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

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• 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 146. More details TBD.

Recursion and Negation

Recap: Datalog

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

Example:

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

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

Non-example:

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

What happens if we allow negation?

EDB is
$$S = \{1\}$$

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

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

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Recursion and Negation Don't Mix

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

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$$S = \{1\}$$

Fixpoint 1:
$$A = \{1\}, B = \emptyset$$
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Pre-fixpoint 3:
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Pre-fixpoint 3:
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A simpler example:

Recursion and Negation

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$$A : \neg B$$

$$B : \neg A$$

Recursion and Negation Don't Mix

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A simpler example:

Recursion and Negation

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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].

Stratified Datalog

Three Examples

Transitive closure of the complement graph:

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

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

Three Examples

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 $T(X, Y) := EC(X, Y)$
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Complement of the transitive closure:

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

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

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

Three Examples

Transitive closure of the complement graph:

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

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

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The Win-Move Game:

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

(will explain it later)

Semi-positive Datalog

EDB atoms may be positive or negated.

IDB atoms can only be positive.

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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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 - ▶ For positive atoms $A(X) :- \cdots \land B(Y) \land \cdots$: $s(A) \ge s(B)$.
 - For any negative atoms $A(X) : \cdots \land \neg B(Y) \land \cdots : s(A) > s(B)$.

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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!

Example

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

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

Stratum 1: T

Stratum 2: Answ

¹Assuming no isolated nodes

Example

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Semantics:

T = transitive closure, Answ = its complement

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

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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:

$$A := \neg B$$

Logic-Based Extensions

Logic-Based Extensions

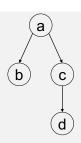
Stable Models

Well Founded Model

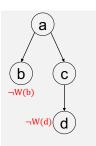
Representative example: the Win-Move Game (next)

- 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?

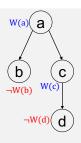
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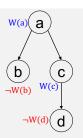
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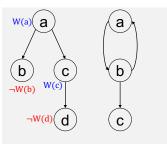


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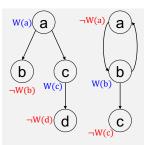
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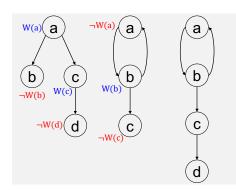
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Logic-Based Extensions 00000000

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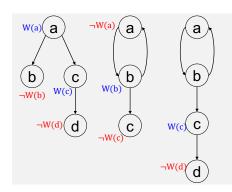
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Logic-Based Extensions 000000000

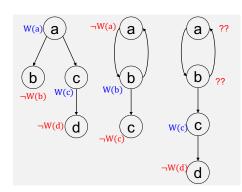
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• Least Fixpoint Logic (LFP) is FO extended with monotone fixpoint. E.g. the win-move game:

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- Hence: need datalog extensions beyond stratified datalog.

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Before that we discuss two simple technical constructs:

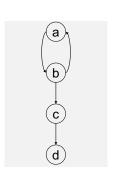
grounded program and reduct

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



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

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

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

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

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

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Topics in DB Theory: Unit 9b

Fall 2023

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

The reduct, P_I 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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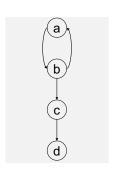
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$$lfp(P_I) = \{W(a), W(b)\}\$$

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

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



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

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

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

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

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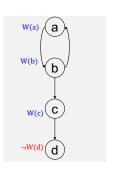
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Example: $J = \{W(a), W(c)\}$

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

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



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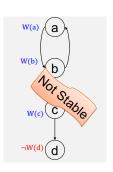
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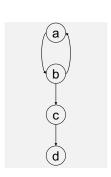
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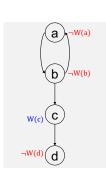
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\end{array}$$

- 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.

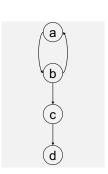
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A(1) := Perfect model: J = \{A(1), C(1)\}
B(1) := \neg A(1)
C(1) := A(1)
Not stable: J = \{A(1), B(1), C(1)\} why?
```

 $C(1) := C(1) \land \neg B(1)$

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

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

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



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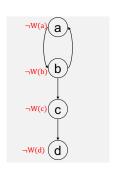
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$$J^{(0)} = \emptyset$$

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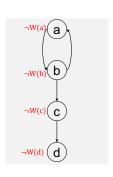
$$W(b) := E(b,c) \land \neg W(c)$$

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

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

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

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



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

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

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

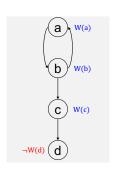
$$W(b) := E(b,c) \land \neg W(c)$$

$$|W(c)| - E(c,d) \wedge \neg W(d)$$
Topics in DB Theory: Unit 9b Fall 2023

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

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

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$$J^{(0)} = \emptyset$$
 $J^{(1)} = \{W(a), W(b), W(c)\}$

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

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

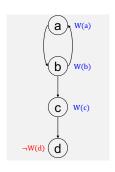
$$W(b) := E(b,c) \land \neg W(c)$$

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Topics in DB Theory: Unit 9b Fall 2023

$$\int_{0}^{1} \int_{0}^{1} \int_{0$$

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

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



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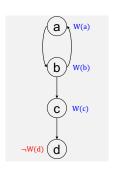
$$W(b) := E(b,c) \land \neg W(c)$$

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

$$\int_{0}^{\infty} \int_{0}^{\infty} \int_{0$$

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

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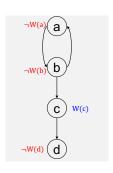
$$W(b) := E(b,c) \land \neg W(c)$$

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 $J^{(1)} = \{W(a), W(b), W(c)\}$
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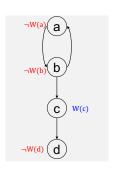
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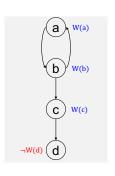
$$J^{(0)} = \emptyset$$
 $J^{(1)} = \{W(a), W(b), W(c)\}$
 $J^{(2)} = \{W(c)\}$

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

$$\int_{0}^{\infty} \int_{0}^{\infty} dt \, dt = \int_{0}^{\infty} \int_{0}^{\infty} dt \, dt = \int_{0$$

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

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

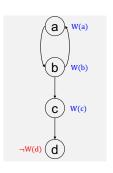


$$\begin{array}{ll} \emph{J}^{(0)} = \emptyset & \emph{J}^{(1)} = \{ \emph{W}(\emph{a}), \emph{W}(\emph{b}), \emph{W}(\emph{c}) \} \\ \emph{J}^{(2)} = \{ \emph{W}(\emph{c}) \} & \emph{J}^{(3)} = \{ \emph{W}(\emph{a}), \emph{W}(\emph{b}), \emph{W}(\emph{c}) \} \\ \end{array}$$

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

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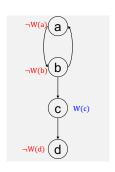
$$W(b) := E(b,c) \land \neg W(c)$$

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

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$$J^{(0)} = \emptyset \qquad J^{(1)} = \{W(a), W(b), W(c)\}$$

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$$J^{(4)} = \{W(c)\} \qquad \dots$$

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

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

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

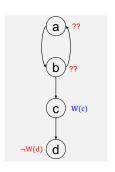
$$W(c) := E(c,d) \land \neg W(d)$$

Alternating Fixpoint:

$$\int_{0}^{1} \int_{0}^{1} \int_{0$$

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

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



$$\begin{array}{ll} J^{(0)} = \emptyset & J^{(1)} = \{W(a), W(b), W(c)\} \\ J^{(2)} = \{W(c)\} & J^{(3)} = \{W(a), W(b), W(c)\} \\ J^{(4)} = \{W(c)\} & \dots \\ \text{Certain facts: } W(c); \end{array}$$

possible facts: W(a), W(b).

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

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

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

$$A(C_1) = E(D,C) \land \neg VV(C_1)$$

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

Dan Suciu

• 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

• Datalog with inflationary fixpoint semantics.

Datalog with partial fixpoint semantics.

Let P be a datalog program, T_P its ICO.

The inflationary fixpoint is $|fp(P)| \stackrel{\text{def}}{=} \bigcup_{t \geq 0} J_t$, where:

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

Fact

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

why?

Inflationary Fixpoint

Let P be a datalog program, T_P its ICO.

The inflationary fixpoint is $| ifp(P) \stackrel{\text{def}}{=} \bigcup_{t \geq 0} J_t |$, where:

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

Fact

ifp(P) can be computed in PTIME in the size of the EDB 1.

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

The partial fixpoint is:

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

where

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

Fact

pfp(P) can be computed in PSPACE in the size of the EDB 1.

why?

The partial fixpoint is:

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

where

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

Fact

pfp(P) can be computed in PSPACE in the size of the EDB 1.

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

Detect non-termination using a counter.

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!

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ifp(P) is incorrect!

Detect the last step:

$$T(X,Y) := E(X,Y)$$
 $T(X,Y) := T(X,Z) \land E(Z,X)$
 $T_{\mathsf{prev}}(X,Y) := T(X,Y)$
 $C() := T(U,V) \land \neg T_{\mathsf{prev}}(U,V)$
 $D() := T(U,V) \land \neg C()$
 $\mathsf{Answ}(X,Y) := V(X) \land V(Y)$
 $\land \neg T(X,Y) \land D()$

Descriptive Complexity

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

Dan Suciu

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

$$E(X, Y) := \operatorname{succ}(X, Z) \wedge \operatorname{succ}(Z, Y)$$

 $E(X, Y) := E(X, Z) \wedge E(Z, Y) // \text{ even-length distance}$
 $Even() := R(X) \wedge \min(X) \wedge E(X, Y) \wedge \max(Y) \wedge R(Y)$

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 <.

- 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^{\neg}(ifp) = datalog^{\neg}(pfp) iff PTIME=PSPACE.
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