Learning Challenges in Natural Language Processing

Swabha Swayamdipta

April 04, 2019

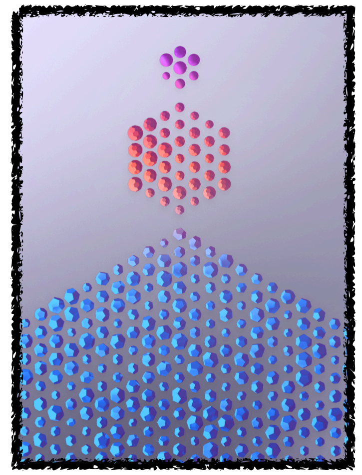
UWNLP

Carnegie Mellon University
Language Technologies Institute

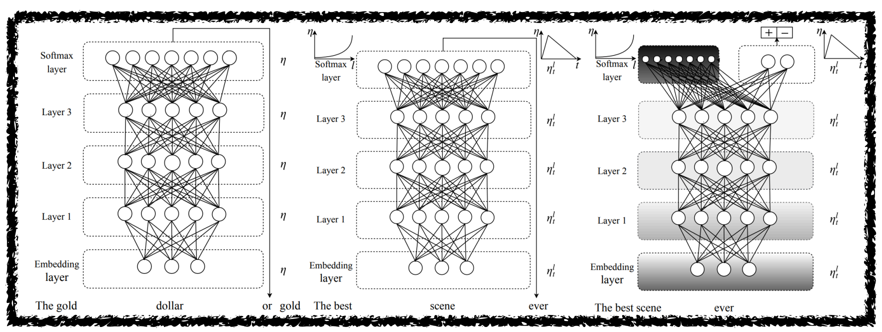
NLP today

NLP today

[Peters et. al., 2018]

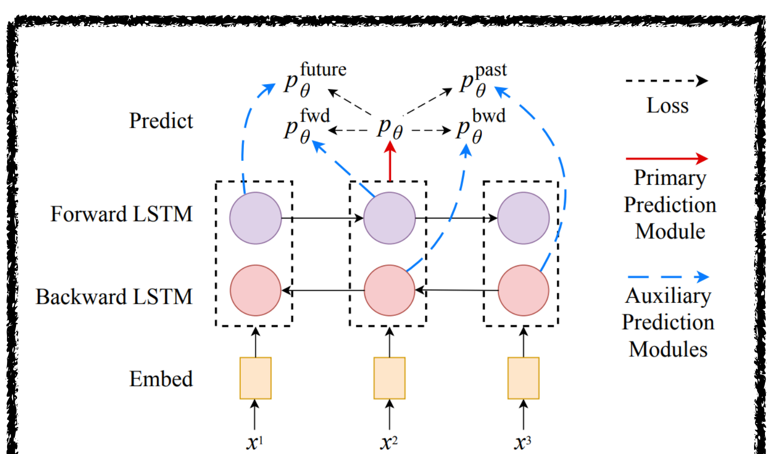


[Radford et. al., 2018]



[Howard & Ruder, 2018]

Contextualized Representations



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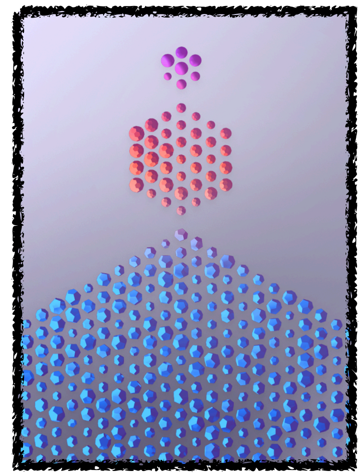

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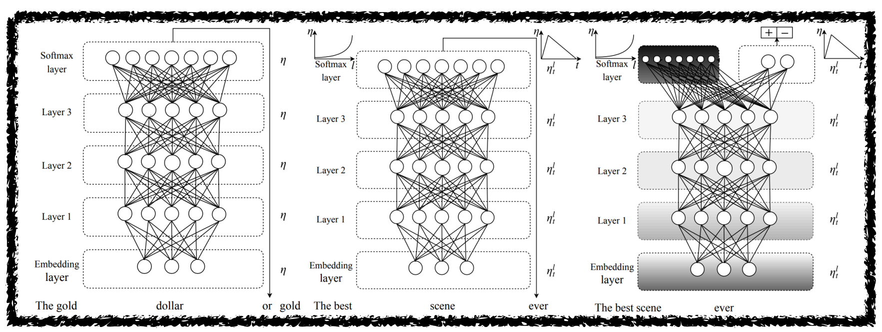
Large Language Model



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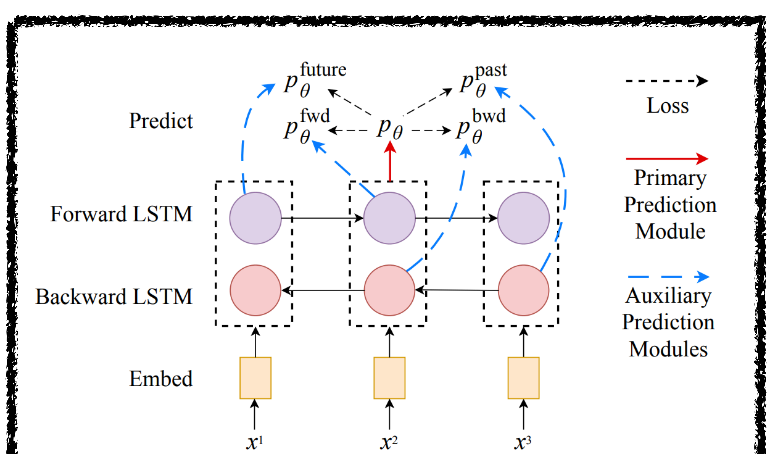

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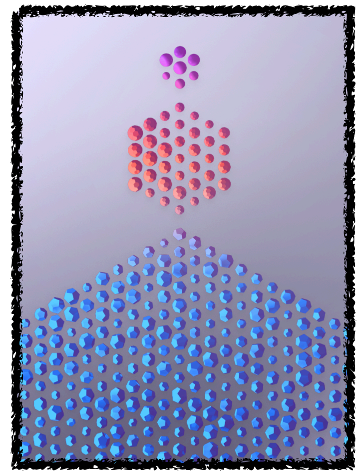

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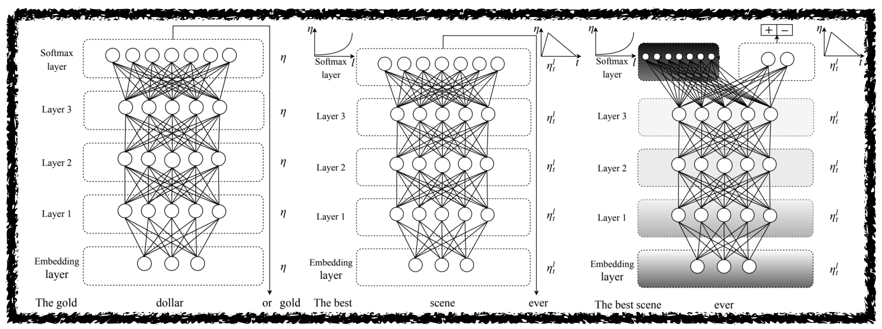

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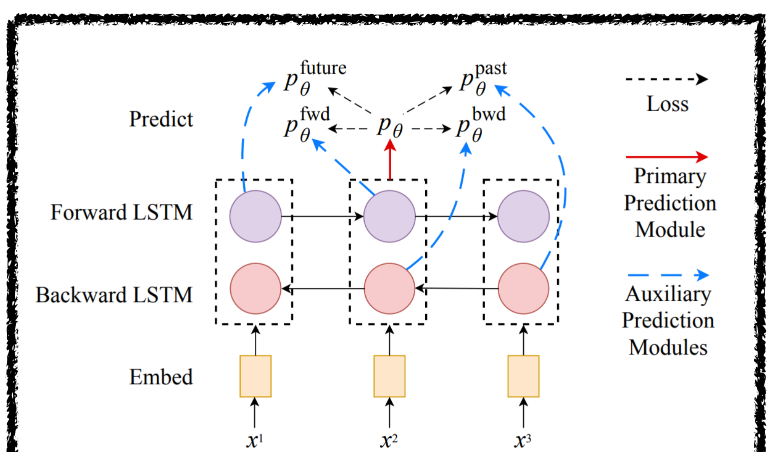
Contextualized Representations

Downstream Tasks



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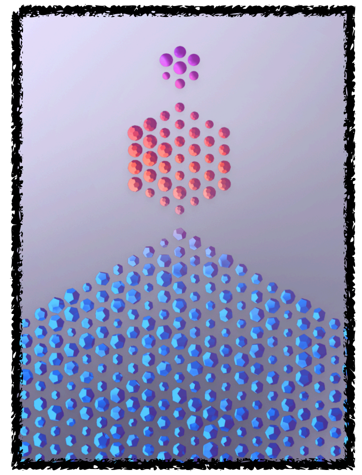

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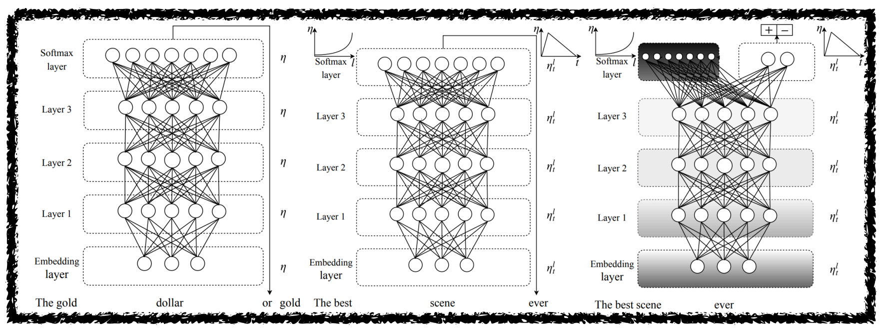

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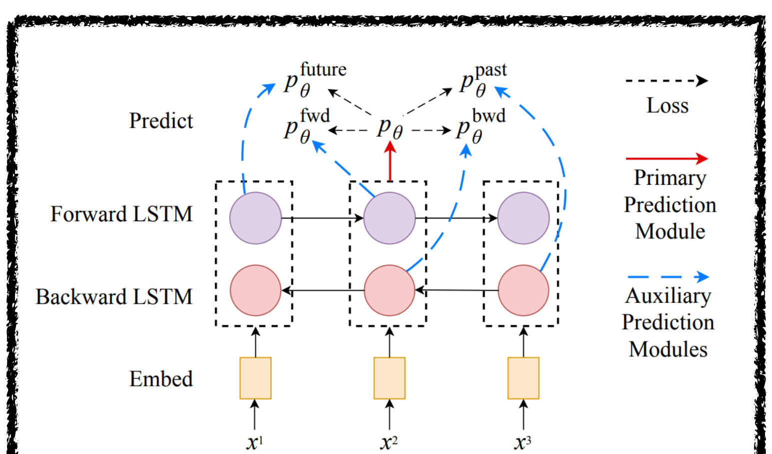

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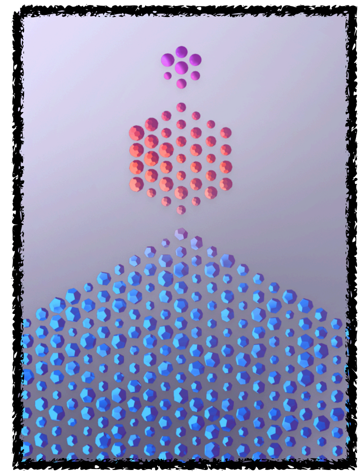

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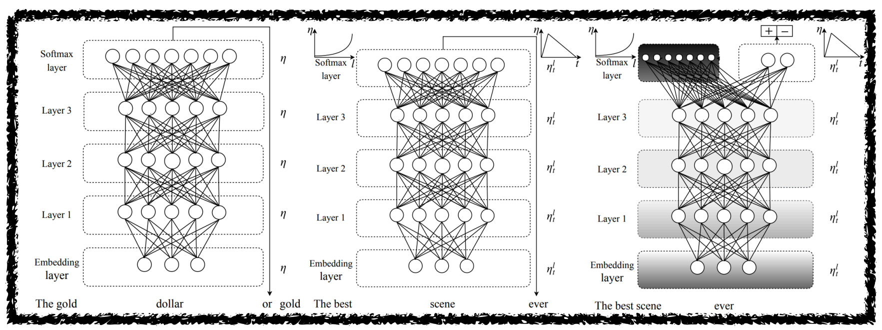

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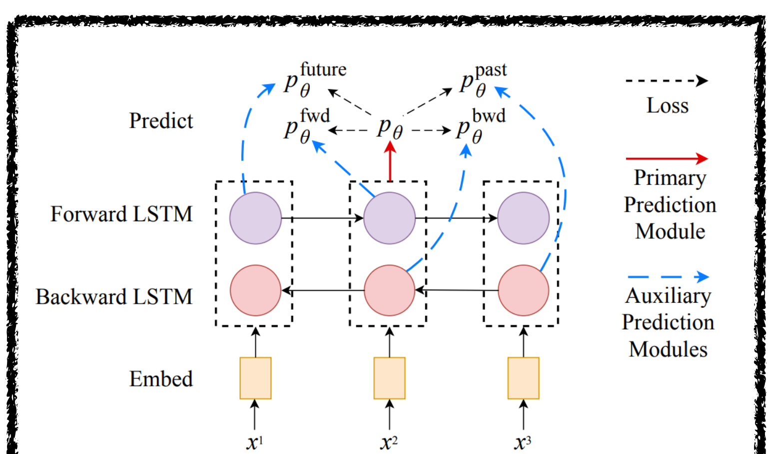

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Large Language Model

Unsupervised

Contextualized Representations

Downstream Tasks

Supervised

A closer look...

Wessex is chivalrous and charming, but semi-betrothed to Lady Ursula Glynde, whom he has not seen since her infancy. Wessex is repelled by the idea of having his wife thrust upon him and purposely avoids Lady Ursula. Unknown to Wessex, the Queen jealously guards him against Ursula, who is extremely beautiful. As soon as she realizes the Queen is keeping her away from Wessex, Ursula is angered. She believes she loves Wessex, for his nobility and goodness, and she is invested heavily in the betrothal. Although Ursula does not want to lose her independence by marrying, she seeks to frustrate the Queen's plans and make Wessex notice her.

Who seeks to frustrate the Queen's plans?

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Part I

Can we incorporate some priors about language to improve our models?

- [ ] Syntactic Scaffolds for Semantic Structures (EMNLP 2018)

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Part II

What in our data is causing models to achieve high performance?

- [ ] Annotation Artifacts in Natural Language Inference Data (NAACL 2018)

Learning Challenge #1

- Can we incorporate some priors about language?

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- One kind of prior - Linguistic Structure

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- Can linguistic structure act as an informative prior?

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Linguistic Structure: Semantics

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- Who did what to whom?

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After encouraging them , he told them goodbye and left for Macedonia

Linguistic Structure: Semantics

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After **encouraging** them , he **told** them goodbye and **left** for Macedonia

encourage.02 tell.01 leave.04

PropBank [Palmer et. al., 05]

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Linguistic Structure: Semantics

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- This talk: **Span**-based semantics.

PropBank [Palmer et. al., 05]

Linguistic Structure: Semantics

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- This talk: **Span**-based semantics.
- Can span-based semantics serve as a linguistic prior?

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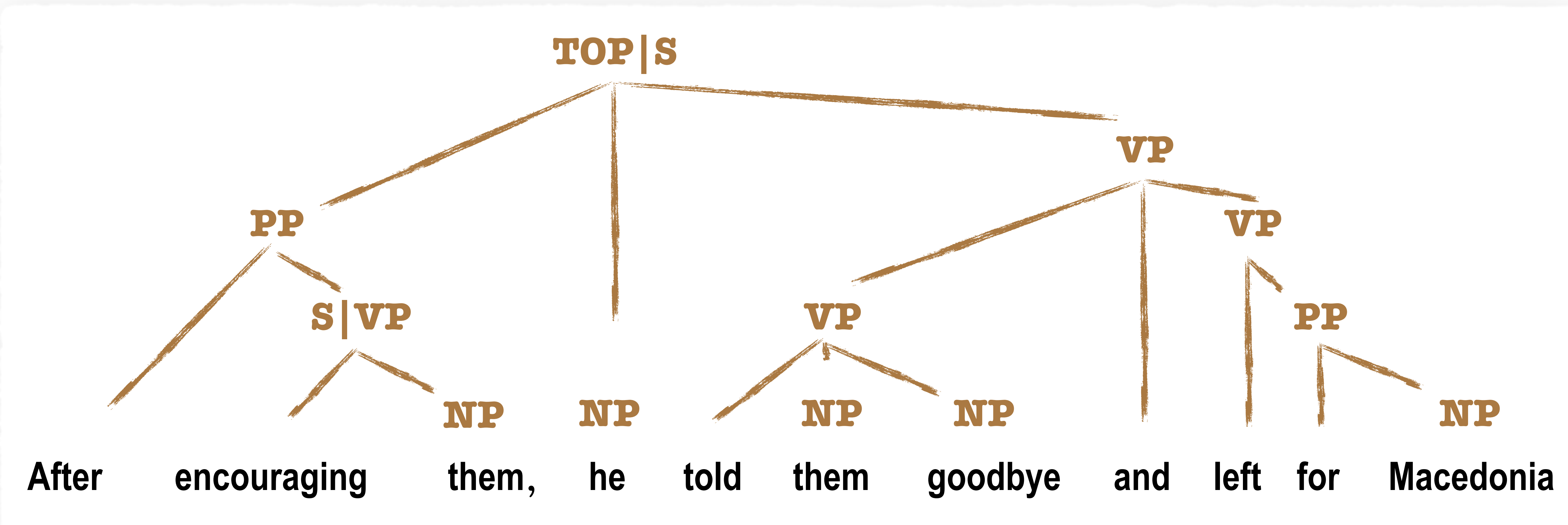

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- **Syntax** - a foundation for sentence meaning / semantics
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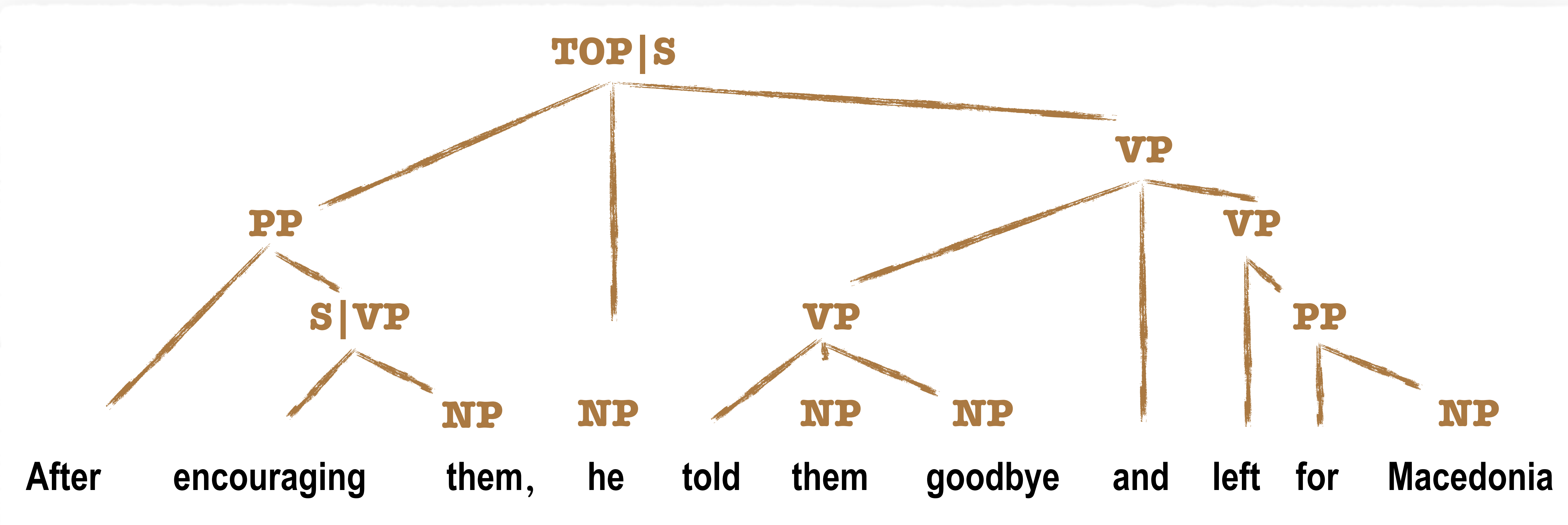

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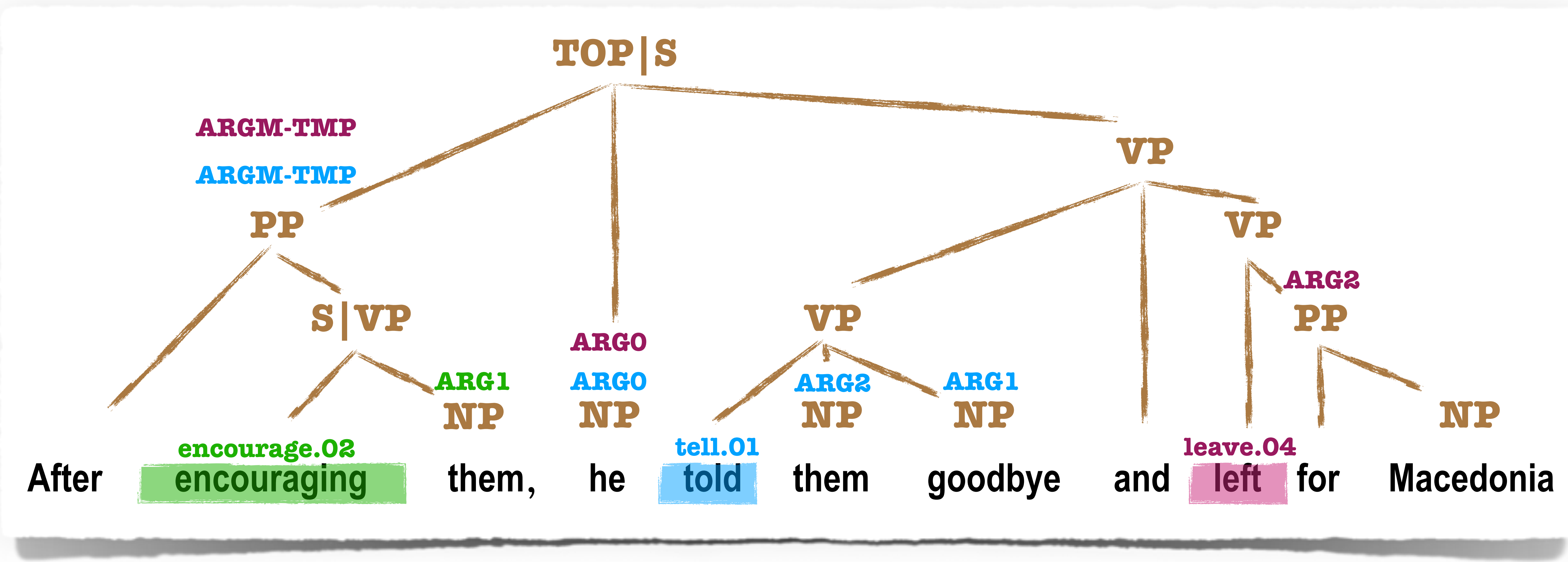
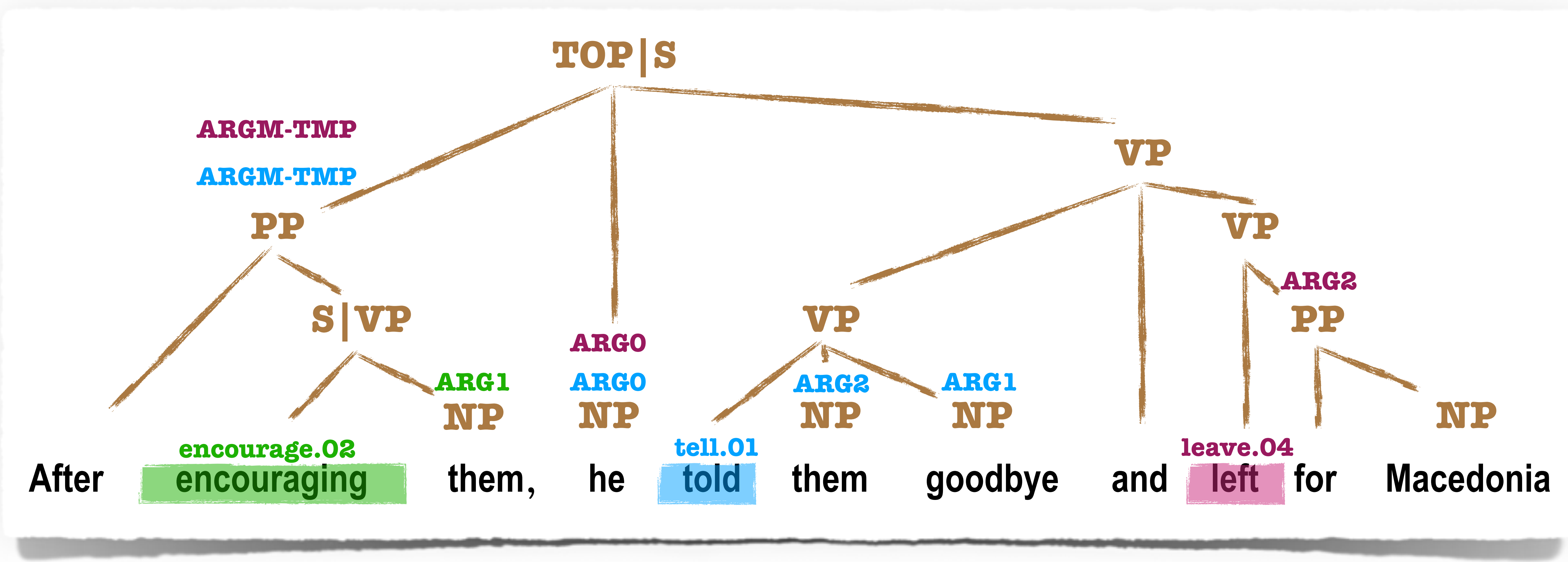
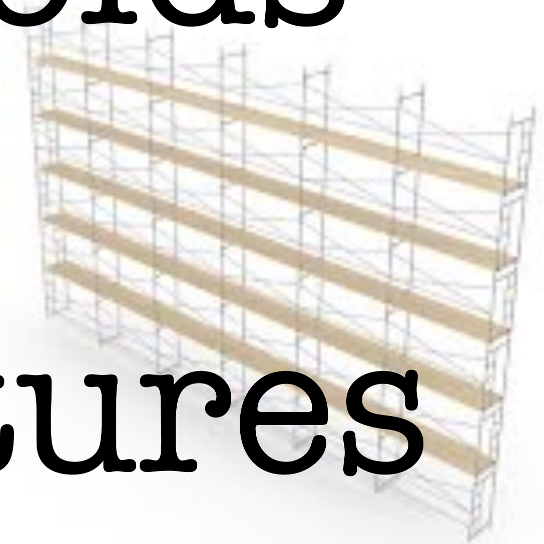


A Prior for Semantics

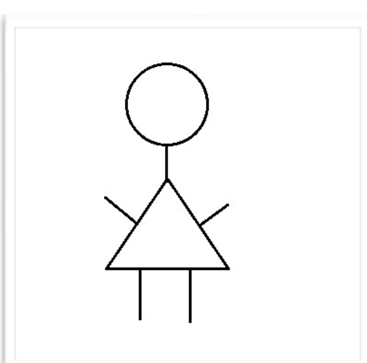
- **Syntax** - a foundation for sentence meaning / semantics
- Phrase-based syntax (node → span)
- Key Intuition: Learn from a **complementary** structure



Syntactic Scaffolds for Semantic Structures

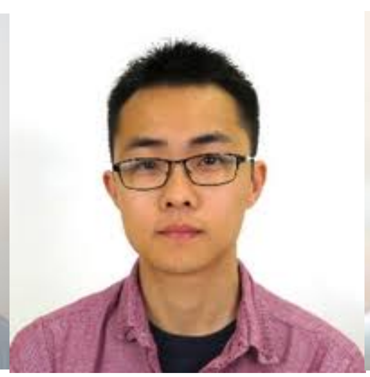


EMNLP 2018



S.

Sam Thomson



Kenton Lee

Luke Zettlemoyer

Chris Dyer

Noah A. Smith

Structured prediction with an auxiliary structure

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- Auxiliary structure: **syntax**

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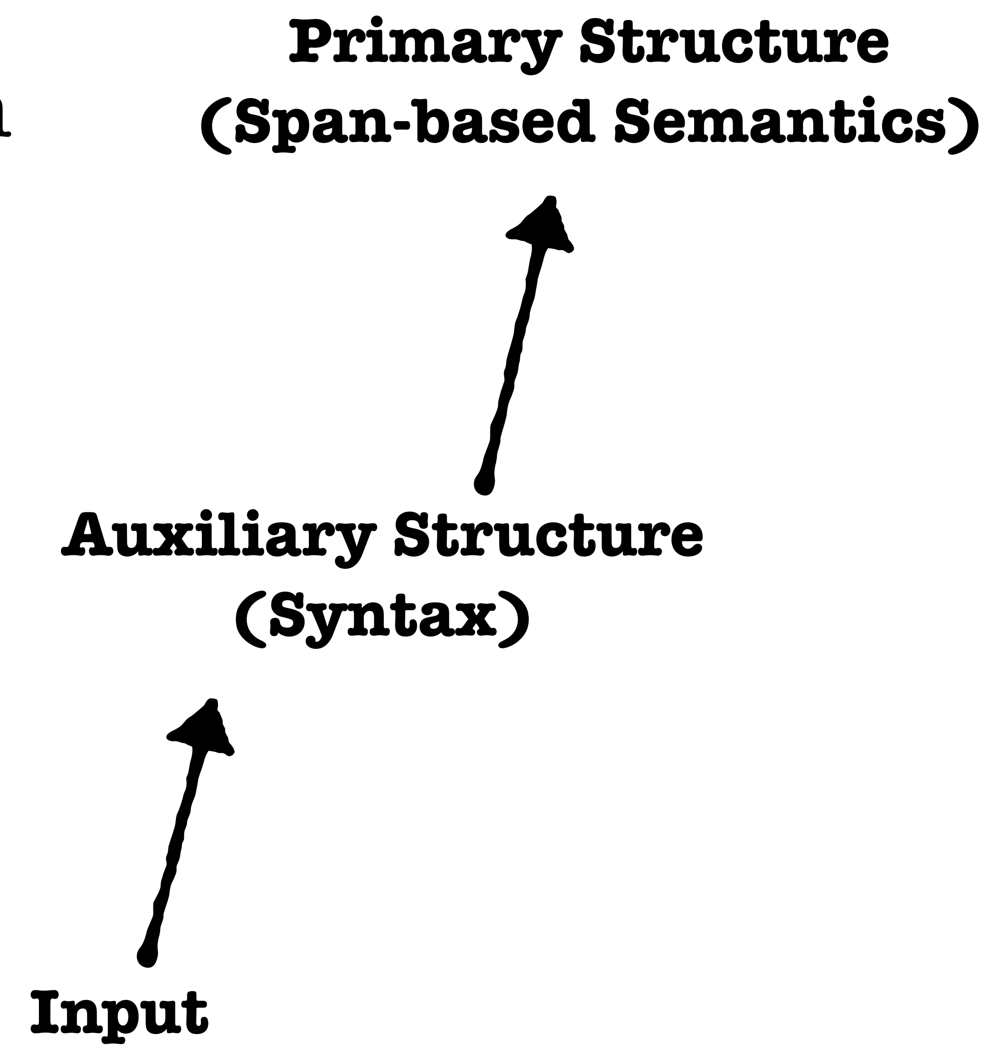
Primary Structure
(Span-based Semantics)

Auxiliary Structure
(Syntax)

Input

Structured prediction with an auxiliary structure

- Auxiliary structure: **syntax**
- Traditionally a pipeline, both at train and test time [Gildea & Jurafsky, 2002]



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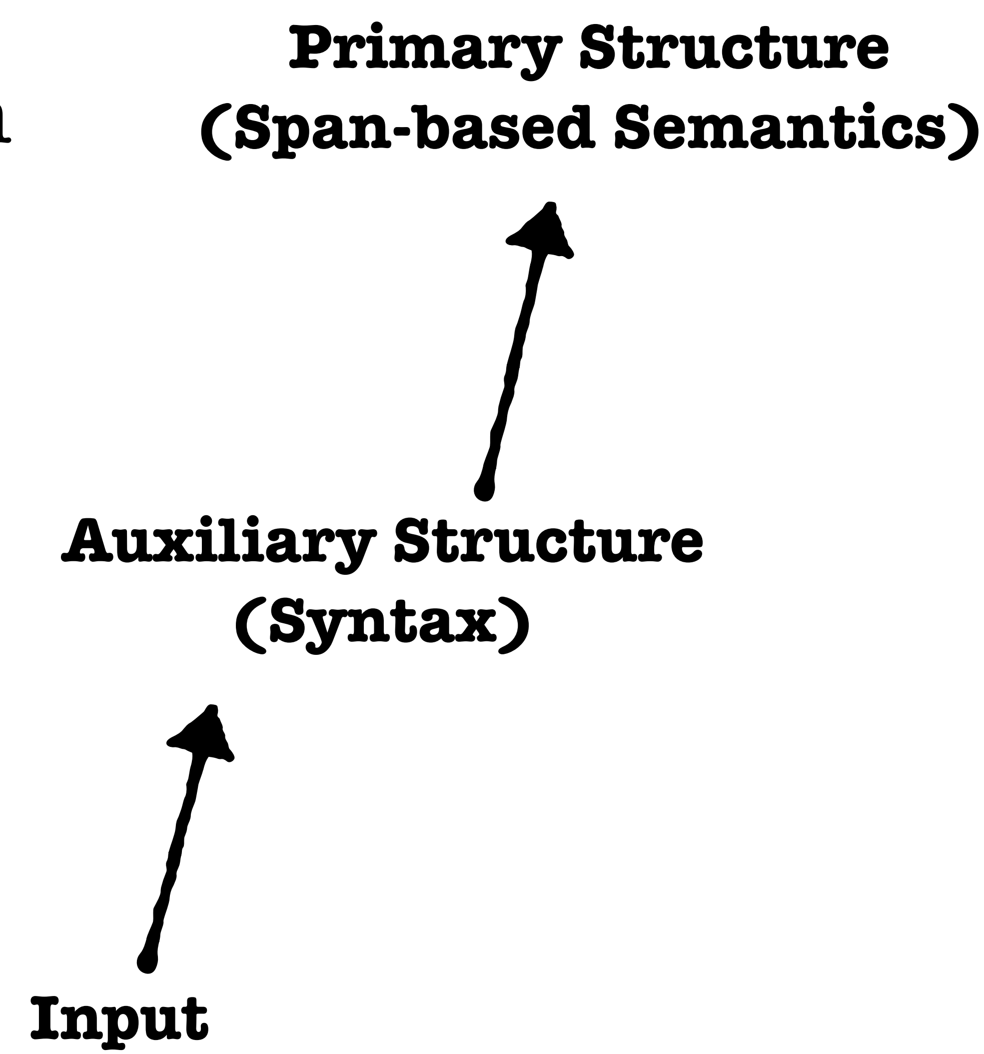

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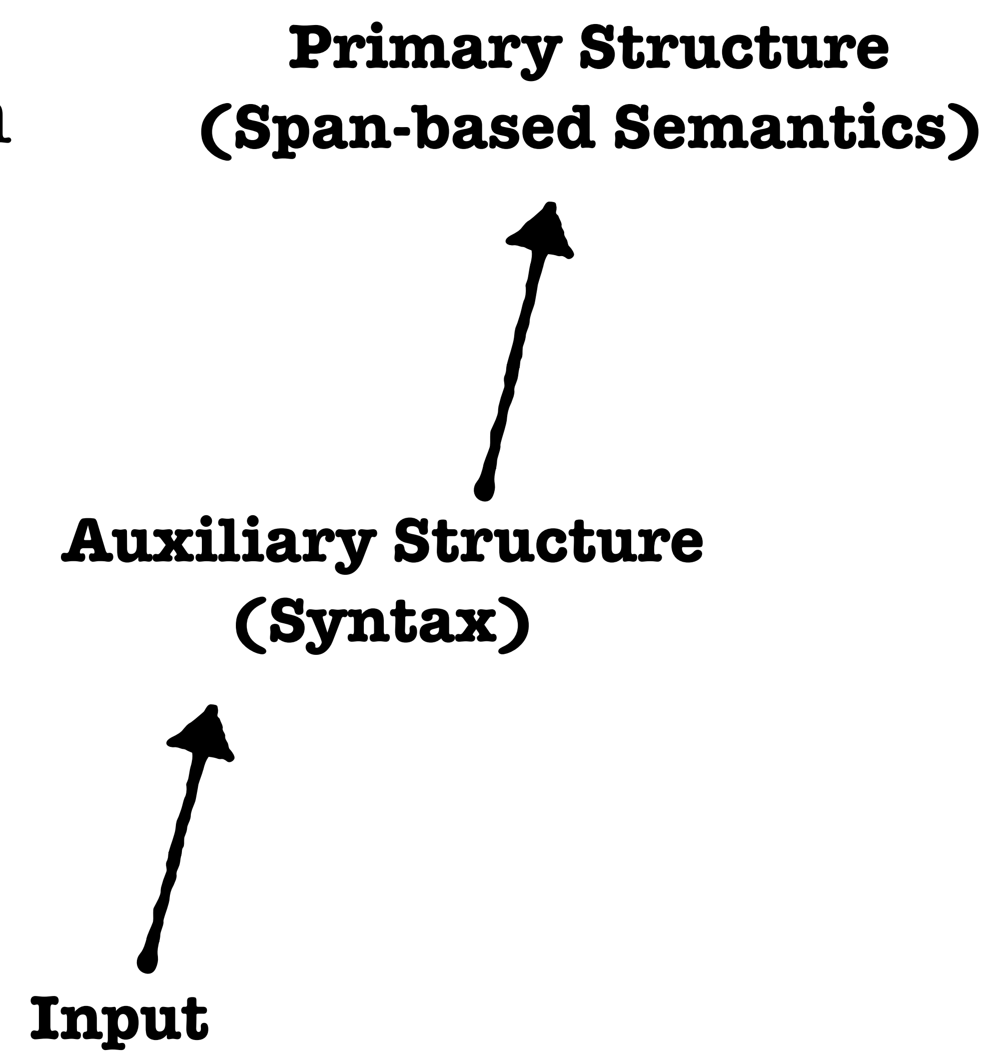

Structured prediction with an auxiliary structure

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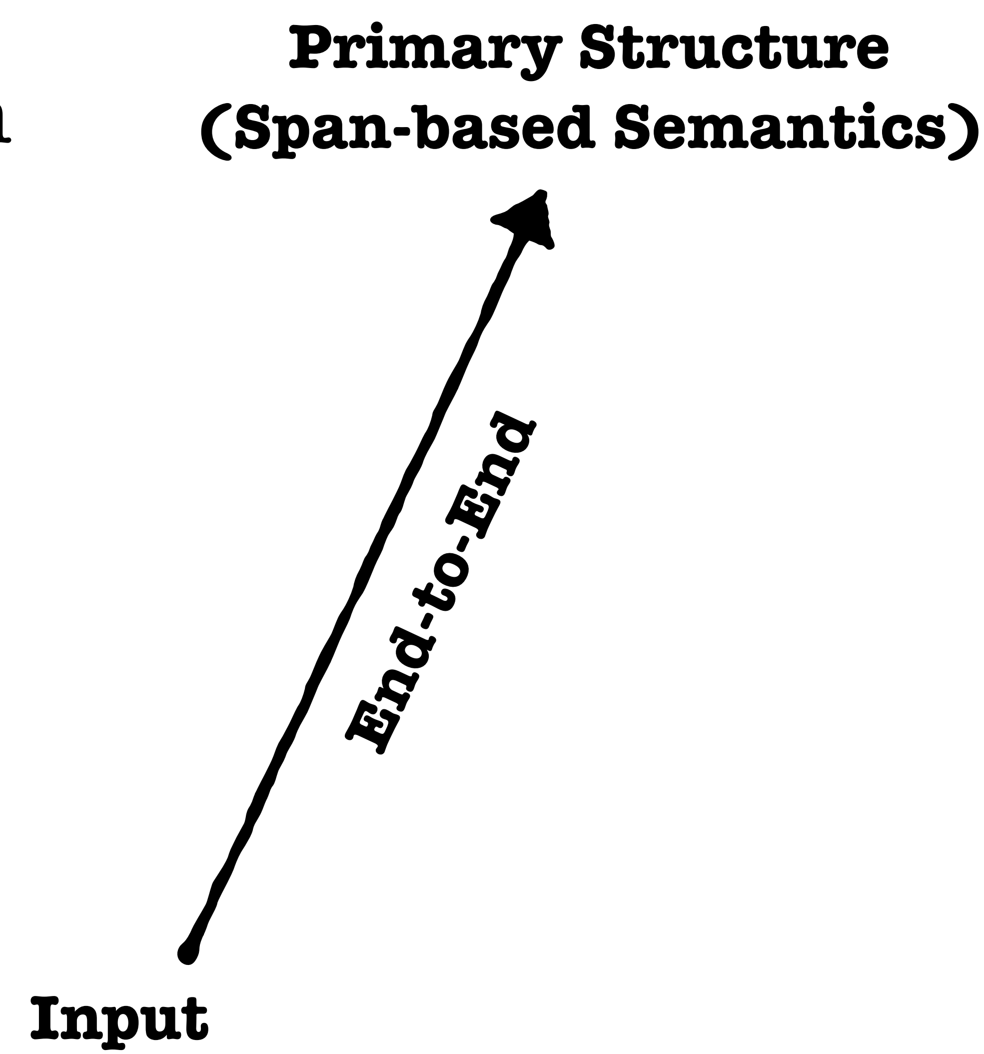
  - More structured data
  - Cascading errors
- Forsaken in most end-to-end models, but at a cost [He et. al, 2017]



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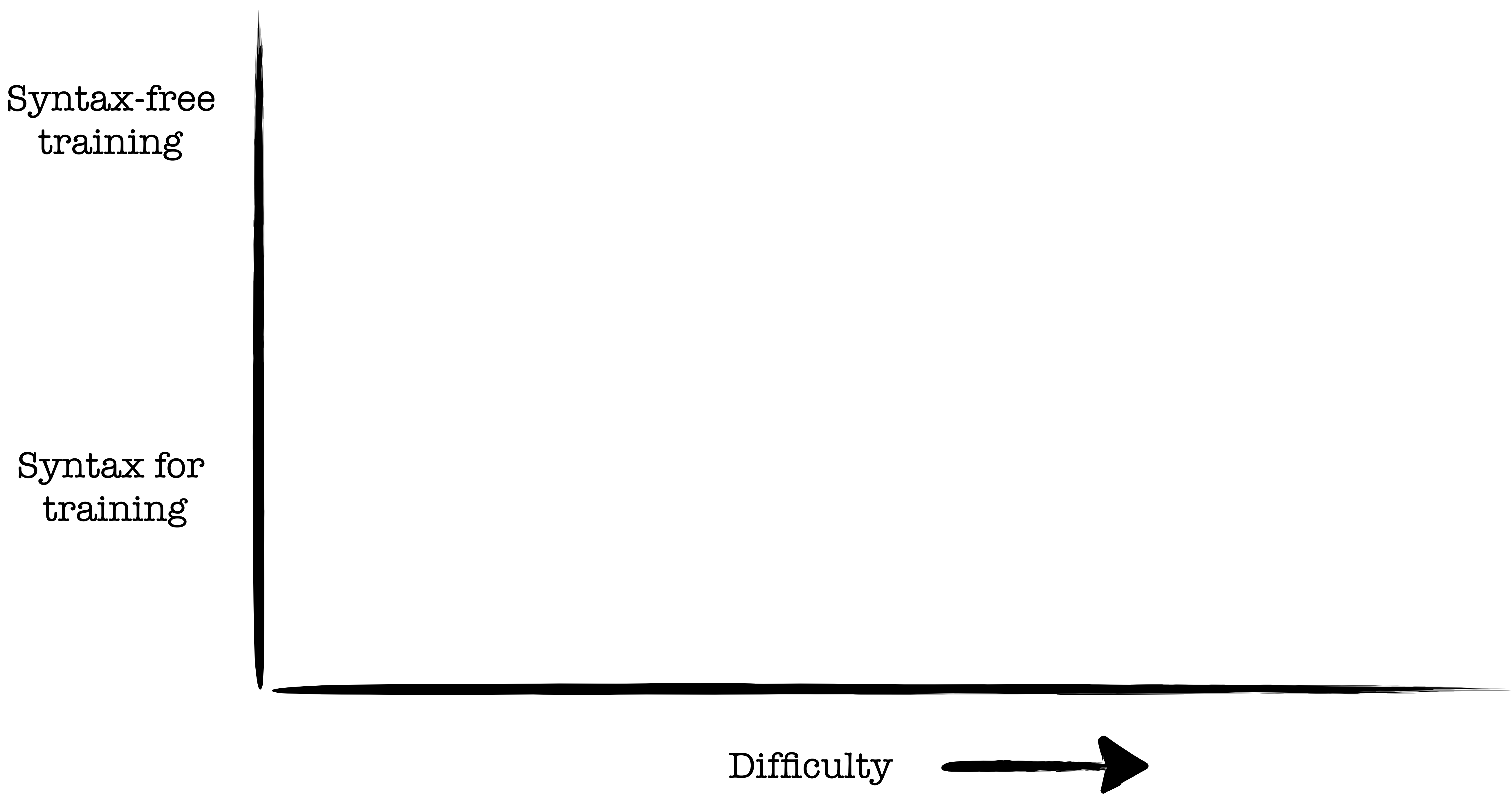

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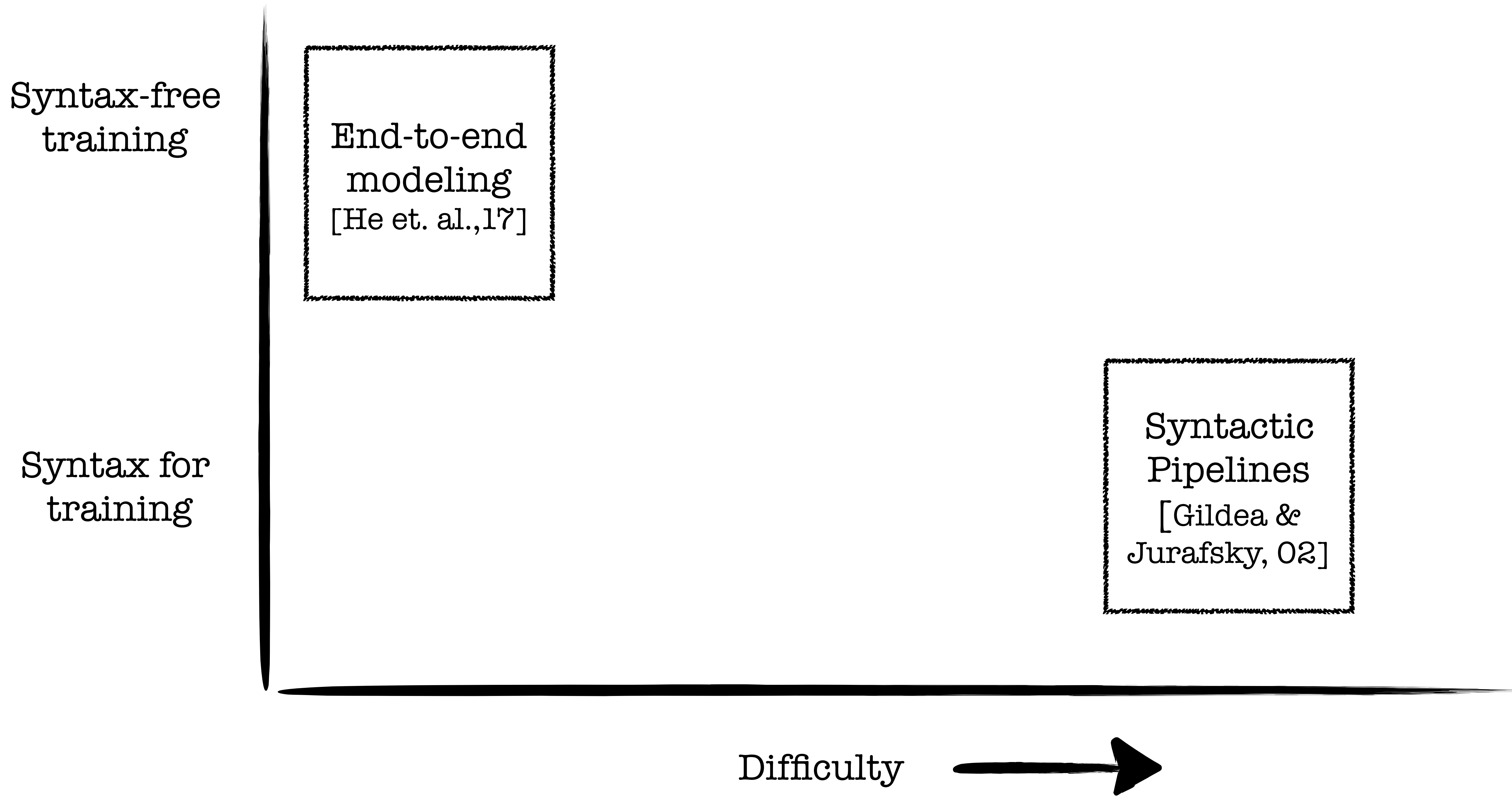

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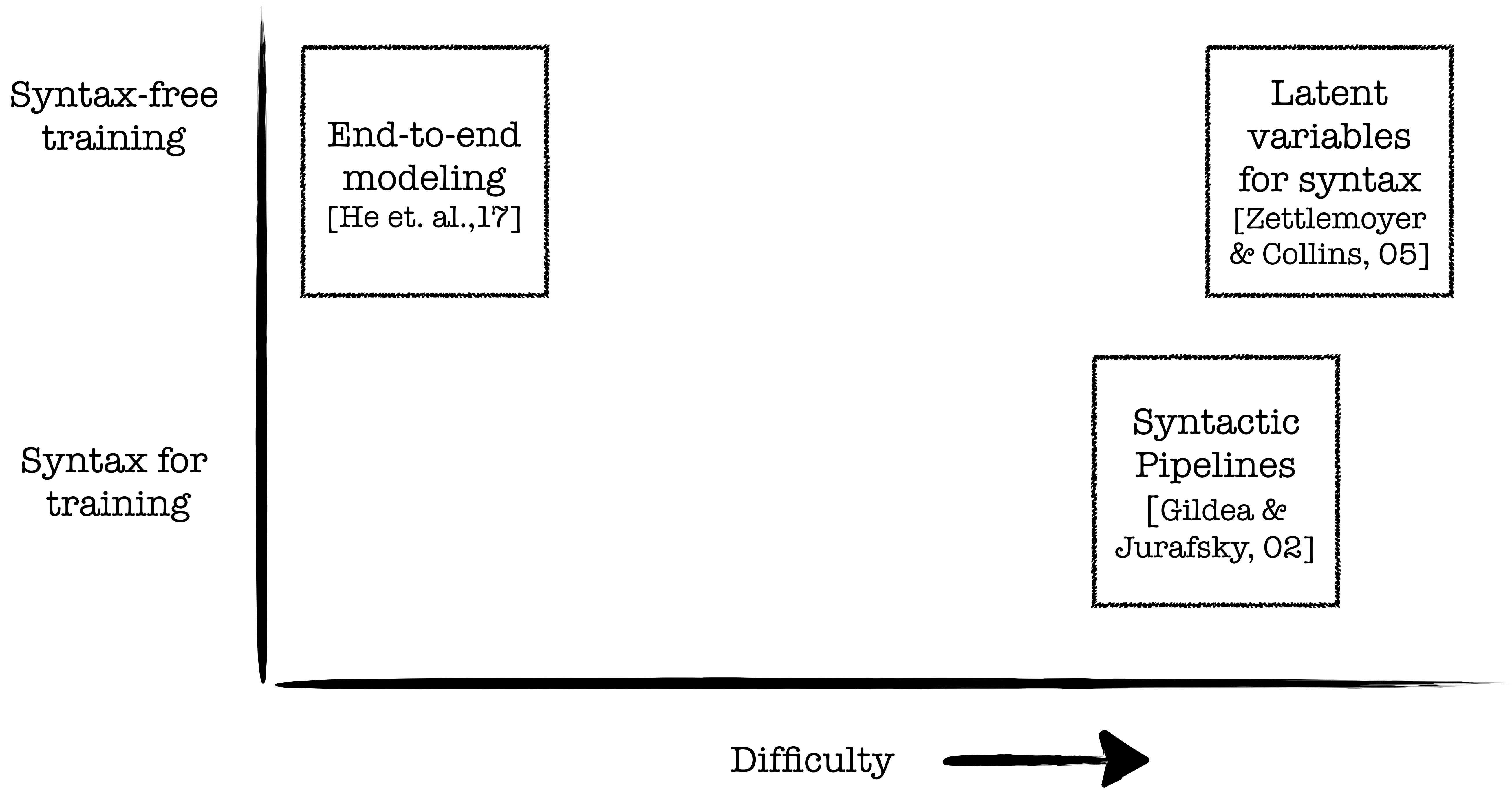

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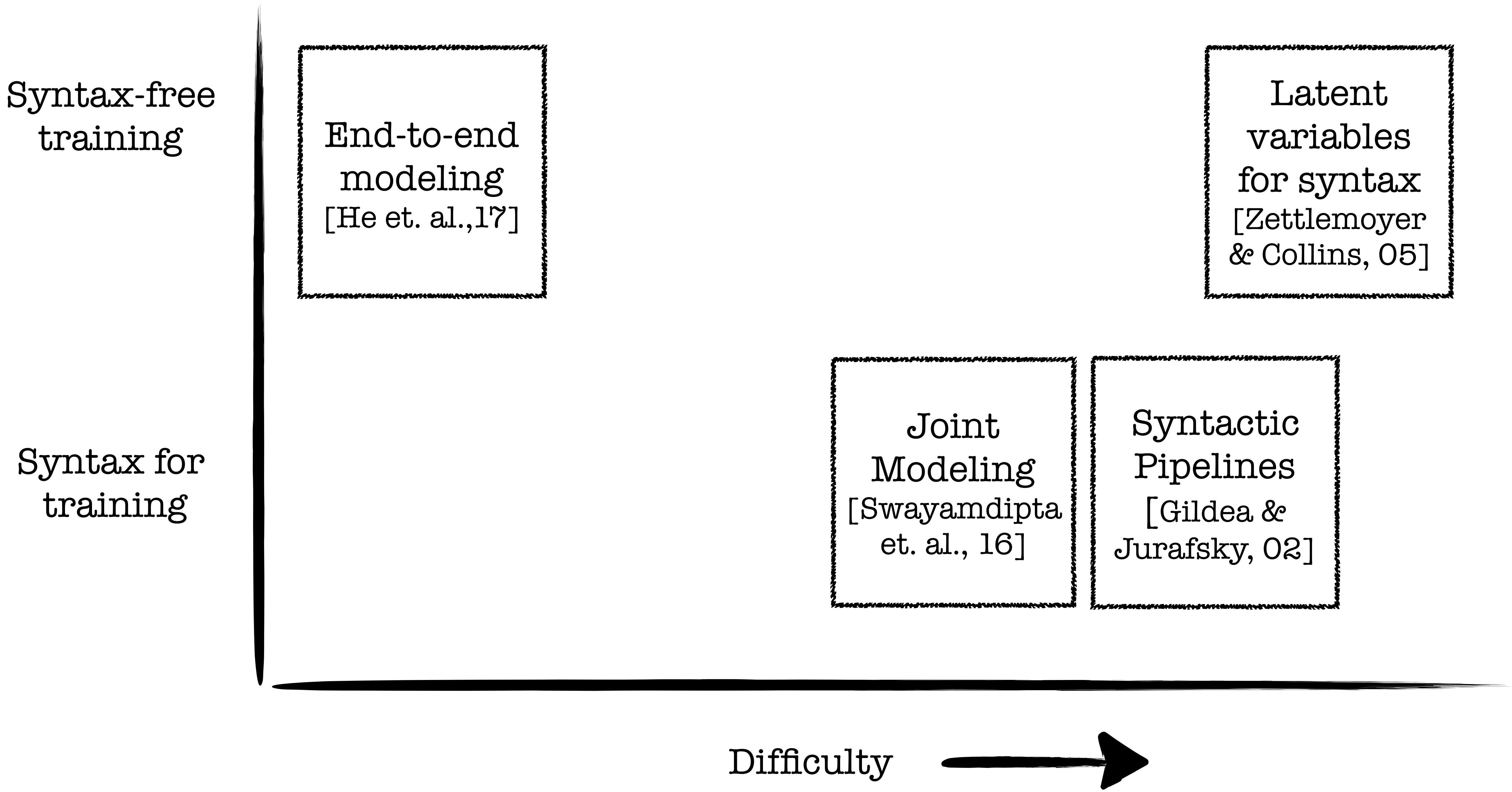

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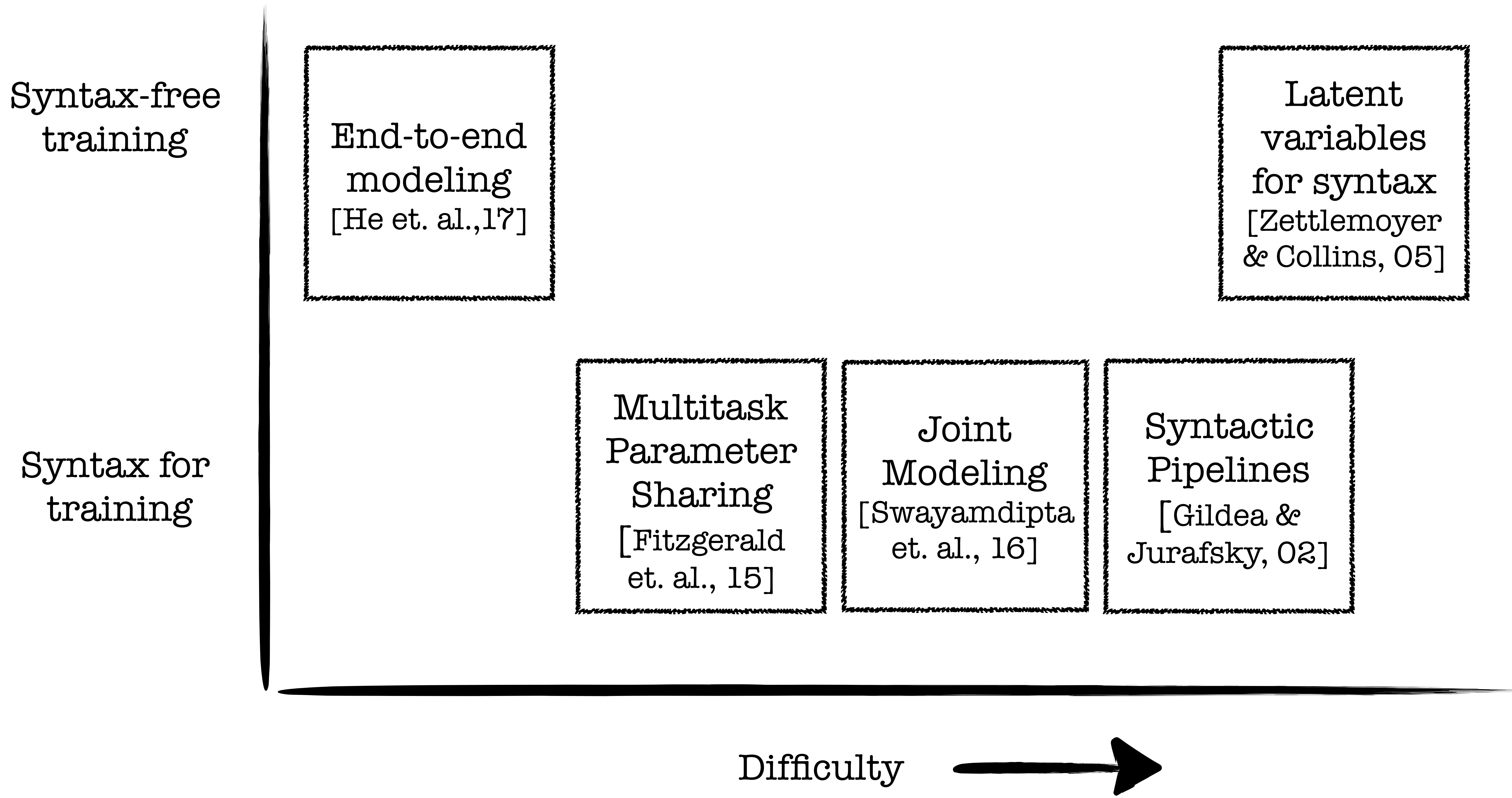

FREDA [Daumé III, 2009]

Training Paradigms

Syntax-free training

End-to-end modeling [He et. al.,17]

Latent variables for syntax [Zettlemoyer & Collins, 05]

Syntax for training

Multitask Parameter Sharing [Fitzgerald et. al., 15]

Joint Modeling [Swayamdipta et. al., 16]

Syntactic Pipelines [Gildea & Jurafsky, 02]

Difficulty →

FREDA [Daumé III, 2009]

Syntactic Scaffolds

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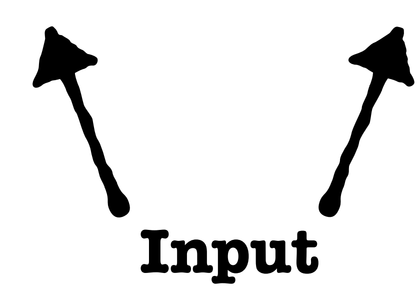
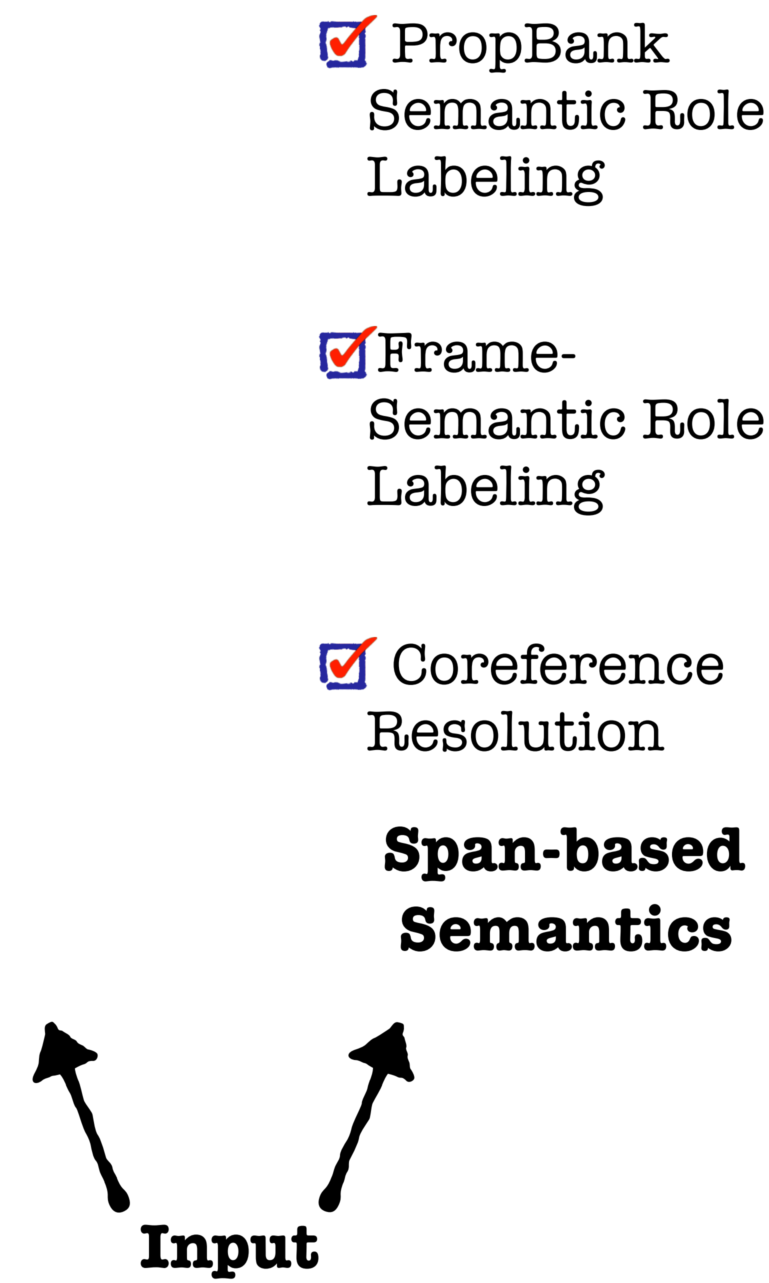
- Multitask setting



Syntactic Scaffolds

- Multitask setting
  - Primary Task → Span-based Semantics



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☑ PropBank Semantic Role Labeling

☑ Frame-Semantic Role Labeling

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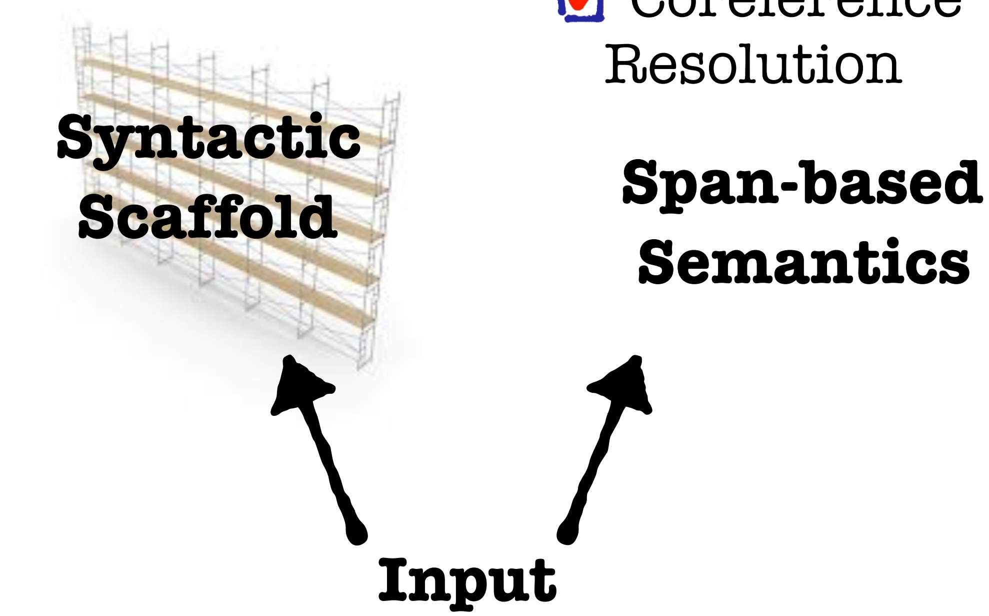

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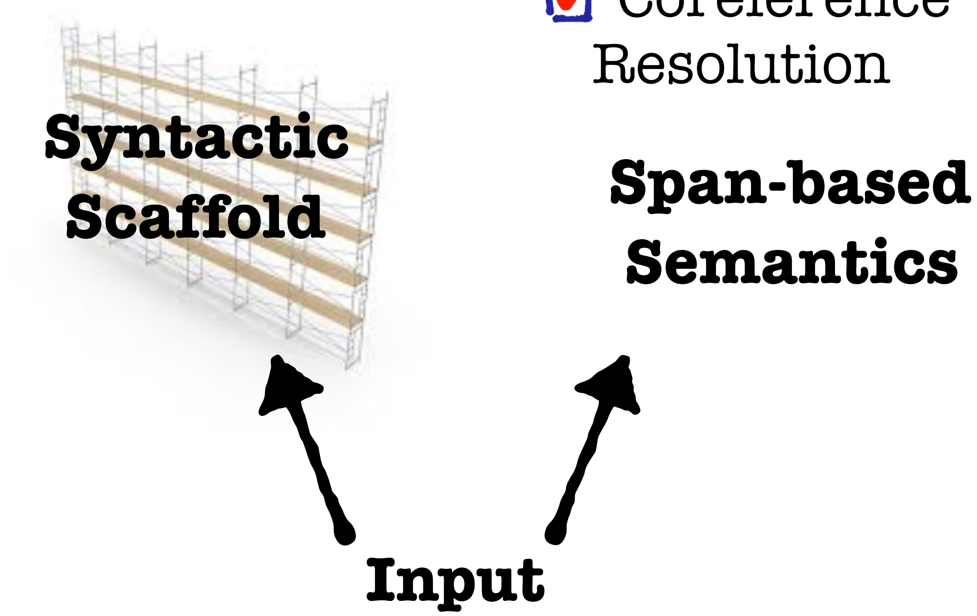

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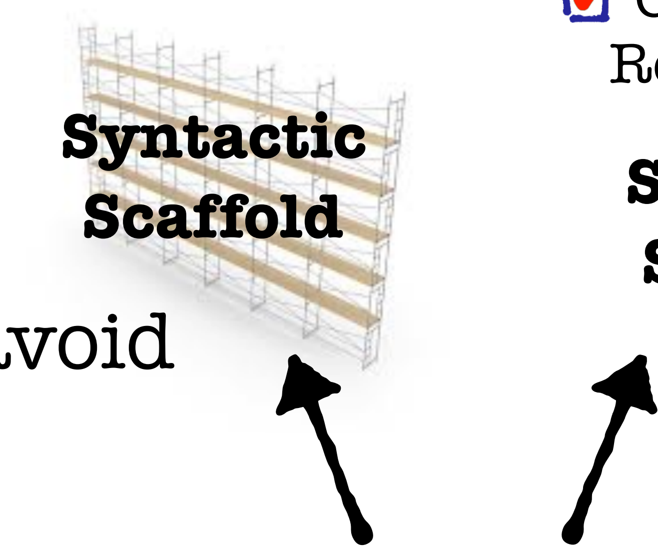

Syntactic Scaffolds

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    - ~~Full Trees~~ Shallow syntax
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- Not required during test

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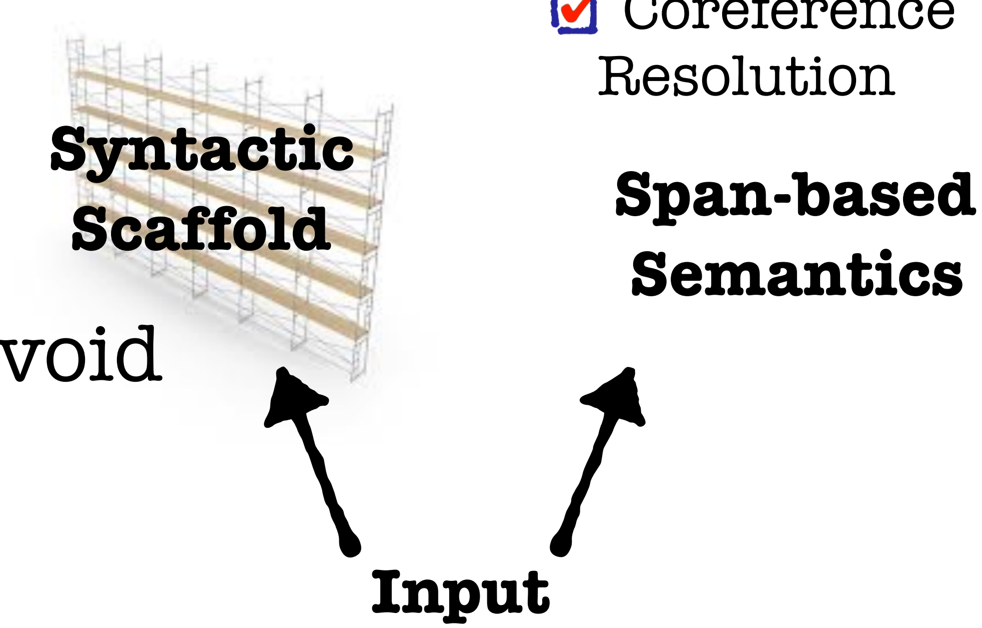
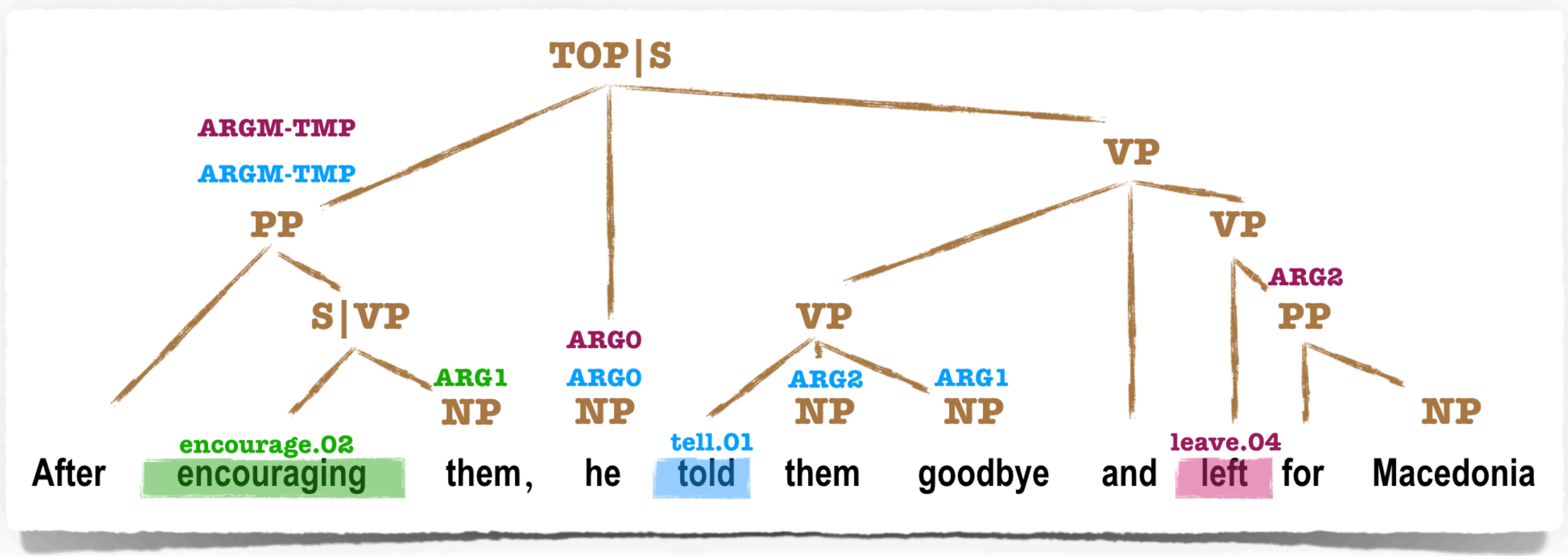


Shallow Syntactic Prediction

- **Desired** parts of syntactic tree:



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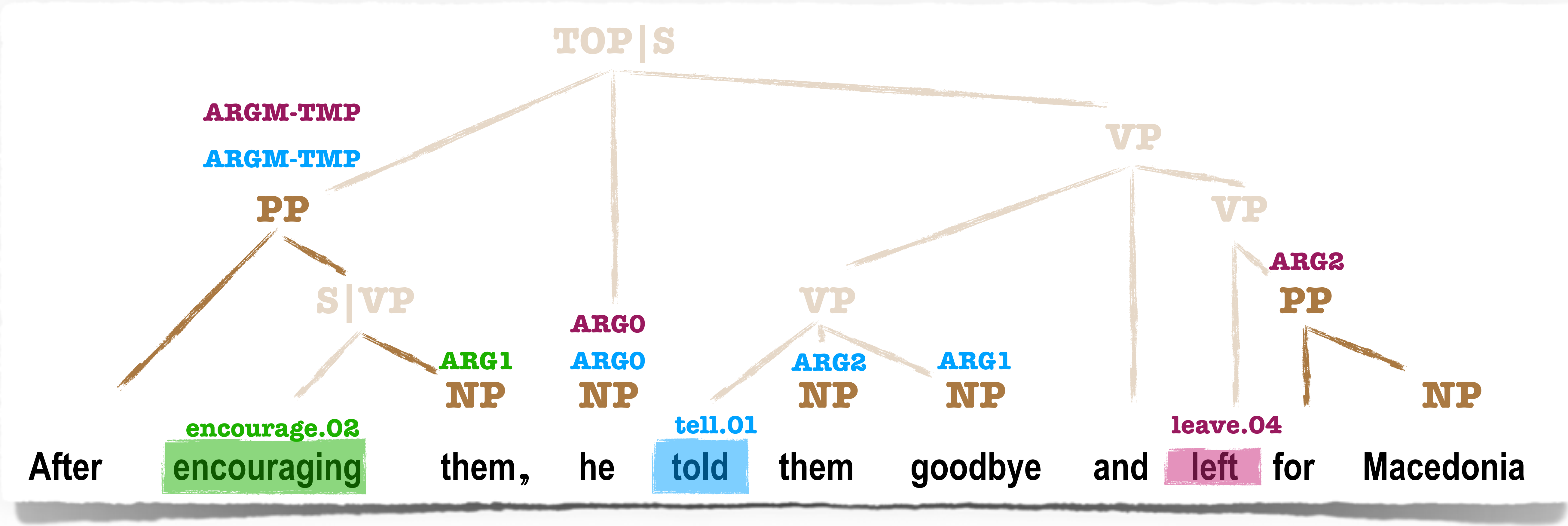

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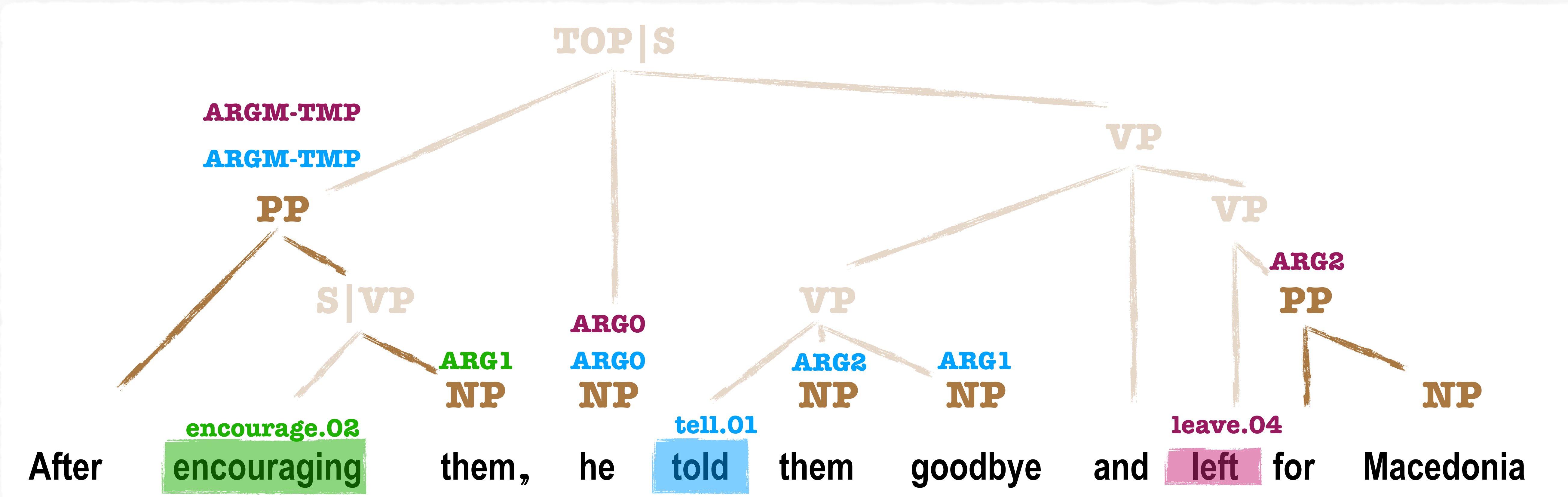

- Span-level classification: For every span, predict phrase category

$$\mathscr{L}_2(\mathbf{x}, \mathbf{z}) = -\sum_{1 \leqslant i \leqslant j \leqslant n} \log p(z_{i:j} \mid \mathbf{x}_{i:j})$$

Training with syntactic scaffolds

x = Input
y = Output Structure
z = Scaffold Structure

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$$\sum_{(\mathbf{x},\mathbf{z}) \in \mathscr{D}_2} \mathscr{L}_2(\mathbf{x}, \mathbf{z}; \theta, \psi)$$

Scaffold Dataset

Scaffold Task Objective

Training with syntactic scaffolds

x = Input
y = Output Structure
z = Scaffold Structure

$$\sum_{(\mathbf{x},\mathbf{y})\in\mathcal{D}_1} \mathcal{L}_1(\mathbf{x}, \mathbf{y}; \theta, \phi)$$

Primary Dataset

Primary Task Objective

$$\sum_{(\mathbf{x},\mathbf{z})\in\mathcal{D}_2} \mathcal{L}_2(\mathbf{x}, \mathbf{z}; \theta, \psi)$$

Scaffold Dataset

Scaffold Task Objective

Training with syntactic scaffolds

x = Input
y = Output Structure
z = Scaffold Structure

$$\sum_{(\mathbf{x},\mathbf{y})\in\mathcal{D}_1} \mathcal{L}_1(\mathbf{x},\mathbf{y};\theta,\phi) + \delta \sum_{(\mathbf{x},\mathbf{z})\in\mathcal{D}_2} \mathcal{L}_2(\mathbf{x},\mathbf{z};\theta,\psi)$$

Primary Dataset

Primary Task Objective

Mixing Ratio

Scaffold Dataset

Scaffold Task Objective

Training with syntactic scaffolds

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$$\sum_{(\mathbf{x},\mathbf{y})\in\mathcal{D}_1} \mathcal{L}_1(\mathbf{x},\mathbf{y};\theta,\phi) + \delta \sum_{(\mathbf{x},\mathbf{z})\in\mathcal{D}_2} \mathcal{L}_2(\mathbf{x},\mathbf{z};\theta,\psi)$$

Primary Dataset

Primary Task Objective

Mixing Ratio

Scaffold Dataset

Scaffold Task Objective

Shared input parameters

The primary objective

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Same structures must be scored in both the primary and the scaffold task.

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- Span-based classification, with aggressive pruning [Lee et. al., 2017]

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- Span-based classification, with aggressive pruning [Lee et. al., 2017]
- Semi-Markov Conditional Random Fields [Sarawagi et. al. 2004]

Semi-Markov CRFs

After encouraging them	he	told	them	goodbye	and	left	for Macedonia
ARGM-TMP	ARG0					leave.04	ARG2

Semi-Markov CRFs

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- Globally normalized model for segmentations (**s**) of a sentence (**x**).

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$$p(\mathbf{s} \mid \mathbf{x})$$

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- Generalization of CRFs:

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$$s = \langle i, j, y_{i:j} \rangle$$

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$$\Phi(\mathbf{x}, \mathbf{s}) = \sum_{k=1}^{m} \phi(s_k, x_{i_k:j_k})$$

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- Generalization of CRFs:
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$$s = \langle i, j, y_{i:j} \rangle$$

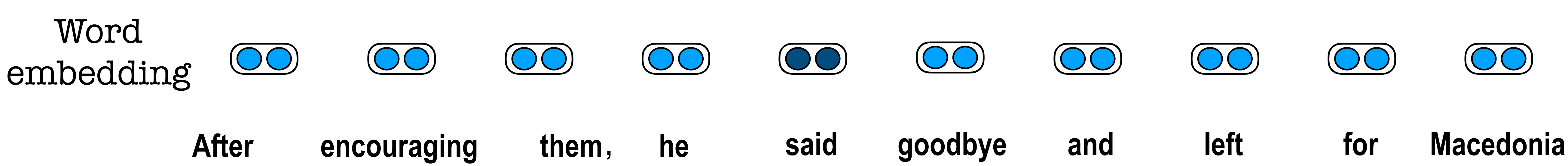
- Training and inference given by O(ndl) dynamic programs, with a 0th-order Markovian assumption.

$$\Phi(\mathbf{x}, \mathbf{s}) = \sum_{k=1}^{m} \phi(s_k, x_{i_k:j_k})$$

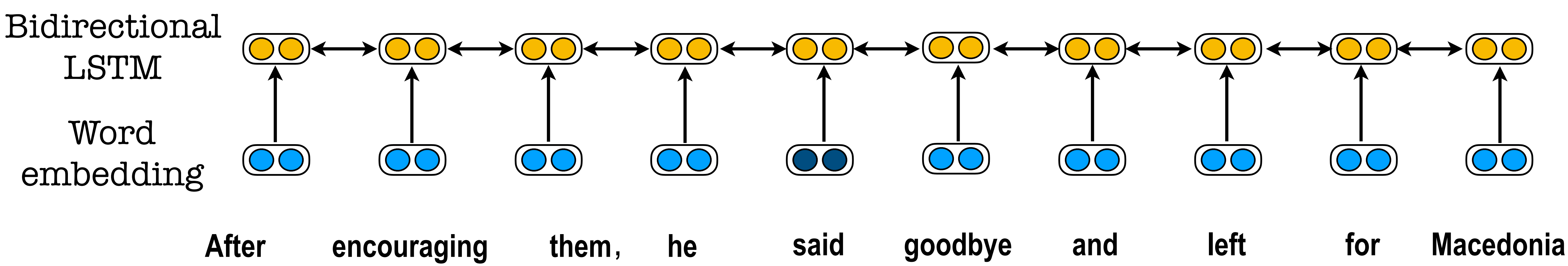
Model architecture

After encouraging them, he said goodbye and left for Macedonia

Model architecture



Model architecture



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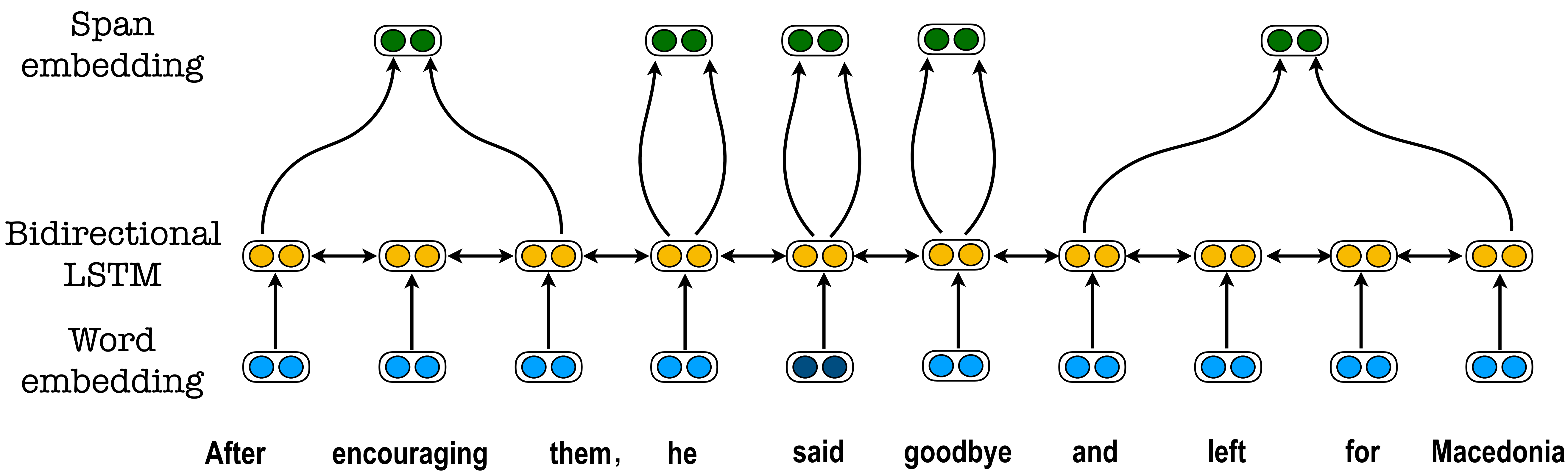

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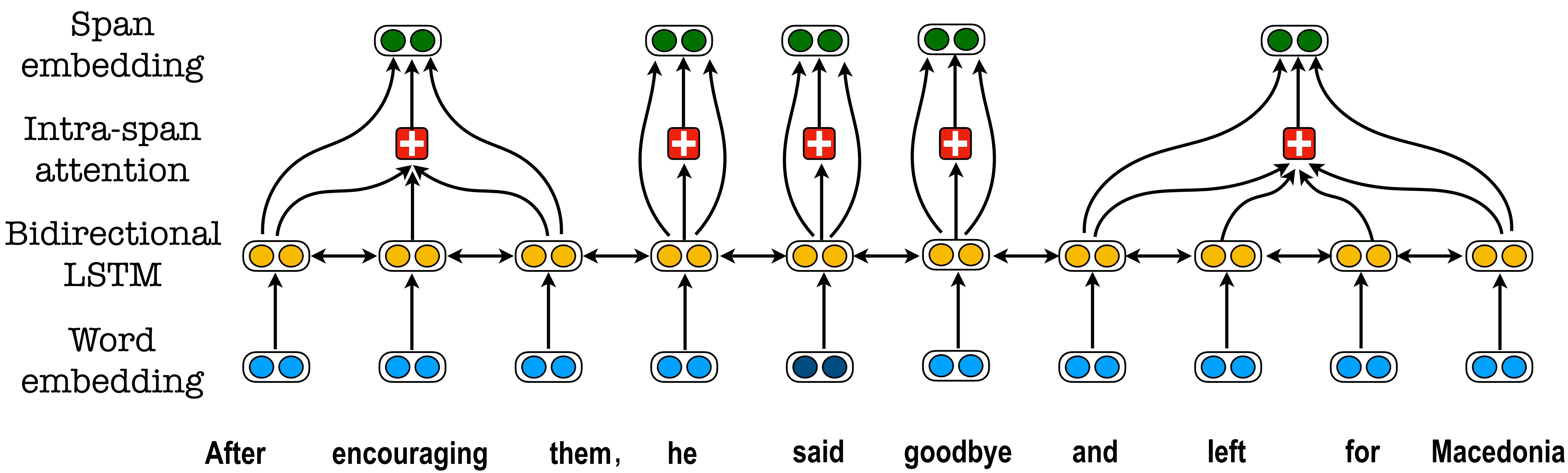

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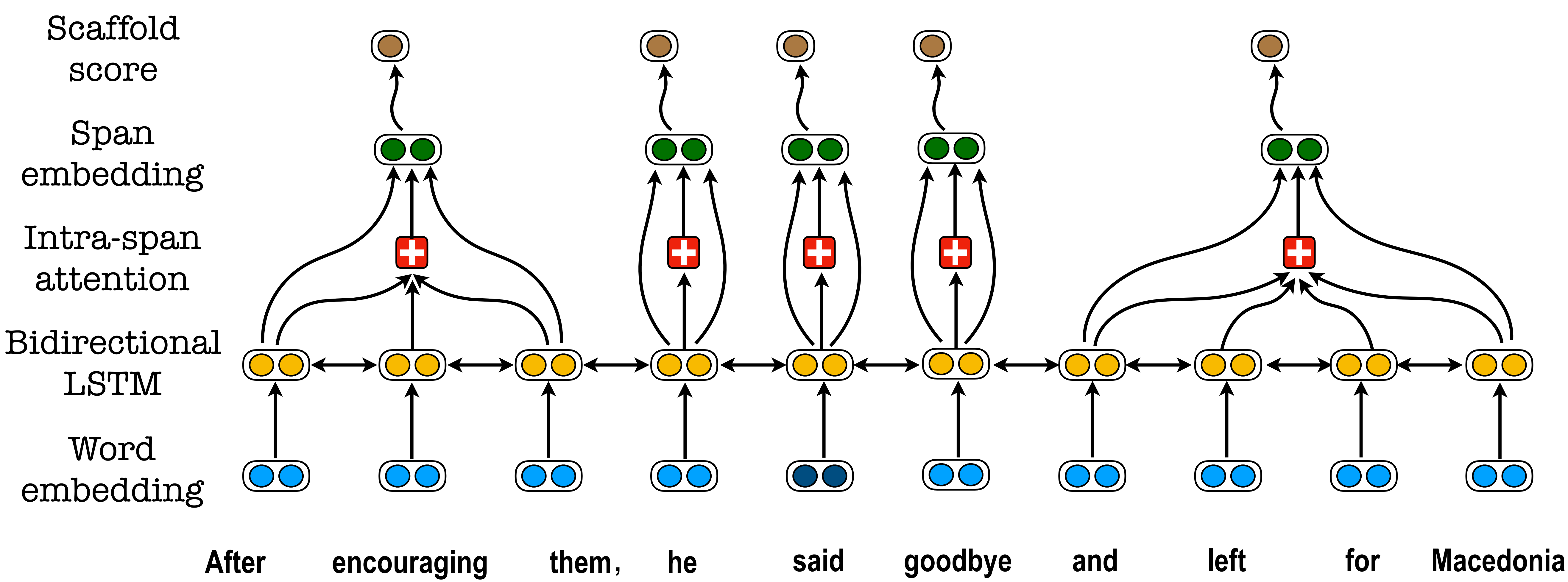

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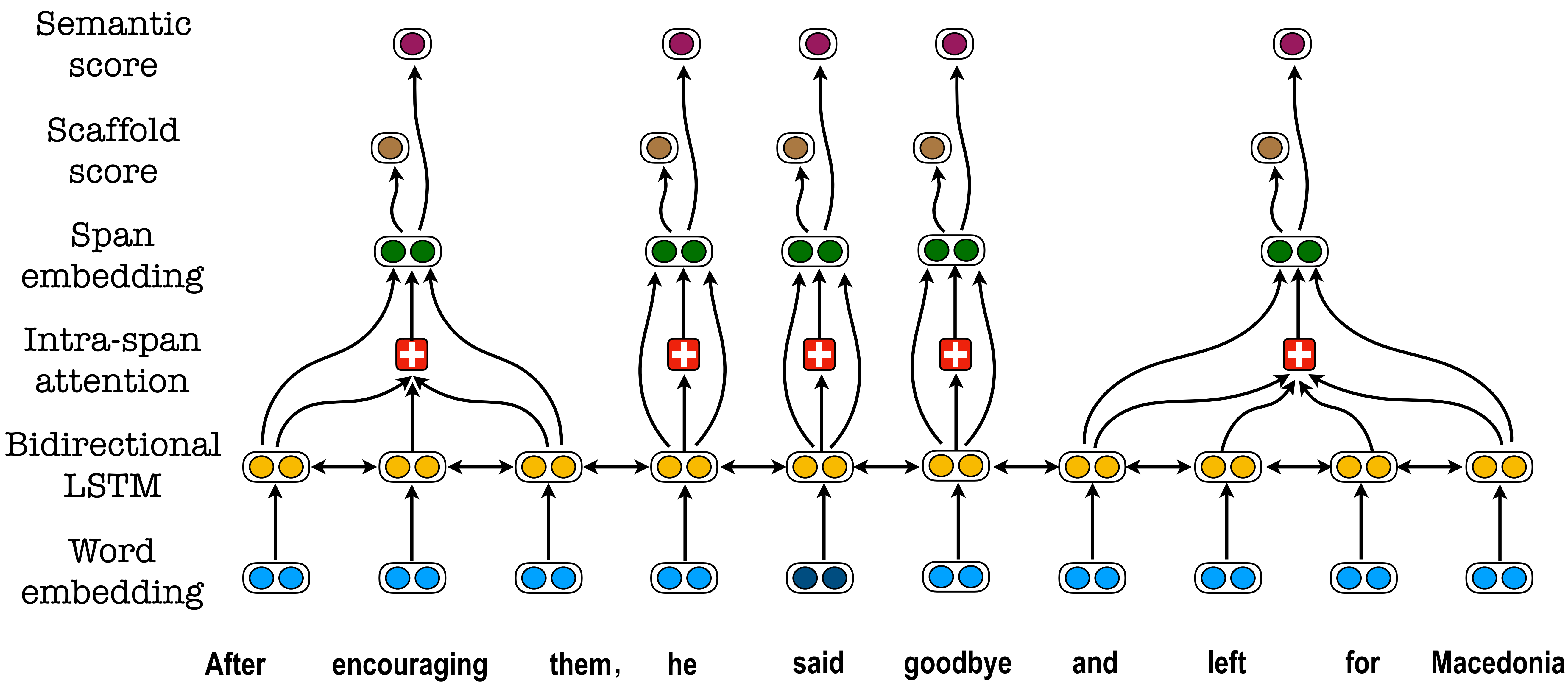

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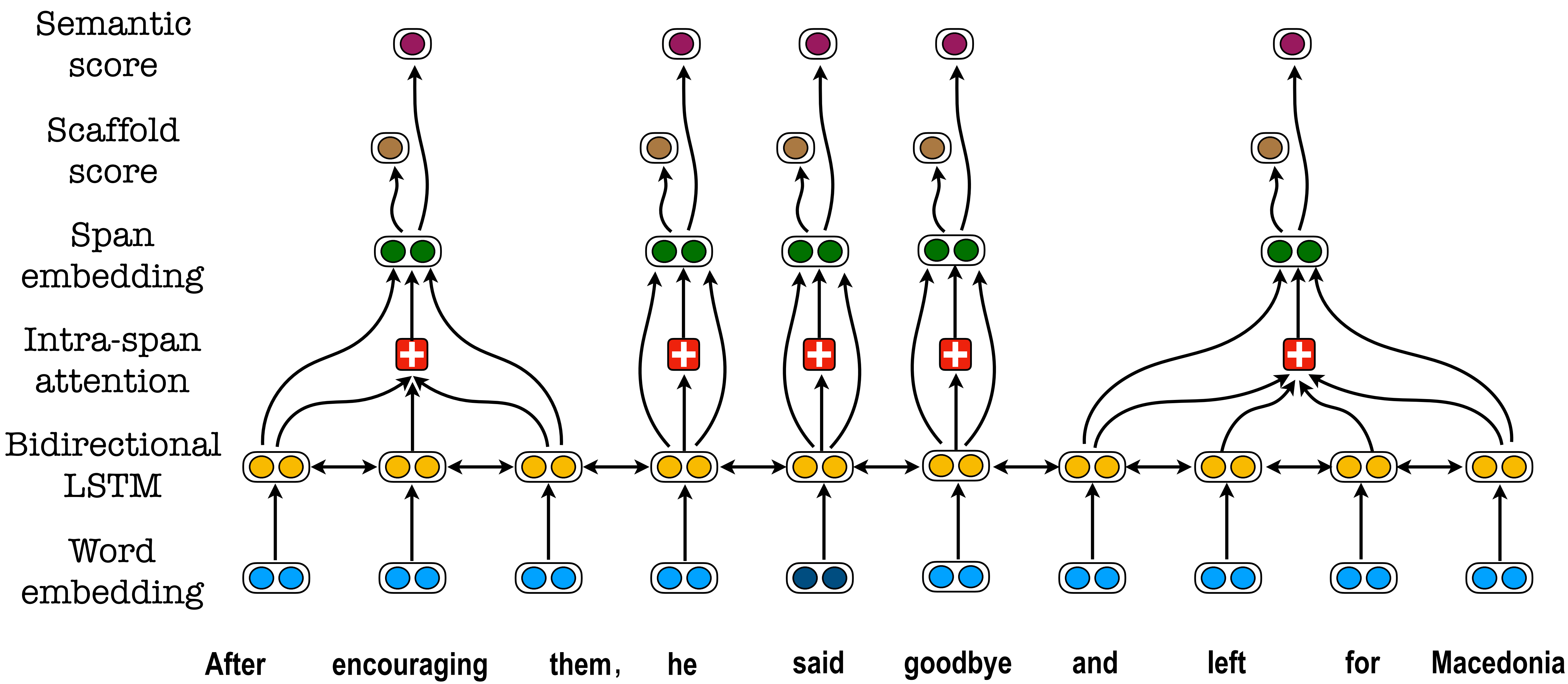
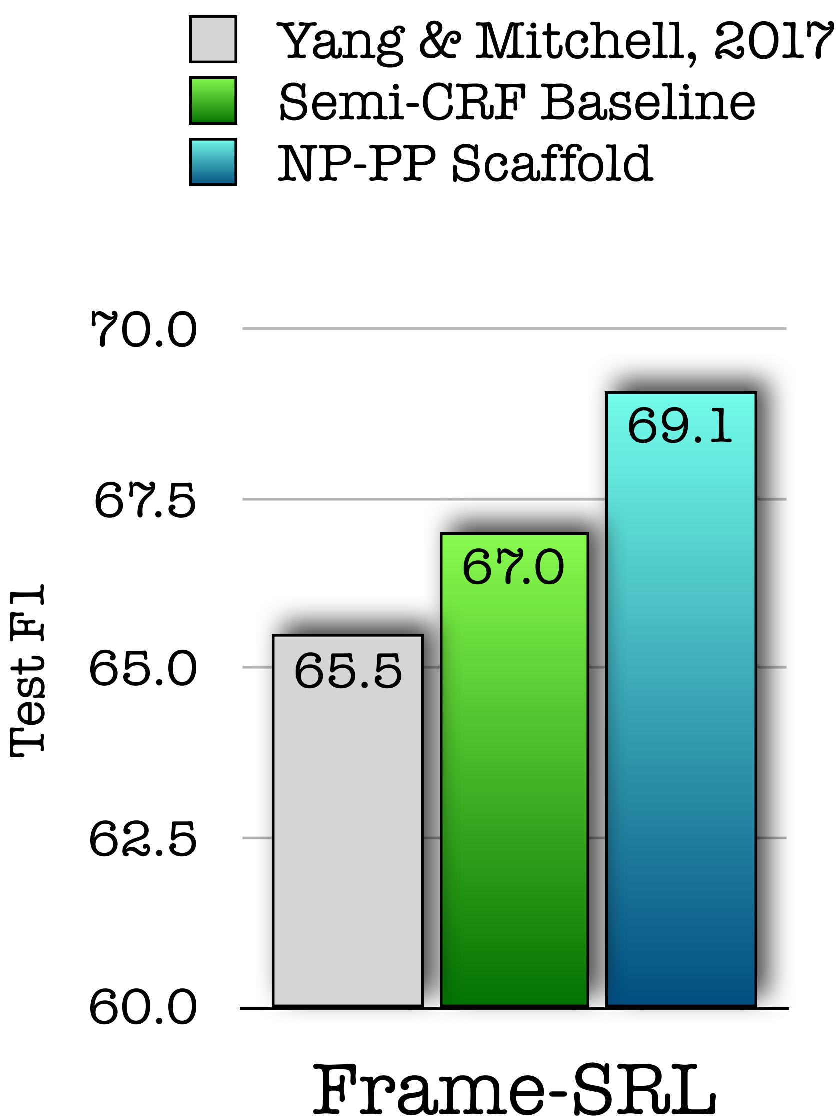


- Learn scaffold score when syntactic annotations available.

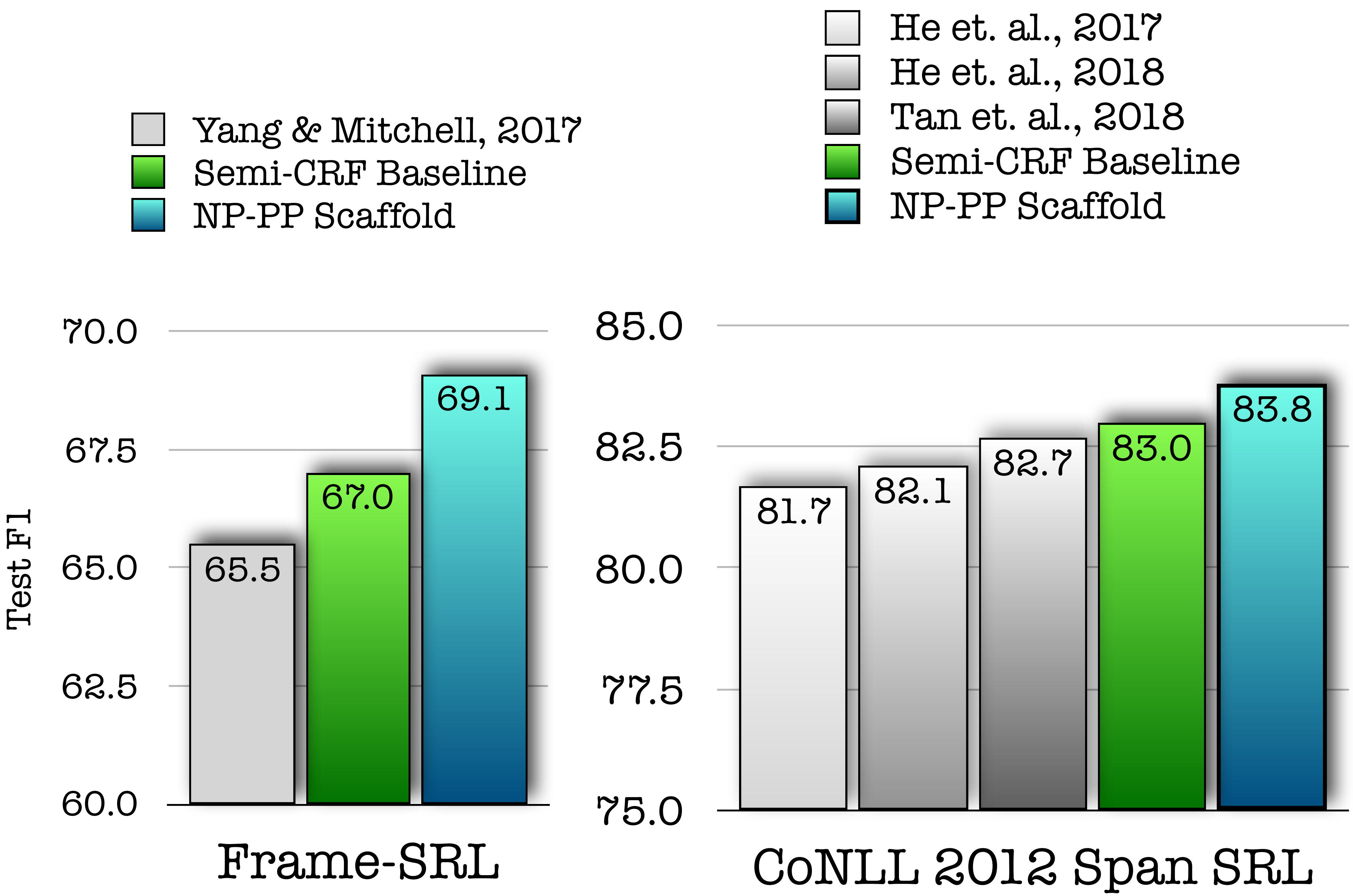
Results

Results



Yang & Mitchell, 2017
Semi-CRF Baseline
NP-PP Scaffold
70.0
67.5
65.0
62.5
60.0
Test F1
65.5
67.0
69.1
Frame-SRL

Results


Yang & Mitchell, 2017
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Frame-SRL
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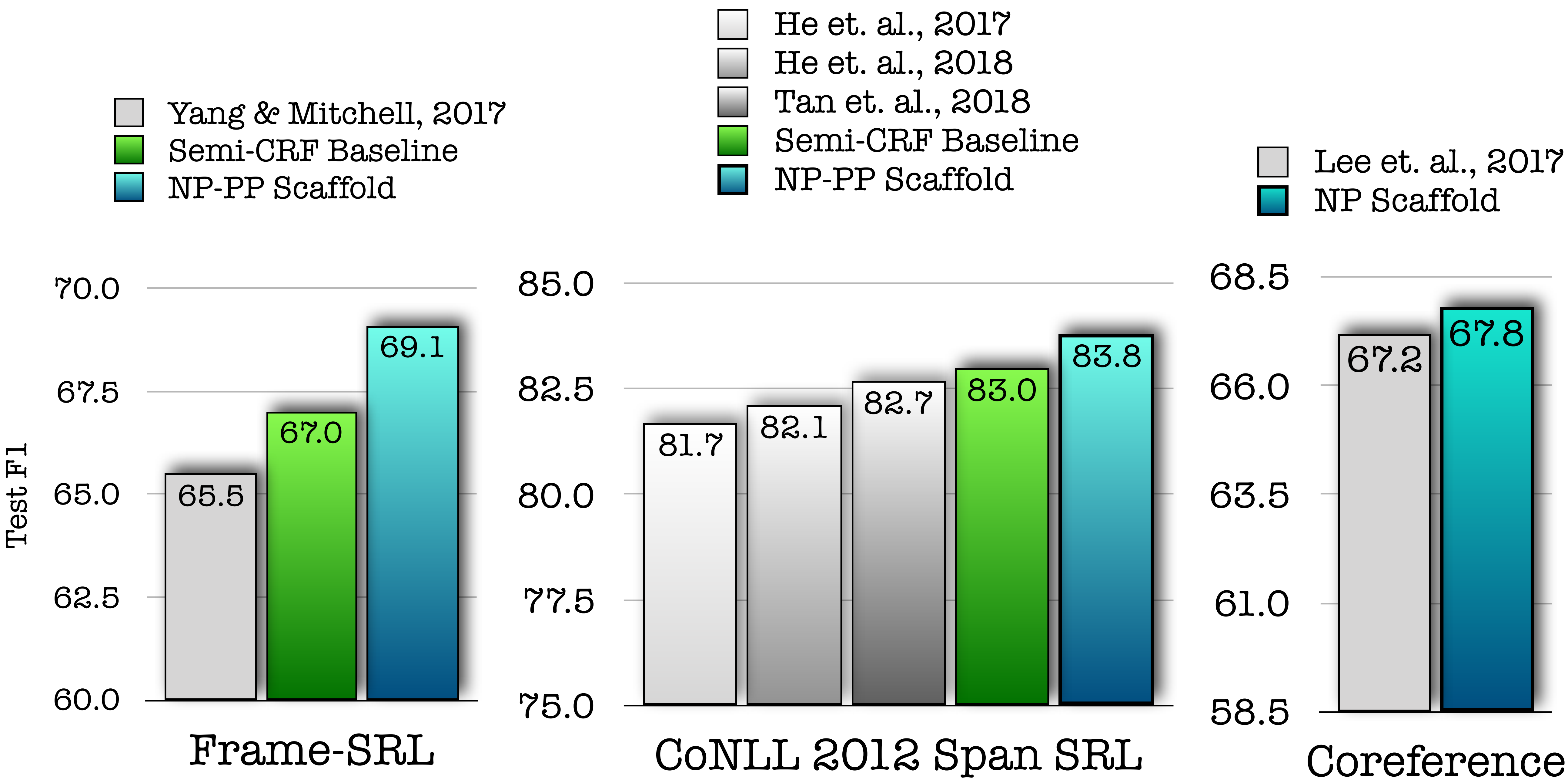
82.5
80.0
77.5
75.0
81.7
82.1
82.7
83.0
83.8
CoNLL 2012 Span SRL

Results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68.5
66.0
63.5
61.0
58.5
67.2
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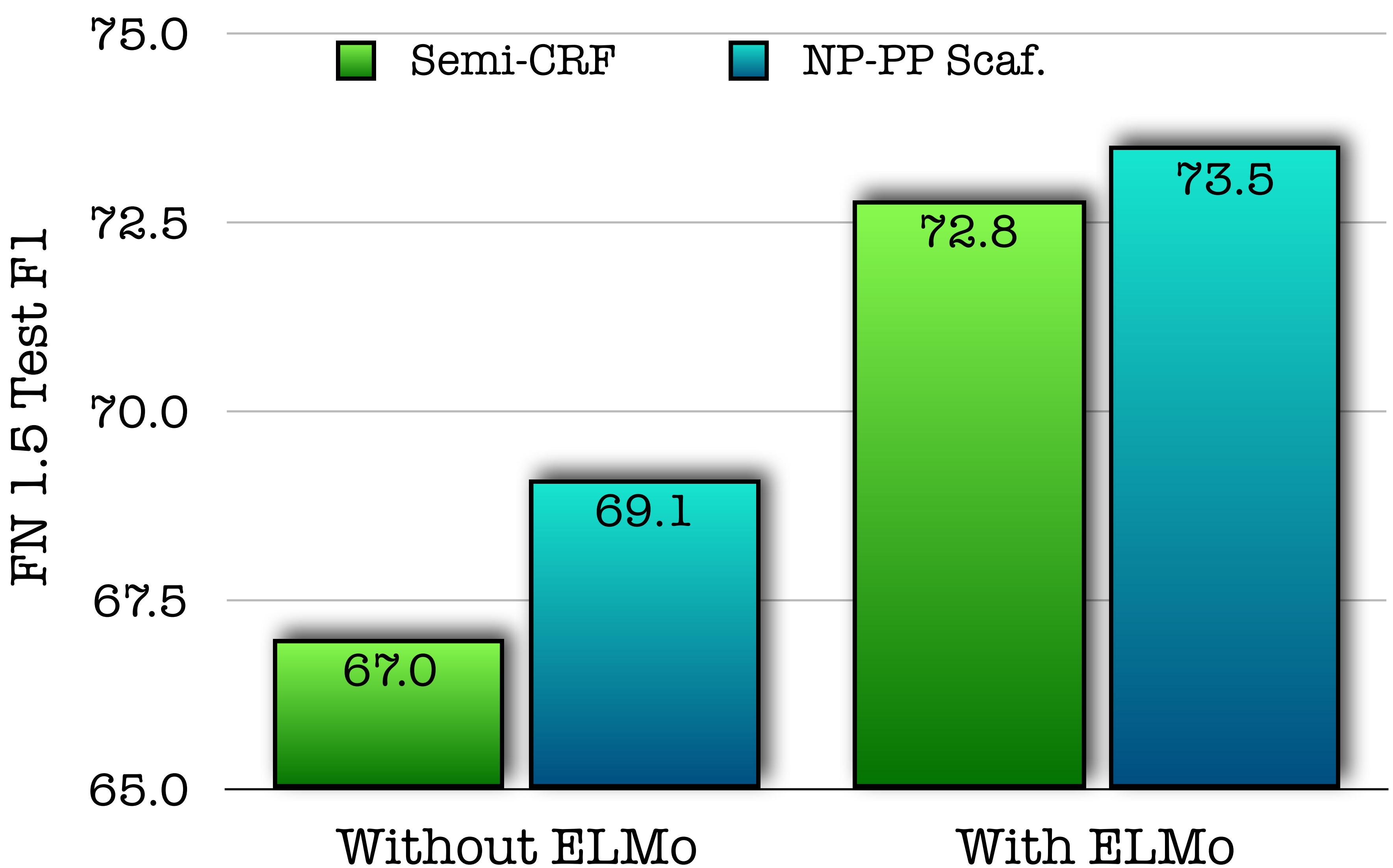
Coreference

Effect of Contextualized Representations



Note: These results are not included in the paper.

Recap: Learning Challenge #1

Can linguistic structure act as an informative prior for improving our models?

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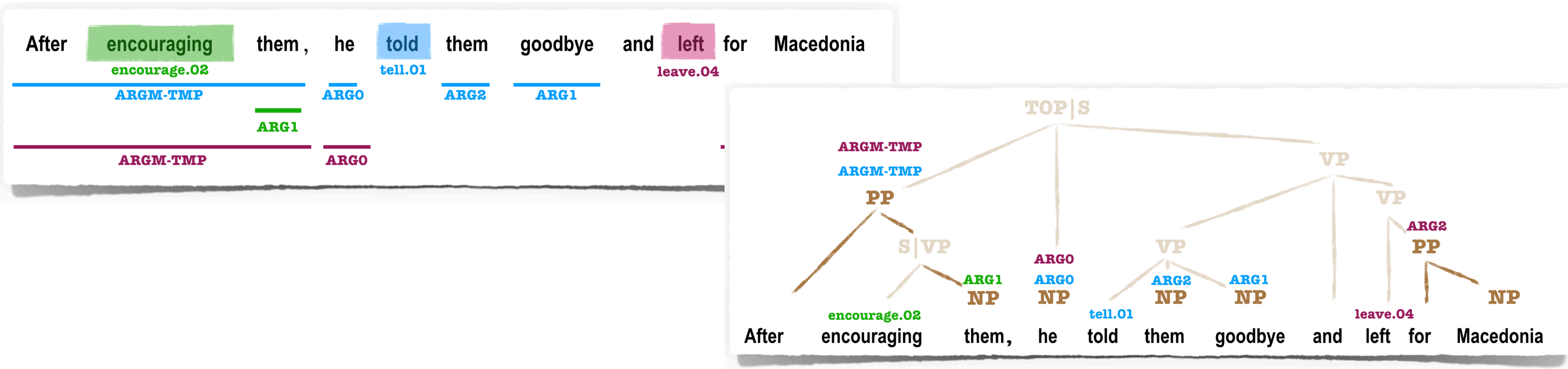

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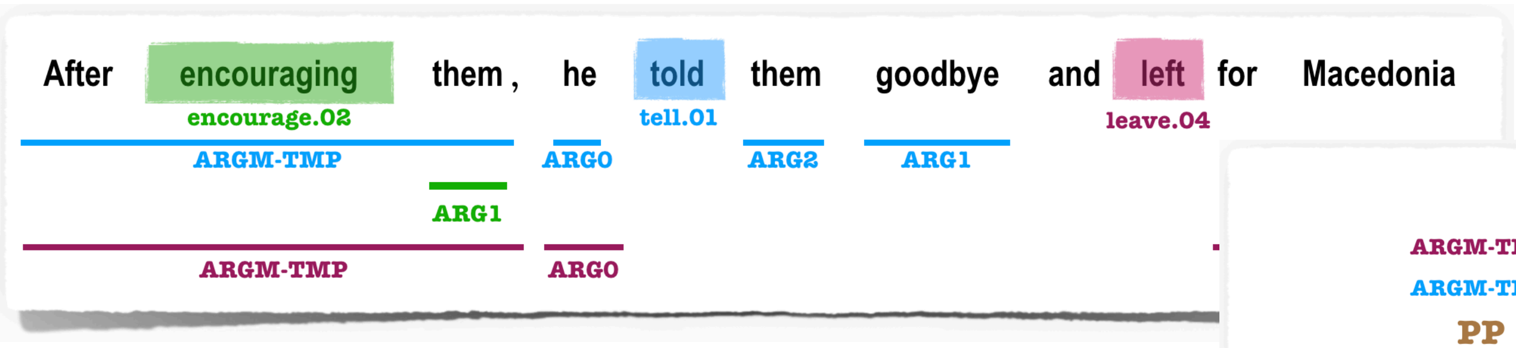

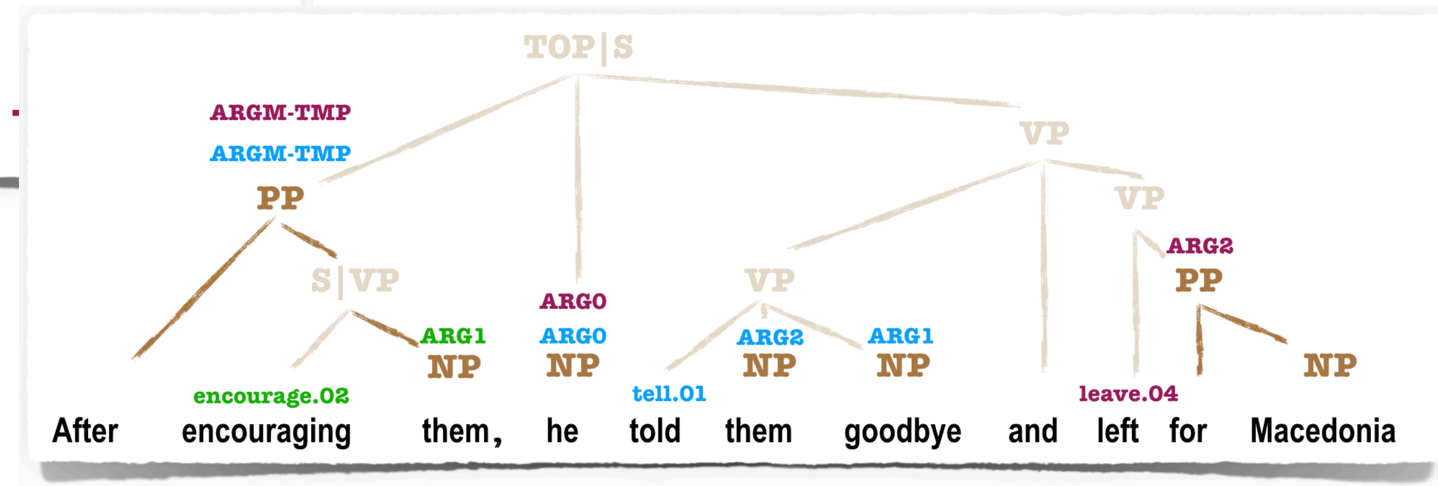

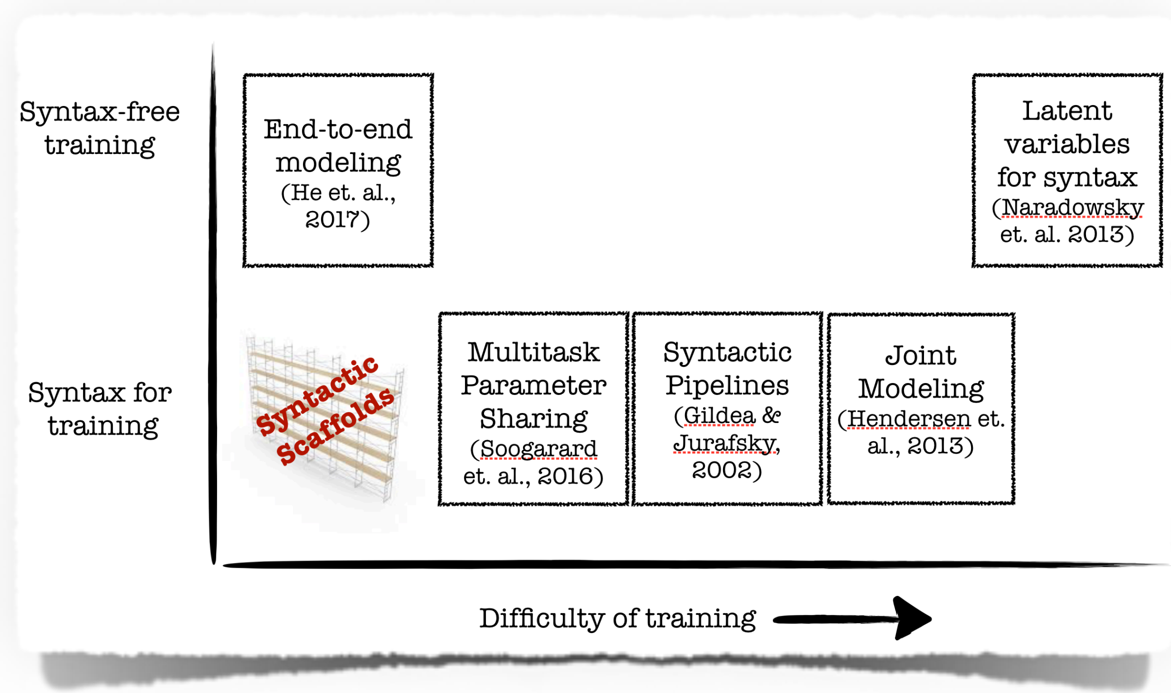

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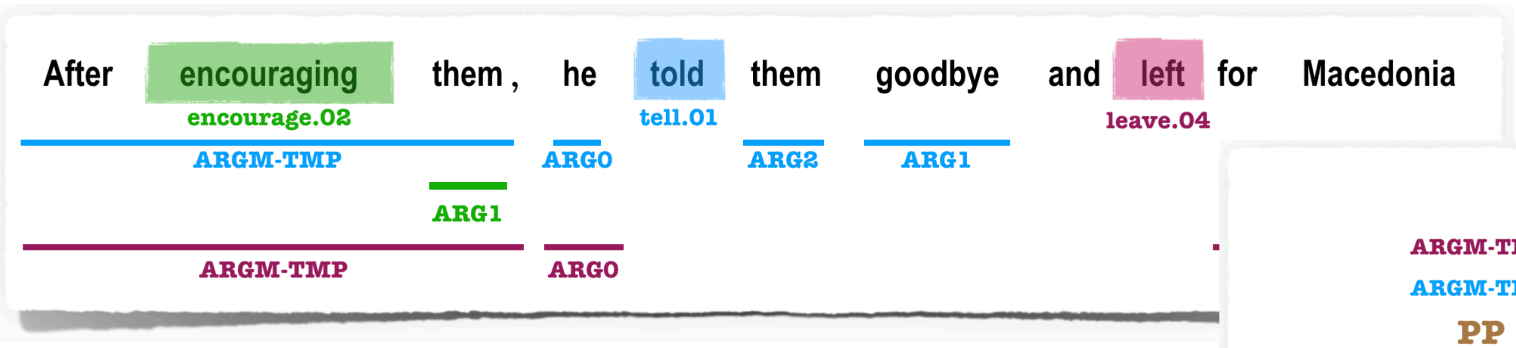
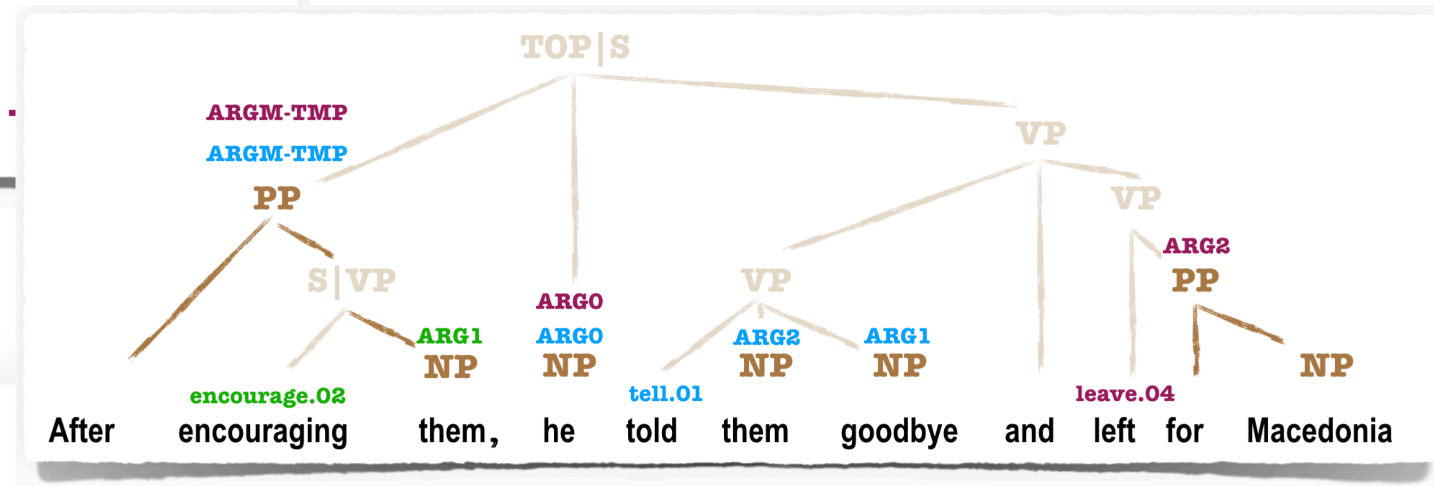
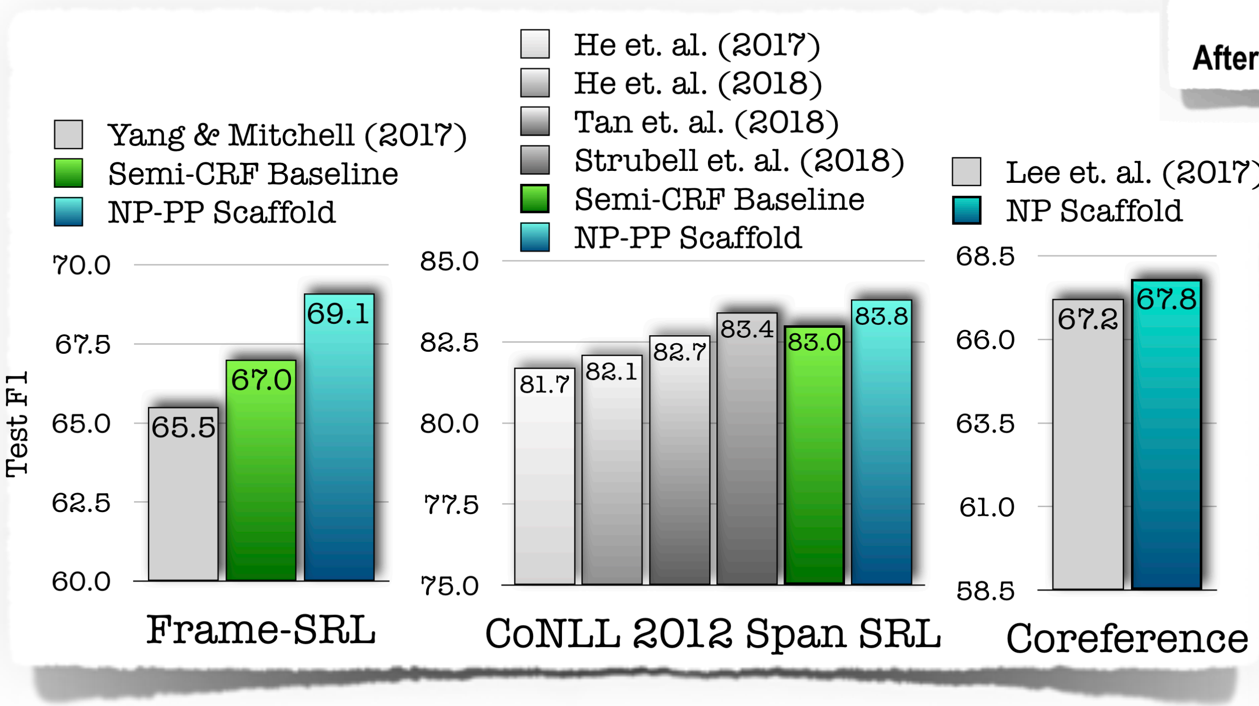
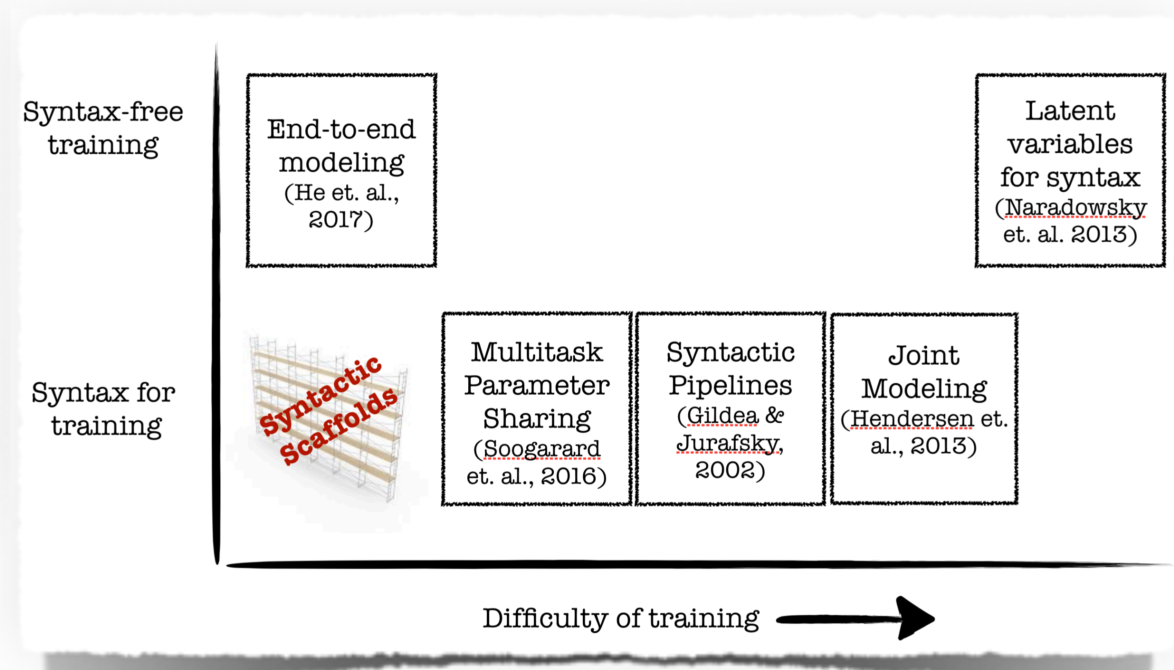
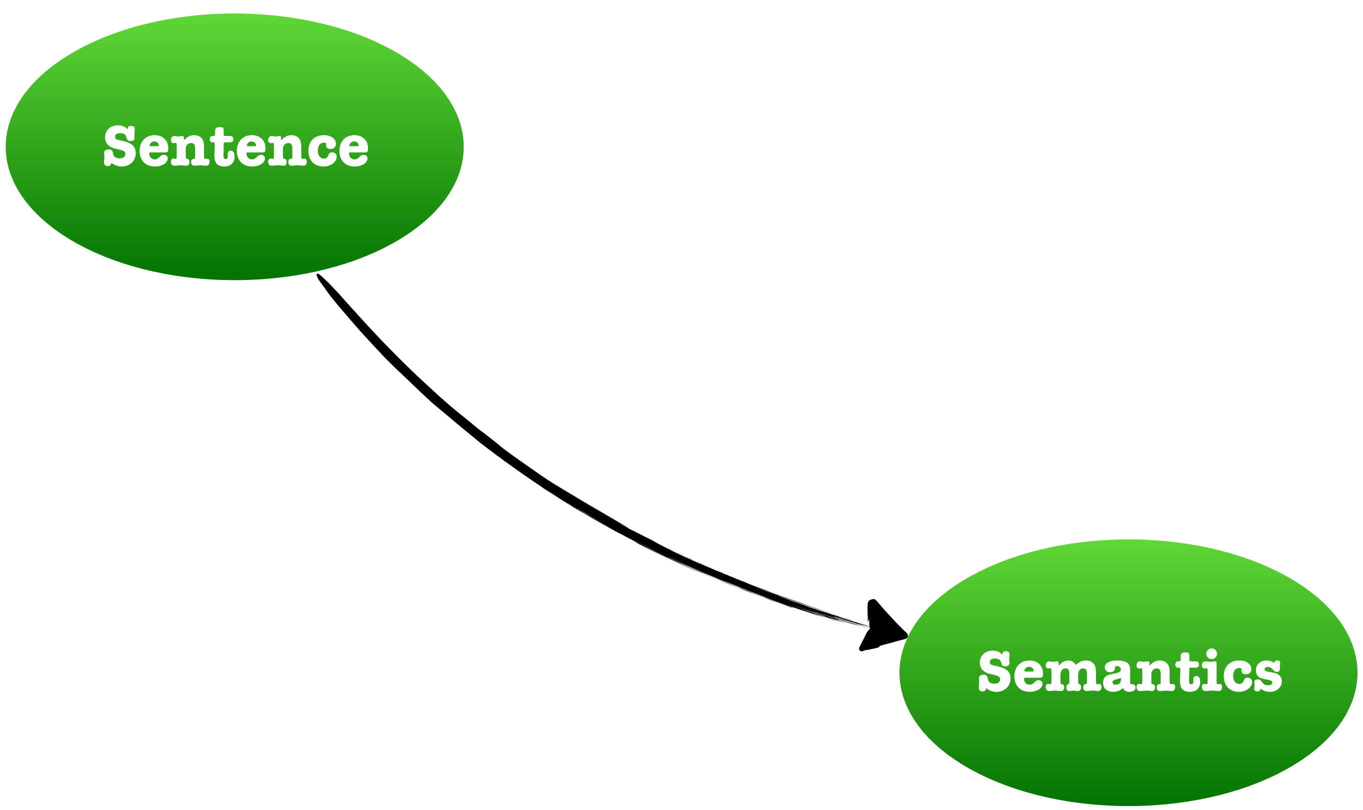








Looking ahead: Predicted Structure



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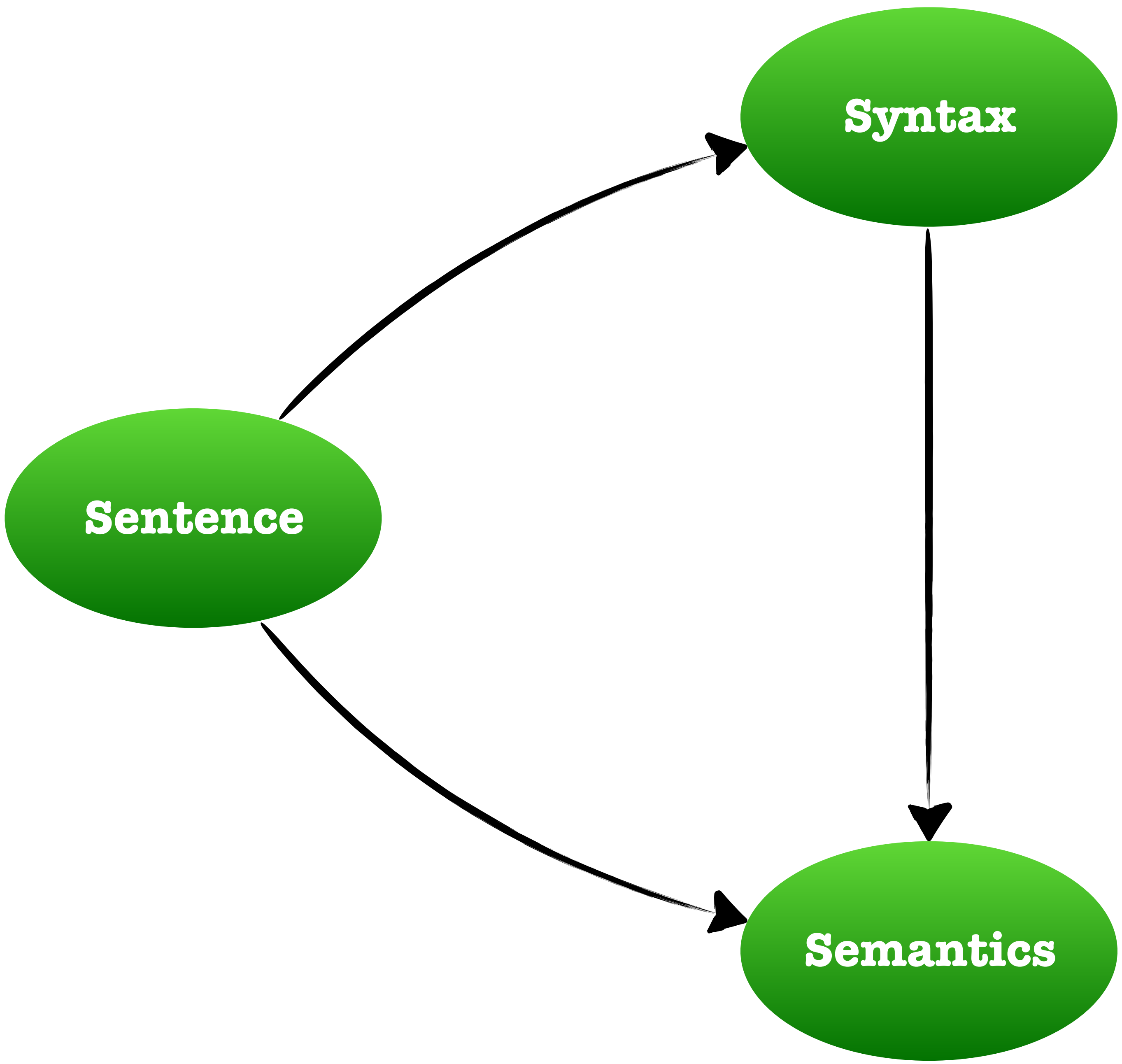

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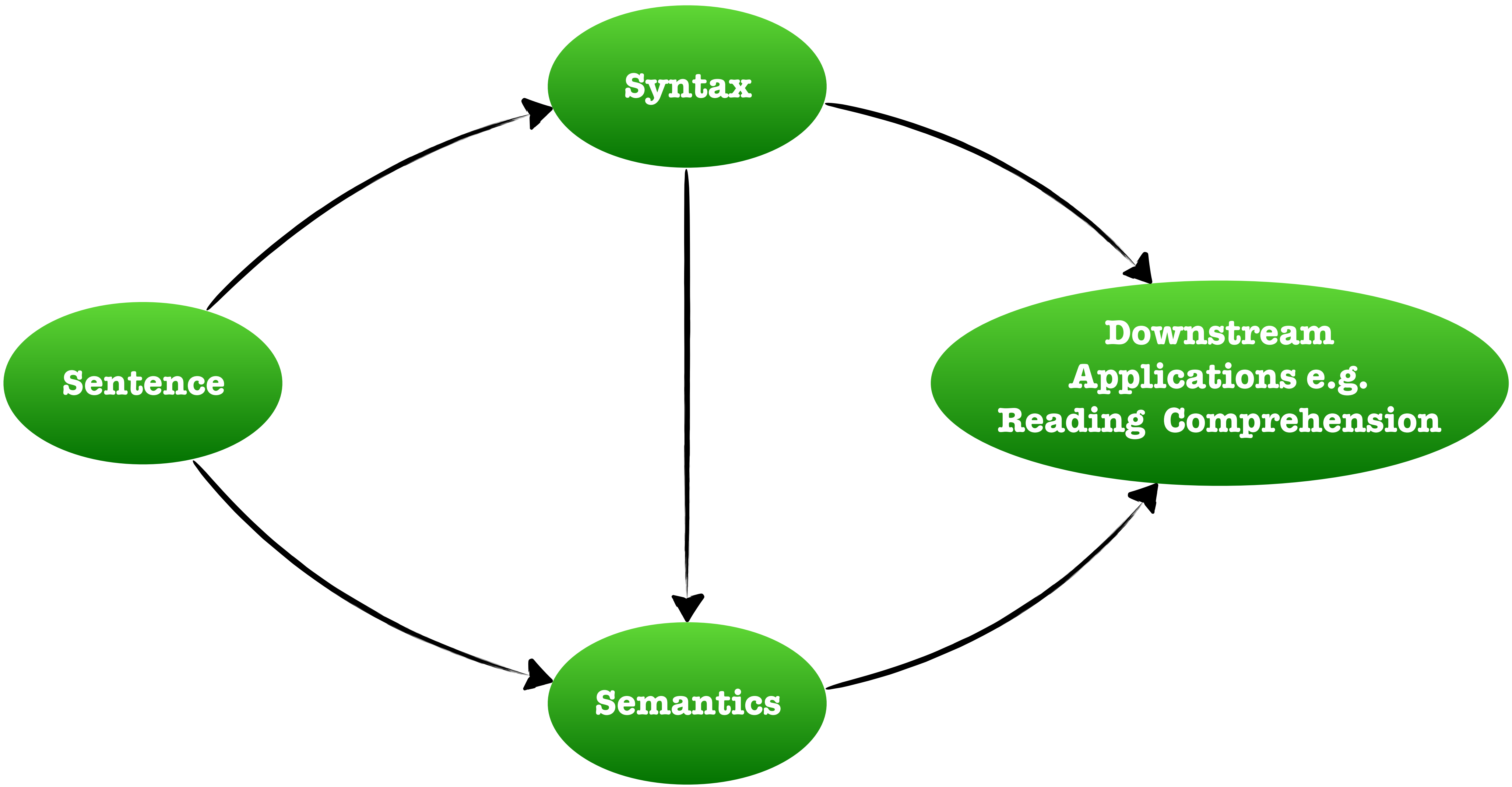
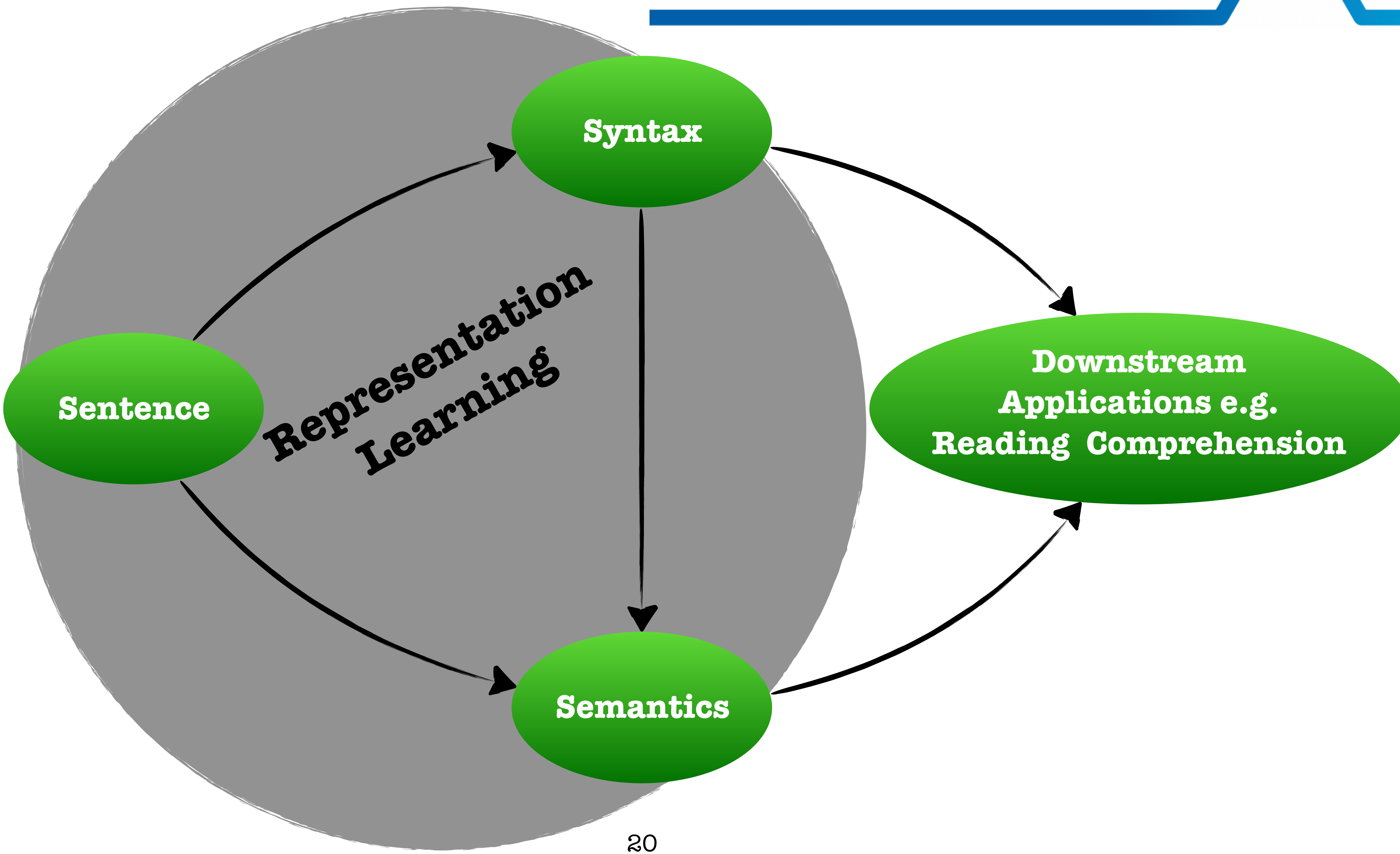
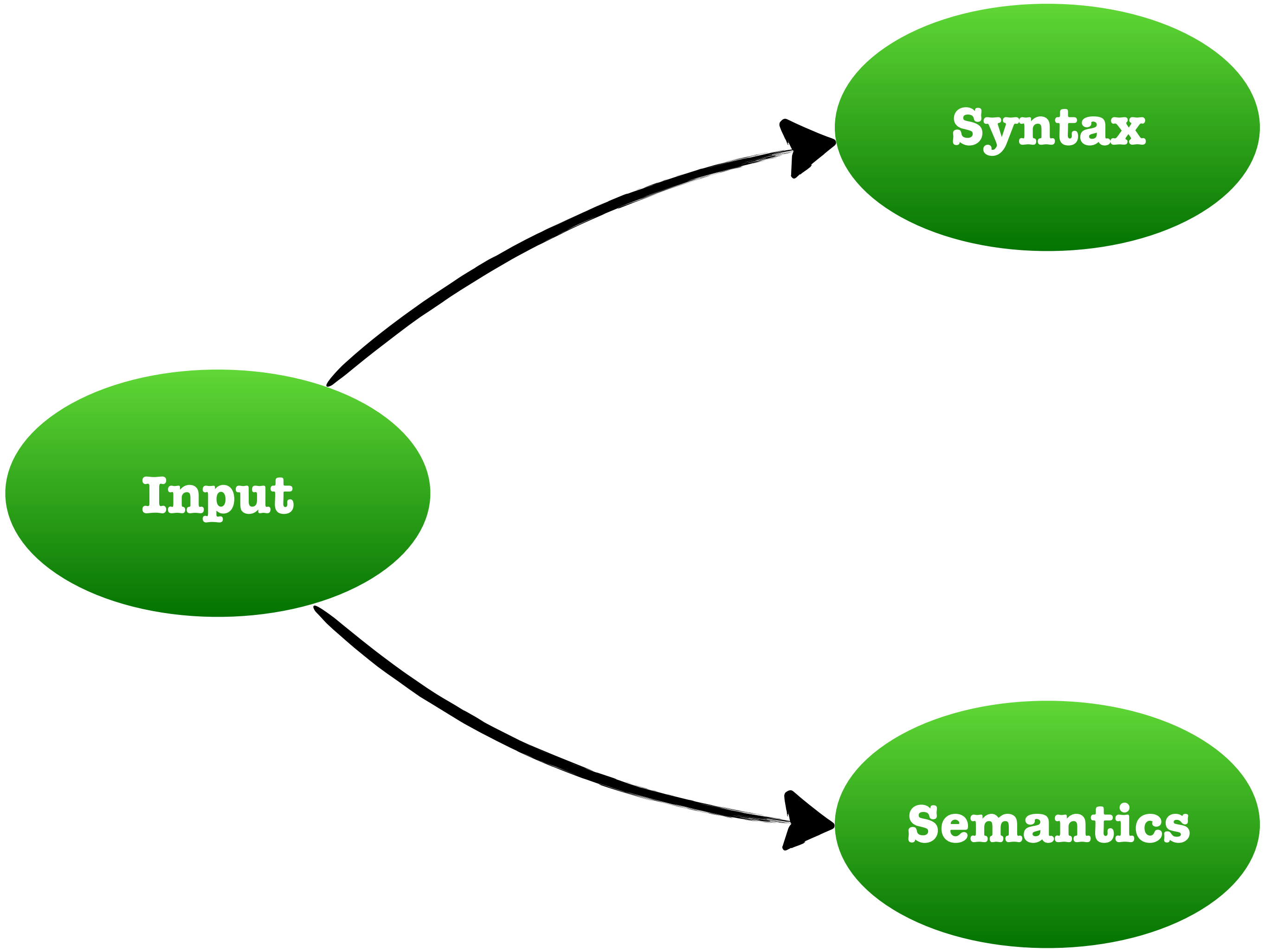


Looking ahead: Predicted Structure



Looking ahead: Structured Transformation



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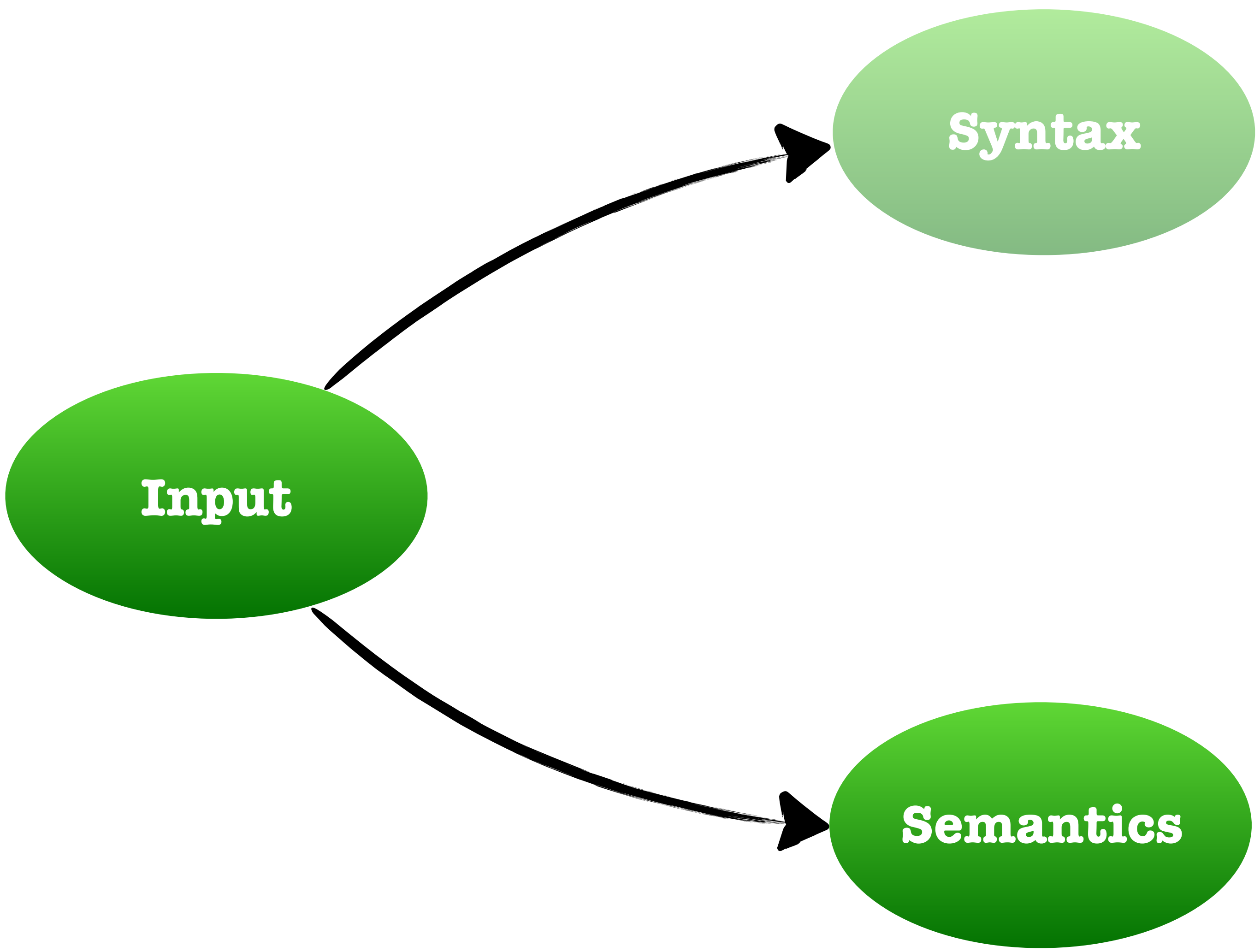
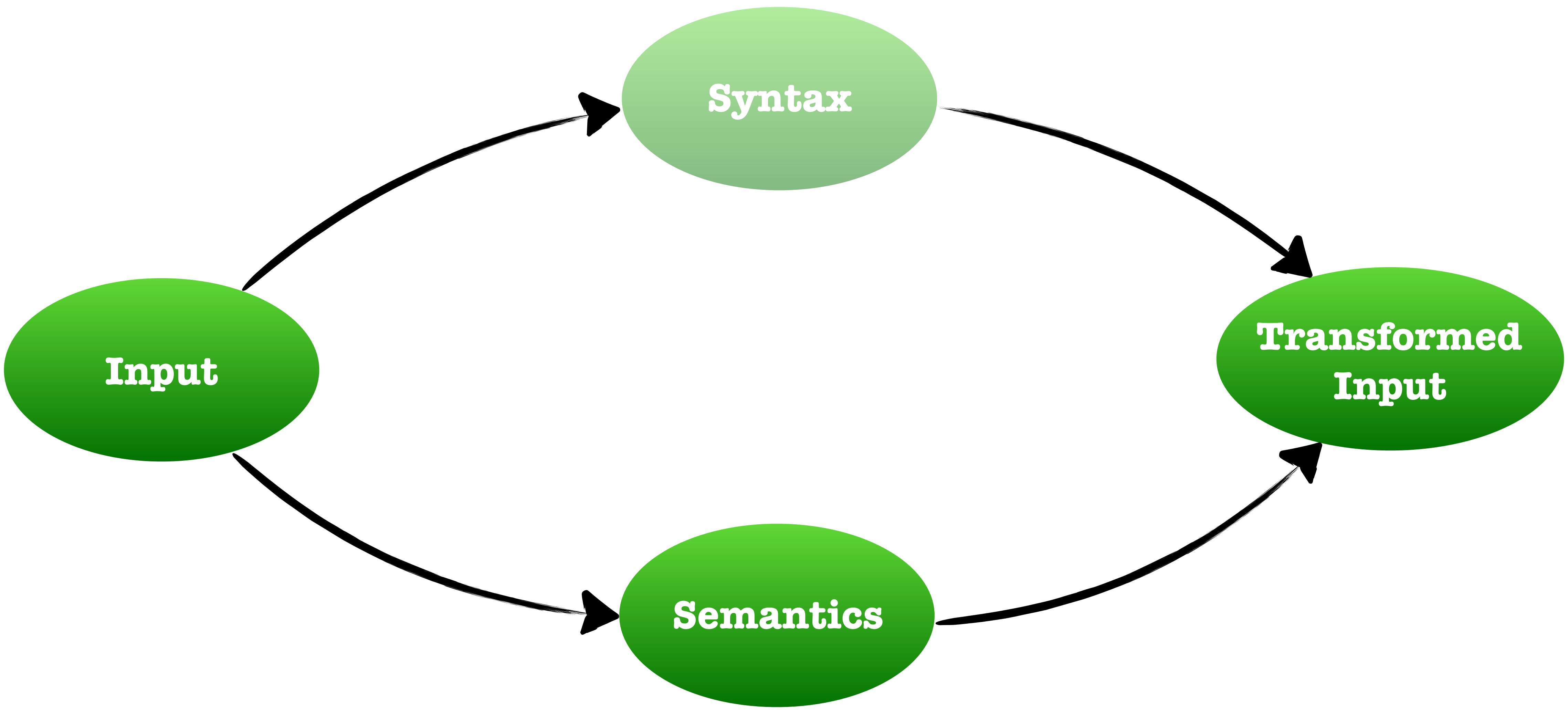


Iyyer et. al. [NAACL 2018]

Looking ahead: Structured Transformation



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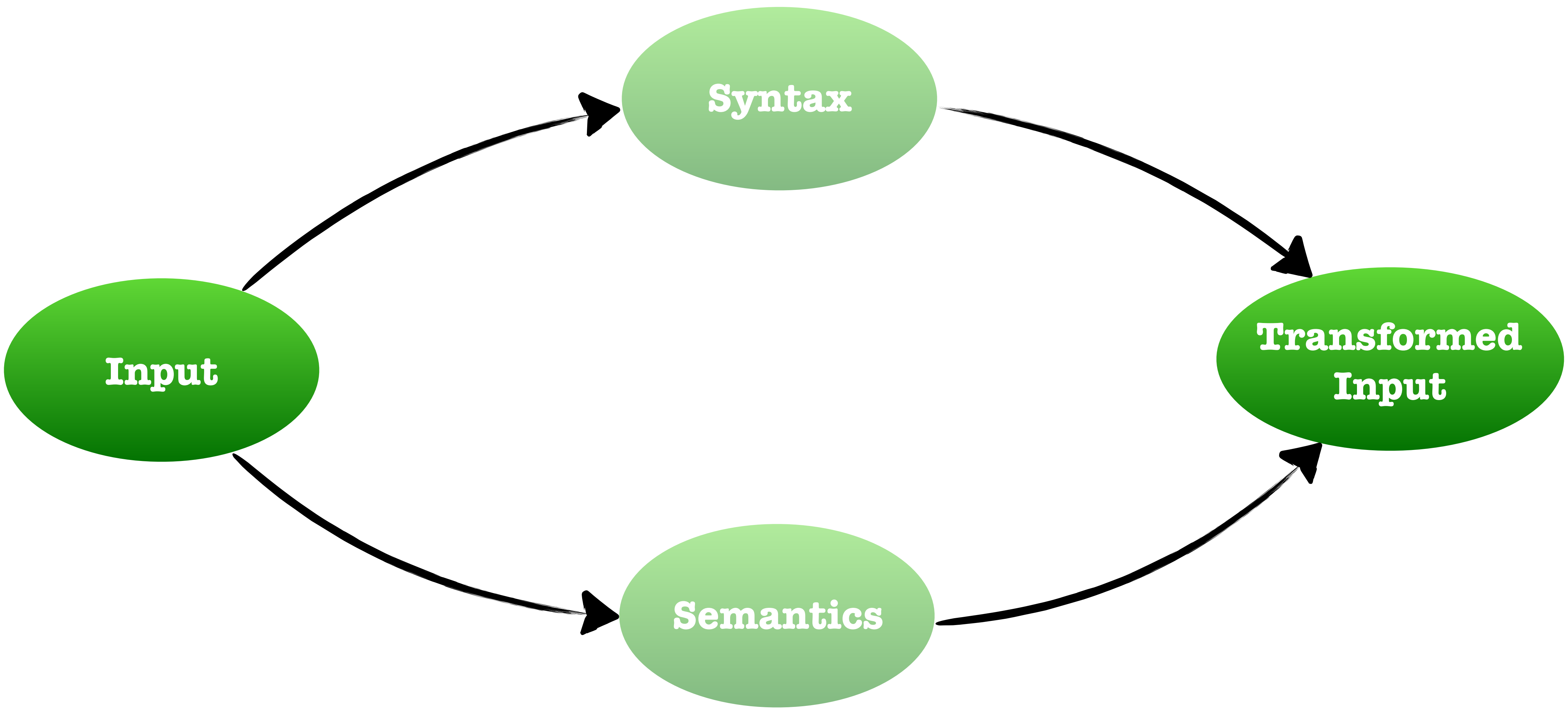
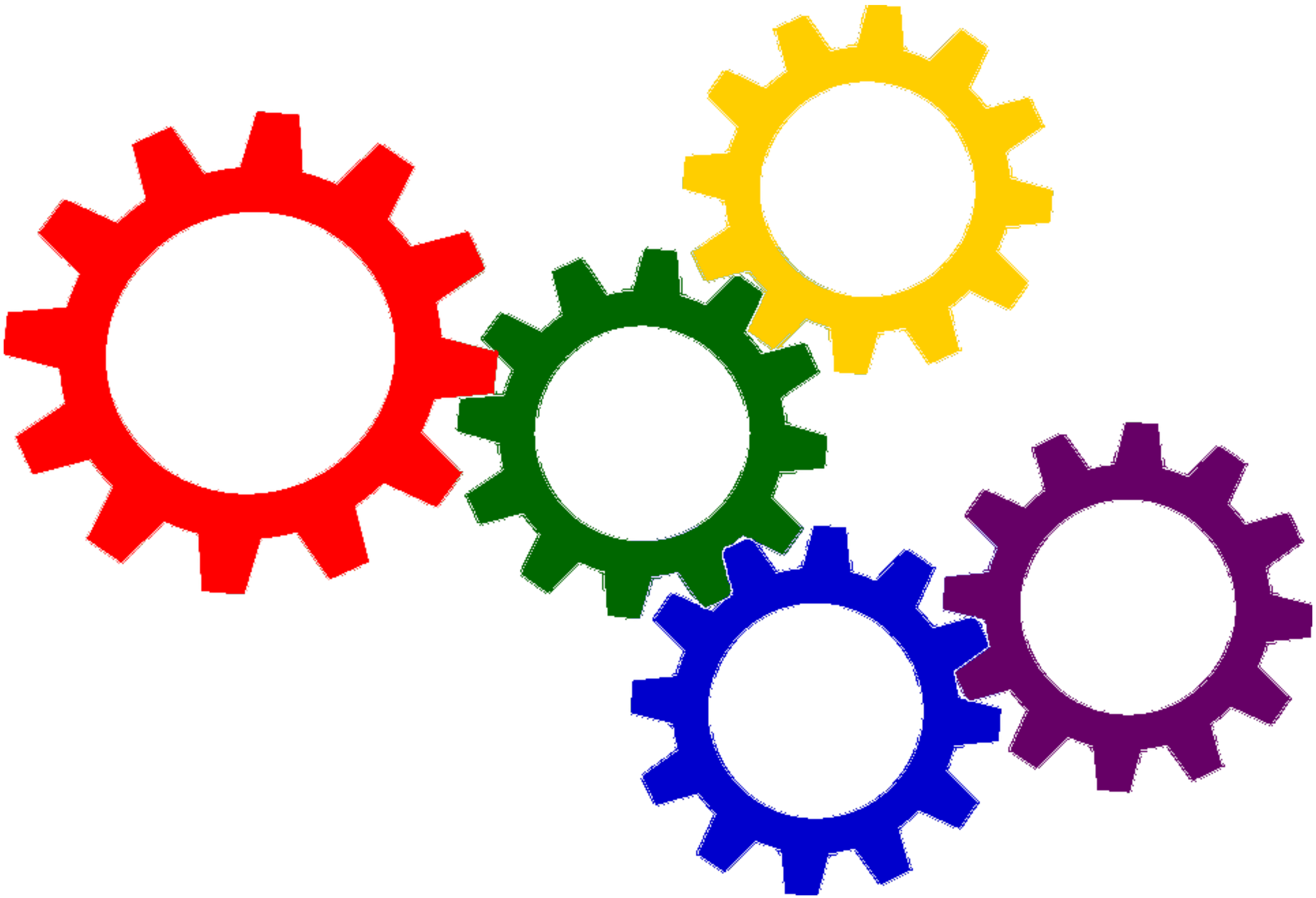


Iyyer et. al. [NAACL 2018]

Part II



Recap: Confusion of the Muppets

Wessex is chivalrous and charming, but semi-betrothed to Lady Ursula Glynde, whom he has not seen since her infancy. Wessex is repelled by the idea of having his wife thrust upon him and purposely avoids Lady Ursula. Unknown to Wessex, the Queen jealously guards him against Ursula, who is extremely beautiful. As soon as she realizes the Queen is keeping her away from Wessex, Ursula is angered. She believes she loves Wessex, for his nobility and goodness, and she is invested heavily in the betrothal. Although Ursula does not want to lose her independence by marrying, she seeks to frustrate the Queen's plans and make Wessex notice her.

Who seeks to frustrate the Queen's plans?

Learning Challenges

Part I

Can linguistic structure act as an informative prior for improving our models?

- [x] Syntactic Scaffolds for Semantic Structures (EMNLP 2018)

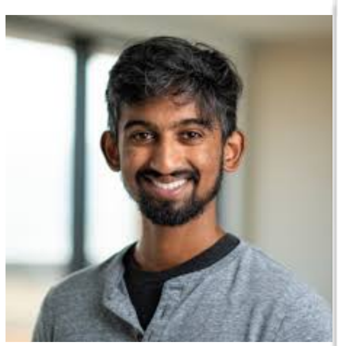
Part II

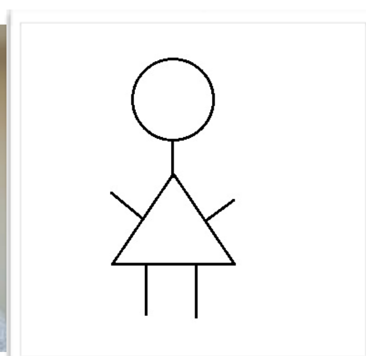
What in our data is causing models to achieve high performance?

- [ ] Annotation Artifacts in Natural Language Inference Data (NAACL 2018)

Annotation Artifacts in Natural Language Inference Data

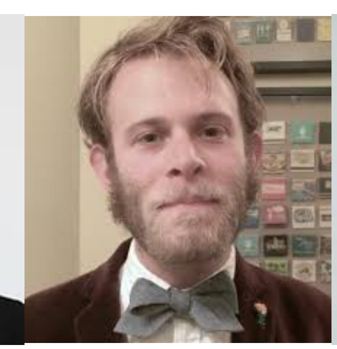
NAACL 2018


Suchin Gururangan*


S.*


Omer Levy


Roy Schwartz


Sam Bowman


Noah A. Smith

*equal contribution

Natural Language Inference (NLI)

Given a premise, is a hypothesis true, false or neither?

Premise	Two dogs are running through a field.
Hypothesis	The pets are sitting on a couch.

- True → **Entailment**
- False → **Contradiction**
- Cannot Say → **Neutral**

NLI Datasets

Stanford NLI [Bowman et. al, 2015]   570 K
Multi-genre NLI [Williams et. al., 2017] 433 K

NLI Datasets

Two dogs are running through a field.

Premise

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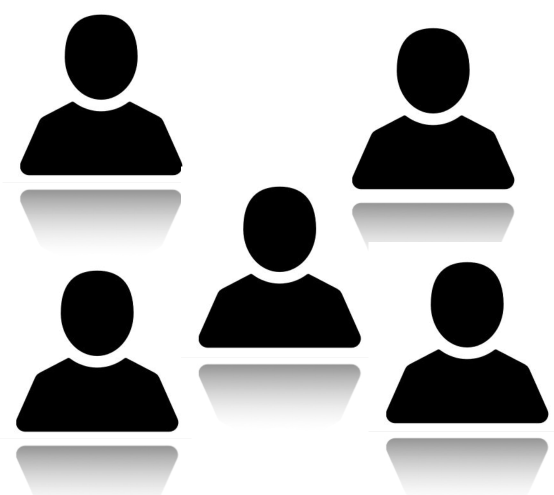

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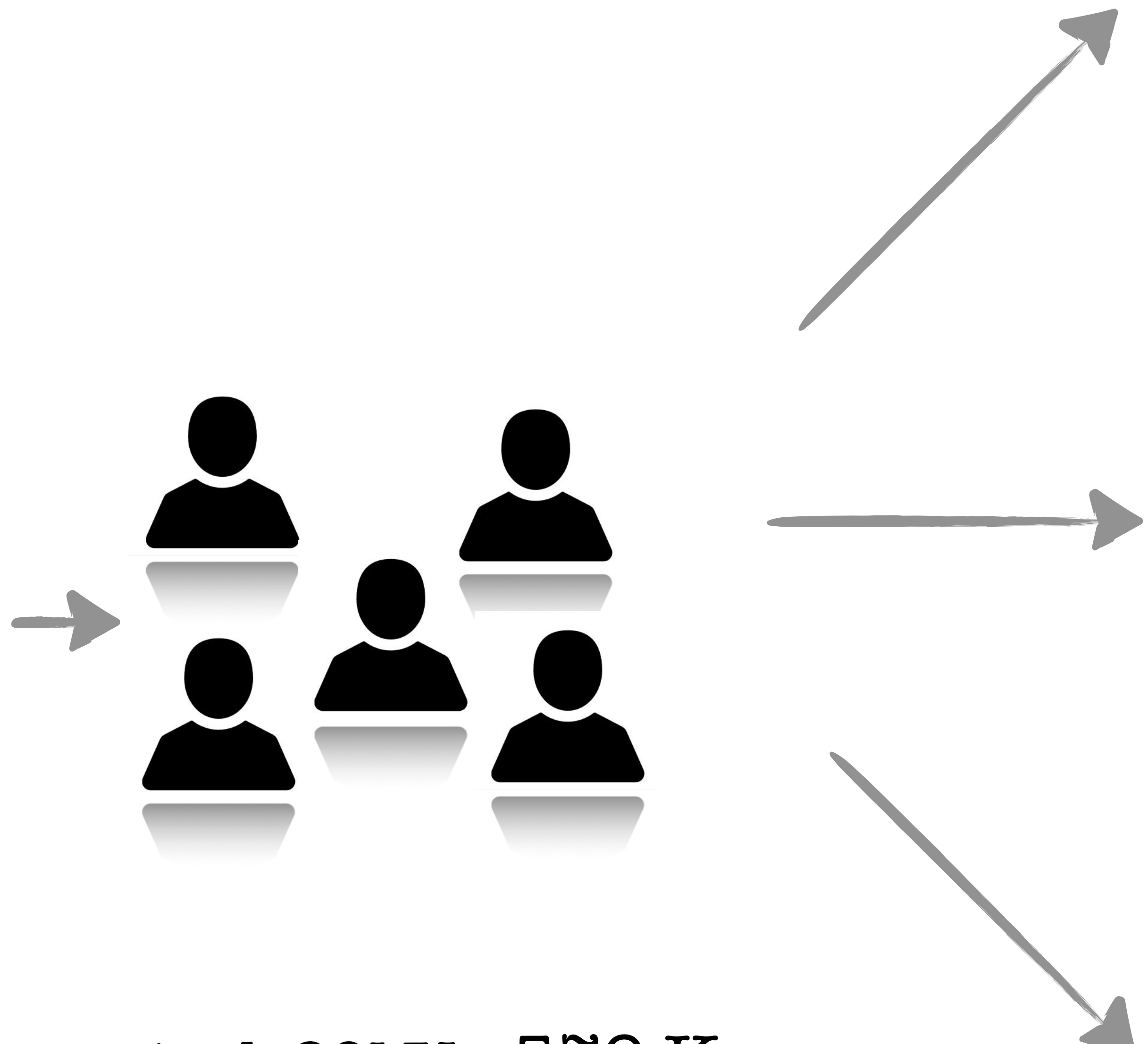

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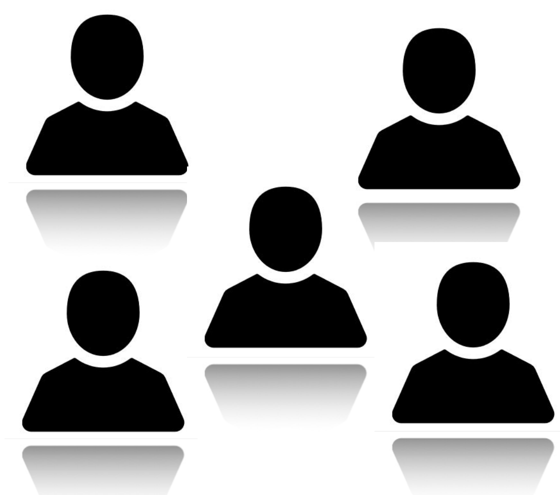
NLI Datasets

There are animals outdoors.

Entailment

Two dogs are running through a field.

Premise



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NLI Datasets

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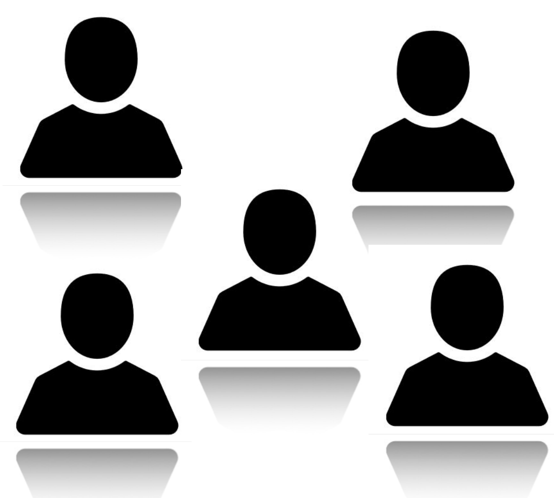
Premise



Entailment

There are animals outdoors.

Neutral

Some puppies are running to catch a stick.

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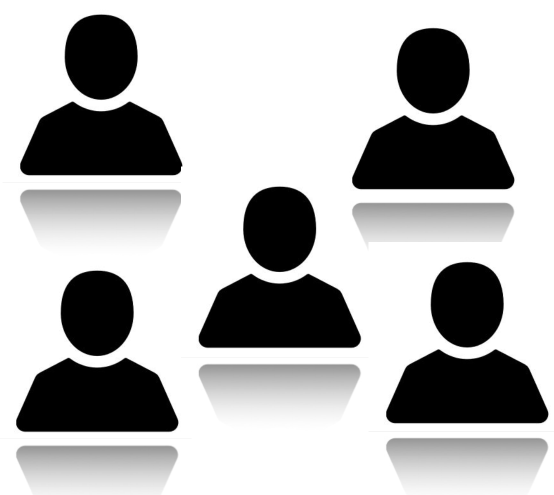
NLI Datasets

Two dogs are running through a field.

Premise



Entailment → There are animals outdoors.

Neutral → Some puppies are running to catch a stick.

Contradiction → The pets are sitting on a couch.

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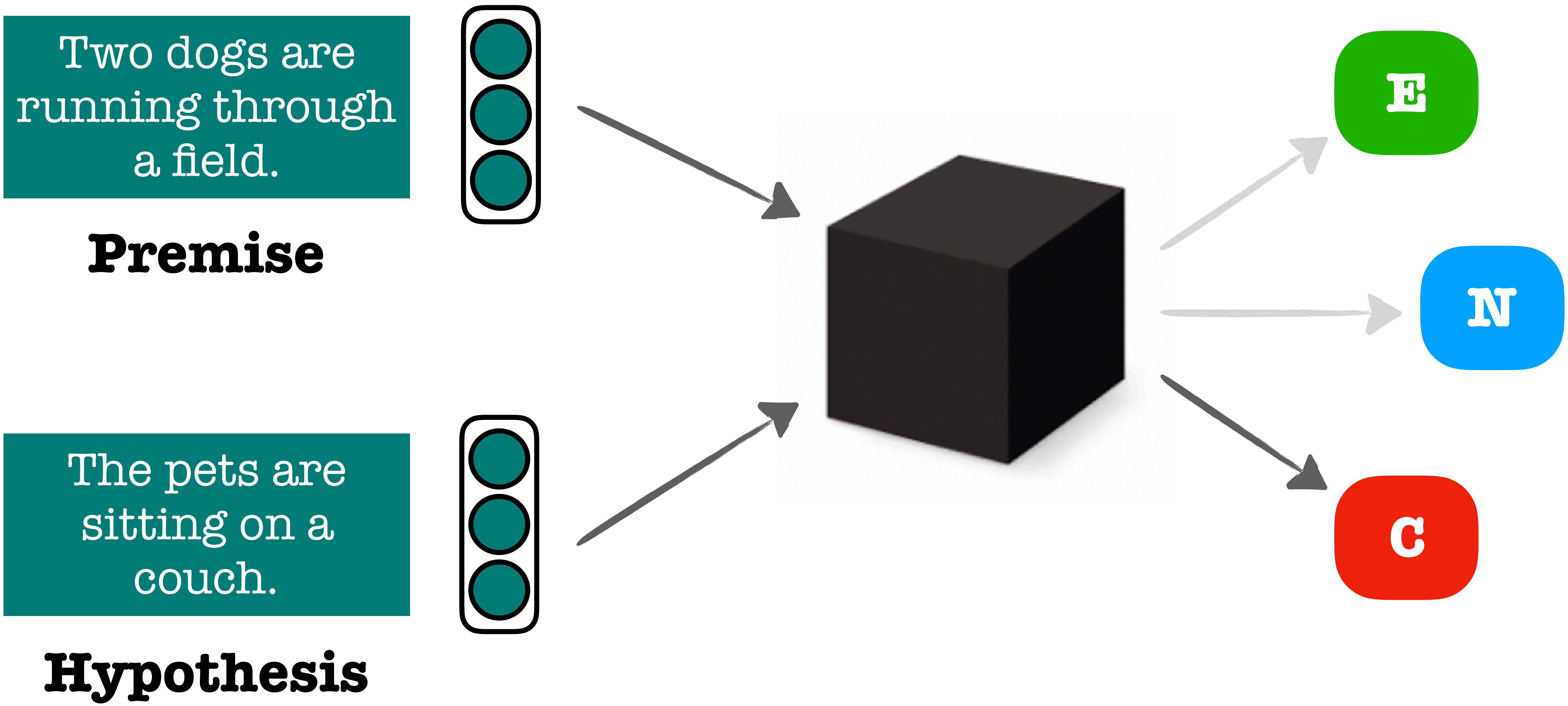
Multi-genre NLI [Williams et. al., 2017] 433 K

Lots of progress

Publication	Model	Parameters	Train (% acc)	Test (% acc)
Feature-based models				
Bowman et al. '15	Unlexicalized features		49.4	50.4
Bowman et al. '15	+ Unigram and bigram features		99.7	*78.2*
Peters et al. '18	ESIM + ELMo	8.0m	91.6	88.7
Boyuan Pan et al. '18	300D DMAN	9.2m	95.4	88.8
Zhiguo Wang et al. '17	BiMPM **Ensemble**	6.4m	93.2	88.8
Yichen Gong et al. '17	448D Densely Interactive Inference Network (DIIN, code) **Ensemble**	17m	92.3	88.9
Seonhoon Kim et al. '18	Densely-Connected Recurrent and Co-Attentive Network	6.7m	93.1	88.9
Zhuosheng Zhang et al. '18	SLRC	6.1m	89.1	89.1
Qian Chen et al. '17	KIM **Ensemble**	43m	93.6	89.1
Ghaeini et al. '18	450D DR-BiLSTM **Ensemble**	45m	94.8	89.3
Peters et al. '18	ESIM + ELMo **Ensemble**	40m	92.1	89.3
Yi Tay et al. '18	300D CAFE **Ensemble**	17.5m	92.5	89.3
Chuanqi Tan et al. '18	150D Multiway Attention Network **Ensemble**	58m	95.5	89.4
Boyuan Pan et al. '18	300D DMAN **Ensemble**	79m	96.1	89.6
Radford et al. '18	Fine-Tuned LM-Pretrained Transformer	85m	96.6	**89.9**
Seonhoon Kim et al. '18	Densely-Connected Recurrent and Co-Attentive Network **Ensemble**	53.3m	95.0	**90.1**

NLI as Text Classification



A simple experiment

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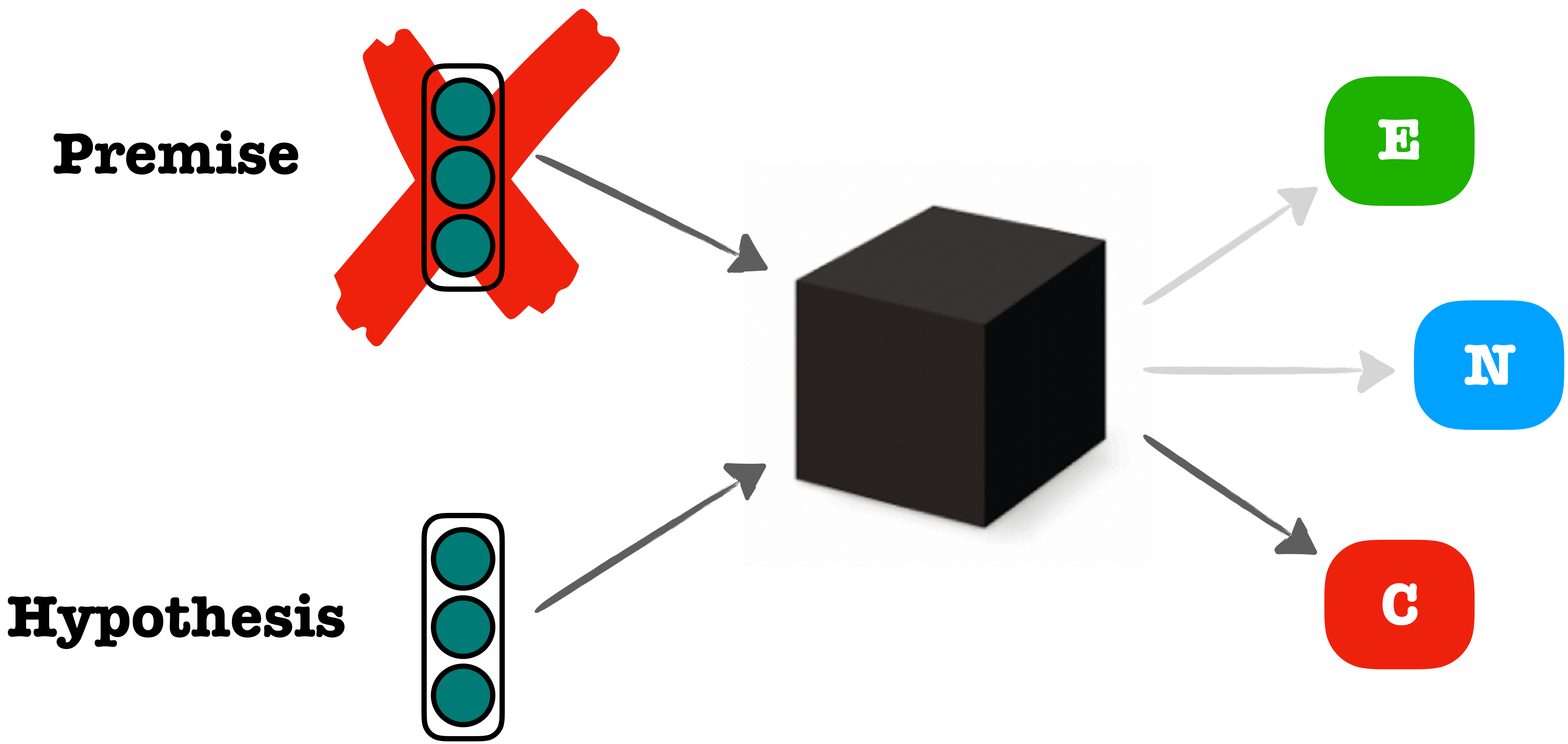
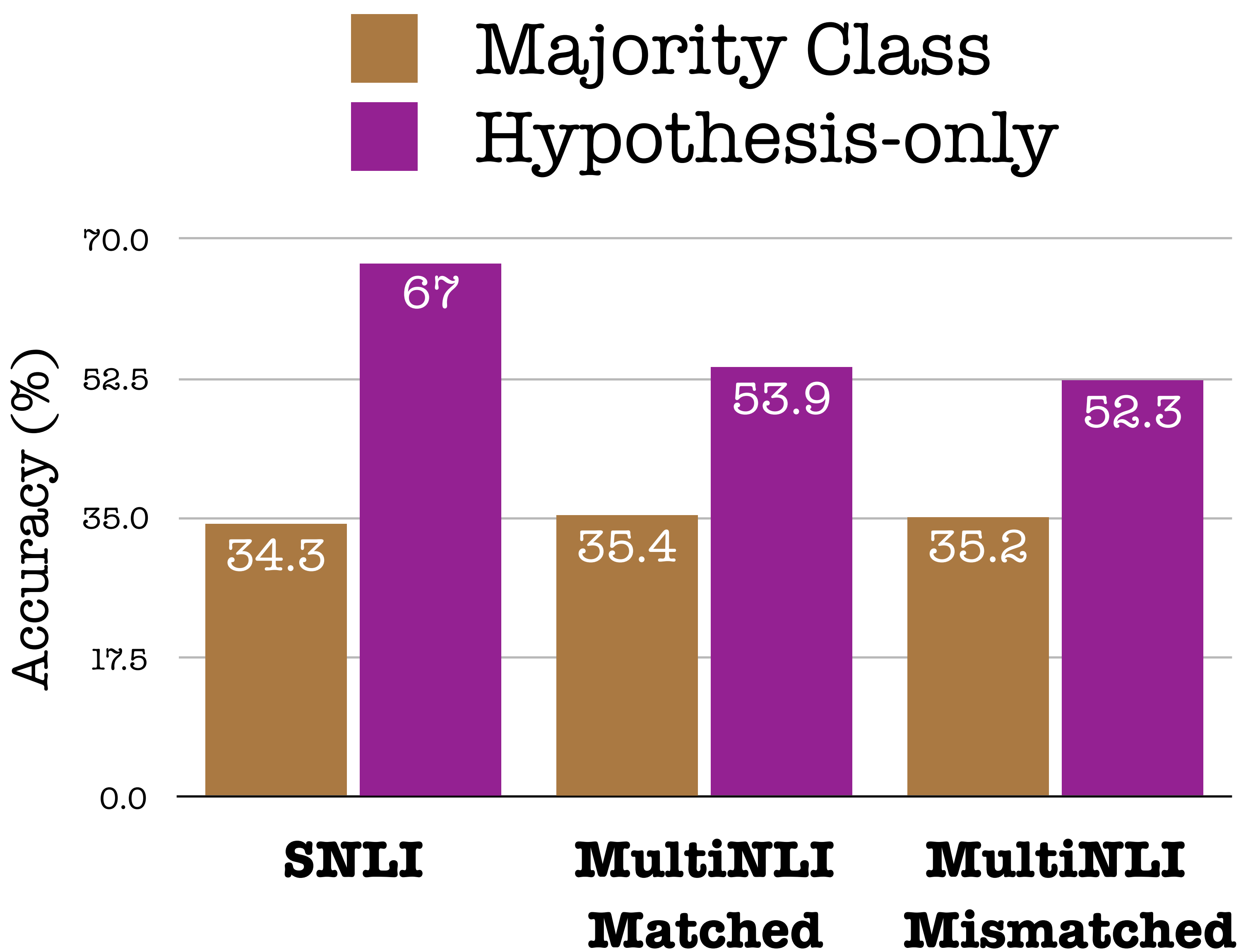


fastText [Joulin et. al. 2017]

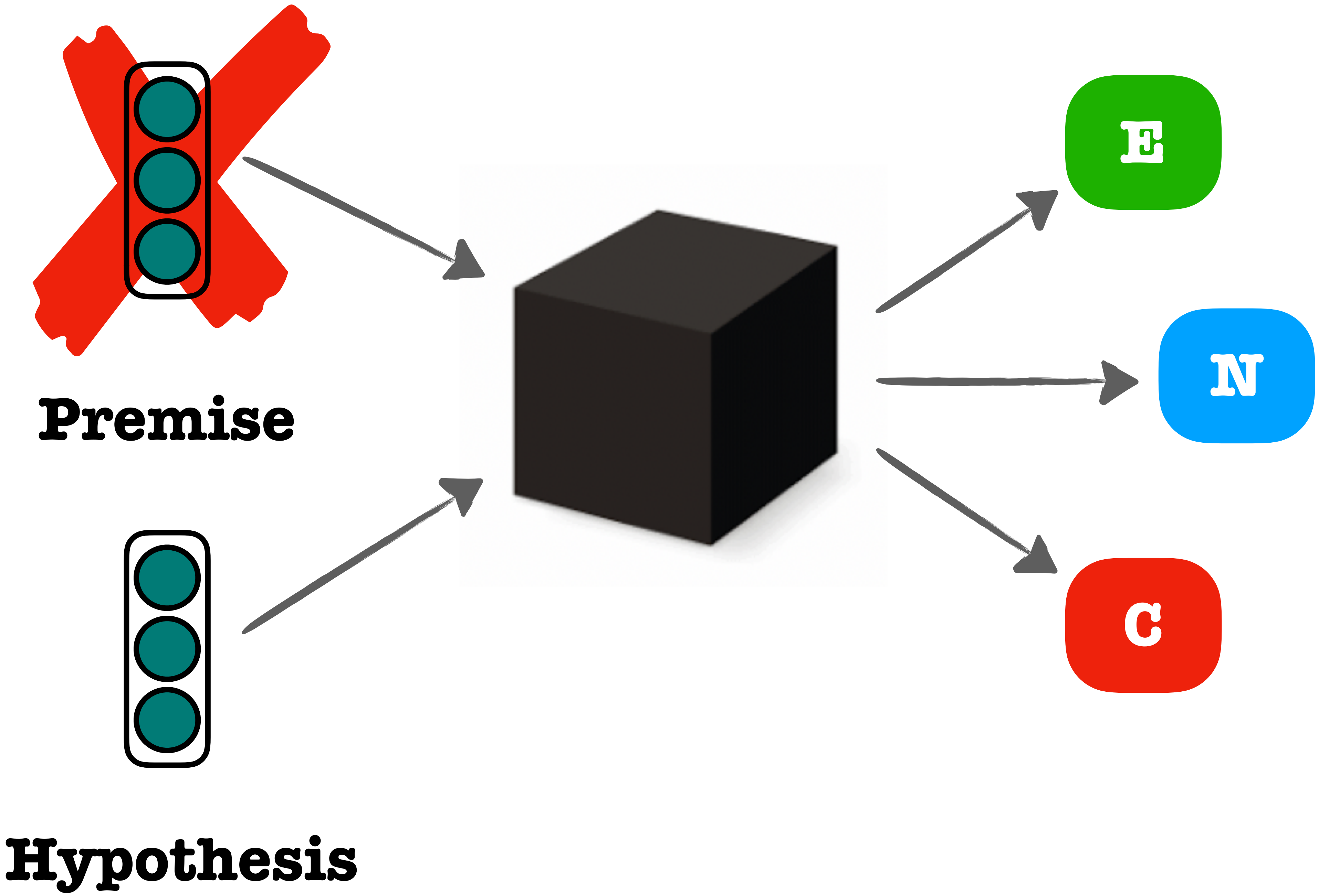
Performance of hypothesis-only



Over 50% of NLI examples can be correctly classified **without** ever observing the premise

[Poliak et. al., 2018, Glockner et. al., 2018]

Can we filter out examples with artifacts?



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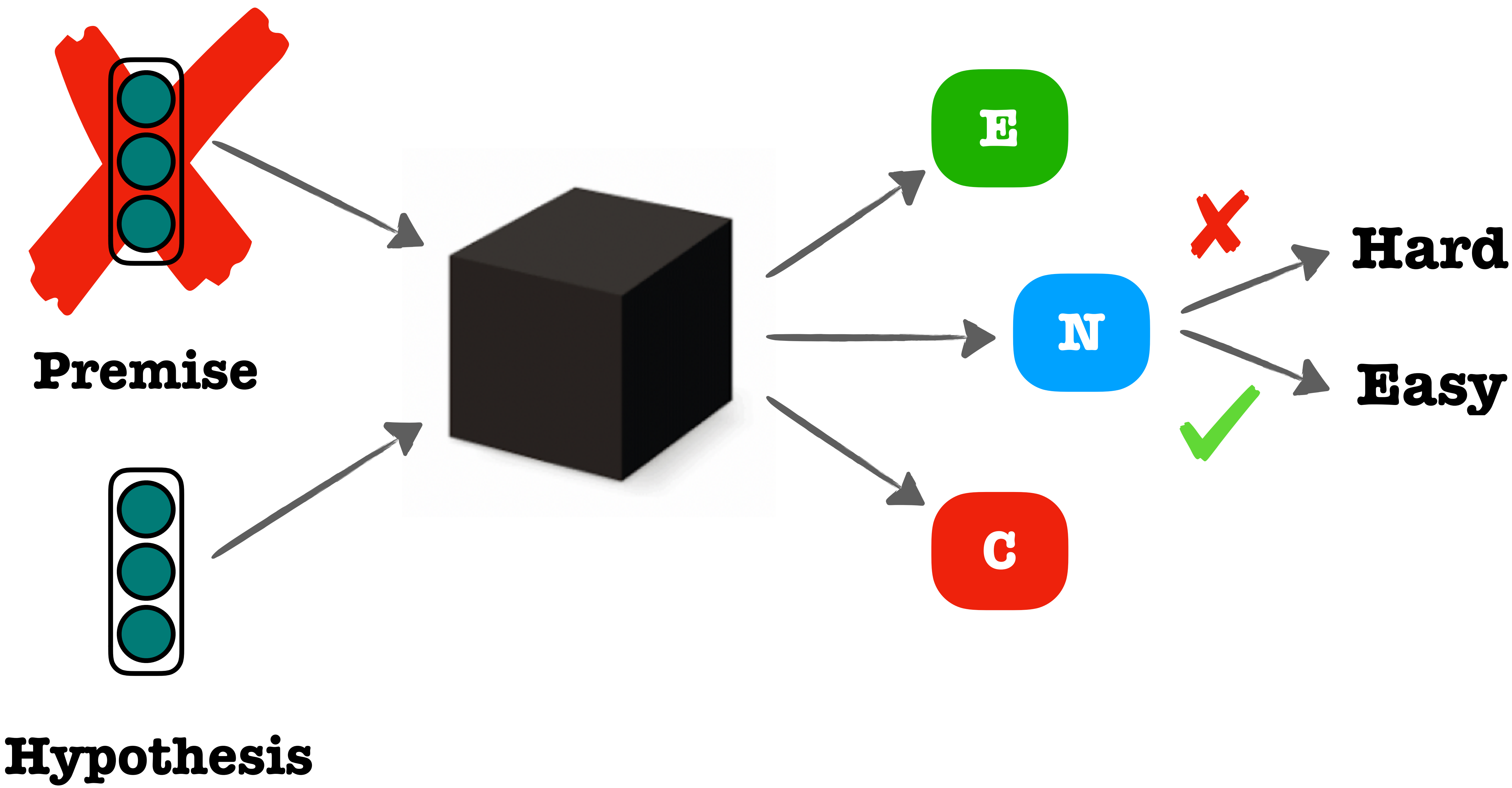
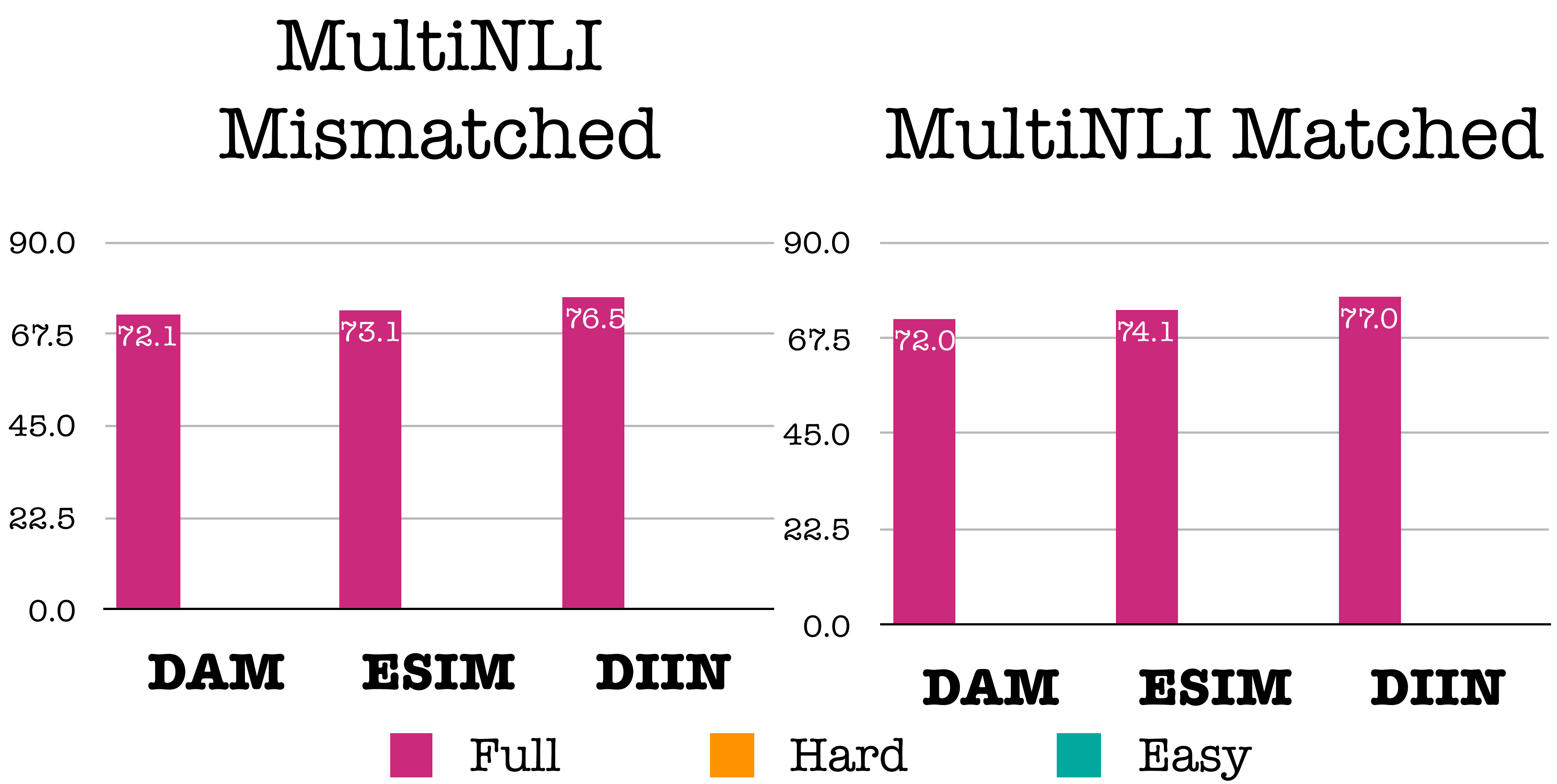


Revisiting NLI models

DAM - Decomposable Attention Model [Parikh et. al. 2016]
ESIM - Enhanced Sequential Inference Model [Chen et. al., 2017]
DIIN - Densely Interactive Inference Network [Gong et. al. 2018]

Revisiting NLI models



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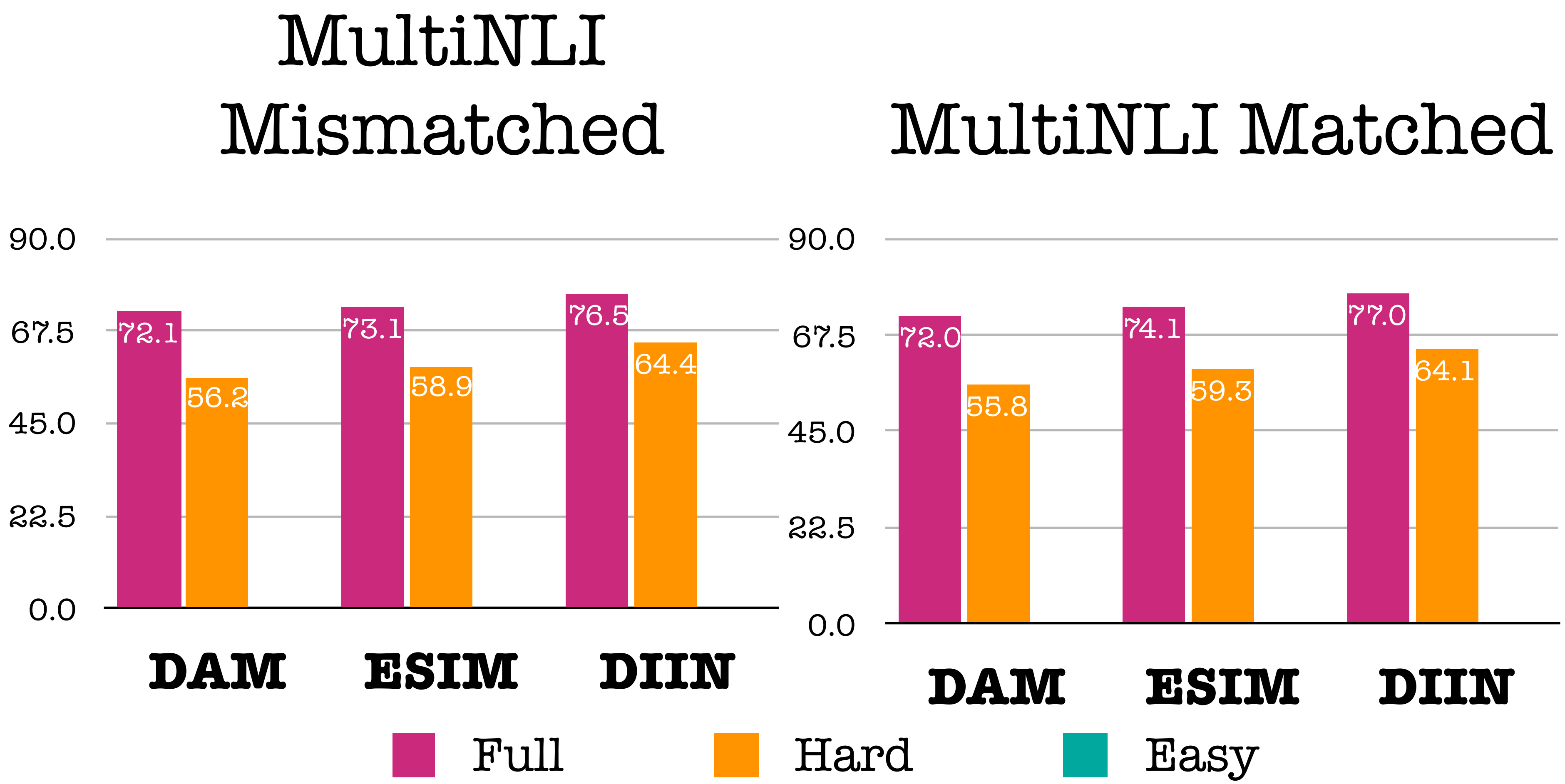
Revisiting NLI models



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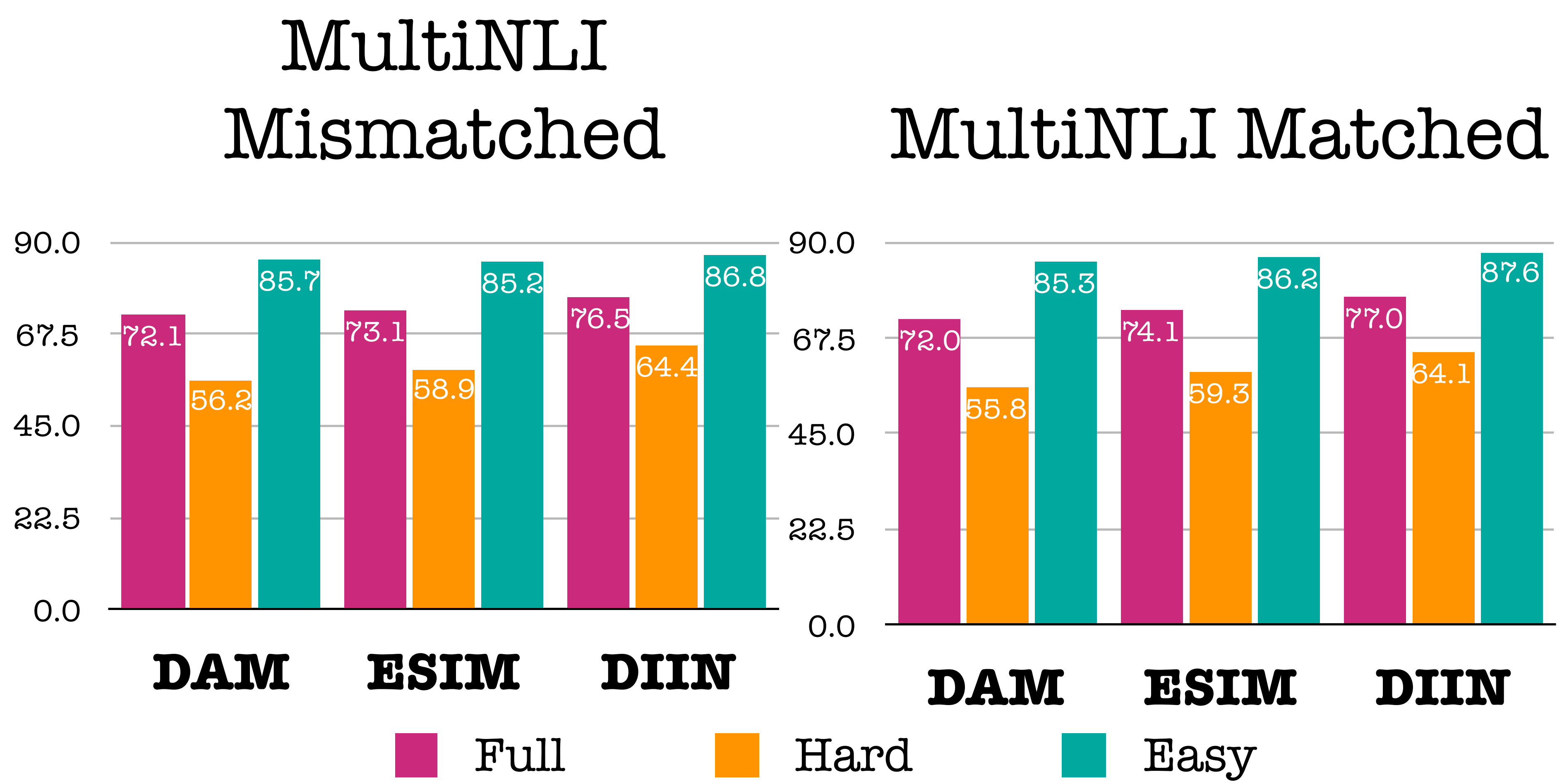

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People play frisbee **outdoors**.

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Three dogs racing on racetrack.

Premise

Cats!

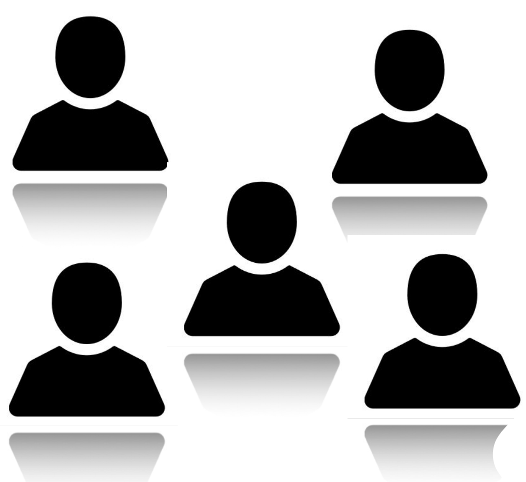
Three **cats** race on a track.

Contradiction Hypothesis

Annotation Artifacts

Two dogs are running through a field.

Premise



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There are **animals** outdoors.

Neutral

Some puppies are running **to catch a stick**.

Contradiction

The pets are sitting on a couch.

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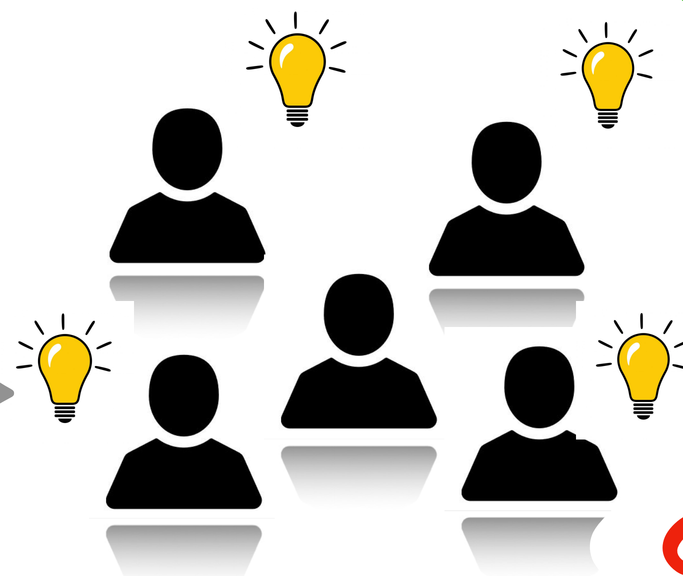

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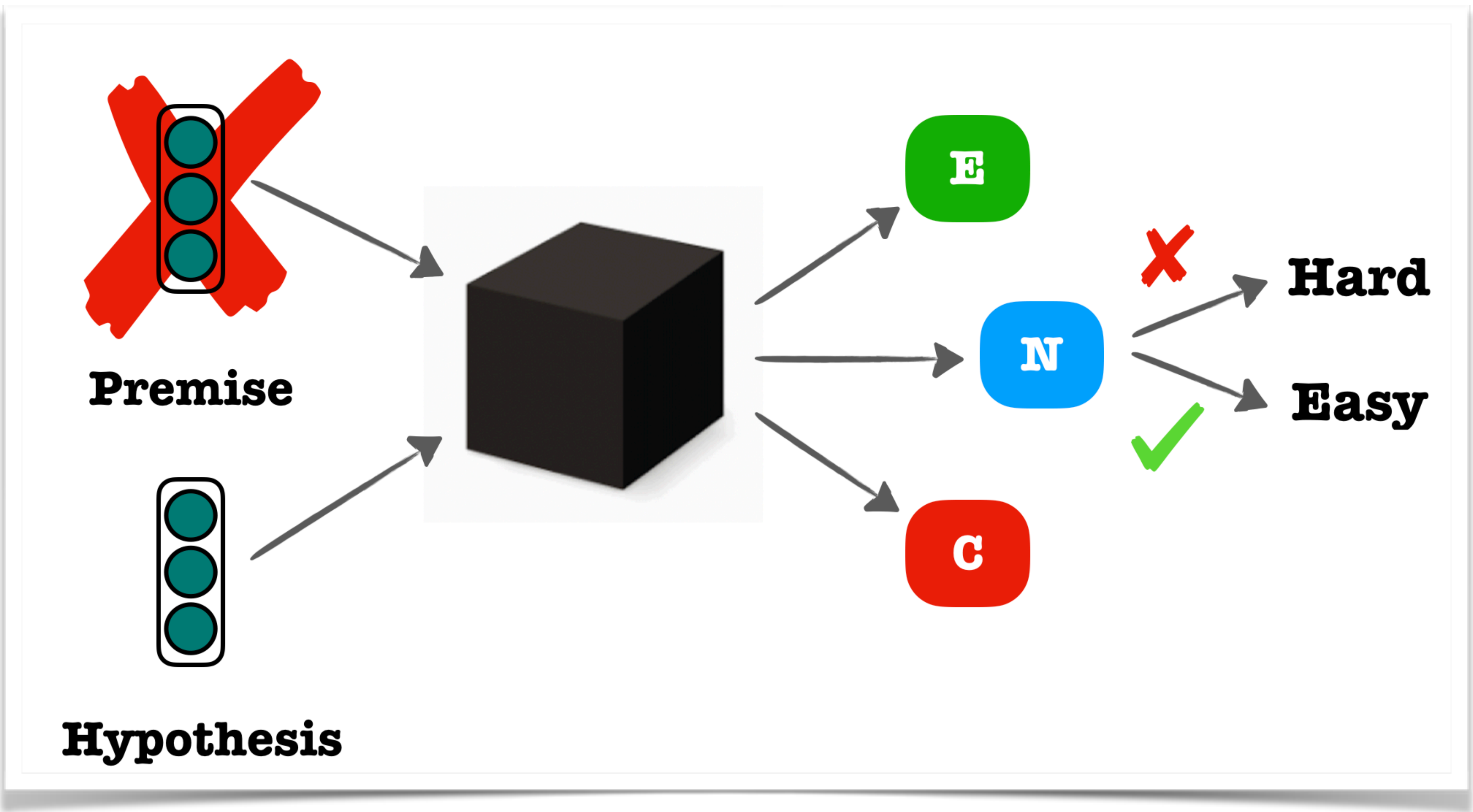

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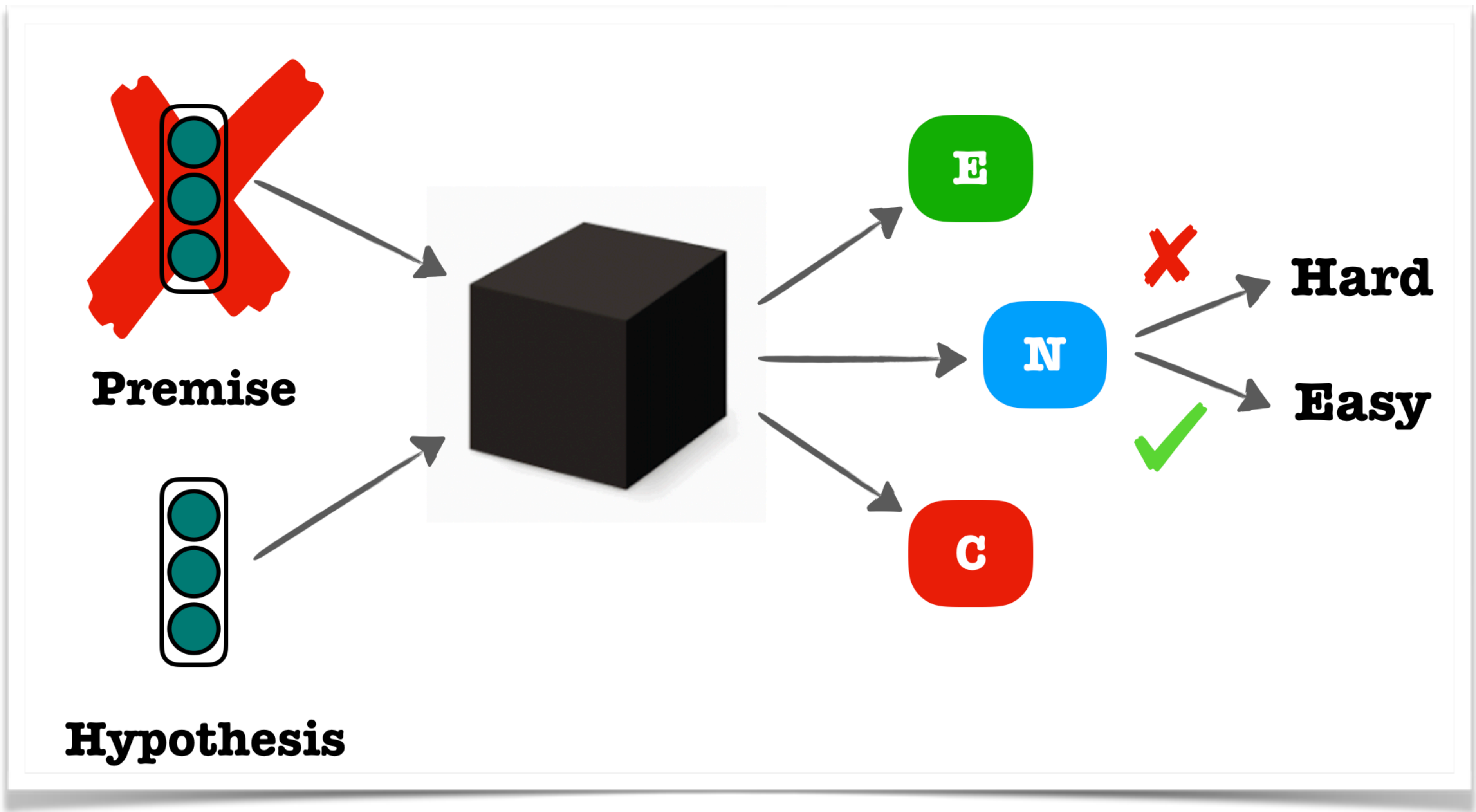

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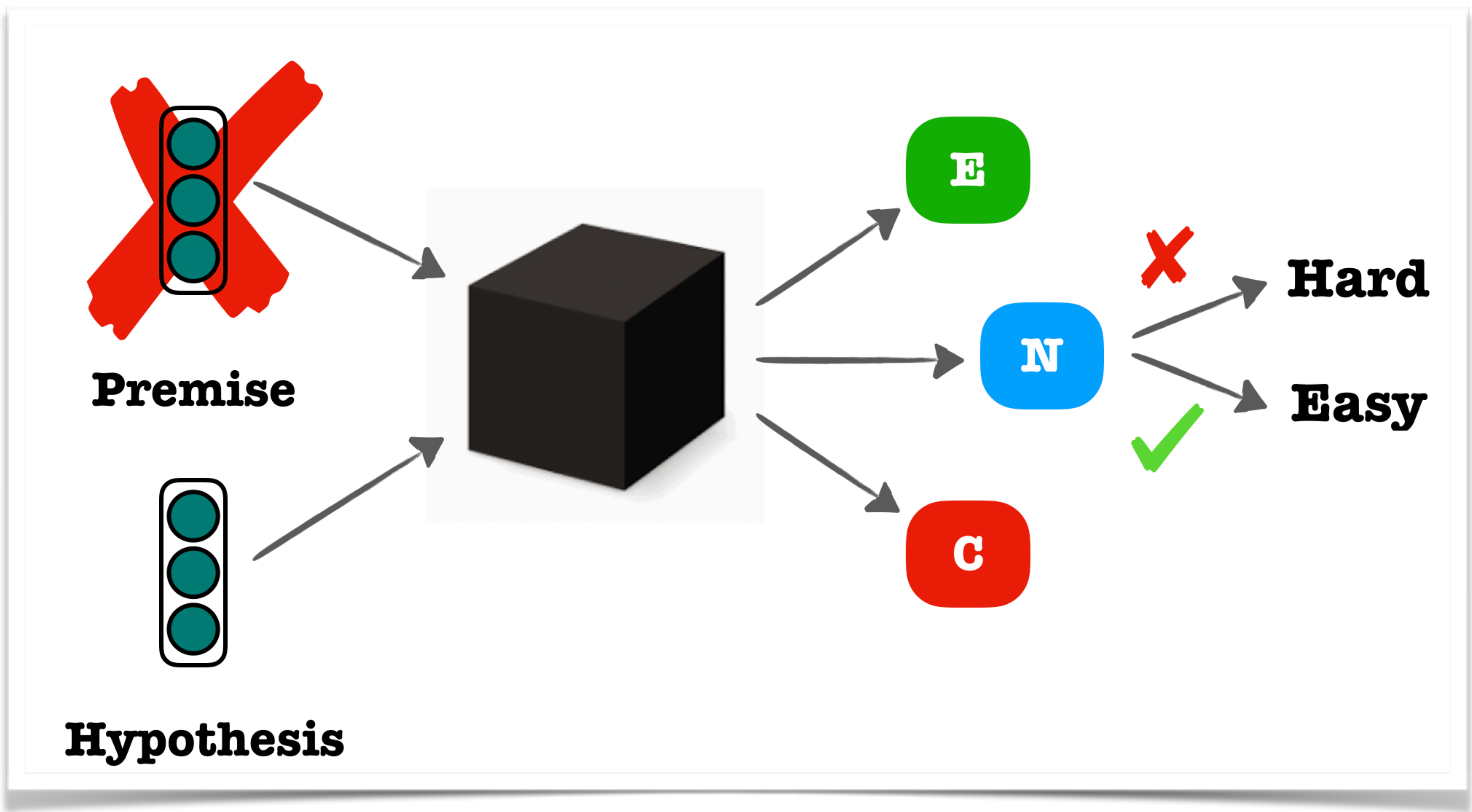

- Hard examples exhibit their own artifacts!
- Artifacts are still valid examples…

Looking ahead: Learning from Datasets with Artifacts

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- Intuition: Models which exploit artifacts == models which can detect artifacts

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Easy  **Hard**

Looking Ahead: Improved Data Collection

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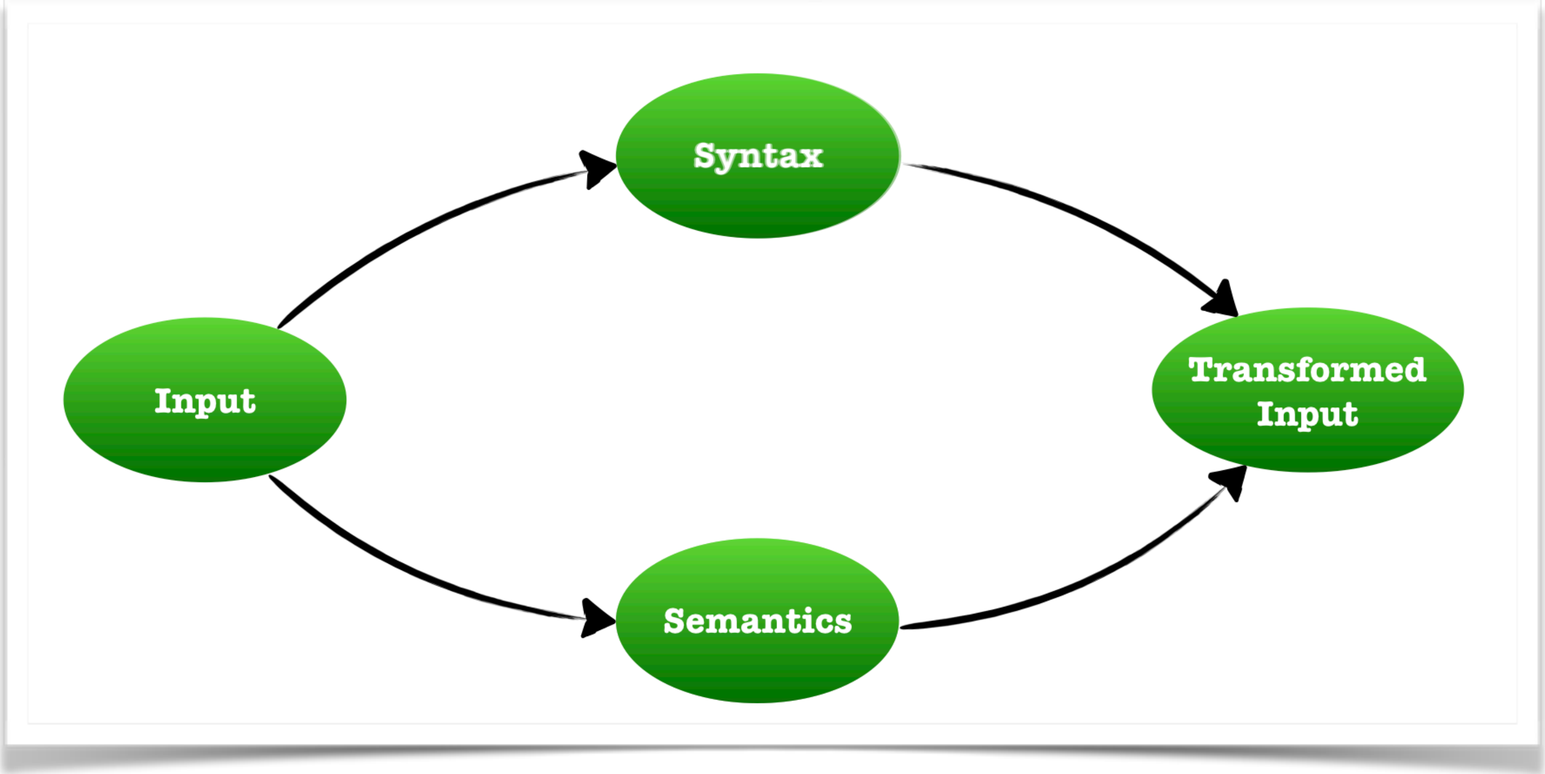

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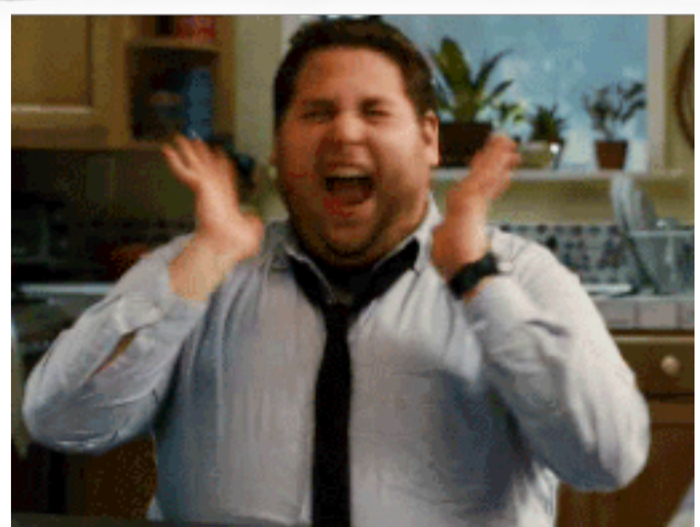
The New York Times

Finally, a Machine That Can Finish Your Sentence

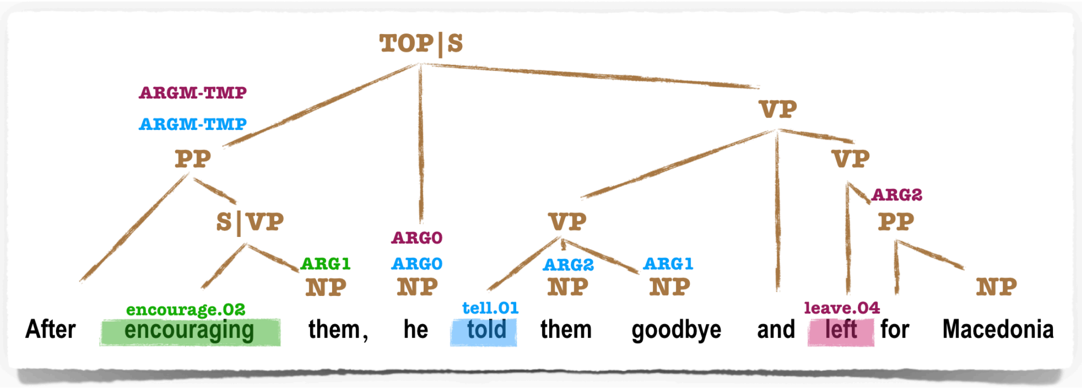
Completing someone else's thought is not an easy trick for A.I. But new systems are starting to crack the code of natural language.



In conclusion - Learning Challenges

Part I

Can linguistic structure act as an informative prior to improve our models?



Predicted structure can help representation learning.

Part II

What in our data is causing models to achieve high performance?

Need models robust to artifacts.

Thanks!

http://www.cs.cmu.edu/~sswayamd

swabhs

swabhz