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# Consistent Human Evaluation of Machine Translation across Language Pairs

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## Abstract

Obtaining meaningful quality scores for machine translation systems through human evaluation remains a challenge given the high variability between human evaluators, partly due to subjective expectations for translation quality for different language pairs. We propose a new metric, XSTS, that is more focused on semantic equivalence. Moreover, we introduce a cross-lingual calibration method that enables more consistent assessment. We demonstrate the effectiveness of these novel contributions in large scale evaluation studies across up to 14 language pairs, with translation both into and out of English.

## 1 Introduction

While machine translation systems are typically evaluated with automatic metrics like BLEU (Papineni et al., 2001), the gold standard for quality assessment is evaluation of machine translation output by human evaluators. In fact, the validity of automatic metrics is justified by correlation to human evaluations.

However, in practice individual human evaluators apply very different standards when assessing machine translation output, depending on their expectation of translation quality, their exposure to machine translation output, their language abilities, the presentation of source or reference translation, and vague category descriptions like "mostly correct". This is especially a problem when the goal is to obtain meaningful scores across language pairs, to assess, for instance, if a machine translation system for any given language pair is of sufficiently high quality to be put to use.

We address this problem of high variability and cross-lingual consistency by two novel contributions: (1) a new scoring metric XSTS that is focused on meaning; and, (2) an evaluation protocol that allows for calibration of scores across evaluators and across language pairs. Our studies show that the XSTS score yields higher inter-annotator agreement compared against a 5-Point Raw Scale. We also show that our calibration leads to improved correlation of system scores to our subjective expectations of quality based on linguistic and resource aspects as well as improved correlation with automatic scores.

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## 2 Related Work

The DARPA evaluation of the 1990s tasked human evaluators to assign scores from 1 to 5 to judge the fluency and adequacy of translations (White and O’Connell, 1996), with vague definitions like *much meaning* for an adequacy score of 3 or the slightly offensive *non-native English* for a fluency score of 3. This scale was also used in the first human evaluation of the Workshop on Statistical Machine Translation (WMT) (Koehn and Monz, 2006).

Note that these evaluations aim at a different goal than the one we are concerned with here: their main purpose is to rank the output of different machine translation systems against one another — without the need to report a meaningful score that is an absolute measure of their translation quality. Hence, it should come as no surprise that the WMT evaluation then moved towards pairwise comparisons of different system outputs (Callison-Burch et al., 2007). For many years, evaluators were asked to rank up to 5 system outputs against each other.

Due to the problem that for  $n$  systems,  $O(n^2)$  pairwise comparisons need to be done (Bojar et al., 2016), recent WMT evaluations switched to Direct Assessment (Graham et al., 2013). Evaluators are required to indicate absolute quality of a machine translated sentence using a slider which is converted into a score on a 100 point scale. Such finer grained scores allow for easier normalization of scores between annotators. Direct Assessment is also used by Microsoft for shipping decisions (Kocmi et al., 2021). Google uses a 5-point scale to evaluate their machine translation systems but specifics have not been published.

Recently, Mariana et al. (2015) proposed the Multidimensional Quality Metrics (MQM) Framework, rooted in the need for quality assurance for professional translators, that aims at generating meaningful scores. In MQM, fine-grained error categories like *omission*, *register* and *capitalization* are assessed and the error counts per category are combined into a single score. Such fine-grained errors can typically only be detected in relatively high-quality translations (Freitag et al., 2021). This metric is predominantly used for quality assurance in the translation industry to evaluate translations from professional translators.

## 3 A New Metric: XSTS

We propose a new metric that is inspired by the Semantic Text Similarity metric (STS) used in research on paraphrase detection and textual entailment (Agirre et al., 2012). The metric emphasises adequacy rather than fluency. We do this for several reasons but mainly because we deal with many low resource language pairs where preservation of meaning during translation is a pressing challenge. Arguably, assessing fluency is also much more subjective and thus leads to higher variance. Another reason is that we are interested in evaluating the translation of social media text where the source and reference translation may be disfluent, so lack of fluency should not be counted against machine translation.

As in many previously proposed scoring rubrics, we use a 5-point scale. For a detailed definition of the meaning of each score, see Figure 1. There are various ways this metric could be used. The examples in the figure show two English sentences, such as machine translation output and a human reference translation, but our core evaluation protocol presents the source sentence and corresponding machine translation to a bilingual evaluator. Different from previous evaluation protocols, XSTS asks explicitly about meaning (semantic) correspondence, all the more while obfuscating which sentence is the source and which is the translation.

Note that the score has a fairly high bar for a score of 4: semantic equivalence, only allowing for differences in style, emphasis, and connotation. This allows us to detect differences in quality at the very high end. We experimented with both this 5 point scale and a reduced scale where the categories 4 and 5 were collapsed.

**1** The two sentences are not equivalent, share very little details, and may be about different topics. If the two sentences are about similar topics, but less than half of the core concepts mentioned are the same, then 1 is still the appropriate score.

Example A (different topics):

Text 1: *John went horseback riding at dawn with a whole group of friends.*

Text 2: *Sunrise at dawn is a magnificent view to take in if you wake up early enough for it.*

Example B (similar/related topics):

Text 1: *The woman is playing the violin.*

Text 2: *The young lady enjoys listening to the guitar.*

**2** The two sentences share some details, but are not equivalent. Some important information related to the primary subject/verb/object differs or is missing, which alters the intent or meaning of the sentence.

Example A (opposite polarity):

Text 1: *They flew out of the nest in groups.*

Text 2: *They flew into the nest together.*

Example B (word order changes meaning)

Text 1: *James voted for Biden.*

Text 2: *Biden voted for James.*

Example C (missing salient information):

Text 1: *"He is not a suspect anymore." John said.*

Text 2: *John said he is considered a witness but not a suspect.*

Example D (substitution/change in named entity)

Text 1: *I bought the book at Amazon.*

Text 2: *The book was purchased at Barnes and Noble by me.*

**3** The two sentences are mostly equivalent, but some unimportant details can differ. There cannot be any significant conflicts in intent or meaning between the sentences, no matter how long the sentences are.

Example A (minor details that are not salient to the meaning):

Text 1: *In May 2010, US troops invaded Kabul.*

Text 2: *The US army invaded Kabul on May 7th last year, 2010.*

Example B (minor verb tense and/or unit of measurement differences):

Text 1: *He bought 2 LBs of rice at Whole Foods.*

Text 2: *He buy 1 KG. of rice at WholeFoods.*

Example C (small, non-conflicting differences in meaning):

Text1: *She loves eating ripe apples in the fall.*

Text2: *She usually eats ripened apple in autumn.*

Example D (omitted non-critical information, but no contradictory info introduced):

Text1: *Several of the sailors set out on a rainy Tuesday morning.*

Text2: *Several of the sailors set out on a Tuesday morning.*

**4** The two sentences are paraphrases of each other. Their meanings are near-equivalent, with no major differences or information missing. There can only be minor differences in meaning due to differences in expression (e.g., formality level, style, emphasis, potential implication, idioms, common metaphors).

Example A (different level of formality):

Text 1: *This is Europe the so-called human rights country*

Text 2: *This is Europe, the country of alleged human rights*

Example B (added sense of urgency, advertising style):

Text1: *Special bike for more info call 0925279927*

Text2: *Special bike for more information call now 0925279927*

**5** The two sentences are exactly and completely equivalent in meaning and usage expression (e.g., formality level, style, emphasis, potential implication, idioms, common metaphors).

Example A (same style and level of formality):

Text 1: *What's up yu'all?*

Text 2: *Howdy guys!*

Example B (disfluency is not penalized):

Text 1: *One two three apples oranges green*

Text 2: *One two three apples oranges green*

Figure 1: Part of the instruction given to evaluators to explain the XSTS scoring rubric. We also used a variant of this scale where 4 and 5 are collapsed into a single category.

Metric Study	Calibration Study	
Arabic	Amharic	Romanian
Estonian	Arabic	Sindhi
Indonesian	Azerbaijani	Slovenian
Mongolian	Bosnian	Swahili
Spanish	Georgian	Urdu
Tamil	Hindi	Zulu
	Brazilian Portuguese	

Table 1: Languages used. Both translation directions into and out of English were evaluated.

#### 4 Cross-Lingual Consistency via Calibration Sets

Even after providing evaluators with instruction and training, they still show a large degree of variance in how they apply scores to actual examples of machine translation output. This is especially the case when different language pairs are evaluated, which necessarily requires different evaluators assessing different output.

We address this problem with a calibration set. Note that we are either evaluating X–English or English–X machine translation systems. In either case, this requires evaluators who are fluent in English. Hence, we construct a calibration set by pairing machine translation output from various X–English systems with human reference translations — so that the evaluators compare two English sentences. The sentence pairs are carefully chosen to cover the whole range of scores, based on consistent judgments from prior evaluation rounds.

Evaluators assess this fixed calibration set in addition to their actual task of assessing translations for their assigned language pair. We then compute the average score each evaluator gives to the calibration set. If this evaluator-specific calibration score is too high, then we conclude that the evaluator is generally too lenient and their scores for the actual task need to be adjusted downward, and vice versa.

There are various ways how scores for each evaluator could be adjusted. After exploring various options, we settled on a simple linear shift (with an option for moderating large calibration shifts or shifts near the edges of the scale if desired). To give an example, if the consensus score for the calibration set is 3.0 but an evaluator assigned it a score of 3.2, then we deduct 0.2 from all their scores for the actual evaluation task.

#### 5 Study Design

We report on two large-scale human evaluation studies to assess the two novel contributions of this work. The first study compares XSTS and its variants against other evaluation methods like a raw 5-Point scale modelled (RAW) after Direct Assessment. The second study assesses the effectiveness of our calibration method.

**Language Pairs** We selected languages with the goal to cover both high-resource languages with good machine translation quality and low-resource languages with weaker machine translation quality. The languages also differ in writing system, morphological complexity, and other linguistic dimensions. See the Table 1 for the list of languages in our studies.

**Selection of Evaluators** Evaluators were selected for each language pair and they evaluated both language directions (English–X and X–English). The evaluators were professional translators who were recruited by a translation agency. They had to have at least three years of translation experience, be native speakers of the language X, high level of English proficiency, and pass through a training process (detailed documentation of the task and training examples).

We speculate, but have not yet tested, that the XSTS protocol may be employable by evaluators with less rigorous translation training than traditional DA; so long as they still have high levels of fluency in both languages being evaluated. This could potentially facilitate the evaluation of low-resource languages where qualified annotators may be difficult to source.

**User Interface and Training** Since we are working with language service providers who subcontract the work to professional translators who differ in their technical setup, we do not always have full control over the way text is presented to them and how they register their evaluations. Throughout our studies, the employed tools vary from simple spreadsheets to a customized annotation tool similar to the one used in WMT evaluations.

**Machine Translation Systems** Most of the machine translation systems used in this studies were trained in-house with fairseq (Ott et al., 2019) on public data sets at different times in 2020 and 2021, each designed to optimized translation quality given available data and technology. The most recent system, used in the calibration study, is a 100-language multilingual system, similar to the one developed for the WMT 2021 Shared Task (Tran et al., 2021).

**Test Set** The translated sentences to be evaluated are selected from social media messages and Wikipedia — the later being part of the FLORES test set which comprises close to 200 languages at the time of writing (Guzmán et al., 2019). Note that social media messages have the additional challenge of disfluency and creative language variation in the source sentence.

## 5.1 Study on Evaluation Metrics

We compare the newly proposed XSTS to RAW and variants of XSTS. We report here on an experiment that used a 4-point XSTS scale but a subsequent study with a 5-point scale confirmed the findings. In all evaluations, the identity of the translation system was hidden and sentence translations of the different systems are randomly shuffled.

**Raw 5-Point Scale (RAW)** In this protocol, the evaluators are required to judge translation output with respect to a source sentence on a 5-point qualitative rating scale. The evaluators render these ratings for machine translations (MT1, MT2, MT3) and a human translation (HT0), while shown the source sentence. This method is based on source-based direct assessment (Graham et al., 2013) — however there are important differences: direct assessment uses a continuous slider scale which internally gets converted into a 100-point scale, while we adapted it to a quantized 5-point scale.

**Cross Lingual Semantic Textual Similarity (XSTS)** XSTS is the cross-lingual variant of STS. Evaluators indicate the level of correspondence between source and target directly. This protocol does not rely on reference translations. We apply XSTS to all directions for all translations (MT\* and HT0).

**Monolingual Semantic Textual Similarity (MSTS)** MSTS is a protocol where the evaluators indicate the level of correspondence between two English strings, a machine translation (MT\*) or human translation (HT0) and an additional human reference translation (HT1), using the XSTS scale. This evaluation was only carried out for translations into English since we have two reference translations for English (HT0, HT1) but not for other languages.

**Back-translated Monolingual Semantic Textual Similarity (BT+MSTS)** BT+MSTS is an attempt to make MSTS work for English-X translation when two reference translations are only available in English. Each translation from the English-X MT systems is manually back-translated into English, which allows us to compare it against the English reference

Language	Morphological complexity	Resource presence	Writing system	Inherent variants	Language family
Arabic (AR)	xxxx	High	Arabic	Yes	Semitic
Estonian (ET)	xxx	Medium	Latin	No	Uralic
Indonesian (ID)	x	Medium	Latin	Yes	Austronesian
Mongolian (MN)	xxx	Low	Cyrillic	No	Mongolic
Tamil (TA)	xxx	Low	Tamil	No	Dravidian
Spanish (ES)	xx	High	Latin	Yes	Indo-European

Table 2: Details on Languages used in the Metrics Study

translations HT1 while also allowing for scoring the back-translation of HT0. Note that the manual back-translation will unlikely have fluency problems but any failures to preserve adequacy of the machine translation system will not be recovered by the professional translator.

**Post Editing with critical errors (PE)** In this protocol, evaluators are required to provide the minimal necessary edits for the translations to render them correspondent to the source. Crucially however, evaluators are required to indicate the number of critical errors rendered in the post editing. The impetus behind this level of annotation is to transcend the traditional count of the number of edits needed to fix a translation. This protocol does not rely on a reference translation. Given the corrections, we computed three scores: critical edit counts, Levenshtein distance, and ChrF.

As test sets we used 250 sentences of social media messages (collected from public Facebook posts). We primarily report on results on this social media test set but an additional study on the Wikipedia test set (FLORES) confirms these findings. We evaluated two internal machine translation systems (MT0 and MT1) and translations obtained from Google Translate (MT2). See Figure 2 for details on the languages involved.

## 5.2 Study on Calibration

In a second study, we examined the introduction of a calibration set to create meaningful scores that can be compared across language pairs. This enables better absolute inter-direction comparison; for instance the decision if a machine translation system for a language pair is good enough to be put into production.

Evaluators judge 1012 sentence pairs for a single language pair in both language directions. In this study, we only use the XSTS score. Translations are judged against the source sentence. Machine translations are generated with a state-of-the-art multilingual machine translation system. Evaluators also judge the human reference translation similar to Fan et al. (2021). The crucial addition to the sentence pairs to be judged is a calibration set of sentence pairs that is common across all languages. It consists of 1000 pairs of a machine translation into English and a corresponding English reference translation. These sentence pairs are carefully selected to span a wide quality range, based on human-scored translations from previous evaluations where multiple evaluators agreed on the score (200 sentence pairs from each quality score).

A fair objection to using such a calibration set is that we are asking evaluators to perform two different tasks — comparing machine translation against a source sentence (English and non-English), and comparing machine translation against a reference (English and English) — but posit that they will use the same standards when making quality assessments.

Because the calibration set is fixed, its quality is fixed, and the average score each evaluator assigns to the sentence pairs in the set should be the same. Hence, we can use the actual score

assigned by each evaluator and the official fixed score as the basis to make adjustments to each evaluator’s score. For instance, if an evaluator gives the calibration too high score, then we detect that they are too lenient and their scores need to be corrected downward. For simplicity and robustness, we applied calibration corrections after taking majority scores across annotators for an evaluation item; correcting for the overall bias of the group rather than a single individual.

Note that there is also a second fixed point that could be used for score adjustment: the average score each evaluator gives to the reference translation. These professionally translated and vetted translations should receive high scores, and we could adjust each evaluator’s scores so that the average adjusted score for reference translations is a fixed value. The underlying assumption here is that reference translations are of identical quality across all language pairs. We opted against utilizing this point, in favor of the monolingual calibration set, because knowing how harsh or generous our annotators are on a set of only high quality translations does not as well inform us as to how they will behave on the intermediate or low quality translations which will likely be in the machine translations they are evaluating. This was backed up by lower correlations between automatic metrics and XSTS when using these human reference translations than when using our calibration set. Additionally such reference translations can be expensive and time consuming if applied to a new use case.

The calibration study generates a set of data points for each assigned score that contain the following information: (1) language pair, (2) machine translation system, reference translation, or calibration set, (3) evaluator, (4) sentence pair, and (5) raw XSTS score.

So far, we discussed calibration to adjust the scores for each evaluator. Our real goal, however, is to adjust scores for each language pair. Hence, we aggregate the individual data points into the following statistics: (1) language pair, (2) machine translation system, reference translation, or calibration set, and (3) average of median raw XSTS scores. We first take judgments of different evaluators for the same translation and determine the median value. Then, we average these scores for each combination of language pair and translation source (machine translation, reference translation, calibration set).

Based on this, we determine an adjustment function

$$f_{\text{language-pair}} : \text{raw-score} \rightarrow \text{adjusted-score} \quad (1)$$

The simplest form of this function is a linear shift  $f(x) = x + \alpha$  where  $\alpha$  is the adjustment parameter. To ensure that adjusted scores agree on the consensus set, we compute  $\alpha$  for each language pair as

$$\alpha_{\text{language-pair}} = \text{consensus-score} - \text{avg-median-score}(\text{language-pair,calibration-set}) \quad (2)$$

With two fix points (score on calibration set and score on human reference translations), we use an adjustment formula  $f(x) = \beta x + \alpha$  and determine the parameters  $\alpha$  and  $\beta$  in a similar fashion.

### 5.3 Proposed Robustness Improvements

As we look towards applying the calibration methodology described above in a variety of circumstances, there are a few undesirable edge cases which we may wish to better handle.

The first of these are large calibration shifts. Our analysis has suggested that when annotators rate a calibration set especially low or high, this is increasingly an indication that their behavior or bias on the calibration set is less indicative of their behavior or bias on the primary translation task, and that the calibration factor may be too large or in error. Large calibration scores ( $\alpha > 0.5$ ) tend to over-correct. Internal experiments limiting the magnitude of the calibration score found an increase in correlation between XSTS scores and automatic metrics (ChrF++, spmBLEU) when applying a calibration shift cap between 0.5 and 1.0 (smaller than

0.5 and we begin to chip away the benefits of calibration and the correlation decreases). To reduce this affect we propose to introduce a moderating term into the calibration calculation.

The second case of concern occurs near the boundaries of the scale. Imagine a simple case where annotators give a mean score of 4.8 to a translation model. But the same annotators are somewhat harsh on the calibration set, giving it a score of 2.7, resulting in a calibration correction term  $\alpha = +0.3$ . Applying calibration in this case yields  $4.8 + 0.3 = 5.1$ , overshooting the end of our 5-point quality scale. An analogous problem can occur at the bottom of the scale. Moreover, small differences in scores near the top of the XSTS quality scale are arguable more meaningful than such differences in the middle (a translation model moving from 4.6 to 4.8 may be of more practical significance than a model moving from 2.4 to 2.6 if the scores are accurate). We would like to be more cautious of overstating model quality near the top of the scale, in particular. To eliminate the possibility of scores being calibrated off the evaluation scale, and to moderate calibrations towards the top end we propose introducing another moderating term to the calibration formula; this one multiplicative the previously moderated score.

- **Simple Calibration:**  $f(x) = x + \alpha$
- **Moderated Calibration:**  $f(x) = x + EA$

where

$$A = \tanh(\alpha)$$

$$E = \begin{cases} -\tanh(x - s_{\text{top}}) = +\tanh(s_{\text{top}} - x) & \text{if } \alpha > 0 \\ 0 & \text{if } \alpha = 0 \\ +\tanh(x - s_{\text{bottom}}) & \text{if } \alpha < 0 \end{cases}$$

For our 5 point implementation of the XSTS protocol,  $s_{\text{top}} = 5$  and  $s_{\text{bottom}} = 1$ .

We selected hyperbolic tangent as our moderating factor because it has the behavior of approaching  $f(x) = x$  for small  $x$ , especially  $x < 0.5$ , and asymptotically approaching 1 for larger values. This behavior allows it to both moderate large calibration shifts as well as to act as the moderation function as points approach the end of our scale. Additionally we had the requirement that the function be monotonic between  $s_{\text{top}}$  and  $s_{\text{bottom}}$ , and never push calibrated scores outside of that same range. Other moderating terms may also be possible.

We are currently piloting this more robust form of calibration and will share results with its application in the upcoming No Language Left Behind paper (NLLB Team et al., 2022).

## 6 Results

### 6.1 Evaluation Metrics

While automatic metrics are typically evaluated against gold standard human evaluation, we do not have such a gold standard when assessing different human evaluation protocols. Instead, we appeal to desirable aspects of human evaluation and assess these. Different evaluators should give the same translation the same score (inter-evaluator reliability). Evaluations should properly detect the quality difference between machine translation and gold standard human translation (meaningfulness). The amount of human effort for evaluations is also a significant factor (cost).

**Inter-Evaluator Reliability** Reliability measures the reproducibility of the measurements obtained during evaluation. Variability in ratings is an indication of complexity of the evaluation, lack of clarity in the guidelines rendering it highly subjective. It should be noted that evaluating translations is inherently subjective, yet protocols that are able to transcend the inherent subjectivity should yield more reproducible measures leading to more reliable protocols.



X-English								
	AR	ES	ET	ID	MN	TA	AVG	Rank
RAW	0.36	0.39	0.26	0.50	0.16	0.40	0.34	3
PE	0.32	0.63	0.54	0.09	0.11	0.15	0.31	4
XSTS	0.64	0.29	0.50	0.12	0.19	0.81	0.43	2
MSTS	0.57	0.48	0.46	0.56	0.52	0.62	0.54	1
English-X								
RAW	0.50	0.63	0.67	0.35	0.23	0.74	0.52	3
PE	0.54	0.56	0.56	0.45	0.37	0.68	0.53	2
XSTS	0.85	0.60	0.49	0.99	0.57	0.50	0.67	1
BT+MSTS	0.46	0.43	0.47	0.43	0.48	0.46	0.46	4

Table 3: **Fleiss Kappa Inter-Evaluator Reliability** averaged across HT0, MT0, MT1, and MT2 per protocol. AVG indicates average Kappa across all language directions per protocol. Rank is based on AVG, the highest rank (1) is a reflection of the protocol that yielded the inter-annotator agreement.

We use Fleiss Kappa to measure three-way inter-evaluator reliability scores. Kappa numbers above 0.4 typically indicate moderate to excellent agreement (the higher the better). Table 3 shows the average Kappa across all evaluators for all translations HT0, MT0, MT1, MT2 for each of the protocols.

In Table 6, we also note the overall average Kappa per protocol across all languages (AVG). MSTS is the highest scoring protocol as it exhibits the highest average Kappa across languages per protocol. BT+MSTS also performs well. For the protocols that apply to both language directions XSTS (0.43 and 0.67, average 0.55) ranks above RAW (0.34 and 0.52, average 0.43) and PE (0.31 and 0.53, average 0.42).

**Score difference between human reference translation and machine translation** A simple test of the meaningfulness of each protocol is whether we can clearly see a distinction between Human level translation quality (manually yielded by humans) and our Machine Translation quality. If a protocol cannot meaningfully distinguish between HT and MT then it will not be very useful as a quality measure. This measure makes two crucial assumptions: (1) human translation is indeed excellent and (2) the data selected for annotation evaluation is reflective of various levels of quality for the machine translation. Accordingly, both within each language, and overall between languages, we expect to see a clear progression of: *human translation (HT0) > better machine translation (MT1) > worse machine translation (MT2)*.

RAW, XSTS, and PE passed this test and were reasonably good at separating the three types of translation. But, at least with our sample sizes MSTS and BT-MSTS had a very difficult time distinguishing between HT0 and MT1 or MT1 and MT2, even in cases where the other protocols did not have that difficulty.

## 6.2 Calibration

The goal of calibration is the adjust raw human evaluation scores so that they reflect meaningful assessment the quality of the machine translation system for a given language pair. When comparing different adjustment methods, we are faced with the problem, that there is no real ground truth. However, we do have some intuitions under which circumstances our machine translation systems will likely do well. More training data, the more related languages are to English in terms of proximity in the language family tree, low degree of syntactic and semantic divergence, or the same writing system should be correlated with better machine translation

Language	Language family	Writing system	Linguistic properties		Training size
Amharic	Semitic	Ethiopian	SOV	fusional	2,011,822
Arabic	Semitic	Arabic	VSO	fusional	51,979,453
Bosnian	Balto-Slavic	Latin	SVO	fusional	14,325,281
Bulgarian	Balto-Slavic	Cyrillic	SVO	fusional	51,044,962
Georgian	Georgian-Zan	Georgian	SOV	agglutinative	950,086
Hindi	Indo-Iranian	Devanagari	SOV	fusional	8,607,078
North Azerbaijani	Southern Turkic	Latin	SOV	agglutinative	869,224
Portuguese (Brazil)	Italic	Latin	SVO	fusional	57,210,510
Romanian	Italic	Latin	SVO	fusional	63,737,708
Sindhi	Indo-Iranian	Arabic	SOV	fusional	420,354
Slovenian	Balto-Slavic	Latin	SVO	fusional	30,300,765
Swahili	Volta-Congo	Latin	SVO	agglutinative	5,529,619
Urdu	Indo-Iranian	Arabic	SOV	fusional	4,767,174
Zulu	Volta-Congo	Latin	SVO	agglutinative	4,117,686

Table 4: Languages used in the calibration study and their properties. Training corpus size is number of sentence pairs of the publicly available parallel data used for training. Note that sometimes a large part of the training corpus is of low quality.

quality, in both English–X and X–English translation systems (Birch et al., 2008). See Table 4 for such details for the languages used in the study. Note that the training data comes of sources of varying quality. For instance, the bulk of the Romanian data comes from Open Subtitles — a notoriously noisy corpus.

Additionally, we can also compute the correlation to automatic scores such as the BLEU score. Of course, BLEU scores are notoriously meaningless, for instance they are highly dependent on the literalness of the human reference translation and typically lower when translating into morphologically richer targeted languages. But note that we are using a test set that is shared across all languages. Thus, BLEU scores for translation systems from any language into English are scored against exactly the same English reference translation.

Table 5 shows how the scores for the language pairs were adjusted from the raw baseline scores by (1) the consensus calibration score, (2) fixing the human translation score to 4.687 (determined by averaging scores given to human translations across all language pairs), and (3) both. Intuitively, one of the easiest language is Portuguese due large amounts of data and closeness to English. After adjusting with the calibration score Portuguese-English ranks above Hindi-English and Arabic-English.

The second method to assess the effectiveness of our calibration methods is by computing correlation. We measure correlation with 3 different statistical methods: Pearson’s R,  $r^2$ , and LinReg<sup>1</sup>. Results are shown in Table 6 and an illustration in Figure 2. Independent of the correlation method, or if we compute correlation into English, out of English, or both, the calibration method of adjusting the score based on the calibration set yields the highest correlation, clearly outperforming the baseline of unadjusted scores.

## 7 Conclusion

We introduced two novel contribution to the human evaluation of machine translation for multiple language pairs and validated their effectiveness in industrial-scale user studies: We proposed

<sup>1</sup>The “LinReg” score was calculated as the mean  $r^2$  goodness of fit metric for training a simple sklearn linear regression model on spmBLEU scores and the calibrated XSTS scores using k-fold Cross-Validation with a 1:1 Train/test split, with the cross-validation split randomly bootstrapped 5000 times.

X-English				English-X			
RAW	CS	HT	CS+HT	RAW	CS	HT	CS+HT
4.94 Hindi	4.73 Bosnian	4.64 Hindi	4.64 Hindi	4.95 Hindi	4.88 Bosnian	4.68 Bosnian	4.68 Bosnian
4.88 Slovenian	4.65 Portuguese	4.57 Slovenian	4.56 Slovenian	4.93 Slovenian	4.82 Portuguese	4.67 Hindi	4.67 Hindi
4.75 Bosnian	4.64 Hindi	4.51 Portuguese	4.53 Portuguese	4.90 Bosnian	4.74 Arabic	4.65 Portuguese	4.65 Portuguese
4.62 Arabic	4.58 Arabic	4.49 Bosnian	4.52 Bosnian	4.79 Arabic	4.66 Hindi	4.63 Slovenian	4.62 Slovenian
4.61 Portuguese	4.47 Slovenian	4.40 Arabic	4.43 Arabic	4.78 Portuguese	4.56 Bulgarian	4.58 Bulgarian	4.58 Bulgarian
4.56 Sindhi	4.34 Sindhi	4.30 Sindhi	4.31 Sindhi	4.41 Swahili	4.52 Slovenian	4.56 Arabic	4.58 Arabic
3.98 Swahili	4.19 Bulgarian	4.19 Bulgarian	4.19 Bulgarian	4.12 Romanian	4.41 Swahili	4.38 Swahili	4.38 Swahili
3.96 Urdu	3.98 Swahili	4.14 Urdu	4.03 Urdu	4.07 Bulgarian	4.27 Romanian	4.26 Romanian	4.26 Romanian
3.74 Romanian	3.89 Romanian	3.98 Swahili	3.98 Swahili	3.97 Urdu	3.86 Urdu	4.14 Urdu	4.03 Urdu
3.70 Bulgarian	3.86 Urdu	3.83 Romanian	3.86 Romanian	3.62 Zulu	3.73 Zulu	3.76 Zulu	3.75 Zulu
2.90 Amharic	2.98 Amharic	3.12 Azerbaijani	2.98 Amharic	3.15 Amharic	3.23 Amharic	3.12 Amharic	3.21 Amharic
2.80 Zulu	2.91 Zulu	3.00 Zulu	2.91 Zulu	2.99 Georgian	2.96 Georgian	3.07 Georgian	2.96 Georgian
2.66 Azerbaijani	2.91 Azerbaijani	2.92 Amharic	2.91 Azerbaijani	2.24 Azerbaijani	2.50 Azerbaijani	2.63 Azerbaijani	2.46 Azerbaijani
1.04 Georgian	1.02 Georgian	1.12 Georgian	0.90 Georgian	2.16 Sindhi	1.94 Sindhi	1.89 Sindhi	1.97 Sindhi

Table 5: Adjustment of average XSTS scores based on fixing the score on the calibration set (CS), the human reference translation (HS) or both (CS+HS), compared to unadjusted scores. The languages Hindi, Portuguese, Arabic, Bulgarian, and Swahili are highlighted. CS adjustment ranks them more closely to our expectations based on corpus size and language similarity.

Method	Pearson's R			$r^2$			LinReg		
	X-EN	EN-X	both	X-EN	EN-X	both	X-EN	EN-X	both
baseline	.897	.711	.797	.804	.506	.635	.715	.288	.566
CS	<b>.946</b>	<b>.772</b>	<b>.854</b>	<b>.895</b>	<b>.595</b>	<b>.730</b>	<b>.833</b>	<b>.342</b>	<b>.650</b>
HT	.926	.749	.834	.858	.561	.696	.767	.276	.604
CS+HT	.934	.757	.839	.874	.573	.704	.803	.283	.612

Table 6: Correlation of XSTS scores with spmBLEU scores fixing the score on the calibration set (CS), the human reference translation (HS) or both (CS+HS), compared to raw scores.

the scoring metric XSTS which is focused on meaning and introduced a calibration method that allows us to achieve meaningful scores that rank the quality of machine translation systems for different language pairs so that they match more closely with our intuition (plausibility) and automatic scores.

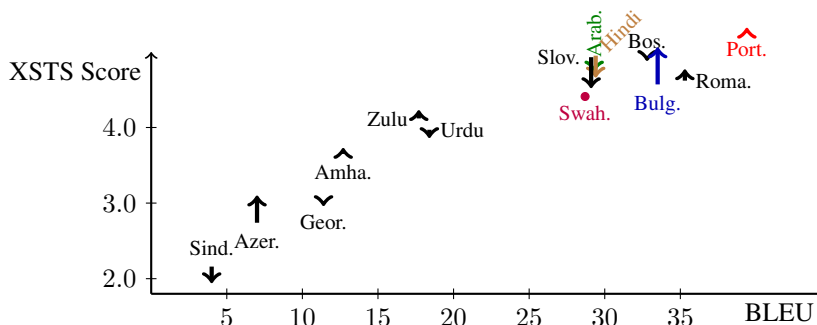


Figure 2: Adjusted X-English scores using calibration set increases correlation with BLEU.

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