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Using Rhetorical Structures to Analyze Argumentation in Scientific Communication Texts

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Abstract

This article explores the role of rhetorical structures in the argument mining task on the material of scientific Internet communication texts in Russian. Two approaches are proposed and studied for argumentative relation prediction: the first one constructs segment vector representations using a Graph Neural Network (GNN) based on rhetorical structure, and the second one uses multitask learning that combines argumentation extraction with rhetorical relations prediction tasks. With proposed approaches three models were implemented: two variations of the model using GNN and one model employing the multitask approach. These models were compared with a simple baseline using the Lonformer model on a dataset annotated with both argumentative and rhetorical structures. Argumentative annotating was performed manually by four experts. Existing resources and tools were used to obtain rhetorical markup. The conducted experiments showed that the approaches using additional rhetorical information improve the quality of argumentative relation prediction, particularly for long-distance relations. The best performance, with an F1 score of 72.32%, was achieved by a model incorporating GNN-enhanced statement representations.

Keywords: argument mining; text corpus; argument annotation; argumentative relation prediction; rhetorical structure theory

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Использование риторических структур для анализа аргументации в текстах научной коммуникации

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Аннотация

В данной работе исследована роль риторических структур в задаче извлечения аргументации на материале текстов научной интернет-коммуникации на русском языке. Предложены и изучены два подхода для предсказания аргументативных отношений: первый использует риторическую структуру при построении векторных представлений сегментов с помощью GNN, а второй использует многозадачное обучение, совмещая извлечение аргументации с предсказанием риторических связей. В рамках предложенных подходов были реализованы три модели: две вариации модели с использованием GNN и одна модель, использующая многозадачный подход. Эти модели сравнивались с простой базовой с использованием модели Lonformer на наборе данных, аннотированном как аргументативными, так и риторическими структурами. Аргументационная разметка выполнялась вручную четырьмя экспертами. Для получения риторической разметки применялись существующие ресурсы и инструменты. Проведенные эксперименты показали, что подходы, использующие дополнительную риторическую информацию, улучшают качество предсказания аргументативных отношений, особенно для дальних связей. Лучшее качество с F1 = 72,32% показала модель, в которой векторные представления утверждений модифицировались с помощью графовой нейронной сети и дополнялись информацией о типе риторической связи.

Ключевые слова: извлечение аргументации; корпус текстов; аргументативная разметка текста; предсказание аргументативных отношений; теория риторических структур

1 Introduction

The analysis of reasoning structures presented in natural language texts has emerged relatively recently as a field of computational linguistics that is attracting increasing attention from researchers. Text fragments are sequences of functional steps that contribute to the presentation of the author's idea, supporting its understanding and/or acceptance. In applied linguistics, the structure of reasoning has been considered from a functional point of view based on the theory of rhetorical structure [1–4] and the theory of argumentation [5].

The study of discourse involves describing its structure in the form of discourse units connected by various relations. One of the most famous models used to solve this problem is the Rhetorical Structure Theory (RST) and its modifications [1, 2]. Under RST, simple sentences, clauses and some collapsed propositions (represented by nominalizations and prepositional groups) are connected by symmetric (multinuclear) and asymmetric (mononuclear) relations. In this case, larger discourse units are formed, thereby creating an integral tree-like structure.

Argumentation presented by the author to convince the audience of a particular position plays a special role in discourse analysis. The most famous study of argumentation that has found application in practical argumentation analysis is the model of Douglas Walton [6], in which a structured argument is defined as a set of statements consisting of premises, conclusion (thesis), and inference from premises to conclusion. Walton introduced the concept of an argument scheme, a form representing a stereotypical model of reasoning. The work [5] provides a compendium containing 60 basic argumentation schemes.

Practical application of argumentation theory is complicated by a number of factors, including the lack of annotated material, the non-obviousness of identifying argumentation zones, the presence of functionally similar arguments that complicate the choice of a scheme in a specific situation, and insufficiency of the set of schemes when it comes to new genres of texts. Such factors lead to ambiguity in text annotation, disagreement between annotators, which worsens the quality of the created datasets to be applied in machine learning methods and, as a consequence, leads to low quality of automation of argumentation analysis in general.

There exist methods to overcome the lack of argumentatively annotated material. In particular, corpora of texts with multi-level annotation are created to explore the correlation between rhetorical structure presented in RST-markup and argumentative structure shown by A-markup, in order to use existing resources and tools of discourse analysis to extract arguments. Thus, in [7] the development and use in experiments of a two-level corpus of 112 argumentative essays is described, in [8] the material is scientific articles from the field of computational linguistics, and [9] is devoted to the comparison of RST-markup and A-markup of popular science texts. In the presence of such a parallel corpus, neural network methods of machine learning can be applied both based on multitasking and considering RST-markup as additional features.

The purpose of this work is to develop methods for automatic construction of argumentation structure based on RST structure for Russian-language texts. Existing resources and tools for rhetorical analysis of Russian-language texts are used to obtain RST-markup.

The following research questions were formulated within the framework of this work.

Q1. How can language models aimed at analyzing argumentation use information about the rhetorical structure of a text?

Q2. To what extent does the quality of argumentation analysis improve when using rhetorical information obtained with the help of rhetorical parsers?

Experimental studies are conducted on a Russian-language corpus of texts related to the field of scientific communication, equipped with A-markup in accordance with the model of D. Walton.

2 Review

In the last few years, research has emerged examining the potential use of tools for automatically constructing the rhetorical structure of the text to solve the problem of argument mining. Most of the researchers below use the formalism proposed by RST, and parsers that allow you to build a rhetorical structure in the appropriate format.

The idea of using the text rhetorical structure to present argumentation is based on the fact that both illustrate the functional structure of displayed thoughts. More precisely, argumentation reflects the structure of reasoning to prove a thought, and the RST structure is a representation of this reasoning.

In both cases, the elements of the structure that form the vertices of the graph representation are text segments expressing the steps of reasoning, which are considered elementary. The function of the segment is displayed in the final structure as a relation linking it with the structure of the entire text. The final structure in both cases is a directed graph, its vertices forming elementary segments, and the arcs being marked with the names of the relations that link the segments. The coincidence of rhetorical and argumentative segmentations is observed for the rhetorical relations Cause-effect, Condition, Contrast, Concession, Purpose and partially for Attribution. In the "classical" set of rhetorical relations, some authors [10, 11] distinguish relations close to those used in argument analysis: Motivation, Evidence, Justify, Antithesis, Concession.

Two methods of presenting the structure of discourse demonstrate not only common properties, but also significant differences. Therefore A-markup cannot be considered as a special case of RST-markup [9, 11, 12]. Differences are revealed at all levels: a) not all text segments are included in the argumentative structure, but only those that relate to the argumentation zone; b) rhetorical segmentation is more fragmented, e.g. segments connected by Joint, Same-unit and Elaboration rhetorical relations are usually embedded in argumentative segments; c) the opposite situation in which a single rhetorical segment is presented in A-markup by several segments can be caused by pragmatic aspects of the context; d) when constructing the argumentative structure, there is no procedure for enlarging units by combining adjacent segments – the argument and the thing being argued (theses) can be located far from each other, which is quite natural for the structure of many scientific texts.

Several ways of using information about the rhetorical structure of text to extract argumentation have been proposed.

Early approaches used handcrafted features based on the rhetorical structure of text, such as the distance between elementary discourse units, the type of rhetorical relation, the presence of children/parents, etc. [13] used expert RST markups and compared three models: (1) a simple tree-transformation model based on heuristics; (2) an RST and argumentation graph alignment model; and (3) a modification of the Evidence Graph model. [14] also trained the Evidence Graph model, where discourse annotation of text was performed by automatic parsers with use of not only RST annotations but also Penn Discourse Treebank ones.

[15] modified the approach based on the biaffine dependency parser [16] and proposed a model in which the edge weights are refined by the corresponding discourse coefficients obtained from the rhetorical tree. In addition, the authors use several variants of RST annotations obtained for paraphrased statements to account for the ambiguity of the discursive interpretation of the text. The highest Unlabeled Attachment Score (UAS) on the Microtexts corpus [17] reached 64.6%.

And in [18], information about the rhetorical structure is used to form prefixes that guide the generation of argumentation structure using the BART model. BART-Encoder and Relational Graph Convolutional Network are used to generate the prefix. The model proposed by the authors achieved a 58.51% F1 score on the AAEC dataset [19] and a 40.46% F1 score on the AbstRCT dataset [20] for argumentative relation classification subtask.

Another approach was considered in [21], where the authors applied transfer learning on the Discourse Dependency TreeBank for Scientific Abstracts (SciDTB) [22] with added argumentation annotation layer. In this approach, a pre-trained model designed to recognize rhetorical relations was adapted on a limited training set for the task of recognizing argumentative relations. This model achieved a 40% F1 score for the argumentative attachment task on the SciDTB.

3 Methods

This paper proposes two methods for using rhetorical structure information in the argument mining process. They are compared with a baseline model that does not take such information into account.

In the first approach, the vector representations of statements were modified using a Graph Neural Network (GNN) to account for structural dependencies, and each type of rhetorical relation was assigned a trainable embedding which was combined with the corresponding segment vectors. In the second approach, the classifier was trained in a multitask mode, simultaneously solving the main task of extracting arguments and the auxiliary task of predicting rhetorical relations. This approach allowed the model to build better representations by transferring knowledge between similar tasks.

3.1 Baseline classifier

Let a text fragment consist of m Elementary Discourse Units (EDUs) EDU_i, where $i \in \{1,2,\cdots,m\}$, each including n_i tokens, and the total number of tokens in the text fragment is n. The contextual vector representations of the tokens obtained using encoder Enc are denoted as $e_i^{(1)}, e_i^{(2)}, \cdots, e_i^{(n_i)}$.

Vector representations of EDUs $h_1, h_2, \cdots, h_m$ are formed by aggregating the vector representations of tokens corresponding to each elementary segment:

$$h_i = AGG\left(e_i^{(1)}, e_i^{(2)}, \cdots, e_i^{(n_i)}\right)$$

The vector representations of EDU_i and EDU_j, are concatenated: $h_{ij} = [h_i; h_j]$, an MLP (Multi Layer Perceptron) classifier is applied to the resulting vector:

$$y_{ij}^{baseline} = Classify(h_{ij})$$

where $y_{ij}^{baseline}$ – the predicted probability of a relation between EDU_i and EDU_j. Cross-Entropy Loss (CE Loss) is used in the training.

3.2 GNN based approach

The main peculiarity of this approach is that the vector representations of the EDUs obtained using Enc are further transformed using a Graph Convolutional Network [23] according to the rhetorical structure. The evolution of vector representations at each layer of the GNN is defined as follows:

$$h_i^{(k+1)} = W_k^T \sum_{j \in \mathcal{N}(i) \cup \{i\}} \frac{h_i^{(k)}}{\sqrt{d_i d_j}}$$

where W_k – trainable weight matrices, $N(i)$ – the neighbors for EDU_i in the graph of rhetorical structure, $d_i = 1 + deg(i)$, and $deg(i)$ – vertex degree.

The vector representations $h_1^{(K)}, h_2^{(K)}, \cdots, h_m^{(K)}$ obtained at the last Kth layer of GNN are final and are used in the classifier: $y_{ij}^{graph} = Classify\left(\left[h_i^{(K)}; h_j^{(K)}\right]\right)$, and the initial representations $h_i^{(0)}$ are set equal to h_i for all $i \in \{1,2,\cdots,m\}$.

Figure 1 shows the architecture of the proposed model with the parameter K is configured equal to one, and the number of EDUs in the text is equal to four. The rhetorical structure graph of the text is depicted by dotted lines.

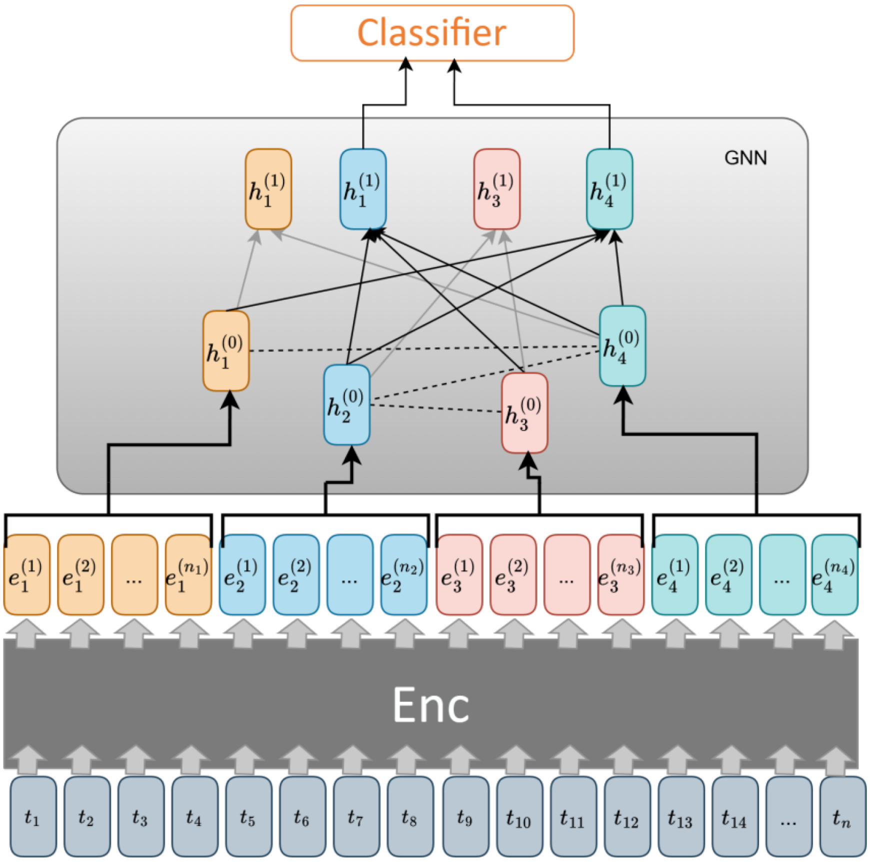

Figure 1: Architecture of the GNN-based model

This model uses only rhetorical structure and not relation types, however, not all rhetorical relations have correspondences in the argumentation structure. To account for the relation type, a trainable embedding e_r of dimension d_r is introduced for each rhetorical relation type r, as well as for an additional type none, denoting the absence of a relation. The updated vector representation for an EDU pair is defined as: $h'_{ij} = \left[h_i^{(K)}; h_j^{(K)}; e_r\right]$. Thus, $y_{ij}^{rel-graph} = Classify\left(h'_{ij}\right)$.

3.3 Multitask based approach

The next approach involves using multitask learning [24, 25], where a single model is trained to solve several related tasks simultaneously. The main idea is that through joint training, the model can build generalized representations improving performance on each task and reducing overfitting [25].

The second (auxiliary) task here is predicting the presence of a rhetorical relation between two EDUs. Thus, the vector representations of EDUs $h^1, h^2, \cdots, h^m$ are used to predict both argumentative and rhetorical relations, contributing to the creation of more informative and generalized representations.

The loss function in this case is the sum of the losses for each task: $L = L^{arg} + \alpha L^{rhet}$, where L^{arg} is the CE Loss for predicting argumentative relations, L^{rhet} is the CE Loss for predicting rhetorical relations, and α is a weighting coefficient that controls the contribution of the rhetorical component to the overall loss function.

4 Annotated Data

The material for the study is a parallel corpus in which texts are provided with RST- and A-markups. Figure 2 shows an example of parallel markup of a text fragment. In this example, there is a one-to-one correspondence between the relation pairs <*Adversative, Logical_Conflict*> and <*Casual, NegativeConsequences_Inference*>.

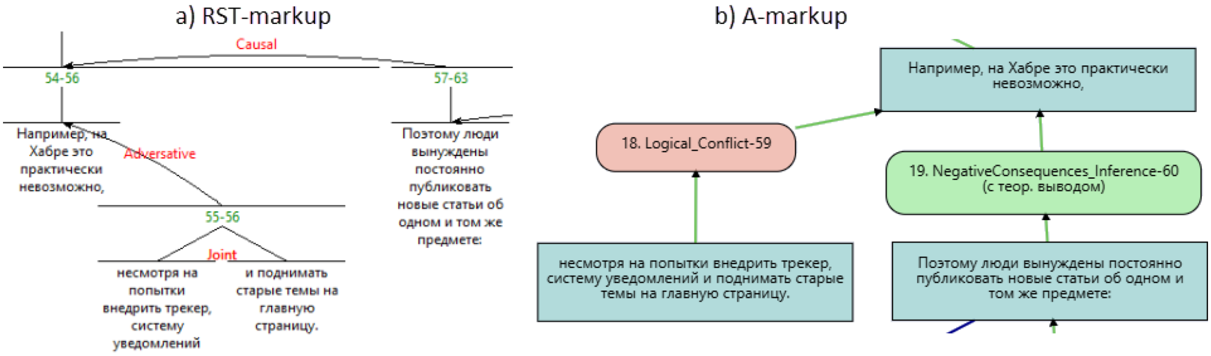

Figure 2: Example of correlation between a) RST-markup and b) A-markup

The corpus consists of 100 texts of Internet communication in several scientific and popular science genres: 1) scientific articles (10 articles, the average volume of the article is 3571 words); 2) scientific reviews (30 reviews, the average volume of the review is 346 words); 3) short articles about science news (30 articles from the website poisknews.ru , the average length of the article is 506 words); 4) long articles (30 articles from the site habr.com/ru , the average length of an article is 1912 words).

A-annotating was performed manually by four experts on the ArgNetBank Studio platform[1] [26], which presents the ontology of argumentation and description of schemes within the framework of D. Walton's approach used in annotating texts. In total, the corpus contains about 10 thousand marked-up arguments.

RST annotating was performed automatically. To build RST structures, the IsaNLP RST Parser analyzer was used [27], which is based on a classifier trained on a bilingual corpus, including annotated texts in Russian and English. The classifier is trained for segmentation, building RST structure and classifying the relations included in it.

A comparative analysis of RST- and A-segmentation statistics conducted for each text and on average by genre shows that there is no text in which the number of A-segments would be equal to the number of RST-segments. Moreover, in most cases this indicator for RST is 2–4 times greater than for A-segmentation. This shows both the presence of non-argumentative fragments in texts and larger granularity of RST-segmentation.

Comparison with the ¾ similarity threshold on the dataset shows that the proportion of A-segments that match RST segments is on average 42.23%. This once again confirms the fact that RST-markup provides significant information for constructing A-markup [12].

Based on RST- and A-markups, a dataset was constructed for experimental comparison of the proposed models, including positive and negative examples of pairs of statements (premise, conclusion). EDUs from RST-markups serve as statements. A pair is considered a positive example if there is an argumentative relation between premise and conclusion in at least one of the expert A-markups (i.e. markups of different experts are combined). Negative examples were formed as follows: for each positive pair of statements, a pair of statements from the same or adjacent paragraphs was selected (in the absence of suitable candidates) between which there is no path in the argumentation graph.

In total, the dataset used for the experiments contains 2722 pairs of statements, a half of them being positive examples and another half negative. 28.14% of positive pairs, i.e. connected by argumentative relation, are also connected by rhetorical relation, and only 12.05% of rhetorical relations are among negative examples. The distribution of types of rhetorical relations among positive and negative examples is presented in Figure 3.

1 https://uniserv.iis.nsk.su/arg/

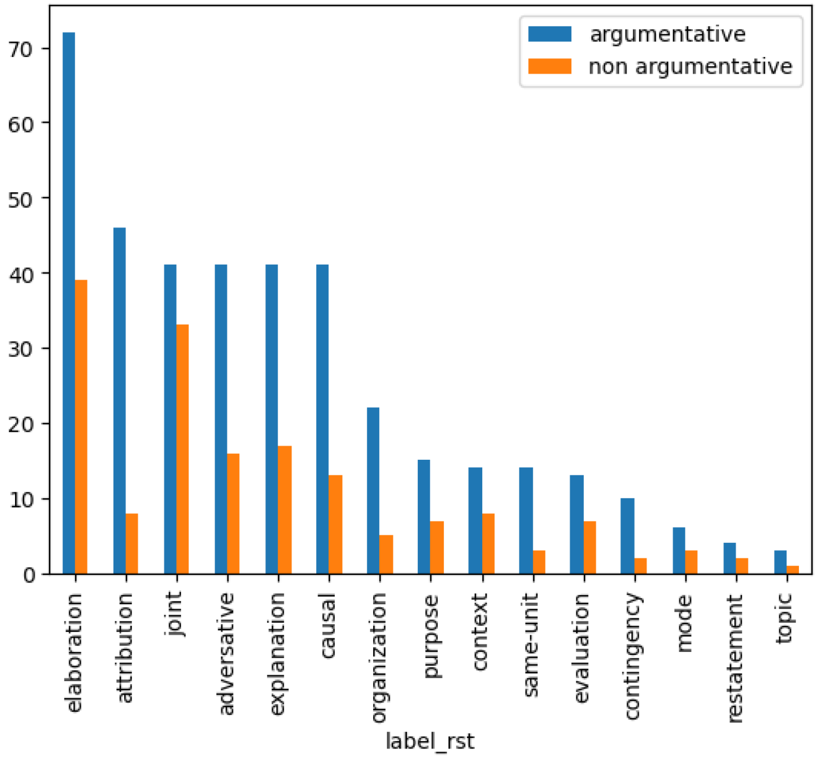

Figure 3: Rhetorical relations between positive pairs of statements (connected by argumentative relations) and negative ones

Additionally, each pair is provided with its paragraph-sized context and a graph of the context's rhetorical structure, constructed on the basis of RST-markup. The graph's vertices are EDUs. If a rhetorical relation in RST structure connects two discourse segments, then the graph connects two vertices that are the roots of these statements. The root of an EDU is itself, the root of a mononuclear relation is the root of the nucleus, and the root of a multinuclear relation is the root of the leftmost segment.

5 Experiments

Experiments were performed using the Longformer model [28] as an encoder (Enc) for long sequences, with all parameters remaining trainable. The max function was used as the aggregation function AGG. To mitigate the impact of data inconsistency, the label smoothing technique [29] with a coefficient of 0.1 was used. The baseline results were obtained with the model proposed in [30], which uses this Longformer model and the label smoothing technique.

The dataset was split into training, development, and test sets (57/20/23 texts), with the test subset including texts from all subcorpora in the dataset. Hyperparameter tuning was performed on the development subset. The size of the hidden layer in the two-layer classifier was set to 256, and the size of the embeddings for rhetorical relations was 32. The GNN module consisted of two layers. All models were optimized using AdamW with an initial learning rate of 5×10^{-6} and a batch size of 4.

Table 1 summarizes the results of the experiments on the use of rhetorical information.

- Baseline is a base model for predicting argumentative relations.
- ArgRhetRelGraph is a model that uses a GNN utilizing the rhetorical structure of a text fragment and trainable embeddings for each type of rhetorical relation.
- ArgRhetGraph is a modification of the previous model that does not use embeddings for rhetorical relations.
- ArgRhetRel is a modification of ArgRhetRelGraph that does not use a GNN.
- ArgRhetMT is a model trained in multitask mode on the tasks of predicting argumentative and rhetorical relations.

Model	P	R	F1
Baseline	74.46	63.97	68.82
ArgRhetRelGraph	**77.37**	**67.90**	**72.32**
ArgRhetGraph	77.05	65.13	70.59
ArgRhetRel	77.29	64.43	70.28
ArgRhetMT	77.09	63.74	69.79

Table 1: Results obtained by the proposed models

Experimental results demonstrated that the use of rhetorical information improves the quality of argument retrieval compared to the baseline version. The ArgRhetRelGraph model showed the best results and achieved F1 = 72.32%.

An analysis of examples where the predictions of the ArgRhetRelGraph differ from those of the Baseline has shown that the most frequent rhetorical relation which decreases the model's confidence in the presence of an argumentative relation is Elaboration (the satellite presents more detailed information about the nucleus). Conversely, among those in which the model became more confident the Attribution relation (the source, the author of the information presented in the nucleus) is more frequent. The Joint relation (a conjunctively related sequence of segments) can either decrease or increase the model's confidence in the presence of an argumentative relation, depending on the specific context.

A comparison of the prediction quality for short- and long-distance relations (see Table 2) showed that, in general, all models predict argumentative relations significantly better for statements within the same paragraph (short-distance relations) than for long-distance relations. Meanwhile, the use of rhetorical information improves prediction quality more strongly for long-distance relations, which can be explained by the fact that, despite the local nature of rhetorical relations, they contribute to the text's cohesion at the global level. Thus, the average linear distance in segments between pairs of statements in the test set is 12.8, while the average distance in terms of transitions between nodes of the rhetorical structure graph is 3.9.

Model	Same paragraph			Long distance		
	P	R	F1	P	R	F1
Baseline	76.34	70.30	73.20	68.82	49.23	57.40
ArgRhetRelGraph	**79.49**	**71.62**	**75.35**	71.96	**59.23**	**64.98**
ArgRhetGraph	79.25	69.31	73.94	71.29	55.38	62.34
ArgRhetRel	78.95	69.31	73.81	**72.63**	53.08	61.33
ArgRhetMT	79.23	67.99	73.18	71.43	53.85	61.40

Table 2: Comparison of the prediction quality of argumentative relations for segments located at different distances

6 Discussion

The most common errors resulting in incorrect argument predictions are categorized below.

Segmentation errors. RST segmentation being too fractional is inherited by the model, although, as the expert analysis given in [12] shows, argumentative segments (ADUs) are often concatenations of rhetorical segments (EDUs). As a correlating parameter, it is necessary to take into account the presence of *joint* type relations in the context: for example, in (1), two EDUs should be combined into a single ADU.

(1) Однако исследователи не могут назвать точный возраст костей, [поскольку это место является объектом Всемирного наследия,] <joint> [а окаменелости охраняются лаосским законодательством.]

However, researchers cannot give an exact age for the bones [since the place is a World Heritage site] <joint> [and the fossils are protected by Laotian law.]

Zoning errors are closely related to segmentation ones: there are examples in which an argumentative relation is based on segments that actually relate to a non-argumentation zone, as evidenced by the rhetorical context. In example (2) below, an argumentative relation is predicted that holds between the purpose segment and the following segment, which is incorrect: the corresponding rhetorical relation is *context* and annotators do not see any area of argumentation here. In the RST, subject matter relations are contrasted with textual presentational relations that facilitate the presentation process. The textual relations such as *elaboration, context, joint* are highly correlated with a larger argumentative segmentation and/or with belonging to the non-argumentation zone.

(2) Исследователи продолжают искать способ [вылечить или хотя бы смягчить симптомы болезни.] <context> [Команда ученых с участием НИУ ВШЭ детально изучила около 40 исследований за последние 20 лет] и предположила, как стимуляция мозга может влиять на целостность ГЭБ, в том числе при болезни Альцгеймера.

Researchers continue to look for a way [to cure or at least alleviate the symptoms of the disease.] <context> [A team of scientists with the participation of the Higher School of Economics has reviewed in detail about 40 studies over the past 20 years] and suggested how brain stimulation can affect the integrity of the BBB, including in Alzheimer's disease.

Errors in predicting the direction of argumentative relations which in the rhetorical representation correspond to subject matter relations such as *causal, purpose, explanation* linking adjacent segments or groups of segments. Most false-positive examples are found for adjacent segments within the same paragraph, when the direction of the predicted argumentative relation is erroneously opposite to the direction of the rhetorical link (in the examples below main segments predicted by the model are underlined).

*(3) [И вот на этом этапе кольцо "обиды" замыкается,] [**так как** публичное выражение обиды и оскорблённости направлено на вызов сопереживания других людей конкретно к вам и вашей ситуации,]*

*[And at this stage the circle of "resentment" closes,] [**since** the public expression of resentment and insult is aimed at evoking empathy from other people specifically towards you and your situation,]*

*(4) [«Во всем мире было проделано огромное количество теоретических и экспериментальных работ,] [**направленных на то, чтобы** понять, что происходит после поглощения фотона.]>*

*[“A huge amount of theoretical and experimental work has been done around the world] [**aimed at** understanding what happens after a photon is absorbed.]>*

*(5) [но некоторые данные о нейронах и глиальных клетках доступны.] [**Так**, [в [[исследовании]] китайских ученых сообщалось,] что магнитные импульсы могут оказывать нейрозащитный эффект.]*

*[but some data on neurons and glial cells are available.] [**For example**, [a [[study]] by Chinese scientists reported that magnetic pulses can have a neuroprotective effect.]*

In the examples given, *causal* (3)*, purpose* (4)*, and explanation* (5) subject matter dependencies are marked by the presence of corresponding discourse markers (highlighted in bold), which are characterized by certain positional characteristics (as indicator of argumentation causal *так как ‘since’* introduces a premise, and *поэтому ‘therefore’* introduces a conclusion, etc.). A combination of the described model with the indicator method (see [31]) would allow us to avoid most of these types of errors.

Errors in predicting long-distance relations. The segments are in different paragraphs or even in different sections of the article. Long-distance relations should not contradict short-distance relations, which is the case in (6).

(6) Результаты подтверждают оценки возраста окаменелостей, найденных ранее в пещере Там Па Линг, [но увеличивают хронологию этого места примерно на 10 000 лет.]

[Пещера находится более чем в 300 километрах от моря,] поэтому открытие предполагает, что наши мигрирующие предки не просто следовали вдоль побережья и островов в своем путешествии из Африки, но пересекали лесные районы и долины рек.

The results confirm age estimates for fossils previously found at Tam Pa Ling Cave, [but push the site's chronology back by about 10,000 years.]

[The cave is more than 300 kilometres from the sea,] so the discovery suggests that our migrating ancestors did not simply follow coastlines and islands on their journey out of Africa, but crossed forested areas and river valleys.

Errors in determining the role of the title. In view of the text organization characteristics, these errors can be considered a special case of the previous ones.

(7) [В лаосской пещере найдена кость человека возрастом 86 тыс. лет]

[В недрах лаосской пещеры ученые обнаружили самые ранние известные свидетельства того,] что наши человеческие предки пробирались через материковую часть Юго-Восточной Азии по пути в Австралию около 86 000 лет назад.

[86,000-year-old human bone found in Laotian cave]

[In the depths of a Laotian cave, scientists have discovered the earliest known evidence] that our human ancestors made their way across mainland Southeast Asia on their way to Australia about 86,000 years ago.

It can be assumed that one of the parameters that must be taken into account is the genre characteristic. Thus, in scientific articles, the last paragraph/heading is more likely to represent the main thesis - the conclusion, to which segments from other paragraphs should be connected as premises. In news articles, on the contrary, the headline may well be the premise – this is how annotators see it in (7).

7 Conclusion

In this paper, we investigate the role of rhetorical structures in the task of argument extraction. Two approaches are proposed and studied: the first one uses rhetorical structure in constructing vector representations of segments using GNN, and the second one uses multitask learning that combines argumentation extraction with rhetorical relations prediction.

The proposed solutions contribute to improving the quality of predicting argumentative relations, including connections between statements located at a significant distance from each other. The best quality was demonstrated by a model in which vector representations of statements were modified using a GNN and supplemented with information about the type of rhetorical relation, and achieved F1 = 72.32%.

This study was limited to predicting the relations between EDUs. In the future, it is planned to expand the approach by using methods that allow combining several EDUs into one argumentative statement. In addition, it is planned to study the role of rhetorical relations in the task of predicting argumentation schemes.

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