

Tulane University

KNOWENG BIG DATA TO KNOWLEDGE CENTER OF EXCELLENCE

Relational Learning and Feature Extraction by Querying over Heterogeneous Information Networks

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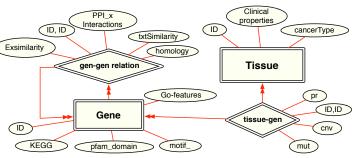
Sameer Singh, University of California, Irvine Daniel Khashabi, University of Illinois at Urbana-Champaign Christos Christodoulopoulos, Amazon Research Cambridge, UK Mark Summons, University of Illinois at Urbana-Champaign Saurabh Sinha, University of Illinois at Urbana-Champaign Dan Roth, University of Illinois at Urbana-Champaign

> Statistical Relational Al August 2017, Sydney, Australia

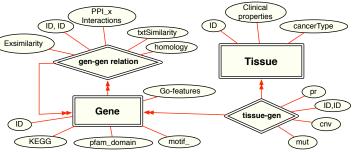
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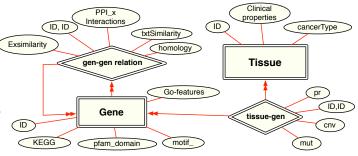
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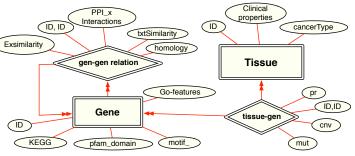


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- **Demand:** Relational data **representation**, **learning** and flexible intelligent data analysis, as well as the **evolution** of these networks based on the analysis outcomes, need to be placed in a well-defined framework.

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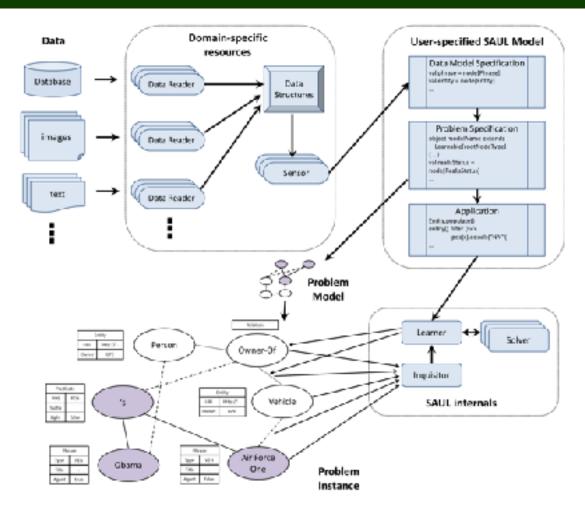
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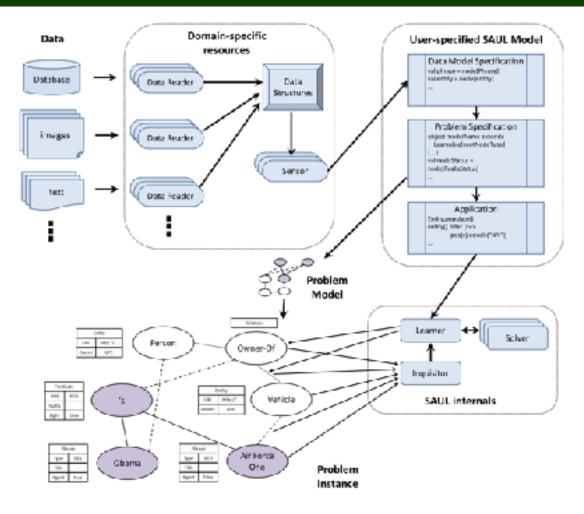
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- Considering expert knowledge at a very high level with a logical representation.

Overview of the components

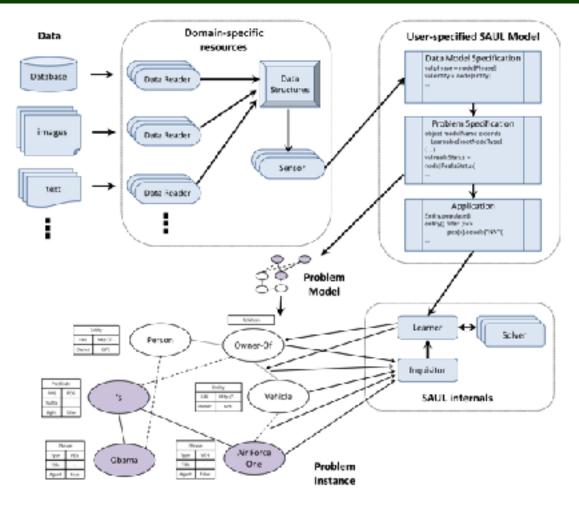


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