What’s in a (Data) Type? Meaningful Type Safety for Data Science

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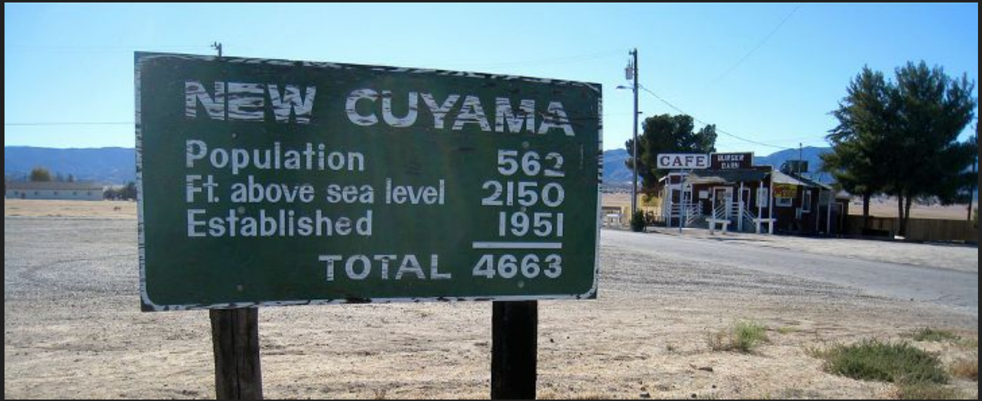
What's in a (Data) Type?

- Data Scientists work with Data that represent real-world concepts
- Important decisions are made based on data scientists' results
- The nuances of these concepts are reduced to integers, strings, etc



Overview

1. **How datatypes fail to typify data**

2. **Why current solutions don’t work**

3. **A framework for meaningful type safety**

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1. **How datatypes fail to typify data**
   I. Mereology
   II. Time
   III. Provenance

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Mereological Troubles

- Mereology is part-whole relation
- Legs are part of a table, Toronto is part of Ontario
- Definition of ‘eligible’ COVID vaccine population changes, comprises new age groups
- Mereology not formally defined within the data, needs to be integrated manually

Time Complications

- Time is a common and important factor in most data

- Data is observed, collected, updated at specific timepoints

- Time is an additional layer of complexity, mereology changes over time
    - Toronto 1985 vs Toronto 2021

- Manual intervention still necessary, time is only values, no reasoning being done

Provenance

- As data is changed, so are the concepts it represents
  - Population vs average population
  - Density = Mass / Volume

- Take Physical Quantities, Units as an example
  - Most approaches just enforce same units and conversion

- Bob’s Height + Mary’s Height : What is this quantity?

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   I. Improving Documentation

   II. Data Provenance

   III. Knowledge Modelling

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Developing Decent Dictionaries

- To better understand data, we can create better documentation standards
  - A meaningful list of questions to be answered about a given dataset

Motivation	Composition	Collection Process	Maintenance
...?	…?	…?	…?

- We have a more complete picture of the dataset, however:
  - Description is still in natural language
  - Description is static
  - Description is not machine readable

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Prospering with Provenance?

- To avoid confusion about semantics, keep track of how our data changes

- Provenance is mainly discussed in two forms:
  - Lineage: What is the data’s history of operations?
  - Where-provenance: What data sources were combined to arrive here?

- Provenance can give us additional info, however:
  - Provenance information won’t warn us of potential errors
  - Provenance information doesn’t ensure initial understanding

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Opportunity for Ontologies?

- Use an ontology as an interlingua for interoperability
  - Allows us to define one ontology and map others to it
  - Requires knowledge modeling experts to maintain

- Ontology Oriented Programming
  - Ontologies integrated into programming languages
  - These tools are not very mature and unstable

- Actual integration varies widely between disciplines & software tools

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    I. Architecture
    II. Knowledge Layer
    III. Typing Layer
    IV. Interface Layer

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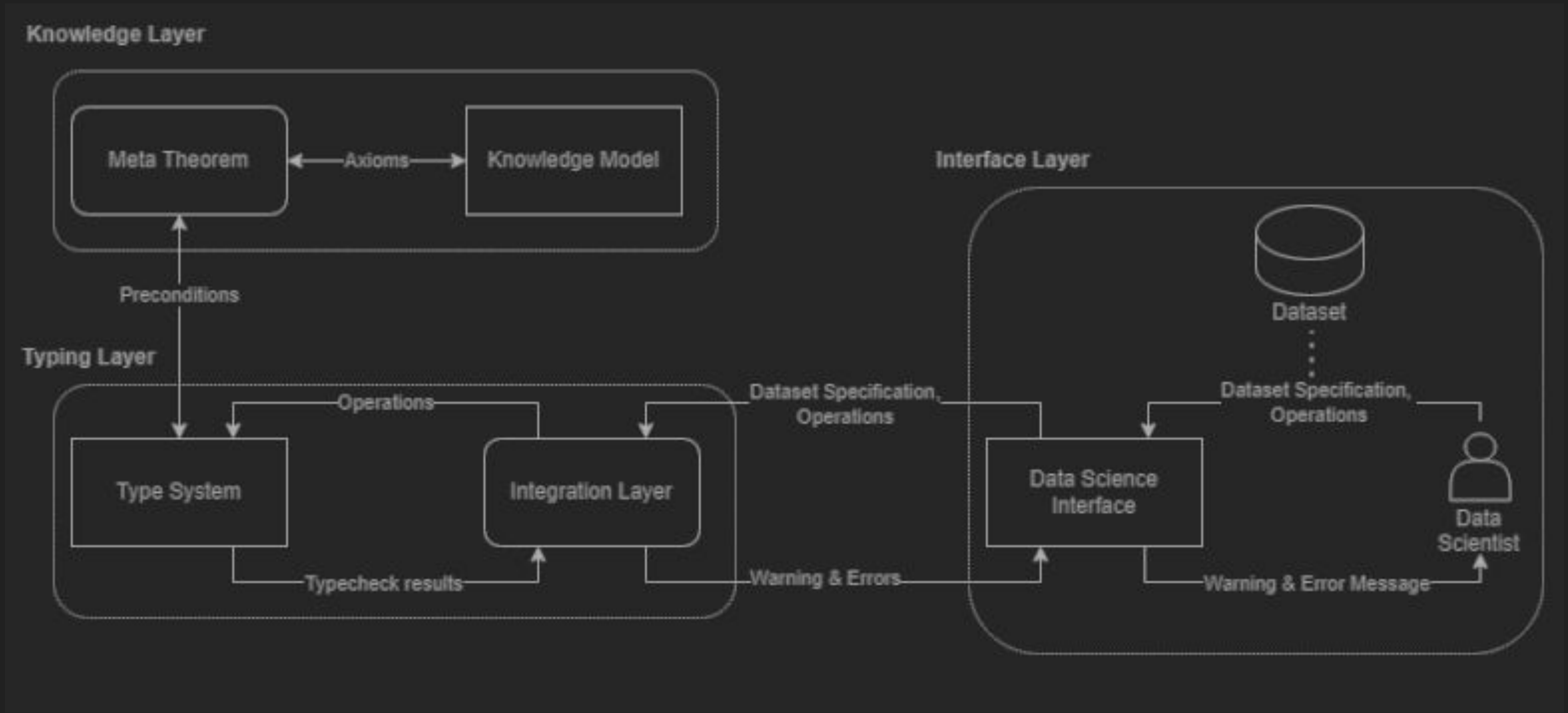
Framework Architecture



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Knowledge Layer

- Formal model of concepts represented in the dataset
- Correspondence between program and logic
- Provides justification for modelling decisions, separate ontological commitments from implementation

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Typing Layer

- Leverage Dependent Typing
  - Construct types which depend on values

- Tuples (m,n) where m < n

$$\sum_{m:\mathbb{N}} \sum_{n:\mathbb{N}} ((m < n) = True)$$

- The type of operations can enforce pre-conditions, post-conditions

Meaningful Types

- Operations enforce relationships between their operands

- Values change after each operation : Provenance-Integrated
    - Averaging populations produces an “Average Population”

```
Plus : List Disjoint Populations -> Population
…

Subtraction : Pop1, Pop2 BothSameKind -> Population
```

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Interface Layer

- Data Scientists should not need to adopt whole new skillsets

- Logic-Based Type System is integrated into data science tools
  - Pandas: meaningful types library
  - Tableau: meaningful types plugin

- Data Scientist specifies the concepts contained in the data
  - Small additional work upfront will pay dividends

Forward-Looking Thoughts

- A complete framework is a big piece of work
- Data Scientists, Type Theorists, and Knowledge Modellers can learn from each other
    - Bridging the gap enriches us all
- Meaningful Data Science is Important
    - Reduce bias
    - Make informed decisions
    - Save lives