

JWSign: A Highly Multilingual Corpus of Bible Translations for more Diversity in Sign Language Processing

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Abstract

Advancements in sign language processing have been hindered by a lack of sufficient data, impeding progress in recognition, translation, and production tasks. The absence of comprehensive sign language datasets across the world’s sign languages has widened the gap in this field, resulting in a few sign languages being studied more than others, making this research area extremely skewed mostly towards sign languages from high-income countries. In this work we introduce a new large and highly multilingual dataset for sign language translation: JWSign. The dataset consists of 2,530 hours of Bible translations in 98 sign languages, featuring more than 1,500 individual signers. On this dataset, we report neural machine translation experiments. Apart from bilingual baseline systems, we also train multilingual systems, including some that take into account the typological relatedness of signed or spoken languages. Our experiments highlight that multilingual systems are superior to bilingual baselines, and that in higher-resource scenarios, clustering language pairs that are related improves translation quality.

1 Introduction

There are around 300 sign languages recorded up to date (United Nations, 2021). However, sign language translation research is extremely skewed towards a limited number of sign languages, primarily those from high-income countries (Müller et al., 2023), while ignoring the vast majority of sign languages used in low and middle-income countries (Gueuwou et al., 2023). A similar phenomenon was observed in the spoken¹ languages machine translation community and was shown by Ògúnremí et al. (2023) to be harmful, calling on the NLP

¹In this work, following Müller et al. (2022a), we “use the word ‘spoken’ to refer to any language that is not signed, no matter whether it is represented as text or audio, and no matter whether the discourse is formal (e.g. writing) or informal (e.g. dialogue)”.

community to do more research on low resource spoken languages (Ranathunga et al., 2023). This issue is exacerbated by the fact that approximately 80% of people with disabling hearing loss in the world reside in middle and low-income countries (World Health Organization, 2023).

Our first contribution towards addressing these challenges is to present *JWSign*, a highly multilingual corpus of Bible translations in 98 sign languages, made accessible through an automated loader. To the best of our knowledge, *JWSign* is one of the largest and most diverse datasets to date in sign language processing (§3).

There is precedent in natural language processing (NLP) for using Bible translations as a starting point for many under-resourced languages that may not have any parallel resources in other domains. Bible corpora have played a major role in research in speech and text areas of NLP (§2).

We complement the *JWSign* dataset with baseline experiments on machine translation, training a Transformer-based system for 36 bilingual pairs of languages in the dataset. Such bilingual systems, trained individually for each language pair (one sign language and one spoken language), are the default procedure in recent literature.

However, sign language translation (SLT) has proven to be a challenging task, due to obstacles such as very limited amounts of data, variation among individual signers and sub-optimal tokenization methods for sign language videos. A potential way to improve over bilingual systems (the predominant kind at the time of writing) is to build multilingual systems. Linguistic studies have suggested a good level of similarity and mutual intelligibility among some sign languages (Power et al., 2020; Reagan, 2021) even from different continents (e.g. Ghanaian Sign Language in Africa and American Sign Language in North America). In this work, we therefore explore different multilingual settings for sign language translation (§4).

2 Related Work

The following section explores the motivation behind the research by examining works that have utilized the Bible in various modalities (§2.1). It delves into the limited coverage of many sign languages within popular existing datasets for sign language translation (§2.2), and provides a comprehensive overview of the state-of-the-art methods employed for automatic translation of sign language videos into text (§2.3).

2.1 Use of Bible corpora in NLP

Previous studies have acknowledged the Bible as a valuable resource for language exploration and processing (Mayer and Cysouw, 2014) with good linguistic breadth and depth (Resnik et al., 1999). In machine translation, Bible translations have proven to be a good starting point for machine translation research of many spoken languages, even if eventually one must move to other more useful domains (Liu et al., 2021). In effect, Bible translations have shown their usefulness across different modalities including text (McCarthy et al., 2020) and audio (Black, 2019; Pratap et al., 2023), and for many low resource spoken languages especially in Africa (Dossou and Emezue, 2020; Adelani et al., 2022; Meyer et al., 2022).

Mayer and Cysouw (2014) showcased a corpus of 847 Bibles and McCarthy et al. (2020) increased it significantly both in terms of the number translations (4,000 unique Bible translations) and number of languages (from 1,169 languages to 1,600 languages) it supported thus forming the Johns Hopkins University Bible Corpus (JHUBC). In the audio domain, the CMU Wilderness Speech Dataset (Black, 2019) is a notable resource derived from the New Testaments available on the www.bible.is website. This dataset provides aligned sentence-length text and audio from around 699 different languages. In a similar effort, Meyer et al. (2022) formed BibleTTS: a speech corpus on high-quality Bible translations of 10 African languages. Pratap et al. (2023) expanded both these works and formed the MMS-lab dataset containing Bible translations in 1,107 languages.

2.2 Sign Language Translation Datasets

Previous studies on sign language translation were predominantly relying on the RWTH-Phoenix 2014T dataset (Camgoz et al., 2018), which contains 11 hours of weather broadcast footage

from the German TV station PHOENIX, covering recordings from 2009 to 2013 (Camgoz et al., 2018; Yin and Read, 2020; De Coster et al., 2021; Zhou et al., 2021; Voskou et al., 2021; Chen et al., 2022b). However, Müller et al. (2023) called into question the scientific value of this dataset. In recent times, TV broadcast datasets have been introduced for several sign languages, including SWISSTXT and VRT (Camgöz et al., 2021), and the BBC-Oxford British Sign Language (BOBSL) dataset (Albanie et al., 2021) for Swiss-German Sign Language, Flemish Sign Language and British Sign Language respectively. Other examples are the How2Sign dataset (Duarte et al., 2021), OpenASL (Shi et al., 2022a) and YouTubeASL (Uthus et al., 2023), featuring American Sign Language.

All datasets mentioned above are bilingual i.e. they contain one single sign language, paired to one spoken language. However, some multilingual datasets have emerged very recently as SP-10 (Yin et al., 2022) and AfriSign (Gueuwou et al., 2023). SP-10 features 10 sign languages but sentences here are extremely short in general (e.g. “How are you?”). AfriSign comprises 6 sign languages which are actually a subset of JWSign. In contrast, JWSign is a valuable resource that surpasses most other sign language translation datasets in terms of duration, signers diversity, and coverage over different sign languages as highlighted in Table 1. Thus, we aim for JWSign to serve as a foundational resource to make sign language translation research more diverse and inclusive going forward.

2.3 Sign Language Translation Methods

SLT is an emerging field which aims to translate sign language videos to text/speech and/or vice-versa. One of the main challenges in SLT is finding an efficient and high-quality representation for sign language. This has resulted in many translation architectures using tokenization methods such as human keypoint estimation (Ko et al., 2019; Kim et al., 2020), CNN feature extraction (Zhou et al., 2021; De Coster et al., 2021; Voskou et al., 2021), linguistic glosses (Müller et al., 2023) or phonetic systems such as SignWriting (Jiang et al., 2023). However, most of these are frame-level tokenization methods and assume implicitly that sign language utterances can be considered as sequences of lexical units, while in reality signing uses complex structures in time and 3-dimensional space.

All things considered, 3D CNN window-level

Dataset	#SL(s)	Vocab	#Hours	Avg	#Signers	Source
PHOENIX (Camgoz et al., 2018)	1	3K	11	4.5	9	TV
KETI (Ko et al., 2019)	1	419	28	6.9	14	lab
CSL-Daily (Zhou et al., 2021)	1	2K	23	4.0	10	lab
BOBSL (Albanie et al., 2021)	1	78K	1467	4.4	39	TV
How2Sign (Duarte et al., 2021)	1	16K	80	8.2	11	lab
OpenASL (Shi et al., 2022a)	1	33K	280	10.5	≈220	web
YouTubeASL (Uthus et al., 2023)	1	60K	984	4.8	>2519	web
SP-10 (Yin et al., 2022)	10	17K	14	4.3	79	web
AfriSign (Gueuwou et al., 2023)	6	20K	152	18.3	160	web
JWSign	98	729K	2530	19.3	≈1500	web

Table 1: Comparing the JWSign dataset to other common datasets in SLT research. Vocab = Vocabulary of target spoken language i.e. number of unique spoken words, PHOENIX = RWTH Phoenix-2014T, #SL = number of sign language pair(s), #Hours = Total duration of the dataset in hours, Avg = Average duration of a sample in the dataset in seconds.

feature extractors have been reported to reach the best results in this task (Chen et al., 2022a; Müller et al., 2022a; Tarrés et al., 2023). The main component of this approach is an inflated 3D convolutional neural network (I3D) (Carreira and Zisserman, 2017) or S3D (Wei et al., 2016). Originally designed for action recognition (Kay et al., 2017), some works (Varol et al., 2021; Duarte et al., 2022; Chen et al., 2022a) have adapted and fine-tuned these networks for sign language recognition datasets such as BSL-1K (Albanie et al., 2020) and WLASL (Li et al., 2020).

3 JWSign

In this section, we give an overview of JWSign (§3.1) and list key statistics, comparing JWSign to other recent datasets (§3.2). Finally, we explain our process of creating fixed data splits for (multilingual) machine translation experiments (§3.3).

3.1 Overview

JWSign is made up of verse-aligned Bible translations in 98 sign languages from the Jehovah’s Witnesses (JW) website². This wide coverage also extends to the racial identities of the signers, with representation from American Indians/Alaska Natives, Asians, Blacks/African Americans, Hispanics/Latinos, Native Hawaiians/Other Pacific Islanders, and Whites (*in alphabetic order*) (illustrated in in Figure 1). Therefore, we believe that JWSign captures a broad range of signer demo-

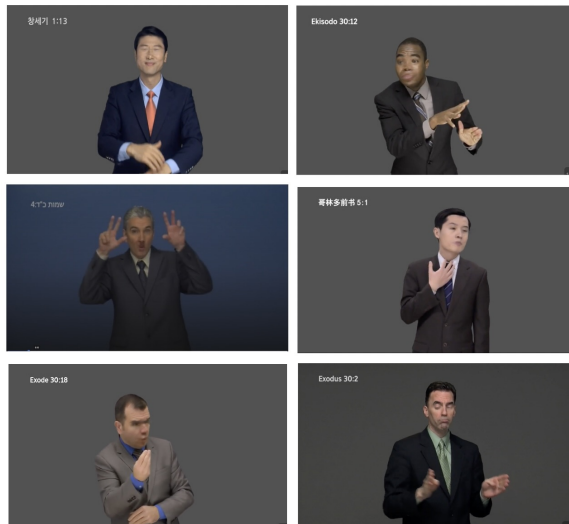


Figure 1: Anecdotal signer diversity in JWSign.

graphics, making it a unique and valuable resource for researchers and practitioners alike.

Translators are either deaf themselves or have grown up in deaf communities, and the recordings are made in a studio on-the-ground in each country. Translations are not only out of English, different spoken languages are used as the source material, depending on the country. Details about the translation process at JW are included in Appendix A.

3.2 Statistics of JWSign

JWSign features 98 sign languages spread across all the 7 continents of the world (Table 2). All languages taken together, it has a total duration of 2,530 hours and contains roughly 1,500 individual

²<https://www.jw.org/>

Europe	31
Asia	21
Africa	19
North America	11
South America	11
Oceania	4
Australia	1

Table 2: Number of sign languages in JWSign per continent.

people, according to our automatic analysis.

Comparison to similar datasets We show a comparison of JWSign to other datasets in Table 1. JWSign contains more sign languages, covering more geographic regions, than any other dataset we are aware of. For instance, SP-10 (Yin et al., 2022) features 10 sign languages mostly from Europe, and AfriSign (Gueuwou et al., 2023) has 6 sign languages from Africa. JWSign has higher signer diversity (§3.1) than most other datasets. We also observe that samples in other datasets generally are shorter than the average duration in JWSign.

On the other hand, we emphasize that JWSign is a corpus of Bible translations only, hence covering a limited linguistic domain. Other datasets such as BOBSL and YouTubeASL are far more broad, covering many domains and genres. Similarly, when comparing the amount of data available for an individual language pair, JWSign does not always offer the most data. For certain high-resource language pairs, other datasets are considerably larger. For example, BOBSL and YouTubeASL contain $\approx 1,500$ hours and $\approx 1,000$ hours of content in English and British Sign language and American Sign language respectively. Nevertheless, for many language pairs, JWSign is an unparalleled resource for training and evaluating sign language translation models.

Per-language statistics JWSign contains at least 2,000 samples for 47 language pairs. The distribution of samples per language pair indicates that some languages are represented better than others (Figure 2). A similar trend is observed with the total duration per language pair (Appendix B).

Naturally, sign languages present a variation in average sample duration across different sign languages, as depicted in Figure 3. This observation sheds light on the linguistic “verbosity” of sign languages, where the same sentence may be signed

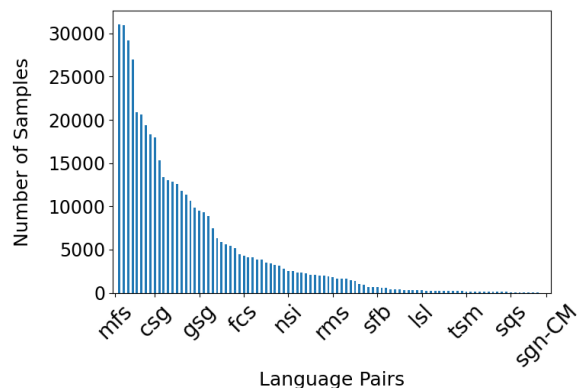


Figure 2: Number of samples per language pair. The x-axis shows language pairs referred to by the ISO code for the sign languages only. All ISO codes are listed in Appendix E. While there are 98 language pairs in total, we show a representative sample of 11, ranging from high-resource to low-resource.

in varying lengths across different sign languages. We envision that JWSign enables linguistic studies such as these across many sign languages.

Cross-lingual frequency To measure the extent of sample overlaps across different sign languages, we measure how many times each sample (Bible verse) appears across all sign languages. The distribution of this analysis is illustrated in Figure 4.

Number of individuals To determine the number of individuals in the dataset, we adopt the signer clustering approach proposed by Pal et al. (2023). We utilize the face recognition toolbox³ to obtain a 128-dimensional embedding for the signer in each video sample. Then, we use the Density Based Spatial Clustering of Application with Noise (DBSCAN) algorithm (Ester et al., 1996) with $\epsilon = 0.2$ to cluster all embeddings of each sign language. This clustering method is based on the reasonable assumption that no signer can appear in videos for two different sign languages, given that videos are recorded on-the-ground in each country. This yielded a grand total of 1,460 signers⁴.

3.3 Data splits and automated loader

For each language pair in JWSign we provide a fixed, reproducible split into training, development and test data, tailored towards machine translation as the main use case.

³https://github.com/ageitgey/face_recognition

⁴We realised this clustering approach works non-optimally for Black/African American and Asian signers and much better on other races. So we expect the ground-truth number of signers in JWSign to be above this value.

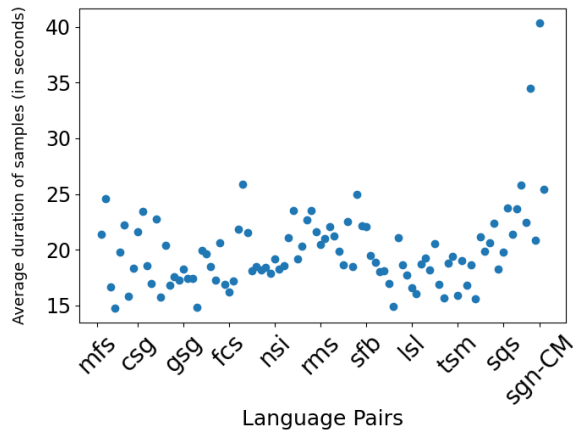


Figure 3: Average duration (in seconds) per language pair. It is worth noting that the two outliers sign languages that exhibit significant deviations from the norm were observed to be those with a very small sample size (less than 10) and long sentences, and are therefore not sufficiently representative of those sign languages.

Splitting procedure Our method for splitting the data into training, development and test sets is designed to eliminate multilingual “cross-contamination” (the same sentence in two different languages appearing both in the train and test set) as much as possible. Multi-way parallel corpora such as the IWSLT 2017 multilingual task data (Cettolo et al., 2017) (where cross-contamination does exist) are known to paint an overly optimistic picture about the translation quality that can realistically be obtained. A second goal is to maintain a reasonable test set size for machine translation.

We select development and test data based on an analysis of cross-lingual frequency (Figure 4). We minimize the chances of a sample in the test set in one sign language being found in the train set in another language, which could lead to cross-contamination when training a multilingual model and possibly inflate the test set evaluation scores. More details on the splitting procedure are given in Appendix C.

Automated loader We do not create new videos nor upload and store them.⁵ Instead, JWSign consists of links to Bible verses on the JW website⁶ itself and we support it with an automated loader integrated in the Sign Language Datasets library (Moryossef and Müller, 2021) for better accessibility and reproducibility. More information about the

⁵Hosting Jehovah’s Witnesses data publicly is not allowed: <https://www.jw.org/en/terms-of-use/>

⁶<https://www.jw.org/en/online-help/jw-library-sign-language/>

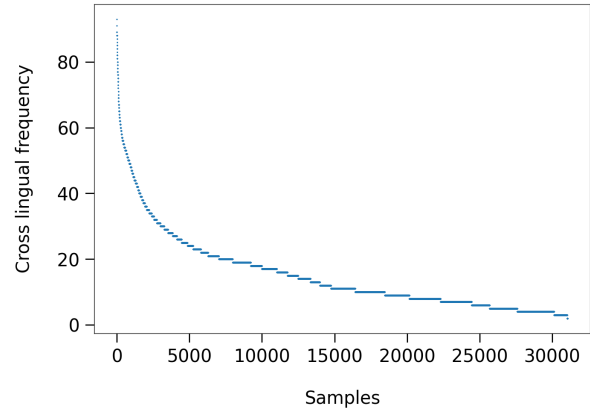


Figure 4: Cross-lingual frequency of Bible verses in JWSign. The y-axis shows the number of sign languages each verse is translated to.

creation of this automated loader⁷ can be found in Appendix D.

4 Experimental setup

We perform preliminary machine translation experiments on the JWSign dataset. In this section we explain our preprocessing steps (§4.1), how different models are trained (§4.2) and our method of automatic evaluation (§4.3).

4.1 Preprocessing

Sign language (video) data All videos have a resolution of 1280×720 and frame rate of 29.97 fps. We first resize the videos to a smaller resolution of 256×256 pixels and then we apply a center crop to the dimensions of 224×224 pixels (the input size expected by the subsequent step). Lastly, we apply color normalization.

The preprocessed videos are then fed into a pre-trained I3D model for feature extraction. We use a window size of 64 and a temporal stride of 8, and the particular I3D model we use was fine-tuned by Varol et al. (2021) on an expanded version of the BSL-1K dataset (Albanie et al., 2020), encompassing over 5,000 sign classes.

Using a fine-tuned I3D model, or more generally, a vision-based approach, for feature extraction is motivated by earlier findings. For example, Müller et al. (2022a) and Tarrés et al. (2023) point out that vision-based approaches outperform alternatives such as feature extraction with pose estimation.

What is more, Shi et al. (2022b) have shown

⁷https://github.com/sign-language-processing/datasets/tree/master/sign_language_datasets/datasets/jw_sign

that a pretrained I3D model fine-tuned on a sign language corpus with a greater diversity of signing categories yields more substantial benefits for sign language translation compared to a corpus with fewer signs.

We extract embeddings before the final classification layer, specifically the “mixed_5c” layer. These embeddings are 1024-dimensional vectors that are stacked together, forming a $w \times 1024$ -dimensional vector for each sample video, where w is the total number of windows in a sample video.

Finally, for multilingual systems only, a 1024-dimensional vector representing the target spoken language is further appended to the extracted embedding stack. This particular vector serves as a continuous analogue of a tag to indicate the associated target spoken language (Johnson et al., 2017) and it is unique for every spoken language.

Spoken language (text) data We remove special noisy characters as “*” and “+”. The resulting preprocessed text is then tokenized using a Sentencepiece model (Kudo and Richardson, 2018).

4.2 Types of models that are compared

In this paper we work exclusively on signed-to-spoken translation, translating from a sign language to a spoken language in all cases. Our models are Transformers (Vaswani et al., 2017) with 6 encoder and 3 decoder layers. Our code is based on Fairseq Sign-to-Text (Tarrés et al., 2023) and is publicly available⁸. All experiments were conducted on a single NVIDIA-A100 GPU.

Bilingual (“B” systems) We developed 36 bilingual models (referred to as **B36**), each focusing on a specific language pair i.e. sign language to spoken language. These language pairs were carefully chosen based on having a substantial number of samples (greater than 1,000 samples) in their respective training sets. We trained the models with a batch size of 32, a learning rate of 1e-3 and applied a dropout rate of 0.3.

We set the Sentencepiece vocabulary size to 1,000 for most language pairs, except for those with a limited number of samples (less than 10,000 in total), where we use a vocabulary size of 500. For languages with a very wide range of characters, such as Chinese and Japanese, we observed many characters are appearing only once (hapax legomena). To counteract this we reduced the character

coverage to 0.995 and expanded the vocabulary size to 1,500 to accommodate the larger character set. Training was done for a maximum of 100,000 updates.

Multilingual systems (“M” systems) We explore three different multilingual settings. First, we train a single multilingual model using the 36 highest-resource language pairs (same as for B36 above) (**M36**). This enables us to compare the effect of training various language pairs separately and jointly. To optimize the training of multilingual models, we employ a larger batch size of 128 and slightly increase the initial learning rate to 1e-06.

We then attempt a naive model trained on all language pairs in JWSign that have training samples (**M91**). This amounts to 91 different language pairs, excluding seven language pairs in the *Zero* category which do not have any training data. We use these zero-resource language pairs only for testing.

Since we anticipate that the naive multilingual strategy of M91 leads to low translation quality for the low-resource language pairs, we further explore a fine-tuning strategy. For this system (**MFT**), we fine-tune the M36 model jointly on all lower-resource language pairs with training data (i.e. all training data that M36 was *not* trained on, 55 language pairs in total). All hyperparameters are kept the same except that we reset the optimizer accumulator and restart from the 0-th step. This allows us to examine cross-lingual transfer from higher-resource to lower-resource languages. By training on a diverse range of language pairs, we can assess the model’s ability to generalize and adapt to unseen sign languages having very little data.

Clustered families (“C” systems) Finally, as another attempt at improving over naive multilingual training, we leverage the phylogeny of spoken languages and sign languages. We cluster the language pairs based on source sign language families (Power et al., 2020; Eberhard et al., 2023) and train on each cluster separately (**CSIG**). Similarly, we cluster the language pairs according to the target spoken language families (Fan et al., 2021) and train on each cluster separately as well (**CSPO**). A sample of each cluster can be found in Table 3 and the full list of clusters is given in Table 6 and Table 7 in the Appendix. The intuition for these clustering experiments is to invoke positive transfer effects stemming from similarities between languages.

⁸<https://github.com/ShesterG/JWSign-Machine-Translation>

Group	Spoken Languages
Germanic	Danish (da), Dutch (nl), English (en), German (de), Norwegian (no), Swedish (sv)
Group	Sign Languages
Old French	Argentinean (aed), Austrian (asq), Belgian French (sfb), Dutch (dse), Flemish (vgt), French (fsl), German (gsg), Greek (gss), Irish (isg), Israeli (isr), Italian (ise), Mexican (mfs), Quebec (fcs), Spanish (ssp), Swiss German (sgg), Venezuelan (vsl)

Table 3: Examples for clustering into language families, showing a sign language cluster and a spoken language cluster.

4.3 Evaluation

During training, we evaluate models every 2 epochs and select the checkpoint with the highest BLEU score (Papineni et al., 2002) computed with SacreBLEU (Post, 2018),⁹ aggregated across languages for multilingual models. At test time, using a beam search of size 5, we evaluate all models on the detokenized text using BLEU computed with SacreBLEU, BLEURT-20 (Pu et al., 2021), and chrF (Popović, 2015). We note that many recent neural metrics, such as COMET (Rei et al., 2020), are not applicable in our case because the source languages (sign languages) are not supported.

5 Results and Discussion

Although all language pairs in this work are considered very low-resourced when compared to spoken languages (Goyal et al., 2022), going forward we use the term *High* to refer to language pairs with more than 10,000 training samples, *Medium* for language pairs with training samples between 1,000 and 9,999 inclusive, *Low* for language pairs with training samples between 500 and 999 inclusive, *Very Low* for language pairs with training samples less than 500 and *Zero* for language pairs with no training samples.

Our main findings are summarized in Table 4. Due to limited computational resources, we conducted single runs for all reported results. To give a better overview over our individual results, for some systems on 98 different test sets, we show results aggregated into different training data sizes. For a comprehensive understanding, we have

⁹BLEU+c.mixed+#.1+s.exp+tok.13a+v.1.4.1.

also provided detailed non-aggregate results in Appendix G.

Performance Variation Across Language Pairs

The table categorizes the language pairs into different groups based on resource availability, namely *High*, *Medium*, *Low*, *Very Low*, and *Zero*. By examining the performance metrics (BLEU, BLEURT, chrF) within each group, we can observe trends in model performance. For example, the *High* and *Medium* groups tend to have higher scores compared to the *Low*, *Very Low*, and *Zero* groups. This suggests that having a larger training dataset, as indicated by the resource availability, positively impacts the translation quality.

Going into more individual bilingual pair results (Table 8 in Appendix G), the highest BLEU was obtained by Japanese Sign Language to Japanese text (7.08), American Sign Language to English text (4.16) and Chinese Sign Language to Chinese (3.96). This suggests some language pairs are easier for a model to learn, for instance because the grammar of Japanese sign language may be more aligned with spoken Japanese, compared to other language pairs.

Impact of multilingual training Here we compare the performance of the “B36” model (bilingual training on 36 language pairs separately) and the “M36” model (multilingual training of one model on the same 36 language pairs together). We observe that our evaluation metrics show conflicting trends, since multilingual training generally reduces BLEU and chrF scores, but increases BLEURT scores. Based on evidence presented in Kocmi et al. (2021) and Freitag et al. (2022), we adopt the view that the neural metric BLEURT is more trustworthy than BLEU and chrF, in the sense of having higher agreement with human judgement. With this interpretation in mind, our results suggest that training on multiple languages simultaneously increases translation quality.

When *Low*, *Very Low* and *Zero* resource language pairs are added to the multilingual training (M91), there is a light drop in scores for *High* and *Medium* language pairs when compared to when they were solely trained together (M36). Thus, while this method may offer advantages for low-resource languages by leveraging knowledge from language pairs with much more data resulting in positive transfer, there is a trade-off between transfer and interference, as increasing the number of

Models	High			Medium			Low			Very Low			Zero			Average		
	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF
B36	2.37	23.36	15.87	1.65	23.43	16.07	-	-	-	-	-	-	-	-	-	1.89	23.4	16
M36	1.6	26.91	14.07	1.38	26.65	13.02	-	-	-	-	-	-	-	-	-	1.45	26.73	13.37
M91	1.59	26.58	13.76	1.37	26.24	12.83	1.01	29.79	13.21	1	27.24	12.77	0.63	30.37	9.84	1.14	27.32	12.73
MFT	0.53	16.18	13.19	0.61	22.76	13.41	1.37	22.83	16.96	1.48	24.2	15.84	1.18	22.12	14.16	1.12	22.62	14.88
CSIG	2.37	26.04	15.35	1.82	27.28	14.98	1	22.82	12.88	0.41	20.47	8.25	0.45	20.49	7.24	1.04	23.01	11.04
CSPO	2.01	27.13	14.69	1.88	28.13	15.32	1.18	24.7	12.84	0.61	21.7	10.29	0.91	22.75	11.27	1.16	24.26	12.34

Table 4: Evaluation results. B36 = Bilingual Training on 36 language pairs separately, M36 = Multilingual Training on the same 36 language pairs as B36 but jointly, MFT = Fine-tuning of the M36 models on all the remaining 55 language pairs available with available training data, M91 = Joint multilingual training on all the 91 language pairs that have any training data, CSIG = Results of the clustered multilingual models when the source sign languages are from the same group, CSPO = Results of the clustered multilingual models when the target spoken languages are from the same group.

languages in the training set can lead to a decline in performance for the *High* and *Medium* resource language pairs (Arivazhagan et al., 2019).

Fine-tuning on additional language pairs The “MFT” model represents the fine-tuning of the “M36” model on all the remaining 55 language pairs with training data available. Comparing its performance with “M36” and “M91”, we observe a marked drop in BLEURT scores across all resource categories. On average, “M91” leads to a BLEURT score of 27.32, “MFT” achieves 22.62 on average. This suggests that for incorporating new additional language pairs with limited resources, training these languages from scratch mixed with *High* and *Medium* language pairs is better than a fine-tuning approach.

Clustered multilingual models The “CSIG” and “CSPO” models represent the results of clustered multilingual models. In the “CSIG” model, the source sign languages are from the same group, while in the “CSPO” model, the target spoken languages are from the same group. In higher-resource settings, clustered multilingual models perform better than non-clustered multilingual models (M36, MFT, M91). For *High* and *Medium* resource language pairs, CSPO leads to the best BLEURT scores among all model types. For lower-resource settings, the opposite is true and clustering languages based on linguistic phylogeny hurts translation quality as measured by BLEURT.

6 Conclusion and Future Work

In this study, we introduced JWSign as a unique resource aimed at promoting diversity in sign lan-

guage processing research which has been so far dominated by few sign languages. We conducted a series of baseline experiments using JWSign to attempt improving the scores of automatic sign translation systems in different scenarios. We demonstrate that multilingual training leads to better translation quality compared to bilingual baselines. On the other hand, our experiments did not show a clear benefit for a fine-tuning approach in lower-resource scenarios. Similarly, we found that clustering data by language family, even though intuitively promising, is only beneficial in higher-resource settings.

More generally, the overall translation quality is still very low. This is in line with other recent studies such as Müller et al. (2022a) who report BLEU scores in a similar range. Regardless, we firmly believe that as we strive to improve translation systems, it is crucial to ensure early diversification of the sign languages used to train these systems. By incorporating a wide range of sign languages during the training phase, we can enhance the inclusivity and effectiveness of the resulting translation systems.

As part of our future research, we aim to develop enhanced models utilizing JWSign that can effectively handle multiple sign languages. Furthermore, JWSign presents a distinctive opportunity to address the existing gaps in sign language processing, such as the development of a sign language identification tool. JWSign can also serve as a valuable tool for linguists to explore and compare various sign languages in an attempt to gain more insights, such as further inquiries into the typological relatedness of sign languages.

Limitations

There are several limitations to this study that need to be considered.

Dataset size Although JWSign is one of the largest dataset that was designed for Sign Language Translation, it is still quite low-resourced when compared to data in other modalities such as text and/or speech.

Limited domain One limitation of the JWSign dataset is that it is focused on the domain of biblical texts, which may not be representative of other types of sign language communication. This could limit the applicability of the dataset to certain types of sign language translation tasks.

Translationese effects Another limitation of the dataset is the presence of translationese effects, which can occur when translated text or speech sounds unnatural or stilted compared to the original (Barrault et al., 2019). This can be a challenge for sign language translation systems, which must accurately convey the meaning of the source sign language in this case while also producing natural and fluent spoken language.

Recording conditions On top, the videos in the JWSign dataset were recorded in a studio setting, which may not fully capture the complexity and variability of sign language communication in real-world settings. Factors such as lighting, camera angles, and the absence of background noise or visual distractions could affect the sign language production and recognition process in ways that differ from natural communication contexts. This could limit the generalizability of the dataset to real-world sign language translation scenarios.

Reproducibility The dataset is not hosted although we circumvent this with an automated loader to increase accessibility. As long as the original videos and website remain online with stable links, our dataset can be reproduced exactly.

Uni-directional models In this work, we reported baseline scores only for signed-to-spoken translation. We did not experiment at all with translation systems that generate sign language utterances, which is also an important research problem.

Ethics Statement

Licensing We do not in any way claim ownership of the JW data. We do not create new videos, nor upload or store them. The data strictly and entirely belongs to JW. Instead, we provide links to Bible verses on the JW website itself and we support this with an automated loader to increase accessibility. To the best of our knowledge, we believe that this usage is in accordance with the JW.org terms of use¹⁰, which explicitly allow the distribution of links, as well as downloads/usage of media for "personal and noncommercial purposes". As we neither upload nor copy the actual data, and our aim is to enable researchers to do noncommercial research, we believe these terms are satisfied.

Nevertheless, we have also taken the step of requesting explicit permission by contacting JW's legal branches in the USA and Switzerland (the Office of the General Counsel in New York and the Rechtsabteilung¹¹ in Thun, Switzerland). However, we have not yet received a reply at the time of writing. Should this permission be refused we certainly plan to abide by their wishes.

Our automated dataset loader includes a usage notice that explicitly informs users of JW's licensing terms.

Privacy and consent We did not reach out to all individuals depicted in our dataset (an estimated 1,500 people) to ask for their consent. We believe our research poses no risk to their privacy because (1) we do not distribute videos and (2) we only train models for signed-to-spoken translation. This means that it is impossible to recover personal information such as faces from a trained model (which we do not share in the first place).

Algorithmic bias On a different note, even though JWSign has signers from all races, the dataset might suffer from other biases such as gender, age representation and handedness. Models trained here are far from usable and reliable, and thus cannot replace a human sign language interpreter.

¹⁰<https://www.jw.org/en/terms-use/>

¹¹<https://www.jw.org/de/rechtlich/rechtsabteilungen-kontakt/schweiz/>

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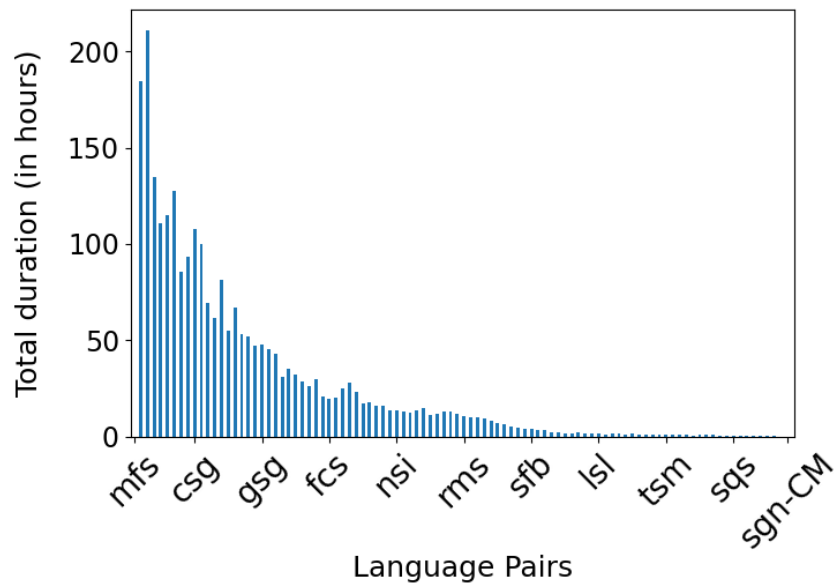


Figure 5: Total duration (in hours) per language pair.

A Translation process at Jehovah’s Witnesses

The Witnesses’ approach to sign language translation is thorough and collaborative¹². Newly recruited translators receive extensive training in translation principles and work in teams, where each member performs a specific role such as translating, checking, or proofreading the material. To ensure the highest quality of translation, a panel of deaf individuals from diverse backgrounds and locations review the translation and provide valuable feedback to refine the signs and expressions used in the final video. This step guarantees that the message is conveyed accurately and naturally.

In addition to their translation work, the sign-language translators participate in congregation meetings and hold Bible studies with non-Jehovah’s Witnesses members of the deaf community, enabling them to stay abreast of language developments and improve their skills. This diligent approach to sign-language translation ensures translators stay up-to-date with the language.

The videos are recorded in a studio with proper lighting and the translation is done from the region’s official spoken language to the country’s sign language verse by verse. This work is incremental and still ongoing - as of January 2023, the complete Bible is only available in three sign languages (American Sign Language, Brazilian Sign Language and Mexican Sign Language).

B Additional Statistics

The distribution of the total number of hours in each language pair can be found at Figure 5.

C Details of data splitting procedure

First, we sort the samples by cross-lingual frequency in descending order, based on the number of sign languages in which they appear. This ensures that samples with the most overlap across sign languages will be found at the top of the list, while samples with the least overlap will be found at the bottom (Figure 4). We proceed by partitioning the samples into three distinct and non-overlapping buckets. The test bucket consists of the 1,500 most frequently occurring samples, followed by the dev bucket containing the next 1,500 samples, and finally the train bucket comprising the remaining samples. For each language, the test, dev, and train sets are formed by intersecting the language-specific samples with their corresponding buckets. This method helps to eliminate the possibility of a sample in the test set in one sign language being found in the train set in another language, which could lead to cross-contamination when training a multilingual model and possibly inflate the test set evaluation scores.

¹²<https://www.jw.org/en/jehovahs-witnesses/activities/publishing/sign-language-translation/>

D Development of automated loader

To create this loader, we followed a few key steps. First, we created an index file that contains a comprehensive list of verses and their attributes, such as the video URL on the JW website, start and end times of the verse in the video, and a link to the corresponding written text on the JW website. We ensured that all selected videos had a frame rate of 29.970 fps (the most common fps used in the videos on the website) and resolution of 1280x720, and we eliminated any duplicates. The index file was stored in JSON format, which has the advantage of being easily updatable when the website gets updated.

Next, we developed a script that utilizes the information in the index file to automatically load frames/poses and corresponding text, aligning them appropriately to form a dataset. With this loader, users have the option to form a dataset for a specific sign language, a set of sign languages, or all sign languages as needed. The human poses estimation can be obtained from Mediapipe Holistic (Lugaresi et al., 2019) or OpenPose (Cao et al., 2017). Human pose estimation refers to a computer vision task that involves detecting, predicting, and monitoring the positions of various joints and body parts. Both OpenPose and Mediapipe Holistic are capable of detecting various keypoints present in videos, including those on the face, hands, and body.

We believe that the automated loader for JWSign integrated in the Sign Language Datasets library will streamline the process of accessing sign language data.

E Dataset Statistics

Table 5 highlights the statistics about all the 98 sign languages in JWSign.

F Language Groupings

Table 7 and Table 6 highlights the sign language groups and spoken language groups respectively, used during Clustering Families Training.

G Results detailed

Table 8 shows the evaluation results on model B36 and model M36, while Table 9 shows the evaluation results on model M91, CSIG, CSPO and MFT.

sign language	iso	spoken	samples	duration	avg	train / dev / test
Mexican	mfs	es	31056	184.473	22	28057 / 1500 / 1499
Brazilian	bzs	pt-br	30949	211.135	25	27957 / 1494 / 1498
American	ase	en	29150	134.655	17	26358 / 1340 / 1449
Russian	rsl	ru	26949	110.571	15	24109 / 1449 / 1391
Italian	ise	it	20882	114.923	20	19376 / 796 / 710
Colombian	csn	es	20644	127.63	23	18506 / 1151 / 987
Spanish	ssp	es	19394	85.207	16	16416 / 1483 / 1495
Korean	kvk	ko	18287	93.322	19	16030 / 1104 / 1153
Argentinean	aed	es	17818	106.856	22	14946 / 1435 / 1437
Chilean	csg	es	15357	100.15	24	12845 / 1282 / 1230
Ecuadorian	ecs	es	13331	68.873	19	10577 / 1368 / 1386
Polish	psp	pl	12994	61.294	17	10085 / 1435 / 1474
Peruvian	prl	es	12843	81.079	23	9890 / 1456 / 1497
British	bfi	en	12538	54.925	16	9557 / 1485 / 1496
Japanese	jsl	ja	11832	67.154	21	8929 / 1409 / 1494
Indian	ins	en	11384	53.298	17	8609 / 1358 / 1417
Venezuelan	vsl	es	10634	51.821	18	7720 / 1420 / 1494
South African	sfs	en	9837	47.159	18	7046 / 1352 / 1439
Zimbabwe	zib	en	9463	47.889	19	6787 / 1313 / 1363
German	gsg	de	9335	45.164	18	6412 / 1432 / 1491
Malawi	sgn-MW	ny	8849	42.815	18	6266 / 1246 / 1337
French	fsl	fr	7415	30.545	15	4735 / 1257 / 1423
Finnish	fse	fi	6303	34.883	20	3432 / 1394 / 1477
Angolan	sgn-AO	pt-pt	5867	32.05	20	3490 / 1100 / 1277
Australian	asf	en	5597	28.75	19	2900 / 1266 / 1431
Cuban	csf	es	5406	25.968	18	2868 / 1145 / 1393
Indonesian	inl	id	5201	29.651	21	3000 / 921 / 1280
Filipino	psp	en	4406	20.638	17	1928 / 1096 / 1382
Chinese	csl	zh-CN	4280	19.278	17	2143 / 778 / 1359
Zambian	zsl	en	4067	24.666	22	1920 / 886 / 1261
Quebec	fcs	fr	4058	19.518	18	1604 / 1056 / 1398
Bolivian	bvl	es	3881	27.864	26	1411 / 1117 / 1352
Paraguayan	pys	gn	3810	22.837	22	1506 / 979 / 1325
Kenyan	xki	en	3452	17.351	19	1286 / 927 / 1239
Czech	cse	cs	3412	17.537	19	1498 / 593 / 1321
Ghanaian	gse	en	3185	16.062	19	1965 / 378 / 842
Hungarian	hsh	hu	3125	16.011	19	851 / 837 / 1437
Taiwanese	tss	zh-TW	2754	13.707	18	799 / 722 / 1233
Swedish	swl	sv	2540	13.532	20	768 / 519 / 1253
Portuguese	psr	pt-pt	2368	12.208	19	466 / 593 / 1309
Nigerian	nsi	en	2347	11.898	19	774 / 593 / 980
Slovak	svk	sk	2302	13.48	22	450 / 505 / 1347
Honduras	hds	es	2290	14.964	24	594 / 405 / 1291
Costa Rican	csr	es	2099	11.177	20	478 / 338 / 1283
Guatemalan	gsm	es	2081	11.763	21	517 / 309 / 1255
Panamanian	lsp	es	2025	12.741	23	397 / 326 / 1302
Nicaraguan	ncs	es	2013	13.152	24	534 / 278 / 1201
Madagascar	mzc	mg	1935	11.624	22	321 / 577 / 1037
Salvadoran	esn	es	1806	10.289	21	458 / 232 / 1116
Romanian	rms	ro	1647	9.632	22	126 / 339 / 1182

Mozambican	mzy	pt-pt	1628	9.596	22	241 / 311 / 1076
Greek	gss	el	1627	10.011	23	102 / 339 / 1186
Thai	tsq	th	1456	8.049	20	143 / 201 / 1112
Congolese	sgn-CD	fr	1334	6.914	19	245 / 216 / 873
Ivorian	sgn-CI	fr	977	6.122	23	103 / 151 / 723
Croatian	csq	hr	960	4.922	19	85 / 113 / 762
Myanmar	sgn-MM	my	666	4.623	25	91 / 99 / 476
Tanzanian	tza	sw	651	4.007	23	80 / 104 / 467
Malaysian	xml	ms	643	3.936	23	57 / 84 / 502
Belgian French	sfb	fr	609	3.292	20	56 / 67 / 486
Vietnamese	hab	vi	606	3.18	19	38 / 90 / 478
Uruguayan	ugy	es	398	1.994	19	19 / 34 / 345
New Zealand	nzs	en	368	1.849	19	52 / 36 / 280
Irish	isg	en	362	1.708	17	23 / 36 / 303
Dutch	dse	nl	330	1.366	15	8 / 27 / 295
Serbian	sgn-RS	sr	328	1.922	22	62 / 46 / 220
Albanian	sqk	sq	310	1.605	19	1 / 10 / 299
Norwegian	nsl	no	275	1.354	18	32 / 29 / 214
Swiss German	sgg	de	270	1.244	17	12 / 29 / 229
Latvian	lsl	lv	257	1.149	17	6 / 22 / 229
Austrian	asq	de	252	1.309	19	1 / 15 / 236
Danish	dsl	da	243	1.301	20	48 / 32 / 163
Ugandan	ugn	en	236	1.192	19	10 / 27 / 199
Nepali	nsp	ne	228	1.301	21	5 / 12 / 211
Jamaican	jls	en	227	1.067	17	16 / 31 / 180
Flemish	vgt	nl	183	0.986	20	7 / 14 / 162
Israeli	isr	he	177	0.782	16	20 / 9 / 148
Turkish	tsm	tr	173	0.913	19	9 / 6 / 158
Lithuanian	lls	lt	170	0.793	17	5 / 7 / 158
Ethiopian	eth	am	162	0.84	19	12 / 18 / 132
Cambodian	sgn-KH	km	145	0.629	16	1 / 5 / 139
Mongolian	msr	mn	129	0.571	16	1 / 8 / 120
Armenian	aen	hy	129	0.763	22	5 / 6 / 118
Estonian	eso	et	122	0.674	20	6 / 9 / 107
Melanesian	sgn-PG	en	117	0.67	21	9 / 7 / 101
Slovenian	sgn-SI	sl	96	0.596	23	1 / 2 / 93
Suriname	sgn-SR	nl	96	0.487	19	2 / 2 / 92
Bulgarian	bqn	bg	87	0.479	20	3 / 2 / 82
Rwandan	sgn-RW	rw	77	0.402	19	13 / 20 / 44
Sri Lankan	sqs	si	61	0.403	24	1 / 1 / 59
Hong Kong	hks	zh-TW	60	0.356	22	2 / 1 / 57
Singapore	sls	en	33	0.217	24	0 / 0 / 33
Fiji	sgn-FJ	en	30	0.215	26	0 / 0 / 30
Lebanese	sgn-LB	ar	28	0.174	23	0 / 0 / 28
Samoan	sgn-WS	sm	8	0.077	35	0 / 0 / 8
Burundi	sgn-BI	fr	3	0.017	21	0 / 0 / 3
Mauritian	lsy	en	2	0.022	41	0 / 0 / 2
Cameroon	sgn-CM	fr	2	0.014	26	0 / 0 / 2
TOTAL	98	51	472529	2530.262	19.3	341334 / 52052 / 79143

Table 5: Comparing the different sign languages in JWSign. iso = ISO 639-3 sign language code, samples = total number of videos, duration = total duration of all videos (in hours), avg = average duration of samples (in seconds).

Group	Languages
Chinese	Chinese mandarin simplified (zh-CN), Chinese mandarin traditional (zh-TW), Japanese (ja), Korean (ko), Vietnamese (vi)
Germanic	Danish (da), Dutch (nl), English (en), German (de), Norwegian (no), Swedish (sv)
Malayo-Polynesian	Indonesian (id), Malagasy (mg), Malay (ms)
Niger-Congo	Amharic (am), Chichewa (ny), Kinyarwanda (rw), Swahili (sw)
Romance	French (fr), Italian (it), Portuguese-brazil (pt-br), Portuguese-portugual (pt-pt), Romanian (ro), Spanish (es)
Slavic	Bulgarian (bg), Croatian (hr), Czech (cs), Polish (pl), Russian (ru), Serbian-roman (sr), Slovak (sk), Slovenian (sl)
Uralic	Estonian (et), Finnish (fi), Hungarian (hu), Latvian (lv), Lithuanian (lt)
Other	Albanian (sq), Arabic (ar), Armenian (hy), Cambodian (km), Greek (el), Guarani-paraguayan (gn), Hebrew (he), Mongolian (mn), Myanmar (my), Nepali (ne), Samoan (sm), Sinhala (si), Thai (th), Turkish (tr)

Table 6: Spoken languages Groups

Group	Languages
America	American (ase), Bolivian (bvl), Burundi (sgn-BI), Cambodian (sgn-KH), Cameroon (sgn-CM), Colombian (csn), Congolese (sgn-CD), Costa Rican (csr), Ecuadorian (ecs), Ethiopian (eth), Filipino (psp), Ghanaian (gse), Guatemalan (gsm), Indonesian (inl), Ivorian (sgn-CI), Jamaican (jls), Kenyan (xki), Malawi (sgn-MW), Malaysian (xml), Myanmar (sgn-MM), Nigerian (nsi), Panamanian (lsp), Peruvian (prl), Rwandan (sgn-RW), Salvadoran (esn), Singapore (sls), Sri Lankan (sqs), Thai (tsq), Ugandan (ugn), Zambian (zsl), Zimbabwe (zib)
British	Australian (asf), British (bfi), Croatian (csq), Fiji (sgn-FJ), Indian (ins), Melanesian (sgn-PG), Nepali (nsp), New Zealand (nzs), Samoan (sgn-WS), Serbian (sgn-RS), Slovenian (sgn-SI), South African (sfs)
Chinese	Chinese (csl), Hong Kong (hks), Japanese (jsl), Korean (kvk), Taiwanese (tss)
Old French	Argentinean (aed), Austrian (asq), Belgian French (sfb), Dutch (dse), Flemish (vgt), French (fsl), German (gsg), Greek (gss), Irish (isg), Israeli (isr), Italian (ise), Mexican (mfs), Quebec (fcs), Spanish (ssp), Swiss German (sgg), Venezuelan (vsl)
Polish	Bulgarian (bqn), Czech (cse), Estonian (eso), Hungarian (hsh), Latvian (lsl), Lithuanian (lls), Mongolian (msr), Polish (pso), Romanian (rms), Russian (rsl), Slovak (svk)
Swedish	Brazilian (bzs), Danish (dsl), Finnish (fse), Madagascar (mzc), Norwegian (nsl), Portuguese (psr), Swedish (swl)
Uruguay	Chilean (csg), Paraguayan (pys), Uruguayan (ugy)
Other	Angolan (sgn-AO), Honduras (hds), Nicaraguan (ncs), Suriname (sgn-SR), Turkish (tsm), Vietnamese (hab), Lebanese (sgn-LB), Albanian (sqk), Armenian (aen), Mauritian (lsy), Mozambican (mzy), Tanzanian (tza), Cuban (csf)

Table 7: Sign languages Groups

Language Pair	B36			M36		
	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF
mfs->es	2.33	21.18	15.33	1.62	27.75	14.74
bzs->pt-br	2.12	18.7	14.96	1.47	21.76	12.75
ase->en	4.16	37.49	18.99	2.48	36.91	15.46
rsl->ru	3.09	26.38	17.81	1.14	24.74	12.21
ise->it	2.58	25.49	16.3	1.33	27.4	12.45
csn->es	2.04	23.73	14.07	1.32	28.03	14.48
ssp->es	2.64	20.42	17.52	1.48	27.17	14.68
kvk->ko	1.37	32.38	9.88	3.68	31.88	16.56
aed->es	2.2	21.37	15.48	1.44	26.91	14.68
csg->es	2.38	19.1	16.63	1.36	28.22	14.8
ecs->es	1.76	16.94	16.38	1.52	26.36	14.64
pso->pl	1.78	17.15	17.06	0.38	15.76	11.44
prl->es	1.92	19.57	15.69	1.44	27.1	14.69
bfi->en	2.89	36.02	18.19	1.99	36.11	15.05
jsl->ja	7.08	23.96	14.77	5.44	25.49	14.83
ins->en	2.87	35.01	18.43	1.82	36.25	15.01
vsl->es	1.83	15.74	16.87	1.3	26.94	14.03
sfs->en	1.99	33.95	16.16	1.75	36.39	14.89
zib->en	1.47	34.43	14.92	1.55	36.69	14.39
gsg->de	1.22	19.34	16.58	0.58	19.9	12.12
sgn-MW->ny	0.93	26.81	19.06	0.31	23.95	12.17
fsl->fr	1.36	0.48	16.28	0.47	-2.24	8.42
sgn-AO->pt-pt	0.73	13.18	13.03	0.78	19.39	11.72
fse->fi	1.2	22.33	18.45	0.35	15.41	8.36
inl->id	1	45.08	19.16	0.23	40.53	13.02
asf->en	1.52	32.72	15.5	1.75	37.18	15.57
csf->es	1.02	12.97	14.75	1.07	26.49	14.06
csl->zh-CN	3.96	33.7	14.49	4.92	34.14	16.32
gse->en	1.22	31.5	16.14	1.15	35.94	14.92
psp->en	1.11	31.88	16.97	1.68	37.1	14.87
zsl->en	1.08	27.51	15.71	1.22	35.58	14.41
fcs->fr	0.8	-1	14.98	0.51	-1.76	8.32
pys->gn	0.64	17.65	15.73	0.17	13.02	12.53
cse->cs	0.38	11.19	12.84	0.02	16.38	4.09
bvl->es	0.57	9.24	14.81	1.08	27.21	14.31
xki->en	0.85	28.98	16.11	1.53	36.33	14.42

Table 8: Evaluation Results on B36 and M36.

Language Pair	M91			CSIG			CSPO			MFT		
	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF
mfs->es	2	28.46	14.42	2.91	26.79	16.02	2.04	27.47	14.56	0.74	15.73	16.08
bzs->pt-br	1.47	20.42	13.34	3.03	20.3	17.02	1.68	22.83	13.66	0.58	10.08	16.75
ase->en	1.84	37.03	15.09	3.06	37.86	16.52	3.86	39.08	18.91	0.87	32.06	15.35
rsl->ru	1.21	22.58	12.63	3.12	25.89	17.8	3.73	26.88	18.63	0.04	7.6	1.48
ise->it	1.33	29.38	12.86	2.37	28.06	14.76	1.33	26.39	12.76	0.03	10.41	8.12
csn->es	1.47	27.87	13.92	2.16	26.96	14.35	1.73	26.04	14.63	0.66	15.93	16.44
ssp->es	1.6	27.23	14.15	2.47	26.23	15.63	1.75	26.1	14.44	0.53	16.66	15.49
kvk->ko	2.85	32.26	14.84	1.27	29.81	8.63	1.43	30.3	9.23	0.83	22.59	10.66
aed->es	1.66	27.39	14.04	2.34	27.04	15.29	1.4	26.38	14.11	0.63	15.8	16.28
csg->es	1.67	28.11	14.65	2.31	16.54	17.73	1.55	26.67	14.52	0.66	17.35	16.81
ecs->es	1.58	26.81	14.07	1.7	26.52	14.17	1.65	25.55	14.38	0.72	17.38	16.08
psa->pl	0.36	11.46	11.12	1.69	20.49	16.3	1.92	21.92	16.4	0.05	12.51	8.76
prl->es	1.74	27.05	14.19	2.02	27.24	14.6	1.51	25.98	14.39	0.61	17.93	16.78
bfi->en	1.62	35.87	14.55	3.13	36.26	18.89	3.04	38.01	17.98	1.05	31.82	15.54
jsl->ja	5.06	24.97	13.78	6.55	24.3	13.19	6.12	23.7	12.52	1.11	22.09	12.98
ins->en	1.47	35.26	14.18	3.14	36.09	18.6	2.9	37.94	17.98	0.85	32.29	15.99
vsl->es	1.37	27.09	13.69	2.05	26.32	14.84	1.42	26.48	13.89	0.58	16.64	15.79
sfs->en	1.45	35.24	14.24	2.32	35.54	18.15	2.64	37.23	17.63	0.88	32.06	15.74
zib->en	1.18	35.76	13.84	1.63	36.14	14.7	2.28	36.69	16.71	1.06	31.73	15.4
gsg->de	0.37	19.85	12.79	0.91	22.51	13.99	1.12	23.48	16.19	0.09	22.76	13.07
sgn-MW->ny	0.21	24.53	13.88	0.48	28.04	15.3	1.31	27.46	18.27	0.03	22.75	7.31
fsl->fr	0.69	1.69	9.23	1.1	3.89	12.2	0.74	0.85	9.78	0.47	-2.69	14.1
sgn-AO->pt-pt	0.86	18.1	12.54	0.88	10.7	13.32	0.89	21.31	12.47	0.68	10.42	13.98
fse->fi	0.45	22.22	7.96	1.46	29.43	16.56	1.35	27.57	18.22	0.08	19.57	10.83
inf->id	0.2	33.68	12.86	0.62	45.08	17.18	1.59	46.86	20.04	0.03	31.09	8.51
asf->en	1.39	36.32	14.75	2.23	34.85	17.93	2.31	37.48	17.31	0.92	32.35	15.85
csf->es	1.23	25.85	13.31	0.74	13.83	13.8	1.37	24.57	13.74	0.51	16.9	15.13
csl->zh-CN	6.54	29.07	16.48	4.25	36.89	13.93	3.52	36.21	13.2	0.18	28.8	5.82
gse->en	1.11	35.17	14.55	1.56	35.43	15.52	1.84	36.38	16.63	0.98	31.39	15.89
psp->en	1.43	36.93	14.2	1.91	36.65	15.13	2.09	37.35	16.41	0.93	31.85	15.71
zsl->en	1.06	35.08	14.03	1.44	35.07	15.07	1.68	34.54	16.16	0.78	30.55	14.97
fcf->fr	0.7	1.77	9.06	1.03	4.61	11.49	0.58	0.29	9.42	0.6	-1.99	13.86
pys->gn	0.25	13.86	11.2	0.52	17.78	14.75	1.12	17.24	16.53	0.09	29.14	8.61
cse->cs	0.04	12.83	4.94	0.47	16.1	11.82	0.62	16.02	11.62	0.12	9.82	7.99
bvl->es	1.22	27.24	13.85	1.53	26.52	13.62	1.42	25.93	14.11	0.84	17.68	16.8
xki->en	1.17	34.31	13.83	1.68	35.51	15.02	1.64	35.56	16.39	1.15	31.32	15.27
hsh->hu	0.02	42.61	6.11	1.23	30.39	14.11	1.25	27.09	15.33	0.95	27.62	15.56
tss->zh-TW	2.02	29.33	26.32	0.68	17.28	6.62	0.67	18.34	6.68	4.6	23.54	21.93
nsi->en	1.31	36.11	14.41	1.88	36.06	15.29	2.43	36.64	16.94	1.29	32.68	16.54
swl->sv	0.02	21.11	3.93	0.75	22.69	12.88	0.25	14.93	9.05	0.58	19.78	15.12
hds->es	0.97	26.6	13.81	0.5	13.37	13.93	0.99	25.81	13.96	0.67	18.72	16.55
ncs->es	1.25	26.32	14.04	0.61	13.79	14.08	1.18	24.91	14	0.73	18.89	16.65
gsm->es	1.49	26.48	13.88	1.35	26.15	13.26	1.5	25.21	13.91	0.76	18.6	16.36
csr->es	1.1	25.35	13.56	1.1	25.04	13.05	0.99	24.54	13.62	0.63	18.26	16.15
psr->pt-pt	0.95	18.77	13.09	1.16	16.82	14.36	0.95	21.1	12.28	0.69	11.12	14.85
esn->es	1.21	26.59	13.79	1.15	26.15	13.23	1.07	24.64	13.88	0.71	18.52	16.36
svk->sk	0.04	22.33	6.29	0.38	17.47	11.66	0.26	16.92	10.65	0.92	16.33	12.96
lsp->es	1.29	26.68	14.02	1.18	25.11	13.84	1.11	24.59	14.21	0.82	18.56	17.03
mzc->mg	0.02	29.21	9.94	0.17	28.19	14.2	0.64	28.87	18.65	0.52	28.93	19.36
sgn-CD->fr	0.64	1.9	8.93	0.01	4.28	0.37	0.52	-0.49	9.07	0.48	-2.01	14.85
mzy->pt-pt	0.55	18.28	12.6	0.6	10.27	13.33	0.75	22.21	12.54	0.58	10.58	14.8
tsq->th	1.34	40.02	25.54	0.03	15.79	4.83	1.24	15.17	13.47	7.09	38.71	27.64
rms->ro	1.19	23.57	8.74	0.06	18.17	9.11	0.01	25.6	4.28	2.22	16.14	13.99
sgn-CL->fr	0.69	0.37	9.5	0.01	4.4	0.3	0.71	-1.08	9.7	0.52	-2.23	14.8
gss->el	1.05	18.05	23.38	0.01	1.86	5.72	0.6	8.12	14.54	6.16	7.52	28.67
sgn-MM->my	4.5	44.03	27.65	0.06	8.75	9.7	1.88	9.6	16.89	7.64	41.13	27.41
csq->hr	0.01	22.21	3.32	0.07	21.07	8.89	0.08	22.5	8.16	0.1	20.28	11.73
tza->sw	0.03	20.47	7.76	0.06	21.66	10.24	0.22	18.46	14.05	0.21	21.73	15.58
sgn-RS->sr	0.02	21.65	3.9	0.07	21.54	7.26	0.09	22.56	8.1	0.16	22.35	11.55
xml->ms	0.06	35.9	12.56	0.67	46.52	15.58	0.42	46.99	18.58	0.41	41.08	16.89
sfb->fr	0.81	1.18	9.1	0.91	4.02	11.24	0.7	-0.76	9.54	0.5	-2.32	14.13
nzs->en	0.96	34.56	12.91	0.91	33.97	14.81	2.09	36.66	15.03	0.94	31.01	14.82
dsl->da	0.05	19.23	2.44	0.31	22.8	12.85	0.08	17.94	6.69	1.56	19.41	15.01
hab->vi	2.46	4.79	16	0.52	7.63	7.55	1.29	6.29	8.21	8.57	-0.18	19.33
nsf->no	0.28	19.46	3.76	0.36	19.04	11.92	0.04	15.3	3.97	1.72	18.07	14.78
isg->en	1.2	36.38	13.52	0.02	26.33	4.31	1.68	37.95	15.28	1.38	32.07	15.24
isr->he	3.3	49.11	30.58	0.14	30.32	5.19	1.09	35.57	14.91	2.42	55.09	29.15
ugy->es	0.81	27.21	12.66	0.93	12.43	13.59	1.12	26.12	13.16	0.63	18.3	15.11
jls->en	0.78	34.97	13.86	1.27	34.65	14.84	1.04	36.14	16.12	0.68	32.17	14.82
sgn-RW->rw	0.13	14.83	6.88	0.03	13.59	4.95	0.23	9.07	11.07	0.09	9.48	10.54
eth->am	0.37	56.43	15.7	0.01	24.34	0.87	0	28.35	1.37	0.3	55.98	14.91
sgg->de	0.81	20.96	13.17	0.59	22.58	13.3	0.65	22.86	14.88	0.15	22.9	13.4
ugn->en	0.28	32.23	11.51	1.08	34.37	14.36	1.1	36.95	15.63	0.48	31.43	14.61
sgn-PG->en	1.13	35.64	13.8	1.61	32.9	16.58	1.74	36.21	15.6	0.93	32.72	16.07

Table 9: Evaluation Results on M91, CSIG, CSPO and MFT.

Language Pair	M91			CSIG			CSPO			MFT		
	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF	BLEU	BLEURT	chrF
tsm->tr	1.17	17.41	10.77	0.01	9.4	7.26	0.09	21.78	11.47	0.48	12.74	8.9
dse->nl	0.08	19.32	4.77	0.02	15.57	3.81	0	13.61	2.83	0.1	16.67	12.31
vgt->nl	0.02	18.54	5.21	0.03	15.41	4.6	0.01	13.42	2.75	0.14	16.99	12.05
lsl->lv	0.19	40.5	4.27	0.03	21.88	3.71	0.14	20.19	8.86	0.83	22.6	10.42
eso->et	0.03	24.41	4.06	0.06	19.88	4.88	0.14	16.79	8.01	0.11	17.87	10.06
aen->hy	3.04	56.72	27.18	0.03	29.38	5.81	0.1	32.28	11.06	0.2	57.51	13.82
lls->lt	1.57	31.09	8.68	0.05	23.8	5.52	0.07	19.25	8.93	0.73	24.97	9.16
nsp->ne	2.25	50.5	28.44	0.02	28.27	3.04	0.04	43.11	8.81	1.79	52.75	23.62
bqn->bg	0.1	18.29	7.7	0.14	22.75	8.04	0.1	17.59	5.14	1.79	29.66	13.83
hks->zh-TW	3.96	25.6	24.22	3.14	17.66	7.72	3.17	17.71	8.33	5	19.37	21.45
sgn-SR->nl	0.03	17.68	4.66	0.01	15.76	2.95	0.01	12.3	2.68	0.12	18.79	13.44
sqk->sq	1.01	34.96	13.84	0.02	21.64	4.51	0.09	18.54	8.97	0.35	26.98	8.08
sgn-KH->km	2.87	49.28	32.52	0	22.58	0.19	0	20.62	0.94	2.84	47.95	28.47
mst->mn	0.91	17.09	4.83	0.04	17.3	2.51	0.06	18.01	2.68	1.36	16.72	6.21
asq->de	0.6	20.8	12.86	0.45	22.57	13.26	0.72	23.81	14.98	0.15	22.87	13.34
sqe->si	2	53.36	25.02	0	27.95	0.03	0	37.97	5.32	4.61	55.27	29.44
sgn-SI->sl	0.01	29.42	3.26	0.05	18.79	6.18	0.11	19.75	8.08	0.08	18.93	8.96
sgn-BI->fr	0.43	5.56	7.9	0.18	5.7	0.16	1.03	-1.39	9.9	1.29	0.09	14.99
sgn-CM->fr	1.13	3.51	9.49	0.27	7.97	0.48	1.4	-3.04	10.23	0.95	-4.75	11.3
sgn-FJ->en	0.34	41.56	13.94	0.69	33.64	16.89	0.72	35.4	15.42	0.94	30.54	16.08
sgn-LB->ar	0.03	37.63	1.47	0.02	16.26	1.56	0.02	32.27	1.95	1.83	24.95	11.12

Table 10: continuation: Evaluation Results on M91, CSIG, CSPO and MFT.