Compositional Semantic Parsing Across Graphbanks

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Research Question

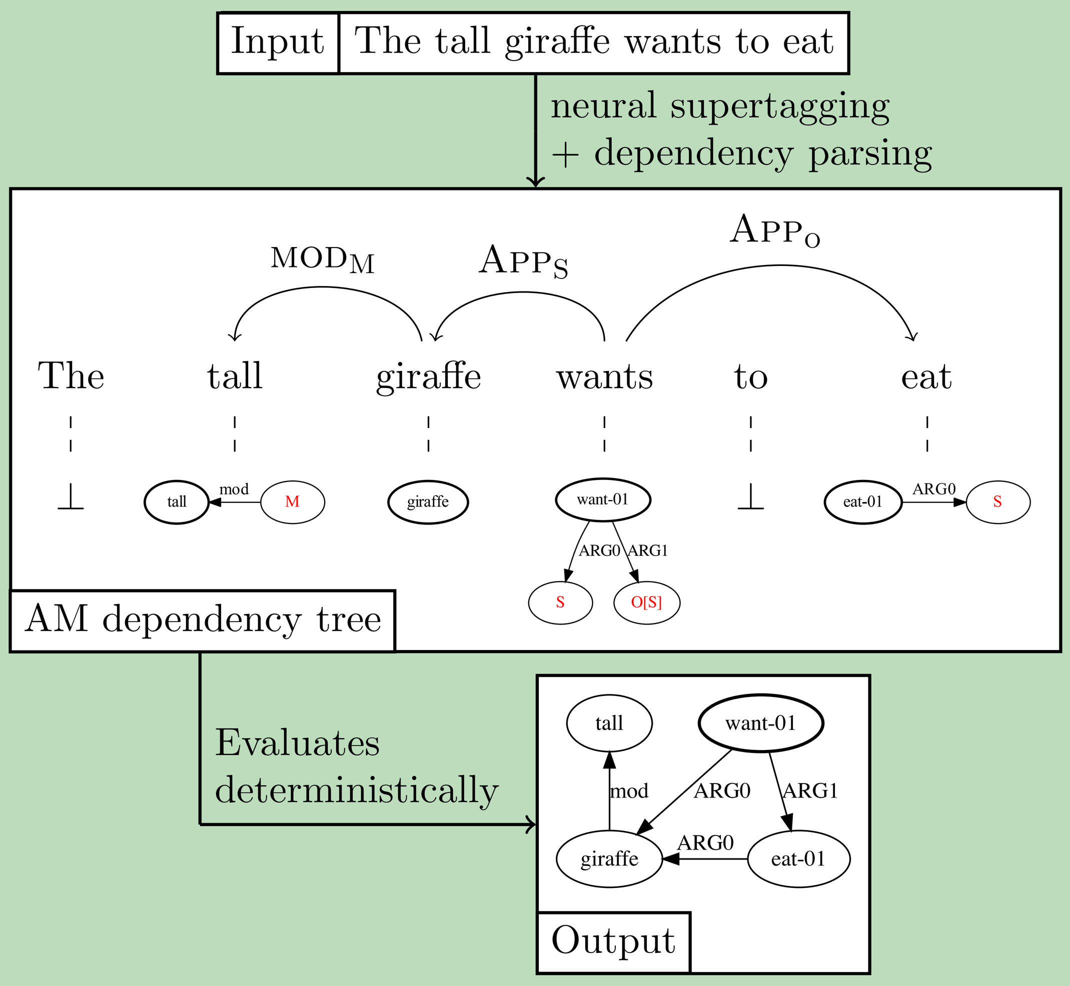
- Groschwitz et al. (2018) introduced *AM dependency parsing* for AMR.
  - → Builds bridge between compositional methods and neural parsing.
  - → Strong parser performance.
- But there are many meaning representations, and so far no parser works for all of them.
- **So, how widely applicable is AM dependency parsing beyond AMR?**

Contribution

- AM dependency parsing achieves competitive results for
  - DM
  - PAS
  - PSD
  - EDS
  - AMR
- With BERT and multi-task learning, we set a new state of the art on most of the datasets.

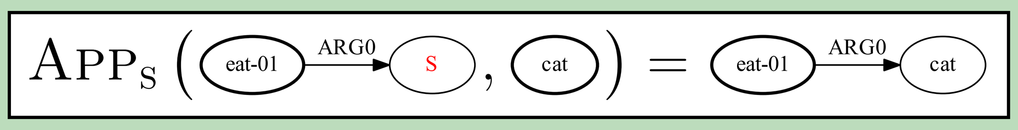
AM dependency parsing

AM dependency parsing (Groschwitz et al. 2018):

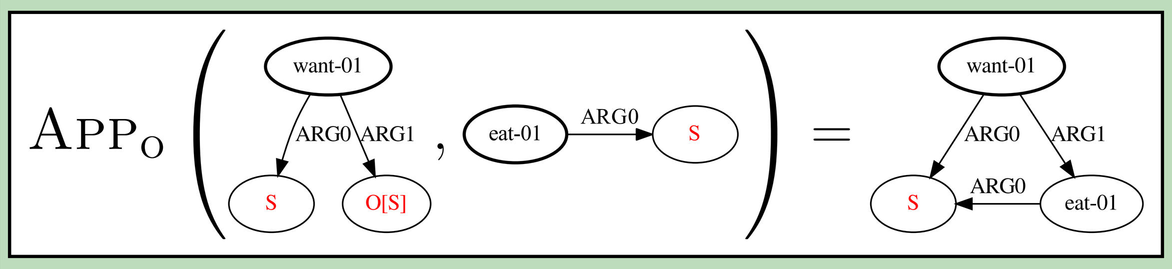


The **AM algebra** (Groschwitz et al. 2017) is a collection of graph-building operations based on

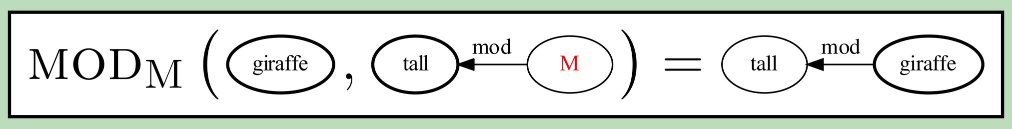
a) argument application (filling 'sources'):



shared sources merge, creating reentrancies:



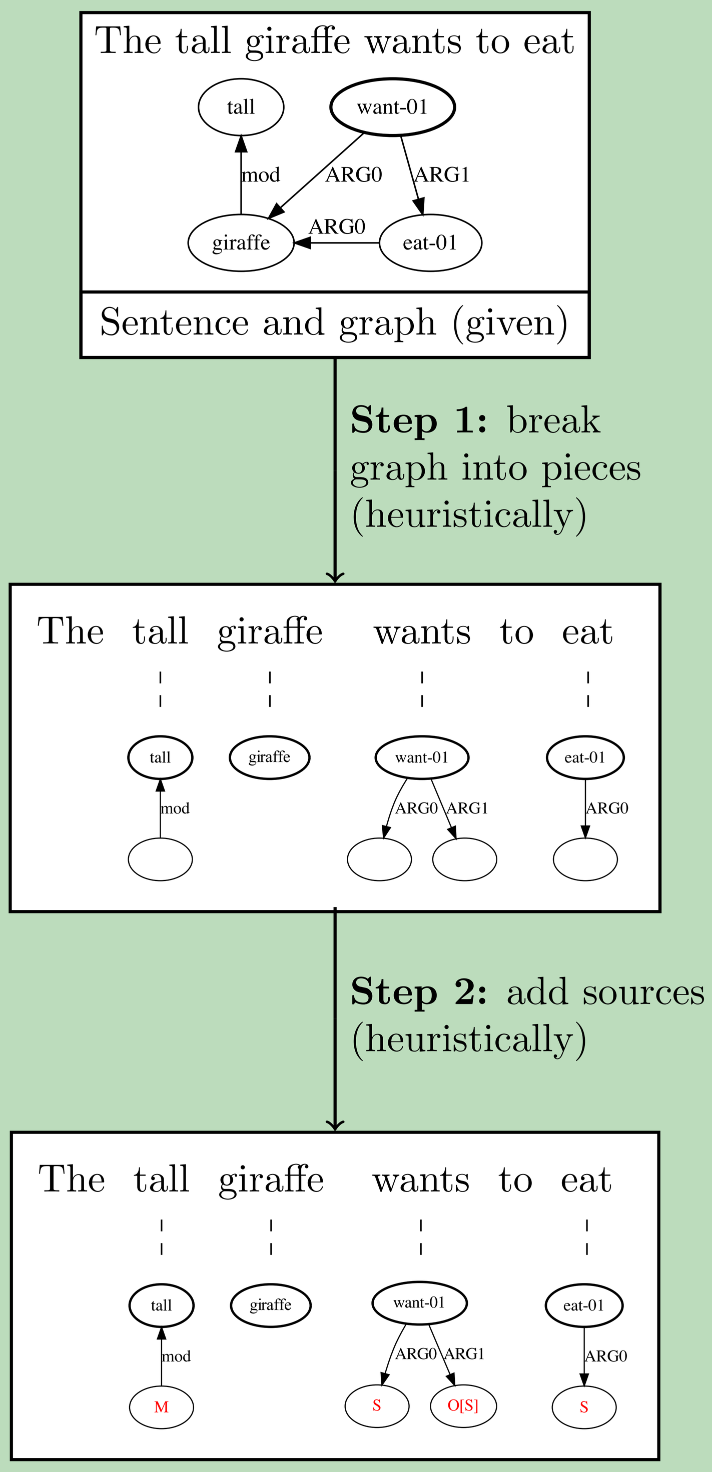
b) modification:



Decomposition

Main challenge: only sentences and graphs are given in the graph banks, but we need the "hidden" AM dependency trees to train our parser.

This is how we did it for AMR:

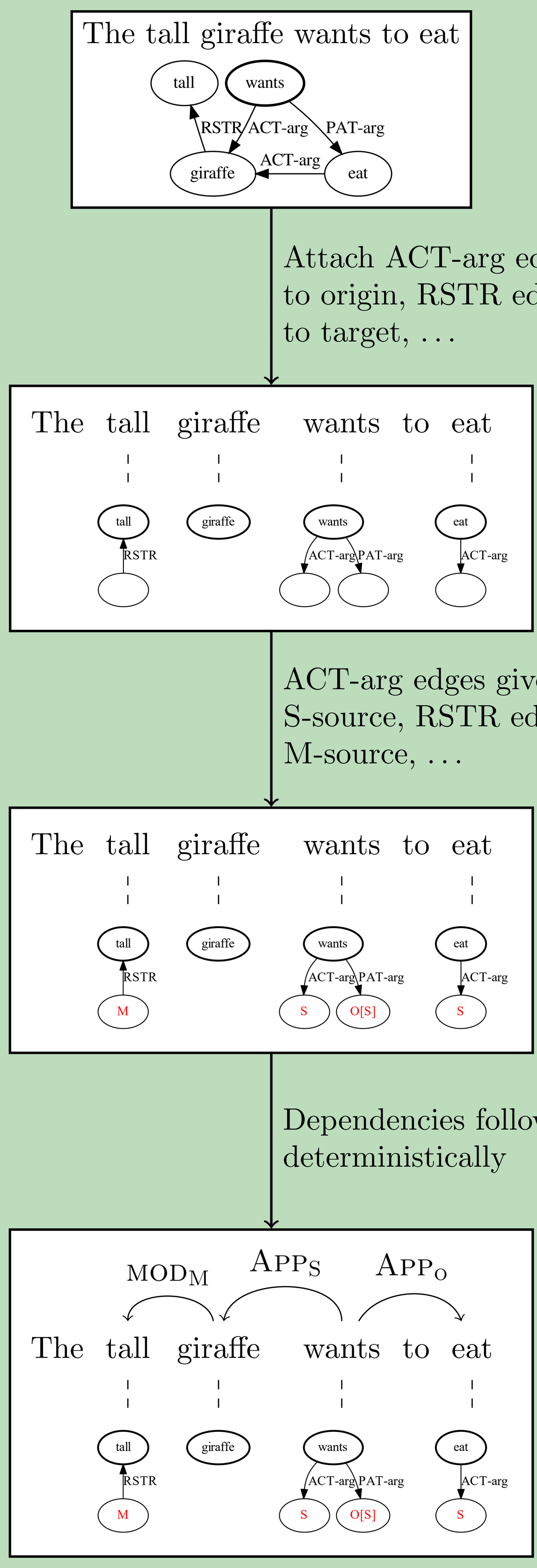


The dependency edges follow deterministically after these two steps.

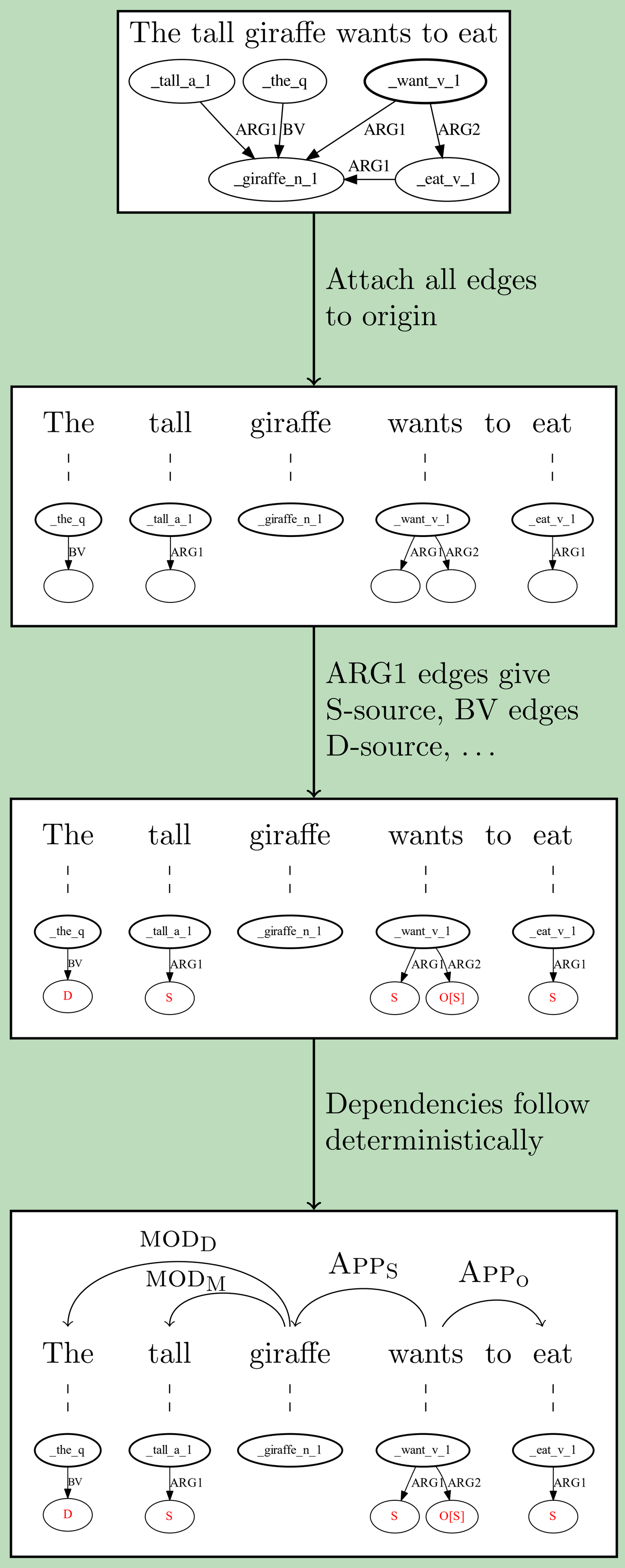
Decomposing DM, PAS, PSD, EDS

Main technical contribution: heuristics for the two decomposition steps for DM, PAS, PSD and EDS.

Example: PSD



Example: EDS



Challenges overcome: coordination, raising, comparatives, ...

One compositional parser.
Diverse semantic graphbanks.
Improved states of the art.

		DM		PAS		PSD		EDS		AMR 2015	AMR 2017
		id F	ood F	id F	ood F	id F	ood F	Smatch F	EDM	Smatch F	Smatch F
Single task	Groschwitz et al. (2018)	-	-	-	-	-	-	-	-	70.2	71.0
	Lyu and Titov (2018)	-	-	-	-	-	-	-	-	73.7	74.4
	Zhang et al. (2019)	-	-	-	-	-	-	-	-	-	**76.3**
	Peng et al. (2017) Basic	89.4	84.5	92.2	88.3	77.6	75.3	-	-	-	-
	Dozat and Manning (2018)	93.7	88.9	94.0	90.8	81.0	79.4	-	-	-	-
	Buys and Blunsom (2017)	-	-	-	-	-	-	85.5	85.9	60.1	-
	Chen et. al (2018)	-	-	-	-	-	-	**90.9**	**90.4**	-	-
	This paper (GloVe)	90.4	84.3	91.4	86.6	78.1	74.5	87.6	82.5	69.2	70.7
	This paper (BERT)	**93.9**	**90.3**	**94.5**	**92.5**	**82.0**	**81.5**	90.1	84.9	**74.3**	75.3
Multi-task learning	Peng et al. (2017) Freda1	90.0	84.9	92.3	88.3	78.1	75.8	-	-	-	-
	Peng et al. (2017) Freda3	90.4	85.3	92.7	89.0	78.5	76.4	-	-	-	-
	This paper (GloVe)	91.2	85.7	92.2	88.0	78.9	76.2	88.2	83.3	(70.4)	71.2
	This paper (BERT)	**94.1**	**90.5**	**94.7**	**92.8**	**82.1**	**81.6**	90.4	85.2	(74.5)	75.3