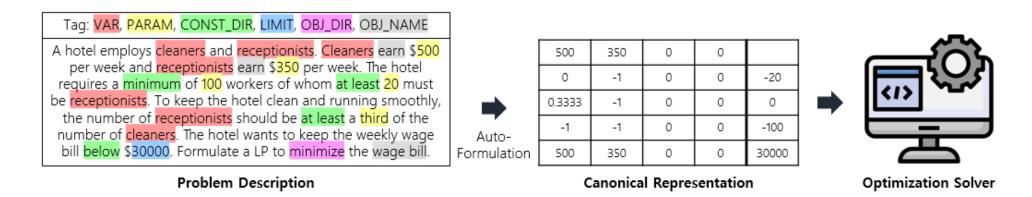
Tag Embedding and Well-defined Intermediate Representation improve Auto-Formulation of Problem Description

[NeurlPS 2022 NL4Opt Competition (Subtask 2) 2nd Place]
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Auto-Formulation of Problem Description

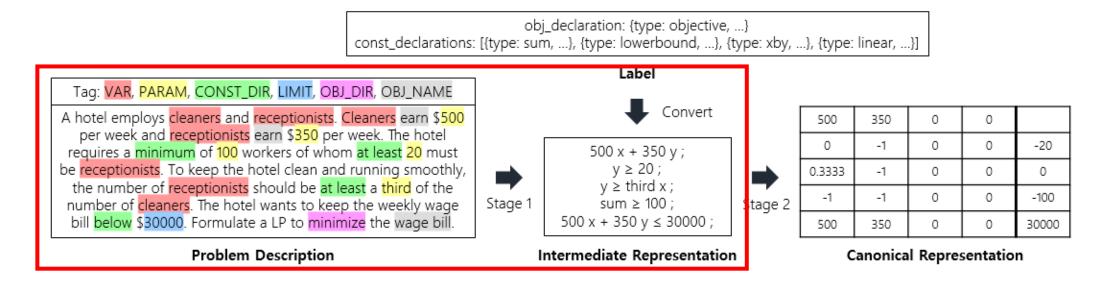
Auto-formulation is the task of converting an optimization problem into a canonical representation.



A problem description and tagged entities are given, and we should extract the objective and constraints.

Two-Stage Auto-Formulation

- We decompose auto-formulation task into two stages.
 - (1) optimization problem → intermediate representation
 - (2) Intermediate representation → canonical representation

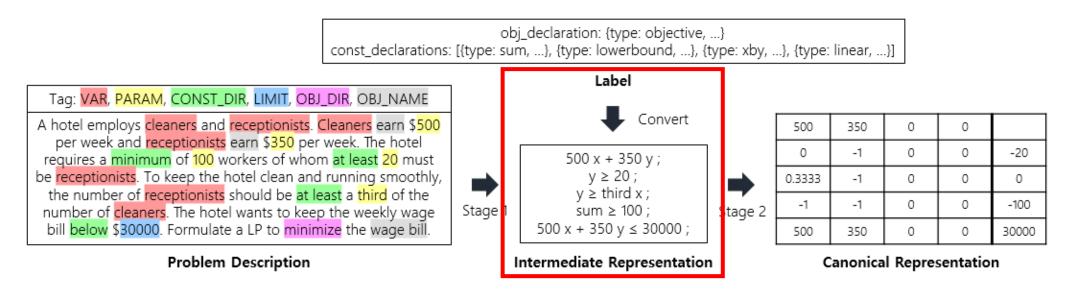


The model only needs to focus on the first stage.



Intermediate Representation

We define intermediate representation to be in the form of mathematical expression.



- The objective and constraints are generated at once to include the relationship between declarations in training.
- To avoid inconsistency in model training, we define the order of generation of declarations.
 - (1) objective \rightarrow constraints (lowerbound \rightarrow upperbound \rightarrow xy \rightarrow xby \rightarrow sum \rightarrow linear \rightarrow ratio)
 - (2) position
 - $(3) \times y \to z \to w$
 - $(4) \leq \rightarrow \geq$



Data Augmentation

- We augment the data by reversing the direction of some constraints.
 - (1) must not, can not, cannot \rightarrow must

The number of train trips must not exceed the number of truck trips. $x \le y$;



The number of train trips must exceed the number of truck trips. $x \ge y$;



Entity Tag Embedding and Embedding Scaling

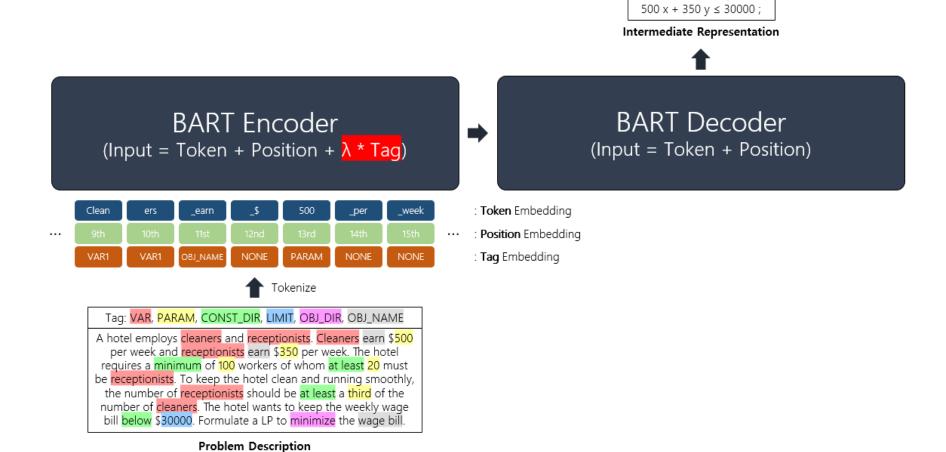
- We finetune pretrained BART_{large} for auto-formulation task.
 - (1) token embeddings: $E_{w_1}^{tok}$, $E_{w_2}^{tok}$, ..., $E_{w_L}^{tok} \in \mathbb{R}^d$
 - (2) position embeddings: $E_1^{pos}, E_2^{pos}, ..., E_L^{pos} \in \mathbb{R}^d$
 - (3) entity tag embeddings: $E_{t_1}^{tag}$, $E_{t_2}^{tag}$, ..., $E_{t_L}^{tag} \in \mathbb{R}^d \to \text{initialize to 0s}$
- We use an embedding scaling hyperparameter λ for entity tag embedding.
 - (1) I-th input embedding: $E_{w_l}^{tok} + E_l^{pos} + \lambda E_{t_l}^{tag}$.



Problem Description



Method Overview



500 x + 350 y; $y \ge 20$; $y \ge third x$; $sum \ge 100$;

Experiments

We use declaration-level mapping accuracy:

$$Accuracy = 1 - \frac{\sum_{i=1}^{N} FP_i + FN_i}{\sum_{i=1}^{N} D_i}$$

Hyperparameters:

Hyperparameters		
Batch Size	16	
Optimizer	AdamW	
Learning Rate	5e-5	
Weight Decay	1e-5	
LR Scheduler	Cosine Annealing	
Max Norm (Gradient Clipping)	1.0	
Num Epochs	100	
Generation	Beam Search	
Num Beams	4	

Ablation Study

- The results demonstrate the effectiveness of the proposed techniques.
 - (1) λ : embedding scaling weight for entity tag
 - (2) p: probability of reversing constraint direction (for data augmentation)

Hyperparameter		Validation	
BART Size	λ	р	Accuracy
Base	0	0	0.5513
Large	0	0	0.7718
Large	1	0	0.8000
Large	5	0	0.8692
Large	5	0.3	0.8846

→ Larger pretrained model

→ Adding entity tag embedding

→ Adjusting weight of entity tag embedding

→ Data augmentation



Result

■ We placed 2nd in NL4Opt competition subtask 2.

Team	Test Accuracy
UIUC-NLP	0.899
Sjang	0.878
Long	0.867
PingAn-zhiniao	0.866
Infrrd AI Lab	0.780
KKKKKi	0.634



Thank You