Chapter 4

AI: Irrevocable Shift from Problem Solving-making to Problem Complexity Analysing

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Abstract

This chapter explores the paradigm shift in applied problem-solving driven by the democratisation of artificial intelligence (AI). The widespread use of AI enables a transition from manual task-solving to goal-setting and managing the complexity of phenomena, thereby reducing uncertainty. Central to this chapter is evaluating the alignment between the complexity of a task and the complexity of the AI method used to address it. Real-world examples, including the 2008 financial crisis, Zillow's price prediction model, and digital footprint credit scoring, demonstrate the practical relevance of the proposed methodology. These cases highlight the risks and challenges of using AI without systematic evaluation of complexity. This chapter emphasises the need for a structured approach to managing complexity, ensuring that AI applications align with societal, ethical, and legal norms while delivering practical value.

Keywords: Artificial intelligence; human–machine interaction; complexity; uncertainty; ethics

1. Introduction

AI is a technology that has received the widest application in completely different spheres of human life due to the implementation of colossal opportunities to increase labour productivity (McKinsey, 2024). Many large corporations have

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Shaping Collaborative Ecosystems for Tomorrow, 65–75

doi:10.1108/978-1-83662-494-320251005

set as their strategic goal the implementation of AI in most business processes, and corporations with the most advanced level of AI maturity are transforming their business, moving from the paradigm of 'AI is the automation of individual elements of a business process' to 'What should my business process look like in the era of AI' (Accenture, 2022). It can be said that AI methods have become so widely used largely due to the increase in the complexity of the tasks to be solved – they have confidently occupied the niche in which all previously invented methods for extracting information from data do not work so effectively (McKinsey, 2022).

However, like any new[1] technology, AI carries risks related to reliability, credibility, and responsibility for the result of its work from an ethical and legal point of view (McKinsey, 2019). Modern technologies distinguish the current era of human life from previous ones mainly by the much longer time that a person spends interacting with a machine. Again, it's worth noting the changing complexity of such interactions (Raikov, 2024; Raikov & Pirani, 2022; Snow et al., 2024): it's one thing to just use the internet to find information, and quite another to be driven by an AI-driven self-driving car at 88 miles per hour on the freeway. Unfortunately, even in deterministic machine systems, a person sometimes overlooks the complex effects of the interaction of their individual modules, which can lead to very tragic consequences (Shrivastava, 2020). It is obvious that the risk control methods developed by humanity to date may not be sophisticated and diverse enough (Ashby, 1956) to ensure the safe and reliable use of such a young (in terms of application) and promising technology as AI applications. This is a problem that people are just beginning to solve at the systemic level (Vorontsov, 2009).

It is important to note another effect brought by AI technology to our lives, especially widespread with the development of deep learning (Krizhevsky et al., 2012; Russel, 2017). People began to ask AI to solve problems formulated in natural language, for example, about proving theorems (Sutskever, 2020). Generative AI has significantly improved the efficiency of a number of tasks. For example, according to GitHub research (GitHub, 2022), developers who use Copilot spend 55% less time on their tasks than before. Another example is a study by Goldman Sachs (Briggs, 2023), according to which generative AI has the potential to automate 26% of work tasks in the arts, design, entertainment, media and sports sectors. Generally speaking, such capabilities have existed before, but they were available mainly to scientists engaged in the development of AI models for solving specific problems. Now everyone who has access to such models, including through chat (McKinsey, 2023), is starting to do this. This is a meta-system transition in the field of decision-making: with the advent of AI, a person moves from solving problems to entrusting the solution of a task to a machine with a trained AI model under the hood.

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[1] Here and below, the term «new» means that the technology has been used on a large scale only relatively recently (one could say, since 2020, when the GPT-3 model was introduced).

A necessary step from the authors' point of view for the effective use of AI and the assignment of a specific task to it is complexity management: a joint assessment of the complexity of the task and the specific AI method that is used to solve it.

2. Background

The main source of ideas on complexity management discussed in this chapter is Stafford Beer's book *The Brain of the Firm* (Beer, 1995). This book presents the concept of corporate governance as a self-organised system that balances centralised management with horizontal connections. A key idea is controlling complex systems through a hierarchical five-level structure, where diversity increases as signals move downward and simplifies when returning upward.

William Ashby's principle of necessary diversity (Ashby, 1956) supports this hierarchical approach, emphasising the importance of amplifiers and simplifiers in managing complexity. Complexity, as defined in this work, refers to Kolmogorov complexity (Kolmogorov, 1963), which represents the minimal amount of information required to characterise a phenomenon. This definition is adapted informally to address applied AI challenges.

In classical AI, approaches like the Vapnik-Chervonenkis dimension (Vapnik, 1971) and Valiant's computational learning theory (Valiant, 1984) provide ways to assess model capacity and limits. These methods estimate the variability of data a model can handle and help refine retraining processes (Vorontsov, 2008).

The rise of AI on an enterprise scale led to MLOps (Sculley et al., 2015), a set of practices ensuring stable operation of models in industrial environments, similar to DevOps (Huttermann, 2012). MLOps addresses challenges like data variability and the continuous updating and retraining of models, ensuring robustness and reliability in corporate settings (Kreuzberger et al., 2023).

With the replication of AI methods, parallels to the Solow paradox (Solow, 1987) emerge: costs of using advanced methods may outweigh their benefits, but the nature of tasks fundamentally shifts. Humanity appears to 'run faster on a treadmill' to address increasingly complex problems using AI (GitHub, 2022).

The financial crisis of 2008 highlighted risks arising from reliance on probabilistic models like value at risk. While these models were transparent and interpretable, their simplified assumptions underestimated rare, high-impact events. The cascading failures that followed illustrate the limitations of such models (BIS, 2010). Compared to today's opaque AI systems, these probabilistic models were relatively simpler, making the 2008 crisis a 'manageable black swan'. The lack of interpretability in AI systems heightens risks, emphasising the need for robust evaluation of task and model complexity.

While much attention has been given to the concept of complexity globally, it remains primarily tied to specific cases and lacks a generalised approach. This chapter advocates using complexity systematically to manage AI models effectively on large datasets (De Mauro et al., 2016).

3. Methodology

3.1. Development of Tools for Working with Complexity

This section presents the authors' original new view on the development of applied tools allowing people to solve problems related to data processing. The key element in this chronological sequence is the informally defined concept of the complexity of the tasks to be solved, which increases with the transition from tool to tool. To illustrate the presentation, we are showing this process in the form of an isometric diagram in three axes (see Fig. 4.1).

Let's take a closer look at the diagram presented in Fig. 4.1. It shows three axes that correspond to the most important areas of tool development: the creation of algorithms, the creation of computers, and the creation (digitisation) of data. In addition, the diagram conventionally shows the chronological order of the appearance of these tools in the hands of man from the point of view of history. In this context, the word 'conditionally' is deliberately used because the boundary of applicability of these tools is blurred, and there is no clear chronology, but from the point of view of the mass use of a particular tool, everything is exactly like this: algorithms - > computers - > digitised data. Let's consider each of these tools in turn.

3.1.1. Algorithms

In this work, this tool is understood as the entire complex of natural sciences and the underlying mathematical apparatus, which was developed by people to solve applied problems. Figuratively speaking, to solve a specific problem, you only need the ability to use this device, empirical knowledge of some aspects of the problem and a pencil and paper.

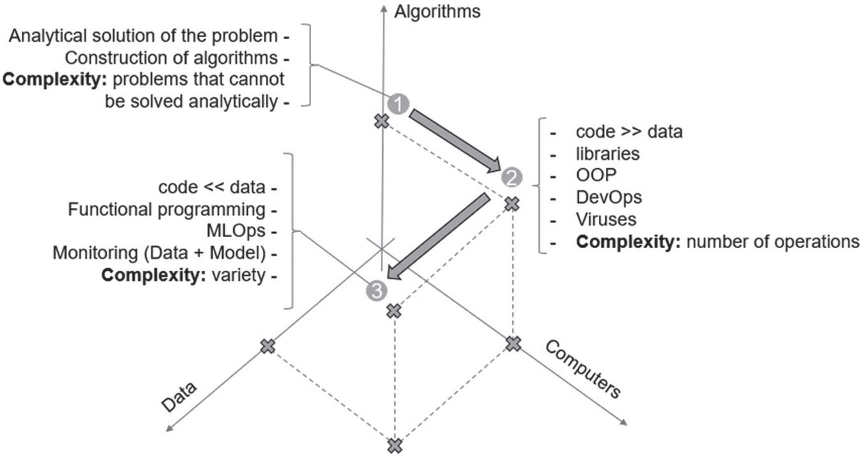

Fig. 4.1. Schematic Representation of Tools That Increase the Complexity of Tasks.

Despite the huge wealth of problems solved with the help of these tools, at some point problems began to appear, the solution of which only with the use of algorithms and mathematical apparatus turned out to be either impossible or incredibly difficult. Examples of such problems are: integrals that are computable only numerically, not analytically; optimisation problems that are also solved only numerically and require a large number of operations per unit of time; space shuttle control systems that require autonomous control depending on feedback (Wiener, 1948); process modelling problems that fundamentally require the implementation of a large number of complex computable scenarios without conducting real experiments (Moiseev, 1979); and others.

Overcoming this 'barrier of complexity' began to occur around the middle of the 20th century with the creation of the Turing machine (Turing, 1936) and, after it, modern computers (Wiener, 1948).

3.1.2. Computers

The era of computers – complexes capable of producing large[2] numbers of calculations per unit of time – gave mankind the opportunity to overcome the barrier of complexity, which turned out to be beyond the control of the classical mathematical apparatus. With the advent of computers, many problems began to be solved numerically; it became possible to implement servo mechanisms (Wiener, 1948) in practice, taking into account feedback from the environment in which they operate, and there were ample opportunities for modelling complex systems.

Computers did not replace the mathematical apparatus but strengthened it. The effective use of both algorithms and computers leads to the emergence of the direction of computer science (Patton, 2009). Programming languages and libraries of ready-made modules appear, which programmers can use all over the world, saving time on their re-creation.

It is important to note that with the advent of computers, the theoretical approach to cognition of the world is significantly enriched by the empirical one (Popper, 1980). If earlier the testing of a hypothesis required knowledge of a powerful mathematical and theoretical apparatus, now testing a hypothesis often consists of writing a few lines of code in Python without the need to have all the knowledge that was previously required. It becomes possible to create models of complex systems (economic, biological, physical, queuing systems) and analyse how the logic of their operation changes depending on the parameters without conducting experiments in reality.

However, as in the case of algorithms, computers as a tool also run into a barrier of complexity – labour intensity. Moreover, labour intensity manifests itself in two aspects at once: the exponential computational complexity of the task and the labour intensity of writing code. In this chapter, we will be more interested in the last aspect related to the automation of code writing with the spread of generative AI methods.

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[2] Significantly more in comparison with human capabilities.

3.1.3. Data

With the advent of petabytes of digitised data, as well as datasets in the public domain and the spread of libraries, including in the Python language, the intensity of the use (McKinsey, 2024) of machine learning methods for solving problems has greatly increased.

It is necessary to note the most interesting effect: the amount of code has become much less than the amount of data. This means that if before 'big data' (De Mauro et al., 2016) each column of the dataset required programmers to write a separate code for processing, now the data scientist simply writes model.fit(x, y) and gets a model that can predict the target variable with good accuracy. The complexity of data processing is 'absorbed' by the complexity of the model used to process it. In this sense, there is a significant change in the principles of working with data – a person determines only the principles of their processing, choosing the architecture of the model. Thus, the machine now automatically processes the 'big data' and generates the 'code' in the form of parameters of the trained model. This model is an object of a completely different complexity than a programme written by a person, which can be verified line by line by another person. The result of the work of a machine that performs billions of operations per unit of time; a person is physically unable to verify in a reasonable time. Therefore, there are practices that allow you to somehow ensure the reliability of the industrial use of AI models on a regular basis in corporations – MLOps (Sculley et al., 2015).

The complexity of the problems to be solved in the context of advanced tools of algorithms, computers, and data digitisation is defined as the Cartesian product of the complexity processed by each of these tools. At this stage, a person loses the ability to control the operation of automated systems within the framework of using only classic software development tools. It is necessary to create tools that allow you to control the quality of separately solved tasks using AI methods, and there is a need for a comprehensive assessment of the complexity of data and models, that is, tools are needed to manage the complexity of the phenomenon.

3.2. Managing the Complexity of a Phenomenon

On the one hand, the use of AI methods on 'big data' makes it possible to extract a significant amount of information from them. On the other hand, the difficulty of processing such volumes of information lies in the fact that a person can no longer verify the quality of the extracted information with the previous tools. In the case of algorithms, it was a logical chain checked by another person. In the case of software development, it was a programme that was tested by another person. When using AI methods, the question arises: how to check the completeness and quality of their work?

The weakness of AI models is their nature – they are 'only' very advanced ways of finding correlations that do not have a reality check mechanism (Pearl, 2019). All that the AI model has is a penalty function for an incorrectly found correlation. At the same time, the AI model does not understand the essence of the phenomena it processes, so in general, its answers can lead to great risks if used without any verification.

One illustrative case is Zillow's use of models (The New *York* Times, 2021) for real estate price prediction through its Zestimate tool. Initially, the model achieved remarkable results by handling vast data sets, but it operated with a significant multiplier effect. Machine learning was applied to an enormous number of operations without sufficient human oversight, which made it difficult to notice errors in real-time. The model began to fail when it encountered market conditions not anticipated during its design phase. These failures multiplied rapidly across thousands of transactions, leading to losses of nearly half a billion dollars and the termination of its iBuying business. Additionally, Zillow laid off approximately a quarter of its employees. A task complexity assessment map could have flagged potential risks by highlighting the mismatch between the variability in market conditions and the limited adaptability of the model. Such an assessment might have prompted Zillow to design safeguards, such as integrating human oversight or limiting the multiplier effect of automated decisions.

Another pertinent case is the use of digital footprints (Berg et al., 2019) for creditworthiness assessments. Such systems enhance prediction accuracy by analysing online behaviour and device usage, but they are vulnerable to manipulation. Borrowers aware of the evaluation criteria can alter their digital footprints to appear more creditworthy, posing significant risks to financial stability. A task complexity assessment map could have identified the high verification complexity associated with this approach, urging designers to implement mechanisms for detecting adversarial manipulation or limiting reliance on easily alterable indicators.

If task complexity and algorithm complexity had been evaluated systematically, risks like those in the Zillow and digital footprint cases might have been mitigated during the initial planning phases. A robust assessment framework could have provided early warning signs and allowed for better alignment between the chosen AI methods and the problem's intricacies.

One of the approaches to managing the complexity of AI models could be the principle of estimating the complexity of tasks based on two components: the complexity of solving a problem and the complexity of verifying this solution. As it is known in the theory of NP-completeness (Korte, 2008), the solution to some problems is computationally complex (performed in exponential time), but verification of the solution is much simpler (performed in polynomial time). An example of a 'task complexity assessment map' is given in Table 4.1.

Each row in Table 4.1 corresponds to different levels of difficulty of the task: 'Without a computer' are those tasks that a person can solve without using a computer at all. 'Needs to be programmed' are those tasks in which a computer is necessary, but a person only needs to write a programme code. 'Artificial intelligence' are those tasks that require the use of AI methods. 'High complexity' refers to tasks that are not solved by existing approaches.

The same categories are given for each column, but their meaning lies in the complexity of verifying the solution. It is important to note that this table should

Table 4.1. Task Complexity Assessment Map.

Solution/Verification	**Without a Computer**	**Needs to Be Programmed**	**Artificial Intelligence**	**High Complexity**
Without a computer	–	–	–	–
Needs to be programmed	–	–	–	–
Artificial intelligence	–	–	–	–
High complexity	–	–	–	–

be perceived individually, taking into account the quality requirements for each task. For example, lots of tasks can be solved by a person without a computer; it would just take him too much time to do this. Therefore, from the point of view of assessing the complexity of the problem, it is always necessary to take into account the criteria for the quality of the solution. An approximate solution with an accuracy slightly different from the ideal solution can be found in practice much faster and is often quite sufficient.

Interestingly, in general, the complexity of verification tools may exceed the complexity of the solution. For example, the problem of extracting named entities from text can be solved using regular expressions, and checking for the completeness of the solution can only be performed using the large language model (LLM) as a generator of a large number of diverse inputs.

Summarising this observation, it can be noted that the basic signal reflecting the underestimation of the complexity of the problem is that the complexity of verification is equal to or greater than the complexity of the solution. Of course, it is necessary to take into account both the requirements for the quality of the decision and the requirements for the acceptable level of risk when making a decision. Nevertheless, such a tool can be used as the first step in assessing and comparing the complexity of the problem and the method used to solve it.

4. Conclusion

This chapter presents a novel methodology for understanding the growth of task complexity alongside the tools and algorithms used to address it. The methodology highlights the progressive increase in complexity from algorithms to modern AI systems and emphasises the need for systematic evaluation of complexity in both tasks and methods. Central to this chapter is the proposed concept for assessing the alignment between task complexity and algorithmic complexity, providing a framework to mitigate risks associated with AI deployments.

The importance and necessity of these contributions are illustrated through practical cases. The Zillow example demonstrates the risks of scaling machine learning without human oversight, leading to significant financial losses. The digital footprint case highlights the vulnerabilities in AI systems when exposed to adversarial manipulation. These examples underscore how inadequate complexity assessment can result in operational and societal risks.

This framework offers a pathway for organisations to make informed decisions about AI applications, ensuring that models align with the intricacies of real-world tasks. By integrating these approaches, AI systems can be developed to address challenges effectively, maintain reliability, and contribute positively to society.

Acknowledgements

The author expresses deep gratitude to Petr Ototsky for the invaluable insights gained during collaborative discussions on the complexity of tasks. The author is also profoundly inspired by the elegance of the ideas consistently shared by Petr throughout the development of this work.

Disclaimer

This chapter reflects the personal position of the authors. The content and results of this report should not be considered, including citing in any publications, as the official position of the Bank of Russia or an indication of the official policy or decisions of the regulator. Any errors in this material are solely the author's.

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