Linguistically Motivated Neural Machine Translation

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Get access to the slides here (update)

https://github.com/prajdabre/eamt24-linguistic-mt

(under construction)

Self Introduction: Haiyue **Song**

- Technical Researcher at National Institute of Information and Communications Technology (NICT)
- Research
  - Low-Resource Machine Translation
  - Subword Segmentation
  - Large Language Models for Machine Translation

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Self Introduction: Hour Kaing (hour.kaing@nict.go.jp)

- Experience
  - 2022 - Present: Researcher at NICT
  - 2018 - 2022 : Technical Researcher at NICT
  - 2018 - 2022 : Ph.D. at Nara Institute of Science and Technology (NAIST), Japan
    - Low-Resource Morphological and Syntax Analysis
  - 2013 - 2014 : M.Sc at University of Grenoble 1, France

- Research interests
  - Machine Translation, Language Modeling, Linguistic Analysis, and Speech Processing
  - Low-Resource and Linguistically-Motivated NLP
  - Cross-Lingual Transfer and Multilingual Learning

Self Introduction: Raj Dabre (raj.dabre@nict.go.jp)

- Experience
  - 2018-present: Researcher at NICT, Japan
    - Adjunct Faculty at IIT Madras
    - Visiting Researcher at IIT Bombay
  - 2014-2018: MEXT Ph.D. scholar at Kyoto University, Japan
  - 2011-2014: M.Tech. Government RA at IIT Bombay, India

- Research
  - Low-Resource Natural Language Processing
    - **Multilingual Machine Translation: 2012-present**
    - **Document Level Machine Translation: 2021-**
    - **Large Scale Pre-training for Generation: 2021-**
  - Efficient Deep Learning:
    - **Compact, flexible and fast models (2018-present)**

Table of Contents

Introduction to Neural Machine Translation

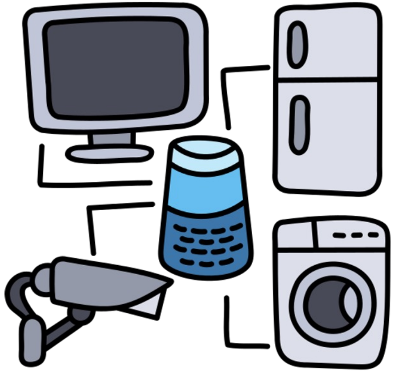
Why Machine Translation is still an important task?

Inclusivity and Accessibility

Bridge gap between low-resource languages (HRL) and high-resource languages (HRL)

Improve language coverage
(only covers ~1K of ~7K in the world)

Data Augmentation for Multilingual Performance Enhancement



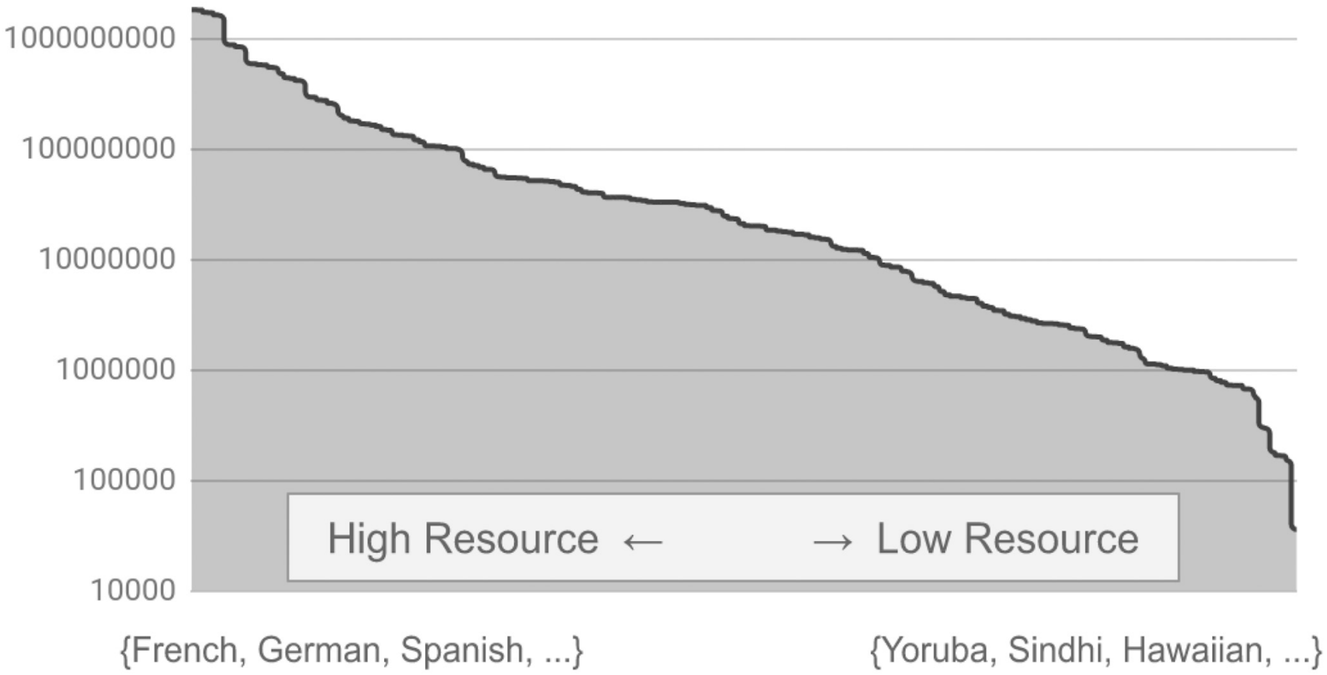
Transfer Learning via Translation

Unlocking Multilingual Capabilities of LLMs

Evolution of Machine Translation

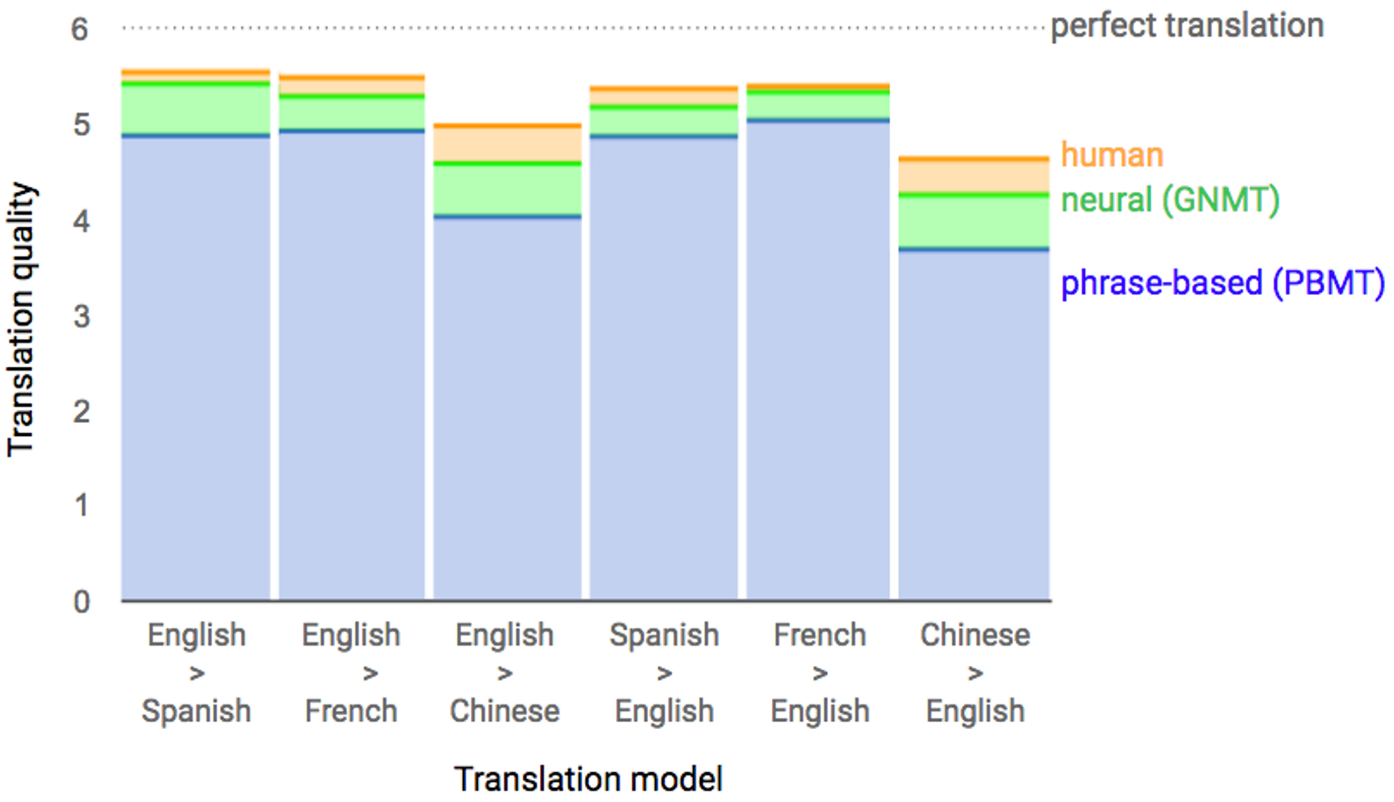
Rule-Based Machine Translation (RBMT)	Example-Based Machine Translation (EBMT)	Statistical Machine Translation (SMT)	Neural Machine Translation (NMT)
• Direct MT • Transfer-based MT • Interlingua MT		• Word-based • Syntax-based • Phrase-based	• RNNs • LSTMs • Transformers
1950 - 1980	1980 - 1990	1990 - 2015	2015 -

Why NMT? (Good for transfer learning)



Data Distribution over language pairs (Arivazhagan et al., 2019)

Quality of NMT Compared to Phrase-based SMT



https://research.googleblog.com/2016/09/a-neural-network-for-

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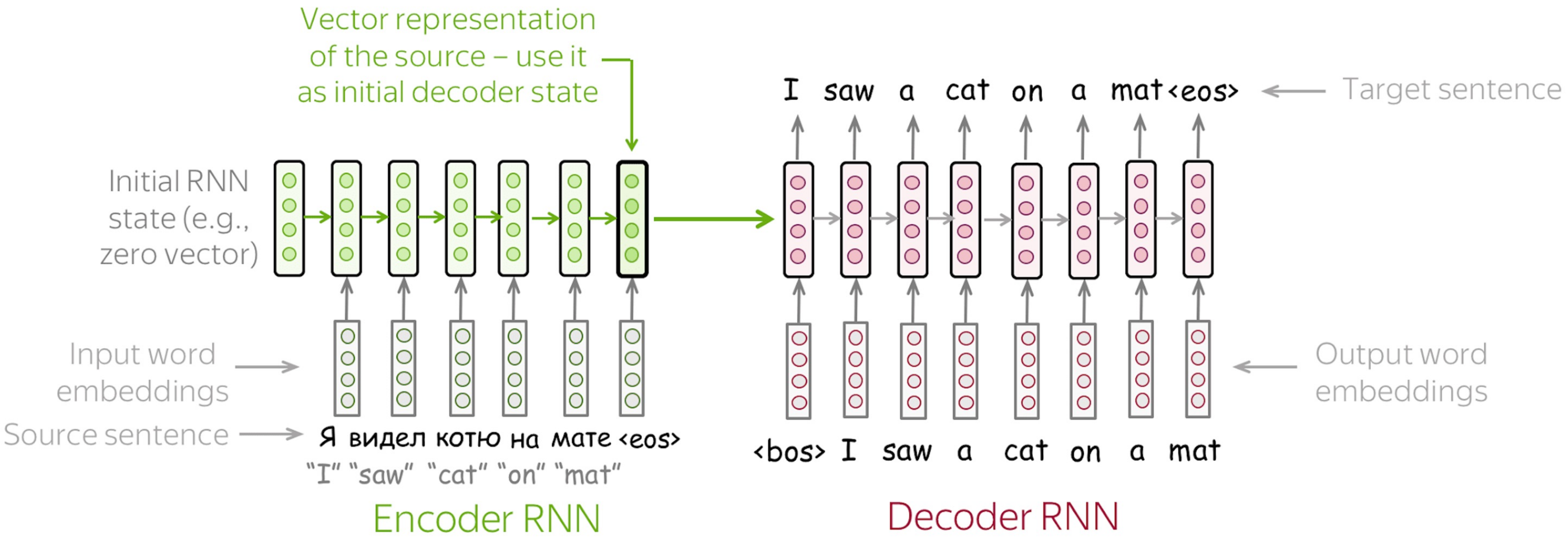
This Tutorial

Neural MT Basics: **Encoder-Decoder Paradigm**



[image credits]

[Sutskever et al. 2014]

Neural MT Basics: **Encoder-Decoder with *Attention***

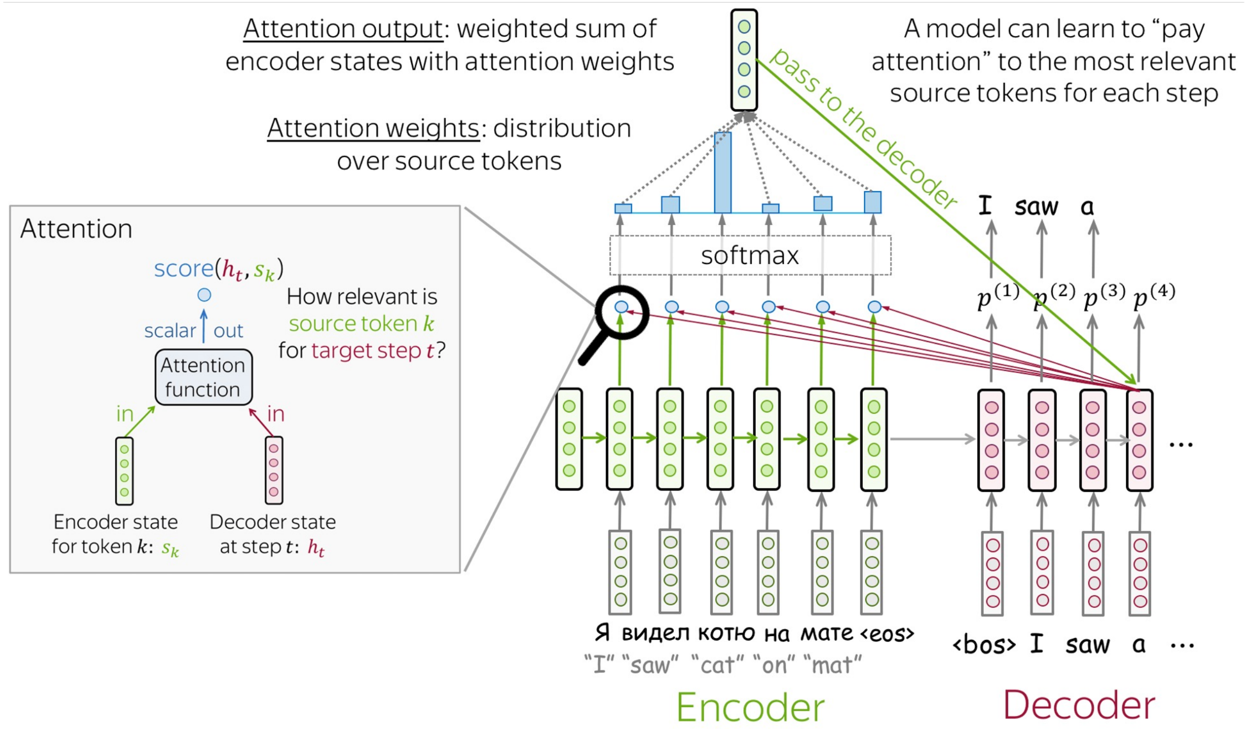


image credits

Bahdanau et al. 2015

Neural MT Basics: **Transformer** Architecture

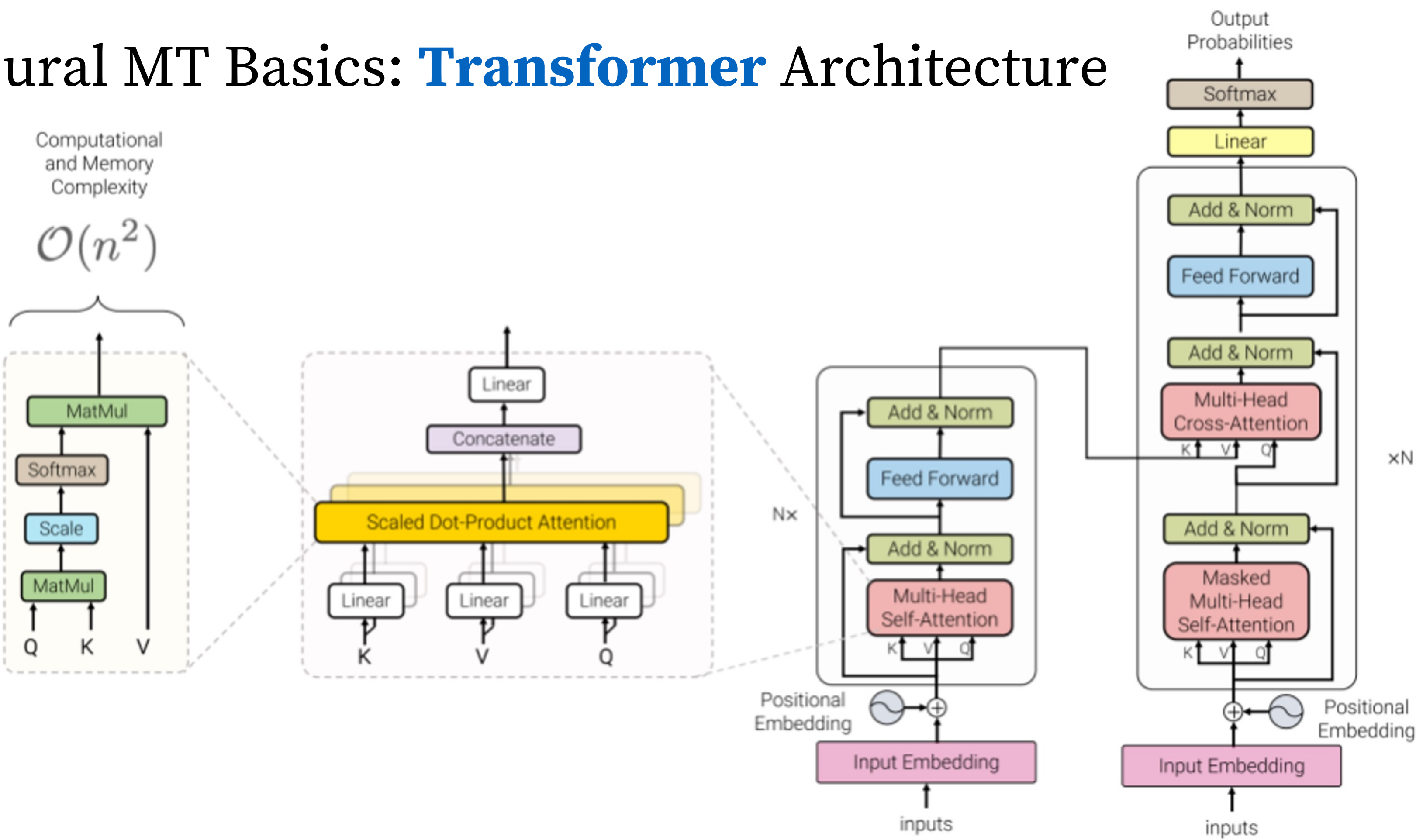


image credits

Vaswani et al. 2017

Is Linguistics **dead**?

No not quite!

Lets re-think!

- Does the model understand
  - **NO!**
- What do they underst
  - **Embedding**
- What are embeddings
  - **Features**

Representing *linguistic info*
as features

- Words: I am a boy
- POS: PRON VERB DET NOUN

Interchangeable?

Why Linguistic Features?

- Supplementary information in low-resource settings

- **Reduce burden** on model to learn *complex features*

- Reuse existing tools rather than waste them

In This Tutorial

- What linguistic features can be leveraged?
- How do we incorporate them in models?
- What is the impact of linguistic features?

Limitations and Future Directions

Limitations

- Mostly impactful in low-resource settings :-(
  - Most languages are low-resource :-)
- Identifying useful features needs exhaustive study :-(
  - In low-resource settings its fine :-)
- Interpretability analysis is hard :-(
  - Extrinsically performance improves :-)
  - But proving it intrinsically is challenging :-(
- Slow speed and error propagation :-(
  - Requires high quality feature extractors (typically available for English)

Future Directions

- Identifying approaches for high-resource settings
    - Also in **multilingual** settings
- Methods to auto-choose features
- Intrinsic analysis of models to show impact of features
- Speed improvement
    - **Latent features** as opposed to explicit features
- Incorporation in LLMs
    - **Mostly open area**

Inco

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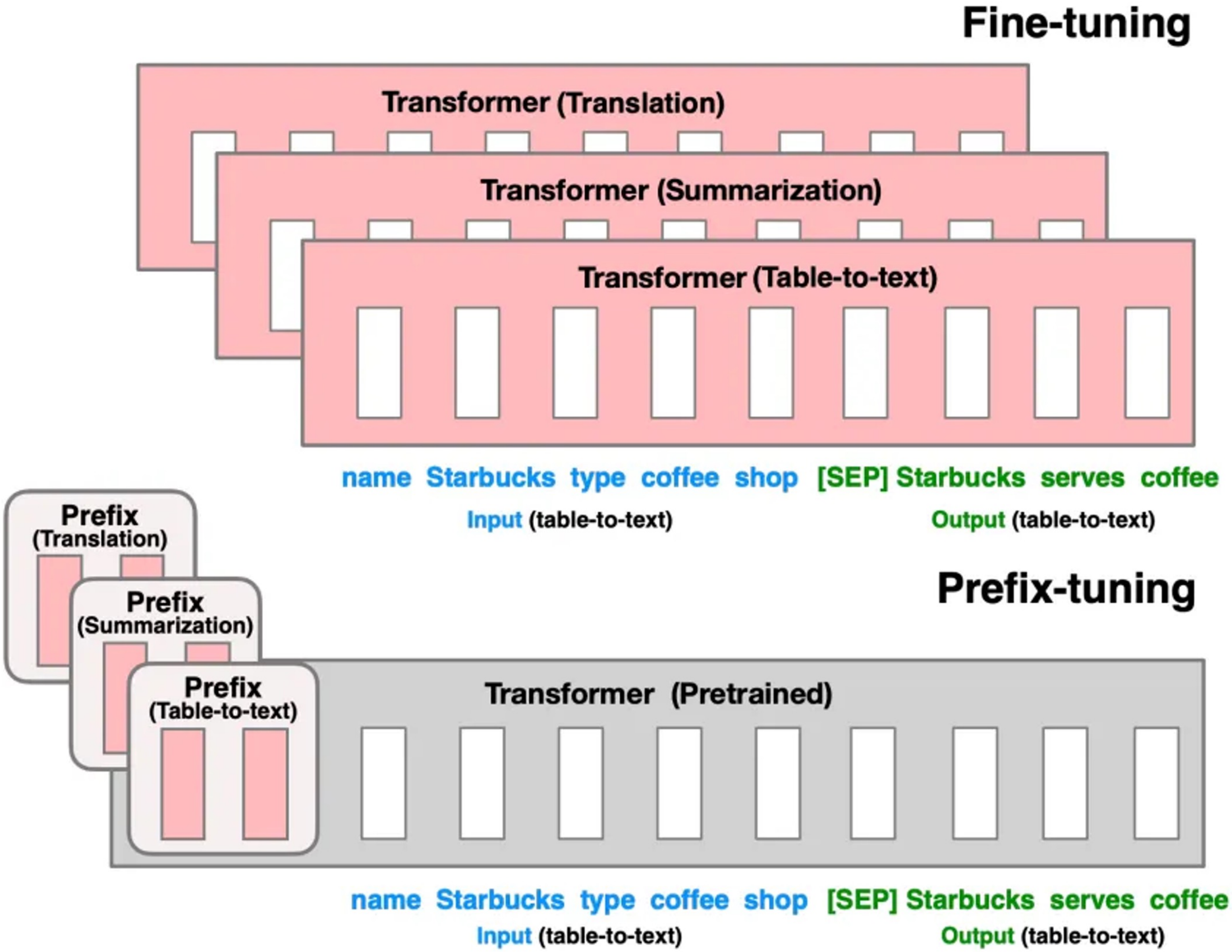

Fine-tuning
Transformer (Translation)
Transformer (Summarization)
Transformer (Table-to-text)
name Starbucks type coffee shop [SEP] Starbucks serves coffee
Input (table-to-text)
Output (table-to-text)
Prefix-tuning
Prefix (Translation)
Prefix (Summarization)
Prefix (Table-to-text)
Transformer (Pretrained)
name Starbucks type coffee shop [SEP] Starbucks serves coffee
Input (table-to-text)
Output (table-to-text)

Summary

Summary

- Basic overview of NMT and motivation

- Methods to incorporate features at various points in the system
    - Data: tokenization and related languages
    - Model: inputs, encoder, representation, and self-attention
    - Decoding: tree-structure decoding
    - Evaluation: linguistic benchmark

- Comparison of effective practices

- Limitations and Future Work

Q&A

Thank You