

An Extension of Datalog for Graph Queries

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- and define a new type of predicates called Multi-Occuring Predicates.

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- $K : [\text{Bexpr}(X, Y)]$ where:
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- $K = ![\text{Bexpr}(X, Y)]$
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- Semantics by using FS-goal and Negation:

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- It is not monotone and requires stratified negation.

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$$total_ref(A) = \sum_{Pno \in paper(A)} reference(Pno)$$

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- Semantics by using Datalog.

```

ref("Bob2012", J) ← lessthan(J, 6).
tref(Author, N) ← N : [author(Author, Pno), ref(Pno, J)].

```

```

lessthan(1, K) ← K ≥ 1.
lessthan(J1, K) ← lessthan(J, K), K > J, J1 = J + 1.

```

Applications

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Some Examples

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Number of paths between two nodes in a Direct Acyclic Graph (DAG).

$$\text{path}(X, Y) : 1 \leftarrow \text{edge}(X, Y)$$
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$$n_path(X, Y) = \sum_{Z \neq X, Y} n_path(X, Z) \times n_path(Z, Y)$$

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Reachability in a directed hyper graph.

A hyperedge $(\{a, b\}, c)$ is represented by the following facts:

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hedgeS(1, a). hedgeS(1, b). hedgeT(1, c).
node(a). node(b). node(c).

```

```

reach(X, X) ← node(X).
reach(X, Y) ← K : [hedgeS(ID, Z), reach(X, Z)],
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- *Dynamic Programming (Knapsak, Viterbi, ...)*
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- a function g denoting how much the number of neighbors influence the change.
- the percentage of neighbors that changed behavior.

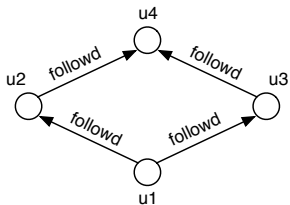
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coeff(X, C) ← K2 = |[followd(Y, X)], bc(X, V1),
                g(K2, V3), C = V1 * V3/K2.
b(X) ← source(X).
b(X) ← coeff(X, C), K ≥ 1/C, K : [followd(Y, X), b(Y)].

```



```

followd(u1, u2).  bc(u1, 1).  g(1, 1.2).
followd(u1, u3).  bc(u2, 0.9). g(2, 2.3).
followd(u2, u4).  bc(u3, 0.5).
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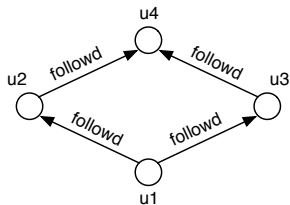
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the program derives the following atoms:

```

coeff(u2, 1.08), coeff(u3, 0.6), coeff(u4, 1.15),
b(u1), b(u2), b(u4).

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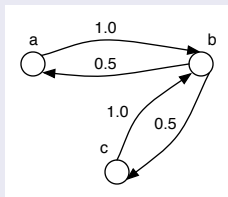
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- Used for Page Rank.

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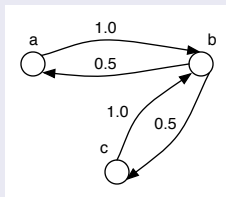
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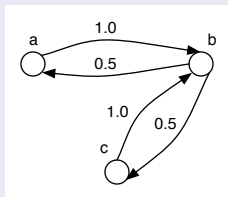
$$w_mat(c, b) : 0.5.$$

$$p_st(a). \quad p_st(b). \quad p_st(c).$$

where:

- $p_st(X) : K$ means the probability of staying in state X is K

Markov chains



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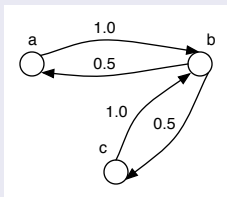
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- Multiplicity predicate: we only store the maximum value of multiplicity.

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- Recent works show how it is possible to use parallel paradigms (Map Reduce) to improve Datalog's performances.
 - Datalog^{FS} and in particular the multiplicity predicates can be also combined with such technologies.

Thank you!
Any question?

Compact way

Compact way of expressing counting goals:

- in Datalog^{FS}

$$\text{sixsubs}(X) \leftarrow \text{detective}(X), 6 : [\text{superior}(X, Y)].$$

- in Datalog

$$\begin{aligned} \text{sixsubs}(X) \leftarrow & \text{detective}(X), \text{superior}(X, Y1), \\ & \text{superior}(X, Y2), \text{superior}(X, Y3), \\ & \text{superior}(X, Y4), \text{superior}(X, Y5), \\ & \text{superior}(X, Y6), Y1 \neq Y2, Y1 \neq Y3, \\ & Y1 \neq Y4, Y1 \neq Y5, Y1 \neq Y6, Y2 \neq Y3, \\ & Y2 \neq Y4, Y2 \neq Y5, Y2 \neq Y6, Y3 \neq Y4, \\ & Y3 \neq Y5, Y3 \neq Y6, Y4 \neq Y5, Y4 \neq Y6, \\ & Y5 \neq Y6. \end{aligned}$$