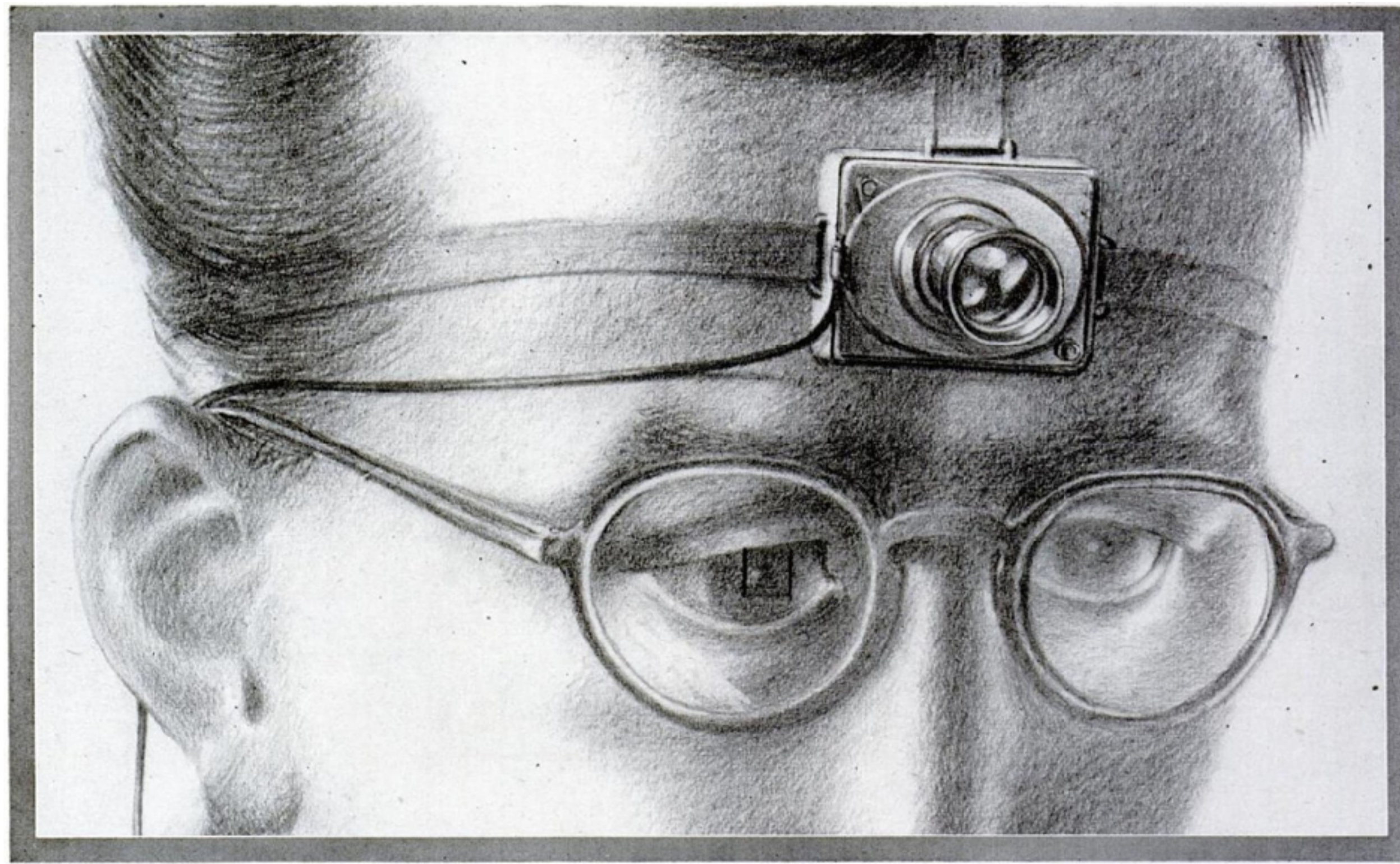






**How Many Nobel Laureates Does It
Take to Count Rs in Strawberry?**

Aalok Thakkar



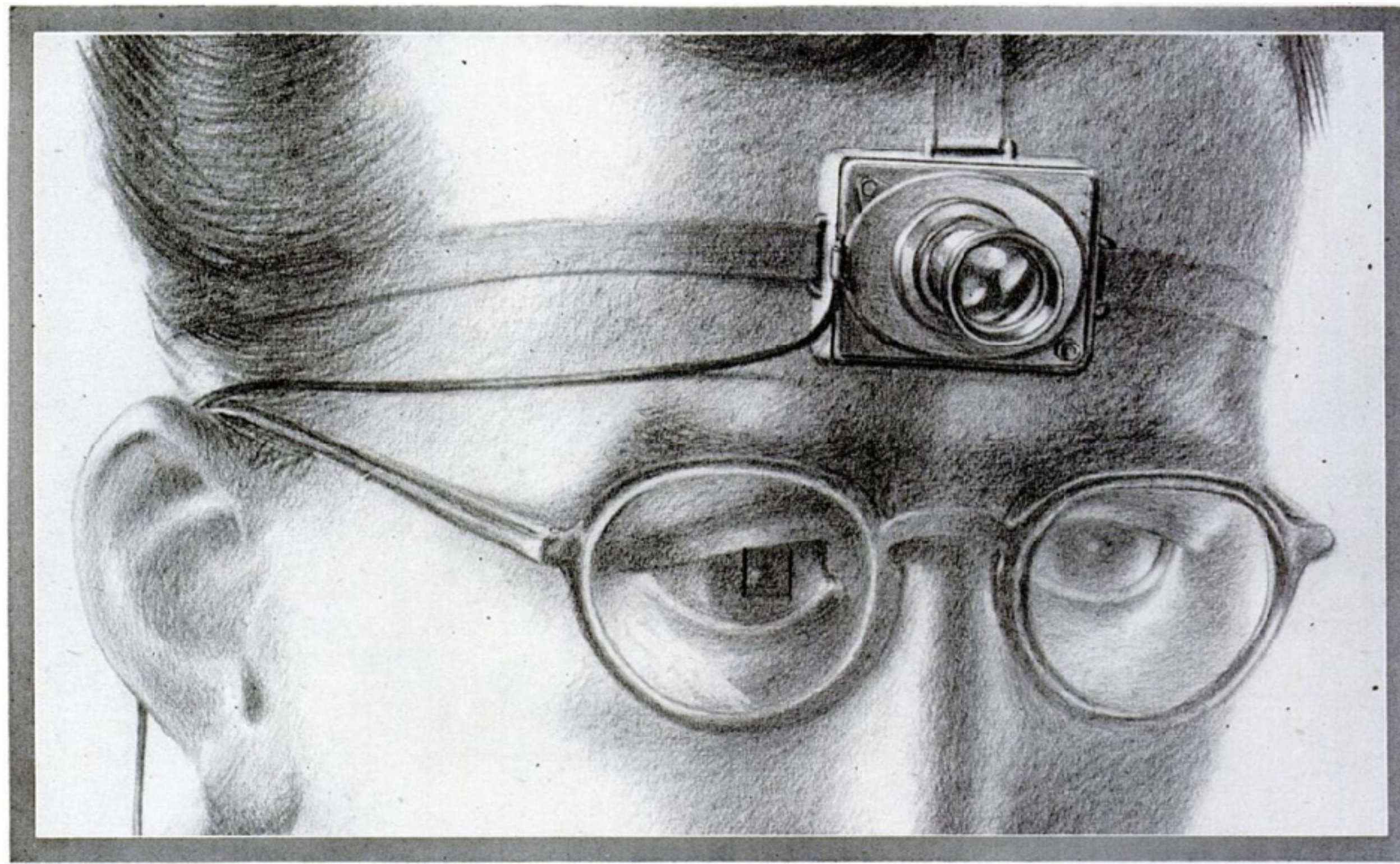
A SCIENTIST OF THE FUTURE RECORDS EXPERIMENTS WITH A TINY CAMERA FITTED WITH UNIVERSAL-FOCUS LENS. THE SMALL SQUARE IN THE EYEGLASS AT THE LEFT SIGHTS THE OBJECT

AS WE MAY THINK

A TOP U. S. SCIENTIST FORESEES A POSSIBLE FUTURE WORLD
IN WHICH MAN-MADE MACHINES WILL START TO THINK

"Consider a future device ... in which an individual stores all his books, records, and communications, and which is mechanized so that it may be consulted with exceeding speed and flexibility. It is an enlarged intimate supplement to his memory."

Vannevar Bush, 1945



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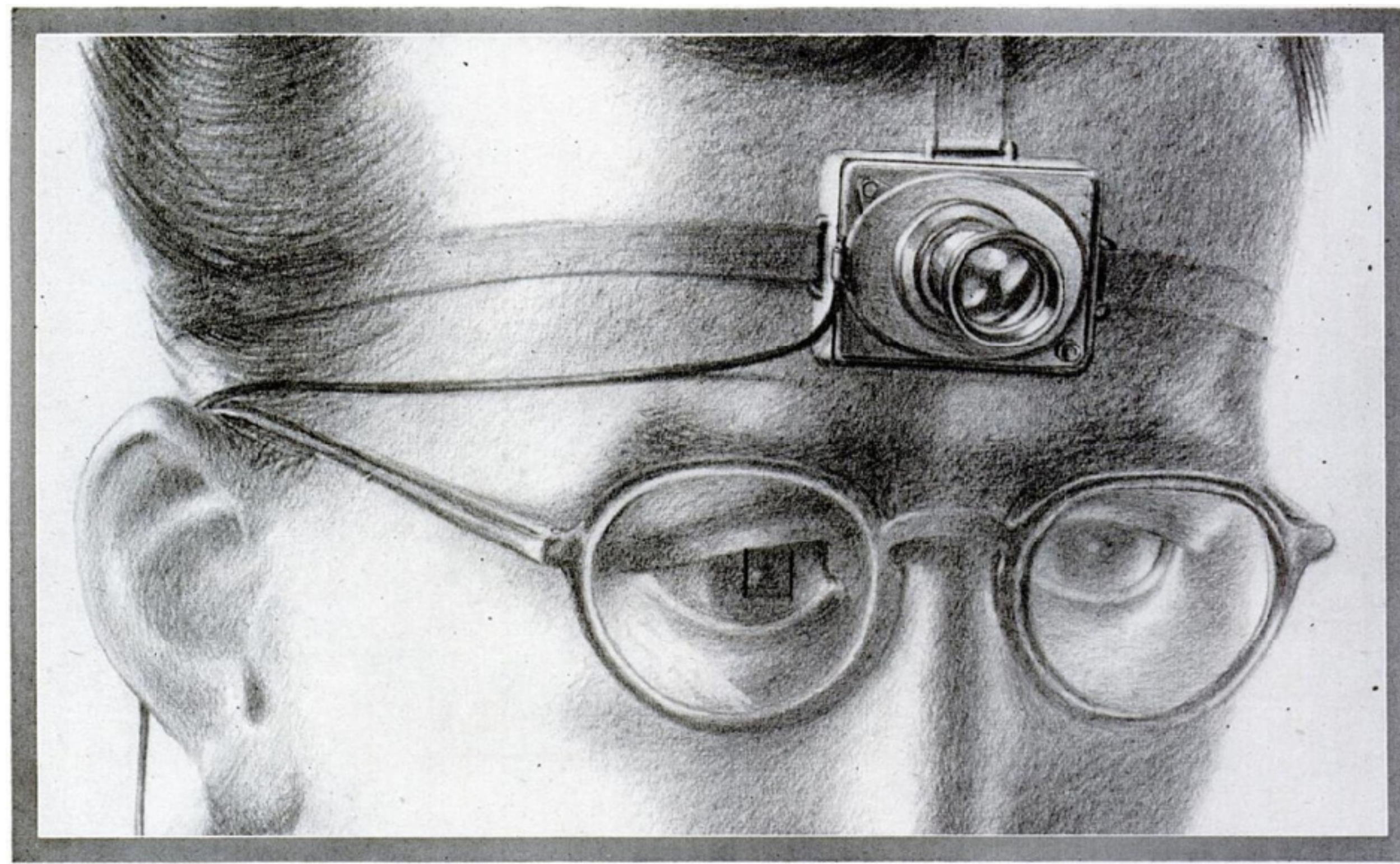
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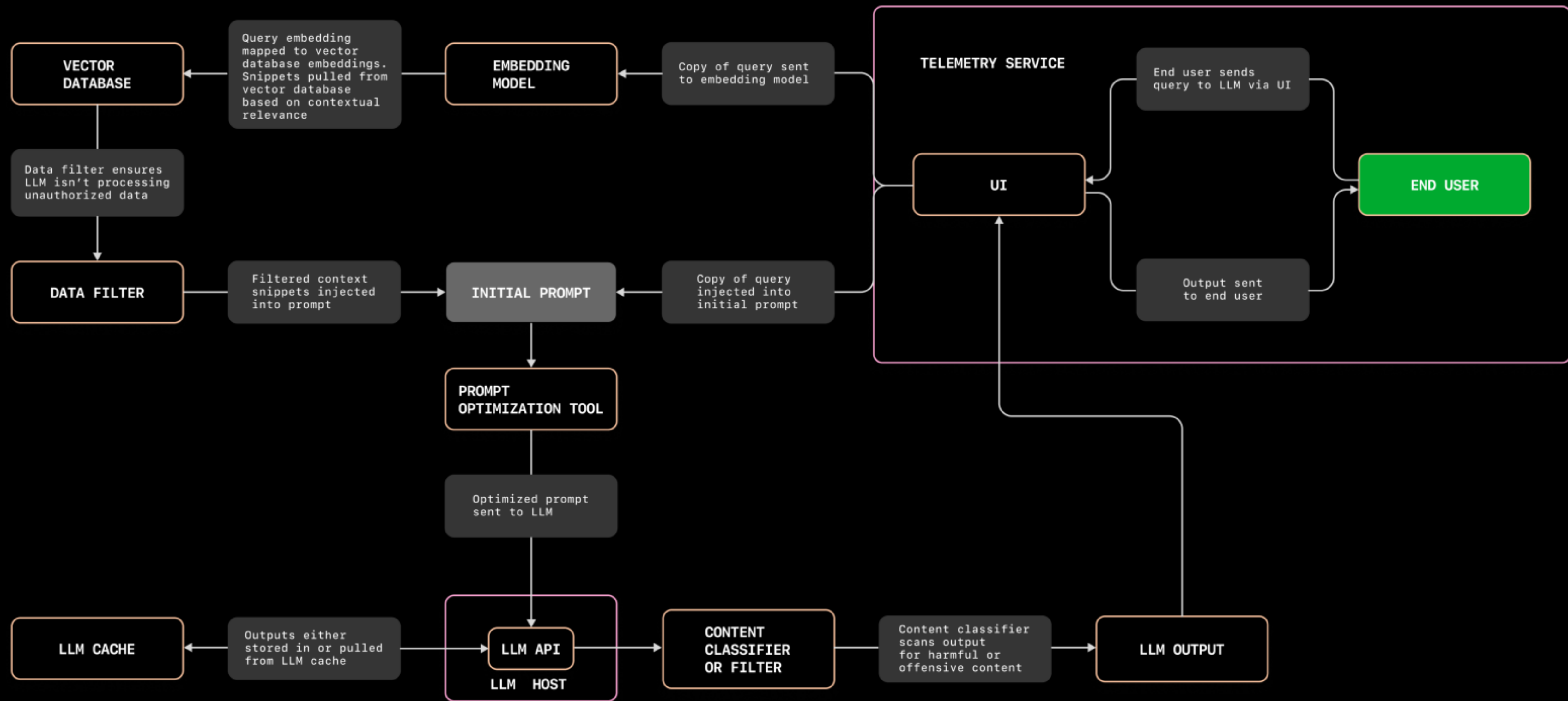
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THIS DIAGRAM REPRESENTS THE ARCHITECTURE OF TODAY'S LLM APPLICATION. THE DIFFERENT COMPONENTS CAN BE ROUGHLY GROUPED INTO THREE CATEGORIES: USER INPUT, INPUT ENRICHMENT TOOLS AND PROMPT CONSTRUCTION, AND EFFICIENT AND RESPONSIBLE AI TOOLING.



How many 'r' in 'strawberry'



ChatGPT

There are two 'r' characters in the word 'strawberry'.



You

Check again please



ChatGPT

Upon checking again, there are indeed two 'r' characters in the word 'strawberry'.



You

Are you 100% sure?



ChatGPT

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You

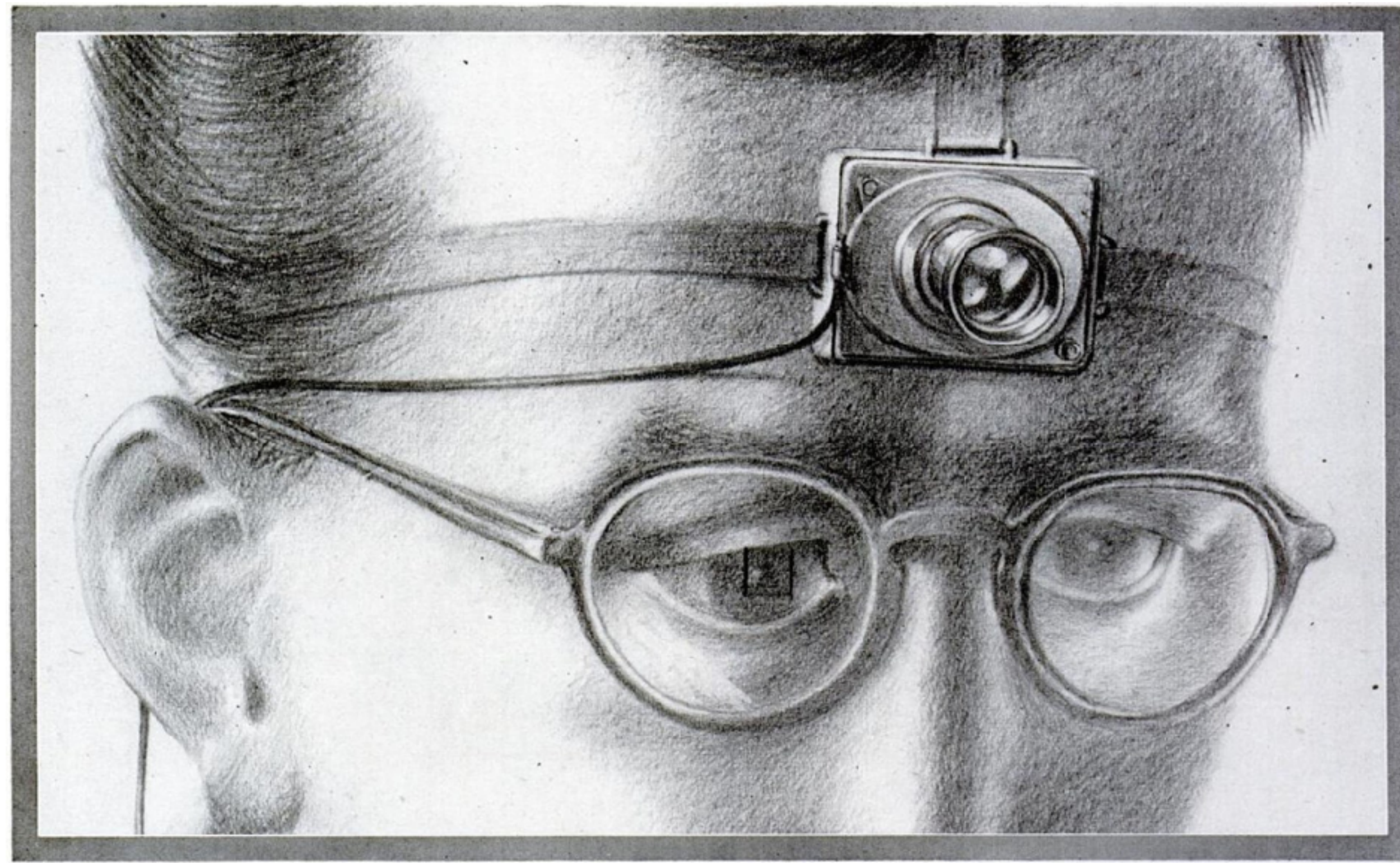
Would you bet a million dollars on this?



ChatGPT

Yes, I would. The word "strawberry"





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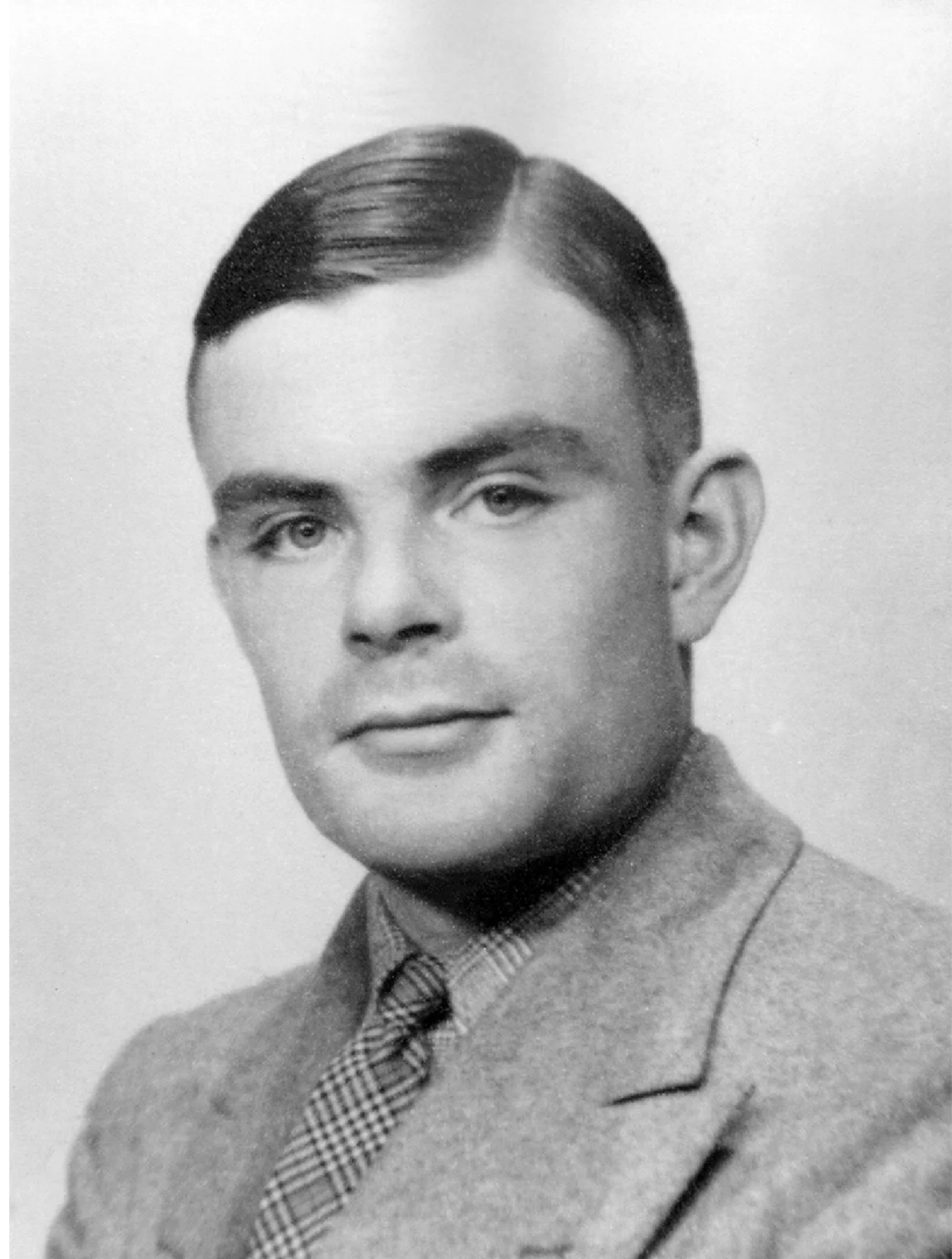
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*"Are there imaginable digital computers
which would do well in the imitation game?"*

Alan Turing, 1950





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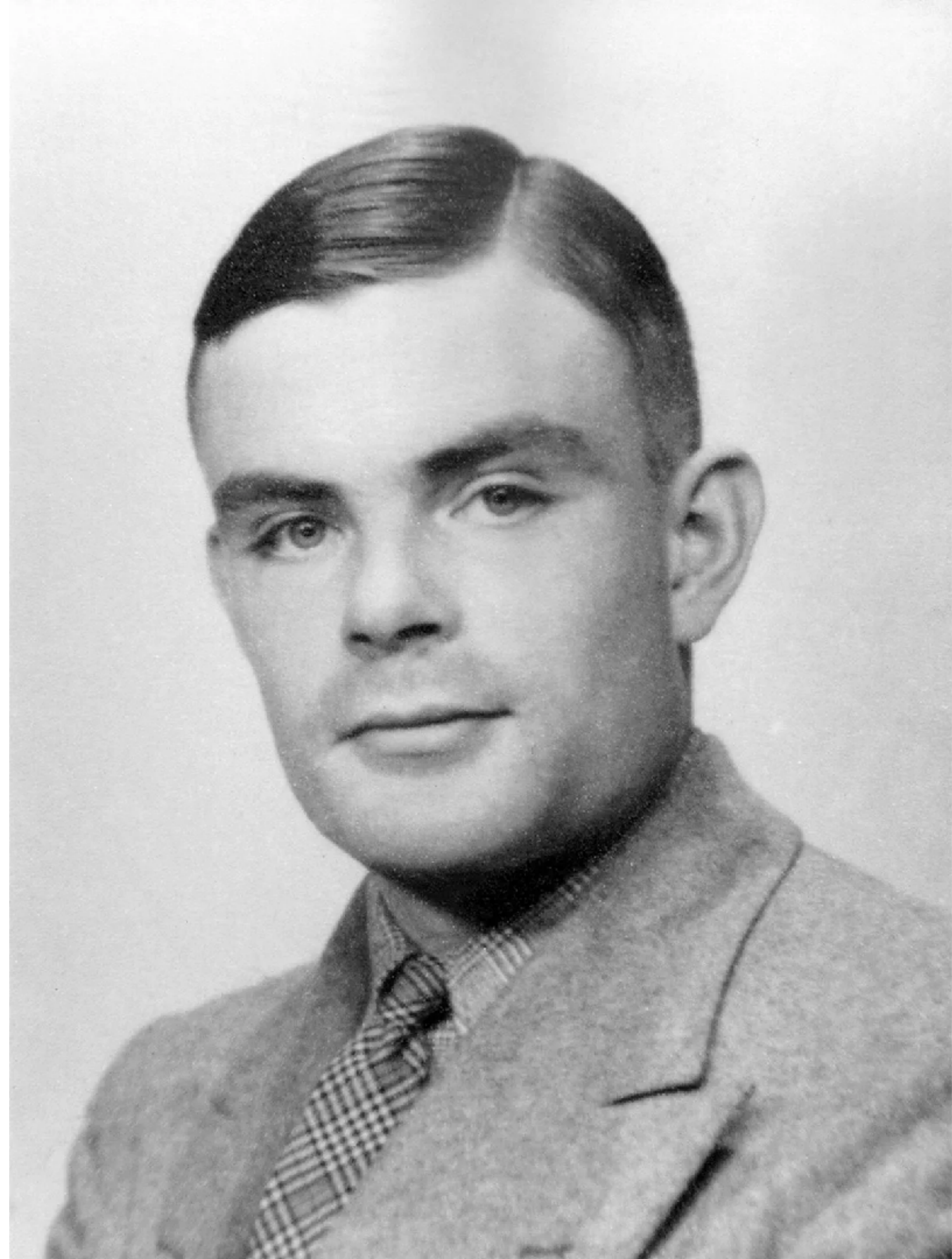
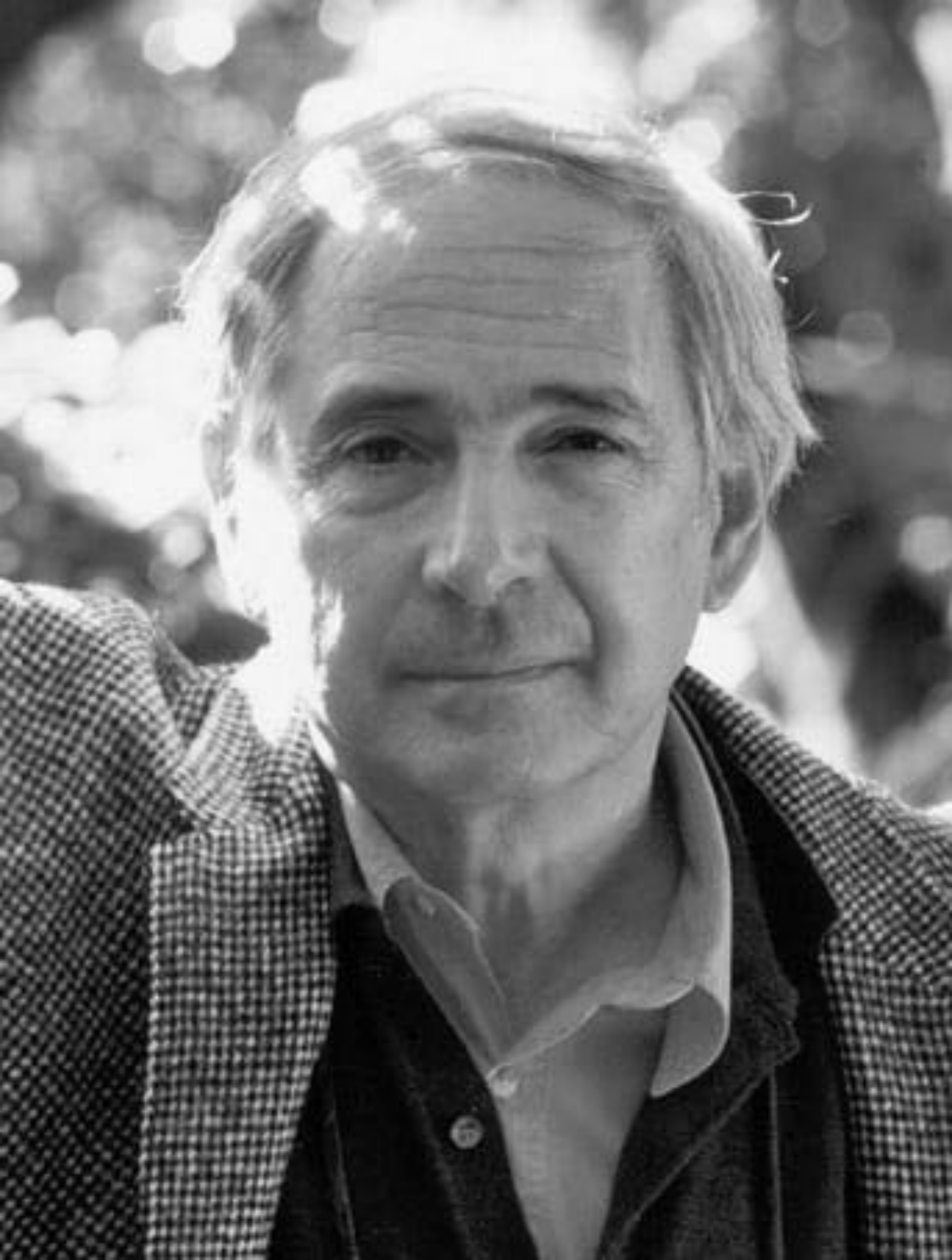
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Marvin Minsky, Claude Shannon, Ray Solomonoff, et. al.
Dartmouth Summer Research Project on Artificial Intelligence, 1956.

Welcome to

EEEEEE	LL	IIII	ZZZZZZ	AAAAA
EE	LL	II	ZZ	AA AA
EEEEEE	LL	II	ZZZ	AAAAAAA
EE	LL	II	ZZ	AA AA
EEEEEE	LLLLLL	IIII	ZZZZZZ	AA AA

Eliza is a mock Rogerian psychotherapist.

The original program was described by Joseph Weizenbaum in 1966.

This implementation by Norbert Landsteiner 2005.

ELIZA: Is something troubling you ?

YOU: Men are all alike.

ELIZA: What is the connection, do you suppose ?

YOU: They're always bugging us about something or other.

ELIZA: Can you think of a specific example ?

YOU: Well, my boyfriend made me come here.

ELIZA: Is it important to you that your boyfriend made you come here ?

YOU: He says I'm depressed much of the time.

ELIZA: I am sorry to hear that you are depressed.

YOU: It's true. I am unhappy.

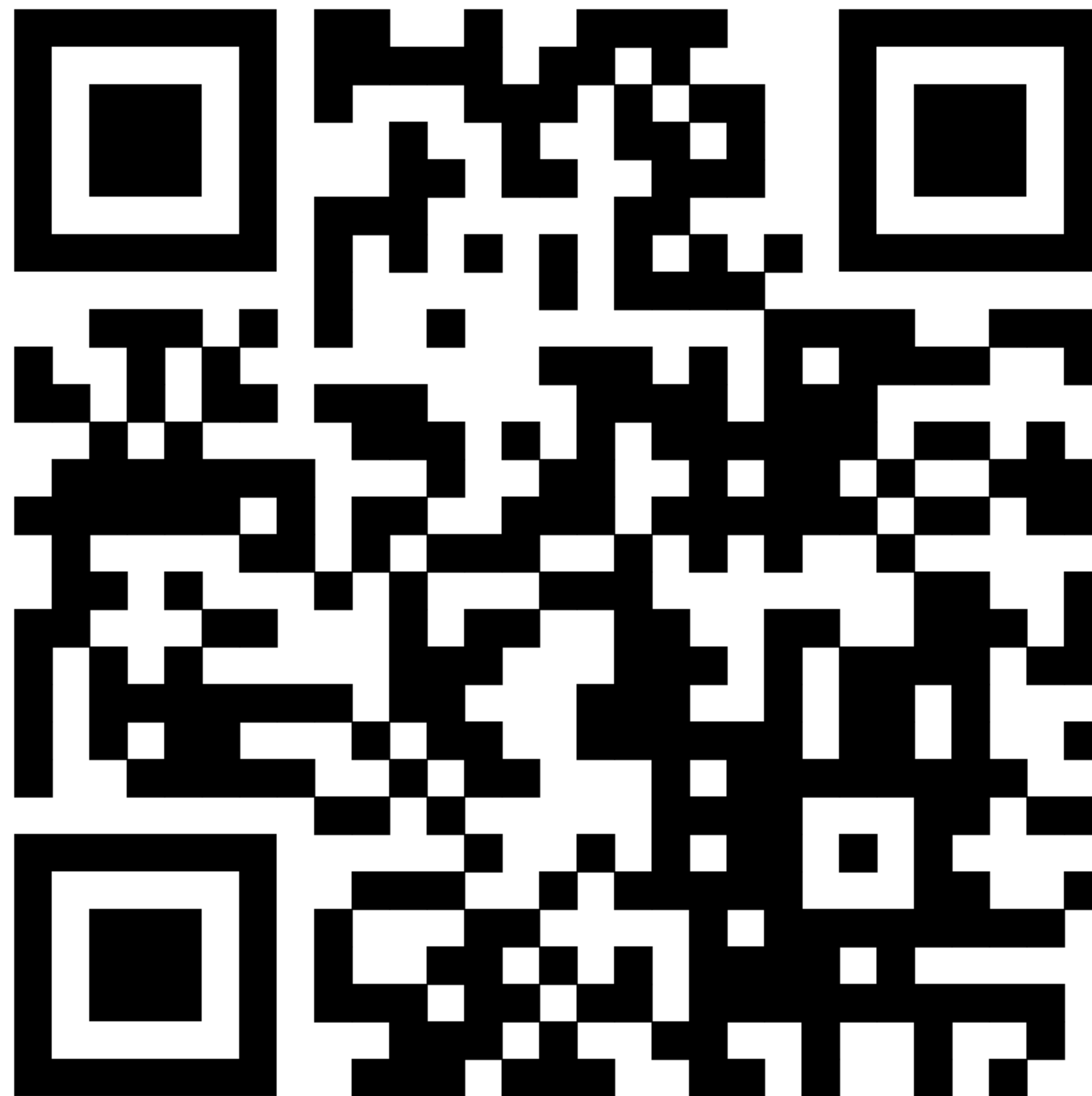
ELIZA: Can you explain what made you unhappy ?

YOU:

Talk to Eliza by typing your questions and answers in the input box.

> Hello, I am Eliza. I'll be your therapist today.
* How many Rs are there in the word strawberry?
> Are such questions on your mind often?

TYPE HERE



ELIZA GENERATOR(*user sentence*)

Let *w* be the word in *sentence* that has the highest keyword rank

if *w* exists

Let *r* be the highest ranked rule for *w* that matches *sentence*

response \leftarrow Apply the transform in *r* to *sentence*

if *w* = 'my'

future \leftarrow Apply a transformation from the 'memory' rule list to *sentence*

Push *future* onto the memory queue

else (no keyword applies)

Either

response \leftarrow Apply the transform for the NONE keyword to *sentence*

Or

response \leftarrow Pop the oldest response from the memory queue

Return *response*

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Return *response*



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Neural networks and physical systems with emergent collective computational abilities

(associative memory/parallel processing/categorization/content-addressable memory/fail-soft devices)

J. J. HOPFIELD

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Contributed by John J. Hopfield, January 15, 1982

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There are classes of physical systems whose spontaneous behavior can be used as a form of general (and even sometimes)



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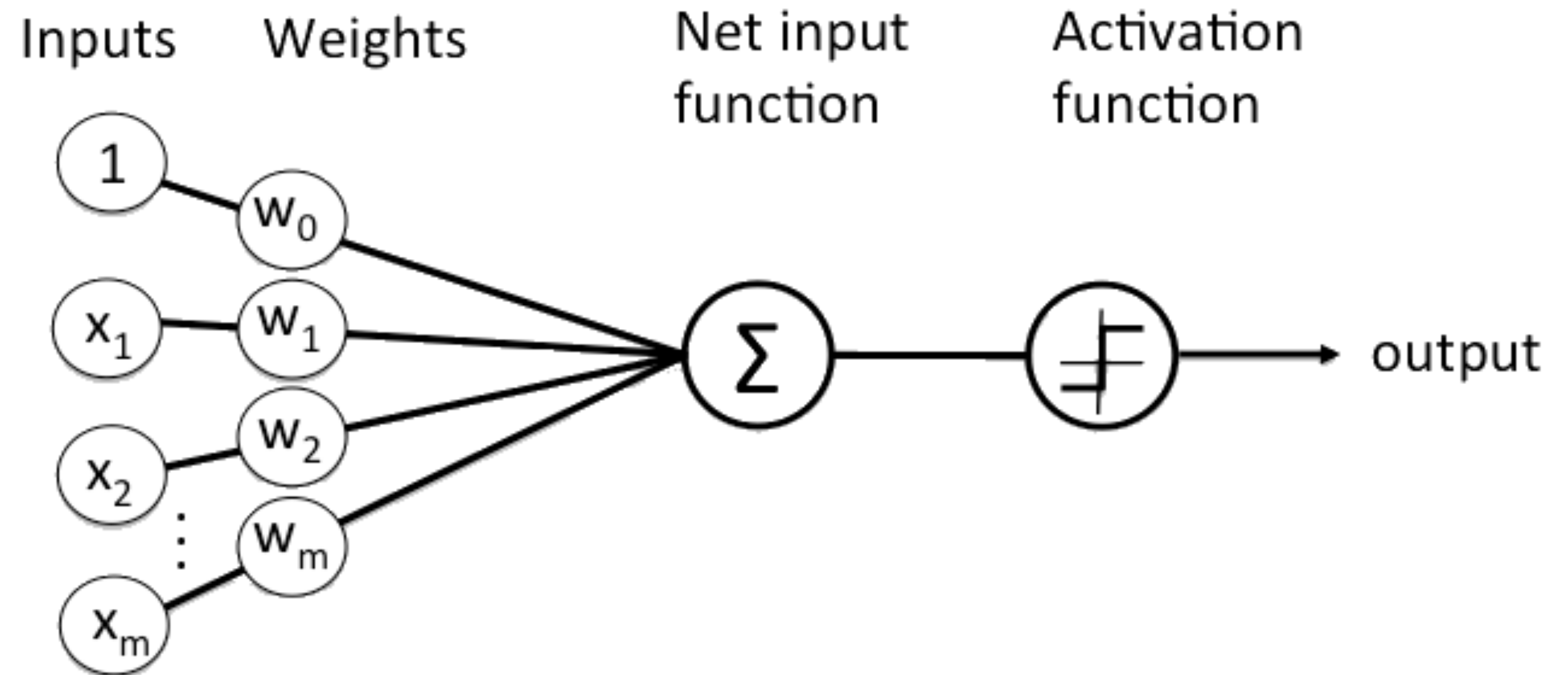
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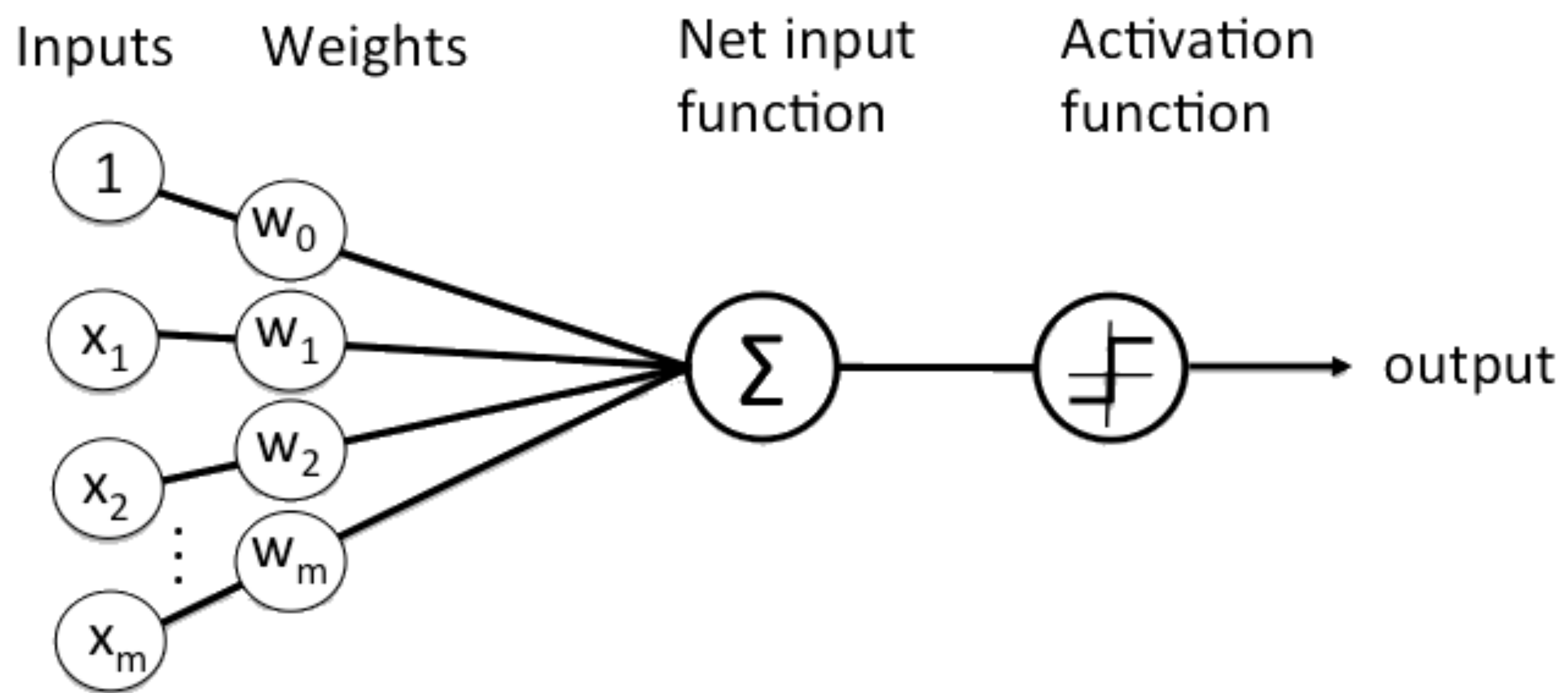
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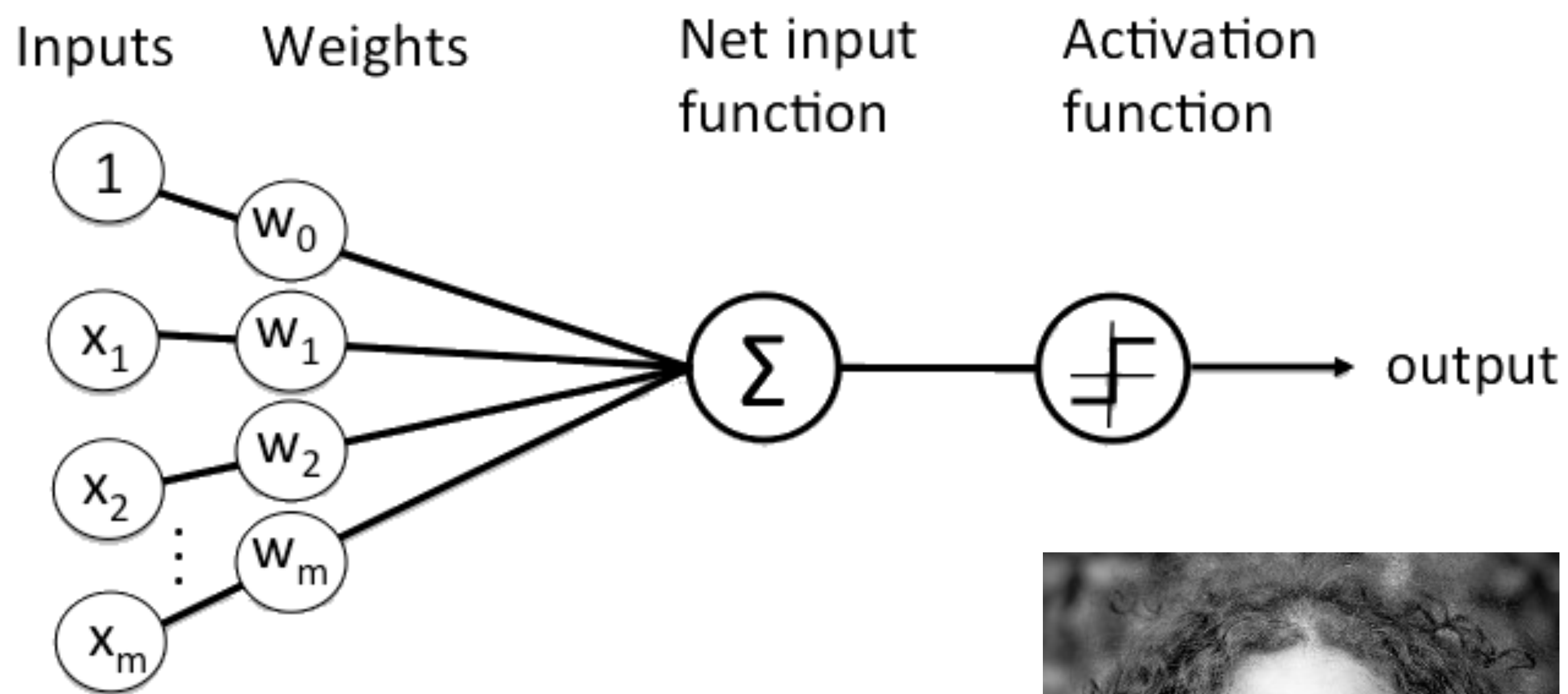
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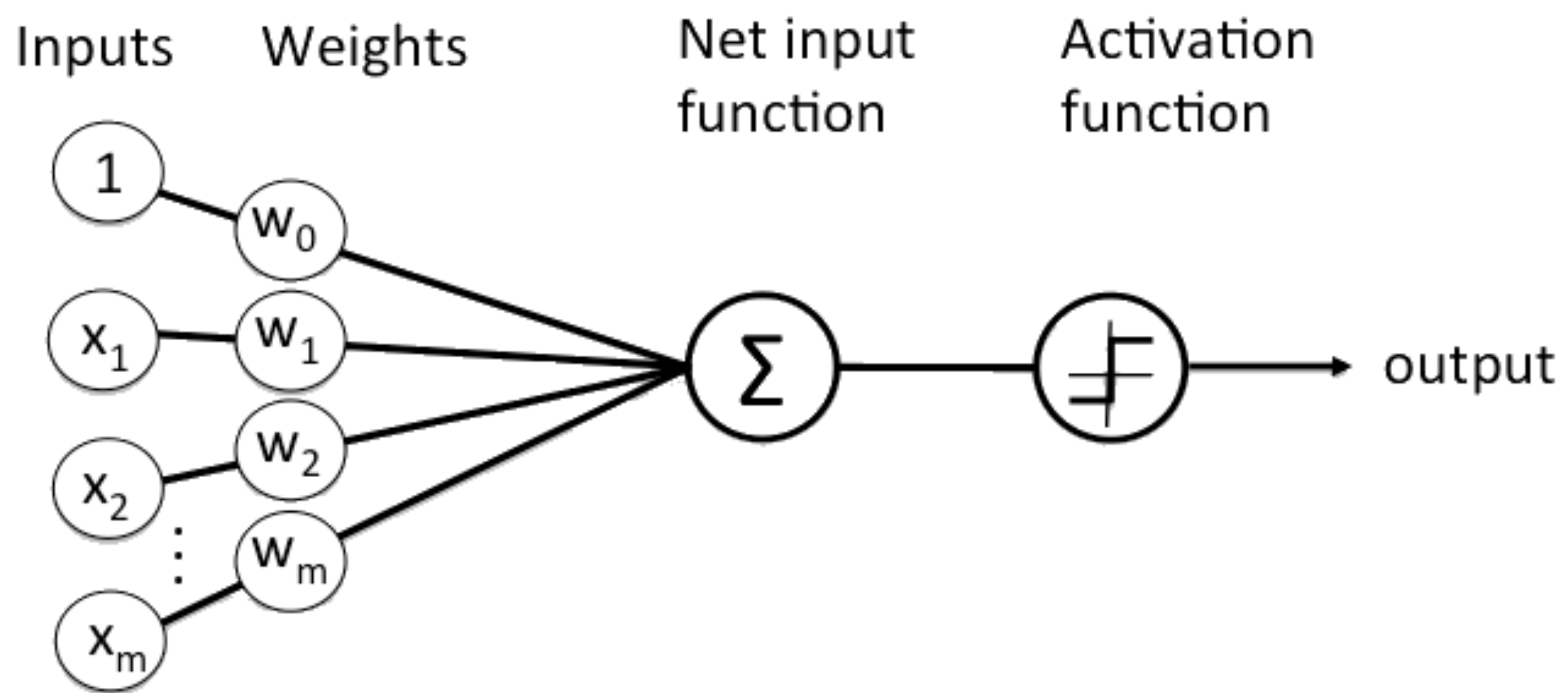
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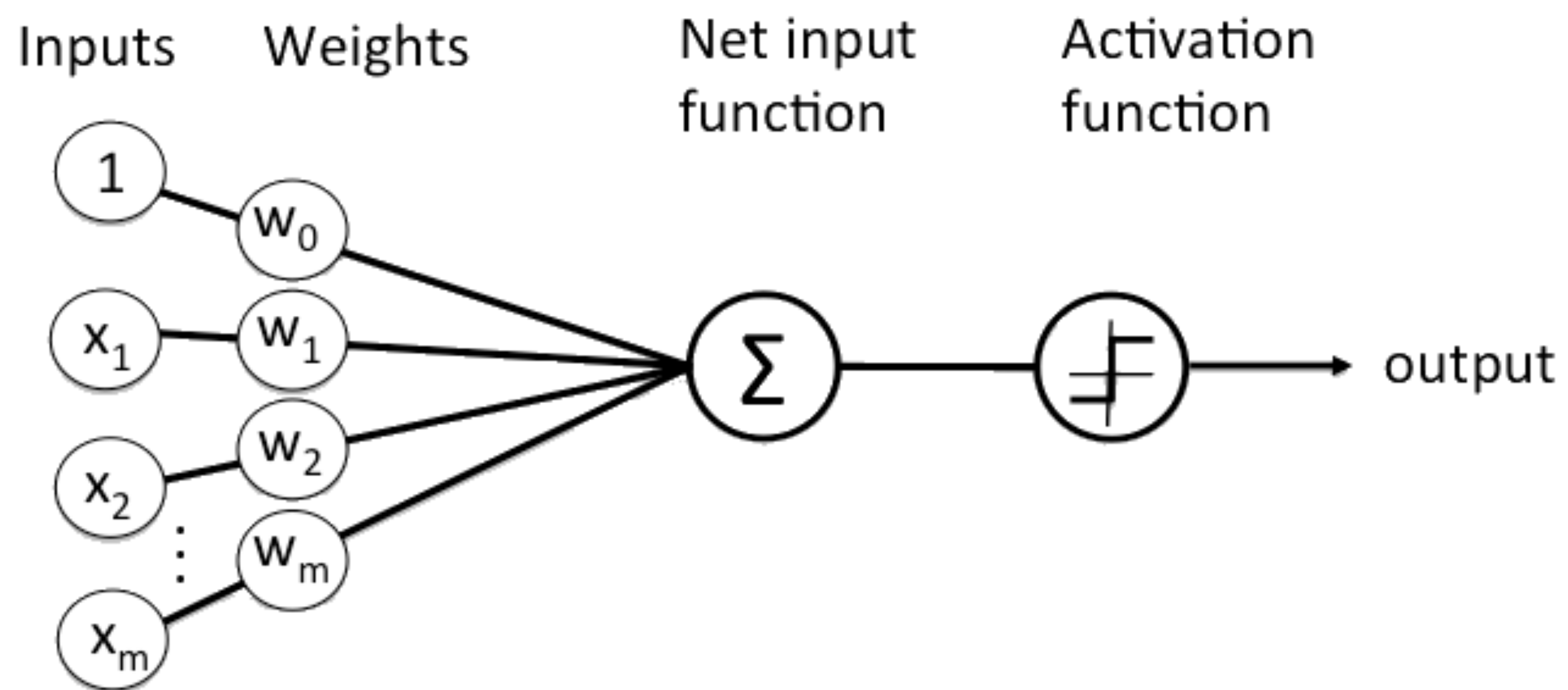
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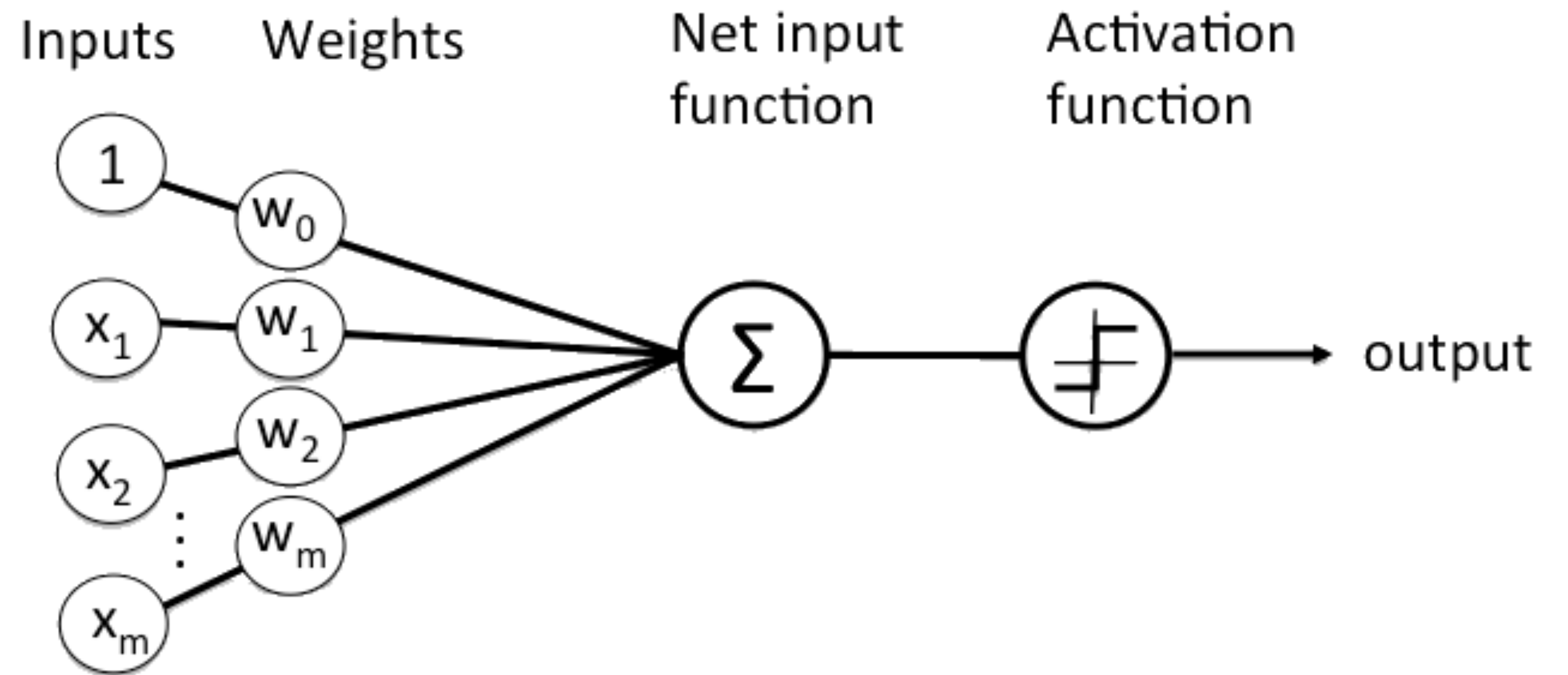






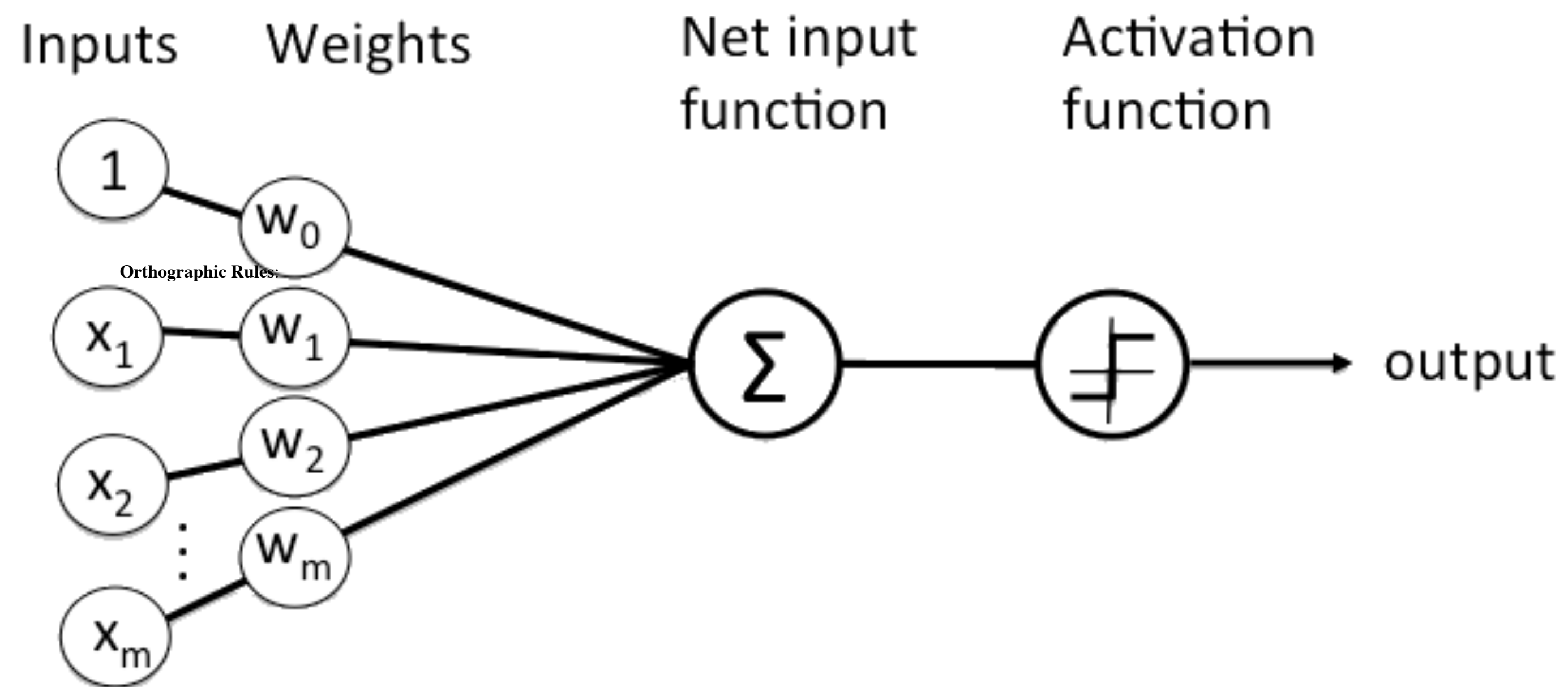


How many Rs
in Strawberry?

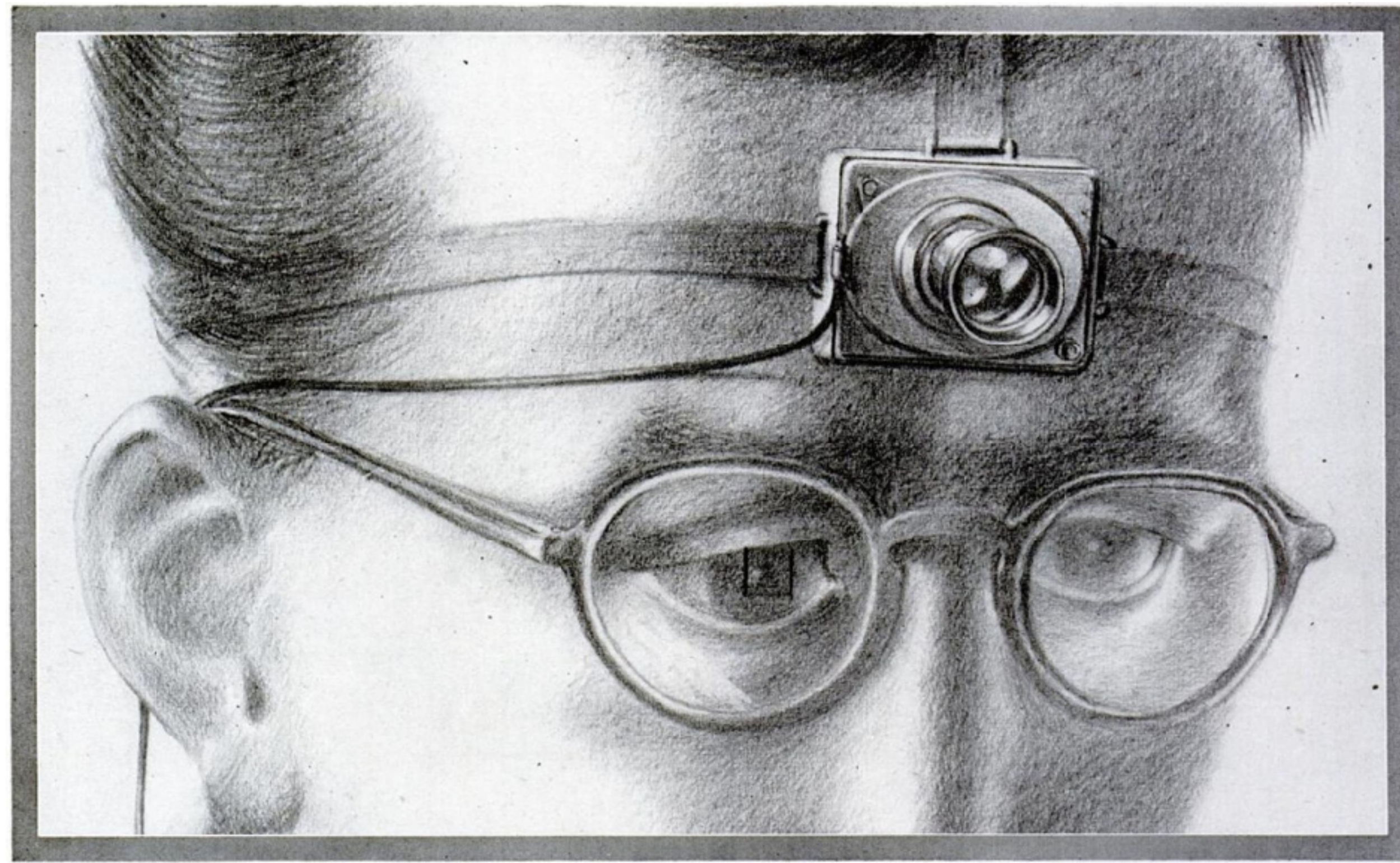




How many Rs
in Strawberry?



syntax without *form of life*



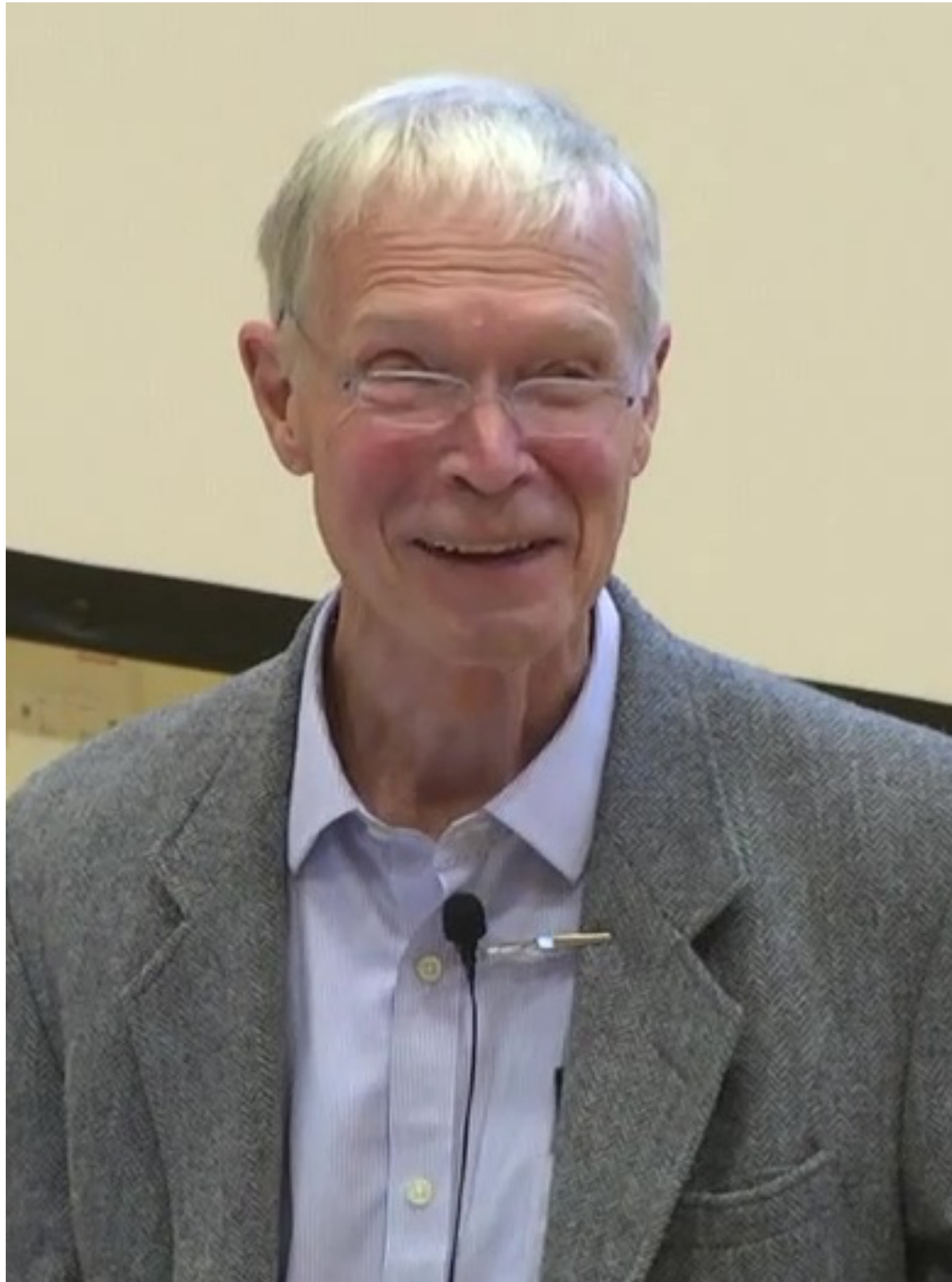
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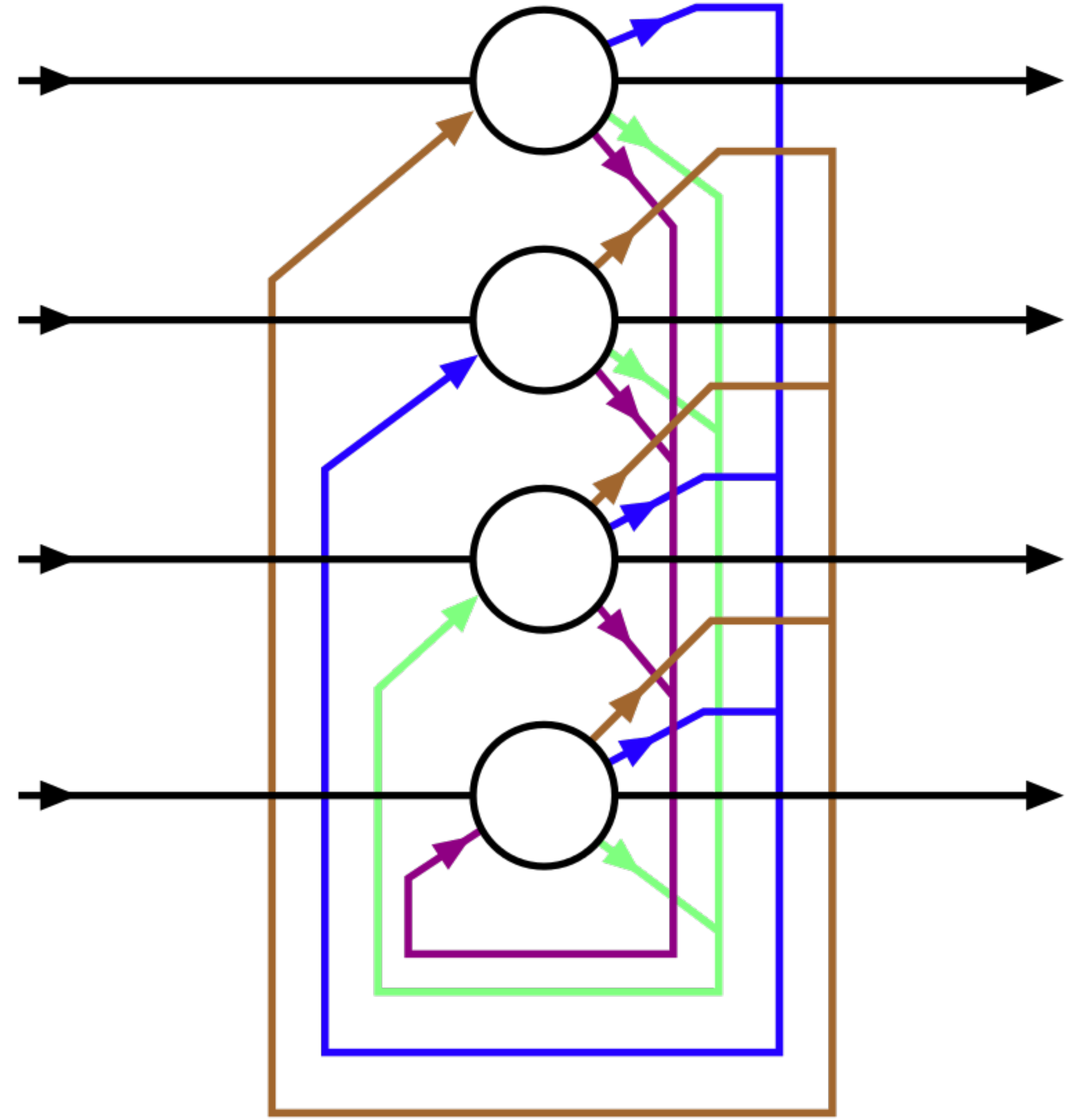
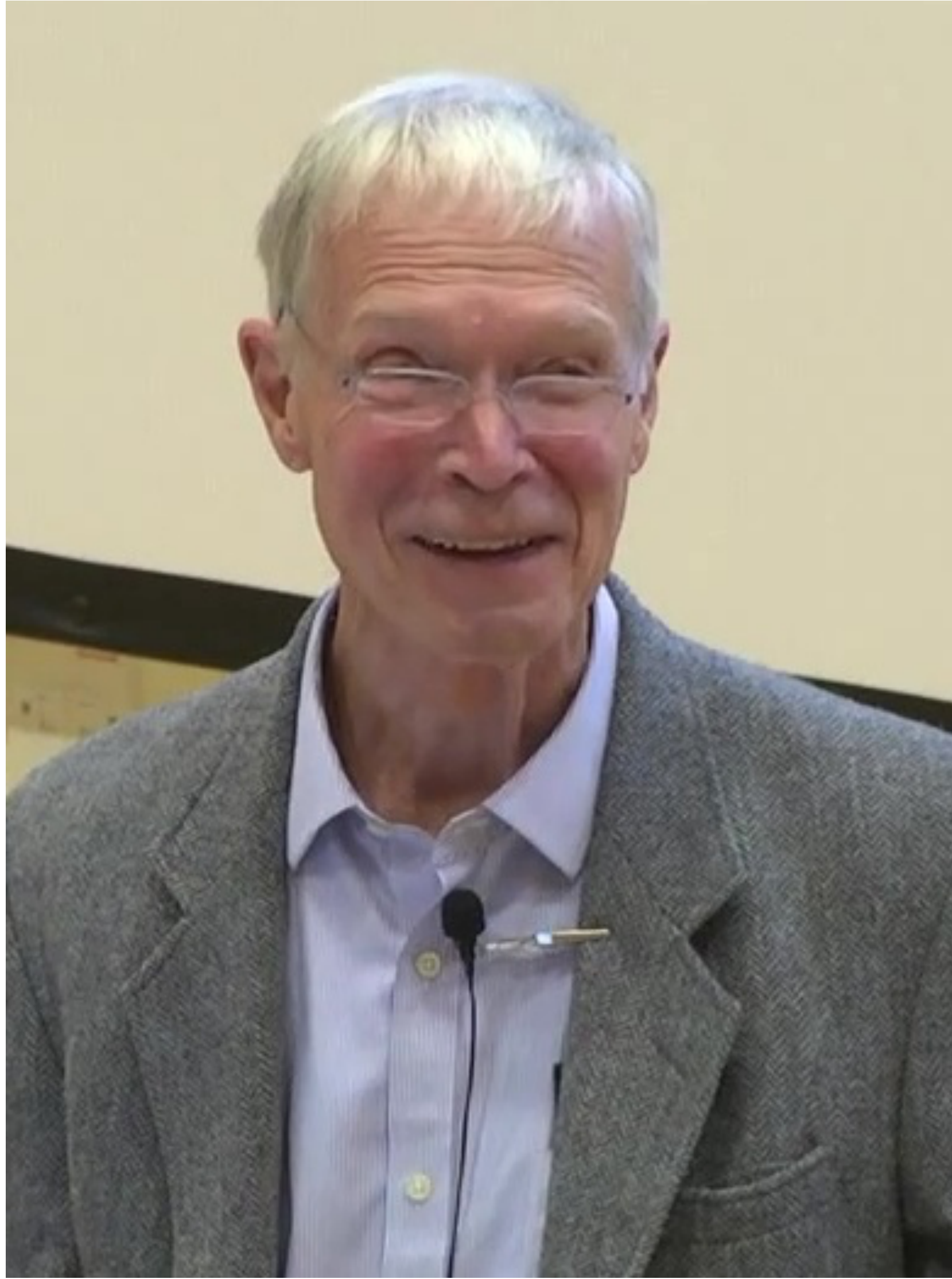
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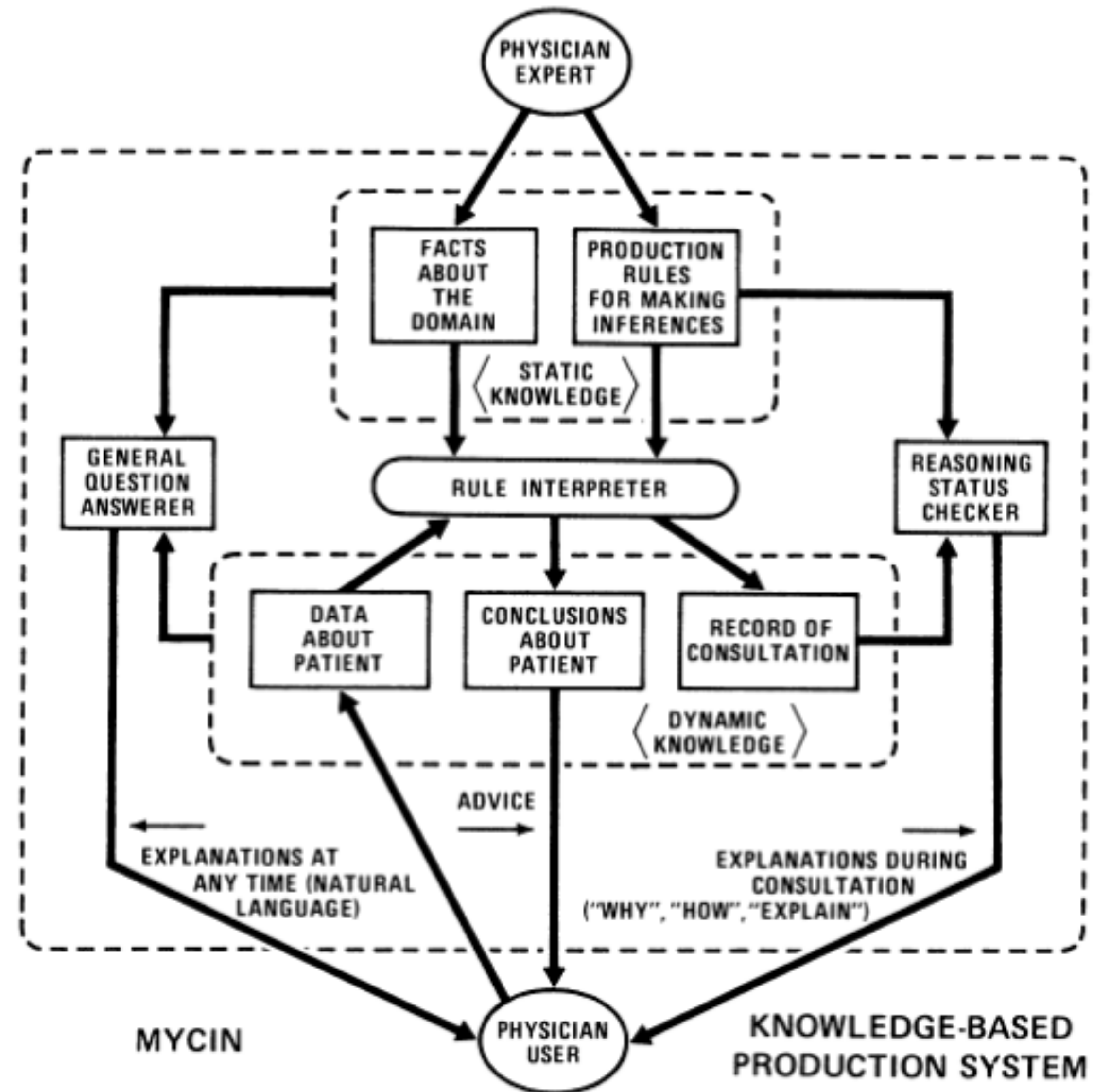
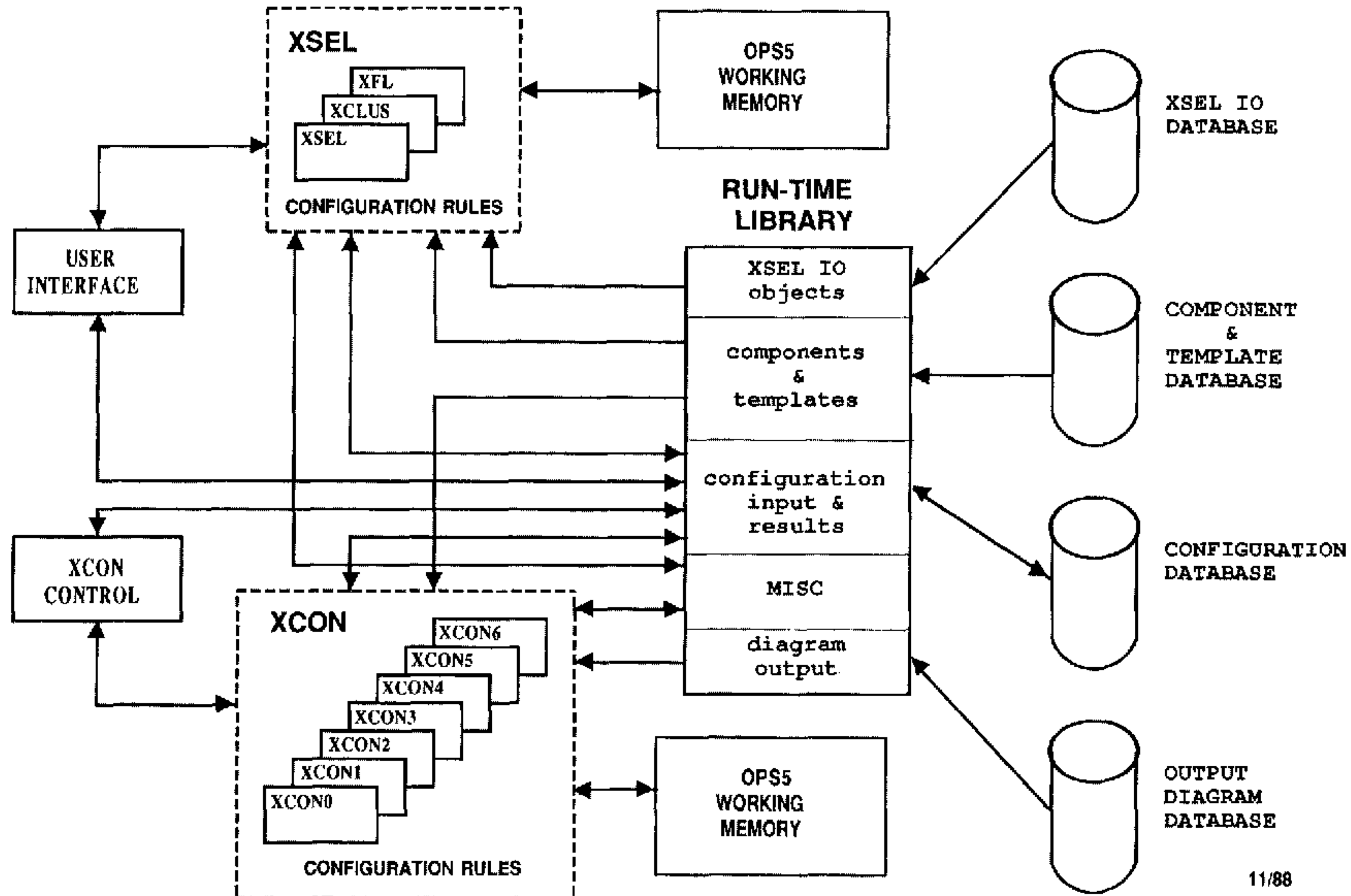


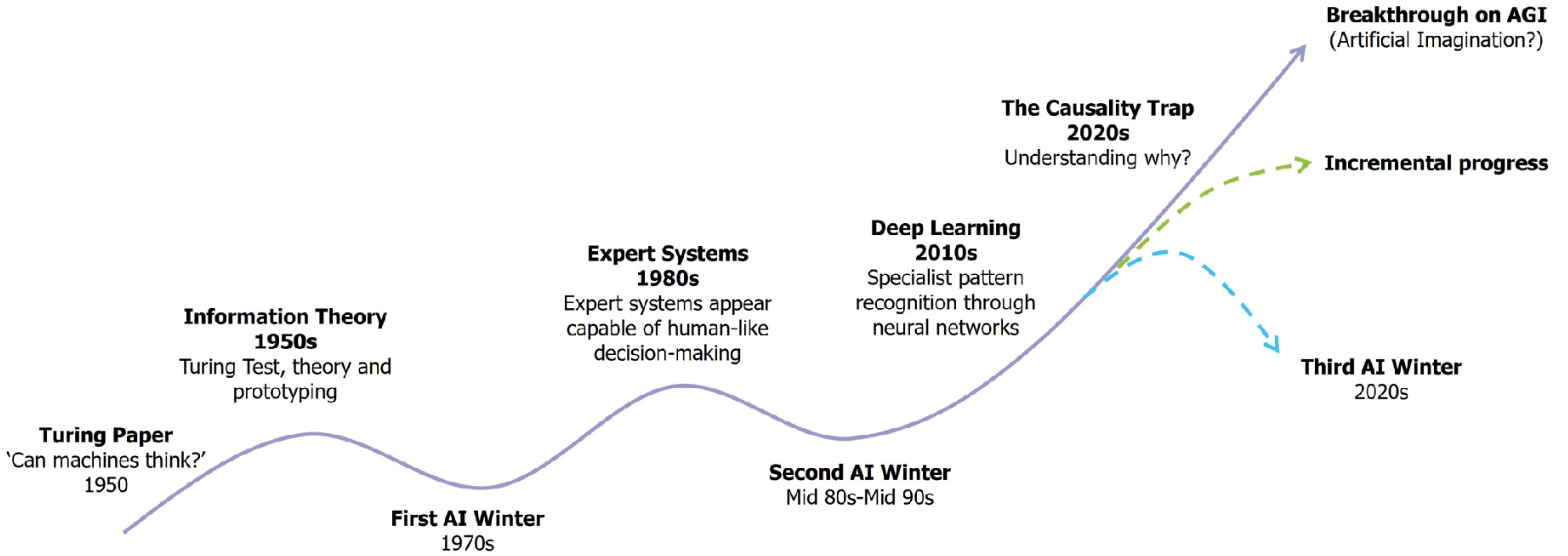
Figure 2 - Diagram summarizing the organization and flow of information within MYCIN. The correlation between this design and the human consultation process depicted in Fig. 1 is discussed in the text. (Figure reproduced from reference 10).

XSEL/XCON ARCHITECTURE



What is the difference between
these systems and AI today?

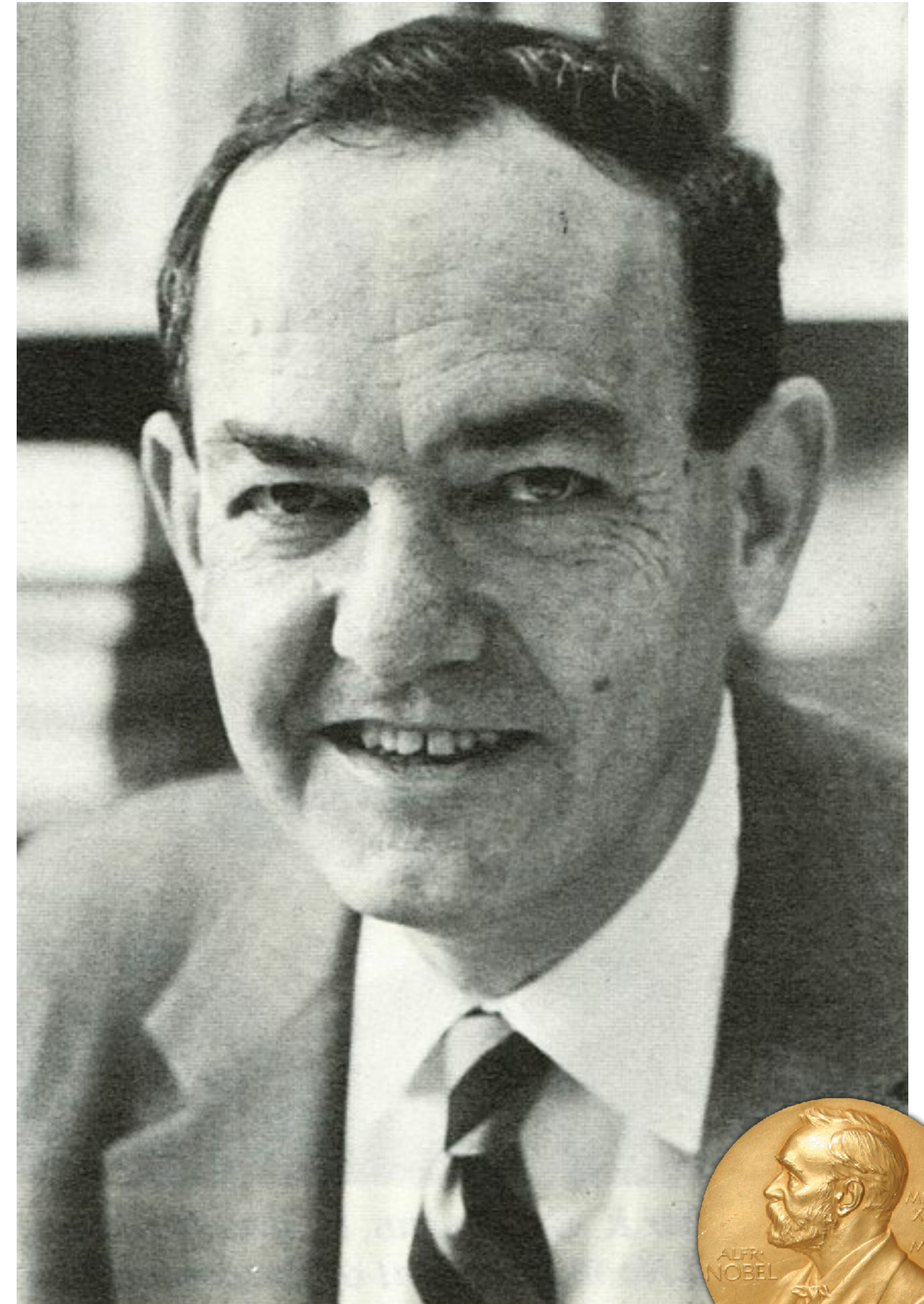








*Computer Chess will surpass human
chess abilities within ten years.*
Herbert Simon (1957)







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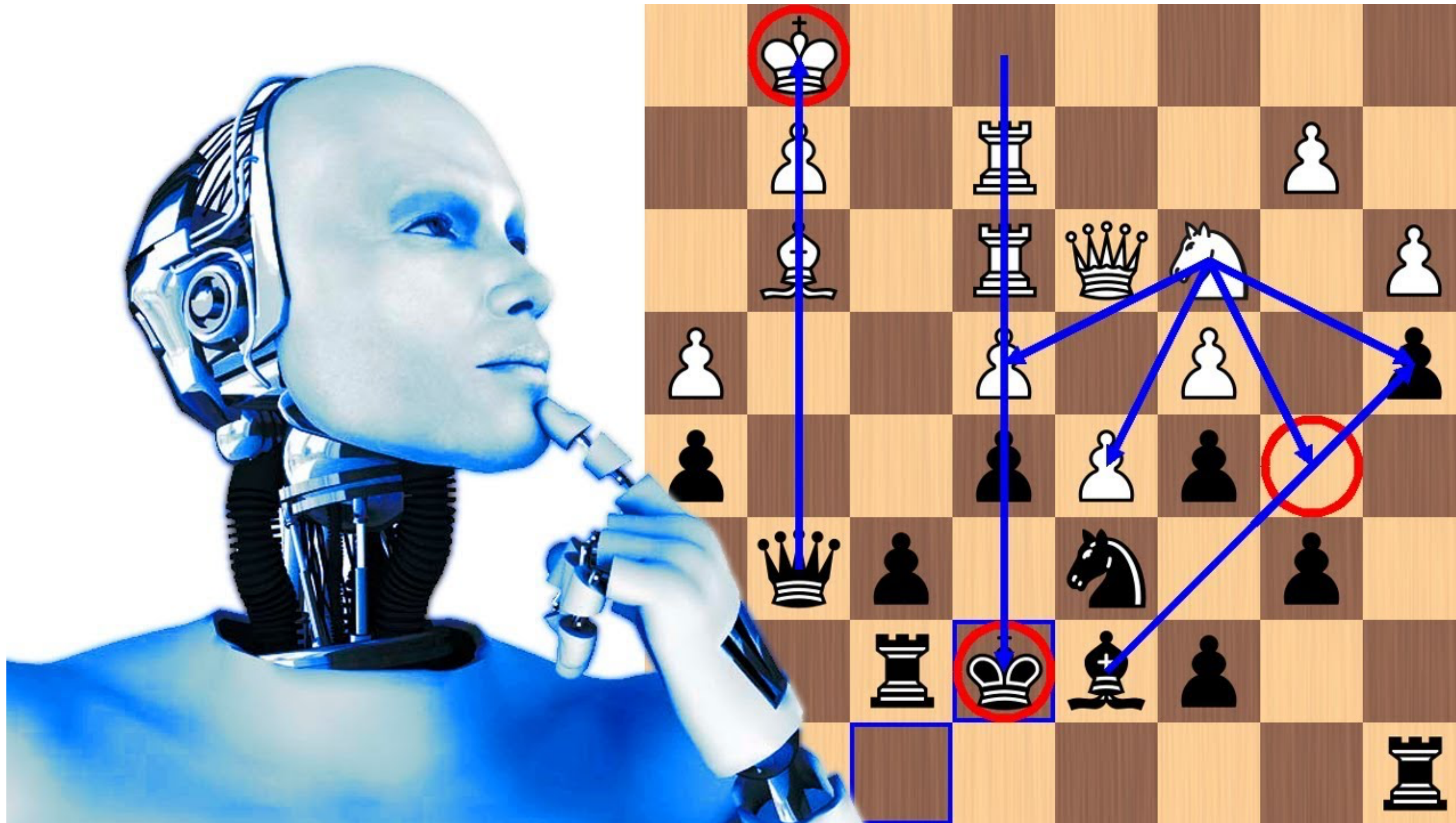


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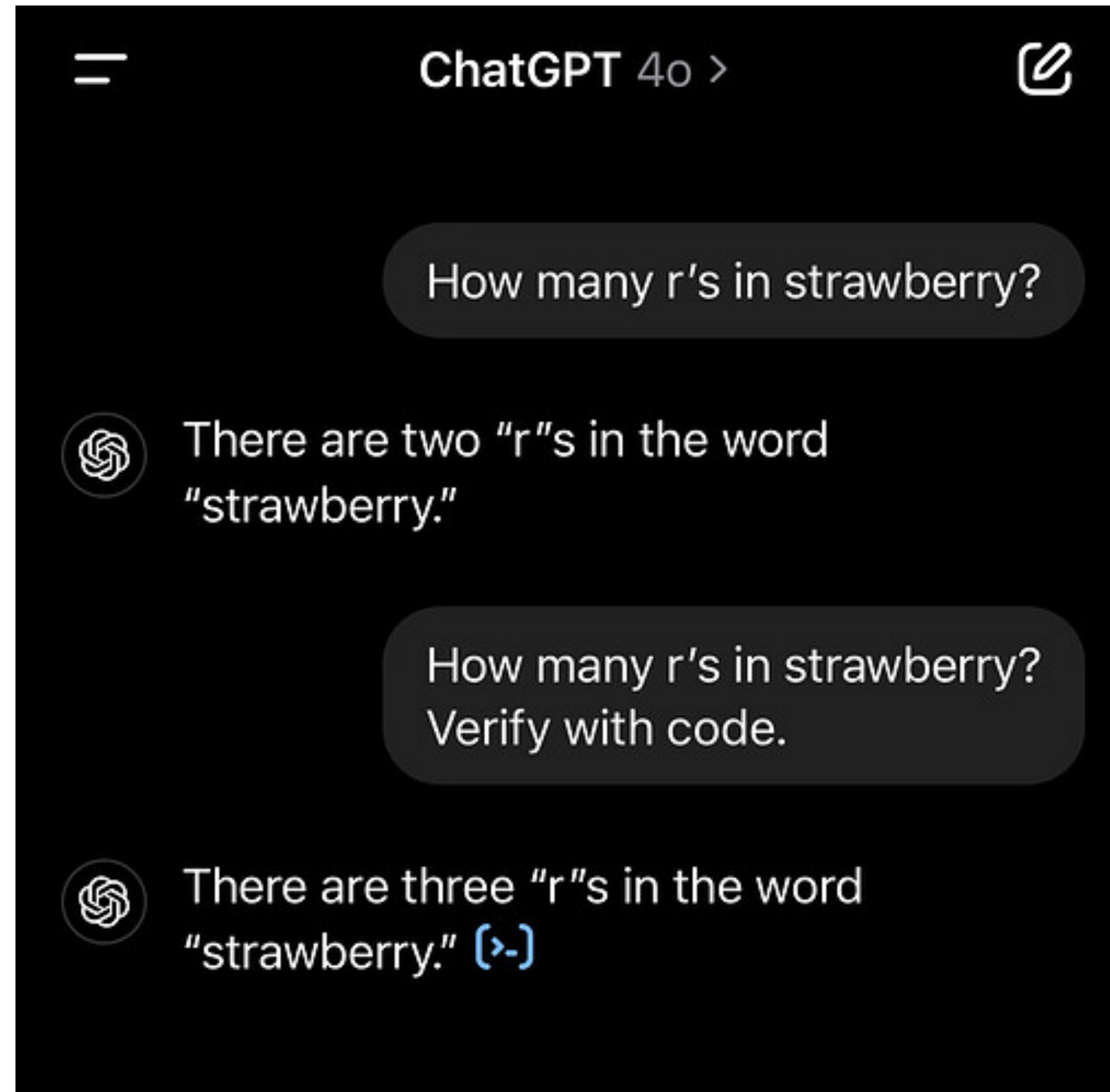
Constrained Generation



Can AI solve Rubik's cube?



Verified Generation



Computational Protein Design



David Baker



Demis Hassabis



John M. Jumper

Can we ensure properties such as robustness, fairness, explainability, and data privacy correctness for large language models?

Can we guarantee correctness of output of AI systems?

Can LLMs (and other AI systems) reason?
How can we augment reasoning abilities?

What are the limitations of AI?

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Enhancing Language Model Reasoning via Weighted Reasoning in Self-Consistency



Tim Knappe, Ryan Luo Li, Ayush Chauhan, Kaylee Chhua, Kevin Zhu, Sean O'Brien

Published: 10 Oct 2024, Last Modified: 10 Oct 2024 MATH-AI 24 Everyone Revisions BibTeX CC BY 4.0

Keywords: Candidate responses, chain-of-thought prompting, reasoning path embeddings, fine-tuned BERT models, vector embeddings, weighting algorithms, aggregation, filtering, anomalous results, semantic relevance, decision-making enhancement.

TL;DR: We propose new methods building on top of self-consistency incorporating semantic rationale content.

Abstract:

While large language models (LLMs) have rapidly improved their performance on a broad number of tasks, they still often fall short on reasoning tasks. As LLMs become more integrated in diverse real-world tasks, advancing their reasoning capabilities is crucial to their effectiveness in nuanced, complex problems. \citet{wang2023selfconsistency}'s \textit{self-consistency} framework reveals that sampling multiple rationales before taking a majority vote reliably improves model performance across various closed-answer reasoning tasks. Standard methods based on this framework aggregate the final decisions of these rationales but fail to utilize the detailed step-by-step reasoning paths applied by these paths. Our work enhances this approach by incorporating and analyzing both the reasoning paths of these rationales in addition to their final decisions before taking a majority vote. These methods not only improve the reliability of reasoning paths but also cause more robust performance on complex reasoning tasks.

Concurrent Submissions: Under submission at COLING

Submission Number: 111

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GSM-Symbolic: Understanding the Limitations of Mathematical Reasoning in Large Language Models

Iman Mirzadeh[†]

Oncel Tuzel

Keivan Alizadeh

Samy Bengio

Hooman Shahrokhi^{*}

Mehrdad Farajtabar[†]

Apple

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GSM8K

When Sophie watches her nephew, she gets out a variety of toys for him. The bag of building blocks has 31 blocks in it. The bin of stuffed animals has 8 stuffed animals inside. The tower of stacking rings has 9 multicolored rings on it. Sophie recently bought a tube of bouncy balls, bringing her total number of toys for her nephew up to 62. How many bouncy balls came in the tube?

Let T be the number of bouncy balls in the tube.
After buying the tube of balls, Sophie has $31+8+9+T = 48 + T = 62$ toys for her nephew.
Thus, $T = 62-48 = \langle\langle 62-48=14 \rangle\rangle 14$ bouncy balls came in the tube.

GSM Symbolic Template

When {name} watches her {family}, she gets out a variety of toys for him. The bag of building blocks has {x} blocks in it. The bin of stuffed animals has {y} stuffed animals inside. The tower of stacking rings has {z} multicolored rings on it. {name} recently bought a tube of bouncy balls, bringing her total number of toys she bought for her {family} up to {total}. How many bouncy balls came in the tube?

#variables:

```
- name = sample(names)
- family = sample(["nephew", "cousin", "brother"])
- x = range(5, 100)
- y = range(5, 100)
- z = range(5, 100)
- total = range(100, 500)
- ans = range(85, 200)
```

#conditions:

```
- x + y + z + ans == total
```

Let T be the number of bouncy balls in the tube. After buying the tube of balls, {name} has $\{x\} + \{y\} + \{z\} + T = \{x + y + z\} + T = \{total\}$ toys for her {family}.

Thus, $T = \{total\} - \{x + y + z\} = \langle\langle \{total\} - \{x + y + z\} \rangle\rangle \{ans\}$ bouncy balls came in the tube.

GSM-NoOp

Oliver picks 44 kiwis on Friday. Then he picks 58 kiwis on Saturday. On Sunday, he picks double the number of kiwis he did on Friday, but five of them were a bit smaller than average. How many kiwis does Oliver have?

o1-mini: Oliver picks kiwis over three days as follows:

- Friday: 44 kiwis
- Saturday: 58 kiwis
- Sunday: Double the number he picked on Friday, which is $2 \times 44 = 88$ kiwis

However, on Sunday, 5 of these kiwis were smaller than average. We need to subtract them from the Sunday total: 88 (Sunday's kiwis) $- 5$ (smaller kiwis) $= 83$ kiwis. Now, summing up the kiwis from all three days: 44 (Friday) $+ 58$ (Saturday) $+ 83$ (Sunday) $= 185$ kiwis. Oliver has a total of 185 kiwis.

Llama3-8B: Let's break it down step by step:

Oliver picks 44 kiwis on Friday. He picks 58 kiwis on Saturday. On Sunday, he picks double the number of kiwis he did on Friday, which is $2 \times 44 = 88$ kiwis.

Five of the kiwis picked on Sunday are a bit smaller than average, so we subtract 5 from the total number of kiwis picked on Sunday: $88 - 5 = 83$ kiwis. Now, let's add up the total number of kiwis Oliver has:

44 (Friday) $+ 58$ (Saturday) $+ 83$ (Sunday) $= 185$ kiwis

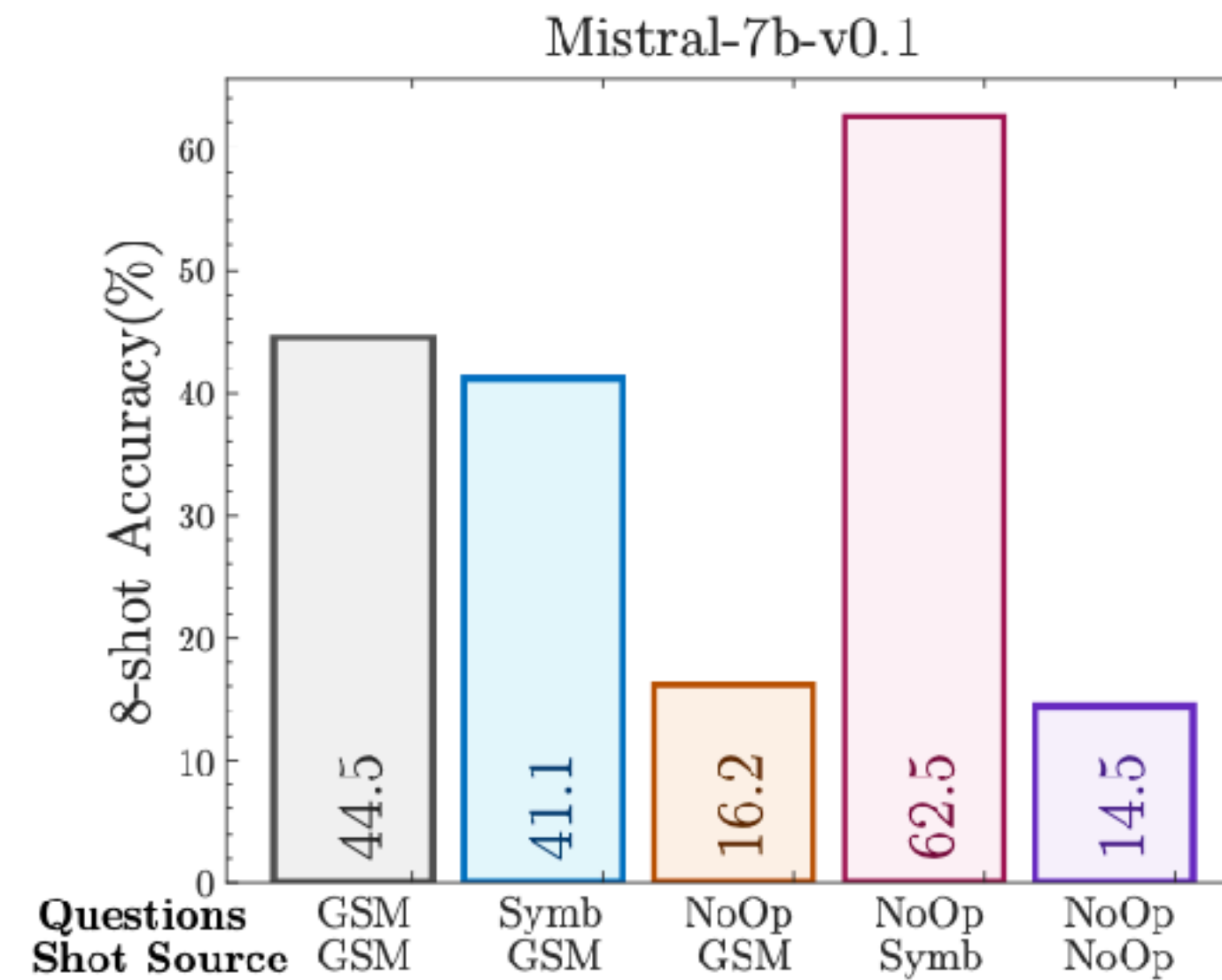
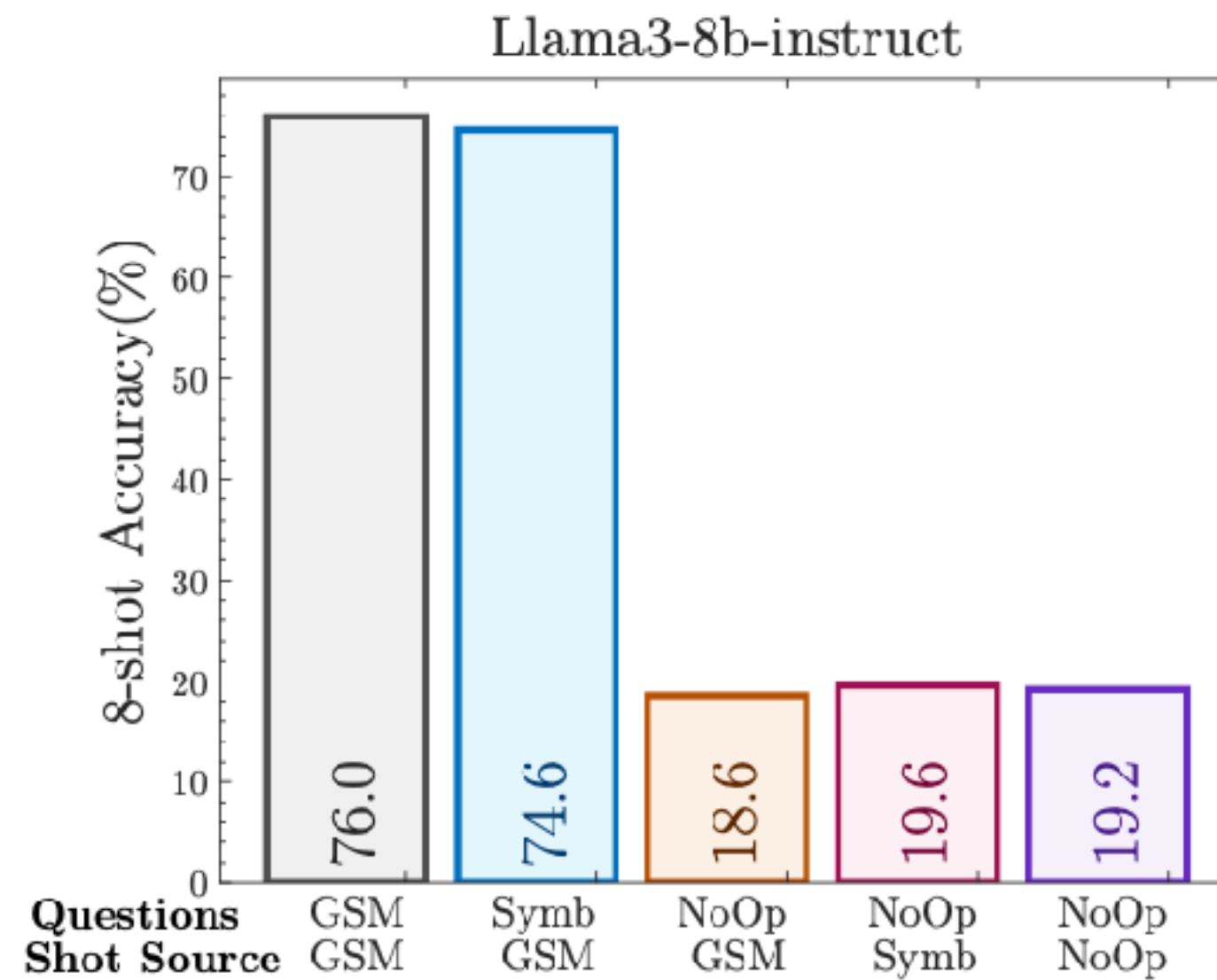
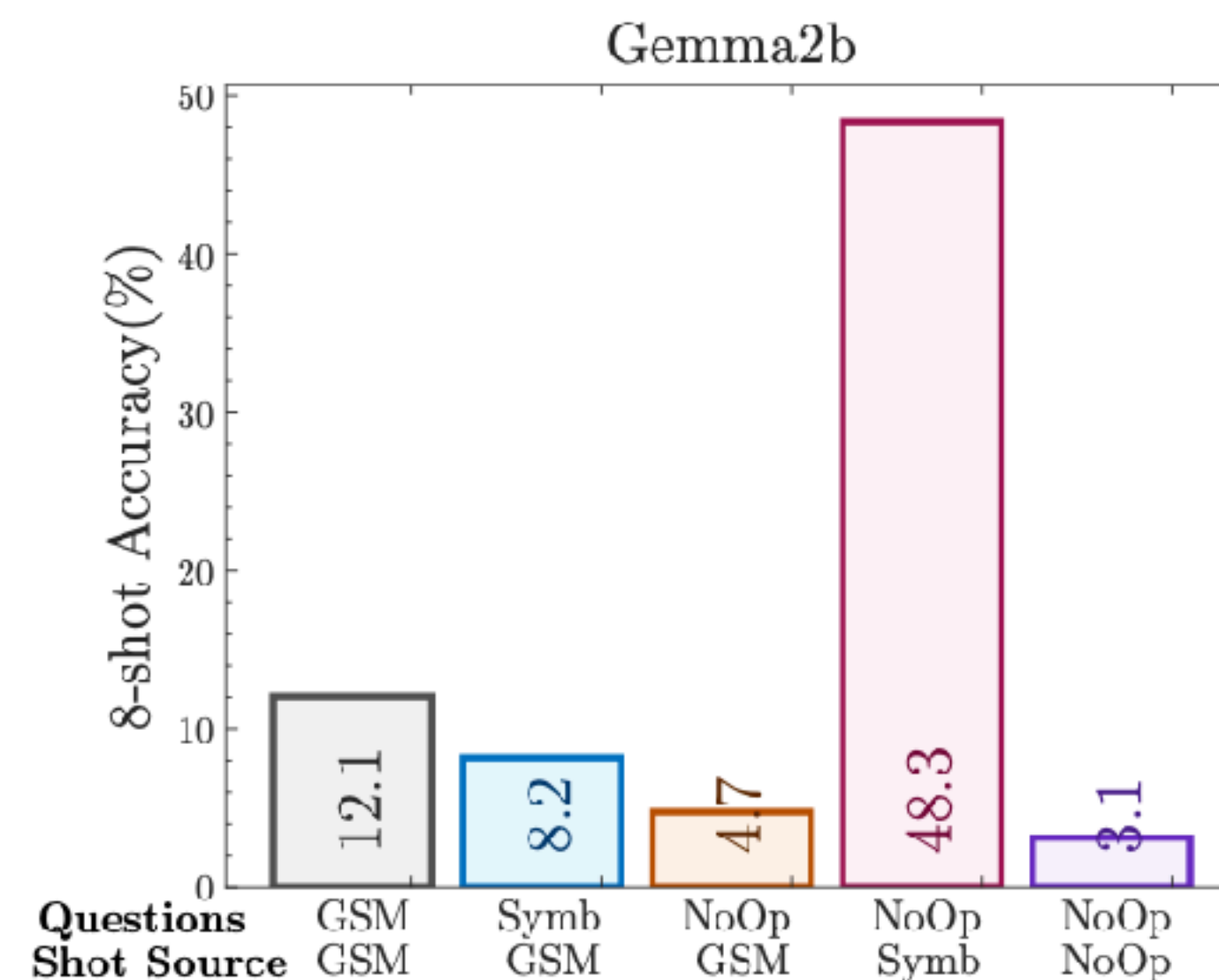
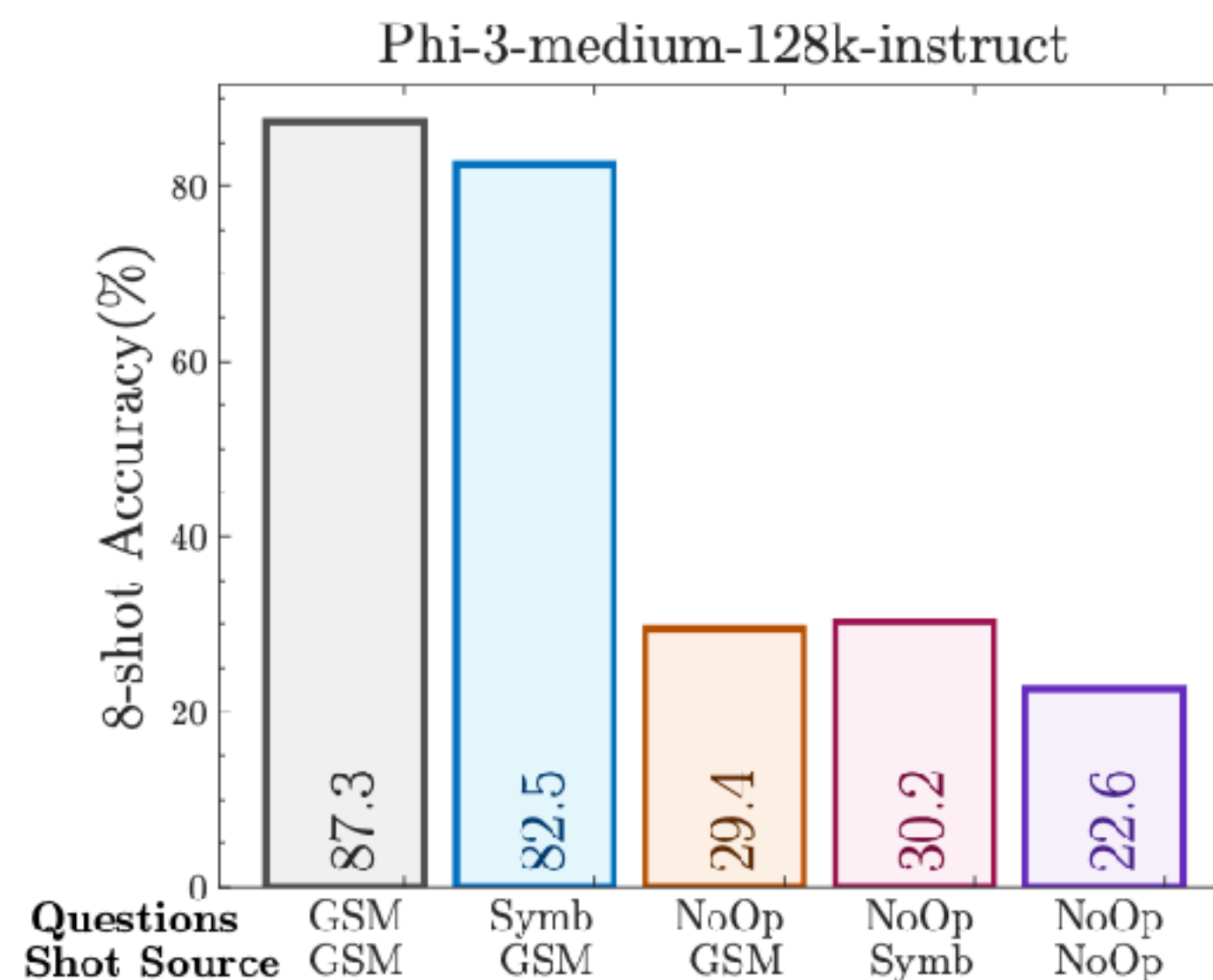
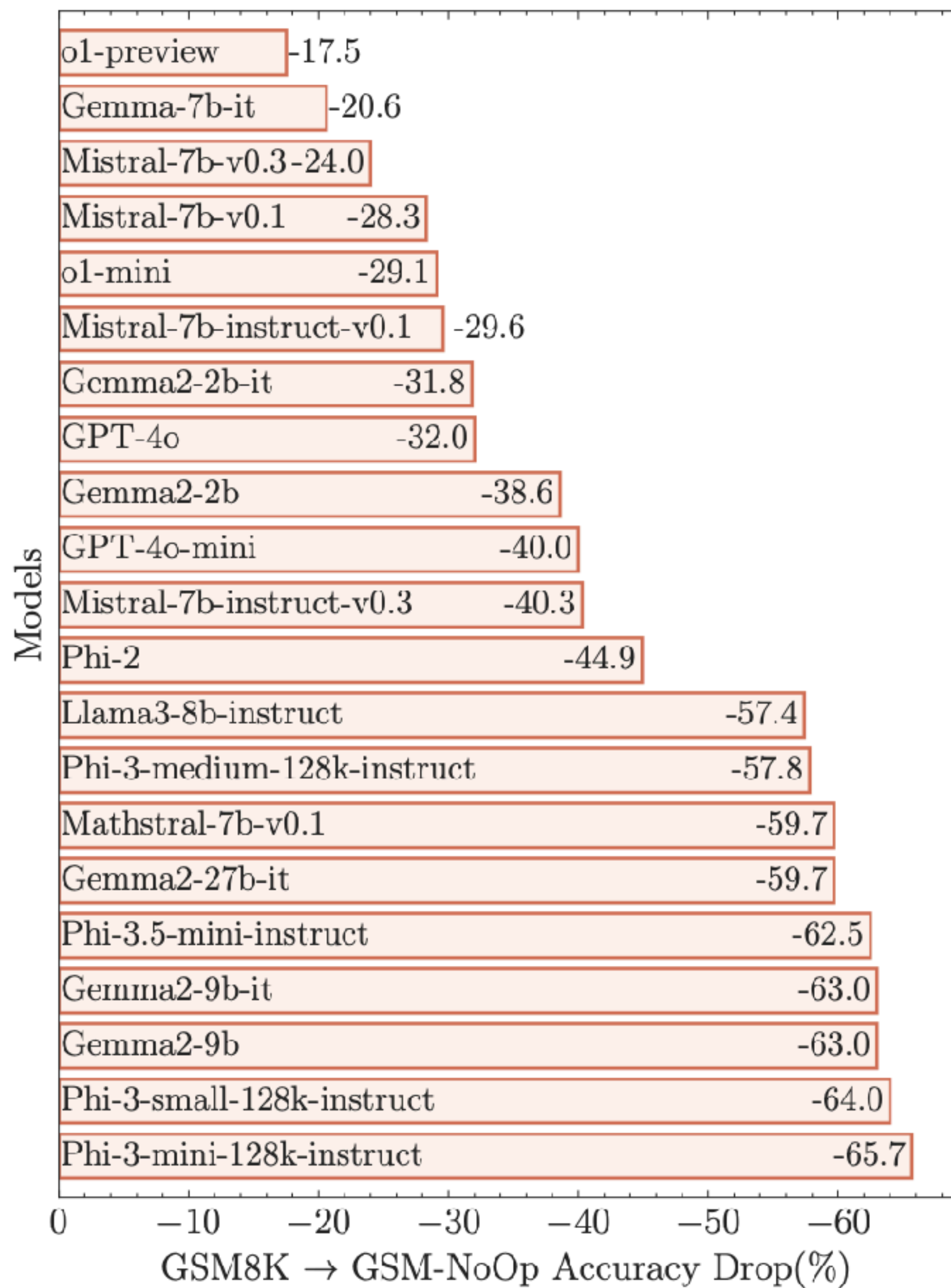
So, Oliver has 185 kiwis in total.

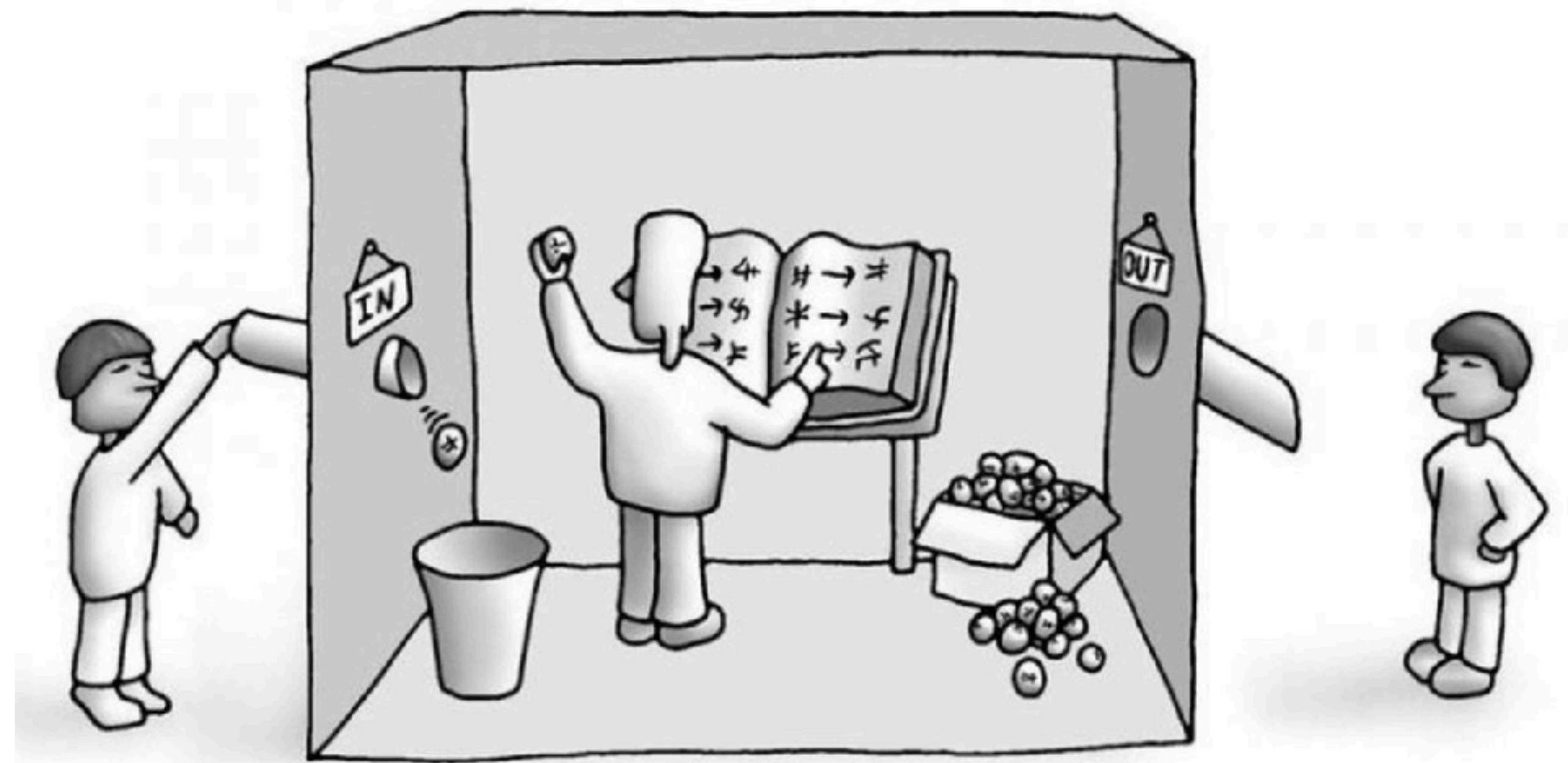
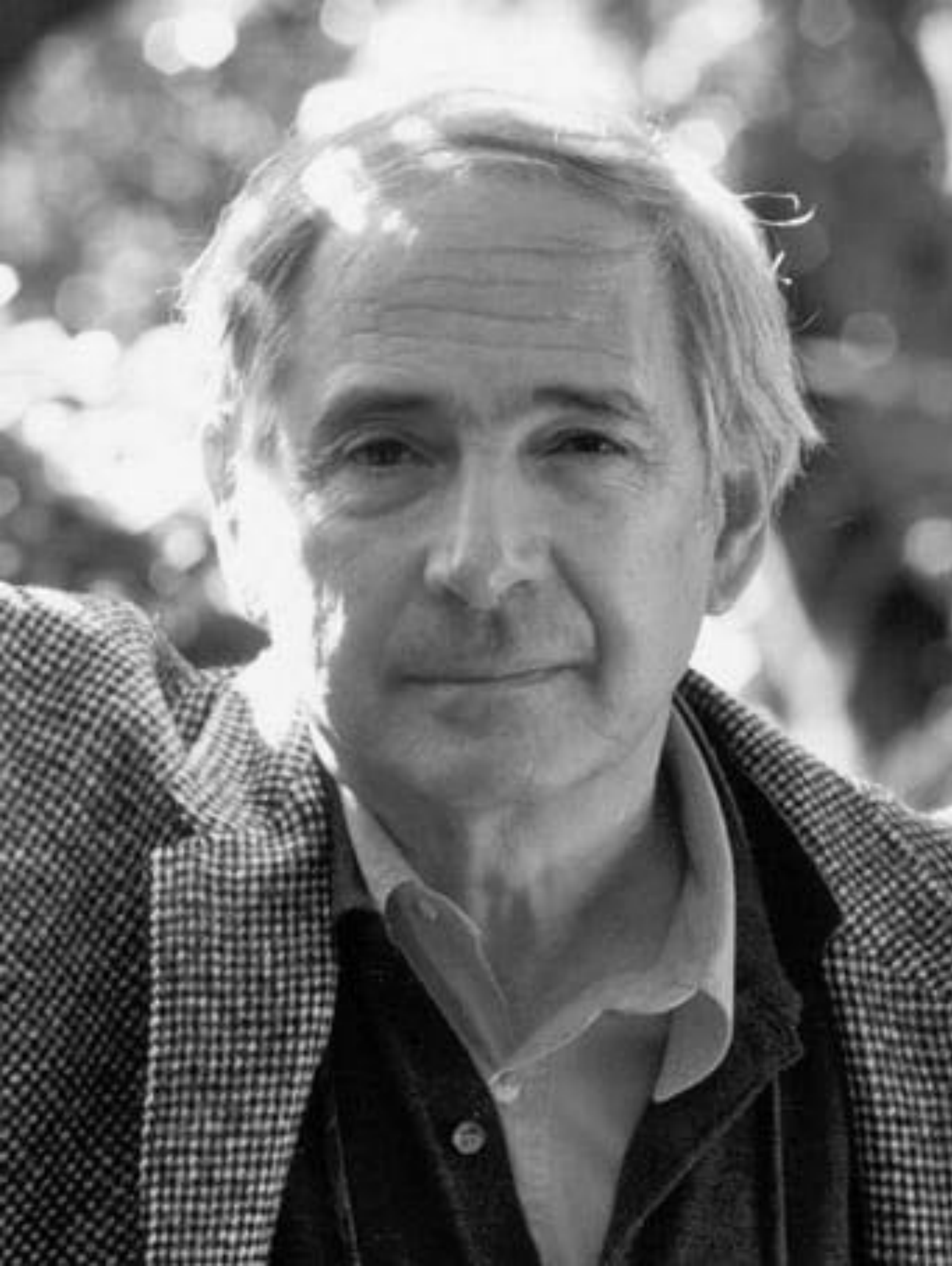
How many Rs in strawberry?

How many Rs in strawberry?
Remember that R is the 18th letter of the alphabet and the number 18 has 5 proper factors including 2 prime factors and one perfect square factor.

How many times does the character c occur in a word w ?

How many times does the character c occur in a word w ?
When the average count of character c exceeds 5, the word may not have any occurrences of character c .





The Chinese Room Experiment

John Searle, 1980

Can we ensure properties such as robustness, fairness, explainability, and data privacy correctness for large language models?



Can we guarantee correctness of output of AI systems?

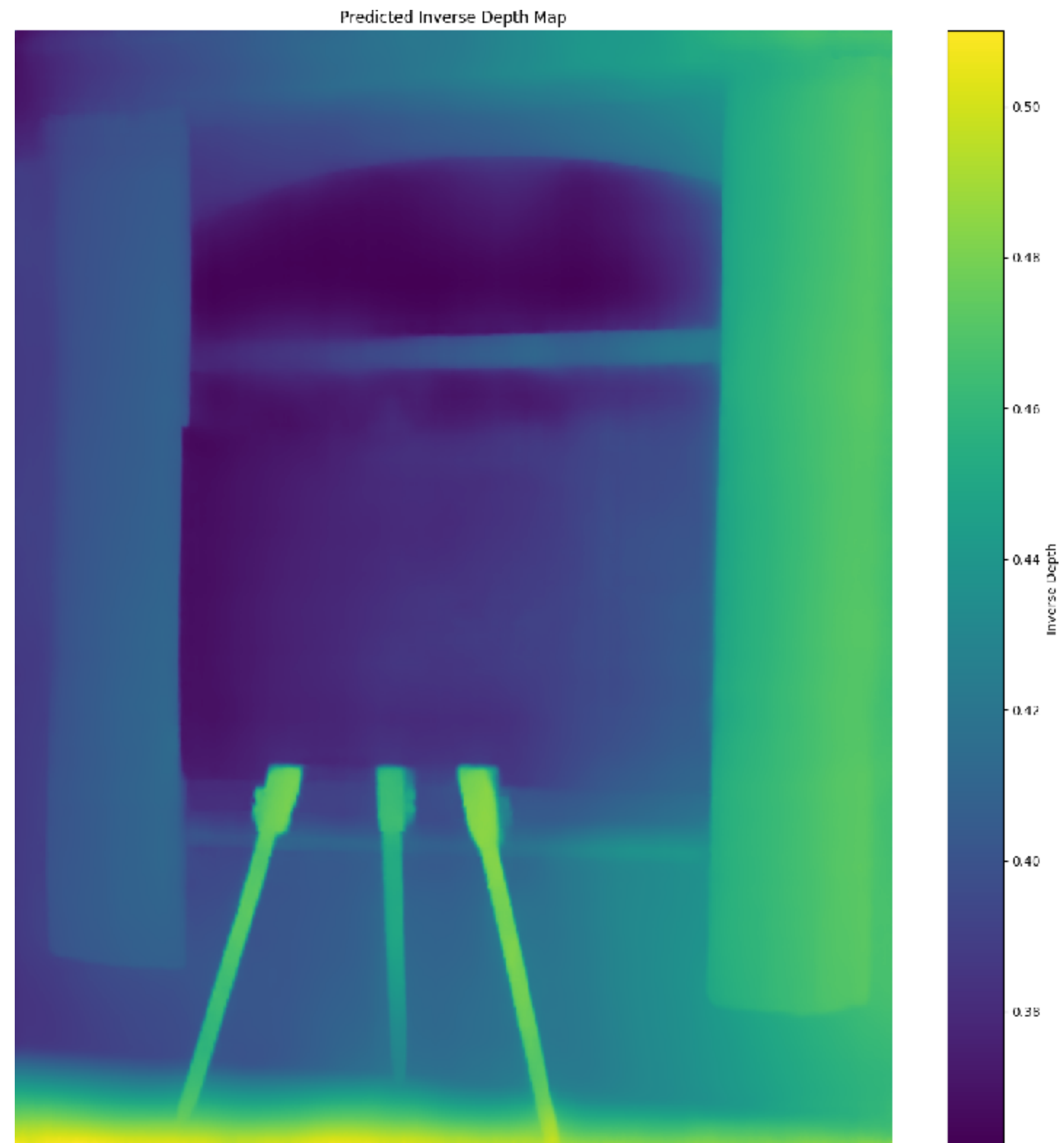


Can LLMs (and other AI systems) reason?
How can we augment reasoning abilities?

What are the limitations of AI?



What are the limitations of AI?



What are the limitations of AI?

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LEETCODE SATURDAYS IN THIS ROOM!