

# Automatic frame-semantic role labeling

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# Outline

**1. Task of frame-SRL**

2. Primary Subtasks

a. Target Identification

b. Frame Identification

c. Frame-Element Identification

3. Advanced Modeling

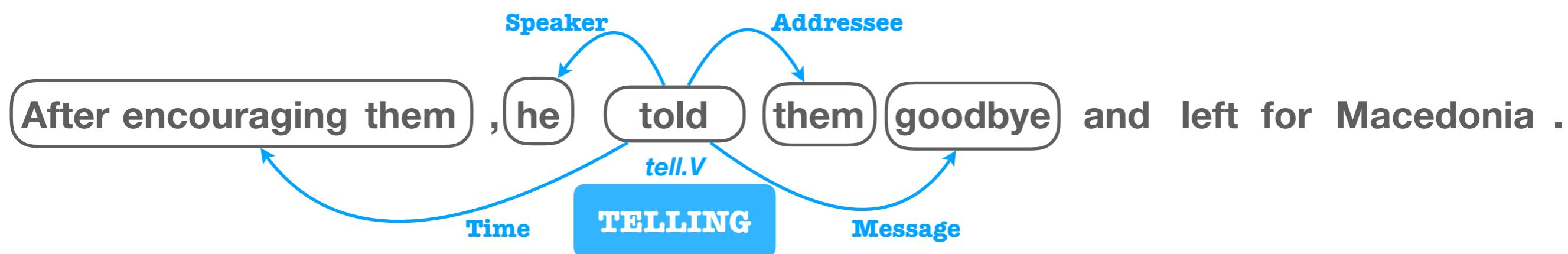
4. Looking forward: Multilingual Extensions

# Frame-Semantic Role Labeling (frame-SRL)

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

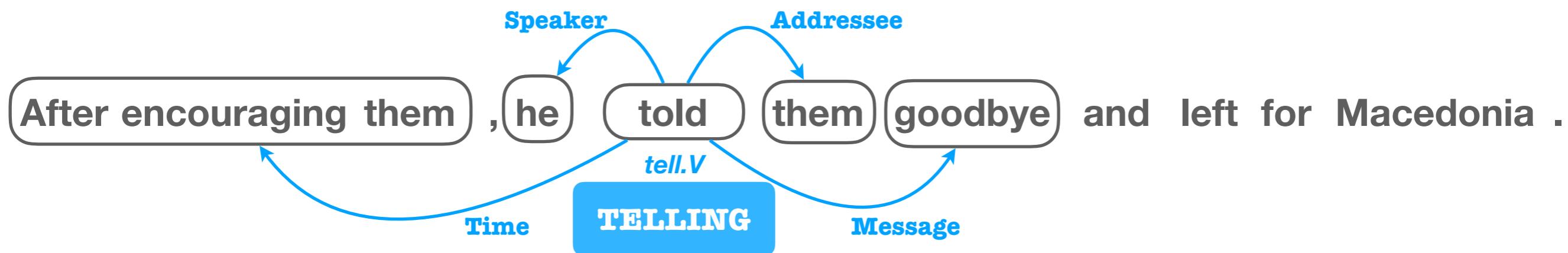
# Frame-Semantic Role Labeling (frame-SRL)

**Sentence → Graph**



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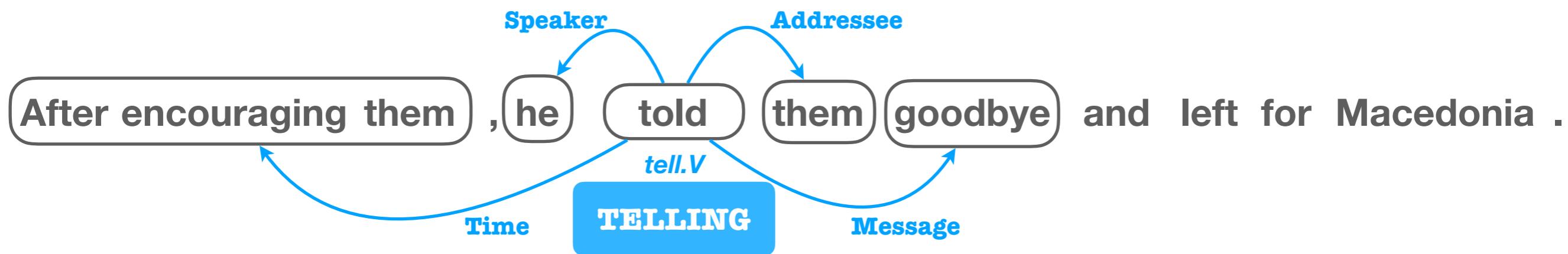
**Sentence → Graph**



- **Nodes:** tokens / spans in the sentence. Could represent both targets and arguments.

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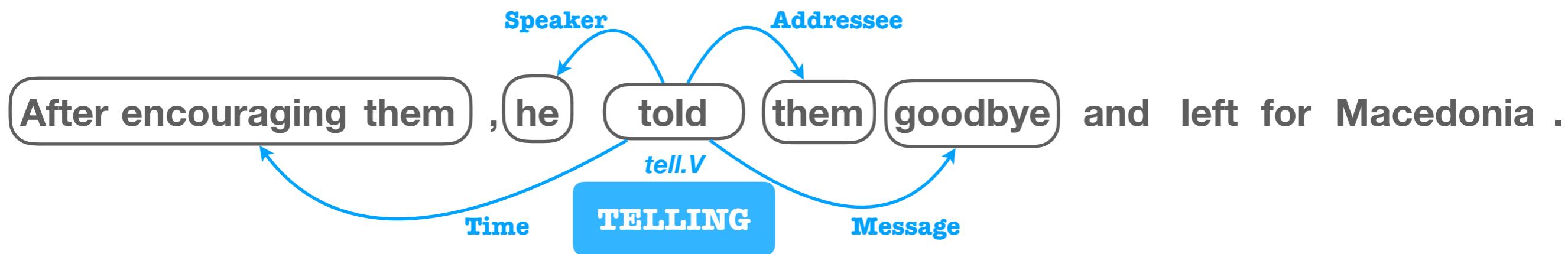
**Sentence → Graph**



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- **Node Labels:** lexical units (LUs) and frames.

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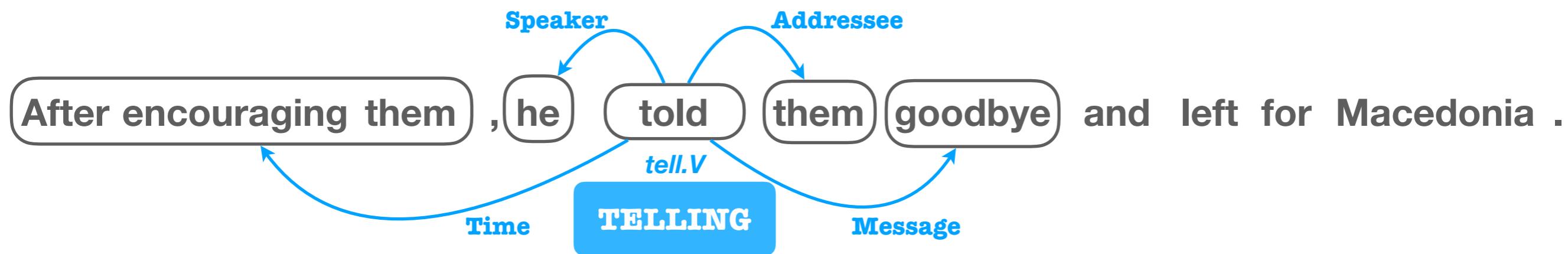
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- **Edges:** Between target nodes and argument nodes

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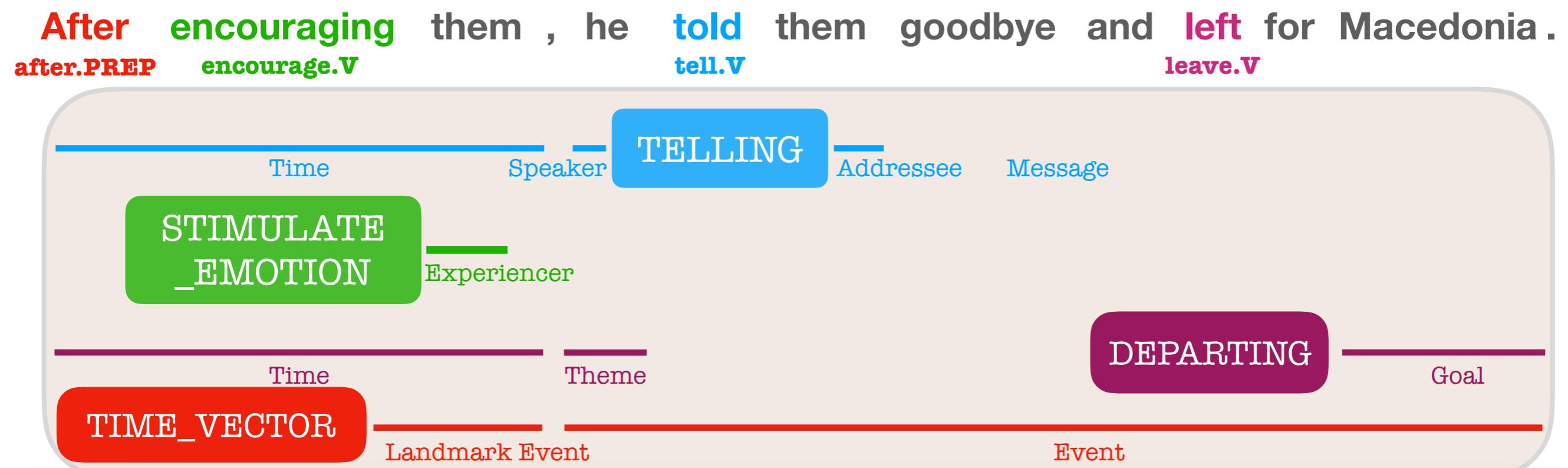
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- **Node Labels:** lexical units (LUs) and frames.
- **Edges:** Between target nodes and argument nodes
- **Edge Labels:** roles of arguments / frame-elements

# Frame-Semantic Graphs: Overlapping Nodes

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



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# Frame-SRL: Subtasks

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STIMULATE  
\_EMOTION

TIME\_VECTOR

## 2. Frame Identification

TELLING

DEPARTING

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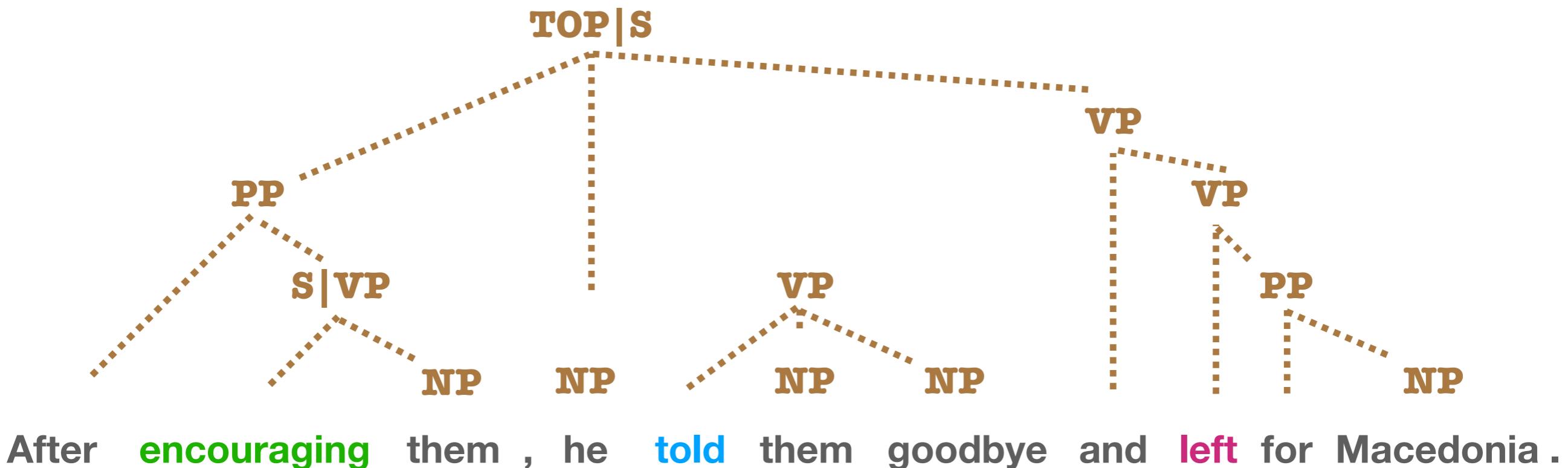
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## 3. Frame-Elements Identification



# A close relative: PropBank SRL

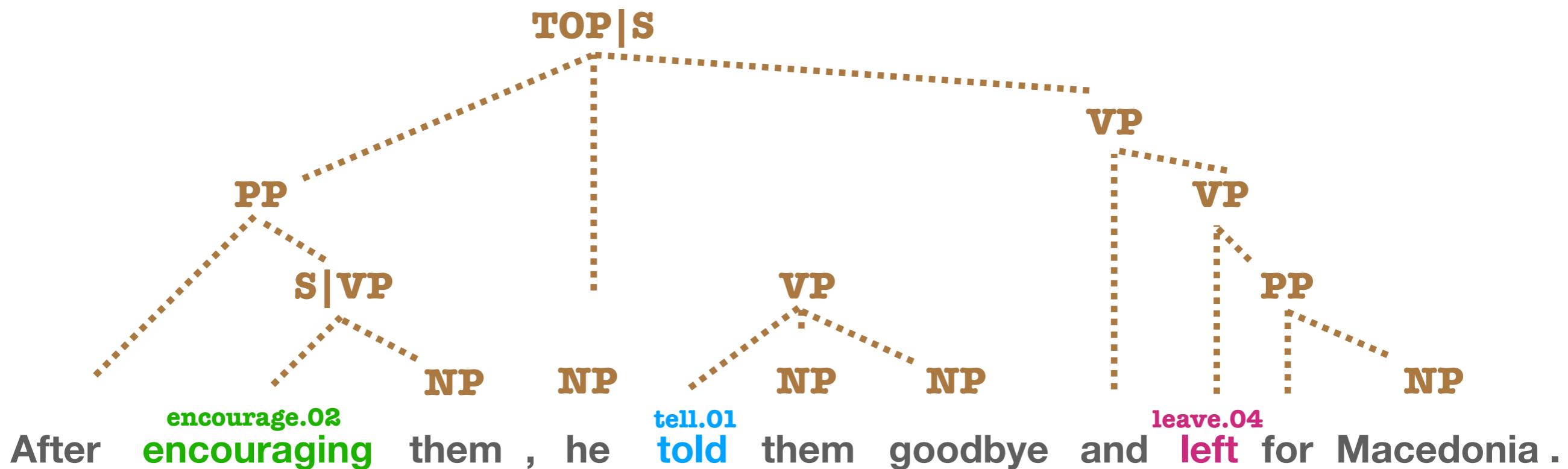
## 1. Target Predicate Identification



# A close relative: PropBank SRL

**1. Target  
Predicate  
Identification**

**2. Frame  
Sense  
Identification**

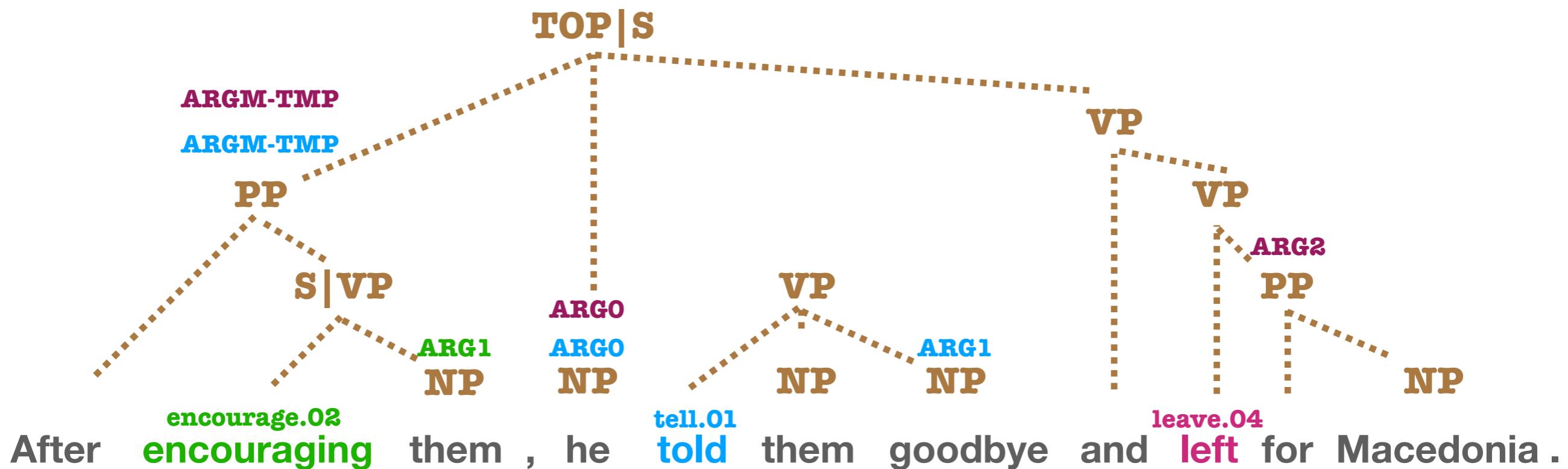


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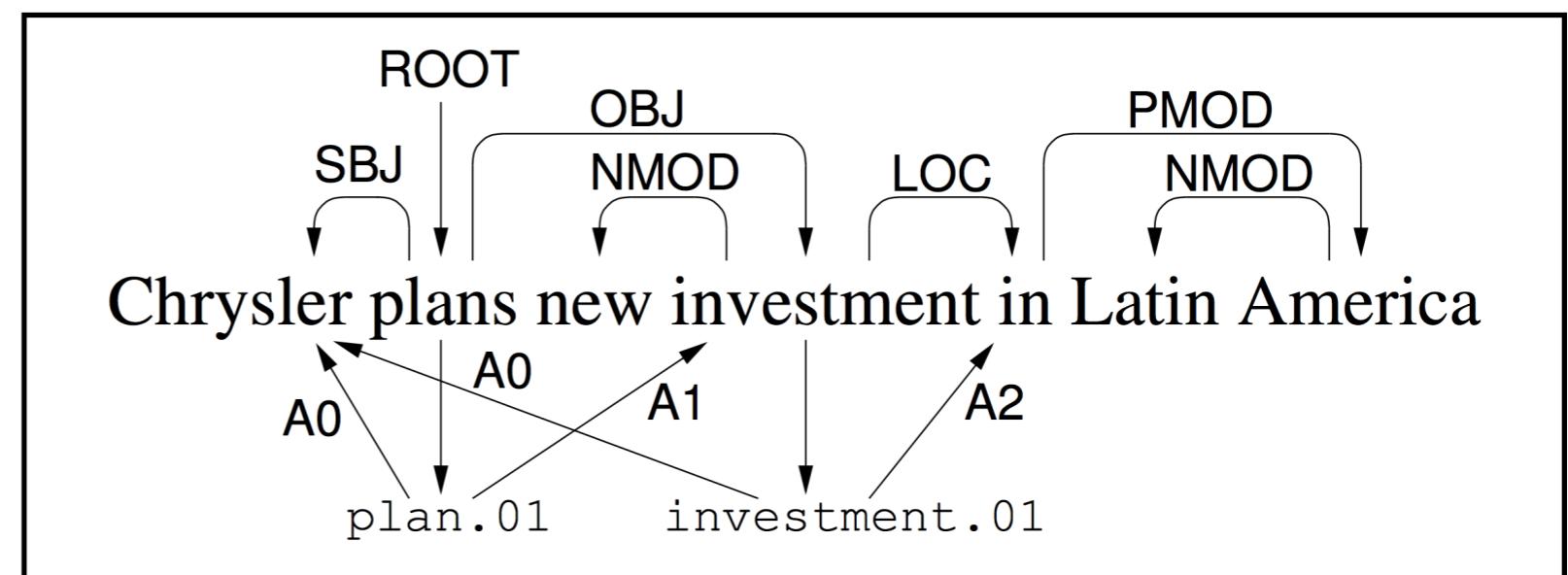
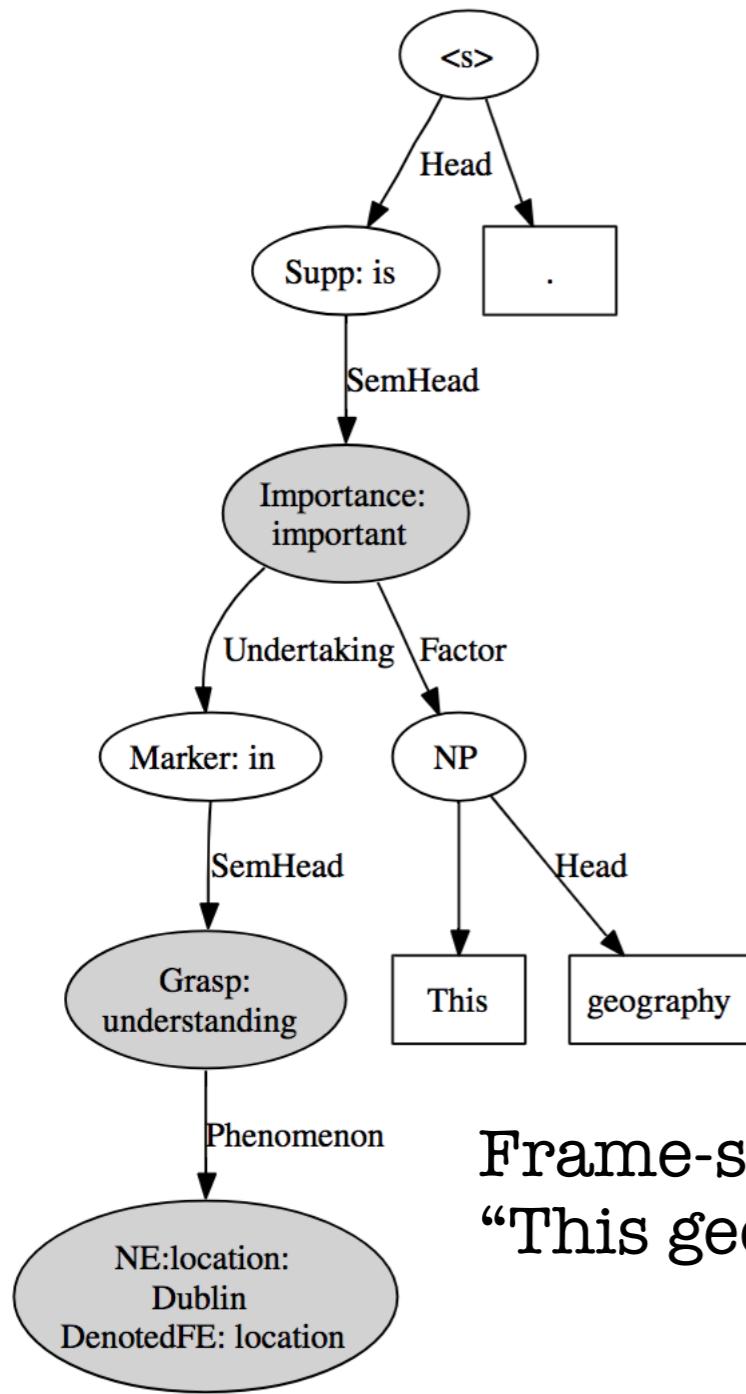
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Identification**



# Dependency Graphs



PropBank-style dependency graph for sentence, along with syntactic dependencies.

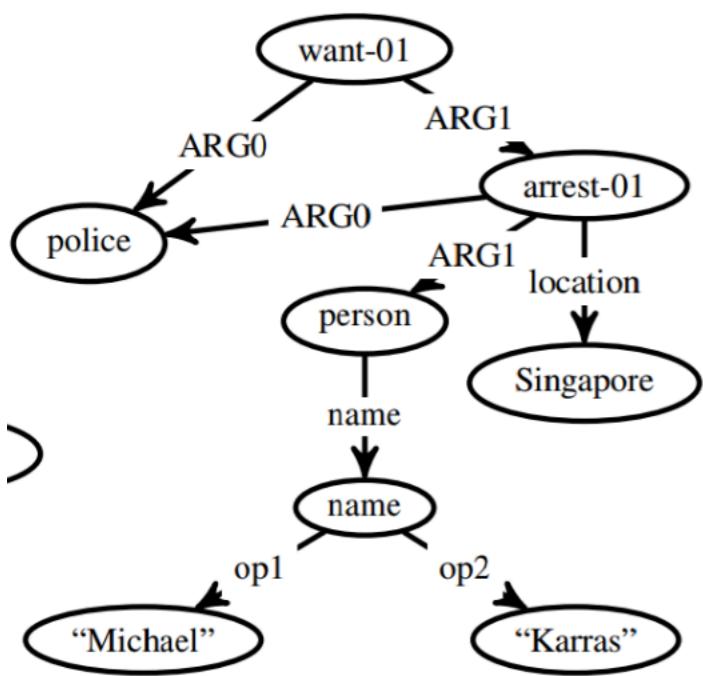
Johannsson & Nugues (ACL, 2008)

Frame-semantic dependency graph for sentence "This geography is important for understanding Dublin.".

Baker et. al. (SemEval, 2007)

# Related tasks

## Abstract Meaning Representation



Banarescu et. al. (2013)

## QA -SRL

A much larger super eruption in Colorado **produced** over 5,000 cubic kilometers of material.

Produced	What produced something?	A much larger super eruption
	Where did something produce something?	in Colorado
	What did something produce?	over 5,000 cubic kilometers of material

He et. al. (2015)  
Fitzgerald et. al. (2018)

## Semantic proto-roles

Sentences	Property	(A)	(B)	(C)
(A) <b>She</b> was untrained and, in one botched job <i>killed</i> a client.	instigated	5	5	5
(B) <b>The antibody</b> then <i>kills</i> the cell.	volitional	2	1	5
(C) <b>An assassin in Colombia</b> <i>killed</i> a federal judge on a Medellin street. PropBank KILL.01, ARG <sub>0</sub> -PAG: killer	awareness	3	1	5
VerbNet MURDER-42.1-1, AGENT: ACTOR in an event who initiates and carries out the event intentionally or consciously, and who exists independently of the event	sentient	5	1	5
FrameNet KILLING, KILLER/CAUSE: (The person or sentient entity) / (An inanimate entity or process) that causes the death of the VICTIM.	moved	3	3	3
	phys_existed	5	5	5
	created	1	1	1
	destroyed	1	3	1
	changed_poss	1	1	1
	changed_state	3	3	3
	stationary	3	3	3

Reisinger et. al. (2015)

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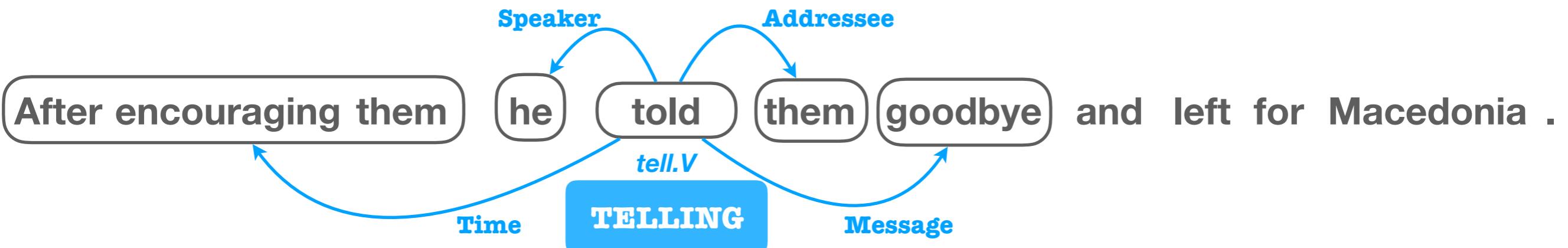
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  - Shared tasks in 2005, 2008, 2009, 2012

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  - Shared tasks in 2005, 2008, 2009, 2012
- SemEval 2007 Shared Task 19 (Baker, Ellsworth & Erk, 2007) sparked interest in automatic frame-SRL.

# Frame-SRL data for supervised training



- Full-text annotations
  - 28 K targets
  - Train (70%) / Dev (10%) / Test (20%)
- Mapping between LUs and frames
  - 13 K LUs : 1.2 K frames
- Mapping between frames and frame-elements:
  - 1.2 K frames : 10 K frame-elements
- Exemplars
  - 192 K

FrameNet 1.7

# Model architectures

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- Most common approach: **Supervised learning**

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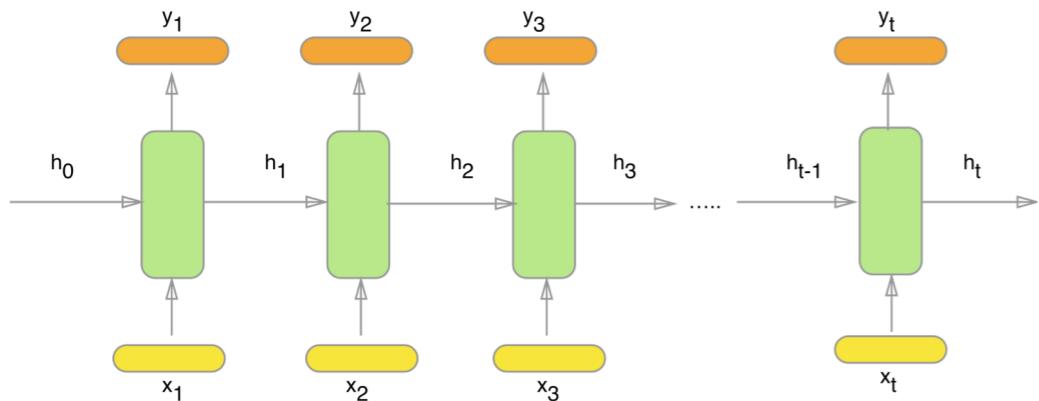
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  - May use distributional representations

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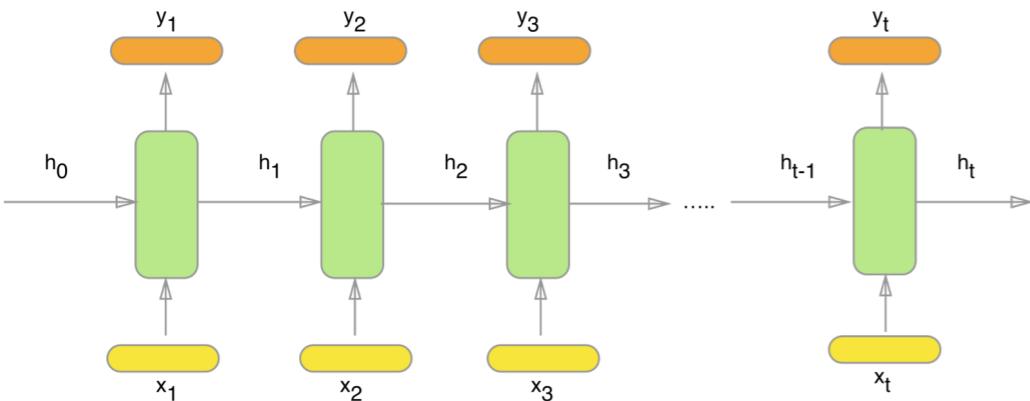
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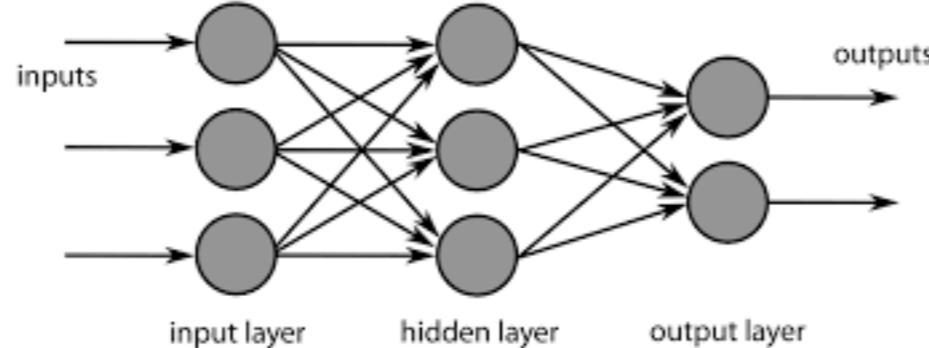
**Recurrent Neural Nets**

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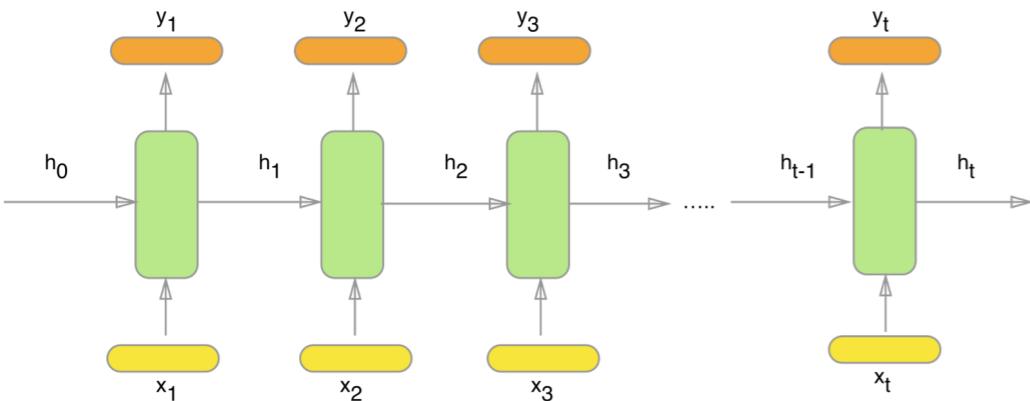
**Recurrent Neural Net**



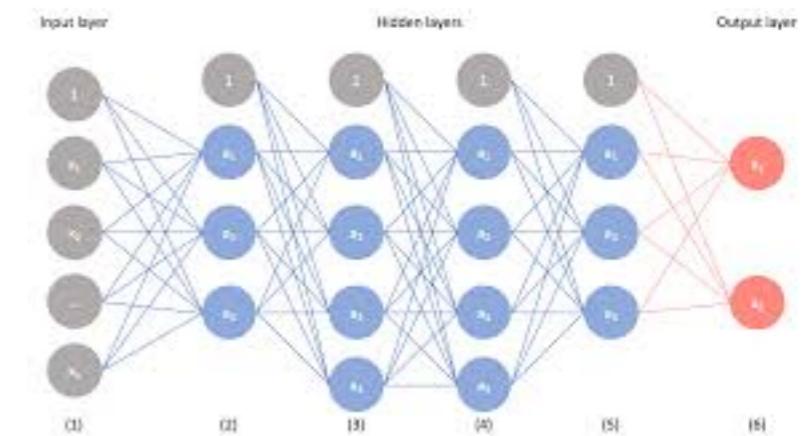
**Feed-forward Nets**

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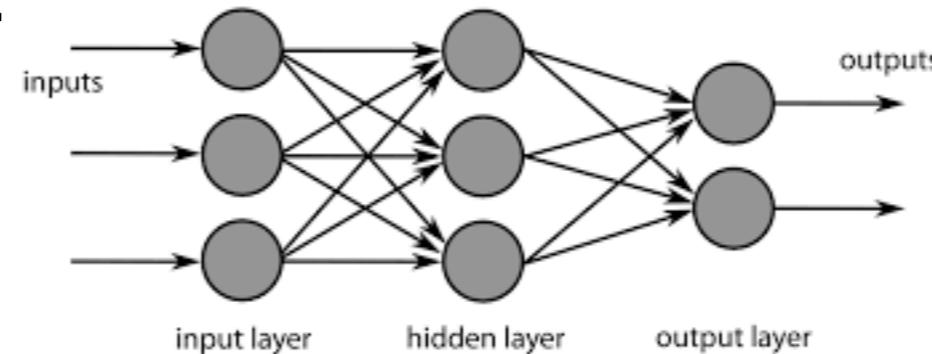
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**Recurrent Neural Net**



**Convolutional Neural Nets**

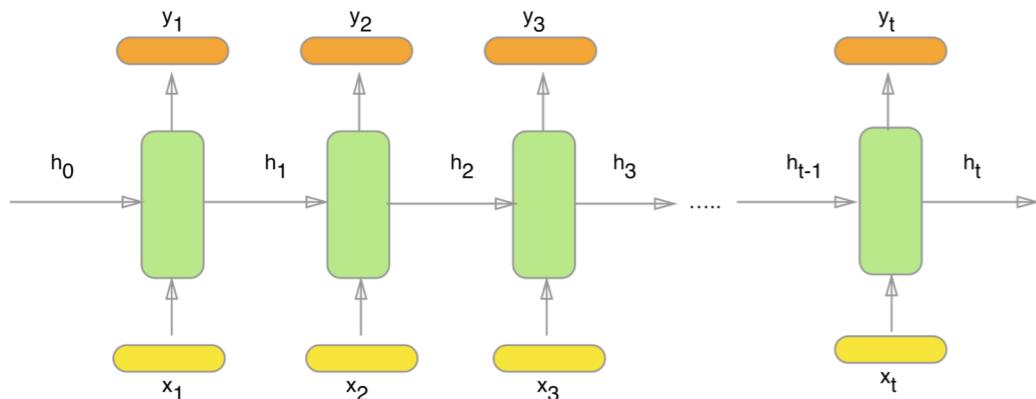


**Feed-forward Nets**

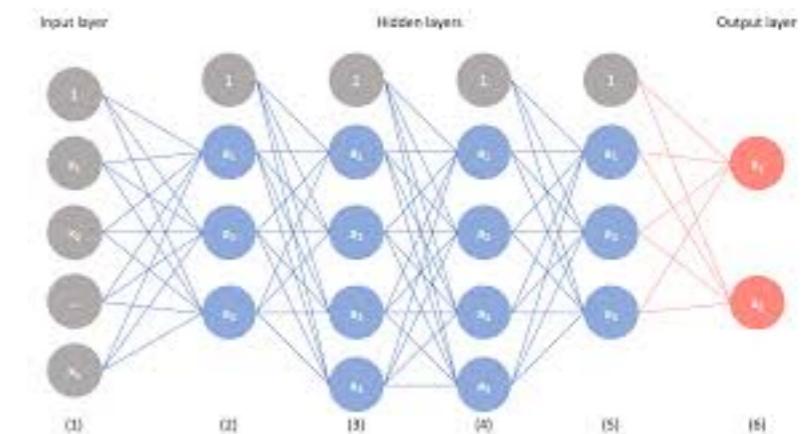
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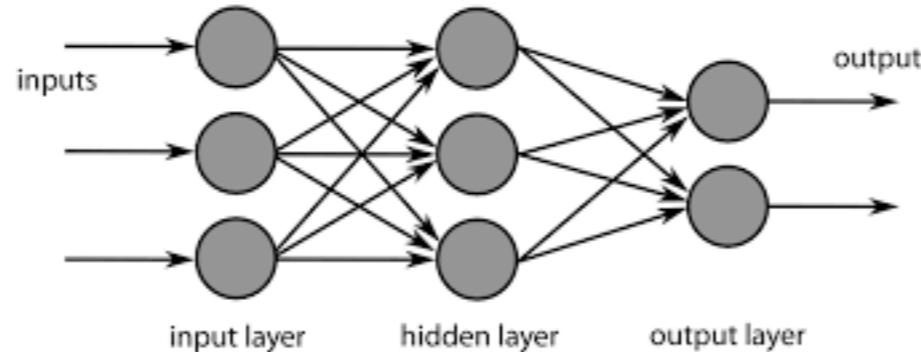
**FrameNet / PropBank  
/ Span-based graphs /  
Dependency Graphs**



**Recurrent Neural Net**



**Convolutional Neural Nets**



**Feed-forward Nets**

# Why automatic frame-SRL?

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- Information extraction (Surdeanu, et al., 2003)
- Textual entailment (Tatu & Moldovan, 2005; Burchardt & Frank, 2006)
- Text categorization (Moschitti, 2008)
- Question answering (Narayanan & Harabagiu, 2004; Frank, et. al., 2007; Moschitti, et. al., 2007; Shen & Lapata, 2007)
- Machine Translation (Wu & Fung, 2009, Marcheggiani et. al., 2017) and its evaluation (Giménez & Márquez, 2007)
- Text-to-scene generation (Coyne et. al., 2012)
- Dialog systems (Chen et. al., 2013)
- Social network extraction (Agrawal et. al., 2014)
- Knowledge Extraction from Twitter (Søgaard et. al., 2015)

# Summary of Part 1

- Frame-SRL as a graph induction task
  - ▶ Subtasks
- Related tasks:
  - ▶ Propbank SRL, QA-SRL, AMR, Semantic Prototypes
- What's in the dataset?
- Supervised Learning: Shift from linear to non-linear models

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1. Task of frame-SRL

## **2. Primary Subtasks**

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4. Looking forward: Multilingual Extensions

# Target Identification

After encouraging them , he told them goodbye and left for Macedonia .  
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- Predict “semantically salient” tokens as targets in the sentence.
- Also, identify the lexical units (LUs) = lemma + POS tag of targets
  - ▶ There might be ambiguity here! Example “**encourage.V**” vs “**encouraging.A**”
- Average in FN 1.5: 6 targets per sentence.

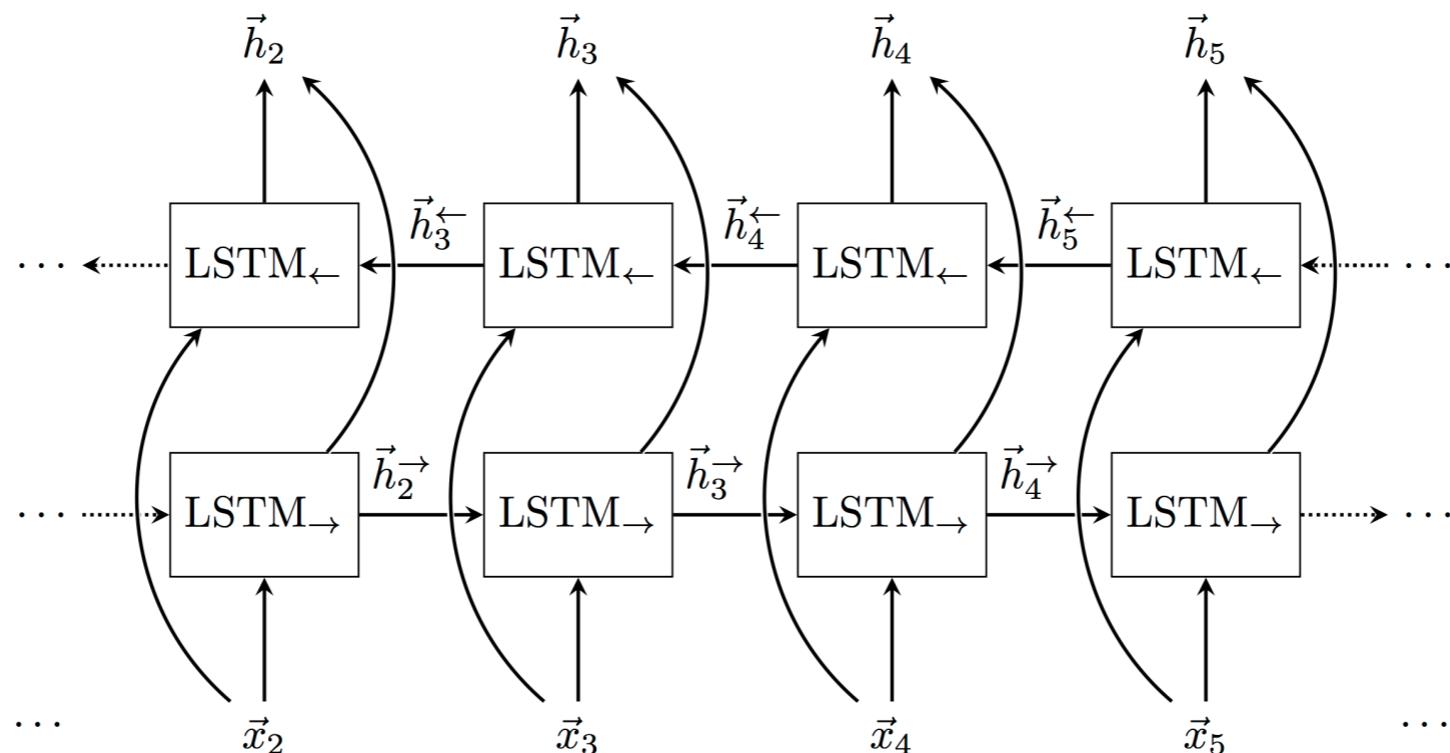
# Target ID: challenges

- Data sparsity, cannot use exemplar data.
- No simple POS tag based bijection, unlike in PropBank, where targets are almost always verbs.
- FrameNet: Verbs, nouns, adjectives and prepositions can be targets, BUT not always!
- Multi-word expressions also considered valid targets. About 4% of all targets in FN 1.5.
  - ▶ Span “**tell apart**” gets labeled with LU “**tell\_apart.V**”
- Targets can be discontinuous
  - ▶ Span “**there would have been**” gets labeled as LU “**there\_be.V**”.

# Target ID: model based on heuristics

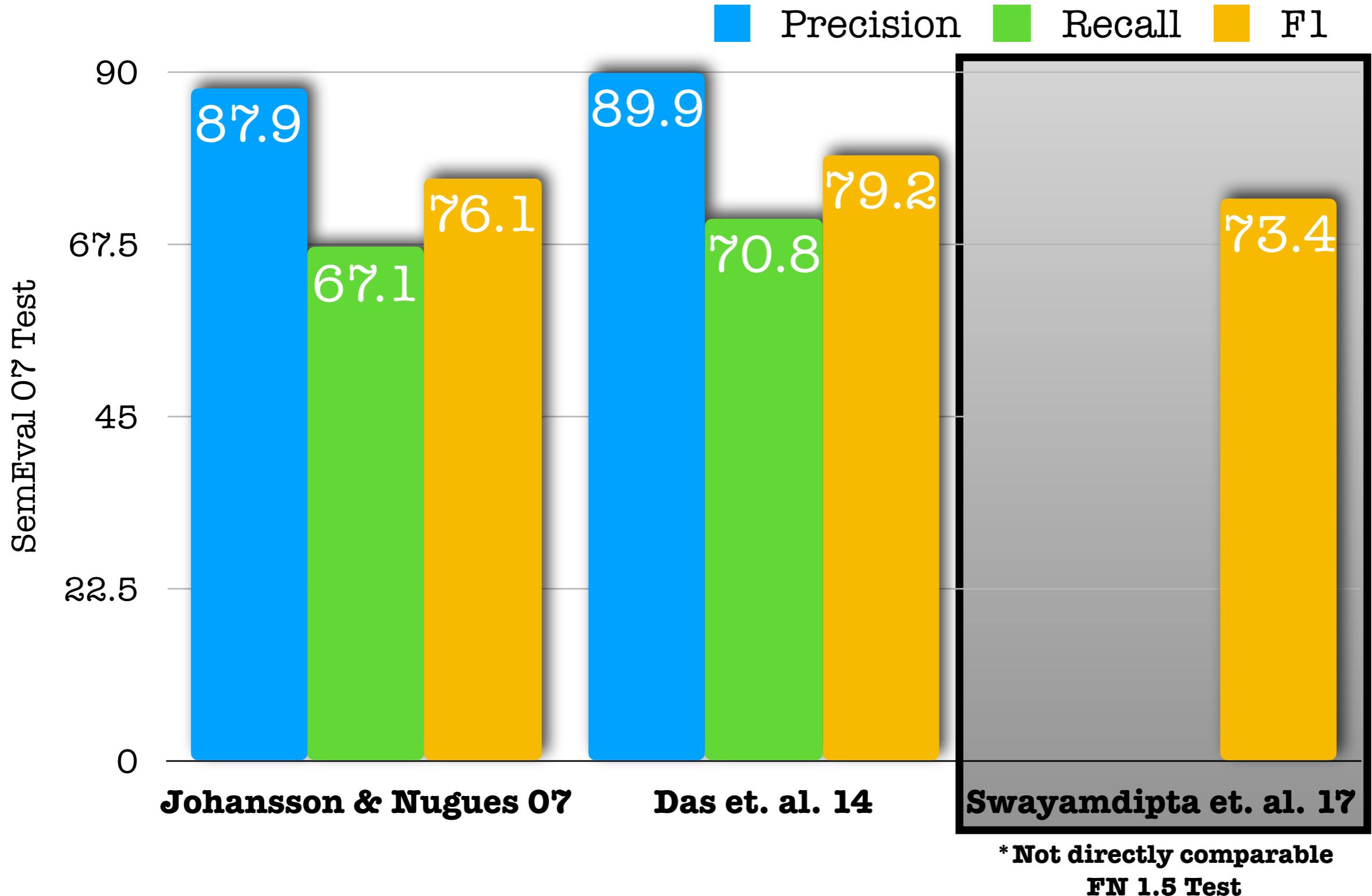
- **have** was retained only if had an object,
- **be** was retained only if it was preceded by **there**,
- **will** was removed in its modal sense,
- **of course** and **in particular** were removed,
- the prepositions **above**, **against**, **at**, **below**, **beside**, **by**, **in**, **on**, **over**, and **under** were removed unless their head was marked as locative,
- **after** and **before** were removed unless their head was marked as temporal,
- **into**, **to**, and **through** were removed unless their head was marked as direction,
- **as**, **for**, **so**, and **with** were always removed,
- because the only sense of the word was the frame PARTITIVE, it was removed unless it was preceded by **only**, **member**, **one**, **most**, **many**, **some**, **few**, **part**, **majority**, **minority**, **proportion**, **half**, **third**, **quarter**, **all**, or **none**, or it was followed by **all**, **group**, **them**, or **us**,
- all targets marked as support verbs for some other target were removed.

# Target ID: Neural Model



- Bidirectional RNNs (Open-SESAME; Swayamdipta et. al., 2017) and no syntax!
- Does significantly worse than heuristics-based model.

# Target ID: Evaluation



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# Frame Identification

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TIME\_  
VECTOR

STIMULATE  
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DEPARTING

- Given a target (lexical unit) token in the sentence, identify the frame evoked by it.
- On an average, about 2 frames per lexical unit.
- Lexical units play a critical role here, because of the mapping between lexical units and frames.
  - ▶ Errors in identifying targets / lexical units directly impact frame identification.

# Frame ID models

- Simple Classification

$$\text{frame} = \arg \max_{\text{frame} \in \text{LU}} p(\text{frame} | \text{target}, \text{LU}, \text{sentence})$$

- When LU is ambiguous:
  - Treat it as another unknown
  - Learn a distribution for it (Das et. al., 2014)

# Linear Frame ID Models

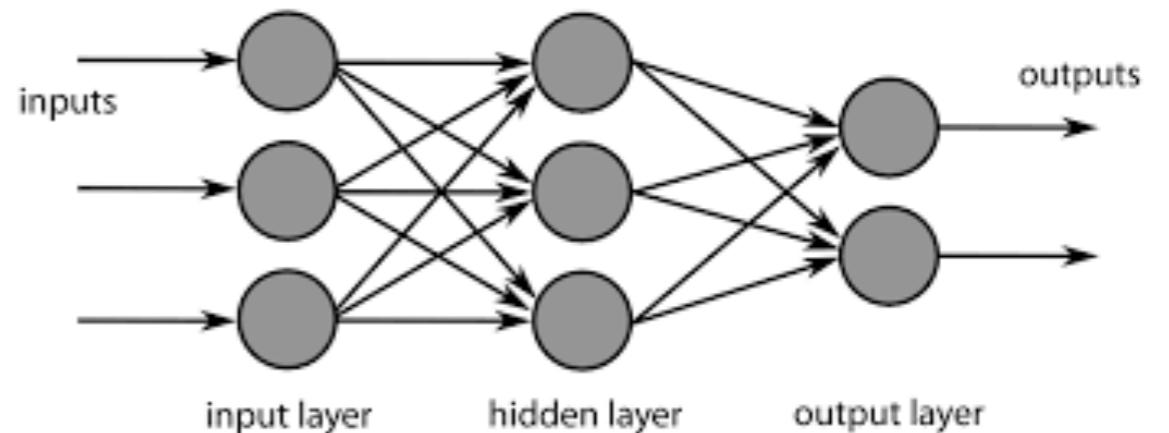
- With features from syntax (Das et. al., CL 2014)
  - the POS of the parent of the head word of  $t_i$
  - \* the set of syntactic dependencies of the head word<sup>21</sup> of  $t_i$
  - \* if the head word of  $t_i$  is a verb, then the set of dependency labels of its children
  - the dependency label on the edge connecting the head of  $t_i$  and its parent
  - the sequence of words in the prototype,  $w_\ell$
  - the lemmatized sequence of words in the prototype
  - the lemmatized sequence of words in the prototype and their part-of-speech tags  $\pi_\ell$
  - WordNet relation<sup>22</sup>  $\rho$  holds between  $\ell$  and  $t_i$
  - WordNet relation<sup>22</sup>  $\rho$  holds between  $\ell$  and  $t_i$ , and the prototype is  $\ell$
  - WordNet relation<sup>22</sup>  $\rho$  holds between  $\ell$  and  $t_i$ , the POS tag sequence of  $\ell$  is  $\pi_\ell$ , and the POS tag sequence of  $t_i$  is  $\pi_t$

# Neural Models for Frame ID

- Feed-forward nets
  - With syntactic features  
(Hermann et. al., 2015)
  - Without syntactic features  
(Swayamdipta et. al., 2017)
- Distributional and visual  
features (Hartmann et. al.,  
2017; Botschen et. al., 2018)
- With Argument ID (Yang et. al.  
2018 ; Peng et. al. 2018)

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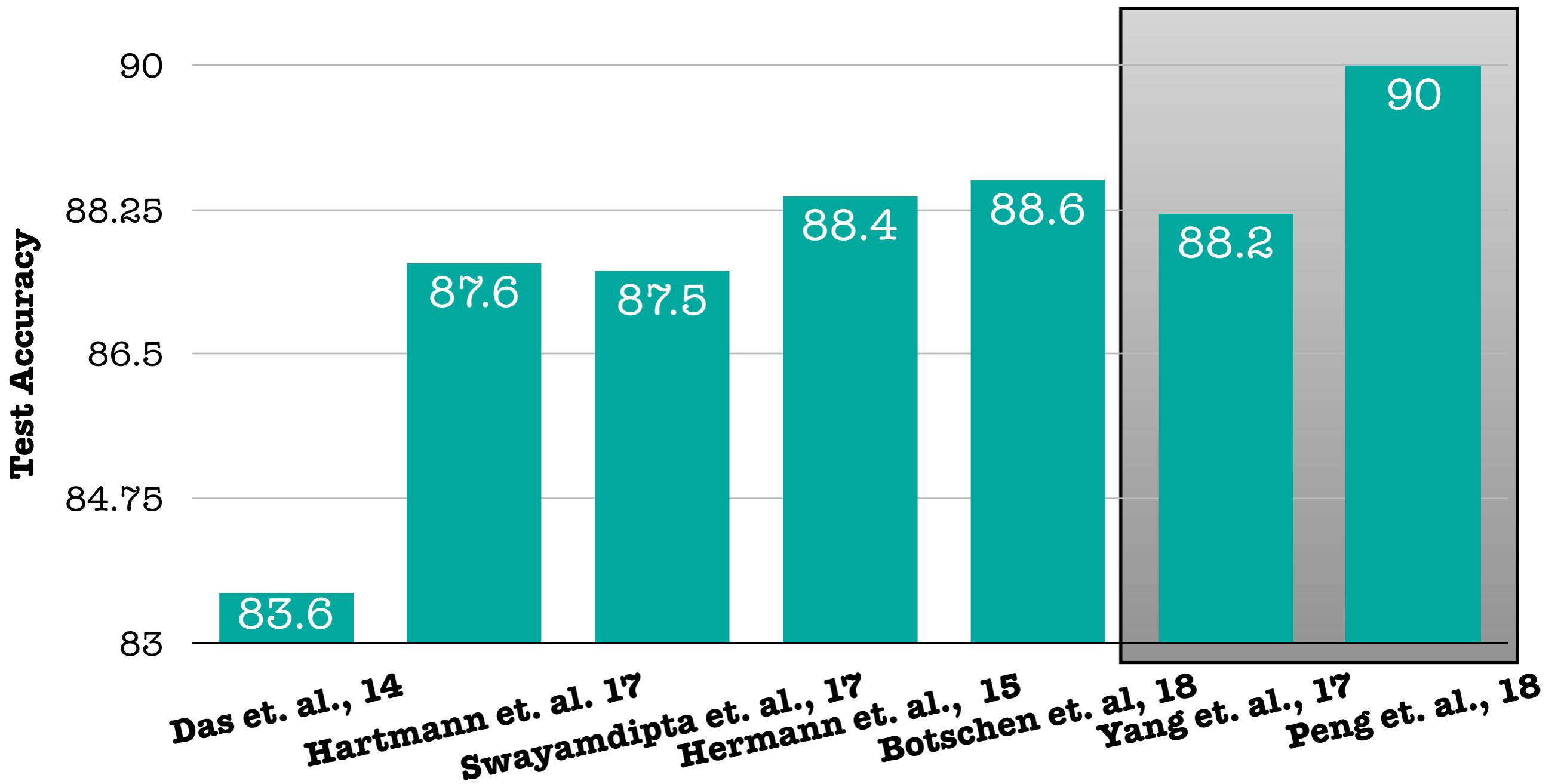
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**Feed-forward Nets**

# Frame ID: Evaluation

Given GOLD targets!



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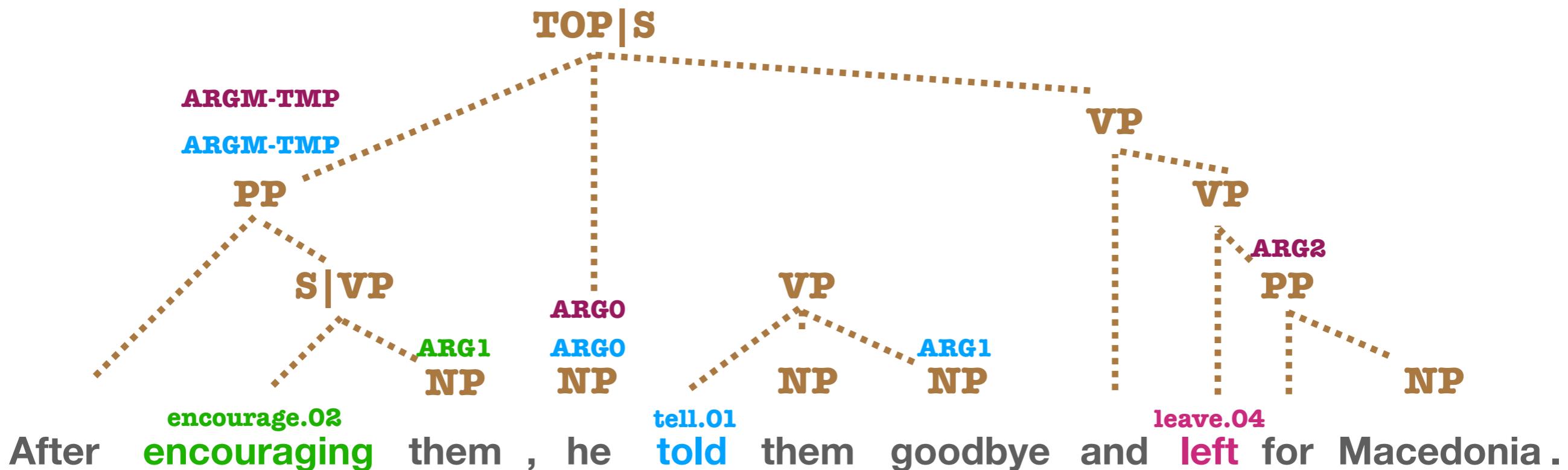
# Argument Identification

After encouraging them , he told them goodbye and left for Macedonia .  
after.PREP encourage.V tell.V leave.V



- Given a target and the frame it evokes, identify
  - ▶ all the spans in the sentence which are arguments to the frame,
  - ▶ and their respective labels (frame-elements)

# PropBank vs FrameNet arguments



- Primary difference between PropBank SRL and Frame SRL arg ID:

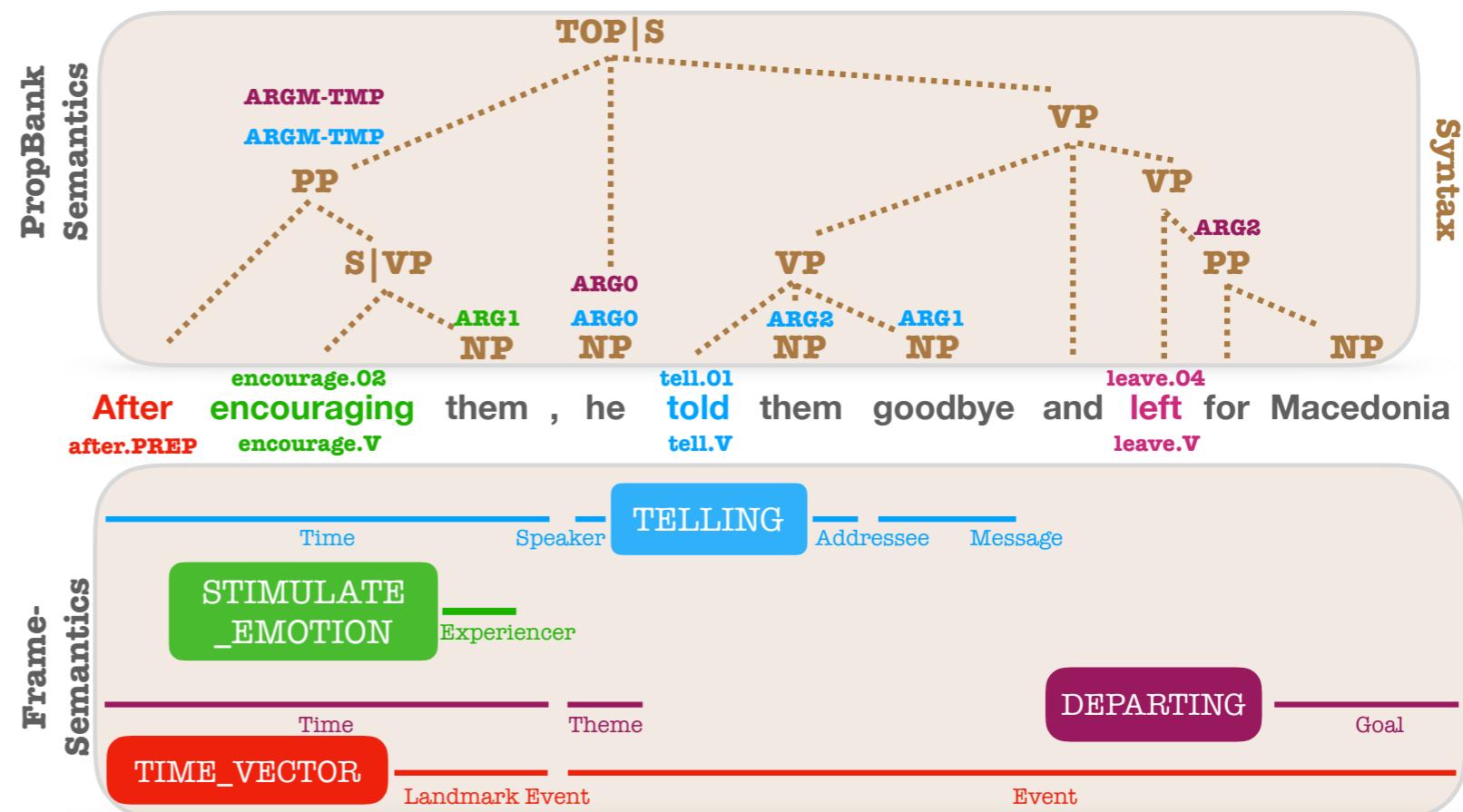
- ▶ PropBank role labels ( $\text{ARG}_0 - \text{ARG}_n$ ) are uniform across predicates.
- ▶  $\text{ARG}_0$  and  $\text{ARG}_1$  correspond to Dowty's (1991) proto-agent and proto-patient, respectively.
- ▶ Higher  $\text{ARG}_n$  have verb-specific definitions.

# Arg ID: Basics

- Arguably, the most challenging task!
- Each predicate/ target (and its frame) considered independently
- Arguments as spans
- Arguments as sequences

# Role of syntax

- Traditional feature design (Das et. al. 2014)
- Heuristics for potential argument identification (Das et. al., 2014)
- Continuous valued features (Roth & Lapata, 2016; Yang et. al., 2017)
- Constraints during decoding (He et. al., 2017)



# Linear Arg ID models

$$\text{role} = \arg \max_{\text{role} \in \text{frame}} p(\text{role} | \text{frame}, \text{LU}, \text{target}, \text{span})$$

- Span classification task
- Candidate spans pruned by syntactic rules
- Features rely heavily on syntax

**Features with both null and non-null variants:** These features come in two flavors: if the argument is null, then one version fires; if it is overt (non-null), then another version fires.

- some word in  $t$  has lemma  $\lambda$
- some word in  $t$  has lemma  $\lambda$ , and the sentence uses PASSIVE voice
- the head of  $t$  has subcategorization sequence  $\tau = \langle \tau_1, \tau_2, \dots \rangle$
- the head of  $t$  has  $c$  syntactic dependents

- some word in  $t$  has POS  $\pi$
- some word in  $t$  has lemma  $\lambda$ , and the sentence uses ACTIVE voice
- some syntactic dependent of the head of  $t$  has dependency type  $\tau$
- bias feature (always fires)

**Span content features:** apply to overt argument candidates.

- POS tag  $\pi$  occurs for some word in  $s$
- the first word of  $s$  has POS  $\pi$
- the last word of  $s$  has POS  $\pi$
- the head word of  $s$  has syntactic dependency type  $\tau$
- $w_{s_2}$  and its closed-class POS tag  $\pi_{s_2}$ , provided that  $|s| \geq 2$
- the head word of  $s$  has lemma  $\lambda$
- the last word of  $s$ :  $w_{s_{|s|}}$  has lemma  $\lambda$
- $w_{s_{|s|}}$ , and its closed-class POS tag  $\pi_{s_{|s|}}$ , provided that  $|s| \geq 3$
- lemma  $\lambda$  is realized in some word in  $s$ , the voice denoted in the span (ACTIVE or PASSIVE)

- the head word of  $s$  has POS  $\pi$
- $|s|$ , the number of words in the span
- the first word of  $s$  has lemma  $\lambda$
- the first word of  $s$ :  $w_{s_1}$ , and its POS tag  $\pi_{s_1}$ , if  $\pi_{s_1}$  is a closed-class POS
- the syntactic dependency type  $\tau_{s_1}$  of the first word with respect to its head
- $\tau_{s_2}$ , provided that  $|s| \geq 2$
- $\tau_{s_{|s|}}$ , provided that  $|s| \geq 3$
- lemma  $\lambda$  is realized in some word in  $s$
- lemma  $\lambda$  is realized in some word in  $s$ , the voice denoted in the span,  $s$ 's position with respect to  $t$  (BEFORE, AFTER, or OVERLAPPING)

**Syntactic features:** apply to overt argument candidates.

- dependency path: sequence of labeled, directed edges from the head word of  $s$  to the head word of  $t$

- length of the dependency path

**Span context POS features:** for overt candidates, up to 6 of these features will be active.

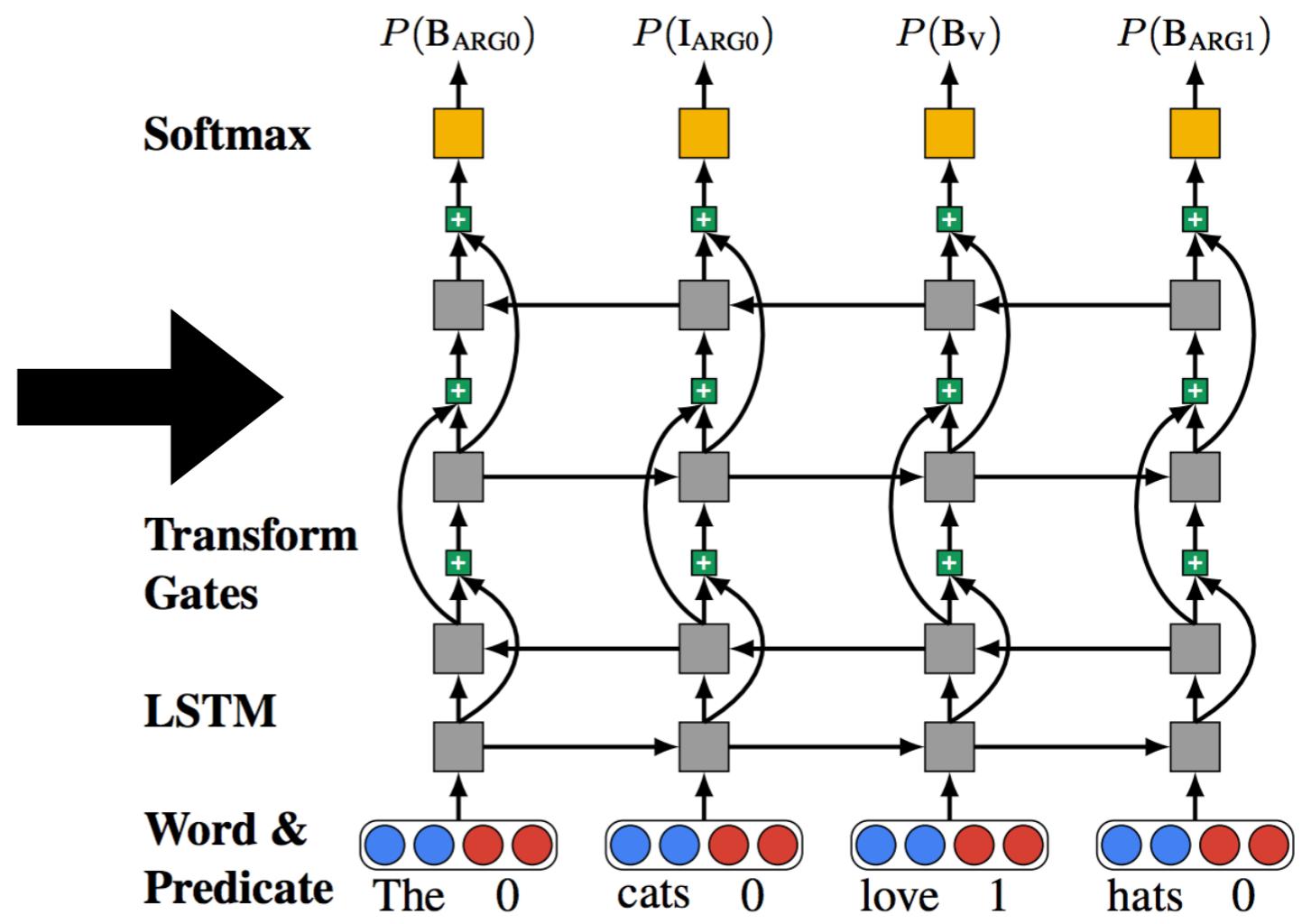
- a word with POS  $\pi$  occurs up to 3 words before the first word of  $s$
- a word with POS  $\pi$  occurs up to 3 words after the last word of  $s$

**Ordering features:** apply to overt argument candidates.

- the position of  $s$  with respect to the span of  $t$ : BEFORE, AFTER, or OVERLAPPING (i.e. there is at least one word shared by  $s$  and  $t$ )
- linear word distance between the nearest word of  $s$  and the nearest word of  $t$ , provided  $s$  and  $t$  do not overlap
- target-argument crossing: there is at least one word shared by  $s$  and  $t$ , at least one word in  $s$  that is not in  $t$ , and at least one word in  $t$  that is not in  $s$
- linear word distance between the middle word of  $s$  and the middle word of  $t$ , provided  $s$  and  $t$  do not overlap

# Neural models for Arg ID

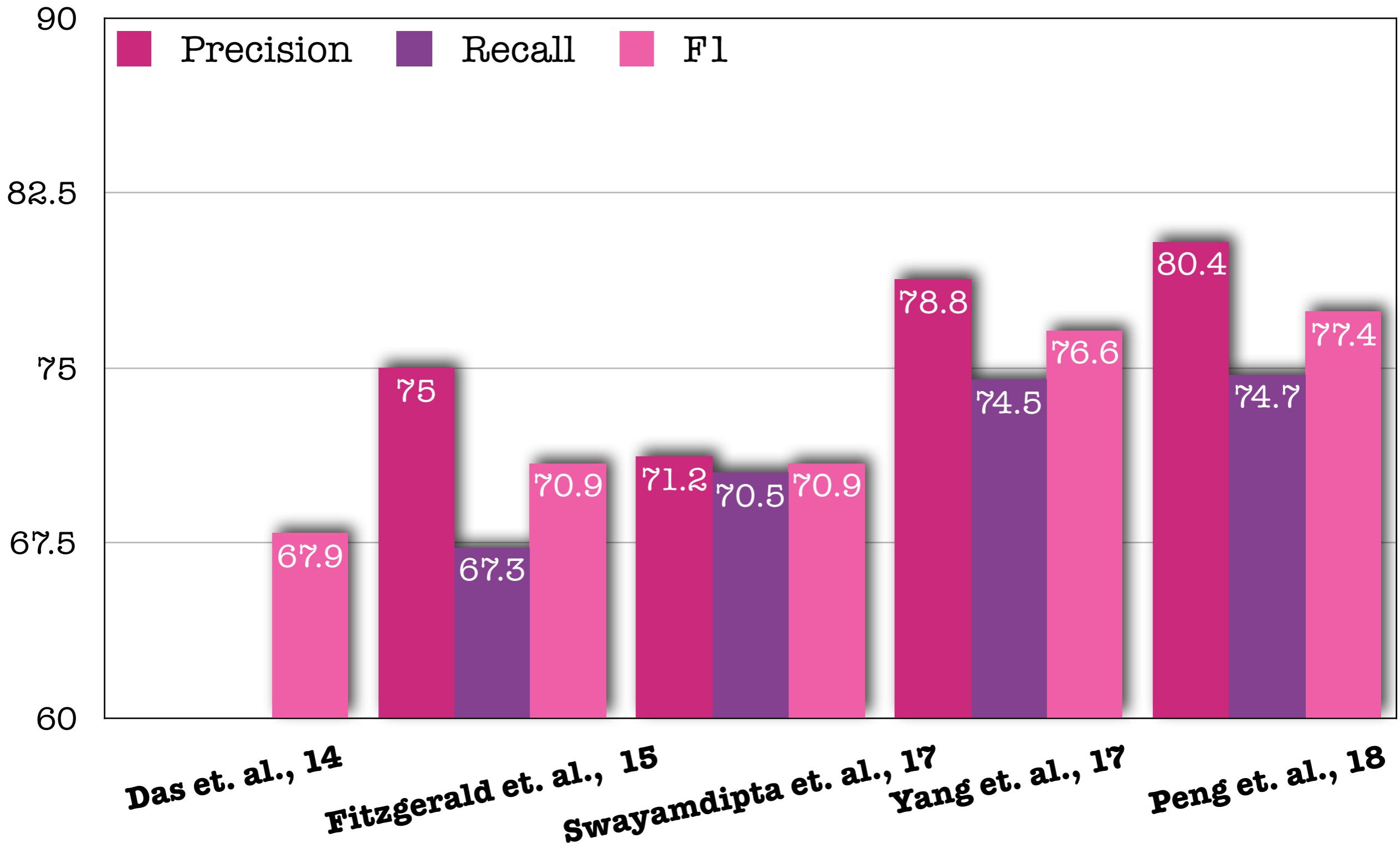
- BIO specification
- Deep bidirectional, highway  
(Zhou & Xu, 2015;  
He et. al. ACL 2017)
- Transformers  
(Tan et. al., AAAI  
2018; Strubell et. al.,  
2018)



He et. al. (2017)

# Frame + Arg ID: Evaluation

Given GOLD targets!



# End-to-end Frame SRL evaluation



# Summary of Part 2

- Subtasks have their own intricacies.
- Automation is coming along fast, we have seen big gains.
- Non-uniformity of evaluation is an issue.
- Can we do better? [Part 3]

# Outline

1. Task of frame-SRL

2. Primary Subtasks

a. Linear

b. Neural models

**3. Advanced Modeling**

4. Looking forward: Multilingual Extensions

# Biggest Challenge

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- Part 3: Make the best of available supervision through advanced modeling
  - ▶ Joint prediction
  - ▶ Multitask learning

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- Availability of data
- Part 3: Make the best of available supervision through advanced modeling
  - ▶ Joint prediction
  - ▶ Multitask learning
- Part 4: Enhance the amount of supervision

# Getting the most out of data

- Frame-semantic parsing with heterogenous annotations  
(Kshirsagar et. al., 2015)
  - Frame Hierarchy
  - Exemplar annotations
  - PropBank
- Relatively unused: Grammatical Functions and Phrase Types of frame-elements
  - Only for gold arguments

# Joint prediction

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  - ▶ Targets, frames, frame-elements are mutually informative!

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  - Approximate prediction with global constraints (AD<sup>3</sup> : Das et. al. 2012)

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- Frames + frame-elements:
  - Approximate prediction with AD<sup>3</sup> (Yang et. al., 2017; Peng et. al., 2018)
- Joint prediction of predicates, senses and arguments (Labeled Span Graphs, He et. al., ACL 2018)

# Multitask learning

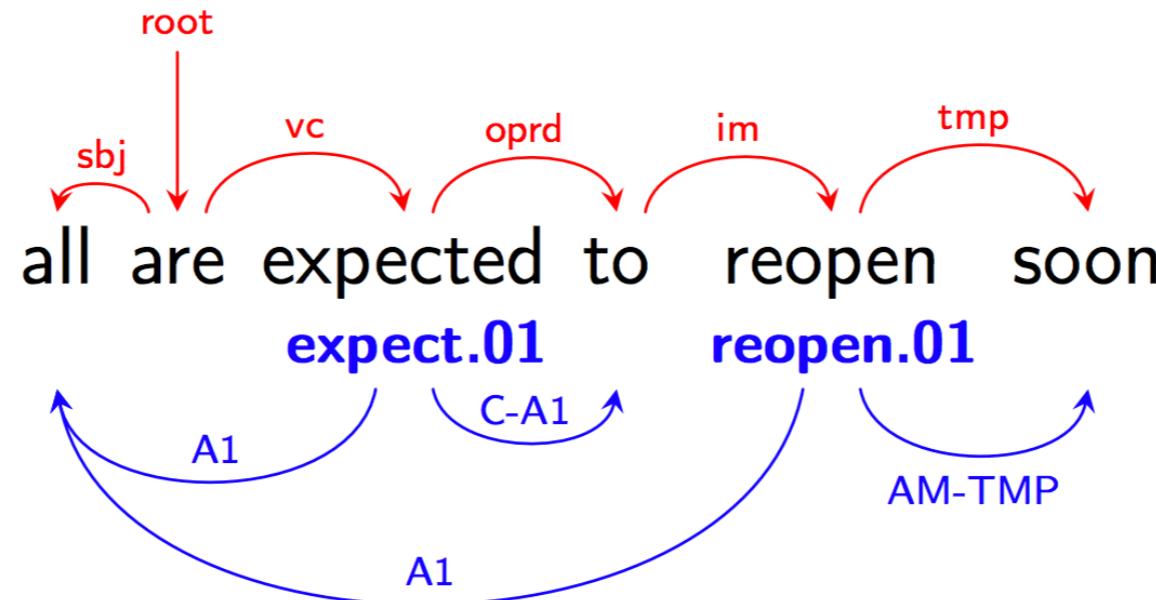
# Multitask learning

- With syntax
  - Full syntactic tree (CoNLL shared tasks 2008, 2009)
  - Only relevant parts -Scaffolding (Swayamdipta et. al., EMNLP 2018)

# Multitask learning

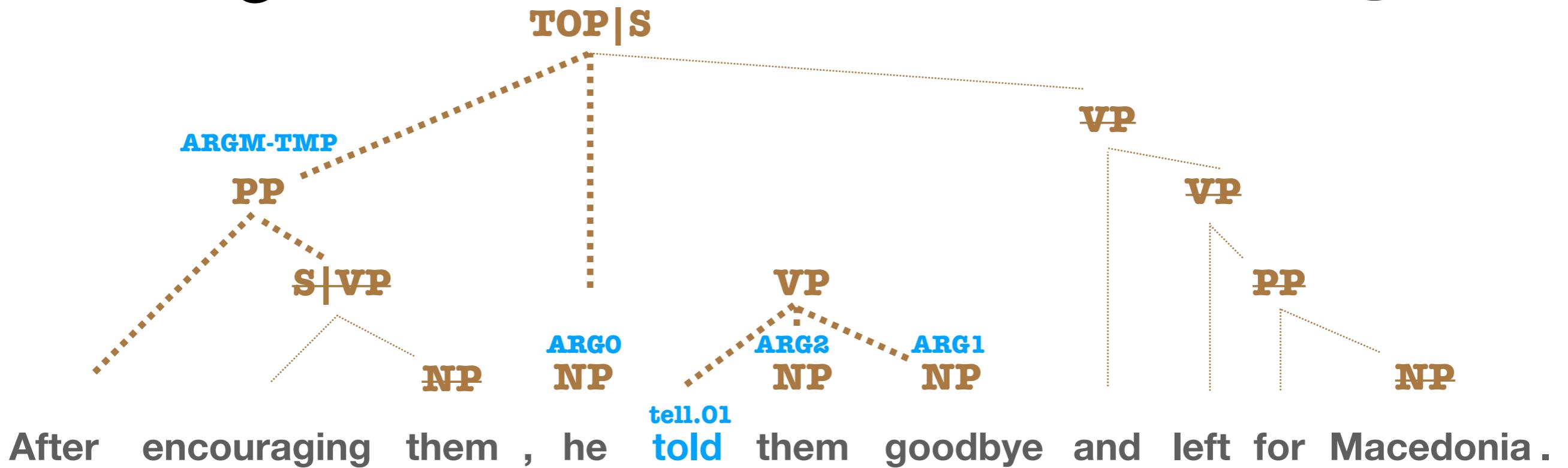
- With syntax
  - Full syntactic tree (CoNLL shared tasks 2008, 2009)
  - Only relevant parts -Scaffolding (Swayamdipta et. al., EMNLP 2018)
- With multiple semantic formalisms:
  - PropBank + FrameNet (Kshirsagar et. al. NAACL 2015; Fitzgerald et. al. EMNLP 2015)
  - Semantic dependencies + FrameNet (Peng et. al. NAACL 2018)

# Syntactic tree + semantic graph

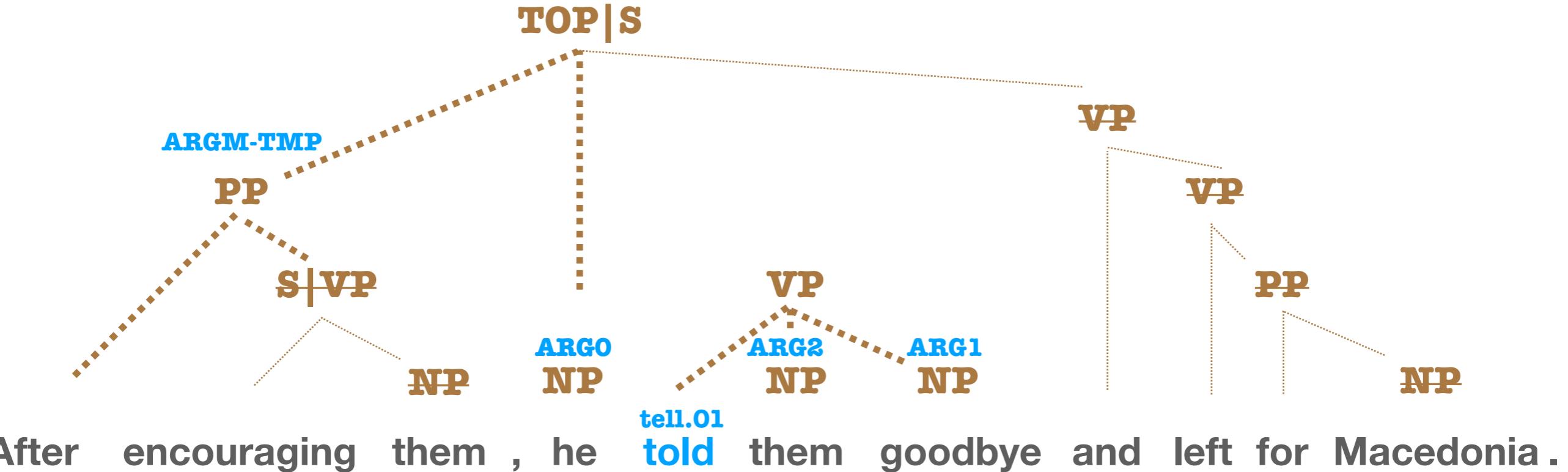


- CoNLL 2008 (Surdeaneau et. al., 2008)
- CoNLL 2009, multilingual (Hajič et. al., 2009)
- Pipelined models : Syntax → Semantics
- Joint models
  - Graph-based (Lluis et. al., 2008, 2013)
  - Transition-based (Titov et. al., 2009; Swayamdipta et. al., 2016)

# Syntactic Scaffolding

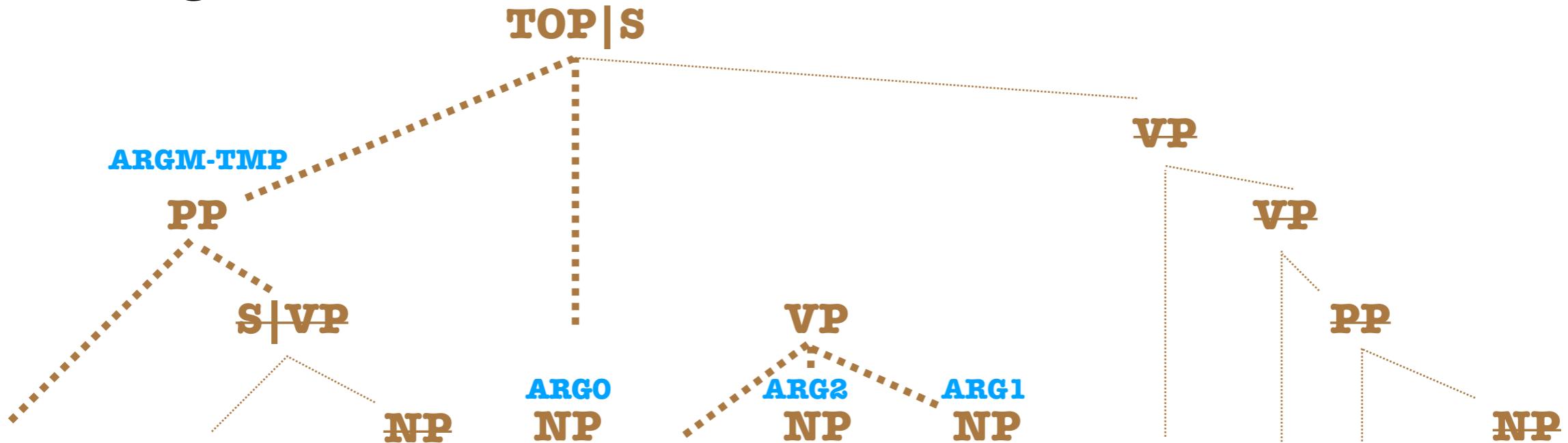


# Syntactic Scaffolding



- Instead of learning entire syntactic trees, **only learn parts of the tree** which are relevant for SRL.

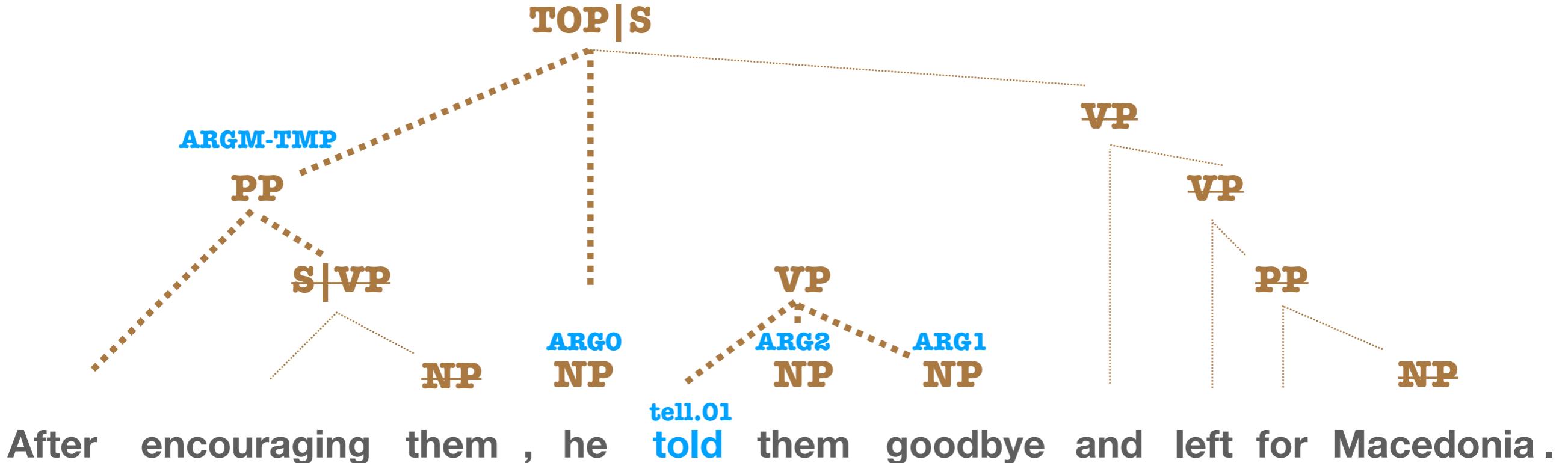
# Syntactic Scaffolding



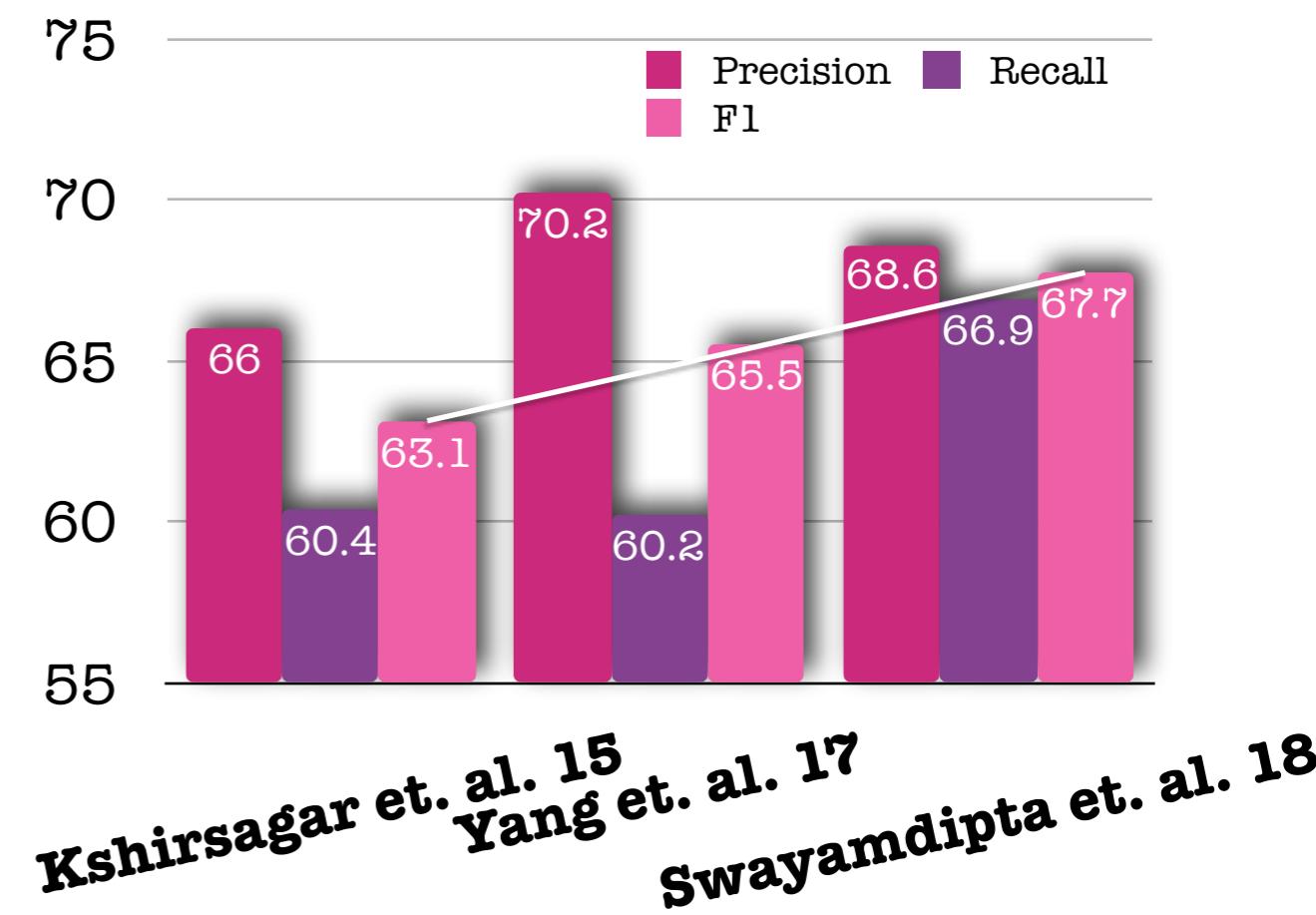
After encouraging them , he told them goodbye and left for Macedonia .

- Instead of learning entire syntactic trees, **only learn parts of the tree** which are relevant for SRL.
- “Scaffold” - can be discarded after training.

# Syntactic Scaffolding

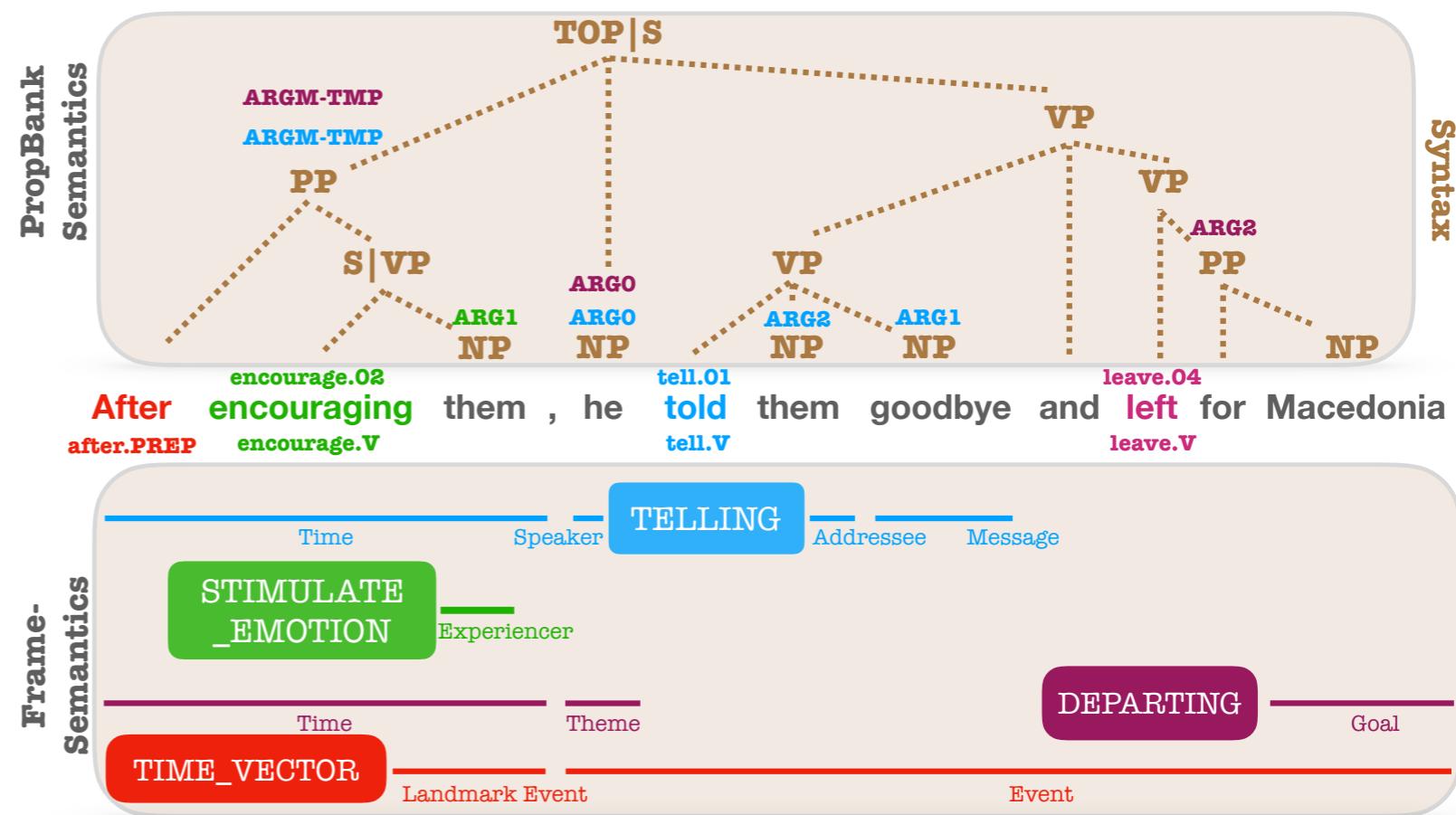


- Instead of learning entire syntactic trees, **only learn parts of the tree** which are relevant for SRL.
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# PropBank + Frame-SRL

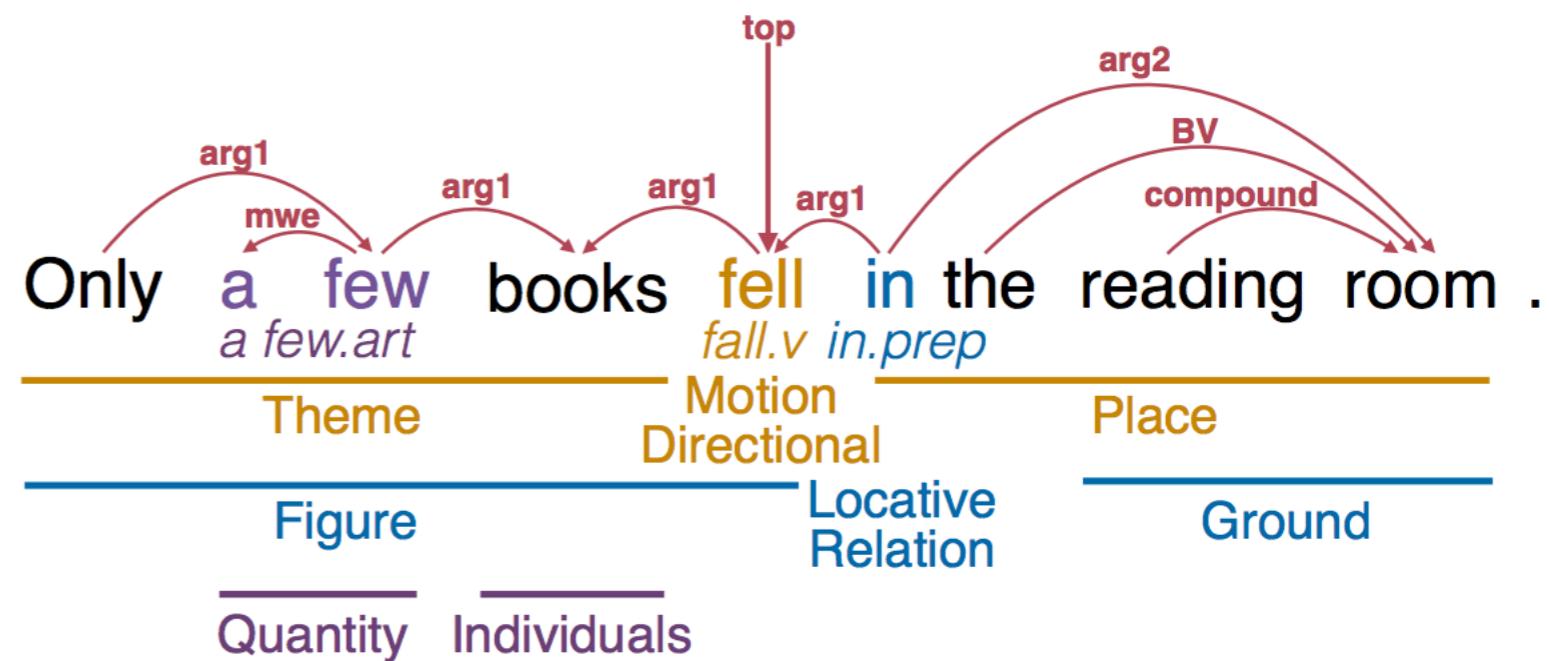
- Significant overlaps between formalisms
- PropBank much larger than FrameNet, so helps FrameSRL performance



Fitzgerald et. al. (2015)  
Kshirsagar et. al. (2015)

# Semantic Dependencies + Frame-SRL

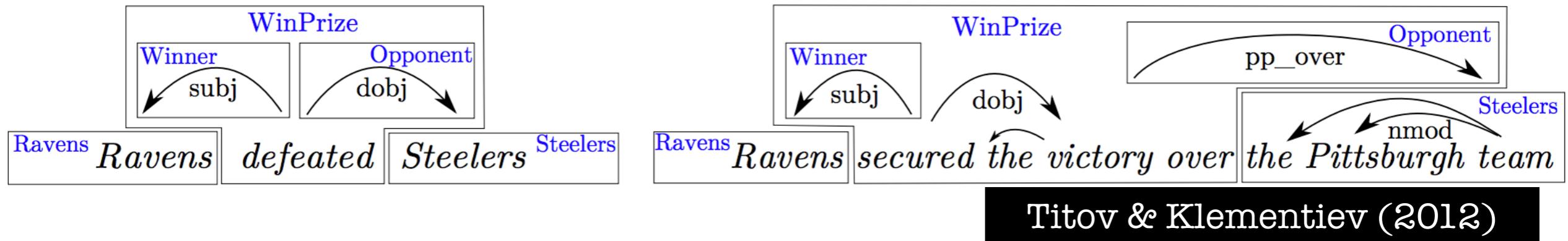
- SemEval 2015 Semantic Dependencies (Oepen et. al., 2015)
- Disjoint formalisms : span-based vs. dependency-based.
- Treat semantic dependencies as “latent” when predicting frame-elements.



Peng et. al. (2018)

# Alternatives to supervised learning

## Unsupervised approaches



- Two different syntactic trees with a common semantic representation.
- Clusters of syntactic structures correspond to semantic roles.

## Semi-supervised approaches

- Pre-trained embeddings, based on language models.
- Seed examples and projection (Fursteau & Lapata, 2012; Das et. al., CL 2014)

# Summary of Part 3

- Vanilla classifiers for subtasks can be improved on.
- Joint prediction
- Multi-task learning
- Still need more data... [Part 4]

# Outline

1. Task of frame-SRL
2. Primary Subtasks
  - a. Linear
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3. Advanced Modeling
- 4. Looking Forward / Multilingual Extensions**

# Increasing supervision

- Coverage (Palmer & Sporleder, 2010)
  - Augmentation via Paraphrases (Pavlick et. al. 2015; Rastogi & Van Durme, 2015)
- Domain Adaptation
  - Distributional methods (Croce et. al., 2010)
  - FrameID (Hartmann et. al. EACL 2017)

# One glaring gap

# One glaring gap

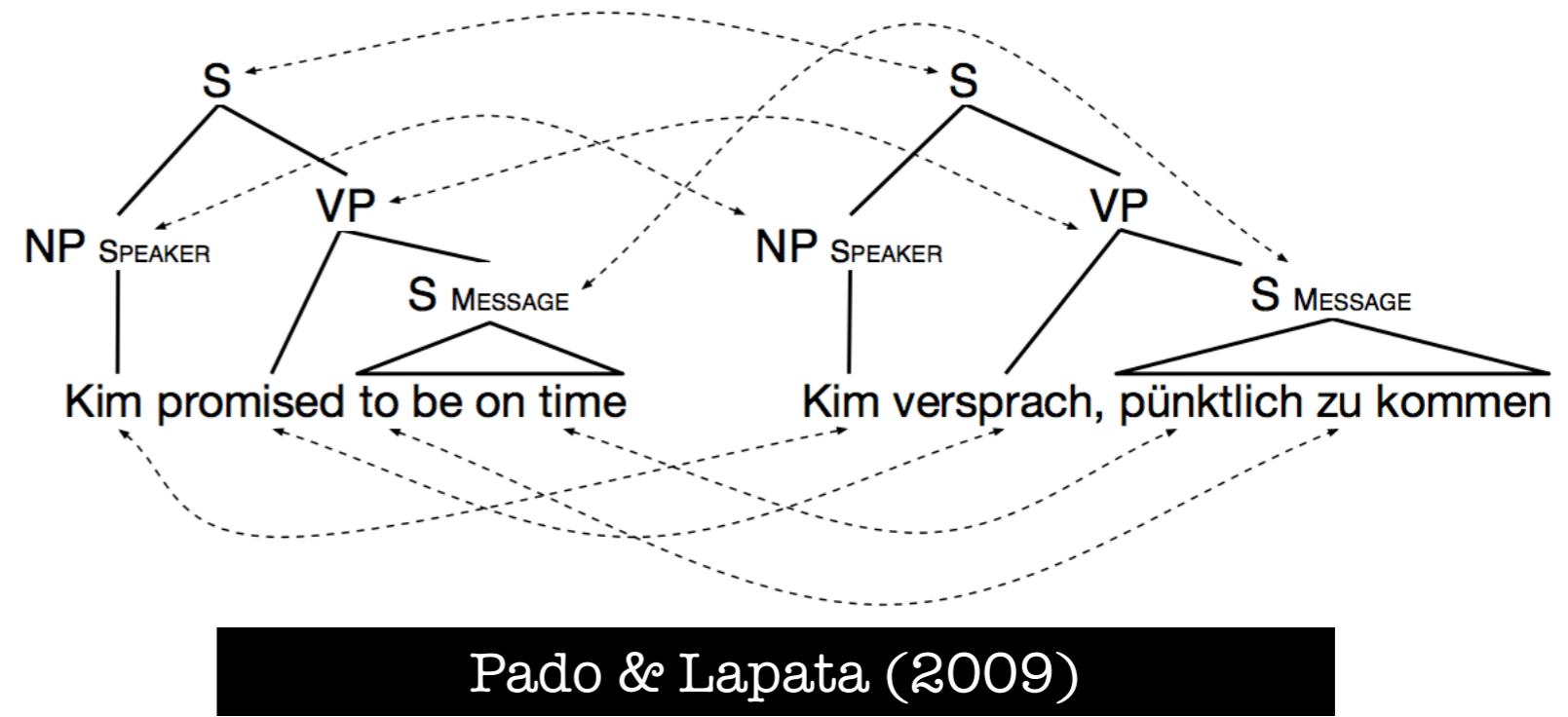


# Multilingual SRL: Generating Annotations via Projection

# Multilingual SRL:

## Generating Annotations via Projection

- Needs parallel corpora
- Projection of annotations via lexical and syntactic alignments between sentences
- Not feasible without parallel data / highly accurate syntax
- Not directly translatable (Akbik et. al., 2015)



SL

A0	need.01	A1			
A0		hold.01	A1	A2	
We	need	to	hold	people	responsible

TL

Il	faut	qu'	il	y	ait	des	responsables
it	needs	that	there		exist	those	responsible
	need.01	A1			exist.01		A1

# Multilingual FN: Generating Annotations

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- Wiktionary + FrameNet for English - German FrameNet  
(Hartmann & Gurevych, ACL 2013)

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# Multilingual FN: Generating Annotations

- Wiktionary + FrameNet for English - German FrameNet (Hartmann & Gurevych, ACL 2013)
- Danish Thesaurus + valencies (Nimb et. al., 2017)
- Any language frame-semantic parsing (Johannsen et. al. 2015)
  - ▶ Using word-word translation
  - ▶ 9 languages in 2 domains
  - ▶ Inter-annotator agreement issues stemming from automatic target identification through word-word translation

# Models for multilingual SRL

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- Encouraged by CoNLL 2009 for PropBank SRL

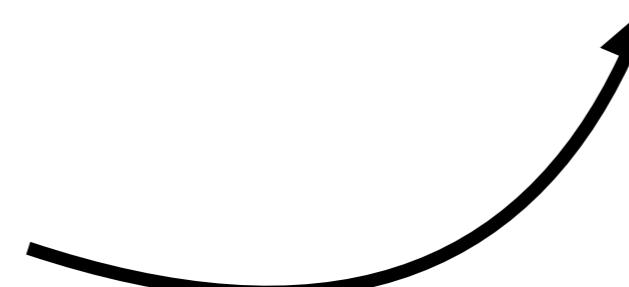
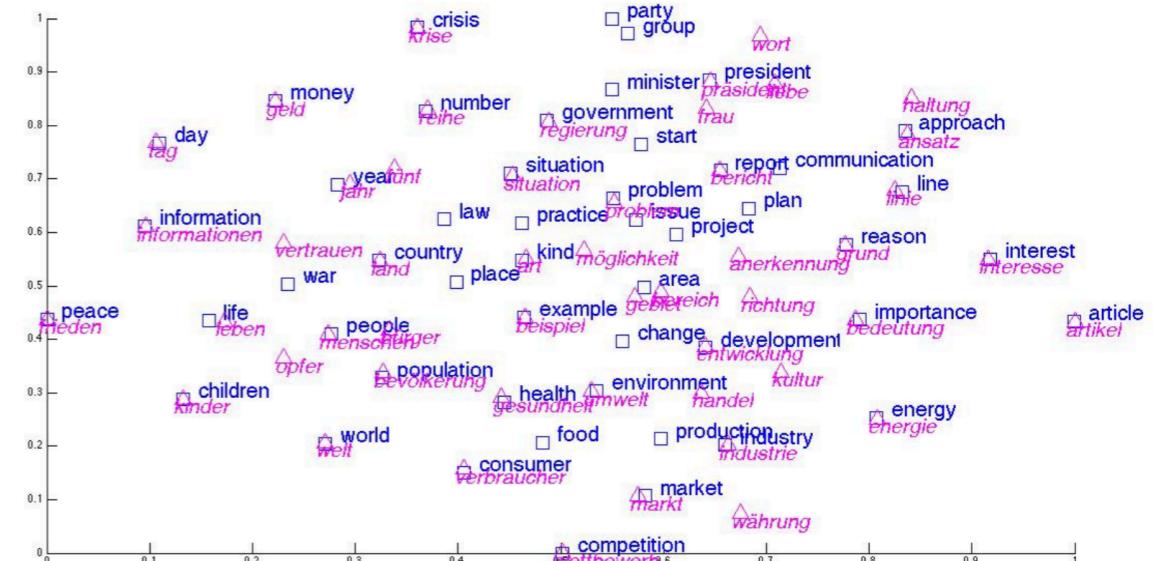
# Models for multilingual SRL

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# Models for multilingual SRL

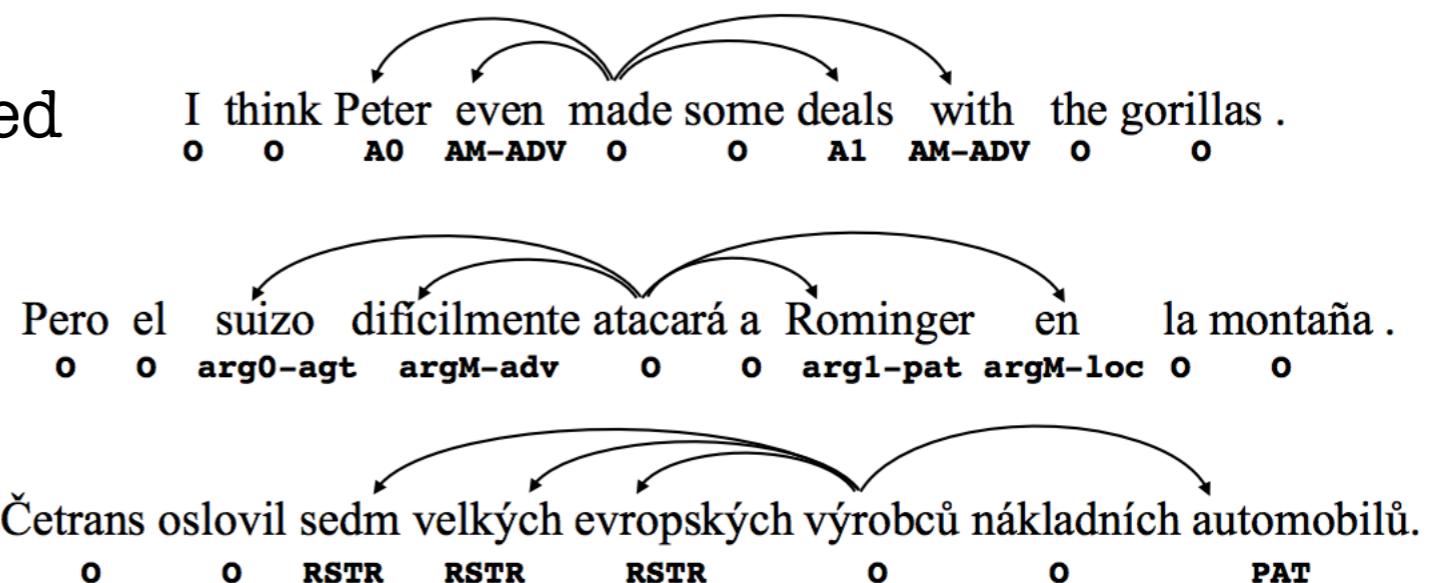
- Encouraged by CoNLL 2009 for PropBank SRL
- Primary approach: One model per language
  - Build a single model for SRL
  - Apply to others via language-specific features / embeddings
- Moving towards single multilingual models: Cross-lingual embeddings learned from cross-lingual alignments (Ammar et. al., 2016)

Luong et. al. (2015)



# Polyglot SRL

- Training data from pairs of CoNLL 2009 languages merged
- Challenge: Differences in annotation schemes across languages.
- Multilingual word embeddings, learned from cross-lingual alignments (Ammar et. al., 2016)
- Maximum benefit reported for low-resource languages such as Catalan, when combined with English.



Mulcaire et. al. (ACL, 2018)

- Label unification helps (Akbik & Li, 2016) but needs more annotation efforts

# Applications of Multilingual FrameNet

- Translation using semantics as pivot.
- Cross-lingual transfer for downstream applications such as knowledge | information | relation extraction.
- Particular benefits for low-resource languages



# Summary

- |   |  |   |
|---|--|---|
| <ul style="list-style-type: none"><li>• Part 1:<br/>Frame-SRL</li><li>a. Graph induction</li><li>b. Supervised Learning</li></ul> | <ul style="list-style-type: none"><li>• Part 2:<br/>Subtasks<ul style="list-style-type: none"><li>a. Target Identification</li><li>b. Frame Identification</li><li>c. Frame-Element Identification</li></ul></li></ul> | <ul style="list-style-type: none"><li>• Part 3:<br/>Advanced Modeling</li><li>• Part 4:<br/>Looking Forward / Multilinguality</li></ul> |
|---|--|---|

Slides and references at

<https://github.com/swabhs/coling18tutorial>