ADAPTIVE WAIT-K POLICY FOR SIMULTANEOUS TEXT-TO-TEXT MACHINE TRANSLATION BASED ON RL

/ML Project 2024-25M

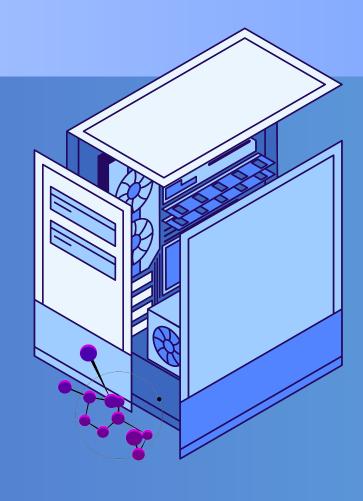
GROUP MEMBERS:

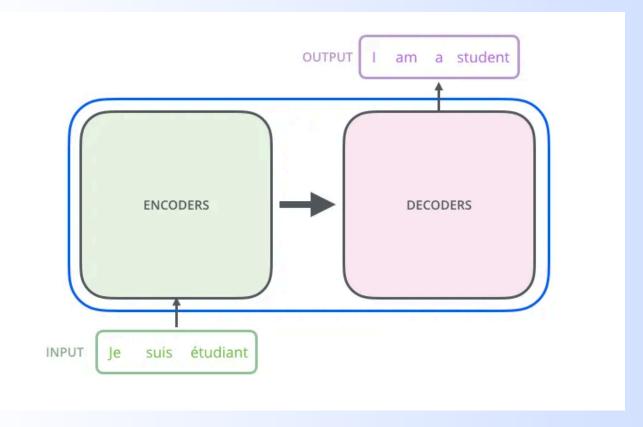
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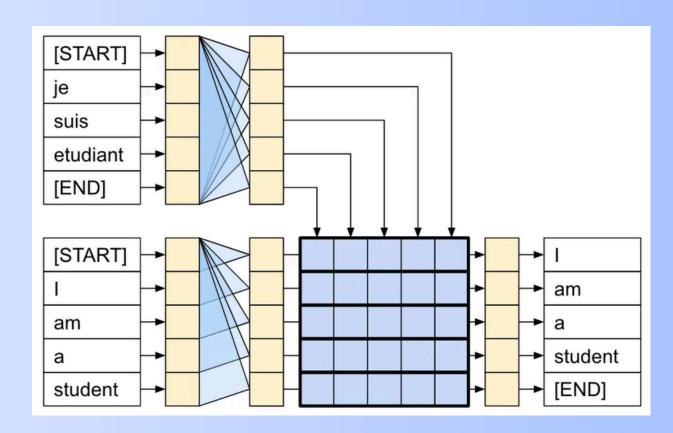


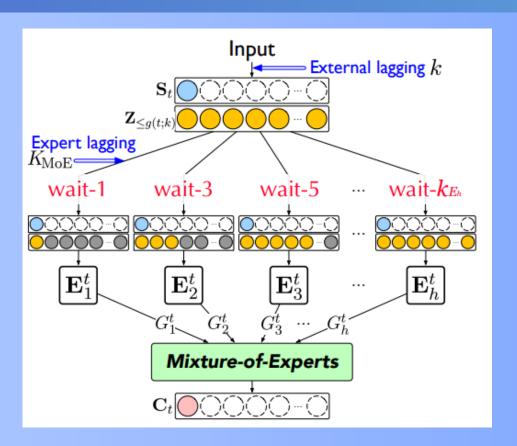
O PROBLEM STATEMENT

Simultaneous Machine Translation (SiMT) aims to generate translations simultaneously with the reading of the source sentence, balancing translation quality with latency. Most SiMT models currently require training multiple models for different latency levels, thus increasing computational costs and, more importantly, limiting flexibility. The new approach is, like Mixture- of-Experts Wait-k policy, training multiple wait-k values in balance between the considerations of both latency and translation quality, leaving the determination of the optimal value of k for unseen data as an open challenge. Moreover, variability in the structure of structure between different languages makes the problem even more complicated because the application of a fixed policy becomes rather ineffective.









The unique contribution of this project is the use of Reinforcement Learning to enable real-time adaptive decision-making in Simultaneous Machine ranslation. Unlike existing models that rely on fixed or pre-defined wait-k values, the proposed method allows the model to dynamically choose the optimal k based on the context and structure of the input sentence. . We are also integrated HMT Transformer (Hidden Markov Transformer) with SCST (Self-Critical-Sequence-Training) RL Algorithm, by this approach it reduces need for training multiple models for different latency levels and improves robustness across different languages.

Dataset Preparation WORKFLOW

Model Training

Tokenization

Dynamic Wait-k Policy(HMT)

> SCST Fine-Tuning

Mathematical Foundations

- ullet Wait-k Policy: $g(t;k) = \min(k+t-1,|Z|)$
- Latency Metric (AL): $AL = rac{1}{ au} \sum_{t=1}^ au [g(t) t 1] \cdot rac{|y|}{|x|}$
- SCST Reward: $R(heta) = \sum_{t=1}^T (r_t b_t) \log P(y_t|x; heta)$

Evaluation

Metrics Assessment

 \Longrightarrow

Model Development







- **Dynamic Wait-k Policy:** Demonstrated significant improvements in balancing latency and quality compared to static methods.
- SCST RL Fine-Tuning: Effectively optimized latency-quality trade-offs through reinforcement learning.
- HMT Integration: The use of HMT provided statistical support for sequence alignment, further improving the model's adaptability in real-time translation scenarios.
- Efficient Performance: The LoRA-enhanced LLaMA model delivered resource-efficient, high-quality translations.
- Robust Evaluation: BLEU and ROUGE scores provided reliable metrics for gauging translation accuracy and informativeness.
- Evaluate translation quality using BLEU and ROUGE metrics while minimizing latency.



CONTRIBUTIONS

Tanmay Kumar Shrivastava: Coding, Ideation and Approach collaboratively handled with Gourav.

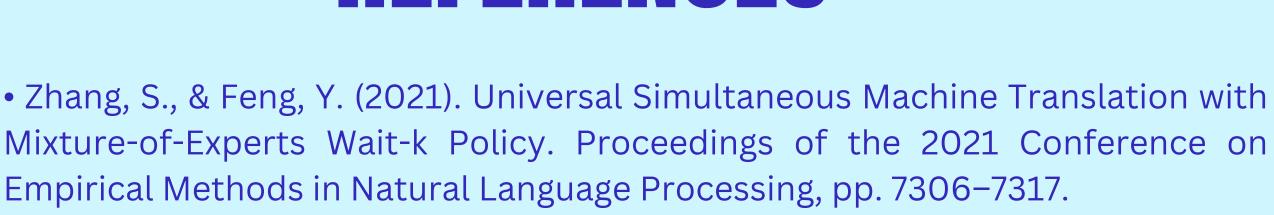
Nagulapalli Shavaneeth Gourav: Report, ppt, Ideation, Approach Collaboratively handled with Tanmay Kumar Shrivastava.

Darsh Mahajan: Ideation of the approach and helped in ppt and report making.

Despite of the specific contributions, whole project was handled by all group members.

REFERENCES

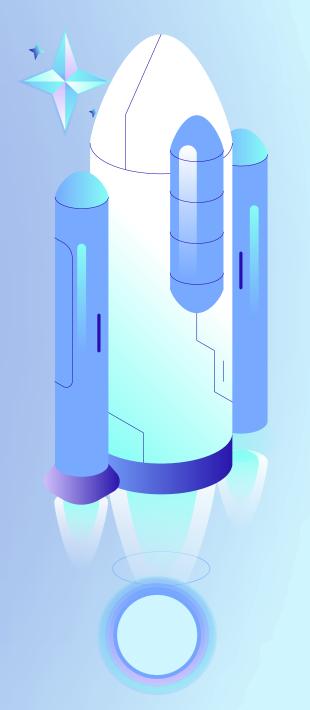
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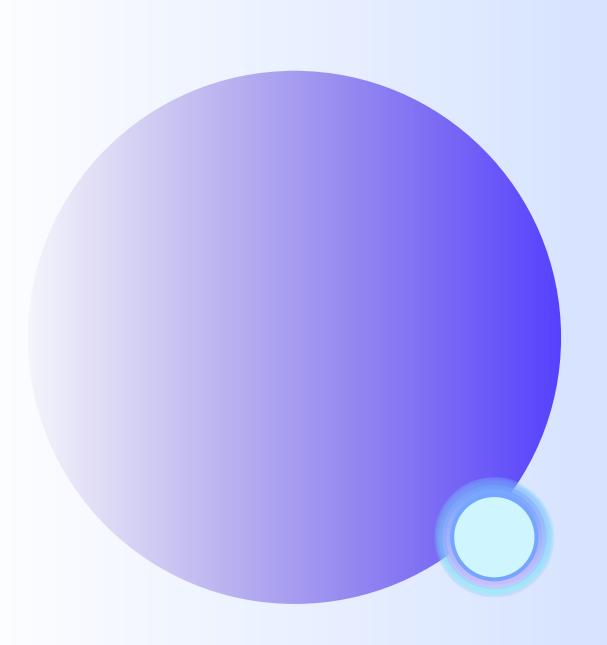
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THANK YOU!