



Introduction

1.1 Problem Definition

Conversation disentanglement aims at identifying threads in multi-party conversations. The figure below shows two threads in different colors, with reply-to links between utterances.

- [12:05] <ydnar> for what reason would a dvd not play if i have libdvcss2 installed?
- [12:05] <gourdin> we will we be able to access an edgy repo ?
- [12:05] <Ng> ydnar: what are you using to play it?
- [12:06] <Anfangs> Edgy Eft is the next codename for Ubuntu dapper+1. See <https://ubuntu.com/0064.html>.
- [12:06] <holycow> because it couldn't crack the encoding for the particular portion of the dvde
- [12:06] <ydnar> tried vlc. holycow, do you have any
- [12:06] <gourdin> I don't think the link works

1.2 Limitation of previous methods

- transformer-based models are not systematically compared with respect to performance, memory consumption and speed
- previous methods don't leverage **dialogue history** effectively
- greedy decoding algorithm recovers threads by finding the parent utterance for each utterance of interest (UOI) **independently**

Methodology

2.1 Pairwise Model

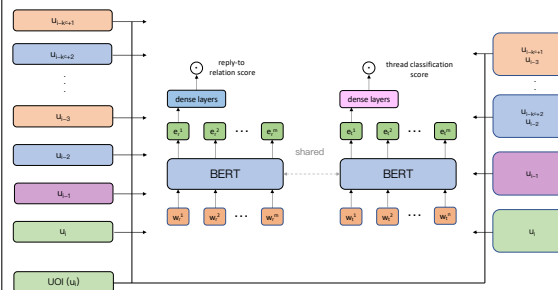
Pairwise models measure the similarity between UOI and each candidate separately. BERT+MF (manual features) is still a strong baseline.

Model	Link Prediction			Ranking			Clustering		
	Precision	Recall	F1	R@1	R@5	R@10	I-1	VI	F
Last Mention	37.1	35.7	36.4	-	-	-	21.4	69.5	4.0
GLOVE+MF	71.5	68.9	70.1	70.2	95.8	98.6	76.1	91.5	34.0
MF	71.1	68.5	69.8	70.2	94.0	97.3	75.0	91.3	31.5
POLY-BATCH	59.3	59.9	58.6	40.8	69.8	80.8	52.9	80.8	9.8
POLY-INLINE	42.2	40.7	41.4	42.8	70.8	81.3	62.0	84.4	13.6
ALBERT	46.1	44.4	45.3	46.8	77.3	88.4	68.6	87.9	22.4
BERT	48.2	46.4	47.3	48.8	75.4	84.7	74.3	89.3	26.3
BERT+FFN	67.9	65.4	66.6	66.9	90.6	95.3	76.9	91.1	34.9
BERT+MF	73.9	71.3	72.6	73.9	95.8	98.6	77.0	92.0	40.9

Model	GPU Mem (GB)	Speed (ins/s)
BERT	18.7	9.4
ALBERT	14.6	9.4
POLY-INLINE	9.9	16.8
POLY-BATCH	5.1	36.4

Poly-encoder is the fastest and most memory efficient model, with a sacrifice of performance.

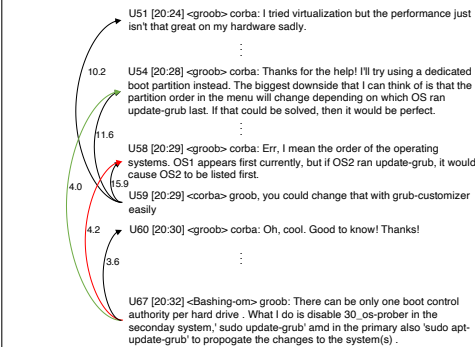
2.2 Context Expansion using Multi-task Learning



Model	Link Prediction			Ranking			Clustering		
	Precision	Recall	F1	R@1	R@5	R@10	I-1	VI	F
BERT	48.2	46.4	47.3	48.8	75.4	84.7	74.3	89.3	26.3
BERT+MF	73.9	71.3	72.6	73.9	95.8	98.6	77.0	92.0	40.9
MULTI ($\alpha = 1$)	65.6	63.2	64.4	66.7	91.8	95.6	64.6	87.7	24.3
MULTI ($\alpha = 5$)	66.9	64.5	65.7	65.4	91.8	95.6	68.7	88.8	27.4
MULTI ($\alpha = 10$)	65.2	62.9	64.0	64.4	91.4	95.6	70.3	89.5	28.1
MULTI ($\alpha = 20$)	64.7	62.4	63.5	63.9	91.0	95.0	68.3	88.8	26.7
MULTI+MF ($\alpha = 1$)	72.8	70.2	71.5	71.9	94.0	96.4	76.3	91.8	36.1
MULTI+MF ($\alpha = 5$)	73.3	70.7	72.0	72.4	94.0	96.5	72.8	90.8	33.1
MULTI+MF ($\alpha = 10$)	72.2	69.6	70.8	70.4	93.4	96.4	71.8	90.2	29.9
MULTI+MF ($\alpha = 20$)	70.8	68.2	69.5	69.4	93.4	97.3	73.2	90.6	28.6

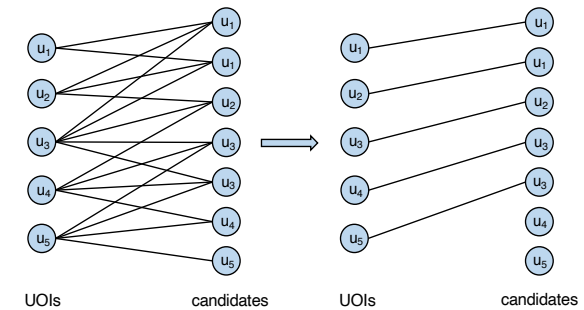
We conduct utterance-to-utterance and utterance-to-thread classification at the same time, which outperforms pairwise models when manual features are unavailable.

2.3 Bipartite Graph Matching for Conversation Disentanglement



U₆₇ chooses U₅₄ as parent in global decoding algorithm but chooses U₅₈ in greedy algorithm.

Bipartite matching-based algorithm recovers threads by identifying the parent utterance of a set of UOIs jointly.



	Precision	Recall	F1
Oracle	88.4	85.2	86.8
Rule-Based	73.7	70.9	72.3
FFN	73.8	71.0	72.3
BERT+FFN	72.9	70.3	71.5

We frame conversation disentanglement as a **maximum-weight bipartite matching** problem. It has the potential to outperform greedy approaches.

Conclusion

- BERT combined with manual features is still a strong baseline for conversation disentanglement
- The multi-task learning framework that conducts utterance-to-utterance and utterance-to-thread classification at the same time outperforms pairwise models when manual features are not available
- Bipartite graph matching-based conversation disentanglement shows potential to outperform greedy approaches.