A method of distributed inference in an intelligently configured network based on category theory*

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Abstract
The article examines a method of distributed inference in an intelligently configured network of a complex system for autonomous navigation in GPS signal format and sensor monitoring of the environment, which category theory builds. The proposed approach provides formalization of knowledge processing and integration processes in a distributed environment of large language models, which allows the system to increase its adaptability and resilience to dynamic changes. The method relies on using categorical structures to describe relationships between content objects, as well as on applying morphisms to construct logical connections between knowledge elements. This ensures the possibility of automated coordination of hardware resources, effective management of information flows, and support for decision-making. The practical significance of the method lies in increasing the efficiency of the complex system of sensor monitoring and autonomous navigation in GPS signal format through the intellectualization of resource management algorithms. Intelligent control allows the formation of a flexible structure of sensors and pseudolites, which change their location and switch from a passive disabled state to an active enabled mode depending on the state of the external environment.

Keywords
Intelligently configured network, intellectualization, knowledge model, distributed inference, category theory.

1. Introduction

Prospective information and communication networks, as the foundation of a complex system for autonomous navigation and sensor monitoring of the environment, require a high level of intellectualization to ensure reliability, adaptability, and resilience to external influences. In current conditions of intensive development of navigation technologies, a need arises for high-precision, reliable, and protected positioning means. Traditional global navigation satellite systems (GNSS) have a number of limitations associated with the impact of interference, signal jamming, multipath propagation, and the absence of stable coverage in complex conditions, particularly in urban development, mountainous terrain, or inside buildings. In military, aviation, and critically important civil infrastructure, these problems can lead to significant risks. Pseudolite systems represent a promising solution for increasing the accuracy and stability of navigation processes. They allow the creation of local navigation fields that supplement or completely replace GNSS signals in case of their unavailability. This opens new possibilities for autonomous vehicles, unmanned aerial vehicles, robotic systems, as well as for monitoring and managing objects under conditions of limited or blocked satellite navigation.

The growing relevance of pseudolite technologies also stems from the need to develop intelligent navigation systems integrated with sensor networks for environmental monitoring, artificial intelligence, and Internet of Things (IoT) technologies. This ensures not only increased accuracy in determining coordinates but also the system's adaptability to changes in the external environment and resilience to the impact of external threats.

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Traditional approaches to processing GPS signal data and sensor information often rely on centralized algorithms, which have limited scalability and sensitivity to dynamic environmental changes. In this regard, the application of distributed inference methods becomes relevant, as they allow the integration of knowledge from heterogeneous sources and ensure flexible system reconfiguration under conditions of uncertainty. One of the promising directions for formalizing integration and knowledge processing processes involves using category theory, which provides a universal apparatus for describing structures and relationships between them. Building an intellectually-configured network of a complex autonomous navigation system on a categorical basis makes it possible to define a unified mathematical model for representing GPS data, sensor information, and inference results in a distributed environment. The proposed approach allows us to combine the potential of large language models with categorical modeling tools to ensure greater consistency, adaptability, and system resilience. Using distributed inference based on categorical logic helps reduce dependence on centralized computational nodes, increases the efficiency of multidimensional data processing, and ensures stable system functioning under conditions of incomplete or contradictory information. Thus, this article examines a method for building an intellectually-configured network of a complex autonomous navigation and sensor monitoring system that uses category theory as a foundation for distributed inference and knowledge formalization. This opens new possibilities for developing cognitive technologies in the field of navigation and monitoring solutions [1, 2]. Similar directions of security-oriented intellectualization are also considered in the context of information technology security platforms, where intelligent mechanisms are used to increase the adaptability and reliability of cybersecurity systems [3].

2. Problem Statement

The idea of creating an intellectually-configured network of a complex autonomous navigation system in the format of GPS signals and sensor monitoring of the environment involves combining existing control systems for corresponding resources with integrated artificial intelligence (AI) tools based on large language models (LLM) [4]. Such a system has a multi-level (hierarchical) structure, as it will include a central control system with LLM and local control systems with LLM connected to it according to hierarchy levels: autonomous navigation systems and sensor monitoring systems. The entire system can operate in isolation from Internet access. Individual local LLMs can exchange information with the central LLM and with other local LLMs. In such isolated and distributed environments, the ability to detect network attacks in reproducible experimental infrastructures becomes especially important for validating the resilience of intelligent communication systems [5]. Both the central LLM and local LLMs can undergo additional training based on information circulating in subsystems at corresponding levels and according to thematic focus. Since each local system undergoes separate training on material from its own domain, the knowledge bases of local LLMs will differ, and for cross-domain queries, we will need to implement distributed inference. At the architectural level, this also corresponds to zero-trust and microsegmentation principles, where network components are logically separated and access between segments is controlled according to security policies [6].

3. Analysis of Publications

In addition to inference and routing challenges, intelligent distributed systems must also address software and infrastructure-level security risks. In particular, uncontrolled storage of secrets in source code may compromise configuration files, API access, deployment pipelines, and other components that are critical for the secure operation of distributed intelligent networks [7].

The theoretical foundation for organizing effective distributed inference includes a set of methods that we can distribute according to the following directions:

1. Federated inference models — each subsystem operates autonomously, but a centralized component (shared manager) exists, which compares semantic embeddings of queries with vector knowledge bases of different LLMs and decides where to best search for an answer. Works [8, 9, 10] provide detailed analysis of approaches to organizing federated inference, present positive aspects of methods and their drawbacks. In particular, they show that this approach does not always achieve the desired convergence of inference algorithms. We should also note that federated inference focuses primarily on training models rather than on synthesizing knowledge. It does not formalize the logic of inference between individual nodes (only transfers model weights or gradients) and does not resolve the problem of knowledge compatibility between domains.

2. Meta-inference — a meta-model or router operates over thematic LLMs, which does not generate an answer but decides: where to direct the query, whether to combine answers from multiple models, whether to apply a clarification loop mechanism. Thus, work [11] proposes the Switch Transformer model, which simplifies the routing algorithm during inference and offers an intuitively understandable algorithm with reduced communication and computation costs. The authors of article [12] propose a different meta-analysis structure, which bases itself on two weighted estimates from different external models and their subsequent combination into an overall estimate using Bayesian methods. At the same time, meta-inference focuses on routing efficiency rather than on formal inference logic. In such models, avoiding semantic conflict between experts proves difficult — clear rules for combining knowledge from different modules do not exist. Limited transparency — tracking why a particular expert answered a query becomes difficult.

3. Bayesian trust models — each LLM has a probability of confidence in its answer. If confidence falls below a certain threshold, then the system activates an external appeal mechanism or combination. This approach allows avoiding "hallucinations" in narrow domains [13]. Article [14] defines a mathematical measure for quantitatively comparing the effectiveness of probabilistic computational trust systems in different environments. And publication [15] develops a trust assessment system using hierarchical Bayesian updating to increase safety awareness of such systems. At the same time, Bayesian models of trust, entropy, and significance operate locally, at the level of a single model or document. They do not describe the interaction of knowledge between models or their semantic mappings. They prove suitable mostly for assessing knowledge, but not for the logic of constructing new knowledge at the intersection of LLMs.

4. Agent-oriented approach. Each LLM represents an agent with its own competence. Agents' responses can coordinate according to the Blackboard Model principle: the system writes a query on the "board," agents read and react [16]. Also, publication [17] applies orchestrated agents based on decision tree search, where the workflow iteratively evolves during the sequential process of distributed inference. At the same time, agent models and the Blackboard approach orient themselves toward centralized coordination where the central "board" creates a vulnerability node and inefficiency with a large number of agents. Weak formal semantics — knowledge presents itself in imperative or heuristic form, which limits the possibilities of automatic verification or inference. Also, models cause difficulties with knowledge typing and scaling to complex domain hierarchies.

4. Research Goal and Objectives

Thus, for formalizing distributed inference in systems with multiple interacting LLMs, under conditions when: knowledge distributes itself between modules (domains: navigation and monitoring); composition of information from different sources occurs; consistency of concepts, structures, processes, and transformations becomes necessary, using a theoretical apparatus free from the above-described drawbacks appears to be an effective approach, specifically — category theory.

Article Goal — to develop a method of distributed inference in an intellectually-configured network of a complex autonomous navigation system in the format of GPS signals and sensor monitoring of the environment based on category theory.

5. Key Concepts of Category Theory

Category theory represents an abstract mathematical language that operates not with elements, but with objects and morphisms (mappings between objects), which allows: modeling knowledge as objects, and connections between them — as morphisms; providing a universal interface for interaction between different knowledge models (LLMs); formalizing inference logic as composition of morphisms [18].

The key concepts of category theory include [19]:

1. categories — abstract mathematical structures that describe a system of objects and connections (morphisms) between them. This provides a universal language for formal description of structures and relationships in any domain where one can discuss "objects" and "interconnections";
2. functors, as translators between knowledge domains. One LLM-domain (for example, the "navigation" knowledge category) can have a functor to another domain (for example, GPS) — this allows formal description of concept transformation;
3. knowledge co-integration through limits/colimits. When several domains provide partial answers, one can compose them into a "global answer" using colimits;
4. knowledge extension through Yoneda Lemma. This enables interpretation of objects through their connections with others, that is, building inference based on context, even when the model does not contain complete information;
5. Fibrations/Indexed Categories. These allow construction of multi-level knowledge models, where local categories (LLM) receive "indexing" by a global category (meta-model or upper level in the hierarchy).

Thus, category theory serves as a meta-framework that allows combining the advantages of previous approaches, eliminating their shortcomings, and building a transparent, modular, semantically consistent system of distributed knowledge inference in military LMS based on LLM.

6. Knowledge representation model in distributed LLM based on category theory

The basic LLM category is a category in which objects and arrows bear labels with natural language phrases that indicate their intended meaning. For knowledge representation in distributed LLM, we use basic categories that include types, aspects, and facts. A type is an abstract concept that one can represent as a block containing an indefinite singular noun phrase. Each of the four blocks shown in Fig. 1 is a type. An aspect of object x is a way of perceiving it, in which one can view or measure x. For example, one can view a pseudolite as a radio navigation point (RNP); therefore, "being an RNP" is an aspect of a pseudolite. A pseudolite has signal power (say, measured in W), so "having power (in W)" is an aspect of the pseudolite. In the category, aspect A receives representation by an arrow $A \longrightarrow B$, where B is the set of possible "answers" or measurement results. For example, when measuring pseudolite signal power, the set of possible results is the entire set of real number or, possibly, the set of real number from 0.001 to 0.5 W (Figure 1-2).

Facts. Path equivalences that exist in categories do not exist in graphs, and therefore make category theory more suitable for describing knowledge in distributed LLMs [20, 21]. The mechanism of diagram commutativity forms the basis of this. Two paths from A to C can be considered equivalent (Figure 3). We know that officers and sergeants are command for a soldier, therefore these two paths $A \longrightarrow C$ must be equivalent.

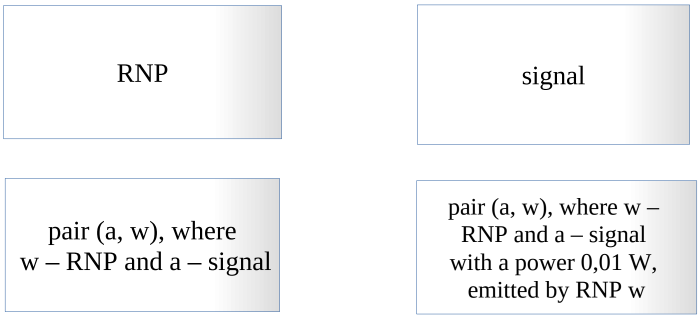

Figure 1: Types of objects.

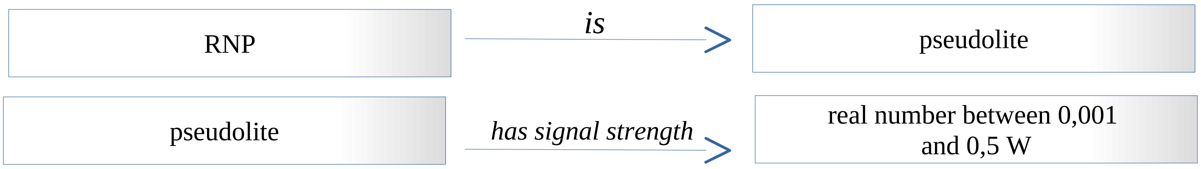

Figure 2: Examples of aspects.

When describing more complex facts, such as "a pseudolite weighs more than a sensor", one can write this as a diagram where both the upper and lower elements commute (Figure 4).

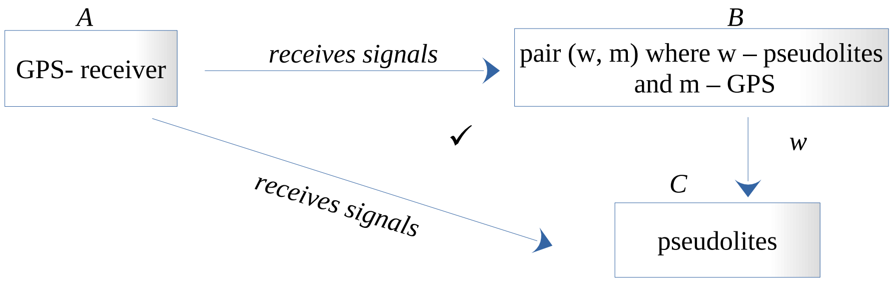

Figure 3: Example of path equivalence

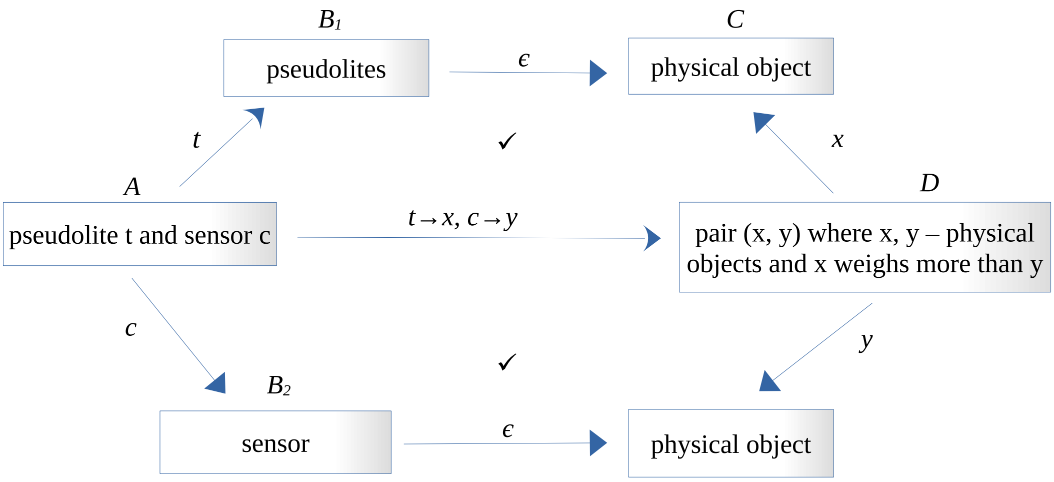

Figure 4: Example of diagram with element commutation

Thus, the improved knowledge representation model for distributed LLM, unlike the existing transformer model of multidimensional vector representations (embeddings), bases itself on category theory — an abstract mathematical language that operates with objects and morphisms (mappings between objects), which allows: modeling knowledge as objects and connections between them as morphisms to provide a universal interface for interaction between different knowledge models (LLMs) and formalization of inference logic as composition of morphisms.

7. Inference method in distributed LLM

Conceptual knowledge in LLM represents its worldview and is encoded in categories that contain concepts, relations, and observations important for this LLM. Fragments of such knowledge can be represented using a graph instance G, rather than a category instance C. A graph instance G — graph morphism $D: G \to |\mathrm{Set}|$, which maps each type x in G to a set D(x) of instances and maps each aspect $e: x \to y$ in G to an instance function $D(e): D(x) \to D(y)$.

For any G-specification E, the influence satisfies the following axioms [16]:

a) basic axiom – if E contains equation ε, then E implies ε;
b) reflexivity axiom – if E implies $(f =_G f): i \to j$, then for any path $f: i \to j$;
c) symmetry axiom – if E implies $(f_1 =_G f_2): i \to j$, then E also implies equality $(f_2 =_G f_1): i \to j$;
d) transitivity axiom – if E implies $(f_1 =_G f_2): i \to j$ and $(f_2 =_G f_3): i \to j$, then E also implies equality $(f_1 =_G f_3): i \to j$;
e) compositionality axiom – if E implies two equalities $(f_1 =_G f_2): i \to j$ and $(g_1 =_G g_2): j \to k$, then E also implies $(f_1; g_1 =_G f_2; g_2): i \to k$;
f) bi-closure axiom – if E implies $(g_1 =_G g_2): j \to k$, then E also implies $(f; g_1 =_G f; g_2): i \to k$ and $(g_1; h =_G g_2; h): j \to l$ for any left-composable path $f: i \to j$ and any right-composable path $h: k \to l$.

From the presented axioms, one can construct the following inference rules.

1. Equivalence rules:

$$(reflexivity)\frac{f: i \to j}{(f =_G f): i \to j}; \tag{1}$$

$$(symmetry)\frac{(f_1 =_G f_2): i \to j}{(f_2 =_G f_1): i \to j}; \tag{2}$$

$$(transitivity)\frac{(f_1 =_G f_2): i \to j, (f_2 =_G f_3): i \to j}{(f_1 =_G f_3): i \to j}; \tag{3}$$

2. Algebra rules:

$$(composition)\frac{(f_1 =_G f_2): i \to j, (g_1 =_G g_2): j \to k}{(f_1; g_1 =_G f_2; g_2): i \to k}; \tag{4}$$

$$(bi-closure)\frac{(g_1 =_G g_2): j \to k}{(f; g_1 =_G f; g_2): i \to k, (g_1; h =_G g_2; h): j \to l}; \tag{5}$$

3. Morphic flow rules:

$$(forward)\frac{(f_1 =_{G_1} f_1'): i_1 \to j_1}{(H^*(f_1) =_{G_2} H^*(f_1')): H(i_1) \to H(j_1)}; \tag{6}$$

$$(backward)\frac{(H^*(f_1) =_{G_2} H^*(f_1')): H(i_1) \to H(j_1)}{(f_1 =_{(G_1)} f_1'): i_1 \to j_1} \tag{7}$$

4. System flow rules:

$$(forward)\frac{(f =_{G_n} f^{'}):i \to j}{(l_n^*(f)=_{\hat{G}} l_n^*(f^{'})):l_n(i) \to l_n(j)}; \tag{8}$$

$$(backward)\frac{(l_n^*(f)=_{\hat{G}} l_n^*(f^{'})):l_n(i) \to l_n(j)}{(f =_{G_n} f^{'}):i \to j} \tag{9}$$

Justification of correctness of inference rules based on category theory. To justify the correctness of the presented inference rules and the overall validity of the method, let us consider their application for forming elementary flow and category specifications.

Elementary flow. A graph morphism $H:G_1 \to G_2$ maps types and aspects of G1 onto types and aspects of G2. Graph morphisms − transformations between categories. A functor $F:C_1 \to C_2$ has a base graph morphism $|F|:|C_1| \to |C_2|$. For any graph morphism $H:G_1 \to G_2$, there exists a fact function $eqn(H):eqn(G_1) \to eqn(G_2)$, that maps G1-equations $f_1 =_{G_1} f_1^{'}:i_1 \to j_1$ onto G2-equations $H^*(f_1) =_{G_2} H(f^{'})_1 : H(i_1) \to H(j_1)$ and a key diagram functor $dgm(H):dgm(G_2) \to dgm(G_1)$ that maps a key diagram $D_2:G_2 \to |\mathrm{Set}|$ to a key diagram $H \circ D_2:G_2 \to |\mathrm{Set}|$.

The fact function is the fundamental unit of informational (formal) flow for categories, and the key diagram functor is the fundamental unit of semantic flow for categories. Formal flow is adjoint to semantic flow — truth is invariant with respect to flow: $dgm(H)(D_2)|=_{G_1} \varepsilon_1$ then and only then, when $D_2|=_{G_2} eqn(H)(\varepsilon_1)$ for any graph morphism $H:G_1 \to G_2$, source fact ε_1 and target diagram D2. We can move specifications along graph morphisms by extending the fact function (equations). For any graph morphism $H:G_1 \to G_2$ we must define a forward flow operator $dir(H)=\wp\, eqn(H):spec(G_1) \to spec(G_2)$ and a reverse flow operator $inv(H)=eqn(H)^{-1}((-)^{\bullet}):spec(G_2) \to spec(G_1)$. Forward and reverse flows are adjoint monotone functions $\langle dir(H) \mapsto inv(H)\rangle : fbr(G_1) \to fbr(G_2)$ with respect to context order: $dir(H)(E_1) \geq_{G_2} E_2$ then and only then, when $E_1 \geq_{G_1} inv(H)(E_2)$. For any graph morphism $H:G_1 \to G_2$, any G1-specification E1 and any G2-specification E2, entailment satisfies the following axioms:

a) forward flow — if E1 entails equality $(f =_{G_1} f^{'}):i \to j$, then $dir(H)(E_1)$ entails $H^*(f_1) =_{G_2} H^*(f_1^{'}):H(i_1) \to H(j_1)$;

b) reverse flow — if E2 entails $H^*(f) =_{G_2} H^*(f^{'}):H(i) \to H(j)$, then $inv(H)(E_2)$ entails equality $(f =_{G_1} f^{'}):i \to j$.

c) The presented axioms are included in the inference rules (1) — (9). A graph morphism $H:G_1 \to G_2$ defines a consequence operator $(-)^{\langle\,\rangle H} = dir(H) \circ inv(H)$ on the context preorder $fbr(G_1)$, where $E_1 \geq_{G_1} E_1^{\bullet} \geq_{G_1} E_1^{\langle\,\rangle H}$.

Specifications. A specification $S=\langle G,E\rangle$ — indexed concept consisting of a graph G and a G-specification $E \in spec(G)$. Sometimes it is convenient to use the symbol "S" instead of "E"; for example, to say that "$S \in spec(G)$". We can derive and present a category C as a specification $spec(C)=\langle G,E\rangle$ consisting of a graph $G=|C|$ containing types and aspects of C, and a collection E of all facts that hold in C. In the other direction, any specification S induces a (cited) category $cat(S)$Earlier, we described the category (Fig. 3) as a specification. A specification morphism

$H=\langle G_1, E_1\rangle \to \langle G_2, E_2\rangle$ – graph morphism $H=G_1 \to G_2$ that preserves embodiment: $E_1 \mapsto_{G_1} \varepsilon_1$ means $E_2 \mapsto_{G_2} eqn(H)(\varepsilon_1)$ for any $\varepsilon_1 \in eqn(G_1)$; or equivalently, that satisfies the adjointness condition $dir(H)(E_1) \geq_{G_2} E_2$, then and only then, when $E_1 \geq_{G_1} inv(H)(E_2)$. Being a graph morphism, it maps types to types and aspects to aspects. Moreover, it also maps facts in E1 to facts in E2; that is, it preserves all declared structure.

We can derive and present a functor $F=C_1 \to C_2$ as a specification morphism $F=spec(C_1) \to spec(C_2)$. Thus, the functor representation form does exactly what the functor does. The context category of specifications Spec has specifications as objects, and specification morphisms as morphisms. Thus, we define it in terms of information flow. There exists a base graph functor $gph:\mathrm{Spec} \to \mathrm{Gph}$ from specifications to graphs $\langle G, E\rangle \mapsto G$. A subcategory over any fixed graph G is the context fbr(G); due to the opposite orientation, one should understand that "the category of specifications is directed downward in the lattice of concepts".

Thus, the developed inference method in distributed LLM based on category theory represents communication between categories as an interaction of corresponding specifications within the framework of introduced truth axioms based on established inference rules (equivalence, algebra, morphic and systemic flows). This approach enables the implementation of direct and reverse information flow between contexts of individual LLMs, ensures the integration of information from individual LLMs and provides the possibility of transferring it back to individual LLMs in the form of a set of local facts from remote categories.

8. Experimental research

We evaluated the developed inference method based on category theory by assessing the quality of the AI-generated structure (topology) of a complex navigation and monitoring system in distributed LLM before and after fine-tuning it on a base network of relevant data. For this purpose, we selected 15 experts from among specialists in the field of radio navigation and sensor networks, who formed a system of 20 criteria for evaluating the effectiveness of the topology of a complex navigation and monitoring system. We built the evaluation system by integrating the Delphi method with T. Saaty's Analytic Hierarchy Process (AHP). Using Delphi ensured the convergence of the expert group's opinions, while applying AHP facilitated the resolution of complex decision-making problems using a hierarchical structure of evaluations. Subsequently, by comparing quality assessments, we drew a conclusion regarding the effectiveness of the proposed distributed inference method.

We performed model fine-tuning on a corresponding dataset of 55 subject-relevant data points. Using the AHP method, we determined the system of indicators and quality weights for the indicators of the AI-generated topology of the complex navigation and monitoring system (Fig. 5).

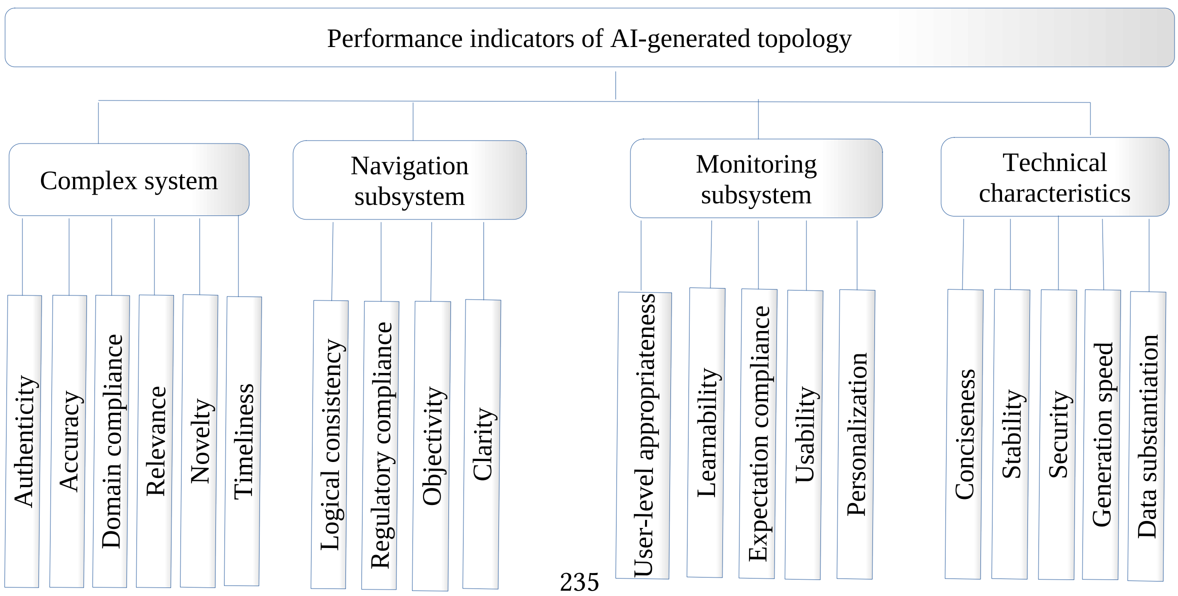

Figure 5: Hierarchical model of performance indicators for AI-generated topology

Experiment stages: 1). Preparatory stage. Formation of expert group. Deployment of simulation model of complex navigation and monitoring system; installation of LLM. Selection of model example for experiment. Formation of set of criteria and indicators for evaluating system topology efficiency. Formation of test sets of questions for LLM. 2). Testing the efficiency of solutions generated in LLM. Expert work — formation of efficiency matrix. Determination of weight of criteria and indicators based on efficiency matrix. 3). Selection of data for fine-tuning. Fine-tuning of LLM. 4). Testing the efficiency of solutions in fine-tuned LLM. Expert work — formation of efficiency matrix. 5). Comparison of results.

9. Analysis of experiment results

In Figure 6 presents a comparison of assessments provided by experts across 20 indicators before and after fine-tuning the LLM.

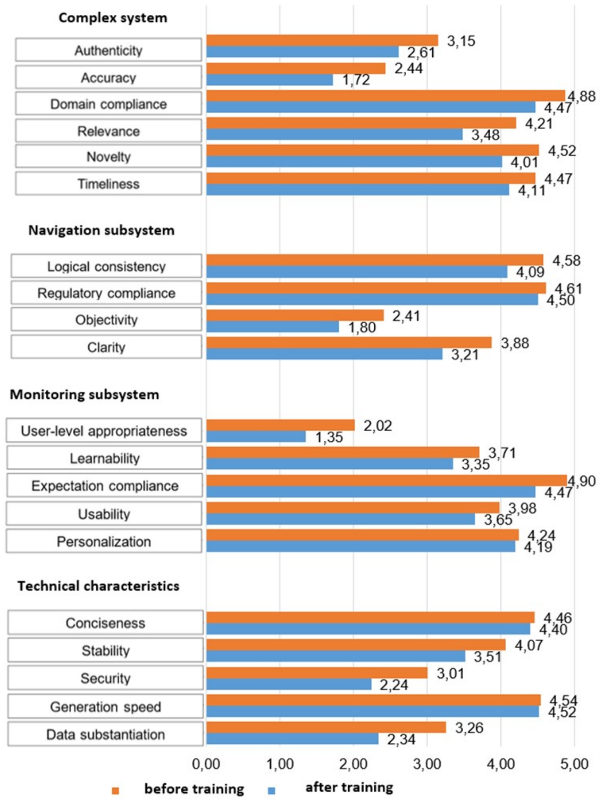

Figure 6. Comparison of quality assessments of AI-generated topology before and after LLM fine-tuning

The involvement of 15 experts ensured sufficient variability of judgments, which allowed us to reduce subjectivity of assessment. The use of 20 indicators covering both substantive and formal aspects of the complex system enabled us to conduct a multidimensional analysis of changes.

Comparing the results of quality assessment of AI-generated topology before and after LLM fine-tuning, we can see that the overall quality of the complex system as a whole improved. Thus, the most significant improvements occurred in the indicators "User-level appropriateness" (+49.3%) and "Accuracy" (+41.9%). Slightly smaller improvements in content quality occurred in the indicators "Data substantiation" (+39.3%), "Security" (+34.4%) and "Objectivity" (+33.9%). At the same time, the indicators "Generation speed" (+0.4%), "Personalization" (+1.1%), "Conciseness"

(+1.4%) remained almost unchanged. The overall (average) increase in efficiency of AI-generated complex navigation and monitoring system based on the results of the conducted experiment amounts to 13.7%.

10. Conclusions

1. The study of known distributed inference methods shows that they focus either on optimizing training and routing processes, or they limit themselves to local knowledge assessment without formal and scalable logic for knowledge integration between nodes. They do not solve the problems of semantic compatibility, typing and controllability of inferred knowledge, and centralized architectures create vulnerability nodes and scale poorly. This substantiates the need to turn to a more abstract and formalized approach, which is "Category Theory", which allows us to describe knowledge and its transformations in the form of strictly defined morphisms and objects, supporting transparency, consistency and the possibility of automatic verification in distributed LLM systems.
2. The proposed knowledge representation model for distributed LLM, unlike the existing transformer model of multidimensional vector representations (embeddings), bases itself on category theory, which allows us to: model knowledge as objects and relationships between them as morphisms to provide a universal interface for interaction between different knowledge models (LLM) and formalize inference logic as composition of morphisms.
3. The method of inference in distributed LLM that we developed based on category theory represents communication between categories as an interaction of corresponding specifications within the framework of introduced truth axioms based on established inference rules (equivalence, algebra, morphic and systemic flows). This allows us to implement direct and reverse information flow between contexts of individual LLMs, ensure the integration of information from individual LLMs and the possibility of transferring it back to individual LLMs in the form of a set of local facts from remote categories.
4. The proposed solutions create a foundation for building a scalable, flexible and fault-tolerant intellectually-configured network of complex autonomous navigation system in the format of GPS signals and sensor monitoring of the environment, capable of functioning effectively under conditions of isolation from global networks and limited computational resources. This approach forms the basis for further integration of promising artificial intelligence technologies into various information and communication networks.
5. Promising directions for further research in this field may include a wide range of issues in developing methods of distributed inference in networks with isolated local LLMs, improving algorithms for dynamic routing taking into account constant changes in the situation and level of communication channel availability, as well as implementing hybrid knowledge representation models capable of integrating semantic, situational and context-dependent data taking into account the specifics of particular tasks.

Declaration on Generative AI

The author(s) have not employed any Generative AI tools.

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