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Artificial intelligence: unpredictable or unprestatable?

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Current AI technologies have demonstrated impressive results, mainly driven by large language models (LLMs). The most diffused applications of LLMs are in the so-called generative AI, which consists in techniques that produce texts, music, pictures or videos–often in a multimodal setting. Challenging the intuition that machines cannot be truly creative, the artefacts produced by LLMs are sometimes considered as surprising, novel and creative. This view is also supported by observing that there are both theoretical and practical limitations on the predictability of AI systems' outcomes. Actual creativity can also be transformative and inventive, hence not just unpredictable but unprestatable: true novelty arises within a process whose evolution of the very possibility space cannot be predicted. Prominent examples of unprestatability are the evolution of the biosphere and can be found in artistic human productions. In this contribution, we elaborate on the notions of predictability and prestatability in the context of current AI systems. We maintain that these systems are, to some extent, unpredictable but not unprestatable. A consequence of our contention is the definition of the limits of what AI systems can and cannot do, and therefore the contexts for which these technologies are best suited.

KEYWORDS
affordance, artificial intelligence, creativity, evolution, novelty, predictability, prestatability

1 Introduction

The problem of prediction in science concerns the capability to anticipate events or phenomena on the basis of prior knowledge, typically formalized in the form of a theory [1]. Prediction plays a key role in scientific discovery since, according to Popper [2], only those theories that generate testable predictions can be considered scientific, precisely because they are falsifiable. We do not discuss here the conceptual and philosophical debates on prediction; rather, we focus on the various challenges involved in achieving prediction. Particularly, we are interested in elaborating on the kinds of unpredictability related to artificial intelligence (AI) systems. The problem of assessing the predictability of artificial systems is long-standing. It became particularly relevant with the advent of digital computers, when questions arose about the extent to which programs can produce sound results in a given amount of time. In the current era of widespread use of systems based on large language models (LLMs), the notion of predictability is challenged by their ability to generate texts and other forms of artifacts—such as images and music—that are often surprising.

In this paper, we elaborate on the diverse facets of unpredictability exhibited by AI systems. Our analysis concerns AI systems implemented on computational architectures with an expressive power equivalent to universal Turing machines (UTMs); in other terms,

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our focus is on hardware and software implementations of algorithms, possibly interacting with users.

Here we focus particularly on LLMs, deep artificial neural networks structures that typically consist of billions of parameters and are trained on large datasets [3,4]. When trained on textual documents, their primary task is to predict the following words of an input sequence. However, their use has gone far beyond this original goal, and they are currently employed in numerous everyday activities, from the generation of reports and code to summarization, across a wide range of applicative domains, such as medicine and finance. We discuss the various sources of unpredictability in relation to the notion of novelty and surprise, as well as emergent properties. Therefore, we concentrate our attention on possibly positive aspects of unpredictability, rather than those—equally important—related to soundness, reliability and explainability.

Our aim is to show that the nature of unpredictability in AI systems, and LLMs in particular, is at a different—lower—level than that of biological systems. Our contention is that current AI systems have some degree of unpredictability, whereas biological systems can in fact be unprestatable, implying not only the impossibility of predicting what will occur, but also what is even possible. The notion of unprestatability has been introduced to characterize the evolution in time of systems for which the typical approach used in physics cannot be applied [5–7]. In physics, the dynamics typically takes place in a prescribed phase space which is generally not affected by the dynamics itself. Even though many modern physics problems, for instance in soft matter, involve the self-consistent coupling between different phenomena interacting over a broad range of scales [8], the phase space is defined once for all and does not change in response to the dynamics of the system. Such systems might still be too hard to compute, simulate or predict in practice, but they are prestatable. Fluid turbulence is an adamant example in point. In some biological processes, first and foremost the evolution of the biosphere, the phase space changes persistently in response to the dynamics of the system, thereby triggering a two-way self-sustained loop that cannot be mathematically modelled *a priori*. In this case, the system is said to be unprestatable because if the phase space changes, the very laws which govern the system dynamics may change as well.

Central to our argument is the notion of affordance [9,10] that expresses the possible actions an organism—or a system—can take in a give situation. This concept is tightly linked to sense-making in organisms [11] and will guide our exploration of the boundary between the unpredictability of AI systems and the unprestatability characteristic of the living world. The outcome of our discussion is that AI systems can demonstrate some elements of novelty—but not originality—and they are confined within the borders of combinatorial and—to some extent—exploratory creativity [12]. Therefore, the innovation they produce is inherently limited.

In Section 2 we examine the principal sources of unpredictability for AI systems, and then discuss them in Section 3. We provide our conclusive statements in Section 4.

2 Unpredictability in AI systems

The problem of predicting the outcomes of an AI system varies depending on the sources of uncertainty that affect it [13].

A first source of unpredictability arises from the fact that AI systems are computational systems—i.e., systems equivalent to UTMs—and consequently subject to issues related to computational complexity, decidability and irreducibility [14]. A prominent case is the so-called halting problem, which states that there is no algorithm that can decide whether any given UTM, initialized with any input data, will eventually halt.[1] The halting problem has tight relations with Gödel theorems, as well as decidability in formal system. In terms of current AI systems, it posits that in general we cannot predict whether a program will eventually stop and return an answer. Besides the halting problem, a prominent issue concerning predictability of computational systems is that of computational irreducibility: there exist systems for which it is impossible to predict the final outcome without executing all the computational steps [15]. In other terms, if we interpret computation as a trajectory of a dynamical system in a discrete state space, there are no shortcuts to reach the end of the trajectory. Computational irreducibility has also been deeply investigated in discrete dynamical systems such as cellular automata [16,17]. The principal implication of computational irreducibility is that there may be cases in which it is impossible to wait for a program's answer because of time constraints. Therefore, we cannot rule out the possibility that an AI system cannot return a solution or an answer in the time allowed, and so we cannot predict its outcome.[2] It is important to remark that we are considering deterministic systems, so this kind of unpredictability does not arise from stochasticity. En passant, we mention a further remarkable case of unpredictability in deterministic dynamical systems: deterministic chaos [18], formally defined in the mid of the 20th century [19], but anticipated by scholars such as Hadamard and Poincaré [20]. Deterministic chaos may affect AI systems in those cases in which their outputs depend on long chains of calculations, where the effects of rounding and approximations might become significant [21].

A second source of unpredictability comes from stochastic components, which introduce uncertainty to the systems, thereby limiting predictability. Nevertheless, as long as the probabilistic models used in a system are known, principled estimates of the expected outcomes can still be made. Therefore, stochastic elements and randomness *per se* do not inherently preclude predictability. Likewise, randomness alone does not constitute a significant source of novelty or originality in artificial systems. However, we remark that LLMs make use of a parameter—usually called temperature—that acts on the diversification of the output. In this way, the variance of possible answers returned by an LLM can be tuned. The sequence of tokens produced is the result of a chain of probabilistic (not independent) decisions. When the LLM model is large and trained on a huge corpus of data, we might face unpredictability due to computational irreducibility, since it is very likely that most paths have low probability and therefore even a probabilistic estimation of the outcome becomes practically unfeasible. One might consider this as an elementary form of

1 The definition of the problem is usually attributed to Turing [50], but, as shown by an accurate historical analysis [51], it may be more correct to regard Church, Kleene and Davis as the main contributors to its formulation.

2 This limitation is tightly linked to the notion of computational complexity [52].

creativity, because the production may turn out to be novel and surprising to the user. Nevertheless, this is simply a stochastic recombination of the possible answers embedded in the internal model. Moreover, in these cases novelty is also likely attributable to the vast datasets used to train commercial LLMs. Indeed, an LLM trained on data limited to a specific topic would likely not surprise a user with expertise in that field.

In contrast to the previous cases, the third source of unpredictability we consider may in fact have a significant impact: it consists in the possibility that new, unforeseen abilities emerge in LLMs. A recent paper discusses such so-called emergent abilities [22], focusing on properties that do not appear in smaller models but arise in larger ones. Hence the rationale for the term "emergent": if an ability is absent in smaller models, it cannot be extrapolated to larger ones. A typical example of such an ability concerns integer arithmetic tasks. These properties are observed to appear as sharp transitions in a given metric. However, these results have been tempered by observing that they are mostly an artifact of the metrics chosen for observing the phenomenon [23]. The arising of unexpected abilities has also been discussed from the perspective of cognitive sciences [24] observing that LLMs often exhibit abilities that go beyond the task they have been originally trained. For example, they achieve excellent results in tasks that, if performed by humans, would require factual knowledge, the ability of performing semantic operations, recognize affordances, and even infer mental states of the characters involved in a text. In a few words: they would require understanding the meaning of a text. These results have been observed by applying cognitive and psychological tests to LLMs. While these tests may provide significant information on human abilities, nothing guarantees that they can do the same for LLMs. One reason is that LLMs are trained on huge corpora of texts and they are able to use the correlations they have found in these data to solve problems for which humans seemingly make use of "compressed concepts that reflect their real-world experiences" [25].

For the sake of completeness, we conclude our overview of principal sources of unpredictability in AI systems by considering a fourth factor: the "human in the loop". The dynamics resulting from the repeated interactions between a human user and an LLM may become rather intricate, given the complexity of the two agents involved. The social implications of the interactions between human users and AI systems are vast and profound, especially in an era in which robots are increasingly autonomous and can now exploit the potential of LLMs. However, this topic lies beyond the scope of this contribution, and we refer the interested reader to the specialized literature (see, e.g., [26–28]).

3 Discussion

The sources of unpredictability that we have examined in the previous section have different impact on AI systems predictability. Theoretical limitations and computational irreducibility mostly affect predicting the outcome of a program and do not directly influence the generative abilities of LLMs. Nevertheless, it is important to acknowledge that LLMs are implemented on structures computationally equivalent to UTMs, therefore they share the same limitations: the universe of their possibilities is bounded by the elementary rules and components on which they are built [29,30]. As a consequence, even if some stochasticity is injected, they cannot generate anything that is not obtainable by the combination of tokens they have extracted during training. Therefore, their ability to generate novel texts relies on their capacity to recombine words according to the linguistic model learned and the query of the user. The skills LLMs exhibit of manipulating and generating text have only to do with linguistic capability rather than reasoning and elaboration of concepts. This difference can be summarized in the statement "language ≠ thought" [31]. This does not prevent an AI-generated text to sound new, surprising and interesting to a user, but its originality is negligible because it is just an elaborated recombination of elementary blocks.

A question connected to the previous observations can be raised about the very meaning of sentences expressed in a language. From a biosemiotic standpoint, meaning in organisms arises from actions on and perceptions of the physical world: meaning is rooted in experiencing the world [32]. In the case of human language, the enactive approach [33] further emphasizes that language is a way of acting, inherently involving embodiment [34]. Therefore, any specific meaning or meaningful intuition we attribute to a text generated by an LLM, is ultimately a reflection of the meaning we ourselves project onto that text. Moreover, it is important to observe that the texts we humans write are a representation of what we experience in the world, which is characterized by correlations. These correlations are seemingly captured syntactically in our discourse and therefore reused in the artificial generation of text. Finally, we observe that LLMs are good at providing average responses [35], which are likely to reproduce the most common regularities and correlations expressed in a language.

The emergence of novel unexpected skills and capabilities in LLMs can certainly be a rich source of unpredictability, similar to discovering a new use for a tool. However, we must observe that the origin of this new use lies in human discovery, rather than in the intrinsic capabilities of AI systems. Pivotal for the discovery of new uses of tools are affordances, a concept first introduced in psychology by Gibson [36], and subsequently further elaborated in various fields, including biosemiotics [37], robotics [38], and philosophy [9]. Broadly speaking, an affordance can be defined as "a possible use of X by an agent to accomplish Y". For example, a river stone provides an affordance as a paperweight. Importantly, affordances are not intrinsic properties of the object, but they depend on agents' goals and repertoire of actions [10,32,39]. In other words, affordances can only be defined through relations, which involve subjective features introduced by the agent. Consequently, affordances are indefinite: (i) they cannot be exhaustively listed, (ii) nor can they be ordered, (iii) nor can they be algorithmically derived from one another [29,40–42].[3] This is the key property that defines the border between unpredictability and unprestatability: affordances are not simply unpredictable but unprestatable, because the very space in which they may arise cannot be predefined. The intuition is that an object is not associated to its uses, but is characterized by an indefinite universe of features that can be exploited in diverse ways, depending on the agent's goals and possible actions.

3 An interesting related perspective is provided by [53] who discuss the increase of complexity in open-ended evolution within the Gödel-Turing-Post recursion-theoretic framework.

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An AI system, such as a program that achieves automatic planning or an LLMs, can find uses of an object in a finite and numerable set or by using an algorithmic procedure for deducing possible uses. In this discovery achieved by AI we can recognize some degree of unpredictability (mostly caused by computational limits or stochasticity), but certainly not the unprestatability that characterizes the livings [6,43].

Affordances are also at the core of artistic works, because they are central to the artistic choices [42,44]. Like the function of an object is not selected among a list associated with it, so artistic choices follow a trajectory whose state space is progressively constructed and depends upon the contingent situation and the goals and intuition of the artists. The pieces of art an AI system can produce are sampled from a bounded space of possibilities. Therefore, the creativity they express is combinational or exploratory, but not transformational [12]. We observe that cases of transformational art in human culture are, in fact, as rare as major evolutionary transitions. Yet they would not be possible in systems whose dynamics are bounded.

Finally, we address a point of paramount importance: the possible contribution of LLMs to science. The use of LLMs to extract knowledge from text and other types of data is tied to the broader question of finding regularities in large datasets. Since the early successes of big data technologies, the question as to whether theories are still necessary has arisen [45]. Today, the ability of LLMs to convert the analysis of a large amount of data into natural language sentences and to identify correlations may seem to reinforce this perspective. The limits of knowledge extraction from big data has been extensively discussed [46,47], especially in the case of data extracted from complex systems dynamics, where factors such as spurious correlations, non-Gaussian statistics, sensitivity to data inaccuracies, and rare events play a crucial role [48,49]. Acknowledging that LLMs can be unpredictable—but in a bounded space—and therefore recognizing that they cannot generate explanations or theories beyond those boundaries, does not mean that we should abandon their use. Rather, it invites us to exploit their potential in combination to our intellectual investigations.

4 Conclusion

In this perspective paper, we have examined the main sources of unpredictability in AI systems—particularly LLMs—focusing on the forms of unpredictability that relate to their generative abilities and might lead us to attribute to them the capability of producing something novel and original. We have identified four sources of unpredictability: theoretical limitations and computational irreducibility, stochastic components, the emergence of new abilities and the interaction with humans. Each of these factors may cause some degree of unpredictability. For this reason LLMs can occasionally produce surprising outcomes. Nevertheless, this kind of uncertainty is fundamentally different from the one characterizing humans–and living organisms in general. In organisms, actions are determined by means of affordances, which are not merely unpredictable, but unprestatable.

LLMs can therefore provide an effective and useful tool for conducting controlled explorations and experiments, or as a source of (limited) alternatives. They should be considered as tools for speeding-up some activities, not a substitute to human intuition and inventiveness. In this regard, we remark that the risks of using LLMs in science come precisely from their tendency toward homogenization and uniformity, which might lead us to a science in which we produce more, but understand less [27].

Data availability statement

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

Author contributions

AR: Conceptualization, Investigation, Writing – original draft, Writing – review and editing. SS: Conceptualization, Investigation, Writing – review and editing. SK: Conceptualization, Investigation, Writing – review and editing.

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Generative AI statement

The author(s) declared that generative AI was used in the creation of this manuscript. ChatGPT (Version 4) was used to find alternative expressions or synonyms, and to improve clarity and conciseness of some sentences.

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