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Multilinguality & Speech Translation

Antonios Anastasopoulos

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The Languages of the World

The Languages of the World

The Languages of the World

- More than **6000** languages:

The Languages of the World

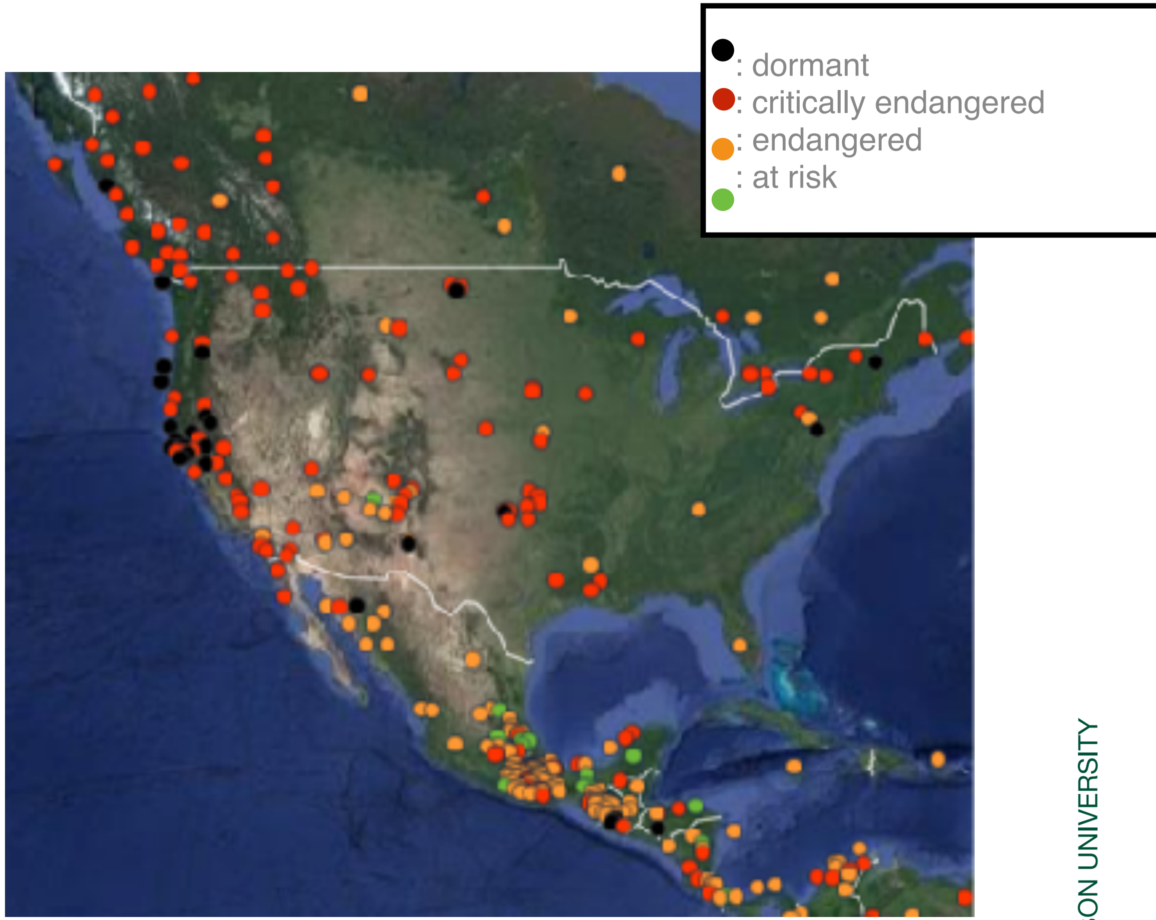
- More than **6000** languages:
  - → 45% oral

A traditional Kyrgyz manaschi performing part of the Epic of Manas at a yurt camp in Karakol

Image Source: Wikipedia

The Languages of the World

- More than **6000** languages:
  - → 45% oral
  - → 43% endangered or vulnerable



Source: the Endangered Languages Project

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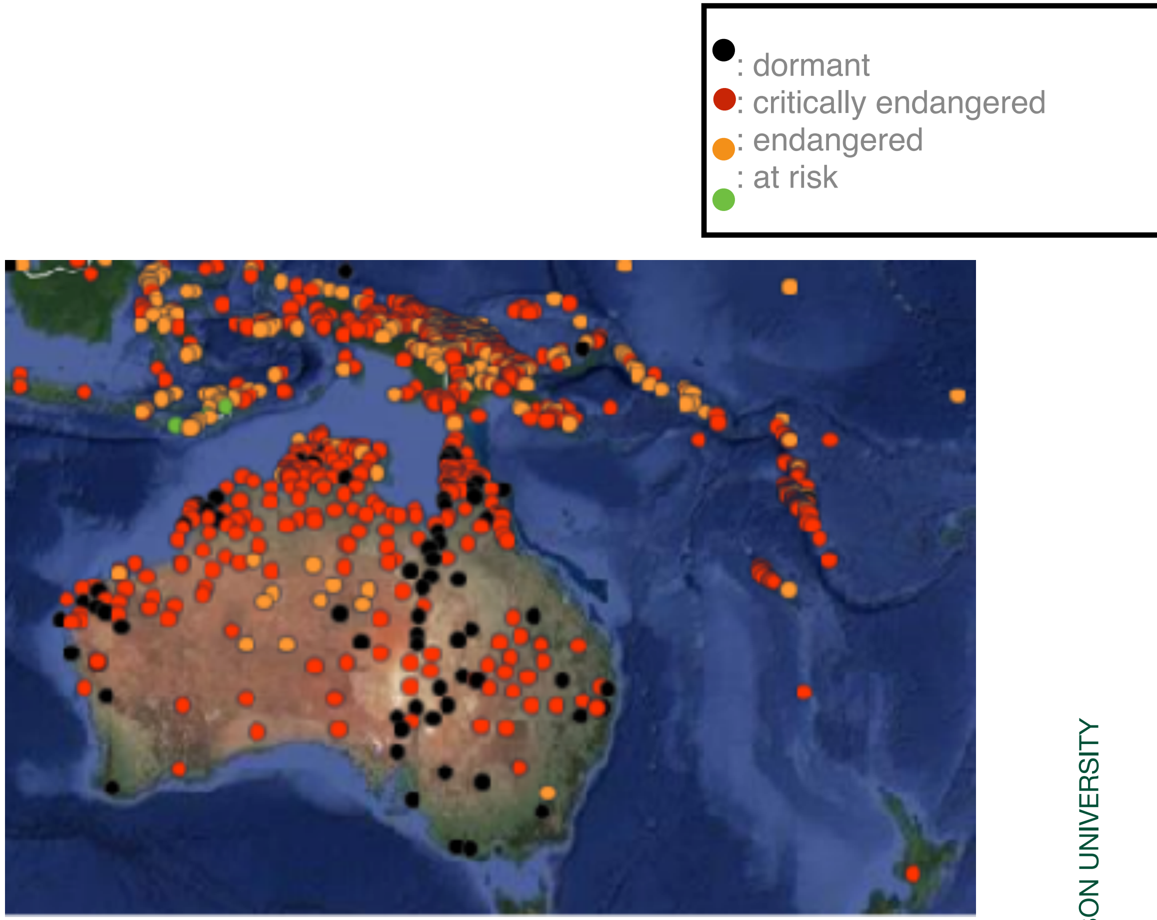

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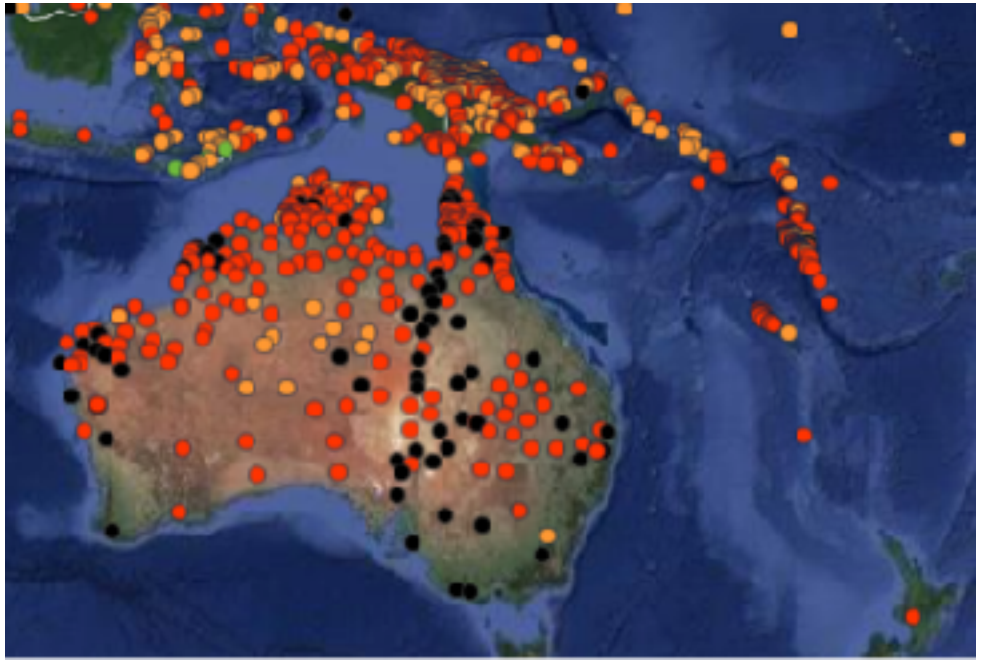
The Languages of the World

- More than **6000** languages:
  - → 45% oral
  - → 43% endangered or vulnerable
  - → differences in culture, vocabulary
  - → differences in morphological complexity, syntax, tonality, word order…

●: dormant
●: critically endangered
●: endangered
●: at risk



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But also…

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But also…

- → regional varieties (dialects)

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But also…

- → regional varieties (dialects)
- → L2 speakers
- → sign languages

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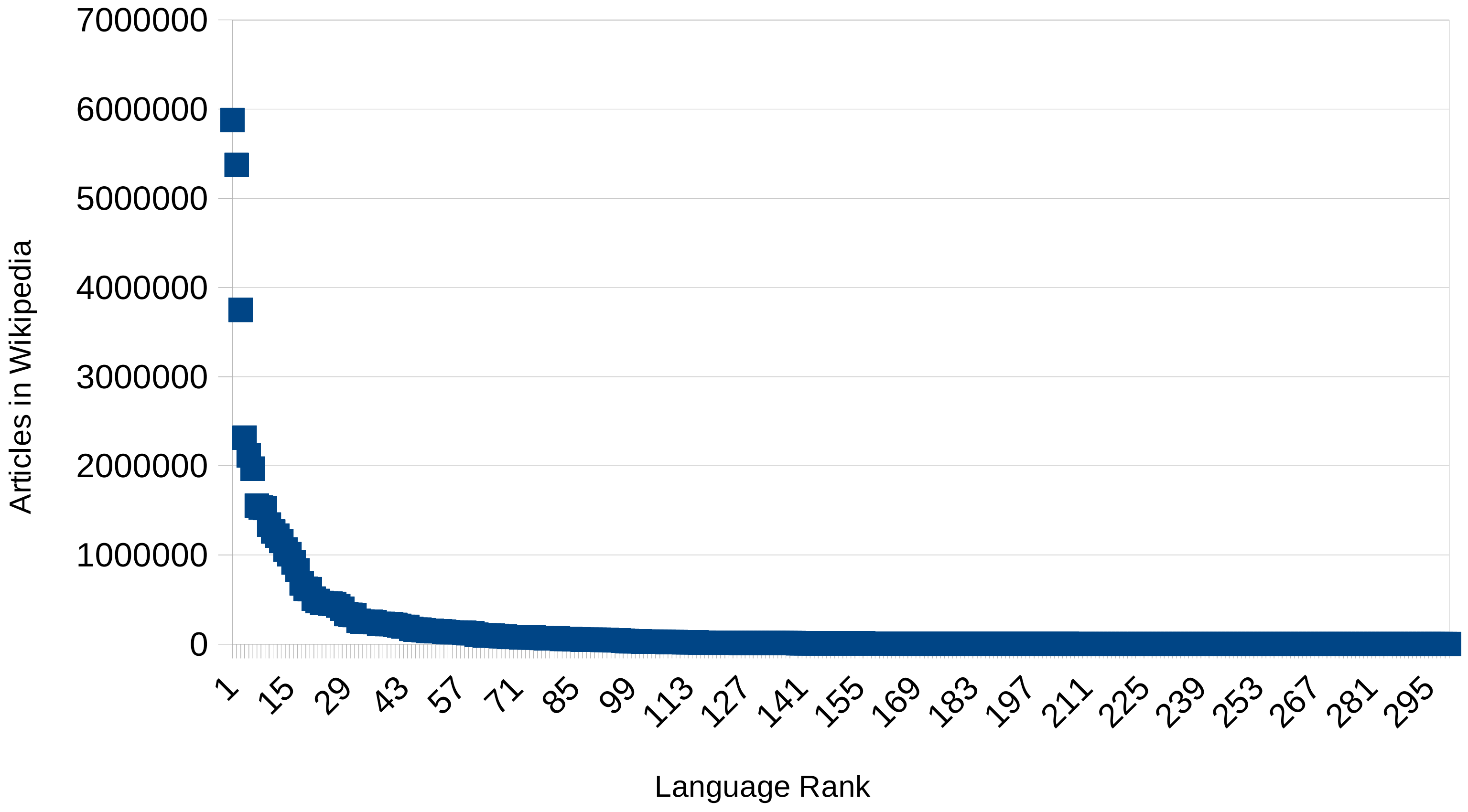
The Long Tail of Data



CASE STUDY: TRANSLATION BETWEEN SIMILAR LANGUAGES

Catalan: Què diu aquesta frase?

Spanish: ¿Qué dice esta oración?

Galician: Que di esta frase?

Portuguese: O que esta frase diz?

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Team	Type	BLEU	TER
MLLPUPV	P	64.7	20.8
UPC-TALP	P	62.1	23.0
NICT	P	53.3	29.1
Uhelsinki	C	52.8	28.6
Uhelsinki	P	52.0	29.4
Uhelsinki	C	51.0	33.1
NICT	C	47.9	33.4
UBC-NLP	P	46.1	36.0
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BSC	P	44.0	37.5

Table 27: Results for *Spanish* to Portuguese Translation

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Uhelsinki	C	59.1	25.5
Uhelsinki	C	58.6	25.1
Uhelsinki	P	58.4	25.3
KYOTOUNIVERSITY	P	56.9	26.9
NICT	C	54.9	28.4
BSC	P	54.8	25.8
UBC-NLP	P	52.3	32.9
UBC-NLP	C	52.2	32.8
MLLPUPV	C	51.9	30.5
MLLPUPV	C	49.7	32.1
BSC	C	48.5	35.1

Table 26: Results for Portuguese to Spanish Translation

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Panlingua-KMI	P	11.5	79.1
CMU_MHAN	P	11.1	79.7
UBC-NLP	P	08.2	77.1
UBC-NLP	C	08.2	77.2
NITS-CNLP	P	03.7	-
NITS-CNLP	C	03.6	-
CFILT_IITB	C	03.5	-
Panlingua-KMI	C	03.1	-
CFILT_IITB	P	02.8	-
CFILT_IITB	C	02.7	-
Panlingua-KMI	C	01.6	-
JUMT	P	01.4	-

Table 28: Results for Hindi to Nepali Translation

CASE STUDY: INDIAN SUBCONTINENT

এই বাক্যটি কী বলে? આ વાક્ય શું કહે છે? ಈ ವಾಕ್ಯ ಏನು ಹೇಳುತ್ತದೆ? ਇਹ ਸਜ਼ਾ ਕੀ ਕਹਿੰਦੀ ਹੈ?

ഈ വാചകം എന്താണ് പറയുന്നത്? यह वाक्य क्या कहता है? हे वाक्य काय म्हणते?

ఈ వాక్యం ఏమి చెబుతుంది? यो वाक्यले के भन्छ? මෙම වාක්‍යය පවසන්නේ කුමක්ද?

- Phonetic and Orthographic Similarity
- Transliteration and Cognate mining
- Character-level translation

Issues: text normalization, tokenization

CASE STUDY: ENGLISH-CHINESE

what does this sentence mean? 這句話是什麼意思?
這句话是什么意思?

Best WMT system: *The NiuTrans Machine Translation Systems for WMT19, Li et al. 2019*

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tokenization?

Character-based decoding can help
when translating to Chinese (Bowden et al, 2019)

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CASE STUDY: ENGLISH-CHINESE

what does this sentence mean?

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Another idea: Modeling sub-character information

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Another idea: Modeling sub-character information

Neural Machine Translation of Logographic Languages
Using Sub-character Level Information, Zhang and Komachi, 2019.

Character	Semantic ideograph	Phonetic ideograph	Pinyin
驰 run	马 horse	也	chí
池 pool	水(氵) water	也	chí
施 impose	方 direction	也	shī
弛 loosen	弓 bow	也	chí
地 land	土 soil	也	dì
驱 drive	马 horse	区	qū

Table 1: Examples of decomposed ideographs of Chinese characters. The composing ideographs of different functionality might be shared across different characters.

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Another idea: Modeling sub-character information

Character-level Chinese-English Transl
through ASCII Encoding,
Nikolov et al., 2019.

Figure 1: Overview of the wubi2en approach to Chinese-to-English translation. A raw Chinese word ('承诺') is encoded into ASCII characters ('bd|yad'), using the Wubi encoding method, before passing it to a Seq2Seq network. The network generates the English translation 'commitment', processing one ASCII character at a time.

CASE STUDY: ARABIC

what does this sentence mean?   ماذا تعني هذه الجمله؟

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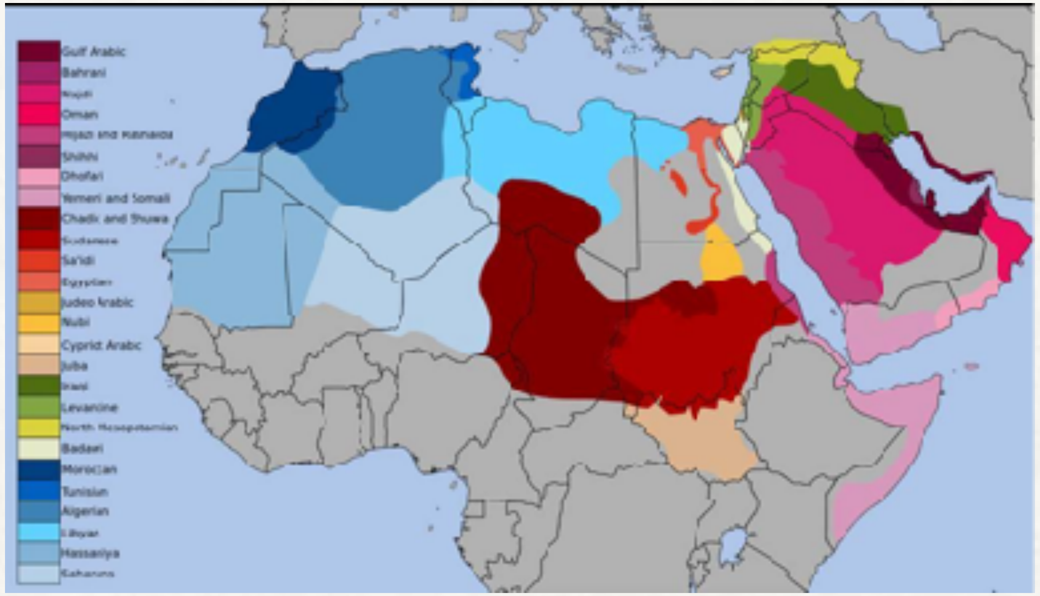

CASE STUDY: ARABIC

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Issue: Root-and-Pattern morphology

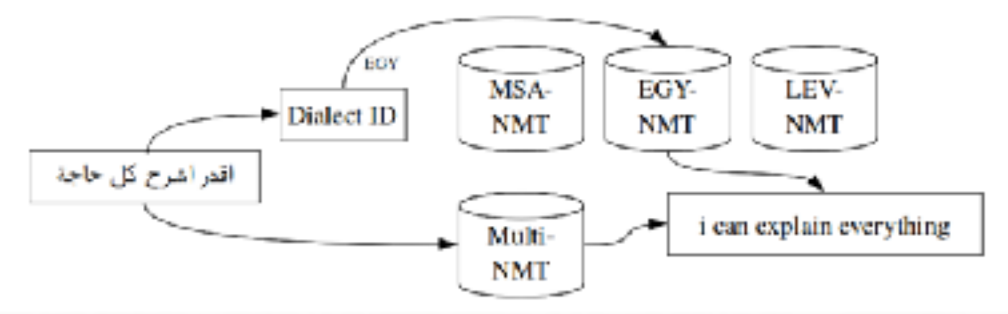
Solution: Morphological Analysis and Disambiguation

Input	wsynhY	Alr}ys	jwlth	bzyArp	AlY	trkyA.	
Gloss	and will finish	the president	tour his	with visit	to	Turkey	.
English	The president will finish his tour with a visit to Turkey.						
ST	wsynhY	Alr}ys	jwlth	bzyArp	AlY	trkyA	.
D1	w+ synhy	Alr}ys	jwlth	bzyArp	<lY	trkyA	.
D2	w+ s+ ynhy	Alr}ys	jwlth	b+ zyArp	<lY	trkyA	.
D3	w+ s+ ynhy	Al+ r}ys	jwlp +P$_{3MS}$	b+ zyArp	<lY	trkyA	.
MR	w+ s+ y+ nhy	Al+ r}ys	jwl +p +h	b+ zyAr +p	<lY	trkyA	.
EN	w+ s+ >nhY$_{VBP}$ +S$_{3MS}$	Al+ r}ys$_{NN}$	jwlp$_{NN}$ +P$_{3MS}$	b+ zyArp$_{NN}$	<lY$_{IN}$	trkyA$_{NNP}$	.

CASE STUDY: ARABIC

what does this sentence mean? ماذا تعني هذه الجمله؟

Handling dialectal data:



CASE STUDY: COMPLEX MORPHOLOGY (E.G. FINNISH, TURKISH)

What about linguistically-informed segmentation?

Words	He admits to shooting girlfriend
BPE	He admits to sho@@ oting gir@@ l@@ friend
Morfessor	He admit@@ s to shoot@@ ing girl@@ friend
Characters	H e _ a d m i t s _ t o _ s h o o t i n g _ g i r l f r i e n d

Table 2: Example with different segmentations.

USING RELATED LANGUAGES

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How can you choose a related language for cross-lingual transfer?

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1. Intuition (maaaayyybe ok)

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2. Geography (could be misleading)

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How can you choose a related language for cross-lingual transfer?

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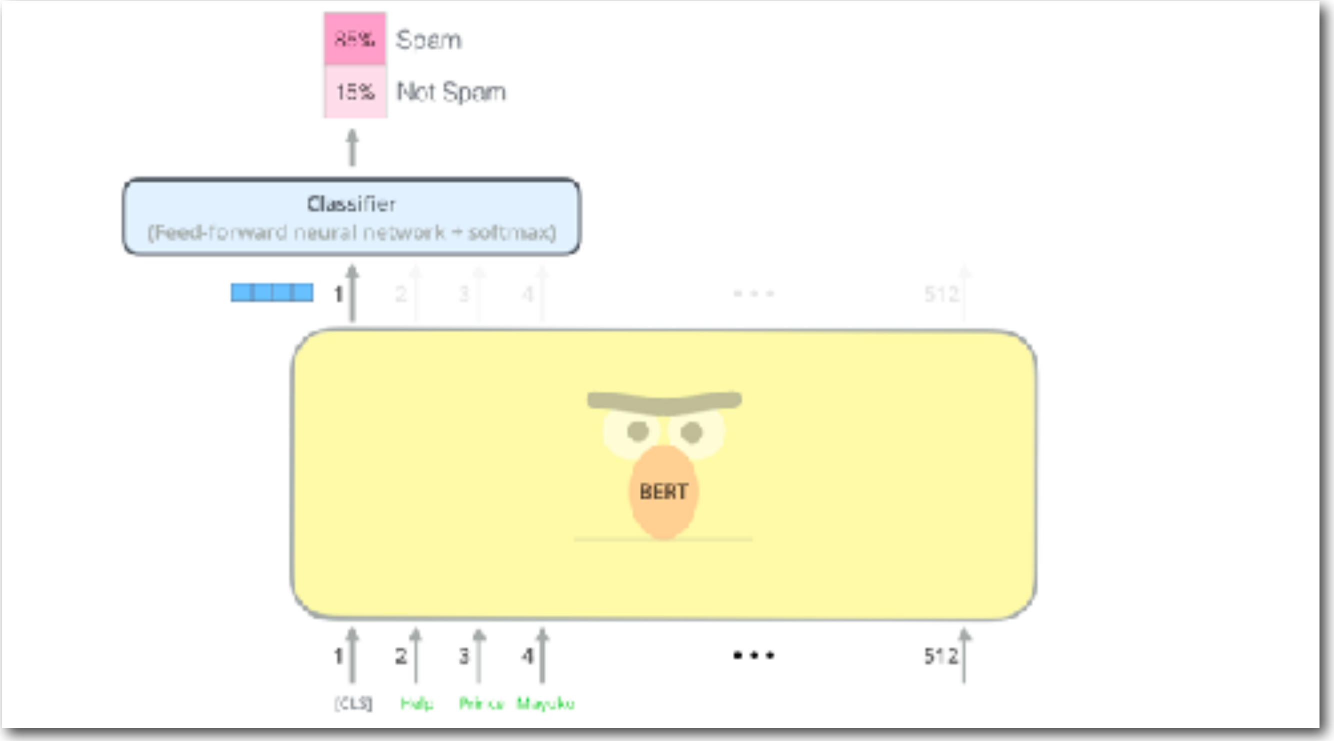
2. Geography (could be misleading)
3. Typological Features

Some recent trends



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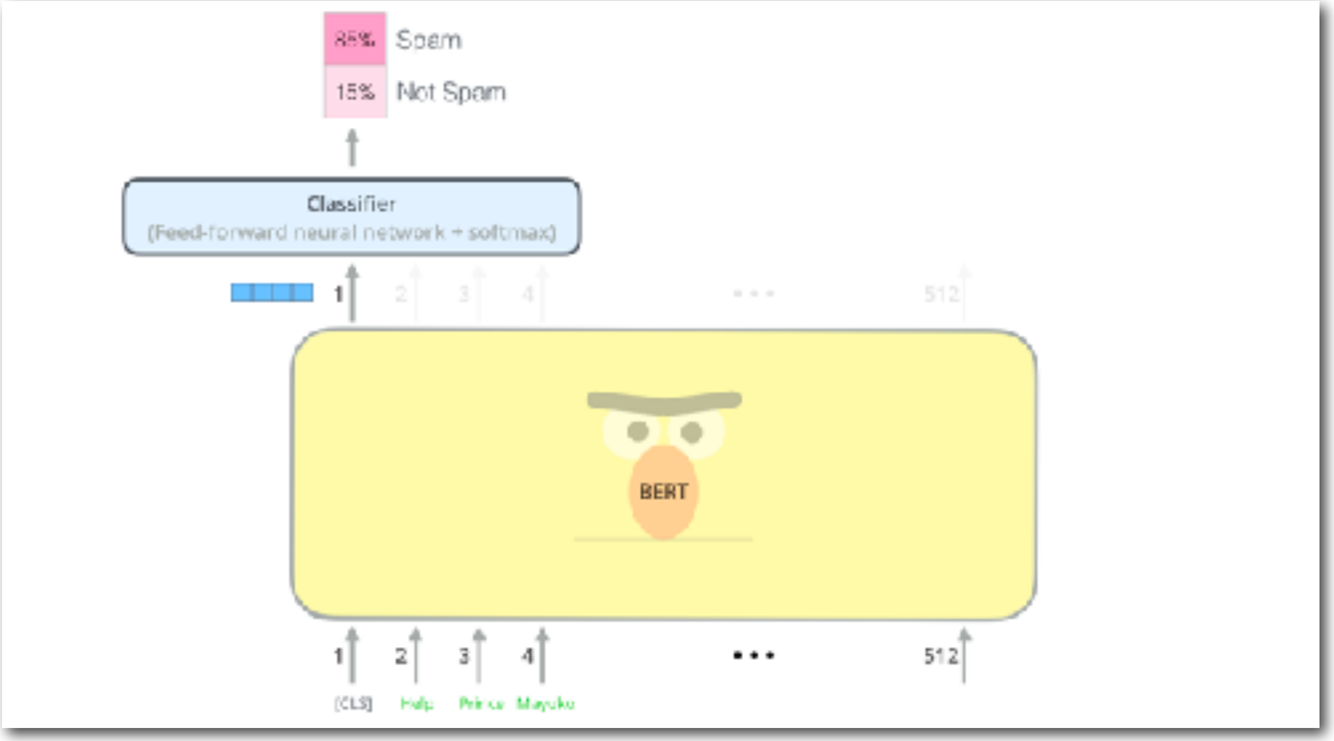


Choose our own adventure

~~Gemini~~

~~GPT-4~~

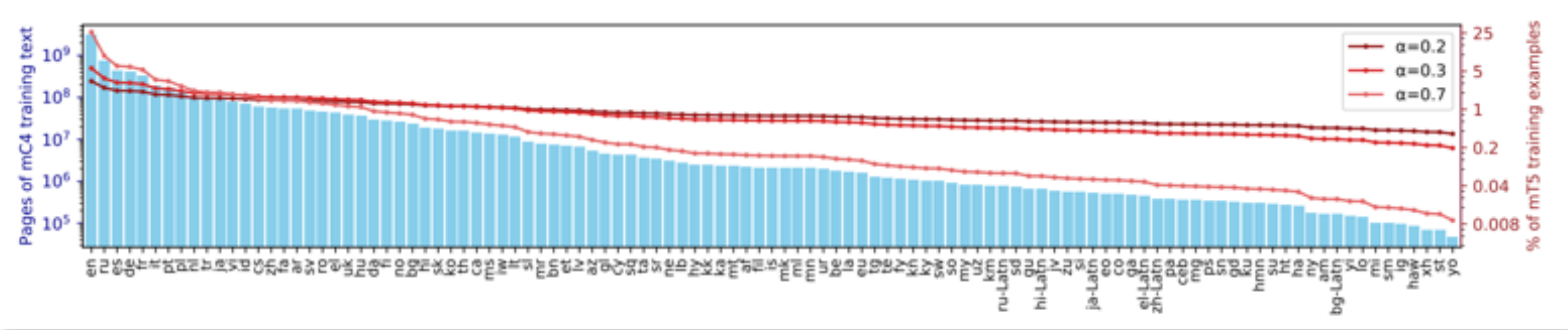
~~Claude~~

~~PaLM~~

~~GPT-2~~

~~XLM-R~~

Make it multilingual!



mT5: A Massively Multilingual Pre-trained Text-to-Text Transformer

NLP beyond the top-100 languages

Going Beyond the top-100 Languages

Going Beyond the top-100 Languages

Dominant
Written (Latin)
Standardized
high(ish)-resource

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Going Beyond the top-100 Languages

Dominant
Written (Latin)
Standardized
high(ish)-resource

Local
Oral
non-Standardized
Very low-resource

Going Beyond the top-100 Languages

Going Beyond the top-100 Languages

Going Beyond the top-100 Languages

Train on all the internet (GPT-4?) → ***incidental multilingualism***

Going Beyond the top-100 Languages

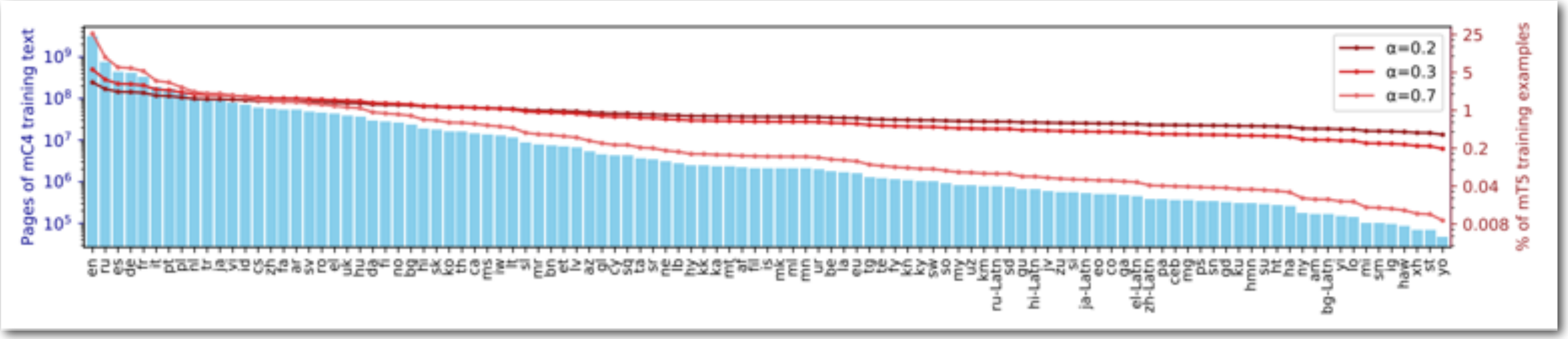
Train on all the internet (GPT-4?) → ***incidental multilingualism***
or

Going Beyond the top-100 Languages

Train on all the internet (GPT-4?) → ***incidental multilingualism***

or

Explicitly collect data in many languages and upsample low-resource ones



Getting Data - Internet Crawling

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Crawling the internet → Language ID

Currently 166 languages

Getting Data - Internet Crawling

Crawling the internet → Language ID
Currently 166 languages

Quality at a Glance:
An Audit of Web-Crawled Multilingual Datasets

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Crawling the internet → Language ID
Currently 166 languages

**Quality at a Glance:
An Audit of Web-Crawled Multilingual Datasets**

Very low quality for some languages
langID far from perfect

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Our Solution: Work with Communities

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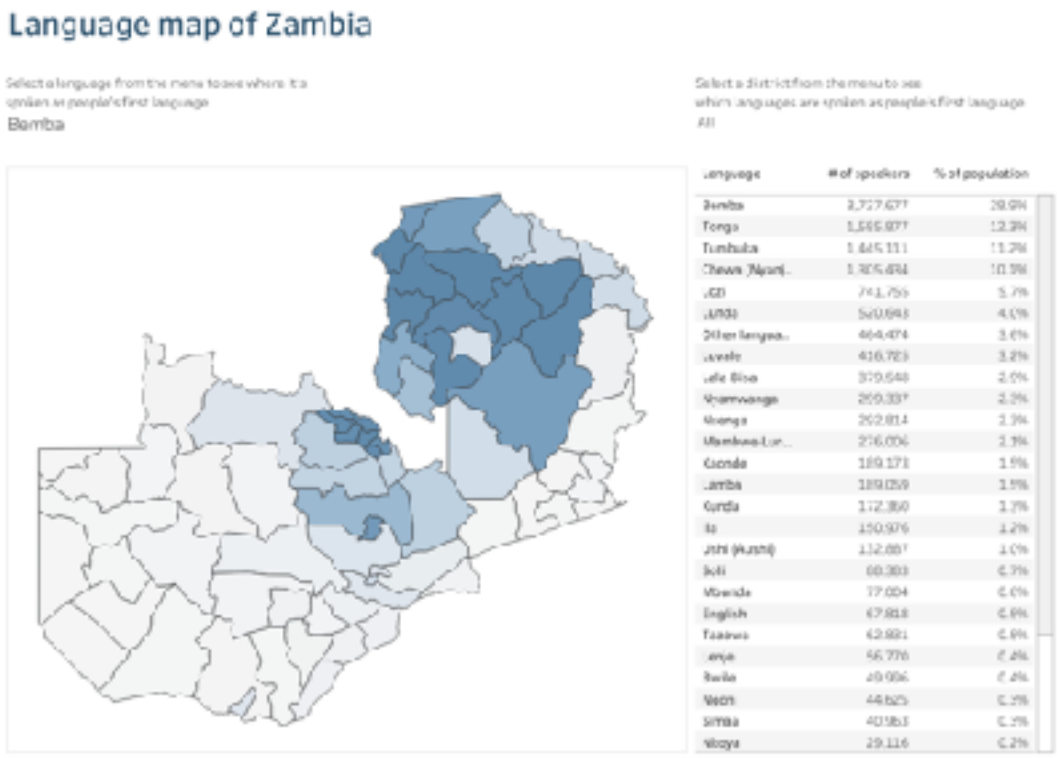
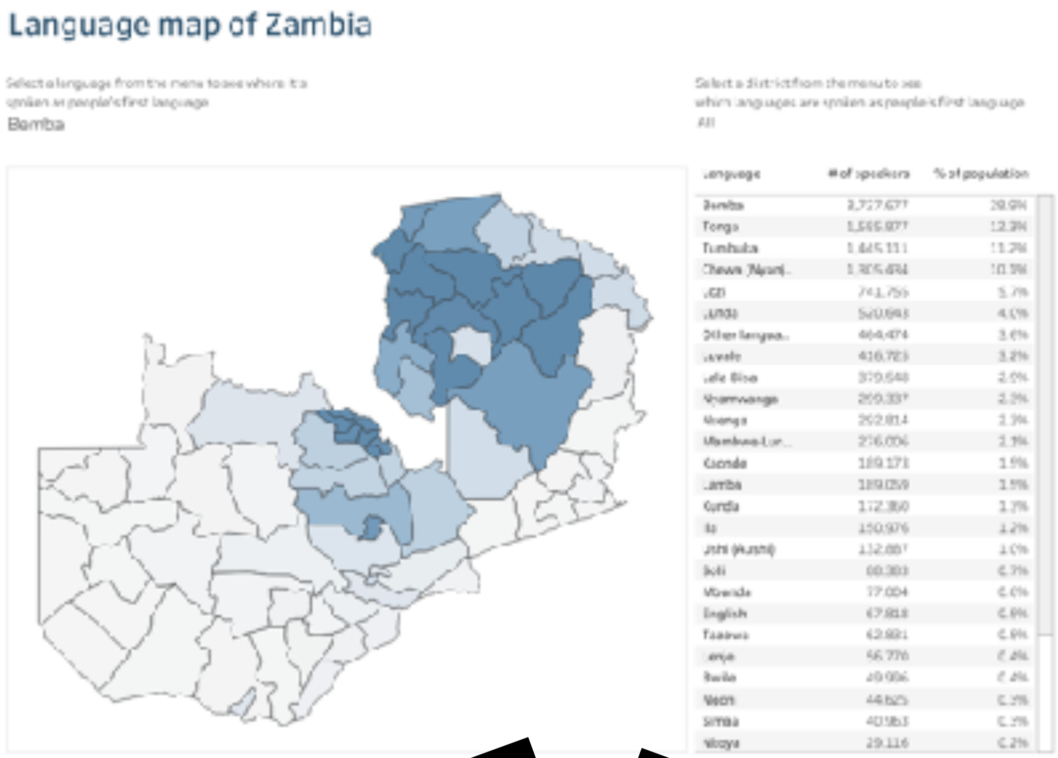


Our Solution: Work with Communities



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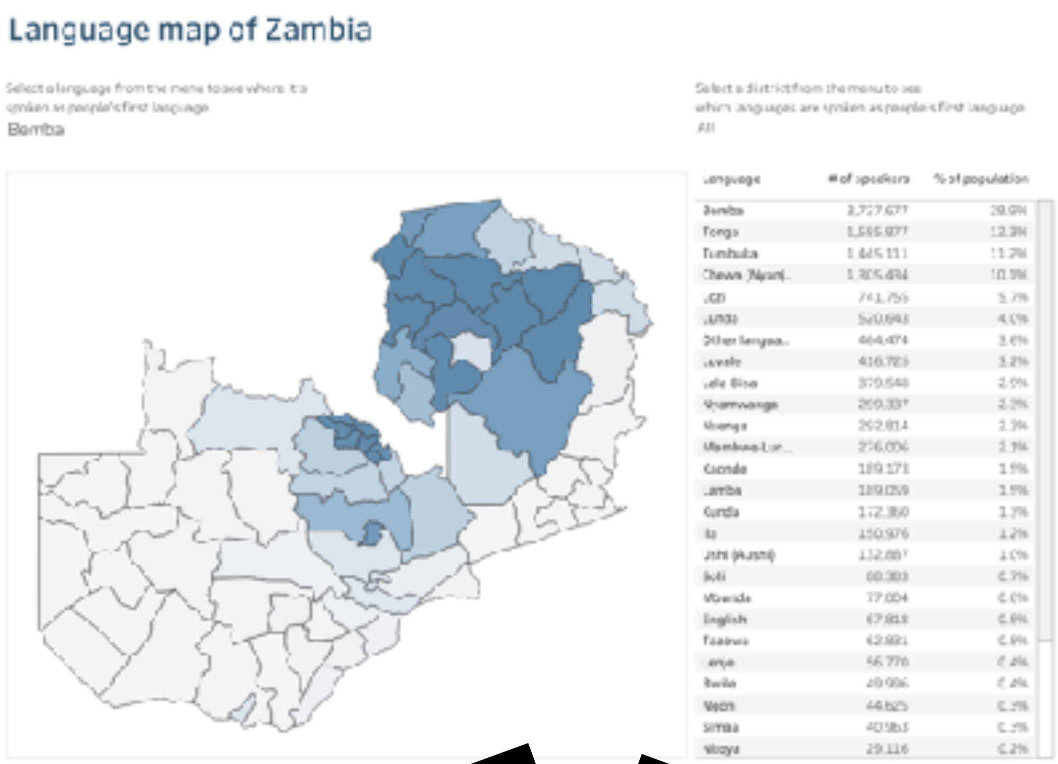

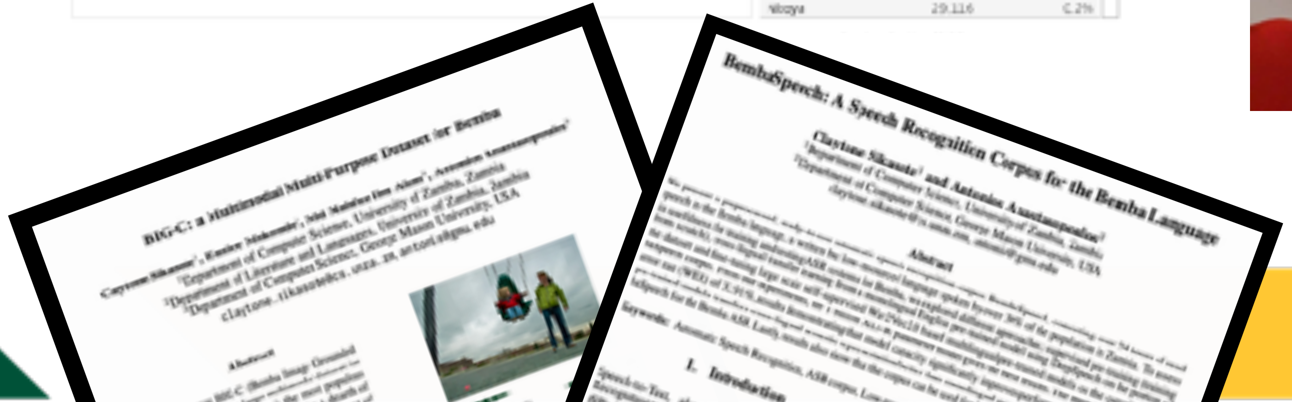

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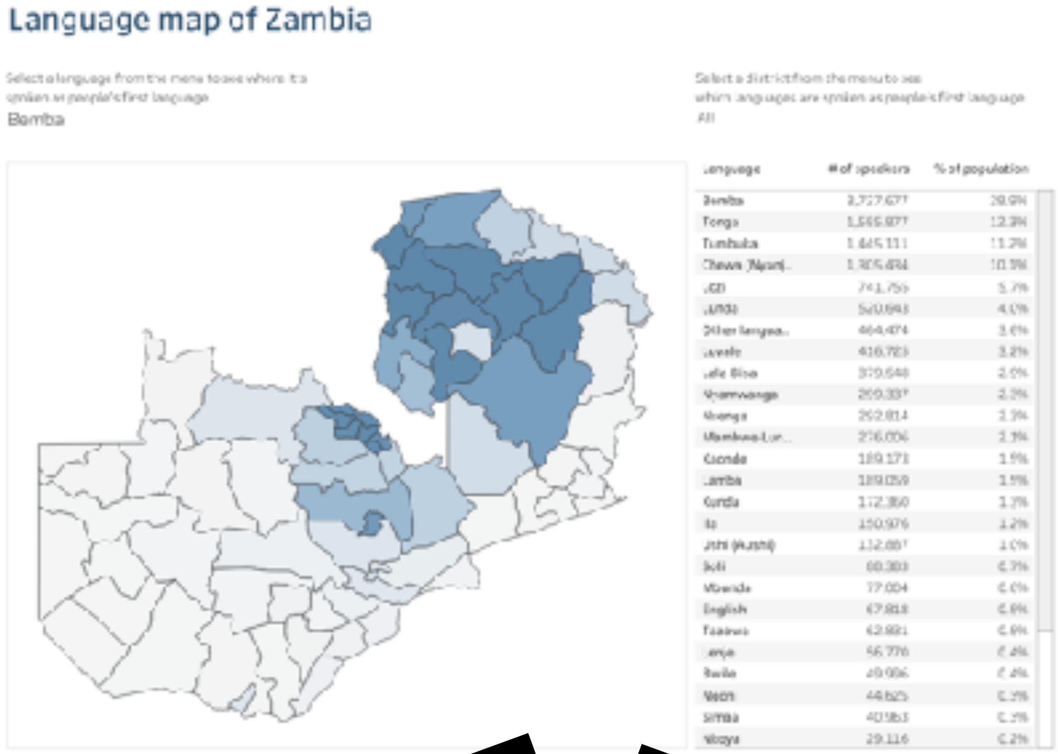
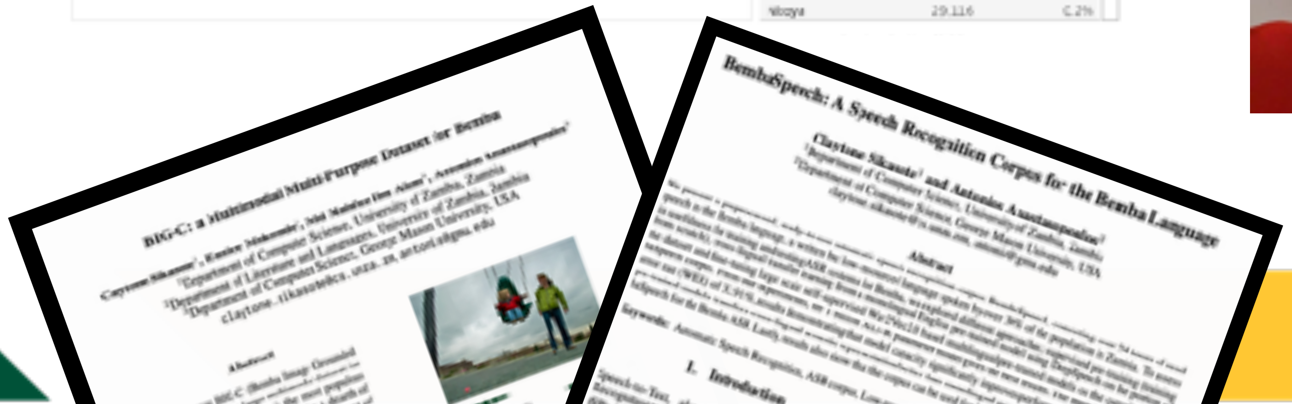



BIG-C: a Multimodal Multi-Purpose Dataset for Bemba

BembaSpeech: A Speech Recognition Corpus for the Bemba Language

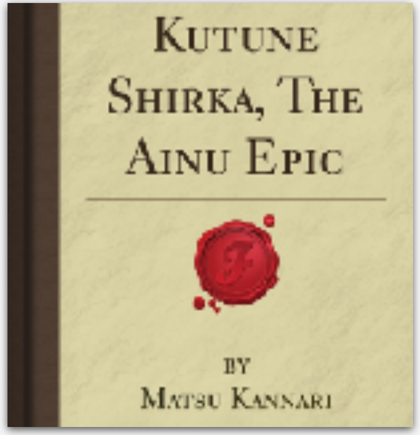
Abstract


Educational Tools for Mapuzugun

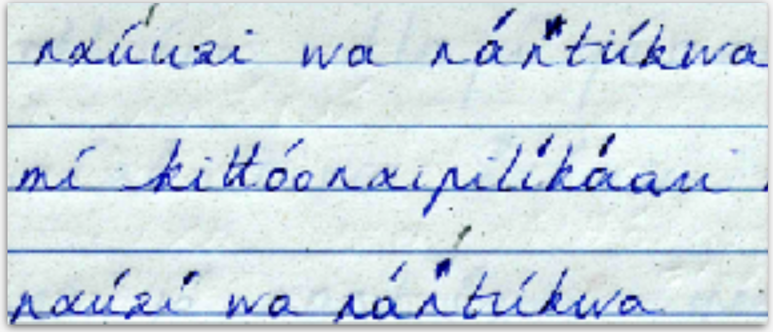
Cristian Ahumada Claudio Gutierrez Antonios Anastasopoulos

Abstract

Our Solution: Make Existing Data ML-Usable

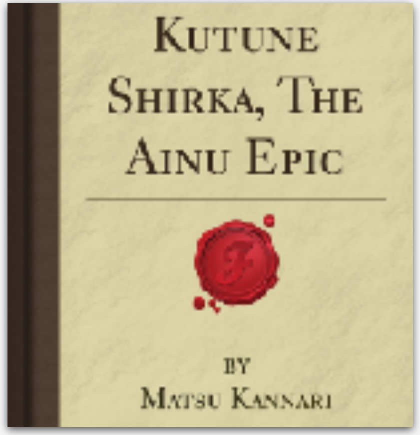


Printed books



Handwritten notes

Our Solution: Make Existing Data ML-Usable



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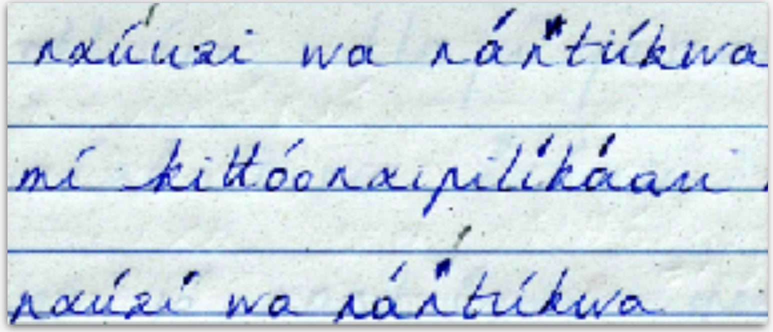

Handwritten notes

Our Solution: Curation at Scale

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Let's get *small, but high quality* data

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PRATHAM BOOKS storyweaver

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Our Solution: Curation at Scale

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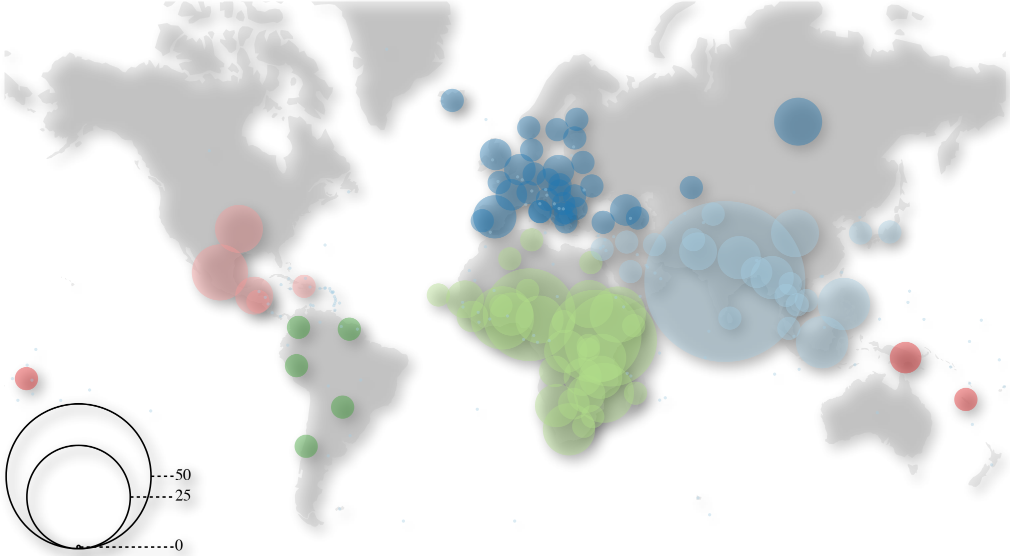
PRATHAM BOOKS
storyweaver

>350 languages



LIMIT: Language Identification, Misidentification, and Translation using Hierarchical Models in 350+ Languages

Milind Agarwal Md Mahfuz Ibn Alam Antonios Anastasopoulos
Department of Computer Science, George Mason University

Abstract

Language ID at Scale

Benchmarking most popular models

Language ID at Scale

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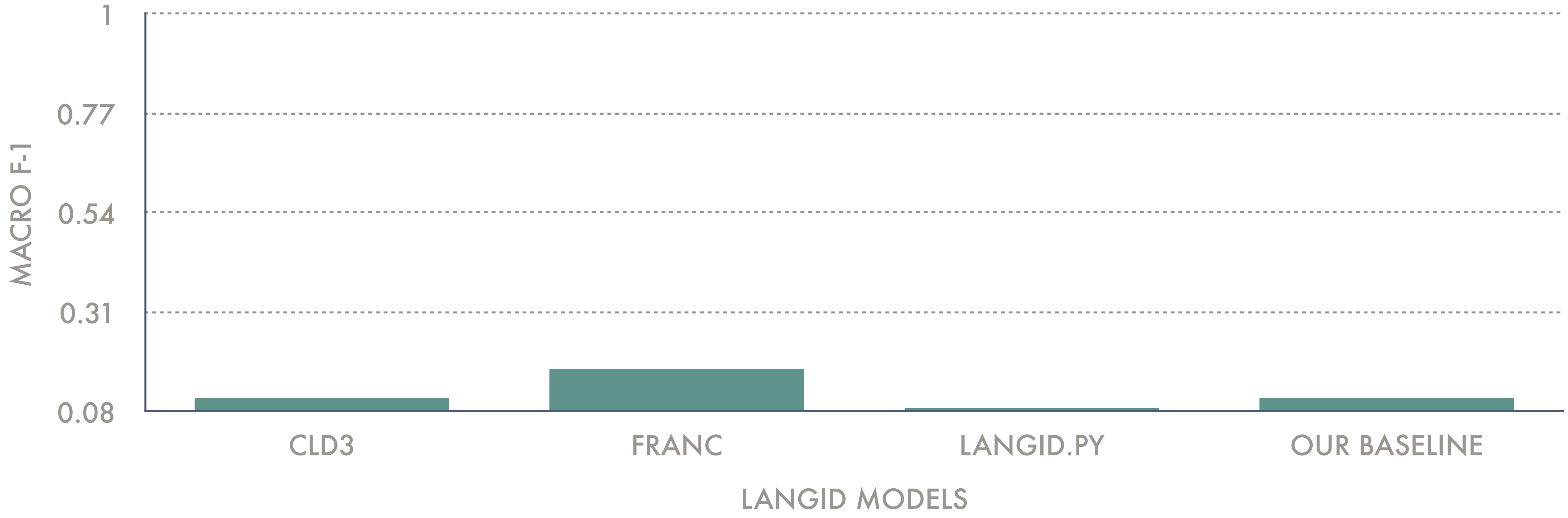
Benchmarking most popular models



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Dialects

Languages are not Monoliths

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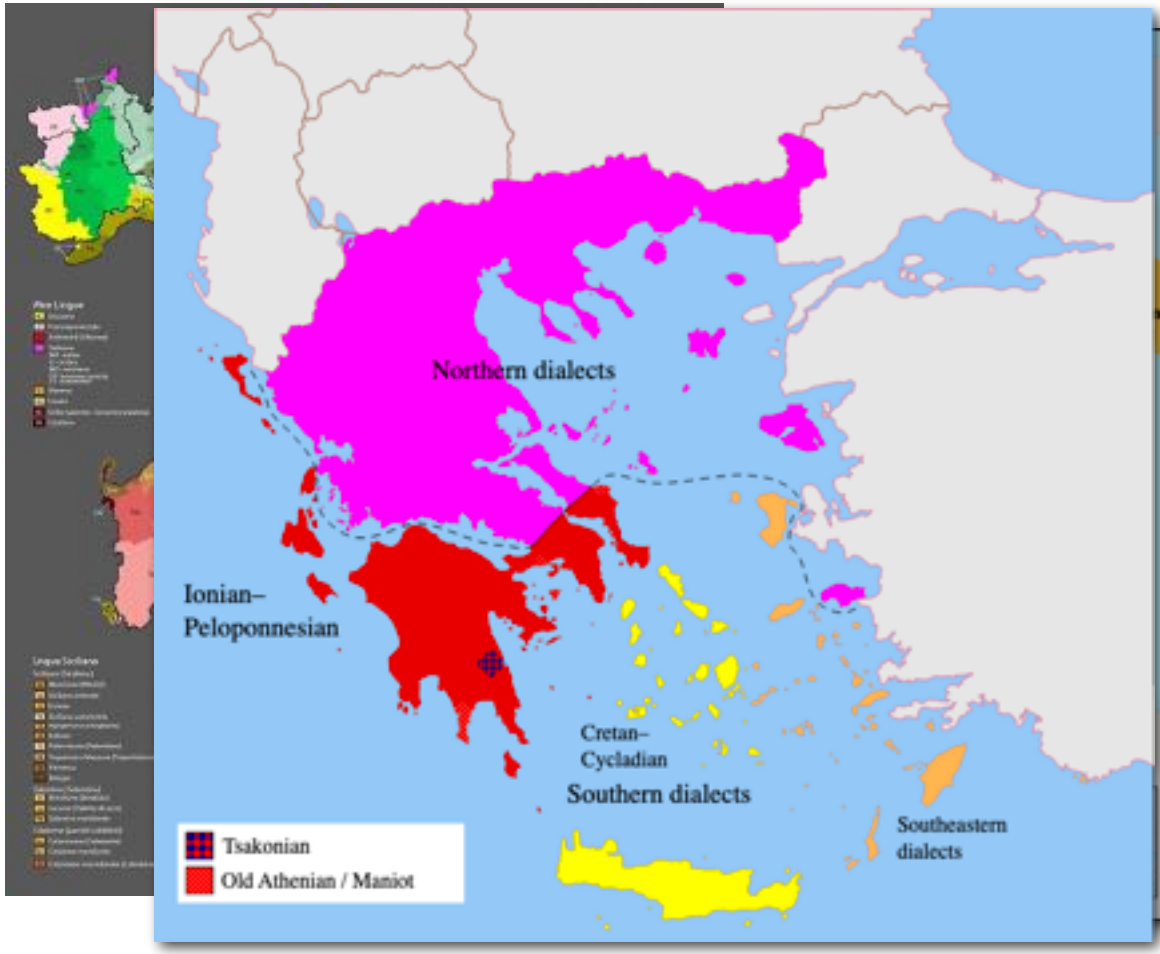
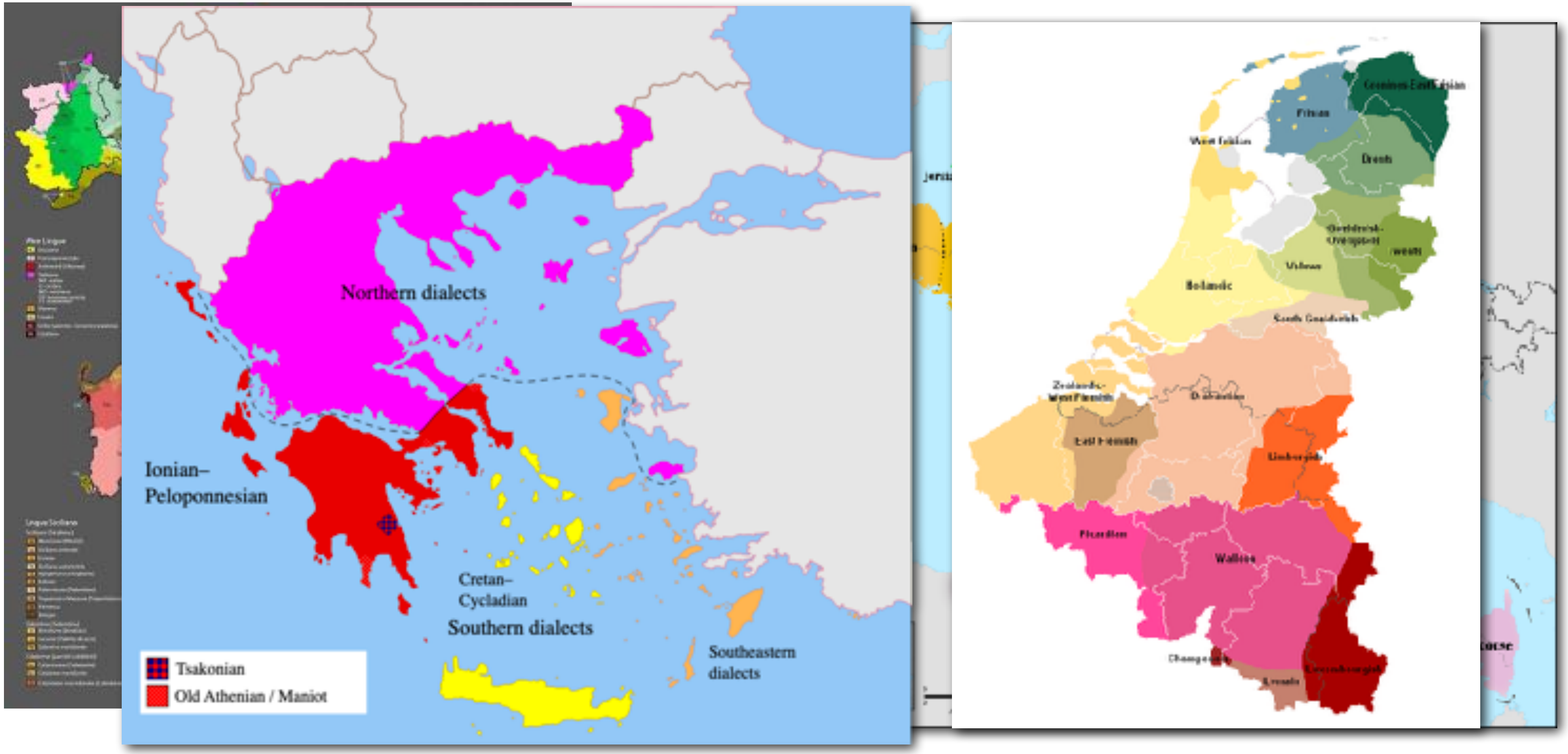


Languages are not Monoliths

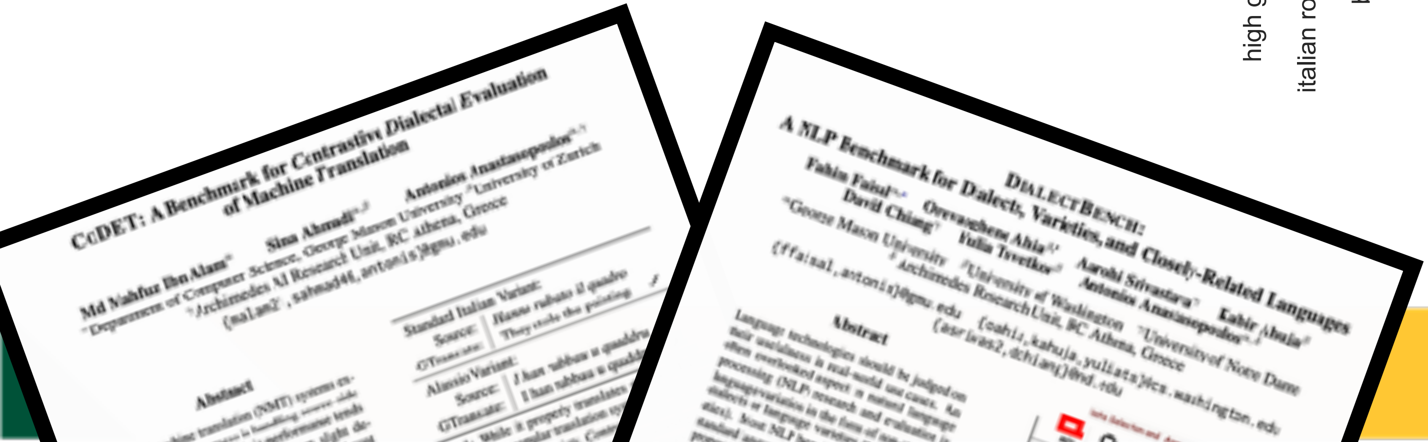


DialectBench

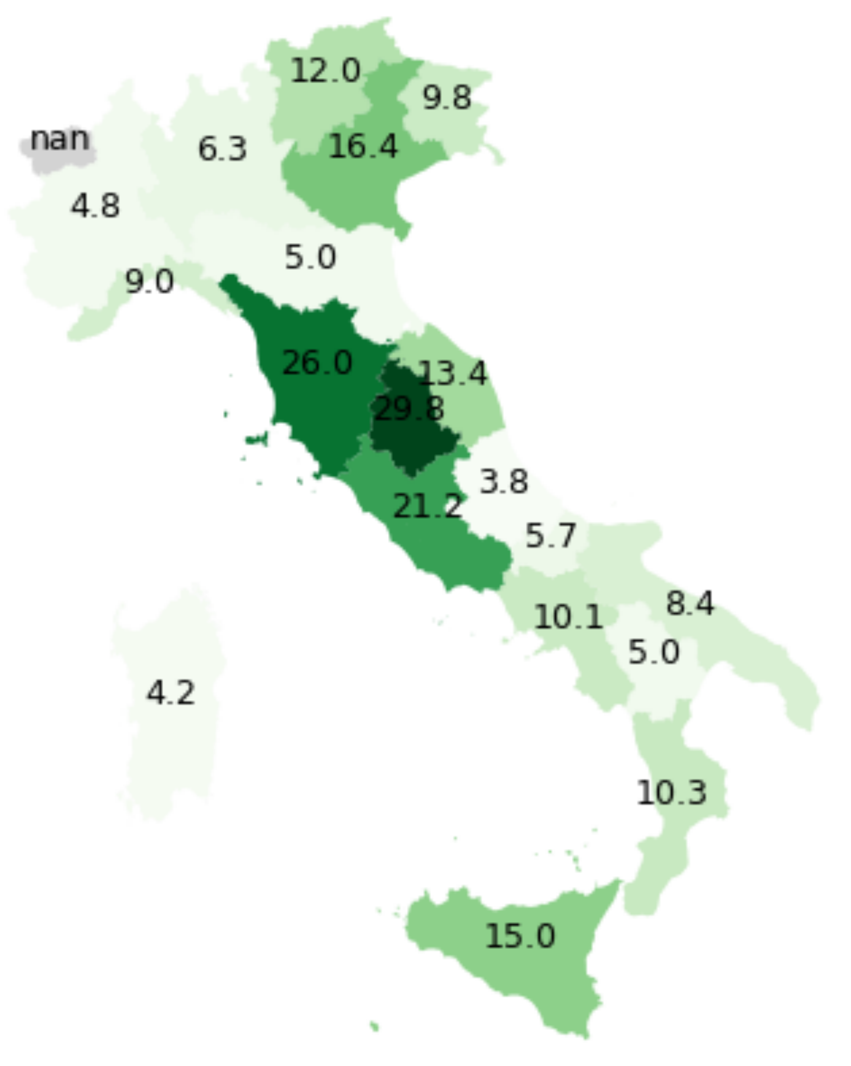
First large-scale benchmark
10 tasks, 40 continua, 281 varieties

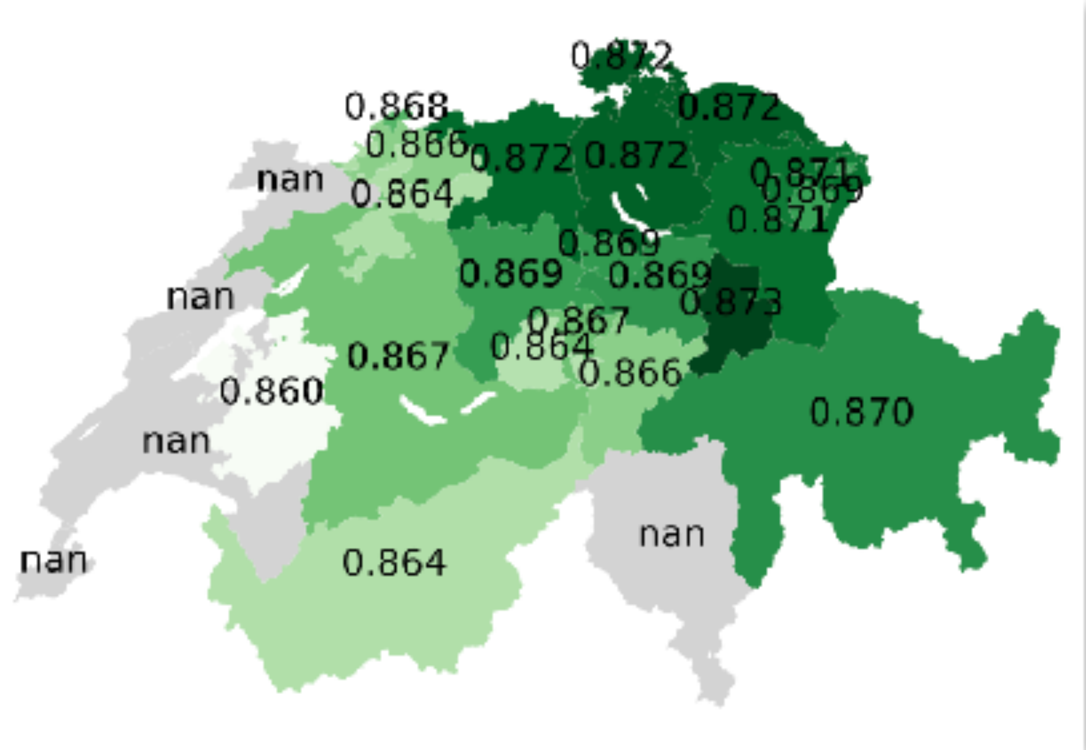
Task	Total	arabic	high german	italian romance	basque	anglic	sinitic	common turkic	sw shift. romance	greek	gallo-rhaetian	norwegian	neva	bengali	gallo-italian	kurdish	komi	serb.-croa.-bosnian	tupi-guarani.	modern dutch	eastern romance	frisian	swahili	Other
DEP.	40	3	2	4		3	3		4		3	3			1		3		3					8
POS.	51	6	2	4		2	3		5		3	3	8		1		3		3					8
NER	85	2	8	4		4	6	4	5	2	6	3			5	2	2	4		3	3	3		19
EQA	24	7				11								2									2	2
MRC	11	6				1	2																	2
NLI	38	9	2	2		1	3	3	4		1	2			3	2				1				5
TC	38	9	2	2		1	3	3	4		1	2			3	2				1				5
SA	9	9																						
DId	49	26	4			3	4		6	6														
MT	114	25	23	20	21			8	1	2		3		5		2								4
Total	281	42	31	26	21	19	13	12	11	11	8	8	8	6	5	5	4	4	3	3	3	3	3	32

Language Clusters



DialectBench Results





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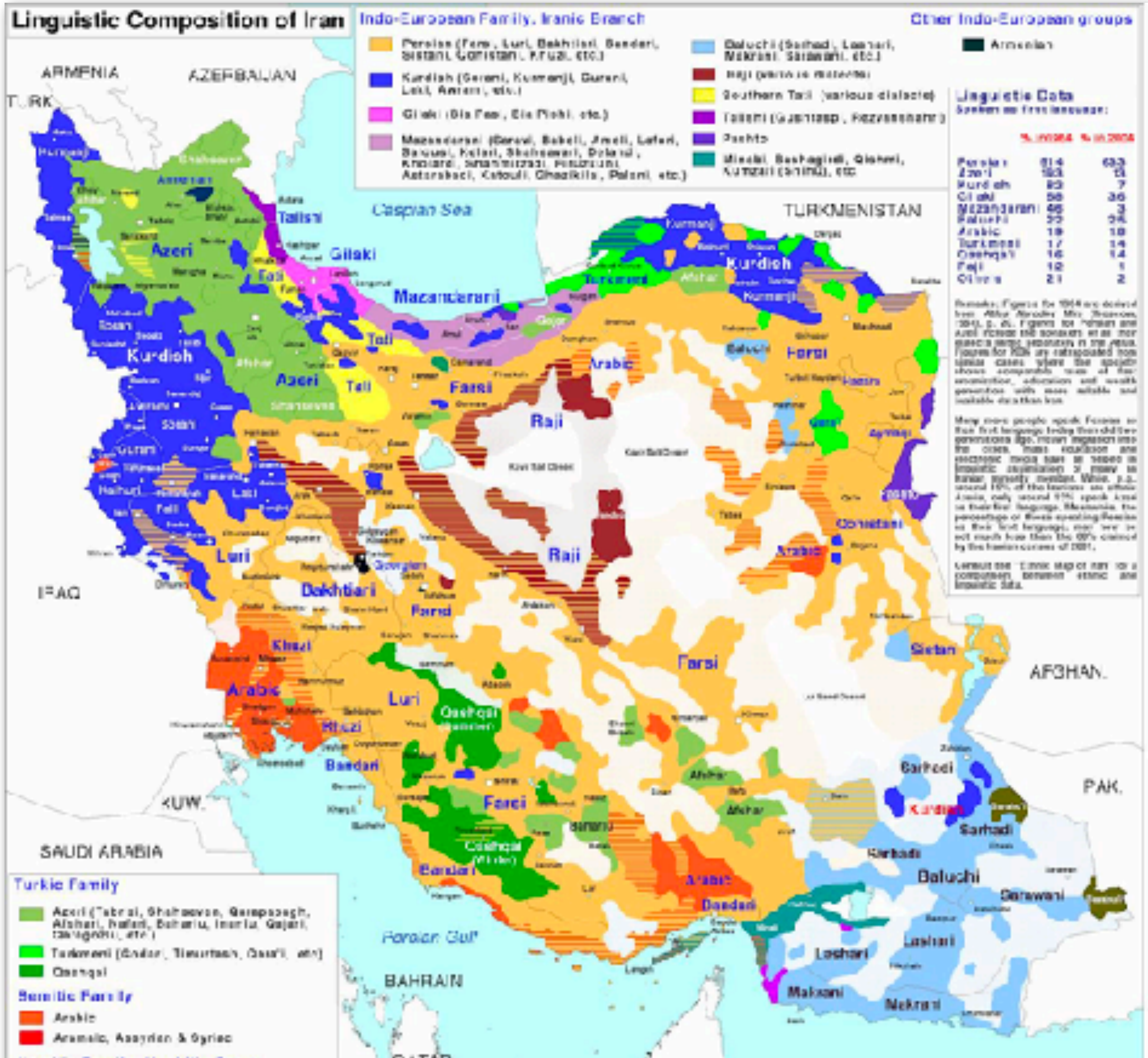
Minority Languages

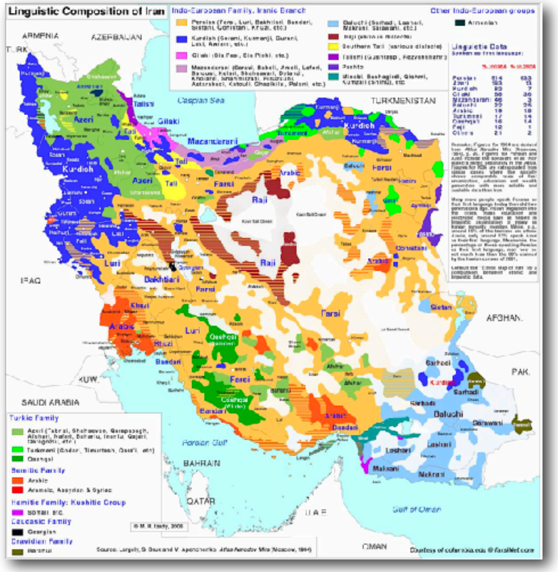
Minority Languages in X-lingual Communities

Minority Languages in X-lingual Communities

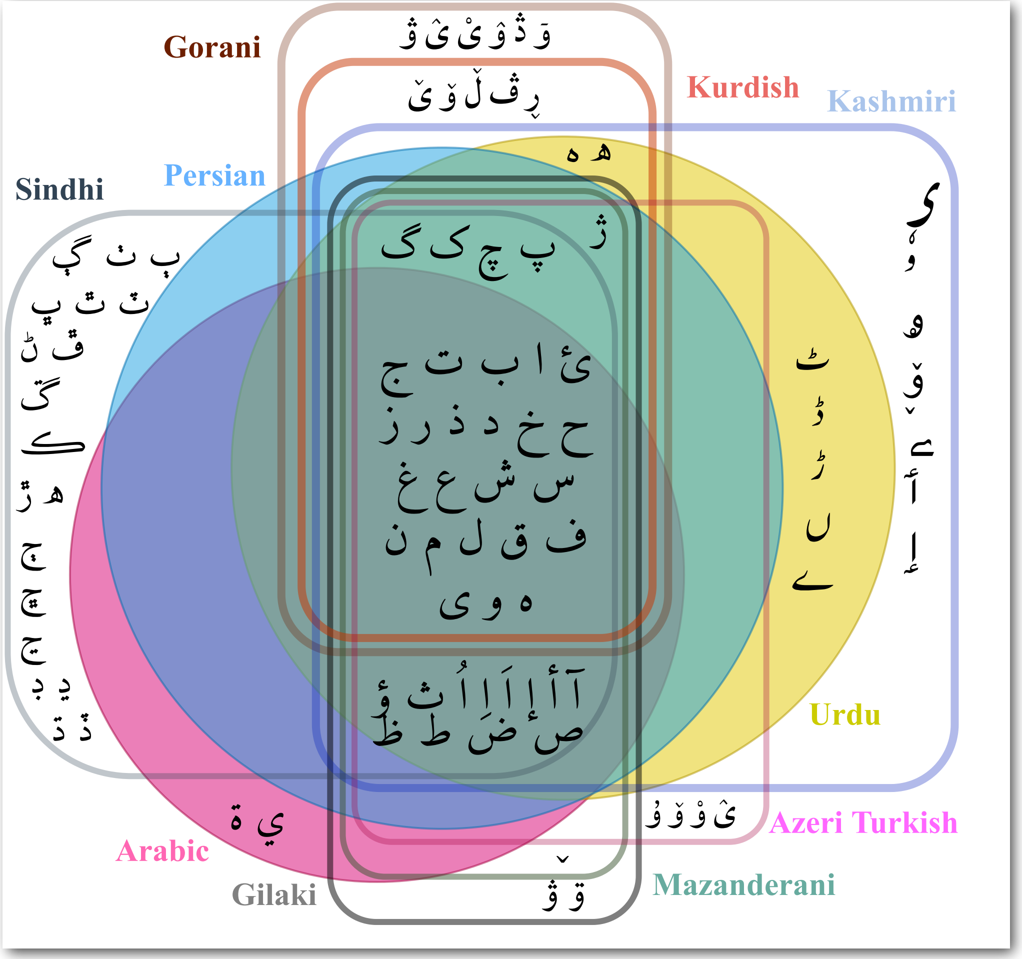


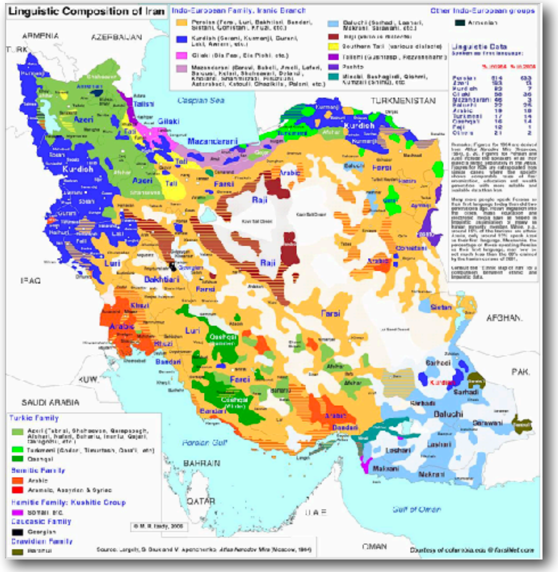
Source:

Minority Languages in X-lingual Communities



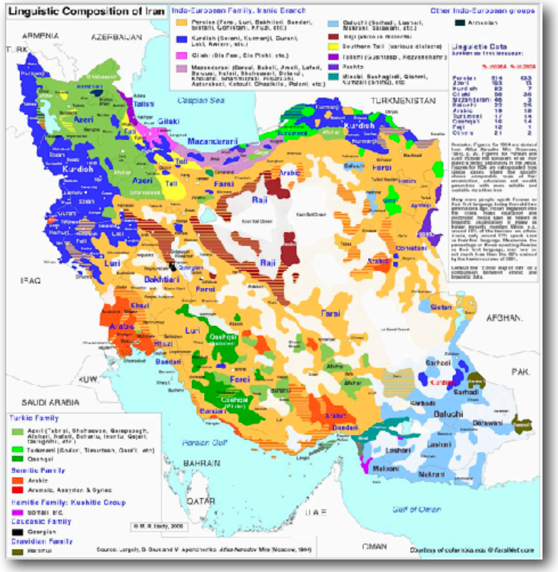
Minority Languages in X-lingual Communities

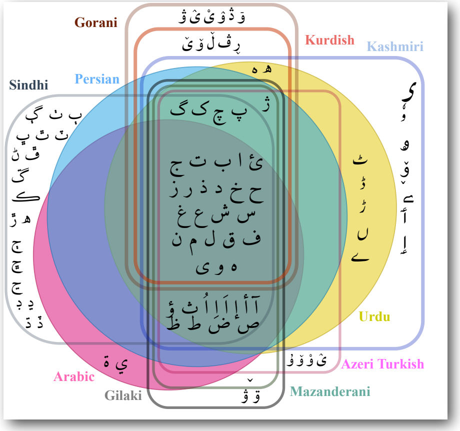




Minority Languages in X-lingual Communities

Dominant language (e.g. Farsi) influences the minority one:

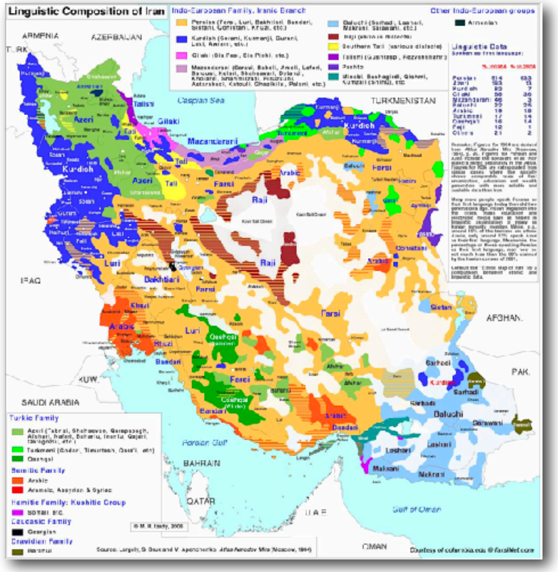


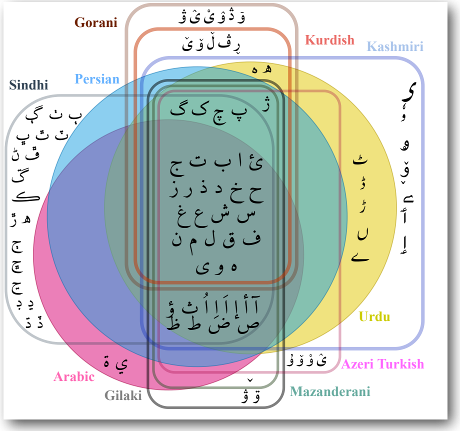


Minority Languages in X-lingual Communities

Dominant language (e.g. Farsi) influences the minority one:

Language	Unconventional script	Unconventional writing	Conventional writing
Gilaki	Persian	يته زون نم هيسه گه گيلكن اون جى گب زنن	يته زوؤنˇ نؤم هيسه گه گيلكؤن اوْنˇ جي گب زنن
Kashmiri	Urdu	برورچھ اکھ وراسے جانور۔	برْور چھُ اَکھ وُرأسۍ جانوَر۔
Kurmanji	Arabic	قايمقام امدي بةرثوا پارزكار دهوك دا	قايمقامێ ئامێديێ بەرسڤا پارێزگارێ دهۆکێ دا
Sorani	Arabic	هةر لة يةكةم شانؤوة ديارة فهديان دةويت	هەر لە یەکەم شانۆوە دیارە فەهەدیان دەوێت
Sindhi	Urdu	مديني ڌانهن هجرت وقت فقط هيء گهرواري سانن گڏ هئي	مديني ڌانهن هجرت وقت فقط هيء گهرواري ساٿن گڏ هئي





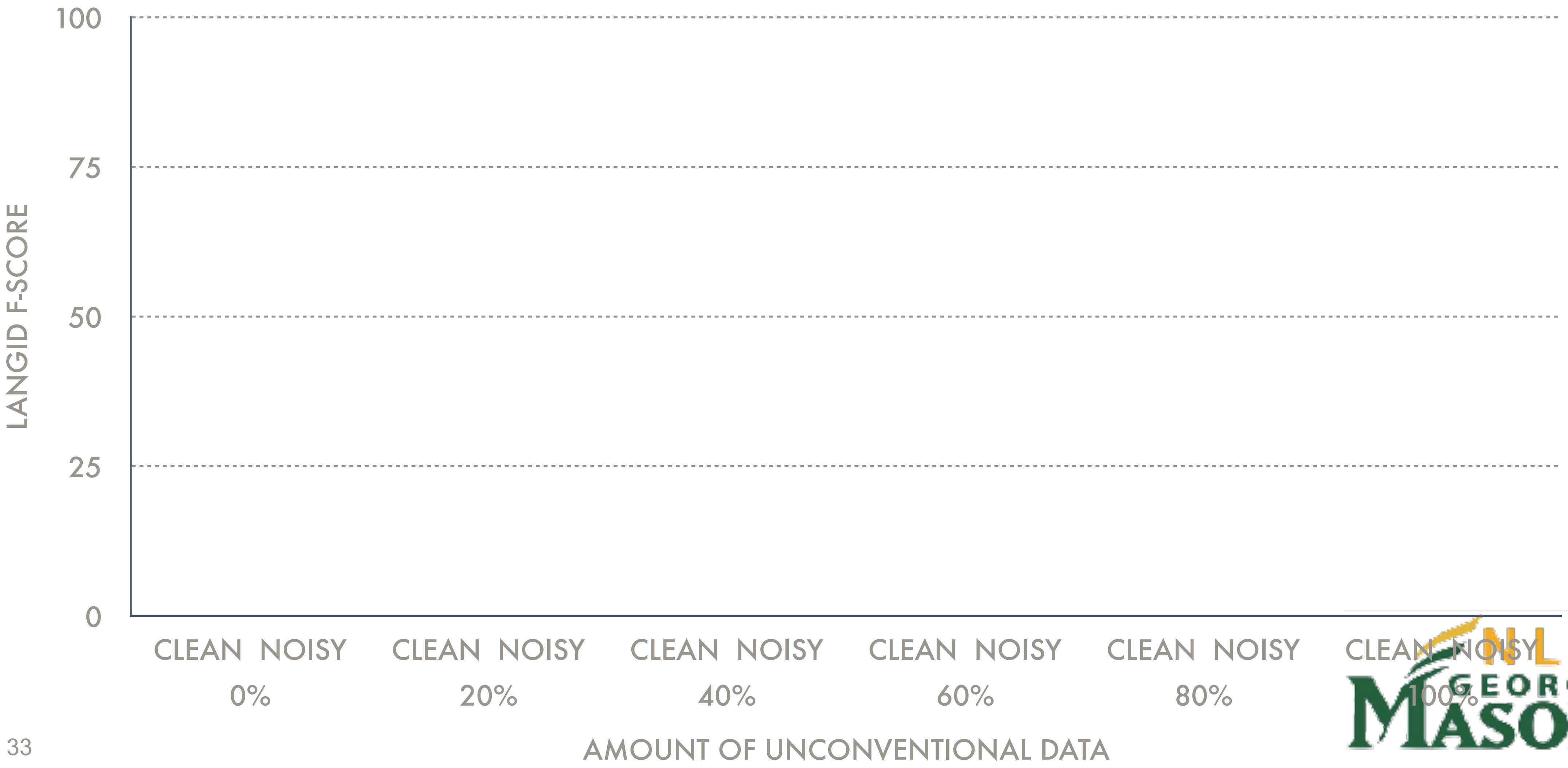
Case Study: Languages using Perso-Arabic Script

Language	639-3	WP	Script type	Diacritics	ZWNJ	Dominant
Azeri Turkish	azb	azb	Abjad	✓	✓	Persian
Gilaki	glk	glk	Abjad	✓	✓	Persian
Mazanderani	mzn	mzn	Abjad	✓	✓	Persian
Pashto	pus	ps	Abjad	✓	✗	Persian
Gorani	hac	-	Alphabet	✗	✗	Persian, Arabic, Sorani
Northern Kurdish (Kurmanji)	kmr	-	Alphabet	✗	✗	Persian, Arabic
Central Kurdish (Sorani)	ckb	ckb	Alphabet	✗	✗	Persian, Arabic
Southern Kurdish	sdh	-	Alphabet	✗	✗	Persian, Arabic
Balochi	bal	-	Abjad	✓	✗	Persian, Urdu
Brahui	brh	-	Abjad	✓	✗	Urdu
Kashmiri	kas	ks	Alphabet	✓	✗	Urdu
Sindhi	snd	sd	Abjad	✓	✗	Urdu
Saraiki	skr	skr	Abjad	✓	✗	Urdu
Torwali	trw	-	Abjad	✓	✗	Urdu
Punjabi	pnb	pnb	Abjad	✓	✗	Urdu
Persian	fas	fa	Abjad	✓	✓	-
Arabic	arb	ar	Abjad	✓	✗	-
Urdu	urd	ur	Abjad	✓	✓	-
Uyghur	uig	ug	Alphabet	✗	✗	-

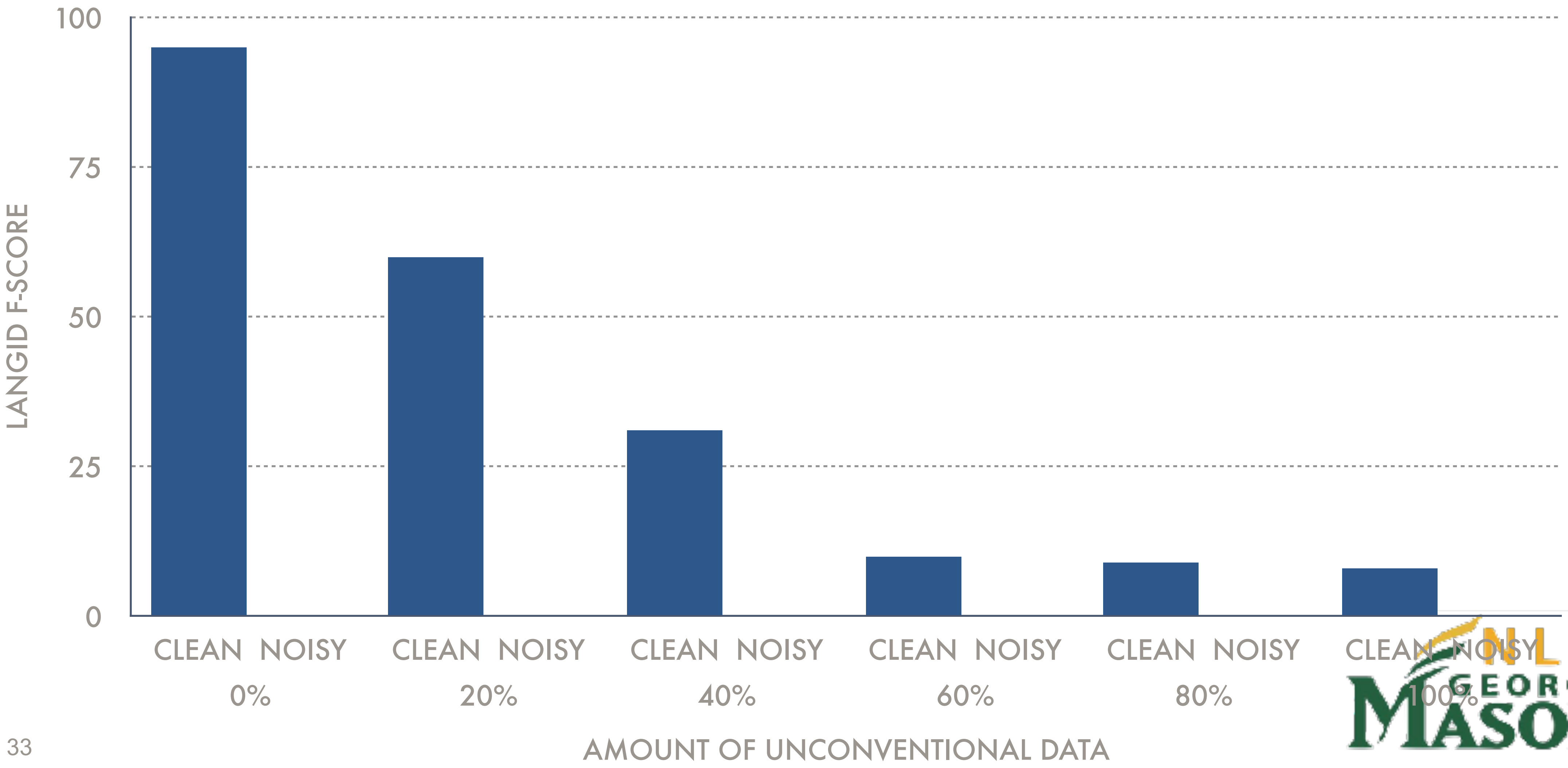
Table 1: Perso-Arabic scripts of the selected languages studied in this paper. Columns 2 and 3 show the codes of the languages in ISO 639-3 and on their specific Wikipedia (WP), if available. The diacritics and zero-width non-joiner (ZWNJ) columns refer to the usage of diacritics (*Harakat*) and ZWNJ as individual characters.

Effect of Unconventional Writing

Effect of Unconventional Writing



Effect of Unconventional Writing



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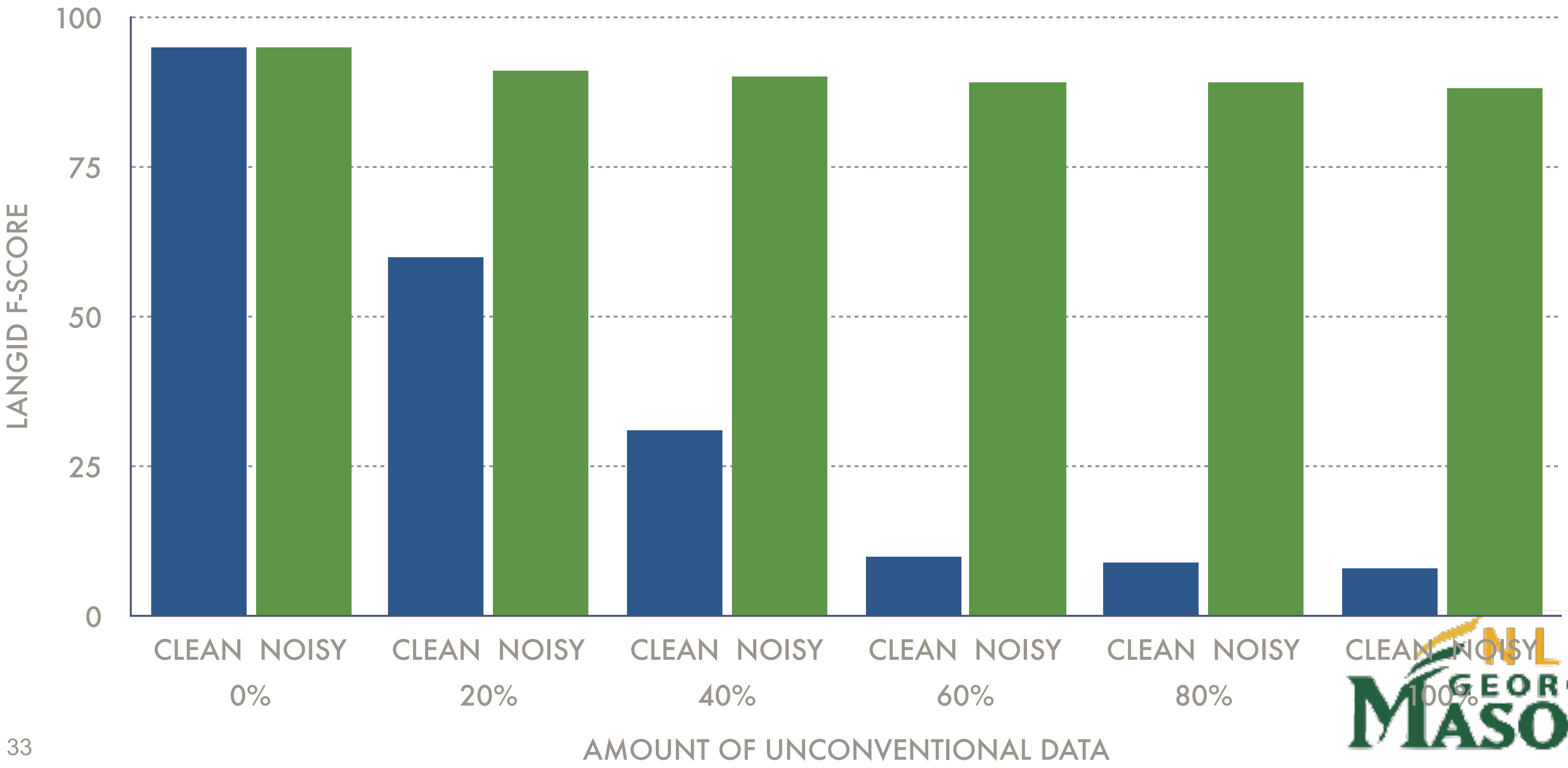
Effect of Unconventional Writing



Mitigating the Effect of Unconventional Writing

Mitigating the Effect of Unconventional Writing

Train a Normalization model
(Encoder-decoder, self-attention based)

Mitigating the Effect of Unconventional Writing

Train a Normalization model
    (Encoder-decoder, self-attention based)
Evaluate its effect on Machine Translation

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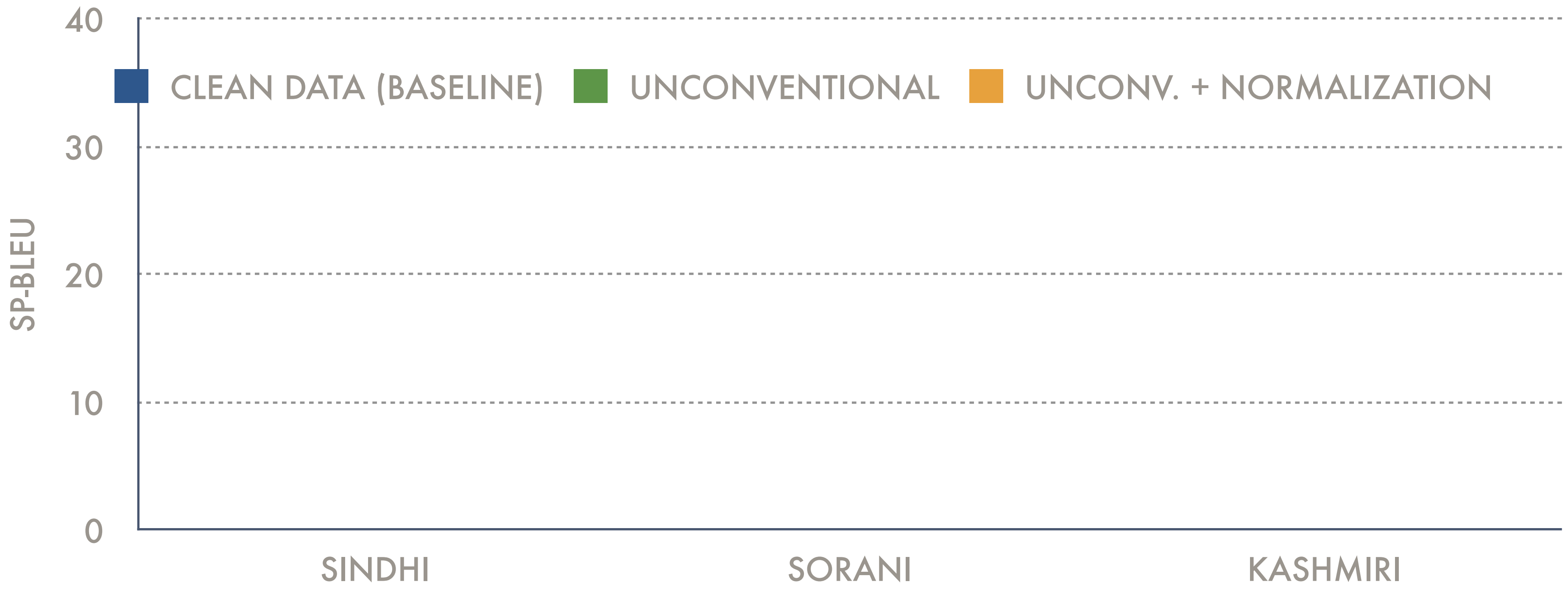
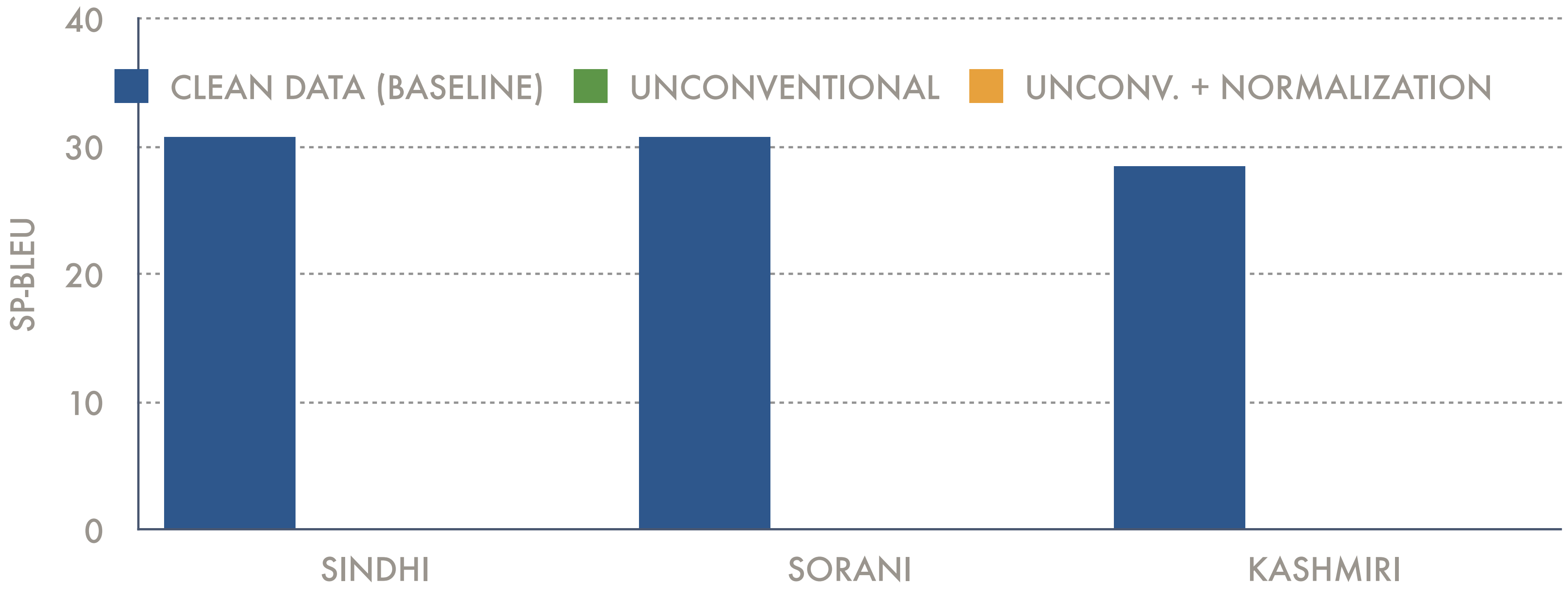


Mitigating the Effect of Unconventional Writing

Train a Normalization model

(Encoder-decoder, self-attention based)

Evaluate its effect on Machine Translation



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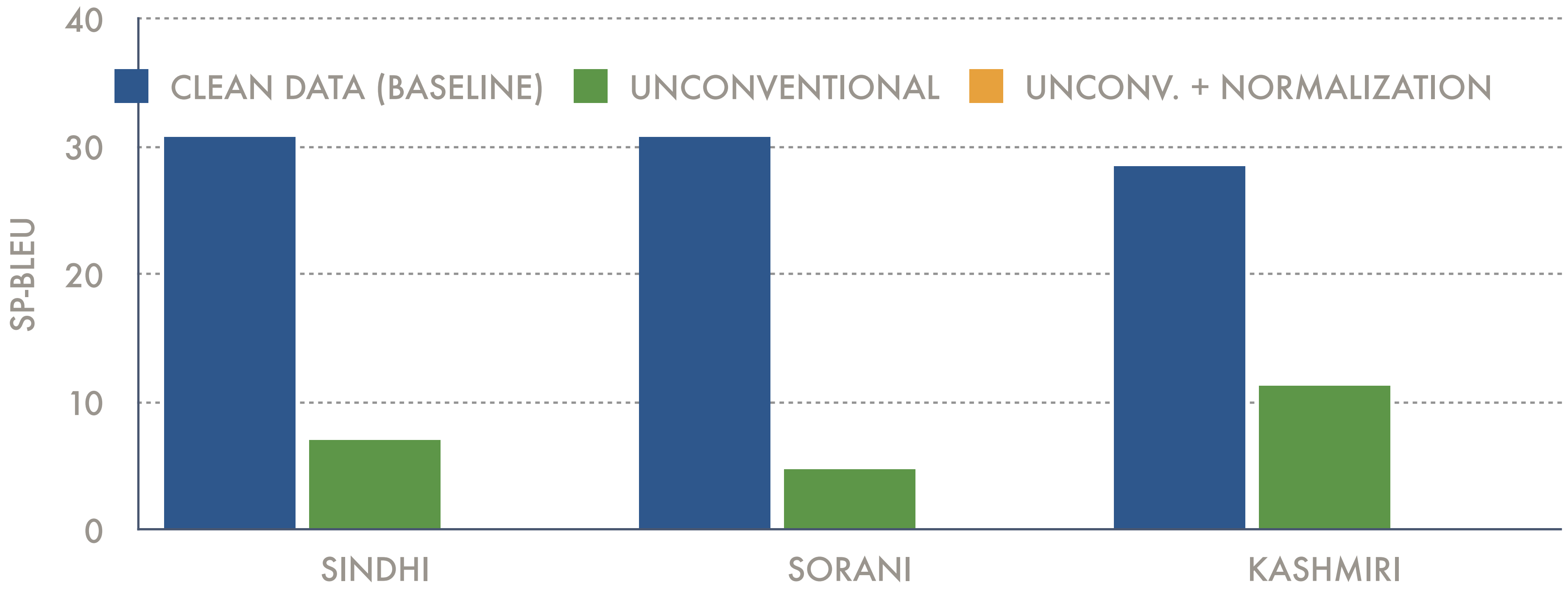

Mitigating the Effect of Unconventional Writing

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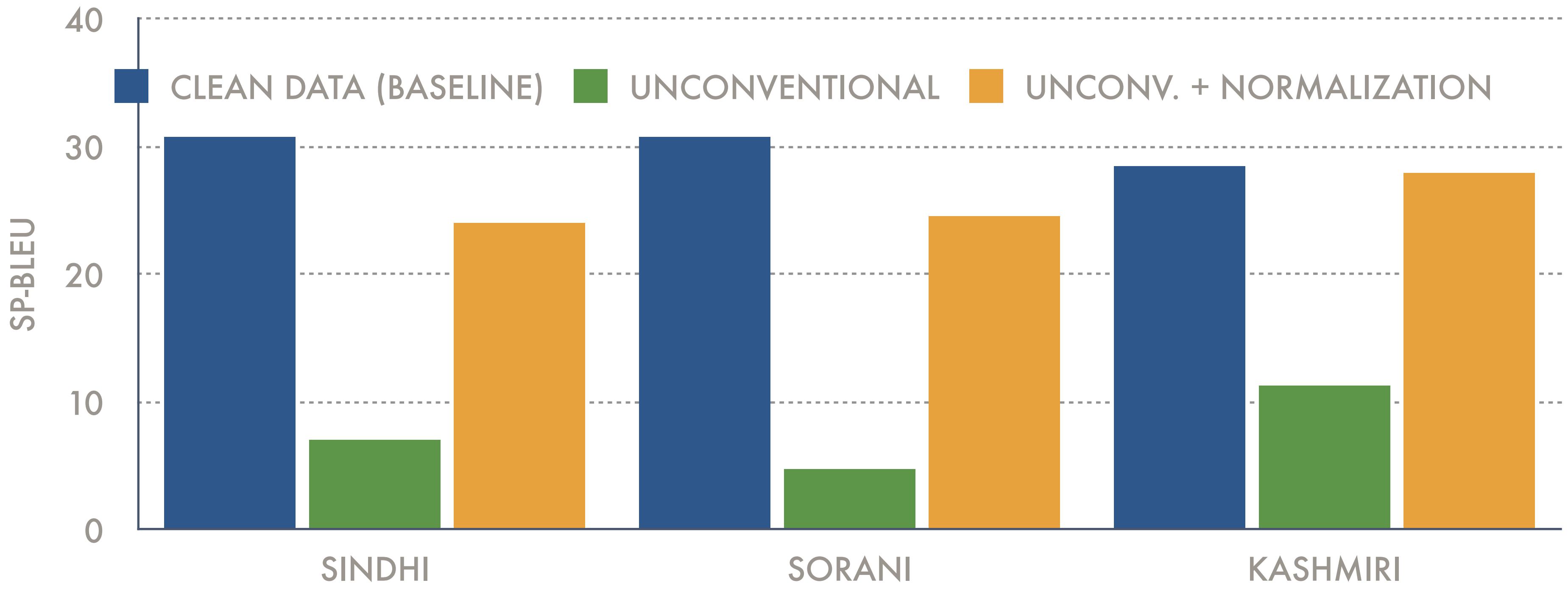


We Need to Handle Speech Input

With many slides from the

"End-to-end-ST tutorial" at EACL 2021

by Jan Niehues, Liz Salesky, Marco Turchi, and Matteo Negri

Speech Translation - History (before e2e)

Late ‘80s: first proofs of concept

Constraints to control language ambiguity (phonetics, syntax, semantics)

- Restricted vocabulary
- Controlled speaking style
- Narrow domain
- Offline processing

‘90s: Less constraints (vocabulary, speaking style)

First spontaneous ST systems (C-STAR, Verbmobil, Nespole,...)

2003-2006: Less constraints (domain)

First open-domain ST systems (STR-DUST, TC-STAR, GALE)

- different scenarios (broadcast news, parliamentary speeches, academic lectures)
- different languages (Zh, Ar, Es)

2006: Less constraints (operating conditions)

First simultaneous translator
(real-time translation of spontaneous lectures and presentations)

Speech Translation - History (the e2e era)

2005: first ST corpora
Small size/language coverage

2016-2017: first e2e ST models
(Duong et al., 2016, Berard et al., 2016, Weiss et al., 2017, ...)
encoder-decoder architectures based on RNNs

2018: first e2e models at IWSLT
8.7 BLEU points below cascade ST solutions on En-De

2019: significant gap reduction at IWSLT
1.6 BLEU points below cascade ST solutions on En-De

2019: ST adaptation of Transformer
(Di Gangi et al., 2019)

2019-2020: new ST corpora
Larger size/language coverage

2020: the gap almost closed?
+0.24 BLEU on unsegmented En-De test data

Sec 1.2

Challenges in Translation of Speech

Challenges in translation of speech

- Audio challenges
  - Multiple speaker
    - e.g. Meetings
    - Challenges:
      - Overlapping voice
  - Background noise
  - Audio segmentation

Challenges in translation of speech

- Audio challenges
- Text-Speech mismatch
  - Disfluencies
    - Hesitations: “uh”, “uhm”, “hmm”,
    - Discourse markers: “you know”, “I mean”,…
    - Repetitions: “It had, it had been a good day”
    - Corrections: “no, it cannot, I cannot go there”

  - No punctuation
    - Let’s eat Grandpa !
    - Let’s eat, Grandpa !

Challenges in translation of speech

- Audio challenges
- Text-Speech mismatch
- Error propagation
  - ASR errors worse after translation
    - More difficult to compensate by human
    - MT adds additional errors

Reden (engl. speeches)

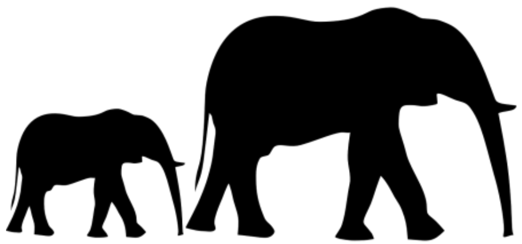
Reben (engl. vines)

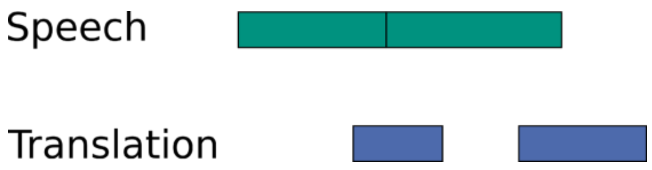
Challenges in translation of speech

- Audio challenges
- Text-Speech mismatch
- Error propagation
- Data
  - End-to-End data:
    - Growing amount but still limited
  - Integration of other data types
    - Speech transcripts
    - Parallel data

Challenges in translation of speech

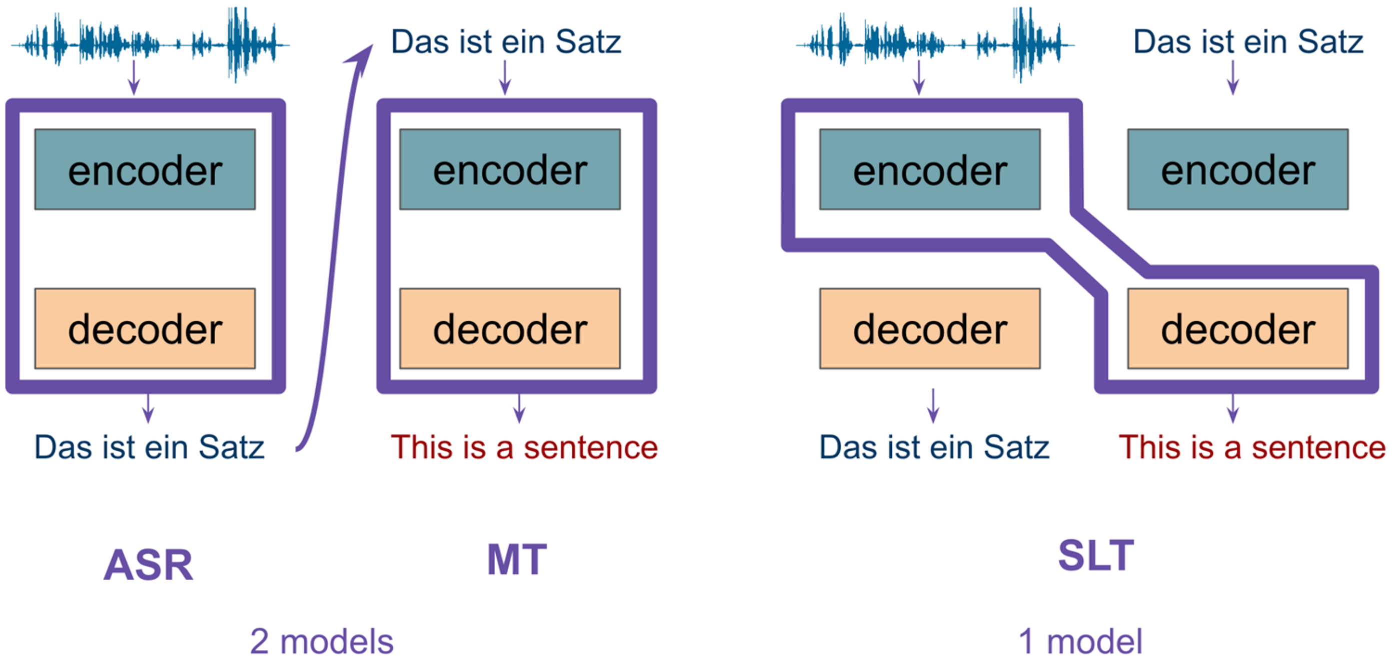
- Audio challenges
- Text-Speech mismatch
- Error propagation
- Data
- Partial information
  - Online: Translate during production of speech
  - Generate translation before full sentence is known



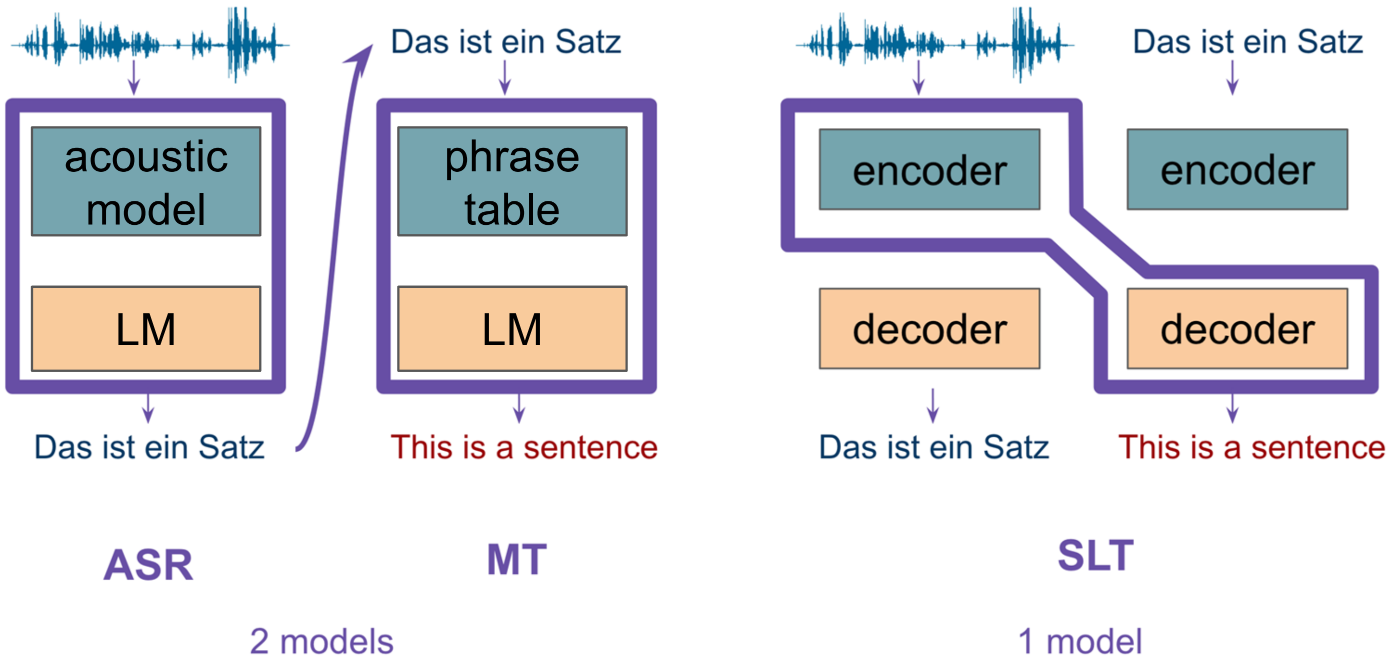


Traditional Cascade Approach

Traditional cascade approach



Traditional cascade approach



Modular, pipeline approach

ASR, MT: isolated objectives

(Waibel et al. 1991; Vidal, 1997; Ney, 1999; Saleem et al. 2004; Matusov et al. 2005; Bertoldi and Federico, 2005; Quan et al. 2005; Kumar et al. 2014; IWSLT Eval Campaigns 2004—)

End-to-End ST

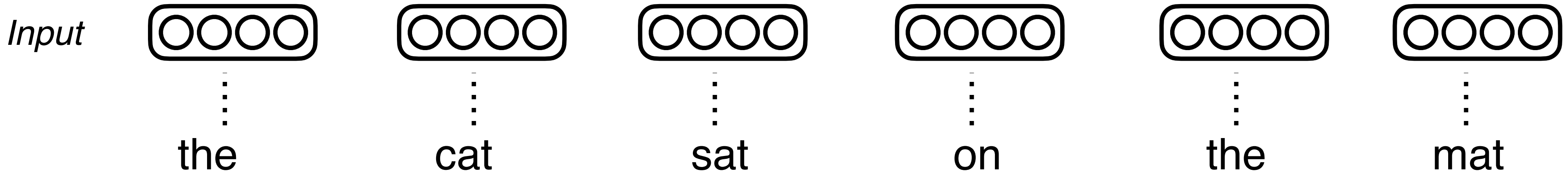
Encoder-Decoder with Attention

the cat sat on the mat

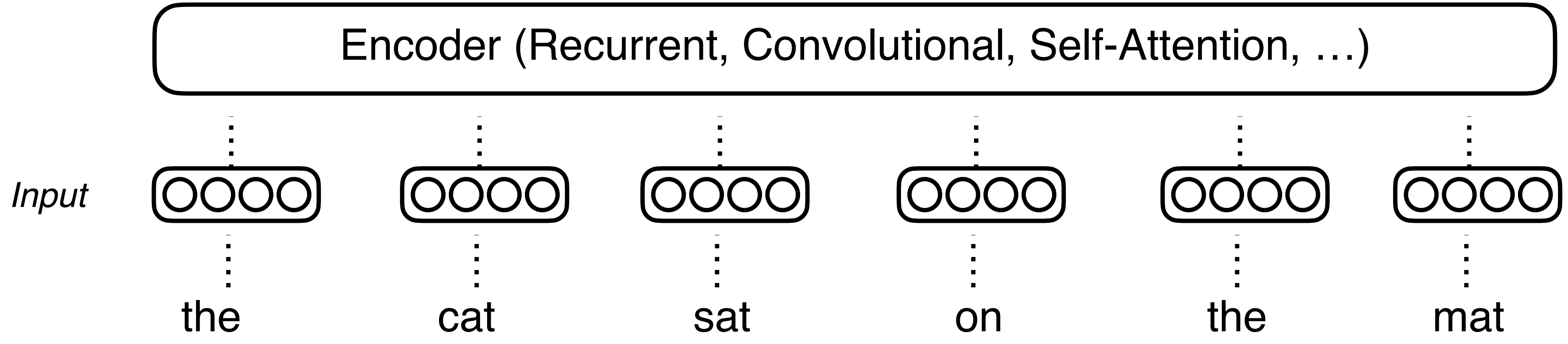
Encoder-Decoder with Attention

the cat sat on the mat

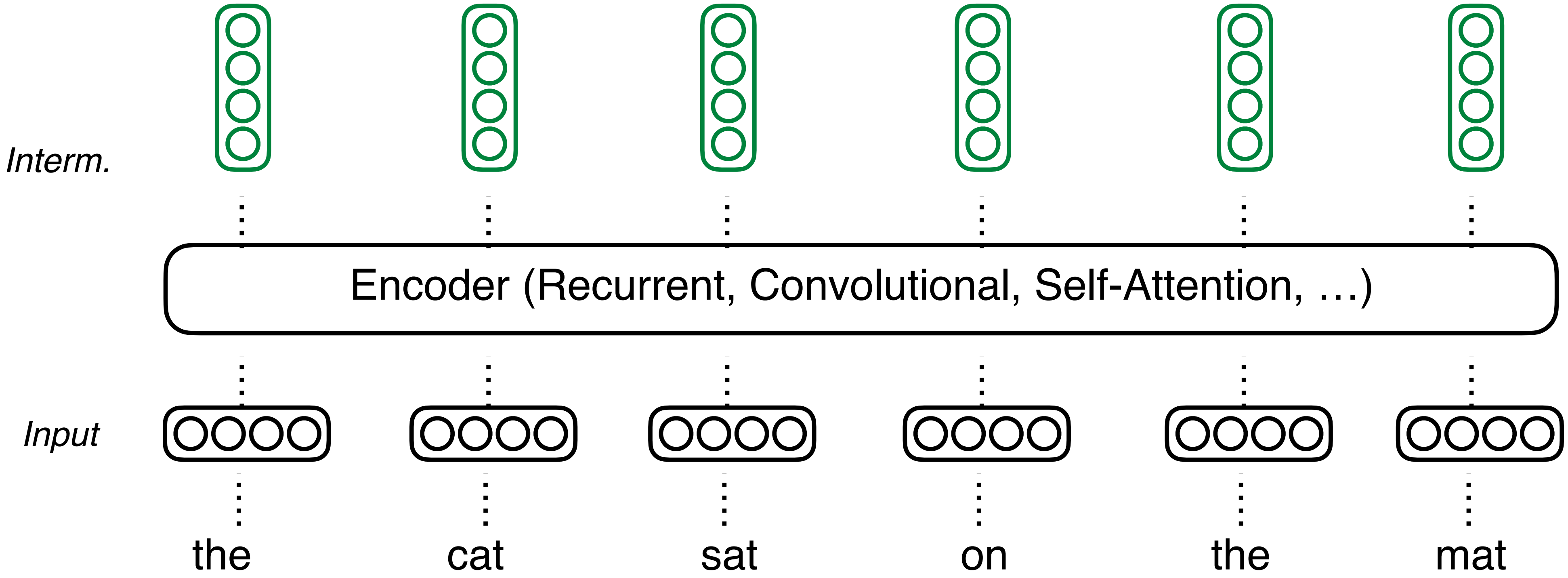
Encoder-Decoder with Attention



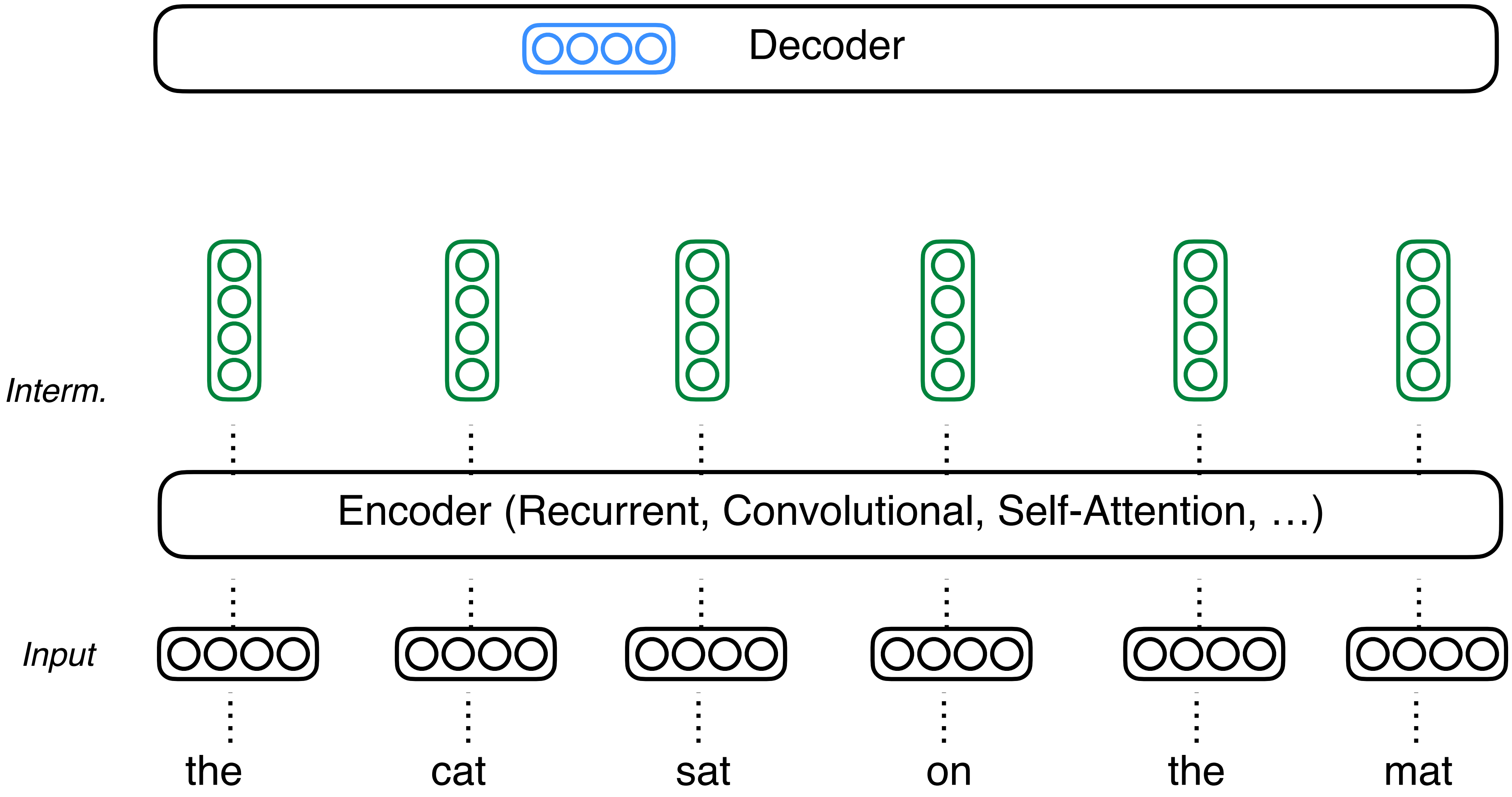
Encoder-Decoder with Attention



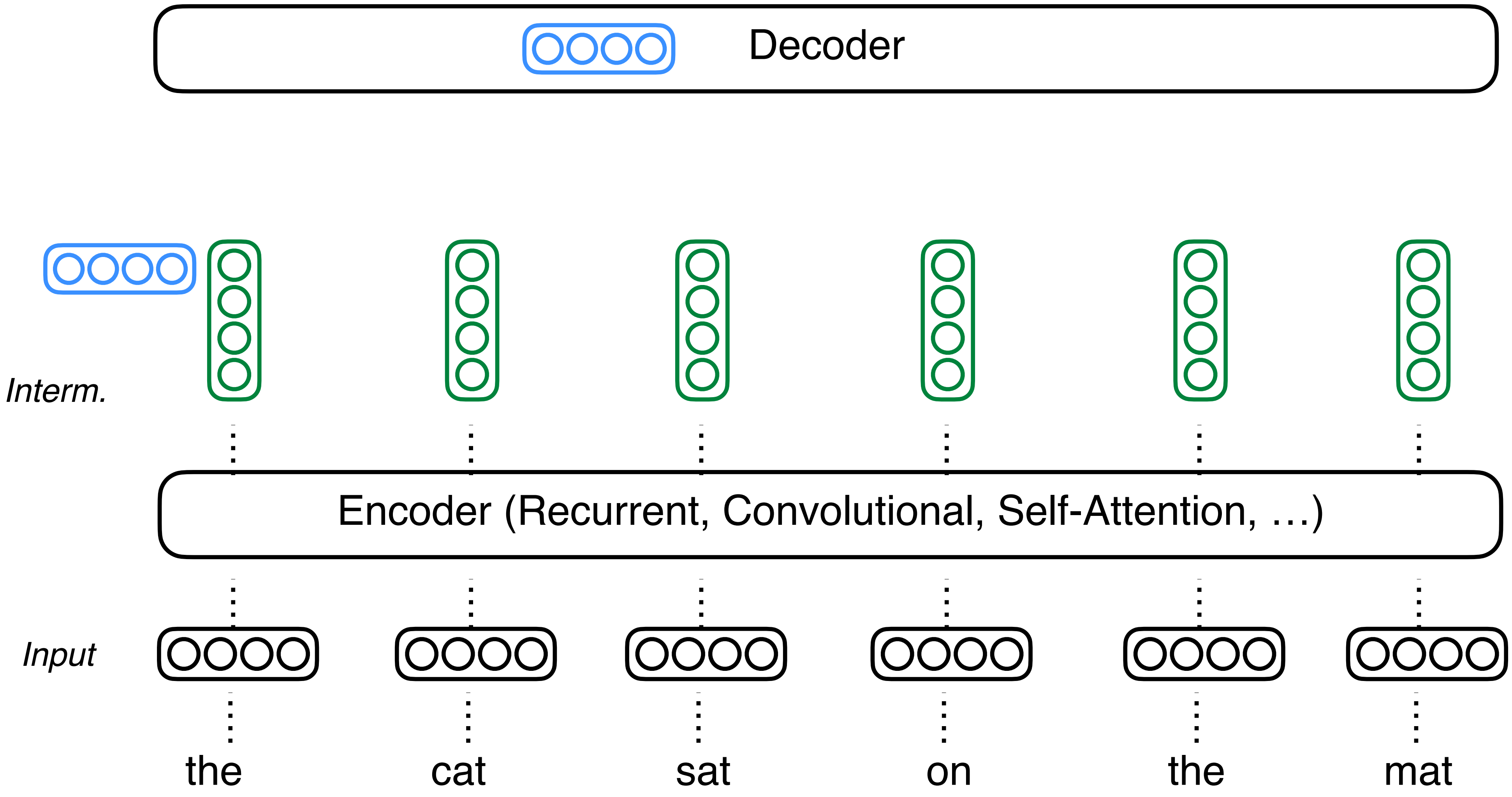
Encoder-Decoder with Attention

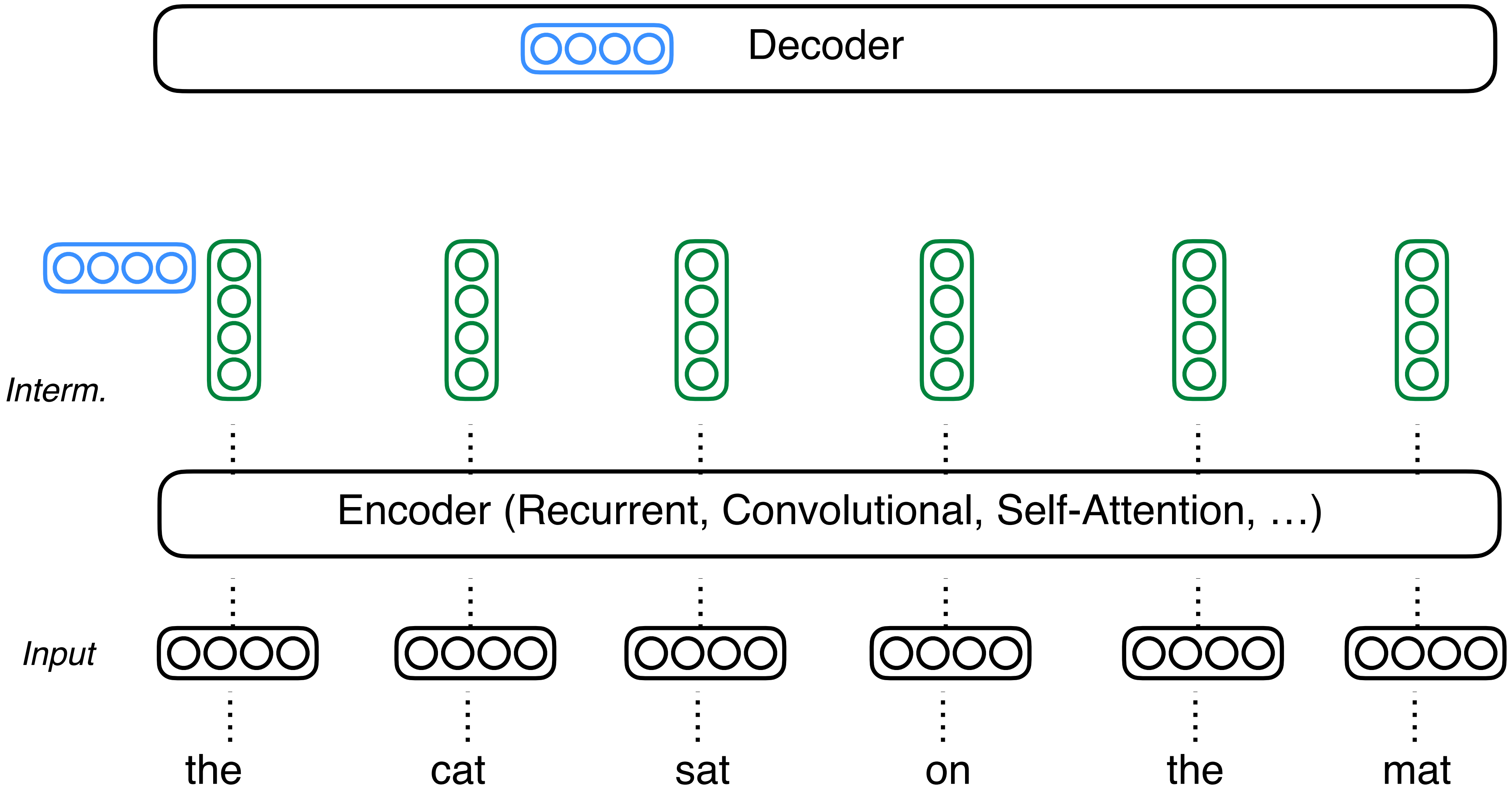


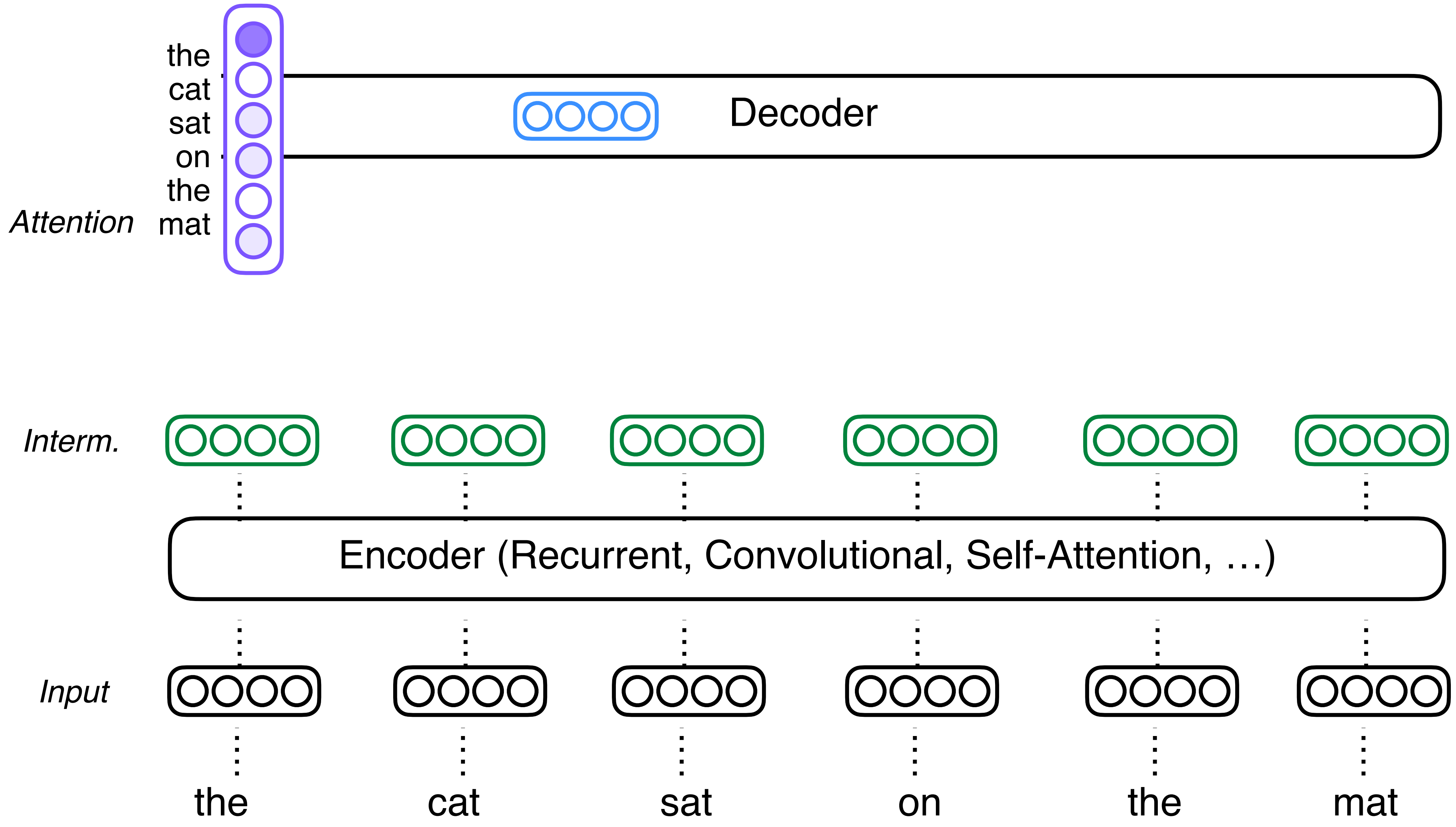
Encoder-Decoder with Attention



Encoder-Decoder with Attention




Decoder
Interm.
Encoder (Recurrent, Convolutional, Self-Attention, …)
Input
the
cat
sat
on
the
mat


the
cat
sat
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mat
Attention
Decoder
Interm.
Encoder (Recurrent, Convolutional, Self-Attention, …)
Input
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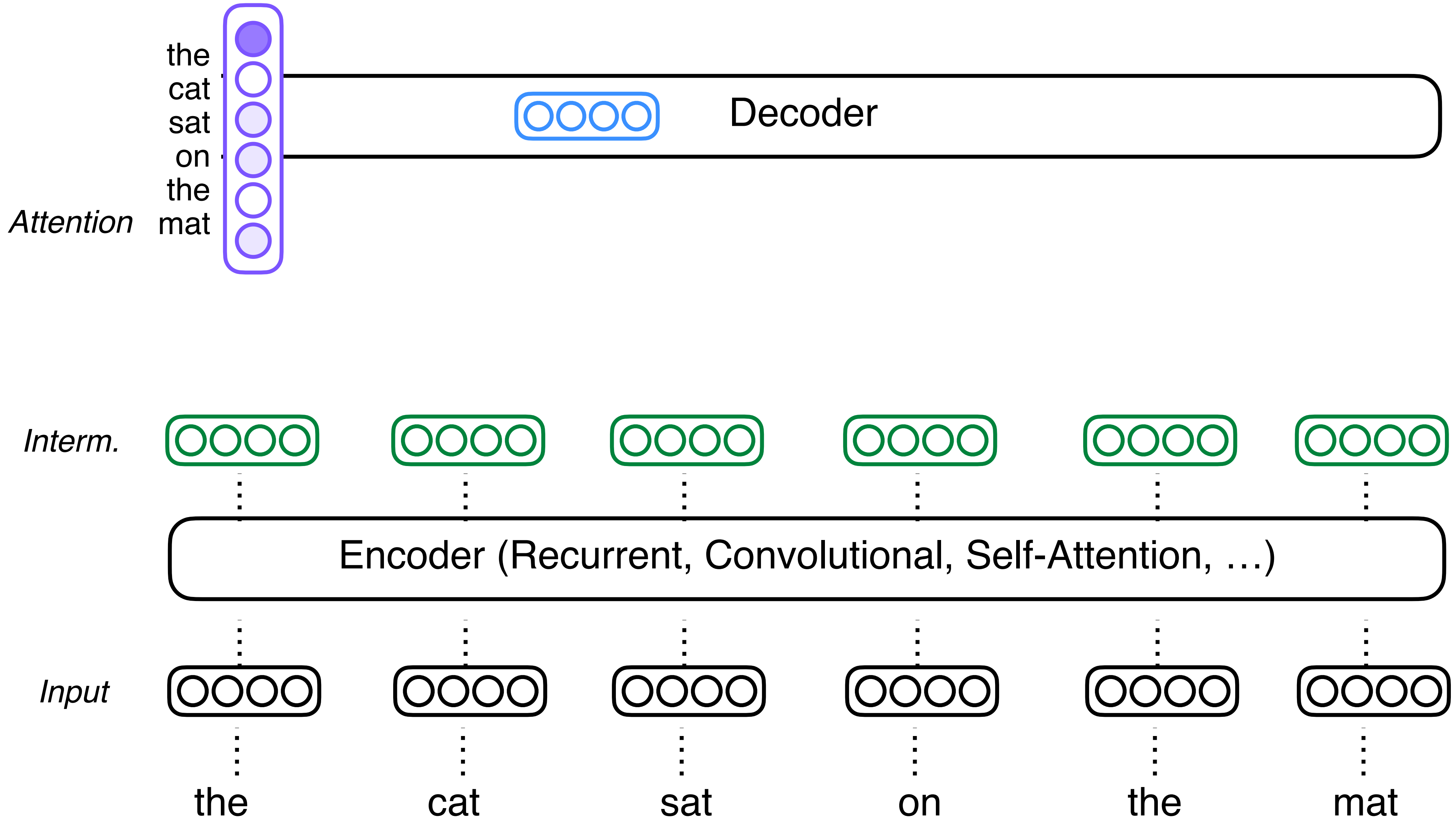

the
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Attention
Decoder
Interm.
Encoder (Recurrent, Convolutional, Self-Attention, …)
Input
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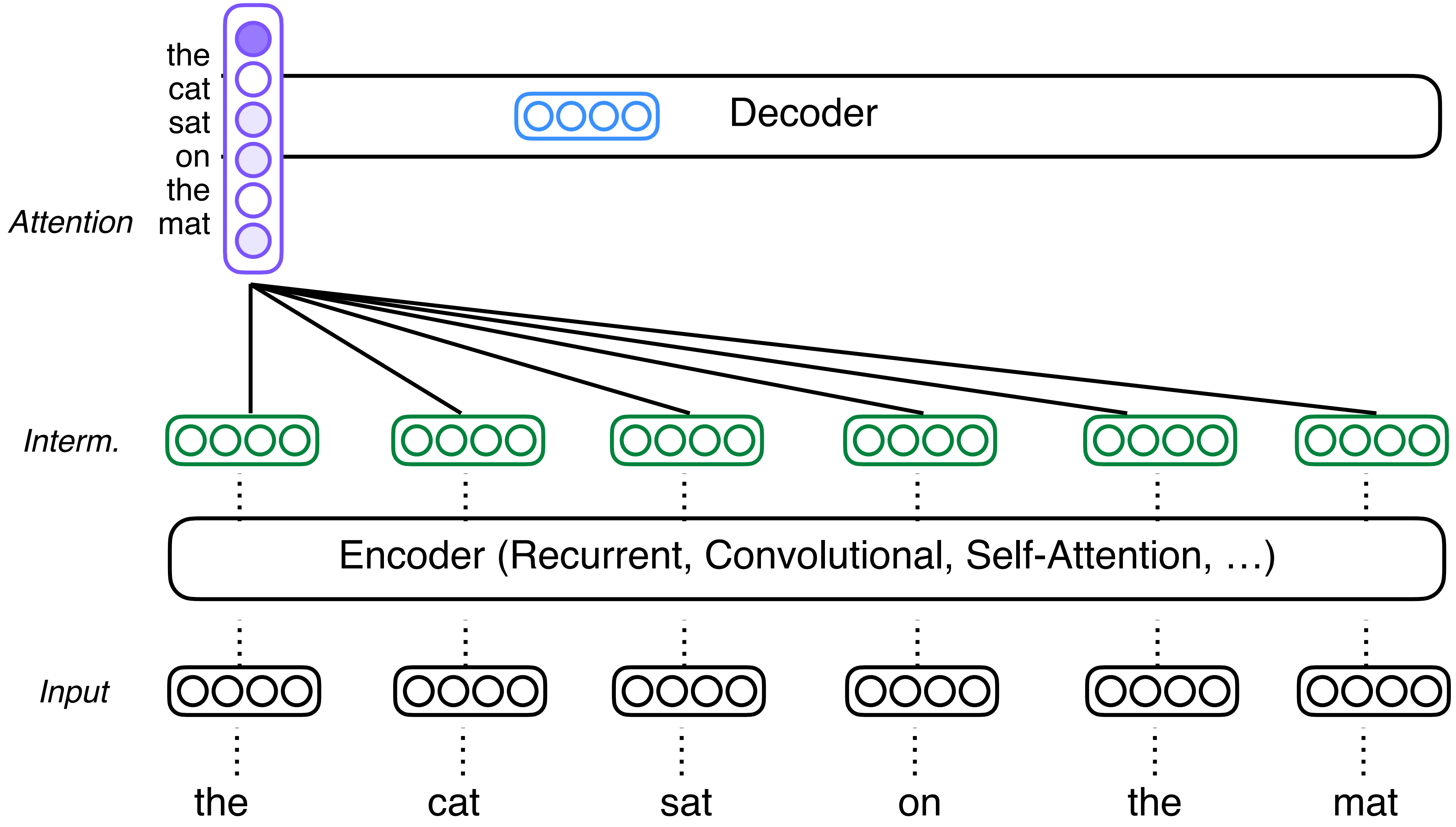

the
cat
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Attention
mat
Decoder
Interm.
Encoder (Recurrent, Convolutional, Self-Attention, …)
Input
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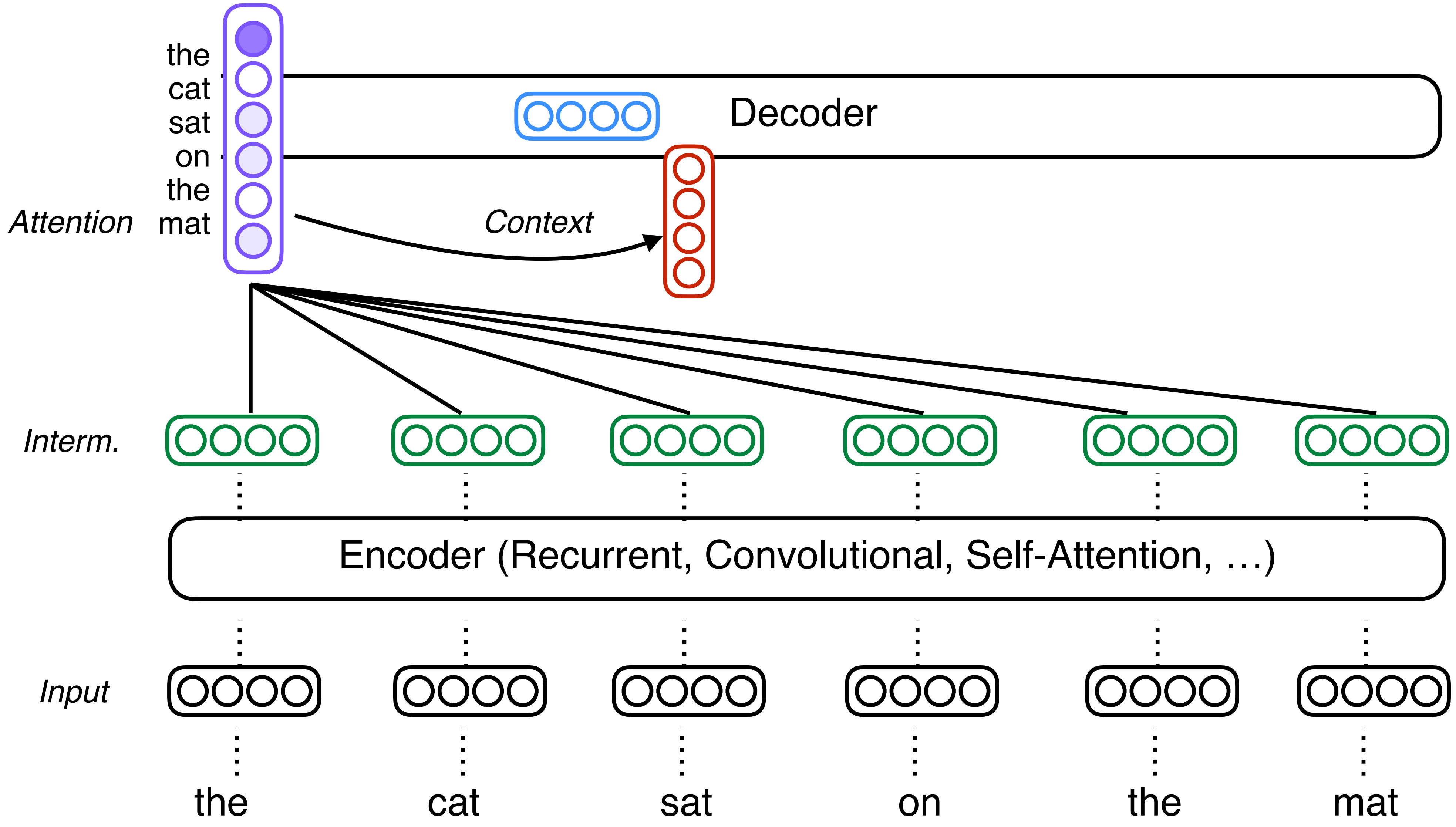
mat


Attention
the
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Decoder
Context
Interm.
Encoder (Recurrent, Convolutional, Self-Attention, …)
Input
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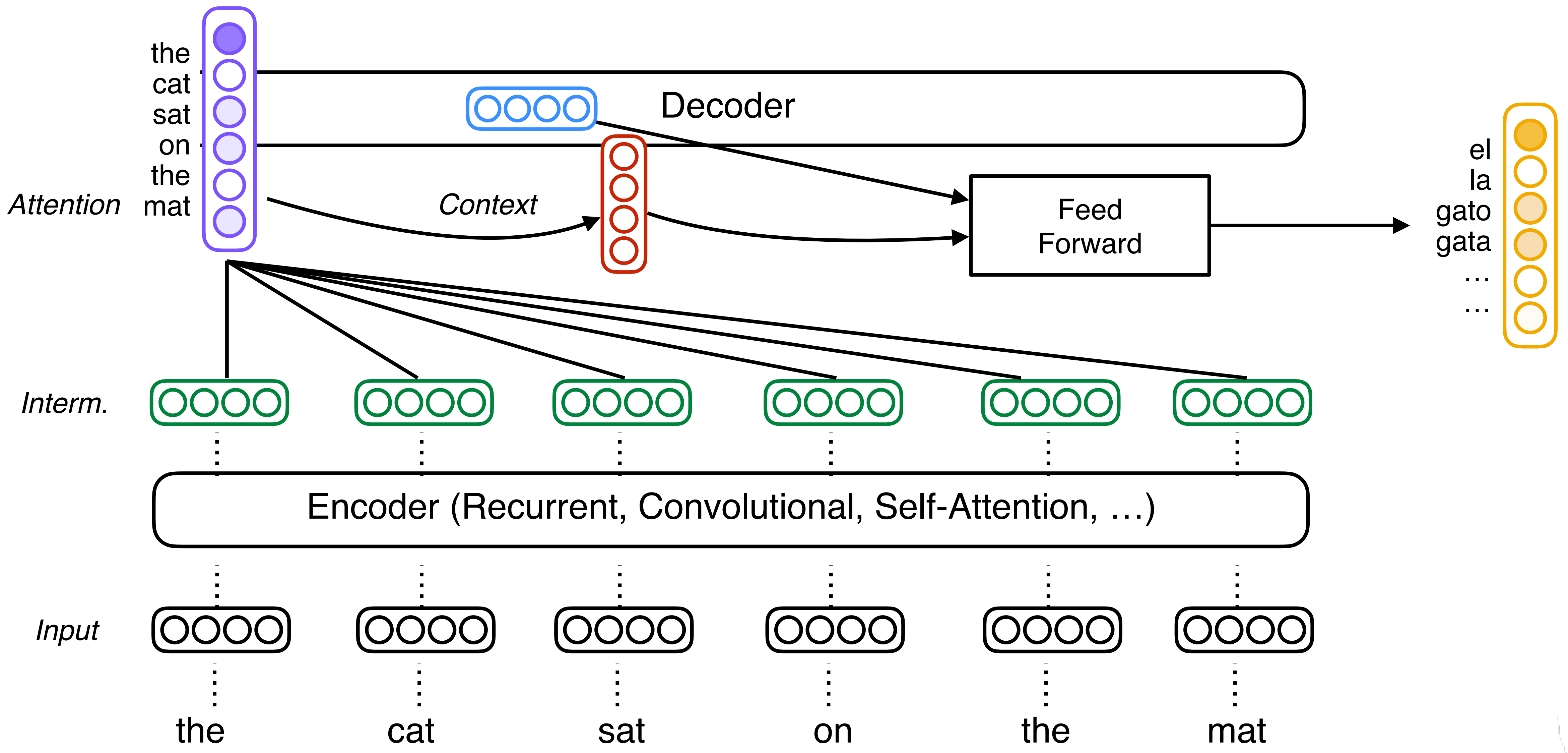
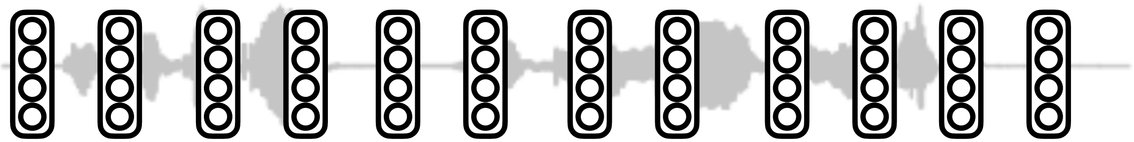
cat
sat
on
the
mat



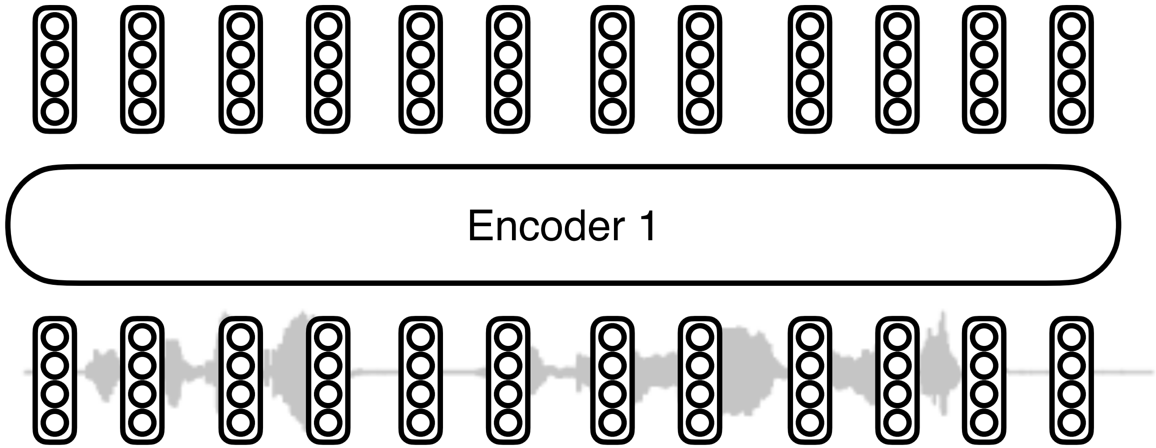
Decoder
the
cat
sat
on
the
mat
Attention
Context
Feed
Forward
el
la
gato
gata
…
…
Interm.
Encoder (Recurrent, Convolutional, Self-Attention, …)
Input
the
cat
sat
on
the
mat

An Audio-Input model

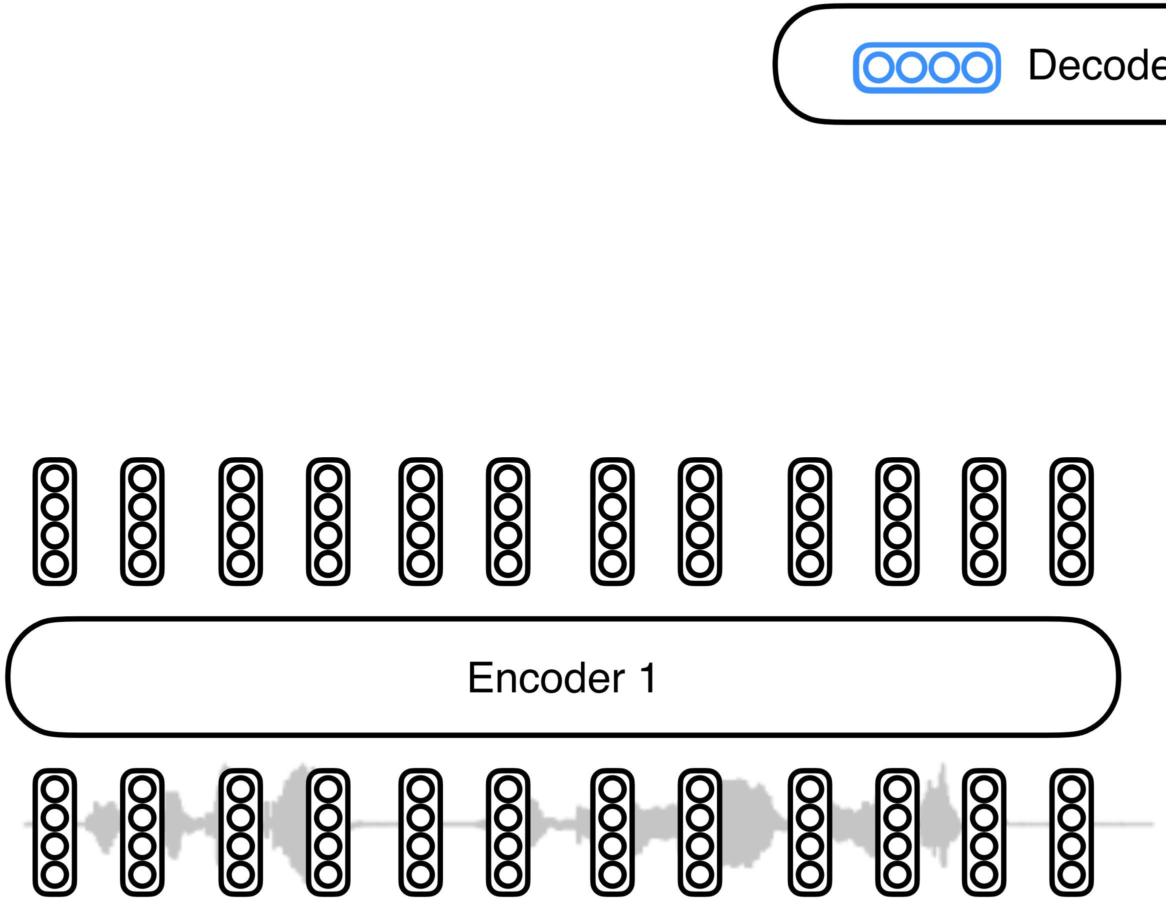
An Audio-Input model

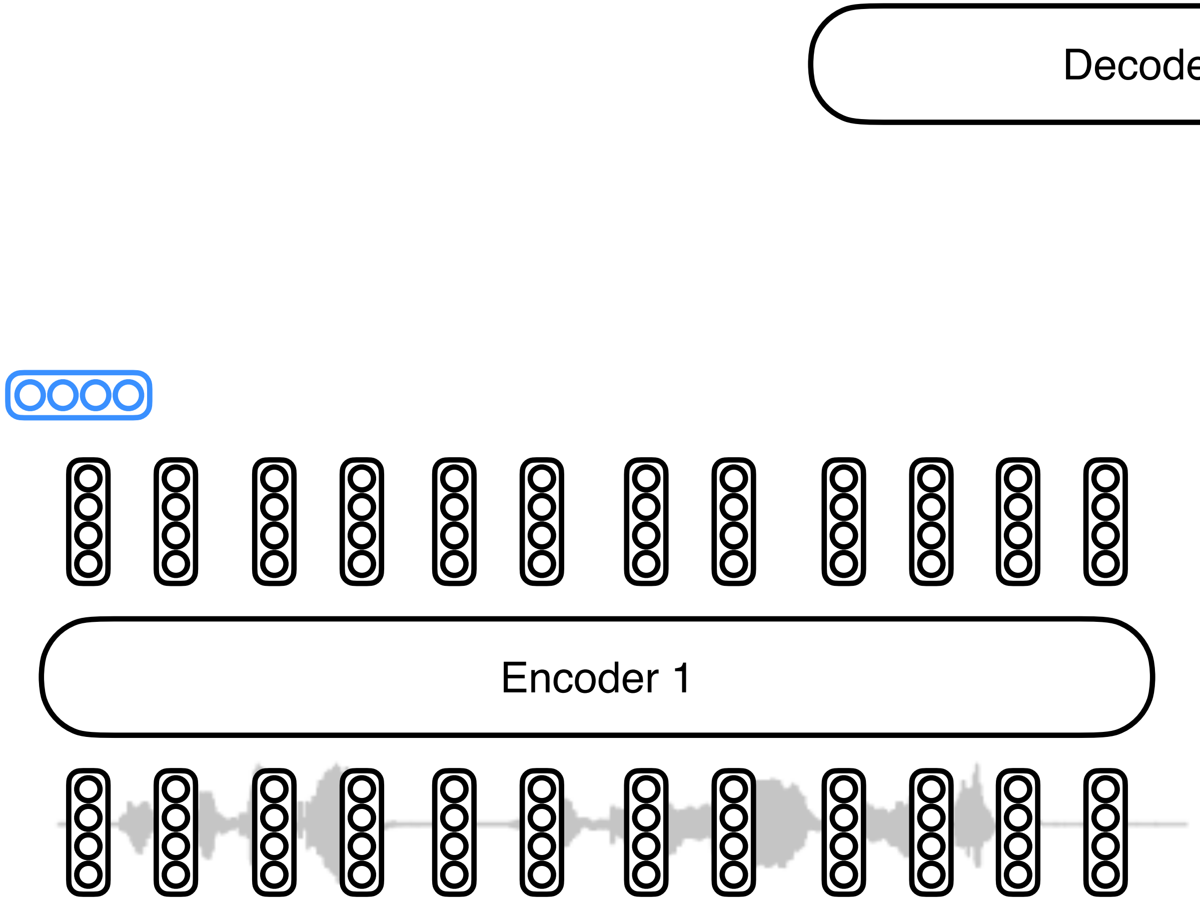


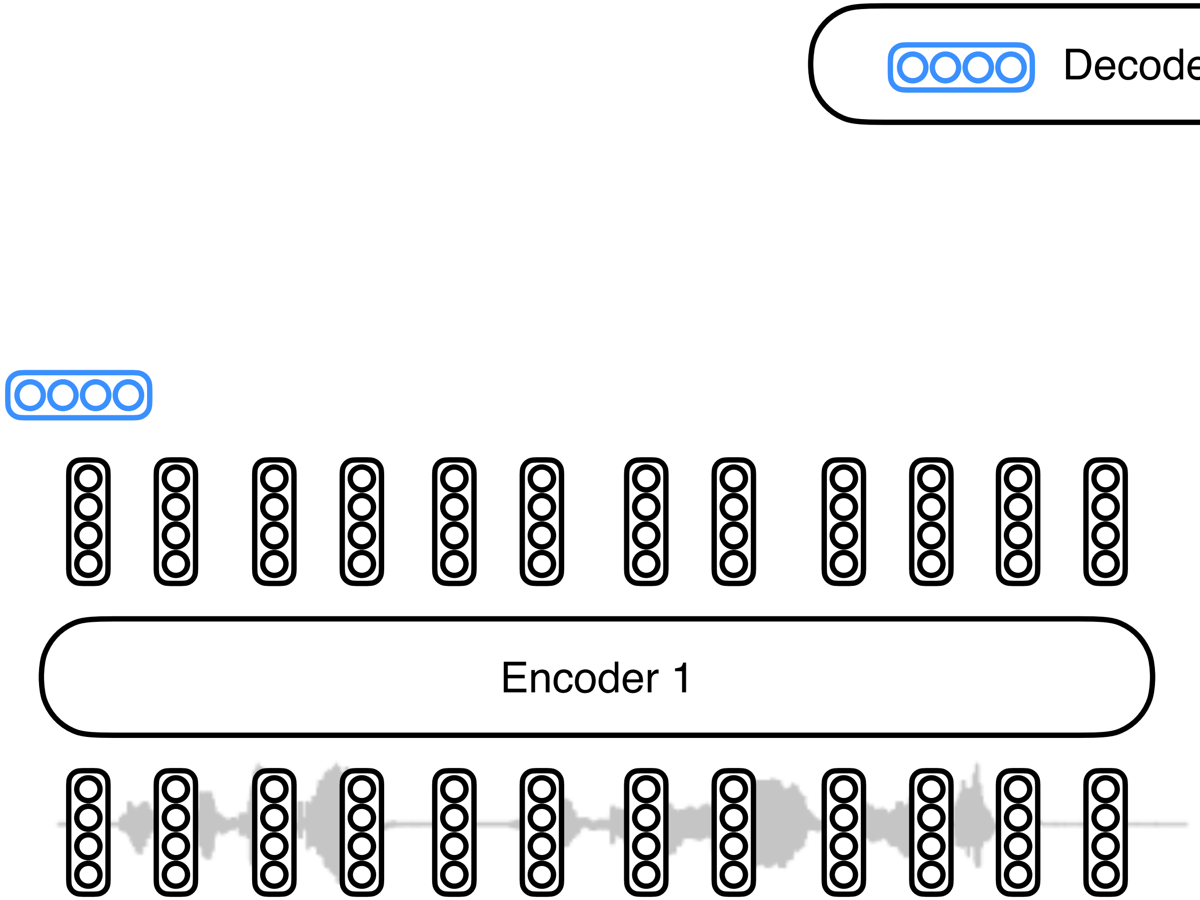
An Audio-Input model

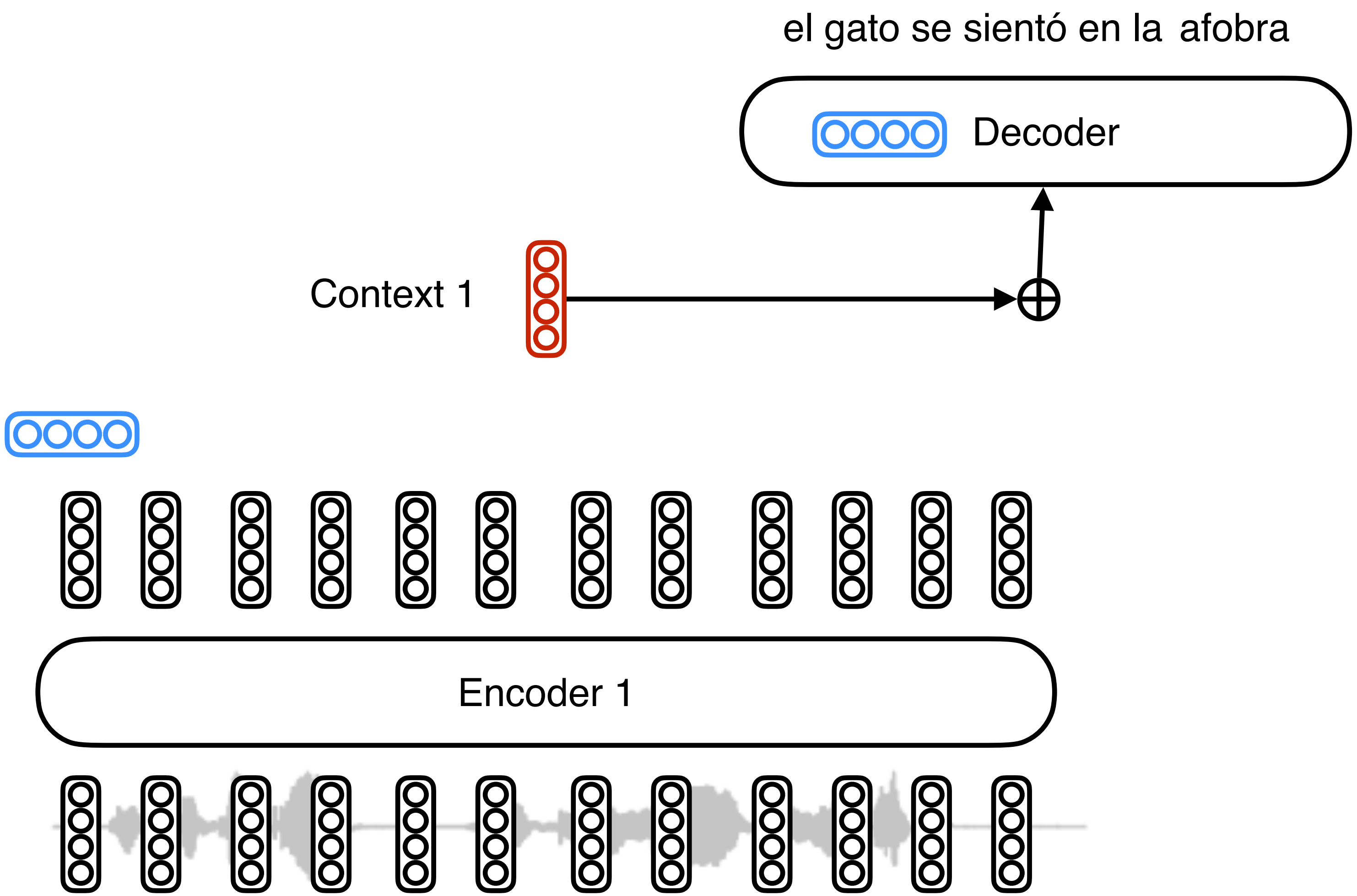


An Audio-Input model



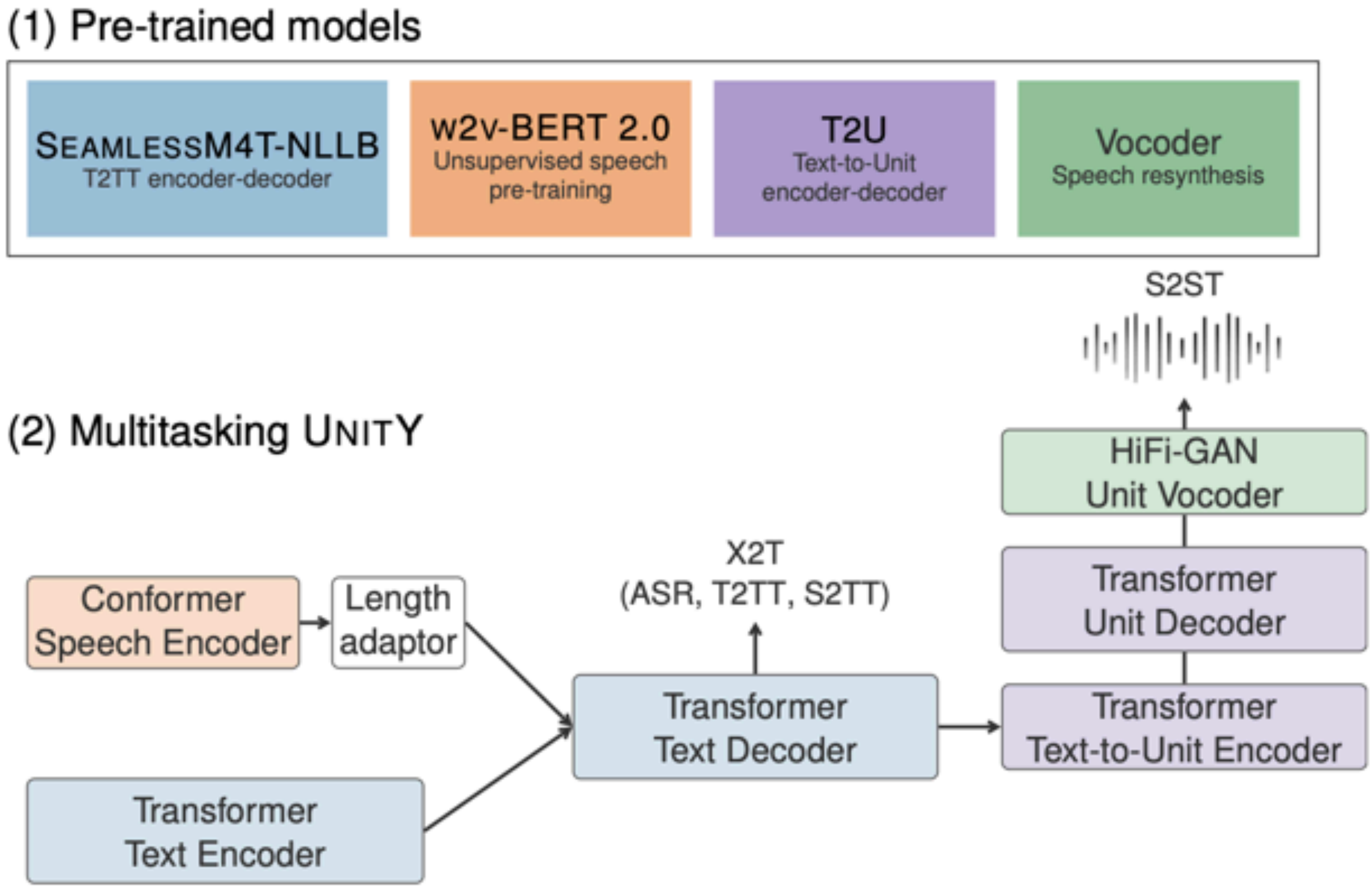

Decoder
Encoder 1


Decoder
Encoder 1


el gato se sentó en la afobra
Decoder
Context 1
Encoder 1

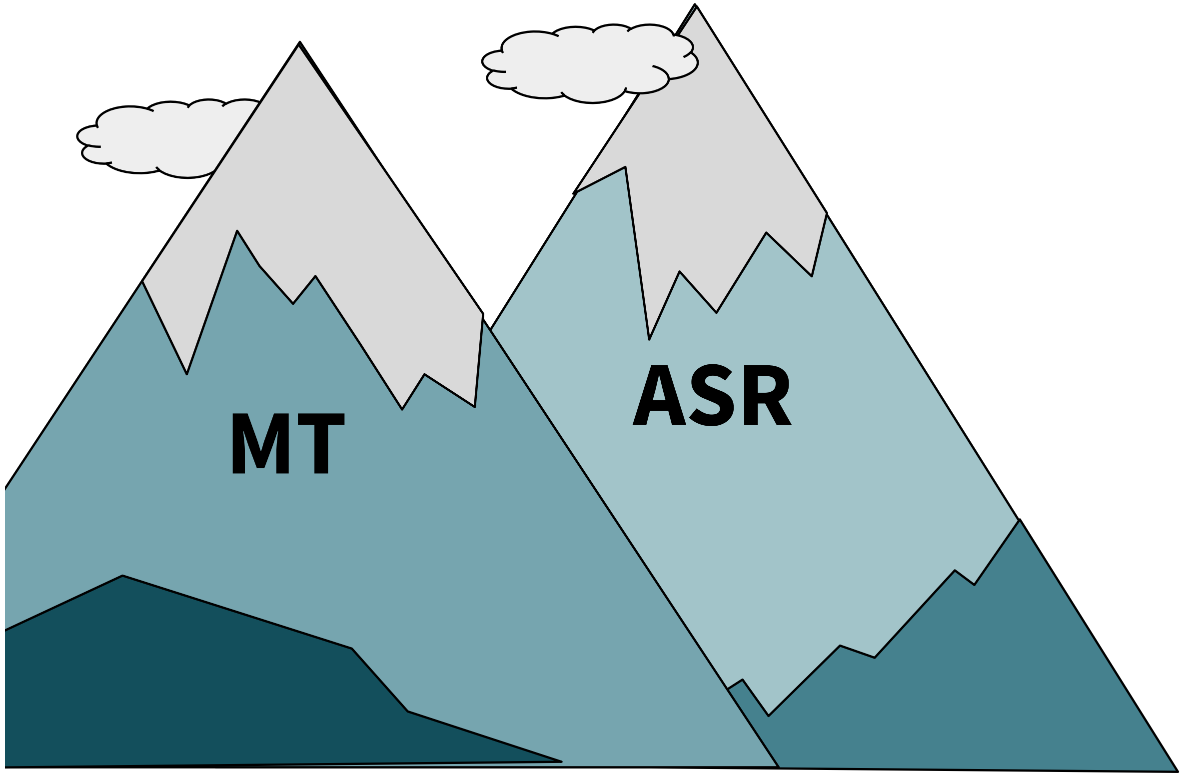
Today: pre-training

The SeamlessM4T model



Today: data mining

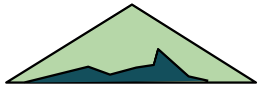
Recap: Available data



(text, translation)

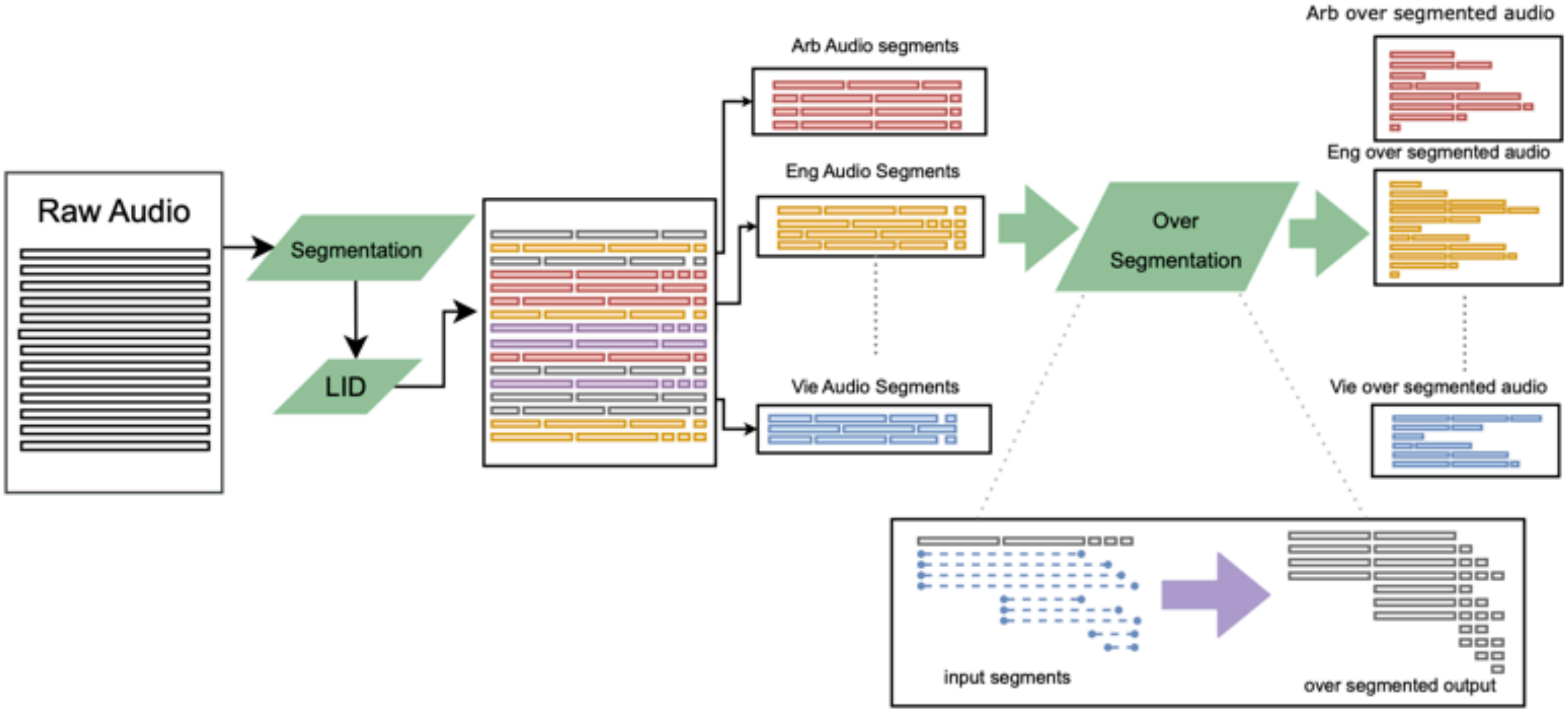
(audio, transcript)

Can we make use of this large amount of data?



(audio, transcript, translation)

Mining Parallel Speech Data



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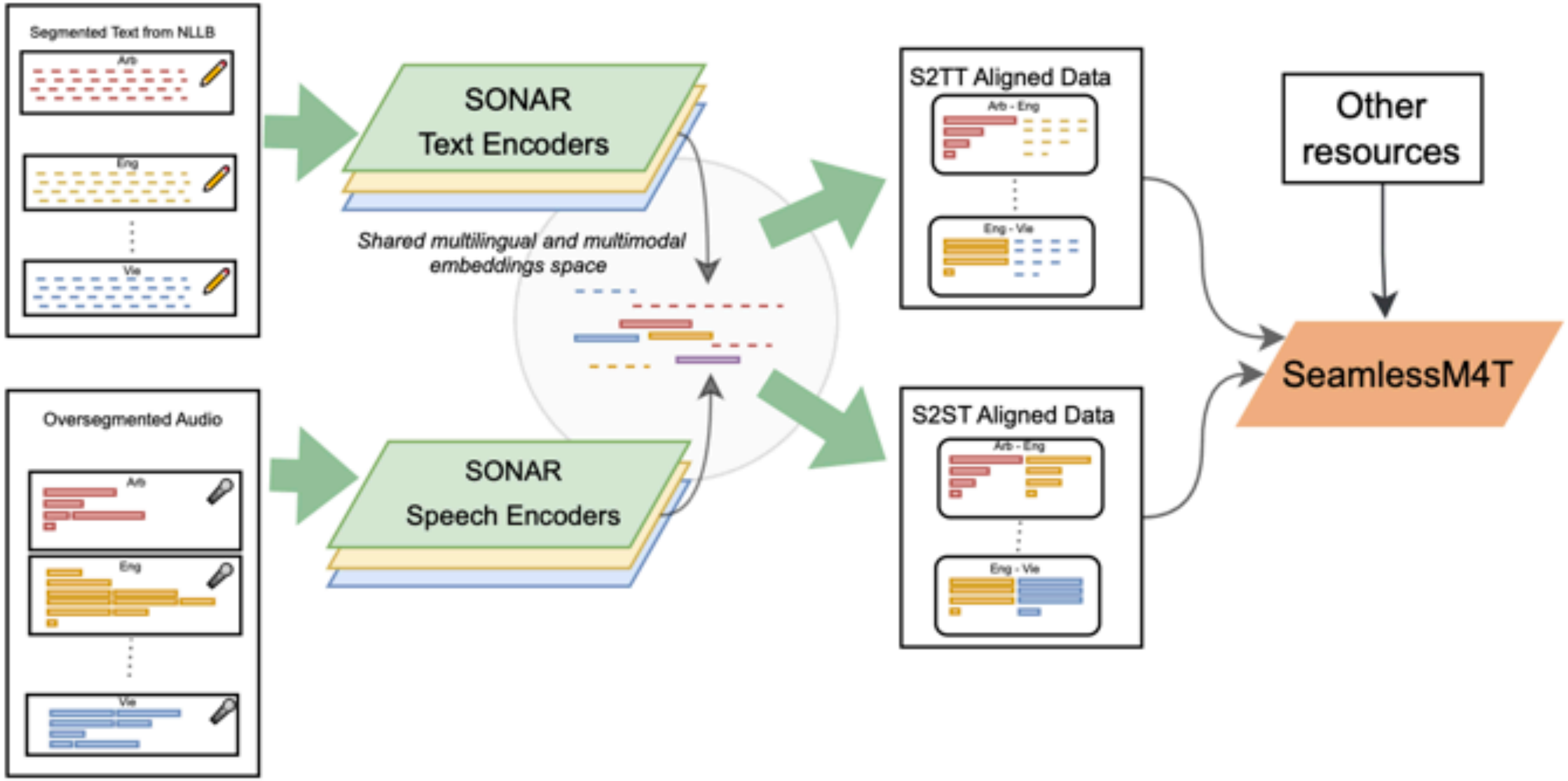
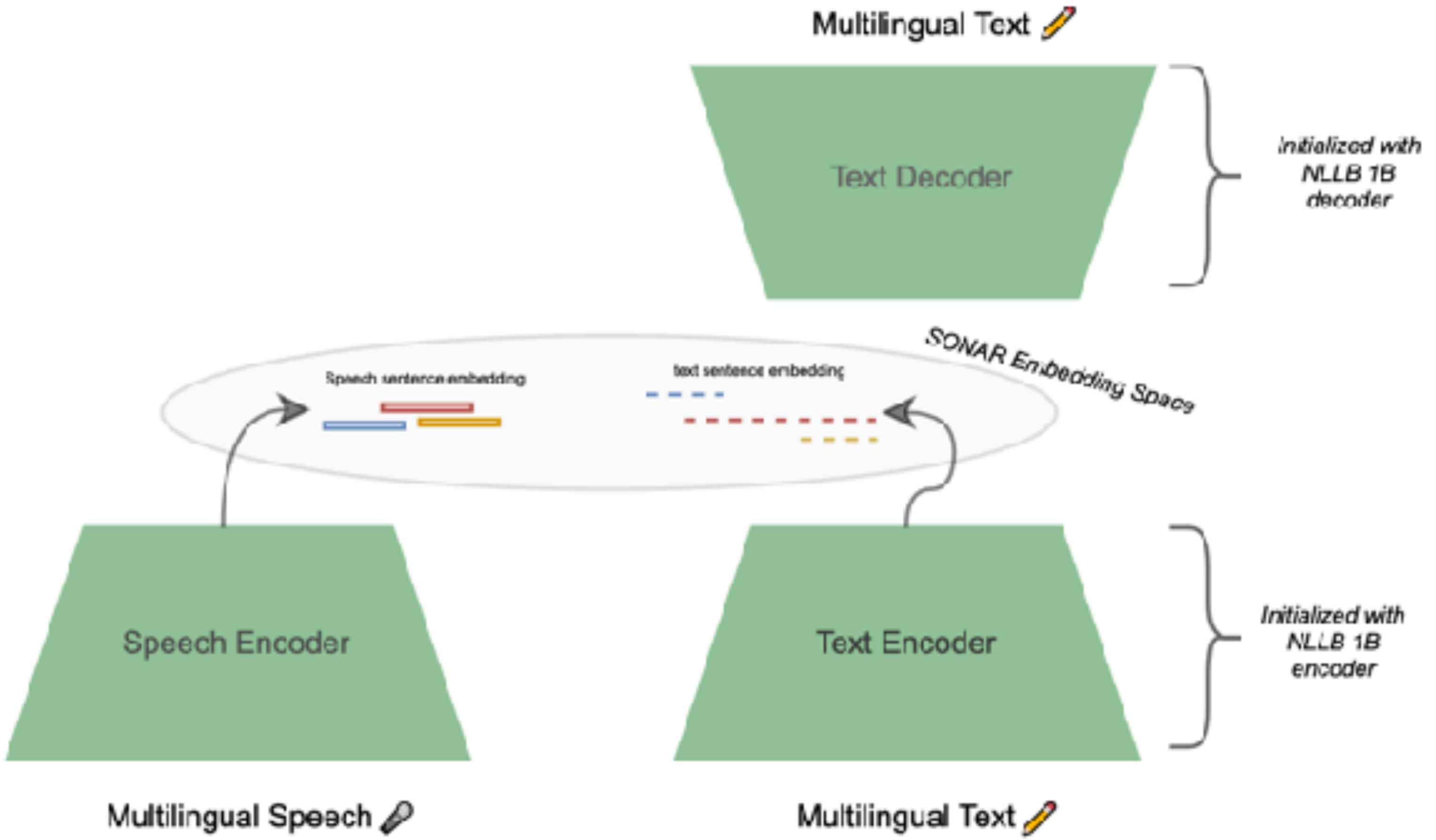
SONAR Representations



SONAR Representations



SeamlessM4T Results

SeamlessM4T Results

tl;dr: it’s great