俺, 僕 or 私?

Machine Translation Robustness to Natural Asemantic Variation

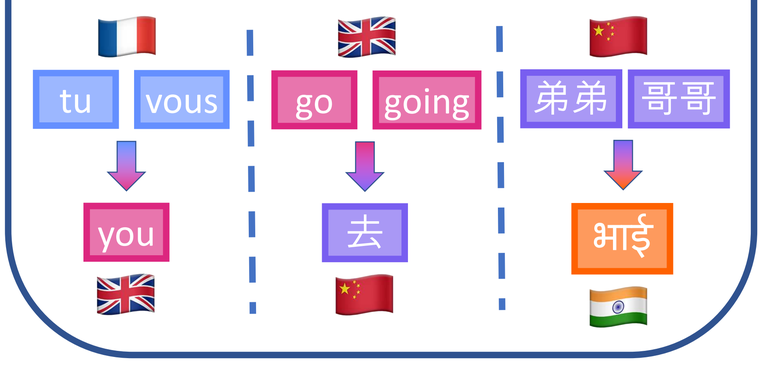
Jacob Bremerman, Xiang Ren, Jonathan May
University of Southern California

USC University of Southern California
USC Viterbi Information Sciences Institute
CUTE LAB NAME

Natural Asemantic Variation (NAV)

NAV refers to "naturally-occurring"[1] variations of a standard sentence, which only slightly alters the meaning such that the nuance difference can't be concisely expressed in the target language.

1: (not typos, 1337 5p34k, emojis, etc.)



This is a Japanese sentence:

彼女は私に本を返しました。

She returned the book to me.

This is a perturbation of a Japanese sentence:

彼女#は私aに本を返しました。

She# returned the book to mea.

She returned the book to me.

This is a NAV perturbation of a Japanese sentence:

彼女は俺に本を返してくれた。

She returned (as a favor) the book to (masculine) me. [informal utterance]

She returned the book to me.

gloss

translation

Sometimes MT models struggle with NAV:

彼女は私に本を返しました。

She returned the book to me.

彼女は俺に本を返してくれた。

She returned (as a favor) the book to (masculine) me. [informal utterance]

She gave me a book.

Presence of extra nuance in source language results in inadequate translation

Evaluation—NAV Robustness Desiderata

She returned the book to me. = S R M B

Input: 4 NAV versions of the same (semantic) sentence

Reference translation in target language

Representation of **reference** translation sequence

彼女は俺に本を返してくれた。

The 4 outputs resemble **reference**

The 4 outputs resemble **each other**

Quality

Consistency

Best model will exhibit both qualities!

Output from NAV variation #1

Output from NAV variation #2

STAPLE (2020) Dataset

彼女は俺に本を返してくれた。
彼女は俺に本を返した。
彼女はわたしに本を返した。
彼女は私に本を返したよ。

She returned the book to me.

~300 NAVariations

5 language pairs

hu ja pt ko vi

train dev test

test

en

Off-the-shelf

M2M-100 model from FAIR

Domain-adapted

Fine-tune M2M-100 on STAPLE data

NAV fine-tuned

Fine-tune M2M-100 on STAPLE data WITH several NAV perturbations

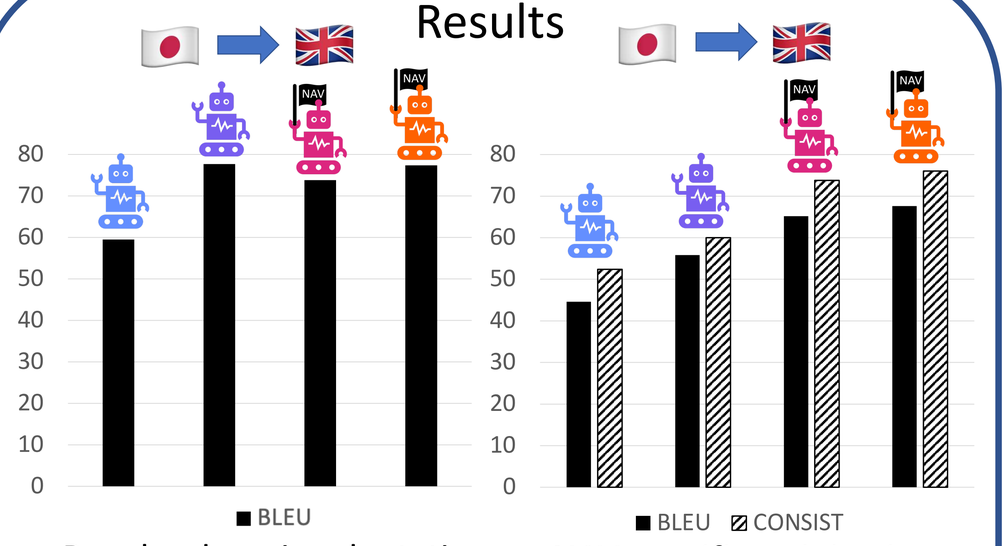
Multilingual NAV fine-tuned

Fine-tune M2M-100 on STAPLE data WITH several NAV perturbations from all THREE language pairs together

Common NAV
0-shot transfer
Uncommon NAV
Synthetic
Synthetic Multilingual

(Additional experimental conditions/data/evaluations shown in full paper)

Results



Regular domain adaptation works just fine for standard MT test data/evaluation

NAV-specific training is necessary to perform maximally on NAV test data

Takeaways

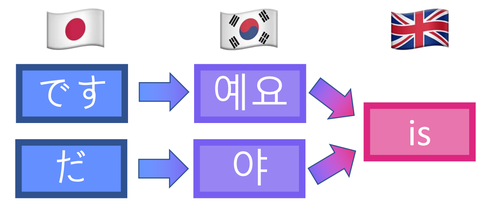
- MT models are brittle to NAV variation
- NAV exposure leads to NAV robustness
- NAV robustness improvements apply cross-lingually
- Synthetic NAV augmentation methods outperform traditional noise augmentation

Future Work

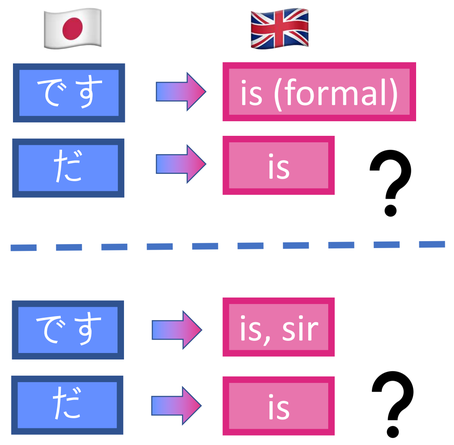
- Handle all types of noise simultaneously without sacrificing performance in other areas
- Work with "set to set" translation pair examples
- Non-English reference languages

Very Future Work

- Maintain nuance differences properly when the target language allows for it



- What to do when the language doesn't allow for it?



What's an example of NAV (w.r.t. English) in ***your*** language?

Link to Full Paper:

This material is based upon work supported by the Defense Advanced Research Projects Agency (DARPA) under Agreement No. HR00112290056. Xiang Ren's research is supported in part by the Office of the Director of National Intelligence (ODNI), Intelligence Advanced Research Projects Activity (IARPA), via Contract No. 2019-19051600007 and NSF IIS 2048211.