Context matters: Self attention for Sign Language Recognition

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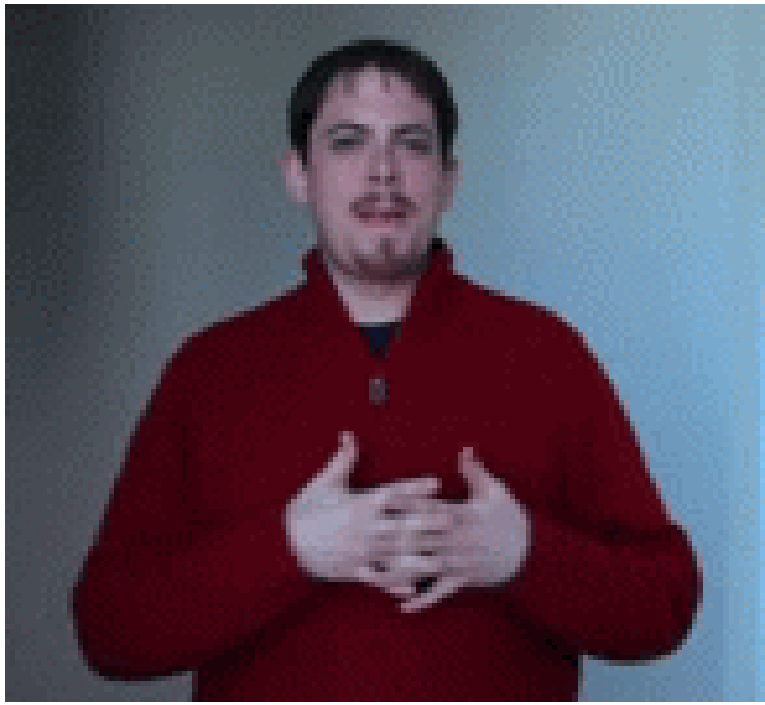
Goal : Sign Language recognition System

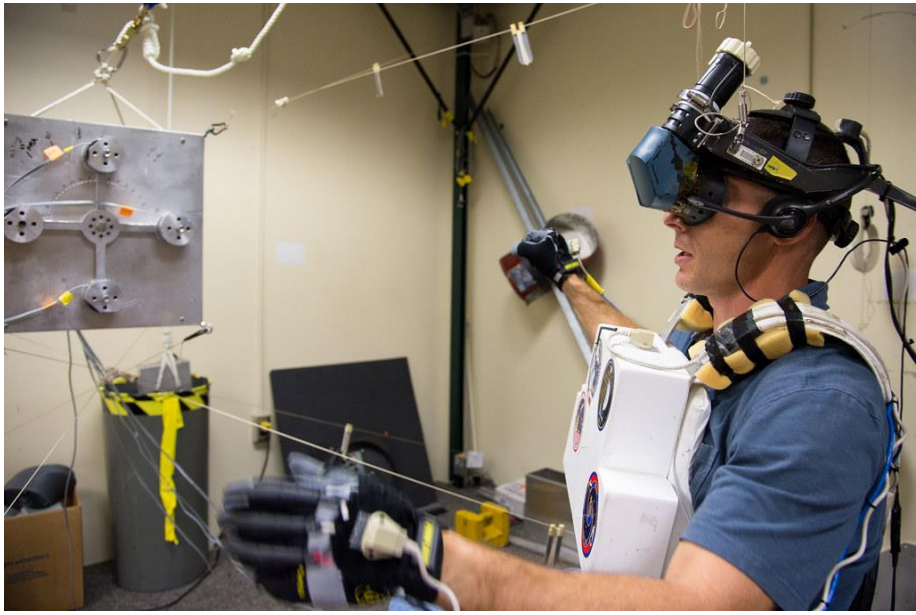
- Recognize continuous SL gestures.
- Capture SL gesture information from space and time.



Input : Only RGB data

Literature on Sign Language Recognition

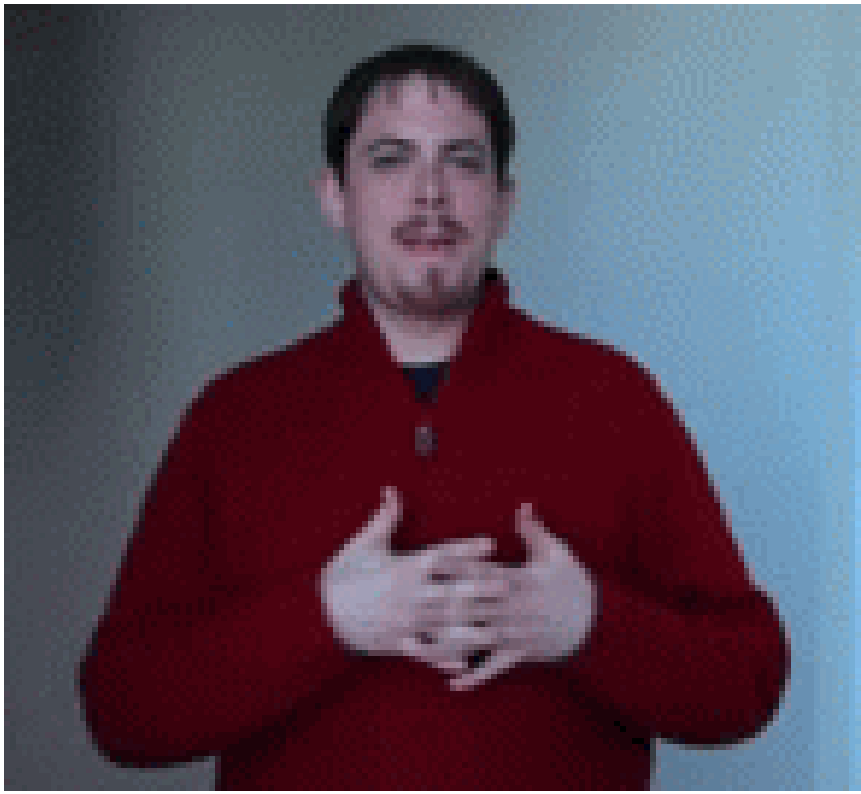
- Glove-based methods.
- Motion tracking gadgets and sensors.



Sign Language Gestures = Hand articulations + non-manual components

→ Multiple channels of information

- Non-manual components provide semantic context to the dominant hand.



VS

Man

Woman

VS

Sit

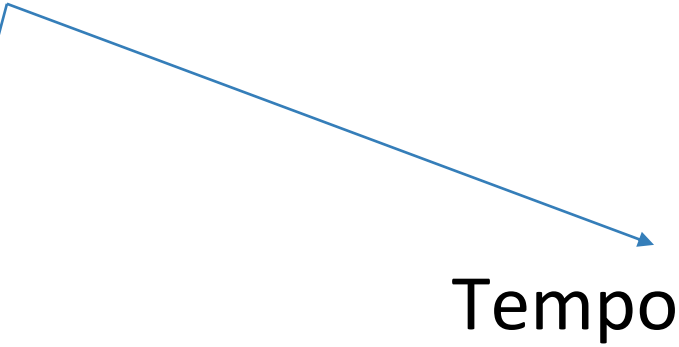
Chair

VS

- "Is it you?"
- "Are you ... ?"
- "Did you?"

- It's *you?!*?!
  (I am surprised that it is you.)

Sign Language Gestures =
Dominant Handshape
+
Contextual Information



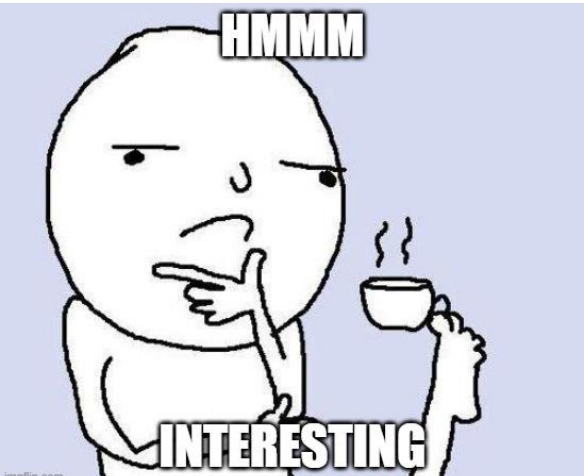
Spatial Information
(Around the handshape)

Temporal Information
(Hand and Body movements)

Key insight

“

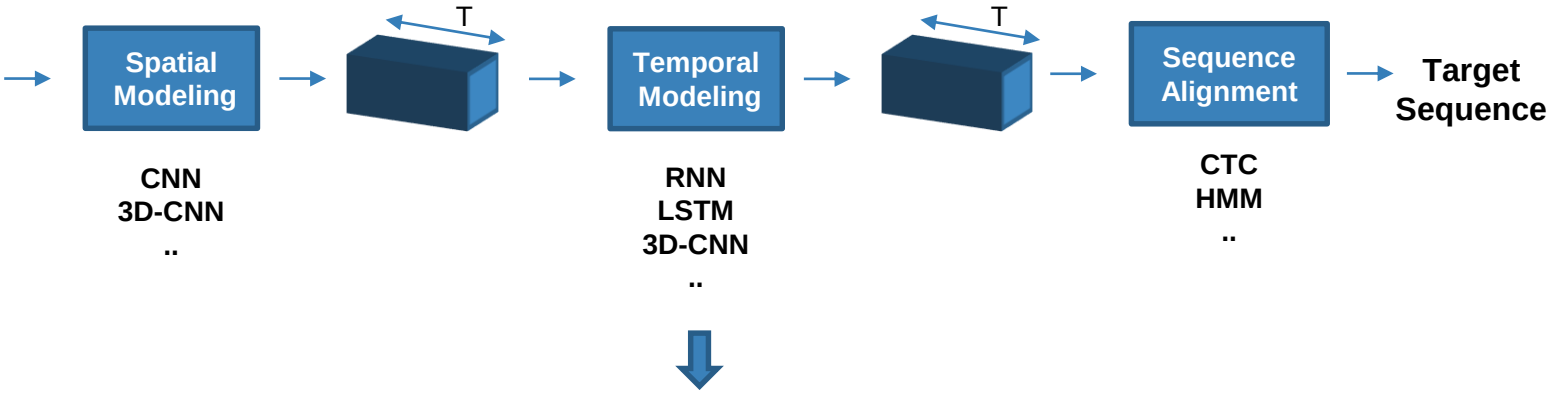
Signs require recognizing the handshape accompanied by its contextual information.



⟹ CONTEXT MATTERS !!

Typical architecture for Sign Language Recognition

Input Clip



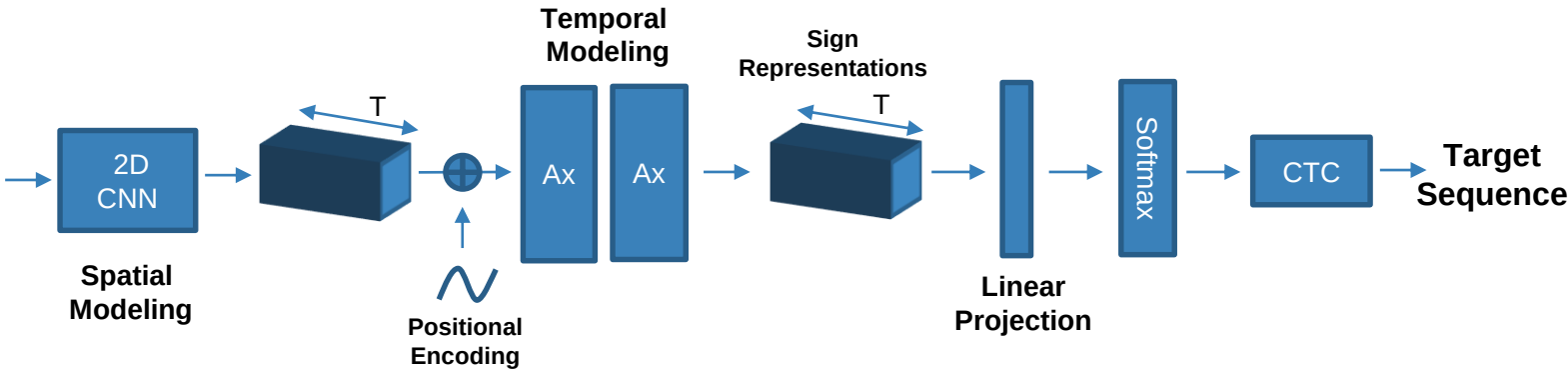
Transformer Network

Attention Is All You Need by Ashish et al.

CTC : Connectionist Temporal Classification
HMM : Hidden Markov Model

SIGN ATTENTION NETWORK (SAN)

Sign Clip



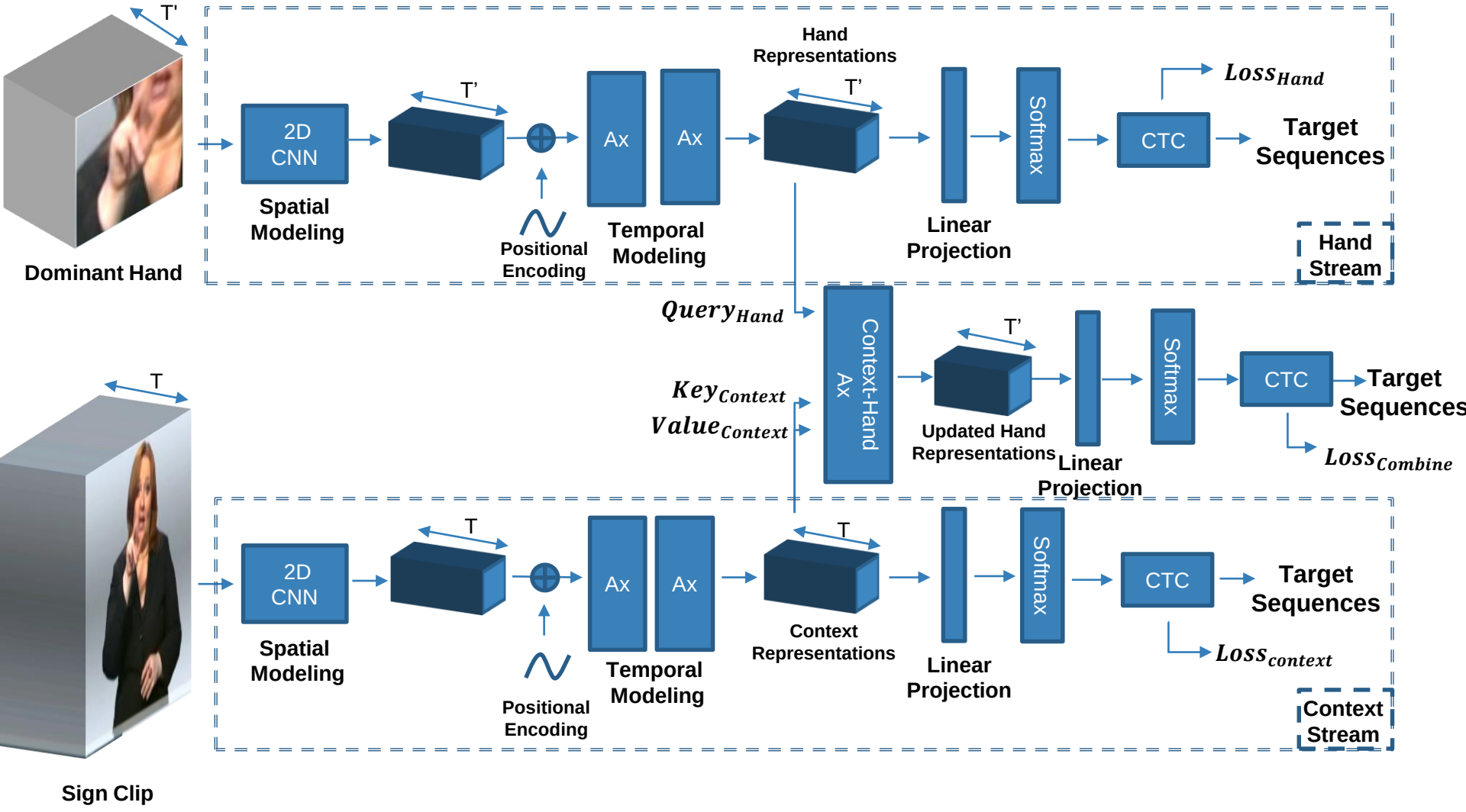
Key insight:

- Signs are recognizable from the state of the body, apart from the handshape

Solution:

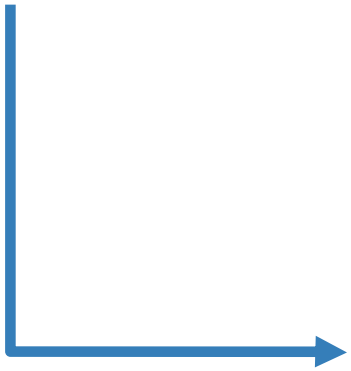
- Exploit spatiotemporal context around the handshape to recognize the sign

SIGN ATTENTION NETWORK
With Hand Stream



SubUNets: End-to-end Hand Shape and Continuous Sign Language Recognition

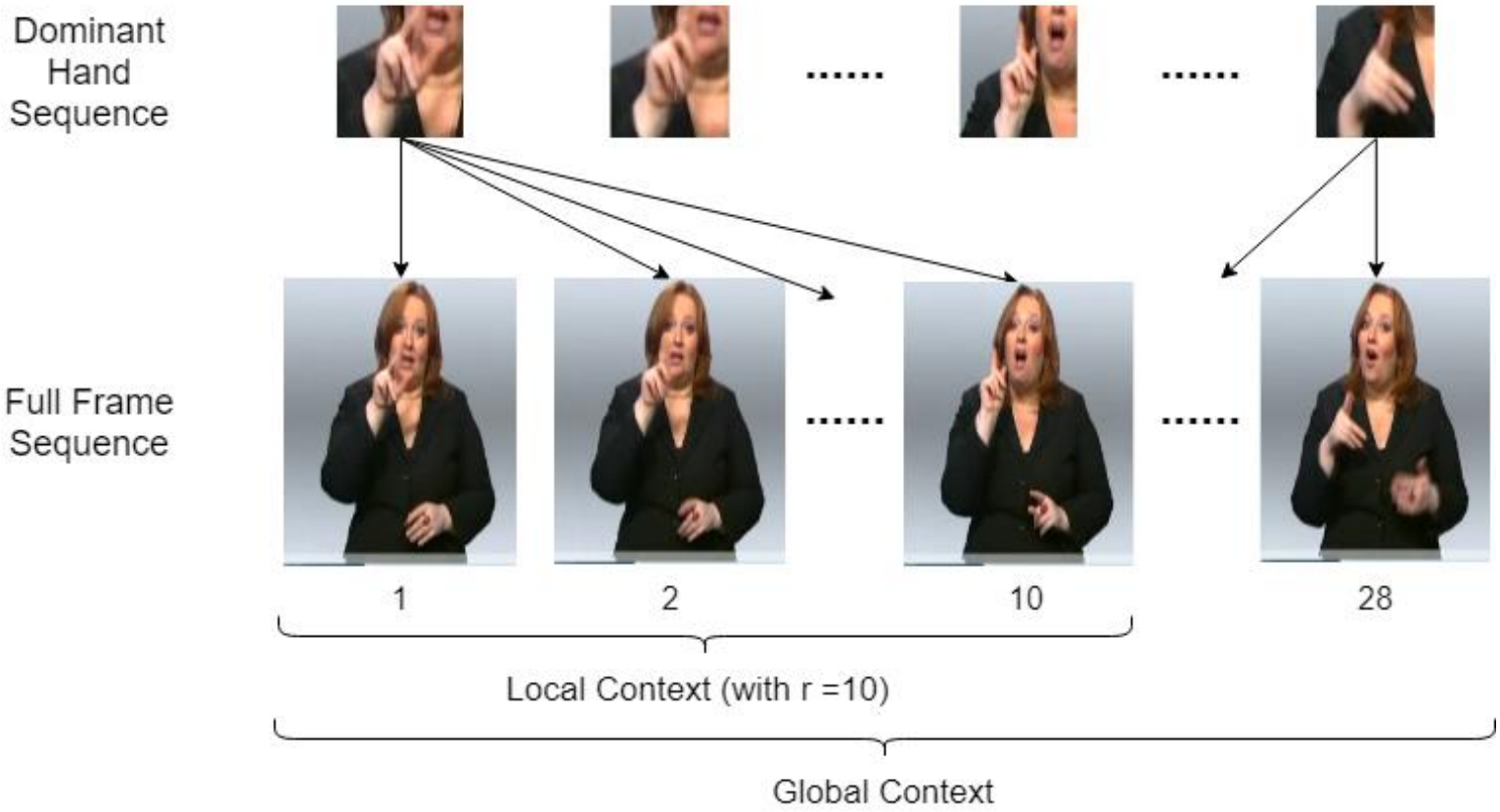
Sign language components have complex relations.



Attention

<u>Efficiently capture dependencies</u> between manual and non-manual components.

SIGN ATTENTION NETWORK
With Relative local Context masking



Implementation Details

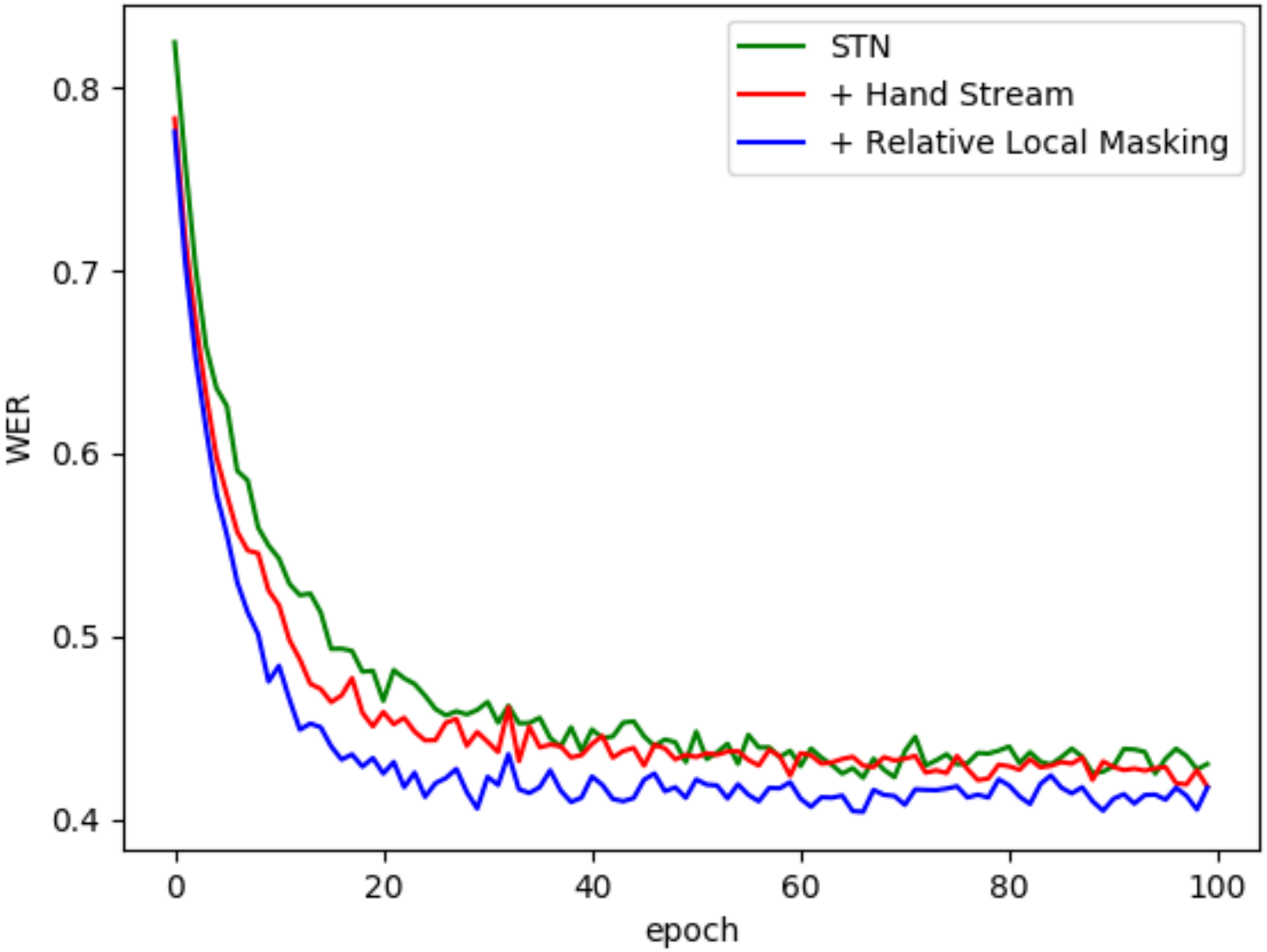
- Extract T keyframes (mostly 64) from original video clip.
- Resize full-frame and hand frames to 224 x 224 and 112 x 112.
- Normalize input images by subtracting the dataset's image pixels mean.
- We use the MobilenetV2 CNN architecture for feature extraction.

Word Error Rate (WER)

$$WER = \frac{\#\text{deletions} + \#\text{insertions} + \#\text{substitutions}}{\#\text{number of reference observations}}$$

Comparison SAN variations

	Dev	Test
SAN	35.33	35.45
+ Hand Stream	33.68	34.12
+ Relative Local Masking	**32.74**	**33.29**


STN
+ Hand Stream
+ Relative Local Masking
WER
0.8
0.7
0.6
0.5
0.4
0
20
40
60
80
100
epoch

Pretraining methods

Pre-Training	Dev	Test
ImageNet	32.74	33.29
RWTH-PHOENIX-Weather 2014	**29.02**	**29.78**

➡ Model is too complex to generalize using our dataset.

Better initialization scheme for our model by firstly training the spatial feature extractor (CNN) on the same dataset.

Quantitative Evaluation on the RWTH-PHOENIX-WEATHER 2014 DATASET in WER %

	Dev	Test
SAN	**29**	**29.7**
Koller et al. (CNN-2BLSTM) [7]	32.7	32.9
Koller et al. (CNN) [7]	33.7	33.3
Huang et al. [9]	-	38.3
Cui et al. [17]	39.4	38.7
Koller et al. [6]	38.3	38.8
Camgoz et al. (HMM-LM) [10]	40.8	40.7
Camgoz et al. (CTC) [10]	43.1	42.1
Koller et al. [35]	47.1	45.1
Koller et al. [27]	57.3	55.6

O. Koller, J. Forster, and H. Ney. Continuous sign language recognition: Towards large vocabulary statistical recognition systems handling multiple signers. Computer Vision and Image Understanding, volume 141, pages 108-125, December 2015.

Qualitative Analysis

SAN

+ Hand Stream

+ Relative Local Masking

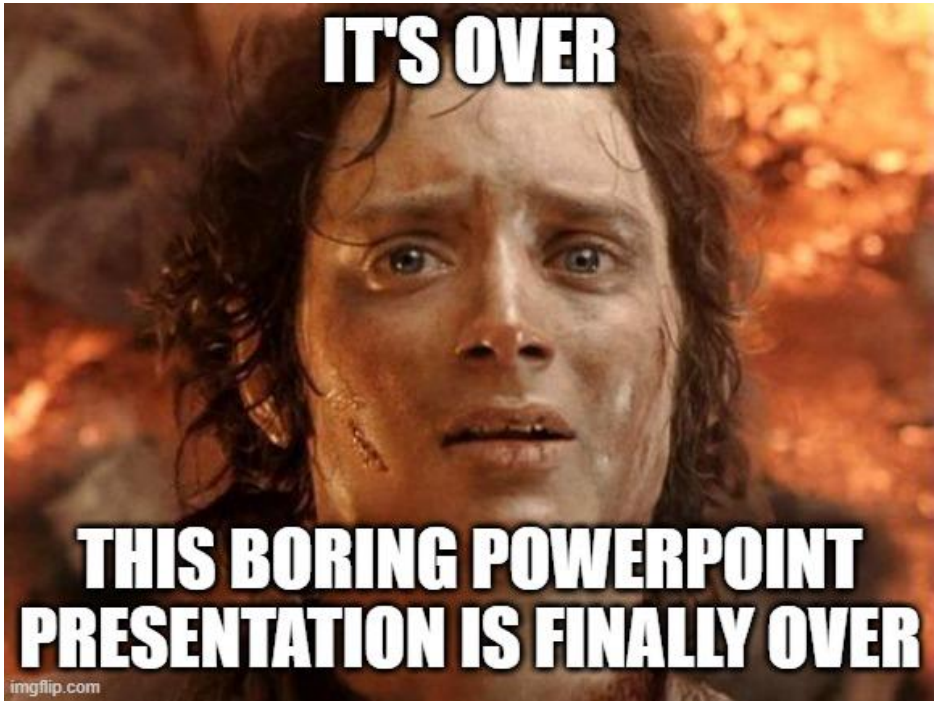
Thank you !!!

References:

- Memes created by : Meme Generator - Imgflip
- SIGN Regonition Dataset: https://www-i6.informatik.rwth-aachen.de/~koller/RWTH-PHOENIX/

Papers:

- Video Action Transformer Network
- Neural Sign Language Translation
- SubUNets: End-to-end Hand Shape and Continuous Sign Language Recognition



Code (GitHub):

The official PyTorch implementation of "Context Matters: Self-Attention for sign Language Recognition"

- **https://github.com/faresbs/slrt**