The Denoised Web Treebank

Evaluating Dependency Parsing under Noisy Input Conditions

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OVERVIEW

- Novel benchmark for dependency parsing of noisy Web data.
- Our contributions:
  - Treebank
  - Evaluation of noise-aware parsing
  - Experiments

MAIN FINDINGS

- Text normalization improves parse quality on noisy content.
- Normalization works better above the word level.
- Treebank and evaluation metric: http://jodaiber.de/DenoisedWebTreebank

DATA

- 500 English Tweets randomly selected from 24h time window (07/01/2012).
- Manual language identification to avoid bias towards well-formed sentences.

TREEBANKS FOR NOISY CONTENT

Name	# Trees	OOV	Style	Norm.
EWT [1]	16.6k	28%	C+D	No
Foster [2]	1k	25%	C	No
Foreebank [3]	1k	29%	C	Yes
Tweebank [4]	929	48%	D	No
This work	**500**	**31%**	**D**	**Yes**

REFERENCES

[1] Slav Petrov and Ryan McDonald. Overview of the 2012 shared task on parsing the web. In *SANCL 2012*.

[2] Jennifer Foster et al. From news to comment: Resources and benchmarks for parsing the language of web 2.0. In *IJCNLP 2011*.

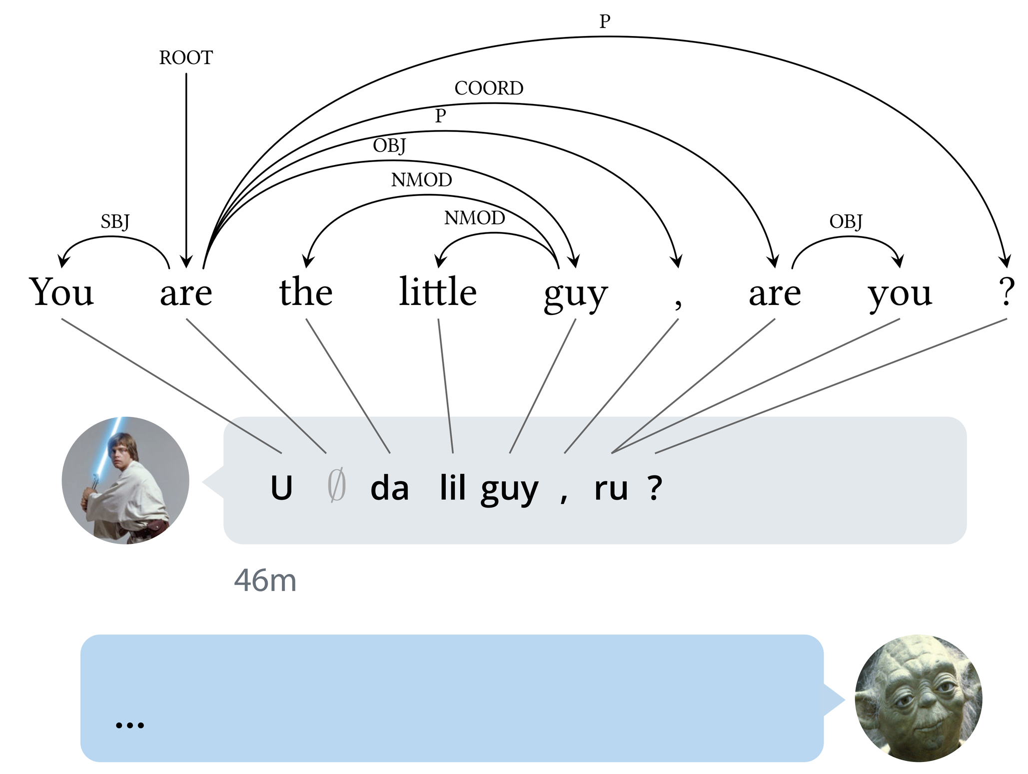
[3] Rasoul Kaljahi et al. Foreebank: Syntactic analysis of customer support forums. In *EMNLP 2015*.

[4] Lingpeng Kong et al. A dependency parser for Tweets. In *EMNLP 2014*.

[5] Ryan McDonald et al. Non-projective dependency parsing using spanning tree algorithms. In *EMNLP 2013*.

[6] Bo Han and Timothy Baldwin. Lexical normalisation of short text messages: Makn sens a #twitter. In *ACL 2011*.

TREEBANK



Normalization

- Spelling
- Abbreviations are split (e.g. *cu*)
- Twitter-specific elements
- Zero copulas: Align to empty surface token
- Keeping alignment information

Syntactic annotation

- Syntactic annotation on normalized layer
- Manually annotated POS tags and dependencies (annotated in 2 passes)
- Careful treatment of Twitter-specific items

EVALUATION OF NOISE-AWARE PARSING

We evaluate:

$D_P = \langle V_P, E_P \rangle \leftarrow$ predicted dependency tree
$D_G = \langle V_G, E_G \rangle \leftarrow$ gold dependency tree
$a_P, a_G \leftarrow$ alignment functions to original text

Aligned precision and recall

- Collect gold and predicted dependencies and the original tokens they align to:

$$M_G = \{\langle a_G(w_i), a_G(w_j)\rangle \mid \langle w_i, r, w_j\rangle \in E_G\}$$
$$M_P = \{\langle a_P(w_i), a_P(w_j)\rangle \mid \langle w_i, r, w_j\rangle \in E_P\}$$

- Calculate gold/predicted overlap:
  - $|M_G \cap M_P|$ true positives
  - $|M_P \setminus M_G|$ false positives
  - $|M_G \setminus M_P|$ false negatives
- Labeled/unlabeled aligned F_1 score:

$$F_1 = 2 \cdot \frac{P \cdot R}{P + R}$$
$$P = \frac{TP}{TP + FP} \qquad R = \frac{TP}{TP + FN}$$

- Only 1-to-1 alignments ⇒ UAS/LAS

EXPERIMENTS: EVALUATING THE EFFECT OF TEXT NORMALIZATION ON PARSING

Normalization method	Unlabeled F_1	Labeled F_1
No normalization (Vanilla MST[5])	72.41	60.16
+ Twitter syntax rules	76.17*	64.38*
Unsupervised lexical normalization [6]	76.36*	64.80*
Machine translation	76.85*	65.38*
Unsupervised lexical normalization + MT	77.08*	65.57*
Gold normalization, predicted tags	78.20*	68.02*
Gold normalization, gold tags	79.28*	69.85*

* statistically significant against non-normalized baseline at p-value < 0.05.

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