Corpus Annotation, Parsing, and Inference for Episodic Logic Type Structure

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What does it mean to understand language?

Al-complete?



To understand language

1. parse the structure



- 2. relate to world knowledge
- 3. consider the participants





Feature of Symbolic Systems

Effect of single interactions on

- complex plans
- model of the world

Major systematic change

Requires modeling of precise relationships

Interface for world model & communicative intent

→ Language Meaning (Bender & Koller 2020)

Symbols for Language Meaning

Shared across languages: purpose + human cognition

- truth/falsity
- predicates
- identity
- generalized quantifiers
- modification
- reification
- event reference
- comparatives

FOL

most, few, many, no, at most 10 very, gracefully, nearly, possibly <u>Beauty</u> is subjective. <u>That exoplanets exist</u> is now certain. Many children had not been vaccinated against measles; <u>this situation</u> caused sporadic outbreaks of the disease.

Doorways are taller than most people



Unscoped Episodic Logical Forms (ULF)

Underspecified Expressive Logic

ULF Parsing

Neural Model Over a Transition System

ULF Inference

Pragmatic Discourse and Natural Logic

Wider Use of ULF

Spatial Reasoning Agent & Schema Learning

Design of ULF



Episodic Logic (EL)

- Extended FOL
- Closely matches expressivity of natural languages
 - Predicates, connectives, quantifiers, equality
 - Predicate and sentence modification
 - Predicate and sentence reification
 - Generalized quantifiers
 - Intensional predicates
 - Reference to events and situations

EL Inference

- Suitable for deductive and uncertain inference
- EPILOG for fast and comprehensive theorem proving

How hard is it to annotate and parse Episodic Logic?





Errors for 1 in 3 verb definitions! (Kim and Schubert, 2016)

What if we leave things that are ambiguous without context?

"I want to dance in my new shoes" 📃



Unscoped Logical Form

(i.pro ((pres want.v) (to (dance.v (adv-a (in.p (my.d ((mod-n new.a) (plur shoe.n))

Episodic Logic

 $(\exists e: [e \text{ at-about Now}]$ [[Gene want1.v (ka (λx : [[x dance1.v] \wedge $(\iota y: [[y \text{ shoes.n}] \land$ $[y \text{ poss-by Gene}] \land$ [x in-wear y]])]))] ** e])

1. Retain ambiguity of

- a. scopes
- b. word sense
- c. anaphora
- d. event relations
- 2. Maintain semantic coherence
- **Reflect syntactic structure** 3.







ULF & Semantics

Basic Ontological Types

- \mathcal{D} Domain
- ${\cal S}$ Situations

2 Truth-value

 $\begin{array}{l} \text{Monadic Predicate} \\ \mathcal{N}: (\mathcal{D} \rightarrow (\mathcal{S} \rightarrow \mathbf{2})) \end{array}$

"Alice thinks that John nearly fell" (|Alice| (((pres think.v) (that (|John| (<u>nearly.adv-a</u> (past fall.v))))))

"You made the order for me" (you.pro ((past make.v) (the.d order.n) (adv-a (for.p me.pro))))

Determiner $(\mathcal{N} \rightarrow \mathcal{D})$: the.d

Modifier Constructor $(\mathcal{N} \to (\mathcal{N} \to \mathcal{N}))$: adv-a

Predicate modifier $(\mathcal{N} \rightarrow \mathcal{N})$: <u>nearly.adv-a</u>

Sentence reifier $((\mathcal{S} \rightarrow \mathbf{2}) \rightarrow \mathcal{D})$: that

"I want to dance in my new shoes" 📃







"I want to dance in my new shoes"







Dataset Annotation



Human ULF annotations

- are fast
 (~8 min/sent)
- are *consistent* (up to 0.88 IAA)



Data (ULF Release)



Trained student annotators + Reviewed by an expert annotator

Text Sources

Tatoeba (crowd-sourced translations)

Project Gutenberg (100 most popular)

Discourse Graphbank (WSJ subset) [Wolf, 2005]

UIUC Question Classification [Li & Roth, 2002]

1,738 sentences





Parsing into ULF





Xin (Lucy) Lu Stanford (formerly UR)



Lenhart Schubert UR

Viet Duong UR

Can we actually learn a parser from English to ULF?

Challenge Relatively modest dataset size

Parser Design ULF-oriented transition system



Neural action selector



Cache Transition System

Initialize with empty stack & cache, buffer of node labels

- 1. Shift: add buffer node to graph
- 2. **Push:** insert shifted node to cache (move prior one to stack)
- 3. Arc: make edges in cache
- 4. **Pop:** remove rightmost cache element (move elements to right)





How do we tailor this to ULF?

Node label regularity

Word-based Node Labels



Structure-based Node Labels

Type-shifter		Operand
k	operates on	noun predicates (k gold.n)
ka		<pre>verb predicates (ka (run.v quickly.adv-a))</pre>
that		<pre>sentences (that (i.pro (past win.v)))</pre>
adv-a		any predicates (adv-a (for.p you.pro))





Transition System Procedure

Initialize with empty stack & cache, buffer of *word* sequence.

- 1. **Gen:** generate a symbol and add to tree
- 2. Push: insert gen'd node to cache
- 3. Arc: make edges in cache
- 4. **Promote:** type-shift rightmost cache element
- 5. **Pop:** remove rightmost cache element (move elements to right)



How do we train an action selector?



Parsing Action Sequence

Oracle

Gen & Arc

Greedy symbol and edge generation while tracking word-symbol alignment

Skip words if their alignment is earlier than predicted

Push

Choose the cache index whose closest edge or path including only promoted symbols into buffer is farthest away

Unaligned symbols may be generated via promote

Promote

If promoted gold edge exists to rightmost cache item and child is fully formed, add it.

Bottom-up enforced for Promote & Type Constrained Decoding






Word Sequence

GloVe + RoBERTa + CharCNN + lemmas + POS + NER



Symbol Sequence

Symbol + CharCNN (of aligned word)





Transition State Features

Always: Current Phase

Pop/*Gen: rightmost cache + leftmost buffer *token, dependency*, and *ULF arc* features

Arc/Promote: two cache position *token, dependency,* and *ULF arc* features; dependencies between them

LSTM



Experimental Details

Data Split (~8/1/1)

1,738 sentences

- 1,378 train
- 180 dev
- 180 test

SemBLEU

Extends BLEU to graphs. Based on overlaps of path segments in a graph. [Song & Gildea 2019]

EL-Smatch

Extends smatch to non-atomic operators. Computes node alignment with highest possible overlap of node and edge labels. [Kai & Knight, 2013; Kim & Schubert, 2016]

Comparison to Baselines



Baselines

Strong AMR parsers w/ minimal AMR-specific assumptions

They struggle on node-label prediction

dataset is too small

Inference with ULF







Sophie SacksteinMuskaan MendirattaBooz Allen HamiltonBarclaysFormerly URFormerly UR



Benjamin Kane UR



Viet Duong William & Mary Formerly UR

Georgiy Platonov Amazon Formerly UR



Lenhart Schubert UR



Generative



((sub what.pro ((past do.aux-s) you.pro (buy.v *h))) ?) **De-topicalization** "what did you buy?" "did you buy what"

((sub what.pro ((past do.aux-s) you.pro (buy.v *h))) ?)

"what did you buy?"

Un-inversion

"did you buy what" "you did buy what"

((sub what.pro ((past do.aux-s) you.pro (buy.v *h))) ?)

"what did you buy?"

De-questioning

"did you buy what?"

"you did buy what?" "you did buy something" (you.pro ((past do.aux-s) (buy.v something.pro))) 52

Experimental Details

Precision

Freely generate inferences and judge a 127 inferences sample with human evaluators

• 3 or 4 evaluations per inference

Recall

Get human inferences for a sample of sentences and check coverage that the automatic inferences achieve

• annotators are trained for these phenomena

698 inferences 406 sentences

Precision Evaluation



Correct 68.5% Contextual 15.0% Incorrect 16.5%

Grammatical 78.0%

Recall Evaluation



1. Basic Inference

2. Paraphrasing & Coordination [In ULF]

"I want you to get that done" + "I expect you to get that done" → "I want and expect you to get that done"

3. Translate to English

(i.pro (((pres want.v) and.cc (pres expect.v)) you.pro (to (get.v that.pro done.a)))) \rightarrow "I want and expect you to get that done"

4. Select closest match with minimal difference

a. Allow 3 character edit distance

Recall Evaluation



Out of 662 inferences, 112 found (~17%)

*Simple baseline ~0%

Natural Logic

Generate natural language inferences based on syntactic structure and local semantic properties

Monotonicity Inference

Specialization and generalization inferences based on contexts imposed by polarity operators

Some delegates (finished the survey on time) \Rightarrow Some delegates finished the survey

I never had a $(girlfriend)^{\checkmark}$ *before* \Rightarrow *I never had a girlfriend taller than me before*

Exactly 12 aliens read (magazines)[■] ⇔ Exactly 12 aliens read (news magazines)[■]

Sánchez Valencia



ULF



Mandar Juvekar UR



Junis Ekmekciu UR



Viet Duong UR



Lenhart Schubert UR

Sánchez Valencia's System

Inference 1 abelard sees a carp, every carp is a fish / abelard sees a fish

Monotonicity

 $(every \ x)^{\#} \ is \ a \ y, F(x^{+}), X \bullet Y$ $(every \ x)^{\#} \ is \ a \ y, F(y), X \bullet Y$



 $abe\ see\ a\ carp$, $every\ carp\ is\ a\ fish$ \bullet $abe\ see\ a\ fish$ $abe\ sees\ (a\ carp)^{\#}$, $(every\ carp)^{\#}$ is a fish \bullet $abe\ sees\ (a\ fish)^{\#}$ marking $abe\ sees\ (a\ fish)^{\#}$, $(every\ carp)^{\#}$ is a fish \bullet $abe\ sees\ (a\ fish)^{\#}$ marking $abe\ sees\ (a\ fish)^{\#}$, $(every\ carp)^{\#}$ is a fish \bullet $abe\ sees\ (a\ fish)^{\#}$ monotonicity

Natural Logic with ULFs



Monotonicity (UMI)

$$\frac{\phi[(\delta P1)^+], ((\text{every.d } P1) (\text{be.v} (= (\text{a.d } P2))))}{\phi[(\delta P2)]}$$

where δ is a determiner.

Data



Premises Some delegates finished the survey on time

Hypothesis Some delegates finished the survey

Label ENTAILMENT

FraCaS Generalized Quantifiers (GQs)

- 1. Curated by linguists
- 2. Largest section of FraCaS (80/346, 23%)
- 3. Quantifiers impose polarities on restrictor and scope

Inference System







Why not a trained 1. Short, grammatical sentences ULF parser? 2. Errors are more regular and predictables



Initial Polarity Marking





Polarity Propagation








1. Monotonicity Substitution

Every A is a $B + S[A+] \Rightarrow S[B]$

2. Conversion

Some A is a B ⇔ Some B is an A

3. Conservativity

DET As are Bs 🗢 DET As are As that/who are Bs

4. Equivalences

e.g., Every dog is happy \Leftrightarrow All dogs are happy





Search: Interleaved heuristic and breadth-first search

maintain completeness with simple/quick heuristic

Heuristic: F1 score between atoms of new formula and goal

ENTAILMENT : exact match

CONTRADICTION : top-level negation + exact match

UNKNOWN : reached max # of steps or exhausted all inferences

Results



FraCaS GQ Performance



Wider Use of ULF



Spatial Reasoning

David



<u>Time</u>	Scene	Memory	Facts (query)	Facts (embed)
Now0 ↑	D A B C	(you ((past ask.v))	(B touching.p A) (B touching.p C) (B touching.p D)	None
Now1 ↑	A B C	(D ((past move.v) (from.p-arg (\$ loc 1 1)) (to.p-arg (\$ loc 2 1))))	(B touching.p A) (B touching.p C)	None
Now2	A B C	(you ((past ask.v))	(B touching.p A) (B touching.p C)	None
 Now3 ↑	B D A C	(B ((past move.v) (from.p-arg (\$ loc 1 0)) (to.p-arg (\$ loc 0 1))))		(B (past move.v))
 Now4 ↑	D B A C	(D ((past move.v) (from.p-arg (\$ loc 2 1)) (to.p-arg (\$ loc 0 2))))		None
 Now5 ↑	D B A C	(you ((past ask.v))		None
Perceive-world.v:		(A at-loc.p (\$ loc 0 0)) (B at-loc.p (\$ loc 1 0)) (C at-loc.p (\$ loc 2 0)) (D at-loc.p (\$ loc 1 1))		
WM/hat blocks did D tayah hafara I may ad it?"				



David



Hey David, what block is next to Target block?

The Starbucks block is next to the Target block



There are no blocks next to the Starbucks block

Schema Learning



Conclusion



ULF Summarized

Type system + syntax for easy access expressive semantics. This enables

- Sufficient data collection speed and consistency
- Parsability with modest data size
- Syntax-related *inferences*
- Use in larger language interfacing systems

Thanks!







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