Outline

100% Independent UD Annotation for Tweets

2 Effect of Normalization Categories on Parsing

3 Master theses



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

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

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

Did this happen before?

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: <u>http://www.perseus.tufts.edu/~ababeu/tlt8.pdf</u>.
- 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: <u>http://www.aclweb.org/anthology/P16-1070</u>.
- 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: <u>http://aclweb.org/anthology/N18-1088</u>.
- Nguyen, Kiem-Hieu (2018), BKTreebank: Building a Vietnamese Dependency Treebank. In: Proceedings of LREC 2018. Miyazaki, Japan, 2164–2168. Available at: <u>http://www.lrec-conf.org/proceedings/lrec2018/pdf/69.pdf</u>.
- 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: <u>http://www.lrec-conf.org/proceedings/lrec2018/pdf/1101.pdf</u>.
- Seyoum, Binyam Ephrem, Yusuke Miyao & Baye Yimam Mekonnen (2018), Universal Dependencies for Amharic. In: Proceedings of LREC 2018. Miyazaki, Japan, 2216–2222. Available at: <u>http://www.lrecconf.org/proceedings/lrec2018/pdf/565.pdf</u>.
- Skjærholt, Arne (2014), A Chance-corrected Measure of Inter-annotator Agreement for Syntax. In: Proceedings of ACL 2014. Baltimore, MD, 934–944. Available at: <u>http://www.aclweb.org/anthology/P14-1088</u>.

Thanks to Amir Zeldes and the corpora-list

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

POS	96.6%
unlabeled dependencies	88.8%
labeled dependencies	84.3%

Different guidelines (me):



Different guidelines (them):



Different guidelines (them):



Different guidelines (me):



Different guidelines (them):



Different guidelines (them):



Bit harder to converge (not done yet)

Other things:

• I leave phrasal abbreviations as is (they acronyms)

- I leave phrasal abbreviations as is (they acronyms)
- emoticon & emoji: SYMB, appos

- I leave phrasal abbreviations as is (they acronyms)
- emoticon & emoji: SYMB, appos
- urls: X, appos versus X, list

- I leave phrasal abbreviations as is (they acronyms)
- emoticon & emoji: SYMB, appos
- urls: X, appos versus X, list
- username mentions: PROPN, vocative

- I leave phrasal abbreviations as is (they acronyms)
- emoticon & emoji: SYMB, appos
- urls: X, appos versus X, list
- username mentions: PROPN, vocative
- RT: X, discourse

- I leave phrasal abbreviations as is (they acronyms)
- 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

first try:

- ID match
- 126 found

second try:

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

why 20% variation?

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

imhome:)
imhome:-)

@user601blueroommay19thfemsfreeanddrinkfreetil11:30\$5alln @iamyungsmilezblueroommay19thfemsfreeanddrinkfreetil11:30

=	=> outputRob	<==						
#	<pre>sent_id = ov</pre>	woputi.4	406.288578	99439				
#	text = Yall	sholl i	is quiet!!	SPEAK	UP lol	RT @MzCH	linezeEyez: @McQS	peaks 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	сор _	Norm=be
5	quiet		ADJ			Θ	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
=	=> outputTwee	ebank.f:	ixed.fixed	<==				
#	<pre>tweet_id = 0</pre>	oct27.28	8857809439					
#	text = Yall	sholl i	is quiet!!	SPEAK	UP lol	RT @MzC⊦	linezeEyez: @McQS	peaks We Still Here!!lol
1	Yall	yall	PRON	0		4	nsubj Norm	Type=contraction NormWord=you_all
2	sholl	shol	l ADV	R		4	advmod _	
3	is	be	AUX	V		4	сор _	
4	quiet	quie	t ADJ	Α		0	root _	SpaceAfter=No
5	!!		PUNCT			4	punct _	
6	SPEAK	speal	k VERB	V		4	parataxis	
7	UP	up	ADP	Т		6	compound:prt	
8	lol	lol	INTJ			6	discourse	

First test, conll18_ud_eval.py:

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

Inbox	Agreements on UD annotation for twitter data
Junk Email	Metric Precision Recall F1 Score AligndAcc
Drafts 1	Tokens 97.57 97.71 97.64
Sent Items	Words 97.38 97.66 97.52
Scheduled	UPOS 90.18 90.44 90.31 92.61 XPOS 29.41 29.49 29.45 30.20
Deleted Items	UFeats 97.38 97.66 97.52 100.00 AllTags 27.55 27.63 27.59 28.29
Archive	Lemmas 0.05 0.05 0.05 0.05 UAS 76.12 76.34 76.23 78.17
betsema	LAS 69.30 69.50 69.40 71.17
Upgrade to Office 365 with premium Outlook features	MLAS 64.29 64.02 64.16 65.71 BLEX 0.00 0.00 0.00 0.00

蔮

aR

Quite dissapointing, I would say.

Now Lam planning to take a closer look at the difference

Answer:

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

Answer:

Thanks for the experiments. The number seemed OK to me .. Conclusion: we do not agree...

eval.pl by Yuval Krymolowski

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 30/67

For now:

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

5 focus words where most of the errors occur:



- head one word after the correct head (after the focus word), correct dependency : 11 times
- ependency "root" instead of "parataxis" : 11 times
- head one word before the correct head (after the focus word), correct dependency : 11 times
- dependency "aux" instead of "cop" : 5 times
- Solution of a second second
- o dependency "advcl" instead of "parataxis" : 5 times

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

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

(Preliminary) conclusion: Most mistakes made for:

- vocative
- discourse
- root
- parataxis

(Preliminary) conclusion: Most mistakes made for:

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

Next:

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

• ..

2 Effect of Normalization Categories on Parsing

3 Master theses



Thesis:

- Evaluating normalization per category
- Effect of normalization on parsing

Thesis:

- Evaluating normalization per category
- Effect of normalization on parsing
- Logical follow up: evaluating effect normalization categories for parsing

Thesis:

- Evaluating Normalization per category
- Effect of normalization on parsing
- Logical follow up: Evaluating effect normalization categories for parsing

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

So why do it again?

Their taxonomy:



Figure 1: Taxonomy of normalization edits

Their taxonomy:



Figure 1: Taxonomy of normalization edits

For automated normalization, the scope is often different!

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*



But how do you classify 'lolllll'?

$\kappa = 0.807$

EMNLP 2018 submission:

- Spelling variants;
 - Typography variants unconscious or intended manyping, section "previewent", "manytimeter".
 - Cognitive variants visitants which occur due to a nurve contention or which of knowledge on the part of New Contention facancet because C., "tounget trapped."
 - Prometry national source of blocks of graphenies, and salivabilities by physical colly similar ones, such as the radiaforever of "passial system".
 - Visual variant: some characters are substrated by smally similar enes, such as "Is's (charaf), "Isl'shawf".
 - Word abbreviation: a large part of a word is clipped, such as "conversion-workation?", "far-theyonder".
 - Pleasal abbreviation: a please is abbreviated rate a single curiant, such as foldaugh out load?. "bithappy buthdars?"
 - Repetitions, suburity some syllables are

- Dialocity/inseign words, words that belong to other languages or dialocit, e.g., "derither" as German word, "noviewi" in a chalecheal word, the unresponding English word are inwele the parentheses.
- Obsolute nords: the words that do not belong to the Modern English and meety sould non-adays, such as "there;year!" "resp haps pottage?"

 Mange: the normal that are used regionally or Dynamic particular groups, with an "mild", a groups way to say "mill;

Next years, the words that are invested onture, sectors Testitude(cut + statude)"

Ensures second referring to named outdars.

 Ran-converses the executination of several words, web-to "Peebdory".

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

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

So I added category annotation to Owoputi treebank

Setup:

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





Next:

- Use automatic normalization
- Test for other tasks?

• ...

2 Effect of Normalization Categories on Parsing



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

Distant supervision for normalization:

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

Automatic prediction of taxonomy categories (Wessel Reijngoud):

- in corpus
- cross-corpus
- cross-language

Why?

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

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

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?

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

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