

The Universal Data Cube

my intended research direction

Curran Kelleher

Outline

- The group I am from – Umass Lowell IVPR
- Relevant past projects
- IVPR's current primary project - Weave
- Data Representation Problems
- The Universal Data Cube
 - I plan to make this my thesis topic
- Data Representation Solutions
- Open discussion

IVPR

IVPR

The Institute for Visualization and Perception Research

Led by Professor Georges Grinstein

At University of Massachusetts Lowell

I've worked there for 4 years on

- The Universal Visualization Platform (UVP)

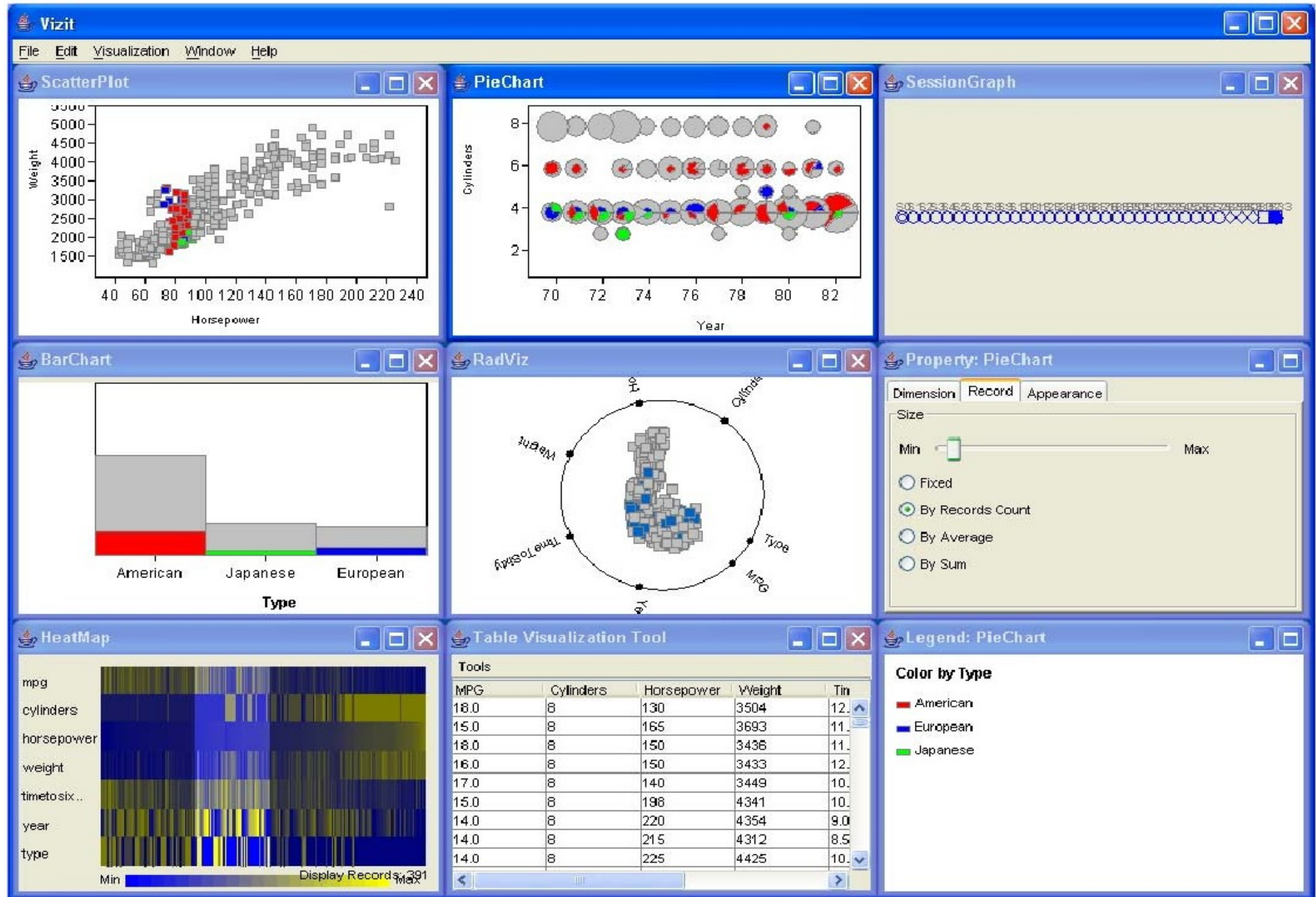
- JyVis

- Weave

- Text Analysis (VAST dataset preprocessing – NER, search)

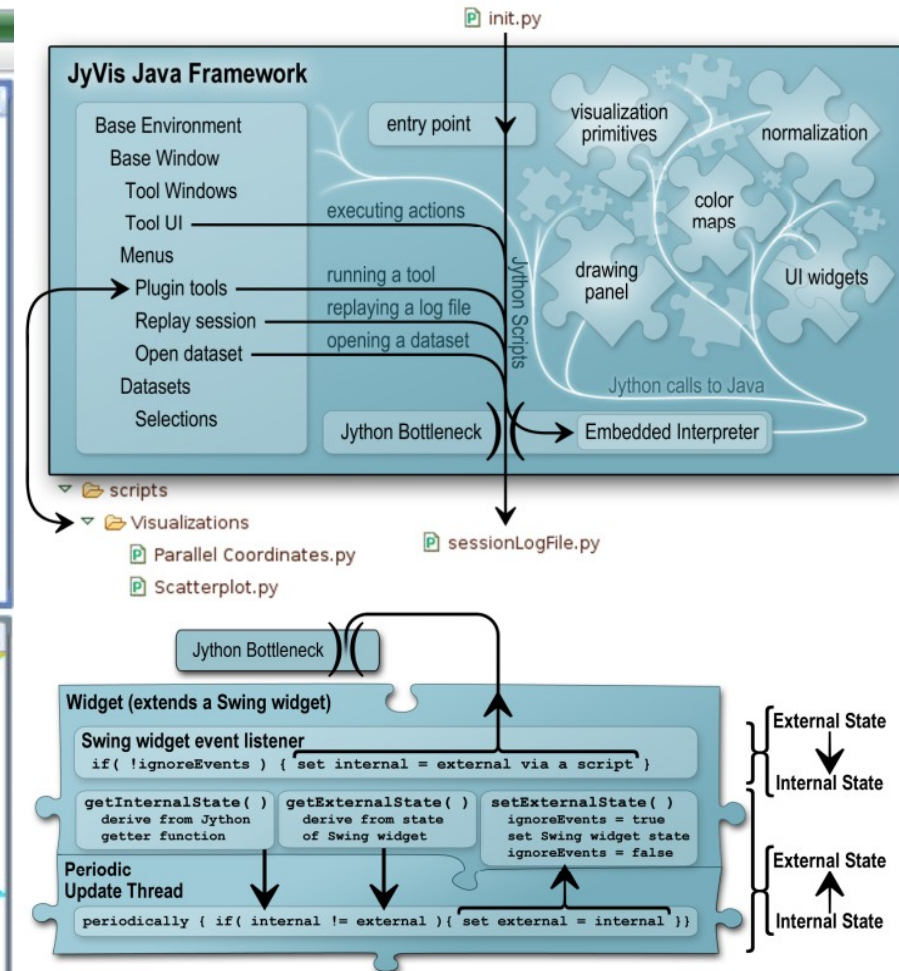
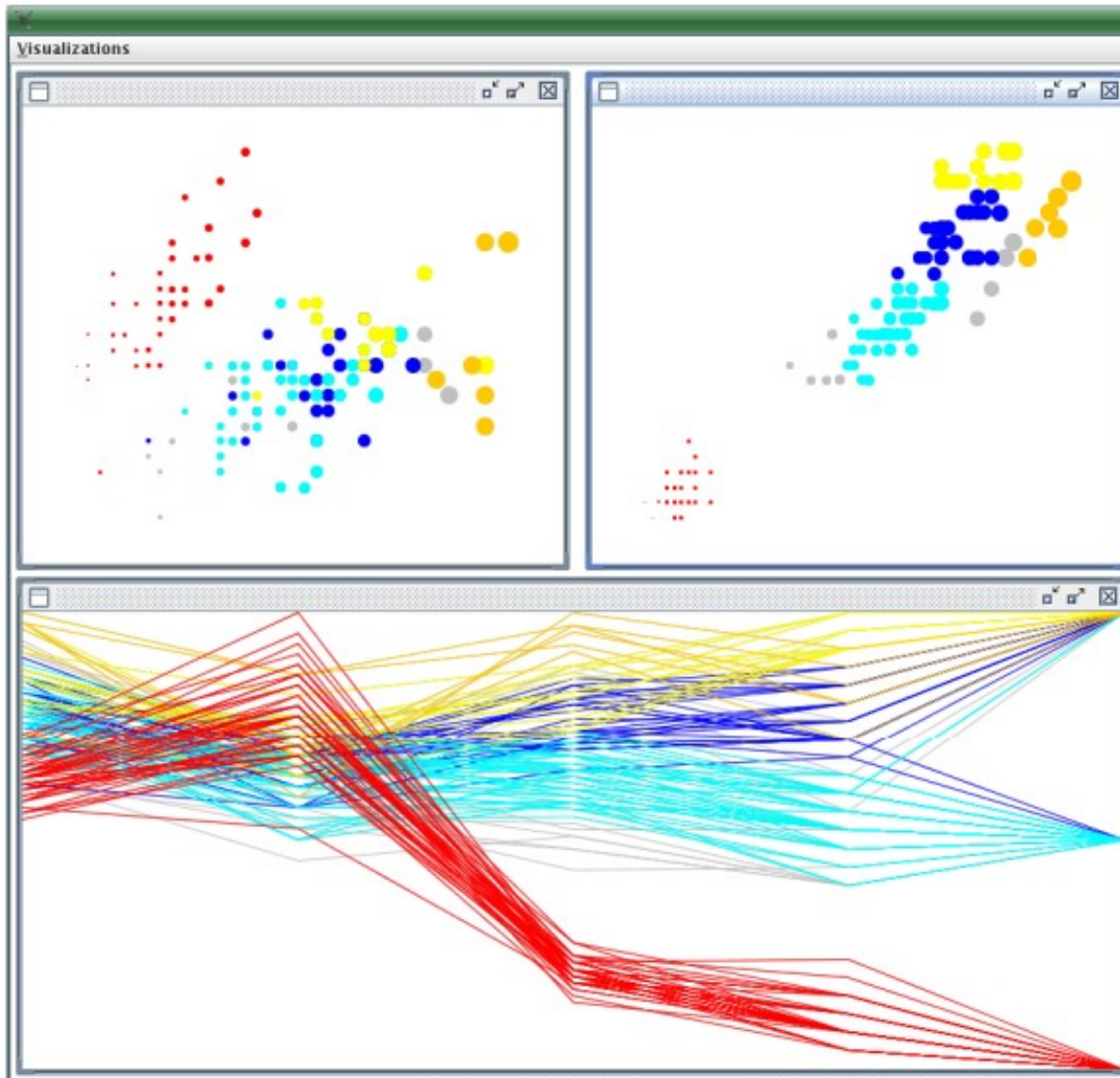
- Miscellaneous smaller projects

The Universal Visualization Platform



Many tools with brushed selection

JyVis



Same functionality as the UVP but with cleaner API, plugin architecture, and session history mechanism

Weave

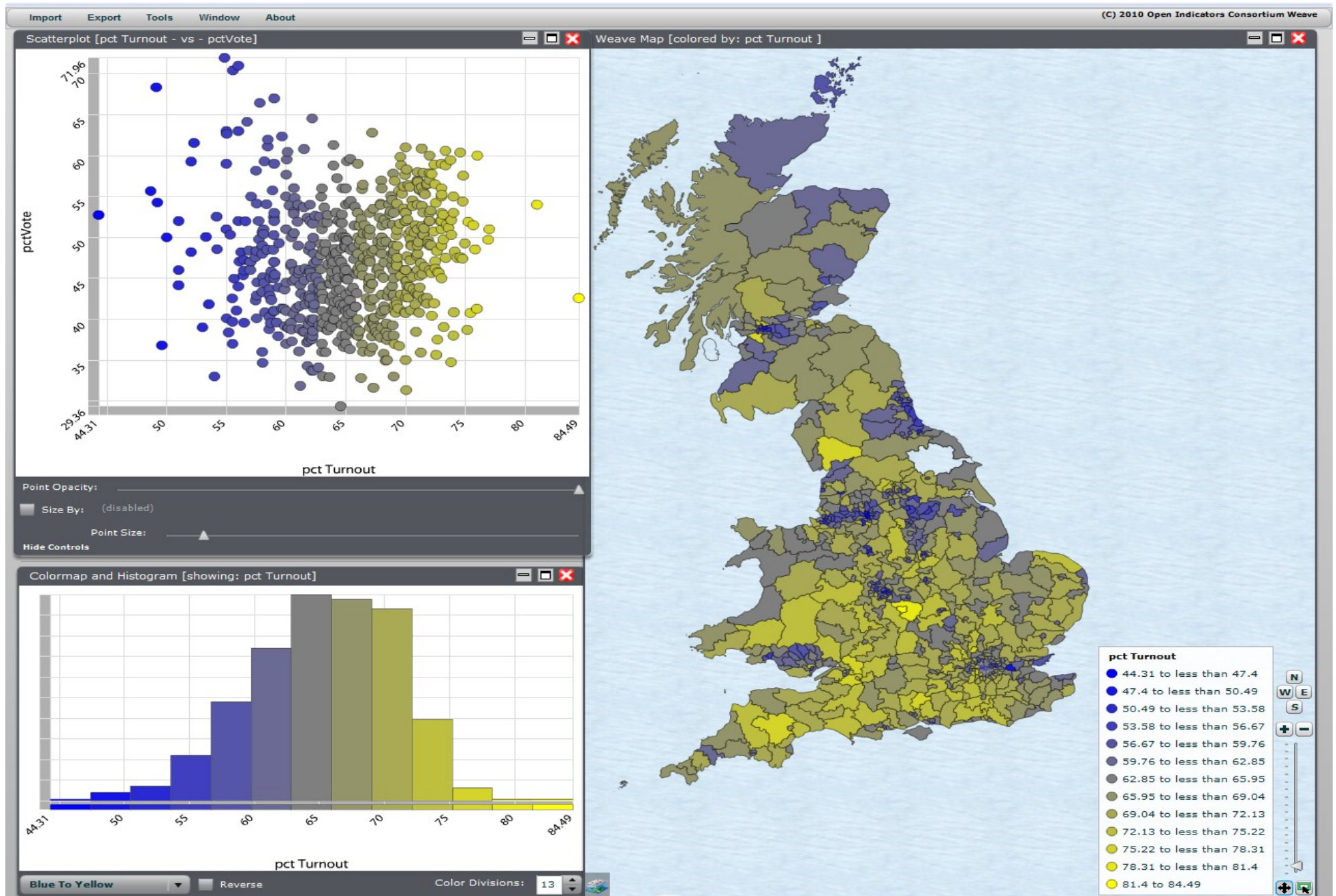
Weave

Web-based Analysis and Visualization Environment

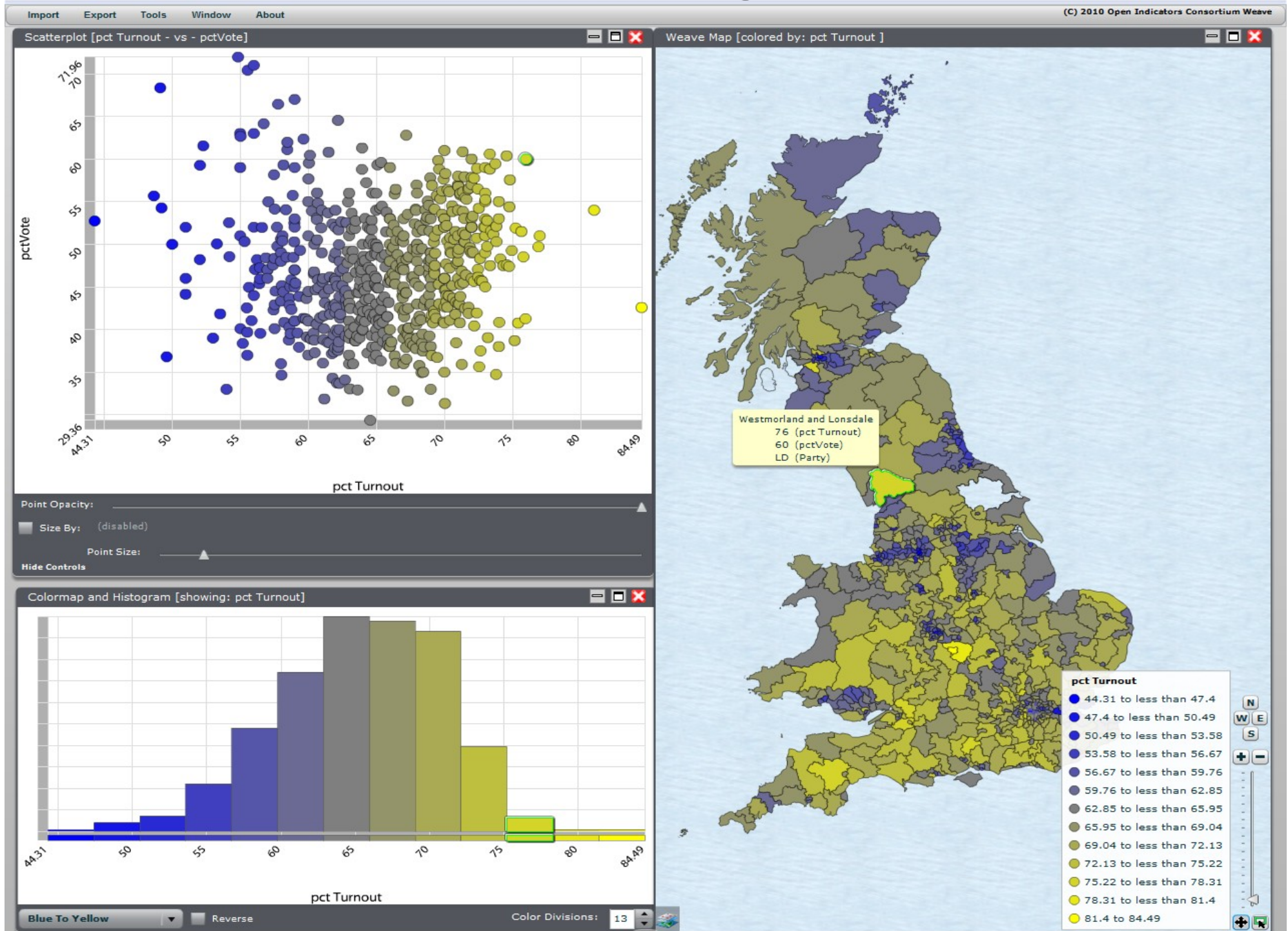
- Developed by the IVPR group
- Funded by the Open Indicators Consortium
- Client written in Adobe Flex
- Server written in Java

British Election Results in May 2010

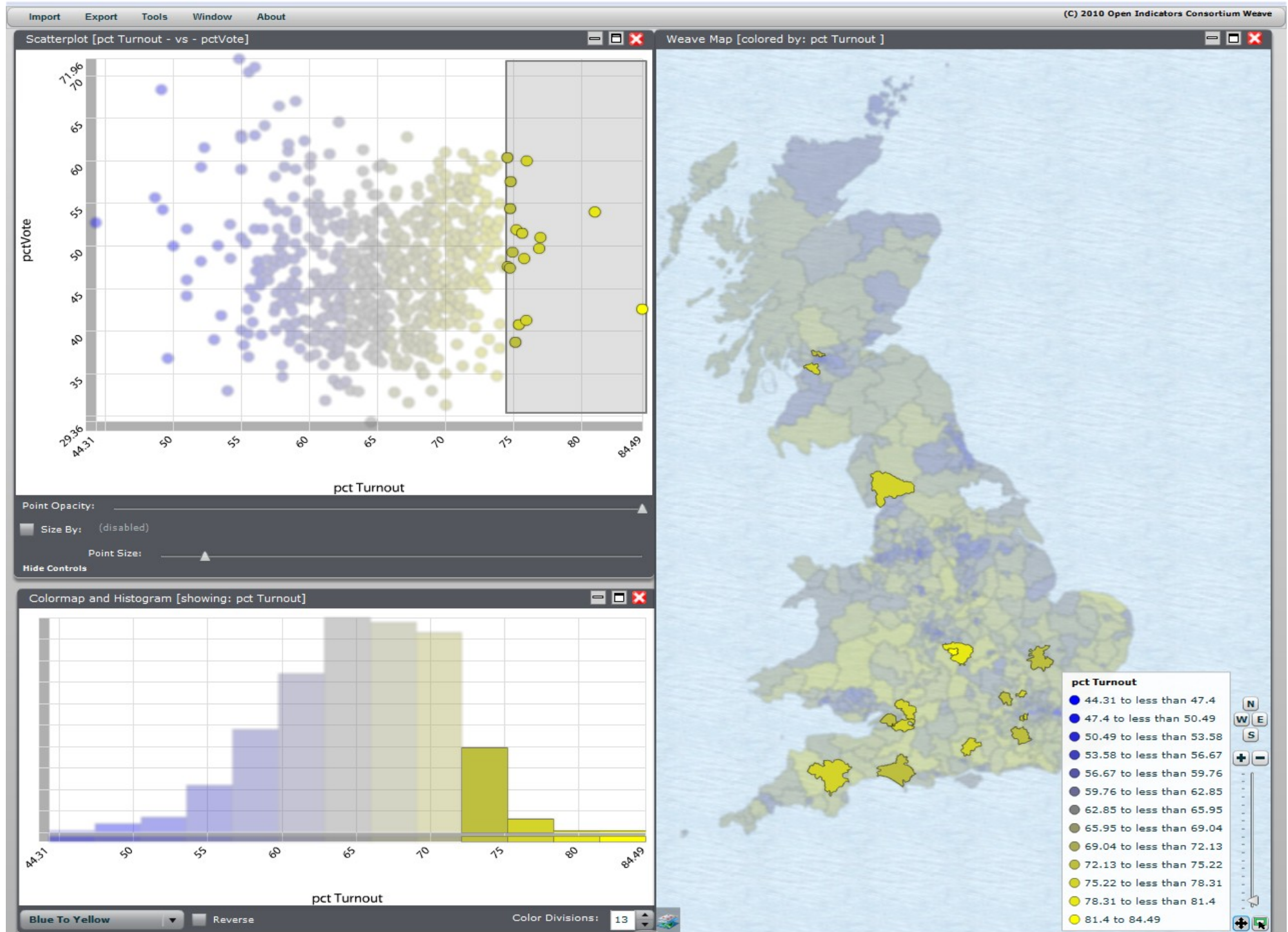
assembled by Jim Giddings



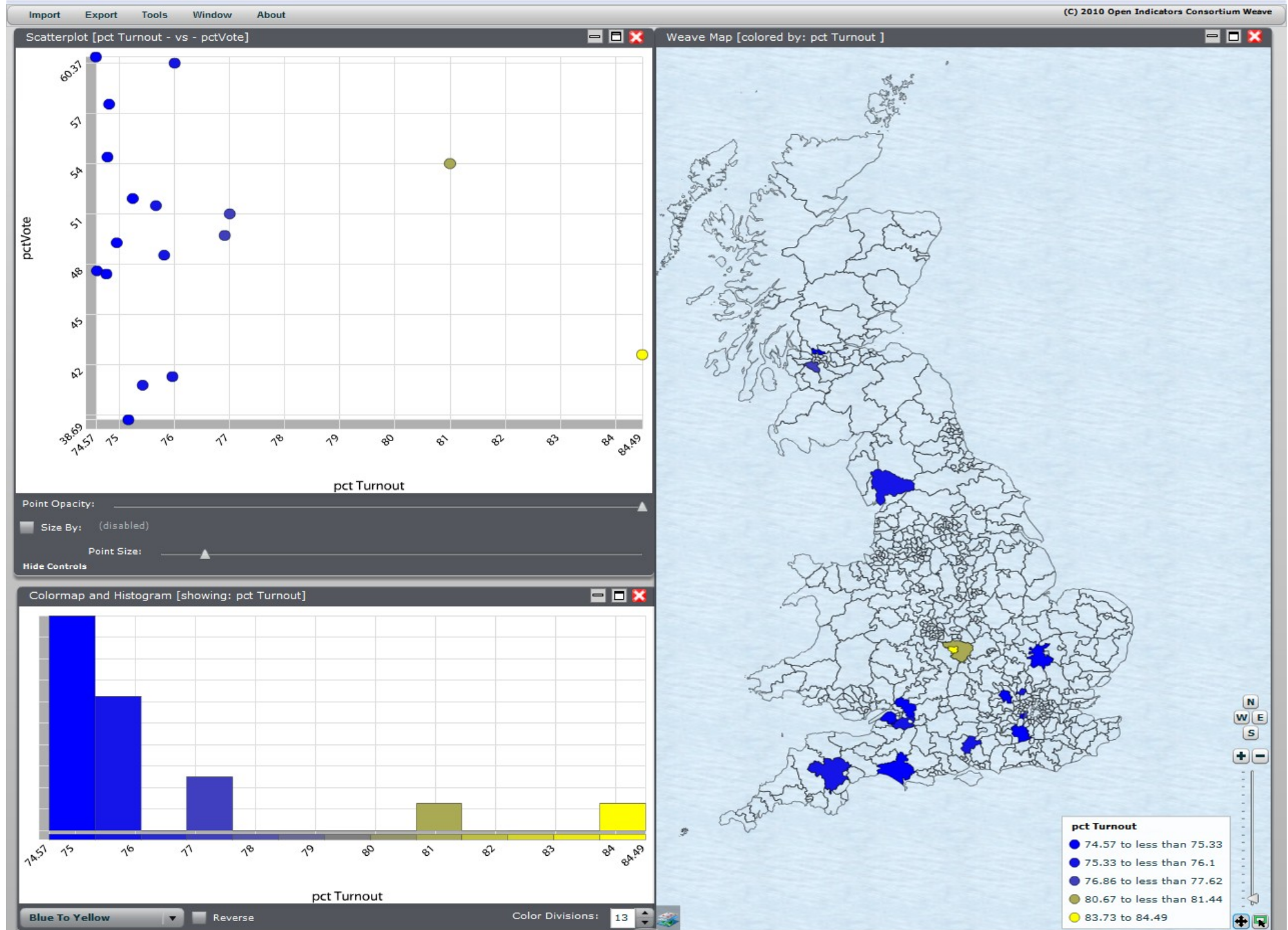
Probing



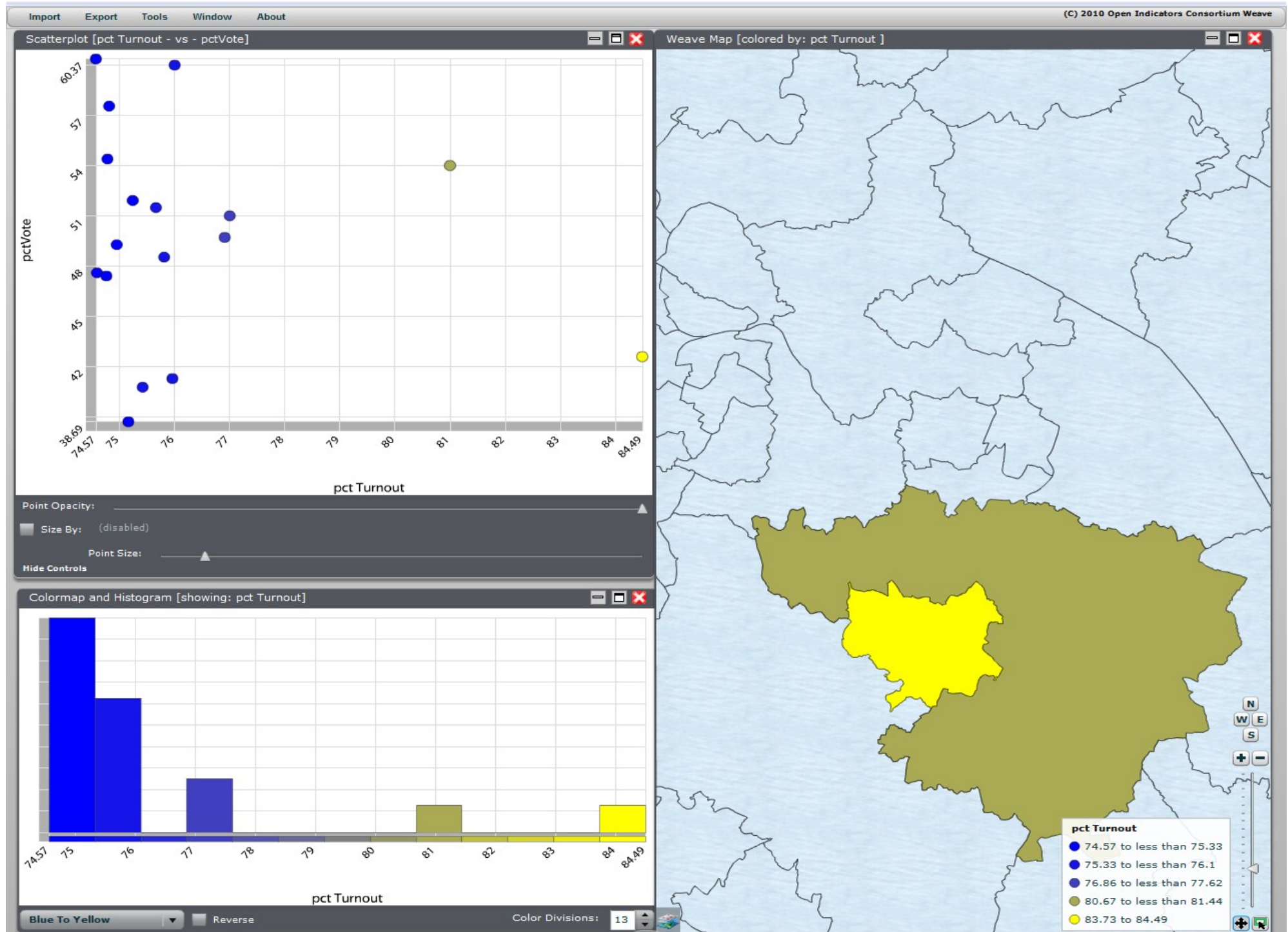
Brushed selection

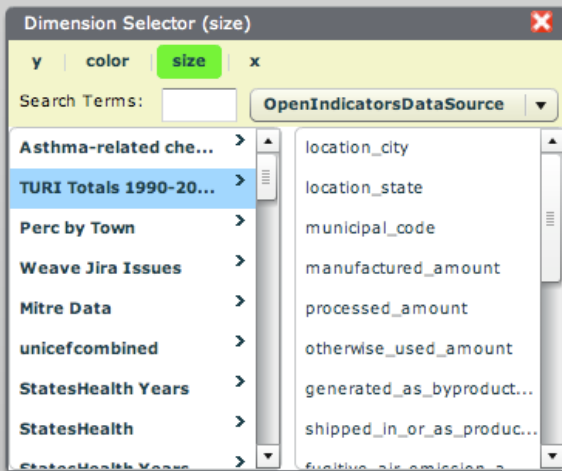
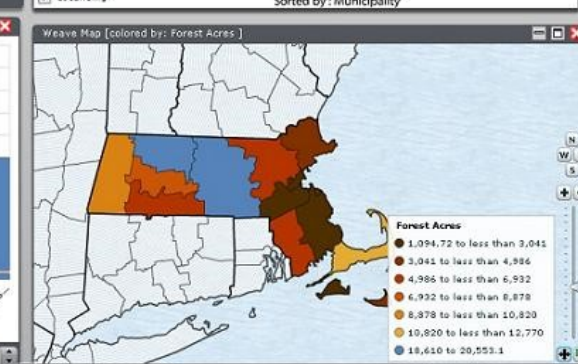
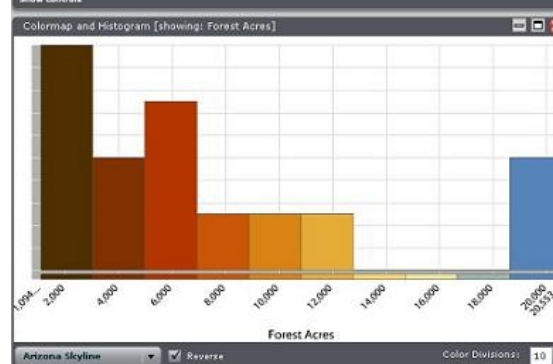
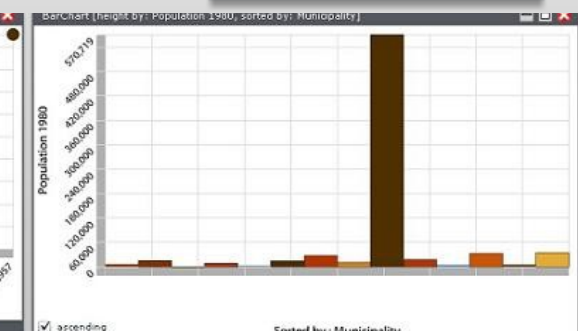
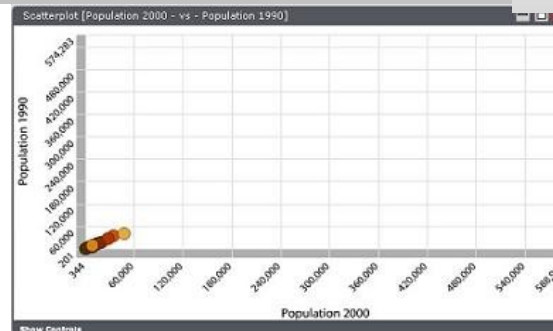
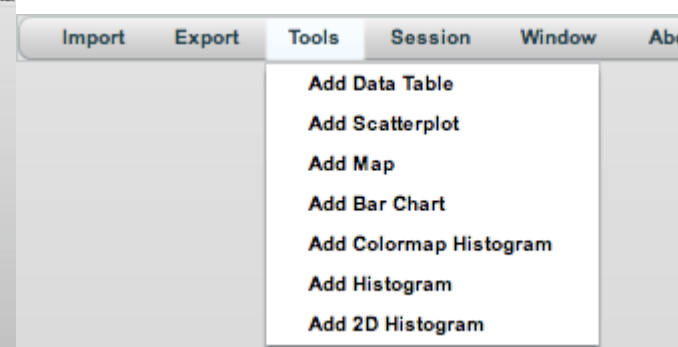
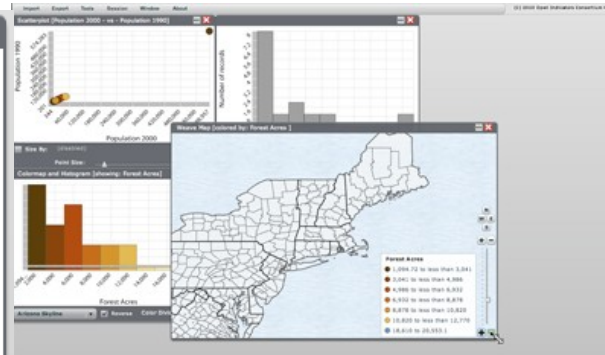
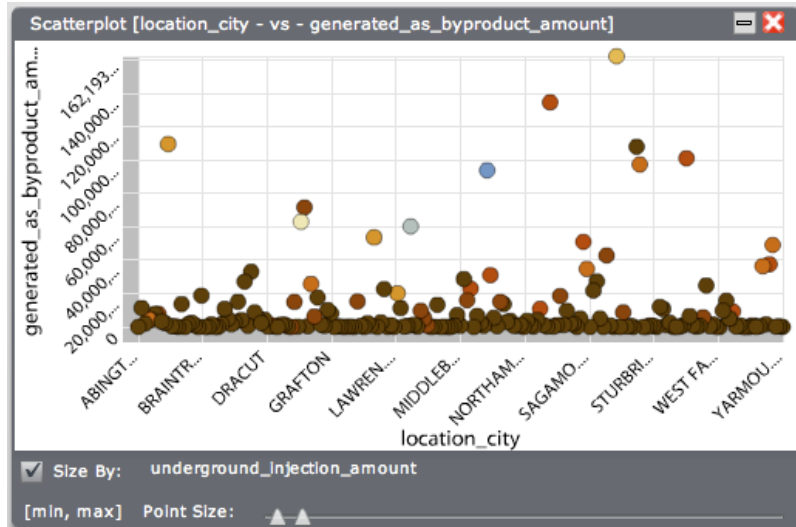
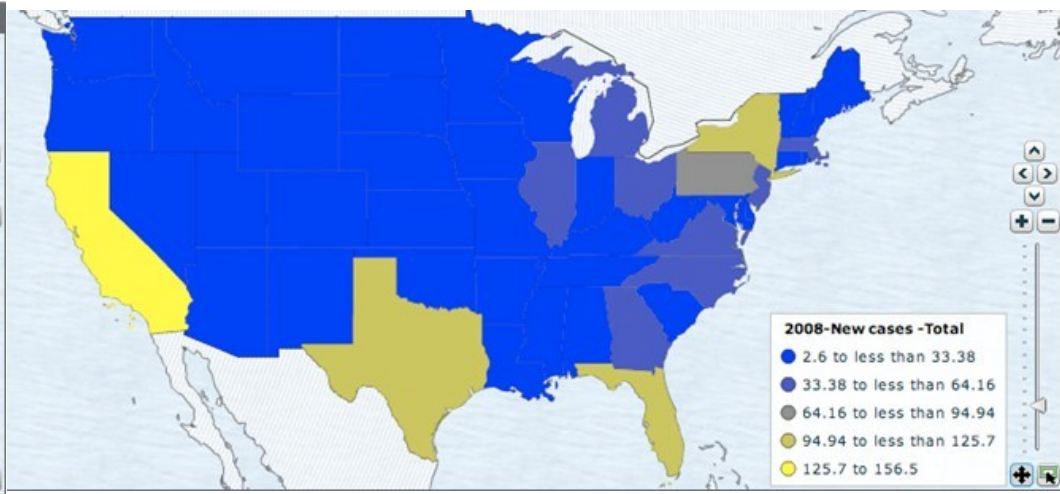
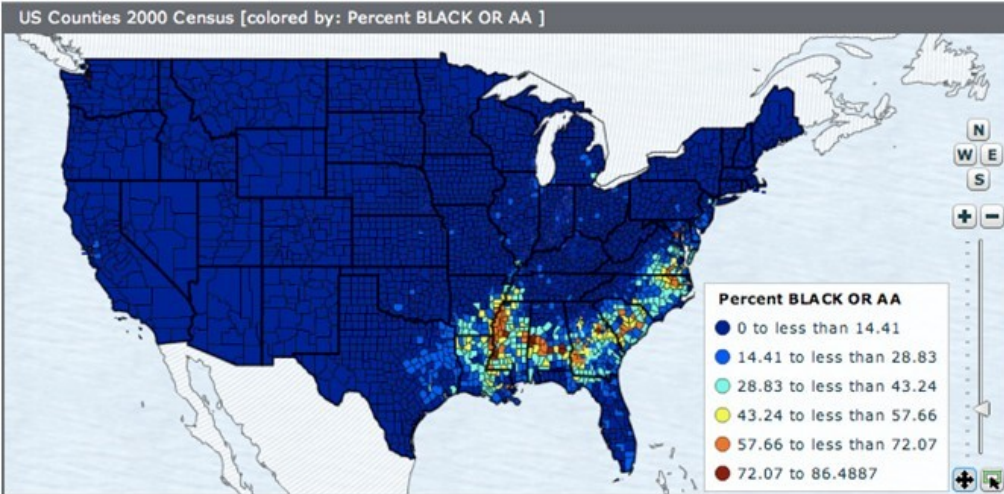


Dynamic filtering



Map navigation





The Weave Data Model

- Data is a collection of columns
 - Multiple simultaneous data sources are supported
- Columns are placed in a category hierarchy
- Columns have names
- Columns have associated key types
- Key type indicates what kind of thing records are
 - For example “US State FIPS code”

Weave Data Model Problems

- Hierarchical key types are not linked
 - US Counties and US States are totally independent
- Key types referring to the same things not linked
 - “US State FIPS” != “US State abbreviations”
- Columns representing the same measure with different units are not compatible
 - Population in thousands not comparable with Population in millions
- No way of resolving when two datasets provide comparable columns
 - Is column “Pop” the same thing in dataset A and B?

Data Cubes

Informative clips from the 2002 paper

Multiscale Visualization Using Data Cubes

by Chris Stolte, Diane Tang, and Pat Hanrahan

2 Related Work

In this section, we review several existing multiscale visualization systems, focusing on how the systems perform both data and visual abstraction. *Data abstraction* refers to transformations applied to the data before being visually mapped, including aggregation, filtering, sampling, or statistical summarization.

Visual abstraction refers to abstractions that change the visual representation (e.g., a circle at an overview level versus a text string at a detailed level), change how data is encoded in the visual attributes of the glyphs (e.g., encoding data in the size and color of a glyph only in detailed views), or apply transformations to the set of visual representations (e.g., combining glyphs that overlap).

Multiscale Visualization in Cartography

Cartography is the source of many early examples of multiscale visualizations. Cartographic generalization [19] refers to the process of generating small scale maps by simplifying and abstracting large scale source material and consists of two steps: (1) combining

data abstractions limited to simple filtering and the ability to add or switch data sources. In addition, these systems primarily only allow for a single viewing path.

Our goal is to develop a system for describing and developing multiscale visualizations that support multiple view paths and both data and visual abstractions. We want to support multiple view paths because many large data sets today are organized using multiple hierarchies that define meaningful levels of aggregation (i.e., details).

Data cubes are a commonly accepted method for abstracting and summarizing relational databases. By representing the database with a data cube, we can switch between different levels of detail using a general mechanism applicable to many different data sets. Combining this general mechanism for performing meaningful data abstractions with traditional visual abstraction techniques enhances our ability to generate abstract views of large data sets, a difficult and challenging problem.

Previously, we presented Polaris, a tool for visually exploring relational databases [15] and later extended for hierarchically struc-

Next, we describe how we can use the data cube to provide a visual representation of the data. We describe how we can use the data cube to provide a visual representation of the data. We describe how we can use the data cube to provide a visual representation of the data.

3.1 Data Abstraction: Data Cubes

Not only are data cubes widely used, but they also provide a powerful mechanism for performing data abstraction that we can leverage. Specifically, data cubes quickly provide summaries of the underlying data at different meaningful levels of detail, rather than arbitrary summarizations such as aggregating every two records. This goal is achieved by building a lattice of data cubes to represent the data at different levels of detail according to a semantic hierarchy and providing mechanisms for data summarizing each cube. We first describe an individual data cube before describing the lattice.

Data cubes categorize information into two classes: dimensions and measures, corresponding to the independent and dependent

variables, respectively. For example, U.S. states are a dimension, while the population of each state is a measure. Within a cube, the data is abstractly structured as an n-dimensional data cube. Each axis corresponds to a dimension in the data cube and consists of every possible value for that dimension. For example, an axis corresponding to states would have fifty values, one for each state. Every "cell" in the data cube corresponds to a unique combination of values for the dimensions. For example, if we had two dimensions, State and Product, then there would be a cell for every unique combination of the two (e.g., one cell each for (California, Oranges), (California, Coffee), (Florida, Oranges), (Florida, Coffee), etc.). Each cell contains one value per measure of the data cube; e.g., if we wanted to know about product production and consumption, then each cell would contain two values, one for the number of products of each type consumed in that state, and one for the number of products of each type produced in that state.

Thus far, we have considered dimensions to be flat structures. However, most dimensions have a hierarchical structure. For exam-

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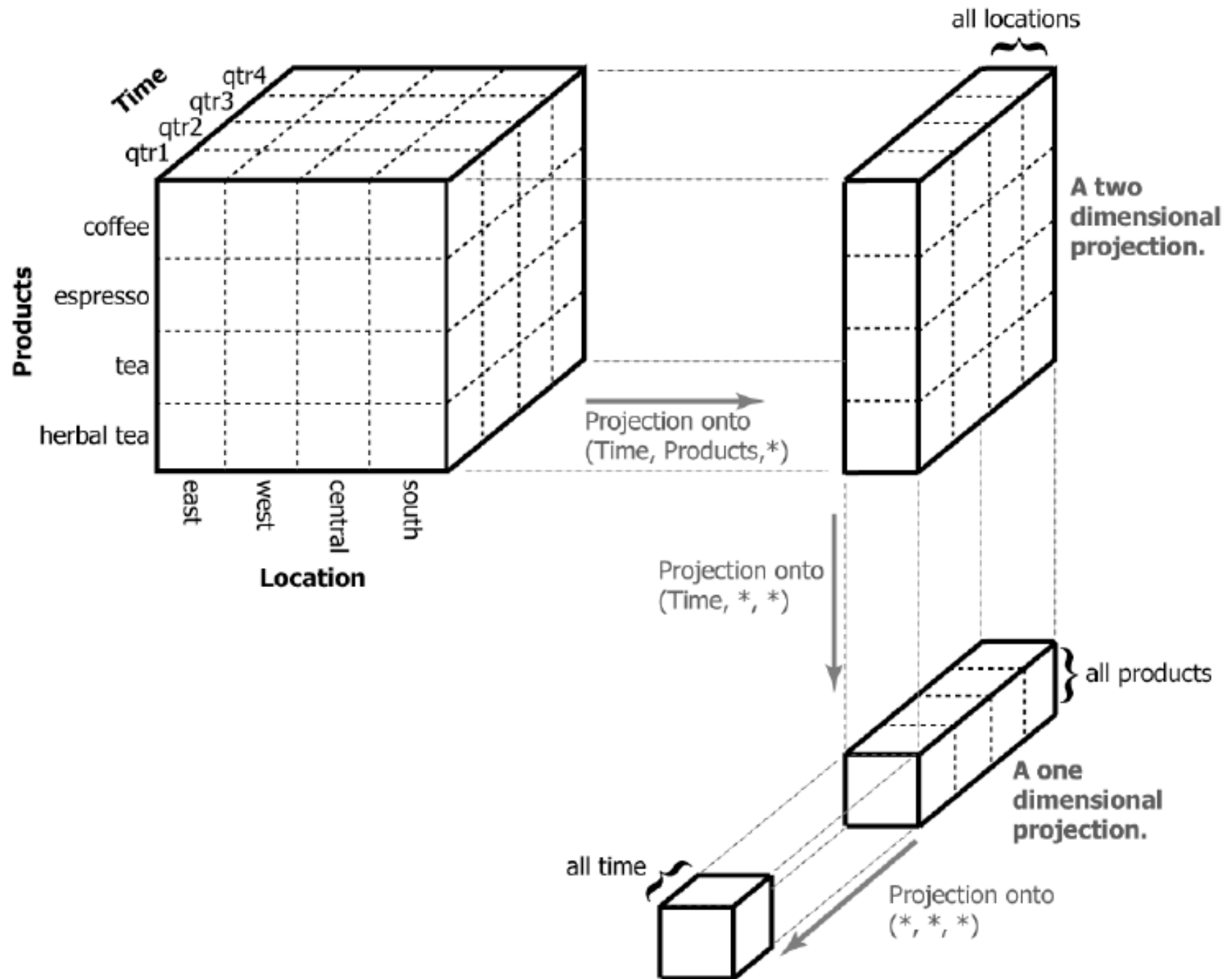
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Thus far, we have considered dimensions to be flat structures. However, most dimensions have a hierarchical structure. For example, the dimension of U.S. states can be broken down into counties, cities, and zip codes.

Projecting a three dimensional data cube



Hierarchical Data Cubes

Thus far, we have considered dimensions to be flat structures. However, most dimensions have a hierarchical structure.

For example, rather than having a single dimension "state", we may have a hierarchical dimension "location" that has levels for country, state, and county. If each dimension has a hierarchical structure, then the data must be structured as a lattice of data cubes, where each cube is defined by the combination of a level of detail for each dimension.

Data abstraction in this model means choosing a meaningful summary of the data. Choosing a data abstraction corresponds to choosing a particular projection in this lattice of data cubes: (a) which dimensions we currently consider relevant and (b) the appropriate level of detail for each relevant dimensional hierarchy. Specifying the level of detail identifies the cube in the lattice, while the relevant dimensions identifies which projection (from a dimension down to the number of relevant dimensions) of that cube is needed. Figure 1 shows a simple lattice and projection.

While identifying a specific projection in the data cube corresponds to specifying the desired data abstraction of the raw data, in

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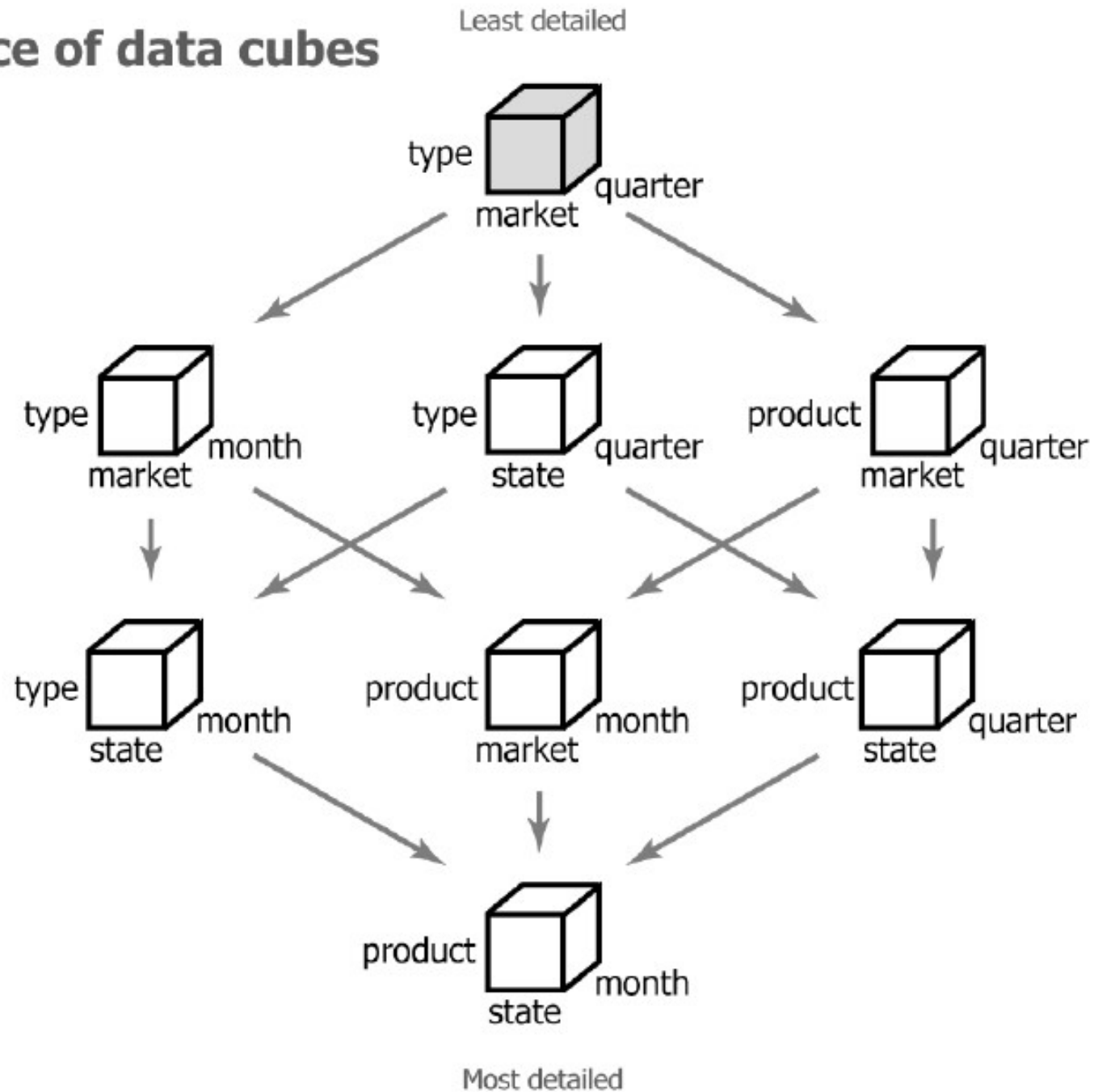
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While identifying a specific projection in the data cube corresponds to specifying the desired data abstraction of the raw data, in multiscala visualizations we need to specify both the data and visual abstractions. Both sets of information are contained in a *thematic*

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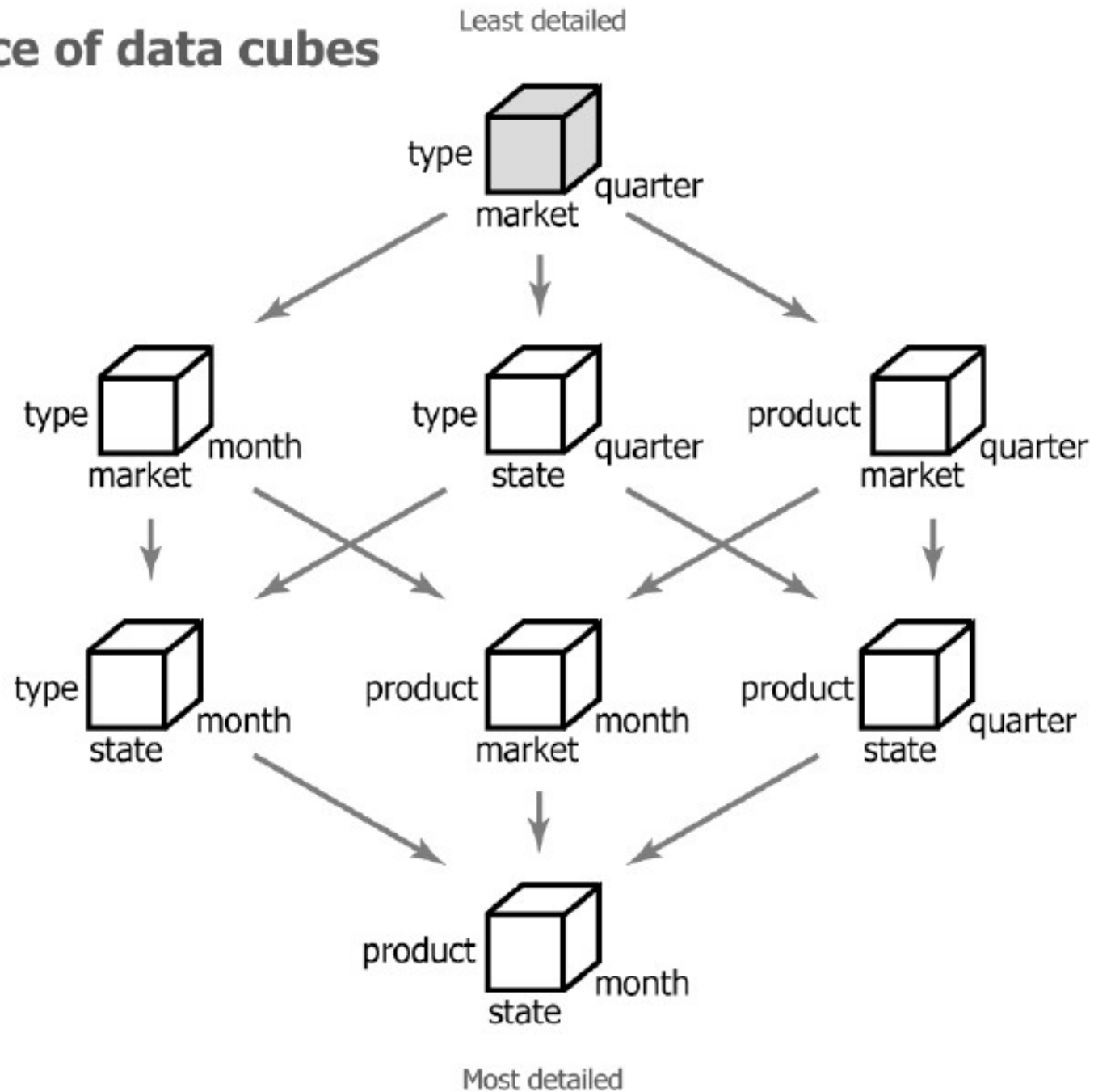
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The lattice of data cubes



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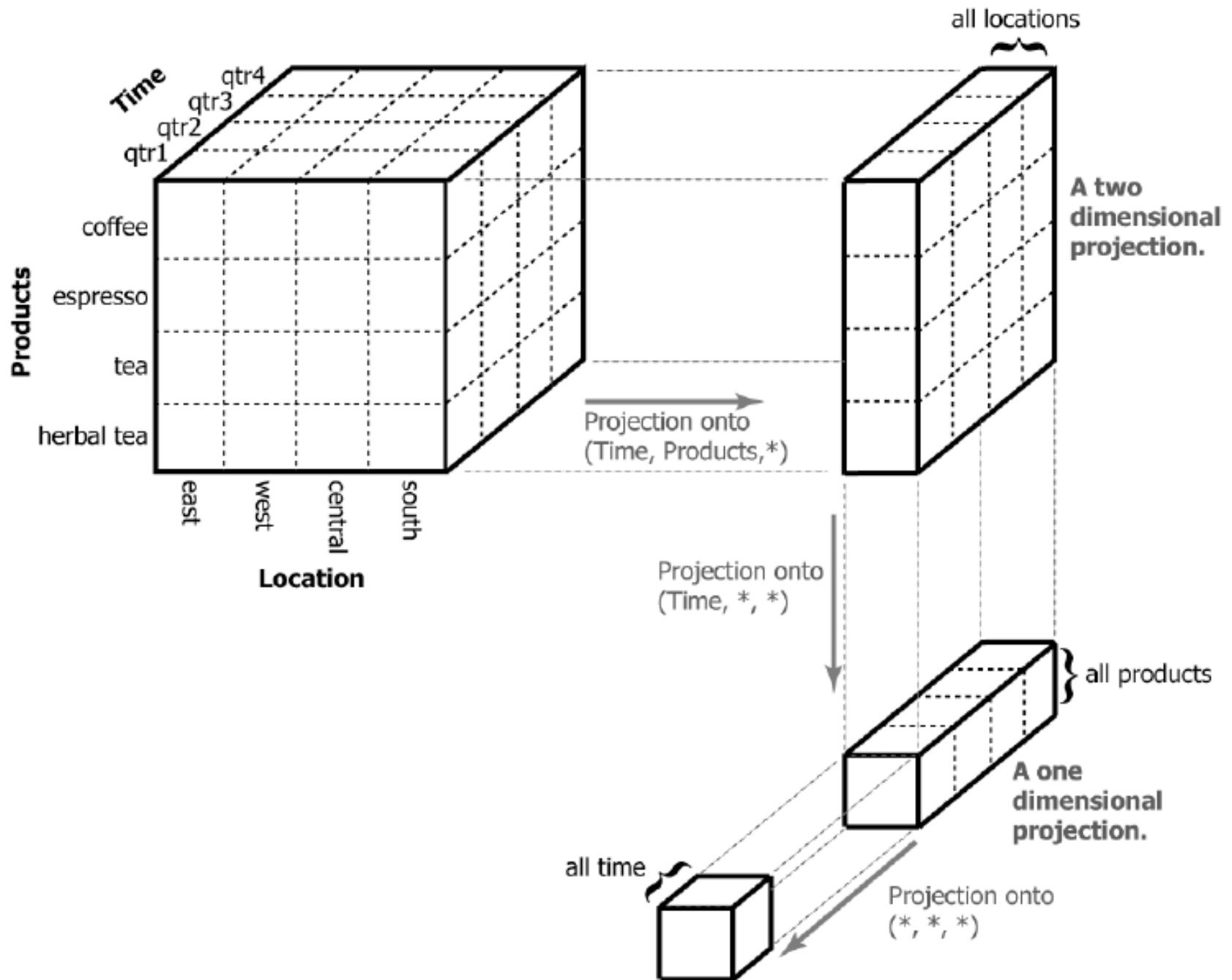
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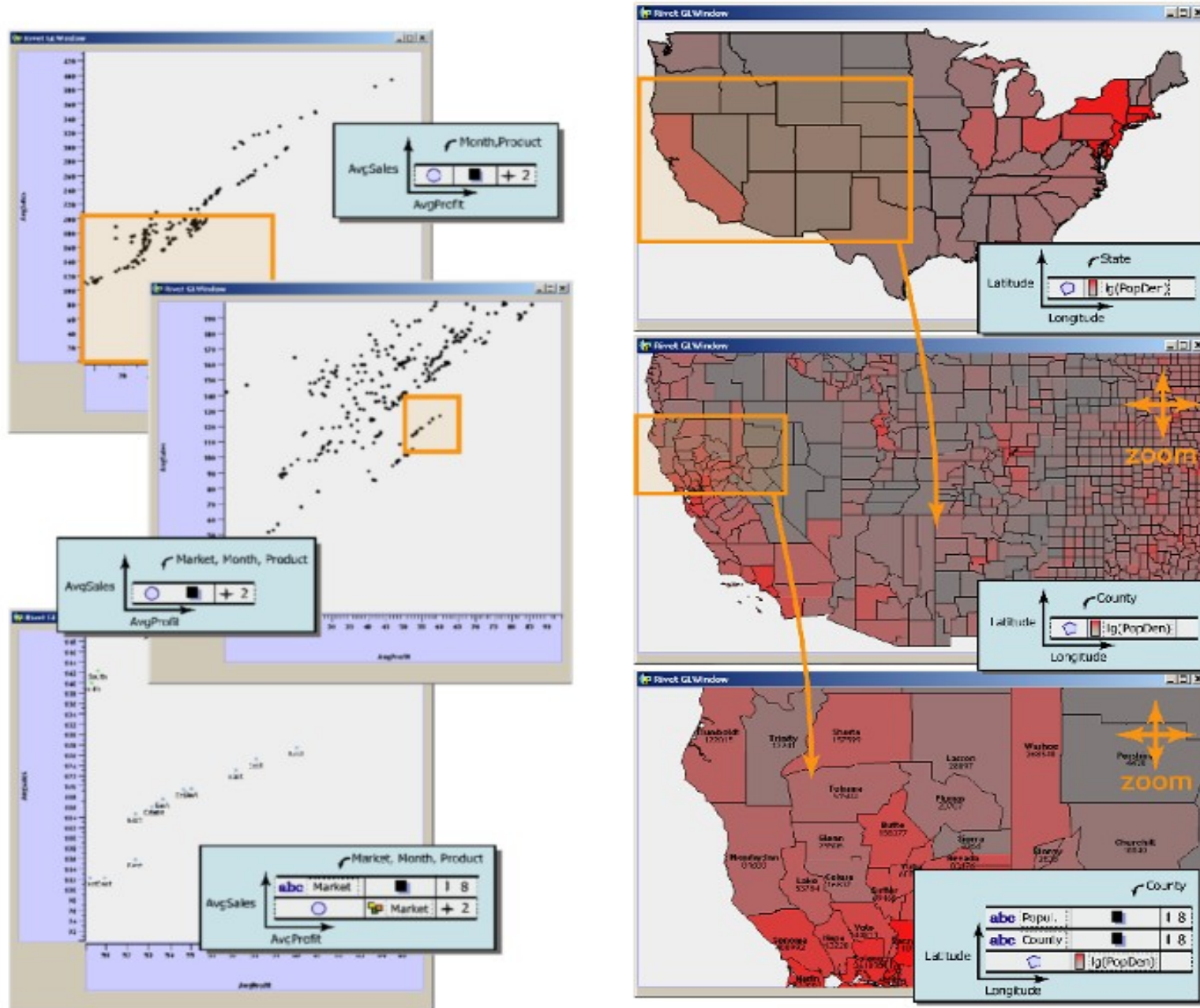
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Projecting a three dimensional data cube



Example: Data Cube Navigation in the Polaris system



an example data cube: the

U.S. Bureau of Labor Statistics (BLS) Employment Dataset

The BLS Employment Dataset

as **dimensions** and **measures**

- Raw data at <ftp://ftp.bls.gov/pub/special.requests/cew/>
- Covers **Time** from 1990 to 2007
 - Data for years, quarters, and months
- Covers **Space** for all US States
 - Data for States and Counties
- Covers the NAICS **Industry** hierarchy
- Covers **Ownership**
 - Government (Federal, State, Local) and Private
- Contains measures **employment, annual pay, total wages, and number of establishments** (among others)

NAICS

North American Industry Classification System

11	Agriculture, Forestry, Fishing and Hunting	
111	Crop Production	
1111	Oilseed and Grain Farming	
11111	Soybean Farming	Soybean Farming
111110		
11112	Oilseed (except Soybean) Farming	Oilseed (except Soybean) Farming
111120		
11113	Dry Pea and Bean Farming	Dry Pea and Bean Farming
111130		
11114	Wheat Farming	Wheat Farming
111140		
11115	Corn Farming	Corn Farming
111150		
11116	Rice Farming	Rice Farming
111160		
11119	Other Grain Farming	Other Grain Farming
111191		Oilseed and Grain Combination Farming
111199		All Other Grain Farming
1112	Vegetable and Melon Farming	
11121	Vegetable and Melon Farming	Vegetable and Melon Farming
111211		Potato Farming
111219		Other Vegetable (except Potato) and Melon Farming
1113	Fruit and Tree Nut Farming	
11131	Orange Groves	Orange Groves
111310		
11132	Citrus (except Orange) Groves	Citrus (except Orange) Groves
111320		
11133	Noncitrus Fruit and Tree Nut Farming	Noncitrus Fruit and Tree Nut Farming
111331		Apple Orchards
111332		Grape Vineyards
111333		Strawberry Farming
111334		Berry (except Strawberry) Farming
111335		Tree Nut Farming
111336		Fruit and Tree Nut Combination Farming
111339		Other Noncitrus Fruit Farming
1114	Greenhouse, Nursery, and Floriculture Production	
11141	Food Crops Grown Under Cover	Food Crops Grown Under Cover
111411		Mushroom Production
111419		Other Food Crops Grown Under Cover
11142	Nursery and Floriculture Production	Nursery and Floriculture Production
111421		Nursery and Tree Production
111422		Floriculture Production
1119	Other Crop Farming	
11191	Tobacco Farming	Tobacco Farming
111910		
11192	Cotton Farming	Cotton Farming
111920		
11193	Sugarcane Farming	Sugarcane Farming
111930		
11194	Hay Farming	Hay Farming
111940		
11199	All Other Crop Farming	All Other Crop Farming
111991		Sugar Beet Farming
111992		Peanut Farming
111998		All Other Miscellaneous Crop Farming
112	Animal Production	
1121	Cattle Ranching and Farming	
11211	Beef Cattle Ranching and Farming, including Feedlots	Beef Cattle Ranching and Farming, including Feedlots
112111		Beef Cattle Ranching and Farming
112112		Cattle Feedlots
11212	Dairy Cattle and Milk Production	Dairy Cattle and Milk Production
112120		
11213	Dual-Purpose Cattle Ranching and Farming	Dual-Purpose Cattle Ranching and Farming
112130		
1122	Hog and Pig Farming	Hog and Pig Farming
11221		
112210		
1123	Poultry and Egg Production	Poultry and Egg Production
11231	Chicken Egg Production	Chicken Egg Production
112310		
11232	Broilers and Other Meat Type Chicken Production	Broilers and Other Meat Type Chicken Production

Industry

Accommodation and food services

Administrative and waste services

Agriculture, forestry, fishing and hunting

All industries

Arts, entertainment, and recreation

Construction

Educational services

Finance and insurance

Health care and social assistance

Information

Management of companies and enterprises

Mining, quarrying, and oil and gas extraction

Other services, except public administration

Professional and technical services

Public Administration

Real estate and rental and leasing

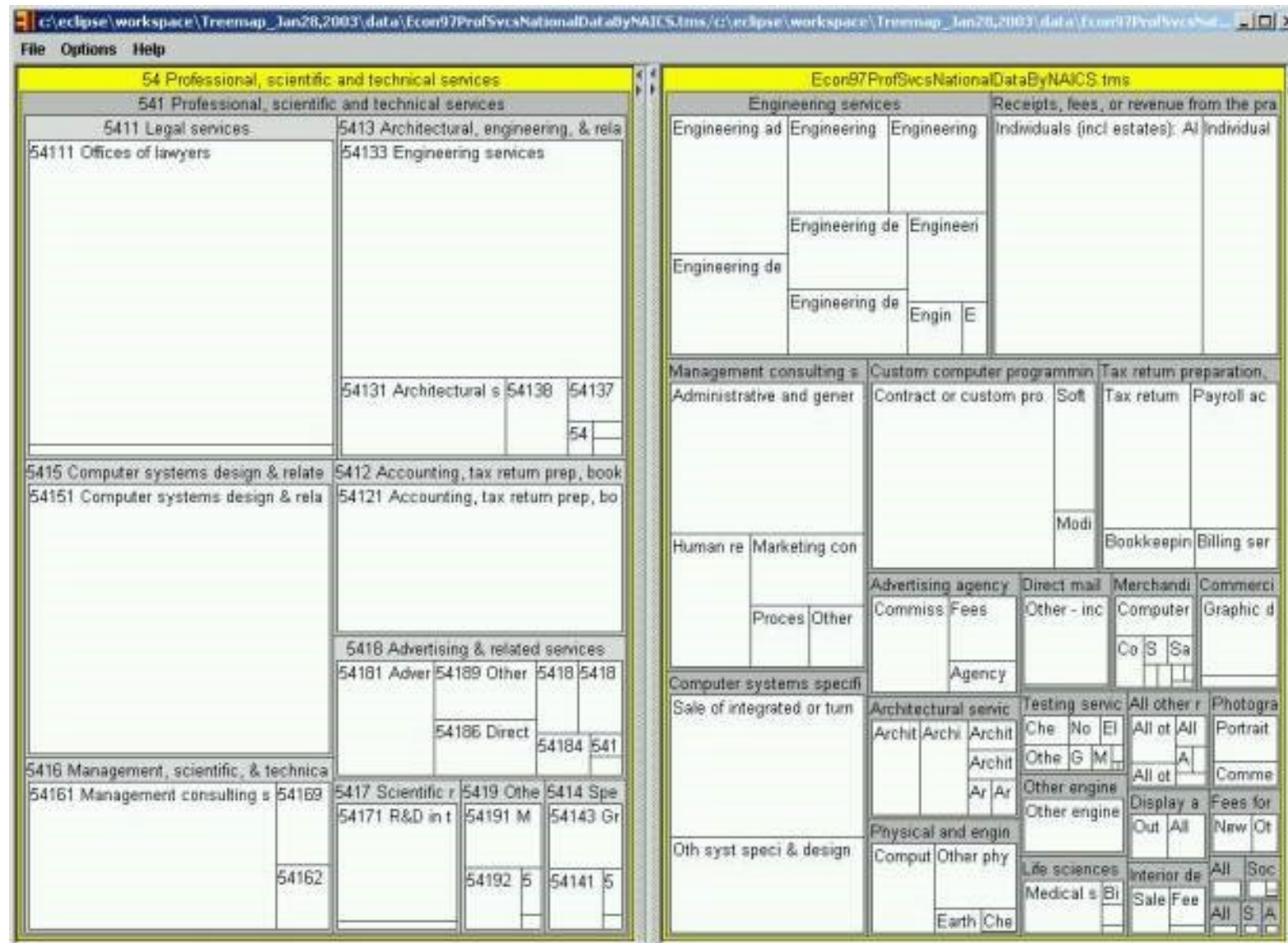
Unclassified

Utilities

Wholesale trade

NAICS Treemap by Revenue

from University of Maryland using US Census data



from <http://hcil.cs.umd.edu/trs/2003-09/2003-09.html>

Tableau

A commercial visual analysis tool

- Uses the data cube model
- From the authors of “Multiscale Visualization using Data Cubes”



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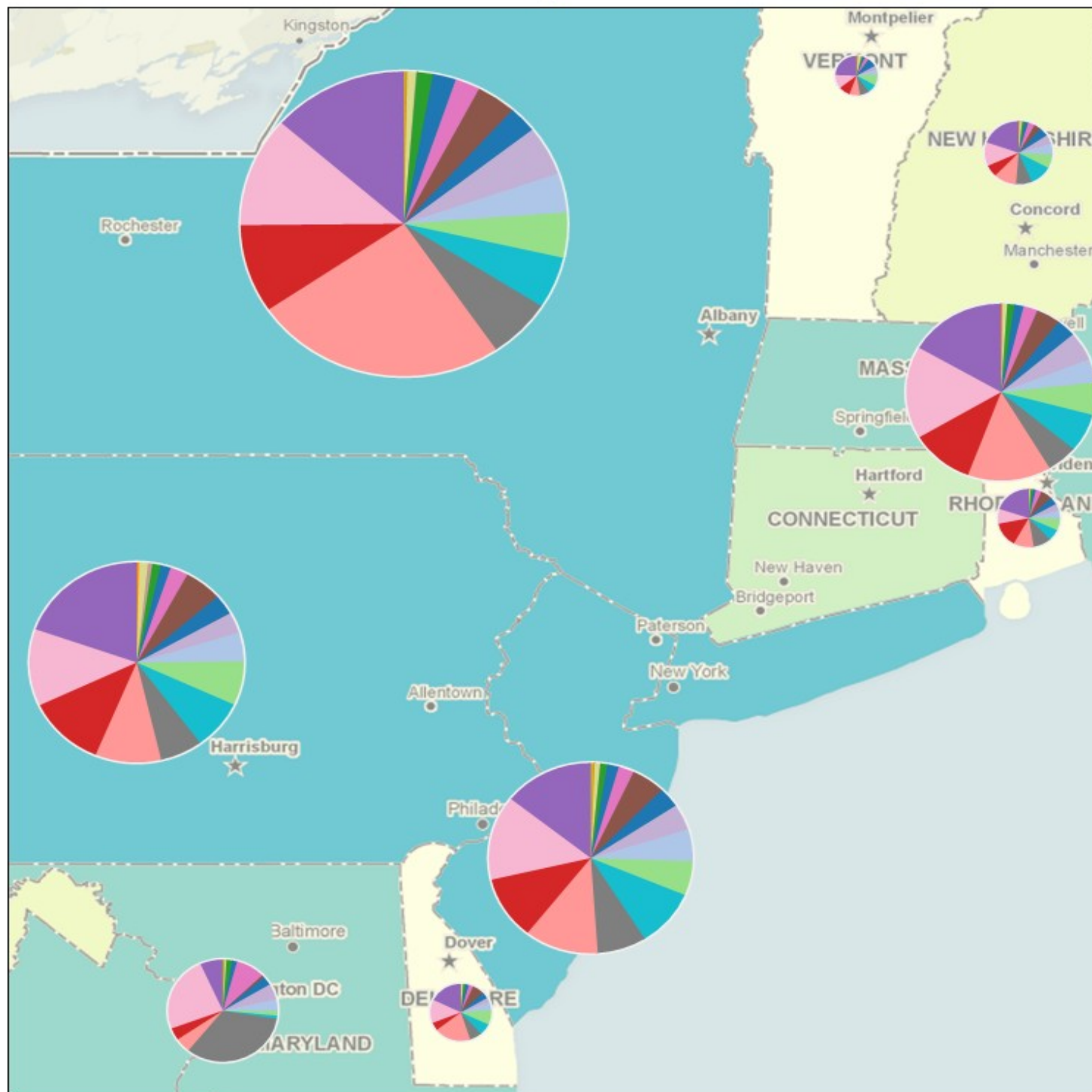
[see it in action](#)



The BLS Employment dataset
Visualized
using
Tableau

from a project by Siva Mohan and Curran Kelleher

New England Pies



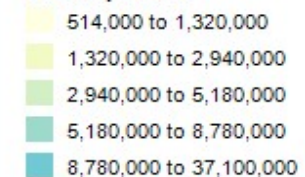
A Total Wages



Industry

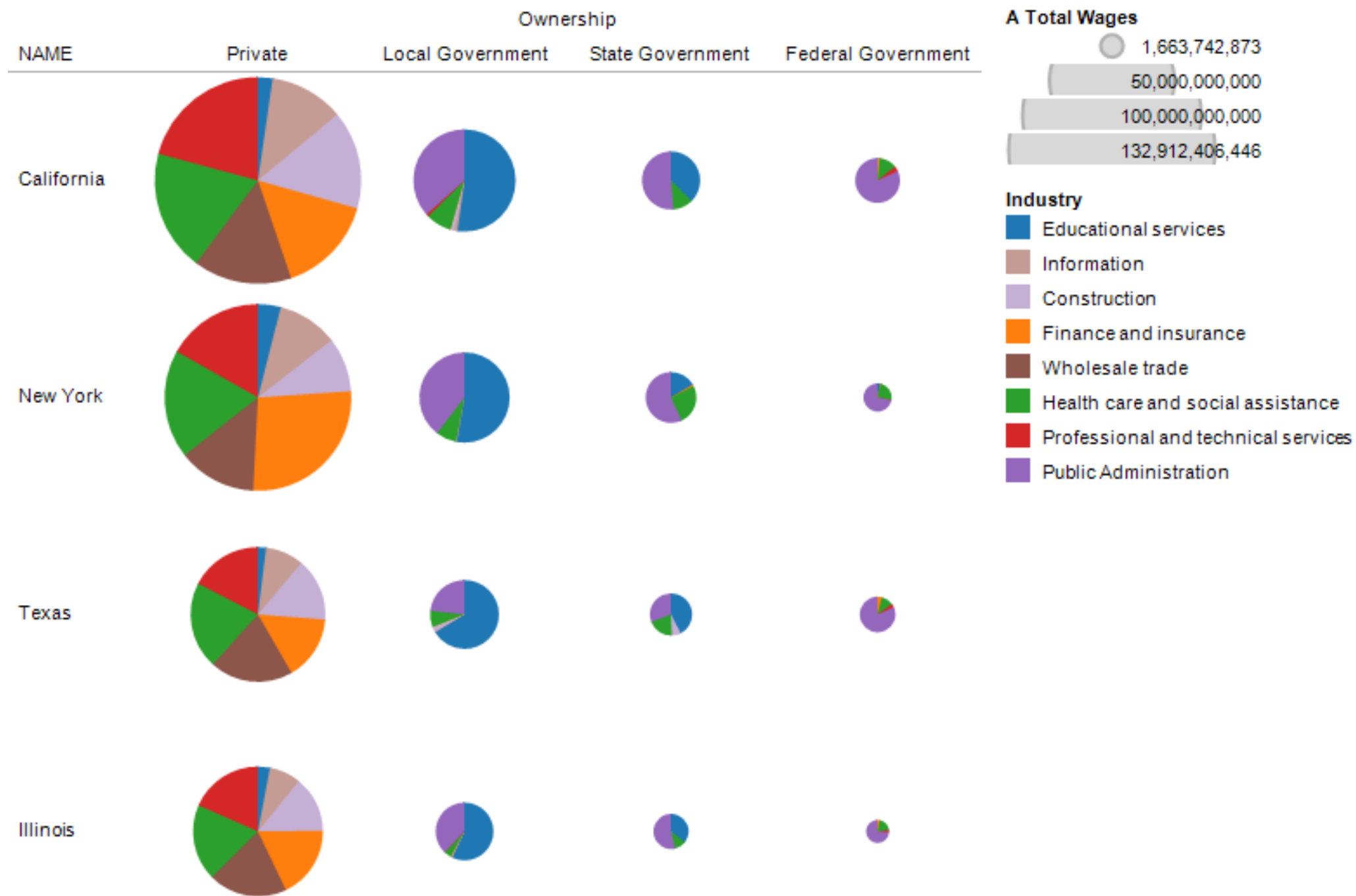


2007 Population



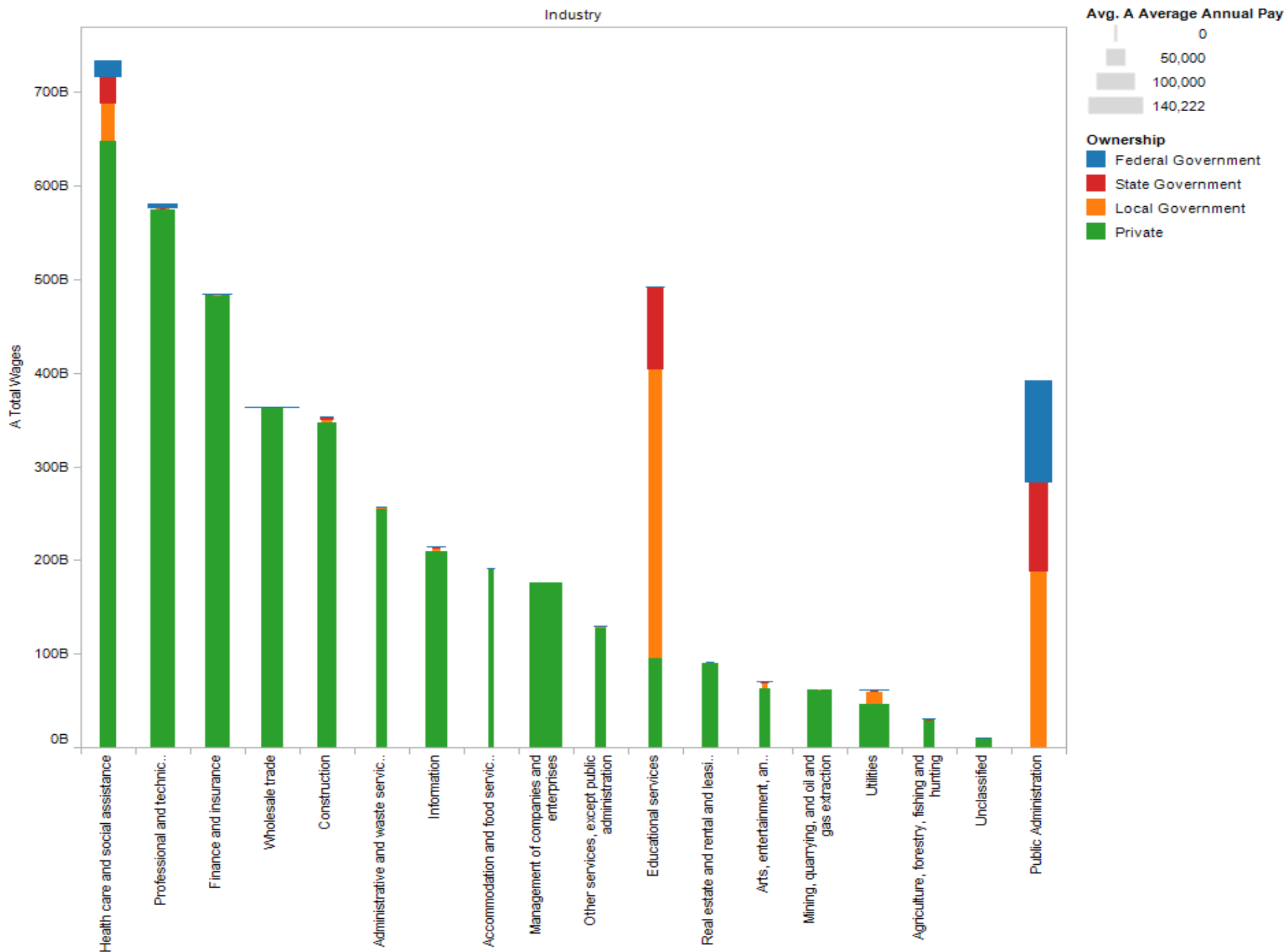
Map based on Longitude (generated) and Latitude (generated). Color shows details about Industry. Size shows sum of A Total Wages. Details are shown for ALPHA. The view is filtered on Industry and Exclusions (ALPHA, Industry). The Industry filter excludes All industries. The Exclusions (ALPHA, Industry) filter specifies a set.

Industry Pies By Ownership



Industry (color) and sum of A Total Wages (size) broken down by Ownership vs. NAME. The view is filtered on NAME and Industry. The NAME filter excludes 48 members. The Industry filter excludes 10 members.

Industries divided by Ownership



Sum of A Total Wages for each Industry. Color shows details about Ownership. Size shows average of A Average Annual Pay. The view is filtered on Industry, which excludes All industries.

Issues with Tableau

- No support for hierarchical data cubes
 - Only a small subset of the dataset usable: states, years, top level industries
- Dealing with Time was problematic
 - Years in different tables
 - Months in different columns
 - Tableau expects single column dimensions

The Semantic Web

Semantic Web Technologies

- Resource Description Framework (RDF)
 - Describes things with subject-predicate-object triples
 - Has a standard XML-RDF encoding
- Web Ontology Language (OWL)
 - Defines vocabularies for use in RDF documents
- Ontologies
 - Define classes and properties
 - Ontology design is much like object oriented design

```

- <rdf:RDF>
  - <foaf:Person rdf:about="http://www.w3.org/People/EM/contact#me">
    <rdf:value>Eric Miller, em@w3.org</rdf:value>
    <foaf:name>Eric Miller</foaf:name>
    <foaf:phone rdf:resource="tel:+1-(617)-258-5714"/>
    <foaf:mbox rdf:resource="mailto:em@w3.org"/>
    <foaf:nick>em</foaf:nick>
    <foaf:img rdf:resource="http://www.w3.org/People/EM/s000782.JPG"/>
    <foaf:workInfoHomepage rdf:resource="http://www.w3.org/People/EM"/>
    <foaf:workplaceHomepage rdf:resource="http://www.w3.org"/>
  - <contact:office>
    - <contact:contactLocation>
      <rdf:value>MIT CSAIL</rdf:value>
      <contact:homePage rdf:resource="http://csail.mit.edu"/>
    - <contact:address>
      - <contact:Address>
        - <rdf:value>
          The Stata Center, Building 32-G516, 32 Vassar Street, Cambridge MA 02139
        </rdf:value>
        <contact:city>Cambridge</contact:city>
        <contact:country>USA</contact:country>
        <contact:postalCode>02139</contact:postalCode>
      - <contact:street>
        The Stata Center, Building 32-G516, 32 Vassar Street
      </contact:street>
      <loc:coordinates>42.361860,-71.091840</loc:coordinates>
    </contact:Address>
  </contact:address>
</contact:contactLocation>
</contact:office>
<foaf:knows rdf:resource="http://www.w3.org/People/Berners-Lee/card#i"/>
<foaf:knows rdf:resource="http://www.w3.org/People/Gunnella/#me"/>

```

An
RDF
example

Another RDF example

from Wikipedia



Linked Data

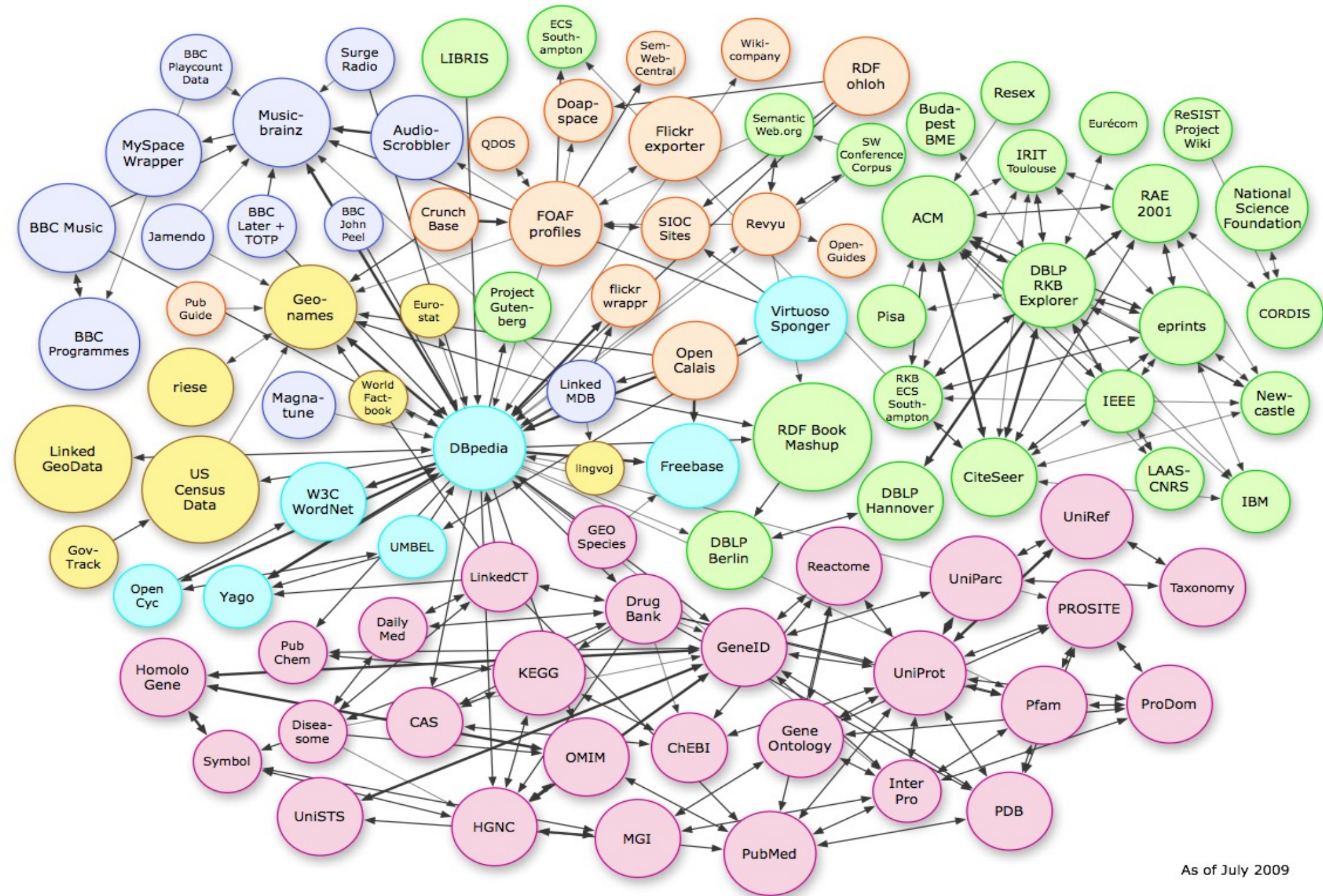
“A term used to describe a recommended best practice for exposing, sharing, and connecting pieces of data, information, and knowledge on the Semantic Web using URIs and RDF.”
– Wikipedia

Linked Data Principles

from Tim Berners-Lee

1. Use URIs as names for things
2. Use HTTP URIs so that people can look up those names.
3. When someone looks up a URI, provide useful information, using the standards (RDF, SPARQL)
4. Include links to other URIs. so that they can discover more things.

The Linked Data Cloud



The Universal Data Cube

The Universal Data Cube System is a vision for a world wide web in which complex data sets are first class citizens, and rich web-based data visualization and analysis tools are commonplace.

Goals

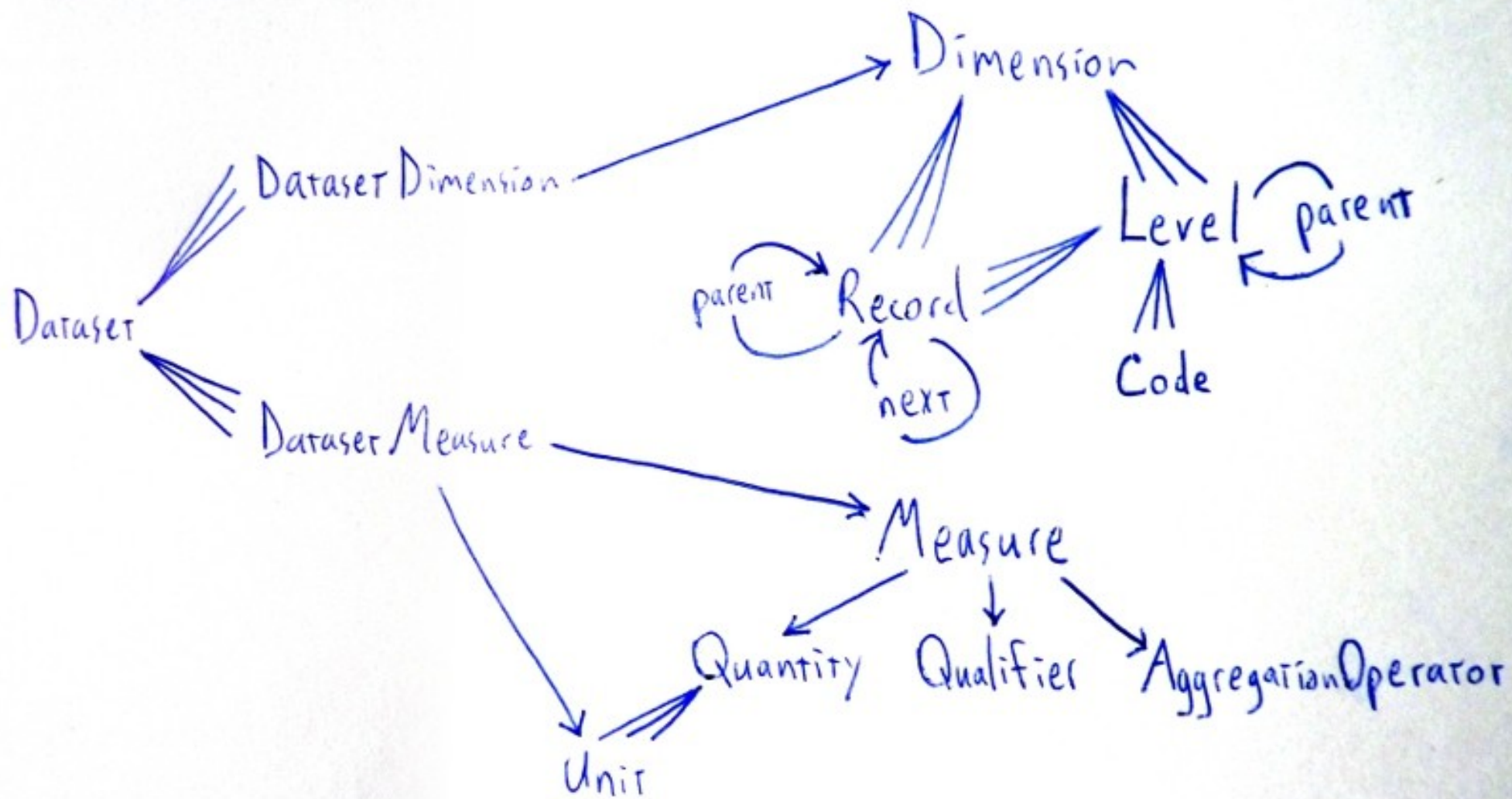
- Design an ontology for hierarchical data cubes
- Develop a system which publishes
 - Data cube metadata in the Linked Data cloud
 - A data cube query endpoint on the web
- Adapt the Weave client to use this system
- Encourage others to build more clients
- Propose it as a web standard for data publishing

The Universal Data Cube Ontology

Competency Questions

that the system must handle

- Show me the average Sepal Width for all iris classes in the Iris dataset (Barchart)
- Show me the average income for the year 2008 for the construction industry for all the US States and the counties of Texas from the BLS dataset. (choropleth map)
- Show me the total wages for top-level industries aggregated across all US States for the years 1990 to 2008 from the BLS dataset (timeseries line chart where lines are industries)



Classes

Classes will follow this pattern:

[class name]

- [property name] [property range type] (multiplicity)
- * [hidden properties internal to the server]

Multiplicity can be one of the following:

- '1' = exactly one
- '+' = one or more
- '*' = zero or more

Dimension

- hasName String (1) //like "Time" or "Space"
- containsRecord Record (*)
//e.g. "Space" containsRecord "Massachusetts"
- containsLevel Level (*)
//e.g. "Space" containsLevel "US State"

Level

- hasName String //like "Year" or "State"
- hasNamePlural String //like "Years" or "States"
- hasParentDimension Dimension (1)
//e.g. "US State" hasParentDimension "Space"
- containsRecord Record (*)
//e.g. "US State" containsRecord
"Massachusetts"
- hasParentLevel Level (0 or 1)
//e.g. "US State" hasParentLevel "Country"

Record

- hasName String (1)
//like "1990" or "Massachusetts"
- hasParentDimension Dimension (1)
- hasLevel Level (1)
- hasParentRecord (0 or 1)
- hasNextRecord (0 or 1)

Quantity

- hasName String (1)
//like "Currency" or "Number of People"
- hasQuantityType String (1)
//either "Magnitude" or "Multitude"
- containsUnit Unit (*)
//e.g. "Currency" containsUnit "US Dollars"

Unit

- hasName String (1)
//like "US Dollars" or "Persons"
- hasParentQuantity Quantity (1)
//e.g. "US Dollars" hasParentQuantity "Currency"

AggregationOperator

- `hasName String (1) //like "Sum" or "Average"`

Measure

- hasName String (1)
//like "Average Income" or "Population"
- hasQuantity Quantity (1)
//e.g. "Average Income" hasQuantity "Currency"
- hasQualifier String (1)
//e.g. "Teenage Girls" hasQualifier "People
which are female and between age 13 and 19"
- usesAggregationOperator AggregationOperator (1)
//e.g. "Average Income" usesAggregationOperator "Average"

DatabaseConnection

- hasName String (1) //like "BLS Database"
- containsDatabaseTable DatabaseTable (*)
- (internal) user, pass, host, and port

DatabaseTable

- hasName String (1) //like "Employment"
- hasParentDatabaseConnection
DatabaseConnection (1)
- containsColumn DatabaseTableColumn (*)
- (internal) hasSQLName String

DatabaseTableColumn

- hasName String (1)
- hasParentDatabaseTable DatabaseTable (1)

Dataset

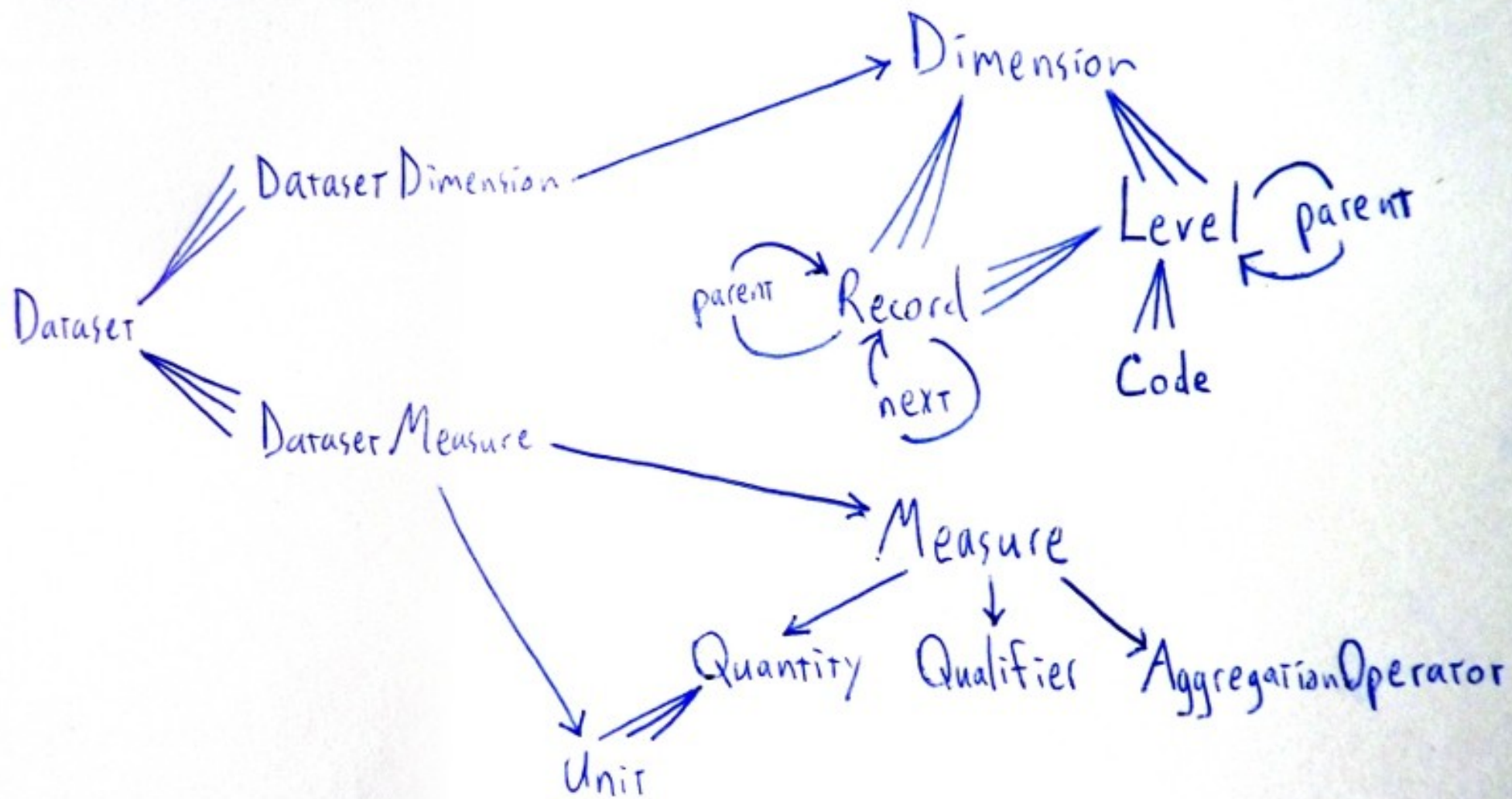
- dc:title String (1) //like "BLS Employment Dataset"
- dc:creator String (0 or 1)
- dc:subject String (0 or 1)
- dc:description String (0 or 1)
- dc:publisher String (0 or 1)
- dc:date String (0 or 1)
- dc:rights String (0 or 1)
- usesDatabaseTable DatabaseTable (*)
- usesDataCubeMapping String (1) //maps data cube metadata to relational tables
- containsDatasetDimension DatasetDimension (*)
- containsDatasetMeasure DatasetMeasure (*)

DatasetDimension

- hasParentDataset Dataset (1)
- representsDimension Dimension (1)
- containsRecord Record (*)
- containsLevel Level (*)

DatasetMeasure

- hasParentDataset Dataset (1)
- representsMeasure Measure (1)
- hasUnit Unit (1)



An Example Knowledge Base

for the BLS Employment Dataset

Dimension time = new Dimension
time hasName "Time"

Dimension space = new Dimension
space hasName "Space"

```
Level year = new Level  
year hasName "Year"  
year hasNamePlural "Years"  
year hasParentDimension time  
time containsLevel year
```

```
Level usState = new Level  
usState hasName "US State"  
usState hasNamePlural "US States"  
usState hasParentDimension space  
space containsLevel usState
```



```
Record year1990 = new Record  
    year1990 hasName "1990"  
    year1990 hasLevel year  
year1990 hasParentDimension time  
time containsRecord year1990
```

```
Record ma = new Record  
ma hasName "Massachusetts"  
  ma hasLevel usState  
ma hasParentDimension space  
  space containsRecord ma
```

Quantity currency = new Quantity
currency hasName "Currency"

Quantity numPeople = new Quantity
numPeople hasName "Number of People"

```
Unit usDollars = new Unit  
usDollars hasName "US Dollars"  
usDollars hasParentQuantity currency  
currency containsUnit usDollars
```

```
Unit persons = new Unit  
persons hasName "Persons"  
persons hasParentQuantity numPeople  
numPeople containsUnit persons
```

Measure avgIncome = new Measure
avgIncome hasName "Average Income"
avgIncome hasQuantity currency

Measure population = new Measure
population hasName "Population"
population hasQuantity numPeople

```
DatabaseConnection blsDatabase = new DatabaseConnection  
blsDatabase hasName "Bureau of Labor Statistics Database"
```

```
DatabaseTable bls2008 = new DatabaseTable  
blsTable hasName "bls2008"
```

blsTable hasColumn "Average Income"
 blsTable hasColumn "Total Wages"
 blsTable hasColumn "Employment"
blsTable hasColumn "Average Income"
 blsTable hasColumn "Population"

blsTable hasParentDatabaseConnection blsDatabase
blsDatabase containsDatabaseTable blsTable


```
Dataset blsDataset = new Dataset  
blsDataset hasName "Bureau of Labor Statistics  
Employment Dataset"  
blsDataset usesDatabaseTable blsTable
```

DatasetDimension blsTimeDimension = new DatasetDimension
blsTimeDimension representsDimension time
blsTimeDimension hasParentDataset blsDataset
blsDataset containsDatasetDimension blsTimeDimension

DatasetRecord bls1990 = new DatasetRecord
 bls1990 representsRecord year1990
bls1990 hasParentDatasetDimension blsTimeDimension
 blsTimeDimension containsDatasetRecord bls1990

DatasetRecord blsMA = new DatasetRecord
blsMA representsRecord ma
blsMA hasParentDatasetDimension blsSpaceDimension
blsSpaceDimension containsDatasetRecord blsMA

DatasetMeasure blsPopulation
blsPopulation representsMeasure population
blsPopulation hasUnit persons
blsPopulation hasParentDataset blsDataset
blsDataset containsDatasetMeasure blsPopulation

DatasetMeasure blsAvgIncome
blsAvgIncome representsMeasure avgIncome
blsAvgIncome hasUnit usDollars
blsAvgIncome hasParentDataset blsDataset
blsDataset containsDatasetMeasure blsAvgIncome

Weave Data Model Problems

- Hierarchical key types are not linked
 - US Counties and US States are totally independent
- Key types referring to the same things not linked
 - Like US State codes and US State abbreviations
- Columns representing the same measure with different units are not compatible
 - Population in thousands not comparable with Population in millions
- No way of resolving when two datasets provide comparable columns

Weave Data Model Solutions

- Hierarchical key types are linked
 - Via the data cube dimension hierarchy structure
- Key types referring to the same things are linked
 - US State codes and US State abbreviations are different RecordCodes for the same record set
- Columns representing the same measure with different units are compatible
 - Population in thousands and Population in millions are two different Units within the same Quantity
- Resolving when two datasets provide comparable columns is possible
 - Because Datasets use universal Measure URIs to describe their contents

Similarities with Category Theory

I know **very little** about category theory,
but the following concepts seem to correlate exactly:

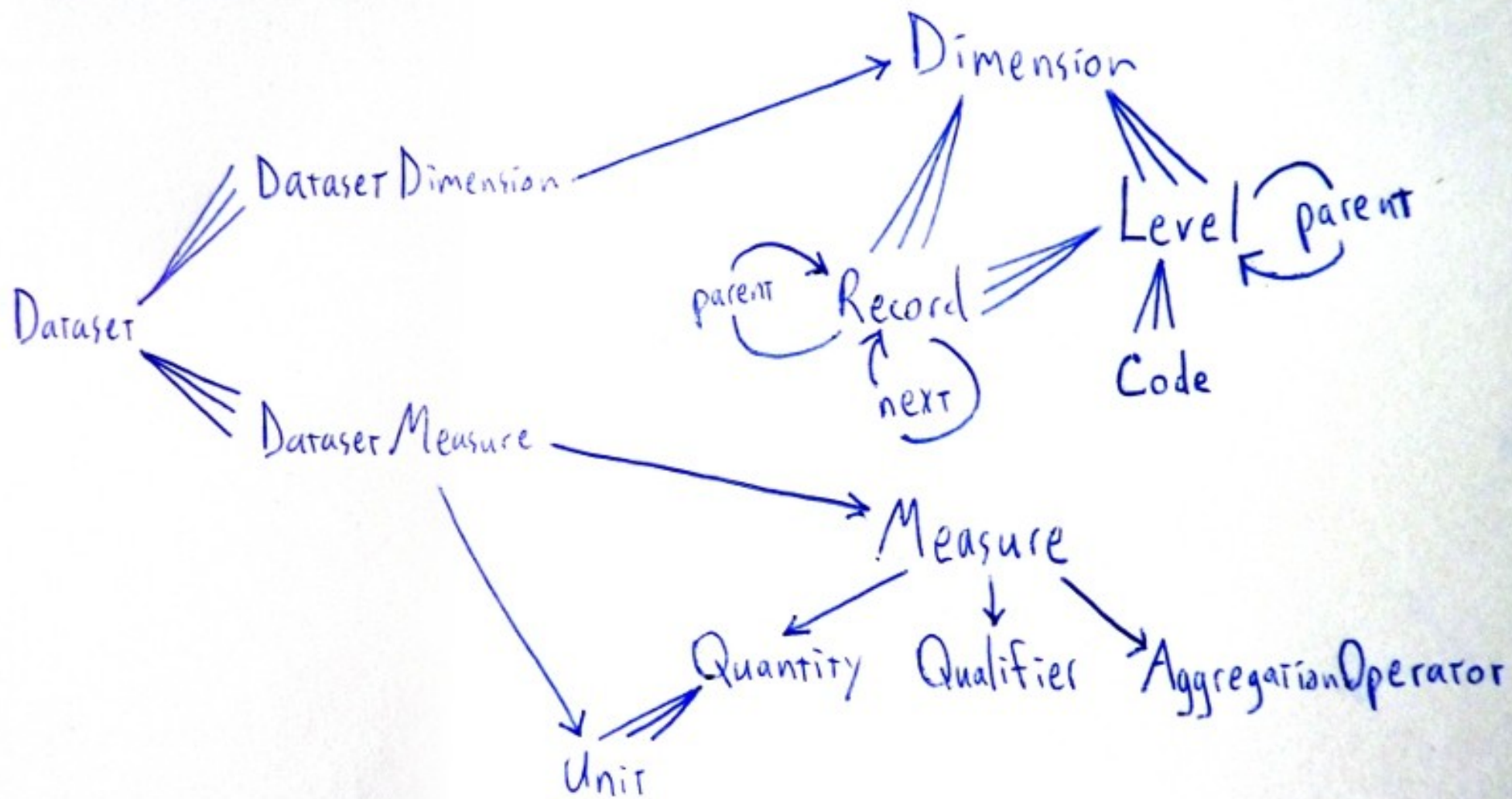
Dimension \rightarrow Category (Poset)

Record \rightarrow Object

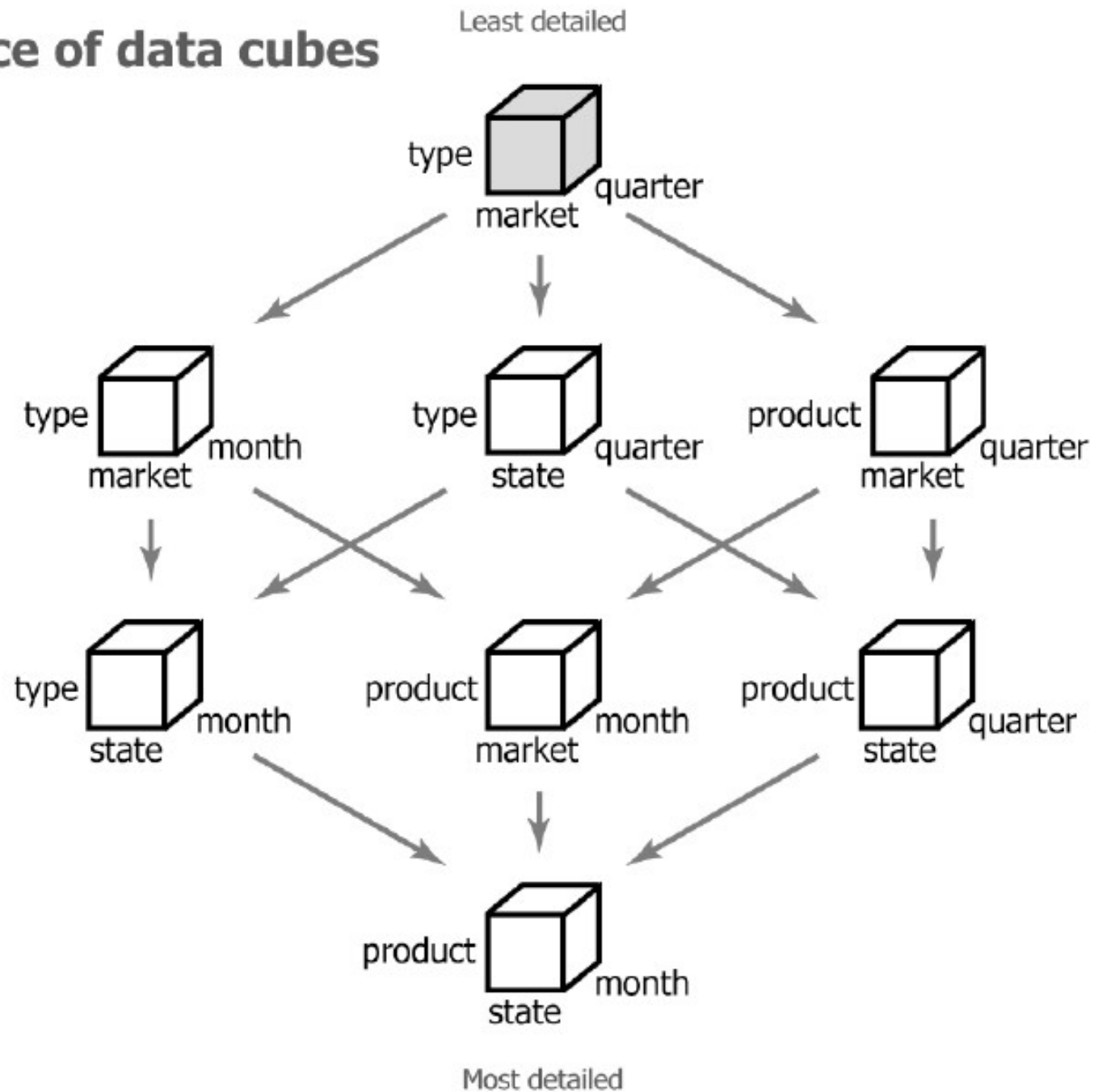
Measure \rightarrow Sheaf

Maybe the ontology should be based on
terminology from category theory.

The end.



The lattice of data cubes



Projecting a three dimensional data cube

