AI training data, model success likelihood, and informational entropy-based value

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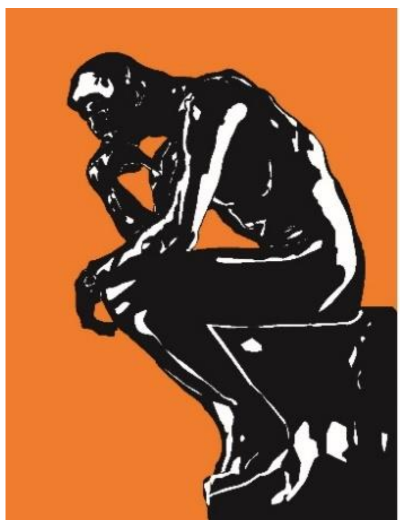

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"Yes, problem-solving is important; the better solution-maker we are, the brighter future we expect.

But we are not such good problem solvers for simple reasons: it is hard to define a genuine problem."

In Meandering Sobriety (2023)

Abstract

Since the release of OpenAI's ChatGPT, the world has entered a race to develop more capable and powerful AI, including artificial general intelligence (AGI). The development is constrained by the dependency of AI on the model, quality, and quantity of training data, making the AI training process highly costly in terms of resources and environmental consequences. Thus, improving the effectiveness and efficiency of the AI training process is essential, especially when the Earth is approaching the climate tipping points and planetary boundaries. It is evident that AI can function better when trained to mimic certain human mental processes. Based on insights from quantum mechanics and the informational entropy-based notion of value, we suggest AI developers can enhance the AI training processes' effectiveness and efficiency by creating and implementing parameter systems that are capable of effectively assigning probabilities to informational quanta. Such systems can help reduce entropy within the system, which lowers the energy required for data storage and processing while decreasing the likelihood of information loss during training. Successfully applying the concept of information entropy-based value in AI development will be crucial for advancing generative AI and achieving AGI in a sustainable manner.

Keywords: AI training; data dependency; entropy; granular interactions thinking; value

Since the release of OpenAI's ChatGPT large language model (LLM) in November 2022, the world has witnessed soaring interest in generative artificial intelligence (AI). With the rising influx of global consumers, the market of generative AI is projected to reach $1.3 trillion by 2032. Due to its potential, giant technology companies like Google, Microsoft, Meta, Apple, Tencent, Alibaba, etc., are racing to develop more capable and powerful AI, including artificial general intelligence (AGI), the AI that can be equally smart or smarter than humans in a wide range of cognitive capabilities.

A major obstacle constraining the development of AI is its heavy dependency on the model, quality, and quantity of training data, making the development of better AI highly costly. Training more powerful and multifunctional AI requires massive computational power. For instance, OpenAI's GPT-4 language model is believed to be operated with 1.76 trillion parameters, while Gemini 1.5 Pro, one of the GPT-4's competitors, also has approximately 1.5 trillion parameters. The more powerful and multifunctional the AI models are, the more extensive resources (e.g., hardware, energy, minerals and metals, data acquisition and processing costs, and maintenance costs) are necessitated for training and operating them.

Besides physical costs, AI development also involves significant and multifaceted negative impacts on the environment at various stages of the AI lifecycle. A vast amount of electricity is required for the computation and cooling of the system. As a result, it also exacerbates the current climate crisis. System cooling also necessitates a significant amount of water, which can strain local water resources, especially in areas where water is scarce.

To keep the development of AI sustainable, improving the effectiveness and efficiency of the AI training process is vital. A recent study in *Nature Human Behaviour* suggests that the AI model, RTNet, trained to mimic variability and confidence similar to the human decision-making process, outperforms other types of convolutional neural networks (Rafiei et al., 2024). The finding implies the potential of learning from humans' mental processes to improve the effectiveness of AI development.

This potential can be elaborated through the lens of quantum mechanics, which examines matter and energy at their fundamental levels (i.e., at and below the scale of atoms). Quantum mechanics posits that the world, including all physical systems on Earth, like humans and AI, is made up of discrete quanta of fields (Rovelli, 2018). A physical system composed of multiple quanta holds a set of information. Given that the world is made up of interacting physical systems, it also forms a network of reciprocal information exchanges among these systems.

A living organism, such as a human, is a physical system that constantly restructures itself to maintain its existence, continuously interacting with its environment. This process relies on managing correlations with the external world—essentially, information management. Information management includes gathering, storing, transmitting, and processing information, aligning with Charles Darwin's views on biological evolution.

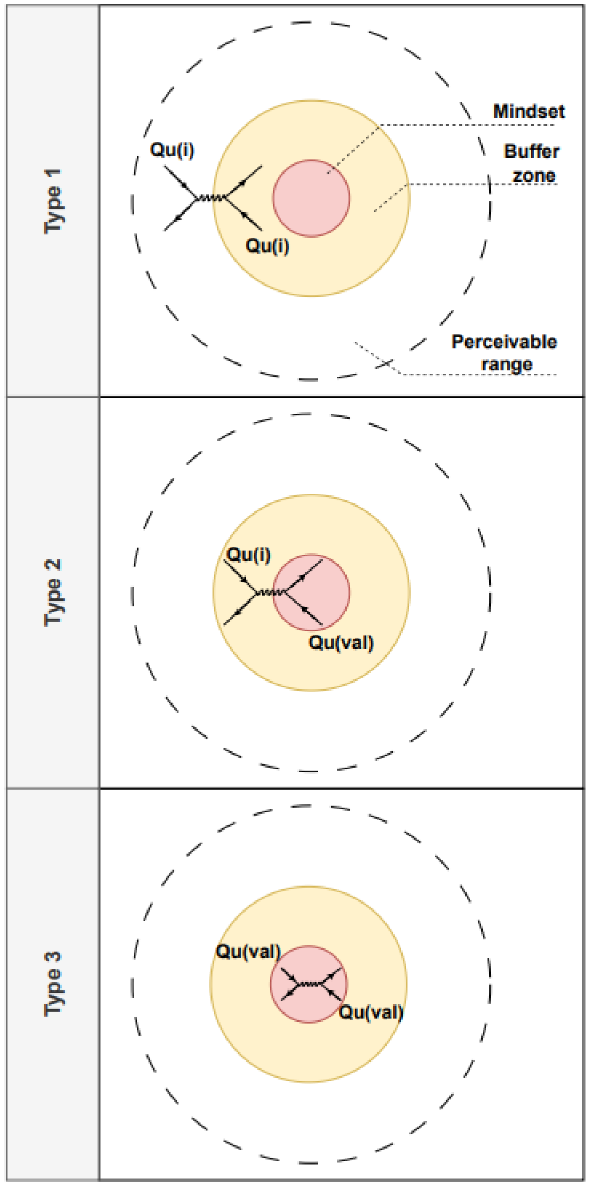

Figure 1: Primary types of interactions between informational quanta, adapted from the Feynman diagram and mindsponge theory (Feynman, 1949; Vuong, 2023). $Qu(i)$ represents the informational quanta, while $Qu(val)$ represents the value quanta (or synthetic informational quanta).

Nevertheless, human energy is limited, and so is our processing capacity. To operate effectively within these energy constraints, humans need to increase information processing efficiency through the development of value systems. This pattern can be referred to as an informational entropy-based notion of value (Vuong & Nguyen, 2024). Through the granular interactions thinking (see Figure 1), humans let informational quanta within the mind and absorbed from the environment interact and create values (or synthetic information). Such values help humans form the priority system, which essentially reduces entropy within the mind, thereby requiring less energy to store and process information.

To better understand the benefit of the priority system, we can look at Shannon's formula for calculating the informational entropy (Shannon, 1948):

$$H(X) = -\sum_{i=1}^{n} P(x_i) \log_2 P(x_i)$$

$H(X)$ is the informational entropy of a random variable X with possible outcomes $\{x_1, x_2, \dots, x_n\}$ and corresponding probabilities $\{P(x_1), P(x_2), \dots, P(x_n)\}$. $P(x_i)$ is the probability of the outcome x_i. Each probability $P(x_i)$ represents how likely each outcome x_i is to occur. In the context of a human's mental process, the variable X can be seen as an individual's mind in its current state, containing i information quanta. Each informational quantum has $P(x_i)$ probability of being stored and processed in the mind. According to the entropy formula, if the number of information units increases without a clear system for differentiating and prioritizing their importance, informational entropy will rise rapidly, peaking when all information is deemed equally important, specifically when $P(x_i) = \frac{1}{n}$. This means individuals face the highest risk of information loss if they fail to establish a priority system. The more information units the mind attempts to store and process, the greater the likelihood of them being lost or forgotten due to memory and energy limits.

Unlike the limitations of humans, the memory and energy that AI can use depend on human provisioning. However, as climate tipping points and planetary boundaries are about to be crossed, it is evident that humanity faces the dilemma between socio-economic development and environmental sustainability, and thus, AI's memory and energy might also be approaching their limits.

Therefore, we believe that the current approach to developing AI models, which heavily relies on large amounts of data and computational power, needs to change. To achieve this, technology companies developing AI must create and implement parameter systems that are capable of effectively assigning probabilities to informational quanta. This will reduce entropy within the system, thereby lowering the energy required to store and process data (i.e., informational quanta) while also decreasing the likelihood of information loss.

Currently, the number of parameters in AI models has reached the trillion milestone, yet they still fall short of achieving the level of general intelligence expected in AGI. Thus, it seems to us that successfully applying the concept of information entropy-based value in AI development and operation will play a crucial role in further upgrading generative AI and realizing AGI within the scope of sustainable development.

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