Interpretable Decision-Making in Smart Environments

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Introduction

Motivation

1. Smart environments are cyber-physical systems with automated sensing, learning, and reasoning capabilities.

2. High-stakes decision-making in smart environments requires interpretability.

3. Existing interpretable machine learning methods are not tailored for large-scale heterogeneous smart environment data, and result in rule explosion.

Research Objectives

1. How to do knowledge discovery over the sensor data and associated semantics in smart environments, without rule explosion?

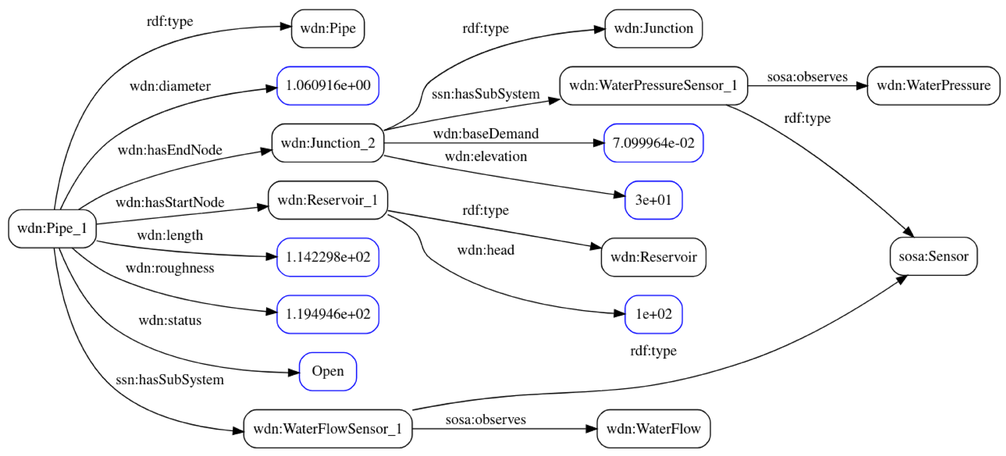
2. How to utilize learned patterns and background knowledge for automated decision-making?

Background

1. Semantics, ontologies and knowledge graphs, are used in system and data modeling.

2. Rule learning, a common interpretable machine learning method, can reveal associations in smart environment data, enable fast inference and easy domain knowledge integration.

Example: Smart Environment Data - Water Distribution Networks



Knowledge Graph

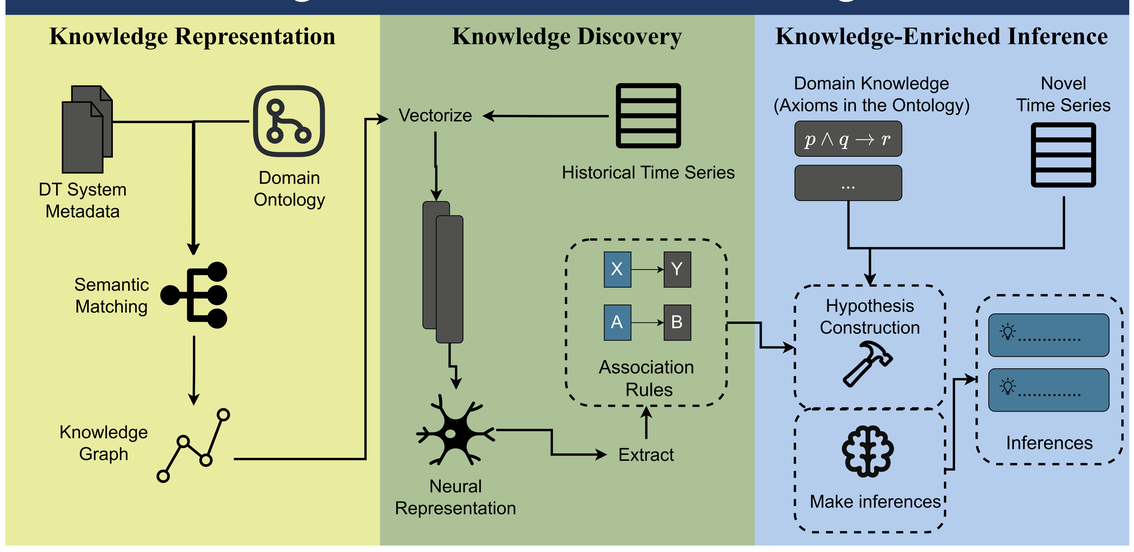
time	value	type	name
2017-12-31 23:30:00.000	187.2	demand	s_Junction_2
2017-12-31 23:30:00.000	3,981.6	flow	s_Pipe_1
2017-12-31 23:00:00.000	4,406.4	flow	s_Pipe_1
2017-12-31 23:00:00.000	205.2	demand	s_Junction_2
2017-12-31 22:30:00.000	4,791.6	flow	s_Pipe_1
2017-12-31 22:30:00.000	205.2	demand	s_Junction_2
2017-12-31 22:00:00.000	212.4	demand	s_Junction_2
2017-12-31 22:00:00.000	5,173.2	flow	s_Pipe_1
2017-12-31 21:30:00.000	5,508	flow	s_Pipe_1
2017-12-31 21:30:00.000	270	demand	s_Junction_2

Timeseries Sensor Data

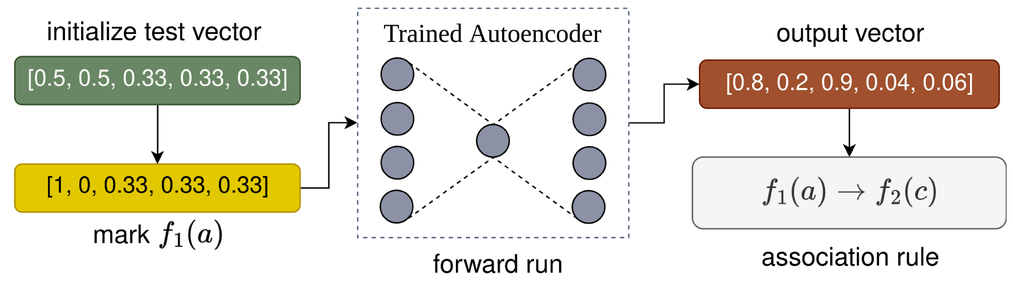
LeakDB - Vrachimis et al. 2018

Method

3K: Knowledge-Enriched Decision-Making



Neurosymbolic Rule Learning



Neurosymbolic Semantic Association Rule Learning

Learn and extract the most prominent associations from neural representations of holistic smart environment data.

Tackles rule explosion and results in substantially lower execution time.

Example: Semantic Association Rules

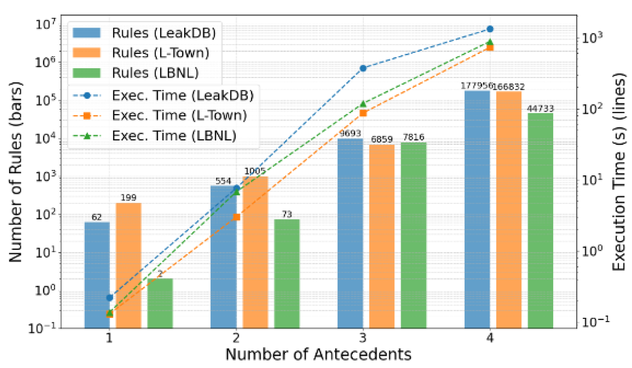
if sensor1 measures a value in range R, then sensor2 must measure a value in the range R2 ✗

if a sensor with type T inside Pipe P measures a value in range R, then a sensor with type T2 inside Junction J must measure a value in range R2 ✓

Results & Discussion

Semantics Enables Generalizability

	# Rules	Support	Cov.	Conf.
	w-s|wo-s	w-s|wo-s	w-s|wo-s	w-s|wo-s
		LeakDB		
FP-G	103K|9K	**0.41**|0.19	**0.43**|0.2	0.95|0.97
Aerial	554|2.5K	**0.54**|0.25	**0.59**|0.3	0.91|0.87
		L-Town		
FP-G	25K|5K	**0.86**|0.36	**0.9**|0.38	0.96|0.96
Aerial	1K|2.5K	**0.59**|0.39	**0.65**|0.45	0.91|0.88
		LBNL		
FP-G	7K|2K	**0.84**|0.73	**0.85**|0.75	0.98|0.99
Aerial	73|258	**0.74**|0.65	**0.74**|0.66	1.0|0.99



High-Quality Concise Rule Sets

Algorithm	# Rules	Sup.	Conf.	Cov.	Zhang
		LeakDB			
Exhaustive	103283	0.41	0.95	1.0	0.82
DE	11841	0.19	0.77	1.0	0.24
GA	663	0.08	0.46	1.0	0.15
PSO	12566	0.08	0.75	1.0	0.16
LSHADE	23605	0.4	0.98	1.0	0.41
jDE	10270	0.25	0.77	1.0	0.29
Aerial	554	0.54	0.91	1.0	0.9
		L-Town			
Exhaustive	25421	0.86	0.96	1.0	-0.18
DE	15163	0.11	0.76	1.0	0.13
GA	1384	0.03	0.37	1.0	0.05
PSO	15651	0.03	0.75	1.0	0.04
LSHADE	22825	0.39	0.96	1.0	0.39
jDE	11255	0.19	0.78	1.0	0.21
Aerial	1005	0.59	0.91	1.0	0.4

Discussion

1. Semantics can help learning generalizable semantic association rules.

2. Neurosymbolic can enable large-scale knowledge discovery.

3. Interpretable machine learning can automate decision-making by domain knowledge integration and knowledge-enriched inference.

4. Better ways of Neurosymbolic integration is needed.

Me

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