Self-Ensemble of N-best Generation Hypotheses by Lexically Constrained Decoding

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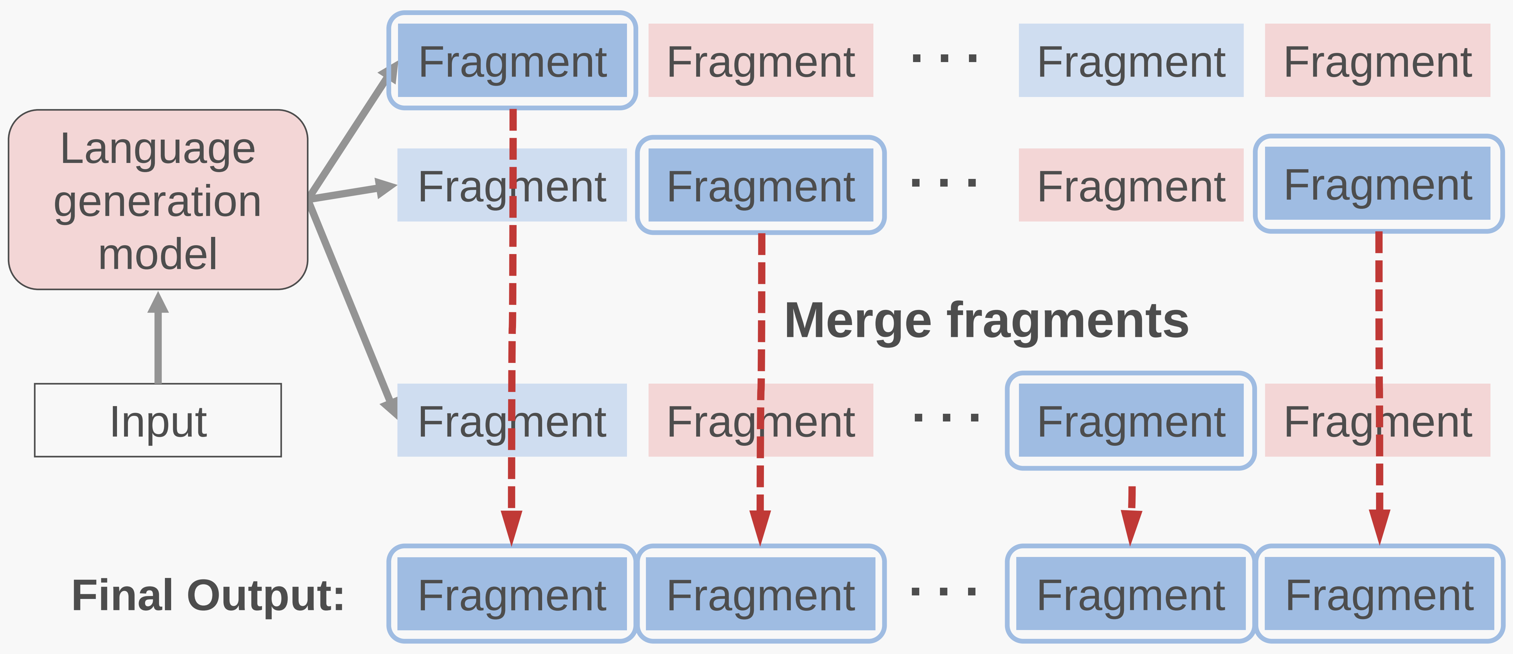
Code, Paper

Introduction

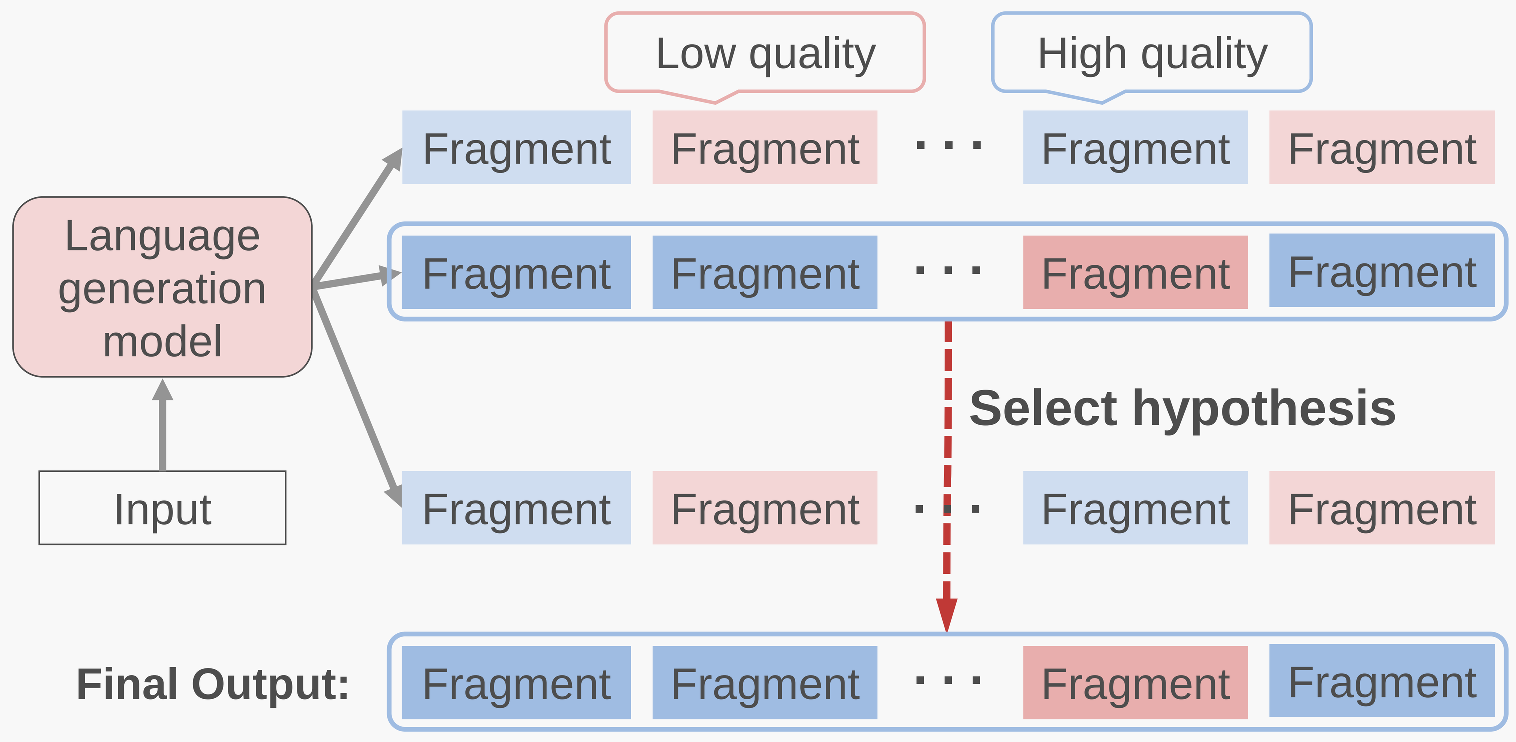
Our approach

- Assumption: There exists ***partly*** higher quality hypotheses
- **Merge high quality fragments** to obtain better output
- Use **lexical constraints** to control output



Existing method – Reranking

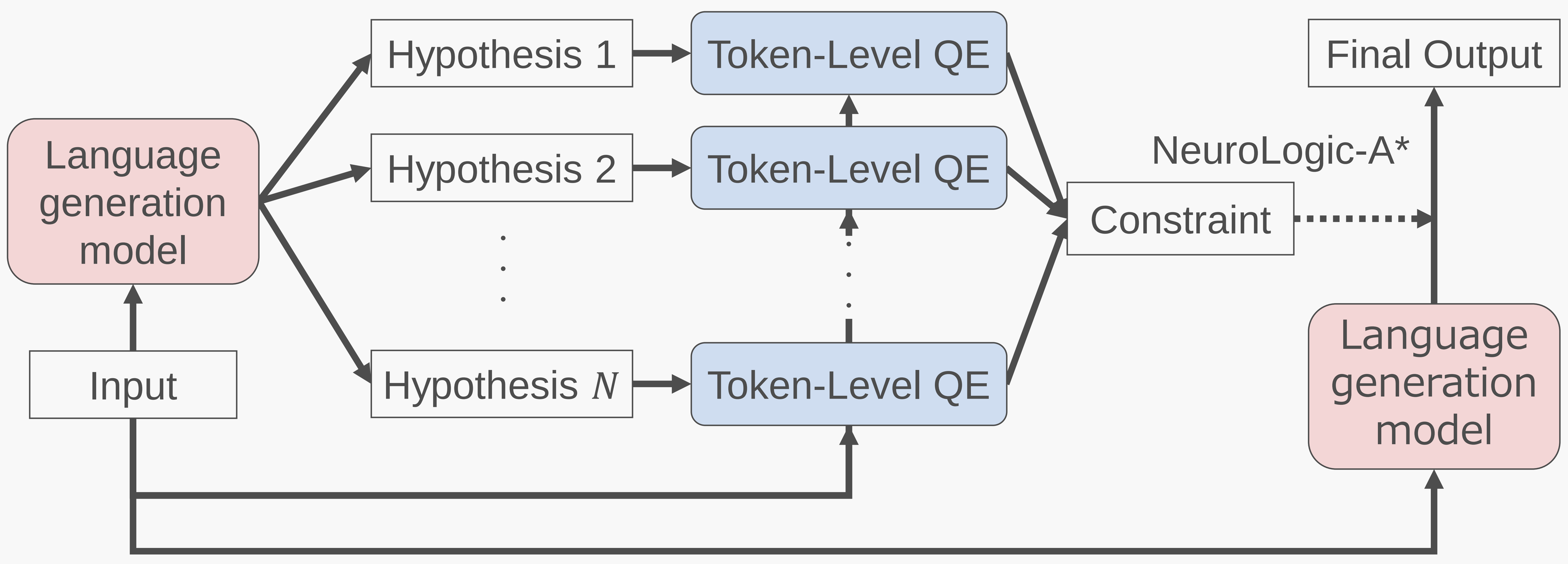
- Assumption: There exists a higher quality hypothesis
- Re-evaluate hypotheses and **select the best hypothesis**



Proposed method

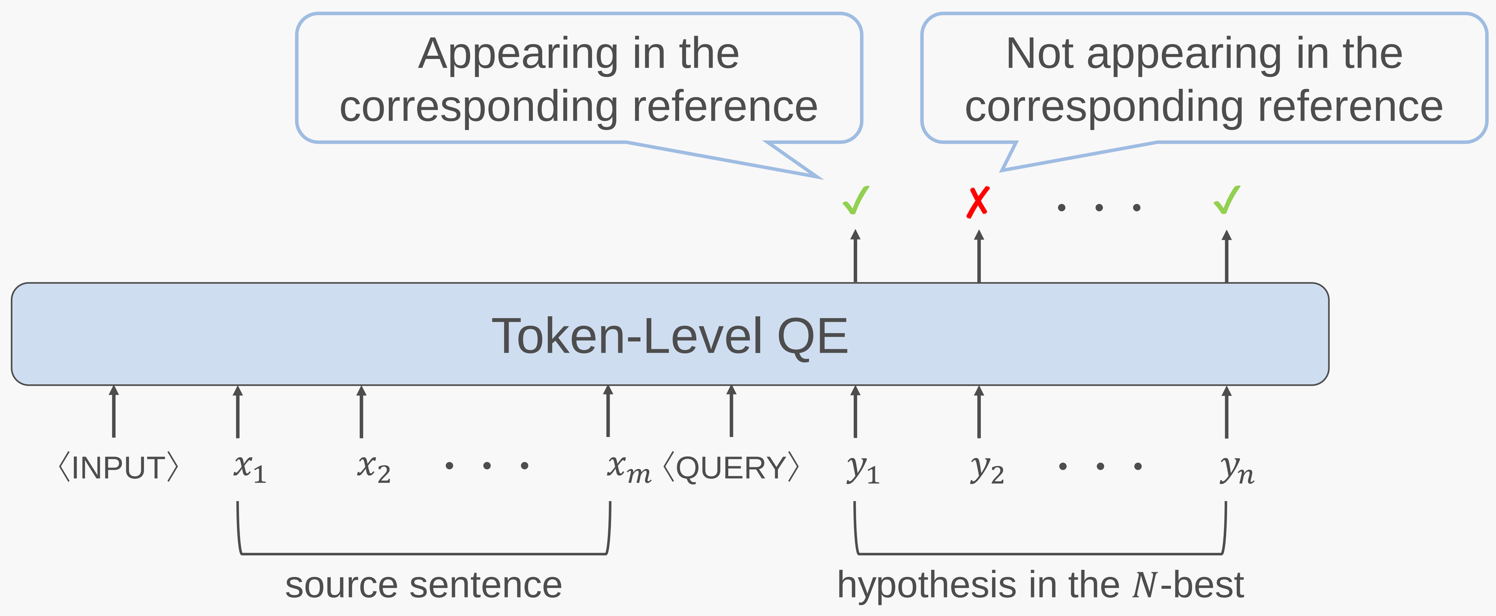
Overview

- Create constraints based on the **token-level QE model**
  - QE model predict whether each token in N-best hypotheses should be used or avoided in the final output
- Generate final output using Lexically constrained decoding
  - NeuroLogic-A* (Lu et al., 2022)



Training of the token-level QE model

- Create training data
  - Generate N-best hypotheses for training sentences using a language generation model
  - Assign positive labels to tokens appearing in the reference and negative labels to tokens not appearing
- Fine-tune a pretrained masked language model

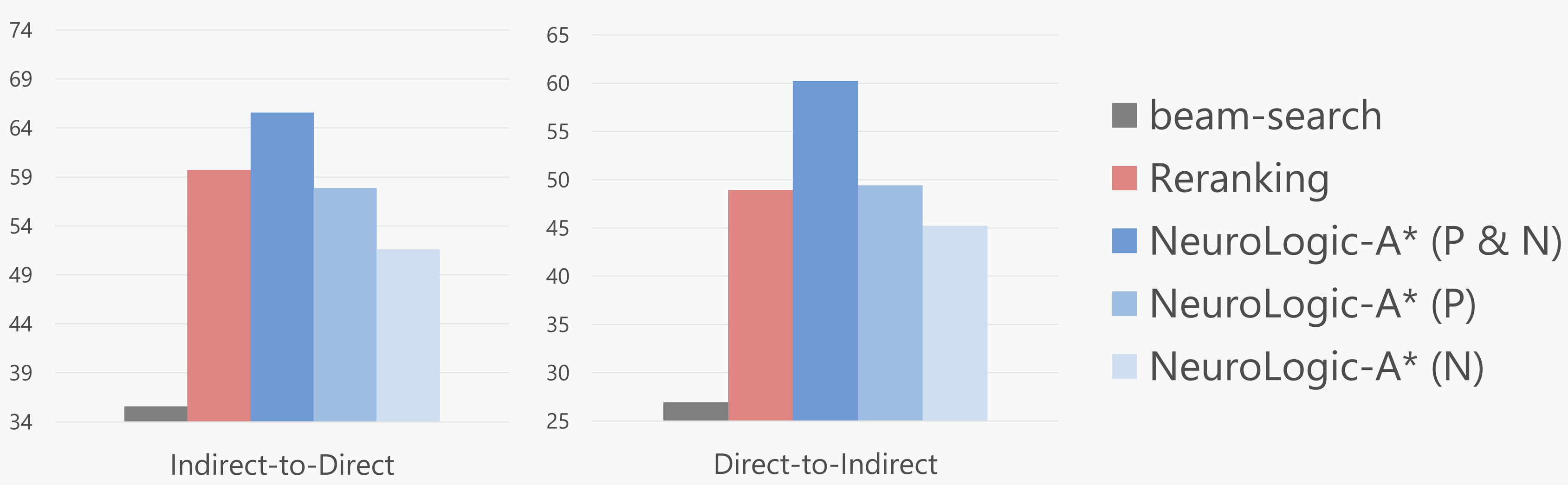


Experiments

Evaluate our method on language generation tasks

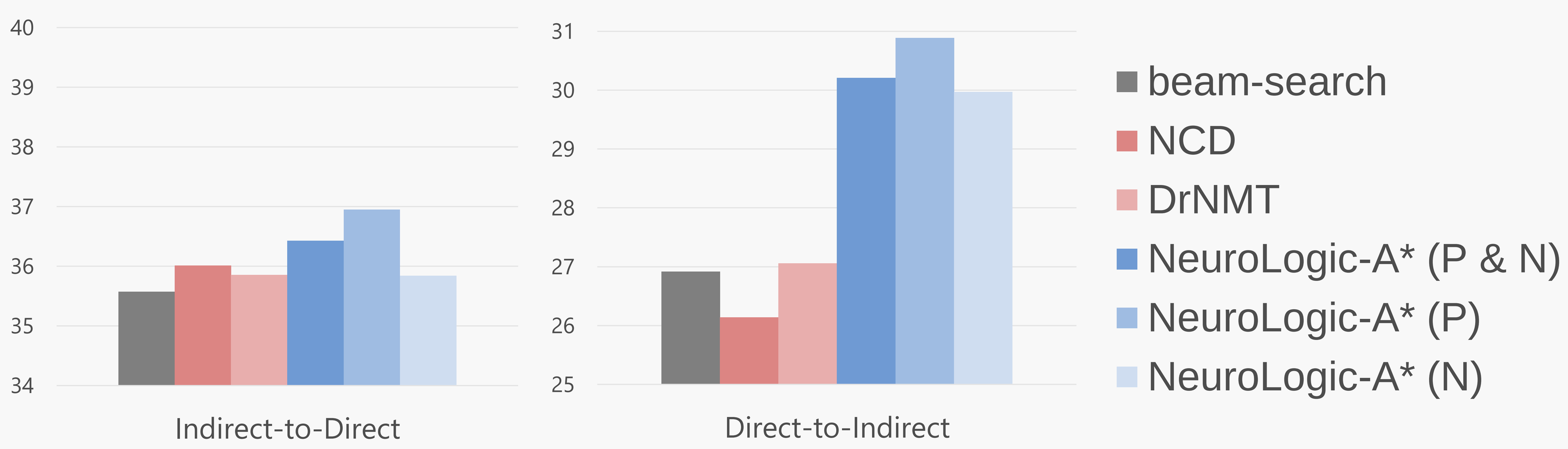
- Paraphrasing
  - Dataset: DIRECT (Takayama et al., 2021)
  - Metrics: BLEU
- Summarisation
  - Dataset: XSum (Narayan et al., 2018)
  - Metrics: ROUGE-L

Paraphrasing - Oracle (Assume the reranker and QE model are ideal)

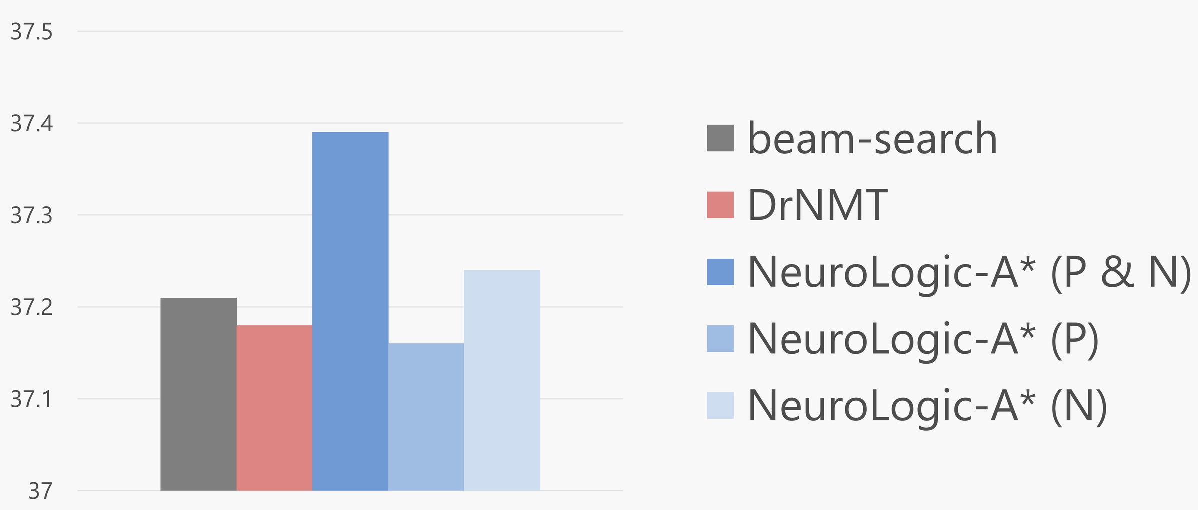


Ensembling N-best hypotheses is more effective than selecting the best hypothesis

Paraphrasing



Summarisation



Proposed method significantly outperforms the strong reranking methods