How to get Metaphor Concept Mapping

정 시 열

목차

Introduction

- 최신 Depression Detection연구들은 성능 향상에 초점을 맞추어 SOTA 모델들을 사용하기에 설명이 어렵다는 단점 존재

- Depression 환자 특징
  - 본인의 감정과 정신 상태를 전문의에게 표현하기 앞서 Social Media에 표현하는 경향이 있음.
  - 본인의 감정과 경험을 *은유적으로 표현함.

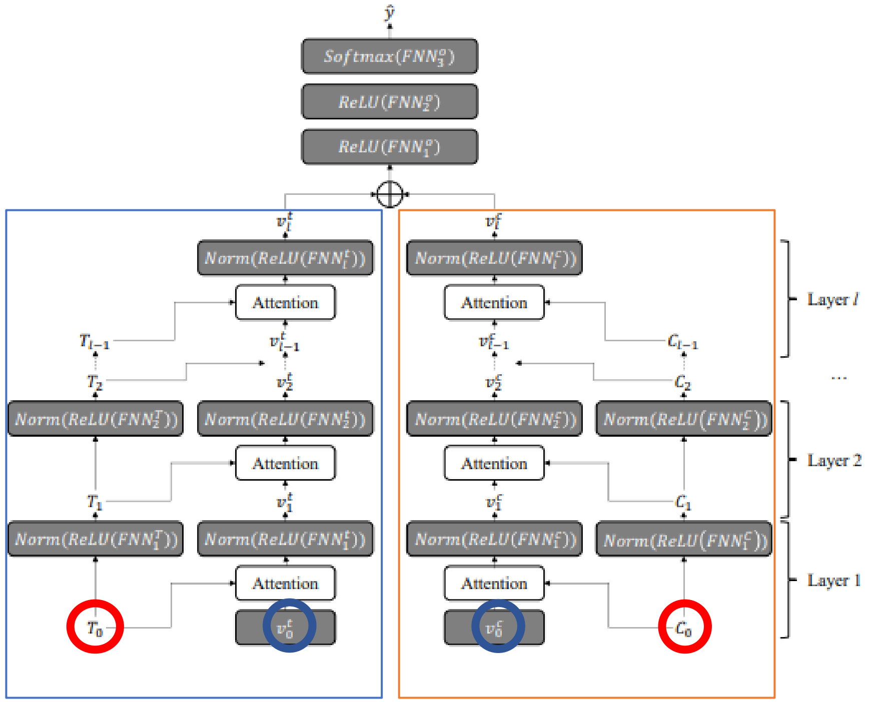
    *Metaphor is not only a linguistic phenomenon, but also a reflection of cognitive **mappings of source and target concept**

  - 환자의 은유 표현은 심리치료에서 중요함.

- "You are ***wasting*** my time" => "**Time** is **Money**"
- "This is the ***core*** of the matter" => "**importance** is **interiority**"

➢MCM을 활용한 설명 가능한 모델 **HAN**을 소개함.

*MCM = Metaphor Concept Mappings (" A is B ") / A: target, B: Source



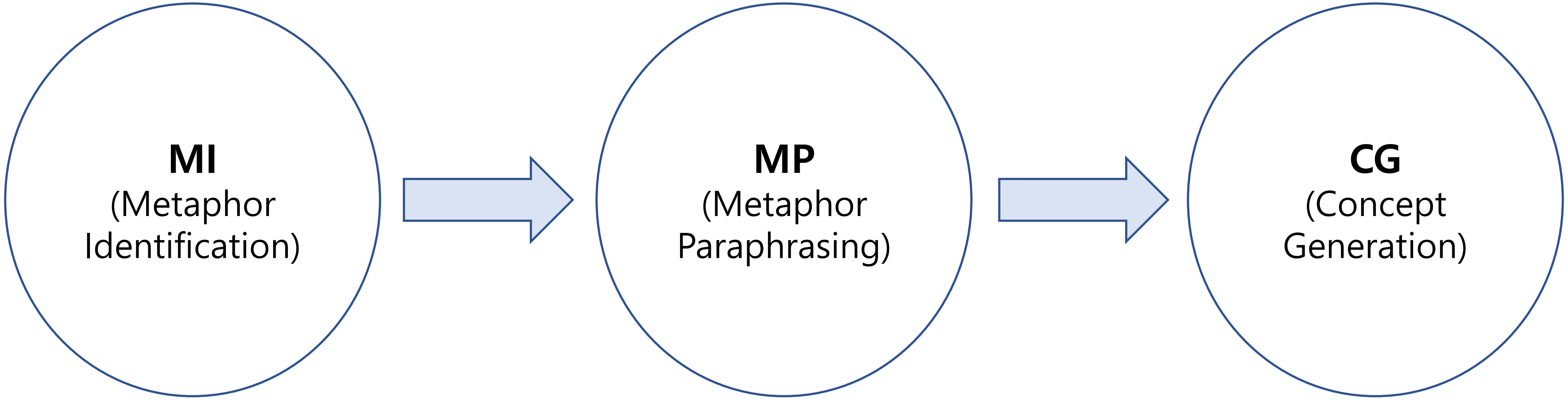
Tweet

MCM

How to get MCM?

Introduction

How to get MCM?

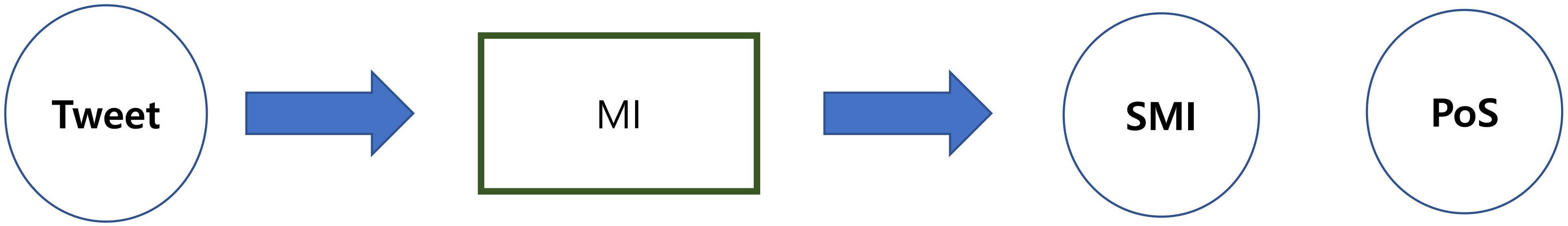


Metaphor Identification (MI)

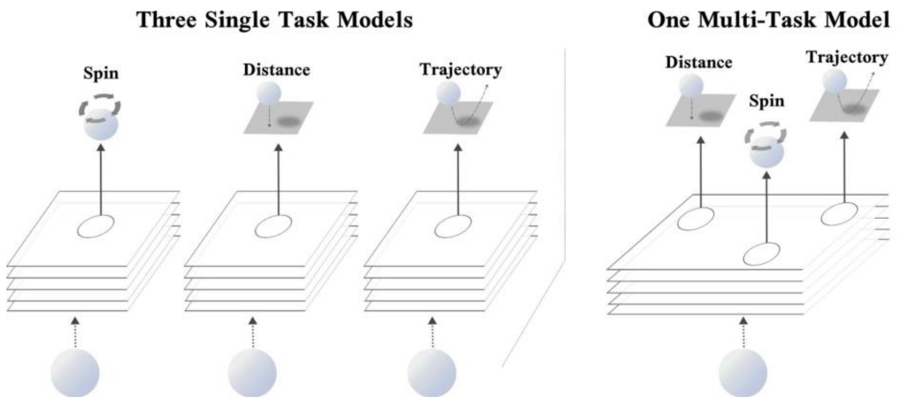
Ex) My car **drinks** gasoline

Input:	I	have	already	passed	the	two	written	exams	.
SMI:	lit	lit	lit	met	lit	lit	lit	lit	lit
PoS:	PRON	AUX	ADV	VERB	DET	NUM	VERB	NOUN	PUNCT

$$r_\epsilon, \rho_\epsilon = MI(\mathbb{x}_\epsilon),$$



Metaphor Identification



Bridging Towers of Multi-task Learning with a Gating Mechanism for Aspect-based Sentiment Analysis and Sequential Metaphor Identification

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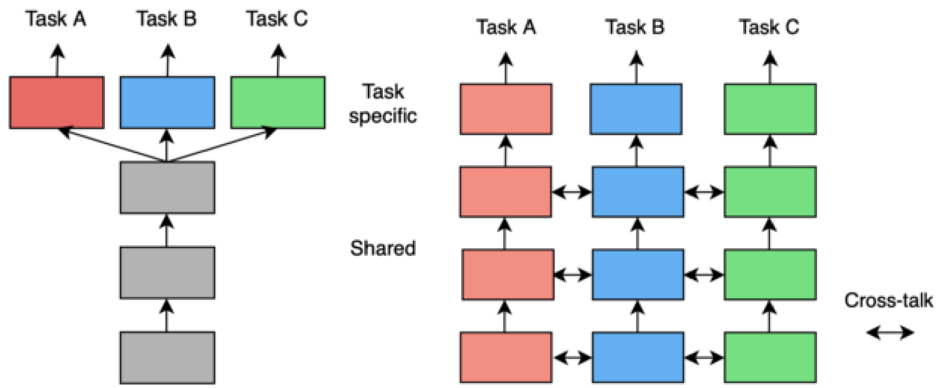


(a) Hard parameter sharing (b) Soft parameter sharing

Metaphor Identification

VU Amsterdam Metaphor Corpora

1. Read the text to get a general understanding of the meaning

2. Determine the lexical units

3a. Establish the contextual meaning of the unit

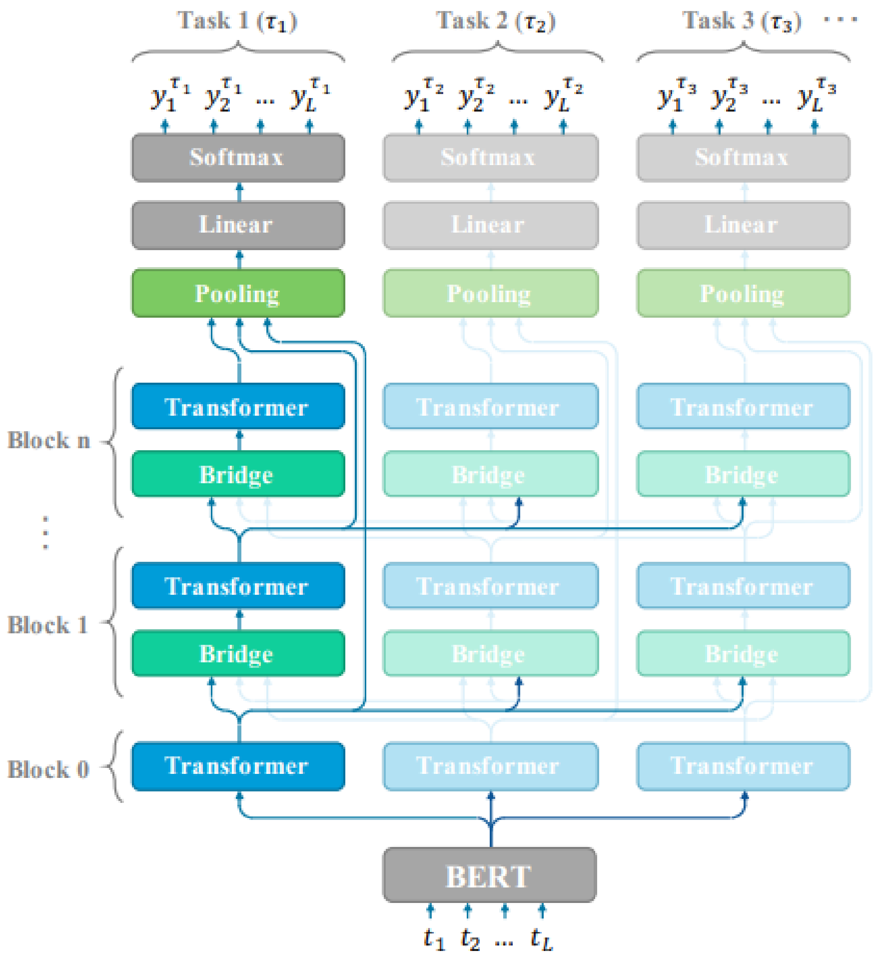
3b. Determine if it has a more basic meaning

more concrete, body-related,
more precise, historically older;
not necessarily the most frequent
meaning!

Does the contextual meaning contrast with the basic meaning but can it be understood in comparison with it?

4. If yes, mark the unit as metaphorical.

Metaphor Identification



$$H^s = BERT(t_1, ..., t_L).$$

$$G_i^{\tau_j} = GBM_{\phi_{i,j}}(H_{i-1}^{\tau_1}, ..., H_{i-1}^{\tau_j}, ...),$$

$$\begin{cases} H_0^{\tau_j} = Trans_{\phi_{0,j}}(H^s), \\ H_i^{\tau_j} = Trans_{\phi_{i,j}}(G_i^j), \quad 0 < i \leq n. \end{cases}$$

$$H_{pool}^{\tau_j} = \sum_{i=0}^{n} \alpha_i^{\tau_j} H_i^{\tau_j},$$

$$\hat{Y}^{\tau_j} = W_{fc}^{\tau_j} H_{pool}^{\tau_j} + b_{fc}^{\tau_j},$$

$$\mathcal{L} = \sum_{\tau_j} \omega^{\tau_j} \text{CrossEntropy}(\hat{Y}^{\tau_j}, Y^{\tau_j}),$$

Metaphor Identification

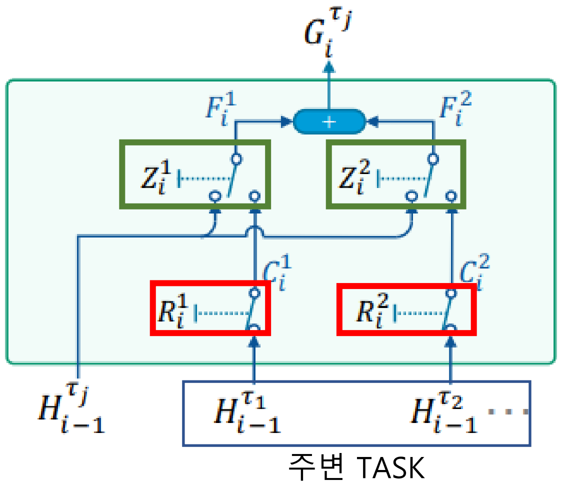


Figure 2: An illustration of the proposed Gated Bridging Mechanism with three subtask examples, where i denotes Block i. H is Transformer hidden states. $\{\tau_j, \tau_1, \tau_2, ...\}$ are different subtasks, where τ_j is the focused task in a multi-task learning tower; R is a reset gate; C is new current states; Z is an update gate; F is the fusion of H^{τ_j} and C. '+' is the element-wise addition. G is the output of GBM.

: Reset gate

: Update gate

$$R_i^m = \sigma(W^m_{\phi_{R,i,j}} H^{\tau_m}_{i-1} + b^m_{\phi_{R,i,j}}),$$

$$C_i^m = tanh(W^m_{\phi_{C,i,j}}(R_i^m \odot H^{\tau_m}_{i-1}) + b^m_{\phi_{C,i,j}}),$$

$$Z_i^m = \sigma(W^m_{\phi_{Z,i,j}} H^{\tau_j}_{i-1} + b^m_{\phi_{Z,i,j}} + V^m_{\phi_{Z,i,j}} C_i^m + d^m_{\phi_{Z,i,j}})$$

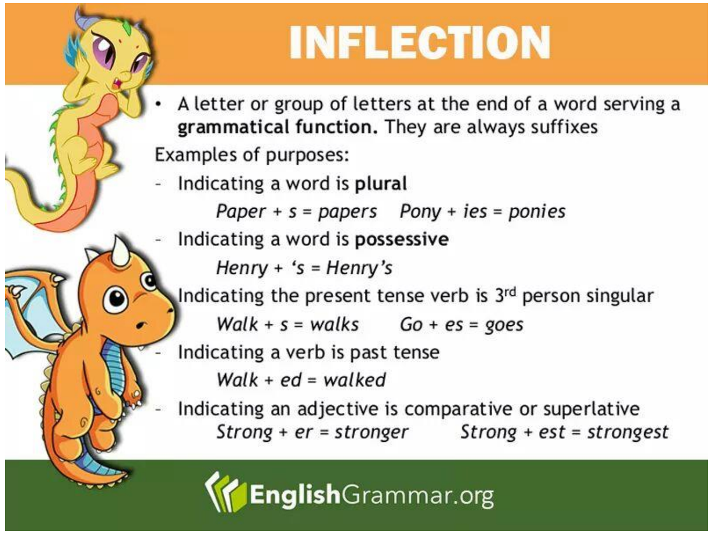
$$F_i^m = Z_i^m \odot H^{\tau_j}_{i-1} + (1 - Z_i^m) \odot C_i^m$$

$$G_i^{\tau_j} = \sigma(W^{\tau_j}_{\phi_{G,i,j}}(\sum_{m \neq j} F_i^m) + b^{\tau_j}_{\phi_{G,i,j}}).$$

Metaphor Paraphrasing

Mp

$$\omega^{\iota}_{\epsilon,j} = MP(\tau_{\epsilon,j}, \rho_{\epsilon,j}).$$



Interpreting Verbal Metaphors by Paraphrasing

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$$p(m_i | w_1, ..., w_{i-1}, w_{i+1}, ..., w_n)$$
$$= \text{BERT}([\text{CLS}], w_1, ..., [\text{MASK}]_i, ..., w_n, [\text{SEP}]),$$

$$b_i = \operatorname*{argmax}_{m_i \in \mathcal{C}_i} p(m_i | w_1, ..., w_{i-1}, w_{i+1}, ..., w_n).$$
$$(\mathcal{C}_i = \{h_{i,j}, h^f_{i,j}, s_{i,k}, s^f_{i,k}\}).$$

Metaphor Concept Mapping CG

$$\mathrm{A}_{\epsilon,j} = CG(\tau^{\iota}_{\epsilon,j}),$$

$$\mathrm{B}_{\epsilon,j} = CG(\omega^{\iota}_{\epsilon,j}).$$

$$\mathrm{MCM}_{\epsilon,j} = \mathrm{B}_{\epsilon,j} \text{ IS } \mathrm{A}_{\epsilon,j}.$$

Explainable Metaphor Identification Inspired by Conceptual Metaphor Theory

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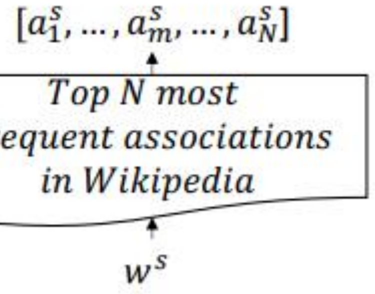
Metaphor Concept Mapping

CG

- 모델 입력 :**Verb-Noun, Adjective-Noun** 등 연관된 단어 2개
  Noun: literal, Verb/Adjective: literal or Metaphoric
- 모델 목표: 단어 사이의 **은유 관계 파악** 및 **Concept Mapping 생성**
- 단어쌍과 은유 관계 여부가 포함된 데이터셋 사용.
  컨셉의 경우 WordNet을 통하여 생성함
- W^t: Noun (-> infer Target Concept)
  W^s: Verb or Adjective (-> Source Concept)

1. 입력된 W^s 와 가장 많이 사용된 명사 N개 찾기

(a)



W^t, W^s의 dependency 고려

Metaphor Concept Mapping

(명사)

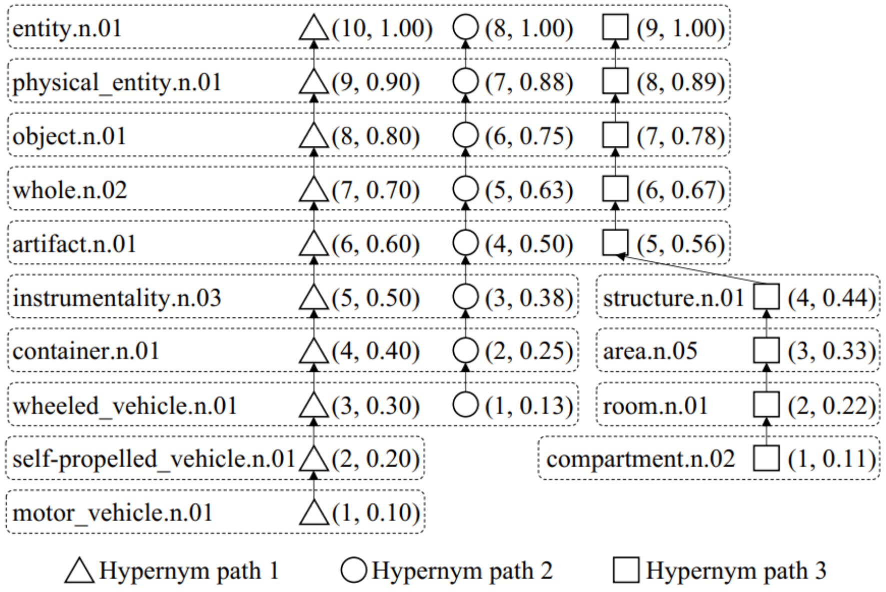


Figure 2: The rating scores of hypernyms of "car" in separate paths. The nodes in the same box denote the same synset in WordNet. The numbers in the parentheses besides a node denote the index of a node in a hypernym path (left), and the rating score in the path (right), respectively.

$$\Theta_{hyper} = \sum_{j} \frac{i_j^{hyper}}{len_j},$$

$$\Theta_{container} = 4/10 + 2/8 = 0.65.$$

Metaphor Concept Mapping CG

(명사)

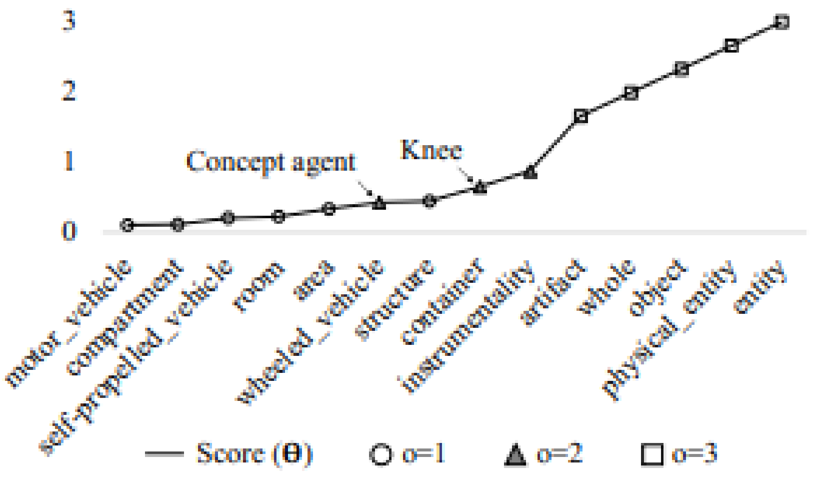
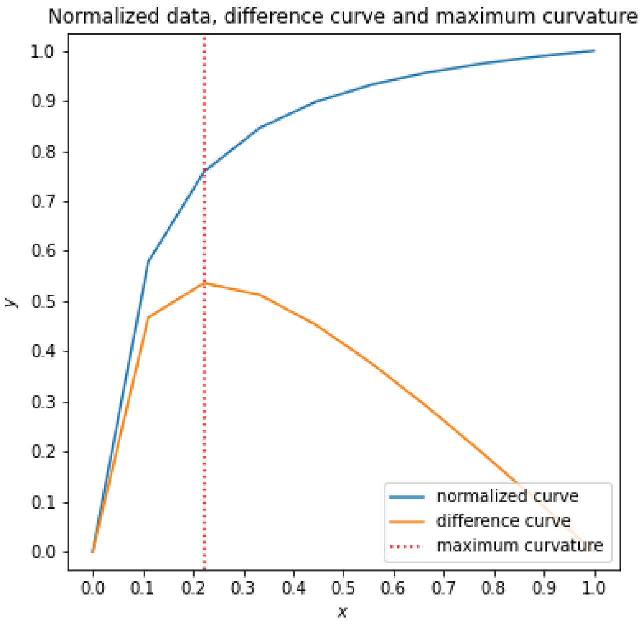
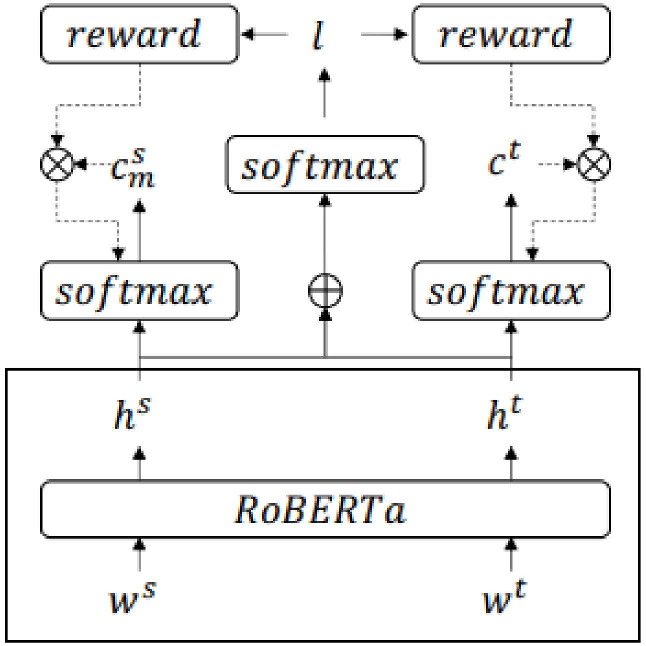


Figure 3: The rating score curve of hypernyms of "car" without smoothing and normalization.



$$c = hyper* = \arg \min_{hyper \in D_{knee}} \Theta_{hyper}.$$

Metaphor Concept Mapping CG



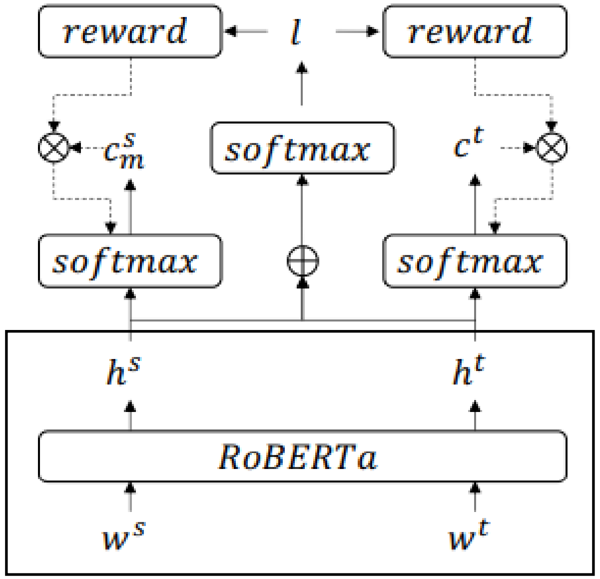
$W^t = C^t$

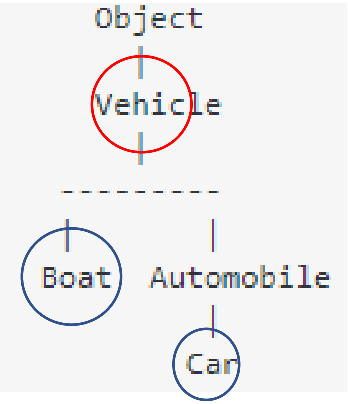
$W^s = (C^s = \{c^s_1, ..., c^s_m, ..., c^s_N\})$

$$h^s, h^t = RoBERTa(<s>, w^s, w^t, </s>),$$

$$P(\hat{c}^s_m) = softmax(W^s h^s + b^s),$$
$$P(\hat{c}^t) = softmax(W^t h^t + b^t),$$
$$P(\hat{l}) = softmax(W^l (h^s \oplus h^t) + b^l),$$

Metaphor Concept Mapping CG





Boat와 Car의 lcs: Vehicle

$$\mathcal{L} = \mathcal{L}^l + \beta\mathcal{L}^s + \beta\mathcal{L}^t$$

$$\beta = \varphi P(\hat{l} = l)^2 + \gamma\mu.$$

$$\begin{cases} \mu = sim(c_m^s, c^t), & if\ literal; \\ \mu = 1 - sim(c_m^s, c^t), & otherwise. \end{cases}$$

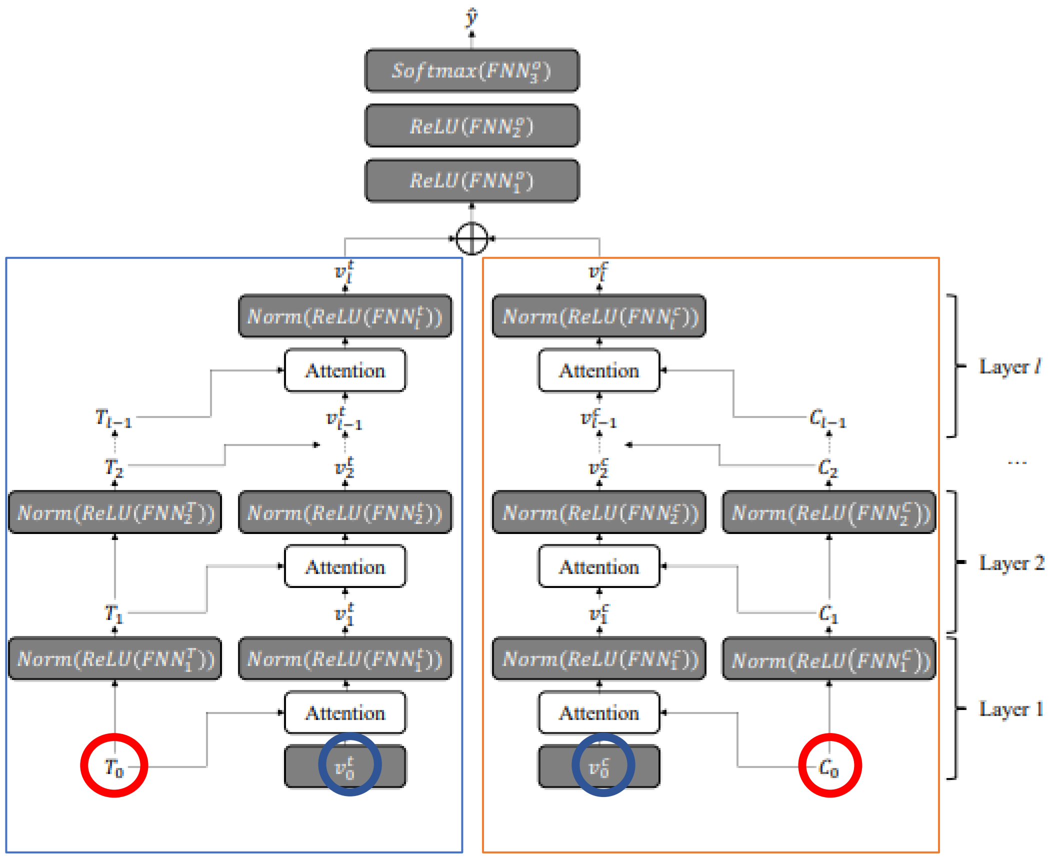
$$sim(c_m^s, c^t) = \frac{2 * N_{lcs \to root}}{N_{c_m^s \to lcs} + N_{c^t \to lcs} + 2 * N_{lcs \to root}}.$$

Inference

Source Concept: $c^{s*} = \arg\max_{\hat{c}_m^s \in C^s} P(\hat{c}_m^s)$

Target Concept : c^t

HAN



Tweet MCM

User: u_k

Set of tweets: $X_k = \{x_{k,1}, \dots, x_{k,n}\}$

Set of MCM in tweets: $M_k = \{m_{k,1}, \dots, m_{k,n}\}$

$$u_k = [X_k, M_k]$$

$$T_0 = BERT(\mathbb{X}).$$

$$C_0 = BERT(\mathbb{M}).$$

$$v_i^t, T_i = HAN_i^t(v_{i-1}^t, T_{i-1}).$$

$$v_i^c, C_i = HAN_i^c(v_{i-1}^c, C_{i-1}).$$

Layer 내부 전개

$K_{i-1} \in \mathbb{R}^{o \times d}$

$(q_{i-1} \in \mathbb{R}^{1 \times d})$

$$w_i = Softmax\left(\frac{q_{i-1} \otimes K_{i-1}^{\mathsf{T}}}{\sqrt{d}}\right)$$

$$q_i = LN(ReLU(FNN_i^{query}(w_i \otimes K_{i-1}))).$$

$$K_i = LN(ReLU(FNN_i^{key}(K_{i-1}))).$$

Results

Model	P	R	F1	Acc.
Gui et al. (2019)	0.900	0.901	0.900	0.900
Lin et al. (2020)	0.903	0.870	0.886	0.884
Zogan et al. (2021)	0.909	0.904	0.912	0.901
HAN$_{ours}$-Avg$_{D1-D5}$	0.975	0.969	**0.972**	**0.971**
D1	0.981	0.965	0.973	0.973
D2	0.988	0.956	0.972	0.971
D3	0.972	0.972	0.972	0.971
D4	0.968	0.970	0.969	0.968
D5	0.964	0.981	0.972	0.971

Table 2: Depression detection results. Our model result is averaged over the five testing sets (D1-D5).

Model	F1 on MDL-validation						F1 on IMDL-validation					
	D1	D2	D3	D4	D5	Avg	D1	D2	D3	D4	D5	Avg
HAN	0.985	0.960	0.971	0.976	0.975	**0.973**	0.939	0.911	0.933	0.927	0.931	**0.928**
HAN-MCM	0.972	0.947	0.963	0.967	0.962	**0.962**	0.914	0.897	0.914	0.905	0.918	**0.909**
Δ	0.013	0.013	0.008	0.009	0.013	**0.011**	0.025	0.014	0.019	0.022	0.014	**0.019**

Table 3: Ablation study results on validation sets, measured by F1 score. Δ is defined by $F1_{\text{HAN}} - F1_{\text{HAN-MCM}}$.

# of HAN layers	1	2	4	8
MDL D1 validation	0.542	**0.985**	0.983	0.979

Table 4: F1 scores for different numbers of encoder layers.

	LSTM	BiLSTM	GRU	BiGRU	TF-first	HAN-TF	HAN
F1 on MDL D1 val. $\uparrow$	0.966	0.965	0.961	0.959	0.898	0.976	**0.985**
# of param. per layer $\downarrow$	4.72M	9.45M	3.54M	7.09M	3.55M	4.14M	**1.18M**

Table 5: Comparison results of different encoder layers. $\uparrow$ denotes that the higher the value is, the better the model is. $\downarrow$ denotes that the lower the value is, the better the model is.

End