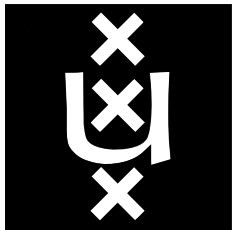


Graph Convolutions over Constituent Trees for Syntax-Aware Semantic Role Labeling

Diego Marcheggiani¹ and Ivan Titov^{2,3}



¹Amazon

²University of Amsterdam

³University of Edinburgh



Semantic Role Labeling

- Predicting the predicate-argument structure of a sentence

Investors appeal to the CEO not to limit their access to sales data

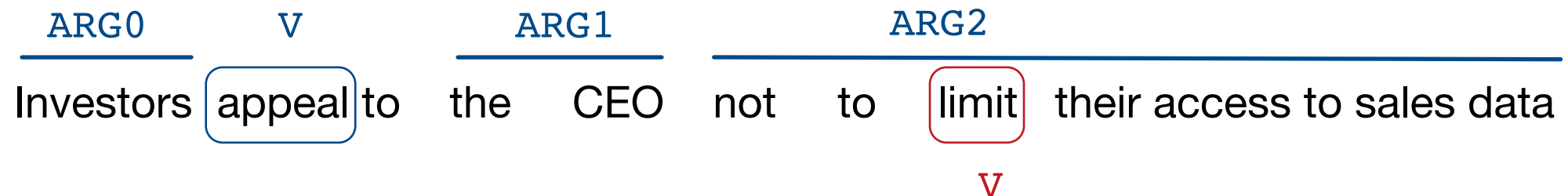
Semantic Role Labeling

- Predicting the predicate-argument structure of a sentence
 - Discover predicates

Investors appeal ^v to the CEO not to limit _v their access to sales data

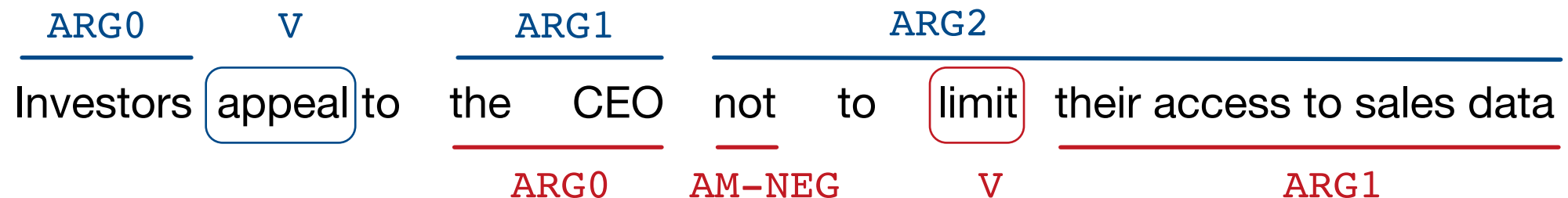
Semantic Role Labeling

- Predicting the predicate-argument structure of a sentence
 - Discover predicates
 - Identify arguments and label them with their semantic roles

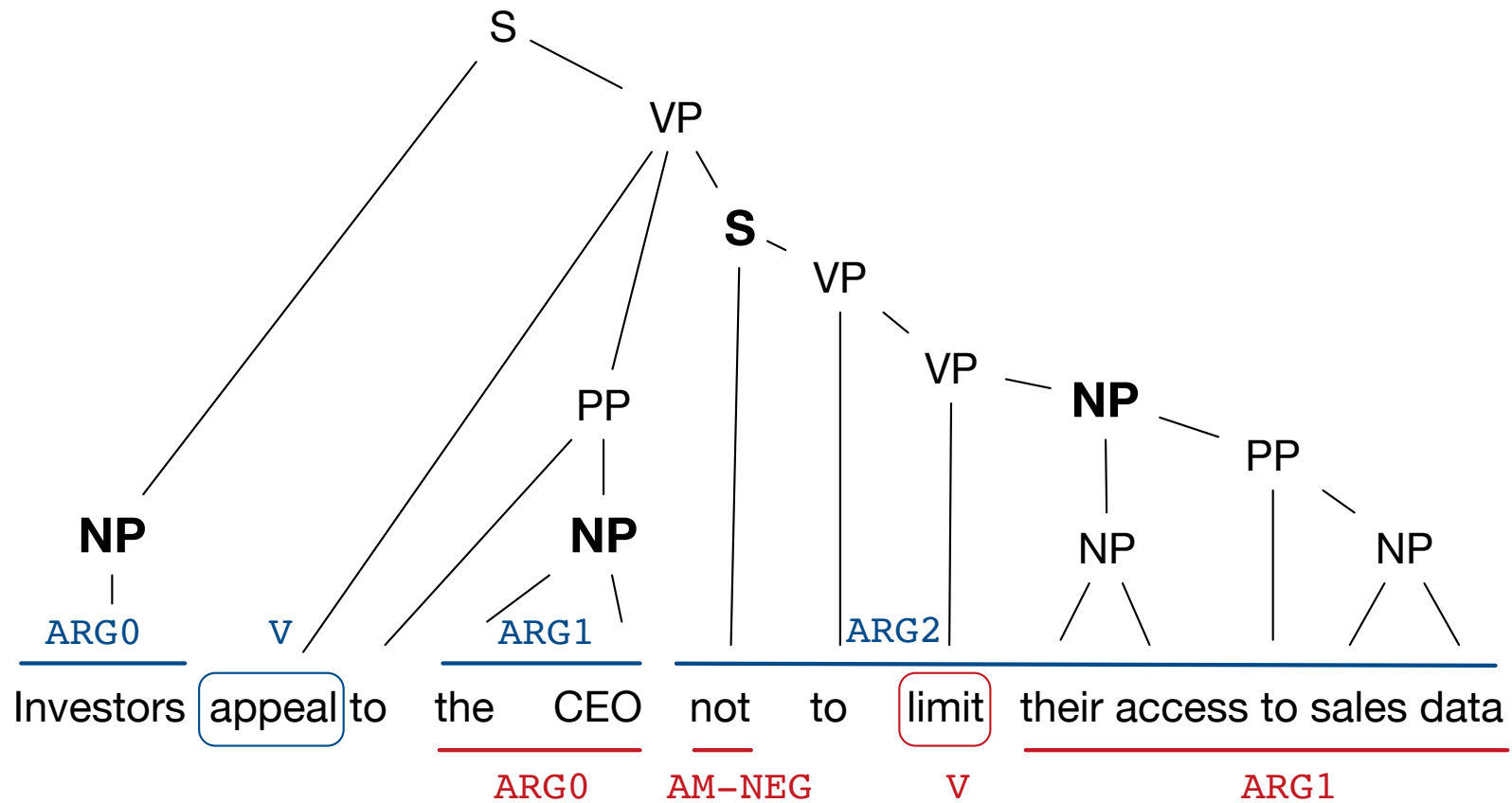


Semantic Role Labeling

- Predicting the predicate-argument structure of a sentence
 - Discover predicates
 - Identify arguments and label them with their semantic roles



Motivation- Importance of syntax in SRL



Previous work

- Converted into dependency trees and encoded with self-attention:
 - Strubell et al. (2018)
- Constituency syntax extracted using heuristics:
 - He et al. (2019)
 - Wang et al. (2019)
- Syntax-agnostic models:
 - He et al. (2017)
 - Tan et al. (2018)
 - Ouchi et al. (2018)

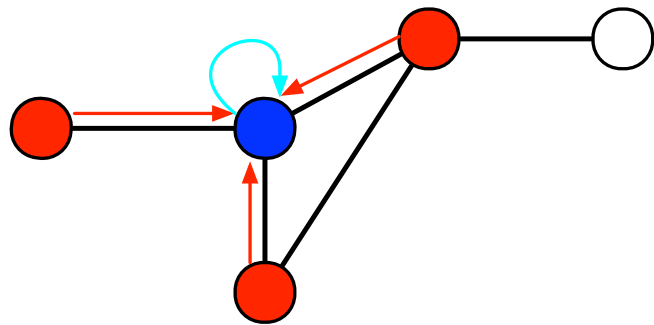
Contributions

- Span Graph Convolutional Networks (SpanGCN)
- Encode constituent structure:
 - efficiently (in a single pass)
 - at the level of words representation (compatible with seq2seq)
 - general and applicable to other span-based structures
- Syntax remains beneficial for SRL

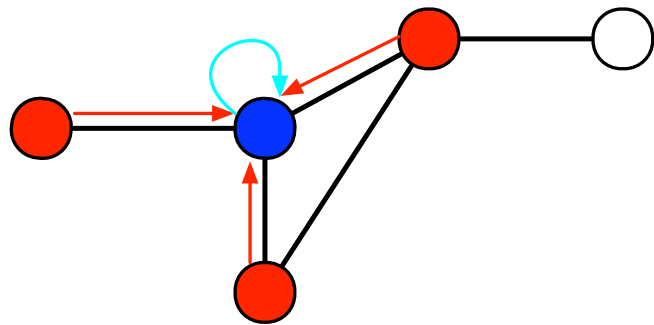
Graph Convolutions over Constituent Trees

- **Graph Convolutional Networks**
- SpanGCN
- Semantic Role Labeling Model
- Experiments
- Conclusions

Graph Convolutional Networks

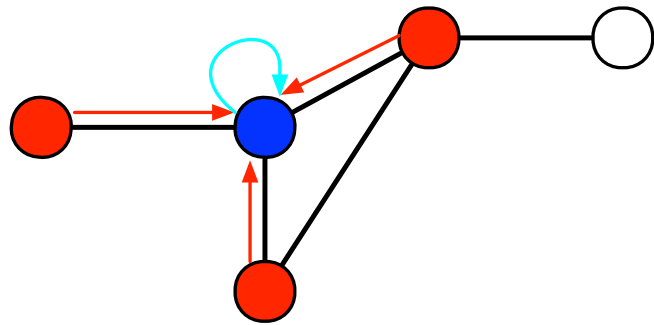


Graph Convolutional Networks



$$h_i = \text{ReLU} \left(W_0 h_i + \sum_{j \in \mathcal{N}(v)} W_1 h_j \right)$$

Graph Convolutional Networks



$$h_i = \text{ReLU} \left(W_0 h_i + \sum_{j \in \mathcal{N}(v)} W_1 h_j \right)$$

combination

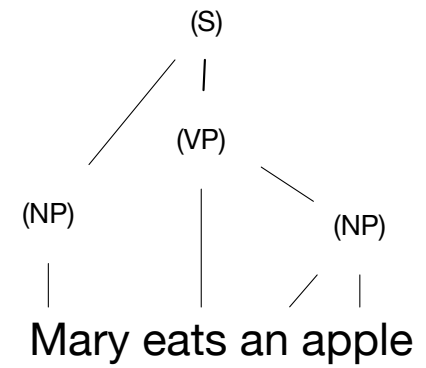
messages

Graph Convolutions over Constituent Trees

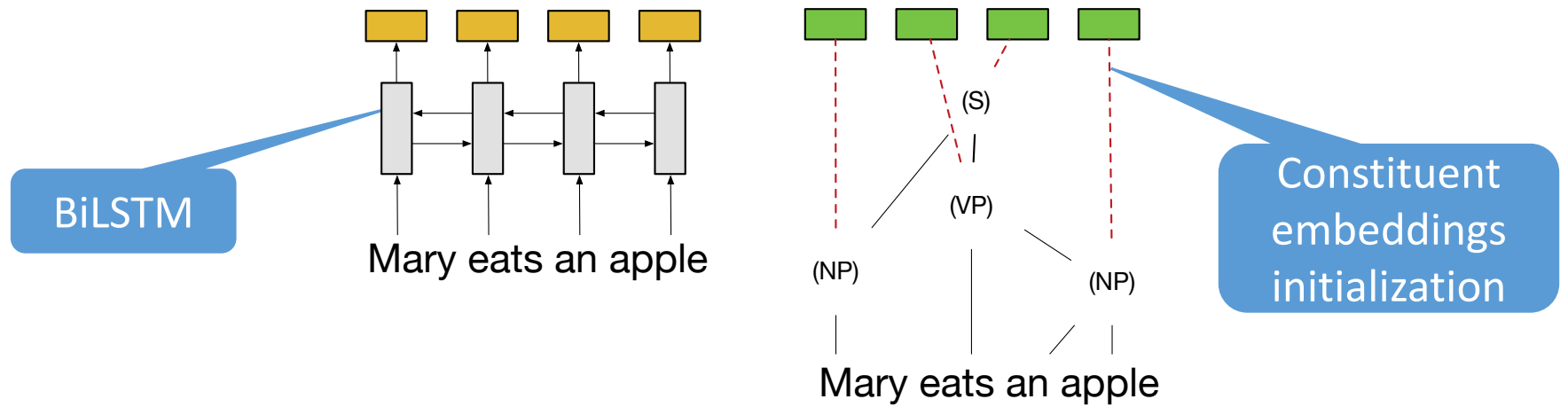
- Graph Convolutional Networks
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Example

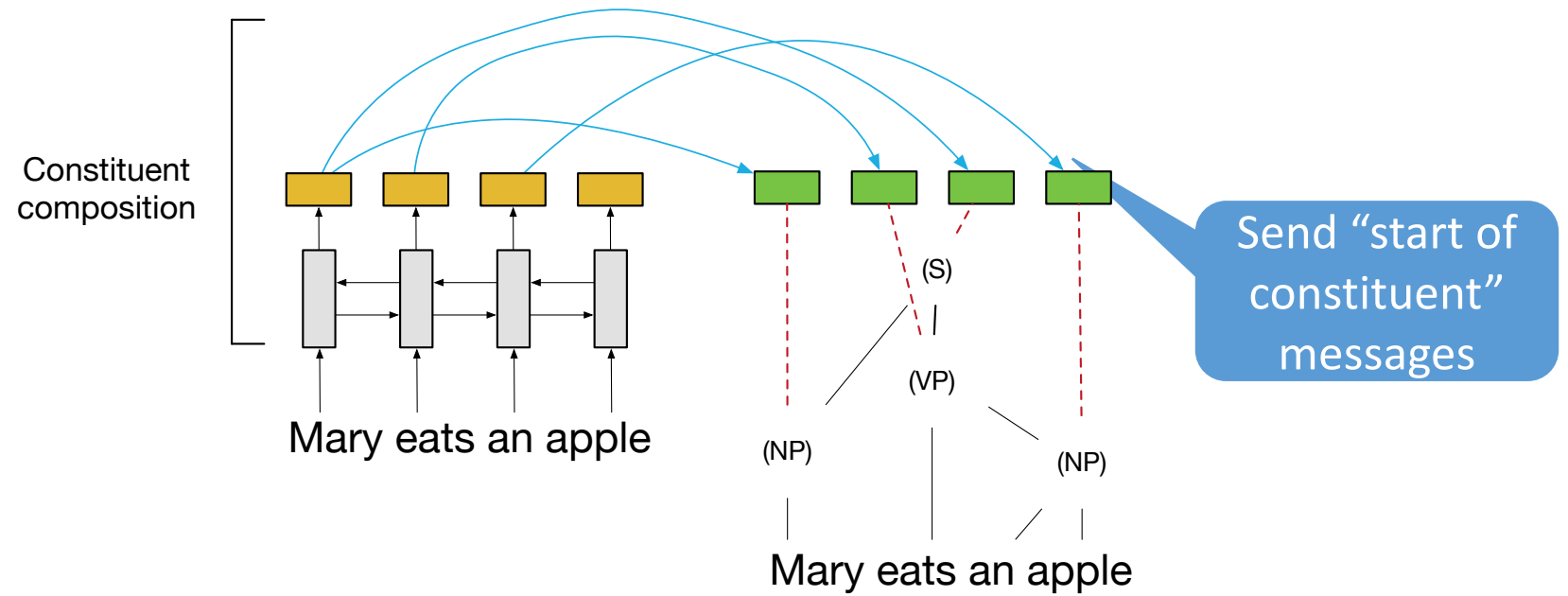
Mary eats an apple



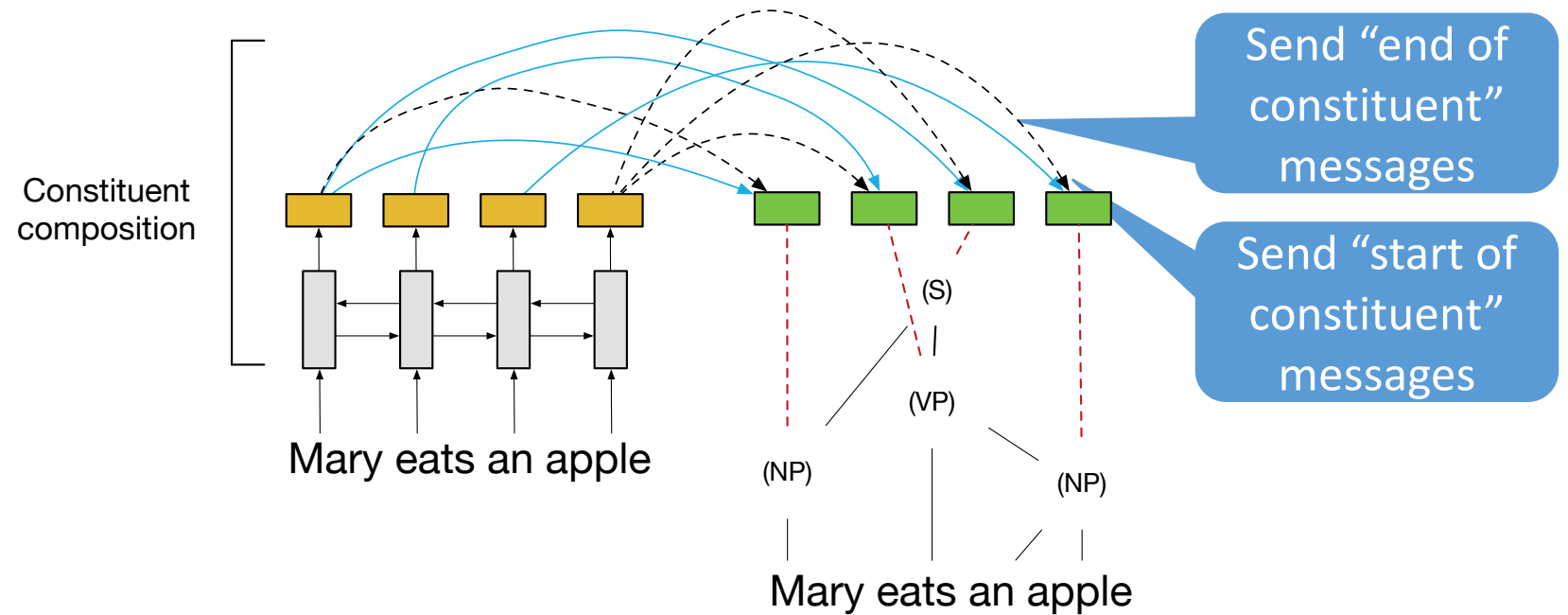
Example



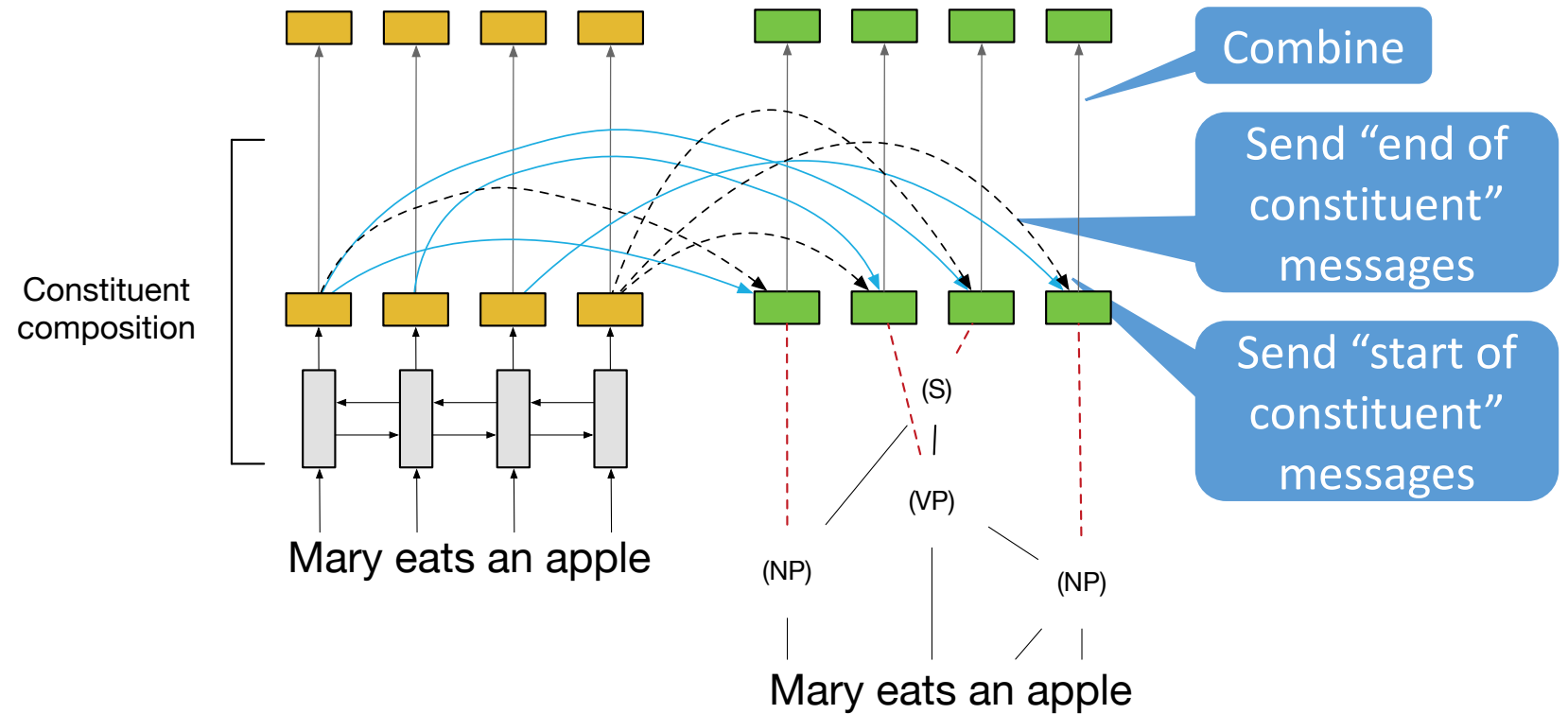
Example



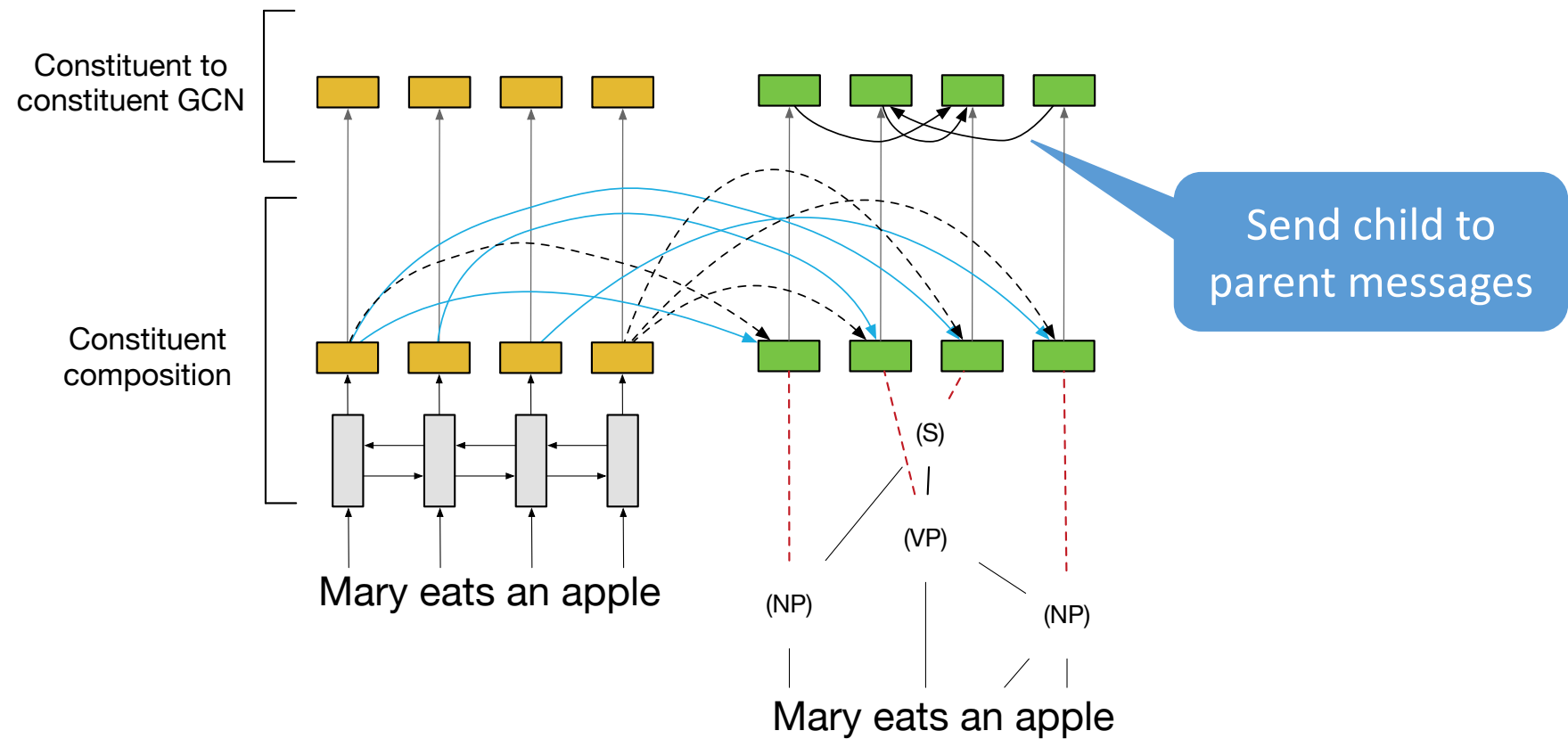
Example



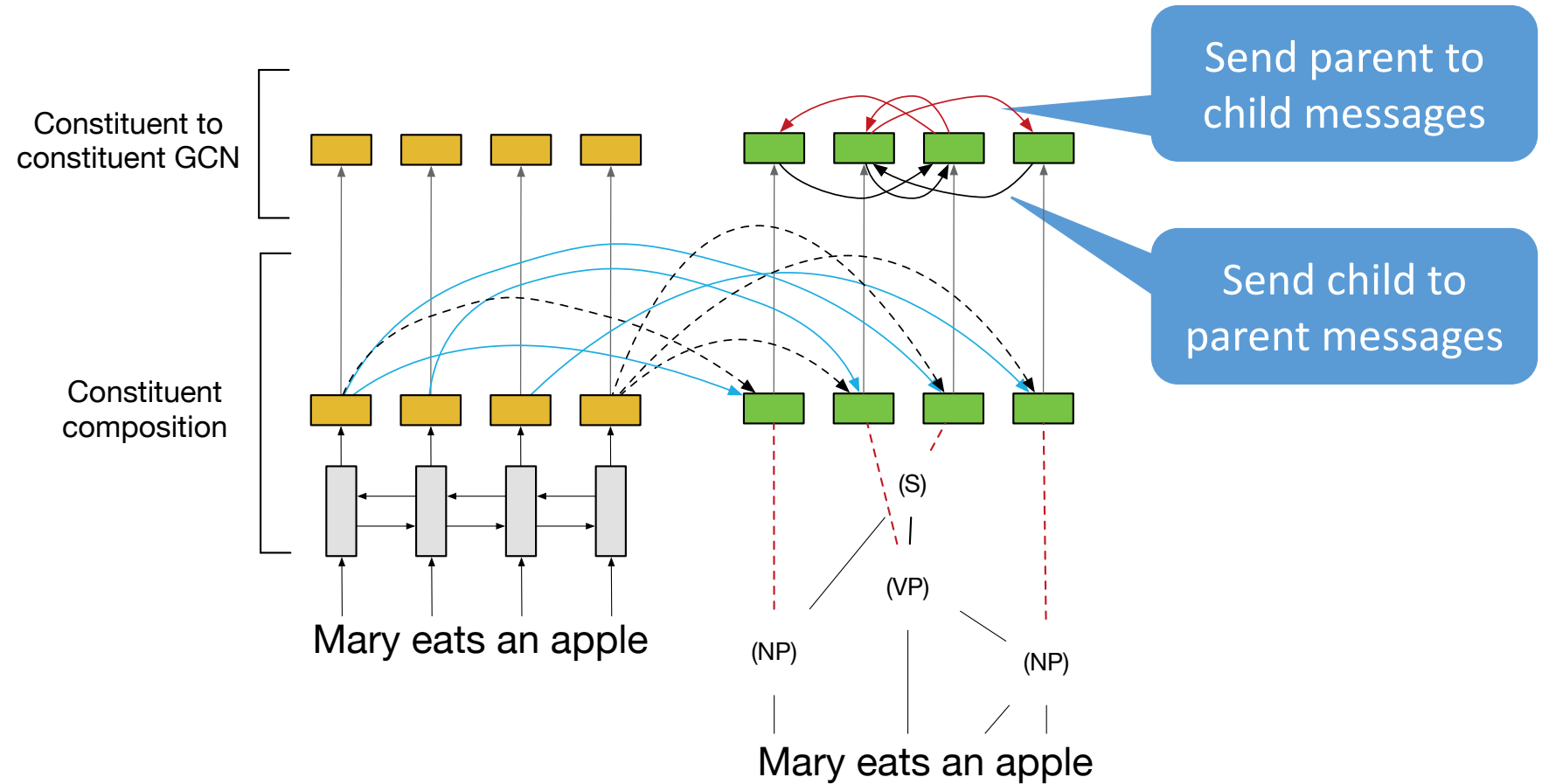
Example



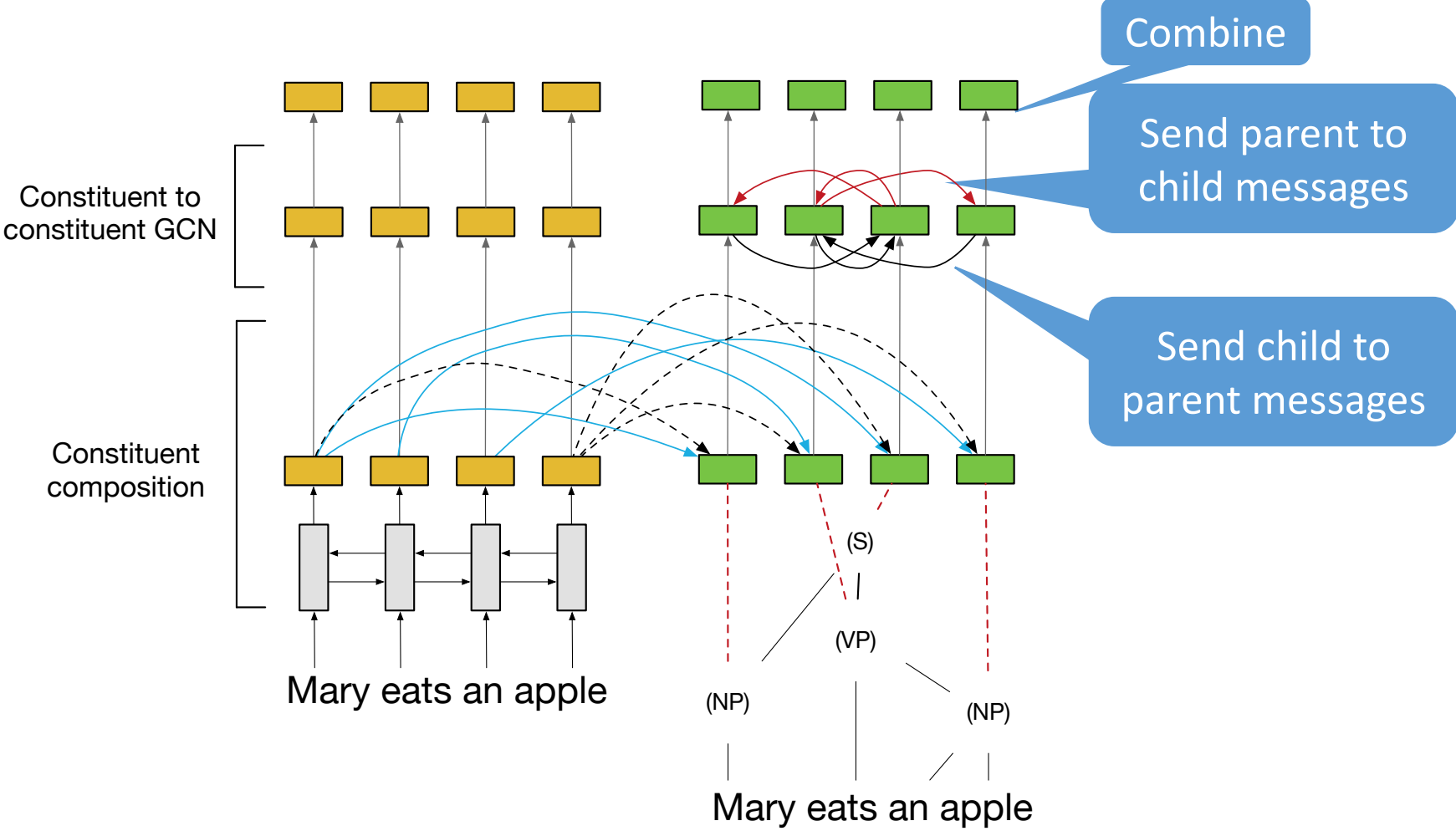
Example



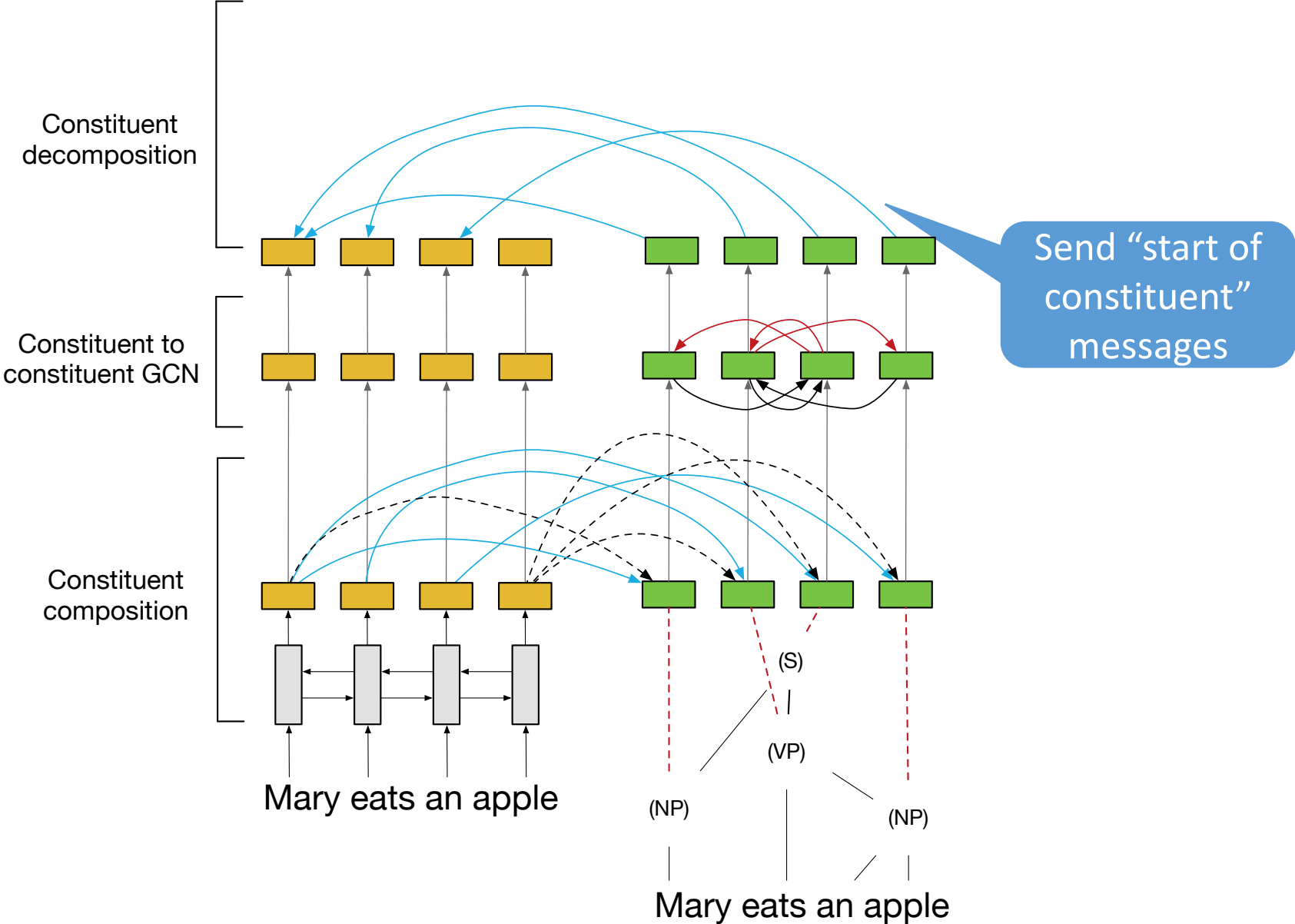
Example



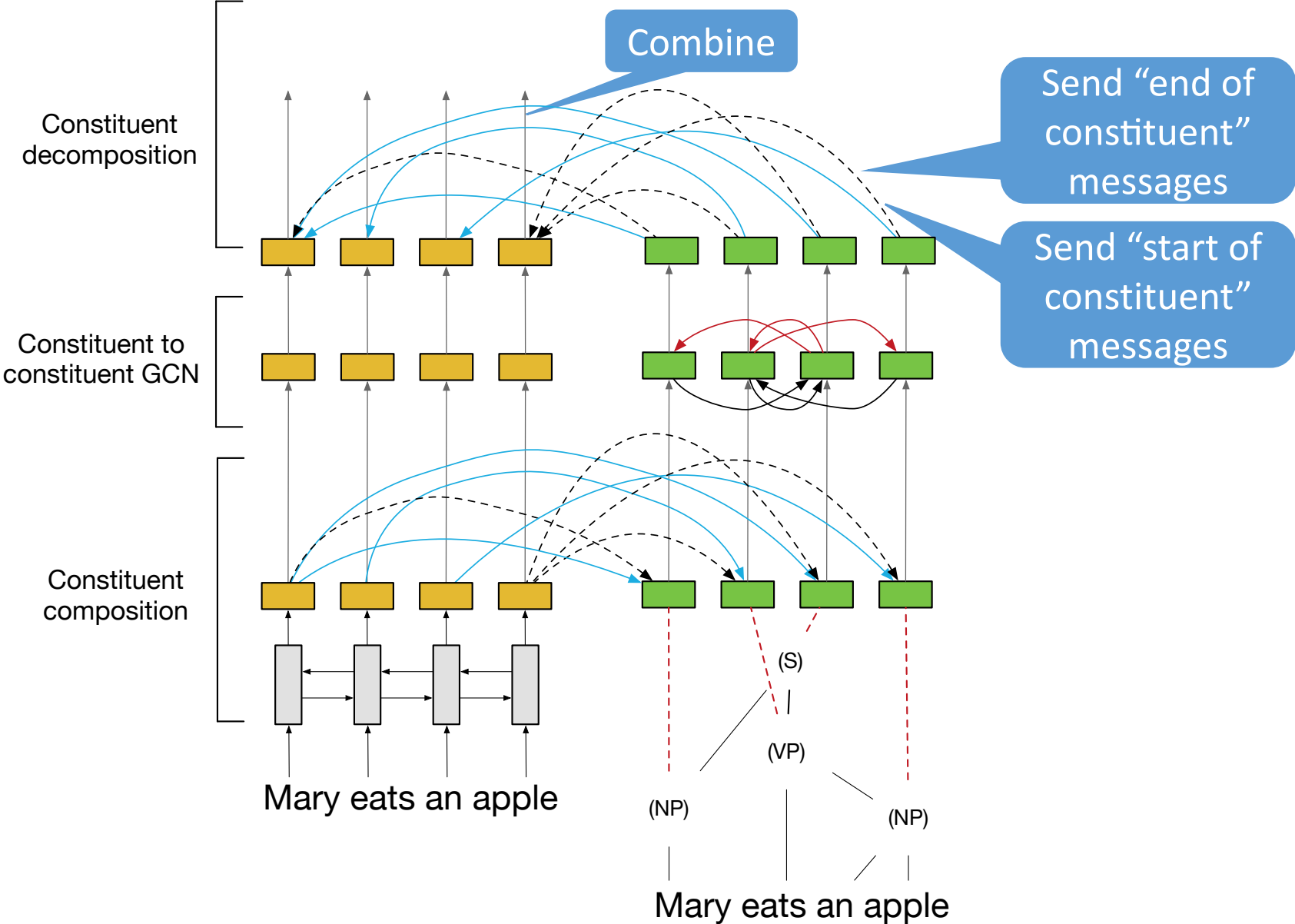
Example



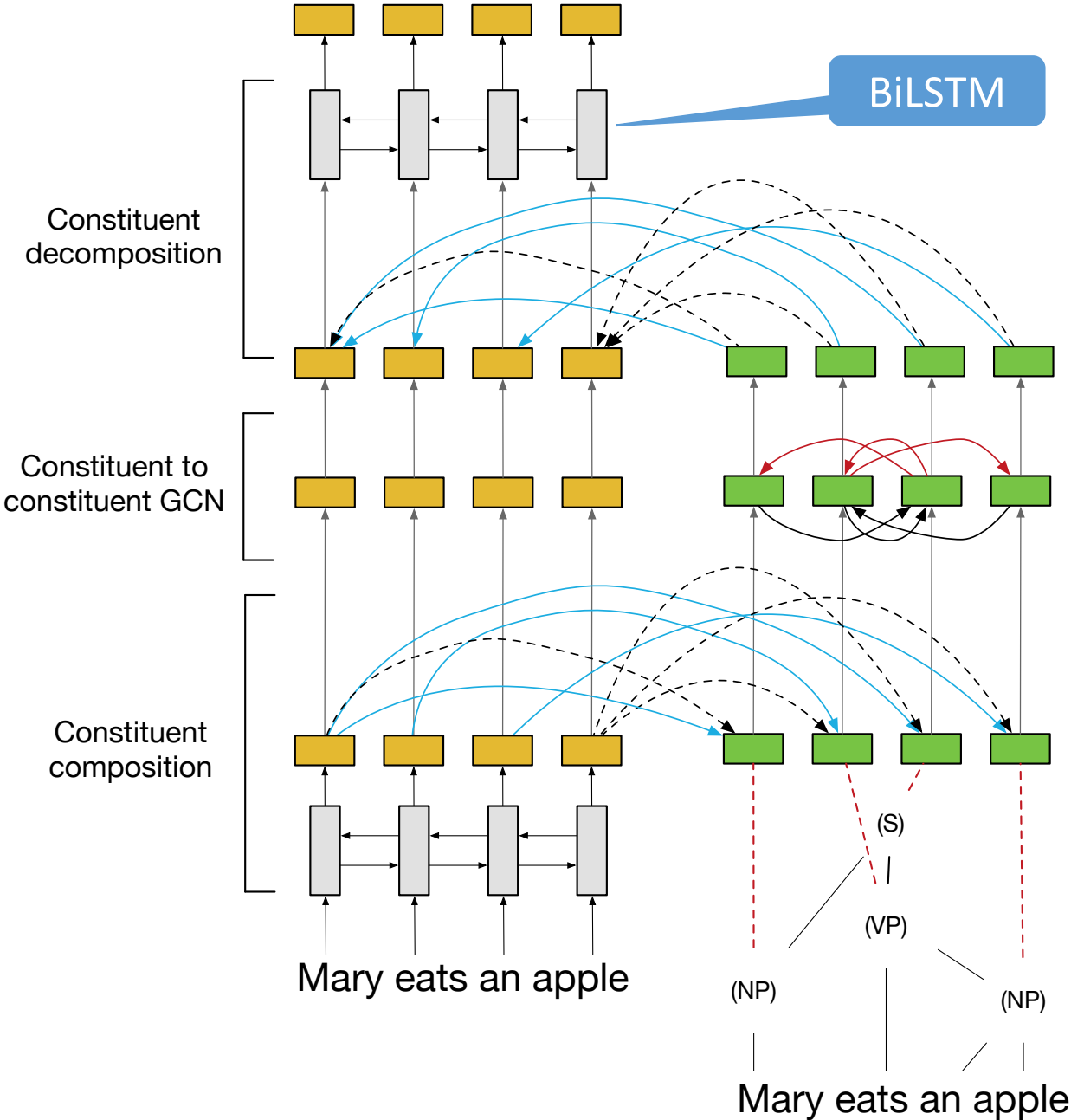
Example



Example



Example



SpanGCN Update

$$h_v = \text{ReLU}\left(\sum_{u \in \mathcal{N}(v)} U_{T_c(u,v)} h_u + b_{T_f(u,v)}\right)$$

SpanGCN Update

Messages

$$h_v = \text{ReLU}\left(\sum_{u \in \mathcal{N}(v)} U_{T_c(u,v)} h_u + b_{T_f(u,v)}\right)$$

SpanGCN Update

$$h_v = \text{ReLU}\left(\sum_{u \in \mathcal{N}(v)} \left[U_{T_c(u,v)} h_u + b_{T_f(u,v)} \right]\right)$$

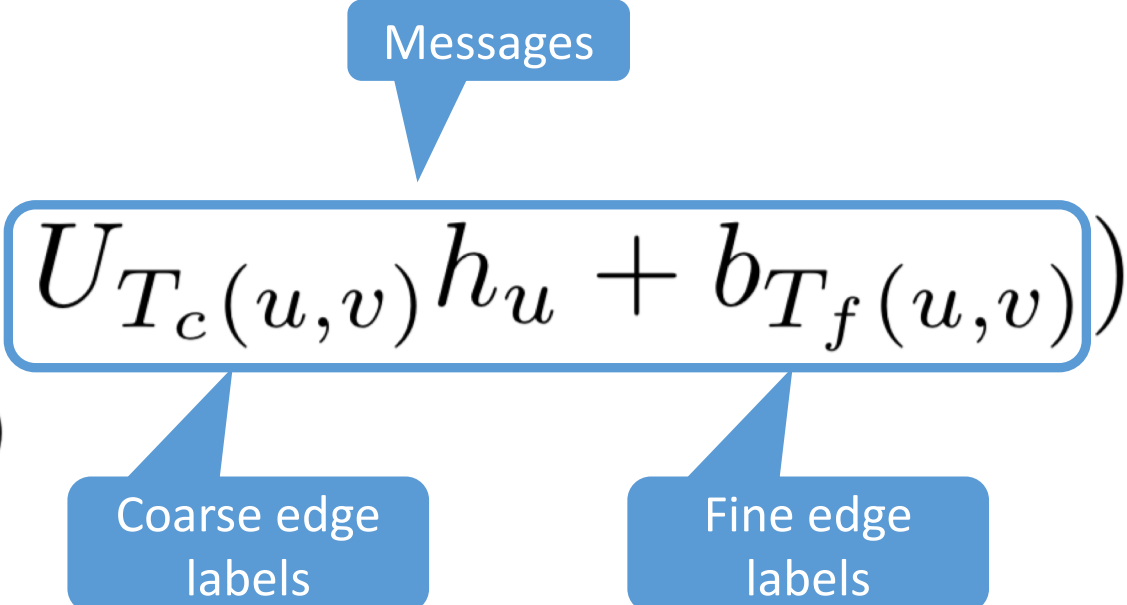
Messages

Coarse edge labels

Fine edge labels

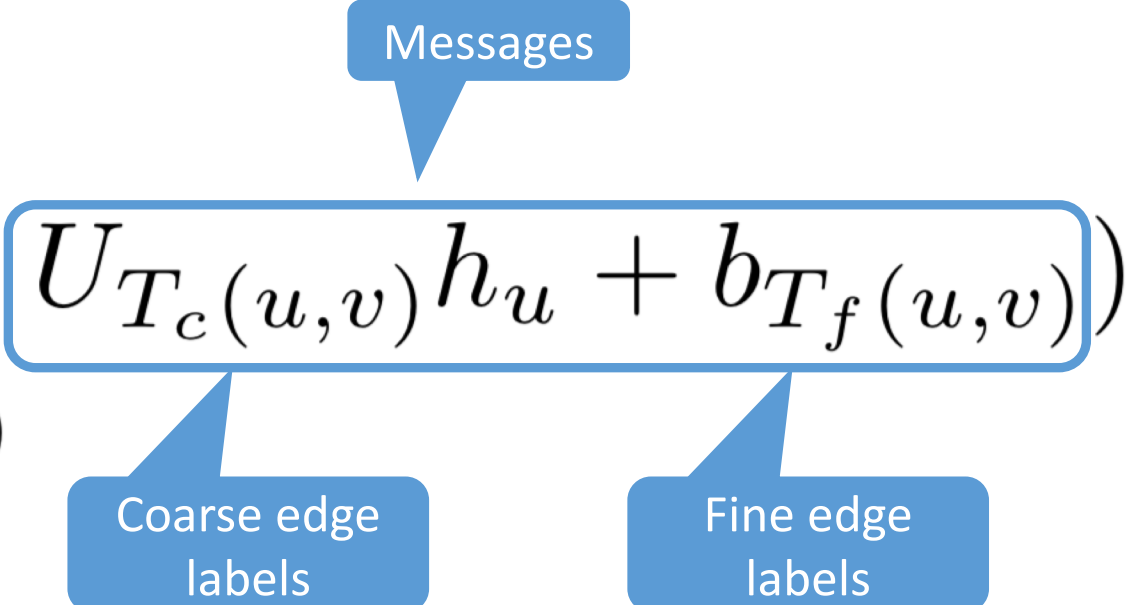
The diagram shows the SpanGCN update equation. The term $U_{T_c(u,v)} h_u + b_{T_f(u,v)}$ is enclosed in a blue rounded rectangle. A blue callout box labeled 'Messages' points to this rectangle. Below the rectangle, two blue callout boxes are present: 'Coarse edge labels' points to $U_{T_c(u,v)}$ and 'Fine edge labels' points to $b_{T_f(u,v)}$.

SpanGCN Update

$$h_v = \text{ReLU}\left(\sum_{u \in \mathcal{N}(v)} \left(U_{T_c(u,v)} h_u + b_{T_f(u,v)} \right)\right)$$


- Composition and Decomposition
 - $T_c(u,v)$ distinguishes between start or end token
 - $T_f(u,v)$ specifies syntactic labels of the constituent

SpanGCN Update

$$h_v = \text{ReLU}\left(\sum_{u \in \mathcal{N}(v)} \left(U_{T_c(u,v)} h_u + b_{T_f(u,v)} \right)\right)$$


- **Composition and Decomposition**
 - $T_c(u,v)$ distinguishes between start or end token
 - $T_f(u,v)$ specifies syntactic labels of the constituent
- **Constituent GCN**
 - $T_c(u,v)$ specifies message directions (parent to child and vice-versa)
 - $T_f(u,v)$ specifies syntactic labels

Graph Convolutions over Constituent Trees

- Graph Convolutional Networks
- SpanGCN
- **Semantic Role Labeling Model**
- Experiments
- Conclusions

SRL Model

- Frozen word representation (Glove, ELMo, RoBERTa)
 - with predicate embeddings
- SpanGCN
- Conditional Random Field
 - Minimize negative conditional log likelihood

Baseline: BiLSTM in place of SpanGCN

Pennington et al., (2014)
Peters et al. (2018)
Liu et al., (2019)

Graph Convolutions over Constituent Trees

- SpanGCN
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Experiments

- Data
 - PropBank (CoNLL 2005)
 - FrameNet 1.5
- Gold predicates are given
- Syntactic parser of Kitaev and Klein, (2018)
- F1 score as metric
- Hyperparameters are tuned on Dev set of CoNLL 2005

PropBank

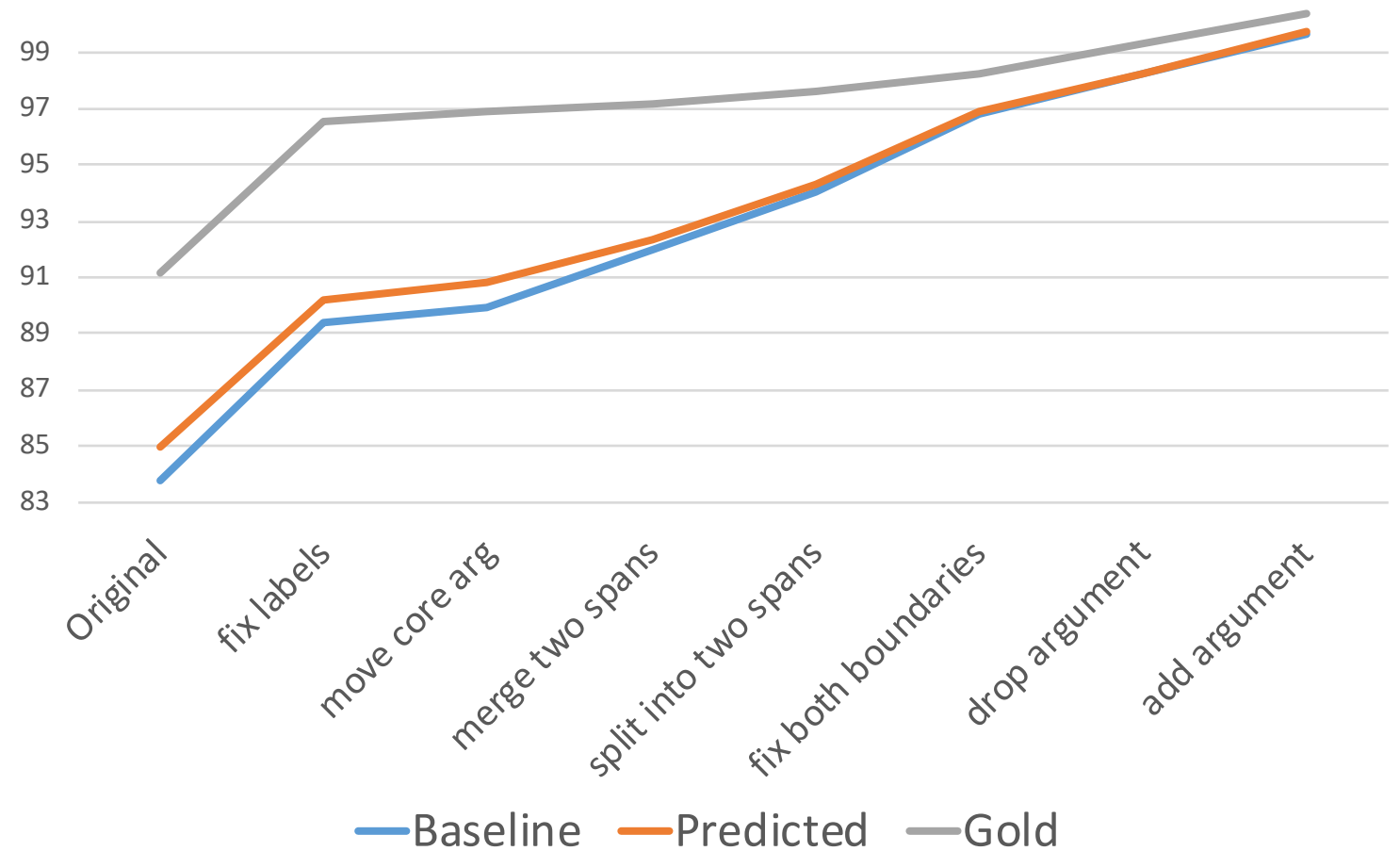
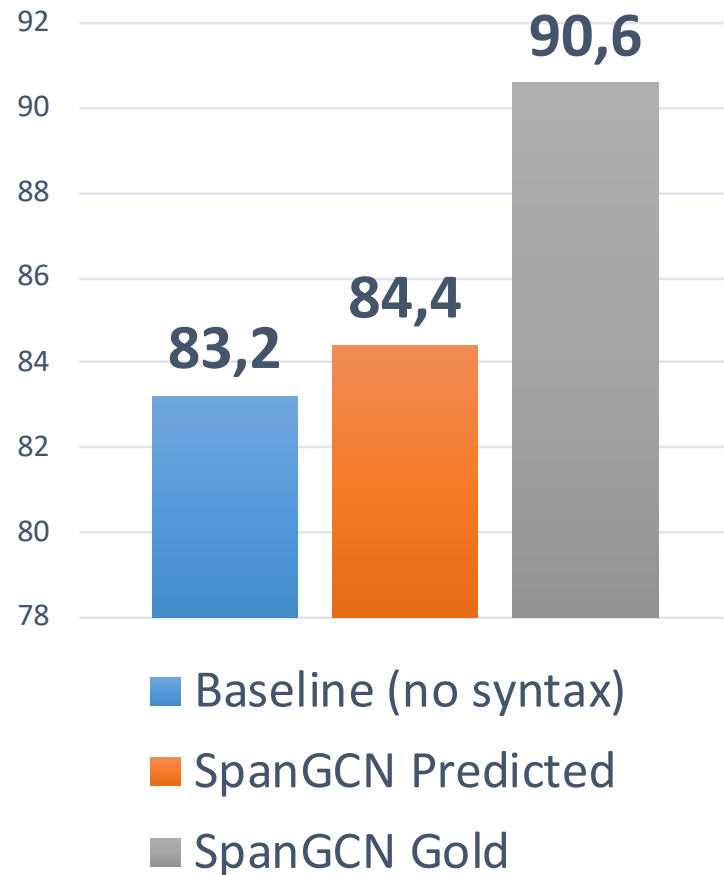
Palmer et al., (2005)

Carreras and Màrquez, (2005)

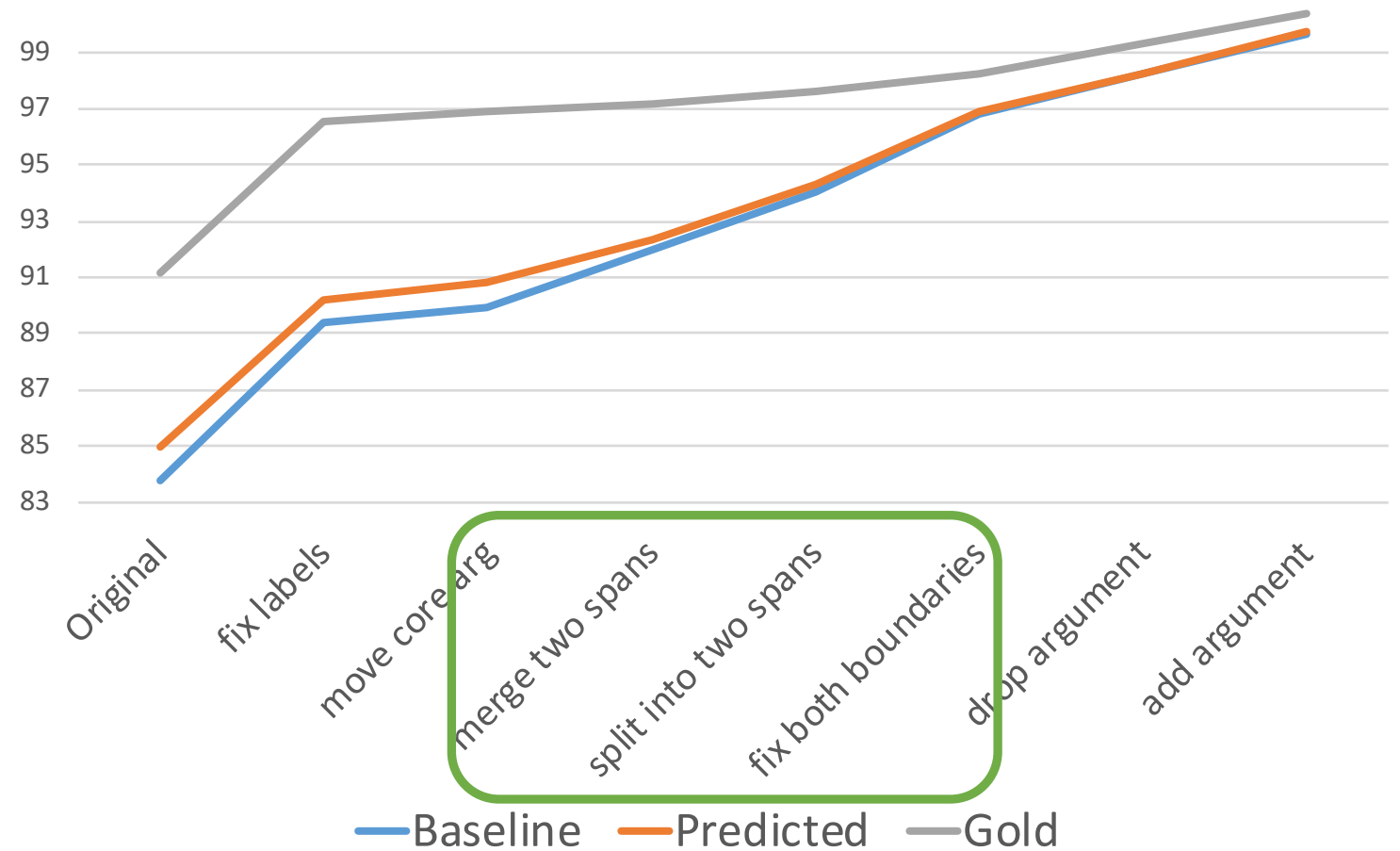
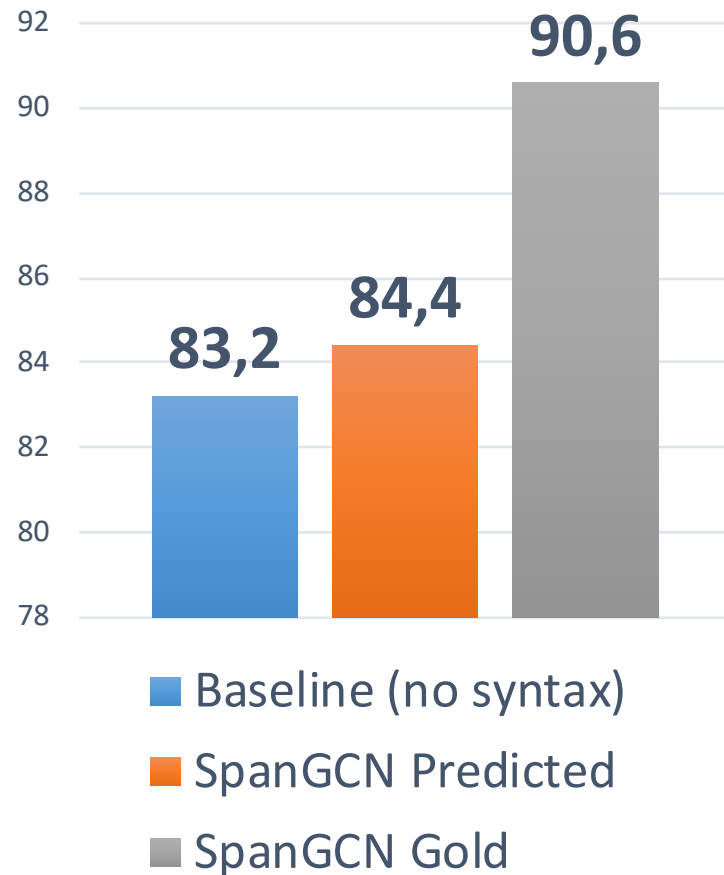
FrameNet

Baker et al., (1998)

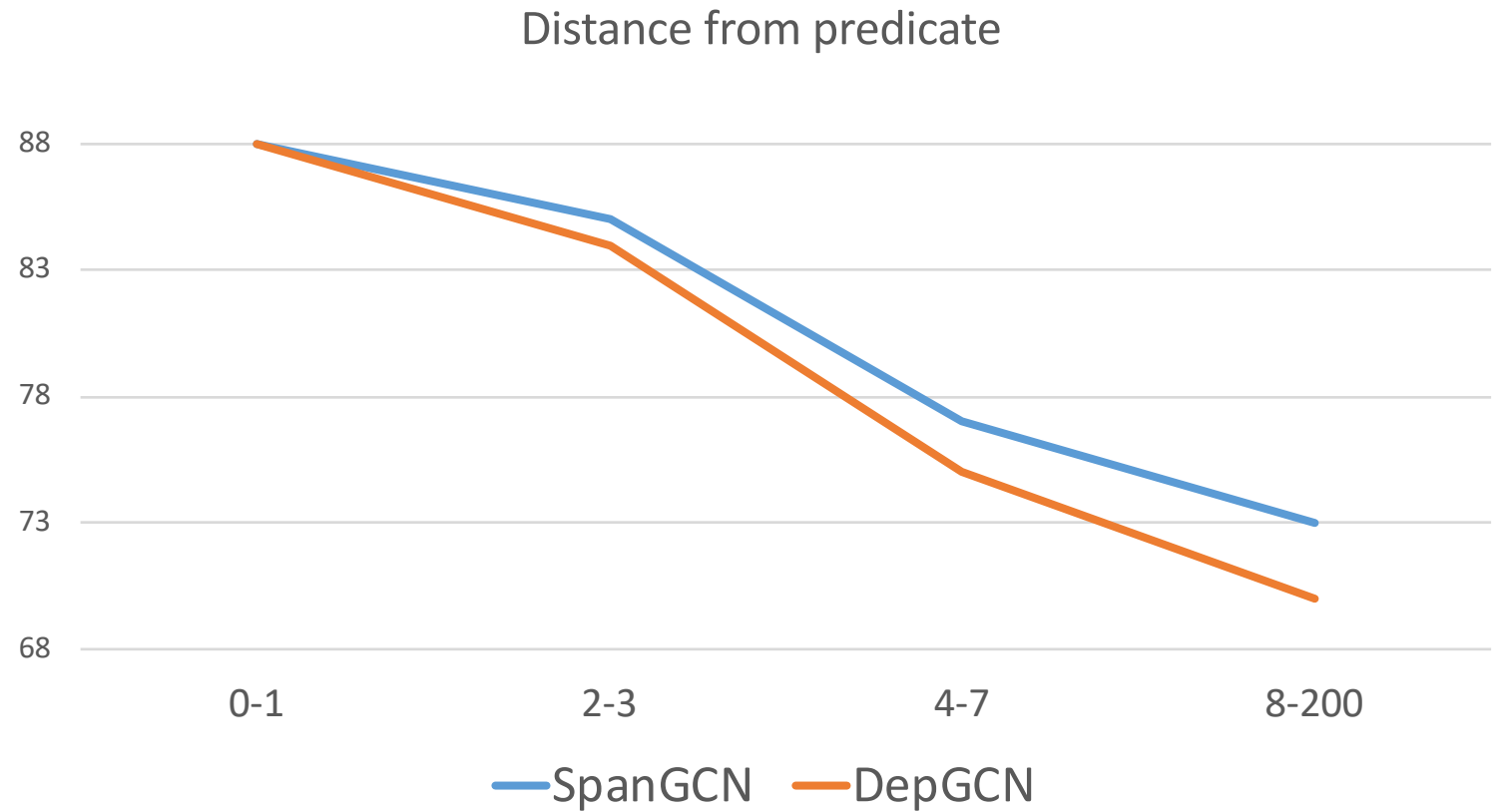
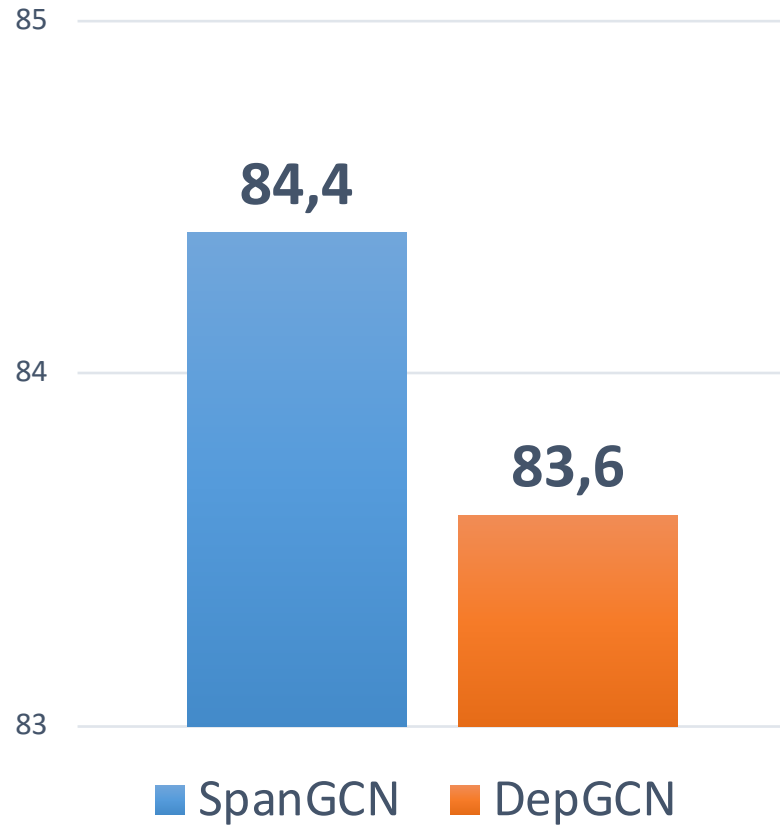
Predicted vs. Gold Syntax (Dev CoNLL 2005)



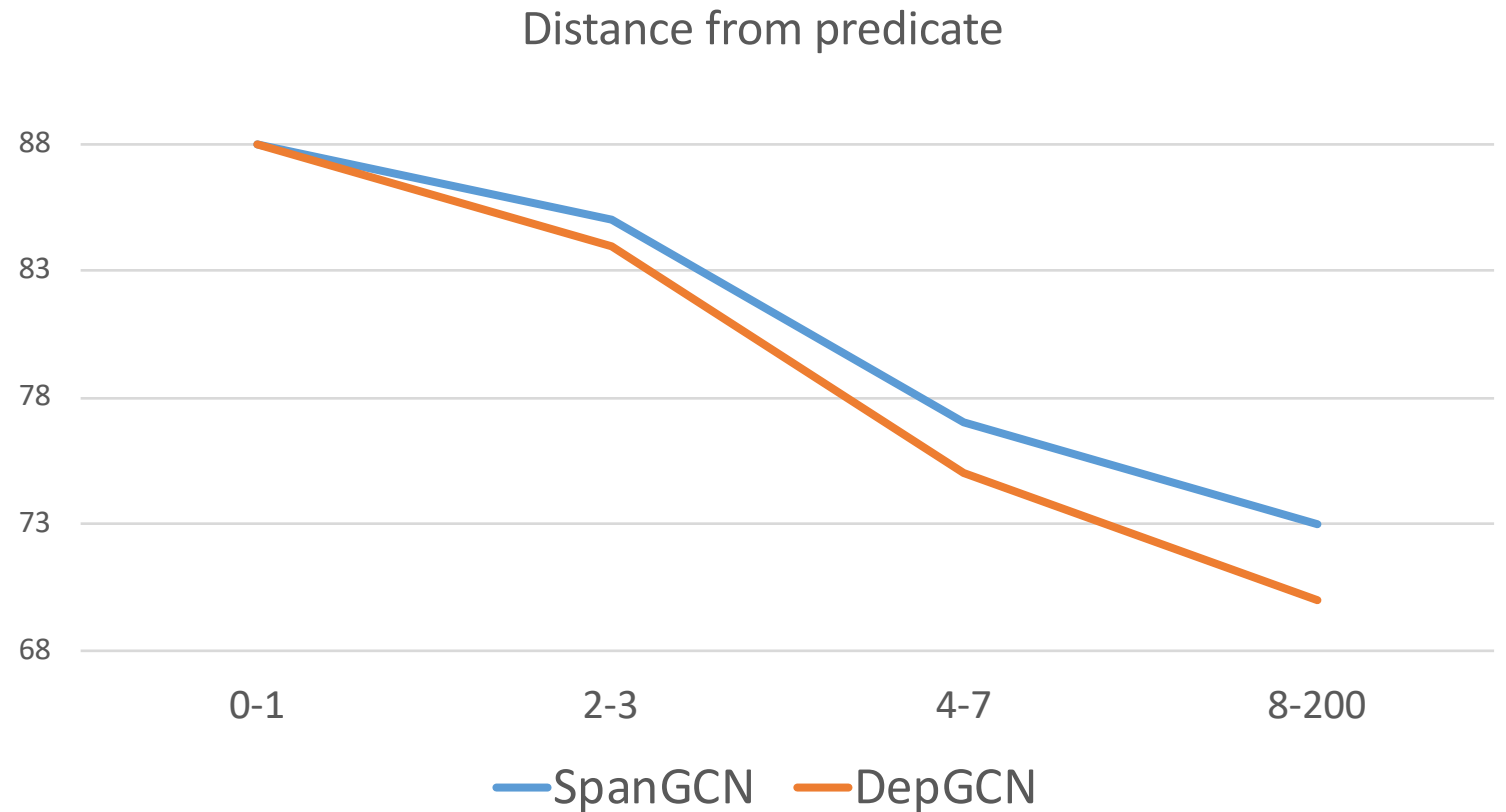
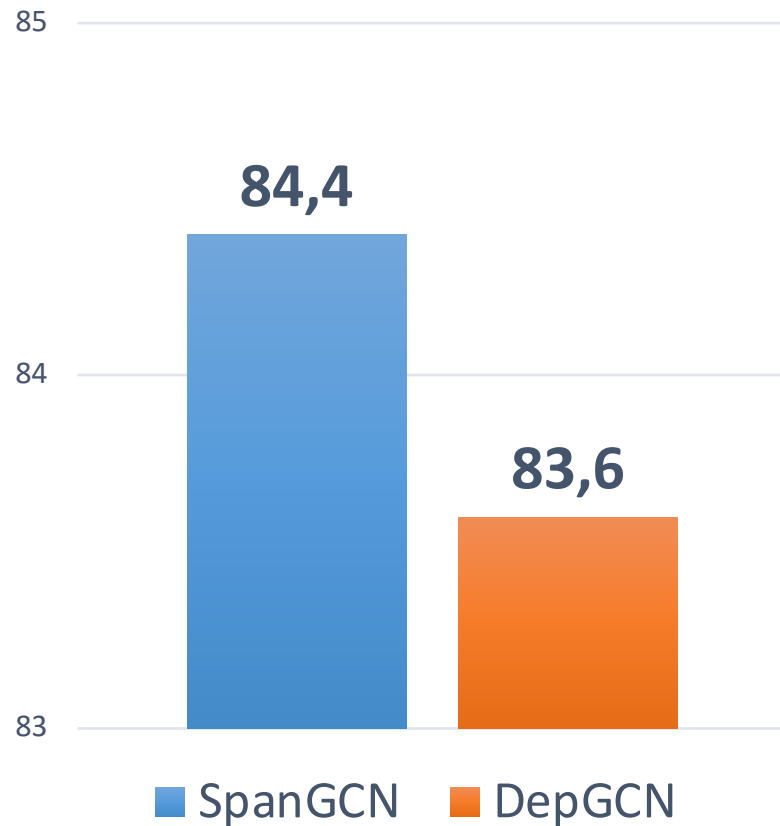
Predicted vs. Gold Syntax (Dev CoNLL 2005)



SpanGCN vs. DependencyGCN (Dev CoNLL 2005)

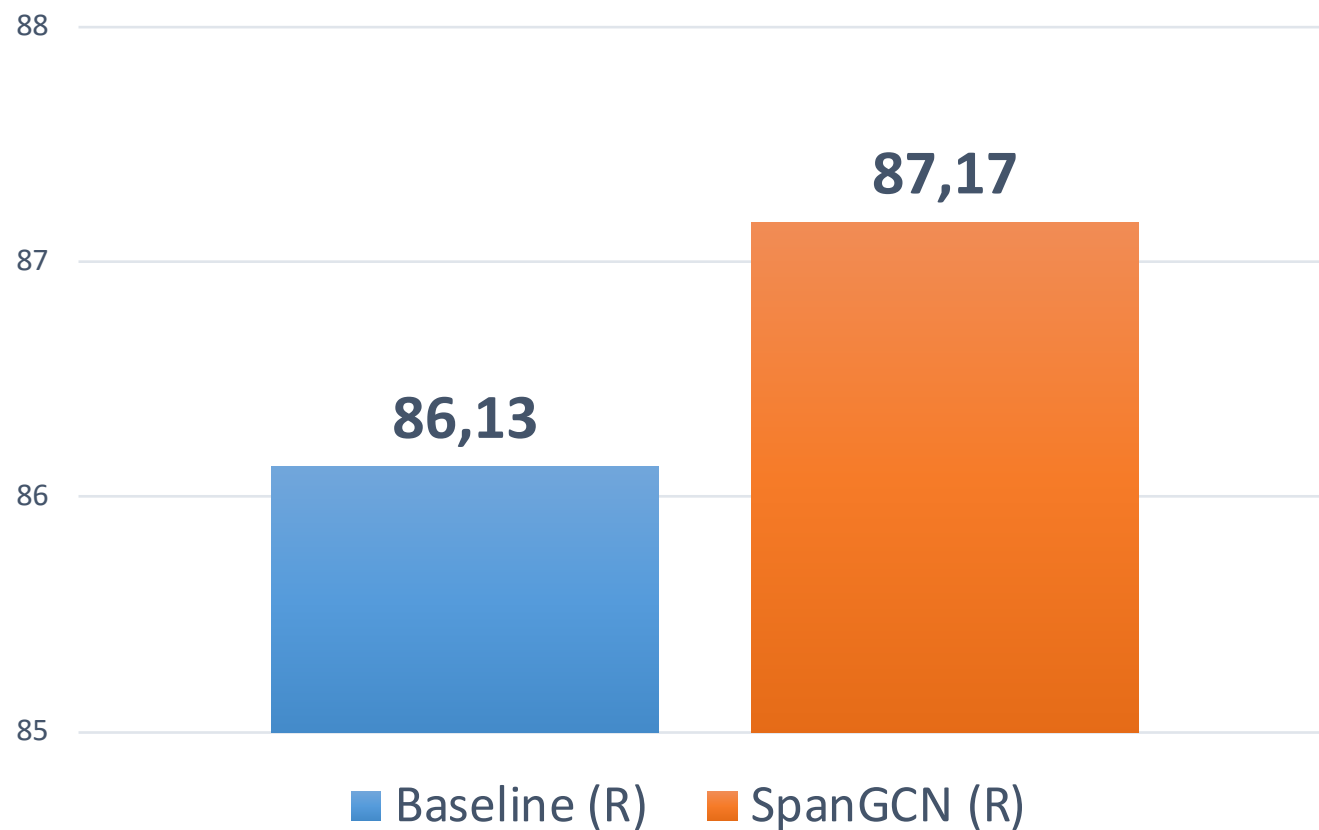


SpanGCN vs. DependencyGCN (Dev CoNLL 2005)

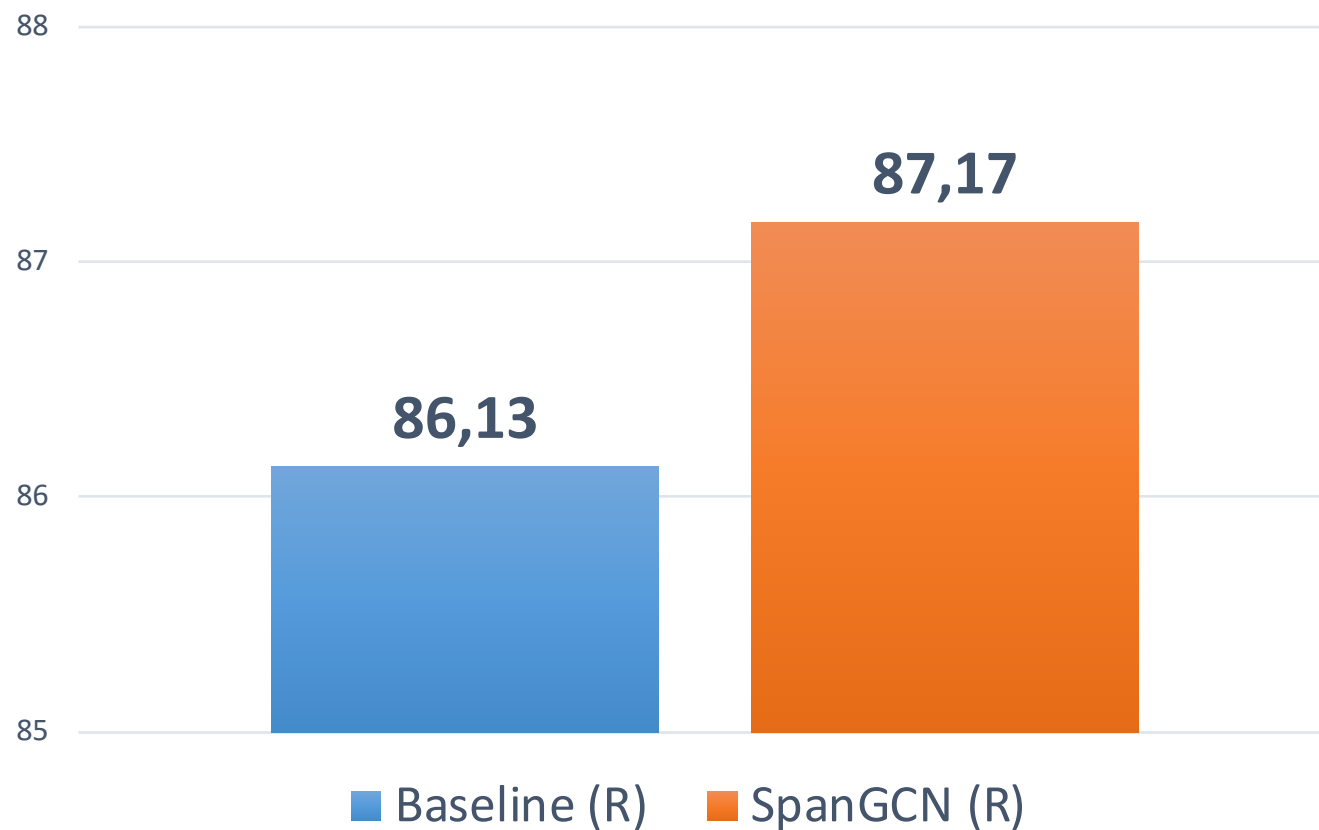


SpanGCN is more effective for distant arguments

RoBERTa + SpanGCN (Dev CoNLL 2005)

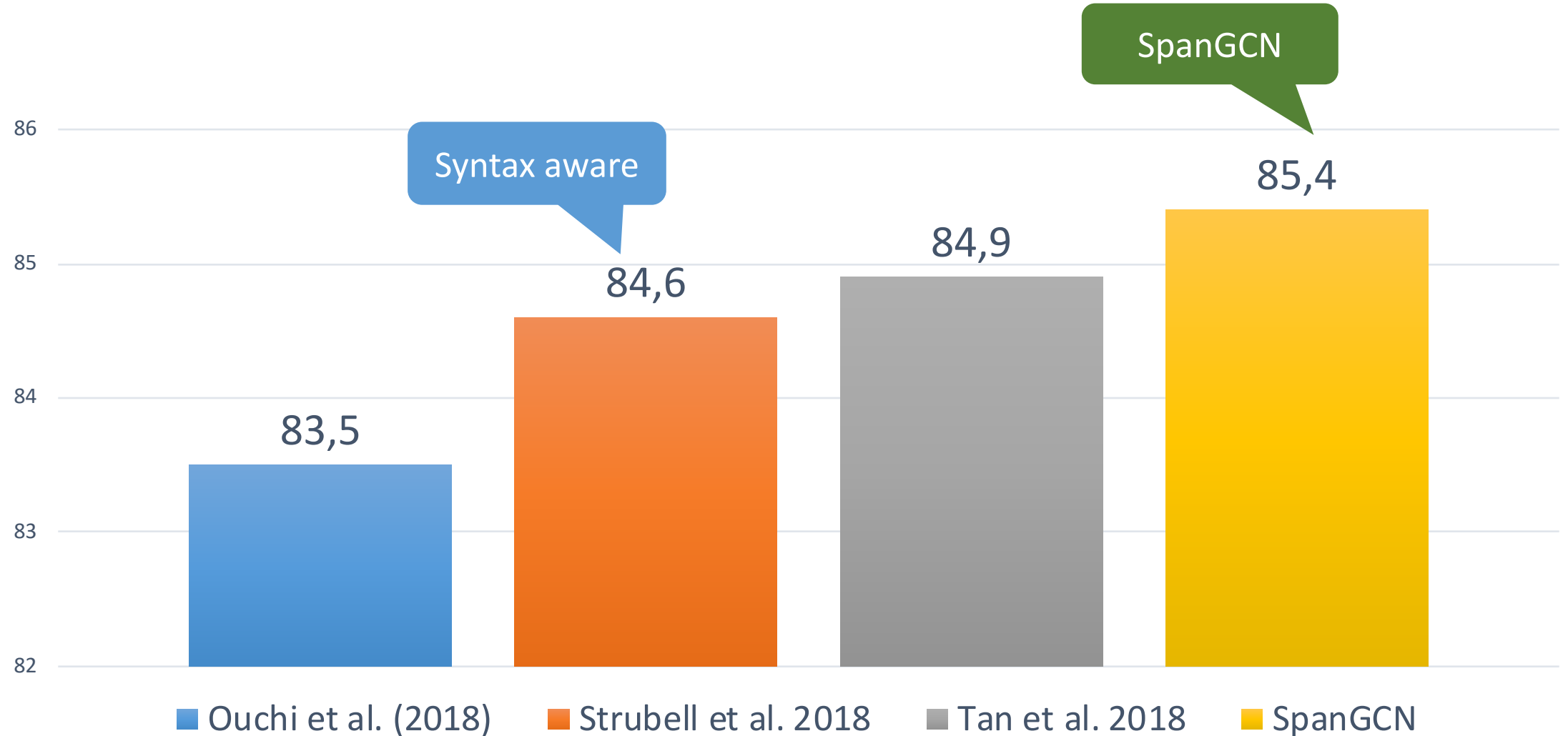


RoBERTa + SpanGCN (Dev CoNLL 2005)



Syntax is still useful with powerful encoders

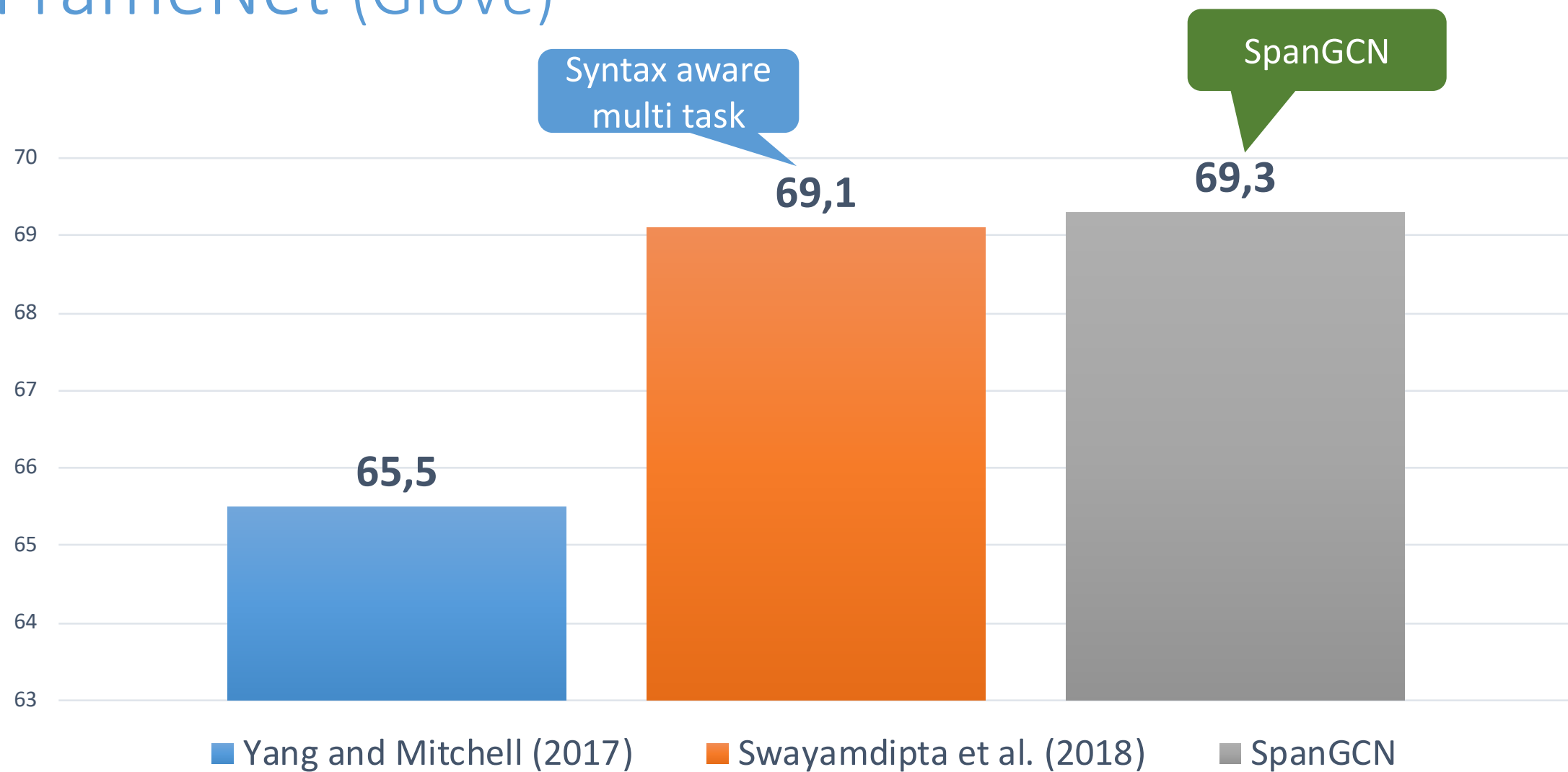
CoNLL 2005 – WSJ (GloVe)



CoNLL 2005 – WSJ (ELMo-RoBERTa)



FrameNet (GloVe)



Conclusions

- GCN-based architecture for encoding constituent structure
 - co-reference, semantic structures, entity graphs, discourse, etc.
- Obtained competitive results on SRL
 - PropBank and FrameNet

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