

Logical Instruments: Regular Expressions, AI and
thinking about thinking

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introduction

1 This chapter revisits the origins of AI in the context of the history of soft-
2 ware and computer science. This might seem an obvious thing to do, but it
3 is not. For one, the period from roughly 1940 to 1960 was a time of relentless
4 fantasizing about the potential of the new calculating machines and the new
5 science appropriate to them—alternately christened cybernetics, automata
6 studies, artificial intelligence, mechanization of thought processes, and com-
7 puter science, among others. Researchers from an incredibly large range of
8 disciplines struggled to understand and define what computers, computa-
9 tion, and the control of mechanical logical processes would come to mean.
10 Proposals for the future and research programs designed to achieved them
11 were abundant and varied, and no one was certain what the computer itself
12 would become: giant brain? industrial calculator? military weapon? au-
13 tomatic linguistic translator? cybernetic organism? experimental device?
14 communications system?

15 It was a period of tremendous experimentation and exploration, and ar-
16 tificial intelligence of the form promoted by John McCarthy, Allan Newell,
17 Herbert Simon and Marvin Minsky was but one fine thread. All of these
18 men were involved in multiple attempts to define the computer, along with a
19 wide range of others, from a youthful Noam Chomsky to John von Neumann
20 from neuroscientist-philosophers to circuit-designing engineers and abstract
21 object-loving mathematicians. All of them played with the ideas and tech-
22 nologies of the time with but vague ideas of what they would become. Hence
23 it is worth looking back to this period from the perspective of the software,

24 networks and computing devices we have created, in order to ask: how does
25 thinking about thinking proceed?

26 The period from 1940-1960 is also witness to a division that haunts com-
27 puter science into the present period: is the computer a tool for thinking,
28 or a replacement for it? Artificial intelligence proponents like Newell and
29 Simon made the leap instantly from rudimentary logic problem solving pro-
30 grams to a autonomous thinking machine. Rather than speak of computers
31 and computational science as aids to thought (as many at the time did, from
32 Vannevar Bush to Warren Weaver to JCR Licklider), they leapt instantly
33 to speaking of them as thinking entities. Later, critics like Dreyfus and
34 Suchman (among many others) would argue that this reduction of human
35 thinking to logical problem solving was philosophically impoverished and an
36 impossible research program [Agre, 1997, Suchman, 1987, Dreyfus, 1992].
37 But close attention to this period reveals that not everyone confronting the
38 computer equated logic and human reasoning. For many, the computer re-
39 mained a tool to think with, a way to try out and test ideas in a mechanical
40 form in order to generate concepts and results which could give meaning
41 and form to the practice of mechanical reasoning. In short, many people in
42 this period treated logical reasoning not as the basis of human thought, but
43 a companion to it, as an instrument to be explored and put to use. As a
44 logical instrument to reason *with* not *against*.

45 This chapter tells the story of one such “logical instrument”: regular
46 expressions. Regular expressions are (today) both a ubiquitous program-
47 ming tool and a keystone in the edifice of theoretical computer science.¹ By

¹Regular expressions are central to the construction of programming languages, es-

48 exploring the history of these arcane tools, it is possible to demonstrate how
49 the development of logic and mechanical reasoning proceeds alongside, and
50 in conversation with human reasoning and exploitation of these tools. As
51 such, this story does not take sides for or against claims made about artifi-
52 cial intelligence (such as the critiques made by Dreyfus), but seeks instead
53 to observe, historically and anthropologically, how thinking proceeds; I use
54 the case of regular expressions to show how concepts evolve and are made
55 concrete, even (and perhaps most significantly) concepts meant to capture
56 the foundations of thought itself. It is this objectification, or “registration”
57 [Smith, 1996] of objects as having a certain stability and tractability which
58 I attempt to demonstrate through the historical analysis of the half-century
59 long transformation of the idea of regular expressions. Such an approach
60 is broadly pragmatic in its understanding of logic, thought and concepts as
61 things concretely tested against reality.²

pecially in tools that partially automate the process, such as compilers, parsers, lexical
analyzers and compiler compilers. By 1969, regular expressions had been incorporated
into computer science curricula in most of the major programs as part of classes on formal
languages and automata theory. The first textbook was Hopcroft and Ullman’s *Formal
languages and their relation to automata* [Hopcroft and Ullman, 1969]; current textbooks
retain much of the same structure and material, e.g. Peter Linz’s *An Introduction to
Formal Languages and Automata* [Linz, 2001]

²In particular, the work Dewey undertook in *Experimental Logic* [Dewey, 2004,
Hester et al., 2007]. Pragmatist approaches to AI seem few and far between, but see
[Burke, 1995]. Recent work by Okrent has extended a Dewey-inspired reading of Heidegger
that focuses on intentionality and tool-use as one way to reformulate the philosophical
basis of rationality. Intentionality as a case of tool-use is close to what is sought here as an
explanation in the case of regular expressions, though the present case does not fit neatly
within Okrent’s explanation of intentionality, in part because the actors discussed here
do not always understand their own manipulations of logical systems as a tool-oriented,
intentional activity. And yet, I argue, it is possible to understand what they have done
within this frame, and that this re-description is a step towards articulating the under-
standing of intentionality necessary to remove logic from the domain of pure reason and
show its function in the domain of practical reason, especially after the advent of software
and programmable computers. See especially [Okrent, 2007, Okrent, 1991]

62 The range of transformations that regular expressions have gone through
63 is impressive and surprising: they emerge out of the work of Rudolph Carnap
64 on the syntax of logic, are transformed by McCulloch and Pitts into a logical
65 calculi of nerve nets, picked up by John von Neumann for his description
66 of the EDVAC computer, and later his theory of automata, formalized (and
67 given the name “regular expressions”) by mathematician Stephen Kleene,
68 used to design state diagrams for circuits by Janusz Brzozowski, imple-
69 mented in software for the first time by Ken Thompson (who also held a
70 patent on their use for pattern matching), re-implemented in a variety of
71 text editors such as emacs and vi, used in a wide variety of basic textbooks
72 in computer science and built into nearly every programming language in
73 use into the present.

74 In telling this story of transformations, I demonstrate how human reason-
75 ing develops in concert with (indeed, through) the logical tools for thinking
76 that we create. Such a claim is increasingly obvious given our contemporary
77 reliance on software and computation to guide thinking, and yet we have no
78 clear understanding of how we have created such a possibility for ourselves.
79 The period 1940-1960 is key to understanding how logics went from being
80 the ultimate basis for all human and mathematical reasoning (in the sense of
81 Hilbert’s program) to domesticated creatures just barely under our control,
82 living alongside us, keeping us company, thinking with us, thinking about
83 thinking.

84 **Regular Expressions, a brief history,**
85 **with backreferences**

86 Regular Expressions are widely known as a powerful and useful tool for
87 matching patterns in text. As is clear from the very popular web-comic *xkcd*
88 (See Fig 1), possessing knowledge of how to use these tools can be powerful,
89 heroic even. The utility and ubiquity of Regular Expressions is a bit of a
90 self-fulfilling prophecy; with the spread of the Internet has come the spread
91 of structured text as a mode of interaction and transfer of data. HTML and
92 XML (and its parent SGML) especially have created the possibility for, and
93 the need for, the automatic processing, manipulation and reformatting of
94 structured text. Regular expressions are the right tool for the job because
95 they permit a programmer to write concise and general expressions that
96 match a wide range of variable terms in structured text.

97 For example, a simple verbatim pattern like 'cat' will match the word
98 *cat*, while a pattern such as `[cat(.*)]` will match any word beginning with
99 *cat*. A regular expression can also match, for instance, the word *cat* at the
100 beginning of a line or *dog* at the end of one, thus:

101 `[(^cat|dog$)]`

102 And sophisticated uses such as matching any email address are also possible:

103 `{\b[A-Z0-9._%+-]+@[A-Z0-9.-]+.([A-Z]{2,4})\b}`

104 Regular Expressions match only syntactic or lexical features; they cannot
105 match semantic features unless they can be tied to some kind of lexical or

106 syntactic pattern. Nonetheless, they are widely used because they are built-
107 in features of the most popular programming languages like C++, Java,
108 Perl and Python. Perl in particular, was one of the first scripting (or 'glue')
109 languages to make extensive use of regular expressions since it was used
110 extensively in the early spread and development of the World Wide Web.
111 Jeffrey Friedl's book *Mastering Regular Expressions* [Friedl, 2006] taught a
112 generation of programmers how to apply regular expressions to problems of



Figure 1: “Regular Expressions” xkcd web-comic by Randall Munroe. Used with permission (Creative Commons Attribution-NonCommercial 2.5 License).

113 all kinds; from pattern matching to text searching, to processing and format-
114 ting streams of data like stock quotes or database queries. What’s more,
115 modern implementations include the ability to “back-reference” patterns,
116 allowing sophisticated ways to search and replace bits and pieces of a patter
117 (such as replacing the '.com' section of an email with '.edu'). Combined
118 with other line-oriented UNIX-based processing tools, regular expressions
119 are now part of an arsenal of text and data manipulation tools that allow us
120 to control at least some of our symbol-saturated information environment
121 today.

122 As a tool, its proliferation is tied to the proliferation of the UNIX op-
123 erating system in the 1980s and the growth of Free Software in the 1980s
124 and 1990s[Kelty, 2008]. Current versions of regular expressions trace their
125 roots to Henry Spencer’s implementation in perl in the 1980s which was
126 widely disseminated via USEnet and the Internet. But prior to this, regular
127 expressions were implemented in a variety of tools in the UNIX Operating
128 System. `grep` is the most famous of these tools—so famous that it is used
129 colloquially by geeks to mean “search” as in “I grepped for my socks.” `grep`
130 is standard on every UNIX operating system, including now the Macintosh
131 OS. The modern forms of `grep`, known as `egrep` and `fgrep` owe their exist-
132 tence to the work of Alfred Aho, who created them for the UNIX operating
133 system during his time at Bell Labs (1963-1990). Aho’s versions of `grep` was
134 combined with a tool called `sed` (Stream EDitor) by Larry McMahon, and
135 led to the creation of a widely used programming language, with Peter Wein-
136 berger, and Brian Kernighan called `awk` (after the initials of its inventors).
137 `awk` emphasized string data types, text processing and regular expressions.

138 `awk` was an inspiration for `perl` in the 1980s.³

139 But what most users of regular expressions as a tool do not know, ex-
140 cept in outline, is the long and peculiar history of regular expressions. All
141 of these implementations in software trace back to the work of Ken Thomp-
142 son, one of the inventors of the UNIX operating system, who was the first
143 to attempt to implement an algorithm for regular expressions in software.
144 Thompson wrote the first UNIX version of what would become `grep` for
145 a text editor called QED. QED was a rudimentary word processor, in an
146 era before word processing—one of the very first tools that actually al-
147 lowed people to directly manipulate a file on a screen or through a tele-
148 type; hence it was natural that some facility for searching text would be
149 a goal [van Dam and Rice, 1971, Meyrowitz and van Dam, 1982]. Indeed,
150 the name `grep`’ itself derives from a set of commands that would have been
151 issued in QED:

152

153 **G/re/P** (**G**lobally search for regular expression *re* and **P**rint it)

154

155 QED was written initially by Butler Lampson and Peter Deutsch [Deutsch and Lampson, 1967],
156 two computer engineers at UC Berkeley working on the DARPA-funded
157 Project GENIE, sister to Project MAC at MIT and one of the origins of
158 many of the innovations that went into UNIX and modern time-sharing,
159 multi-user operating systems [Lee et al., 1992]. That version of QED did

³There is no scholarly historical work on UNIX and its origins at Bell Labs that explores the range of activities underway there. Salus [Salus, 1994] reports on the development of the operating system in outline. Most of this work is available online, however, in various places. See Dennis Ritchie’s web resources, for instance <http://www.cs.bell-labs.com/who/dmr/>

160 not include regular expressions, or even the ability to search for arbitrary
161 fixed strings. Ken Thompson received his BS and M.Sc. at Berkeley (1962-
162 1966) and worked with Lampson and Deutsch on Project Genie. When
163 he was hired to work at Bell Labs, and was sent to MIT to participate
164 in Project MAC, one of the first things he did was to create a version of
165 QED for the famous Compatible Time-Sharing System (later to become
166 Multics).[Vleck, 2008] Thompson went on to create versions of QED for
167 Multics and ultimately for UNIX, for which he dropped the Q and called it
168 simply `ed`. `ed` in turn inspired a generation of powerful and difficult to use
169 text editing programs still in wide use today, such as `EMACS` and `vi` .

170 In 1968, Thompson also published a short “Programming Techniques”
171 paper for the CACM in which he described the “Regular Expression Search
172 Algorithm” he had implemented [Thompson, 1968]. What made regular
173 expressions a more powerful tool for search was that they allowed for a
174 kind of parallel processing. Rather than searching up and down a tree of
175 possibilities through brute force, backtracking every time it fails, regular
176 expressions allow the program to search more efficiently by “looking ahead”
177 and figuring out which paths can be eliminated.⁴

178 It is not at all obvious, however, how Thompson reached this point. Prior
179 to his implementation of this algorithm (which was originally written in As-
180 sembly language for the IBM 7090, on which CTSS ran, and presented in

⁴Russ Cox has written a technical history of the different implementations of the matching engine that Thompson used, and those that are in use to day, demonstrating differences in efficiency and speed that have been lost over time [Cox, 2007]. The Algorithm that Thompson implemented also bears some similarity to the general AI approach to “reasoning as search” given the focus on pattern matching and backtracking. Thompson’s use of regular expressions, however, seems to be the first such implementation and entirely distinct from the AI tradition of problem solving.

181 the paper in Algol), there were no such attempts to use regular expressions
182 in this way. Indeed, not many people would have known of their existence
183 outside a handful of now famous people who had explored them in differ-
184 ent forms—Stephen Kleene, John Von Neumann, Walter Pitts and Warren
185 McCulloch, and Michael O. Rabin and Dana Scott. The link between these
186 individuals and Thompson came from Janusz Brzozowski, who taught for
187 a semester at Berkeley while Thompson was there, and who researched the
188 use of formal languages for circuit design in engineering. Brzozowski in-
189 troduced a method for using regular expressions to create “state-transition
190 diagrams” which were widely used in the 1950s as a mnemonic for designing
191 and implementing programs in circuits and in the computers of the 1950s
192 [Brzozowski, 1964]. Thompson adopted Brzozowski’s ideas at a time when
193 “software” was just emerging as concept and practice.

194 Brzozowski’s work was part of an explosion of research in the late 1950s
195 that forms the basis of abstract computer science today: the formaliza-
196 tion of symbolic processing at the root of the logical operation of computers
197 [Myhill et al., 1960, Nerode, 1958, Arbib, 1961, Copi et al., 1958, Hopcroft and Ullman, 1969].
198 Michael O. Rabin and Dana Scott’s 1959 article “Finite Automata and
199 their Decision Problems” [Rabin and Scott, 1959] is frequently referenced as
200 the apotheosis of this work. It was a formal description that might more
201 accurately be understood as the theoretical ground for modern computers
202 than Turing’s work of 20 years earlier [Turing, 1937]. Though indebted to
203 Turing’s work, the formalization of computing in the late 1950s took the
204 finite nature of existing computing devices as a realistic constraint in de-
205 veloping a formal language that would allow for the manipulation of these

206 devices. Such an approach took as its object of logical manipulation of
207 symbols by *finite* automata (whether human, machine or animal). It was
208 based in no small part on the explorations begun earlier by Turing, Von
209 Neumann, McCulloch and Pitts, and ultimately by Carnap and Whitehead
210 and Russell.

211 What should be clear to the reader is that these earlier attempts were in
212 no way intended to produce a simple tool for matching patterns in text, but
213 instead to explore the very basis of logical reasoning itself. What I show in
214 the next section is that this exploration of logical reasoning is conducted as if
215 it is an investigation into the basis of human reason; but it proceeds instead
216 through the manipulation of objectified “logical instruments” which can be
217 formalized, manipulated, explored and constructed as if they were tools, as
218 if they were material objects.⁵ Attention to the media-specific creation of
219 these tools (in their symbolic expression, their representation in diagrams,
220 and ultimately in programming languages and in machines as running code)
221 can help demonstrate how logical instruments have come into being and are
222 progressively translated or modulated from medium to medium and mind
223 to mind.

224 **From Principia Mathematica to Deus ex Machina**

225 Thompson’s paper on Regular Expressions is frustratingly vague about the
226 origins of his idea. It has only four references: The IBM 7094 Programmer’s

⁵The meaning of materiality is obviously at issue: objectification is probably a better term, or concept-ification. It is not merely the symbolic character that is at stake, but the ability to grasp the instrument as a singularity, as something with parts that can be observed, moved, explored, replaced as if one were looking at a device.

227 manual, the paper by Brzozowski, a single paper about pattern matching in
228 text (by Anthony Oettinger), and Stephen C. Kleene’s “Representations of
229 events in Nerve Nets and finite Automata” [Kleene, 1956]. Kleene’s paper
230 is a kind of hidden classic and the link between theories of automata and
231 the language of “regular events and regular expressions” which Kleene in-
232 troduced. Stephen Kleene was a graduate student at Princeton in the 1930s,
233 where he worked alongside Alonzo Church and Alan Turing and made sub-
234 stantial contributions in the field of “recursive functions.” Kleene wrote per-
235 haps the single most famous textbook on the subject called *Introduction to*
236 *Metamathematics* in 1952. Kleene’s 1956 paper describes what he called an
237 “algebra of regular events.” It was published in a well-known volume called
238 *Automata Studies*, edited by Claude Shannon and John McCarthy. Kleene’s
239 paper is widely cited in the computer science literature, and is some ways
240 one of his most famous works but it was not central to his research project,
241 and he never returned to the subject.

242 Kleene’s interest in the subject was motivated by his own work on the
243 algebra of recursive functions. In the paper, he introduces a trio of mathe-
244 matical operators that represent regular events: $A + B$ (or union), $A \circ B$ (or
245 concatenation), and A^* (or the “Kleene Star” or iterate). Kleene’s paper is
246 generally understood to be significant because it proves two theorems about
247 the equivalence of regular events and finite automata. But what makes it
248 interesting in this context is where the idea to create such an algebra came
249 from. In stating these theorems in the text, the origins of Kleene’s interest
250 become clear:

251 Theorem 3: To each regular event, there is a nerve net which
252 represents the event by firing a certain inner neuron at time p
253 + 2, when started with suitable states of the inner neurons at
254 time 1. If the event is describable by a prepositive and positive
255 regular set of tables, the representation can be by a net started
256 with all inner neurons quiet.

257

258 Theorem 5: In any finite automaton (in particular in a McCul-
259 loch Pitts nerve net), started at time 1 in a given internal state
260 b_1 the event represented by a given state existing at time p is
261 regular. [Kleene, 1956, 0]

262 What Kleene meant by “regular events” was an event processed by a
263 set of nerve cells—an event of perception or of thought. Kleene’s paper
264 says nothing about computers, programming, matching patterns in text or
265 searching for text on a computerthe paper was not even composed on or near
266 a computer, as the typescript would indicate. However, it is clear from the
267 opening line of the article what “automata” are: “anything that receives
268 stimuli, human, machine or animal.” It’s also clear that the inspiration
269 for Kleene’s paper was the famous 1943 paper “A Logical Calculus of the
270 Ideas Immanent in Nervous Activity” by Warren McCulloch and Walter
271 Pitts [McCulloch and Pitts, 1943]. Indeed, Kleene adopted the same graphic
272 diagrammatic representation that McCulloch and Pitts used to present his
273 own definitions (See Fig 2)

274 Kleene had written his paper in 1951, during a summer at RAND, after

275 Merrill Flood, his sponsor at RAND and fellow grad student at Princeton,
276 had given him McCulloch and Pitts paper to read [Kleene, 1979]. Upon
277 reading this paper, Kleene’s first inclination as a mathematician was to push
278 further the model it contained—a model of the brain as a logical calculus.
279 Post-Gödelian logics being Kleene’s metier, he naturally wanted to formalize
280 what McCulloch and Pitts had proposed as a model of the brain in terms
281 of an algebra of recursive functions. In a reflection from 1981, Kleene said:

282 I found [McCulloch and Pitts’] model to be very interesting—
283 an original contribution—but their analysis of it to fall quite
284 short of what was possible. So I did what cried out to be done
285 with it (as it seemed to me) having newly in mind also the idea
286 of a finite automaton, which came to me that summer at RAND
287 through reading in printer’s proof (?) Von Neumann’s Hixon
288 Symposium lecture.[Kleene, 1979, 0].

289 What “cried out to be done” however, was probably not what McCulloch
290 and Pitts would have cried out for. It is worth reflecting here on the misfit
291 of intentions between these two papers. Whereas McCulloch and Pitts were
292 interested precisely in creating a representation of thought (if not neurons
293 *per se*), Kleene was not:

294 our theoretical objective is not dependent on the assump-
295 tions [about the neuro-physiological data] fitting exactly. It is a
296 familiar stratagem of science, when faced with a body of data
297 too complex to be mastered as a whole, to select some limited

CASE 3: G is E^*F . The nets for E' and F are combined as in Figure 24.

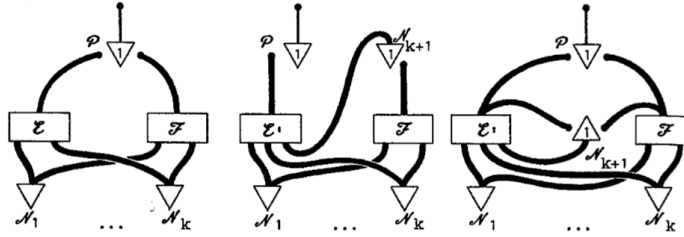


FIGURE 22 $E \vee F$

FIGURE 23 $E'F$

FIGURE 24 E^*F

(a) Kleene's Diagrams

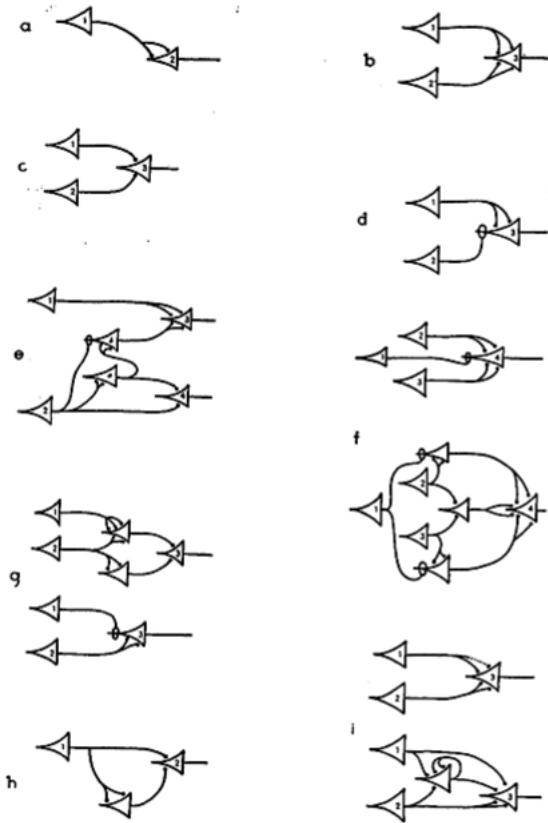


FIGURE 1

(b) McCulloch and Pitt's Diagrams

Figure 2: Kleene and McCulloch and Pitts' diagrams of regular events

298 domain of experiences, some simple situations, and to undertake
299 to construct a model to fit these at least approximately. Having
300 set up such a model, the next step is to seek a through under-
301 standing of the model itself. [Kleene, 1956, page].

302 Kleene was not interested in whether McCulloch and Pitts' model was
303 accurate (that is, whether it really represented the state, function or struc-
304 ture of a brain, or of thought)—what he takes from the paper is a model
305 that just happens to be defined in terms of neurons and sensory inputs and
306 organisms, but that was, for him, not yet fully explored in mathematical
307 terms. In fact, what Kleene proved in his paper was that it wasn't a model
308 of human thought, per se, but a model of any finite automaton, whether
309 animal, human, or machine, which is evident from his reference to von Neu-
310 mann's Hixon Symposium lecture on automata. Von Neumann was among
311 the first to explore the idea of a general theory of automata using the tools
312 of logic. The Hixon symposium is clear that, whereas for centuries we have
313 relied on the mathematics of continuous variation to analyze nature, the
314 emergence of computing technology has created a need for a more power-
315 ful discrete mathematics that might be more amenable to the analysis of
316 thought than that of classical mathematical analysis. Kleene takes this in-
317 sight a step further: the implicit equivalence between the brains of animals,
318 humans and machines in Kleene's approach holds no necessary connection
319 to actual brains or neurons, or even to the actual facts of thinking. Von
320 Neumann intuited this as well when, in writing the famous "First Draft
321 of a Report on the EDVAC." Instead of simply describing the design of a

322 computer in terms of vacuum tubes, wires, plug-boards and relays, von Neu-
323 mann used McCulloch and Pitts diagrams of neurons as its formalism (see
324 Fig. 3).

6.2 The analogs of human neurons, discussed in 4.2–4.3 and again referred to at the end of 5.1, seem to provide elements of just the kind postulated at the end of 6.1. We propose to use them accordingly for the purpose described there: As the constituent elements of the device, for the duration of the preliminary discussion. We must therefore give a precise account of the properties which we postulate for these elements.

The element which we will discuss, to be called an E-element, will be represented to be a circle \bigcirc , which receives the excitatory and inhibitory stimuli, and emits its own stimuli along a line attached to it: $\bigcirc\text{---}$. This axon may branch: $\bigcirc\text{---}\langle$, $\bigcirc\text{---}\leftarrow$. The emission along it follows the original stimulation by a *synaptic delay*, which we can assume to be a fixed time, the same for all E-elements, to be denoted by τ . We propose to neglect the other delays (due to conduction of the stimuli along the lines) aside of τ . We will mark the presence of the delay τ by an arrow on the line: $\bigcirc\text{---}\rightarrow$, $\bigcirc\text{---}\rightarrow\langle$. This will also serve to identify the origin and the direction of the line.

Figure 3: McCulloch-Pitts Neurons in the text of the First Draft of the Report on EDVAC by John von Neumann

325 For von Neumann and Kleene, the formal equivalence demonstrated by
326 McCulloch and Pitts between brains and logical languages was also a formal
327 equivalence suitable to a machine. This is not a metaphor. It is not a sugges-
328 tion that computers should function *like or as if* they are brains, but rather
329 the recognition of a certain utility, testability, or pragmatic rectifiability to
330 this formalism. With the introduction of an algebra of regular events, Kleene
331 created a useful, practicable formalism that within a matter of years would
332 dominate the nascent field of computer science. To a generation of people
333 who would become the first luminaries of computer science, Kleene’s paper
334 was the first step towards a formal theory of actual and possible computer
335 programs.

336 In 1959, for instance, Michael Rabin and Dana Scott would publish “Fi-
337 nite Automata and Their Decision Problems” [Rabin and Scott, 1959] which

338 would become the locus classicus for future research into the classification of
339 computer programs, their complexity and their solvability. What Thompson
340 took from Kleene was not a model of a brain, or even an algebra, but a kind
341 of logical toy, a structure with certain implications that could be explored,
342 an object to think with that could potentially made to fit some new situa-
343 tion. Indeed, somehow Thompson recognized that this algebra was a tool
344 for efficiently matching patterns in text and employed the algebra to create
345 an algorithm and a piece of working software. One might say this is an
346 obvious case of science being “applied” to create technology, but the prob-
347 lem is that whatever it is Kleene’s paper sets out, proleptically, as science,
348 is not the technology that Thompson creates. Rather it is a translation of
349 Kleene’s algebra into an algorithm, a paper and a program.⁶ And Kleene
350 had in turn translated McCulloch and Pitts’ model into an algebra and a
351 formalism now known as regular expressions for regular events, terms ini-
352 tially meant to capture the sensory input experience of an organism or an
353 automaton.

354 Kleene’s formalization of McCulloch and Pitts transformed their ideas
355 from the domain of representations of thought to the domain of representa-
356 tions of automata, and hence made it useful as a tool—both a logical tool
357 for thinking about thinking (i.e. thinking about logical reasoning) and a
358 tool for designing thinking machines (i.e. designing and controlling circuits
359 and eventually software). McCulloch and Pitts’ paper had no such goals in
360 mind. Indeed, the paper is claimed as an origin point variously by cybernet-

⁶And on top of that, a patent which represents the pattern-matching regular expression algorithm in yet another kind of formalism, that of the legal language of claims in a patent (3,568,156)

361 ics, neuroscience, mathematical psychology, cognitive science, mathematical
362 biology, artificial intelligence, and the burgeoning subfield of computer sci-
363 ence that studies neural nets and neural processing, quite in the absence it
364 should be said of any brains other than those of the researchers⁷.

365 McCulloch’s interest was initially in finding what he hypothesized as a
366 “psychon”—or atomic unit of neural activity, which he first sought in his
367 physiological research conducted during the 1930s in partnership with Yale
368 physiologist J.G. Dusser de Barenne. In the early 1940s, McCulloch was
369 introduced to Walter Pitts by Jerome Lettvin, and thereby to Nicholas Ra-
370 shevsky’s Mathematical Biology group at the University of Chicago, where
371 Walter Pitts had been actively working on models of neural activity with
372 Rashevsky and mathematician Alston Householder. The collaboration be-
373 tween the two was lopsided, at best. McCulloch was in his forties, Pitts
374 was 17; McCulloch had spent his career in physiology and philosophy, Pitts
375 was by various and sometimes unreliable accounts a mathematical prodigy
376 who had run away from his home in Detroit and met Bertrand Russell in a
377 park in Chicago [Smalheiser, 2000, Schlatter and Aizawa, 2008]. Together,
378 however, they managed to piece together something that met in the mid-
379 dle, a paper that demonstrated the formal equivalence between a plausible
380 model of neural activity, and a logical calculus. Part of McCulloch and
381 Pitts inspiration for their paper was Turing’s machine. As Tara Abraham
382 puts it “Turing was able to define the complicated process of computation
383 in ‘mechanical’ terms, with the notion of a simple algorithm so exhaustive,

⁷Tara Abraham has recently documented much of the intellectual context and background of this paper [Abraham, 2003, Abraham, 2004, Abraham, 2007]. See also [Kay, 2002] and [Piccinini, 2004]

384 rigorous and unambiguous that the executor would need no 'mathematical
385 knowledge' to carry out its task." [Abraham, 2003, 18] This identification
386 of computation with an automatic procedure provided the inspiration for
387 McCulloch and Pitts to model a set of nerves as something that could also
388 calculate "in the absence of mathematical knowledge."

389 In hindsight, what McCulloch and Pitts achieved was far more influen-
390 tial in engineering, computer science and mathematics than it was in biology
391 or neuroscience. Works that take McCulloch and Pitts logical calculus of
392 nerve nets as a starting point have been extraordinarily bountiful in math-
393 ematics and computer science. Accounts of Artificial Intelligence almost
394 inevitably refer to this paper as one origin point, whether as inspiration
395 or as foundation.⁸ By contrast, neurology and neurobiology have more or
396 less dropped the formalization entirely, beginning at least with McCulloch
397 and Pitts themselves, whose 1947 paper "How we know universals" and
398 the 1959 paper they wrote with Lettvin and Maturana, "What the Frogs
399 Eye Tells the Frog's brain" [Lettvin et al., 1959, Pitts and McCulloch, 1947]
400 both abandon the strict formal equivalence with propositional calculi or the
401 Turing machine, in favor of more complex biological models which are less
402 amenable to logical manipulation.

403 The analogy between logic and thinking is obviously not unique to Mc-

⁸Lily Kay points out that even though their paper is routinely adopted as an origin point for AI, McCulloch was himself "not an AI enthusiast. He was far less interested in machines that try to think than in the mechanical principle of thought (and by mechanical he did not mean physicochemical or reductionist). He was attracted to 'Machines that Think and Want': how we know particulars and universals, the desire for food, woman and bed, music, poetry, mathematics. And he sought a mathematical corrective to the mindless blackbox of behaviorism and the tripartite Platonic conjectures of psychoanalysis." [Kay, 2002, 603-4]

404 Culloch and Pitts. In most of philosophy and mathematics in the early
405 twentieth century, and especially under the influence of the Hilbert pro-
406 gram, logic and mathematics represent the capacity for human reason at its
407 pinnacle. McCulloch and Pitts materialized this assumption in a representa-
408 tion of neurons, adding a concrete formal specificity to an otherwise abstract
409 set of claims about human reason. Like Thompson’s paper on Regular Ex-
410 pressions, McCulloch and Pitts paper is exasperatingly short on citations:
411 it has three, and none refer to previous work in biology or physiology, nor
412 even to Turing’s work, but instead to arguably the three most famous at-
413 tempts to formalize scientific reasoning of the 20th century: Whitehead and
414 Russell’s *Principia Mathematica*, Hilbert and Ackerman’s *Foundations of*
415 *Theoretical Logic* and Rudolph Carnap’s *Logical Syntax of Language*.

416 Despite McCulloch’s polymathic knowledge of physiology, the paper with
417 Pitts is hopelessly imprecise (and avowedly so) in physiological terms. What
418 drives the paper instead is the attempt to transform a logical calculus from
419 one symbolic system to another—a symbolic system inspired by the obser-
420 vation that neurons are connected together in networks and tend to either
421 be firing electrical impulses or not, are either “on” or “off”.

422 Walter Pitts was a student of Rudolph Carnap and had clearly read
423 his work (on the advice of Bertrand Russell himself, so the story goes).
424 However, what was it that McCulloch and Pitts took from Carnap? Was it
425 a particular logical system or a set of propositions and theorems? Or was it
426 the symbolism? What was it that “cried out to be done,” to echo Kleene,
427 with Carnap’s work? I would argue that Carnap provided McCulloch and
428 Pitts with the warrant they were looking for to *creatively* formalize their

429 model.

430 Carnap's book, *The Logical Syntax of Language*, is the pinnacle of his
431 attempts to define a philosophical language suitable to the analysis of scien-
432 tific statements. In it, he constructs two kinds of artificial languages, labeled
433 Language I and Language II. Language I is a highly restricted language that
434 includes only the most basic postulates of the arithmetic of natural num-
435 bers. Language II includes Language I as well as "indefinite" terms for all
436 of mathematics and "the sentences of physics." McCulloch and Pitts chose
437 for their formalism, Language II, a choice widely regarded as unfortunate
438 because of Carnap's impossibly baroque symbolism. Nonetheless, it is not
439 the formalism per se, nor the content, which they draw inspiration from
440 so much as Carnap's insistence that *the choice itself is arbitrary*. Carnap's
441 *Logical Theory of Syntax* is famous for this approach:

442 In [this book], the view will be maintained that we have in ev-
443 ery respect complete liberty with regard to the forms of language;
444 that both the forms of construction for sentences and the rules of
445 transformation (the latter are usually designated as 'postulates'
446 and 'rules of inference') may be chosen quite arbitrarily.... For
447 language, in its mathematical form, can be constructed accord-
448 ing to the preferences of any one point of view represented; so
449 that no question of justification arises at all, but only the ques-
450 tion of the syntactical consequences to which one or another of
451 the choices leads, including the question of non-contradiction.
452 (*Logical Syntax of Language*, p. xv, 1954 ed.)

453 Carnap was justly famous, even among the logical positivists, for his
454 vigorous hatred of metaphysics and of “meaningless” statements—a hatred
455 most clearly visible in the 1932 article “The Elimination of Metaphysics
456 through the Logical analysis of Language” [Carnap, 1932]. So it is perhaps
457 oxymoronic to term this approach to the arbitrariness of logical language
458 the “Principle of Tolerance,” which states: “It is not our business to set up
459 prohibitions, but to arrive at conventions. (p. 51)” and “In logic, there are
460 no morals. Everyone is at liberty to build up his own logic, i.e. his own form
461 of language, as he wishes. All that is required of him is that, if he wishes
462 to discuss it, he must state his methods clearly, and give syntactical rules
463 instead of philosophical arguments. (52)”

464 Only the principle of tolerance, the submission to the arbitrary, Carnap
465 insisted, could lead us to “the boundless ocean of unlimited possibilities”
466 that awaits us[SARKAR, 1996]. Hence, what McCulloch and Pitts picked
467 up on was not that Carnap’s formalism was the most realistic, or accurate,
468 or universal, but that its arbitrariness freed it from any putatively meta-
469 physical presuppositions that might constrain it. It could be made into an
470 experimental tool. It could be made into a brain, a brain-machine, or a
471 brain-language—and the slippage amongst these things could be deliberate
472 and refer implicitly, if not explicitly and precisely, to the activity of human
473 thought.

474 Like Turing’s machine, Carnap’s languages were meant to be the most
475 mechanical and the most rigorous constructions of reason possible—but they
476 were nonetheless constructions of reason. They are not, either in Turing’s
477 case or in Carnap’s, instructions for the creation of machines with which hu-

478 mans might think. For Carnap, the elimination of metaphysics was explicitly
479 about creating protocols that define the understandability and analyzabil-
480 ity of statements; but it was also an implicit ontology of introspection and
481 thinking. Logical analysis provides a way to construct systems by which
482 it is possible to reach valid conclusions without recourse to any inaccessible
483 form of introspection or any revealed knowledge. That is to say, to construct
484 machines that will demonstrate the answer to multiple parties regardless of
485 any mathematical knowledge.

486 Carnap, in a tradition stretching back to Leibniz, wanted his artificial
487 languages to be the ultimate arbiters of dispute. No longer would human
488 frailty, human weakness in its reliance on irrationality or its reference to
489 the supernatural, be responsible for decision making when the best of all
490 possible systems could be constructed to answer questions objectively and
491 mechanically.⁹

492 McCulloch and Pitts seem to have recognized something slightly different
493 in this liberation of logic; they seem to have appreciated that the design
494 of a logical system should not be constrained by our assumptions or our
495 metaphysical beliefs, but should instead be an act of pure construction whose
496 implications and consequences for the task at hand are all that matter.
497 But McCulloch and Pitts did not use Carnap's Language II to test the

⁹Dreyfus locates his original critique of AI in just this age-old desire, which he refers to as Platonic in origin. Dreyfus' book is not a critique of reason per se, however, but an alternative explanation of human reason drawing on concepts of embodiment and background know-how [Dreyfus, 1992]. It does not, however, make any assumptions about whether embodiment or background knowledge are themselves mediated by the presence and proliferation of machines and symbol systems, regardless of whether they were created with the intention of being able to reason autonomously. Thinking with machines seems to me to fit into our "background" know-how in ways that neither AI nor Dreyfus seems to give any credit.

498 soundness of their model, they were not making empirical statements about
499 the brain which Carnap’s logic would verify. Rather what McCulloch and
500 Pitts did was to prove the formal equivalence of their model neuron and
501 that of Carnap’s logic; or to put it differently, they created yet another
502 language—a brain-language or nerve-language—which they showed to have
503 exactly the same expressive possibilities as Carnap’s syntax-language.¹⁰

504 McCulloch and Pitts brain-language is represented in their abstract im-
505 ages of neurons which are carefully correlated with formal propositions from
506 Carnap’s calculus. These abstract neural-net diagrams show up again and
507 again in subsequent formalizations, such as Kleene’s work, and are ulti-
508 mately central to neural network research of all kinds (See again, Fig 2).
509 McCulloch and Pitts translation of Carnap (like Kleene’s translation of Mc-
510 Culloch and Pitts and Thompson’s translation of Kleene) doesn’t try to
511 preserve Carnap’s universal language, nor reduce the brain to it, it invents
512 a new one, it translates it or remediates it.

513 If one examines the work of Carnap, McCulloch and Pitts, Kleene and
514 Thompson and later contributors to the development of regular expressions,
515 one sees a continuity of an instrumental kind, even if that continuity does
516 not map on to one of research programs, institutions or philosophical com-
517 mitments. Indeed, if anything the “principle of tolerance” does not liberate
518 reasoning from metaphysics at all, so much as it creates an entirely new kind
519 of object to think with: logical instruments. McCulloch and Pitts’ insights

¹⁰Lily Kay’s analysis of McCulloch and Pitts confirms this, in part. She argues that what McCulloch and Pitts attempted to do was to bridge the formal analysis of the brain with that of the mind: “Neurophysiology could expand to embrace mind, since that mind—conceptualized within a new discourse of information—could now be embodied in neural nets and investigated experimentally” [Kay, 2002, 600].

520 are mediated through, literally only thinkable through, the liberated logical
521 mechanisms of Carnap or Turing. Just as Kleene’s are mediated through
522 McCulloch and Pitts and Thompson’s through Kleene’s and so on. There
523 is a stability and a coherence to the object registered by these researchers,
524 even if the intentions and justifications for what they are doing seem to
525 diverge or only converge on loosely and serendipitously.

526 **Conclusion**

527 Regular Expressions are everywhere today, which is a strange triumph if
528 one sees in them a vestige of Carnap’s program. The fact that his approach
529 to understanding thought might lead, through a circuitous but very con-
530 crete path, to a tool used everyday to reformat symbolic information in our
531 syntax-saturated, structured language-draped world is a curious fact. The
532 continuity of regular expression raises a question that might be phrased in
533 terms of Bruno Latour’s concept of “immutable mobiles”: what exactly is
534 the “immutable” part of this mobile concept, ontologically speaking? What,
535 if anything, remains of Carnap, in today’s regular expressions?¹¹ Part of
536 what is at stake is a creating a richer description of thinking about think-
537 ing; one in which logical instruments are included as part of our repertoire for
538 exploring ideas, exploring arguments and claims, and constructing concepts.
539 Regular Expressions are a strategic example, since they form the very basis
540 of “formal language” theory in computer science, as well as a ubiquitous
541 tool for matching patters in text. One can also show a similar progression

¹¹Latour’s work on immutable mobiles appears in *Drawing Things Together* [Latour, 1990]; See also Paul Rabinow on the concept of “remediation” [Rabinow, 2008].

542 with the related logical instrument “L-Systems” which similarly transformed
543 from a model of biological growth, to a mathematical formalism, and ulti-
544 mately to a widely used tool for generating computed visual forms, such as
545 images of trees, flowers and neurons [Kelty and Landecker, 2004]. Similarly,
546 one might look to other conventional features of contemporary computing:
547 Bezier curves in illustration (and their origins in numerical controlled de-
548 sign of automobile bodies in the fifties), or filters used in audio-video editing
549 software (and their origins in electrical engineering, communications theory,
550 or speech-processing research). All of these are clear cases of tools based in
551 logic (because based in the construction of effective procedures required by
552 our computing devices) which have come to populate our world.

553 The success of logic, seen in this light, might also be measured oppo-
554 site the putative “failure” of the classic AI program, especially in terms
555 of the productive possibilities that result from research. Alan Newell and
556 Herbert Simon’s famous “Logic Theorist” [Newell and Simon, 1956] was a
557 program designed to prove the theorems of the *Principia Mathematica*. At
558 first glance, this would seem to be another and particularly nice example of
559 the kind of translations seen in the case of regular expressions. However,
560 Newell and Simon’s project made no explicit formal equivalence, it trans-
561 lated nothing. They did invent a new artificial language—a precursor to the
562 programming language LISP—but they did not attempt to prove that that
563 language was equivalent to any other. Rather, the implicit formal equiva-
564 lence maintained in AI is that between the human capacity for reason and
565 proof of theorems by logical inference. Newell, Simon, McCarthy, Minsky
566 and others aimed at a second creation, a robot race of machines more intel-

567 ligent than humans. By contrast, the work of McCulloch and Pitts, Kleene,
568 and especially Thompson led to the creation of something more like a com-
569 panion species of logical instruments; logical instruments with and through
570 which introspection and exploration is conducted. Rather than asking “Can
571 machines think?” as AI relentlessly does, this minor tradition asks “Can
572 humans think?” to which the answer is: not alone. We reason with logics,
573 we form symbiotic relationships with them, we translate them from paper
574 to machine, to patent to software.

575 If one sees AI as the attempt to create a second race of thinking beings,
576 then one can only pronounce its failure; but seen from the perspective of
577 “logical instruments” AI might also be seen as a similarly successful research
578 program—not “degenerative” at all (Dreyfus) but proliferative. Game en-
579 gines, recommendation systems, virtual world non-player characters, and
580 net-based commerce and advertising applications are everywhere. Computer
581 scientists routinely speak of “agents” today instead of humans or thinking
582 entities. The Rodney Brooks-inspired approach of creating large coordinated
583 networks of very simple processes has dominated the research imagination
584 since the early 1990s at least.

585 Understanding AI as part of a tradition of logical instrument fashioning
586 might also help explain the current explosion computer research traditions
587 that surround us today: whatever the computer is, its much more than the
588 machine on our laps or in our homes, and certainly much more than what
589 Turing wrote about in 1936. Today there journals such as *Soft Computing*,
590 *BioSystems Natural Computing*, *The Journal of Applied Soft Computing*,
591 *the IEEE transactions on Evolutionary Computaion* and *The International*

592 *Journal of Unconventional Computing.* There are GRID computers, mesh
593 computers, computers made of DNA, molecular computers and “moleware”,
594 reaction-diffusion chemical computing, quantum computers, spintronic com-
595 puters, protein-based optical memories and processors, “computers” literally
596 made of leech neurons and “membrane” computers (which are not made of
597 membranes at all), tinker toy computers, “amorphous computers,” neural
598 networks and genetic algorithms as well as an increasingly vibrant array of
599 programmable logic devices like the field programmable gate array, to say
600 nothing of a new generation of biological sensors that measure and compute
601 everything from light intensity to fish freshness. All these variations are de-
602 signed with logic instruments and become logical instruments for designing.
603 They proliferate in direct response to the playfulness with which they are en-
604 gaged, and this should tell us something about the history of thinking about
605 thinking. Some of these proliferations tend towards a fantasy world in which
606 everything is a computer. Cells compute, DNA computes, molecules com-
607 pute, waves compute—indeed, this version of computation-as-intelligence is
608 so generalized that its seems impoverished to continue making the implicit
609 connection between logic and thought, and instead start thinking of them as
610 logical instruments without which we cannot think, creatively or otherwise.

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