Enforcing Ontological Commitments:

From Process Mining to Dependent Types

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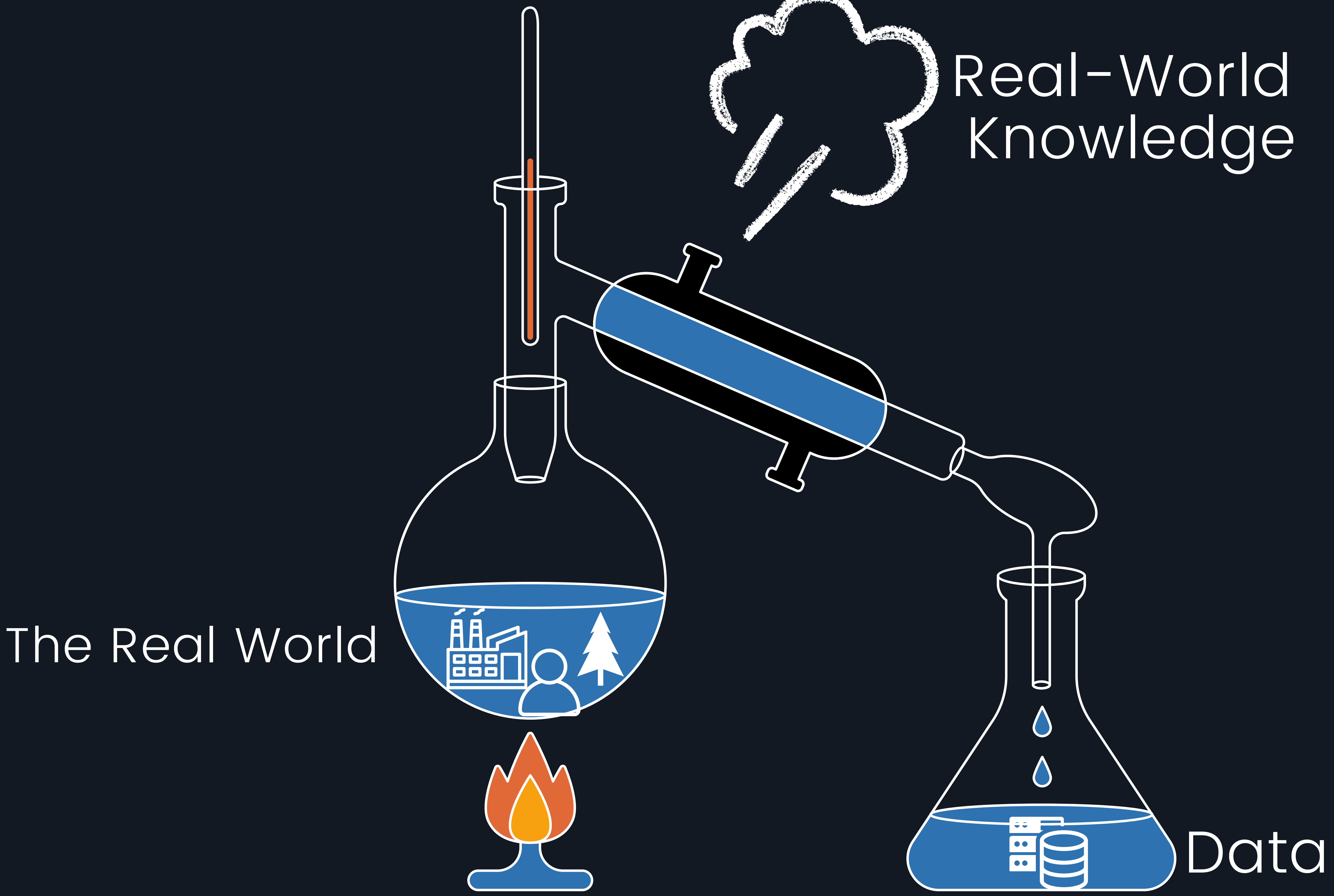
Semantic Technologies Lab

The Semantic Gap

The Semantic Gap



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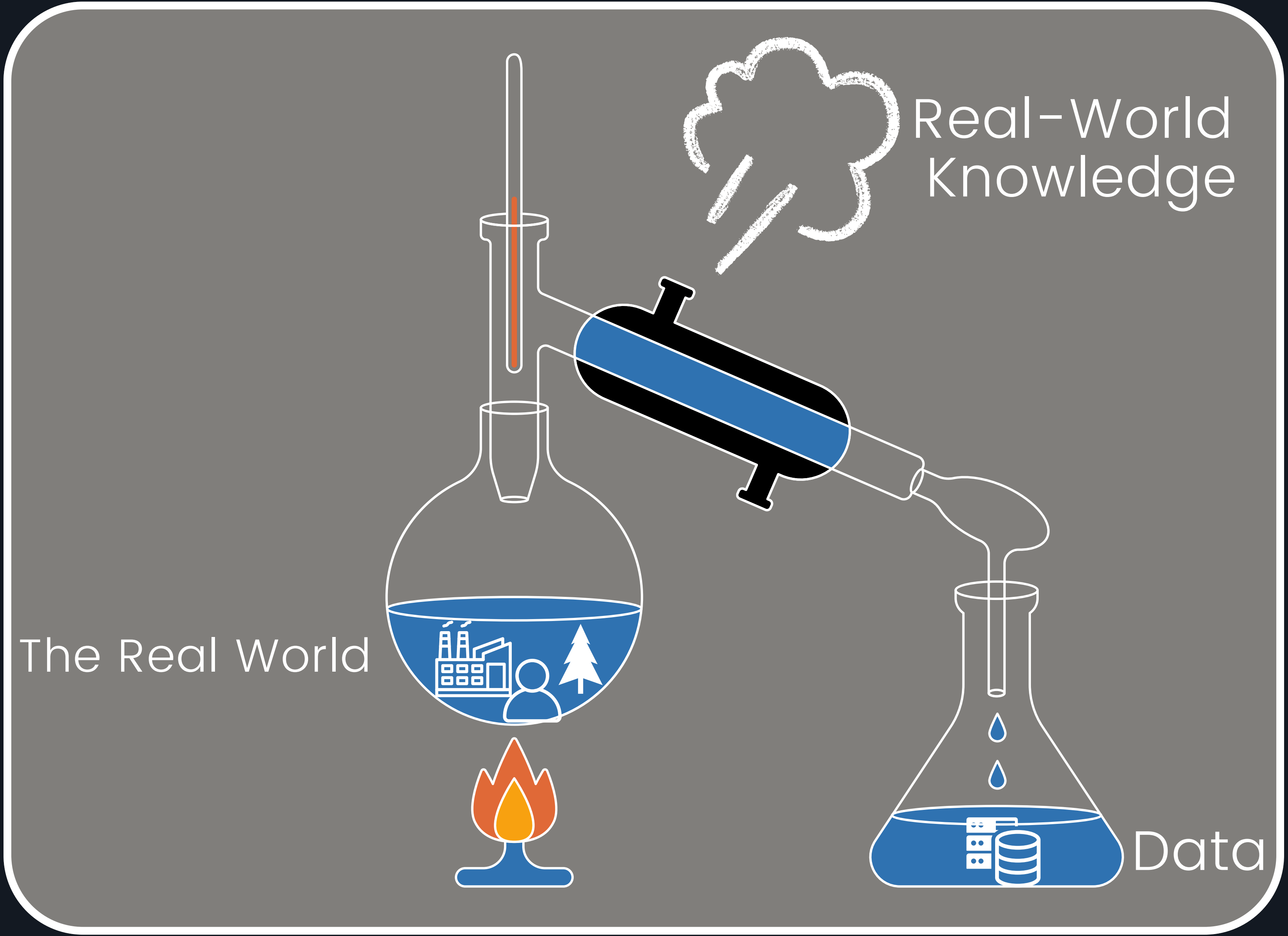
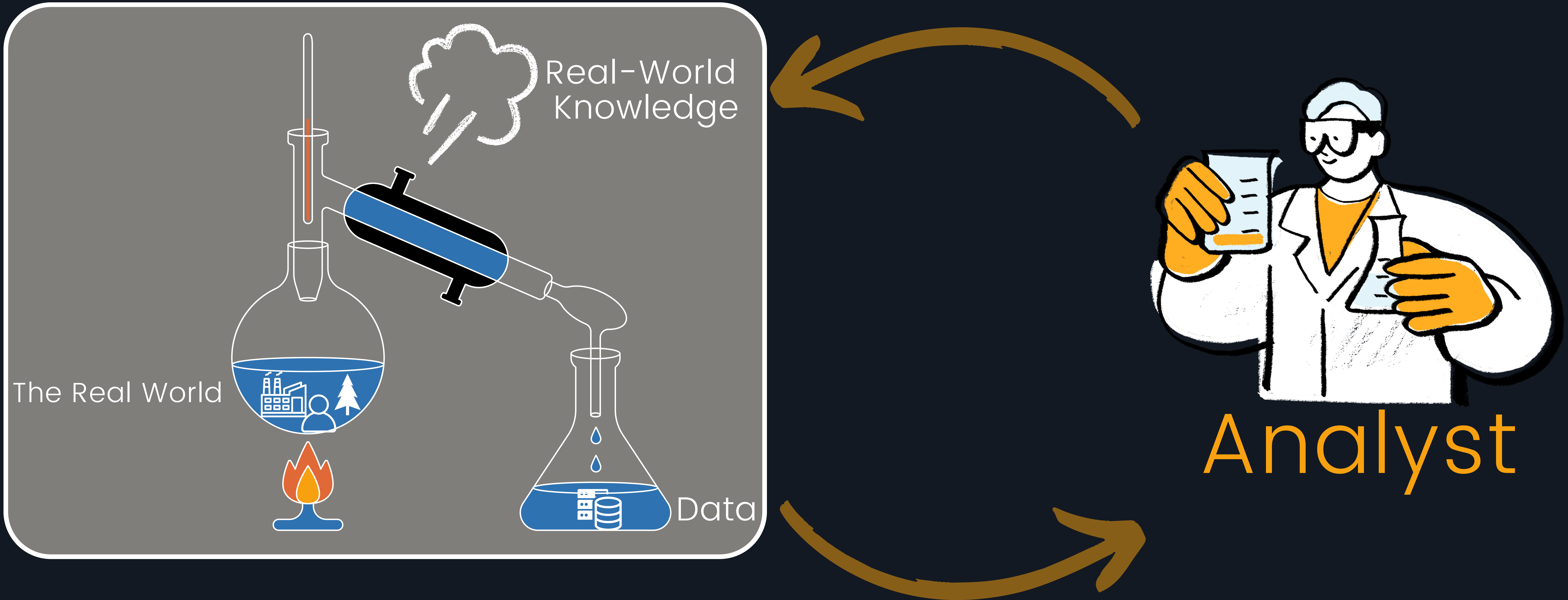


Analyst

The Semantic Gap



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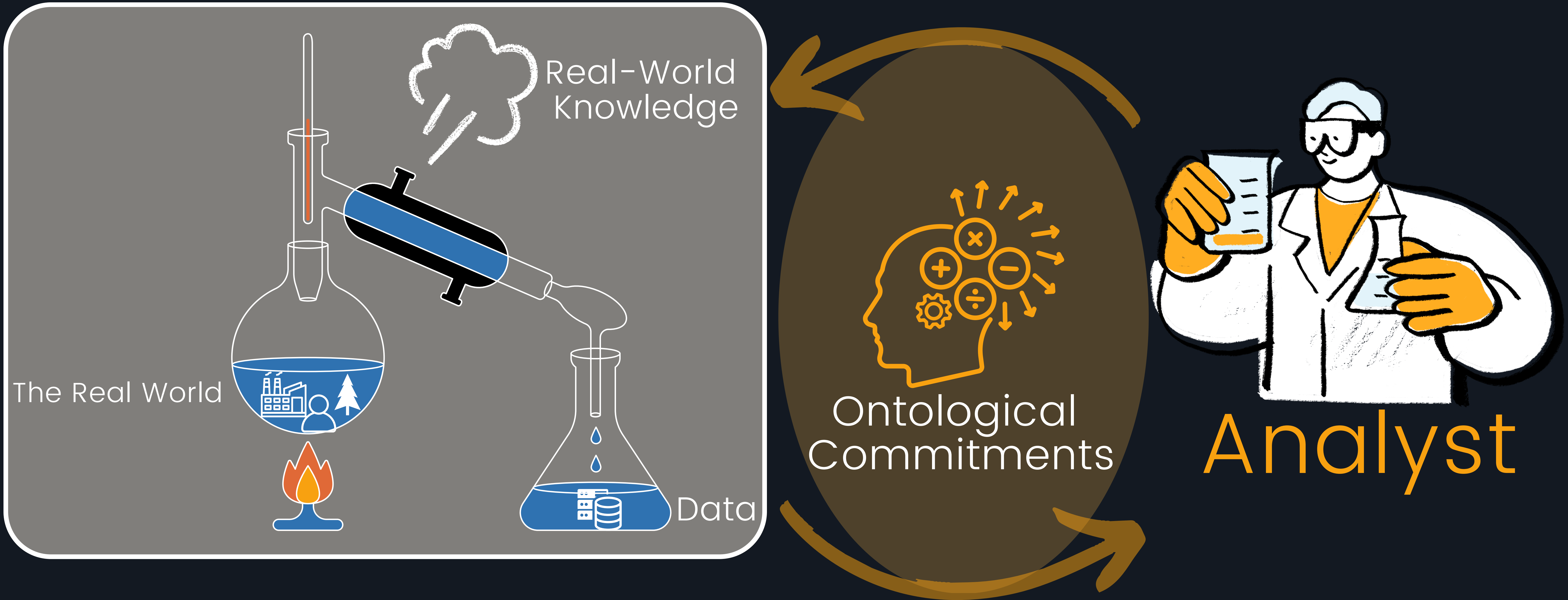

Bridging The Semantic Gap

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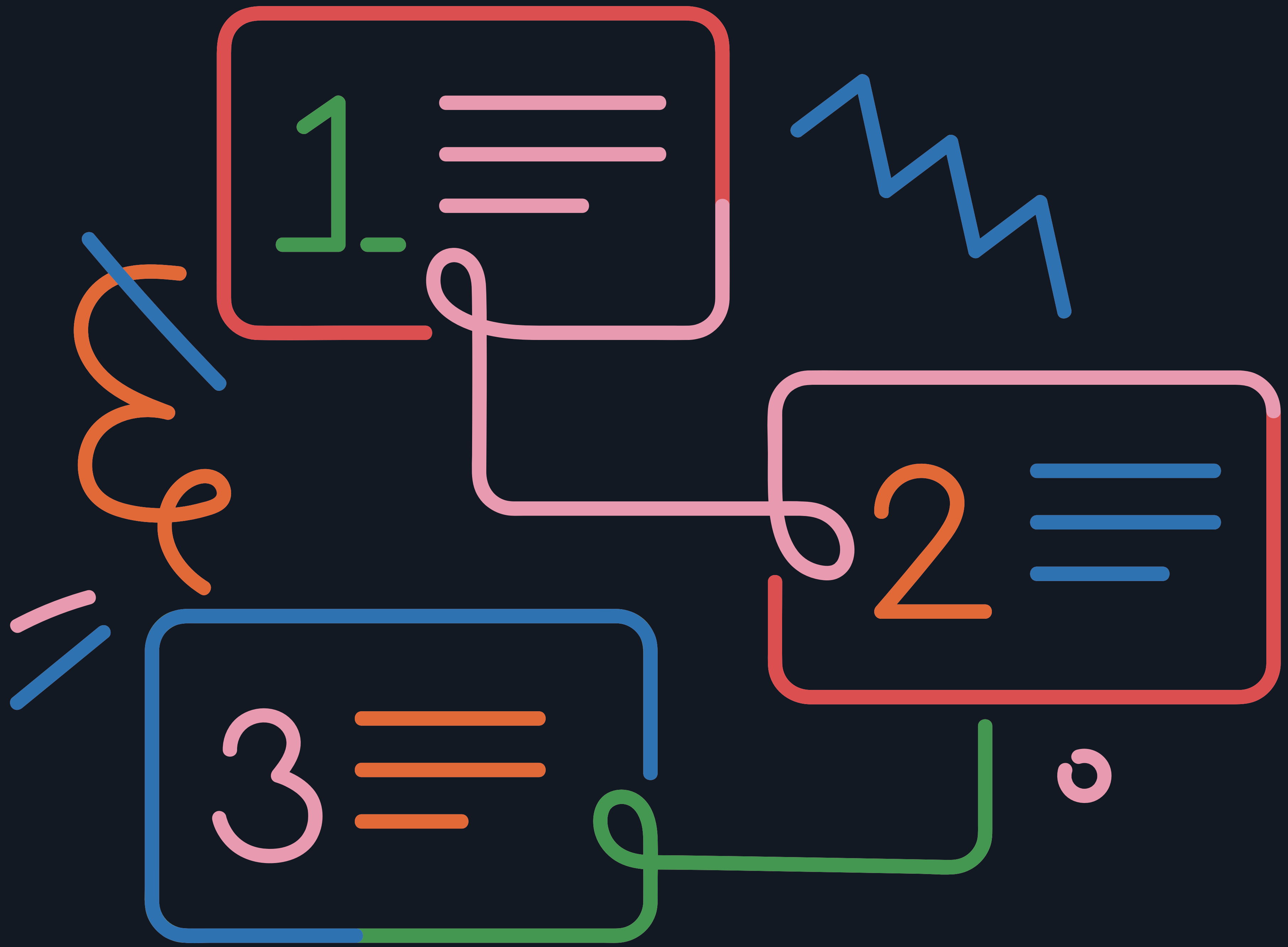
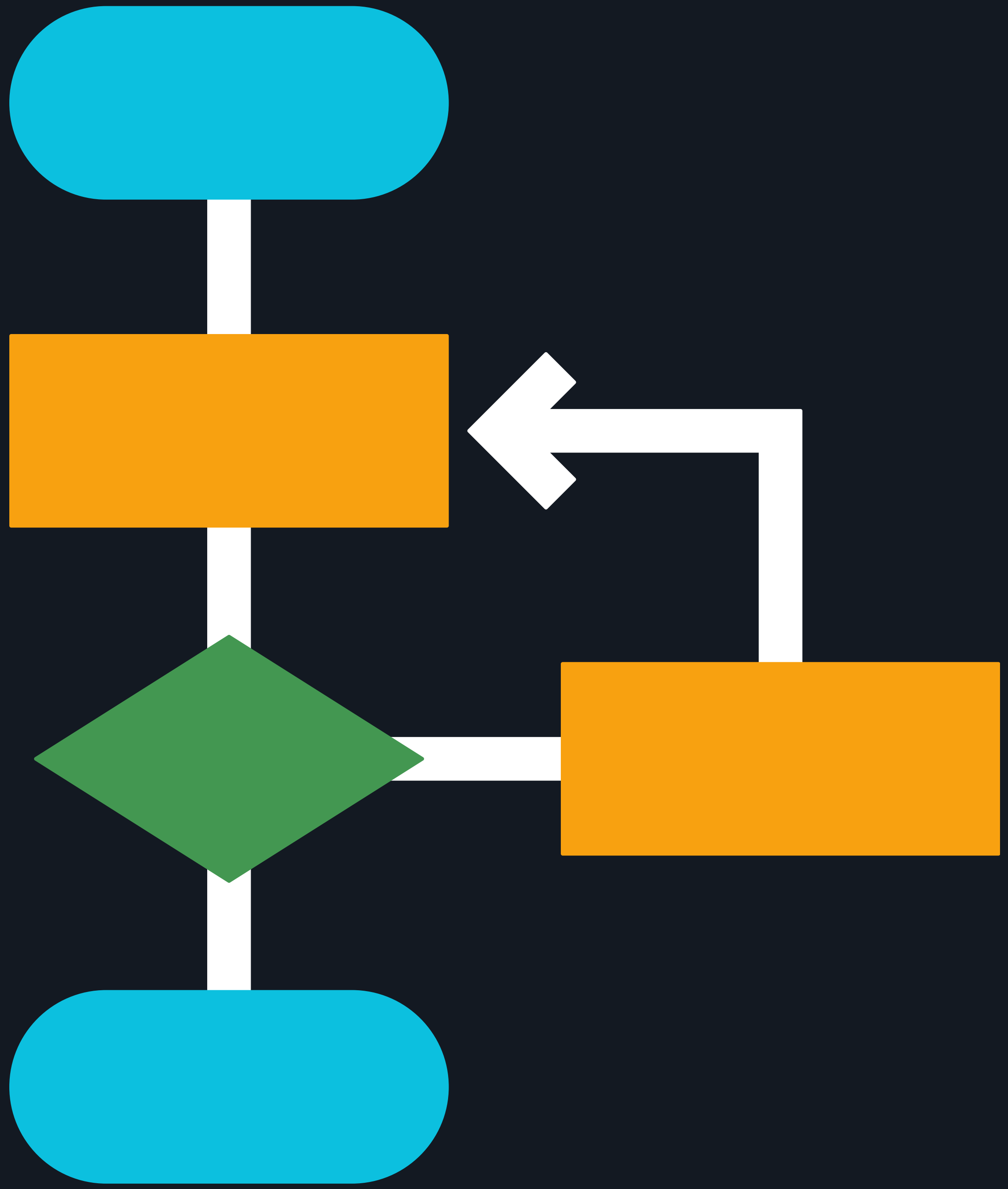
- Process mining
  - Ontological challenges of events
  - Formalizing event data interpretations

- Datatypes & data science
  - The limitations of simple datatypes
  - How to make types meaningful

Part 1:
Mining for Meaning

Business Processes





Processes and Data

Process Data (Event Logs)

Business Rules, Process Knowledge

Models, Compliance Checks, Insights

- Process mining as the analysis engine for event data

Process Mining

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

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

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Process Mining: Events

- “Awaiting Assignment”
- “Document Under Review“
- “Review Document”
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But they have very different process implications

Events are heavily overloaded and require interpretation for analysis

Process Mining

Process Data
(Event Logs)

Business Rules,
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Models,
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1. How does a process ontology fit?

Process Mining

Process Data
(Event Logs)

Business Rules,
Process Knowledge

Models,
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1. How does a process ontology fit?
2. What tools enable that fit?

Process Ontology Application: Challenges

- Current ontology applications are more representational, access-driven, and conceptual

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- Current ontology applications are more representational, access-driven, and conceptual
- Application should instead focus on formalizing the ontological commitments of data analysis
- Operational realization capture this notion
- How do we apply operational realization to process mining?

Ontology-Driven Process Mining

Raw Event Data

Ad-Hoc Interpretations

Business Questions

Business Validations

Knowledge Base

Data Theory

Logical Queries

Logical Proofs

Ontology-Driven Process Mining

Raw Event Data

Ad-Hoc Interpretations

Business Questions

Business Validations

Map

Formalize

Analyze

Knowledge Base

Data Theory

Logical Queries

Logical Proofs

Mapping Event Log Data

- Tabular data from event logs becomes ground facts

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

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Event(e2)
hasActivity(e0, creditCheck)
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Ontology Translations

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

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$$\texttt{hasActivity}(e_s, a) \wedge \texttt{hasActivity}(e_e, a) \wedge$$
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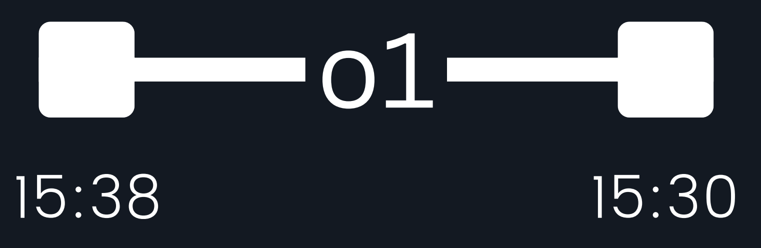
Translated Data

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



Event Log Data Quality

Map
Formalize
Analyze

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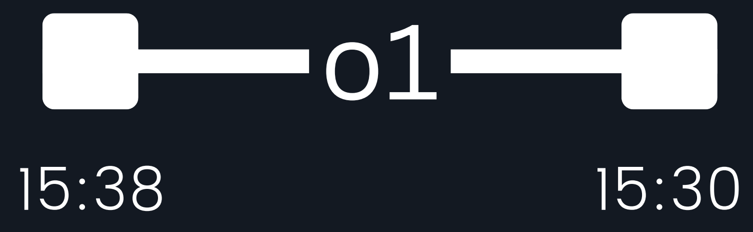

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Ontology

"Activity occurrences start points are less than or equal to their end points"

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$$t_1 \leq t_2$$

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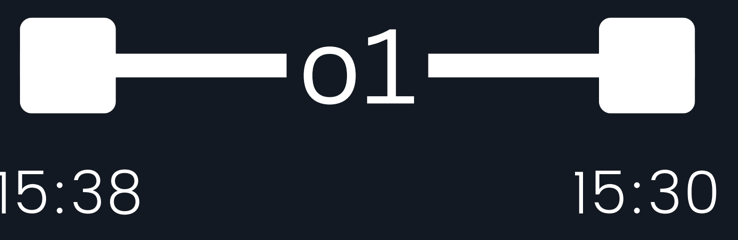

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Proof of Inconsistency

$$t_1 = 15:38$$

$$t_2 = 15:30$$

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

Getting Specific: Knowledge Patterns

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- Focusing on standardization and tractability of these extensions
- Use knowledge patterns to create a data theory

Knowledge Patterns

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Occurrence Constraint

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- “When a fragile object is dropped, it breaks”
- 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

- State-Based Effects (SBE)

$$SBE(a, f_1, f_2) := (\forall o)\, occurrence\_of(o, a) \wedge prior(f_1, o) \implies holds(f_2, o)$$

$$(\forall o)\, occurrence\_of(o, drop) \wedge prior(fragile, o) \implies holds(broken, o)$$

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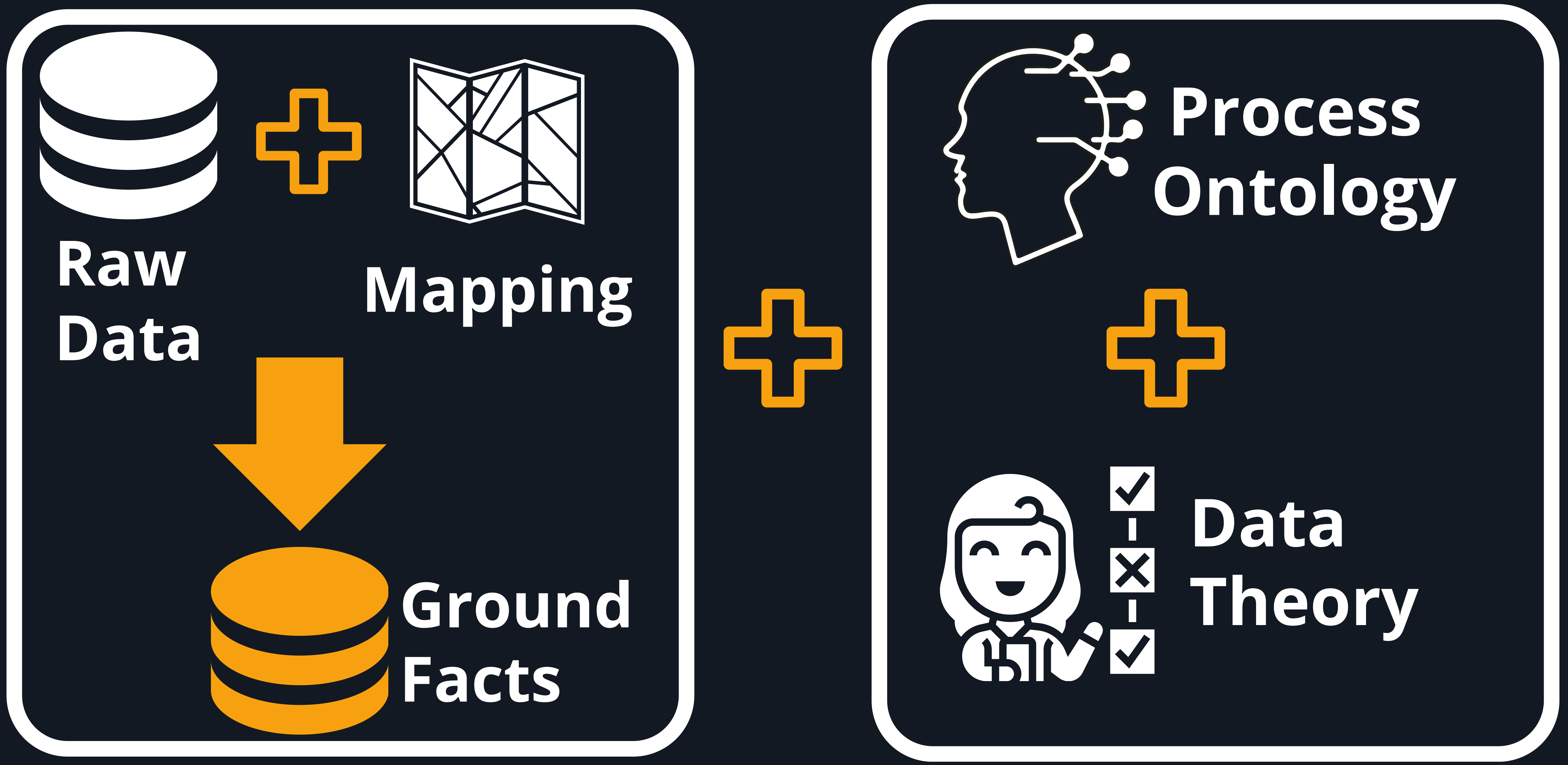
Data Theory

Process Ontology

A-Box

T-Box

Data-Driven Process Ontology



Part 2:
What’s in a (data) type?

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What's in a (data) type?

- Data is representative of real-world phenomena
- Data is represented using simple datatypes
- Datatypes do not typify the real world

Datatype Problems

Datatype Problems

The Real World
- Implicit rules
- Complex concepts and relationships

Simple Datatypes
- Numbers are numbers*
- String OR Integer OR Float OR ...
- Same datatype represents many different concepts

Datatype Problems

Datatype Problems

Geospatial Region

Datatype Problems

Population

Datatype Problems

Distance

Datatype Problems: Mereology

Date	# Fully Vaccinated	% of Eligible Pop. Fully Vaccinated
6/22/2021	1 200 000	3.50%
...	...	...
7/29/2021	1 335 000	2.60%
...	...	...
5/28/2022	1 086 100	2.20%

Datatype Problems: Mereology

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Children become eligible

Datatype Problems: Mereology

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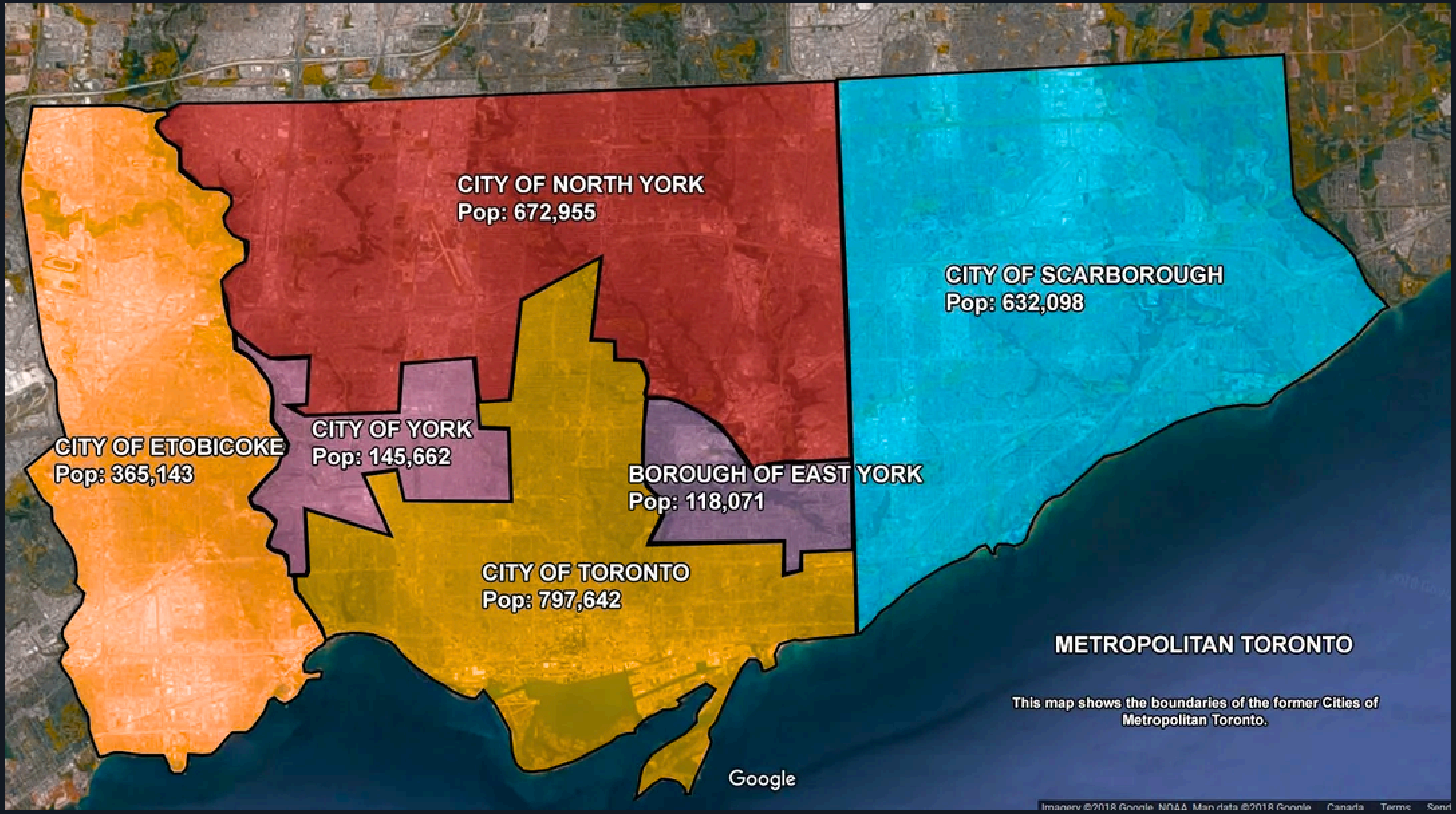
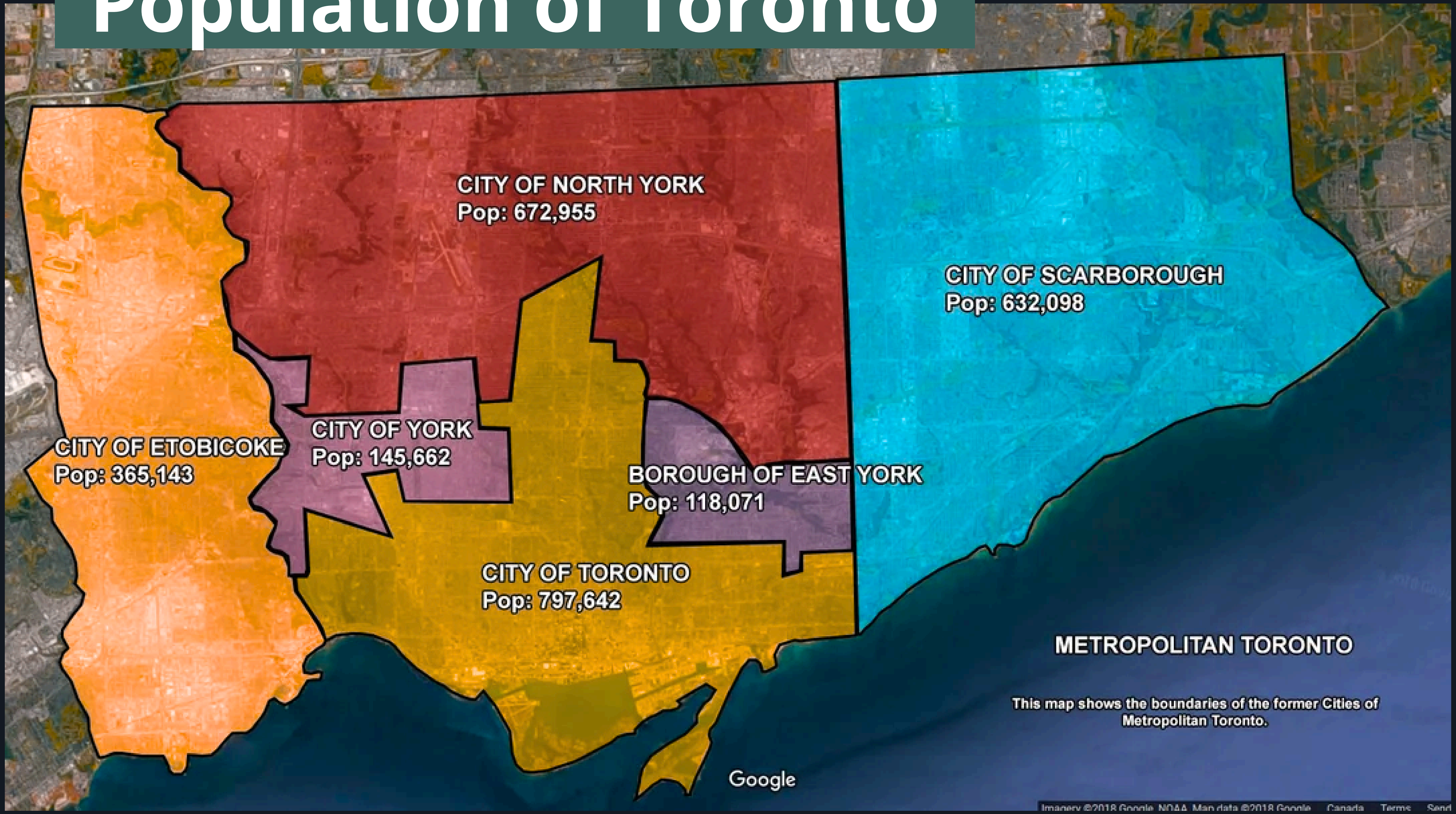
“Fully vaccinated” now defined as 3+ doses

Datatype Problems: Mereology



Datatype Problems: Mereology

"Population of Toronto"



Datatype Problems: Provenance

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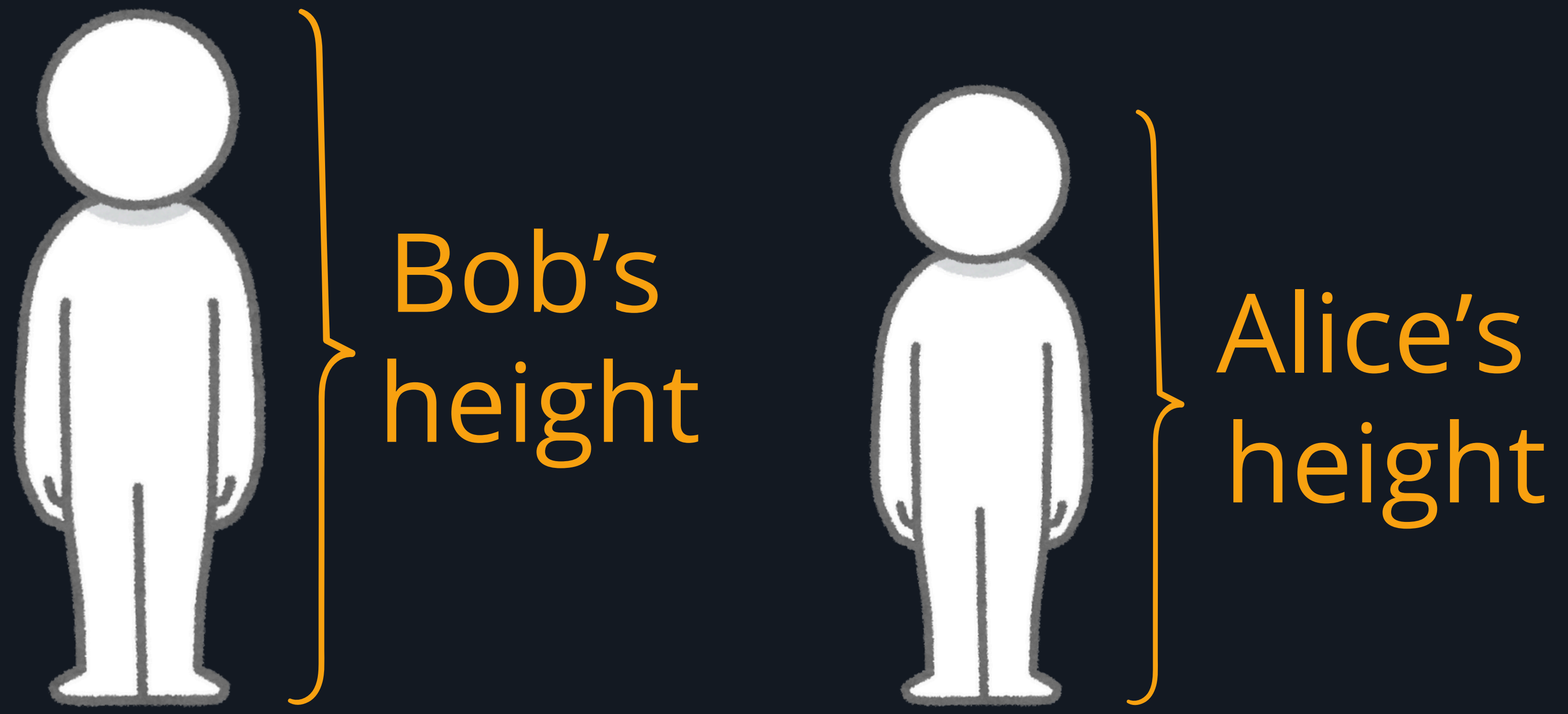

Datatype Problems: Provenance

- How does analysis itself change the meaning of data?

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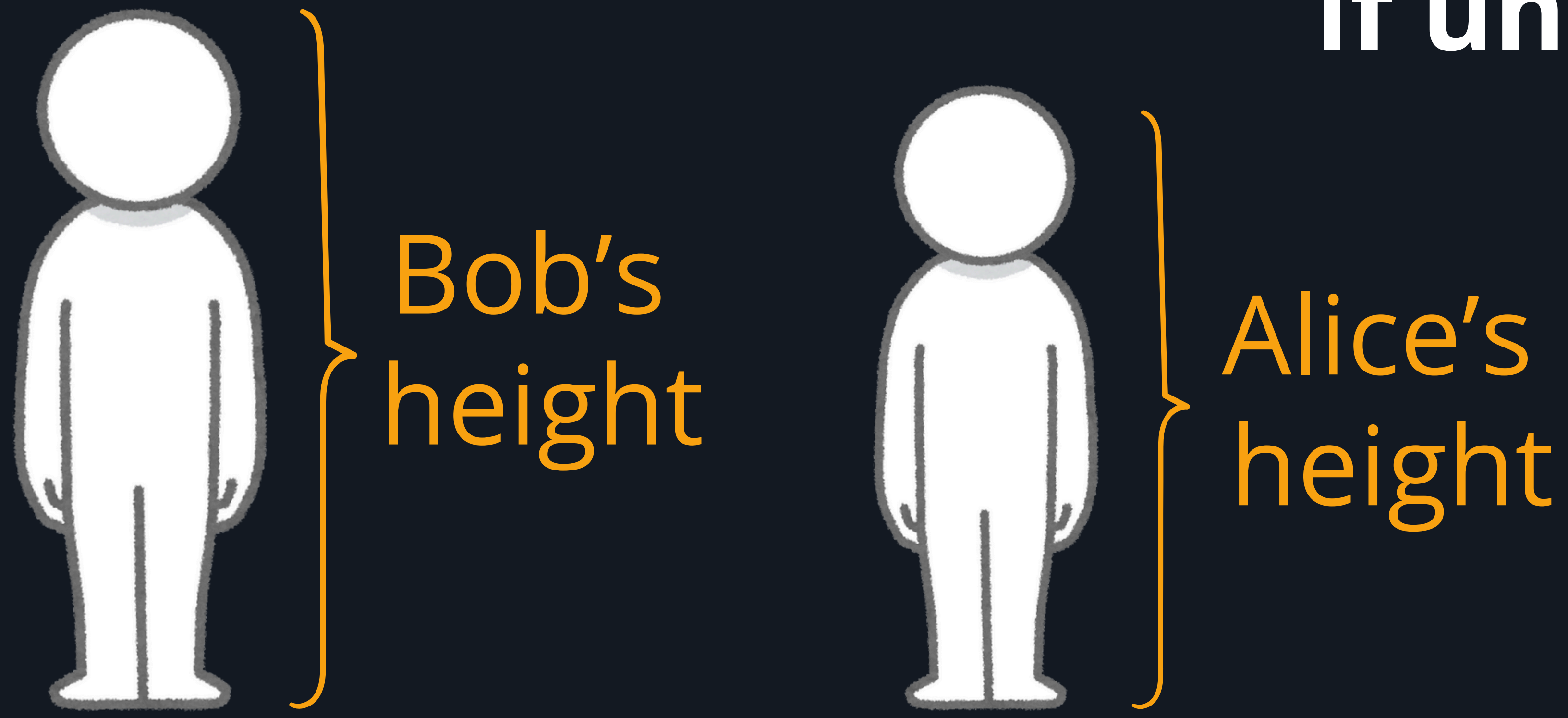
“If units match, all is well!”



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Data Operation Semantics

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Property of (mereological) sum = (arithmetic) sum of properties

$$p(A + B) = p(A) + p(B)$$

Data Operation Semantics

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Datatype Problems: Provenance

- How to formally represent real-world rules about quantitative data?

- How to integrate data provenance?

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Make types stronger!

Meaningful type safety

Meaningful Type Safety

- Leverage the power of dependent types
  - Types depend on values, Natural Numbers (Int >0)

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- Leverage the power of dependent types
  - Types depend on values, Natural Numbers (Int >0)

- Enforce preconditons for operations

```
RegionSum : (Disjoint [Region]) → Region
```

- Integrated provenance → types change after operations

```
PopAvg(regions) = Avg over regions
```

Meaningful Type Safety

- Encoding complex real-world constraints through type-checking

```
PopAvg( (Toronto2024 - Toronto2016),
     (Buffalo2024 - Albany2024))
```

```
PopAvg : ([Population]
(differsOverTime XOR differsOverRegion))
→ Population
```

Formal Ontologies and Type Safety

- Types are propositions, proofs are programs

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- Ontologies can be constructed which represent* type safety

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* Proving this representation is tricky

Takeaways

- We must build the ontological commitments underlying our analysis directly into data pipelines for verifiability, reusability, and transparency.
- Process data theories are a pragmatic & modular way to model event data interpretation, separating data-dependent definitions from foundational logic.
- Meaningful type safety offers a powerful a-priori approach, enforcing foundational rules as type-checks to prevent invalid operations.

Contact / More Details

Looking Ahead

- Process ontology benchmarking - Providing new data-driven challenges for existing foundational ontologies to demonstrate their capabilities for operational realization

- Extensions for object-centric event logs and event knowledge graphs

- Using LLMs as the interface to instantiate knowledge patterns and create data theories

Contact / More Details