# Large-Scale Debugging for Datalog

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Introduction

## Introduction

- ▶ Logic programming (e.g. Datalog) is popular [Aref et al., 2015]
  - Static program analysis
  - Declarative networking
  - Security analysis
- Evaluate at large scale, e.g. hundreds of millions of tuples
- Current debugging approaches do not scale well

We present a new approach to debugging that scales to super large sizes

## Datalog

Declarative programming language - logical rules define computation

#### Example

```
path(x, y) :- edge(x, y).
path(x, z) :- edge(x, y), path(y, z).
```

#### Example Input

```
edge(1, 2), edge(2, 2), edge(2, 3)
```

#### **Example Output**

```
path(1, 2), path(2, 2), path(2, 3), path(1, 3)
```

## **Debugging in Datalog**

#### Debugging Example

Program produces unexpected output path(1, 4) Where does output come from?

- Debugging in Datalog is difficult
- Imperative language debugging:
  - Inspect values of variables at certain points in program
- ▶ In Datalog, we only get the output
  - No notion of variables
  - No notion of time

## Provenance as a Debugging Tool

The answer is provenance!

Data Provenance

A way to explain the origins and derivations of data

 Previous approaches for provenance are expensive [Deutch et al., 2015, Köhler et al., 2012]

How do we compute provenance efficiently?

Provenance Computation

## **Proof Trees**

A form of provenance - a complete explanation for a tuple

#### Definition (Proof Trees)

A *proof tree* for a tuple describes how that tuple is derived The root is the tuple itself, tree explains which rules are applied and which tuples are used

#### Proof trees for path(1, 3)

$$\frac{edge(1,2)}{path(2,3)} \frac{edge(2,3)}{(r_2)} (r_1) \\ \frac{edge(2,2)}{path(2,3)} \frac{edge(2,3)}{(r_2)} (r_2) \\ \frac{edge(2,2)}{path(2,3)} \frac{edge(2,3)}{(r_2)} (r_2) \\ \frac{edge(2,3)}{path(2,3)} (r_2) \\ \frac{edge(2,3)}{(r_2)} (r_2) \\ \frac{edge(2,3)}{path(2,3)} (r_2) \\ \frac{edge(2,3)}{path(2,3)} (r_2) \\ \frac{edge(2,3)}{(r_2)} (r_2) \\ \frac{edge(2,3)}{path(2,3)} (r_2) \\ \frac{edge(3,3)}{path(2,3)} (r_2) \\ \frac{edge(3,3)}{path(2,3)} (r_2) \\ \frac{edge(3,3)}{path(2,3)} (r_2) \\ \frac{edge(3,3)}{path(2,3)} (r_2) \\ \frac{edge(3,3)}{path(3,3)} (r_2) \\ \frac{edge(3$$

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## **Fundamental Question**

#### How do we compute a proof tree?

Apply one step of computation repeatedly

#### One step of computation

- Given a concrete tuple R(a) and rule  $R(X) := R_1(X_1), \ldots R_k(X_k)$
- Want subproof for R(a) tuples for each atom  $R_i(X_i)$  which generate R(a)

If we can do one step of computation, we can apply it recursively to get the full proof tree  $% \left( {{{\left[ {{L_{\rm{s}}} \right]}}} \right)$ 

## **Naïve Encoding**

Directly store the subproof and rule for each tuple

Path program
path(x, y) :- edge(x, y).
path(x, z) :- edge(x, y), path(y, z).

Path	Subproof	Rule
(1,2)	edge(1,2)	$r_1$
(2, 3)	edge(2,3)	$r_1$
(1,3)	edge(1,2), path(2,3)	$r_2$

## **Naïve Encoding**

Directly store the subproof and rule for each tuple

- Can directly query for a subproof
- Storing full provenance is expensive



#### What information do we actually need for a subproof?

- Tuples matching the body of a rule
- ► Form the next level up in a proof tree



#### What information do we actually need for a subproof?

- Tuples matching the body of a rule
- ▶ Form the next level up in a proof tree
- So, we need
  - ► The rule generating the tuple
  - Its level in the proof tree

## **Guided SLD**

A better method - generate annotations for each tuple

- Rule which generated tuple
- Level in proof tree for tuple

#### Path program

path(x, y) :- edge(x, y).
path(x, z) :- edge(x, y), path(y, z).

Path	Rule	Level
(1, 2)	$r_1$	1
(2,3)	$r_1$	1
(1,3)	$r_2$	2

#### Finding a subproof

Search for tuples matching the rule with lower level number

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Advantages:

- Only store 2 extra numbers per tuple
- Finds minimum height proof tree optimality

## **Guided SLD**



Figure: Diagram of guided SLD provenance system

Implementation in Soufflé



 Soufflé [Jordan et al., 2016] is a high-performance, compilation based Datalog engine - used in large-scale real-world applications

Implementation

- Datalog-to-Datalog transformation
- Guided SLD
  - ► Soufflé evaluation modification standard set enforcement fails with annotations
  - Modified existing Soufflé machinery for subproof search

## **Provenance Query System**

#### On-demand query interface



Figure: Provenance Query Interface

Experiments and Results

## **Overhead vs Normal Soufflé on Doop**

Industry standard Doop DaCapo benchmarks

- Points-to analysis framework for Java
- Hundreds of millions of output tuples

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Figure: Runtime overhead of guided SLD



Figure: Memory usage overhead of guided SLD

## Comparisons

Compared to state-of-the-art method (top-k [Deutch et al., 2015])

▶ Instrument Datalog for single query, and run on Soufflé

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Figure: Results of Datalog evaluation time



Figure: Results of Datalog evaluation memory usage

## **Proof Construction Time**



Figure: Distribution of proof tree heights for DaCapo

Figure: Proof tree construction time vs. size

Conclusion

## Conclusion

- Debugging in Datalog is difficult
- Developed a solution to efficiently generate provenance information
- Demonstrated viability with large-scale real world data

#### Future Work

- Optimise Soufflé for guided SLD
- Provenance for negated Datalog

## The End

#### References



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