Better Late Than Never: Evaluation of Latency Metrics for Simultaneous Speech-to-Text Translation

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Abstract

Simultaneous speech-to-text translation (SimulST) systems have to balance translation quality with latency–the delay between speech input and the translated output. While quality evaluation is well established, accurately measuring latency remains a challenge. Existing metrics often produce inconsistent or misleading results, especially in the widely used short-form setting where speech is artificially pre-segmented. In this paper, we present the first comprehensive analysis of SimulST latency metrics across language pairs, systems, and both short- and long-form regimes. We uncover a structural bias in current metrics related to segmentation that undermines fair and meaningful comparisons. To address this, we introduce YAAL (Yet Another Average Lagging), a refined latency metric that delivers more accurate evaluations in the short-form regime. We extend YAAL to LongYAAL for unsegmented audio streams and propose SoftSegmenter, a novel resegmentation tool based on word-level alignment. Our experiments show that YAAL and LongYAAL outperform popular latency metrics, while SoftSegmenter enhances alignment quality in long-form evaluation, together enabling more reliable assessments of SimulST systems.

1 Introduction

Simultaneous speech-to-text translation (SimulST) is the task in which a system has to produce incremental translation concurrently with the speaker's speech (Ren et al., 2020). SimulST models have to balance between quality and latency of the output, which is the time elapsed between when a word is uttered and when its corresponding translation is produced. While translation quality measures are extensively studied both in the offline ST and in the related field of machine translation (Freitag et al., 2022, 2023; Zouhar et al., 2024), there is no study regarding the reliability of latency metrics. The most commonly used latency metrics in SimulST (Cho and Esipova, 2016; Ma et al., 2019; Cherry and Foster, 2019; Polák et al., 2022; Papi et al., 2022; Kano et al., 2023), even though with different approximations, base their calculation on simplifying assumptions such as uniform word duration, absence of long pauses, and strict monotonic alignment between source speech and target translation. However, despite relying on the same assumptions, these metrics often produce very inconsistent assessments of the system's performance. This inconsistency is clearly illustrated in the results of the IWSLT 2023 Shared Task on Simultaneous Translation (Agarwal et al., 2023), where different metrics produced substantially different rankings for the same set of systems (see Figure 1). Such variability raises serious concerns about the validity of current evaluation protocols and their ability to support meaningful comparisons between systems. Moreover, this risk can be further exacerbated when shifting from dealing with already pre-segmented speech input–i.e., *short-form* SimulST–to unsegmented audio streams–i.e., *long-form* SimulST, where information about sentence boundaries is not available, thereby further complicating the systems' evaluation (Papi et al., 2025).

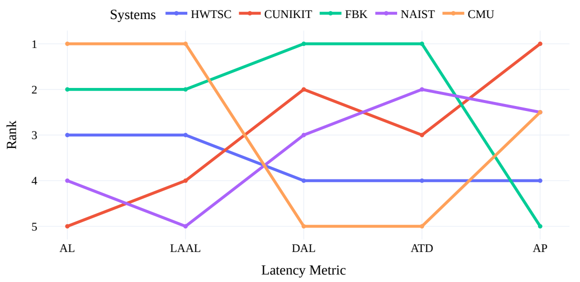

Figure 1: Ranking of the systems submitted to the IWSLT 2023 Simultaneous Speech Translation Track according to the official five latency metrics.

In this paper, we present the first comprehensive evaluation of latency metrics for SimulST under several aspects, including diverse systems, language pairs, and short- and long-form regimes. Through an in-depth analysis of systems submitted to recent IWSLT SimulST Shared Tasks (Anastasopoulos et al., 2022; Agarwal et al., 2023; Ahmad et al., 2024), we reveal that existing metrics can lead to misleading conclusions and hinder effective system design. We show that the inconsistent evaluations are not primarily due to the aforementioned assumptions, but rather to a structural bias in how latency is measured–particularly in how segmentation influences SimulST models' behavior.

Motivated by these findings, we propose YAAL (Yet Another Average Lagging), a refined latency metric designed to mitigate the biases present in existing latency metrics. Our extensive experiments demonstrate that YAAL yields more reliable latency estimates, consistently aligning better with the actual behavior of SimulST systems. Furthermore, we also show that resegmentation–which pairs segment-level predictions with their corresponding reference–is necessary to produce meaningful latency measurements for long-form SimulST. To this end, we introduce SoftSegmenter, a new resegmentation tool, and extend our YAAL to LongYAAL, which deals with audio streams. Compared to the current standard alignment tool used in the speech translation community (Matusov et al., 2005a), SoftSegmenter significantly improves alignment quality, enabling more accurate evaluation in long-form scenarios.[1]

2 Background

In the following, we describe the metrics currently used for both the short-form (§2.1) and long-form (§2.2) regimes. Throughout the paper, we assume incremental SimulST systems, i.e., systems that cannot revise their outputs, as they are not affected by flickering problems, and are leading current research efforts in the topic (Papi et al., 2025).

2.1 Short-Form SimulST Latency Metrics

The short-form is the most common evaluation regime of SimulST (Anastasopoulos et al., 2022; Agarwal et al., 2023; Ahmad et al., 2024), where all recordings of the test set are divided, usually following sentence boundaries, into short segments of a few seconds. Each segment consists of source audio $\mathbf{X} = [x_1, \dots, x_{|\mathbf{X}|}]$, where x_i is a small portion of raw audio–i.e., audio chunk–with a duration T_i, and reference translation $\mathbf{Y^R} = [y^R_1, \dots, y^R_{|\mathbf{Y^R}|}]$. Each audio chunk is incrementally fed to the system, which concurrently outputs a partial translation $\mathbf{Y}_j$ at timestamp $d_j = \sum_{k=1}^{i} T_k$. Under these settings, we describe below the latency metrics operating in the short-form regime.

Average Proportion (AP; Cho and Esipova, 2016) measures the average proportion of input speech read when emitting a target token:

$$\text{AP} = \frac{1}{|\mathbf{X}||\mathbf{Y}|} \sum_{i=1}^{|\mathbf{Y}|} d_i. \quad (1)$$

Average Lagging (AL; Ma et al., 2019) for simultaneous machine translation and modified for speech by Ma et al. (2020) defines the latency as the average delay behind an ideal policy:

$$\text{AL} = \frac{1}{\tau(\mathbf{X})} \sum_{i=1}^{\tau(\mathbf{X})} d_i - d^*_i, \quad (2)$$

where $\tau(\mathbf{X}) = \min\{i | d_i = \sum_{j=1}^{|\mathbf{X}|} T_j\}$ is the index of the hypothesis token when the model reaches the end of the source sentence, also known as the cutoff point. AL considers delays up to and including the one associated with the token at the cutoff point. The i-th delay of the ideal policy is defined as $d^*_i = \frac{i-1}{\gamma}$, where $\gamma = |\mathbf{Y^R}| / \sum_{j=1}^{|\mathbf{X}|} T_j\}$.

Length-Aware Average Lagging (LAAL) is an AL modification that is robust to overgeneration, i.e., when the hypothesis $\mathbf{Y}$ is much longer than $\mathbf{Y^R}$, which makes the original AL produce negative delays when $|\mathbf{Y}| \gg |\mathbf{Y^R}|$. To overcome this problem, which was unduly rewarding overgenerating systems, Polák et al. (2022) and Papi et al. (2022) proposed the modification $\gamma = \max(|\mathbf{Y}|, |\mathbf{Y^R}|) / \sum_{j=1}^{|\mathbf{X}|} T_j\}$.

Differentiable Average Lagging (DAL; Cherry and Foster, 2019) modifies AL by introducing a minimal delay of $1/\gamma$ after each step. Unlike AL and LAAL, DAL considers all delays in the hypothesis, without cutoff after $i > \tau(\mathbf{X})$:

$$\text{DAL} = \frac{1}{|\mathbf{Y}|} \sum_{i=1}^{|\mathbf{Y}|} d'_i - d^*_i, \quad (3)$$

[1]The code for YAAL, its long-form variant LongYAAL, and SoftSegmenter will be released upon the paper acceptance under Apache 2.0 license.

where

$$d'_i = \begin{cases} d_i, & \text{if } i = 1 \\ max(d_i, d'_i + 1/\gamma), & \text{otherwise.} \end{cases} \quad (4)$$

Average Token Delay (AP; Kano et al., 2023) assumes that the source speech, similar to the translation, consists of discrete tokens. ATD defines a fixed duration for speech tokens of 300ms and divides the input speech and translation into C chunks, where the c-th translation chunk y^c is translated conditioned on the source chunk x^c and previous translation chunks $y^1, \dots, y^{c-1}$. ATD is then defined as the average delay between each translation and the corresponding source tokens:

$$\text{ATD} = \frac{1}{|\mathbf{Y}|} \sum_{i=1}^{|\mathbf{Y}|} (T(y_t) - T(x_{a(t)})), \quad (5)$$

where $T(\cdot)$ is the end time of the source/translation token and

$$a(t) = \begin{cases} s(t), & \text{if} s(t) \leq L_{acc}(x^{c(t)}) \\ L_{acc}(x^{c(t)}), & otherwise, \end{cases} \quad (6)$$

is an index of a source token corresponding to translation token y_t, where $L_{acc}(x^c)$ is the number of source tokens in the chunk x^c and $s(t) = t - max(0, L_{acc}(y^{c(t)-1}) - L_{acc}(x^{c(t)-1}))$ handles the case where more tokens are generated than read, i.e., y_t is aligned with $x_{t'}$, $t' < t$.

2.2 Long-Form SimulST Latency Metrics

The long-form evaluation regime evaluates SimulST systems more realistically (Papi et al., 2025), as it assesses their ability to handle long audio streams, often spanning several minutes. Since all metrics were developed for the short-form regime, recent studies exploring the long-form counterpart (Polák and Bojar, 2024; Papi et al., 2024) resorted to re-segmentation of the translations and delays based on the reference translation (Matusov et al., 2005b), and computed the metrics on the segment level. A proposed variant of the LAAL metric for long-form is explained below.

Streaming LAAL (StreamLAAL; Papi et al., 2024) extends the LAAL metric to unsegmented audio streams $\mathbf{S} = [\mathbf{X}_1, ..., \mathbf{X}_{|\mathbf{S}|}]$, paired with a continuous stream of predicted translations $\mathbf{Y_S}$. Since reference translations $\mathbf{Y_1^R}, ..., \mathbf{Y_{|S|}^R}$ are only available at segment-level $\mathbf{X_1}, ..., \mathbf{X}_{|\mathbf{S}|}$, prediction $\mathbf{Y_S} = [\mathbf{Y_1}, ..., \mathbf{Y}_{|\mathbf{S}|}]$ with the corresponding delays is segmented based on reference sentences $\mathbf{Y}_\mathbf{s}^*$ to obtain segment-level predictions. Then, StreamLAAL is computed as:

$$\underset{\text{LAAL}}{\text{Stream}} = \frac{1}{|\mathbf{S}|} \sum_{s=1}^{|S|} \frac{1}{\tau(\mathbf{X_s})} \sum_{i=1}^{\tau(\mathbf{X_s})} d_i - d_i^* \quad (7)$$

Where $d_i^* = (i-1) \cdot |\mathbf{X_s}| / \max\{|\mathbf{Y_s}|, |\mathbf{Y_s^R}|\}$ In practice, the LAAL metric is calculated for every speech segment $\mathbf{X_s}$ of the stream $\mathbf{S}$ and its corresponding reference $\mathbf{Y_s^R}$ with the automatically aligned prediction $\mathbf{Y_s}$ and then averaged over all the speech segments of the stream $\mathbf{X_1}, ..., \mathbf{X}_{|\mathbf{S}|}$.

3 Overcoming the Pitfalls in SimulST Latency Metrics

3.1 The Short-Form Regime

The use of audio segmentation in short-form evaluations significantly affects translation behavior and latency. In practice, short-form SimulST systems are evaluated in a simulated environment where each segment is processed independently (Ma et al., 2020). When the entire source segment has been consumed–i.e., fed to the system–the translation is often still in progress. At that point, the simulator requests the remaining translation, which the model emits without any additional delay. This setup introduces two unrealistic conditions. First, the audio is typically segmented in advance by a human annotator or an automatic model with access to the full audio (*Oracle Segmentation*). Second, the model is allowed to generate the remaining translation (hereinafter, *tail words*) instantaneously once the input segment ends. These factors unduly distort short-form evaluations, by both providing high-quality segmentation and eliminating the delay that would occur in a realistic setting, where the system must wait to confirm that the sentence has ended.

In a more realistic scenario, a model has both to rely on online segmentation and delay final translation steps until it is confident that the input sentence is complete, thereby introducing extra latency. This discrepancy is illustrated in Figure 2. In the *Without Segmentation* and *Simultaneous Segmentation* regimes, the last five words of the first sentence are emitted during the second sentence. In contrast, Oracle Segmentation concludes the first sentence synchronously with the speaker–before the second sentence begins–gaining an artificial latency advantage of approximately 500 ms.

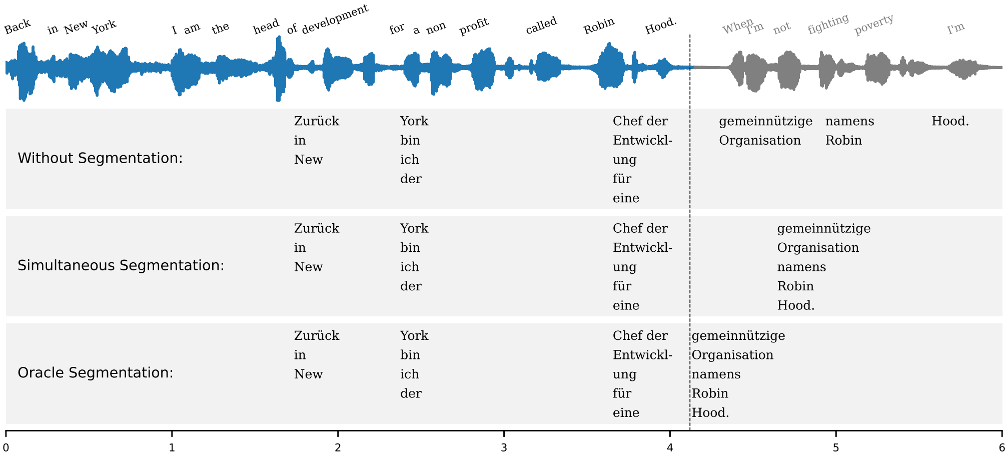

Figure 2: Translations and emission times of a SimulST model. Words in a column were emitted at once. The emission of the last five words ("*gemeinnützige Organisation namens Robin Hood.*") depends on the segmentation. *Without Segmentation*: Model continues translating the second sentence. *Simultaneous Segmentation*: Segmentation model runs concurrently with the translation model. *Oracle Segmentation*: Optimal segmentation is known before.

Based on these observations, we categorize existing short-form latency metrics (§2.1) into two main groups, depending on whether they include all translated words or only a subset in their latency computation. The first group–comprising AP, DAL, and ATD–includes all translated words in the calculation. Among these, DAL attempts to mitigate the impact of tail words by adding a minimum delay of $1/\gamma$ after each generated word (also within the same step), thus "spreading" the tail delays across words. However, $1/\gamma$ simply reflects the average source-to-target length ratio and does not accurately capture the system behavior for tail words in settings without segmentation. If multiple words are emitted as tail words, DAL can significantly overestimate latency. In the edge case of a system that waits for an end-of-segment signal (i.e., an offline system), DAL returns the segment length, failing to capture the system's true behavior–in this case, infinite latency. AP assigns a delay of 1 to each tail word as the entire recording has to be processed to emit that word, thus, the proportion is 1. While AP is marginally less sensitive to segmentation effects than DAL–since it operates on proportions rather than absolute delays–it still fails to model system behavior faithfully for the tail words. ATD also considers all translated words. However, unlike DAL, it does not apply corrections for tail word behavior, making it the most sensitive to segmentation artifacts among the three metrics.

The second group–AL and LAAL–computes latency only for words emitted up to and including the cutoff point $\tau(\mathbf{X})$, which marks the first word generated after the end of the input segment. This corresponds to the word "*gemeinnützige*" in Figure 2. As discussed earlier, in the short-form regime with oracle segmentation, the $\tau(\mathbf{X})$-th and following words are often translated earlier than they would be in a more realistic long-form scenario. As a result, this cutoff introduces a systematic bias in the latency estimate, which may lead to either underestimation or overestimation, depending on the system's policy.[2]

AP, DAL, ATD, AL, and, more recently, LAAL became established metrics in the short-form evaluation of SimulST. However, as discussed above, including any of the tail words in the latency computation leads to a systematic bias that undermines fair comparisons. To cope with this bias, we propose a new metric derived from the LAAL metric:

Yet Another Average Latency (YAAL) We refine the LAAL formulation to better isolate the portion of output that is actually produced under simultaneous settings. Specifically, we define a new cutoff point:

$$\tau_{\text{YAAL}}(\mathbf{X}, D) = \max\{i | d_i < \sum_{j=1}^{|\mathbf{X}|} T_j\}, \quad (8)$$

[2]For instance, systems that continuously produce output may appear faster due to the omission of final tail delays (i.e., underestimation), while systems that delay a large portion of translation until the end of the segment may appear slower than they actually are (i.e., overestimation).

which includes only those words generated strictly before the end of the input stream. For example, in Figure 2, this corresponds to including words up to and including "*eine*", thereby avoiding distortion from tail words and yielding a more reliable latency estimate that remains consistent across different segmentation regimes.

3.2 The Long-Form Regime

The long-form regime offers a more realistic evaluation setting by assessing systems on continuous, unsegmented audio streams that better reflect real-world use cases. However, widely used latency metrics were originally designed for the short-form regime and do not directly extend to this setting.

First, metrics such as AL, LAAL, and DAL rely on a γ parameter, representing the average target-to-source length ratio. In long-form settings, however, γ can vary substantially across different segments within the same audio stream, leading to inconsistent and unreliable latency estimates (Iranzo-Sánchez et al., 2021). Second, AP tends to converge toward 0 for long recordings, as typical speech inputs are significantly longer than their corresponding translations, i.e., $|\mathbf{X}| \gg |\mathbf{Y}|$, leading Equation (1) to approach 0. Finally, ATD assumes that each speech token has a fixed duration and that source and target tokens align monotonically–assumptions that are overly restrictive and especially unrealistic for long-form speech.

To address these challenges, prior work has introduced re-segmenting long inputs into short segments and computing latency on these units, as in StreamLAAL. While StreamLAAL provides the first adaptation of existing metrics to long-form input, it has some limitations. It relies on the mWERSegmenter tool (Matusov et al., 2005a), which may introduce alignment errors (Amrhein and Haddow, 2022; Polák and Bojar, 2024), and computes latency up to the cutoff word $\tau(\mathbf{X_i})$ (Equation (7)), which can lead to the systematic bias (§3.1) as this word is often translated beyond the reference segment. To overcome these limitations, we propose both a new re-segmentation method and an extension of the YAAL metric for the long-form regime.

SoftSegmenter We introduce a new re-segmentation method inspired by Polák and Bojar (2024), employing a softer alignment strategy to more accurately match translation outputs with reference segments. Our method works on the word level, but uses a character-level score to allow a non-exact match. Additionally, we penalize word alignments to punctuation, reducing spurious boundaries and improving alignment robustness. Refer to Appendix B for implementation details.

Long-Form YAAL (LongYAAL) We also extend YAAL to the long-form regime–i.e., LongYAAL. Unlike StreamLAAL, LongYAAL includes all words in the latency computation, even those generated beyond the aligned segment boundaries $\mathbf{X_s}$, i.e., all d_i for $i > \tau(\mathbf{X_s})$. However, we exclude the final tail words produced after the end of the full stream $\mathbf{S}$, i.e., d_i for $i > \tau(\sum_{s=1}^{|\mathbf{X}|} |\mathbf{X_s}|)$. This ensures that we include all words emitted beyond the segment boundaries $\mathbf{X_s}$, but we do not include the tail words generated at the end of the entire stream $\mathbf{S}$. If the stream $\mathbf{S}$ consists of a single segment, LongYAAL coincides with YAAL.

4 Experimental Settings

4.1 Data

For the short-form regime, we use systems submitted to the IWSLT Simultaneous Speech Translation tracks of 2022 and 2023. For the long-form regime, the logs are sourced from IWSLT 2025. Detailed information on the data, the number of systems available for each regime, year, and language pair is presented in Appendix A. All systems were evaluated with SimulEval (Ma et al., 2020).

4.2 Evaluation

True Latency To enable fair comparisons across latency metrics, we require a reference latency reflecting the user experience, i.e., how long the user needs to wait for translation. Since human evaluation is infeasible at scale, we adopt a carefully designed automatic approximation, which we refer to as *true latency*. This is grounded in an intuitive and practical definition of latency in speech translation: *On average, how long does a user have to wait for a given piece of source information to appear in the translation?* Concretely, we define true latency as the average delay between each target word and its corresponding source word.

$$TL = \frac{1}{|\mathbf{Y^A}|} \sum_{i=1}^{|\mathbf{Y^A}|} d_i - d_i^{src}, \tag{9}$$

where d_i is the emission time of the target word y_i and d_i^{src} is the corresponding source delay. We define the source delay as the time that the speaker finished the last word corresponding to the target word: $d_i^{src} = \max_l \{s_l^{end} | (y_i, s_l) \in \mathcal{A}(\mathbf{Y} \rightarrow \mathbf{S})\}$, where s_l^{end} is the end timestamp of the source word s_l and $\mathcal{A}(\mathbf{Y} \rightarrow \mathbf{S})$ is the translation alignment between the target and the source. As discussed in §3.1, computing latency over all words–including tail words–can introduce systematic bias. To mitigate this, we restrict the true latency calculation to words generated strictly during simultaneous decoding, i.e., before the end-of-source signal. Additionally, we consider only the subset of target words $\mathbf{Y^A} \subseteq \mathbf{Y}$ that are aligned to at least one source word, thereby avoiding biases introduced by over- or under-generation (Polák et al., 2022; Papi et al., 2022). The implementation details are provided in Appendix C.

Score Difference For the main evaluation, we adopt the pairwise comparison approach (Mathur et al., 2020). Rather than evaluating each system independently as a standalone data point, we examine the difference between the scores of two systems: $\Delta = score(\text{System A}) - score(\text{System B})$. Pairwise comparison better reflects the typical use case of latency metrics–namely, distinguishing between two systems. In our evaluation, we restrict comparisons to system pairs evaluated on the same test set and language pair.

Accuracy Following Kocmi et al. (2021), we also evaluate the accuracy of binary comparisons between systems: given a pair of systems, which one is better according to the true latency ranking (used as gold labels)? The accuracy is defined as the proportion of system pairs for which the relative ranking according to a metric matches that of the true latency:

$$\text{Accuracy} = \frac{|sign(\Delta\text{TL}) = sign(\Delta\text{M})|}{|\text{all system pairs}|}.$$

This accuracy measure considers only the ranking–not the magnitude–of the latency differences, allowing us to aggregate comparisons across language pairs and test sets. However, this accuracy might be affected if two systems have similar latencies. To avoid this issue, we compute the accuracies in multiple subsets by removing pairs that are not significantly different according to Mann-Whitney U test on their true latencies.[3] We use bootstrap resampling with $N = 10000$ (Tibshirani and Efron, 1993) to estimate confidence intervals and consider all metrics within the 95% confidence interval of the top-performing metric to be statistically tied.

[3] We do not assume normal distribution of delays. Each system has different hypotheses, so we cannot use paired tests.

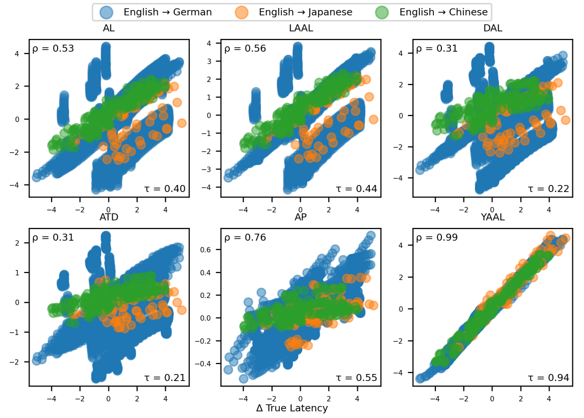

Figure 3: Each point represents the difference between the true latency (x-axis) and the automatic metric (y-axis) for two systems. Reported Pearson and Kendall rank correlations are for illustration only, as each language pair has a slightly different scale.

5 Results

5.1 Short-Form Evaluation

Which is the best Short-form Latency Metric? We present the pairwise comparison of all short-form systems in Figure 3. An important first observation is that a significant portion of system pairs exhibit no or slightly negative correlations–points that create almost vertical lines and lines far off the diagonal. These systems[4] share an *anomalous simultaneous policy*: The lower the latency of the prefix generated simultaneously, the larger the portion of the sentence translated offline. We assume that the underlying reason for this behavior is that the system is too eager to emit outputs at the beginning, but then it gets to a "dead end" of probable outputs and only emits the remaining words at the signaled end of the sentence. This policy, coupled with the bias introduced by the latency metrics, led to a severe overestimation of the systems' actual latency. In particular, the shorter the prefix in low-latency systems, the greater the impact of the $\tau(\mathbf{X})$-th word that has a delay equal to the segment length, causing the low-latency system to

[4] After a manual inspection, we identified that all affected systems were submitted independently by two different teams in IWSLT 2022 and 2023, showing that the metric's negative behavior is not so uncommon.

have higher AL values.[5]

Moving to the metrics, we observe that they all show positive correlations with the true latency, but each language pair has a slightly different scale, which motivates the use of accuracy. Therefore, we compare the latency metrics in terms of accuracy in Table 1. If we consider all system pairs, we see that all metrics significantly underperform YAAL, which reaches 96% accuracy. When we progressively filter out system pairs with similar true latency, the accuracies slightly increase, but the order of metrics does not change. If we consider a subset that has a p-value between 0.001-0.05 (i.e., removing systems with the same true latency and systems that are easily distinguishable), we see that YAAL still remains the most accurate one, but relative ranking of the other metrics changes, which we attribute to the influence of systems with the anomalous policy. Apart from YAAL, AP appears less vulnerable to tail words, likely due to the use of relative delays compared to absolute delays in other metrics. If we remove systems with the anomalous policy, all metrics gain a significant boost in accuracy (bottom part of Table 1). The YAAL metric is the best metric in all subsets based on p-values, achieving 98 and 99% accuracy–even though it relies on assumptions such as uniform source token durations and monotonic source-to-target alignment. Based on these observations, we conclude that ***the automatic YAAL metric is almost as accurate as true latency***. We include more accuracy evaluations by isolating different categories of systems in Appendix D.

Should we use the Short-Form Regime? As discussed in §3 and empirically observed in this section, short-form evaluation can significantly distort latency measurements. In Table 2, we present the average fraction of target words generated *after* the end-of-segment signal. The results reveal that a substantial portion of the translations are tail words, starting at 41% in the low-latency regime (1-2s) and reaching 72% in the high-latency regime (4-5s).[6] ***Short-form evaluation, with artificial segment boundaries absent in real-world scenarios and metrics' problematic handling of tail words, often misrepresents SimulST system behavior.*** This raises serious concerns about its reliability and underscores the need for long-form evaluation, which we analyze in §5.2.

[5]For example, one segment had only one word translated simultaneously, and the rest was translated after the end of the speech in 9.3 s. YAAL for this segment is $(1-0\times0.4)/1 = 1$ s, while AL and LAAL are $(1-0\times0.4+9.3-1\times0.4)/2 = 4.95$ s, where $* \times 0.4$ is the ideal latency for this segment.

[6]Systems with higher-latency behavior have policies leading to deferred delays, and these delays in turn are more likely to overflow the source duration.

p-val	AL	LAAL	DAL	ATD	AP	YAAL	N
all system pairs							
all	0.66	0.69	0.59	0.56	0.74	**0.96**	5326
<0.05	0.67	0.70	0.59	0.56	0.75	**0.98**	5149
<0.01	0.67	0.70	0.59	0.56	0.75	**0.98**	5103
<0.001	0.68	0.70	0.59	0.56	0.76	**0.98**	5048
0.001-0.05	0.40	0.46	0.40	0.43	0.42	**0.71**	101
w/o anomalous policy							
all	0.95	0.97	0.95	0.92	0.85	**0.98**	2100
<0.05	0.96	0.97	0.96	0.92	0.85	**0.99**	2060
<0.01	0.96	0.98	0.96	0.93	0.85	**0.99**	2046
<0.001	0.96	0.98	0.97	0.93	0.85	**0.99**	2025
0.001-0.05	<u>0.71</u>	**0.74**	<u>0.66</u>	**0.74**	<u>0.66</u>	**0.74**	35

Table 1: Accuracy of systems in the short-form regime. Best scores in **bold**. <u>Underlined</u> scores are considered tied with the best metric.

Latency regime [s]	1-2	2-3	3-4	4-5
Tail Words [%]	41	49	63	72

Table 2: Average fraction of words generated after the end-of-segment signal under the short-form evaluation regime, averaged across all systems.

5.2 Long-Form Evaluation

Which Resegmentation is Better? In Table 3, we evaluate two re-segmentation tools: mWERSegmenter (Matusov et al., 2005a) and our proposed SoftSegmenter. The evaluation is done on reconcatenated short-form outputs, allowing us to compare with gold segment boundaries. As we can see in Table 3, ***the accuracy of SoftSegmenter is significantly higher***. When filtering out comparable systems by the p-value, accuracy further decreases with mWERSegmenter, suggesting that the segmentation is not stable. Moreover, both segmentation approaches achieve a very high accuracy of more than 99%, showing that resegmentation does not compromise translation quality measurement.

Do we need Resegmentation? The upper part of Table 4 presents the accuracy of latency metrics on long-form systems evaluated *without resegmentation*. We see that the accuracies are low, not exceeding 66% when considering all systems. Compared to StreamLAAL (first column), the best-performing AL metric loses 15% to 16% absolute points, and

	Latency (StreamLAAL)		MT Quality (COMET)	
p-value	mWERSegmenter	ours	mWERSegmenter	ours
All	86.4	94.1	99.3	99.1
0.05	86.3	95.8	100.0	100.0
0.01	86.2	96.1	100.0	100.0
0.001	86.1	96.5	100.0	100.0

Table 3: Accuracy of latency and quality metrics after re-segmentation.

p-val	Stream LAAL	AL	LAAL	DAL	ATD	AP	YAAL	N
longform + unsegmented								
all	0.82	**0.66**	0.61	0.57	0.61	0.39	0.61	594
<0.05	0.85	**0.69**	0.64	0.59	0.63	0.36	0.64	523
<0.01	0.85	**0.70**	0.65	0.59	0.63	0.35	0.65	496
<0.001	0.87	**0.71**	0.65	0.60	0.63	0.34	0.65	461
0.001-0.05	0.63	0.52	0.55	0.48	**0.60**	0.47	0.55	62

p-val	Stream LAAL	Long AL	Long LAAL	Long DAL	Long ATD	Long AP	Long YAAL	N
longform + resegmented								
all	0.82	0.92	**0.95**	0.94	0.93	0.71	**0.95**	594
<0.05	0.85	0.94	0.96	0.97	0.97	0.72	**0.98**	523
<0.01	0.85	0.95	0.97	0.97	**0.98**	0.72	**0.98**	496
<0.001	0.87	0.95	0.97	0.98	**0.99**	0.74	**0.99**	461
0.001-0.05	0.63	0.85	**0.90**	0.85	0.82	0.60	0.87	62

Table 4: Accuracy of systems in the long-form regime. Best scores in **bold**. Underlined scores are considered tied with the best metric. All metrics in the bottom half use the proposed SOFTSEGMENTER, except for StreamLAAL that uses the original mWERSegmenter.

the gap is even wider compared to LongYAAL, with AL falling short by 29 points. The bottom part of Table 4 reports the accuracy of latency metrics in long-form systems when evaluated *with resegmentation*. Overall, we see that the resegmentation quality significantly influences the accuracy. StreamLAAL and LongLAAL share the same definition, but differ in the resegmentation tool–while StreamLAAL uses the original mWERSegmenter, LongLAAL (and all the other "Long-" metrics) uses our proposed SOFTSEGMENTER. The gap in accuracy is 8% to 10% absolute in all subsets, showing trends similar to those in Table 3. ***These results highlight the critical role of resegmentation in ensuring reliable latency evaluation in the long-form regime.*** Additional observations are provided in Appendix E.

Which is the best Long-form Latency Metric? Table 4 also shows that the proposed LongYAAL metric has the highest accuracy across all subsets. LongATD and LongDAL show slightly worse results, but the differences are not statistically significant. This contrasts with the observations in §5.1, where ATD and DAL are in the fourth and third places. This discrepancy can be explained by the fact that both metrics account for all words, including tail words that rarely occur in the long-form regime. We attribute the marginal difference to LongATD's assumption of 300ms words in the source speech, which is dynamic in LongYAAL and LongDAL in the form of the γ parameter, and the difference in LongDAL is probably caused by the minimum delay of $1/\gamma$ assigned to each word. LongLAAL ties with LongYAAL in most subsets, but appears slightly worse when considering easily distinguishable systems (p-val <0.001), where the metric loses 2% absolute in terms of accuracy. LongLAAL, unlike LongYAAL, disregards words generated beyond the reference segment boundaries. The number of words ignored increases with the true latency of the system (see §5.1), which is more prevalent in the p-val < 0.001 subset. Similarly, LongAL ignores the tail words in the resegmentation and is also vulnerable to overgeneration (Polák and Bojar, 2024; Papi et al., 2024). Finally, AP performs the worst with a loss of more than 21% points compared to the rest of the metrics, which we attribute to the metric's sensitivity to variable segment length. Overall, ***these results position LongYAAL as the most reliable metric for assessing latency in long-form SimulST***.

6 Conclusions

In this paper, we presented the first systematic evaluation of latency metrics for SimulST across several aspects, such as diverse systems, language pairs, and operating under short- and long-form speech processing. We have identified current pitfalls in the SimulST evaluation by isolating issues in the most commonly used metrics. To overcome these limitations, we propose YAAL, a new latency metric better aligned with the short-form evaluation regime. However, our analysis also reveals inherent shortcomings of short-form evaluation, further reinforcing the adoption of long-form evaluation as a more reliable alternative. Moreover, we also demonstrated that resegmentation is necessary to conduct a proper evaluation of systems operating under the long-form regime, and proposed an improved resegmentation tool coupled with the extension of YAAL for these settings–LongYAAL. The results showed that YAAL and LongYAAL improve over all other metrics in both regimes, establishing the new state-of-the-art metric for SimulST.

Limitations

While our study offers a thorough evaluation of latency metrics for SimulST and introduces improved tools for both short- and long-form regimes, some limitations remain. First, our evaluation depends on reference translations and transcriptions, which may not be available or reliable in low-resource or real-time scenarios. Second, although the proposed SOFTSEGMENTER improves alignment robustness, word-level alignment is still susceptible to errors in the presence of disfluencies or speech recognition noise. Third, our experimental analysis focuses on systems from the IWSLT Shared Tasks, which may not fully represent the range of techniques or data conditions used in broader academic or industrial settings. Fourth, our analysis focuses on high-resource languages, for which data were available, but the findings should be reconfirmed under low-resource language settings.

Potential Risks Our work introduces new evaluation tools that could influence future benchmarking of SimulST systems. However, there is a risk that over-reliance on specific metrics–even improved ones like YAAL and LongYAAL–could lead to overfitting system design to particular evaluation settings. For example, systems might be tuned to perform well under LongYAAL but degrade in real-world conditions that are not fully captured by the metric. Additionally, the use of automatic resegmentation methods may inadvertently introduce subtle biases if misaligned with human interpretation of segment boundaries. We encourage the community to use these tools alongside qualitative analysis and human-in-the-loop evaluations where possible.

Computational Budget We did not train any models as part of this study. However, we used several evaluations that required computation. Most of the experiments were conducted on a standard desktop computer equipped with an Intel i7 processor and 32GB of RAM. For forced alignments with neural models, machine translation alignment, and the COMET translation quality metric, we used a GPU cluster. However, these evaluations can be done on a desktop machine with a slightly longer runtime. The proposed SOFTSEGMENTER, YAAL, and LongYAAL can be run efficiently on a CPU.

Use of AI Assistants We used AI-assisted coding (i.e, Copilot) with the bulk written by humans. For writing, we used AI to check grammar mistakes.

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A Evaluated Systems

For the short-form regime, we use systems submitted to the IWSLT Simultaneous Speech Translation tracks of 2022 and 2023. Specifically, we use the SimulEval evaluation logs of the IWSLT 2022 and 2023 test sets (Anastasopoulos et al., 2022; Agarwal et al., 2023), and the logs of the `tst-COMMON` test set of the MuST-C data set (Cattoni et al., 2021) that were submitted to IWSLT 2022. For the long-form regime, the logs are sourced from IWSLT 2025. In particular, for English-to-{German, Chinese, Japanese} the evaluation was done on the development set of the ACL 60/60 dataset (Salesky et al., 2023), and IWSLT 2025 test set. For the Czech-to-English language pair, the evaluation was performed on the IWSLT 2024 development set (Ahmad et al., 2024) and the IWSLT 2025 test set. A portion of the IWSLT 2024 development set contained segmented audio that could not be reconstructed into the original unsegmented audio.

In Tables 5 to 7, we present the number of systems used in the short- and long-form evaluations. The number of systems available to us was slightly larger, but we excluded all systems where the logs were incomplete (e.g., predictions for all recordings were not present, mismatched order of sources and hypotheses). Furthermore, in the long-form regime, we excluded one team entirely from the evaluation due to faulty logs. These logs contained a different number of predicted words and delays, which means that we could not faithfully determine generation timestamps for each predicted word.

Language Pair	Dataset	Teams	Systems
EN→DE	IWSLT 22 test set	5	68
	IWSLT 23 test set	5	5
	tst-COMMON	7	75
EN→JA	IWSLT 22 test set	3	9
	IWSLT 23 test set	4	4
	tst-COMMON	3	14
EN→ZH	IWSLT 22 test set	3	14
	IWSLT 23 test set	3	3
	tst-COMMON	3	14

Table 5: Overview of the short-form systems in our evaluation.

Language Pair	Dataset	Teams	Systems
EN→DE	IWSLT 22 test set	4	40
	IWSLT 23 test set	4	4
	tst-COMMON	6	47
EN→JA	IWSLT 22 test set	3	7
	IWSLT 23 test set	4	4
	tst-COMMON	3	7
EN→ZH	IWSLT 22 test set	3	14
	IWSLT 23 test set	3	3
	tst-COMMON	3	14

Table 6: Overview of the short-form systems in our evaluation after filtering out systems with anomalous policy.

Language Pair	Dataset	Teams	Systems
EN→DE	ACL 6060 dev set	6	20
	IWSLT 25 test set	6	10
EN→JA	ACL 6060 dev set	3	16
	IWSLT 25 test set	2	3
EN→ZH	ACL 6060 dev set	4	16
	IWSLT 25 test set	4	8
CS→EN	IWSLT 24 dev set	2	14
	IWSLT 25 test set	2	4

Table 7: Overview of the long-form systems in our evaluation.

B SoftSegmenter Implementation Details

The main purpose of our SoftSegmenter tool is to mitigate the incorrect alignment and resegmentation of hypotheses. We take inspiration from (Polák and Bojar, 2024). During preprocessing, we lowercase and tokenize both the reference translations and the system hypotheses. This allows for a more precise alignment around the sentence ends, especially in cases where the reference and model differ in sentence segmentation. However, we still keep the original texts in memory so as not to interfere with the machine translation quality evaluation. Additionally, we keep the delay information together with each token, and we use it during the alignment process to prevent alignment of tokens to future segments, which generally leads to spurious negative latencies.

For alignment, we use the following score metric that we maximize during alignment:

$$\mathcal{S}(t_r, t_h) = \begin{cases} -\infty & s_r \geq d_h, \\ -\infty & P(t_r) \oplus P(r_h), \\ \mathcal{S}_{\text{char}}(t_r, t_h) & \text{otherwise}, \end{cases} \tag{10}$$

where t_r and t_h, are the reference and hypothesis tokens, s_r is offset of the reference segment in the recording, d_h is the emission time of the hypothesis token, $P(\cdot)$ is a function that indicates in the token is a punctuation, and finally we define the character-level similarity of the reference and hypothesis tokens as follows:

$$\mathcal{S}_{\text{char}}(t_r, t_h) = \frac{t_r \cap t_h}{t_r \cup t_h}. \tag{11}$$

In case of character-based languages such as Japanese and Chinese, Equation (11) reduces to an exact match.

C True Latency

C.1 Implementation Details

Short-Form Regime To determine the true latency for each system, we follow the definition in §4. First, we tokenize the hypotheses, the reference transcript, and the reference translation using `MosesTokenizer`. For Chinese and Japanese, we split the text into characters. Second, we perform time alignment between the source speech and the golden source transcripts using Montreal Forced Aligner (McAuliffe et al., 2017). This gives us the precise start and end timestamps for every word in the source recording. Third, we use the `awesome-align` tool (Dou and Neubig, 2021) to map each hypothesis word with its most likely counterpart in the source transcript.

Long-Form Regime Same as in the short-form evaluation, we follow the definition of the true latency in §4. However, there are two differences. After initial experiments, we observed that the Montreal Forced Aligner used in the short-form regime is not robust for the challenging conditions of the IWSLT 2025 test set, which is based on ACL presentations. The recordings include frequent restarts, repetitions, domain-specific terminology, and non-native speech. Instead, we use the alignment method implemented within WhisperX (Bain et al., 2023) for forced alignment. This tool leverages neural speech encoders that seem to be robust to the above-mentioned challenges. In particular, we used WhisperX's default settings, i.e., PyTorch's `WAV2VEC2_ASR_BASE_960H` for English and `comodoro/wav2vec2-xls-r-300m-cs-250` for Czech speech forced alignments. Second, we perform re-segmentation of the system hypotheses prior to the machine translation alignment with the reference. This step is necessary because the `awesome-align` tool uses the `bert-base-multilingual-cased` model for the alignment, and this model has a maximum input length of 512 tokens, which is much lower than the system hypotheses.

C.2 Why Not Use True Latency Directly?

A natural question arises: *Why rely on automatic latency metrics at all, when true latency offers a closer approximation of user experience?* In practice, computing true latency requires several requirements that limit its applicability. High-quality transcripts must be available, which is often not the case–particularly for low-resource languages or unwritten languages where transcription is infeasible. Moreover, forced alignment tools and reliable word-level translation alignments are typically available only for a small set of high-resource language pairs. Even when such resources exist, computing true latency involves multiple processing steps and is substantially more complex than evaluating standard automatic metrics. Importantly, as we show in our analysis in §5, several automatic metrics approximate true latency with high accuracy, making them a practical and effective alternative in most evaluation scenarios.

D Short-Form Evaluation

Additional Analysis In Figure 4, we illustrate the trends after filtering out the systems affected by the anomalous policy (see §5.1). Unlike in Figure 3, we see that all metrics and system pairs show a positive correlation with the true latency. As mentioned in §5.1, language pairs exhibit different scales, making the use of the correlation coefficient more cumbersome and motivating the use of accuracy as described in §4.2.

To this end, in Figures 5 and 6, we also offer the accuracy of subsets of system pairs based on the absolute difference in the true latency.

Comparing Related vs. Unrelated Systems We were also interested in the accuracy of latency metrics when comparing related against unrelated systems. In our evaluation, we consider the systems

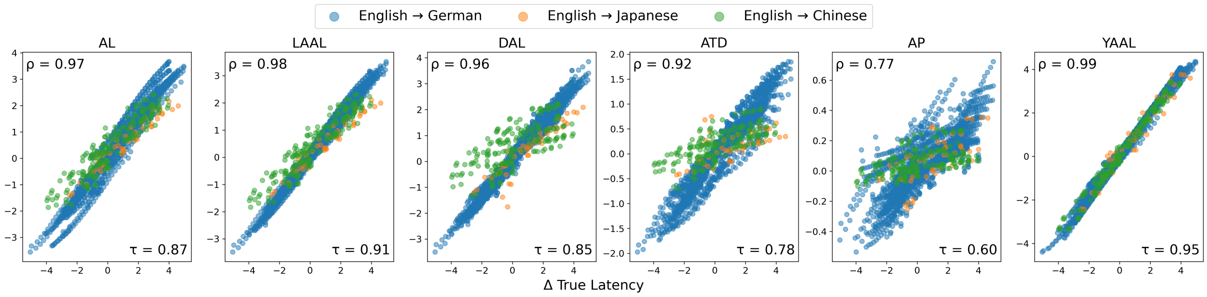

Figure 4: Figure 3 excluding systems affected by the anomalous policy. Each point represents the difference between the true latency (x-axis) and the automatic metric (y-axis) for two systems. In the upper left corner, we report the Pearson correlation coefficient ρ, and in the bottom right corner, we report the Kendall rank coefficient τ. The reported correlations are only for illustration, as different language pairs and test sets have different scales.

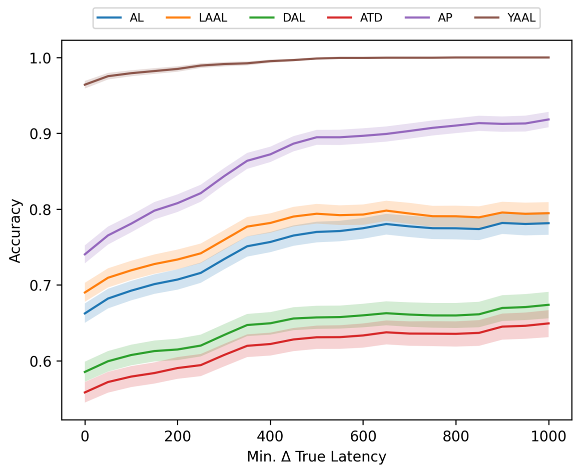

Figure 5: Metric accuracies based on the difference of two systems. Solid lines show the accuracy given the minimal difference in True Latency. The colored strips along the lines show the 95% confidence interval obtained with bootstrap resampling (N=10000).

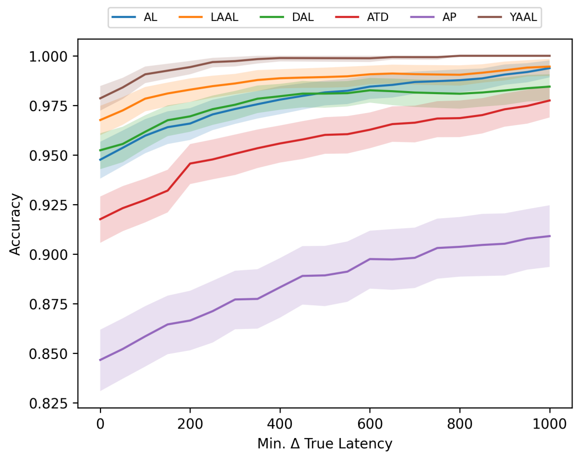

Figure 6: Figure 5 excluding systems affected by the anomalous policy. Metric accuracies based on the difference between two systems. Solid lines show the accuracy given the minimal difference in True Latency. The colored strips along the lines show the 95% confidence interval obtained with bootstrap resampling (N=10000).

p-val	AL	LAAL	DAL	ATD	AP	YAAL	N
related systems							
all	0.99	1.00	0.99	0.96	0.99	1.00	897
<0.05	1.00	1.00	1.00	0.97	0.99	1.00	888
<0.01	1.00	1.00	1.00	0.97	0.99	1.00	888
<0.001	1.00	1.00	1.00	0.97	0.99	1.00	881
0.001-0.05	1.00	1.00	1.00	0.57	1.00	1.00	7
unrelated systems							
all	0.92	0.95	0.92	0.88	0.74	**0.97**	1203
<0.05	0.93	0.96	0.94	0.89	0.75	**0.98**	1172
<0.01	0.93	0.96	0.94	0.89	0.75	**0.98**	1158
<0.001	0.93	0.96	0.94	0.89	0.75	**0.98**	1144
0.001-0.05	<u>0.64</u>	<u>0.68</u>	0.57	**0.79**	0.57	<u>0.68</u>	28

Table 8: Accuracy of systems in the short-form regime when comparing related and unrelated systems. Systems with the anomalous policy were omitted. Best scores in **bold**. <u>Underlined</u> scores are considered tied with the best metric.

submitted by one team as related.[7] We also use only a subset of the systems that were not affected by the anomalous simultaneous policy. The results are in Table 8.

Surprisingly, when evaluating related systems, all metrics perform almost perfectly, reaching accuracy between 97% and 100%. In Figure 7, we report the accuracy of subsets based on the minimal difference in the true latency. Given a difference of at least $\sim$ 250 ms, all metrics except AP achieve 100% accuracy, and AP achieves around 99% accuracy.

The results on unrelated systems (bottom half of Table 8, and Figure 8) are generally similar to

[7]To the best of our knowledge, most teams submitted multiple systems that were based on the same system with varying hyperparameters.

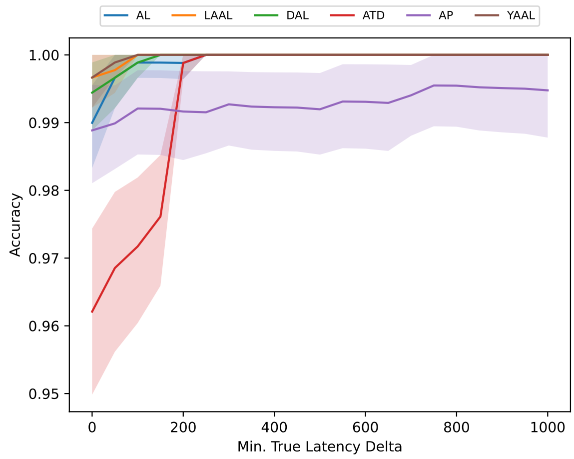

Figure 7: Metric accuracies based on the difference of two related (coming from the same team) systems. Solid lines show the accuracy given the minimal difference in True Latency. The colored strips along the lines show the 95% confidence interval obtained with bootstrap resampling (N=10000).

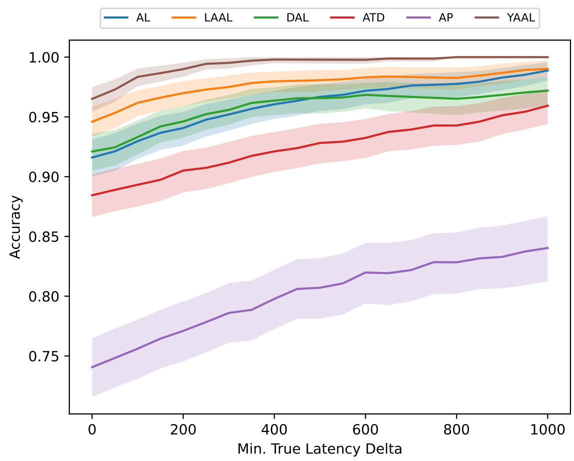

Figure 8: Metric accuracies based on the difference of two unrelated (each system is compared to a system from a different team) systems. Solid lines show the accuracy given the minimal difference in True Latency. The colored strips along the lines show the 95% confidence interval obtained with bootstrap resampling (N=10000).

the observations in §5.1 and Table 1. All metrics show a loss of accuracy of no more than 4% points compared to the results on all systems. The only exception seems to be AP, which loses up to 11% points. The order of the metrics remains the same.

E Long-Form Evaluation

In Figure 9, we show pairwise comparisons of systems evaluated in the long-form regime without resegmentation, and in Figure 10, we show the same systems evaluated in the long-form regime, but after resegmentation. In Figure 11, we report the accuracy of subsets based on the minimal difference in the true latency.

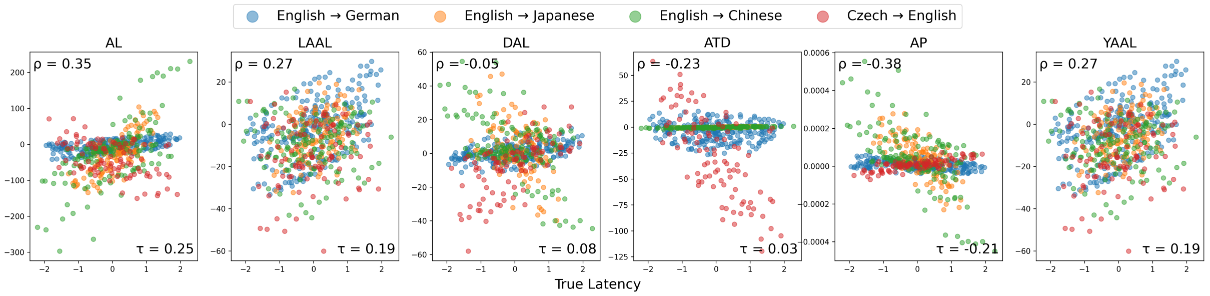

Figure 9: Automatic latency metrics when evaluating in the unsegmented regime without resegmentation.

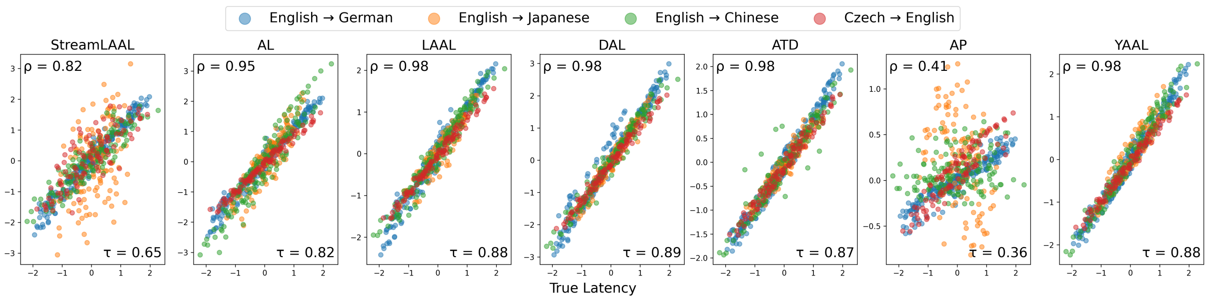

Figure 10: Automatic latency metrics when evaluating in the unsegmented regime without resegmentation.

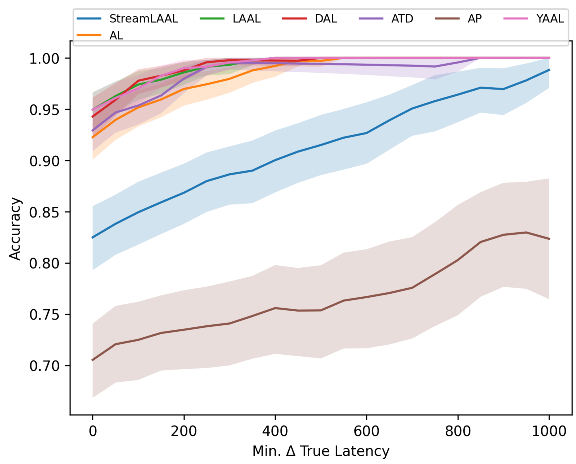

Figure 11: Metric accuracies based on the difference of two systems evaluated in the long-form regime. Solid lines show the accuracy given the minimal difference in True Latency. The colored strips along the lines show the 95% confidence interval obtained with bootstrap resampling (N=10000).