Learnability and Semantic Universals

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(joint work-in-progress with Jakub Szymanik)

Cognitive Semantics and Quantities Kick-off Workshop
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Overview

1. Semantic Universals
2. The Learning Model
3. Experiments
4. Conclusion
Universals in Linguistic Theory

Question
What is the range of variation in human languages? That is: which out of all of the logically possible languages that humans could speak, do they in fact speak?
Sound (phonology):
All languages have consonants and vowels. Every language has at least /a i u/.
Example Universals

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  All languages have verbs and nouns.
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- **Meaning (semantics):**
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- **Grammar (syntax):**
  All languages have verbs and nouns.

- **Meaning (semantics):**
  All languages have syntactic constituents (NPs) whose semantic function is to express generalized quantifiers. (Barwise and Cooper 1981)
Determiners

- Determiners:
  - Simple: every, some, few, most, five, . . .
  - Complex: all but five, fewer than three, at least eight or fewer than five, . . .
Determiners:

- Simple: *every*, *some*, *few*, *most*, *five*, . . .
- Complex: *all but five*, *fewer than three*, *at least eight or fewer than five*, . . .

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For example:

\[
\begin{align*}
\llbracket \text{every} \rrbracket &= \{ \langle M, A, B \rangle : A \subseteq B \} \\
\llbracket \text{most} \rrbracket &= \{ \langle M, A, B \rangle : |A \cap B| > |A \setminus B| \}
\end{align*}
\]
Monotonicity

- Many French people smoke cigarettes
  ⇒ Many French people smoke
Monotonicity

- Many French people *smoke cigarettes* ⇒ Many French people *smoke*
- Few French people *smoke* ⇒ Few French people *smoke cigarettes*
Monotonicity

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- Q is upward (resp. downward) monotone iff:
  if $\langle M, A, B \rangle \in Q$ and $B \subseteq B'$ (resp. $B' \subseteq B$), then $\langle M, A, B \rangle \in Q$
- A determiner is monotone if it denotes either an upward or downward monotone generalized quantifier
Monotonicity Universal (Barwise and Cooper 1981)
All simple determiners are monotone.
Key intuition: determiners denote *general* relations between their restrictor and nuclear scope, not ones that depend on the identities of particular elements of the domain.
Quantity

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- Q is quantitative:
  if $\langle M, A, B \rangle \in Q$ and $A \cap B, A \setminus B, B \setminus A, M \setminus (A \cup B)$ have the same cardinality as their primed-counterparts, then $\langle M', A', B' \rangle \in Q$. 
Quantity

- Keenan and Stavi 1986, p. 311:
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Quantity Universal

All simple determiners are quantitative.
Conservativity

- Key intuition: the restrictor *restricts* what the determiner talks about
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  ≡ Many French people are French people who smoke cigarettes
Conservativity

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- Many French people smoke cigarettes
  \[\equiv\text{ Many French people are French people who smoke cigarettes}\]
- Q is conservative iff:
  \[\langle M, A, B \rangle \in Q \text{ if and only if } \langle M, A, A \cap B \rangle \in Q\]
Conservativity Universal

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Explaining Universals

Natural Question

*Why* do the universals hold? What explains the limited range of quantifiers expressed by simple determiners?
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- Answer 1: *learnability*.
  (Barwise and Cooper 1981; Keenan and Stavi 1986; Szabolcsi 2010)
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• Answer 1: learnability.
  (Barwise and Cooper 1981; Keenan and Stavi 1986; Szabolcsi 2010)
• The universals greatly restrict the search space that a language learner must explore when learning the meanings of determiners. This makes it easier (possible?) for them to learn such meanings from relatively small input.
[Compare: Poverty of the Stimulus argument for UG.]
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  [Compare: Poverty of the Stimulus argument for UG.]
- In a sense must be true, but:
  “Likely, the unrestricted space has many hypotheses which are so implausible, they can be ignored quickly and do not affect learning. The hard part of learning, may be choosing between the plausible competitor meanings, not in weeding out a large space of potential meanings.” Piantadosi 2013, p. 22
Explaining Universals

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- Answer 2: learnability. (Peters and Westerståhl 2006)
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- The universals aid learnability because quantifiers satisfying the universals are *easier* to learn than those that do not.

- **Challenge:** provide a model of learning which makes good on this promise.
  [See Tiede 1999; Gierasimczuk 2007; Gierasimczuk 2009 for earlier attempts.]
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Neural Networks

Source: Nielsen, "Neural Networks and Deep Learning", Determination Press
Gradient Descent and Back-propogation

The learning framework will be a non-convex optimization problem.

- A total loss function, which will be the mean of a ‘local’ error function:

\[
L = \frac{1}{N} \sum \ell(\hat{y}_i, y_i) \\
= \frac{1}{N} \sum \ell(\text{NN}(\theta, x_i), y_i)
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**Gradient Descent and Back-propogation**

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- Back-propagation: calculate $\ell(\cdot, \cdot)$ after a forward-pass of the network. ‘Propagate’ the error backwards through the network to calculate the gradient.
Recurrent Neural Networks

Long Short-Term Memory

Introduced in Hochreiter and Schmidhuber 1997 to solve the exploding/vanishing gradients problem.

The Learning Task

- Our data will be the following:
  - Input: \( \langle Q, M \rangle \) pairs, presented sequentially
  - Output: T/F, depending on whether \( M \in Q \)
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So, this will be a *sequence classification* task.

The loss function we minimize is *cross-entropy*. In our case, with $y \in \{0, 1\}$, very simple:

$$\ell(\text{NN}(\vec{\theta}, x), y) = -\ln(\text{NN}(\vec{\theta}, x)_y)$$
Data Generation

Algorithm 1 Data Generation Algorithm

*Inputs*: max_len, num_data, quants

data ← []

**while** len(data) < num_data **do**

N ∼ Unif([max_len])

Q ∼ Unif(quants)

cur_seq ← Unif({A ∩ B, A \ B, B \ A, M \ (A ∪ B)}, N)

if ⟨Q, cur_seq⟩ ∉ data **then**

data.append(generate_point(⟨Q, cur_seq, Q ∈ cur_seq?⟩))

end if

**end while**

return shuffle(data)
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- Run some number of trials of training an LSTM to learn those quantifiers

Code and Data Available At: [http://github.com/shanest/quantifier-rnn-learning](http://github.com/shanest/quantifier-rnn-learning)
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  500 minibatch running mean total accuracy on test set is $> 0.99$; or mean probability assigned to correct truth-value on test set is $> 0.99$
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Experiment 1: Monotonicity

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- Quantifiers: $\geq 4$, $\leq 4$, $= 4$
Monotonicity: Results
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('at_least_4', 'at_most_4')
('at_least_4', 'exactly_4')
('at_most_4', 'exactly_4')
Monotonicity: Discussion

- \( \geq 4 \) easier than \( = 4 \): ✔
Monotonicity: Discussion

- $\geq 4$ easier than $= 4$: ✓
- $\geq 4$ easier than $\leq 4$, and $\leq 4$ not easier than $= 4$: ???
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  - Upward monotone are generally cognitively easier than downward
    [Just and Carpenter 1971; Geurts 2003; Geurts and Slik 2005; Deschamps et al. 2015]
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  - $= 4$ is a conjunction of monotone quantifiers
- A better measure of learning rate than convergence point?
Experiment 2: Quantity

Quantity Universal

All simple determiners are quantitative.
Experiment 2: Quantity

Quantity Universal

All simple determiners are quantitative.

- Quantifiers: $\geq 3$, first3
Quantity: Results
Quantity: Results
Quantity: Discussion

- Very promising initial results
Quantity: Discussion

- Very promising initial results
- Harder to learn an order-sensitive quantifier than one that is only sensitive to quantity
Experiment 3: Conservativity

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- Quantifiers: nall, nonly
  [Motivated by Hunter and Lidz 2013]
Conservativity: Results
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Conservativity: Discussion

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Conservativity: Discussion

- No way of ‘breaking the symmetry’ between $A \cap B$ and $B \setminus A$ in this model
- More boldly: conservativity as a syntactic/structural constraint, not a semantic universal
  [See Fox 2002; Sportiche 2005; Romoli 2015]
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Towards Meeting the Challenge

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- We showed how to train LSTM networks via backpropagation to verify quantifiers.
- Initial experiments show that this setup may be able to meet the challenge.
Future Work

- More and larger experiments
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- Different models, including baselines for this task
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- Different models, including baselines for this task
- Tools to ‘look inside’ the black box and see what the network is doing
The End

Thank you!