



On Incorporating Structural Information to Improve Dialogue Response Generation

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Motivation

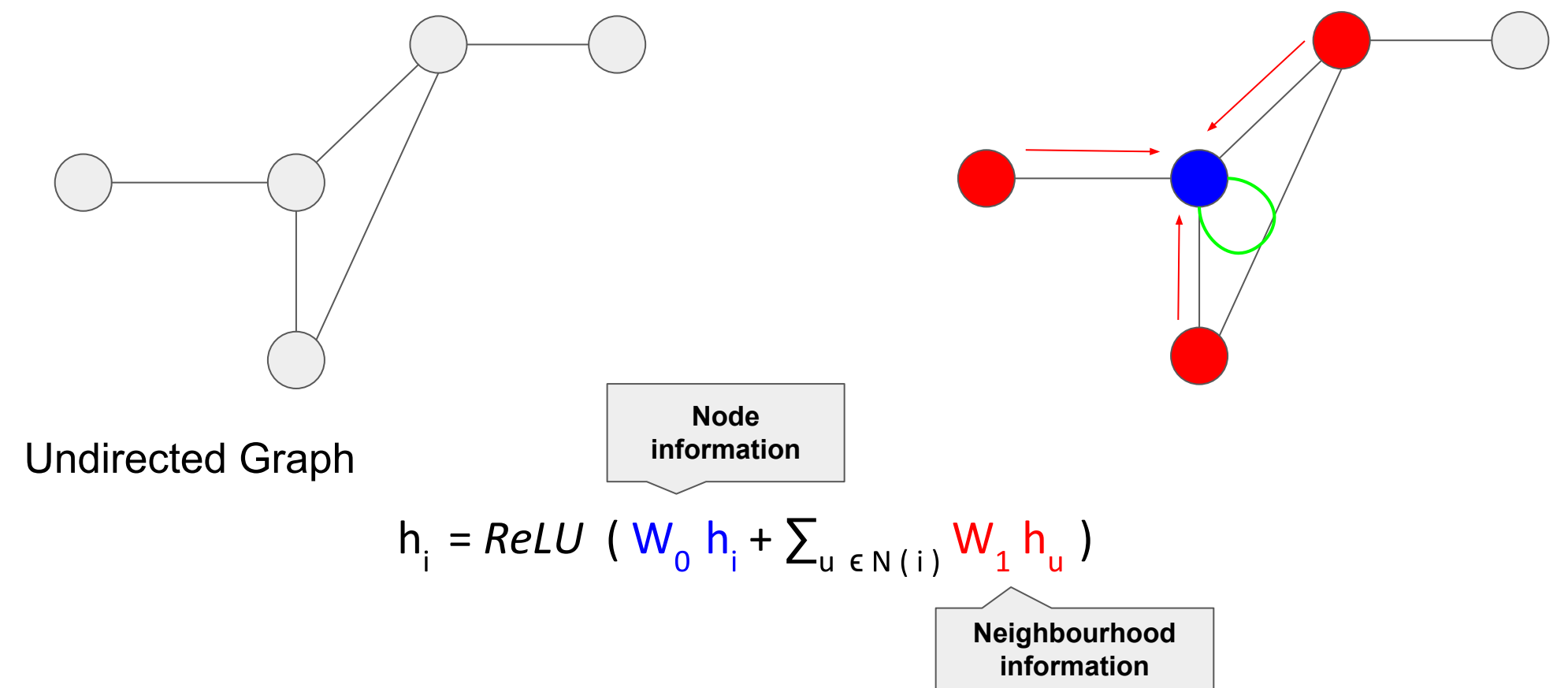
Structural information is ubiquitous in natural language

Dependency parses, constituency trees, co-reference graphs

But deep neural methods hope to learn these linguistic properties implicitly from data during training

Can we *explicitly* incorporate structural information in these neural architectures?

Graph Convolutional Network (GCN)



Background Aware Conversation Systems

Task: Given conversation history and associated background knowledge, generate a response

Dataset: Holl-E Domain: Movies Language: English Stats: ~9k chats, ~90k utterances, ~9k resources
Every alternate response is formed by copying words from the resource with appropriate prefixes/ suffixes

Speaker 1: Yes very true, this is a real rags to riches story. Russell Crowe was excellent as usual

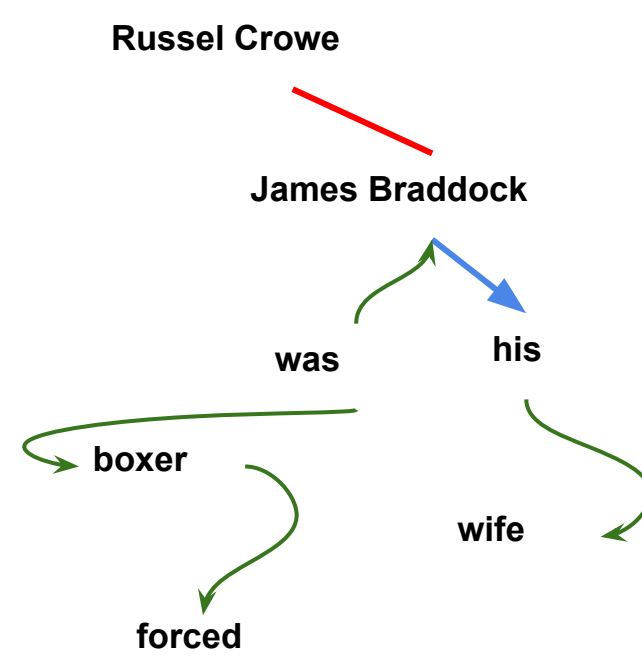
Speaker 2: Russell Crowe owns the character of James Braddock. He's a good fighter turned hack. Injury, bad luck and the Depression sends him down the drain.

Speaker 1: Totally! Oh by the way do you remember his wife ... how she wished he would stop

Speaker 2: Yes! His wife Mae had prayed for years that he would quit boxing, before becoming permanently injured.

Russel Crowe plays the lead. At this point **James Braddock** was a **boxer**, who was **forced** to retired from the ring after breaking his hand in his last fight. **His wife Mae** had prayed for years that he would quit boxing, before becoming permanently injured. To support his family, Braddock works as a laborer at the docks, but he still has a dream to box.

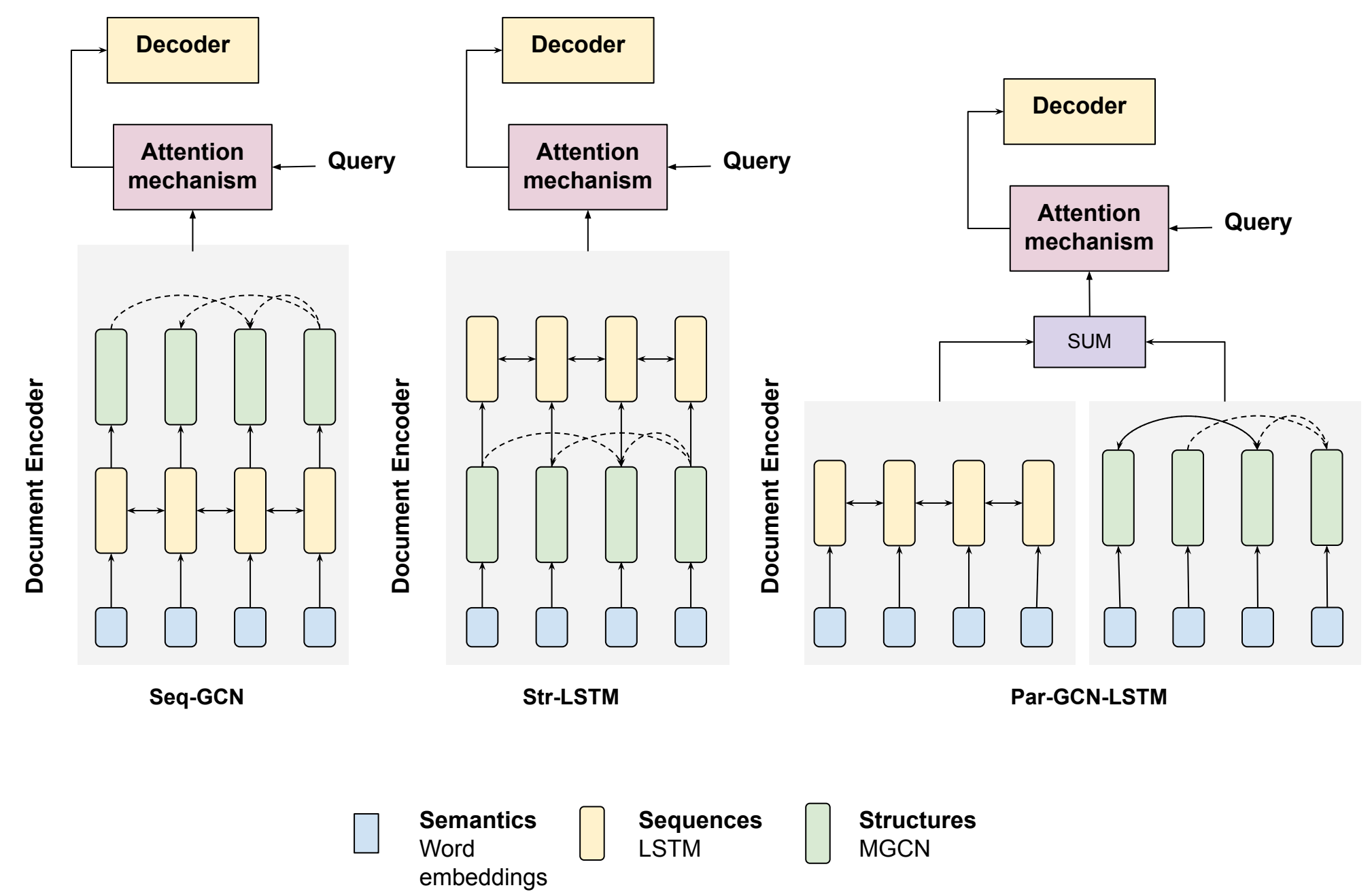
Resource



Dependency graph
Entity graph
Co-reference graph

Conversation

Semantics-Sequences-Structures Framework



Multi Graph GCN: $h_i^{k+1} = \text{ReLU} (W_0^k h_i^k + \sum_{\text{NEG}} \sum_{u \in N(i)} (W_{\text{dir}(i,u)}^k h_u^k + b_{L(i,u)}^k))$

Results

	Model	BLEU	ROUGE		
			1	2	L
	HRED	05.23	24.55	07.61	18.87
	GTPP	13.92	30.32	17.78	25.67
	BiDAF	16.79	26.73	18.82	23.58
GloVe	Sem	04.40	29.72	11.72	22.99
	Sem + Seq	14.83	36.17	24.84	31.07
	Sem + Seq + Str	18.96	38.61	26.92	33.77
ELMo	Sem	14.36	32.04	18.75	26.71
	Sem + Seq	14.61	35.54	24.58	30.71
	Sem + Seq + Str	19.32	39.65	27.37	34.86
BERT	Sem	11.26	33.86	16.73	26.44
	Sem + Seq	18.49	37.85	25.32	32.58
	Sem + Seq + Str	22.78	40.09	27.83	35.20

Analysis

Conclusion and Future Work

- We demonstrate the usefulness of incorporating structural information into the standard semantics+sequential neural models.
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- In future, we can design architectures that have the power of both Recurrent Neural Networks and Graph Convolutional Networks

References

- [1] *Semi-supervised classification with Graph Convolutional Network*, Thomas N Kipf and Max Welling., In International Conference on Learning Representations (ICLR) 2016
- [2] *Towards Exploiting Background Knowledge for Building Conversation Systems*, Nikita Moghe, Siddhartha Arora, Suman Banerjee, and Mitesh M. Khapra. In proceedings of Empirical Methods in Natural Language Processing (EMNLP) 2018