Parsing and Generation as Datalog Queries

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CFG recognition/parsing as Datalog query evaluation



S(i,j) := NP(i,k), VP(k,j). VP(i,j) := V(i,k), NP(k,j). NP(i,j) := Det(i,k), N(k,j). NP(i,j) := John(i,j). V(i,j) := found(i,j). Det(i,j) := a(i,j). N(i,j) := unicorn(i,j).

Datalog program

John(0, 1).

found(1, 2).

a(2, 3).

unicorn(3, 4).

database

?— S(0, 4).

CFG recognition/parsing as Datalog query evaluation



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John(0, 1).

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database

?— S(0, 4).

- Polynomial-time algorithms
 - − CYK ≈ seminaive bottom-up evaluation
 - Earley \approx magic-sets rewriting

Extending Datalog representation

CFG recognition/parsing

recognition/parsing for

grammars with

"context-free" derivations

(MC)TAG

(P)MCFG

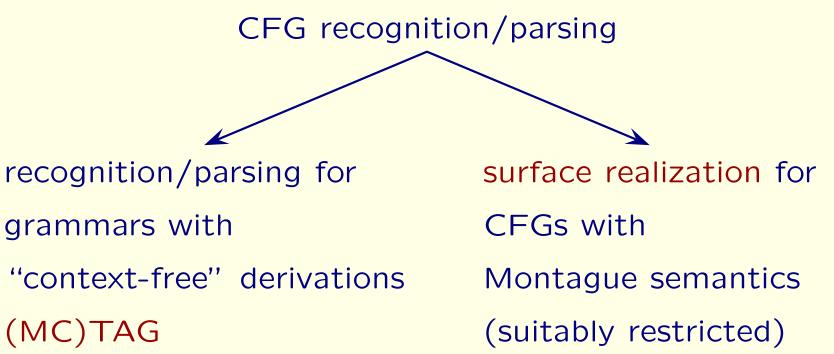
surface realization for

CFGs with

Montague semantics

(suitably restricted)

Extending Datalog representation

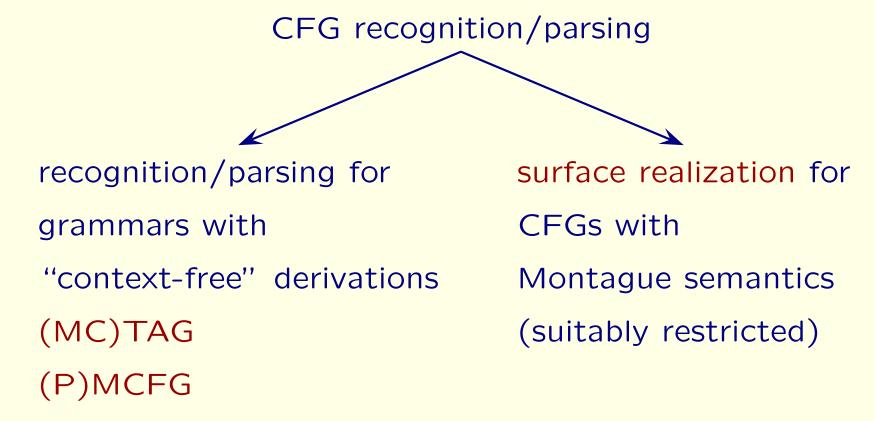


Polynomial-time algorithms

(P)MCFG

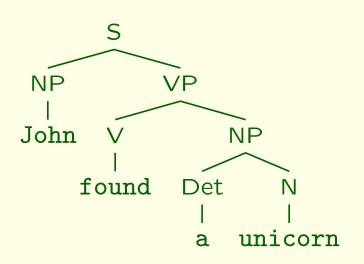
- − CYK ≈ seminaive bottom-up evaluation
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Extending Datalog representation



- Polynomial-time algorithms
 - − CYK ≈ seminaive bottom-up evaluation
 - Earley \approx magic-sets rewriting
- Complexity
 - Polynomial-sized derivation tree \Rightarrow LOGCFL $AC^0 \subseteq NC^1 \subseteq L \subseteq SL \subseteq NL \subseteq LOGCFL \subseteq AC^1 \subseteq NC^2 \subseteq P \subseteq NP$

Context-free grammar with Montague semantics



```
S(X_1X_2) \rightarrow NP(X_1) VP(X_2)
VP(\lambda x. X_2(\lambda y. X_1 yx)) \rightarrow V(X_1) NP(X_2)
V(\lambda yx.X_2(X_1yx)(X_3yx)) \rightarrow V(X_1) \text{ Conj}(X_2) V(X_3)
NP(X_1X_2) \rightarrow Det(X_1) N(X_2)
NP(\lambda u.u John^e) \rightarrow John
\vee (\mathsf{find}^{e \to e \to t}) \to \mathsf{found}
\vee (\mathsf{catch}^{e \to e \to t}) \to \mathsf{caught}
Conj(\Lambda^{t \to t \to t}) \to and
\operatorname{Det}(\lambda uv. \exists^{(e \to t) \to t}(\lambda y. \wedge^{t \to t \to t}(uy)(vy))) \to \mathbf{a}
N(\mathbf{unicorn}^{e \to t}) \to \mathbf{unicorn}
```

$$(\lambda u.u \ \mathsf{John})(\lambda x.(\lambda uv.\exists (\lambda y.\Lambda(uy)(vy))) \ \mathsf{unicorn}\ (\lambda y.\mathsf{find}\ y\ x))$$

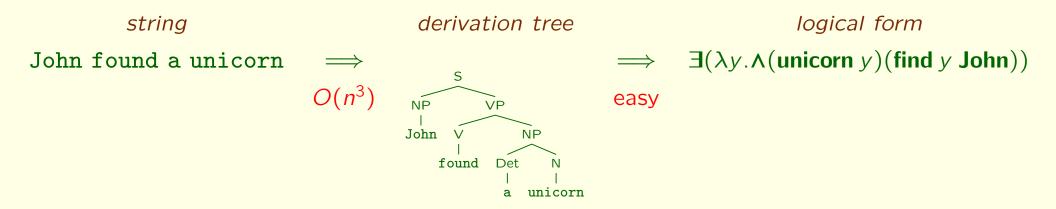
$$\to_{\beta} \ \exists (\lambda y.\Lambda(\mathsf{unicorn}\ y)(\mathsf{find}\ y\ \mathsf{John}))$$

$$\approx \exists y(\mathsf{unicorn}(y)\ \Lambda\ \mathsf{find}(\mathsf{John},y))$$

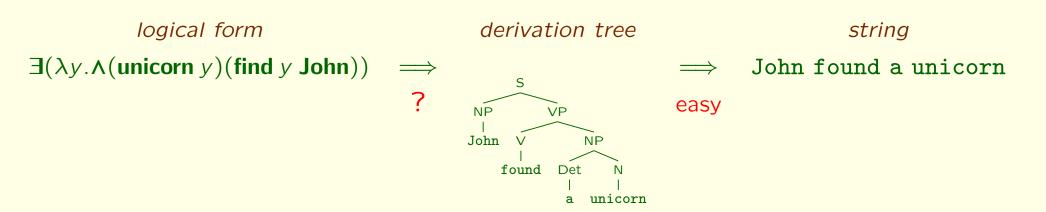
$$\log ical\ form$$

Semantic interpretation and surface realization

Semantic interpretation

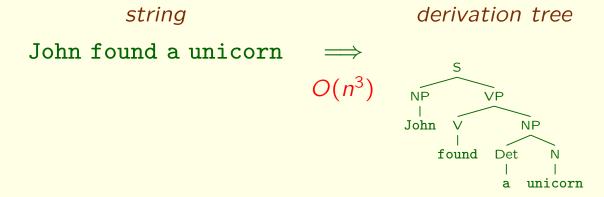


Surface realization (tactical generation)

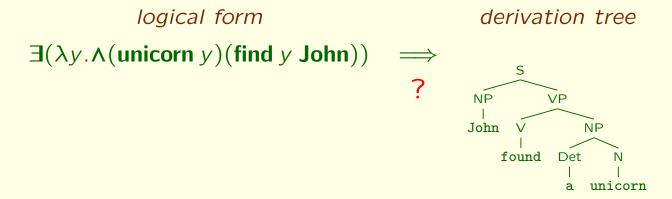


Semantic interpretation and surface realization

Parsing (of input string)



Parsing of input logical form



Semantic interpretation and surface realization

Recognition (of input string)

```
\frac{string}{} \frac{grammatical?}{} John found a unicorn \implies yes/no O(n^3)
```

Recognition of input logical form

Recognition \approx Parsing

My approach to surface realization

• Exact generation, not taking into account logical equivalence.

$$\mathsf{man\ John} \Leftrightarrow \exists y. (\mathsf{man\ } y \land y = \mathsf{John})$$

My approach to surface realization

• Exact generation, not taking into account logical equivalence.

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- The semantic representation language is that of higher-order λ -terms, and the computation of meaning involves β -reduction.
- More faithful to standard linguistic analysis than previous approaches.

Synchronous grammar view

$$S(X_1X_2) \rightarrow NP(X_1) \ VP(X_2)$$
 $VP(\lambda x. X_2(\lambda y. X_1 yx)) \rightarrow V(X_1) \ NP(X_2)$
 $V(\lambda yx. X_2(X_1 yx)(X_3 yx)) \rightarrow V(X_1) \ Conj(X_2) \ V(X_3)$
 $NP(X_1X_2) \rightarrow Det(X_1) \ N(X_2)$
 $NP(\lambda u. u \ John^e) \rightarrow John$
 $V(find^{e \rightarrow e \rightarrow t}) \rightarrow found$
 $V(catch^{e \rightarrow e \rightarrow t}) \rightarrow caught$
 $Conj(\Lambda^{t \rightarrow t \rightarrow t}) \rightarrow and$
 $Det(\lambda uv. \exists^{(e \rightarrow t) \rightarrow t}(\lambda y. \Lambda^{t \rightarrow t \rightarrow t}(uy)(vy))) \rightarrow a$
 $N(unicorn^{e \rightarrow t}) \rightarrow unicorn$

string grammar

$$S o NP VP$$
 $VP o V NP$
 $V o V Conj V$
 $NP o Det N$
 $NP o John$
 $V o found$
 $V o caught$
 $Conj o and$
 $Det o a$
 $N o unicorn$

λ-term grammar

```
S(X_{1}X_{2}) := NP(X_{1}), VP(X_{2}).
VP(\lambda x. X_{2}(\lambda y. X_{1}yx)) := V(X_{1}), NP(X_{2}).
V(\lambda yx. X_{2}(X_{1}yx)(X_{3}yx)) := V(X_{1}), Conj(X_{2}), V(X_{3}).
NP(X_{1}X_{2}) := Det(X_{1}), N(X_{2}).
NP(\lambda u. u John^{e}).
V(find^{e \to e \to t}).
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```

Context-free λ -term grammars (CFLGs)

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• $L(G) = \{ |M|_{\beta} | \vdash_{G} S(M) \}.$

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```

- $L(G) = \{ |M|_{\beta} | \vdash_{G} S(M) \}.$
- An alternative notation for second-order abstract categorial grammars (de Groote 2001), with the restriction to linear λ -terms dropped.
- With linear CFLGs, parsing/recognition complexity is in P (Salvati 2005).

Representing string grammars with CFLGs

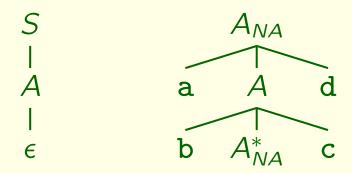
• Linear CFLGs can represent well-known mildly context-sensitive grammar formalisms like TAGs, MCTAGs, and MCFGs through encoding of strings as λ -terms (de Groote 2002, de Groote and Pogodalla 2004):

$$/a_1 \dots a_n/=\lambda z.a_1^{o\to o}(\dots(a_n^{o\to o}z)\dots).$$

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$$S(\lambda y.X_1(\lambda z.z)y) := A(X_1).$$

 $A(\lambda xy.\mathbf{a}^{o\to o}(X_1(\lambda z.\mathbf{b}^{o\to o}(x(\mathbf{c}^{o\to o}z)))(\mathbf{d}^{o\to o}y))) := A(X_1).$
 $A(\lambda xy.xy).$

Almost linear CFLGs

A λ -term M is almost linear if

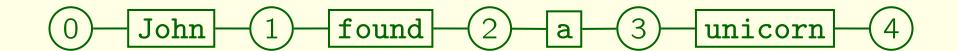
- each occurrence of λ binds at least one occurrence of a variable (M is a λI -term), and
- ullet any variable that occurs more than once in M is of atomic type.

```
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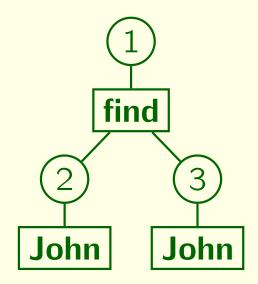
Datalog representation of almost linear CFLGs

- input λ -term \Rightarrow (database, query)
- CFLG rule ⇒ Datalog rule

Hypergraph representations of strings and trees



John found a unicorn

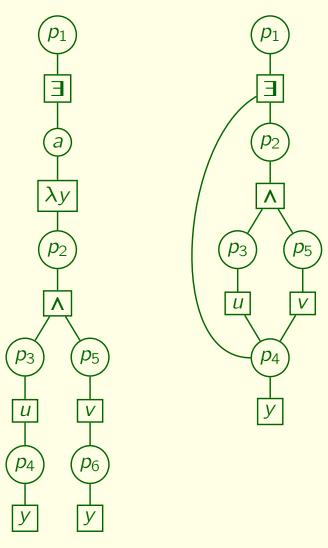


find John John

Hypergraph representations of λ -terms

 $\exists (\lambda y. \land (uy)(uy))$

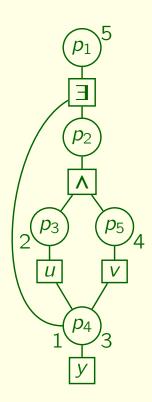
 $\lambda uv. \exists (\lambda y. \land (uy)(uy))$



tree graph

term graph

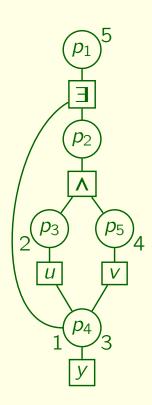
term graph with external nodes



• The graph represents a principal (i.e., most general) typing of the term:

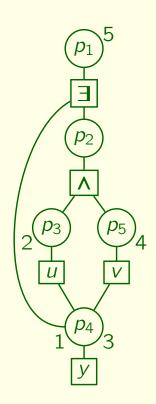
$$\exists : (e \to t) \to t, \land : t \to t \to t$$

 $\vdash \lambda uv. \exists (\lambda y. \land (uy)(vy)) : (e \to t) \to (e \to t) \to t$



• The graph represents a principal (i.e., most general) typing of the term:

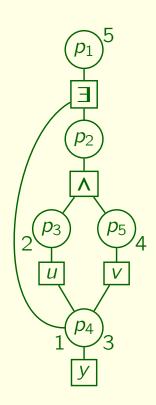
$$\exists : (p_4 \to p_2) \to p_1, \land : p_3 \to p_5 \to p_2$$
$$\vdash \lambda uv. \exists (\lambda y. \land (uy)(vy)) : (p_4 \to p_3) \to (p_4 \to p_5) \to p_1$$



 The graph represents a principal (i.e., most general) typing of the term:

$$\exists : (\bar{p_4} \to \bar{p_2}) \to \bar{p_1}, \Lambda : \bar{p_3} \to \bar{p_5} \to \bar{p_2} \\ \vdash \lambda uv. \exists (\lambda y. \Lambda(uy)(vy)) : (\bar{p_4} \to \bar{p_3}) \to (\bar{p_4} \to \bar{p_5}) \to \bar{p_1}$$

• If the λ -term is almost linear, the typing represented by the graph is negatively non-duplicated (cf. Aoto 1999).



 The graph represents a principal (i.e., most general) typing of the term:

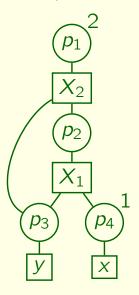
$$\exists : (\bar{p_4} \to \bar{p_2}) \to \bar{p_1}, \Lambda : \bar{p_3} \to \bar{p_5} \to \bar{p_2} \\ \vdash \lambda uv. \exists (\lambda y. \Lambda(uy)(vy)) : (\bar{p_4} \to \bar{p_3}) \to (\bar{p_4} \to \bar{p_5}) \to \bar{p_1}$$

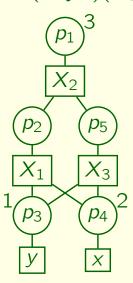
- If the λ -term is almost linear, the typing represented by the graph is negatively non-duplicated (cf. Aoto 1999).
- A negatively non-duplicated typing uniquely determines a λ -term up to $\beta\eta$ -equality (Aoto and Ono 1994).

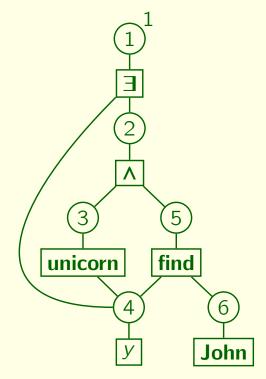
 $\lambda x. X_2(\lambda y. X_1 yx)$

 $\lambda y x. X_2(X_1 y x)(X_3 y x)$

 $\exists (\lambda y. \land (unicorn \ y)(find \ y \ John))$







 $S(p_1) := NP(p_1, p_2, p_3), VP(p_2, p_3).$

 $VP(p_1, p_4) := V(p_2, p_4, p_3), NP(p_1, p_2, p_3).$

 $V(p_1, p_4, p_3) := V(p_2, p_4, p_3), Conj(p_1, p_5, p_2), V(p_5, p_4, p_3).$

 $NP(p_1, p_4, p_5) := Det(p_1, p_4, p_5, p_2, p_3), N(p_2, p_3).$

 $NP(p_1, p_1, p_2) := John(p_2).$

 $V(p_1, p_3, p_2) := find(p_1, p_3, p_2).$

 $V(p_1, p_3, p_2) := \operatorname{catch}(p_1, p_3, p_2).$

Conj $(p_1, p_3, p_2) :- \Lambda(p_1, p_3, p_2).$

 $Det(p_1, p_5, p_4, p_3, p_4) := \exists (p_1, p_2, p_4), \land (p_2, p_5, p_3).$

 $N(p_1, p_2) := \mathbf{unicorn}(p_1, p_2).$

 $\exists (1, 2, 4).$

 $\Lambda(2, 5, 3).$

unicorn(3, 4).

find(5, 6, 4).

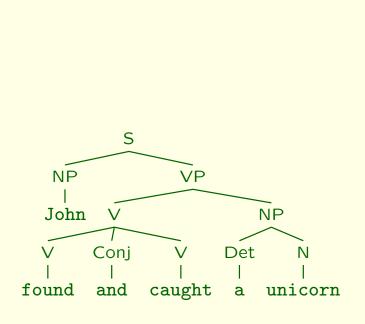
John(6).

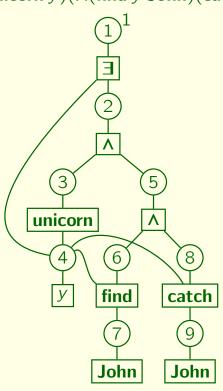
database

?— S(1).

Datalog program

 $\exists (\lambda y. \land (unicorn \ y)(\land (find \ y \ John)(catch \ y \ John)))$





```
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NP(p_1, p_1, p_2) := John(p_2).
V(p_1, p_3, p_2) := find(p_1, p_3, p_2).
V(p_1, p_3, p_2) := catch(p_1, p_3, p_2).
Conj(p_1, p_3, p_2) := \Lambda(p_1, p_3, p_2).
Det(p_1, p_5, p_4, p_3, p_4) := \exists (p_1, p_2, p_4), \Lambda(p_2, p_5, p_3).
N(p_1, p_2) := unicorn(p_1, p_2).
```

catch(8, 9, 4).

John(9).

database

 $\exists (1, 2, 4).$

 $\Lambda(2, 5, 3).$

 $\Lambda(5, 8, 6).$

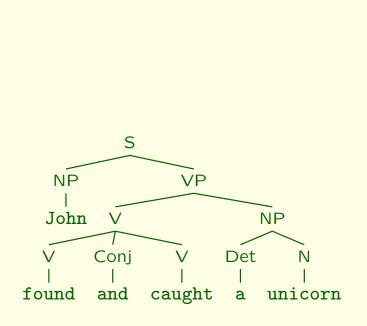
John(7).

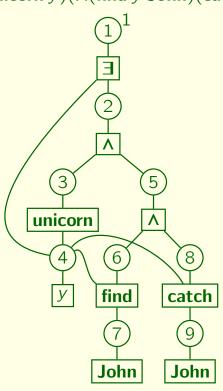
find(6, 7, 4).

unicorn(3, 4).

?— S(1).

 $\exists (\lambda y. \land (unicorn \ y)(\land (find \ y \ John)(catch \ y \ John)))$



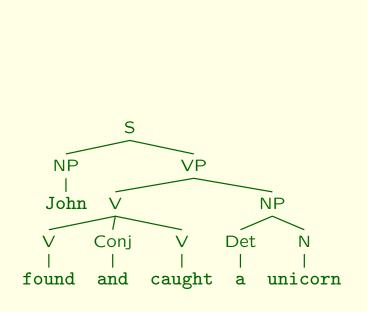


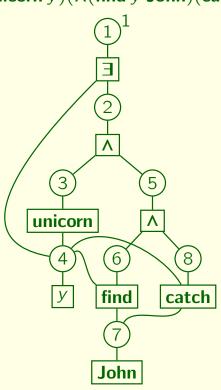
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V(p_1, p_3, p_2) := \text{find}(p_1, p_3, p_2).
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Conj(p_1, p_3, p_2) := \Lambda(p_1, p_3, p_2).
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N(p_1, p_2) := unicorn(p_1, p_2).
                          Datalog program
```

 $\exists (1, 2, 4).$ $\Lambda(2, 5, 3).$ unicorn(3, 4). $\Lambda(5, 8, 6).$ **find**(6, 7, 4). John(7). catch(8, 9, 4). **John**(9). database

?-S(1)No!

 $\exists (\lambda y. \land (unicorn \ y)(\land (find \ y \ John)(catch \ y \ John)))$





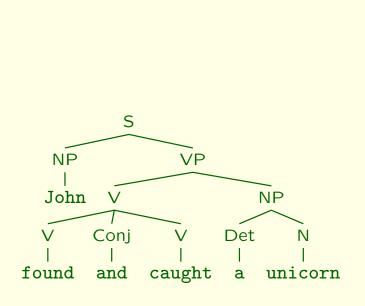
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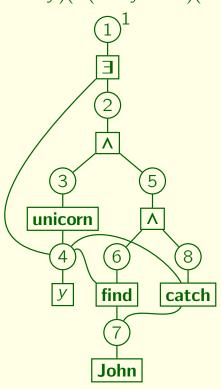
Datalog program

 \exists (1, 2, 4). \land (2, 5, 3). unicorn(3, 4). \land (5, 8, 6). find(6, 7, 4). \exists John(7). catch(8, 7, 4).

?— S(1).

 $\exists (\lambda y. \land (unicorn \ y)(\land (find \ y \ John)(catch \ y \ John)))$





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S(p_{1}) := NP(p_{1}, p_{2}, p_{3}), VP(p_{2}, p_{3}).
VP(p_{1}, p_{4}) := V(p_{2}, p_{4}, p_{3}), NP(p_{1}, p_{2}, p_{3}).
V(p_{1}, p_{4}, p_{3}) := V(p_{2}, p_{4}, p_{3}), Conj(p_{1}, p_{5}, p_{2}), V(p_{5}, p_{4}, p_{3}).
NP(p_{1}, p_{4}, p_{5}) := Det(p_{1}, p_{4}, p_{5}, p_{2}, p_{3}), N(p_{2}, p_{3}).
NP(p_{1}, p_{1}, p_{2}) := John(p_{2}).
V(p_{1}, p_{3}, p_{2}) := find(p_{1}, p_{3}, p_{2}).
V(p_{1}, p_{3}, p_{2}) := catch(p_{1}, p_{3}, p_{2}).
Conj(p_{1}, p_{3}, p_{2}) := \Lambda(p_{1}, p_{3}, p_{2}).
Det(p_{1}, p_{5}, p_{4}, p_{3}, p_{4}) := \exists (p_{1}, p_{2}, p_{4}), \Lambda(p_{2}, p_{5}, p_{3}).
N(p_{1}, p_{2}) := unicorn(p_{1}, p_{2}).
Datalog\ program
```

 $\exists (1, 2, 4).$ $\land (2, 5, 3).$ unicorn(3, 4). $\land (5, 8, 6).$ find(6, 7, 4). $\exists (1, 2, 4).$ $\Rightarrow (3, 4).$ $\Rightarrow (4, 4).$ $\Rightarrow (4, 4).$

?-S(1). Yes!

 \bullet Given an input $\lambda\text{-term},$ find the most compact term graph representing it.

From Datalog derivation to grammar derivation

From grammar derivation to Datalog derivation

• "ε-rule":

B(M)

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$$program(G) \cup database(M) \vdash query(M)$$

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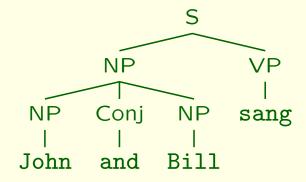
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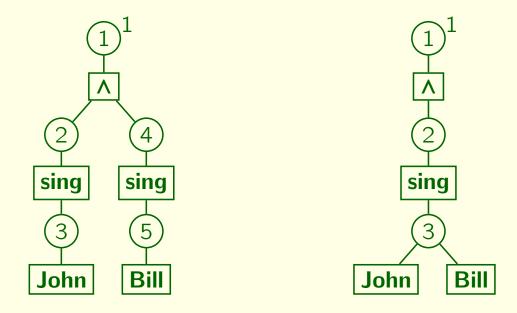
- (database(M), query(M)) can be computed in logspace.
- This implies that L(G) belongs to LOGCFL (cf. Ullman and Van Gelder 1988, Kanellakis 1988).

Limitation

 $NP(\lambda x^{e \to t}.X_2(X_1x)(X_3x)) := NP(X_1), Conj(X_2), NP(X_3).$



∧(sing John)(sing Bill)



not a term graph

Conclusion

- Parsing and surface realization are reduced to Datalog query evaluation, which can be computed in polynomial time in the size of the database.
- The reduction provides a more convincingly uniform architecture for parsing and generation than previous approaches.
- The reduction is to the LOGCFL fragment of Datalog, which implies the existence of fast parallel algorithms.
- Sophisticated evaluation techniques for Datalog can be applied to parsing and generation. In particular, generalized supplementary magic-sets rewriting (Beeri and Ramakrishnan 1991) automatically yields Earley-style algorithms for both parsing and generation.
- Higher-order λ -terms need not be avoided for the purpose of achieving computational efficiency.