Physical-Cyber-Social Computing

An early 21st century approach to Computing for Human Experience

WIMS'13 Keynote, Madrid, Spain. June 2013.

Amit Sheth

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http://knoesis.org

Special Thanks: **Pramod Anantharam**. Ack: Cory Henson, TK Prasad and Kno.e.sis Semantic Sensor Web team

External collaboration: Payam Barnaghi @ Surrey (IoT), many domain scientists/clinicians…

Kno.e.sis Ohio Center of Excellence Wright State University

CHE encompasses the essential role of technology in a human-centric vision

CHE emphasizes the unobtrusive, supportive, and assistive role of technology in improving human experience

A. Sheth: Computing for Human Experience: 2008 -

A glimpse at related visions of computing …

Man-Computer Symbiosis – *J. C. R. Licklider*

Humans and machines cooperate to solve complex problems while machines formulate the problem (advancing beyond solving a formulated problem)

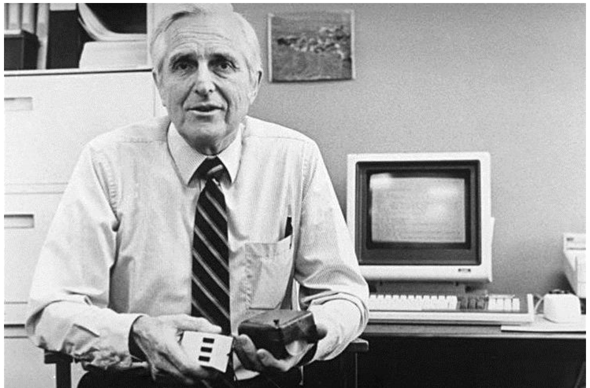
Man-Computer Symbiosis

J. C. R. Licklider
IRE Transactions on Human Factors in Electronics,
volume HFE-1, pages 4-11, March 1960

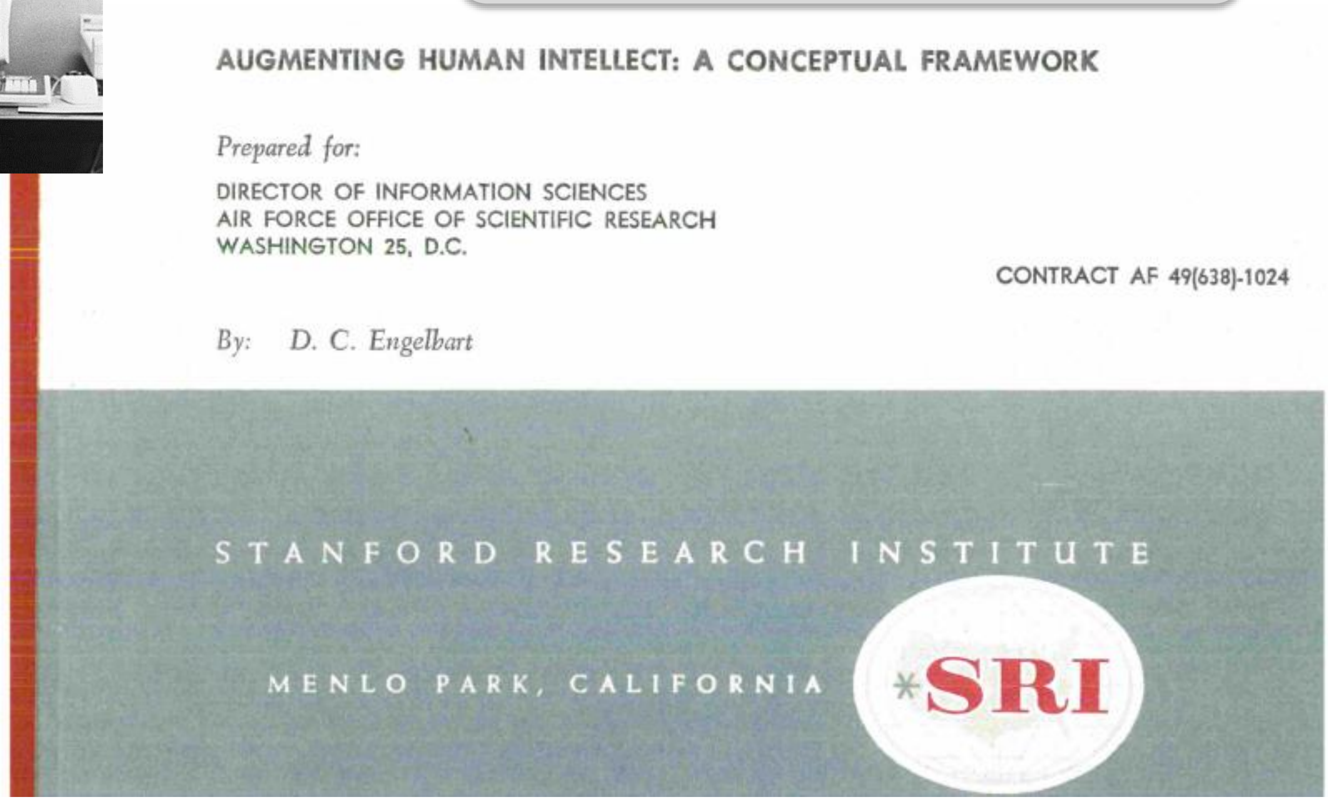
Summary

Man-computer symbiosis is an expected development in cooperative interaction between men and electronic computers. It will involve very close coupling between the human and the electronic members of the partnership. The main aims are 1) to let computers facilitate formulative thinking as they now facilitate the solution of formulated problems, and 2) to enable men and computers to cooperate in making decisions and controlling complex situations without inflexible dependence on predetermined programs. In the anticipated symbiotic

Augmenting Human Intellect – *D. Engelbart*



Humans utilize machines to solve “insoluble” problems


AUGMENTING HUMAN INTELLECT: A CONCEPTUAL FRAMEWORK

Prepared for:

DIRECTOR OF INFORMATION SCIENCES
AIR FORCE OFFICE OF SCIENTIFIC RESEARCH
WASHINGTON 25, D.C.

CONTRACT AF 49(638)-1024

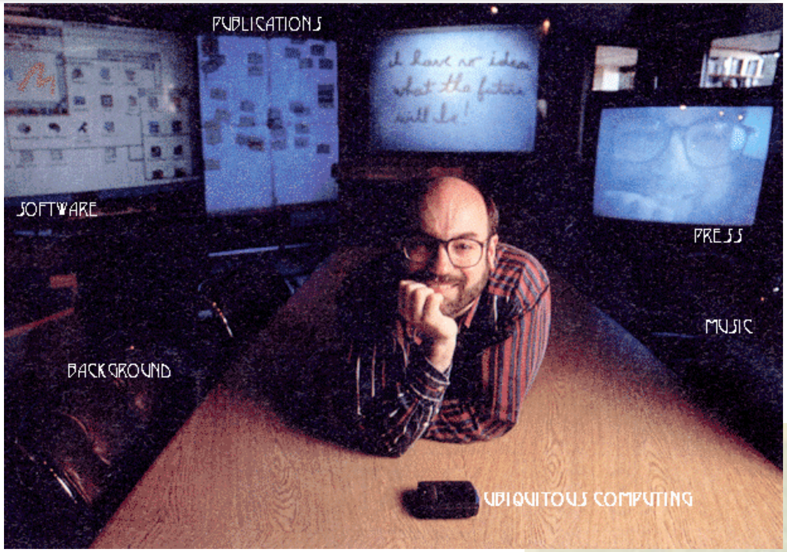
By: D. C. Engelbart

STANFORD RESEARCH INSTITUTE

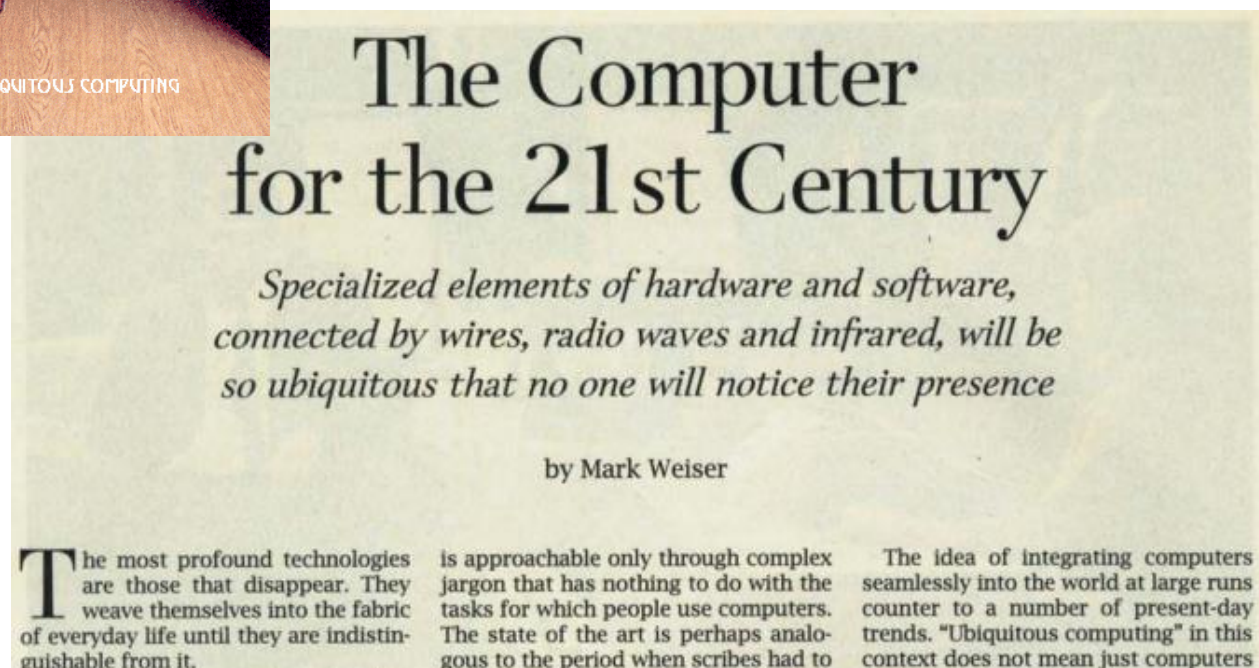
MENLO PARK, CALIFORNIA

SRI

Ubiquitous Computing – *M. Weiser*



Making machines disappear into the fabric of our life



The Computer for the 21st Century

Specialized elements of hardware and software, connected by wires, radio waves and infrared, will be so ubiquitous that no one will notice their presence

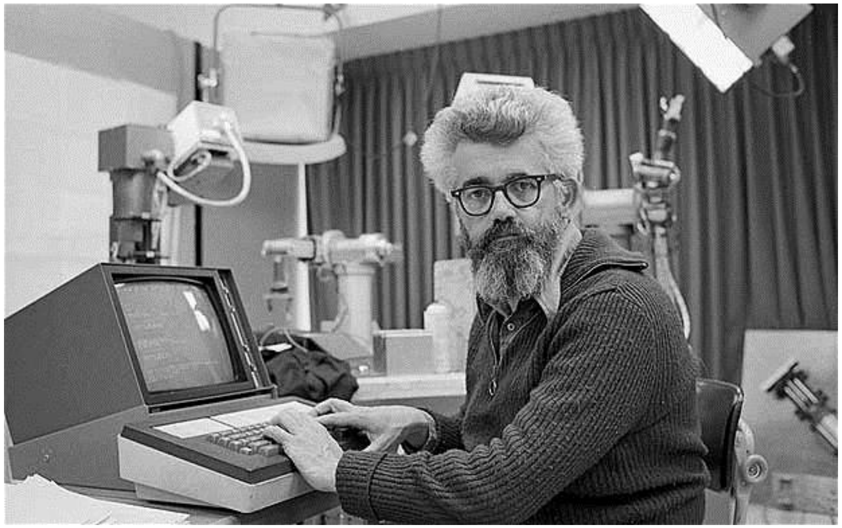
by Mark Weiser

The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it.

is approachable only through complex jargon that has nothing to do with the tasks for which people use computers. The state of the art is perhaps analogous to the period when scribes had to

The idea of integrating computers seamlessly into the world at large runs counter to a number of present-day trends. "Ubiquitous computing" in this context does not mean just computers

Making Intelligent Machines –*J. McCarthy*



WHAT IS ARTIFICIAL INTELLIGENCE?

John McCarthy
Computer Science Department
Stanford University
Stanford, CA 94305
jmc@cs.stanford.edu
http://www-formal.stanford.edu/jmc/

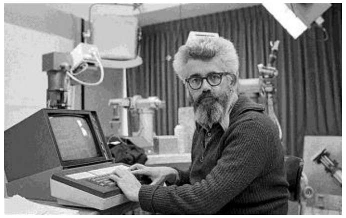
AI

Ambient Intelligence

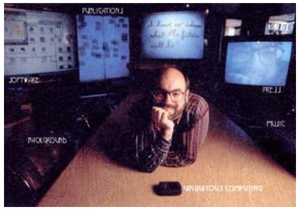
HCI

CHE

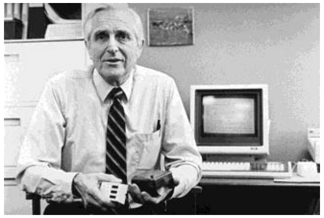
Machine Centric ←-----------------------------------→ Human Centric



J. McCarthy



M. Weiser



D. Engelbart

J. C. R. Licklider

My interest

Imagine the role of computational techniques in solving big challenges

Healthcare

- Hospital readmissions
- Managing chronic conditions
- Drug development

Sustainability

- Traffic management
- Water management
- Crime prevention

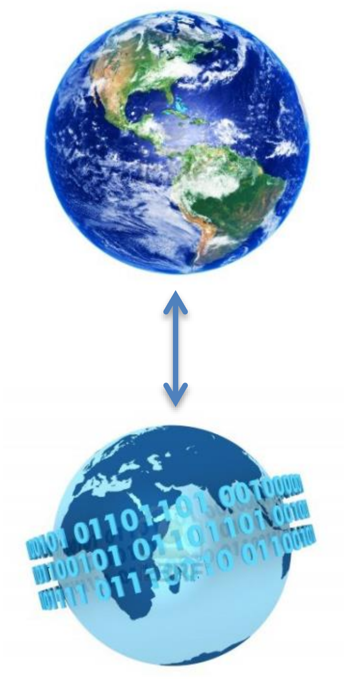
Security

- Border protection
- Intelligence & reconnaissance
- Cyber infrastructure
- Critical infrastructure

Grand challenges in the real-world are complex

If people do not believe that mathematics is simple, it is only because they do not realize how complicated life is.

- John von Neumann



Computational paradigms have always dealt with a simplified representations of the real-world… *

Algorithms work on these simplified representations

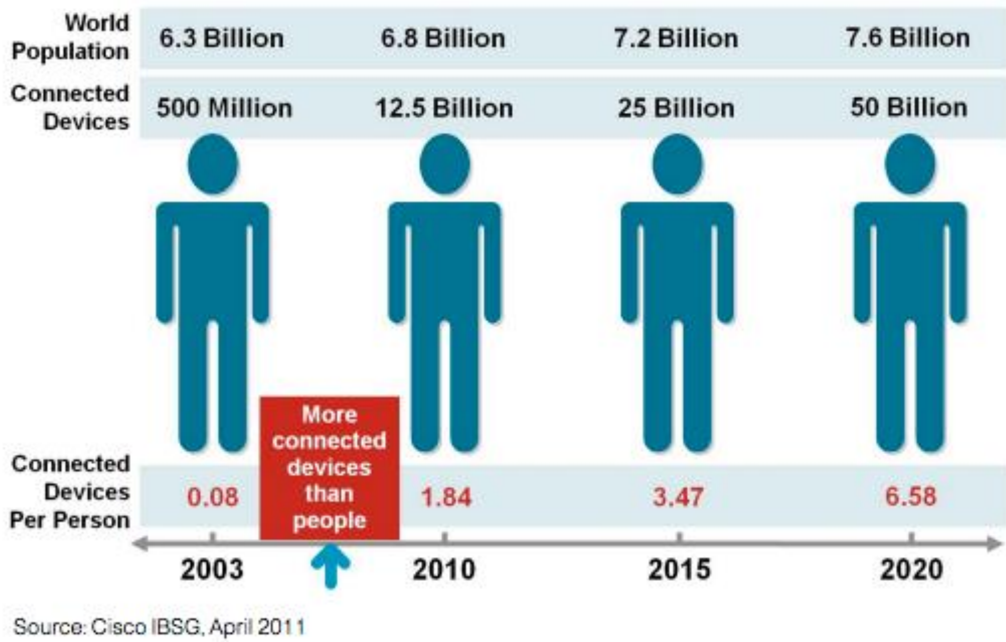
Solutions from these algorithms are transcended back to the real-world by humans as actions

kno.e.sis

* Ack: Ramesh Jain: http://ngs.ics.uci.edu/blog/?p=1501

What has changed now?

About 2 billion of the 5+ billion have data connections – so they perform "citizen sensing". And there are more devices connected to the Internet than the entire human population.

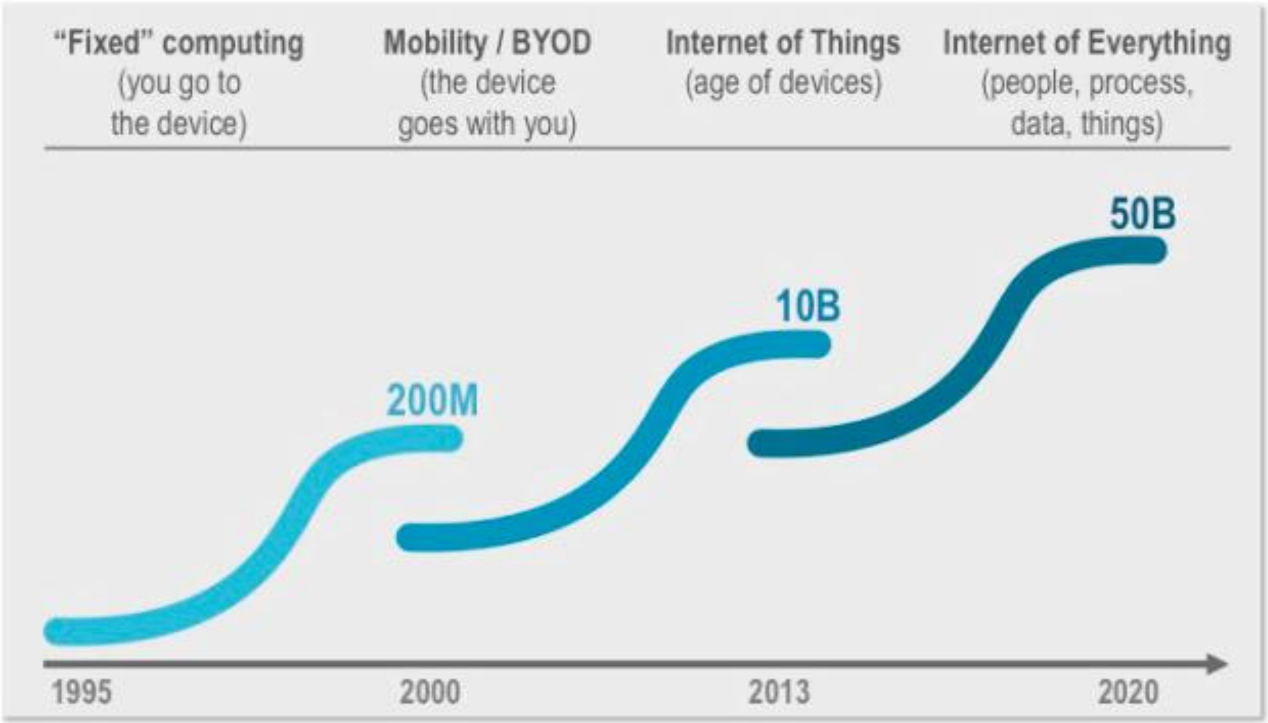


These ~2 billion citizen sensors and 10 billion devices & objects connected to the Internet makes this an era of IoT (Internet of Things) and Internet of Everything (IoE).

http://www.cisco.com/web/about/ac79/docs/innov/IoT_IBSG_0411FINAL.pdf

What has changed now?

"The next wave of dramatic Internet growth will come through the confluence of people, process, data, and things — the Internet of Everything (IoE)."
- CISCO IBSG, 2013



Source: Cisco IBSG, 2013

Beyond the IoE based infrastructure, it is the possibility of developing applications that spans **Physical**, **Cyber** and the **Social** Worlds that is very exciting. Think of **PCS Computing** as the application/semantic layer for the IoE-based infrastructure.

What has *not* changed?

We are still working on the simpler representations of the real-world!

What should change?

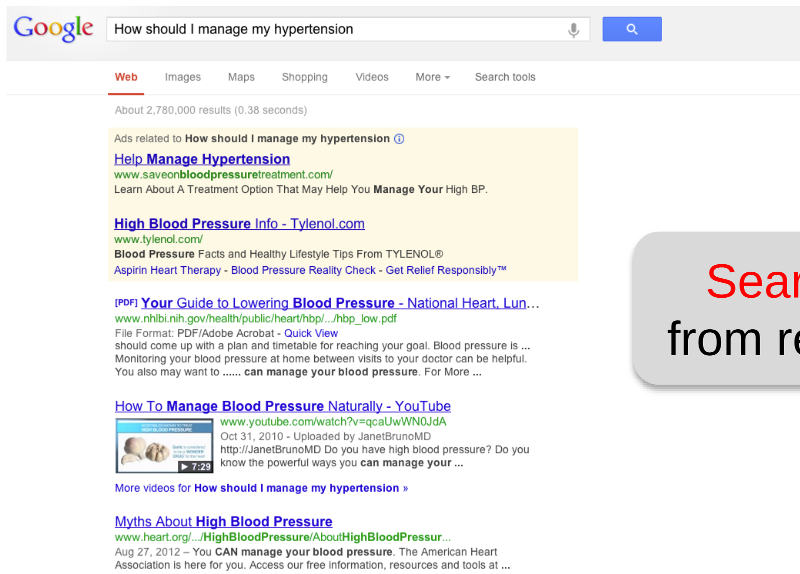
We need computational paradigms to tap into the rich pulse of the human populace

Represent, capture, and compute with richer and fine-grained representations of real-world problems

Consider an example of Mark, who is diagnosed with hypertension

Search based approach

How do I manage my hypertension?



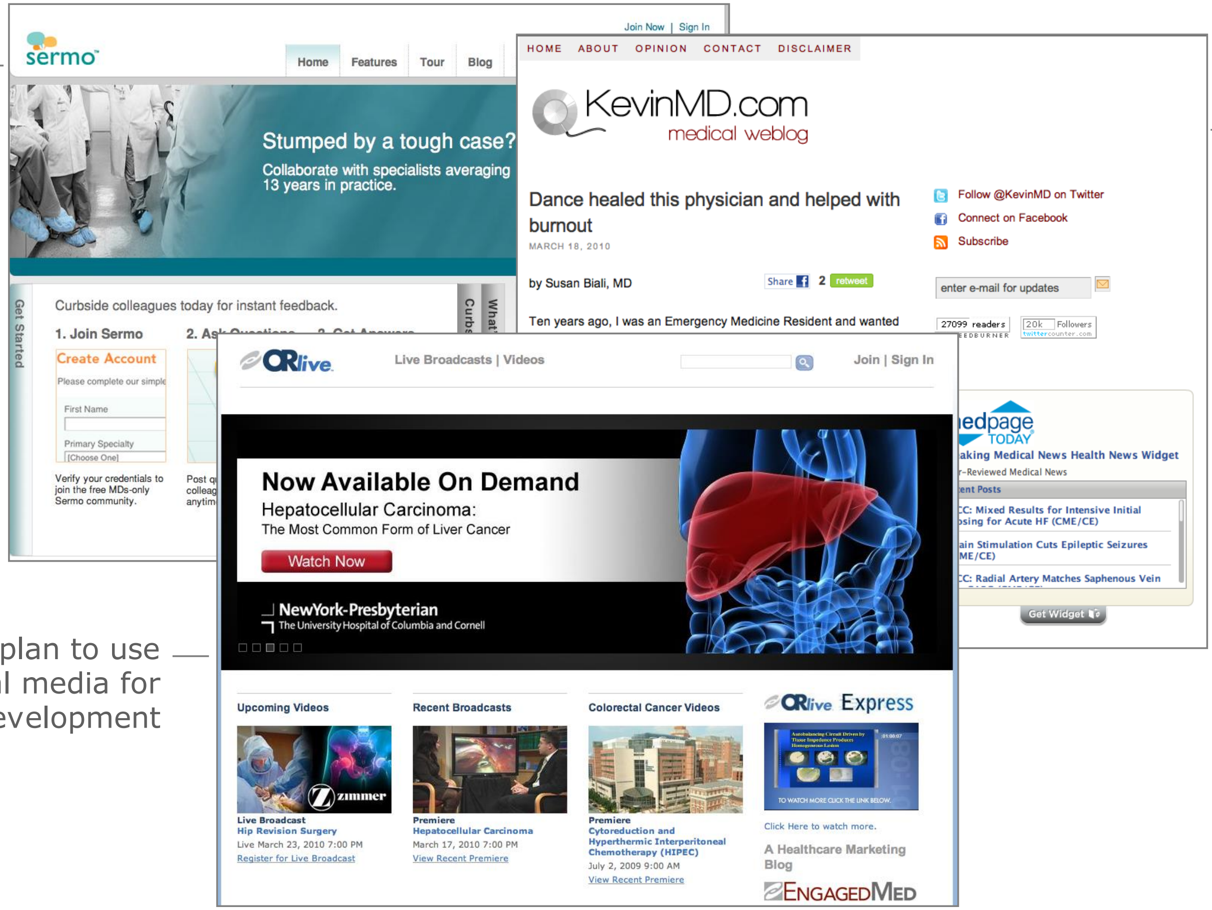
Search for suggestions from resources on the web

There are many suggestions but less insights that Mark can understand and follow

Search based approach

60% of physicians either use or are interested in using social networks

112,000 docs talk to each other on Sermo.



This doc-to-doc blogger has 53,000 readers this month + 20,000 Twitter followers

65% of docs plan to use social media for professional development

Manhattan Research 2009, 2010
Sermo,com
Compete.com

Search based approach

People are turning to each other online to understand their health

50%

Of patients leave a physician's office unsure of what they were told.

61%

Of Americans go online to research health information

41%

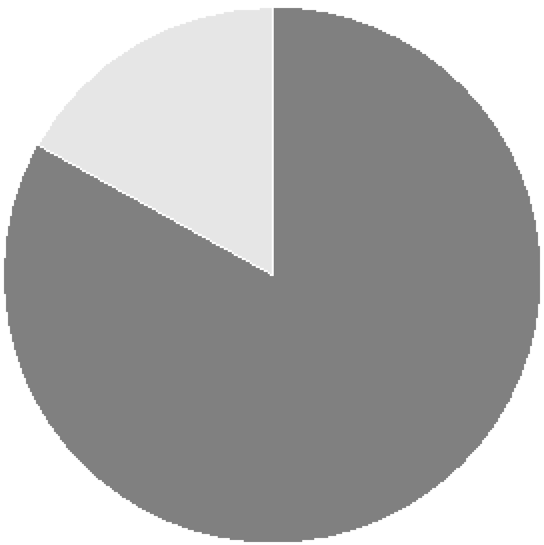
Of them read about other's medical experiences on social websites or blogs.

We look for health information for ourselves online and for each other.
Half of our health searches are on behalf of someone else.
And **two-thirds of us talk with someone else about what we find online.**

The Social Life of Health Information, Pew Internet and American Life Project, 2009

Search based approach

83% of online adults search for health information



66% look up a specific disease or problem

55% a certain medical treatment or procedure

45% information on prescription or over-the-counter drugs

35% alternative treatments or medicines

http://www.slideshare.net/IQLab/social-media-101-for-pharma-3494462

Search based approach

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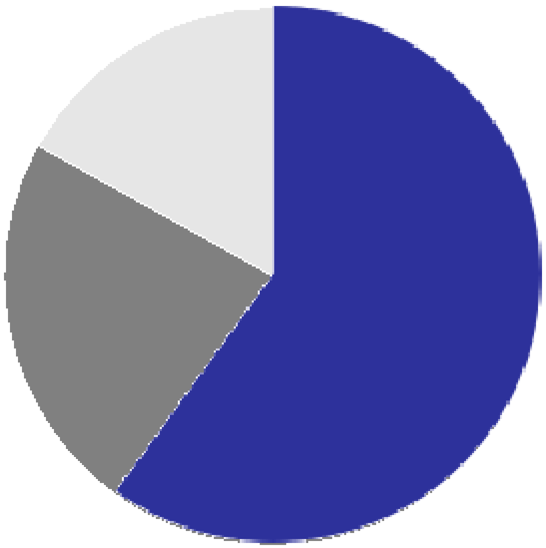


66% look up a specific disease or problem

55% a certain medical treatment or procedure

45% information on prescription or over-the-counter drugs

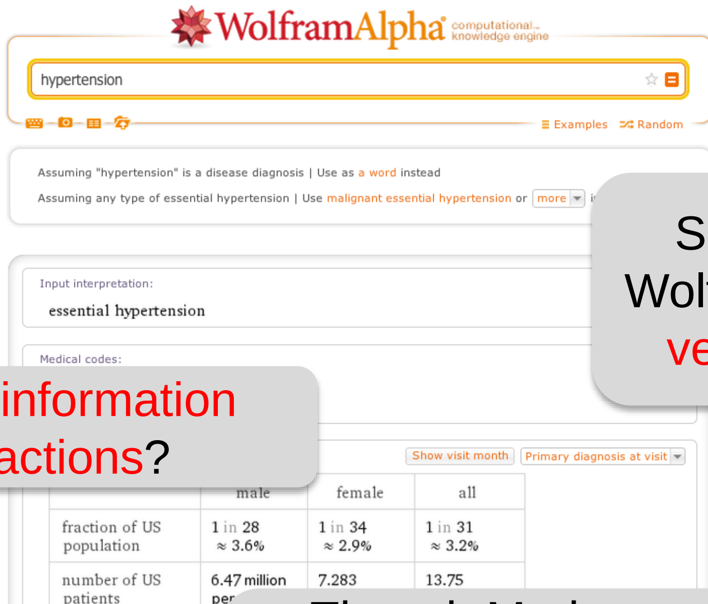
35% alternative treatments or medicines

60% of them look for the experience of "someone like me"

There are many suggestions but less insights that Mark can understand and take action

Solution engine based approach

How do I manage my hypertension?

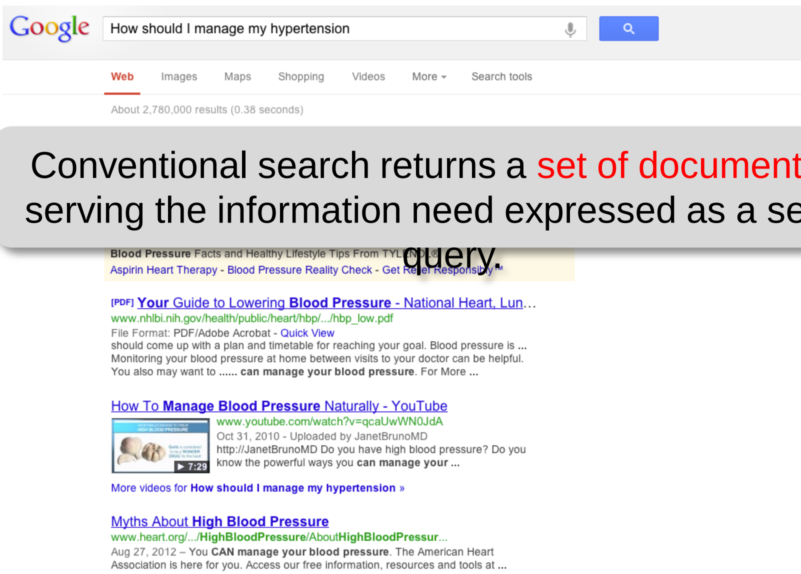


Solution engine such as WolframAlpha would provide very relevant information

Will this relevant information translate into actions?

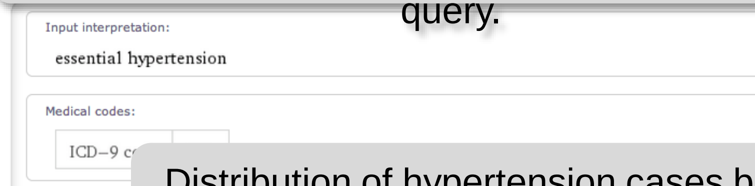
Though Mark acquired knowledge about hypertension, it is not personalized and contextually relevant for taking any action

search vs. solution engine

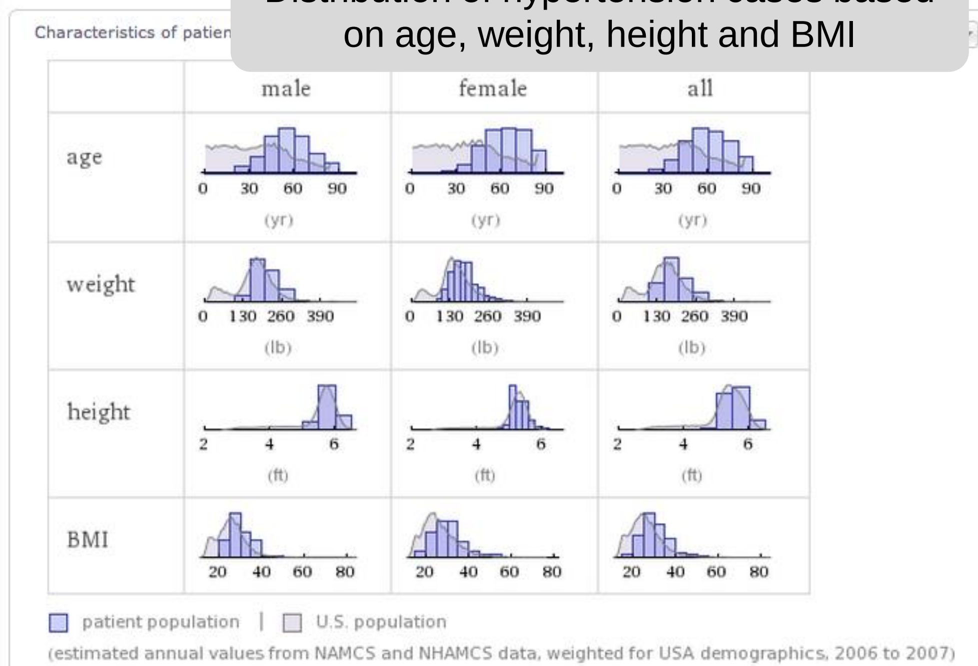


Conventional search returns a set of documents for serving the information need expressed as a search query.

WolframAlpha (which calls itself "Answer engine" provides statistical information when available for a query.



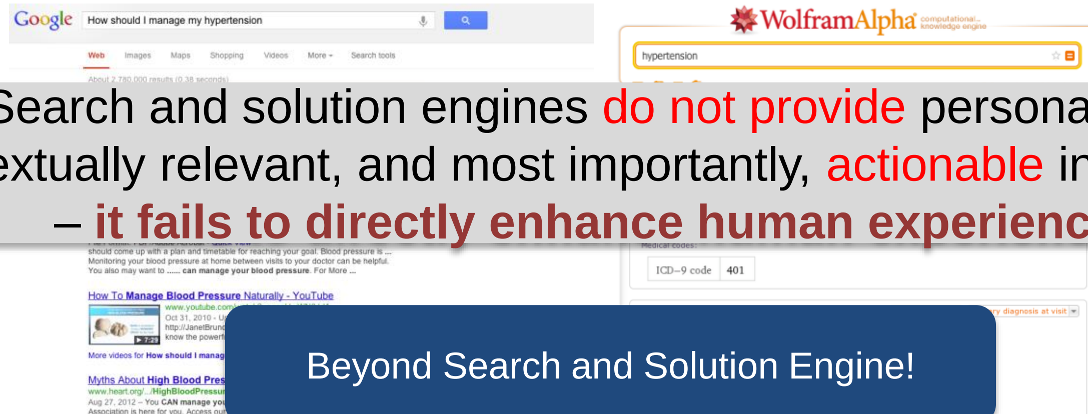
Distribution of hypertension cases based on age, weight, height and BMI



Chances of finding hypertension cases based on ethnicity.

	male	female	all
white	3.7%	2.7%	3.1%
black	4.9%	5.6%	5.3%
Asian	2.4%	3.7%	3.1%
Hispanic or Latino	3.7%	2.4%	2.9%
Amerindian Alaska native	11%	7.4%	8.7%
Pacific Islander	8.4%	7.4%	7.7%
mixed	0.01%	1.6%	0.9%

What do we need to help Mark?



Search and solution engines do not provide personalized, contextually relevant, and most importantly, actionable information – **it fails to directly enhance human experience!**

Beyond Search and Solution Engine!

We need a human-centric computational paradigm that can semantically integrate, correlate, understand, and reason over multimodal and multisensory observations to provide actionable information

Physical-Cyber-Social Computing

An early 21st century approach to Computing for Human Experience

PCS Computing

Physical: Weight, height, Activity, Heart rate, Blood Pressure

P

Cyber: Medical knowledge, Encyclopedia, NIH guidelines

C

Answer to the Mark's question, "How do I manage my hypertension?" lies here

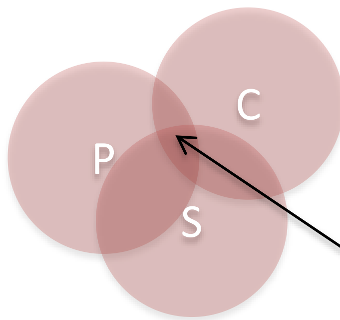
S

Social: Knowledge shared on communities, Similar ethnicity, Socio-economically similar

PCS Computing

Physical: Weight, height, Activity, Heart rate, Blood Pressure

Cyber: Medical knowledge, Encyclopedia, NIH guidelines

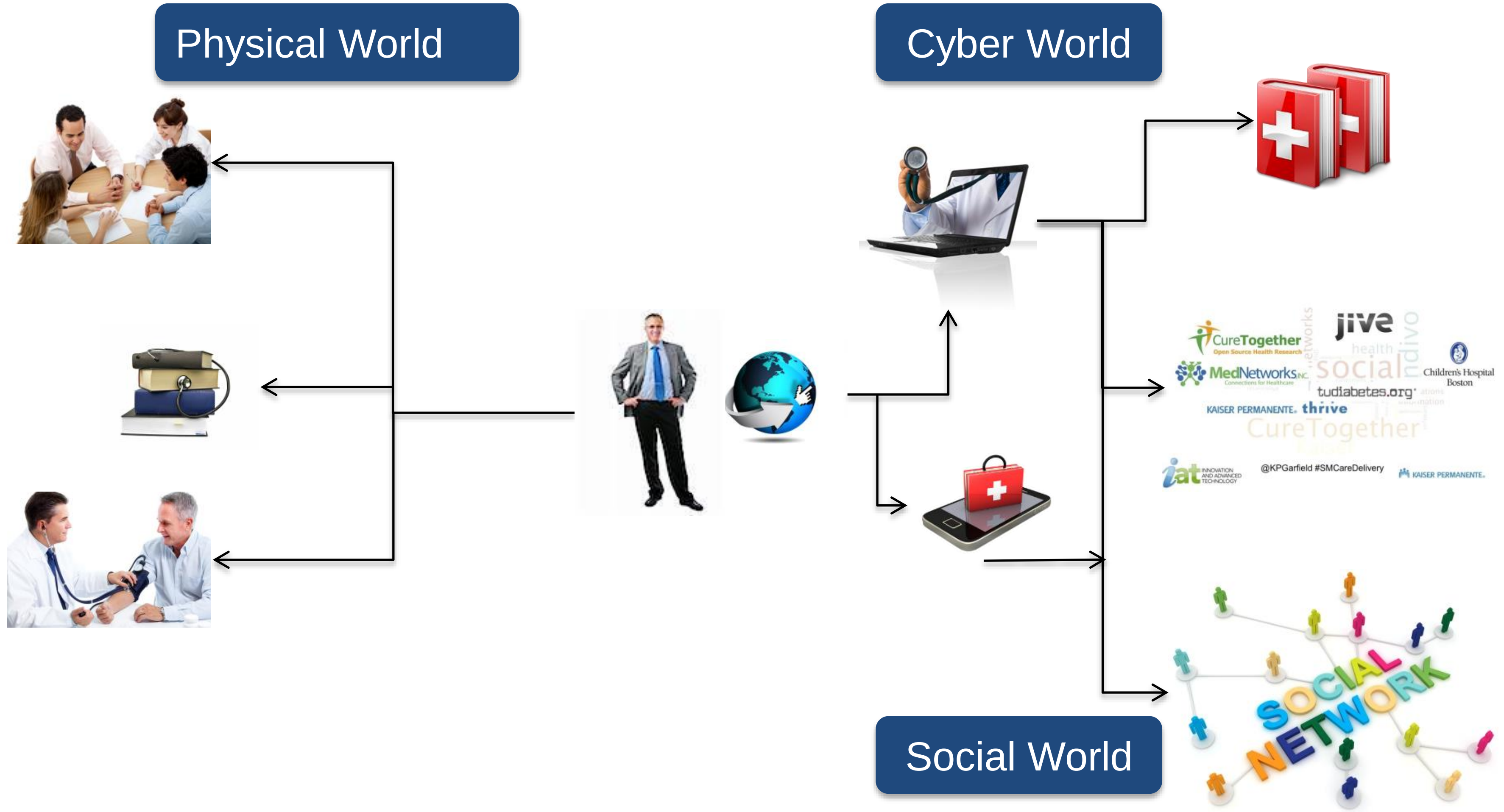


Answer to the Mark's question, "How do I manage my hypertension?" lies here

Social: Knowledge shared on communities, Similar ethnicity, Socio-economically similar

PCS Computing

People live in the physical world while interacting with the cyber and social worlds



PCS Computing

People consider their observations and experiences from physical, cyber, and social worlds for decision making – this is not captured in current computing paradigms

Physical World

Cyber World

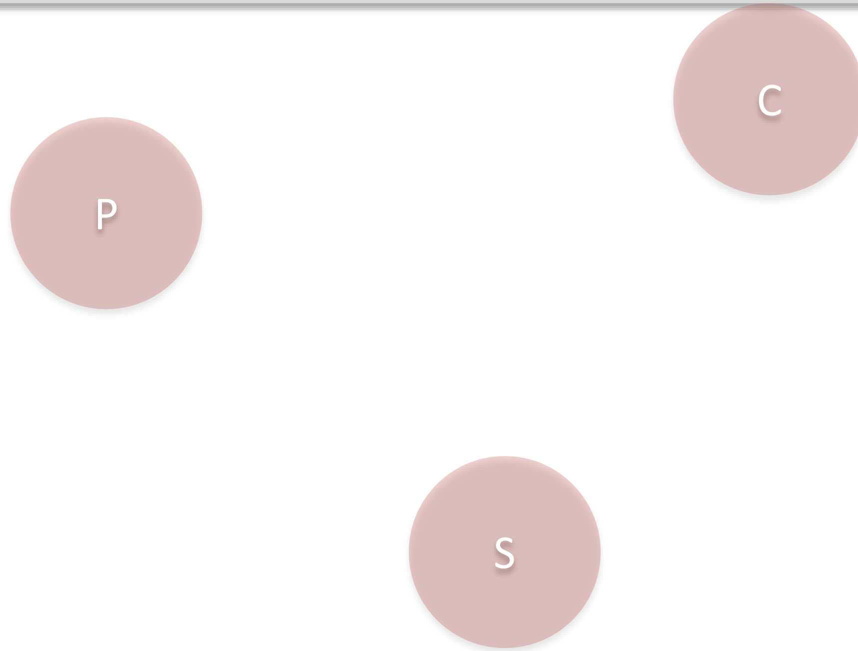
Social World

Substituting spices for salt intake would reduce sodium intake aiding in controlling hypertension

Decision making

PCS Computing

PCS computing is intended to address the seamless integration of cyber world, and human activities and interactions



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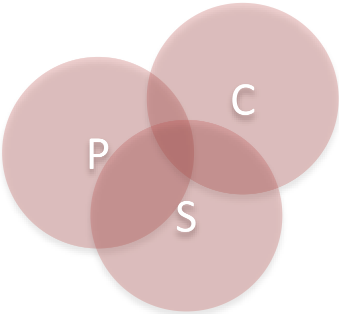
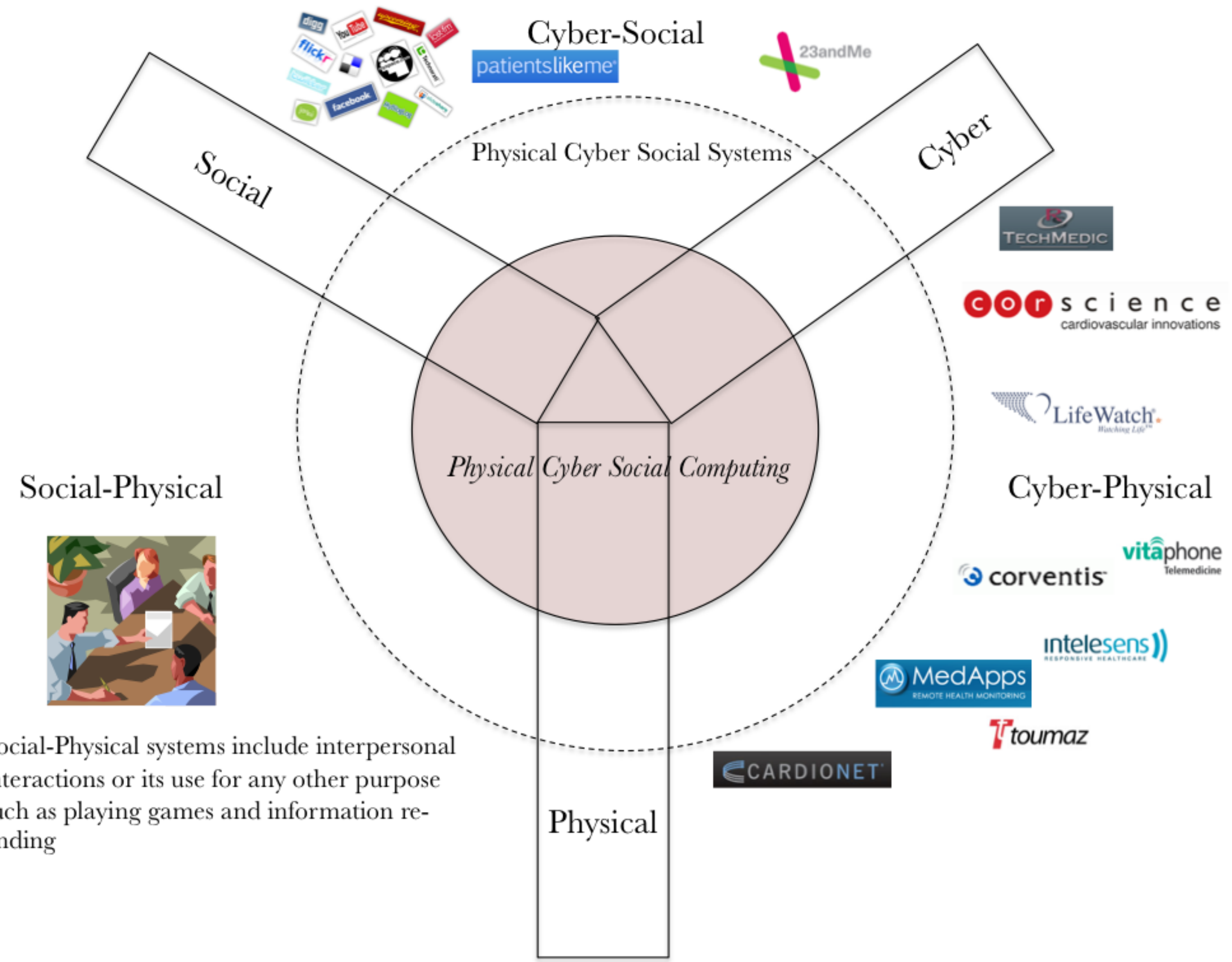


Increasingly, real-world events are:
(a) Continuous: Observations are fine grained over time
(b) Multimodal, multisensory: Observations span PCS modalities

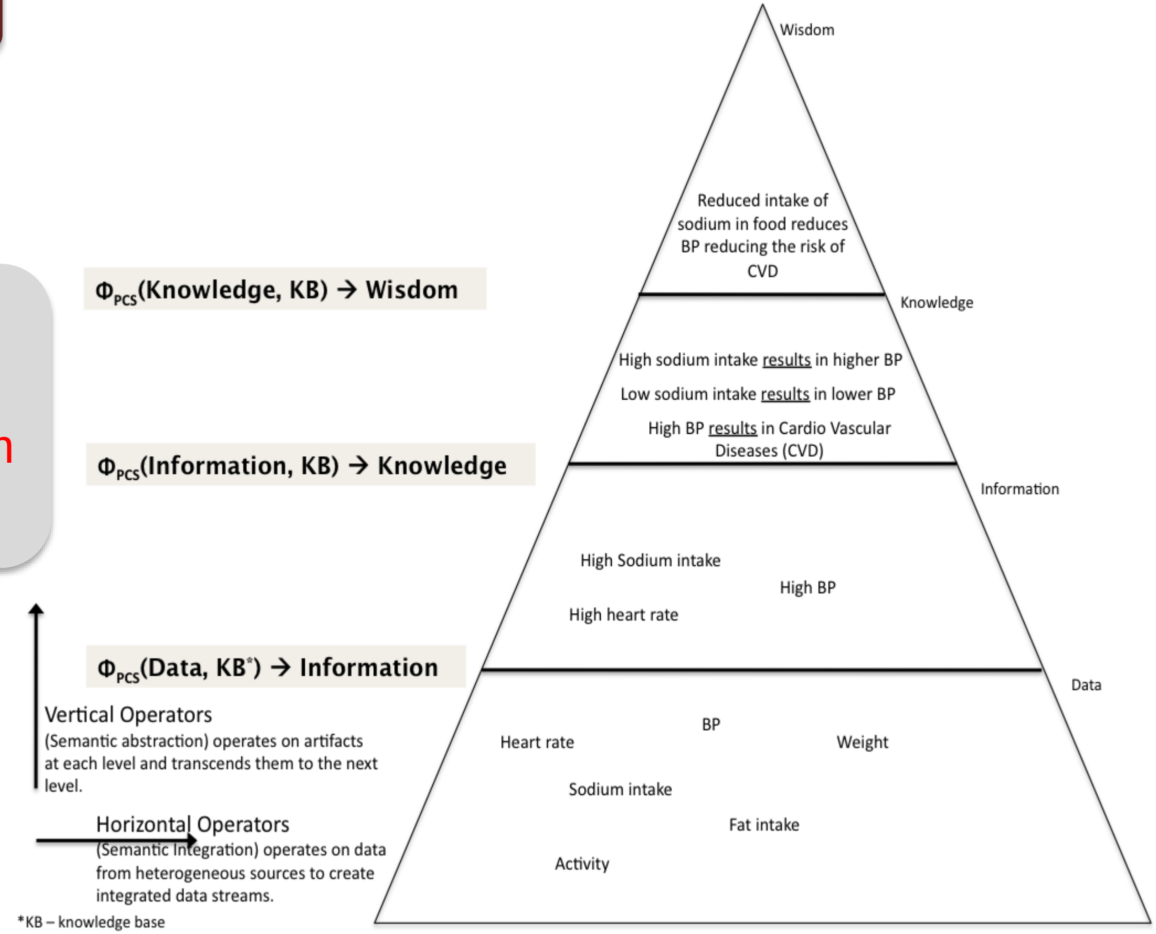


Social-Physical systems include interpersonal interactions or its use for any other purpose such as playing games and information re-finding

PCS computing operators

Vertical operators facilitate transcending from data-information-knowledge-wisdom using background knowledge

Opportunity to do exciting new research here



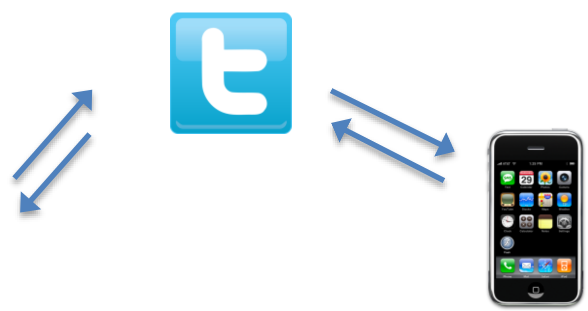
Horizontal operators facilitate semantic integration of multimodal and multisensory observations

We have made more progress along this line

Let’s take progressive steps from existing computing paradigms toward PCS computing…

Physical-Cyber Systems

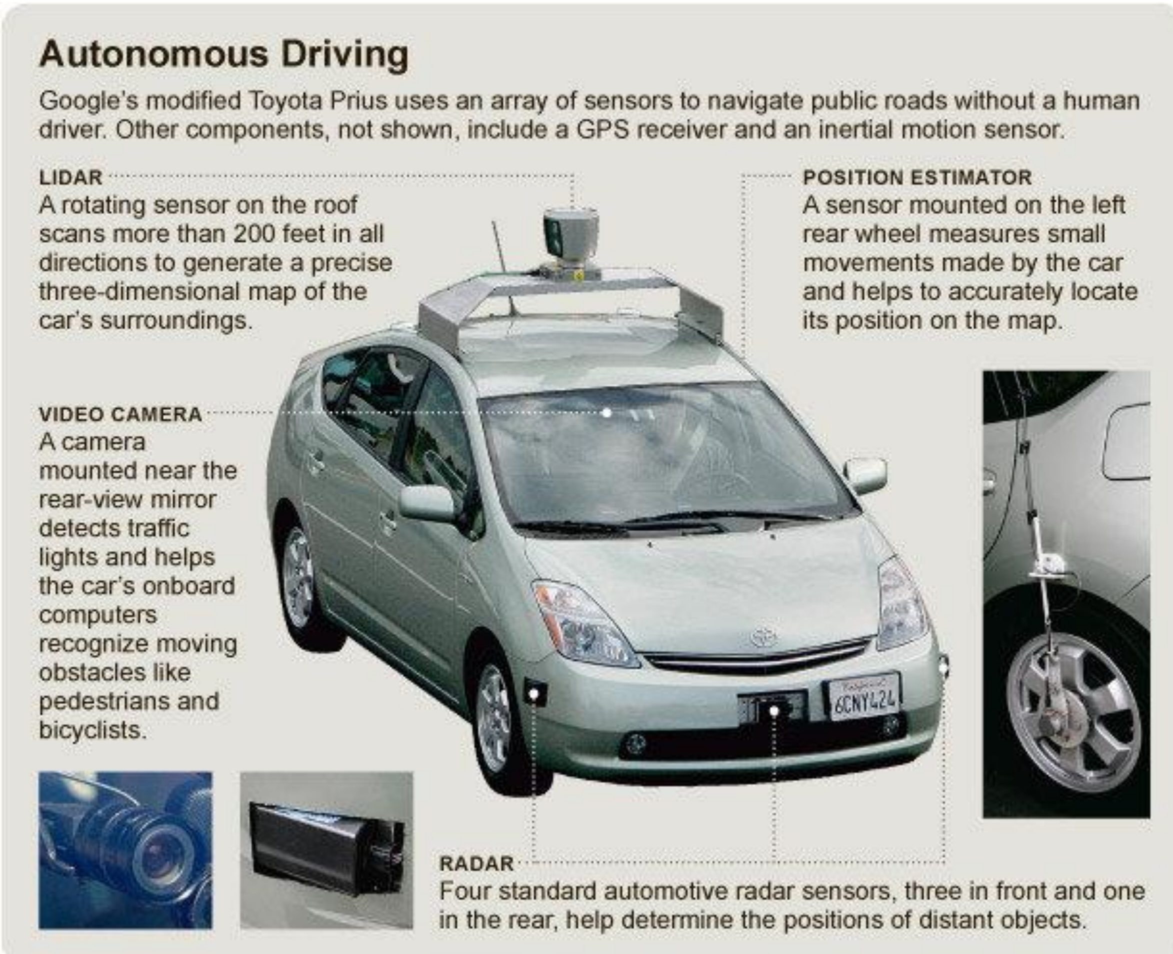
The computational, communication, and control components closely interact with physical components enabling better cyber-mediated observation of and interaction with physical components.



CPS involves sensing, computing, and actuating components

Physical-Cyber Systems

Google's autonomous car needs to sense, compute, and actuate continuously in order to navigate through the city traffic

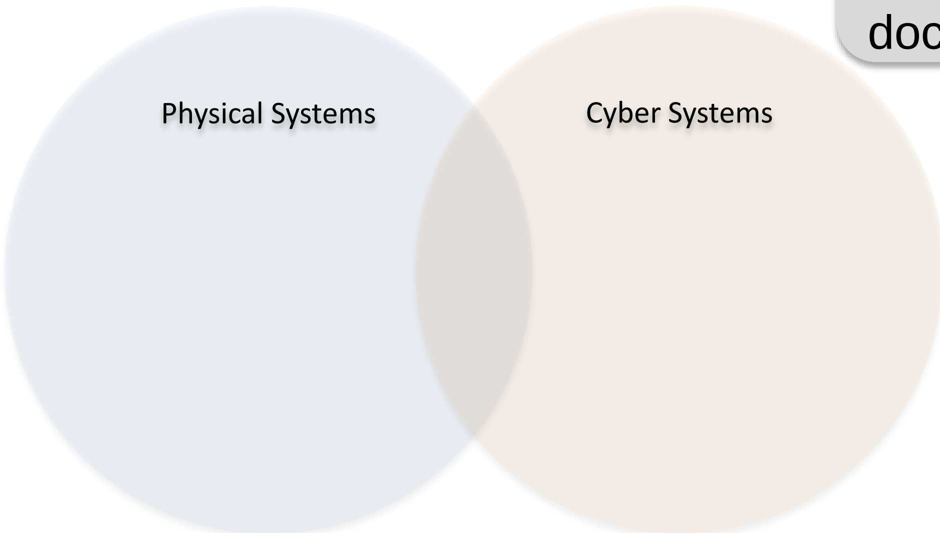


Source: Google

THE NEW YORK TIMES; PHOTOGRAPHS BY RAMIN RAHIMIAN FOR THE NEW YORK TIMES

Physical-Cyber Systems

Health applications and tools that monitor a person physically and connect them to care providers (e.g. doctors)

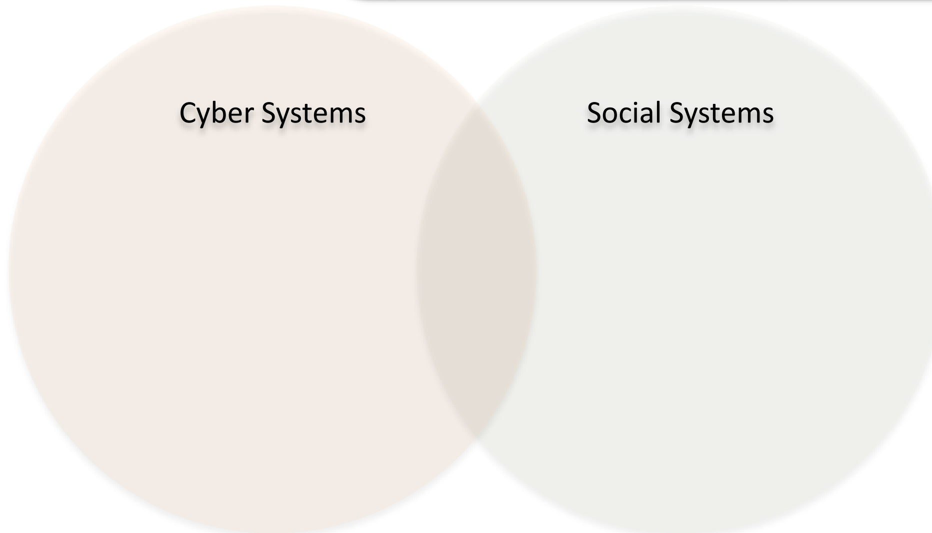


- MedApps — Remote heath monitoring
- CardioNet — Mobile cardiac outpatient telemetry and real time analytics
- vitaphone Telemedicine — Applications integrating telemedicine service
- TechMedic — Remote real-time patient monitoring of vitals
- corscience (cardiovascular innovations) — Offers sensor solutions for monitoring cardiovascular ailments
- LifeWatch — Provides solutions to monitor cardio activity
- intelesens — Non-invasive wearable monitoring of vital signals
- corventis — Cardiovascular patient monitoring
- toumaz — Continuous monitoring of physiological parameters

http://quantifiedself.com/2010/01/non-invasive-health-monitoring/

Cyber-Social Systems

Observations spanning Cyber and Social world – people share their activities, knowledge, experiences, opinions, and perceptions.



patientslikeme

Sharing experiences and management of conditions and their treatments

23andMe

Managing risks and making informed decisions based on gene sequencing

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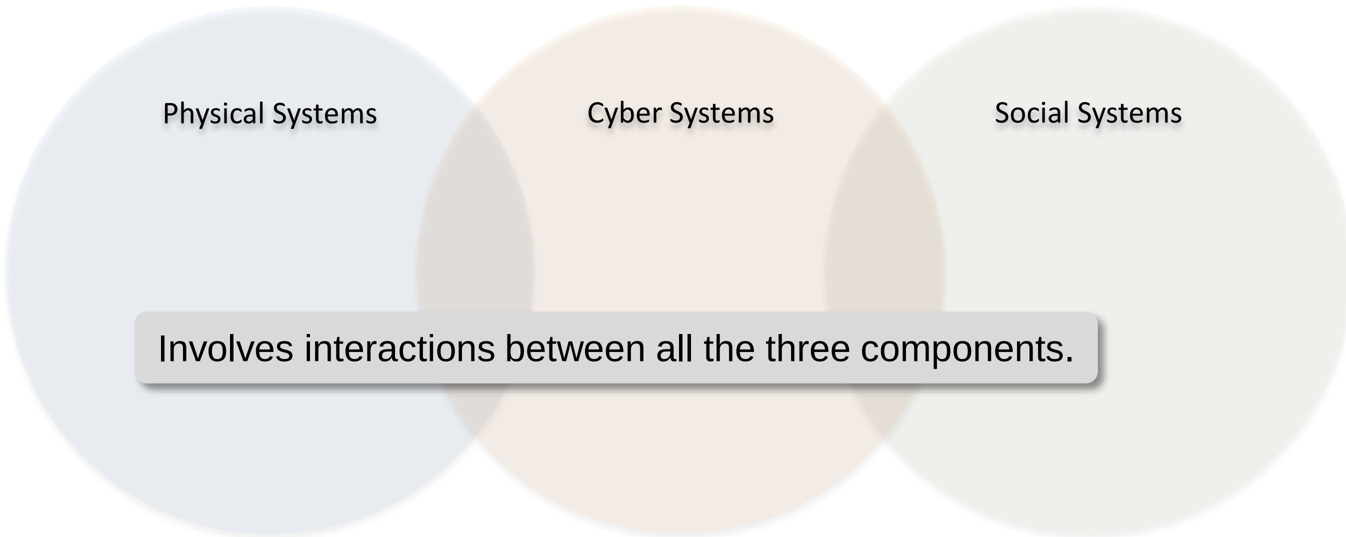
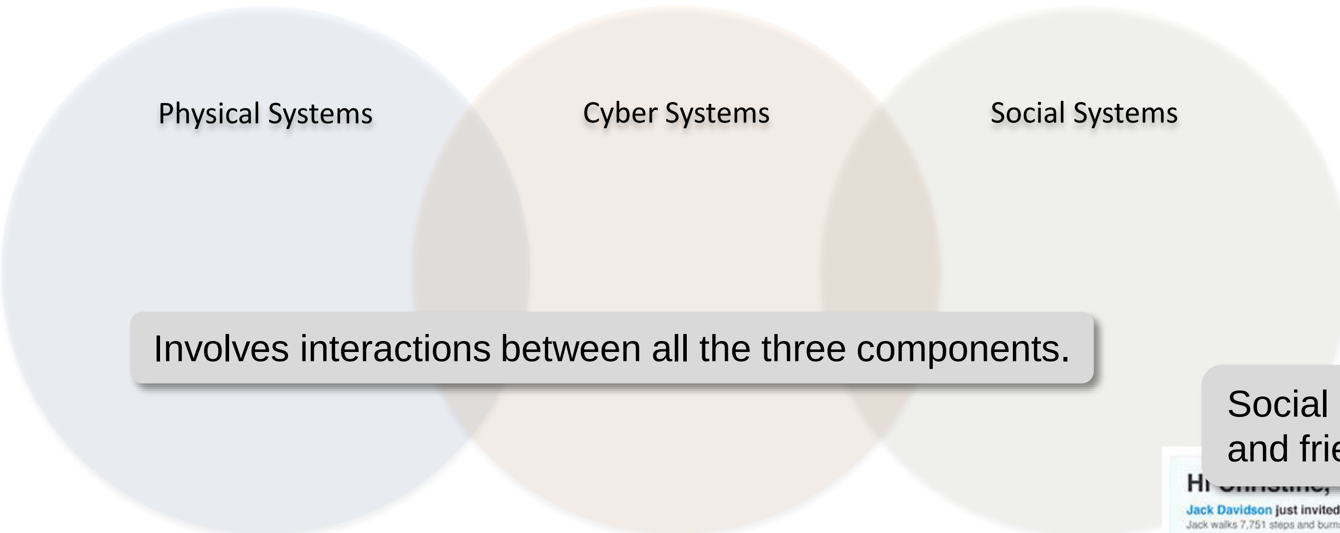
Physical-Cyber-Social Systems



Physical-Cyber-Social Systems



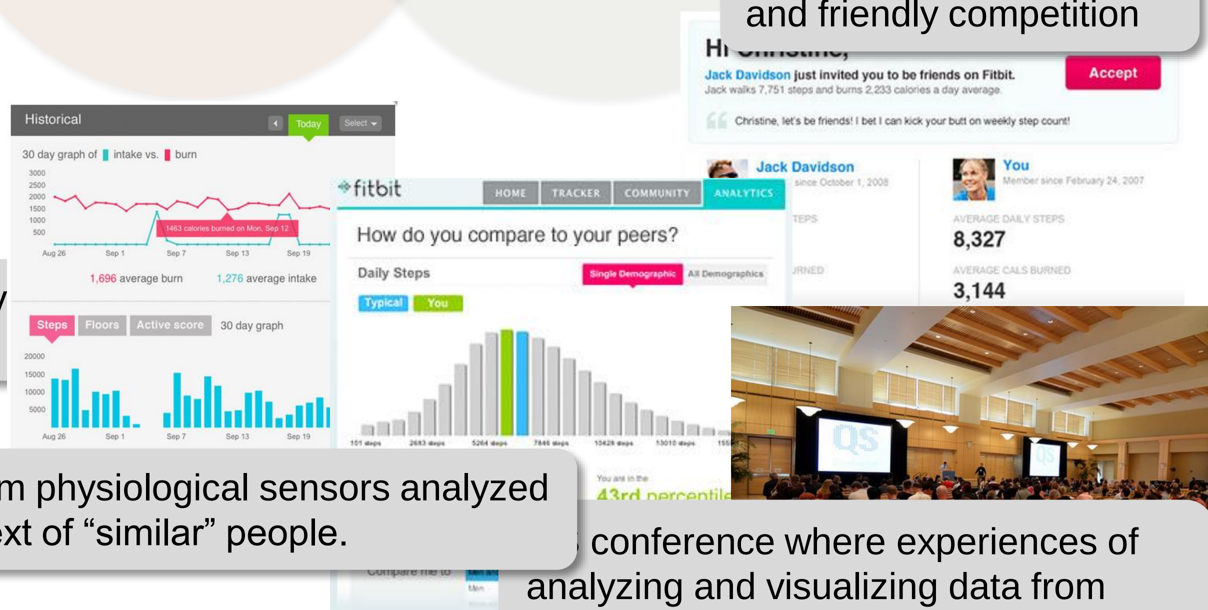
Involves interactions between all the three components.

Social aspect of sharing and friendly competition

Quantified Self

Self knowledge through…

Sensors collecting observ… form the physical world



Data collected from physiological sensors analyzed in the social context of “similar” people.

…s conference where experiences of analyzing and visualizing data from physiological sensors are presented.

http://www.fitbit.com/product/features#social

Physical-Cyber-Social Systems

Physical Systems

Cyber Systems

Social Systems

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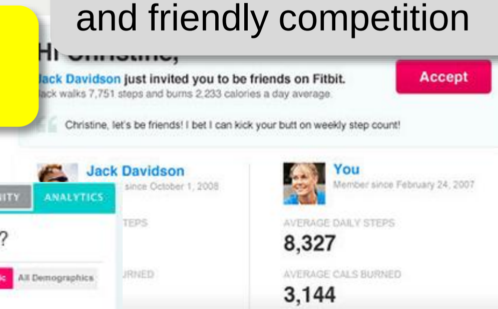
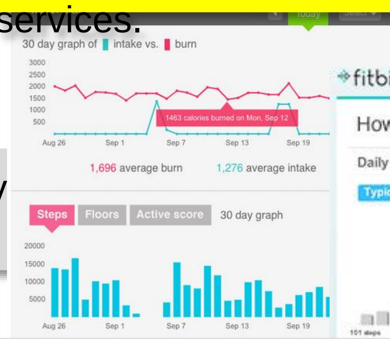
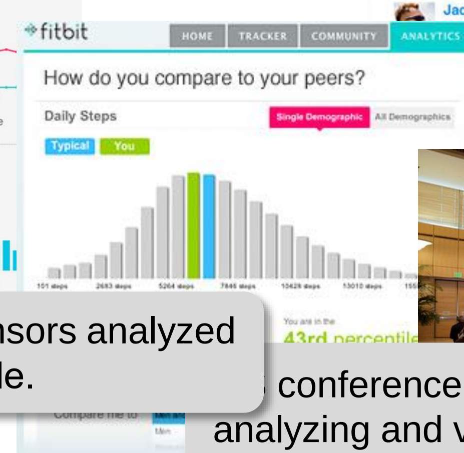


This data is stove piped due to fragmentation in sensor data collection services.





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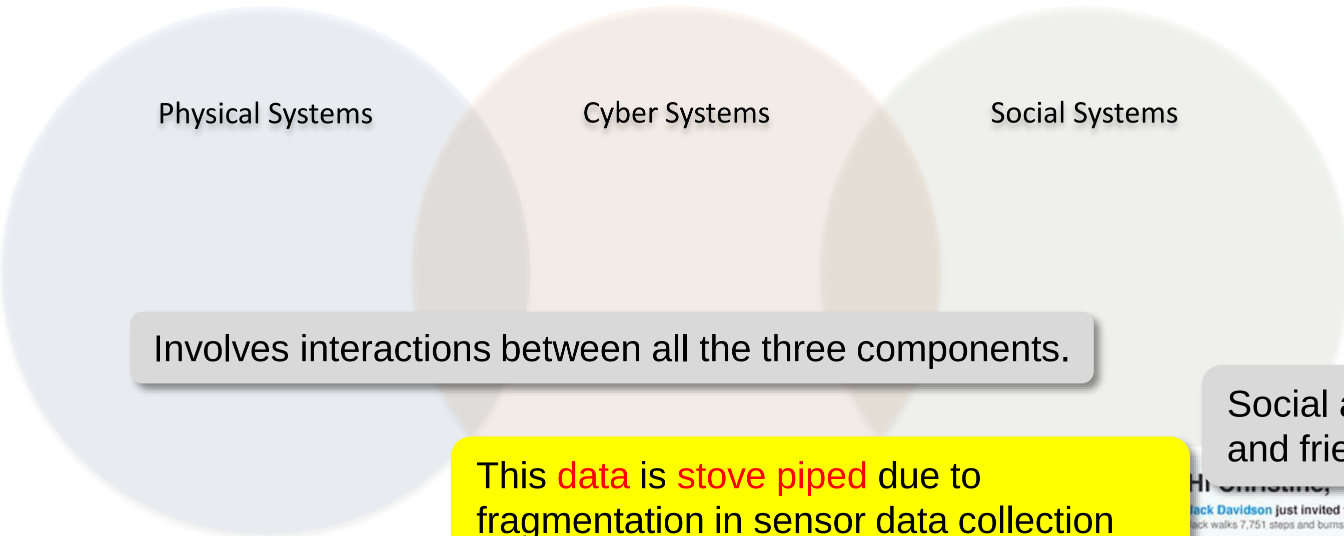

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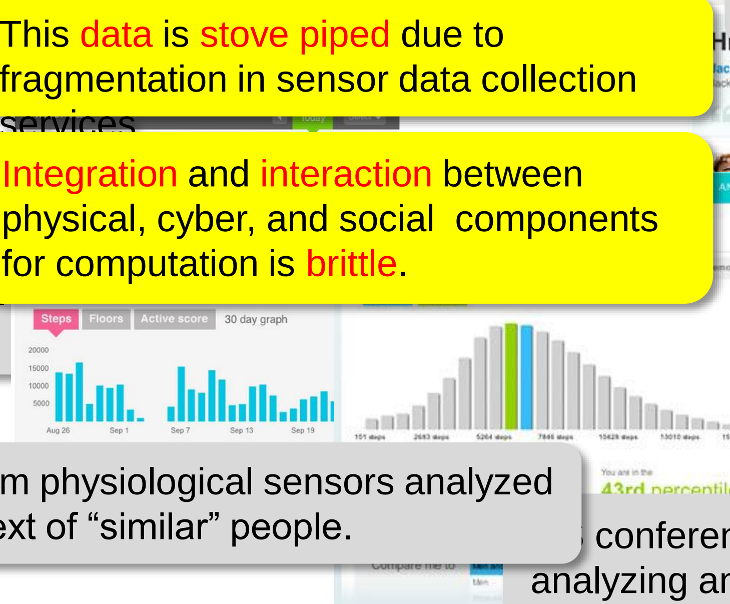
Integration and interaction between physical, cyber, and social components for computation is brittle.



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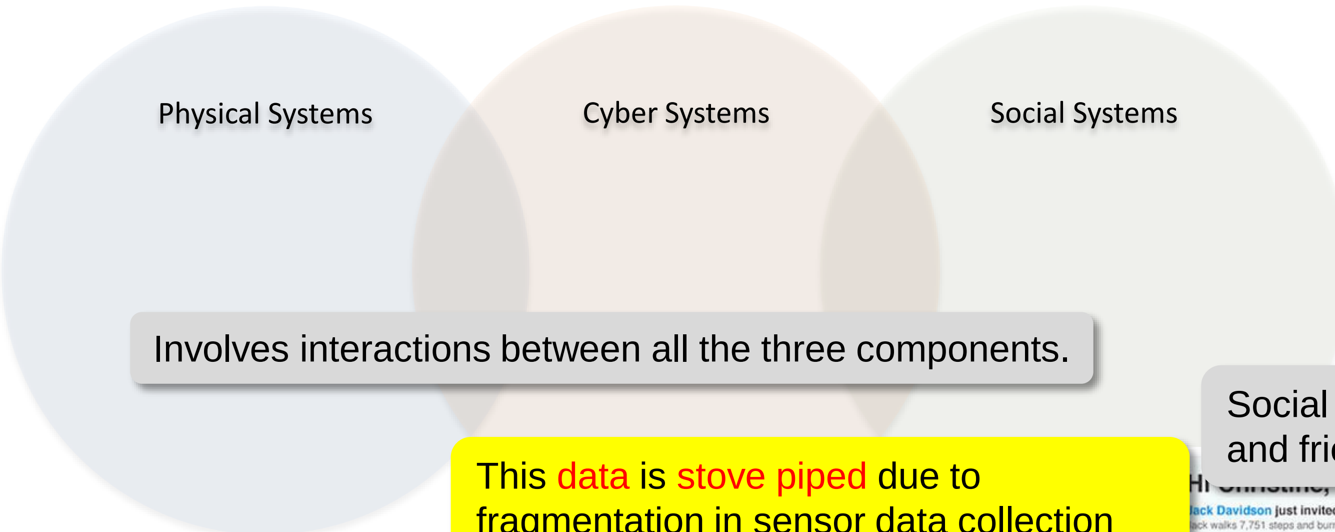

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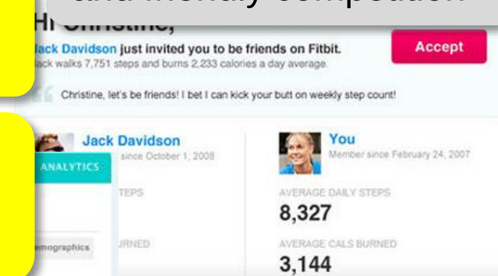

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Integration and interaction between physical, cyber, and social components for computation is brittle.

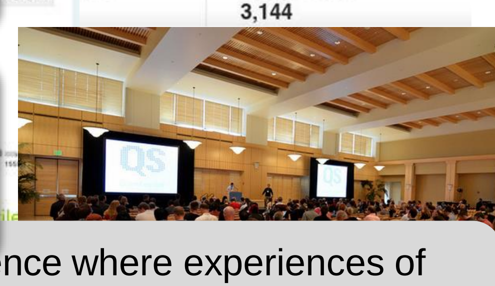
Needs significant human involvement in interpretation of physiological observations using their knowledge of the domain and social experiences.

Quantified Self

Self knowledge through

Sensors collecting obse form the physical world

Data collected fr in the social cont



...ence where experiences of analyzing and visualizing data from physiological sensors are presented.

http://www.fitbit.com/product/features#social

What if?

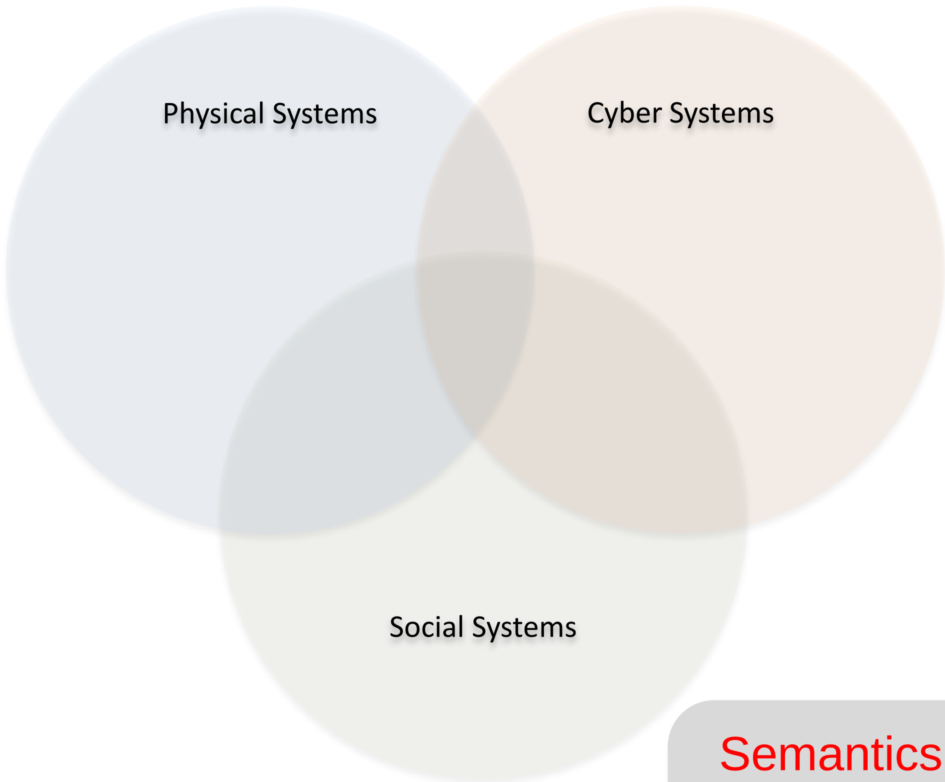
Computations leverage observations form sensors, knowledge and experiences from people to understand, correlate, and personalize solutions.

Physical-Cyber

Social-Cyber

Physical-Cyber-Social

PCS Computing



Semantics play a crucial role in bridging the semantic gap between different sensor types, modalities, and observations to derive insights leading to a holistic solution.

PCS Computing

Physical, Cyber and Social

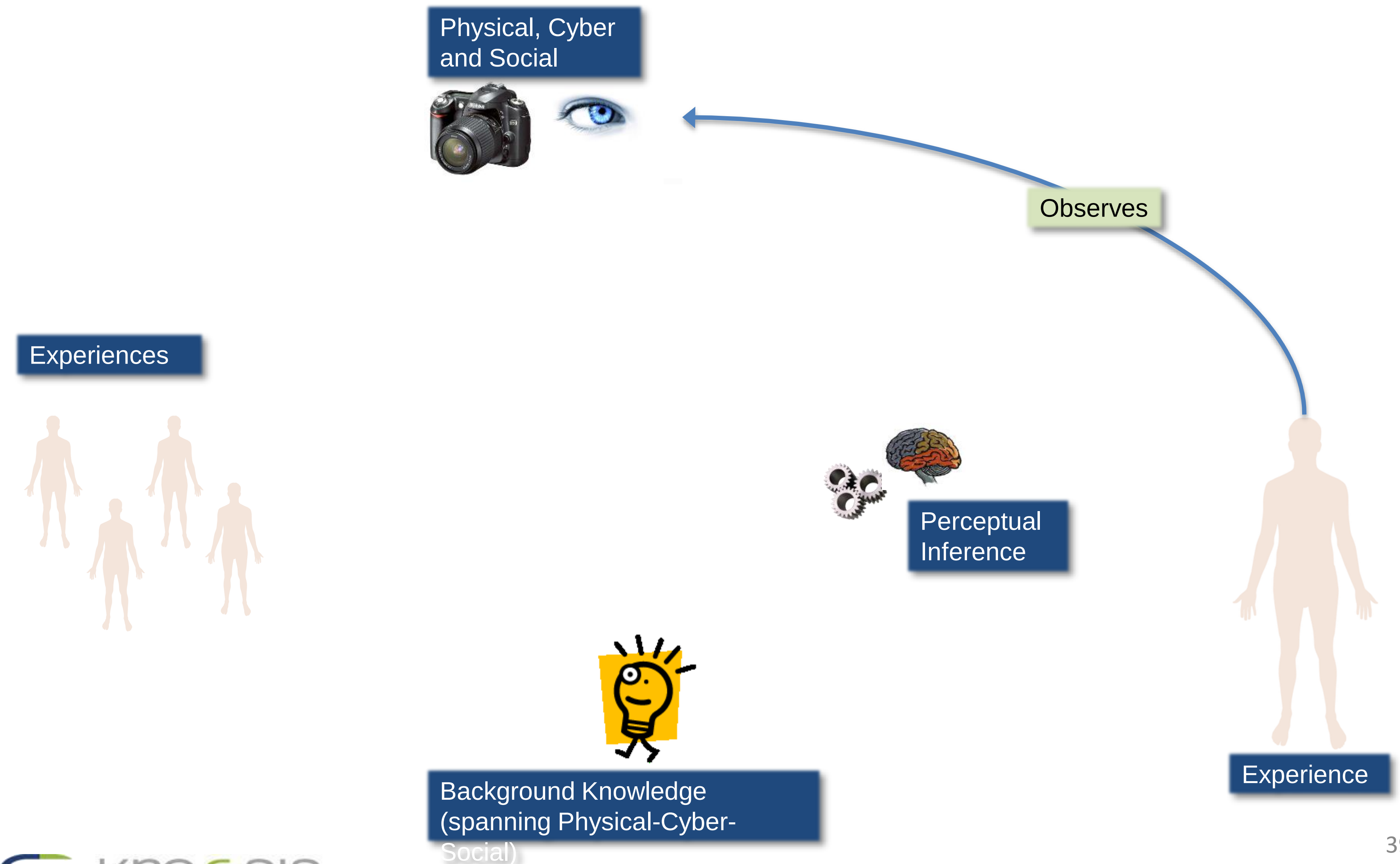
Experiences

Perceptual Inference

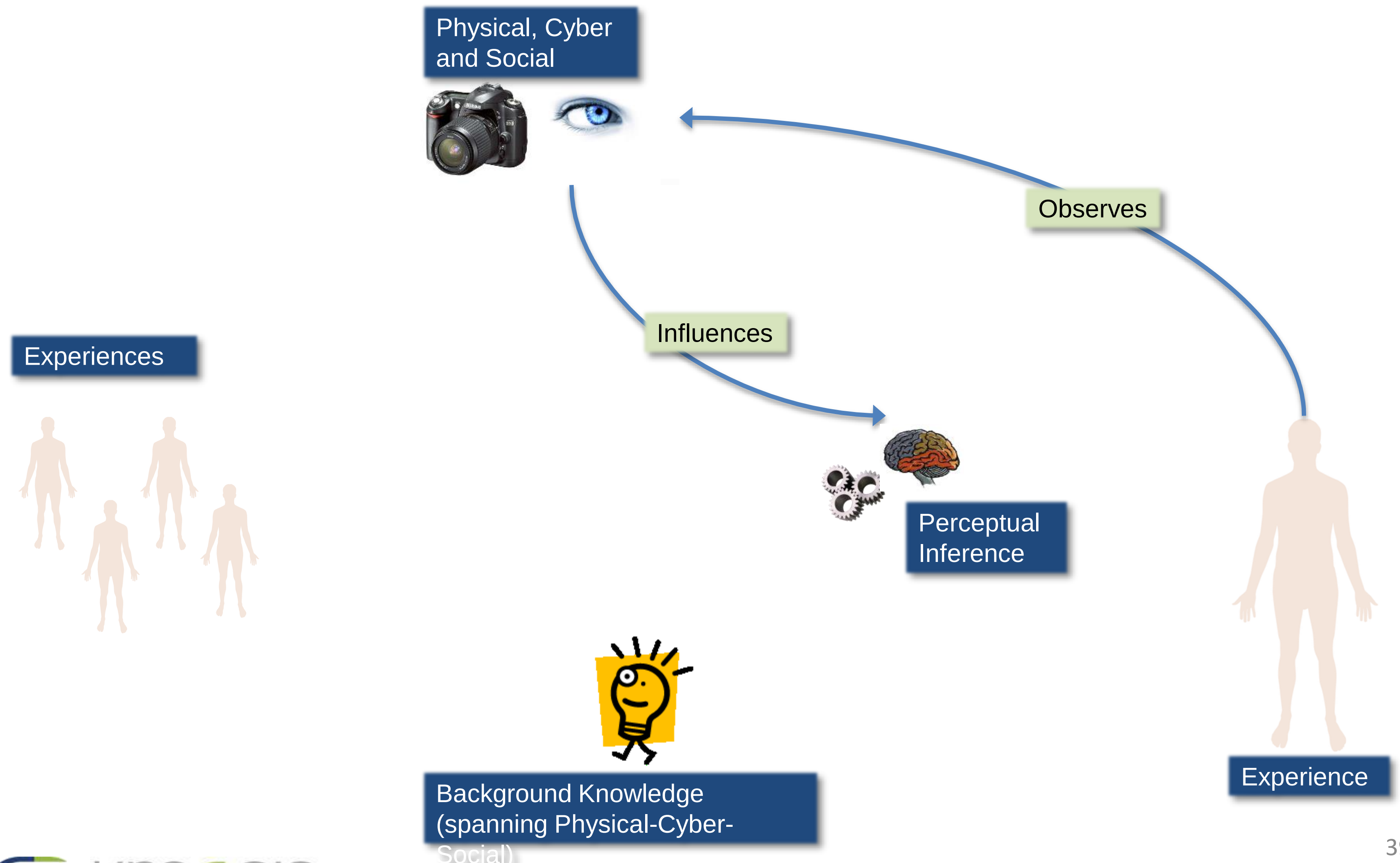
Background Knowledge (spanning Physical-Cyber-Social)

Experience

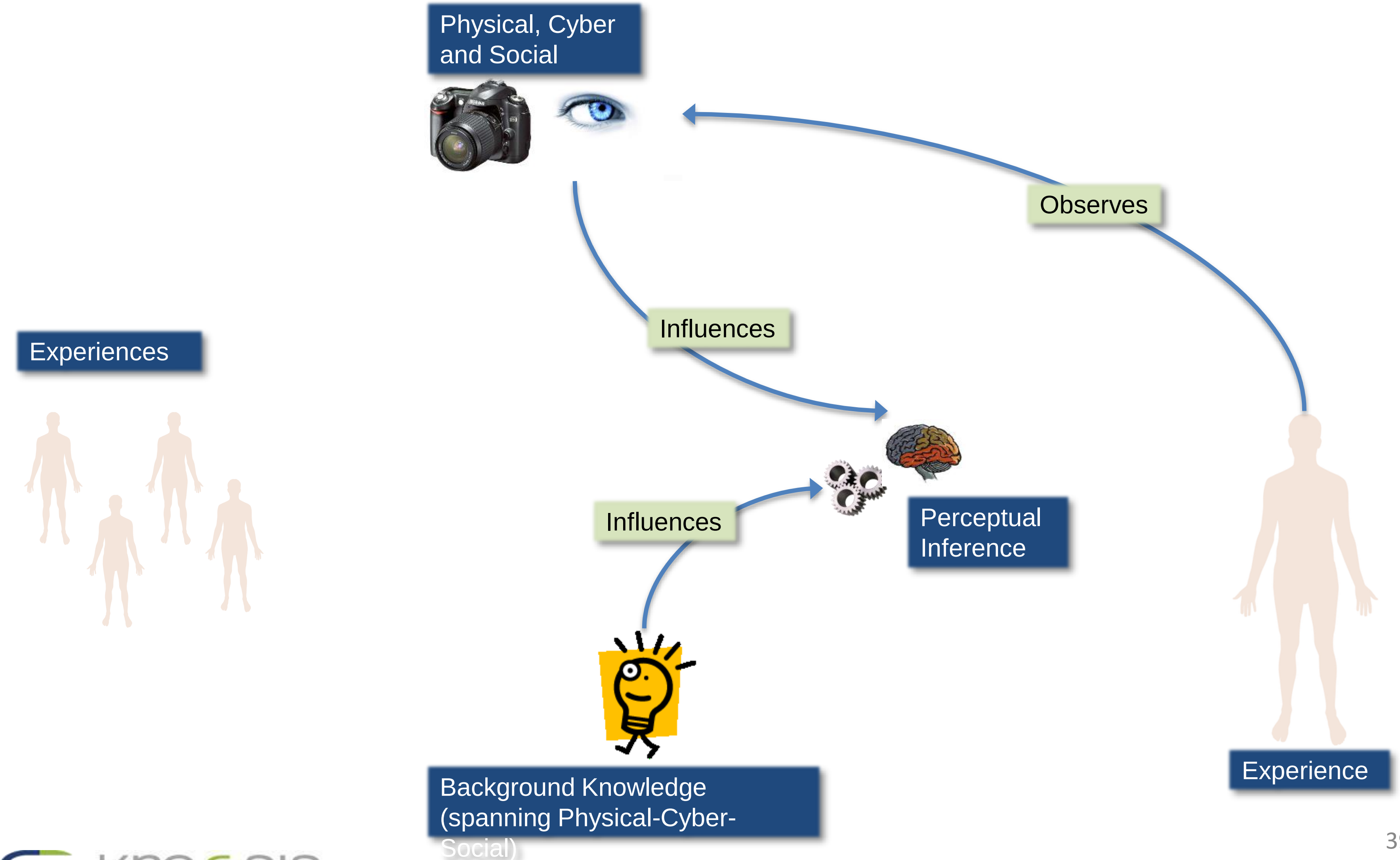
PCS Computing



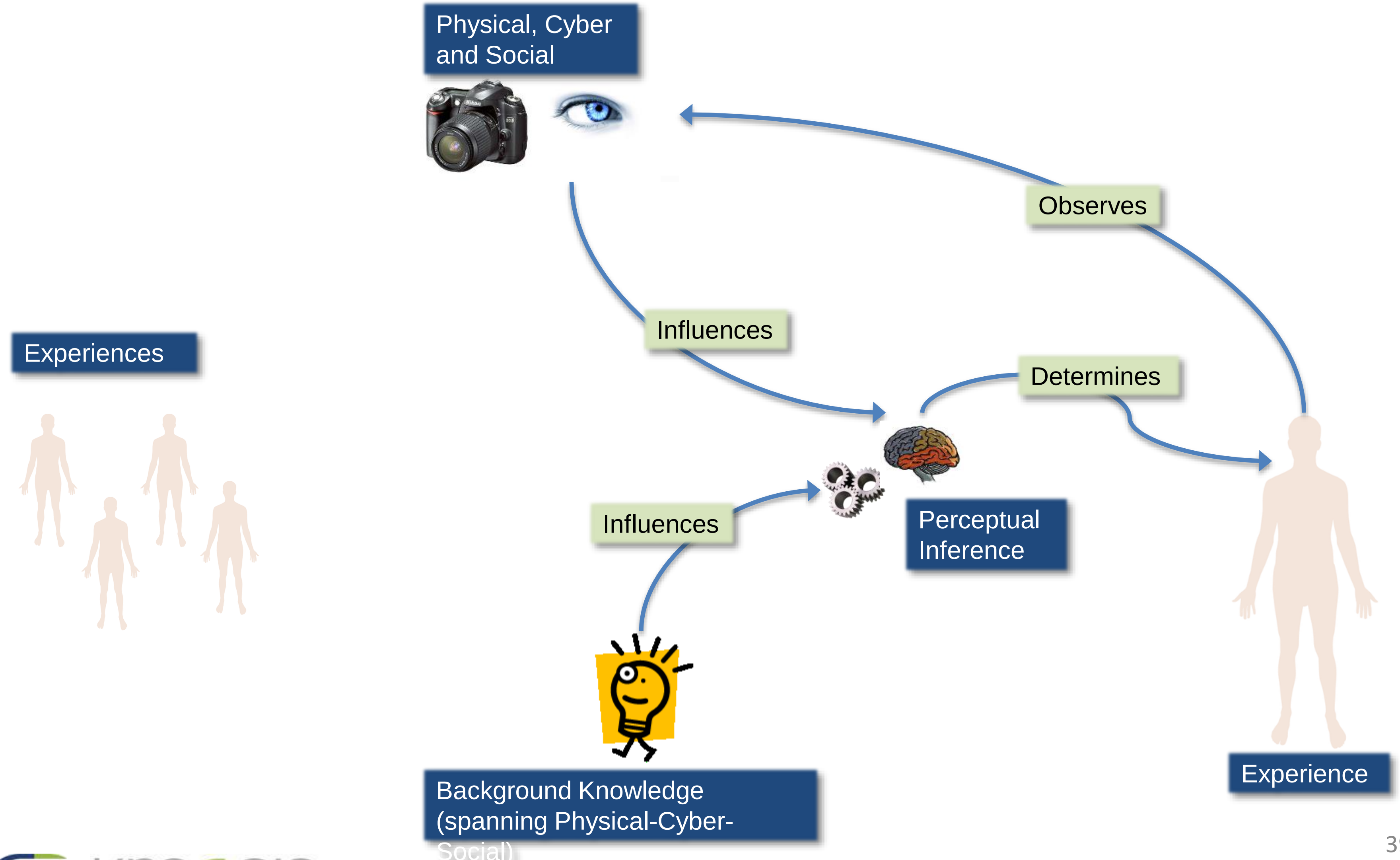
PCS Computing



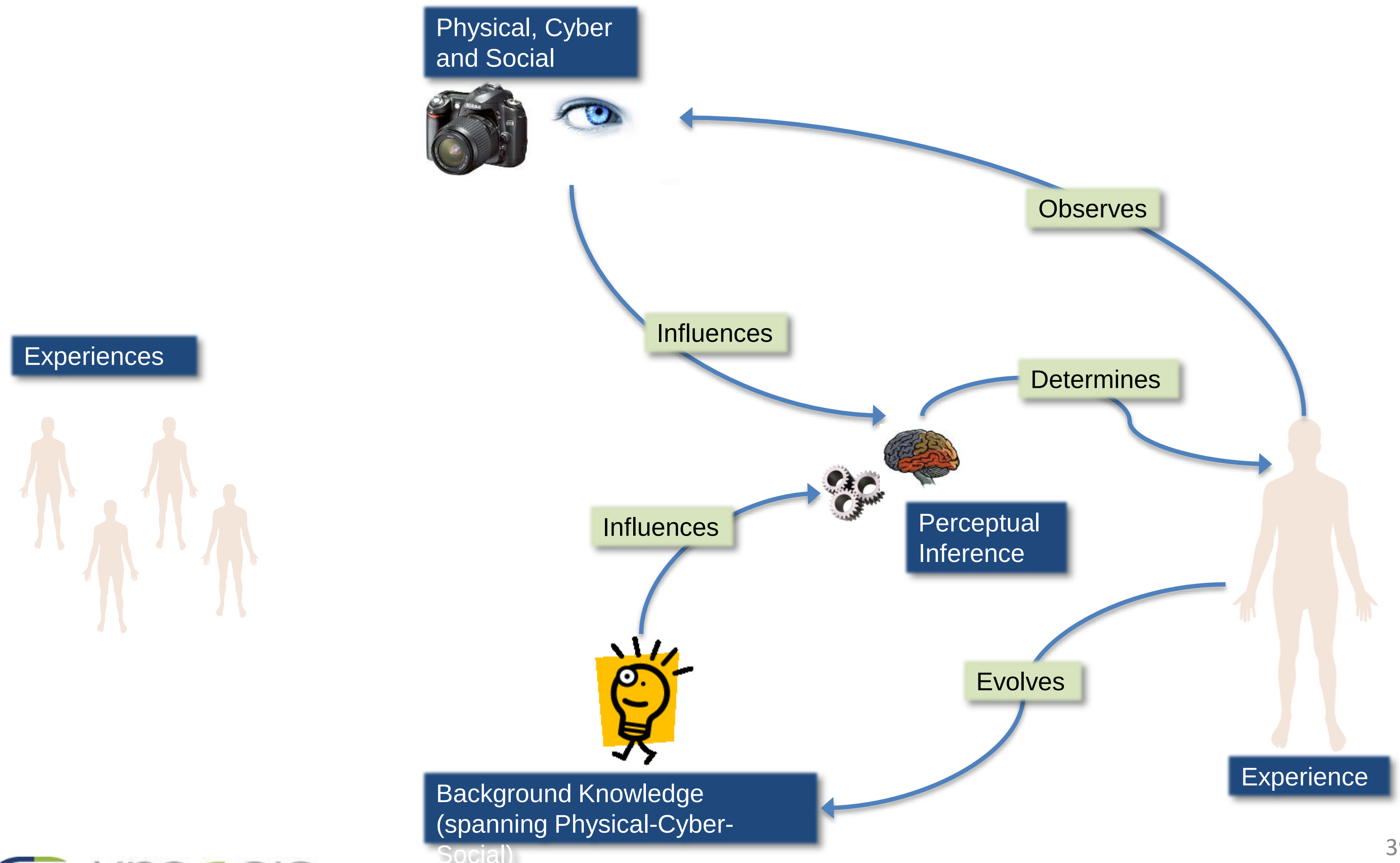
PCS Computing



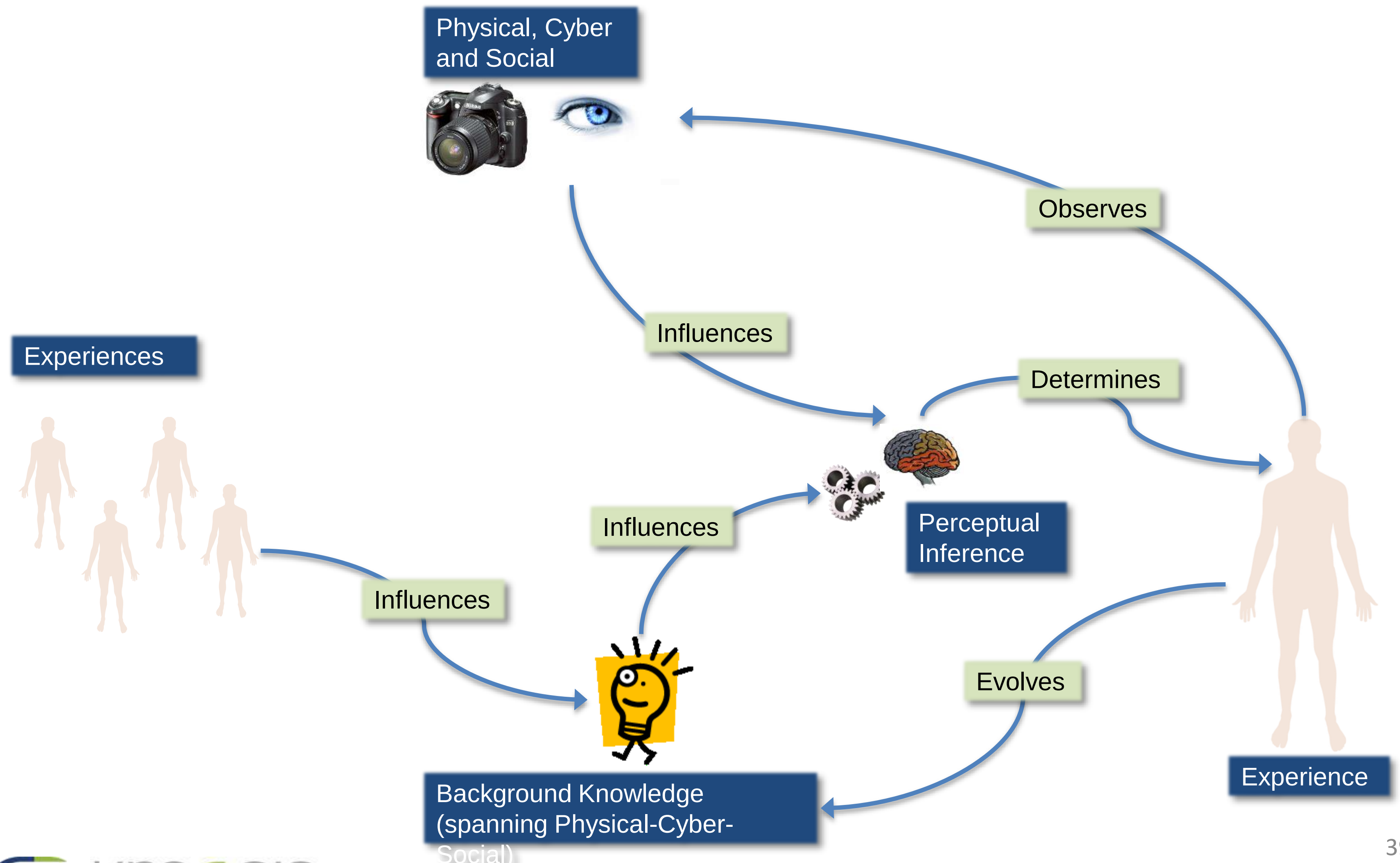
PCS Computing



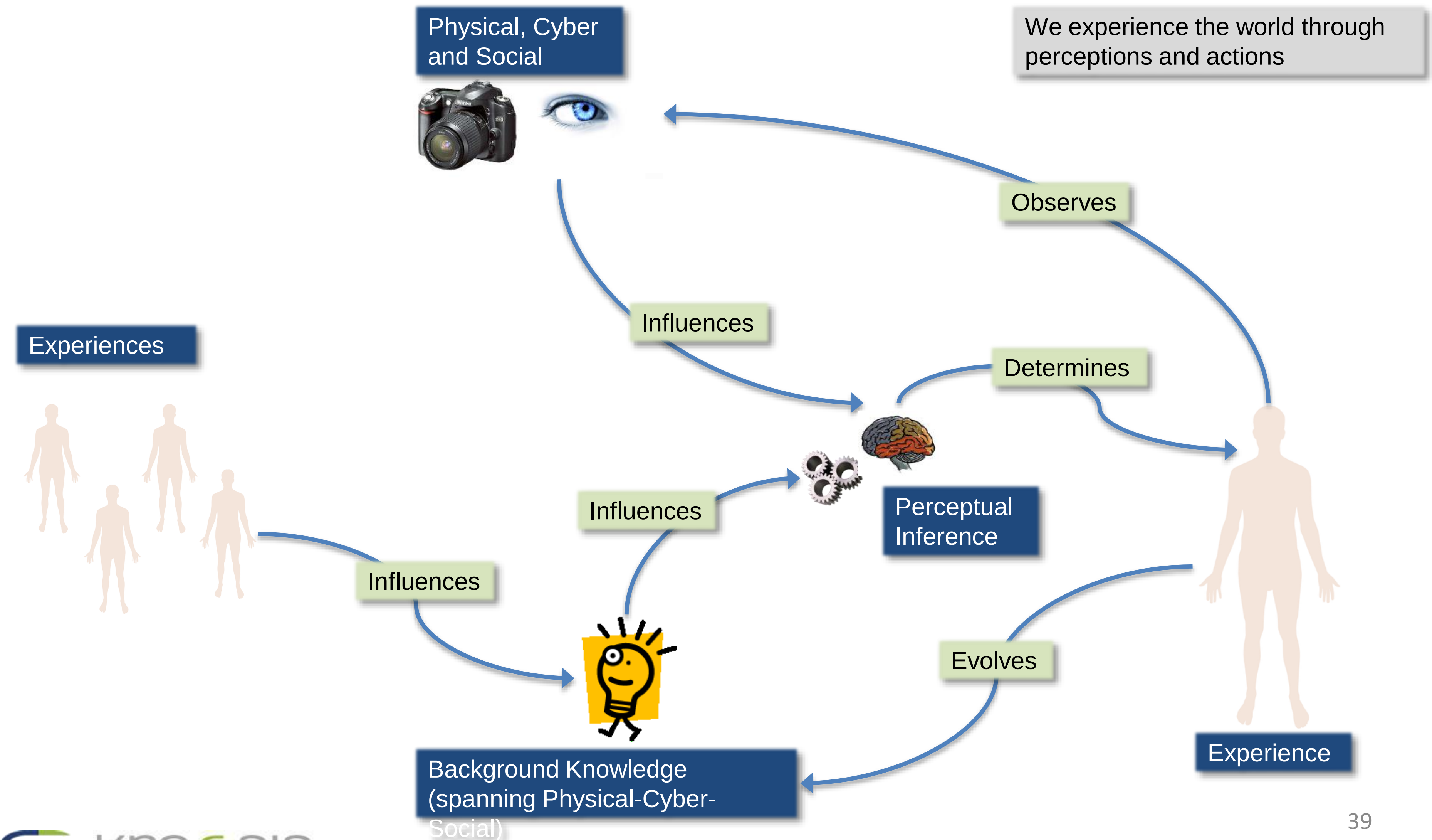
PCS Computing



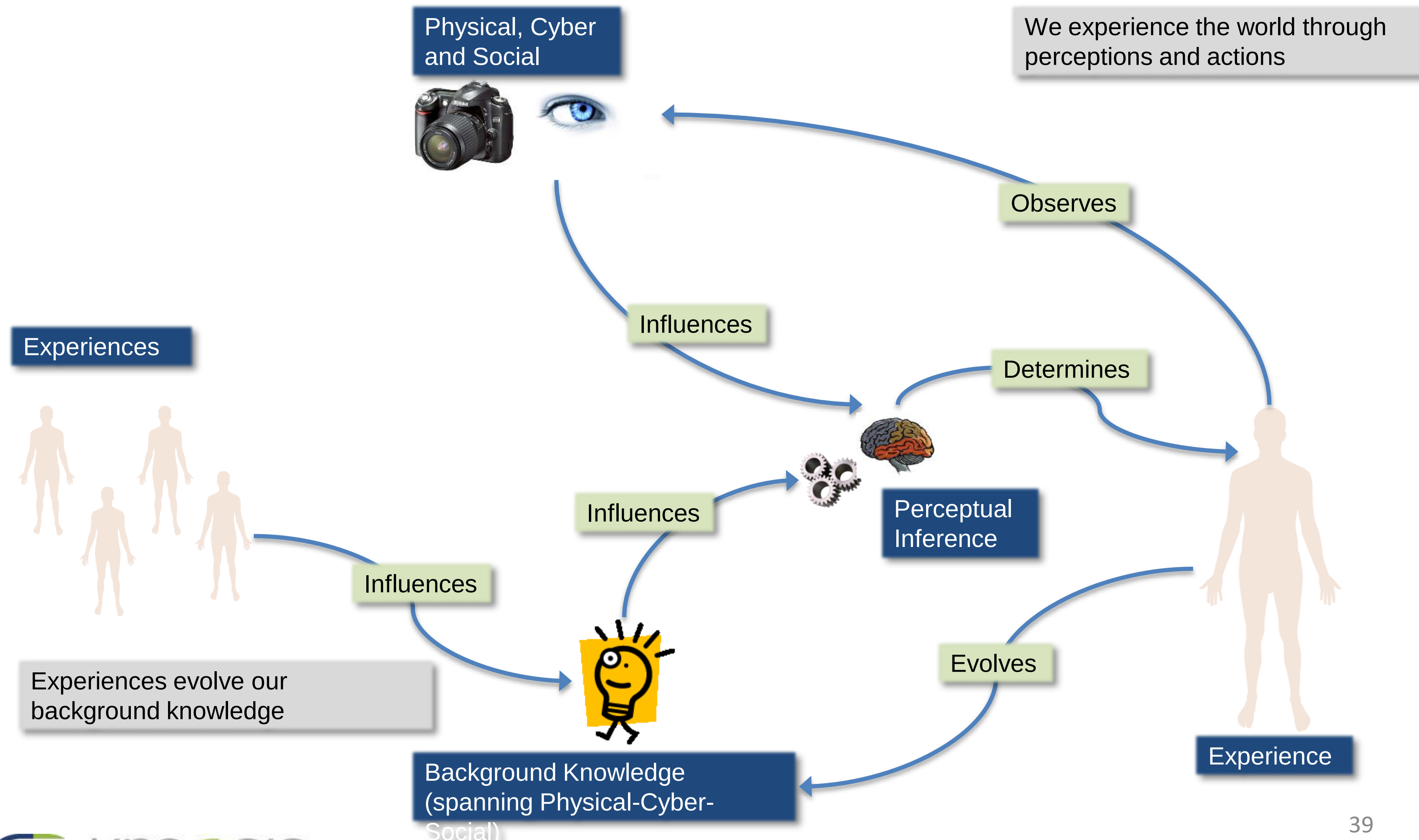
PCS Computing



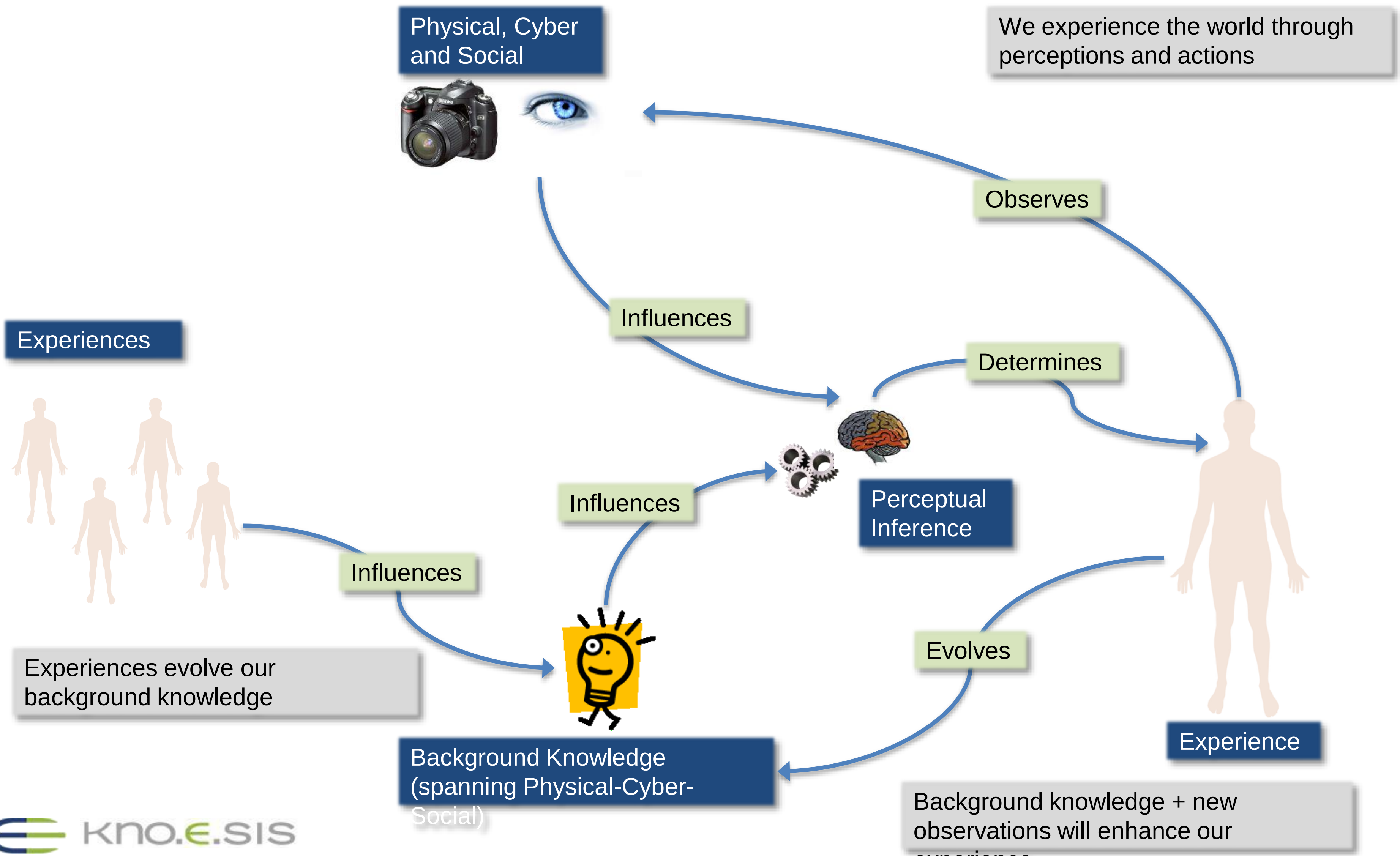
PCS Computing



PCS Computing



PCS Computing



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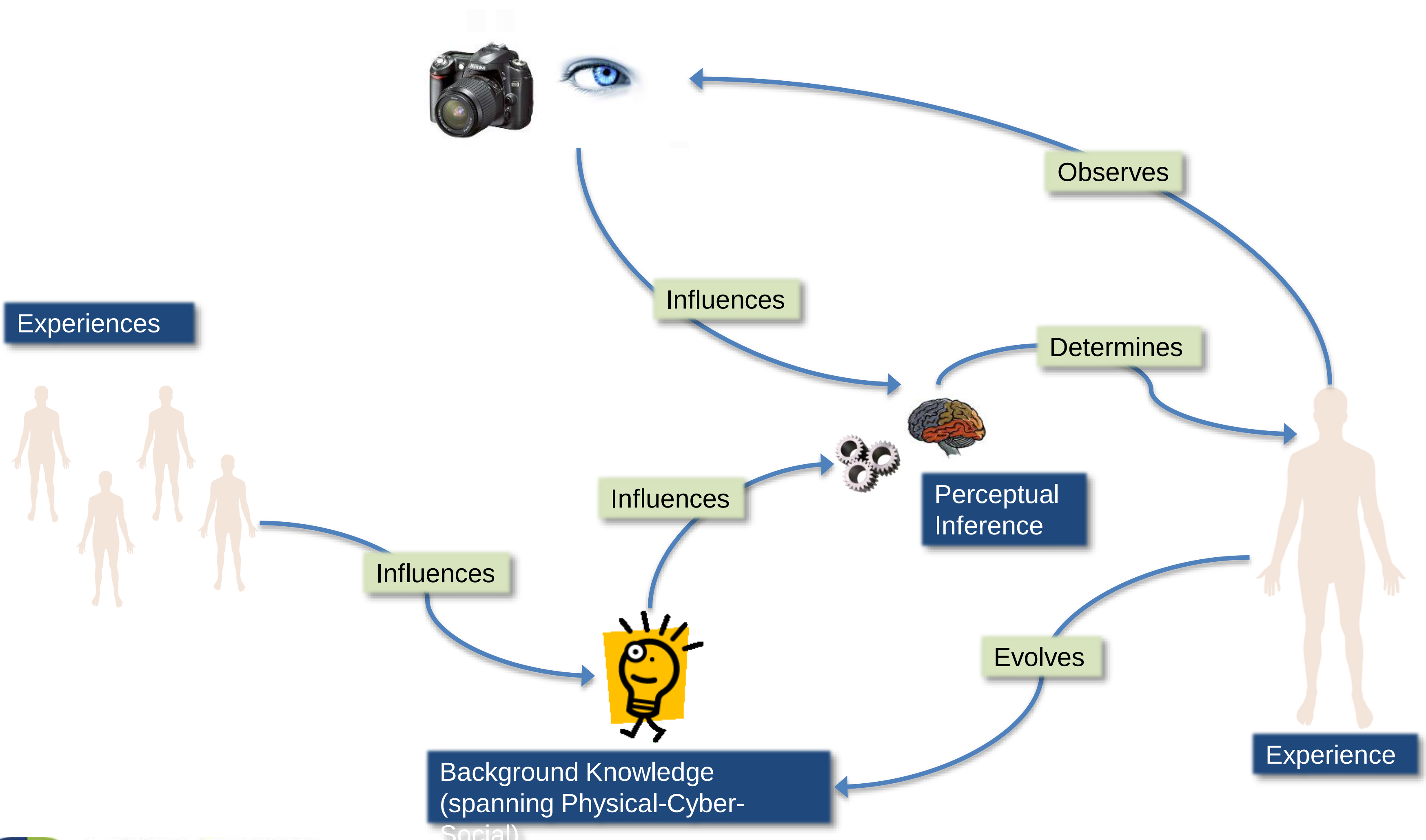
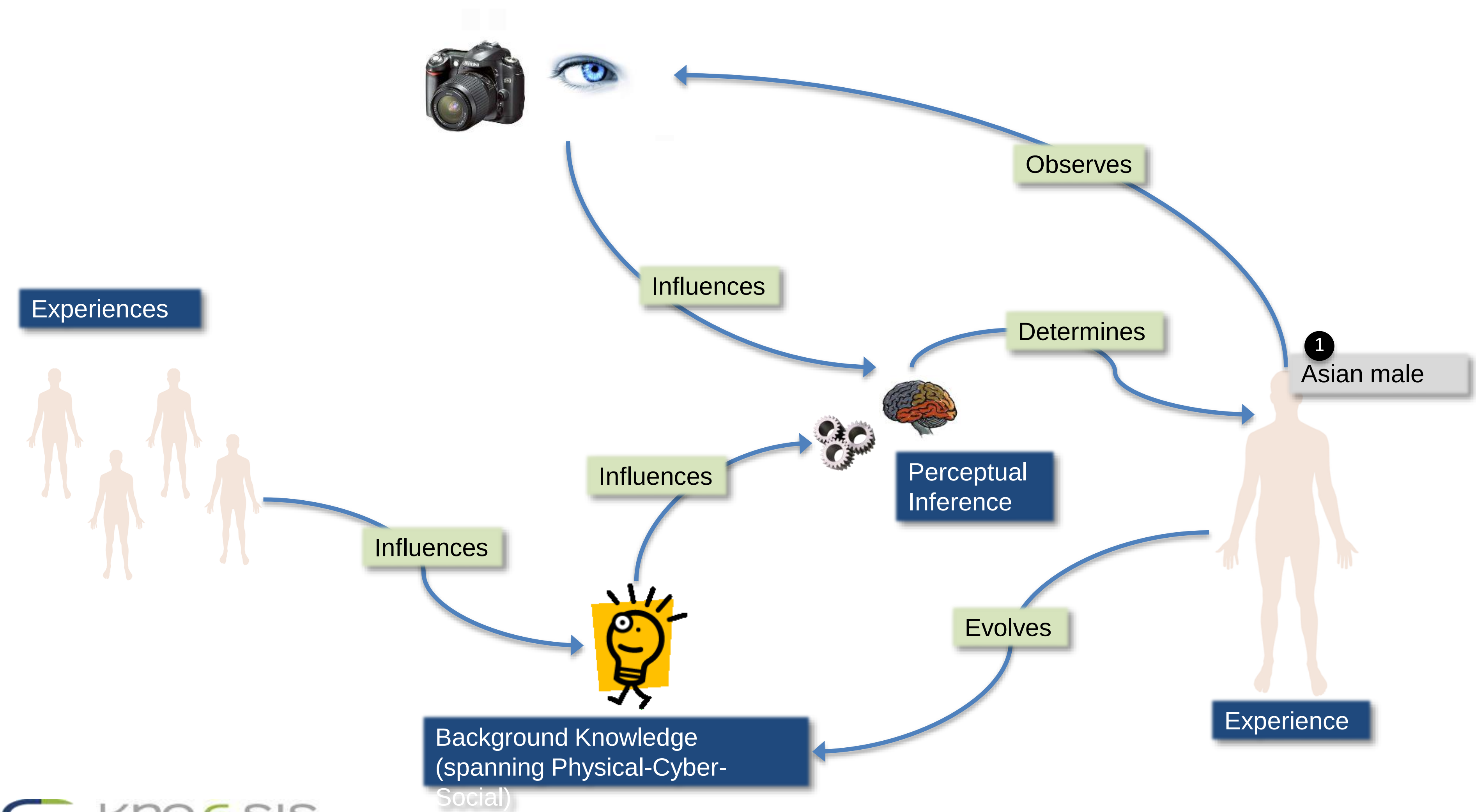
PCS Computing: Scenario of high Blood Pressure (BP)



PCS Computing: Scenario of high Blood Pressure (BP)



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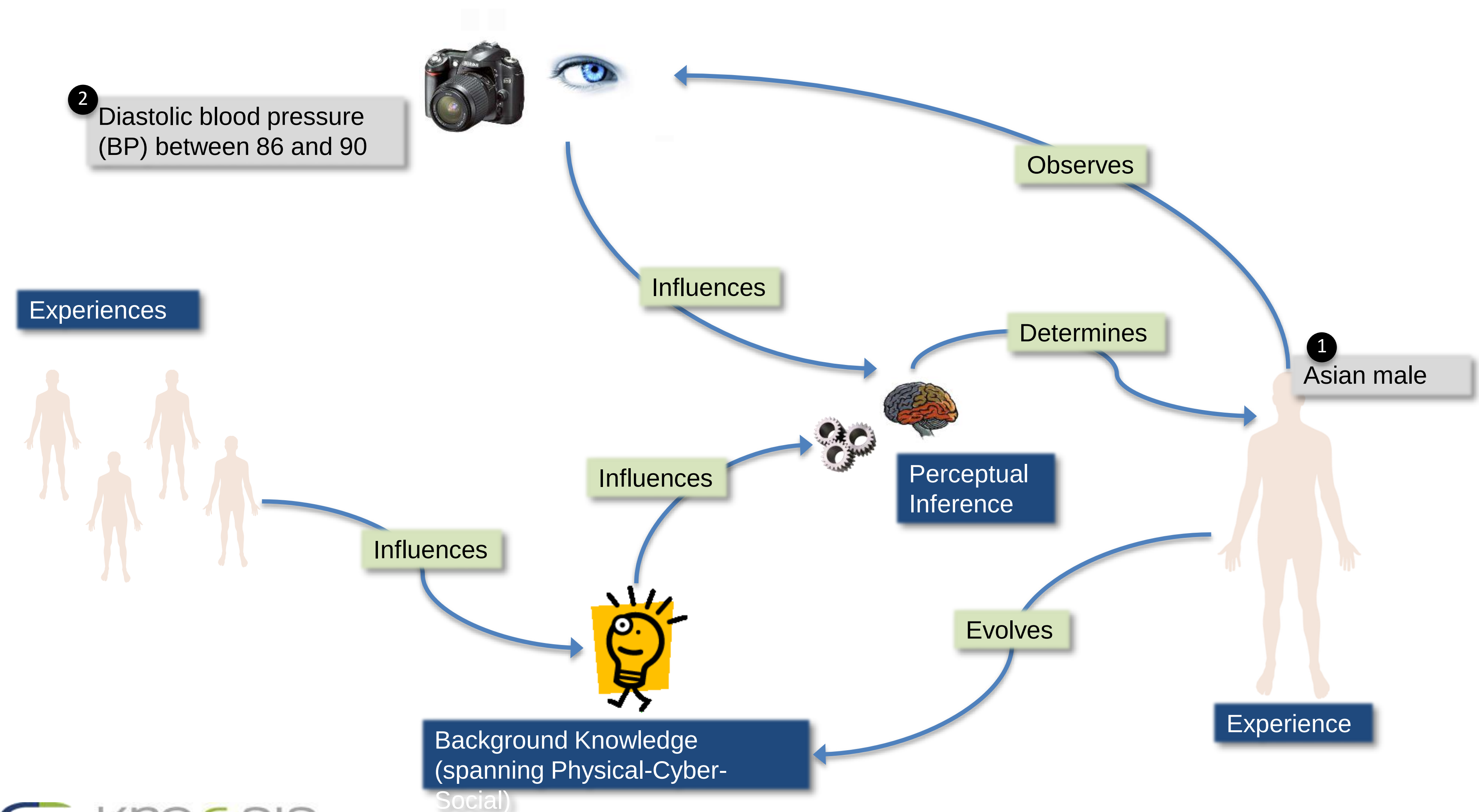
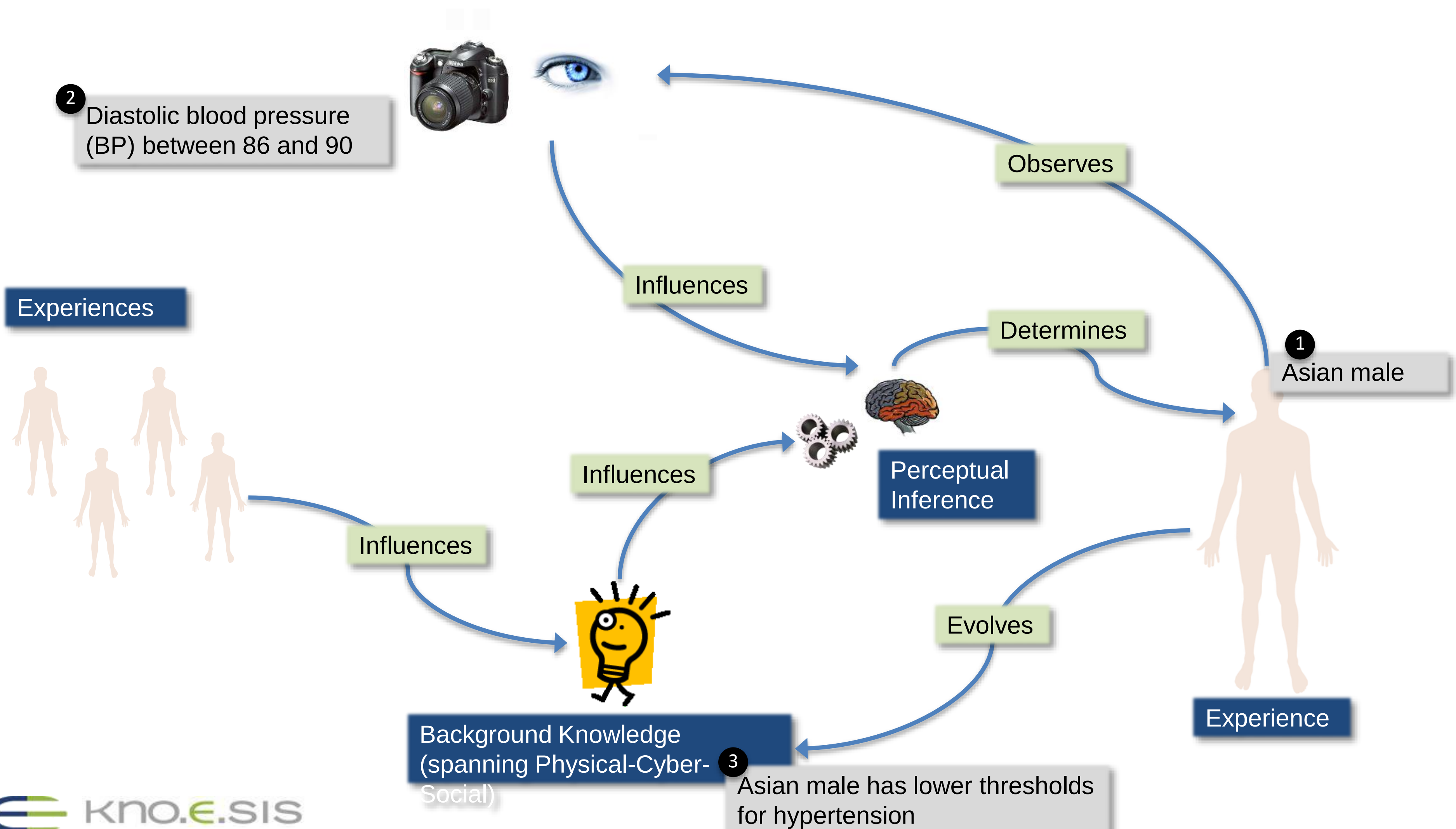


PCS Computing: Scenario of high Blood Pressure (BP)



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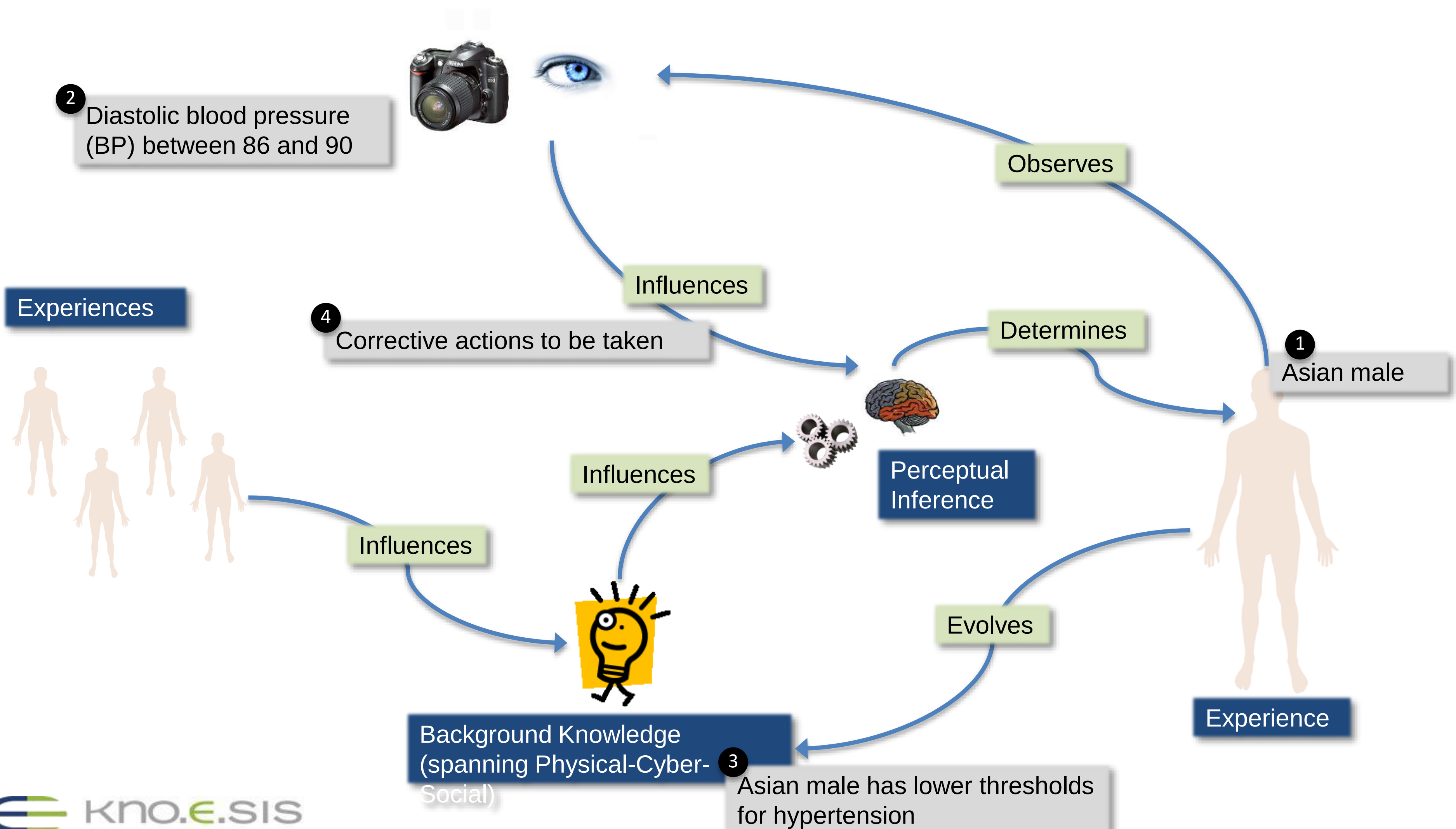
PCS Computing: Scenario of high Blood Pressure (BP)



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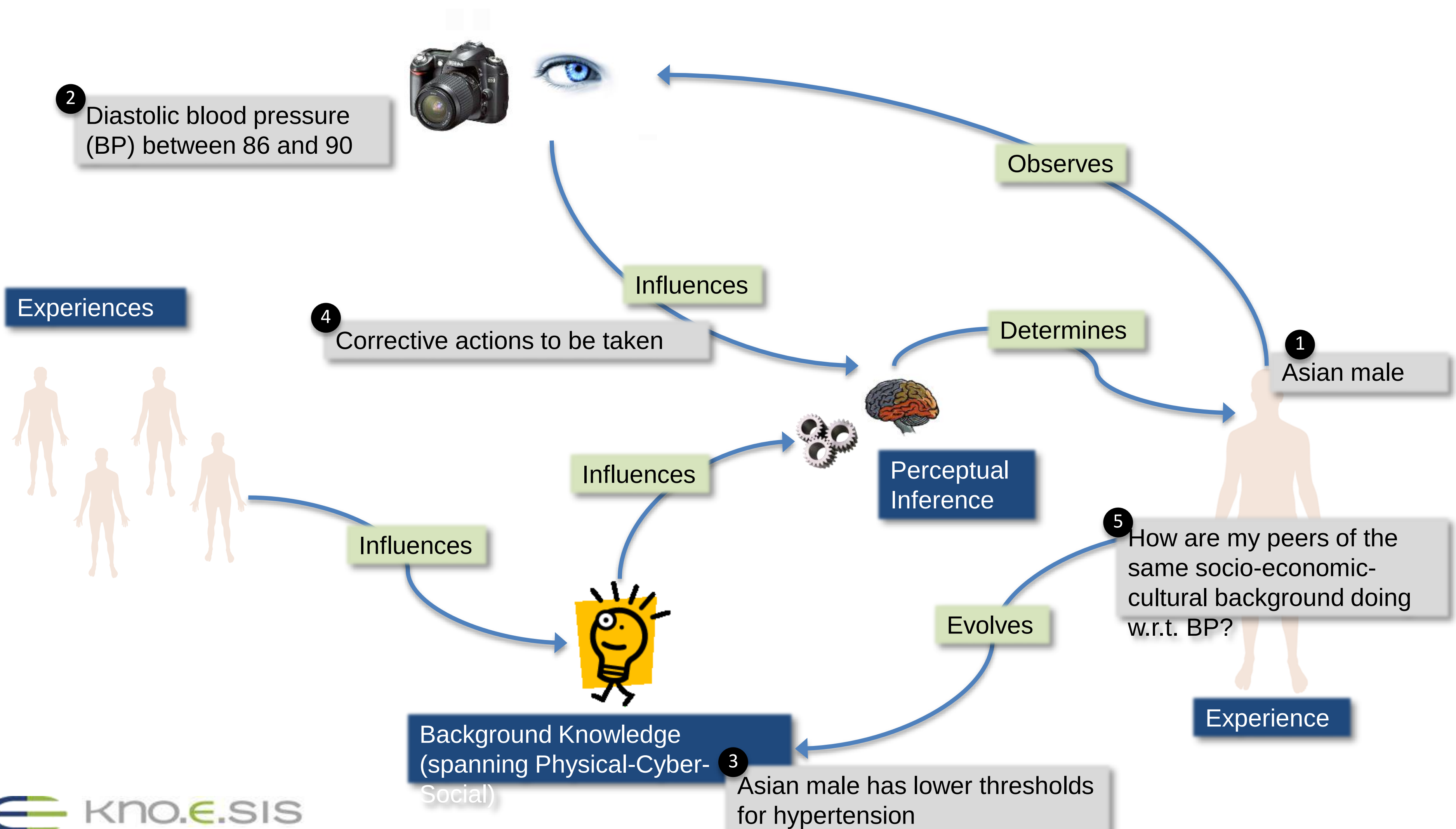
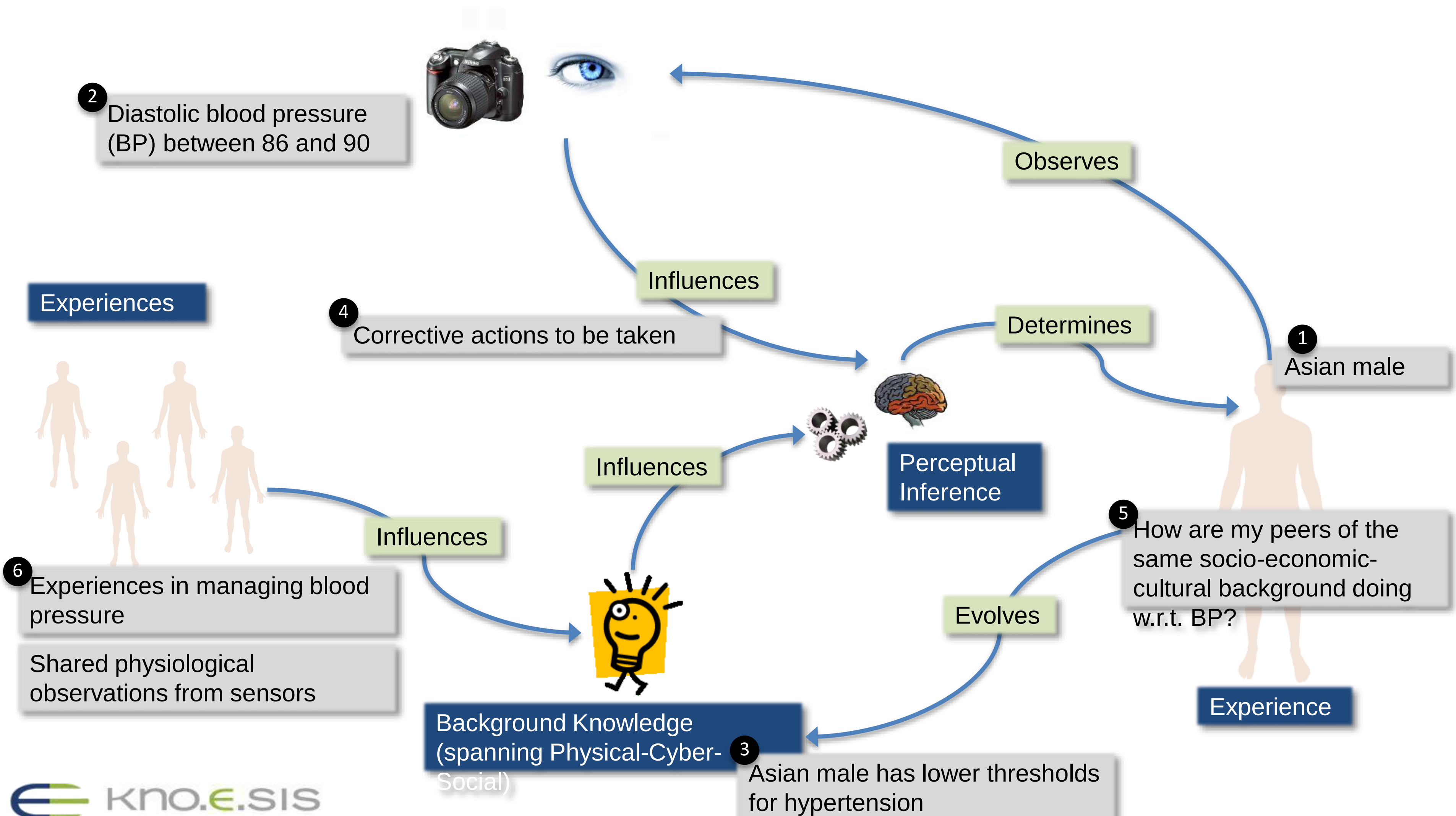
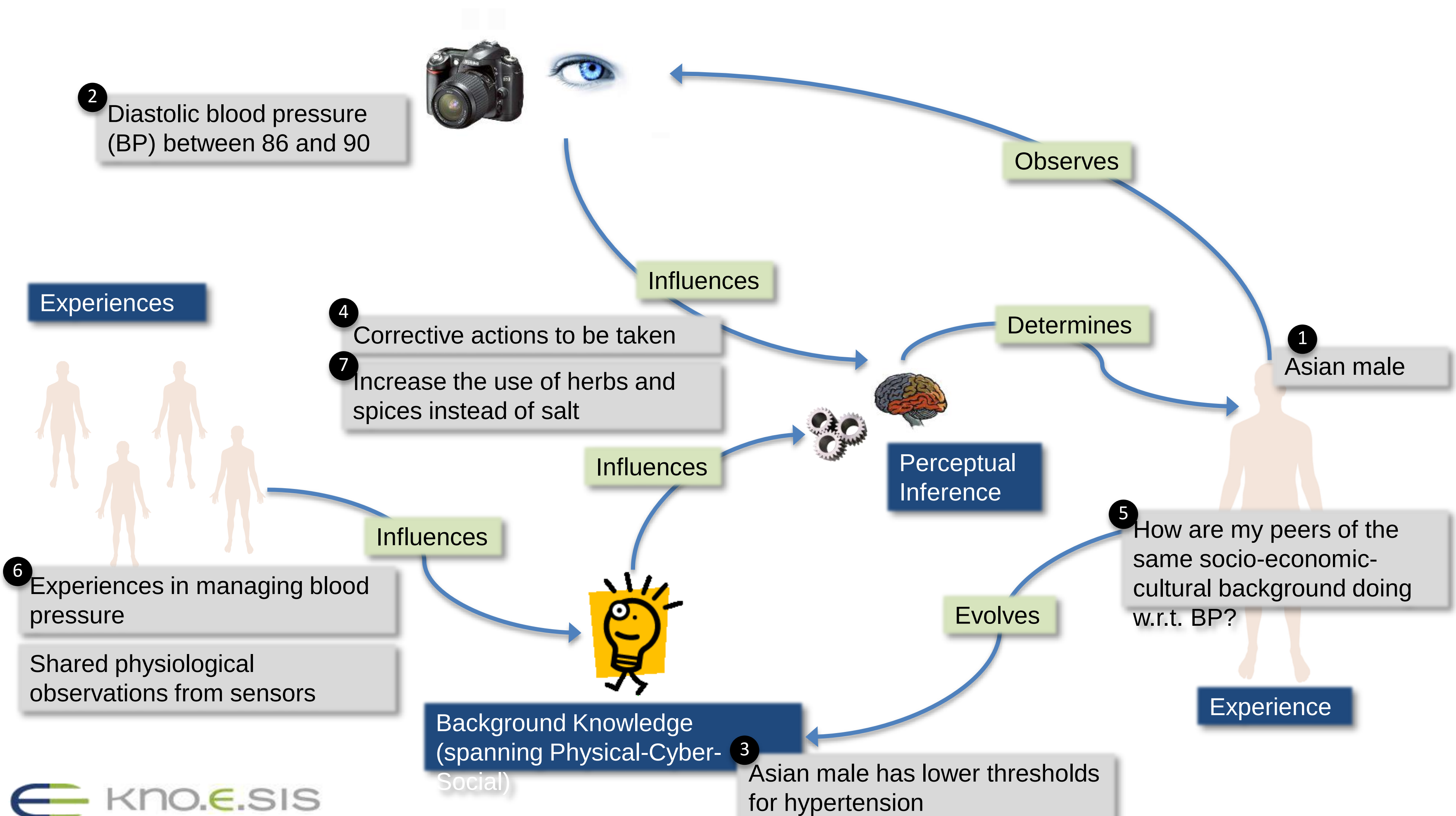
PCS Computing: Scenario of high Blood Pressure (BP)



PCS Computing: Scenario of high Blood Pressure (BP)



PCS Computing: Scenario of high Blood Pressure (BP)



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PCS Computing Operators

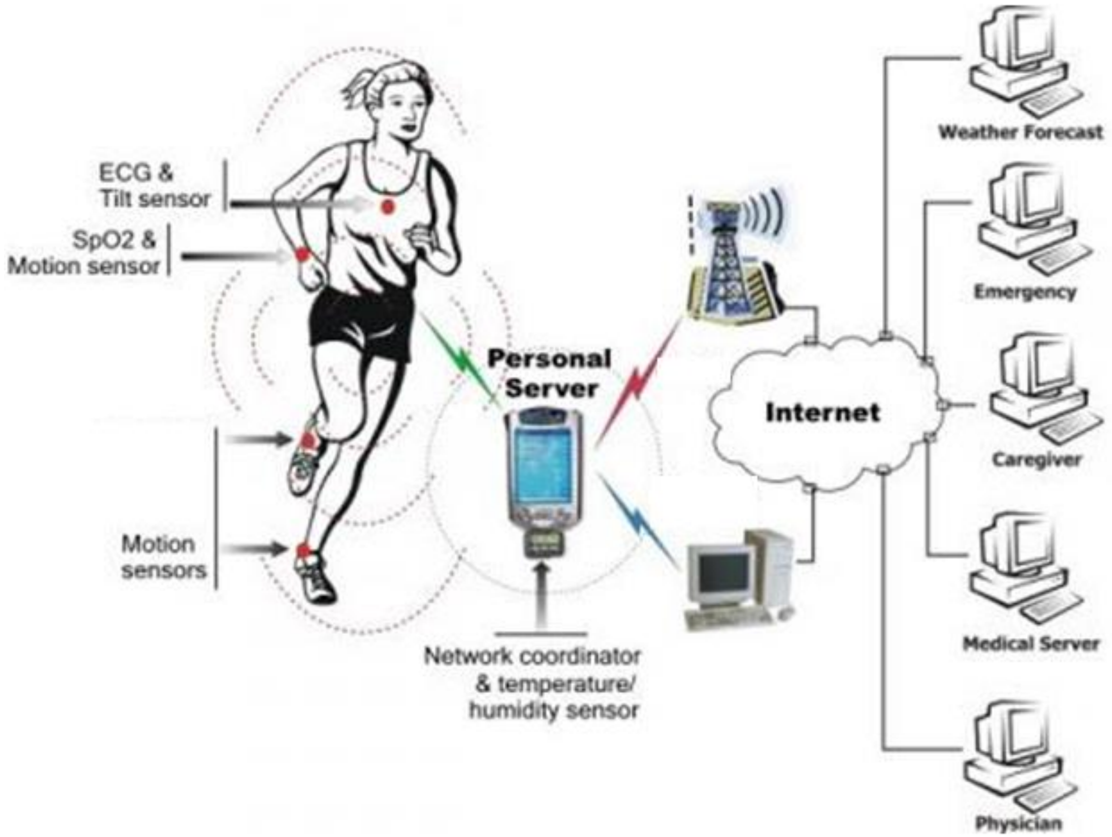
Horizontal Operators

Vertical Operators

Let's look at machine perception, which belongs to the category of vertical operators

Perception (sense making) is the act of engaging in a cyclical process of observation and generation of explanations to transform massive amount of raw data to actionable information in the form of abstractions

Homo Digitus
(Quantified Self)



The Patient of the Future

MIT Technology Review, 2012

http://www.technologyreview.com/featuredstory/426968/the-patient-of-the-future/

Primary challenge is to bridge *the gap between data and knowledge*

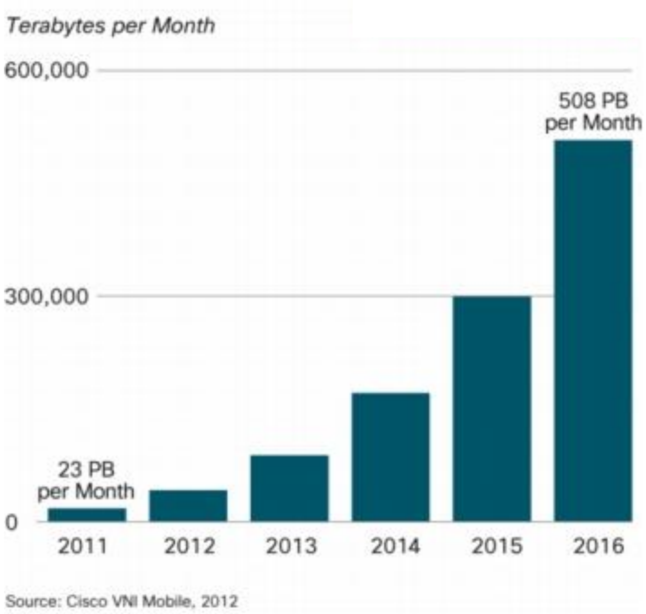
KNOWLEDGE

situation awareness useful
for decision making

DATA

sensor
observations

What if we could automate this *sense making* ability?



… and do it *efficiently* and at *scale*

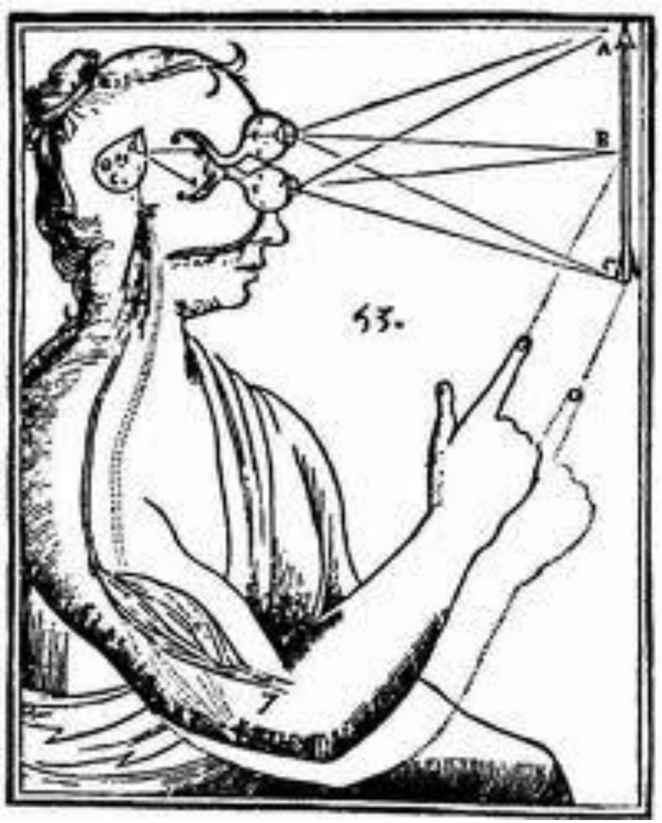
Making sense of sensor data with

intelleg

“to perceive”

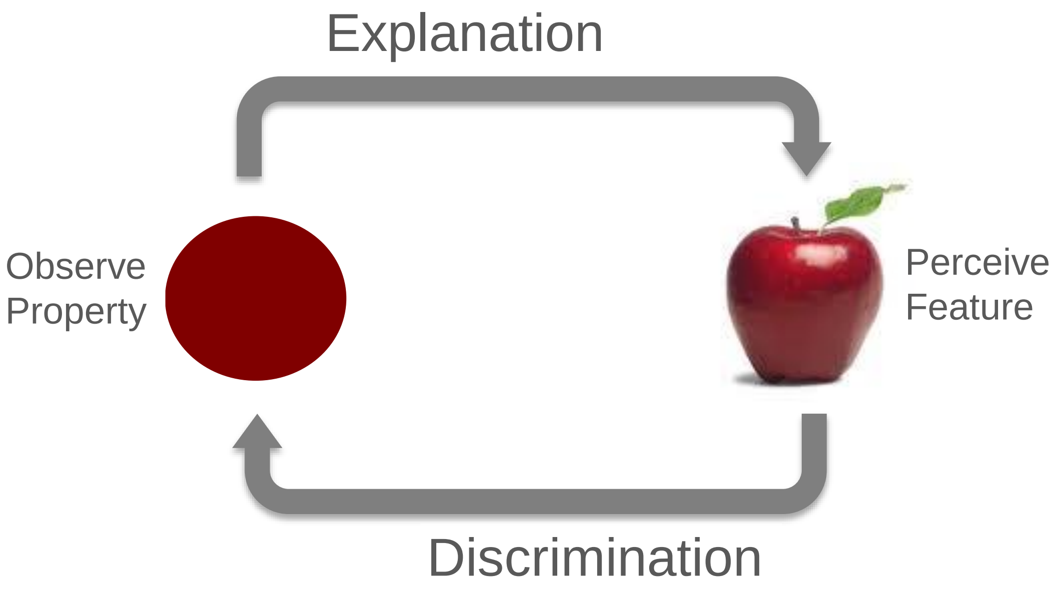
Henson et al An Ontological Approach to Focusing Attention and Enhancing Machine Perception on the Web, Applied Ont, 2011

People are good at *making sense* of sensory input



What can we learn from cognitive models of perception?
The key ingredient is prior knowledge

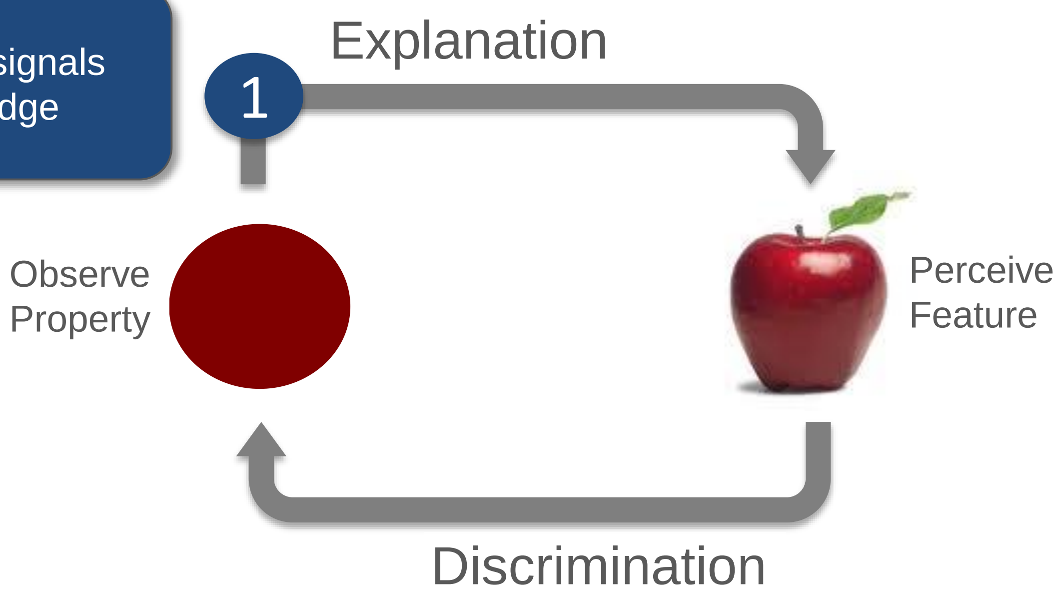
Perception Cycle*



* based on Neisser's cognitive model of perception

Perception Cycle*

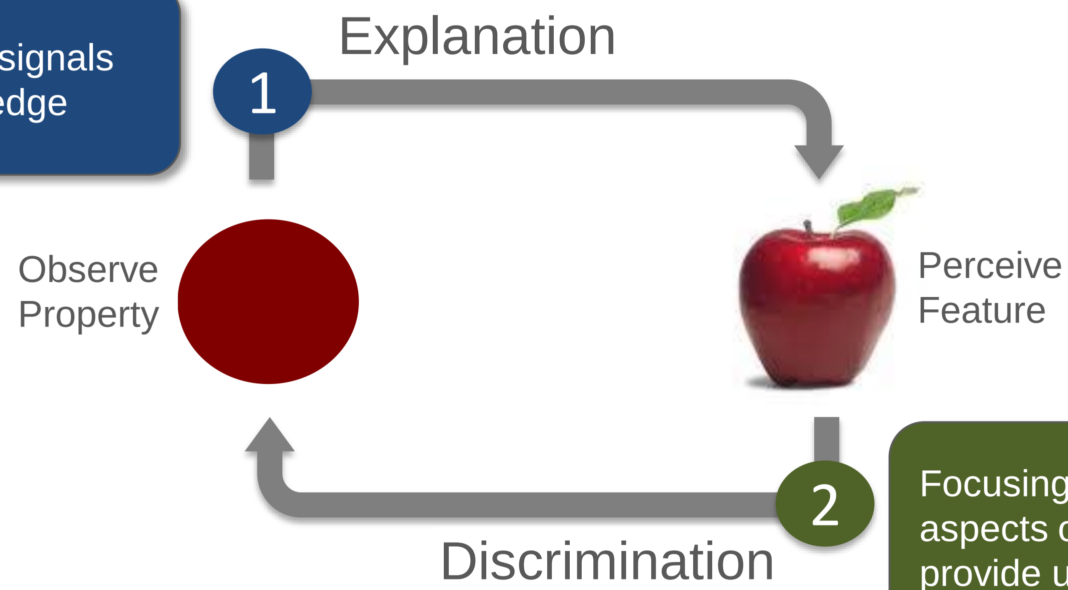
Translating low-level signals into high-level knowledge



* based on Neisser's cognitive model of perception

Perception Cycle*

Translating low-level signals into high-level knowledge



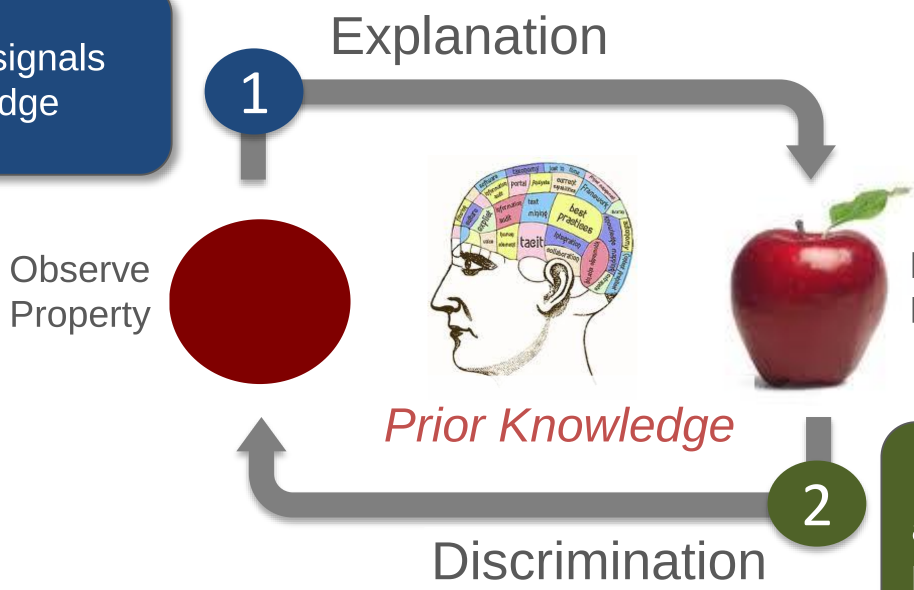
Focusing attention on those aspects of the environment that provide useful information

* based on Neisser's cognitive model of perception

Perception Cycle*

Convert large number of observations to semantic abstractions that provide insights and translate into decisions

Translating low-level signals into high-level knowledge



Focusing attention on those aspects of the environment that provide useful information

* based on Neisser's cognitive model of perception

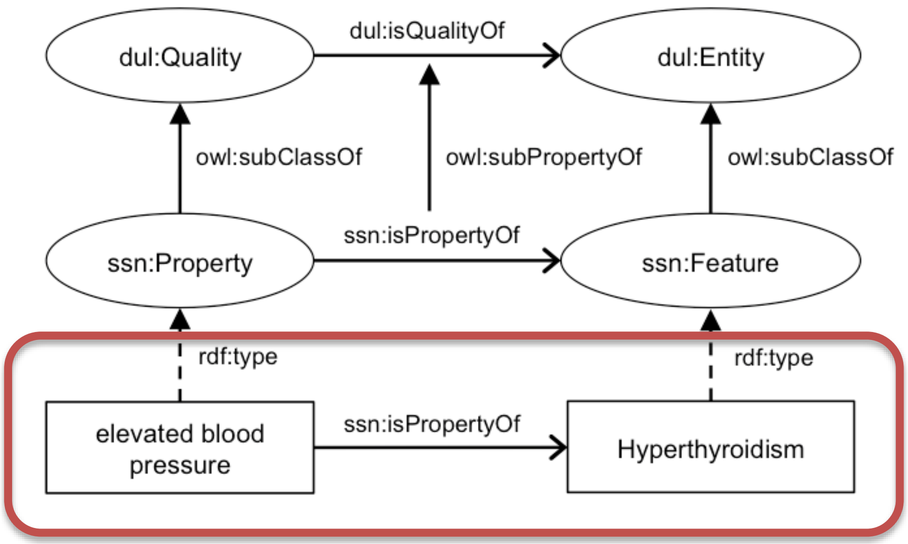
To enable machine perception,

Semantic Web technology is used to integrate sensor data with prior knowledge on the Web

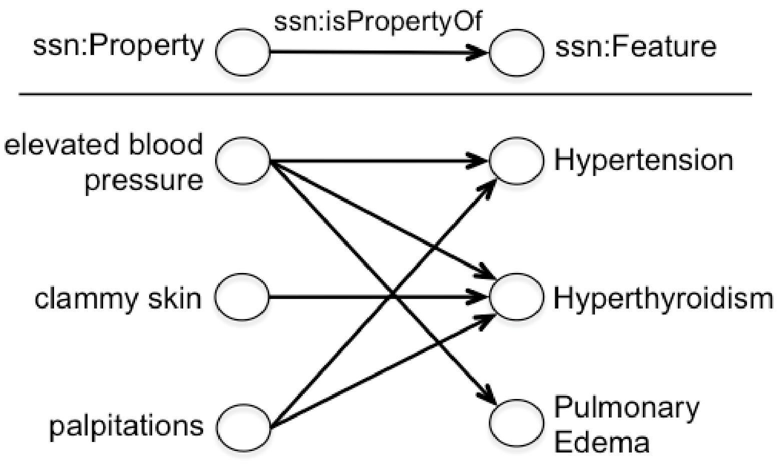
[W3C SSN XG 2010-2011](), [SSN Ontology]()

Prior knowledge on the Web

W3C Semantic Sensor Network (SSN) Ontology

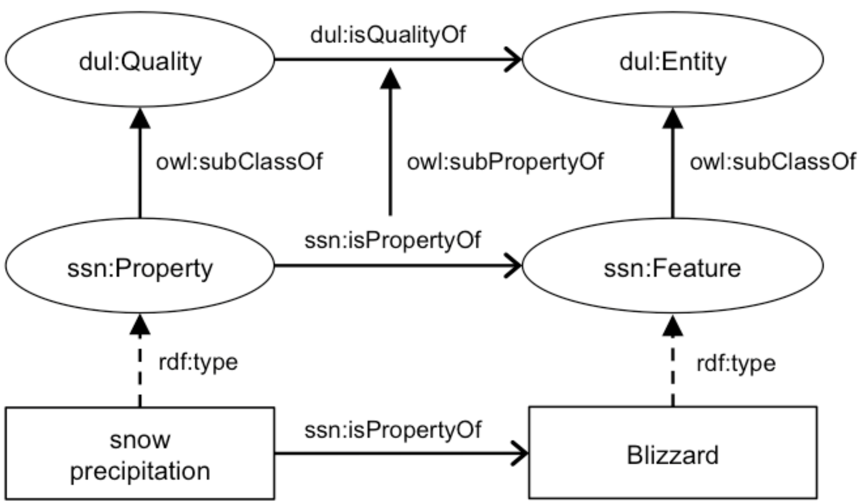


Bi-partite Graph

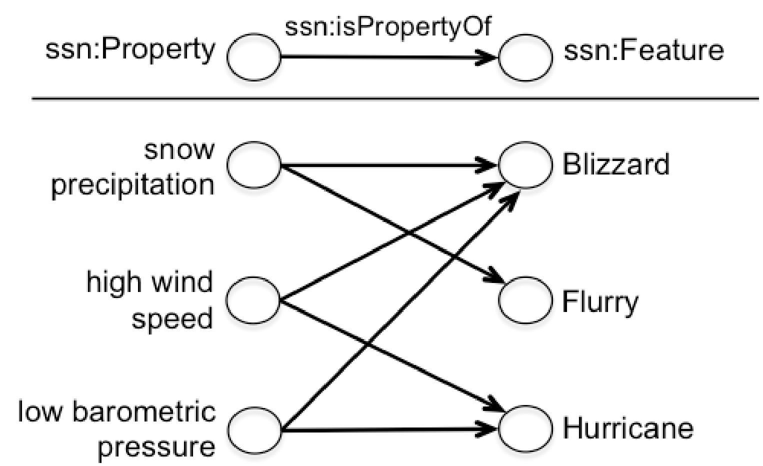


Prior knowledge on the Web

W3C Semantic Sensor Network (SSN) Ontology



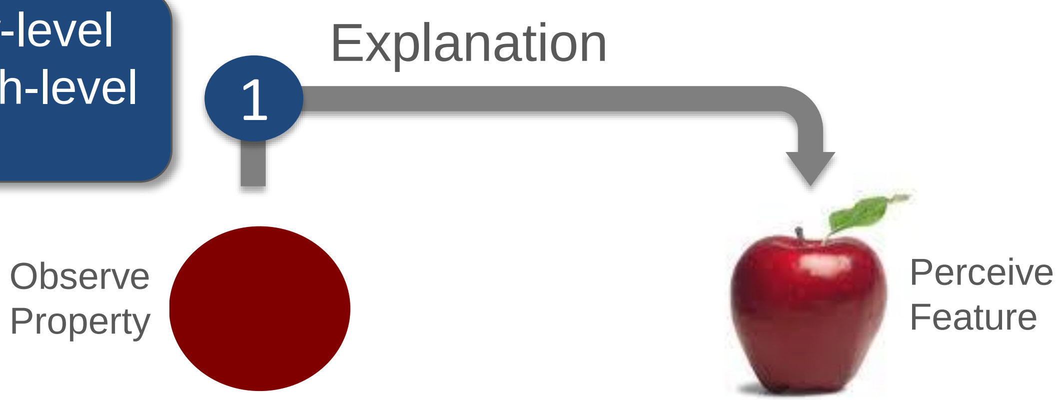
Bi-partite Graph



Explanation

Explanation is the act of choosing the objects or events that best account for a set of observations; often referred to as hypothesis building

Translating low-level signals into high-level knowledge

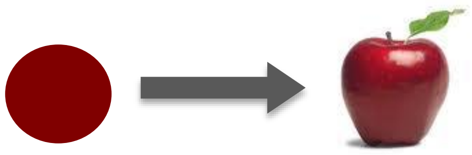


Explanation

Explanation is the act of choosing the objects or events that best account for a set of observations; often referred to as hypothesis building

Inference to the best explanation

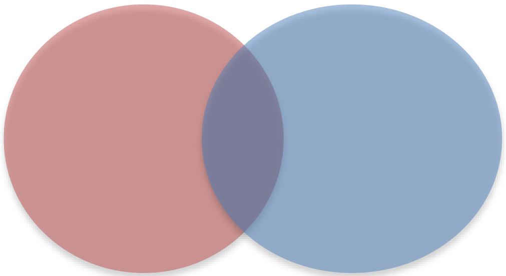
- In general, explanation is an **abductive** problem; and hard to compute



Finding the sweet spot between abduction and OWL

- **Single-feature assumption*** enables use of OWL-DL deductive reasoner

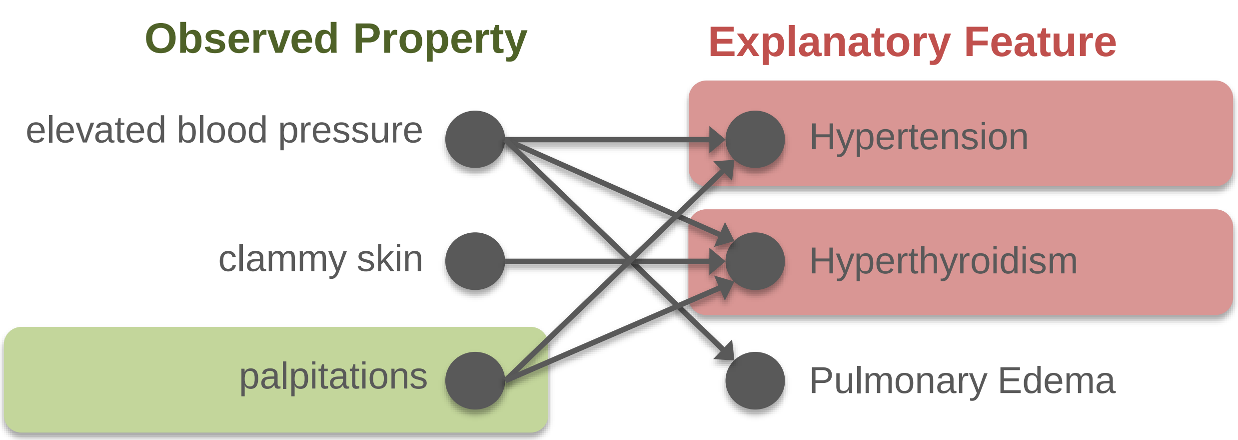
** An explanation must be a single feature which accounts for all observed properties*



Explanation

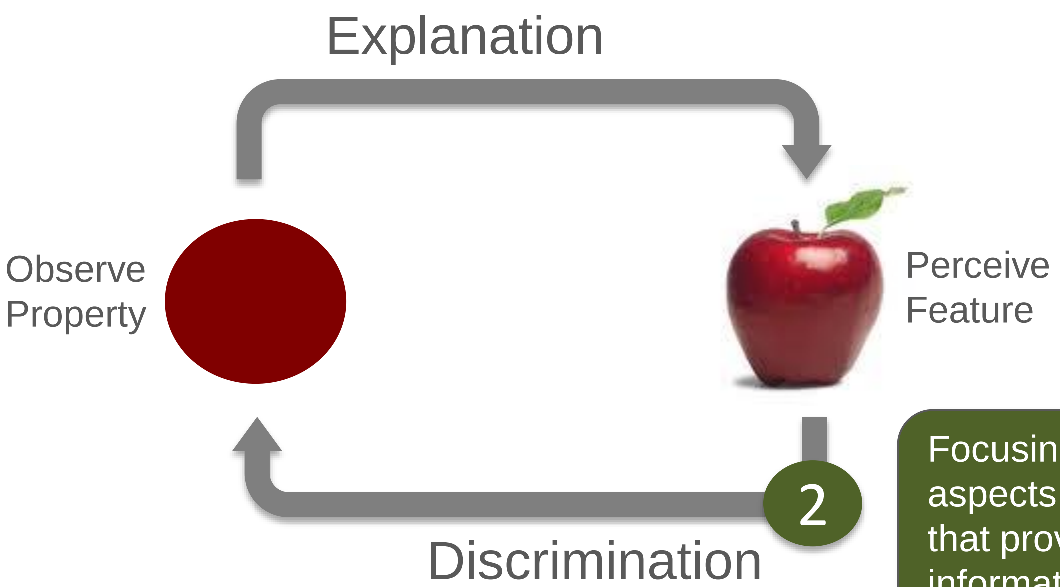
Explanatory Feature: *a feature that explains the set of observed properties*

ExplanatoryFeature ≡ $\exists$ssn:isPropertyOf^{-}.{p_1} ⊓ … ⊓ $\exists$ssn:isPropertyOf^{-}.{p_n}



Discrimination

Discrimination is the act of finding those properties that, if observed, would help distinguish between multiple explanatory features

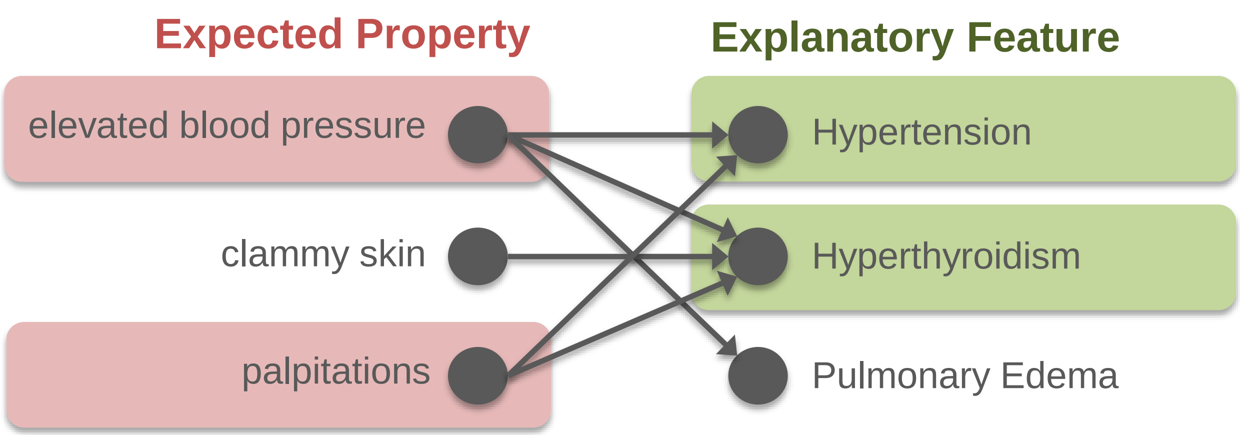


Focusing attention on those aspects of the environment that provide useful information

Discrimination

Expected Property: *would be explained by every explanatory feature*

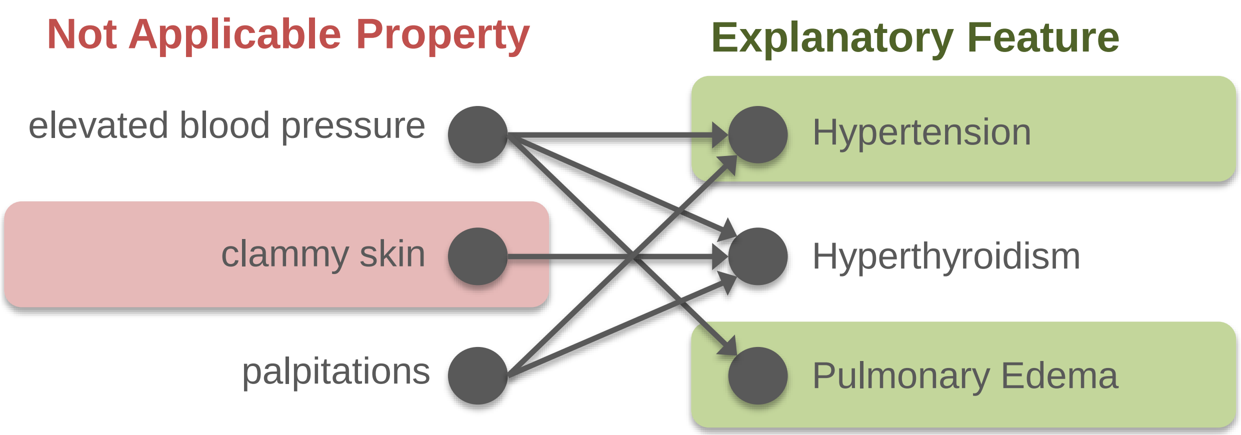
ExpectedProperty ≡ ∃ssn:isPropertyOf.$\{f_1\}$ ⊓ … ⊓ ∃ssn:isPropertyOf.$\{f_n\}$



Discrimination

Not Applicable Property: *would not be explained by any explanatory feature*

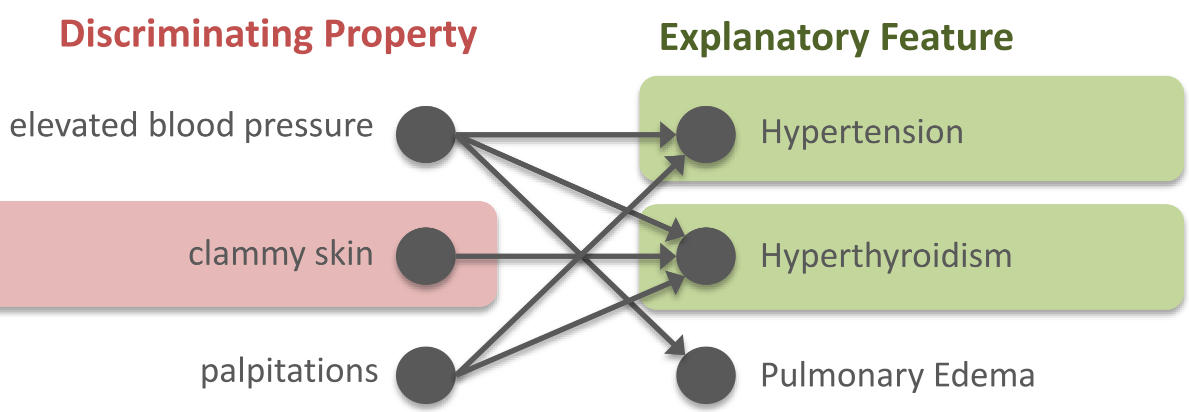
$$\text{NotApplicableProperty} \equiv \neg\exists \text{ssn:isPropertyOf}.\{f_1\} \sqcap \ldots \sqcap \neg\exists \text{ssn:isPropertyOf}.\{f_n\}$$



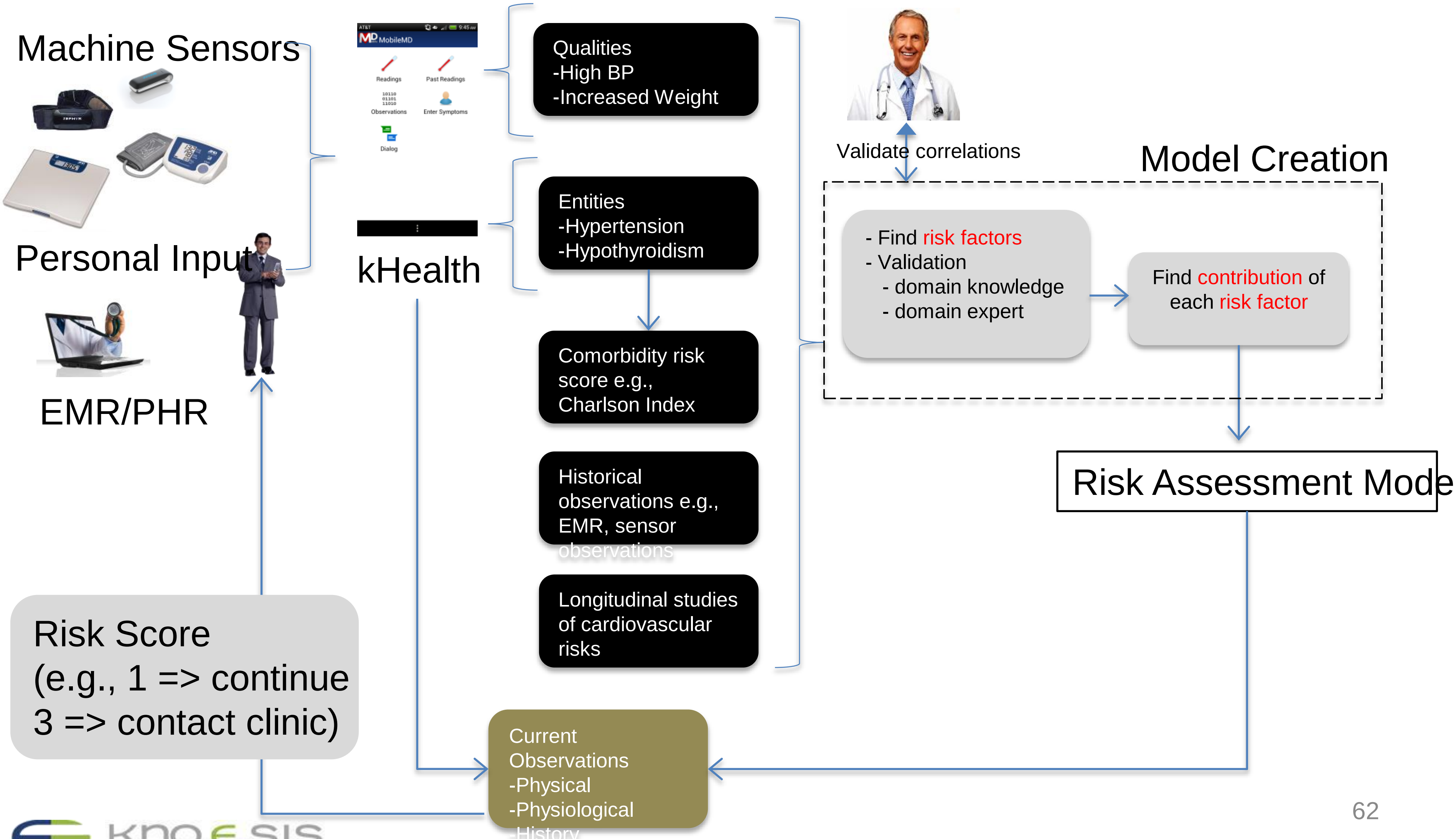
Discrimination

Discriminating Property: *is neither expected nor not-applicable*

DiscriminatingProperty ≡ ¬ExpectedProperty ⊓ ¬NotApplicableProperty



Risk Score: from Data to Abstraction and Actionable Information



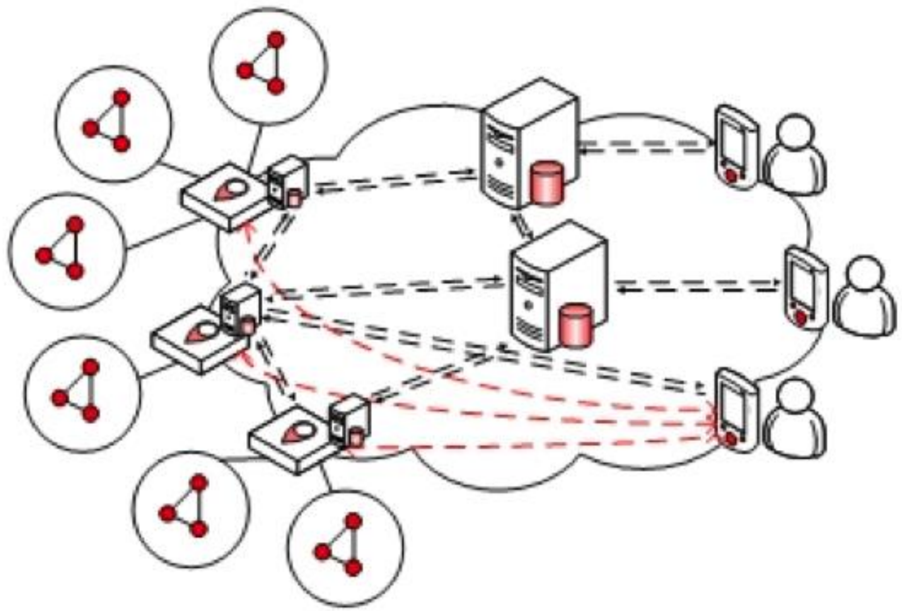
How do we implement machine perception *efficiently* on a resource-constrained device?

Use of OWL reasoner is resource intensive
(especially on resource-constrained devices),
in terms of both memory and time

- Runs out of resources with prior knowledge >> 15 nodes
- Asymptotic complexity: $O(n^3)$

Approach 1: Send all sensor observations to the cloud for processing

Approach 2: downscale semantic processing so that each device is capable of machine perception



intelligence at the edge

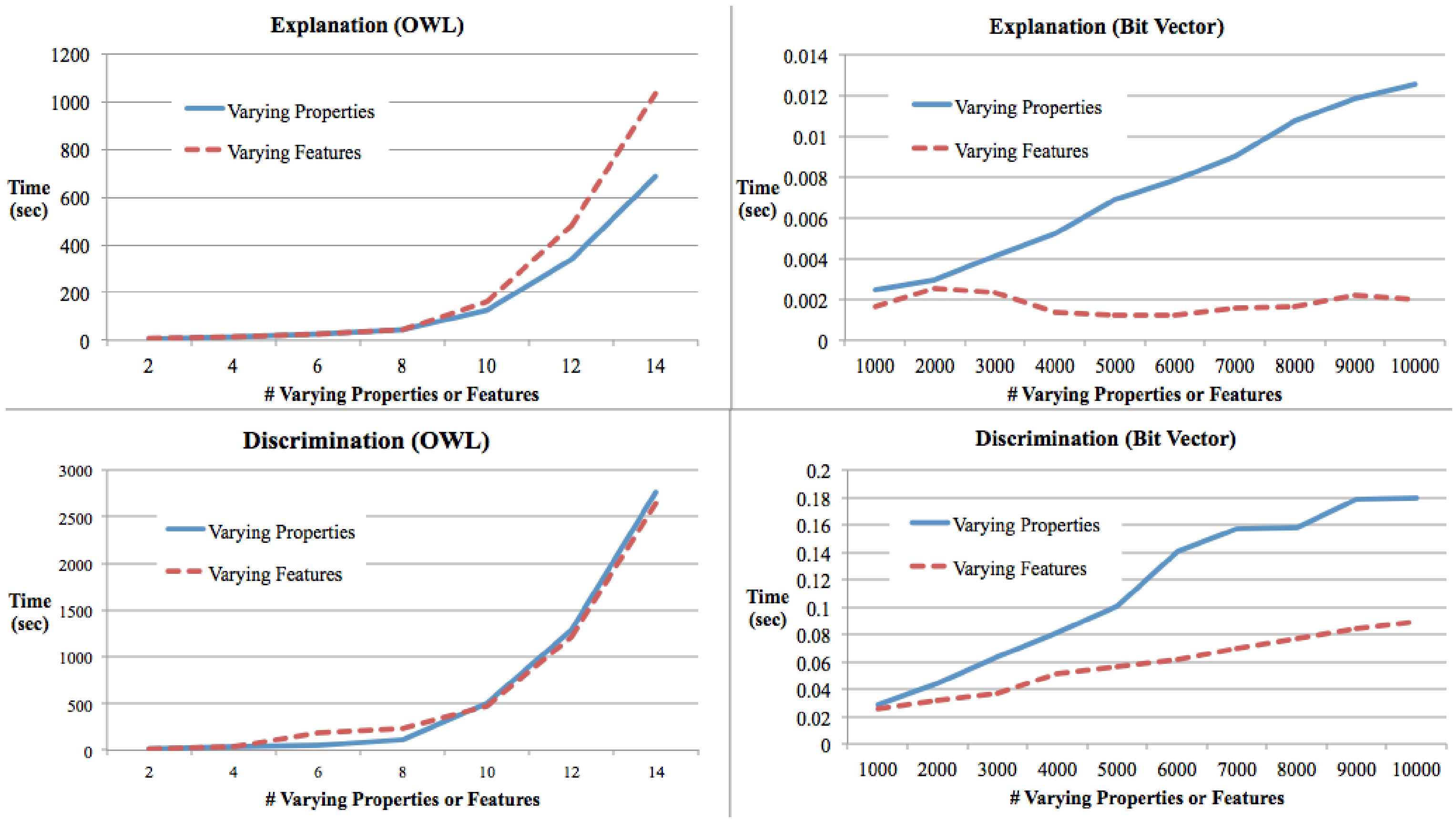
Efficient execution of machine perception

Use *bit vector encodings and their operations* to encode prior knowledge and execute semantic reasoning

010110001101
0011110010101
1000110110110
101100011010
0111100101011
000110101100
0110100111

Henson et al. 'An Efficient Bit Vector Approach to Semantics-based Machine Perception in Resource-Constrained Devices, ISWC 2012.

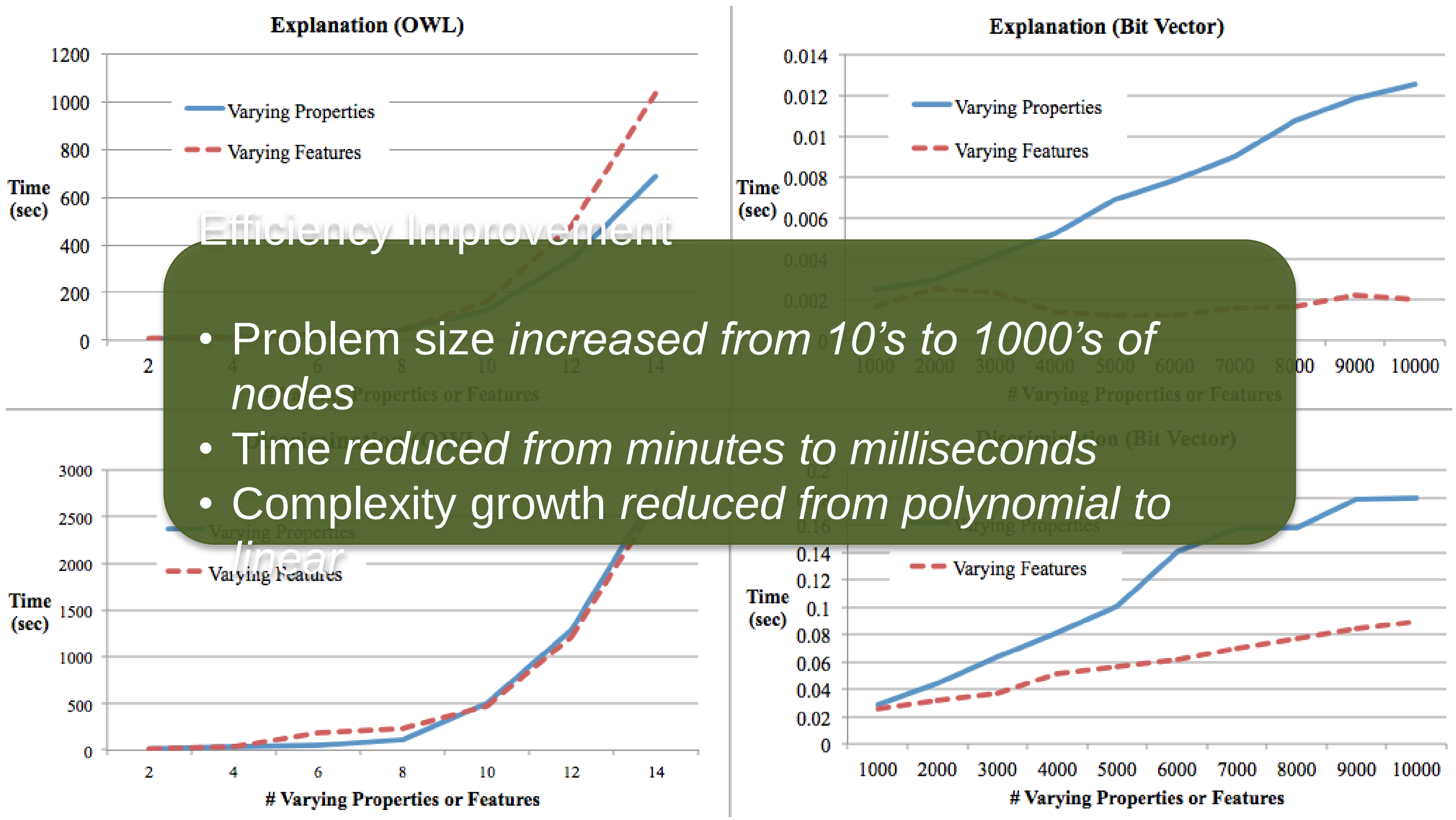
Evaluation on a mobile device



$O(n^3) < x < O(n^4)$

$O(n)$

Evaluation on a mobile device



Efficiency Improvement

- Problem size *increased from 10's to 1000's of nodes*
- Time *reduced from minutes to milliseconds*
- Complexity growth *reduced from polynomial to linear*

$O(n^3) < x < O(n^4)$

$O(n)$

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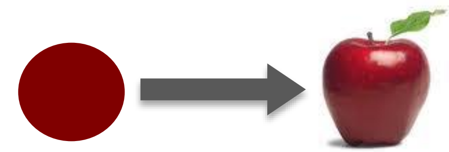
Semantic Perception for smarter analytics: 3 ideas to takeaway

1 *Translate low-level data to high-level knowledge*
Machine perception can be used to convert low-level sensory signals into high-level knowledge useful for decision making



2 *Prior knowledge is the key to perception*
Using SW technologies, machine perception can be formalized and integrated with prior knowledge on the Web

3 *Intelligence at the edge*
By downscaling semantic inference, machine perception can execute efficiently on resource-constrained devices

Application of semantic perception to healthcare…

kHealth

Knowledge-enabled Healthcare

Our Motivation

kHealth: knowledge-enabled healthcare

Through physical monitoring and analysis, our cellphones could act as an early warning system to detect serious health conditions, and provide actionable information

canary in a coal mine

Canary

kHealth – knowledge-enabled healthcare

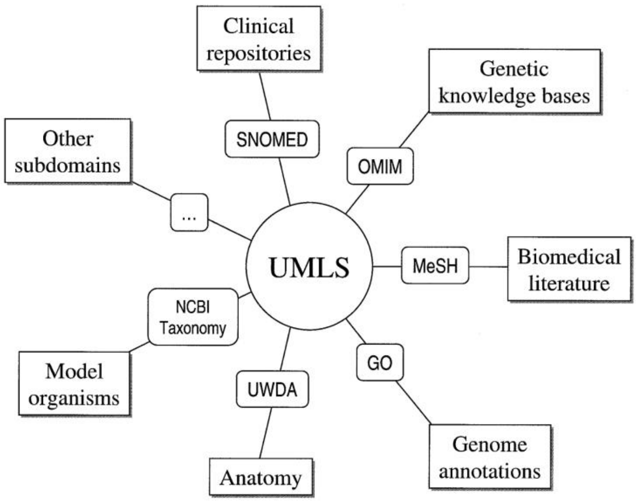
Approach:

- Use semantic perception inference
- with data from cardio-related sensors
- and curated medical background knowledge on the Web

to ask the patient *contextually relevant questions*

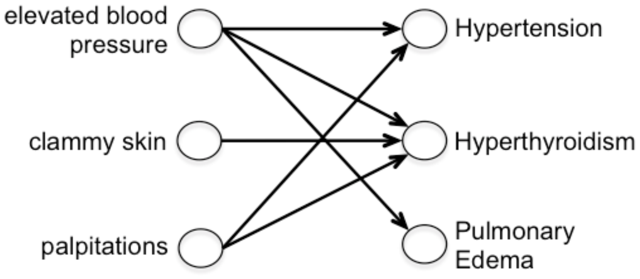
Cardiology Background Knowledge

Unified Medical Language System



Healthline™
Connect to Better Health

Causal Network



- Symptoms: 284
- Disorders: 173
- Causal Relations: 1944

kHealth Kit for the application for reducing ADHF readmission

Android Device
(w/ kHealth App)

Sensors

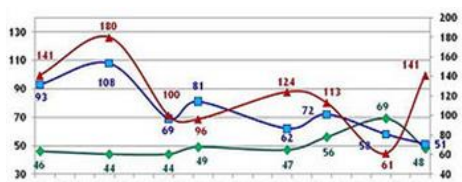
Weight Scale

Heart Rate Monitor

Blood Pressure Monitor

Total cost: < $500

Explanation in kHealth



via Bluetooth

Observed Property

- Abnormal heart rate
- High blood pressure

Explanatory Feature

- Panic Disorder
- Hypoglycemia
- Hyperthyroidism
- Heart Attack
- Septic Shock

Focus in kHealth

Contextually dependent questioning based on prior observations

(*from 284 possible questions*)

Are you feeling lightheaded?

yes

Are you have trouble taking deep breaths?

yes

Observed Property

- Abnormal heart rate
- High blood pressure
- **Lightheaded**
- **Trouble breathing**

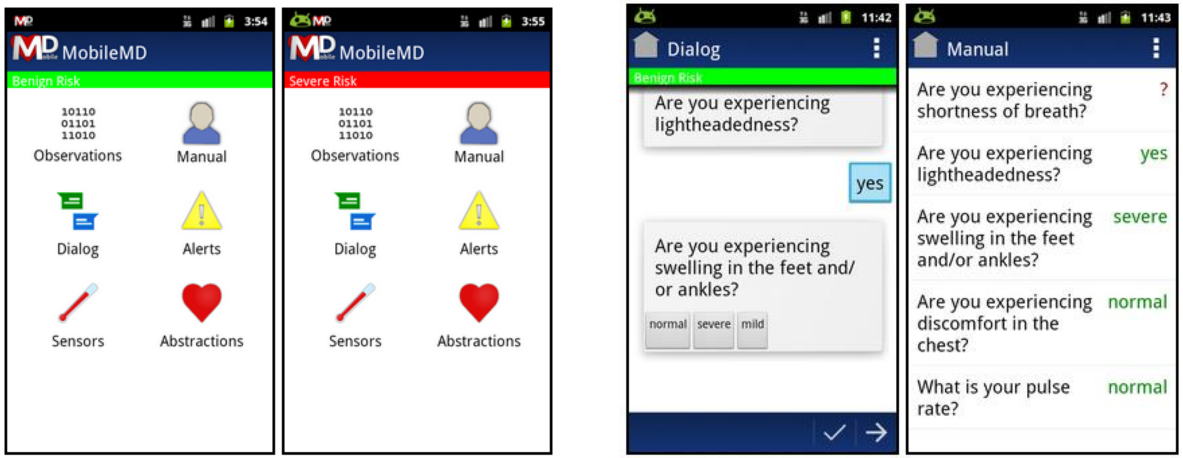
Explanatory Feature

- ~~Panic Disorder~~
- Hypoglycemia
- Hyperthyroidism
- ~~Heart Attack~~
- ~~Septic Shock~~

kHealth Summary

A kHealth application leverage low-cost sensors toward reducing hospital readmissions of ADHF patients

kHealth will continue toward the vision of Physical-Cyber-Social computing to understand, correlate, and personalize healthcare



Paper at ISWC: C. Henson, K. Thirunarayan, A. Sheth, [An Efficient Bit Vector Approach to Semantics-based Machine Perception in Resource-Constrained Devices]

Pre-clinical usability trial

Wexner Medical Center

Dr. William Abraham, M.D.
Director of Cardiovascular Medicine

Other Potential Applications

- Asthma, Stress, COPD, Obesity, GI, etc.

Demos

- Real Time Feature Streams: http://www.youtube.com/watch?v=_ews4w_eCpg
- kHealth: http://www.youtube.com/watch?v=btnRi64hJp4

PCS Computing for Asthma

Asthma: Severity of the problem

25 million	People in the U.S. are diagnosed with asthma (7 million are children)[1].
300 million	People suffering from asthma worldwide[2].
$50 billion	Spent on asthma alone in a year[2]
155,000	Hospital admissions in 2006[3]
593,000	Emergency department visits in 2006[3]

[1]http://www.nhlbi.nih.gov/health/health-topics/topics/asthma/
[2]http://www.lung.org/lung-disease/asthma/resources/facts-and-figures/asthma-in-adults.html
[3]Akinbami et al. (2009). Status of childhood asthma in the United States, 1980–2007. *Pediatrics*,*123*(Supplement 3), S131-S145

Specific Aims

Can we detect asthma/allergy early?

- Using data from on-body sensors, and environmental sensors
- Using knowledge from an asthma ontology, generated from asthma knowledge on the Web and domain expertise
- Generate a *risk measure* from collected data and background knowledge

Can we characterize asthma/allergy progression?

- State of asthma patient may change over time
- Identifying risky progressions before worsening of the patient state

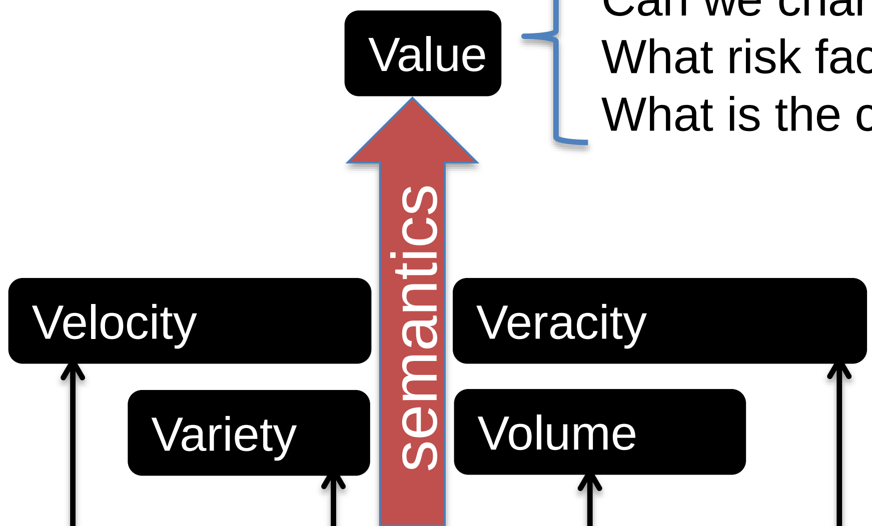
Does the early detection of asthma/allergy, and subsequent intervention/treatment, lead to *improved outcomes*?

- Improved outcomes could be improved health (less serious symptoms), less need for invasive treatments, preventive measures (e.g. avoiding risky environmental conditions), less cost, etc.

Massive Amount of Data to Actions

Asthma is a multifactorial disease with health signals spanning ***personal***, ***public*** health, and ***population*** levels.

Can we detect the asthma severity level?
Can we characterize asthma control level?
What risk factors influence asthma control?
What is the contribution of each risk factor?



Understanding relationships betwee
health signals and asthma attacks
for providing actionable information

Real-time health signals from personal level (e.g., Wheezometer, NO in breath, accelerometer, microphone), public health (e.g., CDC, Hospital EMR), and population level (e.g., pollen level, CO2) arriving continuously in fine grained samples potentially with missing information and uneven sampling frequencies.

Asthma Example of Actionable Information

Asthma Healthcare Application

Personal

Public Health

Population Level

Detection of events, such as wheezing sound, indoor temperature, humidity, dust, and CO_2 level

Action in the Physical World

Close the window at home during day to avoid CO_2 inflow, to avoid asthma attacks at night

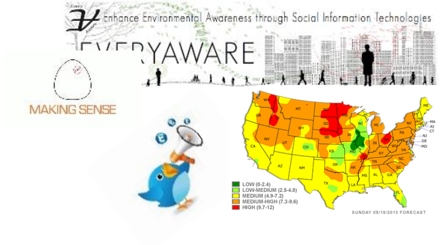
PCS Computing Challenges

Variety: Health signals span heterogeneous sources
Volume: Health signals are fine grained
Velocity: Real-time change in situations
Veracity: Reliability of health signals may be compromised

Personal

Value: Can I reduce my asthma attacks at night?

Population Level



Public Health

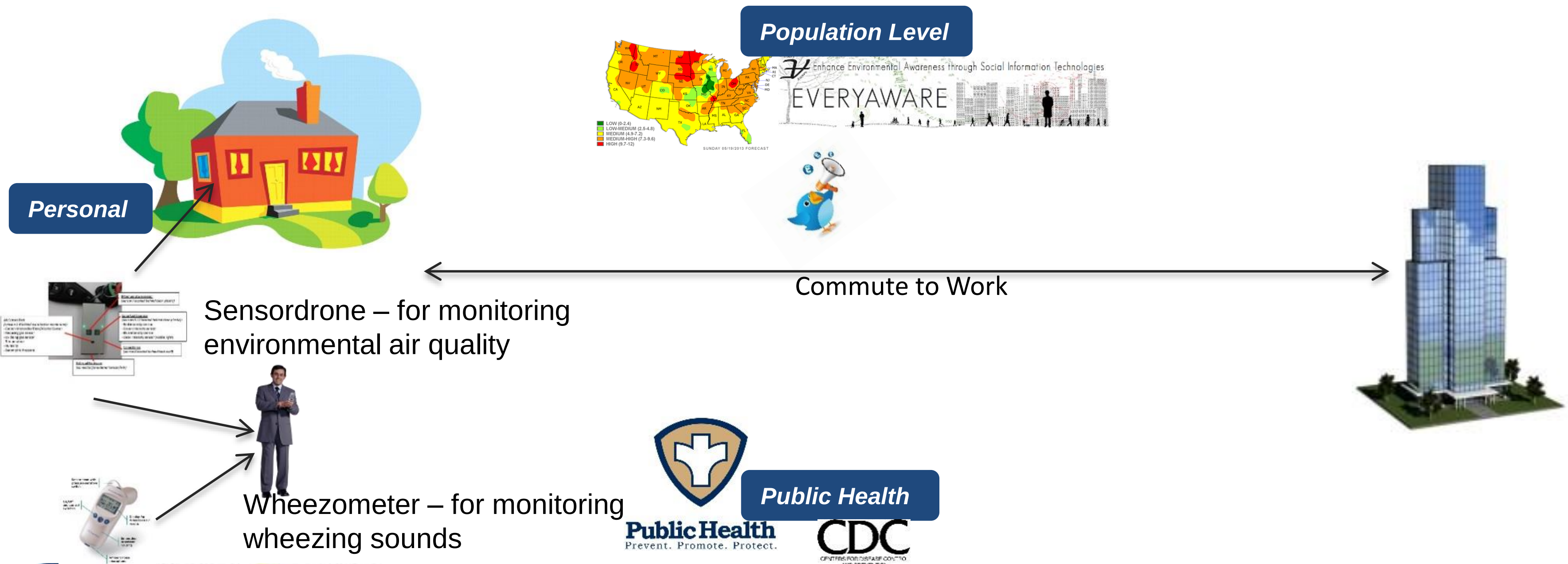
CDC
CENTERS FOR DISEASE CONTROL AND PREVENTION

Public Health
Prevent. Promote. Protect.

Value: Decision support to doctors by providing them with deeper insights into patient asthma care

PCS Computing: Asthma Scenario

Can I reduce my asthma attacks at night?



PCS Computing: Asthma Scenario

What are the triggers?

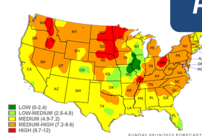
What is the wheezing level?

What is the exposure level over a day?

What is the air quality indoors?

What is the propensity toward asthma?

Population Level



Personal

Commute to Work

Sensordrone – for monitoring environmental air quality

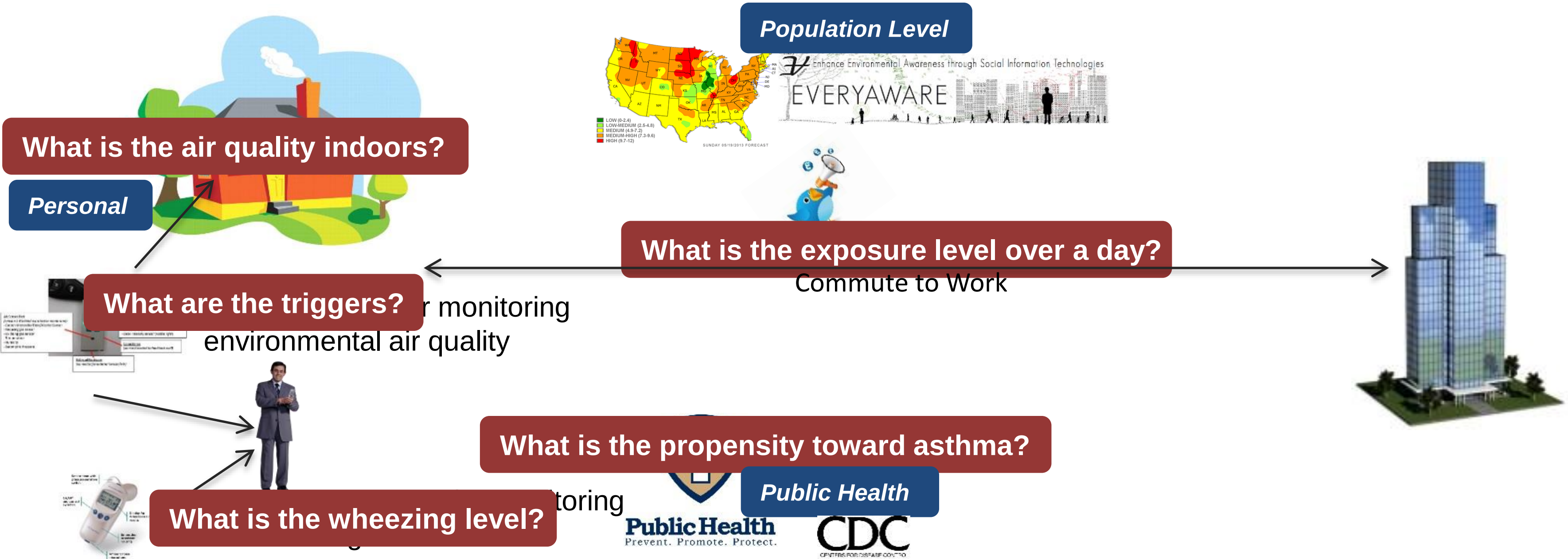
Wheezometer – for monitoring wheezing sounds

Public Health

Public Health
Prevent. Promote. Protect.

CDC

PCS Computing: Asthma Scenario

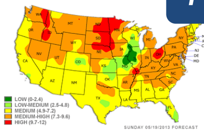


PCS Computing: Asthma Scenario

Actionable Information

Closing the window at home in the morning and taking an alternate route to office may lead to reduced asthma attacks

Population Level



What is the air quality indoors?

Personal

What is the exposure level over a day?

Commute to Work

What are the triggers?

r monitoring environmental air quality

What is the propensity toward asthma?

Public Health

What is the wheezing level?

toring

Public Health
Prevent. Promote. Protect.

CDC

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Personal, Public Health, and Population Level Signals for Monitoring Asthma

Sensors and their observations for understanding asthma

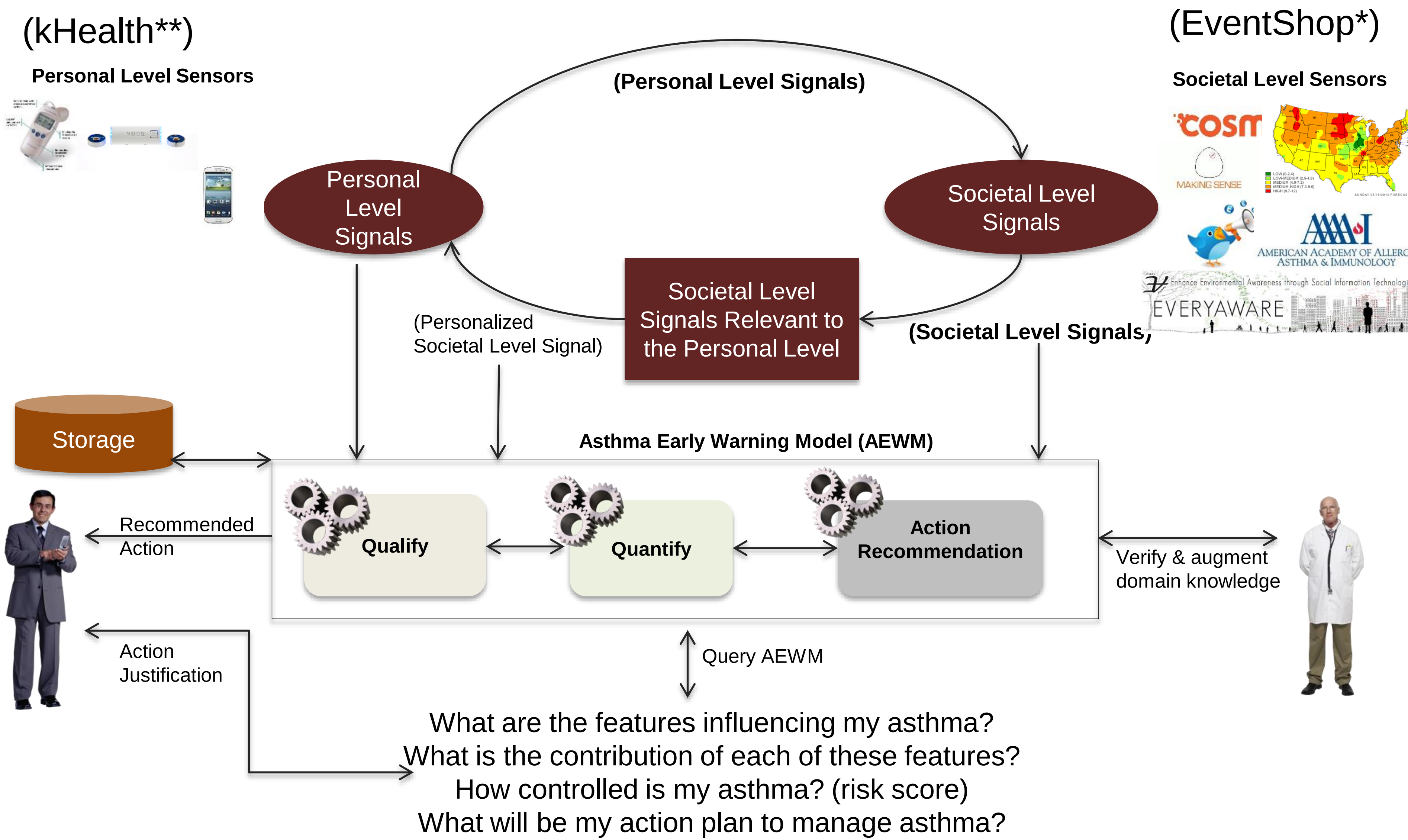
	Data Sources	Health Signals
Personal Level	*Physiological:* Wheezometer [57], Nitric Oxide [60], Accelerometer, Microphone, Contextual Questions *Environmental:* Sensordrone [20], Dust Sensor [59], Location	Wheezing sound, Exhaled Nitric Oxide, Activity level, Coughing sound Personal observations, Temperature, Humidity, CO2, Luminosity, Proximity, Altitude, Pressure, Dust. Particles, Indoor/Outdoor
Public Health	CDC [83], EMR Records	Asthma prevalence based on county, ethnicity, age
Population Level	Everyaware [27], AirQuality Egg [58], Allergy Alerts [61,62], Social Observations (e.g., tweets), Air Quality Index[87]	Community shared air pollution information, Air pollutants outdoors, Pollen level due to weeds, tree, grass, and mold, Air pollution and asthma symptoms and incidents

Asthma Control and Actionable Information

Asthma Control =>	*Daily Medication Choices for starting therapy*	*Not Well Controlled*	*Poor Controlled*
Severity Level of Asthma	*(Recommended Action)*	*(Recommended Action)*	*(Recommended Action)*
Intermittent Asthma	SABA prn	-	-
Mild Persistent Asthma	Low dose ICS	Medium ICS	Medium ICS
Moderate Persistent Asthma	Medium dose ICS alone Or with LABA/montelukast	Medium ICS + LABA/Montelukast Or High dose ICS	Medium ICS + LABA/Montelukast Or High dose ICS*
Severe Persistent Asthma	High dose ICS with LABA/montelukast	Needs specialist care	Needs specialist care

ICS= inhaled corticosteroid, LABA = inhaled long-acting beta$_2$-agonist, SABA= inhaled short-acting beta$_2$-agonist ; *consider referral to specialist

Asthma Early Warning Model



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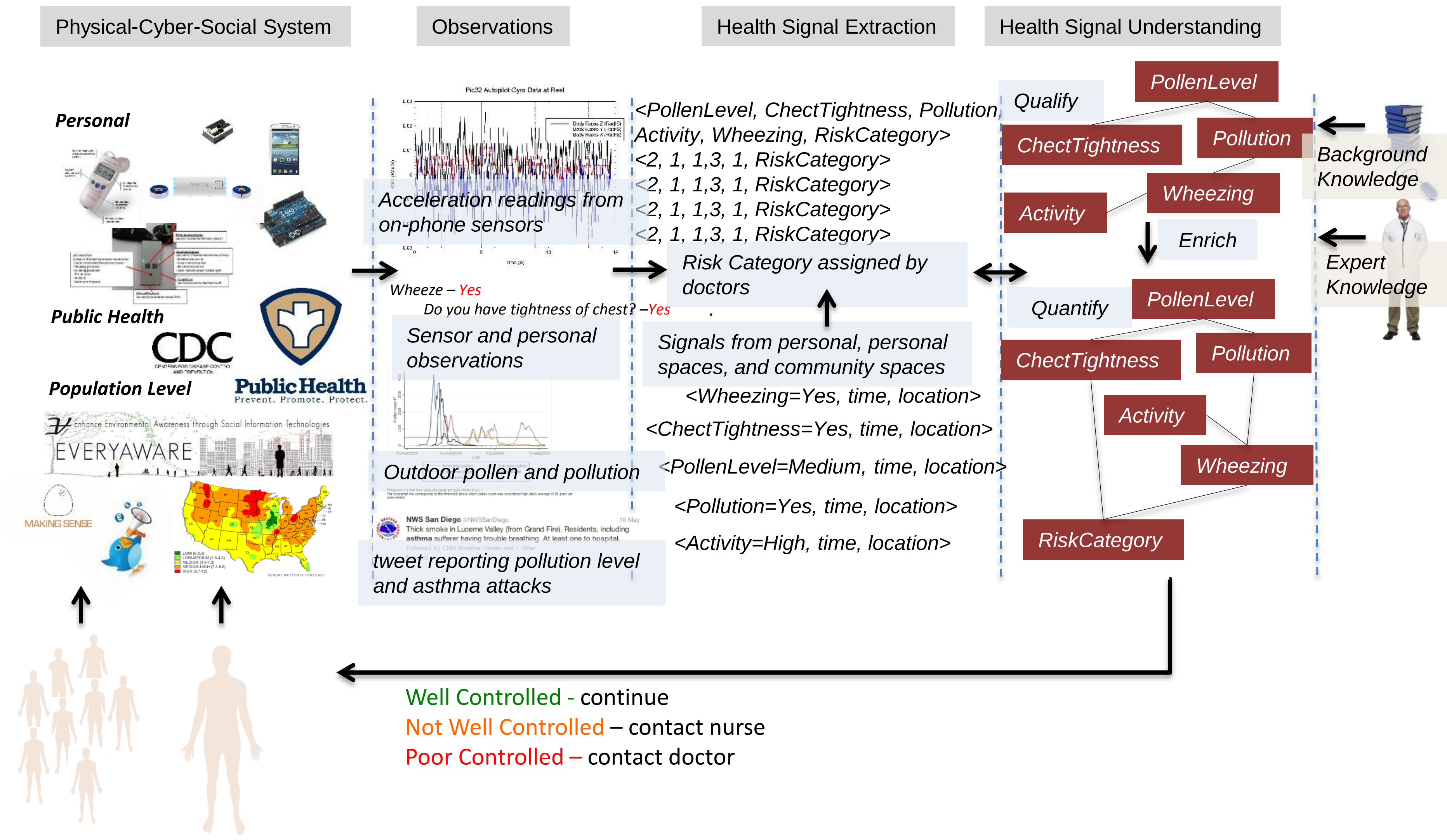
*http://www.slideshare.net/jain49/eventshop-120721, ** http://www.youtube.com/watch?v=btnRi64hJp4

Health Signal Extraction to Understanding



PCS Computing for Parkinson's Disease

Parkinson's Disease (PD): Severity of the problem

1 million Americans live with Parkinson's Disease[1]

10 million People worldwide are living with Parkinson's disease[1].

$25 billion Spent on Parkinson's alone in a year in the US[1]

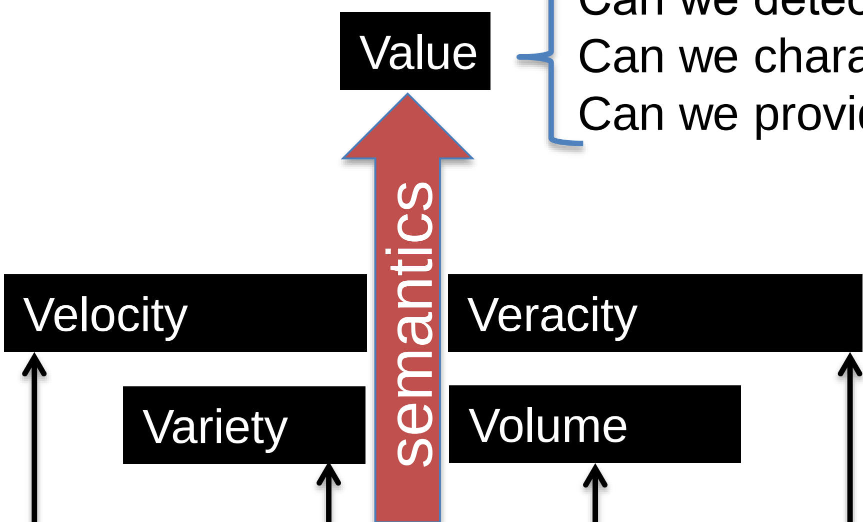
$100,00 0 Therapeutic surgery can cost up to $100,000 dollars per patient[1].

60,000 Americans are diagnosed with Parkinson's disease each year[1].

[1] http://www.pdf.org/en/parkinson_statistics

Massive Amount of Data to Actions

Parkinson's disease (PD) data from The Michael J. Fox Foundation for Parkinson's Research.



Can we detect the onset of Parkinson's disease?
Can we characterize the disease progression?
Can we provide actionable information to the patient

Representing prior knowledge of PD led to a focused exploration of this massive dataset

8 weeks of data from 5 sensors on a smart phone, collected for 16 patients
resulting in ~12 GB (with lot of missing data).

[1]https://www.kaggle.com/c/predicting-parkinson-s-disease-progression-with-smartphone-data

Massive Amount of Data to Actions

Input: Sensor observations such as acceleration, audio, battery, compass, and GPS from smart phones

Output:

- Distinguish patients with and without (control group) Parkinson's
- Categorize disease progression/evolution over time
- Categorize the severity for actionable information

Symptoms to possible manifestations in sensor observations

Mild

Tremors

rapid change in x,y, and z (unlike speed, the x, y, and z will have high variance)

Poor balance

zig-zag movement using GPS? + compass

Moderate

Move slowly

average speed of movement

Move intermittently

x, y, and z coordinates do not change over time

Disturbed sleep

sounds in the night

Slower monotone speech

low energy in the voice recording

Advanced

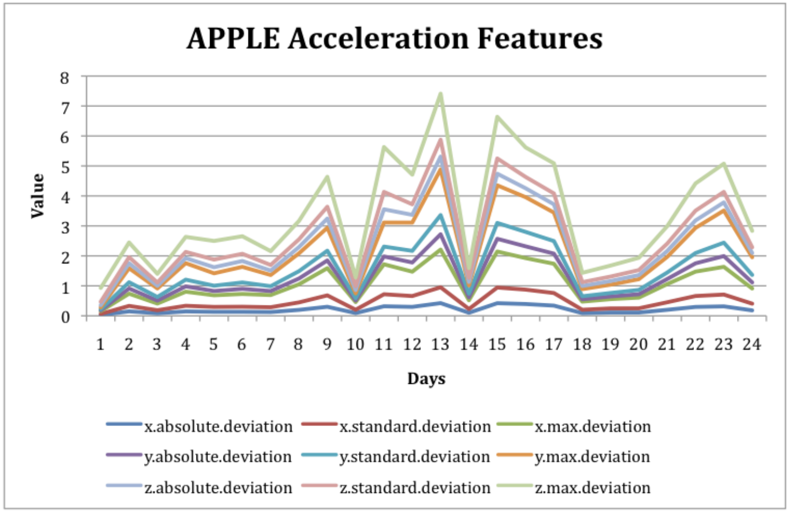
Fall prone

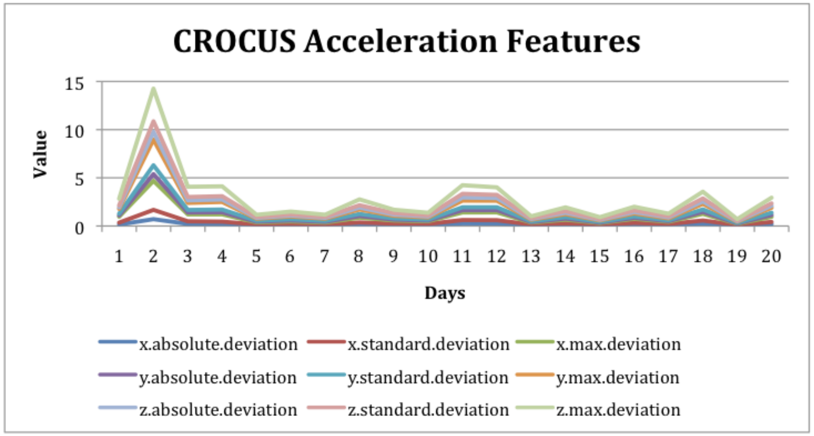
rapid change in z coordinate

Feature extraction (accelerometer)

Control group

PD patient



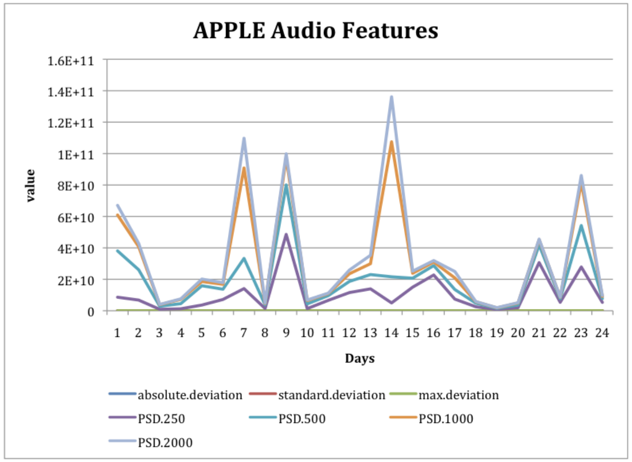


The movement of the control group person is not restricted and exhibits active motion with high variance in acceleration readings

The movement of the PD patient is restricted and exhibits slow motion with low variance in acceleration readings

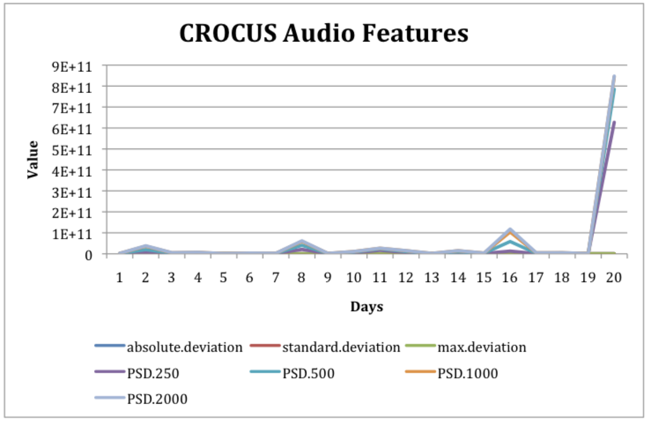
Feature extraction (audio)

Control group



The speech of the control group person is normal and exhibits good modulation in audio energy level

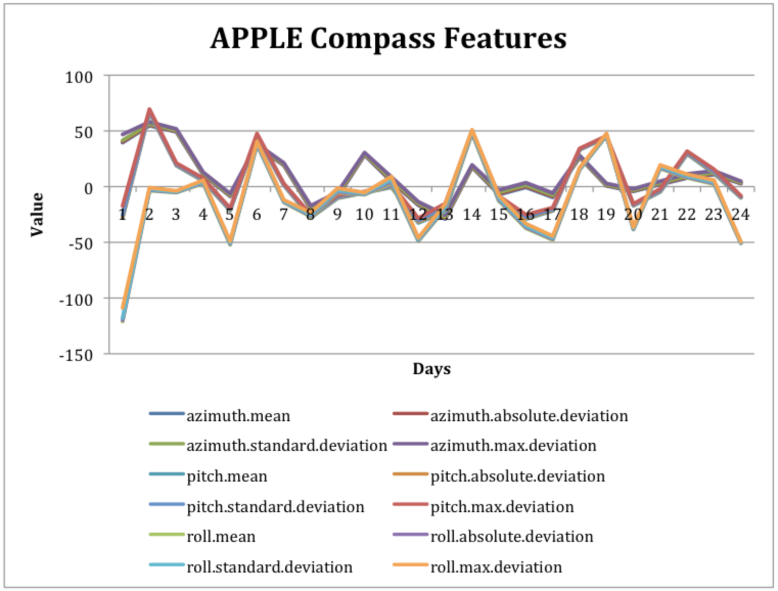
PD patient



The speech of the PD patient is monotone and exhibits low modulation in audio energy level

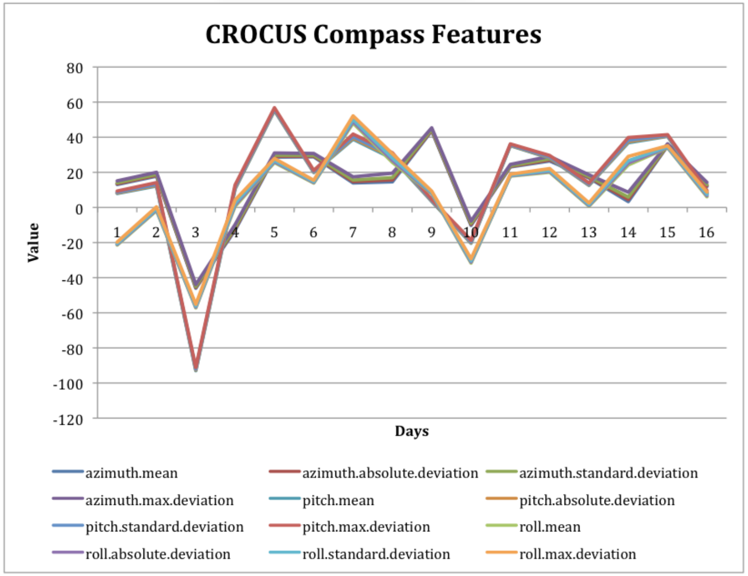
Feature extraction (Compass)

Control group



The walking direction of the control group person is well-balanced and exhibits equal variations in all directions

PD patient



The walking direction of the PD patient is not well-balanced and exhibits “sticky” behavior (stuck in one direction)

Evaluation: run *classification algorithms* on carefully *crafted features* from *knowledge* of PD

Naïve Bayes (Accuracy = 66%)

Predicted =>	Control	PD
Control	25	44
PD	6	75

Bayes Net (Acc. = 74%)

Predicted =>	Control	PD
Control	44	25
PD	13	68

J.48 Decision Tree (Acc. = 72%)

Predicted =>	Control	PD
Control	52	17
PD	24	57

Random Forest (Acc. = 77%)

Predicted =>	Control	PD
Control	57	12
PD	22	59

Random Tree (Acc. = 79%)

Predicted =>	Control	PD
Control	52	17
PD	14	67

Logistic Regression (Acc. = 80%)

Predicted =>	Control	PD
Control	51	18
PD	12	69

Knowledge Based Analytics of PD dataset

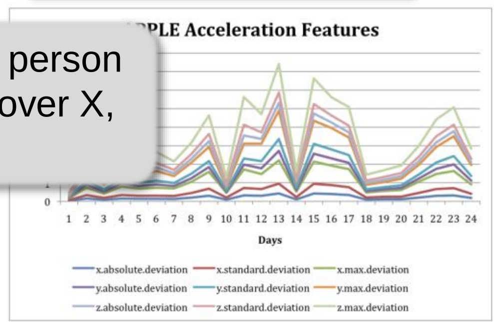
Declarative Knowledge of Parkinson's Disease used to focus our attention on symptom manifestations in sensor observations

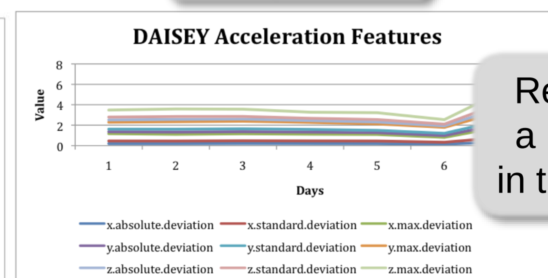
ParkinsonMild(person) = Tremor(person) ∧ PoorBalance(person)
ParkinsonModerate(person) = MoveSlow(person) ∧ PoorSleep(person) ∧ MonotoneSpeech(person)
ParkinsonAdvanced(person) = Fall(person)

Control group

PD patient

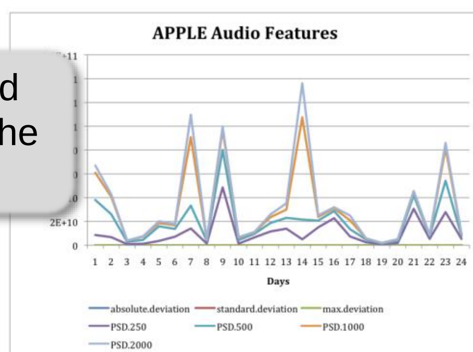
Movements of an active person has a good distribution over X, Y, and Z axis

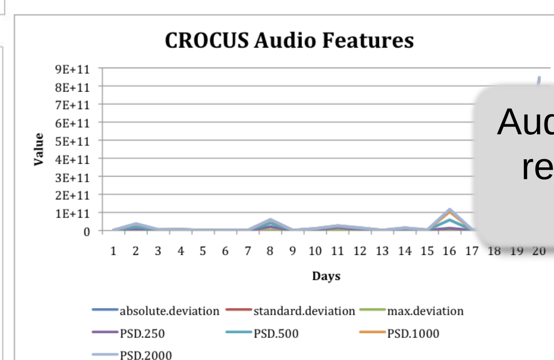




Restricted movements by a PD patient can be seen in the acceleration readings

Audio is well modulated with good variations in the energy of the voice





Audio is not well modulated represented a monotone speech

PCS Computing for Traffic Analytics

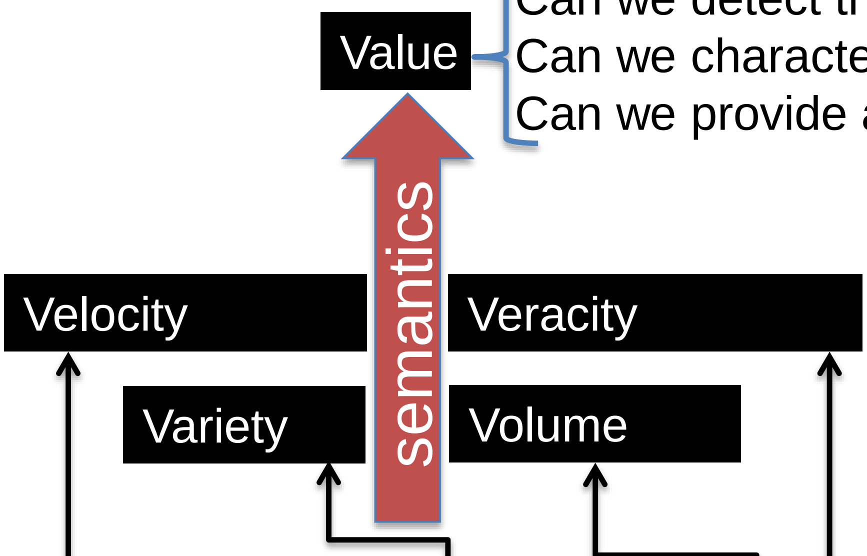
Traffic management: Severity of the problem

1 billion	Cars on road and this number may double by 2020[1]
236%	Increase in traffic from 1981 to 2001[1].
285 million	People lived in cities in India, greater than the entire population of US[2]
91%	Got stuck in traffic with an average delay of 1.3 hours in last 3 years[1].
42%	Have stress related implications due to traffic[1].

[1] http://www.ibm.com/smarterplanet/us/en/traffic_congestion/ideas/
[2]The Crisis of Public Transport in India

Massive Amount of Data to Actions
(traffic data analytics)

Vehicular traffic data from San Francisco Bay Area aggregated from on-road sensors (numerical) and incident reports (textual)



Can we detect the onset of traffic congestion?
Can we characterize traffic congestion based on event
Can we provide actionable information to decision mak

Representing prior knowledge of traffic lead to a focused exploration of this massive data stream

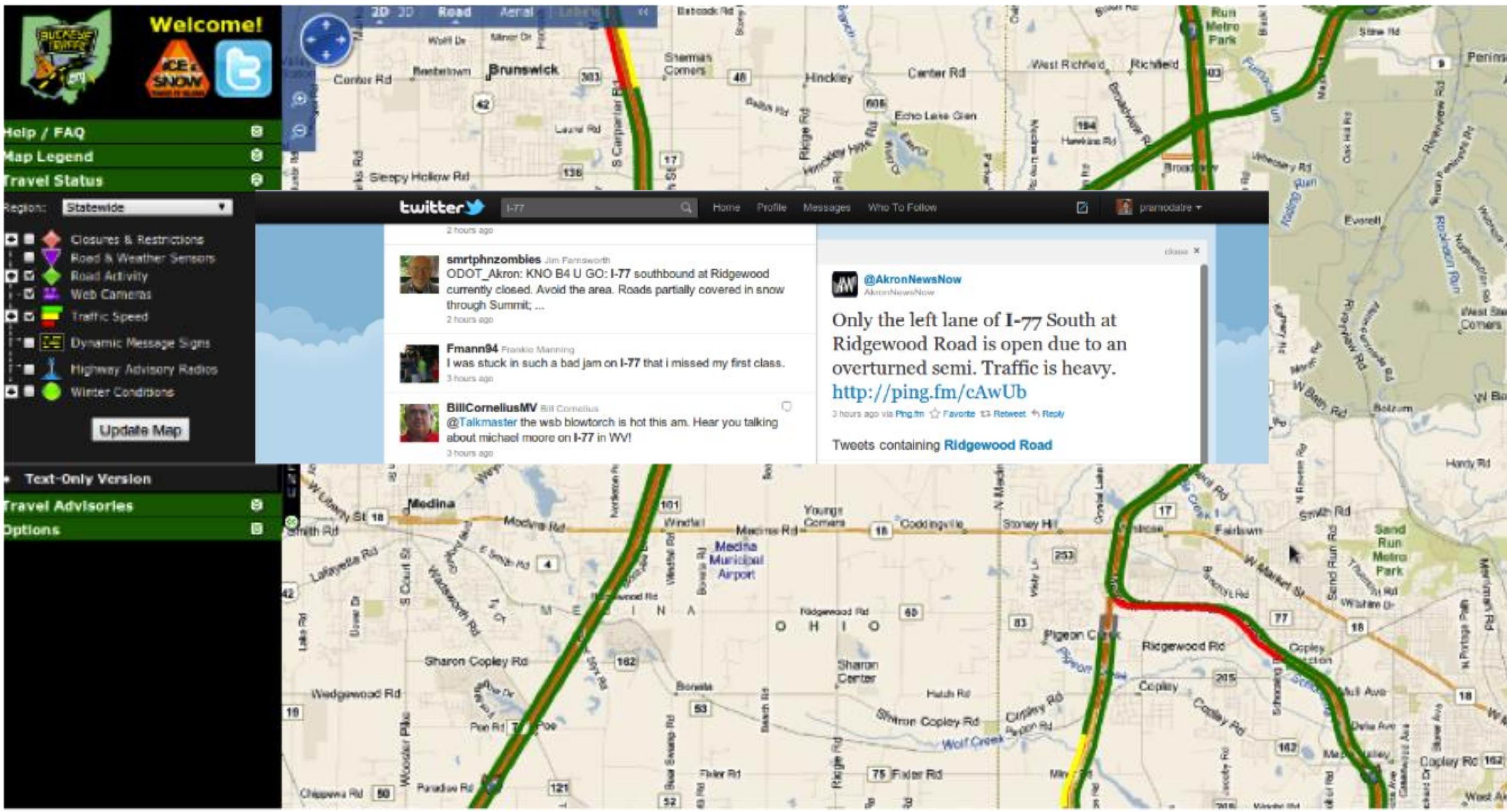
Every minute update of speed, volume, travel time, and occupancy resulting in 178 million link status observations, 738 active events, and 146 scheduled events with many unevenly sampled observations collected over 3 months.

http://511.org/

Heterogeneity leading to complementary observations

Heterogeneity leading to complementary observations

Heterogeneity leading to complementary observations



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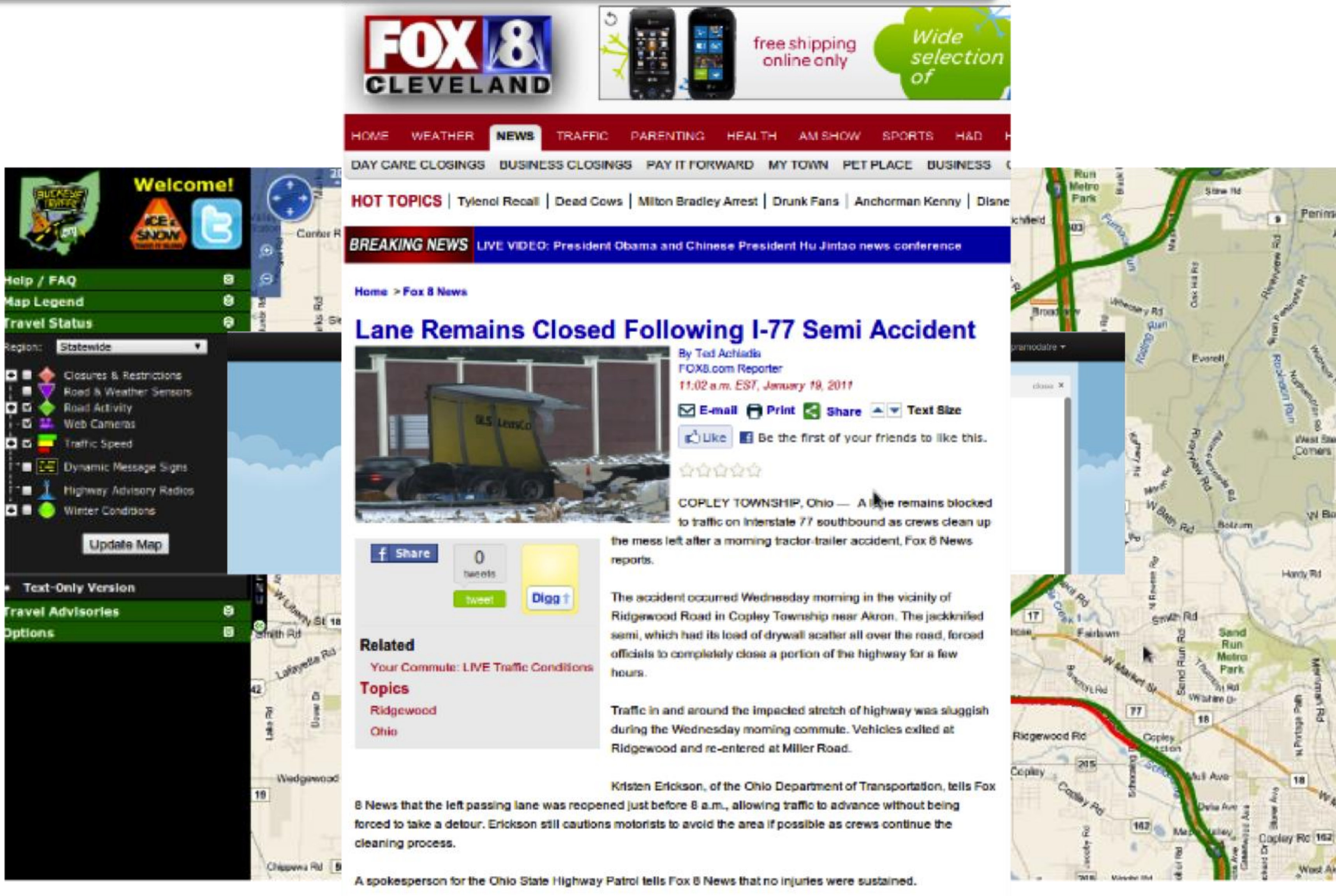
Heterogeneity leading to complementary observations



Home > Fox 8 News

Lane Remains Closed Following I-77 Semi Accident

By Ted Achladis
FOX8.com Reporter
11:02 a.m. EST, January 19, 2011

E-mail Print Share Text Size

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COPLEY TOWNSHIP, Ohio — A lane remains blocked to traffic on Interstate 77 southbound as crews clean up the mess left after a morning tractor-trailer accident, Fox 8 News reports.

The accident occurred Wednesday morning in the vicinity of Ridgewood Road in Copley Township near Akron. The jackknifed semi, which had its load of drywall scatter all over the road, forced officials to completely close a portion of the highway for a few hours.

Traffic in and around the impacted stretch of highway was sluggish during the Wednesday morning commute. Vehicles exited at Ridgewood and re-entered at Miller Road.

Kristen Erickson, of the Ohio Department of Transportation, tells Fox 8 News that the left passing lane was reopened just before 8 a.m., allowing traffic to advance without being forced to take a detour. Erickson still cautions motorists to avoid the area if possible as crews continue the cleaning process.

A spokesperson for the Ohio State Highway Patrol tells Fox 8 News that no injuries were sustained.

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Related
Your Commute: LIVE Traffic Conditions

Topics
Ridgewood
Ohio

511.org

linkid	linkspeed	linkvolume	linkoccupancy	linkdelay	linktraveltime	timestamp
107060	18	-1	-1	-1	74	9/30/12 2:20 PM
107070	18	-1	-1	-1	341	9/30/12 2:20 PM
108150	27	6540	29	-1	244	9/30/12 2:20 PM
108420	36	2548	23	-1	216	9/30/12 2:20 PM
119626	45	-1	-1	-1	51	9/30/12 2:20 PM

Slow moving traffic

511.org

linkid	linkspeed	linkvolume	linkoccupancy	linkdelay	linktraveltime	timestamp
107060	18	-1	-1	-1	74	9/30/12 2:20 PM
107070	18	-1	-1	-1	341	9/30/12 2:20 PM
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108420	36	2548	23	-1	216	9/30/12 2:20 PM
119626	45	-1	-1	-1	51	9/30/12 2:20 PM

Slow moving traffic

Link Description

511.org

linkid	onstreet	fromstreet	tostreet	speedlimit
108150	I-880 S	66TH AVE	HEGENBERGER RD	104

511.org

linkid	linkspeed	linkvolume	linkoccupancy	linkdelay	linktraveltime	timestamp
107060	18	-1	-1	-1	74	9/30/12 2:20 PM
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Slow moving traffic

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511.org

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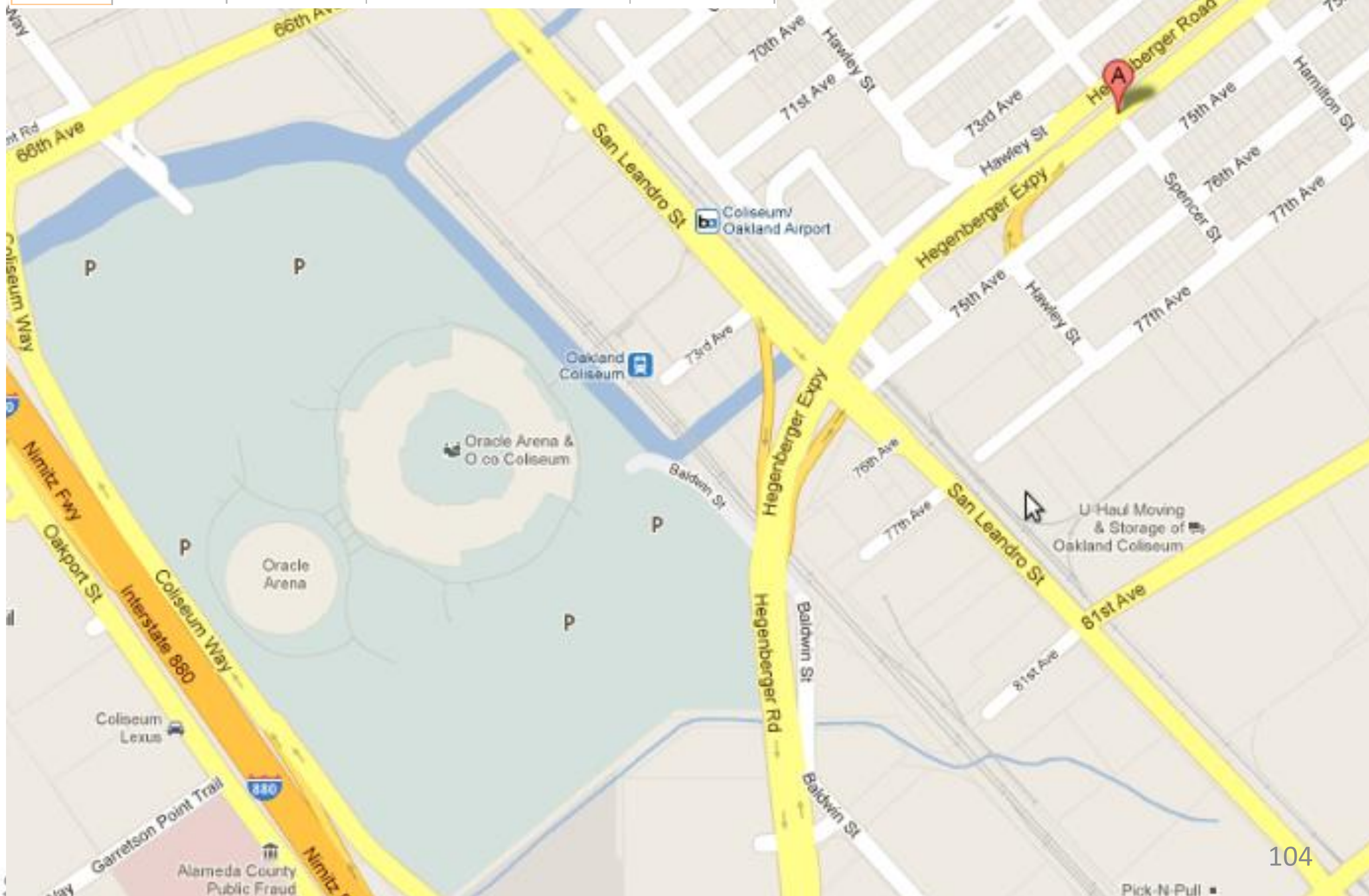

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511.org

Slow moving traffic

Link Description

linkid	onstreet	fromstreet	tostreet	speedlimit
108150	I-880 S	66TH AVE	HEGENBERGER RD	104

511.org

Scheduled Event

scheduleid	eventtype	onstreet	fromstreet	tostreet	eventlat	eventlong	starttime	endtime
2012040510161401002076	baseball-game	*NULL*	*NULL*	*NULL*	37750956	-122202232	2012-09-30T11:59:00.0000	2012-09-30T17:00:00.0000

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linkid	linkspeed	linkvolume	linkoccupancy	linkdelay	linktraveltime	timestamp
107060	18	-1	-1	-1	74	9/30/12 2:20 PM
107070	18	-1	-1	-1	341	9/30/12 2:20 PM
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Slow moving traffic

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511.org

Scheduled Event

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2012040510161401002076	baseball-game	*NULL*	*NULL*	*NULL*	37750956	-122202232	2012-09-30T11:59:00.0000	2012-09-30T17:00:00.0000

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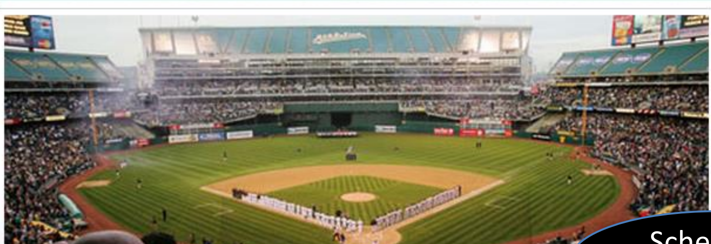
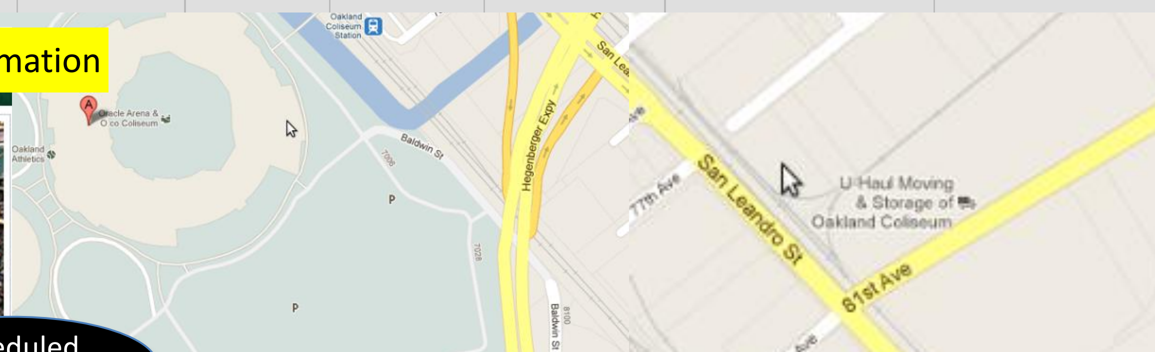
THE COLISEUM

Schedule Information





Scheduled Event

Fri, 9/28	Mariners	[illegible]	89-68	Griffin (7-1)	Beavan (10-11)
Sat, 9/29	Mariners	7-4	90-68	Balfour (3-2)	Perez (1-3)
Sun, 9/30	Mariners	W 5-2	91-68	Doolittle (2-1)	Kelley (2-4)
Mon, 10/1	Rangers	W 4-3	92-68	Parker (13-8)	Perez (1-4)
Tue, 10/2	Rangers	W 3-1	93-68	Blackley (6-4)	Harrison (18-11)

Uncertainty in a Physical-Cyber-Social System

Observation: Slow Moving Traffic

Multiple Causes (Uncertain about the cause):

- Scheduled Events: music events, fair, theatre events, concerts, road work, repairs, etc.
- Active Events: accidents, disabled vehicles, break down of roads/bridges, fire, bad weather, etc.
- Peak hour: e.g. 7 am – 9 am OR 4 pm – 6 pm

Each of these events may have a varying impact on traffic.
A delay prediction algorithm should process multimodal and multi-sensory observations.

Modeling Traffic Events

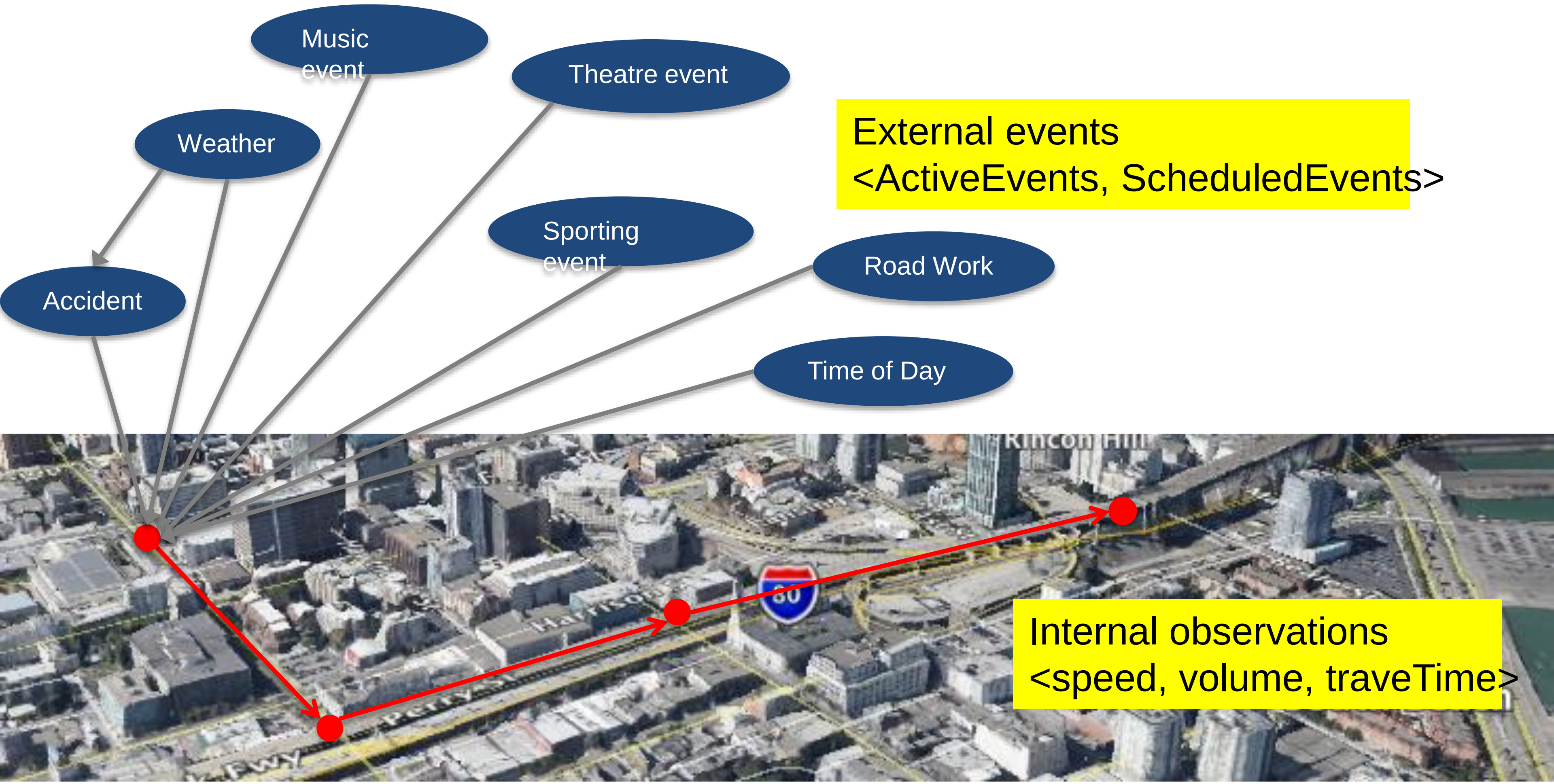
Internal (to the road network) observations

- Speed, volume, and travel time observations
- Correlations may exist between these variables across different parts of the network

External (to the road network) events

- Accident, music event, sporting event, and planned events
- External events and internal observations may exhibit correlations

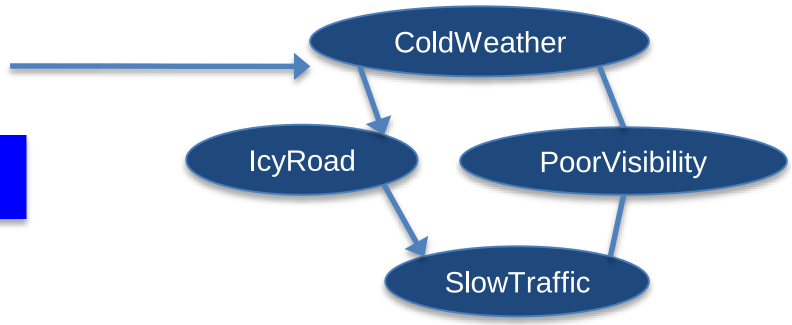
Modeling Traffic Events: Pictorial representation



Combining Data and Knowledge Graph

Combining Data and Knowledge Graph

Domain Experts



Combining Data and Knowledge Graph

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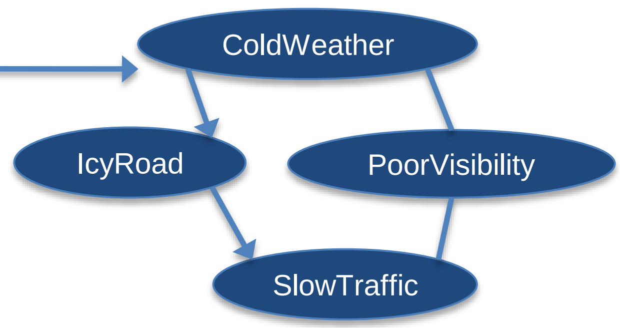


Structure and **parameters**

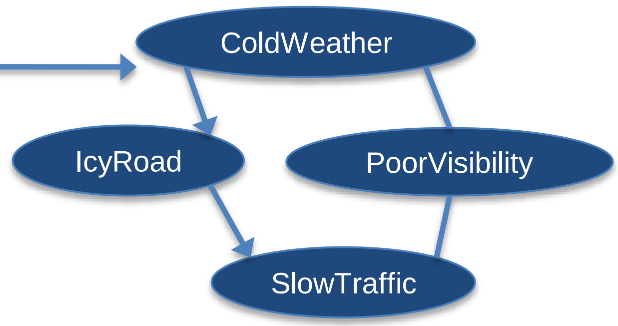
Domain Observations

ColdWeather(YES/NO)	IcyRoad (ON/OFF)	PoorVisibility (YES/NO)	SlowTraffic (YES/NO)
1	0	1	0
1	1	1	1
1	1	1	0
1	0	1	1

Combining Data and Knowledge Graph

Domain Experts

Declarative domain knowledge



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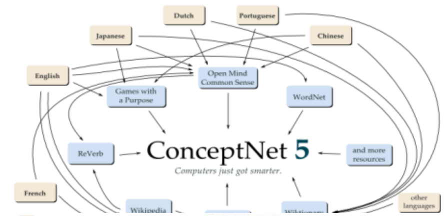
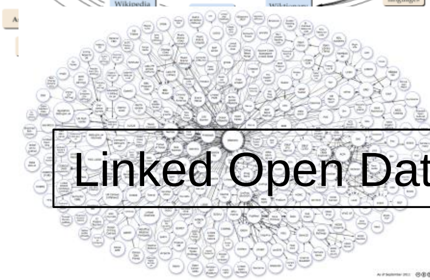
1	0	1	1

Combining Data and Knowledge Graph

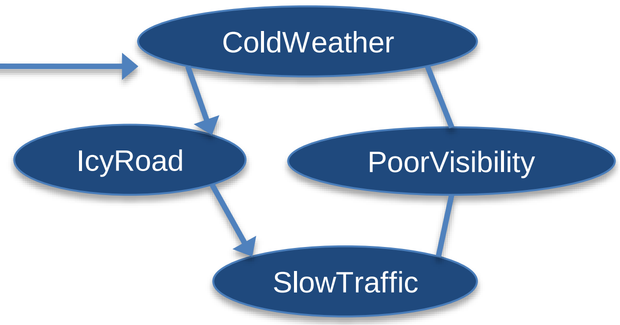
Domain Experts

Declarative domain knowledge





Domain Knowledge



Structure and **parameters**

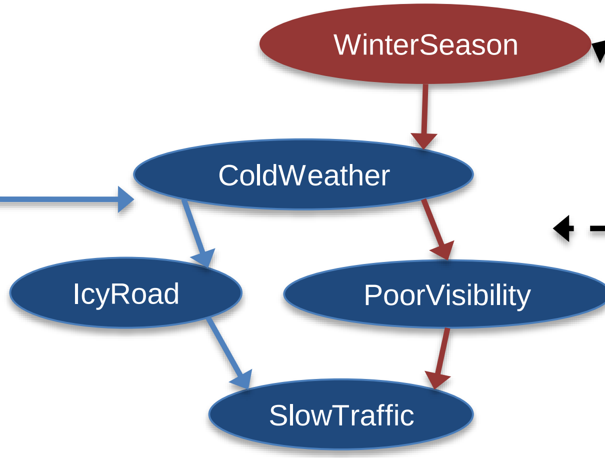
Domain Observations

ColdWeather(YES/NO)	IcyRoad (ON/OFF)	PoorVisibility (YES/NO)	SlowTraffic (YES/NO)
1	0	1	0
1	1	1	1
1	1	1	0
1	0	1	1

Combining Data and Knowledge Graph

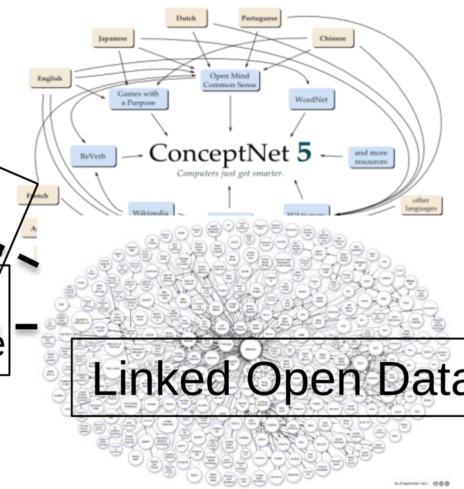
Declarative domain knowledge

Domain Experts



Other knowledge

Causal knowledge



Domain Knowledge

Structure and **parameters**

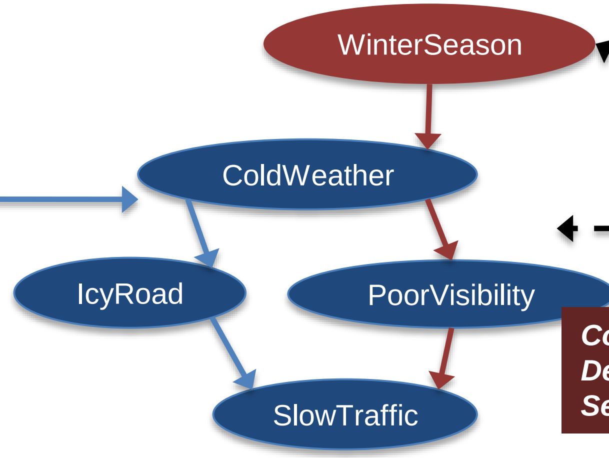
Domain Observations

ColdWeather(YES/NO)	IcyRoad (ON/OFF)	PoorVisibility (YES/NO)	SlowTraffic (YES/NO)
1	0	1	0
1	1	1	1
1	1	1	0
1	0	1	1

Combining Data and Knowledge Graph

Declarative domain knowledge

Domain Experts



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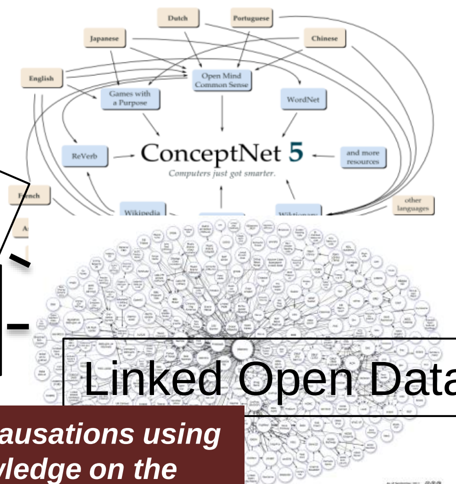


Linked Open Data

Correlations to causations using Declarative knowledge on the Semantic Web

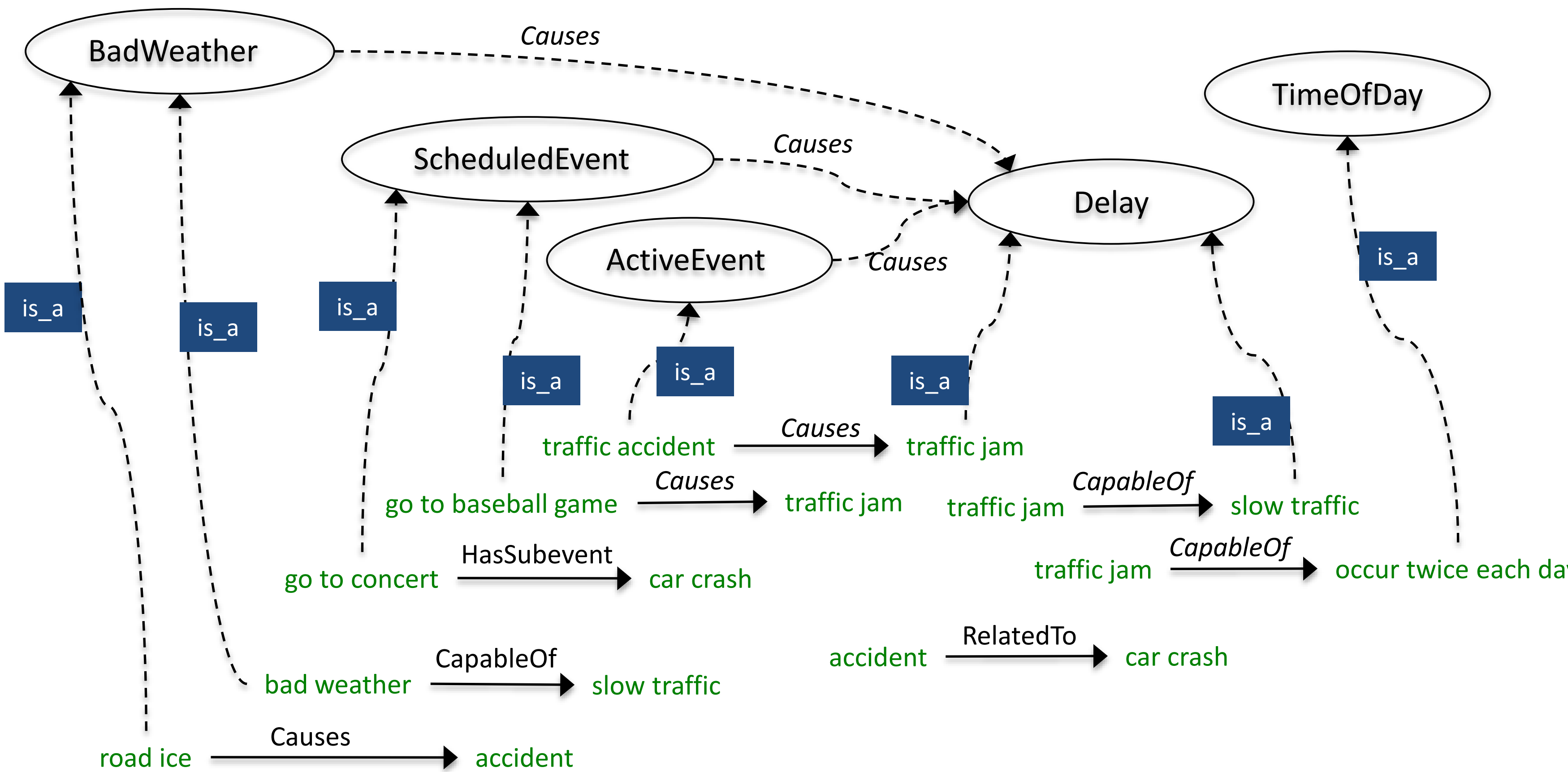
Domain Knowledge

Structure and **parameters**

Domain Observations

ColdWeather(YES/NO)	IcyRoad (ON/OFF)	PoorVisibility (YES/NO)	SlowTraffic (YES/NO)
1	0	1	0
1	1	1	1
1	1	1	0
1	0	1	1

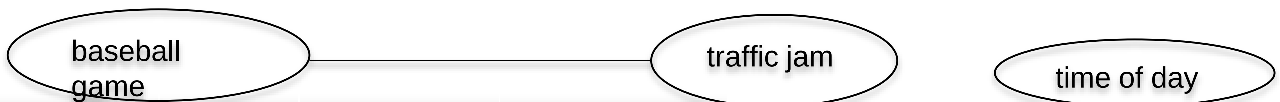
Declarative knowledge from ConceptNet5



http://conceptnet5.media.mit.edu/web/c/en/traffic_jam

Three Operations: Complementing graphical model structure

Three Operations: Complementing graphical model structure



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107070	18	-1	-1	[illegible]	[illegible]	9/30/12 2:20 PM
108150	27	6540	29	-1	244	9/30/12 2:20 PM
108420	36	2548	23	-1	216	9/30/12 2:20 PM
119626	[illegible]	-1	-1	-1	[illegible]	9/30/12

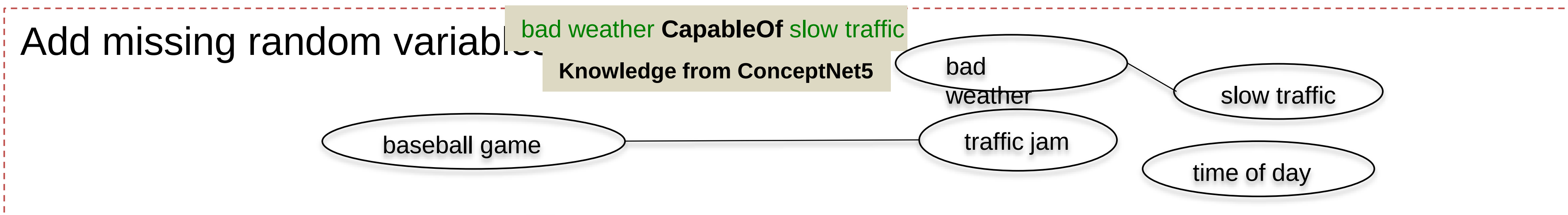
linkid	onstreet	fromstreet	tostreet	speedlimit
108150	I-880 S	66TH AVE	HEGENBERGER RD	104

scheduleid	eventtype	onstreet	fromstreet	tostreet	eventlat	eventlong	starttime	endtime
2012040510161401002076	baseball-game	NULL	NULL	NULL	37750956	-122202232	2012-09-30T11:59:00.0000	2012-09-30T17:00:00.0000

Traffic data from sensors deployed on road network in San Francisco Bay Area

Three Operations: Complementing graphical model structure

Add missing random variables



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108150	27	6540	29	-1	244	9/30/12 2:20 PM
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119626	[illegible]	-1	-1	-1	[illegible]	9/30/12[illegible]

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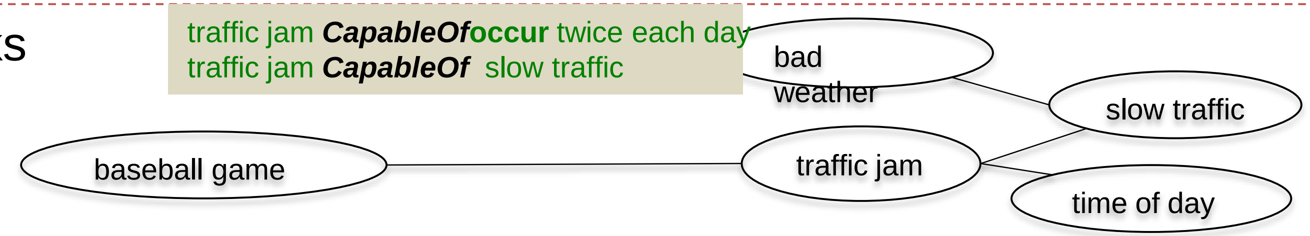
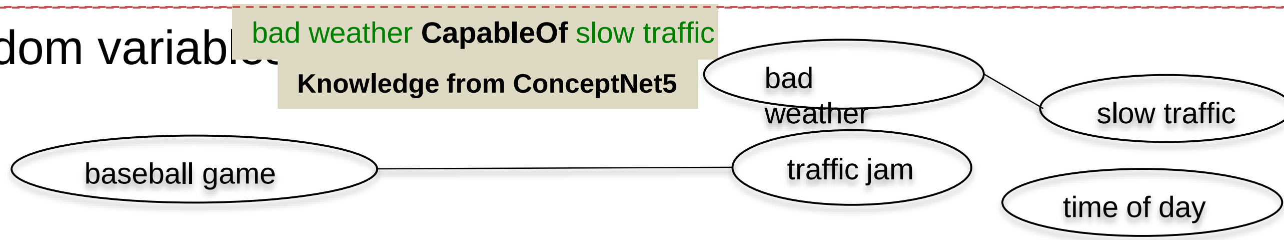
Traffic data from sensors deployed on road network in San Francisco Bay Area

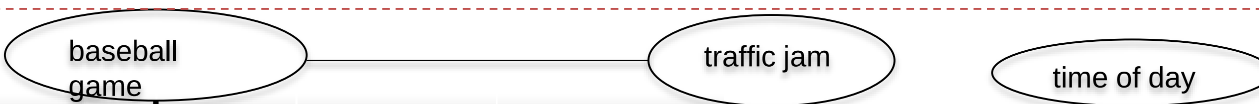
Three Operations: Complementing graphical model structure

Add missing links



Add missing random variables





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107070	18	-1	-1	[illegible]	41	9/30/12 2:20 PM
108150	27	6540	29	-1	244	9/30/12 2:20 PM
108420	36	2548	23	-1	216	9/30/12 2:20 PM
119626	45	-1	-1	-1	51	9/30/12

Traffic jam

Time of day

linkid	onstreet	fromstreet	tostreet	speedlimit
108150	I-880 S	66TH AVE	HEGENBERGER RD	104

Scheduled Event

Link Description

scheduleid	eventtype	onstreet	fromstreet	tostreet	eventlat	eventlong	starttime	endtime
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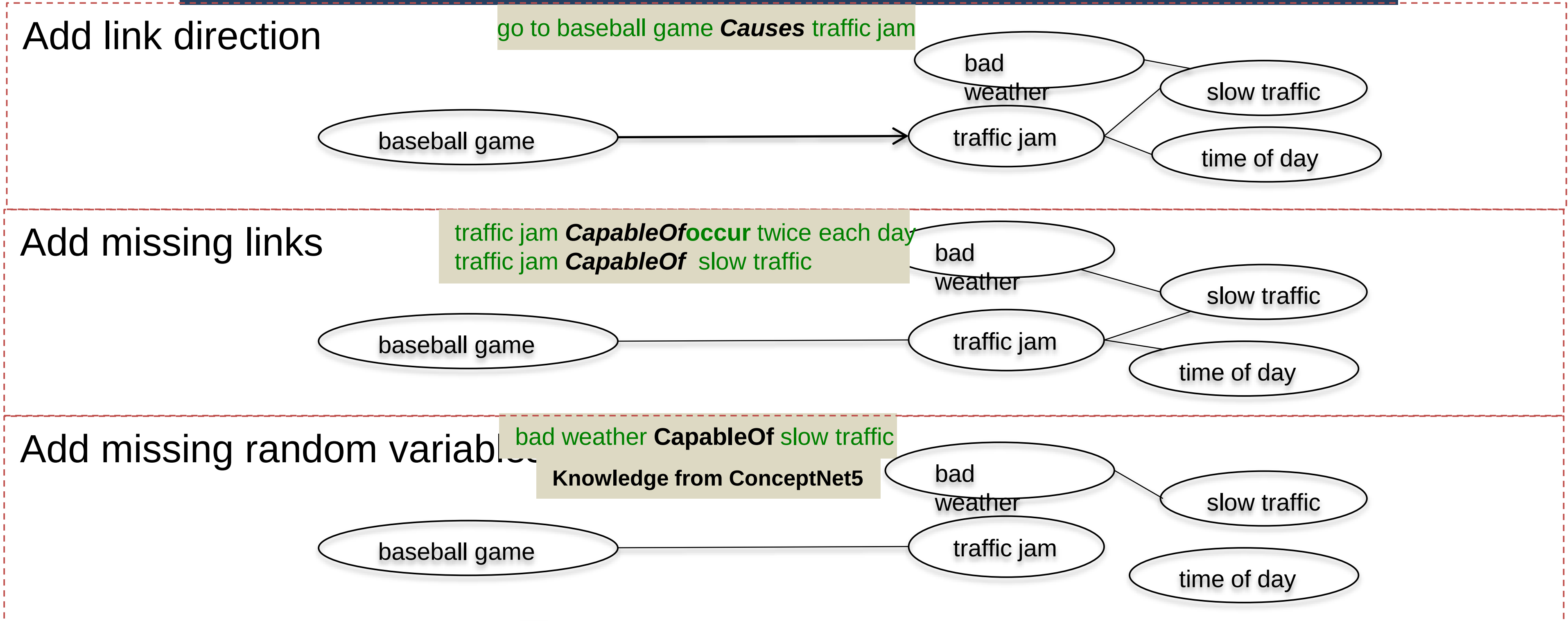
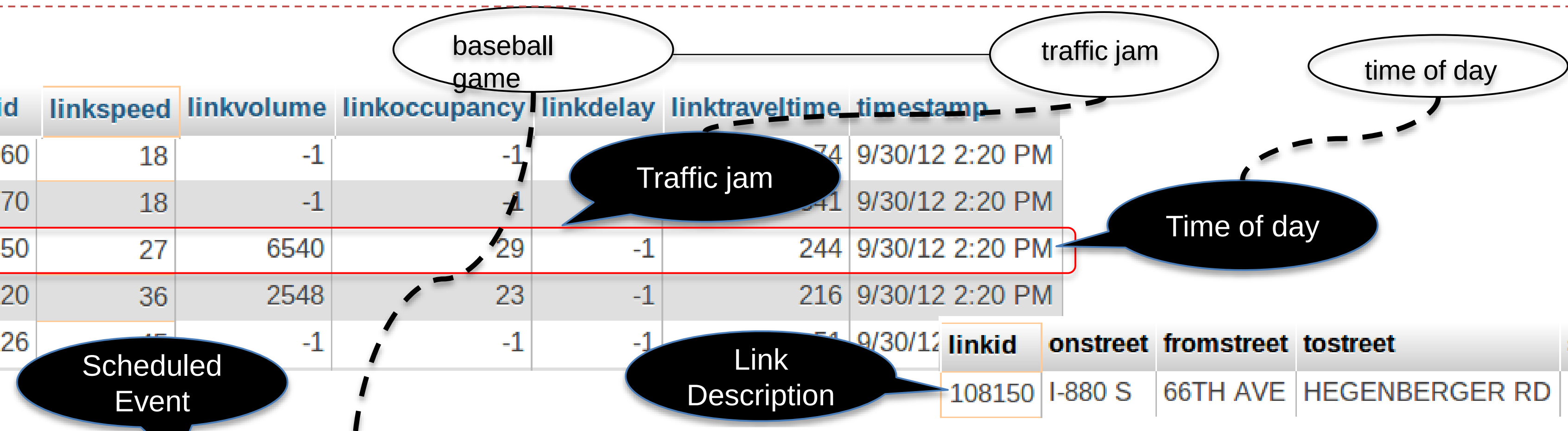
Traffic data from sensors deployed on road network in San Francisco Bay Area

Three Operations: Complementing graphical model structure





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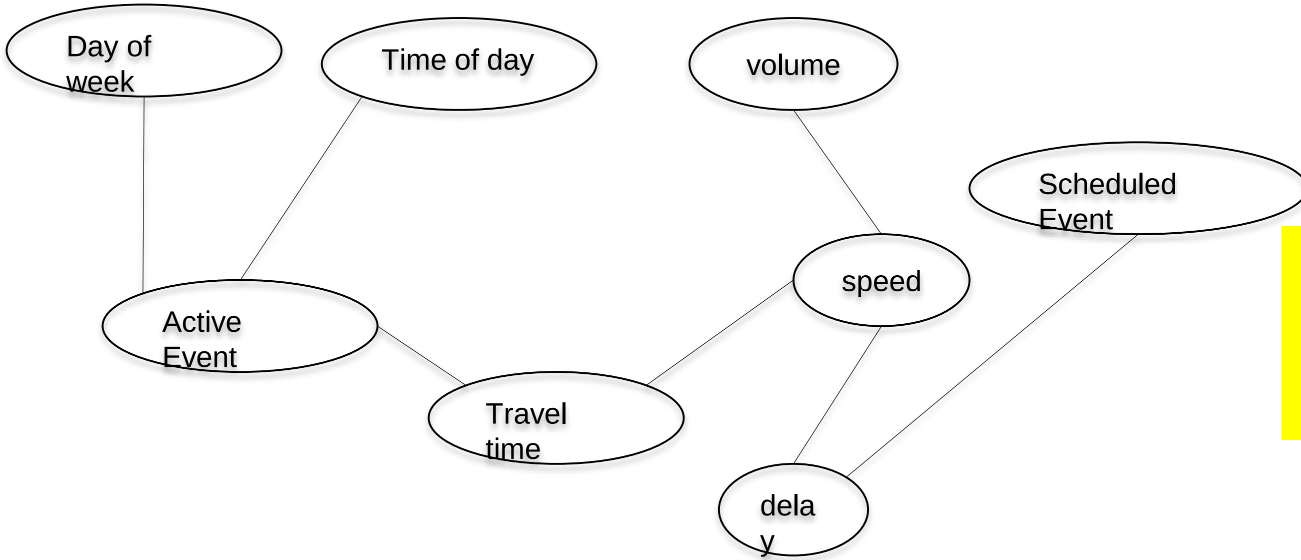
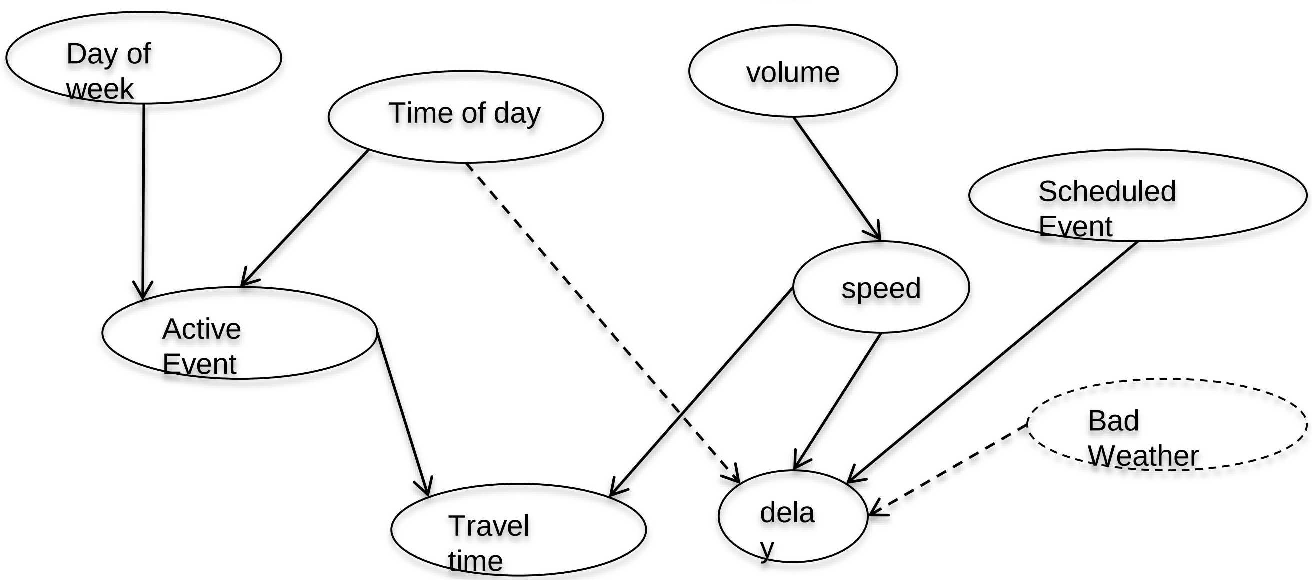
Traffic data from sensors deployed on road network in San Francisco Bay Area

Enriched Probabilistic Models using ConceptNet 5



Structure extracted form traffic observations (sensors + textual) using statistical techniques



Enriched structure which has link directions and new nodes such as "Bad Weather" potentially leading to better delay predictions

Anantharam et al: Traffic Analytics using Probabilistic Graphical Models Enhanced with Knowledge Bases

PCS Computing for Intelligence

PCS Computing for Intelligence

PCS Computing for Intelligence

Observations span physical, cyber, and social space generating massive, multimodal, and multisensory observations

Scenario: Physical Cyber Social Threat

Government Facilities

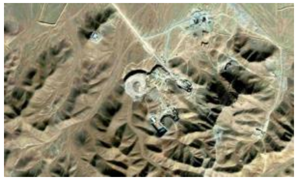
Water Reservoirs

Natural Gas Pipelines

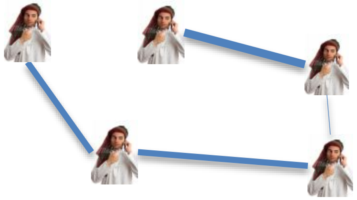
Power Grid

? Threat to physical/cyber infrastructure

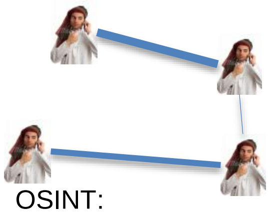
Observations



GEOINT:
Satellite and drone images capturing activities in a geographical area



SIGINT:
Phone logs indicating calling patterns



OSINT:
Communication and group dynamics on social media and emails

IMINT:
Observations from continuous monitoring (e.g., CCTV)

Multi-Int:
Prior knowledge from historical events/threats

Data Sources

GEOINT:
Satellite images

SIGINT:
Mobile Communication

SIGINT:
Sensors on the soldier

OSINT:
Textual message exchanges

SIGINT:
On-ground sensors

OSINT:
News reports, knowledge bases, intelligence databases, history of undesirable events

Scenario
(along with the knowledge required to answer them)

What physical infrastructure may have threats?

Location based knowledge
Physical Infrastructure at a location
Surveillance with high activity (e.g., logs, CCTV)
Prior disposition of infrastructure to risks
Events of high risk near the location (e.g., raid of explosives)

What are the locations currently at high threat level

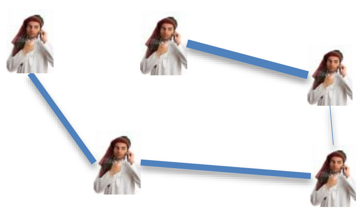
Location based knowledge
Locations with physical infrastructure + suspects
Locations where surveillance logs show frequent attacks

Who are the suspects?

Location based knowledge
People from watch list and making international calls
People from watch list and found near infrastructure through surveillance

Observations

GEOINT:
Satellite and drone images capturing activities in a geographical area



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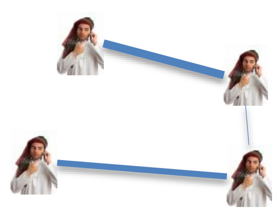

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KNO.E.SIS

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(along with the knowledge required to answer them)

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Locations where surveillance logs show frequent attacks

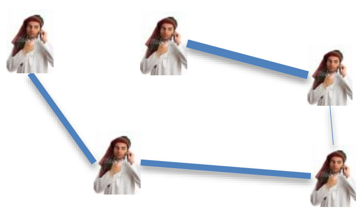
nswering these questions demands semanti integration, annotation, mapping, and interpretation of massive multi-modal and multi-sensory observations.

Who are the suspects?

Location based knowledge
People from watch list and making international calls
People from watch list and found near infrastructure through surveillance

Observations

GEOINT:
Satellite and drone images capturing activities in a geographical area



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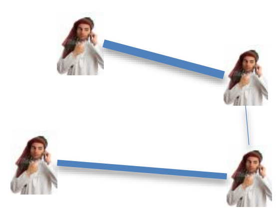

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Communication and group dynamics on social media and emails

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Multi-Int:
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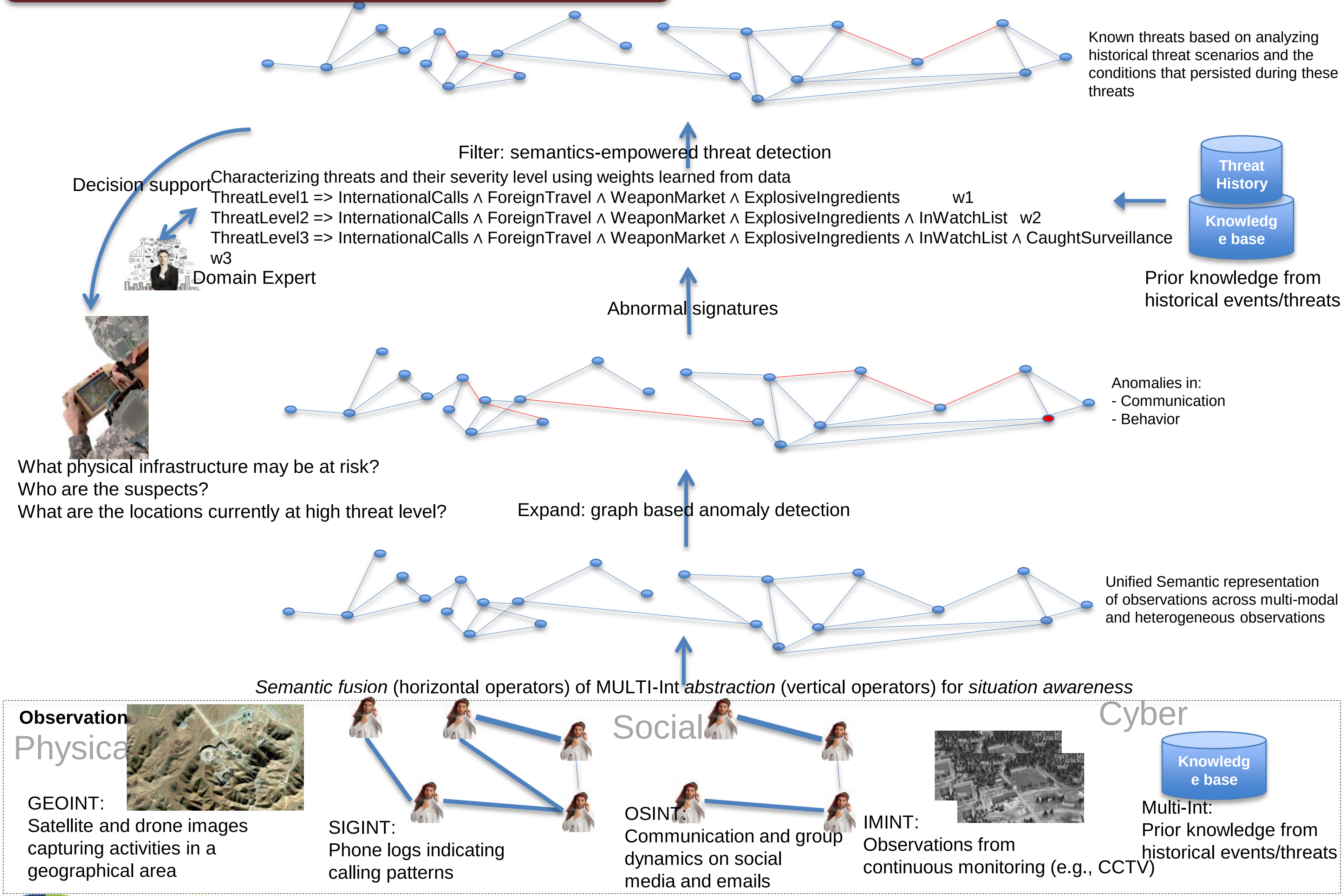
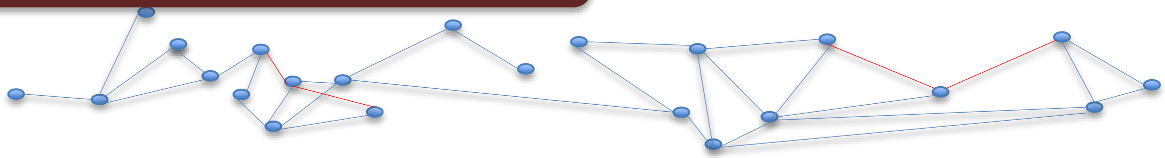
PCS computing for detecting threats



PCS computing for detecting threats



Known threats based on analyzing historical threat scenarios and the conditions that persisted during these threats

Filter: semantics-empowered threat detection

Decision support

Characterizing threats and their severity level using weights learned from data

ThreatLevel1 => InternationalCalls ∧ ForeignTravel ∧ WeaponMarket ∧ ExplosiveIngredients w1

ThreatLevel2 => InternationalCalls ∧ ForeignTravel ∧ WeaponMarket ∧ ExplosiveIngredients ∧ InWatchList w2

ThreatLevel3 => InternationalCalls ∧ ForeignTravel ∧ WeaponMarket ∧ ExplosiveIngredients ∧ InWatchList ∧ CaughtSurveillance w3

Domain Expert

Threat History

Knowledge base

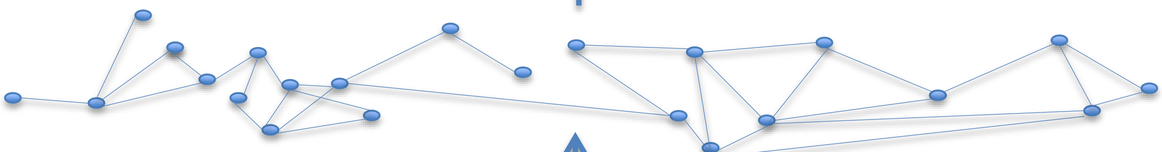
Prior knowledge from historical events/threats

What physical infrastruct
Who are the suspects?
What are the locations currently at high threat level?

Takeaway Points:

- PCS computing is crucial for a holistic interpretation of observations
- Horizontal and vertical operators empowers analytics spanning CPS modalities
- Semantics-empowered graph based anomaly detection algorithms will detect more anomal
- Leveraging prior knowledge from experts and historical data will allow characterization of th

Expand: graph based anomaly detection



Unified Semantic representation of observations across multi-modal and heterogeneous observations

Semantic fusion (horizontal operators) of MULTI-Int *abstraction* (vertical operators) for *situation awareness*

Observation

Physica

GEOINT:
Satellite and drone images capturing activities in a geographical area

SIGINT:
Phone logs indicating calling patterns

Social

OSINT:
Communication and group dynamics on social media and emails

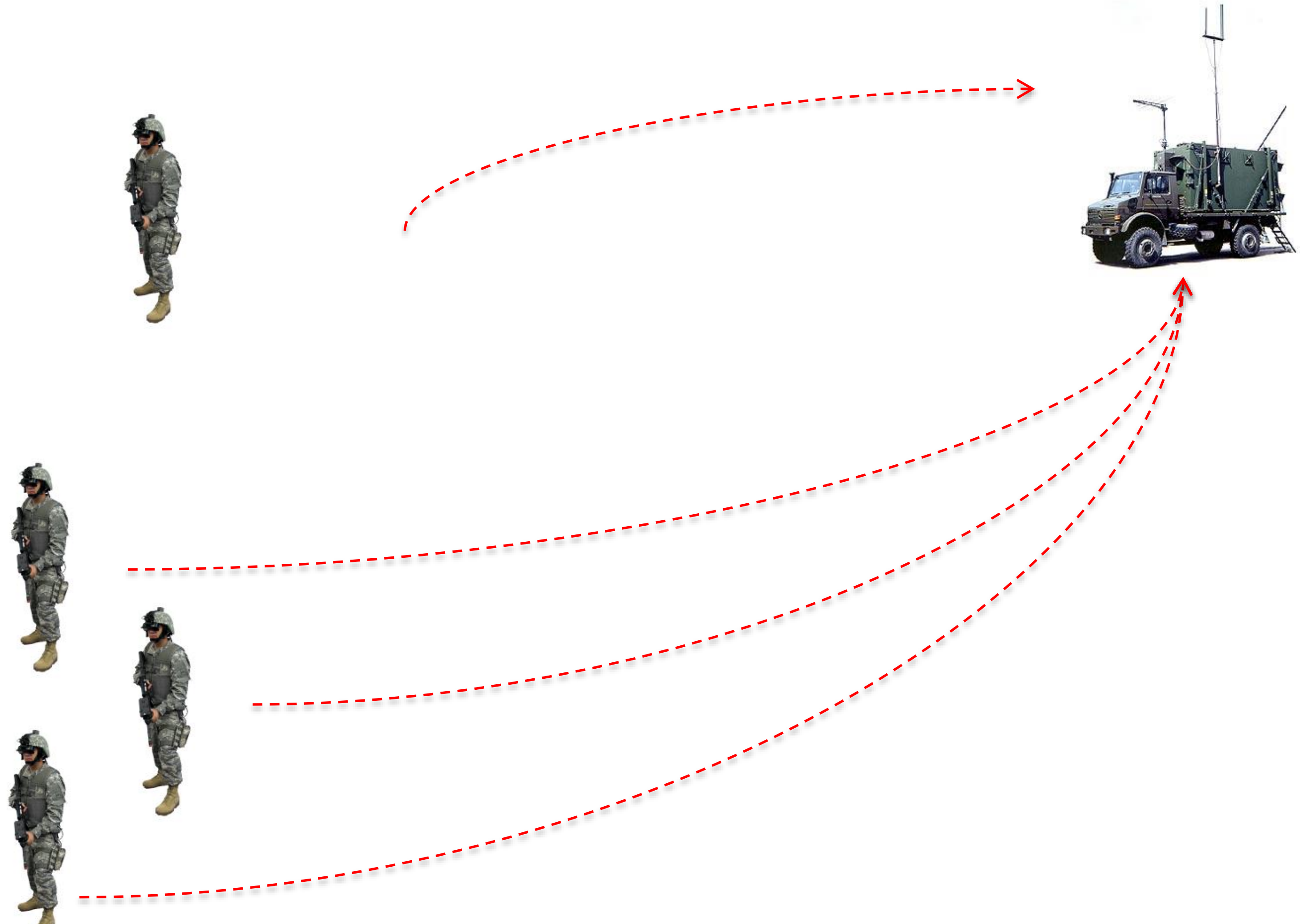
IMINT:
Observations from continuous monitoring (e.g., CCTV)

Cyber

Knowledge base

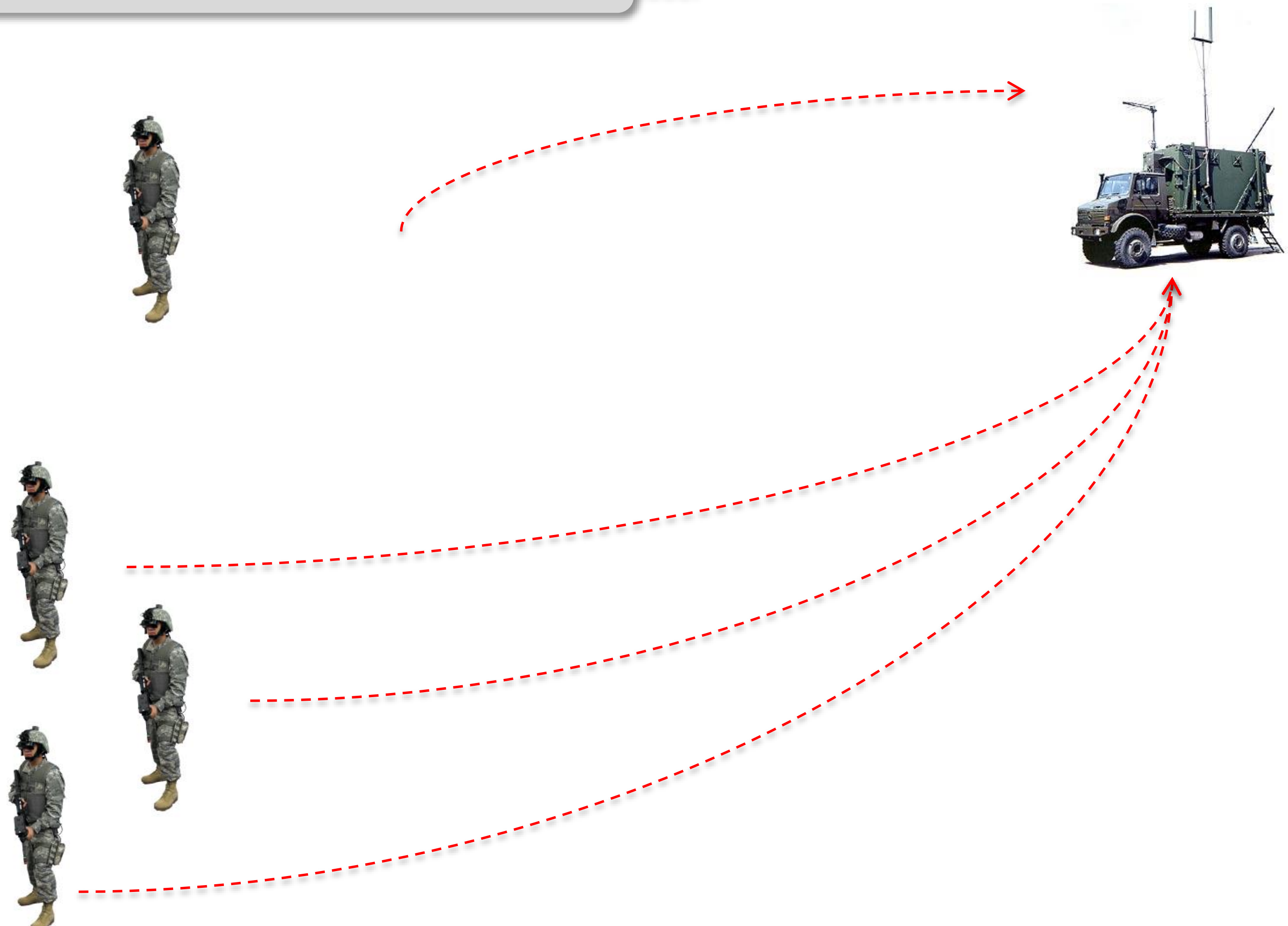
Multi-Int:
Prior knowledge from historical events/threats

PCS computing for soldier health monitoring



PCS computing for soldier health monitoring

There are a variety of sensors used to monitor vitals of soldiers, location, and presence of poisonous gases.



PCS computing for soldier health monitoring

There are a variety of sensors used to monitor vitals of soldiers, location, and presence of poisonous gases.

- Footsteps
- GPS
- O_2
- Accelerometer
- Heart rate
- CO
- CO_2
- Intrusion Detection
- Compass

- Each soldier is augmented with situation awareness of location, poisonous gases, and vitals.
- Cohort health management is crucial for real-time efficient management of stress levels of soldiers
- Data sent to a mobile control center after initial pre-processing and analysis
- Dynamic allocation of units based on their physiological state and stress levels leads to informed decisions

CPS Current State of Art: Limitations

CPS are stovepipe systems with narrow set of observations of the real world.

No knowledge support for informed decision making with Mark’s case.

Social aspects crucial for decision making is ignored

The vision of Physical-Cyber-Social Computing is to provide solutions for these limitations.

Conclusions

Transition form search to solution to PCS computing engines for actionable information.

Seamless integration of technology involving selective human involvement.

Transition from reactive systems (humans initiating information need) to proactive systems (machines initiating information need).

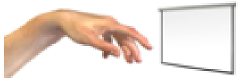
Sharing of knowledge, experiences, and observations across physical-cyber-social worlds lead to informed decision making. Subjectivity, personalization and social aspects are key to convert insight into action.

Physical-Cyber-Social Computing articulates how to achieve this vision. Semantic computing supports integration and reasoning capabilities needed for PCS computing.

AI

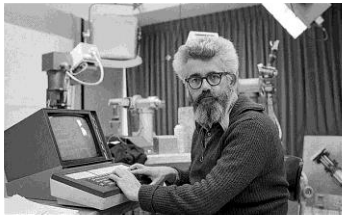
Ambient Intelligence

HCI

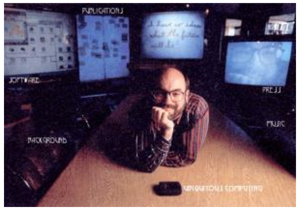


CHE

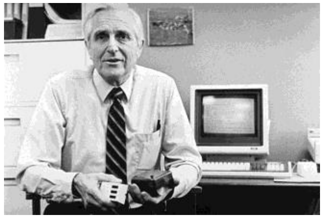
Machine Centric ← - - - - → Human Centric



J. McCarthy



M. Weiser



D. Engelbart

J. C. R. Licklider

A bit more on this topic

Influential visions by Bush, Licklider, Eaglebert, and Weiser.

Amit Sheth, Pramod Anantharam, Cory Henson, 'Physical-Cyber-Social Computing: An Early 21st Century Approach,' IEEE Intelligent Systems, pp. 79-82, Jan./Feb. 2013

Amit Sheth,"Computing for Human Experience: Semantics-Empowered Sensors, Services, and Social Computing on the Ubiquitous Web," IEEE Internet Computing, vol. 14, no. 1, pp. 88-91, Jan.-Feb. 2010, doi:10.1109/MIC.2010.4

A. Sheth, Semantics empowered Cyber-Physical-Social Systems, Semantic Web in 2012 workshop at ISWC 2102.

Cory Henson, Amit Sheth, Krishnaprasad Thirunarayan, 'Semantic Perception: Converting Sensory Observations to Abstractions,' IEEE Internet Computing, vol. 16, no. 2, pp. 26-34, Mar./Apr. 2012, doi:10.1109/MIC.2012.20

Cory Henson, Krishnaprasad Thirunarayan, Amit Sheth. An Ontological Approach to Focusing Attention and Enhancing Machine Perception on the Web. Applied Ontology, vol. 6(4), pp.345-376, 2011.

Cory Henson, Krishnaprasad Thirunarayan, and Amit Sheth, 'An Efficient Bit Vector Approach to Semantics-based Machine Perception in Resource-Constrained Devices,' In: Proceedings of 11th International Semantic Web Conference (ISWC 2012), Boston, Massachusetts, USA, November 11-25, 2012.

Kno.e.sis resources

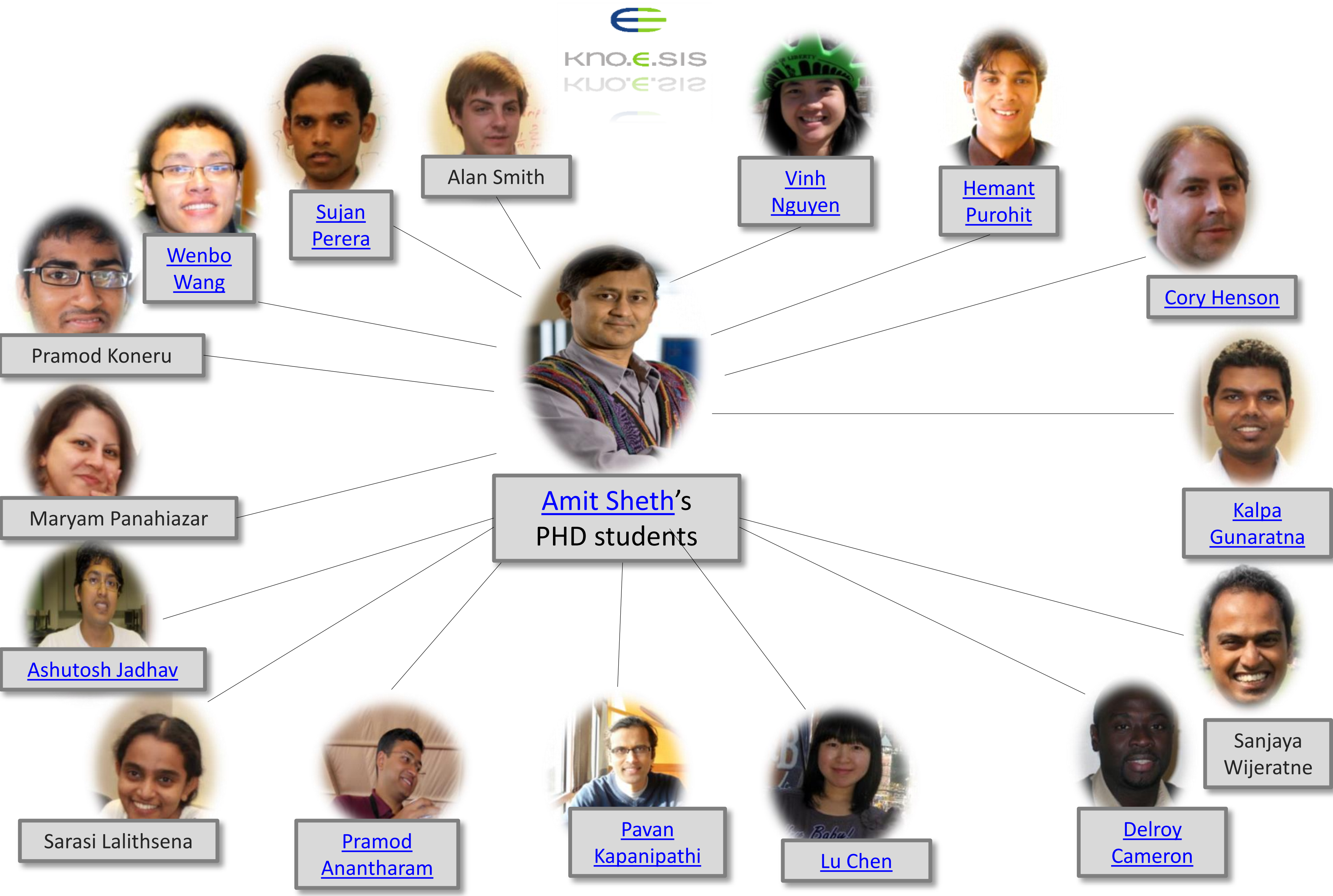
- OpenSource: http://knoesis.org/opensource
- Showcase: http://knoesis.org/showcase
- Vision: http://knoesis.org/vision
- Publications: http://knoesis.org/library
- PCS computing: http://wiki.knoesis.org/index.php/PCS

Acknowledgements

- Collaborators: U-Surrey (Payam Barnaghi), UCI (Ramesh Jain), DERI, AFRL, Boonshoft Sch of Med – WSU (Dr. Forbis, …), OSU Wexner (Dr. Abraham), and several more clinical experts, …
- Funding: NSF (esp. IIS-1111183 "SoCS: Social Media Enhanced Organizational Sensemaking in Emergency Response,"), AFRL, NIH, Industry….

Physical Cyber Social Computing

Amit Sheth, Kno.e.sis, Wright State



Kno.e.sis in 2012 = ~100 researchers (15 faculty, ~50 PhD students)

Physical-Cyber-Social Computing

thank you, and please visit us at

http://knoesis.org

Kno.e.sis – Ohio Center of Excellence in Knowledge-enabled Computing
Wright State University, Dayton, Ohio, USA