Sharpening the empirical claims of generative syntax through formalization

Tim Hunter

University of Minnesota, Twin Cities

ESSLLI, August 2015
Part 1: Grammars and cognitive hypotheses
   What is a grammar?
   What can grammars do?
   Concrete illustration of a target: Surprisal

Parts 2–4: Assembling the pieces
   Minimalist Grammars (MGs)
   MGs and MCFGs
   Probabilities on MGs

Part 5: Learning and wrap-up
   Something slightly different: Learning model
   Recap and open questions
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Part 5

Learning and wrap-up
Motivating question

Components of a learner:

- A formalism ("toolkit") defines a space of grammars for a learner to choose from
- An updating algorithm defines a way to search through such a space (in response to provided input)
Motivating question

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- An updating algorithm defines a way to search through such a space (in response to provided input)

Given two formalisms, F1 and F2, can we construct a learner which

- reaches **one end-state** when used with F1, and
- reaches **a different end-state** when used with F2?
Motivating question

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- A formalism ("toolkit") defines a space of grammars for a learner to choose from.
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Given two formalisms, F1 and F2, can we construct a learner which

- reaches **one end-state** when used with F1, and
- reaches **a different end-state** when used with F2?

With everything else held fixed:

- same (strong) generative capacity
- same updating algorithm
- same training data
Outline

18 Grammatical formalisms and learning

19 Learning with a given grammar

20 Learning with a choice of grammars

21 Conclusion
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Q: How can we provide traction between the learning algorithm and the internals of each $G$?
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A: Probabilities
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Q: How can we provide traction between the learning algorithm and the internals of each $G$?
A: Probabilities
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Learning scenario

Training corpus: some combination of occurrences of the following.

- boys will shave
- boys will shave themselves
- who will shave
- who will shave themselves
- foo boys will shave

- The learner **knows** correct analyses of these sentences, with ‘foo’ as a determiner.
- The learner **must decide** what probabilities to attach to these known sentences.
Grammatical formalisms and learning

Learning with a given grammar

Training corpus:

1. 10 boys will shave
2. 2 boys will shave themselves
3. 3 who will shave
4. 1 who will shave themselves
5. 5 foo boys will shave

193/201
Training corpus:

10  boys will shave
2   boys will shave themselves
3   who will shave
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Training corpus:

10  boys will shave
2   boys will shave themselves
3   who will shave
1   who will shave themselves
5   foo boys will shave

Grammar’s distribution:

<table>
<thead>
<tr>
<th>Probability</th>
<th>Sentence</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.35478</td>
<td>boys will shave</td>
</tr>
<tr>
<td>0.35478</td>
<td>foo boys will shave</td>
</tr>
<tr>
<td>0.14801</td>
<td>who will shave</td>
</tr>
<tr>
<td>0.05022</td>
<td>boys will shave themselves</td>
</tr>
<tr>
<td>0.05022</td>
<td>foo boys will shave themselves</td>
</tr>
<tr>
<td>0.04199</td>
<td>who will shave themselves</td>
</tr>
</tbody>
</table>

Grammar's distribution:

<table>
<thead>
<tr>
<th>Probability</th>
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<tbody>
<tr>
<td>0.35721</td>
<td>boys will shave</td>
</tr>
<tr>
<td>0.35721</td>
<td>foo boys will shave</td>
</tr>
<tr>
<td>0.095</td>
<td>who will shave</td>
</tr>
<tr>
<td>0.095</td>
<td>who will shave themselves</td>
</tr>
<tr>
<td>0.04779</td>
<td>boys will shave themselves</td>
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<tr>
<th></th>
<th>Entropy</th>
<th>Entropy Reduction</th>
</tr>
</thead>
<tbody>
<tr>
<td>---</td>
<td>2.09</td>
<td>---</td>
</tr>
<tr>
<td>who</td>
<td>0.76</td>
<td>1.33</td>
</tr>
<tr>
<td>will</td>
<td>0.76</td>
<td>0.00</td>
</tr>
<tr>
<td>shave</td>
<td>0.76</td>
<td>0.00</td>
</tr>
<tr>
<td>themselves</td>
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<td>2.28</td>
<td>---</td>
</tr>
<tr>
<td>who</td>
<td>1.00</td>
<td>1.28</td>
</tr>
<tr>
<td>will</td>
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<td>0.00</td>
</tr>
<tr>
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- The learner **knows** correct analyses of wh-movement and reflexives.
- The learner **must decide** how to analyze ‘foo’: determiner or wh-phrase?
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MGs

MG-DET

MG-WH

IMGs

IMG-DET

IMG-WH
Training corpus:

5 boys will shave
5 boys will shave themselves
5 who will shave
5 who will shave themselves
5 foo boys will shave
Training corpus:

5 boys will shave
5 boys will shave themselves
5 who will shave
5 who will shave themselves
5 foo boys will shave

\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{3.36 \times 10^{-18}}{4.48 \times 10^{-20}} = 75.0
\]
### MGs and IMGs

<table>
<thead>
<tr>
<th></th>
<th>MG-DET</th>
<th>MG-WH</th>
<th>IMG-DET</th>
<th>IMG-WH</th>
</tr>
</thead>
<tbody>
<tr>
<td>G</td>
<td></td>
<td>G</td>
<td>G</td>
<td>G</td>
</tr>
<tr>
<td>(\hat{g}_{\text{DET}})</td>
<td></td>
<td>(\hat{g}_{\text{WH}})</td>
<td>(\hat{g}_{\text{DET}})</td>
<td>(\hat{g}_{\text{WH}})</td>
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### Training corpus:

- 5 boys will shave
- 5 boys will shave themselves
- 5 who will shave
- 5 who will shave themselves
- 5 foo boys will shave

### Probability Calculations

\[
P(D | \hat{g}_{\text{DET}}) = \frac{3.36 \times 10^{-18}}{4.48 \times 10^{-20}} = 75.0
\]
\[
P(D | \hat{g}_{\text{WH}}) = \frac{3.36 \times 10^{-18}}{2.45 \times 10^{-20}} = 13.7
\]
Training corpus:

18 boys will shave
3 boys will shave themselves
1 who will shave
1 who will shave themselves
1 foo boys will shave

\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{5.82 \times 10^{-14}}{7.27 \times 10^{-11}} = 0.000801
\]

\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{7.64 \times 10^{-14}}{6.85 \times 10^{-10}} = 0.000112
\]
MGs

\[ G \]

\[ \hat{g}_{\text{DET}} \]

\[ \hat{g}_{\text{WH}} \]

MG-DET | MG-WH

IMGs

\[ G \]

\[ \hat{g}_{\text{DET}} \]

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IMG-DET | IMG-WH

Training corpus:

1. boys will shave
2. boys will shave themselves
3. who will shave
4. who will shave themselves
5. foo boys will shave

\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{1.21 \times 10^{-17}}{7.70 \times 10^{-19}} = 15.7
\]

\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{3.46 \times 10^{-17}}{1.19 \times 10^{-16}} = 0.291
\]
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MGs

\[ \hat{g}_{\text{DET}} \]

\[ \hat{g}_{\text{WH}} \]

IMGs

\[ \hat{g}_{\text{DET}} \]

\[ \hat{g}_{\text{WH}} \]

MG-DET

MG-WH

IMG-DET

IMG-WH

Training corpus:

8 boys will shave
1 boys will shave themselves
12 who will shave
1 who will shave themselves
4 foo boys will shave

\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{2.83 \times 10^{-15}}{4.36 \times 10^{-20}} = 64900
\]

\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{1.31 \times 10^{-17}}{1.75 \times 10^{-17}} = 0.749
\]
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\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{2.44 \times 10^{-13}}{4.94 \times 10^{-14}} = 4.94
\]

\[
\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{1.46 \times 10^{-13}}{1.62 \times 10^{-13}} = 0.901
\]
Details of one interesting case

**MG-WH**

- Feature weight: ant=0.000000
- Feature weight: obj=0.000000
- Feature weight: subj=0.306077
- Feature weight: t=-0.895880
- Feature weight: v=0.000000
- Feature weight: wh=0.895880
- Feature weight: merge=-0.000000
- Feature weight: move=-0.000000

\{t29: 0.5, t13_t4: 0.5\}
\{t28: 0.5, t13_t5: 0.5\}
\{t0_t14: 0.077, t21_t7: 0.462, t22: 0.462\}

- t0 : (:: =t c)
- t4 : (:: subj)
- t5 : (:: subj -wh)
- t7 : (:: wh)
- t13 : (: =subj t)
- t14 : (: t)
- t21 : (: =wh c)
- t22 : (: +wh c;: -wh)
- t28 : (: +subj t;:: -subj;:: -wh)
- t29 : (: +subj t;:: -subj)

**IMG-WH**

- Feature weight: ant=0.000000
- Feature weight: obj=0.000000
- Feature weight: subj=-0.860545
- Feature weight: t=-0.434630
- Feature weight: v=-3.324996
- Feature weight: wh=2.050275
- Feature weight: insert=-0.563888
- Feature weight: merge=0.563888

\{t00130005: 0.5, t0028: 0.5\}
\{t0021_t0007: 0.333, t00010016: 0.667\}
\{t00000014: 0.077, t0022: 0.923\}
\{t0013_t0004: 0.900, t00110026: 0.100\}

- t00000014 : (:: +t -c;:: -t)
- t00010016 : (:: +t +wh -c;:: -t;:: -wh)
- t0004 : (:: -subj)
- t0007 : (:: -wh)
- t00110026 : (:: +v +subj -t;:: -v;:: -subj)
- t0013 : (:: +subj -t)
- t00130005 : (:: +subj -t;:: -subj -wh)
- t0021 : (:: +wh -c)
- t0022 : (:: +wh -c;:: -wh)
- t0028 : (:: +subj -t;:: -subj;:: -wh)
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What we’ve done (I hope)

If we accept — as I do — . . . that the rules of grammar enter into the processing mechanisms, then evidence concerning production, recognition, recall, and language use in general can be expected (in principle) to have bearing on the investigation of rules of grammar, on what is sometimes called “grammatical competence” or “knowledge of language”.

(Chomsky 1980: pp.200-201)

The psychological plausibility of a transformational model of the language user would be strengthened, of course, if it could be shown that our performance on tasks requiring an appreciation of the structure of transformed sentences is some function of the nature, number and complexity of the grammatical transformations involved.

(Miller and Chomsky 1963: p.481)
What we’ve done (I hope)

There are ways to have “purely derivational” properties of formalisms make a difference to predictions about sentence processing complexity and generalization in learning
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• ...without saying anything about real-time mental operations

• ... (let alone saying that things like MERGE and MOVE happen in real time).
What we’ve done (I hope)

There are ways to have “purely derivational” properties of formalisms make a difference to predictions about sentence processing complexity and generalization in learning

- ... without saying anything about real-time mental operations
- ... (let alone saying that things like \textsc{merge} and \textsc{move} happen in real time).
- Instead, the derivation tree is the object to be recovered/identified.
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As mentioned above, the MP as a syntactic theory appears to be a step
backwards for psycholinguistics (although perhaps not for syntacticians,
of course). One of the fundamental problems is that the model derives a
tree starting from all the lexical items and working up to the top-most
node, which obviously is difficult to reconcile with left-to-right
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Ferreira (2005: p.369)
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Ferreira (2005: p.369)

- What we’ve done of course leaves questions about real-time operations unanswered.
- But it’s not clear that there is a conflict that needs to be “reconciled”.
Open questions

How realistic is the assumption that there are a finite number of derivational states?

- MGs’ SMC vs. mainstream “minimality”
- Dependencies over arbitrary distances (e.g. Condition C, NPIs)
- ...?

Local vs. global normalization


