Automatic generation of new knowledge based on a Constructionist approach to AGI development

Abstract

In article [1], an approach to developing human-like AI was proposed based on the principle of structural similarity between human intelligence and a five-level model of the human psyche: reflexes, instincts, emotions, thinking, and consciousness. This article specifies the approach to the algorithmic implementation of the thinking function of human intelligence as a mechanism for perceiving information, understanding its semantic content, analyzing accumulated knowledge, and generating hypotheses of new knowledge.

Keywords

Strong Artificial Intelligence, Strong AI, Artificial General Intelligence, AGI, cognitive function of the brain, Knowledge Graph, constructionist approach to AI modeling.

Literature Review

In the scientific literature dedicated to strong artificial intelligence, there is a wide variety of definitions regarding what should be considered intelligence in general, and how weak (narrow, specialized) AI differs from strong (multimodal, broad, universal) AI

Marr's levels of analysis is a conceptual model that interprets artificial intelligence as a three-level system consisting of computational (goal), algorithmic (process), and hardware (implementation) layers [2].

The classical Cattell-Horn-Carroll (CHC) theory [3], a now-classic scientific model of the structure of intelligence and cognitive abilities, represents intelligence as a three-level structure consisting of the General Intelligence level (g-factor), the broad abilities level (about 16 factors), and the narrow abilities level (over 80 specific skills), divided into two types: fluid and crystallized.

Neuro-symbolic Approaches

Dan Hendrycks, in a 2025 article [4], proposes the definition: "AGI is AI that can match or exceed the cognitive versatility and skill of a well-educated adult."

In Tim Genewein's review [5], the term AGI is used to denote a system achieving at least median human performance across a very broad spectrum of cognitive tasks.

A highly relevant and useful quote from Geoffrey Hinton is: "I have always been convinced that the only way to get artificial intelligence to work is to do the computation in a way similar to the human brain.…"

Various approaches to defining what should be considered artificial intelligence and strong AI, and how corresponding automated systems can be implemented, are also discussed in articles [6]–[20].

Human Intelligence and Predictive Properties of the Psyche

If we consider the human psyche from the perspective of biological expediency, we can see that the most important function of a reactive system (which the psyche essentially is) is to generate a forecast of the consequences of events happening to and around a person, and to form a reaction to these events that minimizes potential harm and/or maximizes possible benefits. The higher the complexity of the reaction, the wider the horizon of foresight! Compared to the levels of reflexes, instincts, and emotions, predictions at the level of intelligence are the most long-term and statistically the most reliable.

Following Geoffrey Hinton, it is natural to assume that the development of Strong AI should follow the principle of "similarity to the human brain." This article attempts to outline a path that could lead to the development of a system prototype capable not only of understanding the semantic content of what is said/written and remembering it, and correctly assessing events in the immediate environment, but also of simulating the human thinking process when a person invents something new, formulates hypotheses and ideas, and generates new knowledge.

It is proposed to rely on the assumption that when inventing something new, a person does not do it out of nowhere, but uses their existing stock of knowledge, among which they search for those that might be useful for developing new models, designs, or ideas.

The goal set in this work is to develop a formalized process for generating new knowledge, devices, mechanisms, models, concepts, theories, etc., based on previously known knowledge and a given task. The main condition is that this process must be algorithmizable and allow the use of AI tools to obtain the result.

If one carefully and in detail traces how a person tries to invent something new, for example, the design of a new device, one can notice that they do not build this new device out of nowhere, "from scratch." The desired design usually has defined properties for which the development process is undertaken. Usually, the inventor recalls in memory some similar designs or models that are somewhat analogous to the required one. They try to form a suitable new model with the required properties based on one of the remembered designs. Taking an analogous design as a basis, the inventor tries to refine, modify, and adapt it to the given task. When it is impossible to select one suitable initial analogous model, there remains the possibility of selecting two or more models with the properties of interest, and based on them, by somehow combining them, to assemble a new model "in parts," so that the result is sufficiently close to what is required in the task.

The question of greatest interest was: is it possible to formalize the process of developing new designs and models (knowledge) in such a way that it can be automated, if not for absolutely all tasks, then for a sufficiently broad set of task classes, and at the same time develop a system capable of selecting a suitable set of initial models from the entire body of known knowledge for a given task, and based on them, generate a new model with the expected properties and capabilities.

Tracing the process of inventing new device designs, and more generally, acquiring new knowledge, is very convenient using the example of the history of airplane development at the dawn of the era of aeronautics and aviation.

According to legend, Wilbur Wright, sitting in a coastal cafe, saw a stuffed large seagull with outstretched wings being lifted into the air by the wind blowing from the sea. From this observation, he concluded that due to the special shape of the seagull's wing, the oncoming airflow created a lift force that lifted the seagull off the ground. This, in turn, led to the conclusion that to achieve flight in the air, it is not necessary to construct a "flapping-wing" device—an ornithopter—but instead, one needs to select an airfoil profile for the flying device close to that of a seagull's wing and ensure an oncoming airflow of sufficient intensity, i.e., accelerate the device to the required speed.

On the other hand, observing the flight of a kite launched by children, some inventor might have had the thought that to lift an aircraft into the air, it needs wings like a kite, only larger, and a power unit developing enough thrust to accelerate this device to a speed at which the oncoming airflow creates the required lift force. Such an "accelerating device" could be an internal combustion engine with a propeller, similar to the propellers of marine motors, but shaped to push air rather than water. That is, having a kite and an internal combustion engine with an air propeller in front of their eyes, the inventor would only need to take one step—combining these models—to conceive the idea of an airplane design in their mind.

Based on this example, the process of inventing a new device or creating new knowledge looks as follows:

1. The author formulates a task for themselves in the form of a set of requirements for a new device or model of something. In the case of the airplane, it would have sounded something like this: develop a technical device capable of lifting off the ground on its own, raising a person to a sufficient height, and moving a sufficient distance in a direction determined by that very person.
2. The inventor, having a sufficiently wide set of knowledge in the form of facts, structures, and dynamic models in their memory, seeks a solution to the given task by acting in a certain sequence:

   2.1. Searches among what is already known to them for analogs, something similar, some sample that could be used in some form to solve the new task;

   2.2. Having found something potentially useful, the author tries to change in the chosen sample what will allow obtaining an aggregate with the required properties as a result;

   2.3. If, as a result of the search in step 2.2, a candidate of satisfactory quality appears, work with it continues until the desired result is obtained;

   2.4. If, as a result of the search in step 2.2, it turns out that the required result cannot be achieved with the chosen candidate, this sample is set aside, and the author returns to step 2.1;

   2.5. When the enumeration of candidates available in memory ends, and the result is not achieved, it is natural for the author to move on to enumerating combinations of models, each of which has at least some of the necessary properties, and collectively, all models in the chosen combination provide the entire set of required characteristics.
3. The idea, model, or prototype formed in step 2 is tested in practice, and if it passes the test, it becomes new knowledge; if it fails, another attempt is made to work through step 2.

> Not every inventor, and not every time they set a goal to create something new, can achieve success, but the probability that a specialist with a broad outlook and a trained mind will find at least one acceptable solution through the described enumeration is usually not that small.

The narrowest point in this chain of reasoning is how, out of the entire body of knowledge, designs, and models in a person's memory, they choose those very analogs. Are the signs of "analogy" of interest to the inventor contained within the candidate model (or aggregate of models) in the form of some parameters? What is the process of selecting candidates? What stages of review and evaluation does each candidate model (aggregate of models) go through? And, most importantly for us in the context of our task, can this process be represented as an algorithm that we could implement in the form of software code using modern AI tools?

To answer these questions, it makes sense to trace the process of forming inventions in more detail. And again, it is convenient to do this using the example of the development of the first airplanes.

Inventors striving to develop an aircraft searched among what was already known to them for something suitable for use in the given task—some initial material to assemble something similar to the future device from it. They searched among known objects and devices for something possessing, if not all the required properties, then at least some part of them. It is clear that they a priori discarded things far from the topic of the task. Obviously, when pondering a possible airplane design, it did not occur to them to mentally consider the suitability of, say, a horse-drawn plow or a loom for the role of a future aircraft. Most likely, they first mentally went through everything that has the property of staying in the air without solid support—birds, bees, autumn leaves in the wind, hot air balloons, kites, etc. When thinking about creating thrust to generate lift, they certainly excluded household furniture or board games from consideration. Most likely, they thought of horse-drawn carriages capable of pulling a large kite with a person on a rope, or a steam locomotive doing the same, or even a steam engine suspended from a kite and rotating reduced mill wings.

Whatever combinations came to their minds, it was not difficult to discard obviously unpromising ones, and the circle of possible candidates could easily be narrowed down to a relatively small number. For example, gathering a flock of birds into something resembling a dog sled is possible, but clearly, it would be impossible to control them purposefully—such an option would obviously have to be discarded. Attaching a steam engine to a huge balloon is also possible, but it would most likely lack the power to push the entire structure against the wind—and this option also makes no sense to consider.

Based on this observation, we come to the conclusion that when inventing new devices, the process of selecting from known models the candidates for the role of "analogous" goes through several stages:

1. At the first stage, obviously unsuitable models are discarded without consideration (primary filtering), and potentially suitable ones are selected based on the explicit indication in their description of the presence of a key property, for example, such as the ability to rise and stay in the air without solid support, sufficient load capacity, or the ability to develop sufficient thrust to push the device in the chosen direction.
2. At the second stage, potentially suitable analog prototypes or their combinations are considered based on the presence of the entire set of required properties. For example, a combination of devices ensuring both the ability to stay in the air without solid support, and the ability to develop thrust by pushing off the air, and capable of lifting and carrying

a load comparable in weight to a human. Candidate combinations could be:

a balloon with a rubber motor,
a large kite with ground-based horse traction,
artificial wings, the shape of which repeats the shape of bird wings, with a steam engine and an air propeller,
artificial wings with an internal combustion engine and an air propeller.

3. At the third stage, experimental verification of each such combination for operability is necessary. We will call these combinations of initial models "prototypes."
4. The model combinations (prototypes) that passed the test in step 3 are compared for efficiency, and a choice is made in favor of one of them.

   If we return to the example of the invention of the airplane, it is appropriate to recall that the Wright brothers' experiments with gliders and a wind tunnel logically led to the creation in 1903 of an aircraft with a biplane scheme and an internal combustion engine, while Samuel Langley's experiments with glider models with a rubber motor or steam engine reached a dead end and ultimately proved unviable. Practice filtered out inefficient solutions and left the most promising one.

Based on the above, there are grounds to assume that the process of generating new knowledge in the general case most often goes through the stages described above, and this process can be algorithmized. It would be most interesting to propose an algorithm that would allow automating the process of generating a new device model (in the general case, new knowledge of an arbitrary nature) based on a combination of previously known models, devices, and concepts adapted to a new task and assembled in an appropriate manner. To achieve this goal, we need to:

1. Determine what the body of known knowledge should look like,
2. Understand how the search process in this body of models relevant to the given task should be structured,
3. Figure out how a new model will be formed from the selected candidates in accordance with the given task.
4. Formulate a fundamental scheme for testing the hypothesis for compliance with the given task.

The body of known knowledge must have a structure that will allow efficient processing of this data at all stages of solving the overall task. It is necessary to determine in what form the data constituting the body of known knowledge (the inventor's outlook) should be presented, among which facts, devices, models, concepts, etc., will be represented.

The question of abstract representation of a body of knowledge has already been well studied, and the corresponding structure has been generally developed and described in the scientific literature. This structure is called a Knowledge Graph (hereinafter KG).

The nodes of the KG are the knowledge itself in the form of facts, rules, designs, models, systems, theories, etc., and the edges of the KG are the connections between this knowledge.

For the convenience of algorithmic processing, we will represent the nodes of the KG as models implemented in the form of software objects having a structure traditional for programming, that is, their properties will be represented by fields, and functional capabilities by methods. The connections between knowledge, in our proposed version of the KG, are also conveniently represented in the form of models—software objects with their own fields and methods.

The structure of the knowledge model and the connection model in the KG must be formed in such a way that the search algorithm among already known knowledge for those applicable in a new task as "analogous" would be significantly less labor-intensive than a full enumeration of all graph nodes and their combinations, so that it becomes possible to form a training dataset from sets of KG nodes, which could be used to train a corresponding predictor. The elements of such a training dataset (TD) should be vectorized data of the type:

{[Problem Formulation], [Set of Known Knowledge and Connections between them]} →
(Relevance Score of this set of knowledge to the essence of this task)

Here, "Problem Formulation" (hereinafter PF) is understood as a correct, substantive text describing the properties and functionality of the desired device, design, knowledge, or model, and "Set of Known Knowledge and Connections between them" (hereinafter SKKC) is understood as a complex of models selected from the KG, collectively representing a candidate for the role of an "analog" or "prototype." When the SKKC accurately matches the PF, the Relevance Score (RS) is close to 1, and when the match is only partial, the RS << 1, and if there is no match, the RS is close to 0.

Obviously, [Problem Formulation] + [Set of Known Knowledge and Connections between them] in vectorized form is the input vector (embedding) of the predictor, and the Relevance Score of the set of knowledge to the essence of the given task (RS) is the label of this element.
By collecting a sufficiently large number of TD elements of the form {PF, SKKC → RS}, we will be able to train a predictor that can select, from the set of possible combinations of known knowledge and connections, those combinations that most accurately correspond to the given task.

Let us provide an example of a probable process of inventing an airplane, going through all the described stages.

The inventor must obviously possess an outlook that includes a sufficient number of initial knowledge models and connection models, searching among which could lead to a hypothesis of an airplane design. Suppose that among the models and connections of the inventor's individual knowledge graph remaining after primary filtering, the following are potentially suitable for further consideration:

1. Knowledge / Design Models:

1.1. Air

Properties

1.1.1. Gaseous substance.

1.1.2. Specific weight - 1.225 kgf/m³.

Functionality

1.1.3. Capable of exerting pressure on objects during movement.

1.2. Seagull

Properties

1.2.1. Weight — 5 kg

1.2.2. Wingspan — 1 meter

1.2.3. Lift force — arises as a result of flapping wing movements

1.2.4. Climbing height — several kilometers

1.2.5. Thrust — developed by muscle work

1.2.6. Key factor — heavier than air.

1.2.7. Power unit — muscles.

Functionality

1.2.8. Free flight.

1.2.9. Wing flapping.

1.3. Balloon

Properties

1.3.1. Weight — 50 kg

1.3.2. Diameter — 10 meters

1.3.3. Material — gas-impermeable shell + basket

1.3.4. Lift force — arises due to a large volume of gas lighter than air

1.3.5. Climbing height — determined by the average density of the device.

1.3.6. Key factor — lighter than air.

Functionality

1.3.7. Ability to hover in the atmosphere due to an average density lower than air.

1.3.8. Movement along with the wind.

1.4. Kite

Properties

1.4.1. Wingspan — 0.5 meters

1.4.2. Weight — 300 grams

1.4.3. Material — dense fabric

1.4.4. Lift force — arises from the oncoming airflow during movement [air + movement = lift force].

1.4.5. Thrust — external traction.

1.4.6. Climbing height — determined by the length of the rope and wind strength.

1.4.7. Key factor — heavier than air.

Functionality

1.4.8. Soaring in the atmosphere due to the lift force of the wings.

1.5. Steam engine

Properties

1.5.1. Weight — from 2.9 kg

1.5.2. Power — from 1 hp

1.5.3. Fuel - oil

Functionality

1.5.4. Rotates the propeller shaft

1.6. Rubber motor

Properties

1.6.1. Weight — about 1 kg

1.6.2. Power — about 0.5 hp

1.6.3. Source of torque — elasticity of rubber

Functionality

1.6.4. Rotates the propeller shaft

1.6.5. Started by manual winding

1.7. Horse-drawn carriage with a rope

Properties

1.7.1. Power — from 1 hp

1.7.2. Traction - muscular

Functionality

1.7.3. Thrust due to muscle power

1.8. Internal combustion engine

Properties

1.8.1. Weight - from 1.8 kg

1.8.2. Specific power — from 50 hp

1.8.3. Fuel - gasoline

Functionality

1.8.4. Rotates the propeller shaft

1.9. Pushing water propeller

Properties

1.9.1. Material - metal

1.9.2. Size (diameter) from 0.1 m

Functionality

1.9.3. Converts shaft rotation into a water jet

1.10. Pulling air propeller

Properties

1.10.1. Material - wood

1.10.2. Size (diameter) from 1 m

Functionality

1.10.3. Converts shaft rotation into an air jet

2. Connection Models.

2.1. Connection "air — balloon"

Models

2.1.1. first model - air

2.1.2. second model - balloon

Connection Type

2.1.3. Physical interaction

Rule

2.1.4. The specific weight of the gas-filled balloon is less than the specific weight of air; due to the difference in specific weights, a lift force arises.

2.2. Connection "air – wing"

Models

2.2.1. first model - air

2.2.2. second model - curved profile wing

Connection Type

2.2.3. Physical interaction

Rule

2.2.4. The oncoming airflow flows around the wing at different speeds under and over the wing, due to which a lift force arises.

2.3. Connection "rope - kite"

Models

2.3.1. first model - rope

2.3.2. second model - kite

Connection Type

2.3.3. Physical interaction

Rule

2.3.4. The rope transmits thrust to the kite from a running person or a moving horse-drawn carriage and accelerates the kite.

2.4. Connection "air - kite"

Models

2.4.1. first model - air

2.4.2. second model - kite

Connection Type

2.4.3. Physical interaction

Rule

2.4.4. The oncoming airflow presses on the wing of the kite, due to which a lift force arises.

2.5. Connection "propeller-air"

Models

2.5.1. first model - propeller

2.5.2. second model - air

Connection Type

2.5.3. Physical interaction

Rule

2.5.4. Rotation of the propeller causes air movement, forming a pushing jet.

2.6. Connection "engine — propeller"

Models

2.6.1. first model - engine

2.6.2. second model - propeller

Connection Type

2.6.3. Physical interaction

Rule

2.6.4. Rotation of the engine shaft sets the propeller in motion, which in turn pushes the air, forming an intense jet.

The Problem Formulation for airplane development (PFAD) should presumably sound like this: develop a device for the sufficiently fast and controlled movement of a person through the air over significant distances in an arbitrary direction within an acceptable time. When searching for a solution to the task, rely on the known (listed above) device models, by combining some of them into a single aggregate to attempt to obtain the desired new model.

Upon first consideration of the presented set of models, their properties, and functional capabilities, the following combination options naturally come to mind:

1. Balloon + horse-drawn carriage
2. Balloon + steam engine with a pushing air propeller
3. Balloon + rubber motor with a pushing air propeller
4. Balloon + internal combustion engine with a pushing air propeller
5. Enlarged kite + horse-drawn carriage
6. Enlarged kite + steam engine with a pushing air propeller
7. Enlarged kite + rubber motor with a pushing air propeller
8. Enlarged kite + internal combustion engine with a pushing air propeller

Selection Process:

1. The hypothetical design in the form of the combination "Balloon + horse-drawn carriage" (B + HC) will be capable of lifting a person into

the air and moving them a significant distance, but will not meet the requirement of movement in an arbitrary direction, since a horse-drawn carriage can only move on roads suitable for this. The relevance score should be low, ~0.2.

2. The hypothetical design in the form of the combination "Balloon + steam engine" (B + SE) will be capable of lifting a person into the air, but moving them a significant distance will be difficult for such a model due to the high windage of the structure, and there will be problems with movement in an arbitrary direction since the balloon is subject to wind action, which a steam engine is unlikely to overcome. The relevance score should be low, ~0.1.
3. The hypothetical design in the form of the combination "Balloon + rubber motor" (B + RM) will allow lifting a person into the air, but will not be able to move them a significant distance, as the range using a rubber motor is very small. The relevance score should be low, ~0.1.
4. The hypothetical design in the form of the combination "Balloon + internal combustion engine" (B + ICE) will be capable of lifting a person into the air and moving them a significant distance, but will not meet the requirement of movement in an arbitrary direction within an acceptable time, since with such high windage, movement against the wind may be too slow or even impossible. The relevance score should be low, ~0.3.
5. The hypothetical design in the form of the combination "Enlarged kite + horse-drawn carriage" (EK + HC) is capable of lifting a person into the air and moving them a significant distance, but, just like the design in point 1, will not meet the requirement of movement in an arbitrary direction, since a horse-drawn carriage can only move on suitable roads. The relevance score should be low, ~0.1.
6. The hypothetical design in the form of the combination "Enlarged kite + steam engine" (EK + SE), if it is capable of lifting a person into the air,

then to move them a significant distance, a steam engine would be required, the weight of which would obviously be excessively large. The relevance score should be low, ~0.1.

7. The hypothetical design in the form of the combination "Enlarged kite + rubber motor" (EK + RM) might not even cope with the task of lifting a person into the air, since the thrust of a rubber motor is very small. The relevance score should be low, ~0.05.
8. The hypothetical design in the form of the combination "Enlarged kite + internal combustion engine" (EK + ICE) will be capable of lifting a person into the air and moving them a significant distance, and will be able to move them in an arbitrary direction within an acceptable time. The relevance score should be high, ~0.95.

Thus, we could include embeddings of pairs with labels in the training dataset:

(PFAD), (B + HC) → 0.2
(PFAD), (B + SE) → 0.1
(PFAD), (B + RM) → 0.1
(PFAD), (B + ICE) → 0.3
(PFAD), (EK + HC) → 0.1
(PFAD), (EK + SE) → 0.5
(PFAD), (EK + RM) → 0.05
(PFAD), (EK + ICE) → 0.95

A neural network predictor could easily memorize these elements, and when given a new pair as input:

(PFAD), (Seagull + RM) → it would most likely assign it a relevance score of ~0.05.

To form a knowledge graph for a universal training dataset containing a sufficient number of knowledge models, the already developed and practically used GraphRAG mechanism can be employed. It forms a knowledge graph by automatically collecting data from available documentary sources through indexing the array of sources, i.e., using Entity Extraction, Relationship Mapping, Community Detection, and allows running a query that performs Graph Traversal. Using this approach, new drugs, new methods of treating diseases, new materials for engineering structures, etc., are already being developed.

Using a knowledge graph generated with the help of GraphRAG will allow forming a large universal training dataset, which will consist of sets of pairs of the form:

{[Problem Formulation], [Reliable set of previously known knowledge and connections between them]}

and assigning them a high relevance score for this set of knowledge to the essence of this task.

Further, based on these reliably known inventions and the material on the basis of which they were made, new elements of the form can be synthesized:

{[Problem Formulation], [MODIFIED set of previously known knowledge and connections between them]}

and assigning them a relevance score (RS) for this set of knowledge to the essence of this task with a reduced value, depending on the attributive composition of knowledge models added to this modified set.

The predictor of the new knowledge production system can be formed according to a GAN scheme, in which the discriminator will be trained on the existing TD, and the generator will be trained trying to select a set of suitable known models for a given problem formulation, so that the discriminator would not be able to distinguish this set from the reliable ones.

To select the optimal architecture of the generator, within the framework of the Constructionist approach to Strong AI development [1], genetic algorithms should be used. Generations of bots must compete for the right to proceed to the next stage based on the quality and efficiency of their gene set—fields, predictor architecture, hyperparameters, etc., and at each subsequent stage, these genes must vary, providing the opportunity to select an increasingly better set of genes, including an increasingly improved architecture (number of layers, neurons, skip connections, recurrent blocks, etc.).

The developed system for generating new knowledge will become one of the key components of the large AGI model proposed in [1].

A system developed according to this scheme will not yet be able to easily generate theories on the level of the General Theory of Relativity or design devices on the level of megascience projects, however, it will be capable of generating hypotheses of new knowledge or designs of new devices according to a pre-formulated assignment.

The process of developing an AGI prototype capable of generating hypotheses of new knowledge will have to go through the following stages:

1. Development of the Knowledge Graph structure with nodes in the form of knowledge models, and edges in the form of connection models using GraphRAG.

2. Populating the Knowledge Graph with a sufficient amount of already known knowledge—developed models of this knowledge and connections between knowledge—developed models of these connections using GraphRAG.
3. Formation of a sufficiently large set of training dataset elements in the form of problem formulations and combinations of "prototype" model sets, with labels in the form of relevance scores of the taken set of "prototype" models to the problem formulation.
4. Development of the predictor architecture, which will be trained on this training dataset.
5. Preparation of a virtual test environment in which the verification of generated hypotheses will be carried out, for example, in the form of registering the dynamics of states, movement, and evolution of a digital twin of a new model in a corresponding virtual World Model environment.

   Based on the proposed approach, a prototype of a system is already being implemented, capable of performing a search/selection of a set of knowledge models possessing the properties required in the task condition within a knowledge graph (formed using GraphRAG) based on a problem formulation [https://github.com/Kwoargus/agi_evolution].

Conclusion

The described approach can be developed with the involvement of topological space techniques. For this, knowledge is interpreted as an object having a text description and parameter-properties, for which an embedding can be obtained using vectorization. On the set of embeddings of all known knowledge models, using cosine distance, a metric can be defined, and with its help, a topology can be set on this set.

Such an approach transfers abstract concepts of general and differential topology, as well as data geometry (Data Manifold), to the structure of human knowledge. In essence, a topological space of knowledge models is constructed based on semantic vectors.

Instead of a simple search for similar objects, topology allows studying the generalized structure of the set of knowledge:

a) Search for "voids" as lacunae in knowledge - using Persistent Homologies, topological "holes" (cycles) in the knowledge manifold can be detected. If a dense ring of related concepts exists around a certain area, but the center itself is empty, this indicates a structural gap in science. Filling this hole is the formulation of a fundamentally new hypothesis.

b) Betti numbers Bn - counting the number of independent cycles of different dimensions allows estimating the complexity and connectivity of the entire system of human knowledge or individual disciplines.

c) Clustering through connectivity - knowledge aggregates are defined as connectivity components or regions of high density (topological plateaus).

d) Semantic bridges - in topology, one can identify articulation points or narrow "isthmuses" connecting two large isolated topological components; embeddings that fall into these isthmuses represent hypotheses at the intersection of sciences, capable of transferring methods from one discipline to another.

Many groups of scientists in Russia and abroad are already engaged in the implementation of this approach, but research in this direction is still far from completion.

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