Grammar in Performance and Acquisition: acquisition

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ENS Paris • 2008 • day 4

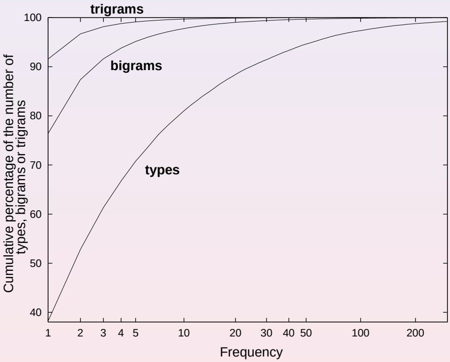
Q1 How are utterances interpreted 'incrementally'?

Q2 How is that ability acquired, from available evidence?

Q3 Why are some constituent orders unattested across languages?

Q4 What kind of grammar makes copying a natural option?

- we don't need to start from zero (start from grammar)
- frame explanations supported by convergent evidence



tb2: ≈40% words unique, 75% bigrams, 90% trigrams, 99.7% sentences

⇒ most sentences heard only once

Parameter setting: methodology

- How are fundamental properties of language learned? Important to distinguish 2 ideas:
  - Uncontroversially, we usually aim to understand how the basic parameters of language variation are set, abstracting away from other properties.
  - A controversial suggestion is that there may be a principled distinction between "core" parameters and "peripheral" parameters of variation, such that universal grammar "will make available only a finite class of possible core grammars, in principle," (Chomsky'81)

  The first idea is assumed here and in virtually all work on learning, in all domains; the second conjecture might or might not be true, and nothing mentioned here will depend on it.

Parameter setting: methodology

- How are fundamental properties of language learned?
- Gibson&Wexler'94: set n binary parameters on basis of input constituent orders
  $\langle vs, vos, vo_1o_2s, \ldots \rangle \mapsto$(spec-final, comp-final, not V2)
- ...in the case of Universal Grammar...we want the primitives to be concepts that can plausibly be assumed to provide a preliminary, prelinguistic analysis of a reasonable selection of presented data. it would be unreasonable to incorporate such notions as **subject of a sentence** or other grammatical notions, since it is unreasonable to suppose that these notions can be directly applied to linguistically unanalyzed data. (Chomsky, 1981)
- Suppose parameters are associated with (functional) heads, in the lexicon. (Presumably tightly constrained – more on this later) The learner needs to identify them...

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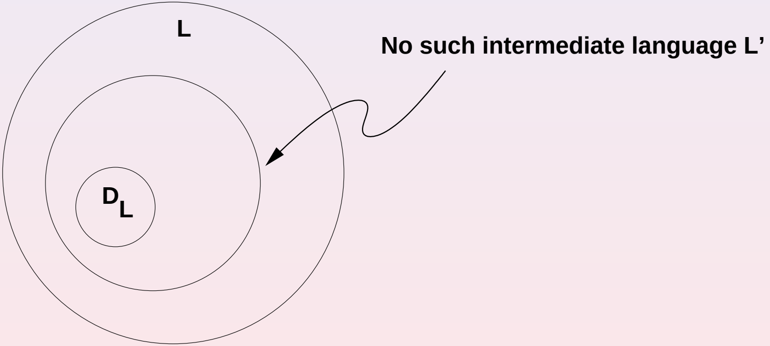
- (Gold, 1967; Angluin, 1980) A collection of languages is *perfectly identifiable from positive text* iff every **L** has finite subset $\mathbf{D_L}$



$\Rightarrow$ no superset of the class of finite languages is learnable in this sense

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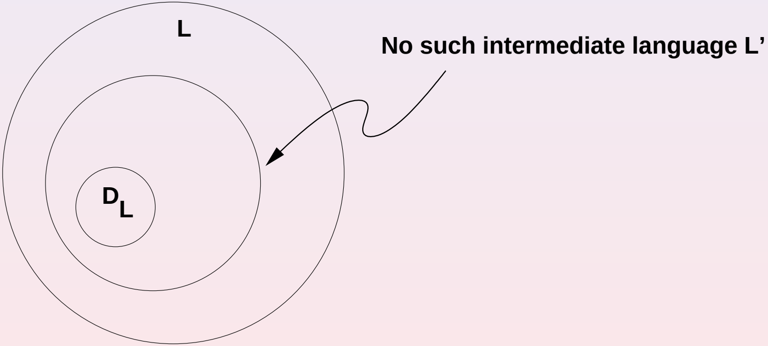

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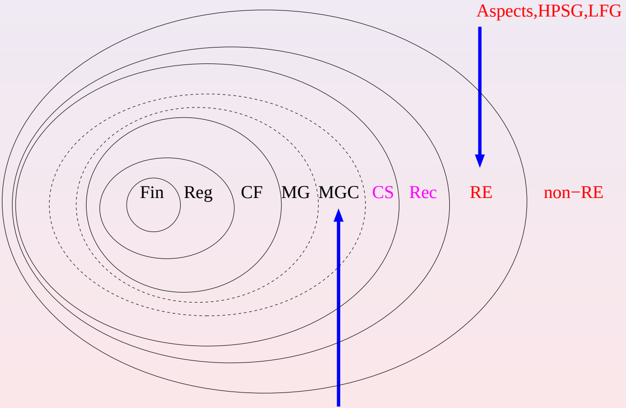
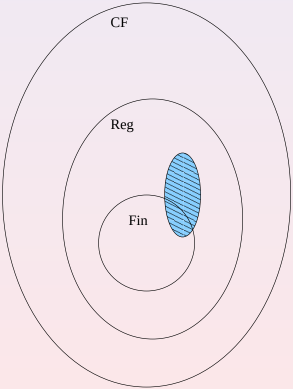


$$\mathrm{CF} \subset \boxed{\mathrm{TAG} \equiv \mathrm{CCG}} \subset \boxed{\mathrm{MCFG} \equiv \mathrm{MG}} \subset \boxed{\mathrm{MGC} \subseteq \mathrm{PMCFG}} \subset \mathrm{CS}$$

A regular language is **0-reversible** iff $xz, yz \in L$ implies $\forall w,\ xw \in L$ iff $yw \in L$

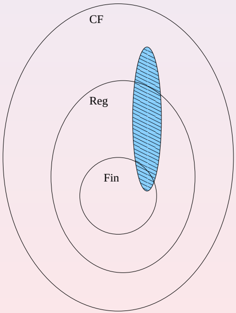


(Angluin'82): 0-reversible languages are learnable from positive text

A CFG is **very simple** iff every rule has form $A \longrightarrow a\alpha$ for pronounced (terminal) symbol a and sequence of categories α, where no two rules have the same pronounced element a.

Example:

S $\longrightarrow$ & S S
S $\longrightarrow$ ¬ S
S $\longrightarrow$ p
S $\longrightarrow$ q

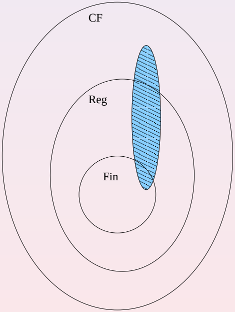


(Yokomori'03): VSLs are learnable from positive text

A CG is *k*-**valued** if no pronounced (terminal) symbol has more than *k* categories.

Example:
&::(S\S)/S
¬::S/S
p::S
q::S

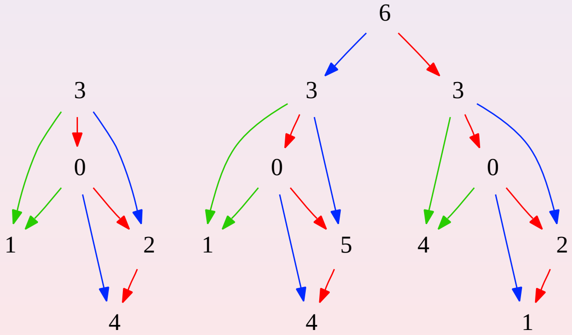
Example:
and::(S\S)/S
saw::(D\S)/D
saw::N
student::N
vegetarian::N
some::D/N
every::D/N



(Kanazawa'94): *k*-valued categorial languages are learnable from function-argument trees (and learnable in principle from strings)

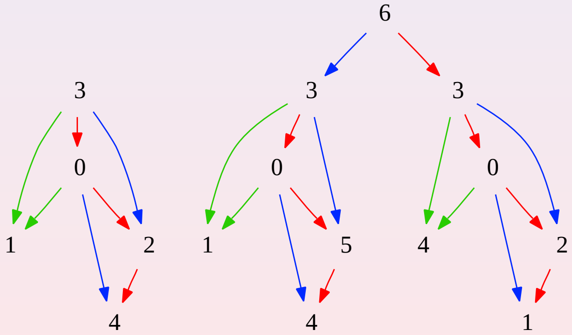
- **input:** 12340, 15340642310,. . .
- **Problem:** What is the language? Does the language have structures you have not seen?

- **input:** 12340, 15340642310,. . .
  dependencies (r,b,g)



- **Problem:** What is the language? Does the language have structures you have not seen?

- **input:** 12340, 15340642310, . . .
  dependencies (r,b,g), MG, lex unambiguous

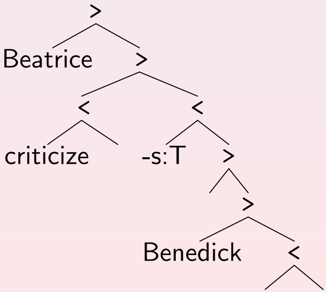


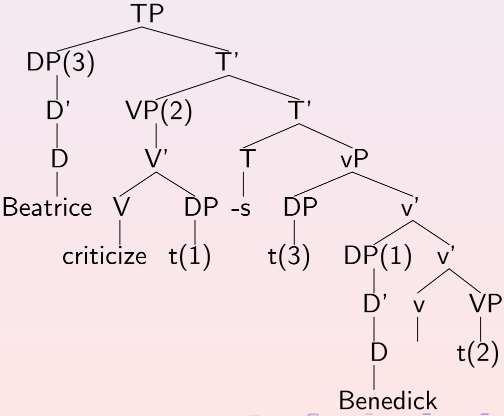
- **Problem:** What is the language? Does the language have structures you have not seen?

criticize::=D V -v　　praise::=D V -v

-s::=v +v +case T　　ϵ::=V +case =D v

Beatrice::D -case　　Benedick::D -case　　and:=T =T T





The same derivation in *tuple form*, fully explicit:

Beatrice criticize -s Benedick:T

criticize -s Benedick:+case T,Beatrice:-case

-s Benedick:+i +case T,criticize:-i,Beatrice:-case

-s::=v +i +case T   Benedick:v,criticize:-i,Beatrice:-case

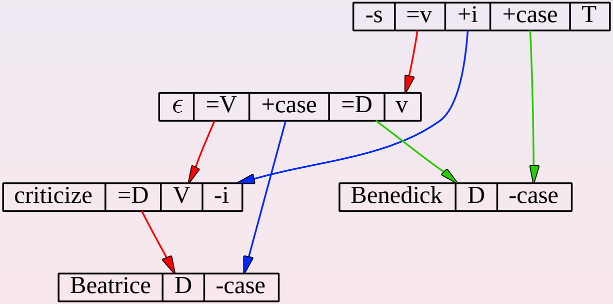
Benedick:=D v,criticize:-i   Beatrice::D -case

ϵ:+case =D v,criticize:-i,Benedick:-case

ϵ::=V +case =D v   criticize:V -i,Benedick:-case

criticize::=D V -i   Benedick::D -case

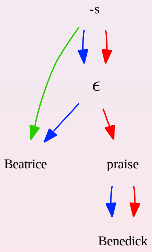
The same derivation as a *matching graph*:



(This graph completely determines the derivation)

- Suppose the learner can identify these dependencies using semantic reasoning, but not the syntactic features. . . what do we have when features are removed?

Let's call these MG *dependency structures*:



- From these, the learner can identify the language.

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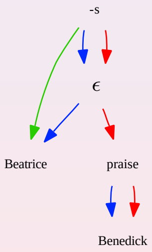
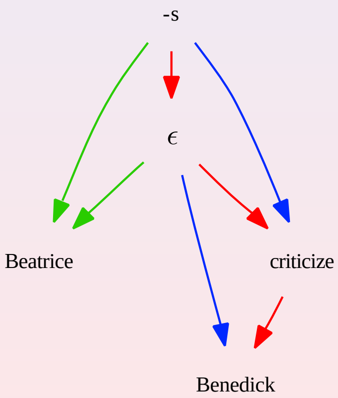


- From these, the learner can identify the language.

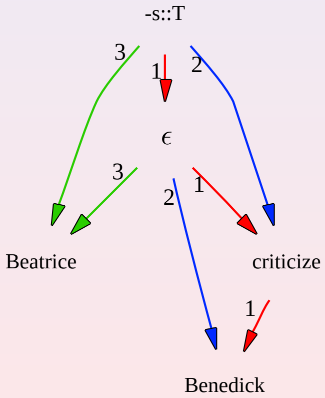
the learner: given a sequence of dependency structures. . .

1. label the root category
2. identify first arcs of non-root nodes, add new category labels
3. add new licensee features for each other incoming arc
4. add pre-category feature to match each outgoing arc
5. collect the lexicon
6. assuming no lexical ambiguity, unify features

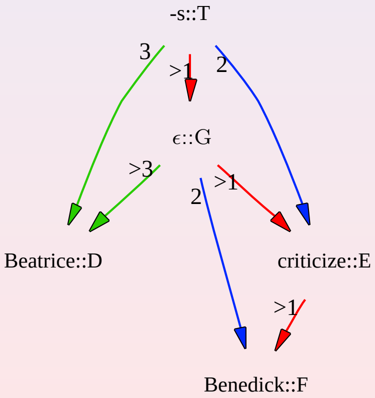
Input: $\langle d_1 \rangle$



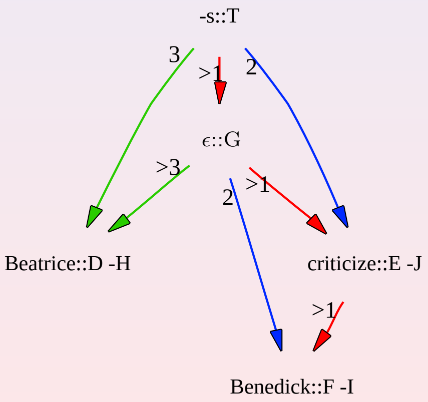
Step 1: Label root category



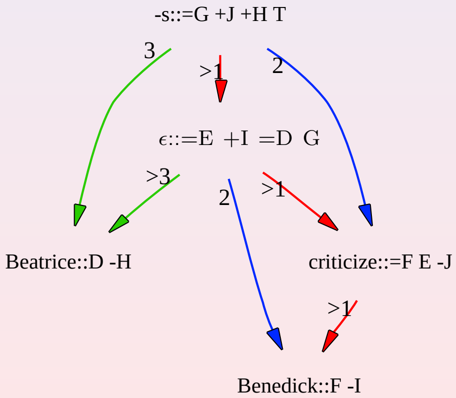
Step 2: Identify least incoming arcs of non-root nodes; add new category labels:



Step 3: Add new licensee features for each later incoming arc:



Step 4: Add precategory features to match other end of each outgoing arc, in order (r,b,g):



Step 5. collect lexicon: $GF(\langle d_1 \rangle)$ is then:

criticize::=F E -J	
-s::=G +J +H T	ϵ::=E +I =D G
Beatrice::D -H	Benedick::F -I

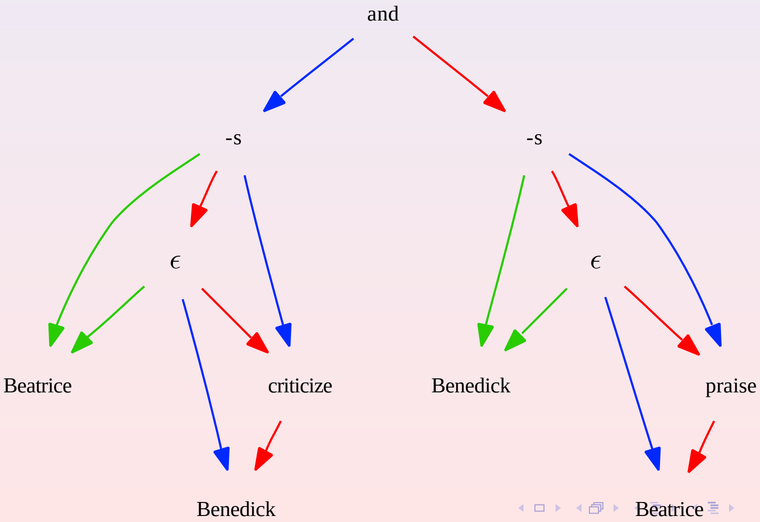
The result of this step is always a grammar that defines exactly the dependency trees given in the input; nothing more. The grammar generates exactly the input string(s).

Step 6. unify to make rigid: $GF(\langle d_1 \rangle)$ already rigid, so $GF(\langle d_1 \rangle) = RG(\langle d_1 \rangle)$

criticize::=F E -J	
-s::=G +J +H T	ϵ::=E +I =D G
Beatrice::D -H	Benedick::F -I

criticize::=D V -v	praise::=D V -v	
-s::=v +v +case T	ϵ::=V +case =D v	
Beatrice::D -case	Benedick::D -case	and::=T =T T

Input: $\langle d_1, d_2 \rangle$



Step 5: $GF(\langle d_1, d_2 \rangle)$ is then:

Beatrice::P -U	Benedick::O -V	and::=L =K T
Beatrice::S -Y	Benedick::C -X	
-s::=M +W +U K	ϵ::=N +V =P M	
criticize::=O N -W	praise::=S R -Z	
-s::=Q +Z +X L	ϵ::=R +Y =C Q	

criticize::=F E -J	
-s::=G +J +H T	ϵ::=E +I =D G
Beatrice::D -H	Benedick::F -I

NB: Again, $GF(\langle d_1, d_2 \rangle)$ does not generalize at all.

Step 6. unify to make rigid: $RG(\langle d_1, d_2 \rangle) =$

criticize::=D E -J   praise::=D E -J
-s::=G +J +H T ϵ::=E +H =D G
Beatrice::D -H   Benedick::D -H   and::=T =T T

criticize::=D V -v   praise::=D V -v
-s::=v +v +case T ϵ::=V +case =D v
Beatrice::D -case   Benedick::D -case   and::=T =T T

This strategy always works

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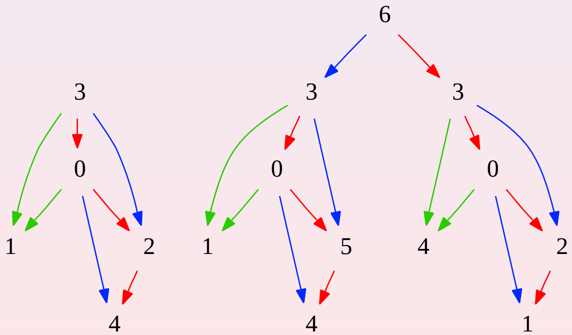
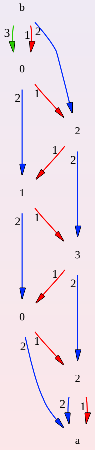
Beatrice::D -case	Benedick::D -case	and::=T =T T

This strategy <u>always</u> works

- **input:** 12340, 15340642310
  Beatrice praise -s Benedick ϵ,
  Beatrice criticize -s Benedick ϵ and Benedick praise -s Beatrice ϵ.
  dependencies (r,b,g), MG, lex unambiguous



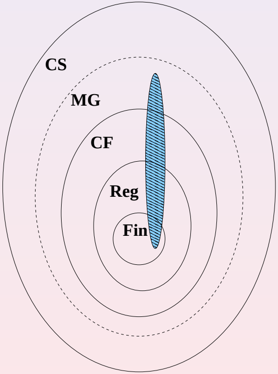
- **Problem:** What is the language?



a::C -r -l	b::=C +r +l T	ϵ::T
2::=C +r A -r	3::=C +r B -r	
0::=A +l C -l	1::=B +l C -l	

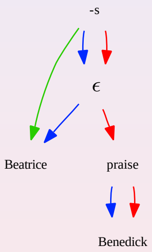
cross-serial dependencies by 'rolling-up' (non-CF)

A MG is **rigid** if each pronounced (terminal) symbol has at most 1 set of syntactic features.



Thm Given any rigid MG G, and any text of dependency structures t defined by G, this learning method will exactly identify the language after finitely many examples

structures from strings



- **Selection:** inferred from cognitively salient events
  - conditioned variation $\longrightarrow$ lexical categories
  - tight constraints on functional categories $\star$
- **Movement:** non-adjacency with related elements

ambiguity

- -s::=v +v +case T -s:=N Num (and more)
  ϵ::=V +case =D v ϵ::=T C (and more)
- read::=D V read::V read::N reed::N (and more)
  bill::=D V bill::V bill::N (and more)
- much ambiguity is systematic
- semantic features reduce syntactic ambiguity
- topic, semantic features from distributions?

ambiguity

- -s::=v +v +case T   -s:=N Num   (and more)
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ambiguity

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- much ambiguity is systematic
- semantic features reduce syntactic ambiguity
- topic, semantic features from distributions?

Summary

- simple formalisms can model many linguistic proposals
  - **Q3** Why are some constituent orders unattested? (perhaps DTC?)
  - **Q4** What grammars make copying a natural option? (MGC?)
    - many open questions

Q1 What performance models allow incremental interpretation (and remnant movement, doubling constructions?)

- a straightforward semantics can value every MGC constituent
- CKY, Earley efficiently parses every MGC
- fit the performance data with a parser that works!

Q2 How is this ability acquired, from available evidence?

- rigid MGs can be learned from structures
- restricted possible structures aids: strings→structures
- many open questions!

Recap: the learner given a sequence of dependency structures. . .

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