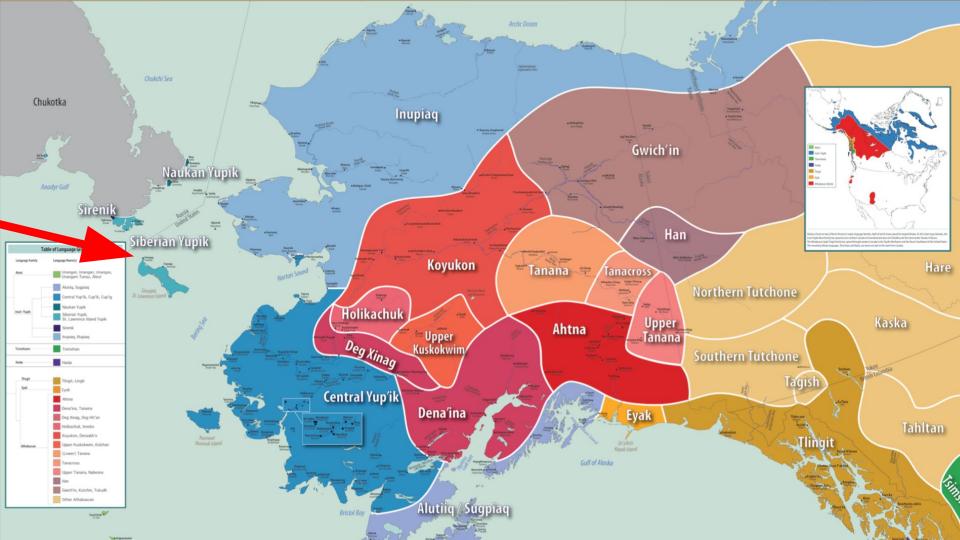
Neural Polysynthetic Language Modelling

JSALT 2019 Opening Presentation











Indigenous Languages

matter for development, peace building and reconciliation

Languages play a crucial role in the daily lives of people, not only as a tool for communication, education, social integration and development, but also as a repository for each person's unique identity, cultural history, traditions and memory. But despite their immense value, languages around the world continue to disappear at an alarming rate. With this in mind, the United Nations declared 2019 The Year of Indigenous Languages (IY2019) in order to raise awareness of them, not only to benefit the people who speak these languages, but also for others to appreciate the important contribution they make to our world's rich cultural diversity.





7 thousand

> Languages spoken worldwide

370 million

Indigenous people in the world

90 countries

With indigenous communities

5 thousand

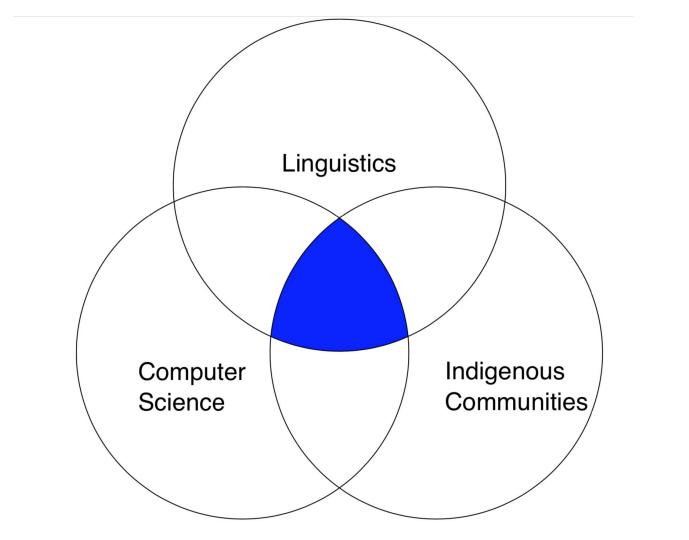
Different indigenous cultures

2680 languages

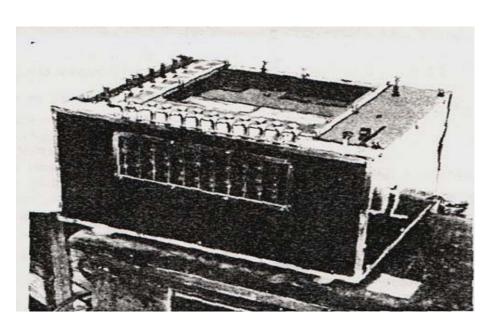
In danger

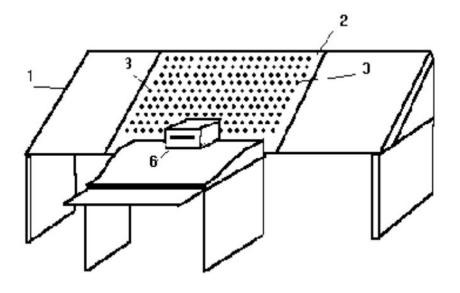


- Increasing understanding, reconciliation and international cooperation.
- Creation of favorable conditions for knowledge-sharing & dissemination of good practices with regards to indigenous languages.
- Integration of indigenous languages into standard setting.
- Empowerment through capacity building.
- Growth and development through elaboration of new knowledge.



Since 1933, NLP technology has overwhelmingly focused on languages & methodologies in which the word is the primary meaning-bearing unit



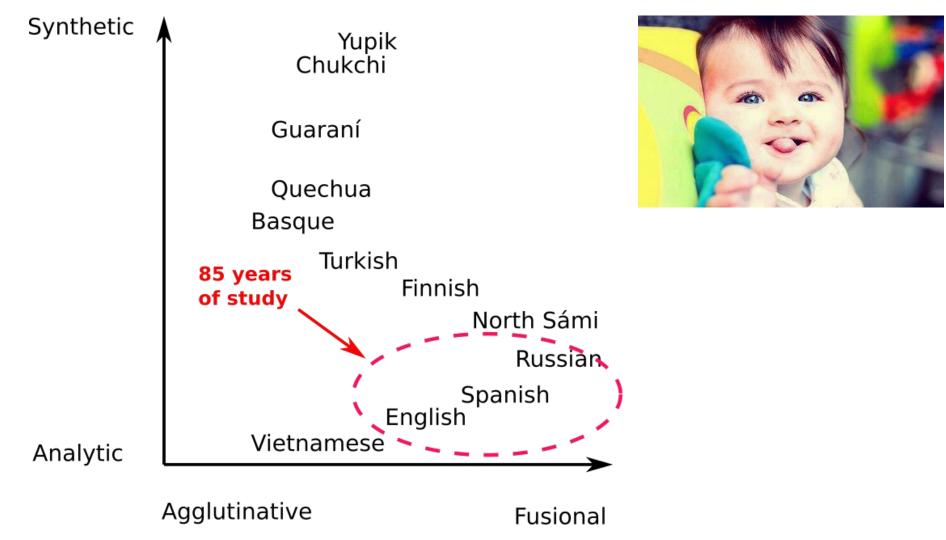


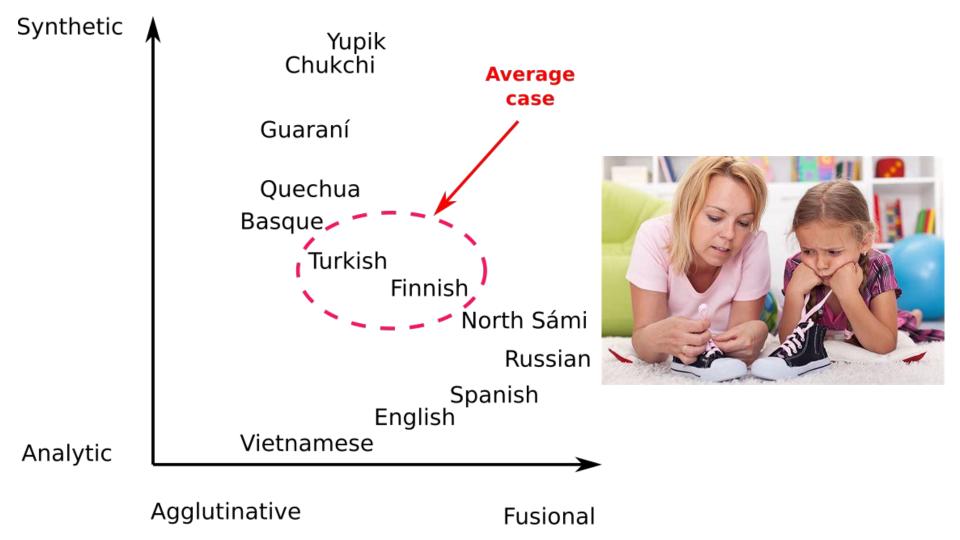
Arstrouni (1933, Paris)

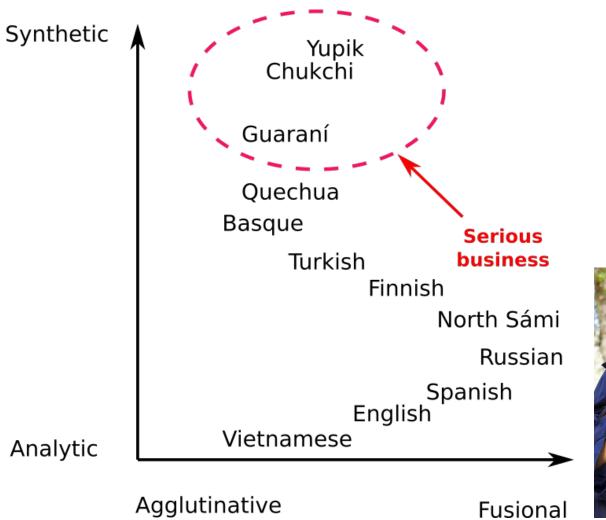
Trojanskij (1933, St. Petersburg)

For *most* human languages, this assumption is fundamentally broken











Analytic Languages:

Little inflectional morphology

- English inflection
 - dog, dogs
 - walk, walks, walked, walking
- English derivation
 - disestablishmentarianism

Isolating Languages:

Little morphology other than compounding

- Chinese inflection
 - few affixes (prefixes and suffixes):
 - 们: 我们, 你们, 他们, 同志们 mén: wǒmén, nǐmén, tāmén, tóngzhìmén plural: we, you (pl.),they, comrades, LGBT people
 - "suffixes" that mark aspect: 着 -zhě 'continuous aspect'
- Chinese derivation
 - 艺术**家** yìshù**jiā** 'art**ist**'
- Chinese is a champion in the realm of compounding—up to 80% of Chinese words are actually compounds.

毒	+	贩	\rightarrow	毒贩
dú		fàn		dúfàn
'poison, drug'		'vendor'		'drug trafficker'

Synthetic Languages:

Lots of morphology relative to analytic languages

- Czech inflection
 - fusional suffixes:

Class	Singular	Plural
1. Nominative	měst o	měst a
2. Genitive	měst a	měst
3. Dative	městu	městům
4. Accusative	město	měst a
5. Vocative	město	měst a
6. Locative	městě	městech
7. Instrumental	městem	městy

Agglutinative Languages:

Verbs in Swahili have an average of 4-5 morphemes, http://wals.info/valuesets/22A-swa

- Words are written without hyphens or spaces between morphemes.
- Orange prefixes mark noun class (like gender, except Swahili has nine instead of two or three).
 - Verbs agree with nouns in noun class.
 - Adjectives also agree with nouns.
 - Very helpful in parsing.
- **Black** prefixes indicate tense.

Swahili	English
m-tu a-li-lal-a	'The person slept'
m-tu a-ta-lal-a	'The person will sleep'
wa-tu wa-li-lal-a	'The people slept'
wa-tu wa-ta-lal-a	'The people will sleep'

Agglutinative Languages:

Turkish

But most words have around three morphemes

uygarlaştıramadıklarımızdanmışsınızcasına

"(behaving) as if you are among those whom we were not able to civilize"

```
"civilized"
uygar
        "become"
+laş
        "cause to"
+tır
        "not able"
+ama
                                                                      Derivational and inflectional
+dık
        past participle
                                                                      morphology.
+lar
        plural
        first person plural possessive ("our")
+ımız
+dan
        ablative case ("from/among")
+mis
        past
        second person plural ("y'all")
+siniz
+casina finite verb \rightarrow adverb ("as if")
```

From the Jurafsky and Martin textbook.

Polysynthetic Languages

- All definitions are problematic
 - "A word means a whole sentence"
- There is no one feature (e.g., noun incorporation) that is in every polysynthetic language
- The definition isn't important
- What is important
 - There is a much larger number of distinct possible words
 - Beyond Turkish and Finnish
 - All languages have some of the properties of polysynthesis
 - Compounding, mild recursion in morphology (operationalization), causative, applicative, passive, negative

Inuit-Yupik Language Family

```
Yupik
St. Lawrence Island
Central Alaskan
Inuit
Inupiaq
Innuinaqtun
Inuktitut
Greenlandic (Kalaallisut)
```



Inuktitut Morphology

And even though it's not snowing a great deal, I'm not going out.

Qanniqlaunngikkaluaqtuqlu aninngittunga.

```
qanniq-+-lak + uq-+-nngit-+-galuaq-+-tuq + lu
to snow a little frequently not although 3rd pers. sg. and
ani-+-nngit-+-junga
to go out not 1st pers. sg.
```

http://en.wikipedia.org/wiki/Inuit grammar + Uqailaut morph analyzer

Inuktitut Morphology

Inuktitut Morphology

Some examples of flipping back and forth between noun and verb

umiaq + juaq + liuq + vik + mi

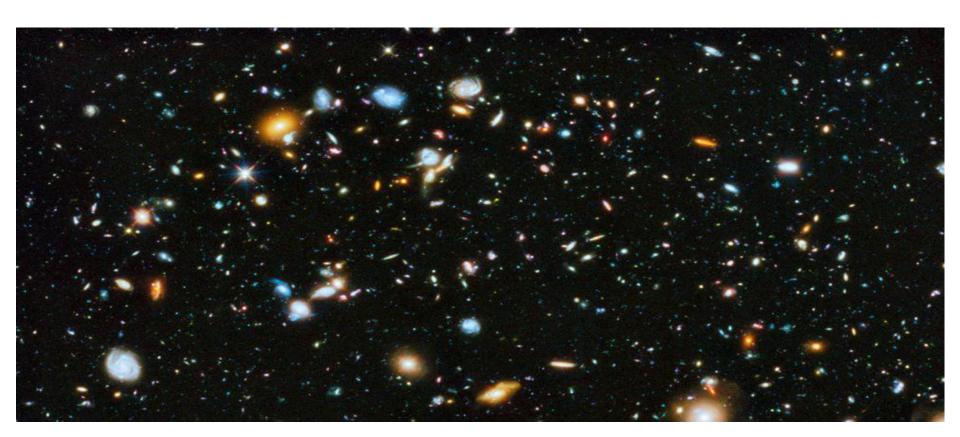
boat (n) + big (adj incorp) + make (n-v, light verb) + place-where (v-n, derivational) + locative "in the shipyard"

ilinniaq+ vik + siuq + junga

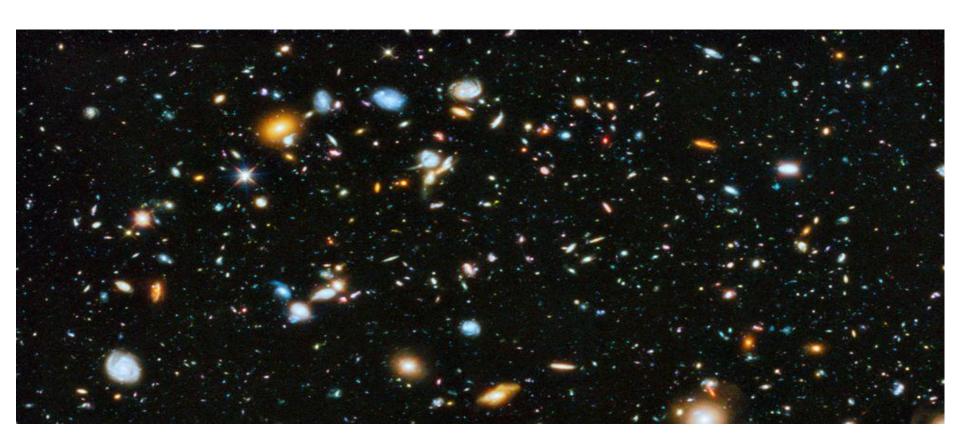
learn (v) + place-where (v-n, derivational) + look for (n-v, light verb) + 1-s "I'm looking for a school"

http://www.inuktitutcomputing.ca/Technocrats/ILFT.php#morphology

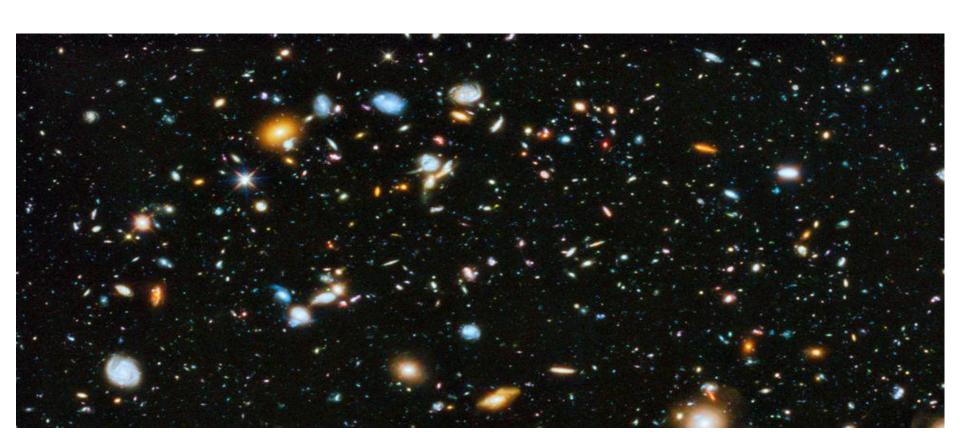
There are 1.2×10^{23} stars in the observable universe



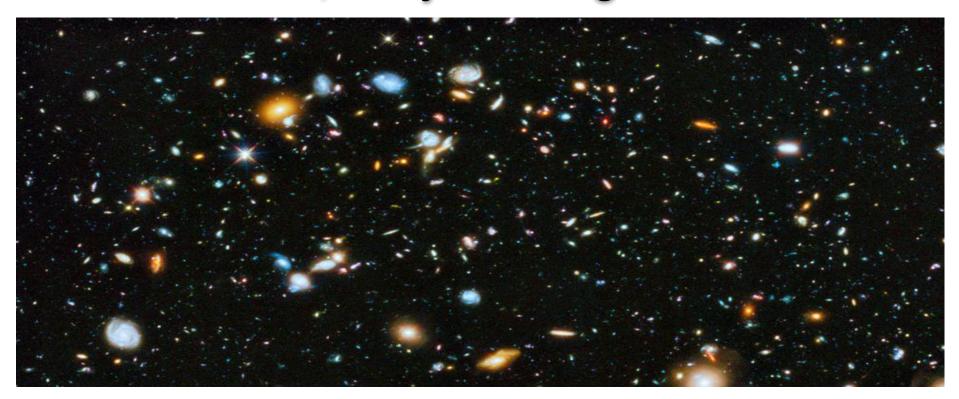
There are 1.2 x 10²³ possible Yupik word forms



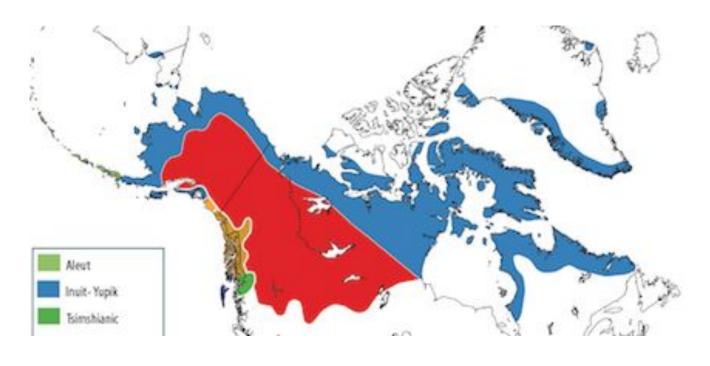
Big data is NOT the solution



We need a language model that sees the stars, not just the galaxies



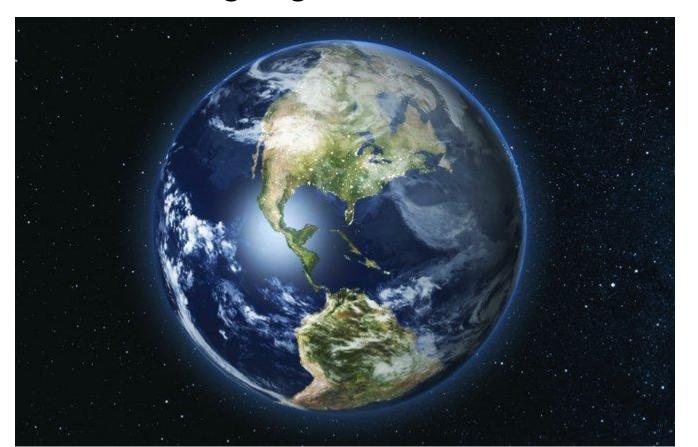
Create a language model that handles the hardest case



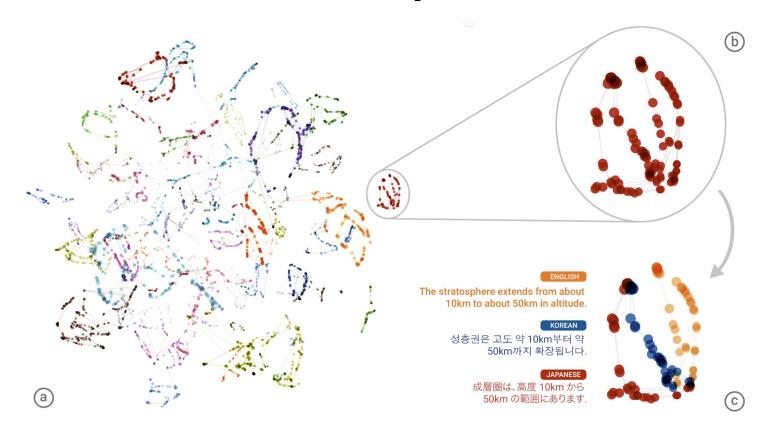
... where every other token is OOV



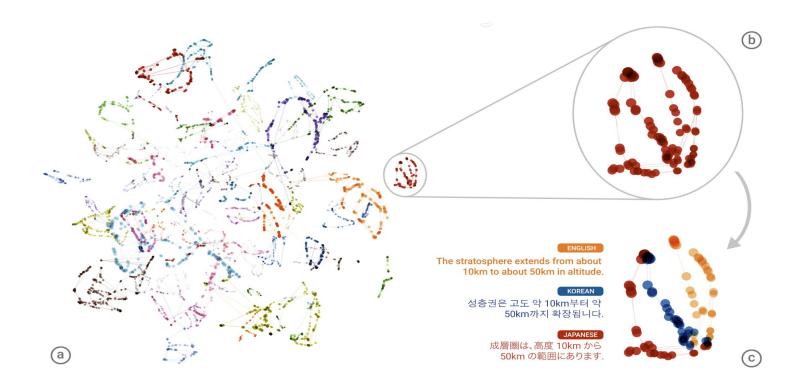
... and you'll learn lessons that will apply to the >6700 human languages that are not like English



Research questions

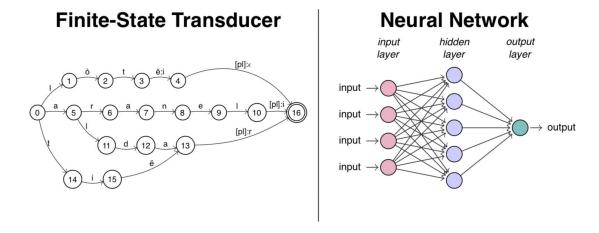


1) What embedding representations are most appropriate for languages with a high ratio of morphemes to words?



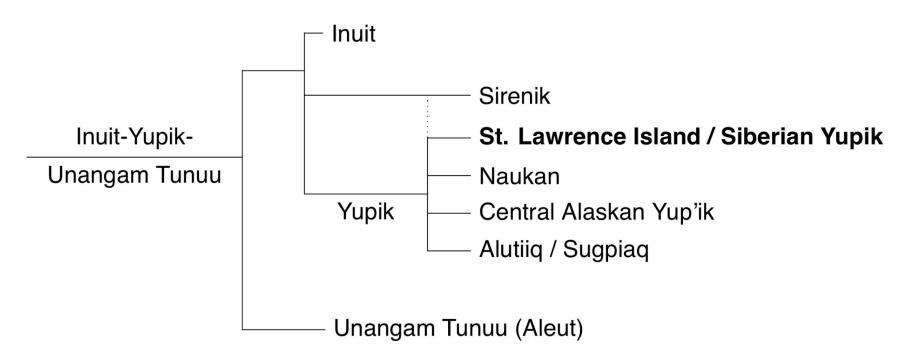
2) Can FST-based morphological analyzers effectively be used to bootstrap *more* effective neural LMs?

Morphological analyzers may be implemented as a



- Neural systems require LOTS of data
 - But Yupik is a low-resource language
 - Very few surface form-lexical form pairs available

3) How can common neural models be developed for closely related languages in order to maximize the utility of sparse digitized resources?



Overview

- Language selection and data collection
- Baseline systems
 - Language modelling
 - Machine translation
 - ASR
- Downstream applications
 - Spell-checkers & on-device morph-aware dictionaries
 - On-device predictive text
 - Audio transcription / search of audio archives
 - Interactive machine translation of monolingual polysynthetic texts

Language selection

Saint	Lawrence	Is	land	Yupik
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Alaskan Yup'ik

North Slope Iñupiaq

Inuktitut

Kalaallisut

Chukchi

Guaraní

Seneca

Mohawk

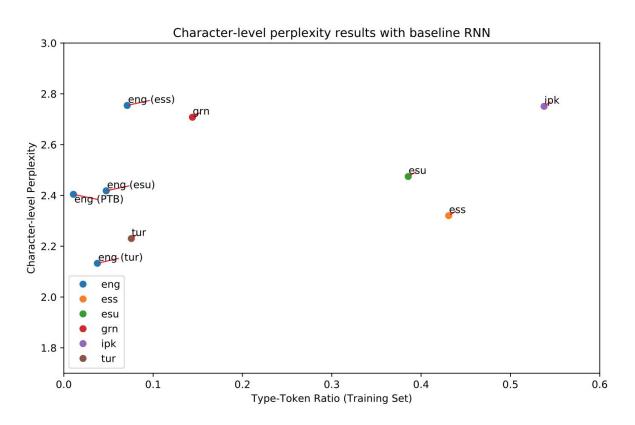
Crow



Data collection

Language	Code	Monolingual	Parallel	FST	Audio
St. Lawrence Island Yupik	ess	24,456	8,002	V	33h*
Alaskan Yup'ik	esu	_	45,254	_	_
North Slope Iñupiaq	esi	4,070	_	V	_
Inuktitut	iku	1,552	1,300,159	(✔)	_
Kalaallisut	kal	5,949	_	V	_
Chukchi	ckt	1,015	_	V	1h30*
Guaraní	grn	_	30,078	V	_
Seneca	see	_	_	_	12h
Mohawk	moh	_	_	_	_
Crow	cro	_	_	_	7h

Baseline system: RNN LM



Baseline system: MT

English → Inuktitut

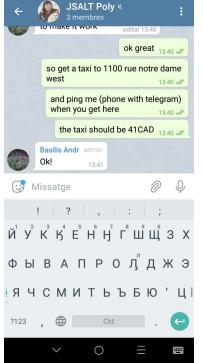
BPE	NMT	SMT
500	16.7	13.1
1000	16.8	14.8
5000	16.9	15.2
15000	17.0	15.1
30000	16.7	15.2
60000	16.8	15.5

Baseline system: ASR

- DeepSpeech ASR baseline for Crow
- Forced aligner trained for SLI Yupik

Downstream applications:

On-device predictive text



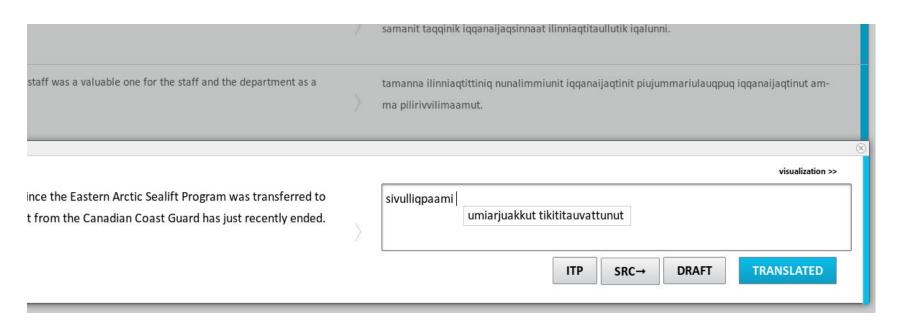
the taxi should be 41 CAD 13:40 we have the t



Downstream applications: Spell-checkers



Downstream applications: Interactive MT



Downstream applications: Audio transcription / search



Workshop goals

 What embedding representations and neural LM architectures are most effective for languages with a high ratio of morphemes per word?

Can rule-based FSTs be used to bootstrap more robust neural models?

 To what extent can common neural models be developed for closely related languages in order to maximize the utility of sparse digitized resources?

NPLM Team Members

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Let's learn lessons that will apply to the >6700 human languages that are not like English

