Exploiting Semantics in Neural Machine Translation with Graph Convolutional Networks

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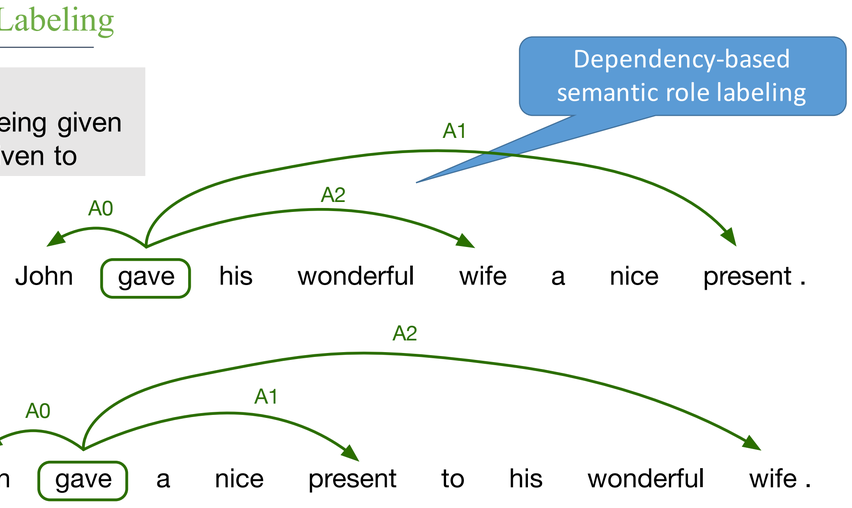
- We use graph convolutional networks (GCNs) to inject semantic structures into neural machine translation.
- The semantic-aware model outperforms the linguistic-agnostic one (EN-DE WMT16).
- Syntax and semantics are complementary.

Semantic Role Labeling

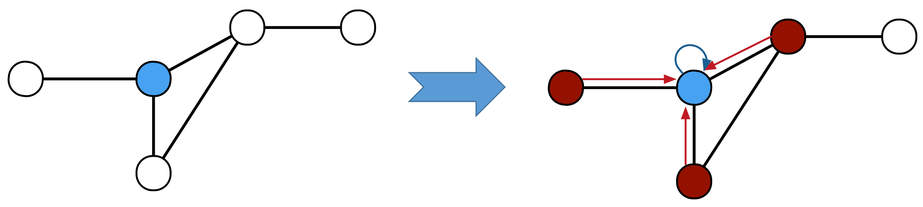
- A0: the giver
- A1: the thing being given
- A2: an entity given to



- Predicate-argument structures define an abstraction which helps to generalize over different surface realizations of the same underlying "meaning".
- We explicitly encode semantic role labeling (SRL) graphs using GCNs.

Graph Convolutional Networks

[Kipf and Welling, ICLR 2016]

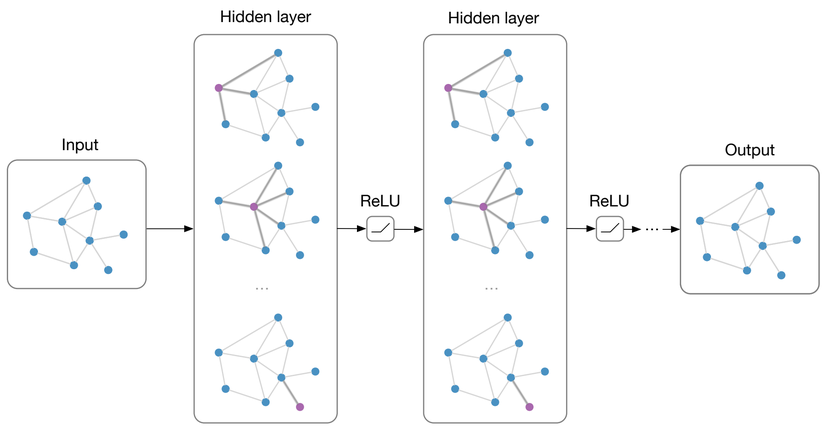


- Nodes are represented as vectors
- Messages are summed up following the graph structure
- Same W for every edge but self loop

$$\mathbf{h}_i^{(l+1)} = \sigma(\mathbf{W}_0^{(l)}\mathbf{h}_i^{(l)} + \sum_{j \in \mathcal{N}_i} \mathbf{W}_1^{(l)}\mathbf{h}_j^{(l)})$$

Self loop

Node neighborhood



Semantic GCN

Marcheggiani and Titov (2017)
Bastings et al. (2017)

- GCNs are used to encode syntactic dependencies for SRL and NMT.
- SRL graphs have directed and labeled edges.
- Message passed through different edges have different meaning.
- Parameterize each message according to syntactic label and edge direction.

$$h_v^{(k+1)} = ReLU\left(\sum_{u \in \mathcal{N}(v)} W_{L(u,v)}^{(k)} h_u^{(k)} + b_{L(u,v)}^{(k)}\right)$$

Self loop is included

Returns label and direction indices

Edge-wise gates

- Not all edges are equally important
- Gates decide the importance of each edge based on edge labels and node representations

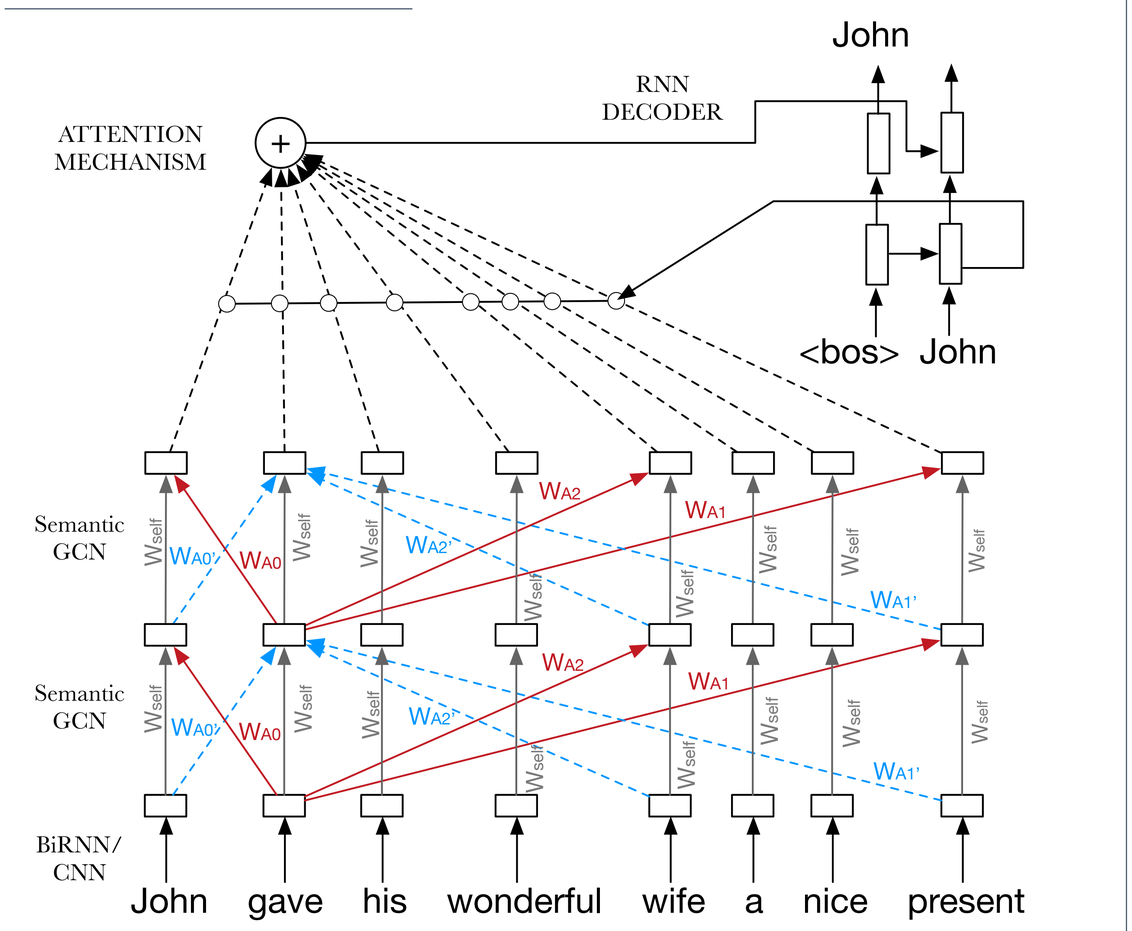
$$g_{u,v}^{(k)} = \sigma\left(h_u^{(k)} \cdot \hat{v}_{L(u,v)}^{(k)} + \hat{b}_{L(u,v)}^{(k)}\right)$$

Scalar gate

Sigmoid function

Resulting update: $h_v^{(k+1)} = ReLU(\sum_{u \in \mathcal{N}(v)} g_{v,u}^{(k)}(W_{L(u,v)}^{(k)} h_u^{(k)} + b_{L(u,v)}^{(k)}))$

GCN Encoder-Decoder Model

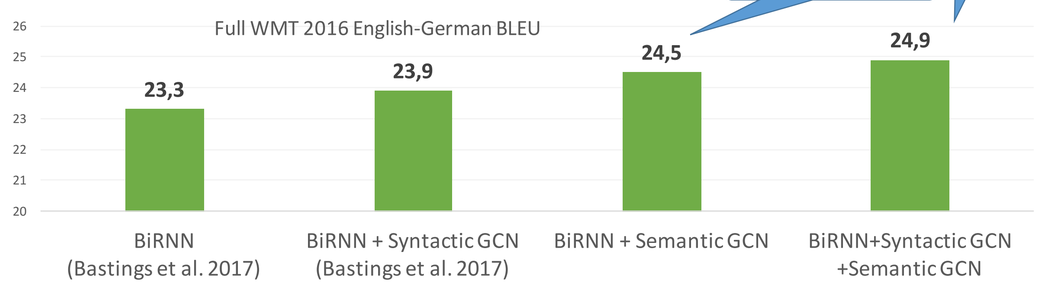


Experiments

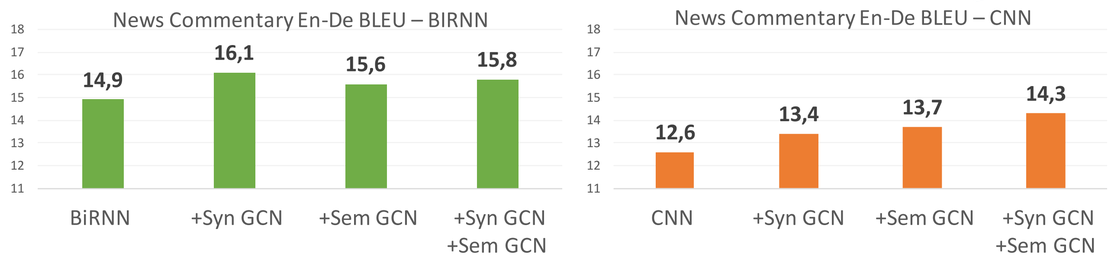
Data:
- Full WMT16 En-De (~4.5 million sentence pairs)
- News Commentary En-De (~226.000 sentence pairs)

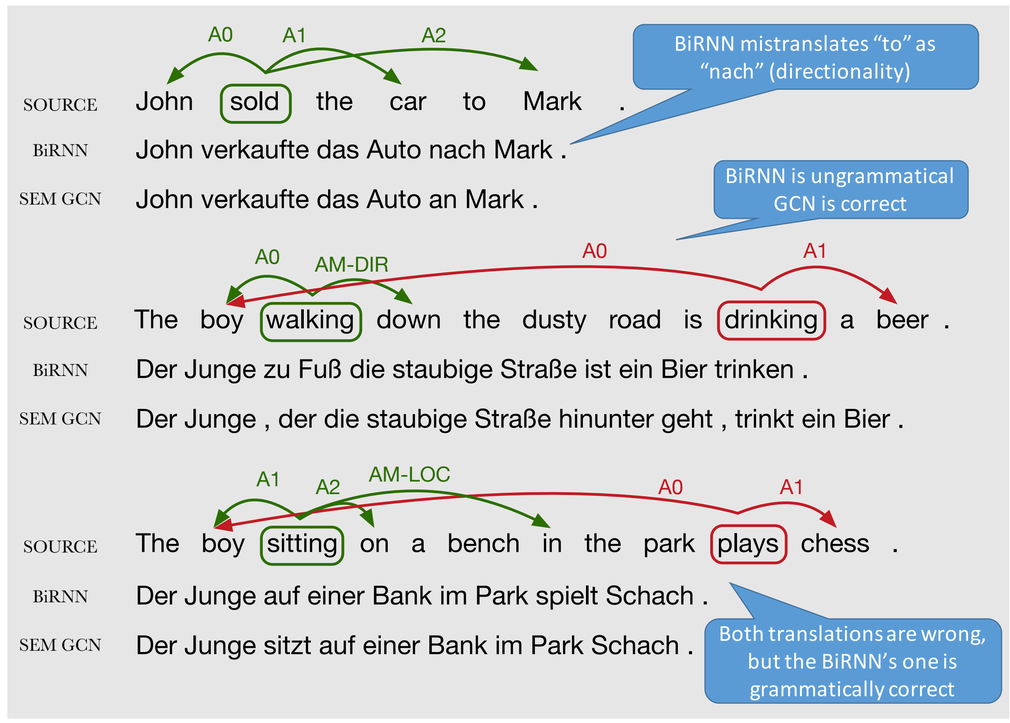
Syntax and semantics are complementary

Semantics is helpful



Weak encoders benefit more from linguistic information





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