

# Big Value Data, Not Just Big Data!

Dr. Joseph Reger

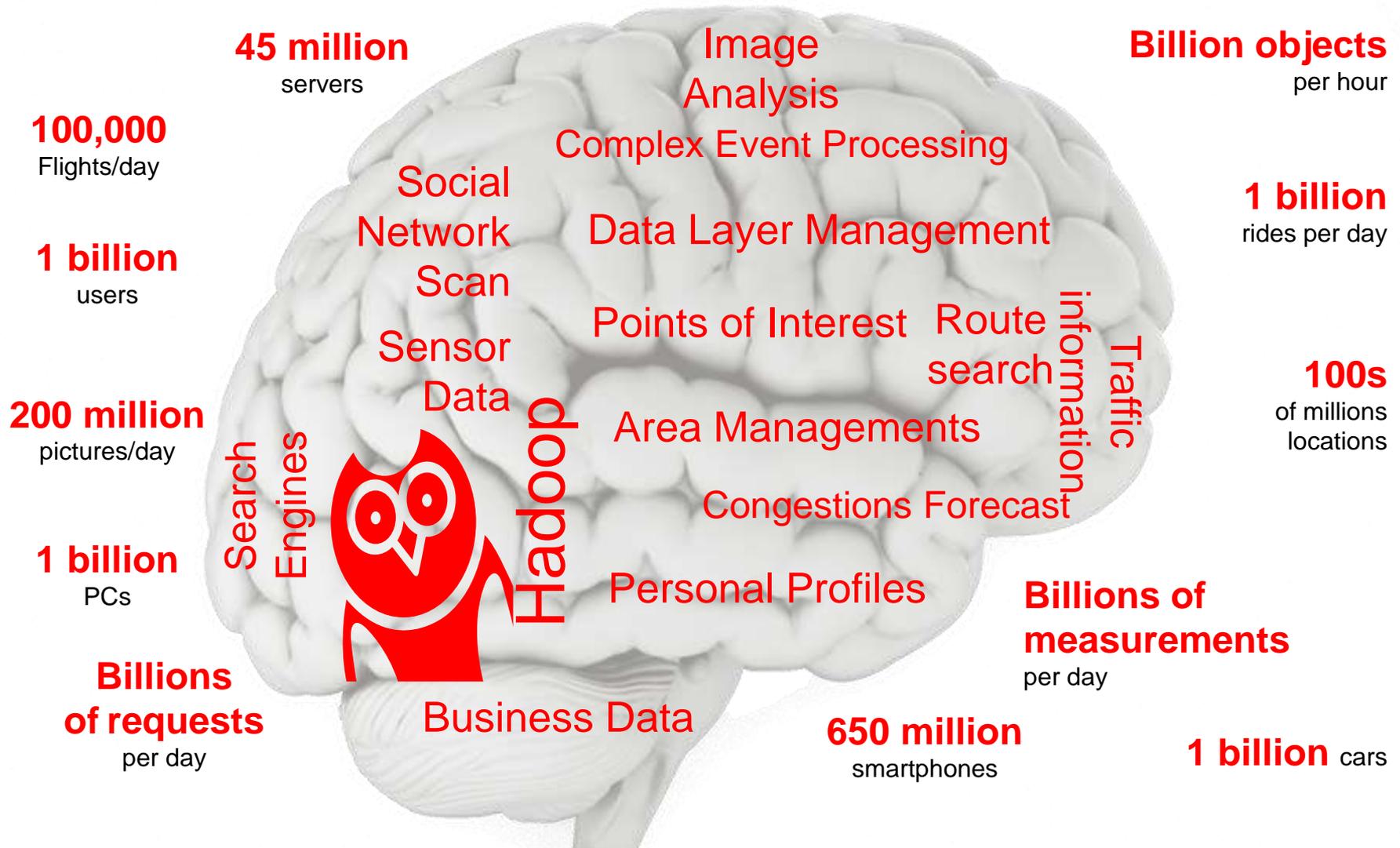
Chief Technology Officer  
Fujitsu Technology Solutions

# Powers of Ten (SI)

Metric prefixes							
Prefix	Symbol	$1000^m$	$10^n$	Decimal	Short scale	Long scale	Since <sup>[n 1]</sup>
yotta	Y	$1000^8$	$10^{24}$	1 000 000 000 000 000 000 000 000	septillion	quadrillion	1991
zetta	Z	$1000^7$	$10^{21}$	1 000 000 000 000 000 000 000	sextillion	trilliard	1991
→ exa	E	$1000^6$	$10^{18}$	1 000 000 000 000 000 000	quintillion	trillion	1975
→ peta	P	$1000^5$	$10^{15}$	1 000 000 000 000 000	quadrillion	billiard	1975
→ tera	T	$1000^4$	$10^{12}$	1 000 000 000 000	trillion	billion	1960
giga	G	$1000^3$	$10^9$	1 000 000 000	billion	milliard	1960
mega	M	$1000^2$	$10^6$	1 000 000	million		1960
kilo	k	$1000^1$	$10^3$	1 000	thousand		1795
hecto	h	$1000^{2/3}$	$10^2$	100	hundred		1795
deca	da	$1000^{1/3}$	$10^1$	10	ten		1795
		$1000^0$	$10^0$	1	one		–

Source: Wikipedia

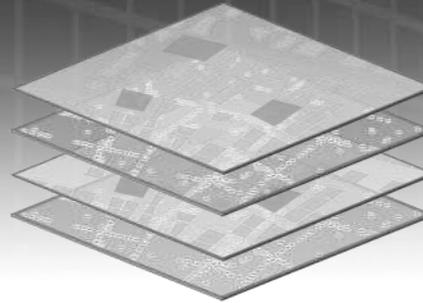
# Big Data?







# Big Value Data!

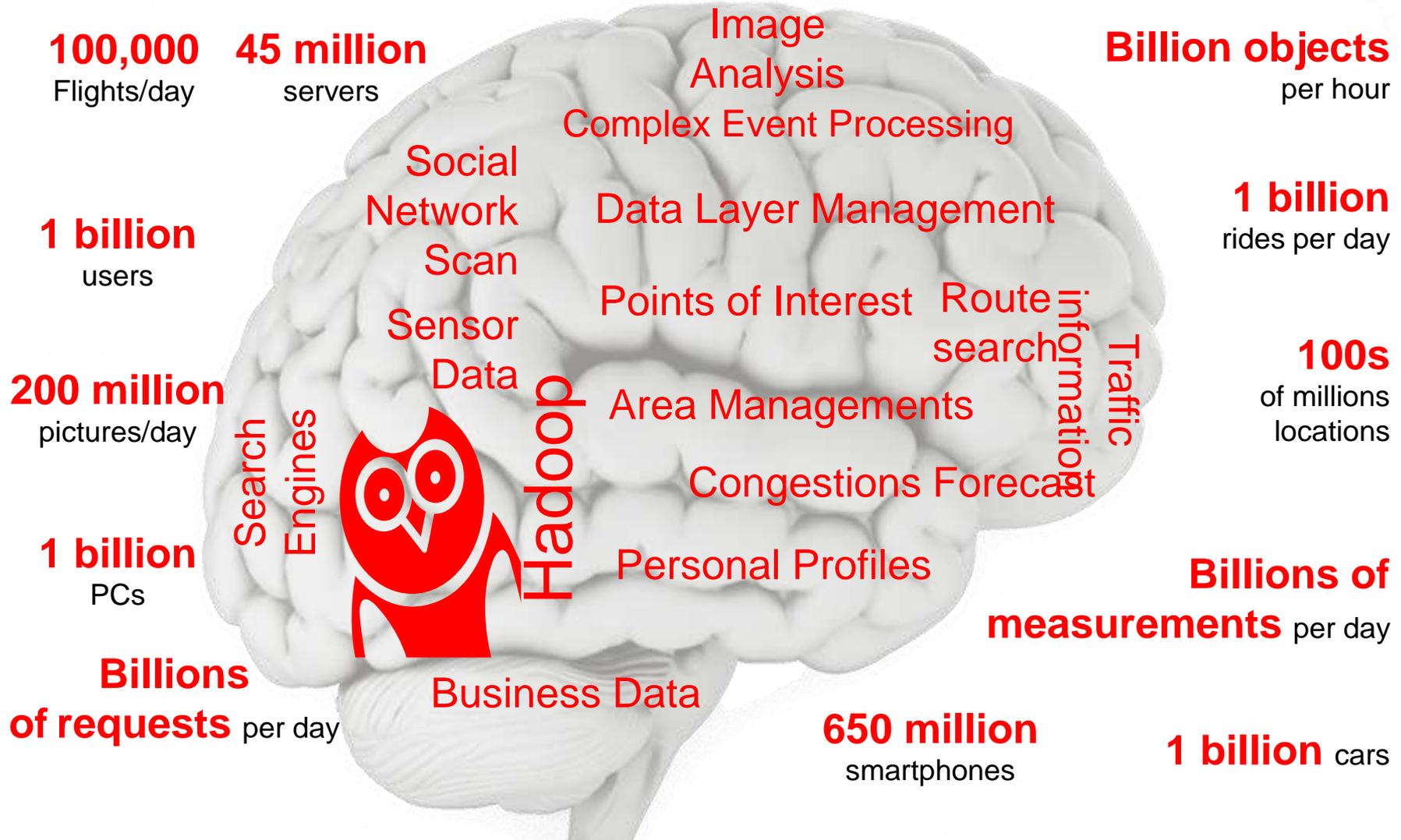


Social Networking  
Services & Sensor  
Data

Business  
Data

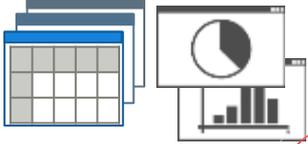


# Big Data?



## Big Data

- Statistics / history



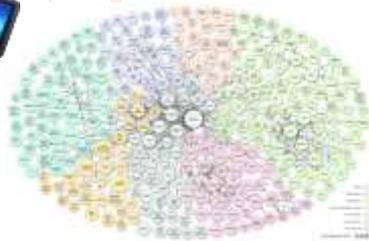
- Social media – Twitter, blogs etc.



- Sensor data – GPS, weather, etc.



- Open data



## Collection

- Distributed data collection

- Privacy security

- Linked open data

## Analysis

Data/text mining  
Analysis platform  
Optimization  
Simulation

### Topics:

- Social media analysis
- Analytic templates
- Optimal area discovery
- Social simulation

## Application

Transportation  
Energy  
Disaster recovery  
Marketing

### Topics:

- Transportation simulation
- Smart grid
- Event detection from SNS

## Data processing

Fast processing of large-scale data

### Topics:

- Incremental data processing
- Parallel complex event processing
- Stream data aggregation

Faster, more intelligent, more secure technologies

# Application Areas

Sectors

Healthcare



Retail



Manufacturing



Government

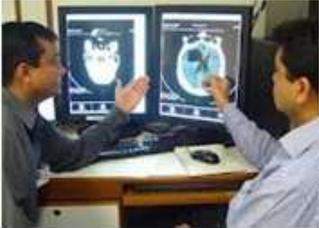


Agriculture



Usage

Disease Prevention



Multi-channel Sales



Behavior Management



Traffic Management



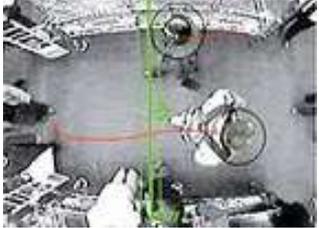
Production Efficiency



New Drug Development



Customer Behavior



Asset Management



Homeland Security



Livestock Reproduction Management



Bio Technology



SCM



New Service M2M



Crime Prevention



Inventory Management



# Research on Big Data use cases by Fujitsu Laboratories & Fujitsu Limited

Kozo Otsuka

Technology Office  
Fujitsu Technology Solutions

## Accurate prediction by the variety of health related data analysis

Medical record data



**12 M**  
over 5 years

Health checkup data

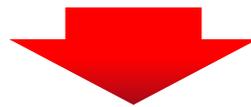


**0.8 M**  
over 5 years

Vital data



**1/4 M**  
from sampling for 1/2 year



- Early detection of signs of habits leading to lifestyle diseases
- Link to expert advice for preventive actions

■ Example: Diabetic patients & candidates in Japan: 33% of male, 23% of female adults (2011)

## Fujitsu developed methodology

### Conventional diag. param.

- HbA1c
- Blood Glucose



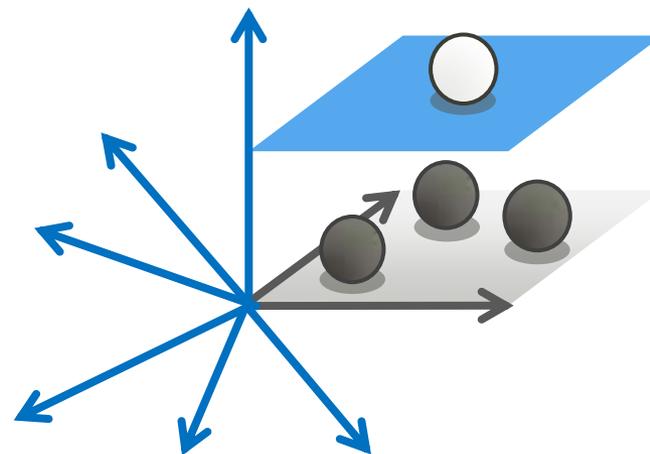
### Reg. health checkup data

- Serum creatinine
- HDL cholesterol
- BMI
- Platelet count
- $\gamma$ -GT( $\gamma$ -GTP)
- Abdom. Circum.
- GOT(AST)
- MCH
- Total protein
- MCV
- White blood cell
- GPT(ALT)
- MCHC
- Serum uric acid
- Diastolic blood pressure
- Neutral fat
- LDL cholesterol
- Total cholesterol
- Systolic blood pressure
- Hematocrit
- Hemoglobin content
- ...

### Medical record data

- Diag./Treatment
- Prescriptions

Machine Learning  
to create rules  
2,000-dimensions



**Finer distinctions for accurate prediction by high dimensional rules**

# Example: predict diabetes

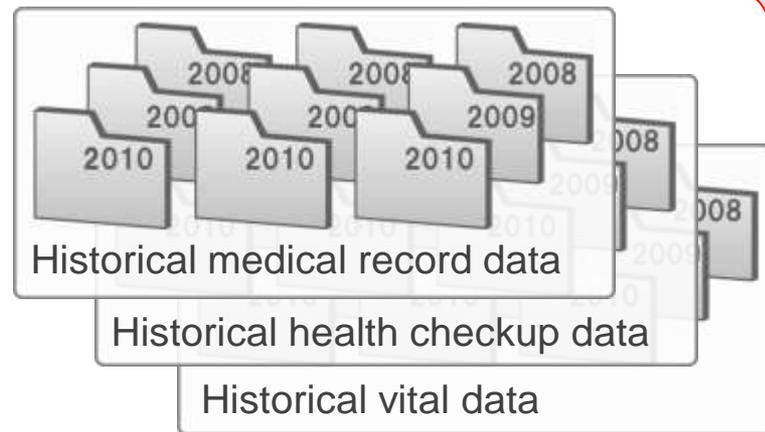
## Test conducted targeting Fujitsu employee volunteers (26,000)



Fujitsu employees  
(Including diabetes patients)



1. Collect and sort relevant data



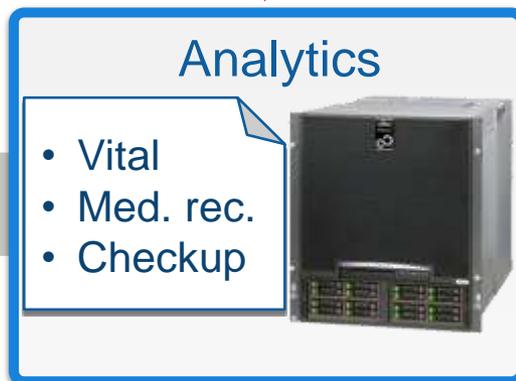
2. Analyze all data to build 'highly probable diabetes model'



- Vital
- Med. rec.
- Checkup



3. Feed target individual's data



4. Compare against model

Outcome



5. Diabetics probability



Reduce medical care cost by accurate prediction

# Extremely high population density in Tokyo

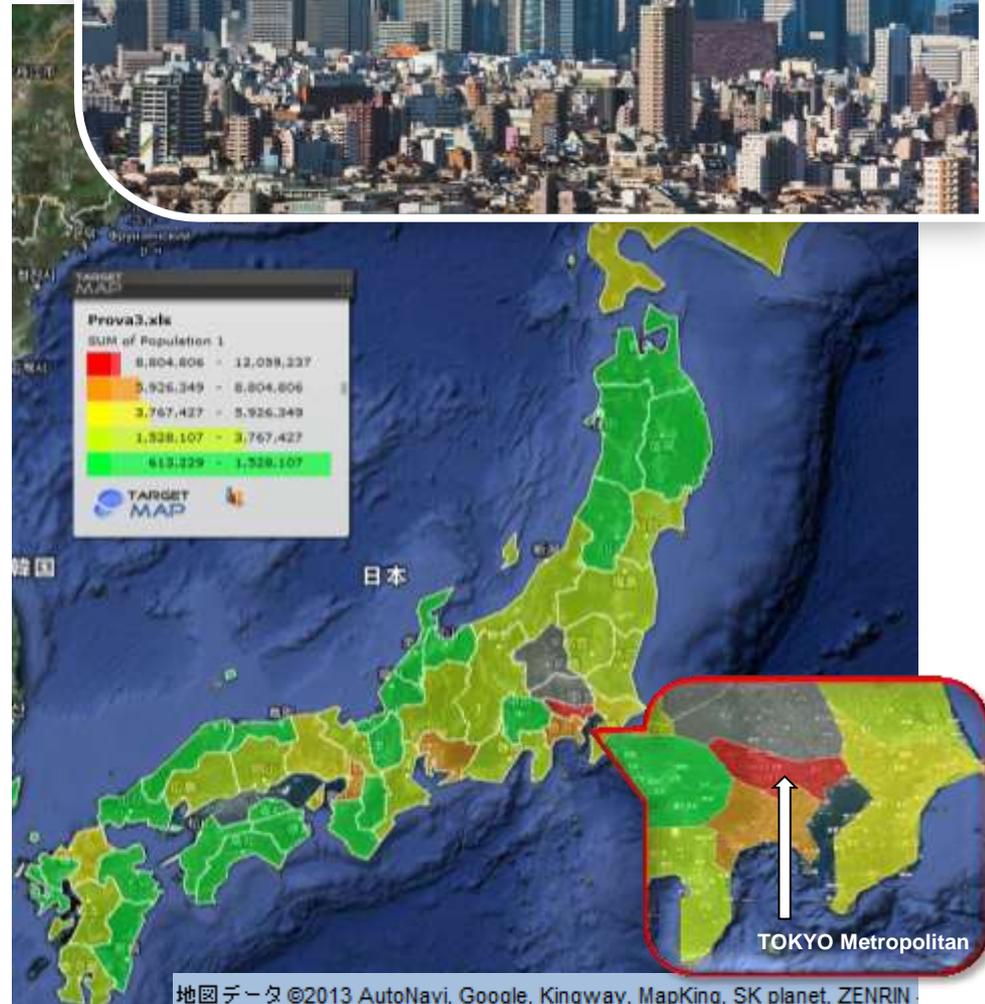
## Tokyo population density

- Over 12 million people in Tokyo metropolitan area (= ca. 10% of the total Japanese population)
- Over 14,000 people / km<sup>2</sup> in Tokyo city (ref. ca. 4,400 people / km<sup>2</sup> in Munich, Germany)

▶ **Small personal space, higher risk for human conflicts**

- Over 6 million people in Tokyo metropolitan area using smartphones during commute, office & private hours

▶ **Huge # of social media data**



<http://www.targetmap.com/viewer.aspx?reportId=5845>

## Visualization of social network information

- Use Twitter (40 mil. tweets / day in Japan) as huge number of event sensors
- Create database of the detected events mapped to geographic locations



- Filtering and selecting tweets for a target topic
- Classify selected tweets into sub-categories
- Identify locations of the events in the tweets

## Criminal activity map

Select tweets related to crimes

①

Correlate crime types, time & locations

②

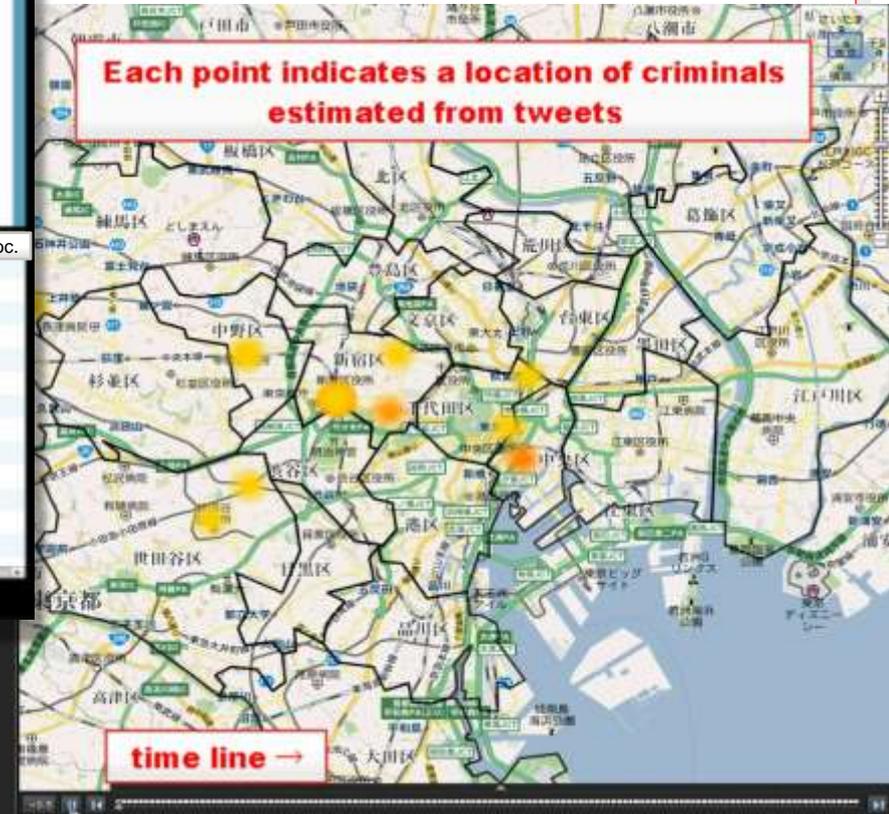
Overlay the correlation data onto a map

③

## Visualization of criminal activity related tweets

Showing the semantic analysis & machine learning phase

Contents	Handle	Date	Typ., Loc.
...	...	2013/08/10 10:12:00	...
...	...	2013/08/10 09:54:00	...
...	...	2013/08/10 09:40:00	...
...	...	2013/08/10 09:39:00	...
...	...	2013/08/10 09:38:00	...
...	...	2013/08/10 09:34:00	...
...	...	2013/08/10 09:32:00	...
...	...	2013/08/10 09:31:00	...
...	...	2013/08/10 09:22:00	...
...	...	2013/08/10 09:21:00	...
...	...	2013/08/10 09:17:00	...



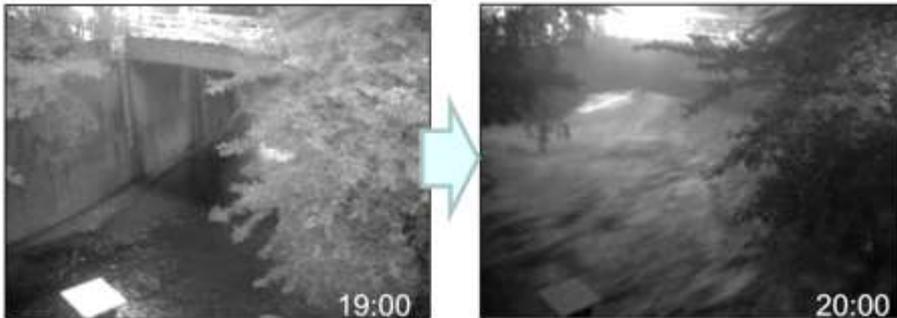
Showing the mapping of criminal activities onto the Tokyo map

## Natural disaster due to rainfall

- Ca. 4 Billion U.S. dollars of property damage annually caused by flooding & inundation
- Over 1,100 landslides annually
- Over 100mm per hour precipitation from torrential rain
- Precipitation increasing every year

 **Strong need for early warnings & preventions**

Water level rose by 3.45 m in 10 minutes from 19:50 to 20:00.

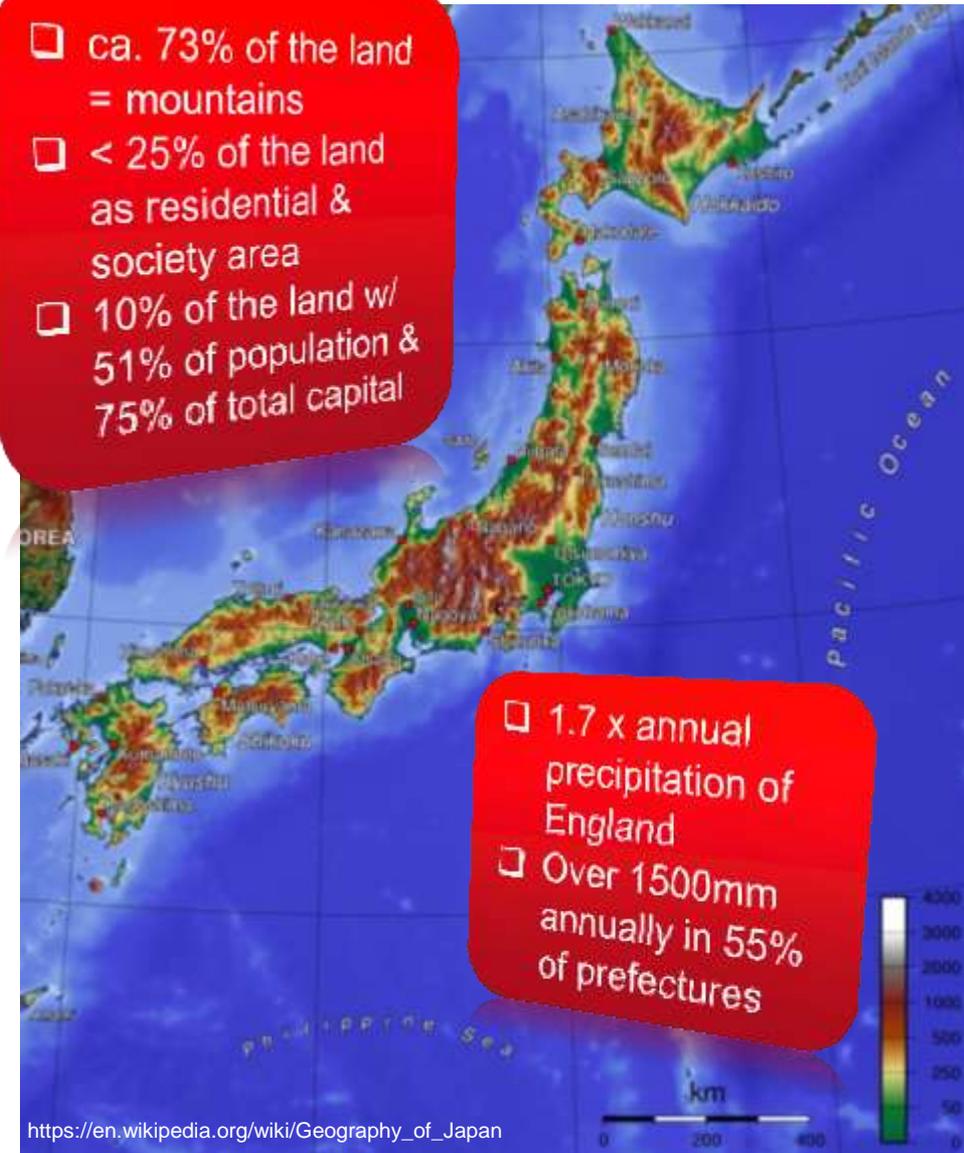


Change of water level in Shakuji River

Based on investigation by Disaster Prevention Office, Fire Disaster Management Agency on September 11, 2009

[http://www.mlit.go.jp/river/basic\\_info/english/pdf/conf\\_01-0.pdf](http://www.mlit.go.jp/river/basic_info/english/pdf/conf_01-0.pdf)

- ❑ ca. 73% of the land = mountains
- ❑ < 25% of the land as residential & society area
- ❑ 10% of the land w/ 51% of population & 75% of total capital



# Finer granularity of rain observation in Japan

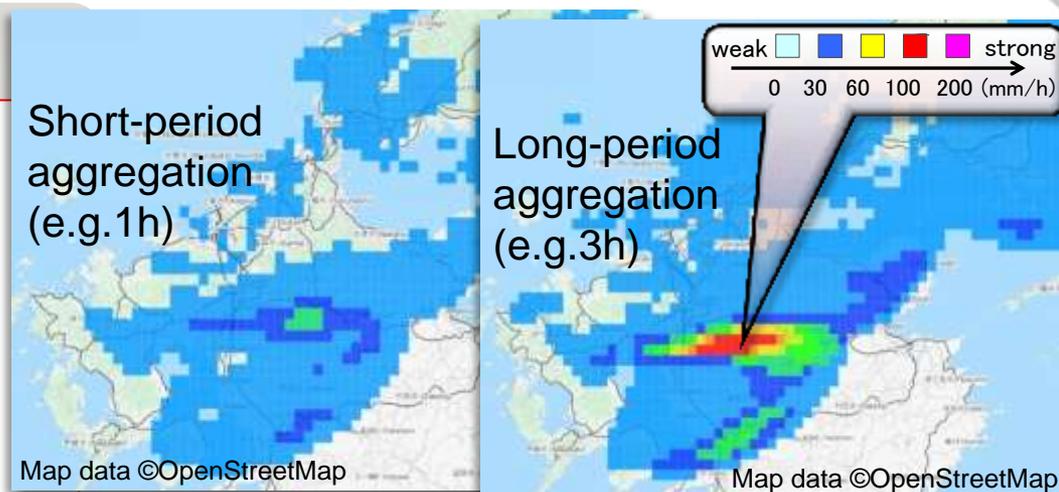
## Leverage “XRAIN”\* radar

- Compared to the conventional:
  - 5x more frequent data (1 min)
  - 16x finer mesh resolution (250m)
  - 3D scan – raindrop information
  - Over 100 times data increase
- Over 500K records per minute per zone (w/ up to 4 radars)

**▶ More precise & more real-time**

- With Fujitsu big data processing:
  - Aggregation of up to 100 mil. records within 10+ secs., updated every 1 min.
  - Real-time aggregation of total rainfall since the 1<sup>st</sup> drop for each mesh

**▶ Detect potential disaster areas w/ the fast data aggregation**



5km-mesh rainfall data by XRAIN (Source: Water & Disaster Mgmt. Bureau, Ministry of Land, Infrastructure, Transport and Tourism)



Figure 1: Radar distributions and their coverages of MLIT X-band MP radar network. Triangles indicate

\*XRAIN = X-band MP radar developed by NIED\* for MLIT\*

\*NIED = National Research Institute for Earth Science and Disaster Prevention, Japan

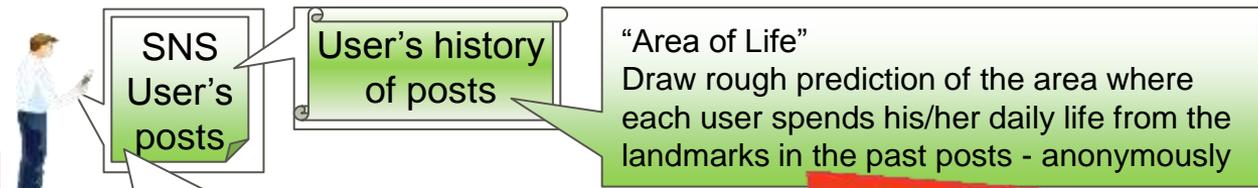
\*MLIT = Ministry of Land, Infrastructure, Transport and Tourism

\*C-band radar = currently, the most popular weather radar type in the world

## Use a certain tendency from large SNS data to identify the status quo

- More precise analysis of location information contained in SNS through “Area of life” analysis to overcome the following challenges:
  - Only 0.5%(\*) of SNS posts including GPS information
  - Only 30%(\*) of posts containing landmark information(e.g. town name vs. neighborhood)
  - Only coarse “resolution”(municipal area, state, prefecture) as SNS user location profile
  - Unreliable ties between contents of posts and user location profiles (e.g. hearsay vs. real experience)

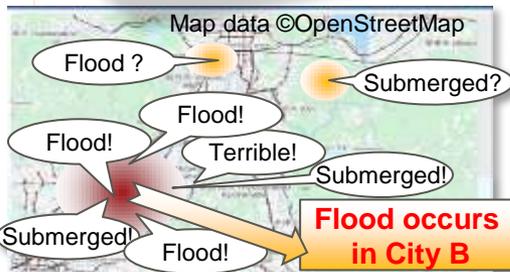
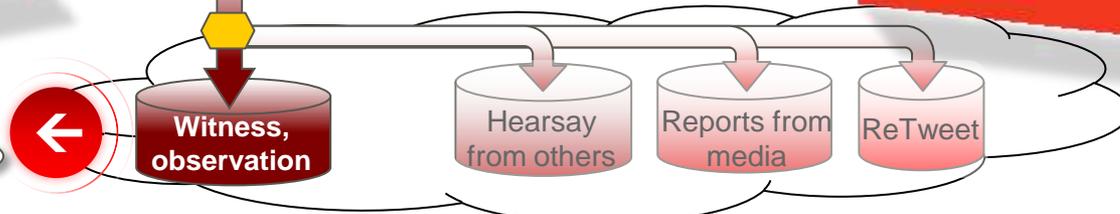
\* According to the analysis on Tweeter tweets conducted by Fujitsu Labs



Machine learning & Natural language processing

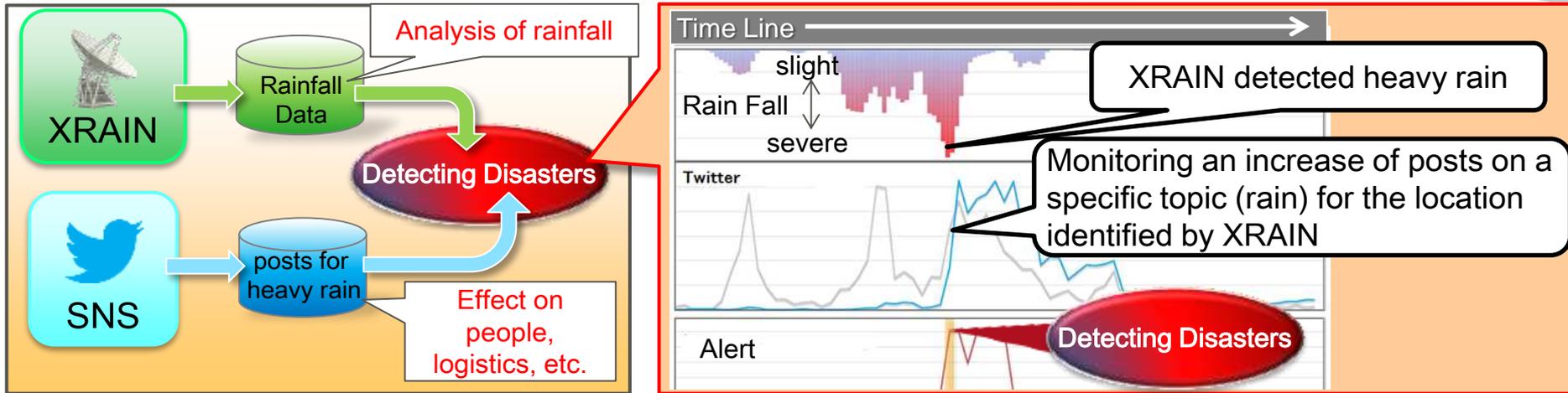
Disaster related posts + “Area of life” (e.g. City B)

“Area of life” helps to estimate location information of 70% of SNS posts.



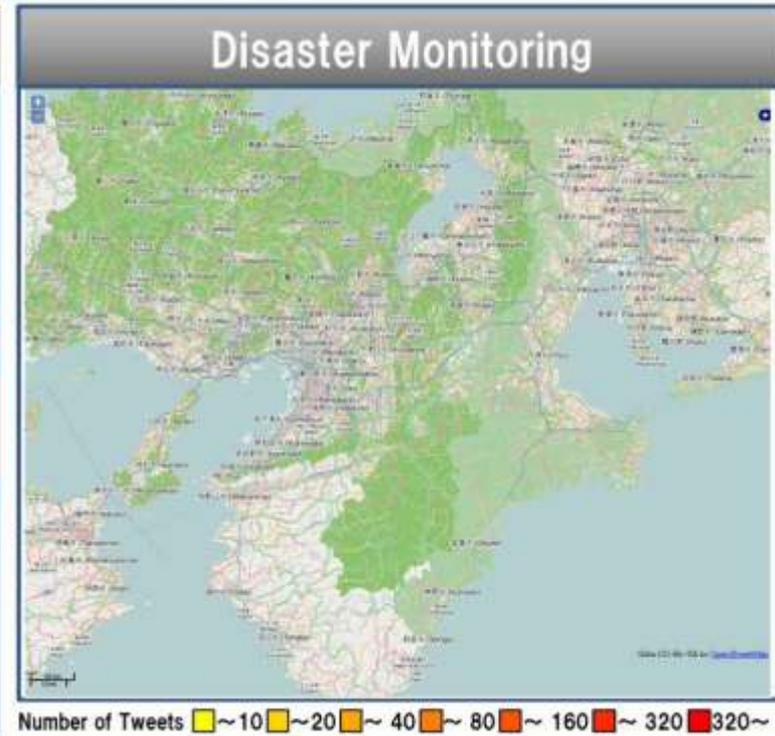
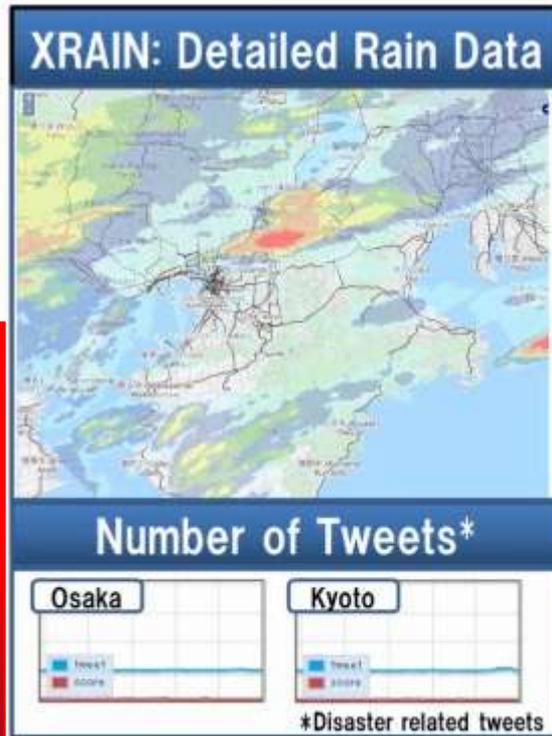
Higher potential of disaster status quo estimated by the large # of posts regarding towns/city

# Big Data use: Disaster alert w/ SNS & XRAIN



\* XRAIN data supplied courtesy of Ministry of Land, Infrastructure, Transportation and Tourism of Japan

**▶ Test run in 2012 for towns in Osaka & Kyoto prefs. raised alerts 3 h earlier than conventional warnings**



## Damages caused by Tsunami

- Epicentral area – ca. 500km long (N-S) and 200km wide (E-W)
- Max. 14.8m Tsunami height, up to 40m Tsunami run-up height
- 535km<sup>2</sup> of land inundated by Tsunami in Tohoku & Kanto region
- ca. 129,000 buildings destroyed
- ca. 15,850 fatalities & 3,282 missing
- Over 20,000 cars swept away – a lot of them were in traffic jams
- Over 179 mil. tweets in that week, many asking for help



### Earthquake simulation initiative by the Japanese government

1) Earthquake & Tsunami simulation: predict power & speed

2) Building response simulation: predict effects on infra.

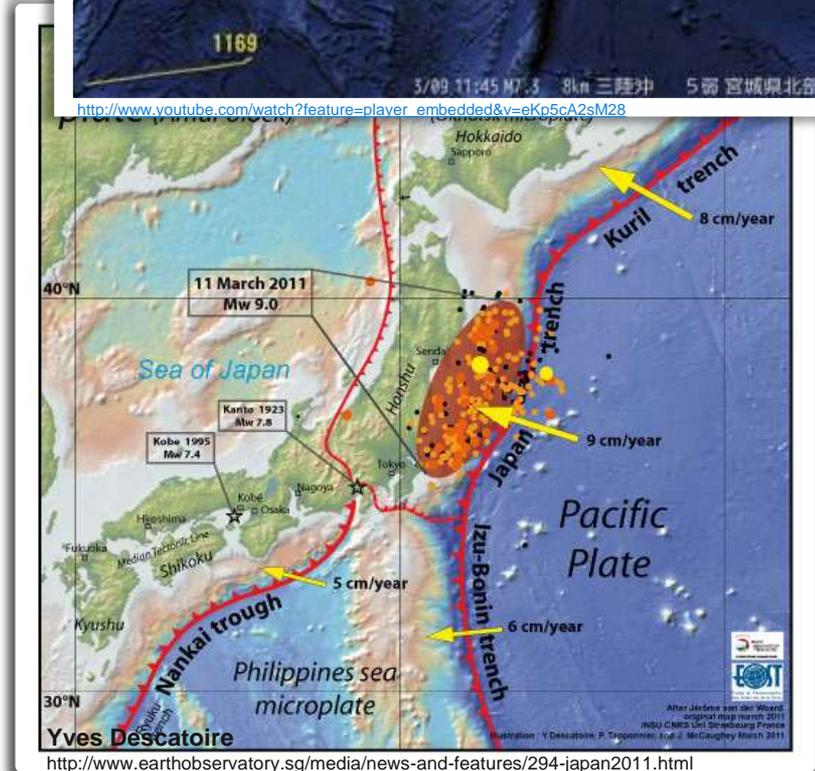
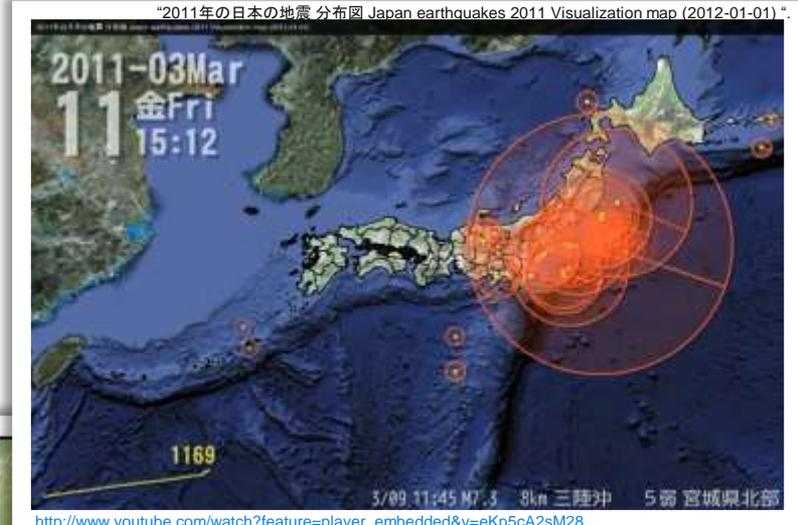
3) Evacuation activity simulation: protect human lives

## 1) Earthquake & Tsunami simulation: predict power & speed

### Fault-line slides trigger Tsunami

- The impact underestimated by the existing Tsunami warning system during Tohoku earthquake on Mar. 11<sup>th</sup>, 2011
- No sensor to measure the amount of fault line slide – no accurate way to predict the Tsunami speed & power, yet
- Urgent need for the alternative real-time Tsunami prediction system leveraging:
  - Sensors on the surface and the bottom of the ocean (GPS buoy, seabed wave gauges, coastal tide gauges, etc.)
  - More accurate real-time analysis on the source area of Tsunami and the Tsunami source model using the new & accurate sensor data input (above)

 **1<sup>st</sup> Step: Solid simulation algorithm based on Tohoku earthquake data**



# Big Data use: Simulation for accurate early warning **FUJITSU**

1) Earthquake & Tsunami simulation: predict power & speed

## Research on real-time & high-res. simulation for more accurate warning



- Using K computer (京)
- Simulation of the 2011 Great Tohoku tsunami
- Simulation resolution ranges over 5 m – 405 m
- The inundated region shown w/ black dotted line
- 5 m resolution used in the red boxes in this simulation focusing on Sendai city

- Non-linear simulation to solve the Tsunami wave & flow
- ca. 16 mil. triangular grids & finer grids over Sendai
- ca. 16 k calc. steps in 120 min. long simulation
- 23 min. for calc. w/ ca. 9.3 % of K computer total core #



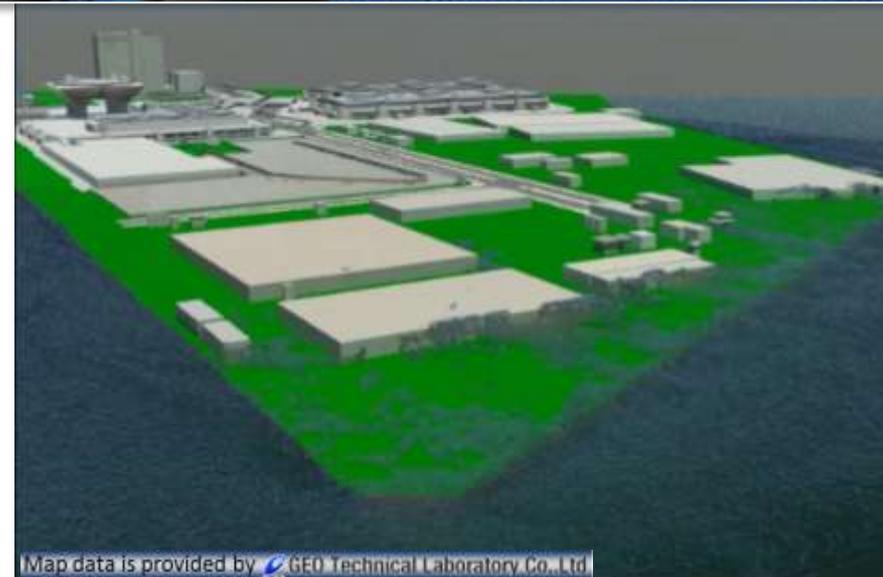
**More accurate & faster  
Tsunami warning**

Oishi *et al.* (2013, JpGU)

2) Building response simulation: predict effects on infra.

## Impact by the Tsunami water flow

- Improve the accuracy on estimation of building damages by Tsunami
- Improve the accuracy on estimation of river/canal overflow by Tsunami flowing upstream direction
- Balance between robust buildings vs. water flow direction & speed
- Help the city/town infrastructure planning to secure the evaluation paths (road, bridges, etc.)
- Helps to better design the evacuation facilities and the way to get there



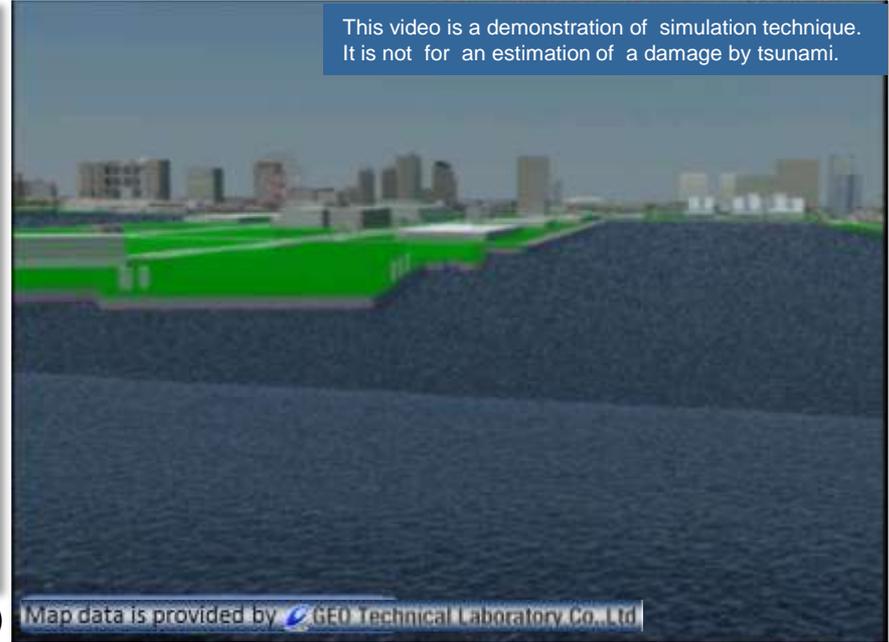
 **2<sup>st</sup> Step: Solid 3D simulation of the water flow to predict damages**

2) Building response simulation: predict effects on infra.

## Accurate 3D replication of invading wave from offshore to shallow sea



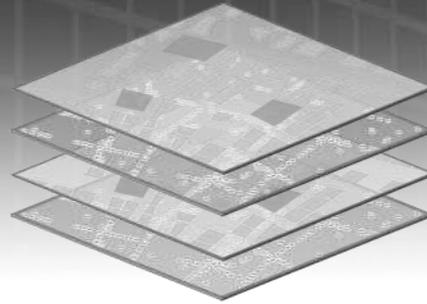
(left: Yokohama, right: Tokyo)



- 3D simulation for wide-area using K computer (京)
- Smoothed-particle hydrodynamic simulation w/ 400 million particles
- The potential use of these research results are:
  - to design levees & evacuation shelters
  - to develop guidelines for hazard maps and evacuation routes

**More effective disaster prevention planning through 3D simulation**

# Big Value Data!



Social Networking  
Services & Sensor  
Data

Business  
Data



## The Rock

...

Where is the Life  
we have lost in living?

Where is the wisdom  
we have lost in knowledge?

Where is the knowledge  
we have lost in information?

...

*T.S. Eliot*



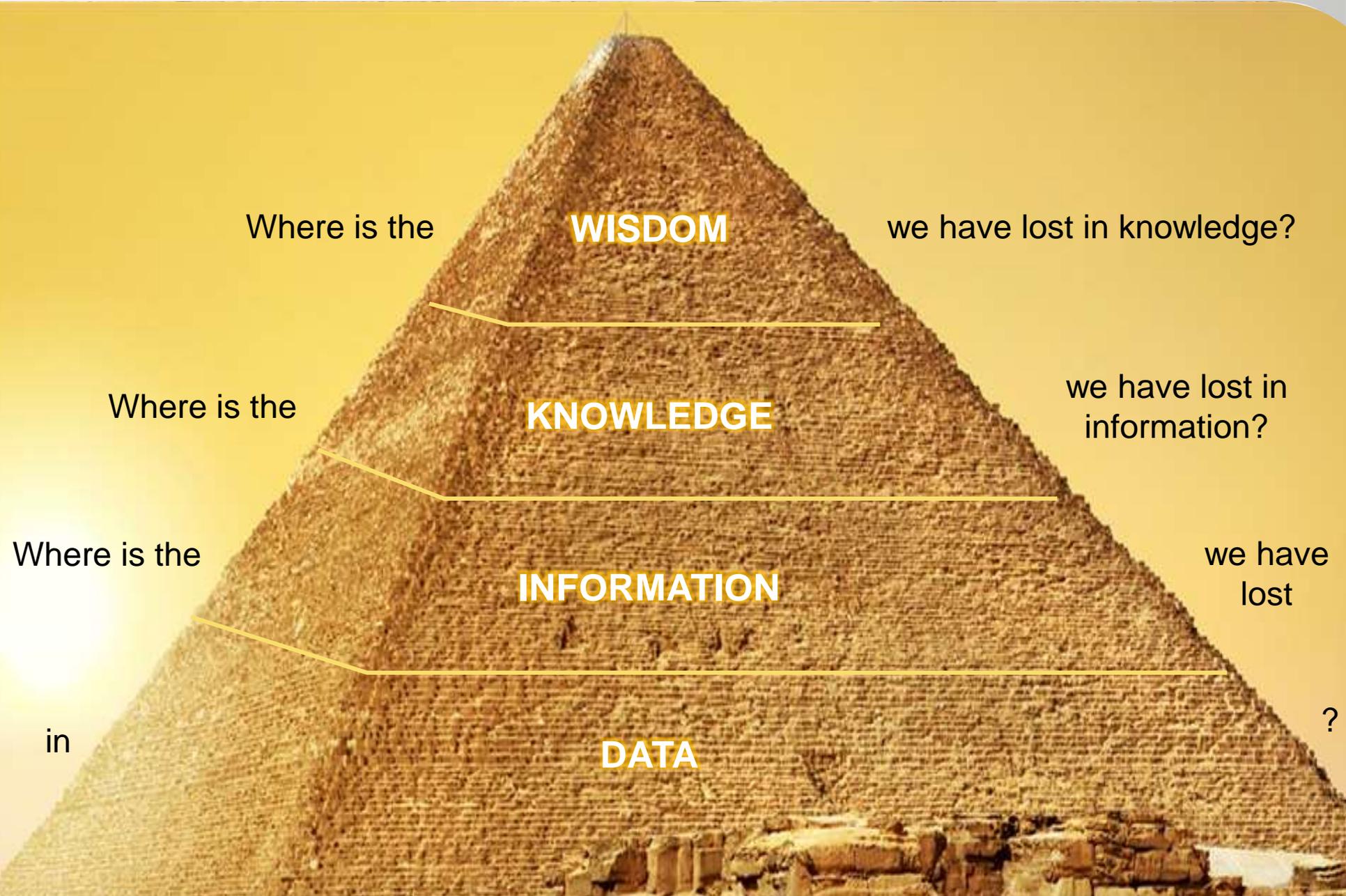
Thomas Stearns Eliot

(1888 – 1965)

publisher, playwright, literary

born American  
naturalized British subject in 1927  
Nobel prize in literature in 1948

# DIKW-Hierarchy



Where is the

**WISDOM**

we have lost in knowledge?

Where is the

**KNOWLEDGE**

we have lost in information?

Where is the

**INFORMATION**

we have lost

in

**DATA**

?



**FUJITSU**

shaping tomorrow with you