Unsupervised Language Learning in OpenCog

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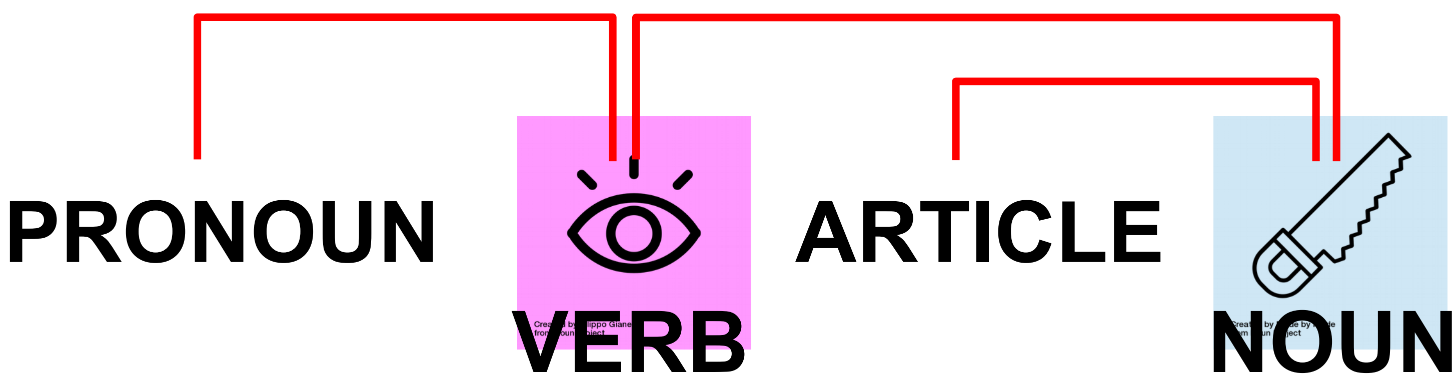
OpenCog
https://opencog.org/

SingularityNET
https://singularitynet.io

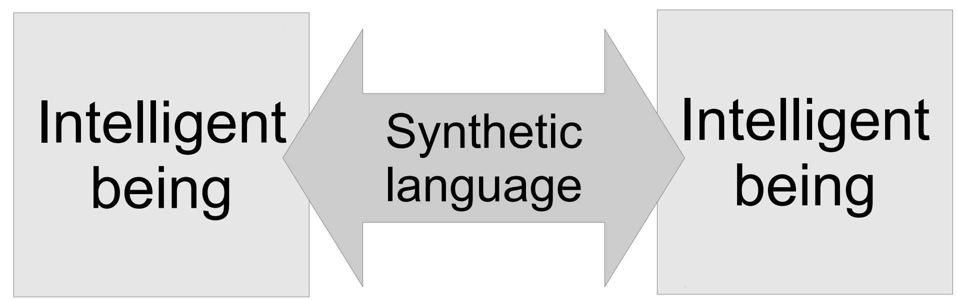
HANSON ROBOTICS
http://www.hansonrobotics.com/

Grammar Learning from scratch - programmatically



Language as beneficial evolutionary property of generic intelligence

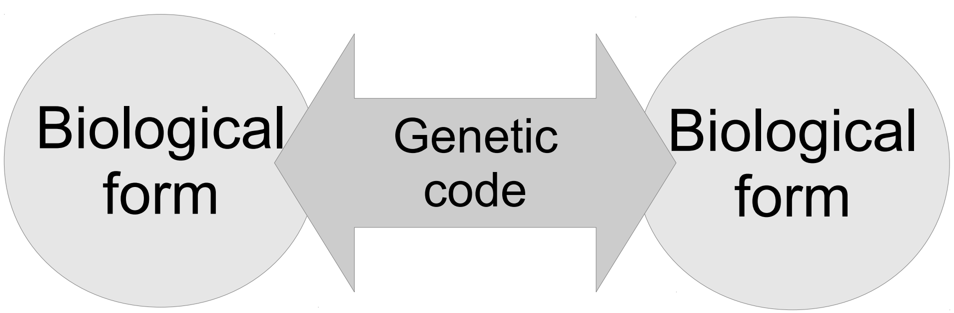
Social transfer of information



Speed of light

Learnable Language

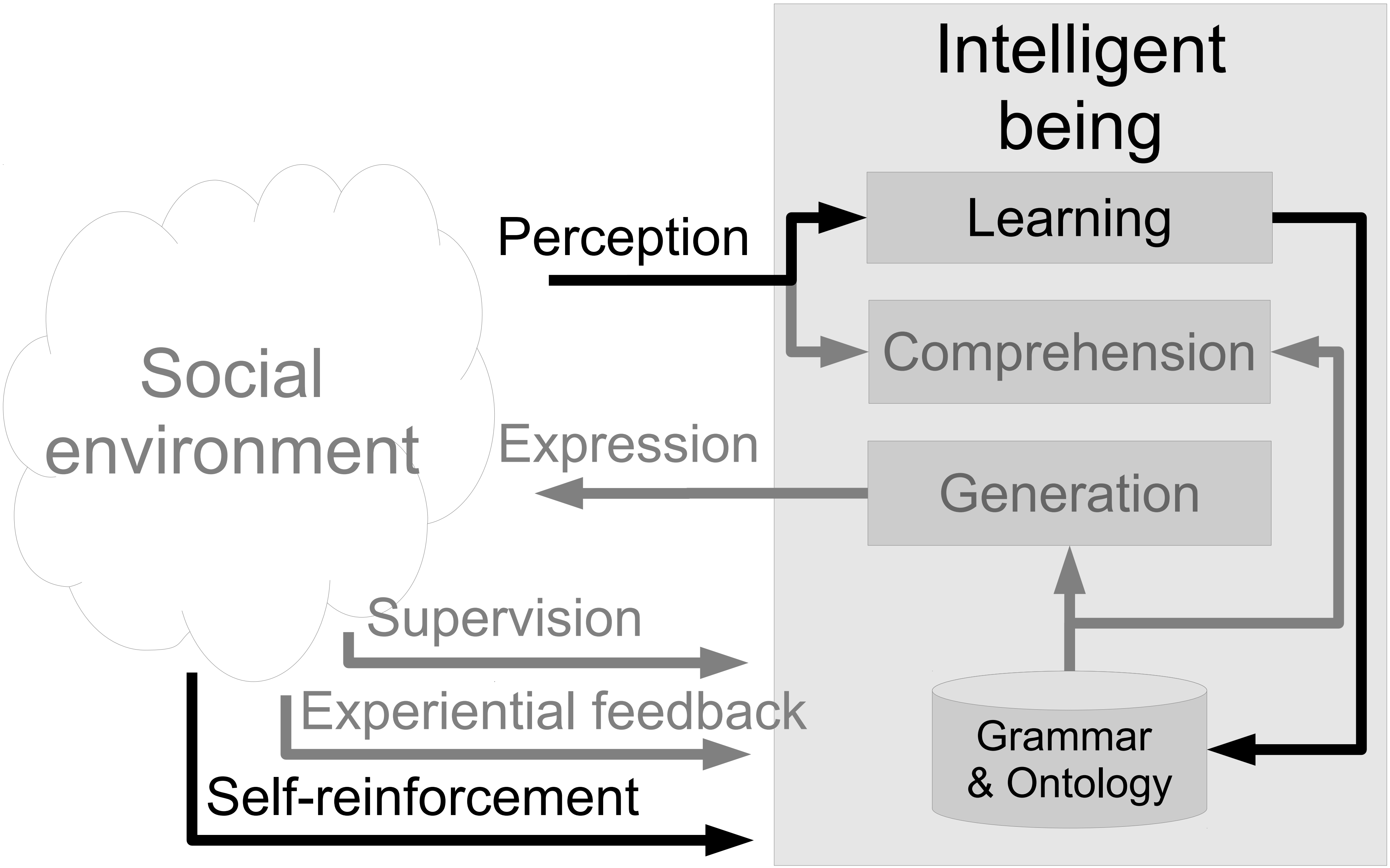
Biological transfer of information



Change of generations

Hardcoded by evolution

Language Learning Environment



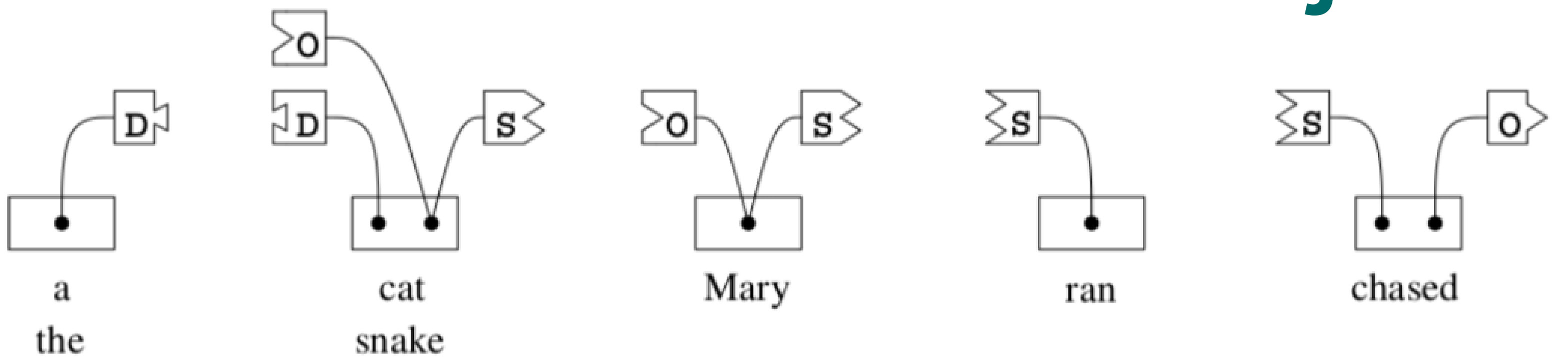
Project goal and applications

- Grammar learning from scratch - programmatically
- Grammar extension/customization for specific domains
- Building dictionaries and patterns for NLP applications
- Parsing texts for NLP applications
- Grammar checking (more than spell checking)

Constraints of the currently explored approach

- Controlled corpora
- Using Link Grammar formalism
- Relying on MST parses
- No account for morphology
- Self-reinforcement with parse-ability
- Test against training data

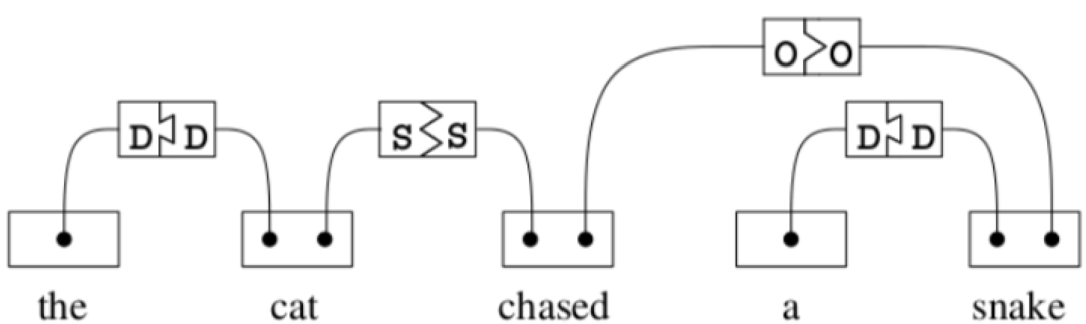
Link Grammar and Disjuncts



An illustration of Link Grammar connectors and disjuncts. The connectors are the jigsaw-puzzle-shaped pieces; connectors are allowed to connect only when the tabs fit together. A disjunct is the entire (ordered) set of connectors for a word. As lexical entries appearing in a dictionary, the above would be written as

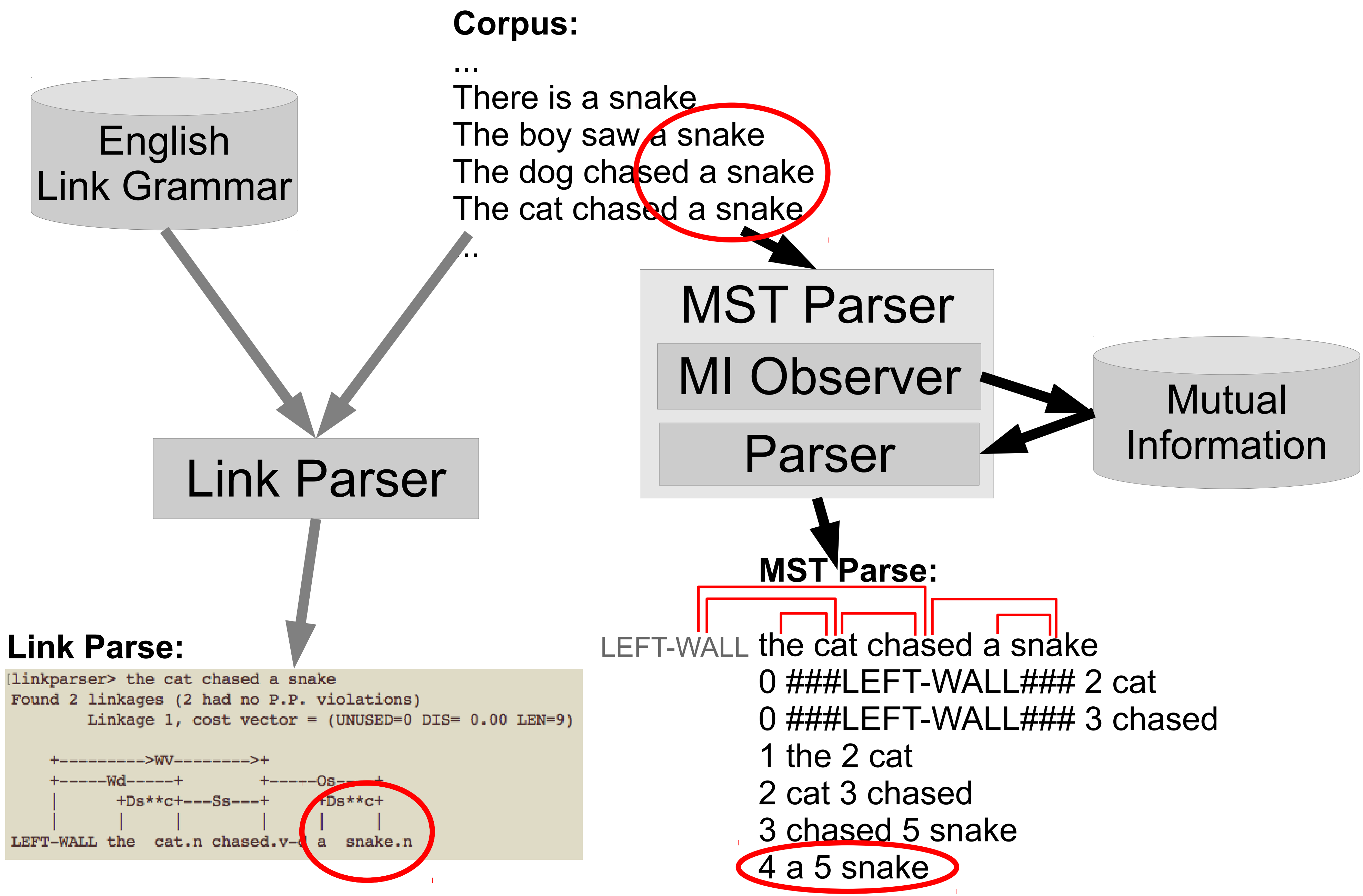
```
a the: D+;
cat snake: D- & (S+ or O-);
Mary: O- or S+;
ran: S-;
chased S- & O+;
```

Note that although the symbols ''&'' and ''or'' are used to write down disjuncts, these are ***not*** Boolean operators, and do ***not*** form a Boolean algebra. They do form a non-symmetric compact closed monoidal algebra. The diagram below illustrates puzzle pieces, assembled to form a parse:



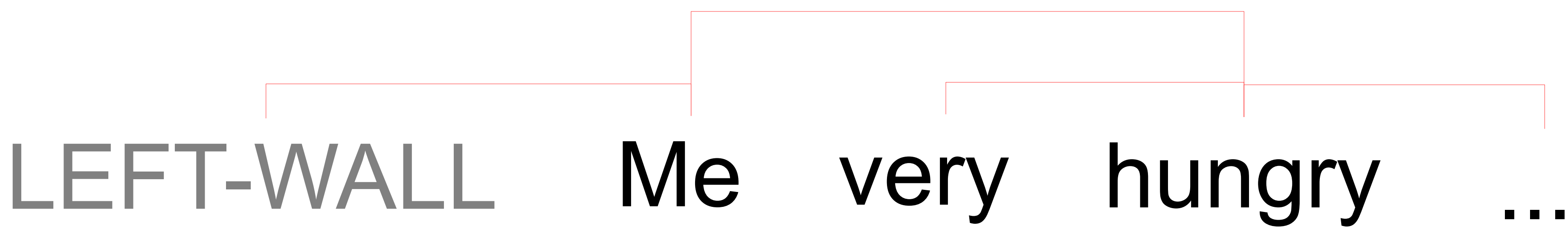
B. Goertzel, L. Vepstas, 2014

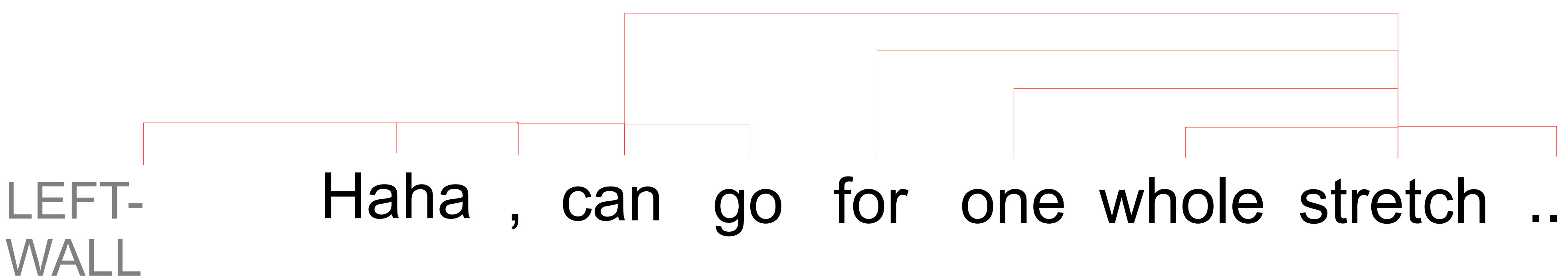
MST Parses vs. Link Parses



MST-Parser parsing SMS text

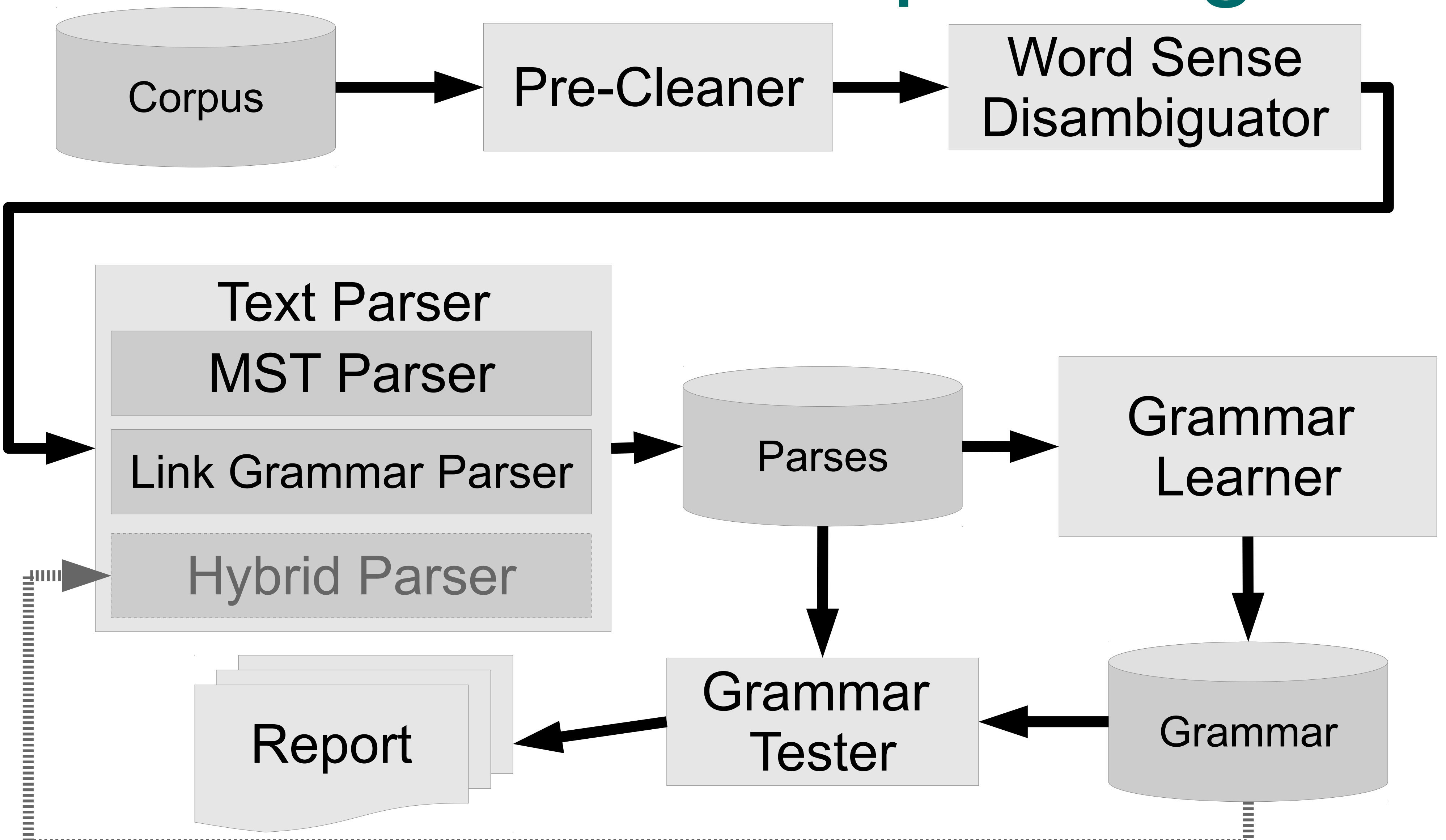
- SMS corpus in English by NUS[1]
- Pre-processed and MST-parsed



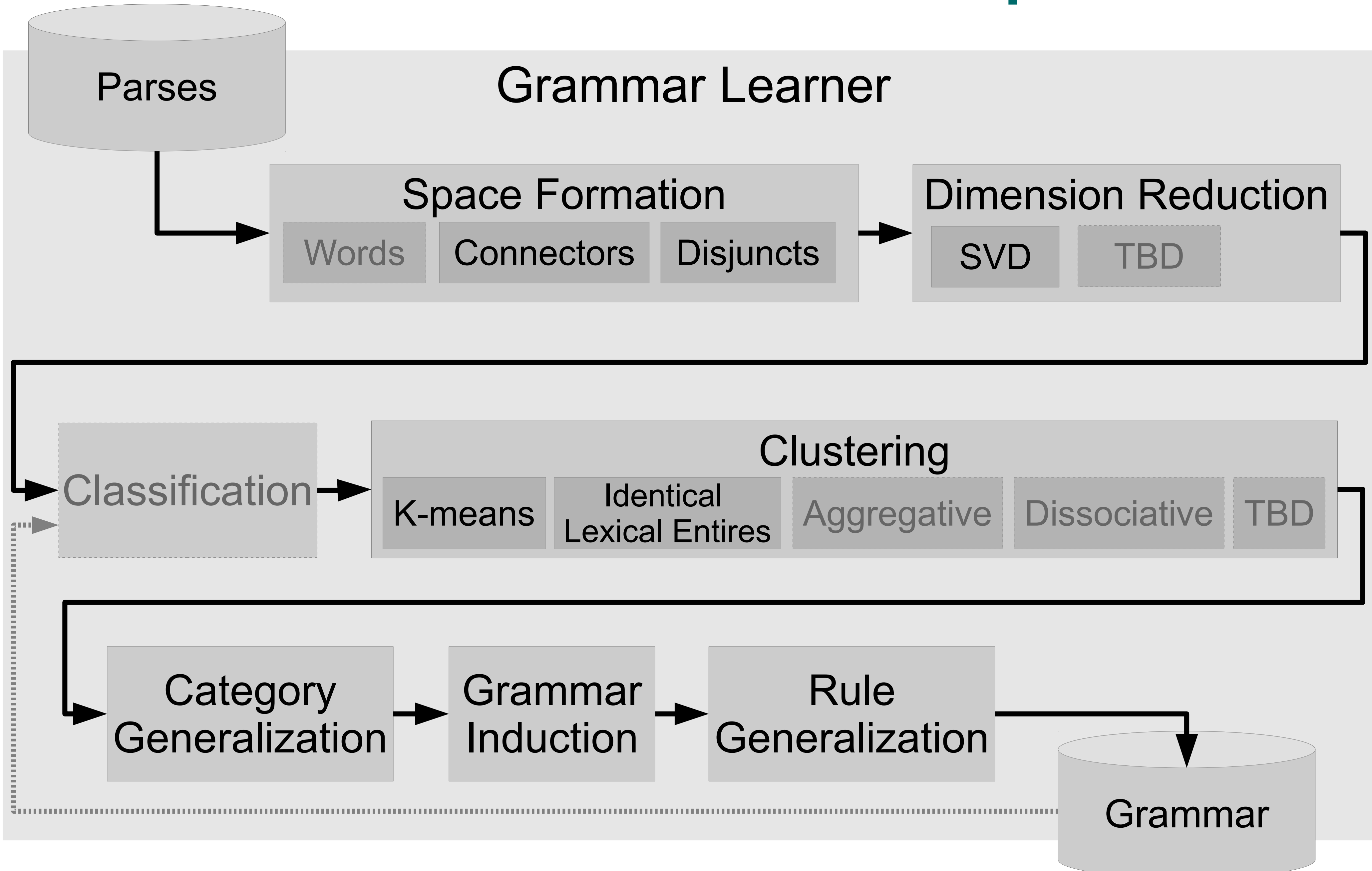


[1] https://www.kaggle.com/rtatman/the-national-university-of-singapore-sms-corpus#smsCorpus_en_2015.03.09_all.json

Unsupervised language learning framework in OpenCog



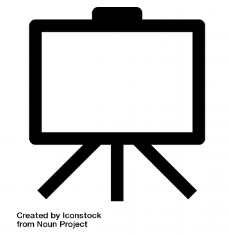
Grammar Learner Pipeline

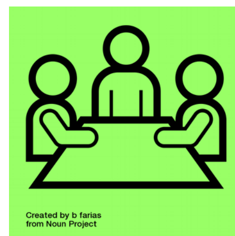


Results: Word-Sense Disambiguation

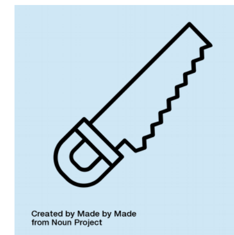
Using AdaGram[1] we disambiguate our POC-English corpus without supervision.

Two ambiguous words in corpus, with only two senses each:





board

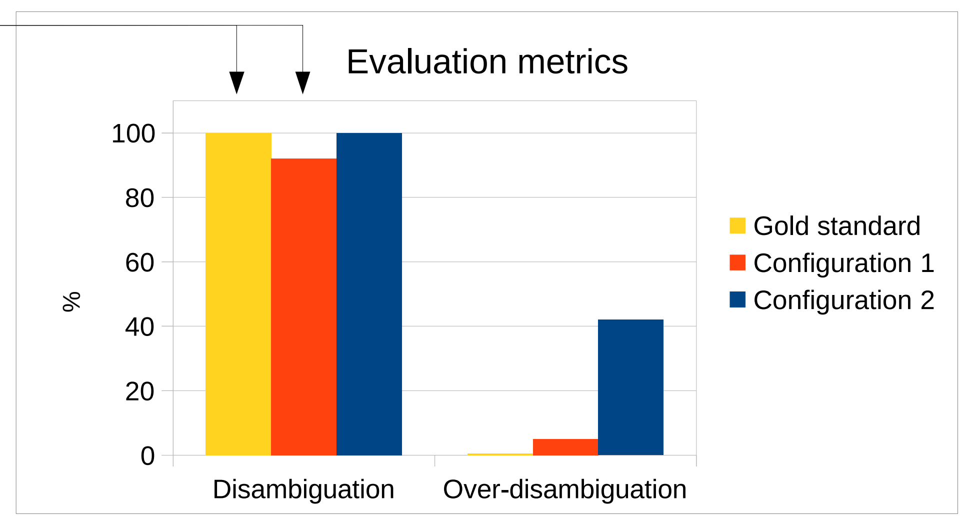


saw

After parameter tuning, we found two promising results:

mom saw@a dad with a saw@b .

mom@a saw@a dad@b with a@c saw@b .



[1] https://github.com/glicerico/AdaGram/tree/take_sentences

Results: Corpora with PA & PQ

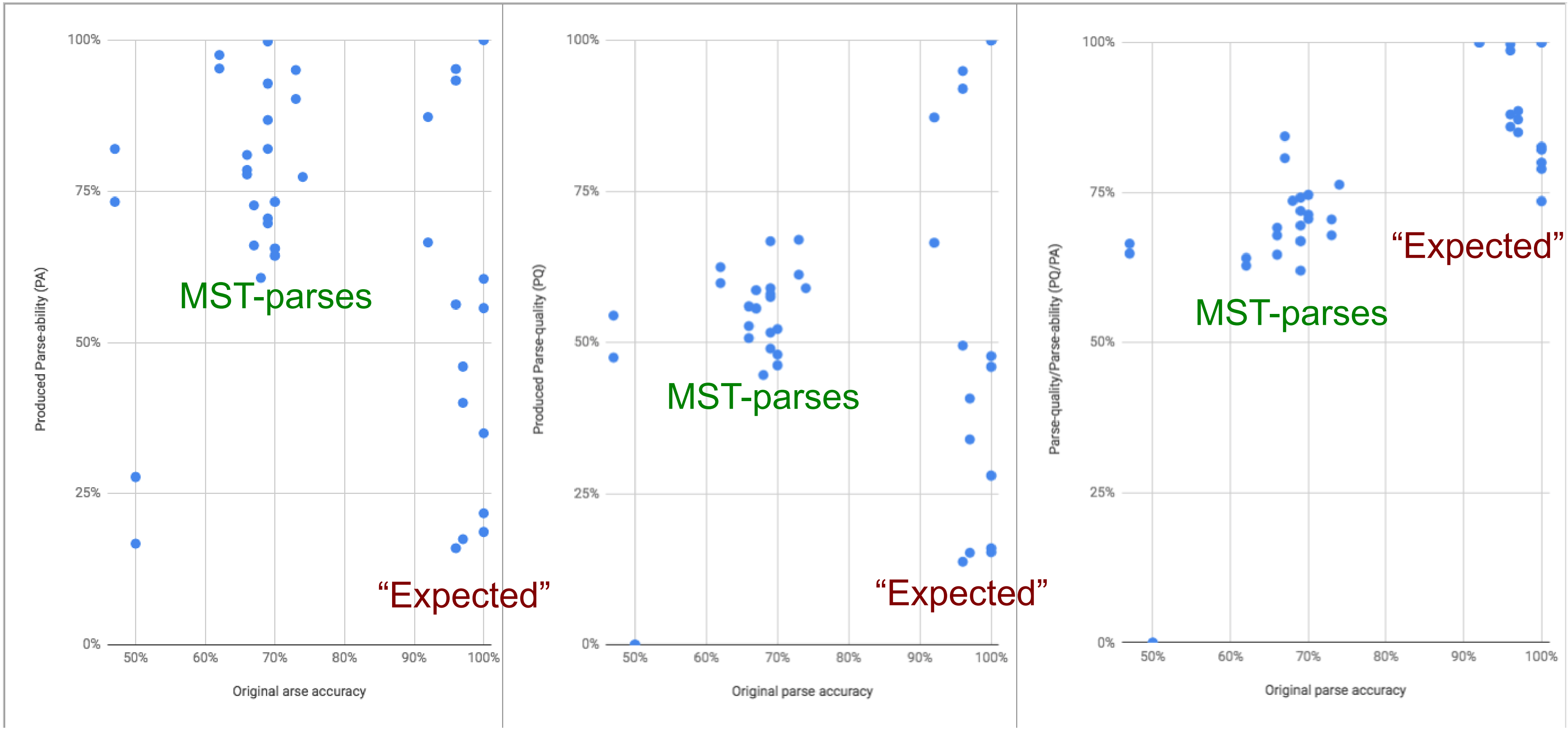
Name	Language	Volume (bytes)	Unique Words	Word Instances	Instances per Word	Sentences	Average sentence length	Best PA	Best PQ	Best PQ/PA
POC-Turtle	Turtle	203	13	36	3	12	3	100%	100%	100%
POC-English (with no ambiguity)	English	789	25	132	5	36	4	100%	68%	68%
POC-English (with ambiguity)	English	1,794	55	388	7	88	4	97%	70%	72%
Child Directed Speech (br-text + brent9mos)	English	633,151	4,717	130,109	27	38,181	3	75%	60%	80%
Gutenberg Children Books	English	30,118,309	54,054	2,695,151	50	207,130	13	99%	62%	63%

Across corpora with the best found configurations, artificially learned grammar makes it possible to

parse 75-100% of text (Parse-ability or PA),
having 60-100% of it parsed properly (Parse-quality or PQ),
with properly parsed fraction of parsed text above 63%

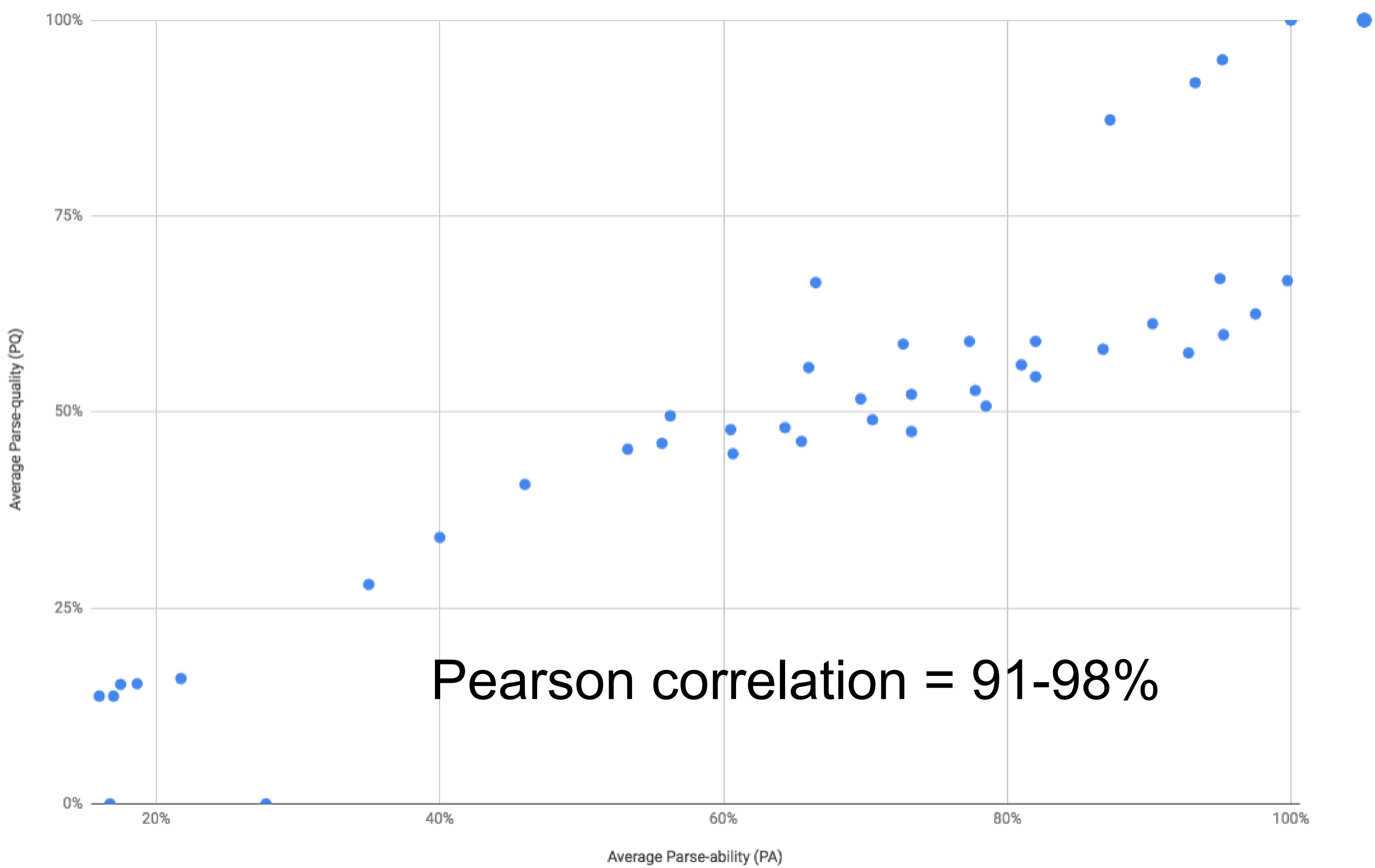
Results: MST Parses

Parse-ability (PA) Parse-quality (PQ) PQ/PA



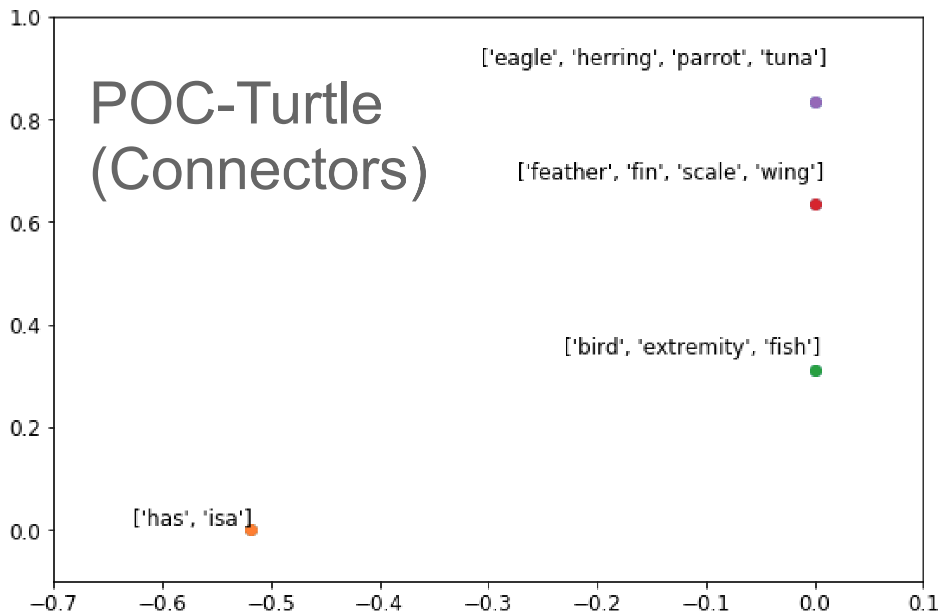
- Better parses – better results (generally, for MST parses - especially)
- Good parses – does not mean good results (for "expected" parses)

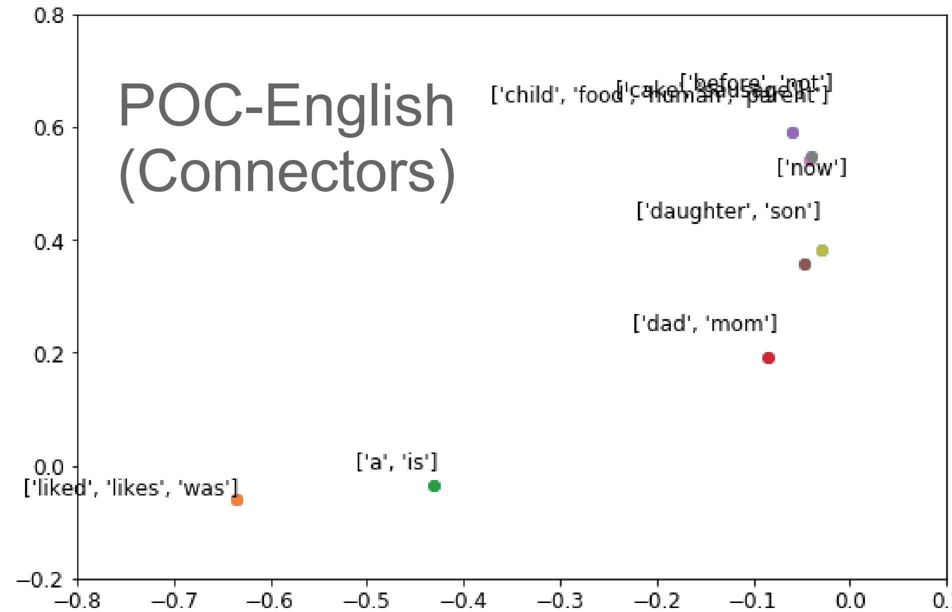
Results: PA and PQ correlation

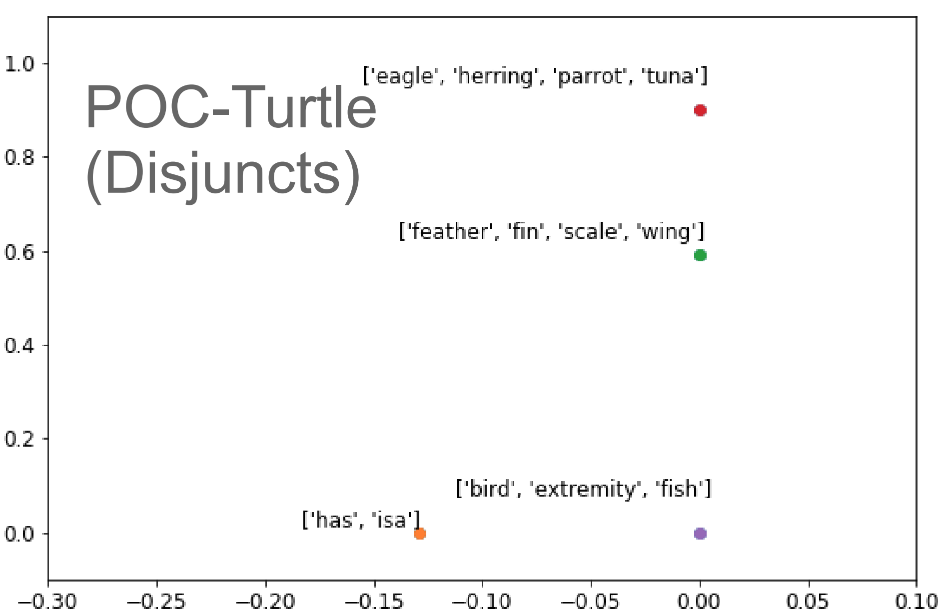


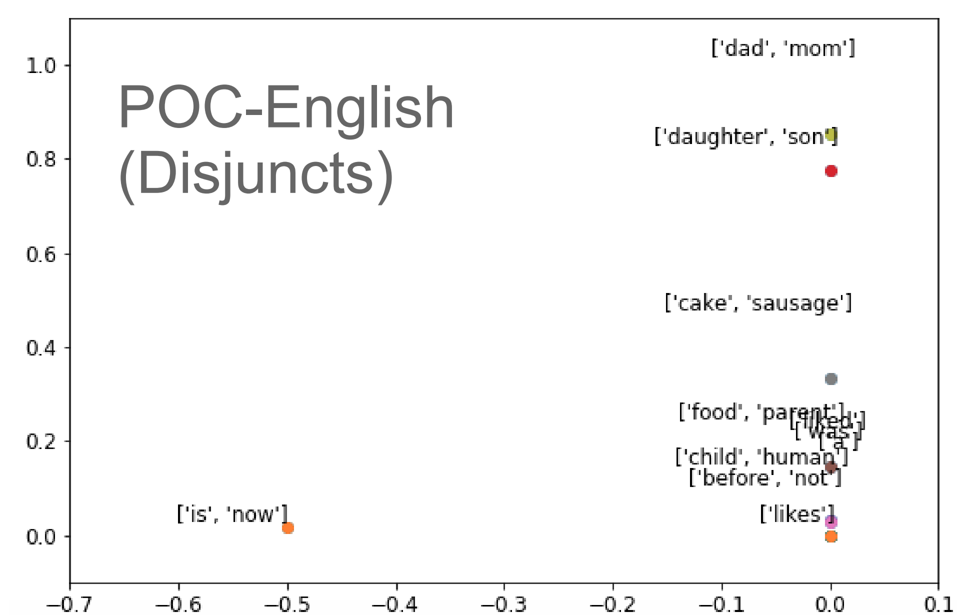
Better Parse-ability (PA) implies better Parse-quality (PQ)

Results: Categorial spaces (POC)

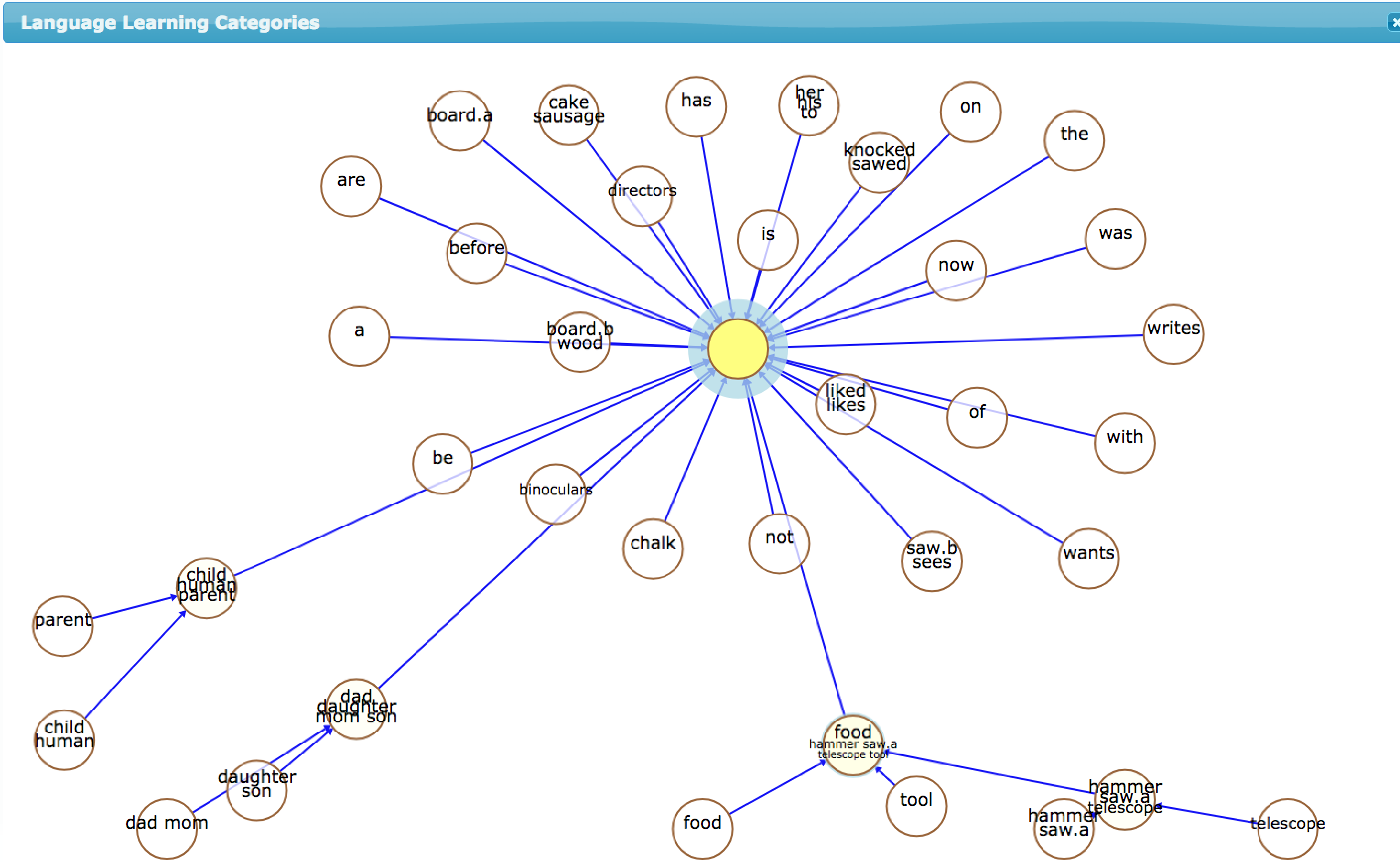






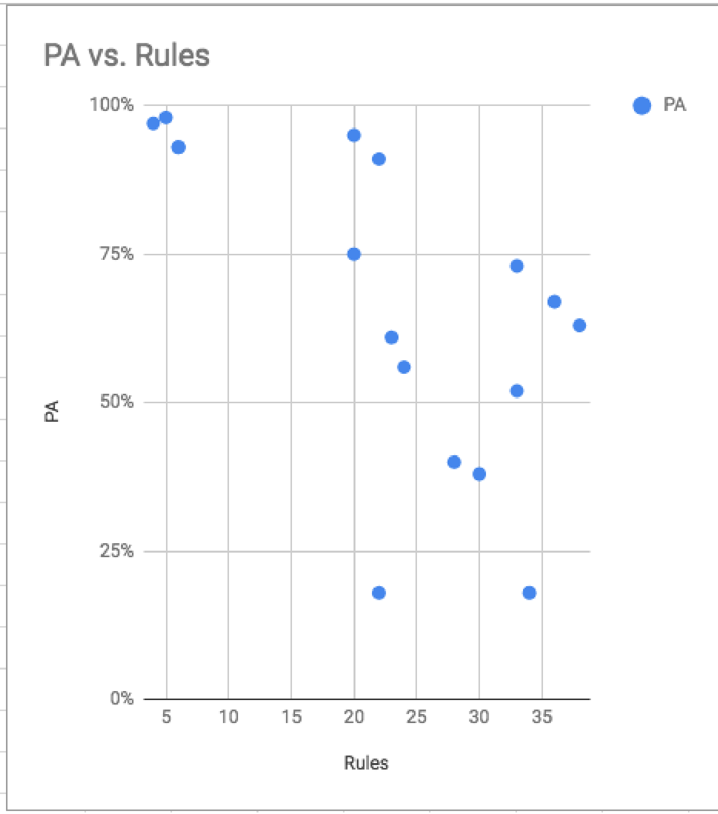


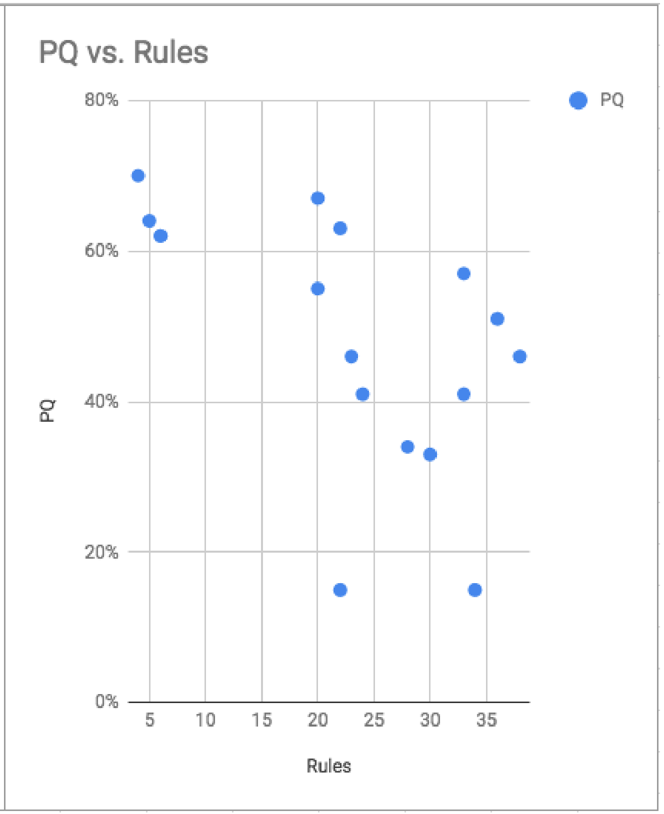
Results: Category trees (POC-English)



Results: Categories and PA and PQ

Parsing	Gene	Space	Rules	PA	PQ
MST-fixed-manually	none	dDRKd	30	38%	33%
MST-fixed-manually	rules	dDRKd	28	40%	34%
LG-English	none	dDRKd	34	18%	15%
LG-English	rules	dDRKd	22	18%	15%
R=6-Weight=6:R-mst-weight=+1:R	none	dDRKd	6	93%	62%
R=6-Weight=6:R-mst-weight=+1:R	rules	dDRKd	6	93%	62%
R=6-Weight=6:R-mst-weight=+1:R	none	dDRKd	38	63%	46%
R=6-Weight=6:R-mst-weight=+1:R	rules	dDRKd	36	67%	51%
R=6-Weight=6:R-mst-weight=+1:R-	rules	dDRKd	4	97%	70%
R=6-Weight=1-mst-weight=+1:R	none	dDRKd	20	75%	55%
R=6-Weight=1-mst-weight=+1:R	none	dDRKd	24	56%	41%
R=6-Weight=1-mst-weight=+1:R	rules	dDRKd	23	61%	46%
R=6-Weight=1-mst-weight=+1:R-ad	rules	dDRKd	33	52%	41%
LG-ANY-all-parses	none	dDRKd	5	98%	64%
LG-ANY-all-parses	none	dDRKd	22	91%	63%
LG-ANY-all-parses	rules	dDRKd	20	95%	67%
LG-ANY-all-parses-adagram	rules	dDRKd	33	73%	57%
Pearson correlation with N of Rules				**-0.6**	**-0.6**





- Fewer categories – better Parse-ability (PA) and Parse-quality (PQ)
- Number of categories vary from upper limit of natural number of identical lexical entries (tens to thousands) to 4-6 basic “parts of speech” - randomly due to uncontrolled nature of K-means clustering which has to be replaced with controlled aggregative/dissociative clustering

Results: Grammar Learning Algorithms

Comparing across all corpora

Grammar Learning Algorithm	Parse-ability (PA)	Parse-quality (PQ)	PQ/PA
Space of Connectors, SVD, K-means, Rules by Connectors	82%	61%	75%
Space of Connectors, SVD, K-means, Rules by Disjuncts	64%	49%	76%
Space of Disjuncts, SVD, K-means, Rules by Disjuncts	61%	47%	77%
Space of Disjuncts, No dimension reduction, Identical Lexical Entries, Rules by Disjuncts	54%	44%	81%

- Connectors - more generalized, less categories, less strict parsing
- Disjuncts - less generalized, more categories, more precise parsing

The next steps

- Incremental probabilistic assessment of parses, clustering, grammar induction
- Fine/tuning MST-parsing parameters or change parsing approach
- Quality assessment procedure (fitness function) idea tolerant to overfitting
- Pipeline made available as CLI tool, web service and SingularityNET adapter

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