Exploiting and Expanding Corpus Resources for Frame-Semantic Parsing

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(with Chris Dyer & Noah A. Smith)
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FrameNet + NLP = <3

• We want to develop systems that understand text

• Frame semantics and FrameNet offer a linguistically & computationally satisfying theory/representation for semantic relations
Roadmap

- A frame-semantic parser
- Multiword expressions
- Simplifying annotation for syntax + semantics
Frame-semantic parsing

SemEval Task 19 [Baker, Ellsworth, & Erk 2007]
Frame-semantic parsing

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  ▸ \textbf{frame} evoked by each LU
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• Given a text sentence, analyze its frame semantics. Mark:
  ▸ words/phrases that are *lexical units*
  ▸ **frame** evoked by each LU
  ▸ **frame elements** (role–argument pairings)

• Analysis is in terms of groups of tokens. No assumption that we know the syntax.
Robots in popular culture are there to remind us of the awesomeness of unbounded human agency.
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Desirability Existence Evoking People Organization
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<table>
<thead>
<tr>
<th>DESIRABILITY</th>
<th>EXISTENCE</th>
<th>EVOKING</th>
</tr>
</thead>
<tbody>
<tr>
<td>Evaluate</td>
<td></td>
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<tr>
<td>Entity</td>
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<tr>
<td>Stimulus</td>
<td>Phenomenon</td>
<td>Cognizer</td>
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</tbody>
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SEMAFOR

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  preprocessing → target identification →
  frame identification → argument
  identification
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• Heuristics + 2 statistical models
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• Preprocessing: syntactic parsing

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• Trained/tuned on English FrameNet’s full-text annotations
Full-text Annotations

+ American National Corpus Texts
1. Berlitz History of Greece
2. Berlitz History of Jerusalem
3. Berlitz History of Las Vegas
4. Berlitz Intro of Dublin
5. Berlitz Intro of Hong Kong
6. Berlitz Intro of Jamaica
7. Berlitz What to Do in Hong Kong
8. Berlitz Where to Go in Hong Kong
9. Children's home fund-raising letter
10. Children’s home fund-raising letter
11. Goodwill fund-raising letter
12. Goodwill fund-raising letter
13. Goodwill fund-raising letter
14. Goodwill fund-raising letter
15. Goodwill fund-raising letter
16. Goodwill fund-raising letter
17. journal_christine
18. journal_patrick
19. journal_ryan
20. journal.pbio.0020001
21. Slate magazine article: Entrepreneur as Madonna
22. Slate magazine article: Stephanopoulous Crimes

+ AQUAINT Knowledge-Based Evaluation Texts
+ LUCorpus-v0.3
+ Miscellaneous
+ Texts from Nuclear Threat Initiative website, created by Center for Non-Proliferation Studies
+ Wall Street Journal Texts from the PropBank Project

https://framenet.icsi.berkeley.edu/fndrupal/index.php?q=fulltextIndex
Full-text annotations

1. Stephanopoulos Analyzes His Own Crime
   Committing crime
2. There was FORMER Heartbroken
   Furrow-browed and
   "Heartbroken"
   Clinton aide George Stephanopoulos on ABC's This Week this morning,
   "with all the Evidence"
   Coming out "against the" the Lewinsky story was only a
   Stephanopoulos popped up on Good Morning America to demonstrate
   his Concern
   "These are Probably"
   The most Serious
   Allegations
   He leveled against the President
   "There is no Question
   They could lead to impeachment proceedings."

...
SEMAFOR

[Das, Schneider, Chen, & Smith 2010]
• SEMAFOR’s models consist of features over observable parts of the sentence (words, lemmas, POS tags, dependency edges & paths) that may be predictive of frame/role labels

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• Full-text annotations as training data for (semi)supervised learning

• Extensive body of work on semantic role labeling [starting with Gildea & Jurafsky 2002 for FrameNet; also much work for PropBank]

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[Das et al. 2013 to appear]
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- State-of-the-art performance on SemEval’07 evaluation (outperforms the best system from the task, Johansson & Nugues 2007)

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• State-of-the-art performance on SemEval’07 evaluation (outperforms the best system from the task, Johansson & Nugues 2007)

• On SE07: \( [F] 74\% \) \( [A] 68\% \) \( [F\rightarrow A] 46\% \)
  On FN1.5: \( [F] 91\% \) \( [A] 80\% \) \( [F\rightarrow A] 69\% \)

[Das et al. 2013 to appear]
SEMAFOR

[Das, Schneider, Chen, & Smith 2010]

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  On FN1.5: [F] 91% [A] 80% [F→A] 69%
  [Das et al. 2013 to appear]

• BUT: This task is really hard. Room for improvement at all stages.
SEMAFOR Demo

http://demo.ark.cs.cmu.edu/parse
How to improve?

• Better modeling with current resources?
• Ways to use non-FrameNet resources?
• Create new resources?
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• Better modeling with current resources?
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Better Modeling?

• We already have over a million features.

• better use of syntactic parsers (e.g., better argument span heuristics, considering alternative parses, constituent parsers)

• recall-oriented learning? [Mohit et al. 2012 for NER]

• better search in decoding [Das, Martins, & Smith 2012]

• joint frame ID & argument ID?
Use Other Resources?

- FN1.5 has just 3k sentences/20k targets in full-text annotations. **data sparseness**
- semisupervised learning: reasoning about unseen predicates with distributional similarity [Das & Smith 2011]
- NER? supersense tagging?
- use PropBank → FrameNet mappings to get more training data?
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Multiword Expressions

Christmas Day.n  Losing it:
German measles.n  lose it.v
along with.prep  go ballistic.v
also_known_as.a  flip out.v
armed forces.n  blow cool.v
bear arms.v  freak out.v
beat up.v
double-check.v
Multiword Expressions

- 926 unique multiword LUs in FrameNet lexicon
  - 545 w/ space, 222 w/ underscore, 177 w/ hyphen
  - 361 frames have an LU containing a space, underscore, or hyphen
- support constructions like ‘take a walk’: only the N should be frame-evoking [Calzolari et al. 2002]
I took an aspirin.

I take aspirin for headaches.
I took an aspirin.

I take aspirin for headaches.
Fred took off his shoes.
Fred took off his shoes.
Fred took off his shoes.

**Correct Model:**
- **Conquering:**
  - **Figure:**
  - **Ground:**
- **Clothing**
  - **Garment:**
- **Locative Relation**
  - Theme
...even though take break.v is listed as an LU!
(probably not in training data)
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...even though \textit{take break.} is listed as an LU!
(probably not in training data)
• There has been a lot of work on specific kinds of MWEs (e.g. noun-noun compounds, phrasal verbs) [Baldwin & Kim, 2010]
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◦ Special datasets, tasks, tools

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  ▸ Special datasets, tasks, tools

• Can MWE identification be formulated in an open-ended annotate-and-model fashion?

  ▸ Linguistic challenge: understanding and guiding annotators’ intuitions
MWE Annotation

• We are annotating the 50k-word Reviews portion of the English Web Treebank with multiword units (MWEs + NEs)
MWE Annotation

It is right on the hustle and bustle of Wisconsin Ave but some might miss it as it is nestled in between Subway Sandwiches and Modell 's.

It is right on the hustle_and_bustle of Wisconsin_Ave but some might miss it as it is nestled in_between Subway_Sandwiches and Modell_'s.
Examples

• My wife had taken her '07 Ford Fusion in for a routine oil change.

• The education is horrible at best, do society a favor, and do NOT send your student here.

• He called the next day to see if everything was to my satisfaction.

• After they showed up there was a little trouble to get my car unlocked, it took quite a bit of time but the job was well done.
MWE Annotation

• Eventual goal: train a system to detect multiword lexical items (including discontiguous ones)

• Replace or supplement SEMAFOR’s target identification phase
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• My wife had taken her '07 Ford Fusion in for a routine oil change.

My > wife > had < [taken in] < ['07 Ford Fusion] < her 
[taken in] < for < [oil change]
a > [oil change] < routine
• My wife had taken her '07 Ford Fusion in for a routine oil change.

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wife :: Personal_relationship
[taken in] :: Bringing
['07 Ford Fusion] :: Vehicle/NE
routine :: Typicality?
[oil change] :: ?
Lightweight Syntax + Semantics

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Full-text Annotations

1. Stephanopoulos Analyzes His Own CRIME Committing crime

2. THERE Locative relation was FORMER HEARTBROKEN furrow-browed and "HEARTBROKEN"

Clinton aide George Stephanopoulos on ABC 's This Week this morning, with all the EVIDENCE Evidence coming out "against the

PRESIDENT Leadership Last WEEK WHEN

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LEAD Leadership THERE

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Amateur Frame Annotation

Stephanopoulos: **NE** Analyzes: **Scrutiny** His Own Crime: **Committing_crime**
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There was: **Existence** *Locative relation* former: **Time vector**
Clinton: NE aide: **Subordinates_and_superiors** *
George Stephanopoulos: NE on ABC: NE 's This_Week: NE this morning: **Calendric_unit**,
furrow-browed: **Observable_body_parts** * and ~~
heartbroken: **Emotion_directed** with all the evidence: **Evidence coming_out:** * " against the president: **People_by_vocation** *Leadership .
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- Is an ‘aide’ someone who is Assisting, or someone who is the object of Employing, or one of Subordinates_and_superiors (like ‘assistant’)?
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- ‘president’: Leadership? or People_by_vocation?
Amateur Frame Annotation

Last week: *Calendric_unit*, when the Lewinsky: *NE* story: *Text* was only a few: *Quantified_mass* hours: *Measure_duration* old: *Age*, Stephanopoulos: *NE* popped_up: *Arrive* on Good_Morning_America: *NE* to demonstrate: *Cause_to_perceive* his concern: *Emotion_directed*.

- want a Journalism frame for ‘story’
- want Make_appearance for ‘pop up’
Amateur Frame Annotation
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• Is this feasible?
Amateur Frame Annotation

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- Challenges: lexicon coverage (LUs & frames); large number of frames; deciding which frame is most appropriate when there are multiple facets of meaning
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• Many open issues in how to structure the annotation: e.g., Should annotators proceed token-by-token, predicate-by-predicate, or frame-by-frame? [cf. Kilgarriff 1998, Garrette & Baldridge 2013]
Summary
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• The SEMAFOR system is state-of-the-art for frame-semantic parsing
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- Others likely due to data sparseness
  - We are exploring relatively cheap forms of semantic annotation that should be useful
- Thanks for listening & discussion!