ABSTRACT

Sign Language Translation (SLT) first uses a Sign Language Recognition (SLR) system to extract sign language glosses from videos. Then, a translation system generates spoken language translations from the sign language glosses. Though SLT has gathered interest recently, little study has been performed on the translation system. This paper focuses on the translation system and improves performance by utilizing Transformer networks. We report a wide range of experimental results for various Transformer setups and introduce the use of Spatial-Temporal Multi-Cue (STMC) networks in an end-to-end SLT system with Transformer.

We perform experiments on RWTH-PHOENIX-Weather 2014T, a challenging SLT benchmark dataset of German sign language, and ASLG-PC12, a dataset involving American Sign Language (ASL) recently used in gloss-to-text translation. Our methodology improves on the current state-of-the-art by over 5 and 7 points respectively in BLEU-4 score on ground truth glosses and by using an STMC network to predict glosses of the RWTH-PHOENIX-Weather 2014T dataset. On the ASLG-PC12 corpus, we report an improvement of over 16 points in BLEU-4. Our findings also demonstrate that end-to-end translation on predicted glosses provides even better performance than translation on ground truth glosses. This shows potential for further improvement in SLT by either jointly training the SLR and translation systems or by revising the gloss annotation system.

1 Introduction

Communication holds a central position in our daily lives and social interactions. Yet, in a predominantly hearing society, the hearing-impaired are often deprived of effective communication. Although the deaf community in various cultures have developed sign language to handily communicate between themselves and others who have learned to sign, it remains uncommon for hearing people to have learned sign language. While advancements have been made in recent years to better accommodate deaf people, such as the captioning of videos and increased use of online text-based communication, the deaf community still face issues of social isolation and miscommunication on a daily basis [55, 49, 14, 63]. Although Sign Language Recognition (SLR) has been an active topic of research over the last two decades [12, 33, 34, 8, 65] it is only in recent years that Sign Language Translation (SLT) has gathered some interest and advancement [9, 32]. For the rest of this paper, we will refer to SLT as the task of translating sign language into spoken language, and will precise the cases in the other direction.

In general, sign languages have developed independently of their spoken counterparts, and learning to sign is not easier than learning a completely different spoken language. There is a significant linguistic variance between spoken and sign languages [59], where sign language usually does not translate its spoken counterpart word by word. For instance, the syntax of ASL shares more with spoken Japanese than English [42]. For this reason, SLR systems do not suffice in capturing the underlying grammar and complexities of sign language, and SLT faces the additional challenge in generating translations while taking into account the different syntactic structures and grammar.

In this paper, we build upon the approach formalized in [9] for SLT that can be divided into two parts: tokenization and translation. The tokenization problem is similar to continuous SLR, where vision methods analyze videos of sign language to generate sign language glosses that capture the meaning of the sequence of different signs. The translation problem is analogous to any translation task between two different languages if we regard the sign language glosses as one language. Recent works [43, 69] have reported improvements in the tokenization system, but currently there has been no study on improving the translation system for this SLT task. We utilize and compare different Neural Machine Translation (NMT) architectures, notably Transformers that have not yet been studied in [9], in the context of SLT.

To evaluate the performance of our NMT approach and compare it with existing works, we perform trans-
lation of ground truth gloss annotations in the RWTH-PHOENIX-Weather 2014T dataset, as well as gloss annotations predicted by the tokenization system of [69] to assess performance in an end-to-end system. Moreover, we also translate ground truth gloss annotations from the ASLG-PC12 corpus to study the behavior of our translation system applied to another language, on a dataset of a different size and gloss annotation scheme.

The contributions of this paper may be summarized as:

- We perform the first thorough study of using the Transformer network for SLT and demonstrate how it outperforms previous NMT architectures for this task
- We make the first use of weight tying, transfer learning with spoken language data and ensemble learning in SLT and report baseline results of Transformers in various setups
- We improve on the state-of-the-art results in German SLT on the RWTH-PHOENIX-Weather 2014T dataset for both sign language gloss to spoken language text translation and end-to-end sign language video to spoken language text translation, and in American SLT on the ASLG-PC12 dataset
- We demonstrate how a Spatial-Temporal Multi-Cue network provides better end-to-end performance when used for CSLR in SLT than previous approaches and even surpass translation using ground truth glosses

Sign Language Glossing  Glossing corresponds to transcribing sign language word-for-word by means of another written language, and is often used by students to remember new signs. Glosses differ from translation as they merely indicate what each part in a sign language sentence mean, and does not form an appropriate sentence in the written language that signifies the same thing. Often, glosses would also include notations that indicate non-manual cues such as facial expressions and body grammar that come with sign language. In general, sign language glosses are annotated by hand by sign language experts, and more recently by continuous SLR systems. However, while various sign language corpus projects have provided different guidelines for gloss annotation [16, 26, 15], there is no single standard agreed on [25, 53] which hinders the easy exchange of data between projects and consistency between different sign language corpora.

Sign Language Recognition  Over the last decade, some progress has been made in SLR as well as Continuous Sign Language Recognition (CSLR), for various sign languages. SLR consists of identifying isolated single signs from videos, while CSLR is a relatively more challenging task that consists of identifying a sequence of running glosses from a given video. Most SLR and CSLR systems make predictions on RGB video data [3, 19], as is the case with the CSLR system we use in our experiments, even though our translation system may be used with any other SLR systems that predict glosses as well, such as those using gloves or accelerometers [67, 52].

Sign Language Translation  SLT differs from SLR as the latter merely detects a sequence of signs without taking into account the linguistic structures and grammar unique to sign language. As illustrated in Figure 1, the SLT system takes CSLR as a first step to detect a sequence of glosses from the input video. Then, an additional task is performed to translate the detected glosses into a valid sentence in the target language. SLT is a novel problem and a difficult task compared to other translation problems because it involves extracting meaningful features from a video of a multi-cue language accurately, then generating translations and infer correct word orders and grammar from an intermediate gloss representation instead of the source language directly.

Figure 1: Sign language translation. This task consists of successively performing CSLR and NMT. Glosses obtained from [36]

2 Methods

Despite considerable advancements made in machine translation between spoken languages, the field of sign language processing falls behind for many reasons. To begin, unlike spoken language, sign language is a multi-dimensional form of communication that relies on both manual and non-manual cues which presents additional computer vision challenges [2]. Signs also vary both in space and in time, where two sequences of the same signs may be performed at different speeds, with gestures of different magnitudes or at different positions from the camera. There is no existing universal convention on transcribing sign language into a written form of sign language glosses, and the number of video frames associated with a single gloss is not fixed either. Also, datasets for sign language processing are often very limited in size and/or vocabulary [41, 58, 54].
3 Related Work

Sign Language Recognition  The first approaches for SLR rely on hand-crafted features [61, 64, 66, 7, 13] and use Hidden Markov Models [20, 21, 33, 57, 56] or Dynamic Time Warping [37] to model sequential dependencies. More recently, 2D convolutional neural networks (2D-CNN) [17] and 3D convolutional neural networks (3D-CNN) [40] have shown to be effective on modelling spatio-temporal representations from sign language videos.

Most existing works on CSLR divide the task into three sub-tasks: alignment learning, single-gloss SLR, and sequence construction [35, 68] while others perform the task in an end-to-end fashion using deep learning architectures [23, 8, 24]. Works in SLR and CSLR, however, merely approach the problem as a visual recognition task and ignores the underlying grammatical and linguistic structures unique to sign language.

Sign Language Translation  SLT is formalized for the first time in [9] where they introduce the RWTH-PHONIX-Weather 2014T dataset and jointly use a 2D-CNN model to extract gloss-level features from video frames, and a sequence-to-sequence model to perform German sign language translation. Subsequent works have been published on this dataset [43, 69], but all of them focus only on improving the CSLR component in SLT. Despite recent advancements in the field of NMT, no study has been made so far seeking to improve the baseline on translating glosses to spoken language text.

Similar work has been done for Korean sign language by [32] where they introduce the KETI dataset and estimate human keypoints to extract glosses, then use sequence-to-sequence models for translation. [1] uses sequence-to-sequence models to directly translate ASL glosses from the ASLG-PC12 dataset [44] without taking sign language data itself or CSLR systems that generates glosses from sign language.

Neural Machine Translation  Neural Machine Translation (NMT) employs neural networks to carry out the task of automated text translation. Recent NMT approaches typically use an encoder-decoder architecture, also known as sequence-to-sequence (seq2seq) models.

Earlier approaches use recurrent networks [28, 60, 4, 10] and convolutional networks [29, 22, 27] for the encoder and decoder. However, standard seq2seq networks are unable to model long-term dependencies in large input sentences without causing an information bottleneck. To address this issue, more recent works use attention mechanisms introduced by [41] and later extended by [39]. Their attention function calculates context-dependent alignment scores between encoder and decoder hidden states. [62] introduces the Transformer architecture, a seq2seq model relying on self-attention that obtains state-of-the-art results in NMT.

While [32] and [43] report results using Transformers in SLT, their works focus on the CSLR system rather than translation, they give little detail on the use of Transformers and the performance of their Transformers is weaker than those of sequence-to-sequence models. Our work is the first to perform various experiments on Transformers and provide parameter recommendations to obtain state-of-the-art performance in SLT as well as experimental results for different model setups.

4 Transformer

Transformer [62] is a seq2seq encoder-decoder network. It differs from previous models in its usage of self-attention layers in place of recurrent networks. Its architecture is illustrated in Figure 2. In this section we will briefly explain its architecture.

![Figure 2: Architecture of a Transformer with two encoder-decoder layers.](image)

4.1 Overall architecture

Transformers are composed of an encoding component and a decoding component. Both the encoder and decoder stacks are composed of \( N \) identical layers. Each word in an input sentence is first embedded into a vector of size \( d_{\text{model}} \) before being passed on to the first layer of the encoder stack. All encoder layers receive a list
of \( n \) vectors of size \( d_{\text{model}} \). The output of the last encoder layer is then used by each decoder layer during its attention operation. At each step, the decoder stack is auto-regressive meaning it uses previously generated symbols as additional input when generating the next symbols.

### 4.2 Multi-head Attention

The attention mapping takes as input a set of \( n \) queries \( Q \in \mathbb{R}^{n \times d_k} \), keys \( K \in \mathbb{R}^{n \times d_k} \) and values \( V \in \mathbb{R}^{n \times d_v} \) to produce an output \( O \in \mathbb{R}^{n \times d_v} \) using the function below:

\[
\text{Attention}(Q, K, V) = \text{softmax} \left( \frac{QK^T}{\sqrt{d_k}} \right) V
\]

The queries, keys and values are linear transforms of the input.

In addition, multi-head attention employs \( h \) parallel attention layers, or heads, to obtain multiple representation subspaces and allow the model to focus on different positions.

\[
\text{MultiHead}(Q, K, V) = \text{Concat}(\text{head}_1, \ldots, \text{head}_h)W^O
\]

where \( \text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, WV_i^V) \) with \( W_i^Q, W_i^K \in \mathbb{R}^{d_{\text{model}} \times d_k}, W_i^V \in \mathbb{R}^{d_{\text{model}} \times d_v} \) and \( W_i^O \in \mathbb{R}^{d_{\text{model}} \times d_{\text{model}}} \).

### 4.3 Encoder

In the encoder, each layer is composed of two sub-layers: a multi-head attention mechanism and a position-wise, fully-connected feed-forward layer. Around each sub-layer is a residual connection followed by layer normalization. That is, the output of each sub-layer is \( \text{LayerNorm}(x + \text{Sublayer}(x)) \) where \( x \) is the encoder input and \( \text{Sublayer} \) denotes the function applied by the sub-layer itself.

### 4.4 Decoder

In addition to the same two sub-layers as in each encoder layer, a decoder layer has an additional “Encoder-Decoder attention” sub-layer. This sub-layer has the same mechanism as multi-head attention, except that it uses queries from the layer below it, and keys and values from the output of the encoder stack. At each time step, the decoder stack outputs a symbol from the output sentence, which is then fed to the first decoder layer in the next time step, until the symbol indicating the end of the sentence is reached. The self-attention layers in the decoder also mask future positions, by setting them to \(-\infty\) for example, so that the predictions for the \( i \)-th symbol can only depend on known outputs at positions less than \( i \).

### 4.5 Positional Encoding

Since the Transformer contains no recurrence or convolution, the network with self-attention has no notion of the word order in a sentence. To address this, positional encoding is summed with the input embeddings at the bottoms of the encoder and decoder stacks. Positional encoding adds information about the relative position of symbols and allows the model to make use of the order of the words. The positional encoding vector \( p = (p_1, p_2, \ldots, p_m) \) with \( p_j \in \mathbb{R}^f \) is obtained using sine and cosine functions of different frequencies:

\[
p_{2i} = \sin \left( \frac{\text{pos} \times 2i}{10000^{2i/d_{\text{model}}}} \right)
p_{2i+1} = \cos \left( \frac{\text{pos} \times 2i}{10000^{2i/d_{\text{model}}}} \right)
\]

where \( \text{pos} \) is the position of the symbol in its sentence.

### 5 Datasets

#### 5.1 RWTH-PHOENIX-Weather 2014T

To evaluate and compare the performance of our model to existing works, we use the RWTH-PHOENIX-Weather 2014T dataset introduced by [9]. The data is extracted from news and weather forecast airings of the German tv station PHOENIX, and to our knowledge it is currently the only publicly available dataset with both gloss level annotations and spoken language translations for sign language videos that is of sufficient size and challenge for deep learning.
Table 2: Statistics of the ASLG-PC12 dataset before and after preprocessing.

| Raw data | Preprocessed data |
|----------|-------------------|
|          | Train | Dev | Test | Train | Dev | Test |
| ASL en   | 15,782| 21,600 | 4,323 | 2,150 | 2,609 | 5,906 |
| en       | 7,712 | 1,163 | 1,254 | 394   | 379   |      |
| Shared vocab. | 10,048 | 2,652 | 1,296 | 4,941 | 899   | 287  |
| BLEU-4   | 20.97 | 21.16  | 20.63 | 38.87 | 38.74 | 38.37 |

This dataset consists of a parallel corpus of German sign language videos from 9 different signers, gloss-level annotations with a vocabulary of 1,066 different signs and translations into German spoken language with a vocabulary of 2,887 different words.

5.2 ASLG-PC12

As can be seen in Table 1, the RWTH-PHOENIX-Weather 2014T dataset only has 7,096 training pairs, while deep learning models, notably Transformers, achieve better results on larger datasets [48]. We would also like to assess the performance of our model on a larger dataset and in a language most of us are familiar with. For this purpose, we conduct NMT of sign language glosses on the ASLG-PC12 corpus proposed in [44]. So far, SLT on this dataset has only been performed using RNN-based sequence-to-sequence attention networks in [1].

This corpus consists of 87,709 pairs of ASL gloss with a vocabulary of 15,782 different signs and English sentences with a vocabulary of 21,601 different words. It is constructed from English data of the Project Gutenberg that has been transformed into ASL glosses following an automatic rule-based approach and validated by human experts. There are no explicit training, development and testing splits published on the dataset so we created our own random splits for our experiments. The splits and our code are made publicly available to encourage and underpin future research.

6 Experiments and Discussions

All of our Transformer models are built using PyTorch [46] and the Open-NMT library [31] with a word embedding size of 512 and sinusoidal positional encoding, recurrent layers containing 512 hidden units, and Transformer feed-forward layers of 2048 hidden units. For optimization, we use Adam [30] with 0.9 beta1 and 0.998 beta2, as well as Noam learning rate schedule, 0.1 dropout, gradient clipping with threshold 0, and 0.1 label smoothing.

During training, the networks are evaluated on the dev set each half-epoch, and early stopping with patience 5 is used to halt training and save the model. Decoding using a trained model is performed using beam search with a beam width of 5. During decoding, generated <unk> tokens for unknown words are also replaced by the source token having the highest attention weight. This is useful when <unk> symbols correspond to proper nouns that can be directly transposed between languages [31]. As our architecture varies highly from previous works on SLT, and especially since Transformers are highly sensitive to hyperparameter and architecture settings, we perform a series of experiments to find the optimal setup. We equally experiment with various techniques often used in classic NMT to SLT such as transfer learning, weight tying and ensembling to improve model performance.

To evaluate the performance of our translation models, we use BLEU [45], ROUGE [38] and METEOR [5] scores, which are commonly used to measure machine translation performance. We use three different metrics as finding a single adequate automatic method to evaluate translation performance is an ongoing challenge where natural language is often highly ambiguous. For BLEU, we report BLEU-1,2,3,4 scores and as ROUGE score we report the ROUGE-L F1 score.

All reported results unless otherwise specified are averaged over 10 runs with different random seeds. The variance between experiments with different seeds under $10^{-1}$ points on each score.

We organize our experiments into two groups:

1. Gloss2Text (G2T) in which we translate ground truth gloss annotations to simulate perfect tokenization, on both RWTH-PHOENIX-Weather 2014T and ASLG-PC12 datasets
2. Sign2Gloss2Text (S2G2T) in which we translate glosses tokenized by an existing SLR system to evaluate end-to-end performance on the RWTH-PHOENIX-Weather 2014T dataset

6.1 Gloss2Text

We first carry out training and evaluation using the ground truth glosses taken from the RWTH-PHOENIX-Weather 2014T and the ASLG-PC12 datasets. This allows us to assess the performance of our translation model when used with a perfect CSLR system. Though

[1] https://github.com/kayoyin/transformer-slt
Table 3: G2T performance comparison of Transformers on RWTH-PHOENIX-Weather 2014T with different number of enc-dec layers.

| Layers | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | ROUGE-L | METEOR | BLEU-1 | BLEU-2 | BLEU-3 | BLEU-4 | ROUGE-L | METEOR |
|--------|--------|--------|--------|--------|---------|--------|--------|--------|--------|--------|---------|--------|
| 1      | 43.39  | 32.47  | 24.27  | 20.26  | 44.66   | 42.64  | 43.26  | 32.23  | 25.59  | 21.31  | 45.28   | 42.56  |
| 2      | 45.31  | 33.65  | 26.73  | 22.23  | 45.74   | 43.92  | 44.57  | 33.08  | 26.14  | 21.65  | 40.47   | 42.97  |
| 4      | 44.32  | 32.87  | 26.15  | 21.78  | 45.86   | 43.31  | 44.10  | 32.82  | 25.99  | 21.57  | 45.44   | 42.92  |
| 6      | 44.04  | 32.46  | 25.67  | 21.34  | 44.09   | 42.32  | 43.74  | 32.44  | 25.67  | 21.32  | 41.69   | 42.58  |

we use ground truth glosses for translation, this task remains non-trivial and challenging because of the high linguistic variance between sign language glosses and spoken language, as well as how gloss annotations are an intermediate representation of sign language videos that may present imprecisions and information loss. Experiments on ASLG-PC12 also allows us to explore the behavior of Transformers on a larger dataset. Moreover, Table 2 shows that the source and target corpora in ASLG-PC12 are more similar to each other with many shared vocabulary and a relatively high BLEU-4 score on raw data. This will also allow us to compare the performance of Transformers on a less challenging dataset. The input phrases are tokenized to gloss level and we initialize the embedding matrix randomly, which is then trained in an end-to-end manner along with the whole model. For ASLG-PC12, many of the ASL glosses are English words with an added prefix so during data preprocessing we remove all such prefixes as we deem them unessential for training and inference. We also set all words that appear less than 5 times during training as an unknown token which allows us to reduce the vocabulary size considerably, as seen in Table 2.

6.1.1 Model size

The original setup of the Transformer architecture in [62] uses 6 identical layers each in the encoder and the decoder to obtain their WMT results. However, our task may differ from a standard machine translation task between two spoken languages so our first experiment trains Transformer models with 1, 2, 4 and 6 encoder-decoder layers. All networks are trained with a batch size of 2,048 token and an initial learning rate of 1.

To choose the best model, we will mainly take into account the BLEU-4 score, as it is the most widely used metric in machine translation currently. Table 3 shows that on RWTH-PHOENIX-Weather 2014T, the architecture with 2 layers obtains the highest performance on both the development and testing sets. Though the model with 4 layers obtains better ROUGE score, this metric places more emphasis on recall and is more interpretable in summarization tasks. Moreover, a smaller model has the advantage of taking up less memory and computation time. A reason why the smaller model than the more common one with 6 layers is more effective for our task is likely because the German sign language glosses are more similar to spoken German compared to two different spoken languages such as English and German. Also, because our dataset is much smaller than those used in standard machine translation tasks, larger networks may be disadvantaged. Repeating the same experiment on ASLG-PC12, we also find 2 layers to be the optimal model size. We carry out the rest of our experiments on this dataset with networks of 2 enc-dec layers.

6.1.2 Batch size

The recommended batch size by [31] to train Transformers is 4,096 tokens, which did not fit into our GPU memory so we initially decreased the batch size to 2,048. [48] recommends to set the batch size as high as possible when training Transformers, while [9] reports the best results with small batch size when training sequence-to-sequence models for SLT. We therefore train Transformer models using batch size 2,048, 1,024, 256, 128, 32 and 1.

We can also perform gradient accumulation which is approximately equivalent to increasing the batch size by the number of times we accumulate gradients without needing additional GPU memory. We perform additional experiments with batch size 2,048 and 2, 3, 5 or 10 gradient accumulations.

Figure 3: G2T performance on RWTH-PHOENIX-Weather 2014T with different batch size and gradient accumulation. Gn stands for batch size 2048 with n gradient accumulations.

Figure 3 seems to confirm that the higher the batch size, the better. Batch size 2,048 gives the best performance when used with 3 gradient accumulations for both RWTH-PHOENIX-Weather 2014T and ASLG-PC12, while more gradient accumulation does not seem to nec-
Table 4: G2T performance comparison using different embedding schemes on RWTH-PHOENIX-Weather 2014T.

| Model       | Dev Set | Test Set |
|-------------|---------|----------|
|             | BLEU-1  | BLEU-2   | BLEU-3  | BLEU-4  | ROUGE-L | METEOR  | BLEU-1  | BLEU-2   | BLEU-3  | BLEU-4  | ROUGE-L | METEOR  |
| Vanilla     | 45.81   | 34.06    | 27.05   | 22.49   | 46.68    | 44.35   | 45.29   | 33.74    | 26.70    | 22.22   | 46.08    | 43.75   |
| Tied decoder| 45.90   | 34.10    | 27.09   | 22.49   | 46.76    | 44.51   | 45.30   | 33.82    | 26.82    | 22.22   | 46.14    | 44.61   |
| GloVe       | 44.37   | 32.65    | 27.90   | 22.49   | 44.53    | 43.28   | 43.85   | 32.58    | 26.38    | 21.74   | 45.83    | 43.45   |
| fastText    | 44.91   | 33.23    | 26.60   | 22.04   | 46.17    | 43.70   | 44.85   | 33.95    | 26.95    | 22.22   | 45.55    | 43.04   |

Table 5: G2T performance comparison using different embedding schemes on ASLG-PC12.

| Model       | Dev Set | Test Set |
|-------------|---------|----------|
|             | BLEU-1  | BLEU-2   | BLEU-3  | BLEU-4  | ROUGE-L | METEOR  | BLEU-1  | BLEU-2   | BLEU-3  | BLEU-4  | ROUGE-L | METEOR  |
| Vanilla     | 90.15   | 84.92    | 80.27   | 75.94   | 94.72    | 94.58   | 90.49   | 85.64    | 81.31    | 77.33   | 94.75    | 95.16   |
| Tied dec    | 91.00   | 86.26    | 82.00   | 78.02   | 95.24    | 95.12   | 91.25   | 86.76    | 82.76    | 79.02   | 95.32    | 95.75   |
| GloVe dec   | 90.13   | 85.14    | 80.67   | 76.49   | 94.16    | 94.65   | 90.51   | 85.83    | 81.65    | 77.74   | 94.80    | 95.27   |
| GloVe enc-dec| 89.65   | 84.33    | 79.72   | 75.48   | 93.02    | 93.62   | 90.01   | 85.15    | 80.88    | 76.95   | 93.00    | 94.14   |
| fastText dec| 90.64   | 85.63    | 81.14   | 76.94   | 94.75    | 95.02   | 91.20   | 86.62    | 82.53    | 78.72   | 94.73    | 95.57   |
| fastText enc-dec| 90.02   | 85.01    | 80.56   | 76.41   | 93.68    | 94.10   | 90.94   | 86.58    | 82.01    | 76.23   | 93.61    | 94.42   |
| fastText tied dec| 90.16   | 85.26    | 80.85   | 76.72   | 95.03    | 94.60   | 90.44   | 85.25    | 81.69    | 77.28   | 95.11    | 95.04   |

It is necessary to improve performance. We also invite others to try using an even bigger batch size on a larger GPU as using a bigger batch size may be more efficient than its equivalent using gradient accumulation. The remaining experiments are performed with batch size 2,048 and 3 gradient accumulations.

6.1.3 Embedding schemes

[50] shows that tying the input and output embeddings during the training of language models may provide better performance. In our model, the decoder is also a language model that is conditioned on the encoding of the source sentence and the previous words of the generated sentence. We therefore tie the embeddings in the decoder by using a shared weight matrix for the input and output word embeddings.

In addition, pre-trained embeddings are a widely used method in NLP transfer learning where we initialize our models using pre-trained word embeddings. These word embeddings are typically trained in an unsupervised manner on a large corpus of text in the desired language, such as Wikipedia articles. They help bring in outside information at the start of training and can be useful when dealing with a small dataset.

Since German is a high-resource language where many German data resources exist, several pre-trained German embeddings are available publicly. We perform experiments on RWTH-PHOENIX-Weather 2014T using two popular word embeddings: GloVe [47] where we use the vectors published by [18], and fastText [6]. To the best of our knowledge, pre-trained embeddings have never been used in SLT in previous works.

As shown in Table [3], there is only one matching token between the German glosses and the pre-trained embeddings, while over 90% of the words in the German text appear in both pre-trained embeddings. For this reason, in this part of the experiment we initialize with the pre-trained embeddings for the decoder only, and keep random initialization for the encoder. We do not freeze the embedding layers and fine-tune them during training for our task.

Table 4 shows that the new embedding schemes do not actually help in improving performance on RWTH-PHOENIX-Weather 2014T. It may be because pre-trained embeddings are shown to be more effective when used on the encoding layer [51], but we have no available pre-trained embeddings in German sign language glosses. Another possible reason is the difference between the domain of our dataset and of the corpus the embeddings were trained on, as our dataset has a specific domain of weather forecasts. We therefore keep random initialization of word embeddings for the rest of our experiments on RWTH-PHOENIX-Weather 2014T. Using this setting, we run a parameter search over the learning rate and warm-up steps, and we use initial learning rate 0.5 with 3,000 warm-up steps for the remaining experiments. Details of the parameter search are included as an appendix.

On ASLG-PC12, we also try tying the decoder embeddings as well as using English pre-trained GloVe and fastText embeddings. Table [7] shows that both GloVe and fastText English vectors have a reasonable overlap with the vocabulary of ASL glosses as well as the English targets. We therefore load pre-trained embeddings on only the decoder side as well as on both the encoder and decoder sides in our experiments.

Table 6: German pre-trained embeddings statistics

|         | GloVe | fastText |
|---------|-------|----------|
| Dimension | 300   | 300      |
| Source match | 0.08% | 0.08%    |
| Target match | 90.53% | 94.57%   |

Table 6 shows that the new embedding schemes do not actually help in improving performance on RWTH-PHOENIX-Weather 2014T. It may be because pre-trained embeddings are shown to be more effective when used on the encoding layer [51], but we have no available pre-trained embeddings in German sign language glosses. Another possible reason is the difference between the domain of our dataset and of the corpus the embeddings were trained on, as our dataset has a specific domain of weather forecasts. We therefore keep random initialization of word embeddings for the rest of our experiments on RWTH-PHOENIX-Weather 2014T. Using this setting, we run a parameter search over the learning rate and warm-up steps, and we use initial learning rate 0.5 with 3,000 warm-up steps for the remaining experiments. Details of the parameter search are included as an appendix.

On ASLG-PC12, we also try tying the decoder embeddings as well as using English pre-trained GloVe and fastText embeddings. Table [7] shows that both GloVe and fastText English vectors have a reasonable overlap with the vocabulary of ASL glosses as well as the English targets. We therefore load pre-trained embeddings on only the decoder side as well as on both the encoder and decoder sides in our experiments.

Table 7: English pre-trained embeddings statistics
|    | GloVe | fastText |
|----|-------|----------|
| Dimension | 300   | 300      |
| Source match | 96.23% | 94.64%  |
| Target match | 97.71% | 96.32%  |

Table 4 shows that fastText pre-trained embeddings for the decoder improves performance compared to the vanilla embedding scheme, while using tied decoder embeddings without pre-trained embeddings gives the best performance in our experiment. We also performed an additional experiment using fastText pre-trained embeddings and embeddings tying on the decoder, but it does not surpass tied embeddings without pre-trained embeddings. For the remaining experiments, we used tied decoder embeddings with an initial learning rate of 0.2 and 8,000 warm-up steps which are the optimal parameters empirically.

6.1.4 Beam width

A naive method for decoding a sequence of words is greedy search, where the model simply chooses the word with the highest probability at each time step of the sequence. However, this simple approach may be suitable for one time step, but becomes sub-optimal in the context of the entire sequence. Beam Search is a widely used method to address this problem, in which at each time step, the decoder expands with all possible candidates and keeps a number of most likely sequences, or the beam width. Large beam widths do not always result in better performance and take more space in memory and decoding time. We therefore use our best performing model to decode using different beam widths and find the optimal beam width value to be 4 on RWTH-PHOENIX-Weather 2014T and 5 on ASLG-PC12.

![Figure 4: G2T decoding on RWTH-PHOENIX-WEATHER 2014T using different beam width. Beam width = 1 is equivalent to greedy search.](image)

6.1.5 Ensemble decoding

Ensemble methods combine the predictions of multiple models and shows in various settings to improve the overall performance. We propose to employ ensemble decoding, where we use a group of models that have been trained separately during the decoding phase together. Ensemble decoding combines the predictions made by different models by averaging. We chose 9 models from our experiments that gave the highest BLEU-4 during testing on RWTH-PHOENIX-Weather 2014T. The number of models is chosen empirically, as using fewer models will lead to less ensembling but including too many weaker models may lessen the quality of the ensemble model. These models are of the same architecture, but are initialized with different seeds and were trained using different batch sizes and/or learning rates. Alone, these models give a BLEU-4 on testing between 22.92 and 23.41.

Table 8 gives a performance comparison on RWTH-PHOENIX-Weather 2014T of the recurrent seq2seq model from [9], our single best performing model, and our ensemble model. We also provide the scores on the gloss annotations themselves, to give an idea of the difficulty of this task.

Without any additional training, ensembling different models improves the BLEU-4 score on testing by over 1 point. Also, we report an improvement of over 5 BLEU-4 points on the current state-of-the-art. A single Transformer also gives an improvement of over 4 BLEU-4 points more than the state-of-the-art, which shows the advantage of Transformers over previous seq2seq networks for SLT.

We also use 5 of the best models from our experiments on ASLG-PC12 in an ensemble. These models report a BLEU-4 testing score between 81.72 and 82.41 individually. Table 9 compares the performance of our best single Transformer and ensemble model to the recurrent seq2seq model from [1]. The performance of a single Transformer surpasses the previous model by over 16 BLEU-4 points and the ensemble model reports an improvement of 0.46 BLEU-4 points over the single model.

6.2 German Sign2Gloss2Text

We would also like to simulate an end-to-end system where both the tokenization into glosses and the translation of glosses to text are carried out by automatic methods. To achieve this, we will use the spatial-temporal multi-cue (STMC) network proposed in [69] for tokenization, which gives state-of-the-art results in CSLR on this dataset.

The STMC network is composed of a spatial multi-cue (SMC) module and a temporal multi-cue (TMC) module. The SMC module models spatial features of different cues while the TMC models temporal correlations within and between cues. The two are trained in an end-to-end fashion in order to analyze multi-cue data such as sign language that relies on both manual and non-manual gestures. SLR performance is often measured by word error rate (WER) between the output and ground truth phrases, where the lower the WER, the more accurate the outputs are. The STMC network obtains WER 19.6 and 21.0 on the dev and test sets of RWTH-PHOENIX-Weather 2014T.
Table 8: G2T on RWTH-PHEONIX-WEATHER 2014T final results.

| Model            | Dev Set | Test Set |
|------------------|---------|----------|
|                  | BLEU-1  | BLEU-2   | BLEU-3  | BLEU-4  | ROUGE-L | METEOR |
| Raw data         | 13.01   | 6.23     | 3.03    | 1.71    | 24.23   | 13.69  |
| Seq2seq          | 44.40   | 31.93    | 24.61   | 20.16   | 46.02   | --     |
| Transformer      | 49.05   | 36.20    | 28.53   | 23.52   | 47.36   | 46.09  |
| Transformer Ens. | 48.85   | 36.62    | 29.23   | 24.38   | 49.01   | 46.96  |

Table 9: G2T on ASLG-PC12 final results

| Model            | Dev Set | Test Set |
|------------------|---------|----------|
|                  | BLEU-1  | BLEU-2   | BLEU-3  | BLEU-4  | ROUGE-L | METEOR |
| Raw data         | 54.60   | 39.67    | 28.92   | 21.16   | 76.11   | 61.25  |
| Preprocessed data| 69.25   | 56.83    | 46.94   | 38.74   | 83.80   | 78.75  |
| Seq2seq          | --      | --       | --      | --      | --      | --     |
| Transformer      | 92.98   | 89.09    | 83.55   | 85.63   | 82.41   | 95.93  |
| Transformer Ens. | 92.67   | 88.72    | 85.22   | 81.93   | 96.18   | 95.95  |

For the next part of the experiments, we use the glosses predicted by a trained STMC model on the training set to train our translation models. We report the translation model’s performance on the output of the STMC model on the development and the testing sets.

6.2.1 S2G → G2T

To begin, we use the best performing model from the last experiment on German G2T, and we simply feed the output of the STMC network to this model to obtain German translations. In Table 10 we can see that despite having no additional training, this model already obtains a relatively high score that beats the current state-of-the-art in German S2G2T by over 5 BLEU-4 points.

6.2.2 Recurrent sequence-to-sequence networks

Since there is no existing work performing S2T with the STMC network, we also train and obtain the performance of attention-based seq2seq networks on glosses predicted by the STMC model. The seq2seq networks are built using four stacked layers of Gated Recurrent Units (GRU) [11], and we compare models that use Luong [39] and Bahdanau [4] attention mechanisms.

Table 10: SLT performance using STMC for CSLR. The first set of rows correspond to the current state-of-the-arts included for comparison.

| Model            | Dev Set | Test Set |
|------------------|---------|----------|
|                  | BLEU-1  | BLEU-2   | BLEU-3  | BLEU-4  | ROUGE-L | METEOR |
| G2T [9]          | 44.40   | 31.93    | 24.61   | 20.16   | 46.02   | --     |
| S2G → G2T [9]    | 41.08   | 29.10    | 22.16   | 17.86   | 43.76   | --     |
| S2G2T [9]        | 42.88   | 30.30    | 23.03   | 18.40   | 44.14   | --     |
| S2G → G2T        | 46.73   | 34.99    | 27.79   | 23.06   | 47.29   | 45.23  |
| Bahdanau         | 45.89   | 32.24    | 24.93   | 20.52   | 44.46   | 43.48  |
| Luong            | 45.81   | 32.54    | 26.33   | 21.00   | 46.19   | 44.93  |
| Transformer      | 48.27   | 35.20    | 27.47   | 22.47   | 46.31   | 44.95  |
| Transformer Ens. | 50.31   | 37.60    | 29.81   | 24.68   | 48.70   | 47.45  |

Table 10 shows that the recurrent seq2seq model obtains slightly better performance with Luong attention. What is surprising, however, is that this end-to-end SLT system using STMC and seq2seq networks outperforms the previous G2T result that simulates a system with a perfect CSLR network and a seq2seq model.

6.2.3 Transformer

Finally, we train Transformer models with the same architecture as the last experiment. We run a parameter search over the learning rate and the beam size and find an initial learning rate of 1 with 3,000 warm-up steps and beam size 4 to be the optimal one for this task. Then, we use our 8 best models in an ensemble as before to obtain the final result. Individually, the models included in the ensemble give a BLEU-4 score between 23.51 and 24.00.

Again, we observe that the system using jointly STMC and Transformer outperforms the previous system with ground truth glosses simulating a perfect CSLR network with Transformer. This result could be explained by how while the STMC network performs imperfect CSLR, its gloss predictions are more useful than ground-truth annotations during SLT and are more readily analyzed by the Transformer model. Again, the
ground truth glosses represent merely a simplified intermediate representation of what the actual sign language says so it is not entirely unexpected that translating ground truth glosses does not give the best performance. We include in the Appendices translation examples comparing qualitatively the outputs of German G2T and S2G2T using Transformers. Moreover, Transformer models outperform recurrent seq2seq networks in this end-to-end system as well. Finally, an STMC network and an ensemble of Transformers give an improvement of over 7 BLEU-4 points on the current state-of-the-art for S2G2T SLT.

7 Conclusions and Future Work

In this paper, we proposed using Transformer models in sign language translation and also the joint use of Transformer with a spatio-temporal multi-cue (STMC) network to perform end-to-end sign language translation from videos. We performed experiments using different Transformer setups and training schemes, and demonstrated how they surpass performance on SLT compared to previous RNN-based translation networks. We equally achieved new state-of-the-art results on different translation tasks on the RWTH-PHOENIX-Weather 2014T dataset as well as the ASLG-PC12 dataset.

We notably obtained superior performance in an end-to-end system using an STMC network to extract glosses from videos compared to a system that simulates perfect CSLR using ground truth glosses. As future work, we suggest either an approach that trains a CSLR model to output glosses easily usable by an NMT model, or training the CSLR model on ground truth glosses that are adapted to make the NMT task simpler. For the second approach, it would be worthwhile to device a gloss annotation scheme that optimizes translation before creating a new dataset.

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### A Appendices

#### A.1 Experiments on German G2T learning rate

A learning rate that is too low results in a notably slower convergence, but setting the learning rate too high risks leading the model to diverge. To prevent the model from diverging, we applied gradient clipping with threshold 0, and apply the Noam learning rate schedule where the learning rate increases linearly during the first training steps, or the warmup stage, then decreases it proportionally to the inverse square root of the step number. The number of warmup steps is a parameter that has shown to influence Transformer performance [48] therefore we first run a parameter search over the number of warmup steps.

![Graph showing BLEU-4 scores for G2T performance on RWTH-PHEONIX-WEATHER 2014T with different warmup steps. Initial learning rate is fixed to 0.2.]

**Figure 5:** G2T performance on RWTH-PHEONIX-WEATHER 2014T with different warmup steps. Initial learning rate is fixed to 0.2.

![Graph showing BLEU-4 scores for G2T performance on RWTH-PHEONIX-WEATHER 2014T with various initial learning rate.]

**Figure 6:** G2T performance on RWTH-PHEONIX-WEATHER 2014T with various initial learning rate.

#### A.2 Comparison of German G2T and S2G2T outputs

Because quantitative metrics provide only a limited evaluation of translation performance, manual evaluation by viewing the translation outputs directly may give a better assessment of the quality of translations. In Table [12] we share examples of translation on the RWTH-PHEONIX-WEATHER 2014T dataset by the G2T and S2G2T networks accompanied by the respective gloss annotations, ground truth German translation, and English translations for the reader.

The examples show that the translations are of generally good quality, even for those with lower BLEU-4 scores. Most translations may have slight differences in word choice that do not change the overall meaning of the sentence, or present grammatical errors in German. As for the comparison between the G2T and S2G2T networks, there does not seem to be a clear pattern between cases where S2G2T outperforms G2T and vice versa. The difference between ground truth and predicted glosses are also often within a single gloss. Overall, qualitative results are quite satisfactory for human comprehension and are encouraging for practical applications of sign language translation.

#### A.3 Qualitative G2T Results on ASLG-PC12

Table [12] provides examples of SLT output on the ASLG-PC12 dataset. Here we can see how ASL glosses include prefixes that are not necessary to capture the meaning of the phrase, which we have removed during data pre-processing before training. With a BLEU-4 testing score of 82.87, most predictions by our system are very close to the target English phrases and are able to convey the same meaning. We have also selected translation examples with lower BLEU-4 score and we can see that common errors include mistranslation of numbers and proper nouns. These are likely corner cases with infrequent examples during training.
| german | bleu-4 | german | bleu-4 |
|--------|--------|--------|--------|
| T1: JETZT WETTER WEI- AUSSCHNIT MORGEN SAMSTAG ZWITTER APRIL (NOW WEATHER LIKE-ZWITTER MONDAY MORNING WEEKEND APRIL) | 100.00 | T4: JETZT WETTER WEI- AUSSCHNIT MORGEN SAMSTAG ZWITTER APRIL (NOW WEATHER LIKE-ZWITTER MONDAY MORNING WEEKEND APRIL) | 100.00 |
| GLEICH WETTER AUSSCHNIT Donnerstag (SAME WEATHER AS-MONDAY) | 100.00 | WIND SCHWACH UNTERSCHIEH-KOMMEN (WIND WINDY DIFFERENCE-KOMMEN) | 65.80 |
| WIND SCHWACH UNTERSCHIEH-KOMMEN (WIND WINDY DIFFERENCE-KOMMEN) | 31.02 | MONTAG WECHSELSTATT MAL SONNE WOLKE DES ROUGER SCHWIERIG GUTTER (MONDAY VARIABLE-SUN CLOUDS PARTICULARLY REGION HUNGARY DECISIONS) | 65.80 |
| MONTAG WECHSELSTATT MEHR SONNE WOLKE DES ROUGER SCHWIERIG GUTTER (MONDAY VARIABLE-SUN CLOUDS PARTICULARLY REGION HUNGARY DECISIONS) | 55.90 | WOCHENENDE SONN-SAMATAM SCHR-NED TEMPERATUR BIS 17 DEGREASI JEDER GANZEN REGION (WEEKEND-SATURDAY TEMPERATURE AND WIND DEGREASI WIND REGION) | 49.38 |
| GT: AM-SONNEN-SAMATAM SCHR-NED WIND WIND.MEISTEN SONNEN-DEGREASI WIND REGION (AND THE WIND IS MOSTLY SUN WIND REGION) | 13.49 | GT: ES GELTEN-EN MARGAN UNTERSCHIEH.DEN DEMEN-MORALEGRATEN (APPROPRIATE WARNINGS FROM THE GERMAN WEATHER SERVICE APPLY) | 54.91 |
| GT: AM-SONNEN-SAMATAM SCHR-NED WIND WIND.MEISTEN SONNEN-DEGREASI WIND REGION (AND THE WIND IS MOSTLY SUN WIND REGION) | 49.38 | GT: ES GELTEN-EN MARGAN UNTERSCHIEH.DEN DEMEN-MORALEGRATEN (APPROPRIATE WARNINGS FROM THE GERMAN WEATHER SERVICE APPLY) | 13.49 |
| GT: OST MEITENS SONNE (EAST EAST SUN) | 47.47 | GT: ES GELTEN-EN MARGAN UNTERSCHIEH.DEN DEMEN-MORALEGRATEN (APPROPRIATE WARNINGS FROM THE GERMAN WEATHER SERVICE APPLY) | 49.38 |
| GT: OST MEITENS SONNE (EAST EAST SUN) | 49.38 | GT: ES GELTEN-EN MARGAN UNTERSCHIEH.DEN DEMEN-MORALEGRATEN (APPROPRIATE WARNINGS FROM THE GERMAN WEATHER SERVICE APPLY) | 47.47 |
| GT: AM-TAG VOGEL LAND (IN-THE DAY BIRD LAND) | 14.74 | GT: ES GELTEN-EN MARGAN UNTERSCHIEH.DEN DEMEN-MORALEGRATEN (APPROPRIATE WARNINGS FROM THE GERMAN WEATHER SERVICE APPLY) | 44.69 |
| GT: AM-TAG VOGEL ZWEI [ELEVEN BIRD DUBBLY] | 14.74 | GT: ES GELTEN-EN MARGAN UNTERSCHIEH.DEN DEMEN-MORALEGRATEN (APPROPRIATE WARNINGS FROM THE GERMAN WEATHER SERVICE APPLY) | 14.74 |
| GT: BISCHER SCHNEI A-KOMMEND WACHEN-ODER BIRD REGION BAYERN REGION MÖGLICH SCHNIE (MAY SNOW IN COMING SNOW OR MOUNTAIN REGION BAVARIA REGION POSSIBLE SNOW) | 18.13 | GT: ES GELTEN-EN MARGAN UNTERSCHIEH.DEN DEMEN-MORALEGRATEN (APPROPRIATE WARNINGS FROM THE GERMAN WEATHER SERVICE APPLY) | 18.13 |
| GT: BISCHER SCHNEI A-KOMMEND WACHEN-ODER BIRD REGION BAYERN REGION MÖGLICH SCHNIE (MAY SNOW IN COMING SNOW OR MOUNTAIN REGION BAVARIA REGION POSSIBLE SNOW) | 18.13 | GT: ES GELTEN-EN MARGAN UNTERSCHIEH.DEN DEMEN-MORALEGRATEN (APPROPRIATE WARNINGS FROM THE GERMAN WEATHER SERVICE APPLY) | 18.13 |

Table 11: Qualitative comparison of G2T and S2G2T on RWTH-PHEONIX-WEATHER 2014T. GT refers to the ground truth German translation.

| BLEU-4 | BLEU-4 |
|--------|--------|
| ASL: X-I BE DESC-PARTICULARLY DESC-GRATEFUL FOR EUROPEAN PARLIAMENT DESC-CHIEF DESC-DIRECT-AGAINST Y Y DESC-DIRECT-AGAINST Y | 100.00 |
| GT: i am particularly grateful for the european parliament’s driving role where the baltic sea cooperation is concerned. | 100.00 |
| Pred: i am particularly grateful for the european parliament’s driving role where the baltic sea cooperation is concerned. | 100.00 |
| ASL: DESC-REFO DESC-MUCH WORK NEED TO BE DO IN ORDER TO DESC-FURR SIMPLIFY RULE | 100.00 |
| GT: therefore , much work needs to be done in order to further simplify the rules . | 100.00 |
| Pred: therefore , much work needs to be done in order to further simplify the rules . | 100.00 |
| ASL: THIS PRESSURE BE DESC-PARTICULARLY DESC-GREAT ALONG UNION DESC-SOUHER DESC-DOWN AND DESC-EASTERN DESC-BORDER | 100.00 |
| GT: this pressure is particularly great along the union’s southern and eastern borders . | 100.00 |
| Pred: this pressure is particularly great along the union’s southern and eastern borders . | 100.00 |
| ASL: MORE WOMAN DRI FROM AGGRESSION DESC-DIRECT-AGAINST Y Y | 73.15 |
| GT: more women die from the aggression directed against them than the death from cancer . | 73.15 |
| Pred: more women die from the aggression directed against them than the death from cancer . | 73.15 |
| ASL: XT FEU WAR IN CAMBODIUM IN 1990 AND XT FEU BE DENMOCRACY | 21.29 |
| GT: it fuelled the war in cambodia in the 1990s and it is an enemy of democracy. | 21.29 |
| Pred: it fuelled the war in cambodia in the 1990s and it is an enemy of democracy. | 21.29 |
| ASL: DESC-N CHIEF INVESTIGATOR X-HIMSELF BE TARGET DESC-HOUSE DESC-CARD DESC-LAPSE. | 15.93 |
| GT: otherwise we have to vote on the corresponding part of amendment thank you nos picus , we take due note of your observation . | 15.93 |
| Pred: mr president , we took due note of your observation. | 15.93 |