

Lexical Substitution as Causal Language Modeling

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Introduction

Lexical Substitution Task (LST) is to identify suitable replacements for a target word while preserving the contextual meaning of the sentence.

$LST(S, w_x) = y$

Sentence (S) = "Let me begin again."; Target Word (w_x) = "begin"

Substitutes (y) = ["start", "commence", "open", ...]

Existing methods involve contextualized representations and sequence-to-sequence generation; however, several **limitations** remain.

We provide the first single-step, end-to-end generative solution for LST that can also address existing limitations.

Methodology

We solve LST by reducing the problem to **Word Prediction (WP)**, which we solve via **Causal Language Modelling (CLM)**.

Lexical Substitution, $LexSub(S, w_x, w_y) :=$ "the word w_x can be replaced by the word w_y in the sentence S without altering its meaning"

$LexSub(\text{"Let me begin again."}, \text{"begin"}, \text{"start"}) = \text{True}$

$WP(S, w) :=$ "the word w has the same meaning as the masked word in the sentence S"

Task Reduction from **LexSub** to **WP**:

$LexSub(S, w_x, w_y) \Leftrightarrow WP(S, w_x) \wedge WP(S, w_y)$

Limitations of Prior Work

Semantic Change:

Predicted substitutes may align well with the context but significantly *change the original meaning* of the sentence.

"Let me carry on again." vs. "Let me originate again."

Pipeline Approach:

- (1) Manually defined heuristics and tuned thresholds
- (2) Extensive pre-processing and post-processing steps
- (3) Dependence on expert knowledge and external resources

Misalignment: Pre-training (language modeling) vs. Fine-tuning (LST)

Model Architecture (e.g., GeneSis):

Let me begin again. \rightarrow Encoder-Decoder \rightarrow start, commence, open, ...

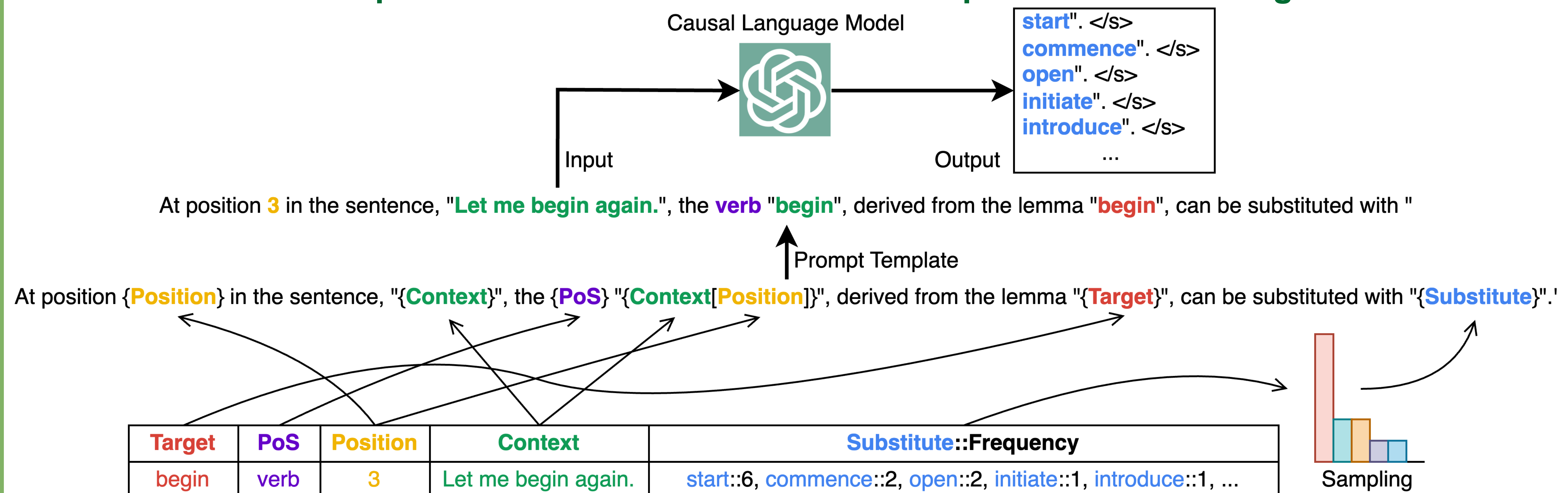
(a) GeneSis

The "{Target}" in the sentence "{Context}" can be substituted with "{Substitute}".

The "begin" in the sentence "Let me begin again." can be substituted with "

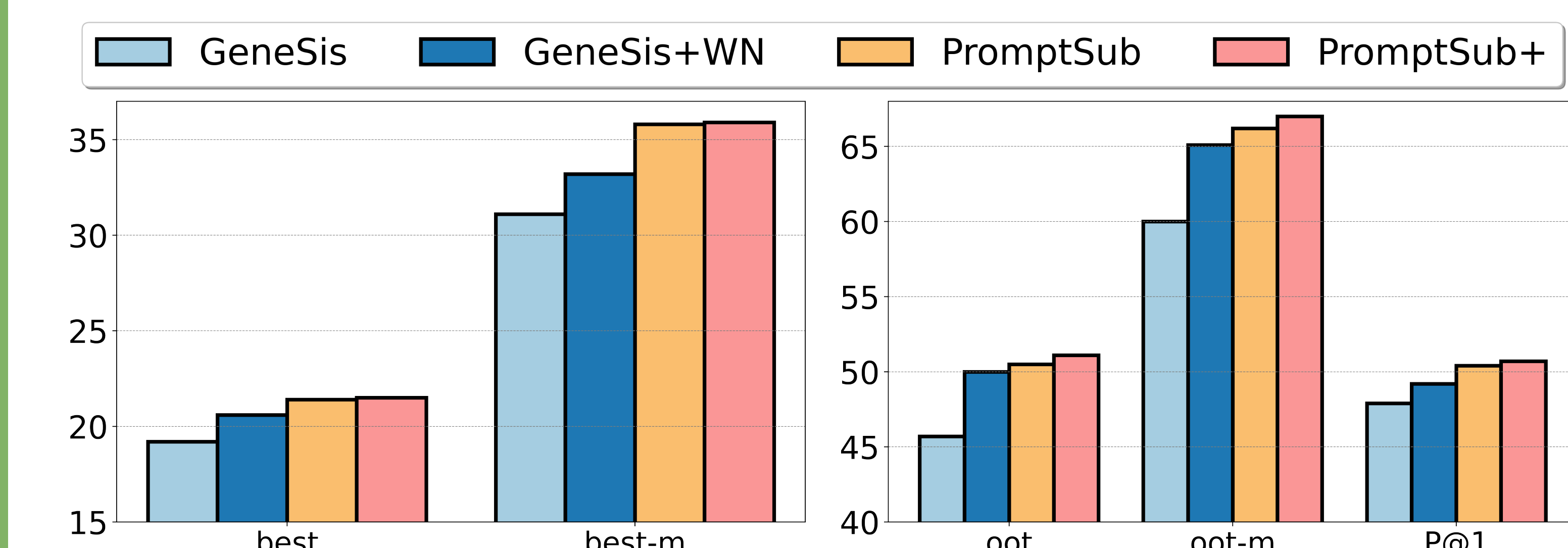
Decoder-Only \rightarrow start".
...
(b) PromptSub

PromptSub: Lexical Substitution via Prompt-aware Fine-tuning



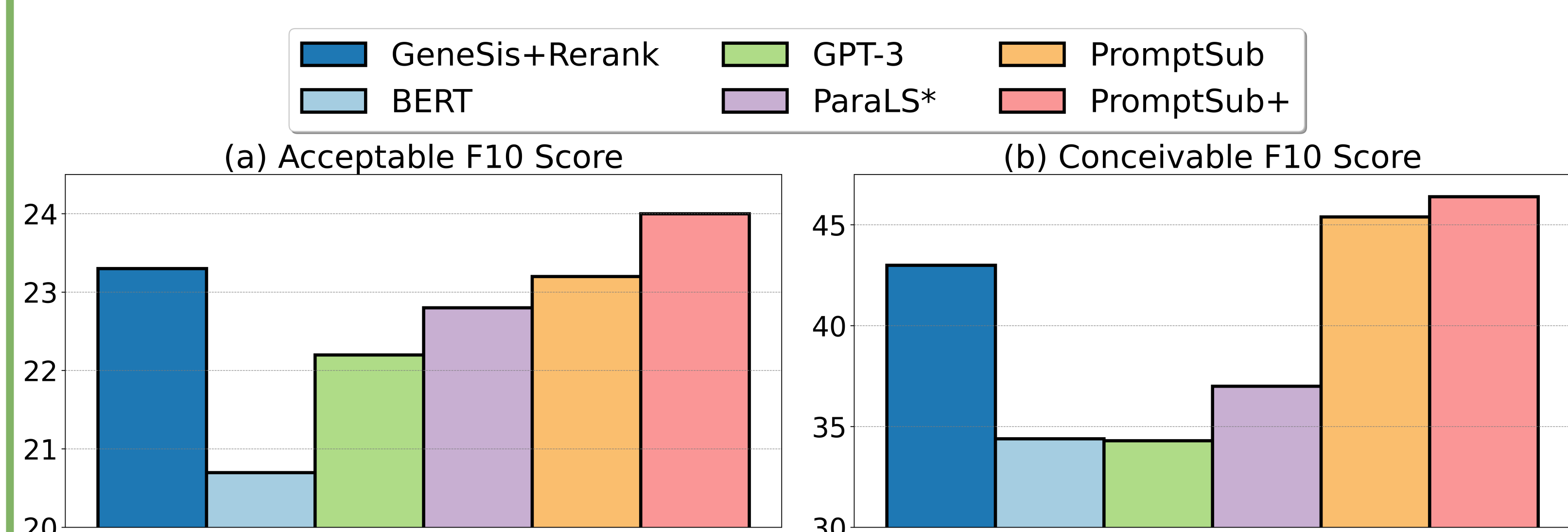
LS07 Results

PromptSub+ augments the training set by incorporating the dev set.



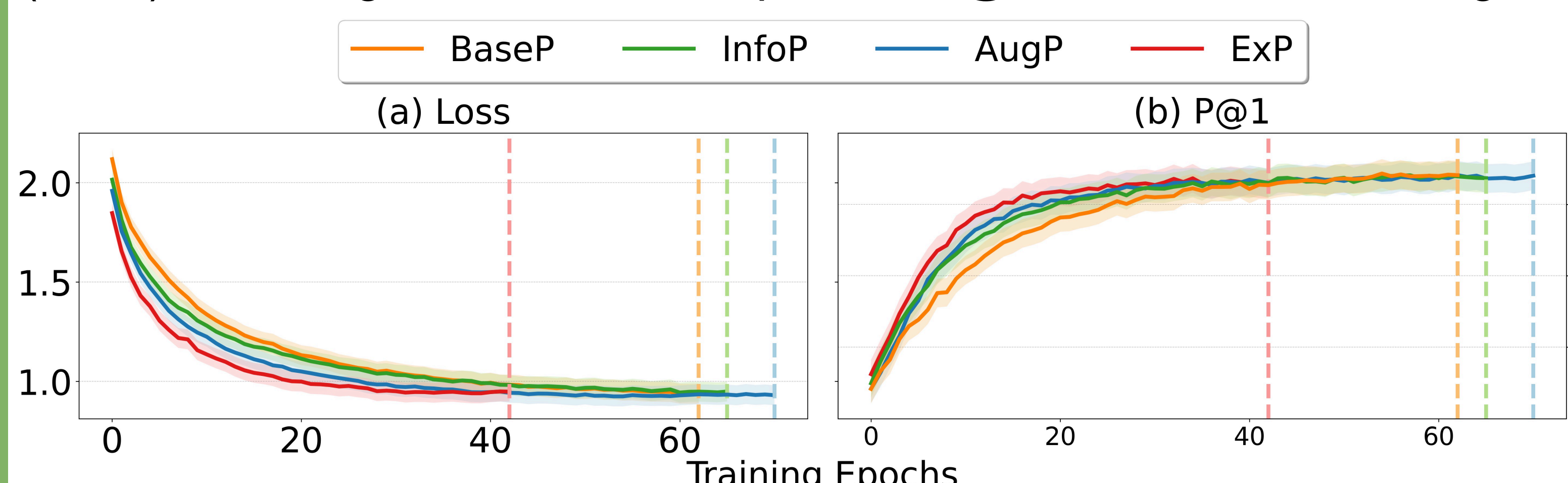
LS21 Results

We reproduced GeneSis+Rerank, which incorporates post-processing steps to refine the results.



Analysis

ExP retrieves WordNet synsets for retrieval-augmented generation (RAG), resulting in lower loss, improved P@1, and earlier convergence.



Conclusion

- An innovative and successful attempt to apply CLM to LST through a formally defined task reduction.
- A new state of the art on the LS21 benchmark by a large margin.
- Scalability via data resources, model capacity, and RAG.

github.com/ShiningLab/PromptSub

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