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MULTI-ASPECT ANALYSIS OF EMOTIONAL CONTEXT FOR TEXT DOCUMENT CATEGORIZATION

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КАТЕГОРИЗАЦИЯ ТЕКСТОВЫХ ДОКУМЕНТОВ НА ОСНОВЕ МНОГОАСПЕКТНОГО АНАЛИЗА ЭМОЦИОНАЛЬНОГО КОНТЕКСТА

The problem of texts intellectual analysis to identify their emotional context is considered. Presents the results of a review of modern approaches to the identifying emotions in texts problem, the key limitations and issues in processing complex linguistic constructions are outlined. A hypothesis is advanced: to increase the quality of digital texts categorization by emotional tone, it is necessary to account for semantic and pragmatic characteristics of their representation (sarcastic statements, emoji, contextual dependencies and other linguistic markers). A method for multi-aspect text analysis for document categorization based on identification of their emotional context is proposed. A multi-modular architecture of the method is presented, the principal component of which is a classifier built on a transformer-based language model. A description of the developed software tools using contemporary approaches is provided. The main results of computational experiments confirming the hypothesis and demonstrating the proposed approach effectiveness are discussed. Further steps for research are outlined.
Keywords: Natural Language Processing, Sentiment Analysis, Emotional Context, Document Categorization, Transformer-based Models, RoBERTa.

Рассматривается проблема интеллектуального анализа текстов с целью выявления их эмоционального контекста. Представлены итоги обзора современных подходов к задаче выявления эмоций в текстах, обозначены ключевые ограничения и проблемы при обработке сложных лингвистических конструкций. Выдвигается гипотеза: для повышения качества категоризации цифровых текстов по эмоциональному фону необходимо учитывать семантические и прагматические особенности их представления (саркастические высказывания, эмодзи, контекстуальные зависимости и другие лингвистические маркеры). Предложен метод многоаспектного анализа текста для категоризации документов на основе выявления их эмоционального контекста. Представлена многомодульная архитектура метода, основным компонентом которой является классификатор, построенный на языковой модели на основе трансформатора. Представлено описание разработанного программного средства с использованием современных подходов. Обсуждаются основные результаты вычислительных экспериментов, подтвердившие гипотезу и продемонстрировавшие эффективность предложенного подхода. Обозначены дальнейшие шаги для исследований.
Ключевые слова: обработка текста, сентимент-анализ, эмоциональный контекст, категоризация документов, трансформерные языковые модели, RoBERTa.

Introduction

Automatic text documents classification represents one of the most pressing and challenging tasks in modern computational linguistics. And when we consider contextual categorization (for example, emotional categorization), the task complication increases of the essence. In the context of exponential growth in textual information volumes across social networks, feedback systems, and digital communication platforms, there is an increasing demand for accurate and efficient methods of analyzing the emotional context of messages. Modern users of social networks and other digital communication tools actively share their thoughts, feelings, and experiences in online environments. Digital platforms daily serve as venues for exchanging textual messages and documents among millions of people. Automated analysis of textual emotional background enables businesses to understand audience sentiment, track trends, and respond to customer inquiries more quickly and effectively. An important aspect of the considered problem is that texts posted online can serve as indicators of mental health, providing opportunities to identify warning signals, depression, stress, and other issues.

Traditional approaches are often limited to simple categorization of positive and negative sentiments and consider only direct mood markers [1]. Traditional statistical methods, such as naive Bayes classifiers and support vector machines, demonstrate limited effectiveness when processing complex cases. These approaches are primarily based on analyzing the frequency of individual words or their combinations, which does not adequately account for contextual features and semantic dependencies [2]. The importance of considering emotional state in personality analysis and information processing has been the subject of numerous studies. For example, the paper [3] explores the problem of emotional expression and the multifaceted nature of its manifestation.

Natural language (NL) is complex and rich in nuances such as sarcasm, hidden meanings, metaphors, and subjective evaluations. Sarcasm and irony create contradictions between literal and implied meaning of statements, significantly complicating the interpretation of emotional content [4]. Contextual dependencies require analysis not only of individual lexical units but also their interaction within broader semantic structures. The emergence of transformer architectures such as BERT and RoBERTa has opened new possibilities for solving Natural Language Processing (NLP) tasks due to their ability to model long-term dependencies and contextual connections [5]. Contemporary research demonstrates high effectiveness of deep learning methods for emotion recognition in texts. However, even these advanced models experience difficulties when working with Russian-language texts containing sarcasm, mixed emotions, or non-standard methods of emotional expression. Analysis of the current state of the field shows the necessity of developing a comprehensive approach that combines the advantages of deep learning with specialized methods for processing complex linguistic constructions. Experience in applying various ensemble and multi-aspect text analysis methods for identifying implicit characteristics in solving various applied tasks has shown the effectiveness of such a comprehensive approach [6].

The key idea constituting the theoretical foundation of the work is the development and application of a multi-modular approach to emotional context analysis. Substantial improvement in emotion classification efficiency is proposed to be achieved through combining such key methodological components as sarcasm processing, emoji analysis, and identification of contextual features [7]. The research assumes critical importance of integrating specialized components for processing complex linguistic phenomena characteristic of modern digital communication. An important role in analyzing texts from internet sources today is played by accounting for emoji that accompany the text itself. The emoji analyzer represents an important component of emotion analysis that allows considering the semantic load of graphic symbols and their interaction with textual content [8]. The theoretical rationale behind the proposed approach arises from the insight that contemporary texts are characterized by multilayered emotional expression and employ a wide variety of linguistic means, including nonverbal elements. Conventional approaches to emotion analysis, which rely either on straightforward lexical classification or basic neural network architectures, prove insufficient for effectively capturing the complexity and richness of modern emotional expression in texts. Integration of global analysis covering the entire textual document as a unified semantic structure for identifying dominant emotional orientation with local analysis focusing on detailed investigation of emotional coloring of individual text sentences or other smaller fragments is proposed.

The main hypothesis underlying this work is the possibility of significantly improving the accuracy of determining emotional coloring in text through combined application of specialized components for processing various text features.

1 Text Analysis Method using Transformer-based Model

A method for multi-aspect analysis of NL texts is proposed to determine the spectrum of emotions in the analyzed texts. The method is based on a multi-module architecture that includes the following major components: an emotion classifier, an emoji analyzer, a sarcasm detector, a contextual analyzer, and a compositional mechanism. The interaction between components is organized according to the principle of sequential modification of the base emotion vector, considering additional factors revealed at each stage of analysis (Figure 1). The key component of the proposed method is the emotion classifier. The classifier involves using a transformer-based model that implements the modern RoBERTa encoder architecture [9]. The encoder architecture was specially adapted and additionally trained for solving emotion recognition tasks in texts. Transformer models demonstrate effectiveness in multilingual emotion analysis tasks [10].

Text input to the RoBERTa classifier undergoes preprocessing. After cleaning and normalization, tokenization is performed using the RoBERTa Tokenizer tool, ensuring preservation of text structure and its contextual connections. Using the «Byte Pair Encoding» text segmentation algorithm allows the model to effectively process rare or unknown words by breaking them into more understandable and frequently occurring parts, helping the model work with a sufficiently wide range of texts.

The model is trained to recognize nine emotional states: eight basic ones (wariness, delight, admiration, horror, astonishment grief, disgust, and anger) as well as a neutral undefined state. For training the developed model the modern AdamW optimization algorithm is applied, representing an improved version of the classic Adam optimizer with correct implementation of weight decay. This algorithm demonstrates high characteristics in transformer architecture training tasks due to its ability to effectively manage the gradient descent process when working with high-dimensional parameter spaces. AdamW ensures accelerated model convergence to optimal parameter values through adaptive learning rate management for each parameter individually, allowing the model to more effectively adapt to complex patterns in data [11].

The emoji analyzer component (step 2 in Figure 1) represents a classifier of emoji symbols identified in the text. Each emoji symbol is matched with a predetermined dictionary where each symbol is assigned a specific emotional category. Thus, coefficients for correcting the basic emotion vector are formed. When calculating the contribution of emoji to the document's emotional context, not only quantitative indicators are considered, but also their application methods (combinations, placement throughout the text, etc.).

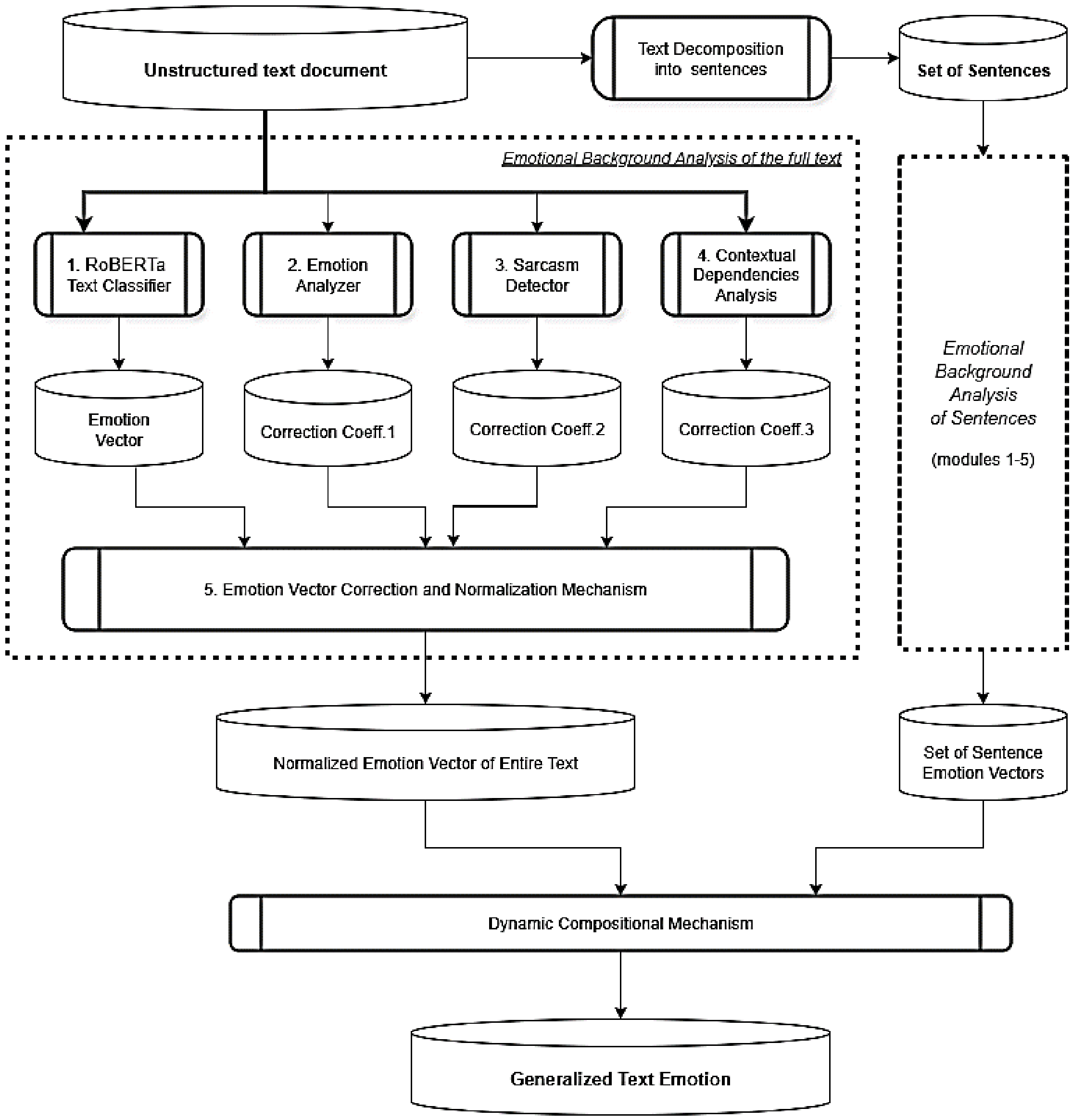

Figure 1. General structural scheme of the proposed method.

The sarcasm detector is based on recognizing characteristic linguistic patterns typical of sarcastic statements [12]. At this stage, a dictionary of markers and typical features is used, including special intensification markers. To identify sarcasm features, sentence structure analysis and syntactic analysis of punctuation mark combinations are performed. All identified sarcasm features are combined using weighted evaluation, where the weight of each feature is determined based on its statistical significance for sarcasm detection. With high sarcasm probability, emotion vector inversion or its substantial modification is possible. The contextual analyzer serves to identify logical and emotional connections between sentences – how they develop, strengthen, or change the emotional line of the text.

Contextual analysis plays a key role in modern NLP systems. The obtained set of coefficients is applied to the emotion vector for correction.

The final component of the developed architecture is the compositional mechanism, representing an intelligent system for synthesizing results. This mechanism functions as a central coordination node, ensuring mathematically justified combination of results from all specialized system components into a unified holistic and consistent assessment of the emotional context of the analyzed text. The compositional mechanism implements multilevel logic for weighting and integrating heterogeneous factors identified at previous analysis stages, including basic emotional vectors from the transformer model, corrections from the sarcasm detector, modifications from the emoji analyzer, and contextual adjustments from the specialized contextual analyzer. A key feature of this mechanism is its ability for adaptive management of weight coefficients depending on the characteristics of the specific analyzed text and the confidence level of each system component. The overall emotion score of a text is calculated as a weighted sum of all emotion vectors and their weighting coefficients. The weighting coefficients are determined based on the confidence of the classifiers. A distinctive feature of the compositional mechanism is the implementation of a dynamic weight coefficient correction system based on confidence metrics of individual classification components. This software functions according to the principle of adaptive trust, where components demonstrating high confidence in their predictions (determined through analysis of output vector probability distributions) automatically receive increased weight coefficients in the process of forming the final assessment.

After completing all stages of correction and composition of results, a procedure for normalizing the final emotion vector is performed. This operation is carried out using L1-normalization. The normalization procedure incorporates additional measures ensuring mathematical correctness, specifically by verifying the absence of negative values, controlling numerical stability throughout operations, and addressing specific edge cases like zero or infinite vector component values. The final normalized emotion vector represents the ultimate product of the entire analytical system, embodying a comprehensive multi-factor assessment of the emotional context of the analyzed textual document. This vector integrates the results of basic transformer classification, specialized processing of sarcasm and irony, semantic analysis of emoji and graphic elements, contextual analysis of linguistic features, and considers all identified factors of emotional expressiveness and communicative characteristics of the source text.

2 Software Tools for Emotional Background Detection

The proposed models and methods are implemented in the form of a specialized software tools. The developed software represents a comprehensive system for automated analysis of textual data emotional context, built on principles of modular architecture and modern approaches to NLP. The software is implemented using the Python programming language and integrates advanced machine learning libraries and NLP tools to ensure high precision in emotion classification.

The technical foundation of the software is based on the PyTorch framework, which enables efficient work with transformer architectures and support for graphics processing unit (GPU) computations to accelerate training and inference processes. Integration with the Transformers library from Hugging Face provides access to pre-trained RoBERTa models and tools for their fine-tuning for specific emotion classification tasks. For loading and executing the transformer model, performing emotion classification in text, text tokenization, manipulation of emotion vectors, and carrying out mathematical operations, libraries such as PyTorch (torch), Transformers, nltk, NumPy and scikit-learn (sklearn) were employed. For working with emojis, specifically for extraction and identification of emojis in text, the Emoji library (emoji) was used. Methods from the tqdm and Matplotlib libraries (tqdm, matplotlib) were also used for visualization of the training process and presentation of analysis results. The software tool is organized as a set of interconnected modules, each responsible for a specific aspect of textual data processing and analysis.

The data preprocessing module performs normalization of input text, including cleaning from irrelevant symbols, correction of common typos, unification of emoji and special symbol representation. Tokenization is performed using RoBERTa Tokenizer, which ensures correct text splitting while maintaining semantic integrity.

The main classification module represents a system component that implements the interaction logic with a modified RoBERTa transformer architecture that has undergone specialized additional training for multi-class emotion classification tasks within eight target categories of the emotional spectrum. RoBERTa-type models, considering their size and complexity, require significant computational resources, especially when training on large datasets. It was considered when designing the software architecture. The classification module includes numerous functional capabilities: automated mechanisms for loading and initializing pre-trained model weight parameters, a system for performing inference procedures on new input textual data, generation of multidimensional probabilistic vectors of emotional states with accompanying quantitative metrics of reliability and confidence of classification decisions. The module provides dynamic computational resource management, automatic determination of optimal execution device (CPU or GPU), and implements exception handling mechanisms to ensure system stability under various operating conditions.

The emoji analysis module implements semantic matching of graphic symbols with textual content based on the CLIP model. The component extracts emoji from text, calculates their semantic proximity to textual content through cosine distance in vector space, and generates corrective coefficients for the basic emotional vector.

To identifying sarcastic statements, a combination of linguistic rules and statistical patterns is used (the "sarcasm detector" module). To context analysis dictionaries of linguistic markers and rules for their combination are used to generate contextual corrections.

The software tools provide several interaction interfaces for various usage scenarios. The following operating modes are supported: real-time mode for analyzing individual messages with minimal delay; batch mode for processing large document collections with performance optimization; and continuous monitoring mode for analyzing streaming data from social networks or other open external sources.

The software architecture ensures a high degree of configurability through a system of configuration files in JSON and YAML formats. Users can configure weight coefficients of various components, threshold values for sarcasm detection, emotional marker dictionaries, and other system parameters without the need to modify source code. The software tool configuration allows organizing assembly for efficient operation on both personal computers and high-performance server systems. GPU acceleration support through CUDA provides significant acceleration of analysis processes when working with large data volumes. The software includes mechanisms for caching intermediate results and memory optimization for processing long texts and large data batches. The architecture supports horizontal scaling through distributing computational load among multiple worker processes or servers, allowing the application to be adapted to various performance requirements and volumes of processed data.

3 Computer Experiment and Discussion

To evaluate the effectiveness of the proposed method and the software developed based on it, a computer experiment was conducted. Within the framework of the experiment, the task was set to assess the proposed approach in comparison with existing classification methods, models, and services.

For conducting the experiment, a specialized dataset «ru_go_emotions» was used, containing annotated Russian-language texts with emotional categories [13]. Additionally, a test sample was formed from social network comments that includes examples of sarcasm, metaphorical expressions, and ambivalent statements. Such a dataset is indicative for evaluating the method's capabilities to handle ambiguous cases. The experiment was conducted on a sample that included 1000 randomly selected texts from the «ru_go_emotions» dataset. For each text from the set, emotional context assessment was performed using two software solutions:

– A service based on the modern generative language model GPT;

– Software based on the proposed multi-aspect emotional context analysis method.

To ensure correctness of result comparison, adaptation of the dataset classification scheme to the "Flower of Emotions" model variation using a palette of eight emotions, which was used in this work, was performed. Evaluation was carried out by comparing predictions of each solution with expert annotations of the dataset.

Detailed analysis of prediction distribution revealed fundamental differences in architectural approaches and methodological principles of the two systems for solving multi-class emotion classification tasks, demonstrating critical limitations of universal generative models and advantages of specialized emotional analysis systems. GPT demonstrated serious problems with classification balancing, manifested in extremely uneven distribution of predictions across emotion categories (Table 1).

Table 1 – Number of detected documents (for each of selected emotion)

Emotion	Expert assessment	GPT Service	Software of the Proposed Method
Wary	147	443	51
Delight	168	383	62
Admiration	291	56	70
Horror	117	0	287
Astonishment	72	5	298
Grief	68	17	124
Disgust	90	50	68
Anger	47	46	33

At the same time, the software proposed in this work demonstrated a fundamentally different classification paradigm based on deep understanding of emotional structure and specialized balancing algorithms. A significant achievement of the developed approach is the complete elimination of classification "dead zones" characteristic of GPT. The phenomenon of absolute ignoring of the horror emotion (zero detections from the dataset) by GPT represents a fundamental architectural problem of generative model’s incapable of adequate categorization of intense negative emotional states.

The series of experiments allows concluding that the software complex presented in this work demonstrated superiority over the modern generative GPT model. On the test sample of thousand texts, the authors’ method achieved a classification accuracy of over 56 percent, which is eighteen percentage points higher than GPT's performance (with GPT achieving thirty-eight percent). Various non-trivial cases were examined: sarcastic use of emoji and negation of reliability, mixed emotions and technical terminology, mixed emotions in long text, contradictory emotions in short sentences, and others (Table 2).

Coefficient of variation – a dimensionless indicator, calculated as the ratio of standard deviation to the arithmetic mean of the number of predictions across 8 emotion classes. Standard deviation – measured in the number of predictions, shows the absolute spread from the mean value of 125 predictions per class. Herfindahl concentration index – a dimensionless indicator from 0 to 1, calculated as the sum of squares of each class's proportions, shows the degree of prediction concentration. Maximum deviation from uniformity – represents the largest deviation of any class proportion from the ideal uniform distribution of 12.5% for 8 classes (measured in percentages).

Table 2. Detailed analysis of four key statistical metrics.

Metric	GPT-based Approach	Proposed Approach	Enhancement
Coefficient of variation	0.89	0.31	x 2.8
Standard deviation	128.4	37.2	x 3.5
Herfindahl concentration index	0.26	0.13	x 2
Maximum deviation from uniformity	22.8%	6.4%	x 3.5

The conducted experiments validated the efficacy of the proposed method in handling diverse configurations of complex texts across multiple datasets. For example, when analyzing text with heavy emotional context. In this case, the GPT model showed uncertain classification with low probabilities, while multi-aspect analysis correctly determined the final emotion value as the negative emotion of sadness with confidence of seventy-eight hundredths. "Sarcasm Detector" module showed remarkable effectiveness in handling complex cases. Specific test scenarios included the use of quotation marks around keywords, ironic juxtapositions, and inconsistencies between positively phrased sentences and negatively connoted emojis.

The results indicate substantial progress in solving the task of automatic emotion classification in texts. The achieved accuracy improvement of approximately thirty percent compared to commercial solutions demonstrates the effectiveness of a specialized approach for specific NLP tasks. Comparison with commercial solutions reveals advantages the research approach's superior accuracy in processing complex linguistic constructions. Commercial products often use simplified algorithms to ensure high processing speed, which negatively affects the quality of analysis of non-standard cases.

The developed software showed high effectiveness in working with hidden emotional contexts, the ability to distinguish neutral declarative tone from emotionally colored. The tool demonstrates the capability to accurately determine the overall emotion of a text and its variations, even in cases where individual sentences yield conflicting analyses. The ability to correctly interpret conflicts between textual content and graphic elements is critically important for analyzing messages in Social Net and messengers, where such contradictions occur regularly. Experimental validation confirms the feasibility of the proposed approach to adaptive adjustment of initial predictions based on contextual factors. Particular attention was paid to analyzing stability with rare emotion classes and performance indicators in scenarios where emotions overlap or are distributed among different parts of the text.

It's important! Limitations of the method are related to the computational complexity of transformer architectures and the need for significant resources for training.

Conclusion

Application areas of the developed method include social media monitoring systems for public opinion analysis and identification of potential crisis situations, e-commerce platforms for automatic customer review analysis and service quality improvement, psychological support systems for early detection of some mental disorders through text messages analysis, and content moderation tools for automatic identification of aggressive or destructive messages.

The scientific results of this research work include the development of a specialized sarcasm detector for Russian-language texts, integration of an emoji analyzer based on the CLIP model for semantic matching of graphic symbols and textual content. The hypothesis about the effectiveness of using multi-aspect text analysis to improve the quality of document categorization was experimentally confirmed. The developed architecture can serve as a foundation for creating more complex NLP systems with in-depth analysis of human emotions and intentions. The obtained results open perspectives for further development of emotion analysis methods toward supporting multilingualism, integrating additional modalities, and expanding the spectrum of recognizable emotional states.

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RESUME

A. I. Paramonov, K. A. Pavluchenko

Multi-Aspect Analysis of Emotional Context for Text Document Categorization

Background: Traditional sentiment analysis methods are limited to simple positive/ negative categorization and fail to adequately process complex linguistic constructions. Statistical approaches like naive Bayes and support vector machines demonstrate limited effectiveness due to their reliance on word frequency analysis without accounting for contextual features and semantic dependencies. Modern texts contain nuanced elements such as sarcasm, mixed emotions, emoji, and contextual dependencies that significantly complicate emotional content interpretation.

Materials and methods: A multi-aspect text analysis method is proposed, based on a multi-modular architecture integrating specialized components: an emotion classifier built on the RoBERTa transformer-based model trained to recognize nine emotional states, an emoji analyzer using the CLIP model for semantic matching of graphic symbols with textual content, a sarcasm detector based on linguistic patterns and statistical markers, a contextual analyzer for identifying logical and emotional connections between sentences, and a compositional mechanism for intelligent synthesis of results through weighted combination of all components. The software implementation uses Python with PyTorch, Transformers library, and AdamW optimization algorithm. Evaluation was conducted on the ru_go_emotions dataset containing 1000 annotated Russian-language texts.

Results: The proposed method achieved classification accuracy of 56%, exceeding the GPT-based commercial solution by 18 percentage points (GPT: 38%). Statistical analysis revealed significant improvements: coefficient of variation decreased 2.8-fold, standard deviation improved 3.5-fold, and Herfindahl concentration index improved 2-fold. The method demonstrated complete elimination of classification "dead zones" characteristic of generative models, successfully handling complex cases including sarcastic emoji usage, mixed emotions in long texts, and contradictory emotions in short sentences.

Conclusion: The computational experiments validated the effectiveness of combining neural network models with postprocessing algorithms for emotional context analysis. The method successfully accounts for subtle aspects of natural language including contextual

mentions, sarcasm, and ambiguous cases. The developed architecture provides a foundation for creating advanced natural language understanding systems with in-depth emotion and intention analysis, with applications in social media monitoring, e-commerce review analysis, psychological support systems, and content moderation tools.

РЕЗЮМЕ

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Категоризация текстовых документов на основе многоаспектного анализа эмоционального контекста

В данной статье разработан метод многоаспектного анализа текстов на естественном языке для определения спектра эмоций в анализируемых документах на основе многомодульной архитектуры. Предложена архитектура, включающая классификатор эмоций на базе трансформерной модели RoBERTa, анализатор эмодзи с использованием модели CLIP для семантического сопоставления графических символов с текстовым содержимым, детектор сарказма на основе распознавания характерных лингвистических паттернов, контекстуальный анализатор для выявления логических и эмоциональных связей между предложениями и композиционный механизм для интеллектуального синтеза результатов всех компонентов системы. Разработано программное средство с использованием языка Python, библиотек PyTorch и Transformers, алгоритма оптимизации AdamW. Проведены вычислительные эксперименты на датасете ru_go_emotions, содержащем 1000 аннотированных русскоязычных текстов. Результаты экспериментов показали точность классификации 56%, что превышает показатели коммерческого решения на основе GPT на 18 процентных пункта. Коэффициент вариации улучшен в почти 3 раза, стандартное отклонение – в 3,5 раза, а индекс концентрации Херфиндаля – в 2 раза. Метод продемонстрировал полное устранение «мёртвых зон» классификации и эффективную обработку сложных случаев, включая саркастическое использование эмодзи, смешанные эмоции в длинных текстах и противоречивые эмоции в коротких высказываниях. Разработанные модели и методы позволяют решить задачу повышения качества категоризации цифровых текстов по эмоциональному фону за счёт учёта семантических и прагматических особенностей их представления и могут быть использованы в системах мониторинга социальных сетей, анализа отзывов в электронной коммерции, психологической поддержки и модерации контента.

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