

Improving Sign Language machine translation results by using linguistic features and other data augmentation methods: A series of studies on Spanish Sign Language (LSE) and German Sign Language (DGS)



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Background

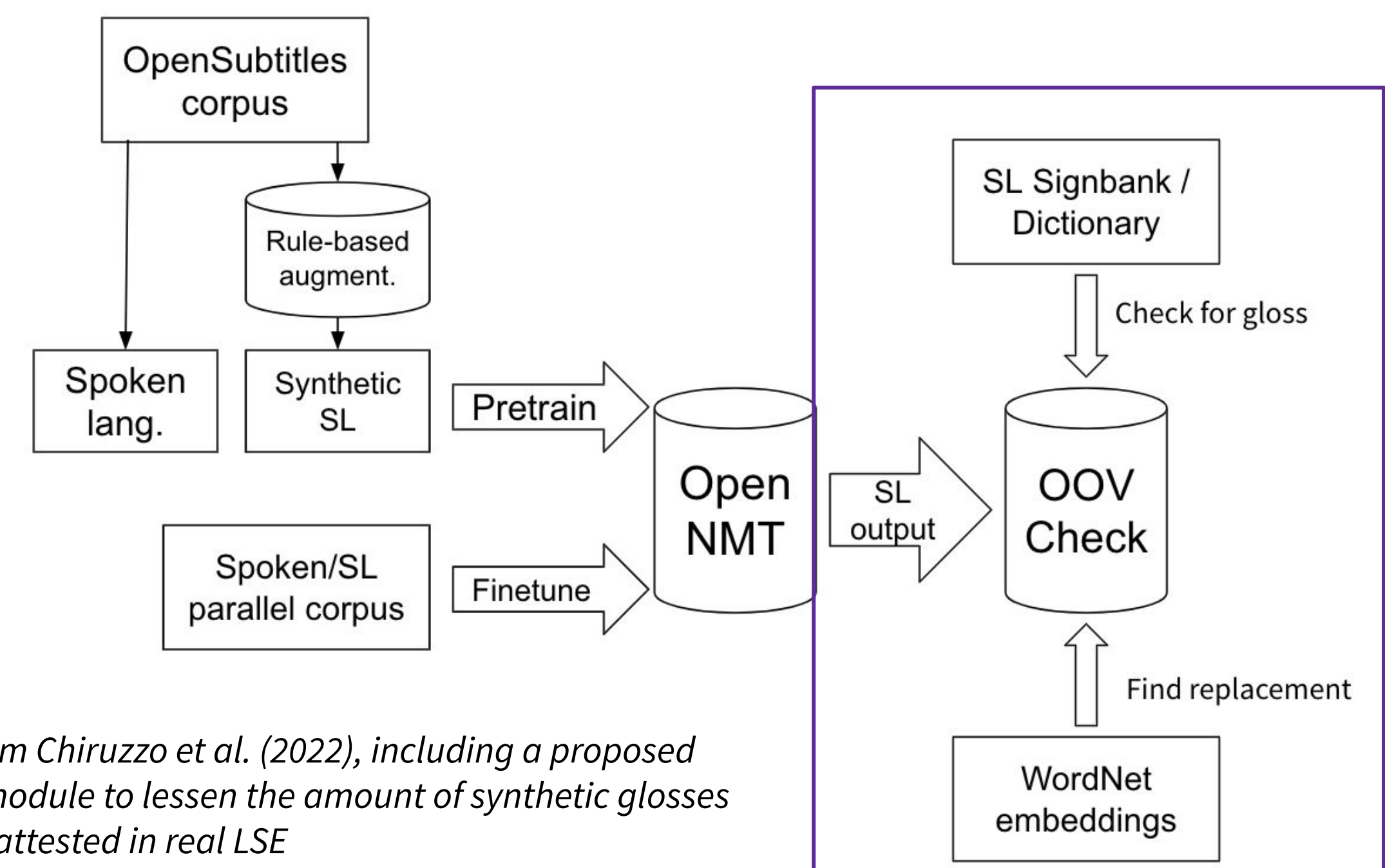
There are approximately **466M¹** people worldwide who experience hearing loss of some kind, of whom **70M²** communicate predominantly through one of **400+** attested³ Sign Languages (SLs). SLs are fully-fledged languages with their **own complex grammar**, and are not typologically related to the spoken languages which coexist in the areas where they are used.

SLMT, or machine translation for signed languages, is a nascent technology, existing for little over 20 years compared with MT for spoken languages which has been studied since the 1950s. There are a few reasons for this:

- (1) d/Deaf and Hard-of-Hearing (**DHH**) communities tend to be marginalised in society - with SLs only becoming officially recognised in European countries in the last few years.
- (2) SLs are produced in the **visual-spatial modality** and in a **non-linear** manner where signs may co-occur in time and space and some of these grammatical features are still not fully understood by linguists.
- (3) There is a **lack of writing system** which is widely used in SLs, so we often use **glosses** which provide a semantically lacking lexeme-based representation.
- (4) The **data problem** - parallel datasets for SLMT are severely limited (De Sisto et al., 2022) in size, scope (SLMT is inherently **multimodal** between visual and textual representations (Bragg et al., 2019)), and standardisation of transcription methods (Cormier et al., 2016).

Our work intends to improve **text-to-gloss** and **gloss-to-text** translation, where glosses act as the **intermediate step** between SL video and spoken language text in the translation pipeline. End-to-end systems exist (e.g. Camgöz et al., 2020), but they are not yet optimally performing for all SL data, particularly that which is *extremely* low resource (Moryossef et al., 2021). We **inject linguistic features** into neural encoder-decoder translation models. This method is known as the **‘factored transformer’** (Sennrich & Haddow, 2016) and has shown particular promise in improving low-resource MT results (Armegnot-Estapé et al., 2021).

For LSE, we also expand small SL datasets using a **rule-based transformation** to monolingual spoken language corpora into **synthetic glosses** based on the **grammatical rules** of a given SL.

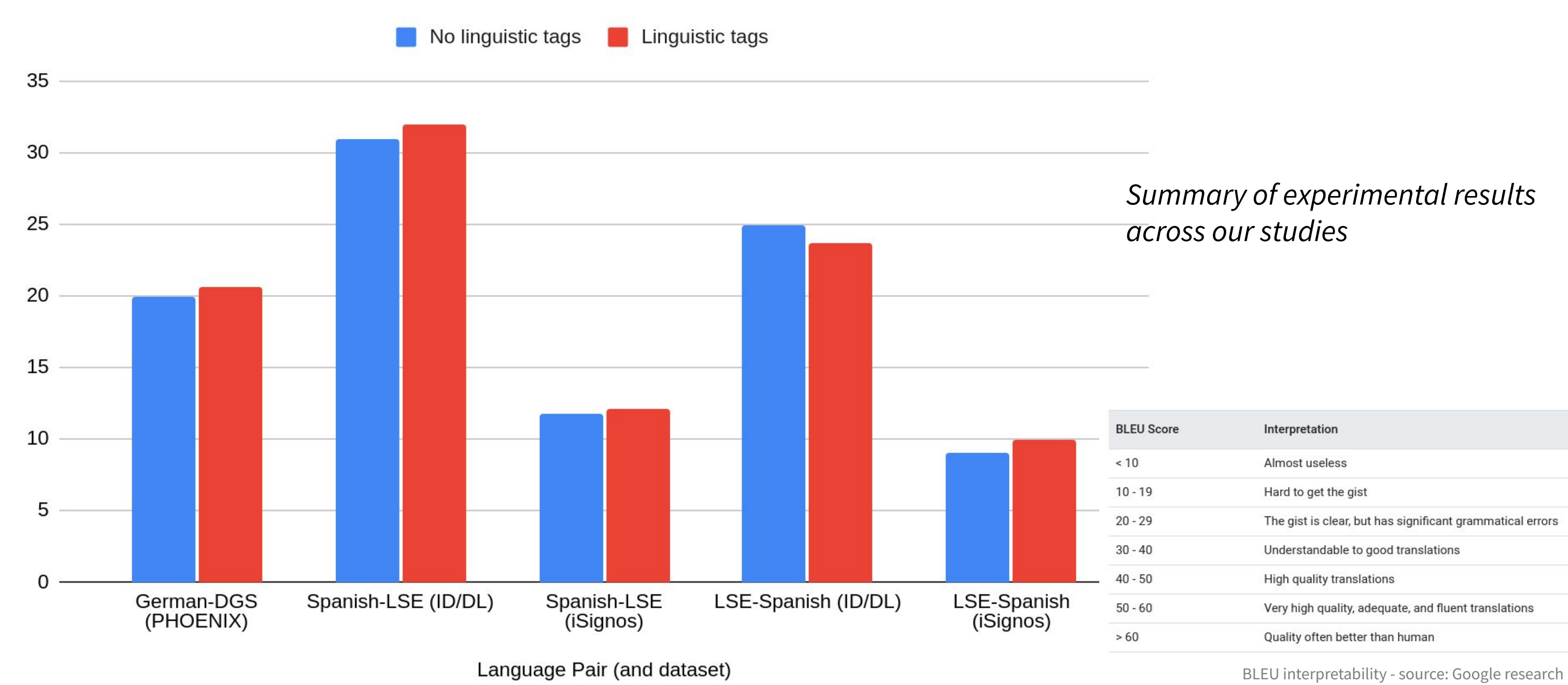


Model dgm from Chiruzzo et al. (2022), including a proposed OOV-checker module to lessen the amount of synthetic glosses which are not attested in real LSE

Spanish↔LSE Text2Gloss and Gloss2Text with linguistic features, pretrained with synthetic gloss data

We first **pre-trained** our model with parallel Spanish-*synthetic* LSE gloss data which we created with a **rule-based** strategy before fine-tuning on Spanish-LSE two different parallel corpora in each study respectively (Chiruzzo et al., 2022; McGill et al., 2023). We again found that linguistic features improved translation performance, but **only Text2Gloss** - this is likely because we used Spanish features for the unrelated language LSE, as there is **no NLP support** for LSE.

Our 2023 work manually PoS-tags LSE data, opening the door for **SL NLP** (Yin et al., 2021) techniques such as creating UD treebanks in future. When using these tags, we now saw improvements in translations in **both Gloss2Text** and Text2Gloss. We plan to do more work in future on automatically tagging SL data.



List of mentioned work:

- McGill, E., Chiruzzo, L., Egea Gómez, S., & Saggion, H. (2023) “Part-of-Speech tagging Spanish Sign Language data and its applications in Sign Language machine translation” *RESOURCEFUL@NoDaLiDa*
- Chiruzzo, L., McGill, E., Egea Gómez, S., & Saggion, H. (2022) “Translating Spanish into Spanish Sign Language: Combining Rules and Data-driven Approaches” *LoResMT@COLING*
- Egea Gómez, S., Chiruzzo, L., McGill, E., & Saggion, H. (2022) “Linguistically Enhanced Text to Sign Gloss Machine Translation” *NLDB@ACM*
- Egea Gómez, S., McGill, E. & Saggion, H. (2021) “Syntax-aware Transformers for Neural Machine Translation” *BUCC@RANLP*

Key references:

- Kearsy Cormier et al. (2016) “Digging into Signs: Emerging Annotation Standards for Sign Language Corpora”
- Rico Sennrich & Barry Haddow (2016) “Linguistic Input Features Improve Neural Machine Translation”
- Danielle Bragg et al. (2019) “Sign Language Recognition, Generation and Translation: An Interdisciplinary Perspective”
- Necati Cihan Camgöz et al. (2020) “Sign Language Transformers: Joint End-to-end Sign Language Recognition and Translation”
- Jordi Armegnot-Estapé et al. (2021) “Enriching the Transformer with Linguistic Factors for Low-Resource Machine Translation.”
- Amit Moryossef et al. (2021) “Data Augmentation for Sign Language Gloss Translation”
- Kayo Yin et al. (2021) “Including Signed Languages in Natural Language Processing”
- Mirella De Sisto et al. (2022) “Challenges with Sign Language Datasets for Sign Language Recognition and Translation”

German→DGS Text2Gloss with linguistic features

Our first experiments in this area (Egea Gómez et al., 2021; 2022) involved enriching gloss representations with syntactic **dependency**, part-of-speech (**PoS**), and **morphological** information (model shown above). We used the ubiquitous PHOENIX-Weather corpus for comparability with other Text2Gloss studies.

Our 2022 study also experimented with different **feature aggregation** methods, or ways of including these linguistic features in the model. We found that using **convolutional block aggregation**, as well **transfer learning** of pre-trained model weights (rather than random initialisation) substantially improved translation performance. Our **best sacreBLEU score was 20.57**, comparable with the highest E2E strategies available at the time.

1) World Health Organisation
2) World Federation of the Deaf
3) SIL International