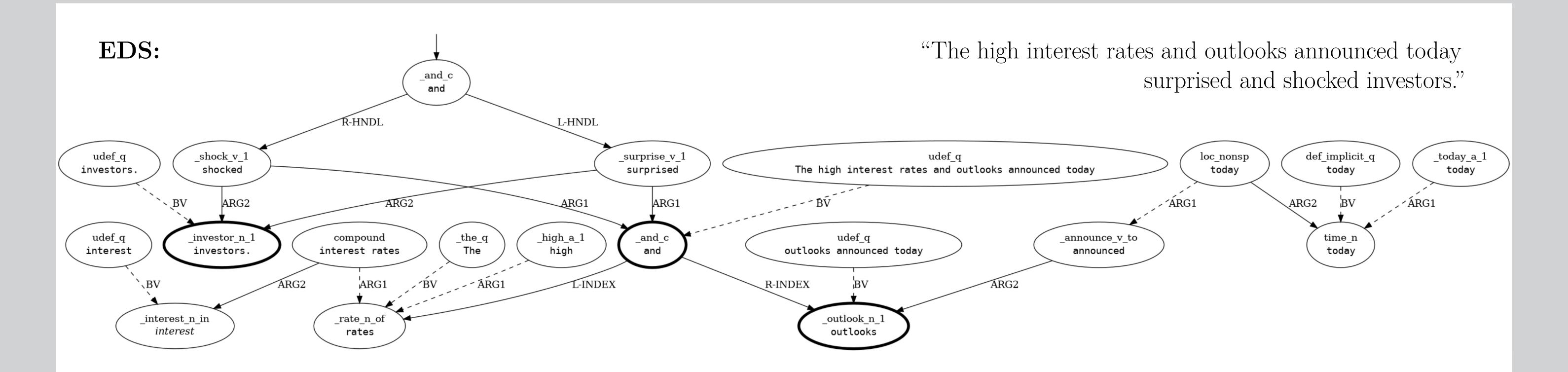


# Argument Sharing in AMR, EDS & PTG

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### Introduction and motivation

In parsing into graph-based meaning representations, the widely accepted wisdom is that parsing accuracy deteriorates with growing structural complexity. However, the *why?* is still not clear.

Previous work shows a discrepancy in parser performance with growing graph complexity, between AMR & PTG vs. EDS.

RQ1: Is this caused by shared arguments and reenrant nodes?

By expanding our understanding of framework design decisions, we can inform future annotation efforts, as well as parser development.

#### Graph structure and reentrancy

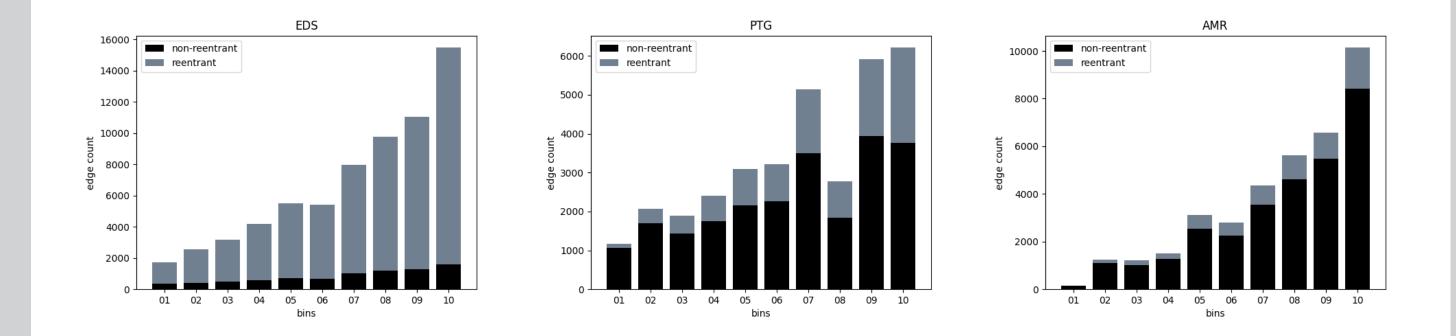
#### Annotation – 3 samples of 150 sentences

RQ2: Is the discrepancy due to the types of reentrancies?

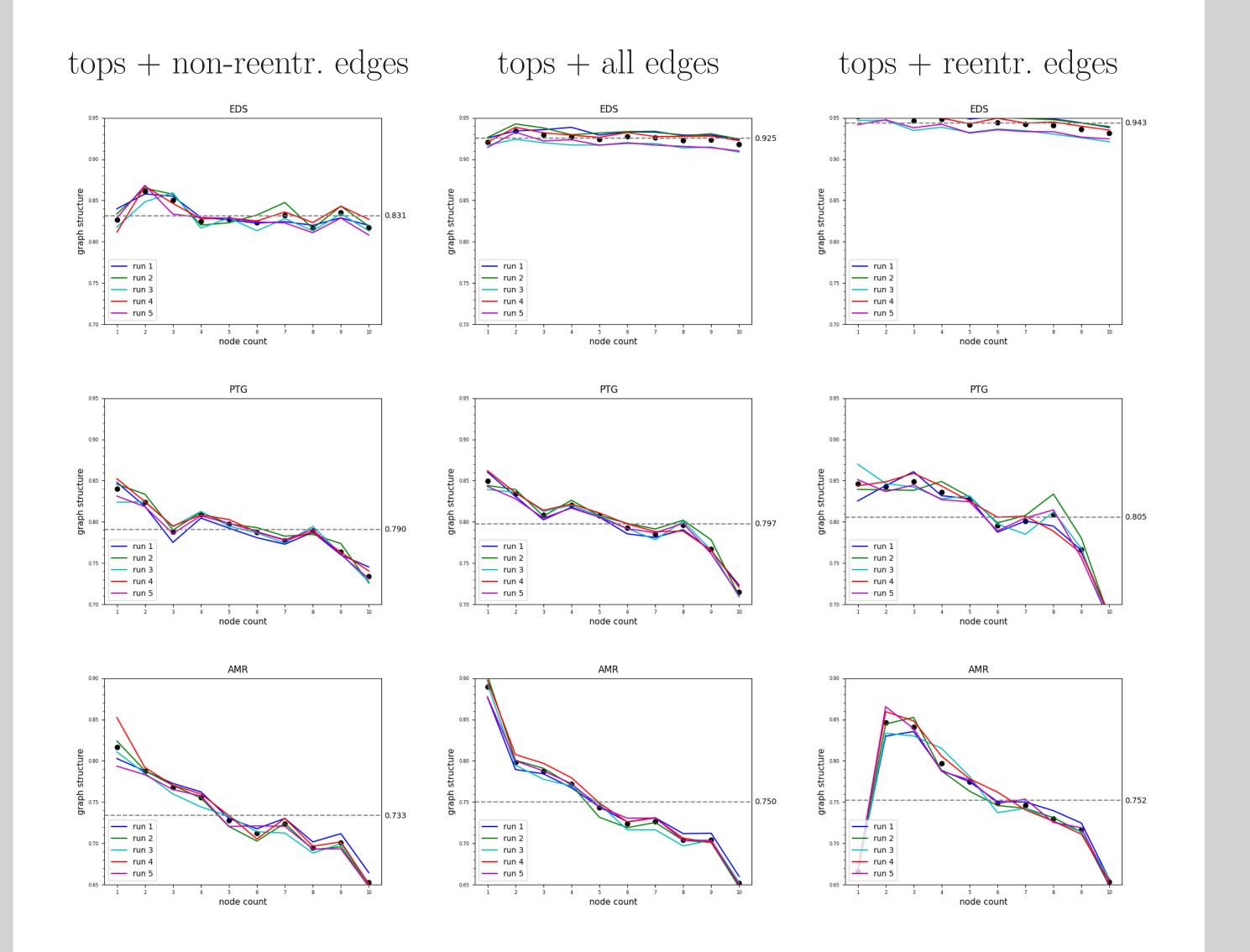
Previous work on linguistic phenomena that give rise to reentrancies informs our pilot annotation and performance analysis.

### Edges – reentrant and non-reentrant

There is a marked difference between the frameworks in proportions of non-reentrant vs. reentrant edges, including "predictable" ones.



We approximate sentence-level graph complexity by number of nodes, group sentences into 10 decile bins, and compare F-scores for unlabelled graph structure contrasting by the reentrant status of edges.



#### Types of "non-predictable" reentrancies

	EDS		$\mathbf{PTG}$		AMR	
Type	Freq.	Error	Freq.	Error	Freq.	Error
clause-like structures	.067	.058	_	_	.039	.428
comparative	.027	.000	-	-	-	-
control structures	.063	.250	.136	.291	.106	.342
coordination	.127	.125	.165	.258	.134	.166
coreference	.027	.142	.401	.382	.243	.436
modal	.011	.333	.014	.400	.008	.333
modification	.167	.071	.176	.451	-	-
named entity	-	-	.031	.818	-	-
partitive	-	-	-	-	.058	.285
possessive	.039	.500	.008	.666	.008	.666
relative clause	.183	.065	.022	.125	.008	.666
verbalisation	.159	.075	.002	.000	.326	.358
other	.122	.173	.039	.571	.067	.541

EDS parsing accuracy remains stable across complexity bins.

Reentrant edges actually seem easier to predict, in particular for EDS, and to an extent also for AMR.

Little difference for PTG, but slight improvement for less complex sentences when scoring reentrant edges only.

#### Findings and future work

AMR & PTG, coreference  $\rightarrow$  frequent and hard to predict. AMR, verbalisation  $\rightarrow$  frequent and non-uniform. All three frameworks, possessives  $\rightarrow$  high error rate. EDS, lowest error rate  $\rightarrow$  grammar-guided annotations.

Next steps: alternative approximations of graph complexity (reentrancies), expanded annotated dataset.

#### https://github.com/cfmrp/mtool

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