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[FOCI 2007 Tutorial]
Computational Intelligence in Everyday Life
~ Probabilistic Human Modeling and Behavior Sensing ~

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Project page:
http://www.openlife.jp/

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Messages

- **Sensing and modeling everyday life:**
  as a grand challenge in Computational Intelligence
  - Now, computers should work for supporting **human's whole** everyday life not only for office work,
  - Everyday life information has much higher degree of freedom than specific task in office work.
  - Huge, hetero, multi-modal, multi-dimensional information is related to everyday life.
- **Key points:**
  - **Sensing** comprehensive data related everyday life
  - **Modeling** principal structure from such data
  - **Application** focused on as an essential problem

(Application driven basic researches are necessary to select sensing data and structure of the model.)

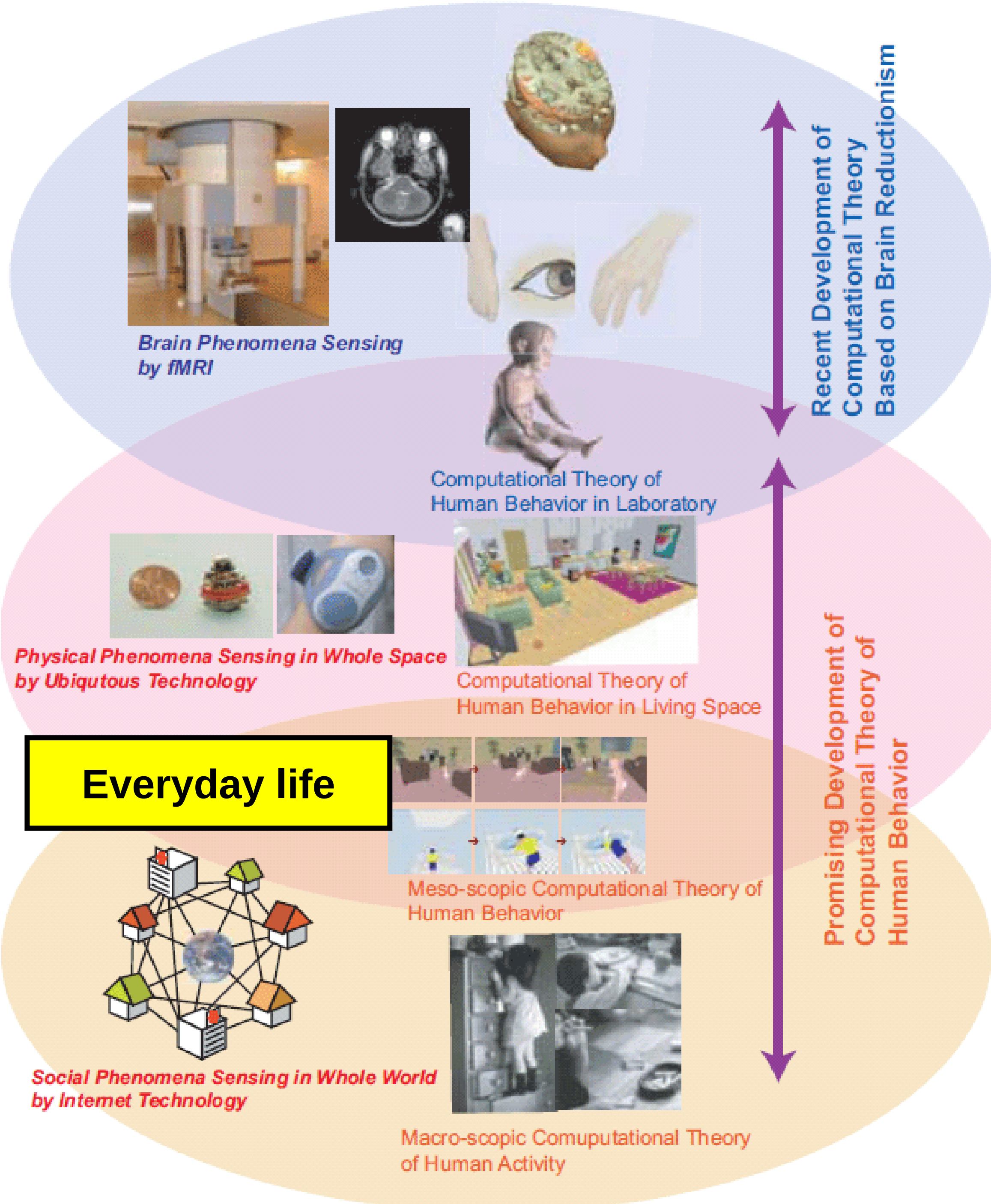
Contents

- Introduce our research in everyday life computing

- Application: Childhood Injury prevention and surveillance
- Behavior Sensing: Ubiquitous, Wearable and Internet sensors
- Probabilistic Human Modeling: Bayesian networks

We have little understanding everyday life

Development of computational theory of human



Three perspectives

1. New observing device
2. New representing device
3. Meso-scopic phenomena

In case of brain science

1. fMRI
2. Computer
3. Neuron (micro) ⇔Brain functions(macro)

Everyday behavior science

1. Ubiquitous sensor
   Wearable
   Internet sensor
2. Game, CG, Robot
3. Everyday behavior
   – Behavior(micro) ⇔Injury(macro)

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Application:

Childhood Injury Prevention and surveillance

Trend of cause of child death

The leading cause is injury

-900 children died par year in Japan

-Social cost is estimated as $ 5 billion par year in Japan

Age	First(%)	Second (%)	Third (%)	Forth(%)	Fifth (%)
0	Birth defect (36.3)	Respiratory disturbance (16.1)	Sudden death syndrome (8.1)	Accident (5.9)	Fetal hemorrhagi c disorder (4.1)
1-4	Accident (24.8)	Birth defect (17.6)	Malformatio n neoplasma (7.5)	heart disease (6.0)	Pneumonia (5.0)
4-9	Accident (35.0)	Malformation neoplasma (17.2)	Birth defect (7.9)	Heart disease (5.5)	Murder (3.8)
10 -14	Accident (22.0)	Malformation neoplasma (21.2)	Heart disease (9.5)	Suicide (9.2)	Birth defect (6.5)

in Japan

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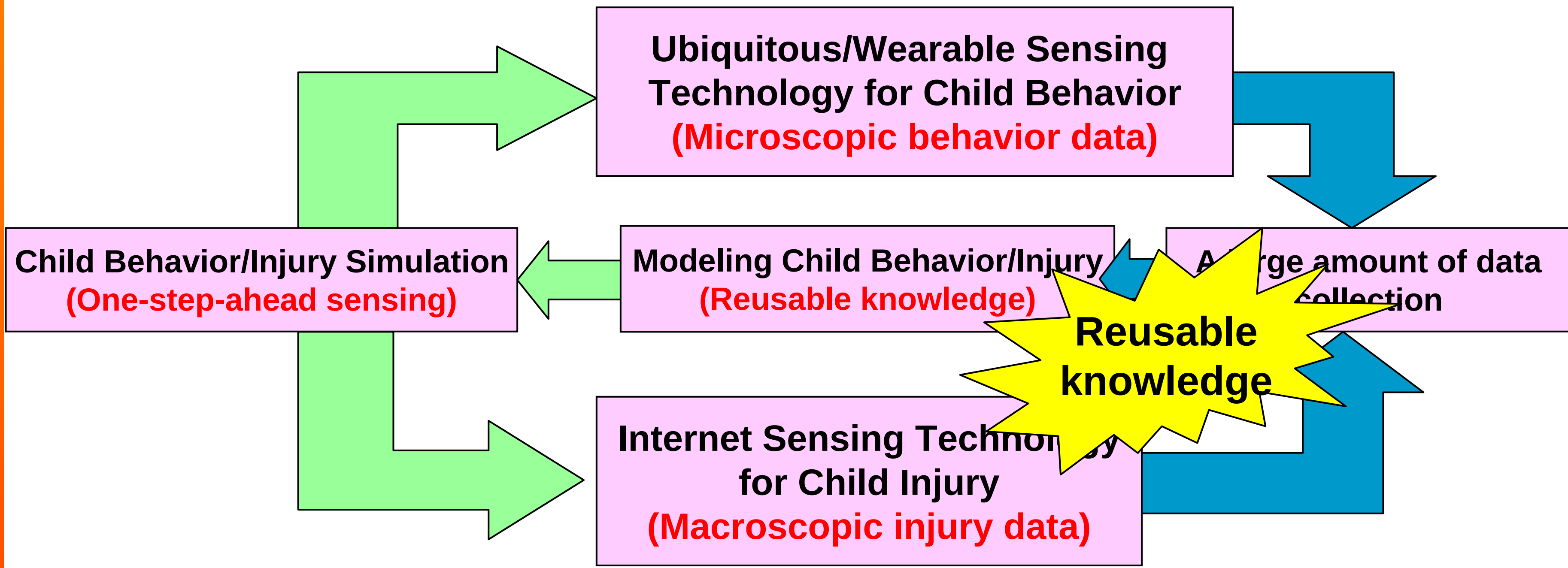
Research approach



Generative model

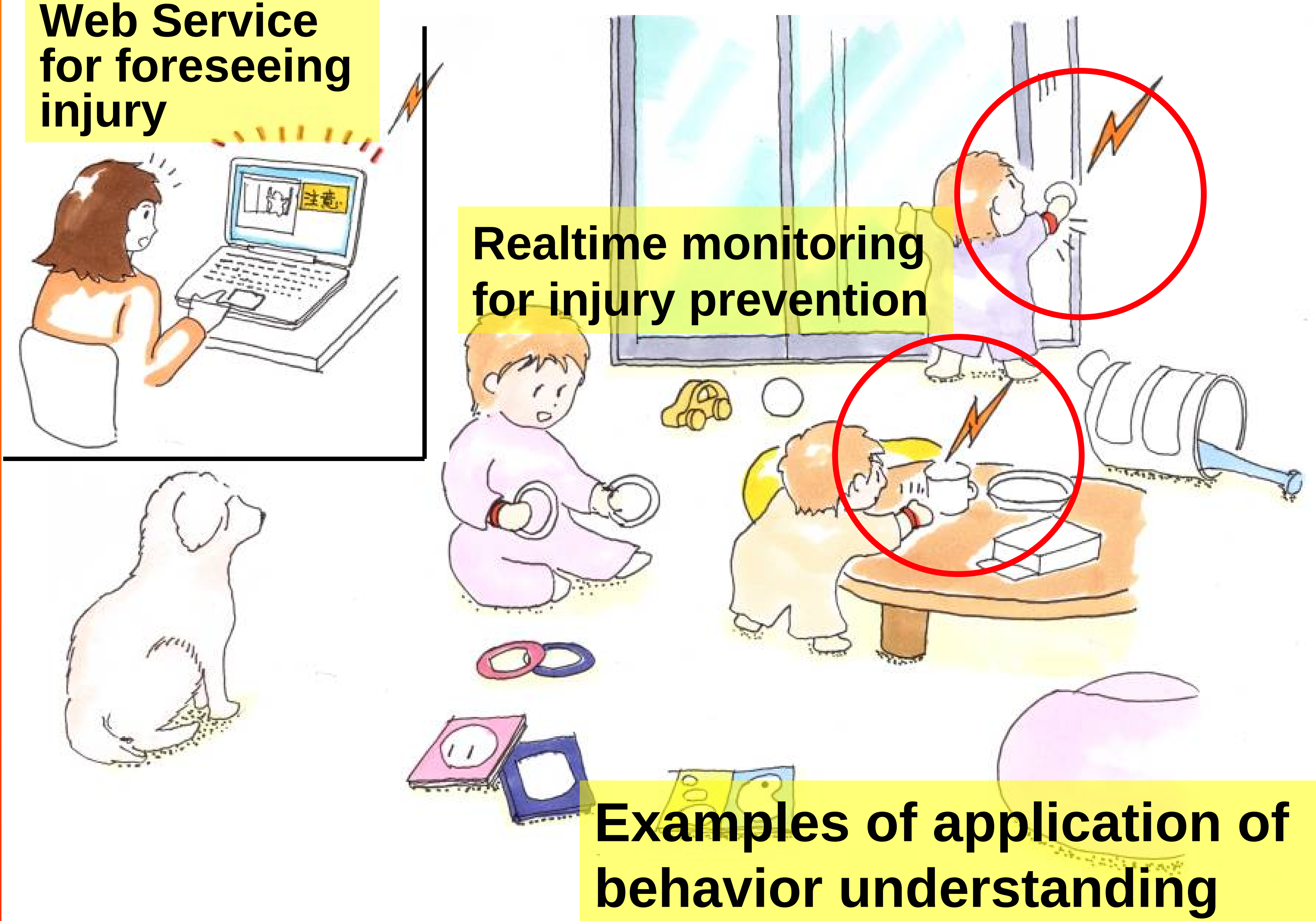
Sensing everyday life

Generative Model of everyday life behavior by sensing technology + modeling technology

Examples of service

Web Service for foreseeing injury

Realtime monitoring for injury prevention

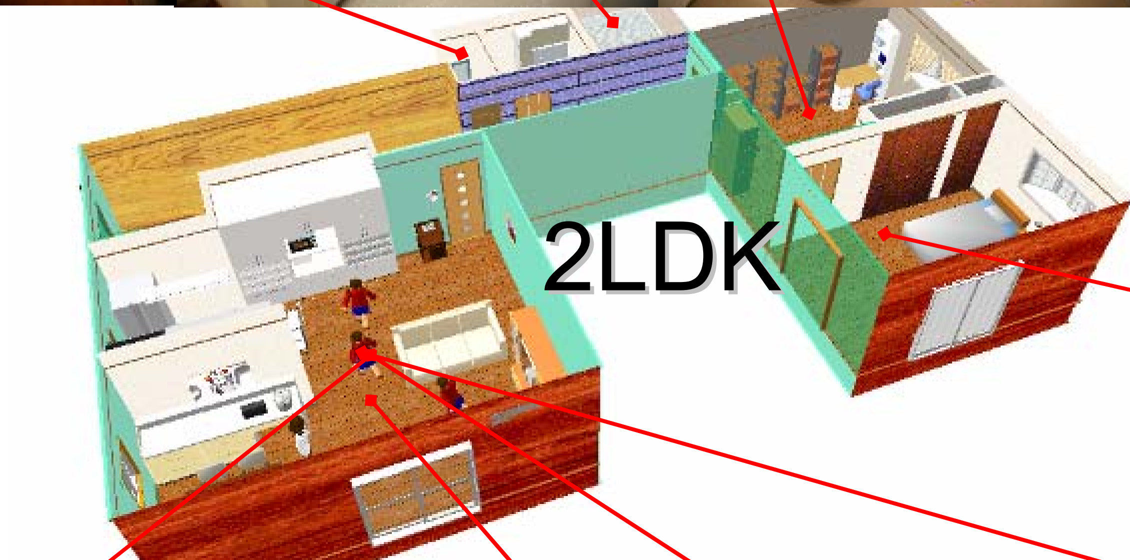


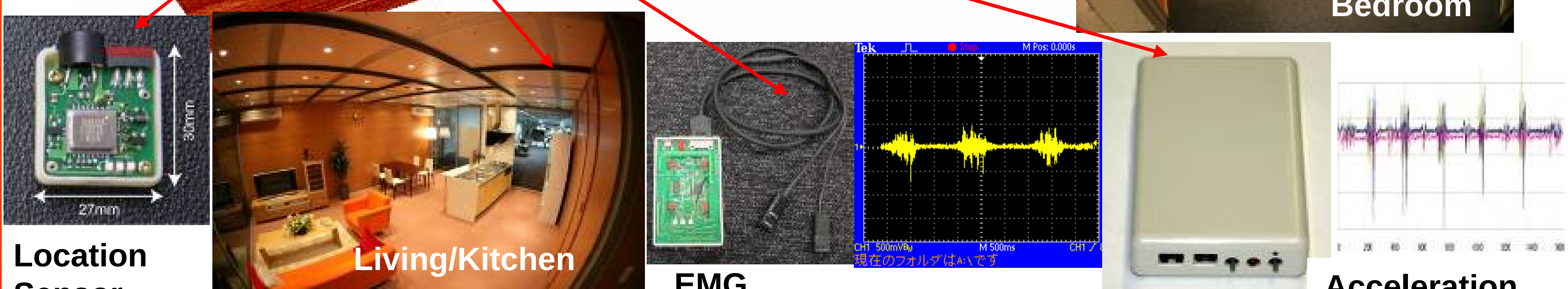
Examples of application of behavior understanding

Ubiquitous, wearable and Internet sensors

Ubiquitous Sensor 1/4
for observing everyday life

- Home-shaped system
  - Living/Kitchen, Bathroom, Toilet, Bedroom
- Embedded sensor
  - 1000 Ultrasonic 3D location sensor
  - Camera, Microphone
- Wearable sensor
  - Wearable EMG
  - Wearable acceleration





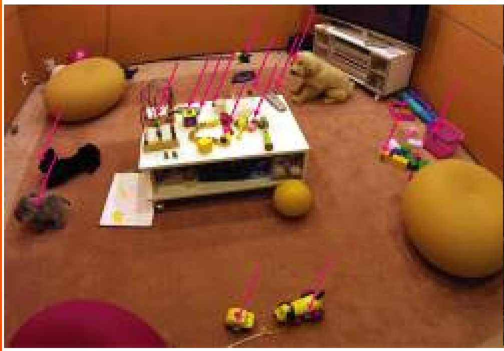
Location Sensor

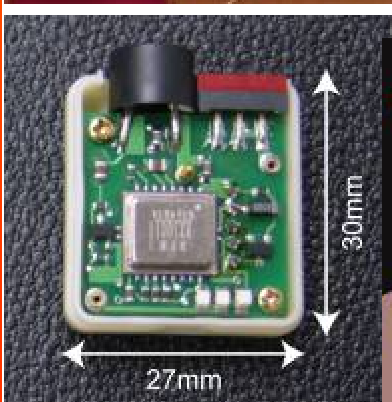
EMG

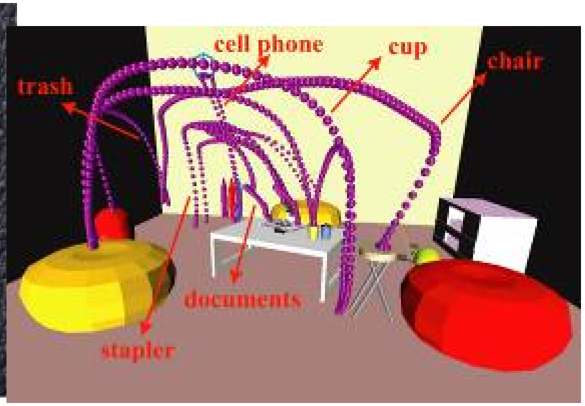
Acceleration

Ubiquitous Sensor 2/4
for observing everyday life

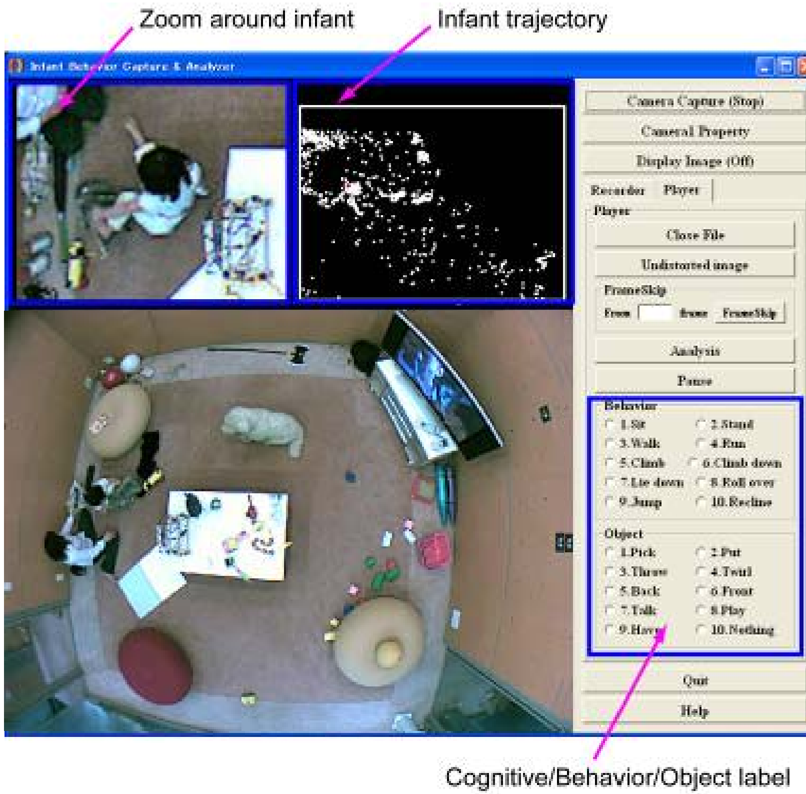
- **Child's everyday behavior data** in a laboratory
- Extract **behavior characteristics**







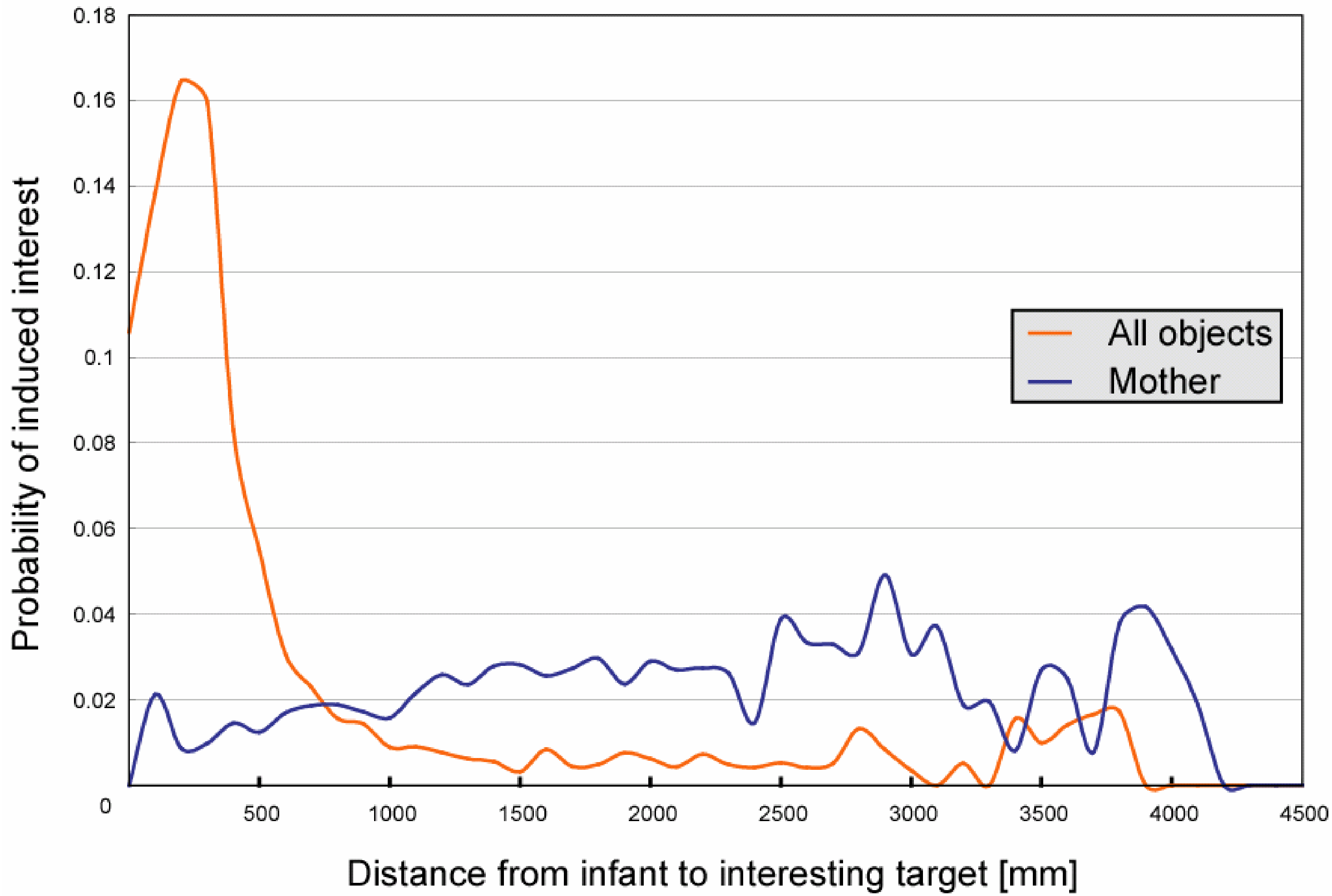
Behavior data from 100 children



Ubiquitous Sensor 3/4

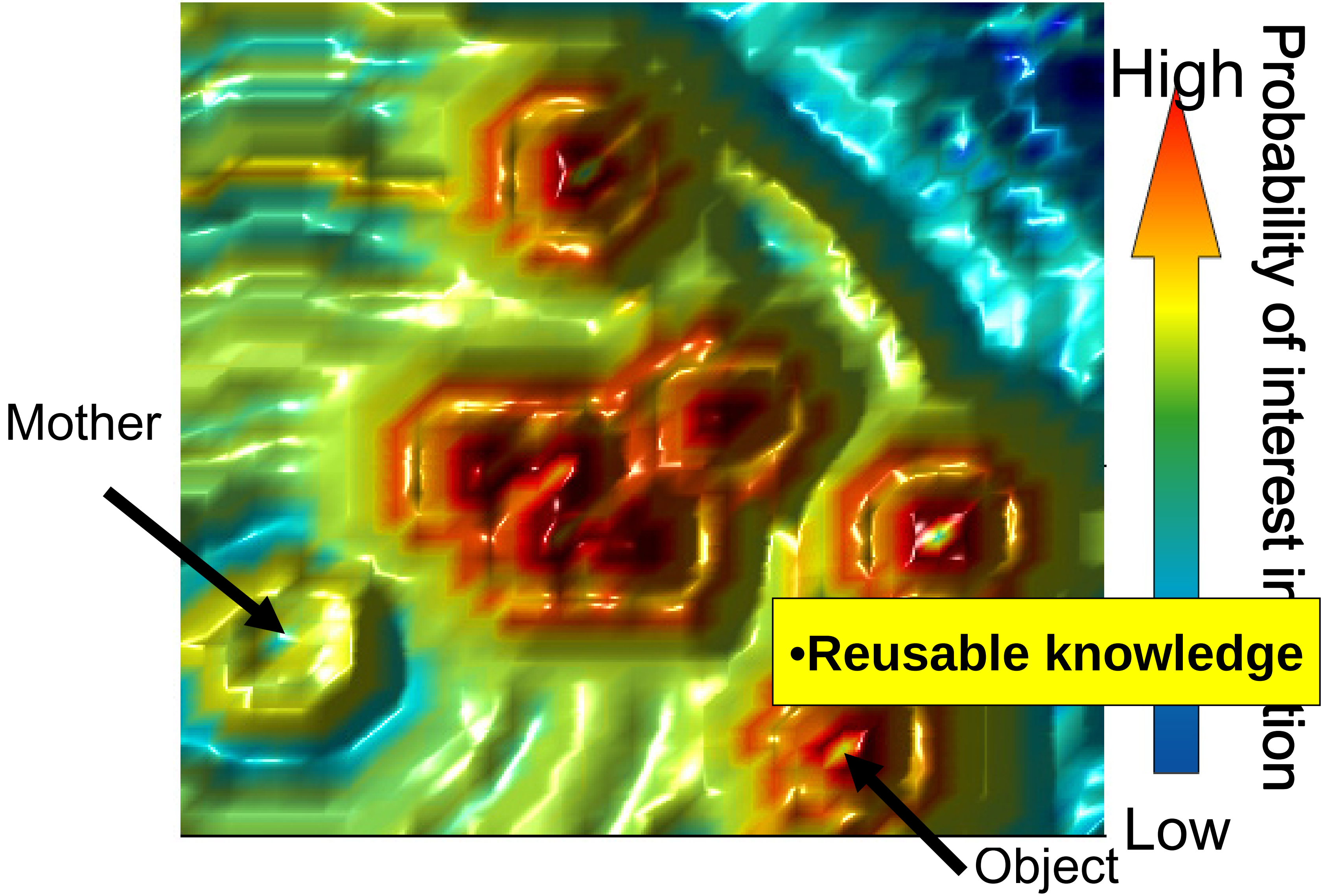
Example of behavior characteristics :

- Relationship between infant's interest and distance to objects



Ubiquitous Sensor 4/4

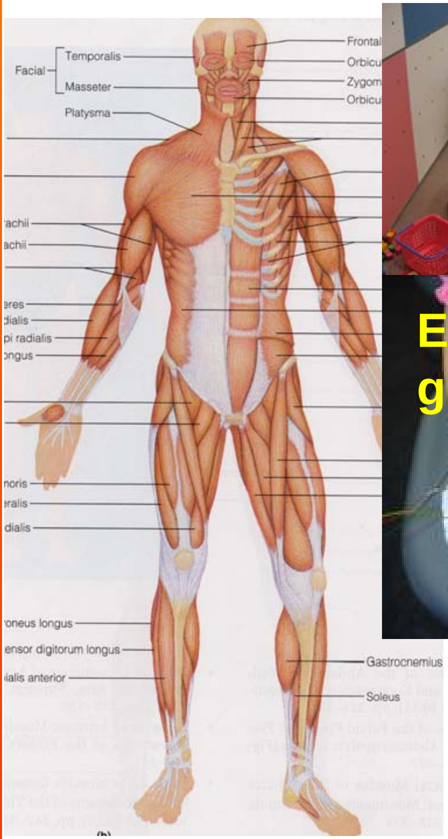
Visualization of interest induction



- **Reusable knowledge**

Wearable Sensor 1/2
for everyday life sensing

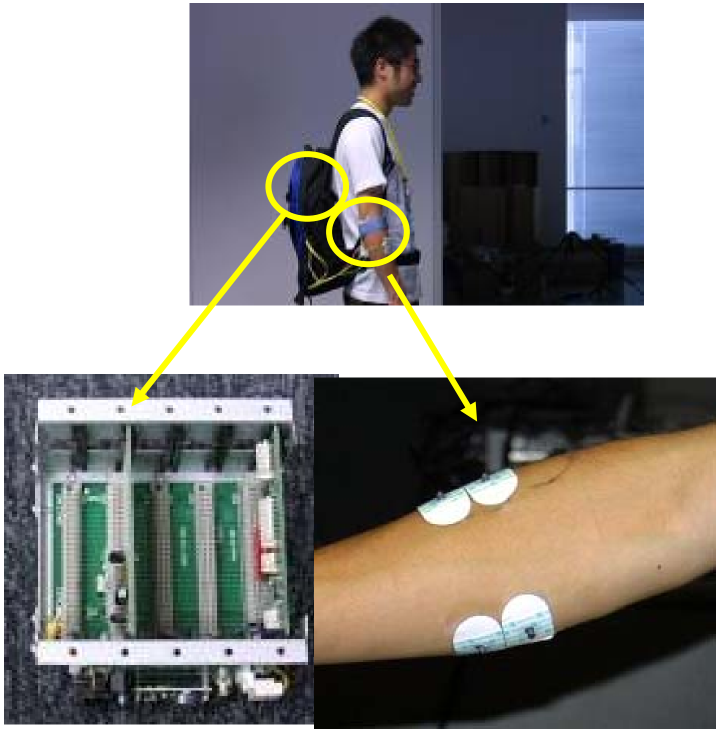
- From lab. to **real home environment**
- Systematic methodology of child measurement

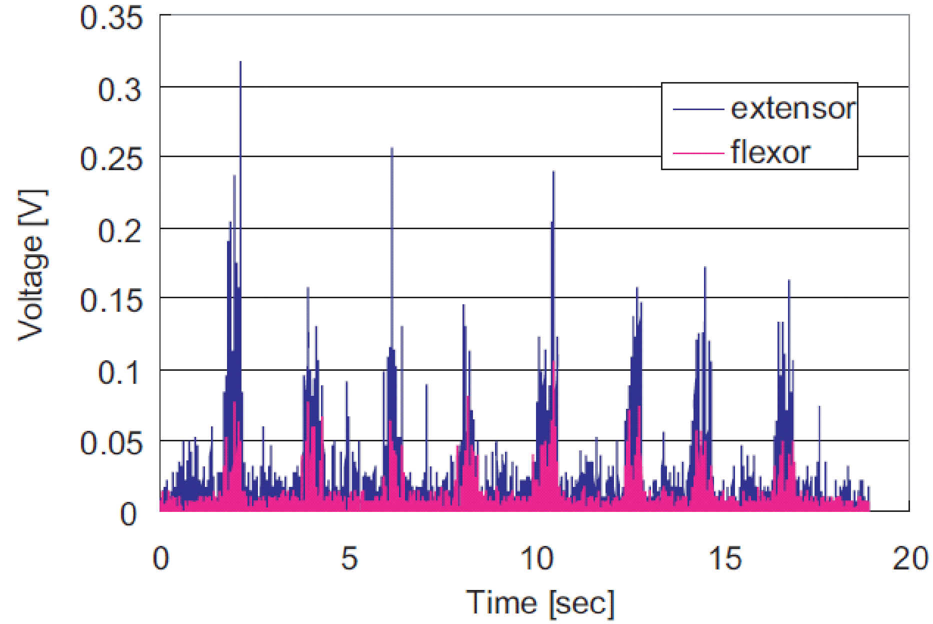


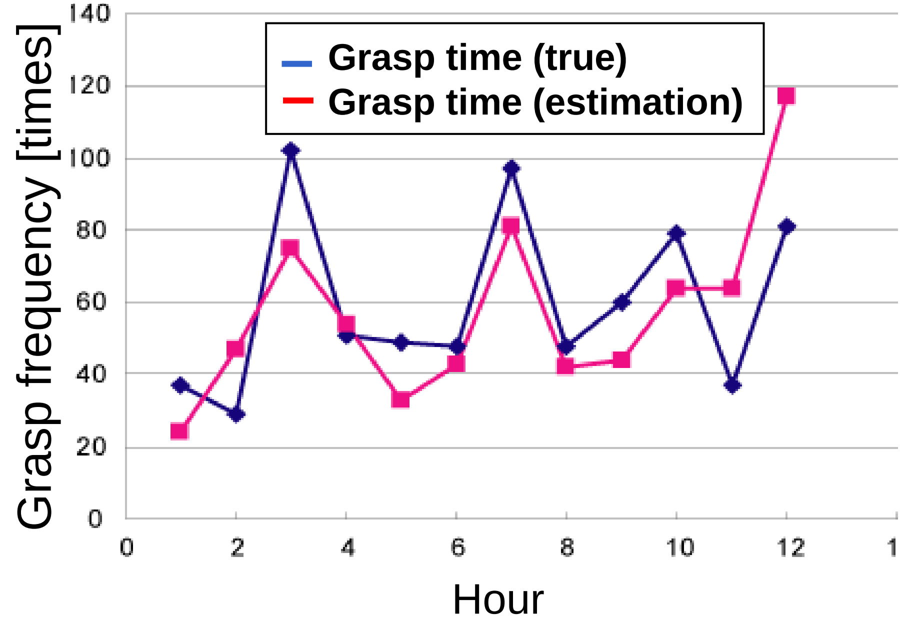
For example,

- **How many times does child grasp?**
- **How many times does child fall?**
- **When does child perform a certain behavior?**

Wearable Sensor 2/2

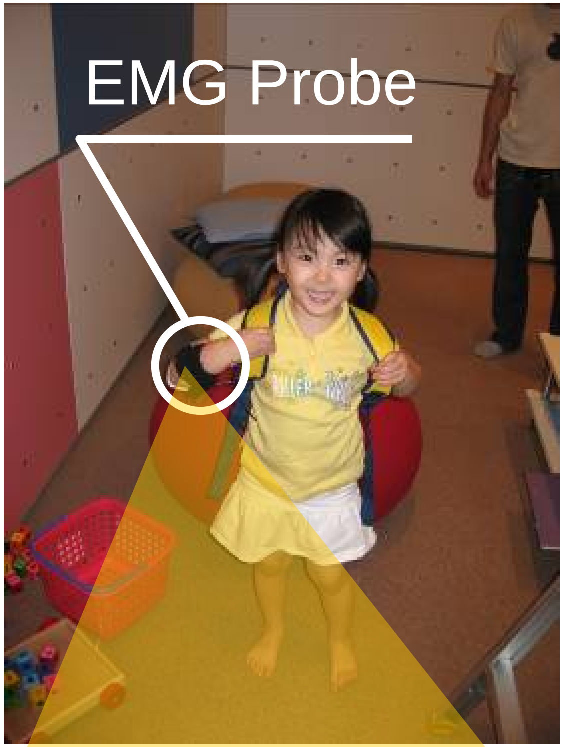






A system can estimate the times of grasp within an error of 25%.

EMG Map = EMG + Location



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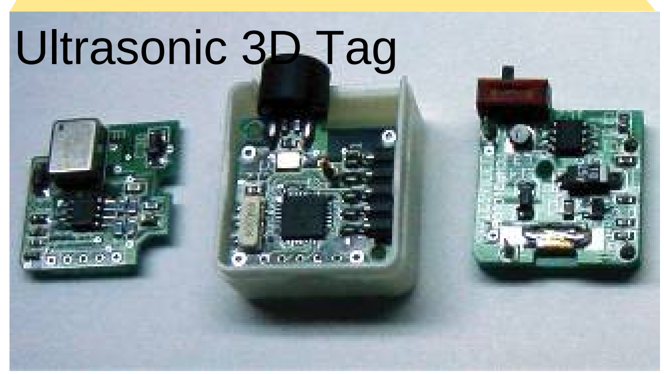
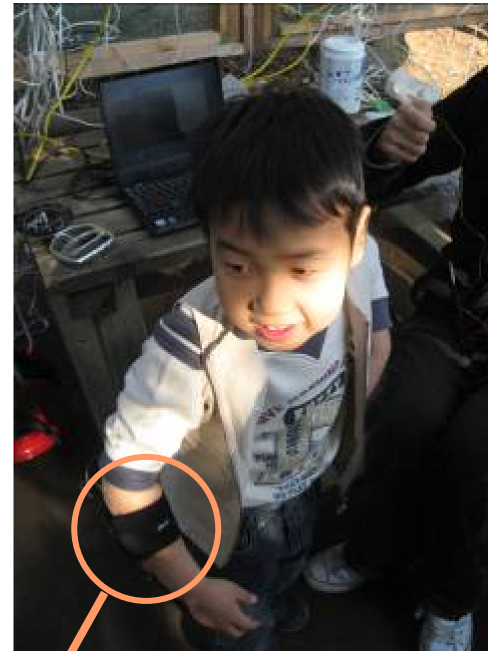


- Record EMG with location
- Useful for understanding when/where/ how EMG occurs

Science of “Playing” Child with EMG map

“Stone wall” type of play equipment

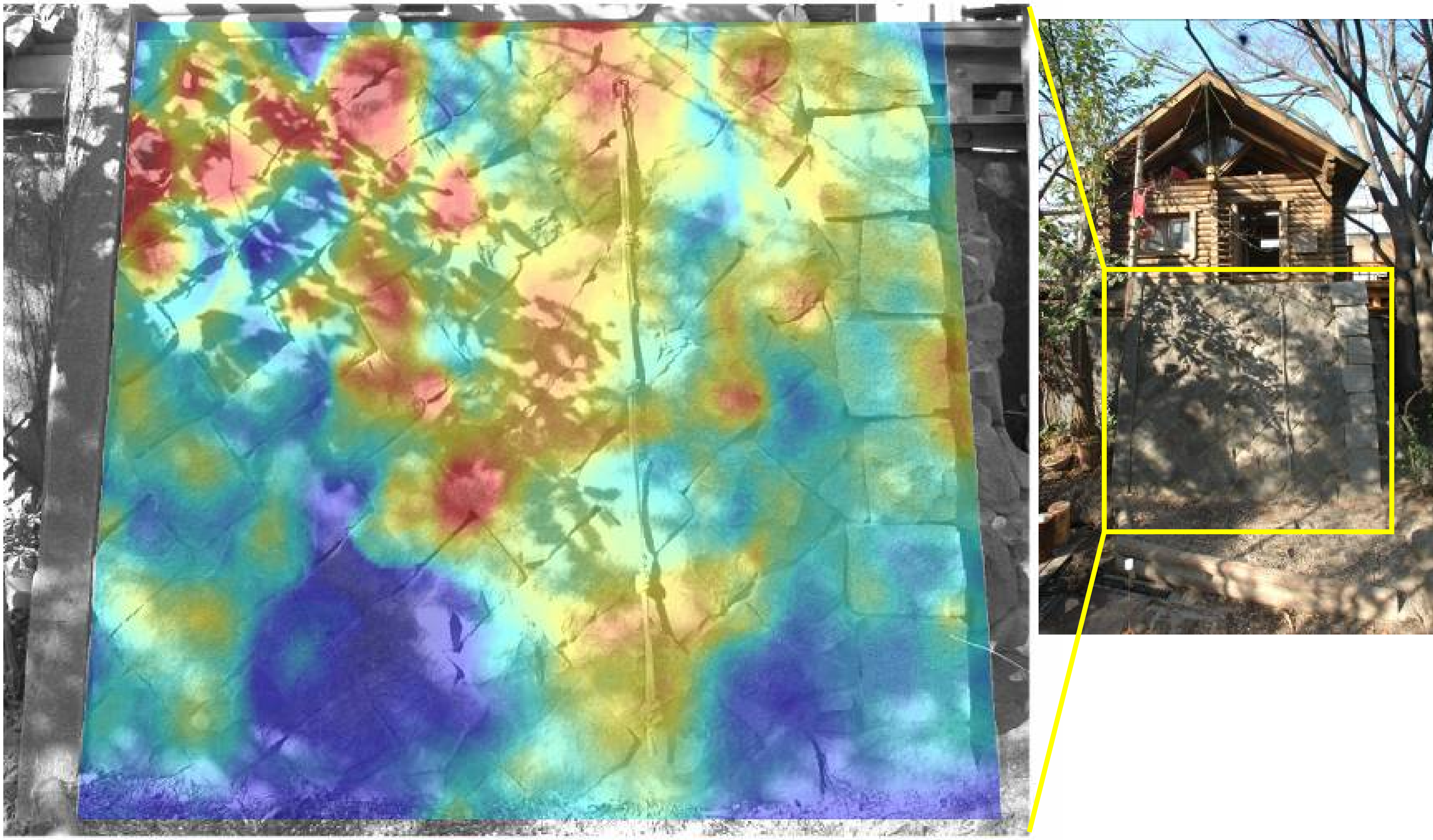


Ultrasonic 3D Tag
(location sensor)

Wearable EMG
(physiological data)

Experimental results of EMG map

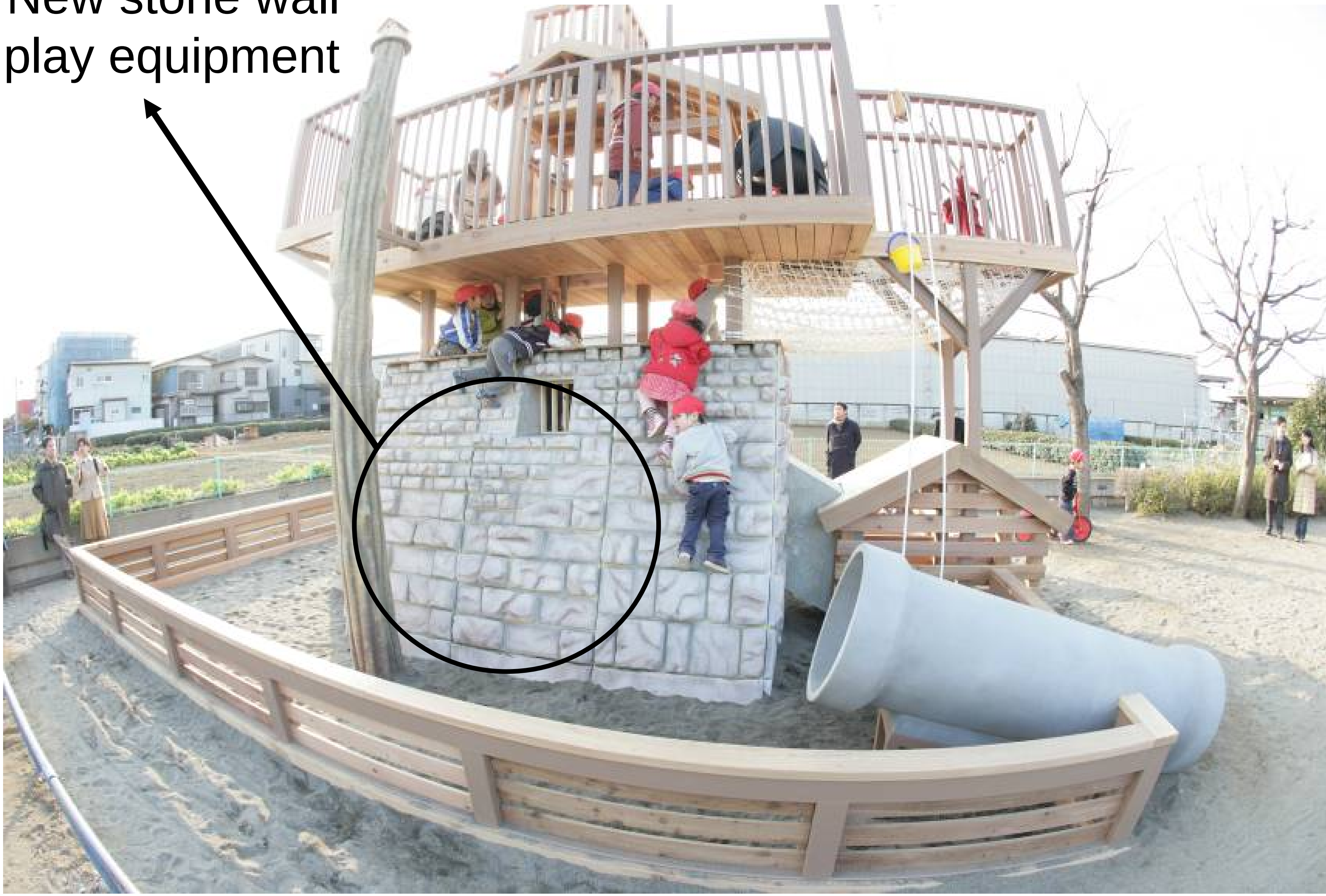
We can understand where is dangerous parts for child.



Red area indicates that large muscle power is used

New design for children based on EMG map

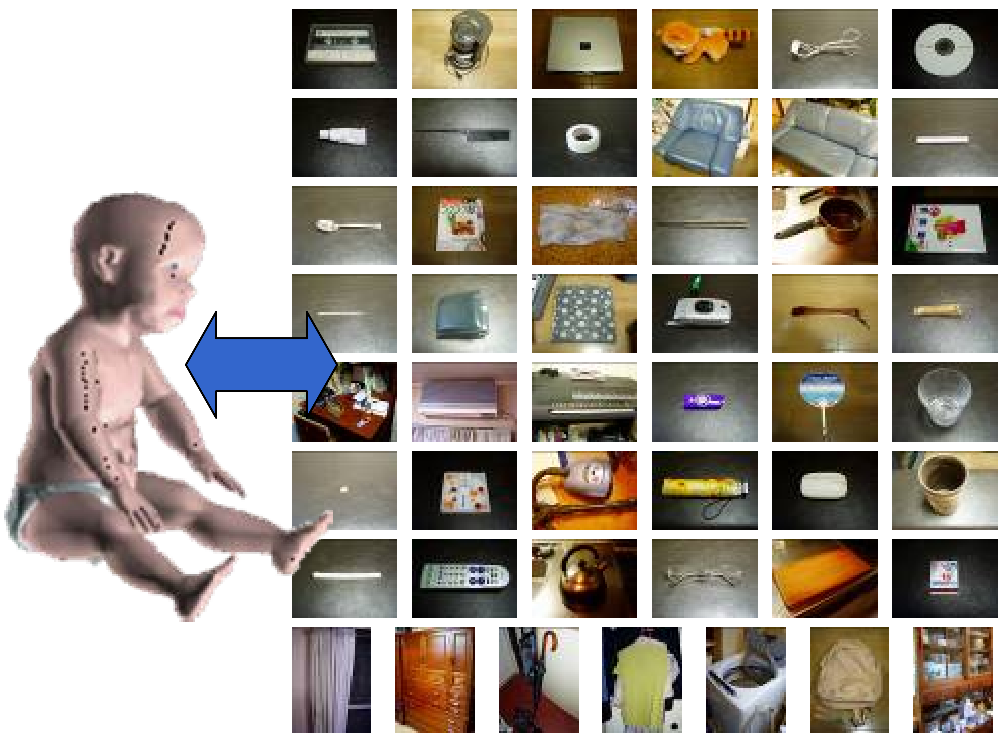
New stone wall
play equipment



Kuwanomi kindergarten Feb. 2007

Internet Sensor
for social phenomena sensing

- from lab/home to Society
- Actual interaction between child and objects in a everyday lives



- Small size
  - Rokuen Children's Clinic
- Middle size
  - National Children's Medical Center

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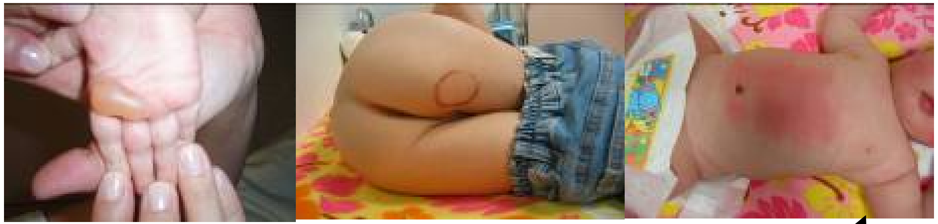
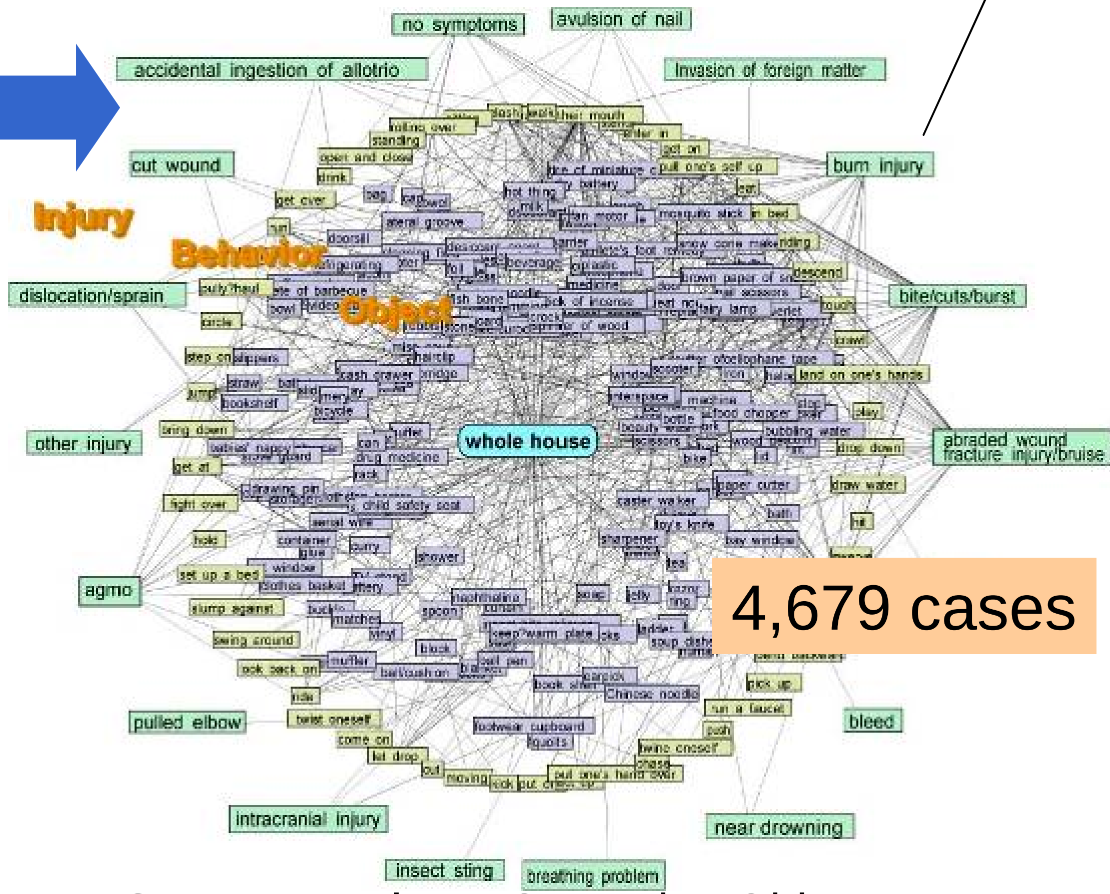
Data, Knowledge, Action, and Service

Advanced Injury Surveillance System and Database





4,679 cases

Collect injury data
At hospitals

Age, Sex, Date, Place, Causative Object, Behavior, Injury, Accident, Hospital Visit for Complete Cure

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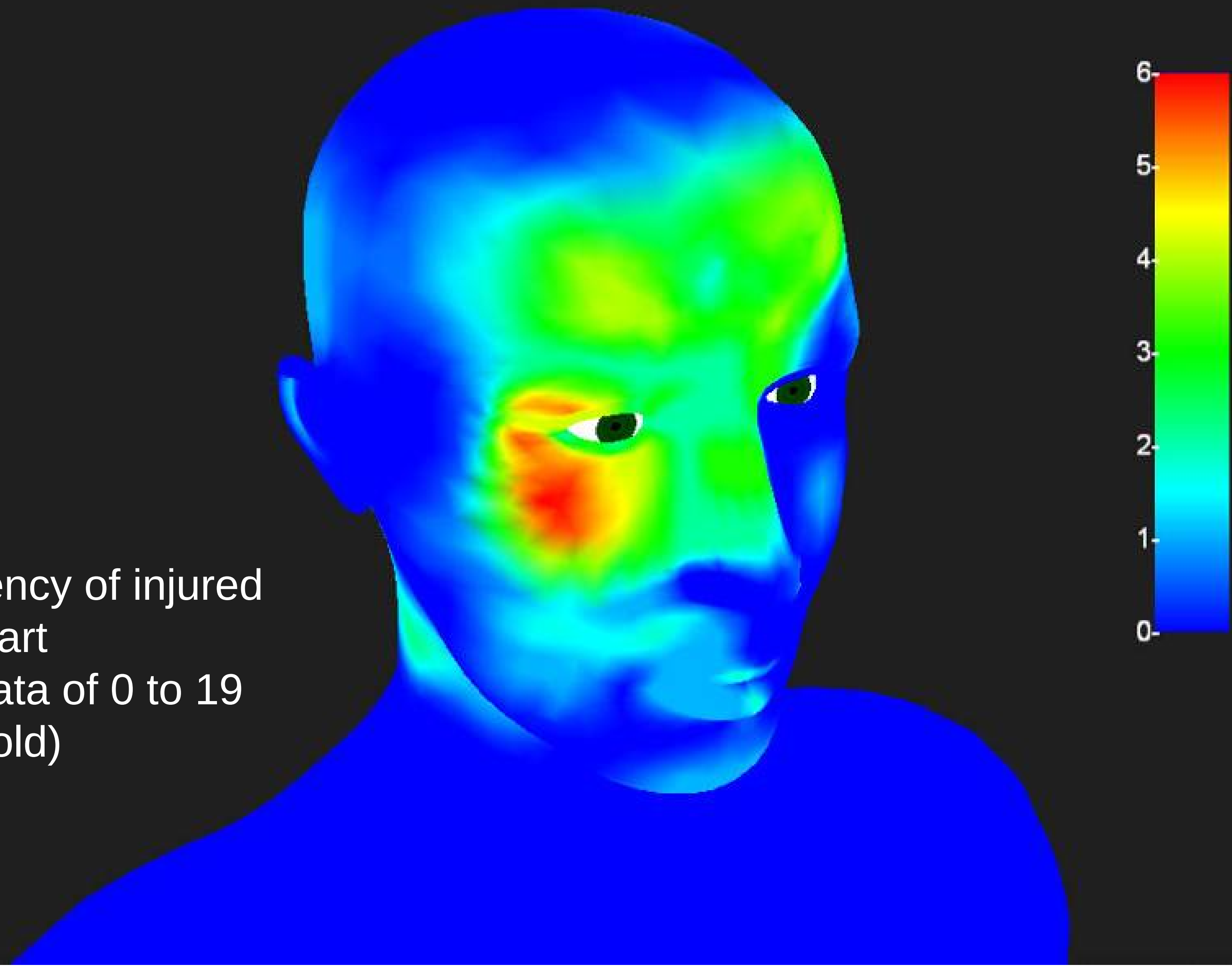
Human-GIS enables to describe and visualize size, area, and position of injury.



Frequency of injured body part
(169 data of 0 to 19 year-old)

Medical Cost

Expectation of medical cost
when injury due to object occurs

$

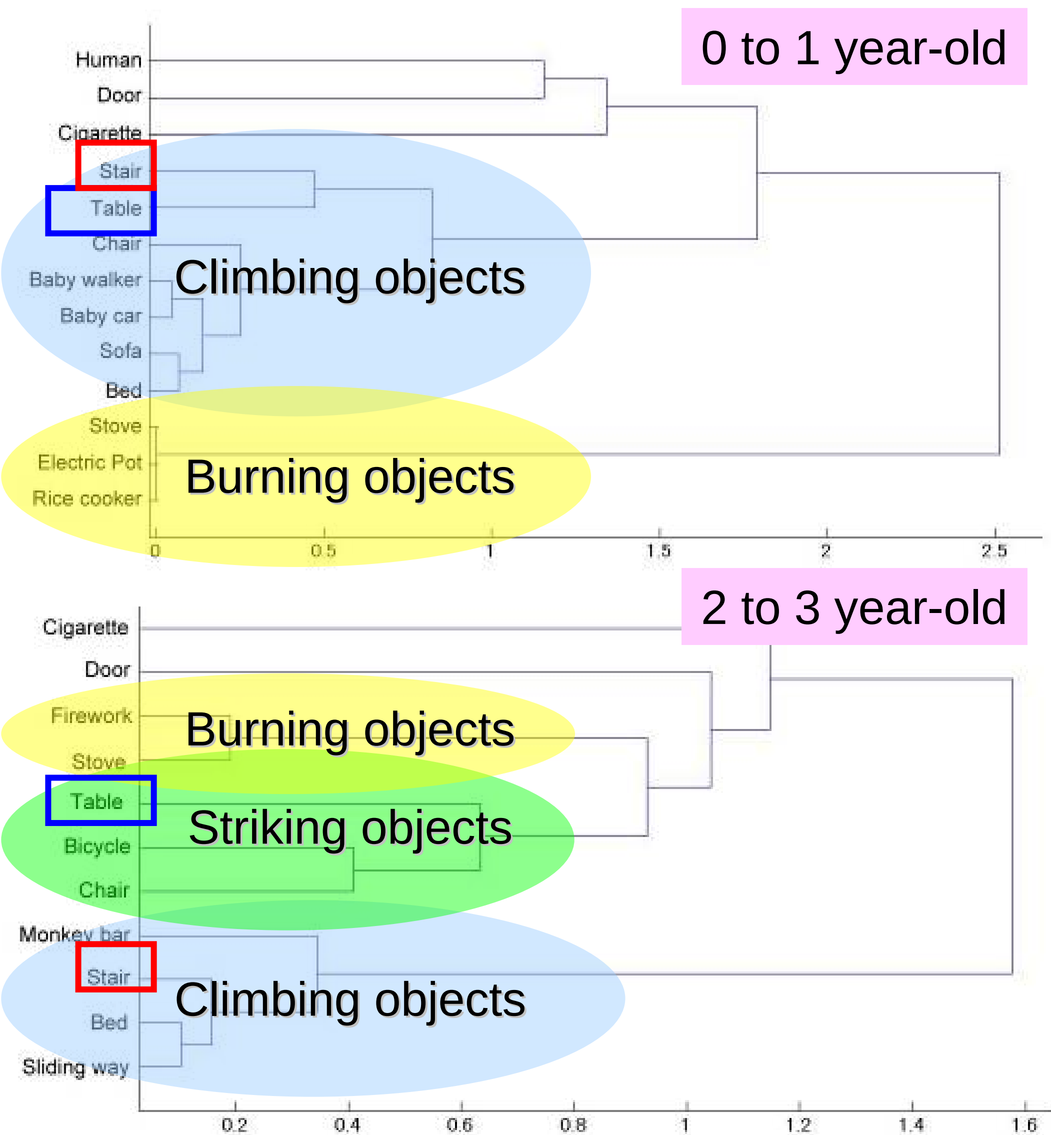
Chair	774
Electric Pot	694
Stove	676
Miso Soup	661
Coffee	480
Razor	431
Rice Cooker	421
Firework	395
Bed	382
Fan Heater	338
Pillar (柱)	331

Monkey bar	326
Iron	314
Sliding way	197
Sofa	181
Toy	158
Bicycle	151
Toy	136
Window	136
Cigarette	127
Baby car	79
Human	78

- Calculated from MHLW DB and AIST Injury DB

Everyday Cognitive Science

Object classification from child's point of view



- Define injury frequency as feature vector of each object
- Cluster analysis
- Object cluster changes by child's age
- Imply that the way of seeing/using object changes

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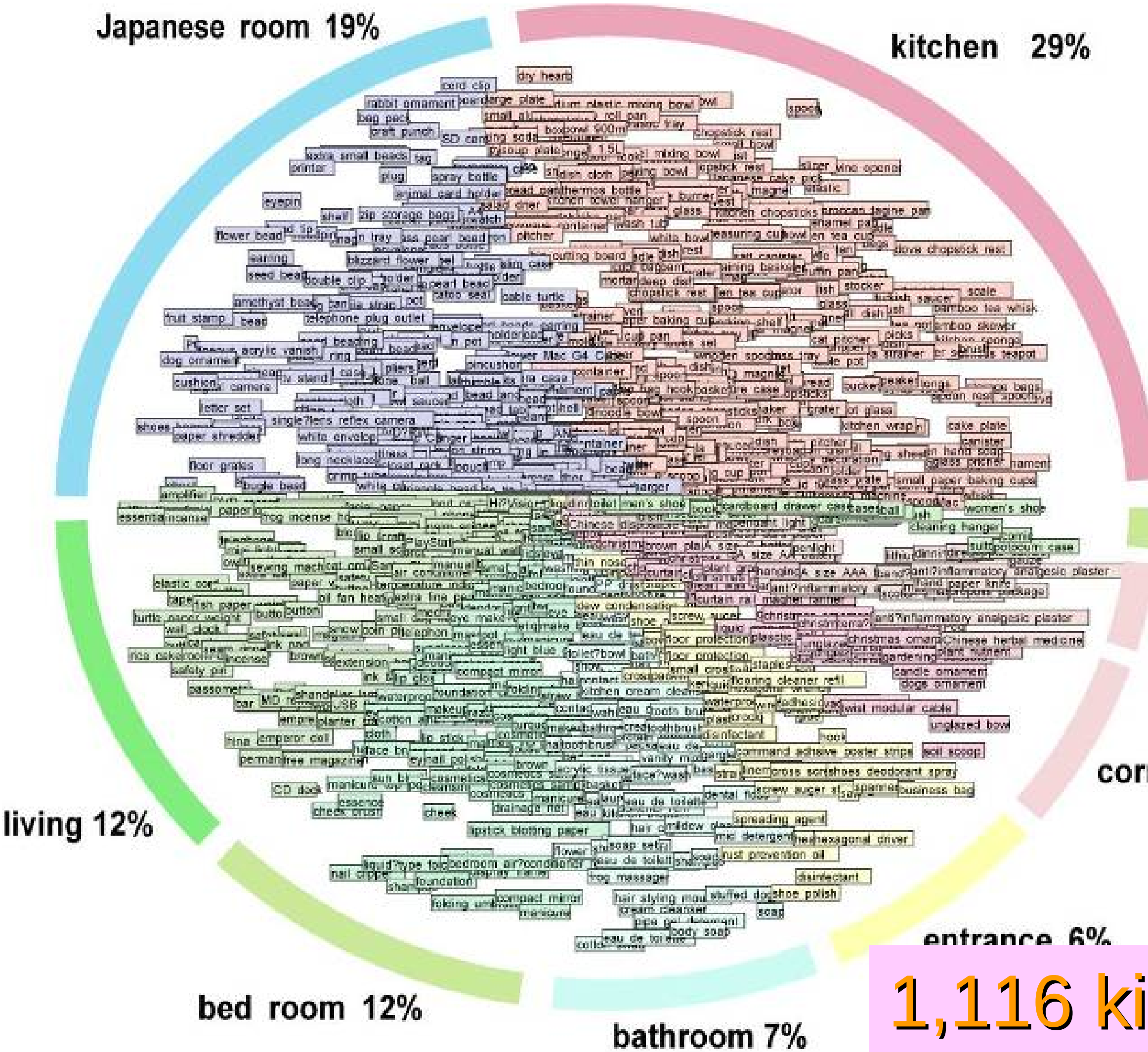
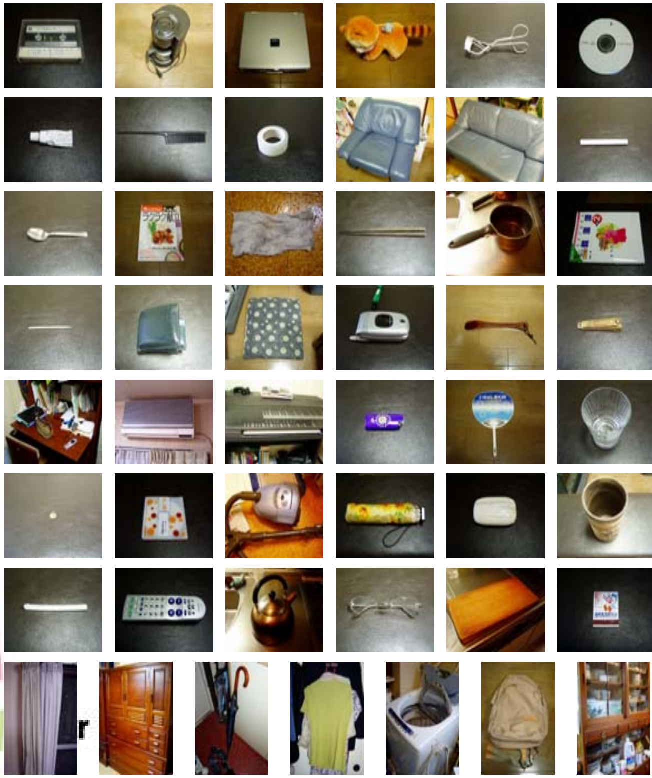
DHRC Object database
(Objects existing in one home)





1,116 kinds, 4,289 objects
(Sampled from home of "family of two")

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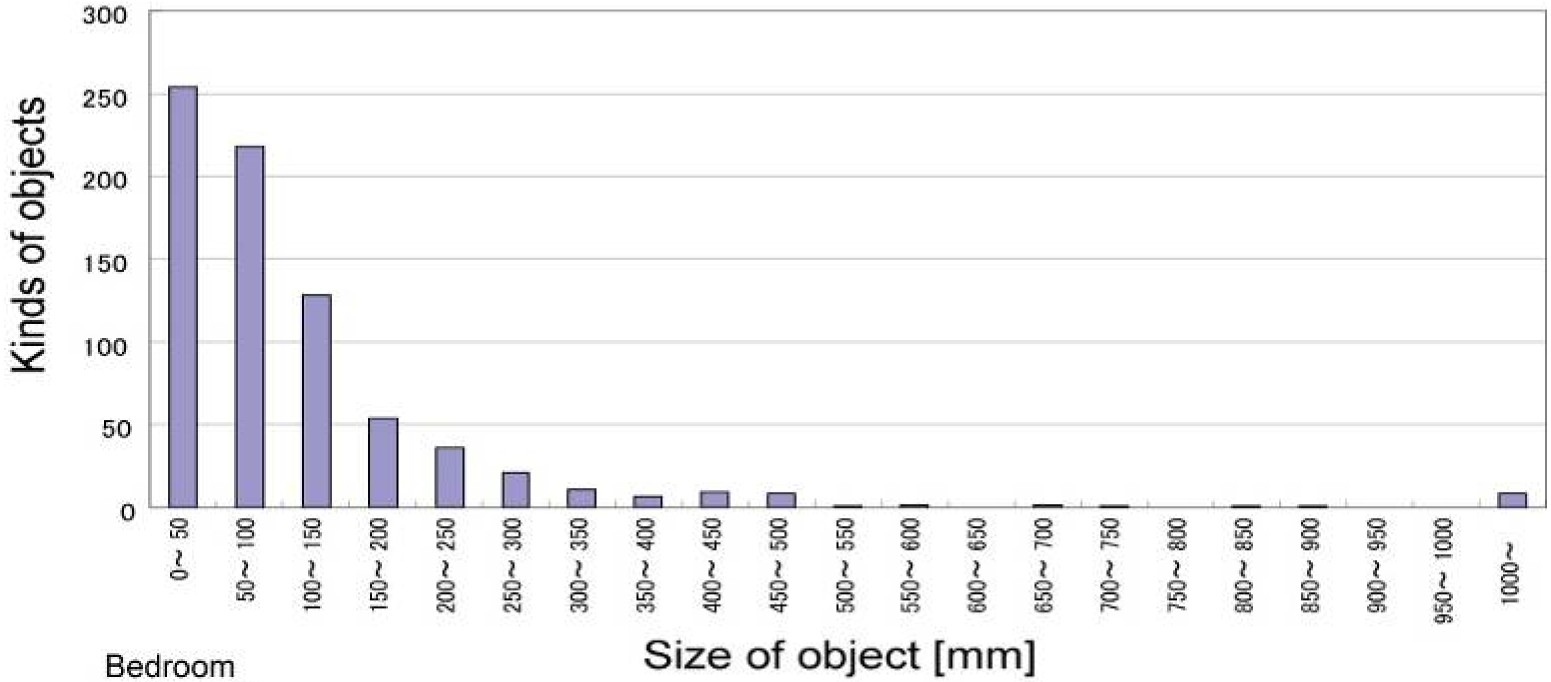
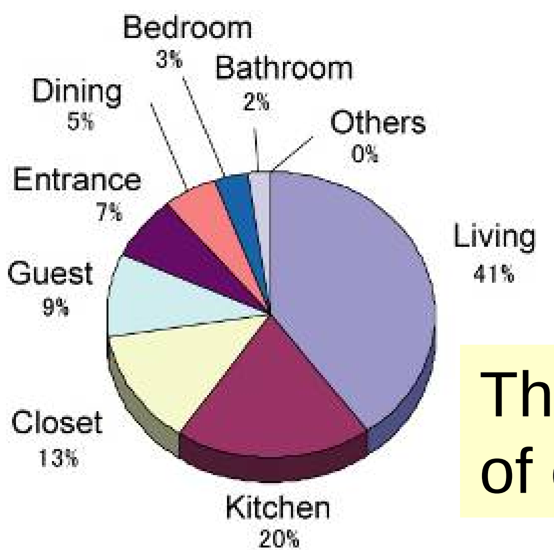
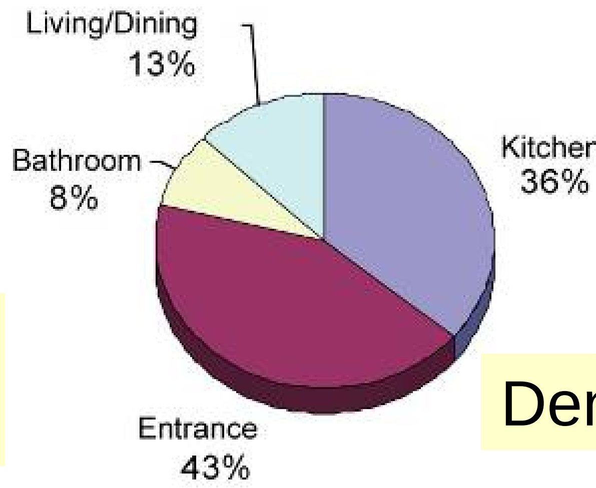
Probability Distribution of Everyday Object





The number of objects



Density

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AIST

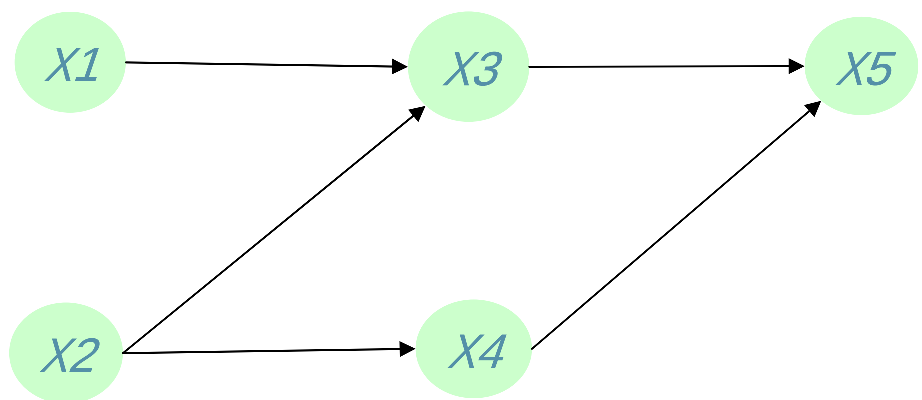
Probabilistic Human modeling to make re-usable computational knowledge

- Problem:
  - Data, Statistics can not explain what we should do next.

- Solution: Causality, Graphical modeling and Computer simulation (re-usability and computation)
- Method: modeling and applying Bayesian networks

Bayesian networks

- Node：(X:{true,false}/{Mon,Tue,…}), discrete random variables
  Observed or unobservable (predicted variable)
- Directed arc：conditional dependency
- Conditional probability: defined by Tables
  (Conditional Probability Table:CPT)



CPT: $P(X4|X2)$

X4 \ X2	0	1
0	0.8	0.4
1	0.2	0.6

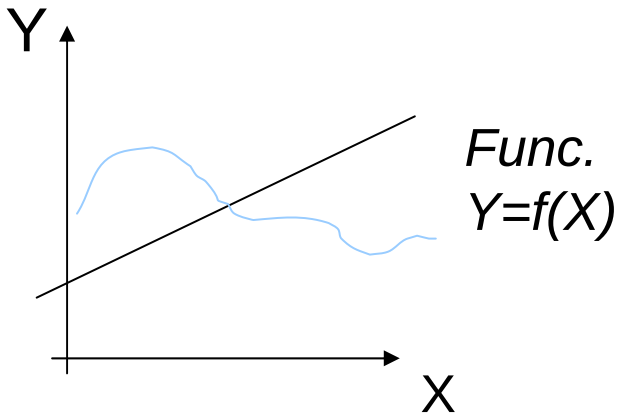
$$P(X1,X2,X3,X4,X5)$$
$$=P(X5|X3,X4)P(X4|X2)P(X3|\ldots)P(X2)P(X1)$$

Decomposed to make the model tractable

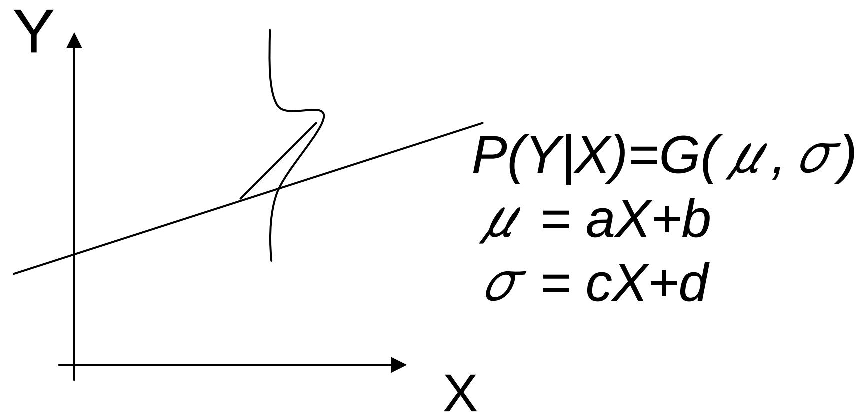
Why Bayesian network?

- Statistical learning (flexible modeling)
- Probabilistic reasoning (simulation available)
- Sophisticated algorithms and softwares
- Easy to understand semantics of models

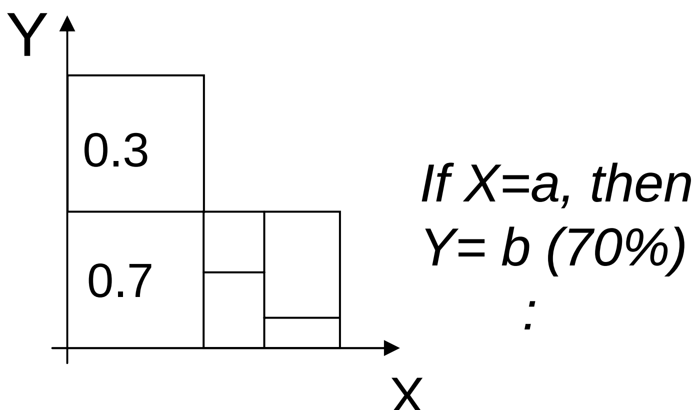
More flexible representation power than other models



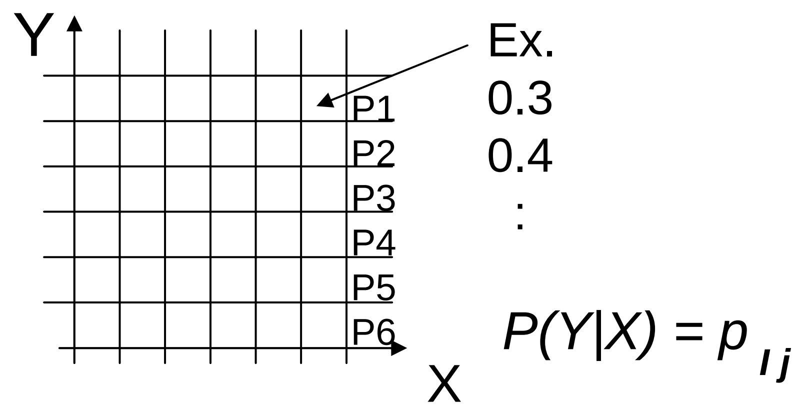
Linear : regression model
Non linear : neural network



Gaussian model（normality）



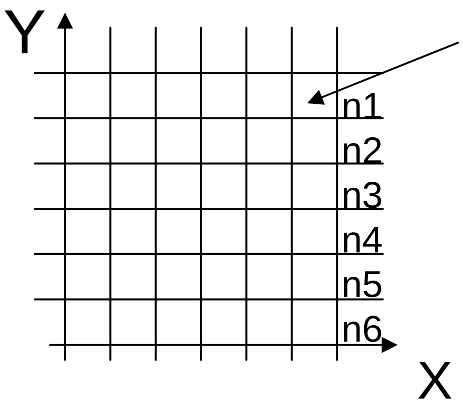
Decision tree



Bayesian network

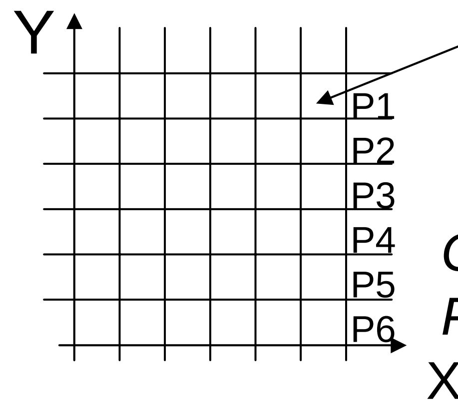
Graph structure learning from data

$X \qquad Y$? OR $X \longrightarrow Y$?



Ex.
3
4
:
Cross table
$|Y, X| = n_{xy}$

χ 2 testing



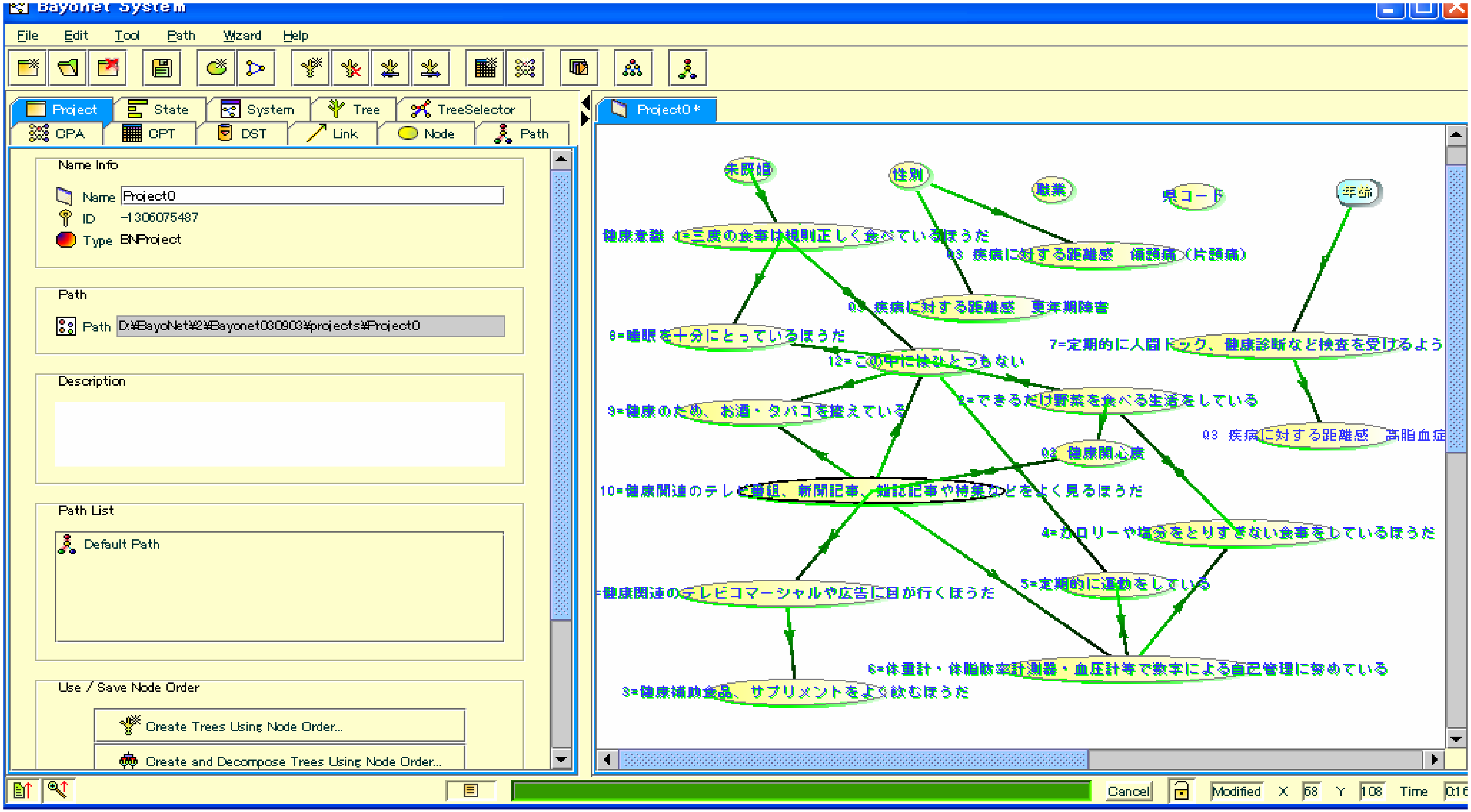
Ex.
0.3
0.4
:
Cond.Prob.Table
$P(Y|X) = p_{xy}$

Bayesian network

Model selection using
Information criteria (AIC, BIC=MDL)

Repeat model selection to all child nodes in the graph

Graph structure learning software BayoNet (BN software) developed by AIST (1996-2007) http://staff.aist.go.jp/y.motomura/bayonet/



Fast learning from huge SQL database and reasoning

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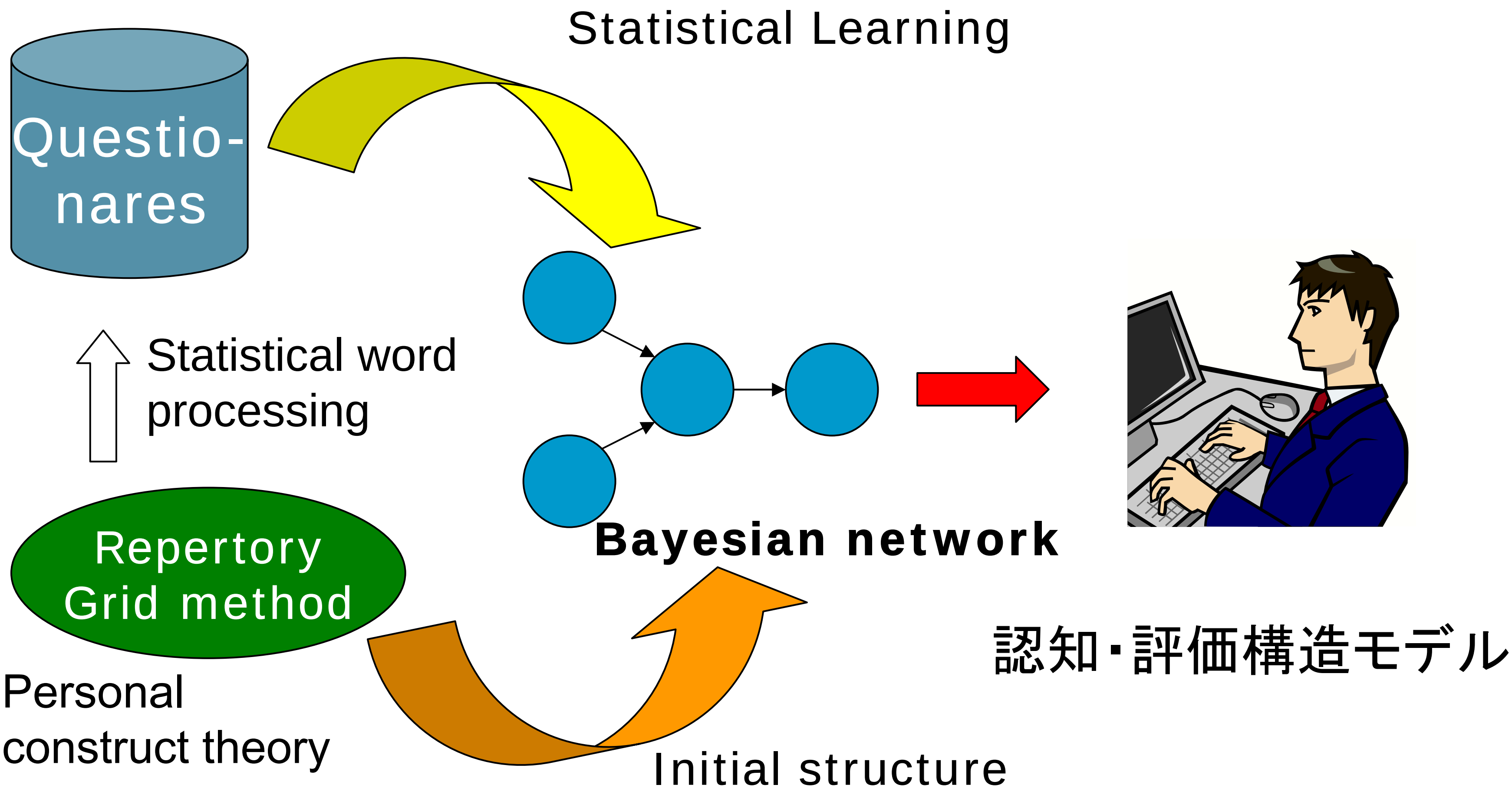
Cognitive modeling using Bayesian networks

"Y.Motomura, T.Kanade :Probabilistic Human Modeling based on Personal Construct Theory", Journal of Robot&Mechatronics, 17/6, (2005).



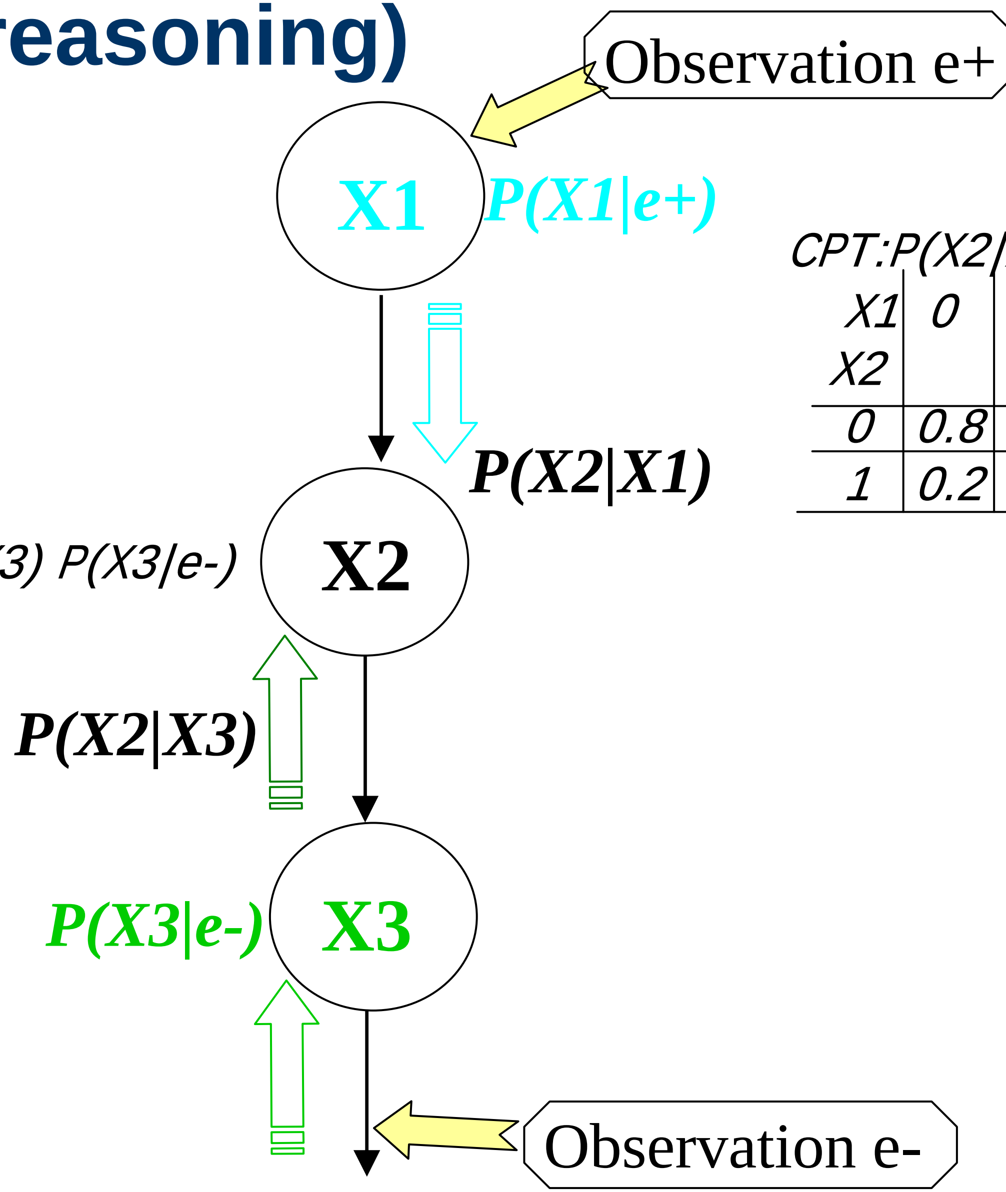
Belief propagation 1/2 (Probabilistic reasoning)

Basic fomula

Belief(X2)

$$= P(X2|e+, e-)$$

$$= P(X2|X1)\ P(X1|e+) \cdot P(X2|X3)\ P(X3|e-)$$



CPT:P(X2|X1)

X1 / X2	0	1
0	0.8	0.4
1	0.2	0.6

Belief propagation 2/2

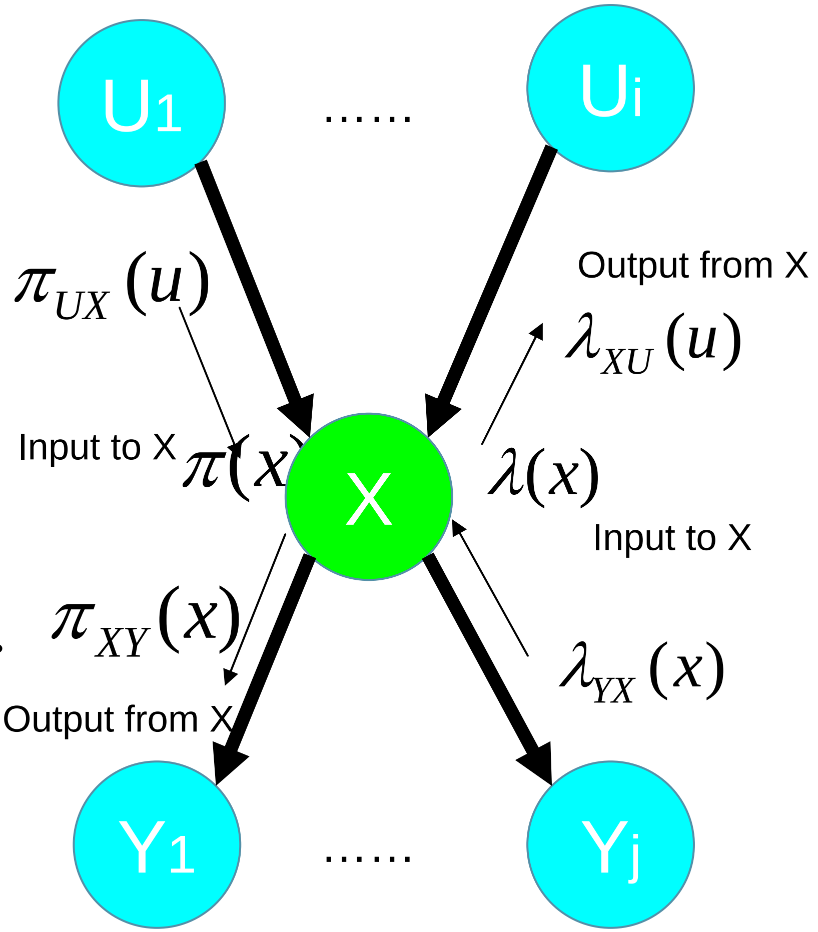
$$\Pr(X=x)=\alpha\lambda(x)\pi(x).$$

$$\pi(x)=\sum_u P(X\,|\,U=u)\prod_{Ui}\pi_{UiX}(Ui),$$

$$\lambda(x)=\prod_{Yj}\lambda_{YjX}(x),$$

$$\pi_{XYj}(x)=\pi(x)\prod_{k\neq j}\lambda_{YkX}(x),$$

$$\lambda_{XUi}(u)=\sum_x\lambda(x)\sum_{k\neq i}P(x\,|\,U)\prod_{k\neq i}\pi_{UkX}(u_k).$$



Loopy BP

- Apply belief propagation to multiply connected Bayesian networks.
- Not guarantee convergence and precision.
- But it can give adequate results in many cases (experimentally).
- Fast and less memory space (good properties for embedded IT systems like mobile phone and car-navigation systems)

Computational speed of Loopy BP

- CPU: Pentium III 975 MHz、Memory: 512 MB 、OS: Windows2000, language: C++

No. of nodes	Loopy BP	Junction tree	Systematic sampling
20	119 ms	112 ms	445 ms
50	314 ms	997 ms	1845 ms
100	2283 ms	10820 ms	4197 ms
300	4765 ms	impossible	20367 ms

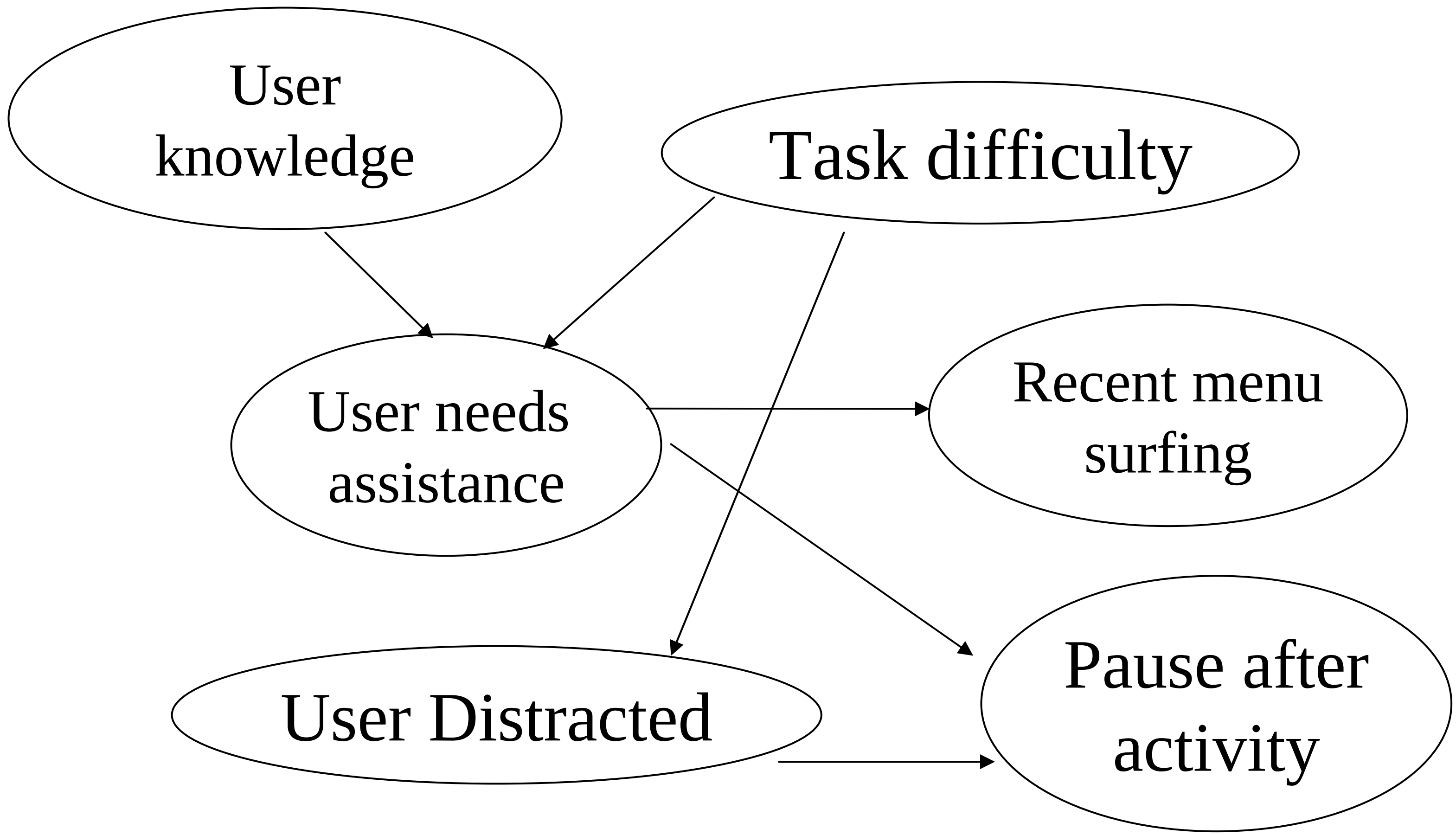
Fast enough for real world applications

Probabilistic user modeling using Bayesian networks

- User modeling (office assistant in PC)
- Human modeling and analysis
  (Customer/Market-analysis, Computer Graphic etc.)

Applications:
Personalized and situated information recommendation
n car-navigation systems or cell phones, etc.

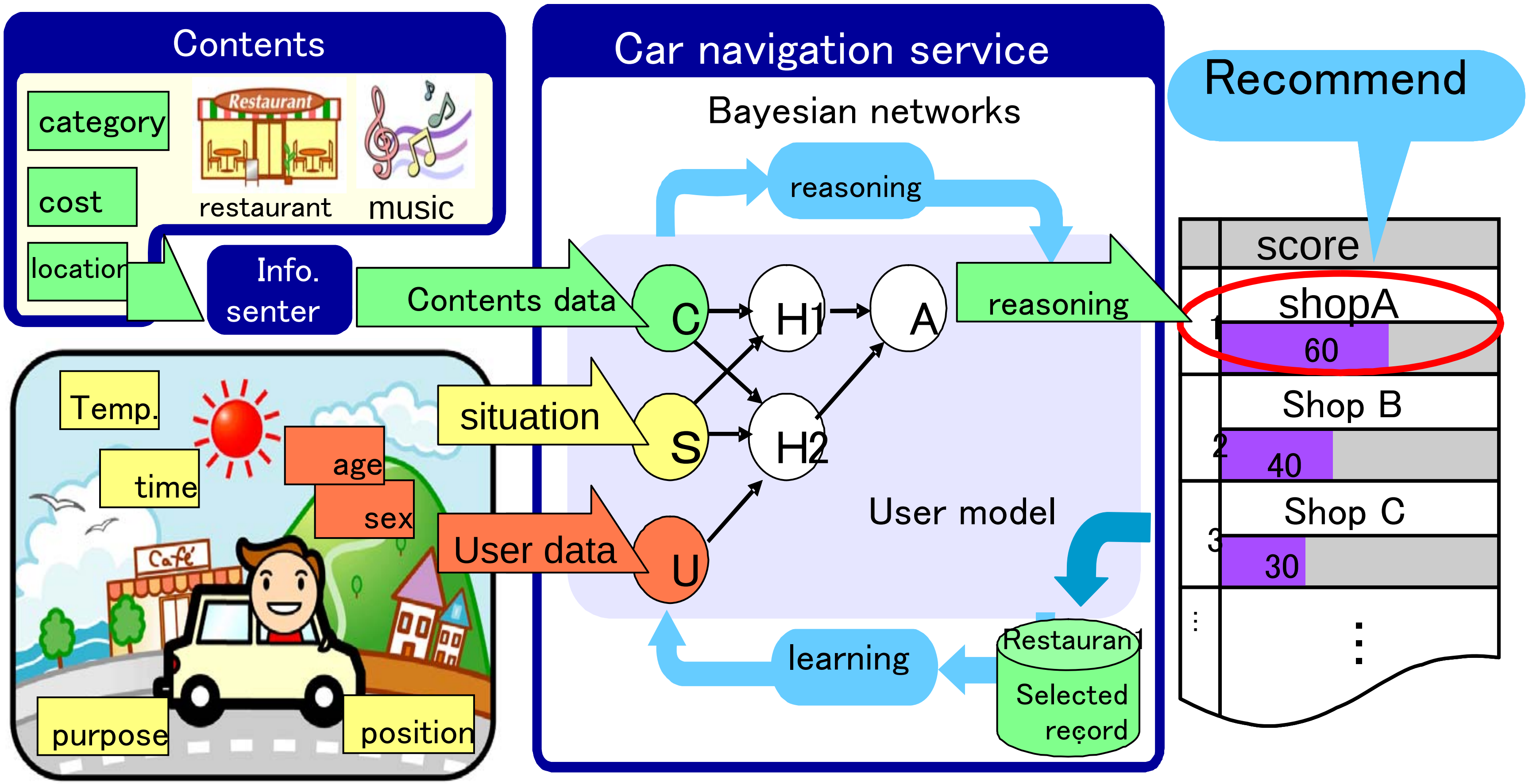
Microsoft：Office Assistant:Horvitz, E.
"Lumiere Project: Bayesian Reasoning for Automated assistance“, (1998). http://research.microsoft.com/research/dtg/horvitz/lum.htm



P(assist | difficulty, knowledge, recent menu, pause)

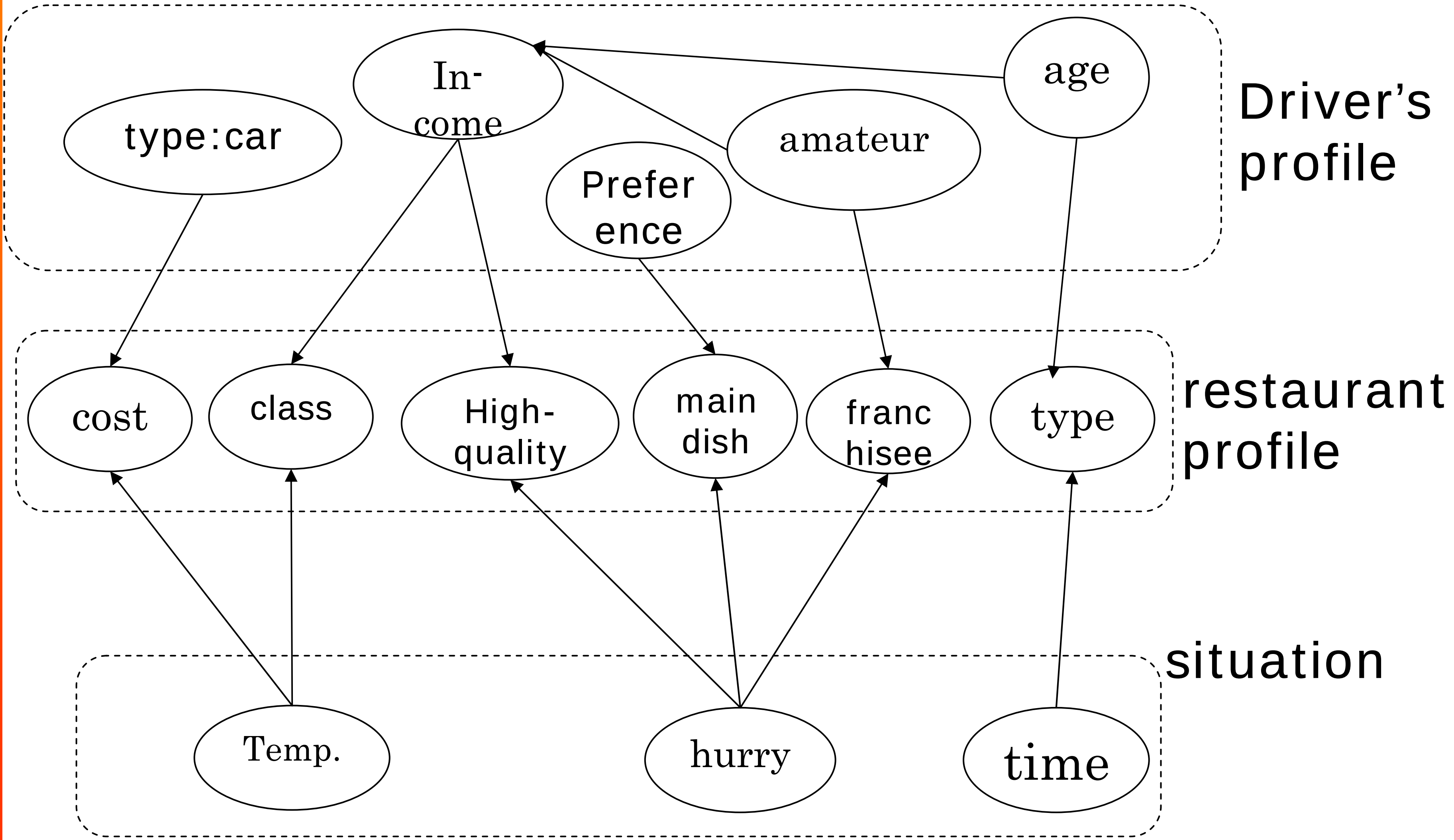
Car-navigation: personalized, situated restaurant-navigation

Y.Motomura and T.Iwasaki (2006)



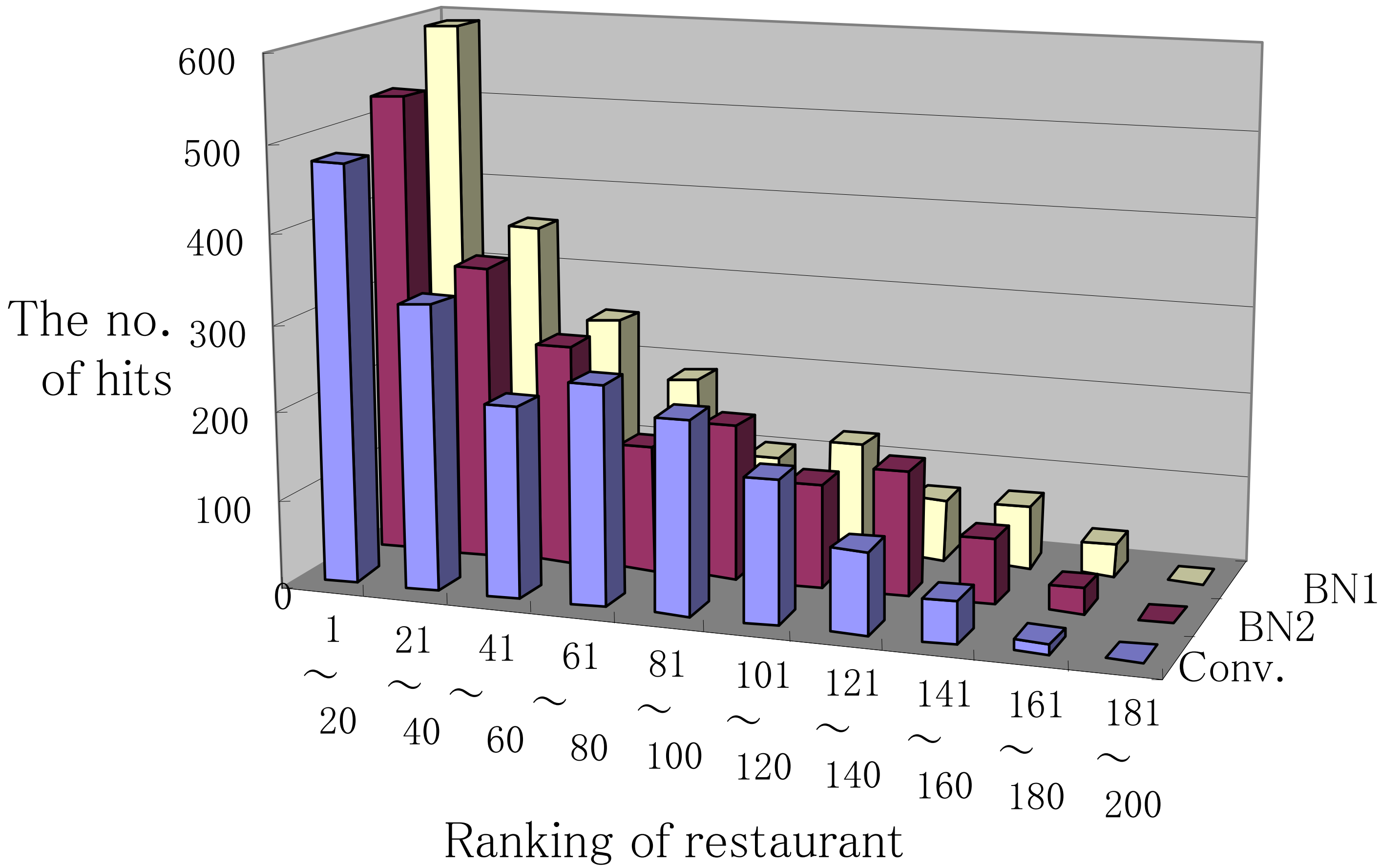
Human/User Models in personalized, situated restaurant-navigation

P(restaurant| driver,situation)

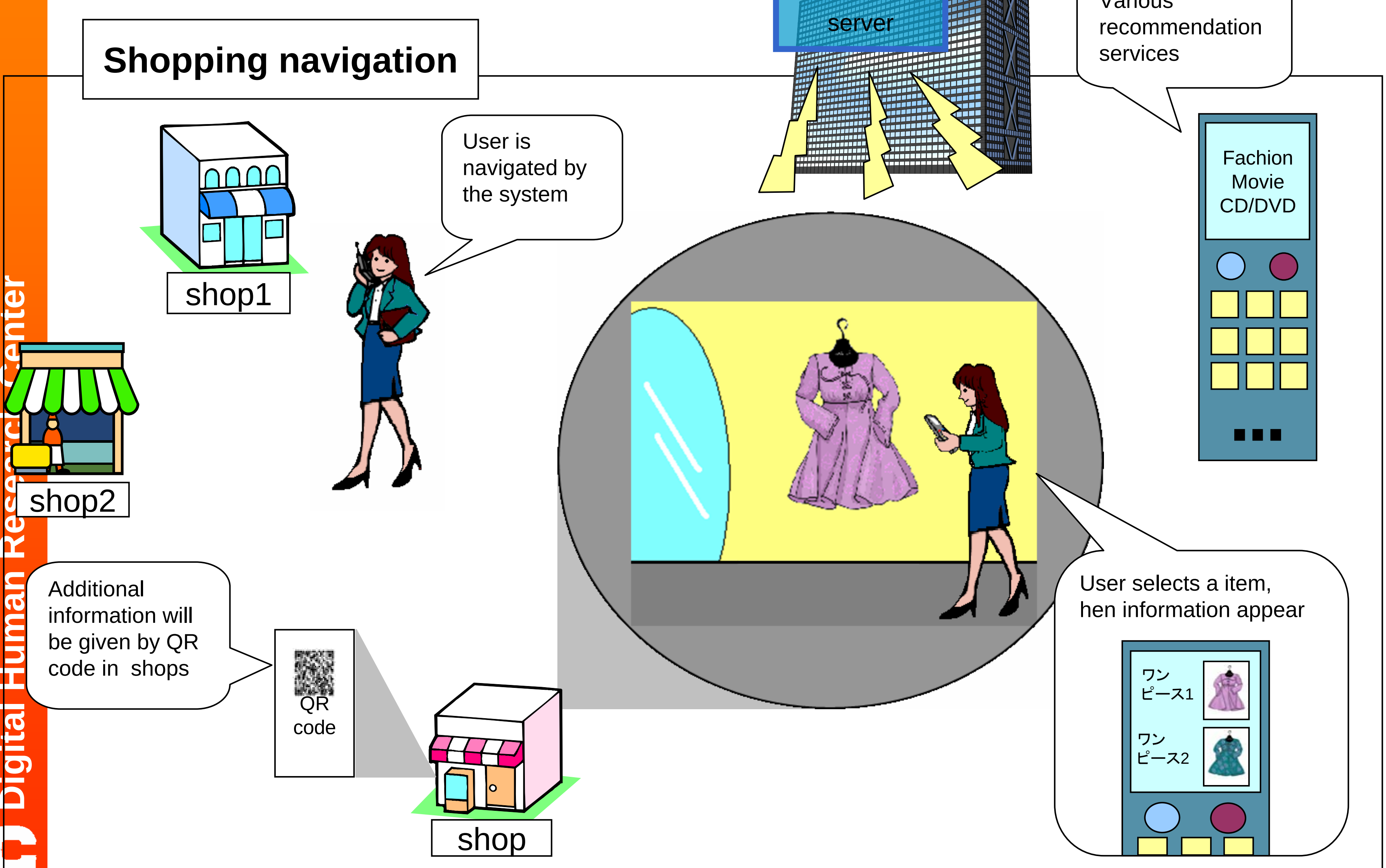


Car-navigation: Comparison Bayesian network vs conventional (conv.)

Prediction rate：BN1(EBA) 32.8%, BN2 29.3%, conv. 26.4%



Personalized and situated service
Using cell phone with human/use models
AIST & KDDI (2005-2007)



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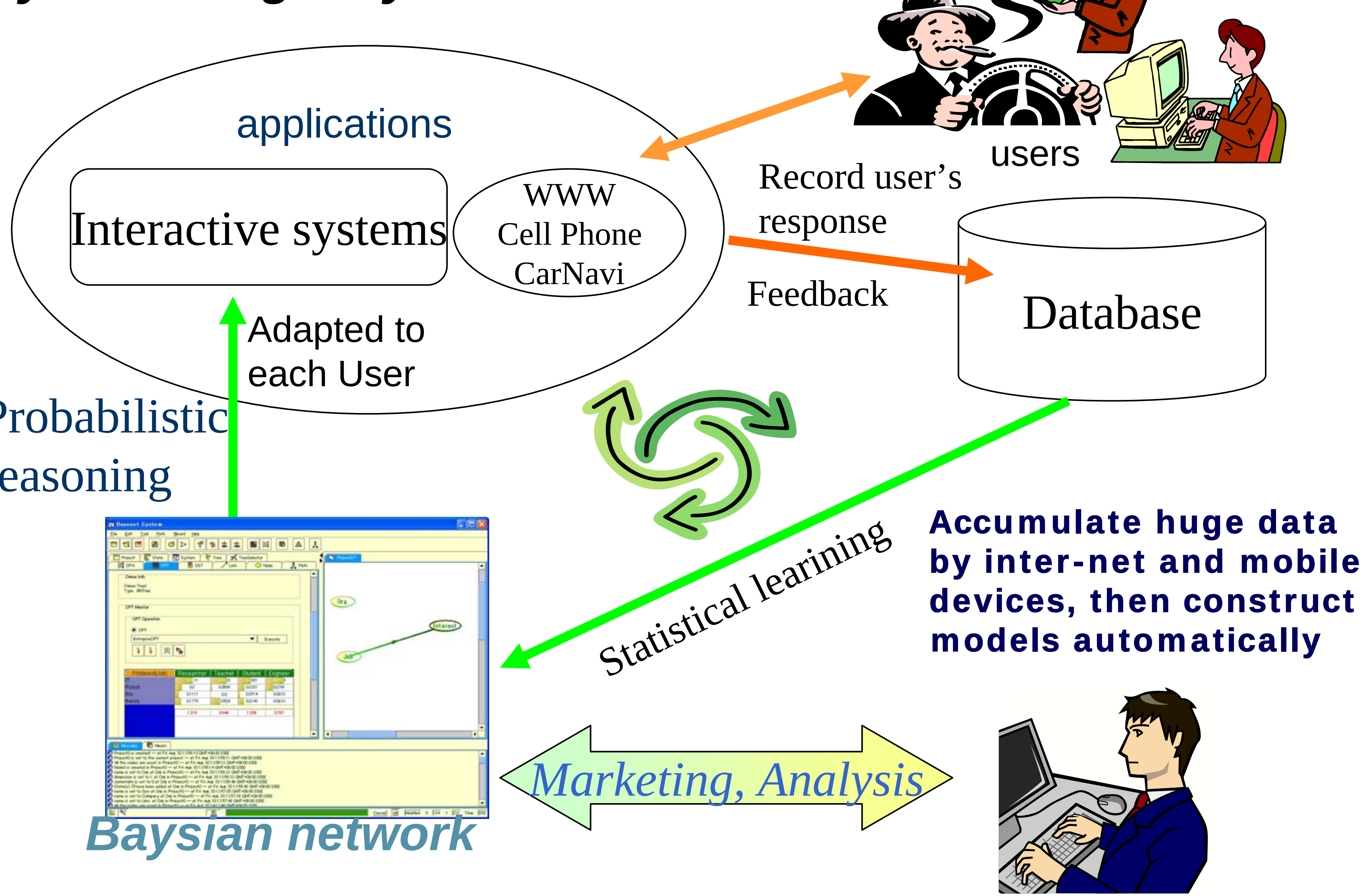
Interaction – User Modeling - Service Cycle using Bayesian networks



Applying to Childhood Injury simulation

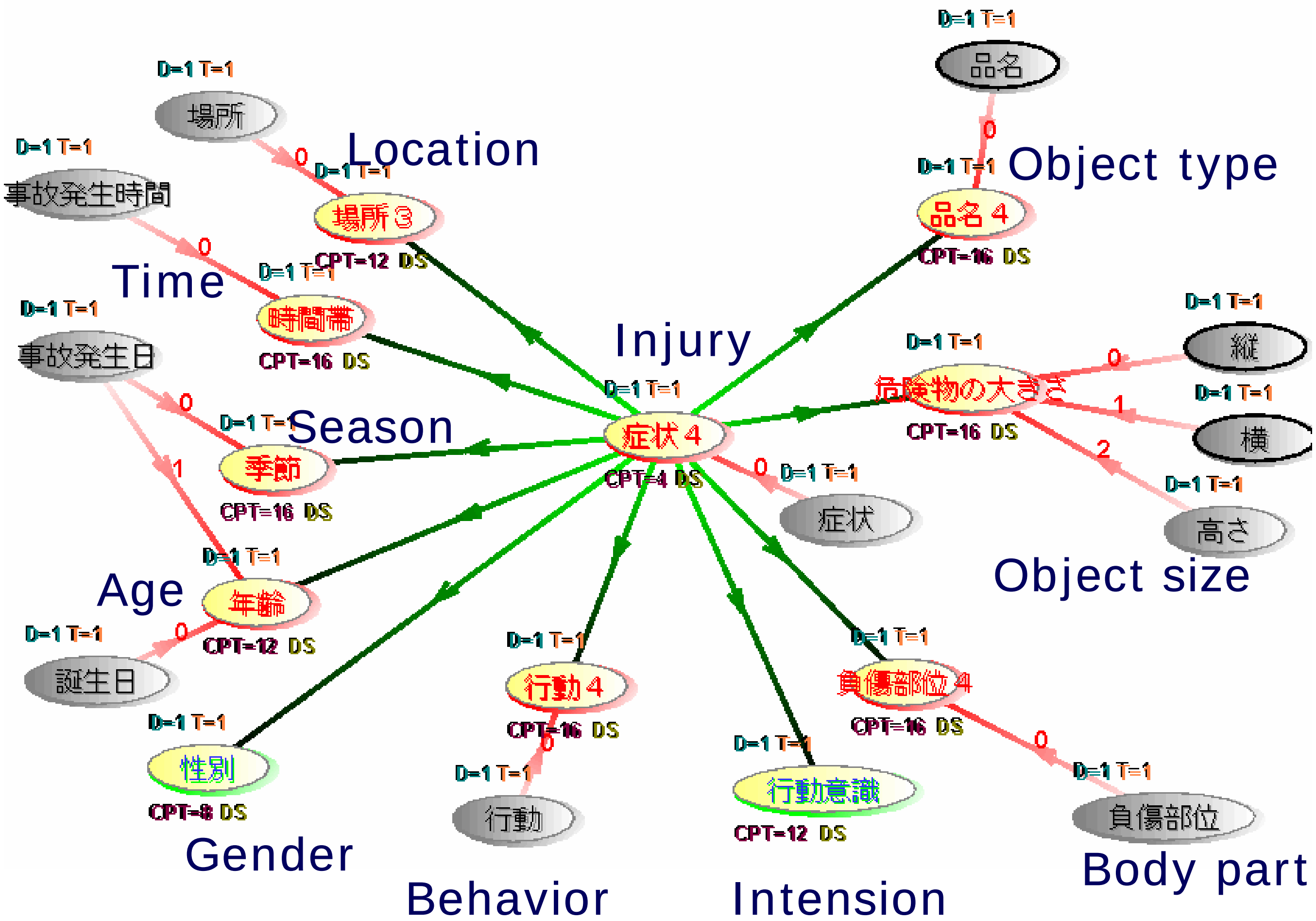
Simulate and evaluate how much dangerous in this situation.
How about for 1 year old boy? If he grows up?
How about when his mother behaves some actions?
What’s happen if new stove will be set?

We should understand what were causes and relational factors (for simulation and evaluation).

Injury surveillance and prevention project

- Accumulate sensing data of children's behavior in house
- Add labeled data by hand to sensing data
- Discretize(clustering) sensor data
- Learning Bayesian networks (Find causal structure)
- Use probabilistic reasoning in computer simulation
- Realize most possible behavior and situations.
- Evaluate risks and show movies for safety promotions

Constructed relational model from child injury record in a hospital in Japan (200 samples)



Simulate:
girl, 1 year,
winter,
By electrical product

Reasoning: (highest):
Burn 94%
WO intention 67%
Arm 90%
Living 62%
Day 67%

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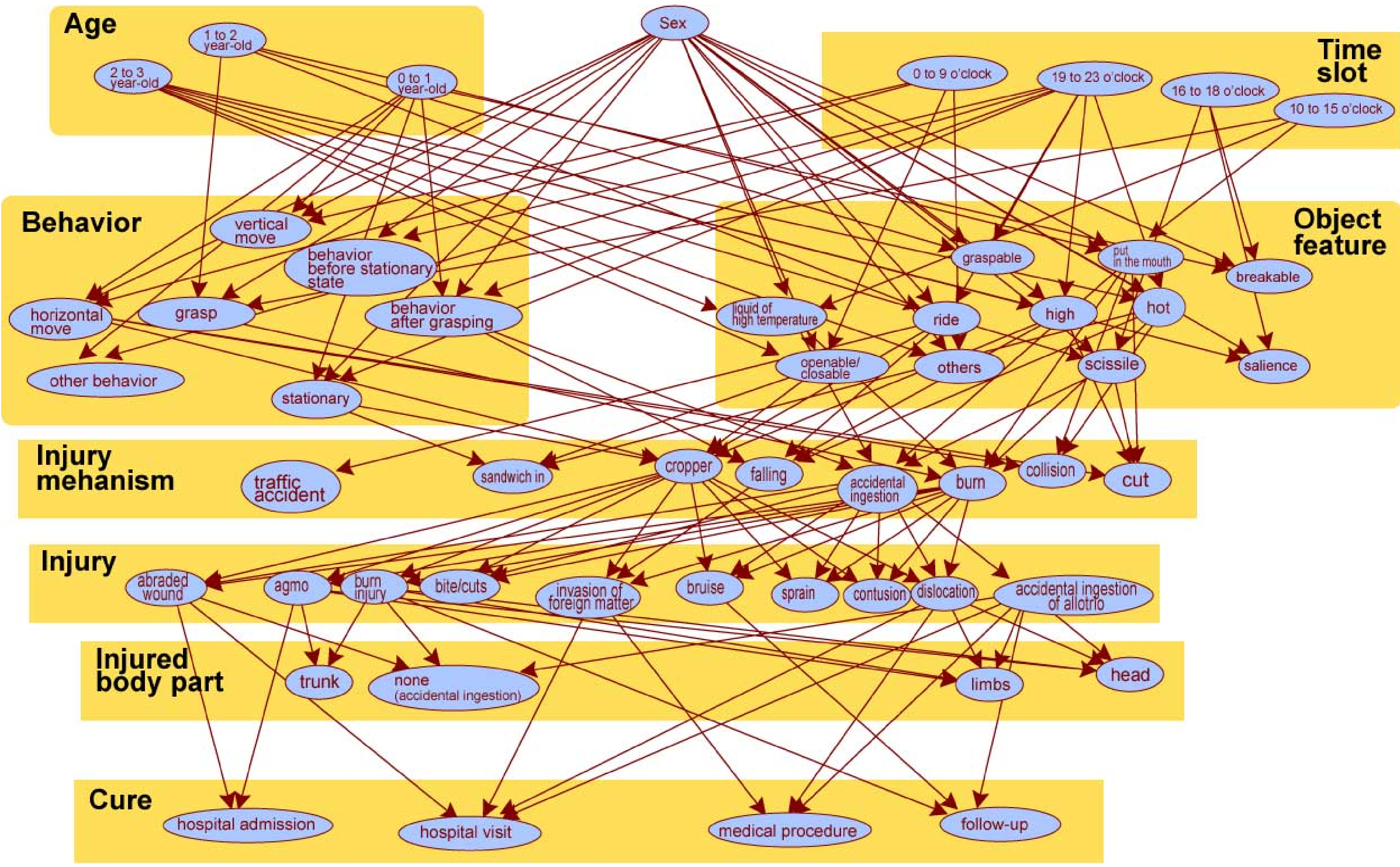
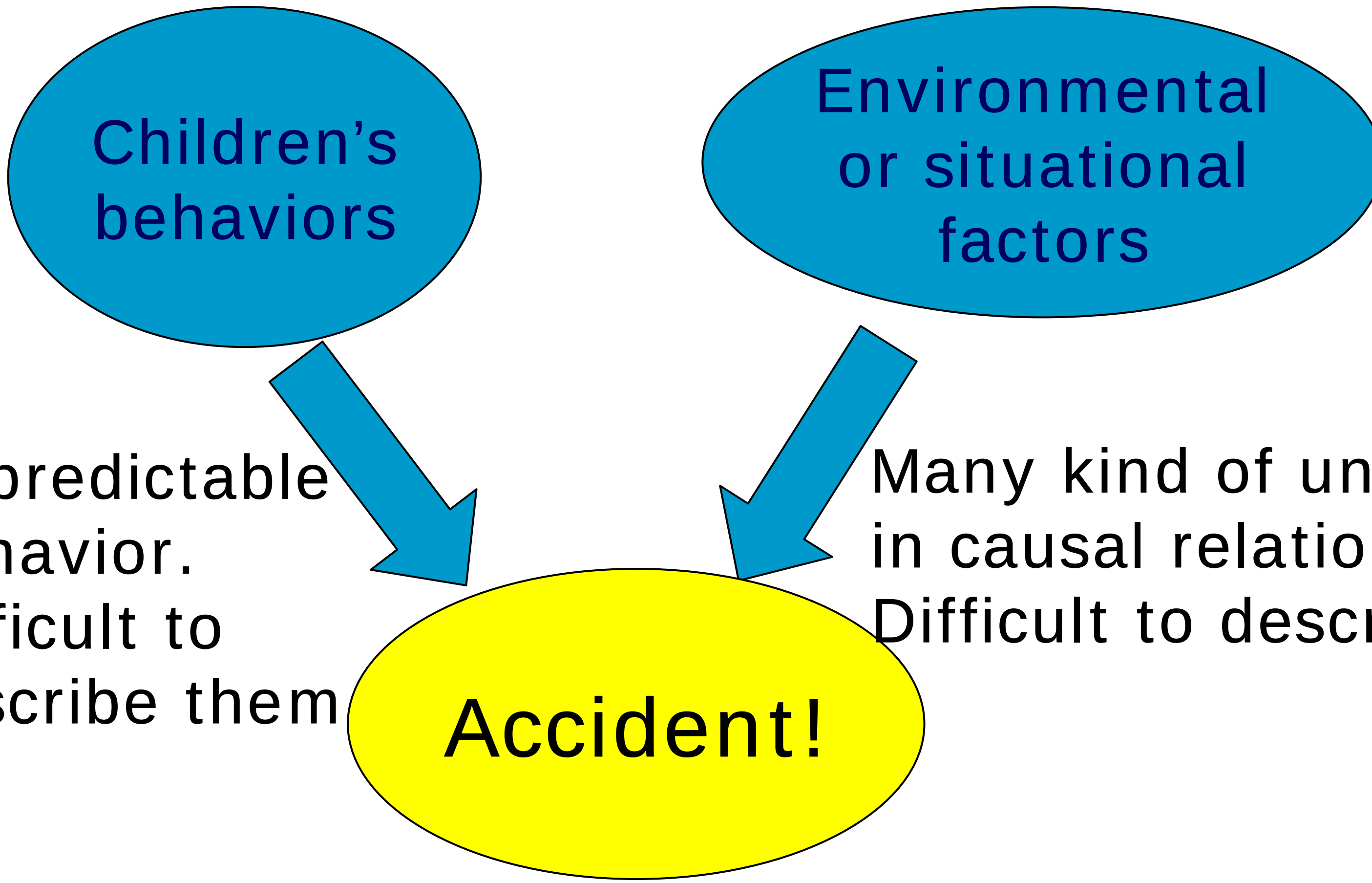
Constructed relational model from child injury record in hospitals in Japan (2788 samples:2007)



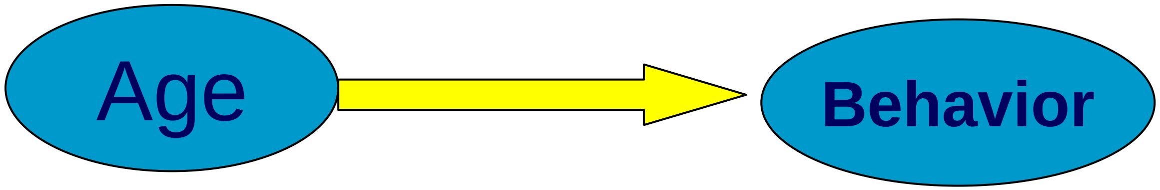
Uncertainty in Relational model between accidents and children's behavior



Unpredictable Behavior.
Difficult to describe them

Many kind of uncertainty in causal relationship
Difficult to describe all.

Probabilistic behavior model according to chilren's development



Behavior	age	7	8.4	9.7	11.1
Standing		0.25	0.5	0.75	0.9
Not yet		0.75	0.5	0.25	0.1

- From statistical research: DENVER(USA), DENVER-II(Japan)
- P(Standing=yes|Age=11.1)= 90%
- P(Standing=yes|Age=7)= 25%

Modeling more precise children's behavior

- Accumulate sensing data of children's behavior in house
- Add labeled data by hand to sensing data
- Discretize (clustering) sensor data
- Learning Bayesian networks (Find major causal structure)
- Use probabilistic reasoning in computer simulation
- Realize most possible behavior and situations
- Evaluate risks and show movies for safety promotions

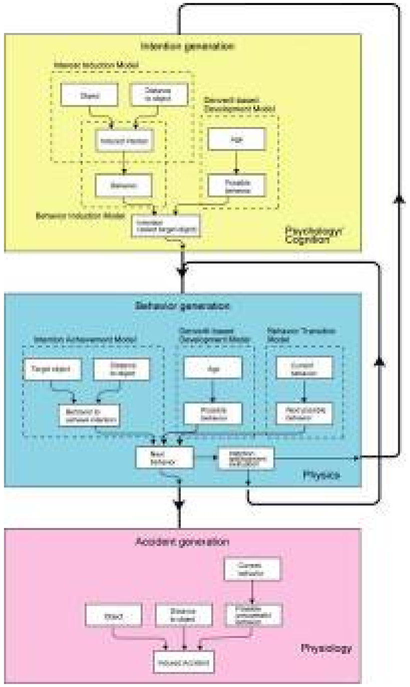
Child Behavior Simulator

Reusable and Comprehensive Model of Infant Behavior

Micro-analysis of child behavior (Denver II) (ubiquitous sensor)

Macro-analysis of child injury (Internet sensor)

Integration



$$P(Behavior_t, Variable_{Env}, Variable_{Dev})$$
$$Variable_{Env} = \{Distance, InterestObj\}$$
$$Variable_{Dev} = \{Age, Behavior_{t-1}\}$$

$$\begin{aligned}
&P(Behavior_t, Distance, InterestObj, Age, Behavior_{t-1}) = \\
&P(Behavior_t \mid InterestObj)\times \\
&P(InterestObj \mid Distance)\times \\
&P(Behavior_t \mid Age)P(Behavior_t \mid Behavior_{t-1})\times \\
&P(Distance)P(Age)P(Behavior_{t-1})P(InterestObj)
\end{aligned}$$

- **Data to Model**
- **Explanation to Generation (Generative Model)**

Sensing, Modeling, Application, and then

Start the next cycle (knowledge circulation)

Socialized Sensing Technology

Distribute infant injury movies to parents for safety promotion

家での事故を防ぐ！

危険予防を考えるWEBサービス

世界初!

子どもの危険行動シミュレーション

将来につながる力を育むうえで、思いきり遊べる環境はとても大切。そこで〈こどもちゃれんじ〉では、独立行政法人・産業技術総合研究所との共同研究により、事故予防のためのシミュレーション（疑似体験）サービスを開発しました。発達段階に合わせて、お子さまがどんな行動をとりどんな危険があるのかを動画でシミュレーションできます。シミュレーション結果に対する予防アドバイスも参照でき、成長をふまえた家での危険ポイントがリアルにわかり、危険回避のヒントがわかります。

- Cooperation with Benesse Corp. which has 1.4 million club member

Service started in December 12, 2005

https://www.shimajiro.co.jp/ikuji/kiken/login.php

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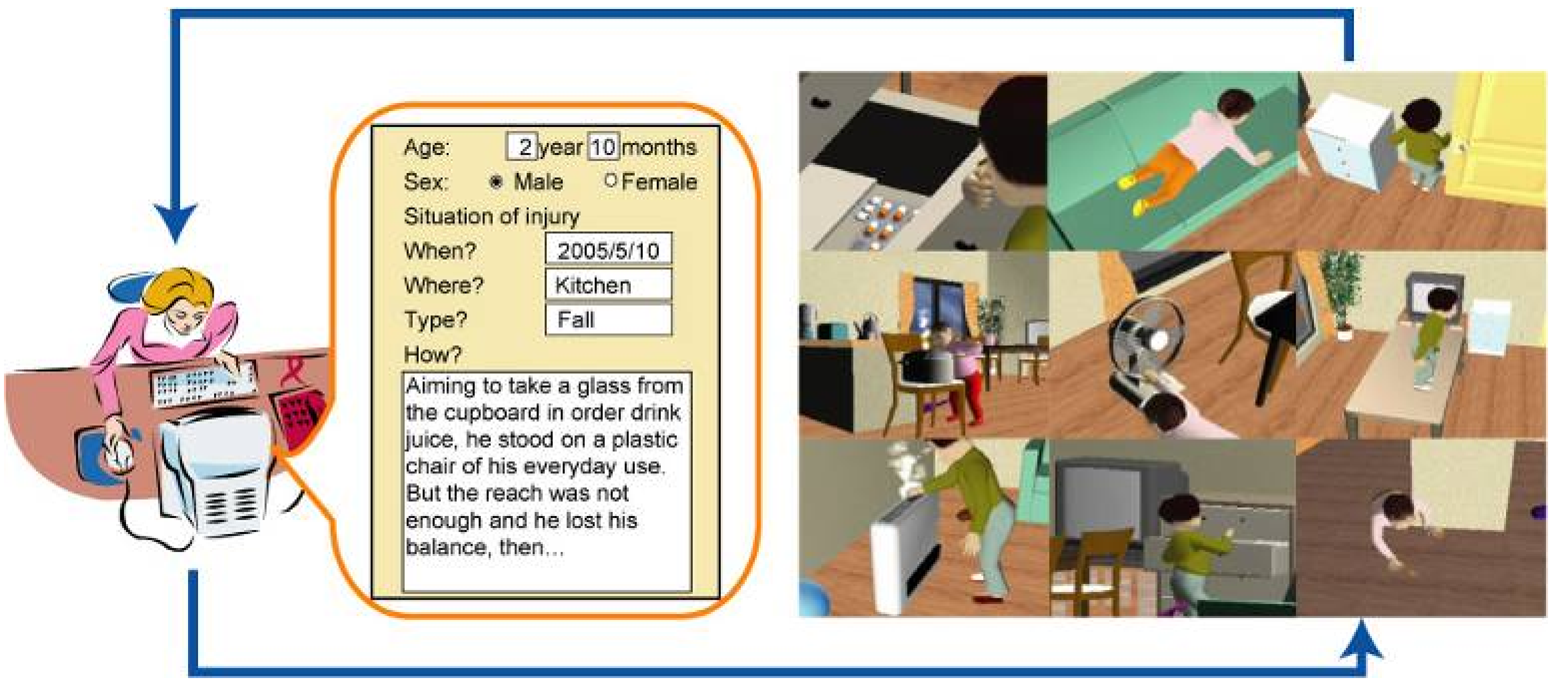
Socialized Sensing Technology

Sustainable Development

of sensing and modeling



$$Sim(User_a, User_i) = \frac{\sum_{f_k \in F_a \cap F_i} (q_{a,k} - \bar{q}_a)(q_{i,k} - \bar{q}_i)}{\sqrt{\sum_{f_k \in F_a \cap F_i} (q_{a,k} - \bar{q}_a)^2} \sqrt{\sum_{f_k \in F_a \cap F_i} (q_{i,k} - \bar{q}_i)^2}}$$

Mutual evolution of Service & Sensor

-Sensing by providing service

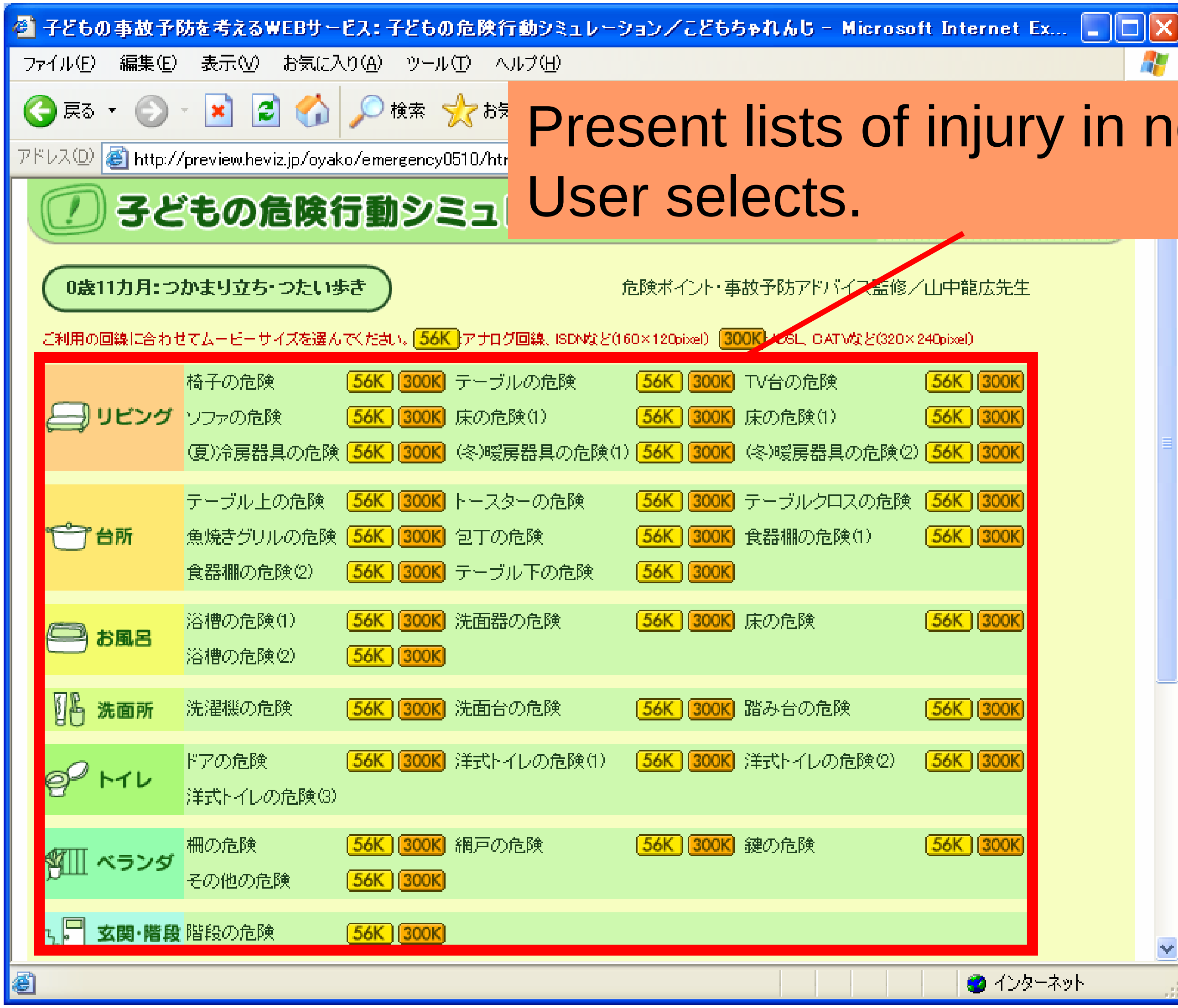
-Improving service by sensing

Injury Precognition Support Service 1/4

Input child's age and developmental stage of behavior

(Benesse Corp.)

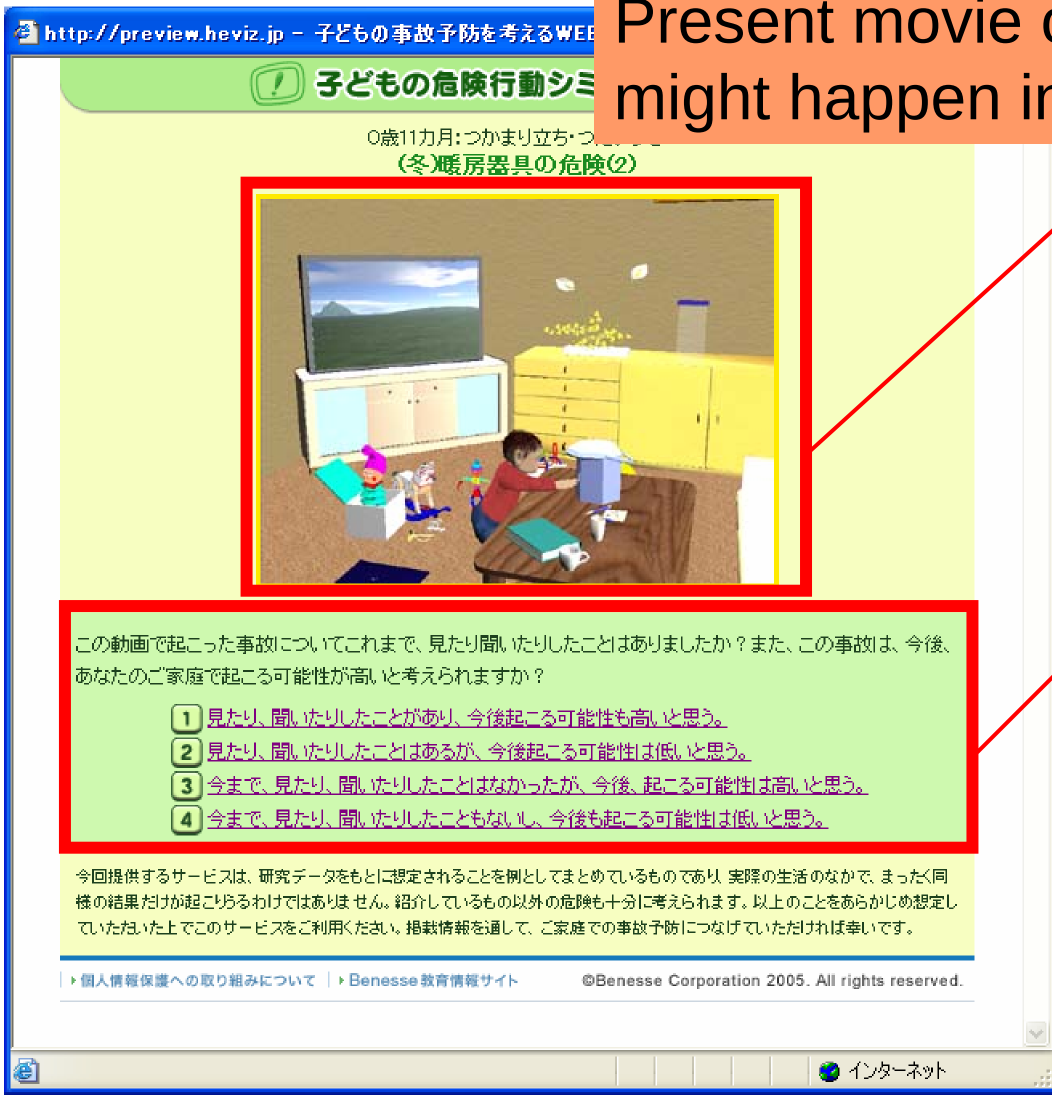
Injury Precognition Support Service 2/4



Present lists of injury in near future
User selects.

(Benesse Corp.)

Injury Precognition Support Service 3/4

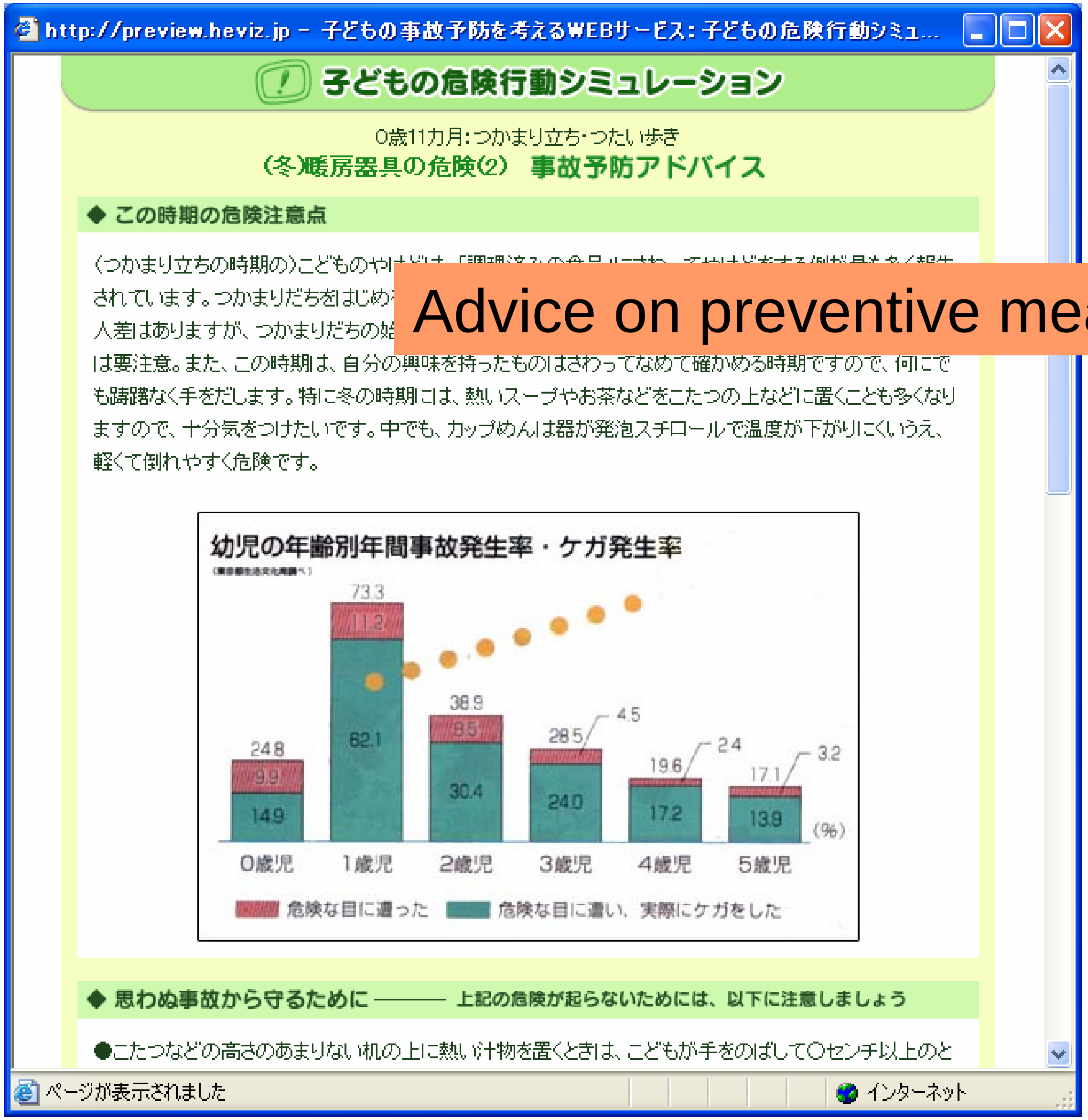


Present movie on injury which might happen in near future

Questionnaire

(Benesse Corp.)

Injury Precognition Support Service 4/4



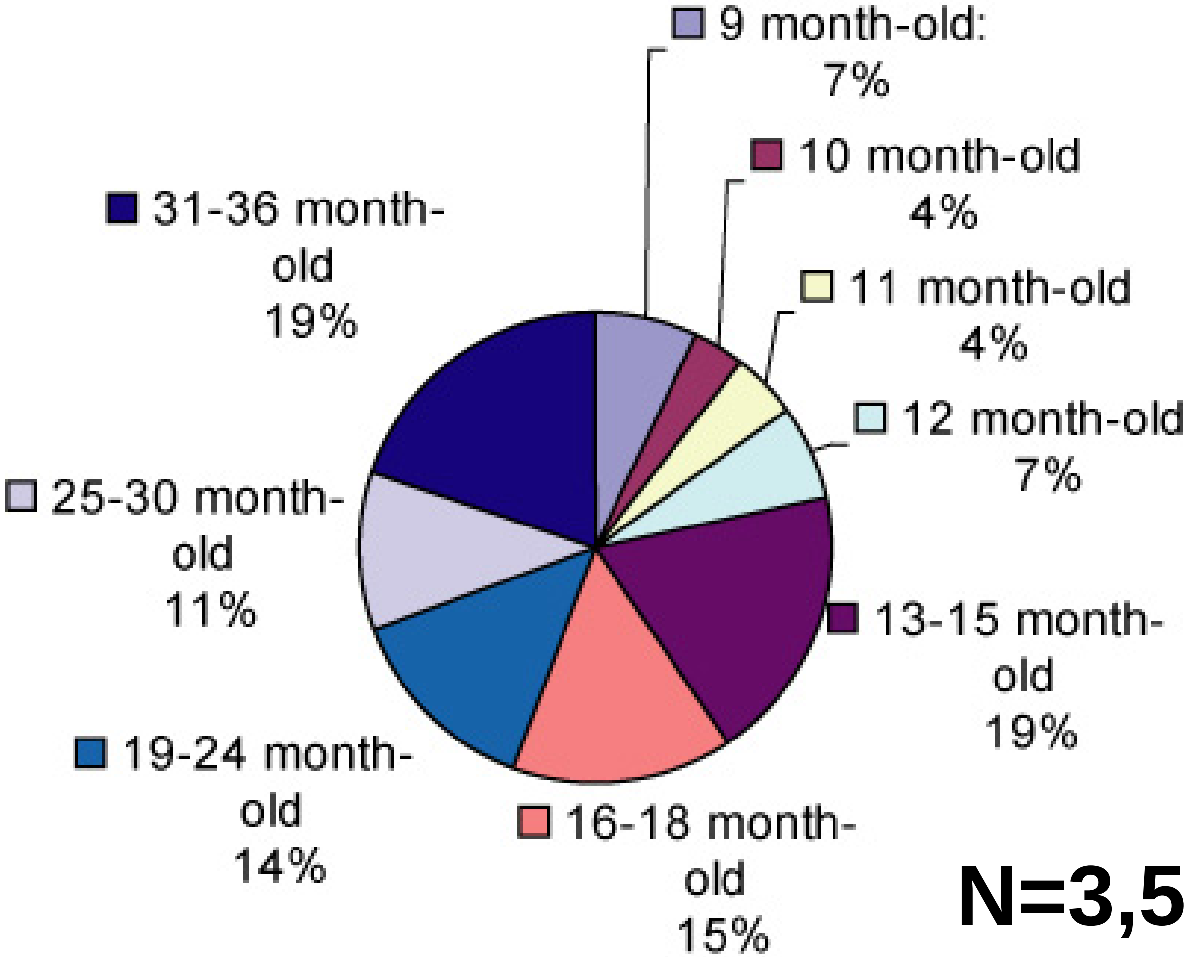
Advice on preventive measure

(Benesse Corp.)

Epidemiology by Internet

4,933 parents accessed, 61,147 movies were distributed

21,482 movies were evaluated



N=3,510

Child's age of parents who utilized Web service

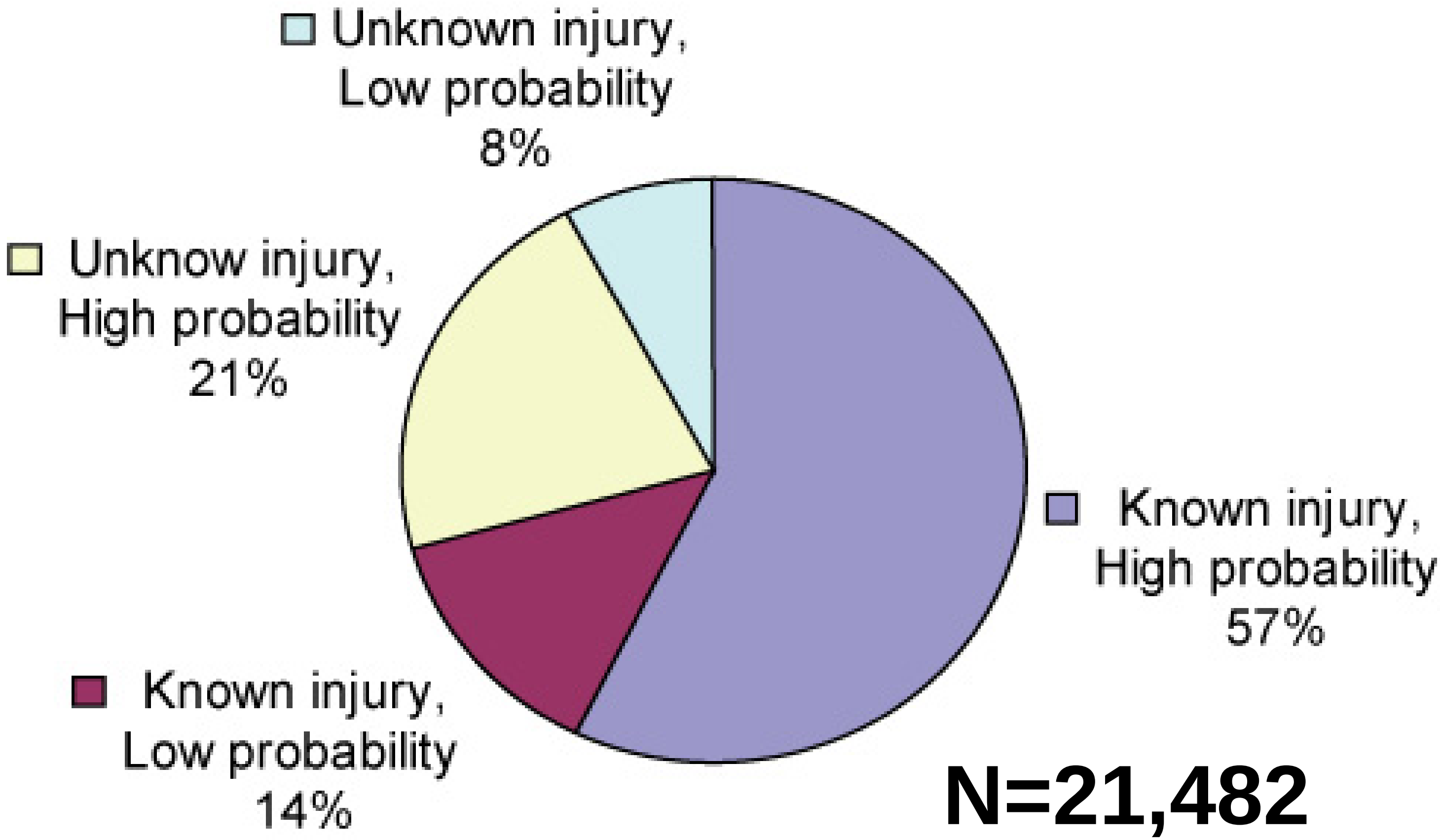
Digital Human Research Center

AIST

Epidemiology by Internet

4,933 parents accessed, 61,147 movies were distributed

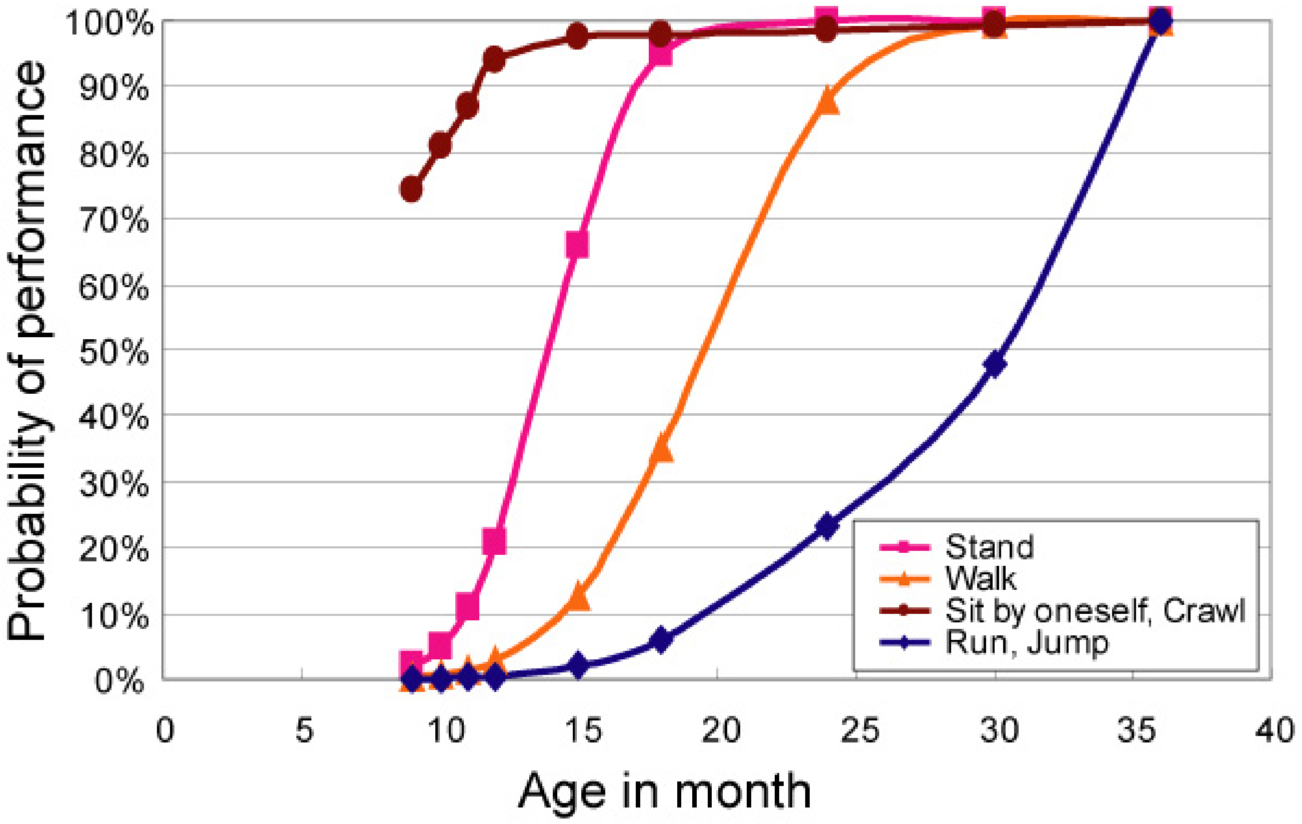
21,482 movies were evaluated



N=21,482

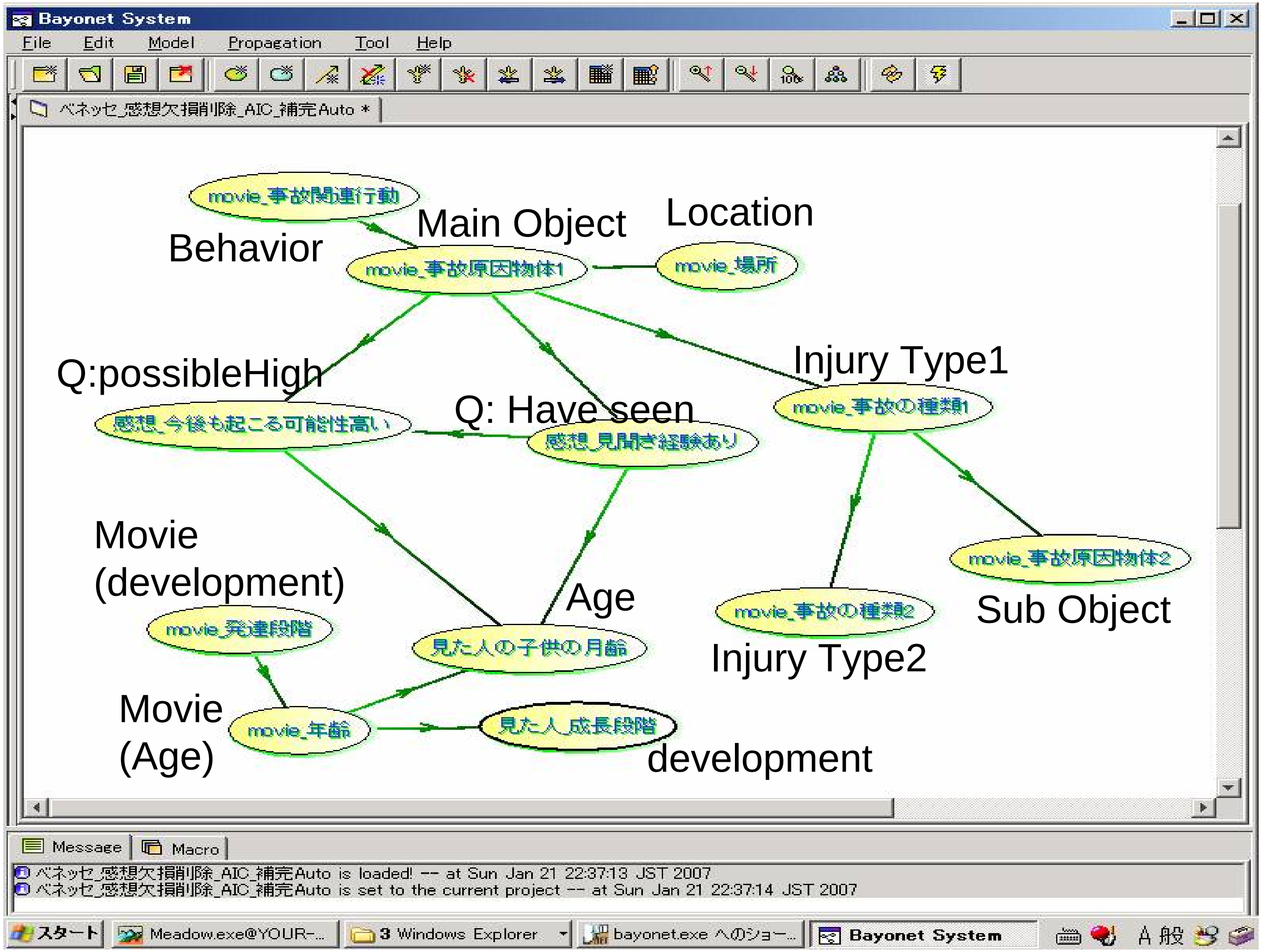
29% of injuries were unfamiliar to parents.
At least 21% of movies change parents' awareness.

Knowledge Obtained by Internet sensing data



- Relation between age and behavior was obtained.
- It takes only 102 days to exceed N=1,819(4,471>1,815(DenverII))
- World's Biggest database
- Internet is a strong tool for research.

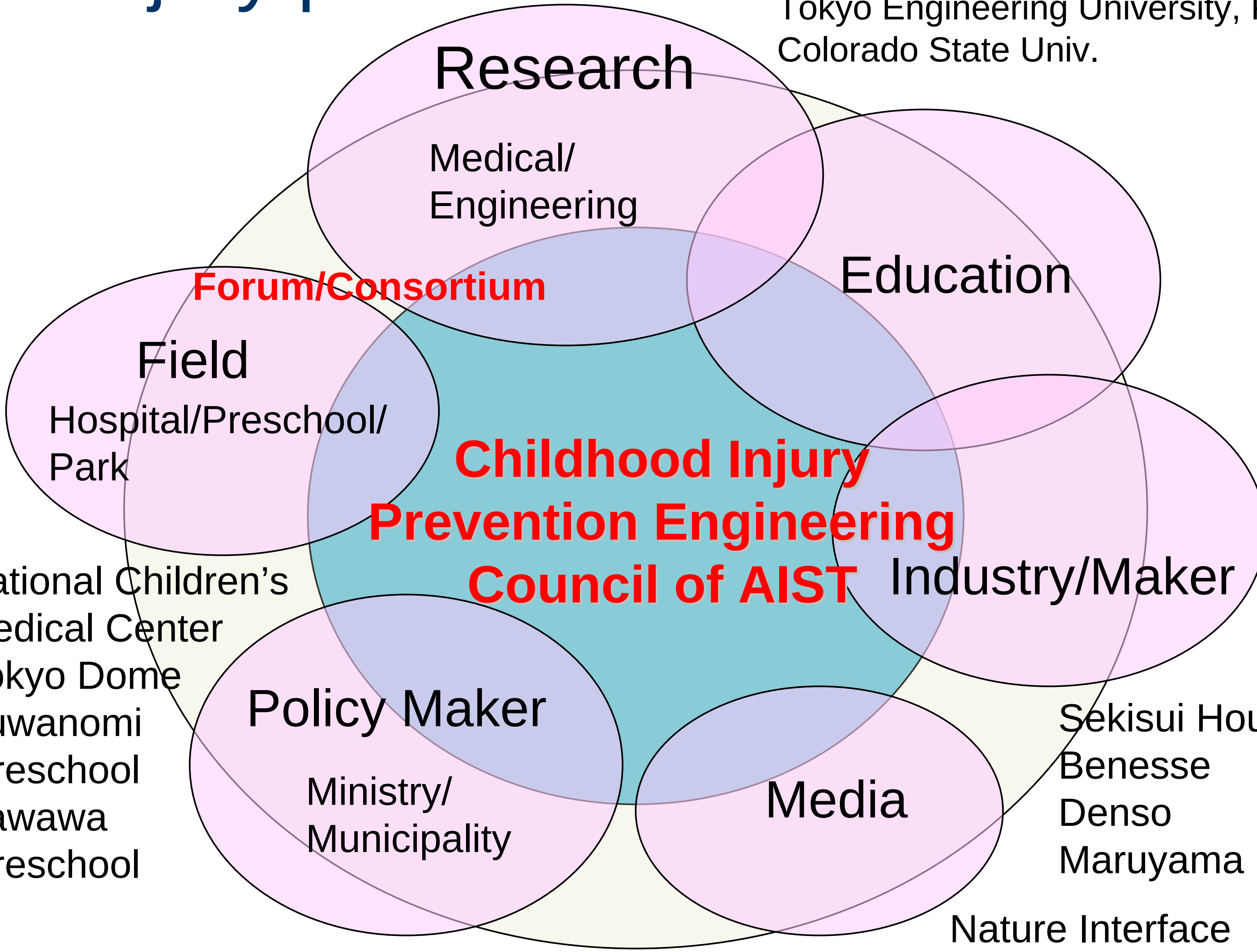
Modeling parent's awareness of child injury constructed from Internet sensing data



Everyday life computing research
as a challenge of project driving scheme

Research Scrum for Injury prevention

Tokyo Univ. of Science,
Kanazawa Univ., Tohoku Univ.
Tokyo Engineering University, Keio Univ.
Colorado State Univ.



National Children's
Medical Center
Tokyo Dome
Kuwanomi
 preschool
Kawawa
 preschool

Sekisui House
Benesse
Denso
Maruyama

Nature Interface
NHK

Tokyo, METI, WHO

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Sharing sensing data, tools, web service

http://www.openlife.jp

- Object data in houses
- Life log data in our sensor-house
- Bayesian network (web service)
- probabilistic reasoning and image processing softwares
- Community place (Mach making for seeds and needs)

Science & Technology of everyday life