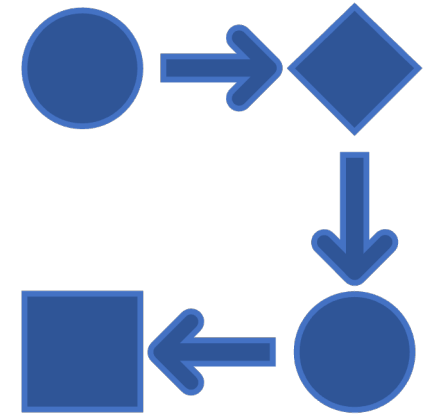


An Ontology Design Pattern for Representing Causality



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BOSCH

AI

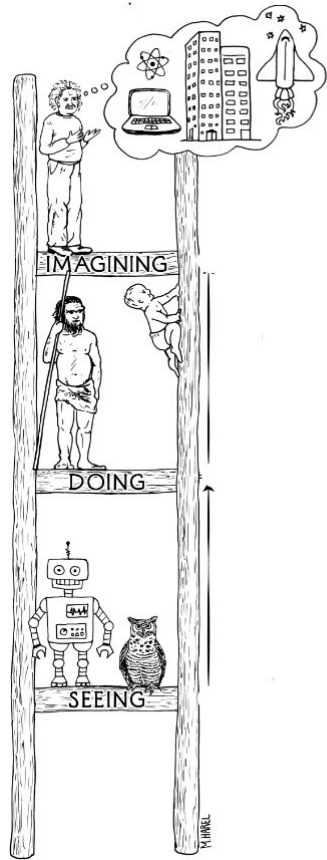
INSTITUTE



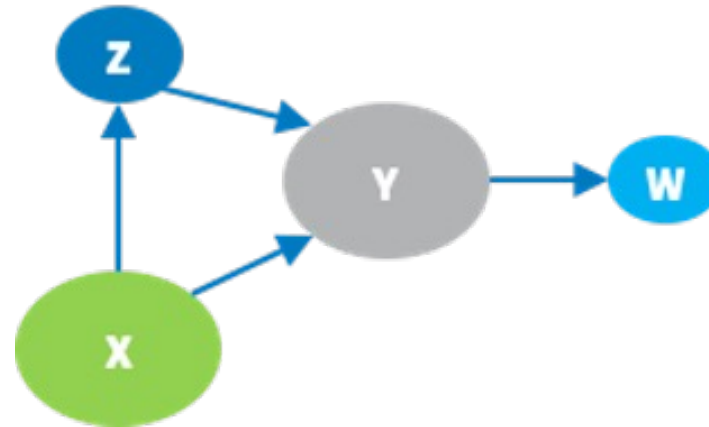
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Causality



Ladder of causation



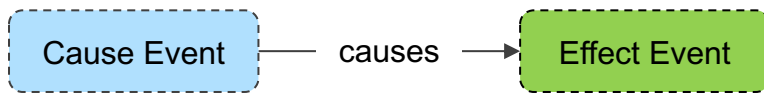
- Node represents events
- Edge represents causal association between events
- Event role: Treatment, Mediator and outcome
- Causal effect weights determine the importance of edges

Causal Bayesian Networks (CBN)

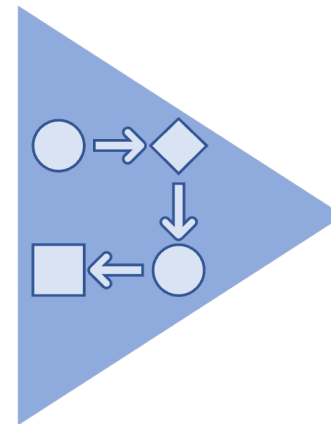
$$\begin{aligned} & f(V, U) \\ & X \leftarrow f_x(U_x) \\ & Z \leftarrow f_z(X, U_z) \\ & Y \leftarrow f_y(X, Z, U_y) \\ & W \leftarrow f_w(Y, U_w) \\ & P(U) \end{aligned}$$

Structural Causal Model

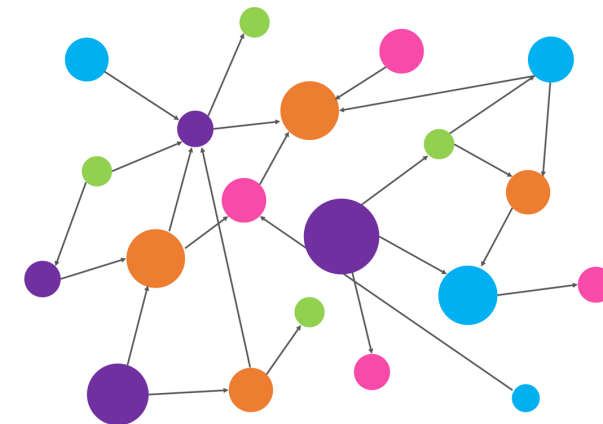
Causality in semantic web



Causal triple



Causal Pattern



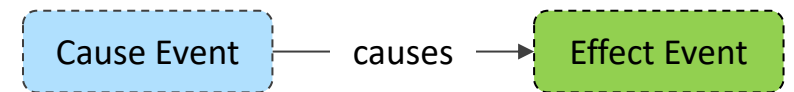
Causal Knowledge Graph

Knowledge Graph enriched with causal information from Causal Bayesian Network which can be used for Causal reasoning

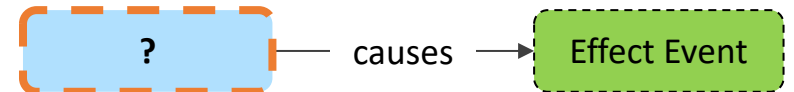
The causal pattern is the first attempt to model concepts from Causal Bayesian Networks within an ontology design pattern.

Use cases for Causal Pattern

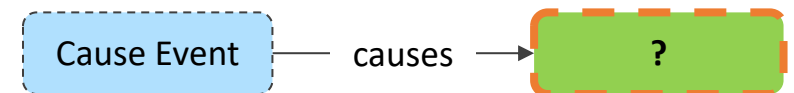
- Information from CBN allows query on a conformant Knowledge Graph.
- Grounding the causal pattern in CBN enables compatibility with causal reasoning.
- Causal knowledge graph can be used for causal reasoning, such as
 - Causal explanation
 - Causal prediction
- Application
 - Healthcare: Understanding the cause of an asthma symptom
 - Smart manufacturing: cause of anomaly in the assembly pipeline
 - Autonomous driving: root cause of a collision



Causal triple



Causal explanation



Causal prediction

Causal Pattern



Represents the structure of causal relations in a knowledge graph.



Grounded in the concepts defined and used by the Causal AI community

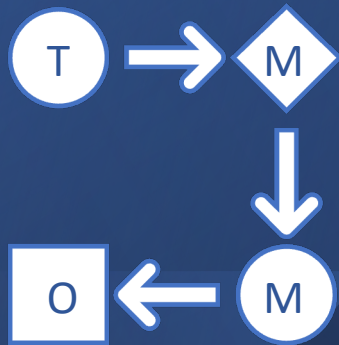
Causal Bayesian Networks and Do-calculus.



Models three primary concepts:

Causal relations,
Causal event roles, and
Causal effect weights

Causal Pattern



Causal relation

- Represents a relation between events such that the occurrence of one event leads to the occurrence of the other.

Causal event role

- Represents the role an event plays within the context of a causal relation.
- Events play three distinct causal roles: *treatment*, *mediator*, and *outcome*.

Causal effect weight

- Represents strength of a causal relation.

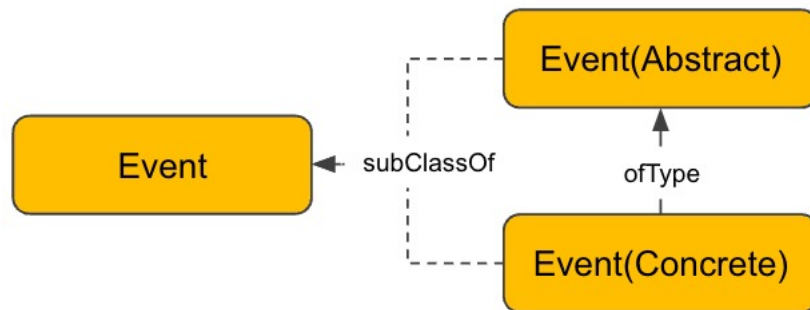
Event



An event can have more than one cause (i.e., *treatment*) and may cause more than one effect (i.e., *outcome*).



An event may either be **abstract** or **concrete**.



$\text{Event(Concrete)} \sqsubseteq \text{Event}$

$\text{Event(Concrete)} \sqsubseteq \text{Event}$

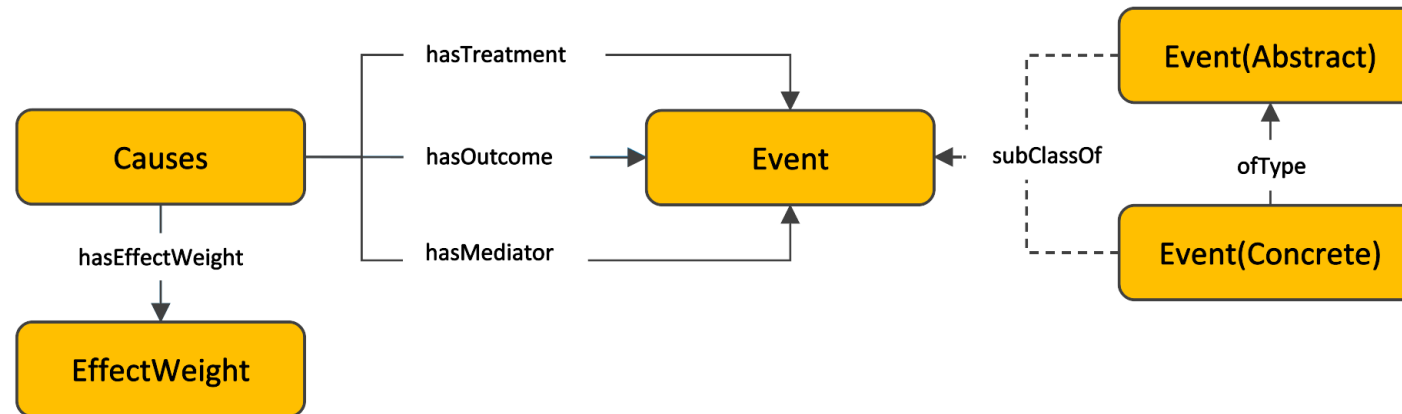
$\exists \text{ofType.Event(Concrete)} \sqsubseteq \text{Event(Concrete)}$

$\text{Event(Concrete)} \sqsubseteq \forall \text{ofType.Event(Concrete)}$

(Scoped Domain)

(Scoped Range)

Causal Relation: Causes



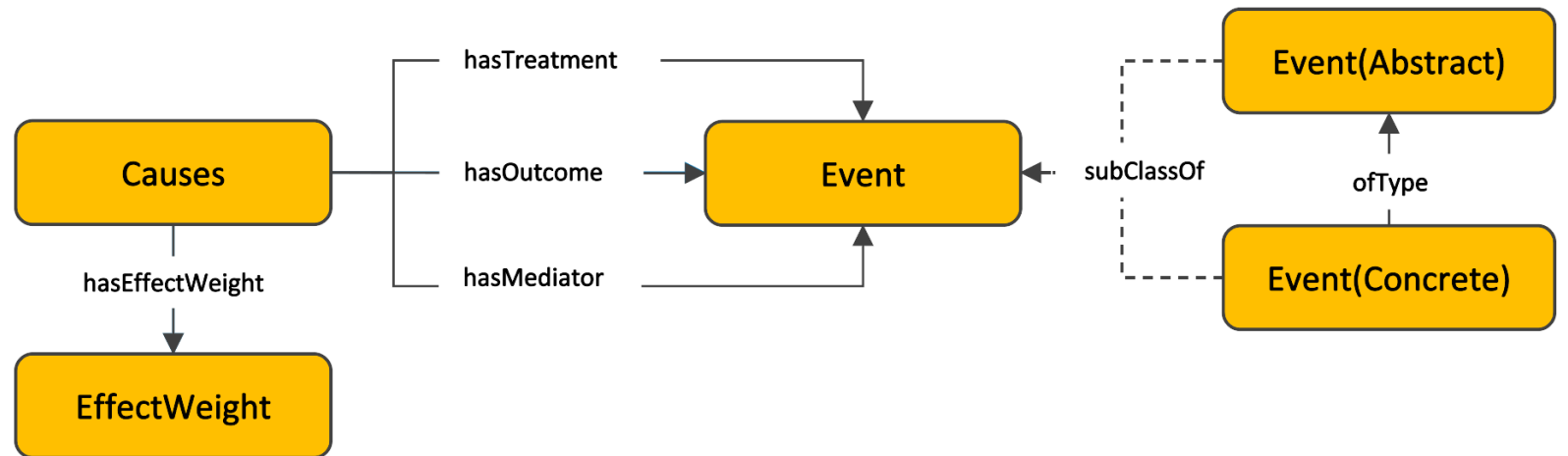
The schema diagram for the Causal pattern

- In the causal pattern, the causal relation is reified as a class, **Causes**.
- **Events** are linked through Causes using the causal role properties.
- **Causal relation** has **effect weight**.

Causal Event Role



- An Event can have a specific role in the causal relation
- The causal roles are represented as object properties with the Causes class as the domain and Event as the range.
 - hasTreatment ,
 - hasOutcome , and
 - hasMediator



Causal Event Role: hasTreatment

- The *treatment* role is defined as the initial event that is responsible for the occurrence of some subsequent event.
- It is represented as an object property, hasTreatment, with the domain Causes and range Event.

$\exists \text{hasTreatment.Event} \sqsubseteq \text{Causes}$ (Scoped Domain)
 $\text{Causes} \sqsubseteq \forall \text{hasTreatment.Event}$ (Scoped Range)
 $\text{Causes} \sqsubseteq \geq 1 \text{hasTreatment.Event} \sqcap \leq 1 \text{hasTreatment.Event}$

Causal Event Role: hasOutcome

- The outcome role is defined as the event which occurs as a result of the treatment event.
- It is represented as an object property, hasOutcome, with the domain Causes and range Event.

$\exists \text{hasOutcome.Event} \sqsubseteq \text{Causes}$ (Scoped Domain)

$\text{Causes} \sqsubseteq \forall \text{hasOutcome.Event}$ (Scoped Range)

$\text{Causes} \sqsubseteq \geq 1 \text{hasOutcome.Event} \sqcap \leq 1 \text{hasOutcome.Event}$

Causal Event Role: hasMediator

- Transitive causal relation
 - For given events {A, B, C}, if A causes B causes C, then this would imply that A causes C
 - The causal relation between A and C is mediated by B
- A causal relation may have zero-or-more mediator events
- The mediator role is represented as an object property, hasMediator, with the domain Causes and range Event.

$\exists \text{hasMediator.Event} \sqsubseteq \text{Causes}$

(Scoped Domain)

$\text{Causes} \sqsubseteq \forall \text{hasMediator.Event}$

(Scoped Range)

$\text{Causes} \sqsubseteq \geq 0 \text{Mediator.Event}$

Causal Effect Weight

- Causal effect weight represents the strength of a causal relation; i.e.,
 - Higher effect weight implies higher level of responsibility is assigned to the treatment event for the occurrence of the outcome event.
- Effect weights can be of three types:
 - Total causal effect (TCE),
 - Natural direct effect (NDE), and
 - Natural indirect effect (NIE)
- Represented as a property, `hasEffectWeight`, with domain `Causes` and range `EffectWeight`.

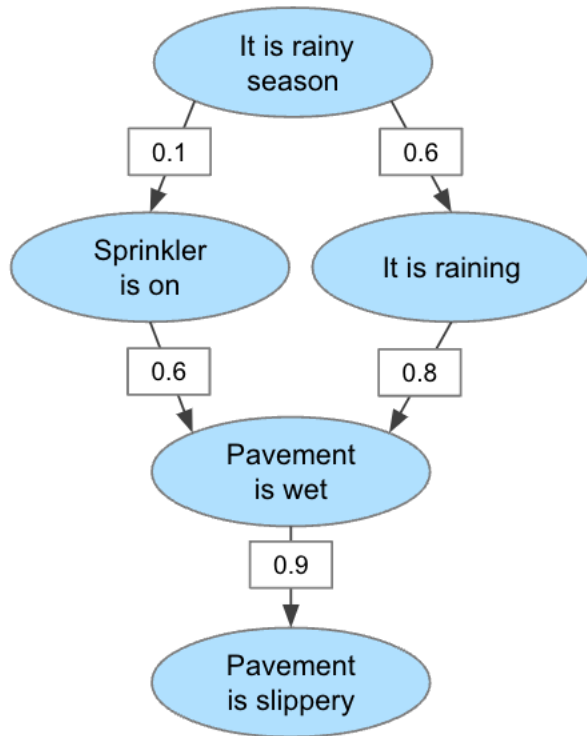
$\exists \text{hasEffectWeight.EffectWeight} \sqsubseteq \text{Causes}$

(Scoped Domain)

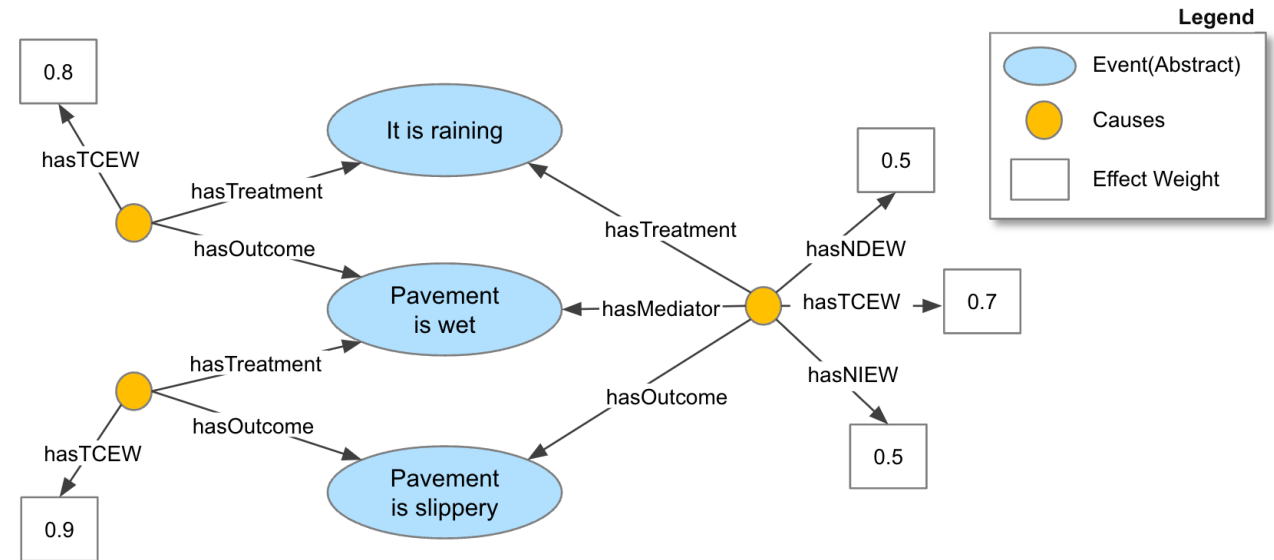
$\text{Causes} \sqsubseteq \forall \text{hasEffectWeight.EffectWeight}$

(Scoped Range)

Sprinkler CBN in Causal Pattern



Sprinkler causal Bayesian network

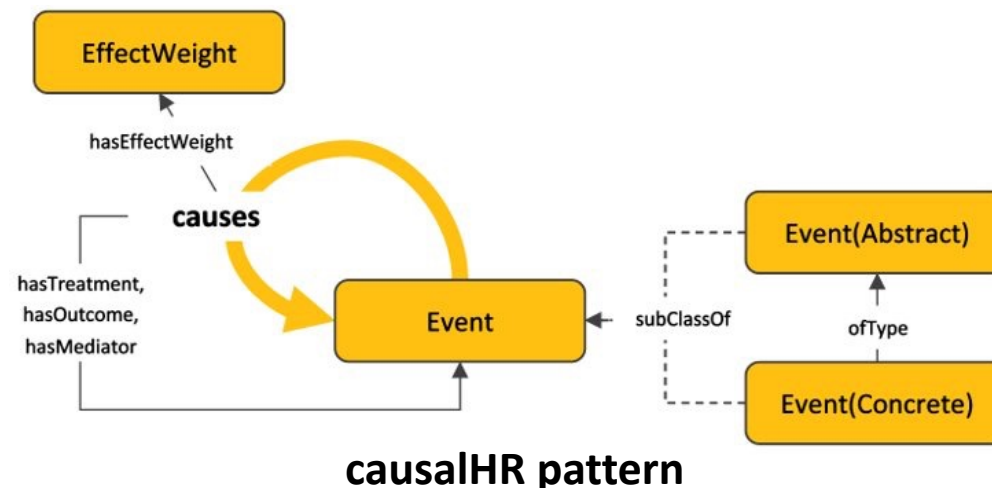


Sprinkler causal Bayesian network represented using Causal Pattern

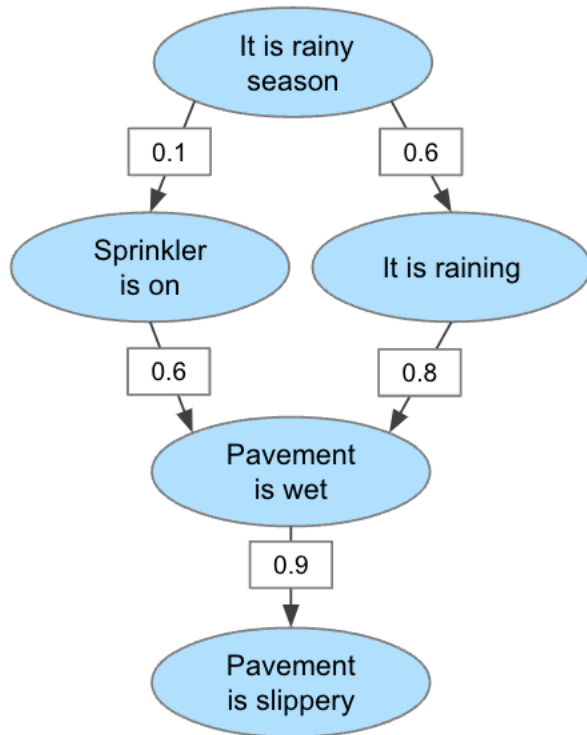
causalHR

Causal pattern for hyper-relational knowledge graphs

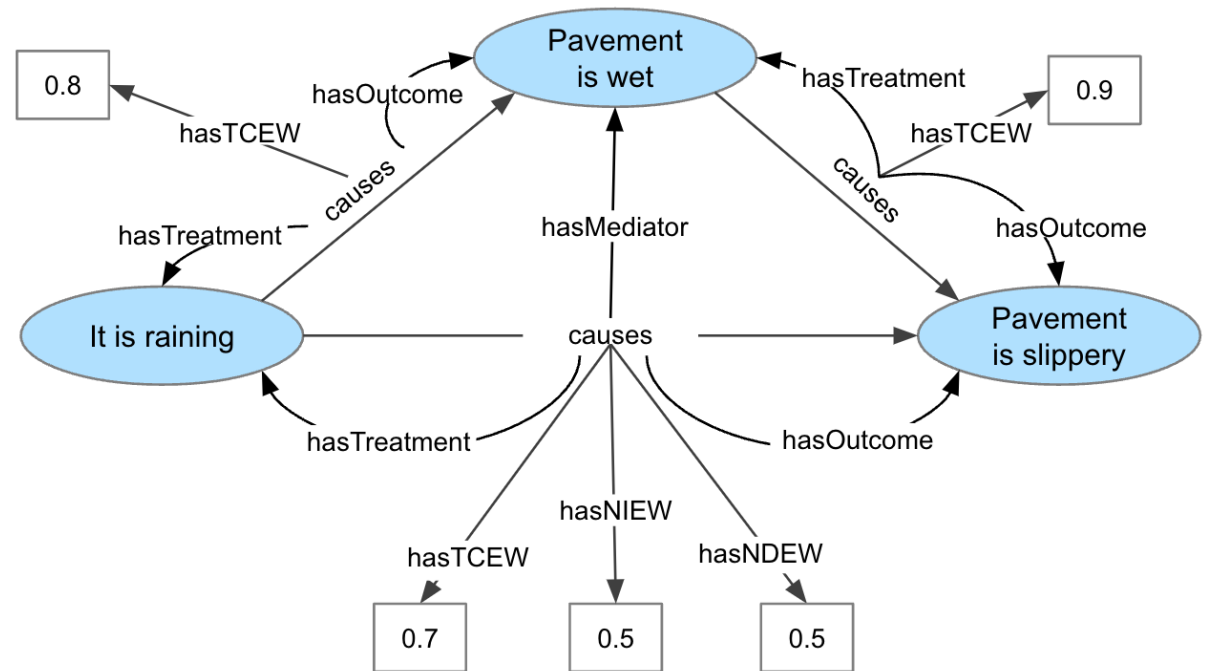
- Interest in the representation and use of hyper-relations has grown over the past few years, along with official standards and tooling with RDF-star and SPARQL-star.
- Additional statements can be made about a causal relation, with the causal triple acting as the subject of these statements.
 - In RDF-star syntax, «event1 causes event2» hasEffectWeight “0.7”.
- The causalHR pattern axioms can only be partially formalized in description logic.
- causes hyper-relation should be the domain of the causal event role relations and the causal effect weight relations.



Sprinkler CBN in causalHR



Sprinkler causal Bayesian network



Sprinkler causal Bayesian network represented using causalHR

Future work

- Extensions to integrate other types of knowledge such as
 - **Provenance:** The structure of a CBN may be either learned from data using existing structure learning algorithms or determined by domain experts.
 - Explicit representation of this type of provenance information may be of critical importance; e.g., for confidence and trust in the assignment of responsibility for a patient's asthma symptoms.
 - **Time:** Causality is also strongly associated with time.
 - A causal relation between events implies a temporal ordering of the events
 - Define a temporal constraint on the causal relation stating that the
 - Treatment event always precedes the outcome event

Conclusion

- Proposed an ontology design pattern to represent the causal relation using concepts grounded in CBN and do-calculus
- Pattern was exemplified through an intuitive and common sprinkler use case
- Discussed how the causal pattern can be represented as a hyper-relation, causalHR pattern
- In the future, the **causal pattern** template can be extended to integrate other types of relevant information, such as provenance and time.

Thanks for
listening



Causal Pattern



Questions are welcomed!!!!

