# A probabilistic approach to Lexical-Functional Grammar 

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Based on joint work with
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## Linguistic Theories provide

## Representations



Formal encoding of grammatical relations

## Rules

$$
\begin{array}{ccc}
S & \rightarrow \begin{array}{c}
\text { NP } \\
\\
\\
(\uparrow \text { SUBJ })=\downarrow
\end{array} & \begin{array}{l}
\text { VP } \\
\text { VP }
\end{array} \\
& \left.\rightarrow \begin{array}{cc}
\mathrm{V} & \text { NP } \\
& \uparrow=\downarrow \\
\hline
\end{array} \uparrow \text { OBJ }\right)=\downarrow
\end{array}
$$

Determine representations for all possible utterances

Usual goal: minimal, nonredundant set of independent generalizations with free interactions

Carry explanatory burden

## Competence Hypothesis

- Language user applies internalized rules to produce internal representations
- Language user acquires rules by abstraction of grammatical experience guided by universal principles and constraints


## Alternative view: Representations only, no rules

- Language user acquires examples of representations from syntactic experience
- Language user applies operations on representations to produce representations for new utterances
- Linguistic theory specifies representations and operations
- Rules perhaps appear in scientific discourse, but are not part of native speaker's "competence"


# Productivity from examples (following Scha, Bod: Data Oriented Parsing) 

Given: corpus annotated with representations (e.g. phrase structures)

1. Break structures into fragments--remember them
2. Combine fragments to get structures for new sentences

## DOP illustration

Given: corpus annotated with representations:


1. Break structures into fragments


## 2. Combine fragments to get structures for new utterances



In DOP, $\circ$ is left-most substitution

8. R. M. Kaplan, A probabilistic approach to LFG, LFG Colloquium and Workshops, Rank Xerox Research Centre, Grenoble, August 1996.

## Another derivation of the same structure:



## Observations

- Fragments are not minimal
- Range from context-free rule equivalent ( $\mathrm{S} \rightarrow \mathrm{NP}$ VP) to whole-utterance structure.
- Some large fragments may represent idiosyncratic constructions, others may not. We don't care.
- We don't even care how many fragments there are (in principle).

TAG?

- Fragments are redundant, with overlapping information.

is in

- Multiple results, not derivations, correspond to ambiguity


## Probabilities

Resolve ambiguities, implicitly identify most useful fragments

- Frequency affects language-user interpretations: governs choice among several grammatical alternatives

Mehler \& Carey (68)....Tanenhaus and Trueswell (95)

- Typically, probabilities are defined on rules (stochastic grammars)
- DOP: Probabilities are defined on representations, not rules Scha (90) .... Bod (95)


## A corpus-oriented, representation-based approach requires

1. A theory of well-formed utterance representations.
2. A definition of productive representation fragments.
3. A definition of a fragment-combination operation ${ }^{\circ}$.
4. A probability model for utterance representations.

A linguistic theory provides 1, 2, 3
but no other descriptive devices
12. R. M. Kaplan, A probabilistic approach to $L F G$, LFG Colloquium and Workshops, Rank Xerox Research Centre, Grenoble, August 1996

## For DOP

1. Representations: phrase structure trees.
2. Fragments: connected subtrees.
3. Operation ${ }^{\circ}$ : substitution of leftmost matching category.
4. Probability model: ...later.

## For LFG:

1. Representations: valid* c-structures and f-structures in correspondence.

*No nonbranching dominance chains
2. Fragments: loosely, connected subtrees in correspondence with connected sub-f-structures


etc.

Intuition says: some possible fragments are implausible

## Examples of theory-based restrictions

Lexical predicates: If a fragment includes an f-structure lexical predicate, the fragment must also include a corresponding lexical node.

Head chains: If a f ragment includes node $n$ corresponding to f -structure $f$, then all other nodes under $n$ corresponding to $f$ must be included.

Control: If a fragment contains one path of a control identity, it must contain the other.

Sisters: If a fragment includes a node $n$, it must include all of $n$ 's sisters (from DOP).

## 3. Operation: Left-most substitution of matching categories followed by unification of corresponding fragment f -structures



[^0]
## Derivation

A derivation for an utterance $u$ is a sequence of fragments $\left\langle f_{1}, f_{2} \ldots f_{\mathrm{n}}\right\rangle$ such that the composition operator ${ }^{\circ}$ applied from left to right results in a valid representation $R$ whose yield is $u$ :

$$
\begin{aligned}
R & =\left(\ldots\left(\left(f_{1} \circ f_{2}\right) \circ \ldots\right) \circ f_{\mathrm{n}}\right) \\
& =<\mathrm{c} \text {-structure, } \phi, \text { f-structure }>
\end{aligned}
$$

Theory of representation defines "valid":
e.g. no nonbranching dominance chains, complete and coherent f-structure.

Theory of representation defines "yield":
e.g the terminal string of the c-structure.

## 4. Probability Model

Let $C$ be a corpus of structures and $\operatorname{Bag}(C)$ be the bag containing all fragments derived from $C . \#(f)$ is the number of times that fragment $f$ appears in the bag.

The probability of each fragment is estimated by its corpus frequency:

$$
P(f)=\frac{\#(f)}{\sum_{\left.g \in \operatorname{Bag}(C)^{\#( } g\right)}}
$$

## Probability of a derivation

A derivation for an utterance $u$ results in a representation $R$ whose yield is $u$.

- We assume a fragment sequence $s=\left\langle f_{1}, f_{2} \ldots f_{\mathrm{n}}>\right.$ is constructed from the bag by random sampling with replacement. Then its sequence probability is

$$
P(s)=\prod_{i} P\left(f_{i}\right)
$$

- There may be infinitely many sequences that result in no representation or which result in a representation whose yield is not $u$. We are not interested in those. For a given derivation $d$ of $u$ we obtain

$$
P(d \mid d \text { yields } u)=\frac{P(d)}{\sum_{s \text { yields } u} P(s)}
$$

The linguistic theory must guarantee for every $u$ a maximum derivation length. (E.g. no nonbranching chains)

## Probability of an utterance representation

In general there are many derivations of a particular representation $R$ for an utterance $u$. Assuming these derivations are independent, we have

$$
P(R)=\sum_{d \text { results in } R} P(d \mid d \text { yields } u)
$$

We assign the most probable $R$ as the best analysis of $u$.

The most probable $R$ : the one most likely to have been derived.

## Other approaches

- Stochastic grammars: Assign probabilities to rules

The most probable $R$ : the one with the most probable derivation

- Johnson (1996): Assign probabilities to f-structure relations

The most probable $R$ : the one with the most probable f -structure independent of any derivation
"Model theory vs. proof theory"

## Summary

- A productive system based on representations, not rules
- Clear, but different, role for linguistic theory
- Different claims about what a native-speaker "knows", what needs to be explained
- Theory of acquisition combined with theory of processing (Although it may be impractical...)


[^0]:    17. R. M. Kaplan, A probabilistic approach to $L F G$, LFG Colloquium and Workshops, Rank Xerox Research Centre, Grenoble, August 1996.
