

# **Knowledge Structuring for Cross-disciplinary Data Exchange and Collaboration**

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## Yamanishi Team

Discovering Deep Knowledge from Complex Data  
and Its Value Creation

### Variety

- Deep learning based on behavioral models
- Optimal integration and prediction of relational data

Theory of Discovering Deep Knowledge

**Yamanishi Group**  
**Masuda Group**

- Latent dynamics
- Change detection
- Temporal network
- Time dependent centrality

### Velocity

Application of Deep Knowledge

**IBM Group**  
**Ohsawa Group**

- Optimization of sequential decision making
- Evaluation of data
- Platform of Data Market

### Value

**Ohsawa Group**  
Methods for Creating Data Market to Evaluate Utility Value of Data and Deep Knowledge

# Introduction

## Big Data

- Increasing capacity of storage
- Analysis method for heterogeneous data

## Personal Devices

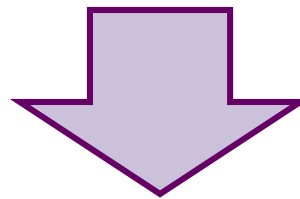
- High granularity personal data
- Purchase logs, life logs, etc.

## Open Data

- The use of secondary data
- Massive amounts of data from the governments are available

## Sensors

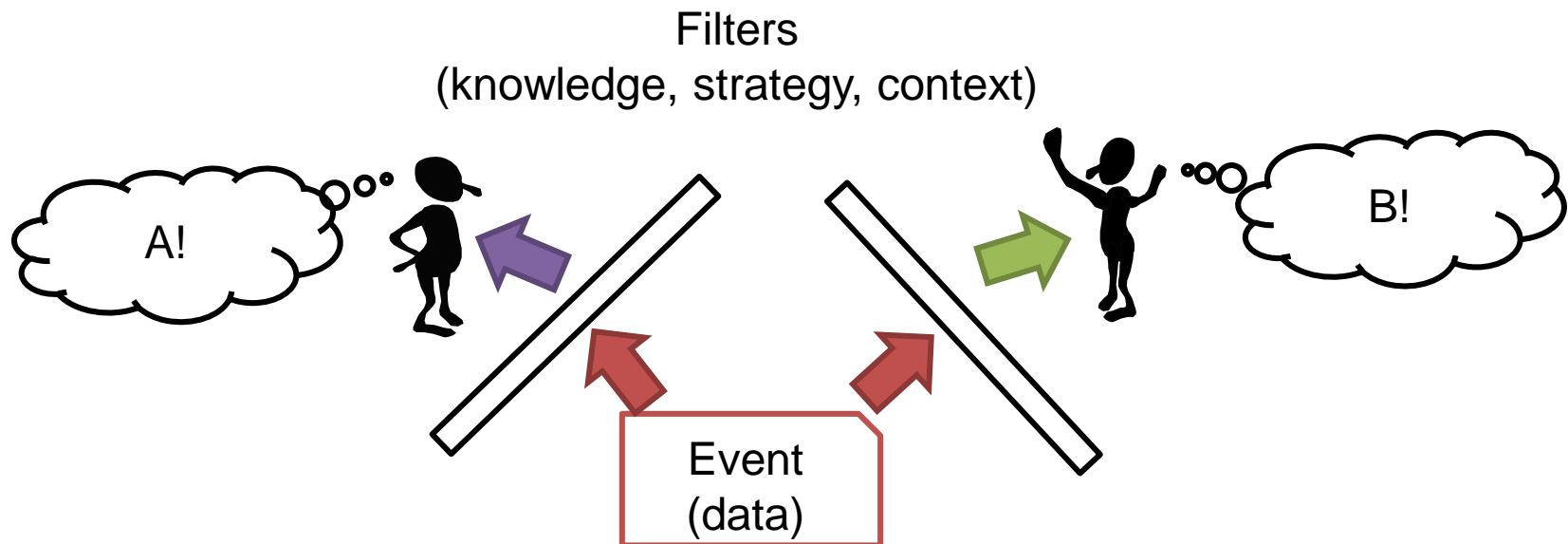
- Internet of Things
- High density data are available



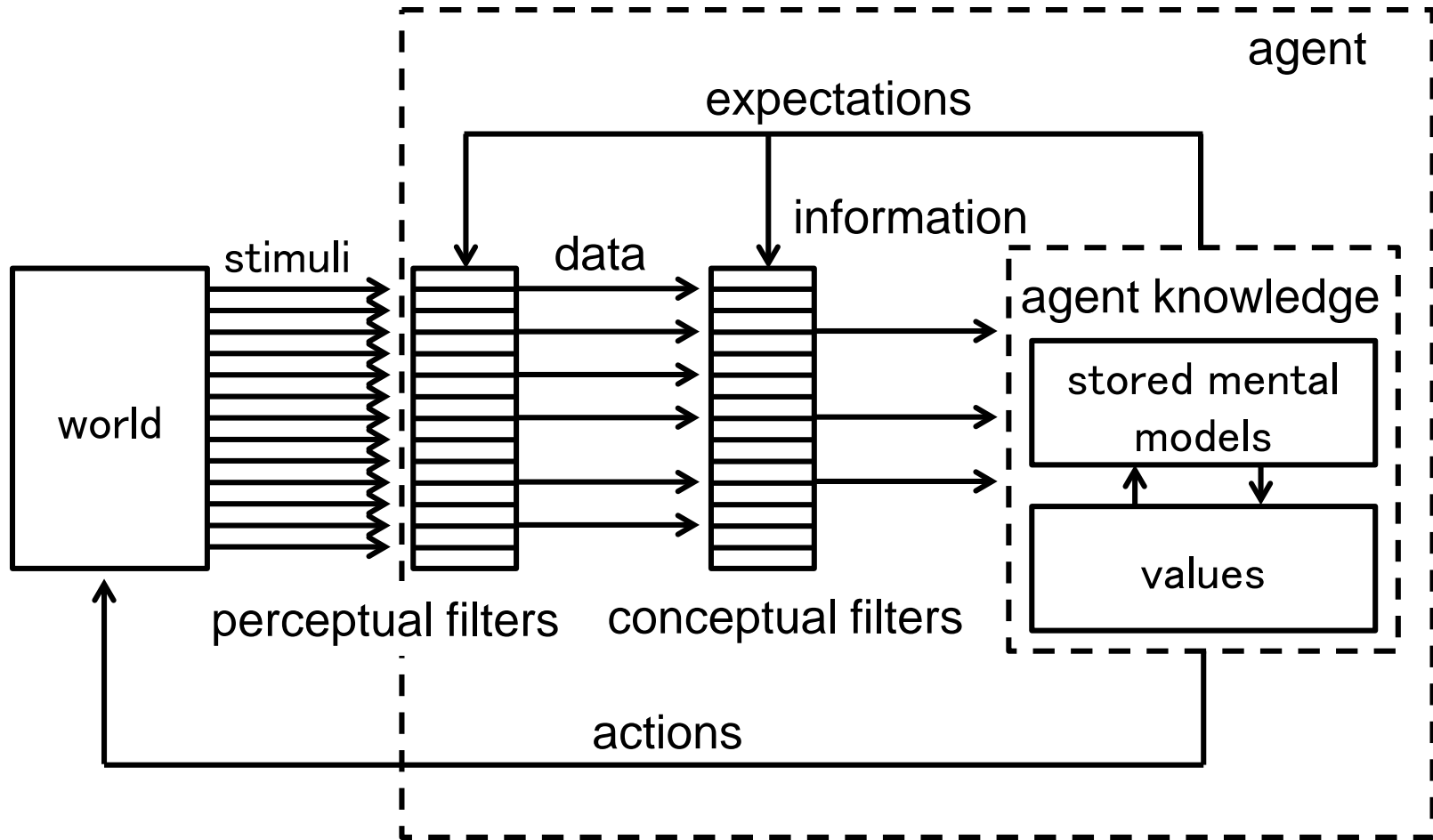
The potential benefits of reusing and analyzing massive amounts of data have been discussed by various stakeholders from diverse domains.

# Why Data Exchange?

- ❑ Decision makers in the society recognize the different world, even though they see the same world (Metcalf, 1998)
  - ❑ background knowledge and available opportunities
- ❑ The two problem solvers may construct different facts even if they observe the same event (data) (Hayashi et al., 2006)
  - ❑ the different perspectives, contexts and background knowledge



# Why Data Exchange?

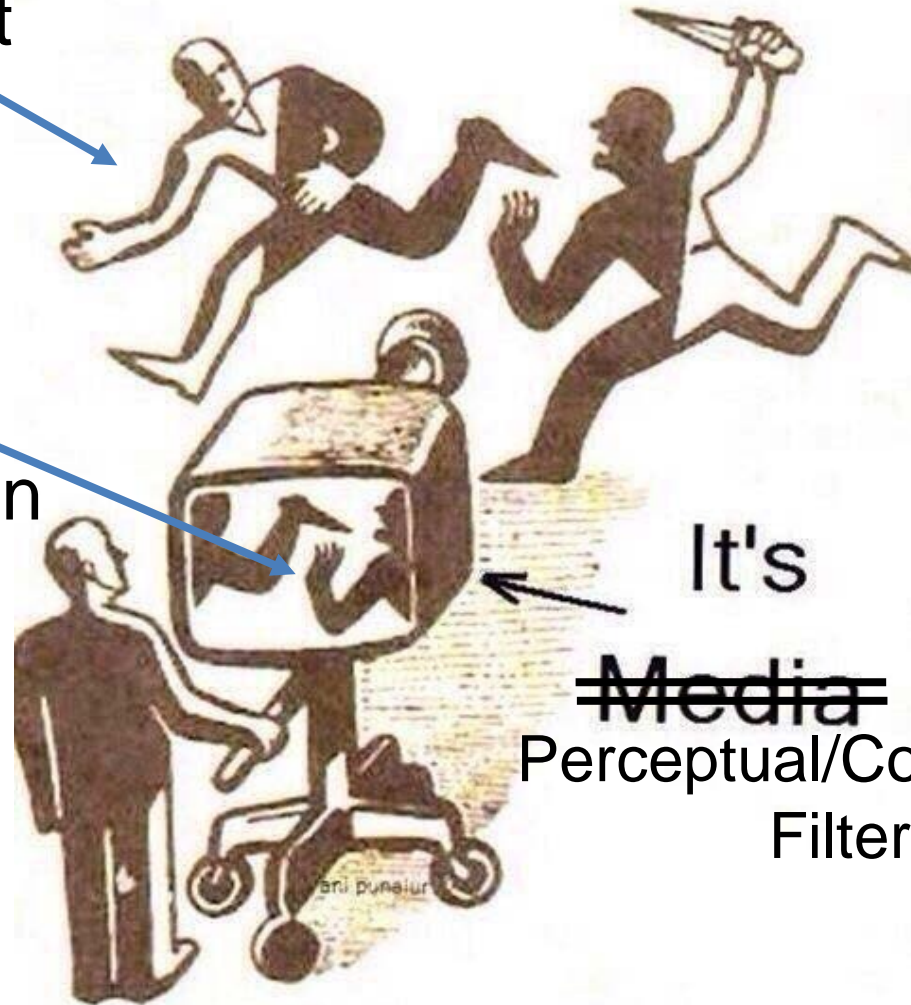


The agent-in-the-world (Boisot & Canals, 2004)

# Why Data Exchange?

It's Event

It's  
Data/Information



It's  
~~Media~~  
Perceptual/Conceptual  
Filter

Data exchange are important to recognize the world correctly, and to encourage the cross-disciplinary data driven innovation.

# Our Approach

To encourage cross-disciplinary data exchange and collaboration...

It is important to understand the events in the world and the relationships of obtained data correctly.



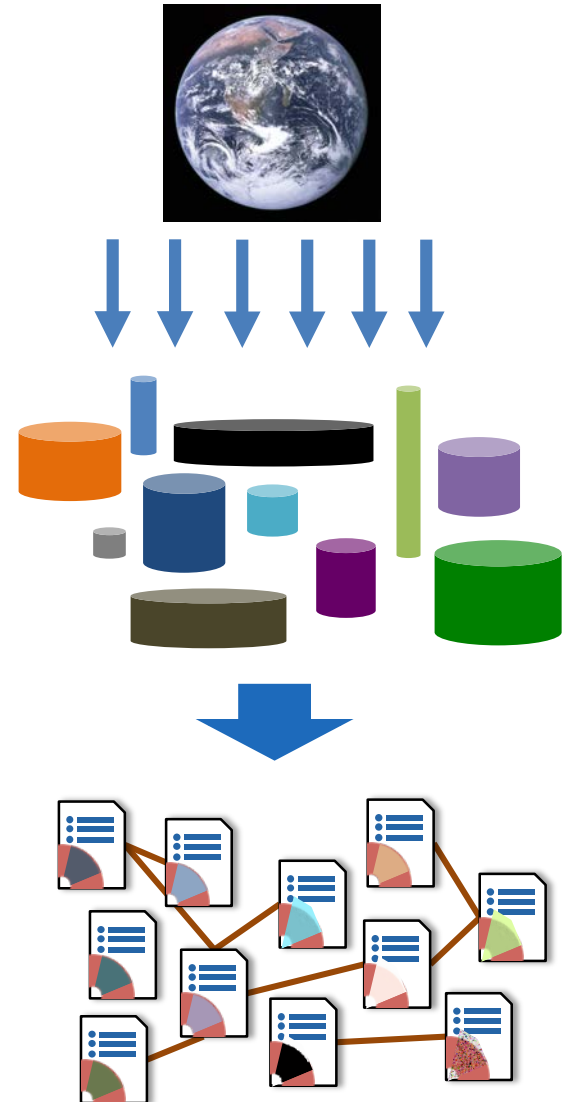
Analyzing the structural features of the population of data from different domains, rather than analyzing individual data



A data model to discuss different data on the same field is necessary to quantitatively evaluate the trends and features of the population of data.

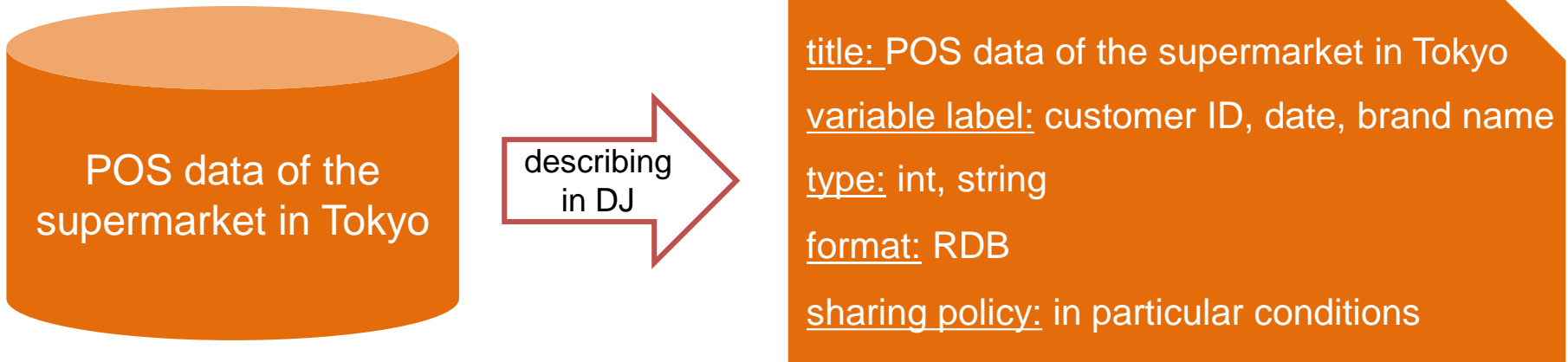


It is effective to use metadata (data of data) obtained from different domains as the analysis subject.



# Data Jacket (DJ)

- **a structured summary of data described in natural language**
- DJ has been developed as a technique for sharing information about data and for considering the potential value of datasets, with the data itself hidden.
- Even if data itself is not open, by publishing DJ, data could be recognizable and understandable not only for humans, but also for machines.
- Published DJs enable data owners, data users and data analysts to understand the contents of each dataset, and start to communicate about data utilizations among stakeholders.





# Examples of DJs

## Earthquake and related disaster information

### ID

262

### OUTLINE

This is the summary of earthquakes and related disasters. Will be updated for several times after the first release as new knowledge is obtained through investigation.

### VARIABLE LABEL

Summary of the earthquake   Date and time of occurrence   Depth   Magnitude   Abolition time  
Latitude (20:25 '14" to 45.33 '19")   Longitude (122:55 '59" to 153:59 '25")   Number of injured  
Number of demolished houses   Number of partial damaged houses   Installation time   Epicenter  
Local seismic intensity around the country   Number of deaths   House damage   Other damages  
Presence or absence of the tsunami   Number of missing   Number of houses with the floor flooded  
Number of inundation above floor level   Emergency Response Headquarters installation conditions

### SHARING POLICY

With anyone

### COLLECTING COST

Available at the website of Fire and Disaster Management Agency of Japan.

### FORMAT

PDF

### TYPE

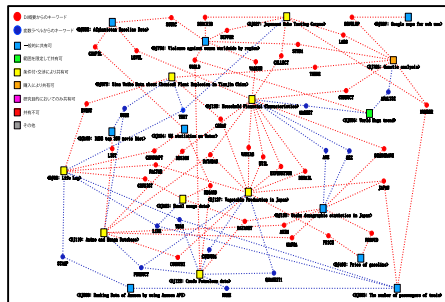
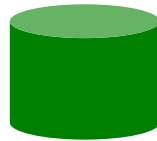
TEXT, TABLE

# What We can do with DJs

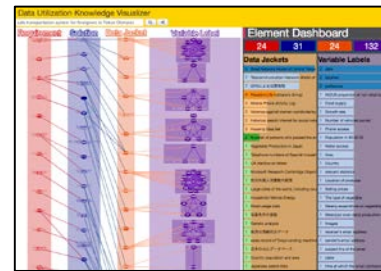
We can...

- ❑ understand who owns the data we are interested in.
- ❑ handle datasets in standardized format by describing each dataset in metadata.

## Understanding Data



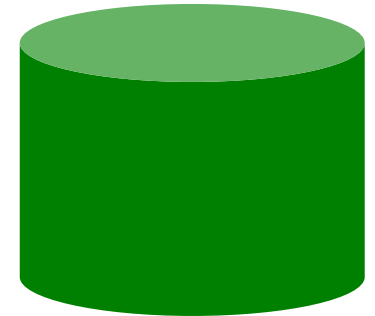
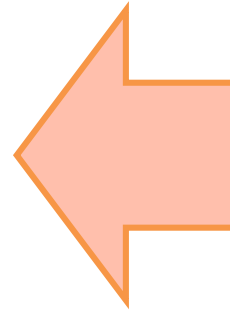
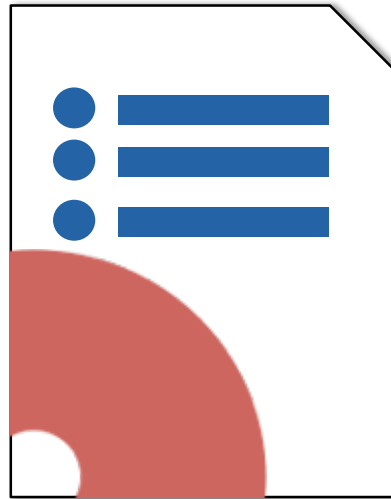
## Support Systems



## Discussion for Data Utilization



# Understanding Data



# Visualization of Data

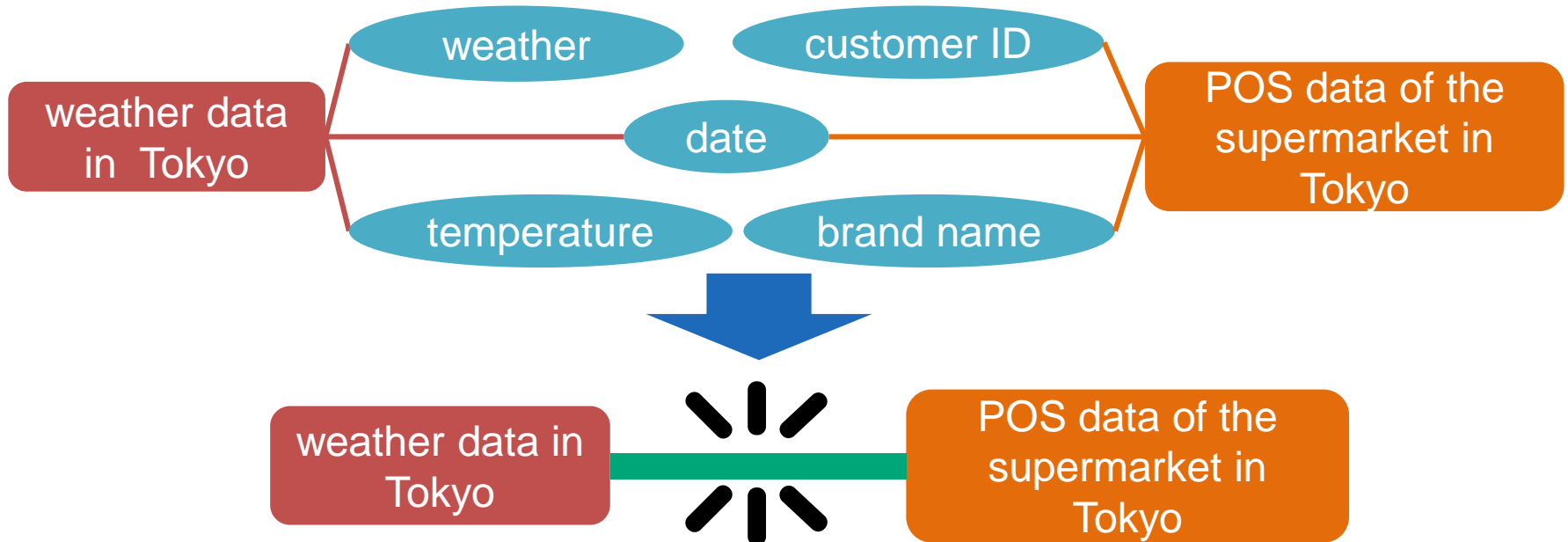
## Linkage of Data:

achieved by the combinations of variables in data



datasets having common Variable Labels are highly likely to be combined

Assuming that each node is a DJ, a link between DJ nodes connects when both DJs have a common Variable Label.



# Visualization of Data



features	value
The number of links	11077
The number of nodes	652
Average degree	33.98
Density	0.0522
Average cluster coefficient	0.703
assortativity	0.561
diameter	11
Average shortest path	3.442

## High average cluster coefficient and low density

- ❑ close each other locally and sparse globally
- ❑ Similar data tends to connect strongly and consists the locally dense network

## Shorter average shortest path and high assortativity

- ❑ The structure is similar to the network of human relations

# Visualization of Data

## Degree centrality

The indicator that how a node has linkages with other nodes

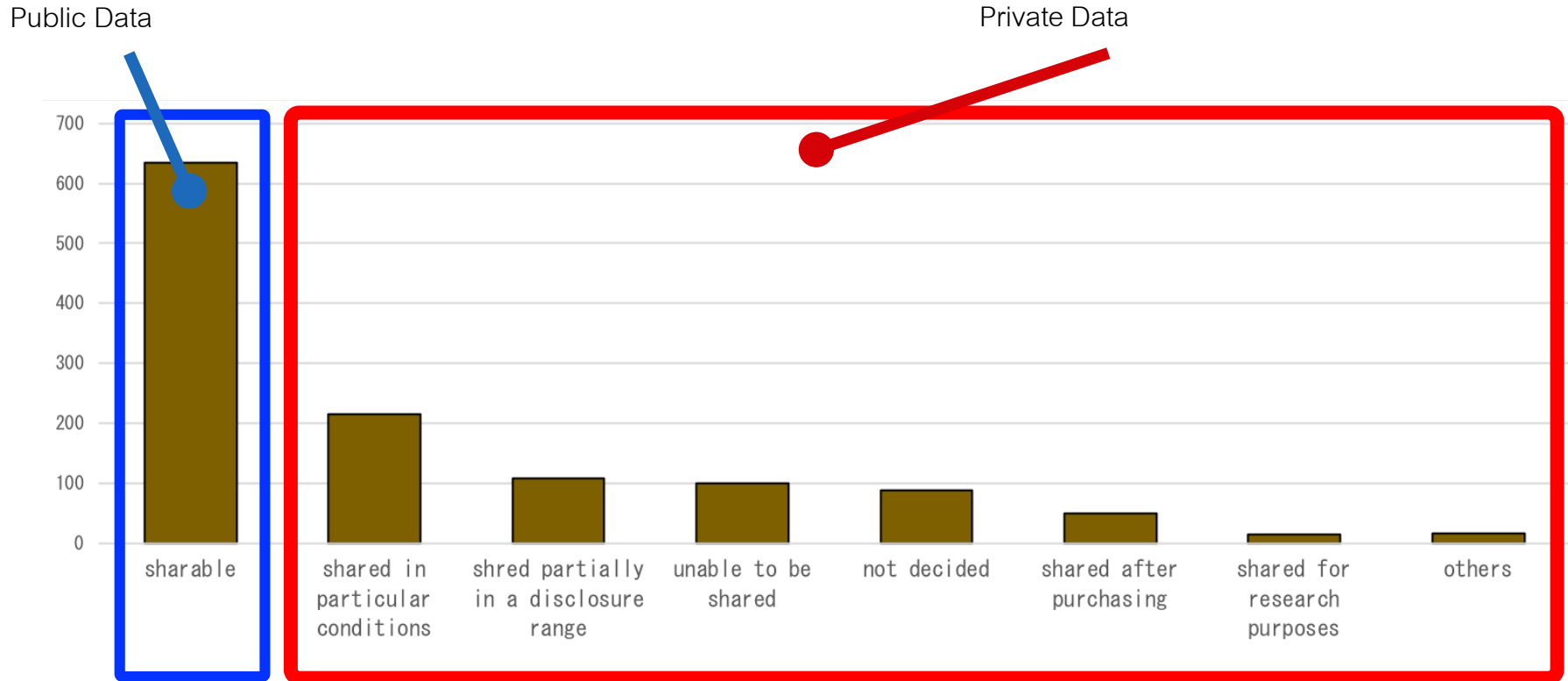
Data name	Value
Facebook data	0.192
The locational information of public toilets	0.187
Twitter data	0.186
The data of earthquakes	0.181
The observation data of ozone layers	0.180

## Betweenness centrality

The indicator that how a node bridges the nodes of other groups

Data name	Value
The traffic data of highways	0.221
Social Networking Service data	0.071
Sales data of food consumption by areas	0.064
Happiness around the World	0.054
The book records data	0.035

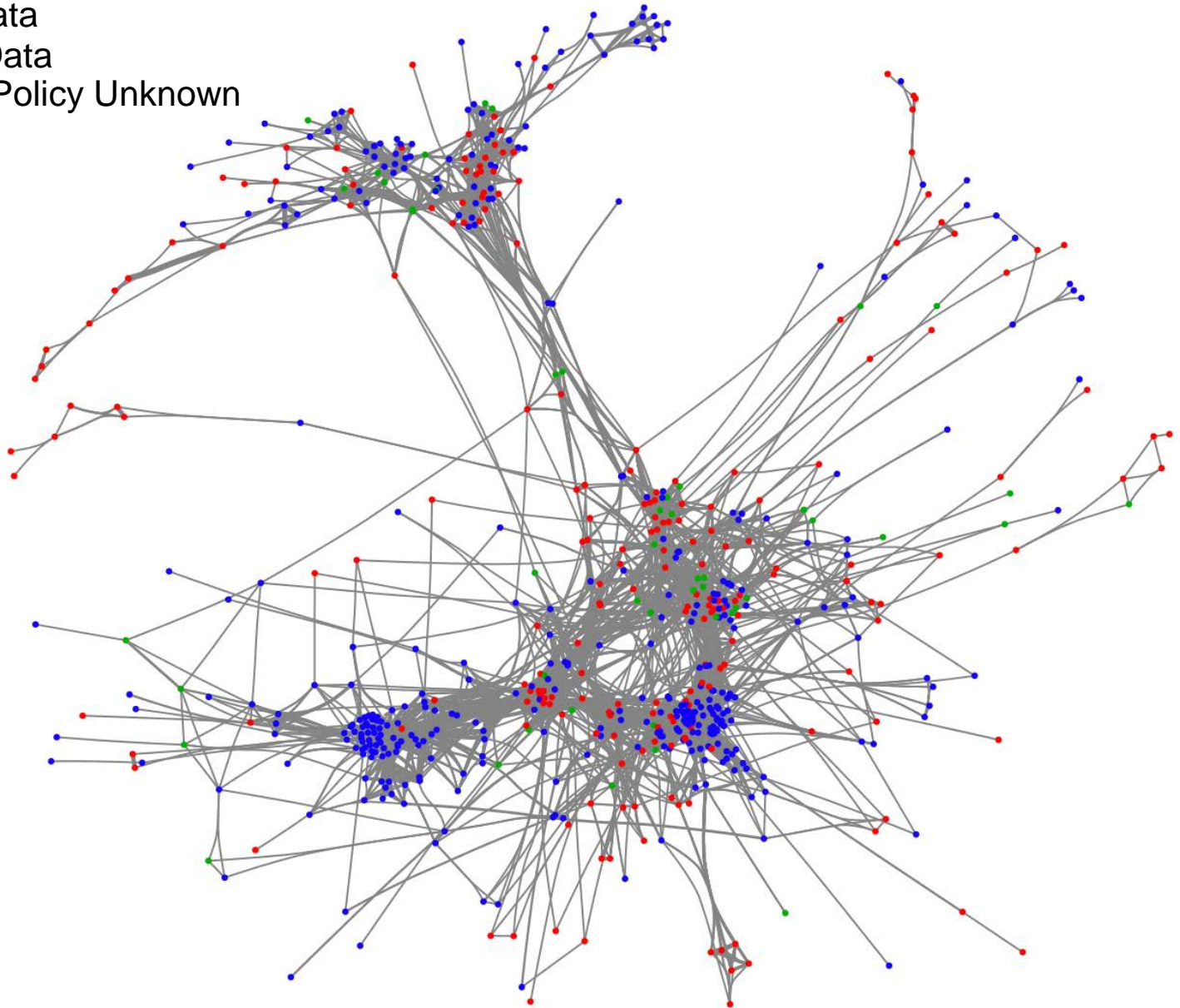
# Network Analysis with Sharing Policy



- ❑ Data is **the economic goods** in the Data Market
- ❑ **The sharing policy** is one of the important attributes of the data
- ❑ We analyzed the network of data considering the sharing policy

# Network Analysis with Sharing Policy

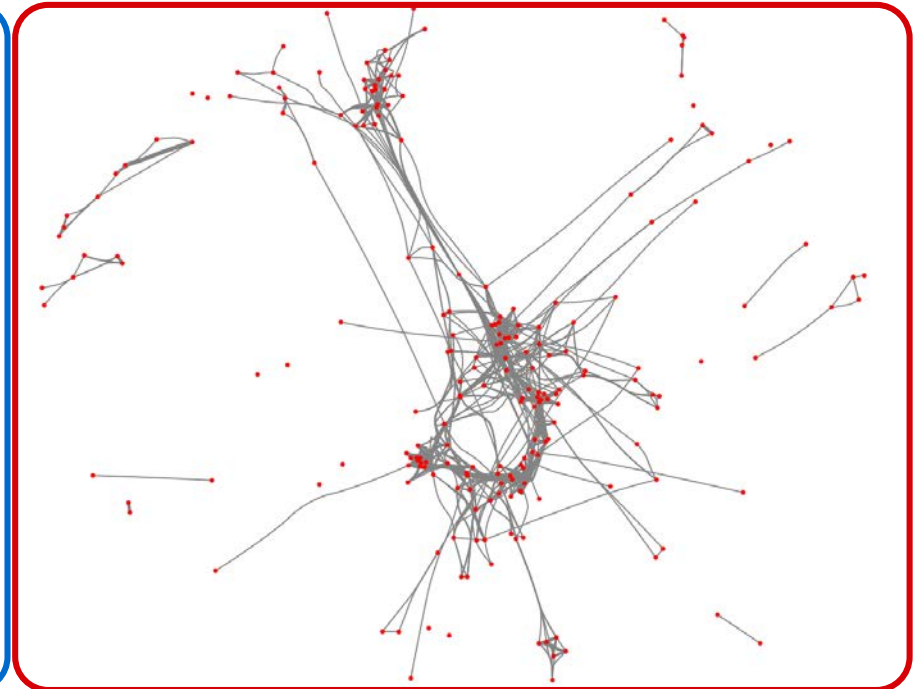
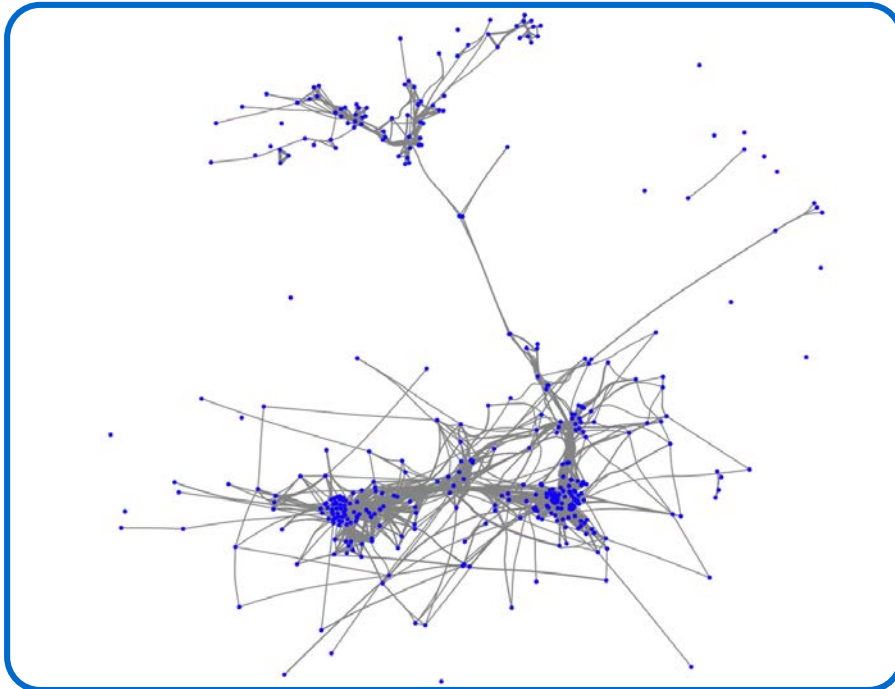
- : Public Data
- : Private Data
- : Sharing Policy Unknown





# Network Analysis with Sharing Policy

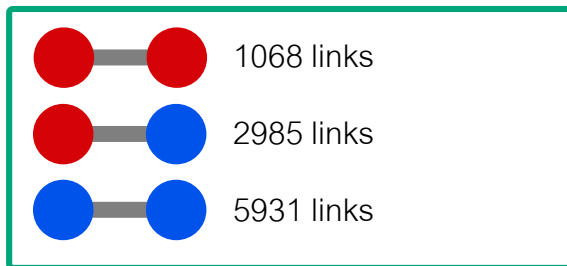
Features	Public Data	Private Data
The number of links	5931	1068
The number of nodes	388	216
Average degree	30.57	9.89
Density	0.079	0.046
Average cluster coefficient	0.719	0.611
assortativity	0.556	0.456



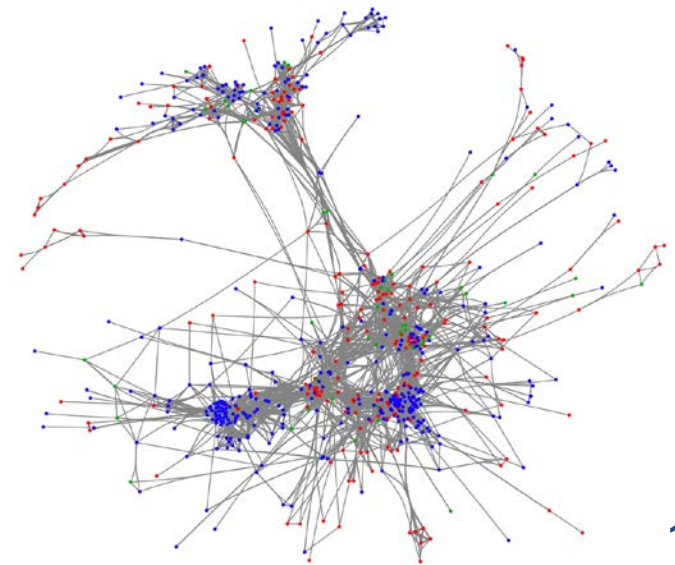
# Network Analysis with Sharing Policy

Degree Centrality	Betweenness Centrality
Facebook data	The traffic data of highways
The locational information of public toilets	Social Networking Service data
Twitter data	Sales data of food consumption by areas
The data of earthquakes	Happiness around the World
The observation data of ozone layers	The book records data

**Private Data** exists more between **Public Data** than between **Private Data**.



This result suggest that **Private Data** may play a role of combining data of different areas.





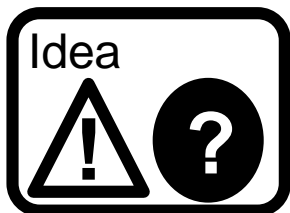
# Necessity of Support Systems

It is difficult for users to accurately obtain data corresponding to their own interests.

- ❑ the combination of databases may occur a serious violation of privacy (Acquisti & Gross, 2009; Xu et al., 2014)
- ❑ the size of the datasets is meaningless, and understanding the values of small data is more important (Boyd & Crawford, 2012)
- ❑ It is difficult to learn the kinds of data that are related to our interests as well as the means to obtain and utilize them (Hayashi & Ohsawa, 2016).

We want to hold the beer party towards the Tokyo Olympic Games.  
BUT, I wonder what kinds of data should we collect...?

I want to solve my health problem related to blood.  
BUT, how I can find the related data?



Data User



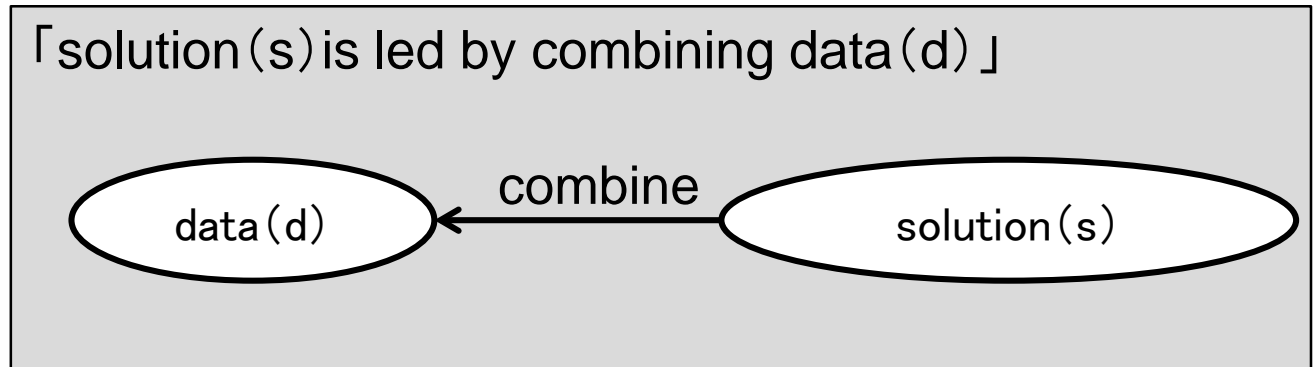
Data Holder



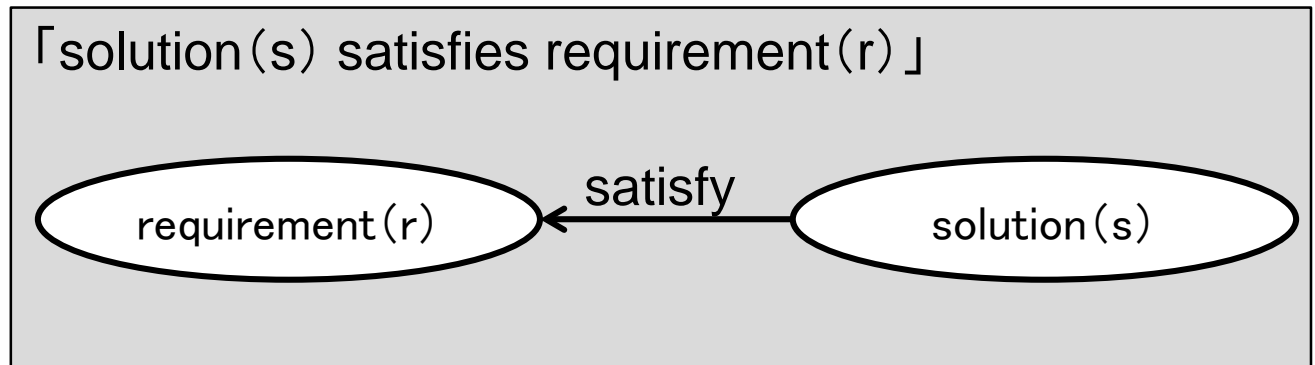
# Retrieval of Data

Structuring Knowledge of Data Utilization created in the data utilization workshops (Innovators Marketplace on Data Jackets)

data utilization  
knowledge 1  
*combine*(*s*, *d*)

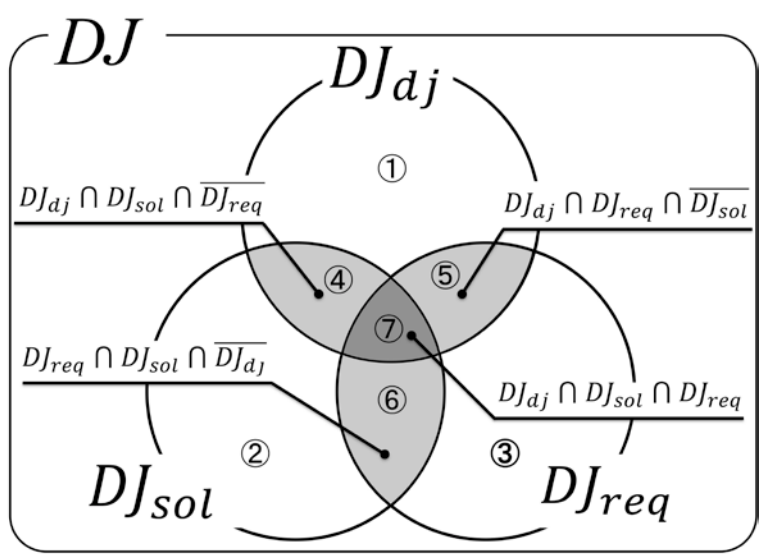
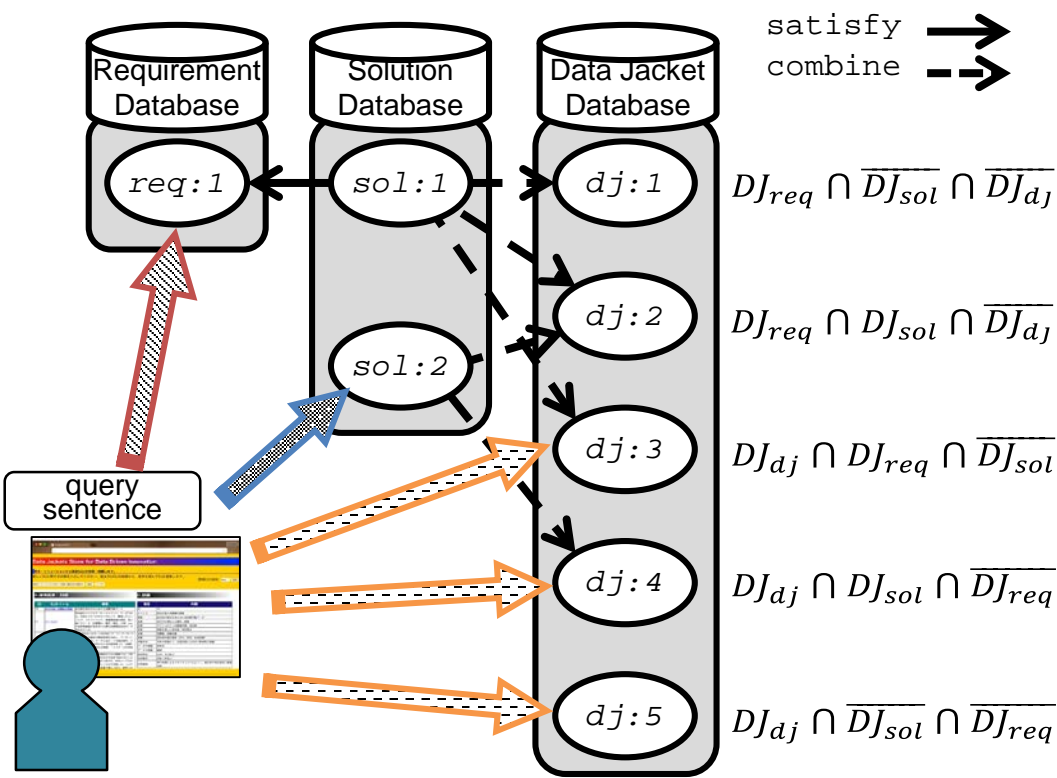


data utilization  
knowledge 2  
*satisfy*(*s*, *r*)



Reusing data utilization knowledge may be useful for Data Users to retrieve information about data related to their interests.

# Retrieval of Data



query sentence:  $D_i = \{word_1, word_2, \dots, word_j\}$  ( $i, j \in \mathbb{N}$ )

return from DJ database:  $DJ_{dj(D_i)} = \bigcup_{j \in \mathbb{N}} DJ_{dj(word_j)}$

return from Sol database:  $DJ_{sol(D_i)} = \bigcup_{j \in \mathbb{N}} DJ_{sol(word_j)}$

return from Req database:  $DJ_{req(D_i)} = \bigcup_{j \in \mathbb{N}} DJ_{req(word_j)}$



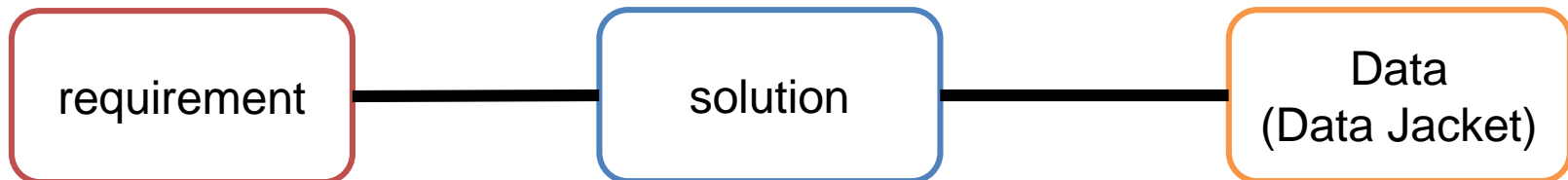
Set of DJs considering the numbers of retrieving.

# Implementation

Knowledge graph of data utilization is represented based on a undirected graph ( $G_W$ )

$$G_W = (V_W, E_W)$$

$V_W = \bigcup_{w \in \{req, sol, dj\}} V_w$ $(V_i \cap V_j = \emptyset (i \neq j), V_i \neq \emptyset)$	a set of nodes
$E_W = \{\{req_i, sol_j\}, \{sol_k, dj_l\}   req, sol, dj \in W\}$	a set of edges



# Knowledge Graph of Data Utilization

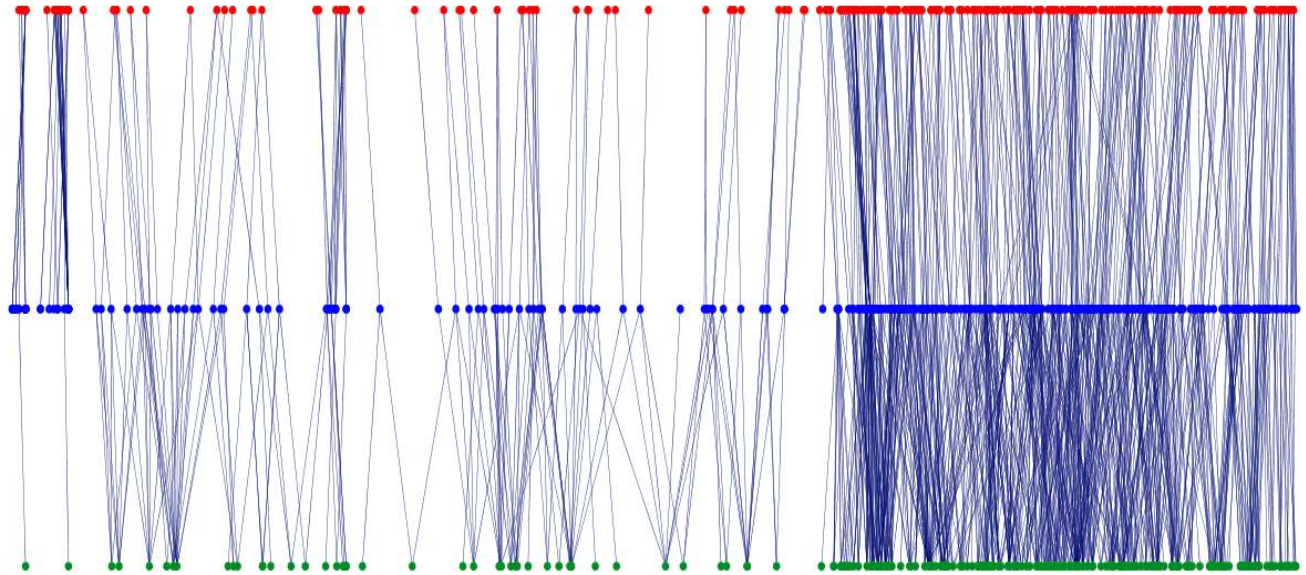


Data User

requirement

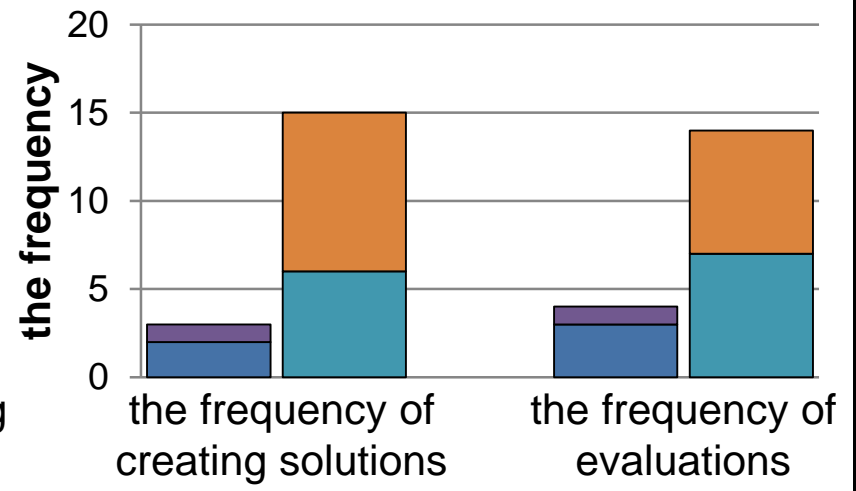
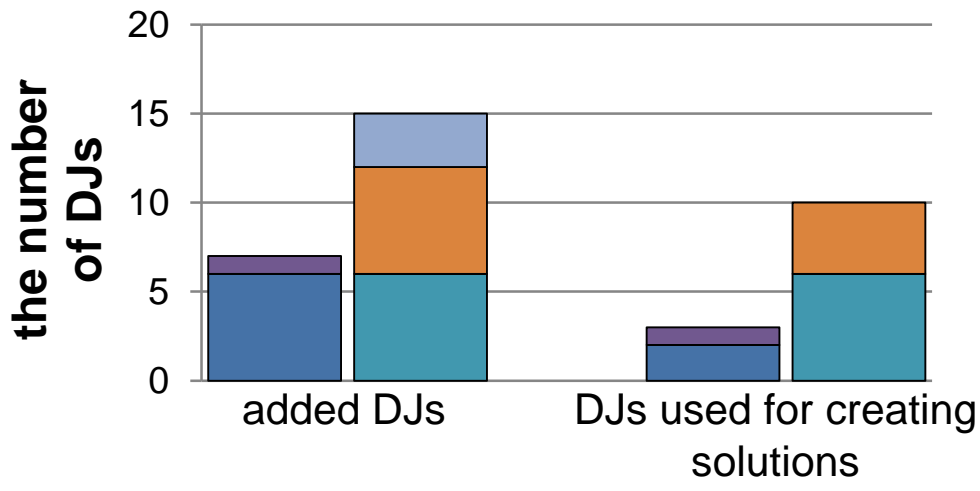
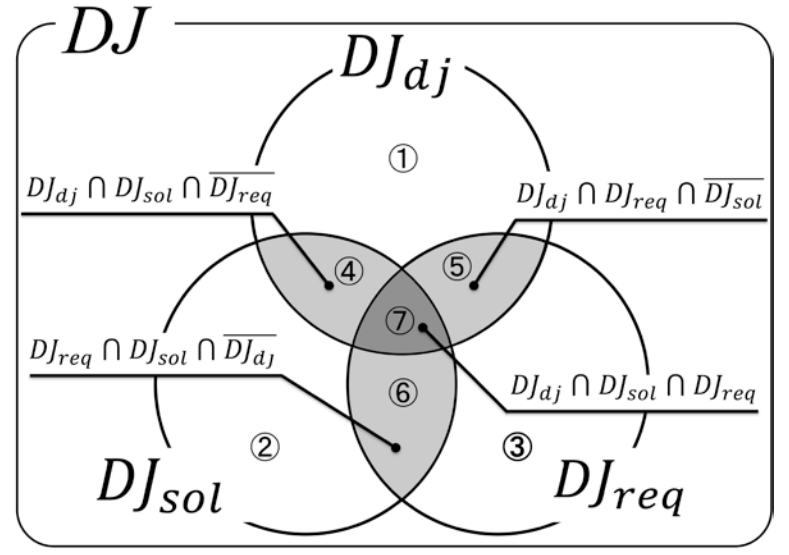
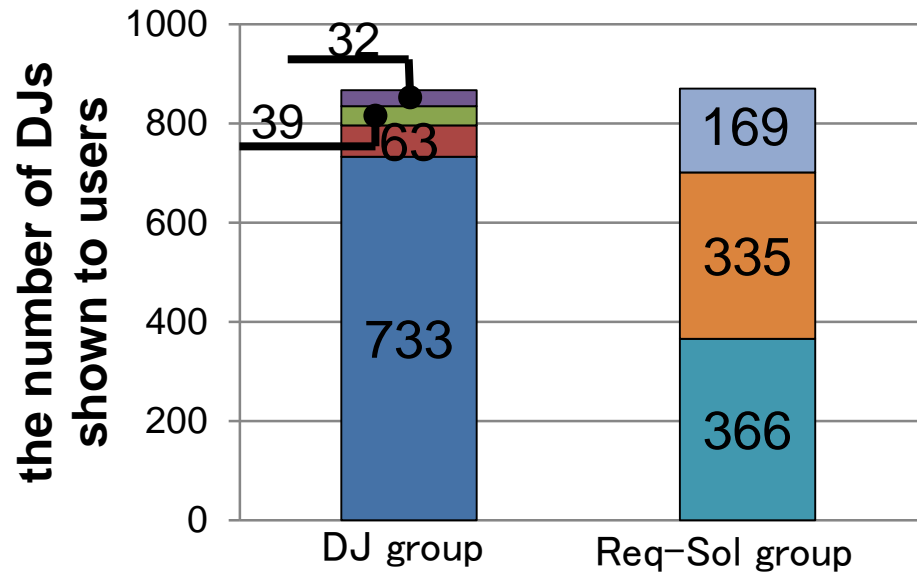
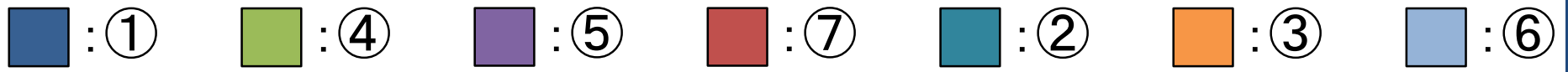
solution

Data Jacket



Data Holder

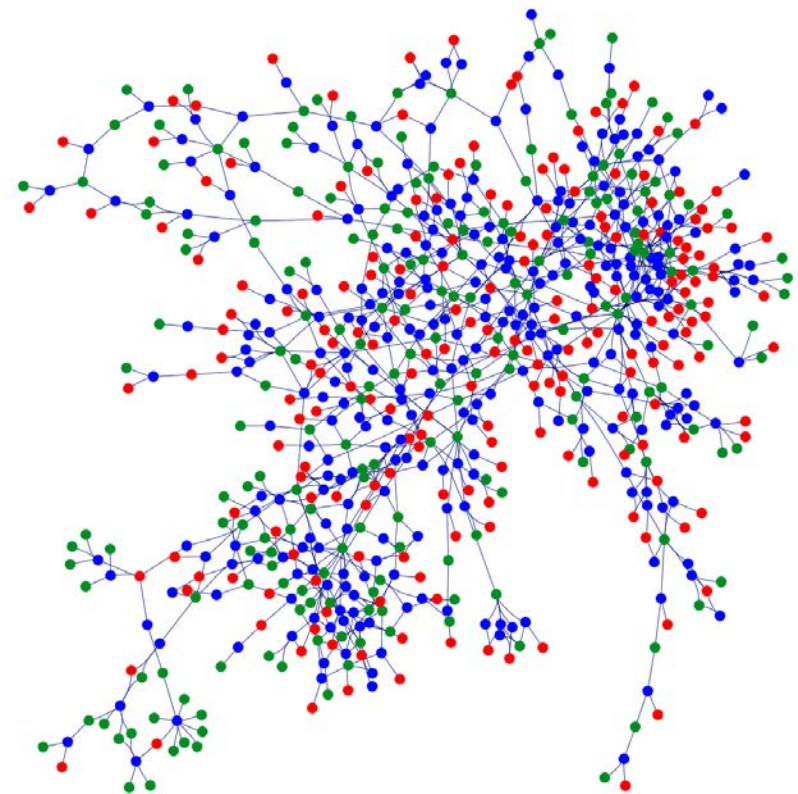
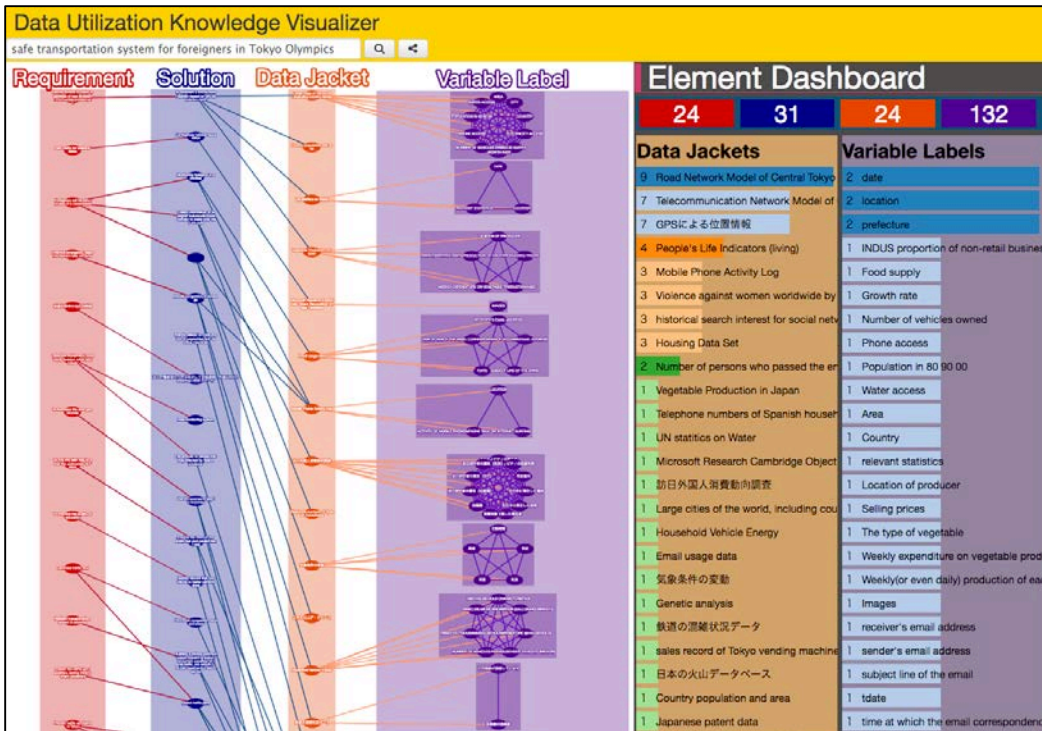




□ The result shows that the structured knowledge of data utilization may support the significant discovery of data related to users' interests, even if users do not have sufficient knowledge of the data.

# Improving the Transparency of the Retrieval Process

Data/Knowledge Retrieval System (Data Jacket Store) by showing the retrieval process

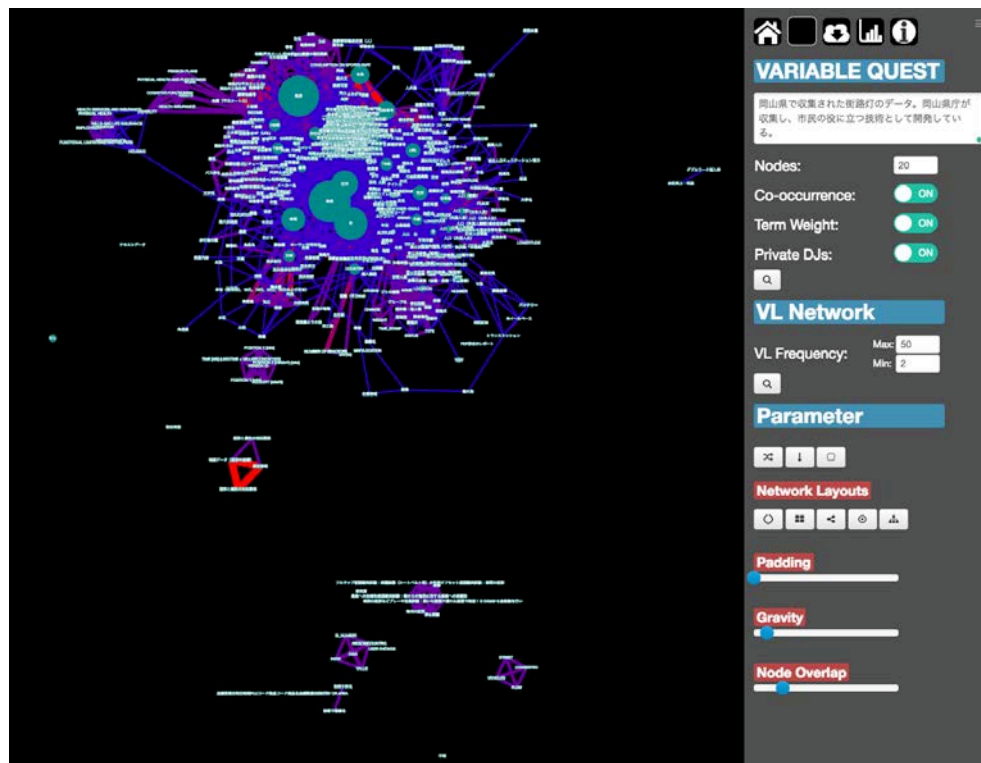


Structural analysis for evaluating knowledge elements in the data driven innovation

T. Hayashi, Y. Ohsawa, "Retrieval System for Data Utilization Knowledge Integrating Stakeholders' Interests," AAAI Spring symposium 2018 Beyond Machine Intelligence: Understanding Cognitive Bias and Humanity for Well-being AI, 2018.

# VARIABLE QUEST (VQ)

- ❑ VARIABLE QUEST (VQ) is the network visualization of VLs using the matrix-based inferring method of VLs by unifying co-occurrence graphs [Hayashi & Ohsawa, 2017].



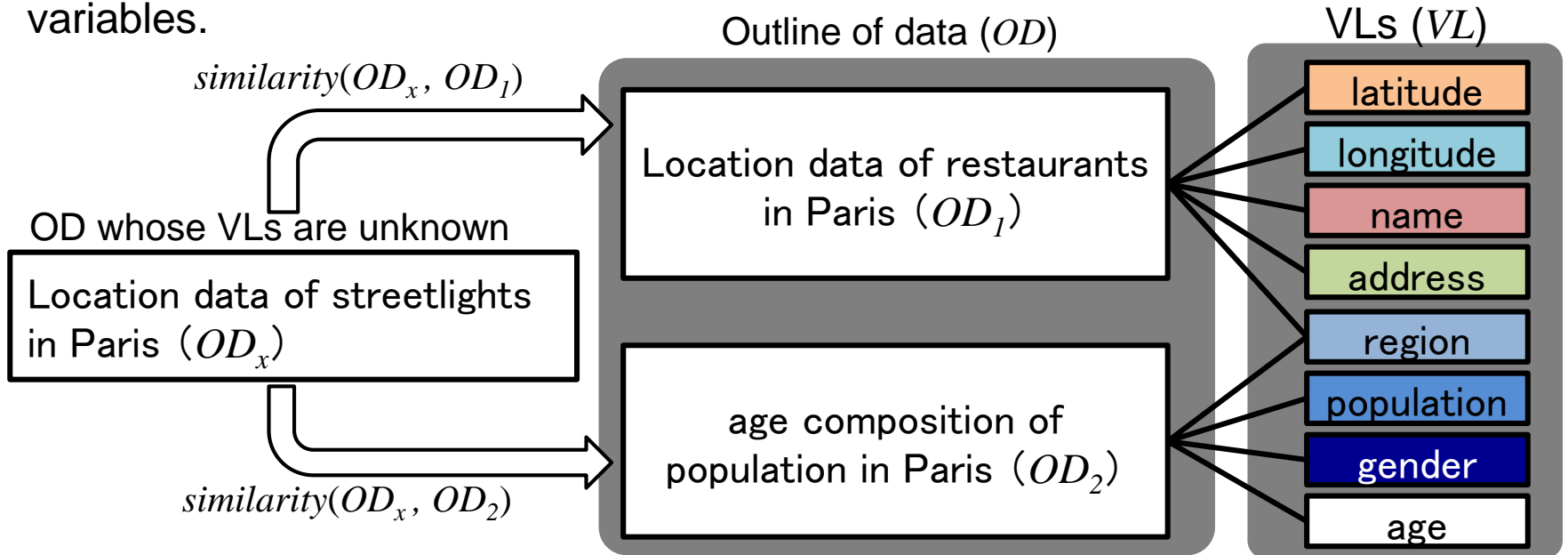
T. Hayashi, Y. Ohsawa, “Matrix-based Method for Inferring Variable Labels Using Outlines of Data in Data Jackets,” The Pacific-Asia Conference on Knowledge Discovery and Data Mining 2017 (PAKDD2017), 2017.

T. Hayashi, Y. Ohsawa, “VARIABLE QUEST: Network Visualization of Variable Labels Unifying Co-occurrence Graphs,” IEEE-ICDM Workshops 2017, pp.577-583, 2017.

# Inferring VLs

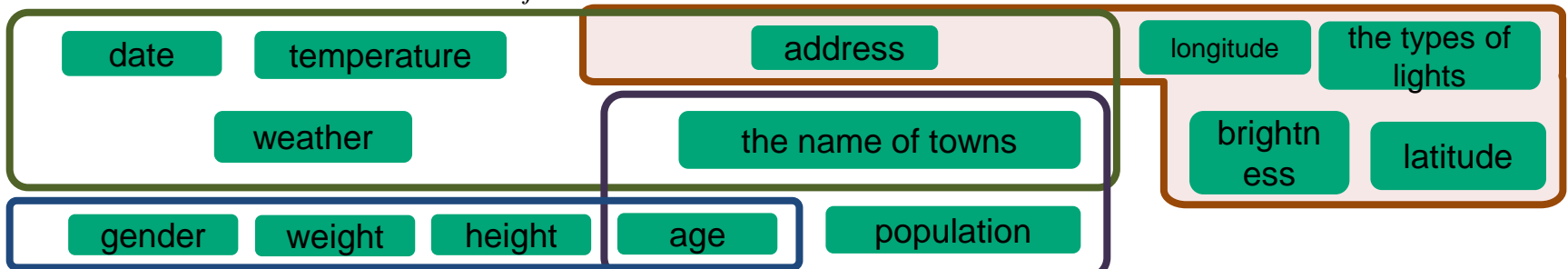
## Model 1:

When a pair of datasets is similar each other, the datasets have the similar variables.

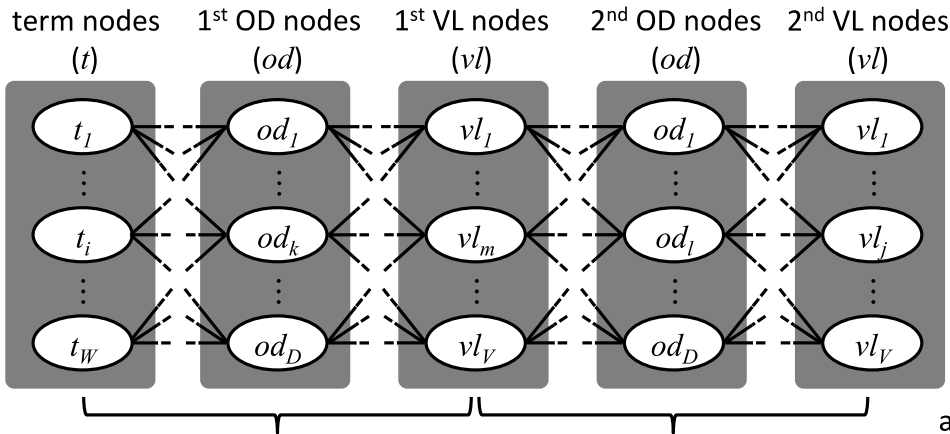


## Model 2:

A pair of variables ( $vl_i$  and  $vl_j$ ) appearing frequently in the same datasets.



# Term-VL Matrix EC



a Term-VL matrix  $E (=MR^T)$

$$\begin{matrix} & vl_1 & \cdots & vl_m & \cdots & vl_V \\ \begin{matrix} t_1 \\ \vdots \\ t_i \\ \vdots \\ t_w \end{matrix} & \begin{bmatrix} e_{11} & \cdots & e_{1m} & \cdots & e_{1V} \\ \vdots & & \vdots & & \vdots \\ e_{i1} & \cdots & e_{im} & \cdots & e_{iV} \\ \vdots & & \vdots & & \vdots \\ e_{w1} & \cdots & e_{wm} & \cdots & e_{wV} \end{bmatrix} \end{matrix}$$

a VL co-occurrence matrix  $C (=RR^T)$

$$\begin{matrix} & vl_1 & \cdots & vl_j & \cdots & vl_V \\ \begin{matrix} vl_1 \\ \vdots \\ vl_m \\ \vdots \\ vl_V \end{matrix} & \begin{bmatrix} c_{11} & \cdots & c_{1j} & \cdots & c_{1V} \\ \vdots & & \vdots & & \vdots \\ c_{m1} & \cdots & c_{mj} & \cdots & c_{mV} \\ \vdots & & \vdots & & \vdots \\ c_{V1} & \cdots & c_{Vj} & \cdots & c_{VV} \end{bmatrix} \end{matrix}$$



a Term-VL matrix  $EC (=MR^T R R^T)$

$$\begin{matrix} & vl_1 & \cdots & vl_j & \cdots & vl_V \\ \begin{matrix} t_1 \\ \vdots \\ t_i \\ \vdots \\ t_w \end{matrix} & \begin{bmatrix} g_{11} & \cdots & g_{1j} & \cdots & g_{1V} \\ \vdots & & \vdots & & \vdots \\ g_{i1} & \cdots & g_{ij} & \cdots & g_{iV} \\ \vdots & & \vdots & & \vdots \\ g_{w1} & \cdots & g_{wj} & \cdots & g_{wV} \end{bmatrix} \end{matrix}$$

1. When  $OD_x$  is given, a  $W$ -dimensional feature vector of  $OD_x$  ( $od_x$ ) is obtained after the pre-processing.
2. By comparing the similarity of  $od_x$  and each  $W$ -dimensional feature vector of VL ( $vl_j$ ) in the matrix  $EC$ , a scored set of VLs are obtained.

$$c_{ij} = \sum_{k=1}^{|D|} r_{ik} r_{kj}$$

$$g_{ij} = \sum_{m=1}^{|V|} \left( \sum_{k=1}^{|D|} v_{ik} r_{km} \right) \left( \sum_{l=1}^{|D|} r_{ml} r_{lj} \right)$$

The Term-VL matrix  $EC$  is equivalent to the adjacency matrix of the 5-partite graph, which consists of 5-disjoint sets of nodes.

$g_{ij}$  represents the number of paths from the  $i$ th term ( $t_i$ ) to the  $j$ th VL ( $vl_j$ ) in the 2<sup>nd</sup> VL nodes, by way of the 1<sup>st</sup> OD nodes, the 1<sup>st</sup> VL nodes, and the 2<sup>nd</sup> OD nodes.

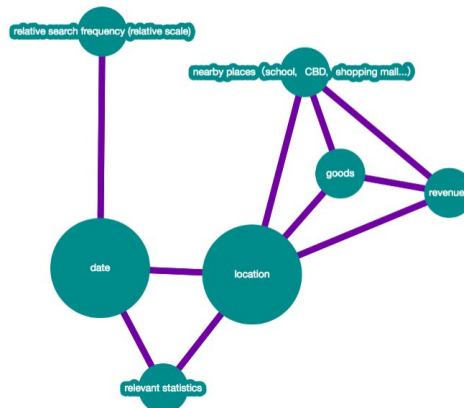
# Implementation

Co-occurrence graph of VLs is represented based on a weighted undirected graph ( $G_S$ )

$$G_S = (V_S, E_S, f, h)$$

$$f: V_S \rightarrow L_{V_S}, h: E_S \rightarrow L_{E_S}$$

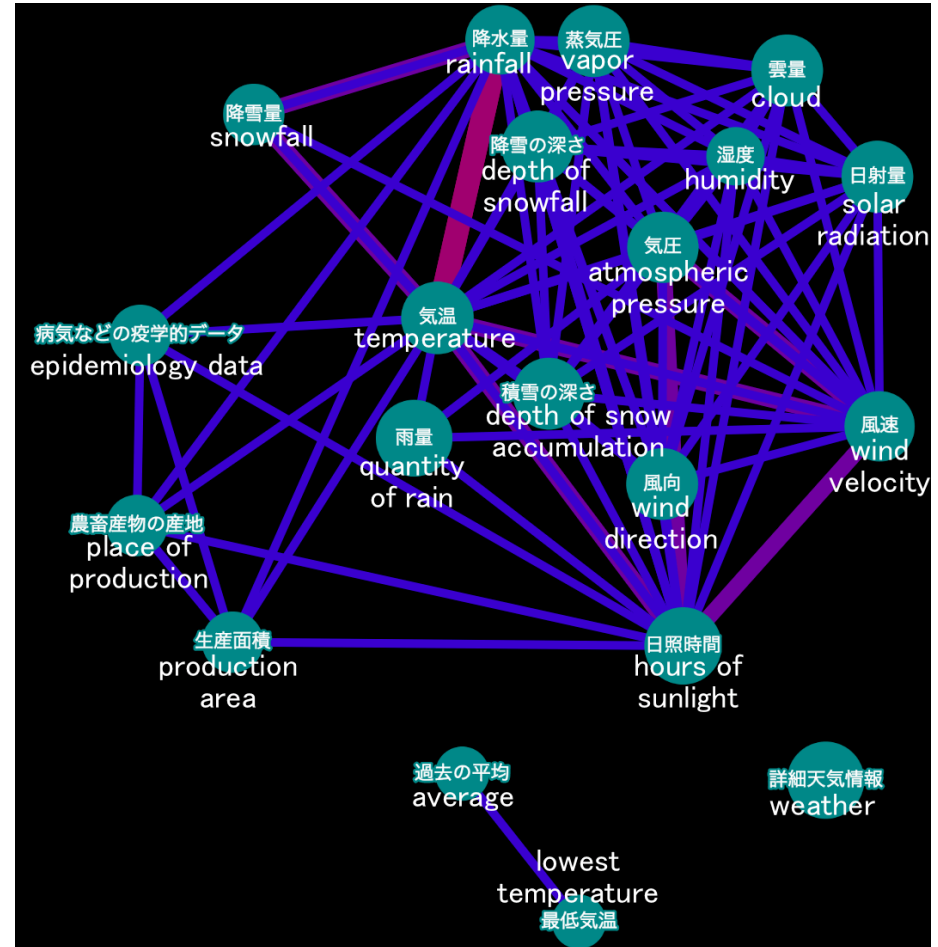
$V_S = \{vl_i \in S\}$	a set of nodes
$E_S = \{(vl_i, vl_j)_{d_{jk}}   vl_i, vl_j \in S, vl_i \neq vl_j\}$	a set of edges
$L_{V_S} = \{\text{frequency}(vl_i)   vl_i \in S\}$	the frequency of VLs
$L_{E_S} = \{\text{link}(vl_i, vl_j)   vl_i, vl_j \in S, vl_i \neq vl_j\}$	the frequency of co-occurrences of a pair of VLs
$\text{link}(vl_i, vl_j) = \sum_{k=1}^D  vl_i _{d_{jk}}  vl_j _{d_{jk}}$	



# Example 1

OD<sub>x</sub>. Japan weather data provided by Japan Meteorological Agency, which includes information about the temperature and weather of prefectures.

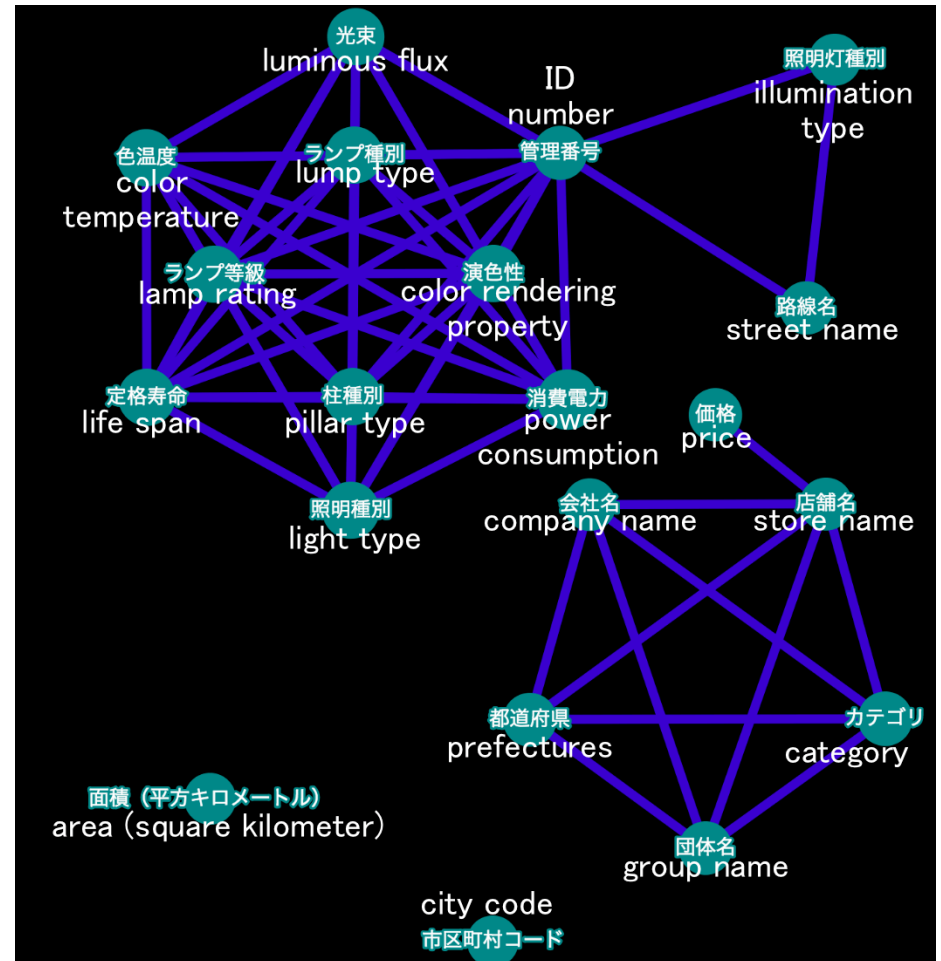
Term-VL Matrix EC	
VL	Similarity
weather	0.318
hours of sunlight	0.313
rainfall	0.307
temperature	0.293
vapor pressure	0.293
solar radiation	0.293
depth of snowfall	0.293
wind velocity	0.293
weather	0.318
hours of sunlight	0.313
⋮	⋮



# Example 2

$OD_x$ : The information about location and installation of streetlights in Paris.

Term-VL Matrix EC	
VL	Similarity
light type	0.557
life span	0.557
color temperature	0.557
lump type	0.557
color rendering	0.557
pillar type	0.557
luminous flux	0.557
power consumption	0.533
ID number	0.505
illumination types	0.465
⋮	⋮





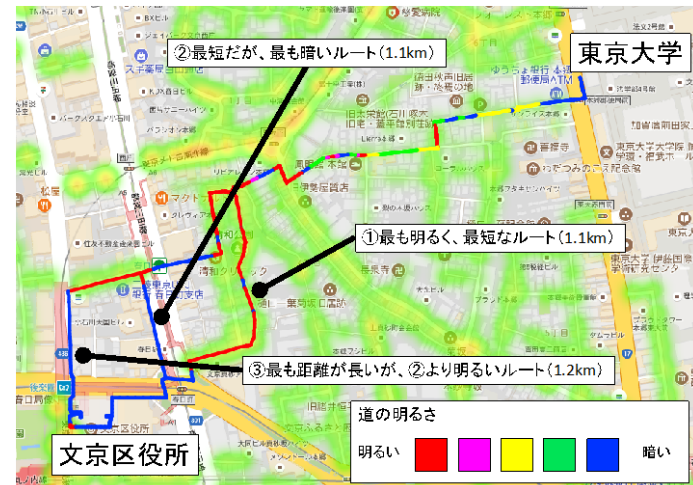
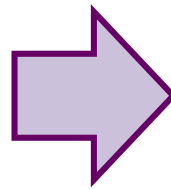
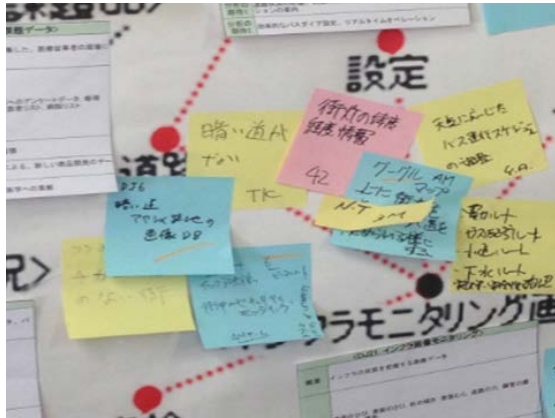
# Discussion for Data Utilization



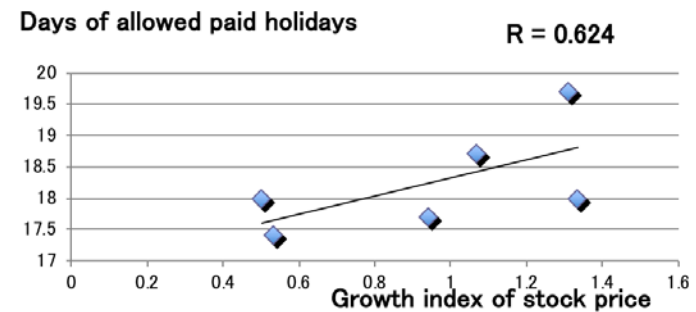
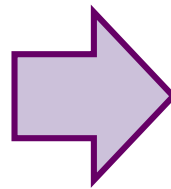


# Examples of Use Cases (1/2)

## Streetlight data & map data

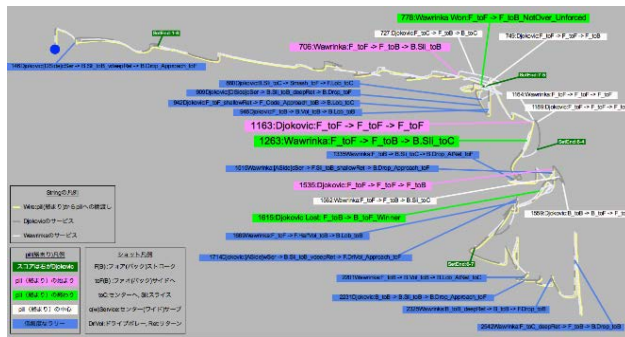


## Paid holidays & stock price data



# Examples of Use Cases (2/2)

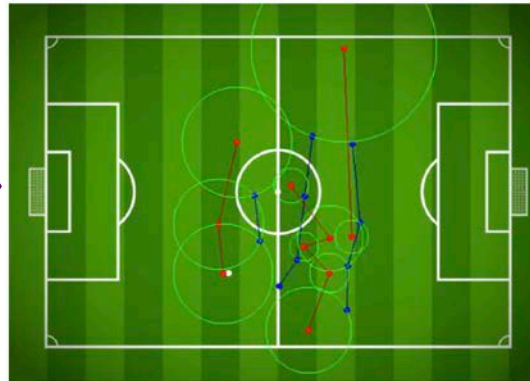
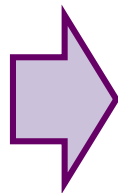
Visualizing the sequence of tennis and strategies



Understanding the latent dangerous locations from the history of bike data



Support system for football players and trainers



# Summary

- ❑ The potential benefits of reusing and analyzing massive amounts of data have been discussed by various stakeholders from diverse domains.
- ❑ However, it is difficult to learn the kinds of data that are related to our interests.
- ❑ We introduce our latest technologies for activating cross-disciplinary data exchange and collaboration by structuring the knowledge of data utilization using Data Jacket (DJ).

Thank you for your listening!