Meaningful Datatypes: Ontologically-Sound Dependent Type Systems for Data Science

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The Role of Data Science

Data Science is increasingly important and valuable

It drives important decisions

Understanding data is critical

What's in a (Data) Type?

• All data is representative of real-world phenomena

Important decisions are made based on data scientists' results

• The nuances of the real world are reduced to integers, strings, etc.

1. Why are datatypes problematic for data science?

2. What are my contributions to solving this problem?

3. What is the significance of these contributions?

4. What are the directions for future work?

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 - II. The gaps in current work

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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 Problem Classes

1. Time

2. Mereology

3. Provenance

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Datatype Issues: Time

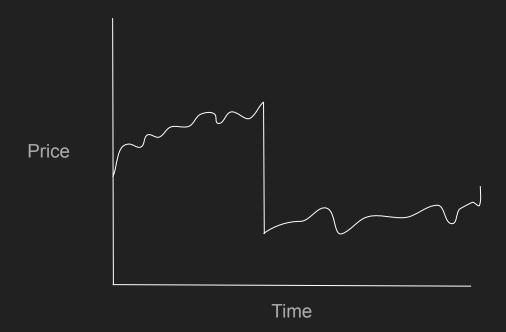
• Time is common and important in most data

• Ex: House Prices

| Date | Average House Price |
|------------|---------------------|
| 1960-05-20 | 12 000 |
| | |
| 2022-01-01 | 850 000 |

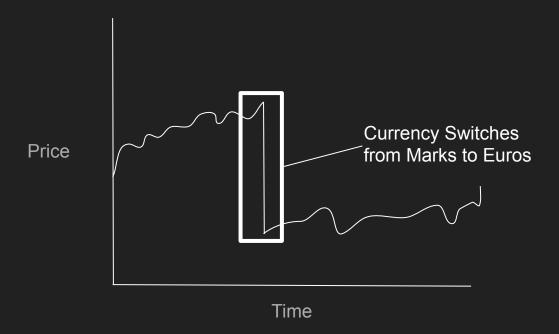
Datatype Issues: Time

Ex: Frankfurt Stock Exchange Quote



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Datatype Issues: Mereology

Mereology in data exists in many different forms

Ex: COVID-19 Vaccination Data

| Date | Fully Vaccinated | % of Eligible Population Fully Vaccinated |
|------------|------------------|---|
| 2021-06-22 | 1 200 000 | 3.5% |
| | | |
| 2021-07-29 | 1 335 000 | 2.6% |
| | | |
| 2022-05-28 | 1 086 100 | 2.2% |

Datatype Issues: Mereology

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Ex: COVID-19 Vaccination Data

| Date | Fully Vaccinated | % of Eligible Population Fully Vaccinated |
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| 2021-06-22 | 1 200 000 | 3.5% |
| Children Become Part of Eligible Population | | |
| 2021-07-29 | 1 335 000 | 2.6% |
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Datatype Issues: Mereology

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| | | |
| 2021-07-29 | 1 335 000 | 2.6% |
| "Fully Vaccinated" definition changes to 3+ doses | | |
| 2022-05-28 | 1 086 100 | 2.2% |

Datatype Problem Classes

1. Time

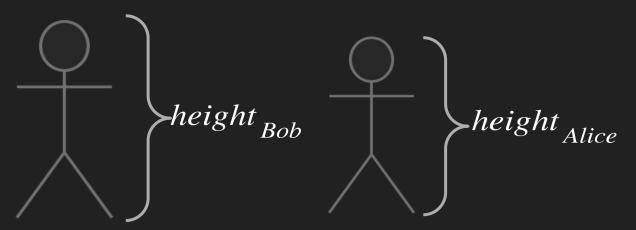
2. Mereology

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Datatype Issues: Provenance

Data science operations transform real-world interpretations

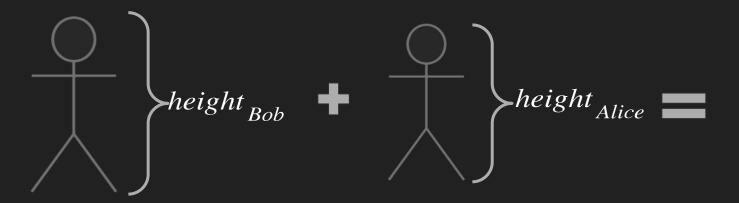
Ex: Height Measurements



Datatype Issues: Provenance

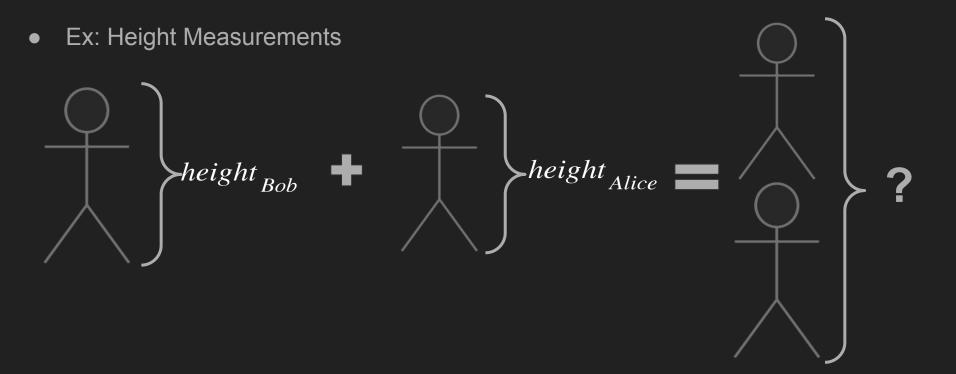
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• Ex: Height Measurements



Datatype Issues: Provenance

Data science operations transform real-world interpretations



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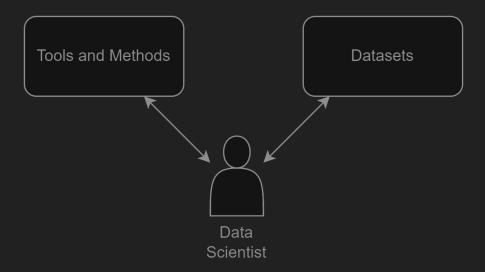
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These approaches supplement datatypes with external knowledge and tools

Applied in informal, ad-hoc, opaque, laborious ways



1. Documentation

2. Provenance Tracking

3. Knowledge Representation

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3. Knowledge Representation

Documentation Standards

- Understand data through documentation standards
 - Provide list of important questions to be answered about the dataset

| Motivation | Composition | Collection Process | Maintenance |
|------------|-------------|-----------------------|-------------|
| ? | ? | ? | ? |

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| 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

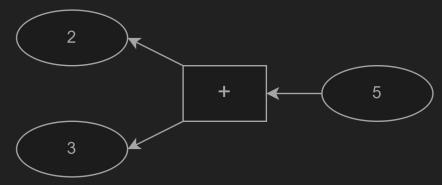
1. Documentation

2. Provenance Tracking

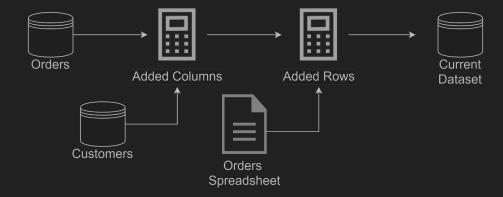
3. Knowledge Representation

Provenance Tracking

• Lineage-Provenance (What, How?)

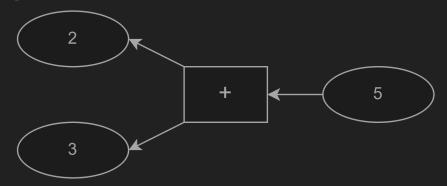


• Where-Provenance (Where From?)

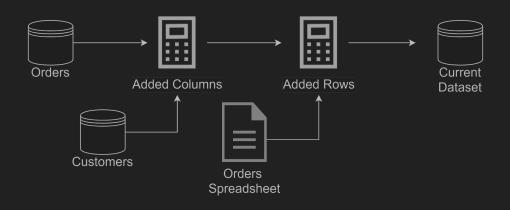


Provenance Tracking

Lineage-Provenance (What, How?)



Where-Provenance (Where From?)



No automatic error detection

 Does not encode real-world semantics

 Human verification still necessary

1. Documentation

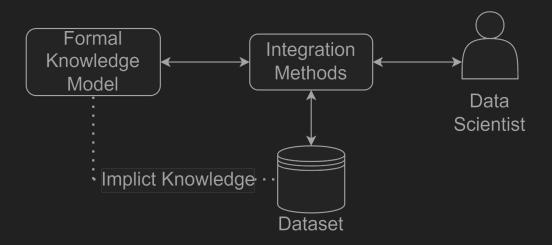
2. Provenance Tracking

3. Knowledge Representation

Knowledge Representation

Diverse knowledge can be represented at many levels of detail

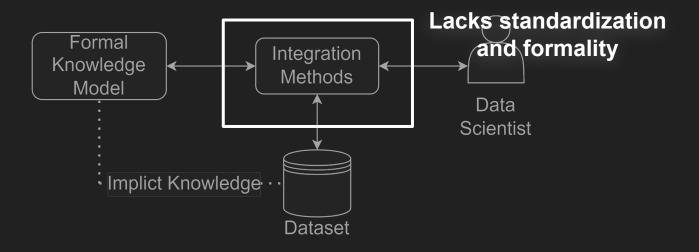
Integration method and role of data science operations is problematic



Knowledge Representation

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Integration method and role of data science operations is problematic



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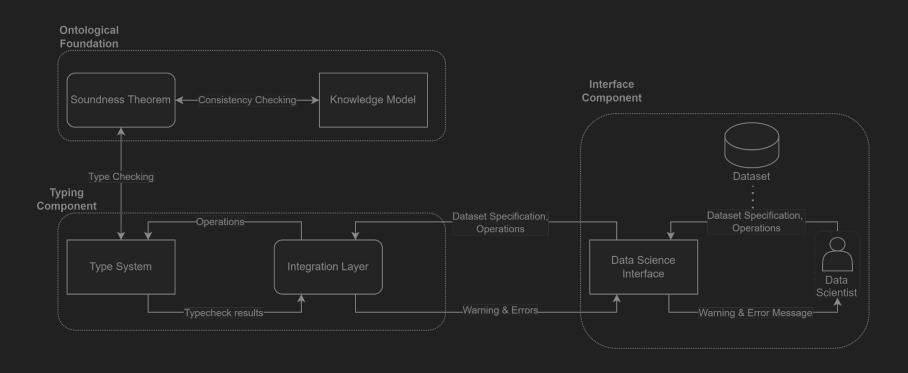
4. What are the directions for future work?

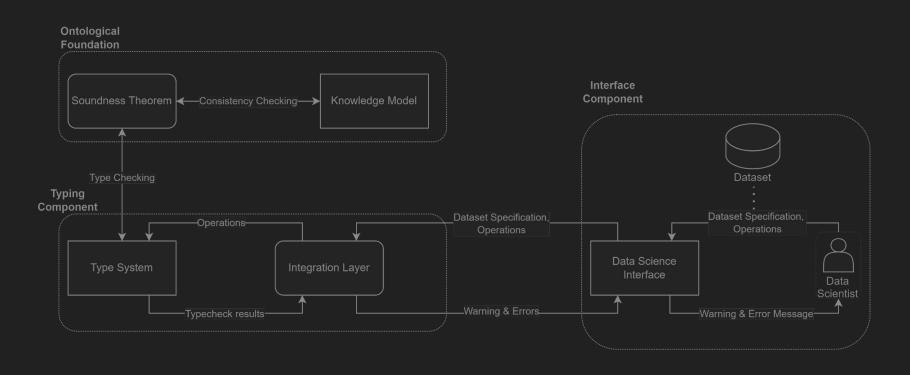
The Meaningful Type Safety Framework (MeTS)

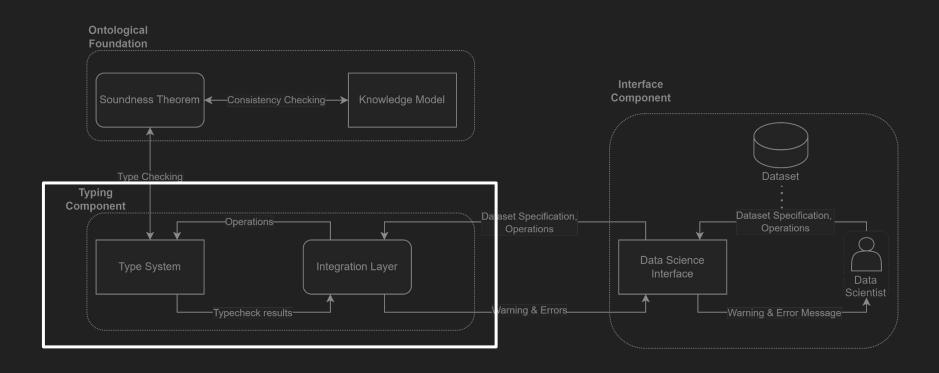
Ontologically-Sound Dependent Type Systems for Data Science

The Meaningful Type Safety Framework (MeTS)

Ontologically-Sound Dependent Type Systems for Data Science







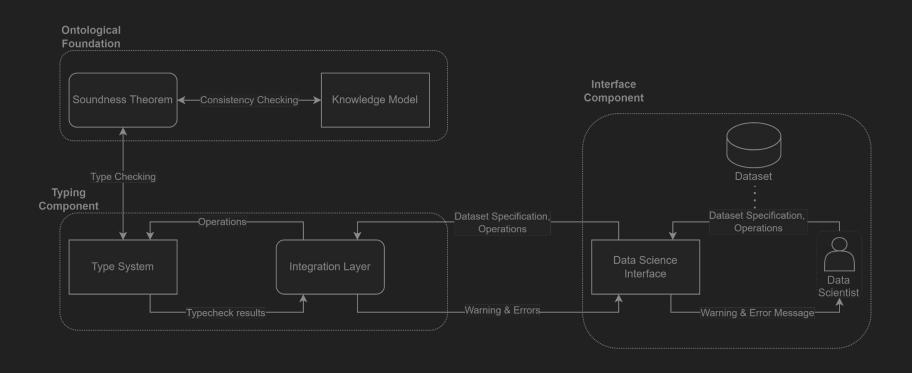
MeTS Type System

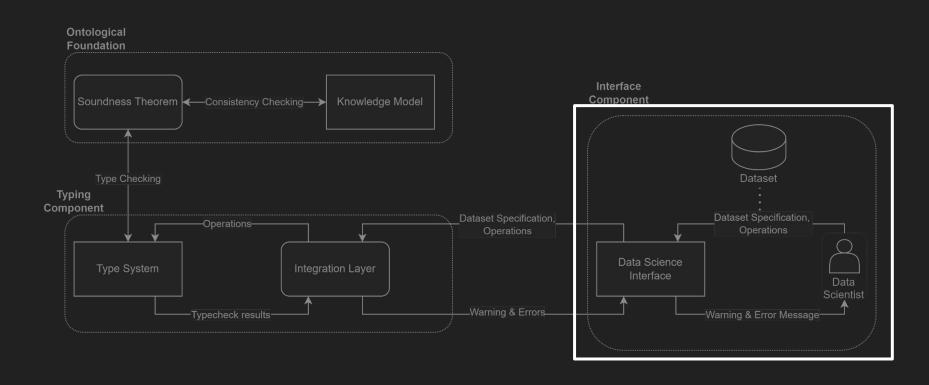
Dependent pair types enforce operation preconditions

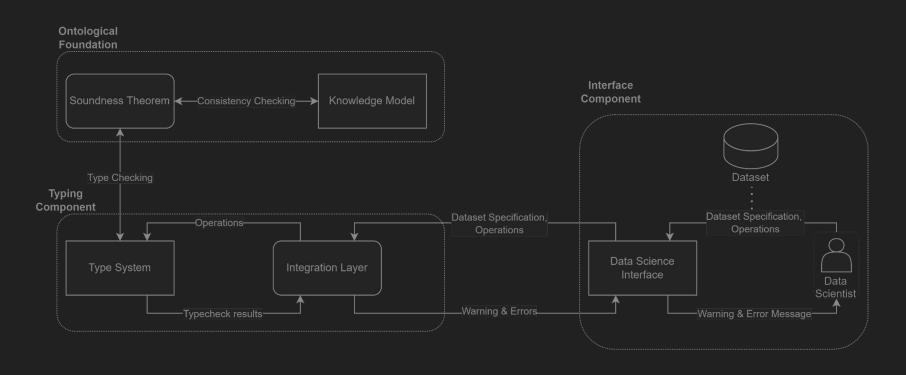
```
RegionSum : List Disjoint Region -> Region
```

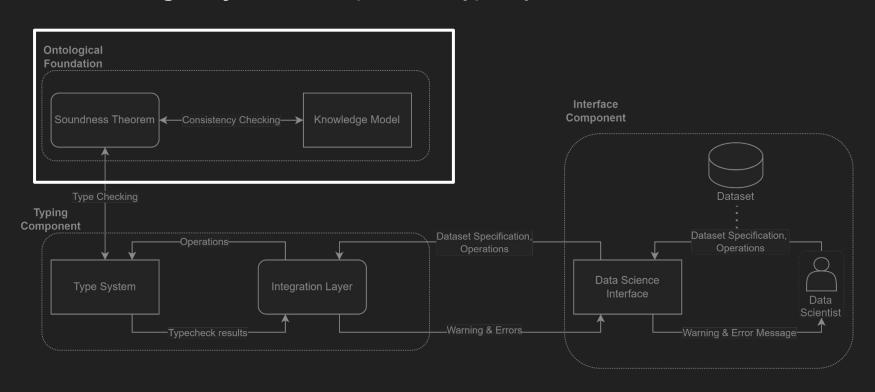
Values change after each operation : Provenance-Integrated

```
PopAvg(operands) = Avg Over operands
```



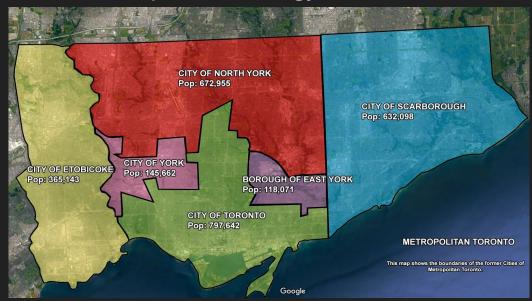






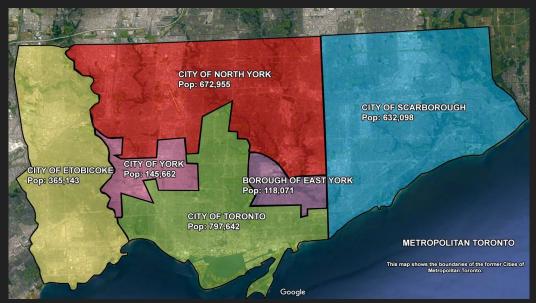
- Represents the fundamental factors of census data
 - Movement of People
 - Crowd mereology
 - Geopolitical occupation
 - Geospatial mereology

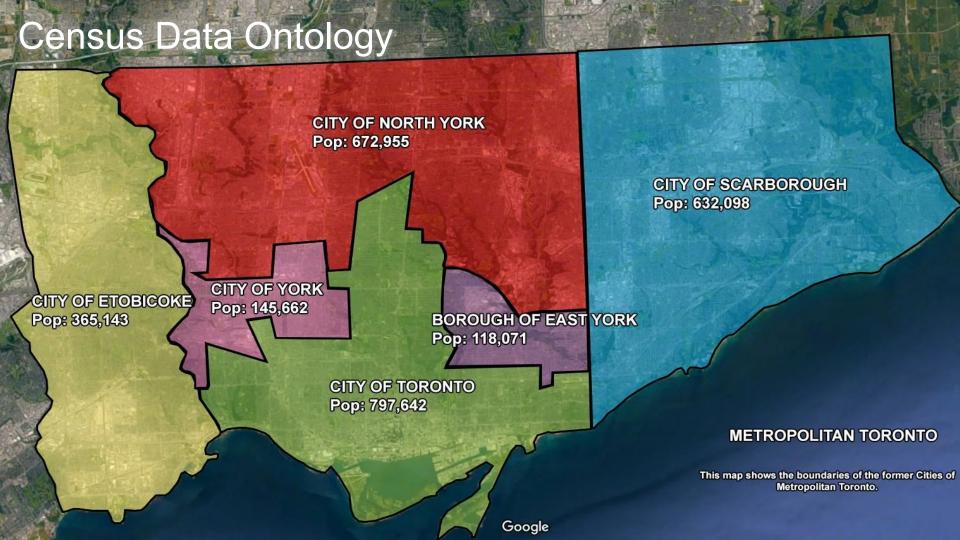
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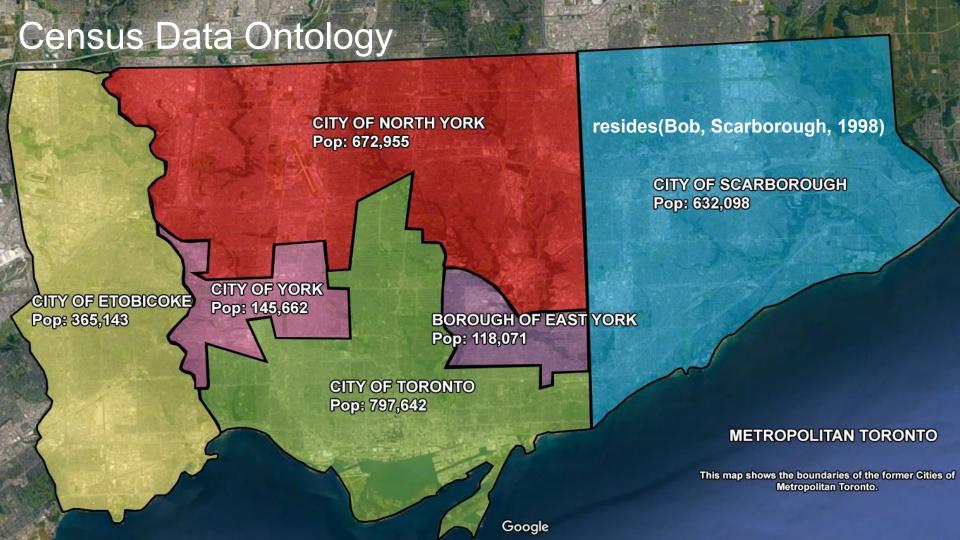


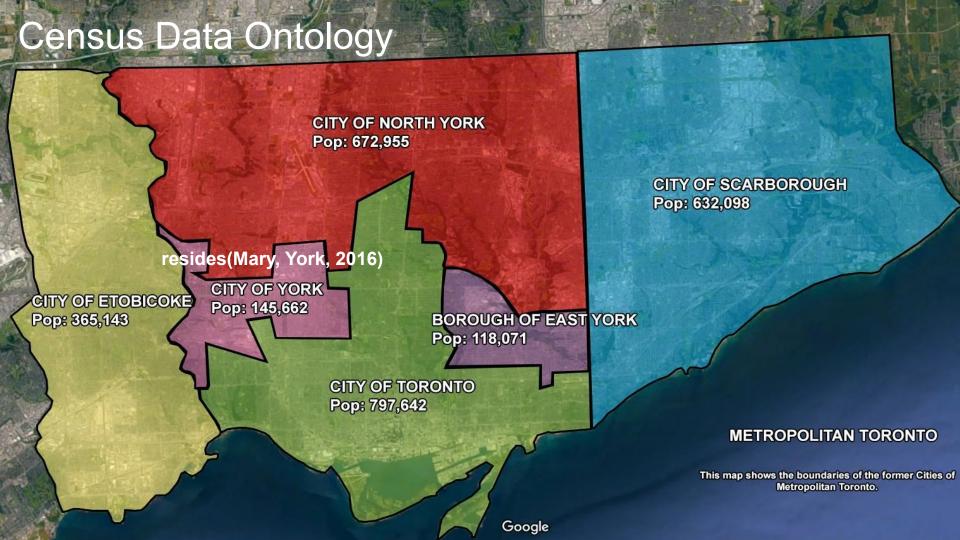
"I live in Toronto" - different interpretations over time

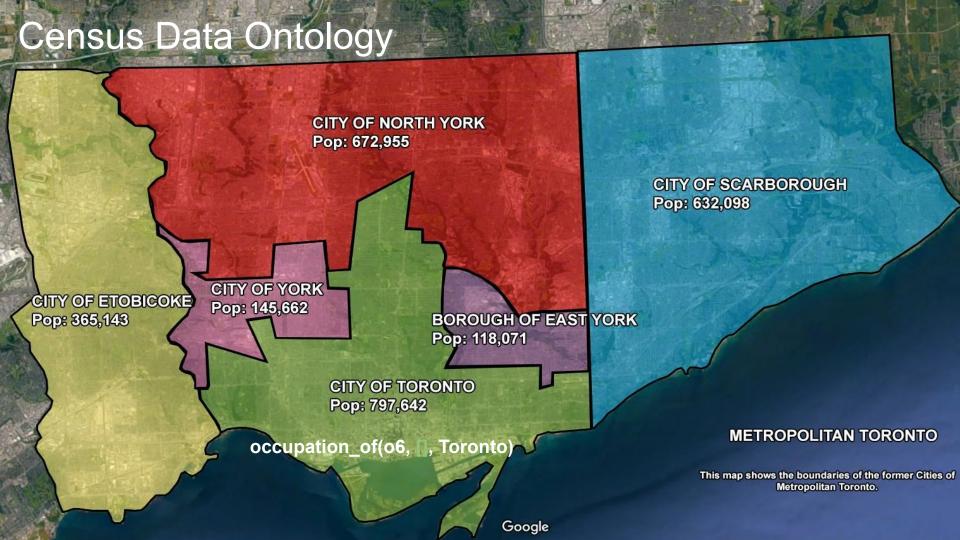
Toronto as a region of land vs the geopolitical entity

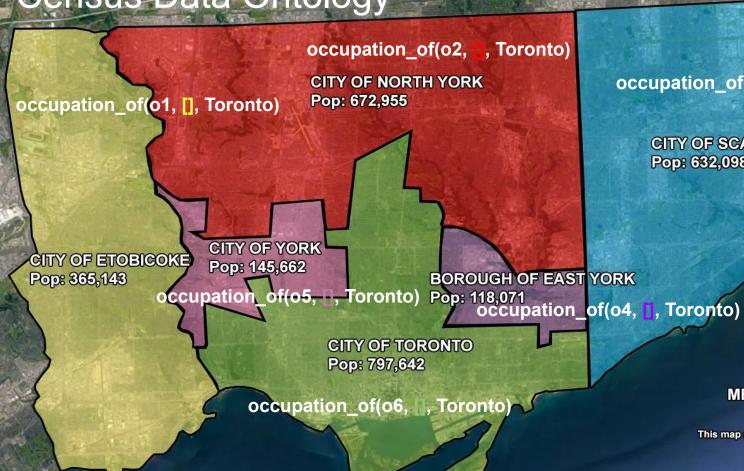












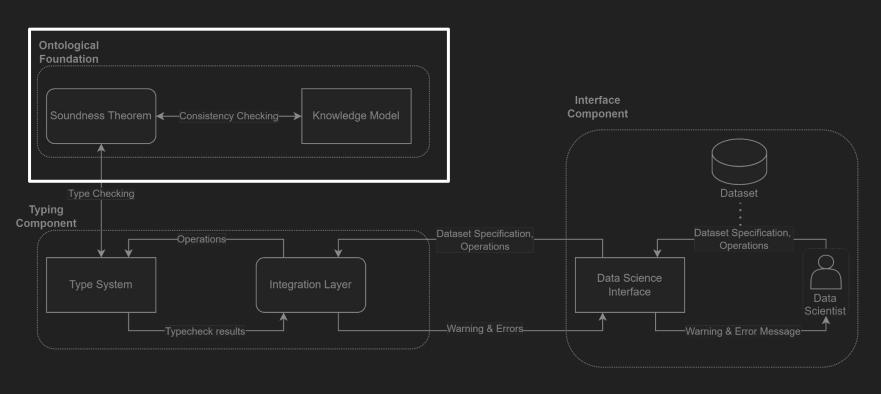
occupation_of(o3, 1, Toronto)

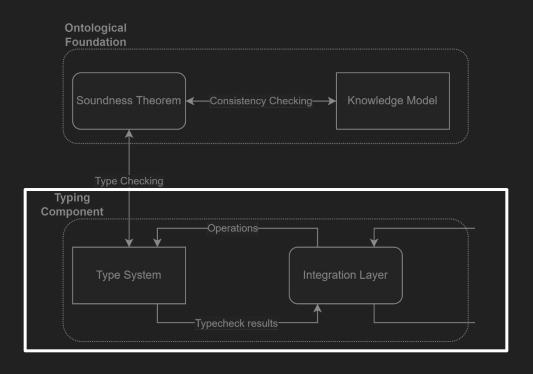
CITY OF SCARBOROUGH Pop: 632,098

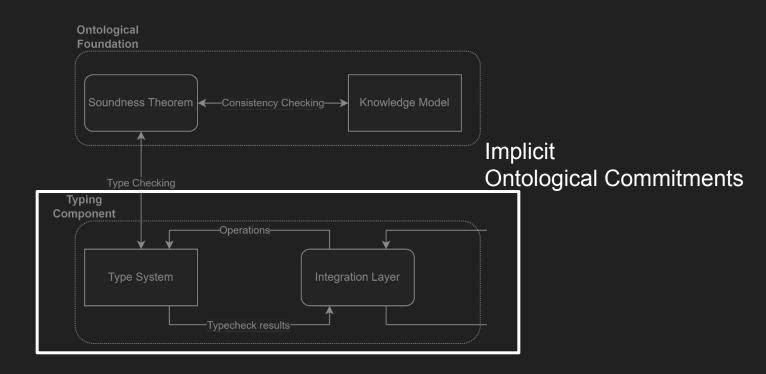
METROPOLITAN TORONTO

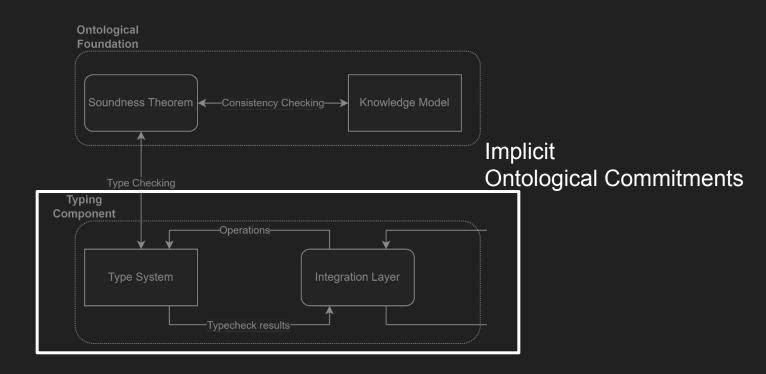
This map shows the boundaries of the former Cities of Metropolitan Toronto.

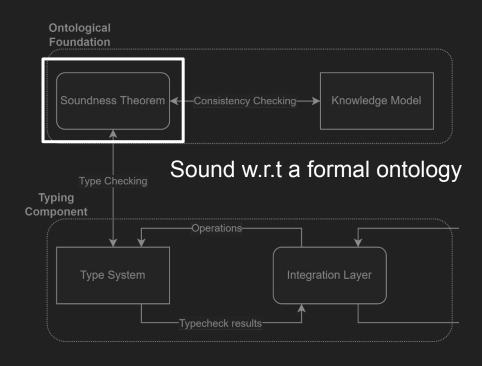
Google











Outline

1. Why are datatypes problematic for data science?

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1. MeTS Framework

2. Census Data Ontology

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1. MeTS Framework

- I. Applies dependent types to model real-world knowledge for data science
- II. Elevates type safety to a meaningful result
- III. Ensures real-world interpretation is upheld throughout the data science pipeline

Census Data Ontology

1. MeTS Framework

2. Census Data Ontology

1. MeTS Framework

2. Census Data Ontology

- I. Models fundamental factors of census data
- II. Provides exceptional expressiveness
- III. Models census data operations

1. MeTS Framework

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- 3. MeTS Soundness Theorem
 - I. Decouples ontological commitments from type system implementation
 - II. Enables increased knowledge sharing
 - III. Creates opportunities for efficient alternative reasoning

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1. Correspondence Theorem

2. Ontology for Data Quantities

- 1. Correspondence Theorem
 - I. Soundness AND completeness
 - II. Requires detailed specification for logic and type systems
 - III. New methods of collaboration

2. Ontology for Data Quantities

1. Correspondence Theorem

2. Ontology for Data Quantities

1. Correspondence Theorem

- 2. Ontology for Data Quantities
 - I. Meta-model of existing ontologies
 - II. Provenance and operation-centric
 - III. Guides development of future ontologies and MeTS

1. Correspondence Theorem

2. Ontology for Data Quantities

1. Correspondence Theorem

2. Ontology for Data Quantities

- I. Minimal change to data scientists workflow
- II. Integrate MeTS into existing data science tools
- III. Enable increased adoption

Thank you!

Questions?

References

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