

Linguistically Motivated Evaluation of Machine Translation Metrics based on a Challenge Set

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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 7th Conference for Machine Translation. The challenge set includes about 20,000 items extracted from 145 MT systems for two language directions (German \leftrightarrow English), covering more than 100 linguistically-motivated phenomena organized in 14 categories. The best performing metrics are YiSi-1, BERTScore and COMET-22 for German-English, and UniTE, UniTE-ref, MetricX-XL-DA19 and MetricX-XXL-DA19 for English-German. Metrics in both directions are performing worst when it comes to named-entities & terminology and particularly measuring units. Particularly in German-English they are weak at detecting issues at punctuation, polar questions, relative clauses, dates and idioms. In English-German, they perform worst at present progressive of transitive verbs, future II progressive of intransitive verbs, simple present perfect of ditransitive verbs and focus particles.

1 Introduction

Automatic evaluation metrics have been valuable tools for Machine Translation (MT), allowing quick evaluation and suggesting directions for further development. Many metrics have been suggested throughout the years, which in turn sets the requirement for their evaluation.

Whereas MT metrics so far have been evaluated based on the agreement of their scores with human judgments on test sets drawn from broad text, little research has taken place on investigating whether the performance of the metrics generalizes enough when evaluating particular cases. A more target way of evaluating metrics is using *challenge sets*. These are targeted test sets, which have been devised in such a way, so that they benchmark the ability of metrics to score particular translation phenomena.

In this paper we present empirical results on the performance of MT metrics, using an extensive challenge set, which includes thousands of test items aiming to test the performance over more than one hundred linguistically-motivated phenomena in two language directions. It is based on thousands of manually created test items, their translation outputs from dozens of MT systems and semi-automatically evaluated with the supervision of linguists. Through this analysis we attempt to reveal strengths and weaknesses of several state-of-the-art MT metrics considering their background methods with regards to linguistic aspects.

The rest of the paper is structured as follows. In Section 2 related work is briefly described. In Section 3 we describe the construction of the challenge set and the evaluation protocol. The empirical results are outlined in Section 4, followed by a conclusion in Section 5.

2 Related work

The need for a thorough evaluation of Natural Language Processing (NLP) tools has lately received increased interest in the research community, indicated by a big amount of publications, among them several which received best paper awards (Ribeiro et al., 2020; Avelino et al., 2022; Campolongo et al., 2022). When focusing on MT, first efforts were made in the 1990s with the introduction of test suites (King and Falkedal, 1990), which were revived after the latest advances in the field (Guillou and Hardmeier, 2016). To the best of our knowledge, the first efforts relevant to the application of challenge sets on MT metrics was presented as an analysis at the Findings paper of the Metrics shared task of the 6th Conference of Machine Translation (Freitag et al., 2021), based on our test suite (Macketanz et al., 2022) that we are using on this paper.

Hereby we are advancing as to that preliminary analysis by (a) increasing the number of challenge

items to about 9,000-10,000, including outputs from state-of-the-art systems from 2021, (b) adding a second language direction (English-German) (c) presenting a more fine-grained analysis, not only in the category level but also on the phenomenon level. This way we can get more confident and more generalisable empirical conclusions.

3 Method

3.1 Test suite for MT systems

The challenge set is based on our test suite (Macketanz et al., 2022), a manually devised test suite for MT for German-English and its recently developed extension for English-German (Macketanz et al., 2021).¹ The German-English side consists of 5,540 German test sentences covering 107 linguistically motivated phenomena, organized in 14 categories. The English-German side consists of 4,438 English test sentences covering 105 phenomena, organized in 12 categories.

The chosen phenomena do not follow a particular linguistic theory but their definition has been inspired by observing linguistic aspects which are relevant for MT. Each phenomenon is represented by at least 20 source test sentences to guarantee a balanced test set. The test suite is used to evaluate MT systems with regard to their performance on the phenomenon-targeting test sentences. The evaluation operates semi-automatically and it occurs based on a set of handwritten rules which contain regular expressions and fixed string tokens.

The above described test suite has been used to evaluate the outputs of 116 German-English and 29 English-German systems, submitted at the translation task of the Conference of Machine Translation (WMT) for four consequent years (2018-2021; Macketanz et al., 2018; Avramidis et al., 2019, 2020; Macketanz et al., 2021), including a preliminary system comparison in 2017 (Burchardt et al., 2017).

3.2 Challenge set for MT metrics

Here we describe how the aforementioned test suite, along with inputs from previous shared tasks, is used in order to evaluate MT metrics. A challenge set for metrics requires contrastive pairs of correct/incorrect translations and a reference, whereas our original test suite contained only source sentences and handwritten rules for the outputs, but

no reference translations. We therefore use the collected MT outputs to construct the challenge items for the metrics task in order to create the required challenge sets as following. For every source sentence of the test suite we create a tuple including:

- one correct translation, to be given to the metrics as reference translation; and a pair of
- another correct translation and
- one incorrect translation, the latter two intended to be given to the metrics for scoring.

In order to generate these tuples we perform random combinations of correct and wrong translations from the WMT outputs. Also, before collecting MT outputs, we filter out a part of the original test items, to be reserved for future evaluations.

The above process resulted into a metrics challenge set with 10,402 items for German-English and 8,945 items for English-German. The fact that the correct and incorrect translations have been sampled from real MT system outputs of the last 4 years, implies that these challenge set is closer to the real MT system ecosystem, as compared to artificially created challenge sets, which may contain translations that would never be produced by state-of-the-art MT.

3.3 Evaluation of metrics

As explained, the challenge set consists of subsets of challenge items, where every subset has been deliberately created so that it can detect the metrics' performance to a particular phenomenon. For every challenge item, the two MT outputs (correct/incorrect) are given unlabelled to the metrics as two separate MT hypotheses so that they score them against the aforementioned references and/or the source. The item is considered correctly scored, if the metric gives to the correct MT output a higher score than the incorrect MT output. Then the following statistics are calculated:

Accuracy per phenomenon is given by the ratio of all correctly-scored challenge items per phenomenon to the total number of challenge items for this phenomenon

Accuracy per category is given by the ratio of all correctly-scored challenge items per category to the total number of challenge items for this category (after aggregating the underlying phenomena of this category in one set).

Significant tests for comparisons: the highest metric accuracy for every phenomenon is compared to all other metric accuracies of the same

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

phenomenon. For this, a one-tailed Z-test with $\alpha = 0.95$ is calculated. The metrics whose accuracies that are not significantly worse than the highest accuracy, are considered to share the winning position for this phenomenon. The best accuracies per category are calculated in the same way, after aggregating the challenge items from the underlying phenomena of every category.

Statistics for metric categories: We repeat this significance testing in two levels: one for all metrics participating in the shared task, and then separately for each one of the three metric categories (baseline, QE as a metric, reference-based). 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.

Finally, we report three kinds of average scores: **Micro-average** treats all items equally, aggregating all test items to compute the average percentages; **Category macro-average** treats all categories equally by computing the percentages independently for each category and then averaging them **Phenomenon macro-average** treats all phenomena equally, by computing the percentages independently for each phenomenon and then averaging them

4 Results

The results are displayed in detail in Tables 1 and 3 in the category level and in Tables 4 and 5 for the phenomenon level, for both language directions German-English and English-German 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 best performing metrics for German-English are YiSi-1 (Lo, 2019), BERTScore (Zhang et al., 2020) and COMET-22 (Rei et al., 2022), achieving the significantly highest micro- and macro-average accuracies (84-85%), whereas for the macro-average, UniTE-ref (Wan et al., 2022) is also included in the first significance cluster. The two QE based metrics of HWTSC (Liu et al., 2022) get the lowest accuracies, together with the baseline BLEU (Papineni et al., 2002).

When considering the systems performance with regards to particular categories, one can see that different metrics win in different combinations of

categories. Most reference-based metrics perform best for at least four categories, apart from MS-COMET which only gets two.

Interestingly enough, one QE method is outperforming reference-based metrics for one category: HWTSC-TLM is the best performing system for *punctuation*. Additionally, UNITE-src performs equally well to reference-based metrics for coordination and ellipsis.

English-German UniTE and UniTE-ref are the winning metrics based on the macro-average (82%), whereas the former seems to be stronger than the latter, winning 5 categories. MetricX-XL-DA19 and MetricX-xxl-DA19 are the winning metrics when it comes to micro-average (78%). Their average accuracies are close to 80%, which raises concerns, as this indicates that 2 out of 10 challenge items in average are not scored correctly in this language direction, even for the best performing metrics. The lowest scoring metric is MATESE (Perrella et al., 2022) in both QE and reference-based versions, very close to REUSE (Mukherjee and Shrivastava, 2022).

Also in this direction, QE methods manage to outperform submitted reference-based metrics in a few categories. REUSE is the best performing metric for *false friends* and UNITE-src for *function words*. COMET-kiwi (Rei et al., 2022) and UniTE-src are on par with reference-aware metrics when it comes to *subordination* and Cross-QE (Liu et al., 2022) for *verb tense/aspect/mood*.

4.2 Linguistically motivated analysis

Here we are looking closer to the results for particular phenomena or categories.

4.2.1 German-English

Category-level The overall average accuracy of all metrics with regards to the linguistically motivated categories is at 78% for German-English. This indicates that the metrics failed in average to predict properly the scores for about one out of four challenge items that we provided. Even for the best categories, the accuracy achieved by most metrics is considerably below the acceptable limit of 90%.

The best performing category in *negation* with 86% average accuracy. For the rest of the categories, the average accuracy is less than 82%. The worst performing categories in average are *named entity* and *terminology* and *punctuation* with only 67% accuracy, whereas *subordination* comes next

ling. category	#	baselines						QE as a metric						ref. based metrics											
		BERTScore	BLEU	BLEURT-20	COMET-20	YiSi-I	chrF	f101spBLEU	f200spBLEU	COMETKiwi	Cross-QE	HWTSC-TLM	HWTSC-TS	KG-BERT	MS-COMET-QE	UniTE-src	COMET-22	MS-COMET	UniTE-ref	UniTE	XL-DA19	XL-MQM20	XXL-DA19	XXL-MQM20	avg
Ambiguity	298	90	71	88	86	89	80	81	79	82	73	60	65	67	82	80	87	85	89	89	88	90	83	86	81
Composition	252	88	65	87	85	90	74	70	71	76	77	73	76	59	72	75	83	86	82	83	86	82	87	82	79
Coordination & ellipsis	316	79	74	79	77	80	77	72	73	82	78	69	72	78	69	83	84	75	79	80	79	83	78	78	77
False friends	90	91	64	93	82	92	78	69	70	88	74	81	91	87	63	44	91	88	92	92	90	90	87	88	82
Function word	586	83	72	83	78	81	73	73	73	81	77	78	81	70	68	77	83	81	86	84	84	79	83	82	79
LDD & interrogatives	1014	85	75	84	85	85	76	74	74	84	83	72	75	63	81	82	86	83	84	85	85	82	85	82	80
MWE	610	85	73	85	85	86	78	74	75	76	76	70	60	56	60	73	86	82	89	90	88	88	87	81	78
Named entity & termin.	861	74	62	68	68	76	67	70	71	65	71	64	61	55	61	61	70	66	67	64	67	75	70	72	67
Negation	76	95	84	88	92	91	88	83	80	93	78	62	74	87	88	92	91	88	93	93	89	78	88	83	86
Non-verbal agreement	419	77	74	83	81	76	75	75	76	75	72	66	63	62	78	73	84	77	84	85	83	81	85	83	77
Punctuation	293	74	77	70	68	73	69	78	80	55	75	81	73	62	61	69	68	65	65	61	61	53	59	47	67
Subordination	679	76	69	77	77	74	69	68	69	72	75	59	62	65	64	73	80	77	77	78	75	70	78	74	72
Verb tense/aspect/mood	4697	88	69	85	86	89	77	71	71	81	87	63	71	78	81	82	86	83	85	85	84	79	85	81	80
Verb valency	211	91	70	88	88	90	72	69	69	86	72	64	64	62	75	82	94	88	91	91	91	88	91	88	81
macro avg.	10402	84	71	83	81	84	75	73	74	78	76	69	70	68	72	75	84	80	83	83	82	80	82	79	78
micro avg.	10402	84	70	82	82	85	75	72	72	78	81	66	70	70	75	78	84	80	83	82	82	79	82	79	78

Table 1: Accuracy of the metrics (%) with regards 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.

with 72%. The lowest performing score for all systems and all categories is achieved by MetricX-XL-MQM20, which can only score correctly almost half of the punctuation challenge items (53%).

Phenomenon-level The best accuracy for this language pair is achieved for *Transitive, future I* where the metrics get an accuracy of 95%-100%. Another 13 phenomena score more than 85%. Four of them also refer to the future tenses of the transitive, in particular future I and future II in both the plain and their subjunctive form. Additionally, one can see good performance in *Intransitive-present, Modal-future I, pied-piping, comma, negation, passive voice, and the negated modal for future I subjunctive II*.

The lowest accuracy of all metrics in average is given for *polar questions* (61%), followed by *quotation marks* (63%). An average accuracy of less than 65% is given for some more phenomena, such as the ones including *measuring units, relative clauses, dates* and *idioms*.

The lowest phenomenon accuracies are given by QE methods, and particularly when it comes to *idioms*, where HWTSC-TLM achieves the lowest performance of 17%. This is explainable by the fact that idioms require resolving rather rare semantic relations between the source and the MT

output (used for QE), but can be easily resolved with lexical matching on the reference (used by reference-aware metrics). Idioms have shown to be a particular challenge for MT systems as well.

4.2.2 English-German

Category-level The overall average accuracy of all metrics (Table 3) with regards to the linguistically motivated categories is at 69-72% for English-German. This is 6% lower than the respective average accuracy for German-English, indicating that the metrics for this MT language direction perform worse.

The category where all metrics perform best in average is *negation* (86%), whereas the one where they perform worse is *Named entity & terminology* (59%). The rest of the categories lie in rather mediocre accuracies, between 66% and 82%. The performance of metrics in English-German is worse than German-English in all categories apart from *function words, punctuation* and *subordination*, although the comparisons between the language directions have to be taken with a grain of salt, due to the fact that the two directions consist of different items.

Phenomenon-level The English-German phenomena, where metrics perform best in average are

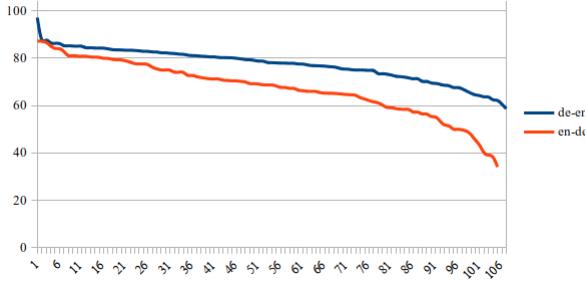


Figure 1: Plot of the accuracy of all phenomena per language direction. The accuracy percentage is shown on the vertical axis and the phenomena on the horizontal

the *Contact clause*, *Negation*, *Ditransitive - present progressive* and *question tags*, achieving more than 85% of accuracy. The most difficult phenomena to score are the *Intransitive - future II progressive* and the *Transitive - present progressive*, as they achieve less than 40% average accuracy, followed by *Ditransitive - present perfect simple*, *measuring units* and *focus particles*.

Interestingly enough, in this language direction there are metrics which scored zero accuracies in several phenomena, something that we didn't see in the opposite language direction.² These zero accuracies are mostly relevant to rare verb-related phenomena (e.g. intransitive constructions). A comparative plot of the accuracies for all phenomena for both language directions can be seen in Figure 1. It is very clear that English-German lacks considerably, with its lowest scored phenomena having an accuracy at half of the lower-scored phenomena of the opposite direction.

Finally, some examples of incorrectly scored challenge items from the phenomena that have the lowest accuracies can be seen in Table 2. Whereas is hard to know why each metric score in a wrong way, in many cases we may assume that it was misled by a part of the sentence which seemed distant to reference (or the source for QE), but it was correct.

5 Conclusion

In this paper we analyzed the performance of several state-of-the-art metrics with regards to particular linguistically-motivated phenomena for two language pairs, German-English and English-German. The analysis gave a multitude of observations, re-

garding both the performance of the metrics and the corresponding linguistic observations.

In an effort to draw conclusions after averaging accuracies, we conclude that the best performing metrics are YiSi-1, BERTScore and COMET-22 for German-English, and UniTE, UniTE-ref, MetricX-XL-DA19 and MetricX-xxl-DA19 for English-German.

The metrics are particularly good at scoring the German-English verb tense *Transitive, future I* and the category of *negation*. Concerning English-German, the best performing phenomena are *contact clause* and *negation*.

On the contrary, metrics in both directions are performing worst when it comes to *named-entities & terminology*. Particularly in German-English they are weak at detecting issues at *punctuation (quotation marks)*, *polar questions*, *measuring units*, *relative clauses*, *dates* and *idioms*. In English-German at *present progressive of transitive verbs*, *future II progressive of intransitive verbs*, *present perfect of ditransitive verbs*, *measuring units* and *focus particles*.

We believe that further investigation on particular phenomena or categories can provide explanations for the relevant observations and possibly lead to suggestions for technical improvements in the development of the metrics in the future. For example, many observations are also relevant to whether the metrics take into account for scoring the reference translation or the source (QE as a metric). Additionally, having seen several low accuracies regarding punctuation, we note that this issue is often handled via pre-processing scripts. The low percentages of scoring punctuation issues, show that the metrics should improve their engineering on that direction.

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²again this should take into consideration that English-German set has a participation of less systems and therefore less diversity than German-English

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Appendix

German-English			
idiom	src	Ich glaube, Tim hat ein Auge auf Lena geworfen.	
	ref	I think Tim has a crush on Lena.	
	✓	I think Tim has cast an eye on Lena.	
	✗	I think Tim has an eye on Lena.	
polar question	src	Willst du mit mir ins Kino gehen?	
	ref	Do you want to go to a movie with me?	
	✓	Do you want to go with me into the cinema?	
	✗	You want to go to the cinema with me?	
measuring unit	src	Ein ausgewachsener Afrikanischer Elefant wiegt etwa sechs Tonnen.	
	ref	An adult African elephant weighs about six tons.	
	✓	A fully grown African elephant weighs about six tons.	
	✗	An adult African elephant weighs about six tonnes.	
comma	src	Er fragte sich, welches Auto er kaufen sollte.	
	ref	He wondered what car to buy.	
	✓	He wondered which car to buy.	
	✗	He asked himself, which car he should buy.	
quotation marks	src	"Wann sollen wir uns treffen?", wollten sie wissen.	
	ref	"When are we supposed to meet?" they asked.	
	✓	"When shall we meet?" they wanted to know.	
	✗	When are we going to meet? They wanted to know.	
English-German			
Intransitive .	src	They will have been running.	
future II progr	ref	Sie werden gelaufen sein.	
	✓	Sie werden gerannt sein.	
	✗	Sie würden gelaufen sein.	
Focus particle	src	He even drank four bottles of wine.	
	ref	Er habe sogar vier Flaschen Wein getrunken.	
	✓	Er trank sogar vier Flaschen Wein.	
	✗	Er trank noch vier Flaschen Wein.	
Transitive	src	They are playing the piano.	
present progr.	ref	Sie spielen auf dem Klavier.	
	✓	Sie spielen Klavier.	
	✗	Sie spielen das Klavier.	
measuring unit	src	Potatoes are sold in hundredweights.	
	ref	Kartoffeln werden in Zentnergewichten verkauft.	
	✓	Kartoffeln werden in Zentner verkauft.	
	✗	Kartoffeln werden in Hundertgewichten verkauft.	

Table 2: Indicative examples of incorrectly scored challenge items for the phenomena that have the lowest accuracies

		ref. based metrics																																																	
		baseline					QE as a metric					MS-COMET																																							
#		BERTScore		BLEU		BLEURT-20		COMET-20		YISI-1		f101sBLEU		P200sBLEU		COMETKWI		Cross-QE		HWTSC-TLM		HWTSC-TS		KG-BERT		MATESE-QE		REUSE		COMET-22		MATESE		MEB		ME4		MS-COMET		UnitE-ref		UnitE		XL-MQM20		XXL-DA19		XXL-MQM20		avg	
ling. category		ref. based metrics																																																	
Ambiguity	146	87	71	90	82	87	89	87	88	55	47	81	47	25	38	15	36	84	40	73	88	91	78	97	93	94	88	95	87	72																					
Coordination & ellipsis	836	69	61	80	76	73	61	64	62	76	71	72	70	60	33	70	38	74	79	37	59	62	78	79	78	81	83	81	80	68																					
False friends	225	66	63	70	73	67	72	66	67	60	64	73	68	52	73	89	64	69	35	69	79	88	76	71	71	71	68	69	69	69																					
Function word	200	90	76	90	94	78	72	74	73	91	92	78	90	66	92	66	94	90	90	90	91	78	80	85	90	78	82	82	82																						
MWE	829	79	72	87	82	85	77	74	73	78	81	79	82	37	71	32	78	86	78	81	87	86	86	79	79	77	75	75	75																						
Named entity & termin.	1272	58	55	66	63	64	61	63	64	55	59	56	53	54	21	55	43	53	61	30	59	63	63	62	69	68	73	70	73	72	59																				
Negation	174	87	83	89	90	93	85	82	84	92	86	87	91	43	92	78	90	91	79	84	92	90	94	82	81	82	78	86	86	90	90	90	73																		
Non-verbal agreement	375	75	72	81	84	78	70	74	75	70	59	63	59	34	79	39	72	90	48	61	73	76	84	87	86	88	90	90	90	73																					
Punctuation	336	70	79	76	77	77	74	71	68	68	72	70	51	50	68	46	79	79	75	64	75	74	73	81	81	67	60	72	68	69	69																				
Subordination	994	77	74	80	83	78	74	75	73	86	82	81	84	82	47	83	48	85	84	53	73	77	78	82	85	85	84	82	79	77	76																				
Verb tense/aspect/mood	3081	67	62	70	69	64	64	64	64	70	77	51	58	41	61	54	70	77	43	71	71	69	64	70	72	78	74	76	73	76	73																				
Verb valency	480	73	64	84	74	76	71	66	70	82	74	65	69	68	30	70	48	72	82	42	62	70	76	79	80	79	78	85	81	80																					
macro avg.	8945	75	69	80	79	77	73	72	75	73	70	69	68	40	71	50	72	81	44	69	75	77	82	82	80	79	80	78	72	72																					
micro avg.	8945	70	65	76	74	73	69	68	73	74	63	65	64	38	67	48	71	78	42	68	71	72	72	77	79	79	77	78	76	69																					

Table 3: Accuracy of the metrics (%) with regards to the 12 linguistically motivated categories for English-German

	#	BERTScore	BLEU	BLEURT-20	COMET-20	YISI-1	chrF	f101spBLEU	f200spBLEU	COMETKivi	Cross-QE	HWTSC-TLM	HWTSC-TS	KG-BERT	MS-COMET-QE	MS-COMET	COMET-22	COMET-22	MS-COMET	UmitTE-src	UmitTE-ref	UmitTE	XL-DAT19	XL-MQM20	XXL-DAT19	XXL-MQM20	avg
	baselines	QE as a metric												ref. based metrics													
Ambiguity	ling. category												ling. phenomenon														
Composition	Ambiguity												Lexical ambiguity	Structural ambiguity													
Phrasal verb	Ambiguity												Structural ambiguity	Compound				Compound									
Gapping	Ambiguity												Compound	Phrasal verb				Phrasal verb									
Right node raising	Ambiguity												Phrasal verb	Coordination & ellipsis				Coordination & ellipsis									

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

ling. category	ling. phenomenon	baselines	QE as a metric	ref. based metrics	avg
#					
BERTScore	Sluicing	128 80	75 77 78 79 73	80 66 77 79 81 76 73 78 81 76 79	70/76
BLERU	Stripping	70 76 74 84 79	80 76 73 73 77	81 80 77 89 71 81/78	
BLERUT-20	False friends	90 91 64 93 82	92 78 69 70 77	91 88 92 90 90 88/82	
COMET-20	Function word	64 86 75 83 89	88 75 72 83 70	81 74 81 75 84 86 88 88 87 81/81	
MWE	LDD & interrogatives	166 87 79 85 83	86 77 80 81 82	75 69 81 83 67 83 89 88 89 83 82	
	Extended adjective construction	356 80 69 82 74	78 71 69 69 81	79 84 80 61 65 75 81 79 84 81 81/77	
	Extraposition	320 87 80 88 87	88 80 80 90 93	79 82 61 91 88 90 87 88 89 86 88/85	
	Multiple connectors	92 73 74 75 82	77 83 72 73 67	74 65 79 62 63 75 76 74 67 77 80 84 78/74	
	Pied-piping	87 74 79 63 72	76 76 80 79 70	68 69 64 69 70 68 79 61 63 66 57 66 53/69	
	Polar question	162 94 78 93 96	93 77 75 75 96	90 73 74 70 79 94 95 94 94 94 94 94 94 94 90/87	
	Scrambling	51 71 43 63 61	67 45 45 47 69	49 49 53 61 69 78 67 55 65 71 61 75 61	
	Topicalization	144 90 72 90	87 88 74 69 69	90 88 82 81 51 90 81 98 90 93 90 96 92 95 95/85	
	Wh-movement	61 85 85 87 84	87 84 87 87 87	77 69 66 70 77 82 74 82 74 80 82 70 85 79/80	
	Collocation	190 87 72 91	89 88 79 74 74	84 82 82 65 67 73 79 89 79 92 93 90 91 89 83	
	Idiom	133 82 67 76 85	83 69 67 65 44	55 36 17 20 31 33 75 77 87 88 89 86 86 75 65	
	Prepositional MWE	146 84 79 85 84	86 84 79 81 82	84 82 84 72 71 85 85 78 84 86 86 85 77/82	
	Verbal MWE	141 86 74 87	80 84 77 77 77	89 81 77 68 57 60 91 92 95 93 91 87 87 84 82/82	
	Named entity & termin. Date	203 67 50 65	66 58 58 57 70	70 63 68 66 67 63 67 63 67 63 69 74 68 72/65	
	Domain-specific term	214 71 63 71 74	71 68 68 67 77	63 57 59 66 60 72 64 72 71 68 75 71 70/68	
	Location	181 78 65 70 75 82	66 71 74 62 57 76	64 38 56 54 75 71 66 61 68 80 70 78/68	
	Measuring unit	203 75 67 61 64	77 72 81 84 57	73 54 51 56 56 55 63 62 59 55 62 67 66 66/64	
	Proper name	60 90 75 85 87	92 73 77 78 88 72 70 50 70 83 85 90 83 83 78 85 90 88/80		
	Negation	76 95 84 88 90	82 91 88 83 80 93 78 62 74 87 88 92 91 88 93 89 78 88 83 86		
	Non-verbal agreement	251 74 68 90 85 75	75 72 71 81 77 73 69 66 84 78 91 82 90 90 91 88 92 91		
Punctuation	Coreference	104 84 88 75 76	82 88 85 86 70 68 50 58 68 74 76 73 70 71 75 70/73		
	External possessor	64 80 80 72 72	67 78 83 61 59 62 58 52 67 53 69 61 73 77 72 69 72/69		
	Internal possessor	46 91 91 93 85	89 87 91 91 85 91 83 85 87 80 80 89 85 87 83 89 80 91 83/87		
	Comma	247 71 75 66 64	70 65 76 77 49 72 81 71 57 57 67 64 61 60 57 56 48 53 40/63		
	Quotation marks	87 71 70 82 75	72 67 66 70 74 66 68 70 69 66 77 67 74 72 70 74 75 68/71		
	Adverbial clause	109 73 73 67 71	66 66 70 69 66 48 64 62 55 71 72 75 66 69 66 64 65 61 66		
	Cleft sentence	70 63 67 77 71	67 71 74 71 60 70 50 56 63 69 77 83 80 81 74 54 76 67/70		
	Free relative clause	119 76 64 81 80	71 70 62 63 80 75 58 58 57 62 70 87 87 86 83 65 84 82/73		
	Indirect speech	64 78 77 77 72	78 77 75 73 73 70 62 67 73 72 70 67 73 70 75 66 80 67/72		
	Infinitive clause	54 85 74 85 91	89 81 72 72 76 89 69 69 94 67 80 93 87 91 89 80 87 85 82		

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

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

(Continued on next page)

#	ling. category	ling. phenomenon	baselines	QE as a metric										ref. based metrics									
				BERTScore	BLEU	BLEURT-20	COMET-20	YiSi-I	chRF	f101spBLEU	f200spBLEU	COMETkwi	Cross-QE	HWTSC-TM	HWTSC-TS	KG-BERT	MS-COMET-QE	MS-COMET	XL-DA	XL-MQM	xxL-DA19	xxL-MQM20	avg
126	Modal negated - perfect	Modal negated - pluperfect	71	50	66	73	72	62	52	73	88	60	71	63	70	63	66	63	60	63	51	66	
126	Modal negated - pluperfect	Modal negated - pluperfect subjunctive II	94	87	90	96	94	99	87	90	95	83	93	55	75	79	88	84	85	88	75	81	76
81	Modal negated - pluperfect subjunctive II	Modal negated - present	75	65	73	72	78	74	69	68	59	84	64	79	84	84	73	86	74	72	79	75	74
33	Modal negated - present	Modal negated - preterite	70	79	73	70	70	64	45	45	64	88	48	67	64	61	58	67	67	70	73	79	
61	Modal negated - preterite	Modal negated - preterite subjunctive II	90	66	90	92	89	87	56	56	90	82	38	75	95	95	90	85	87	80	79	80	
77	Modal negated - preterite subjunctive II	Progressive	88	66	91	87	86	83	65	65	91	95	47	75	86	88	84	91	87	83	78	83	
76	Progressive	Reflexive - future I	84	66	71	75	75	67	67	75	67	50	64	64	70	76	75	76	75	78	67	79	
85	Reflexive - future I	Reflexive - future I subjunctive II	76	89	87	82	80	74	74	86	85	84	81	75	78	88	89	92	88	87	81	88	
96	Reflexive - future I subjunctive II	Reflexive - future II	82	70	79	77	84	66	66	65	78	89	71	79	80	74	85	85	86	85	80	84	
116	Reflexive - future II	Reflexive - future II subjunctive II	97	83	77	81	97	85	81	80	67	73	40	43	72	75	67	87	69	83	84	79	
107	Reflexive - future II subjunctive II	Reflexive - perfect	93	74	81	89	93	77	71	70	79	92	66	77	91	82	87	89	76	87	86	85	
109	Reflexive - perfect	Reflexive - pluperfect	81	64	81	84	82	62	69	68	86	85	53	54	78	72	88	86	80	87	85	82	
90	Reflexive - pluperfect	Reflexive - pluperfect subjunctive II	98	76	79	87	97	80	78	78	70	81	66	70	88	80	80	76	81	88	92	77	
125	Reflexive - present	Reflexive - present	81	59	90	86	80	74	70	70	88	92	72	75	74	94	86	92	88	87	85	89	
117	Reflexive - present	Reflexive - preterite	86	69	85	83	88	75	70	71	83	54	56	66	85	83	88	76	90	91	85	85	
124	Reflexive - preterite	Reflexive - preterite subjunctive II	92	77	86	85	91	70	75	72	83	54	55	65	79	81	95	100	100	100	100	100	
43	Transitive - future I	Transitive - future I subjunctive II	98	95	100	100	100	95	95	100	95	100	100	100	100	100	100	100	100	100	100	100	
37	Transitive - future I	Transitive - future II	100	81	95	100	100	84	86	92	86	54	89	100	95	97	95	95	97	94	97	91	
33	Transitive - future II	Transitive - future II subjunctive II	100	76	94	94	100	94	79	79	88	64	70	94	88	94	76	94	88	94	97	95	
50	Transitive - future II subjunctive II	Transitive - perfect	100	84	88	94	100	88	82	80	92	90	90	98	98	94	92	90	90	92	76	90	
99	Transitive - perfect	Transitive - pluperfect	85	64	81	88	88	80	67	74	79	76	73	86	78	71	93	81	90	80	75	81	
22	Transitive - pluperfect	Transitive - pluperfect subjunctive II	91	73	82	91	91	82	73	73	73	77	73	77	68	77	91	91	86	82	86	73	
39	Transitive - pluperfect subjunctive II	Transitive - present	100	85	64	85	100	97	87	87	49	54	69	67	92	87	54	72	74	74	62	72	
33	Transitive - present	Transitive - preterite	94	58	94	85	91	73	58	61	88	94	82	79	88	94	88	91	91	88	94	91	
57	Transitive - preterite	Transitive - preterite subjunctive II	82	51	86	86	82	63	68	67	95	91	67	68	93	93	95	100	89	86	91	100	
97	Transitive - preterite subjunctive II	Case government	82	40	86	80	84	60	57	54	73	80	73	74	86	79	85	86	84	84	85	77	
80	Case government	Mediopassive voice	89	65	88	86	89	62	64	64	94	75	71	66	50	64	60	68	90	82	88	86	
50	Mediopassive voice	Passive voice	82	64	82	84	80	66	62	60	74	79	64	61	64	82	91	94	94	91	91	88	
33	Passive voice	Resultative predicates	94	85	91	94	82	82	79	77	79	81	67	69	75	73	73	83	96	92	94	94	
48	Resultative predicates		100	73	94	90	98	85	77	79	81												
10402			86	71	83	83	86	76	72	72	79	82	65	71	73	77	79	84	82	84	83	79	
10402			84	70	82	82	85	75	72	72	78	81	66	70	75	78	84	80	83	82	79	82	

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

	ling. category	ling. phenomenon	QE as a metric	ref. based metrics	avg
#	BERTScore				
	BLEU				
	BLEURT-20				
	VIS-1				
	f101sBLEU				
	f200sBLEU				
	COMETkwi				
	Cross-QE				
	HWTSC-TLM				
	HWTSC-TS				
	KG-BERT				
	MATESE-QE				
	REUSE				
	UniTE-src				
	COMET-22				
	MATESE				
	ME2				
	ME4				
	MS-COMET				
	XL-D				
	XL-MQM20				
	XXL-DA19				
	XXL-MQM20				

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

(Continued on next page)

ling. category	QE as a metric	QE as a metric	ref. based metrics	avg																															
				#	baseline	BERTScore	BLEU	BLURT-20	YISI-1	f10spBLEU	f200spBLEU	COMET-20	Cross-QE	HWSC-TLM	HWSC-TS	KG-BERT	MATESE-QE	MS-COMET-QE	REUSE	UniTE-Src	COMET-22	MATESE	ME2	ME4	MS-COMET	XL-DA	XL-MQM	xxL-DAI9	xxL-MQM20						
Verb tense /aspect/mood	Subject clause	148	86	90	89	91	90	91	91	89	89	87	89	89	47	91	33	85	86	71	87	92	93	89	88	84	82	89	85						
	Conditional	106	74	77	94	90	91	70	75	75	92	87	86	89	89	31	81	18	92	83	75	92	92	84	88	89	80	89	80						
	Ditransitive - conditional I progr.	72	65	49	93	89	83	61	56	57	99	99	94	99		79	50	92	74	100	92	47	64	60	62	81	90	92	93	81	100	89	79		
" - conditional I simple	34	94	74	65	85	97	94	74	79	100	97	41	41	44	26	91	91	100	100	18	100	94	97	85	100	97	97	94	100	91	82				
" - conditional II progr.	51	75	78	88	78	80	82	82	82	65	67	51	55	49	24	59	63	86	90	27	86	82	78	82	88	86	84	82	86	92	73				
" - conditional II simple	59	71	64	76	78	66	68	64	73	69	56	53	49	47	36	63	59	78	73	25	78	71	75	78	80	78	81	81	78	67					
" - future I progr.	61	52	51	62	57	57	62	51	51	92	51	84	75	49	11	80	90	97	66	8	59	61	33	59	66	79	75	57	66	61					
" - future I simple	88	60	51	56	55	60	50	45	66	50	52	53	48	40	70	90	85	58	38	56	57	60	53	56	60	65	64	51	60	57					
" - future II progr.	91	70	64	66	57	47	60	65	62	71	45	84	91	11	78	56	77	82	14	89	73	76	54	86	77	65	62	95	92	68					
" - future II simple	49	71	94	86	94	65	94	92	100	92	76	71	65	8	65	88	92	18	96	94	94	65	100	98	86	39	88	76	79						
" - past perfect progr.	91	60	44	60	67	66	58	53	48	65	75	51	59	65	11	75	37	60	71	33	62	59	63	52	67	75	78	73	73	67	60				
" - past perfect simple	112	63	62	65	56	72	71	61	56	79	37	37	54	8	58	43	46	70	39	56	64	53	64	53	62	68	71	57	58	49	57				
" - past progr.	83	58	57	70	58	59	61	57	57	61	37	39	37	37	37	12	42	71	33	70	12	39	55	60	42	66	64	72	67	72	69	53			
" - present perfect progr.	48	85	54	85	75	92	88	56	60	85	94	90	100	100	21	77	52	100	92	35	75	81	81	71	94	79	73	92	77	78					
" - present perfect simple	54	65	37	56	43	30	41	37	44	33	33	31	26	35	28	33	33	31	48	22	44	44	48	33	57	56	65	65	70	69	43				
" - present progr.	72	76	38	94	97	90	68	36	49	100	100	99	99	94	88	35	99	96	71	72	86	83	97	97	88	88	92	88	83						
" - simple past	77	77	56	77	83	56	66	56	57	97	94	69	75	88	36	73	82	94	45	73	78	84	87	82	83	79	84	82	78	75					
" - simple present	54	72	30	83	70	83	56	41	41	67	70	67	67	67	67	54	70	28	70	59	48	56	67	69	65	80	80	81	83	89	86				
Gerund	161	92	85	96	96	92	80	83	82	97	99	58	87	87	19	97	78	99	97	25	83	85	88	98	96	96	96	96	97	87	85				
Imperative	50	70	50	96	94	70	70	58	64	100	92	78	86	86	80	94	82	88	96	60	70	76	94	92	96	90	94	92	82	82					
Intransitive - conditional I progr.	9	56	89	89	100	100	78	78	89	100	44	0	22	22	67	44	100	100	89	56	78	78	89	78	100	100	33	56	89	78	72				
" - conditional I simple	3	100	0	67	100	100	33	0	33	100	33	33	100	67	33	100	67	0	100	100	0	67	100	67	67	67	67	67	67	67					
" - future I progr.	7	71	86	100	100	57	100	86	86	57	57	0	29	29	86	57	71	71	86	0	71	86	100	100	71	100	100	73							
" - future I simple	24	67	75	75	71	50	67	71	96	100	71	46	46	29	92	96	100	62	42	58	67	67													
" - future II progr.	4	25	50	25	50	50	50	50	50	50	75	0	75	25	0	50	25	0	50	0	75	25	25	25	25	25	25	25	25	25	25				
" - future II simple	7	71	100	86	100	100	100	100	100	100	57	71	0	43	100	71	100	14	71	86	100	86	31	31	31	31	31	31	31	31	31	31			
" - past perfect progr.	16	56	50	38	62	69	62	81	69	50	69	38	44	44	0	75	38	44	50	6	56	62	62	69	31	31	31	31	31	31	31	31	31	31	
" - past perfect simple	18	78	72	89	72	61	78	61	61	94	50	89	78	0	56	44	39	83	17	89	78	78	83	72	78	67	89	78	78	78	78	78			
" - past progr.	28	43	57	71	71	54	57	54	54	68	50	46	36	36	29	61	46	57	50	25	50	61	54	50	57	57	54	61	57	52	52				
" - present perfect simple	2	100	50	100	100	100	100	80	80	100	80	80	80	0	0	0	20	80	80	60	100	100	0	50	100	100	50	100	100	84					
" - present progr.	5	80	100	80	80	80	100	80	80	100	96	100	100	46	71	96	88	71	46	38	62	71	67	83	88	62	58	79	79	79	79	79	79	79	79
" - simple past	24	58	38	62	58	58	46	38	38	100	100	40	40	40	40	70	40	60	70	40	70	70	50	20	30	70	50	50	50	50	50	50	50	50	50
" - simple present	10	40	30	50	40	40	40	40	40	70	40	40	40	40	40	70	40	60	70	40	70	70	50	20	30	70	50	50	50	50	50	50	50	50	50

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

ling. category	baseline	QE as a metric	ref. based metrics													
			ling. phenomenon				QE score				BERT score					
#	BERTScore	Modal	20	70	60	40	60	45	55	60	50	15	55	0	25	
		Modal negated	20	35	65	70	75	65	60	70	65	95	50	100	90	
		Reflexive - conditional I progr.	65	66	52	48	45	45	46	71	38	63	15	23	23	
		" - conditional I simple	112	76	70	48	67	58	70	72	32	100	9	27	27	
		" - conditional II progr.	97	71	72	66	67	61	69	71	64	80	10	20	20	
		" - conditional II simple	109	61	68	52	55	54	61	58	59	50	92	11	21	27
		" - future I progr.	70	67	67	70	54	84	79	66	66	60	77	77	47	69
		" - future I simple	83	69	67	71	54	76	86	77	61	61	45	78	63	66
		" - future II progr.	81	65	56	64	73	75	80	57	57	73	88	54	89	80
		" - future II simple	56	71	66	77	61	88	88	64	64	79	98	61	59	59
		" - past perfect progr.	98	60	50	67	63	71	66	60	51	66	82	33	46	46
		" - past perfect simple	53	62	47	68	62	74	55	57	64	98	25	34	34	66
		" - past progr.	5	100	100	40	100	100	100	100	80	60	20	20	40	
		" - present perfect progr.	33	76	48	88	82	76	76	48	100	100	64	61	100	45
		" - present perfect simple	39	59	46	67	69	69	72	44	44	74	92	79	72	21
		" - present progr.	99	62	51	54	54	67	56	60	62	36	77	27	26	26
		" - simple past	119	71	70	73	76	73	77	71	89	83	37	69	76	40
		" - simple present	138	65	65	67	62	88	63	68	67	44	89	39	54	62
		Transitive - future II progr.	11	73	82	73	73	64	82	82	73	55	82	91	9	91
		" - conditional I progr.	11	55	91	45	73	36	82	91	91	55	18	36	45	45
		" - conditional I simple	9	67	100	89	89	56	100	100	100	67	56	67	67	100
		" - conditional II progr.	20	70	55	75	70	80	55	60	75	40	35	50	0	40
		" - conditional II simple	2	50	100	100	100	100	100	100	50	50	50	100	100	100
		" - future I progr.	12	42	83	75	67	25	50	75	75	50	50	42	42	42
		" - future I simple	22	64	95	64	64	59	77	95	36	41	18	18	18	18
		" - future II simple	39	62	92	59	72	67	85	90	82	64	72	3	69	46
		" - past perfect progr.	16	50	69	50	56	81	69	69	62	75	38	38	6	75
		" - past perfect simple	9	44	78	89	78	33	89	78	100	56	89	78	0	56
		" - present perfect progr.	5	20	80	80	20	80	80	40	100	60	0	100	20	60
		" - present perfect simple	9	33	67	78	56	44	78	67	78	33	100	78	44	44
		" - present progr.	10	30	70	20	30	40	50	50	40	40	20	40	40	40
		" - simple past	23	61	43	96	78	35	57	48	52	87	57	13	91	61
		" - simple present	16	31	62	38	44	69	62	56	94	44	31	31	44	100
Verb valency	Case government		57	82	67	75	79	82	70	70	75	86	79	72	77	63
		avg														
		xxL-MQM20														
		xxL-DA19														
		XL-MQM														
		XL-Da														
		UniTE-ref														
		MS-COMET														
		MEE4														
		MEE2														
		MEE														
		MATSE														
		COMET-22														
		UniTE-sre														
		REUSE														
		MS-COMET-QE														
		KG-BERT														
		HWTSC-TS														
		HWTSC-TLM														
		Cross-QE														
		COMETKIWI														
		f101sBLEU														
		f200sBLEU														
		YISI-1														
		BLURT-20														
		BLURT-20														
		COMET-20														

(Continued on next page)

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

ling. category	ling. phenomenon	baselines		QE as a metric		ref. based metrics																										
		#	BERTScore	MEE	MS-COMET	ME4	xxL-MQM20																									
Catenative verb	Catenative verb	177	69	58	86	61	70	62	60	77	67	71	71	25	60	28	60	76	29	62	64	62	65	68	70	67	72	89	64			
Middle voice	Middle voice	29	90	69	93	79	83	83	79	76	90	83	83	21	48	31	62	83	45	83	90	97	97	97	97	97	97	93	93	86	79	
Passive voice	Passive voice	70	64	51	67	74	66	71	53	61	87	74	76	71	21	70	47	70	87	43	50	61	63	86	71	70	79	71	76	77	67	
Resultative	Resultative	147	76	74	90	85	86	80	73	80	84	80	45	61	59	24	84	76	88	88	48	63	73	76	87	92	91	89	87	84	73	76
macro avg.		8945	67	65	74	74	70	70	66	67	75	72	60	62	61	35	69	53	71	79	39	65	70	70	72	74	75	77	73	78	74	68
micro avg.		8945	70	65	76	74	73	69	68	68	73	74	63	65	64	38	67	48	71	78	42	68	71	72	72	77	77	79	77	78	76	69

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