NLP for Signed Languages: Challenges and Opportunities

Kayo Yin

Berkeley NLP

Berkeley AI Research

Arguments for today's talk

1. The linguistic complexity of signed languages gives rise to unique NLP challenges

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2. Awareness of the language and the community helps us build practical NLP models

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Common misconceptions of signed languages

- Not just gestures for spoken language

“Name”

American Sign Language

British Sign Language

Common misconceptions of signed languages

- Not just gestures for spoken language
- Not just hand gestures

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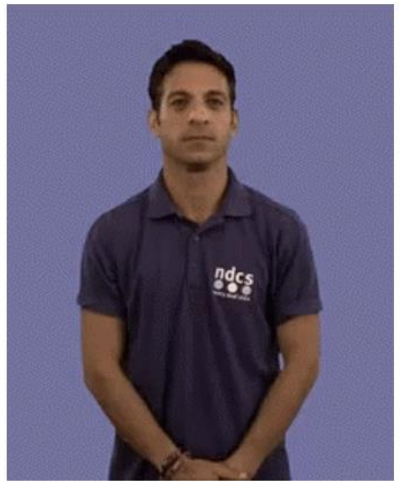
American Sign Language



British Sign Language

Common misconceptions of signed languages

- Not just gestures for spoken language
- Not just hand gestures
- Not just 1 universal sign language

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Common misconceptions of signed languages

- Not just gestures for spoken language
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- Not just 1 universal sign language
- Not slower than speaking

“Name”

American Sign Language

British Sign Language

Signed languages are crucial

- Only 30-40% of English speech can be lipread

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- Cochlear implants do not provide complete access to spoken language

Signed languages are crucial

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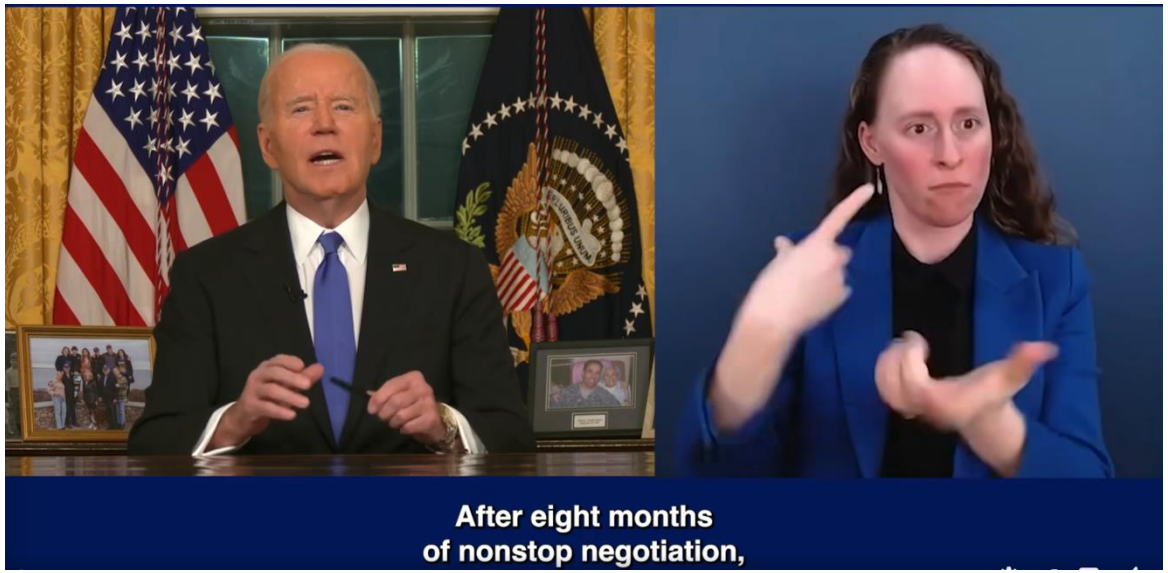
- Cochlear implants do not provide complete access to spoken language
- Integral to Deaf culture

Why not just use subtitles / text?



- Convey tone, emotion

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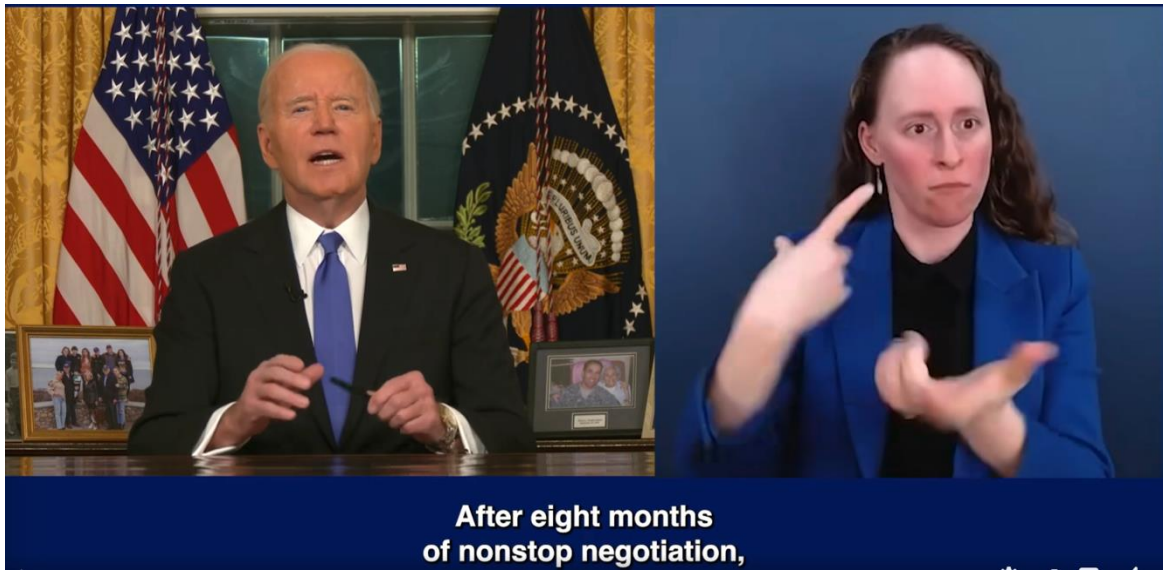

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- Literacy levels vary among signers

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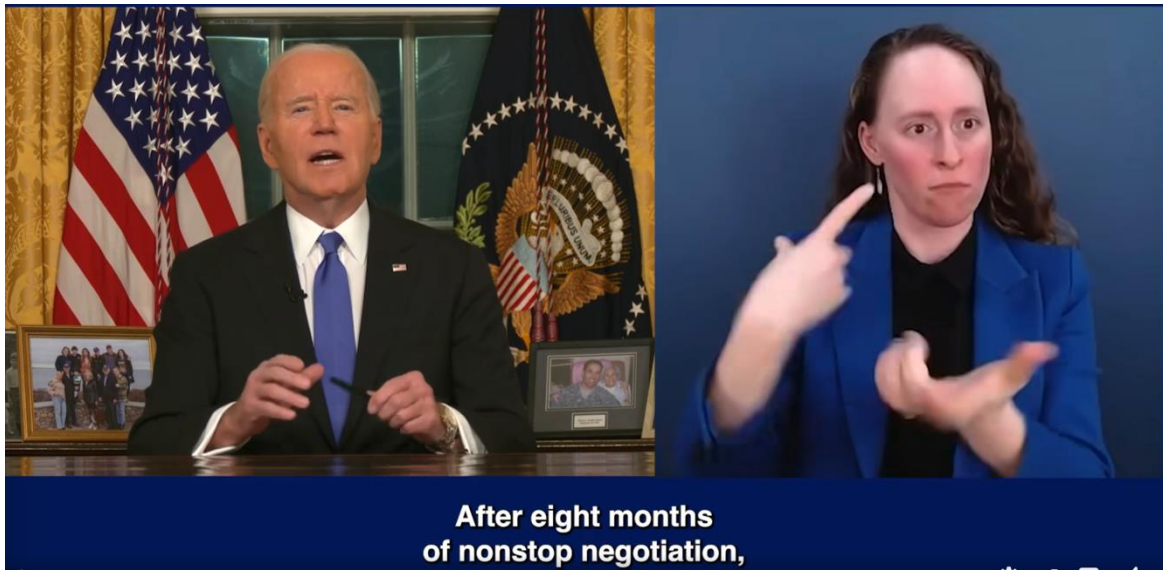


- Convey tone, emotion
- Literacy levels vary among signers
- Primary / most accessible language for many

Possible applications of AI

Translation

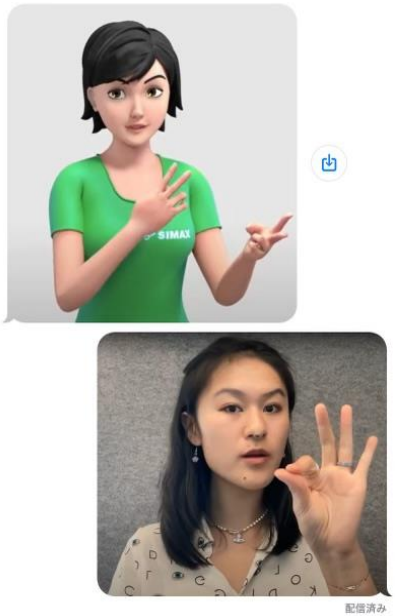
Possible applications of AI

Translation

Education

Possible applications of AI

Translation

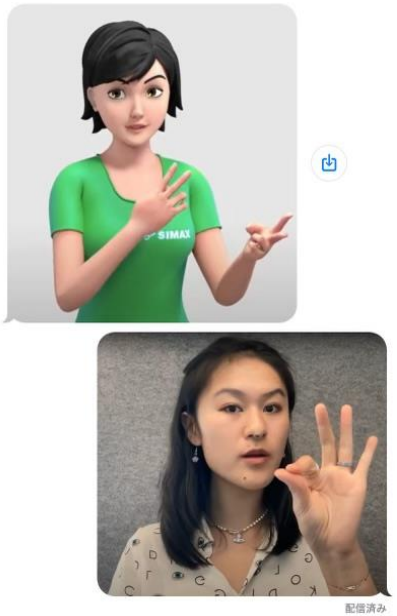


Chatbots

Education

Possible applications of AI

Translation



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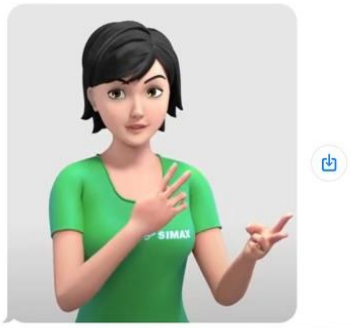

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Information retrieval

Current progress in AI for signed languages

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- 101 papers between 2021-2023 (Desai et al., 2024)

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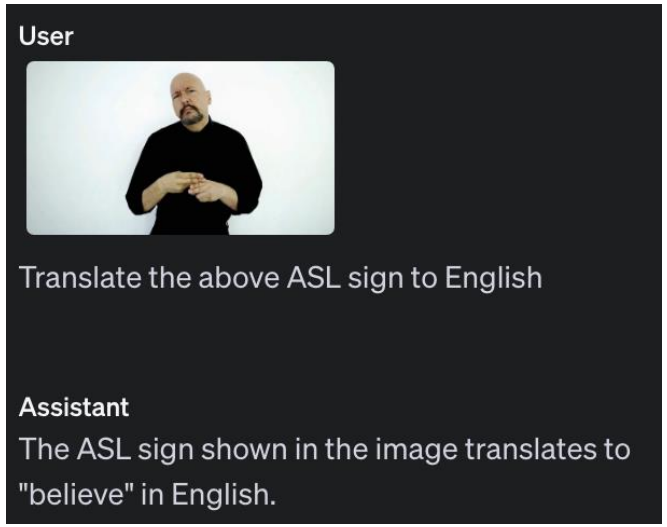

GPT-4o
(OpenAI, 2024)

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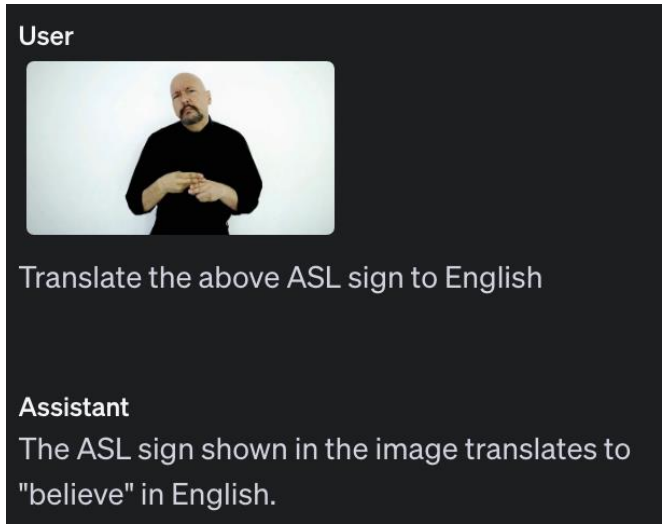

GPT-4o
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“Sign language gloves”

Challenge: data

- ~ 40 public datasets
  - Largest: ~1000 hours

BOBSL dataset
(Albanie et al., 2021)

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- Lack of experts
- Consent and privacy?

BOBSL dataset
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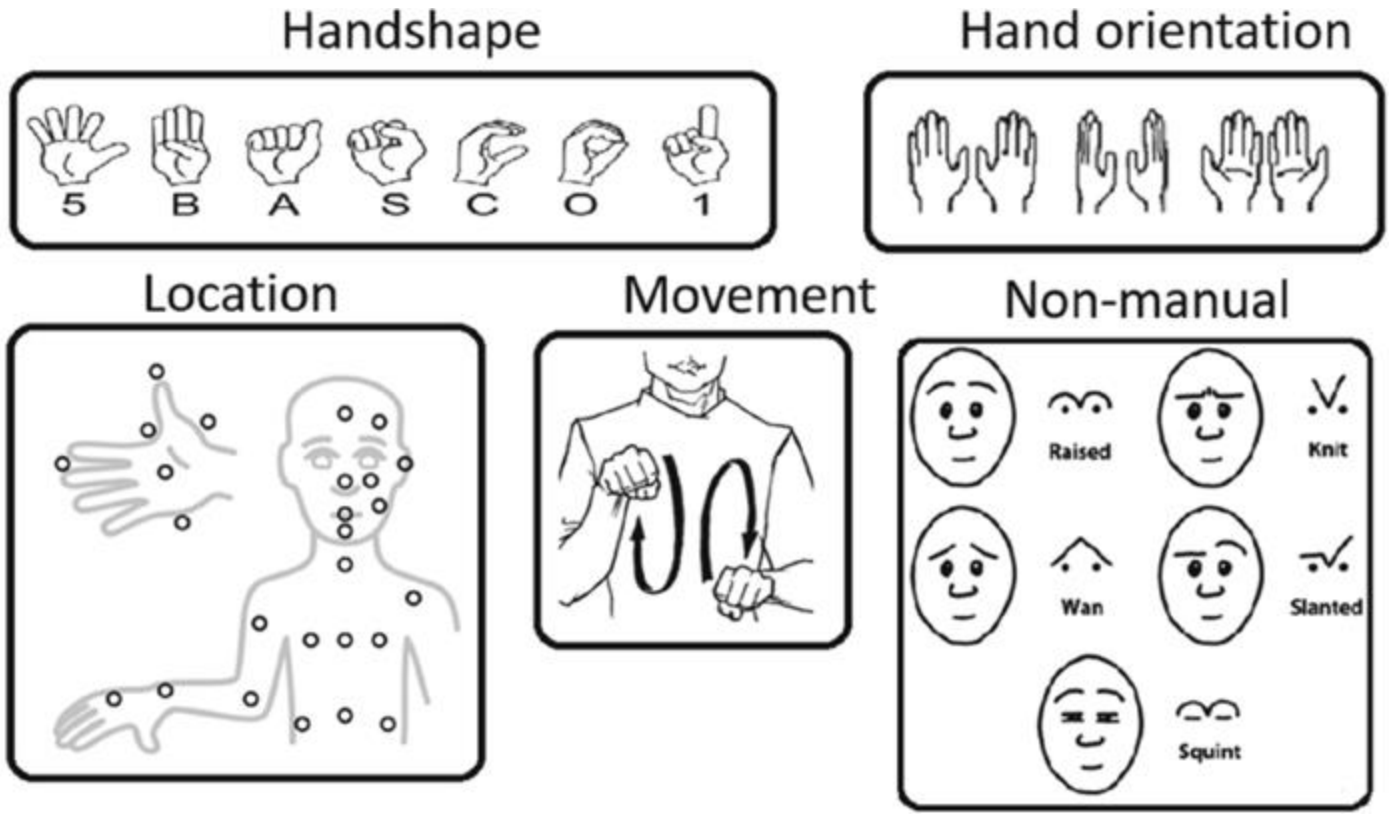
Challenge: simultaneous channels



5 phonological parameters of ASL

Challenge: spatial dependencies

Directional verbs in ASL

Challenge: Deaf-centric design

April 12, 2016

UW undergraduate team wins $10,000 Lemelson-MIT Student Prize for gloves that translate sign language

Wearable-tech glove translates sign language into speech in real time

The device is inexpensive, flexible and highly durable, UCLA bioengineers say

Matthew Chin
June 29, 2020

Hand-ear co-ordination: Interactive glove translates sign language into speech

Infinity Glove, a Lebanon-based start-up, seeks to help translate sign-language into speech by using a high tech glove solution. Cody Combs / The National

Cody Combs
Feb 21, 2024

Listen In English Listen in Ar

Powered by automated trans

Challenge: Deaf-centric design

Why Sign-Language Gloves Don't Help Deaf People

Wearable technologies that claim to translate ASL overlook the intricacies of the language, as well as the needs of signers.

By Michael Erard

Sign Language Translating Devices Are Cool. But Are They Useful?

Emily Matchar

Innovation Correspondent

February 26, 2019

News & Views | Published: 15 July 2020

WEARABLE TECHNOLOGY

Do deaf communities actually want sign language gloves?

Joseph Hill

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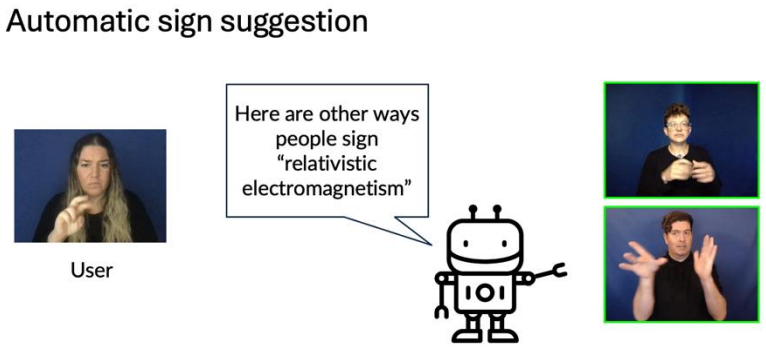
ASL STEM Wiki




Dataset to support
DHH students in STEM

ASL STEM Wiki: Dataset and Benchmark for Interpreting STEM Articles. Yin et al. (2024)

ASL STEM Wiki



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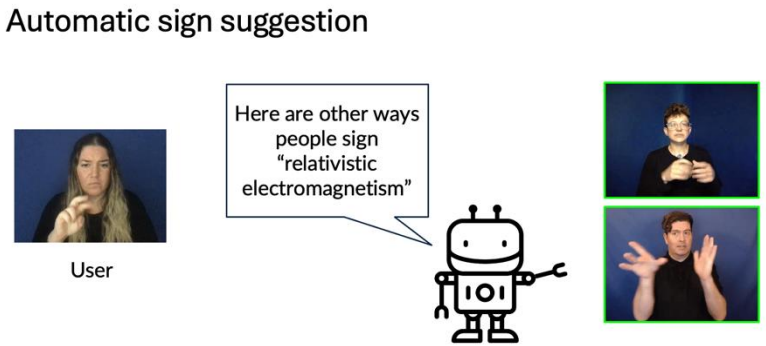

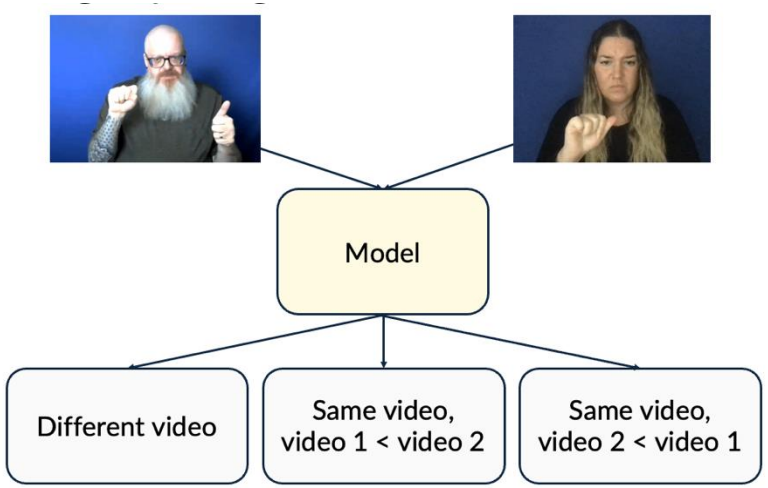

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Tool to assist ASL interpreters, informed by linguistic properties and Deaf pedagogy

Self-supervised sign language modeling for data efficiency

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Barriers to STEM education for DHH students

- ASL -> primary and most accessible language for many deaf and hard-of-hearing (DHH) students in the US

“Relativistic electromagnetism”

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“Relativistic electromagnetism”

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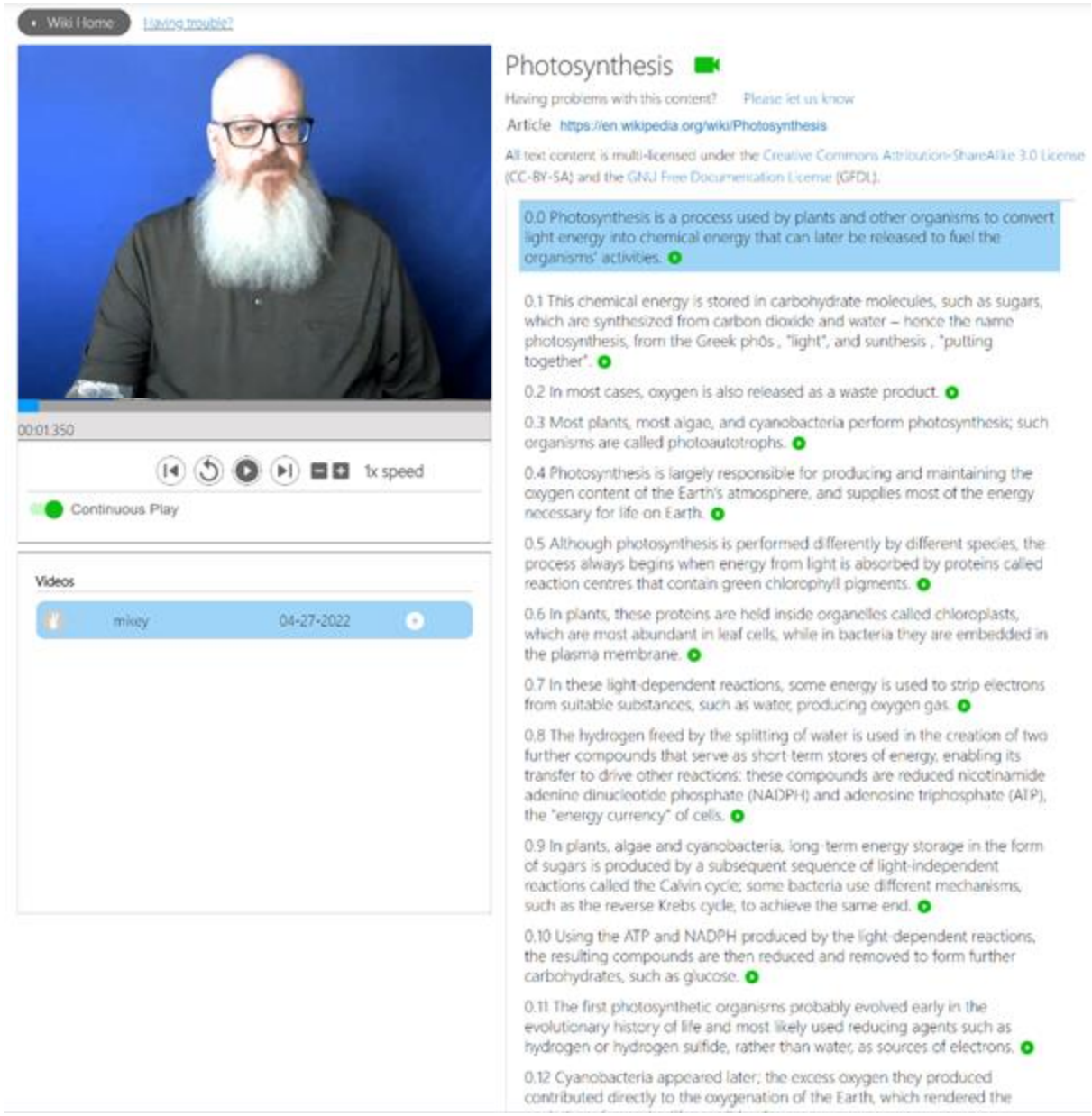
- STEM resources in ASL are **scarce**
- Lack of **standardized ASL signs** for technical words

“Relativistic electromagnetism”

ASL STEM Wiki

- 254 Wikipedia articles
  - Science, technology, mathematics, medicine, geography



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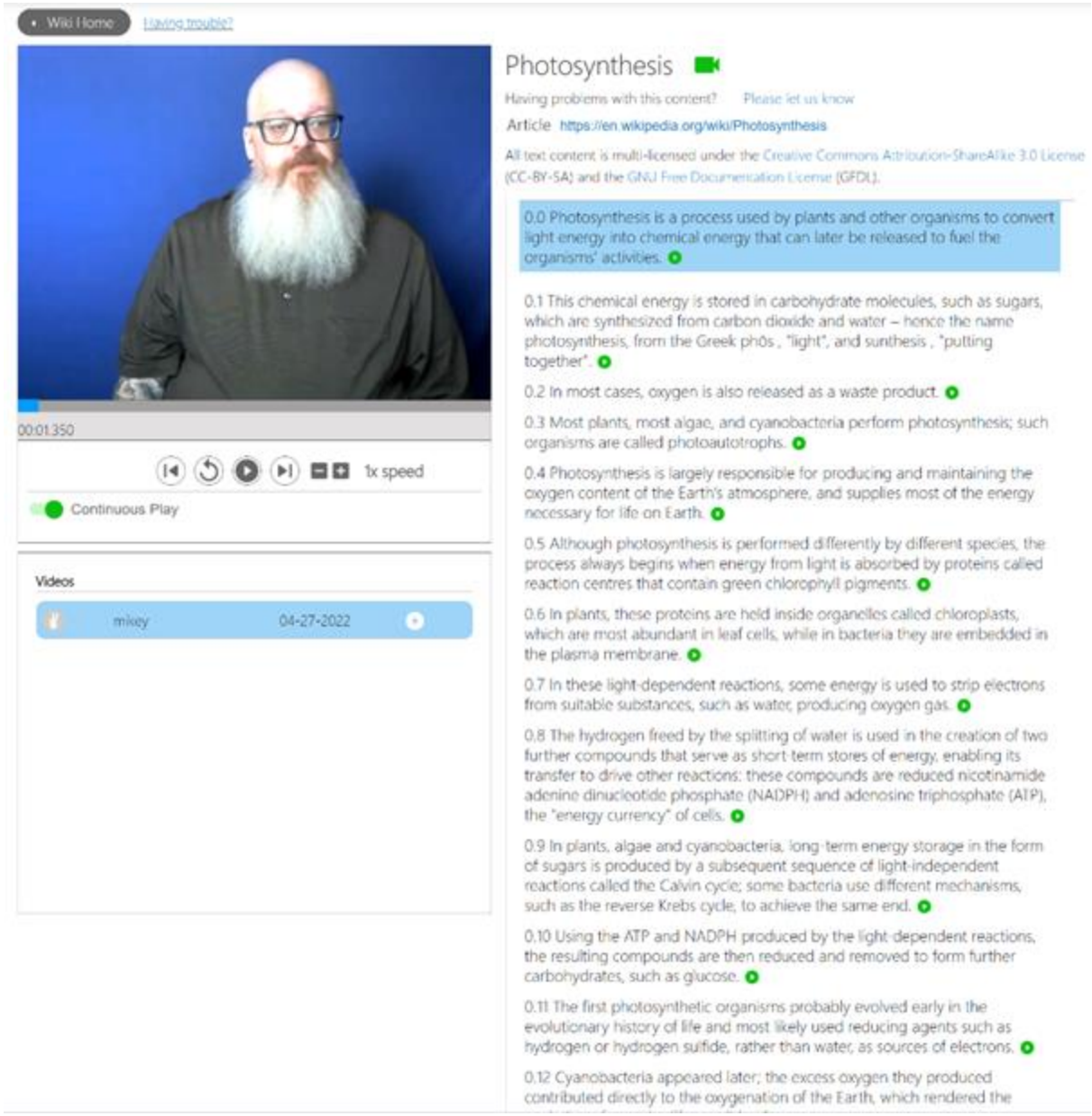
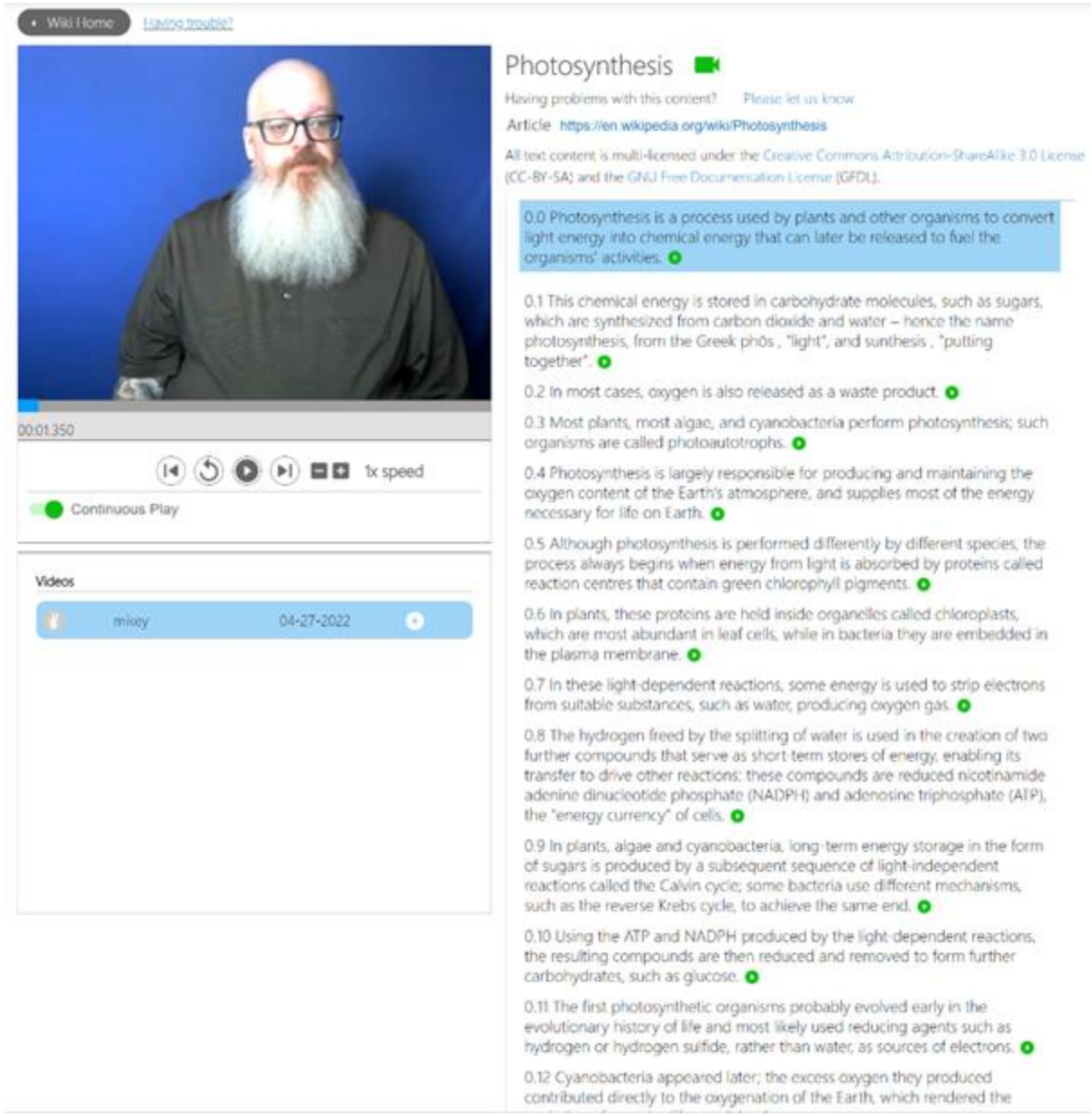
- 254 Wikipedia articles
  - Science, technology, mathematics, medicine, geography
- 37 certified ASL interpreters



ASL STEM Wiki

- 254 Wikipedia articles
  - Science, technology, mathematics, medicine, geography
- 37 certified ASL interpreters
- 300+ hours



Contributions

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3. New AI tool: **automatic sign suggestion**
4. New modeling technique: **contrastive learning** for signed language

Linguistic analysis – fingerspelling in ASL STEM Wiki

High rate of fingerspelling in ASL STEM Wiki

“Relativistic electromagnetism”

- **Fingerspelling**: spell out an English word using letter signs

High rate of fingerspelling in ASL STEM Wiki

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- ~6.4% of ASL (Morford and MacFarlane, 2003)

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- **Fingerspelling**: spell out an English word using letter signs
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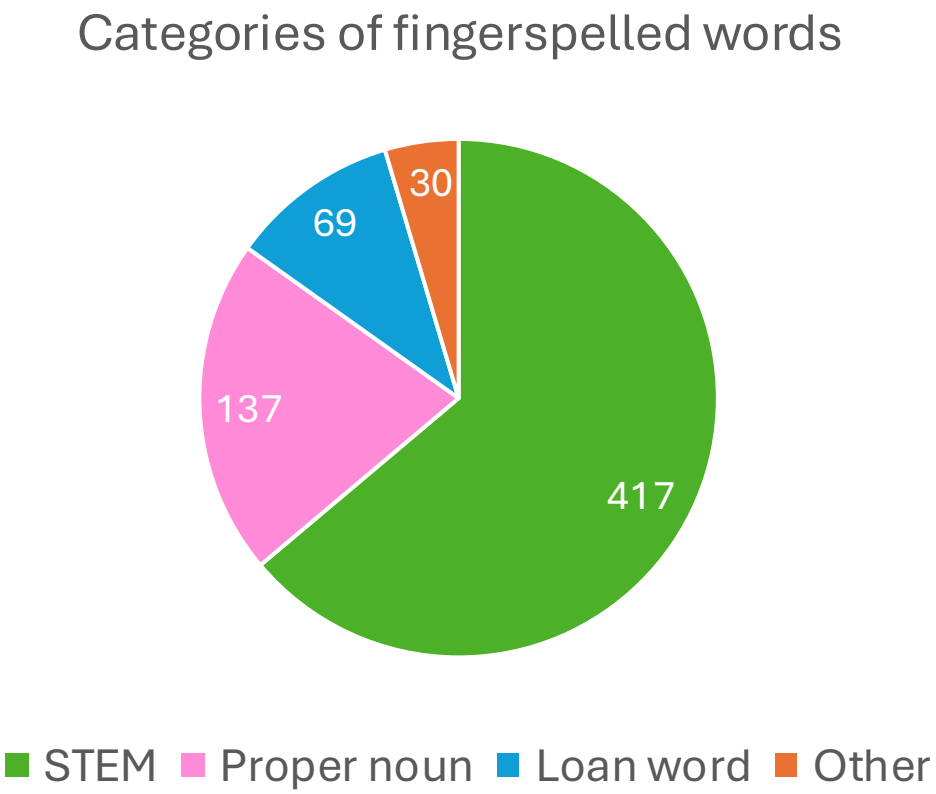
- **~31.5%** of ASL STEM Wiki

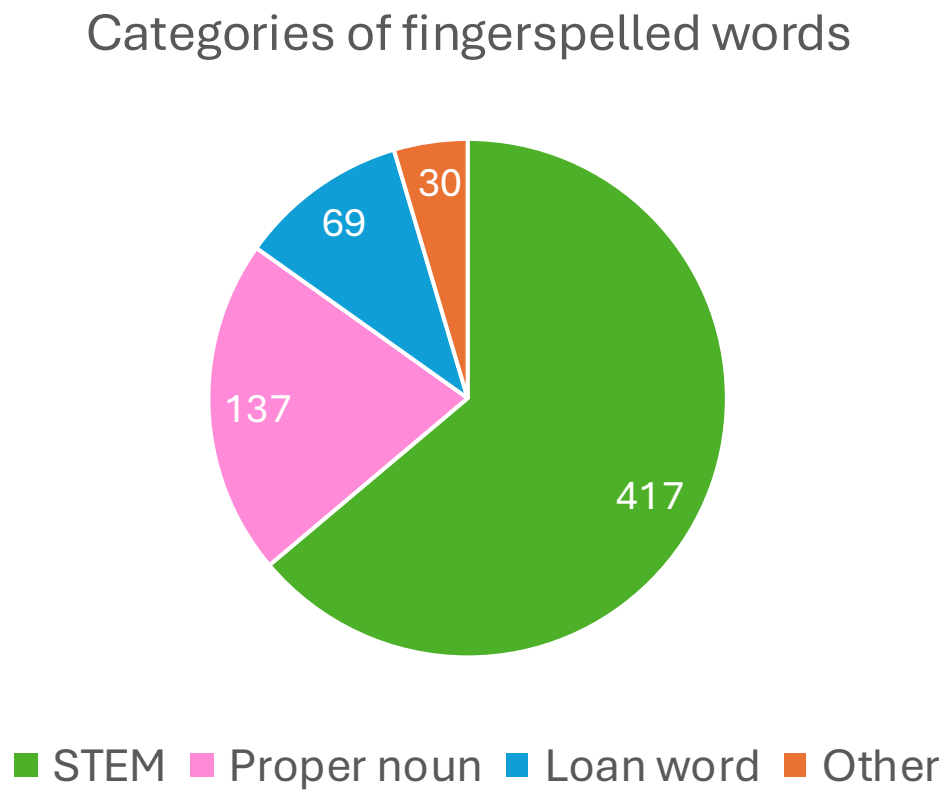
High rate of fingerspelling in ASL STEM Wiki

- **63.9%** of fingerspelling is **STEM** words



High rate of fingerspelling in ASL STEM Wiki

- **63.9%** of fingerspelling is **STEM** words
- Interpreters often resort to fingerspelling when a technical sign is not known



High rate of fingerspelling in ASL STEM Wiki

- 63.
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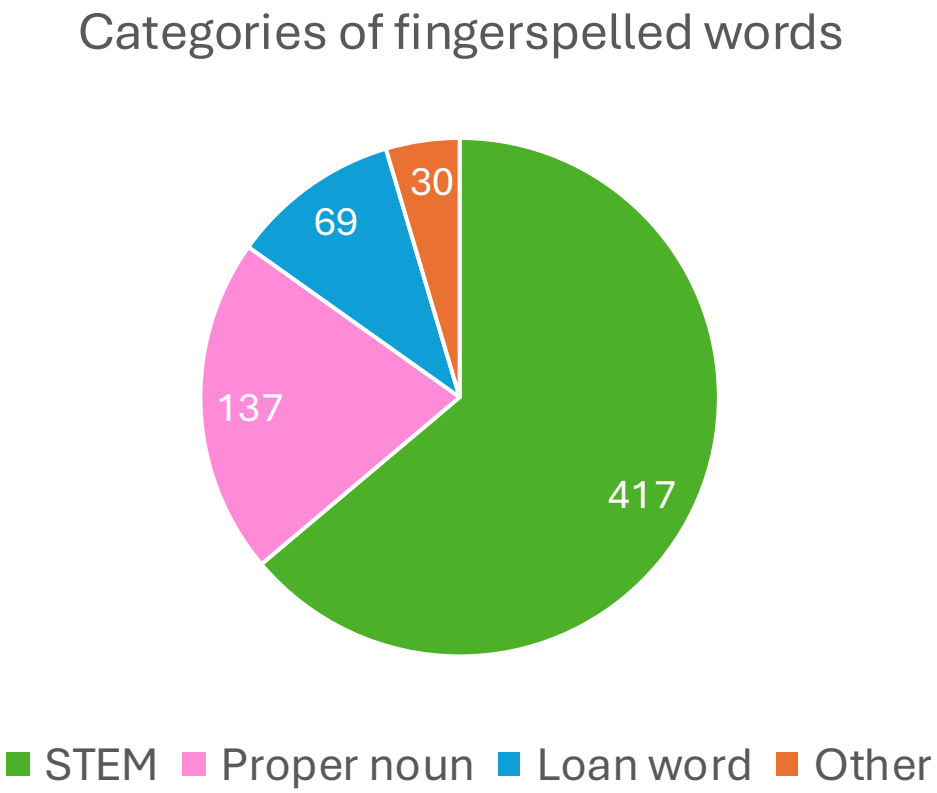
> Development of American Sign Language Guidelines for K-12 Academic Assessments



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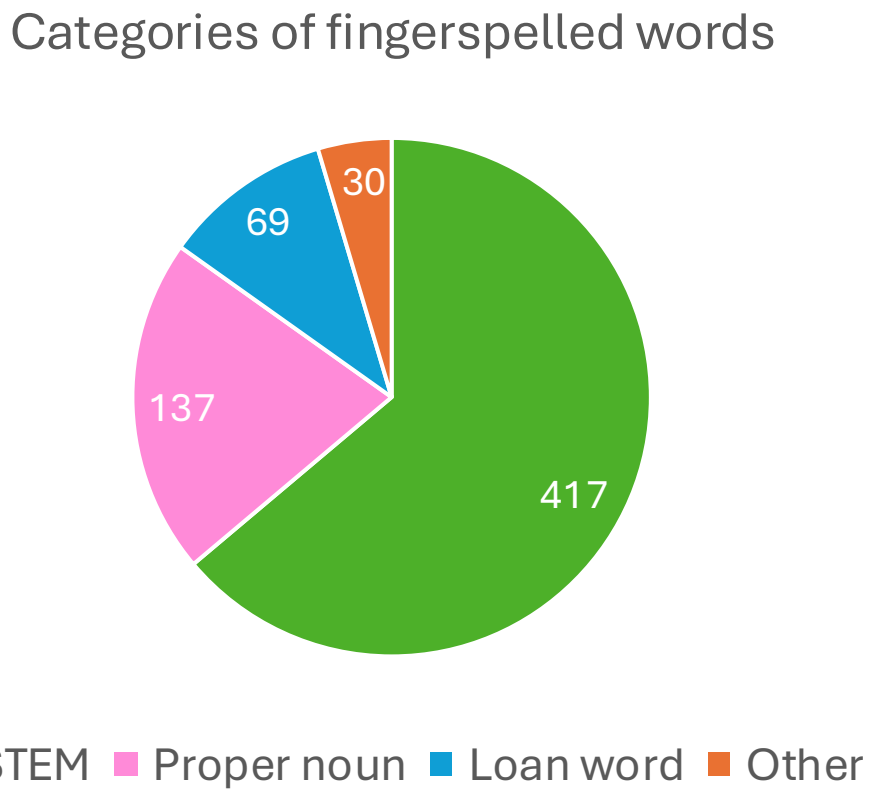


-> NLP tool to address the high rate of fingerspelling in STEM

Automatic sign suggestion: task setup

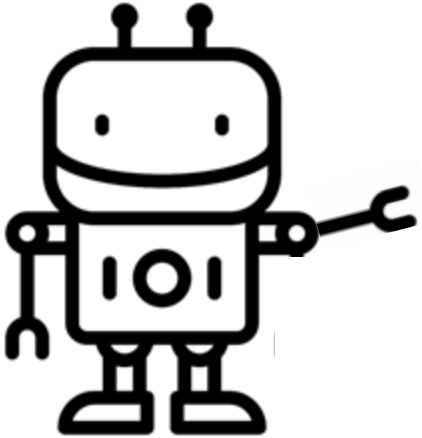
Automatic sign suggestion

User

Automatic sign suggestion

User

Here are other ways people sign “relativistic electromagnetism”



Automatic sign suggestion

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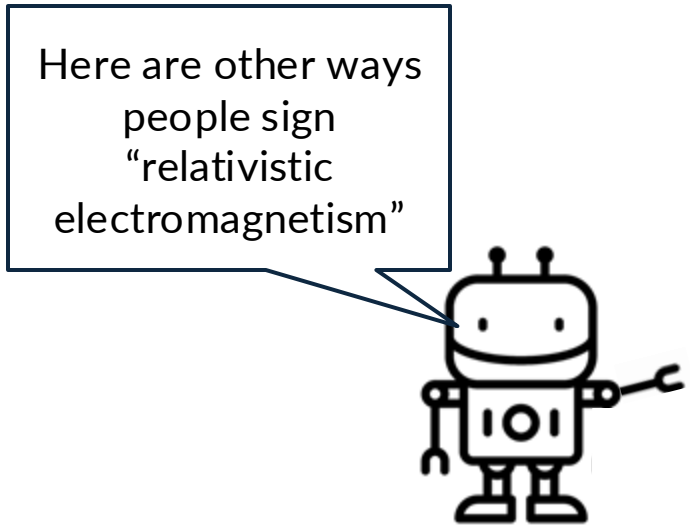

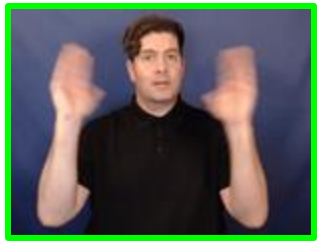

3 steps:

1. Fingerspelling detection
2. Fingerspelling alignment
3. Sign retrieval

Automatic sign suggestion

1. Fingerspelling detection
2. Fingerspelling alignment
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Relativistic electromagnetism is a physical phenomenon due to Coulomb's law and Lorentz transformations.

1. Fingerspelling detection

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Relativistic electromagnetism

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Relativistic electromagnetism

ASL database

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Relativistic electromagnetism

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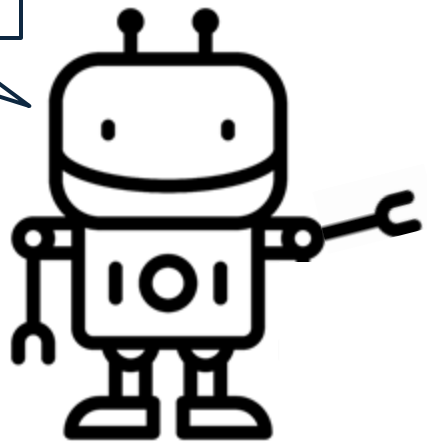

3. Sign retrieval

Self-supervised learning for fingerspelling detection

- Need fingerspelling labels

Automatic sign suggestion

1. Fingerspelling detection
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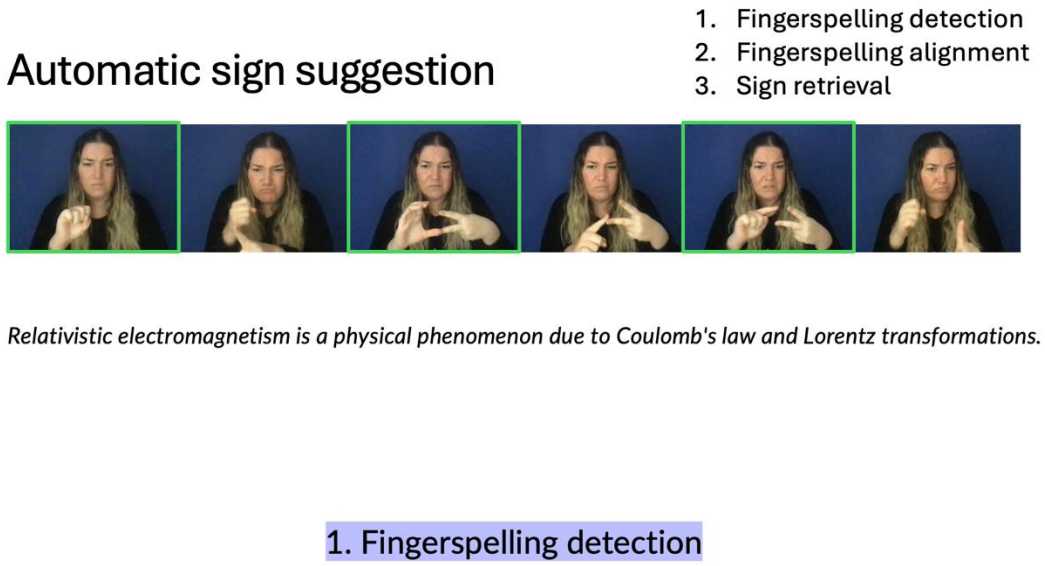
1. Fingerspelling detection

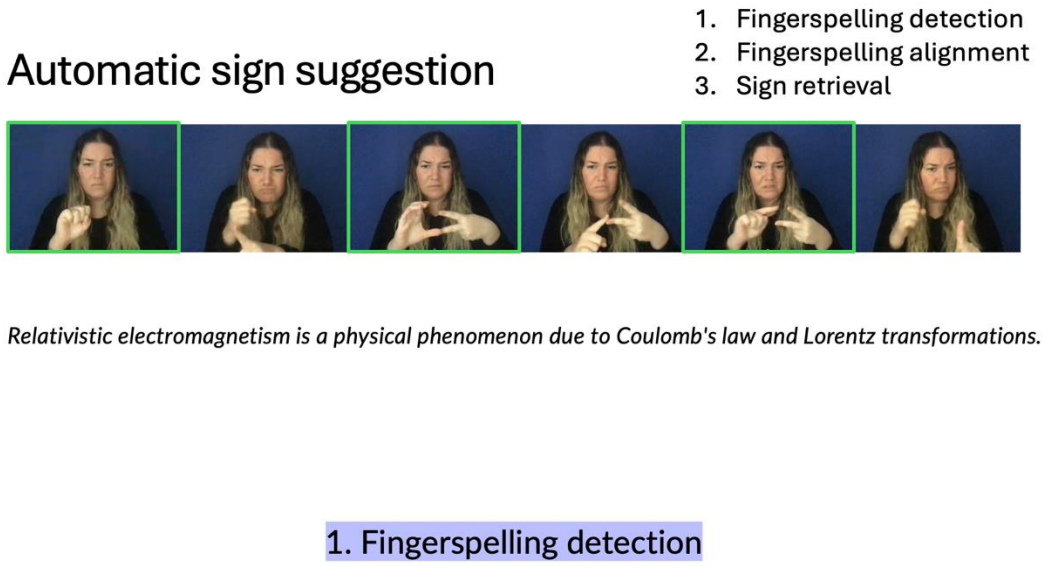
Self-supervised learning for fingerspelling detection

- Need fingerspelling labels
  - We annotated 507 videos

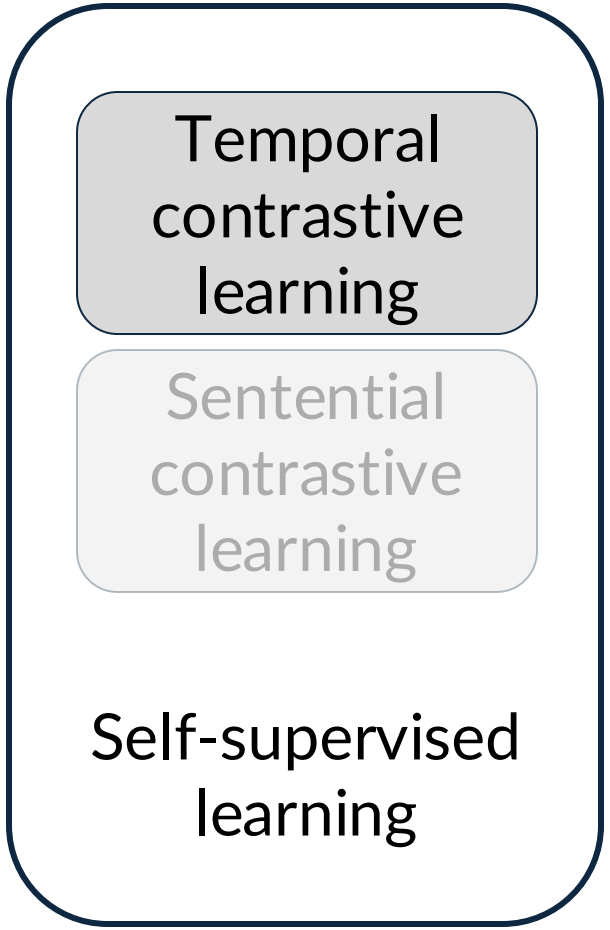


Self-supervised learning for fingerspelling detection

- Need fingerspelling labels
  - We annotated 507 videos
  - 63,759 unannotated videos



Self-supervised learning



Self-supervised learning

Temporal contrastive learning

Sentential contrastive learning

Self-supervised learning

Self-supervised learning

Model

Temporal contrastive learning

Sentential contrastive learning

Self-supervised learning

Self-supervised learning

Model

Different video

Same video,
video 1 < video 2

Same video,
video 2 < video 1

Temporal contrastive learning

Sentential contrastive learning

Self-supervised learning

Self-supervised learning

Learn representations of the structure and timing of signs

Model

Different video

Same video,
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Same video,
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Temporal contrastive learning

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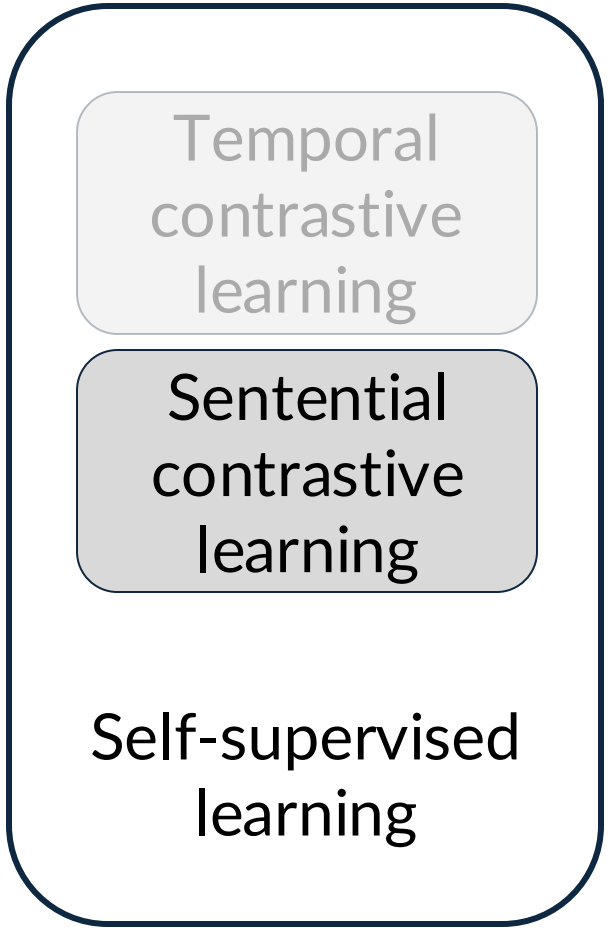
Self-supervised learning

Self-supervised learning



Self-supervised learning

Relativistic electromagnetism is a physical phenomenon due to…

An observer at rest with respect to a system of static, free charges will…

Temporal contrastive learning

Sentential contrastive learning

Self-supervised learning

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Temporal contrastive learning

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Model

Video = sentence 1

Video = sentence 2

Temporal contrastive learning

Sentential contrastive learning

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Relativistic electromagnetism is a physical phenomenon due to…

An observer at rest with respect to a system of static, free charges will…

Learn associations between ASL videos and English text

Model

Video = sentence 1

Video = sentence 2

Temporal contrastive learning

Sentential contrastive learning

Self-supervised learning

Fingerspelling detection

Relativistic electromagnetism is a physical phenomenon due to…

Graph convolutional network

⊕

CANINE
(Clark et al., 2022)

Temporal contrastive learning

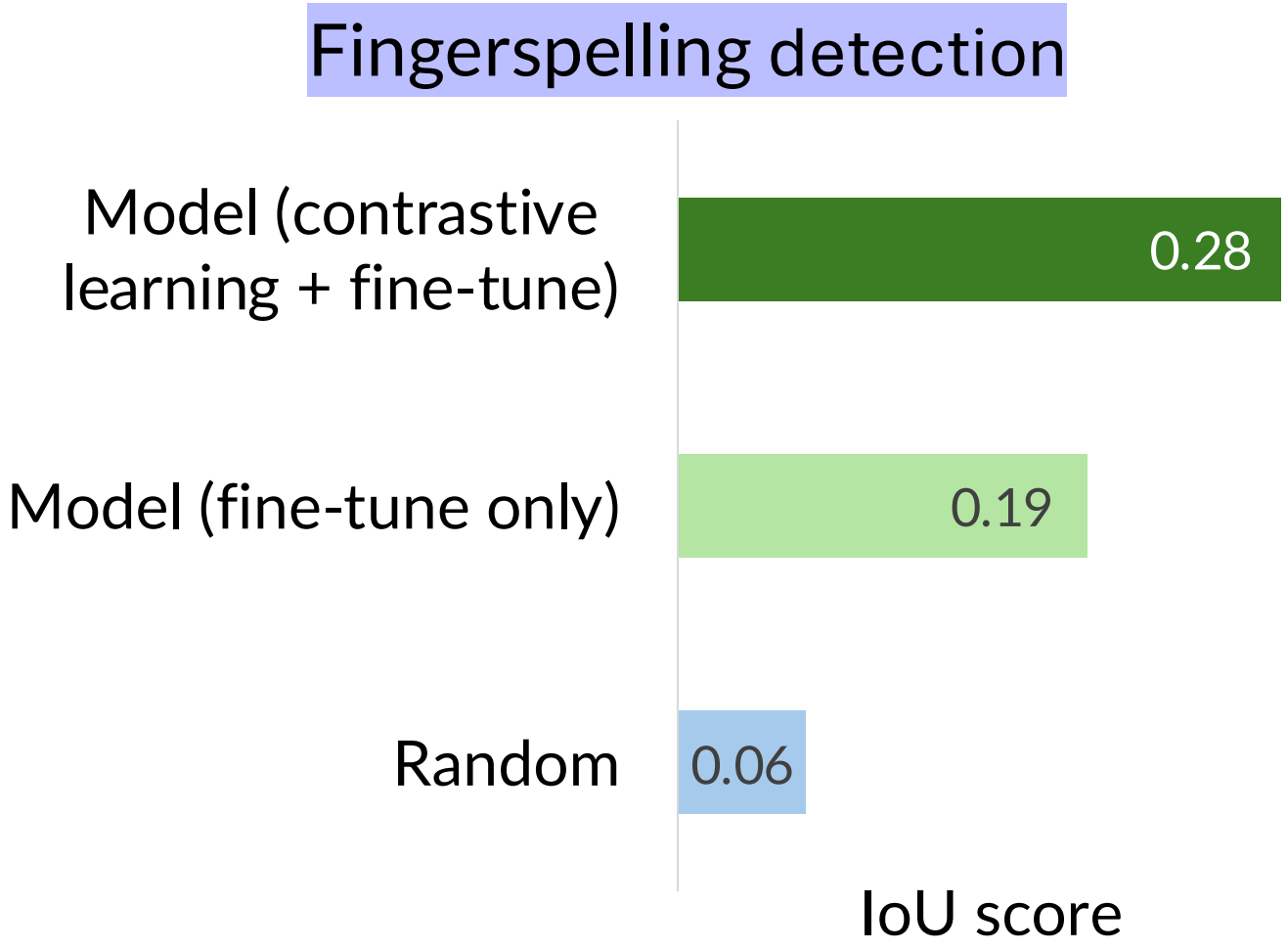
Sentential contrastive learning

Self-supervised learning

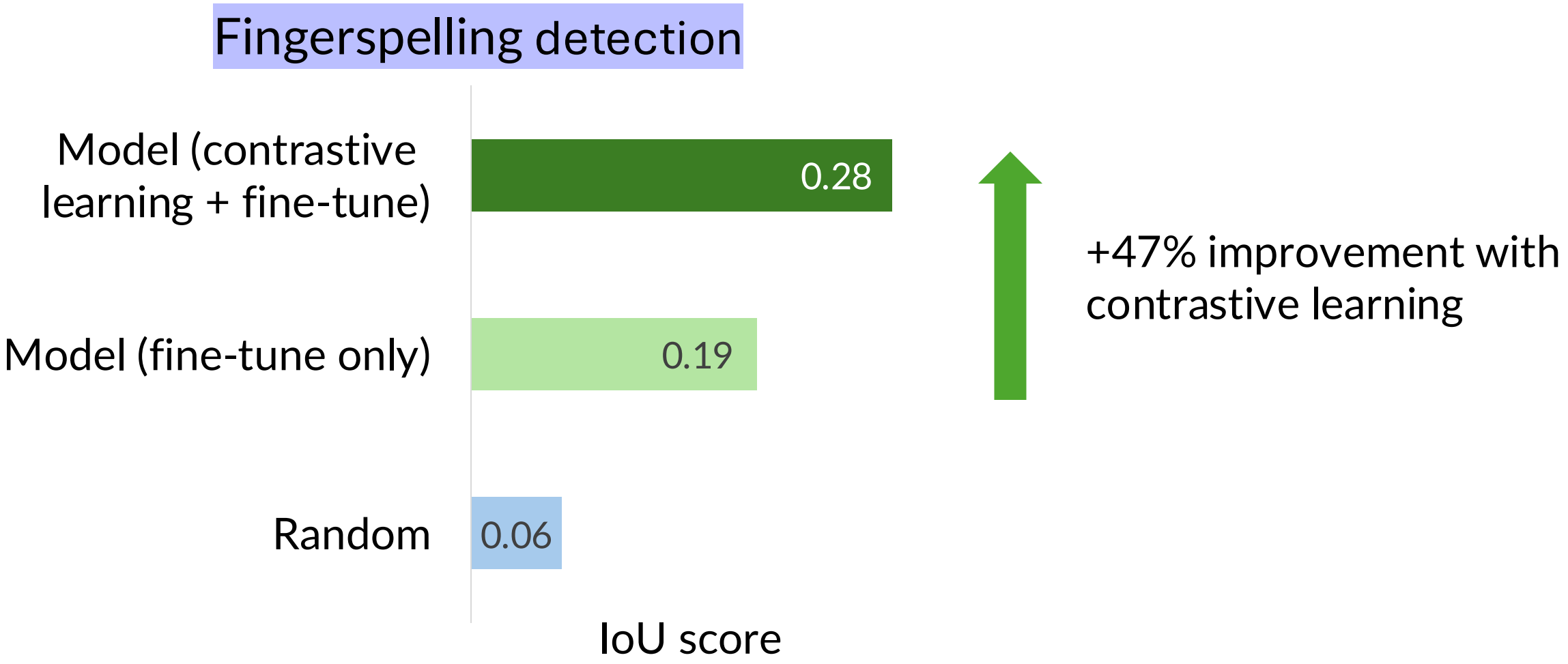
Fingerspelling detection

Fine-tuning

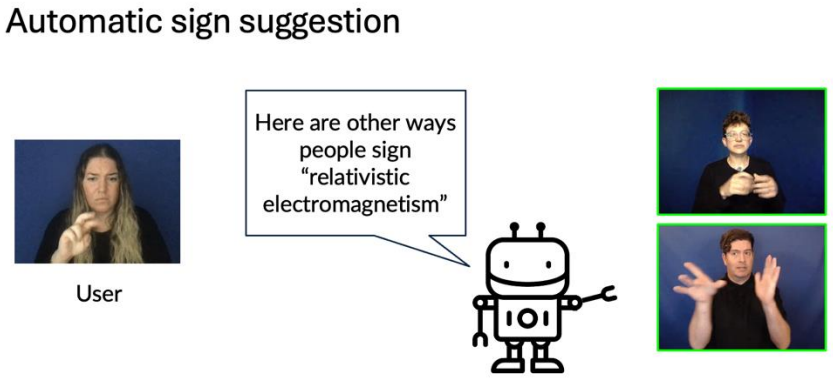
Does contrastive learning work?

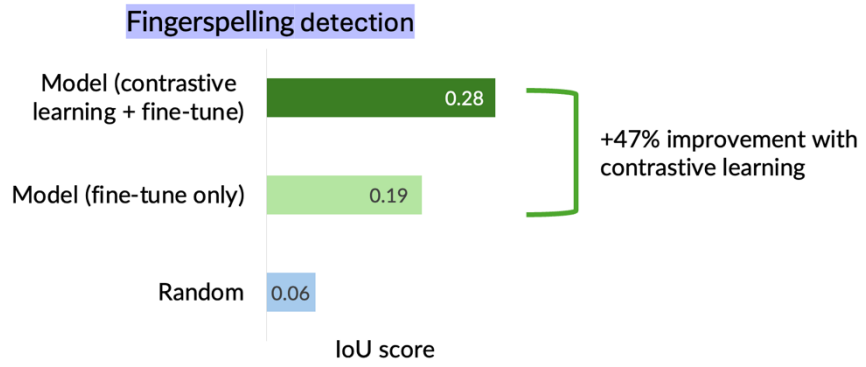


Does contrastive learning work?



Summary





New dataset to support DHH students in STEM

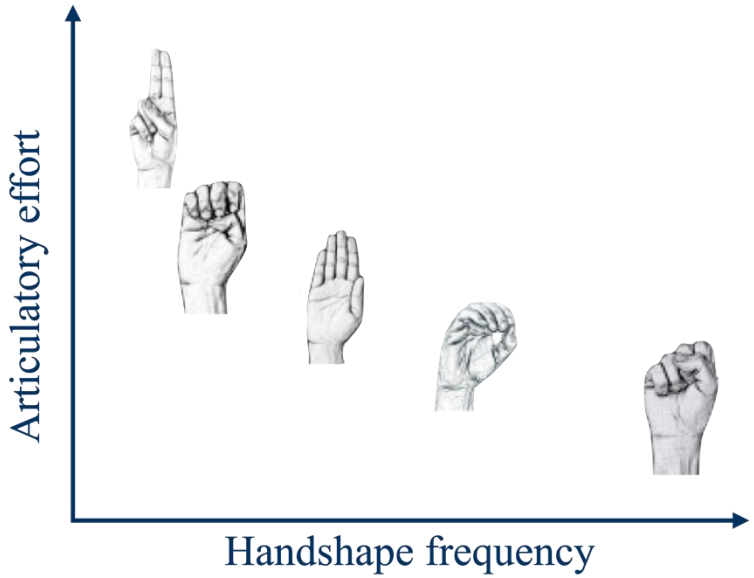
New task to enhance ASL STEM interpretations

Contrastive learning for sign language modeling

Arguments for today's talk

1. The linguistic complexity of signed languages gives rise to unique NLP challenges
2. Awareness of the language and the community helps us build practical NLP models
3. NLP can help answer open questions in sign linguistics

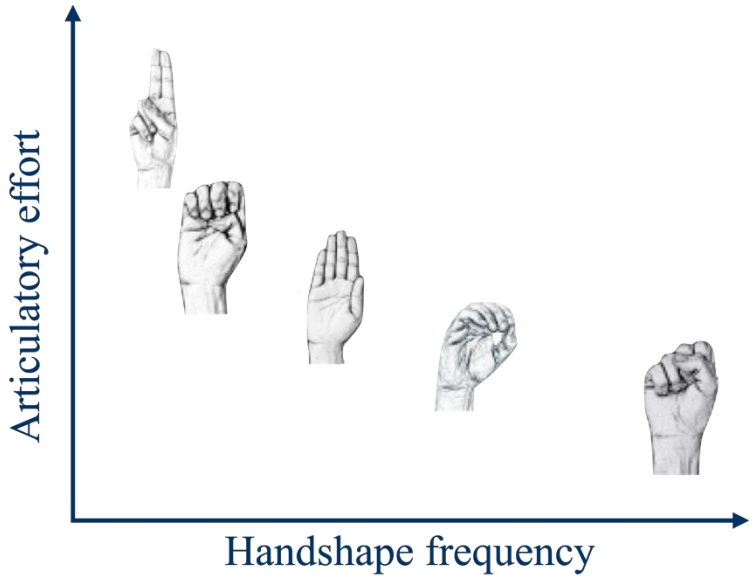
Communicative efficiency in ASL handshapes



Compare ASL handshape frequency and signer effort

Pressures for Communicative Efficiency in American Sign Language. Yin et al. (2024)

Communicative efficiency in ASL handshapes



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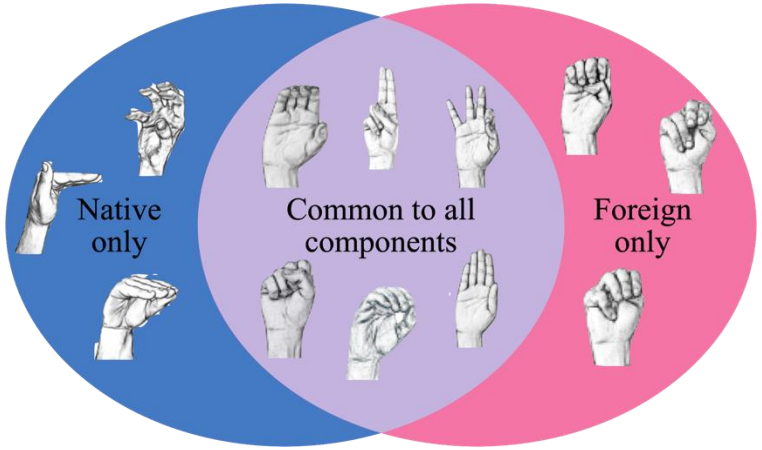

Compare efficiency pressures from native ASL signs vs. signs borrowed from English

Pressures for Communicative Efficiency in American Sign Language. Yin et al. (2024)

Efficiency shapes human language

Efficiency: successful communication with **minimal effort** by sender + receiver

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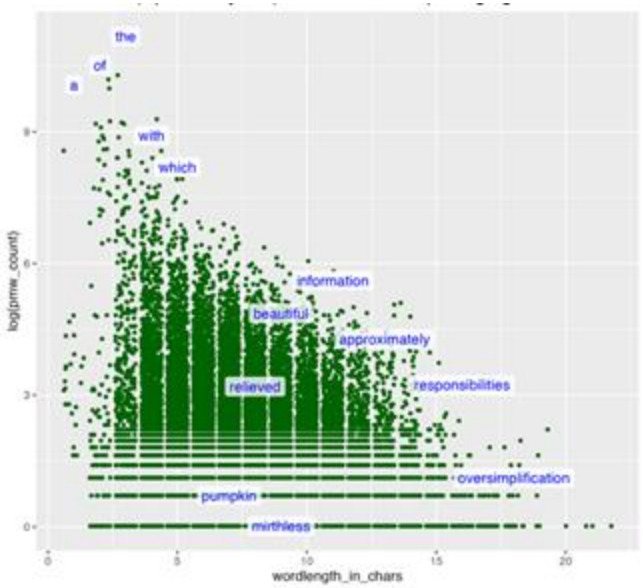
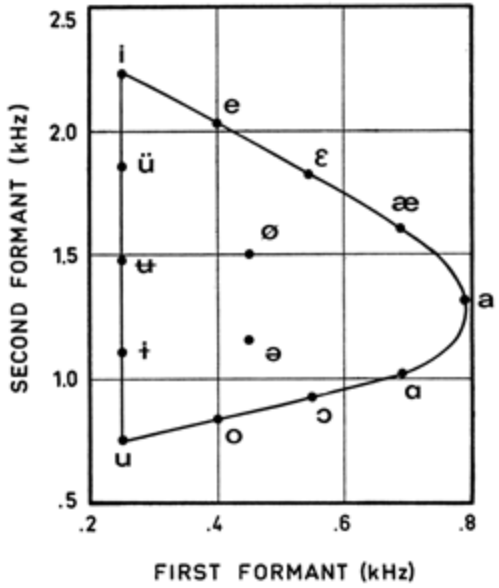


Frequent/informative words are shorter

(Zipf, 1935; Piantadosi et al., 2011)



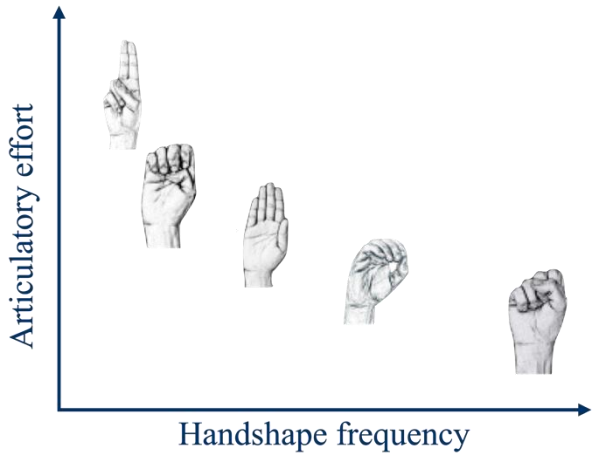
Vowel space maximizes perceptual contrast

(Liljencrants & Lindblom, 1972)

Efficiency shapes human language

Efficiency: successful communication with **minimal effort** by sender + receiver

What would communicative efficiency look like in the visual modality?



Language contact in ASL

Fingerspelling

Language contact in ASL

Fingerspelling

Loan signs

Language contact in ASL

Fingerspelling

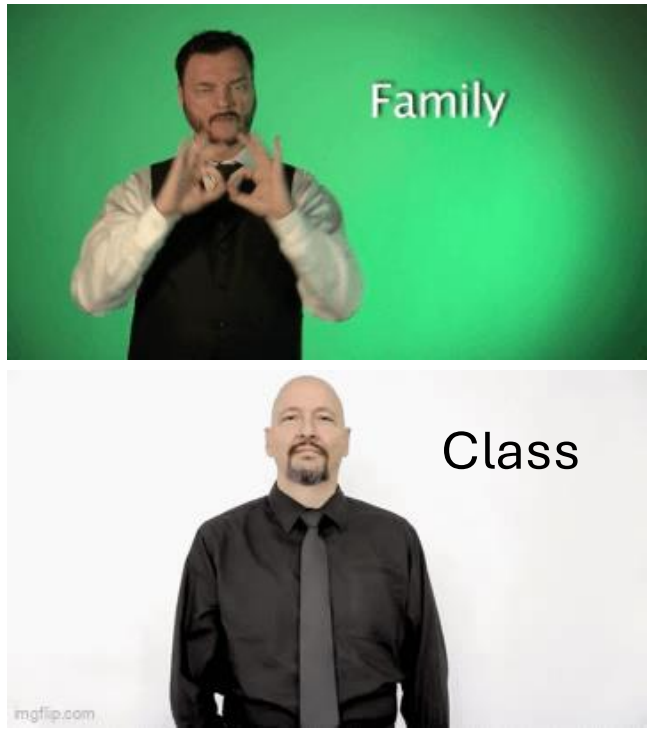
Loan signs

Initialized signs

Language contact in ASL

Fingerspelling

Loan signs



Initialized signs

How do different language sources compare in communicative efficiency?

Research questions

RQ1. Do ASL handshapes reflect pressures for **communicative efficiency**?

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RQ2. If so, do we find communicative efficiency mostly in **native signs**, or also in signs **borrowed from English**?

Research questions

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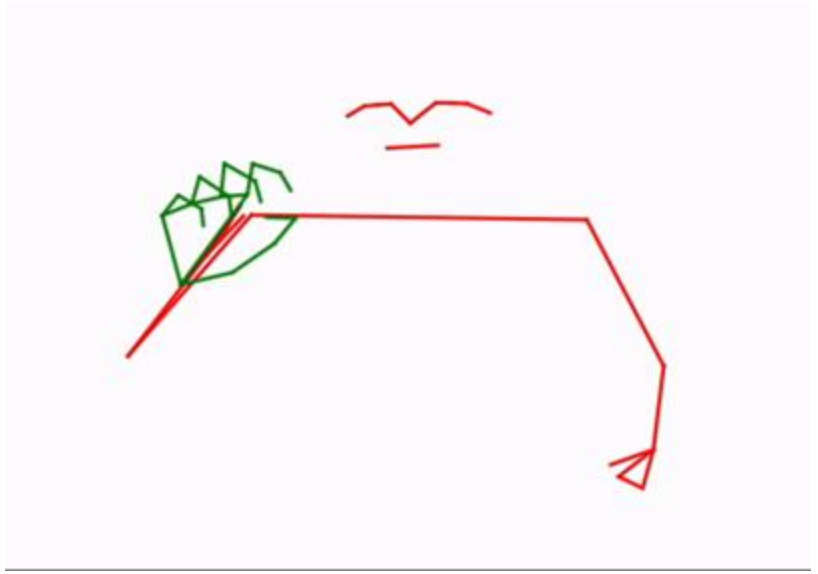
RQ2. If so, do we find communicative efficiency mostly in **native signs**, or also in signs **borrowed from English**?

→ Compare handshape frequency and sender / receiver effort

Data

ASL Fingerspelling Recognition Corpus

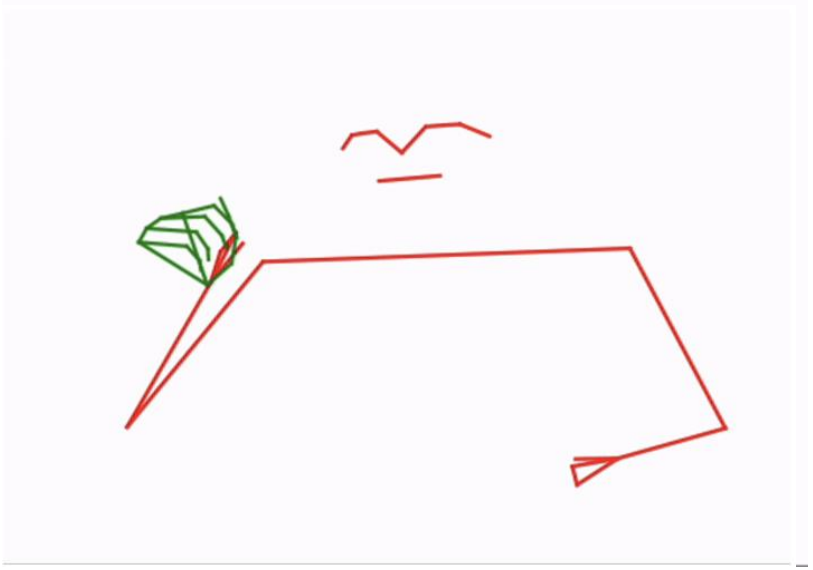


did you have a good time

Data

ASL Fingerspelling Recognition Corpus

- 100k+ fingerspelled phrases, no character-level labels

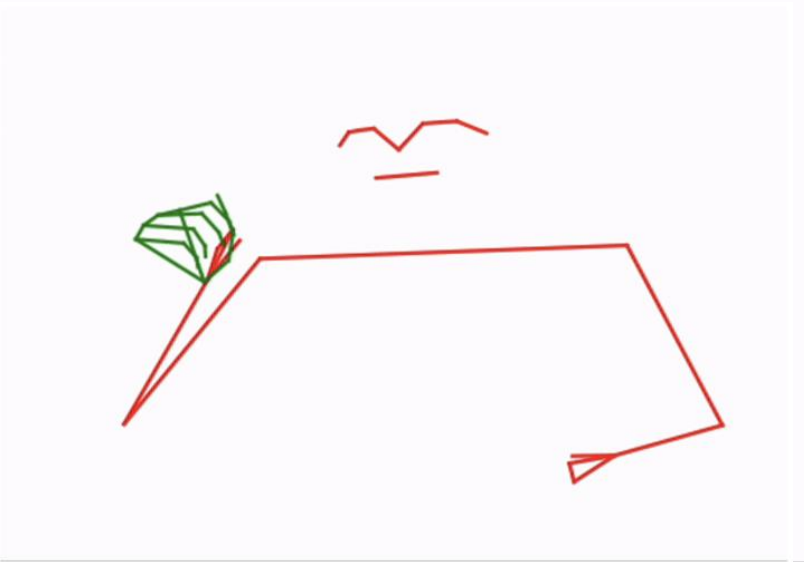


did you have a good time

Data

ASL Fingerspelling Recognition Corpus

- 100k+ fingerspelled phrases, no character-level labels
- Heuristic algorithm + manual post-correction
  - 1062 letters extracted



did you have a good time

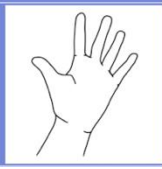
Data

ASL-LEX (Caselli et al., 2017)

Alternate English Translations:

cheese, dairy, food

About the sign:

Entry ID	cheese
English Word Frequency	3.299
Frequency	5.63
Deaf Signer Iconicity	1.55
Initialized Sign	0
Fingerspelled Loan Sign	0
Compound	0
Number Of Morphemes	1
Handshape Image	

Data

ASL-LEX (Caselli et al., 2017)

- Handshape categories

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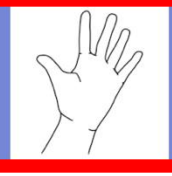
Handshape Image	

Data

ASL-LEX (Caselli et al., 2017)

- Handshape categories
- Sign frequency

Data

ASL-LEX (Caselli et al., 2017)

- Handshape categories
- Sign frequency
- Native / initialized / loan sign

Effort metrics

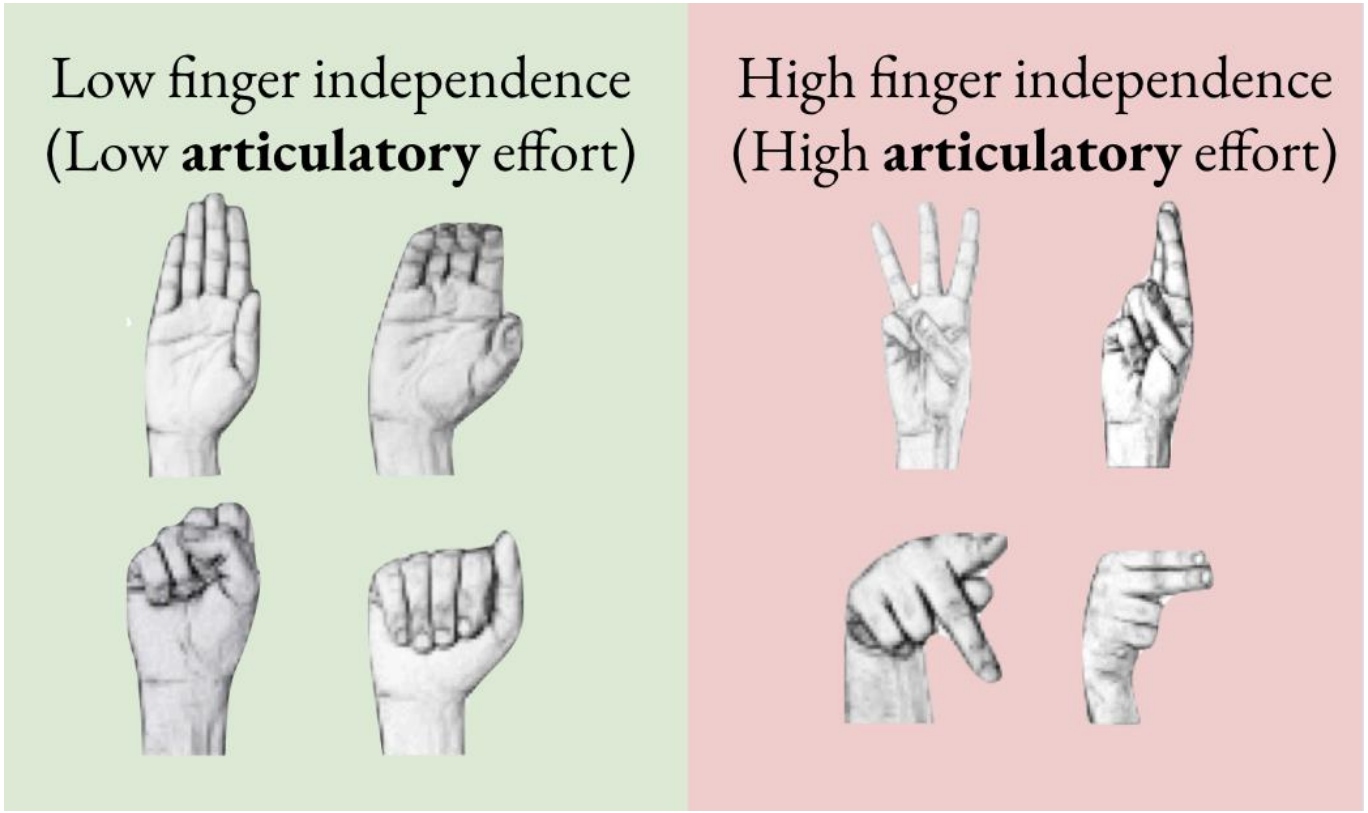
Articulatory effort

Perceptual effort

Effort metrics

Articulatory effort

- Finger independence



Perceptual effort

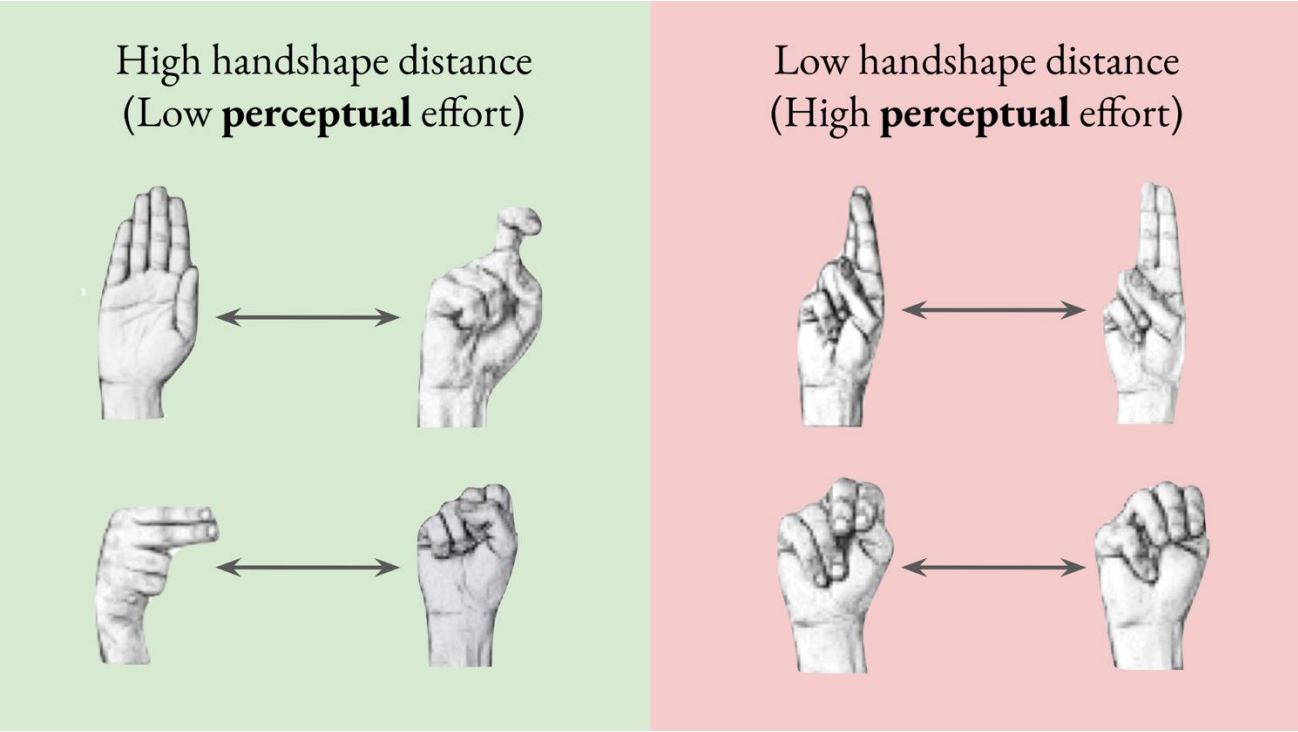
Effort metrics

Articulatory effort

- Finger independence

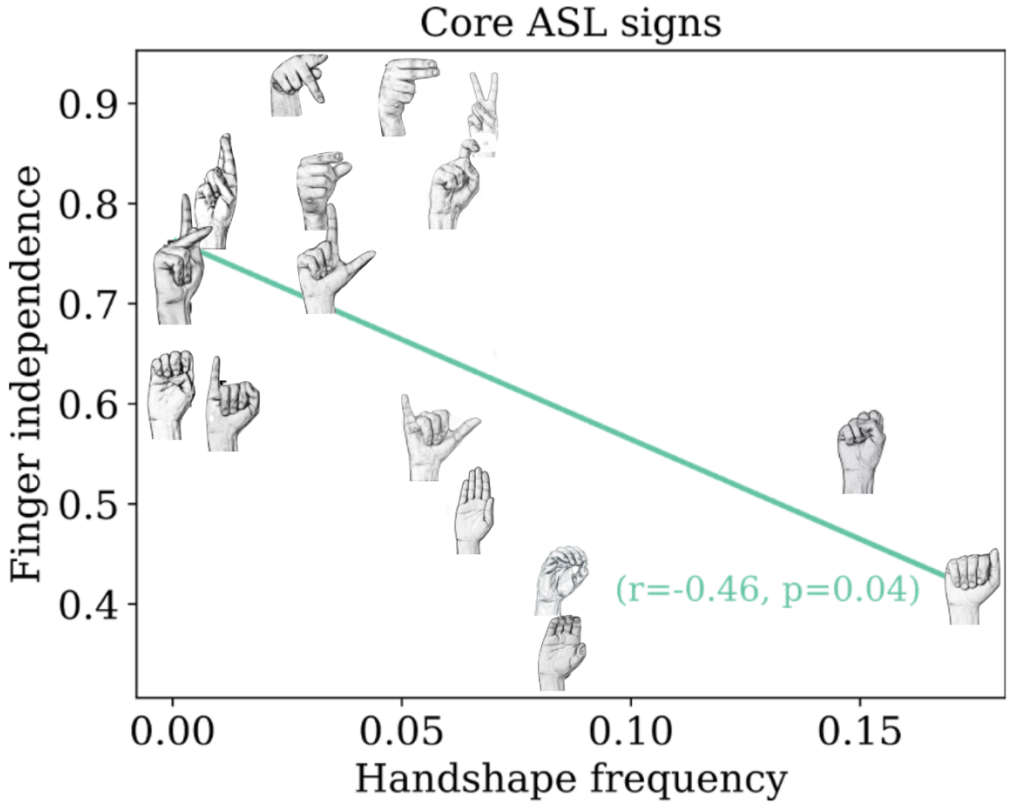
Perceptual effort

- Handshape distance



Results

Handshape frequency vs. articulatory effort： native ASL signs



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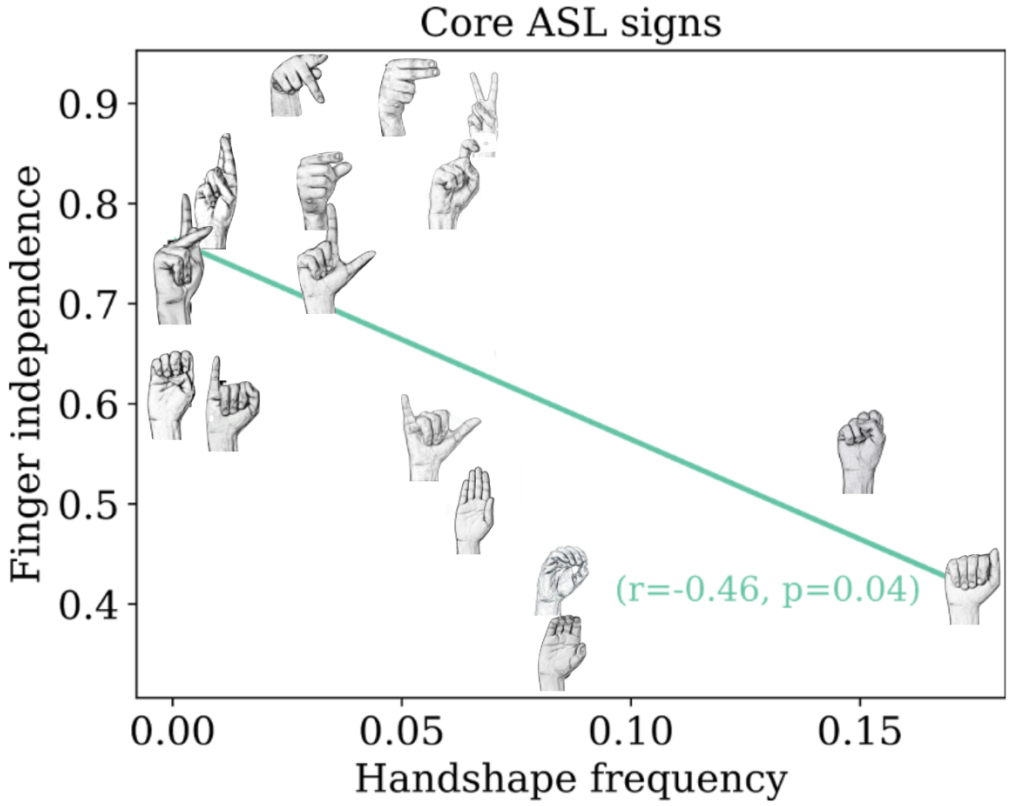


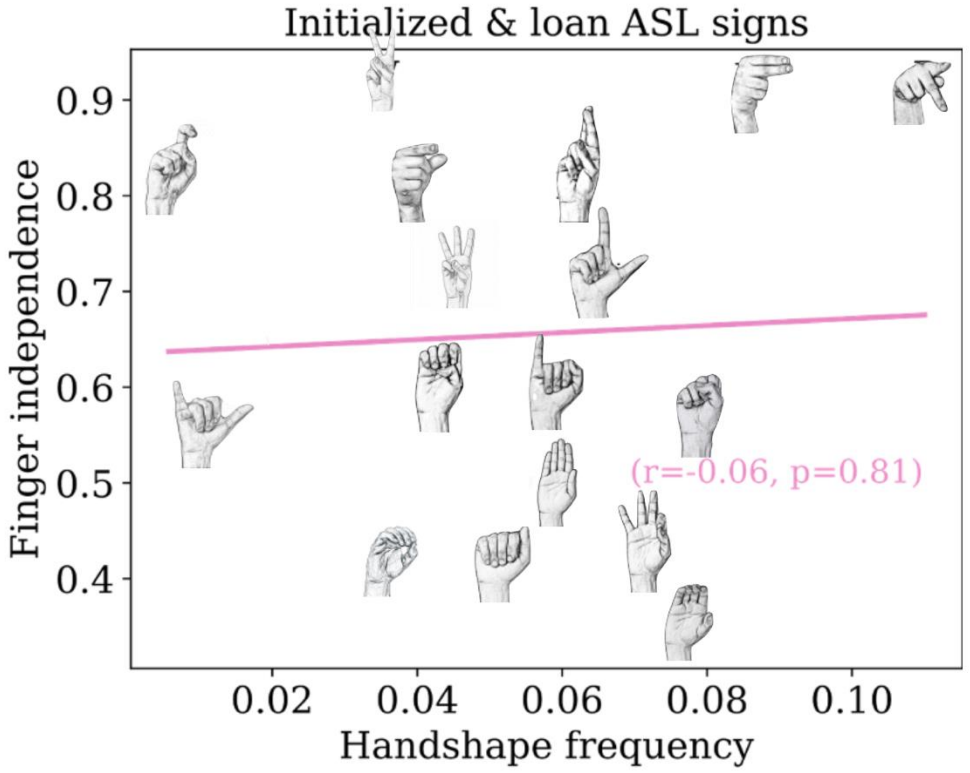
Pearson’s r=-0.46,p=0.04
→strong correlation

✓

Results

Handshape frequency vs. articulatory effort： borrowed ASL signs

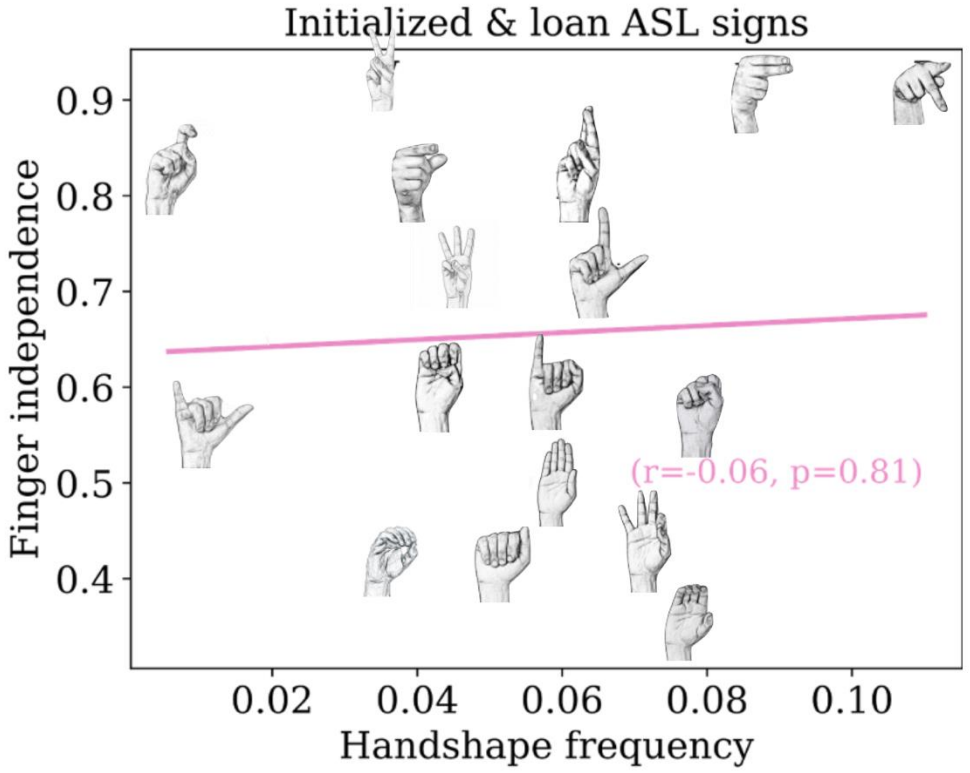
(initialized / fingerspelled loan signs)



Results

Handshape frequency vs. articulatory effort： borrowed ASL signs

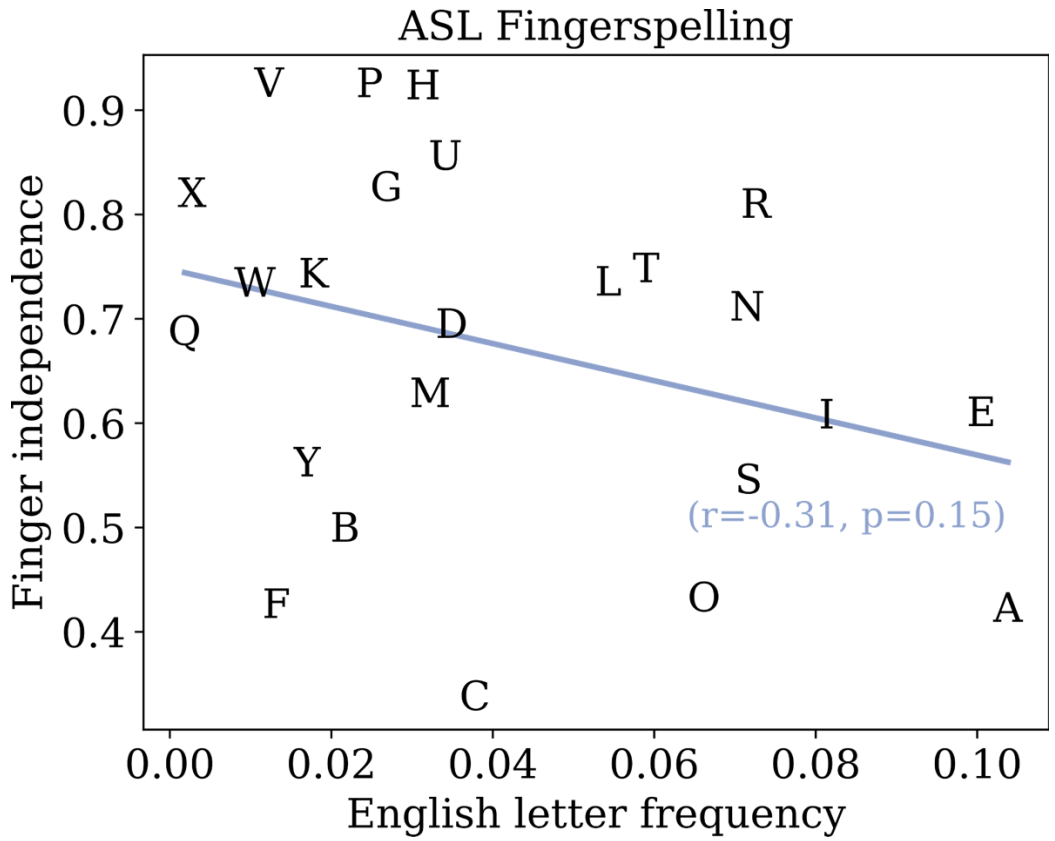
(initialized / fingerspelled loan signs)



Pearson’s r=-0.06,p=0.81
→no correlation

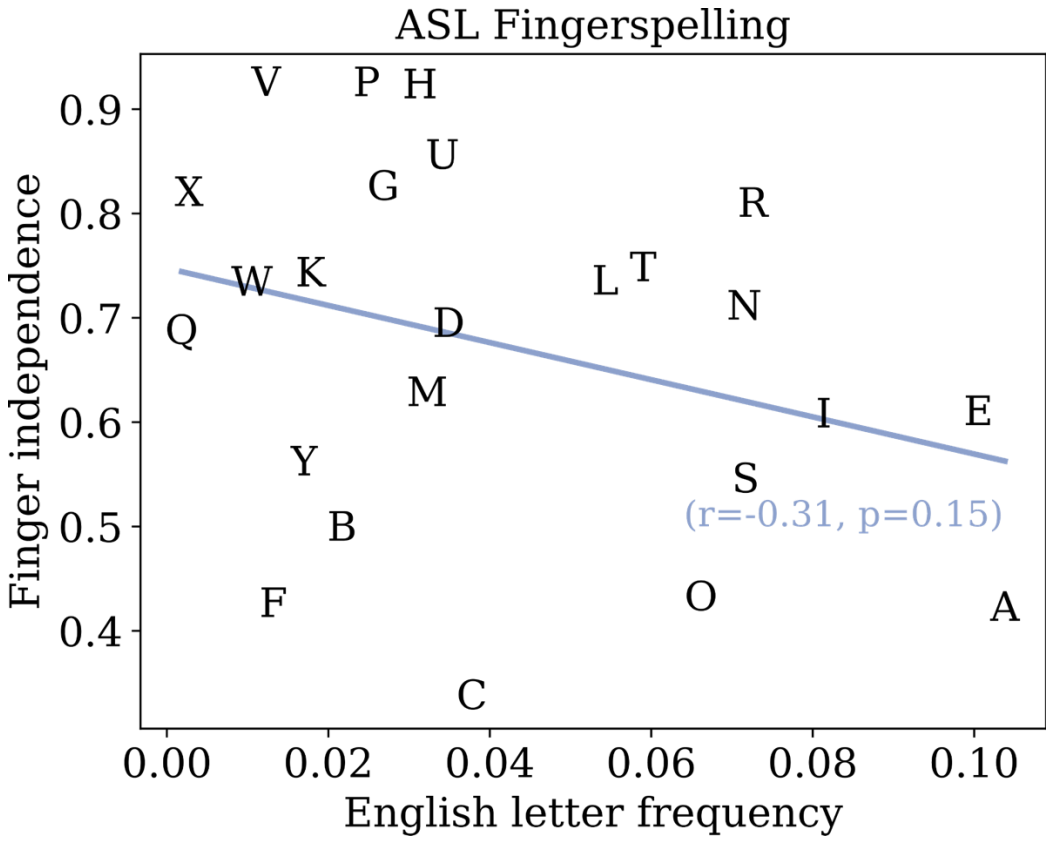
Results

English letter frequency vs. articulatory effort (fingerspelling)



Results

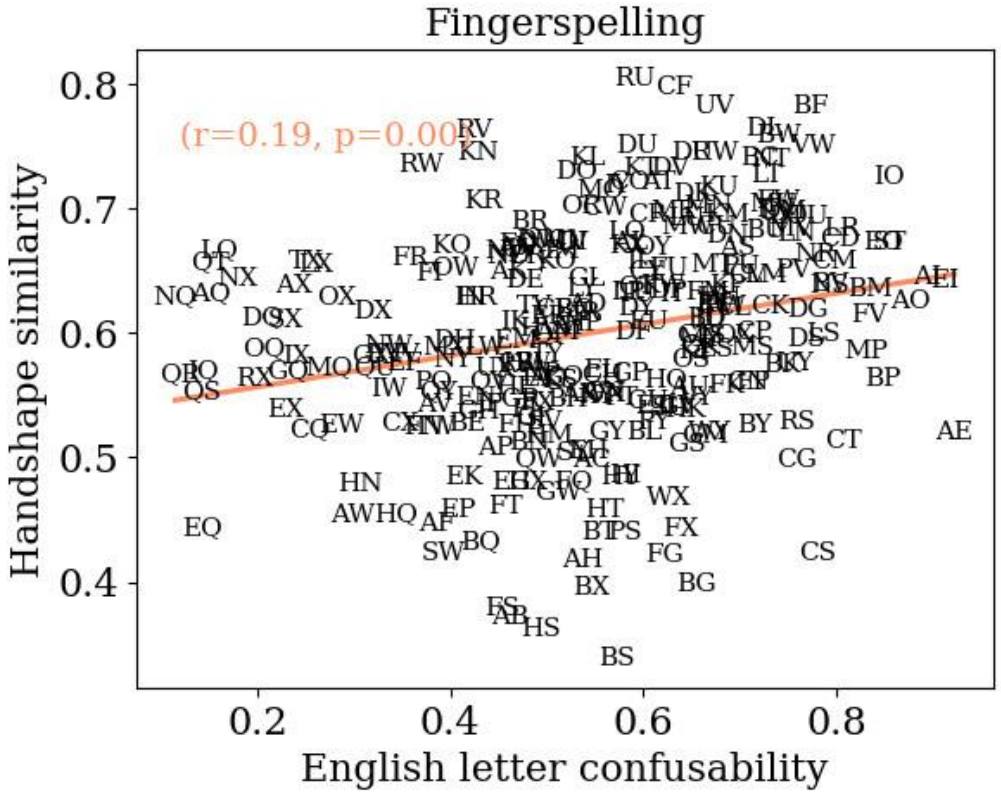
English letter frequency vs. articulatory effort (fingerspelling)



Pearson’s r=-0.31,p=0.15
→no correlation

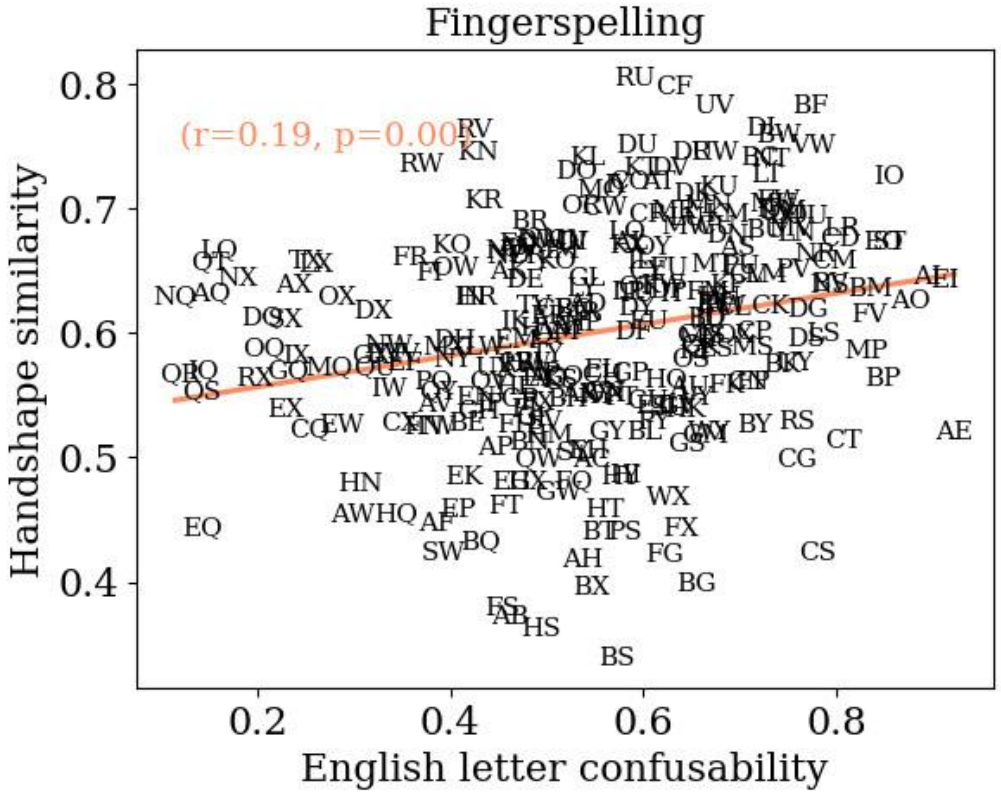
Results

English letter confusability vs. perceptual effort (fingerspelling)



Results

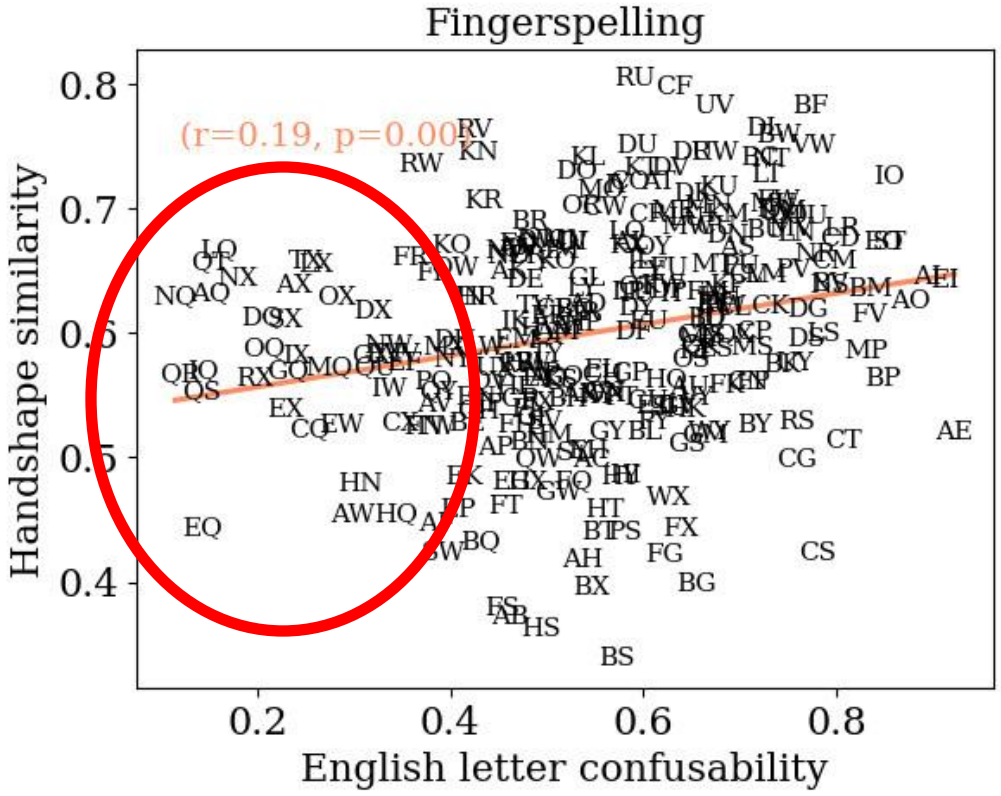
English letter confusability vs. perceptual effort (fingerspelling)



Pearson's r=0.19,p=0.00
→weak correlation?

Results

English letter confusability vs. perceptual effort (fingerspelling)



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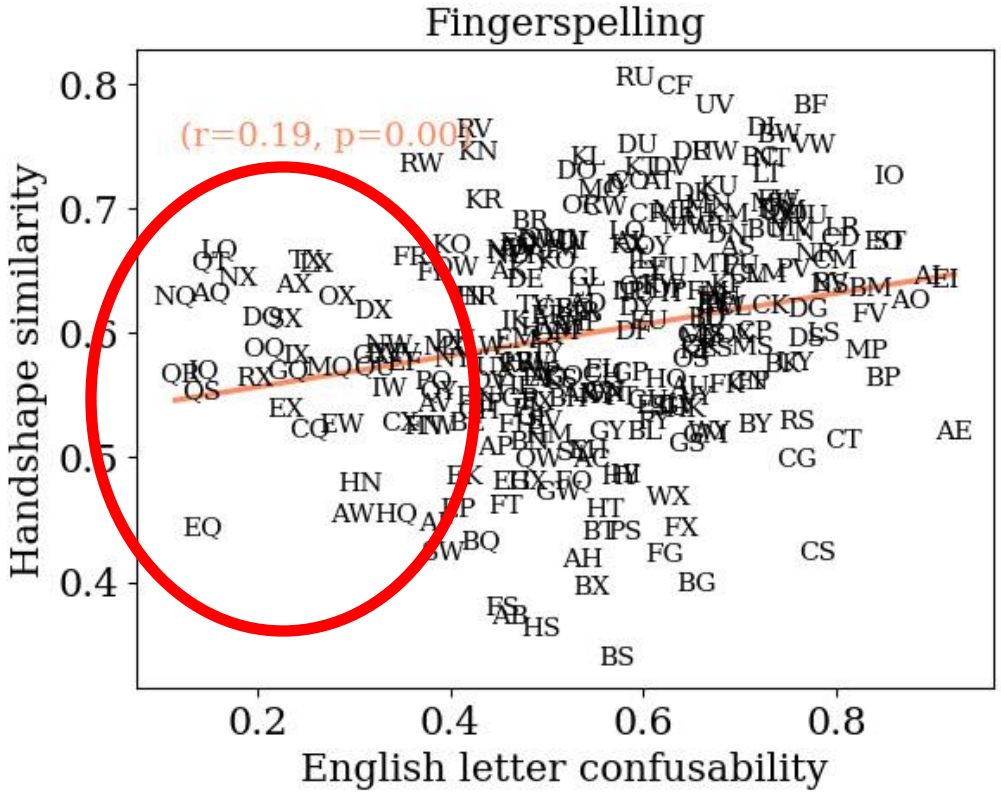
Confusability and letter frequency are highly correlated

Results

English letter confusability vs. perceptual effort (fingerspelling)



Pearson's r=0.19,p=0.00

→no correlation once we partial letter frequency out!

Confusability and letter frequency are highly correlated

What we learned

RQ1. Do ASL handshapes reflect pressures for **communicative efficiency**?

Yes!

RQ2. If so, do we find communicative efficiency mostly in **native signs**, or

also in signs **borrowed from English**? Only in native signs!

What we learned

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Why?

What we learned

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Why?

- ASL fingerspelling is invented by hearing educators (Padden and Gunsauls, 2003)

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Why?

- ASL fingerspelling is invented by hearing educators (Padden and Gunsauls, 2003)
- Frequent words undergo faster language change (Bybee, 2015; Caselli et al., 2022)

What we learned

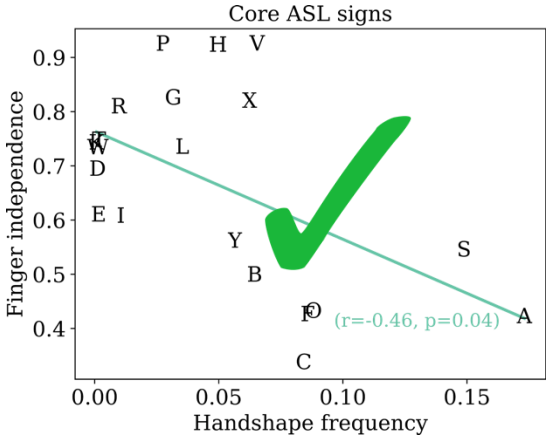
RQ2. If so, do we find communicative efficiency mostly in **native signs**, or also in signs **borrowed from English**? Only in native signs!

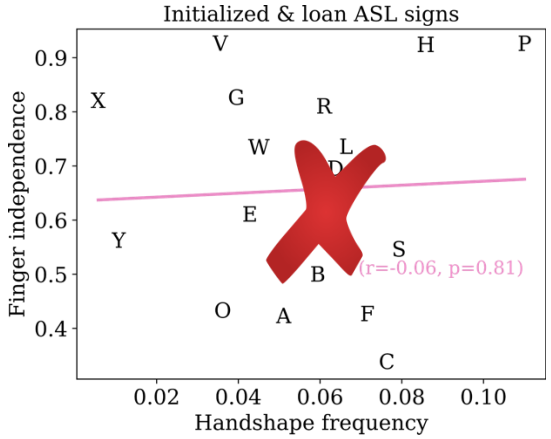
Why?

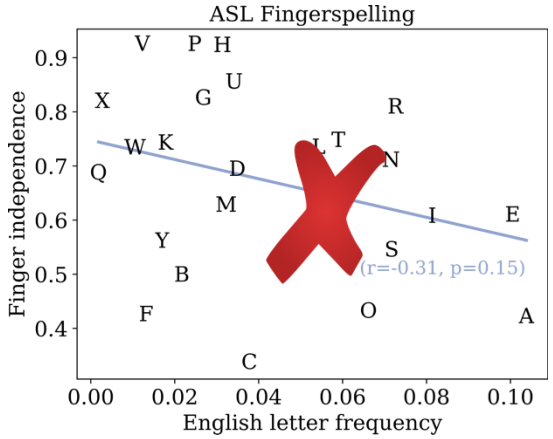
- ASL fingerspelling is invented by hearing educators (Padden and Gunsauls, 2003)
- Frequent words undergo faster language change (Bybee, 2015; Caselli et al., 2022)
- Foreign components obey fewer phonological rules (Brentari and Padden, 2001)

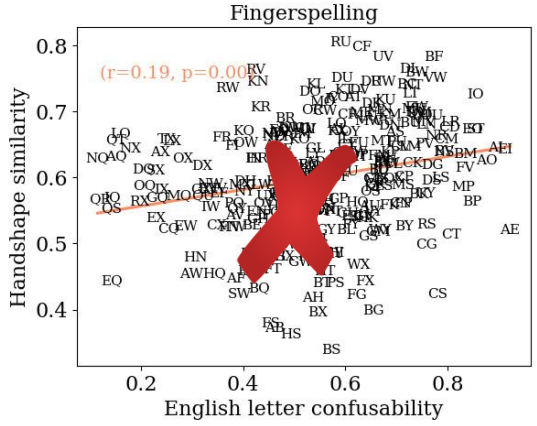
Summary

- Compare the frequency and effort of ASL handshapes
- Automatic metrics to quantify production/recognition effort
- We observe communicative efficiency in only handshapes of native signs, not signs borrowed from English









Takeaways from this talk

1. The linguistic complexity of signed languages gives rise to unique NLP challenges
2. Awareness of the language and the community helps us build practical NLP tools
3. NLP can help answer open questions in sign linguistics

Takeaways from this talk

1. The linguistic complexity of signed languages gives rise to unique NLP challenges – testbed for general multimodal intelligence!
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1. The linguistic complexity of signed languages gives rise to unique NLP challenges – testbed for general multimodal intelligence!
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Takeaways from this talk

1. The linguistic complexity of signed languages gives rise to unique NLP challenges – testbed for general multimodal intelligence!
2. Awareness of the language and the community helps us build practical NLP tools – accessibility + language revitalization!
3. NLP can help answer open questions in sign linguistics – legitimize signed languages + advance science!

Future directions

Ongoing work (sneak peek)


Do sign recognition models rely on meaningful phonological features?

Ongoing work (sneak peek)


Do sign recognition models rely on meaningful phonological features?

- Minimal pairs contrasting in phonology

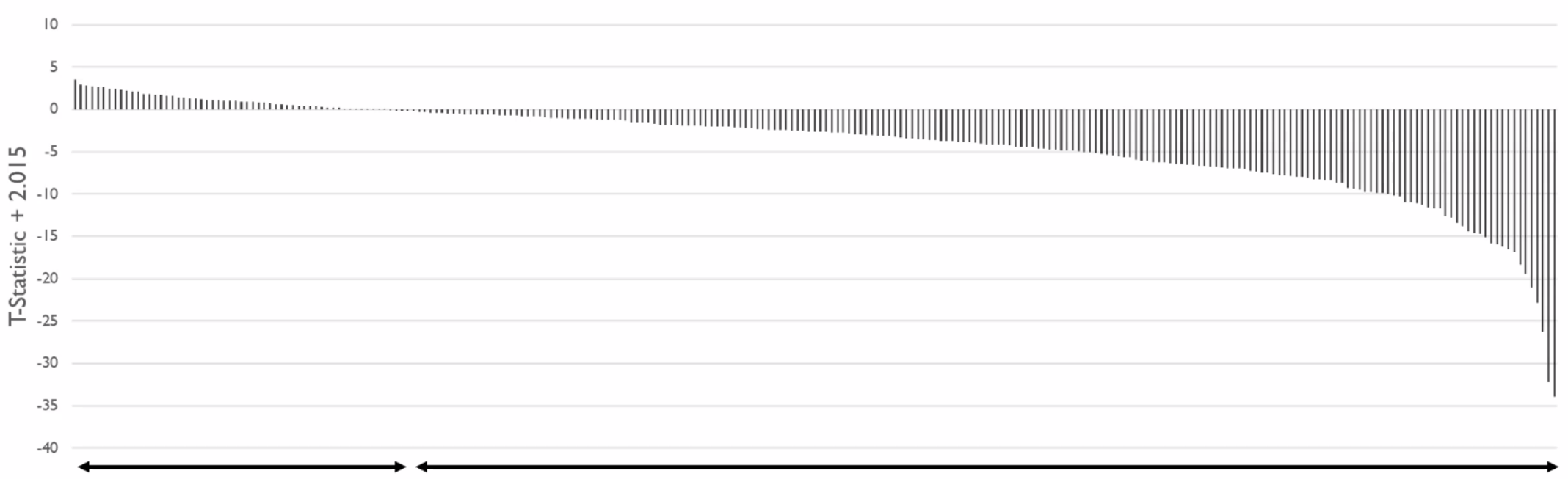
Handshape contrast

Location contrast

Movement contrast

Ongoing work (sneak peek)


- Model embeddings can distinguish most minimal pairs



200 of 254 minimal pairs (78.7%) induce significantly higher distances in embeddings across 5 pairs of signers ($p < 0.05$)

Ongoing work (sneak peek)


- Model embeddings can distinguish most minimal pairs
- No correlation between model perception and human expert perception

Ongoing work (sneak peek)


- Model embeddings can distinguish most minimal pairs
- No correlation between model perception and human expert perception – why?

Ongoing work (sneak peek)


- Model embeddings can distinguish most minimal pairs
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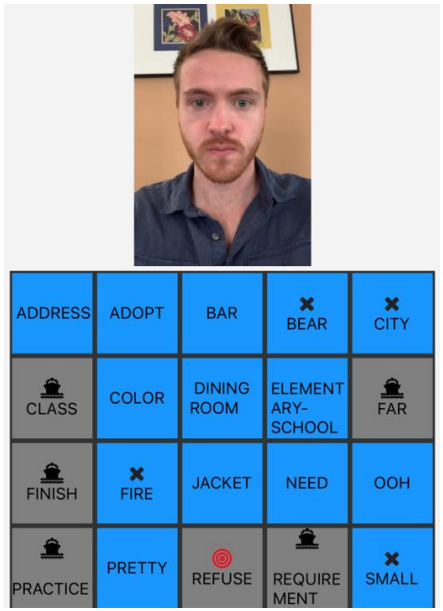
Contributions: evaluation, interpretability, data-efficient training

Future challenges

- Efficient data collection
- Better multimodal architectures
- Spatial reasoning

the world if we had sign foundation models:

Data collection

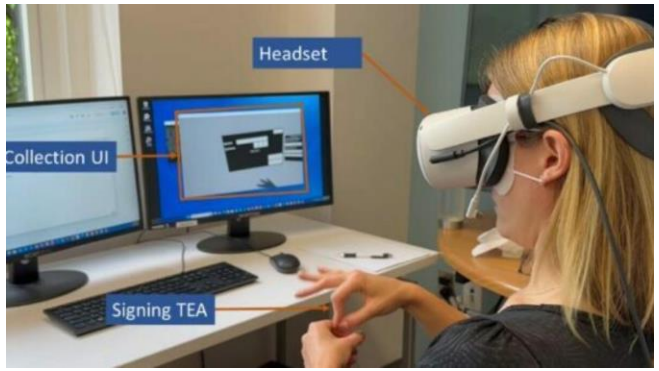


ASL Sea Battle
(Bragg et al., 2021)

- HCI interfaces for data collection
- AI tools to assist data annotation
- AI video anonymization
- Data augmentation

Education

- What environment to learn signed language digitally?
- Adaptive AI for personalized learning
- Educational content delivery, real-time classroom support



ASL Champ
(Gallaudet, 2024)

Signed language generation

Here Comes Mavo!
(Gallaudet, 2025)

- What does a good signing avatar look like?
- Translation between signed languages
- Storytelling

The end!