Leveraging Heterogeneous Data Sources for Relational Semantic Parsing

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Summary

Semantic parsing of natural language sentences consists of identifying semantic concepts and labeling their arguments. FrameNet and PropBank are both popular linguistic resources for semantic annotations, and were a result of substantial annotation efforts. Semantic parsing systems have so far used one of these resources to train models. Leveraging the knowledge from multiple resources will improve a parser's coverage of the semantic space. In this work, we present a preliminary exploration of the opportunities and challenges of learning semantic parsers from heterogeneous semantic annotation sources.

The goal of this work is to improve the performance of the frame-semantic parsing system called SEMAFOR[1] by tapping into PropBank-style annotations.

Towards this, we present:

- An analysis of the differences in the semantic coverage of two resources: FrameNet (FN) and PropBank (PB)
- An analysis of the mappings between FN and PB provided by another independent resource called SemLink[2]
- Candidate models for jointly learning a parser on the two resources

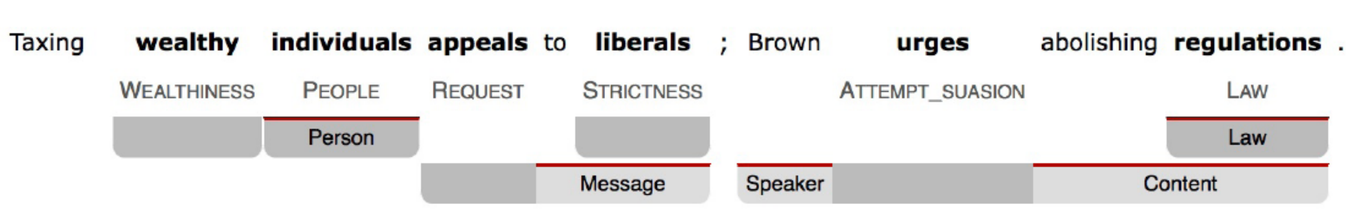
The main challenges that any joint model will need to address are:

- The annotations provided by each resource use a different schema: i.e. the label-spaces of the relations and the arguments differ
- Most concepts do not have a one-to-one mapping between the two resources despite being semantically related. This makes it difficult to transfer the annotations from one schema to the other
- The sentence-level annotation densities of the two resources is different and will influence learning
- A mechanism to incorporate the available noisy SemLink mappings

Another related challenge is that of evaluating such a joint model.

Background

Frame semantic parse from the SEMAFOR system for an example sentence:

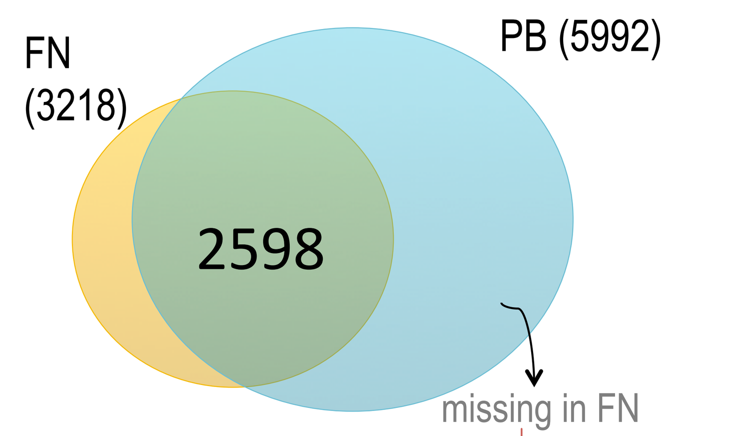


The semantic parse errors seen in the above sentence are for the following reasons:

- **appeals** is annotated with the wrong frame label, the correct being EXPERIENCER_OBJ. This frame currently has several predicates without annotations and "appeal" is one of them.
- **abolishing** is not associated with any frame label, because it is absent from the FN lexicon. It should be recognized as evoking the PROHIBITING frame, which contains synonymous verbs.
- **taxing** is not identified as a target. It is absent from the FN lexicon; further, none of the existing frames can accommodate it.

Coverage difference: FN and PB

Verb coverage:
FrameNet 1.5
– 3218 verb types
PropBank 1.7
– 5992 verb types



PB has ~6000 rolesets.

assign.01
ARG0 (assigner) ARG1 (thing assigned) ARG2 (assigned to)

FN has ~1100 frames.

GIVING
Donor Theme Recipient

involve
nominate
lurk
entice

assign
allot
allocate
designate

Potential frame:
GIVING

SemLink data analysis

- SemLink[2] maps multiple semantic resources: FrameNet, VerbNet, PropBank
- **Sentence-level mappings:** available on PB-WSJ section
  - PB-WSJ section has ~75,000 annotations
  - 50% have SemLink mappings
  - Of these 20% are usable due to noise and inconsistencies

Patient — liquidate.01
[McMoRan Energy Partners] will be [liquidated]
Victim — KILLING

- **Concept-level mappings:**

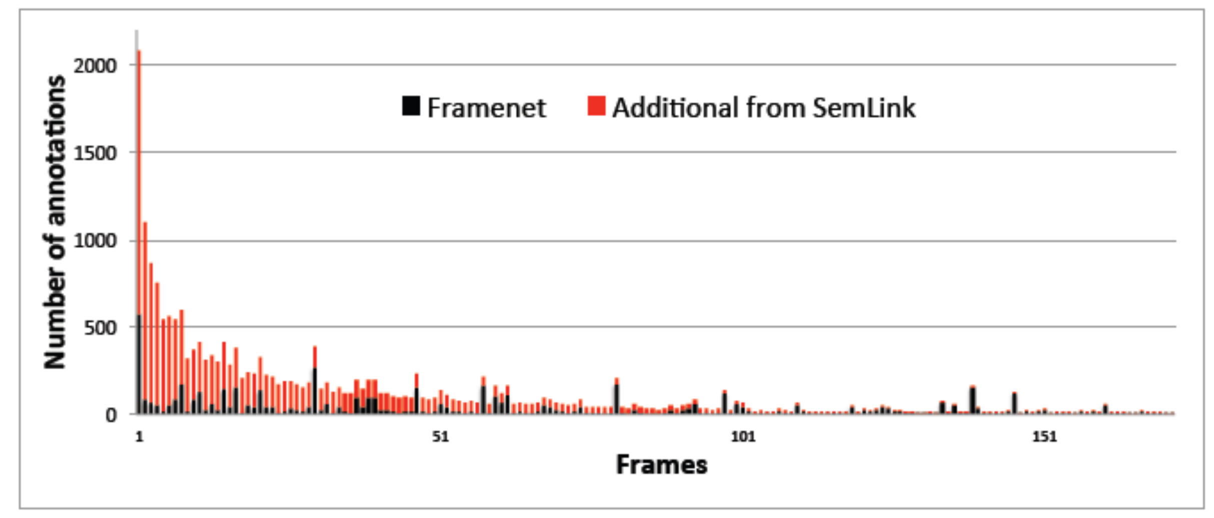
FrameNet frames		VerbNet role		PropBank rolesets
CURE EMPTYING WAKING_UP	⟷	45.4	⟷	bloody.01 capsize.01 christianize.01 ....

Statistics of PB-WSJ sentence-level mappings

FN frame annotation	PB verb tokens	% of all
Frame label = NF	14,624	20%
Frame label = IN	22,982	31%
Frame with no arguments	15,533	21%
Frame with at least 1 mappable argument	15,323	20%
Instances not mapped due to other issues	6,516	9%
Total	74,977	100%

- 51% of the frame labels are NF (no frame) suggesting there isn't an equivalent frame or IN (indefinite) suggesting ambiguity in mapping to an appropriate frame

Statistics of new mappings obtained from SemLink

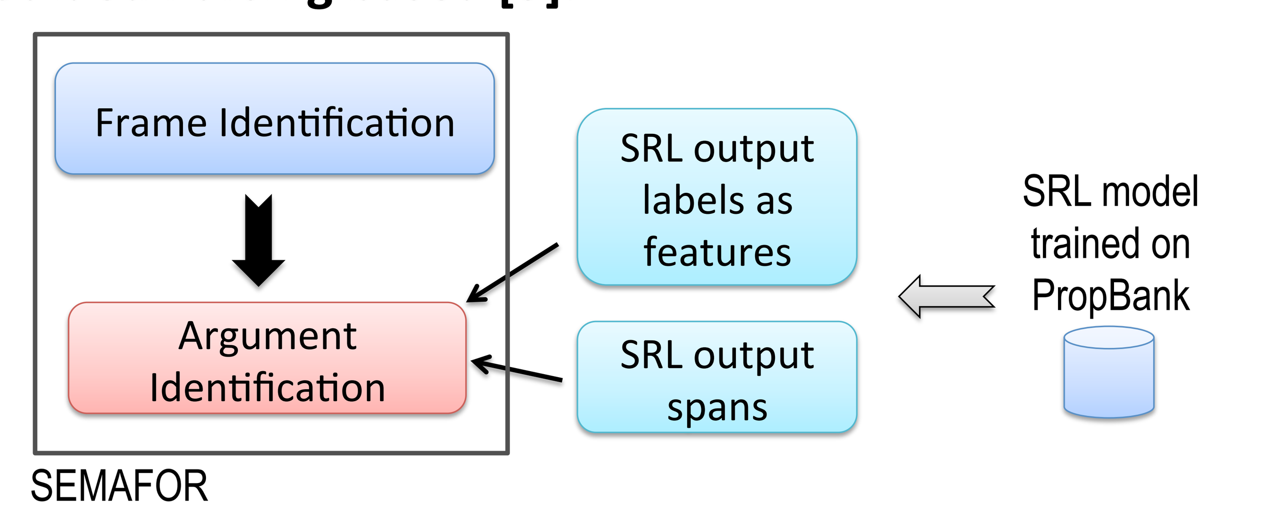


- The red portion of each bar shows the additional annotations obtained for that frame upon processing the SemLink mappings.
- FN has a total of ~1100 frames. 173 frames get additional annotations. STATEMENT frame gets the highest new annotations.

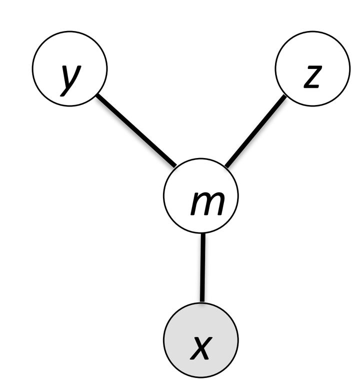
Models

The goal of this work is to improve the performance of the SEMAFOR system. The current system works in two key phases.
Frame Identification: selecting a frame for each target
Argument Identification: finding arguments and labeling them

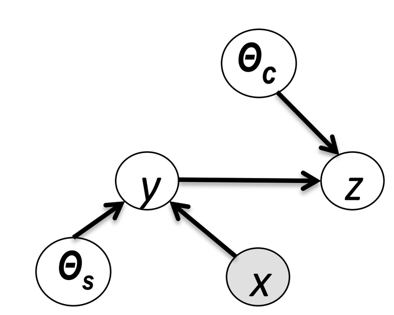
Guided Parsing based [3]:



Latent variable based:



x : features on the observed sentence
y : argument label from FN
z : argument label from PB
m : latent variable representing the semantic concept. Example: "kidnapper" and "abductor" are both "perpetrator" (hidden semantic concept)



Bayesian Decipherment[4] based model

Θ_c : channel parameters
Θ_s : source parameters

$$P(y|z, x) = P(z|y,x)\, P(y|x)$$

Multi-task learning based:

$$L_{fn}(\theta) + L_{sl}(\theta) + \lambda \, || \theta ||_2$$

L_{fn} : likelihood over FN data
L_{sl} : likelihood over SemLink

References

[1] Dipanjan Das, Nathan Schneider, Desai Chen, and Noah A. Smith. *Probabilistic frame-semantic parsing.* NAACL-HLT 2010.
[2] Claire Bonial, Kevin Stowe, and Martha Palmer. *Renewing and revising SemLink.* ACL 2014.
[3] Richard Johansson. *Training parsers on incompatible treebanks.* NAACL-HLT 2013.
[4] Sujith Ravi and Kevin Knight. *Deciphering Foreign Language.* ACL 2011.