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Metric for evaluating mathematical models natural language words for machine translation

Muftakh Khakimov

[1]*Mirzo Ulugbek National University of Uzbekistan, Uzbekistan.*

(*Email:* muftakh@gmail.com)

Abstract

The purpose of this study is to describe and analyze a new metric for evaluating the effectiveness of mathematical models of natural language words based on an extensible input language in machine translation. A new SSM (Structural Semantic Metric) metric has been developed and researched, the methodology of which includes a description (requirement, calculation principle, analytical model, calculation algorithm) and group experiments on six types of mathematical models of words in three natural languages (Uzbek, English, Russian). The metric is implemented in Python, the software products at the input accept a mathematical model represented as a string of characters of an extensible input language, and at the output numerical values for the formula parameters and a general metric estimate. The result of the metric is a numerical value in the range of 0 and 1. A gradation of degrees of reflection of the structural and semantic relationships of mathematical models relative to the range of 0 and 1 is recommended. The experiments obtained prove the high semantic adequacy of mathematical models with reference structures of words in each of the natural languages, which can provide a very high degree (90% - 95%) of translation of words used in machine translation texts between the above languages in 6 directions. The results also highlight the possibility of expanding the model base with new mathematical models of natural language words using this methodology.

Keywords: English, Evaluation, Extensible input language, Machine translation, Mathematical model, Natural language, Russian language, Semantics, SSM metric, Terminal symbol, Uzbek language.

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1. Introduction

Machine translation (MT) currently plays an important role in the modern world. It is used for automatic translation of texts of various kinds – scientific, artistic, official business, journalistic and colloquial, as well as for instant translation of oral speech. Progress in natural language processing and machine learning is making MT more and more accurate, but there are still significant difficulties in conveying the context and preserving the stylistic features of the original text [1].

MT systems have become firmly embedded in everyday life, becoming one of the main tools of interlanguage communication in all spheres of life. The development of globalization and internationalization contributes to the growing demand for high-quality translation of texts of various orientations. The traditional approach to translation involving qualified translators requires significant time and financial resources, which makes automated solutions increasingly attractive [2]. Modern MT systems can significantly reduce information processing time, automate real-time translation and process large amounts of data, which ensures their use in a wide range of tasks, from localization of websites and mobile applications to translation of technical and scientific documentation. Despite significant progress in this area over the past 20 years, current systems still face challenges related to translation accuracy and quality. The lack of contextual awareness, the inability to correctly interpret idioms and stable expressions, lead to incompleteness and incorrect translation.

Optimization of the MT process also helps to increase the availability of information resources for people who do not speak foreign languages and allows all structures to effectively communicate with an international audience. It has been proven that the integration of such systems into business processes increases labor productivity, reducing the need for manual work with content translation. Thus, improving the efficiency of MT systems is an important task in the modern world, as it not only improves the accuracy and quality of translations, but also provides a wider range of information access, simplifying communication at the global level.

Improving the efficiency of MT systems is necessary to overcome existing disadvantages. This includes improving text processing algorithms and introducing new quality assessment metrics for translation models. The development of more reliable quality assessment metrics for translation models will allow us to create high-quality machine translations that can more accurately convey the meaning and context of the source text.

The MT should not only convey the meaning of the source text, but also preserve its stylistic features, context and intonation. Achieving these goals involves improving models and, accordingly, text processing algorithms, adapting systems to different styles and developing more accurate metrics for evaluating the quality of word and sentence processing models that will lead to high-quality automatic translation. To achieve a high level of quality and efficiency, MT systems must use advanced natural language processing techniques, including traditional NLP, LLM, deep learning, and neural networks instead of formalized models. Due to the difference between these technologies, it is possible to identify and correctly convey complex contextual and semantic features of the source text.

Meanwhile, one of the approaches to solving the problem of high-quality translation, in our opinion, is the formalization of natural languages, building a system of linguistic, logical and mathematical models of words and sentences [3-5] that accurately convey the structure and semantics of words in a language using an extensible input language. Extensible Input Language (EIL) is an artificial language developed by the author of this article, the main purpose of which is to formalize natural languages and transform them into formal logical structures.

"EIL is designed to present expressions and concepts of natural language in a form that computers can understand. It serves as a link between natural language and logical formal systems. The main characteristics are:

Extensibility. The language can easily perceive and expand new concepts and structures;

Formalism. Expressions in natural language are presented in a logical and structured form, with clear and single meaning.

Ease of mutual understanding between humans and machines. Although this language is understanddable to computers, it was also designed to be read and understood by humans.

Linguistic versatility. The language is designed to create a common logical framework between different natural languages.

Fields of application – automatic machine translation. Logical analysis and modeling of knowledge;

Semantic network, ontologies.

1.2. Intelligent Information Systems

Focused automatic translation is a method of automatic translation based on the composition of syntactically and semantically important (focus) components with weighting coefficients, through which the influence on improving the accuracy of the translation of the input sentence is carried out. This method is based on logic and computable models of EIL. EIL based models have theoretical advantages through the rules of logical formation and the focus task of syntactic analysis" [6].

Mathematical models of words and sentences should be carefully evaluated beforehand to ensure that they fully reflect the structure and semantics of the language.

Thus, the urgent task is to develop new metrics that take into account the peculiarities of words and sentences in the colloquial, artistic, journalistic, scientific and official business style of the text, as well as the creation of software for automated translation analysis. The purpose of this paper is to describe a new metric for evaluating the quality of mathematical models of words that will help achieving more accurate machine translation close to human translation.

To achieve this goal, it is necessary to conduct a comparative analysis of existing metrics, identify their advantages and disadvantages and propose a developed metric that takes into account the features of different languages and their models.

2. Materials and Methods

2.1. Research Overview

Modern MP systems allow you to process large amounts of data and speed up communication between people, but they do not always accurately interpret the meaning of the source words and sentences. However, evaluating the quality of machine translation is one of the key tasks in the development of natural language processing systems. To date, there are about 100 active indicators that are automated to assess the quality of translation. We will look at the most well-known indicators in terms of their ability to evaluate the quality of mathematical models of words before proceeding with the machine translation process.

The BLEU metric (Bilingual Evaluation Understanding) is one of the first automated metrics for evaluating translation quality. It is based on a comparison of the n-grams present in the translation and the reference text made by a human. The BLEU assessment system has become widespread due to its simplicity and effectiveness. However, it also has drawbacks, the metric does not take into account the context, sentence order and semantic connections between phrases [7-10].

Metrics of the ROUGE class (Recall-Oriented Understanding for Gisting Evaluation) were developed to evaluate automatic text abstraction, but they also found application in evaluating the quality of machine translation. The most well-known metric is ROUGE-N, which measures the number of n-gram matches between the translated text and the reference. The ROUGE-L metric evaluates the longest Common LCS sequence, which makes it possible to identify the global structure of the text. ROUGE-S measures the presence of a common Skip intersection (Skip-Bigrams), which gives flexibility in evaluating word permutations. ROUGE-1, based on the matching of unigrams (individual words), offers a simple but informative assessment of translations. ROUGE-1 is effective in analyzing a large number of texts, maintaining a balance between accuracy and completeness. Despite the advantage in flexibility, all metrics of the ROUGE class do not always accurately reflect the meaning of the source text [7, 11].

The METEOR metric (Metric for Evaluation of Translation with Explicit Ordering) was created to overcome the disadvantages of BLEU and ROUGE. It takes into account the coincidence not only by the exact match of n-grams, but also by root forms, synonyms and spelling variants of words, allowing for a more detailed assessment of the quality of translation, according to several parameters, including synonyms, morphology and takes into account the correct sequence of words. METEOR also includes penalties for reordering words to more accurately reflect semantic proximity to the original text. This makes the metric one of the most adaptive to different languages [7, 12, 13].

The TER (Translation Edit Rate) metric measures the number of changes required to bring the translation fully in line with the benchmark. Changes include adding, deleting, reordering, and replacing words. However, this metric can be difficult to interpret due to the difficulty of identifying all possible variations [14].

The ChrF (Character F-measure) metric is based on symbols. It measures the matching of characters and substrings in the translation and the reference. This approach is especially useful for languages that are not based on the Latin alphabet. ChrF is advantageous for languages where word segmentation is complex, i.e. morphologically rich languages [14].

The combined Phrase Custom AI metric consists of several automated metrics for evaluating the quality of machine translation – BLEU, TER, ChrF and COMET, where each of the metrics, taking into account various aspects of translation, plays a role in improving the quality of translation, which leads to a reduction in post-editing time [9].

The NIST (National Institute of Standards and Technology) metric is used to assess the proximity of two texts. In the NIST calculation, each word and phrase match (n-gram) in machine translation and in the reference is assigned a certain weight, depending on the frequency of occurrence of this n-gram in the language into which the translation was performed [13].

The COMET metric (Cross-lingual Optimized Metric for Evaluation of Translation) is a new generation metric used to evaluate automatic translation models. In particular, transformer and neural mode models are used. It is possible to work on other platforms [15].

The LEPOR (Length Penalty for Ordered Word) metric is used to evaluate the quality and accuracy of translation, it takes into account the correct sequence of words and accuracy [15].

GLUE (General Language Understanding Evaluation) is a standardized set of diverse natural language processing (NLP) tasks for evaluating the effectiveness of various language models [16].

The RIBES metric (Rank-based Intuitive Bilingual Evaluation Score) is used as an alternative version of the BLEU metric. It calculates the order between the translated and reference text [13].

The SARI (Sentence-level Alignment-based Re-ranking Evaluation) metric is based on the context of the test and has a great adaptability. It takes into account the processes of new adapted words [17].

The BERTScore metric is adapted to the BERT architecture and is aimed at analyzing semantic correspondence and context [15].

WMT (Workshop on Machine Translation) metrics is a "work store" that offers special metrics for various types of translation models, such as BLEU, TER, METEOR, ChrF/ChrF++, BERTScore, COMET and BLEURT. Since 2020, the COMET and BLEURT neuron-based metrics functioning in WMT have proven to have a high correlation with human scores [8].

Thus, each of the metrics is distinguished by its own field of application and a specific approach to evaluation. While some metrics are focused on the accuracy of transmitting n-grams or characters, others seek to identify global semantic structures of the text. However, they are not able to fully assess the semantic and contextual correspondence of the translation. This leads to situations where a grammatically correct but semantically incorrect translation can be highly appreciated. Existing metrics are not always able to correctly evaluate different text styles, such as colloquial, artistic, or scientific. Evaluating the quality of translation in such genres requires a deeper analysis of the context and stylistic features, which are not always available through comparing n-grams or words. Key problems and limitations of existing metrics include contextual and semantic insufficiency, ignoring word order, the impact of translation length, and a limited number of reference translations. Meanwhile, each of the above metrics has unique advantages and is able to identify different aspects of translation. Their combined use provides a comprehensive and reliable assessment, taking into account both the lexical and structural characteristics of the translation. Modern MT systems often combine several metrics to provide a more objective assessment of translation quality.

As can be seen from the above analysis of the literature, only the new generation COMET metric can be used to evaluate automatic translation models using transformer and neural mode models. But the transformer models, and even more so the neural mode, have nothing to do with RVN, and even more so with models of any type based on it.

This proves that it is impossible to use the COMET metric to evaluate mathematical models based on RVN. By virtue of the above, it follows that it is necessary to develop new metrics that evaluate the models of words and sentences themselves, which include morphological, semantic, stylistic and basic aspects of words and sentences that will adapt to different genres of text and perform better automatic translations.

Such models should be evaluated prior to the implementation of the automatic translation process, regardless of the instrument on which they are presented, which will ensure high-quality machine translation.

2.2. Description of the SSM Metric

Requirement. The SSM (Structural Semantic Metric) metric is necessary to evaluate mathematical models of words by the types of words expressed in English. The models are designed to describe the structural and semantic characteristics of natural languages. As natural languages, we will consider the agglunative, inflectional, and West Germanic groups of Germanic languages written in the Latin and Cyrillic alphabets.

The metric can operate with formulas that have a special form and are written in English as a sequence of terminal symbols. Terminal symbols include symbols that function on the PC.

The principle of calculation. In this way, metrica can work with consecutive characters, breaking them down into separate parsings. Next, it analyzes each parsing in accordance with the metric formula and performs appropriate calculations for each parameter of the formula.

There are 5 main parameters in the formula, each parameter is calculated according to the specified conditions. The arithmetic mean of these parameters is calculated.

Penalties are determined depending on whether a natural language belongs to its category, for example, for models of agglunative languages, a penalty score of 0.03 is applied, and for models of other languages, a "soft" sanction of 0.015 points is applied.

In the end, the metric value is calculated. The metric value is in the range [0, 1]. Table 1 shows the estimates of the structural and semantic connections of the word.

Table 1.
Gradation of grades according to the SSM metric.

Min SSM value	Max value of SSM	Is the degree of reflection of the structural and semantic relationships of mathematical models
0.90	1.0	Accurate
0.80	0.899	Good
0.75	0.799	Medium
0.65	0.749	Weak
0.499	0.644	Not Satisfactory

2.3. The Analytical Model

The formula of the SSM metric that evaluates the structural and semantic relationships of mathematical models of words has the following form (1):

$$\text{SSM} = (\text{Mor} + \text{Sq} + \text{Mav} + \text{Qb} + \text{Muk}) / \text{Count} - \text{Penalty} \qquad (1)$$

where Mor – it takes into account the base of the word according to condition (2); Sq is a structural parameter that examines the depth of the word and takes into account all additions, prefixes, suffixes calculated by formula (3); Mav is a structural parameter that takes into account the complexity of all additions, calculated by formula (4); Qb is a parameter that takes into account all links to word addition databases are calculated using the formula (5); Muk is a parameter that takes into account the complexity of the word composition; Count is the number of parameters Mor, Sq, Mav, Qb and Muk that are not equal to 0. Penalty is a parameter that takes into account "penalties" for complexity or a large number of additions, calculated using the formula (6).

The condition for determining the value of the parameter could:

$$\textbf{Mor} = \begin{cases} \textbf{1}, & \text{if the base of the word is taken into account} \\ \textbf{0}, & \text{otherwise} \end{cases} \qquad (2)$$

The formula for determining the value of the Sq parameter:

$$\text{Sq} = \frac{(a_1 + a_2 + \dots + a_n)}{\text{n}} \qquad (3)$$

where, a1, a2, ... are all types of affixes included in the mathematical model of the word. If the mathematical model is designed for an agglunative language, then a1=1.00, a2=1.05, a3=1.1 ... and Sq gets the arithmetic mean of n terms.

And for mathematical models of words in other natural languages, prefixes and prefixes starting with the terminal letter "T", suffixes starting with the terminal letter "C", prepositions starting with the letter "D", conjunctions ("Y"), interjections ("E"), modal words ("L") and any other additions – each of them gets a value of 0.65, which is determined by expert analysis, and then their arithmetic mean (Sq) is calculated. If there are more than two bases of a word in the model, then everything except the first one is counted as an addition.

The condition for determining the value of the Mav parameter:

a) in the mathematical model of a word, if the type of the word and/or the base of the word is specified, the value 1.00 is applied. The type of the word or the base of the word begins with the following terminal characters "C", "P", "G", "M", "N", "F", "K".

b) in the mathematical model of a word, the total number n of each terminal sign ↓ is calculated, indicating that the element of the word following it will either be present or not. The formula for calculating the Mav parameter has the following form:

$$\text{Mav} = \frac{1.00 + 1.05 * n}{n+1} \qquad (4)$$

The Qb parameter calculates the average weight of terminal signs based on their total number m. In this case, terminal characters starting with the $ sign are taken into account, for example, $[i,1-5], indicating that there is a choice from the word complement database, i.e. there is a semantic connection with various word additions by type. The formula for calculating terminal signs (5) has the following form:

$$\text{Qb} = \frac{\sum_{k=1}^{m}(1.00+0.05*k)}{m} \qquad (5)$$

The Muk parameter calculates the semantic complexity of the mathematical model, i.e. it calculates the arithmetic mean of the participants in the operation ⊕.

The Penalty parameter is calculated relative to the total number of all word additions (Qs) in the mathematical model, according to the following formula:

$$\text{Penalty} = \lambda * \max(0, \text{Qs} - 3) \qquad (6)$$

If the Penalty value = 0, then, for mathematical models of words of agglunative languages, it gets a value of 0.03, and for other mathematical models of words of natural languages it gets a value of 0.015. The value of λ equal to 0.055 balances penalties for each addition to a word, especially in mathematical models of words of agglunative languages, and for other mathematical models of words of natural languages it gets a value of 0.015. All of the above values have been determined experimentally.

The Qs variable calculates the total number of parsings that start with the following terminal characters EIL: A – all types of affixes, or for example C(A) – noun affix; B – postfix, D – preposition, G(?) – here the sign is ?, this is any terminal letter, P3 – participle 1, P4 – participle 2, K - root, D4 - article, D5 – imprecise article, M3 – demonstrative pronouns and their affixes, M4 – interrogative pronouns and their affixes, M5 – determinative pronouns, M6 – negation pronouns, M7 – indefinite pronouns, M8 – morphemes, M10 – subject pronoun, O – ending, S – suffix, SF – suffixes forming words, T – prefixes and prefixes, U – particles, X – all kinds of suffixes, Z – suffixes of singular numbers. If there are more than two bases of a word in the model, then everything except the first one is counted as an addition.

The calculation algorithm. The calculation algorithm was repeatedly adjusted and identified by the author during the execution of tasks for this metric in Python by the bot [6].

3. Results

To demonstrate the operability and applicability of the proposed metric, appropriate experiments were conducted on mathematical models of words belonging to three different language groups – Uzbek, English and Russian. 25% of mathematical models of words for each type of word were selected from each language group.

Group 1. a) Mathematical models of Uzbek words by the "noun" type:

1. $\downarrow\$_{[j,1-33]}C(A_j) \oplus \$_{[i,1-h1]}C_i \oplus \downarrow\$_{[j,1-33]}C(A_j) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
2. $\$_{[i,1-h3]}G_i \oplus \$_{[j,1-33]}C(A_j) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
3. $\$_{[i,1-h2]}P_i \oplus \$_{[i3,1-6]}C(A4_{i3}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
4. $\$_{[j,1-h4]}F_j \oplus \$_{[i3,1-6]}C(A4_{i3}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
5. $\$_{[i1,1-h5]}M_{i1} \oplus \$_{[i3,1-6]}C(A4_{i3}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
6. $\$_{[i2,1-h6]}N_{i2} \oplus \$_{[i3,1-6]}C(A4_{i3}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
7. $\$_{[i,1-h1]}C_i \oplus \downarrow\$_{[j,1-33]}C(A_j) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
8. $\downarrow\$_{[j,1-33]}C(A_j) \oplus \$_{[i,1-h1]}C_i \oplus \downarrow\$_{[j,1-33]}C(A_j) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
9. $\$_{[i,1-h7]}Q(P4_i) \oplus \$_{[i,1-h8]}Q(P3_j) \oplus \downarrow\$_{[j,1-h9]}Q(X6_j) \oplus \downarrow\$_{[j,1-33]}C(A_j) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$

The results of testing mathematical models of Uzbek words by the type of "noun" are presented in Table 2.

Table 2.
Results of testing mathematical models of Uzbek words by the type of “noun”.

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	1.125	1.050	1.125	1.0	0.165	0.953
Model 2	1.0	1.075	1.050	1.100	1.0	0.110	0.928
Model 3	1.0	1.075	1.125	1.100	1.0	0.110	0.946
Model 4	1.0	1.075	1.125	1.100	1.0	0.110	0.946
Model 5	1.0	1.075	1.125	1.100	1.0	0.110	0.946
Model 6	1.0	1.075	1.125	1.100	1.0	0.110	0.946
Model 7	1.0	1.100	1.125	1.100	1.0	0.110	0.946
Model 8	1.0	1.125	1.125	1.125	1.0	0.110	0.946
Model 9	1.0	1.125	1.050	1.125	1.0	0.165	0.897

b) Mathematical models of Uzbek words by the type of “adjective”:

1. $\$_{[i,1-h1]}C_i \oplus \$_{[j,1-75]}P(A_j) \oplus \downarrow\$_{[i1,1-5]}P(P1_{i1}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
2. $\$_{[i,1-h1]}C_i \oplus \$_{[i1,1-5]}P(P1_{i1}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
3. $\$_{[j,1-h2]}P_j \oplus \downarrow\$_{[i1,1-5]}P(P1_{i1}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
4. $\$_{[i,1-4]}P(P2_i) \oplus \$_{[j,1-h2]}P_j \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
5. $\$_{[i,1-h3]}G_i \oplus \$_{[j1,1-75]}P(A_{j1}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$
6. $\$_{[j,1-h6]}N_j \oplus \$_{[j1,1-75]}P(A_{j1}) \oplus \downarrow X \oplus \downarrow\$_{[j,1-10]}X2_j \oplus \downarrow\$_{[i,1-5]}X3_i \oplus \downarrow\$_{[i1,1-16]}U(A_{i1})$

The results of testing mathematical models of Uzbek words by type “adjective” are presented in Table 3.

Table 3.
Results of testing mathematical models of Uzbek words by type “adjective”.

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	1.100	1.100	1.125	1.0	0.110	0.955
Model 2	1.0	1.075	1.075	1.100	1.0	0.055	0.995
Model 3	1.0	1.100	1.100	1.100	1.0	0.110	0.950
Model 4	1.0	1.100	1.075	1.100	1.0	0.110	0.965
Model 5	1.0	1.100	1.075	1.100	1.0	0.110	0.965
Model 6	1.0	1.100	1.075	1.100	1.0	0.110	0.945

The results of the calculation of the SSM metric according to the Table 2 and Table 3 are presented in the form of histograms in Figures 1 and 2.

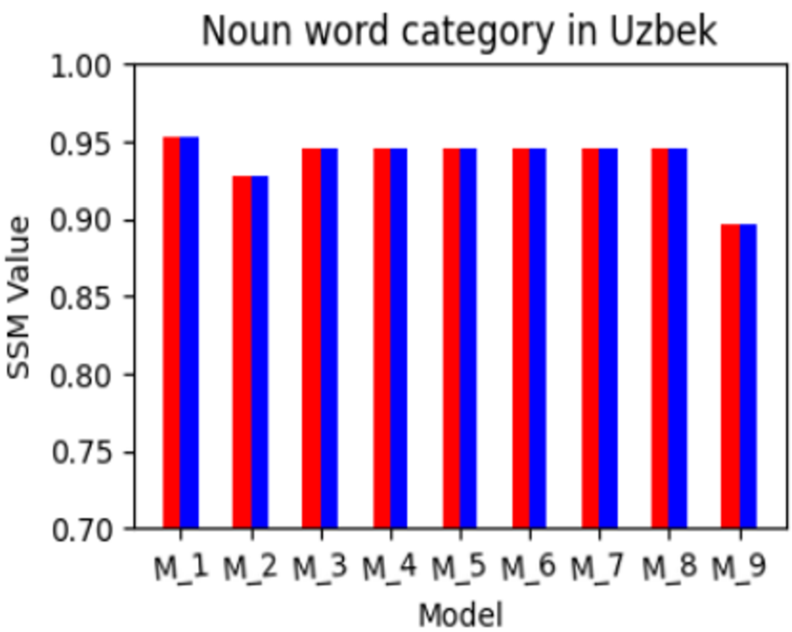

Figure 1. Histogram of the Table 2.

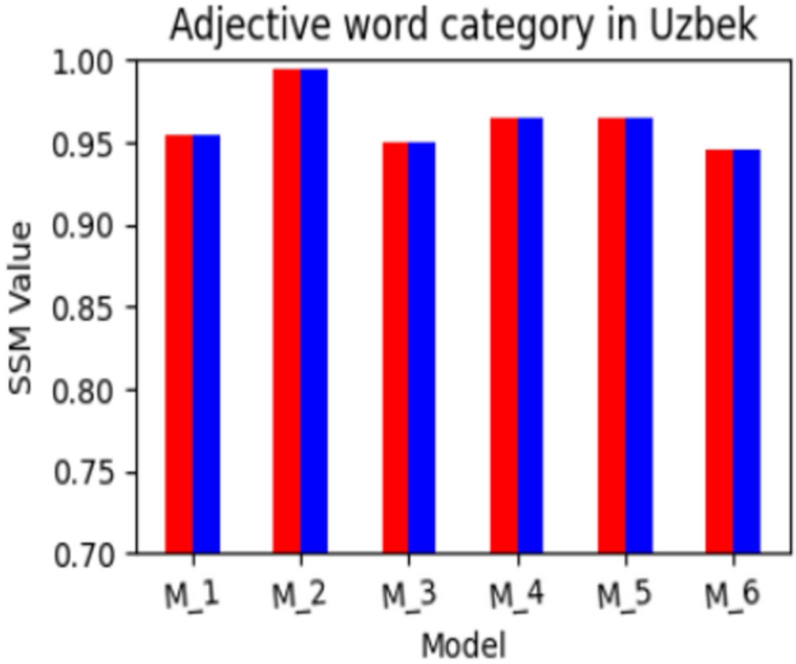

Figure 2. Histogram of the Table 3.

c) Mathematical models of Uzbek words of the "verb" type:

1. $\$_{[j,1\text{-}h3]}G_j \oplus \$_{[j,1\text{-}24]}G(A_j) \oplus \downarrow\$_{[j1,1\text{-}4]}G(U1_{j1}) \oplus \downarrow\$_{[j2,1\text{-}31]}G(U4_{j2}) \oplus \downarrow\$_{[j3,1\text{-}23]}G(U5_{j3}) \oplus \downarrow\$_{[j4,1\text{-}16]}U(A_{j4})$
2. $\$_{[\,j,1\text{-}h1]}C_j \oplus \$_{[i1,1\text{-}24]}G(A_{i1}) \oplus \downarrow\$_{[i2,1\text{-}4]}G(U1_{i2}) \oplus \downarrow\$_{[i3,1\text{-}30]}\,G(U3_{i3})$
3. $\$_{[i,1\text{-}h6]}N_i \oplus \$_{[j,1\text{-}24]}G(A_j) \oplus \downarrow \$_{[j1,1\text{-}4]}G(U1_{j1}) \oplus \downarrow\$_{[j2,1\text{-}26]}G(U2_{j2}) \oplus \downarrow\$_{[i,1\text{-}16]}U(A_i)$
4. $\$_{[i,1\text{-}h1]}C_i \oplus \$_{[j,1\text{-}h3]}G_j \oplus \downarrow\$_{[i1,1\text{-}24]}G(A_{i1}) \oplus \downarrow\$_{[j1,1\text{-}4]}G(U1_{j1}) \oplus \downarrow\$_{[j2,1\text{-}26]}G(U2_{j2}) \oplus \downarrow\$_{[j4,1\text{-}16]}U(A_{j4})$
5. $\$_{[j,1\text{-}h3]}G_j \oplus \$_{[i,1\text{-}h3]}G_i \oplus \downarrow\$_{[i1,1\text{-}24]}G(A_{i1}) \oplus \downarrow\$_{[j1,1\text{-}4]}G(U1_{j1}) \oplus \downarrow\$_{[j3,1\text{-}23]}G(U5_{j3}) \oplus \downarrow\$_{[i3,1\text{-}30]}G(U3_{i3}) \oplus \downarrow\$_{[j2,1\text{-}26]}G(U2_{j2}) \oplus \downarrow\$_{[j4,1\text{-}16]}U(A_{j4})$
6. $\$_{[i,1\text{-}h1]}C_i \oplus \downarrow \$_{[j,1\text{-}11]}G(A_j)$

The results of testing mathematical models of Uzbek words by the "verb" type are presented in Table 4.

Table 4.
Results of testing mathematical models of Uzbek words by the "verb" type.

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.000	1.100	1.075	1.125	1.000	0.165	0.895
Model 2	1.000	1.050	1.025	1.075	1.000	0.055	0.975
Model 3	1.000	1.075	1.050	1.100	1.000	0.055	0.990
Model 4	1.000	1.100	1.075	1.125	1.000	0.055	0.990
Model 5	1.000	1.125	1.125	1.175	1.000	0.165	0.920
Model 6	1.000	1.000	1.000	1.025	1.000	0.030	0.975

d) Mathematical models of Uzbek words by the type of "pronoun":

1. $\$_{[i,1\text{-}6]}\,M(M1_i) \oplus \downarrow X \oplus \downarrow\$_{[i1,1\text{-}5]}X3_{i1} \oplus \downarrow\$_{[j1,1\text{-}16]}U(A_{j1})$
2. $M(M2) \oplus \downarrow X \oplus \downarrow\$_{[j,1\text{-}10]}X2_j \oplus \downarrow\$_{[i,1\text{-}5]}X3_i \oplus \downarrow\$_{[i1,1\text{-}16]}U(A_{i1})$
3. $M(M8) \oplus \downarrow\$_{[i,1\text{-}10]}\,M(M4_i) \oplus \downarrow\$_{[j,1\text{-}10]}X2_j \oplus \downarrow\$_{[i1,1\text{-}5]}X3_{i1}$

The results of testing mathematical models of Uzbek words by the type of "pronoun" are presented in Table 5.

Table 5.
Results of testing mathematical models of Uzbek words by the type of "pronoun".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.000	1.050	1.050	1.050	1.000	0.030	1.000
Model 2	1.000	1.075	1.075	1.050	1.000	0.055	0.983
Model 3	1.000	1.050	1.050	1.050	1.000	0.030	1.000

The results of the calculation of the SSM metric according to the Table 4 and Table 5, in the form of histograms are shown in Figures 3 and 4.

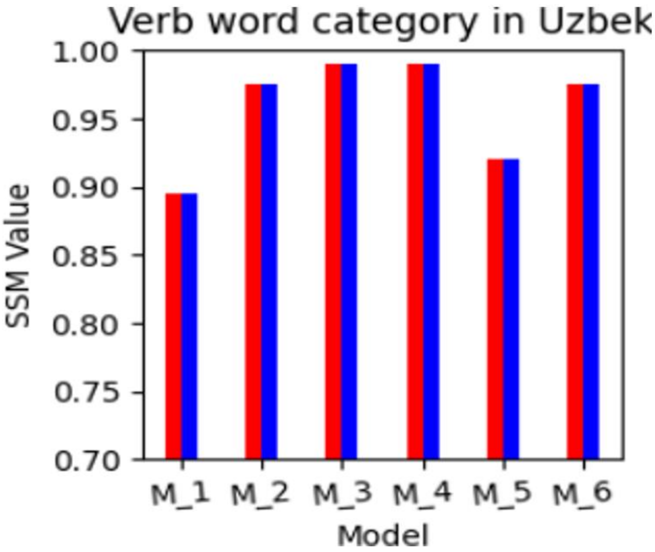

Figure 3. Histogram of the Table 4.

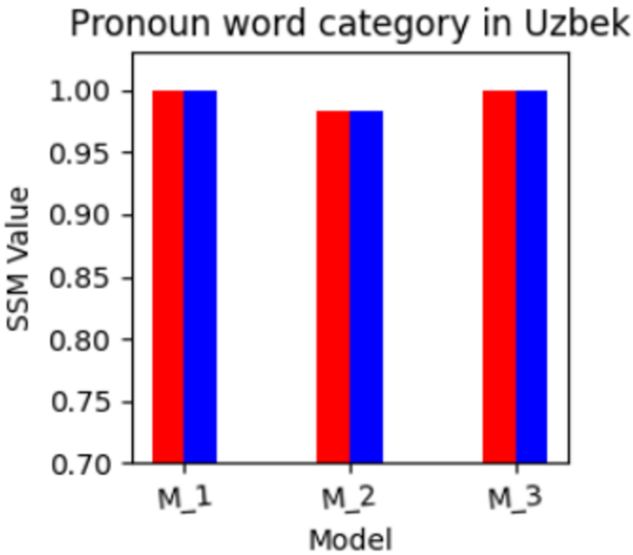

Figure 4. Histogram of the Table 5.

e) Mathematical models of Uzbek words by the type of “adverb”:

1. $\$_{[i,1-h1]}C_i \oplus \downarrow \$_{[i4,1-20]}N(A_{i4})$
2. $\$_{[i1,1-h5]}M_{i1} \oplus \downarrow \$_{[i4,1-20]}N(A_{i4})$
3. $\$_{[i3,1-h6]}N_{i3} \oplus \downarrow \$_{[i4,1-20]}N(A_{i4})$

The results of testing mathematical models of Uzbek words by the type of “adverb" are presented in Table 6.

Table 6.
Results of testing mathematical models of Uzbek words by the type of “adverb".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSM_Final
Model 1	1.000	1.000	1.000	1.000	1.000	0.030	0.970
Model 2	1.000	1.000	1.025	1.000	1.000	0.030	0.975
Model 3	1.000	1.000	1.025	1.000	1.000	0.030	0.975

f) Mathematical model of Uzbek words by the “numeral” type:

$\$_{[i,1-h4]}F_i \oplus \downarrow \$_{[j,1-10]}F(A_j) \oplus \downarrow X \oplus \downarrow \$_{[i1,1-5]}X3_{i1} \oplus \downarrow \$_{[j1,1-16]}U(A_{j1})$

The results of testing the mathematical model of Uzbek words by type “numeral” is presented in Table 7.

Table 7.
Results of testing the mathematical model of Uzbek words by type “numeral”.

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSM_Final
Model 1	1.000	1.075	1.125	1.000	3.000	0.055	0.970

The results of the calculation of the SSM metric according to the Table 6 and Table 7 are presented as histograms in Figures 5 and 6.

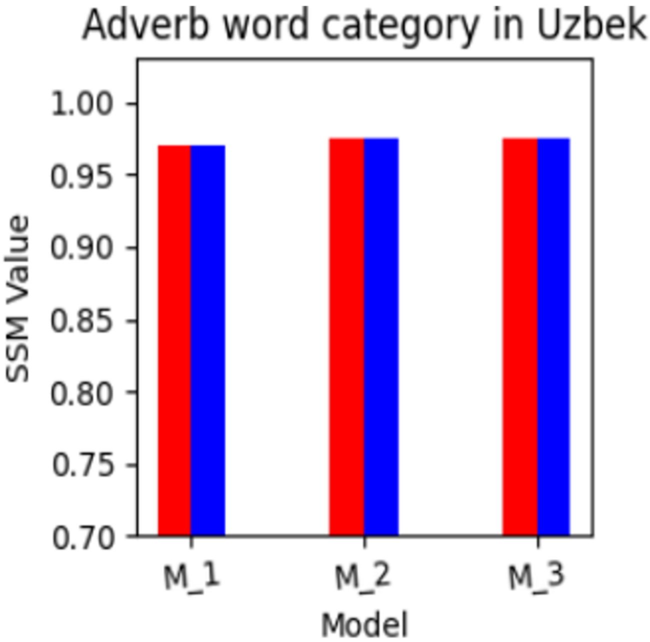

Figure 5. Histogram of the Table 6.

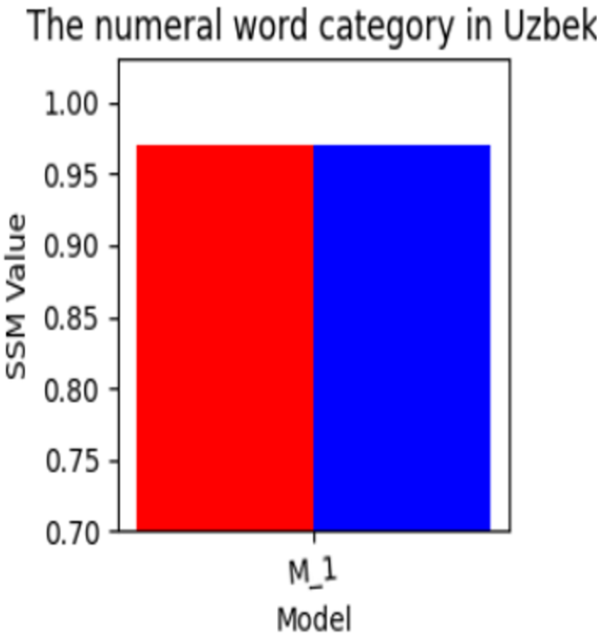

Figure 6. Histogram of the Table 7.

Group 2. a) Mathematical models of English words by the "noun" type:

1. $\$_{[i,1\text{-}h1]}K(C_i) \oplus \downarrow\$_{[j,1\text{-}77]}C(S_j)$
2. $\$_{[i,1\text{-}h1]}K(C_i) \oplus \$_{[i1,1\text{-}h1]}K(C_{i1}) \oplus \$_{[j,1\text{-}77]}C(S_j)$
3. $\$_{[i,1\text{-}h1]}K(C_i) \oplus \$_{[j1,1\text{-}52]}D_{j1} \oplus \$_{[i1,1\text{-}h1]}K(C_{i1})$
4. $\$_{[j,1\text{-}h3]}K(G_j) \oplus \$_{[j1,1\text{-}77]}C(S_{j1}) \oplus \downarrow\$_{[j2,1\text{-}77]}C(S_{j2})$
5. $\$_{[i,1\text{-}h3]} D_i \oplus \downarrow\$_{[j,1\text{-}46]}M10_j \oplus \downarrow\$_{[i1,1\text{-}h]}C_{i1} \oplus \downarrow\$_{[j1,1\text{-}h]}C(AC_{j1}) \oplus \downarrow\$_{[i2,1\text{-}10]}X_{i2}$
6. $\$_{[i,1\text{-}h3]}D_i \oplus \downarrow\$_{[j,1\text{-}h]}M10_j \oplus \downarrow\$_{[i1,1\text{-}10]} N_{i1} \oplus \downarrow\$_{[j1,1\text{-}10]}C(AN_{j2}) \oplus \downarrow X_1$
7. $\$_{[i,1\text{-}h3]}D_i \oplus \downarrow\$_{[j,1\text{-}h]}M10_j \oplus \downarrow\$_{[i1,1\text{-}10]}X5_{i1} \oplus \downarrow\$_{[j1,1\text{-}10]}C(AX5_{j2}) \oplus \downarrow X_1$
8. $\$_{[i,1\text{-}h]}G_i \oplus \downarrow\$_{[j,17\text{-}h77]} C(A_j) \oplus \downarrow X_1 \oplus \downarrow\$_{[i1, 29\text{-} h58]}D_{i1}$

The results of testing mathematical models of English words by the "noun" type are presented in Table 8.

Table 8.
Results of testing mathematical models of English words by the "noun" type.

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSM_Final
Model 1	1.000	0.65	1.000	1.000	1.000	0.015	0.915
Model 2	1.000	0.65	1.050	1.025	1.000	0.015	0.975
Model 3	1.000	0.65	1.075	1.038	1.000	0.015	0.937
Model 4	1.000	0.65	1.000	1.033	1.000	0.015	0.921
Model 5	1.000	0.65	1.075	1.040	1.000	0.015	0.938
Model 6	1.000	0.65	1.075	1.040	1.000	0.015	0.938
Model 7	1.000	0.65	1.075	1.040	1.000	0.015	0.938
Model 8	1.000	0.65	1.050	1.038	1.000	0.015	0.932

b) Mathematical models of English words by the type of "adjective":

1. $\$_{[i,1\text{-}h2]}\, K(P_i) \oplus \$_{[i,1\text{-}h1]} K(C_i) \oplus \$_{[i1,1\text{-}48]} P(S_{i1})$
2. $\$_{[j,1\text{-}22]} P(T_j) \oplus \$_{[i,1\text{-}h2]}\, K(P_i)$
3. $\$_{[i,1\text{-}h1]} K(C_i) \oplus \$_{[i1,1\text{-}h1]} K(C_{i1}) \oplus \$_{[j,1\text{-}48]} P(S_j) \oplus$ "d"
4. $\$_{[i,1\text{-}h6]} K(N_i) \oplus \$_{[i1,1\text{-}h1]} K(C_{i1}) \oplus \$_{[j,1\text{-}48]} P(S_j) \oplus$ "d"
5. $\$_{[i,1\text{-}h4]}\, K(F_i) \oplus \$_{[j,1\text{-}h1]} K(C_j) \oplus$ "ed"

The results of testing mathematical models of English words by type "adjective" are presented in Table 9.

Table 9.
Results of testing mathematical models of English words by type "adjective".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSM_Final
Model 1	1.000	1.000	1.000	1.033	1.000	0.015	0.992
Model 2	1.000	1.000	1.000	1.025	1.000	0.030	0.975
Model 3	1.000	1.025	1.025	1.033	1.000	0.030	0.987
Model 4	1.000	1.025	1.025	1.033	1.000	0.030	0.987
Model 5	1.000	0.65	1.000	1.025	1.000	0.015	0.920

The results of the calculation of the SSM metric according to the Table 8 and Table 9 are represented as histograms in Figures 7 and 8.

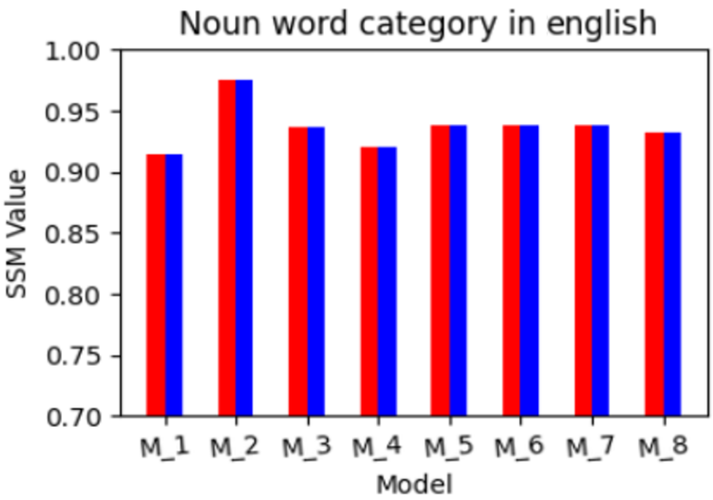

Figure 7. Histogram of the Table 8.

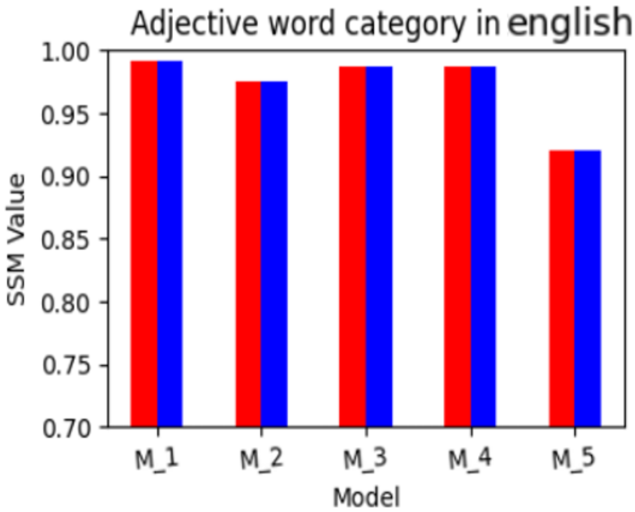

Figure 8. Histogram of the Table 9.

c) Mathematical models of English words of the "verb" type:

1. $\$_{[i1,1\text{-}h3]}K(G_{i1}) \oplus \$_{[j,1\text{-}h2]}K(P_j)$
2. $\$_{[i,1\text{-}h3]}K(G_i) \oplus \$_{[j,1\text{-}52]}D_j \oplus \$_{[i1,1\text{-}h3]}K(G_{i1})$
3. $\$_{[j,1\text{-}27]}G(T_j) \oplus \$_{[i,1\text{-}h3]}K(G_i)$
4. $\$_{[i,1\text{-}h2]}K(P_i) \oplus \$_{[j,1\text{-}11]}G(S_j)$

The results of testing mathematical models of English words by type "verb" are presented in Table 10.

Table 10.
Results of testing mathematical models of English words by type "verb".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	0.65	1.025	1.025	1.00	0.015	0.925
Model 2	1.0	0.65	1.050	1.050	1.00	0.015	**0.935**
Model 3	1.0	0.65	1.025	1.025	1.00	0.030	0.910
Model 4	1.0	0.65	1.025	1.025	1.00	0.030	0.910

d) Mathematical models of English words by the type of "pronoun":

1. $\$_{[j,1\text{-}h5]}K(M_j) \oplus \$_{[i,1\text{-}5]}M(S_i)$
2. $\$_{j,\,[1\text{-}h5]}K(M_j) \oplus \$_{[i,1\text{-}2]}M(M5_i)$

The results of testing mathematical models of English words by the type of "pronoun" are presented in Table 11.

Table 11.
Results of testing mathematical models of English words by the type of "pronoun".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	0.65	1.0	1.025	1.0	0.03	0.905
Model 2	1.0	0.65	1.0	1.025	1.0	0.03	0.905

The results of the calculation of the SSM metric according to Tables 10 and 11 are presented in the form of histograms in Figures 9 and 10.

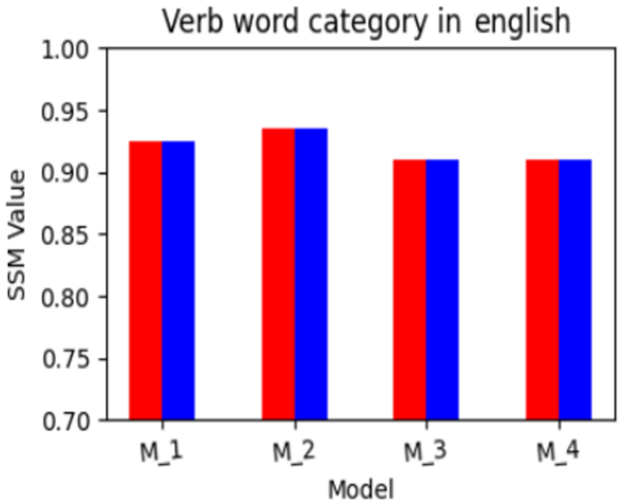

Figure 9. Histogram of the Table 10.

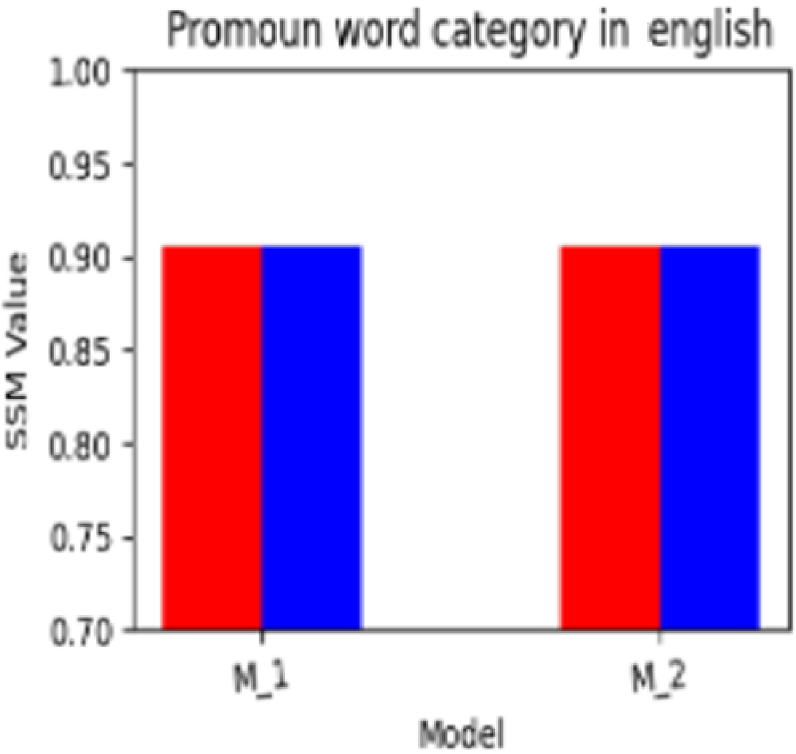

Figure 10. Histogram of the Table 11.

e) Mathematical models of English words by the type of “adverb”:

1. $\$_{[i,1\text{-}h1]}K(C_i) \oplus \$_{[j,1\text{-}10]}N(S_j)$
2. $\downarrow\$_{[i1,1\text{-}18]}N(D_{i1}) \oplus \$_{[i,1\text{-}h1]}K(C_i) \oplus \$_{[j,1\text{-}10]}N(S_j)$

The results of testing mathematical models of English words by the type of “adverb" are presented in Table 12.

Table 12.
Results of testing mathematical models of English words by the type of “adverb".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	0.65	1.0	1.0	1.0	0.015	0.915
Model 2	1.0	0.65	1.05	1.025	1.0	0.015	0.921

f) Mathematical model of English words of the “numeral” type:

1. $\$_{[i,1\text{-}h4]}F_i \oplus \downarrow \$_{[j,1\text{-}10]}F(A_j)$
2. $\$_{[i,1\text{-}h4]}F_i \oplus \downarrow \$_{[j,1\text{-}10]}F(A_j) \oplus \downarrow\$_{[i1,1\text{-}h4]}F_{i1}$

The result of testing the mathematical model of English words by type “numerical” is presented in Table 13.

Table 13.
Results of testing mathematical models of English words by type "numerical".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	0.65	1.05	1.025	1.0	0.015	0.921
Model 2	1.0	0.65	1.075	1.05	1.0	0.015	0.940

The results of the calculation of the SSM metric according to Tables 12 and 13 are presented in the form of histograms in Figures 11 and 12.

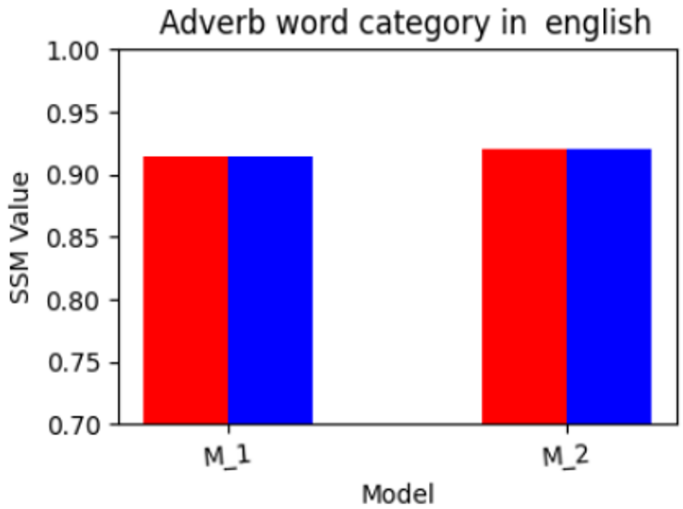

Figure 11. Histogram of the Table 12.

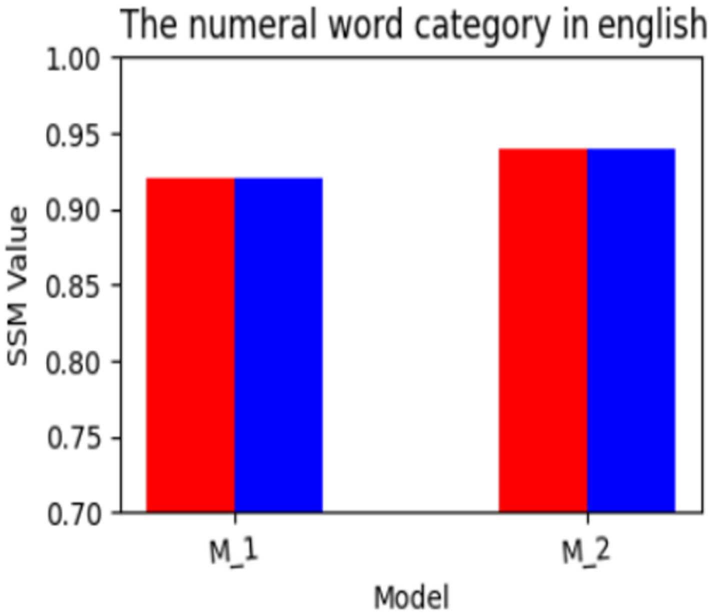

Figure 12. Histogram of the Table 13.

Group 3. a) Mathematical models of Russian words by the type of "noun":

1. $\downarrow\$_{[i,1\text{-}85]}U_i \oplus \downarrow\$_{[j,1\text{-}91]}T_j \oplus \$_{[i1,1\text{-}h4]}K_{i1}(C,P,G,M,N) \oplus \downarrow\$_{[i2,1\text{-}h0]}K_{i2}(C,P,G,M,N) \oplus \downarrow\$_{[j1,1\text{-}241]}S_{j1} \oplus \downarrow(\$_{[j2,1\text{-}241]}S_{j2} \oplus \downarrow\$_{[i3,1\text{-}163]}O_{i3}$
2. $\$_{[j5,1\text{-}h0]}K_{j5}(C,P,G,M,N,F) \oplus \$_{[i,1\text{-}2]}W_i \oplus \$_{[j6,1\text{-}h0]}K_{j6}(C,P,G,M,N,F)$
3. $\downarrow\$_{[i,1\text{-}16]}C(T_i) \oplus \$_{[j,1\text{-}h1]}K(C_j) \oplus \$_{[i1,1\text{-}120]}C(S_i) \oplus \downarrow\$_{[j1,1\text{-}120]}C(S_{j1}) \oplus \downarrow\$_{[i2,1\text{-}28]}C(O_{i2})$
4. $\downarrow\$_{[j2,1\text{-}h2]}K(P_{j2}) \oplus \$_{[j3,1\text{-}h1]}K(C_{j3}) \oplus \downarrow\$_{[j4,1\text{-}h3]}K(G_{j4}) \oplus \downarrow\$_{[i,1\text{-}120]}C(S_i) \oplus \downarrow\$_{[i1,1\text{-}28]}C(O_{i1})$

The results of testing mathematical models of words of the Russian language by the type of "noun" are presented in Table 14.

Table 14.
Results of testing mathematical models of words of the Russian language by the type of "noun".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	0.65	1.05	1.05	1.0	0.06	0.890
Model 2	1.0	0.65	1.05	1.025	1.0	0.015	0.930
Model 3	1.0	0.65	1.05	1.0	1.0	0.03	0.930
Model 4	1.0	0.65	1.1	1.05	1.0	0.03	0.930

Note: b) Mathematical models of words of the Russian language by the type of "adjective":

1. $\downarrow\$_{[i,1\text{-}25]}P(T_i) \oplus \$_{[j,1\text{-}h2]}K(P_j) \oplus \$_{[i1,1\text{-}65]}P(S_{i1}) \oplus \downarrow\$_{[i2,1\text{-}42]}P(O_{i2})$
2. $\downarrow\$_{[i,1\text{-}25]}P(T_i) \oplus \$_{[j,1\text{-}h2]}K(P_j) \oplus \downarrow\$_{[i3,1\text{-}h1]}K(C_{i3}) \oplus \downarrow\$_{[j1,1\text{-}h2]}K(P_{j1}) \oplus \$_{[i1,1\text{-}65]}P(S_{i1}) \oplus \$_{[i2,1\text{-}42]}P(O_{i2})$
3. $\$_{[j,1\text{-}h2]}K(P_j) \oplus \$_{[i4,1\text{-}2]}W_{i4} \oplus \$_{[j1,1\text{-}h2]}K(P_{j1}) \oplus \downarrow\$_{[i1,1\text{-}65]}P(S_{i1}) \oplus \downarrow\$_{[i2,1\text{-}42]}P(O_{i2})$

The results of testing mathematical models of Russian words by the type of "adjective" are presented in Table 15.

Table 15.
Results of testing mathematical models of Russian words by the type of "adjective".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	1.05	1.025	1.050	1.0	0.015	0.970
Model 2	1.0	1.10	1.025	1.075	1.0	0.045	0.875
Model 3	1.0	1.075	1.025	1.075	1.0	0.030	0.925

The results of the calculation of the SSM metric according to Tables 14 and 15 in the form of histograms are shown in Figures 13 and 14.

c) Mathematical models of Russian words by the type of "verb":

1. $\downarrow\$_{[i,1\text{-}85]}U_i \oplus \downarrow\$_{[j,1\text{-}30]}G(T_i) \oplus \$_{[i1,1\text{-}h3]}K(G_{i1}) \oplus \$_{[j1,1\text{-}43]}G(S_{j1}) \oplus \downarrow\$_{[j2,1\text{-}43]}G(S_{j2}) \oplus \downarrow\$_{[i2,1\text{-}37]}G(O_{i2})$
2. $\downarrow\$_{[j,1\text{-}30]}G(T_i) \oplus \$_{[i,1\text{-}h1]}K(C_i) \oplus \$_{[j1,1\text{-}43]}G(S_{j1}) \oplus \downarrow\$_{[i2,1\text{-}37]}G(O_{i2})$
3. $\downarrow\$_{[j,1\text{-}30]}G(T_i) \oplus \$_{[i,1\text{-}h2]}K(P_i) \oplus \$_{[j1,1\text{-}43]}G(S_{j1}) \oplus \downarrow\$_{[j2,1\text{-}43]}G(S_{j2}) \oplus \downarrow\$_{[i2,1\text{-}37]}G(O_{i2})$

Figure 13. Histogram of the Table 14.

Figure 14. Histogram of the Table 15.

The results of testing mathematical models of Russian words by the type of “verb" are presented in Table 16.

Table 16.
Results of testing mathematical models of Russian words by the type of “verb".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.000	0.650	1.100	1.075	1.000	0.015	0.950
Model 2	1.000	0.650	1.050	1.075	1.000	0.015	0.940
Model 3	1.000	0.650	1.050	1.100	1.000	0.030	0.930

d) Mathematical models of Russian words by the type of “pronoun”:

1. $\$_{[i,1\text{-}48]}D_i \oplus \$_{[j,1\text{-}h5]}K(M_j)$
2. $\$_{[j,1\text{-}h5]}K(M_j) \oplus \$_{[i,1\text{-}h1]}K(C_i) \oplus \downarrow\$_{[i1,1\text{-}35]}M(O_{i1})$
3. $\$_{[j,1\text{-}h5]}K(M_j) \oplus \$_{[i,1\text{-}h4]}K(F_i) \oplus \downarrow\$_{[i1,1\text{-}35]}M(O_{i1})$

The results of testing mathematical models of Russian words by the type of “pronoun" are presented in the Table 17.

Table 17.
Results of testing mathematical models of Russian words by the type of “pronoun".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	0.650	1.033	1.025	1.0	0.015	0.9266
Model 2	1.0	0.650	1.025	1.033	1.0	0.015	0.9266
Model 3	1.0	0.650	1.025	1.033	1.0	0.015	0.9266

The results of the calculation of the SSM metric according to Tables 16 and 17 in the form of histograms are shown in Figures 15 and 16.

Figure 15. Histogram of the Table 16.

Figure 16. Histogram of the Table 17.

e) Mathematical models of Russian words by the type of "adverb":

1. $\$_{[i,1\text{-}21]}N(T_i) \oplus \downarrow\$_{[j,1\text{-}h4]}K(F_j) \oplus \downarrow\$_{[i1,1\text{-}h6]}K(N_{i1}) \oplus \downarrow\$_{[j1,1\text{-}13]}N(S_{j1}) \oplus \downarrow\$_{[i2,1\text{-}21]}N(O_{i2})$
2. $\$_{[i1,1\text{-}h6]}K(N_{i1}) \oplus \downarrow\$_{[i2,1\text{-}h1]}K(C_{i2}) \oplus \downarrow\$_{[j,1\text{-}h2]}K(P_j) \oplus \downarrow\$_{[j1,1\text{-}13]}N(S_{j1}) \oplus \downarrow\$_{[i,1\text{-}21]}N(T_i)$
3. $\$_{[i,1\text{-}21]}N(T_i) \oplus \downarrow\$_{[i2,1\text{-}h1]}K(C_{i2}) \oplus \downarrow\$_{[j,1\text{-}h2]}K(P_j) \oplus \downarrow\$_{[j1,1\text{-}h4]}K(F_{j1}) \oplus \downarrow\$_{[j2,1\text{-}h5]}K(M_{j2})$

The results of testing mathematical models of Russian words by the type of "adverb" are presented in the Table 18.

Table 18.
Results of testing mathematical models of Russian words by the type of "adverb".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	0.65	1.04	1.038	1.0	0.03	0.915
Model 2	1.0	0.65	1.04	1.038	1.0	0.03	0.915
Model 3	1.0	0.65	1.04	1.038	1.0	0.03	0.915

f) Mathematical models of words of the Russian language by the type of "numeral":

1. $\$_{[j,1\text{-}h4]}K(F_j) \oplus \$_{[i,1\text{-}43]}F(S_i) \oplus \downarrow\$_{[j1,1\text{-}h7]}F_j$
2. $\$_{[j,1\text{-}h4]}K(F_j) \oplus \$_{[i,1\text{-}43]}F(S_i) \oplus \downarrow\$_{[i1,1\text{-}43]}F(S_{i1})$

The results of testing mathematical models of Russian words by the type of "numeral" are presented in Table 19.

Table 19.
Results of testing mathematical models of Russian words by the type of "numeral".

Model	Mor	Sq	Mav	Qb	Muk	Penalty	SSS_Final
Model 1	1.0	0.65	1.0	1.05	1.0	0.015	0.925
Model 2	1.0	0.65	1.05	1.033	1.0	0.015	0.931

The results of the calculation of the SSM metric according to Tables 18 and 19 in the form of histograms are shown in Figures 17 and 18.

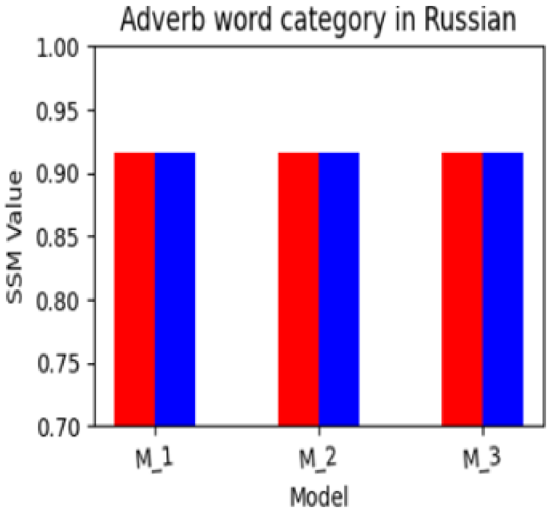

Figure 17. Histogram of the Table 18.

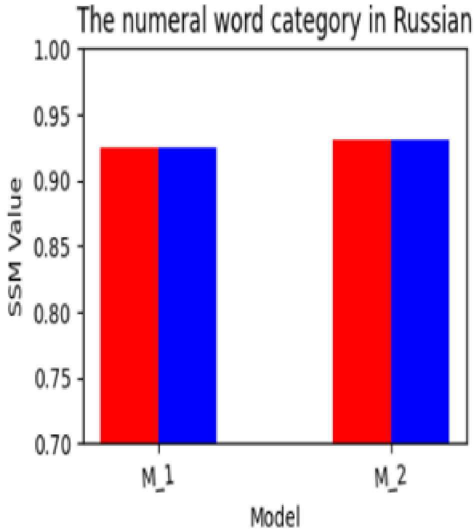

Figure 18. Histogram of the Table 19.

4. Discussion

Evaluation tables and histograms of mathematical models of words show the complexity of mathematical models by type of words, i.e. typological and morphological difference. For example, in agglunative (Uzbek) languages, due to the many additions, the values of the Sq, Mav, and Qb parameters can be high and the overall score of the mathematical model of the word will be in the range [0.9, 1.0].

And in mathematical models of English words, all word models also received high marks in the range [0.9, 1.0], due to the "soft" penalty. This shows that in English language words are based on the root of words and there can be 1 or 2 additions.

In mathematical models of Russian language words, all the models also showed excellent structural and semantic connections.

This proves that all mathematical models correctly reflect structural and semantic relationships, and the metric itself functions correctly, reliably, and universally in this version. It takes into account all the structural components (base, additions, role and complexity) of the word. Using the parameters Mor (root), Sq (additions), Mav (complexity), Qb (links to the bases of fundamentals and additions), Muk (semantic roles), Penalty (penalty), morphology, syntax and semantics are combined. If the classical BLEU and METEOR metrics pay attention only to the result and the correctness of words, then the SSM metric takes into account the structure and interrelationships of the components.

However, there are some disadvantages of the SSM metric. If mathematical models are poorly formalized, or all additions are not taken into account and terminal symbols are used inaccurately, the metric may not work effectively. If the structure of the natural language is not precise enough and is not classified, then it will be difficult for the metric to carry out an automatic accurate assessment of the mathematical model.

5. Conclusion

The result of the research is a new proprietary metric, which makes it possible to evaluate formal mathematical models in terms of structural and semantic connections of a word with all types of endings, prefixes and suffixes. Formal mathematical models devided by types of words were presented in the form of sequences of terminal symbols in Russian. The metric's analytical record, as well as a number of its advantages such as versatility, mathematical reliability and interlanguage objectivity, fair comparison and the solidity of the complexities of accounting for additions to the structure of words in different natural languages, allow it to be used as part of complex mathematical tools for evaluating mathematical models of machine translation words.

The experiments conducted on the metric confirm its operability in the interests of evaluating mathematical models of words, as well as form an important platform for the automatic assessment of syntactic and semantic complexities of words by type, functional suitability and general relevance in the field of international computational linguistic research.

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