

Frame-Semantic Parsing

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May 31, 2015 ■ FrameNet Tutorial at NAACL-HLT

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

Frame-semantic Parsing

SemEval Task 19 [Baker, Ellsworth, & Erk 2007]

- 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.

FrameNet SRL, Parsing: Early Work

- The original SRL paper actually used FrameNet (Gildea & Jurafsky 2002).
Also Thompson et al. 2003 (w/ frame ID),
Fleischman et al. 2003, Padó & Lapata 2005,
Erk & Padó 2006, Matsubayashi et al. 2009,
Fürstenauf & Lapata 2009.
- SemEval 2007 shared task (Baker et al. 2007): full-text annotations.
Best system by Johansson & Nugues.

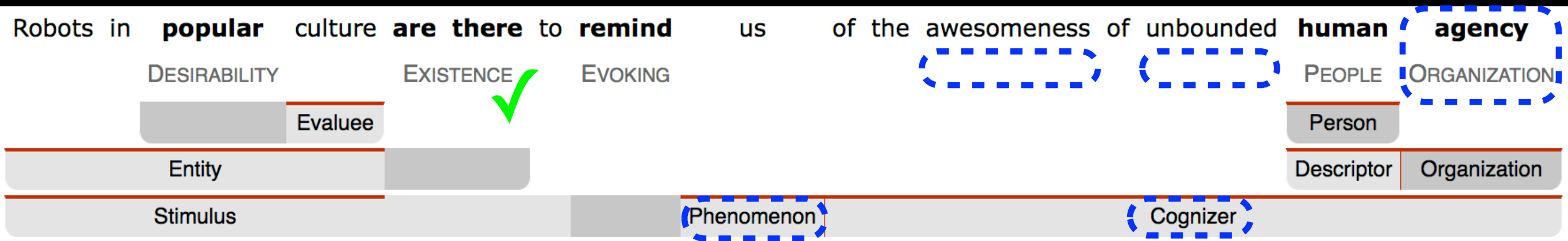
SEMAFOR

[Das, Schneider, Chen, & Smith 2010]

Robots in **popular** culture **are there** to **remind** us of the awesomeness of unbounded **human** **agency**

SEMAFOR

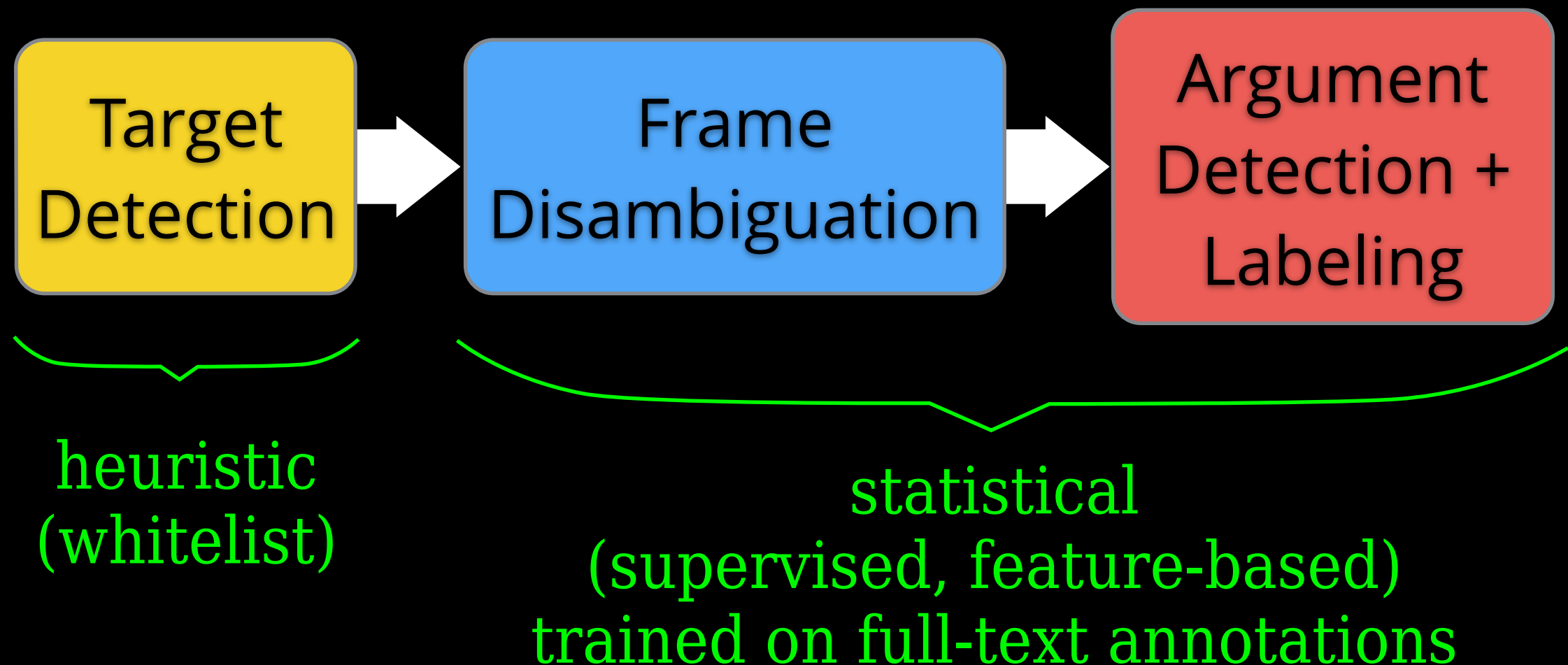
[Das, Schneider, Chen, & Smith 2010]



The SEMAFOR Pipeline

[Das, Schneider, Chen, & Smith 2010]

Preprocessing: syntactic dependency parser



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: Stephanopoulos 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**_{Locative_relation} was **FORMER**_{Time_vector} **Clinton** aide **George Stephanopoulos** on **ABC** 's **This Week this morning** ,
furrow-browed and `` **HEARTBROKEN**_{Emotion_directed} with all the **EVIDENCE**_{Evidence} coming out " against the
PRESIDENT_{Leadership} . Last **WEEK**_{Calendric_unit} , **WHEN**_{Temporal_collocation} the **Lewinsky** story was only **A**_{Quantified_mass}
FEW_{Quantified_mass} **HOURS**_{Measure_duration} **OLD**_{Age} , **Stephanopoulos** popped up on **Good Morning America** to demonstrate
his **CONCERN**_{Emotion_directed} . `` These are **PROBABLY**_{Likelihood} the most **SERIOUS**_{Importance} **ALLEGATIONS**_{Statement} yet
leveled against the **PRESIDENT**_{Leadership} . **THERE**_{Existence} 'S_{Existence} no **QUESTION**_{Point_of_dispute} that , if they 're true ,
they ... could **LEAD**_{Causation} 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**
- 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]

SEMAFOR

[Das, Schneider, Chen, & Smith 2010]

- 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→A] 46%
On FN1.5: [F] 91% [A] 80% [F→A] 69%
[Das et al. 2014]
- BUT: This task is really hard. Room for improvement at all stages.

SEMAFOR Demo

<http://demo.ark.cs.cmu.edu/parse>

So Amelia Bedelia sat right down
and she drew those drapes.



How to improve?

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



Karl Moritz
Hermann



Oscar
Täckström



Dipanjan Das

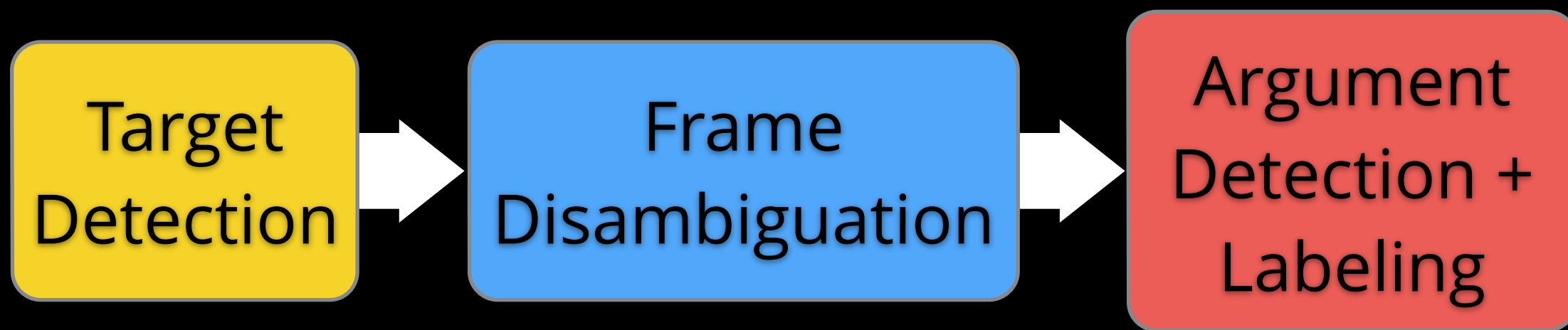


Sam
Thomson

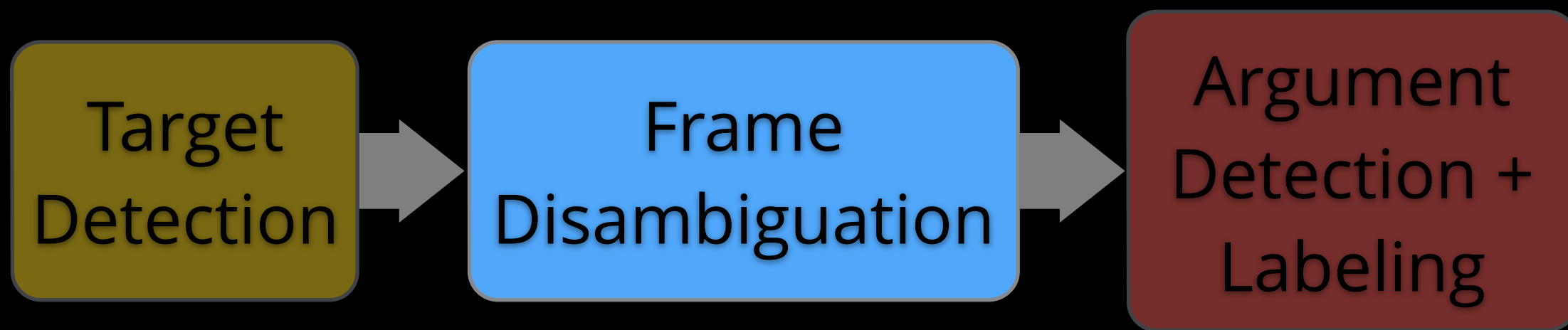


Meghana
Kshirsagar

Advances in Modeling



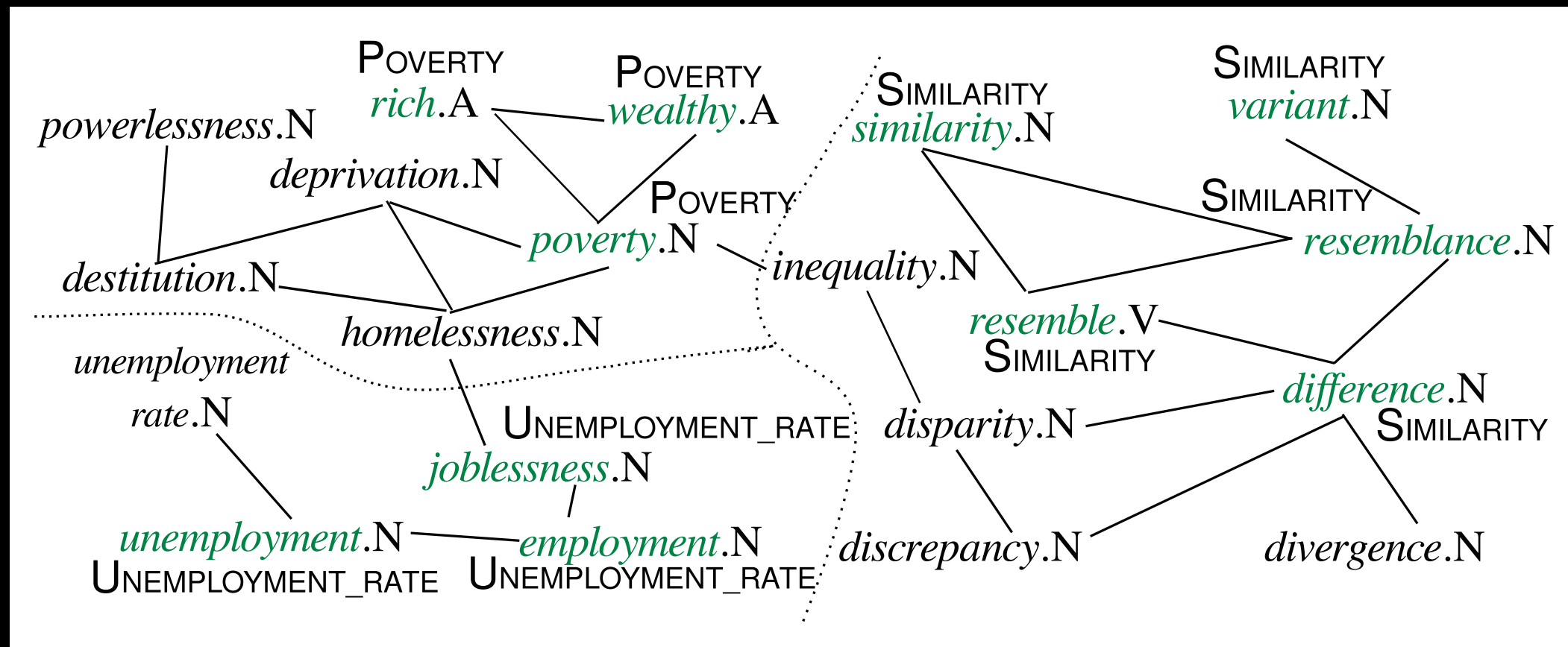
Advances in Modeling



Unknown Predicates

- **Problem:** Many frame-evoking predicates are seen neither in lexicon nor training data. How, then, to assign the correct frame?
- **Solution:** Propagate frame labels from known predicates to unknown predicates in a similarity graph. [Das & Smith 2011, 2012 / 2014]

Unknown Predicates



Word Representations

- **Problem:** With little training data, many features are too infrequent to be useful—particularly for rare/unseen words.
- **Solution:** Learn word embeddings that are predictive of frame labels (neural network).
[Hermann et al. 2014]

Advances in Modeling



Constraints on Argument Combinations

- **Problem:** A frame's arguments should not overlap, but this means classification decisions are not independent.
 - Also, some frames define hard Requires/Excludes constraints over role pairs.
- **Solution 1:** Beam search (approximate).
[Das et al. 2010 / 2014]
- **Solution 2:** Dual decomposition (exact).
[Das et al. 2012 / 2014]
- **Solution 3** (Google's variant of SEMAFOR): Label arguments with dynamic programming. [Täckström et al. 2015]

Constraints on Argument Combinations

Agent
Austria , once expected to **waltz** SELF_MOTION smoothly into the European Union , is elbowing COLLABORATION its partners ,
Self_mover Manner Manner Goal CONDUCT Partner_1 Partner_2
treading on toes and pogo-dancing in a most un-Viennese **manner** .

Conclusion

- SEMAFOR system from CMU has been applied to tasks as diverse as stock prediction and spoken dialogue segmentation

<http://www.ark.cs.cmu.edu/SEMAFOR/>

<http://demo.ark.cs.cmu.edu/parse>

- Ongoing research at CMU, Google, & elsewhere!

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