EE-608: Deep Learning For Natural Language Processing: Graph-to-Graph Transformers

James Henderson

Idiap Research Institute

DLNLP, Lecture 5

Outline

Outline

Why do we need sentence structure?

Humans communicate complex ideas by composing words together into bigger units to convey complex meanings

Human listeners need to work out what modifies [attaches to] what

A model needs to understand sentence structure in order to be able to interpret language correctly

Slide from Diyi Yang

Prepositional phrase attachment ambiguity

San Jose cops kill man with knife

Text Paper Translate Listen Close

San Jose cops kill man with knife

Ex-college football player, 23, shot 9 times allegedly charged police at fiancee's home

By Hamed Aleaziz and Vivian Ho

A man fatally shot by San Jose police officers while allegedly charging at them with a knife was a 23-year-old former football player at De Anza College in Cupertino who was distraught and depressed, his family said

Thursday.

Police officials said two officers opened fire Wednesday afternoon on Phillip Watkins outside his fiancee's home because they feared for their lives. The officers had been drawn to the home, officials said, by a 911 call reporting an armed home invasion

shortly after she called a suicide intervention hotline in hopes of get-

ed help from police."

She said Watkins was on the sidewalk in front

ing for their safety and defense of their life, fired at the suspect."

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Science & Environment

Scientists count whales from space

By Jonathan Amos
BBC Science Correspondent

Slide from Diyi Yang

Prepositional phrase attachment ambiguity

Scientists count whales from space

✓

Scientists count whales from space

✗

Slide from Diyi Yang

PP attachment ambiguities multiply

- A key parsing decision is how we 'attach' various constituents
  - PPs, adverbial or participial phrases, infinitives, coordinations, etc.

The board approved [its acquisition] [by Royal Trustco Ltd.]
[of Toronto]
[for $27 a share]
[at its monthly meeting].

- Catalan numbers: $C_n = (2n)!/[(n+1)!n!]$
- An exponentially growing series, which arises in many tree-like contexts:
  - E.g., the number of possible triangulations of a polygon with $n+2$ sides
    - Turns up in triangulation of probabilistic graphical models (CS228)….

Slide from Diyi Yang

Coordination scope ambiguity

Shuttle veteran and longtime NASA executive Fred Gregory appointed to board

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Slide from Diyi Yang

Coordination scope ambiguity

THE NEWS-GAZETTE

NATION / WO

PRESIDENT'S FIRST PHYSICAL

Doctor: No heart, cognitive issues

But Trump needs to reduce his cholesterol, lose weight

By JILL COLVIN

6-foot-3 president weighed in at 239 pounds — three pounds heavier than he was in September 2016, the last time Trump revealed his weight to the public.

Trump's blood pressure was 122 over 74, and his

with no medical issues." Trump has no heart disease and no family history of it.

The 71-year-old president performed "exceedingly well" on cognitive screening, which is not

White H

reporter

Slide from Diyi Yang

Adjectival/Adverbial Modifier Ambiguity

numbers, including some that featured a bucket and bells brigade of performers who beat rhythms on buckets and trash cans with drums sticks and hammer mallets. PHOTO BY JENNIFER STULTZ

MENTORING DAY

Students get first hand job experience

By Gale Rose
grose@pratttribune.com

Eager students invaded businesses all over Pratt Tuesday, October 24 as they looked for future job opportunities on Disability Mentoring Day.

The 97 students from 12 schools fanned out across Pratt and got first hand experience what it would be like to work at those 40 businesses. They asked questions and got some hands on experience with various operations.

Paola Luna of Pratt High School, Gina Patton of Kingman High School and America Fernandez of St. John chose the Main Street Small Animal Veterinarian Clinic for their business. Students got a tour of the facility, learned what happens in an examination, got to handle various animals and watched a snake eat a mouse.

Luna said she was interested in animal health and wanted to know more about caring for hurt animals. Patton likes all kinds of animals and said she learned a lot from the experience. Watching the snake eat the mouse impressed her the most.

Fernandez wants to become a veterinarian and enjoyed learning everything that veterinarians

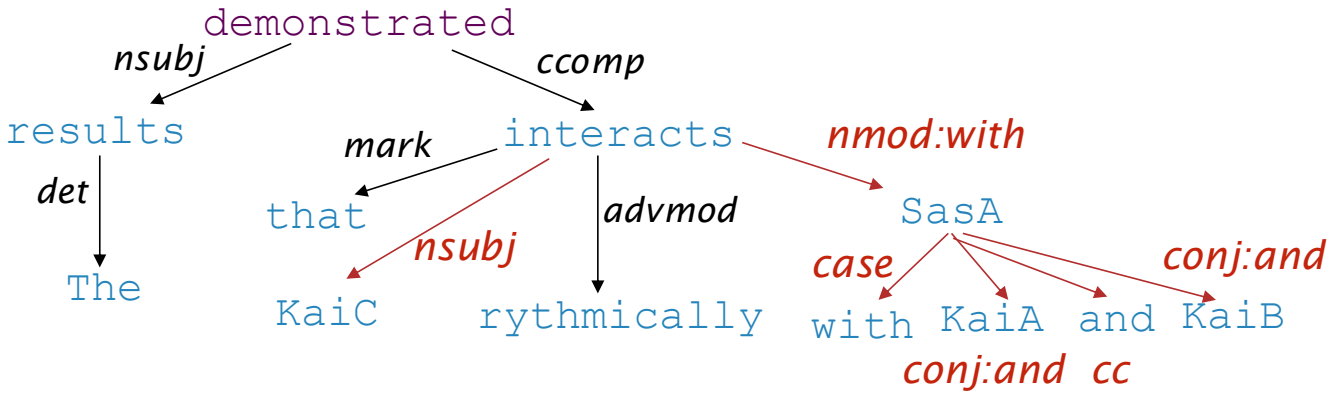
SEE MENTORING, 6

Slide from Diyi Yang

Verb Phrase (VP) attachment ambiguity

Slide from Diyi Yang

Dependency paths help extract semantic interpretation – simple practical example: extracting protein-protein interaction



KaiC ←nsubj interacts nmod:with → SasA

KaiC ←nsubj interacts nmod:with → SasA conj:and→ KaiA

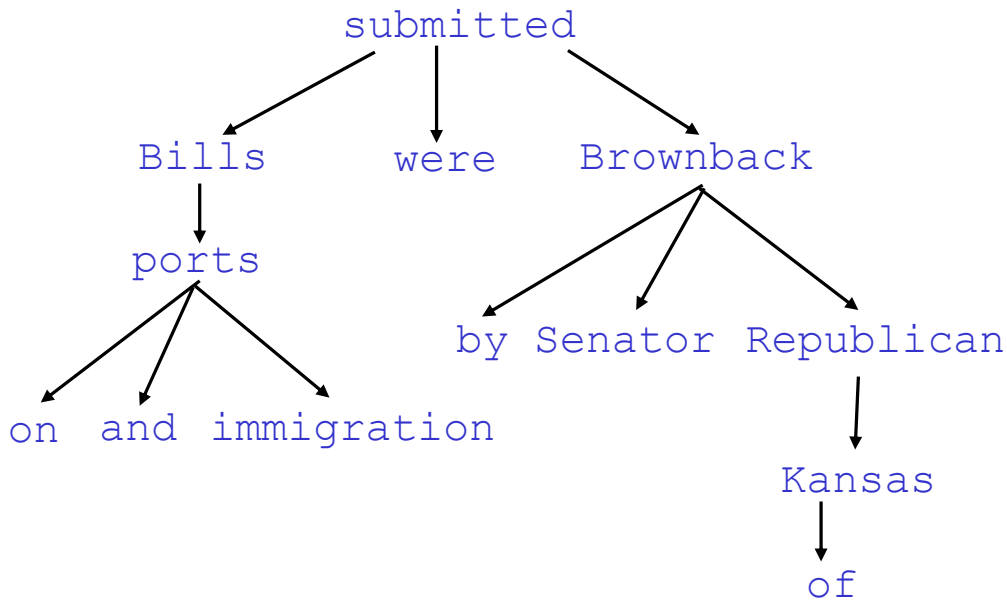
KaiC ←nsubj interacts nmod:with → SasA conj:and→ KaiB

[Erkan et al. EMNLP 07, Fundel et al. 2007, etc.]

Slide from Diyi Yang

2. Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of relations between lexical items, normally binary asymmetric relations ("arrows") called dependencies

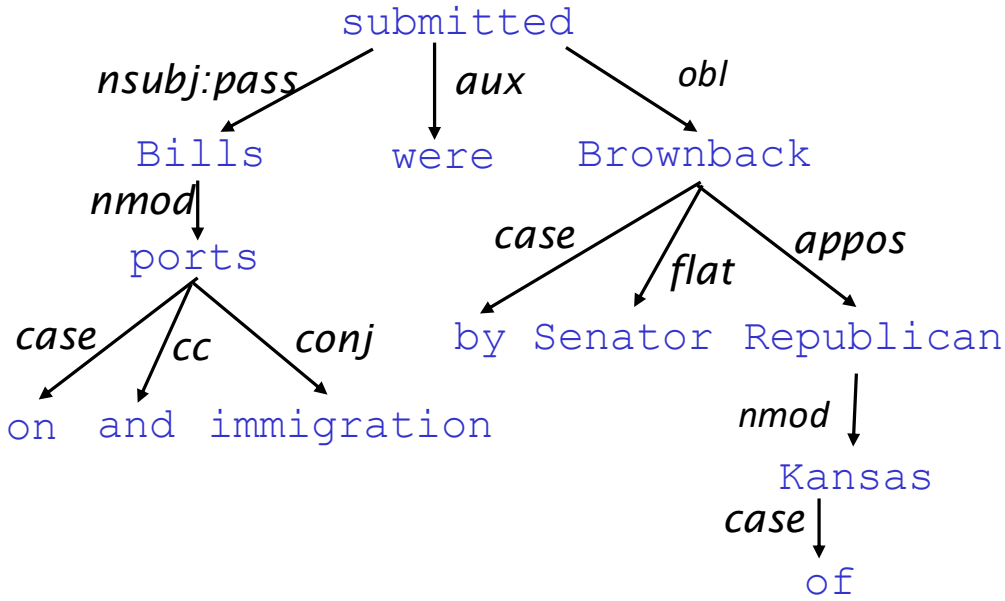


Slide from Diyi Yang

Dependency Grammar and Dependency Structure

Dependency syntax postulates that syntactic structure consists of relations between lexical items, normally binary asymmetric relations ("arrows") called dependencies

The arrows are commonly typed with the name of grammatical relations (subject, prepositional object, apposition, etc.)



Slide from Diyi Yang

Dependency Grammar and Dependency Structure

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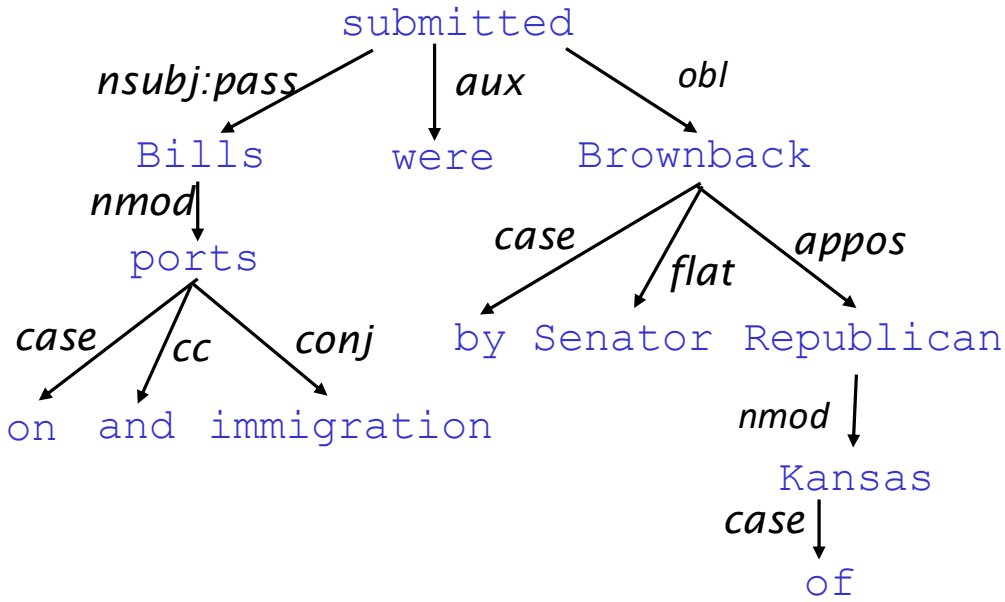
An arrow connects a head with a dependent

Usually, dependencies form a tree (a connected, acyclic, single-root graph)



Slide from Diyi Yang

Summary of Syntactic Structure

- Syntactic structure is a fundamental property of all natural languages
- Syntax is an interface between the meanings of words and the meaning of text
- Two modern traditions for syntactic structure:
  - Constituency structure:
    group words into phrases, recursively
  - Dependency structure:
    link words by their roles, in a tree

Outline

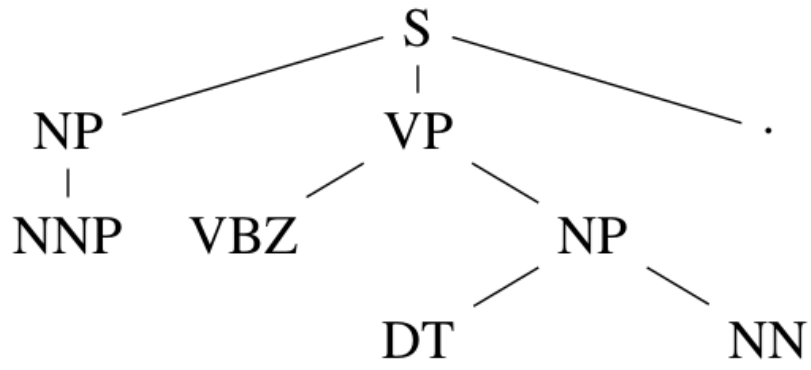
Overview of Syntactic Dependency Parsing

- Syntactic parsing is a benchmark task for ML models of structured prediction
- Dependency parsing finds the syntactic dependencies for a sentence
- Two ways to decompose the score of a parse:
  - Graph-based:
    estimate scores independently, then choose the optimal combination with dynamic programming (MST)
  - Transition-based:
    estimate scores conditioned on history, and search greedily (or with beam search)
- Transition-based parsing tends to be faster, but graph-based is more accurate

Outline

Sequence-to-Sequence Parsing (Vinyals et al. NIPS 2015)

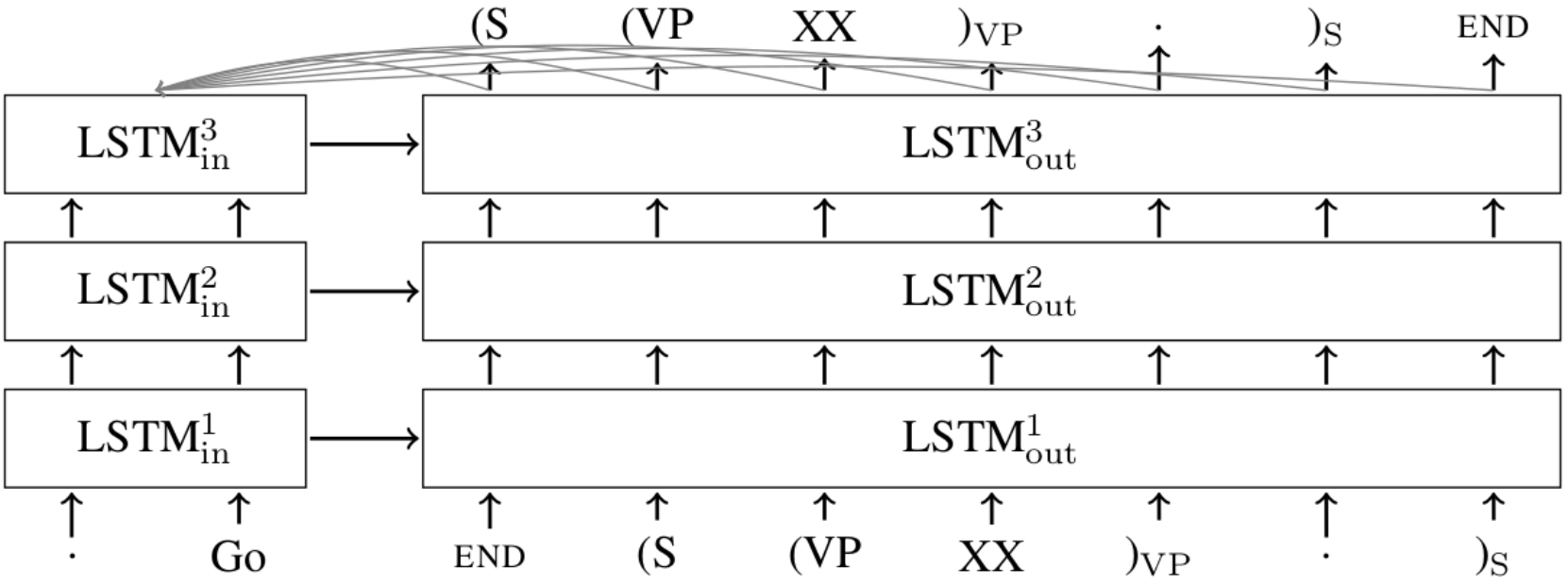
John has a dog . $\rightarrow$



John has a dog . $\rightarrow$ (S (NP NNP)$_{\text{NP}}$ (VP VBZ (NP DT NN)$_{\text{NP}}$)$_{\text{VP}}$.)$_{\text{S}}$

- Parses can be represented as bracketed sequences
- Neural networks can generate sequences
- Why not do parsing like machine translation?

Sequence-to-Sequence Parsing (Vinyals et al. NIPS 2015)



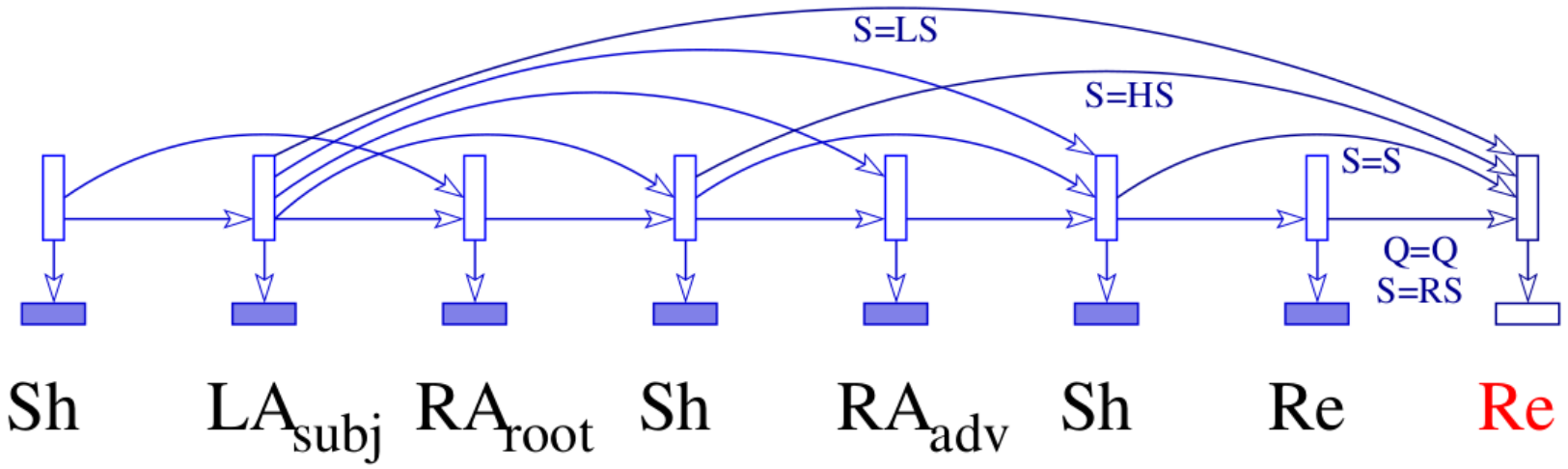
- Use a 2015-SoA neural machine traslation system
- stacked LSTM encoder, stacked LSTM decoder with attention to encoder
- Train it to generate valid bracketed sequences

Sequence-to-Sequence Parsing (Vinyals et al. NIPS 2015)

Parser	Training Set	WSJ 22	WSJ 23
baseline LSTM+D	WSJ only	< 70	< 70
LSTM+A+D	WSJ only	88.7	88.3
LSTM+A+D ensemble	WSJ only	90.7	90.5
baseline LSTM	BerkeleyParser corpus	91.0	90.5
LSTM+A	high-confidence corpus	**92.8**	**92.1**
Petrov et al. (2006) [12]	WSJ only	91.1	90.4
Zhu et al. (2013) [13]	WSJ only	N/A	90.4
Petrov et al. (2010) ensemble [14]	WSJ only	92.5	91.8
Zhu et al. (2013) [13]	semi-supervised	N/A	91.3
Huang & Harper (2009) [15]	semi-supervised	N/A	91.3
McClosky et al. (2006) [16]	semi-supervised	92.4	**92.1**

- Given a sentence, generate a bracketed string
- Convert the string into a parse tree
- Measure accuracy of the resulting parses
- (Optionally, constrain predictions to valid sequences at test time)

Output-Dependent Model Structure



- Need a bias towards learning correlations which are structurally local
- Structure is determined by the parser output
- $\Rightarrow$ Model structure can be incrementally constructed based on output structure

Neural Network Augmentations of Symbolic Models

(Henderson, NAACL 2003; Henderson and Titov, JMLR 2011)

- Recurrent neural networks (RNN)
  - powerful probability estimators
  - induced history representations
  - inductive bias in model structure
- Symbolic models
  - unbounded generalisation
  - domain-appropriate structural locality bias
  - efficient decoding strategies
- Incremental Neural Networks (INN) (a.k.a. SSN, ISBN)
  - RNN estimates derivation decision probabilities
  - with incrementally-specified model structure
  - and efficient beam search decoding

This is the ground breaking work on integrating decoding and structured prediction with neural networks.

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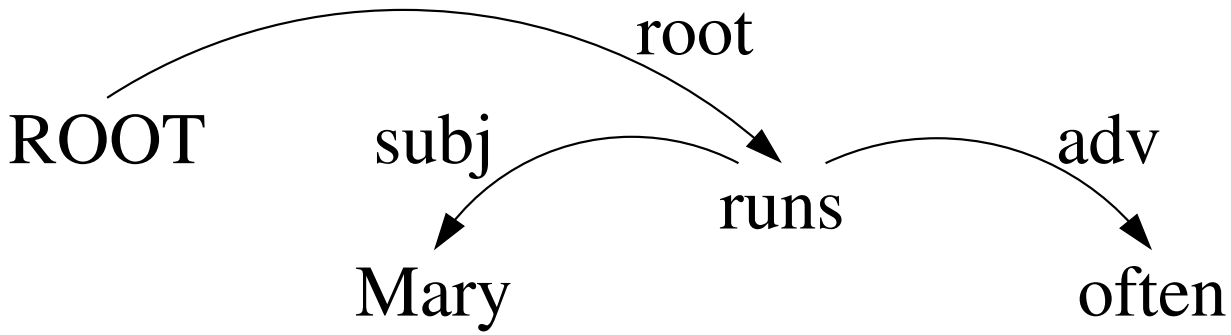
Syntactic parsing with INNs

- Constituency parser with left-corner derivations (Henderson, NAACL 2003)
- Dependency parser with arc-eager derivations (Titov and Henderson, IWPT 2007)
- Faster beam search with discriminative training (Yazdani and Henderson, CoNLL 2015)

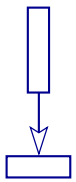
The worlds best parser in 2017 (from Google) was based on the design from (Titov and Henderson, IWPT 2007).



INN dependency parsing example

(Titov and Henderson, IWPT 2007)

ROOT **NNP/Mary** VBZ/runs



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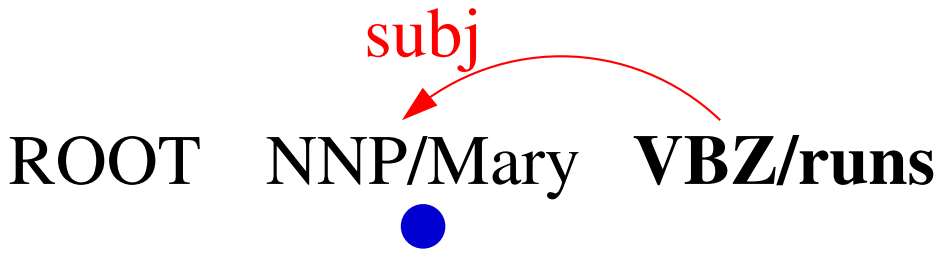
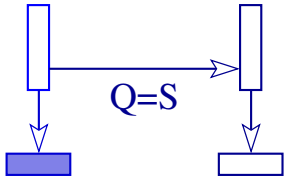
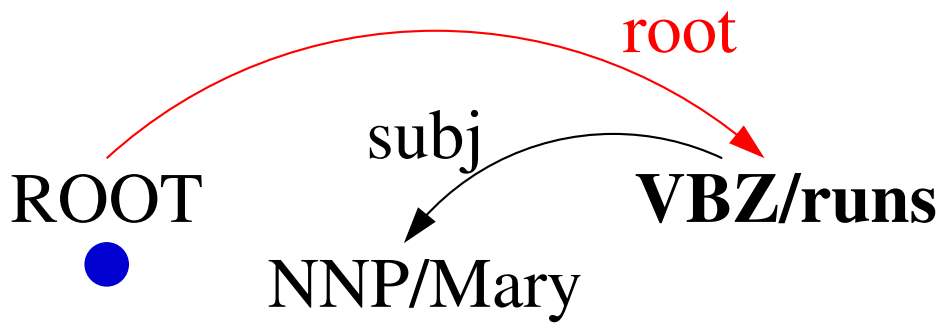


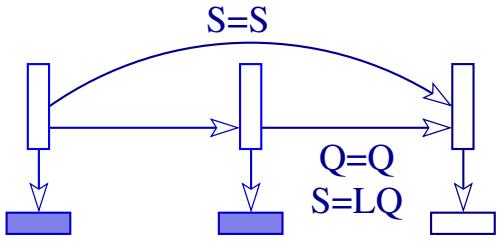


Sh LA_{subj}

INN dependency parsing example

(Titov and Henderson, IWPT 2007)





Sh LA_{subj} RA_{root}

INN dependency parsing example

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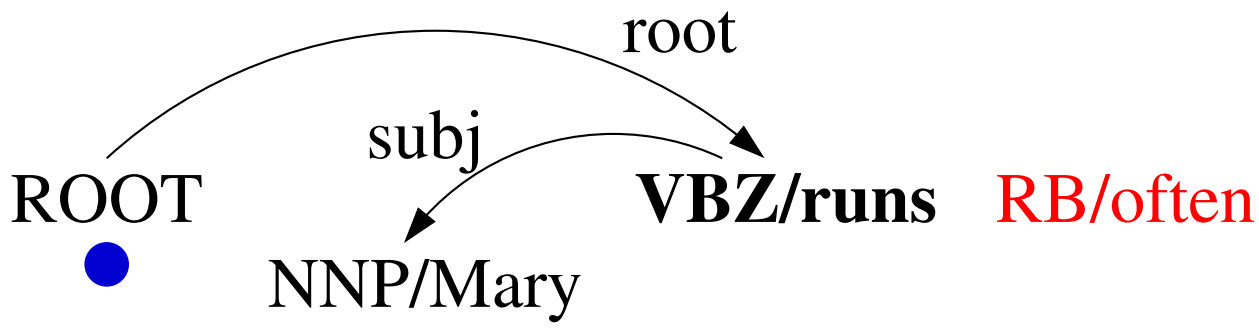

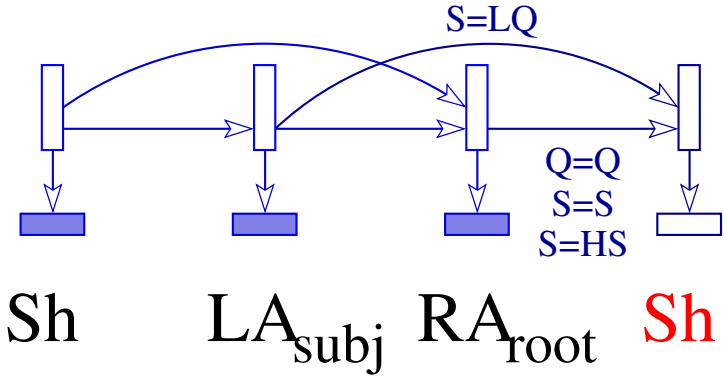

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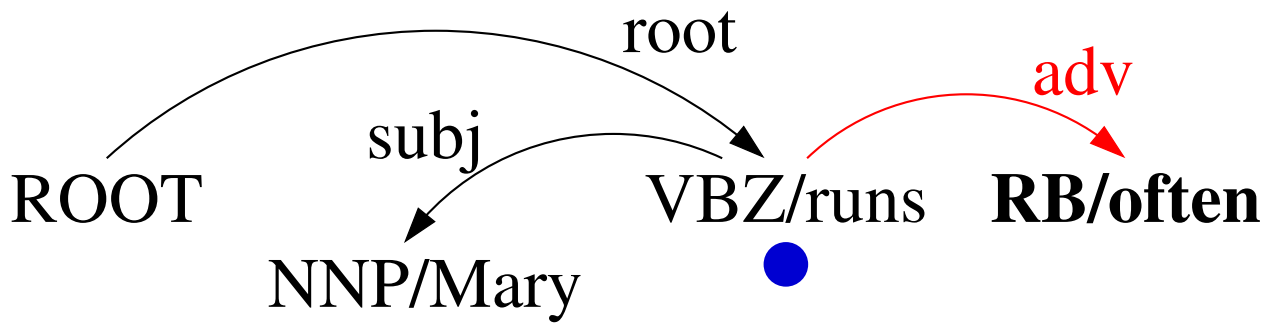

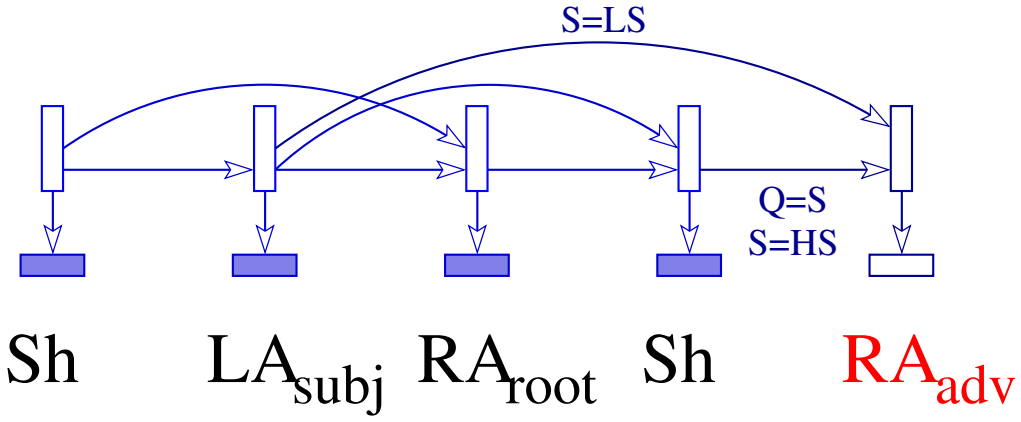

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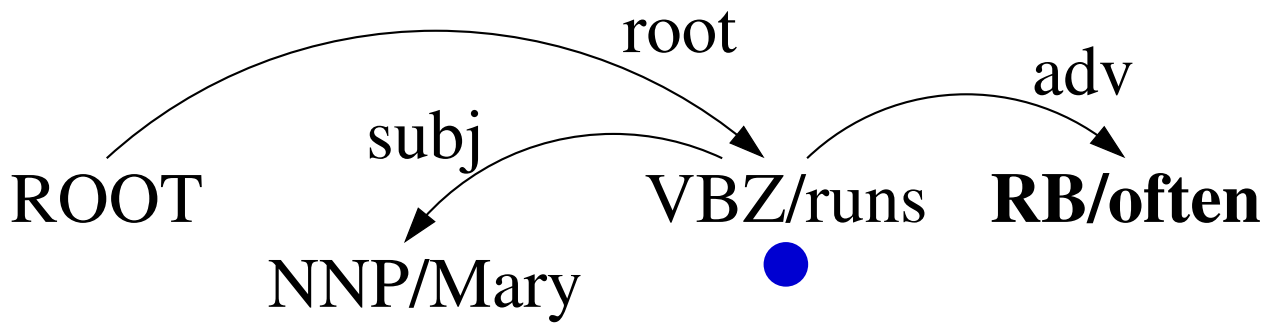

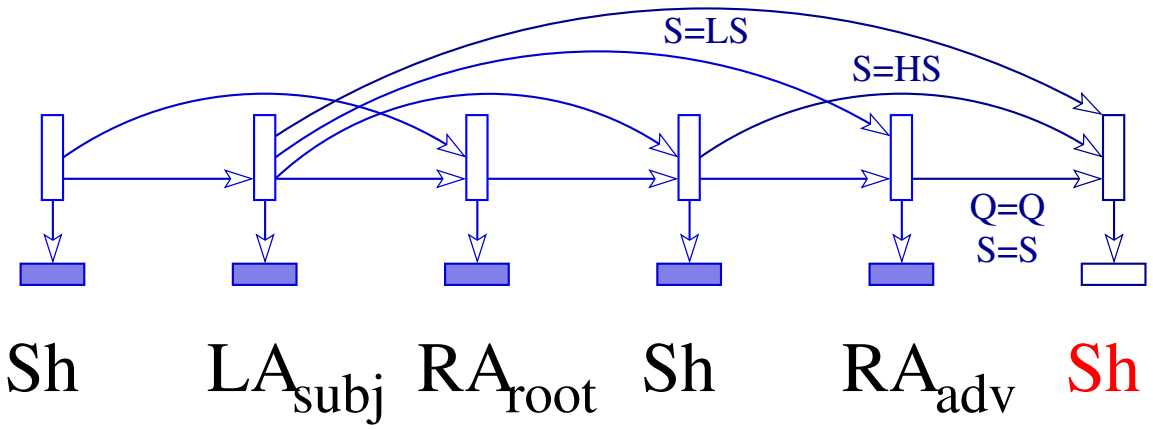

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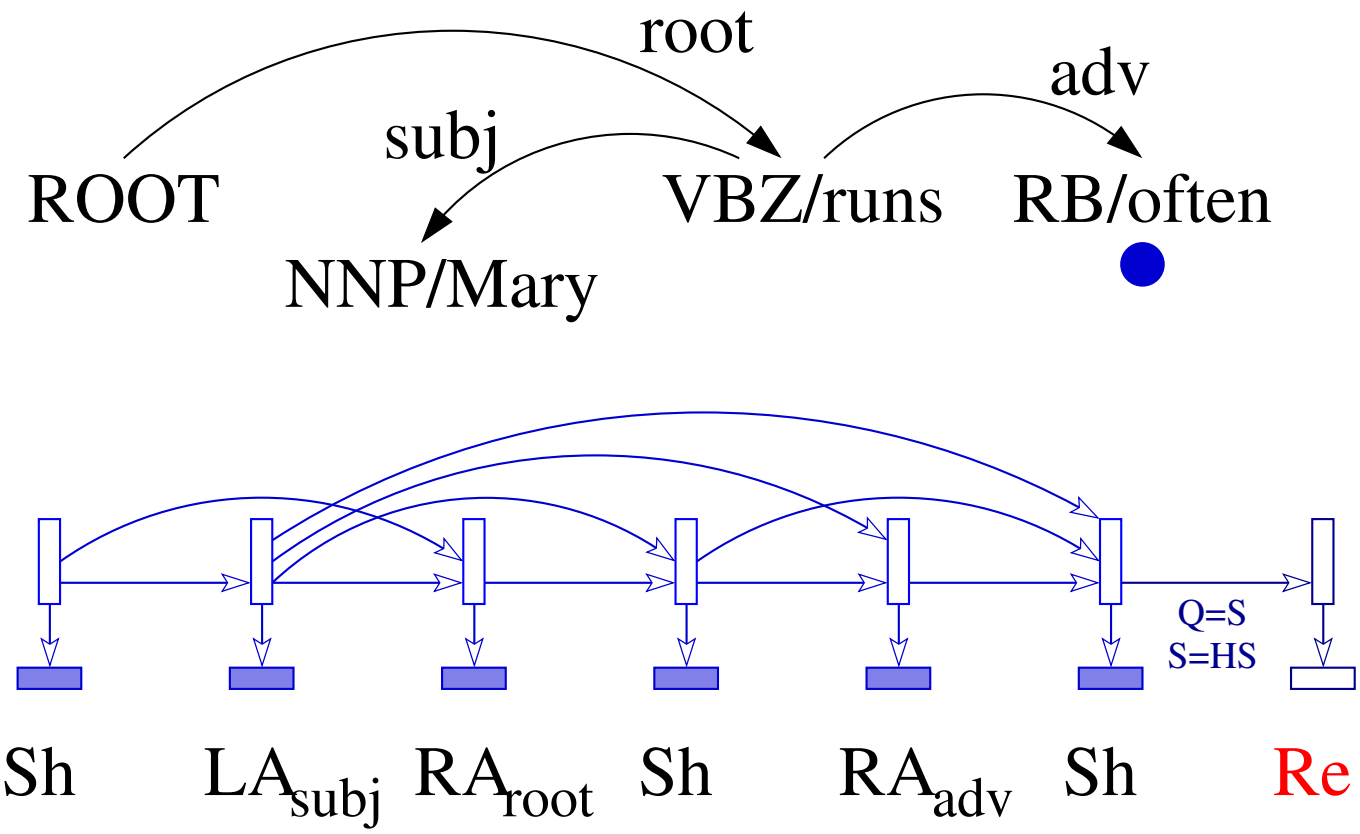

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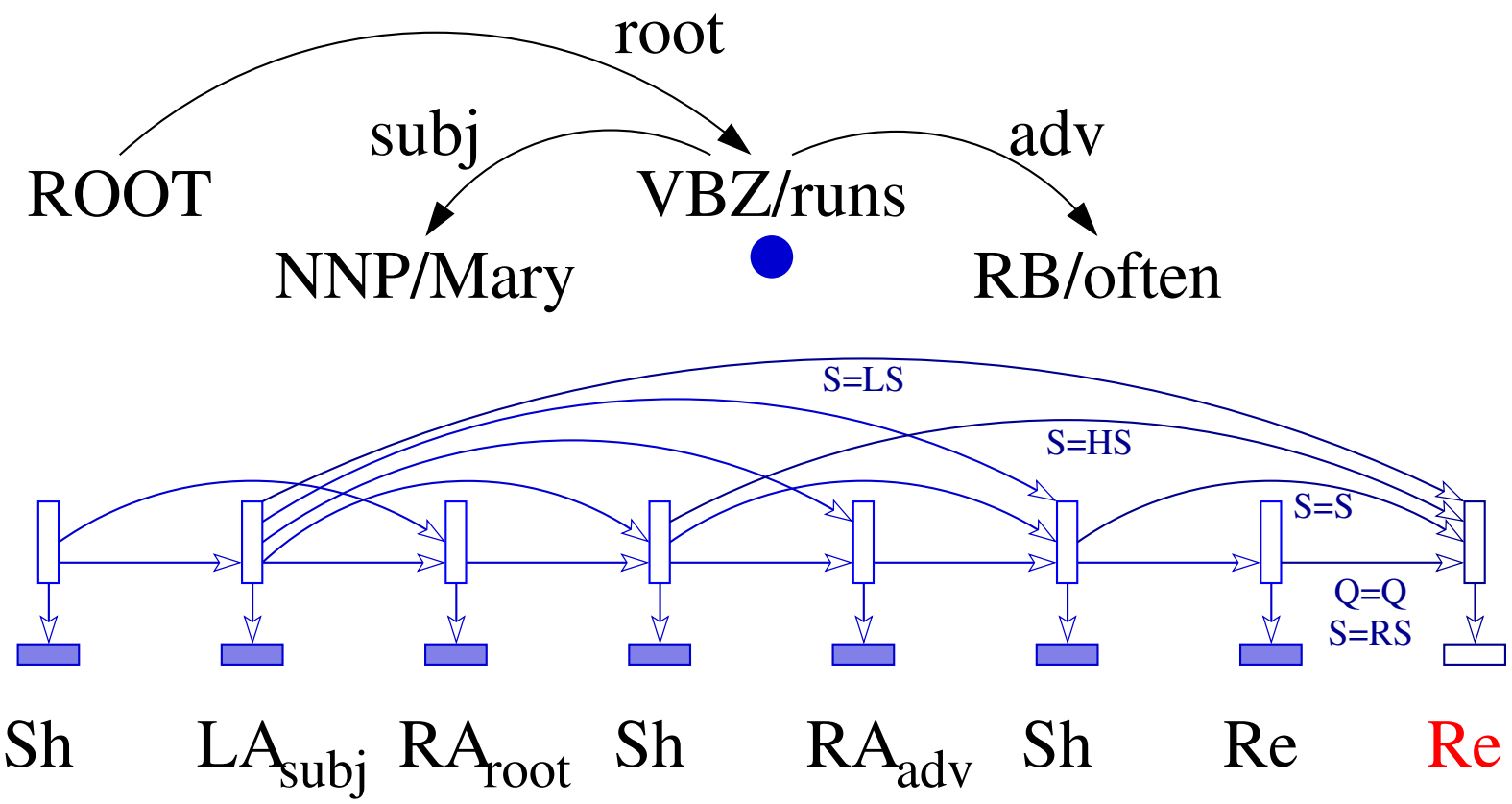

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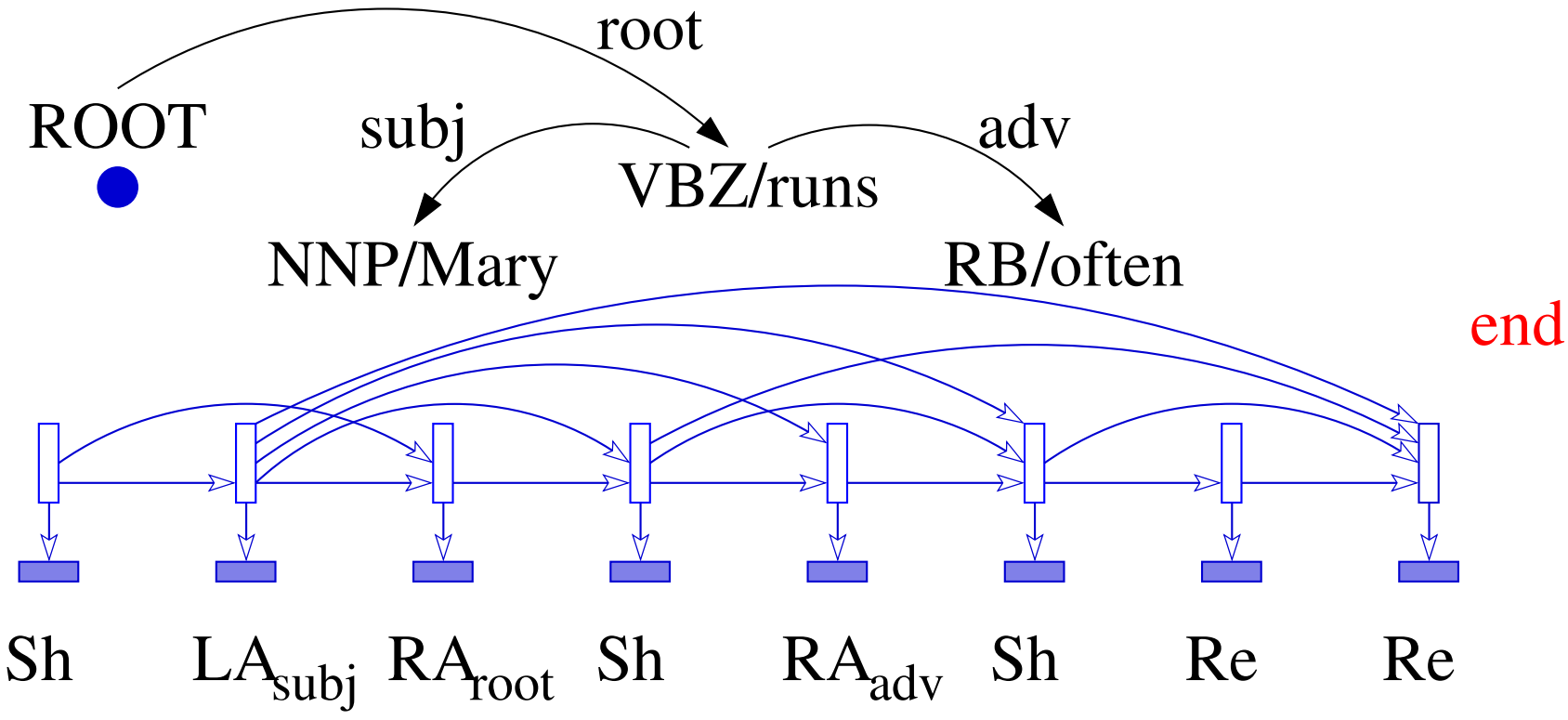

Discriminative modelling of beam search

(Yazdani and Henderson, CoNLL 2015)

Replace the word predictions of the generative model with a ***Correctness Probability*** output

- Trained discriminatively to **distinguish between correct and incorrect parse prefixes**
- Allows beam search with pruning just at *Shift* actions

Better feature parametrisation:

- Low-frequency word-role pair features are factorised into word vectors multiplied by role matrices

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Results on English

better than (Yazdani and Henderson, CoNLL 2015)

CoNLL 2009 English syntactic dependencies:

Model	LAA	wrd/sec
$MALT_{AE}$	86.0	7549
Chen&Manning	86.5	**9589**
MST	87.1	290
Generative **INN**, beam 1	77.8	1122
Generative **INN**, beam 10	87.7	107
Generative **INN**, large beam	**88.7**	NA
D**INN**, beam 1	*89.0*	4890
D**INN**, beam 10	***89.8***	544

- Discriminative parser with a beam of 1 is **50 times faster** than the generative model with beam 10, with higher accuracy.

Multilingual Results

Diverse CoNLL 2009 languages, syntactic dependencies:

Model	German	Spanish	Czech
Chen&Manning	81.9	81.5	58.5
MALT	80.7	82.4	67.3
MST	84.1	82.7	73.4
D**INN**	**86.0**	**85.4**	**77.5**

- Better at generalising to new languages without feature engineering.

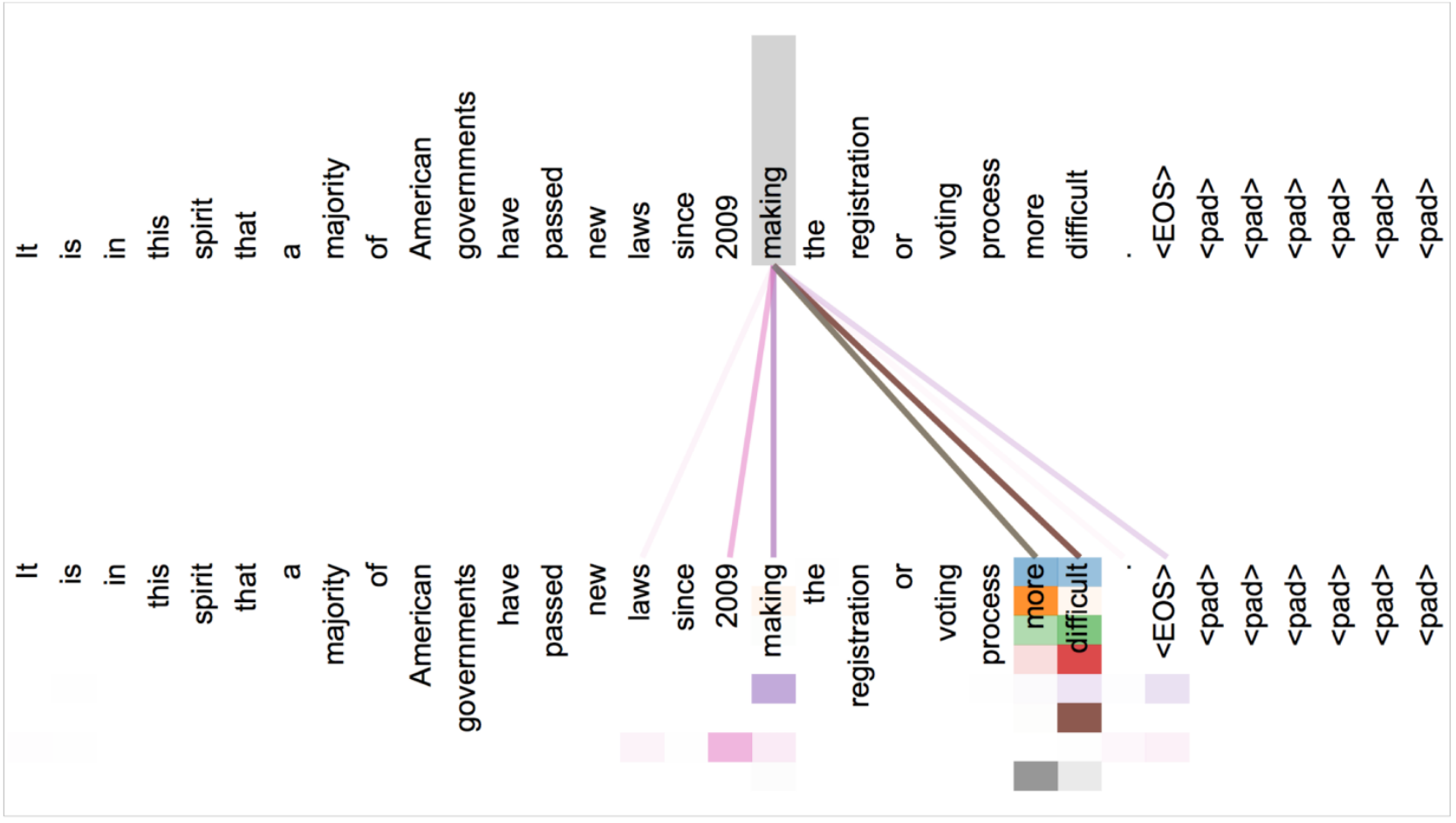
Stack-LSTM Dependency Parser

"Transition-Based Dependency Parsing with Stack Long Short-Term Memory", Dyer, Ballesteros, Ling, Matthews and Smith. ACL 2015.

- Model structure is defined in terms of the parser's data structures
- General mechanism for applying LSTMs to stack data structures

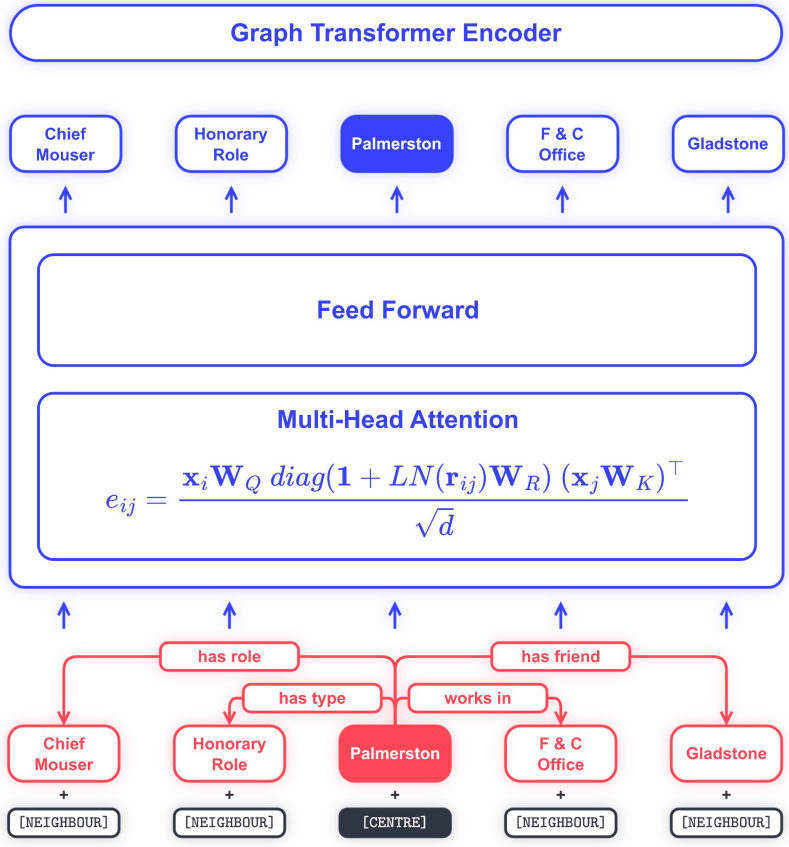
Attention is an Induced Graph

- Graphs specify correlations between nodes
- Attention weights specify correlations between tokens
- Attention induces a latent graph

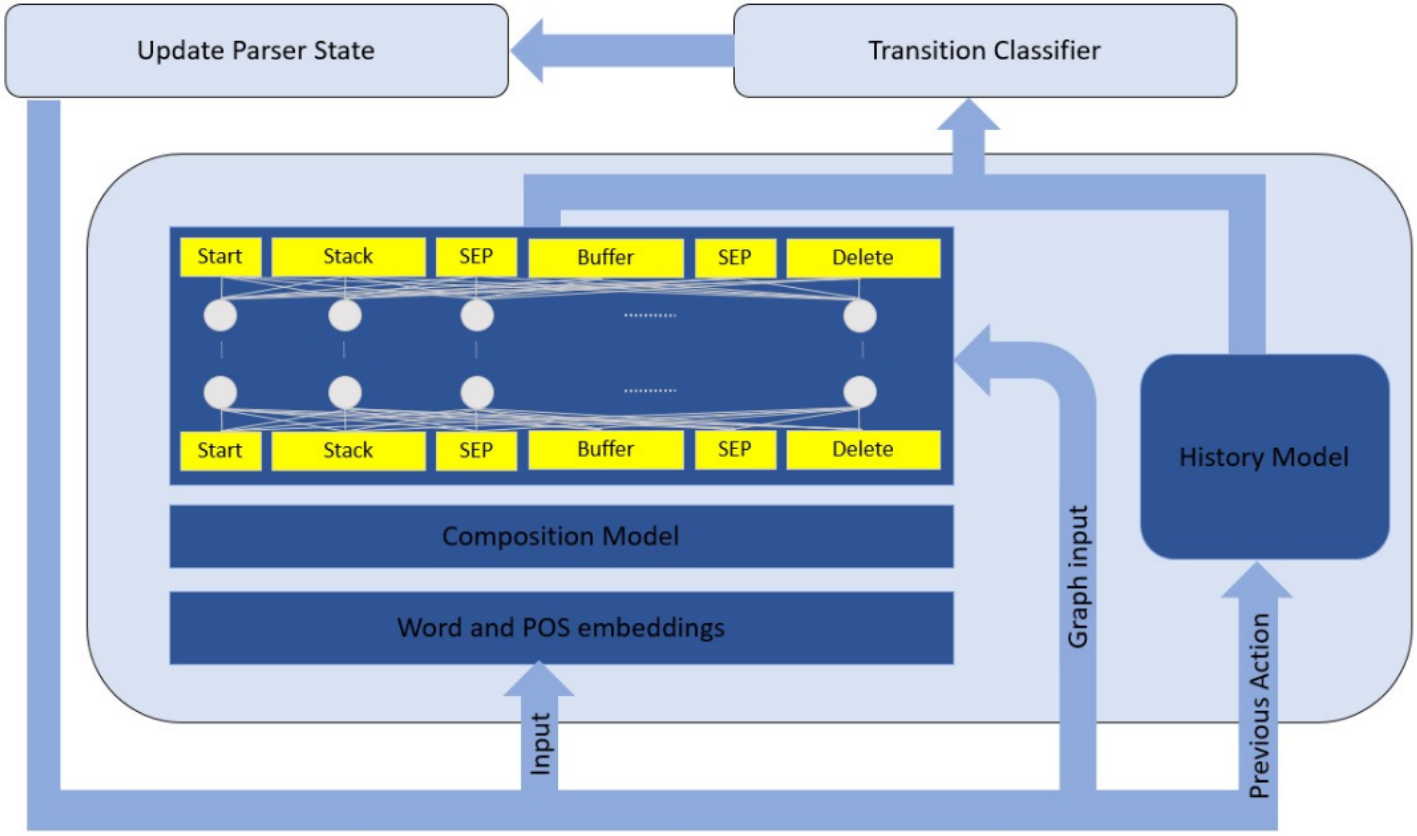


Graph-to Graph Transformers

- Transformers are latent graph models.
- How can we use them to model graphs?



Transformer Transition-Based Dependency Parsing



"Graph-to-Graph Transformer for Dependency Parsing", Mohammadshahi and Henderson, 2020

- Transformer computes token embeddings for parser state
- Additional inputs to reflect parser state and history
- Parser actions predicted from relevant tokens (top of stack)

Agenda

- Motivation
- Graph-to-Graph Transformer
  - Transition-based Dependency Parsing
  - Graph-based Iterative Refinement
  - Semantic Role Labelling
- Compression of Massively Multilingual Models
  - Impacts on different biases
  - Distillation of these models for low-resource languages
- Conclusion and Future Directions

Slide from Alireza Mohammadshahi

Graph-to-Graph Transformer for Transition-based Dependency Parsing

Findings of EMNLP 2020

Authors:

Alireza Mohammadshahi

James Henderson

Slide from Alireza Mohammadshahi

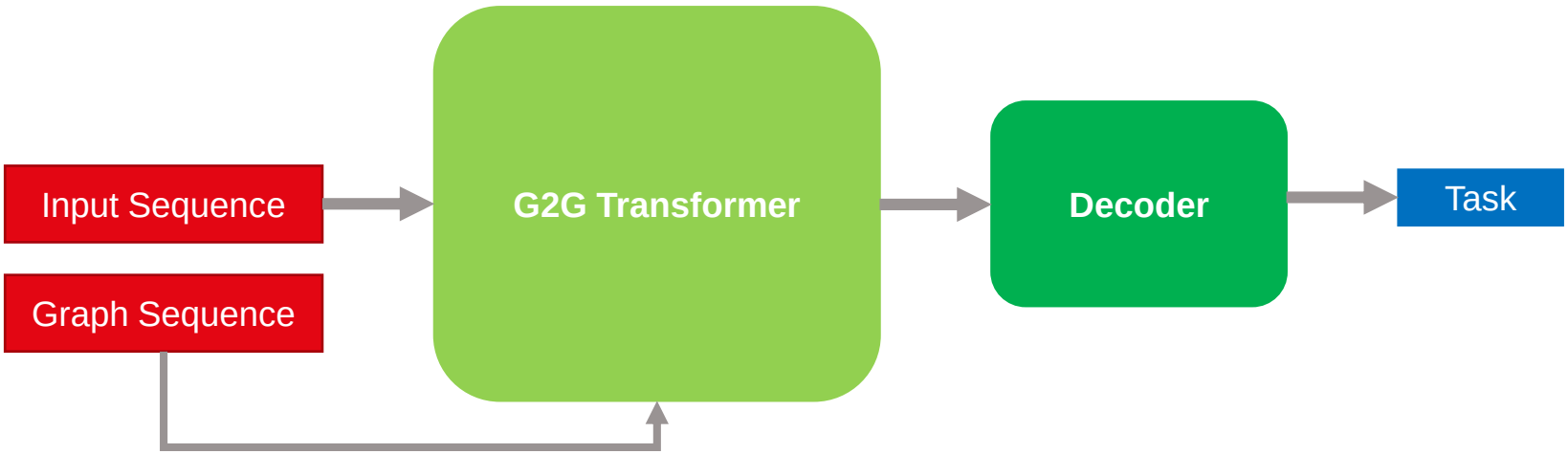
Previous Work

- Add a Graph Encoder on top of sequence encoder (Ji et al,2019)

- Add a hard bias toward graph structure (strubell et al,2018)
- Recursively use neural networks (Dyer et al,2015)

Slide from Alireza Mohammadshahi

Graph-to-Graph Transformer



Slide from Alireza Mohammadshahi

Graph-to-Graph Transformer

- Input arbitrary graph in addition to input sequence
- Output a graph for the downstream task
- Combines both sequence encoder and graph encoder into one general encoder
- Add a soft bias toward attention heads (no hard coding)

Slide from Alireza Mohammadshahi

Graph-to-Graph Transformer

Compute output representations of input sequence by stack of multi-head self-attention layers

Each Layer:

- Multi-head attention layer
- Feed-forward position-wise NN

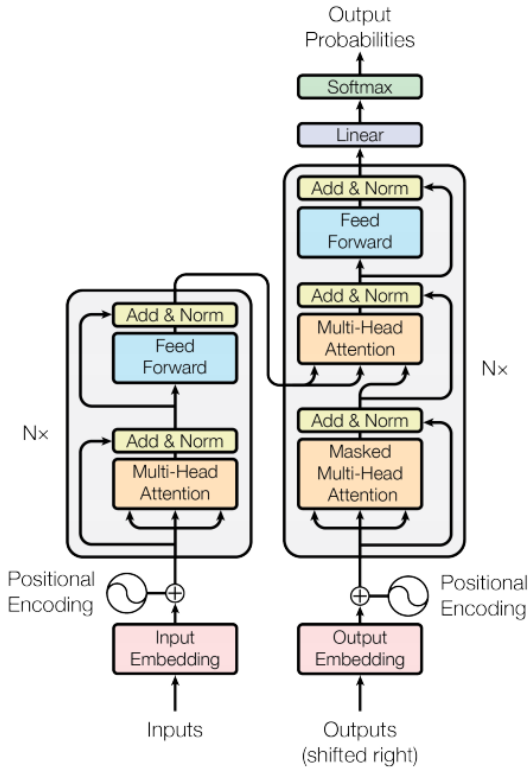


Photo by Vaswani et al, 2017

Slide from Alireza Mohammadshahi

Graph-to-Graph Transformer

We have input sequence X, Transformer finds Output representation Z:

$$z_i = \sum_j \alpha_{ij}(x_j W^v)$$

Attention weights are calculated as:

$$\alpha_{ij} = \frac{\exp(e_{ij})}{\sum_k \exp(e_{ik})}, \qquad e_{ij} = \frac{(x_i W^Q)(x_j W^k)}{\sqrt{d}}$$

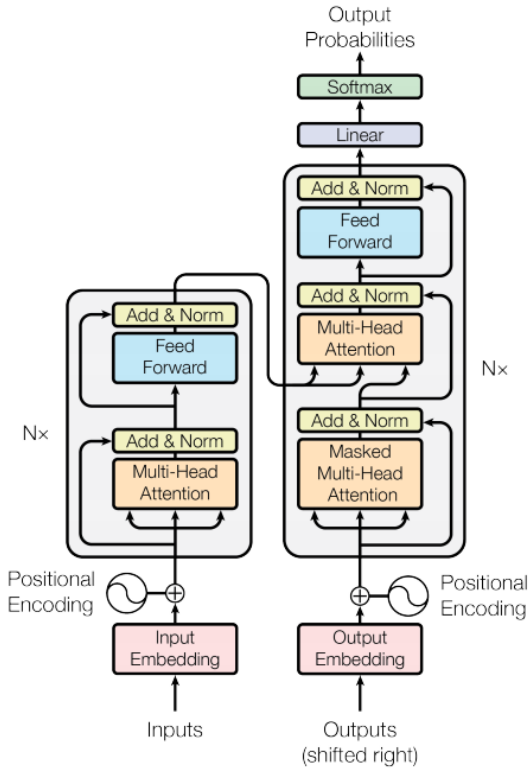


Photo by Vaswani et al, 2017

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Graph-to-Graph Transformer

To input a graph, we modify equations of original Transformer:

$$z_i = \sum_j \alpha_{ij}(x_j W^v + p_{ij} W_L^2)$$

$$e_{ij} = \frac{(x_i W^Q)(x_j W^k + p_{ij} W_L^1)}{\sqrt{d}}$$

p_{ij} is the relation between token x_i and x_j

Slide from Alireza Mohammadshahi

Graph-to-Graph Transformer

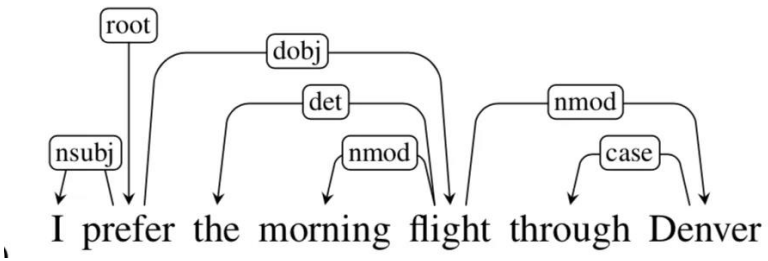
- Matrix P can be any input graph
- **Soft Bias**. Each attention head can easily learn to attend only to positions in a given relation, but it can also learn other structures in combination with other input
- Output value representation can have both token-level and graph-level information
- Can be applied to any NLP tasks which require to input a graph or produce a graph over the same nodes

Slide from Alireza Mohammadshahi

Dependency Parsing

- Extracting a dependency parse of a sentence that represents its grammatical structure

- Defines the relationships between “head” words and words, which modify those heads.



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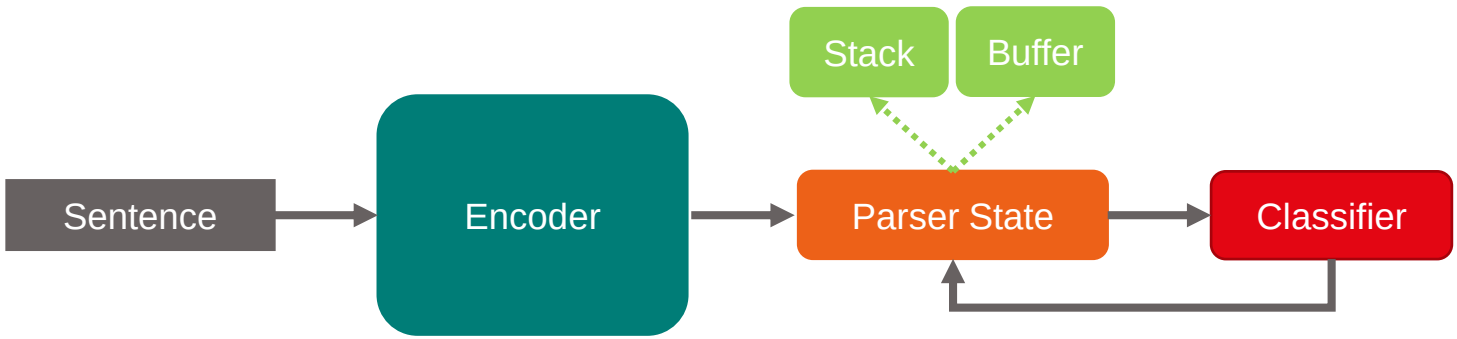
Transition-based Models

- Iteratively build the dependency graph by predicting a new transition at each step

- Transition classifier predicts the new action based on parser state



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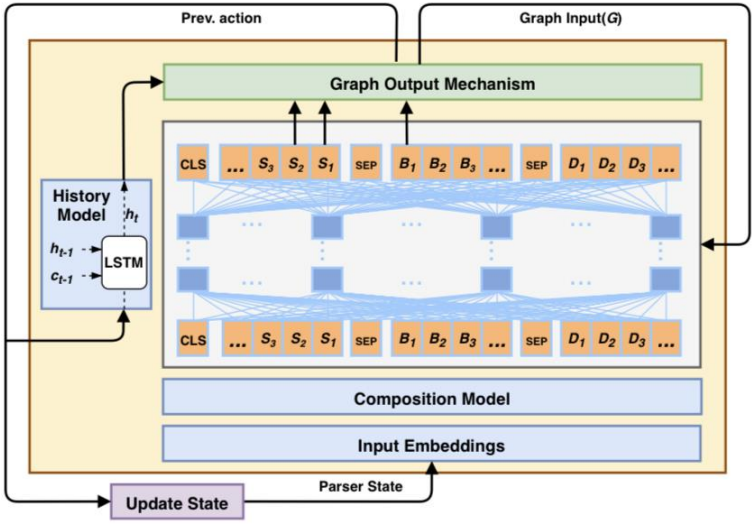
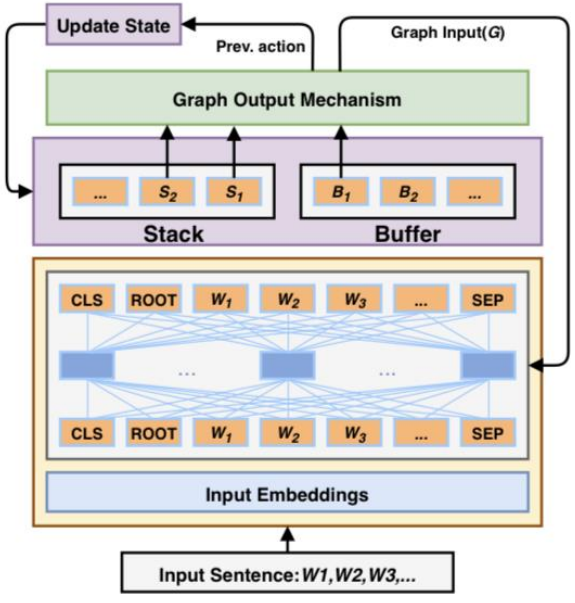
Baselines + G2G-Tr

StateTr+G2G-Tr



SentTr+G2G-Tr



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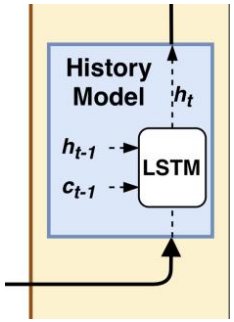
Baselines + G2G-Tr

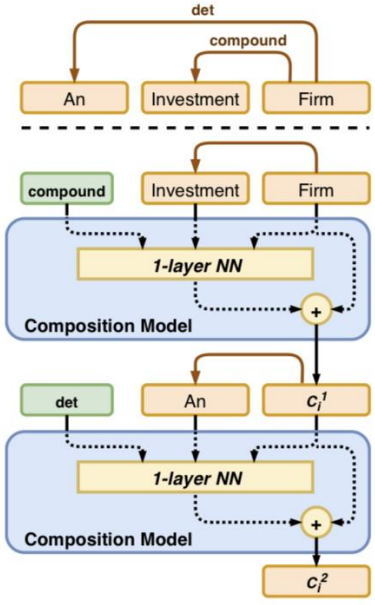
History Model



$$h^t,\ c^t = \mathrm{LSTM}((h^{t-1}, c^{t-1}), a^t + l^t)$$

a^t and l^t are predicted action and dependency label.

Composition Model



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Results

We evaluated our model on:

- English WSJ Penn Treebank (Marcus et al,1993)
- 13 Languages of UD Treebanks (Nivre et al,2018)

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Results

- G2G-Tr integration
- BERT pre-training
- Graph output mechanism
- Replacement with composition model
- UD Benchmark

Language	Kulmizev et al. (2019)	BERT StateTr+G2GTr	BERT SentTr+G2GTr
Arabic	81.9	82.63	**83.65**
Basque	77.9	74.03	**83.88**
Chinese	83.7	85.91	**87.49**
English	87.8	89.21	**90.35**
Finnish	85.1	80.87	**89.47**
Hebrew	85.5	87.0	**88.75**
Hindi	89.5	93.13	**93.12**
Italian	92.0	92.6	**93.99**
Japanese	92.9	95.25	**95.51**
Korean	83.7	80.13	**87.09**
Russian	91.5	92.34	**93.30**
Swedish	87.6	88.36	**90.40**
Turkish	64.2	56.87	**67.77**
Average	84.87	84.48	**88.06**

	Dev Set		Test Set	
	UAS	LAS	UAS	LAS
Transition-based:				
Dyer et al. (2015)			93.10	90.90
Weiss et al. (2015)			94.26	91.42
Cross and Huang (2016)			93.42	91.36
Ballesteros et al. (2016)			93.56	92.41
Andor et al. (2016)			94.61	92.79
Kiperwasser and Goldberg (2016)			93.90	91.90
Yang et al. (2017)			94.18	92.26
Seq2Seq-based:				
Zhang et al. (2017)			93.71	91.60
Li et al. (2018)			94.11	92.08
StateTr	91.94	89.07	92.32	89.69
StateTr+G2GTr	92.53	90.16	93.07	91.08
BERT StateTr	94.66	91.94	95.18	92.73
BERT StateCLSTr	93.62	90.95	94.31	91.85
BERT StateTr+G2GTr	**94.96**	**92.88**	**95.58**	**93.74**
BERT StateTr+G2CLSTr	94.29	92.13	94.83	92.96
BERT StateTr+G2GTr+C	94.41	92.25	94.89	92.93
BERT SentTr	95.34	93.29	95.65	93.85
BERT SentTr+G2GTr	**95.66**	**93.60**	**96.06**	**94.26**
BERT SentTr+G2GTr-7 layer	**95.78**	**93.74**	**96.11**	**94.33**

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Conclusion

- Propose Graph-to-Graph Transformer Architecture
- Applied to transition-based dependency parsing
- Compatible with BERT pre-training
- Outperforms previous work in the transition-based parsing

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Outline

Graph-based dependency parsers

- Compute a score for every possible dependency relation, in the context of the rest of the sentence.
- Given $O(n^2)$ scores $\text{score}(i, j|x)$ (for first-order algorithms), find:

$$\underset{\hat{y} \in Y(x)}{\text{argmax}} \sum_i \text{score}(i, \hat{y}_i|x)$$

- where $Y(x)$ is the set of trees over x
- using an algorithm like Minimum Spanning Tree ($O(n^3)$)

Syntax-Aware Graph-to-Graph Transformer for Semantic Role Labelling

Rep4NLP at ACL 2023

Authors:

Alireza Mohammadshahi
James Henderson

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Motivation

Semantic Role Labelling (SRL)

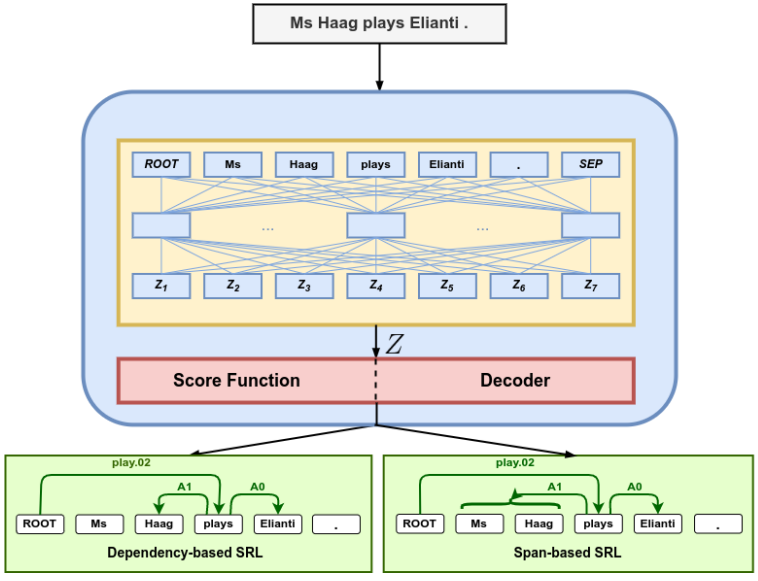
- Provides a shallow representation of the semantics in a sentence

Graph-Types:

- ❑ Dependency-based
- ❑ Span-based

Applications:

- ✓ Question Answering
- ✓ Machine Translation
- ✓ Natural Language Inference (NLI)
- ✓ …



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Motivation

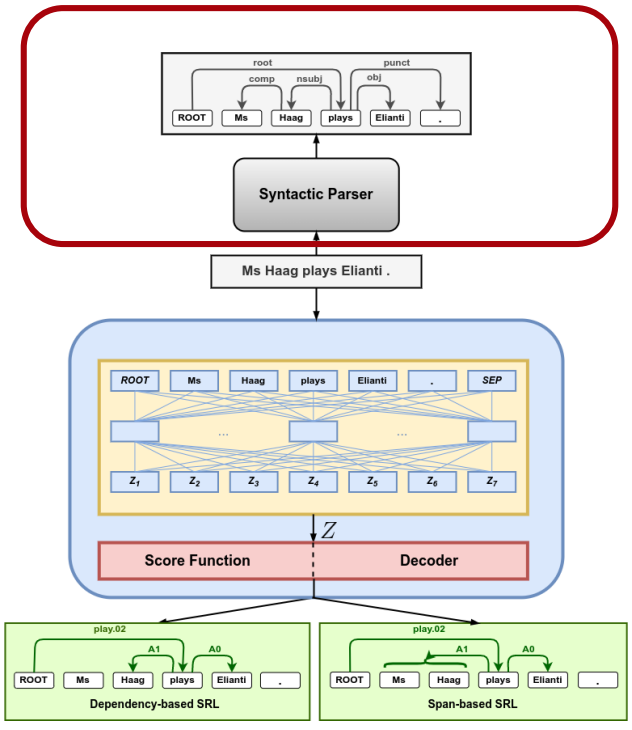
Syntactic Knowledge for SRL

Open Questions:

- Is Syntax beneficial for SRL?
- How can one efficiently encode it?

Previous Work:

- Use separate graph encoder (e.g. GNN)
- Hard coding of attention heads in Transformer
- Joint Training of Syntax and Semantic



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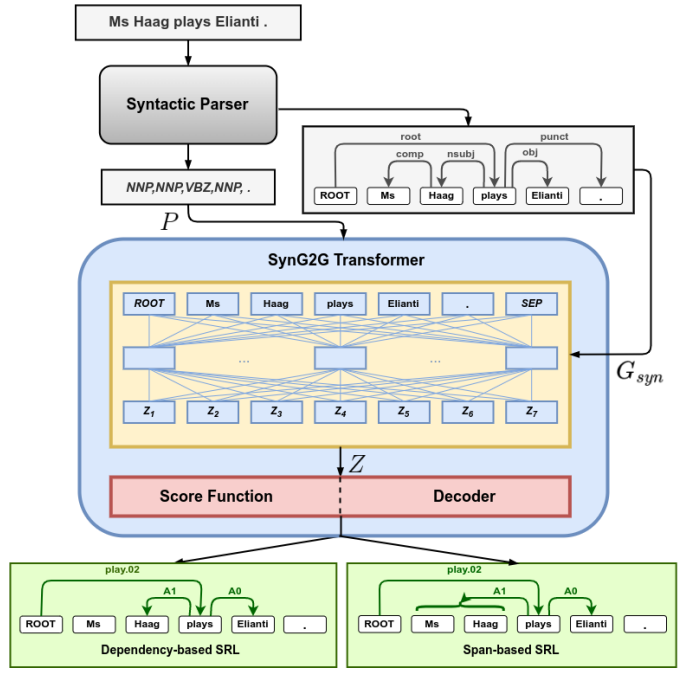
Syntax-Aware Graph-to-Graph Transformer (SynG2G-Tr)

- Integrate the graph relations into the self-attention mechanism
- Soft bias (the model can still learn other structures)
- Efficient as it adds linear complexity to the computation

❖ In this work, we use syntactic dependency graph



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Attention Mechanism

To input a graph, we modify equations of original Transformer:

$$z_i = \sum_j \alpha_{ij}(x_j W^v)$$

$$e_{ij} = \frac{1}{\sqrt{d}}[(x_i W^Q)(x_j W^K)^T + x_i W^Q (r_{ij} W^R)^T + r_{ij} W^R (x_j W^K)^T]$$

r_{ij} is the relation between token x_i and x_j

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Results

Span-based SRL

Evaluation data: CoNLL 2005 benchmark

Without BERT:

- SynG2G-Tr outperforms Strubell et al. (2018)
- Benefit of soft bias instead of hard-coding

With BERT:

- Outperforms by 5.4%/8.8% F1 relative error reduction (RER) on average in both in-domain and out-of-domain settings
- Compatibility with BERT initialisation

Model	SA	WSJ (in-domain)			Brown (out-of-domain)		
		P	R	F1	P	R	F1
end-to-end							
He et al. (2017)	✗	85.0	84.3	84.6	74.9	72.4	73.6
He et al. (2018a)	✗	81.2	83.9	82.5	69.7	71.9	70.8
Strubell et al. (2018)	✓	85.53	84.45	84.99	75.8	73.54	74.66
Li et al. (2019)	✗	-	-	83.0	-	-	-
Xia et al. (2019)	✓	84.3	83.8	84.1	73.7	72.0	72.9
Xia et al. (2020)	✓	83.05	84.49	84.49	73.47	74.92	74.19
SynG2G-Tr (w/o BERT)	✓	84.48	86.46	**85.45**	73.92	76.65	**75.26**
+pre-training							
He et al. (2018a)	✗	84.8	87.2	86.0	73.9	78.4	76.1
Strubell et al. (2018)†	✓	87.13	86.67	86.9	79.02	77.49	78.25
Li et al. (2019)	✗	85.2	87.5	86.3	74.7	78.1	76.4
SynG2G-Tr	✓	86.86	88.3	**87.57**	80.01	81.07	**80.53**
given predicate							
Tan et al. (2017)	✗	84.5	85.2	84.8	73.5	74.6	74.1
He et al. (2018a)	✗	-	-	83.9	-	-	73.7
Strubell et al. (2018)†	✓	86.02	86.05	86.04	76.65	76.44	76.54
Ouchi et al. (2018)	✗	84.7	82.3	83.5	76.0	70.4	73.1
Xia et al. (2020)	✓	85.12	85.0	85.06	76.3	75.42	75.86
SynG2G-Tr (w/o BERT)	✓	86.46	86.56	**86.50**	77.73	77.18	**77.45**
+pre-training							
He et al. (2018a)	✗	-	-	87.4	-	-	80.4
Ouchi et al. (2018)	✗	88.2	87.0	87.6	79.9	77.5	78.7
Li et al. (2019)	✗	87.9	87.5	87.7	80.6	80.4	80.5
Jindal et al. (2020)	✗	87.70	88.15	87.93	81.52	81.36	81.44
Zhang et al. (2021)	✗	88.70	88.00	87.90	80.30	80.10	80.20
Jia et al. (2022)	✗	-	-	88.25	-	-	81.90
SynG2G-Tr	✓	89.11	88.74	**88.93**	83.93	82.50	**83.21**

Slide from Alireza Mohammadshahi

Results

Dependency-based SRL

Evaluation data: CoNLL 2009 benchmark

Without BERT:

- Outperforms previous work in both in-domain and out-of-domain settings

With BERT:

- Significantly outperforms previous work in end-to-end setting with 3.2%/10.4% F1 RER in both in-domain and out-of-domain
- Has competitive performance in given-predicate setting
- Outperforms Fei et al. (2021), which shows the benefit of SynG2G-Tr compared to GNN

Model	SA	WSJ (in-domain)			Brown (out-of-domain)		
		P	R	F1	P	R	F1
end-to-end							
He et al. (2018b)	✓	83.9	82.7	83.3	-	-	-
Cai et al. (2018)	✗	84.7	85.2	85.0	-	-	72.5
Li et al. (2019)	✗	-	-	85.1	-	-	-
SynG2G-Tr (w/o BERT)	✓	84.10	87.07	**85.59**	73.66	72.56	**73.11**
+pre-training							
Li et al. (2019)	✗	84.5	86.1	85.3	74.6	73.8	74.2
SynG2G-Tr	✓	86.38	89.78	**88.05**	80.35	83.57	**81.93**
given predicate							
Marcheggiani et al. (2017)	✗	88.7	86.8	87.7	79.4	76.2	77.7
M&T(2017)	✓	89.1	86.8	88.0	78.5	75.9	77.2
He et al. (2018b)	✓	89.7	89.3	89.5	81.9	76.9	79.3
Cai et al. (2018)	✗	89.9	89.2	89.6	79.8	78.3	79.0
Cai and Lapata (2019c)	✓	90.5	88.6	89.6	80.5	78.2	79.4
Kasai et al. (2019)	✓	89.0	88.2	88.6	78.0	77.2	77.6
SynG2G-Tr (w/o BERT)	✓	89.78	90.28	**90.03**	81.32	82.15	**81.73**
+pre-training							
Li et al. (2019)	✗	89.6	91.2	90.4	81.7	81.4	81.5
Kasai et al. (2019)	✓	90.3	90.0	90.2	81.0	80.5	80.8
Lyu et al. (2019)	✗	-	-	90.99	-	-	82.18
Chen et al. (2019)	✗	90.74	91.38	**91.06**	82.66	82.78	82.72
He et al. (2019)	✓	90.41	91.32	90.86	86.15	86.70	**86.42**
Cai and Lapata (2019a)	✓	91.1	90.4	90.7	82.1	81.3	81.6
Munir et al. (2021)	✓	91.2	90.6	90.9	83.1	82.6	82.8
SynG2G-Tr	✓	91.31	91.16	**91.23**	86.40	86.47	**86.43**
gold syntax							
Fei et al. (2021)	✓	92.5	92.5	92.5	85.6	85.3	85.4
SynG2G-Tr+Gold	✓	92.71	93.37	**93.03**	88.27	88.31	**88.29**

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Conclusion

- Propose SynG2G-Tr model for encoding the dependency parsing graph in the SRL task
- Evaluated our model on CoNLL 2005 and CoNLL 2009 datasets and outperform previous comparable models in most cases of both in-domain and out-of-domain sets

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Graph Transformer Encoder

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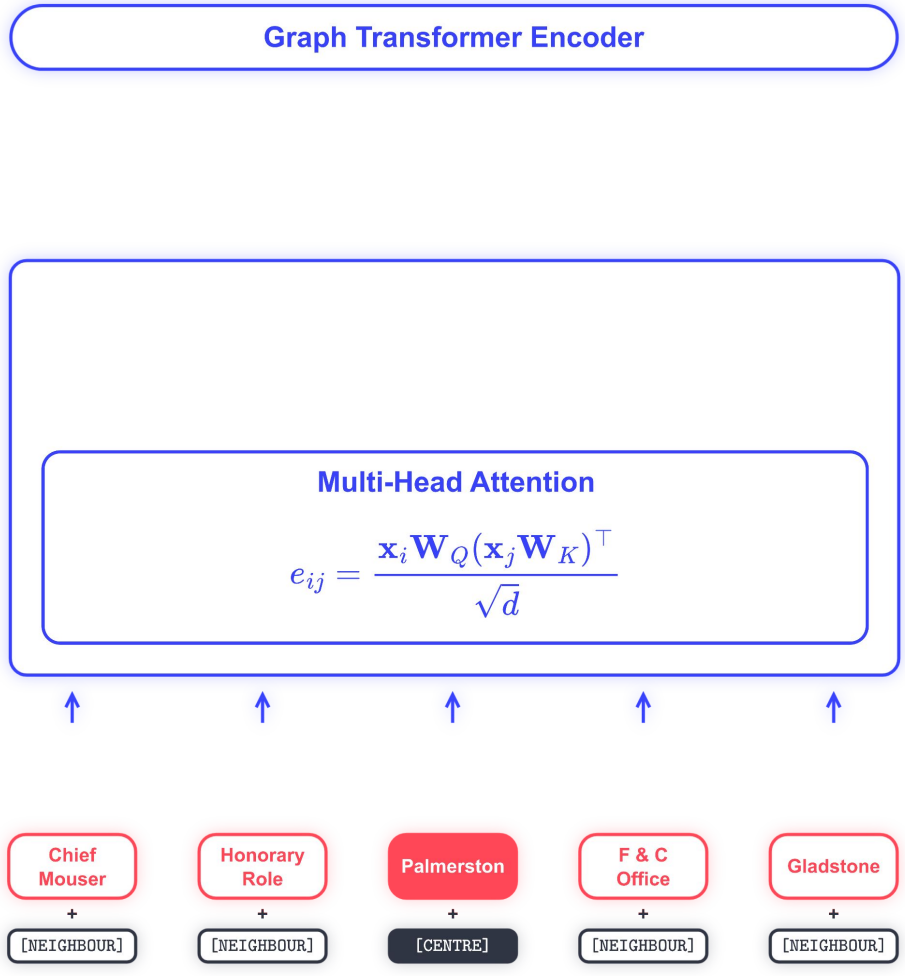

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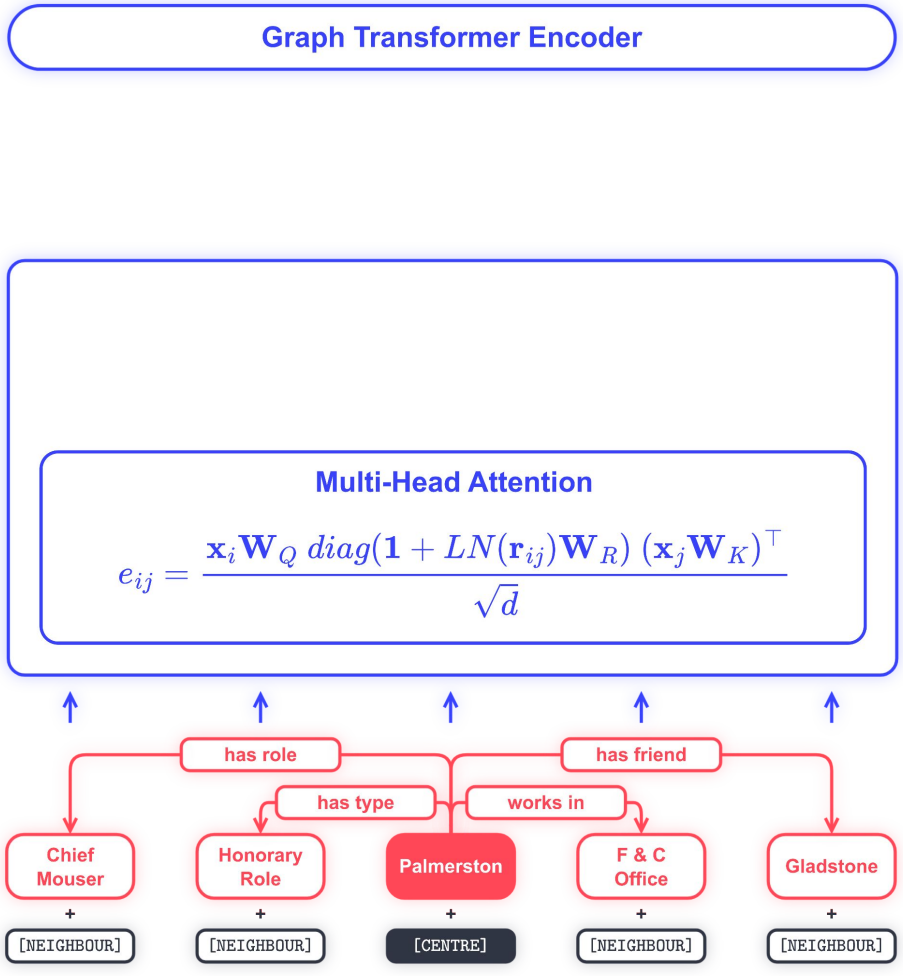

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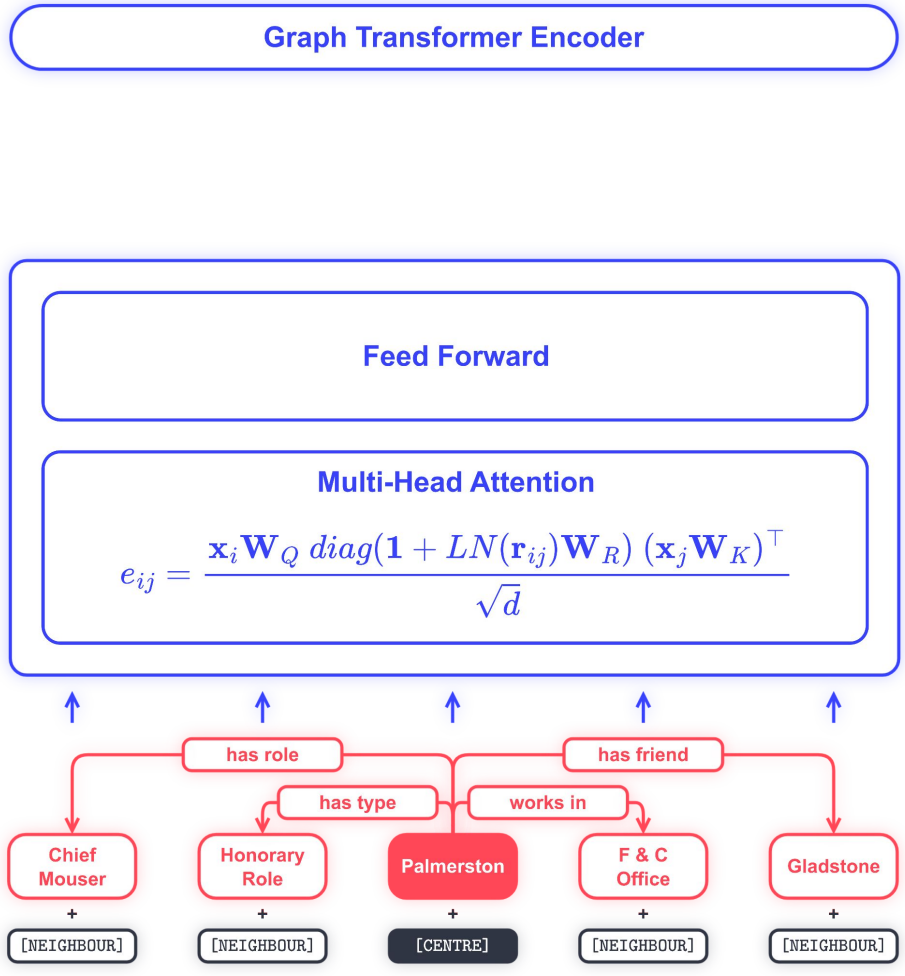

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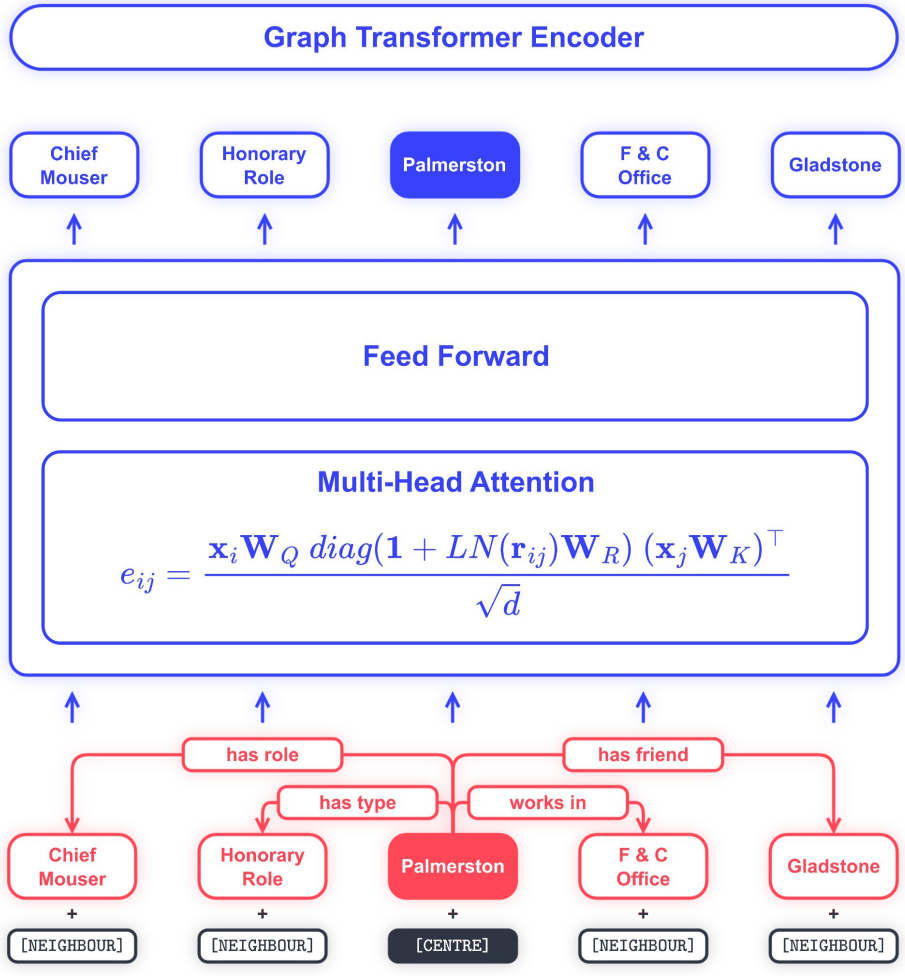

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Outline

Recursive Non-Autoregressive Graph-to-Graph Transformer for Dependency Parsing with Iterative Refinement

Transactions of ACL 2021

Authors:

Alireza Mohammadshahi

James Henderson

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Motivation

Need an architecture to find the graph structure:

Model types
- Autoregressive
- Non-Autoregressive ✓

Non-Autoregressive Structure Prediction:

Predict all edges of the graph in parallel

Problem: Not considering between-edge information!

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Our Proposal

We propose **Recursive Non-Autoregressive Graph-to-Graph Transformer (RNGTr)** architecture:

- **Refines arbitrary graphs** in an **iterative non-autoregressive** manner with conditioning on the complete graph.
- Defines a general Transformer-based encoder to input both sequences and graphs.
- Evaluated on dependency parsing and achieved SOTA on UD and Penn Treebanks.

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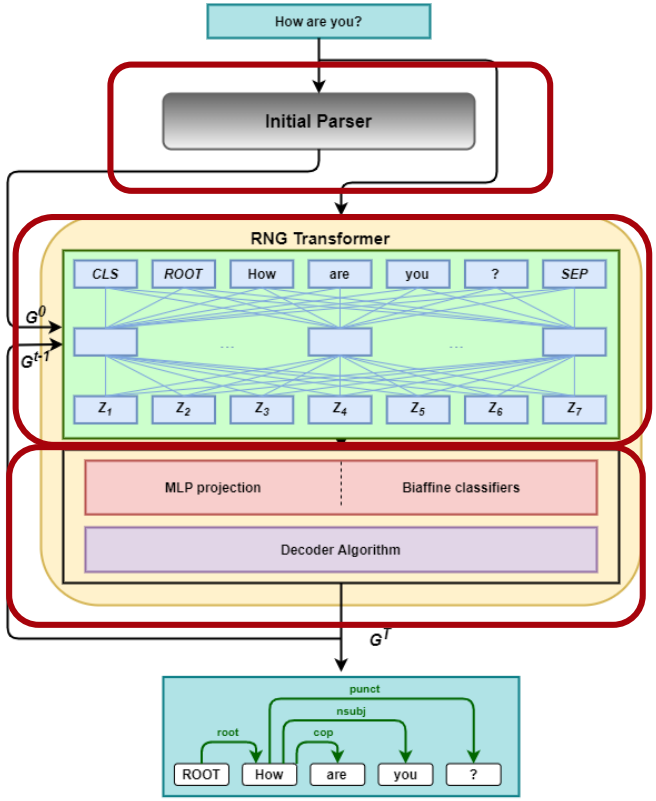
RNGTr Model

- Start with an initial parser (G^0)
- Refinement mechanism:

$$Z^t = E^{RNG}(W, P, G^{t-1})$$

$$G^t = D^{RNG}(Z^t)$$

- $t = 1, \ldots, T$
- G^T is the final graph



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Attention Mechanism

To input a graph, we modify equations of original Transformer:

$$z_i = \sum_j \alpha_{ij}(x_j W^v + r_{ij} W_L^2)$$

$$e_{ij} = \frac{(x_i W^Q)(x_j W^k + LN(r_{ij} W_L^1))}{\sqrt{d}}$$

r_{ij} is the relation between token x_i and x_j

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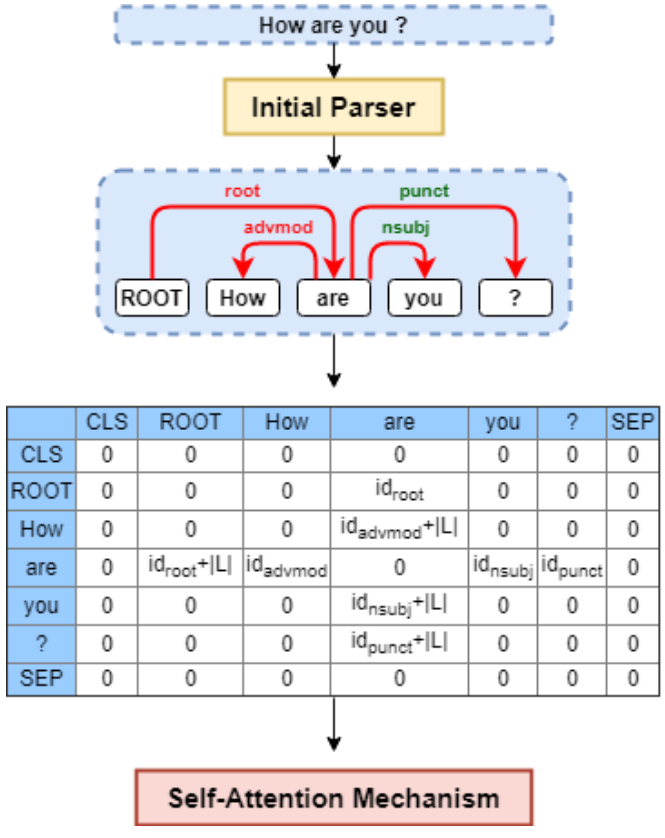
Attention Mechanism

For labelled dependency graph:

$$\left(i \rightarrow^{l} j\right)_t : \begin{cases} r_{ij}^t = ind_l \\ r_{ji}^t = ind_l + |L| \end{cases}$$



	CLS	ROOT	How	are	you	?	SEP
CLS	0	0	0	0	0	0	0
ROOT	0	0	0	id_{root}	0	0	0
How	0	0	0	$id_{advmod}+\|L\|$	0	0	0
are	0	$id_{root}+\|L\|$	id_{advmod}	0	id_{nsubj}	id_{punct}	0
you	0	0	0	$id_{nsubj}+\|L\|$	0	0	0
?	0	0	0	$id_{punct}+\|L\|$	0	0	0
SEP	0	0	0	0	0	0	0

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Initial Parsers

- Syntactic Transformer:
  - RNGTr model without the graph input

$$Z^0 = E^{RNG}(W, P)$$

$$G^0 = D^{RNG}(Z^0)$$

- For UD Treebanks: UDify
- For Penn Treebank: Biaffine parser
- Empty parser

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UD Treebanks

- Integration with UDify
- Integration with SynTr
- Empty Parser

Language	Train Size	Mono [1]	Multi UDPipe	Multi UDify	Multi+Mono UDify+RNGTr	Mono SynTr	Mono SynTr+RNGTr	Mono Empty+RNGTr
Arabic	6.1K	81.8	82.94	82.88	**85.93** (+17.81%)	**86.23**	**86.31** (+0.58%)	**86.05**
Basque	5.4K	79.8	82.86	80.97	87.55 (+34.57%)	87.49	**88.2** (+5.68%)	**87.96**
Chinese	4K	83.4	80.5	83.75	89.05 (+32.62%)	89.53	**90.48** (+9.08%)	89.82
English	12.5K	87.6	86.97	88.5	91.23 (+23.74%)	**91.41**	**91.52** (+1.28%)	91.23
Finnish	12.2K	83.9	87.46	82.03	**91.87** (+54.76%)	**91.80**	**91.92** (+1.46%)	**91.78**
Hebrew	5.2K	85.9	86.86	88.11	90.80 (+22.62%)	**91.07**	**91.32** (+2.79%)	90.56
Hindi	13.3K	90.8	91.83	91.46	93.94 (+29.04%)	93.95	**94.21** (+4.3%)	93.97
Italian	13.1K	91.7	91.54	93.69	94.65 (+15.21%)	**95.08**	**95.16** (+1.62%)	**94.96**
Japanese	7.1K	92.1	93.73	92.08	**95.41** (+42.06%)	**95.66**	**95.71** (+1.16%)	**95.56**
Korean	4.4K	84.2	84.24	74.26	**89.12** (+57.73%)	**89.29**	**89.45** (+1.5%)	**89.1**
Russian	48.8K	91.0	92.32	93.13	**94.51** (+20.09%)	**94.60**	**94.47** (−2.4%)	94.31
Swedish	4.3K	86.9	86.61	89.03	92.02 (+27.26%)	92.03	**92.46** (+5.4%)	**92.40**
Turkish	3.7K	64.9	67.56	67.44	72.07 (+14.22%)	**72.52**	**73.08** (+2.04%)	71.99
Average	–	84.9	85.81	85.18	89.86	90.05	90.33	89.98

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Penn Treebank

- Integration with Biaffine
- Integration with SynTr

Model	Type	English (PTB) UAS	English (PTB) LAS	Chinese (CTB) UAS	Chinese (CTB) LAS	German (CoNLL) UAS	German (CoNLL) LAS
Chen and Manning (2014)	T	91.8	89.6	83.9	82.4	–	–
Dyer et al. (2015)	T	93.1	90.9	87.2	85.7	–	–
Ballesteros et al. (2016)	T	93.56	91.42	87.65	86.21	88.83	86.10
Cross and Huang (2016)	T	93.42	91.36	86.35	85.71	–	–
Weiss et al. (2015)	T	94.26	92.41	–	–	–	–
Andor et al. (2016)	T	94.61	92.79	–	–	90.91	89.15
Mohammadshahi and Henderson (2020)	T	96.11	94.33	–	–	–	–
Ma et al. (2018)	T	95.87	94.19	90.59	89.29	93.65	92.11
Fernández-González and Gómez-Rodríguez (2019)	T	96.04	94.43	–	–	–	–
Kiperwasser and Goldberg (2016)	G	93.1	91.0	86.6	85.1	–	–
Wang and Chang (2016)	G	94.08	91.82	87.55	86.23	–	–
Cheng et al. (2016)	G	94.10	91.49	88.1	85.7	–	–
Kuncoro et al. (2016)	G	94.26	92.06	88.87	87.30	91.60	89.24
Ma and Hovy (2017)	G	94.88	92.98	89.05	87.74	92.58	90.54
Ji et al. (2019)	G	95.97	94.31	–	–	–	–
Li et al. (2020)+ELMo	G	96.37	94.57	90.51	89.45	–	–
Li et al. (2020)+BERT	G	96.44	94.63	90.89	89.73	–	–
Biaffine (Dozat and Manning, 2016)	G	95.74	94.08	89.30	88.23	93.46	91.44
Biaffine+RNGTr	G	96.44	94.71	91.85	90.12	94.68	93.30
SynTr	G	**96.60**	**94.94**	92.42	90.67	**95.11**	**93.98**
SynTr+RNGTr	G	**96.66**	**95.01**	**92.98**	**91.18**	**95.28**	**94.02**

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Conclusion

- We proposed a **general structure refinement model**, based on Transformer architecture.
- We evaluated the model on the dependency parsing task.
- We achieved **state-of-the-art** results on UD and Penn Treebanks.

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Summary of Neural Network Syntactic Parsing

- Deep NNs are very good at encoding the context of a parsing decision
- Deep NNs are very good at scoring dependency relations
- Iterative refinement with Graph2Graph Transformer improves accuracy on complex graphs

Outline

Summary of Graph Processing in Transformers

Transformers are latent graph processing models
(not only sequence-to-sequence models)

- self-attention does processing over a latent graph
- observed graph relations can be output with attention-like functions
- observed graph relations can be input as features in the attention function
- predicted graphs relations can be iteratively predicted and encoded

G2G Transformers can jointly encode latent, observed and predicted graphs in one set-of-vectors embedding