

STACL: Simultaneous Translation with Integrated Anticipation and Controllable Latency*

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Abstract

Simultaneous translation, which translates sentences before they are finished, is useful in many scenarios but is notoriously difficult due to word-order differences and simultaneity requirements. We introduce a very simple yet surprisingly effective “wait- k ” model trained to generate the target sentence concurrently with the source sentence, but always k words behind, for any given k . This framework seamlessly integrates anticipation and translation in a single model that involves only minor changes to the existing neural translation framework. Experiments on Chinese-to-English simultaneous translation achieve a 5-word latency with 3.4 (single-ref) BLEU points degradation in quality compared to full-sentence non-simultaneous translation. We also formulate a new latency metric that addresses deficiencies in previous ones.¹

1 Introduction

Simultaneous translation has the potential to automate simultaneous interpretation. Unlike a consecutive interpreter who waits until the speaker pauses (usually at sentence boundaries) to start translating, and thus doubling the time needed, a simultaneous interpreter performs translation *concurrently* with the speaker’s speech, with a delay of only a few (~ 3) seconds. This *additive* overhead is much more desirable than the *multiplicative* overhead of $2\times$ in consecutive interpretation.

With this appealing property, simultaneous interpretation has been gradually replacing consecutive interpretation ever since the famous Nuremberg Trials (The Nuremberg Trials, 1946; Palazchenko, 1997), and has been widely used in many scenarios including multilateral organizations (such as UN and EU), international

summits (such as APEC and G-20), and bilateral/multilateral negotiations. However, due to the concurrent comprehension (in the source language) and production (in the target language), it is an extremely challenging and exhaustive task for human-beings: there are reportedly only a few thousand qualified simultaneous interpreters worldwide, and each can only last for about 20-30 minutes in one turn whose error rates grow exponentially after just minutes of interpreting (Moser-Mercer et al., 1998). Moreover, limited memory forces human interpreters to routinely omit source content (He et al., 2016), and the best of them can only retain about 60% of source material. Therefore, there is a huge demand for simultaneous interpretation but not nearly enough supply, leaving a critical need to develop simultaneous machine translation techniques to reduce the burden of human interpreters (United Nations, 1957) and make this service more accessible and affordable.

Unfortunately, simultaneous translation is also notoriously difficult for machines, due in large part to the diverging word order between the source and target languages. For example, think about simultaneously translating an SOV or underlyingly SOV language such as Japanese or German to an SVO language such as English or Chinese: you have to wait until you see the source language verb. As a result, existing commercial “real-time” translation systems resort to conventional full-sentence translation, causing an undesirable latency of at least one sentence. Researchers, on the other hand, have attempted to reduce latency by explicitly predicting the sentence-final German verb (Grissom II et al., 2014) which is limited to this particular case, or unseen syntactic constituents (Oda et al., 2015) which requires incremental parsing on the source sentence. Others use reinforcement learning to prefer (rather than enforce) a specific latency (Gu et al., 2017), which

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¹ Online demos: <https://simultrans-demo.github.io/>

and k to represent the word-level translation latency which means that decoder is always k word(s) behind the encoder. Our decoding time step t starts from 1 and $(t + k - 1)$ always capped with $|x|$. Then we have the following decoding strategy:

$$S_k(\mathbf{x}, \mathbf{y}) = \sum_{t=1}^{|\mathbf{y}|} \log p(y_t | \mathbf{x}_{<(t+k)}, \mathbf{y}_{<t}) \quad (2)$$

To have a more general definition which can be applied to any arbitrary policy, we replace the above $(t + k)$ with $p(t)$ to describes the number of source words that have been processed by encoder at decoding time step t :

$$p(t) = \begin{cases} k + t - 1 & 1 \leq t < |x| - k \\ |x| & |x| - k \leq t \end{cases} \quad (3)$$

then our training objective becomes:

$$S_k(\mathbf{x}, \mathbf{y}) = \sum_{t=1}^{|\mathbf{y}|} \log p(y_t | \mathbf{x}_{\leq p(t)}, \mathbf{y}_{<t}) \quad (4)$$

where $\mathbf{x}_{\leq p(t)}$ represents the processed source sequence $(x_1, \dots, x_{p(t)})$.

Eq.3 describes the number of words that are observed by decoder from source side. When our model decodes the first word, there are k words are observed at encoder. Since the second decoder step, every later step will observe one more word on source side. After time step $|x| - k$, encoder receives the entire source sentence and the number of observed words stops increasing.

The above decoding strategy in Eq. 4 is different from Eq. 1 and defines an encoding-decoding policy which first waits k words on the source side, then starts to decode the first translated word on target. Thenceforth the decoder will generate a new target word every time another source word is fed into the encoder.

Below we detail two different instantiations of this simple framework, with RNN and Transformer being the underlying models, respectively.

3.1 Wait- k with RNNs

We first introduce our uni-directional RNN-based approach as one baseline to set up a fair comparison with other methods.

3.1.1 Full Sentence Translation with RNNs

For the basic RNN-based framework, on the encoder side, the RNN maps a sequence \mathbf{x} into a sequence of hidden states as follows:

$$\vec{h}_i = \text{RNN}(x_i, \vec{h}_{(i-1)}; \theta_e),$$

Then we collect a list of hidden states \mathbf{h} to represent the source side. Since we are using uni-directional RNN, we could easily append the new coming word with constant time to the encoder.

On the other side, the decoder takes another RNN to generate the target side's hidden representations at t^{th} step as follows:

$$\vec{s}_t = \text{RNN}(\vec{s}_{(t-1)}, \mathbf{h}; \theta_d) \quad (5)$$

The encoder and decoder are parameterized by θ_e and θ_d , respectively. Note that the decoder takes the entire source context \mathbf{h} as input during generation for each step.

3.1.2 Simultaneous Translation with RNNs

Different from conventional translation, in the scenario of simultaneous translation, the source words are feed into the system one-by-one after k words delay. As mentioned above, during encoding, we could just simply append the new coming words to the end of the existing encoder.

For the decoder side, we need to change Eq.5 into following definition:

$$\vec{s}_t = \text{RNN}(\vec{s}_{(t-1)}, \mathbf{h}_{\leq p(t)}; \theta_d)$$

where $\mathbf{h}_{\leq p(t)}$ indicates that the decoder only can observe the first $p(t)$ hidden states from encoder. Decoder waits for k words on source side, then starts generating a new word once there is another words are feed into the encoder side.

Beside RNN-based, in order to improve our system's performance even further, we also design a Transformer-based framework.

3.2 Wait- k with Transformer

Due to the remarkable performance of Transformer (Vaswani et al., 2017), we renovate the Transformer framework into an simultaneous machine translation framework with arbitrary latency constraints. We first briefly review the Transformer architecture with per-stepwise point of view to highlight the difference between the conventional and our proposed Transformer.

3.2.1 Full Sentence Translation with Transformer

The encoder of Transformer works in a self-attention fashion and takes an input sequence \mathbf{x} , and produces a new sequence of hidden states

$\mathbf{z} = (z_1, \dots, z_n)$ where $z_i \in \mathbb{R}^{d_z}$ as follows:

$$z_i = \sum_{j=1}^n \alpha_{ij} P_{W_V}(x_j) \quad (6)$$

where $P_{W_V}(\cdot)$ is a project function between input space to value space with parameter W_V , and α_{ij} denotes the attention weights which are computed with a softmax function:

$$\alpha_{ij} = \frac{\exp e_{ij}}{\sum_{l=1}^n \exp e_{il}} \quad (7)$$

The above e_{ij} measures the similarity between two elements:

$$e_{ij} = \frac{P_{W_Q}(x_i) P_{W_K}(x_j)^T}{\sqrt{d_x}} \quad (8)$$

where $P_{W_Q}(x_i)$ and $P_{W_K}(x_j)$ project x_i and x_j to query and key space correspondingly with parameters W_Q and W_K . When more self-attention layers are needed, these projection parameters are unique for each layer and attention head. We use 6 layers of self-attention in our model and \mathbf{h} to represents the top layer output sequence which is known for source context.

On the decoder side, during training time, the given gold output sequence $\mathbf{y}^* = (y_1^*, \dots, y_m^*)$ is operated with same above self-attention fashion in the first place to generate hidden self-attended state sequence $\mathbf{c} = (c_1, \dots, c_m)$. Note that on decoder side, we let $e_{ij} = 0$ if $j > i$ in Eq.8 to restrict the self-attention to previously generated words.

In each layer, after we gather all the hidden representations for each target word through self-attention, we then operate the target-to-source attention as follows:

$$c'_i = \sum_{j=1}^n \beta_{ij} P_{W_V}(h_j)$$

similar to self-attention, β_{ij} measures the similarity between h_j and c_i as in Eq.7 and Eq.8. After stacking several layers of above operations, we use \mathbf{s} to denote the top layer's output.

3.2.2 Simultaneous Translation with Transformer

As mentioned above, simultaneous translation needs to start generating translations before the input sentence finishes. This would require our model feed the source sentence incrementally to

the encoder, and the decoder also needs to predict a new target word once the encoder gets a new source word. Obviously, training the incremental encoder and decoder is inefficient. In order to train our framework with above requirements efficiently, we need to make several modifications on both encoder and decoder sides.

For encoder side, during training time, we still feed the entire sentence at one time to the encoder. But different from the self-attention layer which is defined in Eq.7 and Eq.8 in conventional Transformer, we constrain each word to attend only to the prefix of sentence as follows:

$$\alpha_{ij} = \frac{\exp e_{ij}}{\sum_{l=1}^{t+k} \exp e_{il}}$$

when both i and j are within $t + k$, where $k \in [1, n]$ is latency constraint, e.g., wait 3 words, and α_{ij} is 0 otherwise. The translation time step is represented by t . For example, when we are at the 4th translation step with 3-words latency, there are 7 words in the stack of encoder and 4 words have been translated by decoder. And we redefine the Eq.8 as follows:

$$e_{ij} = \begin{cases} \frac{P_{W_Q}(x_i) P_{W_K}(x_j)^T}{\sqrt{d_x}} & \text{if } i, j \leq t + k \\ 0 & \text{otherwise} \end{cases}$$

The above self-attention layer only allows each word attends to its' prefix, which generates equivalent representations to the incremental scenario since every word is blind to the latter words. When we stack more prefix self-attention blocks as in conventional Transformer, the former words are still immune to the future words' information. In this way, we simulate the incremental environment when the full source sentence are observable during training time.

However, there is still another problem for encoder's context representation generation.

3.2.3 Context Caching

The way Transformer generating context representation is different from RNN-based framework, especially uni-directional RNN-based models. In uni-directional RNN-based model, since each word's hidden representation only depends on previous state, when there is an new word which is append to the source sentence, all the representation from prefix words are unchanged. However, this is different in Transformer due to the self-attention mechanism.

As we observe from the definitions of α_{ij} and e_{ij} , when there is another word that has been fed into encoder, the translation time step increments from t to $t + 1$. Every word which is prior to the new word $k + t + 1$ on the source side needs to adjust its' existing representation to a new representation in order to absorb the new word's information. Therefore, different from conventional Transformer, our framework has a list of incremental source side context information instead of only one tensor \mathbf{h} in previous section to represent the entire source side. Our source side context is defined as follows:

$$\mathbb{L} = [\mathbf{h}_{[:k]}, \mathbf{h}_{[:k+1]}, \dots, \mathbf{h}_{[:n-k]}]$$

where n is the total length of source sentence, and $\mathbf{h}_{[:k+i]}$ represents the context representation of the first $(k + i)^{th}$ words. Note that $\mathbf{h}_{[:n-k]}$ equals to \mathbf{h} in previous section.

On the other hand, for the source-target attention on decoder side, at translation step t , the decoder only can observe the t^{th} context in \mathbb{L} .

4 Refinements: Wait- k with Catchup

In aforementioned section, the decoder of proposed "wait- k " process is always k words behind the incoming source stream. In the ideal case which the source and target sentences are in the same length, the last k words on target side will be generated without waiting the encoder since there is no new word is expected on encoder side (for example, a period on source side indicates the source sentence finishes).

From the user perspective, all the previous words are decoded in a one-by-one fashion while the last k words are shown at one time on the screen (this phenomenon can be easily observed in our on-line demo). This increases the user reading work load suddenly at the end of the sentence. This kind of increases of work load might be fine when k is small. However, when target side are expected to be much longer than source side, this phenomenon becomes displeasing for users when there are much more than k words are threw to users to digest at one time.

Based on the previous study of translation ratio from Huang et al. (2017); Yang et al. (2018), it is well known that the target side could be much longer than source side between some certain translation pairs, e.g., Chinese-to-English. In

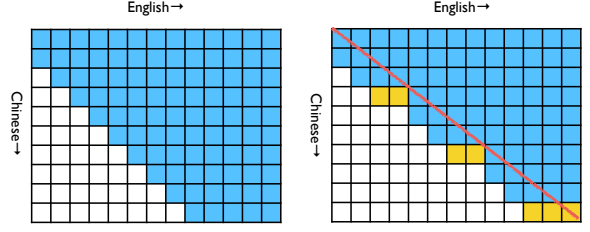


Figure 2: Regular "wait- k " process on the left side. Catchup strategy on the right side. There two words less at the last translation step.

a widely used Chinese-to-English translation corpus, NIST dataset, the target side sentence with English is always more than 1.27 times longer than Chinese source sentence.

Fig. 2 shows one example of translation from Chinese to English. Note that there are 13 words on English side while there are only 10 words on Chinese side. Left figure shows that in wait 2 words policy, the translated English sentence is always 2 words behind Chinese inputs. After wait 2 words gap, every English word corresponds to one Chinese input. However, the last row indicates that there five English words have been translated at one time during the last step. The sudden appearance of these five English words would increase the readers' work load. Therefore, we propose to "amortize" these sudden increased word loads to previous translation steps.

For example, assume the translation ratio is 1.3 which can get from training corpus, we design another read and write action sequence pattern as $1 - 1 - 2$. This means that the decoder will decode 4 words when there are 3 new coming words. And the extra one word will always be in the third decoding step for every 3 translation time step. In this way, we only expect to generate 3 words instead of 5 words. Note that when sentence gets longer, this different would be more significant.

The formal definition is as follows:

$$S_k(\mathbf{x}, \mathbf{y}) = \sum_{t=1}^{|\mathbf{y}|} \log p(y_t | \mathbf{x}_{\leq p_c(t)}, \mathbf{y}_{<t-1})$$

where we use $p_c(t)$ to describes the number of source words that have been processed by encoder in catchup mode:

$$p_c(t) = \begin{cases} k + t - 1 - ct & 1 \leq t < |x| - k \\ |x| & |x| - k \leq t \end{cases} \quad (9)$$

where we use ct to represent the index for extra decoding. For example, in Fig.2, catchup index

ct is 3. The initialization value for ct is 0, and ct increases by one when $t = 3 \times ct$. In this way, during training time, for the example in Fig. 2, the second and third decoded words share the same context information from source side. The desired ct can be learned from training corpus. For example, assume we have a length ratio of 1.3, then we know we should have one extra decoding at time step 3 since $4/3$ is 1.3.

5 A New Latency Metric

Beside accuracy, latency is another crucial measurement for judging how much time is wasted waiting for the translation. This section first introduce the existing metrics for latency measurements. We then show the problems of existing latency metrics. At the end, we propose our new defined latency metrics.

5.1 Existing Metrics: CW and AP

Consecutive Wait (CW) defines the consecutive waits while translating each target word. It describes the length of silence between two translated adjacent words. For each READ or WRITE action, we have the CW definition as follows:

$$c_t = \begin{cases} c_{t-1} + 1 & a_t \text{ is READ} \\ 0 & a_t \text{ is WRITE} \end{cases}$$

where a_t is the action at t^{th} time step and c_t is the number of waited words between two adjacent translated words.

Another latency measurement, Average Proportion (AP) (Cho and Esipova, 2016) focuses on the global latency which is defined as follows:

$$AP = \frac{1}{|X| |Y|} \sum_t p(t) \quad (10)$$

Same with Eq. 3, $p(t)$ from above equation measures the number of source words been waited when decoding the t^{th} on target side.

We observe from the above definitions that CW only defines the local latency and hard to define the global delays.

AP is defined to show the global delays but there is an obvious flaw of it. For example, we have an translation policy which decodes one target word once there is a new coming source word on the decoder side. More explicitly, the action sequence is “RWRWRWRW...”, where the number of “R” equals to the length of source words, and “W”

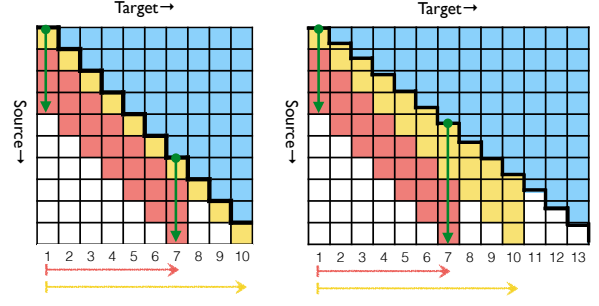


Figure 3: Illustration of our proposed Average Lagging. Left figure shows a simply case when $|x| = |y|$ while right figure shows a more general case when $|x| \neq |y|$.

equals to the length of target words. Assume we have two source words and they can be translated into another two words in target language. Following Eq. 10, we have a latency of 0.75. However, when we increase the length for both source and target side infinity, we then will have a different latency for the same policy whose AP almost equals to 0.5. Furthermore, it is still not obvious to the user about the actual delays in number of words when AP is defined in percentage.

Therefore, AP is very sensitive to the actual length on both side and it only can make a fair comparison between two policies which are operated on the same source and target length. In order to have a global latency definition which is not correlated with the source and target sides’ length and more easy to understand by users, we propose another latency measurements Average Lagging (AL).

5.2 New Metric: Average Lagging

Fig. 3 shows the basic idea of intuition of our proposed metric. The left figure shows a special case when $|x| = |y|$ for simply demonstration. The thick black line indicates the policy which decoder is always one word ahead of encoder and we define this policy have the AL of 0. The yellow squares are on the diagonal represents the “wait-1” policy which starts translating every new words from the first source word. In this case, our AL is 1 which measures these averaged yellow areas which are below the thick black line across different steps. When we have “wait-4” policy which starts translating every new words from the third source word, we use all the red area and the first 7 yellow square (start from left) to represents the lagging whose AL is 4.

When we have the cases on the right side of Fig. 3 when $|x| < |y|$, we notice that there are more and more delays that are cumulated when target sentence grows. For example, for the yellow “wait-1” policy, here are more than 3 delay at decoding step 10 while we only have 1 word delay on the left case. This difference is mainly caused by translation ratio. For the right example, there are 1.3 words that are generated for each source word.

Based on the above observation, we need to define a more general latency measurement that takes length ratio in to consideration. More formally, we have the AL definition as follows:

$$AL = \frac{1}{\tau} \sum_{t=1}^{\tau} p(t) - \frac{t}{\gamma} \quad (11)$$

where we use $\tau = \text{argmin}_{\tau}(p(\tau) = |x|)$ to find the earliest point when encoder observes the full source sentence and $\gamma = |y|/|x|$ to represent the target-to-source length ratio. For the right example in Fig. 3, τ are 10 and 7 for the yellow policy and the red policy respectively.

Eq. 11 describes the average delayed words. Note that we sum the laggings up to τ since when we can decode all the rest words without extra waiting after the entire source sentence are observed. “wait-1” policy’s AL on right figure is greater than the one on the left side, which shows that our AL is more sensitive to the actual γ ratio.

6 Experiments

This section first showcases the accuracy and latency of our proposed “wait-k” model. Then, we demonstrate that our catchup model reduces the latency even further with a little sacrifice of accuracy.

The performance of our models are demonstrated on both English-to-German and Chinese-to-English translation tasks. We use the parallel corpora available from WMT15² for English-to-German translation (4.5M) and NIST corpus for Chinese-to-English translation (2M). We first apply BPE (Sennrich et al., 2015) on both sides in order to reduce the vocabulary for both source and target sides. We then exclude the sentences pairs whose length are longer than 50 and 256 words for English-to-German and Chinese-to-English respectively. For English-to-German, we have the

²<http://www.statmt.org/wmt15/translation-task.html>

development and testing set with the sizes of 3003 and 2169. For Chinese-to-English, we use NIST 06 (616 sentence pairs) and NIST 08 (691 sentence pairs) as our development and testing set.

In the following experiments, we report single reference, three references and four references BLEU score to make comparison with different models and human performance.

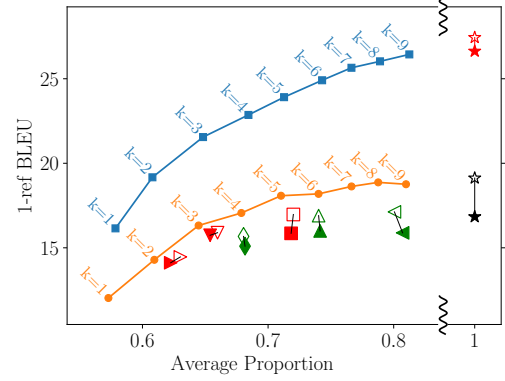


Figure 4: Performance comparison for “wait-k” models on EN2DE test set with AP as Latency measurement. ★★ are greedy decoding and beam-search (beam-size = 11) results with transformer model. Line plots ■ and ● are our results with transformer and RNN models with different wait-k. Point-pairs are the results of simultaneous greedy decoding and beam-search (beam-size = 5) respectively with models(?) trained with various delay targets: ★☆:Wait-Until-End baseline, ◀▶:CW=8, ▲△:CW=5, ◆◇:CW=2, ▶▷:AP=0.3, ▼▽:AP=0.5, ◻◻:AP=0.7

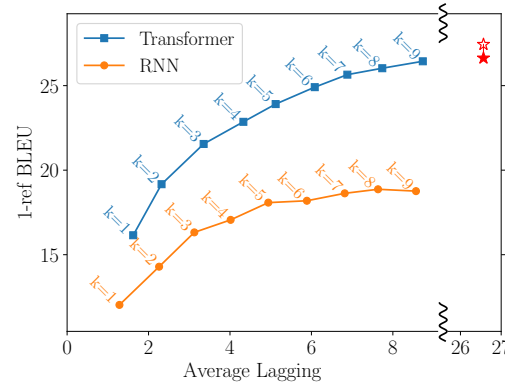


Figure 5: Performance comparison for “wait-k” models on EN2DE test set with AL as Latency measurement. ★★ are greedy decoding and beam-search (beam-size = 11) baseline results with transformer model.

Our Transformer’s parameters are as the same as the base model’s parameter settings in the original paper (Vaswani et al., 2017).

6.1 Performance of “Wait- k ” Model

For Fig. 4, we compare the BLEU score and AP with the model from (Gu et al., 2017) on test set for English-to-German task. From the results we can tell that our RNN-based model outperforms the model from Gu et al. (2017). Our transformer achieves much better performance. In Fig. 5, we also compare the BLEU score together with AL between RNN and Transformer-based models.

For Fig. 6 and Fig. 7, we compare the accuracy and different latency measurements for both “wait- k ” and “catchup” models on development set. As it is shown, we note that the “wait-4” catchup model has similar latency with “wait-1” model. This demonstrates that our catchup model indeed improves the latency especially for the long sentences. Our test set data comparison is shown in Table 1.

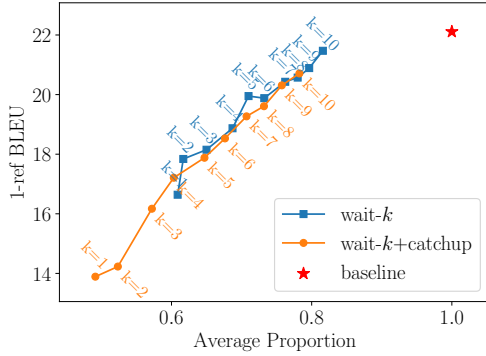


Figure 6: Accuracy for “wait- k ” and catchup models with 1-ref BLEU. Latency is measured by AP.

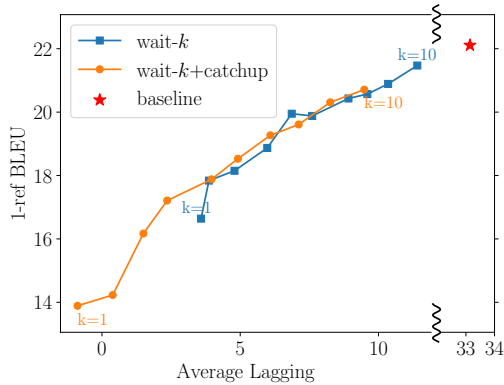


Figure 7: Accuracy for “wait- k ” and catchup models with 1-ref BLEU. Latency is measured by AL.

6.2 Sample Analysis

We showcase some real running examples which are generated from our proposed model and baseline framework for demonstrating the effectiveness of our system. For all the following tables, the first line is Chinese inputs which are represented by pinyin for easier reference to non-Chinese speaker. The second line is the “gloss” which is the word-by-word translation. Our “wait-3” system’s outputs are in the third line of the table with 3 words behind the inputs. Baseline method which starts generating words after the entire source sentence are encoded in the last row.

Table.2 demonstrates that our system could move the prepositional phrase to the end of the sentence depend on the situation. For the case in Table.2, the year information is the 3th word on source side, while the first decoding step only can see the first three words. Then the decoder move the time information to the end of the sentence. Table.3 shows that our model also can move reason clause to the beginning of the sentence and location clause to the middle of sentence.

Table.4 shows another comparison between “wait-3” and “wait-5” models. During decoding time, “wait-3” can not observe any sentimental information at 5th decoding time since the sentimental information “yíhàn” (means regret) only shows up at the end of sentence. Therefore, the “wait-3” model makes the prediction of “appreciation” based on training experience. For “wait-5” model which can observe the sentimental information at the 5th decoding step, the model can correctly predict the word “regret”.

We also make further analysis about the probability difference between these two words: “wait-3” model predict “appreciation” with probability of 18.2% while the word “regret” ranks at the 20th with the probability of 0.0047%. For the “wait-5” model, after the model observed the sentimental information “yíhàn” (means regret) from the source side, the word “appreciation” was degraded to 21th place with a confident of 0.0026% and the model promotes “regret” to the first place with confident of 24.2% which is higher probability than the word “appreciation” in “wait-3” model.

7 Conclusions

We have presented a very simple framework of “wait- k ” predictive policy that can achieve simultaneous translation with arbitrary low latency

		k	1	2	3	4	5	6	7	8	9	10	∞^\dagger	∞^\ddagger
Transformer	wait- k	AP	0.63	0.61	0.68	0.70	0.74	0.76	0.79	0.80	0.82	0.84	1	1
		AL	3.68	2.96	5.03	5.35	6.76	7.27	8.61	9.03	9.87	11.0	33.1	33.1
		1-ref BLEU	13.31	13.46	15.28	15.33	16.93	16.74	16.84	17.14	17.18	18.00	19.03	20.29
		4-ref BLEU	25.73	25.24	29.36	29.20	30.73	30.86	31.66	32.03	32.69	32.95	36.29	38.34
RNN	wait- k	AP	0.63	0.61	0.68	0.70	0.74	0.76	0.79	0.80	0.82	0.84	1	1
		AL	3.68	2.96	5.03	5.35	6.76	7.27	8.61	9.03	9.87	11.0	33.1	33.1
		1-ref BLEU	13.31	13.46	15.28	15.33	16.93	16.74	16.84	17.14	17.18	18.00	19.03	20.29
		4-ref BLEU	25.73	25.24	29.36	29.20	30.73	30.86	31.66	32.03	32.69	32.95	36.29	38.34
Transformer	+catchup	AP	0.50	0.55	0.60	0.62	0.68	0.72	0.73	0.76	0.79	0.81	1	1
		AL	-1.05	1.26	1.76	2.34	4.31	5.43	5.99	6.95	8.27	9.36	29.5	29.5
		1-ref BLEU	10.12	11.90	12.95	13.40	14.47	15.69	15.88	16.73	16.63	17.09	19.03	20.29
		4-ref BLEU	18.55	22.03	24.09	25.23	27.37	29.49	29.72	30.97	31.25	32.24	36.29	38.34

Table 1: Our “wait- k ” and “catchup” model’s performance with different number of waited words (first row) and AP in one-reference and four-reference BLEU on test set. ∞^\dagger means baseline with greedy search. ∞^\ddagger represents the baseline with beam search when beam is 11.

	1	2	3	4	5	6	7	8
Chinese	奥运会	将	于	2008	年	在	北京	举行
Pinyin	Àoyùnhuì	jiāng	yú	2008	nián	zài	Běijīng	jǔxíng
Gloss	Olympics	will	in	2008	year	in	Beijing	hold
Wait-3	the olympic games will be held in beijing in 2008							
+catchup	the olympic games will be held in beijing in 2008							
Baseline [†]	the olympic games will be held in beijing in 2008							
Baseline [‡]	the olympic games will be held in beijing in 2008							

Table 2: Our “wait-3” model moves the adverbial (“in 2008”) to the end, which is fluent in the English word order, and produces a translation identical to the non-simultaneous baseline. Baseline[†] represents greedy decoding and Baseline[‡] represents decoding with beam size 11.

	1	2	3	4	5	6	7	8	9	10	11
Chinese	中东	地区	因为	局势	动荡	所以	爆发	了	一	系列	冲突
Pinyin	zhōngdōng	dìqū	yīnwéi	júshì	dòngdàng	suǒyǐ	bàofā	le	yí	xìliè	chōngtū
Gloss	mid-east	area	because	situation	turbulent	so	break	-	a	series	conflicts
Wait-3	the middle east , a series of conflicts have occurred										
+catchup	the middle east , a series of conflicts broke out										
Baseline [†]	a series of conflicts broke out in the middle east										
Baseline [‡]	a series of conflicts broke out due to turbulence in the middle east region										

Table 3: Our “wait-3” also can move the reason clause (“because of the ...”) to the beginning of the sentence and the location clause (“in the middle ...”) to the middle of sentence. Baseline[†] represents greedy decoding and Baseline[‡] represents decoding with beam size 11.

	1	2	3	4	5	6	7	8
Chinese	江	泽民	对	布什	的	发言	表示	遗憾
Pinyin	jiāng	zémín	duì	bùshí	de	fāyán	biǎoshì	yíhàn
Gloss	jiang	zemin	to	bush	's	speech	express	regret
Wait-3	jiang zemin expressed his appreciation for bush 's speech							
Wait-5	jiang zemin expressed regret over bush 's speech							
Baseline [†]	jiang zemin expressed regret over bush 's speech							
Baseline [‡]	jiang zemin expressed regret over bush 's speech							

Table 4: Outputs difference between “wait-3” and “wait-5” words models. When “wait-3” model decodes to the 5th word, the encoder only can see the first 7 words while “wait-5” model can see the entire source sentence. This is the reason why “wait-5” model made a correct prediction of “regret” while “wait-3” model predicted “appreciation” based on training experience. Baseline[†] represents greedy decoding and Baseline[‡] represents decoding with beam size 11.

while maintaining high translation quality.

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