Multilingual Machine Translation

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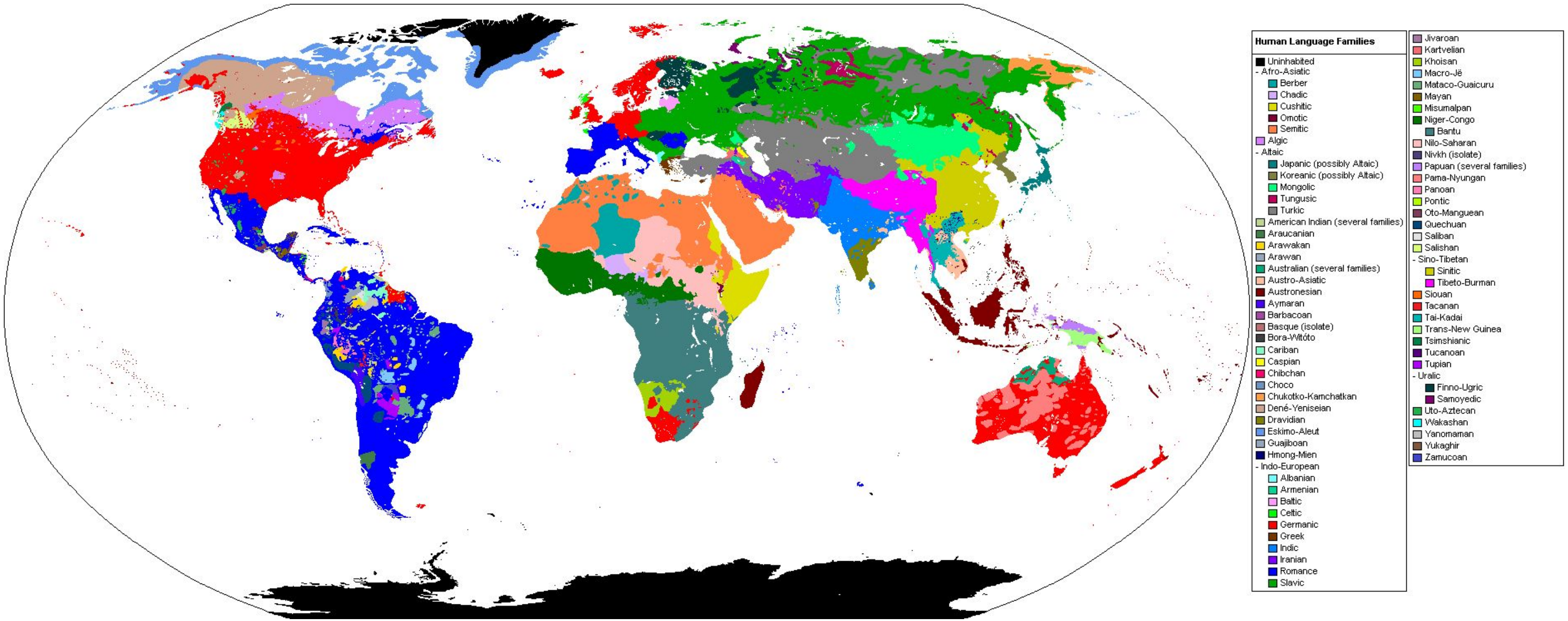


Ethnologue: > 7000 languages are spoken in the world. Figure source: Wikimedia (CC)

Talk Outline

- Overview of Multilingual/Neural Machine Translation
- Translation Tasks & Progress in NMT
- NMT Methods, Experiments, Results and Key Takeaways
- Conclusion, Current and Future Trends (Q&A's)

Overview

Neural Machine Translation

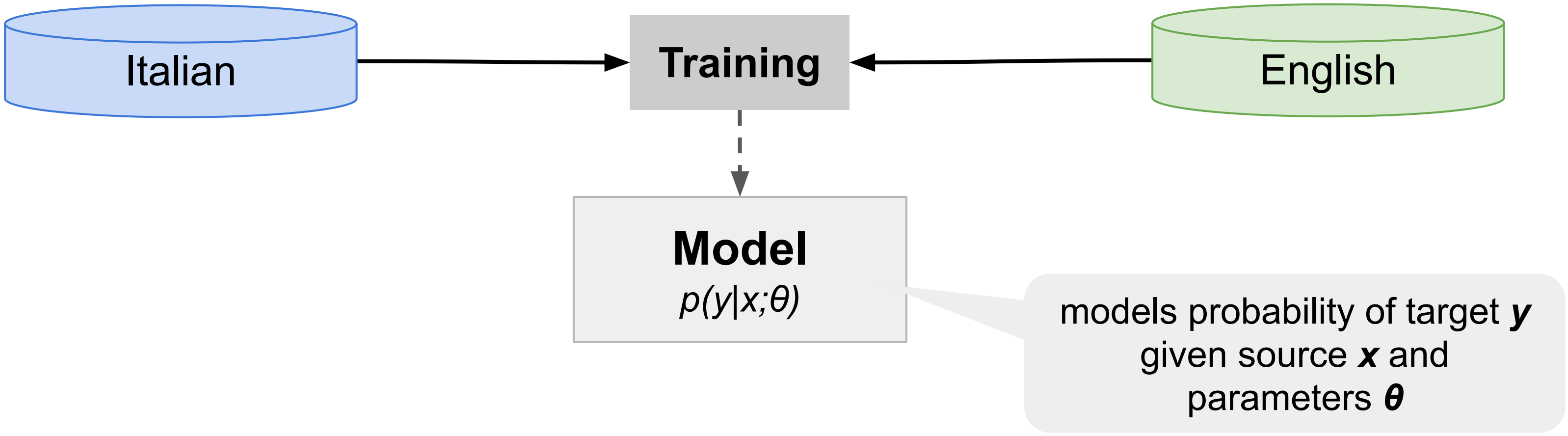
Multilingual
Neural Machine Translation

Task Overview

Neural Machine Translation

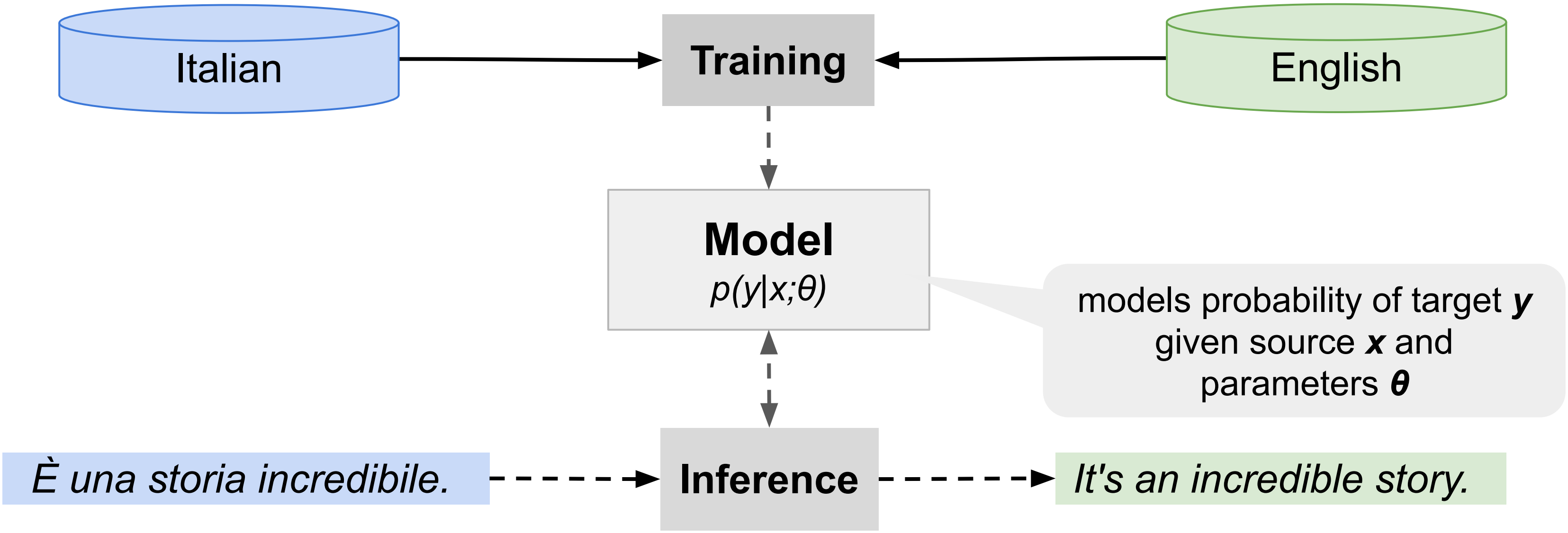
Requires sentence aligned parallel training data between the source (Italian) and target(English) language pairs.

Neural Machine Translation



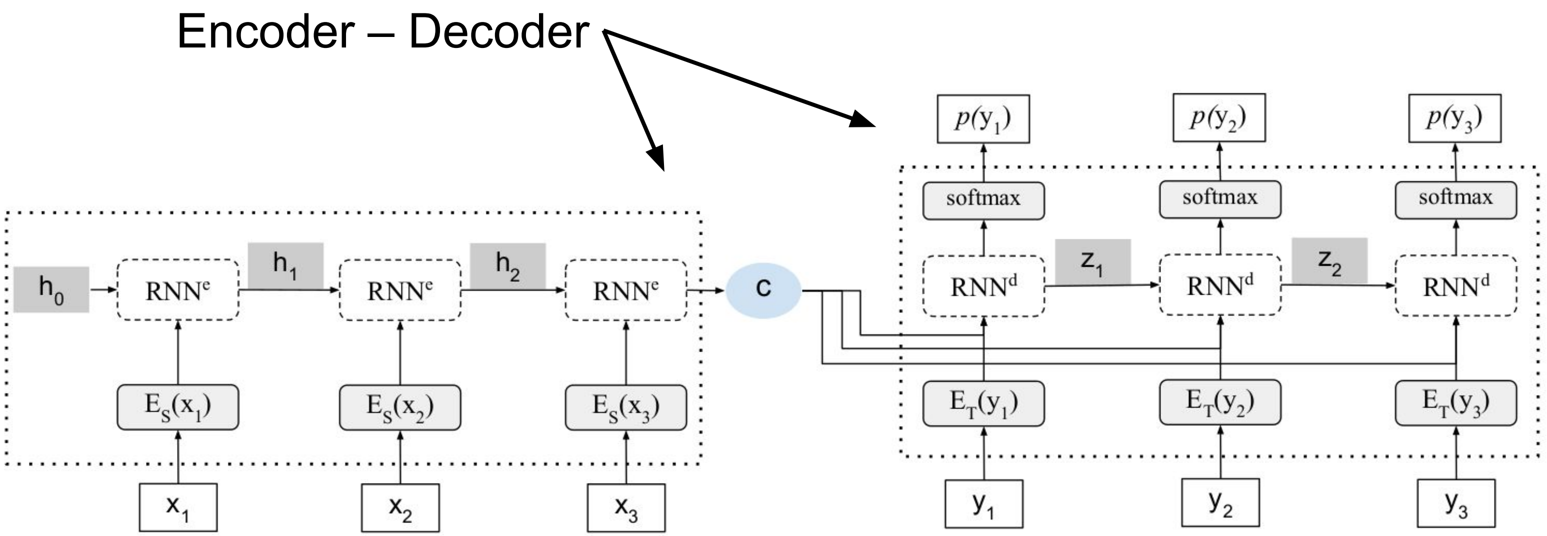
The NMT model is parameterized with a **seq2seq (encoder-decoder)** neural network.

Neural Machine Translation



The NMT translation performance depends on several factors, ranging from the training data size and domain to the model type and capacity.

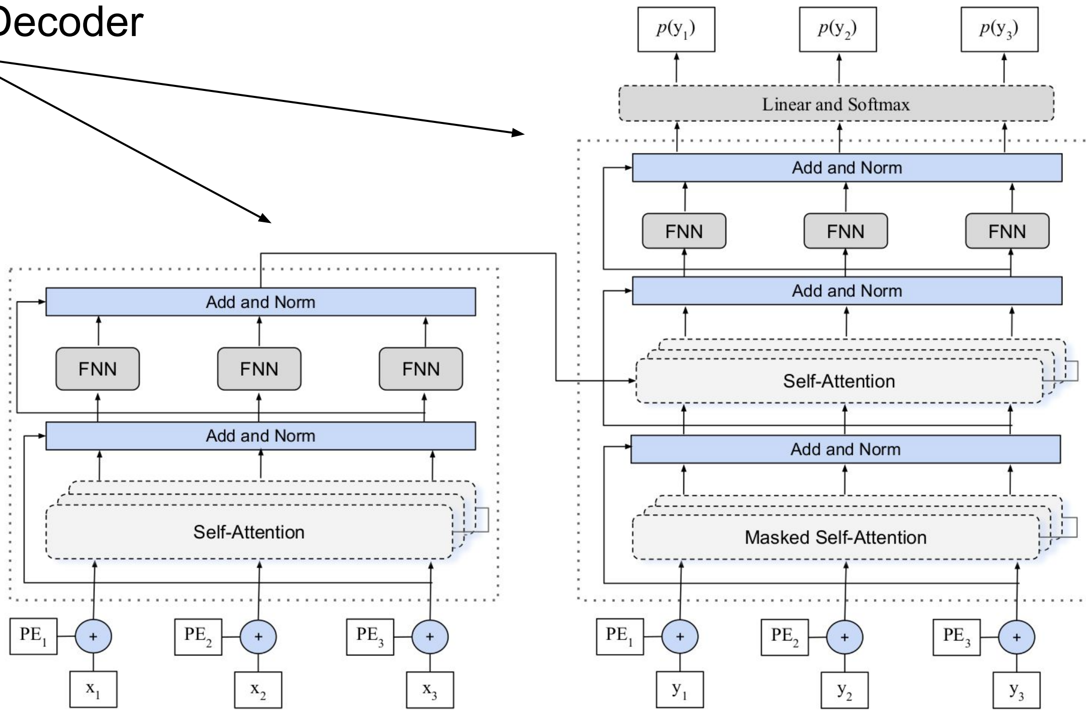
Machine Translation with Recurrent NN



Sutskever et al. 2014

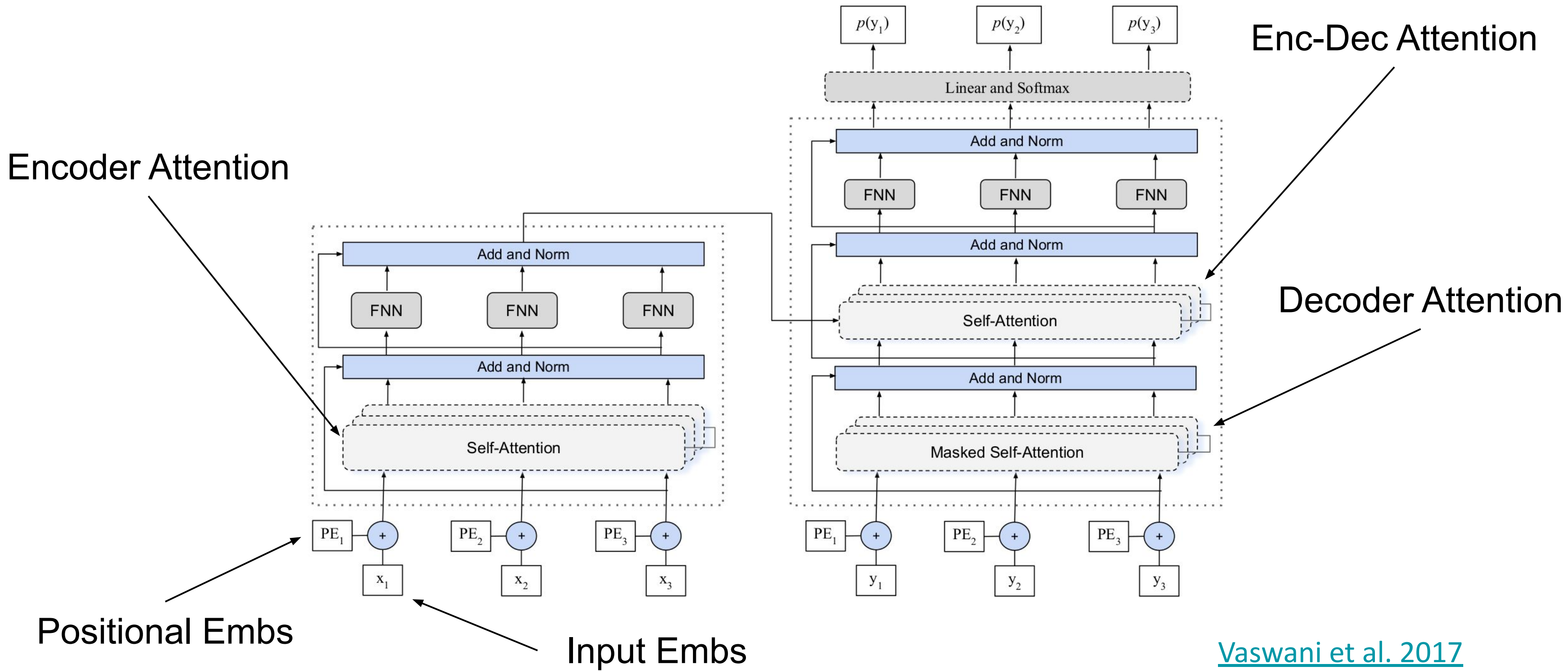
Machine Translation with Transformer NN

Encoder – Decoder



Vaswani et al. 2017

Machine Translation with Transformer NN



Vaswani et al. 2017

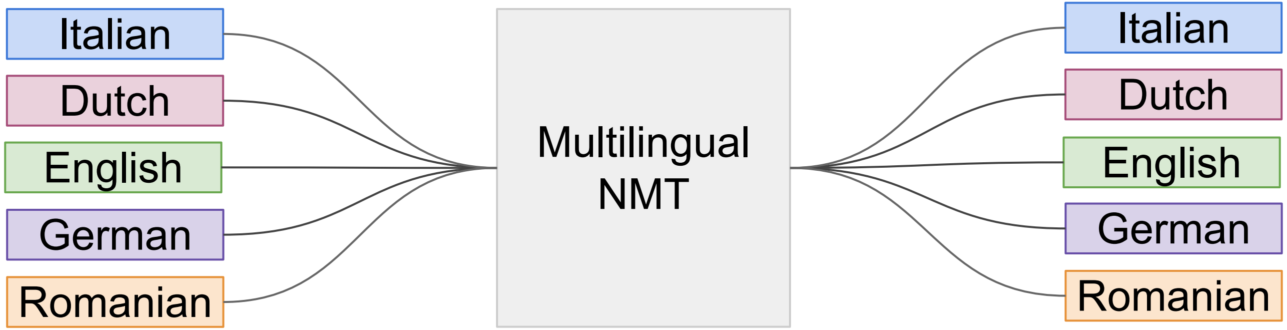
Overview

Neural Machine Translation

Multilingual
Neural Machine Translation

Overview of NMT Tasks

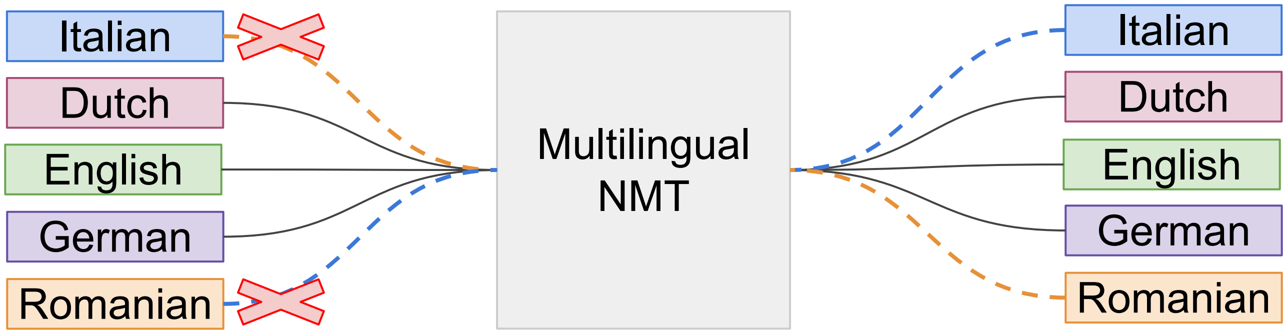
Multilingual Neural Machine Translation



Modeling a single NMT model to translate between multiple languages

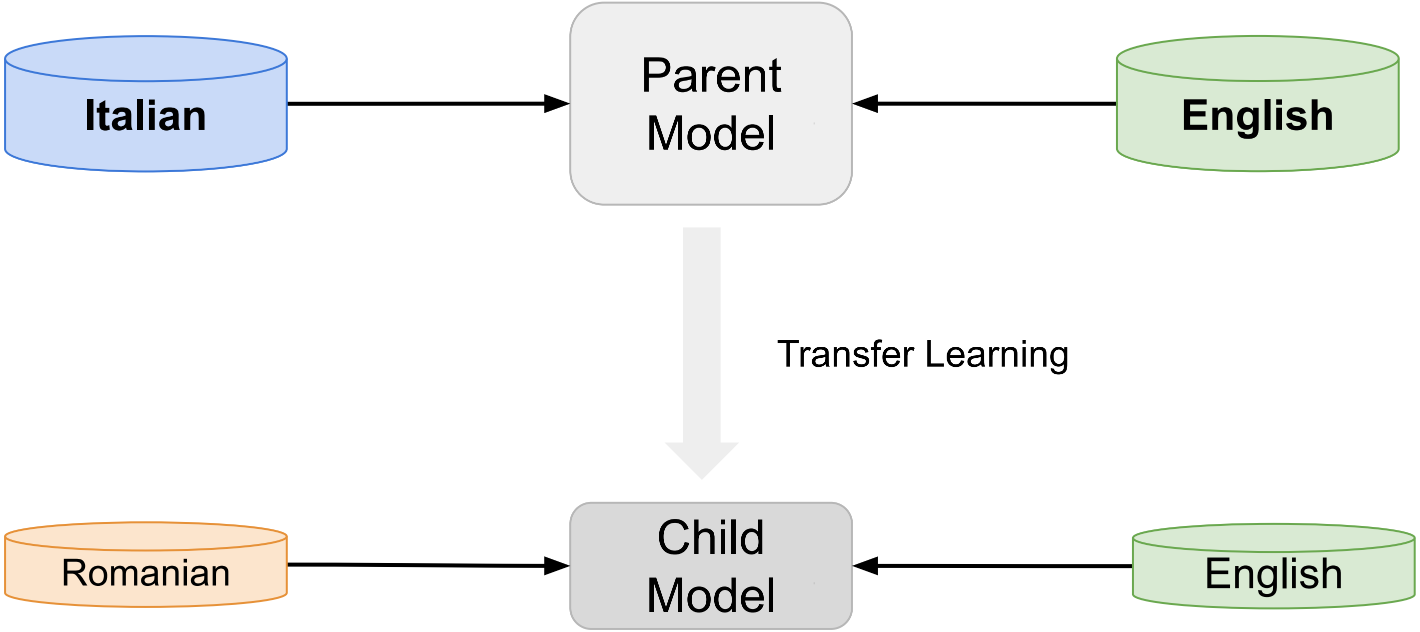
Johnson et al. 2016, Ha et al., 2016

Zero Resource NMT



In the absence of parallel examples, we use monolingual or/and multilingual data.

Low-Resource NMT

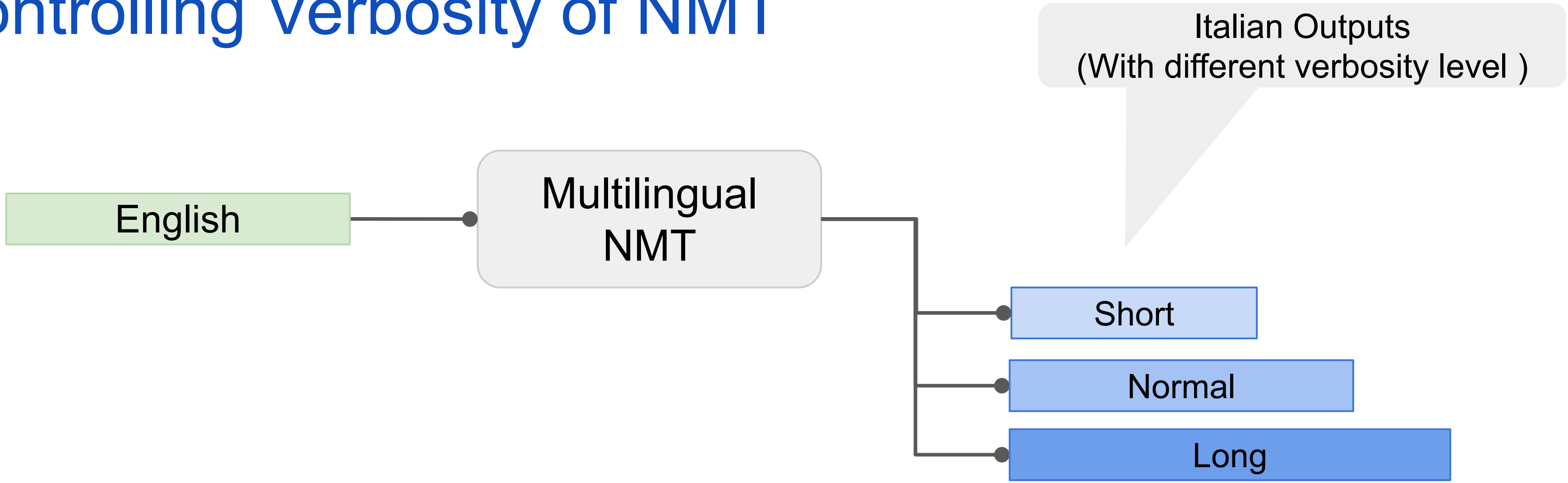


Improving low-resource tasks by leveraging high-resource language pairs.

NMT into Language Varieties

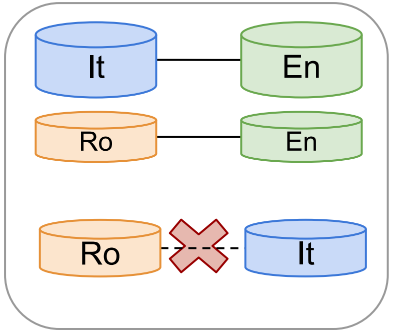
Multilingual NMT repurposed to translate into language varieties.

Controlling Verbosity of NMT



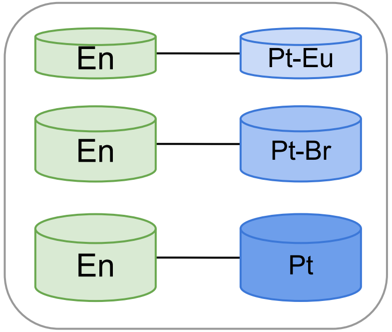
Multilingual NMT repurposed to translate into different verbosity level.

Overview of Tasks: what makes them similar?

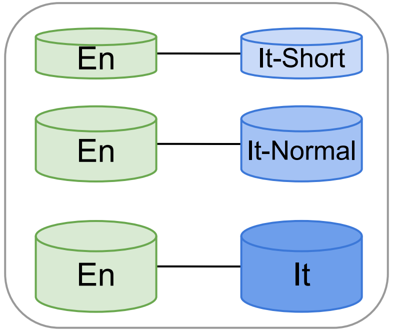


Low-Resource

Zero-Resource



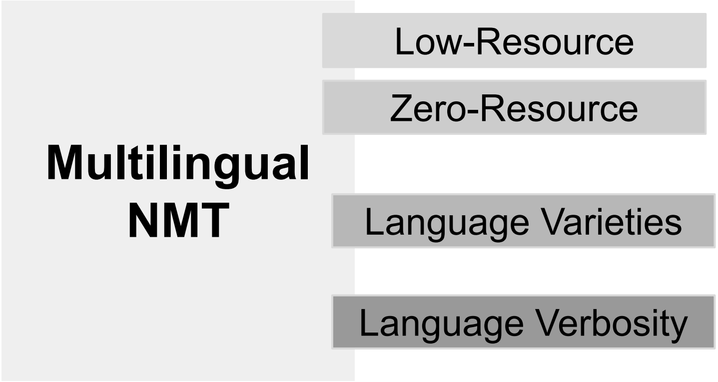
Language Varieties



Language Verbosity

Unbalanced/Unavailable resources across languages, varieties and styles.

Overview of Tasks: what makes them similar?



Modeling multiple tasks in a single model and enabling positive transfer-learning.

Progress in NMT

Tasks and Approaches

Zero Resource NMT

Dynamic Transfer Learning for NMT

NMT into Language Varieties

Controlling NMT Verbosity

Zero-Resource NMT

Previous Work:

2015

Emergence of Multilingual NMT

Dong et al., an encoder - multi. attn. & decoder.

Luong et al., multiple encoder - decoder.

2016.v1

Towards Multilingual NMT

Firat et al., multi. encoder - attn - multi. decoder
Zoph & Knight., multi-source - attn - decoder
Lee & Cho., many to one, single enc-attn-dec

2016.v2

Single Encoder-Attn-Decoder

Firat et al., zero-resource NMT
Johnson et al., large multilingual & zero-shot
Ha et al., multilingual, pivot and zero-shot

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Single Encoder-Attn-Decoder

Firat et al., zero-resource NMT
Johnson et al., large multilingual & zero-shot
Ha et al., multilingual, pivot and zero-shot

Does multilingual NMT improve in low-resource conditions?

Can we further improve Zero-Shot translation of a multilingual NMT?

Lakew et al. 2017

Low-Resource NMT

Previous Work:

2016

Parent - Child TL

Zoph et al., initialize child model with parent parameters.

2017

TL across related languages

Nguyen et al., transfer across related languages.

2018

TL both for src & tgt languages

Neubig & Hu., pre-train multilingual model.
Kocmi & Bojar., update both src & tgt sides

2019

Data-Augmentation, Multilinguality

Xia et al., combine TL with back-translation.
Aharoni et al., massive multilingual model.

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Does dynamic transfer-learning improves over fixed parent model transfer ?

Can we do better transfer-learning with relevant data selection ?

Lakew et al., 2019

NMT into Language Varieties

Previous Work:

2017

SMT vs. NMT b/n LV

Costa-Jussa., RNN improves Catalan-Spanish MT over PBSMT.

2018

NMT b/n LV

Costa-Jussa et al., NMT b/n EU and BR Portugues.

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NMT b/n LV

Costa-Jussa et al., NMT b/n EU and BR Portugues.

Does modeling multiple varieties in a single model is achievable?

How to handle unlabeled LV data?

Lakew et al., WMT 2018

Controlling the Verbosity of NMT

Previous Work:

2016

NMT, MNMT, Summarization

Sennrich et al.,: politeness in NMT
Kikuchi et al.,: summarization

2017

Summarization

Fan et al.,: conditioning the output on a length token

2018

Customized NMT

Michel & Neubig.: personalized NMT

2019

Summarization, Pos. encoding

Sho & Naoaki.,: adapt positional encoding to length encoding.

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Can we bias length of an NMT output, while keeping the translation quality ?

Can we make it versatile to any pre-trained model?

Lakew et al., IWSLT, *2019.*

Approaches & Applications

Methods, Experiments, Results and Findings

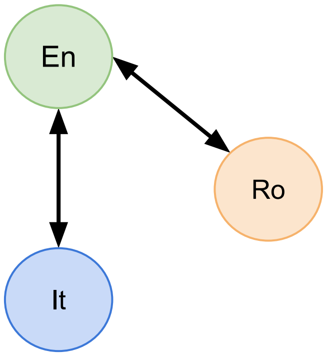
Zero-Shot NMT Modeling

Dynamic Transfer Learning

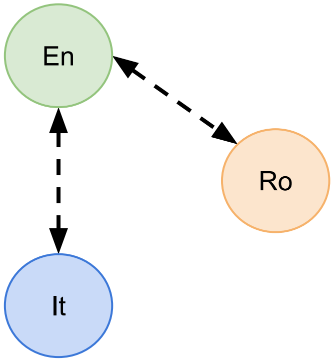
NMT into Language Varieties

Controlling NMT Verbosity

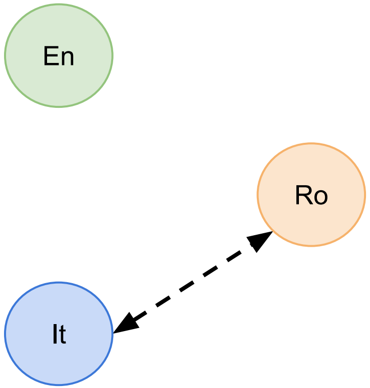
Zero-Shot Translation



Multilingual Training



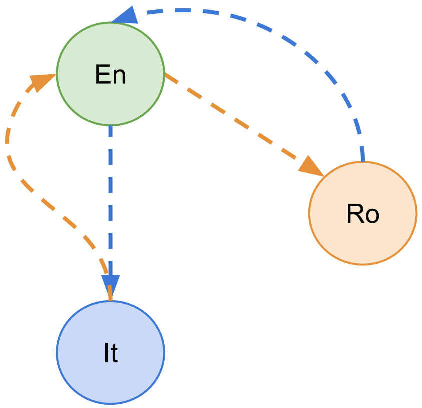
Non Zero-shot Inference



Zero-Shot Inference

Zero-Shot Translation is among the advantages of Multilingual NMT

Pivoting Translation as Alternative



Pivot (N-step) Inference

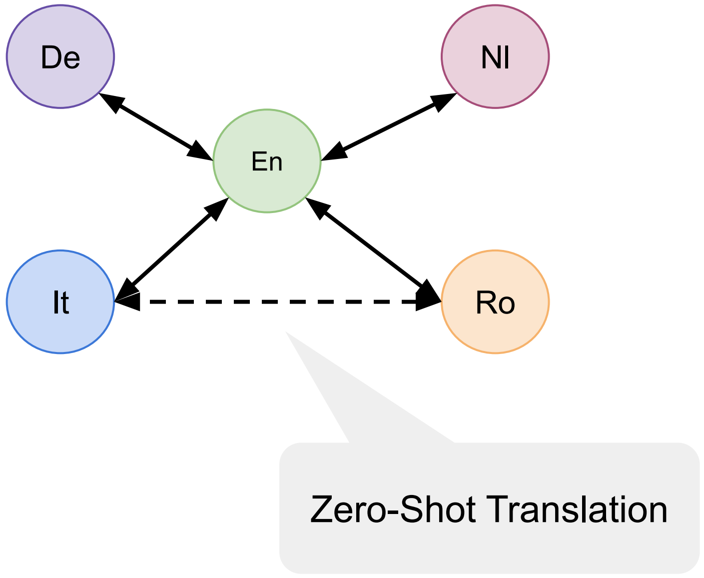
Research Questions

Does multilingual NMT improve low/zero-resource translation ?

Can we further improve Zero-Shot translation of a multilingual NMT ?

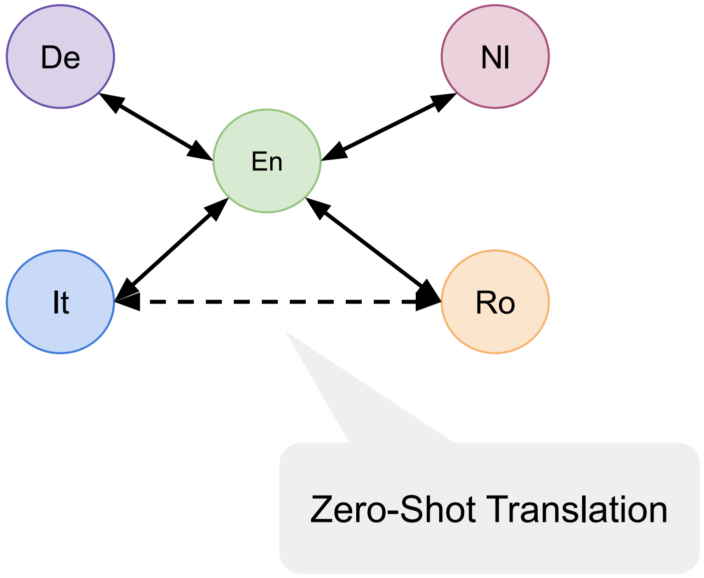
Zero-Shot NMT Modeling

Available Resource and ZST Task



Zero-Shot NMT Modeling

Available Resource and ZST Task

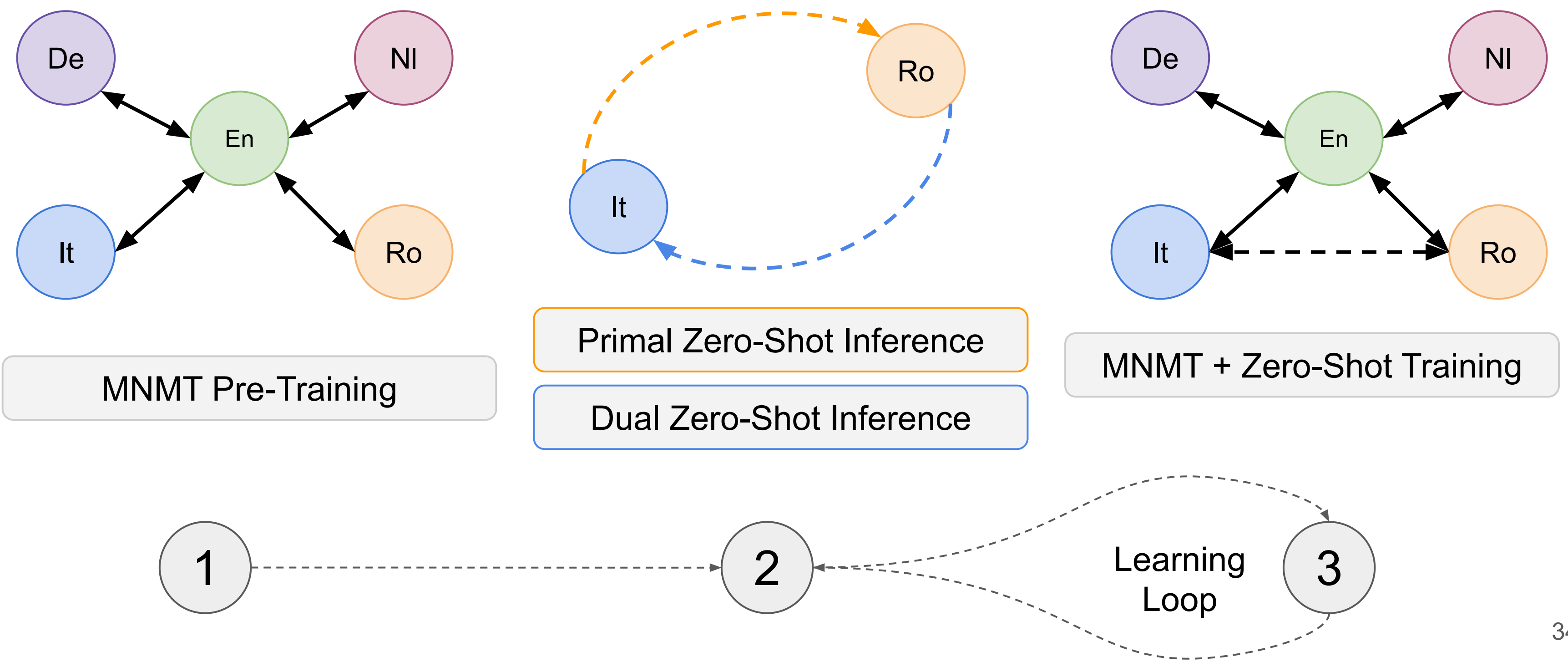


Zero-Shot NMT Learning Steps

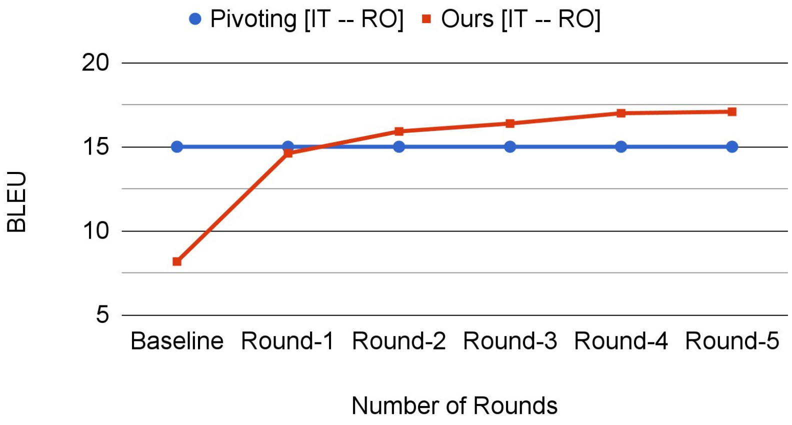
- Leverage monolingual data
- Perform dual back-translation
- Self-Learning using iterative data augmentation & learning with supervised tasks.

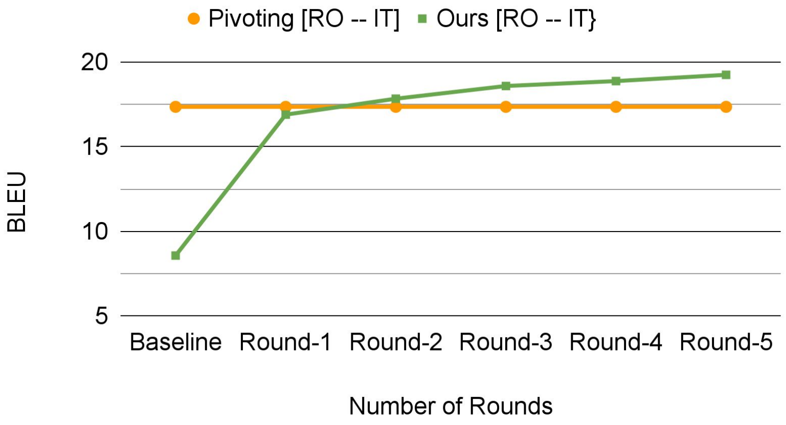
Lakew et al., *IWSLT, 2017*

Zero-Shot NMT Modeling: Three Steps



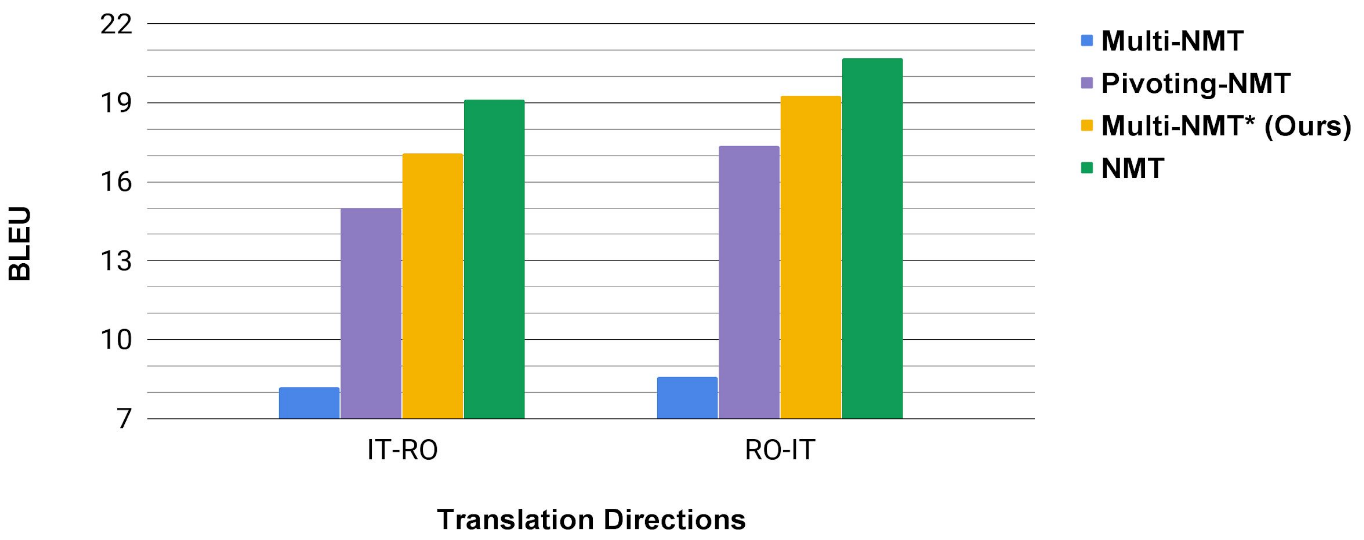
Results





Results of the Italian <> Romanian zero-shot directions on IWSLT test-2017

Comparative Results



Zero-Shot NMT modeling outperformed the baseline **Multilingual NMT** and the **Pivoting** mechanism on IWSLT *test-2017.*

Key Takeaways

- Improves over the initial zero-shot translation only approach
- Learns through the different round of training and inference
- Shows better performance than pivoting
- Signals the universality of multilingual NMT
- Zero-shot translation is an active research area showing improvements not only in NMT but across several ML domains.

Approaches & Applications

Zero-Shot NMT Modeling

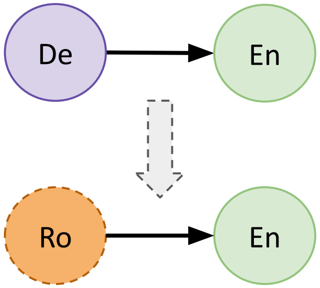
Dynamic Transfer Learning

NMT into Language Varieties

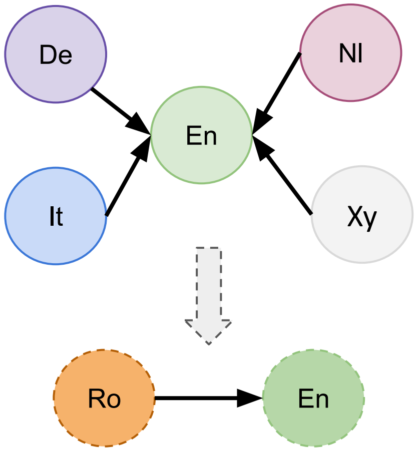
Controlling NMT Verbosity

Transfer Learning

Parent > Child



Transfer from M-NMT



Notice: the parent model parameters are fixed following a one-size-fits-all approach.

Research Questions

Does dynamic transfer-learning improves over fixed parent model transfer-learning?

Can we expand pre-trained NMT into unseen languages directions?

Can we do better transfer-learning with data selection?

Dynamic Transfer Learning: Two Approaches

Progressive Adapt (ProgAdapt)

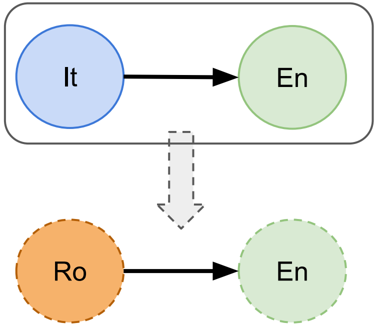
- Transfer parent model parameter to child model with new language pair.

Progressive Grow (ProgGrow)

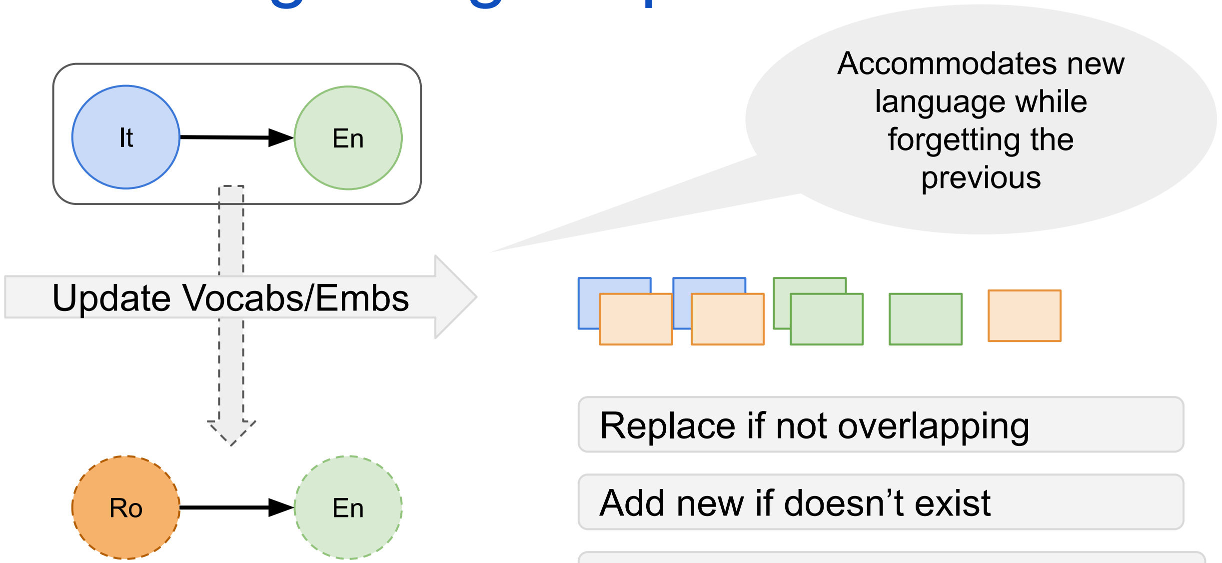
- Accommodate new language pairs when data becomes available.

Lakew et al., *IWSLT, 2018*

Dynamic Transfer Learning: ProgAdapt



Existing TL Approach



Replace if not overlapping

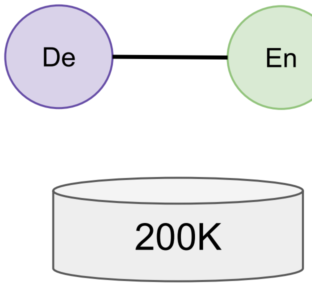
Add new if doesn't exist

Initialize params with 0's/randomly

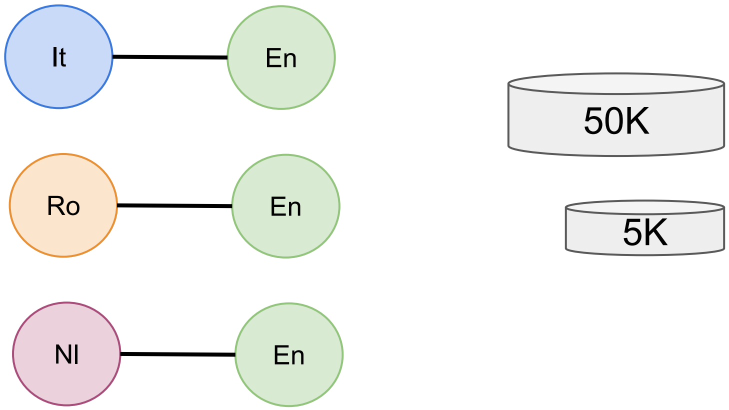
Proposed ProgAdapt Transfer Learning

Experimental Settings

Parent Language pairs / Model



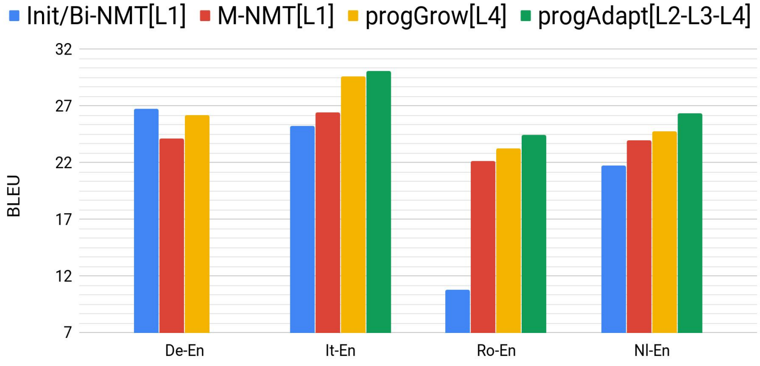
Child Language Pairs / Two Settings



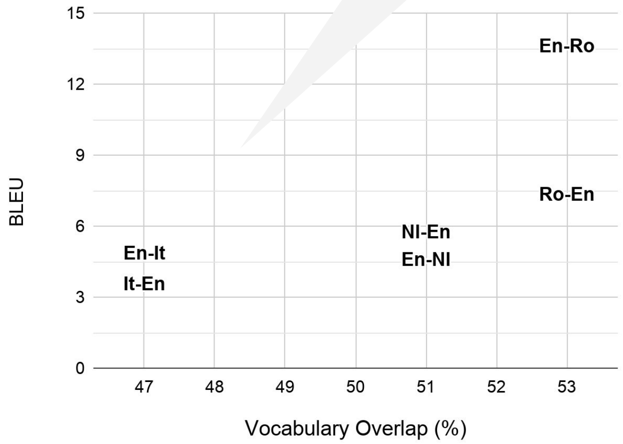
Results

DTL approach outperform both single-pair NMT and M-NMT approaches

In ProgAdapt parent model vocab size is ~10% larger



Low-Resource Results



Key Takeaway

A higher % of shared vocabulary b/n consecutive models in progAdapt shows better gain.

Compared to a model trained from scratch, DTL takes 4% to 20% training steps with significantly higher performance.

Dynamic Transfer Learning

Two Additional Proposals

Multilingual Model

- Train a large scale multilingual parent model to dynamically transfer parameters.

Data selection for TL

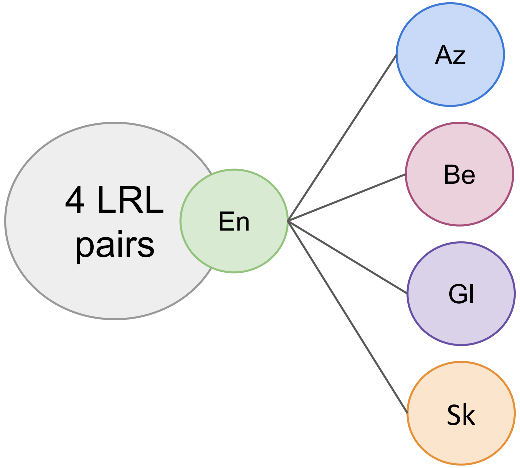
- Train language model on the test language (child) to select relevant data for the TL stage.

Lakew et al., 2019

Experimental Settings

54 languages paired with English

Used to pre-train 108 direction multilingual (parent) model



5.9k

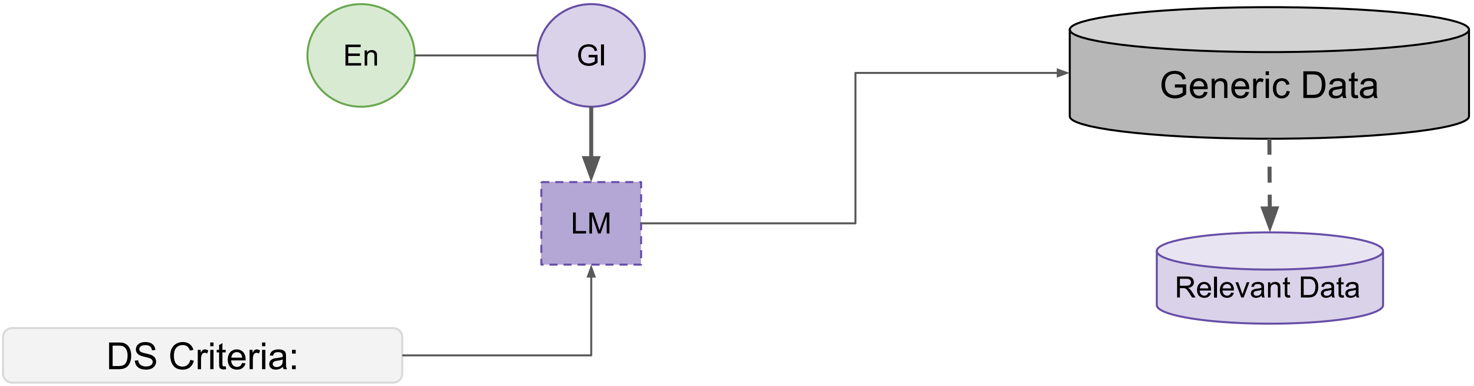
4.5k

10k

61.5k

Low-resource language pairs (child)

Dynamic Transfer Learning: Data Selection Strategies



Select-pplx: select data with lowest pplx from HRLs pool

Select-one: select all data from one HRL related to the LRL

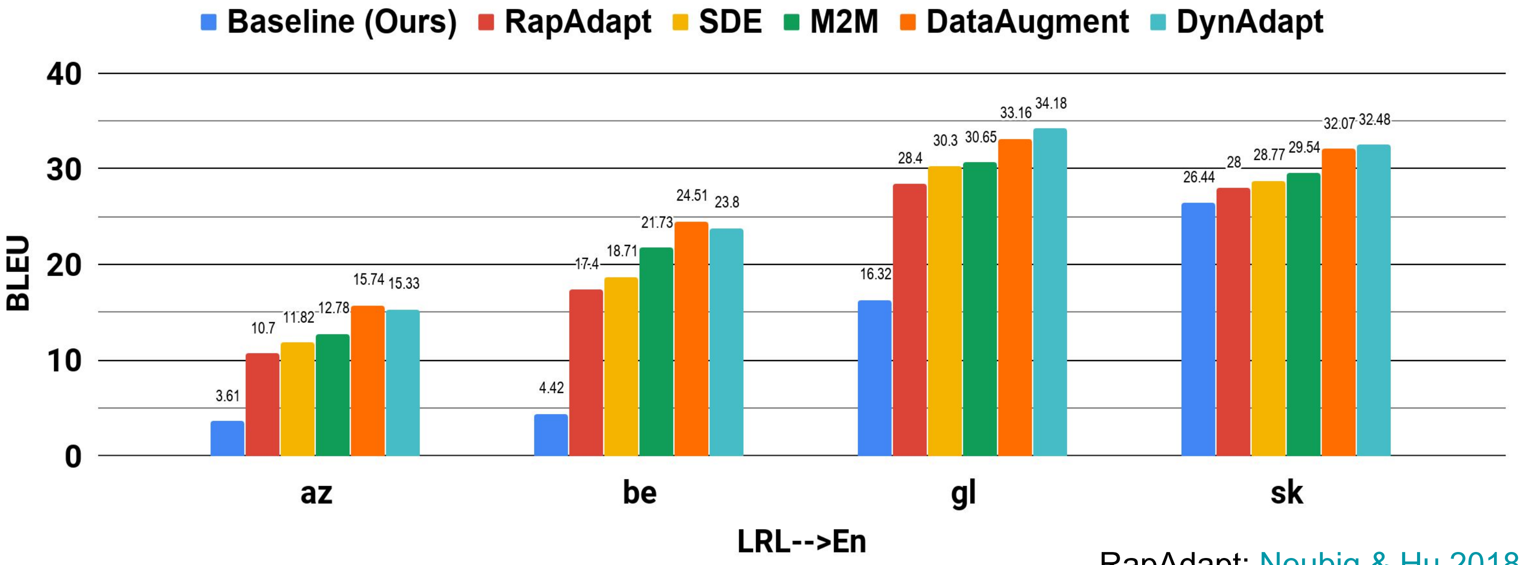
Select-rand: randomly sample from HRLs related/family to the LRL

Select-fam: select all data from a set of HRLs related/family to LRL

*except for Select-fam, other selection strategies pick equal proportion of data.

Results

Using Select-One strategy



RapAdapt: Neubig & Hu 2018
SDE: Wang et al., 2018
M2M: Aharoni et al., 2019
DataAugment: Xia et al., 2019
DynAdapt: Lakew et al., 2019

Key Takeaways

- Utilizing a universal pre-trained multilingual model improves dynamic/TL for LRL’s.
- Relevant data-selection further improves dynamic adaptation & cheaper to acquire.
- DynAdapt + Data selection approaches can provide the best performance over the other data augmentation and transfer-learning approaches.

Approaches & Applications

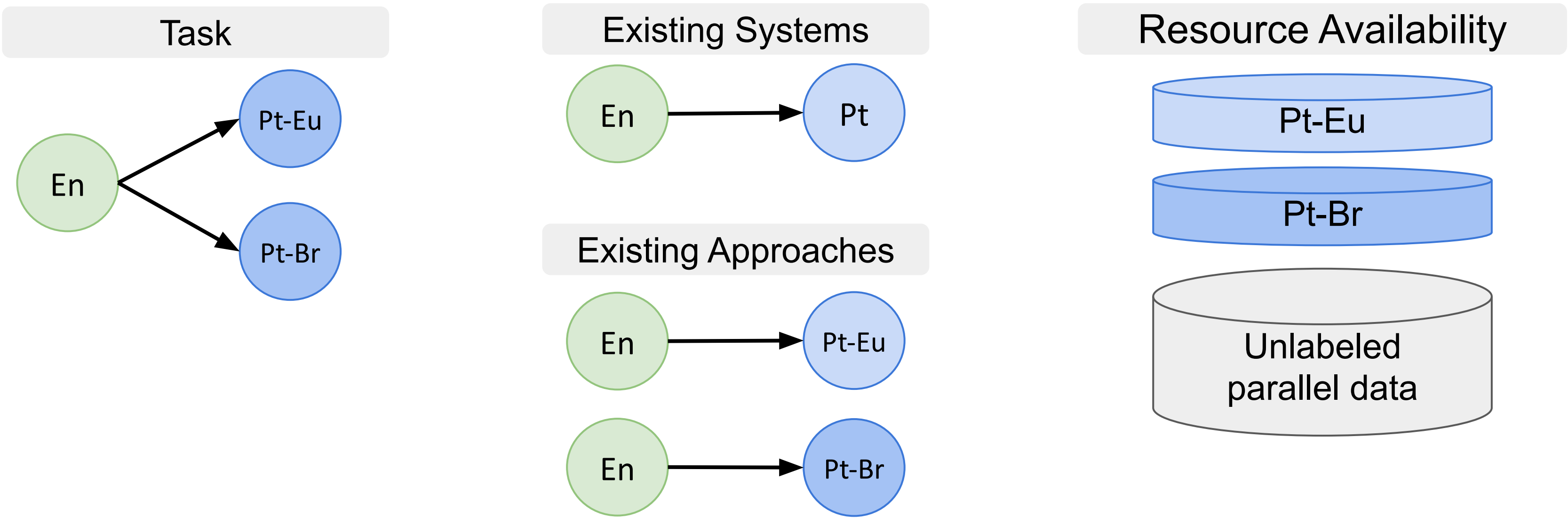
Zero-Shot NMT Modeling

Dynamic Transfer Learning

NMT into Language Varieties

Controlling NMT Verbosity

NMT into Language Varieties: A scenario



A large scale unlabeled data can lead to poor performance when translating to a specific language variety/dialect.

Research Questions

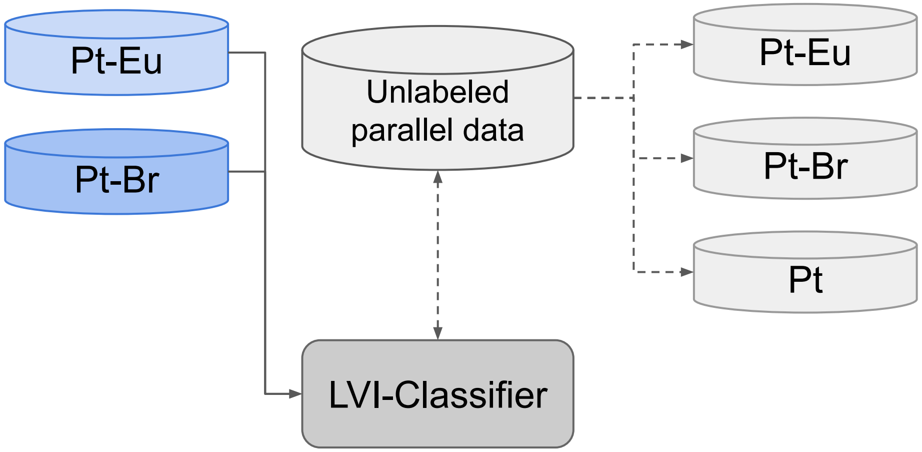
Can we model translation in to multiple language varieties/dialects using a single model?

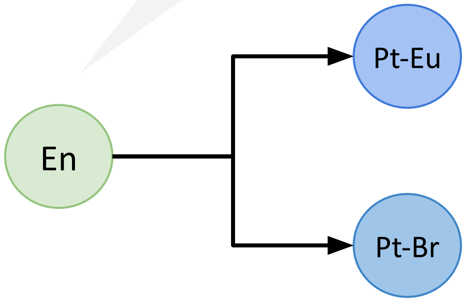
Can we further improve over the baseline single LV models?

How to handle majority of LV unlabeled parallel data?

Modeling NMT into Language Varieties

We use a similar principles as in multilingual NMT



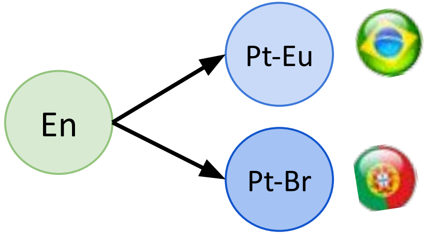


Offline labeling using an LVI classifier

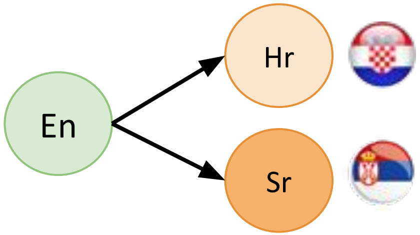
A single LV aware NMT model Training

[Lakew et al., WMT, 2019]()

Experimental Settings: Two Scenarios



Dialects



Closely Related Languages

Experimental Settings: Data regimes & model types

Gen: unsupervised NMT model trained with the union of unlabeled data

Spec: supervised models trained with variety specific data

Mul: supervised model trained with the union of labeled data

M-U: semi-supervised trained with the union of both labeled and unlabeled data

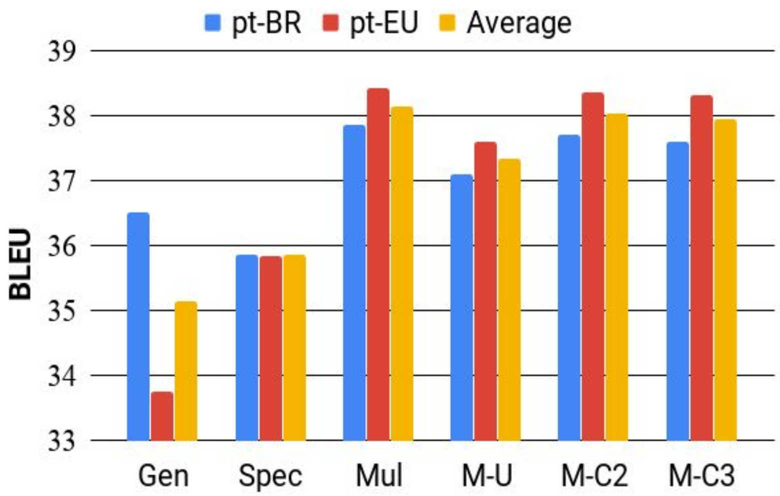
M-C2: semi-supervised training using LVI to map the unlabeled segments to variety classes

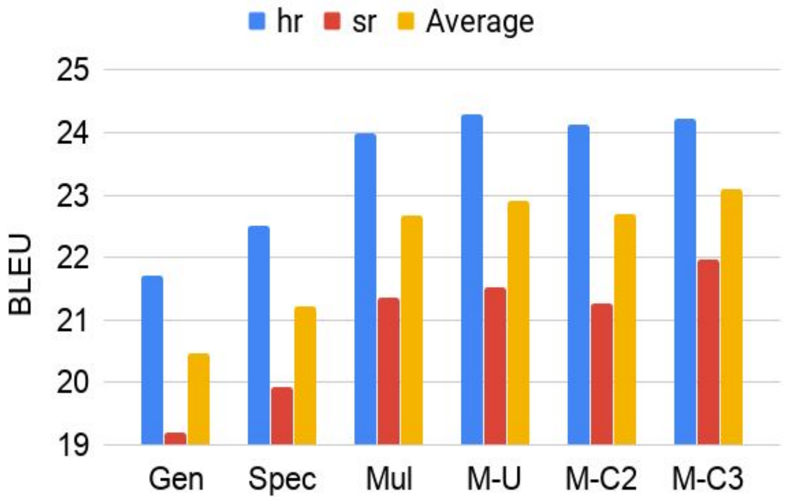
M-C3: trained similarly as M-C2, ambiguous sentences with low classifier confidence are not labeled

Results

Mul (supervised) shows the largest improvement, with comparable performance from semi-supervised (M-C2/3)

Semi-supervised approaches are better than Mul





Key Takeaways

- Presented NMT from English into dialects & related languages, comparing models that can be trained under unsupervised, supervised, and semi-supervised settings.

- Multilingual model (M-C3) trained using labels from LVI module can perform very close to its supervised (Mul) version.

- The approach keeps resource together maximizing transfer-learning b/n the high and low-resourced variety.

- Delivers simplified modeling, in addition to improved performance & translation quality.

Approaches & Applications

Zero-Shot NMT Modeling

Dynamic Transfer Learning

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Controlling NMT Verbosity

Length Control of NMT Outputs: A Scenario

What if translations have to fit a given layout?
E.g. translating subtitles, dubbing script, headlines.

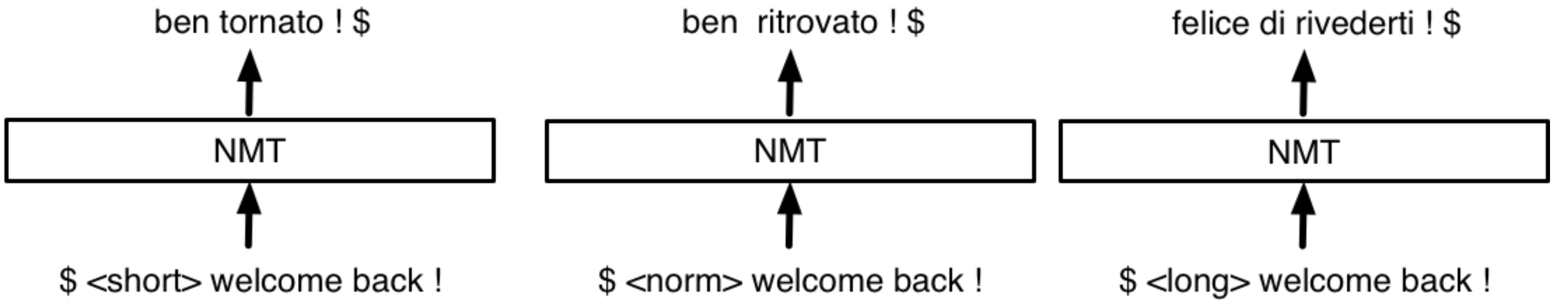
SRC	It is actually the true integration of the man and the machine.
MT	Es ist tatsächlich die wahre Integration von Mensch und Maschine.
MT*	Es ist die wirkliche Integration von Mensch und Maschine.------
SRC	So we thought we would look at this challenge and create an exoskeleton that would help deal with this issue.
MT	Quindi abbiamo pensato di guardare a questa sfida e creare un esoscheletro che potesse aiutare ad affrontare questo problema.
MT*	Pensavamo di guardare a questa sfida e creare un esoscheletro che potesse aiutare a risolvere il problema.---

Research Questions

Can we control length of an NMT output, while keeping the translation quality ?

Can we make it versatile to any pre-trained model ?

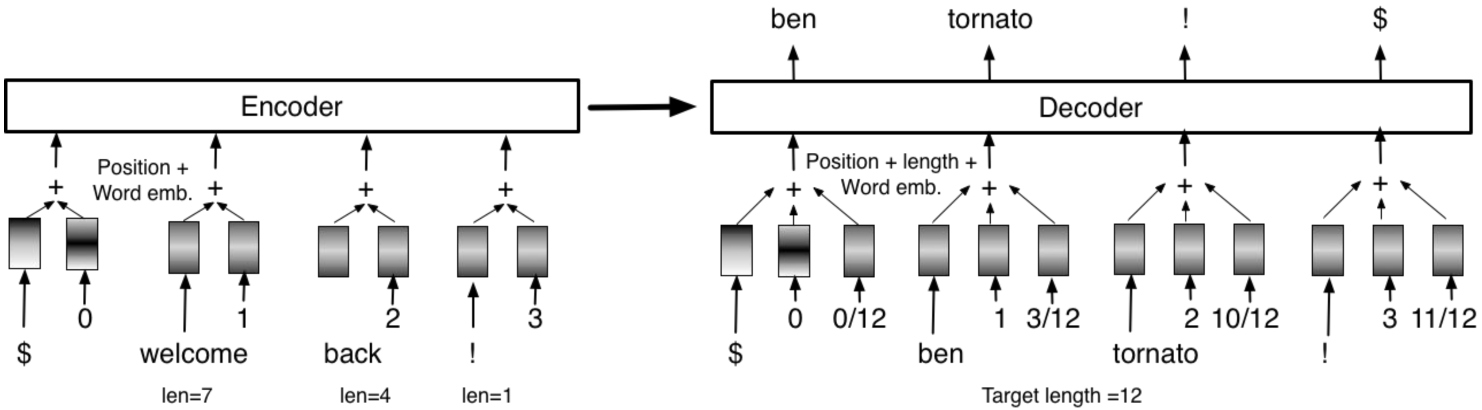
Controlling Verbosity of NMT: Length-Token



Approach conditions the output of NMT to a given target-source length-ratio class

[Lakew et al., 2019]

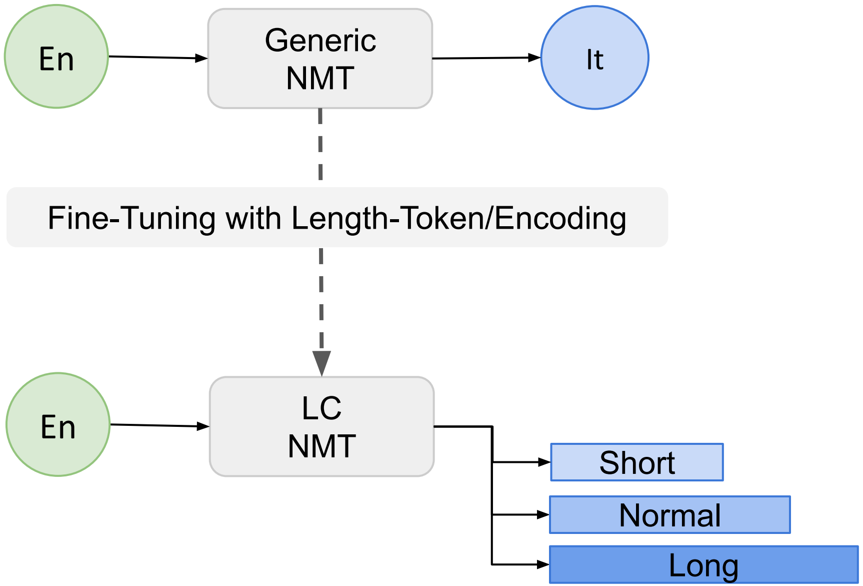
Controlling Verbosity of NMT: Length-Encoding



Approach enriches the positional embedding of NMT with length information.

[Lakew et al., 2019]

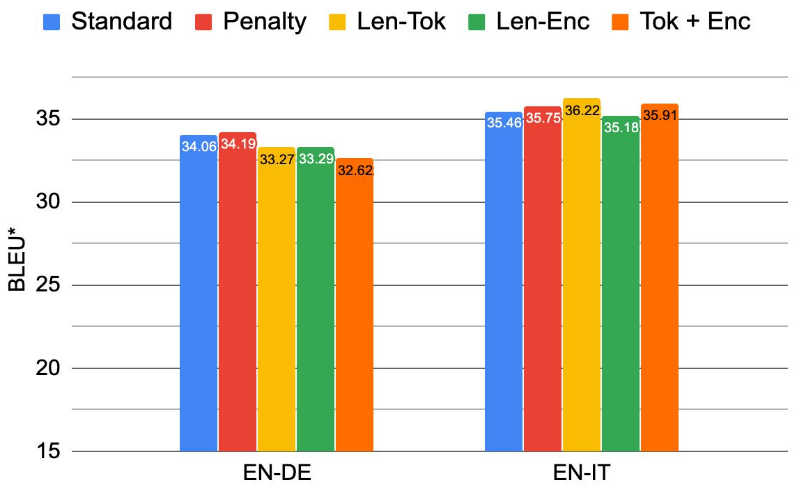
Controlling Verbosity of NMT: as a Fine-Tuning Task

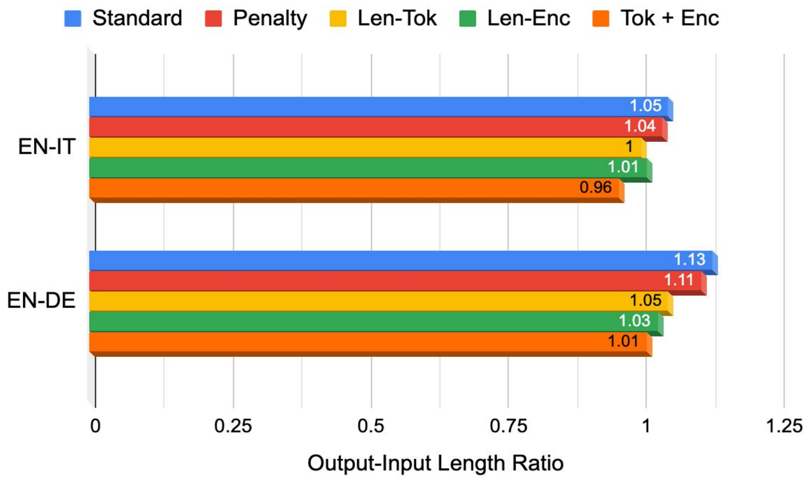


Advantages:

- Versatile to any pre-trained model
- Better performance than training from scratch
- Faster training and language independent

Experimental Results





Models performance (left) with respect to output length (right)

Examples

English > Italian

SRC	**And we in the West** couldn’t understand
NMT	*E noi occidentali* non riuscivamo a capire
LC-NMT	*In occidente* non riuscivamo a capire -----
SRC	how much **this would restrict** freedom
NMT	quanto questo avrebbe limitato la libertà
LC-NMT	quanto limitasse la libertà -------------------
SRC	**this** is a **really** extraordinary honor for me
NMT	questo è un onore davvero straordinario per me
LC-NMT	per me è un onore straordinario ----------------------

Examples of shorter translations obtained by (linguistic variations) paraphrasing, drop of words, and change of verb tense.

Key Takeaways

Proposed solutions for controlling the output length of NMT:

Length-Tok: coarse-grained control without degradation in quality

Length-Enc: fine-grained control with a slight decrease in the translation quality

Fine-Tuning: versatile to any pre-trained model

Conclusions

Multilingual Neural Machine Translation

Conclusions

- Leveraging monolingual data and self-learning improves zero-shot translation by large margin.

- Dynamic transfer-learning that tailors the parent (multilingual) model to the child model improves translation performance.

- Multilingual model can be repurposed to enable translation into language varieties (dialects), and verbosity control of the NMT model outputs.

Current and Future Trends

Two primary directions

- Specialization
  - Improving a model performance on a specific task or language.
- Generalization
  - Improving a model performance on several tasks or languages.

Current and Future Trends

Among current trends (reading material):

- Large scale model training/pre-training
  - Kim et al., 2021 Scalable and Efficient MoE Training for Multitask Multilingual Models
- Multimodal/Multi-task training
  - Bapna et al., 2022 mSLAM: Massively multilingual joint pre-training for speech and text
- Self-Learning for multilingual training
  - Siddhant et al., 2022 Towards the Next 1000 Languages in Multilingual Machine Translation

Thank You! Q&A’s …

Slides: https://github.com/surafelml/talks/[machine-translation/multilingual_mt_*]

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