Outline

100% Independent UD Annotation for Tweets

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MoNoise treebank (van der Goot and van Noord, 2018)

- 632 weets, 10,015 words
- Train on EWT (domain-adaptation)
- 1 annotator
- Paper: effect of normalization

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Tweebank 2.0 (Liu et al, 2018)

- 3550 tweets, 111,214 words
- Train on tweets (+EWT)
- 18 annotators
- Paper: Build ensemble, and make this more efficient

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Both contain data from Owoputi et al. (2013)!

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Did this happen before?

100% Independent UD Annotation for Tweets

Did this happen before?

- Bamman, David, Francesco Mambrini & Gregory Crane (2009), An ownership model of annotation: The Ancient Greek dependency treebank. In: *Proceedings of the Eighth International Workshop on Treebanks and Linguistic Theories (TLT 8)*. Groningen, 5–15. Available at: http://www.perseus.tufts.edu/~ababeu/tlt8.pdf.
- Berzak, Yevgeni, Yan Huang, Andrei Barbu, Anna Korhonen & Boris Katz (2016), Anchoring and Agreement in Syntactic Annotations. In: *Proceedings of EMNLP 2016*. Austin, TX, 2215–2224.
- Berzak, Yevgeni, Jessica Kenney, Carolyn Spadine, Jing Xian Wang, Lucia Lam, Keiko Sophie Mori, Sebastian Garza & Boris Katz (2016), Universal Dependencies for Learner English. In: *Proceedings of ACL 2016*. Berlin, Germany, 737–746. Available at: http://www.aclweb.org/anthology/P16-1070.
- Liu, Yijia, Yi Zhu, Wanxiang Che, Bing Qin, Nathan Schneider & Noah A. Smith (2018), Parsing Tweets into Universal Dependencies. In: *Proceedings of NAACL 2018*. New Orleans, LA, 965–975. Available at: http://aclweb.org/anthology/N18-1088.
- Nguyen, Kiem-Hieu (2018), BKTreebank: Building a Vietnamese Dependency Treebank. In: *Proceedings of LREC 2018*. Miyazaki, Japan, 2164–2168. Available at: http://www.lrec-conf.org/proceedings/lrec2018/pdf/69.pdf.
- Seddah, Djamé, Eric De La Clergerie, Benoît Sagot, Héctor Martínez Alonso & Marie Candito (2018), Cheating a Parser to Death: Data-driven Cross-Treebank Annotation Transfer. In: *Proceedings of LREC 2018*. Miyazaki, Japan, 4535–4539. Available at: http://www.lrec-conf.org/proceedings/lrec2018/pdf/1101.pdf.
- Seyoum, Binyam Ephrem, Yusuke Miyao & Baye Yimam Mekonnen (2018), Universal Dependencies for Amharic. In: *Proceedings of LREC 2018*. Miyazaki, Japan, 2216–2222. Available at: http://www.lrec-conf.org/proceedings/lrec2018/pdf/565.pdf.
- Skjærholt, Arne (2014), A Chance-corrected Measure of Inter-annotator Agreement for Syntax. In: *Proceedings of ACL 2014*. Baltimore, MD, 934–944. Available at: http://www.aclweb.org/anthology/P14-1088.

Thanks to Amir Zeldes and the corpora-list

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For tweets (inter-annotator agreement in 1 paper):

POS	96.6%
unlabeled dependencies	88.8%
labeled dependencies	84.3%

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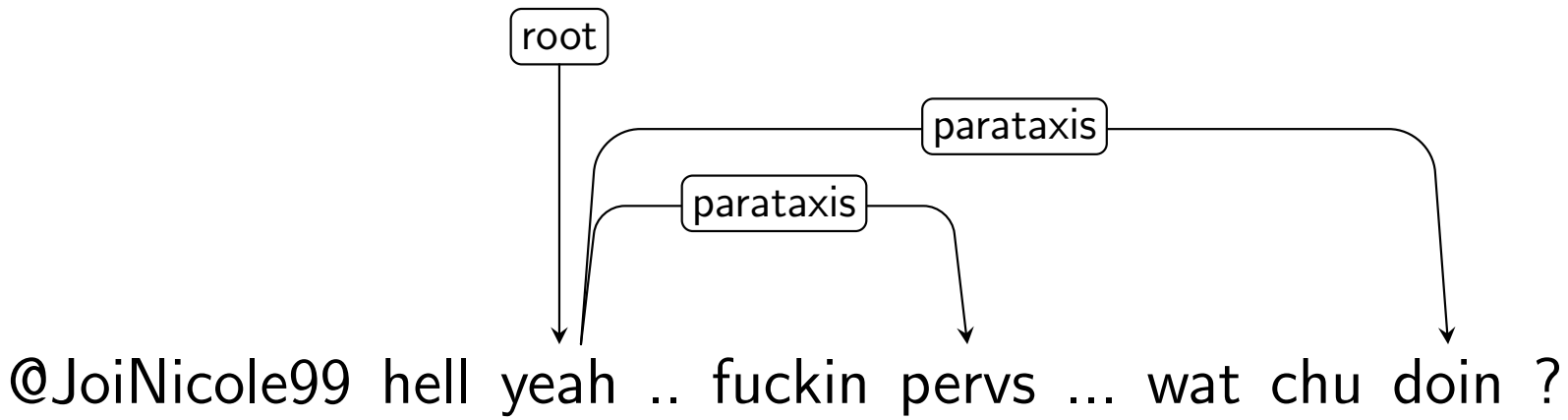
Different guidelines (me):



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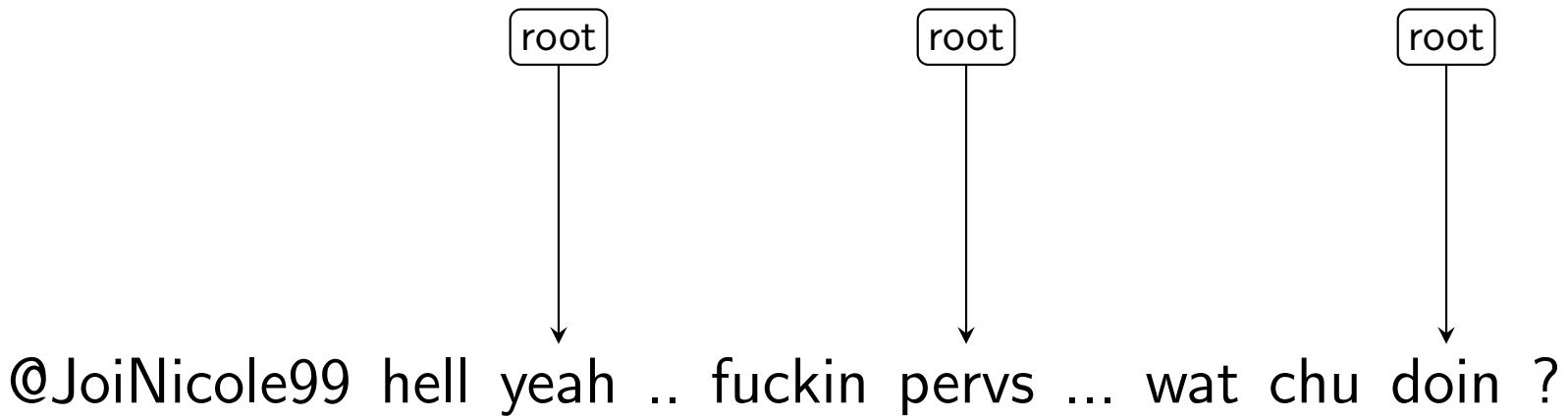
Different guidelines (them):



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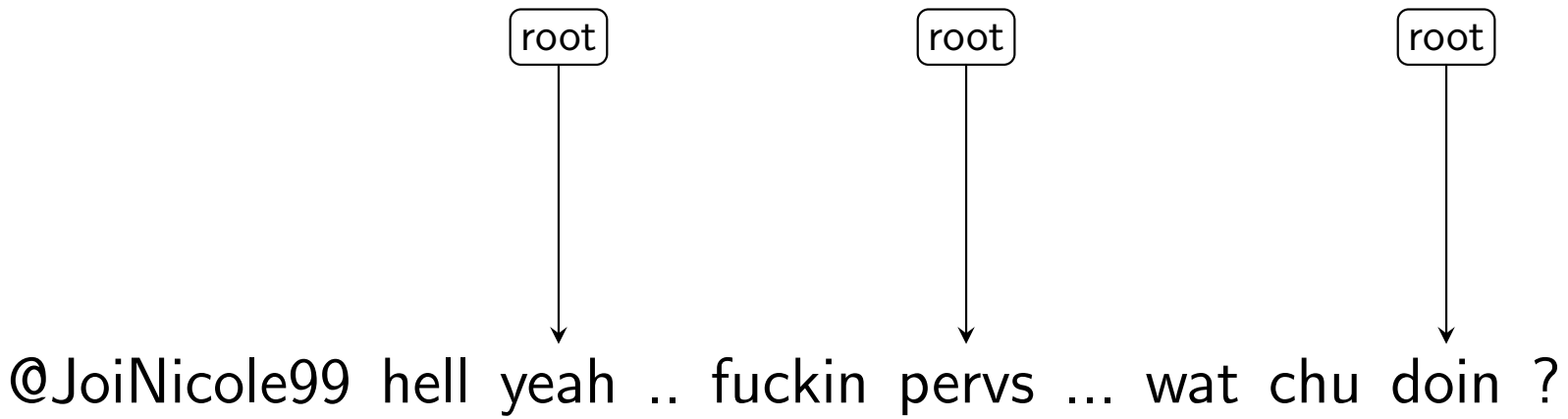
Different guidelines (them):



Easy to converge (rule-based)

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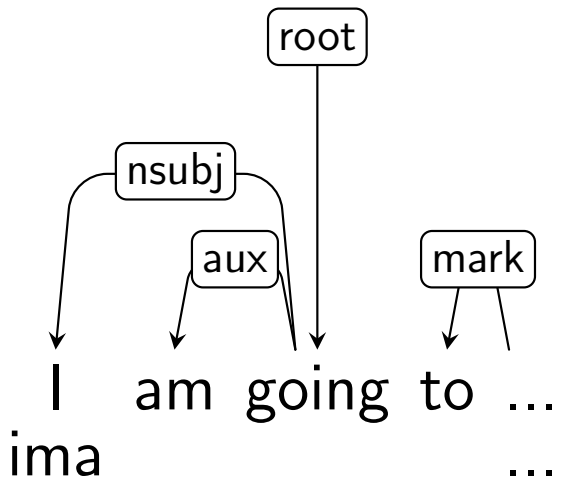
Different guidelines (me):



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Different guidelines (them):

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Different guidelines (them):

Bit harder to converge (not done yet)

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Other things:

- I leave phrasal abbreviations as is (they acronyms)

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- urls: `X, appos` versus `X, list`

100% Independent UD Annotation for Tweets

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- RT: `X, discourse`

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Other things:

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- emoticon & emoji: `SYMB, appos`
- urls: `X, appos` versus `X, list`
- username mentions: `PROPN, vocative`
- RT: `X, discourse`
- Annotate accordingly when above things are used in syntactic context

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first try:

- ID match
- 126 found

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second try:

- character edit distance
- Ignore whitespace, username and allow for 20% variation
- 142 found

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why 20% variation?

```
rt@userwho'seversmokedbeforetheytookatestatschool?/*raise
rt@userwho'seversmokedbeforetheytookatestatschool?/*raise

imhome:)
imhome:-)

\@user601blueroommay19thfemsfreeanddrinkfreetil11:30$5all
\@iamyungsmilezblueroommay19thfemsfreeanddrinkfreetil11:3
```

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```
==> outputRob <==
# sent_id = owoputi.406.28857809439
# text = Yall sholl is quiet!! SPEAK UP lol RT @MzCHinezeEyez: @McQSpeaks We Still Here!!....lol
1       Y       _       PRON    _       _       5       nsubj   _       Norm=you|SpaceAfter=No
2       all     _       DET     _       _       1       det     _       Norm=all
3       sholl   _       AUX     _       _       5       aux     _       Norm=should
4       is      _       AUX     _       _       5       cop     _       Norm=be
5       quiet   _       ADJ     _       _       0       root    _       Norm=quiet|SpaceAfter=No
6       !!      _       PUNCT   _       _       5       punct   _       Norm=!!
7       SPEAK   _       VERB    _       _       5       parataxis       _       Norm=SPEAK
8       UP      _       ADP     _       _       7       compound:prt    _       Norm=UP

==> outputTweebank.fixed.fixed <==
# tweet_id = oct27.28857809439
# text = Yall sholl is quiet!! SPEAK UP lol RT @MzCHinezeEyez: @McQSpeaks We Still Here!!....lol
1       Yall    yall    PRON    O       _       4       nsubj   NormType=contraction|NormWord=you_all
_
2       sholl   sholl   ADV     R       _       4       advmod  _       _
3       is      be      AUX     V       _       4       cop     _       _
4       quiet   quiet   ADJ     A       _       0       root    _       SpaceAfter=No
5       !!      !       PUNCT   ,       _       4       punct   _       _
6       SPEAK   speak   VERB    V       _       4       parataxis       _       _
7       UP      up      ADP     T       _       6       compound:prt    _       _
8       lol     lol     INTJ    !       _       6       discourse       _       _
```

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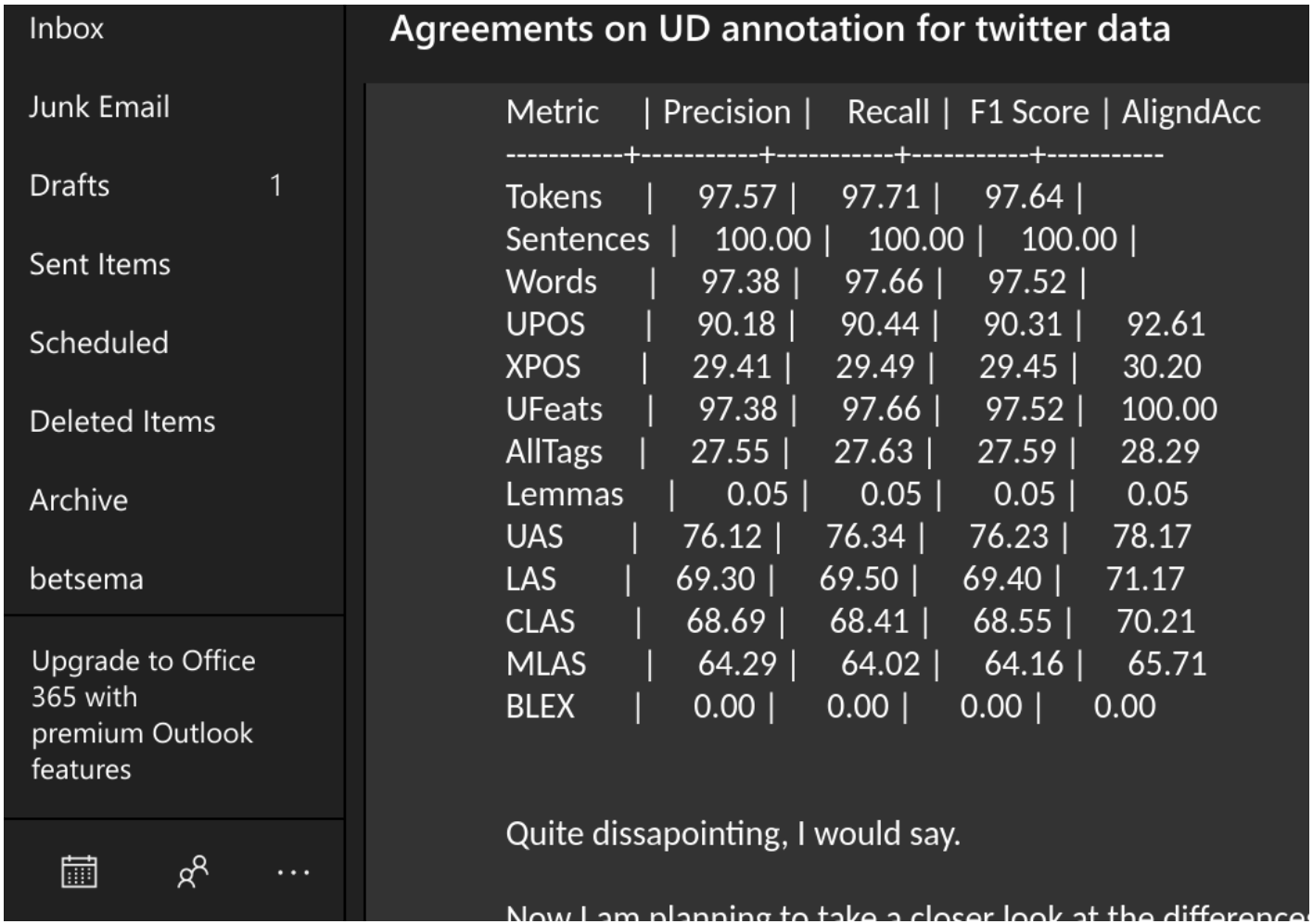
First test, `conll18_ud_eval.py`:

Metric	Precision	Recall	F1 Score	AligndAc
Tokens	97.57	97.71	97.64	
Sentences	100.00	100.00	100.00	
Words	97.38	97.66	97.52	
UPOS	90.18	90.44	90.31	92.6
UAS	76.12	76.34	76.23	78.1
LAS	69.30	69.50	69.40	71.1
CLAS	68.69	68.41	68.55	70.2

100% Independent UD Annotation for Tweets



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Answer:

```
Thanks for the experiments. The number seemed OK to me ..
```

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Answer:

`Thanks for the experiments. The number seemed OK to me ..`

Conclusion: we do not agree...

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`eval.pl` by Yuval Krymolowski

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```
p270396@vesta1:udNew$ perl eval.pl -g outputTweebank.fixe
Word/pos mismatch, line 1:
 gold: # tweet_id = oct27.28857809439
 sys : # sent_id = owoputi.406.28857809439
Word/pos mismatch, line 3:
 gold: 1    Yall    yall    PRON    O    _    4    nsubj    N
 sys : 1    Y    _    PRON    _    _    5    nsubj    _    Norm=
Word/pos mismatch, line 4:
 gold: 2    sholl    sholl    ADV R    _    4    advmod    _    _
 sys : 2    all _    DET _    _    1    det _    Norm=all
Word/pos mismatch, line 5:
 gold: 3    is  be  AUX V    _    4    cop _    _
 sys : 3    sholl    _    AUX _    _    5    aux _    Norm=shou
Word/pos mismatch, line 6:
 gold: 4    quiet    quiet    ADJ A    _    0    root    _    S
 sys : 4    is  _    AUX _    _    5    cop _    Norm=be
```

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For now:

- Filtered, only tweets with same tokenization
- 114 tweets left

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5 focus words where most of the errors occur:

	any	head	dep	both
lol / _	4	4	1	1
it / _	4	1	4	1
RT / _	4	4	0	0
that / _	4	1	3	0
me / _	4	3	4	3

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1. head one word after the correct head (after the focus word), correct dependency : 11 times
2. dependency "root" instead of "parataxis" : 11 times
3. head one word before the correct head (after the focus word), correct dependency : 11 times
4. dependency "aux" instead of "cop" : 5 times
5. dependency "discourse" instead of "parataxis" : 5 times
6. dependency "advcl" instead of "parataxis" : 5 times

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Incoming labels I used where they did not:

parataxis	46
discourse	24
root	22
obj	18
nsubj	16
xcomp	12
advcl	9
compound	9
obl	9
advmod	8

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Incoming labels they used where I did not:

vocative	23
discourse	22
root	22
advcl	20
advmod	17
nsubj	17
obl	15
compound	13
ccomp	12
aux	9

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(Preliminary) conclusion: Most mistakes made for:

- vocative
- discourse
- root
- parataxis

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(Preliminary) conclusion: Most mistakes made for:

- vocative
- discourse
- root
- parataxis
- LAS might sketch a too negative image

100% Independent UD Annotation for Tweets

Next:

- Get parser performance for both (train on EWT)
- MaltEval
- More manual analysis
- Merge styles
- ...

Outline

Effect of Normalization Categories on Parsing

Effect of Normalization Categories on Parsing

Thesis:

- Evaluating normalization per category
- Effect of normalization on parsing

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- Logical follow up: evaluating effect normalization categories for parsing

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Effect of Normalization Categories on Parsing

Tyler Baldwin, Yunyao Li. 2015. An In-depth Analysis of the Effect of Text Normalization in Social Media. In *Proceedings of NAACL*.

Effect of Normalization Categories on Parsing

So why do it again?

Effect of Normalization Categories on Parsing

Their taxonomy:

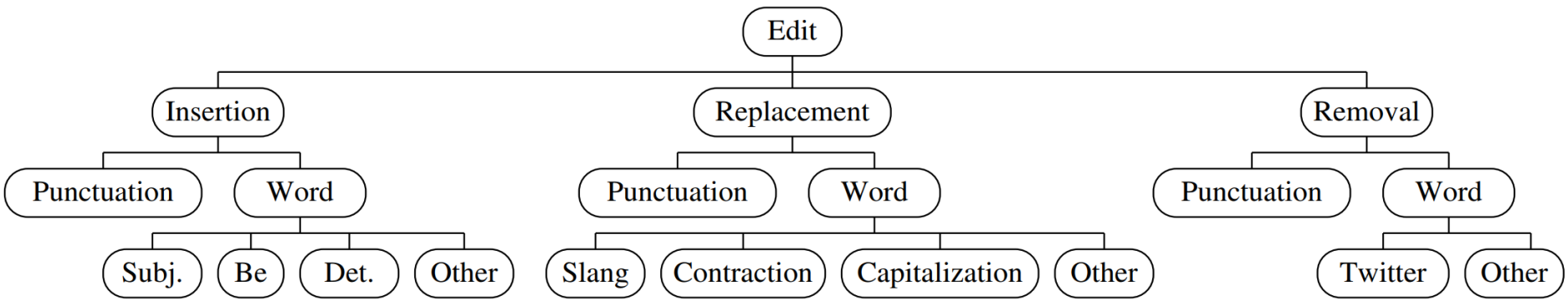


Figure 1: Taxonomy of normalization edits

Effect of Normalization Categories on Parsing

Their taxonomy:

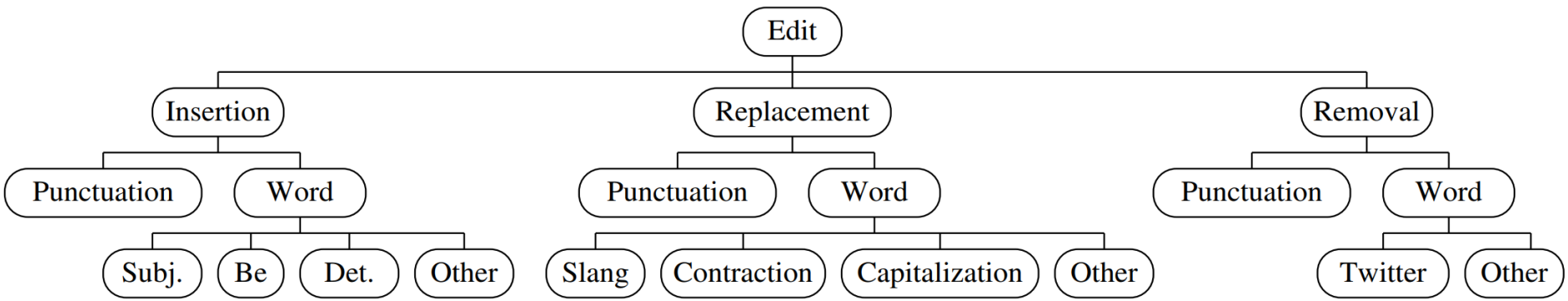


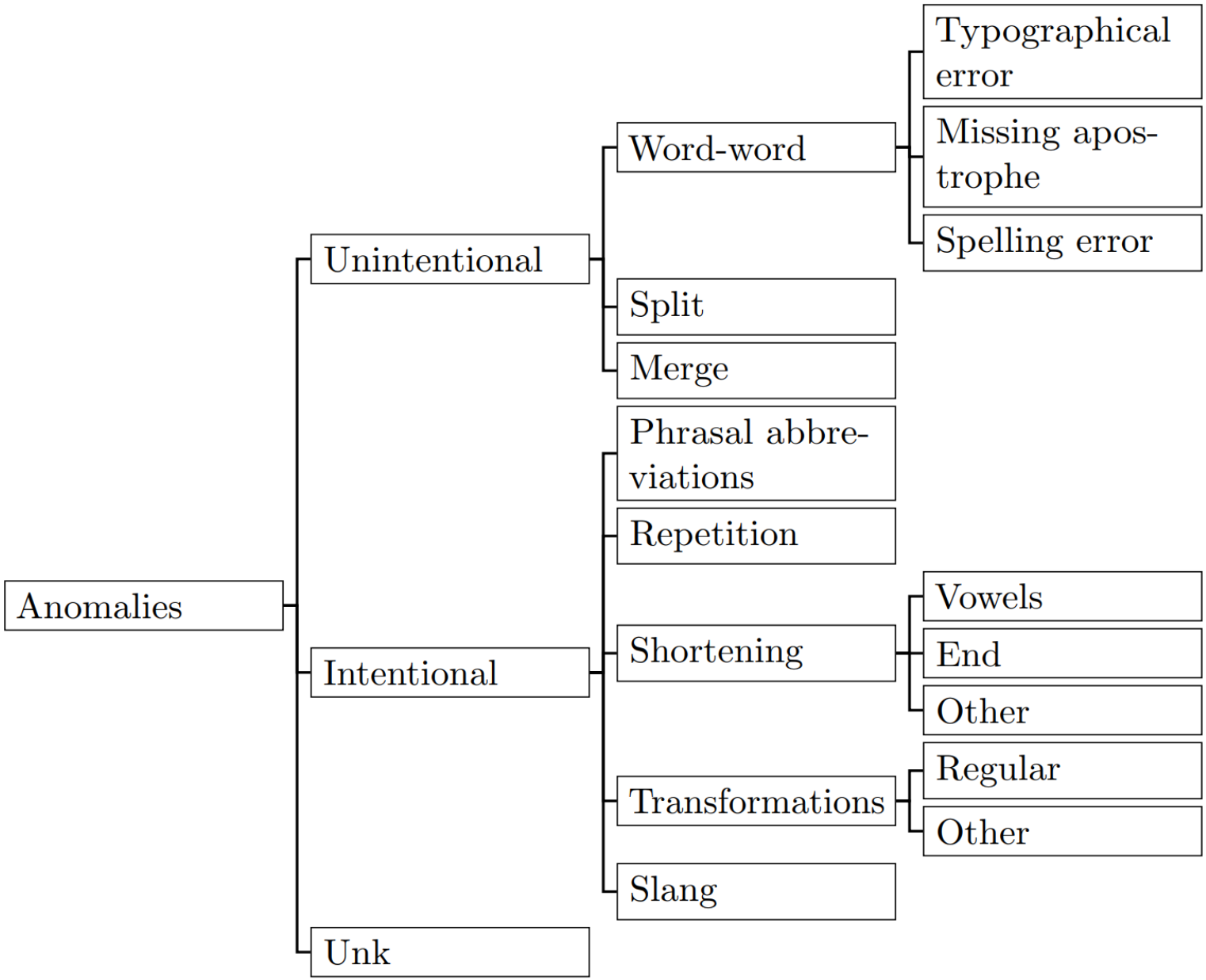
Figure 1: Taxonomy of normalization edits

For automated normalization, the scope is often different!

Effect of Normalization Categories on Parsing

Rob van der Goot, Rik van Noord and Gertjan van Noord. 2018. A Taxonomy for In-depth Evaluation of Normalization for User Generated Content. In *Proceedings of LREC*

Effect of Normalization Categories on Parsing



Effect of Normalization Categories on Parsing

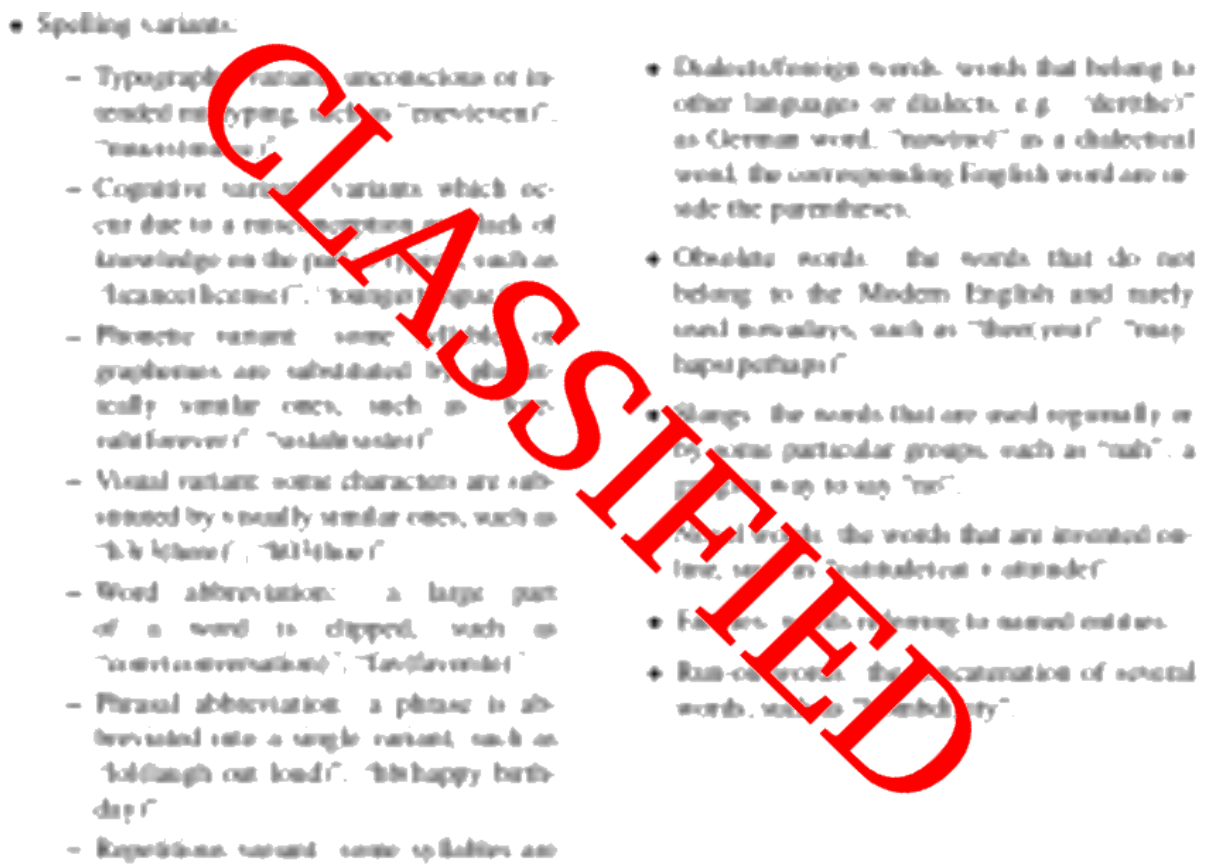
But how do you classify ‘lollllll’?

Effect of Normalization Categories on Parsing

$$\kappa = 0.807$$

Effect of Normalization Categories on Parsing

EMNLP 2018 submission:



Effect of Normalization Categories on Parsing

But I annotated lexnorm2015 with categories, and Owoputi and Lexnorm with UD...

Effect of Normalization Categories on Parsing

But I annotated lexnorm2015 with categories, and Owoputi and Lexnorm with UD...
So I added category annotation to Owoputi treebank

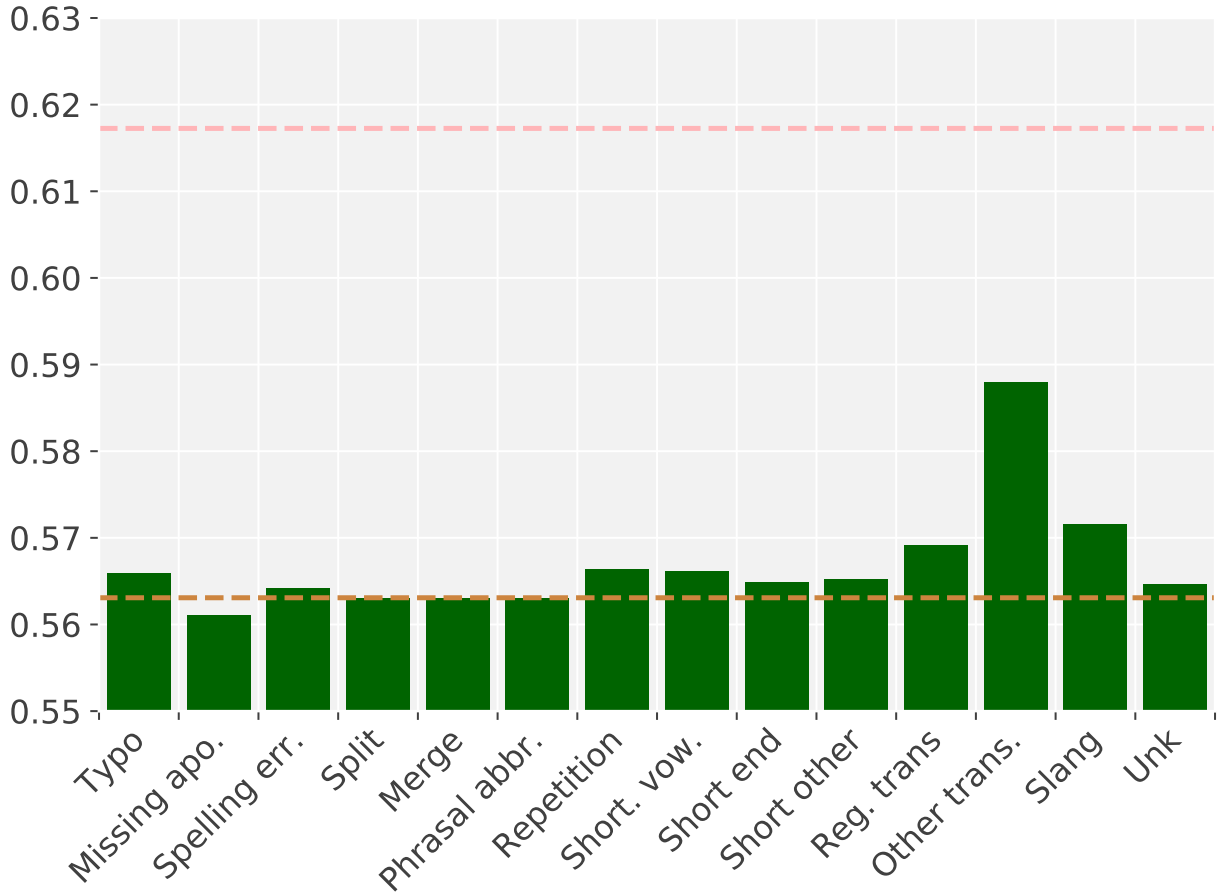
Effect of Normalization Categories on Parsing

Setup:

- UUParser 2.0
- Use gold normalization only for specific categories:
  - in isolation
  - ablation

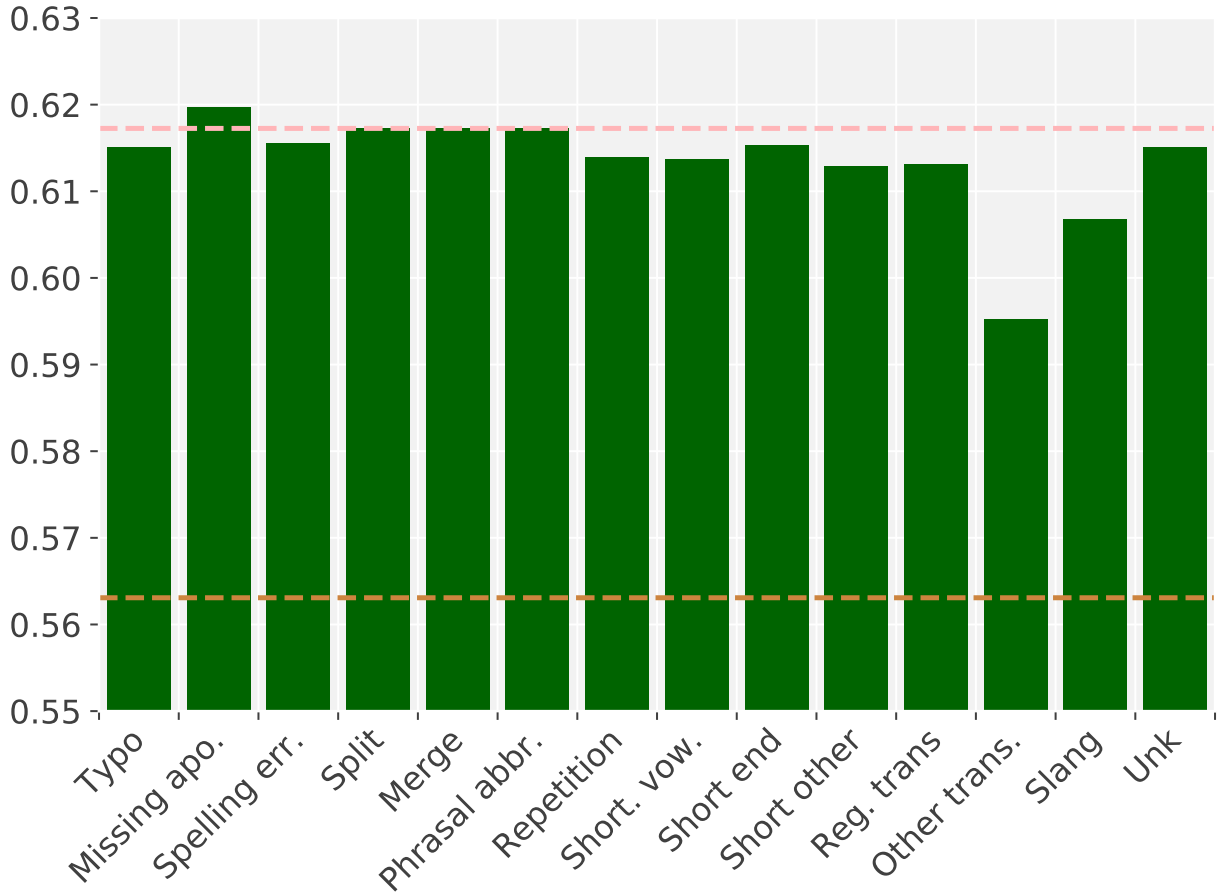
Effect of Normalization Categories on Parsing

Results: (isolation)



Effect of Normalization Categories on Parsing

Results: (ablation)



Effect of Normalization Categories on Parsing

Next:

- Use automatic normalization
- Test for other tasks?
- ...

Outline

Master theses

- Distant supervision for normalization (* 2)
- Automatic prediction of taxonomy categories
- The effect of lexical normalization on POS tagging for Dutch

Master theses

Distant supervision for normalization:

- Ian Matroos: 14:45
- Kelly Dekker: +Human evaluation

Master theses

Automatic prediction of taxonomy categories (Wessel Reijngoud):

- in corpus
- cross-corpus
- cross-language

Master theses

Why?

- Compare corpora (languages?)
- Evaluate normalization models in more detail for multiple languages

Master theses

The effect of lexical normalization on POS tagging for Dutch (youri schuur):

- van der Goot et al. (2017). English. BiLSTM with pre-trained embeds: small gain
- Schulz et al. (2016). Dutch. Treetagger: huge gain

Master theses

The effect of lexical normalization on POS tagging for Dutch (youri schuur):

- van der Goot et al. (2017). English. BiLSTM with pre-trained embeds: small gain
- Schulz et al. (2016). Dutch. Treetagger: huge gain
- Is this an effect of language? or setup?

Master theses

Additional benefits:

- First work to annotate tokenization and normalization as separate layer
- Correct capitalization
- Publicly available evaluation set for Dutch UGC normalization and POS tagging
- Improve MoNoise for Dutch
- Can be used for all the other master theses

Master theses

Thanks, Questions? (you may leave the easy ones for tomorrow)