# Empathetic Dialogue Generation via Sensitive Emotion Recognition and Sensible Knowledge Selection

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code: https://github.com/wlr737/EMNLP2022-SEEK

2022.11.26 • ChongQing

**2022\_EMNLP** 











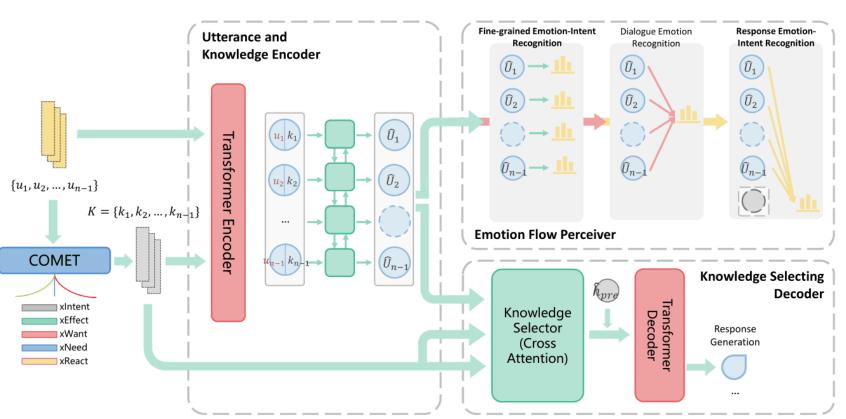


Figure 2: An overall architecture of our proposed model.

Task Formulation

$$C = [C_1, ..., C_{N-1}]$$

$$oldsymbol{EI} = [oldsymbol{ei}_1,...,oldsymbol{ei}_{N-1},oldsymbol{ei}_Y]$$

### Utterance and Knowledge Encoder

**Utterance Encoding** 

$$C_i = [w_{CLS}, w_1, w_2, ..., w_{L_i}]$$

$$\boldsymbol{H}_{U_i} = \mathbf{TRS}_{Enc}(EMB_{C_i}), \tag{1}$$

$$\boldsymbol{U}_i = \boldsymbol{H}_{U_i}[0]. \tag{2}$$

Knowledge Encoding

$$\mathbf{H}_{K_i} = \mathbf{TRS}_{Enc}(\mathbf{K}_i) 
\mathbf{K}_i = \mathbf{Mean}(\mathbf{H}_{K_i})$$
(3)

### **CEM:** Commonsense-aware Empathetic Response Generation

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Code and dataset are available at https://github.com/Sahandfer/CEM











Reported by Yabo Yin

happy entertained

excited

- satisfied - relaxed

buy a ticket
 go to the theater

- go to theater - to buy a ticket - to go to the theater

buys a ticket
 goes to theater

goes to the theater gets bored none

+ <xReact>

+ <xIntent>

+ <xNeed>

+ <xEffect>

+ <xWant>

COMET

#### a movie Method As a result, PersonX feels see Eric wants to Effects on PersonX As a result, PersonX wants PersonX then Emotion Classification Affection-Refined Context Encoder Encoder Knowledge Response Concat Context C Response R Selector Generator Knowledge Cognition-Refined Acquisition Encoder Generate 5 commonsense Calculate average of hidden Append relation token inferences for each relation representations for all tokens

Affective

Encoder

Cognitive

Encoder

Get CLS hidden representation

Figure 2: Overview of our model (CEM).

xReact sentences

xIntent sentences

xNeed sentences

xEffect sentences

xWant sentences

$$D = [u_1, u_2, u_3, ..., u_{k-1}]$$

$$u_i = [w_1^i, w_2^i, w_3^i, ..., w_{M_i}^i]$$

### **Context Encoding**

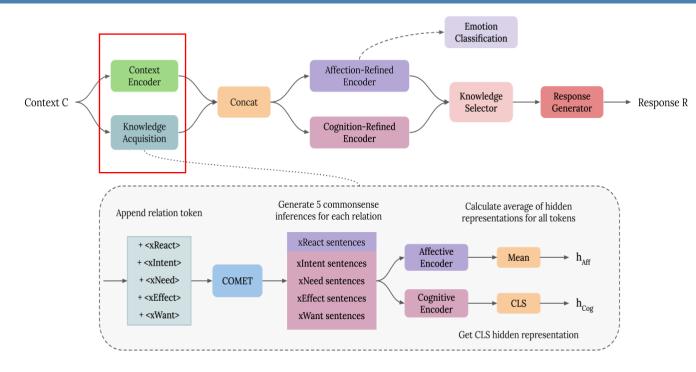
$$C = \texttt{[CLS]} \oplus u_1 \oplus u_2 \oplus u_3 \oplus ... \oplus u_{k-1}$$

$$oldsymbol{H}_{CTX} = \mathbf{Enc}_{CTX}(oldsymbol{E}_C) \quad oldsymbol{H}_{CTX} \in \mathbb{R}^{L imes d}$$

### **Knowledge Acquisition**

use COMET to generate five commonsense inferences  $[cs_1^r, cs_2^r, ..., cs_5^r]$  per relation r.

$$CS_r = cs_1^r \oplus cs_2^r \oplus ... \oplus cs_5^r.$$



$$\boldsymbol{H}_{xReact} = \mathbf{Enc}_{Aff}(\boldsymbol{E}_{CS_{xReact}}) \tag{2}$$

$$\boldsymbol{H}_r = \mathbf{Enc}_{Coq}(\boldsymbol{E}_{CS_r}) \tag{3}$$

 $oldsymbol{H}_{xReact} \in \mathbb{R}^{l_{xReact} \times d}, oldsymbol{H}_r \in \mathbb{R}^{l_r \times d}, \\ r \in \{xWant, xNeed, xIntent, xEffect\}.$ 

$$\boldsymbol{h}_{xReact} = \text{Average}(\boldsymbol{H}_{xReact})$$
 (4)

$$\boldsymbol{h}_r = \boldsymbol{H}_r[0] \tag{5}$$

$$h_{xReact}, h_r \in \mathbb{R}^d$$
.

## **COSMIC: COmmonSense knowledge for eMotion Identification in Conversations**

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**—EMNLP2020** 











Figure 2: Illustration of COSMIC framework. *CSK*: Commonsense knowledge from COMET. In practice we use Bidirectional GRU cells. However, for clarity unidirectional cells are shown in the sketch.



we take the pretrained COMET model on ATOMIC knowledge graph and discard the phrase generating decoder module. We treat utterance U as the subject

核心:为一个句子和对应的5种关系通过Comet的Encoder <sub>k,r</sub> 来获取5个不同的向量表示.并拼接到句子向量上

$$q_{s(u_t),t} = GRU_Q(q_{s(u_t),t-1}, (a_t \oplus \mathcal{ES}_{cs}(u_t)))$$
(3)

$$q_{j,t} = GRU_Q(q_{j,t-1}, (a_t \oplus \mathcal{EL}_{cs}(u_t))); \forall j \neq s(u_t)$$
(4)

$$r_{s(u_t),t} = GRU_R(r_{s(u_t),t-1}, (a_t \oplus x_t \oplus \mathcal{RS}_{cs}(u_t)))$$
(5)

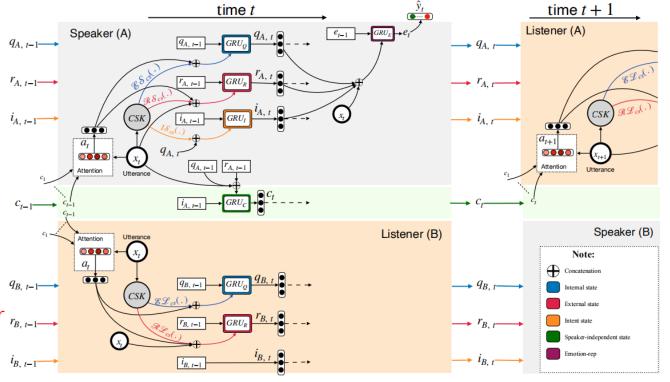


Figure 2: Illustration of COSMIC framework. *CSK*: Commonsense knowledge from COMET. In practice we use Bidirectional GRU cells. However, for clarity unidirectional cells are shown in the sketch.

$$r_{j,t} = GRU_R(r_{j,t-1}, (a_t \oplus x_t \oplus \mathcal{RL}_{cs}(u_t)));$$

$$\forall j \neq s(u_t)$$

$$(6)$$

$$i_{s(u_t),t} = GRU_I(i_{s(u_t),t-1}, (\mathcal{IS}_{cs}(u_t) \oplus q_{s(u_t),t}))$$
(7)

### Topic-Driven and Knowledge-Aware Transformer for Dialogue Emotion Detection

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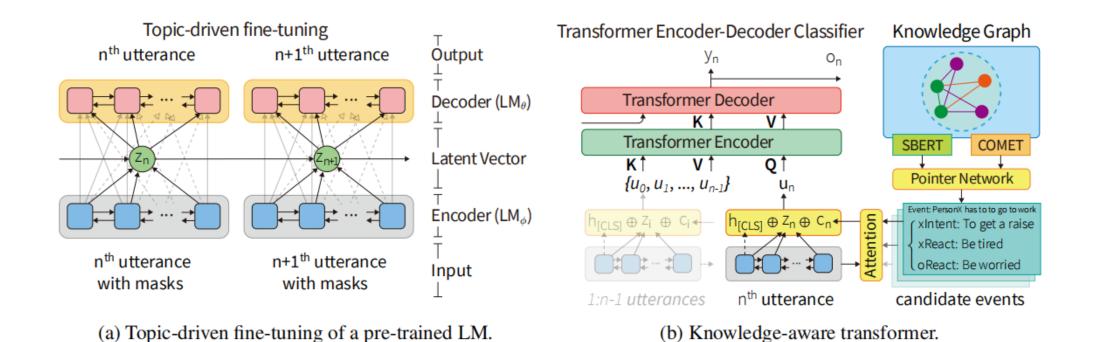


Figure 2: TOpic-Driven and Knowledge-Aware Transformer (TODKAT).



tuned language model. We use COMET to generate the K most likely events, each with respect to the three event relation types. The produced events are denoted as  $\{g_{n,k}^{sI}, g_{n,k}^{sR}, g_{n,k}^{oR}\}, k = 1, \ldots, K$ .

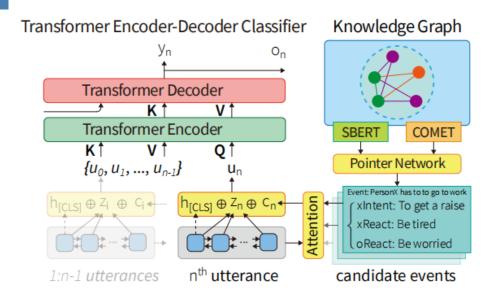
核心:从Comet生成的句子要与原始的Utterance 进行相关性计算充当注意力权重,从而聚合出一个Cn,再将二者拼接起来,进行encode

$$v_k = \tanh([\boldsymbol{c}_{n,k}, z_{n,k}] \mathbf{W}_{\alpha}),$$
 (9)

$$\alpha_k = \frac{\exp(v_k[z_n, u_n]^\top)}{\sum_k \exp(v_k[z_n, u_n]^\top)}, \quad (10)$$

$$\boldsymbol{c}_n = \sum_{k=1}^K \alpha_k \boldsymbol{c}_{n,k}.$$
 (11)

Here, we abuse  $c_n$  to represent the aggregated knowledge phrases. We further aggregate  $c_n$  by event relation types using a self-attention and the final event representation is denoted as  $c_n$ .



(b) Knowledge-aware transformer.

edge-Aware Transformer (TODKAT).

### Past, Present, and Future: Conversational Emotion Recognition through Structural Modeling of Psychological Knowledge

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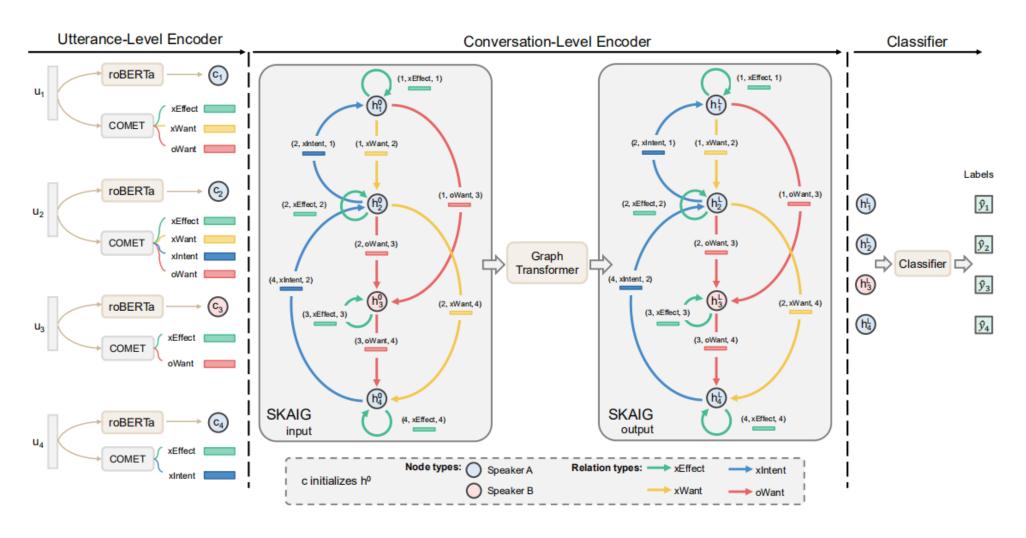


Figure 2: The framework of our model. The utterances are encoded by the utterance-level encoder to produce the utterance representations and the edge representations. The conversation-level encoder processes the SKAIG whose window size is 1. Finally, the classifier predicts the emotion for every utterance. Especially, edges and their representations with different relations are in different colors.

核心: 自己自定义节点之间的关系,关系的表征使用Comet进行学习关系的representation

We concatenate  $u_n$  and a relation with mask tokens (e.g.  $u_n$  [MASK] <xWant>) in the inputting format of COMET, and then COMET processes the input. Following Ghosal et al. (2020), we take the hidden state of the relation token from the last layer of COMET transformer encoder as the relation's representation. For an edge

- 1,不同speaker之间的utterances关系被定义为Owant
- 2,speaker的自环被定义为Oeffect
- 3,同一speaker的不同utterances,当前一个utterance指向后一个utterance时被定义为Xwant
- 4,同一speaker的不同utterances,后一个utterance指向当前一个utterance时 被定义为Xintent

coder as the relation's representation. For an edge  $e_{i,j} = (u_i, xWant, u_j)$ , the corresponding representation is  $a_{i,j}$ , whose dimension is mapped from 768 to  $d_u$  with a following linear unit.

We update the node representation  $h_i^{(l)} \in \mathbb{R}^{d_u}$  of each node  $u_i \in \mathcal{V}$  by:

$$h_i^{(l+1)} = (1 - \beta_i) \left( \sum_{j \in \mathcal{N}(i)} \alpha_{i,j} m_j \right) + \beta_i W_s h_i^{(l)}$$

Eq3利用节点特征和边的特征进行聚合操作,丰富节点的特征表示

