence of doubts about "the long-range
507 potential for this work"[36, p. 14].

508 Nilsson's conclusion was that research activity in AI to date (including Brooks' work) should
509 be considered merely as development of tools to be used in the future by systems that display more
510 general intelligence. Such hybrid approaches to AI have produced strong results in robotics research.
511 For example Brooks describes how the Mars exploration unit Pathfinder takes Brooks' architecture as
512 low level processing of information, with a classical AI-based representation of cognition at a higher
513 level of processing. This layered model bears strong resemblance to the general perception of our
514 minds as having higher level cognitive processes such as for playing chess, and lower level processes
515 such as reacting to unstable ground when walking. The successes demonstrated with this approach
516 are at least in part due to how different approaches to cognition apply on wider scales:

517 “[The hope of Traditional AI] is that the ideas used will generalize to robust behavior in
518 more complex domains. ... [The hope of Nouvelle AI] is that the ideas used will generalize
519 to more sophisticated tasks.

520 Thus the two approaches appear somewhat complementary. It is worth addressing the
521 question of whether more power may be gotten by combining the two approaches.”¹² [8]

522 Clark made a similar point:

523 “As tasks become more representation-hungry - more concerned with the distal, abstract and
524 non-existent - we will see more and more evidence of *some kinds* of internal representation
525 and inner models.” [34, p. 349]

526 Brooks has inspired research both within the field of robotics [30, e.g.] and more broadly, within
527 cognitive theory [54]. Brooks’ theories have contributed to research areas such as [26] Artificial Life
528 (where emergent behaviour is a fundamental demonstration of intelligence) [25, e.g.] and adaptive
529 behaviour approaches [55, e.g.]. His ideas sat alongside related contemporary research movements
530 such as the *animat* approach (where the initial intelligent system start with simple behaviour and
531 gradually the complexity of intelligence is built up, mimicking how life on Earth has evolved) [56],
532 and Braitenburg’s *Vehicles* [57], which similarly evolved complex behaviour from simple principles
533 and has inspired fields such as swarm intelligence [58, e.g.]. Overall, the growth of evolutionary and
534 adaptive approaches to AI e.g. [44,45,59, e.g.] has contributed to a broader perspective on AI beyond
535 traditional AI and connectionism.

536 Brooks’ advancement in academic circles to the post of Director of the Computer Science and
537 Artificial Intelligence Laboratory at MIT shows how his work was taken seriously in academia. He
538 has received various accolades, including the prestigious *IJCAI Computers and Thought Award* in 1991,
539 presented to “outstanding young scientists in artificial intelligence”.¹³ The title of this award is
540 interesting given Brooks’ critique of the metaphor of computation in cognition. In response, Brooks
541 reflected [16] that “Computers and Thought are the two categories that together define Artificial
542 Intelligence as a discipline. It is generally accepted that work in Artificial Intelligence over the last
543 thirty years has had a strong influence on aspects of computer architectures. In this paper we also
544 make the converse claim; that the state of computer architecture has been a strong influence on our
545 models of thought.”

546 His 2002 book *Flash and Machines* [60], aimed at non-academics as well as academics, shows the
547 extent to which Brooks’ behaviour-based research has progressed his views. In this book, Brooks stated
548 that humans are intelligent machines (biological machines, but machines nonetheless):

549 “I believe myself and my children all to be mere machines. But this is not how I treat them. I
550 treat them in a very special way, and I interact with them on an entirely different level ... I
551 maintain two sets of inconsistent beliefs and act on each of them in different circumstances.
552 It is this transcendence between belief systems that I think will be what enables mankind to
553 ultimately accept robots as emotional machines.”[60]

554 To date, Brooks continues to advocate behaviour-based robotics and the principles behind
555 *Intelligence Without Representation*. In 2008 he moved to industry, starting up Rethink Robotics ¹⁴
556 as CTO, while still retaining some presence in academia as emeritus professor at MIT. He was part of
557 the panel behind the 2016 ‘One Hundred Year Study on Artificial Intelligence (AI100)’ Stanford report

¹² Although Brooks later goes on to say that it is best to use his approach on its own rather than in combination with other AI approaches [14]

¹³ <https://www.ijcai.org/awards>, last accessed June 2020.

¹⁴ <http://rethink.ai>

558 [61]. At Rethink Robotics, Brooks has recorded several patents since 2012 that employ behaviour-based
559 robotics commercially.¹⁵

560 6.2. Brooks' views on other areas in current AI research

561 What of Brooks' views comments on other areas of AI research today?

562 Brooks has expressed vocal opinions on various other topics in modern day AI research. For
563 example, one way in which autonomous robotics research has entered modern-day consciousness with
564 the move towards self-driving cars. While he has confidence in the technicalities of self-driving cars
565 being realised, Brooks has voiced concerns about how people's behaviour will have negative effects
566 on the pace of technical development. In an ironic twist, he sees that human behaviour will evolve to
567 hinder robotic developments [37].

568 Machine learning is a currently popular area of Artificial Intelligence that heavily relies upon
569 statistical representations. Perhaps unsurprisingly, Brooks has shown negativity towards this style of
570 approach, issuing a scathing attack in his blog:

571 "In 1991 I wrote a long ... paper¹⁶ on the history of Artificial Intelligence and how it
572 had been shaped by certain key ideas. In the final paragraphs of that paper I lamented
573 that there was a bandwagon effect in Artificial Intelligence Research, and said that "[m]any
574 lines of research have become goals of pursuit in their own right, with little recall of the
575 reasons for pursuing those lines".

576 "I think we are in that same position today in regard to Machine Learning. The papers in
577 conferences fall into two categories. One is mathematical results showing that yet another
578 slight variation of a technique is optimal under some carefully constrained definition of
579 optimality. A second type of paper takes a well know learning algorithm, and some new
580 problem area, designs the mapping from the problem to a data representation ... and show
581 the results of how well that problem area can be learned.

582 "This would all be admirable if our Machine Learning ecosystem covered even a tiny
583 portion of the capabilities of human learning. It does not. And, I see no alternate evidence
584 of admirability.

585 "Instead I see a bandwagon today, where vast numbers of new recruits to AI/ML have
586 jumped aboard after recent successes of Machine Learning, and are running with particular
587 versions of it as fast as they can. They have neither any understanding of how their tiny
588 little narrow technical field fits into a bigger picture of intelligent systems, nor do they care.
589 They think that the current little hype niche is all that matters, are blind to its limitations,
590 and are uninterested in deeper questions." [Postscript to [65]]

591 Brooks has also expressed scepticism over deep learning, an area of Artificial Intelligence currently
592 strongly in favour and gaining large traction. In a 2012 Nature comment, Brooks warned that:

593 "we are in an intellectual cul-de-sac, in which we model brains and computers on each other,
594 and so prevent ourselves from having deep insights that would come with new models."
595 [66]

596 This reads partly as an unspoken attack on the then-emerging area of deep learning. Deep learning
597 relies heavily on multi-level ('deep') representations, often based around neural networks.

598 Brooks is not alone in his concern over the specificity of current machine-learning-focussed
599 approaches to AI, and a lack of adaptability in AI applications to date. For example, as expressed in
600 2019 by Judea Pearl:

¹⁵ e.g. patents [62] granted 2019, [63] granted 2016, [64] granted 2015.

¹⁶ The paper that Brooks refers here to is [16]

601 “The dramatic success in machine learning has led to an explosion of artificial
602 intelligence (AI) applications and increasing expectations for autonomous systems that
603 exhibit human-level intelligence. These expectations have, however, met with fundamental
604 obstacles that cut across many application areas. One such obstacle is adaptability, or
605 robustness. Machine learning researchers have noted current systems lack the ability to
606 recognize or react to new circumstances they have not been specifically programmed or
607 trained for.” [67]

608 Brooks invests more faith in artificial general intelligence (AGI), though he warns that in his
609 opinion, progress in the area of AGI is lacking at present [68]. AGI research investigates how AI
610 can operate with general intelligence that can apply across multiple domains or tasks, rather than
611 intelligence focused on specific tasks or domains. This is certainly an area where one can see the
612 principles behind *Intelligence without Representation* contributing [69, e.g.], though it is not the case that
613 AGI thus far has required a behaviour-based approach [70,71, e.g.].

614 In 2018, Brooks made several predictions for various aspects of artificial intelligence [72]. These
615 include several attacks on deep learning, concluding that by 2027 we will reach the end of “the era of
616 Deep Learning” and the “[e]mergence of the generally agreed upon “next big thing” in AI beyond
617 deep learning.” In contrast, he sees developments in self-driving cars and other robotics continuing
618 over future decades. He is appraising these predictions annually; only time will tell as to how correct
619 his predictions are.

620 7. Concluding remarks

621 As noted above, the goal of artificial intelligence prior to *Intelligence without Representation* [1]
622 was to replicate human intelligence in a computational system [5,7,8]. Taking a modern and widely
623 cited definition of artificial intelligence, Russell and Norvig define AI as “the designing and building
624 of intelligent agents that receive percepts from the environment and take actions that affect the
625 environment” [73]. This definitional shift is a sign that, even if Brooks’ ideas are not directly responsible
626 for the change, they are part of a broadening in how artificial intelligence is conceptualised.

627 Brooks is an elegant writer with a clear and well-presented style, put forward in a persuasive
628 manner. His views have gained significant traction. The evolution of the human mind has been
629 taking place over an extremely large time-scale. Given our current lack of a complete and agreed
630 understanding of what intelligence is and how our mind works, should we be aiming so high in
631 building computerised intelligent systems to display human-level intelligence? The principles of
632 Occam’s razor (where a parsimonious and simple approach is favoured where possible) is often of
633 use in furthering academic progress. This has been demonstrated in countless examples, from the
634 preference of Copernicus’ simpler planetary model over the convoluted Ptolemaic system, to heuristics
635 for good practice in medical diagnosis. So Brooks’ simple, ‘bottom-up’ approach could be considered
636 as the practice of good scientific method. **Perhaps a simpler approach is needed.**

637 But has Brooks discovered a definitive method of explaining and modelling the mind? Brooks’s
638 work showed impressive results at first. But, as the sophistication of the robots has increased and
639 their behaviour has become more complex, development has slowed in pace somewhat. But this is
640 reminiscent of the pattern of development of traditional or ‘good old fashioned’ AI. As noted above,
641 Brooks now predicts that the currently popular AI approach of deep learning will follow a similar
642 pattern [72].

643 Perhaps Brooks himself best summarises the situation between the competing paradigms in AI.
644 Although written in 1990, this observation still holds:

645 “Can there be a theoretical analysis to decide whether one organization for intelligence is
646 better than another? Perhaps, but I think we are so far away in understanding the correct
647 way of formalizing the dynamics of interaction with the environment that no such theoretical
648 results will be forthcoming in the near term.” [8, p. 13]

649 All is not doom and gloom, though, for AI research:

650 “We have only just begun to explore the space of computational possibilities [for modelling
651 our minds]. Changes of direction, and even the occasional dead end, should not be scorned
652 as folly. Science grows not only by conjectures, but also by refutations.” [26, p. 9]

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