

Challenging the state-of-the-art Machine Translation Metrics from a Linguistic Perspective

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Abstract

We employ a linguistically motivated challenge set in order to evaluate the state-of-the-art machine translation metrics submitted to the Metrics Shared Task of the 8th Conference for Machine Translation. The challenge set includes about 21,000 items extracted from 155 machine translation systems for three language directions (German \leftrightarrow English, English \rightarrow Russian), covering more than 100 linguistically-motivated phenomena organized in 14 categories. The metrics that have the best performance with regard to our linguistically motivated analysis are the COMETOID22-WMT23 (a trained metric based on distillation) for German-English and METRICX-23-C (based on a fine-tuned mT5 encoder-decoder language model) for English-German and English-Russian. Some of the most difficult phenomena are *passive voice* for German-English, *named entities*, *terminology* and *measurement units* for English-German and *focus particles*, *adverbial clause* and *stripping* for English-Russian.

1 Introduction

Most NLP evaluation has relied for years on testing the system performance on randomly picked test sets and producing a single generic score. Yet, machine learned systems learn to make abstractions and due to these, phenomena who are on the long tail of the training and test data may be overlooked hidden behind a very high generic score. Additionally, generic scores are often helpful to show relative improvement and reflect overall quality, but cannot explain the performance in a comprehensive way.

For example, old-style machine translation (MT) metrics measuring lexical overlap would equally penalize the omission of an article and the omission of the particle forming the negation in a sentence, although negation is more crucial for its meaning. While the evaluation of so obvious errors has been

addressed by the trained MT metrics, their evaluation relies on correlations with human judgments on randomly picked test-sets. In this case, a single correlation score may not be able to explain the strengths and weaknesses of the metrics with regard to the functioning of language.

Motivated by these considerations, we employ a multifold test set with linguistically-motivated challenges that will allow us to understand the metric performance from a linguistic perspective. These challenges are organized in smaller sets, one set per phenomenon, whereas the phenomena are organized in broader categories. By measuring the ability of the metrics to detect the errors in these challenge sets, we can get scores that indicate different aspects of linguistic performance.

This paper describes the application of such a challenge set on the evaluation of the MT metrics submitted at the relevant shared task of the 8th Conference of Machine Translation (Freitag et al., 2023). The rest of the paper is structured as following: Section 2 describes related work, and section 3 describes the way the challenges were selected. In Section 4 the results are presented and described, first from the perspective of metric comparison and then focusing on the performance for particular linguistically-motivated categories and phenomena per language direction. Some conclusions are given in Section 5.

2 Related work

There has been a growing interest for more fine-grained evaluation of Natural Language Processing (NLP) tools, as shown by the increasing number of publications many of whom have received distinctions (Ribeiro et al., 2020; Avelino et al., 2022; Campolungo et al., 2022). Concerning machine translation (MT), initial efforts were made in the 1990s with the introduction of test suites (King and Falkedal, 1990), and these efforts have been revitalized in light of recent advancements in the

field (Guillou and Hardmeier, 2016). To the best of our knowledge, the first endeavours related to the use of challenge sets in a meta-level in order to evaluate MT metrics were applied to Quality Estimation metrics (Avramidis et al., 2018), based on the first version of our linguistically-motivated test suite (Macketanz et al., 2018). The analysis was broadened to cover a broader range of MT metrics, including reference-based ones, as appeared in the Findings paper of the Metrics shared task of the 6th Conference on Machine Translation (Freitag et al., 2021), which was based on a later version of our test suite on German-English (Avramidis et al., 2019, 2020; Macketanz et al., 2021, 2022a), a resource also employed in this paper.

With the occasion of the first challenge set sub-task for the metrics shared task of the 7th Conference on Machine Translation (Freitag et al., 2022), a few more challenge sets emerged. ACES (Amrhein et al., 2022) for example, focuses on 68 accuracy errors. Similarly, Alves et al. (2022) evaluate the robustness of MT metrics by generating translations with critical errors. In a more linguistic direction, Chen et al. (2022) examine the capability of the metrics to correlate synonyms in different areas and to discern catastrophic errors at both word- and sentence-levels.

Our submission at that sub-task (Avramidis and Macketanz, 2022) augmented the preliminary analysis appearing at Freitag et al. (2021) by adding the language direction of English-German and presenting a more fine-grained analysis, not only in the category level but also on the phenomenon level. This year’s submission, explained on our paper, includes that same challenge set as last year, whereas English-Russian has been added as an additional language direction.

3 Method

3.1 Test suite for MT systems

Here, we are going to explain how we created the pool of MT sentences that were used for the challenge set. The selection was based on a linguistically-motivated test suite (Macketanz et al., 2022a)¹. The test suite contains a set of source sentences focusing on particular phenomena, each of them accompanied by some rules or regular expressions that can detect which translations would be accepted for these source sentences. This allows a

¹<https://github.com/DFKI-NLP/mt-testsuite>

semi-automatic evaluation when new translations are provided, whereas a human annotator resolves cases not covered by the rules.

For this experiment, we employed the test suite on three language directions: German-English (Avramidis et al., 2020), English-German (Macketanz et al., 2021) and English-Russian (Macketanz et al., 2022b). The German-English side consists of 5,539 German test sentences covering 107 linguistically motivated phenomena, the English-German side consists of 4,782 English test sentences covering 126 phenomena, and the English-Russian side consists of 1,225 English test sentences covering 64 phenomena. All language directions are organized in 14 categories, which nevertheless differ among the directions.

The above described test suite has been used to evaluate the outputs of 116 German-English, 29 English-German systems and 10 English-Russian systems submitted at the translation task of the Conference of Machine Translation (WMT). German-English outputs were collected from systems submitted in the years 2018-2021, English-German outputs in the years 2020-2021 and English-Russian in 2022.

3.2 Challenge set for MT metrics

The sentences selected with the help of the test suite are consequently used to create the challenge set. The source sentences and the system outputs have to be organized in contrastive pairs of correct/incorrect translations and a reference. In order to achieve this, for every source sentence from the test suite selection we create a challenge item including:

- one correct translation to be used as a reference translation,
- another correct translation to be used as the first translation candidate
- one incorrect translation to be used as the contrastive translation candidate

The two candidate translations and the reference consist one challenge item. Since source and translations were collected as a result of testing for a particular phenomenon, the same phenomenon will be what the challenge item will test.

Given that we may have many correct and wrong translations for the same source, the reference and the translations of the challenge items result from random combinations of correct and wrong translations from the collected WMT outputs. Therefore,

the same source sentence may appear many times.

As a result, we get a challenge set with 10,402 items for German-English, 8,945 items for English-German and 1,727 items for English-Russian.

3.3 Evaluation of metrics

For each challenge item, the two machine translation (MT) outputs, are provided to the metrics as separate MT hypotheses. Which output is correct, and which is incorrect, is hidden from the metrics. These hypotheses are then evaluated against the previously mentioned reference and/or the source. An item is deemed correctly scored when the metric assigns a higher score to the correct MT output compared to the incorrect one. Following this, the statistics below are computed:

- i) **Accuracy per Phenomenon:** the ratio of all correctly-scored challenge items per phenomenon to the total number of challenge items for that particular phenomenon.
- ii) **Accuracy per Category:** the ratio of all correctly-scored challenge items per category to the total number of challenge items for that category, after consolidating the underlying phenomena of that category into a single set.

Significance tests are performed to compare the highest metric accuracy for each phenomenon with all other metric accuracies for the same phenomenon. This is a one-tailed Z-test, conducted with a significance level of $\alpha = 0.95$. Metrics with accuracies that are not significantly worse than the highest accuracy are considered to share the top position for that phenomenon. A similar approach is used to identify the best accuracies per category, after aggregating the challenge items from the underlying phenomena within each category.

Metric categories We conduct this significance testing in two stages: first, for all metrics involved in the shared task, and then separately for each of the three metric categories (baseline, Quality Estimation (QE) as a metric, reference-based). Systems that are significantly superior per phenomenon across all metrics are highlighted with a gray background, while those that are significantly superior per metric category are denoted in boldface.

Averaging Lastly, we provide three types of averaging scores:

- i) **Micro-average:** This approach considers all items equally, aggregating all test items to compute the average percentages.
- ii) **Category macro-average:** Here, all categories are treated equally, with the percentages being computed independently for each category and then averaged.
- iii) **Phenomenon macro-average:** This average treats all phenomena equally, with the percentages being computed independently for each phenomenon and then averaged.

4 Results

The results are displayed in detail in Tables 1, 2 and 3 for the category level and in Tables 4, 5 and 6 for the phenomenon level, for the three language directions respectively.

4.1 Metric performance analysis

Here we are observing the statistics with a focus on comparing the performance of various metrics on the challenge set.

German-English The accuracies of the metrics, as measured for several categories in German-English, can be seen in Table 1. The best performing metric for German-English is COMETOID22-WMT23 (Gowda et al., 2023), which, wins significantly based on both the micro-average (83%) and the macro-average (87%). This metric is a distilled QE model that has been trained on COMET (Rei et al., 2020) scores of WMT outputs, including the ones of WMT23. For this reason, we include it into the reference-aware metrics. We notice that its performance among the other metrics is impressive. It is the first metric in 6 categories and among them the only one who wins at *Verb tense/aspect/mood* and *function words*, achieving 93% and 91% accuracy respectively.

Another two reference-based baseline metrics, COMET and PRISMREF (Thompson and Post, 2020a,b) share the first position when the category macro-average is considered (82%). None of the other reference-aware metrics submitted this year managed to compete with the metrics with the highest accuracy mentioned above.

The lowest performing metric is the reference-less random baseline RANDOM-SYSNAME, provided by the organizers (44%), followed by XL-SIMQE (55-58%; Mukherjee and Shrivastava,

2023) and MATESE (57-58%; Perrella et al., 2022).

When considering the metric performance with regard to particular categories, one can see, again this year, that different metrics win in different combinations of categories. Here, only COMETOID22-WMT23 as mentioned above, wins 6 metrics, followed by PRISMREF and METRIC-23-C, which win 4 categories. 17 metrics do not win any category, ranging in accuracies around 75%.

English-German The accuracies of the metrics, as measured for several categories in English-German, can be seen in Table 2. The best performing metric in English-German is METRICX-23-C, which is in the first significance cluster based on both the micro-average (81%) and the category macro-average (84%). This metric uses the mT5 encoder-decoder language model, which is fine-tuned using direct assessment data, MQM (Lommel et al., 2014) data and synthetic data. The categories to which its success may be mostly attributed are the *multi-word expressions* (MWE; with 92%) and the non-verbal agreement (95%).

Another three metrics share the first position, when the micro average is considered, namely the QE version of the latter, *MetricX-23-QE-c* and also *mbr-metricx-qe* (Naskar et al., 2023) and XCOMET-Ensemble. It is impressive that QE methods manage to reach high accuracy without access to reference content.

When looking at the worse-performing metrics, MATESE here performs worse than the baseline (36-38%), followed by PARTOKENGRAM_F (55-56%; Dreano et al., 2023b).

In English-German it is even harder to say which metrics perform well in multiple categories, as only one of them, XCOMET-QE-ENSEMBLE, achieves the highest performance in 3 categories (*function words, non-verbal agreement and subordination*). The rest of the metrics show a good performance in 2 categories or fewer.

English-Russian The accuracies of the metrics, as measured for several categories in English-German, can be seen in Table 3. For this language pair, variants of the MetricX achieve significantly higher accuracies than all the other metrics. In particular, METRICX-23-C achieves the highest accuracy based on both micro-average and category macro-average, whereas METRICX-23-B and METRICX-23-QE-C achieve a slightly

lower macro-average, which is nevertheless not significantly worse than the one of the former. MATESE is again by far the lowest performing metric (32/34%), lower than the random baseline. We may assume that this metric has not been optimized for this language direction.

4.2 Linguistically motivated analysis

In this section, we are focusing on the results for particular phenomena or categories.

4.2.1 German-English

Category-level The overall average accuracy of all metrics with regard to the linguistically motivated categories is at 76% for German-English, which is two percentage points lower than last year’s average. It is still a fact, that the metrics in average fail to predict properly the scores for one out of four challenge items that we provided. Luckily, there has been noticeable accuracy for some categories, for example METRICX reference-based variants achieved an accuracy of 96% for *false friends*, whereas *negation* errors have been scored correctly with a 98.5

The worse performing category is *Verb valency*, where the best metrics achieved only 66% accuracy, and the rest of the metrics averaged to a mere 56%. In this category one can observe the lowest accuracy, given by an LLM-based metric, EMBED_LLAMA (Dreano et al., 2023a) with 41%.

Phenomenon-level The best accuracy for this language pair (Table 4) is achieved this year at several variations of verb tenses, i.e. *Transitive - future II, Modal negated - present, Reflexive - preterite subjunctive II* and *Intransitive - pluperfect* which get more than 85% in average.

The lowest accuracy of all metrics in average is given for *passive voice*, where the highest accuracy achieved by several metrics is only 54.5%. Errors related to *commas, domain-specific terms* and *locations* have also been scored with a less than 65% accuracy.

4.2.2 English-German

Category-level The overall average accuracy of all metrics with regard to the linguistically motivated categories is at 71-73% for English-German. The category where all metrics perform better in average is *negation* (83%), where 11 of the metrics achieve more than 90% accuracy. Negation is closely followed by *function words Non-verbal agreement* (80%).

The worse performing category in average is *named entities and terminology* (58,8%), where most metrics' accuracies are close to 50%, except for BLEURT (Yan et al., 2023) (80.3%). The rest of the categories lie in rather mediocre accuracies, between 58.8% and 80%.

Phenomenon-level The English-German phenomena, where metrics perform best in average (Table 5) are the *transitive conditional II simple, gerunds, contact clause* and the *intransitive present perfect simple*, achieving more than 85% of accuracy. The phenomena which incur the lowest average accuracies are the *transitive present progressive, measuring units, modals* and *intransitive - future II progressive* with less than 50% accuracy. The former and the latter were observed as the most difficult phenomena to score also last year.

4.3 English-Russian

This analysis for English-Russian occurs for the first time this year, based on the MT outputs collected at last year's shared task. For this purpose the test instances are much fewer than the other language pairs and therefore the numbers are not very conclusive. Therefore, categories and phenomena that have only a handful of samples will not be included in our analysis, although they appear in the tables.

Category-level Here, the average accuracy over all metrics is much lower than the other language directions, reaching only 66%, only 20% above the random baseline. The best performing category is *ambiguity* (86,3%), more than 13% better than the following categories. The worst performing categories are *function words* and *punctuation*, with less than 55%. The rest of the categories range in accuracies between 53 and 73%.

Phenomenon-level The good performance of the *ambiguity* category is also confirmed in the table on the phenomenon level (Table 6), as in Russian this is the only phenomenon of this category, as opposed to other language pairs where we also have examples of structural ambiguity. The most difficult phenomena to score appear to be the *focus particles, adverbial clause* and *stripping* with less than 50% average accuracy, in many cases lower than the random baseline.

5 Conclusion

In this paper we analysed the performance of several state-of-the-art metrics with regard to particular linguistically-motivated phenomena for three language pairs, German-English, English-German and for the first time, English-Russian. The analysis gave a multitude of observations, regarding both the performance of the metrics and the corresponding linguistic observations.

The metrics demonstrating the best performance in average are COMETOID22-WMT23 for the German-English language pair, and METRICX-23-C for both the English-German and English-Russian language pairs. Quality estimation methods have impressively good performance in several phenomena. Some metrics that report usage of LLMs (EMBED_LLAMA) have not scored very high in overall, indicating that more work is required in this direction.

Among the various linguistic phenomena, we could identify some of the particularly challenging ones. In German-English, metrics have difficulties scoring the *passive voice* properly. In English-German *named entities and terminology* as well as specific *measurement units* pose the most difficulties. In English-Russian translation, translations with *focus particles, adverbial clause, and stripping* phenomena emerge as particularly complex challenges.

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ling. category	baselines														QE as a metric														ref. based metrics													
	BERTscore	BLEU	BLEURT-20	COMET	YSI-1	chrF	prtmRef	spBLEU	CometKiwi-XL	CometKiwi-XXL	CometKiwi	GEMBA-MQM	MS-COMET-QE	MetricX-23-QE-b	MetricX-23-QE-c	MetricX-23-QE	Random-synname	XCOMET-QE-Ensemble	XLsimQE	cometoid22-wm11	cometoid22-wm12	prtmSrc2	KG-BERT	MEE4	MEE4_sisb_xlm	MaTSE	MetricX-23-b	MetricX-23-c	MetricX-23	XCOMET-Ensemble	XCOMET-XL	XCOMET-XXL	XLsim	cometoid22-wm13	eBLEU	embed_llama	partokengram_F	tokengram_F	avg			
Ambiguity	87	71	89	90	90	81	91	79	78	90	85	77	82	78	86	80	46	87	61	86	85	66	85	83	88	74	87	90	88	89	92	84	91	74	56	48	80	81				
Composition	90	66	88	87	88	74	86	71	83	87	80	81	75	85	90	81	44	86	40	81	81	70	80	85	86	69	85	90	85	87	84	83	79	87	74	65	61	75	79			
Coordination & ellipsis	316	81	74	81	78	83	78	82	74	83	75	84	69	78	77	78	45	79	59	75	73	79	84	81	77	49	81	82	81	79	70	77	81	73	68	58	78	75				
False friends	90	64	91	92	88	76	84	69	82	82	82	77	72	89	90	88	47	80	51	87	83	86	82	87	80	73	96	96	84	84	74	74	93	72	68	51	72	80				
Function word	586	82	73	83	83	82	73	84	73	84	87	76	77	68	80	86	47	86	60	84	87	81	76	79	76	57	87	83	86	87	83	72	80	91	79	66	55	75	78			
LDD & interrogatives	1014	84	74	85	87	84	76	86	74	80	81	84	72	81	83	83	45	80	61	81	79	72	84	81	76	53	82	83	82	84	72	77	87	76	68	54	77	77				
MWE	610	82	72	84	84	85	76	86	73	74	83	77	73	59	80	87	45	83	53	72	73	65	76	80	81	67	84	86	87	84	84	80	75	85	75	66	54	76	76			
Named entity & termin.	861	73	64	69	74	76	69	73	72	65	67	66	61	62	65	70	66	44	67	59	66	67	69	66	72	70	58	72	74	72	72	75	66	69	71	64	57	52	70	67		
Negation	76	79	78	91	93	84	82	84	76	91	91	93	75	84	91	95	86	50	93	55	91	89	92	93	86	84	51	91	95	92	95	91	79	76	91	75	59	45	82	82		
Non-verbal agreement	419	78	78	85	84	78	78	79	79	78	80	77	67	78	78	81	79	43	80	64	77	79	74	76	78	75	59	81	84	81	77	72	70	81	76	60	74	77	76			
Punctuation	293	75	74	69	69	70	65	80	76	62	62	63	59	59	61	60	39	65	67	66	66	86	63	76	67	48	62	55	62	66	66	44	69	67	65	66	67	67	65			
Subordination	679	75	70	76	78	75	70	78	69	79	78	78	64	65	77	77	78	43	79	53	75	75	68	78	77	75	50	77	78	77	79	75	64	70	79	73	62	71	71	72		
Verb tense/aspect/mood	4697	88	69	85	88	89	76	90	71	83	84	85	84	81	85	87	81	43	82	60	74	75	80	85	84	84	56	82	87	83	85	83	78	78	93	76	62	77	77	79		
Verb valency	211	64	54	63	64	64	55	65	52	59	54	59	45	51	60	58	55	39	57	33	57	48	59	62	56	44	62	63	61	62	61	53	61	66	55	41	56	56	56			
macro avg.	10402	81	70	81	82	81	73	82	72	77	79	78	70	78	81	77	44	79	55	76	77	74	78	79	77	58	81	82	81	81	79	71	74	83	72	62	59	74	74			
micro avg.	10402	83	70	82	84	84	75	85	72	79	80	80	75	74	80	83	78	44	80	58	75	76	75	80	81	79	57	81	83	81	82	81	74	76	87	74	63	67	75	76		

Table 1: Accuracy of the metrics (%) with regard to the 14 linguistically motivated categories for German-English. The significantly best systems per phenomenon over all metrics are indicated with a gray background, whereas the significantly best systems per metrics category are indicated with boldface.

ling. category	#	baselines												QE as a metric												ref. based metrics																				
		BERTscore	BLEU	BLEURT-20	COMET	YSI-1	chrf	prismRef	spBLEU	Calibri-COMET2-QE	CometKwi-XL	CometKwi-XXL	CometKwi	GEMBA-MQM	KG-BERT	MS-COMET-QE	MetricX-23-QE-b	MetricX-23-QE-c	MetricX-23-QE	Random-synname	XCOMET-QE-Ensemble	XLSimQE	cometoid2-wm11	cometoid2-wm12	cometoid2-wm13	mbr-metricx-qe0p2p1-qe	mbr-metricx-qexv1p-qe	prismStrc2	Calibri-COMET2	MEB4	MEF4_sbs_xlm	MATESe	MetricX-23-b	MetricX-23-c	MetricX-23	XCOMET-Ensemble	XCOMET-XL	XCOMET-XXL	XLSim	eBLEU	embed_llama	mftRegressor	partokengram_F	tokengram_F	avg	
Ambiguity	146	84	71	90	84	86	88	97	88	42	77	60	42	77	42	39	75	85	82	46	56	38	59	58	87	86	86	95	14	84	90	92	50	88	95	88	82	88	62	93	70	62	81	62	88	73
Coordination & ellipsis	836	69	61	80	78	69	61	74	63	73	74	75	74	60	74	71	78	79	80	48	77	38	75	74	76	83	80	58	75	62	63	33	76	81	72	79	81	64	75	61	56	72	49	62	69	
False friends	225	65	63	69	74	71	71	67	65	71	61	75	71	65	71	73	64	80	66	46	76	82	64	52	66	76	63	68	74	83	87	30	60	82	62	65	59	53	76	66	55	56	52	68	67	
Function word	200	90	78	79	90	82	74	93	74	92	94	92	90	82	90	78	86	72	85	36	95	62	94	94	94	90	67	84	86	82	76	60	86	86	84	94	86	64	76	70	52	76	60	76	80	
MWE	829	79	72	87	90	86	77	85	74	74	86	79	73	66	73	71	88	89	85	45	83	37	78	78	90	88	89	47	89	76	78	18	86	92	85	90	93	76	81	69	69	72	54	78	76	
Named entity & termin.	1272	57	54	66	64	62	61	67	62	54	51	49	55	56	54	55	61	65	58	44	54	46	60	54	68	62	80	56	62	60	63	30	72	74	71	62	60	60	71	60	48	54	49	60	59	
Negation	174	87	83	89	92	84	84	84	86	90	90	84	89	76	89	92	83	88	78	47	84	40	90	90	96	89	91	90	91	91	58	85	91	80	84	85	79	80	86	67	88	52	86	83		
Non-verbal agreement	372	74	72	81	88	78	70	83	75	82	90	84	81	83	81	78	95	93	91	45	95	43	93	91	93	82	94	71	87	76	69	57	90	95	87	94	91	88	73	72	65	84	54	69	80	
Punctuation	336	69	73	74	70	66	72	77	69	82	72	76	82	60	82	65	73	66	73	42	60	44	81	82	81	75	70	75	65	74	72	28	74	70	67	65	65	46	68	74	49	57	44	73	68	
Subordination	994	78	74	81	84	78	75	86	74	89	88	89	76	89	80	83	85	83	86	83	84	76	83	79	83	86	83	84	76	83	79	78	16	83	84	83	89	85	79	75	71	75	56	76	78	
Verb tense/aspect/mood	3081	68	62	70	70	69	69	67	64	71	72	75	75	71	75	61	82	84	85	43	83	52	62	65	75	71	77	61	70	70	74	46	77	77	78	83	76	71	69	72	55	71	62	69	70	
Verb valency	480	73	64	82	79	74	70	79	69	77	81	85	77	62	77	71	86	80	86	42	87	52	79	80	77	87	88	66	77	70	36	84	81	85	85	80	75	79	66	69	65	70	70	74		
macro avg.	8945	74	69	79	80	76	73	80	72	75	78	77	75	70	75	70	80	80	79	44	78	48	76	75	82	81	81	64	79	76	76	38	80	84	79	81	79	68	76	70	60	71	55	73	73	
micro avg.	8945	70	65	75	76	72	69	74	68	73	74	75	74	68	74	67	79	81	80	44	78	47	71	71	78	77	81	62	74	71	73	36	79	81	78	81	77	70	73	69	59	69	56	70	71	

Table 2: Accuracy of the metrics (%) with regard to the 12 linguistically motivated categories for English-German

ling. category	baselines												QE as a metric												ref. based metrics															
	BERTscore	BLEU	BLEURT-20	COMET	YsI-1	chrf	prismRet	spBLEU	CometKiwI-XL	CometKiwI-XXL	CometKiwI	GEMBA-MQM	KG-BERT	MS-COMET-QE	MetricX-23-QE-b	MetricX-23-QE-c	MetricX-23-QE	Random-sysname	XCOMET-QE-Ensemble	XLsimQE	cometoid22-wm11	cometoid22-wm12	cometoid22-wm13	prismSrc2	MATSE	MetricX-23-b	MetricX-23-c	MetricX-23	XCOMET-Ensemble	XCOMET-XL	XCOMET-XXL	XLsim	eBLEU	embed_llama	partokengram_F	tokengram_F	avg			
Ambiguity	80	67	100	97	88	67	83	73	100	94	100	100	100	100	95	100	100	100	39	100	30	100	100	100	56	69	55	21	98	100	100	100	100	100	88	77	44	59	70	86
Coordination & ellipsis	84	73	68	73	76	67	77	69	73	64	68	38	68	76	62	79	64	45	64	41	64	70	67	69	55	21	61	69	56	67	64	50	74	80	60	57	67	64		
False friends	100	17	100	100	100	17	83	50	0	0	0	100	0	0	0	100	17	17	17	0	17	33	33	100	0	17	100	100	100	33	33	100	83	100	50	83	33	50		
Function word	59	69	69	59	53	38	48	72	53	55	50	51	50	36	66	55	48	44	72	39	73	64	54	28	9	63	57	60	60	60	60	22	49	61	52	53	38	53		
MWE	122	70	64	79	80	74	64	79	67	72	70	77	57	77	77	75	88	75	40	67	35	75	70	77	23	57	87	91	85	70	73	69	75	66	59	59	64	69		
Named entity & termin.	243	79	69	95	91	79	76	85	76	84	62	59	54	59	69	63	73	73	49	64	53	85	86	95	31	51	89	86	86	91	91	71	84	75	65	58	75	73		
Negation	34	74	74	79	68	74	85	68	74	68	85	85	91	85	41	71	100	9	59	91	9	62	29	59	91	0	94	71	94	79	71	74	65	76	85	85	69			
Non-verbal agreement	61	69	56	82	77	67	61	57	84	100	54	72	54	74	72	72	98	66	41	77	26	95	100	85	62	43	92	92	85	79	31	64	61	66	69	69	70			
Punctuation	121	42	46	53	68	86	41	73	55	66	29	65	27	65	87	55	66	43	41	61	44	66	67	36	56	1	60	71	52	66	57	12	63	66	84	45	45	54		
Subordination	499	62	62	61	70	67	66	63	63	72	66	66	41	66	75	65	66	61	45	77	32	68	61	65	37	18	60	84	58	80	70	52	63	54	57	65	65	61		
Verb tense/aspect/mood	135	79	62	76	85	76	84	81	74	79	79	73	61	73	64	67	65	66	39	74	60	70	59	85	38	50	90	94	90	85	92	74	79	70	73	82	82	73		
Verb valency	121	70	67	70	75	76	67	56	68	71	88	79	66	79	71	76	85	76	36	76	26	63	61	65	25	45	79	81	78	72	70	65	84	76	64	69	69	68		
macro avg.	1727	72	60	78	79	76	61	71	66	69	66	65	63	65	64	64	81	58	41	69	34	72	66	74	42	34	81	83	79	74	72	60	73	72	62	65	64	66		
micro avg.	1727	69	64	72	76	73	65	70	67	74	67	68	51	68	71	67	74	64	44	72	39	73	68	71	40	32	73	82	71	77	74	55	71	67	62	63	66	66		

Table 3: Accuracy of the metrics (%) with regard to the linguistically motivated categories for English-Russian

ling. category	ling. phenomenon	#	baselines												QE as a metric												ref. based metrics																							
			BERTscore	BLEU	BLURT-20	COMET	YISI-1	chrF	prismRef	sBLEU	CometKiwi-XL	CometKiwi-XXL	GEMBA-MQM	MS-COMET-QE	MetricX-23-QE-b	MetricX-23-QE-c	MetricX-23-QE	Random-synname	XCOMET-QE-Ensemble	XLsimQE	cometoid22-wm11	cometoid22-wm12	prismSrc2	KG-BERT	MEE4	MEE4_snb_xlm	MATSE	MetricX-23-b	MetricX-23-c	XCOMET-Ensemble	XCOMET-XL	XCOMET-XXL	XLsim	cometoid22-wm13	eBLEU	embed_llama	partokengram_F	tokengram_F	avg											
80	Subject clause		82	78	80	86	84	74	86	76	88	86	84	80	85	85	84	84	84	71	86	88	82	84	82	81	49	85	81	84	80	74	75	88	78	59	74	74	79											
50	Verb tense/aspect/mood		90	68	92	88	66	84	64	90	96	94	76	80	92	88	88	84	88	64	80	80	82	96	74	81	70	88	92	86	78	90	80	74	75	88	78	59	74	74	79									
121	Conditional		89	69	88	87	91	74	90	71	95	97	94	96	93	92	95	92	56	80	81	91	94	79	74	63	91	95	89	91	95	82	89	81	93	74	57	74	84											
84	Ditransitive - future I subj. II		96	62	86	90	94	75	89	68	100	94	100	100	100	100	98	95	35	95	52	75	80	94	100	79	82	57	80	92	86	96	88	88	63	95	65	57	75	83										
97	Ditransitive - future II		98	65	84	90	96	72	84	66	93	94	97	94	96	88	99	79	41	85	66	77	86	97	72	73	68	84	91	87	92	90	82	68	99	67	53	71	71	81										
88	Ditransitive - future II subj. II		90	69	88	94	94	77	91	73	98	98	94	95	92	97	80	39	95	67	91	90	92	98	78	78	81	93	97	93	93	93	93	93	76	93	80	55	76	86										
72	Ditransitive - perfect		89	64	78	88	90	72	79	62	88	83	83	75	79	89	76	83	50	75	58	72	72	83	68	75	42	75	81	69	75	71	60	74	89	76	69	72	72	75										
86	Ditransitive - pluperfect		91	69	72	90	90	86	78	69	55	66	64	64	72	52	74	43	51	55	49	52	76	64	78	76	43	73	72	71	69	66	45	71	97	74	67	87	87	69										
107	Ditransitive - pluperfect subj. II		82	68	91	87	83	80	88	70	89	89	84	93	79	93	95	82	40	84	55	69	93	84	82	90	91	93	93	92	90	91	78	92	74	64	79	79	81											
90	Ditransitive - present		87	58	87	86	89	77	83	64	88	90	89	82	92	97	92	53	82	51	69	70	69	89	80	81	69	93	88	90	97	93	90	79	89	70	69	79	79	81										
110	Ditransitive - preterite		83	76	93	92	89	83	95	76	79	88	84	86	76	95	94	48	89	59	83	84	81	92	89	85	81	96	97	96	95	98	88	76	97	73	68	85	85											
98	Ditransitive - preterite subj. II		84	59	94	93	91	74	95	63	94	90	95	94	94	94	93	44	94	57	94	93	84	95	90	84	73	95	92	90	95	92	90	95	91	92	79	96	76	59	77	85								
32	Imperative		91	66	94	91	91	75	100	75	97	100	88	97	78	100	97	97	47	66	69	81	81	88	94	91	62	100	97	88	94	75	94	75	72	84	75	94	75	72	78	86								
56	Intransitive - future I		84	61	93	88	91	73	96	70	82	82	77	80	62	77	86	80	36	86	32	66	68	59	77	89	95	59	89	95	91	84	80	77	95	80	75	94	75	72	78	86								
62	Intransitive - future II		92	69	89	95	97	89	97	76	92	96	92	69	82	90	97	44	85	73	71	77	68	92	95	98	55	85	94	82	85	82	77	89	98	88	76	97	73	73	77									
94	Intransitive - future II subj. II		88	65	90	82	90	72	84	63	82	82	83	88	71	83	86	82	44	83	54	80	73	83	80	83	80	84	83	80	84	83	80	79	84	83	80	84	83	80	84	65	54	71	77					
61	Intransitive - perfect		85	70	82	84	89	82	89	69	70	69	77	85	64	93	85	82	39	61	74	75	61	77	82	92	34	77	80	74	69	64	80	92	87	82	82	82	82	82										
85	Intransitive - pluperfect		98	86	96	95	95	88	98	82	92	86	93	92	73	88	91	88	44	87	62	79	82	61	93	96	99	74	92	95	94	88	91	94	98	85	62	91	91	87										
79	Intransitive - pluperfect subj. II		91	75	92	96	99	78	97	72	92	87	94	97	86	97	95	96	43	87	78	84	78	84	91	76	74	46	87	91	83	81	85	70	93	63	63	76	85											
54	Intransitive - present		72	50	85	83	74	61	87	57	81	74	91	85	87	78	74	46	74	76	83	89	74	91	76	74	46	87	91	83	81	85	70	93	67	63	63	76	85											
46	Intransitive - preterite		78	43	83	85	80	52	80	63	83	89	93	80	85	72	83	50	89	52	91	89	87	93	87	83	67	91	91	91	83	72	87	70	85	74	61	57	77											
100	Intransitive - preterite subj. II		89	69	88	92	88	77	95	76	85	84	89	81	87	85	83	79	44	84	52	68	72	89	93	89	64	85	89	86	88	79	80	81	94	88	69	81	81	81										
42	Modal - future I		98	74	93	98	95	95	98	93	83	79	57	69	74	76	67	50	76	62	33	38	57	79	90	98	29	67	74	74	86	81	55	98	100	83	95	95	78											
86	Modal - future I subj. II		86	77	81	78	88	76	90	79	85	79	78	65	71	86	81	50	85	44	42	94	94	78	83	90	31	65	79	67	84	74	72	80	91	79	57	77	77	75										
149	Modal - perfect		91	83	77	87	90	84	93	83	85	83	56	81	83	56	83	76	37	79	61	44	73	83	81	89	21	52	68	56	77	66	62	86	98	83	66	85	85											
75	Modal - pluperfect		80	81	92	92	84	95	77	66	79	76	80	75	81	76	85	67	37	73	77	83	80	84	80	85	92	47	85	80	77	69	67	89	95	81	76	83	79											
61	Modal - pluperfect subj. II		85	57	89	80	85	74	95	66	80	85	87	84	89	72	84	46	87	59	69	74	92	87	85	89	46	75	82	74	90	84	82	72	80	84	70	74	78											
30	Modal - present		93	67	90	90	93	87	100	73	90	83	90	77	90	97	97	43	90	40	73	80	97	90	93	93	53	100	97	100	97	93	97	90	93	90	63	87	86											
72	Modal - preterite		85	78	82	88	88	76	94	78	94	83	85	93	89	88	78	46	90	57	62	69	83	86	88	86	44	75	78	83	82	68	79	89	86	72	76	80												
30	Modal - preterite subj. II		100	80	93	100	93	93	97	87	87	90	87	90	87	87	90	30	80	73	63	63	73	90	93	100	40	70	83	80	77	67	47	87	100	97	77	93	93	83										
43	Modal negated - future I		95	91	88	95	98	93	98	91	91	95	98	88	93	93	95	48	91	56	58	77	98	88	95	42	79	91	81	91	84	65	95	95	91	77	93	93	86											
73	Modal negated - future I subj. II		78	60	77	74	78	73	82	59	85	67	84	68	88	89	75	75	47	71	63	59	78	84	79	78	33	59	71	64	75	70	64	84	92	63	52	75	71											
126	Modal negated - perfect		81	67	71	82	80	77	87	71	79	71	75	64	80	79	75	77	46	67	54	54	56	75	84	83	33	61	66	65	67	58	52	80	94	75	63	78												

ling. category	ling. phenomenon	#	baselines										QE as a metric										ref. based metrics																					
			BERTscore	BLEU	BLURT-20	COMET	YIS-1	chrF	prismRef	spBLEU	CometKiwi-XL	CometKiwi-XXL	CometKiwi	GEMBA-MQM	MS-COMET-QE	MetricX-23-QE-b	MetricX-23-QE-c	MetricX-23-QE	Random-synname	XCOMET-QE-Ensemble	XLsimQE	cometoid22-wm11	cometoid22-wm12	prismSrc2	KG-BERT	MEE4	MEE4_snb_xlm	MATESe	MetricX-23-b	MetricX-23-c	MetricX-23	XCOMET-Ensemble	XCOMET-XL	XCOMET-XXL	XLsim	cometoid22-wm13	eBLEU	embed_llama	partokengram_F	tokengram_F	avg			
	Reflexive - future II subj. II	107	90	67	84	93	92	71	93	70	89	93	91	93	76	84	88	79	41	92	63	84	92	83	91	75	82	55	86	84	88	94	93	82	69	93	69	57	73	73	81			
	Reflexive - perfect	188	85	61	83	85	80	60	85	64	82	88	90	80	78	83	90	80	46	88	58	79	84	84	90	76	74	63	84	91	88	86	83	82	69	91	70	57	60	60	77			
	Reflexive - pluperfect	109	96	74	76	91	94	67	86	71	70	77	80	84	75	66	84	62	43	73	55	72	71	81	80	80	81	55	69	83	67	79	74	70	77	96	72	75	72	72	75			
	Reflexive - pluperfect subj. II	90	90	68	87	90	87	74	92	74	78	87	87	92	88	89	83	78	38	86	64	89	84	88	87	84	86	58	79	82	79	84	81	84	76	92	83	69	76	76	81			
	Reflexive - present	125	82	55	90	86	82	72	88	66	79	84	88	81	91	89	92	87	46	85	58	89	86	91	88	81	78	62	87	90	84	92	87	86	69	88	70	58	70	70	80			
	Reflexive - preterite	117	92	75	86	85	90	77	92	77	71	68	74	89	83	80	80	73	39	71	61	81	80	78	74	92	82	64	90	93	86	77	82	79	71	85	85	79	80	70				
	Reflexive - preterite subj. II	124	94	89	90	93	97	81	96	85	86	81	90	96	88	93	86	93	44	85	55	82	88	90	95	90	77	98	98	88	96	92	77	97	85	73	83	83	87					
	Transitive - future I	43	98	84	95	95	100	86	98	86	84	93	77	88	91	84	81	79	44	93	51	84	84	93	77	95	91	60	93	98	93	93	86	86	86	95	65	56	86	86	85			
	Transitive - future I subj. II	37	97	81	86	95	100	89	95	81	95	95	84	81	100	95	97	89	43	92	68	70	95	100	84	89	89	62	86	89	84	89	89	73	84	97	81	54	84	84	85			
	Transitive - future II	33	97	82	94	94	100	91	94	79	91	94	97	91	85	94	97	82	45	94	67	76	85	100	97	85	97	61	97	97	94	88	79	94	97	73	36	94	94	87				
	Transitive - future II subj. II	50	96	62	78	80	86	82	68	74	92	98	70	92	66	96	98	56	96	54	90	88	86	70	72	88	70	50	82	76	82	80	80	80	82	96	68	56	82	82	79			
	Transitive - perfect	99	88	73	76	91	95	85	96	77	70	77	72	84	82	82	83	72	43	73	60	62	69	86	72	88	94	58	83	84	84	81	78	73	85	96	80	72	86	86	79			
	Transitive - pluperfect	22	82	41	86	86	86	59	95	50	77	91	82	95	95	91	91	77	27	91	45	68	68	91	86	82	64	77	82	82	86	91	91	77	68	91	64	32	55	55	75			
	Transitive - pluperfect subj. II	39	90	64	92	90	90	72	92	69	79	87	92	95	95	92	90	92	49	82	51	82	85	85	92	97	87	87	97	100	97	87	90	90	85	95	85	59	72	84				
	Transitive - present	33	73	52	85	91	82	67	91	70	82	88	91	100	91	85	97	82	48	85	70	88	91	70	91	94	88	88	97	94	97	88	85	94	79	97	85	64	76	76	83			
	Transitive - preterite	57	82	39	84	79	77	56	77	54	84	81	81	63	72	77	77	40	79	58	81	81	74	81	77	70	58	77	79	75	82	75	84	68	84	74	53	58	58	72				
	Transitive - preterite subj. II	97	81	48	88	88	89	59	88	54	82	87	92	94	84	85	94	77	41	88	65	82	85	79	92	78	77	92	91	95	93	95	92	74	88	64	62	62	62	80				
	Case government	80	89	74	86	91	85	72	90	70	84	74	84	60	70	82	78	78	57	76	50	79	80	71	84	84	70	57	86	86	86	86	89	74	80	92	70	51	75	75	77			
	Mediopassive voice	50	94	72	92	90	96	78	94	72	90	84	88	84	86	90	96	88	54	94	40	88	94	72	88	90	88	68	90	90	94	90	90	84	92	94	86	58	80	80	84			
	Passive voice	33	55	55	55	55	55	55	55	55	39	39	42	18	27	45	39	30	27	39	27	42	39	27	42	42	55	55	36	52	55	39	48	36	33	55	55	52	55	55	45			
macro avg.		10402	84	69	82	84	85	75	86	71	80	81	81	76	75	81	83	79	43	80	57	74	75	76	81	81	80	56	81	84	81	83	80	73	76	87	74	62	69	75	76			
micro avg.		10402	83	70	82	84	84	75	85	72	79	80	80	75	74	80	83	78	44	80	58	75	76	75	80	81	79	57	81	83	81	82	81	74	76	87	74	63	67	75	76			

Table 4: Accuracy of the metrics(%) with regard to the linguistically-motivated phenomena for German-English

ling. phenomenon	baselines													QE as a metric													ref. based metrics													#							
	BERTscore	BLEU	BLEURT-20	COMET	YSI-1	chrf	prismRef	spBLEU	Calibrn-COMET22-QE	CometKwi-XL	CometKwi-XXL	CometKwi	GEMBA-MQM	KG-BERT	MS-COMET-QE	MetricX-23-QE-b	MetricX-23-QE-c	MetricX-23-QE	Random-sysname	XCOMET-QE-Ensemble	XLsimQE	cometoid22-wm12	cometoid22-wm13	cometoid22-wm13-ge	cometoid22-wm13-ge	prismStrc2	Calibrn-COMET22	MEE4	MEE4_ssb_xlm	MaTESe	MetricX-23-b	MetricX-23-c	MetricX-23	XCOMET-Ensemble	XCOMET-XL	XCOMET-XXL	XLsim	eBLEU	embed_llama		mltRegressor	partokengram_F	tokengram_F	avg			
Reflex. - future II progr.	65	56	64	64	75	80	88	88	88	85	85	77	85	52	85	89	89	86	51	83	37	44	49	72	64	85	41	67	72	79	57	84	73	80	86	81	81	68	79	38	68	77	77	69			
Reflex. - future I simple	56	71	66	77	54	88	88	88	88	85	85	88	88	52	98	98	98	98	50	100	66	66	68	48	54	85	38	52	52	75	82	61	89	80	91	81	81	64	64	88	64	79	89	89	73		
Reflex. - past perf. progr.	98	60	50	67	64	71	66	49	51	81	79	70	88	83	74	73	83	39	77	48	48	61	63	67	77	43	65	67	69	61	66	69	61	70	81	70	73	61	72	49	63	65	65	66			
Reflex. - past perf. simple	53	62	47	68	55	74	55	49	57	70	89	85	77	64	77	81	79	38	98	60	45	51	68	70	83	49	58	62	58	49	81	70	91	92	83	72	57	77	47	83	53	53	66	96			
Reflex. - past progr.	5	100	100	40	100	100	100	80	100	0	60	60	40	40	100	100	100	100	40	40	60	40	40	40	60	40	60	100	100	100	60	80	60	60	60	60	100	100	100	100	40	100	100	72	96		
Reflex. - pres. perf. progr.	33	76	48	88	67	76	76	45	48	61	100	88	88	85	88	88	88	42	100	27	61	79	82	67	100	24	67	79	85	52	97	79	100	100	97	100	67	100	33	73	79	79	76				
Reflex. - pres. perf. simple	39	59	46	67	59	69	72	46	44	44	97	72	69	64	69	31	74	85	38	82	62	38	67	59	74	31	59	69	79	28	79	69	85	74	77	82	67	90	54	69	69	65					
Reflex. - pres. progr.	99	62	51	54	56	67	56	37	62	51	75	66	46	91	46	39	58	76	70	41	79	51	58	52	57	44	45	58	57	64	51	71	69	74	73	76	70	59	72	42	61	58	58	59			
Reflex. - simple past	119	71	70	73	73	73	77	64	71	63	73	81	82	82	82	46	95	98	100	34	86	55	55	60	75	61	54	63	72	71	77	57	73	84	71	85	82	77	74	79	56	82	78	78	72		
Reflex. - simple pres.	138	65	65	67	67	88	63	64	67	55	70	75	58	87	58	47	78	97	73	49	71	31	56	72	78	54	64	67	69	80	43	70	67	70	77	72	67	77	83	54	67	64	64	67			
trans. - future II progr.	11	73	82	73	91	64	82	82	100	73	100	100	91	100	91	100	100	36	91	73	91	82	91	100	100	64	91	55	55	55	55	82	73	73	100	100	91	82	91	73	82	73	82	82	84		
trans. - cond. I progr.	11	55	91	45	64	82	55	91	36	91	100	55	36	55	82	91	45	100	36	91	73	73	64	100	100	55	55	55	55	55	55	82	73	73	82	73	82	55	45	55	18	82	82	88			
trans. - cond. II simple	9	67	100	89	89	56	100	22	100	67	89	100	56	56	89	100	67	89	33	89	89	44	33	89	100	0	67	67	56	56	100	67	100	100	100	78	67	67	67	67	56	100	100	75	55	70	
trans. - cond. II progr.	20	70	55	75	65	80	55	85	60	70	95	95	70	70	40	75	85	90	40	85	40	65	60	85	95	60	65	100	100	100	100	100	100	90	70	90	85	85	65	55	55	55	55	55	70		
trans. - cond. II simple	2	50	100	100	100	100	100	100	100	100	100	100	50	100	100	100	100	100	100	100	50	50	50	100	100	50	100	100	100	100	100	100	100	100	100	100	100	100	50	50	100	100	100	100	90		
trans. - future I progr.	12	42	83	75	83	25	50	75	75	75	75	75	58	75	58	92	67	92	58	75	67	75	75	92	92	58	75	50	50	58	67	92	67	92	92	92	50	42	42	42	42	67	67	69			
trans. - future I simple	22	68	95	64	68	68	77	50	95	73	86	36	77	5	77	86	95	73	100	50	59	73	77	73	68	64	91	59	64	68	68	73	86	50	86	77	91	73	45	68	59	41	86	86	71		
trans. - future II simple	39	62	92	59	77	67	85	62	90	85	72	79	87	54	87	69	74	69	72	38	97	72	49	44	87	67	62	33	77	82	79	33	67	62	67	79	69	69	74	69	59	74	87	87	70		
trans. - past perf. progr.	16	50	69	50	81	81	81	56	69	94	94	38	94	31	94	75	81	50	81	38	50	62	75	69	62	44	75	62	81	56	56	69	50	75	75	81	38	75	81	38	75	62	50	44	75	75	66
trans. - past perf. simple	5	20	80	80	80	20	80	20	80	80	100	100	0	100	100	100	100	20	80	60	100	20	100	100	100	40	80	20	0	80	60	100	100	100	60	100	80	80	20	20	20	0	80	80	66		
trans. - pres. perf. progr.	9	33	67	78	78	44	78	44	67	100	89	100	100	22	100	100	100	44	100	33	89	67	78	78	100	44	78	33	22	56	78	100	78	89	89	89	22	22	33	33	33	78	78	70			
trans. - pres. perf. simple	10	30	70	20	40	30	40	30	40	30	40	30	20	30	40	90	60	90	50	60	50	50	50	30	40	40	40	50	40	30	20	40	60	40	40	70	70	60	40	20	40	50	50	45			
trans. - pres. progr.	23	61	43	96	70	35	57	87	52	91	78	91	96	61	96	91	96	74	83	48	96	39	74	74	87	96	96	70	65	70	52	96	100	91	96	91	100	57	48	43	70	57	57	75			
trans. - simple past	16	31	62	38	75	69	62	56	56	94	50	81	100	62	100	100	94	94	75	50	81	50	100	94	100	81	81	62	38	50	81	75	75	56	81	69	75	56	44	75	62	62	70				
trans. - simple pres.																																															
Verb valency																																															
Case government	57	82	67	75	82	86	70	86	75	75	74	81	75	75	75	72	86	91	82	40	82	40	81	79	84	84	89	65	75	77	75	42	82	82	79	81	75	79	81	65	79	75	72	72	76		
Catenative verb	177	71	62	87	75	68	63	68	63	73	91	94	73	34	73	66	88	63	90	44	92	60	77	81	67	92	89	58	72	65	68	19	81	71	84	90	85	77	80	64	64	63	64	64	72		
Middle voice	29	83	62	97	93	72	76	93	72	93	79	97	93	86	93	62	100	100	55	100	21	100	93	100	97	100	31	90	90	83	59	100	100	100	100	100	90	79	59	83	83	76	76	84	84		
Passive voice	70	66	54	69	70	67	74	81	61	74	71	63	79	94	79	69	96	99	90	40	79	30	67	63	70	74	89	87	70	64	69	33	89	81	87	71	59	51	80	57	69	60	71	71	71		
Resultative	147	73	69	84	83	81	75	86	76	79	76	84	78	71	78	80	78	84	77	37	83	65	82	84	88	84	73	83	73	69	51	84	88	86	82	80	80	75	67	61	75	67	61	75	75	77	
macro avg.	8945	67	65	74	75	70	71	73	67	73	76	77	78	67	78	68	84	80	83	43	82	52	71	72	77	78	82	62	74	70	72	42	79	80	77	84	79	71	70	67	58	69	59	71	71		
micro avg.	8945	70	65	75	76	72	69	74	68	73	74	75	74	68	74	67	79	81	80	44	78	47	71	71	78	77	81	62	74	71	73	36	79	81	78	81	77	70	73	69	59	69	56	70	71		

Table 5: Accuracy of the metrics(%) with regards to the linguistically-motivated phenomena for English-German

ling. category	ling. phenomenon	baselines													QE as a metric										ref. based metrics										#				
		BERTscore	BLEU	BLEURT-20	COMET	Yst-1	chrf	prismKet	sBLEU	Cometkiwi-XL	Cometkiwi-XXL	Cometkiwi	GEMBA-MQM	KG-BERT	MS-COMET-QE	MetricX-23-QE-b	MetricX-23-QE-c	MetricX-23-QE	Random-synname	XCOMET-QE-Ensemble	XLsimQE	cometoid22-wm12	cometoid22-wm12	cometoid22-wm13	prismSrc2	MATSE	MetricX-23-b	MetricX-23-c	MetricX-23	XCOMET-Ensemble	XCOMET-XL	XCOMET-XXL	XLsim	eBLEU		embed_llama	parTokengram_F	tokengram_F	avg
Ambiguity	Lexical ambiguity	80.67	100.97	88.77	88.67	83.73	73.83	73.83	100.94	100.86	66.30	66.30	100.66	95.43	100.63	98.49	100.63	100.63	100.63	100.63	30.30	100.63	100.63	100.63	56.56	98.98	100.45	100.45	100.57	100.57	100.57	88.88	77.77	44.44	59.59	70.70	86.86		
Coordination & ellipsis	Gapping	80.75	68.77	91.89	91.89	67.73	73.73	73.73	93.87	80.86	66.30	66.30	100.66	95.43	100.63	98.49	100.63	100.63	100.63	100.63	34.34	73.73	68.78	68.78	53.53	14.14	100.45	100.45	100.57	100.57	100.57	88.88	77.77	44.44	59.59	70.70	86.86		
	Pseudogapping	87.78	89.91	87.91	87.91	66.77	73.73	73.73	93.87	80.86	66.30	66.30	100.66	95.43	100.63	98.49	100.63	100.63	100.63	100.63	41.41	53.53	67.67	67.67	88.88	13.13	64.64	73.73	60.60	64.64	60.60	89.89	84.84	78.78	80.80	70.70	66.66		
	Sluicing	64.55	82.45	55.55	64.55	64.55	55.55	55.55	18.55	55.36	64.36	64.36	64.36	64.36	82.82	82.82	82.82	82.82	82.82	82.82	73.73	55.55	55.55	27.27	0.00	55.55	27.27	55.55	55.55	55.55	0.00	91.91	64.64	45.45	64.54	54.54	64.54		
	Stripping	78.63	59.48	63.56	81.52	41.26	56.81	52.41	26.56	86.72	57.86	47.86	82.63	93.93	95.43	62.32	74.74	74.74	74.74	74.74	46.39	79.79	82.79	68.62	61.61	67.67	85.85	22.22	47.47	47.47	67.67	67.67	45.45	70.70	61.61	68.68	50.50		
	VP-ellipsis	100.17	100.100	100.100	100.100	17.83	50.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	17.17	33.33	33.33	100.100	0.00	17.17	100.100	100.100	100.100	100.100	33.33	100.100	83.83	100.100	50.50	83.83	33.33		
False friends	False friends	56.44	36.30	52.36	56.46	42.24	42.24	18.48	44.62	24.24	42.24	42.24	18.48	44.62	44.62	44.62	44.62	44.62	44.62	44.62	34.34	48.48	36.36	20.20	42.42	16.16	66.66	70.70	42.42	42.42	42.42	52.52	56.56	38.38	42.42	52.52	38.38		
Function word	Focus particle	62.88	94.82	53.39	42.91	62.79	56.74	56.50	80.64	38.44	85.42	92.88	14.31	47.58	70.79	24.55	76.76	79.24	55.76	52.52	61.61	47.58	70.79	24.55	76.76	13.13	64.64	73.73	60.60	64.64	60.60	89.89	84.84	78.78	80.80	70.70	66.66		
MWE	Question tag	71.68	81.82	76.67	73.72	86.87	90.90	65.90	90.90	82.86	85.39	85.34	85.85	85.85	82.82	86.86	84.84	89.89	84.84	81.81	70.70	72.72	70.70	65.65	67.67	90.90	100.100	100.100	100.100	100.100	83.83	100.100	45.45	39.39	45.45	50.50			
	Collocation	61.45	65.68	58.42	84.42	26.13	39.39	68.50	92.92	17.83	50.00	92.92	17.83	50.00	92.92	17.83	50.00	92.92	17.83	50.00	16.16	52.52	32.32	52.00	0.00	90.90	100.100	100.100	100.100	100.100	13.13	35.35	81.81	45.45	39.39	45.45			
	Idiom	83.83	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	92.92	75.75	67.67	82.82	8.42	83.83	100.100	100.100	100.100	100.100	83.83	100.100	45.45	39.39	45.45	50.50			
	Verbal MWE	60.47	87.69	58.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	80.49	38.38	82.82	80.80	58.58	9.94	84.84	67.67	84.84	67.67	84.84	67.67	84.84	67.67	53.53	64.64	70.70	61.61		
Named entity & terminology	Date	82.71	97.99	85.79	93.81	93.57	53.53	65.53	92.69	42.42	42.42	60.60	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	9.92	29.29	59.59	91.91	8.68	97.97	100.100	97.97	95.95	99.99	94.94	85.85	81.81	65.65	51.51	79.79	77.77		
	Domain-specific term	87.84	100.84	82.89	62.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	84.84	53.53	67.67	82.82	53.53	11.11	62.62	60.60	60.60	60.60	60.60	60.60	60.60	60.60	60.60	60.60	60.60	60.60	60.60	
	Measuring unit	100.67	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	33.33	100.100	100.100	100.100	33.33	67.67	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100
Negation	Proper name	74.74	79.68	74.85	68.74	85.68	74.85	68.74	68.85	85.91	85.91	85.91	85.91	85.91	85.91	85.91	85.91	85.91	85.91	85.91	9.92	29.29	59.59	91.91	8.68	97.97	100.100	97.97	95.95	99.99	94.94	85.85	81.81	65.65	51.51	79.79	77.77		
Non-verbal agreement	Negation	68.54	86.77	67.67	67.67	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	25.25	100.100	100.100	100.100	50.50	0.00	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75	75.75
	Conference	121.42	46.53	68.86	41.73	55.66	29.29	65.65	27.27	65.65	27.27	65.65	27.27	65.65	27.27	65.65	27.27	65.65	27.27	65.65	61.61	44.44	66.66	39.39	56.56	1.00	60.60	92.44	64.64	43.43	80.80	39.39	30.30	39.39	45.45	45.46	45.46		
Punctuation	Adverbial clause	43.52	32.47	55.46	48.47	49.74	41.32	41.32	41.32	41.32	41.32	41.32	41.32	41.32	41.32	41.32	41.32	41.32	41.32	41.32	16.16	48.48	16.16	39.39	2.50	60.60	92.44	64.64	43.43	80.80	39.39	30.30	39.39	45.45	45.46	45.46			
Subordination	Cleft sentence	71.54	92.92	92.92	75.79	54.96	79.75	88.75	79.92	96.100	54.100	40.100	40.100	40.100	40.100	40.100	40.100	40.100	40.100	40.100	46.46	88.88	88.88	67.67	79.79	33.33	100.100	100.100	100.100	100.100	100.100	92.92	92.92	75.75	54.54	62.62	80.80		
	Contact clause	60.30	90.100	70.60	100.30	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100	60.100
	Infinitive clause	71.75	67.96	79.96	67.67	67.67	96.96	67.67	96.96	54.83	62.83	83.83	71.88	75.38	83.83	75.75	75.75	75.75	75.75	75.75	37.37	100.100	100.100	100.100	50.50	0.00	82.82	70.70	70.70	70.70	70.70	70.70	70.70	70.70	70.70	70.70	70.70	70.70	
	Object clause	66.80	73.83	67.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	79.84	21.21	34.34	100.100	100.100	50.50	0.00	26.26	80.80	26.26	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100
	Participle clause	70.82	67.79	94.76	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	42.82	9.90	30.30	9.90	30.30	9.90	30.30	9.90	30.30	9.90	30.30	9.90	30.30	9.90	30.30	9.90	30.30	9.90	30.30	
	Pseudo-cleft sentence	84.78	86.86	78.65	73.73	65.65	65.65	65.65	65.65	65.65	65.65	65.65	65.65	65.65	65.65	65.65	65.65	65.65	65.65	65.65	55.55	94.94	84.84	88.88	43.43	35.35	75.75	78.78	76.76	78.78	63.63	92.92	67.67	58.58	60.60	71.71	64.64		
	Relative clause	66.56	66.71	63.63	74.66	67.67	81.81	64.64	35.35	64.91	85.78	86.47	83.36	62.74	66.25	32.54	85.68	84.85	32.54	85.68	50.50	68.37	84.87	47.53	45.45	50.50	68.37	84.87	47.53	45.45	79.79	50.50	62.62	80.80	62.62	80.80			
Verb tense/aspect/mood	Subject clause	55.53	53.55	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	61.45	67.67	17.17	17.17	67.67	0.00	83.83	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	
	Conditional	100.67	100.100	100.100	100.100	83.83	100.83	100.83	100.83	100.83	100.83	100.83	100.83	100.83	100.83	100.83	100.83	100.83	100.83	100.83	69.69	92.92	69.69	92.92	31.31	85.85	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	
	Diransitive	85.69	77.100	69.92	100.69	92.100	69.92	100.69	92.100	69.92	100.69	92.100	69.92	100.69	92.100	69.92	100.69	92.100	69.92	100.69	62.62	92.92	69.69	92.92	31.31	85.85	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	100.100	
	Gerund	82.74	100.100	88.91	85.91	88.91	85.91	88.91	85.91	88.91	85.91	88.91	85.91	88.91	85.91	88.91	85.91	88.91	85.91	88.91	91.91	94.38	100.100	100.100	18.18	74.74	91.91	97.97											