Analyzing Parser Errors

To Improve Parsing Accuracy And To Inform Treebanking Decisions

Samar Husain*, Bhasha Agrawal§

*University of Potsdam, Germany
§IIITDM-Jabalpur, India

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  - Better parser performance is always welcome!

Background: Factors that affect parser performance

- What affects dependency parser performance?
  - Algorithm
  - Grammar/Learner/Parameterization
  - Training data size
  - Feature space
  - Tagset size
  - Linguistic features
  - ...

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  - many linguistic phenomena have competing (and equally compelling) analyses
    - eg. coordination

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2. Are there certain linguistic cues implicit (or missing) in the current treebank that can be made explicit (or added) in order to make the parsing of complex constructions easier?

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- Can some of this process be automated?
  - Whether alternative structures for a linguistic phenomenon can be obtained from the original analysis deterministically via transformations?

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  - Dependency annotation
  - Propbanking
  - Phrase structure annotation
- The dependency framework used in the dependency treebank is inspired by Panini's grammar of Sanskrit. (Bharati et al., 1995), (Begum et al., 2008)

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- Experimental results obtained using 5-fold cross-validation on the complete data-set
- Features and parameters for MaltParser adapted from Ambati et al (2010b). Their setup also gives us our baseline score.

Error Classification

All the wrong attachment instances are classified using

- Edge type and Non-projectivity
- Edge length
- Edge depth

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- Non-projectivity: an arc in a dependency tree is projective if there is a directed path from the head word x to all the words between the two endpoints of the arc (Kuebler et al., 2009)

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- Edge depth: the level in the tree at which an edge is situated wrt root

Error Classification

Edge Type			No. of edges	No. of non-projective edges	No. of edges with correct label
Main (3.25%)			11	0	0
Intra Clausal (83.13%)	Verb Argument Structure (51.18%)	Complement (21%)	71	4	9
		Adjunct (30.18%)	102	10	45
	Non-verbal (23.67%)	Noun-modifier (14.79%)	50	1	3
		Adjective mod. (1.48%)	5	0	0
		Apposition (0.30%)	1	0	0
		Genitive(7.10%)	24	2	6
	Others (8.28%)	Co-ordination (6.80%)	23	1	0
		Complex Predicate (0.59%)	2	0	0
		Others(0.89%)	3	0	1
Inter Clausal (13.61%)	Co-ordination (0.89%)		3	0	0
	Sub-ordination (12.72%)	Conjunction (1.18%)	4	0	0
		Relative Clause (3.55%)	12	11	0
		Clausal Complement (3.85%)	13	6	0
		Apposition (1.48%)	5	4	0
		Verb Modifier (2.66%)	9	3	0

Error Analysis: Intra-clausal Errors

- Verbal complements and adjuncts
- Noun modifications (including apposition and genitive)
- Coordination
- Complex predicates

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- Ambiguous post-position of a nominal child node
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- The non-finite clause gets split due to shared arguments.

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- Children can be sub-trees (e.g. a coordination of multiple non-finite verbs that take their own arguments, genitives, etc.).
  - This again creates long distance dependencies

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- Complex interactions of different conjunctions that can lead to long distance dependencies are another source of error.

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  - We tried to neglect errors due to learning problems, data sparsity.
  - Focused only on those errors that we thought are due to lack of robust features or diffcult to learn structures
  - Not a trivial task.

Experiments

- Use of patterns identified in the error analysis
  - to simplify dependency structures
  - to incorporate additional linguistic information and investigate ways to represent/encode this information

Experiment I: Exploring alternative analysis via structural transformations

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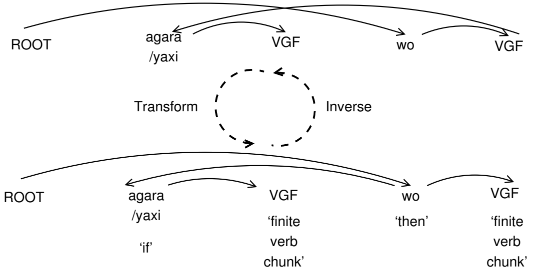
- Can the original structure be successfully recovered again after transformation?

Experiment I: Exploring alternative analysis via structural transformations

- Transformations lead to structural changes in a dependency tree when relations between nodes are modified leading to a new dependency tree

Structural transformations: Paired Connectives

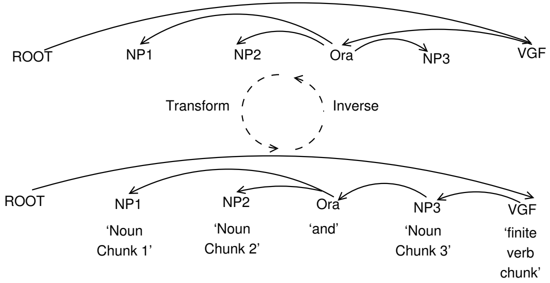


Ex:

'agara'	rAjA	kuCa	'cAhawe'	hEM	'wo'
'if'	'king'	'something'	'demand'	'is'	'then'
usa par	vicAra	'kiya'	jAnA cahie		
'it'	'consider'	'did'	'should'		

' If the king demands something , it should be considered. '

Structural transformations: Intra-clausal Coordination



Ex:	unake	alavA	kaI	'maMwrI'	'Ora'	'vipakRa'	ke
	'them'	'apart from'	'many'	'ministers'	'and'	'opposition'	'of'
	newA	mOjUxa	We				
	'leaders'	'present'	'were'				

' Apart from them, many ministers and leaders of opposition were present. '

Experiment I: Exploring alternative analysis via structural transformations

	Transformation	Transformation Cue Availability	Inverse Transformation	Use of a tool
1	Paired Connective	Yes	Yes	No
2	Relative Clause	Yes	Not 100%	MaxEnt
3	Complement Clause	Yes	Yes	No
4	Intra-clausal Coordination	Yes	Yes	No
5	Complex Predicate argument (with genitive case marker)	Yes	Yes	No

Table: Experiment I: Alternative structures using structure transformation.

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- Analyzing a sentence not only involves identification of such information but also exploring ways to encode this information during annotation.
- If there are multiple ways to encode some information, is one encoding strategy better than the other?

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    - Agreement not explicitly annotated. But morphological features are present.

Experiment II: Encoding linguistic information

	Addition/ Modification	**Encoded through**	**Cue Availability**	**Inverse**	**Use of a resource**
1	Encoding verb-argument agreement	Dependency label	Yes (morphological)	Yes	No
2	Encoding conjunction valency	POS Tag	Yes (lexical)	Yes	Valency lexicon
3	Encoding verbal valency	POS Tag	Yes (lexical)	Yes	Bilingual Dictioanry, VerbNet

Table: Experiment II: Encoding linguistic information

Effect on parsing accuracy

	Experiments	LAS	UAS	LA	Statistical Significance
	Baseline Accuracy	77.58	88.97	80.48	-
Experiment I	*Paired Connectives	**77.70**	**89.15**	**80.61**	UAS,LAS,LA
	*Corelative and extraposed relative clauses	77.59	89.02	**80.72**	LA
	Clausal Complement	77.47	88.89	80.39	-
	Complex predicate argument (with genitive case marker)	77.50	88.77	80.43	-
	*Intra-clausal coordination	78.21	**89.06**	**81.21**	LAS,LA
Experiment II	Encoding agreement via dependency labels	74.15	88.87	79.98	-
	Encoding conjunction valency through POS	77.60	89.00	80.46	-
	Encoding verb's valency through POS	77.53	88.92	80.42	-

Table: Effect of Experiment I and II on parser accuracy. * shows statistical significance with McNemar's test ($p \leq 0.01$), computed using MaltEval. UAS: Unlabeled Attachment Score, LAS: Labeled Attachment Score, LA: Label Accuracy

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  - But we think that the low coverage (only 196 verbs out of 267 were found in the dictionary) of the bilingual dictionary for verbs affected the experiment where we tried to encode verbal valency.
  - The lexical information for conjunctions is sufficient to disambiguate the coordination vs. subordination structures correctly; the added valency information seems to be redundant

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- Does this make treebanks biased to specific parser development?
  - As long as the linguistic integrity of the analysis is maintained, this will not be a disadvantage.
- This not only leads to an increase in parser accuracy but also helps create better treebanks