

# The Universal Data Cube

Curran Kelleher

# Outline

- Weave
- Problems
- The Universal Data Cube
- Solutions
- Open discussion

Weave

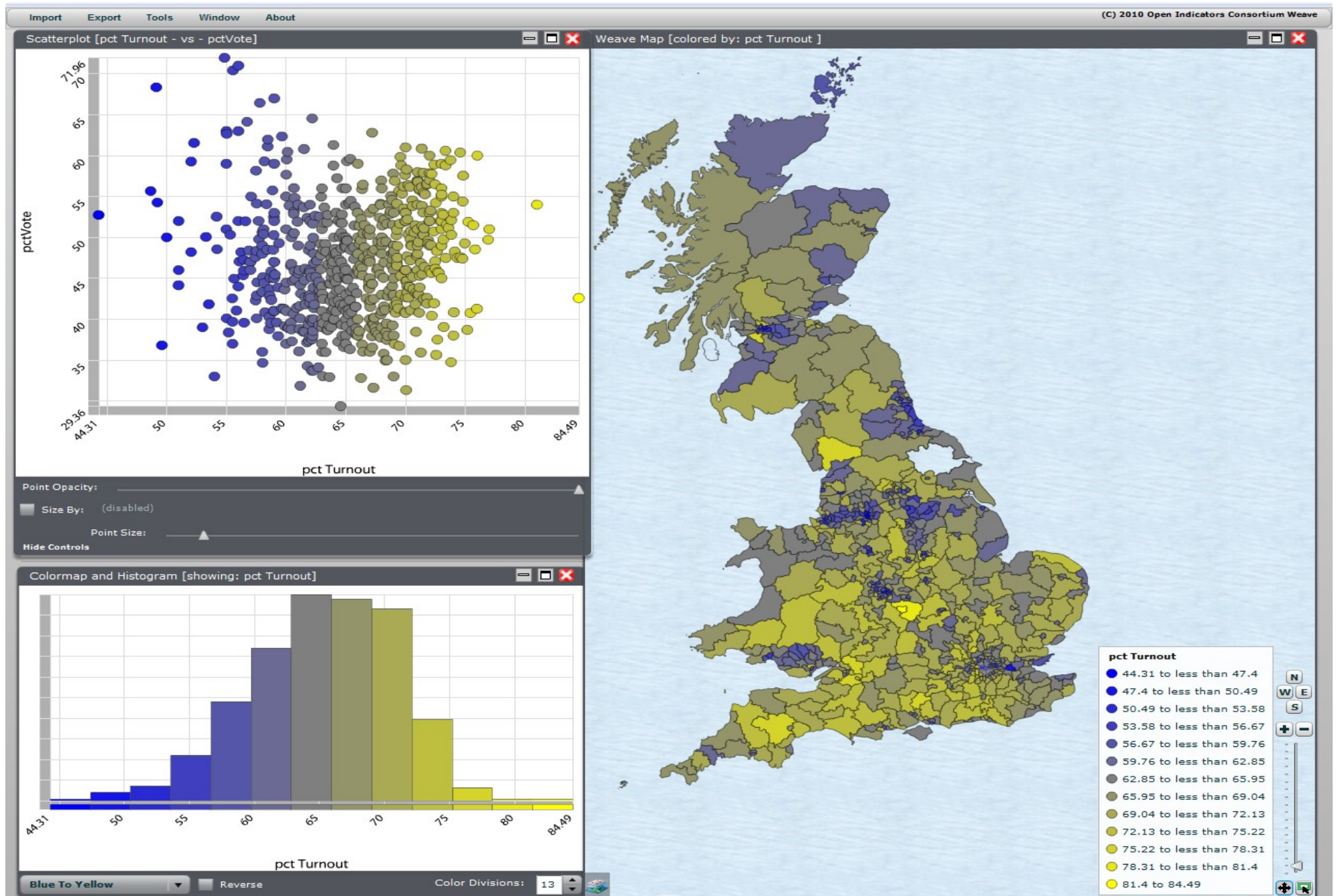
# Weave

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

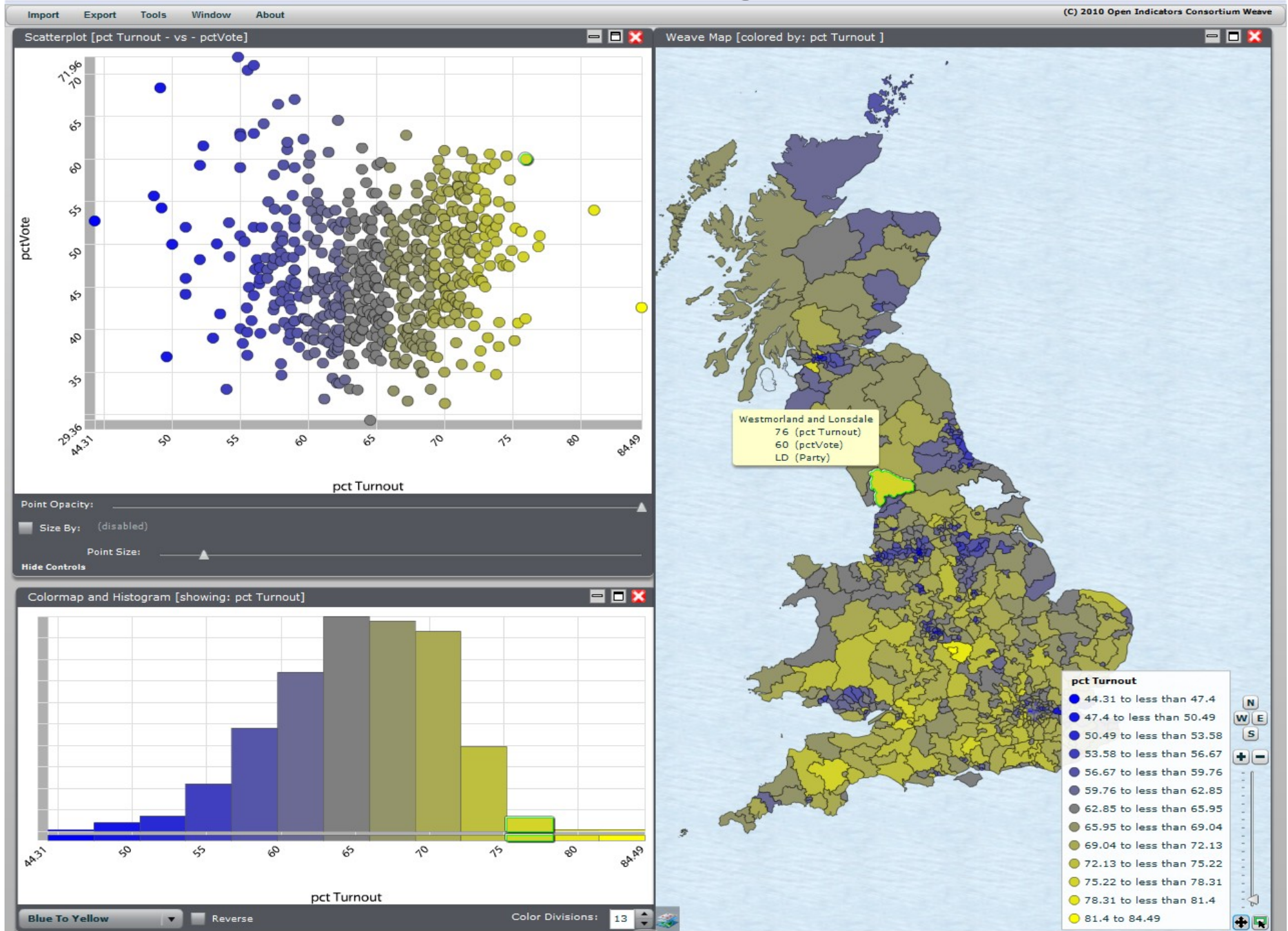
# British Election Results in May 2010

assembled by Jim Giddings

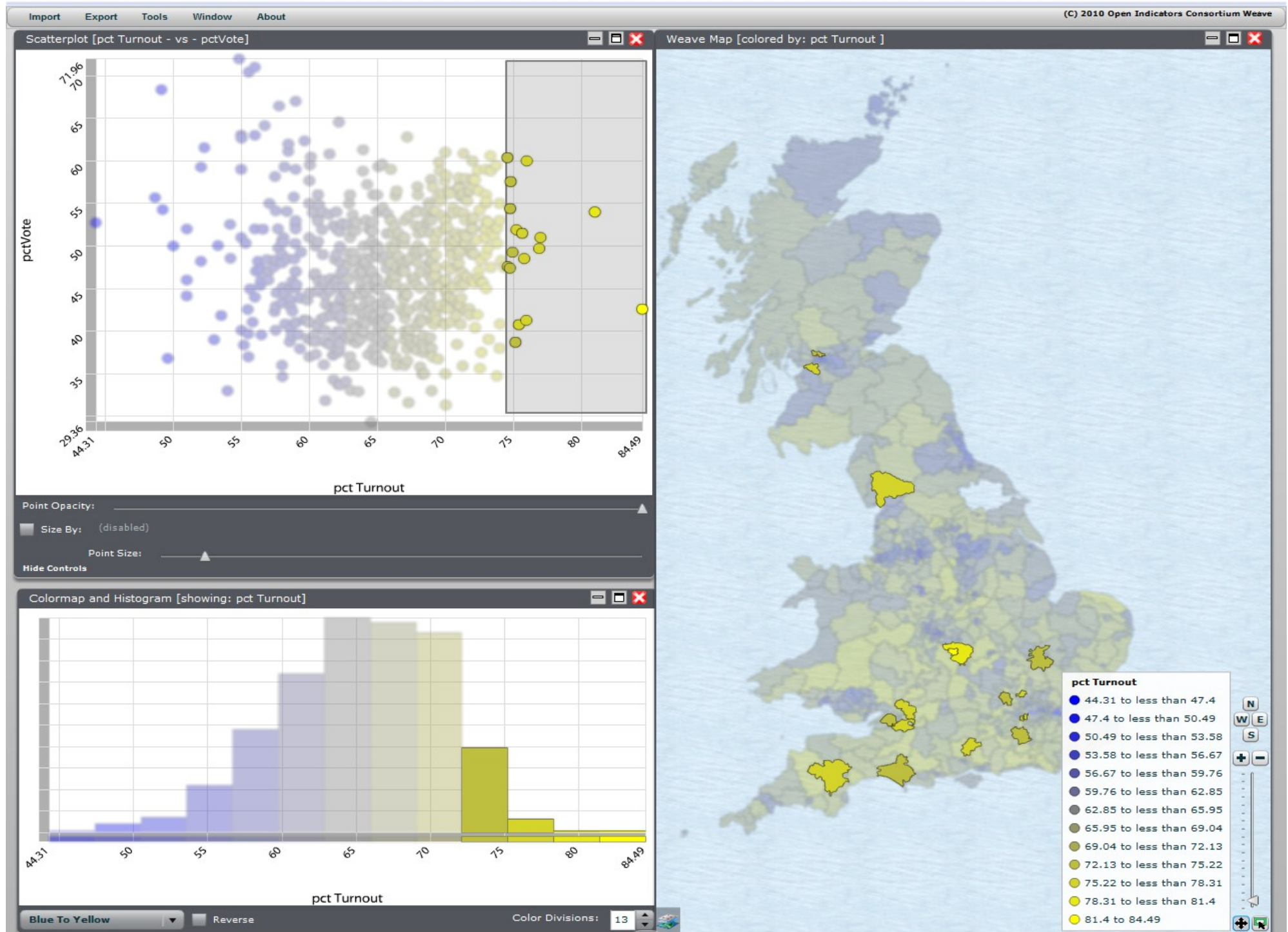




# Probing

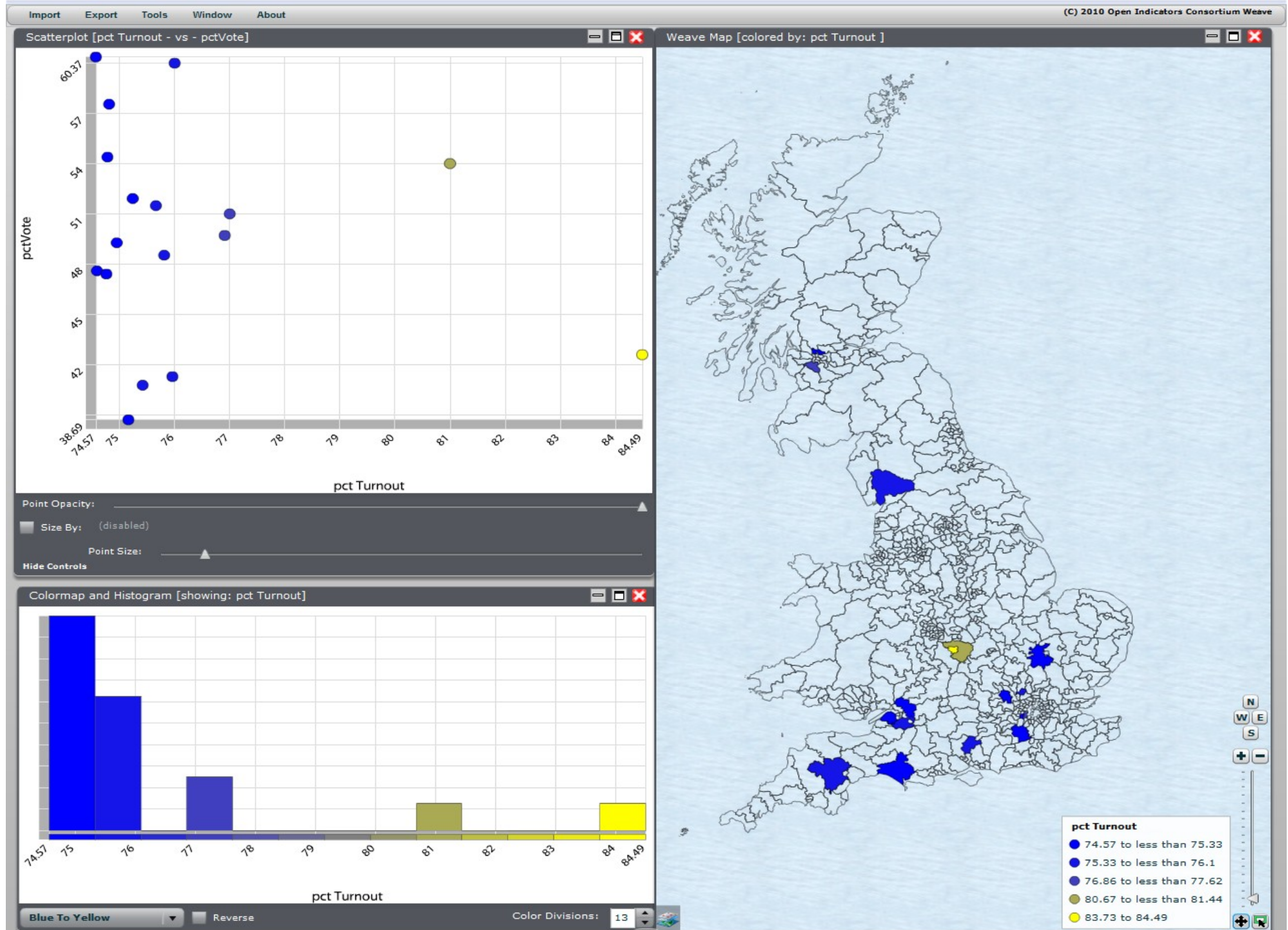


# Brushed selection



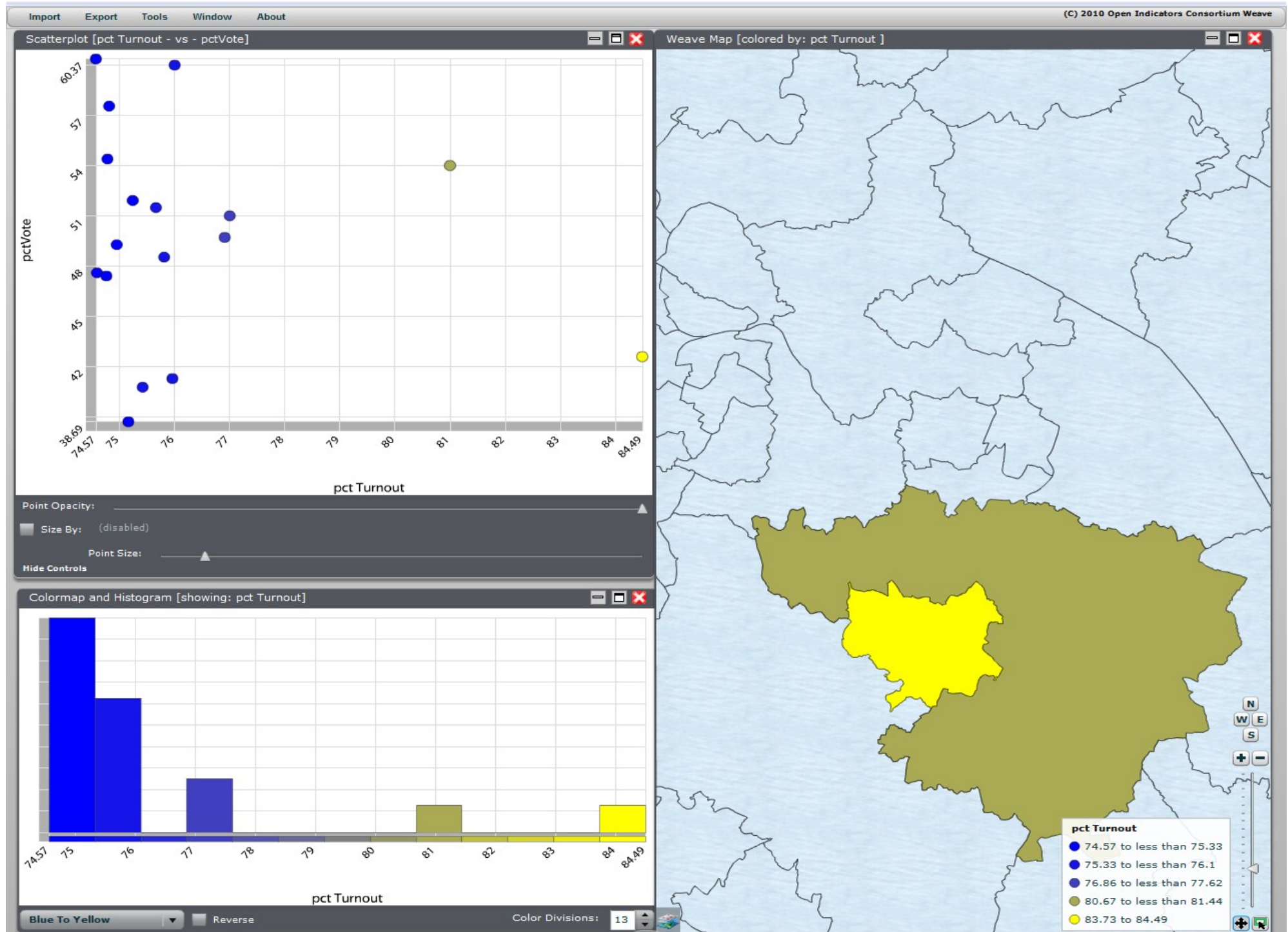


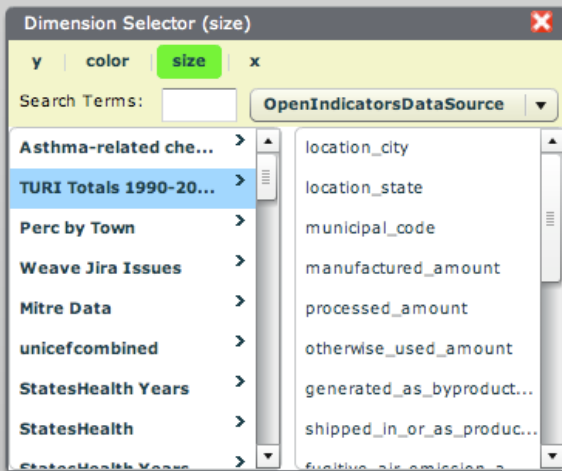
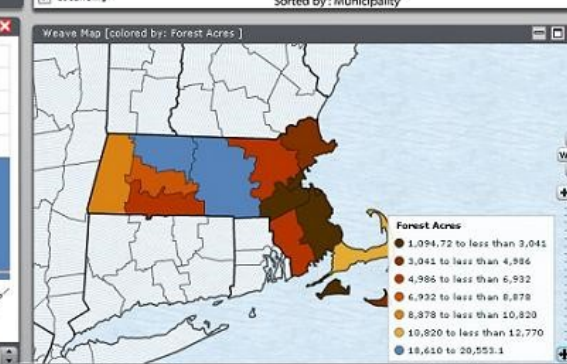
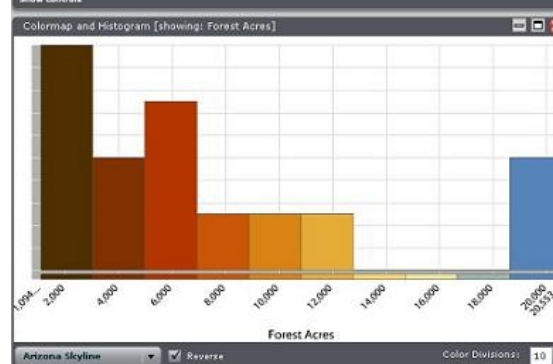
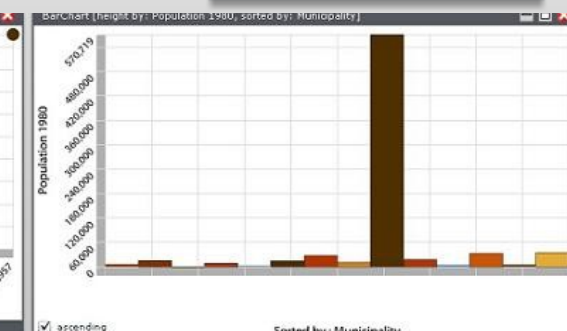
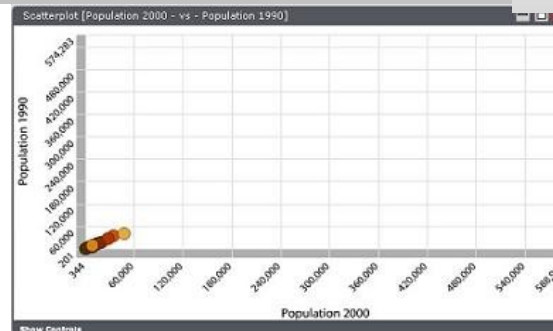
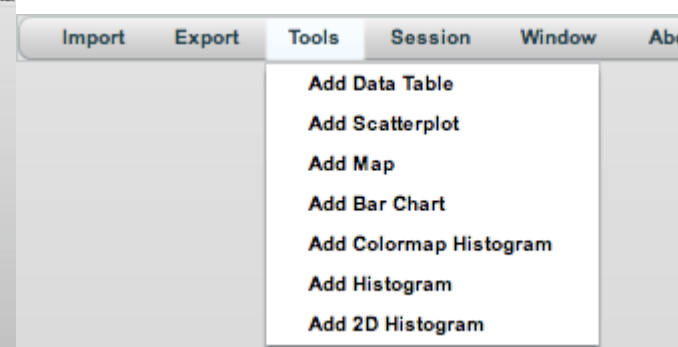
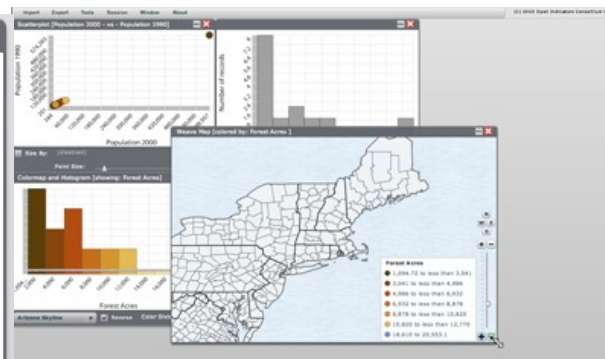
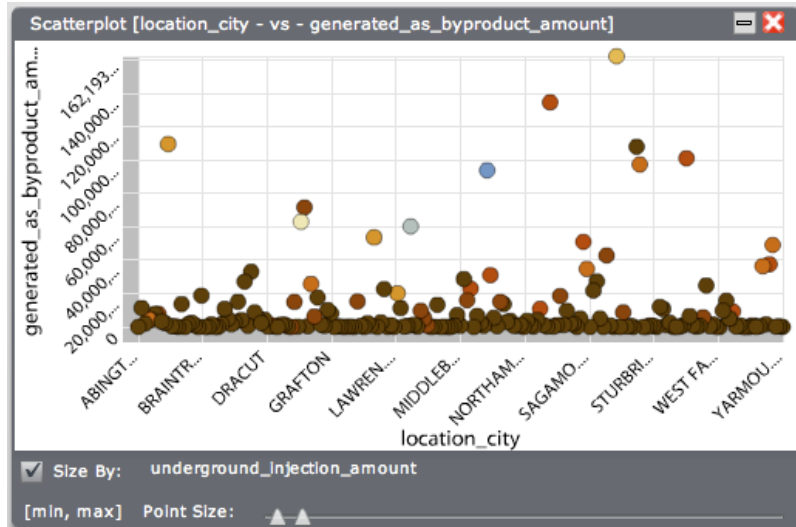
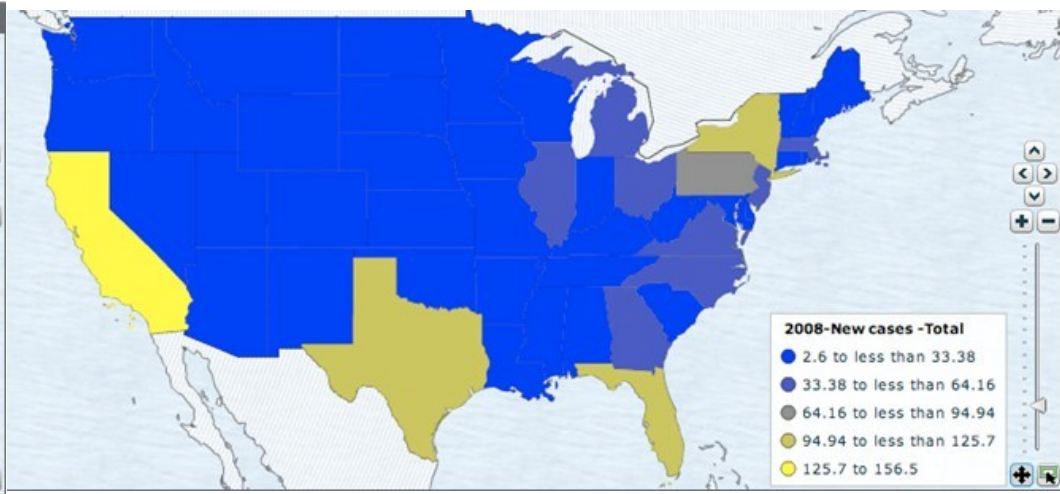
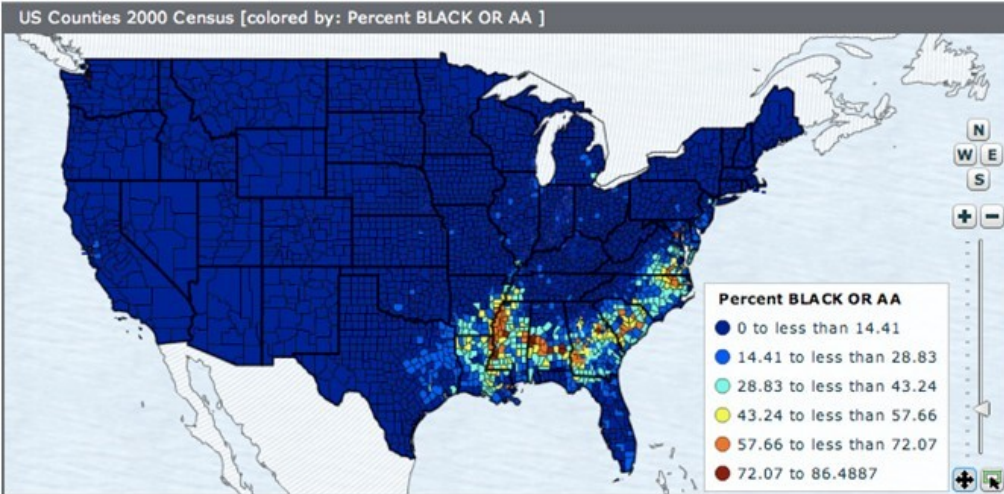
# Dynamic filtering





# 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 answer a query. We provide specifications to describe a multiscale visualization of a hierarchical data set, as well as how we can easily implement such visualizations within our system.

## 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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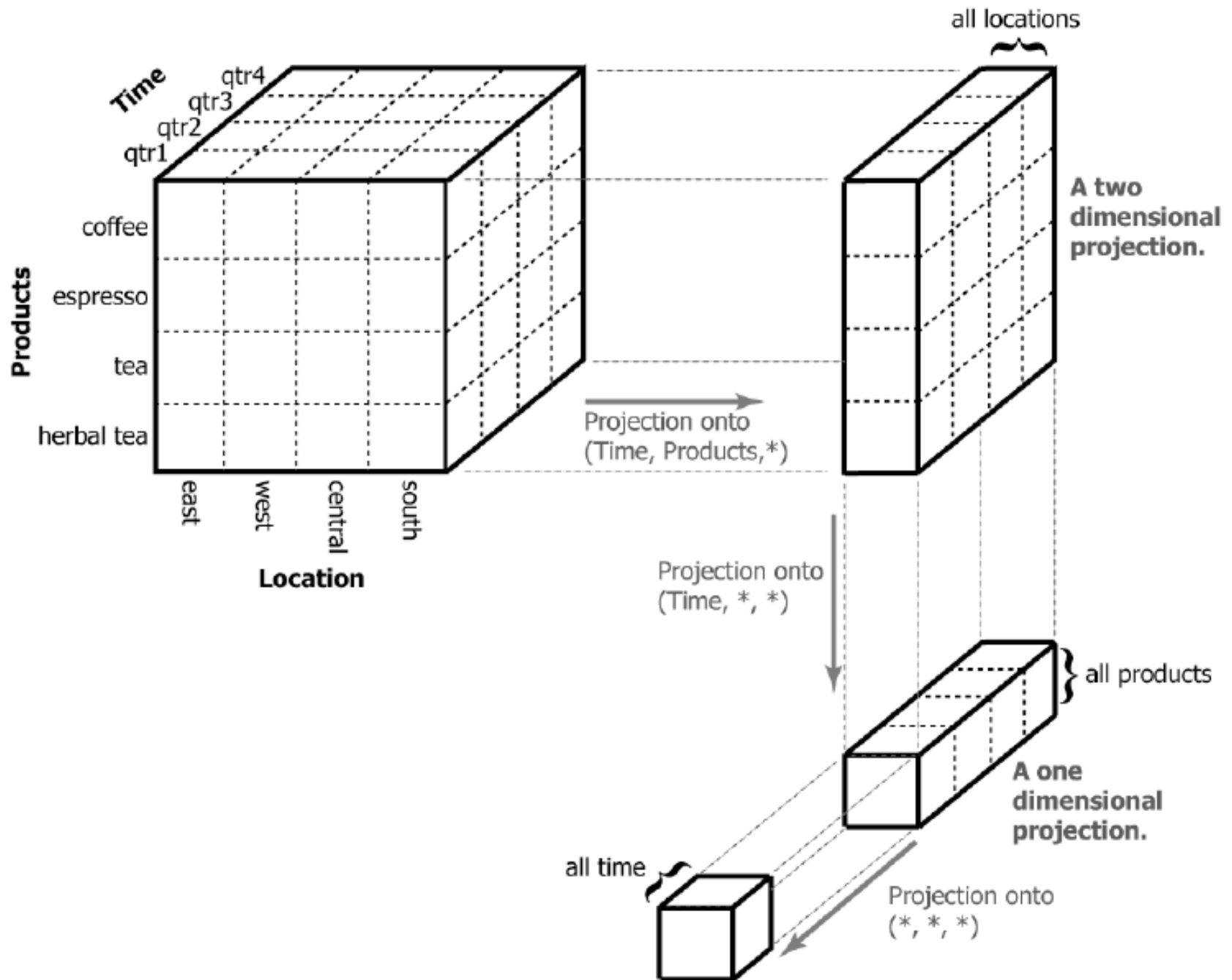
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Thus far, we have considered dimensions to be flat structures. However, most dimensions have a hierarchical structure. For example, the dimension of time can be structured hierarchically as



# 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

not as products of each type product as was said.

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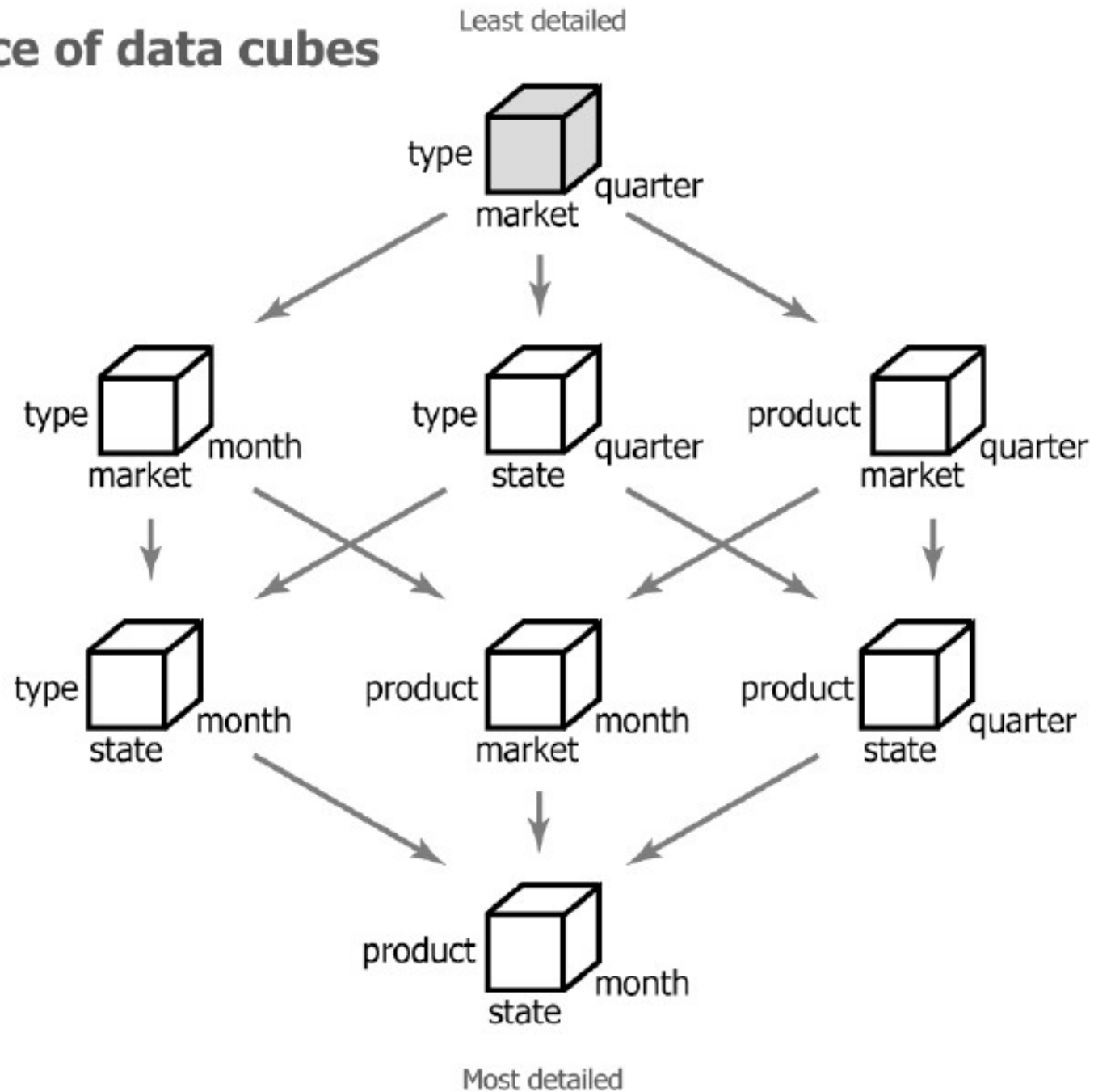
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# The lattice of data cubes



however, some dimensions may be hierarchical themselves. 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 (down 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 multiscala visualizations we need to specify both the data and visual abstractions. Both sets of information are contained in a *projection*.

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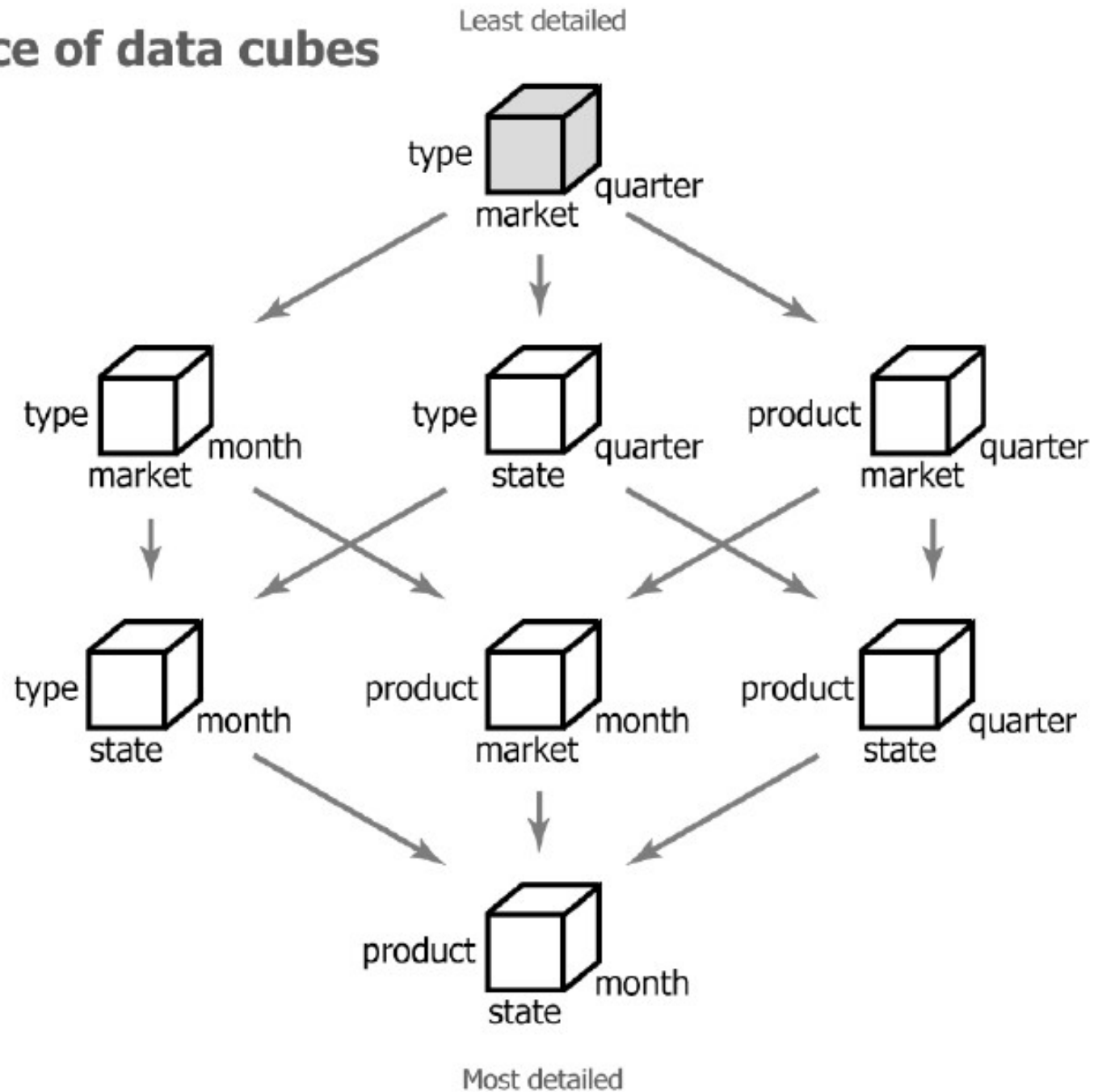
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One abstraction in this model means choosing a meaningful summary of the data. Choosing a data abstraction corresponds to choosing a particular projection in this lattice of data cubes: (a) which dimensions we currently consider relevant and (b) the 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.

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# The lattice of data cubes



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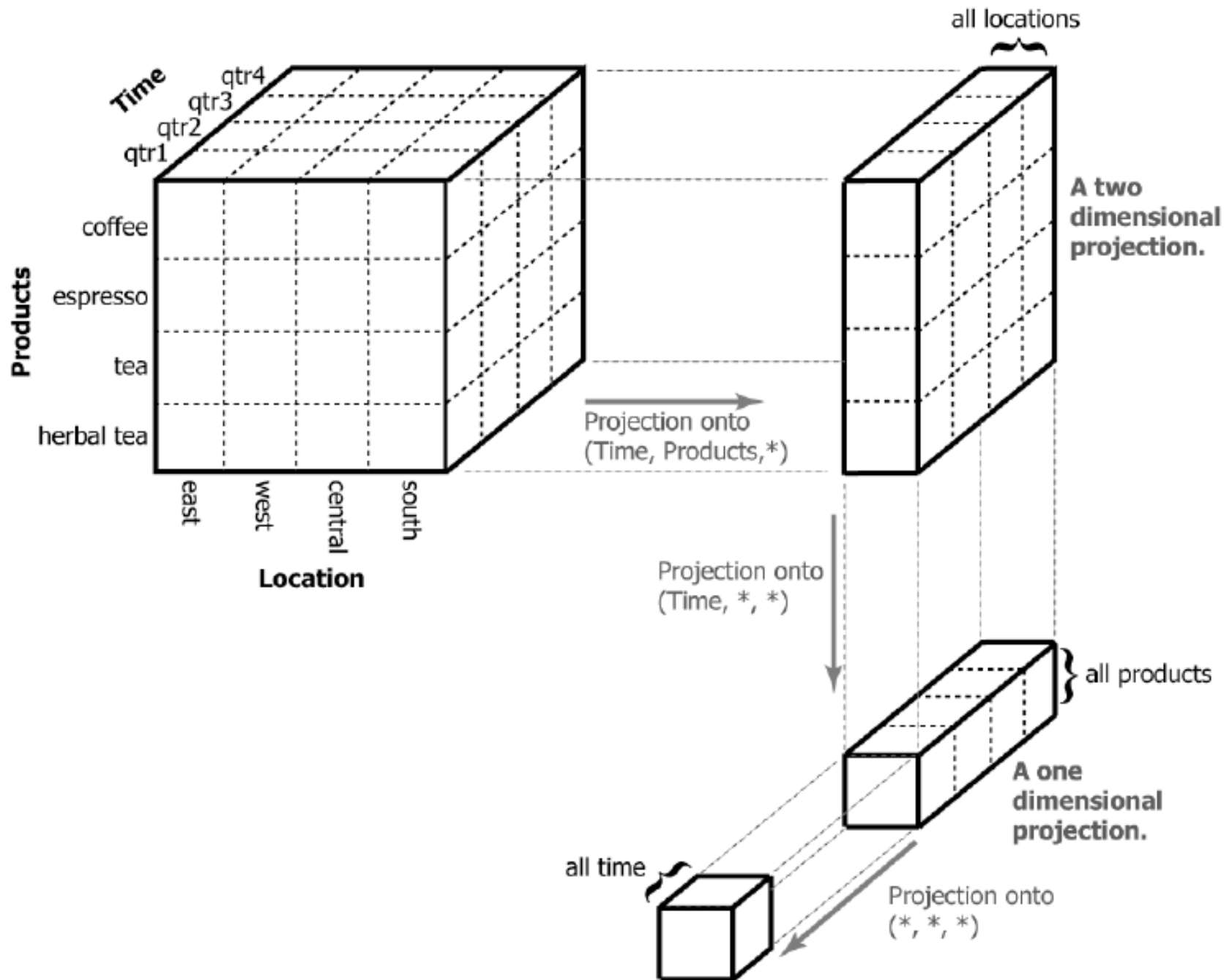
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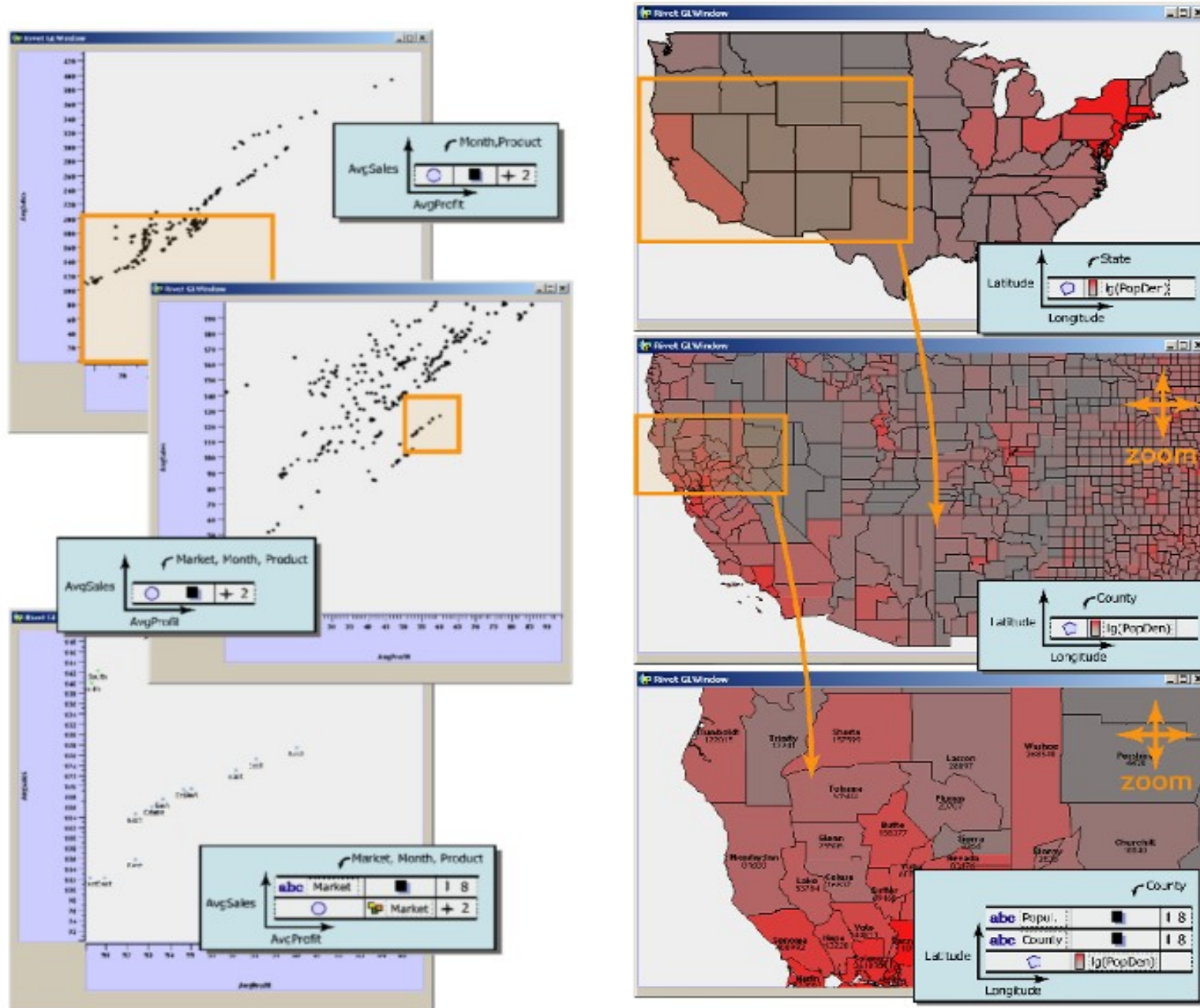
while the relevant dimensions identifies which projection of that cube is needed. Figure 1 shows a simple lattice and projection.

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

# 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	
111110	Soybean Farming	
11112	Oilseed (except Soybean) Farming	
111120	Oilseed (except Soybean) Farming	
11113	Dry Pea and Bean Farming	
111130	Dry Pea and Bean Farming	
11114	Wheat Farming	
111140	Wheat Farming	
11115	Corn Farming	
111150	Corn Farming	
11116	Rice Farming	
111160	Rice Farming	
11119	Other Grain Farming	
111191	Oilseed and Grain Combination Farming	
111199	All Other Grain Farming	
112	Vegetable and Melon Farming	
1121	Vegetable and Melon Farming	
11211	Potato Farming	
11219	Other Vegetable (except Potato) and Melon Farming	
113	Fruit and Tree Nut Farming	
1131	Orange Groves	
11310	Orange Groves	
1132	Citrus (except Orange) Groves	
11320	Citrus (except Orange) Groves	
1133	Noncitrus Fruit and Tree Nut Farming	
11331	Apple Orchards	
11332	Grape Vineyards	
11333	Strawberry Farming	
11334	Berry (except Strawberry) Farming	
11335	Tree Nut Farming	
11336	Fruit and Tree Nut Combination Farming	
11339	Other Noncitrus Fruit Farming	
114	Greenhouse, Nursery, and Floriculture Production	
1141	Food Crops Grown Under Cover	
11411	Mushroom Production	
11419	Other Food Crops Grown Under Cover	
1142	Nursery and Floriculture Production	
11421	Nursery and Tree Production	
11422	Floriculture Production	
119	Other Crop Farming	
1191	Tobacco Farming	
11910	Tobacco Farming	
1192	Cotton Farming	
11920	Cotton Farming	
1193	Sugarcane Farming	
11930	Sugarcane Farming	
1194	Hay Farming	
11940	Hay Farming	
1199	All Other Crop Farming	
11991	Sugar Beet Farming	
11992	Peanut Farming	
11998	All Other Miscellaneous Crop Farming	
12	Animal Production	
121	Cattle Ranching and Farming	
1211	Beef Cattle Ranching and Farming, including Feedlots	
12111	Beef Cattle Ranching and Farming	
12112	Cattle Feedlots	
1212	Dairy Cattle and Milk Production	
12120	Dairy Cattle and Milk Production	
1213	Dual-Purpose Cattle Ranching and Farming	
12130	Dual-Purpose Cattle Ranching and Farming	
122	Hog and Pig Farming	
1221	Hog and Pig Farming	
12210	Hog and Pig Farming	
123	Poultry and Egg Production	
1231	Chicken Egg Production	
12310	Chicken Egg Production	
1232	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

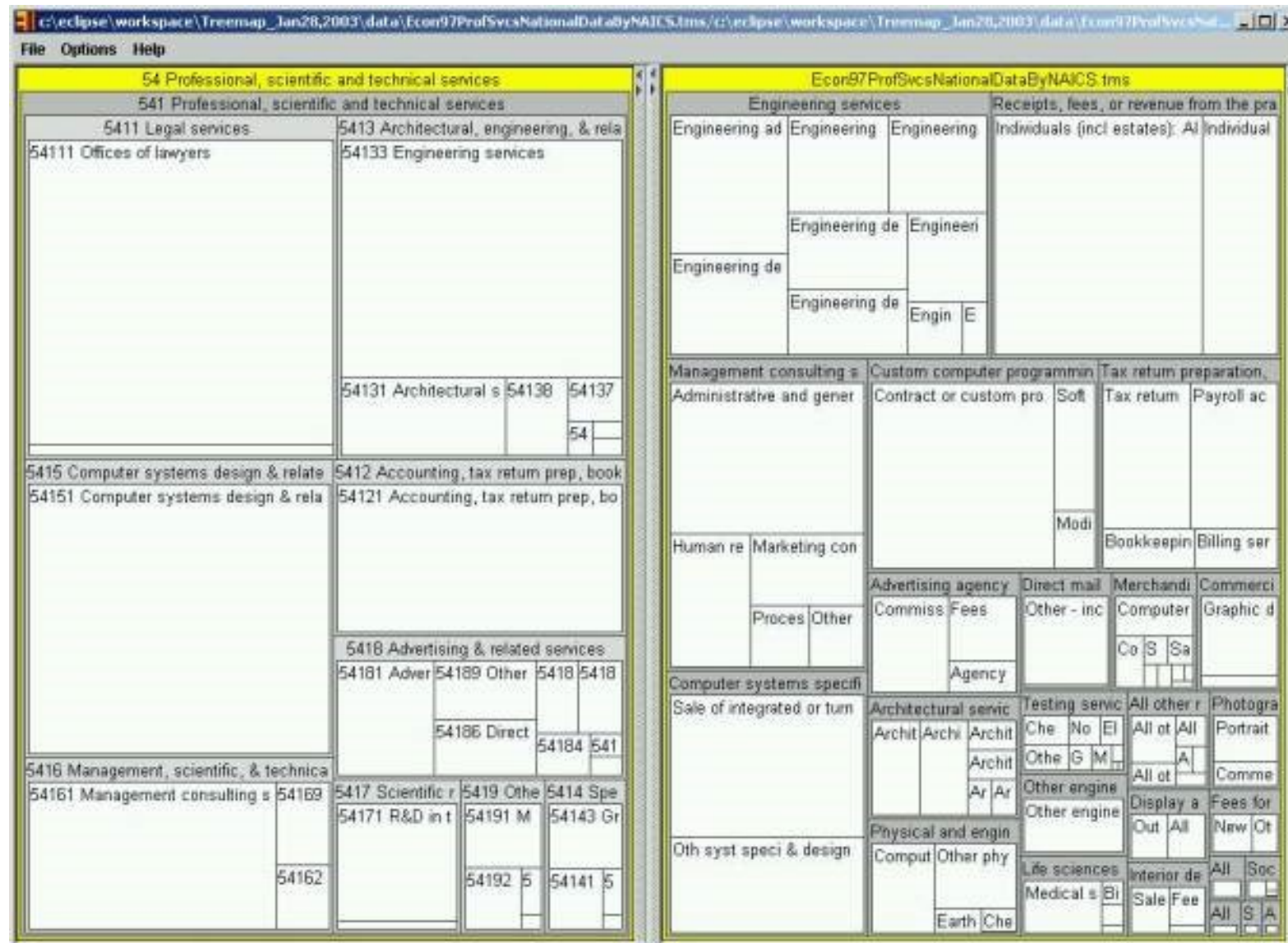
Unclassified

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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Browser-based analytics and data visualization anyone can use. At a fraction of the cost of traditional business intelligence software.

see it in action

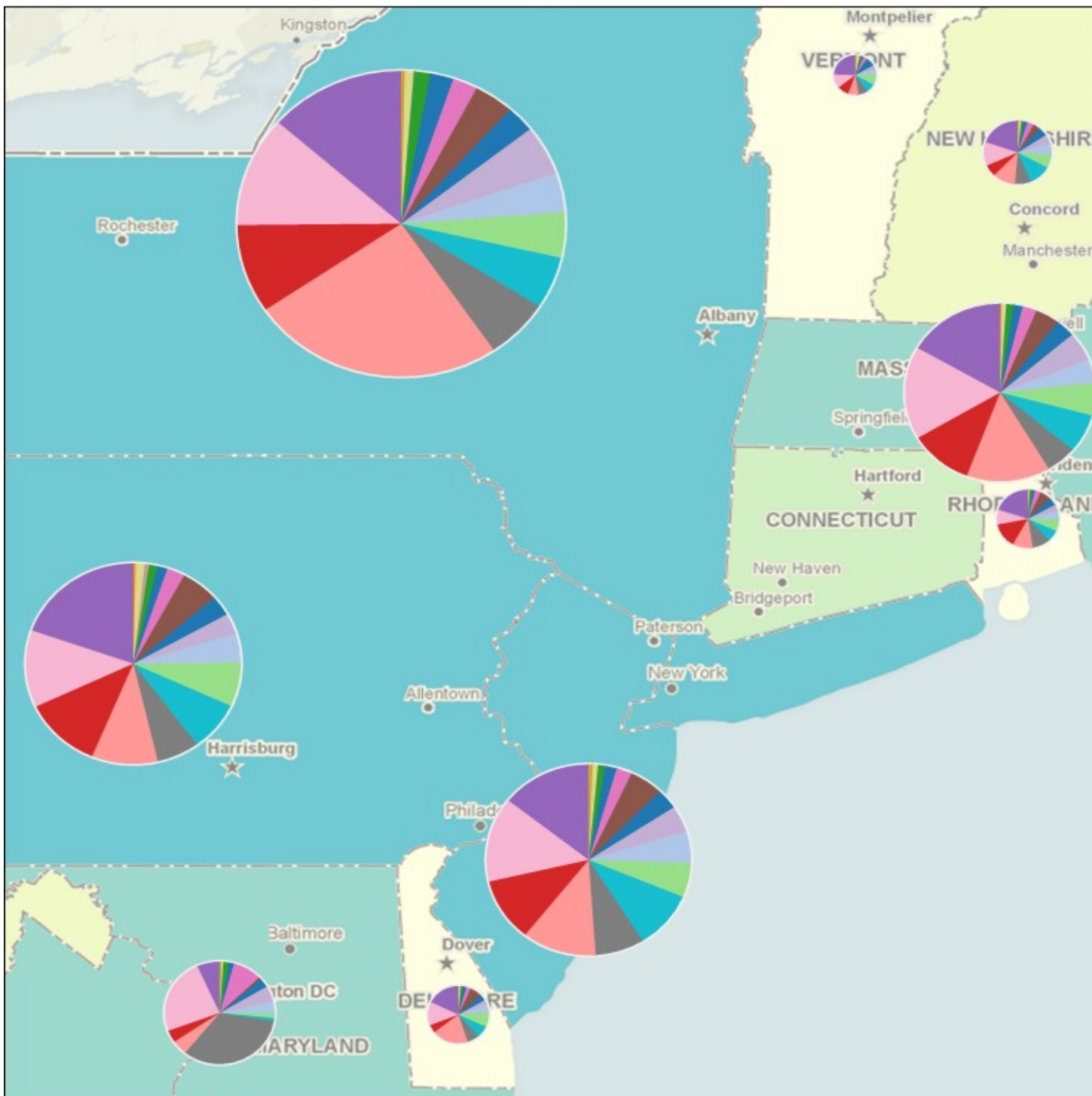


The BLS Employment dataset  
**Visualized**  
using  
**Tableau**

from a project by Siva Mohan and Curran Kelleher



## New England Pies



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.

### A Total Wages



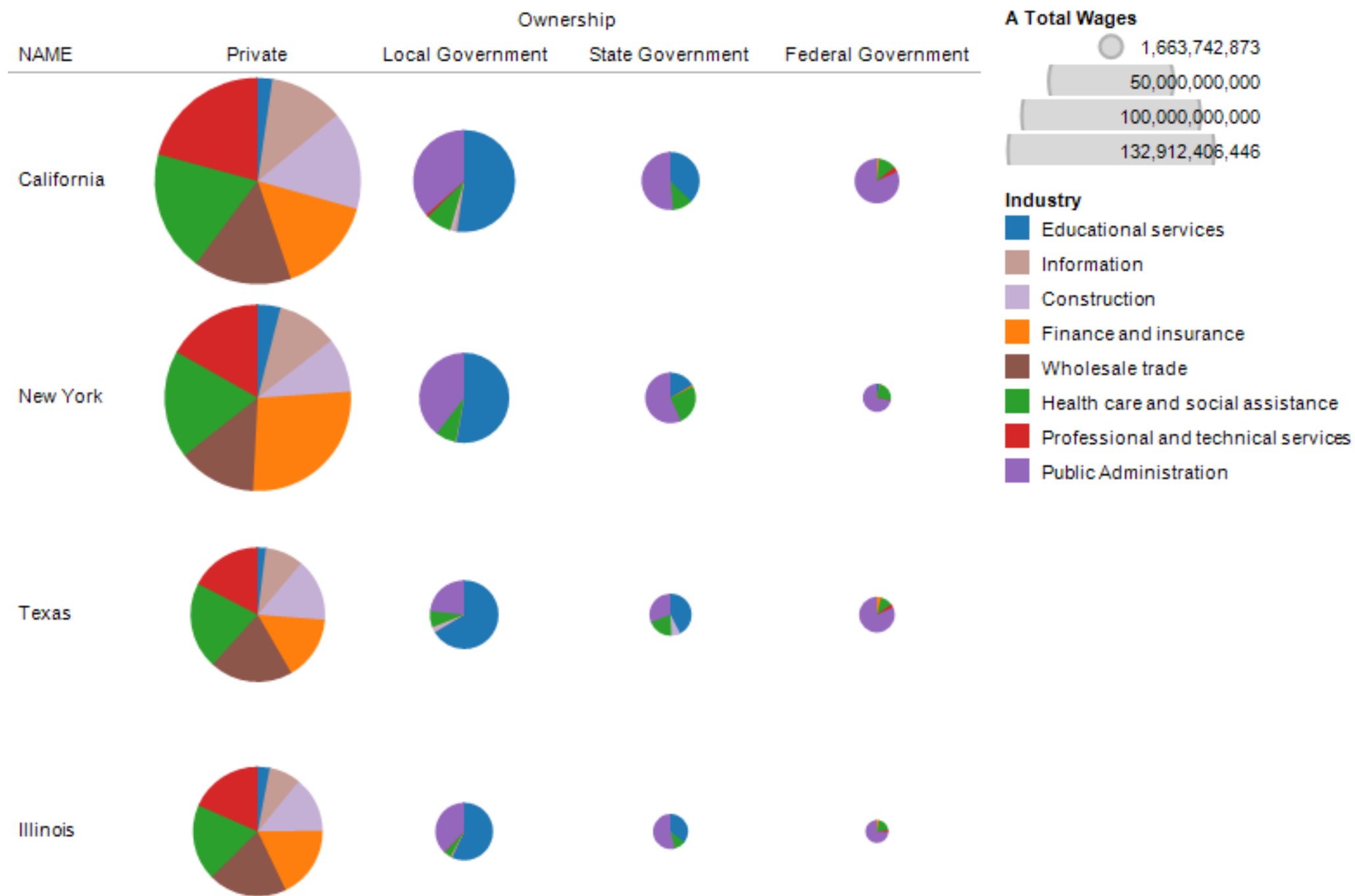
Industry

- Unclassified
- Agriculture, forestry, fishing and hunting
- Utilities
- Mining, quarrying, and oil and gas extraction
- Arts, entertainment, and recreation
- Real estate and rental and leasing
- Other services, except public administration
- Management of companies and enterprises
- Accommodation and food services
- Information
- Administrative and waste services
- Construction
- Wholesale trade
- Public Administration
- Finance and insurance
- Educational services
- Professional and technical services
- Health care and social assistance

### 2007 Population

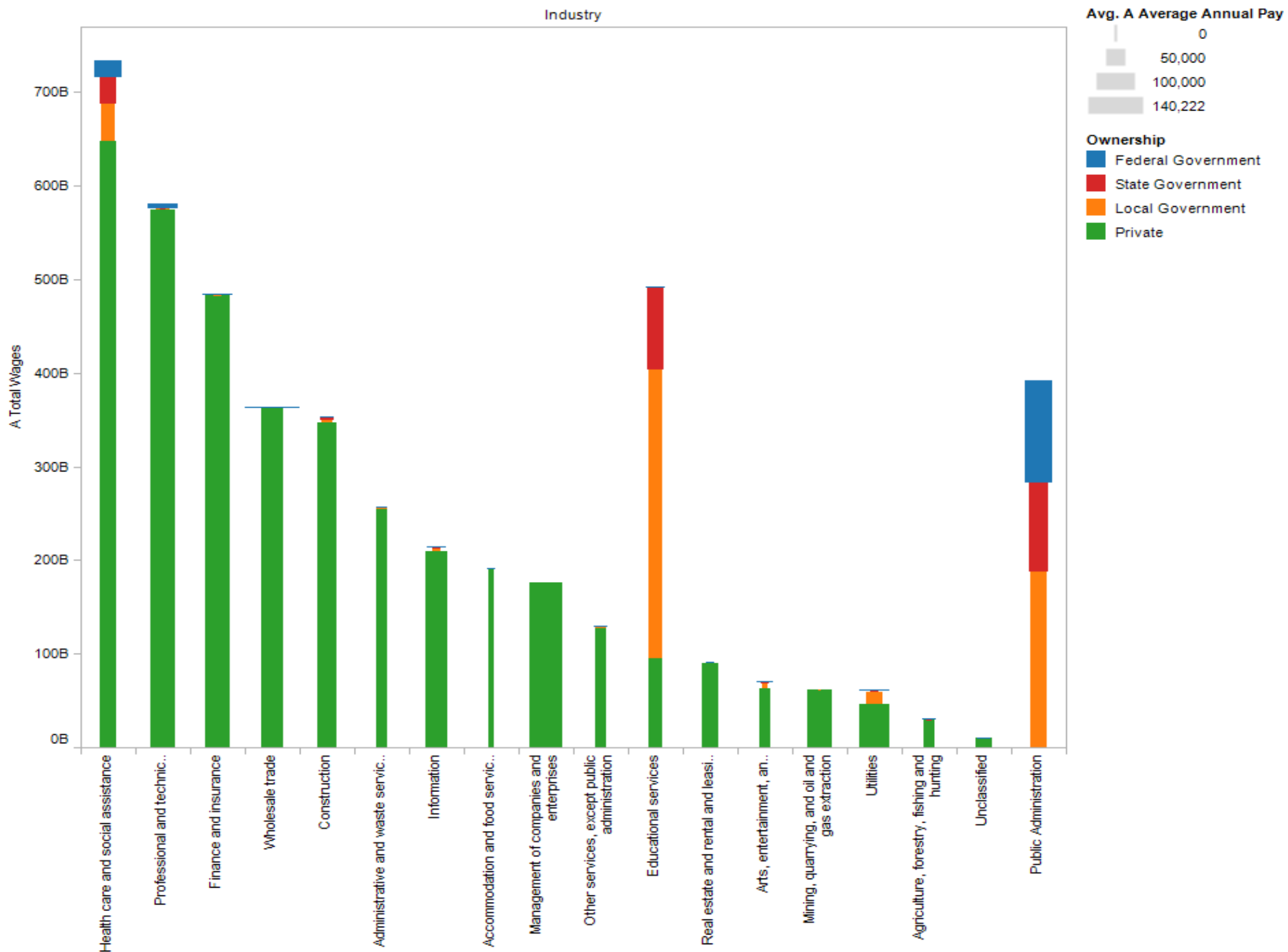
- 514,000 to 1,320,000  
1,320,000 to 2,940,000  
2,940,000 to 5,180,000  
5,180,000 to 8,780,000  
8,780,000 to 37,100,000

# 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>
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    <contact:homePage rdf:resource="http://csail.mit.edu"/>
  - <contact:address>
    - <contact:Address>
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      <contact:country>USA</contact:country>
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    <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

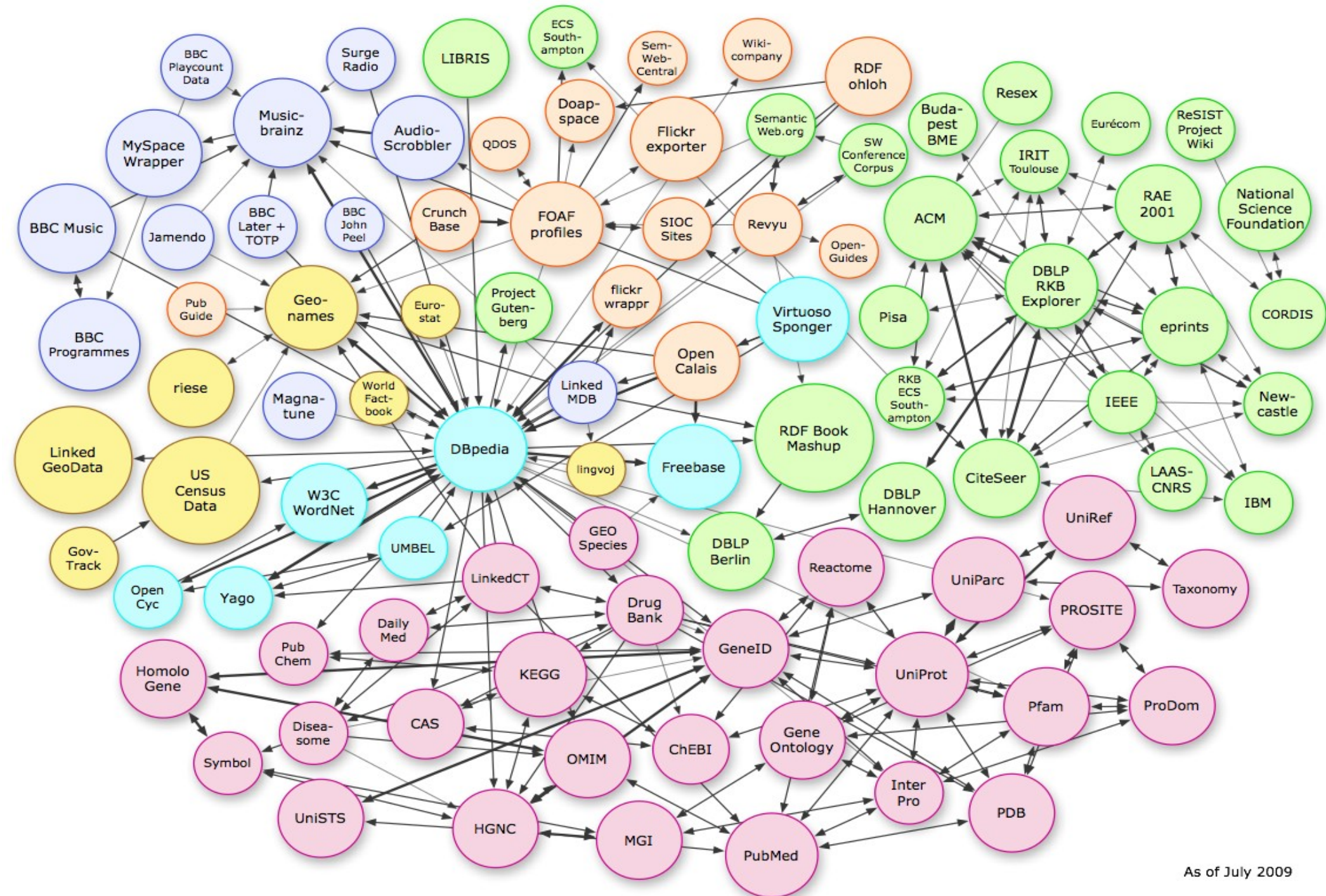
“A term used to describe a recommended best practice for exposing, sharing, and connecting pieces of data, information, and knowledge on the Semantic Web using URIs and RDF.”  
– Wikipedia

# 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



As of July 2009

# 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

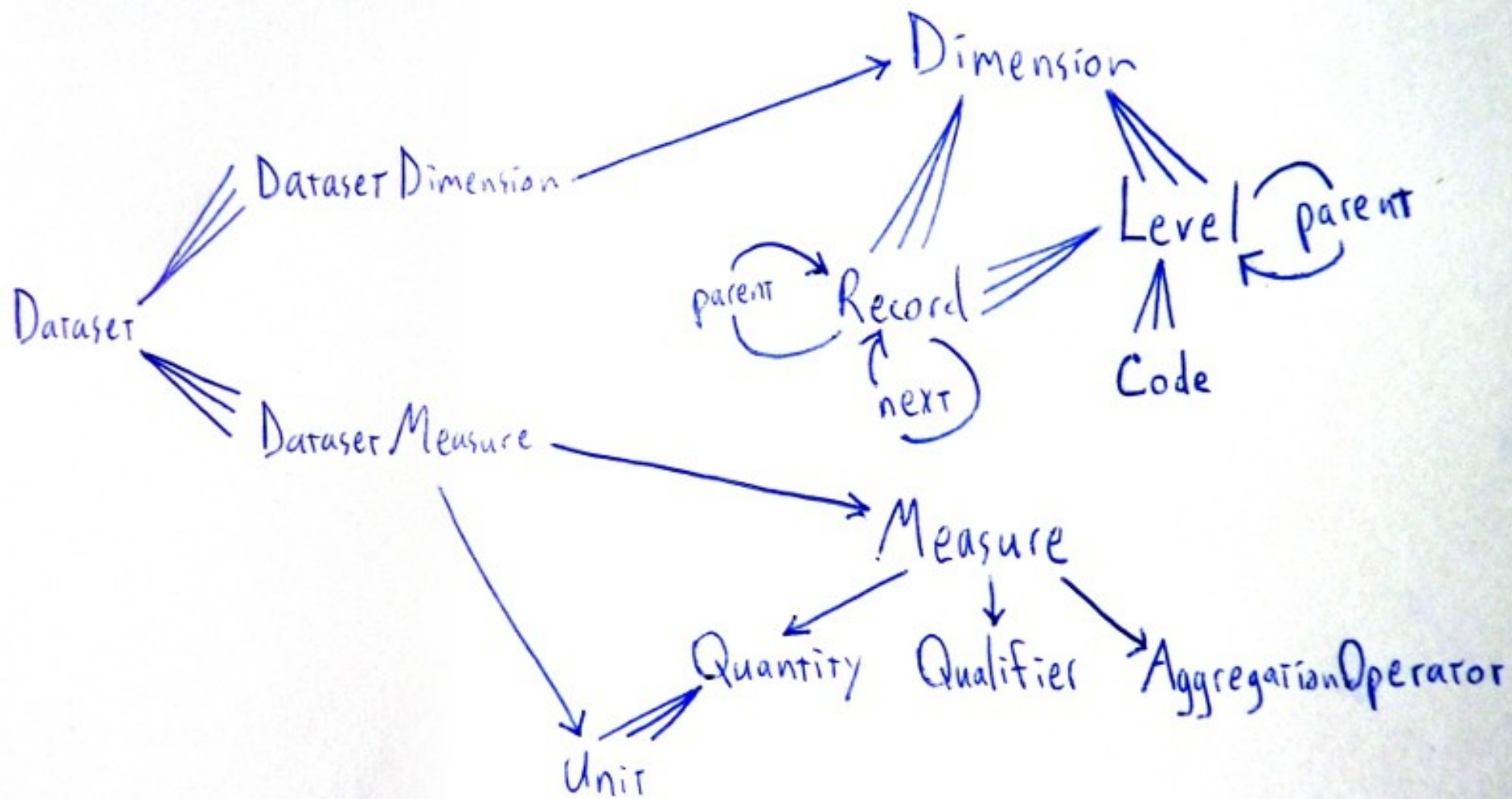
- Design an ontology for hierarchical data cubes
- Develop a system which publishes
  - Data cube metadata in the Linked Data cloud
  - A data cube query endpoint on the web
- Adapt the Weave client to use this system
- Encourage others to build more clients
- Propose it as a web standard for data publishing

# 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

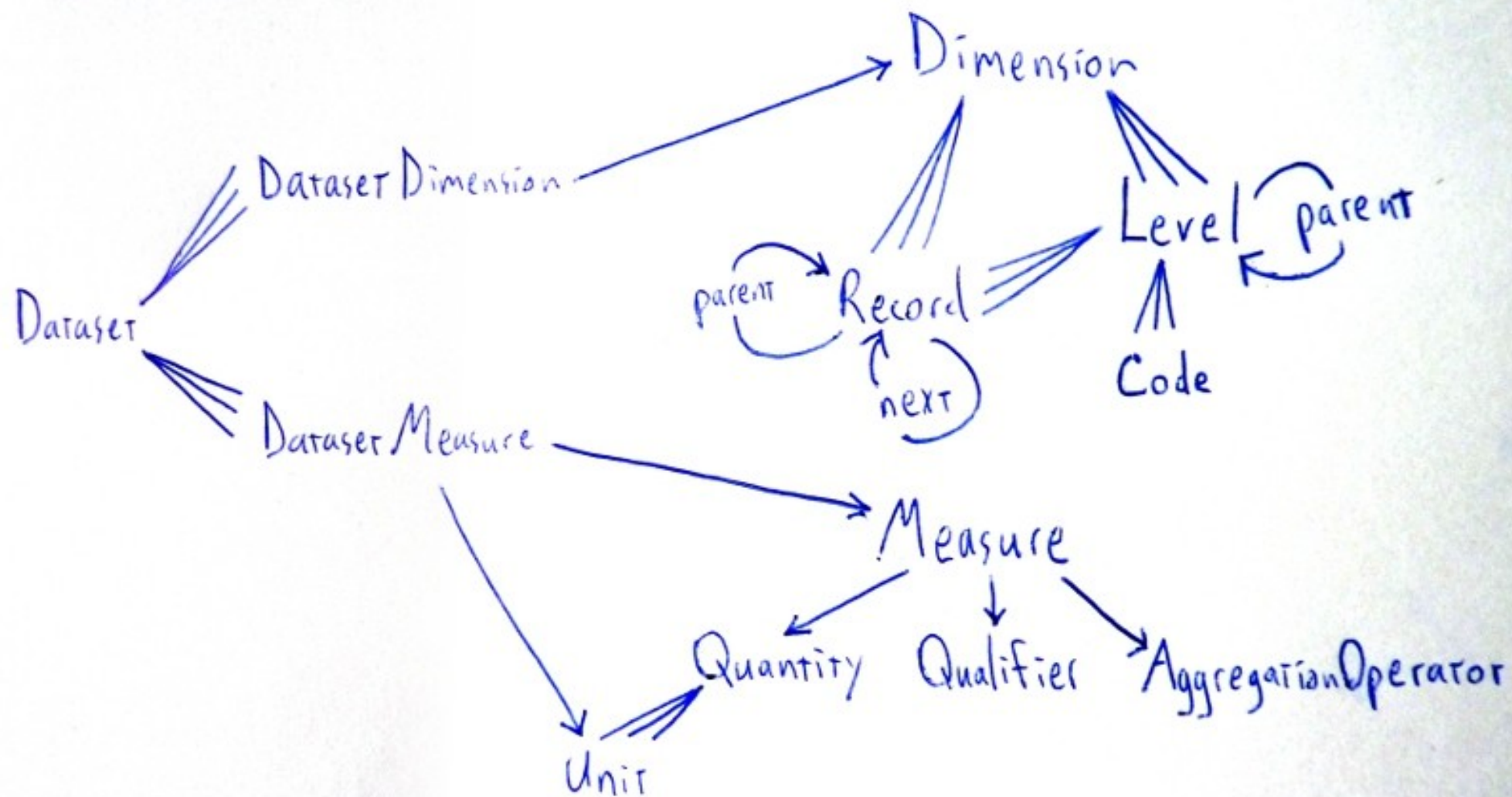
- dc:title String (1) //like "BLS Employment Dataset"
- dc:creator String (0 or 1)
- dc:subject String (0 or 1)
- dc:description String (0 or 1)
- dc:publisher String (0 or 1)
- dc:date String (0 or 1)
- dc:rights String (0 or 1)
- usesDatabaseTable DatabaseTable (\*)
- usesDataCubeMapping String (1) //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

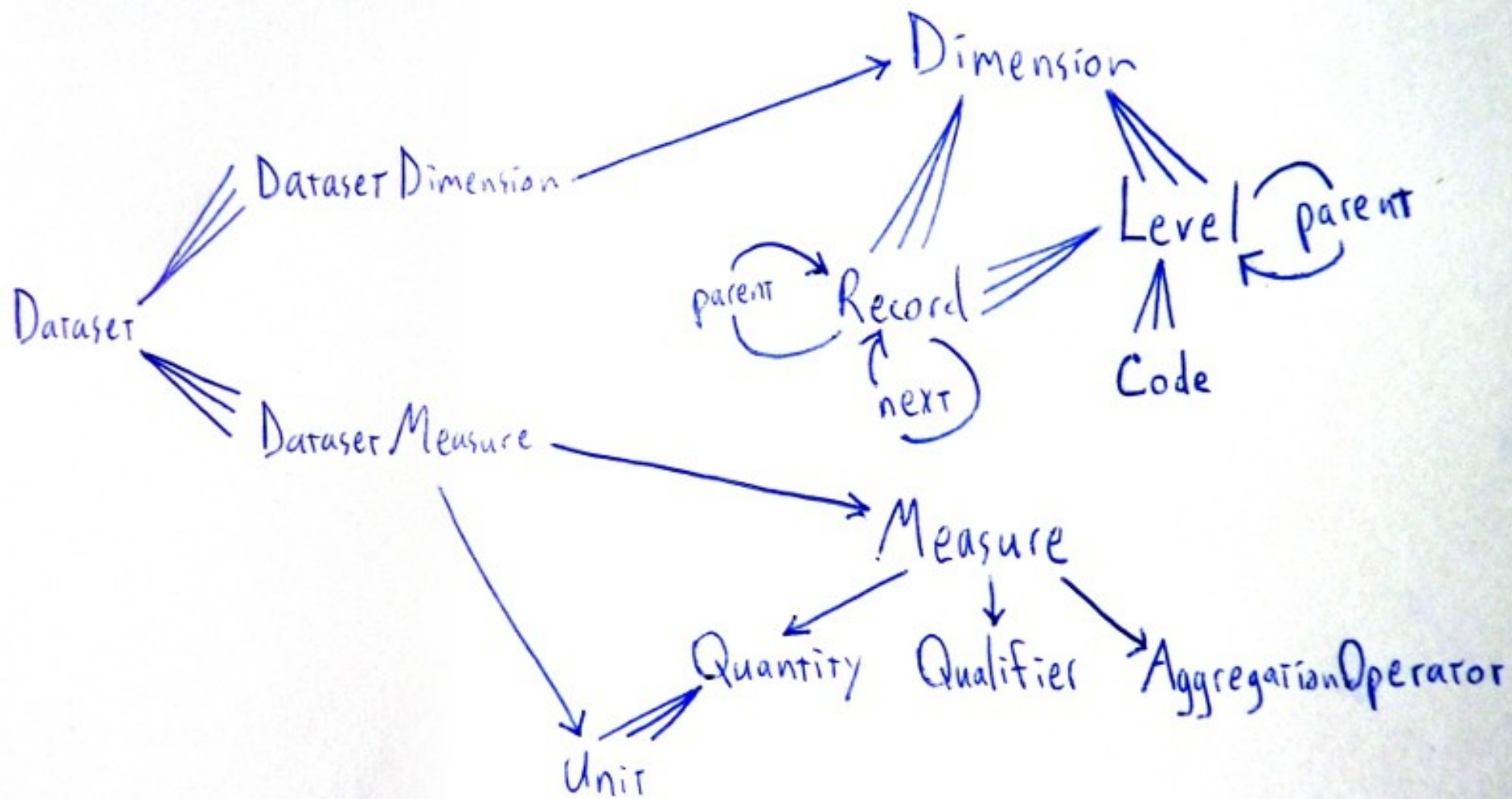
# Weave Data Model Problems

- 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

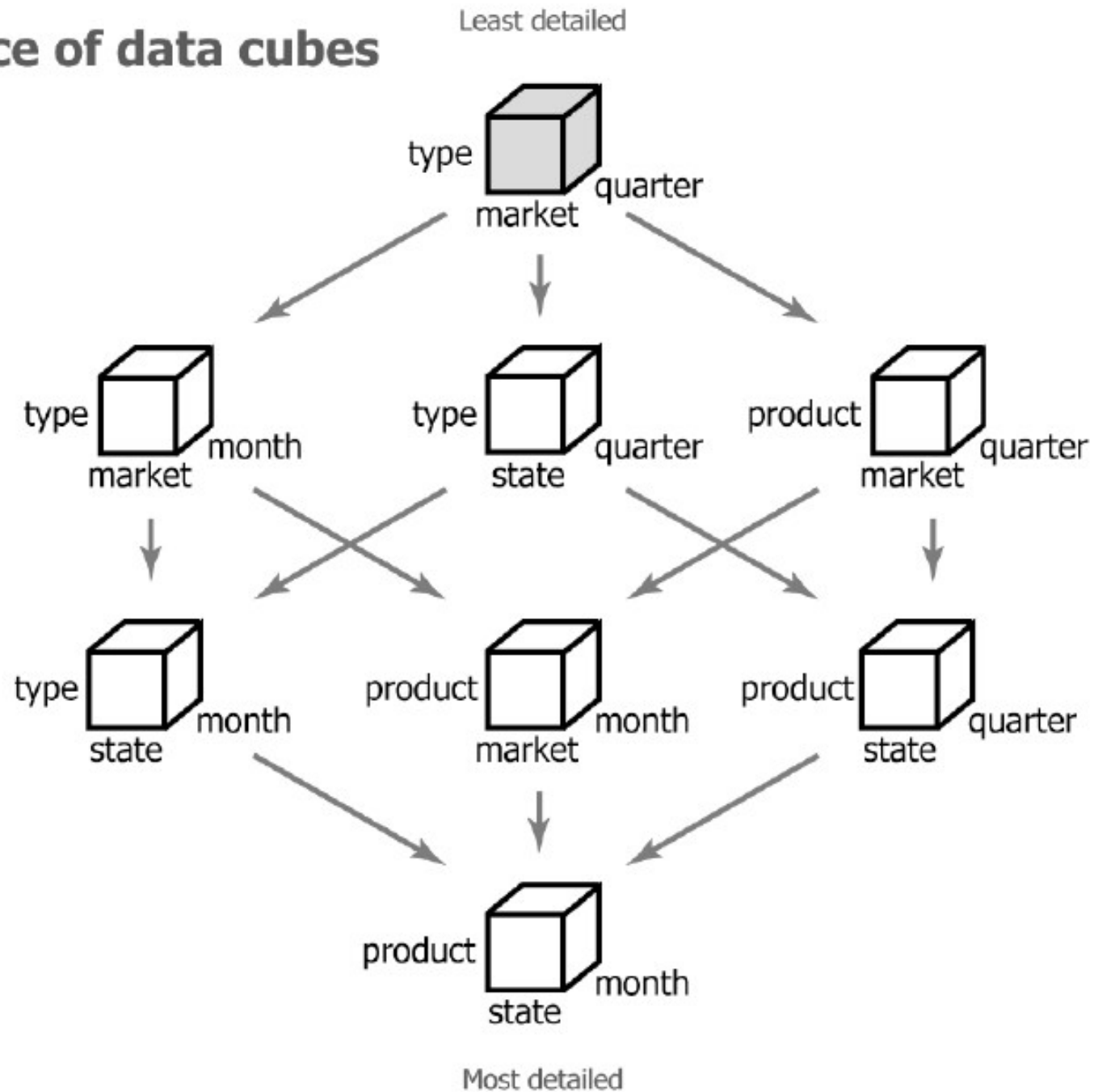
# Weave Data Model Solutions

- 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

The end.



# The lattice of data cubes



# Projecting a three dimensional data cube

