Named Entity-Based Enrichment with BART

NL4Opt Subtask 2, NeurIPS 2022 (nl4opt.github.io)

Neeraj Gangwar (gangwar2@illinois.edu)

Nickvash Kani (kani@illinois.edu)

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University of Illinois at Urbana-Champaign







Task Overview

The goal of this task is to formulate the meaning representation of a linear programming word problem, given the problem description, labeled semantic entities, and the order mapping of variables.



Output Formulation



Upperbounds. Invert the signs in the case of lowerbound.

farm 1: 0, farm 2: 1

- The dataset for this subtask consists of 1101 linear programming word problems.
- The train, dev, and test splits contain 713, 99, and 289 problems, respectively.
- These problems are from advertising, investment, sales, production, science, and transportation domains.
- The training split contains problems only from the first three domains, whereas the dev and test splits contain problems from all six domains.

Our approach is built on top of the baseline method, which uses BART with Copy Mechanism¹, with two modifications:

- The input is enriched to incorporate the named-entity information.
- · The model outputs the objective and constraints at once.

Named Entity-Based Enrichment

Add tags around the named entities in the input (XML-like tagging with start and end tags). For example, the problem shown earlier will be augmented as shown below:

A berry picker must pick <CONST_DIR> at least </CONST_DIR> <LIMIT> 3000 </LIMIT> strawberries and <LIMIT> 15000 </LIMIT> raspberries. He visits two farms. For each <OBJ_NAME> hour </OBJ_NAME> at <VAR> farm 1 </VAR> he spends, ... the <OBJ_NAME> amount of time </OBJ_NAME> he spends at both farms?

¹transformers.BartForConditionalGeneration (v4.3.0)

Model Output Format

The model output is in XML format, consisting of objective and constraint declarations.

<DECLARATION><OBJ_DIR> minimize </OBJ_DIR><OBJ_NAME> amount of time </OBJ_NAME> [is] <VAR> farm 2 </VAR> [TIMES] <PARAM> ONE </PARAM><VAR> farm 1 </VAR> [TIMES] <PARAM> ONE </PARAM></DECLARATION><DECLARATION><CONST_DIR> at least </CONST_DIR><OPERATOR> GREATER_OR_EQUAL </OPERATOR><LIMIT> 3000 </LIMIT><CONST_TYPE> [LINEAR_CONSTRAINT] </CONST_TYPE> [is] <VAR> farm 2 </VAR> [TIMES] <PARAM> 70 </PARAM><VAR> farm 1 </VAR> [TIMES] <PARAM> 50 </PARAM></DECLARATION><DECLARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION></PARATION>

Experiments

Training Details

- 1. Used BART-large² as the pre-trained model and fine-tuned it on the subtask 2 dataset.
- 2. The model was trained on one A100 GPU with 40GB VRAM.

Metrics

The model was evaluated based on declaration-level accuracy.

Results

Our (submitted) best model achieved an accuracy of 0.874 with greedy decoding and 0.882 with a beam size of 5 on the validation set. On the test set, it achieved an accuracy of 0.899 with a beam size of 5.

Sensitivity to Optimization

The model achieved varied accuracy values when initialized with different seeds. The fine-tuning was very sensitive to hyperparameter values including seeds with the large version of BART.

²huggingface.co/facebook/bart-large

We ran our approach with pre-trained models BART-base and BART-large and 10 different seeds (5 common and 5 different seed values)³. Below are the accuracy values achieved by the model on the validation set with greedy decoding.

BART-large ⁴	85.9	89.0	61.3	84.4	56.2	75.4	74.9	75.1	62.1	35.9
BART-base ⁵	80.8	81.5	76.2	80.8	79.2	81.5	81.0	79.7	81.2	80.8

The standard deviation values for BART-large and BART-base are 15.47 and 1.52, respectively.

For these runs, only pre-trained models were switched between BART-base and BART-large. Other hyperparameters were kept the same.

³Ran on one V100 GPU with 32GB VRAM.

⁴huggingface.co/facebook/bart-large

⁵huggingface.co/facebook/bart-base

As we used the baseline model as a starting point for our approach, we faced two major challenges with the baseline code.

Evaluation Batch Size

The validation part of the training failed if the evaluation batch size was increased from 1. This issue affected the speed of training, and the fix helped speed up our training pipeline.

Reproducibility

Even after fixing the seeds in the code, the results were different for different runs with the same seed values. The reason for this was the scatter_add_ method that does not have a deterministic implementation in PyTorch 1.12 or earlier versions. We used PyTorch 1.14 (the dev version) and added torch.use_deterministic_algorithms(True) statement in addition to fixing the seeds. Note that this statement resulted in errors with versions 1.12 or before, due to not having a deterministic implementation of scatter_add_. It works with PyTorch 1.13 and later versions.

Following Shin et al. (2021)⁶, we tried converting the output to a more natural text looking format.

<DECLARATION>The objective is amount of time which is defined as the sum of 1 times farm 2, 1 times farm 1. minimize the objective.</DECLARATION><DECLARATION>Constraint of type linear with direction at least is that sum of 70 times farm 2, 50 times farm 1 is GREATER_OR_EQUAL to 3000</DECLARATION><DECLARATION> ... </DECLARATION>

In our initial experiments, this approach did not show an improvement compared to the approaches that used XML-looking model output.

⁶Shin et al., "Constrained Language Models Yield Few-Shot Semantic Parsers".

Code at **Q**/mlpgroup/nl4opt-eq-generation



Thank you for listening! Questions?