Sharpening the empirical claims of generative syntax through formalization

Tim Hunter

University of Minnesota, Twin Cities

NASSLLI, June 2014

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
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- reaches a different end-state when used with F2?

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- 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

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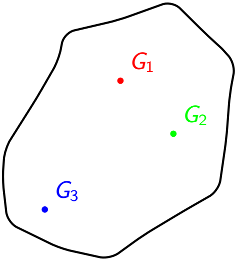
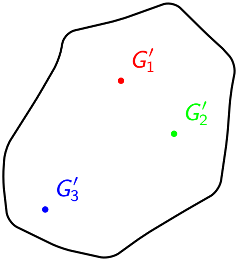
Formalism F1



Formalism F2



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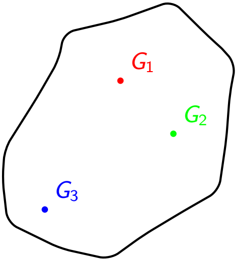
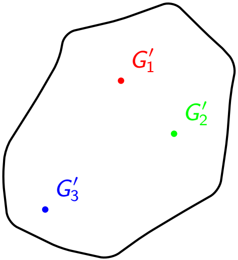


Formalism F2



A "good sentence vs. bad sentence" learner will treat these two formalisms equivalently — it won't "see" the internal differences in how they generate what they generate.

(Gibson and Wexler 1994)

Q: How can we provide traction between the learning algorithm and the internals of each G?

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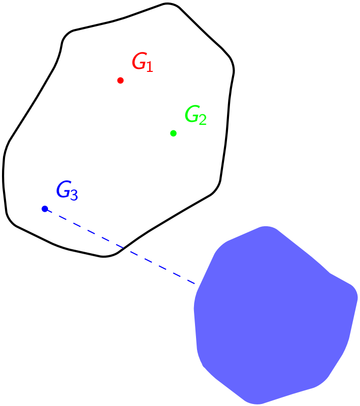
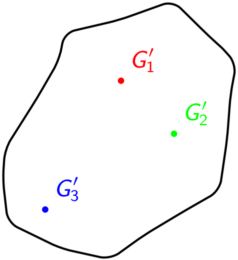


Formalism F2



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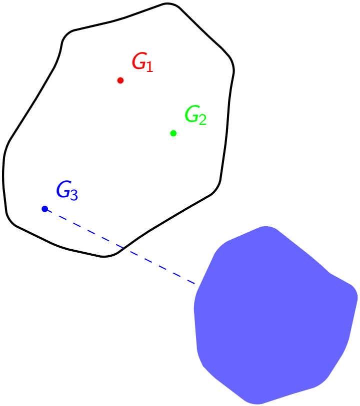
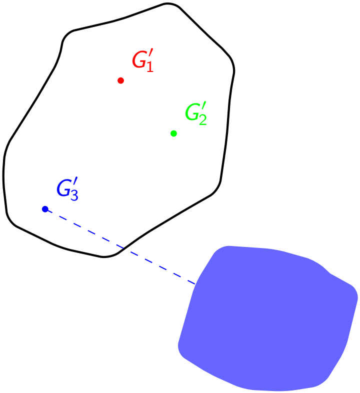


Formalism F2



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Q: How can we provide traction between the learning algorithm and the internals of each *G*?
A: Probabilities

Outline

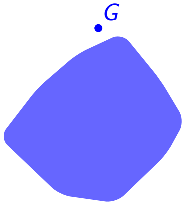
Learning scenario

Training corpus: some combination of occurrences of the following.

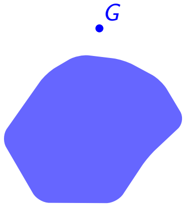
boys will shave	boys will shave themselves
who will shave	who will shave themselves
foo boys will shave	

- 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.

MGs



IMGs



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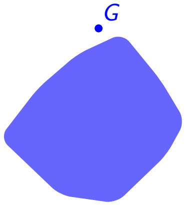

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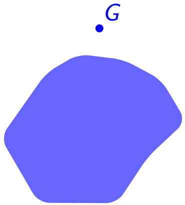
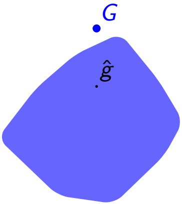
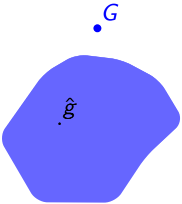


Training corpus:

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

MGs	IMGs
	

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1	who will shave themselves
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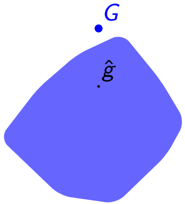
Grammar's distribution: (MGs)

0.35478	boys will shave
0.35478	foo boys will shave
0.14801	who will shave
0.05022	boys will shave themselves
0.05022	foo boys will shave themselves
0.04199	who will shave themselves

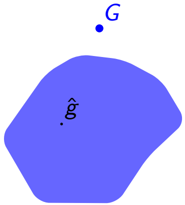
Grammar's distribution: (IMGs)

0.35721	boys will shave
0.35721	foo boys will shave
0.095	who will shave
0.095	who will shave themselves
0.04779	boys will shave themselves
0.04779	foo boys will shave themselves

MGs



IMGs



Training corpus:

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

	Entropy	Entropy Reduction
—	2.09	—
who	0.76	1.33
will	0.76	0.00
shave	0.76	0.00
themselves	0.00	0.76

	Entropy	Entropy Reduction
—	2.28	—
who	1.00	1.28
will	1.00	0.00
shave	1.00	0.00
themselves	0.00	1.00

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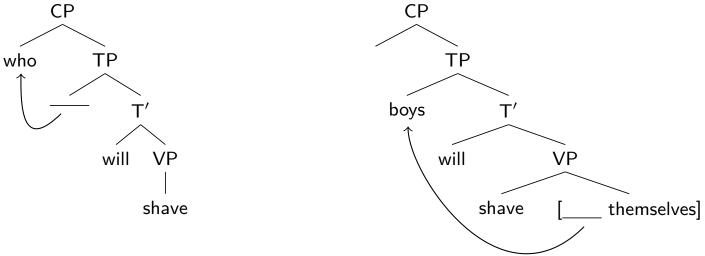

Learning scenario

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boys will shave	boys will shave themselves
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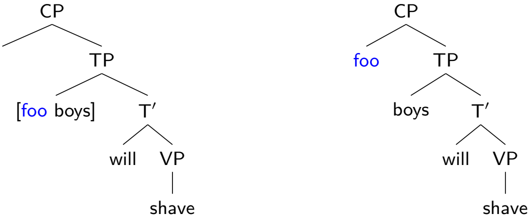
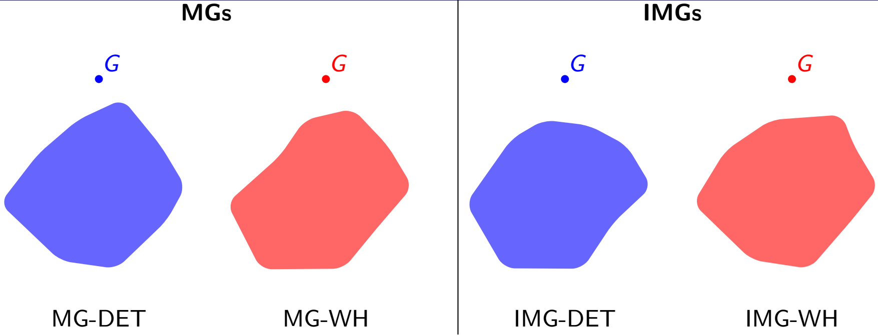
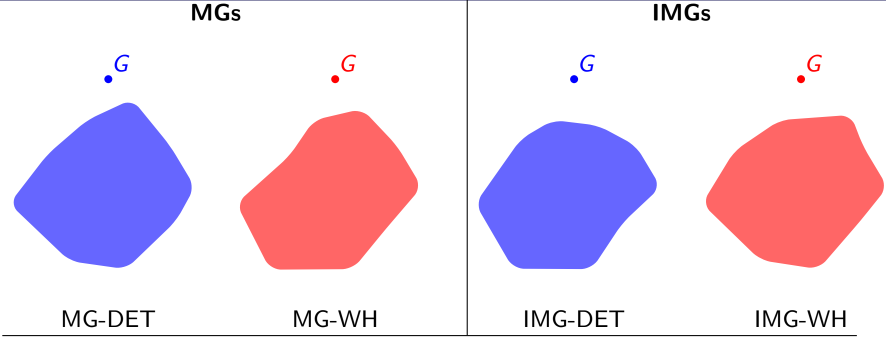
- The learner knows correct analyses of wh-movement and reflexives.
- The learner must decide how to analyze 'foo': determiner or wh-phrase?

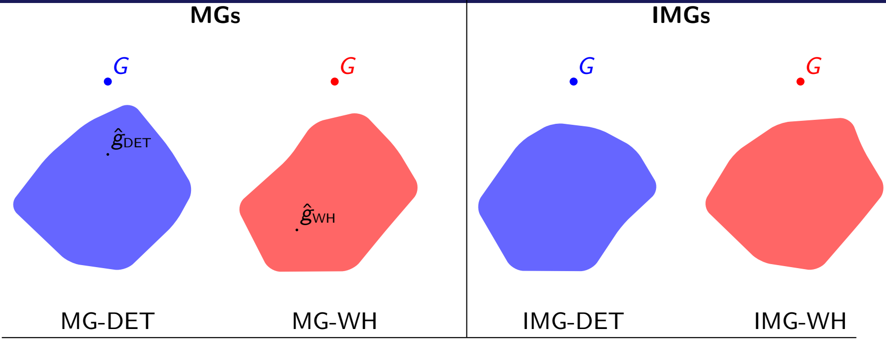



MGs
IMGs
G
G
G
G
MG-DET
MG-WH
IMG-DET
IMG-WH



Training corpus:

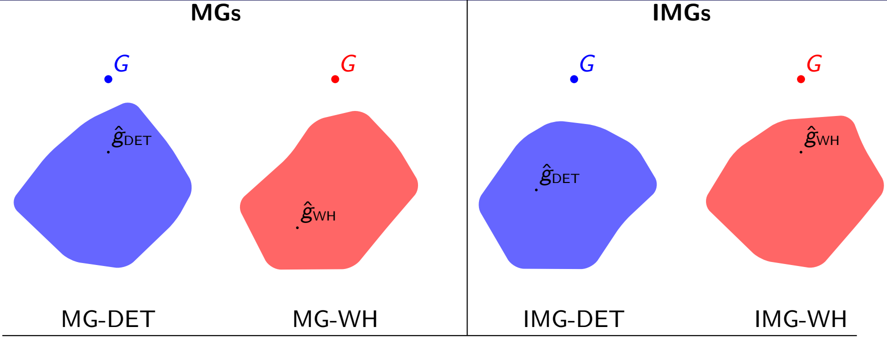
5	boys will shave
5	boys will shave themselves
5	who will shave
5	who will shave themselves
5	foo boys will shave



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

$$\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{3.36 \times 10^{-18}}{4.48 \times 10^{-20}} = 75.0$$



Training corpus:

5	boys will shave
5	boys will shave themselves
5	who will shave
5	who will shave themselves
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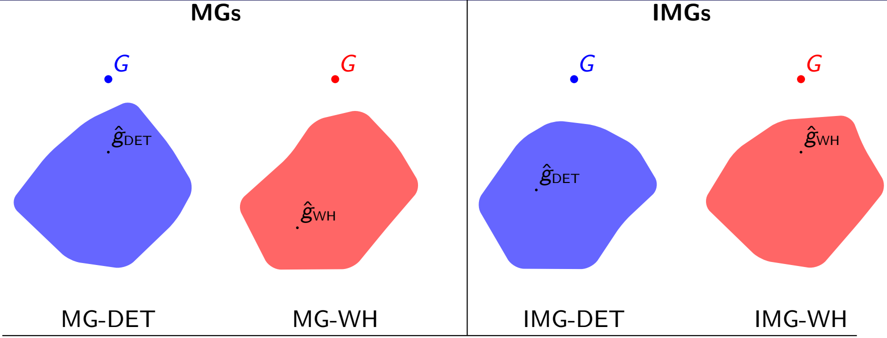
$$\frac{P(D|\hat{g}_{\mathrm{DET}})}{P(D|\hat{g}_{\mathrm{WH}})} = \frac{3.36 \times 10^{-18}}{2.45 \times 10^{-19}} = 13.7$$

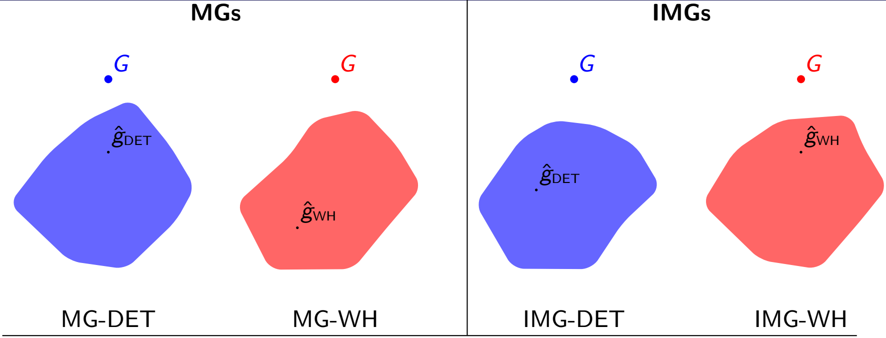


Training corpus:

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

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

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

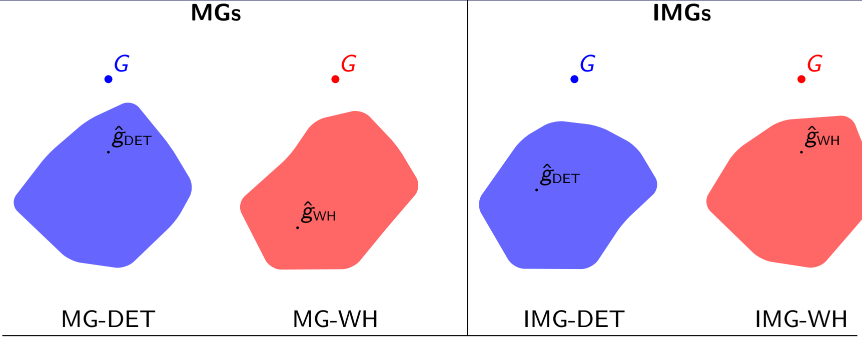


Training corpus:

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

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

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



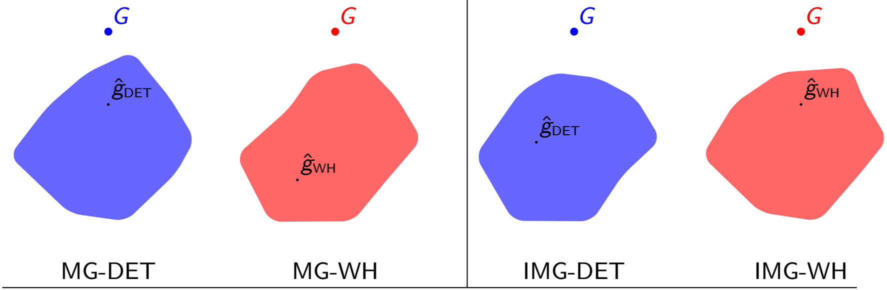
Training corpus:

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

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

$$\frac{P(D|\hat{g}_{\text{DET}})}{P(D|\hat{g}_{\text{WH}})} = \frac{1.31 \times 10^{-17}}{1.75 \times 10^{-17}} = 0.749$$

MGs | **IMGs**



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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)
```

Outline

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)

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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).
- 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 incremental parsing*
>
> *Ferreira (2005: p.369)*

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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 incremental parsing

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

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