NATURAL LANGUAGE & INFORMATION PROCESSING LAB

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భారతీయ సాంకేతిక విజ్ఞాన సంస్థ హైదరాబాద్
भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

CharSpan: Utilizing Lexical Similarity to Enable Zero-Shot Machine Translation for Extremely Low-resource Languages

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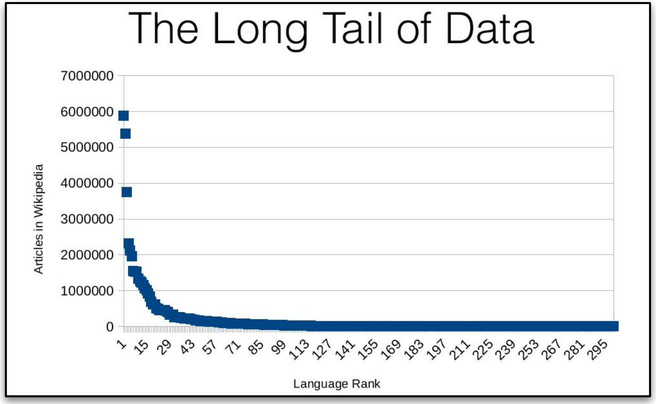
Work conducted during first author's internship at Microsoft, India

Outline

- Introduction and Motivation
- Problem Statement
- Methodology
- Experimental Setup and Results
- Conclusion and Future Work

Introduction: Landscape of Low-resource Languages

- 7000+ languages across the globe [3]
- Only ~300 languages has wikipedia page
- The majority of NLP research focuses on English [3, 4] only - less inclusive and less diverse.
- The majority of the global population—roughly 95%—does not speak English as their primary language, and a staggering 75% do not speak English at all[1]



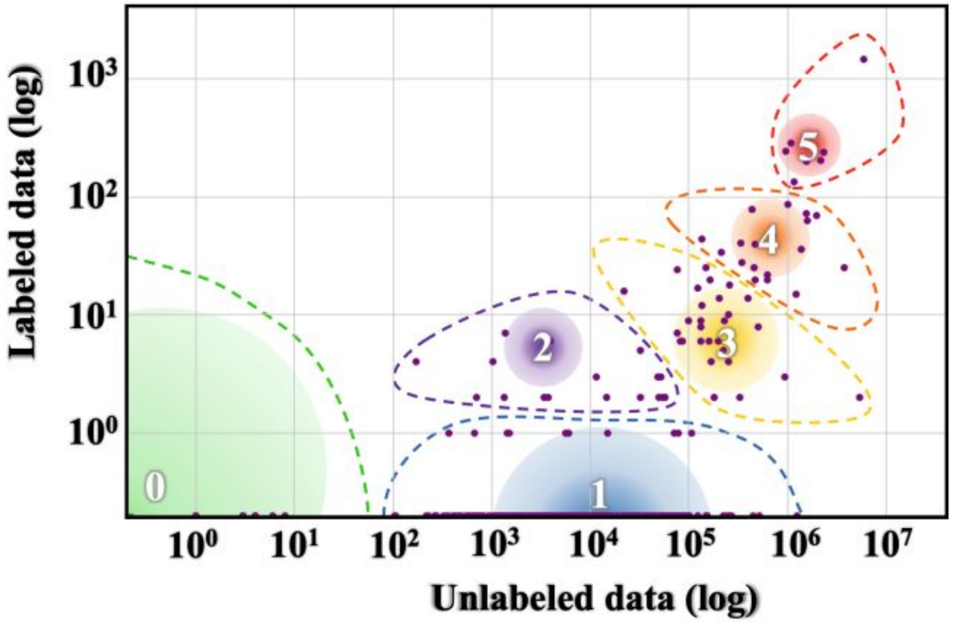
[3] Joshi et al., ACL 2020; [4] E. Bender, The Gradient, 2019

[1] https://en.wikipedia.org/wiki/List_of_languages_by_total_number_of_speakers

Introduction: Limited data for LRLs

- 88% languages fall into class 0 and untouched by language technology [3]

- Only ~100 languages are part of existing large language model, even for those languages, NLG (MT) adaptability is challenging [5]



[3] Joshi et al., ACL 2020; [5] Ahuja et al. 2023

Introduction: Extremely LRLs (ELRLs)

- Lacks parallel data
- Lacks monolingual data
- Representations are absent from existing multilingual pre-trained language models

Problem Statement

"Machine Translation from ELRL to English in the zero-shot setting."

Literature Review: MT for LRLs

- Cross lingual transfer among languages: Multilingual NMT
- Reduce reliance of parallel data: Unsupervised NMT
- Monolingual corpus incorporated NMT: Back-translation
- Data augmentation approaches for MT:
  - Word level perturbation
  - BPE vocabulary overlapping among related languages [23]

Limited Efforts has been made for ELRL for MT task

[23] Patil et al., ACL 2022

Motivation: Hopeful direction

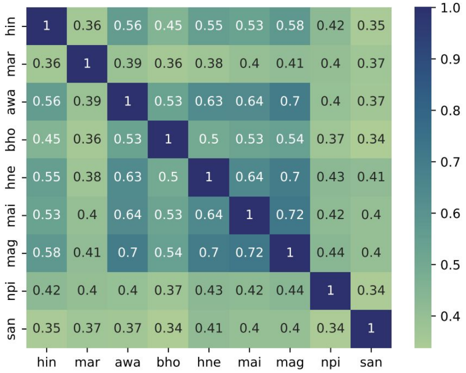
- Utilize relatedness among languages
  - Dialectal variations
  - Vocabulary sharing
  - Similarities due to Geographical proximity

- Many ELRLs are related with some High resource Language (HRL)

Hindi: कनाडियन के खिलाफ नडाल का सीधा रिकॉर्ड 7-2 है।

Bhojpuri: कनाडा के खिलाफ़ नाडाल के हेड-टू -हेड रिकॉर्ड 7-2 के बा।

Lexical level similarity between Hindi and Bhojpuri languages

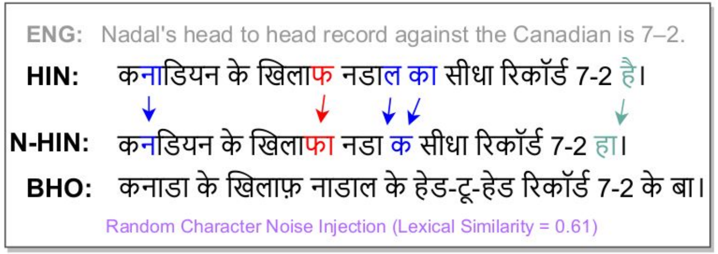


Lexical Similarity heatmap

Motivation: Hopeful direction

Earlier Success for ELRL:

- Recall: Exploit lexical similarity through char-noise augmentation [24]



Limitations:

- Studies limited to NLU tasks only
- Applied with LLM vocab which hinders scalability
- Char Noise augmentation may be suboptimal

[24] Aepli et al., ACL 2022 (Findings)

Motivation: Beyond Character Noise Augmentation

HRL (HIN): इस सीज़न में बीमारी के शुरुआती मामले जुलाई के आखिर में सामने आए थे।
ENG: The initial cases of the disease this season were reported in late July.

HRL (HIN)+CSN: ए_ सीज़न म बीमारी के __प_ मामले जुलाई के आखिर म सामने आए _।

ELRL1 (BHO): ए सीजन में ई बीमारी क पहिला मामला जुलाई क आखिर में सामने आ गइल रहले।

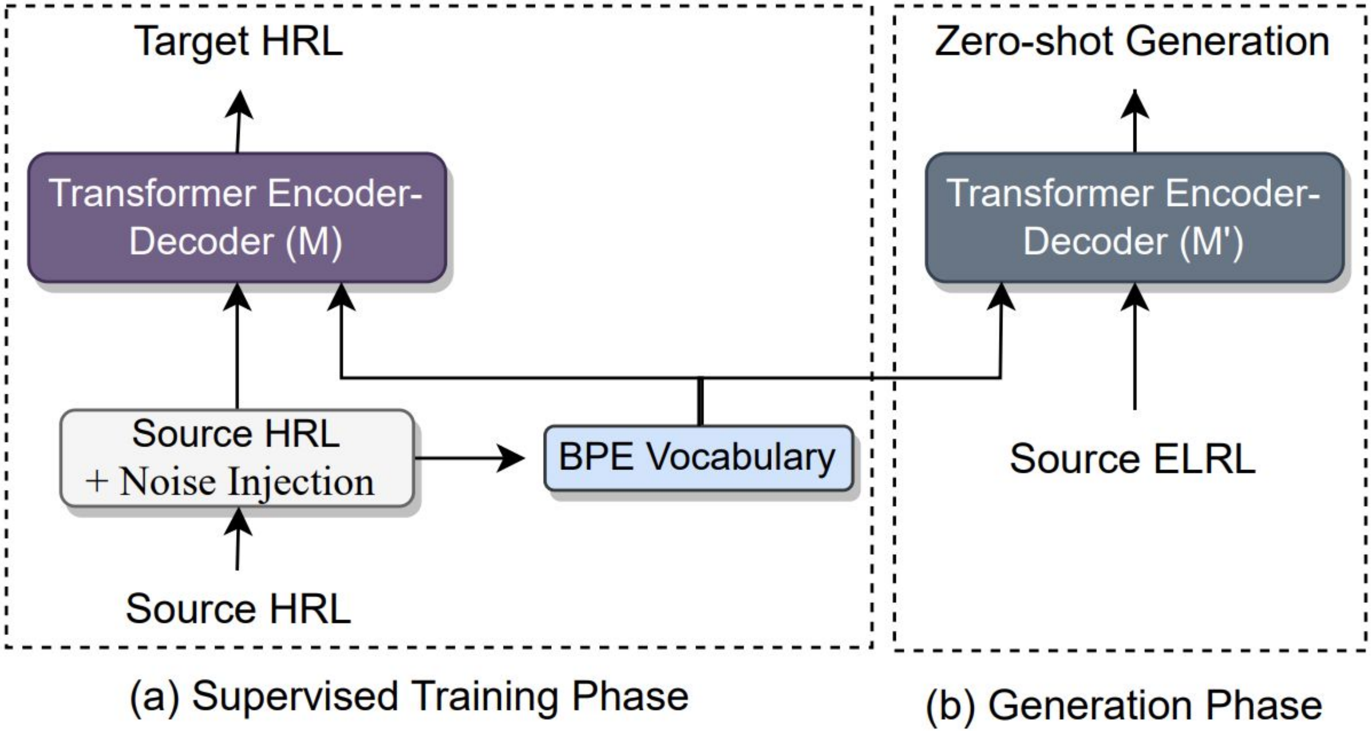
ELRL2 (HNE): ए सीजन म ए बीमारी के पहिला मामला जुलाई के आखिर म सामने आए रहिस।

Character-span Noise Augmentation

Candidate Alphabets

'ं', 'ृ', 'प', 'ॆ', 'ु', 'ञ', 'ऐ', 'अ', '॰', 'र', 'फ', 'ग', 'ह', 'इ' 'न', 'ँ',
'स', 'ए', 'ऑ', 'ल', 'ध', 'ई', 'ऊ', 'ौ', 'ा', 'ঠ', 'म', 'ी', 'छ', 'ॉ' 'ि',
'क', 'ण', 'भ', 'ट', 'ॅ', 'ळ', 'ऋ', 'ष', 'ङ', 'ै', 'ठ', 'ऌ', 'श', 'ब', 'ल',
'ी', 'ও', 'त', 'झ', 'ख', 'ज', 'थ', 'उ', 'ू', 'े', 'ओ', 'ड', 'ी', '़', 'T',
'ऐ', 'ॠ', 'ो', 'ओ', 'ा', 'द', 'ह', 'ो', 'घ', 'च', 'ढ', 'ू', '২', 'य', 'औ',
'व', 'आ', 'ऍ'

Methodology: CharSpan Model



Methodology: CharSpan Model

- Constraints: HRLs and LRLs should be closely related
- Data Sources:
  - No monolingual or parallel data for ELRLs.
  - Used only HRL's alphabets.
- Model Training: No pre-trained LLMs, trained from scratch.
- Noise Augmentation Span: Applied 1-3 character grams.
- Operations: Delete and n-gram to single character insertion.
- Noise Injection Percentage: Injected noise at 10-11%.
- Zero-shot Evaluation:
  - Trained on proxy HRL parallel data.
  - Evaluated with unseen ELRLs

Methodology: Algorithm

Algorithm 1 CharSpan: Character-span Noise Augmentation Algorithm

Require: **[Inputs]** high resource language data ($\mathcal{D}_{\mathcal{H}}(\mathcal{X}, \mathcal{Y})$) from H-En parallel corpus, range of noise augmentation percentage $[P1, P2]$, set of noise augmentation candidates C (see Fig. 3), largest character n-gram size N that will be considered for noising

Ensure: **[Output]** Noisy high resource language data ($\mathcal{D}_{\mathcal{H}}^{'}$)

Augmentation percentage (I_p) = random float(P1, P2) # find a random float value between $P1$ and $P2$
Augmentation factor (α) = int(I_p/N)
for each h in $\mathcal{X}$ **do**
    Let sz be the number of characters in h.
    Let $Indices = \{\lceil(N/2)\rceil, \cdots, sz - \lceil(N/2)\rceil\}$ # Leaving $\lceil(N/2)\rceil$ character indices from beginning and end
    Randomly select $S = N * \alpha$ character indices from $Indices$
    for each k in S **do**
        Span gram (Sp_N) = sample character-span size uniformly from $\{1, 2, \ldots, N\}$ with equal probability
        Operation (O_p) = sample operations uniformly from { delete, replace } with equal probability
        C_d ={}
        if (O_p) is replace **then**
            Candidate char (c) = single sample character uniformly from C with equal probability
            Append candidate char c in C_d
        end if
        if $Sp_N == 1$ **then**
            Perform the operation (O_p) with C_d at the index k
        else
            Perform the operation (O_p) with C_d at the indexes from $k - int((Sp_N - 1)/2)$ to $k + int((Sp_N - 1)/2)$
        end if
    end for
end for

Methodology: Intuition

- Noise augmentation act as regularizer
- Facilitate better a cross-lingual transfer from HRL to ELRL in source side
- Char-Span Noise augmentation enable cross-lingual transfer to distant languages i.e., transfer to less lexically similar to HRLs

Experimental Setup

Indo-Aryan

HRL: Hin and Mar — EU4 Bharat [9]

- Bhojpuri (bho)
- Chhattisgarhi (hne)
- Sanskrit (san)
- Maithili (mai)
- Magahi (mag)
- Awadhi (awa)
- Nepali (npi)
- Kashmiri (kas)
- Konkani (GOM)

FLORES 200 (ELRLs)

Romance

HRL: Esp and Por — Rapp (2021) [10]

- Catalan (cat)
- Galician (glg)

FLORES 200 (ELRLs)

Malay-Polynesian

HRL: Ind and Mal — OPUS

- Javanese (Jav)
- Sundanese (sun)

FLORES 200 (ELRLs)

Automatic evaluation

- BLEU
- ChrF
- BLEURT
- COMET

Human evaluation

- XSTS

- Vanilla NMT [11] [12]
- Word-drop [6]
- SubwordDropout [6]
- BPE-drop [12]
- SwitchOut [13]
- SubwordSwitchOut
- OBPE [14]
- BPE-Dropout [15]
- Random Char Noise [7]

3 Families | 12 ELRLs & 6 HRLs | Datasets | Evaluation Metrics | 9 Baselines

Evaluation Results [ChrF Scores]

Models	Indo-Aryan								Romance		Malay-Polynesian		Average
	Gom	Bho	Hne	San	Npi	Mai	Mag	Awa	Cat	Glg	Jav	Sun	
BPE*	26.75	39.75	46.57	27.97	30.84	39.79	48.08	46.28	33.32	53.75	31.44	32.21	38.06
WordDropout	27.01	39.57	46.19	28.13	31.91	40.31	47.37	46.48	34.20	52.21	32.03	32.52	38.16
SubwordDropout	27.91	40.11	46.26	29.46	32.56	40.99	47.91	47.43	35.09	52.28	33.38	33.47	38.90
WordSwitchOut	25.17	38.81	45.87	26.21	29.95	39.69	47.53	44.54	32.98	51.81	31.84	32.49	37.24
SubwordSwitchOut	26.08	38.84	45.84	28.19	30.81	40.19	47.28	45.93	33.26	53.71	31.24	32.06	37.78
OBPE	27.90	40.57	47.46	28.52	31.99	40.71	49.10	47.16	32.33	52.77	29.98	30.88	38.28
SDE	28.01	40.91	47.88	28.66	32.03	40.82	48.96	47.30	33.72	53.95	31.84	31.24	38.77
BPE-Dropout*	28.65	40.84	46.58	28.80	31.88	40.79	47.86	47.32	34.56	55.83	32.01	32.97	39.00
unigram char-noise**	28.85	42.53	49.35	29.80	34.61	42.67	50.97	49.43	43.16	54.81	35.42	36.69	41.52
BPE $\rightarrow$ SpanNoise*** (*ours*)	28.66	41.94	49.48	30.49	35.66	44.75	50.55	49.21	43.11	54.89	36.12	37.11	40.16
CHARSPAN (*ours*)	29.71	43.75	51.69	**31.40**	36.52	45.84	51.90	50.55	43.51	55.46	36.24	37.31	42.82
CHARSPAN + BPE-Dropout (*ours*)	**29.91**	**44.02**	**51.86**	30.88	**37.15**	**46.52**	**52.99**	**51.34**	**44.93**	**55.87**	**36.97**	**38.09**	**43.37**

Zero-shot chrF scores for ELRLs → English

- Similar improvements in BLEU, COMET and BLEURT metrics

Results Observations

- The proposed model shows the huge improvement over BPE and traditional sub(word) based perturbation models
-

Analysis: Cross-lingual Transfer

Models	Bho	Hne	San	Npi	Mai	Mag	Awa
BPE	0.761	0.793	0.701	0.744	0.762	0.809	0.792
UCN	0.853	0.888	0.765	0.821	0.849	0.897	0.883
CHARSPAN	**0.871**	**0.909**	**0.789**	**0.858**	**0.868**	**0.913**	**0.901**

Average cosine similarity between representations of source HRLs and source ELRLs for Indo-Aryan family.

Observation: The latent representation space between HRL and ELRL(s) is more aligned with the CharSpan model, facilitating better cross-lingual transfer.

Analysis: Mitigate Zero-shot Translation Errors

Examples	Sentence Type	Source/Target/Generation
BHO to ENG	Source Input	उ आगे कहलन,"हमनीं के पास एगो 4-महीना क मूस बा जवन पहिल मधुमेह के बीमारी से ग्रसित रहल लेकिन अब ऊ इ बीमारी से मुक्त बा"
	Reference Target	We now have 4-month-old mice that are non-diabetic that used to be diabetic," he added.
	BPE	"We have Ago 4-month-old Mous Ba Jawan Pahil, who is suffering from diabetes, but now get rid of the disease," "he added."
	UCN	"We had a 4-month-old daughter who was first suffering from diabetes, but now we are free from a disease," "he added.
	CharSpan	We had 4-month-old mice that are non-diabetic, but now free from the diabetic," "he added."
HNE to ENG	Source Input	हामी USOC को कथनसँग सहमत छौं कि विघटन भन्दा बरू हाम्रा एथ्लेट र क्लबहरूको हित र तिनीहरूको खेल सायद हाम्रो सङ्घ भित्र अर्थपूर्ण परिवर्तनको साथ अघि बढेर अझ राम्रो सेवा दिन सकिन्छ।
	Reference Target	We agree with the USOC's statement that the interests of our athletes and clubs, and their sport, may be better served by moving forward with meaningful change within our organization, rather than decertification.
	BPE	Hami agreed to the USOC that dissolution Bhanda Baru Hamra Ethlite Club interested in Tiniharuko Play Syed Hamro Bhitra meaningful changes along with Ah Ramro Service Day Sakinch.
	UCN	Hami agrees with the USOC that dissolution Bhanda Baru Hamra Athlete Club Bahruko interested in Tinihruko Games Sayyid Hamro Sangha Change with Azhi Ramro Seva Day Sakinch.
	CharSpan	We agreed with the USOC that the dissolution would be in the interest of athletes and clubs, and their sport and grow a friendly, meaningful transformation and celebrate rather than decertification in organization.

Observation: Char-Span Model Successfully mitigate the translation error from BPE and UNC models.

Conclusion & Future Work

- CharSpan Model outperforms strong baselines across 12 ELRLs for ELRLs → English MT task
- The proposed model does not required monolingual data, parallel data and LLM multilingual representation.
- Highly Scalable
- Cumulative gain of 12.34% chrF over Vanilla-NMT (BPE) model

Future works:

- Extend to other NLG tasks
- Potential impact for English → ELRLs MT task

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