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## **The development of a natural language reasoning system for a companion robot**

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### **Abstract**

The natural language inference system allows the robot to go from the meaning of the incoming text (from a visual or tactile stimulus) to the derived meaning—the inference. This system uses a rule-based parser, and pairs of semantic representations constructed by the parser are combined into a scenario. In this paper, we represent the robot's natural language inference space as a graph, where the robot can move from the premise of a scenario to the consequence, and from the consequence of one scenario to the premise of another. We involve annotators who propose derived sentences (semantic components) for a given premise and, in the annotator interface, immediately evaluate the proximity of the proposed sentence to the available scenarios. This procedure allows us to develop the graph of scenarios, to evaluate its connectivity and the absence of dead ends (deadlock vertices), as well as the adequacy of the analysis of incoming texts by scenarios within this graph. The graph contains 5,000 scenarios and approximately 22,000 nodes. We estimate that a graph consisting of 7,000 scenarios can be sufficient for modelling the mechanism of human natural language reasoning.

**Keywords:** Companion robot, emotional robotics, cognitive models, dialog support, human-machine interaction

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## **Развитие системы естественно-языковых рассуждений для работа-компаньона**

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### Аннотация

Система естественно-языкового вывода позволяет роботу перейти от смысла поступившего текста (от визуального или тактильного стимула) к производному смыслу — выводу. Данная система использует парсер, основанный на правилах, а пары семантических представлений, построенных парсером, объединяются в сценарий. В работе мы представляем пространство естественно-языкового вывода робота как граф, где робот может перейти от посылки сценария к его следствию, а также от следствия одного сценария — к посылке другого. Мы привлекаем разметчиков, которые предлагают производные предложения (компоненты смысла) для некоторой посылки и в интерфейсе разметчиков сразу же оценивают близость предложенного предложения к имеющимся сценариям. Эта процедура позволяет нам развивать граф сценариев, оценивать его связность и отсутствие в нём тупиков (висячих вершин), а также адекватность анализа входящих текстов с помощью сценариев в составе данного графа. Граф содержит 5000 сценариев и около 22 000 узлов. По нашим оценкам, граф, состоящий из 7000 сценариев, может считаться достаточным для моделирования механизма естественно-языкового рассуждения человека.

**Ключевые слова:** робот-компаньон, эмоциональная робототехника, когнитивные модели, поддержание диалога, человеко-машинное взаимодействие

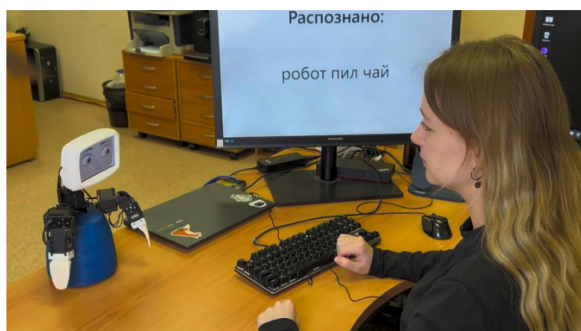
## 1 Introduction

Despite the significant progress of ‘large language models’ (LLMs) in the task of text generation [1], these models are relatively poorly applied to the modelling of reasoning [2]. At their core, LLMs aim to reconstruct the next word of a text based on a context window, so LLMs are usually improved by expanding the context window and by enlarging the training text database. Classical artificial intelligence models oriented towards problem solving or text understanding had a different architecture: they used an enumeration of paths in the problem space [3] or in the space of storylines [4]. To overcome these limitations of LLMs and to create the so-called *Large Reasoning Models* (LRM), *Chain-of-Thought* methods are proposed, where the solution of the problem is performed in several steps: each step is provided by a LLM, but the results of each step can be added to the solution protocol or combined with each other for the next step of the LLM operation [5].

At the same time, there is a relevant task to design a reasoning process, where intermediate representations are connected by a more compact mechanism that does not use LLMs. In classical models such as SOAR [3,4] and CogAff [5], such a transition between two representations has been described in terms of *productions* or *scenarios*. An individual *scenario* relates a typical stimulus (*premise*) to a possible *consequence* and allows the cognitive model (robot) to move in its reasoning process from the current situation to the inferred situation, thus reconstructing the context of the received message or making plans for actions in the environment. The aim of our work is to create a companion robot and to develop a cognitive model for the robot that allows it to mimic various cognitive functions when interacting with humans. These are primarily planning and discussing of actions in the real world [6], as well as the robot’s ability for natural language inference. An example of interaction with the robot using natural language inference is shown in Figure 1.

Following the CogAff model, the robot constructs possible causes and effects from an incoming event<sup>1</sup>, and then evaluates these derived meanings according to their emotionality (significance). In future versions of the system, this should allow the agent to plan its communicative or actual activity in such a way that it approaches positive situations and avoids or compensates for negative situations, e.g., to evaluate the situation ‘robot is well fed’ as positive and ‘robot was sick’ as negative. In the current version (Figure 1), the robot reports all the possible causes and effects in the dialogue based on the incoming utterance, without considering their significance. In this paper we present a scenario architecture for the natural language inference mechanism for companion robots.

<sup>1</sup> For the purposes of this paper, text messages are considered as incoming events, but these events can also be visual or tactile, which are constructed by the vision system or the touch registration system, respectively.



(a) Пользователь: *Робот пил чай.*

(User: *The robot was drinking tea.*)

Робот: *Робот пил чай. Робот налил чай в чашку. Робот заварил чай. Робот вскипятил термос. Робот насытился.*

(Robot: *The robot was drinking tea. The robot poured tea into the cup. The robot made the tea. The robot boiled the thermos.<sup>2</sup> The robot is well fed.*)

(b) Пользователь: *Робот пил водку.*

(User: *The robot was drinking vodka.*)

Робот: *Робот пил водку. Кто-то типа уго-  
стить робота водкой. Робот купил водку. Ро-  
бот налил водку к стопке. Робот опьянел. Ро-  
бот отравился. Тошило робота. Робот бу-  
хал.*

(Robot: *The robot was drinking vodka. Someone like to give vodka to the robot. The robot bought vodka. The robot poured vodka by the shot of glass. The robot got drunk. The robot got poisoned. The robot was sick. The robot was drinking.*)

Figure 1: Interaction with the companion robot controlled by the natural language inference system. The video is available in the repository [7].

## 2 Semantic parser

The basic data block for the scenario system is the semantic representation. The semantic representation of an individual sentence clause contains the valencies for the actants: agent – *ag*, patient – *pat*, instrument – *instr* etc.<sup>3</sup>, as well as the semantic markers for each actant. This semantic representation for an incoming utterance is built by the parser [8,9]. For visual and tactile events, the semantic representations are similar to the text semantics – but without homonymy (are unambiguous) [10,11].

The semantic parser follows the three-level linguistic architecture of Meaning-to-Text Theory [12] and consists of morphological, syntactic and semantic components. **The morphological component** includes a vocabulary of 100,000 lexemes (about 1.5 million word forms) based on the OpenCorpora dictionary [13]. The dictionary lexemes are annotated with semantic markers. During the text analysis, the markers of each word are copied to the semantic valency that the word occupies in the syntactic tree. The markers of the verb are copied to the valency *p* (predicate). In **the syntactic component**, we use a left-to-right parser. Segments of a sentence (words) are sequentially placed on a stack for syntactic parsing, with a morphological annotation assigned to each segment. For each homonymic word form, the stack is duplicated: each copy of the stack contains a different variant of parsing for the homonymic segment. The syntactic component compares the top of the stack with the Russian language grammar, which consists of approximately 800 syntXML rules [14]. If the sequence of segments on the stack meets the requirements of a syntactic rule, then a syntactic link is established between these words. If the syntactic relation can be established ambiguously (in the case of syntactic homonymy), the stack is also duplicated, and a different syntactic relation is established in each copy of the stack. By the end of the sentence, a stack with successful parsing should collapse into a syntactic tree with a single root. The parser then builds a semantic representation for each successful stack (Figure 2). The simultaneous processing of multiple stacks<sup>4</sup> outputs a set of syntax trees from the syntax component, and then each semantic predication is matched to the scenarios: i.e. the most regular semantics for the sentence is selected

<sup>2</sup> Semantic or syntactic errors in utterance synthesis in Russian are underlined.

<sup>3</sup> An inventory of 24 valency types is used, based on [21].

<sup>4</sup> The number of homonymous stacks is usually limited to 256 or 512 units. On each step the stacks are evaluated and only a limited number of “best” stacks is preserved for further analysis.

as better matching to the regular situations – scenarios. The parallel processing of speech ambiguity also allows us to approach the problems of ambiguous representations, such as computer humor, computer imagination and the theory of mind [15].

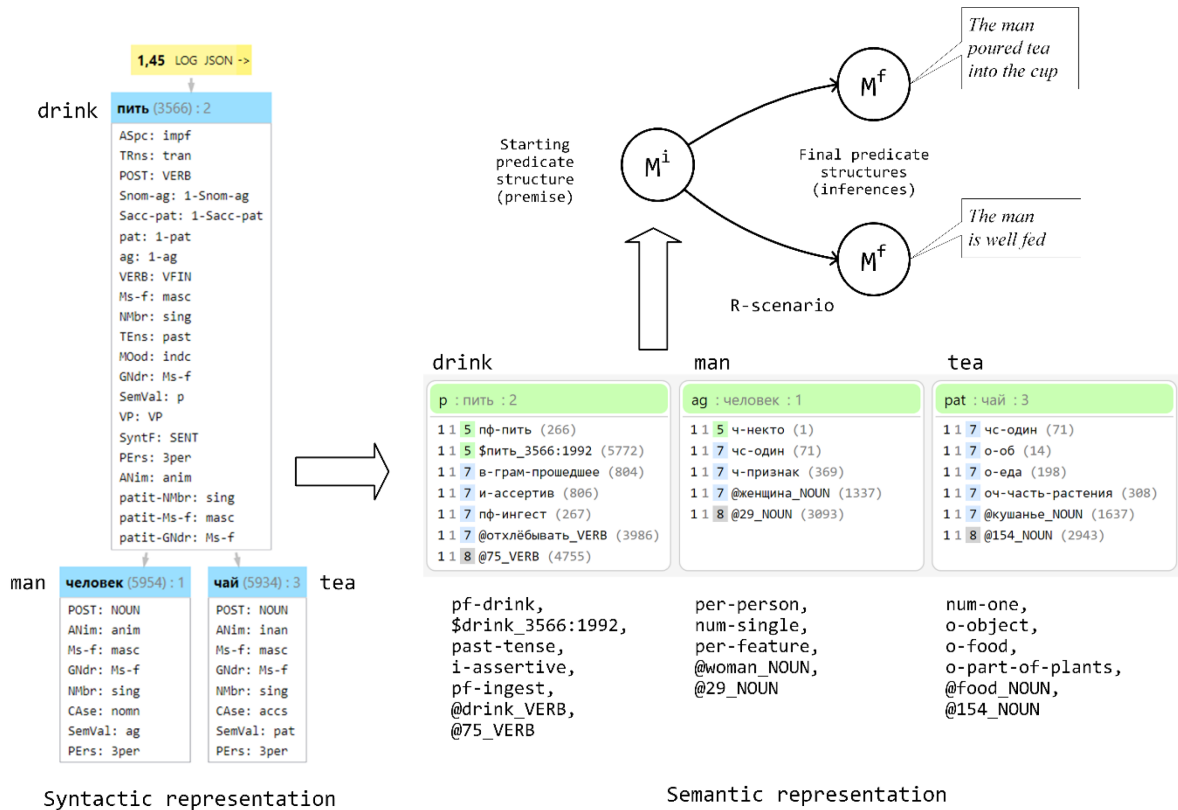


Figure 2: Syntactic tree and semantic representation for the utterance *a man drinks tea*, and its comparison with the premise (initial predicate structure) of the closest scenario.  $M^i$  is the initial predicate structure,  $M^f$  are the final predicate structures of the scenario.

As can be seen in Figure 2, the semantic representation is a set of valencies ( $p$ ,  $ag$ ,  $pat$ ), where each valency is filled with markers of the corresponding lexeme. Unlike *word2vec* semantic vector models, we use markers from a fixed inventory (about 13,000 items), with an average of four markers<sup>5</sup> assigned to individual words in the dictionary. We use several methods to construct the marker inventory: (a) markers based on the categories of Shvedova’s Semantic Dictionary, e.g. *per-person* [16], (b) markers based on emotional markup [17], (c) markers based on clustering of *word2vec* vectors, e.g., *@drink VERB* and *@food NOUN*<sup>6</sup>, and (d) markers based on synsets, e.g., *\$drink\_3566:1992*<sup>7</sup>. A word may be homonymous, in which case the word has different meanings 1:1, 1:2, 1:3, ..., 2:1, 2:2, 2:3, etc. Different semantic markers can be assigned to each of the meanings<sup>8</sup>. The same feature may have different weight (rank)<sup>9</sup> for different words.

In order to determine the correspondence between the incoming semantic representation and the scenario premise, a proximity measure is calculated that takes into account the coincidence of markers in

<sup>5</sup> For 83,000 lexemes from the dictionary, 318,000 links were established with markers from a dictionary of 8,500 features. Thus, each word has 3.91 features.

<sup>6</sup> Marker names are chosen automatically by the closest word to the cluster center. So, *a man* corresponds to the class *@woman\_NOUN*. Here the marker name represents a member of the category, not a hypernym, and should be interpreted as ‘a woman and similar entities’. This procedure is described in more detail in [8].

<sup>7</sup> This marker is assigned to all words of the synset *drink / sip* (Russian synonyms: *пить, выпивать, потягивать, лакать, хлестать, тянуть, попивать*). If a word is homonymic and has several meanings, the marker is assigned to the meaning of the word that is included in the given synset.

<sup>8</sup> In Figure 2, all lexemes are unambiguous and have only meaning 1:1.

<sup>9</sup> For example, the feature *per-person* (‘person’) has more weight for the noun *a man* than for the noun *a tailor*.

the valencies. Each valency of a scenario premise contains a set of semantic markers annotated according to their importance:

- *marker\_value* — the weight of the marker in the scenario premise (the higher the value, the more important is the marker).
- *attr* — attribute of the marker in the incoming representation (the smaller the value, the higher is the semantic *value*).

For each valency, the degree of matching between the markers of the premise  $P$  and the input representation  $C$  is calculated using a modified Jaccard measure (here  $Q = P \cap C$ ):

$$v(P, Q) = \frac{\sum_Q m}{\sum_{P \setminus Q} a + \sum_Q n}$$

where  $v$  lies in the range  $[0, 1]$ . The following normalising factors are used here. For matching markers:

$$m = \frac{\text{marker\_value}}{\ln(\text{attr} + e)}$$

$$n = \text{marker\_value}$$

where  $e$  is the base of the natural logarithm. For non-matching markers:

$$a = \frac{\text{marker\_value}}{\ln(\text{attr\_avg} + e)}$$

where *attr\_avg* is the average attribute value for the corpus.

To calculate the final degree of closeness of the semantic representations, a Jaccard measure modified as follows is used:

$$p(P, Q) = \frac{\sum_Q wv(P, Q)}{\sum_P w}$$

where  $p$  lies in the range  $[0, 1]$ . Here  $P$  is the valency set in the premise,  $Q$  is the valency set present in both representations,  $w$  are valency weights representing their contribution to the scenario.

### 3 Reasoning system

The robot's reasoning system is based on scenarios. Each scenario contains semantic representations of two types:

- (a) premise or *initial predicate structure*;
- (b) consequence or *final predicate structure* (there can be from none to several structures).

If the meaning of the incoming text is close to the initial predicate structure, the scenario is triggered and builds its final predicate structures. It is this mechanism that ensures the construction of the inferred semantic representation '[previously] the robot boiled the kettle' from the incoming utterance *The robot drinks tea*. This 'rational' inference is provided by a system of *r-scenarios* (rational scenarios). Initially, the set of r-scenarios was formed in the following way: semantic representations of diverse natural texts (10 million clauses) were clustered, and after manual checking, about 3,000 r-scenarios (their initial predicate structures) were formed for the approved clusters. Currently, the number of r-scenarios has been brought to 5,300. Each scenario recognizes some typical situation in texts, for example: 'a person's heart is beating', 'a person has a toothache', 'a person drinks tea', etc. From this point of view, r-scenarios are similar to FrameNet's frame inventory [18] or Framebank government models [19]. The difference in our project is that, when the parser is running, the scenarios are automatically recognized in the incoming texts: the closest scenario is assigned to each clause. For example, the @sick\_292\_VERB\_1 scenario (~'the man's tooth hurts') is automatically detected in the utterances:

- *I tried to lift her up, but she couldn't, she said, 'my back hurts.'* (proximity 0.2820).<sup>10</sup>
- *— and my throat hurts too.* (proximity 0.2869)
- *Svetlichnaya has been very seriously ill in recent years.* (proximity 0.2120)

Attributing this scenario to statements such as *Roma, we are all rooting for you and our national team!*<sup>11</sup> is incorrect, because this situation has different causes, consequences and emotional evaluations. Usually, such a misclassification indicates that the scenario system lacks a specific scenario responsible for recognizing this particular meaning 'to root for'.

For emotional processing of incoming meaning, an inventory of d-scenarios (*dominant scenarios*) is used, based on the speech influence model [17]. D-scenarios recognize emotional situations, such as 'nobody needs me', 'something is being plotted against me', 'I feel nauseous', or 'everyone looks at me with admiration', 'I am smarter than other robots', 'I am satiated'.

According to the CogAff architecture, an incoming event can be evaluated by the agent both emotionally and rationally. This is ensured by the competition between d- and r-scenarios. Furthermore, according to CogAff, the result of the agent's reasoning can serve as the material for the next reasoning step or as an object of emotional evaluation. In this case, the secondary emotional mechanism is activated [20]: the emotion is not triggered by the perceived stimulus, but by the reasoning result. To implement this mechanism, the final predicate structures of r-scenarios are passed to the input of the model for the next analysis step (see Figure 3).

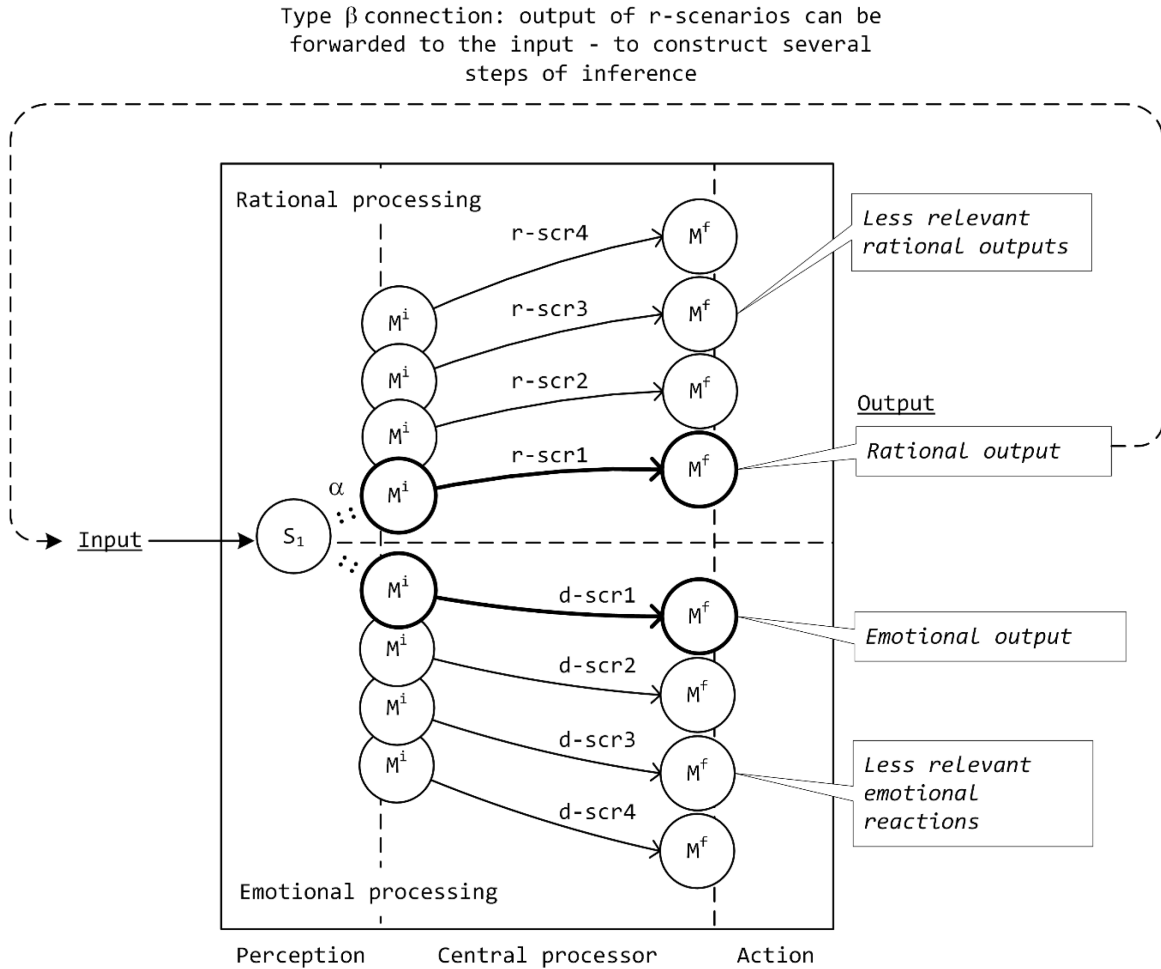


Figure 3: Processing of stimulus  $S_1$  by the scenario system. R-scr – r-scenarios, d-scr – d-scenarios,  $M^i$  – initial predicate structures,  $M^f$  – final predicate structures.

<sup>10</sup> As demonstrated further – the level 0.25 is considered as a *good* proximity, so values above 0.25 are *excellent*.

<sup>11</sup> In Russian *болеть* has at least two meanings – 'to be sick' and 'to root for someone'.



To obtain the final predicate structures for each r-scenario, i.e. semantic representations related to the initial one, annotators were employed. We offered annotators prototypical (initial) utterances for each r-scenario and asked them to write down new utterances denoting: (a) the antecedent situations that led to the initial one – predicate structures of the type BEFORE, (b) the consequent situations caused by the initial one (AFTER), and (c) interpretations of the initial situation (INTERP) – i.e. syntactic conversions ('a house is built by workers' = 'workers build a house') and figurative interpretations (e.g. 'a man was running on the field' = 'a man was playing football'). The annotators' utterances in the annotation environment were immediately parsed by the parser, which established co-referentiality<sup>12</sup> between the actants in the initial and final predicate structures (the same person who was running on the field was playing football). The conference information was also added to the scenario, allowing the robot to mention in derived utterances the same referents that were present in the original stimulus.

When receiving new utterances from the annotators, it is important to check whether these utterances correspond to r-scenarios already present in the scenario apparatus. With a closed set of scenarios, each output result corresponds to some 'input' – the initial predicate structure of another scenario (Figure 4), which should allow the robot to move in its reasoning along some graph (Figure 5).

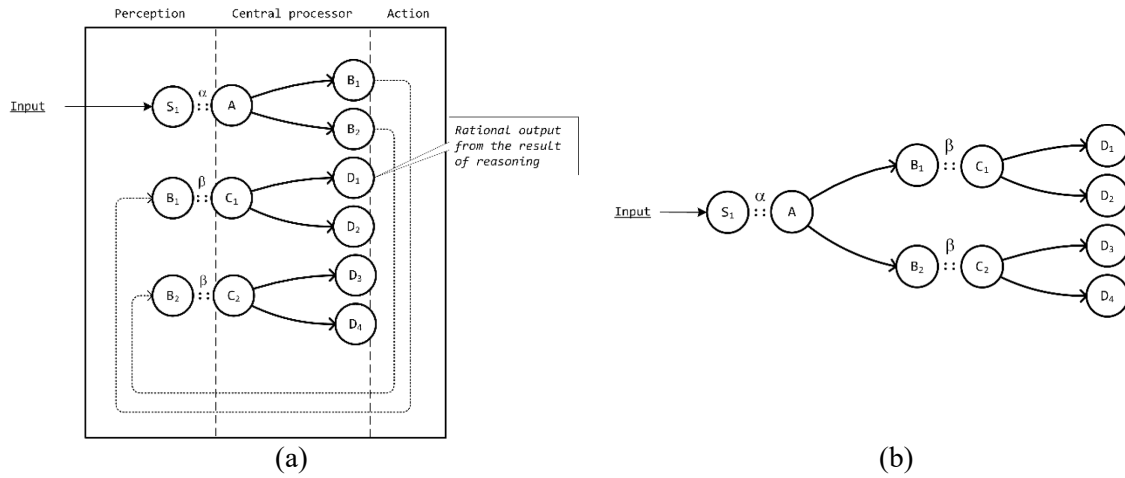


Figure 4: (a) stimulus  $S_1$  is matched to the initial predicate structure  $A$  of a scenario. The constructed inference results  $B_1$  and  $B_2$  can be mapped to the initial predicate structures  $C_1$  and  $C_2$ , which can lead to inferences  $D_1, D_2, D_3, D_4$  on the next reasoning step; (b) the same reasoning mechanism can be represented as a graph induced by the initial stimulus  $S_1$ .

This approach allows us to construct a general graph – the robot's natural language inference space – in which all the inferred semantic representations (predicate structures) are reconstructed for a given initial stimulus. The nodes of this graph correspond to the initial and final predicate structures, while the edges correspond (a) to the links between the initial and final structures within the same scenario and (b) to the links between different scenarios, calculated by the proximity of the final structures to the initial structures. For example, Figure 5 shows the graph constructed from the stimulus *man was drinking tea* at depth 3. The Figure 3 shows that an inference from r-scenarios can be matched with d-scenarios: the robot can infer 'previously someone made tea' (and *It's nice that someone cares about the man!*) and 'someone poured tea into a cup' (and *It's nice that someone brings tea to the man!*) – inferred semantic representations here are constructed by r-scenarios, and emotional evaluations – by d-scenarios.

<sup>12</sup> The annotators were instructed to repeat in their utterances the lexemes used in the initial utterance. If for the initial utterance *man drank vodka* the annotator suggests the interpretation *man was intoxicated*, the parser establishes co-reference between the two occurrences of the word *man*. If the incoming utterance *robot drank vodka* is matched to this scenario, the parser will match the referent 'robot' with the valency 'man' and construct the output *the robot was intoxicated*.

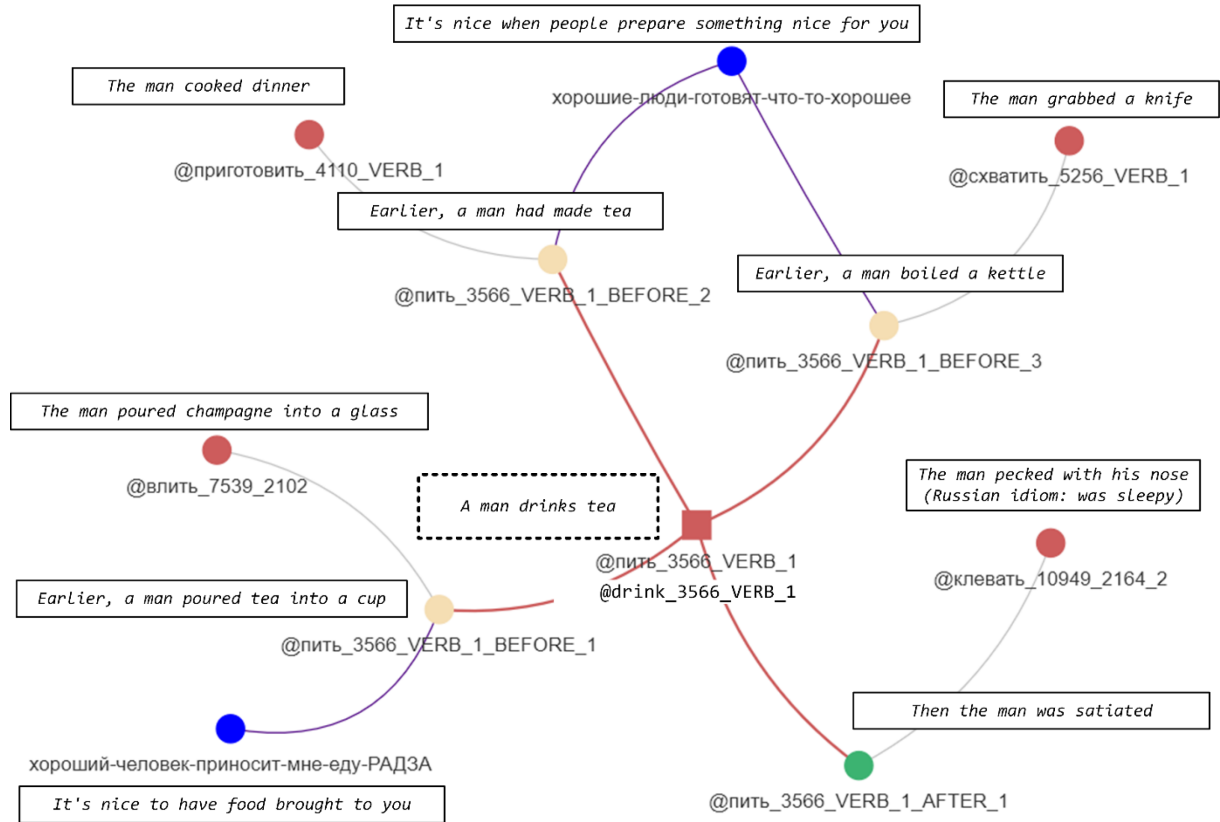


Figure 5: Example of a reasoning subgraph for the initial predicative structure ‘the man drank tea’ (scenario @drink\_3566\_VERB\_1). R-scenarios are marked with “@”, d-scenarios are not. The implications ‘the man was satiated’ and ‘the man boiled the kettle’ are misclassified by the scenarios, which is an argument for creating a separate scenario for these representations when filling the inventory.

The work of the annotators in adding to the scenario inventory should produce such a set of scenarios (such a natural language inference space) that fulfils a number of criteria. First, the inventory of scenarios should be accurate and complete when processing real texts – each clause of the text should be correctly matched to some scenario: proximity of the type  $\alpha$  in Figures 3 and 4. This will allow the robot to correctly classify the incoming stimulus and correctly select possible causes and effects for it. Second, the inventory of scenarios should be closed: each final predicate structure should map to some initial predicate structure: proximity of the type  $\beta$  in Figures 3 and 4. Then the robot will be free to develop reasoning without stopping at representations that have no counterparts among the initial predicate structures of the scenarios.

In order to come close to meeting these requirements, during the annotators’ work the parser immediately parsed each proposed utterance, compared it with the existing set of scenarios and returned the constructed semantic representation with the closest scenarios. The annotator then had to evaluate whether the utterance entered matched the closest scenarios suggested by the parser. Thus, the proximity evaluation of  $\beta$  was collected directly during the work of annotators. If the annotator agreed with the proposed scenario for the entered utterance, it can be assumed that the  $\beta$  scenario graph has connectivity: the robot can freely move in its reasoning from the final predicate structure proposed by the annotator to the initial predicate structure of another scenario. If the annotator finds that none of the three closest scenarios matches his utterance, then the  $\beta$  proximity requirement is not fulfilled: among the available scenarios there is no one that correctly classifies the input text, and this is an argument for creating a new scenario. For example, if the parser offered the best scenario ‘the person had a toothache’ for the annotator’s sentence *the fans were rooting for the team* (in Russian: *were ill for the team*), then a specific



scenario should be created for the situation ‘the fans were rooting for the team’. Such scenarios were created on the basis of the markers’ evaluations, after which the new scenario was given to the annotators to suggest derived meanings, such as BEFORE/AFTER and INTERP.

During the last phase of annotation, 5333 new utterances for scenarios were proposed by the annotators; 2484 utterances were proposed as candidates for the creation of new scenarios (some of them were approved), for 2856 utterances we have collected evaluations of the proximity to the closest scenario. The work on adding to the scenario inventory increased the number of nodes and edges in the scenario graph (Figure 6a) and reduced the number of isolated nodes and connectivity components (Figure 6b).

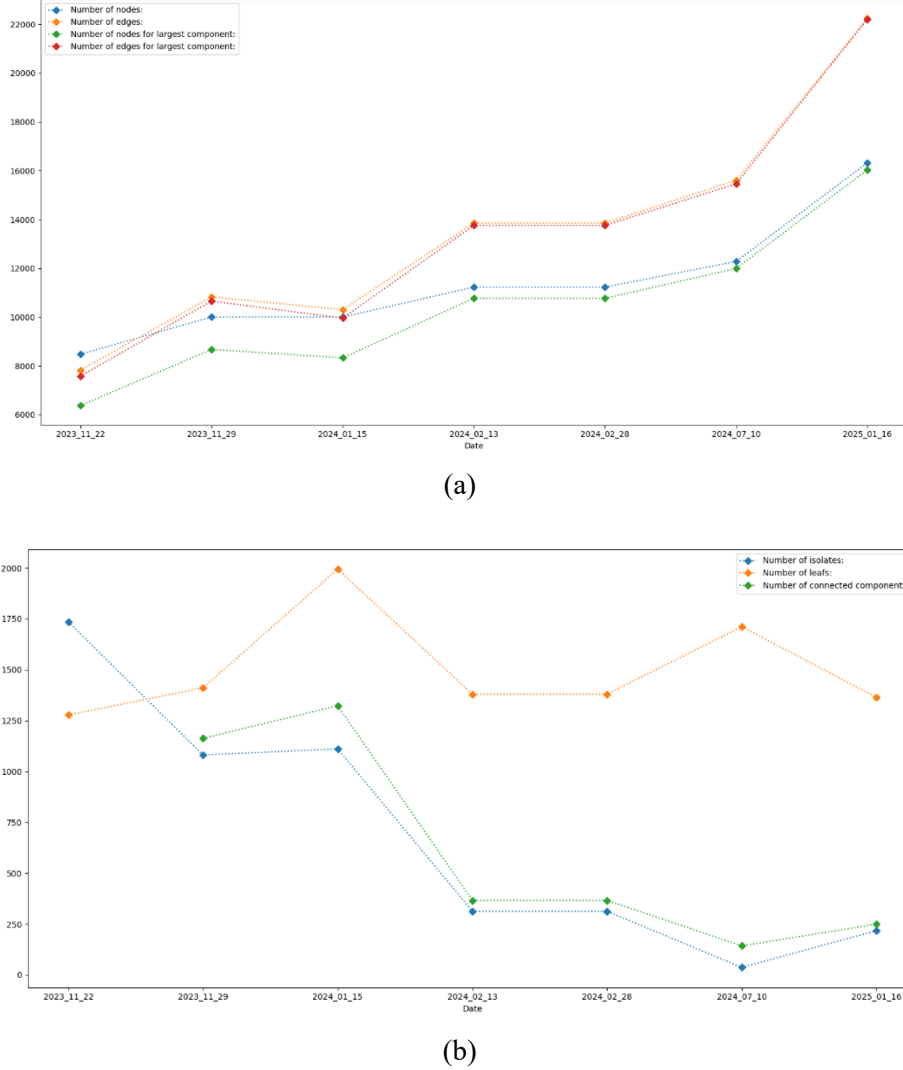


Figure 6: Variation of basic graph characteristics during the addition process: (a) the number of nodes and edges of the whole graph and the largest component: steadily increasing; (b) the number of isolated nodes and connected components decreases.

When extending the graph of the natural language inference space, a natural question is what size of this graph is sufficient to analyze the whole collection of real texts ( $\alpha$ -connectivity). For this purpose, we propose to use the annotators’ evaluation: Figure 8 shows a histogram of the similarity between the annotators’ utterances and the closest scenario where the annotator found the proposed scenario satisfactory. The histogram shows that at a proximity of about 0.25 the annotators most often approve the scenario as corresponding to their utterance (the level of optimal  $\beta$ -connectivity). The main graph (Figure 7) shows the average proximity of clauses of real news texts parsed daily by the parser [9] to the scenarios for different versions of the scenario inventory – i.e., proximity of the  $\alpha$  type (proximity of the semantics of real texts to scenarios). As the scenario inventory has been constantly updated and

refined, this proximity has increased, but it still lags behind the 0.25 level that the annotators consider optimal, according to the estimates on the histogram.

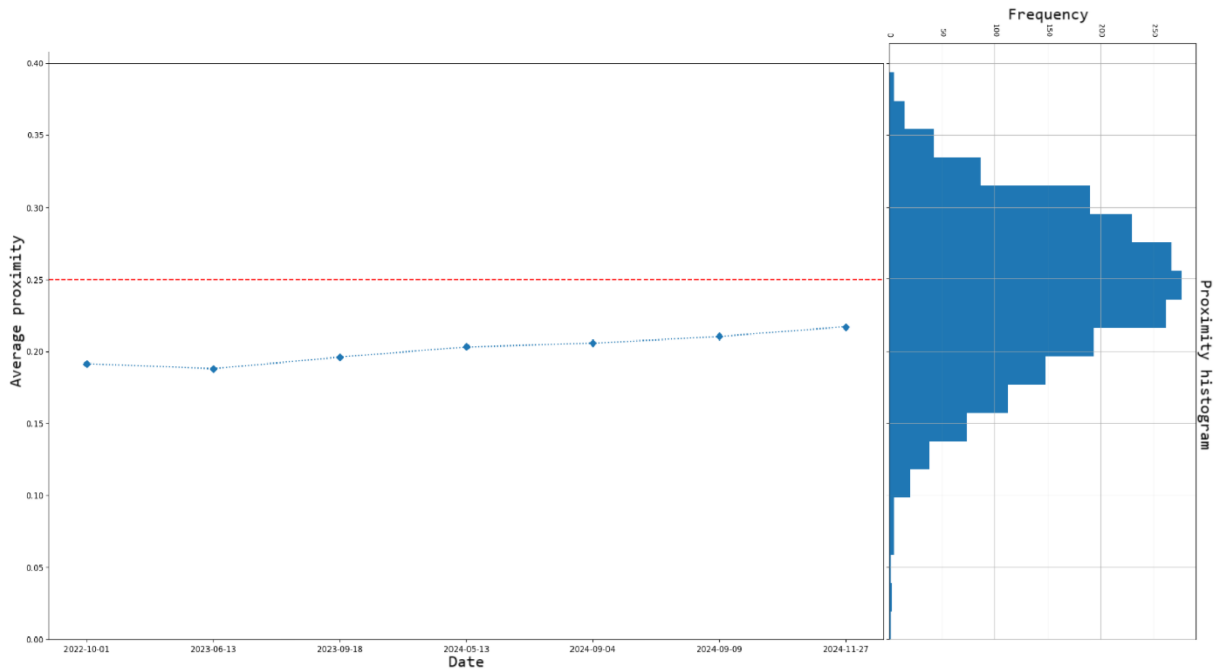


Figure 7: Average proximity of daily news text clauses to scenarios ( $\alpha$ -connectivity); red dashed line is the derived estimate of high  $\beta$ -connectivity (from the histogram of new utterances' proximity to scenarios on the right)

Linear extrapolation was used to estimate the number of scenarios for which a high value of optimal proximity in text parsing would be achieved. Since the set of points  $X$  (number of scenarios at a given point in time) and the corresponding set of points  $Y$  (average proximity to the scenarios) are known, we can approximate a function  $F: Y = F(X)$  expressing the dependence of proximity on the number of scenarios. And if we extrapolate it beyond the interval  $X$ , we can estimate such  $X_\alpha$ :  $F(X_\alpha) = 0,25$ . In our case  $X_\alpha \approx 7000$  scenarios.

## Conclusion

We modelled the process of human natural language reasoning as a transition from one semantic representation to another. We represented the space of possible transitions as a graph containing about 5,000 scenarios. The involvement of annotators allows us to populate the inventory of scenarios and to evaluate the connectivity of the overall graph within the space of the natural language reasoning. Based on our estimates in this paper, we suggest that an inventory of approximately 7,000 scenarios would be sufficient for basic modelling of human natural language inference. This estimate answers the question of how many frames a reasonably complete semantic model should contain.

## Data availability

Scenario annotation intermediate results and robot videos are available from: Scenario Inference Data and Behavioral Protocols // OSF. March 31. doi:10.17605/OSF.IO/9HMP8

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