



Contrast and Generation Make BART a Good Dialogue Emotion Recognizer

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<https://github.com/whatissimondoining/CoG-BART>.

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Experiments

Dataset	MELD		EmoryNLP		IEMOCAP		DailyDialog	
Model	Weighted -Avg-F1	Micro-F1	Weighted -Avg-F1	Micro-F1	Weighted -Avg-F1	Micro-F1	Weighted -F1-neutral	Micro -F1-neutral
BERT	62.28	63.49	34.87	41.11	60.98	-	53.41	54.85
RoBERTa	62.51	63.75	35.90	40.81	63.38	-	52.84	54.33
HiTrans	61.94	-	36.75	-	64.50	-	-	-
DialogXL	62.41	-	34.73	-	65.94	-	-	54.93
XLNet	61.65	-	34.13	-	61.33	-	-	53.62
BART-large	63.57	64.41	35.98	38.93	56.14	56.67	54.83	55.34
CoG-BART	64.81 (± 0.19)	65.95 (± 0.44)	39.04 (± 0.10)	42.58 (± 0.94)	66.18 (± 0.45)	66.71 (± 0.49)	56.09 (± 0.01)	56.29 (± 0.17)

Table 2: The overall results of CoG-BART with pre-train-based baseline models on four datasets.



Speaker-Guided Encoder-Decoder Framework for Emotion Recognition in Conversation

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Experiments

Dataset	Conversations			Utterances		
	Train	Val	Test	Train	Val	Test
IEMOCAP	120		31	5810		1623
MELD	1038	114	280	9989	1109	2610
EmoryNLP	713	99	85	9934	1344	1328

Table 1: The statistics of three datasets.

Model	MELD	EmoryNLP	IEMOCAP
KET	58.18	33.95	59.56
COSMIC	65.21	38.11	65.28
DialogueRNN + RoBERTa	57.03 63.61	- 37.44	62.75 64.76
DialogueCRN + RoBERTa	58.39 63.42	- 38.91	66.20 66.46
RoBERTa	62.88	37.78	63.38
SGED + RoBERTa	63.34	38.47	64.11
bc-LSTM+att + RoBERTa	- 62.95	- 38.28	- 64.51
SGED + bc-LSTM+att	63.37	38.89	65.03
DialogueGCN + RoBERTa	58.10 63.02	- 38.10	64.18 64.91
SGED + DialogueGCN	64.55	39.73	65.90
DAG-ERC	63.65	39.02	68.03
DAG-ERC*	63.39	38.84	67.45
SGED + DAG-ERC*	65.46	40.24	68.53

Table 2: Overall performance on the three datasets. We choose weighted-average F1 to evaluate each method. DAG-ERC* means that we use the one-layer DAG-ERC.



Supervised Prototypical Contrastive Learning for Emotion Recognition in Conversation

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<https://github.com/caskcsg/SPCL>



Experiment

Models	IEMOCAP	MELD	EmoryNLP
COSMIC(Ghosal et al., 2020)	65.28	65.21	38.11
DialogueCRN (Hu et al., 2021)	66.46	63.42	38.91
DAG-ERC (Shen et al., 2021)	68.03	63.65	39.02
TODKAT (Zhu et al., 2021)	61.33	65.47	38.69
Cog-BART (Li et al., 2021)	66.18	64.81	39.04
TUCORE-GCN_RoBERTa(Lee and Choi, 2021)	-	65.36	39.24
SGED + DAG-ERC(Bao et al., 2022)	68.53	65.46	40.24
EmotonFlow-Large (Song et al., 2022)	-	66.50	-
CoMPM (Lee and Lee, 2021)	69.46	66.52	38.93
SPCL-CL-ERC(Ours)	69.74	67.25	40.94

Table 1: Performance comparisons on three datasets.



Mutual Conversational Detachment Network for Emotion Recognition in Multi-Party Conversations

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Code: <https://github.com/circle-hit/MuCDN>

Experiment

Model	EmoryNLP	MELD
ERMC Methods		
ConGCN	-	57.40
DialogXL	34.73	62.41
ERMC-DisGCN	36.38	64.22
ERC Methods with CSK		
KET	34.39	58.18
KAITML	35.59	58.97
KI-Net	-	63.24
SKAIG	38.88	65.18
COSMIC	38.11	65.21
COSMIC w/o CSK	37.10	64.28
ERC Methods without CSK		
DialogueRNN	31.7	57.03
DialogueGCN	-	58.1
IEIN	-	60.72
RGAT	34.42	60.91
DialogueCRN	-	58.39
DAG-ERC	39.02	63.65
MuCDN (Ours)	40.09	65.37

Table 2: Comparison of our model against state-of-the-art baselines. CSK represents the commonsense knowledge utilized in COSMIC. Weighted F1 score is adopted as evaluation metrics.

Model	EmoryNLP	MELD
MuCDN	40.09	65.37
w/o explicit detachment	38.45	64.45
w/o implicit detachment	38.84	64.47
w/o E2I interaction	39.28	64.61
w/o I2E interaction	39.54	64.56

Table 3: Results of ablation study on the two ERMC datasets. E2I interaction is the relative position embedding provided by explicit detachment, while I2E interaction is the complementary global information from implicit detachment.



CauAIN: Causal Aware Interaction Network for Emotion Recognition in Conversations

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Code: <https://github.com/circle-hit/CauAIN>

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Experiments

Model	IEMOCAP	DailyDialog		MELD
	weighted-F1	micro-F1	macro-F1	weighted-F1
ICON	58.54	-	-	-
DialogueRNN	62.57	55.95	41.8	57.03
DialogueGCN	64.18	-	-	58.1
IEIN	64.37	-	-	60.72
DialogueCRN	66.2	-	-	58.39
RGAT	65.22	54.31	-	60.91
COSMIC	65.28	58.48	51.05	65.21
DialogXL	65.94	54.93	-	62.41
KI-Net	66.98	57.3	-	63.24
SKAIG	66.96	59.75	51.95	65.18
CauAIN (Ours)	67.61	58.21	53.85	65.46
w/o Inter Cause	64.61	54.23	49.53	62.83
w/o Intra Cause	64.66	55.24	48.7	59.52
w/o Causal Clue	63.77	57.2	51.73	65.2
	66.36	57.59	52.70	64.81

Table 2: Comparison of our model against state-of-the-art baselines. Intra Cause and Inter Cause are the process of intra- and inter cause detection, respectively and Causal Clue refers to causal clue generated from COMET.