Progressive Transformers for End-to-End Sign Language Production

Ben Saunders, Necati Cihan Camgoz, and Richard Bowden

University of Surrey
{b.saunders,n.camgoz,r.bowden}@surrey.ac.uk

Abstract. The goal of automatic Sign Language Production (SLP) is to translate spoken language to a continuous stream of sign language video at a level comparable to a human translator. If this was achievable, then it would revolutionise Deaf hearing communications. Previous work on predominantly isolated SLP has shown the need for architectures that are better suited to the continuous domain of full sign sequences. In this paper, we propose Progressive Transformers, a novel architecture that can translate from discrete spoken language sentences to continuous 3D skeleton pose outputs representing sign language. We present two model configurations, an end-to-end network that produces sign direct from text and a stacked network that utilises a gloss intermediary. Our transformer network architecture introduces a counter that enables continuous sequence generation at training and inference. We also provide several data augmentation processes to overcome the problem of drift and improve the performance of SLP models. We propose a back translation evaluation mechanism for SLP, presenting benchmark quantitative results on the challenging RWTH-PHOENIX-Weather-2014T (PHOENIX14T) dataset and setting baselines for future research.

Keywords: Sign Language Production, Progressive Transformers, Continuous Sign Generation, End-to-End

1 Introduction

Sign language is the language of communication for the Deaf community, a rich visual language with complex grammatical structures. As it is their native language, most Deaf people prefer using sign as their main medium of communication, as opposed to the written form of spoken language. Sign Language Production (SLP), converting spoken language to continuous sign sequences, is therefore essential in involving the Deaf in the predominantly spoken language of the wider world.

In this paper, we propose a Progressive Transformer model for SLP that is trained on human translation data consisting of continuous sign pose sequences. An overview of our approach is shown in Figure 1. We evaluate two different configurations, first translating from spoken language to sign pose via gloss intermediary (T2G2P), as this has been shown to increase translation performance

1 Glosses are a written representation of sign, defined as minimal lexical items.
In the second configuration we go direct, translating end-to-end from spoken language to sign (T2P).

Our Progressive Transformer is the first SLP model to translate from text to continuous sign pose in an end-to-end manner. Our novelties include an alternative formulation of transformer decoding for continuous variable sequences such as motion capture, where there is no easily defined vocabulary. Furthermore, we introduce a counter encoding into the network which allows prediction of sequence length and the ability to drive the timing at inference. We also propose several data augmentation methods that assist in reducing drift in model production.

In both configurations, to evaluate performance, we propose a back translation evaluation method for SLP, using a Sign Language Translation (SLT) back-end to translate back to spoken language (right hand block of Figure 1). We evaluate on the challenging RWTH-PHOENIX-Weather-2014T (PHOENIX14T) dataset, presenting several benchmark results to underpin future research. We also share qualitative results to give further insight of the models performance to the reader, producing accurate sign pose sequences of an unseen text sentence.

The rest of this paper is organised as follows: In Section 2 we go over the previous research on SLT and SLP and the state-of-the-art in the field of machine translation. In Section 3 we discuss our Progressive Transformer approach for SLP. Section 4 outlines the evaluation protocol and presents quantitative results, whilst Section 5 showcases qualitative examples. Finally, we conclude the paper in Section 6 by discussing our findings and possible future work.
2 Related Work

Sign Language Recognition & Translation: Sign language has been a focus of computer vision researchers for over 30 years [1, 7, 50], primarily on isolated Sign Language Recognition (SLR) [41] and, relatively recently, the more demanding task of Continuous Sign Language Recognition (CSLR) [29]. However, in both cases the majority of work has relied on manual feature representations (based on the hands) [10] and statistical temporal modelling [52]. The availability of larger datasets, such as RWTH-PHOENIX-Weather-2014 (PHOENIX14) [15], have enabled the application of deep learning approaches such as Convolutional Neural Networks (CNNs) [31, 33] and Recurrent Neural Networks (RNNs) [5, 32].

Distinct to SLR, the task of SLT was recently introduced by Camgoz et al. [6], aiming to directly translate sign videos to spoken language sentences. SLT is more challenging than CSLR due to the differences in grammar and ordering between sign and spoken language. Encoder-decoder Neural Machine Translation (NMT) models are the current state-of-the-art in SLT, trained end-to-end from spatial sign embeddings via an intermediate gloss representation [6].

Sign Language Production: Previous approaches to SLP have extensively used animated avatars [18, 26, 38] that can generate realistic sign production, but rely on phrase lookup and pre-generated sequences. Statistical Machine Translation (SMT) has also been applied to SLP [27, 34], relying on static rule-based processing that can be difficult to encode.

Recently, deep learning approaches have been applied to the task of SLP [13, 53]. Stoll et al. present an initial SLP model using a combination of NMT and a Generative Adversarial Network (GAN) [48]. The authors break the problem into three separate processes that are trained independently, producing a concatenation of isolated 2D skeleton poses mapped from sign glosses via a look-up table. Contrary to Stoll et al., our paper focuses on automatic sign production and learning the mapping between text and skeleton pose sequences directly, instead of providing this a priori.

The closest work to this paper is that of Zelinka et al., who build a neural-network-based translator between text and synthesised skeletal pose [54]. Zelinka et al. produce a single sign for each word with a set size of 7 frames, generating sequences with a fixed length and ordering. In contrast, our model allows a dynamic length of output sign sequence, learning the correct length and ordering of each word from the data, whilst using a progress counter to determine the end of sequence generation. Unlike [54], who work on a proprietary dataset, we produce results on the publicly available PHOENIX14T, providing a benchmark for future SLP research.

Neural Machine Translation: NMT aims to learn a mapping between language sequences, generating a target sequence from a source sequence of another language. RNNs were first proposed to solve the sequence-to-sequence problem, with Kalchbrenner et al. [25] introducing a single RNN that iteratively applied
a hidden state computation. Further models were later developed [9,19] that introduced encoder-decoder architectures mapping both sequences to an intermediate embedding space. Bahdanau et al. [3] overcame the bottleneck problem by adding an attention mechanism that facilitated a soft-search over the source sentence for the context most useful to the target word prediction.

Transformer networks [51], a recent NMT breakthrough, are based solely on attention mechanisms, generating a representation of the entire source sequence with global dependencies. Multi-Headed Attention (MHA) is used to model different weighted combinations of an input sequence, improving the representation power of the model. Transformers have achieved impressive results in many classic Natural Language Processing (NLP) tasks such as language modelling [11,55] and sentence representation [12] alongside other domains including image captioning [37,56] and action recognition [17].

Applying NMT methods to continuous output tasks is a relatively underresearched problem. Encoder-decoder models and RNNs have been used to map text to a human action sequence [1,44] whilst adversarial discriminators have enabled the production of realistic pose [16,36]. In order to determine sequence length of continuous outputs, previous works have used a fixed output size [54], which limits the models flexibility, a binary end-of-sequence (EOS) flag [21] or a continuous representation of an EOS token [40]. Related to this work, transformer networks have been applied to many continuous output tasks such as image generation [42], music production [23] and speech recognition [8,45].

3 Progressive Transformers

In this section we introduce Progressive Transformers, which learn to translate spoken language sentences to continuous sign pose sequences. Our objective is to learn the conditional probability $p(Y|X)$ of producing a sequence of signs $Y = (y_1, ..., y_U)$ with $U$ time steps, given a spoken language sentence $X = (x_1, ..., x_T)$ with $T$ words. Gloss can also be used as intermediary supervision for the network, formulated as $Z = (z_1, ..., z_N)$ with $N$ glosses, where the objective is then to learn the conditional probabilities $p(Z|X)$ and $p(Y|Z)$.

Producing a target sign sequence from a reference text sequence poses several challenges. Firstly, the sequences have drastically varying length, with the number of frames being much larger than the number of words ($U >> T$). The sequences also have a non-monotonic relationship due to the different vocabulary and grammar used in sign and spoken languages. Finally, the target signs inhabit a continuous vector space requiring a differing representation to the discrete space of text or gloss.

To address the production of continuous sign sequences, we propose a progressive transformer-based architecture that allows translation from a symbolic to a continuous sequence domain. We first formalise a Symbolic Transformer architecture, converting an input to a symbolic target feature space, as detailed in Figure 2a. This is used in our Text to Gloss to Pose (T2G2P) model to convert
from spoken language to gloss representation as an intermediary step before pose production, as seen in Figure 1.

We then describe the Progressive Transformer architecture, translating from a symbolic input to a continuous output representation, as shown in Figure 2b. We use this model for the production of realistic and understandable sign language sequences, either via gloss supervision in the T2G2P model or direct from spoken language in our end-to-end Text to Pose (T2P) model. To allow sequence length prediction of a continuous output, we introduce a counter mechanism that allows the model to track the progress of sequence generation. In the remainder of this section we describe each component of the architecture in detail.

3.1 Symbolic Transformer

We build on the classic transformer [51], a model designed to learn the mapping between symbolic source and target languages. As per the standard NMT pipeline [39], we first embed the source, $x_t$, and target, $z_n$, tokens via a linear embedding layer, to represent the one-hot-vector in a higher-dimensional space where tokens with similar meanings are closer. Symbolic embedding, with weight, $W$, and bias, $b$, can be formulated as:

$$w_t = W^x \cdot x_t + b^x, \quad g_n = W^z \cdot z_n + b^z$$ (1)
where $w_t$ and $g_n$ are the vector representations of the source and target tokens.

Transformer networks do not have a notion of word order, as all source tokens are fed to the network simultaneously without positional information. To compensate for this and provide temporal ordering, we apply a temporal embedding layer after each input embedding. For the symbolic transformer, we apply positional encoding, as:

$$\hat{w}_t = w_t + \text{PositionalEncoding}(t) \quad (2)$$

$$\hat{g}_n = g_n + \text{PositionalEncoding}(n) \quad (3)$$

where PositionalEncoding is a predefined sinusoidal function conditioned on the relative sequence position $t$ or $n$.

Our symbolic transformer model consists of an encoder-decoder architecture. The encoder first learns the contextual representation of the source sequence through self-attention mechanisms, understanding each input token in relation to the full sequence. The decoder then determines the mapping between the source and target sequences, aligning the representation sub-spaces and generating target predictions in an auto-regressive manner.

The symbolic encoder ($E_S$) consists of a stack of $L$ identical layers, each containing 2 sub-layers. Given the temporally encoded source embeddings, $\hat{w}_t$, a MHA mechanism first generates a weighted contextual representation, performing multiple projections of scaled dot-product attention. This aims to learn the relationship between each token of the sequence and how relevant each time step is in the context of the full sequence. Formally, scaled dot-product attention outputs a vector combination of values, $V$, weighted by the relevant queries, $Q$, keys, $K$, and dimensionality, $d_k$:

$$\text{Attention}(Q, K, V) = \text{softmax}(\frac{QK^T}{\sqrt{d_k}})V \quad (4)$$

MHA stacks parallel attention mechanisms in $h$ different mappings of the same queries, keys and values, each with varied learnt parameters. This allows different representations of the input to be generated, learning complementary information in different sub-spaces. The outputs of each head are then concatenated together and projected forward via a final linear layer, as:

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

where $\text{head}_i = \text{Attention}(QW_i^Q, KW_i^K, VW_i^V)$

and $W^O, W_i^Q, W_i^K$ and $W_i^V$ are weights related to each input variable.

The outputs of MHA are then fed into the second sub-layer of a non-linear feed-forward projection. A residual connection [22] and subsequent layer norm [2] is employed around each of the sub-layers, to aid training. The final symbolic encoder output can be formulated as:

$$h_t = E_S(\hat{w}_t | \hat{w}_{1:T}) \quad (6)$$
where $h_t$ is the contextual representation of the source sequence.

The symbolic decoder ($D_S$) is an auto-regressive architecture that produces a single token at each time-step. The positionally embedded target sequences, $\hat{g}_n$, are extracted and passed through an initial MHA self-attention layer similar to the encoder, with an extra masking operation. Alongside the fact that the targets are offset from the inputs by one position, the masking of future frames prevents the model from attending to subsequent time steps in the sequence.

The decoder contains a further MHA sub-layer, which maps representations from the encoder and decoder and learns the alignment between the source and target sequences. The final sub-layer is a feed forward layer, with all sub-layers followed by a residual connection and layer normalisation as in the encoder. After all encoder layers are processed, a final non-linear feed forward layer is applied, with a softmax operation to generate the most likely output token at each time step. The output of the symbolic decoder can be formulated as:

$$z_{n+1} = \arg\max_i D_S(\hat{g}_n|\hat{g}_{1:n-1}, h_{1:T})$$ (7)

where $z_{n+1}$ is the output at time $n + 1$, from a target vocabulary of size $i$.

### 3.2 Progressive Transformer

We now adapt our symbolic transformer architecture to cope with continuous outputs, so that it can be used to convert source sequences to a continuous target domain. In this work, Progressive Transformers (Figure 2b) translate from the symbolic domains of gloss or text to continuous skeleton pose sequences that represent the motion of a signer producing a sentence of sign language. The model must produce skeleton pose outputs that can both express a realistic sign pose sequence and an accurate translation of the given input sequence.

We represent each sign frame, $y_u$, as a continuous vector of 3D joint positions of the signer. These continuous joint values are first passed through a linear embedding layer, allowing sign poses of similar content to be closely represented in the dense space. The continuous embedding layer can be formulated as:

$$j_u = W^y \cdot y_u + b^y$$ (8)

where $j_u$ is the embedded 3D joint coordinates of each frame, $y_u$.

With continuous sign pose as a target, we apply a counter encoding layer as temporal embedding, determining the progress of sequence generation and allowing timing to be driven at inference. The counter, $c$, holds a continuous value between 0 and 1 and represents the frame position relative to the total sequence length. At training time, the joint embeddings, $j_u$, are concatenated with the respective counter value, $c_u$. The counter encoding is formulated as:

$$\hat{j}_u = [j_u, \text{CounterEncoding}(u)]$$ (9)

where CounterEncoding is a function producing the counter value for frame $u$, and $\hat{j}_u$ is the concatenated counter joint embeddings. At each time-step, counter
values are predicted alongside the skeleton pose, \( \hat{y}_u \), and counter, \( \hat{c}_u \in \{0 : 1\} \), with \( \hat{c} = 1 \) denoting end of sequence.

The counter provides the model with information relating to the length and speed of each sign pose sequence, determining the sign duration. At inference, we drive the sequence generation by replacing the predicted counter value, \( \hat{c} \), with the ground truth timing information, \( c^* \), to produce a stable output sequence.

The Progressive Transformer model also consists of an encoder-decoder architecture. Due to the input coming from a symbolic source, the encoder has a similar setup to the symbolic transformer, learning a contextual representation of the input sequence. As the representation will ultimately be used for the end goal of SLP, they must contain sufficient context to fully and accurately reproduce sign. Taking as input the temporally embedded source embeddings, \( \hat{w}_t \), the encoder can be formulated as:

\[
    r_t = E_S(\hat{w}_t|\hat{w}_{1:T})
\]

where \( r_t \) is the encoded contextual representation.

The progressive decoder \( (D_P) \) is an auto-regressive model that produces a skeleton pose state at each time-step, alongside the counter value described above. Distinct from symbolic transformers, the progressive decoder produces continuous sequences that hold a sparse representation in a large continuous sub-space. The counter-concatenated joint embeddings, \( \hat{j}_u \), as extracted as target input, representing the sign information of each frame.

A self-attention MHA sub-layer is first applied, with target masking to avoid attending to future positions. A further MHA mechanism is then used to map the symbolic representations from the encoder to the continuous domain of the decoder, learning the important alignment between spoken and sign languages.
A final feed forward sub-layer follows, with each sub-layer followed by a residual connection and layer normalisation as before. No softmax layer is used as the skeleton joint coordinates can be regressed directly and do not require stochastic prediction. The progressive decoder output can be formulated as:

\[
[\hat{y}_{u+1}, \hat{c}_{u+1}] = DP(\hat{j}_u | \hat{j}_{1:u-1}, r_{1:T})
\]

where \( \hat{y}_{u+1} \) corresponds to the 3D joint positions representing the produced sign pose of frame \( u + 1 \) and \( \hat{c}_{u+1} \) is the respective counter value. The decoder learns to generate one frame at a time until the predicted counter value reaches 1, determining the end of sequence. Once the full sign pose sequence is produced, the Progressive Transformer model is trained on the Mean Squared Error (MSE) loss between the predicted sequence, \( \hat{y}_{1:U} \), and the ground truth, \( y^*_1:U \):

\[
L_{MSE} = \frac{1}{u} \sum_{i=1}^{u} (y^*_i:U - \hat{y}_i:U)^2
\]

The progressive transformer outputs, \( \hat{y}_{1:U} \), represent the 3D skeleton joint positions of each frame of a produced sign sequence. Animating a video from this sequence is then a trivial task, plotting the joints and connecting the relevant bones, with timing information provided from the counter. These 3D joints could subsequently be used to animate an avatar \[29,38\] or condition a GAN \[24,57\].

### 4 Quantitative Experiments

In this section we share our SLP experimental setup and report experimental results. We first provide dataset and evaluation details, outlining back translation. We then evaluate both symbolic and progressive transformer models, demonstrating results of data augmentation and model configuration.

#### 4.1 Sign Language Production Dataset

Forster et al. released RWTH-PHOENIX-Weather-2012 (PHOENIX12) \[14\] and the extended PHOENIX14 \[15\] as large video-based corpora containing parallel sequences of German Sign Language - Deutsche Gebärdensprache (DGS) and spoken text extracted from German weather forecast recordings. These datasets are ideal for computational sign language research due to the provision of gloss level annotations, becoming the primary benchmark for both SLR and CSLR.

In this work, we use the publicly available PHOENIX14T dataset introduced by Camgoz et al. \[6\], a continuous SLT extension of the original PHOENIX14. This corpus includes parallel sign videos and German translation sequences with redefined segmentation boundaries generated using the forced alignment approach of \[33\]. 8257 videos of 9 different signers are provided, with a vocabulary of 2887 German words and 1066 different sign glosses from a combined 835,356 frames.

We train our progressive transformer to generate sequences of 3D skeletons. 2D joint positions are first extracted from each video using OpenPose \[7\]. We
then utilise the skeletal model estimation improvements presented in [54] to lift the 2D joint positions to 3D. An iterative inverse kinematics approach is applied to minimise 3D pose whilst maintaining consistent bone length and correcting misplaced joints. Finally, we apply skeleton normalisation similar to [48] and represent 3D joints as $x$, $y$ and $z$ coordinates. An example is shown in Figure 4.

4.2 Evaluation Details

In this work, we present back-translation as a means of SLP evaluation. Back translation, the dual mapping between source and text sequences, has been predominantly used to generate new data and improve the performance of monolingual corpus translation [20, 46]. Recent work on SLP used an SLR discriminator to determine whether generated skeletons were identifiable [53], but did not measure the translation performance. We utilise the state-of-the-art SLT [6] as our back translation model, generating the spoken language prediction of a produced sign pose sequence. BLEU and ROUGE scores can then be computed on the predicted text sequences, providing BLEU n-grams from 1 to 4 for completeness.

In the following experiments, our symbolic and progressive transformer models are built with 2 layers, 8 heads and embedding size of 256. All parts of our network are trained with Xavier initialisation [19] and Adam optimization [28] with default parameters and a learning rate of $10^{-3}$. Our code is based on Kreutzer et al.’s NMT toolkit, JoeyNMT [35], and implemented using PyTorch [43].

4.3 Symbolic Transformer: Text to Gloss

Our first experiment measures the performance of the symbolic transformer architecture for sign language understanding. We train our symbolic transformer to predict the gloss representation of a source spoken language text. Table 1 shows our model achieves state-of-the-art results, significantly outperforming that of Stoll et al. [48] who use an encoder-decoder network with 4 layers of 1000 Gated Recurrent Units (GRUs). This supports our use of the proposed transformer architecture for sign language understanding.
### Table 1. Results of the Symbolic Transformer for text to gloss translation

| Approach       | DEV SET | TEST SET |
|----------------|---------|----------|
|                | BLEU-4  | BLEU-3   | BLEU-2   | BLEU-1   | ROUGE    | BLEU-4  | BLEU-3   | BLEU-2   | BLEU-1   | ROUGE    |
| Stoll et al.   | 16.34   | 22.30    | 32.47    | 50.15    | 48.42    | 15.26   | 21.54    | 32.25    | 50.67    | 48.10    |
| Ours           | 20.23   | 27.36    | 38.21    | 55.65    | 55.41    | 19.10   | 26.24    | 37.10    | 55.18    | 54.55    |

### Table 2. Results of the Progressive Transformer for gloss to sign pose production, with multiple data augmentation techniques

| Approach       | DEV SET | TEST SET |
|----------------|---------|----------|
|                | BLEU-4  | BLEU-3   | BLEU-2   | BLEU-1   | ROUGE    | BLEU-4  | BLEU-3   | BLEU-2   | BLEU-1   | ROUGE    |
| Base           | 7.04    | 9.10     | 13.12    | 24.20    | 25.53    | 5.03    | 6.89     | 10.81    | 23.03    | 23.31    |
| Future Prediction | 9.96   | 12.71    | 17.83    | 30.03    | 31.03    | 8.38    | 11.04    | 16.41    | 28.94    | 29.73    |
| Just Counter   | 11.04   | 13.86    | 19.05    | 31.16    | 32.45    | 9.16    | 11.96    | 17.41    | 30.68    | 30.41    |
| Gaussian Noise | 11.88   | 15.07    | 20.61    | 32.53    | 34.19    | 10.02   | 12.96    | 18.58    | 31.11    | 31.83    |
| FP & GN        | 11.93   | 15.08    | 20.50    | 32.40    | 34.01    | 10.43   | 13.51    | 19.19    | 31.80    | 32.02    |

### 4.4 Progressive Transformer: Gloss to Pose

In our next set of experiments, we evaluate our progressive transformer and its capability to produce a continuous sign pose sequence from a given symbolic input. As a baseline, we train a progressive transformer model to translate from gloss to sign pose, with results shown in Table 2 (Base).

We believe our base progressive model suffers from prediction drift, with erroneous predictions building over time. As transformer models are trained to predict the next time-step of all ground truth inputs, they are often not robust to noise in target inputs. At inference time, with predictions based off previous outputs, errors are propagated throughout the full sequence generation, quickly leading to poor quality production. The impact of drift is heightened due to the continuous distribution of the target skeleton poses. As neighbouring frames differ little in content, a model learns to just copy the previous ground truth input and receive a small loss penalty. We thus experiment with various data augmentation approaches in order to overcome drift and improve performance.

**Future Prediction** Our first data augmentation method is conditional future prediction, requiring the model to predict more than just the next frame in the sequence. Experimentally, we find the best performance comes from a prediction of all of the next 10 frames from the current time step. As can be seen in Table 2, prediction of future time steps increases performance from the base architecture. We believe this is because the model now can rely on just copying the previous frame, as there are more considerable changes to the skeleton positions in 10 frames time. The underlying structure and movement of signing has to be learnt, encoding how each gloss is represented and reproduced in the training data.

**Just Counter** Inspired by the memorisation capabilities of transformer models, we next experiment with a pure memorisation approach. Only the counter values are provided as target input to the model, as opposed to the usual full 3D
Table 3. Results of the Text2Pose (T2P) and Text2Gloss2Pose (T2G2P) network configurations for text to sign pose production

| Configuration | BLEU-4 DEV | BLEU-3 DEV | BLEU-2 DEV | BLEU-1 DEV | ROUGE DEV | BLEU-4 TEST | BLEU-3 TEST | BLEU-2 TEST | BLEU-1 TEST | ROUGE TEST |
|---------------|-----------|-----------|-----------|-----------|----------|-----------|-----------|-----------|-----------|----------|
| T2P           | 11.82     | 14.80     | 19.97     | 31.41     | 33.18    | 10.51     | 13.54     | 19.04     | 31.36     | 32.46    |
| T2G2P         | 11.43     | 14.71     | 20.71     | 33.12     | 34.05    | 9.68      | 12.53     | 17.62     | 29.74     | 31.07    |

joint positions. We show a further performance increase with this approach, considerably increasing the BLEU-4 score as shown in Table 2.

We believe the just counter model setup helps to allay the effect of drift, as the model now must learn to decode the target sign pose solely from the counter position, without relying on the ground truth joint embeddings it previously had access to. Setup is then identical at both training and inference, with the model only having to generalise to new data rather than new prediction inputs.

**Gaussian Noise** Our final augmentation experiment examines the effect of applying noise to the skeleton pose sequences during training, increasing the variety of training data in order to build a more robust model. For each joint, statistics on the positional distribution of the previous epoch are collected, with randomly sampled noise applied to the inputs of the next epoch. Applied noise is multiplied by a noise factor, \( r_n \), with empirical validation suggesting \( r_n = 5 \) gives the best performance. An increase of Gaussian noise causes the model to become more robust to prediction inputs, as it must learn to correct the augmented inputs back to the target outputs. However, as \( r_n \) increases even further, model performance starts to degrade.

Table 2 (FP & GN) shows that the best BLEU-4 performance comes from a combination of future prediction and Gaussian noise augmentation. The model must learn to cope with both multi-frame prediction and a noisy input, building a firm robustness to drift. We continue with this setup for further experiments.

4.5 **Text2Pose v Text2Gloss2Pose**

Our final experiment evaluates the two network configurations outlined in Figure 1, sign pose production either direct from text or via a gloss intermediary. Text to Pose (T2P) consists of a single progressive transformer model with spoken language input, learning to jointly translate from the domain of spoken language to sign and subsequently produce meaningful sign representations. Text to Gloss to Pose (T2G2P) uses an initial symbolic transformer to convert to gloss, an important intermediary step to provide correct sign ordering [6], which is then input into a further progressive transformer to produce sign pose sequences.

As can be seen from Table 3, the T2P model outperforms that of T2G2P, with a BLEU-4 of 11.82 and 10.51 for dev and test respectively. This is surprising, as a large body of previous work has suggested that using gloss as intermediary helps networks learn [6]. However, we believe this is because there is more
information available within spoken language compared to a gloss representation, with more tokens per sequence to predict from. Gloss representation can result in a bottleneck where important information is lost, whereas regressing directly from text provides more useful context.

The success of the T2P network shows that our progressive transformer model is powerful enough to complete two sub-tasks: firstly mapping spoken language sequences to a sign representation, then producing an accurate sign pose recreation. This is important for future scaling and application of the SLP model architecture, as many sign language domains do not have gloss availability.

Furthermore, our final BLEU-4 scores outperform the state-of-the-art in the similar Sign to Text task outlined in Camgoz et al. (9.94 BLEU-4). Note: this is an unfair direct comparison, but it does provide an indication of model performance and the quality of the produced sign pose sequences.
5 Qualitative Experiments

In this section we report qualitative results for our progressive transformer model. We share snapshot examples of produced sign pose sequences in Figure 5, with more examples provided in supplementary material. The unseen spoken language sequence is shown as input alongside the sign pose sequence produced by our Progressive Transformer model, with ground truth video for comparison.

As can be seen from the provided examples, our SLP model produces visually pleasing and realistic looking sign with a close correspondence to the ground truth video. Body motion is smooth and accurate, whilst hand shapes are meaningful if a little under-expressed. We find that the most difficult production occurs with proper nouns and specific entities, due to the lack of grammatical context and examples in the training data.

These examples show that regressing continuous sequences can be successfully achieved using an attention-based mechanism. The predicted joint locations for neighbouring frames are closely positioned, showing that the model has learnt the subtle movement of the signer. Smooth transitions between signs are produced, highlighting a difference from the discrete generation of spoken language.

6 Conclusions

The production of continuous sign language sequences from spoken language is an important task to improve communication between the Deaf and hearing. Previous work has focused on producing concatenated isolated signs instead of continuous sign sequences. In this paper, we proposed Progressive Transformers, a novel architecture that translates from discrete spoken language sequences to continuous skeleton pose outputs representing sign. We presented two model configurations, an end-to-end network that produces sign direct from text and a stacked network that utilises a gloss intermediary. Additionally, we introduced a counter that allowed continuous sequence generation at training and inference.

We evaluated our approach on the challenging PHOENIX14T dataset, setting baselines for future research with a back translation evaluation mechanism. We found that regressing continuous sequences can be successfully achieved using a self-attention-based model, helping to learn the correct skeleton pose representation of a signer. Our experiments showed the importance of several data augmentation techniques to improve the performance of SLP models. Furthermore, we have shown that a direct text to pose translation configuration can outperform a gloss intermediary model, meaning SLP models are not limited to only training on data where expensive gloss annotation is available.

As future work, we would like to expand our network to multi-channel sign production, focusing on non-manual aspects of sign language such as body pose, facial expressions and mouthings. It would be interesting to condition a GAN to produce sign videos, learning a prior for each sign represented in the data.

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1 Sequence IDs: 05September_2009_Saturday_tagesschau4078, 05January_2010_Tuesday_tagesschau2672
Acknowledgement

This work received funding from the SNSF Sinergia project SMILE (CRSII2 160811), the European Unions Horizon2020 research and innovation programme under grant agreement no. 762021 Content4All and the EPSRC project ExTOL (EP/R03298X/1). This work reects only the authors view and the Commission is not responsible for any use that may be made of the information it contains.

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A Appendix

In this appendix we show further qualitative results for our progressive transformer model. We share snapshot examples of produced sign pose sequences in Figure 6 and 7. The unseen spoken language sequence is shown as input alongside the sign pose sequence produced by our Progressive Transformer model, with ground truth skeleton pose and video provided for comparison. We also provide videos of produced sign pose sequences in the supplementary materials file, highlighting the quality of production against both ground truth video and skeleton pose.

A.1 Qualitative Results

Fig. 6. Examples of produced sign pose sequences showing spoken language input, produced sign pose and ground truth pose and original video.
Fig. 7. Examples of produced sign pose sequences showing spoken language input, produced sign pose and ground truth pose and original video.

1. das hoch über den azoren stehet sich über mittel europa nach ostern aus und sorgt morgen kurzzeitig für meist freundliches wetter
   (trans: the high above the azores stretches eastwards over central europe and tomorrow will provide mostly friendly weather)

2. am dienstag in der südhalfe wehre etwas vereinzelt auch gewitter in der nordhalfe freundliche abschnitte
   (trans: on tuesday in the southern half more showers occasionally thunderstorms in the northern half friendly sections)

3. in der westhalte geht der regen in schauer über in den bergen schneeschauer
   (trans: in the western half the rain turns into showers in the mountains snow showers)