The SLMT pipeline

SignON and EASIER Final Event 29/11/2023, Brussels



Cloud Platform Architecture



SLR

extract information from input videos containing signed utterances and process it into a suitable format for any downstream task

МТ

convert an input sequence in one language (the source) into another language (target) while preserving its meaning SLS

generate signed utterances in the target sign language. Output: an animation or a video representing a sign language utterance

SLR output/MT input: a symbolic or vectorial representation of signs as tokens MT output/SLS input: a spatio-temporal representation of signs that could be rendered (or interpreted) as a signed utterance.



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017255

3

SLR

extract information from input videos containing signed utterances and process it into a suitable format for any downstream task SLR is the task of extracting information from an input video containing signs, and processing this information into a form suitable for any downstream task, e.g. MT

End-to-end, as with most AI tasks is the preferred way. However, no sufficient high-quality annotated data => feature extractor → sign language classifier



SLR

extract information from input videos containing signed utterances and process it into a suitable format for any downstream task SLR is the task of extracting information from an input video containing signs, and processing this information into a form suitable for any downstream task, e.g. MT

End-to-end, as with most AI tasks is the preferred way. However, no sufficient high-quality annotated data => feature extractor → sign language classifier













This project has receive the European Union's research and innovation programme under grant agreement No 101017255

SLR

extract information from input videos containing signed utterances and process it into a suitable format for any downstream task SLR is the task of extracting information from an input video containing signs, and processing this information into a form suitable for any downstream task, e.g. MT

Isolated SLR = each data example corresponds to a single sign; the objective is to learn how to classify each such sample.

Continuous SLR = data samples contain one or more signs, i.e. a video of continuous signing. The task is then to both locate and recognize signs deriving a sequence of representative tokens.

Train an isolated SLR \Rightarrow

extract SL representations from the data \Rightarrow

use these representations for downstream tasks such as SLMT



SLR model and training



Embedding network ~ Cleaned keypoints Conv-Dense neural network Transformer neural network [0.13,-1.72,...,1.22] Embedding vector

Available gloss-labeled training data

	VGT	NGT	ISL	BSL
Samples (sign videos)	24967	68854	4103	2635
Classes (different glosses)	292 [*]	458 [*]	224**	124**
Different signers	111	82	37	48

* : only glosses with at least **20 examples** **: only glosses with at least **5 examples**



SLR: evolution since mid-term review

New model was developed*:

> powerful/efficient model architecture> significant improvement for all SLs

Mitigating limited data set size:

- multi-language pre-training + fine-tuning for each language
- pre-training on largest dataset (NGT), only training classification head for target language
 - > improvement for ISL/BSL
 > worse for VGT
- pre-training on largest dataset (NGT), transfer & fine tuning for target language

> Best results thus far!

*: Kaggle competition (ASL-ISLR):

> 94,000 samples with 250 glosses
 > SignON ranked 16th/1165 - 86.6% accuracy



Top-5 accuracy

Very high for NGT/VGT

Embeddings contain relevant information about gloss Mistakes are often confusions between similar glosses

SLR model predictions

Example 1



Annotation: SCHILDPAD EERST AANKOMEN Prediction: SCHILDPAD EERST AANKOMEN



Annotation: WANNEER MOETEN AUTO HALEN WETEN-NIET IK Prediction: WANNEER WG-3 MAAR ROLLEN AUTO-RIJDEN PAKKEN WG-3 OK WETEN-NIET IK Only glosses with predicted probability >0.4 kept red = wrong, *light green cursive* = similar, **dark green** = correct



Annotation: WAT WILLEN ETEN JIJ Prediction: VINDEN WAT <missing> <missing> JIJ ZOEKEN MOOI

Testing on newly recorded phrases:

- **Example 1:** perfectly predicted
- Example 2:

some wrong glosses instead of missed gloss (MOETEN), some glosses not exact but very close

Example 3:

some spurious glosses (start and end of recording) some glosses missed (each *predicted as 3rd option*)

-> analyses/user feedback will be used to make further improvements



Machine translation is the process of automatically translating content from one language (the source) to another (the target) without human intervention.

RBTM	(PB)SMT	NMT - RNN	NMT - Transformer	NOW
Human-crafted rules. Difficult to update. But can work (relatively well) for low-resource languages.	Data-driven. Phrase-based translation probabilities. Translation and language models. Decoder. Noisy Channel.	Encoder-decoder architecture. LSTMs and attention to solve problems with long sequences. One token after another.	Self-attention. Positional encoding. Feed-forward networks. Can be parallelised. Efficient and high quality. Mimics the way humans would translate a	BERT, ELMO, GPT, XLM, NLLB Unsupervised models. Better data preprocessin Multi-lingual, multimodal models.
	First commercial breakthroughs. Has reached its limits	Cannot be parallelised.	sentence.	Pay more attention to linguistics. Control bias

Machine Translation Module





This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017255

[1] Camgöz, N. C., Saunders, B., Rochette, G., Giovanelli, M., Inches, G., Nachtrab-Ribback, R., & Bowden, R. (2021, December). Content4all open research sign language translation datasets. In *2021 16th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2021)* (pp. 1-5). IEEE.

Machine Translation Module



	Text-to-text results on Paracrawl					
Metric / Data	EN-GA	GA-EN	EN-ES	ES-EN	EN-NL	NL-EN
BLEU	48.56	55.38	40.68	41.21	43.97	48.75
TER	0.50	0.46	0.50	0.51	0.59	0.55

Sign-to-text results			
Metric / Data	Phoenix2014T	Content4All VRT-NEWS	
BLEU	22.66	0.44	
CHRF	48.58	16.5	
ROUGE	43.86	8.94	



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017255

[1] Camgöz, N. C., Saunders, B., Rochette, G., Giovanelli, M., Inches, G., Nachtrab-Ribback, R., & Bowden, R. (2021, December). Content4all open research sign language translation datasets. In *2021 16th IEEE International Conference on Automatic Face and Gesture Recognition (FG 2021)* (pp. 1-5). IEEE.

Machine Translation Module

SLT results on Content4All's VRT-NEWS VGT-Dutch dataset

- Much lower than SLT results on Phoenix2014T.
- Similar to the SLT results obtained...
 - in the original paper.
 - in the WMT shared task (although the dataset is not the same) [2].

Reasons for the low results

- Insufficient amount of data (~7,000 video-sentence pairs for training).
- Phoenix2014T has a narrower domain (weather forecast), smaller vocabulary (~2,000-3,000 subwords).
 - Moreover, glosses were used in the training.
- The domain of the datasets used for SLR and SLT do not match.

Conclusions

- Results comparable to the state of the art.
- Continuous model / architectural improvements

	BLEU			
Submission	all	SRF		
UZH (baseline)	$0.12{\pm}0.06$	$0.09{\pm}0.03$	0.	
DFKI-SLT	$0.08{\pm}0.01$	$0.10{\pm}0.04$	0.	
DFKI-MLT.1	$0.07 {\pm} 0.05$	$0.05{\pm}0.02$	0.	
DFKI-MLT.2	$0.11 {\pm} 0.06$	$0.08{\pm}0.03$	0.	
DFKI-MLT.3	$0.08{\pm}0.04$	$0.06{\pm}0.02$	0.	
DFKI-MLT.4	$0.02{\pm}0.01$	$0.02{\pm}0.01$	0.	
DFKI-MLT.5	$0.04{\pm}0.02$	$0.03{\pm}0.00$	0	
MSMUNICH.1	$0.44{\pm}0.21$	$0.34{\pm}0.18$	0.	
MSMUNICH.2	$0.56{\pm}0.30$	$0.28{\pm}0.13$	0.	
NJUPT-MTT.1	$0.09 {\pm} 0.01$	$0.13 {\pm} 0.03$	0.	
NJUPT-MTT.2	$0.10{\pm}0.01$	$0.13{\pm}0.03$	0.	
OF ADDIC 1	0.051.0.10	0.20 1.0.10	0	



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017255

[2] Mathias Müller et al. (2022) [Swiss German Sign Language -> German] Findings of the First WMT Shared Task on Sign Language Translation (WMT-SLT22) Sign language synthesis (SLS) or sign language production is the task of generating a synthetic representation that can exhibit properties of a human signer and utter a message in a SL through the expression of manual features (hand configuration, location, and orientation) and non-manual features (including facial expressions, mouthing and mouth gestures, gaze and torso direction).

SLS

generate signed utterances in the target sign language. Output: an animation or a video representing a sign language utterance

- 3D animation-based approach which resolves in generating a 3D animated character, commonly referred to as an avatar
- a (video of a) virtual human that can be synthesised with generative AI methods based on real human video/image data (see the work of Stoll et al. (2020)).



Sign language synthesis (SLS) or sign language production is the task of generating a synthetic representation that can exhibit properties of a human signer and utter a message in a SL through the expression of manual features (hand configuration, location, and orientation) and non-manual features (including facial expressions, mouthing and mouth gestures, gaze and torso direction).

SLS

generate signed utterances in the target sign language. Output: an animation or a video representing a sign language utterance

- 3D animation-based approach which resolves in generating a 3D animated character, commonly referred to as an avatar
- a (video of a) virtual human that can be synthesised with generative AI methods based on real human video/image data (see the work of Stoll et al. (2020)).



Text to AMR

- Abstract meaning representation (Banarescu et al., 2013)
- Represents ("extracts") meaning from a given sentence
- Lexicon is in "English" regardless of input language
- We developed EN/NL/ES → AMR multilingual (91.8% acc) and EN → AMR monolingual (93.6% acc) neural model (based on mBART)

Ex. The girl eats the cookies that her mother baked

1. Linearized AMR form

eat-01 girl cookie bake-01 person have-rel-role-91 mother

2. Concepts only:

eat girl cookie bake mother



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017255

¹Demo: <u>https://huggingface.co/spaces/BramVanroy/text-to-amr</u>



Look up concepts in modified SignBanks

We modified the NGT/VGT SignBanks to include English "translations" so we can do reverse look-ups (English word \rightarrow gloss)

- Multilingual WordNet
- ChatGPT: "context-sensitive" translations
- Similarity filtering with LABSE vectors

So continuing with English concepts extracted from AMR... eat girl cookie bake mother

3. Reverse look-up the English AMR concepts \rightarrow gloss (ex. is VGT)

ETEN-A MEISJE-B KOEK-C BAKKEN-A MOEDER-A

4. Remove regional identifier

ETEN MEISJE KOEK BAKKEN MOEDER



SignON Synthesis Pipeline



-18



Focus Tasks

Top-to-bottom Synthesis Strategy

Top: sign animations

Automatic estimation of NMFs

Edition of NMF behaviours

Exportability of final animation

MFs edition with IK solvers



Bottom: spatial behaviours



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017255 Substantial work on supporting available datasets in HamNoSys and SiGML encoding.

- + Contribution to reduce the scarcity of data in sign language.
- + Support of previous sign projects.
- + Support of sign language research groups.



SignON is not only about sign to sign translation













Cloud Platform Architecture



Thank you!

SIGNON



This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 101017255

25