Types, Networks & Stuff

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LoLa 2019

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Overview

The paper starts with Lambek Calculus, some how uses dependancy labels in some of its semantic types, provides a parsing algorithm for it; there are neural networks and vectors used and some accuracy results provided, but I am still unsure about the contributions of the paper and their relevance

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- λ Abstract Syntax with NLP
- λ Extracting & Learning Type Assignments
- λ Navigating proofs with neural nets
- λ Lexicalized syntax in language modeling

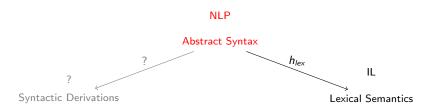
This Timeline



Alternative Timeline



Alternative Timeline



NLP

Grammar

IILL + Structural Control Modalities

$$\mathcal{T}:=A\mid \diamond^d T_1 \to T_2$$

 $A \in \mathcal{A}$:: Atoms denoting complete phrases (NP, S, ...)

 $d \in \mathcal{D}$:: Grammatical relations (subject, object, ...)

 $\diamond^d T$:: Type demarkated by dependency domain d

 $T_1 \rightarrow T_2$:: Linear functor from T_1 to T_2

Why?

- Easier to extract from corpora
- Drastic reduction in lexical ambiguity
- More informative for semantics
- ► Built-in Interpretability
- ▶ Diamonds can regulate parsing (?)

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How?

$$\frac{\Gamma \vdash M : A \to B \quad \Delta \vdash N : A}{\Gamma, \Delta \vdash (M \mid N) : B} \to E$$

$$\frac{\Gamma, x : A \vdash M : B}{\Gamma \vdash \lambda x . M : A \to B} \to I$$

$$\frac{\Gamma \vdash A}{\langle \Gamma \rangle^d \vdash \diamond^d A} \diamond^d I$$

$$\frac{\Delta \vdash \diamond^d A \quad \Gamma, \langle A \rangle^d \vdash B}{\Gamma, \Delta \vdash B} \diamond^d E$$

A dataset of types & proofs

Extracting (1/3)

Algorithm

Graph flooding on syntactic parse graphs Init with maps:

- from POS/Phrasal-tags to atoms
- dependency labels to diamond operators

Two subroutines; each selects untyped nodes and types them

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Two subroutines; each selects untyped nodes and types them

```
function TypeDag: DAG D 	o DAG D \leftarrow DetachNonLocal(D) while D is not fully typed do D \leftarrow TypeStandaloneNodes(D) D \leftarrow TypeHeadsAndMods(D) end while return AttachNonLocal(D) end function
```

Extracting (2/3)

$\lambda 1$ Stand-Alone Nodes

select untyped nodes with

- 1 no incoming head/mod edge
- 2 no untyped daughters (except heads/mods)

type translate pos/tag to atom

λ 2 Heads and Mods

select untyped nodes that

- 1 incoming head/mod edge
- 2 have a typed parent
- 3 have all sisters (except head/mods) typed

type endofunctor of parent if mod, else functor from vector of arguments¹ to parent type



¹minus hypotheses

Extracting (3/3)

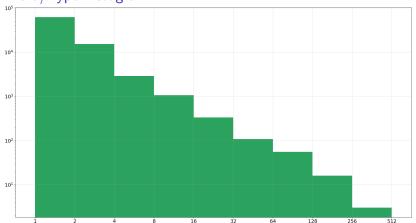
Non-Local Dependencies

```
function DetachNonLocal: DAG D 	oup Tree for each e \in Filter(Reentrant, D.edges) do c \leftarrow copy(e.target) D.nodes \leftarrow D.nodes \cup \{c\} D.edges \leftarrow D.edges - \{e\} D.edges \leftarrow D.edges \cup \{(e.source, e.label, c)\} end for return D end function
```

Mommy, where do types come from?

Lexical Type Ambiguity





Supertagging (1/3)

General idea

$$p(t_1,t_2,\ldots t_n|w_1,w_2,\ldots w_n,\theta)$$

Markov Assumption

$$pprox \prod_{i=1}^n p(t_i|w_1, w_2, \dots w_n, \theta)$$

- Seq2Seq Classification
- © Single Answer
- © Sample Sparsity
- © Closed Domain Assumption

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Supertagging (2/3)

General idea

$$p(t_1,t_2,\ldots t_n|w_1,w_2,\ldots w_n,\theta)$$

Markov Assumption

$$\approx \prod_{i=1}^{n} p(t_i|t_1,\ldots t_{i-1},w_1,\ldots,w_n,\theta)$$

- Seq2Seq Transduction
- Many Answers
- © Sample Sparsity
- © Closed Domain Assumption

Supertagging (3/3)

A step further

The syntax of the type system forms a simple CFG

$$S \Longrightarrow A \qquad \forall A \in \mathcal{A}$$

 $S \Longrightarrow d S S \qquad \forall d \in \mathcal{D}$

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 $\forall A \in \mathcal{A}$ $S \Longrightarrow d S S$ $\forall d \in \mathcal{D}$

- Supertagging as conditional CFG generation
- CFG terminals as decoding targets

$$\approx \prod_{i=1}^{m} p(\sigma_{i}|\sigma_{1}, \dots \sigma_{i-1}, w1, \dots, w_{n}, \theta)$$
$$\sigma \in \mathcal{A} \cup \mathcal{D} \cup \{\langle SEP \rangle\}$$

Supertagging (3/3)

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- Sample Sparsity Many (sub)type examples
- © Closed Domain Assumption Inductive construction of any type



Structural Ambiguity

Navigating Proofs

Parse State

- ► A logical judgement (premises & conclusion)
- ▶ Word associations for (some) premise formulas
- A single element stack

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Framework

Given a parse state:

- 1 Decide between introduction \oplus elimination
- 2 Perform either
- 3 Update state(s)
- 4 Repeat

Proof Ambiguity

The Problem

- Introduction steps are deterministic
- ▶ Eliminations are not

Proof Ambiguity

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Key Insight

Elimination branching \sim binary sequence chunking Semantic content can help disambiguate structure

Vectorizing Types

Types are trees

$$\Diamond^{body}(\Diamond^{su}NP \to S) \to \Diamond^{mod}NP \to NP$$

$$\downarrow \qquad \qquad \qquad \downarrow \qquad \qquad \qquad \downarrow \qquad \qquad \qquad \downarrow$$

$$\downarrow \qquad \qquad \qquad \downarrow \qquad \qquad \downarrow \qquad \qquad \downarrow$$

$$\downarrow \qquad \qquad \qquad \downarrow \qquad \qquad \downarrow$$

Vectorizing Types

Types are trees

- ightharpoonup Atoms as vectors in \mathbb{R}^n
- ▶ Dependencies as functions $\mathbb{R}^n \to \mathbb{R}^n \to \mathbb{R}^n$

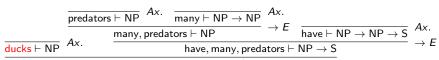
ΝP

$$\frac{ \frac{ \text{predators} \vdash \text{NP} }{Ax.} \quad \frac{Ax.}{\text{many} \vdash \text{NP} \to \text{NP}} \quad \frac{Ax.}{Ax.} }{ \frac{ \text{many}, \text{predators} \vdash \text{NP}}{Ax.} \quad \frac{Ax.}{\text{have}, \text{many}, \text{predators} \vdash \text{NP} \to \text{S}} \quad \frac{Ax.}{Ax.} }{ \text{have}, \text{many}, \text{predators} \vdash \text{NP} \to \text{S}} } \quad \frac{Ax.}{Ax.}$$

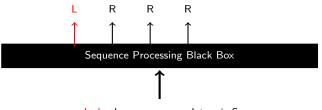
 $\mathsf{ducks}, \mathsf{have}, \mathsf{many}, \mathsf{predators} \vdash \mathsf{S}$

Sequence Processing Black Box

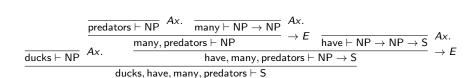
ducks, have, many, predators $\vdash \mathsf{S}$



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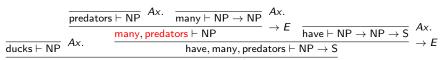
ducks, have, many, predators $\vdash S$



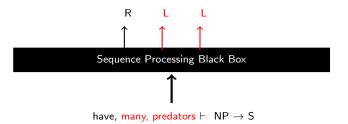
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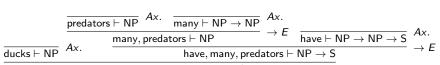


have, many, predators $\vdash \ \mathsf{NP} \to \mathsf{S}$



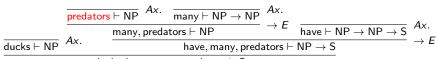
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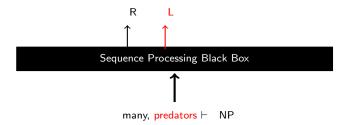


 $\mathsf{ducks}, \mathsf{have}, \mathsf{many}, \mathsf{predators} \vdash \mathsf{S}$





 $\mathsf{ducks}, \mathsf{have}, \mathsf{many}, \mathsf{predators} \vdash \mathsf{S}$



 $\frac{\frac{\mathsf{predators} \vdash \mathsf{NP}}{\mathsf{Ax}.} \quad \frac{\mathsf{Ax}.}{\mathsf{many} \vdash \mathsf{NP} \to \mathsf{NP}} \quad \frac{\mathsf{Ax}.}{\mathsf{have} \vdash \mathsf{NP} \to \mathsf{NP} \to \mathsf{S}} \quad \frac{\mathsf{Ax}.}{\mathsf{have} \vdash \mathsf{NP} \to \mathsf{NP} \to \mathsf{S}} \quad \frac{\mathsf{Ax}.}{\mathsf{Ax}.} \quad \frac{\mathsf{many}, \mathsf{predators} \vdash \mathsf{NP}}{\mathsf{have}, \mathsf{many}, \mathsf{predators} \vdash \mathsf{NP} \to \mathsf{S}} \quad \frac{\mathsf{Ax}.}{\mathsf{Ax}}.$

 $\mathsf{ducks}, \mathsf{have}, \mathsf{many}, \mathsf{predators} \vdash \mathsf{S}$

Sequence Processing Black Box

Proof Traversal

have, many, predators $\vdash \mathsf{NP} \to \mathsf{S}$

ducks, have, many, predators $\vdash S$

Sequence Processing Black Box

Training sample : Elimination branching
Sentence : N independent samples

Training Parallelism

Proof Traversal

 $\underbrace{\frac{\overline{\mathsf{predators} \vdash \mathsf{NP}} \ Ax. \quad \overline{\mathsf{many} \vdash \mathsf{NP} \to \mathsf{NP}}_{\mathsf{Arv.}} \ \frac{Ax.}{\mathsf{many}, \, \mathsf{predators} \vdash \mathsf{NP}}_{\mathsf{have}, \, \mathsf{many}, \, \mathsf{predators} \vdash \mathsf{NP} \to \mathsf{S}} \ \frac{Ax.}{\mathsf{have}, \, \mathsf{many}, \, \mathsf{predators} \vdash \mathsf{NP} \to \mathsf{S}}_{\mathsf{ducks}, \, \mathsf{have}, \, \mathsf{many}, \, \mathsf{predators} \vdash \mathsf{S}}} \ \frac{Ax.}{\mathsf{have}, \, \mathsf{many}, \, \mathsf{predators} \vdash \mathsf{S}}}$

Sequence Processing Black Box

Parsing in $\mathcal{O}(1)^2$

$$\textit{np}, \textit{np} \rightarrow \textit{np} \rightarrow \textit{s}, \textit{np} \rightarrow \textit{np}, \textit{np} \vdash \textit{s}$$

$$\textit{np}_1, \textit{np}_2 \rightarrow \textit{np}_3 \rightarrow \textit{s}_1, \textit{np}_4 \rightarrow \textit{np}_5, \textit{np}_6 \vdash \textit{s}_2$$

$$np_1^+, np_2^- \to np_3^- \to s_1^+, np_4^- \to np_5^+, np_6^+ \vdash s_2^-$$

$$np_1^+, np_2^- \to np_3^- \to s_1^+, np_4^- \to np_5^+, np_6^+ \vdash s_2^-$$

$$P = [np_1, s_1, np_5, np_6] \quad N = [np_2, np_3, np_4, s_2]$$

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$$\frac{|np_{2}| |np_{3}| |np_{4}| |s_{2}|}{|np_{1}| |0| |1| |0| |0|}$$

$$R \in \mathbb{B}^{4 \times 4} = \frac{|np_{2}| |np_{3}| |np_{4}| |s_{2}|}{|np_{5}| |1| |0| |0| |0|}$$

$$\frac{|np_{5}| |1| |0| |0| |0|}{|np_{6}| |0| |0| |1| |0|}$$

$$match(N) = PR^T$$

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$$match(N) = PR^T$$

▶ R is discrete

$$np_1^+, np_2^- \to np_3^- \to s_1^+, np_4^- \to np_5^+, np_6^+ \vdash s_2^-$$

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$$\mathcal{R} \in \mathbb{B}^{4 imes 4} = egin{array}{c|cccc} & np_2 & np_3 & np_4 & s_2 \ \hline np_1 & 0 & 1 & 0 & 0 \ s_1 & 0 & 0 & 0 & 1 \ np_5 & 1 & 0 & 0 & 0 \ np_6 & 0 & 0 & 1 & 0 \ \end{array}$$

$$\mathsf{match}(N) = P\mathcal{R}^T$$

- ▶ R is discrete
- but its continuous relaxations can be approximated (Sinkhorn-Knopp)



References

Grammar & Extraction

► ÆTHEL: Automatically Extracted Type-Logical Derivations for Dutch link

Supertagging & Parsing

- Constructive Type-Logical Supertagging with Self-Attention Networks link
- Deductive Parsing with an Unbounded Type Lexicon link

Permutations

- ► Sinkhorn-Knopp Algorithm link
- Learning Latent Permutations with Gumbel-Sinkhorn Networks link