A Type-coherent, Expressive Representation as an Initial Step to Language Understanding

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May 2019
Unscoped {Episodic} Logical Form (ULF)

- An underspecified Episodic Logic (EL)
- Starting point for EL parsing
- Enables situated inferences
Motivation

Semantic representation desiderata

1. Adequately models the complexity of language semantics
2. Enables the production of general inferences
3. Can be recovered accurately
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1. Adequately models the complexity of language semantics
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Episodic Logic
- Extended FOL
- Closely matches expressivity of natural languages
  - Predicates, connectives, quantifiers, equality $\rightarrow$ FOL
  - Predicate and sentence modification (e.g. very, gracefully, nearly, possibly)
  - Predicate and sentence reification (e.g. Beauty is subjective, That exoplanets exist is now certain)
  - Generalized quantifiers (e.g. most men who smoke)
  - Intensional predicates (e.g. believe, intend, resemble)
  - Reference to events and situations (Many children had not been vaccinated against measles; this situation caused sporadic outbreaks of the disease)
- Suitable for deductive, uncertain, and Natural-Logic-like inference
- A fast and comprehensive theorem prover, EPILOG, is already available.
Language understanding is a growing area of interest in NLP

**Question Answering**: AI2 Reasoning challenge, RACE, SQuAD, TriviaQA, NarrativeQA...

**Dialogue**: Amazon Alexa Challenge, Google Home, Microsoft Cortana...

**Inferring from Language**: JOCI, SNLI, MultiNLI...

**Semantic Parsing**: AMR, DRS Parsing (IWCS-2019 Shared Task), Cross-lingual Semantic Parsing
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Current state-of-the-art systems often end up modeling artifacts

SQuAD question answering and reading comprehension (*Jia & Liang 2017*)

- **Unrelated Information:** 80.0% → 34.2%

Inferring from language (*Gururangan et al., 2018; Poliak et al., 2018*)

- **Hypothesis Only:** SNLI - majority class baseline: 34.3% → 69.0%
Our Driving Hypotheses

1. A divide-and-conquer approach to semantic parsing will ultimately lead to more precise and useful representations for reasoning over language.

Hypothesis 1: Divide-and-conquer
1. A divide-and-conquer approach to semantic parsing will ultimately lead to more precise and useful representations for reasoning over language.

2. An expressive logical representation with model-theoretic backing will enable reasoning capabilities that are not offered by other semantic representations available today.
Our Driving Hypotheses

1. A divide-and-conquer approach to semantic parsing will ultimately lead to more precise and useful representations for reasoning over language.

2. An expressive logical representation with model-theoretic backing will enable reasoning capabilities that are not offered by other semantic representations available today.

3. Better language understanding and reasoning systems can be built by combining the strengths of statistical systems in converting raw signals to structured representations and symbolic systems in performing precise and flexible manipulations over complex structures.

Hypothesis 3: Combine Statistical and Symbolic Methods
Our Driving Hypotheses

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3. Better language understanding and reasoning systems can be built by combining the strengths of statistical systems in converting raw signals to structured representations and symbolic systems in performing precise and flexible manipulations over complex structures.

Hypothesis 3: Combine Statistical and Symbolic Methods
What is ULF?

A minimal step across from syntax to semantics in Episodic Logic

“Alice thinks that John nearly fell”

ULF

(|Alice| (((pres think.v) (that (|John| (nearly.adv-a (past fall.v)))))))

Syntax (simplified)

(S (NP Alice.nnp) (VP thinks.vbz (SBAR that.rb (S (NP John.nnp) (ADVP nearly.rb) (VP fell.vbd))))))
A minimal step across from syntax to semantics in Episodic Logic

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(ULF
 (Alice
   (pres think.v)
   (that
     (John
       (nearly.adv-a (past fall.v)))
   )))

Syntax (simplified)

(S (NP Alice.nnp) (VP thinks.vbz
   (SBAR that.rb (S (NP John.nnp) (ADVP nearly.rb) (VP fell.vbd)))))

Proper Nouns
A minimal step across from syntax to semantics in Episodic Logic

“Alice thinks that John nearly fell”

ULF

\[
\text{(|Alice|} (\text{((pres think.v)} \text{(that (|John|} (\text{nearly.adv-a (past fall.v)}))))))
\]

Syntax (simplified)

\[
(S \text{ (NP Alice.nnp) (VP thinks.vbz}} \text{(SBAR that.rb (S (NP John.nnp) (ADVP nearly.rb) (VP fell.vbd))))})
\]

Verbs
A minimal step across from syntax to semantics in Episodic Logic

“Alice thinks that John nearly fell”

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(|Alice| (((pres think.v) (that (|John| (nearly.adv-a (past fall.v)))))])

Syntax (simplified)
(S (NP Alice.nnp) (VP thinks.vbz (SBAR that.rb (S (NP John.nnp) (ADVP nearly.rb) (VP fell.vbd))))))

Adverbs
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Syntax (simplified)

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   (SBAR that.rb (S (NP John.nnp) (ADVP nearly.rb) (VP fell.vbd))))))

Not just syntax!
What is ULF?

A minimal step across from syntax to semantics in Episodic Logic

“Alice thinks that John nearly fell”, “Could you dial for me?”

ULFs

(|Alice| (((pres think.v)
   (that (|John| (nearly.adv-a (past fall.v)))))))))

(((pres could.aux-v) you.pro
  (dial.v {ref1}.pro (adv-a (for.p me.pro)))) )

Basic Ontological Types

\[ \mathcal{D} \rightarrow (\mathcal{S} \rightarrow 2) \]

Monadic Predicate
What is ULF?

A minimal step across from syntax to semantics in Episodic Logic

“Alice thinks that John nearly fell”, “Could you dial for me?”

ULFs

\[
(|Alice| \ (\ (\ \ )
 (that \ (|John| \ (nearly.\ (past \ fall.\ )))))

\((\ \ )
 (\ ((pres \ could.aux-v) \ you.pro
 (dial.v \ (ref1}.pro \ (adv-a \ (for.p \ me.pro))))) ?)

Entity(\(\mathcal{D}\)):\ |Alice|, |John|, you.pro, {ref1}.pro, me.pro
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Entity(D): |Alice|, |John|, you.pro, {ref1}.pro, me.pro

n-ary predicate(D^n → (S → 2)): think.v, fall.v, dial.v, for.p

Basic Ontological Types

D Domain
S Situations
2 Truth-value

Monadic N : D → (S → 2)
A minimal step across from syntax to semantics in Episodic Logic

“Alice thinks that John nearly fell”, “Could you dial for me?”

ULFs

\[
\begin{align*}
&|\text{Alice}| ((\text{pres think.v}) \kern0.5em \\
&\quad \text{(that } |\text{John}| \text{ (nearly.adv-a (past fall.v)))))) \\
&((\text{pres could.aux-v}) \text{ you.pro} \kern0.5em \\
&\quad \text{(dial.v } \{\text{ref1}.pro \text{ (adv-a (for.p me.pro))}) \})
\end{align*}
\]

Entity(\(D\)): |Alice|, |John|, you.pro, {ref1}.pro, me.pro

n-ary predicate(\(D^n \rightarrow (S \rightarrow 2)\)): think.v, fall.v, dial.v, for.p

Predicate modifier(\(N \rightarrow N\)): nearly.adv-a, (adv-a (for.p me.pro))
What is ULF?

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“Alice thinks that John nearly fell”, “Could you dial for me?”

ULFs

\[ |Alice| (((\text{pres} \ \text{think.v} )
\quad \text{(that} \ (|John| (\text{nearly.adv-a} \ (\text{past} \ \text{fall.v})))))) \]

\[ (((\text{pres} \ \text{could.aux-v}) \ \text{you.pro} 
\quad \text{(dial.v} \ \{\text{ref1}.pro \ (\text{adv-a} \ (\text{for.p} \ \text{me.pro})))))) \]

**Entity**\(D\): \(|Alice|, \ |John|, \ \text{you.pro}, \ \{\text{ref1}.pro, \ \text{me.pro} \)

**n-ary predicate**\(D' \rightarrow (S \rightarrow 2)\): \text{think.v}, \ \text{fall.v}, \ \text{dial.v}, \ \text{for.p} 

**Predicate modifier**\(\mathcal{N} \rightarrow \mathcal{N}\): \text{nearly.adv-a}, \ (\text{adv-a} \ (\text{for.p} \ \text{me.pro}))

**Sentence reifier**\((S \rightarrow 2) \rightarrow D\): \text{that}
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(((\text{pres} \ \text{could.aux-v}) \ \text{you.pro})
    
    (\text{dial.v} \ \{\text{ref1}. \ \text{pro} \ (\text{adv-a} \ (\text{for.p} \ \text{me.pro}))\}))
\]

**Basic Ontological Types**

- **Domain** \( \mathcal{D} \)
- **Situations** \( \mathcal{S} \)
- **Truth-value** \( \mathcal{2} \)

**Monadc Predicate** \( \mathcal{N} : \mathcal{D} \rightarrow (\mathcal{S} \rightarrow \mathcal{2}) \)

**Entity** \( \mathcal{D} \): \(|Alice|, \ |John|, \ \text{you.pro}, \ \{\text{ref1}. \ \text{pro}, \ \text{me.pro} \)

**n-ary predicate** \( \mathcal{D} \rightarrow (\mathcal{S} \rightarrow \mathcal{2}) \): \text{think.v}, \text{fall.v}, \text{dial.v}, \text{for.p}

**Predicate modifier** \( \mathcal{N} \rightarrow \mathcal{N} \): \text{nearly}. \ \text{adv-a}, \ (\text{adv-a} \ (\text{for.p} \ \text{me.pro}))

**Sentence reifier** \( (\mathcal{S} \rightarrow \mathcal{2}) \rightarrow \mathcal{D} \): \text{that}

**Tense** \( (\mathcal{S} \rightarrow \mathcal{2}) \rightarrow (\mathcal{S} \rightarrow \mathcal{2}) \): \text{pres}, \ \text{past}
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“What Alice thinks that John nearly fell”, “Could you dial for me?”

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Entity(D): |Alice|, |John|, you.pro, {ref1}.pro, me.pro
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Predicate modifier(ŋ→ŋ): nearly.adv-a, (adv-a (for.p me.pro))
Sentence reifier((S→2)→D): that
Tense((S→2)→(S→2)): pres, past
Modifier constructor(ŋ→(ŋ→ŋ)): adv-a
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\end{align*}
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\text{Entity}(\mathcal{D}): & \ |Alice|, \ |John|, \ \text{you.pro}, \ {\text{ref1}.pro}, \ \text{me.pro} \\
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\text{Tense}((S → 2) → (S → 2)): & \ \text{pres}, \ \text{past} \\
\text{Modifier constructor}(\mathcal{N} → (\mathcal{N} → \mathcal{N})): & \ \text{adv-a}
\end{align*}
\]

Also... determiner, sentence modifier, connective, lambda abstract, predicate reifier
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Captures the full predicate argument structure!

Basic Ontological Types

\[ \mathcal{D} \quad \text{Domain} \]

\[ \mathcal{S} \quad \text{Situations} \]

\[ \mathcal{2} \quad \text{Truth-value} \]

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Predicate modifier(\(\mathcal{N} \rightarrow \mathcal{N}\)): nearly.adv-a, (adv-a

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

Tense((\(\mathcal{S} \rightarrow \mathcal{2}\) \rightarrow (\(\mathcal{S} \rightarrow \mathcal{2}\))): pres, past

Modifier constructor(\(\mathcal{N} \rightarrow (\mathcal{N} \rightarrow \mathcal{N})\)): adv-a
How does ULF fit into EL interpretation?

ULF sets the foundation, but there’s a lot left!
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We still have

1. Word sense disambiguation

“Chell eats a cake” vs “This situation is eating at me”
How does ULF fit into EL interpretation?

ULF sets the foundation, but there’s a lot left!

We still have

2. Anaphora

Who does “she” refer to?
ULF sets the foundation, but there's a lot left!

We still have

3. **Scoping**

“Every child loves a dog”
Is there a single dog?
Or a different dog for each child?
How does ULF fit into EL interpretation?

ULF sets the foundation, but there’s a lot left!

We still have

4. Event structure

What are the events and how are they related causally and temporally?
How does ULF fit into EL interpretation?

ULF sets the foundation, but there's a lot left!

We still have

5. Canonicalization

Reduce formulas to minimal propositions for inferential flexibility
Using ULF Directly for Inference

**Wh-questions** (presuppose that something happened)

“Who did you see yesterday?”   >  >  >   presupposes   >  >  >   You saw someone yesterday.
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"Who did you see yesterday?"  >  >  >  presupposes  >  >  >  You saw someone yesterday.

**Inference**

"If a wh-question is uttered, the some-version of that sentence is true"

\[
\text{all_wfulf } w \\
\text{ (((w ?) and (wh-sent? w))} \\
\Rightarrow \text{ (uninvert-sent! (wh-sent-to-some-sent! w)))}
\]

Starting with  "Who did you see yesterday?"  -  ((sub who.pro ((past do.aux-s) you.pro (see.v *h yesterday.adv-e))) ?)

We conclude  "You saw someone yesterday"  -  (you.pro ((past see.v) someone.pro yesterday.adv-e))
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“Who did you see yesterday?” > > > presupposes > > > You saw someone yesterday.

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We conclude “You saw someone yesterday” - (you.pro ((past see.v) someone.pro yesterday.adv-e))

Also can do counterfactuals “If I were rich …” means that I am not rich
and clause-taking verbs “I denounce x as y” means that I probably believe that x is y and I want my listener to believe that x is y
and more!
Human ULF annotations...

“She wants to eat the cake”

(she.pro ((pres want.v) (to (eat.v (the.d cake.n))))))
Human ULF annotations...
● are fast (~8 min/sent)

“*She wants to eat the cake*”

Human Annotator

(she.pro ((pres want.v) (to (eat.v (the.d cake.n)))))
Human ULF annotations...
● are fast (~8 min/sent)
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- number over 2000 sentences
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- are fast (~8 min/sent)
- are consistent (up to 0.88 IAA)
- number over 2000 sentences
- preliminary trained parsing results are promising

---

**Annotation and Parsing**

"She wants to eat the cake"

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---

**System Outline**

1. Oracle Token Generator
   - "She wants to eat the cake"
   - 900 sentence dataset
   - No ULF-specific features

2. Cache Transition Parser for AMR
   - (she.pro ((pres want.v) (to (eat.v (the.d cake.n)))))

3. Syntactic Rewriting
   - (she.pro ((pres want.v) (to (eat.v (the.d cake.n)))))
Conclusions

- We presented an underspecified variant of Episodic Logic, ULF
- ULF is an intermediary representation to EL capturing predicate-argument structure while retaining some syntax
- ULF forms the foundation for further EL resolution, which can be done in context
- Annotating ULF is fast and reliable and automatic parsing seems feasible
We would like to thank Burkay Donderici, Benjamin Kane, Lane Lawley, Tianyi Ma, Graeme McGuire, Muskaan Mendiratta, Akihiro Minami, Georgiy Platonov, Sophie Sackstein, and Siddharth Vashishtha for raising thoughtful questions about prior iterations of this work. This work was supported by DARPA CwC subcontract W911NF-15-1-0542.
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**Others**: GLUE
Current state-of-the-art systems end up modeling artifacts rather than learning robust representations
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Question Answering/Reading Comprehension (Jia & Liang 2017)

Question: “What is the name of the quarterback who was 38 in Super Bowl XXXIII?”
Article: Super Bowl 50
Paragraph: “Peyton Manning became the first quarterback ever to lead two different teams to multiple Super Bowls. He is also the oldest quarterback ever to play in a Super Bowl at age 39. The past record was held by John Elway, who led the Broncos to victory in Super Bowl XXXIII at age 38 and is currently Denver’s Executive Vice President of Football Operations and General Manager.”

Original Prediction: John Elway

Accuracy: 80.0%
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**Prediction under adversary**: Jeff Dean

**Accuracy**: 34.2%
Current state-of-the-art systems end up modeling artifacts rather than learning robust representations

Inferring from Language (Gururangan et al., 2018)

Premise
Two dogs are running through a field

Entailment
There are animals outdoors

Neutral
Some puppies are running to catch a stick

Contradiction
The pets are sitting on a couch
Current state-of-the-art systems end up modeling artifacts rather than learning robust representations.

**Problems**

Inferring from Language *(Gururangan et al., 2018)*

- **Premise**: Two dogs are running through a field

  - **Entailment**: There are animals outdoors
  - **Neutral**: Some puppies are running to catch a stick
  - **Contradiction**: The pets are sitting on a couch

**Accuracy**:
- 52.3% *(MultiNLI)*
- 67.0% *(SNLI)*
A few approaches to deal with these problems are being explored

1. **Inducing bias**
   Bias toward relevance, style, repetition, and entailment… somehow

2. **Common sense**
   Current system look like a “mouth without a brain”, let’s add a brain

3. **Evaluate the model on unseen tasks**
   Check if the model generalizes beyond the exact dataset format
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(All of the above assume a core neural/machine learning architecture)

4. **Symbolic semantic representation**
   Directly encode linguistic information and logical reasoning through the representation
Cache Transition Parser

A transition system for parsing graphs using a fixed-sized cache.

Pop: pops the top element from stack to its indexed position in cache

Shift: moves the front of the buffer by one and adds a vertex to the graph for the front element

Push: moves the front of the buffer to the cache and pushes the old cache value to the stack

Arc: forms an arc between a given index of the cache and the rightmost element of the cache
Annotation and Parsing

Human ULF annotations...
- are fast (~8 min/sent)
- are consistent (up to 0.88 IAA)
- number over 2000 sentences

Preliminary parsing experiment
- Based on an AMR cache transition parser (Peng et al. 2018)
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0.738 Average partial match
What is ULF?

Relaxations/Macros

TODO