CS294-248 Special Topics in Database Theory Unit 9: Datalog (Part 2)

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Announcements

• Next Tuesday, Nov. 28: office hours 2pm-4:30pm.

• Please submit a short report on your project by Wednesday, Nov. 29.

• Project presentations: Thursday, Nov. 30, 9:30am, Calvin 116. More details TBD.

Recursion and Negation

Computation-Based Extensions

Recap: Datalog

- Datalog = set of rules.
- Immediate consequence operator
- Least fixpoint semantics
- Naive algorithm $J^{(0)} \subseteq J^{(1)} \subseteq \cdots$

Example:

$$T(X, Y) \coloneqq E(X, Y)$$

$$T(X, Y) \coloneqq T(X, Z) \land E(Z, X)$$

Non-example:

$$C(X) := A(X) \land \neg B(X)$$

What happens if we allow negation?

Three Examples

Transitive closure of the complement graph:

$$\begin{split} & \mathsf{EC}(X,Y) \coloneqq V(X) \land V(Y) \land \neg \mathsf{E}(X,Y) \\ & \mathsf{T}(X,Y) \coloneqq \mathsf{EC}(X,Y) \\ & \mathsf{T}(X,Y) \coloneqq \mathsf{T}(X,Z) \land \mathsf{EC}(Z,X) \end{split}$$

Computation-Based Extensions

Three Examples

Transitive closure of the complement graph:

Complement of the transitive closure:

$$EC(X, Y) := V(X) \land V(Y) \land \neg E(X, Y)$$

$$T(X, Y) := EC(X, Y)$$

$$T(X, Y) := T(X, Z) \land EC(Z, X)$$

$$T(X, Y) \coloneqq E(X, Y)$$

$$T(X, Y) \coloneqq T(X, Z) \land E(Z, X)$$

$$Answ(X, Y) \coloneqq V(X) \land V(Y) \land \neg T(X, Y)$$

Computation-Based Extensions

Three Examples

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$$Answ(X, Y) := V(X) \land V(Y) \land \neg T(X, Y)$$

The Win-Move Game:

 $W(X) := E(X,Y) \land \neg W(Y)$

(will explain it later)

Computation-Based Extensions

But Recursion and Negation Don't Mix

EDB is $S = \{1\}$

$$A(X) := S(X) \land \neg B(X)$$

 $B(X) := S(X) \land \neg A(X)$

Computation-Based Extensions

But Recursion and Negation Don't Mix

EDB is $S = \{1\}$

Fixpoint 1:
$$A = \{1\}, B = \emptyset$$
.

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Computation-Based Extensions

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$$\begin{array}{c} A(X) := S(X) \land \neg B(X) \\ B(X) := S(X) \land \neg A(X) \end{array}$$
 Fix

Fixpoint 1: $A = \{1\}, B = \emptyset$.

Fixpoint 2:
$$A = \emptyset, B = \{1\}$$

Computation-Based Extensions

But Recursion and Negation Don't Mix

EDB is $S = \{1\}$

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Fixpoint 2:
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Pre-fixpoint 3:
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Computation-Based Extensions

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Pre-fixpoint 3:
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A simpler example:

 $A(X) := S(X) \land \neg B(X)$ $B(X) := S(X) \land \neg A(X)$

Computation-Based Extensions

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ICO not monotone! Need new semantics

Outline

Semi-positive, stratified datalog

• Semantics motivated by logic.

• Semantics motivated by computation.

Mostly based on [Abiteboul et al., 1995].

Semi-Positive and Stratified Datalog

Semi-positive Datalog

EDB atoms may be positive or negated.

IDB atoms can only be positive.

Example: transitive closure of the complement graph:

$$EC(X, Y) := V(X) \land V(Y) \land \neg E(X, Y)$$

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The Immediate Consequence Operator is monotone.

Semantics: least fixpoint of the ICO.

• Stratification: assign to each IDB predicate a stratum $s(R) \in \mathbb{N}$.

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- A program *P* is stratified if there exists a stratification such that:

For positive atoms
$$A(\mathbf{X}) := \cdots \land B(\mathbf{Y}) \land \cdots$$
: $s(A) \ge s(B)$.

► For any negative atoms $A(\mathbf{X}) := \cdots \land \neg B(\mathbf{Y}) \land \cdots : s(A) > s(B).$

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- Semantics: for each stratum s = 1, 2, ..., view it as a semi-positive datalog program, compute its fixpoint.
- The output is called perfect model; it is not a minimal model!

Stratified Datalog

ogic-Based Extensions

Computation-Based Extensions

Example

T(X,Y) := E(X,Y) $T(X, Y) := T(X, Z) \wedge E(Z, X)$ $\mathsf{Answ}(X,Y) := V(X) \land V(Y) \land \neg T(X,Y)$

Stratum 1: *T* Stratum 2: Answ

¹Assuming no isolated nodes

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Stratified Datalog

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Stratum 1: *T* Stratum 2: Answ

Semantics:

T = transitive closure, Answ = its complement

This is not the least fixpoint (minimal model) why??

¹Assuming no isolated nodes

Stratified Datalog

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Stratum 1: *T* Stratum 2: Answ

Semantics:

T = transitive closure, Answ = its complement

This is not the least fixpoint (minimal model) why?? The following is also a fixpoint:¹ $T = V \times V$, Answ = \emptyset

¹Assuming no isolated nodes

Discussion

 Stratified datalog is by far the most popular extension of datalog with negation.

• It is limited: it completely prevents the interleaving of recursion and negation. The following is not allowed:

$$A := \neg B$$
$$B := \neg A$$

Computation-Based Extensions

Logic-Based Extensions

Stable Models

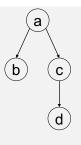
• Well Founded Model

Representative example: the Win-Move Game (next)

- Players I, II take turns moving a pebble in a graph.
- Player who cannot move loses.
- For each node X, does Player I have a winning strategy?

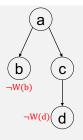
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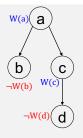
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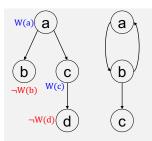
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Computation-Based Extensions

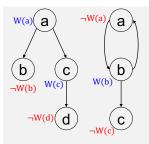
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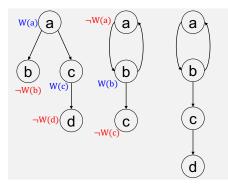
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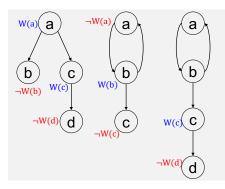
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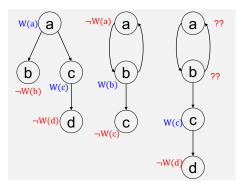


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Computation-Based Extensions

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- For each node X, does Player I have a winning strategy?



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• Least Fixpoint Logic (LFP) is FO extended with monotone fixpoint. E.g. the win-move game:

$$\mathsf{lfp}_{W(x)}(\exists y(E(x,y) \land \forall z(E(y,z) \Rightarrow W(z))))$$

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Before that we discuss two simple technical constructs:

grounded program and reduct

Computation-Based Extensions

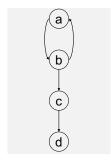
The Grounded Datalog Program

A grounded atom, or a fact, is an atom without variables

A grounded rule is a rule whose atoms are grounded.

The grounding of a program P consists of all possible groundings of its rules

$$W(X) := E(X, Y) \land \neg W(Y)$$



$$W(a) := E(a, b) \land \neg W(b)$$

$$W(b) := E(b, a) \land \neg W(a)$$

$$W(b) := E(b, c) \land \neg W(c)$$

$$W(c) := E(c, d) \land \neg W(d)$$

The Reduct

 $P \stackrel{\text{def}}{=}$ the grounded program, J = any set of grounded atoms;

The reduct, P_J is obtained as follows:

- Remove all rules with a negated atom in *J*.
- Remove all remaining negated atoms.
- P_J is monotone; $Ifp(P_J)$ exists; $J_1 \subseteq J_2$ implies $Ifp(P_{J_1}) \supseteq Ifp(P_{J_2})$

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 $W(a) := E(a, b) \land \neg W(b)$ $W(b) := E(b, a) \land \neg W(a)$ $W(b) := E(b, c) \land \neg W(c)$ $W(c) := E(c, d) \land \neg W(d)$

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 P_J is monotone; $Ifp(P_J)$ exists; $J_1 \subseteq J_2$ implies $Ifp(P_{J_1}) \supseteq Ifp(P_{J_2})$ $J = \{W(a), W(d)\};$

$$\begin{split} & \mathcal{W}(a) \coloneqq E(a,b) \land \neg \mathcal{W}(b) \\ & \mathcal{W}(b) \coloneqq E(b,a) \land \neg \mathcal{W}(a) \\ & \mathcal{W}(b) \coloneqq E(b,c) \land \neg \mathcal{W}(c) \\ & \mathcal{W}(c) \coloneqq E(c,d) \land \neg \mathcal{W}(d) \end{split}$$

$$\begin{array}{c} W(a) := E(a, b) \\ W(b) := E(b, a) \land \neg W(b) \\ \hline W(b) := E(b, c) \\ W(c) := E(c, d) \land \neg W(c) \\ \end{array}$$

 $\mathsf{lfp}(P_J) = \{W(a), W(b)\}$

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The reduct, P_J is obtained as follows:

- Remove all rules with a negated atom in J.
- Remove all remaining negated atoms.

 $P_{J} \text{ is monotone;} \qquad \mathsf{lfp}(P_{J}) \text{ exists;} \qquad J_{1} \subseteq J_{2} \text{ implies } \mathsf{lfp}(P_{J_{1}}) \supseteq \mathsf{lfp}(P_{J_{2}})$ $J = \{W(a), W(d)\}; \qquad J = \{W(a), W(b), W(d)\};$

 $W(a) := E(a, b) \land \neg W(b)$ $W(b) := E(b, a) \land \neg W(a)$ $W(b) := E(b, c) \land \neg W(c)$ $W(c) := E(c, d) \land \neg W(d)$

$$\begin{array}{|c|c|c|c|} \hline W(a) & :- & E(a,b) \\ \hline W(b) & :- & E(b,a) \land \neg W(a) \\ \hline W(b) & :- & E(b,c) \\ \hline W(c) & :- & E(c,d) \land \neg W(d) \\ \end{array}$$

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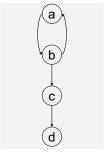
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Computation-Based Extensions

Stable Models

J is a stable model if
$$J = lfp(P_J)$$



$$W(X) := E(X, Y) \land \neg W(Y)$$

$$W(a) := E(a, b) \land \neg W(b)$$

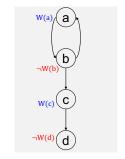
 $W(b) := E(b, a) \land \neg W(a)$
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Computation-Based Extensions

Stable Models

J is a stable model if $J = lfp(P_J)$

Example: $J = \{W(a), W(c)\}$



$$W(X) := E(X, Y) \land \neg W(Y)$$

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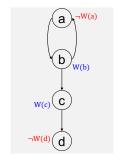
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Stable Models

J is a stable model if
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Example: $J = \{W(a), W(c)\}$

Example: $J = \{W(b), W(c)\}$



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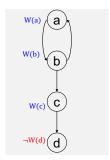
$$W(c) := E(c, d) \land \neg W(d)$$

Computation-Based Extensions

Stable Models

J is a stable model if
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Example: $J = \{W(a), W(c)\}$
Example: $J = \{W(b), W(c)\}$
Non-example: $J = \{W(a), W(b), W(c)\}$ why??



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Computation-Based Extensions

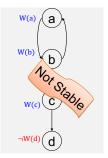
Stable Models

J is a stable model if
$$J = Ifp(P_J)$$

Example: $J = \{W(a), W(c)\}$

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Non-example: $J = \{W(a), W(b), W(c)\}$ why??



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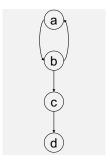
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Computation-Based Extensions

Stable Models

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Computation-Based Extensions

Stable Models

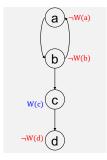
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Example:
$$J = \{W(a), W(c)\}$$

Example:
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Non-example:
$$J = \{W(a), W(b), W(c)\} \text{ why}??$$

Non-example:
$$J = \{W(c)\}$$



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- Stable models introduced by [Gelfond and Lifschitz, 1988]
- Elegant, principled definition.
- But: NP-hard to check if there exists any stable model.

A stratified program has a unique stable model, which is the perfect model.

A(1) :=Perfect model: $J = \{A(1), C(1)\}$ $B(1) := \neg A(1)$ C(1) := A(1)C(1) := A(1)Not stable: $J = \{A(1), B(1), C(1)\}$ why? $C(1) := C(1) \land \neg B(1)$

Computation-Based Extensions

Well-Founded Model

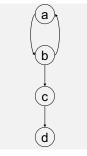
Alternating Fixpoint:

$$J^{(0)} \stackrel{\mathsf{def}}{=} \emptyset, \; J^{(t+1)} \stackrel{\mathsf{def}}{=} \mathsf{lfp}(P_{J^{(t)}})$$

$$J^{(0)} \subseteq J^{(2)} \subseteq J^{(4)} \subseteq \cdots \subseteq J^{(5)} \subseteq J^{(3)} \subseteq J^{(1)}.$$

$$W(a) := E(a, b) \land \neg W(b)$$

 $W(b) := E(b, a) \land \neg W(a)$
 $W(b) := E(b, c) \land \neg W(c)$
 $W(c) := E(c, d) \land \neg W(d)$



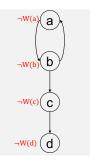
Computation-Based Extensions

Well-Founded Model

Alternating Fixpoint:

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 $\bigcup_{t} J^{(2t)} \stackrel{\text{def}}{=} \text{certain-} \ \bigcap_{t} J^{(2t+1)} \stackrel{\text{def}}{=} \text{possible-facts}$

 $J^{(0)} = \emptyset$

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Computation-Based Extensions

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| ¬W(a) a | |
|---------|--|
| ¬w(b) b | |
| ¬W(c) C | |
| ¬W(d) d | |

 $\bigcup_{t} J^{(2t)} \stackrel{\text{def}}{=} \text{certain-} \ \bigcap_{t} J^{(2t+1)} \stackrel{\text{def}}{=} \text{possible-facts}$

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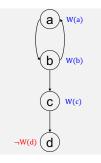
Topics in DB Theory: Unit 9b

Well-Founded Model

Alternating Fixpoint:

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Topics in DB Theory: Unit 9b

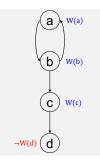
Computation-Based Extensions

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$$J^{(0)} = \emptyset \qquad J^{(1)} = \{W(a), W(b), W(c)\} \qquad W(a) := E(a, b) \land \neg W(b) \\ W(b) := E(b, a) \land \neg W(a) \\ W(b) := E(b, c) \land \neg W(c) \\ W(c) := E(c, d) \land \neg W(d)$$

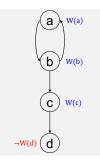
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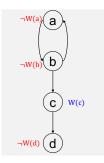
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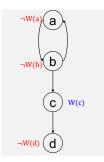
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$$\begin{array}{|c|c|c|c|c|} \hline W(a) & :- & E(a, b) \\ \hline W(b) & :- & E(b, a) \\ \hline W(b) & :- & E(b, c) \\ \hline W(c) & :- & E(c, d) \\ \hline & & \wedge \neg W(d) \\ \hline \end{array}$$

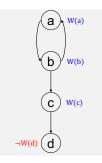
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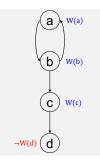
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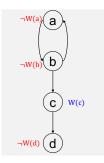
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$$\begin{array}{l} W(a) := E(a,b) \land \neg W(b) \\ W(b) := E(b,a) \land \neg W(a) \\ W(b) := E(b,c) \land \neg W(c) \\ \hline W(c) := E(c,d) \land \neg W(d) \end{array}$$

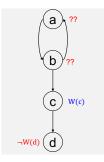
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• Well-founded models can be computed in PTIME.

• Yet, I don't know of any system that supports it. Maybe because of the 3-valued logic?

Next: two other semantics motivated by computation.

Computation-Based Extensions

 $\underset{0 \bullet 00000}{\text{Computation-Based Extensions}}$

Computation-Based Extensions

• Datalog with inflationary fixpoint semantics.

• Datalog with partial fixpoint semantics.

Inflationary Fixpoint

Let P be a datalog[¬] program, T_P its ICO.

The inflationary fixpoint is if
$$p(P) \stackrel{\text{def}}{=} \bigcup_{t \ge 0} J_t$$
, where:

$$J_0 \stackrel{\text{def}}{=} \emptyset, \quad J_{t+1} \stackrel{\text{def}}{=} J_t \cup T_P(J_t)$$

Fact

ifp(P) can be computed in PTIME in the size of the EDB I.

why?

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Fact

ifp(P) can be computed in PTIME in the size of the EDB I.

why? Because $J_0 \subseteq J_1 \subseteq \cdots \subseteq (ADom(I))^k$

 $\underset{0000000}{\text{Computation-Based Extensions}}$

Partial Fixpoint

The partial fixpoint is:

$$\mathsf{pfp}(\mathsf{P}) \stackrel{\mathsf{def}}{=} egin{cases} J_{t_0} & ext{if } J_{t_0} = J_{t_0+1} \ \emptyset & ext{if } J_t
eq J_{t+1}, orall t \end{cases}$$

where

$$J_0 \stackrel{\text{def}}{=} \emptyset$$
, $J_{t+1} \stackrel{\text{def}}{=} T_P(J_t)$

Fact

pfp(P) can be computed in PSPACE in the size of the EDB I.

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 $\underset{0000000}{\text{Computation-Based Extensions}}$

Partial Fixpoint

The partial fixpoint is:

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, $J_{t+1} \stackrel{\text{def}}{=} T_P(J_t)$

Fact

pfp(P) can be computed in PSPACE in the size of the EDB I.

why? each $|J_t|$ has size polynomial in ADom(1).

Detect non-termination using a counter.

Computation-Based Extensions

How To Express Negation

It's harder than one may think!

Complement of the TC:

T(X, Y) := E(X, Y) $T(X, Y) := T(X, Z) \land E(Z, X)$ $Answ(X, Y) := V(X) \land V(Y)$ $\land \neg T(X, Y)$

ifp(P) is incorrect!

Computation-Based Extensions

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ifp(P) is incorrect!

Detect the last step [Abiteboul et al., 1995, Ex.14.4.2]

```
T(X, Y) := E(X, Y)
T(X, Y) := T(X, Z) \land E(Z, Y)
T_{prev}(X, Y) := T(X, Y)
T_{prev-not-last}(X, Y) := T(X, Y) \land
\land T(X', Z') \land E(Z', Y') \land \neg T(X', Y')
Answ(X, Y) := V(X) \land V(Y) \land \neg T(X, Y)
\land T_{prev}(X', Y') \land \neg T_{prev-not-last}(X', Y')
```

Descriptive Complexity

• Datalog[¬] cannot express parity, no matter which semantics we adopt.

²Exercise: express succ(X, Y), min(X), max(Y) using <.

Descriptive Complexity

- Datalog[¬] cannot express parity, no matter which semantics we adopt.
- If we have access to an order relation < then we can express parity as:²

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Descriptive Complexity

- Datalog[¬] cannot express parity, no matter which semantics we adopt.
- If we have access to an order relation < then we can express parity as:²

$$\begin{split} & E(X,Y) := \operatorname{succ}(X,Z) \wedge \operatorname{succ}(Z,Y) \\ & E(X,Y) := E(X,Z) \wedge E(Z,Y) \quad // \text{ even-length distance} \\ & \operatorname{Even}() := R(X) \wedge \min(X) \wedge E(X,Y) \wedge \max(Y) \wedge R(Y) \end{split}$$

Theorem (Descriptive Complexity [Vardi, 1982, Immerman, 1986])

- Datalog[¬](<, ifp) expresses precisely queries in PTIME.
- Datalog[¬](<, pfp) expresses precisely queries in PSPACE.

²Exercise: express succ(X, Y), min(X), max(Y) using <.

| Dan | |
|-----|--|
| | |

- Datalog: simple, elegant, appealing. New resurgence after a 40 years history.
- Stratified datalog[¬] is a simple and practical extension.
- Beyond that, it becomes questionable.
- But the theory is beautiful. A famous result:

Theorem ([Abiteboul et al., 1992]) $datalog^{(ifp)} = datalog^{(pfp)}$ iff PTIME=PSPACE.

Computation-Based Extensions



Abiteboul, S., Hull, R., and Vianu, V. (1995).

Foundations of Databases. Addison-Wesley.



Abiteboul, S., Vardi, M. Y., and Vianu, V. (1992).

Fixpoint logics, relational machines, and computational complexity.

In Proceedings of the Seventh Annual Structure in Complexity Theory Conference, Boston, Massachusetts, USA, June 22-25, 1992, pages 156–168. IEEE Computer Society.



Chandra, A. K. and Harel, D. (1985).

Horn clauses queries and generalizations.

J. Log. Program., 2(1):1-15.



Gelfond, M. and Lifschitz, V. (1988).

The stable model semantics for logic programming. In Kowalski, R. A. and Bowen, K. A., editors, Logic Programming, Proceedings of the Fifth International Conference and Symposium, Seattle, Washington, USA, August 15-19, 1988 (2 Volumes), pages 1070–1080. MIT Press.



Immerman, N. (1986).

Relational queries computable in polynomial time. *Inf. Control.*, 68(1-3):86–104.



Kolaitis, P. G. (1991).

The expressive power of stratified programs. *Inf. Comput.*, 90(1):50–66.



Vardi, M. Y. (1982).

The complexity of relational query languages (extended abstract).

In Lewis, H. R., Simons, B. B., Burkhard, W. A., and Landweber, L. H., editors, *Proceedings of the 14th Annual ACM Symposium on Theory of Computing, May 5-7, 1982, San Francisco, California, USA*, pages 137–146. ACM.