RRG-based semantic frame parsing

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Motivation

- ⋆ Goal: data-driven frame-semantic parsing for Role and Reference Grammar (RRG, Van Valin and LaPolla (1997); Van Valin Jr. (2005))

  → learn tree-frame pairs and argument linking

- ⋆ Semantic annotation of RRGparbank is still ongoing

  → Implementation of a prototypical semantic parser based on data from Parallel Meaning Bank (PMB, Abzianidze et al. (2017))

Approach

1. Parse sentences in PMB with statistical TWG parser ParTAGe to obtain RRG structures
2. For each frame trigger (verbal predicate) and each role filler assign a corresponding frame based on VerbAtlas
3. Extract a TWG grammar from parsed data and assign simplified supertags for each word in all sentences
4. Create argument linking between the supertag and the role labels
5. Learn supertags, dependencies, role labels, frames and argument linking with a statistical model

Resources: ParTAGe, VerbAtlas, PMB (1)

- ParTAGe (Waszczuk (2017); Bladier et al. (2020b))

  → Neural statistical parser for TWG, multilingual BERT model

  → Based on supertagging and a subsequent A* parsing step

  → The sentences in PMB are about 6.38 tokens long

  → ParTAGe performance on sentences < 7 tokens (avg. sent. length 6.69) from gold RRGparbank data is 93.52 (labeled F1) and 94.25 (unlabeled F1)

Resources: ParTAGe, VerbAtlas, PMB (2)

- VerbAtlas (Di Fabio et al. (2019))

  → hand-crafted lexical-semantic resource mapping verbal synsets from BabelNet into semantically-coherent frames

  → 499 frames, no distinction between core and non-core roles, distinction between syntactically realized, implicit, and shadow arguments

  → We use frames to create frame lexicon

Resources: ParTAGe, VerbAtlas, PMB (3)

- Parallel Meaning Bank (PMB, Abzianidze et al. (2017))

  $\rightarrow$ gold semantically annotated data for evaluation of the prototype

  $\rightarrow$ PMB is a corpus of translations annotated with shared DRSs, over 11 million words, four languages (English, German, Italian, and Dutch)

  $\rightarrow$ verbal predicates in PMB are annotated with WordNet senses

  $\rightarrow$ frames in VerbAtlas are mapped to the WordNet senses

Learn tree-frame pairs (1)

- TWG extraction as described in Bladier et al. (2020a)

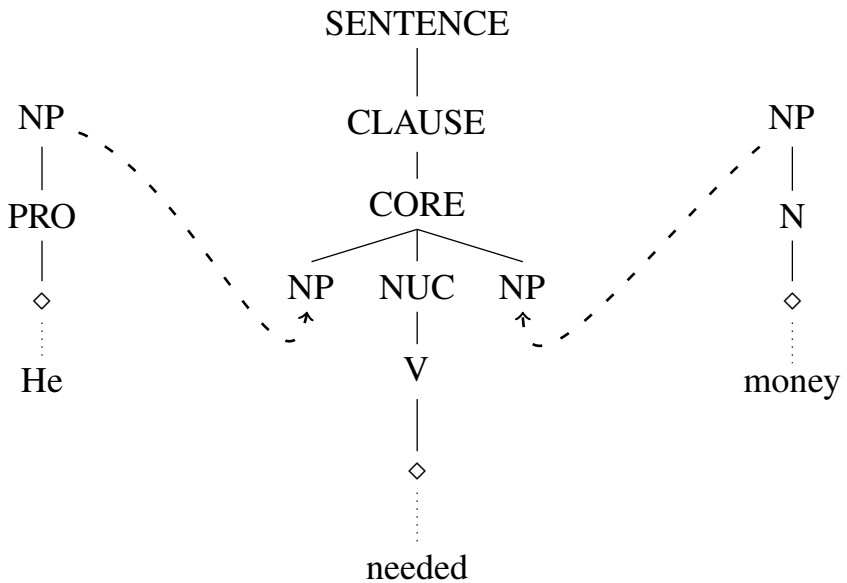


Figure 1: Extracted TWG supertags

Learn tree-frame pairs (2)

- Simplify supertags: all supertags have the tree height 3, only the root node is left and the substitution slots plus the lexical anchor

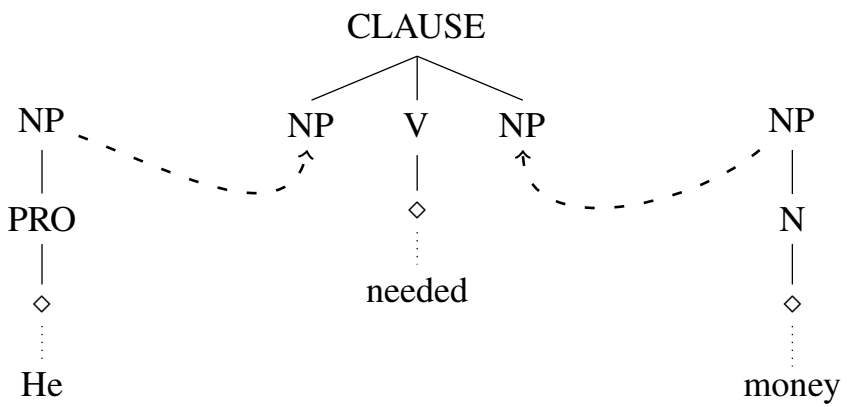
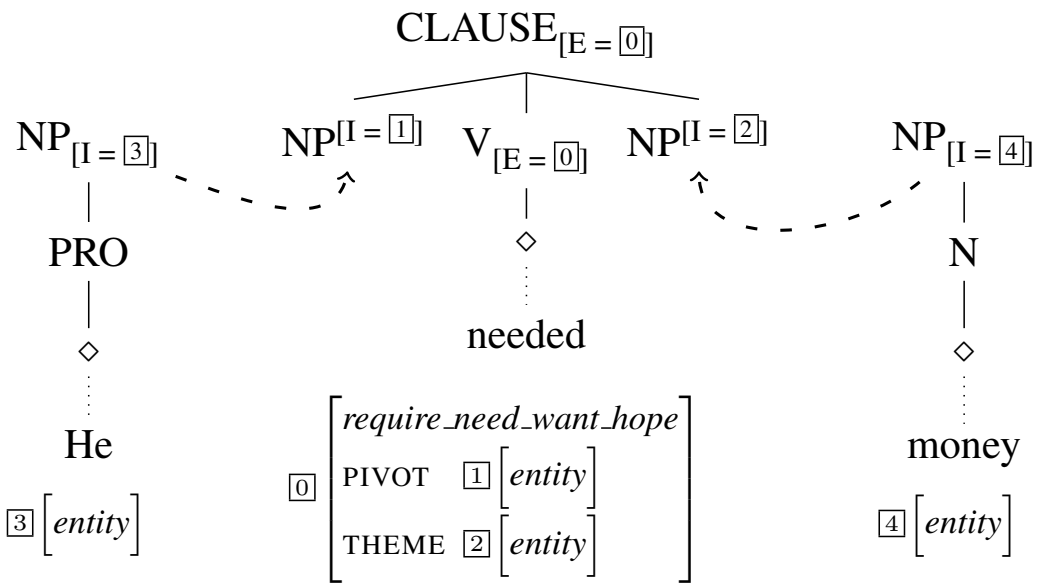


Figure 2: Simplified TWG supertags

Learn tree-frame pairs (3)

- Pair supertags with frames, after Kallmeyer and Osswald (2013)



Resulted frame:

$$\begin{bmatrix} \textit{require\_need\_want\_hope} \\ \text{PIVOT} & \begin{bmatrix} \textit{entity} \\ \text{ENTITY} & \textit{He} \end{bmatrix} \\ \text{THEME} & \begin{bmatrix} \textit{entity} \\ \text{ENTITY} & \textit{money} \end{bmatrix} \end{bmatrix}$$

Figure 3: Simplified TWG supertags mapped to frames

Learn tree-frame pairs (4)

	Token	Head	Supertag	Frames	Argument Linking
1	He	2	(NP (PRO <>))	(entity)	(–)
2	needed	0	(CLAUSE (NP) (V <>) (NP))	(require_ _need_ _want_ _hope)	((1, 'Pivot'), (2, 'Theme'))
3	money	2	(NP (N <>))	(entity)	(–)
4	.	0	(CLAUSE* (. <>))	(–)	(–)

Table 1: Training data

Insights: Most common predicate supertags

- 175 distinct predicative stags, 7955 annotated frames in 7894 gold training sentences
- Most common predicative stags:

Supertag	**Percent**
(CLAUSE (NP) (V <>) (NP))	38.82
(CLAUSE (NP) (V <>))	14.37
(CLAUSE (NP) (V <>) (PP))	10.62
(CLAUSE (NP) (V <>) (NP) (PP))	7.6
(CLAUSE (NP) (V <>) (P) (NP))	5.28
(CLAUSE (NP) (V <>) (NP) (NP))	2.8
(CLAUSE* (V <>) (NP))	1.6
(CLAUSE (NP) (V <>) (PRT) (NP))	1.3
(CLAUSE* (NP) (V <>) (NP))	1.3
(CLAUSE (NP) (V <>) (PRT))	1.12

Insights: Frame annotations

- 399 VerbAtlas frames in PMB
- 7955 predicates annotated with frames
- 18 frames are not seen in train data
- Most common frames:

Frame	Occ.	Example
STAY_DWELL	388	*The famous conductor lives in New York*
MATCH	339	*My name is Robert Johnson*
EXIST-WITH-FEATURE	255	*This painting by Rembrandt is a masterpiece*
LIKE	209	*I love rock music*
SPEAK	174	*You told a lie*
EAT_BITE	165	*Tom is chewing bubble gum*
GO-FORWARD	125	*I 'm travelling to Paris tomorrow*
HIT	122	*He hammered nails into the plank*
BUY	118	*I bought the book yesterday*
LEAVE_DEPART_RUN-AWAY	113	*The plane took off*

Experiments on PMB data

- Train, development, test split: 6 331, 800, and 824 sentences (gold data, only frame-annotated)
- Average sentence length: 6.38
- 4 single task experiments
- NER model from simpletransformers, fine-tuning of BERT multilingual cased model

Experiment	Accuracy (dev)
Stag predictions	94.03
Dependency predictions	93.51
Frame predictions	83.5
Linking predictions	71.38

Table 2

Frame predictions

- 848 predicted frames out of gold 895 frames in development set
- Most frequent mistake: auxiliary 'be' is confused with full verb 'be', false positive and false negative predictions of the 'exist-with-feature' frame
- Long tail of prediction errors

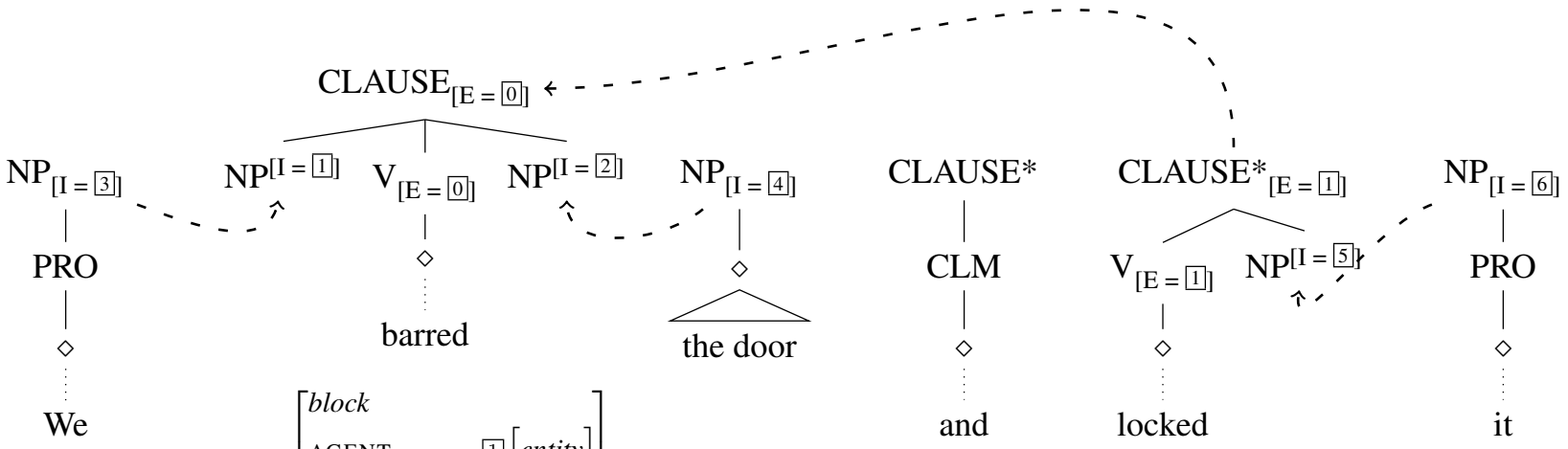
Gold frame	Predicted frame	Example
REMEMBER	HEAR_LISTEN	*I don't remember your name*
CONTINUE	OVERCOME_SURPASS	*We survived!*
LOWER	DECREASE	*Tom lowered the bucket into the wall*
CHASE	REQUIRE_NEED_WANT_HOPE	*He wants the money*
WASH_CLEAN	EMPTY_UNLOAD	*She's cleaning the book*

Models: linking predictions

- Accuracy: 71.38 (449/629) exact matches
- Partial accuracy: 98.4 (at least one linking is predicted correctly)
- Room for improvement: enforce coherence with predicted supertags and the frame

Gold linking	Predicted linking	Example
((1, 'Agent'), (2, 'Patient'))	((1, 'Agent'))	*He is opening the window*
((1, 'Experiencer'))	((1, 'Experiencer'), (2, 'Stimulus'))	*Comfort him*
((1, 'Agent'), (2, 'Theme'))	((1, 'Agent'), (2, 'Patient'))	*I skipped breakfast*
((1, 'Agent'), (0, 'Theme'))	((1, 'Agent'))	*She joined us*

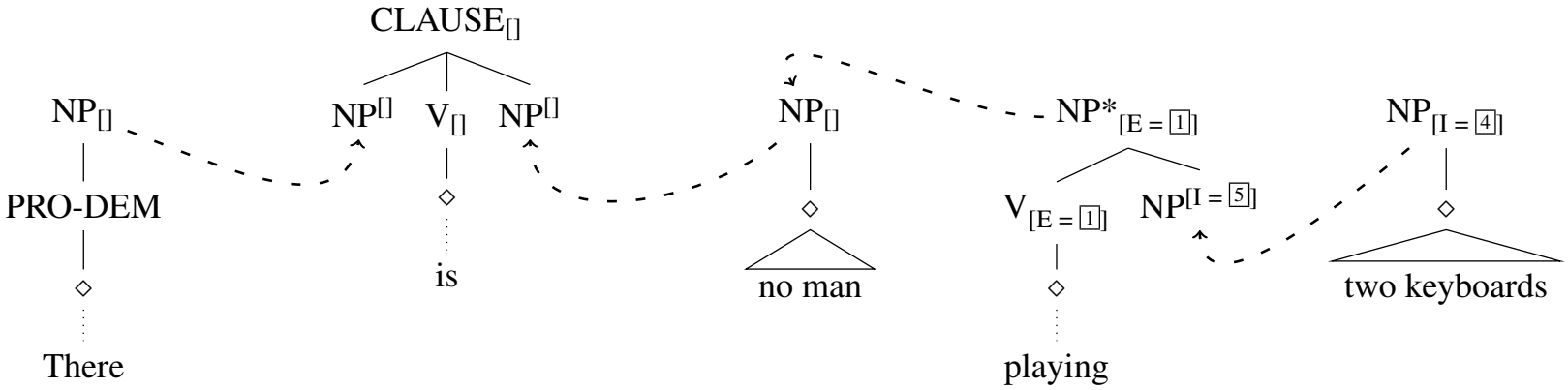
Some decisions: predicate conjunction



Resulted frames:

$$\begin{bmatrix} block \\ \text{AGENT} & \begin{bmatrix} entity \\ \text{ENTITY} \quad We \end{bmatrix} \\ \text{THEME} & \begin{bmatrix} entity \\ \text{ENTITY} \quad the\ door \end{bmatrix} \end{bmatrix} \quad \begin{bmatrix} lock \\ \text{AGENT} & \begin{bmatrix} entity \\ \text{ENTITY} \quad We \end{bmatrix} \\ \text{PATIENT} & \begin{bmatrix} entity \\ \text{ENTITY} \quad it \end{bmatrix} \end{bmatrix}$$

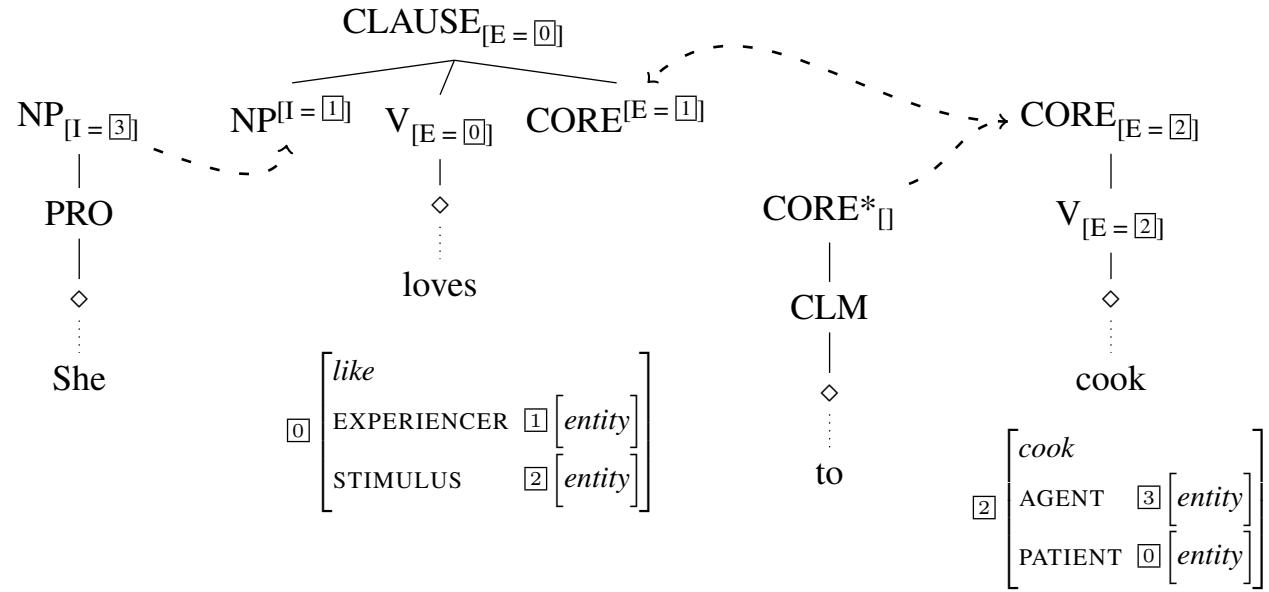
Some decisions: perifery elements



Resulted frame:

$$\begin{bmatrix} \textit{perform} & \\ \text{AGENT} & \begin{bmatrix} \textit{entity} \\ \text{ENTITY} \quad \textit{No man} \end{bmatrix} \\ \text{THEME} & \begin{bmatrix} \textit{entity} \\ \text{ENTITY} \quad \textit{two keyboards} \end{bmatrix} \end{bmatrix}$$

Some decisions: subject and object control



Resulted frame:

$$\begin{bmatrix} like \\ \text{EXPERIENCER} & \boxed{1}\begin{bmatrix} entity \\ \text{ENTITY} \quad she \end{bmatrix} \\ \text{STIMULUS} & \begin{bmatrix} cook \\ \text{AGENT} \quad \boxed{1} \end{bmatrix} \end{bmatrix}$$

Conclusions

- Learning of tree-frame pairs seems to go well
- There is also some room for improvement which we will explore next

Future Work

- Seq2seq model for linking predictions
- Multitasking model to jointly predict all data
- Enforce coherence on linking predictions
- Experiments with RRGparbank data
- Multilingual experiments

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