Mining for Meaning

Knowledge Representation Methods in Process Mining for Transparency, Verifiability, and Replicability.

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23.07.2025
CPMC Annual Meeting

UNIVERSITY OF TORONTO

Semantic Technologies Lab

What’s wrong here?

Timestamp	Event	Patient
12:02	Patient Intake	John Smith
12:05	Patient Intake	John Smith
12:06	Diagnostic	John Smith

What's wrong here?

- Issue: Patient Intake should only occur once for the same patient.

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What's wrong here?

- Issue: Patient Intake should only occur once for the same patient.
- Solution: The event label was wrong

Timestamp	Event	Patient
12:02	Patient Intake	John Smith
12:05	Additional Screening	John Smith
12:06	Diagnostic	John Smith

What's wrong here?

Timestamp	Event	Lifecycle Transition
14:20	Process Application	Start
15:30	Credit Check	Complete
15:38	Credit Check	Start

What's wrong here?

- Issue: Activities cannot end before they begin

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What's wrong here?

- Issue: Activities cannot end before they begin
- Solution: Fix the timestamp with the correct ordering

Timestamp	Event	Lifecycle Transition
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- Interpretations rely on process **knowledge**
- Process knowledge comes in many **different forms**

Idea: provide the means to capture these interpretations & knowledge

Agenda

- What does it mean to represent knowledge?
- What's so special about process knowledge?
- How do we apply this to process mining?

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Knowledge Representation (KR)

- As humans, we can easily understand, interpret, and reason with knowledge
- We leverage that knowledge every day to achieve goals in the real world
- How can machines do the same?

Knowledge versus Data

- Storage =/= Representation

Knowledge versus Data

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- KR enables inference and verification

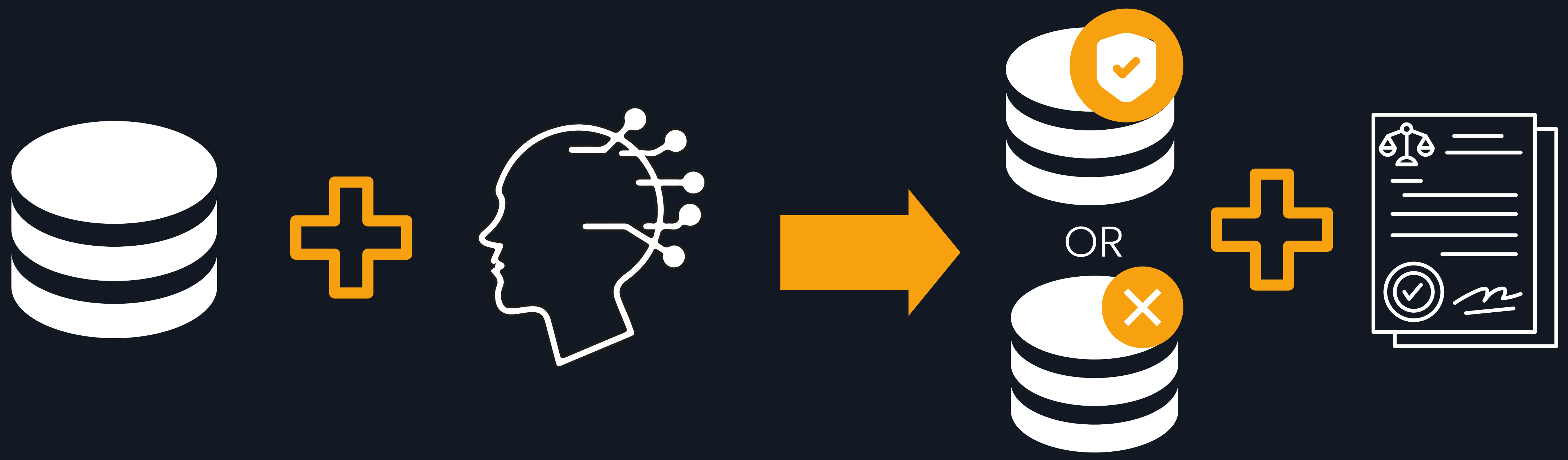
Knowledge versus Data

Inference

Facts and rules produce
new facts

Verification

Facts and rules produce
proofs of compliance or
non-compliance.



Knowledge versus Data

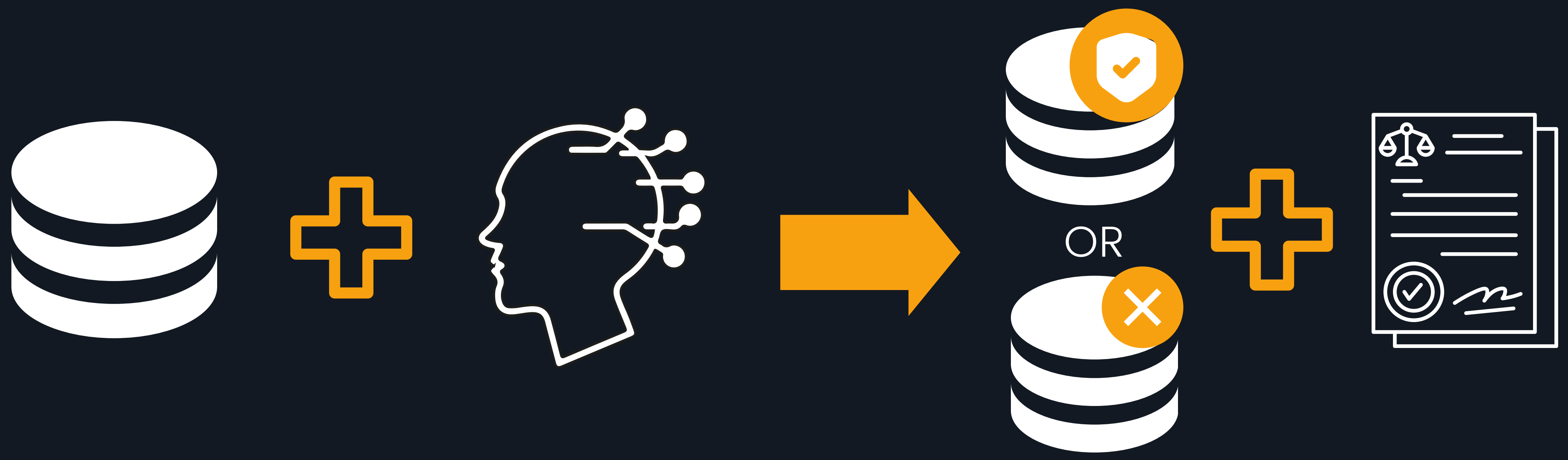
But what does this actually look like?

Inference

Facts and rules produce new facts

Verification

Facts and rules produce proofs of compliance or non-compliance.



KR in practice

- Data is translated into a set of logically represented facts

- Rules about a domain are given by an ontology

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- Data is translated into a set of logically represented facts
- Rules about a domain are given by an ontology
- What is an ontology?
  - A structured vocabulary for a domain
  - An unambigious model of knowledge
  - Rules for entities and their relationships

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- What's so special about process knowledge?
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Process Knowledge

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- Levels of knowledge - both domain-level and fundamental

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- Levels of knowledge - both domain-level and fundamental
- Overloaded concepts - the event

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- “An atomic granule of an activity that has been observed” - XES definition of an event
- “Awaiting Assignment”, “Loan Approval”, “Create Purchase Order Item“
- How do events relate to tasks, resources, processes, occurrences?

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Ontology-Aware Process Mining

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- Enable new kinds of reasoning over event log data
- Done by mapping data to a knowledge base, and augmenting it through knowledge patterns

Mapping and Formalization

Raw Event Data	Knowledge Base
Ad-Hoc Interpretations	Data Theory
Business Questions	Logical Queries
Business Validations	Logical Proofs

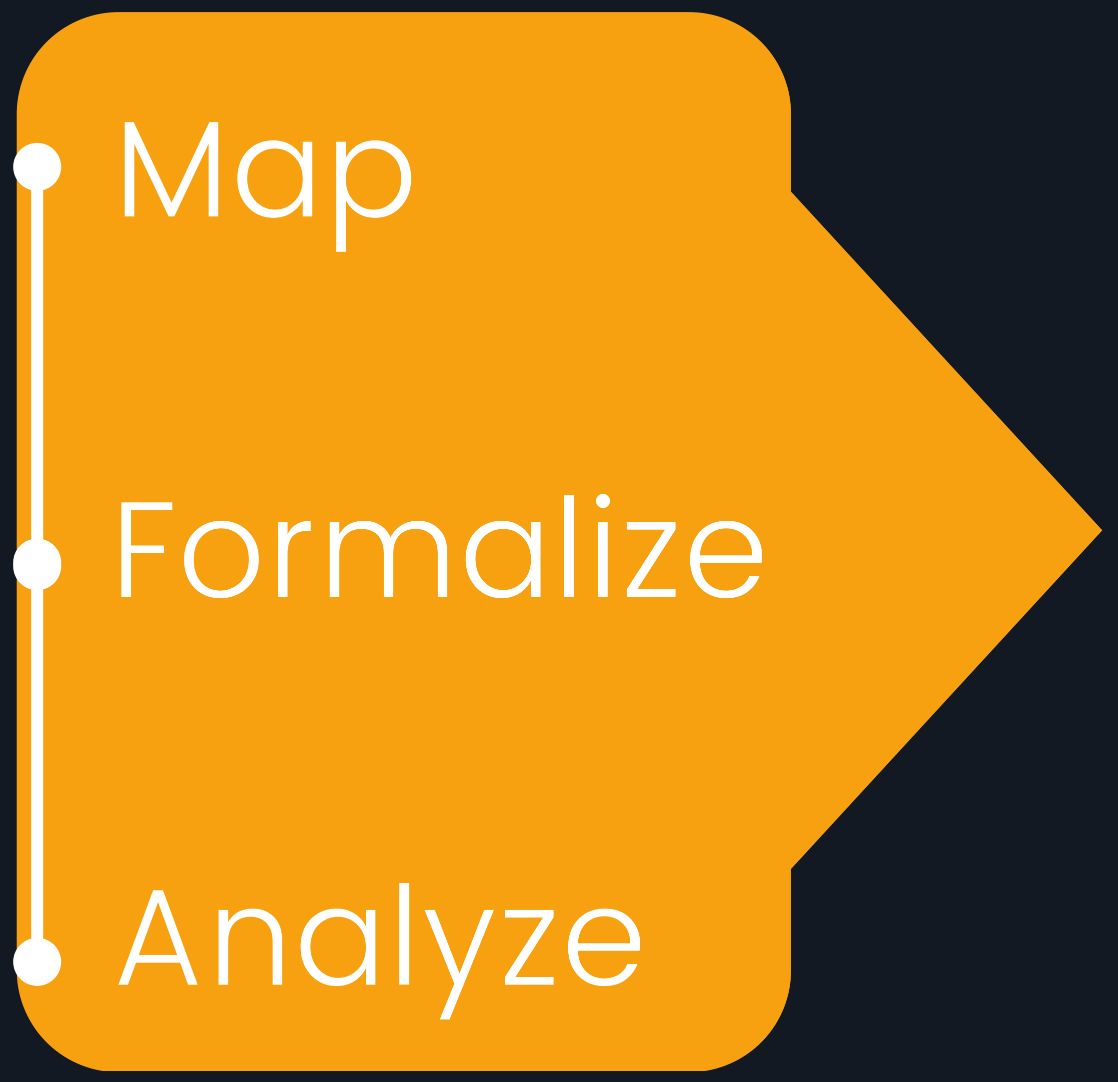
Mapping and Formalization

Raw Event Data

Ad-Hoc Interpretations

Business Questions

Business Validations

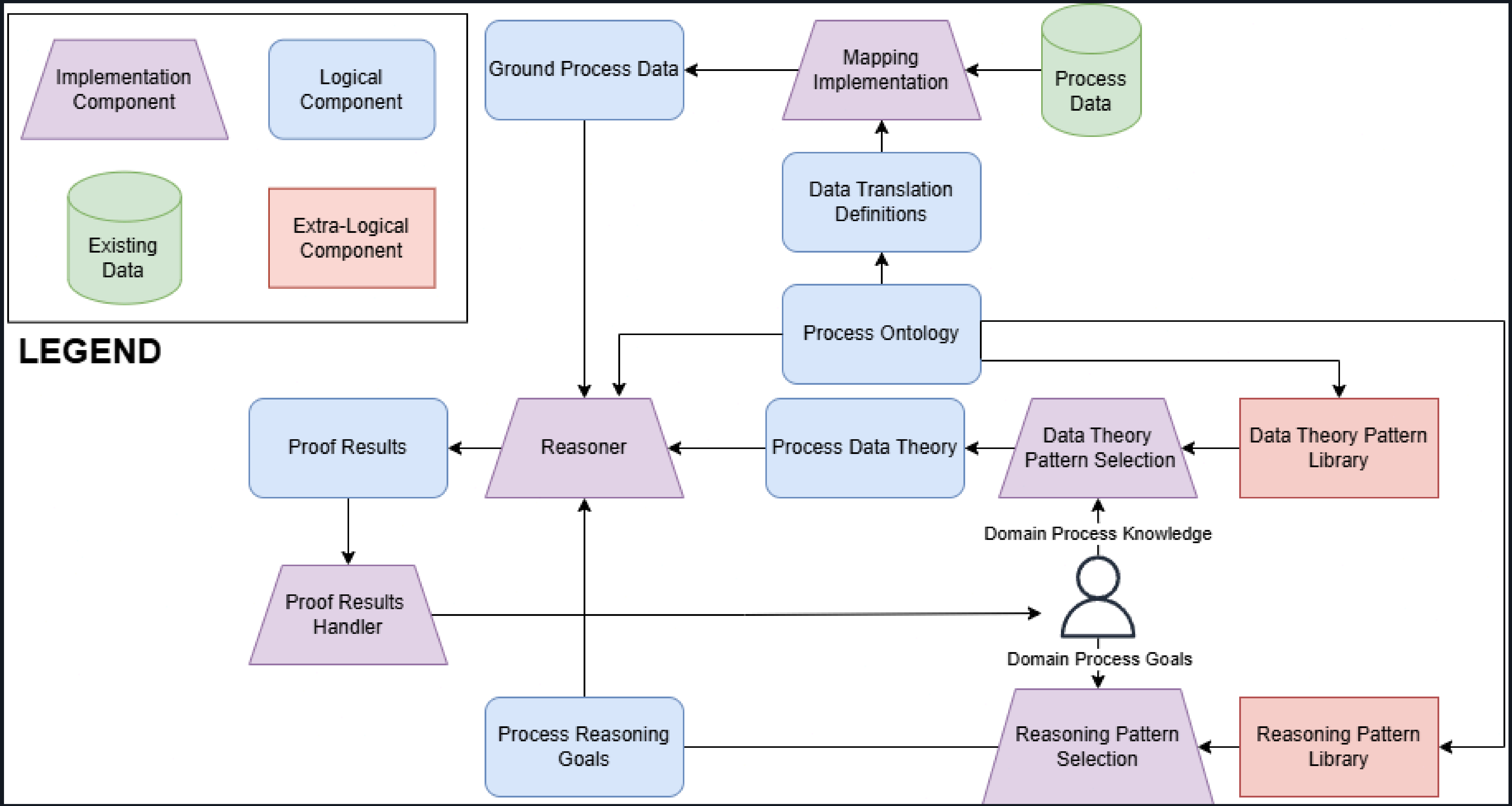


Knowledge Base

Data Theory

Logical Queries

Logical Proofs



Implementation Component
Logical Component
Existing Data
Extra-Logical Component
LEGEND
Ground Process Data
Mapping Implementation
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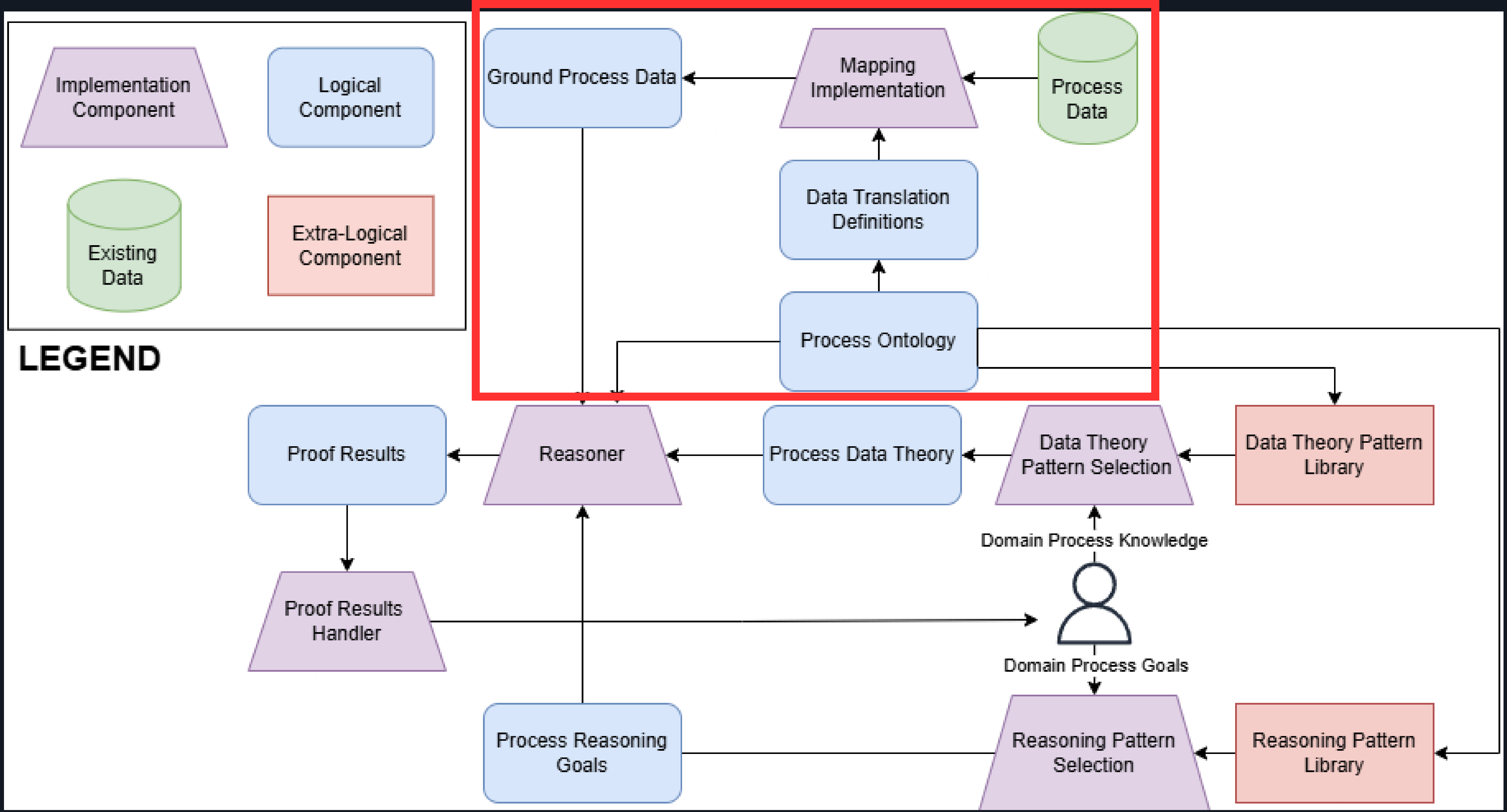

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approval	10:23	c1
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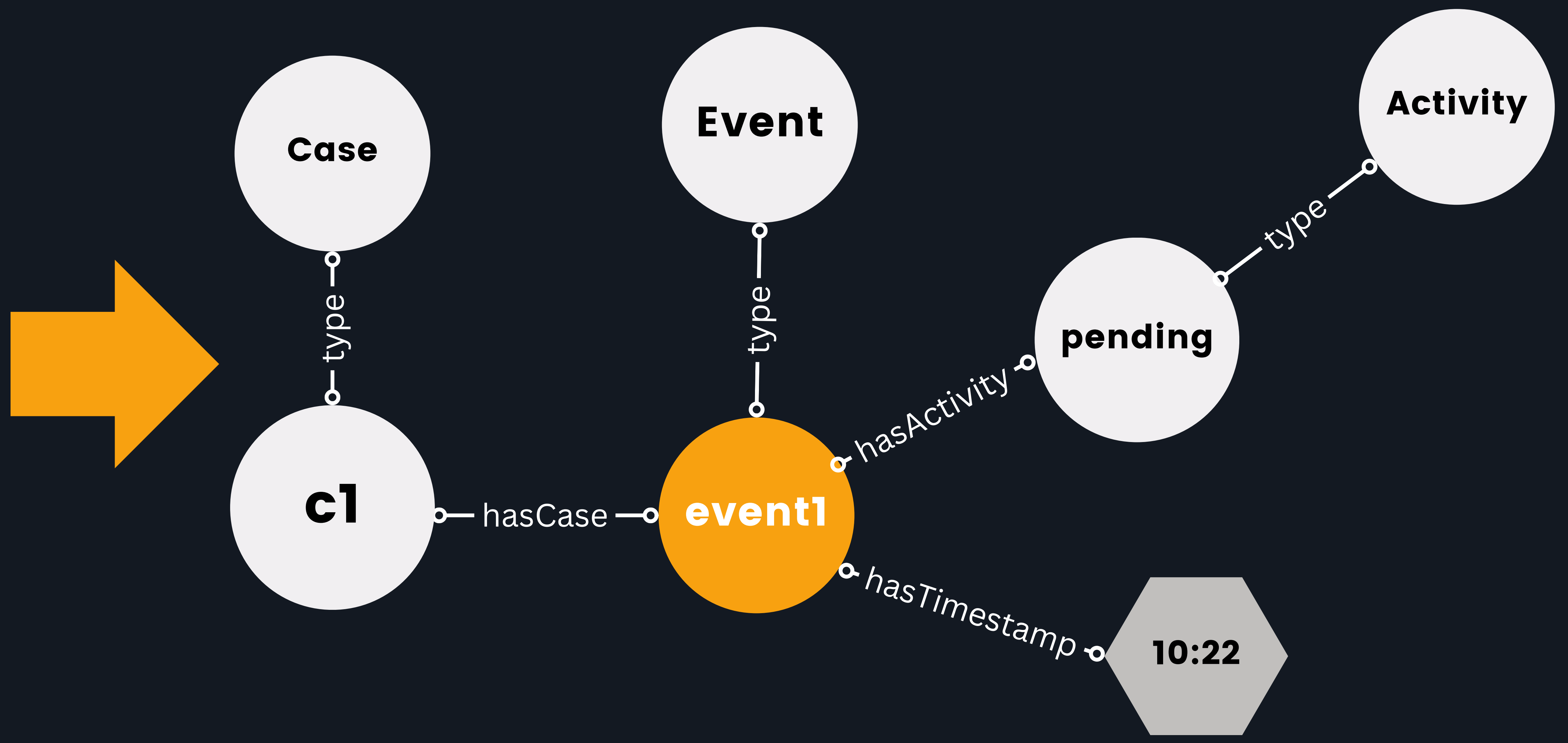

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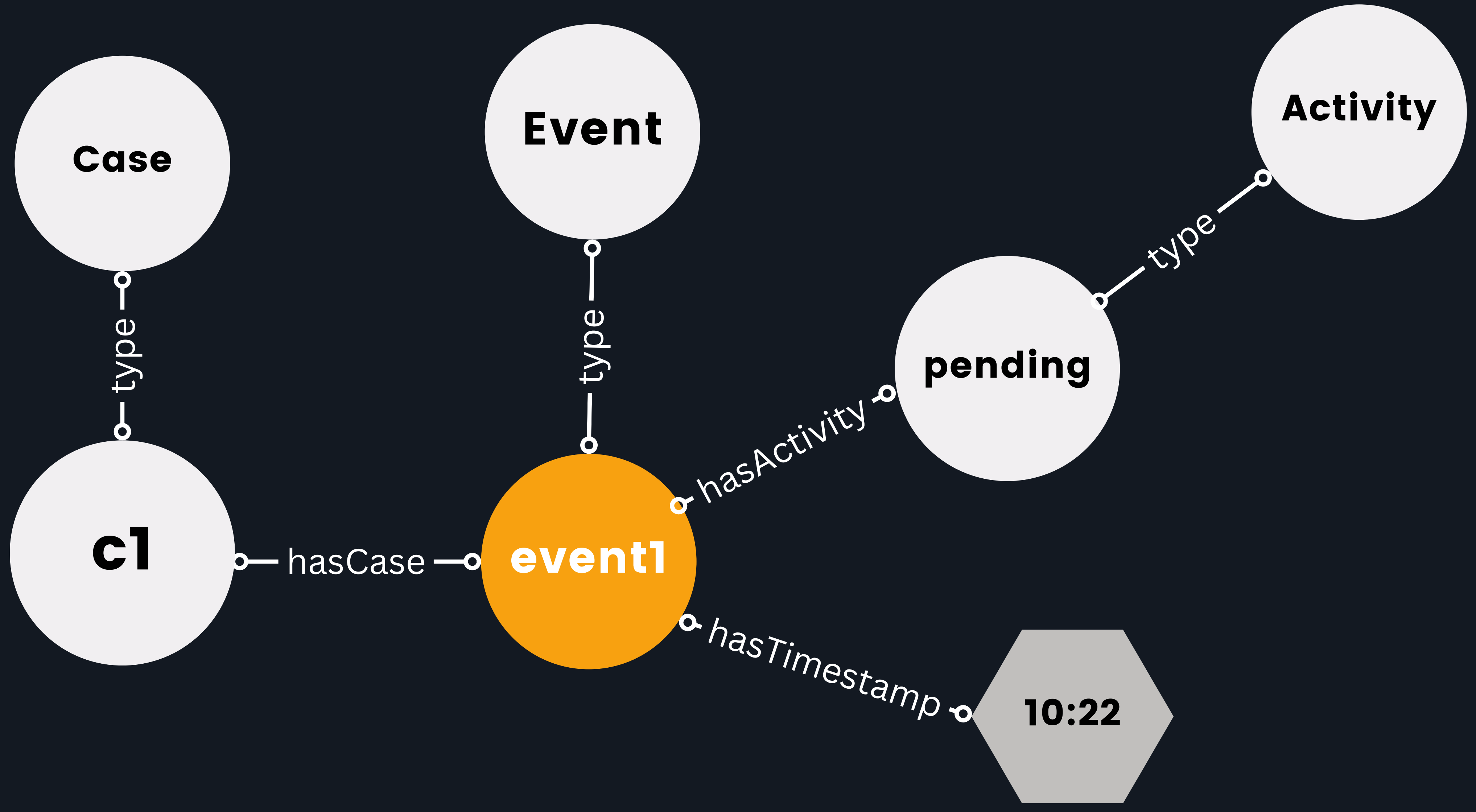

This forms our ground process data

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- Analyze

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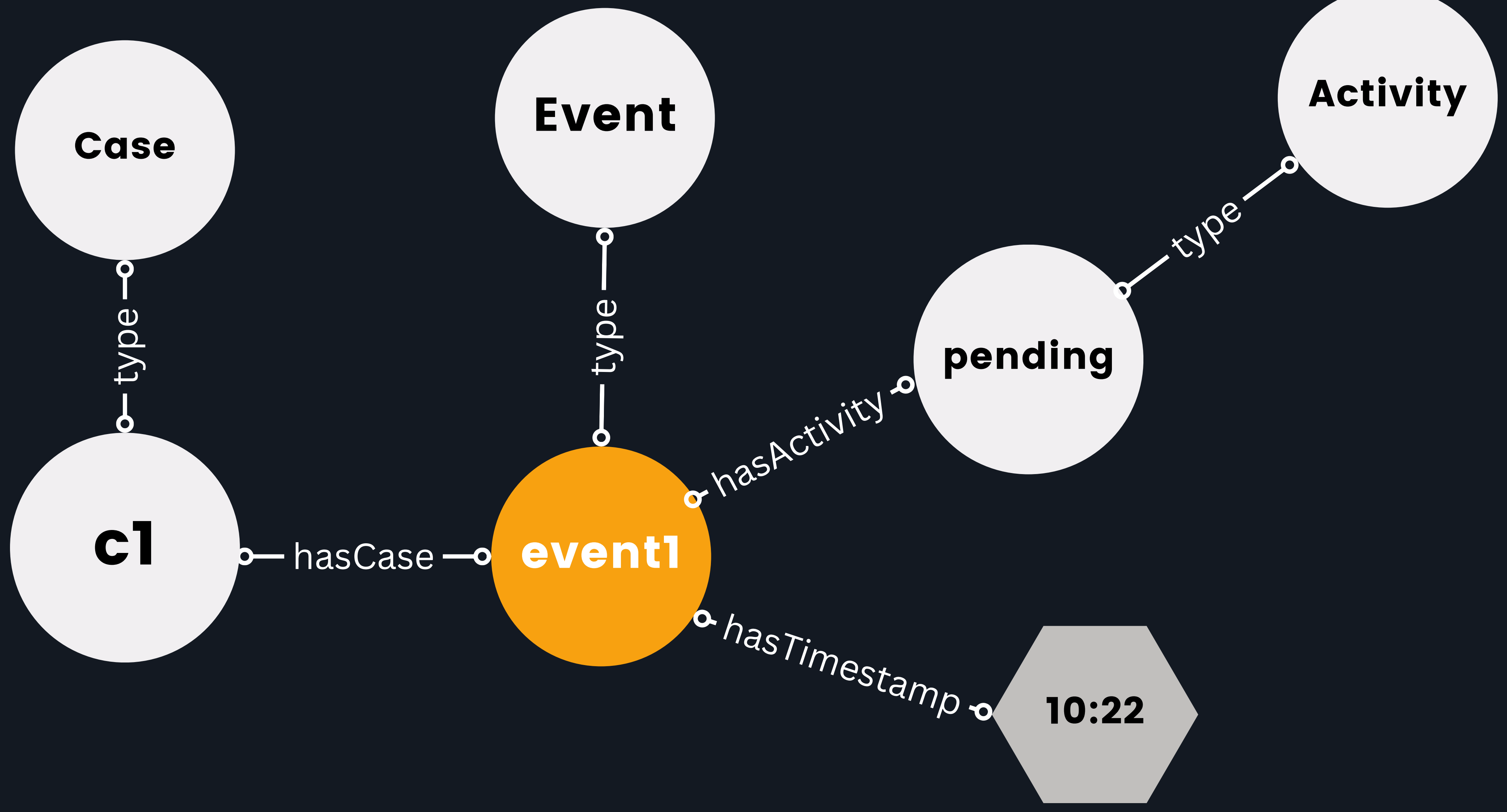

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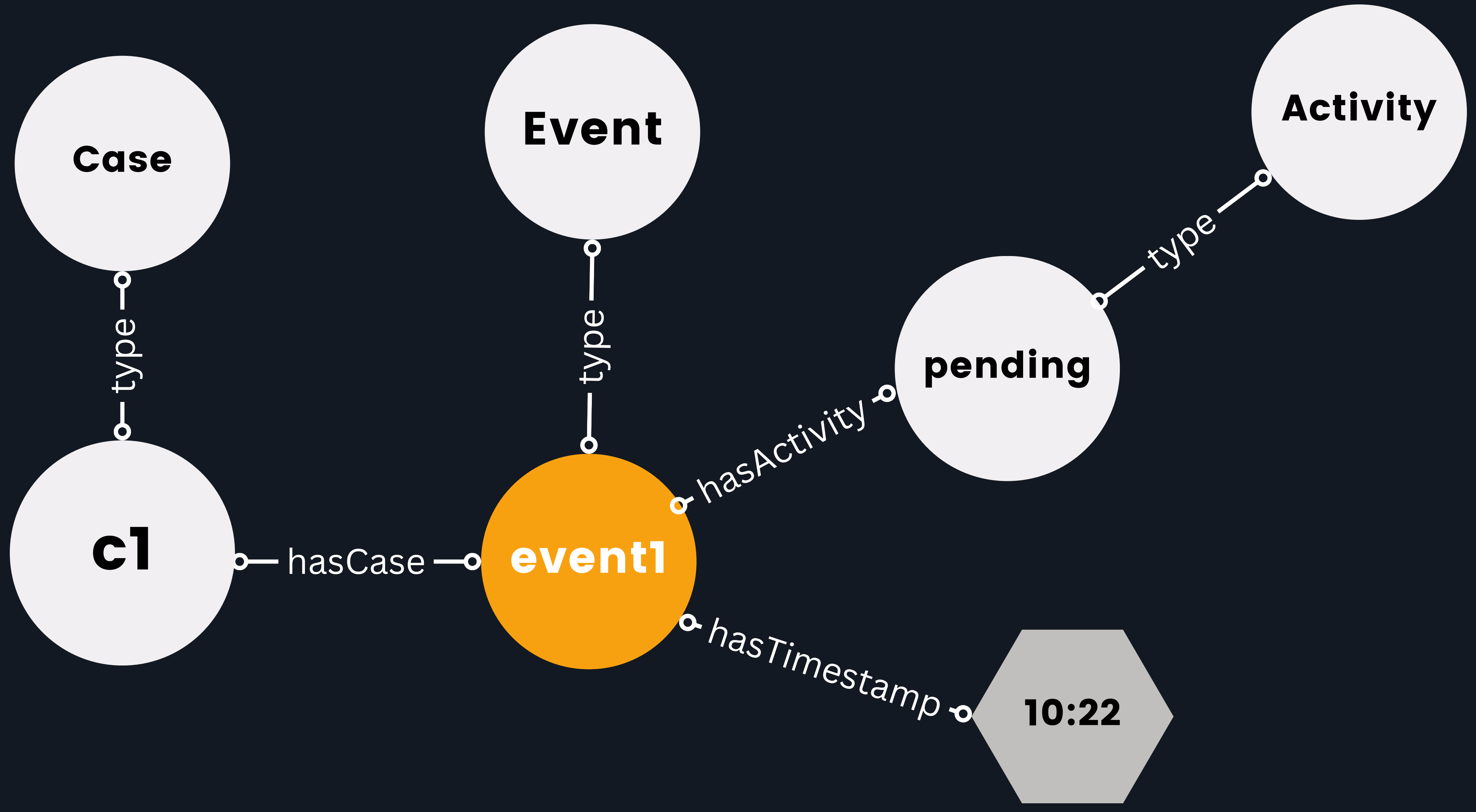

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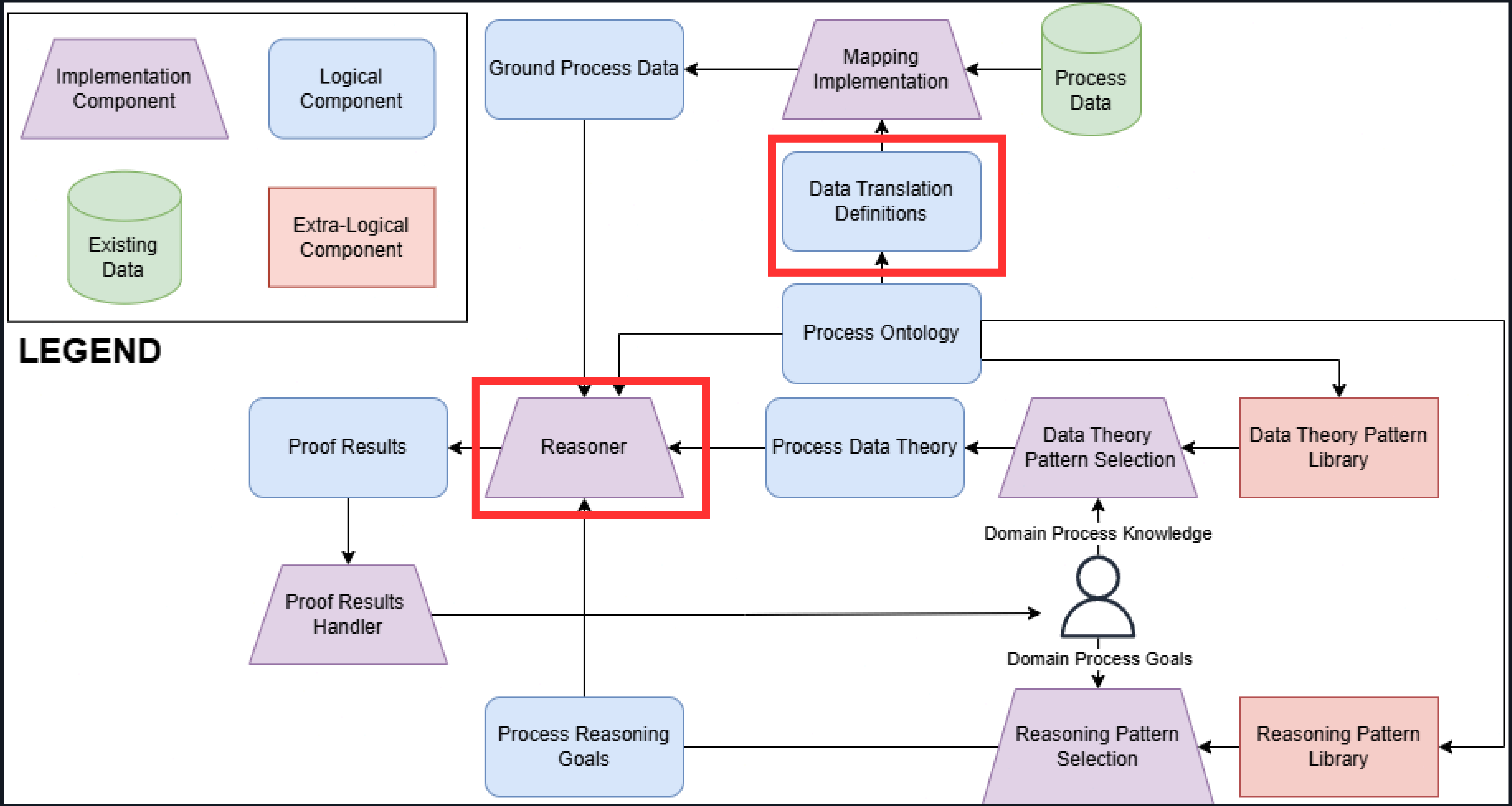

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- How can we formally (and automatically) identify ordering errors?

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"Two events sharing an activity each with a start and end transition indicates an acitivty occurrence"

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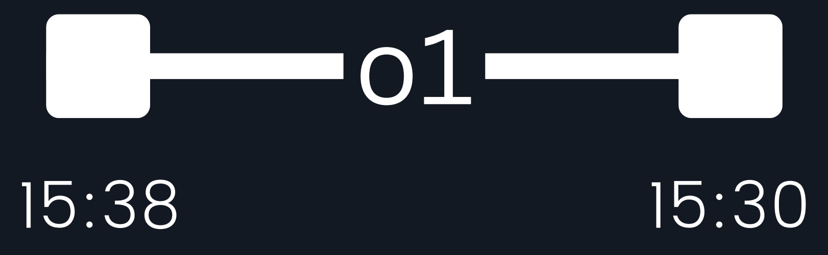
Translated Data

occurrence(o1)
beginOf(o1, 15:38)
endOf(o1, 15:30)



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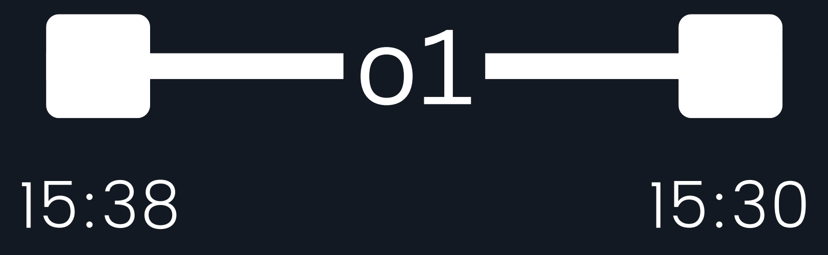

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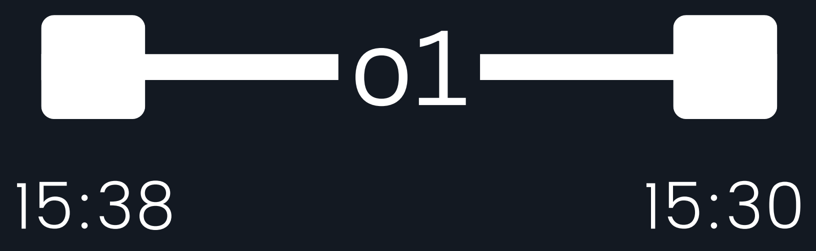

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$$t_1 \leq t_2$$

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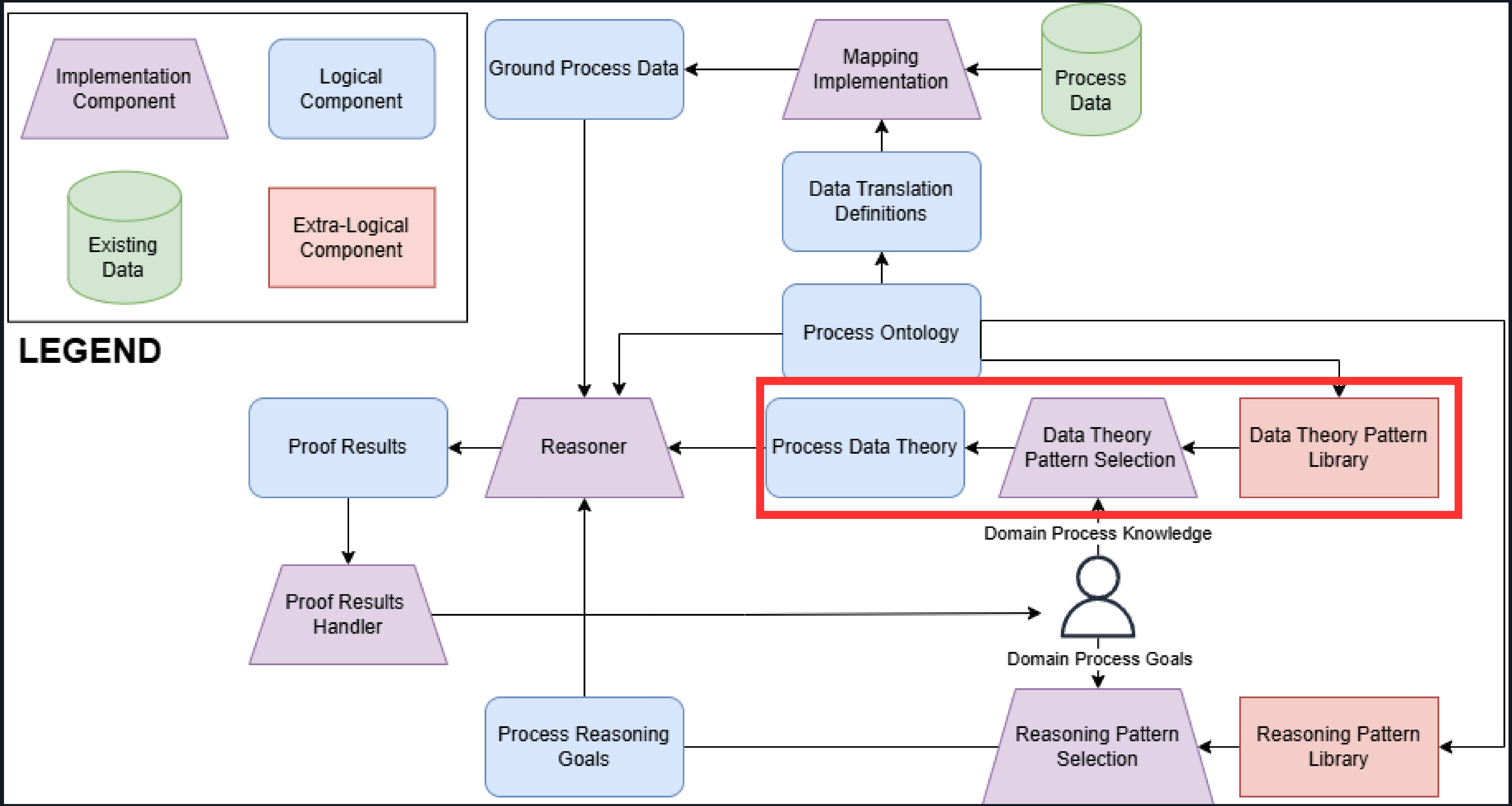
Proof of Inconsistency

$$t_1 = 15:38$$

$$t_2 = 15:30$$

$$\boxed{\begin{array}{c} t_1 > t_2 \\ t_1 \leq t_2 \end{array}}$$

What about domain-specific analysis?



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Knowledge Patterns

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- State-Based Effects (SBE)
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- While some initial condition holds, and an occurrence happens, some resulting condition holds afterwards
- Patterns abstract common process knowledge
- SBE(c1, a, c2)

Knowledge Patterns in Reasoning

- For domain specific reasoning problems
  - Use patterns to declare business rules, data interpretations (the data theory)
  - “Patient Intake occurs exactly once for one patient visit”

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- For domain specific reasoning problems
  - Use patterns to declare business rules, data interpretations (the data theory)
  - "Patient Intake occurs exactly once for one patient visit"
- For general reasoning problems
  - The process ontology contains fundamental knowledge about how processes work
  - "Occurrences cannot end before they begin"

Ontology-Driven Process Mining

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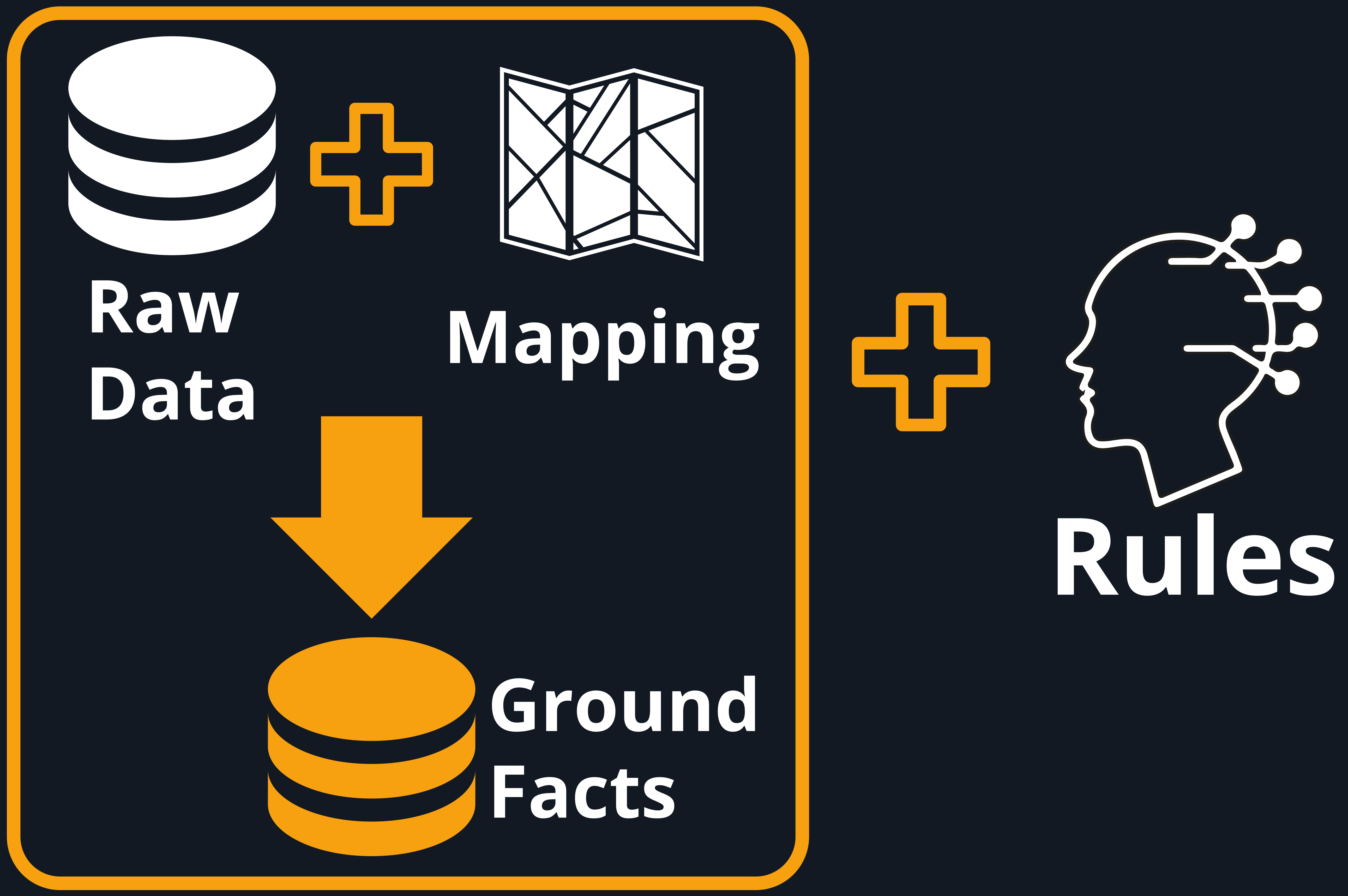
Data Rules

Ontology-Driven Process Mining

Ontology-Driven Process Mining



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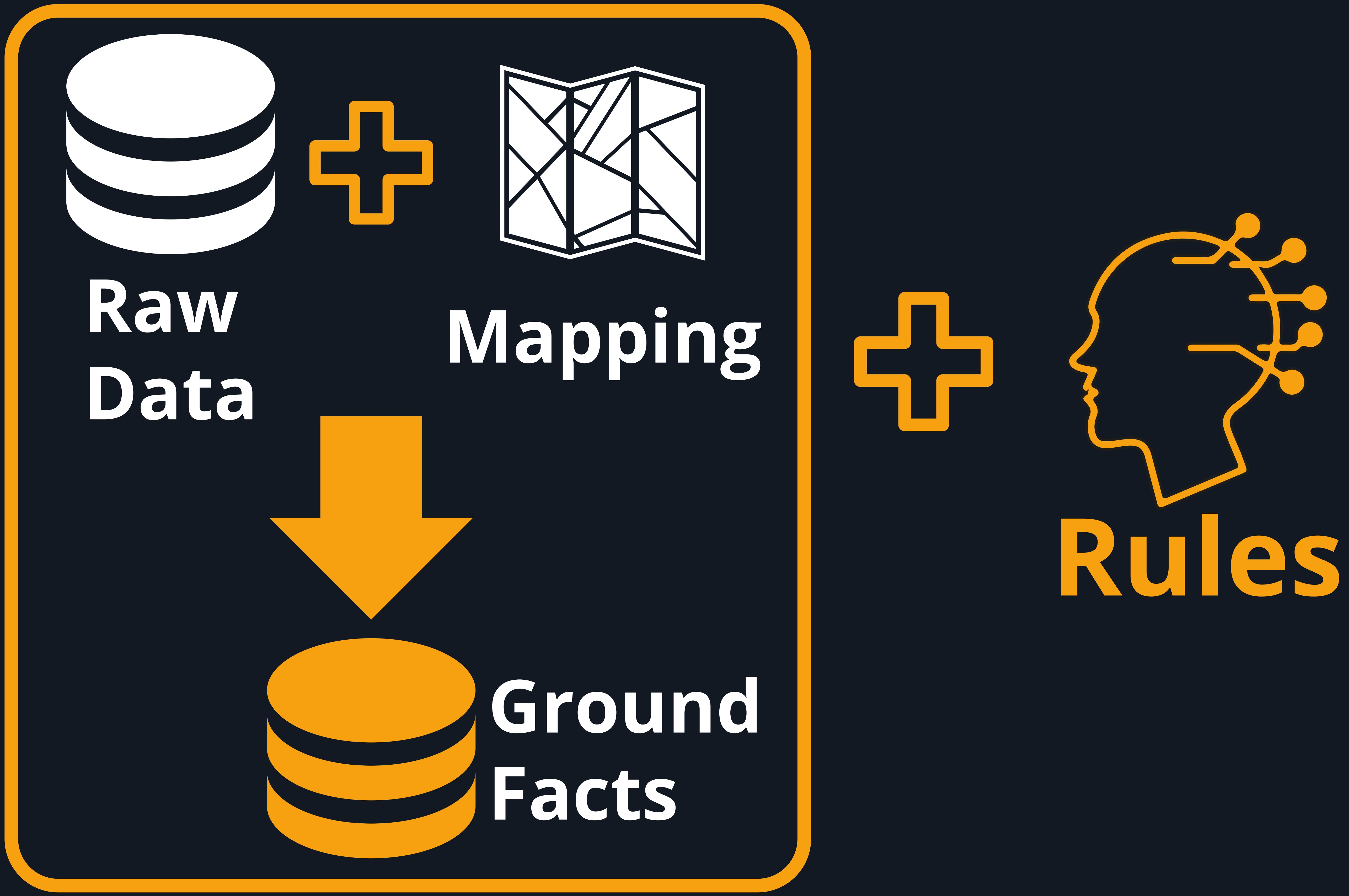

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Thank you!