Graph-to-Sequence Learning using Gated Graph Neural Networks

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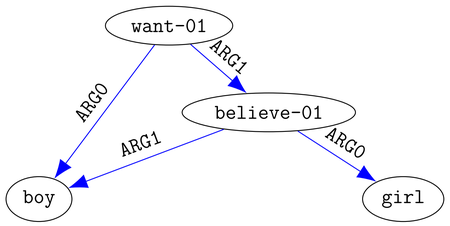
Code available at: github.com/beckdaniel/acl2018_graph2seq

Introduction

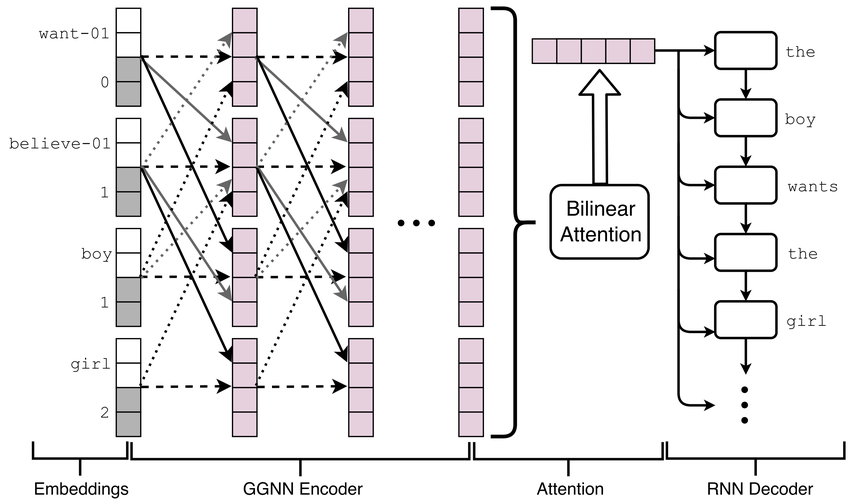
Goal: generate natural language sentences from *graphs*.

- Generation from structured representations.
- Neural Machine Translation with source syntax information.



⇒ "The boy wants the girl to believe him."

- Previous work linearise graphs and apply off-the-shelf sequence-to-sequence networks.
- **Our approach:** replace the sequential encoder with a *Gated Graph Neural Network* [Li et al., ICLR 2016].



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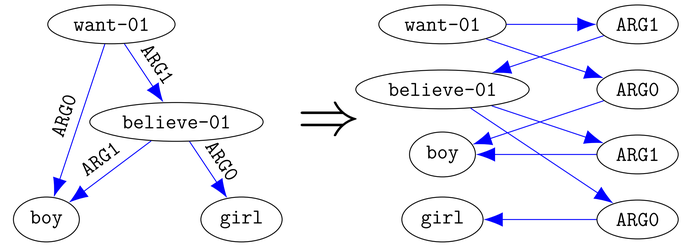
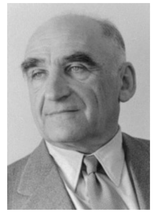
Graph Transformations

Standard GGNN caveats:

- Parameters increase quadratically with number of edge labels.
- Does not generate hidden vectors for edges.
- Does not encode sequential information.

Levi graphs [Levi,1942]

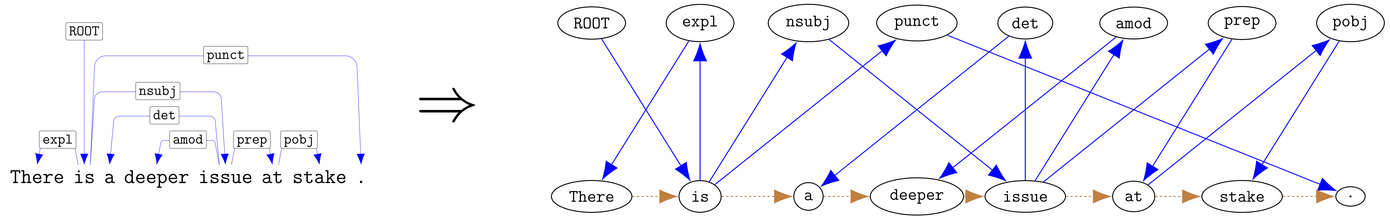




Friedrich Wilhelm Levi

(source: University of Leipzig)

For sequential information we add extra edges to the Levi graph.



Translation: *"Doch steht etwas Grundlegenderes auf dem Spiel ."*

Experiments and Discussion

Data and preprocessing

AMR generation: LDC2017T10 with default splits. Graph simplification and anonymisation [Konstas et al., ACL 2017]

Syntax-based NMT: same settings as in [Bastings et al. EMNLP 2017]. News Commentary V11, English-German and English-Czech. Source side parsed using SyntaxNet and target side segmented using Byte-Pair Encoding.

Models

s2s: sequence-to-sequence baseline.

g2s: our graph-to-sequence model.

g2s+: as above but with extra sequential connections.

Main conclusions

- g2s consistently outperforms s2s in AMR generation
- For NMT, performance drops for standard g2s but g2s+ outperforms the baselines. *Sequential biases added as a graph transformation: no RNNs required in the encoder.*

	BLEU	CHRF++	#params
AMR Generation			
s2s	21.7	49.1	28.4M
g2s	**23.3**	**50.4**	28.3M
NMT English-German			
PB-SMT	12.8	**43.2**	–
s2s	15.5	40.8	41.4M
g2s	15.2	41.4	40.8M
g2s+	**16.7**	42.4	41.2M
NMT English-Czech			
PB-SMT	8.6	**36.4**	–
s2s	8.9	33.8	39.1M
g2s	8.7	32.3	38.4M
g2s+	**9.8**	33.3	38.8M