

Motivations

- Information from the **conversational context** is essential to ensure an accurate understanding of emotions in a dialog between humans.
- There already exist models that perform **Emotion Recognition in Conversation** (ERC), but they often consist in intricate architectures that require high computing power.

We propose a **lightweight yet efficient model based on contrastive learning** to perform ERC

Research Questions

- RQ1:** How to use the information from the conversational context to guide ERC?
- RQ2:** Does taking into account the conversational context help to improve ERC in dyadic dialogues?

Approach - the Training Procedure

(1) builds contextual utterance representations by deploying attention, (2) specifies contextual information for emotion prediction and (3) performs prediction on utterance triplets (A, P, N) where A and P are from the same class and N is from another one.

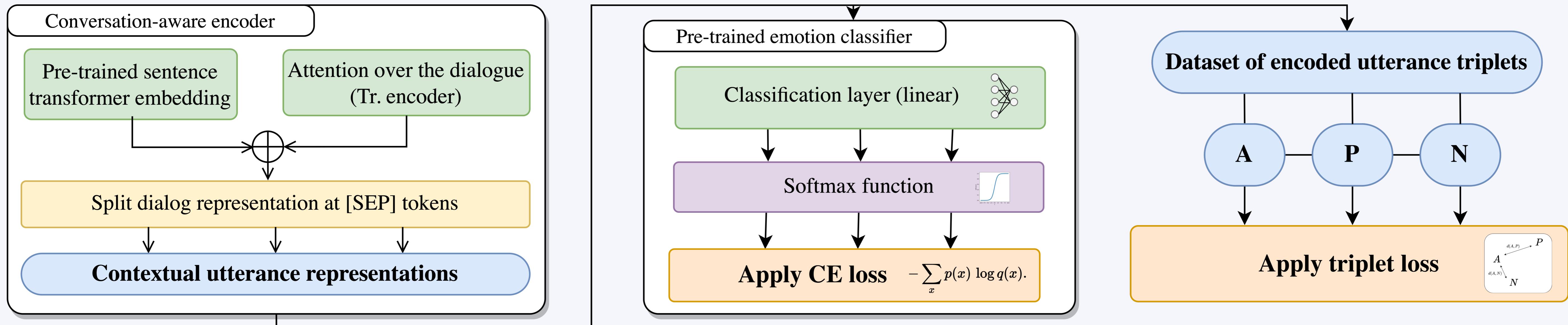


Figure 1: Training procedure for conversation-aware emotion predictions. Both losses (CE and triplet) backpropagate to train the encoder.

Experimental Setup

The DailyDialog dataset (Li et al., 2017)

- 13,118 dyadic dialogues in English about daily life concerns
- Utterance-wise** emotion annotation (no emotion, happiness, anger, disgust, fear, surprise, sadness)

Metric learning with Siamese Networks (Koch et al., 2015)

- Flexible classification framework: learns **relations between labels**, adapts to unseen classes
- Intrinsic adaptation to few-shot learning to learn little-represented emotions
- Weight updates using **triplet loss** help mitigate **class imbalance** issue

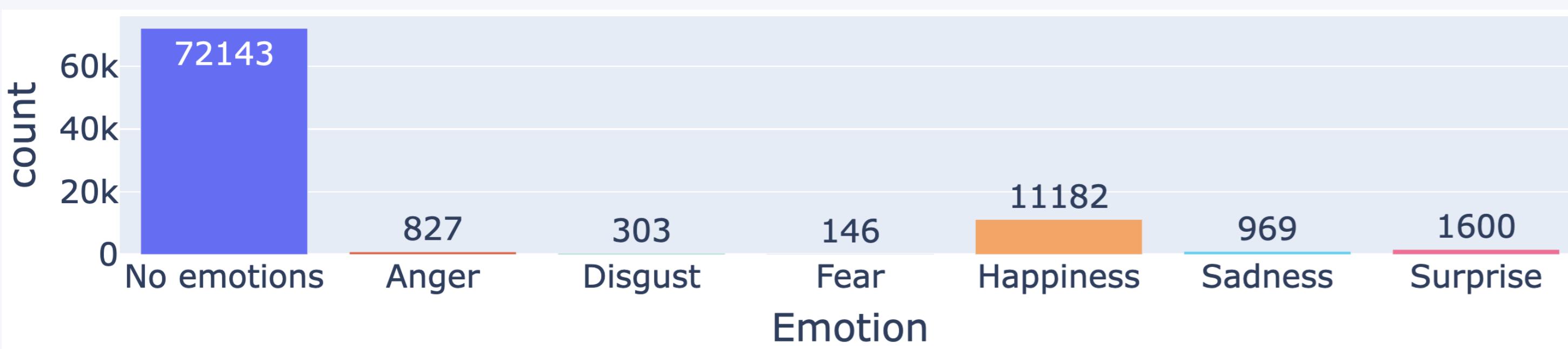


Figure 2: Label distribution in DailyDialog training set.

Evaluation metrics in addition to microF1

- Macro F1:** more demanding metric that favors versatile emotion recognition
- MCC (Matthews Correlation Coefficient):** correlation coefficient between actual and predicted samples for a given class

Results

Model name	macro F1*	micro F1*	MCC
<i>State-of-the-art models on ERC</i>			
CNN+cLSTM (Poria et al., 2017)	–	50.24	–
KET (Zhong et al., 2019)	–	53.37	–
COSMIC (Ghosal et al., 2020)	51.05	58.48	–
RoBERTa (Ghosal et al., 2020)	48.20	55.16	–
Rpe-RGAT (Ishiwatari et al., 2020)	–	54.31	–
Glove-DRNN (Ghosal et al., 2021)	41.8	55.95	–
roBERTa-DRNN (Ghosal et al., 2021)	49.65	57.32	–
CNN (Ghosal et al., 2021)	36.87	50.32	–
DAG-ERC (Shen et al., 2021)	–	59.33	–
TODKAT (Zhu et al., 2021)	52.56	58.47	–
SKAIG (Li et al., 2021)	51.95	59.75	–
Sentic GAT (Tu et al., 2022)	–	54.45	–
CauAIN (Zhao et al., 2022)	–	58.21	–
DialogueRole (Ong et al., 2022)	–	60.95	–
S+PAGE (Liang et al., 2022)	–	64.07	–
DualGAT (Zhang et al., 2023)	–	61.84	–
CD-ERC (Pereira et al., 2023)	51.23	–	–
MCM-CSD (Xu and Yang, 2024)	–	60.70	–
<i>Ours</i>			
SentEmoContext	57.71	57.75	0.49

Table 1: All results for ERC on DailyDialog. * indicates metrics do not include neutral label.

Comparison with Large Language Models (LLMs)

Model name	macro F1*	micro F1*	MCC
llama2-7b-chat-hf	9.70	24.92	0.08
llama2-13b-chat-hf	22.26	43.37	0.15
falcon-7b-instruct	07.54	42.75	0.01
<i>Ours</i>			
SentEmoContext	57.71	57.75	0.49

- The tested LLMs performed poorly in zero-shot emotion prediction, while being far bigger than SentEmoContext
- Finding the right prompting strategy is challenging
- The MCC values suggest that the emotion predictions are close to random in that case: the task is not well understood in such setting

Take Home Messages

- We propose a novel metric-based approach to perform emotion recognition in conversation
- SentEmoContext is state-of-the-art in Macro F1, and consists in a versatile and efficient emotion prediction
- Incorporating context information leads to instability issues because of noise propagation

