DFKI-MLST at DialAM-2024 Shared Task

Arne Binder[1*], Tatiana Anikina[2*], Leonhard Hennig[1], Simon Ostermann[2]

[1] SLT department, DFKI Berlin, [2] MLT department, DFKI Saarbrücken, Germany

The DialAM-2024 Shared Task is about **dialogue argument mining**. It focuses on the **relation extraction** (RE) part using the Inference Anchoring Theory (IAT) to represent the data. DialAM subtasks require detection of:

- **argumentative (ARI) relations**: *Inference*, *Conflict*, *Rephrase*
- **illocutionary (ILO) relations**: *Asserting*, *Agreeing*, etc.

DialAM Data

Inference Anchoring Theory (IAT) uses a bipartite-like representation to model argumentative and dialogue-related information in a single framework.

Propositions (I-nodes, left side) are linked by **argumentative relations** (S-nodes, left side) and both are anchored in **dialogue** (right side) by **illocutionary relations** (YA-nodes, center).

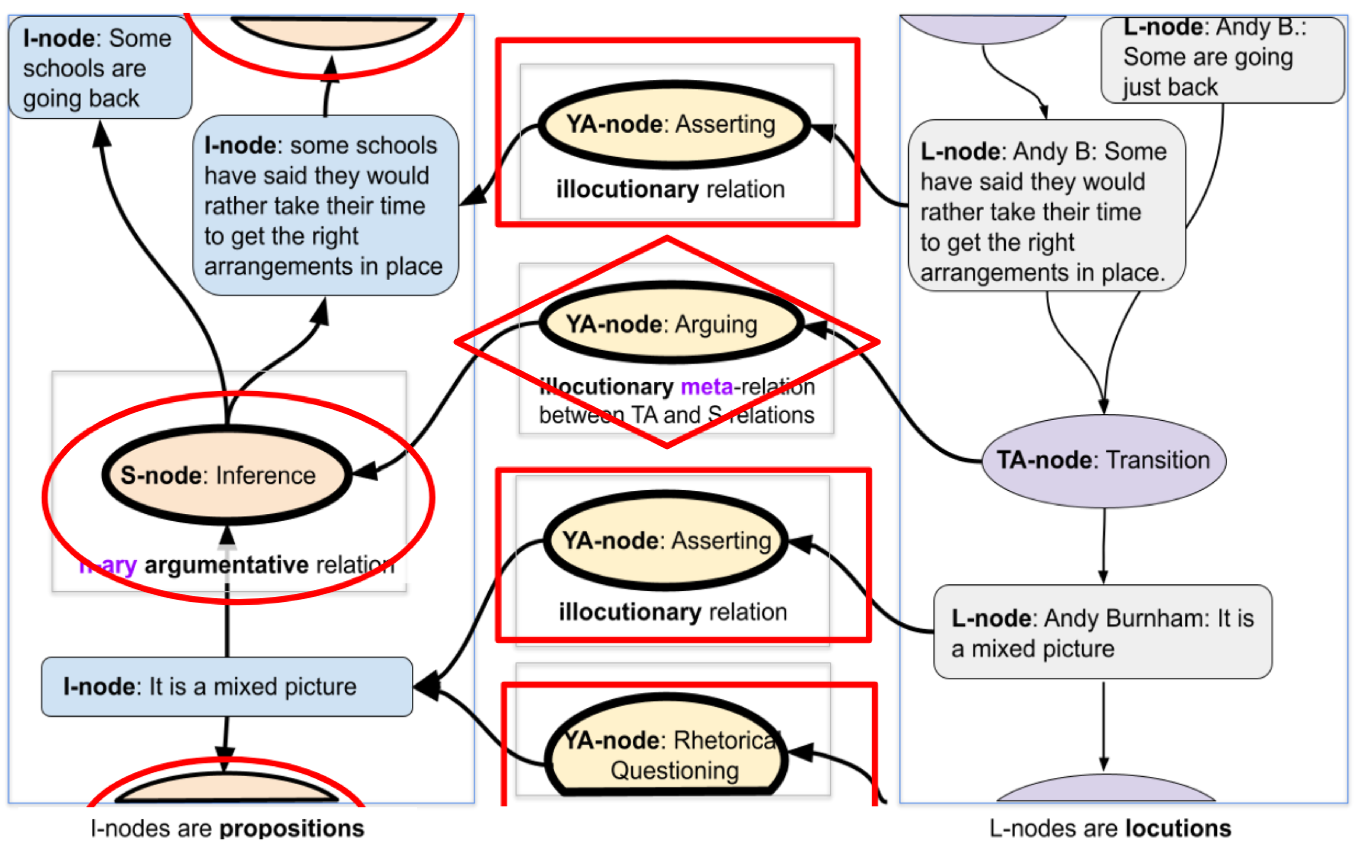

Figure 1: The DialAM 2024 shared task requires identification as well as classification of (1) argumentative S node relations (ARI; ⬭) and (2) illocutionary YA node relations (ILO; ▭ and ◇), see bold circles and arrows.

DialAM Challenges

- **Meta-relations:** some illocutionary relations (YA-nodes) **anchor argumentative relations** (S-nodes) in dialogue.
- **N-ary relation** type of the argumentative relation *Inference* (S-node) since it can have **multiple output nodes**.
- The **direction of argumentative relations** labeled as *Inference* may not follow the direction of dialogue flow.

Our Approach

We train a **single model for both subtasks** by framing them as **n-ary relation extraction on the locution nodes** (L-nodes):

1. Construct relation **candidate tuples** for all relation categories, i.e., ▭, ⬭, and ◇ (see right side).
2. Encode candidate tuples as **contiguous text**:
   1. **Serialize the locution nodes** along the dialogue flow.
   2. **Encode each candidate tuple**: Mark the respective locution node texts with special tokens (see right side).
3. Pass the annotated texts to a **BERT-like model with a linear classification head** (e.g. *DeBERTa-v3*).
4. During training: Assign **gold labels** by matching candidate tuples with gold tuples or use *NONE* if this is not possible.

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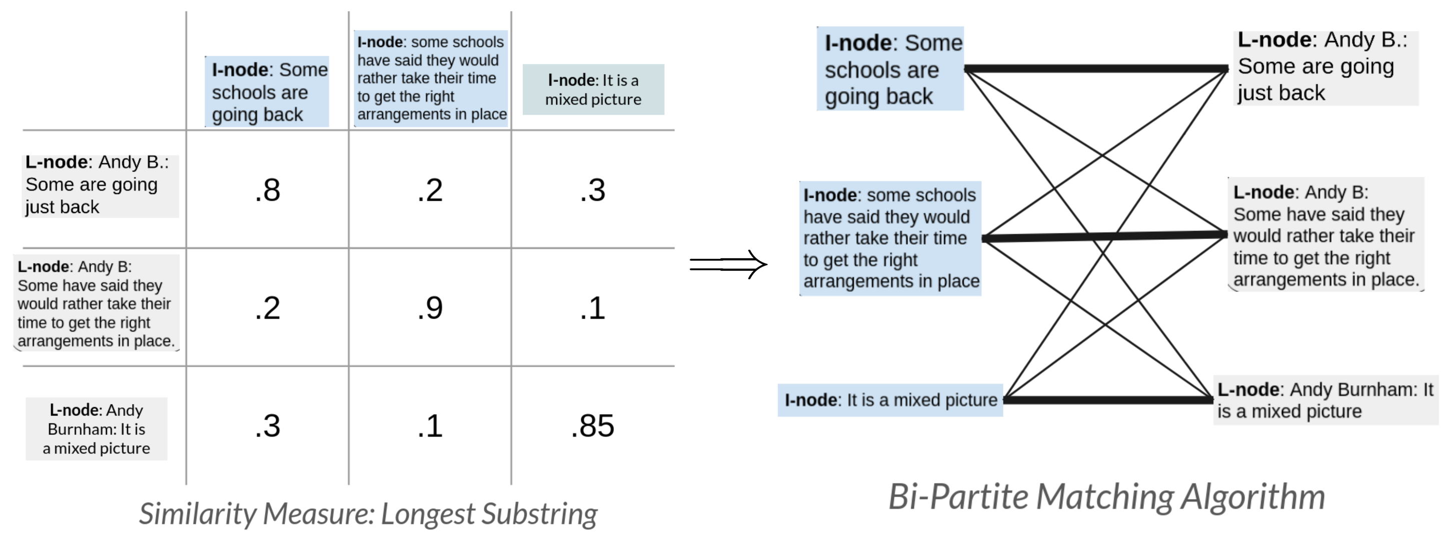
Candidate Tuple Construction

We construct relation argument **tuples consisting of nodes with roles** (arc directions, i.e., *incoming* or *outgoing*) for all relation categories.

▭ **Illocutionary YA-relations (L-node → I-node):** Construct a **bipartite matching between proposition and locution nodes** based on the longest common substring.



⬭ **Argumentative S-relations:** Use the same matching to **map the dialogue *TA relations*** along their relation arguments.

◇ **Illocutionary YA-relations (TA-node → S-node):** Connect the new **argumentative *S-relations* with the dialogue *TA relations*** from which they originate in the previous step.

Encoding Candidate Tuples

We encode the candidate tuples by marking the respective L-node (locution) texts with special tokens: **<{relation category}:{argument role}>**, e.g., **<illo–ta–s:in>**. We determine the L-nodes and roles as follows:

▭ **Illocutionary YA-relations (L-node → I-node)**: Unary relation with the anchoring L-node as the only argument.

⬭ **Argumentative S-relations**: N-ary relation with the L-nodes that anchor its arguments.

◇ **Illocutionary YA-relations (TA-node → S-node)**: N-ary relation with the arguments of the anchoring TA-node.

Some text before.</S><illo-ta-s:in>Andy B.: Some are going just back</illo-ta-s:in>
</S><illo-ta-s:in>Andy B.: Some have said [...] to get the right arrangements in place.
</illo-ta-s:in></S><illo-ta-s:out>Andy B.: It is a mixed picture.</illo-ta-s:out></S>
Some more text. relation label: *illo-ta-s:Arguing*

Figure 2: Encoding of a candidate tuple for an **illocutionary YA-relation (TA-node → S-node)** with roles ***in**coming* and ***out**going*. Role markers and relation labels are prefixed with the relation category, e.g. *illo-ta-s* for *Illocutionary YA-relations (TA-node → S-node)*, so all three cases are distinct. This results in **20 different relation labels** and **40 relation argument roles**.

Results & Conclusion

Model	ARI		ILO		GLOBAL	
	Focused	*General*	*Focused*	*General*	*Focused*	*General*
baseline	22.80	26.46	**72.09**	45.75	47.45	36.10
best-competitor	**35.89**	46.22	69.95	**81.17**	45.23	63.70
dfki-mlst (ours)	30.40	**55.33**	66.10	78.78	**48.25**	**67.05**

Table 1: Argumentative (ARI), illocutionary (ILO) and combined (GLOBAL) relation detection performance (macro F1).

- We frame the dialogue argument mining task as **n-ary relation classification** over dialogue turns (locutions).
- We apply **data simplification and normalization** to solve the task in a unified manner.
- DFKI-MLST achieves **the best scores** in the global setting of the Shared Task: 48.25 F1 Focused and 67.05 F1 General.