

# Machine Translation with Large Language Models: Decoder Only vs. Encoder-Decoder

Team: Machine Translators  
Mentor: Yash Bhaskar

Abhinav P M, University of Calicut  
Sujay Kumar Reddy M, Vellore Institute of Technology, Vellore  
C. Oswald, Assistant Professor, National Institute of Technology, Tiruchirappalli.

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# Problem Statement

To perform Machine Translation Task with respect to:

- Types of LLM: 1. **Decoder Only** (1-1 and 1-Many) Architecture  
2. **Encoder-Decoder** (1-1, Many-1, 1-Many and Many-Many) Architecture

## Objectives:

To investigate on the following:

1. Behaviour of the model with respect to **bi-lingual** (1-1) and **multilingual** (Many-1, 1-Many and Many-Many) language translations
2. Performance of Encoder-Decoder based Transformer models for Neural Machine Translation (NMT) compared with smaller Decoder-only models, such as LLMs, when trained using the same data and similar parameters.
3. To quantify the role of context (no. of tokens) in translation with these two architectures.

# Literature Review

## Multilingual Machine Translation

- Multilingual machine translation with large language models: Empirical results and analysis - [Zhu Wenhao et al. \(arXiv, 2023\)](#) [1]
- Massively multilingual neural machine translation - [Aharoni et al. \(arXiv, 2019\)](#) [2]
- Massively multilingual neural machine translation in the wild: Findings and challenges - [Naveen Arivazhagan et al. \(arXiv, 2019\)](#) [3]

## Learning Resources

- BERT - J. Devlin et al. (arXiv, 2018) [4]
- Attention - A Vaswani et al. (NeurIPS 2017) [5]

# Our Proposed Approaches for Multilingual NMT

1. In-Context Learning (ICL) using Few-Shot Learning
2. Fine-Tuning of LLMs
3. Baseline Model Development from Scratch

# 1. In-Context Learning (ICL) using Few-Shot Learning

# In-Context Learning – How it works?

- A way to use language models to learn tasks given **only a few examples**. [6]
- Prompt Engineering Tasks for **Few-Shot Learning**.
- Examples of MT pairs ( $\langle X \rangle = \langle Y \rangle$ ) with a template T, X - Source Sentence, Y - Target Sentence. [1]
- **In-Context Exemplars:**
  - $\langle X \rangle = \langle Y \rangle$  - Strong recipe for best outputs from the model - Wu et al. (2023) [7]
- Prompt  $P = T(X_1, Y_1) \oplus T(X_2, Y_2) \oplus \dots \oplus T(X_n, Y_n)$  where  $\oplus$  - concatenation, n - number of samples [1]

# Our Approach - ICL

How a prompt to the model is structured?

```
{  
  "1": "After submitting your application, you should receive a registration certificate within several business days. आवेदन जमा करबाक बाद, अहाँकेँ किछु व्यावसायिक दिनक भीतर एक टा पंजीकरण प्रमाण-पत्र भेटि सकैत अछि।"  
  "2": "Early pregnancy bleeding is usually from a maternal source, rather than a fetal one, प्रारंभिक गर्भावस्था में रक्तस्राव आमतौर पर भ्रूण के बजाय मातृ स्रोत से होता है।",  
  "3": "The bride's father symbolically offers to the bridegroom a cow as a present. एहन रोगीक लेल, जनिक संक्रमण आ कैंसरक नैदानिक संदेह न्यून रहैत अछि, एक्स-रे एकटा कम महग प्रारम्भिक विकल्पक अछि आ प्रयोगशालाक अध्ययनक सङ्ग एकर व्याख्या होइत अछि।",  
}
```

- Evaluation:

**Low-Resource Languages:** Hindi, Telugu, Malayalam, Marathi and Tamil

**LLM's:** On 3 sentence pairs using XGLM and MT5.

**Metric:** BLEU.

# Datasets

## BPCC Wiki MT Dataset [9]:

- 16k – 50k Translation Samples.
- English to 22 Indian Language Pairs.
- Context Length of each sentence pair is 40-200 characters long.



# In-Context Learning – Experimentation Results (1/2)

Models Chosen:

## 1. Decoder Only - XGLM

Why? Generates moderate translation with 500 million parameters,  
Builds bi-lingual mapping between non-English to English. [1]

## 2. Encoder-Decoder - mT5

Why? Capability for multilingual translation (mT5-base),  
Contains 300 million parameters.

Reference	Predicted (mT5)	Predicted (XGLM)
_After _sub mitting _your _application , _you _should _receive _a _registration _certificate _within _several _business _days .	_अपना _आवेदन _जमा _करने _के _बाद, _आपको _कई _व्यावसायिक _दिनों _के _भीतर _पंजीकरण _प्रमाणपत्र _प्राप्त होना _चाहिए। _हिंदी में	_आवेदन _जमा _कर बा क _बाद , _अ हाँ के ँ _कि छु _व्यावसायिक _दिन क _भीतर _एक _टा _पं जी करण _प्रमाण - पत्र _भेट ि _सक ै त _अ छि ।

## In-Context Learning – Experimental Results (2/2)

Language-Pair	BLEU - Decoder Only	BLEU - Encoder-Decoder
eng-hin	<b>1.096078</b>	<b>1.04442</b>
hin-eng	0.443236	0.384031
eng-tel	0.307206	0.292951
tel-eng	0.379685	0.378953
eng-tam	0.307206	0.292951
tam-eng	0.349053	0.364626
eng-mal	0.307206	0.292951
mal-eng	0.330114	0.364626

## 2. Fine-Tuning of LLMs

# Work Flow of Encoder-Decoder Model: mT5 Fine-Tuning

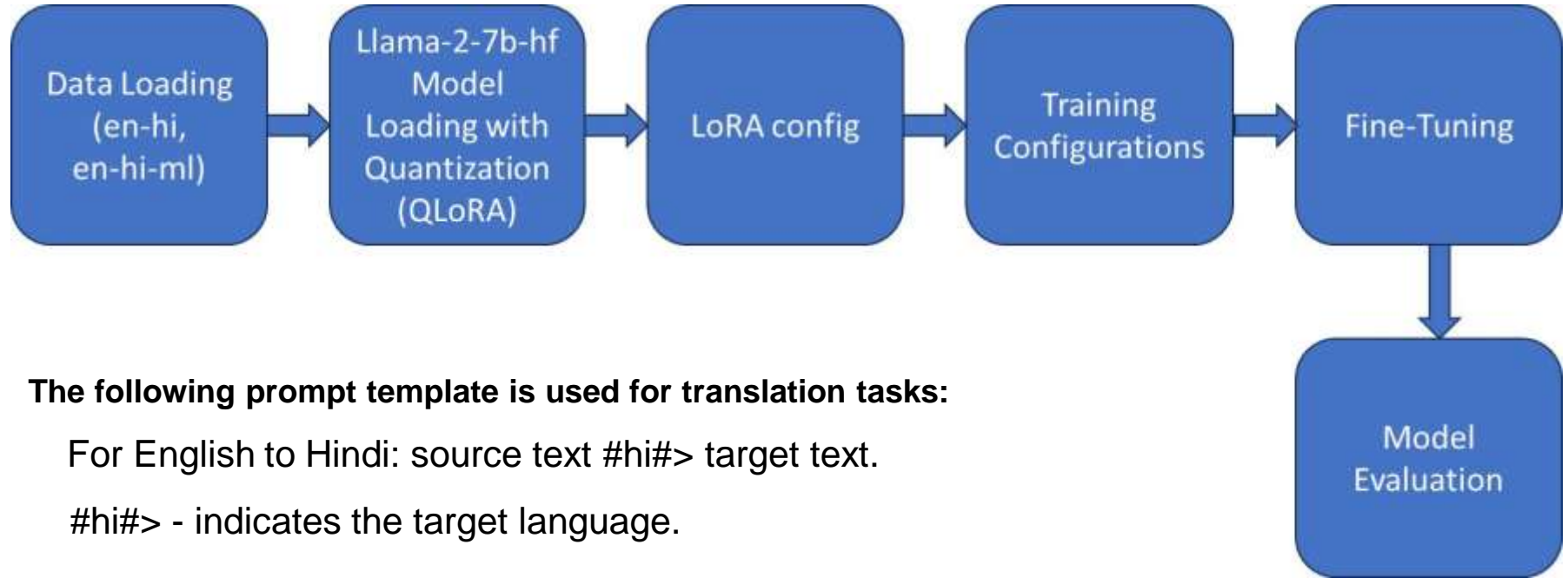
**1-1 Task :** 'en-hi' from **BPCC-Wiki dataset** [9]

**1-Many Task:** 'en-hi-bg' from **ALT dataset** [8]



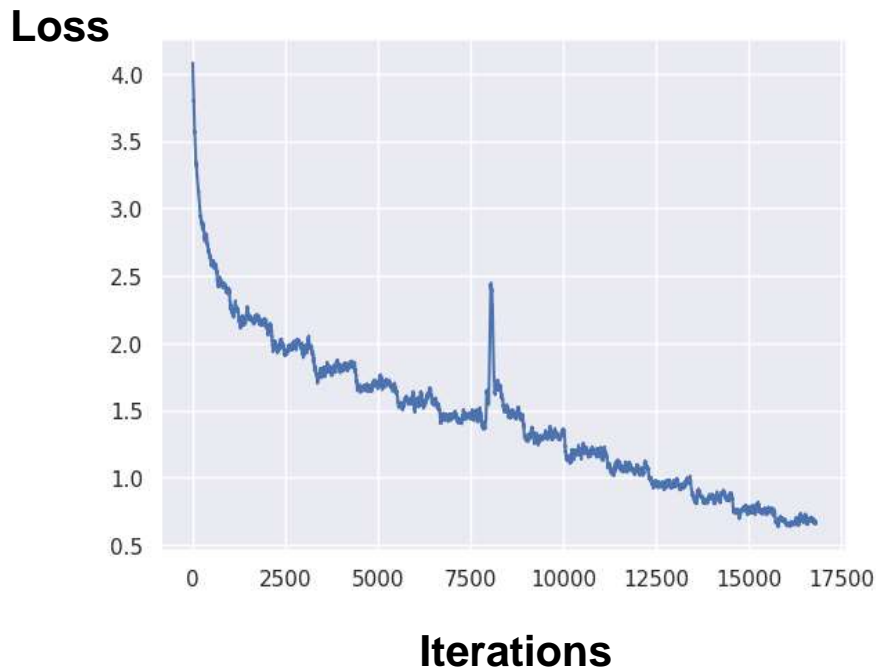
**Figure 1. Work Flow of mT5 Fine-Tuning**

# Work Flow of Decoder-Only Model: Llama2 Fine-Tuning

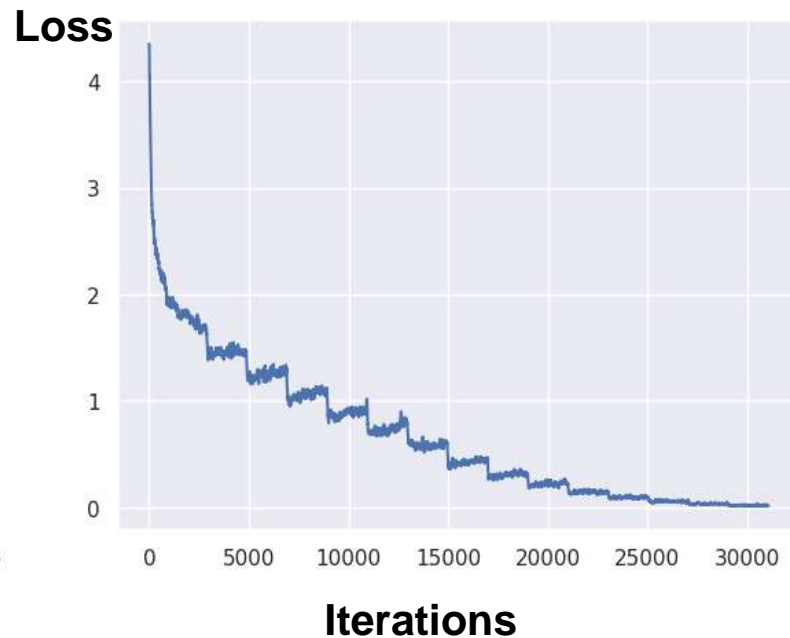


**Figure 2. Work Flow of LLaMA2 Fine-Tuning**

# Experimental Results: mT5 Fine-Tuning



**Figure 3. mT5 Multilingual (en-hi-bg)**



**Figure 4. mT5 Bi-lingual (en-hi)**

# Experimental Results: Llama2 and mT5 Fine-Tuning

Model	BLEU	chrF	TER
Llama2-finetuned-one-many(en-hi)	0.0265	7.1217	94.0950
Llama2-finetuned-one-many(en-ml)	0.0409	6.8530	96.4312
Llama2-finetuned-one-one(En-Hi)	0.0955	9.2282	90.4864
mT5-bi-lingual(en-hi)	11.7107	31.0639	74.1626
mT5-bi-lingual(hi-en)	<b>14.1444</b>	<b>33.8278</b>	74.7157
mT5 many-many(en-hi)	3.4802	19.6184	84.7821
mT5 many-many(en-bg)	1.0885	16.2382	91.9398
mT5 many-many(hi-bg)	0.7545	15.6990	92.9326
mT5 many-many(hi-en)	5.2237	23.2258	84.6685
mT5 many-many(bg-en)	3.9469	21.5855	86.7228
mT5 many-many(bg-hi)	2.1458	16.9235	88.2083

## Sample Results: mT5 Fine-Tuning (1/2)

Model	Type	Source Text	Translated Text	Target Text
mT5	Bi-Lingual	यह किताब मुझे बहुत पसंद है।	This book I really like.	I like this book very much.
		He loves his parents.	वह अपने माता-पिता को पसंद करती है।	वह अपने माता-पिता से प्यार करता है.
mT5	Many-Many	He loves his parents.	उसे अपने माता-पिता की प्यास है।	वह अपने माता-पिता से प्यार करता है.
		He has bought a new car.	তিনি একটি নতুন গাড়ি কিনে কিনেছেন।	তিনি একটি নতুন গাড়ি কিনেছেন।
		यह किताब मुझे बहुत पसंद है।	This book is very suitable for me.	I like this book very much.
		वह अपने माता-पिता से प्यार करता है।	তিনি তার বাবার কাছে খুবই পছন্দ করেন।	সে তার বাবা-মাকে ভালোবাসে।
		तुमि केमन आछो?	तुम कौन हो?	आप कैसे हैं
		आमि आजके बासाय थाकव।	I will be at home today.	I will stay at home today.



## Sample Results: mT5 Fine-Tuning (2/2)

Model	Type	Source Text	Translated Text	Target Text
Llama2	1-Many	Kerala, a state on India's tropical Malabar Coast	ഇന്ത്യയിലെ മലബാർ കോ	ഇന്ത്യയുടെ ഉഷ്ണമേഖലാ മലബാർ തീരത്തുള്ള ഒരു സംസ്ഥാനമാണ് കേരളം
			"भारत की तटीय मलबार कोष्ठ"	केरल, भारत के उष्णकटिबंधीय मालाबार तट पर स्थित एक राज्य
Llama2	1-1	Hello, what is your name?	नमस्ते, आपका नाम क्या है?	नमस्कार, आपका नाम क्या है?
		Today is my birthday	आज मेरी जन्मदिन है	आज मेरा जन्मदिन है
		Click the "Search" button to begin the search	खोज करने के लिए "खोज" बटन क	खोज शुरू करने के लिए "खोजें" बटन पर क्लिक करें

## Analysis: Llama2 and mT5 Fine-Tuning

- mT5 is trained with 32,216 data points for the English to Hindi (en-hi) pair.  
**Reason:** Increased data.
- For the decoder-only model (Llama2 finetuned), it performs poorly on 1-Many tasks.
- For 1-1 tasks, the Llama2 finetuned model performs better compared to the Llama2 1-Many model.  
**Reason:** Llama2 needs to be trained with more high-quality data.

### 3. Baseline Model Development from Scratch

## Challenges so, far ...

- Pre-trained models are trained on large data. For example: mT5

## Now,

- To compare the Encoder-decoder and decoder-only models with similar training setting to evaluate the model's performance in the [multi-task learning](#) paradigms.
- To compare the context length of both the models by some quantitative metrics which provides some Interpretation of the models.

# Proposed Methodology of our Baseline Model Development

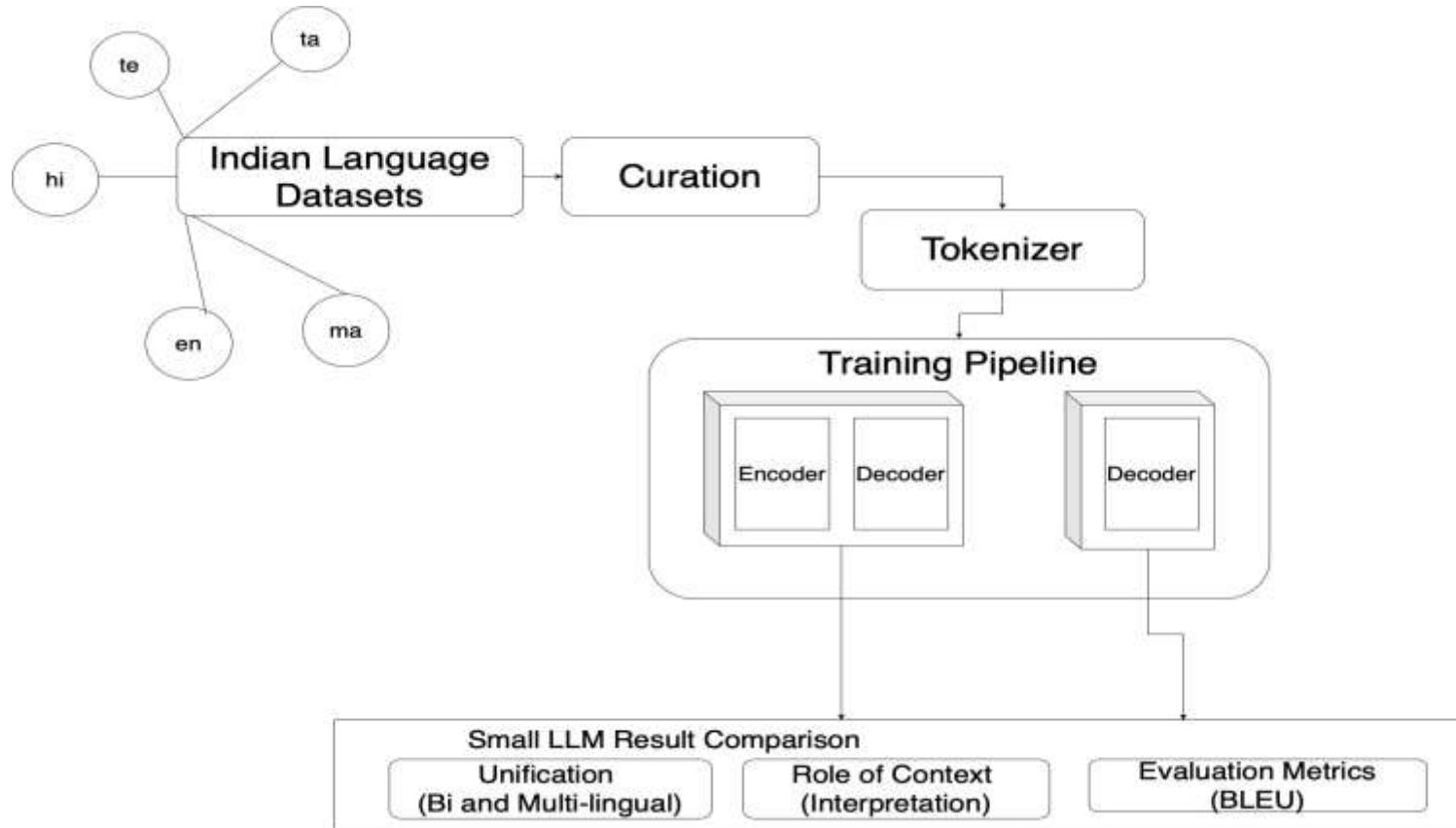


Figure 2. Proposed Methodology of our Baseline Model Development

# Baseline Model Development

- To train a model from scratch - Pretrained model is **more black boxed** and less interpretable.
- Took stable baseline models and equated the parameters.
- Decoder-Only Model - **XLNet** as a base model (Wu et al., 2021) [10]
- Encoder-Decoder model - **IndicBART** as a base model (Dabre et al., 2021) [11]
- Tokenizer is shared across both the architectures.

Model Name	Trainable Parameters
XLNet Baseline	147,490,318
Indic-BART Baseline	145,339,392

# Take Aways and Future Prospects

- Encoder-Decoder model provides **trustable results**, while the Decoder-only models are trained differently as next word/char.
- The learning paradigms for both the Architectures are different:  
**How do we converge for Multilingual Machine Translation?**
- The Decoder-only model treats the starting tokens of the source text and the translated text separately.
- A recent new method - **Streaming Self-Attention (SSA)** helps the model decide when it has enough of the original text to start translating accurately.

## Decoder-only Streaming Transformer for Simultaneous Translation

Shoutao Guo<sup>1,2</sup>, Shaolei Zhang<sup>1,2</sup>, Yang Feng<sup>1,3,4\*</sup>

<sup>1</sup>Key Laboratory of Intelligent Information Processing,  
Institute of Computing Technology, Chinese Academy of Sciences (ICTCAS)

<sup>2</sup>Key Laboratory of AI Safety, Chinese Academy of Sciences

<sup>3</sup>University of Chinese Academy of Sciences, Beijing, China

guoshoutao@ict.ac.cn, zhangshaolei@ict.ac.cn, feiyoung@ict.ac.cn

### Abstract

Simultaneous Machine Translation (SMT) generates translations while reading source tokens, essentially producing the target prefix based on the source prefix. To achieve good performance, it leverages the relationship between source and target prefixes to extract a policy to guide the generation of translations. Although existing SMT methods primarily focus on the Encoder-Decoder architecture, we explore the potential of Decoder-only architecture, owing to its superior performance in various tasks and its inherent compatibility with SMT. However, directly applying the Decoder-only architecture to SMT poses challenges in terms of training and inference. To alleviate the above problems, we propose the first Decoder-only SMT model, named Decoder-only Streaming Transformer (DOST). Specifically, DOST separately encodes the positions of the source and target prefixes, ensuring that the positions of the target prefix remain unaffected by the expansion of the source prefix. Furthermore, we propose a Streaming Self-Attention (SSA) mechanism tailored for the Decoder-only architecture. It is capable of obtaining translation policy by assessing the sufficiency of input source information and integrating with the self-attention mechanism to generate translations. Experiments demonstrate that our approach achieves state-of-the-art performance on three translation tasks.

### 1 Introduction

Simultaneous Machine Translation (SMT) [Gu et al., 2017; Ma et al., 2019] is designed for generating translations in real-time scenarios such as online conferences and real-time subtitles. It predicts the target tokens (i.e., target prefixes) based on the already read source tokens (i.e., source prefixes), aiming to achieve good tradeoffs between latency and translation quality. During training, SMT models

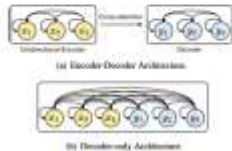


Figure 1: Comparison of Encoder-Decoder architecture and Decoder-only architecture.

need to learn the correspondence between source and target prefixes, crucial for extracting policies that ensure superior performance during inference [Zhang and Feng, 2022].

Existing research on SMT primarily focuses on the Encoder-Decoder architecture and is categorized into fixed and adaptive policies. For fixed policy [Shi et al., 2018; Ma et al., 2019; Elabbadi et al., 2020], the model utilizes heuristic rules to determine the source prefix used for generating translations, which ignores the correspondence between the source and target prefixes. This may lead to redundant or missing source information during translation, resulting in inferior performance [Zhang and Feng, 2022a]. For adaptive policy [Ma et al., 2019], the model dynamically decides whether to read or output tokens based on the relationship between the source and target prefixes. This dynamic adjustment of policy in response to the translation status allows for improved tradeoffs [Zhou et al., 2022]. However, there is a lack of exploration in SMT regarding the Decoder-only architecture.

With the rise of language models, the Decoder-only architecture has exhibited superior performance across diverse tasks [Touvron et al., 2023; Toussaint et al., 2024]. As illustrated in Figure 1,

\* Corresponding author: Yang Feng.

Code is at <https://github.com/ShaoleiZhang>

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