

Evaluation

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TbiLLAI 2019 in Tbilisi, Georgia

### Previous lecture

Syntactic types

Intro

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### Lambda Logical Forms (LLFs):

- Simply typed  $\lambda$ -terms with e and t basic types;
- No logical constants, only lexical terms and λ-abstraction;
- Similar to syntactic trees of natural language expressions.

### Natural tableau system:

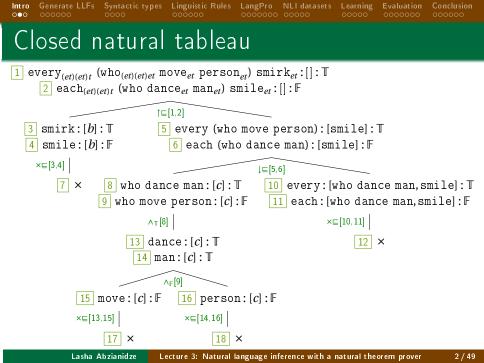
• Tableau entries: LLF:argumentList:truthSign

Binary format of a term

NLI datasets

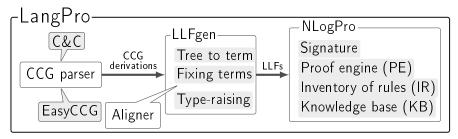
Evaluation

 Monotonicity reasoning achieved with special monotonicity rules



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A natural tableau theorem prover:



Solving natural language inference problems with the prover

## LLFs and Categorial Grammar

Generate LLFs

Lasha Abzianidze

LLFs are similar to formal derivations studied in Categorial Grammars (CGs) [Ajdukiewicz, 1935, Hillel, 1953].

- CGs treat each lexical item as a function;
- Categorial Type-Transparency principle links syntactic types to semantic ones.

Combinatory Categorial Grammar (CCG) [Steedman, 2000] is the only CG that is scaled up for wide-coverage text processing:

- CCG is well-studied from linguistic perspectives;
- There exists robust and accurate wide-coverage parsers for CCG, e.g., C&C parser [Clark and Curran, 2007] and EasyCCG

From CCG Trees to LLFs

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Generate LLFs Syntactic types Linguistic Rules LangPro

## Producing an LLF from a CCG derivation consists of several steps:

Evaluation

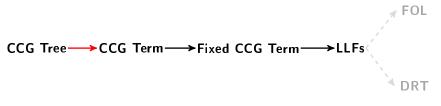
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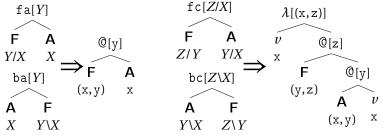
## FOL CCG Tree→CCG Term→Fixed CCG Term→LLFs

## CCG Tree $\rightarrow$ CCG term

Generate LLFs

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### CCG Tree→CCG Term→Fixed CCG Term→LLFs

$$\begin{split} [\text{Dow}_{n,n}^{\text{PER}} \, \text{Jones}_n^{\text{PER}}]_{np} & & \rightarrow \text{Dow}\_\text{Jones}_{np} \\ & \text{nobody}_{np} & & \rightarrow \text{no}_{n,np} \, \text{person}_n \\ & [\text{ice}_n]_{np} & & \rightarrow \text{a}_{n,np} \, \text{ice}_n \\ & [\text{two}_{n,n} \, \text{dogs}_n]_{np} & & \rightarrow \text{two}_{n,np} \, \text{dogs}_n \\ & [\text{working}_{np,s}]_{n,n} & & & \text{who}_{(np,s),n,n} \, \text{working} \end{split}$$

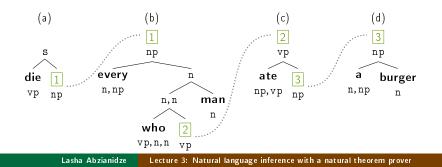
## fixed CCG term $\rightarrow$ LLFs

Generate LLFs

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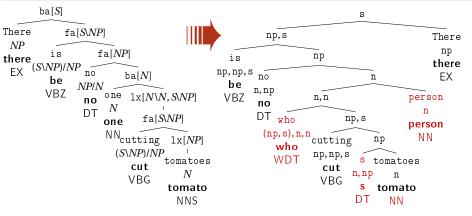
Every man who ate a burger died die<sub>vp</sub> (every<sub>n,np</sub>(who<sub>vp,n,n</sub> (eat<sub>np,vp</sub> ( $a_{n,np}$  burger<sub>n</sub>)) man<sub>n</sub>))  $\rightarrow$ EVERY<sub>n,vp,s</sub>(who ( $\lambda x. A_{n,vp,s}$  burger ( $\lambda y. eat y_{np} x_{np}$ ))man)die A<sub>n,vp,s</sub> burger( $\lambda y. EVERY_{n,vp,s}$ (who ( $\lambda x. eat y_{np} x_{np}$ )man)die)

NLI datasets

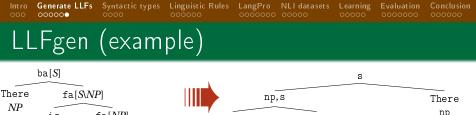


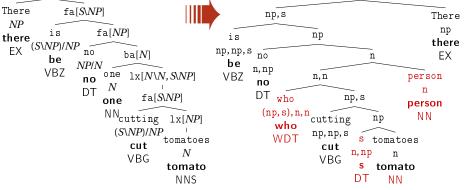
Intro Generate LLFs Syntactic types Linguistic Rules LangPro NLI datasets Learning Evaluation Conclusion

### LLFgen (example)



### There is no one cutting tomatoes $\rightsquigarrow$ $be(no(who(cut(s \ tomato))person))there$





be(no(who(cut(s tomato))person))there  $\rightsquigarrow$ no(who ( $\lambda x$ . s tomato ( $\lambda y$ . cut y x)) person)( $\lambda z$ . be z there) s tomato ( $\lambda y$ .no(who (cut y) person)( $\lambda z$ . be z there)) Uninformative *et*-based types

Syntactic types

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Semantic types based on e and t are uninformative from a syntactic point of view:

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 $\operatorname{cat}_{\rho t}: [C_{\rho}]$  $h_{ot}: [c_o]$  or  $sleep_{et}: [c_e]$ little<sub>(et)et</sub> bird<sub>et</sub>: [c<sub>e</sub>]  $A_{(et)et} B_{et} : [c_e]$ or high<sub>(et)et</sub> fly<sub>et</sub>: [c<sub>e</sub>] quietly<sub>(et)et</sub> (follow<sub>eet</sub> john<sub>e</sub>):  $[c_e]$  $a_{(et)et}(b_{eet}c_e):[c_e]$ or wife<sub>(et)et</sub> (of<sub>eet</sub> john<sub>e</sub>):  $[c_e]$ 

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### Extending the type system

Add syntactic types to semantic ones:

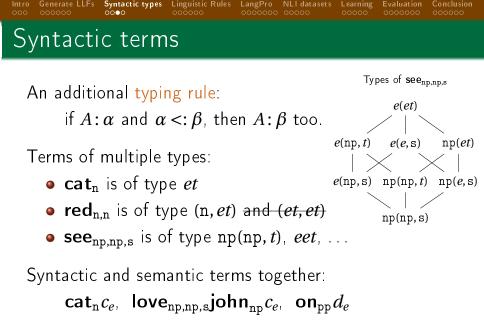
 $\{e, t\} + \{np, s, n, pp\}$ 

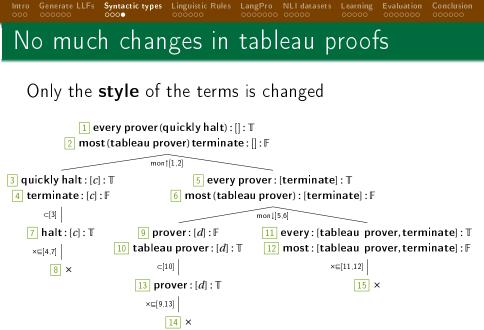
Syntactic types

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A partial order subtyping relation (<:) serves as an interface between syntactic and semantic types:

- s<:t
- *e* <: np
- n <: *et*
- pp <: *et*
- $(\alpha_1, \alpha_2) <: (\beta_1, \beta_2)$  iff  $\beta_1 <: \alpha_1$  and  $\alpha_2 <: \beta_2$





## Linguistic Rules

Linguistic rules, in contrast to the algebraic rules, account for a certain syntactic constructions.

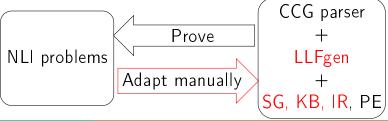
Linguistic Rules

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We will also include the rules that *remedy* errors introduced in the syntactic derivation trees.

Most of the linguistic rules are collected in a data-driven fashion:

NLI datasets



Rules for prepositions

Linguistic Rules

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$$\begin{array}{c} \mathtt{PP@N}_{\mathbb{T}} \\ p_{\mathtt{np},\mathtt{n},\mathtt{n}}^{\mathtt{IN}} dN : [c] : \mathbb{T} \\ N : [c] : \mathbb{T} \\ p_{\mathtt{np},\mathtt{pp}} : [d,c] : \mathbb{T} \end{array}$$

with<sub>np,n,n</sub>  $g_e$  bicycle<sub>n</sub>:  $[c_e]$ :  $\mathbb{T}$ 

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**bicycle**: [c]:  $\mathbb{T}$ with<sub>np,pp</sub>: [g, c]:  $\mathbb{T}$ 



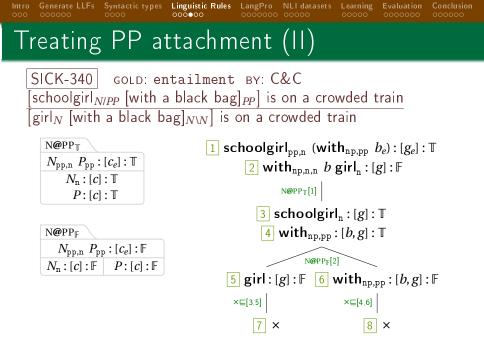
Treating PP attachment

Syntactic types Linguistic Rules

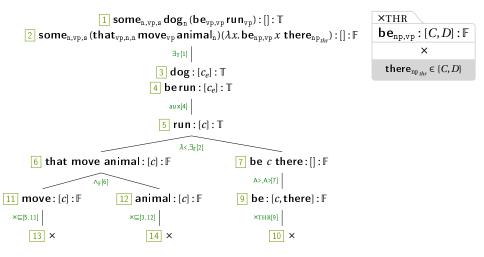
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$$\begin{array}{c} V @ \mathsf{PP} \\ \hline V_{\mathsf{pp},\alpha} \left( p_{\mathsf{np},\mathsf{pp}}^{\mathsf{IN}} D \right) : [\vec{C}] : \mathbb{X} \\ p_{\mathsf{np},\alpha,\alpha}^{\mathsf{IN}} D V_{\alpha} : [\vec{C}] : \mathbb{X} \\ \alpha = (\mathsf{np}^*, \mathsf{vp}) \end{array}$$

$$\begin{array}{c} \mathsf{lie}_{\mathsf{pp},\mathsf{vp}} \ (\mathsf{in}_{\mathsf{np},\mathsf{pp}} \ o_e) : [c] : \mathbb{F} \\ \\ \\ \mathsf{in}_{\mathsf{np},\mathsf{vp},\mathsf{vp}} \ o_e \ \mathsf{lie}_{\mathsf{vp}} : [c] : \mathbb{F} \end{array}$$



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## Other closure rules

Syntactic types Linguistic Rules

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### Open compound nouns:

 $\begin{array}{c} \times \text{CPN} \\ & N_{n} : [d] : \mathbb{T} \\ H_{\text{pp,n}}(prp \ d) : [c] : \overline{\mathbb{X}} \\ & A_{n,n} \ H_{n} : [c] : \mathbb{X} \\ & \times \\ & N \approx A \text{ or } N \approx_{d} A \end{array}$ 

$$\begin{array}{c} \mathsf{protection}_{n} : [d_{e}] : \mathbb{T} \\ \mathsf{gear}_{pp,n}(\mathsf{for}_{np,pp} \ d_{e}) : [c_{e}] : \mathbb{F} \\ \\ \hline \mathsf{protective}_{n,n} \ \mathsf{gear}_{n} : [c_{e}] : \mathbb{T} \\ \times \end{array} (\times \mathbb{CPN}^{*})$$

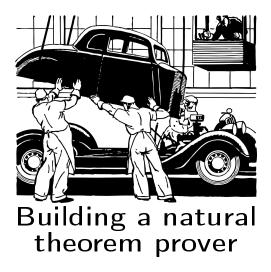
### Light verb constructions:

×LVC  

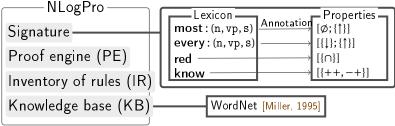
$$l_{\vec{\alpha},vp}: [c, \vec{D}]: \mathbb{X}$$
  
 $u_n: [c]: \mathbb{T}$   
 $v_{\vec{\alpha},s}: [D]: \mathbb{X}$   
×  
 $l \in \{\text{do, get, give, have, make, take}\}$ .  
 $\vec{\sigma}$  is formed by pp and pp and  $u \approx v$ 

$$\frac{\mathsf{do}_{\mathrm{np},\mathrm{vp}}:[d_e,h_e]:\mathbb{T}}{\mathsf{dance}_{\mathrm{n}}:[d_e]:\mathbb{T}} \\ \frac{\mathsf{dance}_{\mathrm{vp}}:[h_e]:\mathbb{F}}{\times} (\times \mathrm{LVC}^*)$$

Syntactic types Linguistic Rules LangPro NLI datasets Learning ••••••







KB uses 4 relations from WordNet 3.0:

- derivation
- similarity
- hyponymy/hypernymy
- antonymy
- 🛕 No word sense disambiguation system is used.

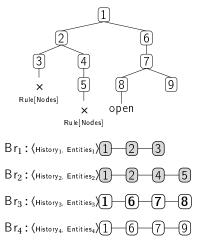
## Two data structures

The proof engine builds both a tree and a list structures:

LangPro

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NLI datasets



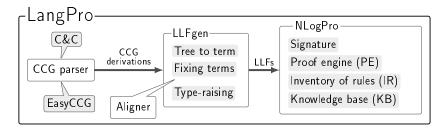
## Natural language theorem prover

Chaining a CCG parser, the LLF generator and NLogPro results in a theorem prover for natural language.

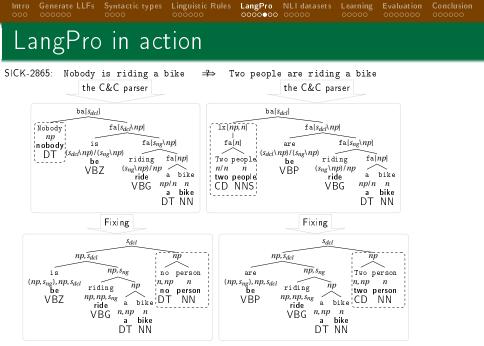
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Evaluation

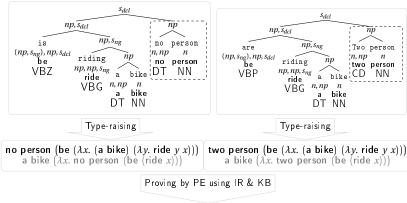


Online demo at: http://naturallogic.pro git clone: https://github.com/kovvalsky/LangPro



Lasha Abzianidze Lecture 3: Natural language inference with a natural theorem prover





intial nodes for entailment checking: no person (be  $(\lambda x. (a bike) (\lambda y. ride y x))): []: \mathbb{T}$ two person (be  $(\lambda x. (a bike) (\lambda y. ride y x))): []: \mathbb{T}$ two person (be  $(\lambda x. (a bike) (\lambda y. ride y x))): []: \mathbb{T}$ 

### Syntactic types Linguistic Rules LangPro NLI datasets Learning Evaluation 000000 LangPro in action (3) no person (be( $\lambda x$ . (a bike) ( $\lambda y$ . ride y x))): []: T 2 two person (be ( $\lambda x$ . (a bike) ( $\lambda y$ . ride y x))):[]: $\mathbb{T}$ ∃<sub>T</sub>[2] 3 person: $[c]:\mathbb{T}$ 4 be( $\lambda x$ . (a bike) ( $\lambda y$ . ride y x)): [c]: $\mathbb{T}$ $\operatorname{no}_{\mathbb{T}}^{n}[1,4]$ 5 person: $[c]:\mathbb{F}$ 6 × $N^{CD} A B: []: \mathbb{T}_{P}$ **no** $A B: []: \mathbb{T}$ $A: [c]: \mathbb{T} \\ --- \operatorname{no}_{\mathbb{T}}^{n}$ $A: [c]: \mathbb{T}$ $B: [c]: \mathbb{F}$ $B: [c]: \mathbb{T}$

Lasha Abzianidze Lecture 3: Natural language inference with a natural theorem prover

## The SICK dataset

Syntactic types

SICK [Marelli et al., 2014b] contains Sentences Involving Compositional Knowledge:

• 10K Text-Hypothesis pairs annotated by humans with three labels: E, C, & N.

NLI datasets

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Evaluation

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- Contains no encyclopedic knowledge, no named entities, relatively small vocabulary, less multiword expressions and no lengthy sentences (9 words per sentence).
- SemEval-14 RTE benchmark [Marelli et al., 2014a]
- 84% of crowd workers' labels match the majority, i.e, gold labels.

### SICK construction

Generate LLFs Syntactic types Linguistic Rules LangPro NLI datasets

Original pair			
S0a: A sea turtle is hunting for fish	S0b: The turtle followed the fish		
Normalized pair			
<b>S1a</b> : A sea turtle is hunting for fish	S1b: The turtle is following the fish		
Ex panded pair			
Similar meaning S2a: A sea turtle is hunting for food S2b: The turtle is following the red fish			
		tisn	
	at least highly contrasting meaning	ch	
S3a: A sea turtle is not hunting for fish S3b: The turtle isn't following the fish Lexically similar but different meaning			
S4a: A fish is hunting for a turtle in the sea S4b: The fish is following the turtle			
Normalized senter		Score	Label
	<b>52a:</b> A sea turtle is hunting for food	4.5	E
	<b>51a</b> : A sea turtle is hunting for fish	3.4	c
	<b>1a:</b> A sea turtle is hunting for fish	3.9	Ν
	<b>1b</b> : The turtle is following the fish	4.6	Ë
S1b: The turtle is following the fish S	<b>3b</b> : The turtle isn't following the fish	4	С
S1b: The turtle is following the fish S	4b: The fish is following the turtle	3.8	С
S1a: A sea turtle is hunting for fish S	<b>2b</b> : The turtle is following the red fish	4	N
S1a: A sea turtle is hunting for fish S	<b>3b</b> : The turtle isn't following the fish	3.2	Ν
S4b: The fish is following the turtle S	51a: A sea turtle is hunting for fish	3.2	Ν
S1b: The turtle is following the fish S	2a: A sea turtle is hunting for food	3.9	N
S1b: The turtle is following the fish S	<b>3a</b> : A sea turtle is not hunting for fish	3.4	Ν
S4a: A fish is hunting for a turtle in the sea S	51b: The turtle is following the fish	3.5	Ν
S1a: A sea turtle is hunting for fish S	<b>1b</b> : The turtle is following the fish	3.8	N

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SICK examples and stats

SICK-1241 GOLD: neutral A woman is dancing and singing with other women A woman is dancing and singing in the rain

Generate LLFs Syntactic types Linguistic Rules LangPro NLI datasets Learning

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Evaluation

SICK-341 GOLD: contradiction There is no girl with a black bag on a crowded train A girl with a black bag is on a crowded train

SICK-8381 GOLD: entailment The young girl in blue is having fun on a slide The young girl in blue is enjoying a slide

### The FraCaS dataset

Syntactic types

The FraCaS test suite [Cooper et al., 1996]:

Linguistic Rules

- Contains 346 problems (45% multi-premised)
- Covers GQs, plurals, anaphora, ellipsis, adjectives, comparatives, temporal reference, verbs and attitudes.

NLI datasets

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Evaluation

- Three-way annotated by the authors of the dataset.
- Requires almost no lexical or world knowledge

The NLI dataset derived from FraCaS [MacCartney and Manning, 2007].

FraCaS NLI problems

FraCaS-26GOLD: entailmentMost Europeans are resident in EuropeAll Europeans are peopleAll people who are resident in Europe can travel freely within EuropeMost Europeans can travel freely within Europe

FraCaS-61 GOLD: undefined Both female commissioners used to be in business. Both commissioners used to be in business.

FraCaS-171 GOLD: entailment

John wants to know how many men work part time.

And women.

John wants to know how many women work part time.

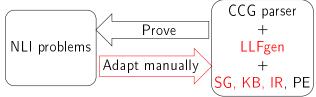
NLI data sets

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# Intro Generate LLFs Syntactic types Linguistic Rules LangPro NLI datasets Learning Evaluation Conclusion

The prover LangPro is (semi-automatically) trained on the NLI datasets [Abzianidze, 2016a].

• Adaptation



Used datasets: SICK-trial and FraCaS

• Development:

Finding optimal values for certain parameters of the prover based on its performance on SICK-train

# Intro Generate LLFs Syntactic types Linguistic Rules LangPro NLI datasets Learning Evaluation Conclusion

The problems that were solved by upgrading one of the components of the prover:

 Treat few as ↓ in its 1st arg (absolute reading): FraCaS-76 GOLD: entailment Few committee members are from southern Europe Few female committee members are from southern Europe

### • Introduce $fit \sqsubseteq apply$ and $food \sqsubseteq meal$ :

SICK-4734 GOLD: entailment A man is fitting a silencer to a pistol

A man is applying a silencer to a gun

SICK-5110 GOLD: entailment

A chef is preparing some food

A chef is preparing a meal

### Development phase

Optimal values are searched for:

- The number of word senses to consider;
- The max number of rule application limit (RAL);
- Whether to use a term aligner:
  - Weak aligner aligns everything but terms of type np: SICK-727 GOLD: contradiction The man in a grey t-shirt is sitting on a rock in front of the waterfall There is no man in a grey t-shirt sitting on a rock in front of the waterfall

NLI datasets Learning

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**Evaluation** 

 Strong aligner aligns everything but terms of type terms of type np with ↓arg.
 SICK-423 GOLD: contradiction Two men are not holding fishing poles
 Two men are holding fishing poles
 Aligner

#### Greedy search for optimal parameters

Evaluation

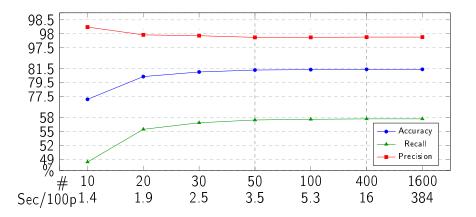
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Generate LLFs Syntactic types Linguistic Rules LangPro NLI datasets Learning

Acc%	Prec%	Rec%	Sense	Efficiency criterion	Aligner	RAL	Parser
75.09	98.5	43.6	1	[nonP,nonB,equi,nonC]	No	200	C&C
76.42	98.3	46.8	1-5	-	-	-	-
76.89	97.8	48.1	All	-	-	-	-
78.44	97.9	51.7	-	[equi,nonB,nonP,nonC]	-	-	-
79.33	97.9	53.8	-	-	Weak	-	-
81.5	97.7	59.0	-	-	Strong	-	-
81.53	97.7	59.1	-	-	Strong	400	-
81.38	98.0	58.5	-	-	Strong	400	EasyCCG
82.6	97.7	61.6	-	-	Strong	400	Both

The results are given on the SICK-train problems.

Efficient and optimal RAL



Learning

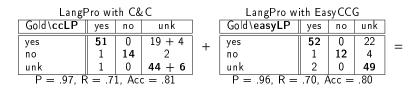
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Evaluation

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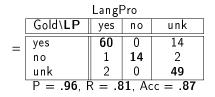
The results are given on the SICK-train problems.

### Solving FraCaS [Abzianidze, 2016b]



NLI datasets

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FraCaS-109GOLD: contradictionLP: entailmentJust one accountant attended the meetingSome accountants attended the meeting

[MacCartney and Manning, 2008] and [Angeli and Manning, 2014] employ a natural logic that is driven by sentence edits.

Evaluation

[Lewis and Steedman, 2013] employ Boxer-style [Bos et al., 2004] translation into FOL, Prover9 and distributional relation clustering.

[Mineshima et al., 2015] also uses the Boxer-style translation but some HOGQs are treated as higher-order terms. Their inference system is implemented in the proof assistant Coq.

[Tian et al., 2014] and [Dong et al., 2014] uses abstract denotations obtained from DCS trees [Liang et al., 2011]:  $man \subset \pi_{subj}(read \cap (W_{subj} \times book_{obj}))$ 

[Bernardy and Chatzikyriakidis, 2017] uses Grammatical Framework and Coq. They use gold standard GF trees.

Sec (Sing/All)			Single-premised (Acc %)								Overall (Acc %)							
		BL	NLO	7,08	LS I	P/G	NLI	T14	la,b	M15	LP	ΒL	LS	P/G	T14	la,b	M15	LΡ
1 GQs	(44/74)	45	84	98	70	89	95	80	93	82	93	50	62	85	80	95	78	95
2 Plur	(24/33)	58	42	75	-	-	38		-	67	75	61		-	-	-	67	73
5 Adj	(15/22)	40	60	80	-	-	87	.	-	87	87	41		-		-	68	77
9 Att	(9/13)	67	<del>56</del>	89	-	-	22		-	78	100	62		-		-	77	92
1,2,5,9	(92/142)	50	-	88	-	-	-	-	-	78	88	52		-		-	74	87

Evaluation

NL07 [MacCartney and Manning, 2007], NL08 [MacCartney and Manning, 2008], NLI [Angeli and Manning, 2014], LS [Lewis and Steedman, 2013], M15 [Mineshima et al., 2015], T14a [Tian et al., 2014] and T14b [Dong et al., 2014]

Advantages of our approach over the related ones include:

- Reasoning (with the semantic tableau) over multiple-premises;
- Logical forms close to surface forms;
- Underlying expressive high-order logic.

### Curing SICK [Abzianidze, 2015]

Gold LangPro SICK-test	Ent	Cont	Neut
Entailment	805	0	609
Contradiction	2	482	236
Neutral	26	7	2760

Evaluation

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P=97.4%, R=60.3%, Acc=82.14%

Mainly the usage of WordNet and noisy gold labels are blamed for false proofs.

ID G/LP	Premise	Conclusion
		A woman is cutting <b>shrimps</b>
4443 N/E	A man is singing to a <b>gir</b> l	A man is singing to a <b>woman</b>
	Two people are riding a motorcycle	
	A couple is not looking at a map	
262 010	P: A soccer ball is not rolling into a g C: A soccer ball is rolling into a goal i	oal net
303 C/C	C: A soccer ball is rolling into a goal i	net



Reason for false neutrals are knowledge sparsity (ca 50%), a lack of rules (ca 25%), wrong labels and parsing mistakes.

ID G/LP	Premise	Conclusion
4974 E/N	Someone is holding a hedgehog	Someone is holding a small animal
6258 E/N	P: A policeman is sitting on a motor	
	C: The cop is sitting on a police bike	
4553 E/N	C. A man is emptying a plastic conta	ainer
4720 E/N	A monkey is practicing martial arts	A chimp is practicing martial arts
6447 C/N	P: [A small boy [in a yellow shirt]] is	
	C: There is no small boy [in a yellow	<pre>v shirt [laughing on the beach]]</pre>

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### Comparison on SICK

SemEval-14 systems	Prec%	Rec%	Acc%	(+LP)	NWS%
Baseline (majority)	-	-	56.69		39.7
Illinois-LH	81.56	81.87	84.57	(+0.65)	72.8
ECNU	84.37	74.37	83.64	(+1.77)	72.7
UNAL-NLP	81.99	76.80	83.05	(+1.48)	71.2
SemantiKLUE	85.40	69.63	82.32	(+2.84)	71.5
The Meaning Factory	93.63	60.64	81.59	(+2.78)	73.0
UTexas (Prob-FOL)	97.87	38.71	73.23	(+9.44)	62.5
LangPro	97.35	60.31	82.14		74.8

The problems from SICK-test that were proved correctly by both ccLangPro and easyLangPro but failed by all the top five systems at the SemEval-14 task.

ID	G	Text Hypothesis
247	C	T: The woman is not wearing glasses or a headdress
241		H: A woman is wearing an Egyptian headdress
406	Е	T: A group of scouts are hiking through the grass
406   E		H: People are walking
2895	С	The man isn't lifting weights The man is lifting barbells
3527	Е	T: A person is jotting something with a pencil
3521		H: A person is writing
3570	С	The piece of paper is not being cut Paper is being cut with scissors
3608	Ν	T: A monkey is riding a bike
		H: A bike is being ridden over a monkey
3806	Е	A man in a hat is playing a harp A man is playing an instrument
4479	Е	The boy is playing the piano The boy is playing a musical instrument

Natural Tableau is a wide-coverage but still logic-based reasoning system inspired by Natural Logic.

It represents a proof-theoretic approach to NLI.

Natural tableau was successfully scaled up for the NLI task: CCG parser + LLFgen + theorem prover

Pros and cons of Natural Tableau:

- Employs higher-order logic to model linguistic semantics;
- Allows deep logical and shallow (e.g. monotonicity) reasoning;
- Getting logical form is similar to syntactic parsing;
- Heavily hinges on CCG parsing;
- ✓ Proofs are highly reliable ( $\leq 3\%$  false proofs);
- Suffers from multi-sense words;
- X No fully automated learning from data yet;
- Its decision procedure is transparent and explanatory;

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There are really many directions for future work:

- Explore different types of RTE data, e.g., the newswire or human generated data [Bowman et al., 2015];
- Incorporate more knowledge in KB, e.g., paraphrase database [Ganitkevitch et al., 2013].
- Model different phenomena: comparatives, anaphora, cardinals, etc.
- Pairing with distributional semantics: R(w1, w2, r) and weighted closure branches;
- Acquisition of lexical knowledge: abductive reasoning;
- Generate LLFs from Universal Dependency trees

   + the Universal Semantic Tagging [Abzianidze and Bos, 2017]
   →? Multilingual Natural Tableau



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