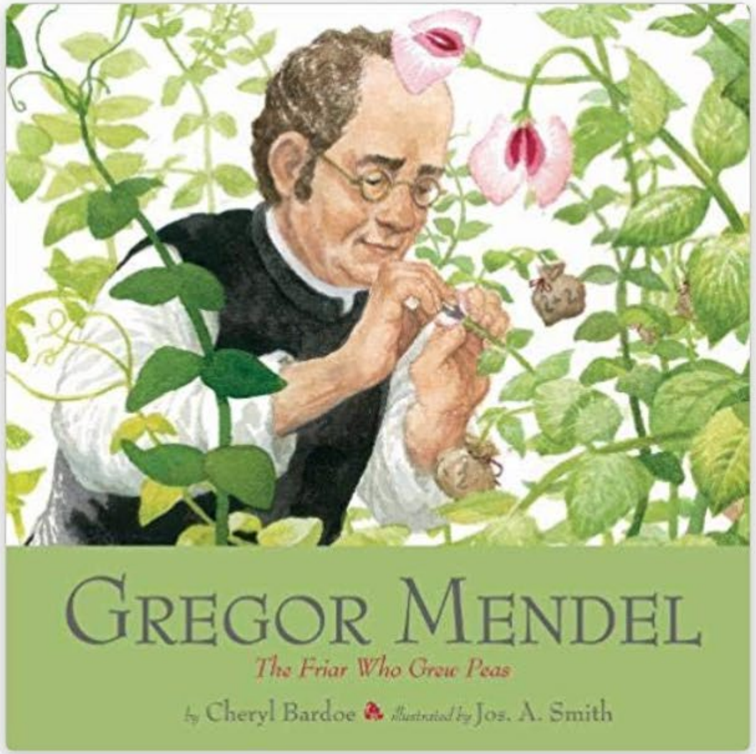
PEAS is mnemonic borrowed from the literature on Agent based systems (ABS) designed (modeled) to address systems performance (P) in the context of environment (E) of operation, events or processes or systems, to be actuated (A), based on information from primary sources, for example, sensor (S) data. http://bit.ly/P-E-A-S and https://link.springer.com/chapter/10.1007/978-981-10-8258-0_8

Gregor Mendel: The Friar Who Grew Peas



PEAS

Platform for the Agro-Ecosystem

Eric Scott McLamore[1] and Shoumen Palit Austin Datta[1,2,3]

[1] Nano-Bio Sensors Lab, Department of Agricultural and Biological Engineering, University of Florida, Gainesville, FL 32611
[2] Auto-ID Labs, Department of Mechanical Engineering, Massachusetts Institute of Technology, Cambridge, MA 02139
[3] MDPnP Lab, Department of Anesthesiology, Massachusetts General Hospital, Harvard Medical School, Cambridge, MA 02139

– Performance

– Environment

– Actuators

– Sensors

http://bit.ly/P-E-A-S

PEAS PLATFORM for the Agro-Ecosystem

Decision Science for Agriculture and Agri-Business

https://prezi.com/go_0ow_w-3n6/agroecosystem-analysis-aesa/

– Performance

KIDS

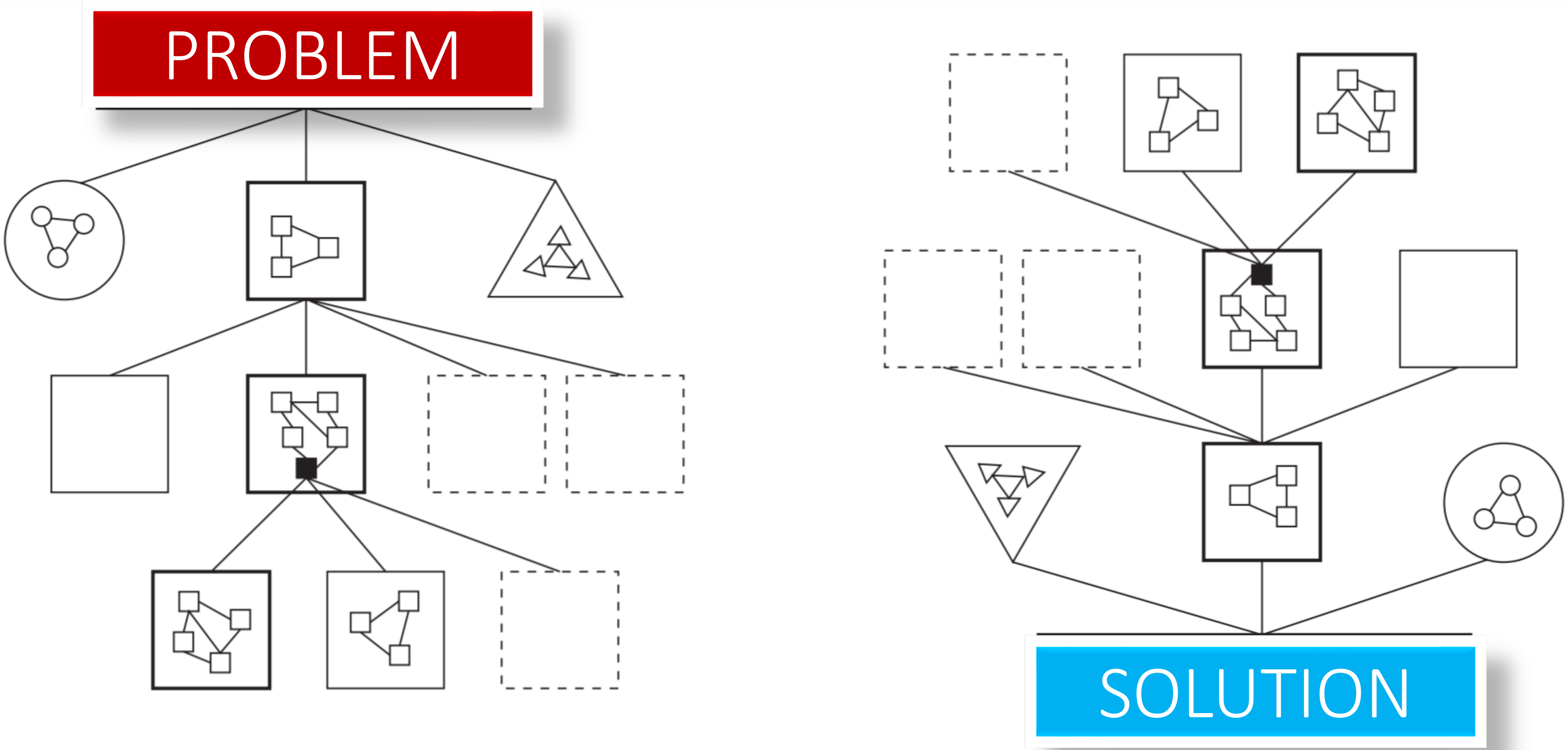
– Sensors

Knowledge-Informed Decision as a Service

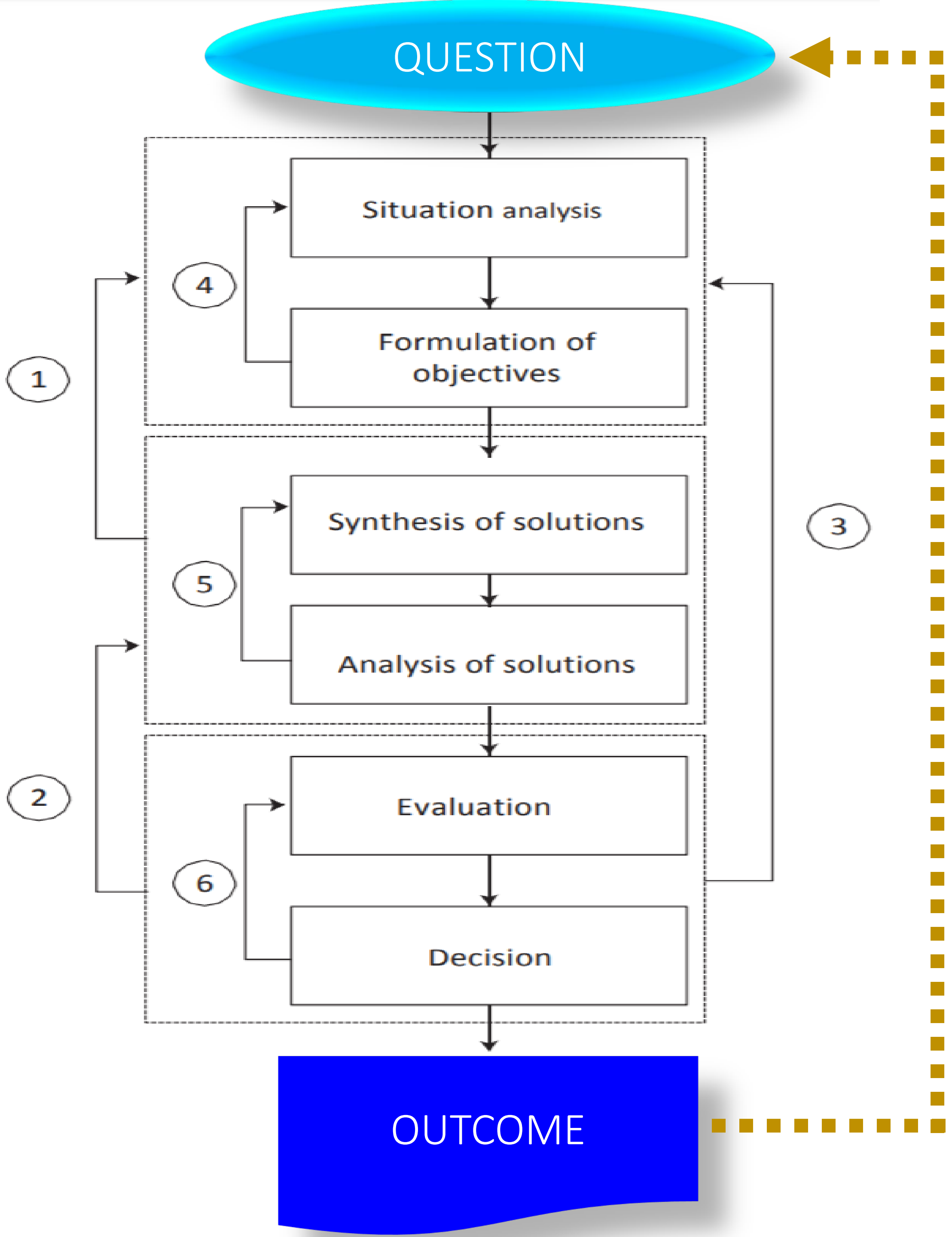
KIDS

The outcome and the value of the service is the key performance indicator.

De-construction and Re-construction



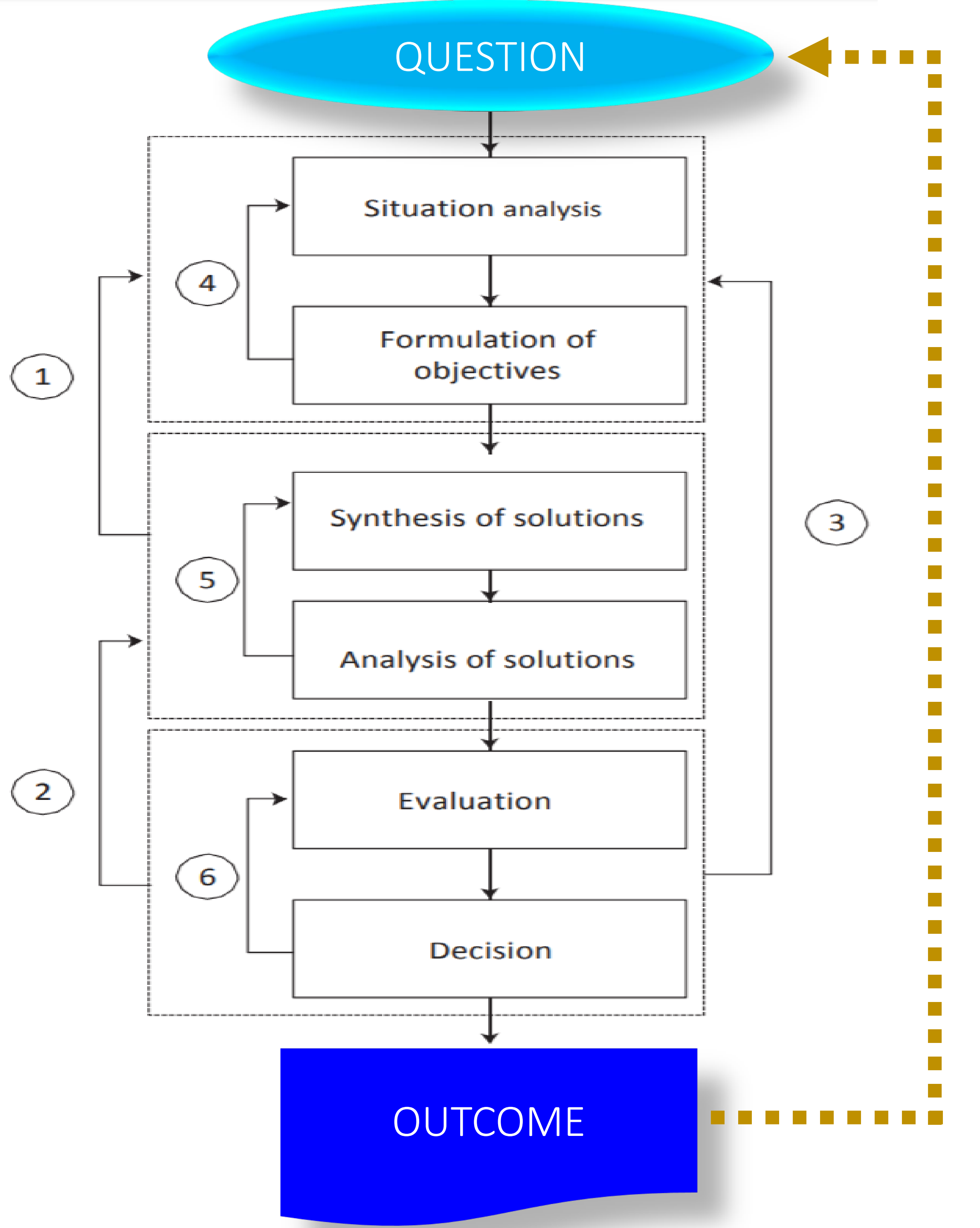
A Systems Engineering Approach? https://link.springer.com/book/10.1007/978-3-030-13431-0



QUESTION
Situation analysis
Formulation of objectives
Synthesis of solutions
Analysis of solutions
Evaluation
Decision
OUTCOME
1
2
3
4
5
6

A Systems Engineering Approach?

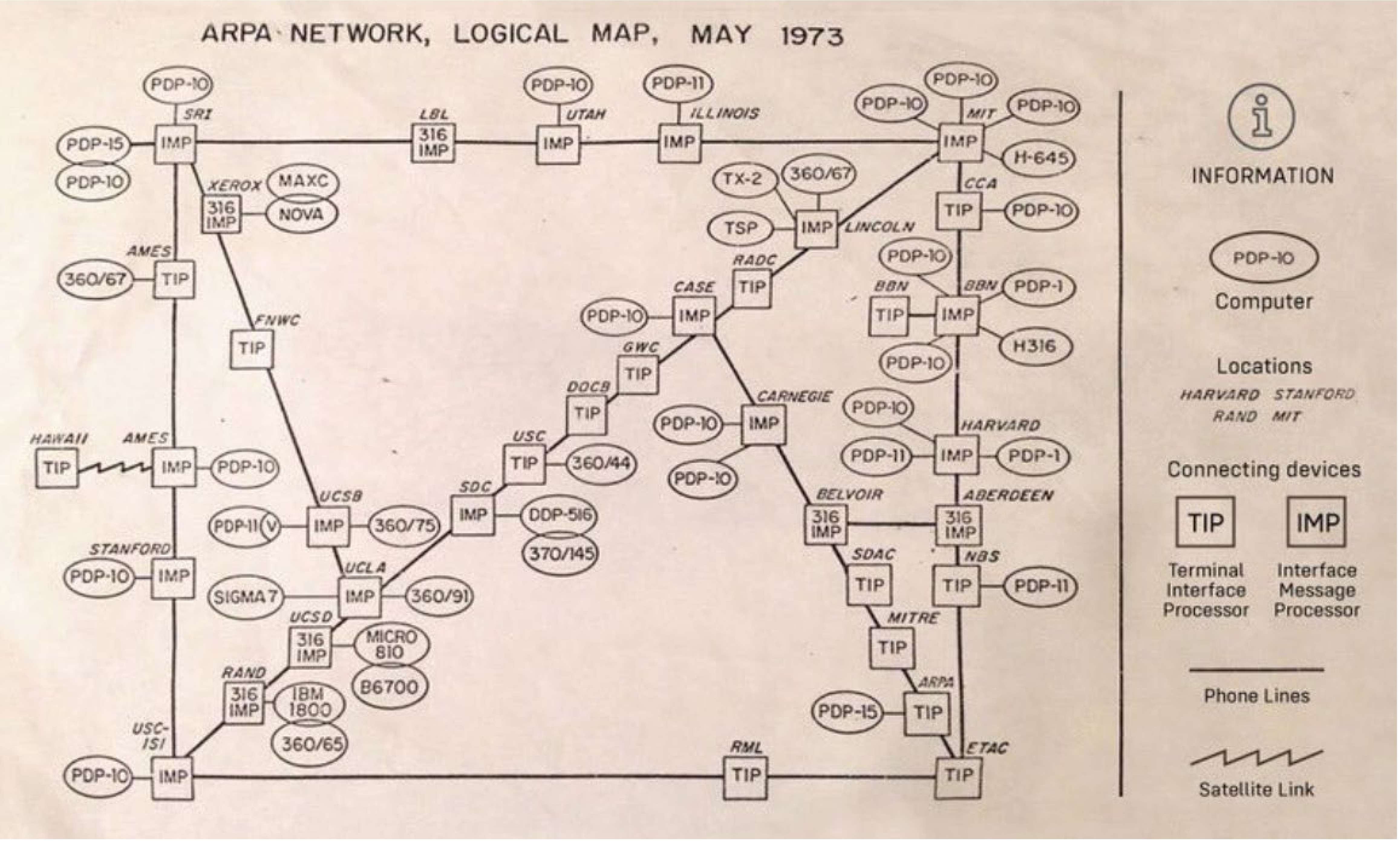
– What is the problem? Is it the correct problem to address?
– Boundaries of the problem space (dynamic vs static).
– Principal influences/mechanisms relative to the context of the problem and problem space.
– Needs a new or re-configured solution?
– What are the solution/system boundaries?
– Requirements of the solution space (system, design goals)
– Feasibility (contextual, technical, economic, social, ecological)
– Solution space to be reconstructed based on existing system or create/innovate architecture to execute solution system?



What is

KIDS

Knowledge-Informed Decision as a Service


ARPA NETWORK, LOGICAL MAP, MAY 1973
SRI
PDP-10
PDP-15
PDP-10
IMP
LBL
316 IMP
UTAH
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ILLINOIS
PDP-11
IMP
MIT
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H-645
XEROX
MAXC
NOVA
316 IMP
TX-2
360/67
TSP
IMP
LINCOLN
CCA
TIP
PDP-10
AMES
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H316
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FNWC
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GWC
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DOCB
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CARNEGIE
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PDP-10
HARVARD
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PDP-11
IMP
PDP-1
HAWAII
TIP
AMES
IMP
PDP-10
USC
TIP
360/44
SDC
IMP
DDP-516
370/145
BELVOIR
316 IMP
ABERDEEN
316 IMP
UCSB
PDP-11
V
IMP
360/75
STANFORD
PDP-10
IMP
UCLA
SIGMA 7
IMP
360/91
SDAC
TIP
NBS
TIP
PDP-11
UCSD
316 IMP
MICRO 810
B6700
MITRE
TIP
RAND
316 IMP
IBM 1800
360/65
ARPA
PDP-15
TIP
USC-ISI
PDP-10
IMP
RML
TIP
ETAC
TIP
INFORMATION
PDP-10
Computer
Locations
HARVARD STANFORD
RAND MIT
Connecting devices
TIP
IMP
Terminal Interface Processor
Interface Message Processor
Phone Lines
Satellite Link

PLATFORM

KIDS

Knowledge-Informed Decision as a Service

PLATFORM

KIDS is an open plan platform concept. Platforms are comprised of multiple applications and integrated solutions with embedded tools and databases that function as complete, seamless environments. Product innovation platforms are intended to support groups of users collaborating across various levels, domains, business units, and the ecosystem. These capabilities are increasingly needed throughout the entire extended enterprise in almost every vertical, agnostic of the type of application or function or users, including farmers, meat packers, produce growers, retail stores, customers, suppliers, and business partners. Developing open platform tools and technologies are not limited to any one domain because graph networks can overlay and configured for use, almost anywhere. KIDS also includes error correction, search engine algorithms, NLU/NLP (natural language processing), automated feature engineering, drag and drop functions, data analytics, workflows, and open services with plug & play interfaces. Human-computer interactions and data interoperability between system of systems are key elements in the KIDS model.

What are the questions?

ABOUT AGRO-ECOSYSTEM

This discussion is about FEWS. But we focus on a tiny part of the science and engineering issues at the nexus of food, energy, water and sanitation (FEWS). Our emphasis is on agriculture and food.
<u>KIDS aims to answer questions from end-users.</u>

For KIDS, food growers and farmers in the field, are the customers.

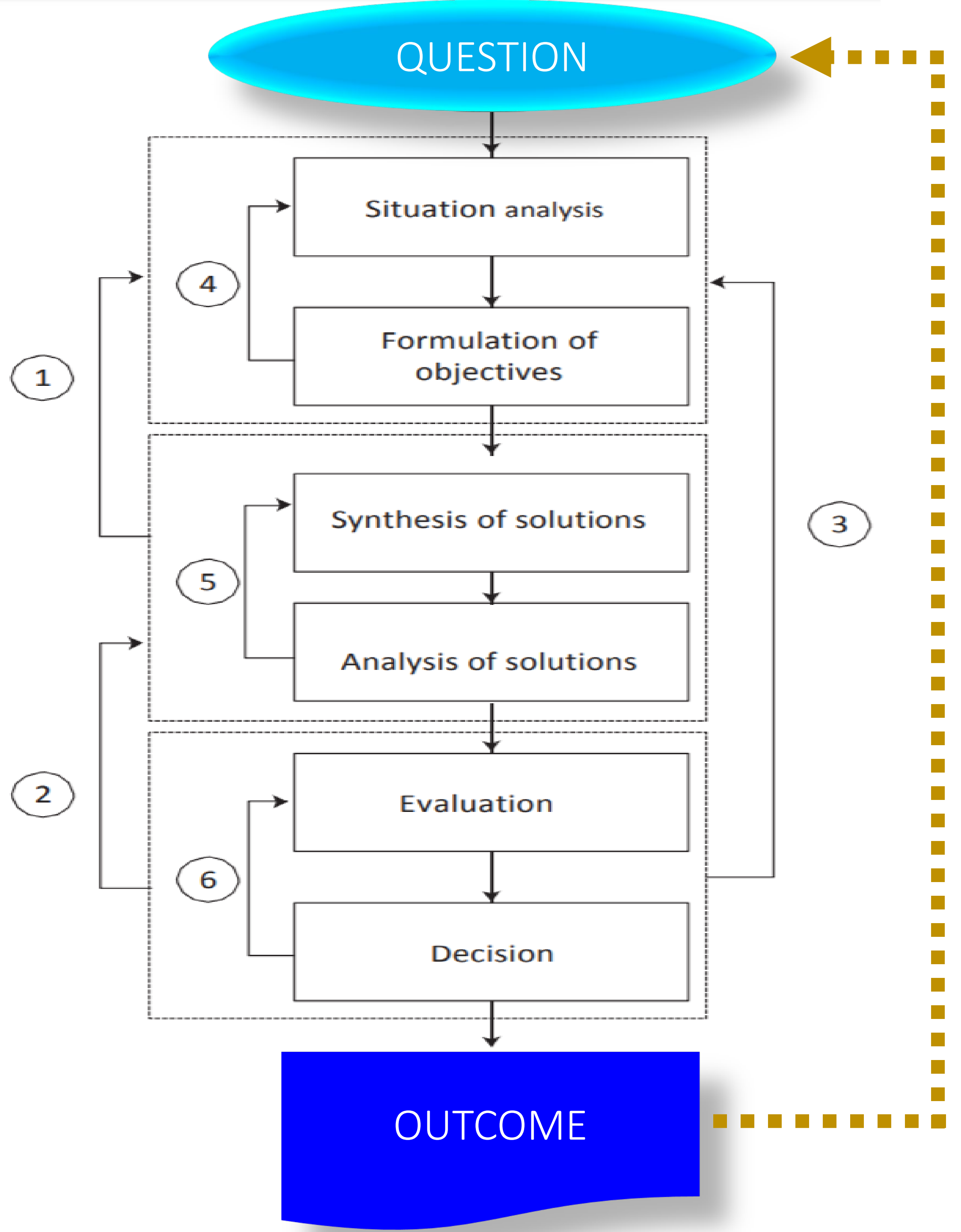
An educated consumer is the best customer.

Example of question from end-user

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Systems engineering approach can guide but it is woefully inadequate. Cannot stay in the "box" if we wish to answer.

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater ?



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

The complexity of this question indicates the challenge for decision support system

Systems engineering approach may need several cycles of
deconstruction and reconstruction to analyze the question and disassemble
the sub-systems, components and data, necessary to attempt to answer the question.

Beyond the horizon of data-informed decision as a service (decision support system)

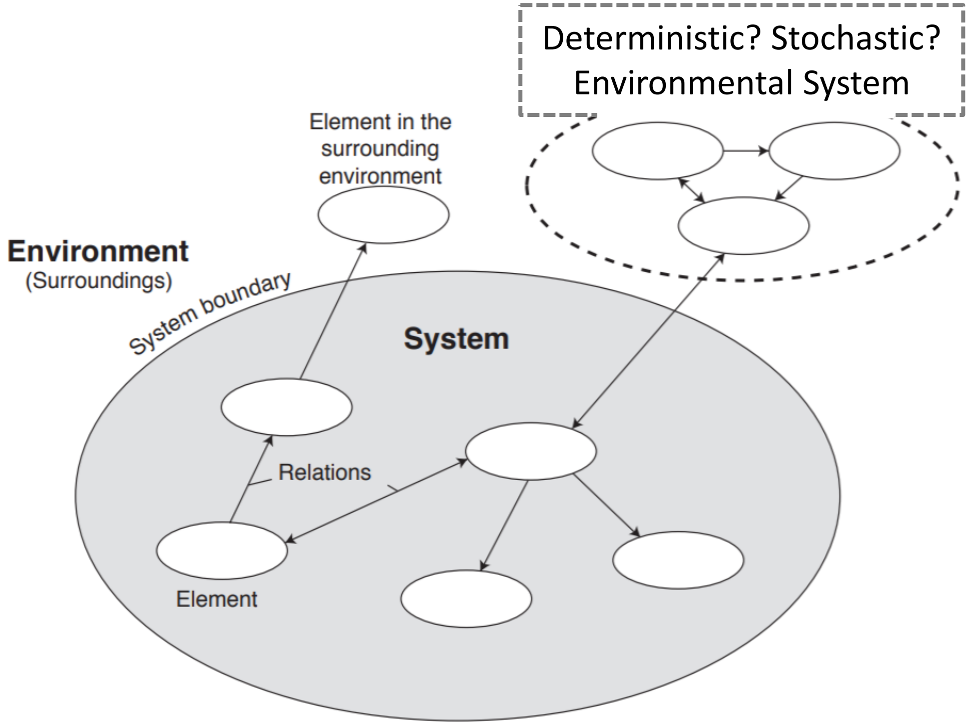
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

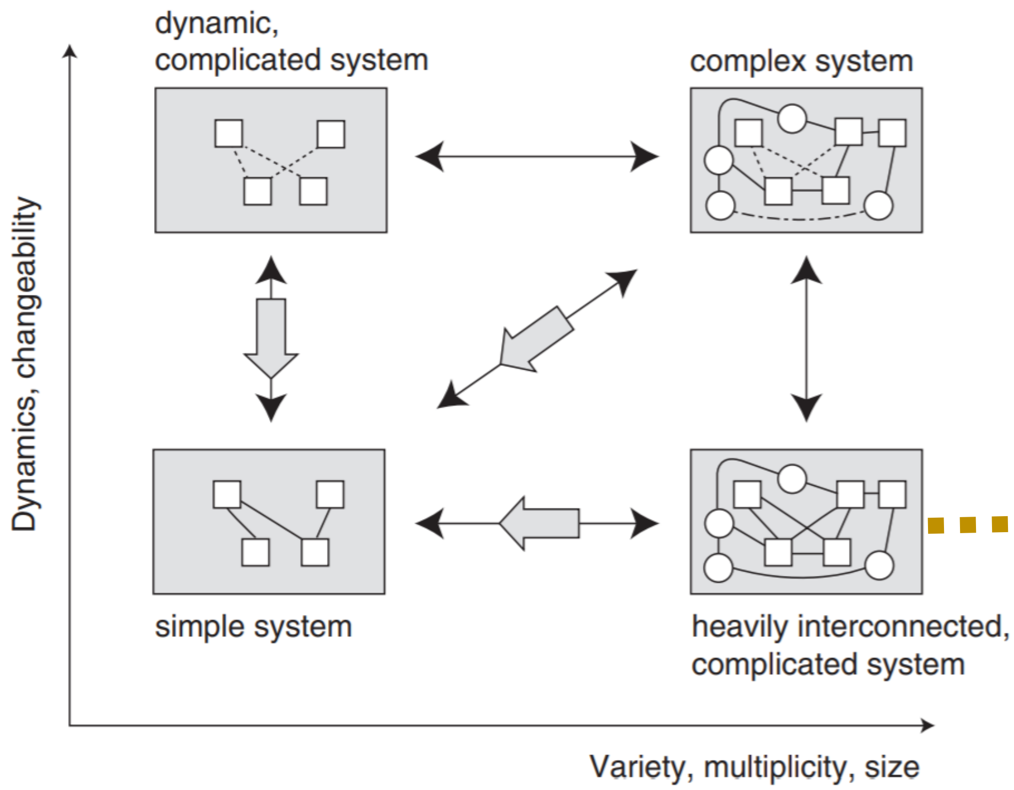
“*sacrificing my values*”

Prevailing decision systems are **data-informed**. Even extraction of actionable “information” stretches the reality. The semantics of this question represents an ecosystem of social “values” with respect to “sacrifices” which are personal in context of the user and her community. There are no tools or systems that can even attempt to answer the first part of the question to any degree of user satisfaction. In the short term, any answer may fail to meet an appreciable quality of service [QoS] level for which the user may recognize the value and may be willing to pay a fee (to receive the service). The best we are capable of delivering is the data-informed decision as a service (**DIDA’S**) which may be relevant to the cost and quality of the waste water which the user is seeking.

Beyond the horizon of data-informed decision as a service (decision support system)

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?





From a systems perspective, we have a heavily interconnected, complicated system

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

What happened to KIDS?

We initiated this discussion with **KIDS**, knowledge-informed decision as a service, but the user's question is compelling us to admit systemic inadequacies. Hence, we are stepping down, considerably, to recognize that the best outcome, at the present, may be limited to **DIDA'S** or data-informed decision as a service and stretch (?) our abilities to extract actionable information.

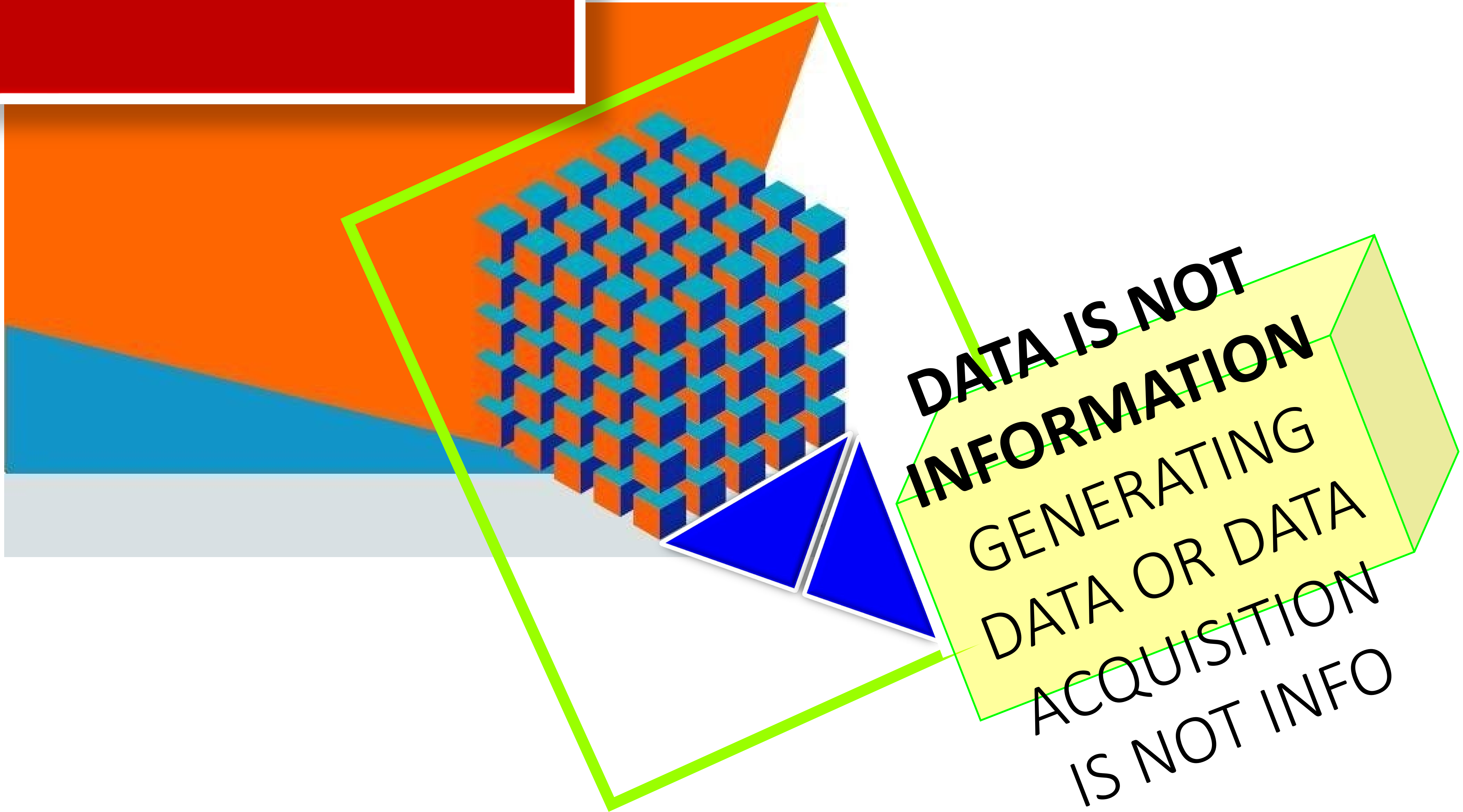
SUMMARY

1) Data ≠ Information ≠ Knowledge

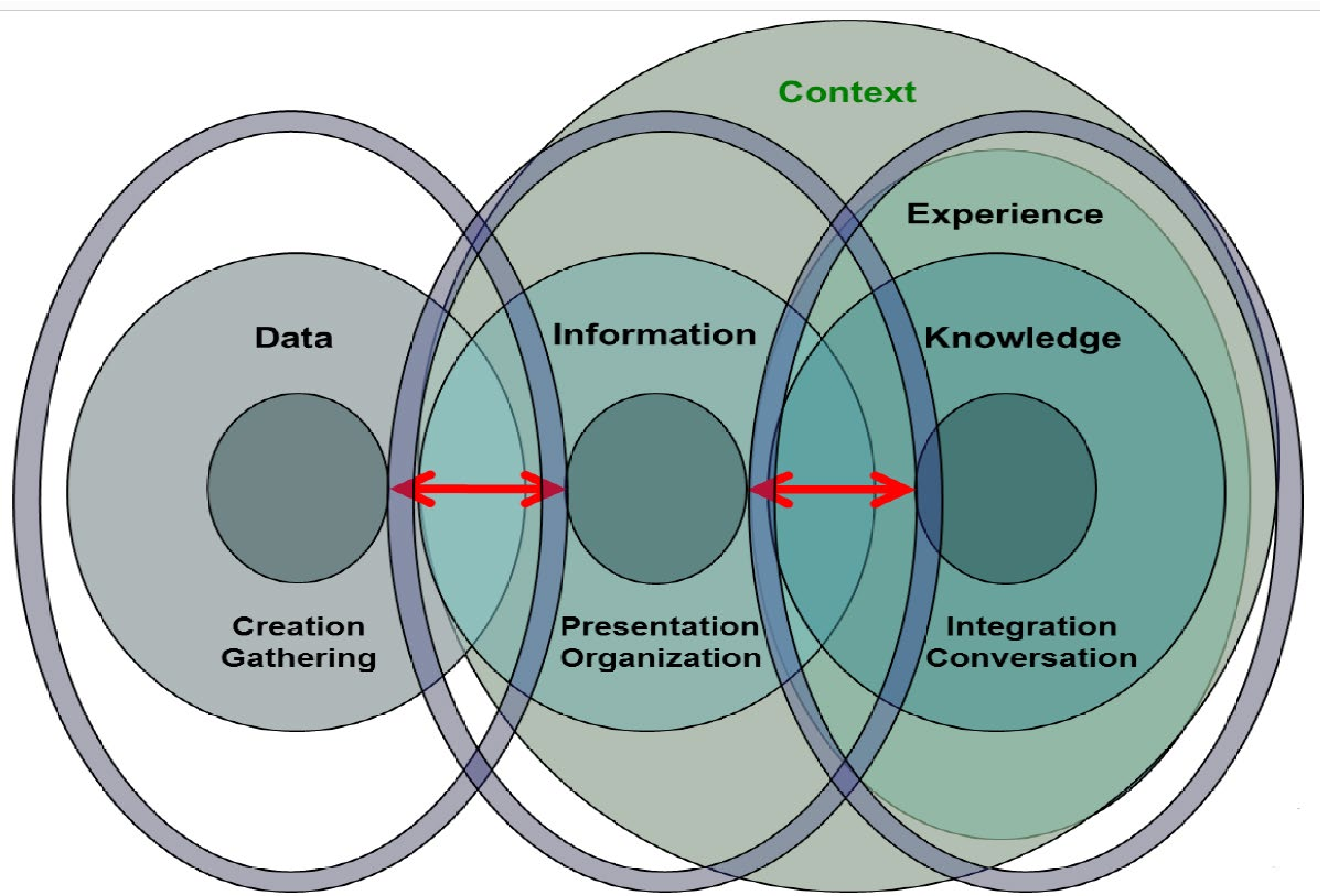
2)

3)

4)



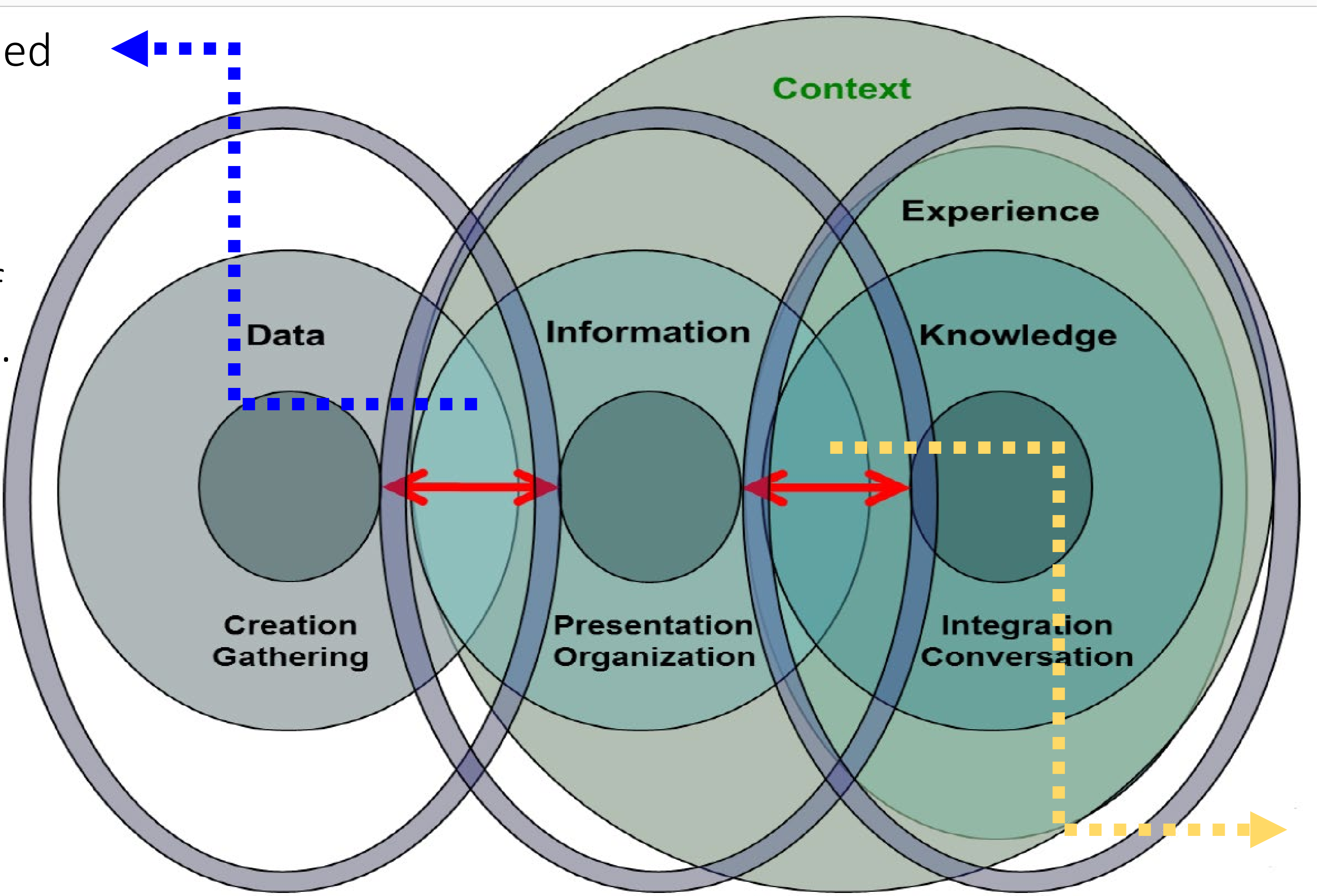
In terms of knowledge from data, our current status is analogous to 1950's, when TV was fuzzy black, greyish white, grainy & dull.



Cartoon: Jim Hendler

In terms of knowledge from data, our current status is analogous to 1950's, when TV was fuzzy black, greyish white, grainy & dull.

Data-informed may be the best case scenario at this stage of our systems.



Knowledge-informed is the Holy Grail. It may be decades away from reality. KIDS may aspire to reach this zone if artificial reasoning can escape the AI mis-information assault and move beyond classical expert systems.

Mind the Gap

There is a

vast

chasm between

data-informed

vs

knowledge-informed

http://www.kr.tuwien.ac.at/staff/tkren/pub/2008/rowschool2008.pdf

KIDS

Knowledge-Informed Decision as a Service

Convergence → *A Sense of the Future*

PLATFORM

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

DIDA'S

Data-Informed Decision as a Service

First, successfully deploy DIDA'S and create tools to extract actionable information.
Then we may re-visit how to create KIDS, knowledge-informed decision as a service.

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to cost, quality of wastewater and wastewater treatment.

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

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If we dissect deeper with our reductionist approach, we determine the need to answer the user's question in terms of water quality. What data DIDA'S may require for water quality?

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SENSOR DATA

DIDA'S

In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to performance, environment, actuators and sensors (PEAS).

DIDA'S

- **P**erformance
- **E**nvironment
- **A**ctuators
- **S**ensors

In the context of DIDA'S (Data-Informed Decision as a Service), re-visit the user's question with respect to performance, environment, actuators and sensor data.

DIDA'S

- **P**erformance
- **E**nvironment
- **A**ctuators
- **S**ensors

http://bit.ly/P-E-A-S

DIDA'S

KIDS

- **P**erformance
- **E**nvironment
- **A**ctuators
- **S**ensors

https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-825-techniques-in-artificial-intelligence-sma-5504-fall-2002/

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If we dissect deeper with our reductionist approach, we determine the need to answer the user's question in terms of water quality. What data DIDA'S may require for water quality?

1. Data from multiple sensors for water quality monitoring
2. Cost and pricing data for comparative analysis
3. Wastewater treatment tools and technologies

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Even the apparently simpler part of the question requires **multiple** sources of **data** and **convergence** of information to provide a sufficiently data-informed service to the user.

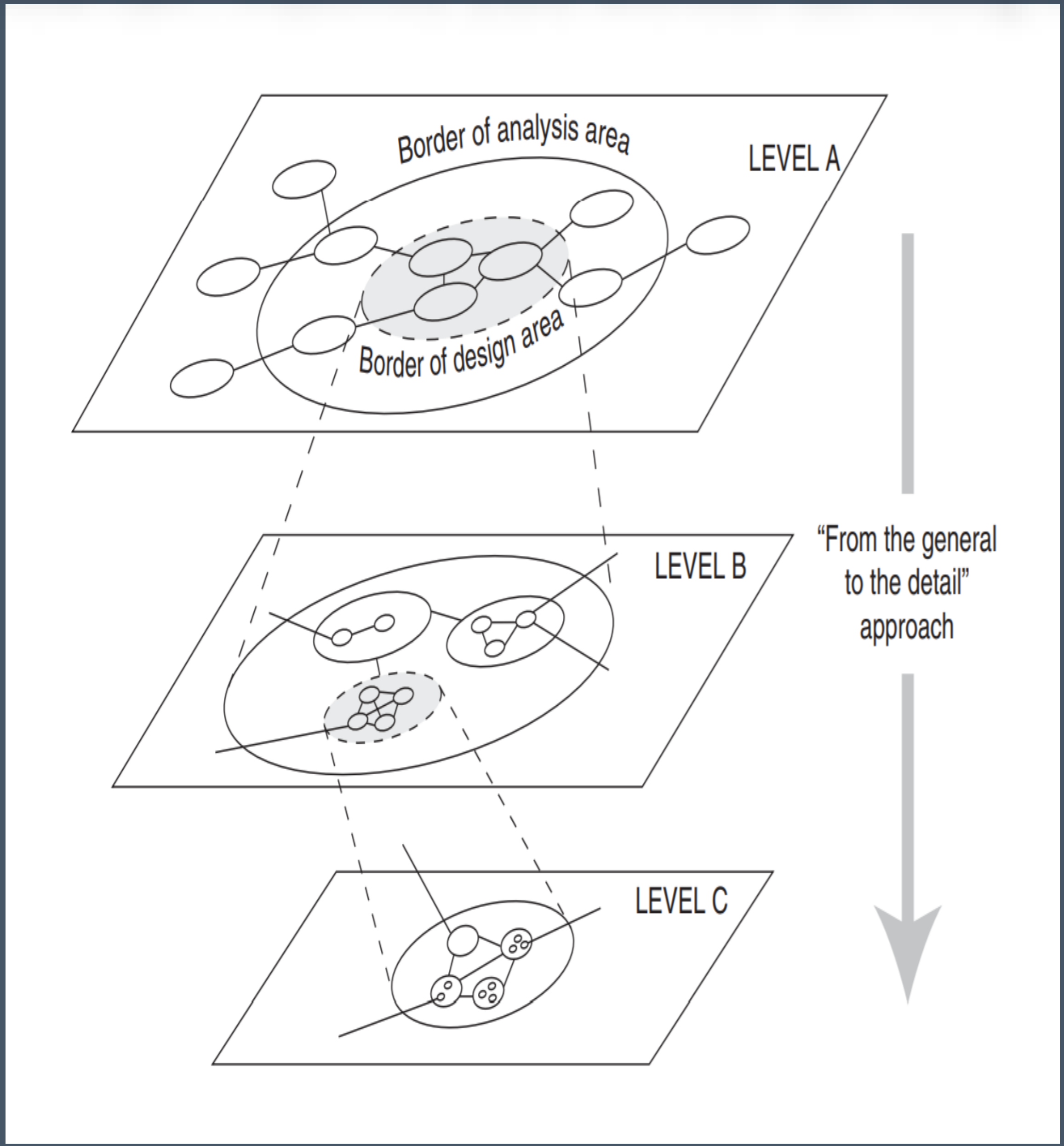
1. Data from multiple sensors for water quality monitoring
2. Cost and pricing data for comparative analysis
3. Wastewater treatment tools and technologies

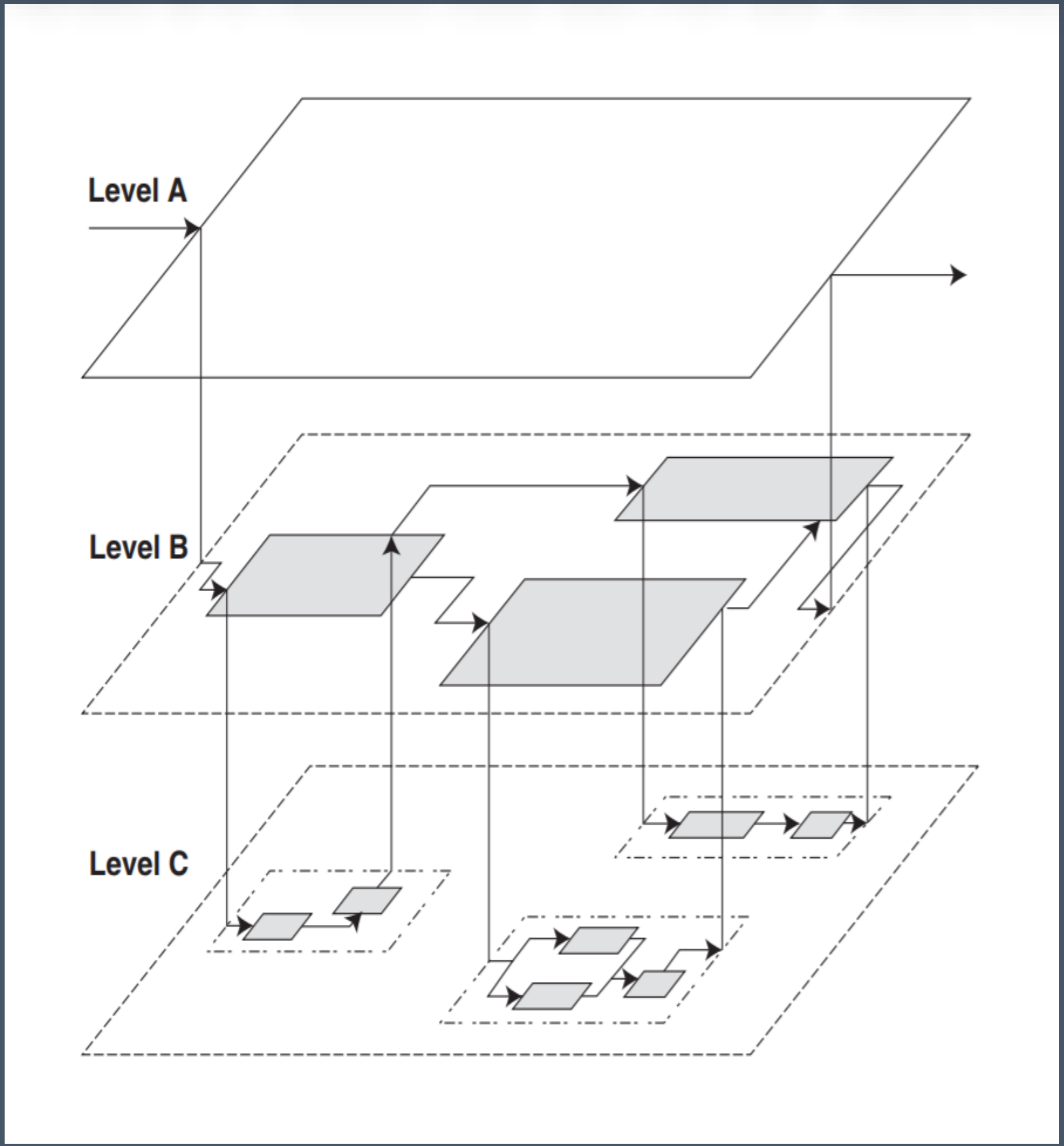
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Data fusion and convergence of information are only a part of the data-informed ***service*** users expect. The tasks are to delineate relationships germane to the question, select relevant data, connect, catalyze data fusion, synthesize information, extract "actionable" information, and deliver to a mobile device, in time, contextually relevant recommendation, of value, to the end-user.

1. Data from multiple sensors for water quality monitoring
2. Cost and pricing data for comparative analysis
3. Wastewater treatment tools and technologies

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

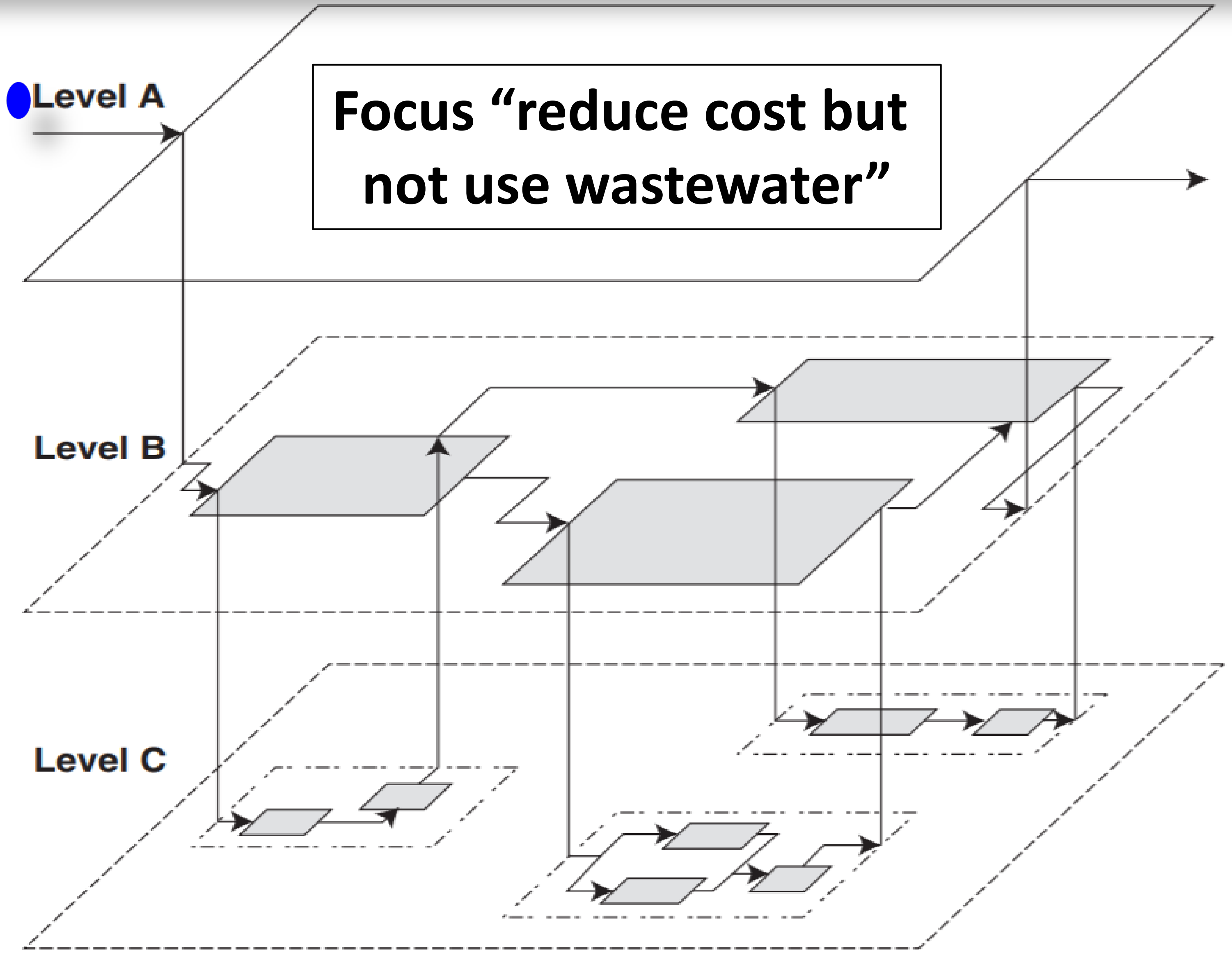




From a systems engineering approach, deconstruct the question in terms of data granularity.

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

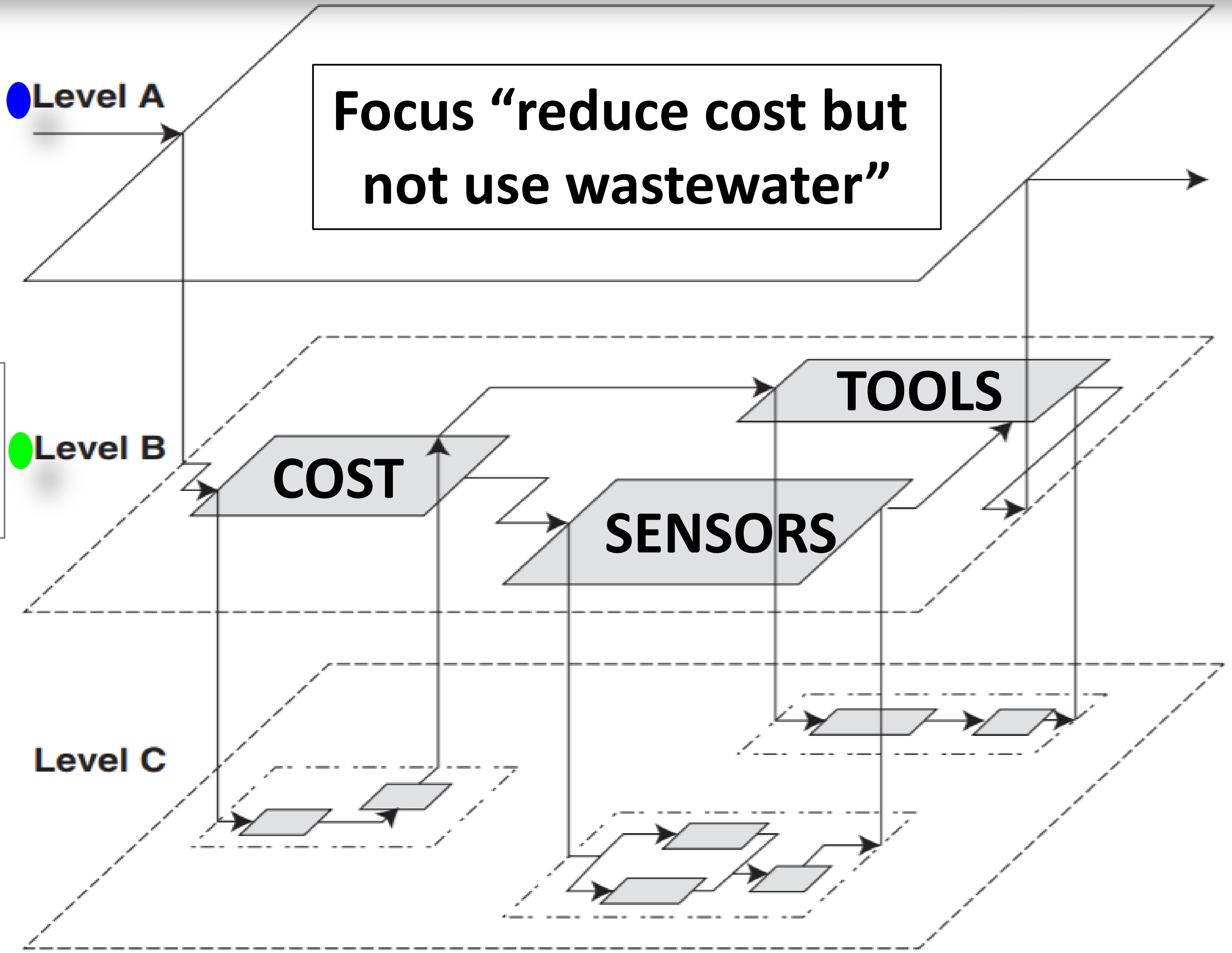
Focus “”reduce cost but not use wastewater



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Focus “”reduce cost but not use wastewater

-Factors affecting cost
-Sensors to determine water quality
-Tools necessary for treatment of wastewater



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

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-Factors affecting cost
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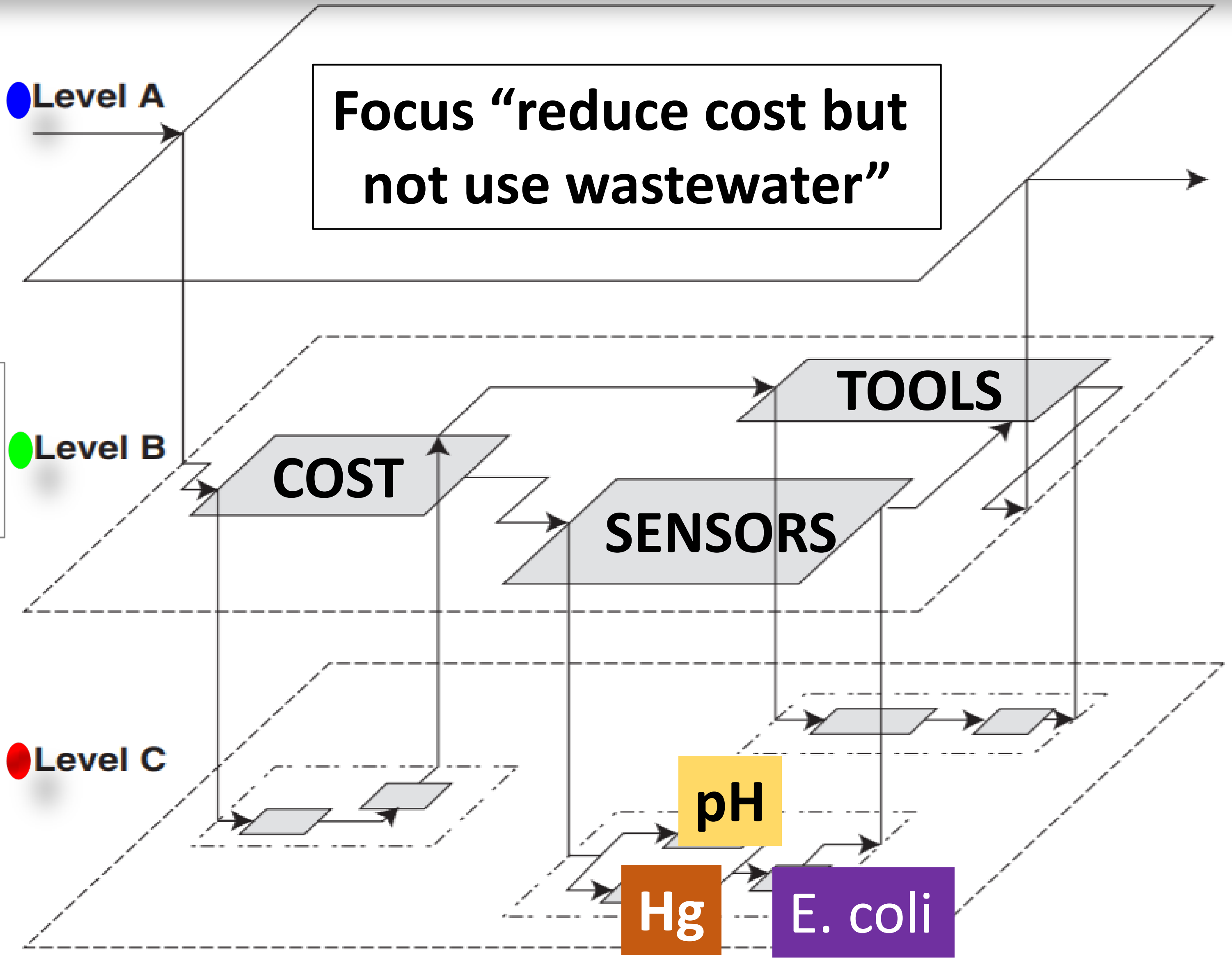
- Sensors to determine water quality
  - Heavy metal pollution (Mercury)
  - Microbial contaminants (E. coli)
  - Chemical characteristics (pH)



Granular Deconstruction – Lowest Common Denominator

Raw Data Source

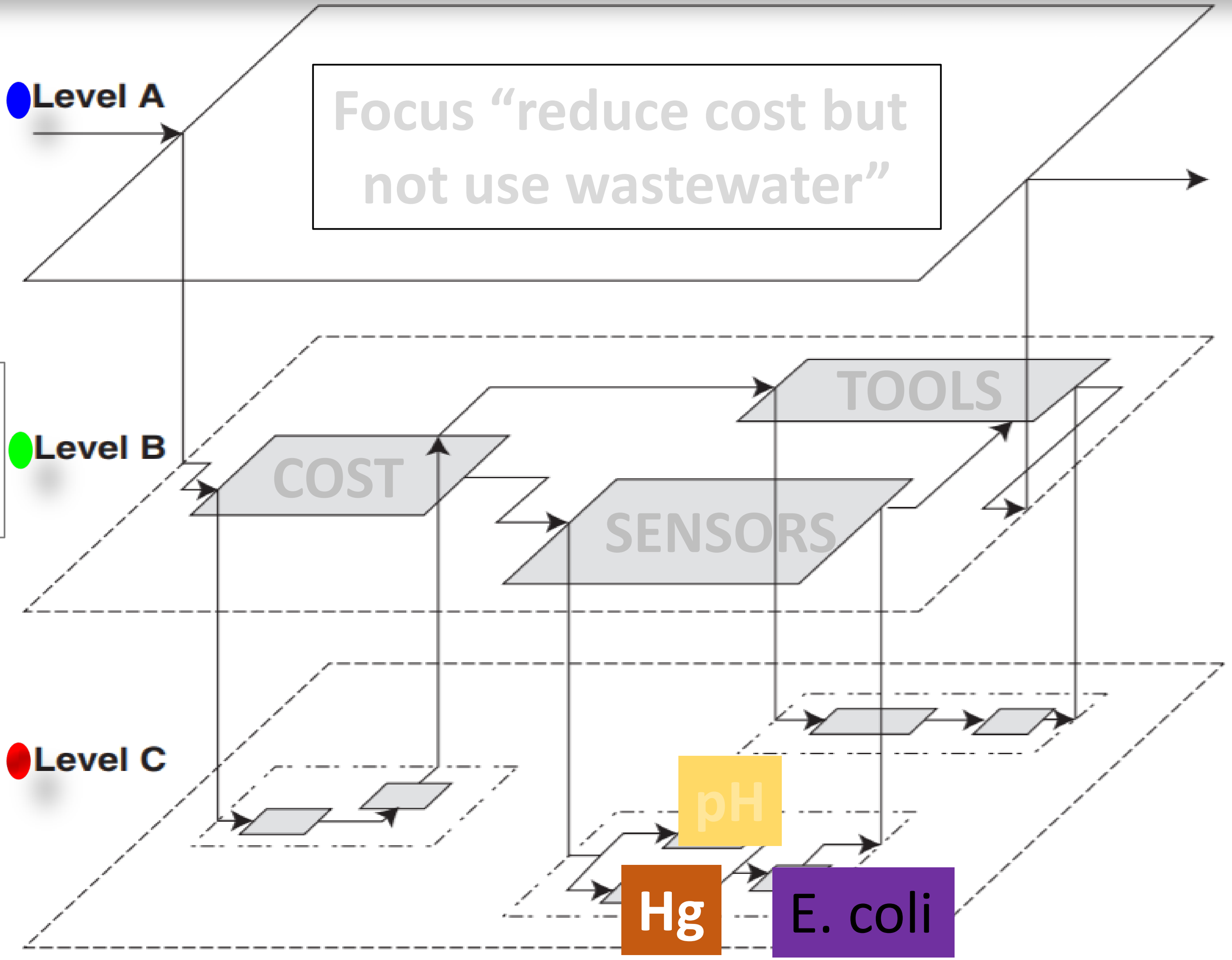
Denominator

Granularity of Deconstruction – Where is the data source?

Focus “”reduce cost but not use wastewater

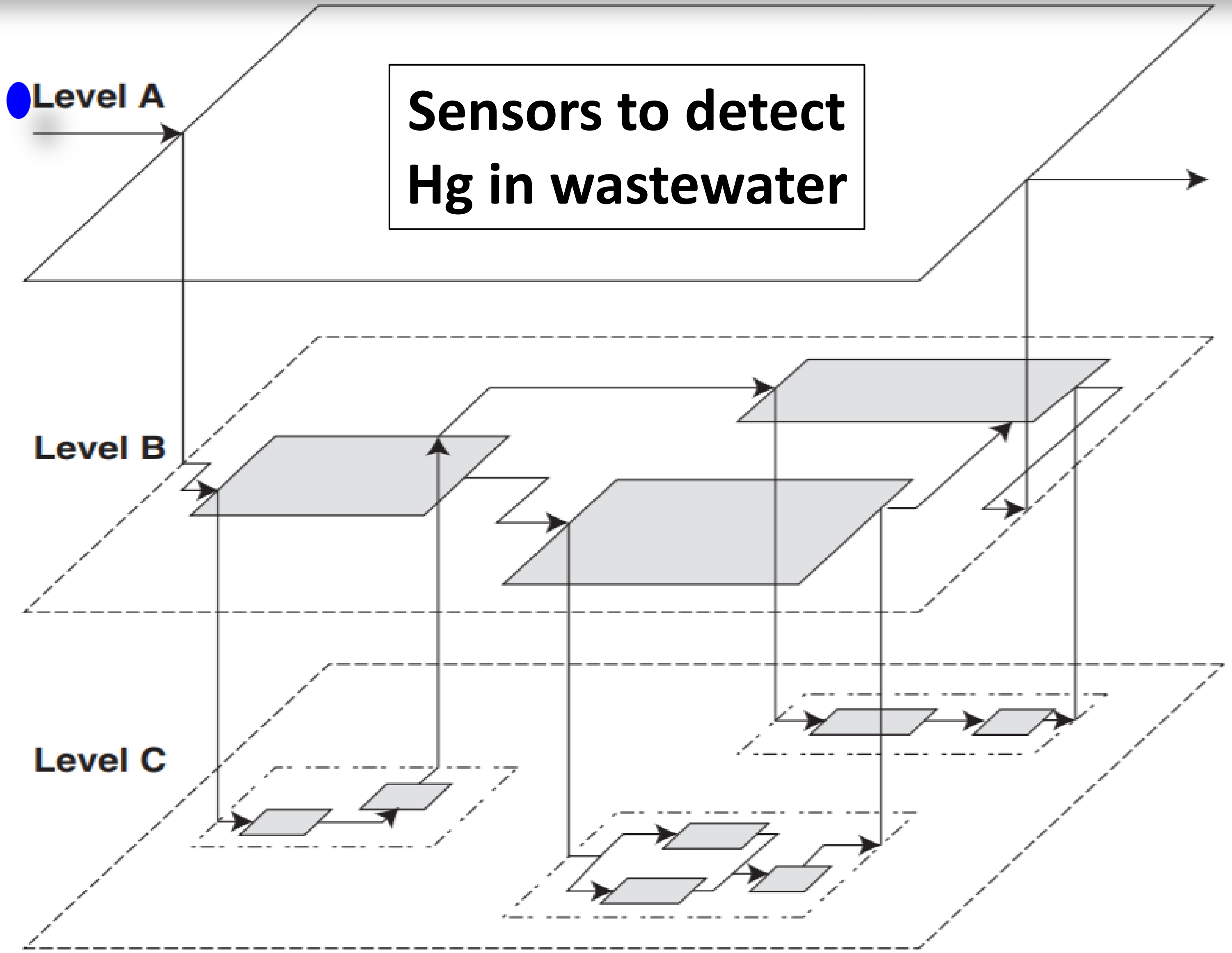
-Factors affecting cost
-Sensors to determine water quality
-Tools necessary for treatment of wastewater

- Sensors to determine water quality
  - Heavy metal pollution (Mercury)
  - Microbial contaminants (E. coli)
  - Chemical characteristics (pH)



Granularity of Deconstruction – Sensors to Detect Mercury

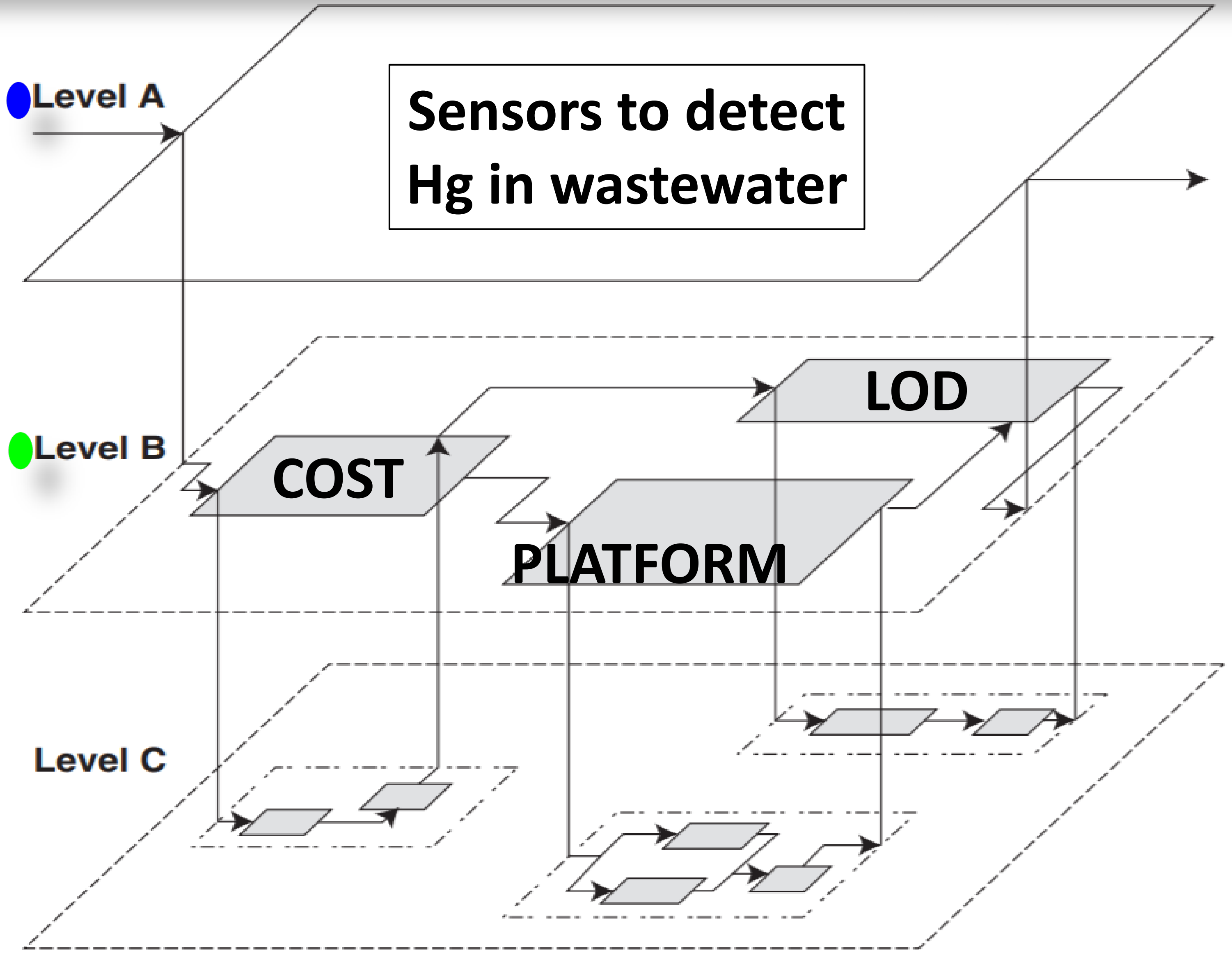
Sensors to detect Mercury (Hg) in wastewater



Granularity of Deconstruction – Sensors to Detect Mercury

Sensors to detect Mercury (Hg) in wastewater

-Cost of sensors
-Limit of Detection (LOD) necessary for use
-Which platform is best for the specific use

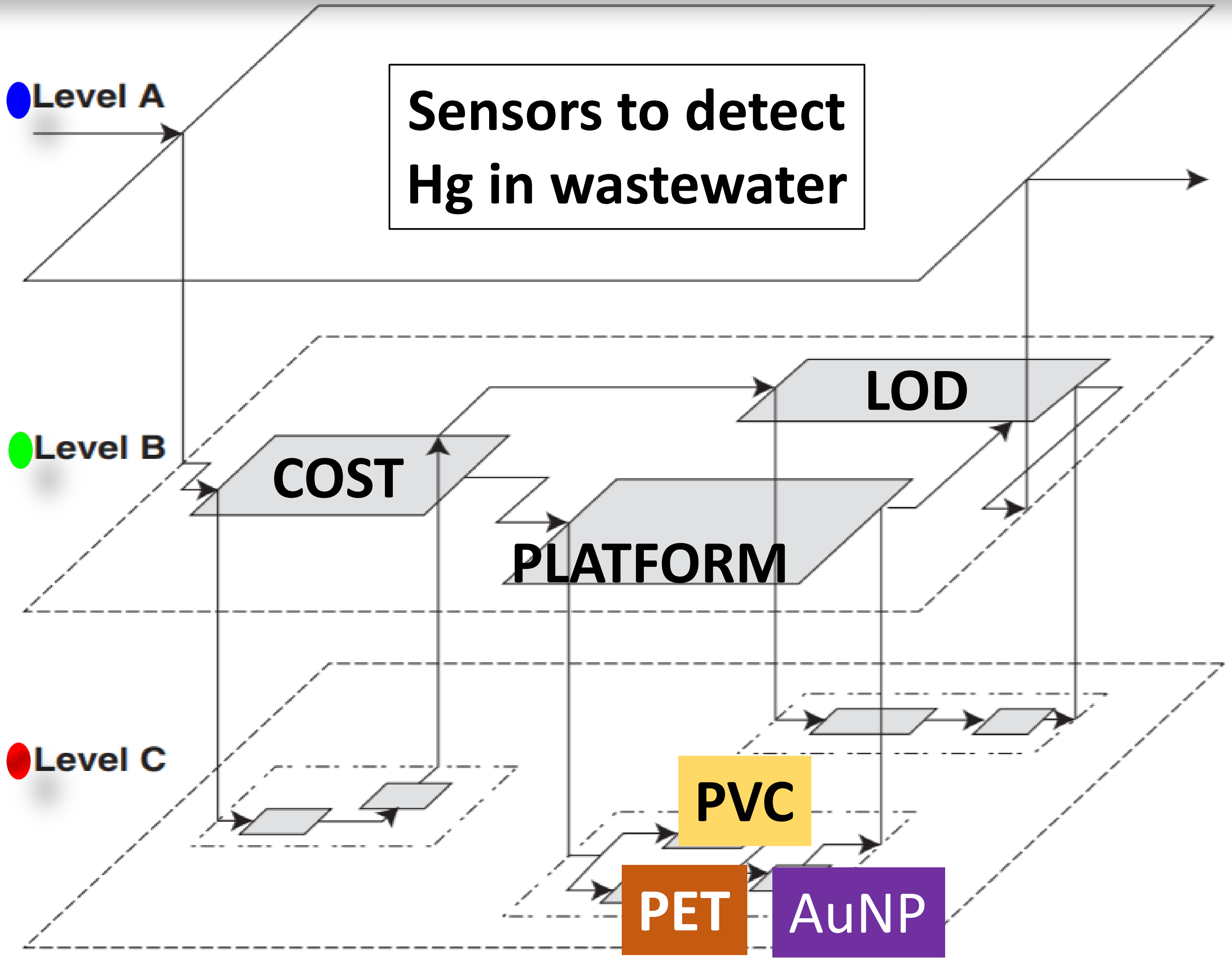


Granularity of Deconstruction – Sensors to Detect Mercury

Sensors to detect Mercury (Hg) in wastewater

-Cost of sensors
-Limit of Detection (LOD) necessary for use
-Which platform is best for the specific use

- Platforms for Mercury (Hg) sensor
  - Poly(vinyl chloride) (PVC) membrane
  - Photoinduced electron transfer (PET)
  - Gold-nanoparticle (AuNP)



https://onlinelibrary.wiley.com/doi/abs/10.1002/elan.1140090609
https://pubs.acs.org/doi/10.1021/ja037995g#
https://pubs.acs.org/doi/10.1021/nl0100116

Granularity of Deconstruction: Several types of sensors to detect Mercury

A	B	C	D	E	F	G	H	I	J
Device number	**MW [Da]**	**Category**	**Target**	**Recognition-transduction scheme**	**Platform**	**Range (LOD)**	**Range (max tested)**	**Selectivity (interferent species tested)**	**Response time [sec]**
1	201	heavy metal	mercury (Hg2+)	AuNP		1.00E-08	NR	NR	60
2	201	heavy metal	mercury (Hg2+)	MIP??	Sol gel	5.00E-06	NR	NR	600
3	201	heavy metal	mercury (Hg2+)	Rhodamine		1.00E-07	NR	NR	60
4	201	heavy metal	mercury (Hg2+)			5.00E-07	NR	95%	60
5	201	heavy metal	mercury (Hg2+)	foldamer	micelle	5.00E-07	NR	99%	60
6	201	heavy metal	mercury (Hg2+)	corroloe derivative	PVC	5.60E-06	NR	NR	300
7	201	heavy metal	mercury (Hg2+)	tetraarylborate		3.00E-07	NR	NR	60
8	201	heavy metal	mercury (Hg2+)			1.00E-07	NR	poor over Ag+	60
9	201	heavy metal	mercury (Hg2+)	polythiophene		3.00E-05	NR	90%	**60**
10	201	heavy metal	mercury (Hg2+)	thiosemicarbazone		5.00E-06	NR	NR	60
11	201	heavy metal	mercury (Hg2+)	dansylcarboxamide		1.00E-05	5.00E-04	NR	60
12	201	heavy metal	mercury (Hg2+)	quenching		3.00E-06	5.50E-05	excellent	60
13	201	heavy metal	mercury (Hg2+)	DNAzyme		2.40E-09	NR	excellent (transition/heavy metals)	60
14	201	heavy metal	mercury (Hg2+)	chromo-ionophore assembly	PVC	3.40E-08	NR	poor (heavy metals)	60
15	201	heavy metal	mercury (Hg2+)	AuNP		5.00E-09	1.00E-05	excellent (transition/heavy metals)	600
16	201	heavy metal	mercury (Hg2+)			1.00E-08	2.00E-04	excellent (transition/heavy metals)	60
17	201	heavy metal	mercury (Hg2+)	Rhodamine 6G	AuNP	6.00E-11	3.60E-08	excellent (transition/heavy metals)	60
18	201	heavy metal	mercury (Hg2+)	Cholic acid		5.00E-08	NR	good (MeHg/transition/heavy metals)	60
19	201	heavy metal	mercury (Hg2+)	thiacalixarene		2.00E-06	8.50E-06	good (poor over Ag+)	60
20	201	heavy metal	mercury (Hg2+)			7.00E-07	NR	poor over Cu+	60
21	201	heavy metal	mercury (Hg2+)	anthraquinone/urea		5.0E-05	2.0E-04	poor	60
22	201	heavy metal	mercury (Hg2+)	anthracene/ionophore hybrid	PET	1.0E-06		poor over Fe3+	60
23	201	heavy metal	mercury (Hg2+)	oligonucleotide	AuNP	1.0E-07	1.0E-06	poor over Pb3+	60
24	201	heavy metal	mercury (Hg2+)	oligonucleotide		4.2E-08	6.7E-07	moderate	60
25	201	heavy metal	mercury (Hg2+)			5.0E-08		excellent (transition/heavy metals)	60
26	201	heavy metal	mercury (Hg2+)	phosphorescent iridium(III) complex		2.0E-05		excellent (transition/heavy metals)	60
27	201	heavy metal	mercury (Hg2+)	MerR protein		1.0E-08		NR	60
28	201	heavy metal	mercury (Hg2+)			1.0E-06		NR	60

Which sensor to choose? Which sensor has the lowest limit of detection?

Which sensor to choose? Which sensor has the lowest limit of detection?

Users wish to explore sensor categories and attributes ?

Which sensor to choose? Which sensor has the lowest limit of detection?

Users wish to explore sensor categories and attributes ?

End-users, as well as experts, may benefit from information about different sensors, by categories and list of attributes, which may be suitable for use.

Which sensor to choose? Which sensor has the lowest limit of detection?

SENsor SEarch Engine

Which sensor to choose? Which sensor has the lowest limit of detection?

SENsor SEarch Engine

SENSEE

Delving deeper into the granularity of the data necessary for DIDA’S to be sufficiently data-informed, we arrive at one data source:

SENSORS
for
DIDA’S

Sensor data as a source of data for data-informed decision as a service (DIDA’S)

Sensor data still remains a key denominator when we move from data-informed (DIDA'S) to knowledge-informed (KIDS)

SENSORS
for
DIDA'S KIDS

Sensors for knowledge-informed decision as a service (KIDS)

SKIDS

In granular terms, DIDA'S and KIDS, still needs to choose sensor type.

SENsor **SE**arch **E**ngine

SENSEE

In granular terms, the outcome from DIDA'S and KIDS, depends on data.

Data from Sensors

SENSEE

At the most granular level, first we need to *choose the sensor* and then proceed to harvest *data* from specific sensor(s).

FOR SOME OF THE QUESTIONS, THIS IS A PRE-REQUISITE FOR DIDA'S and KIDS.

Hence, we start searching for suitable sensor categories and attributes.

SENsor SEarch Engine

SENSEE

Then, we seek data from sensors (relevant to the real world questions).

Data from Sensors

SENSEE

Before we can think about information or digital design

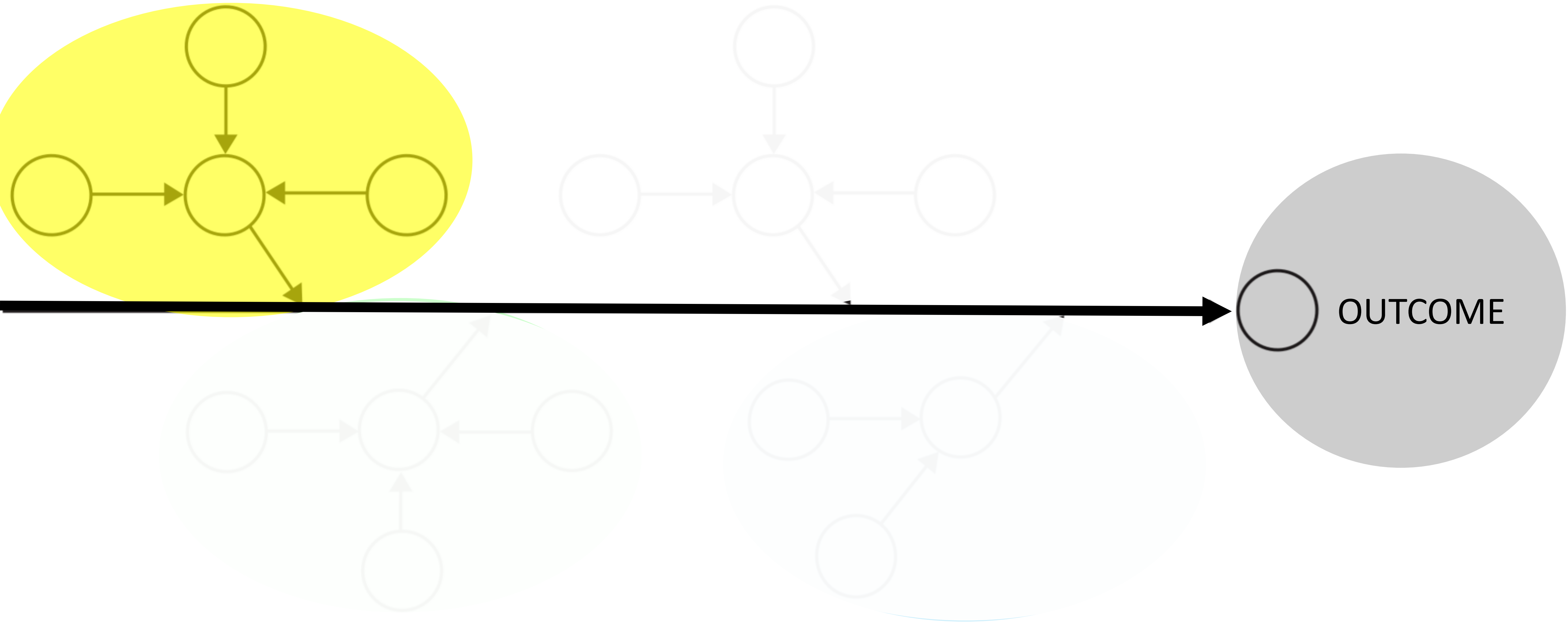
We need sensors, and sensor data, to fuel the outcome.

Data-informed (DIDA’S)

Knowledge-informed (KIDS)

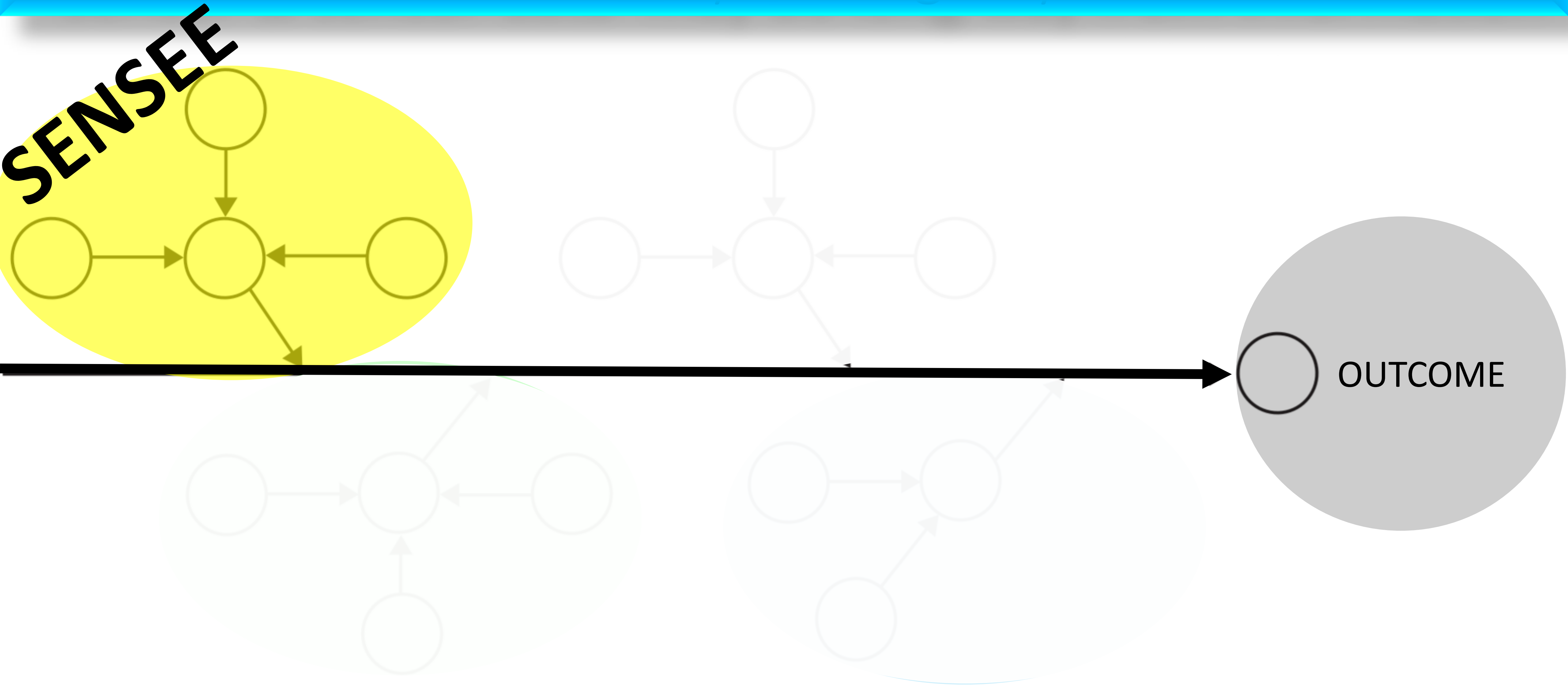
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Sensor & sensor data



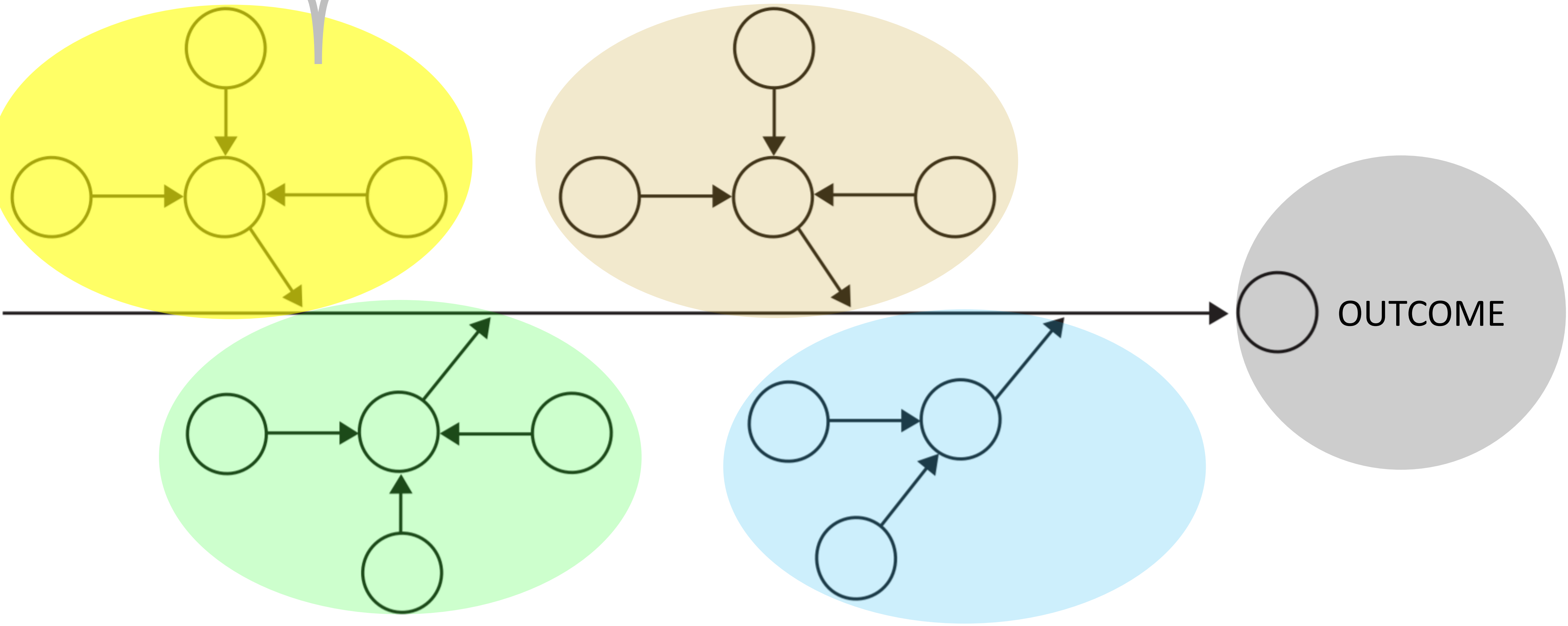
How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Sensor & sensor data



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

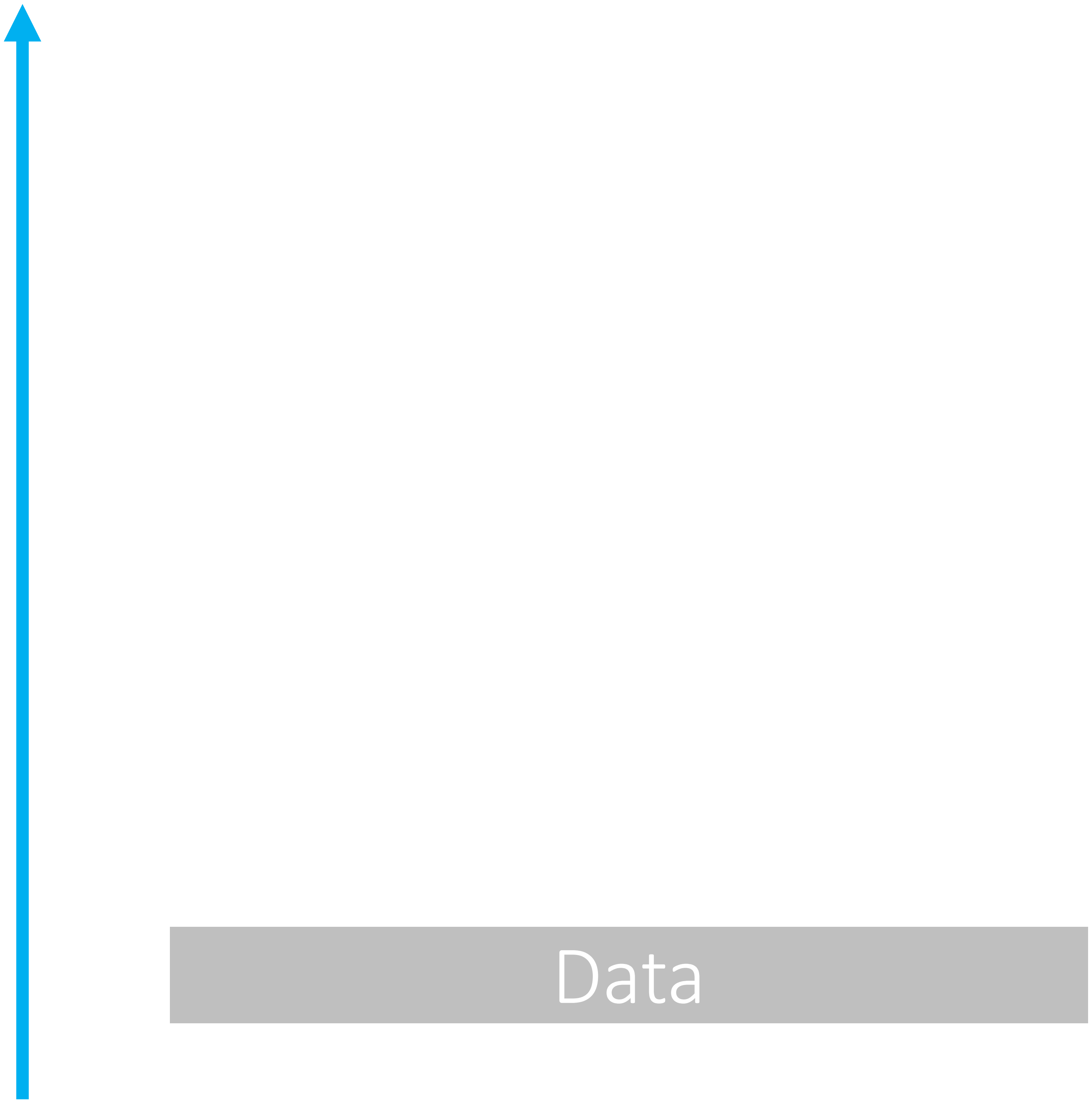
Sensor & sensor data may be long way from information



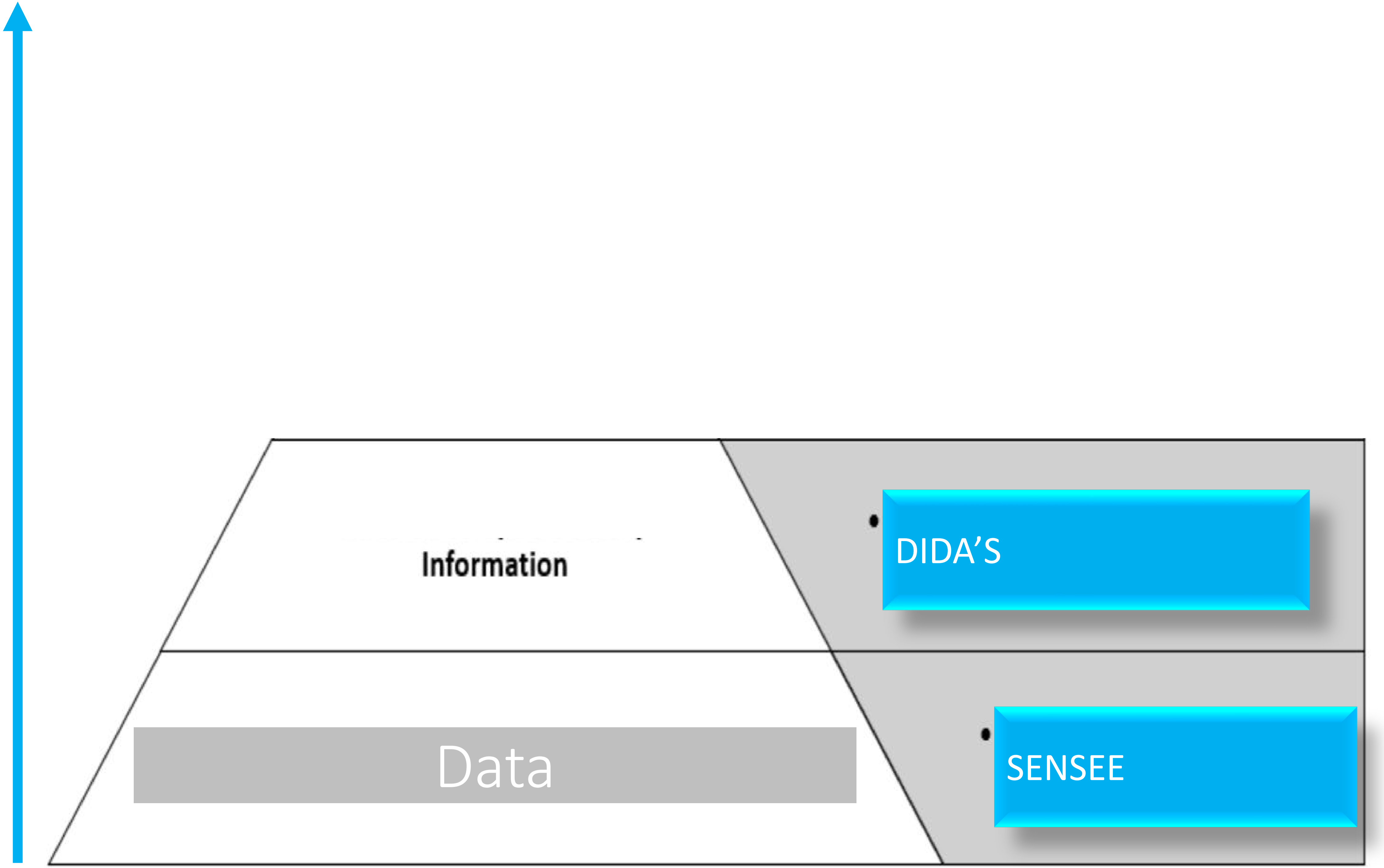
http://www.ihi.org/education/IHIOpenSchool/resources/Assets/CauseandEffect_Instructions.pdf

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

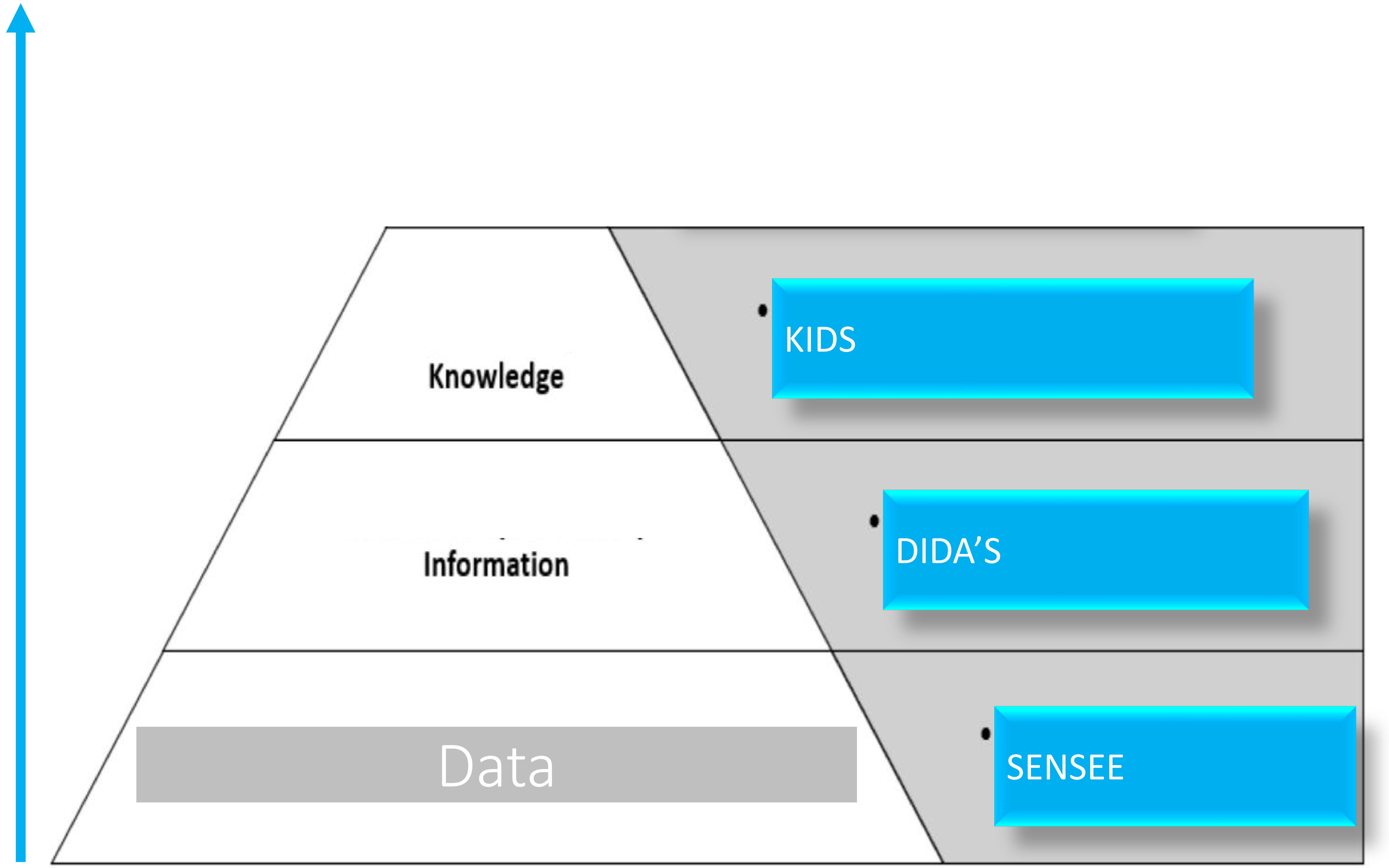
To summarize the steps

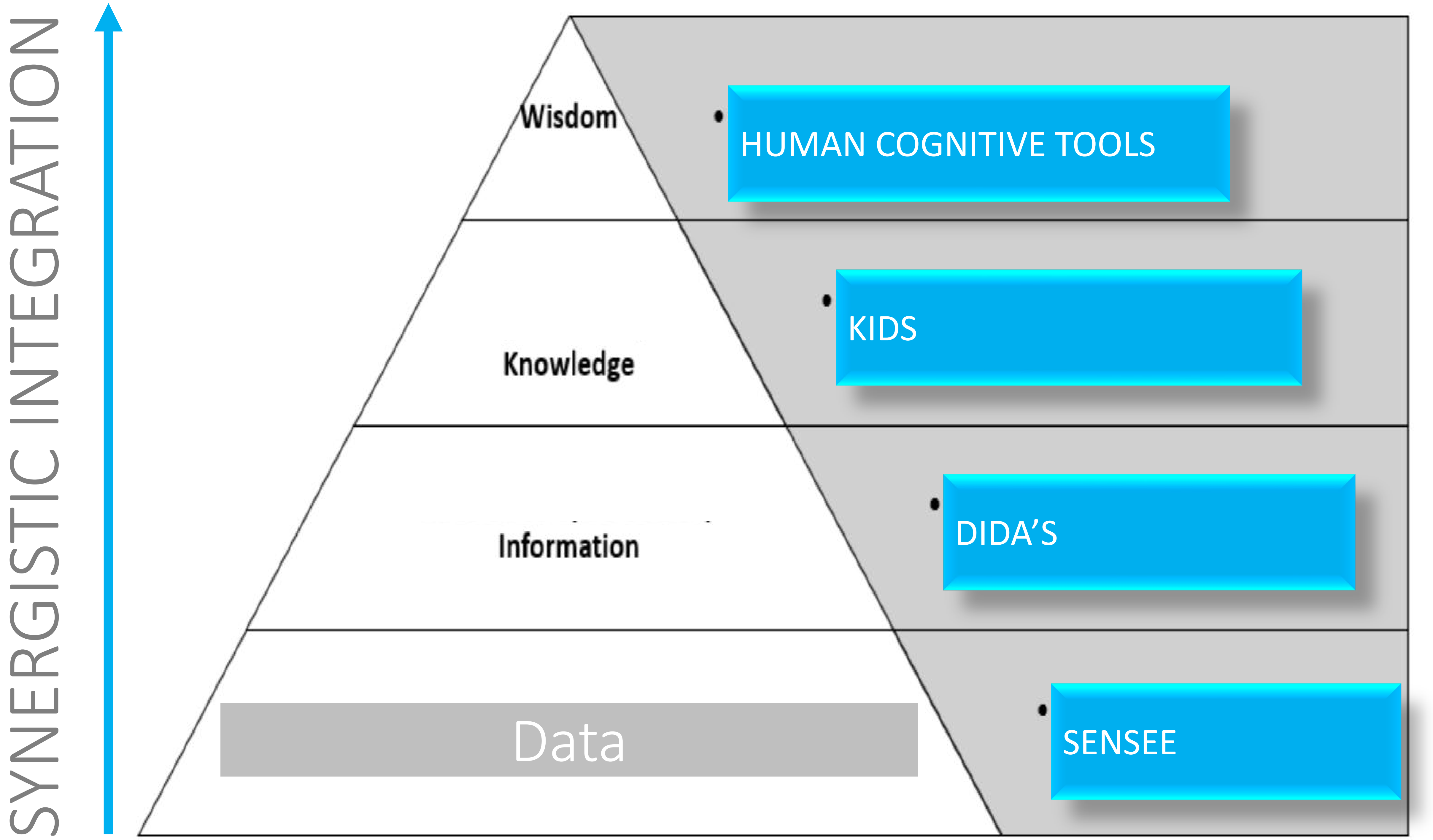

Data

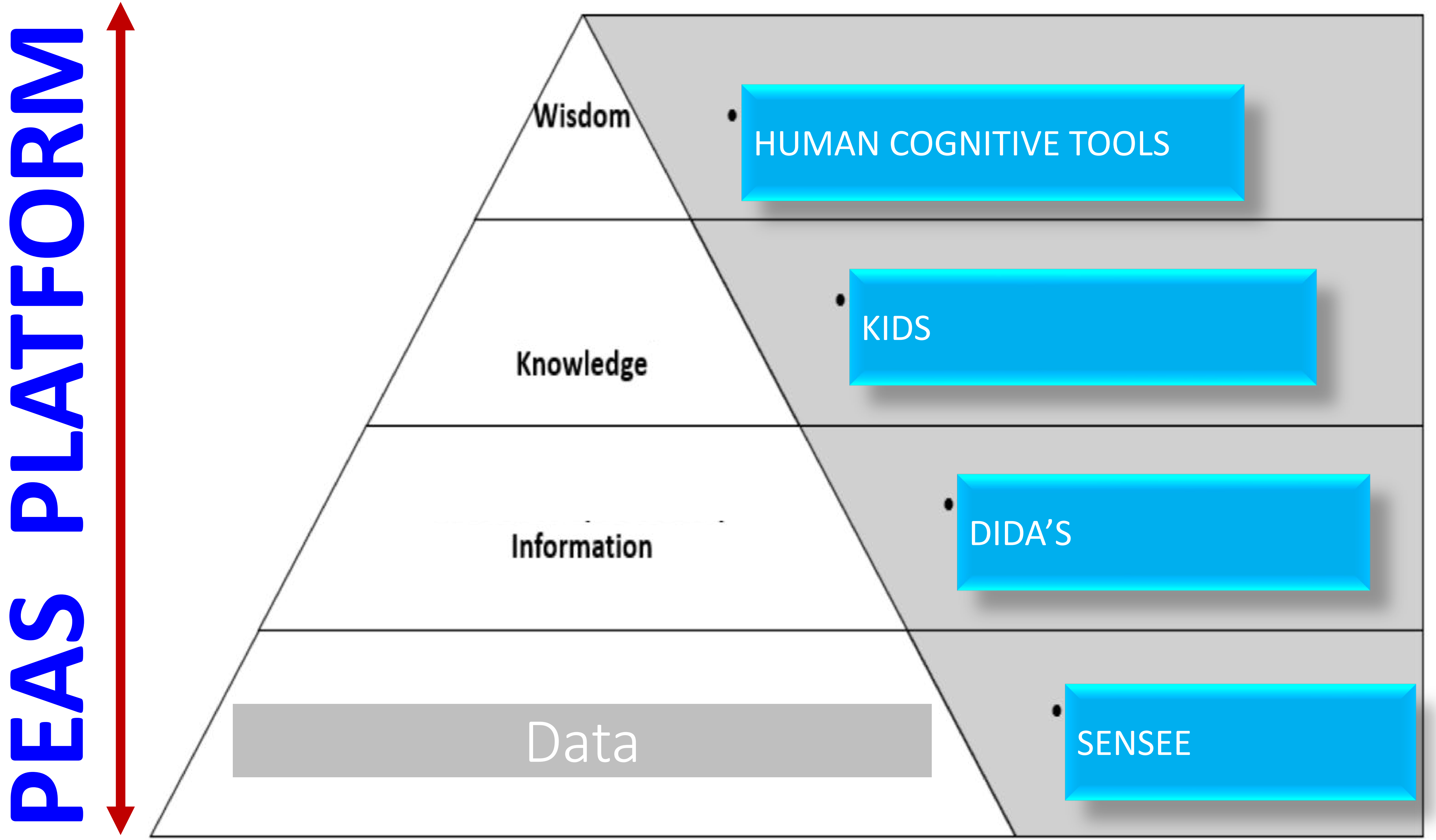

Data
SENSEE



Information
Data
DIDA’S
SENSEE


Knowledge
Information
Data
KIDS
DIDA'S
SENSEE


SYNERGISTIC INTEGRATION
Wisdom
Knowledge
Information
Data
HUMAN COGNITIVE TOOLS
KIDS
DIDA'S
SENSEE


PEAS PLATFORM
Wisdom
Knowledge
Information
Data
HUMAN COGNITIVE TOOLS
KIDS
DIDA’S
SENSEE

Digital Transformation

is about the life cycle of data as it transforms to information and contributes to better decisions

Are we immersed in **data** swamps?
Actions depend on **information**.
Informed by **knowledge**.
Learn from **experience**.

Unbeknownst to us, we are in a perpetual quest for knowledge. Every day, in every action, we undertake the journey from data and information to knowledge. In the process we are learning, in each step, from our experiences, no matter how small and agnostic of the scenarios (social actions, academic activities, business pursuits, ideas and opinions).

Convergence

every step of the journey

Social Domain

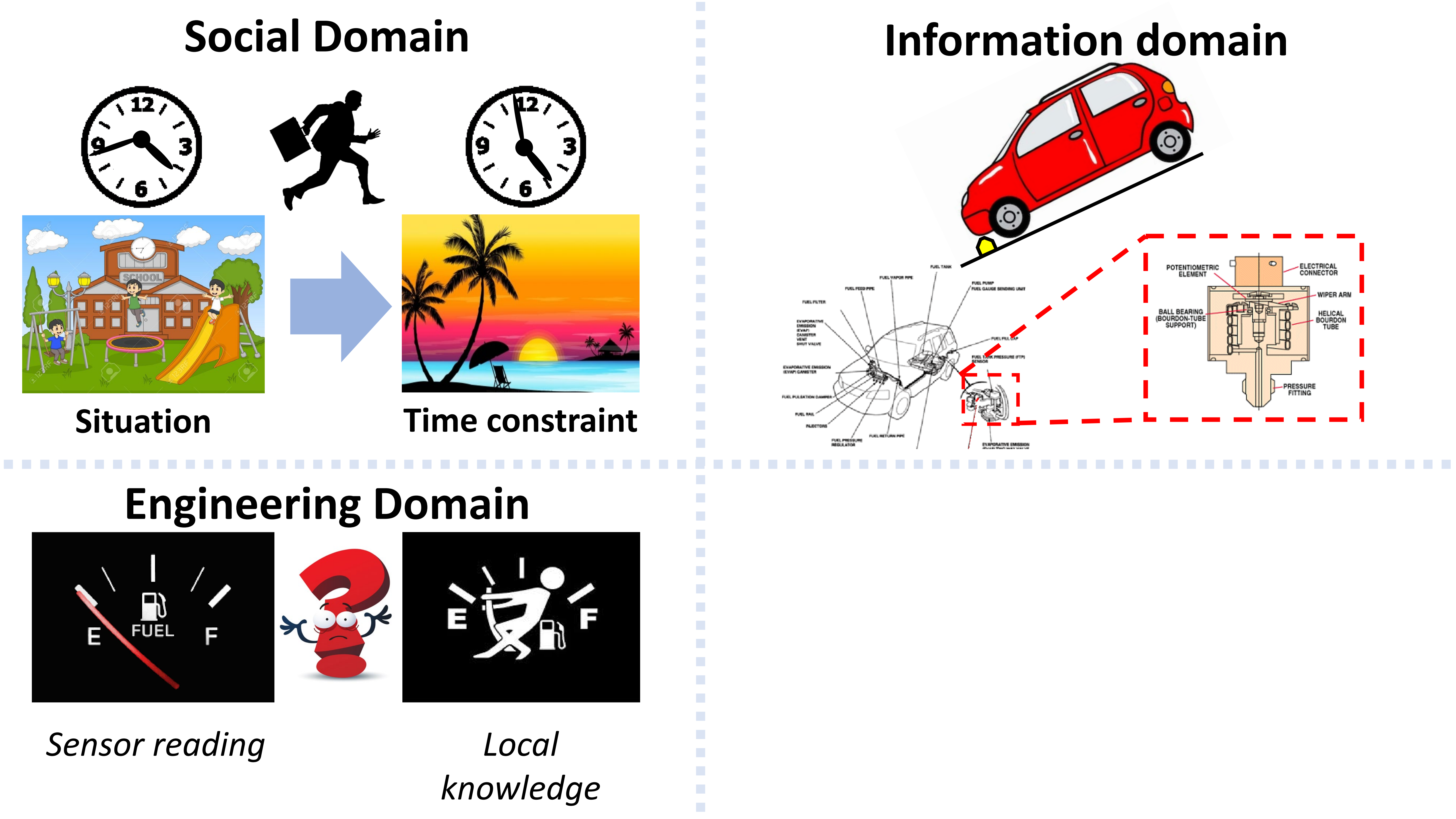
Situation **Time constraint**

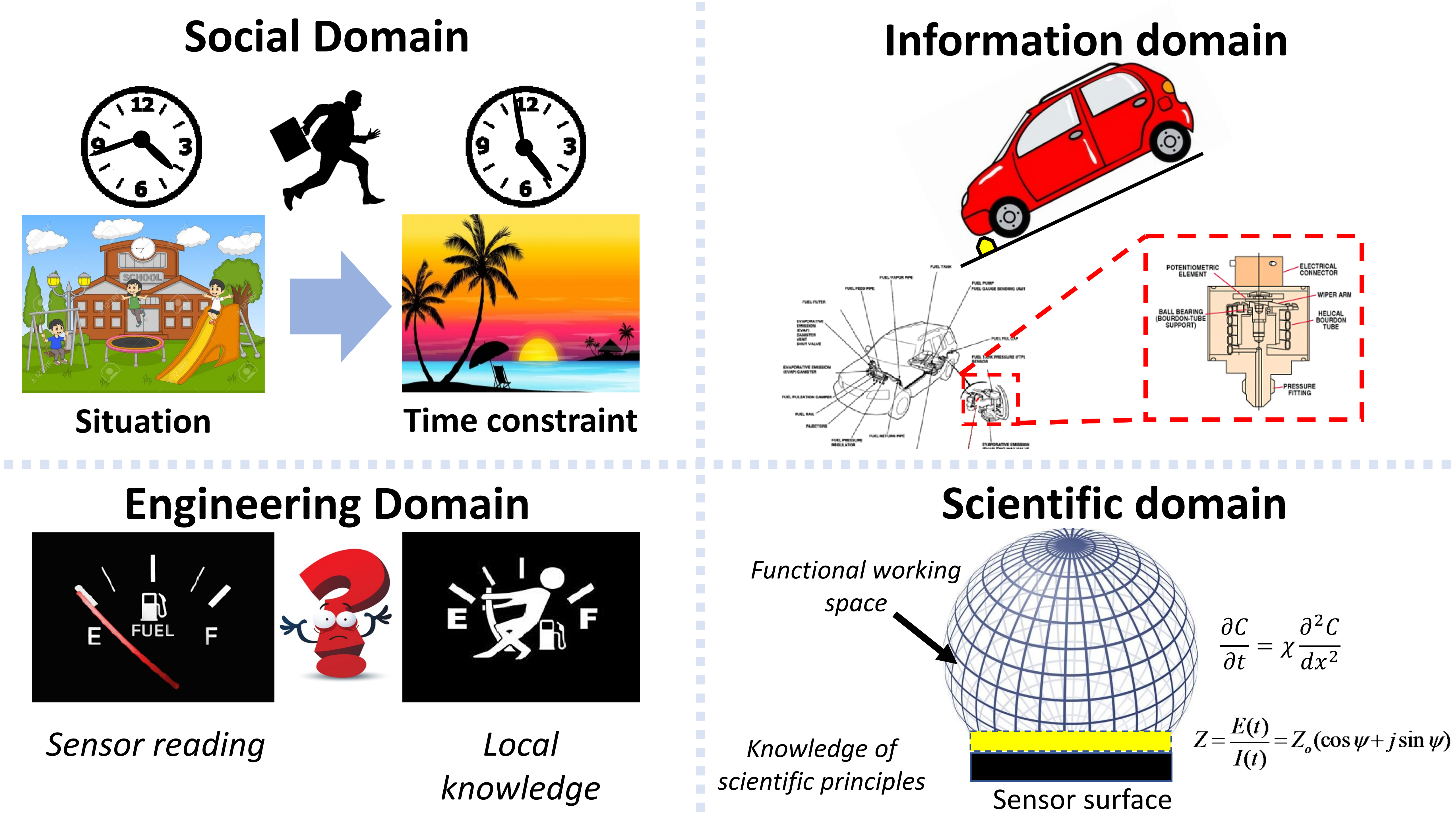
Social Domain

Situation **Time constraint**

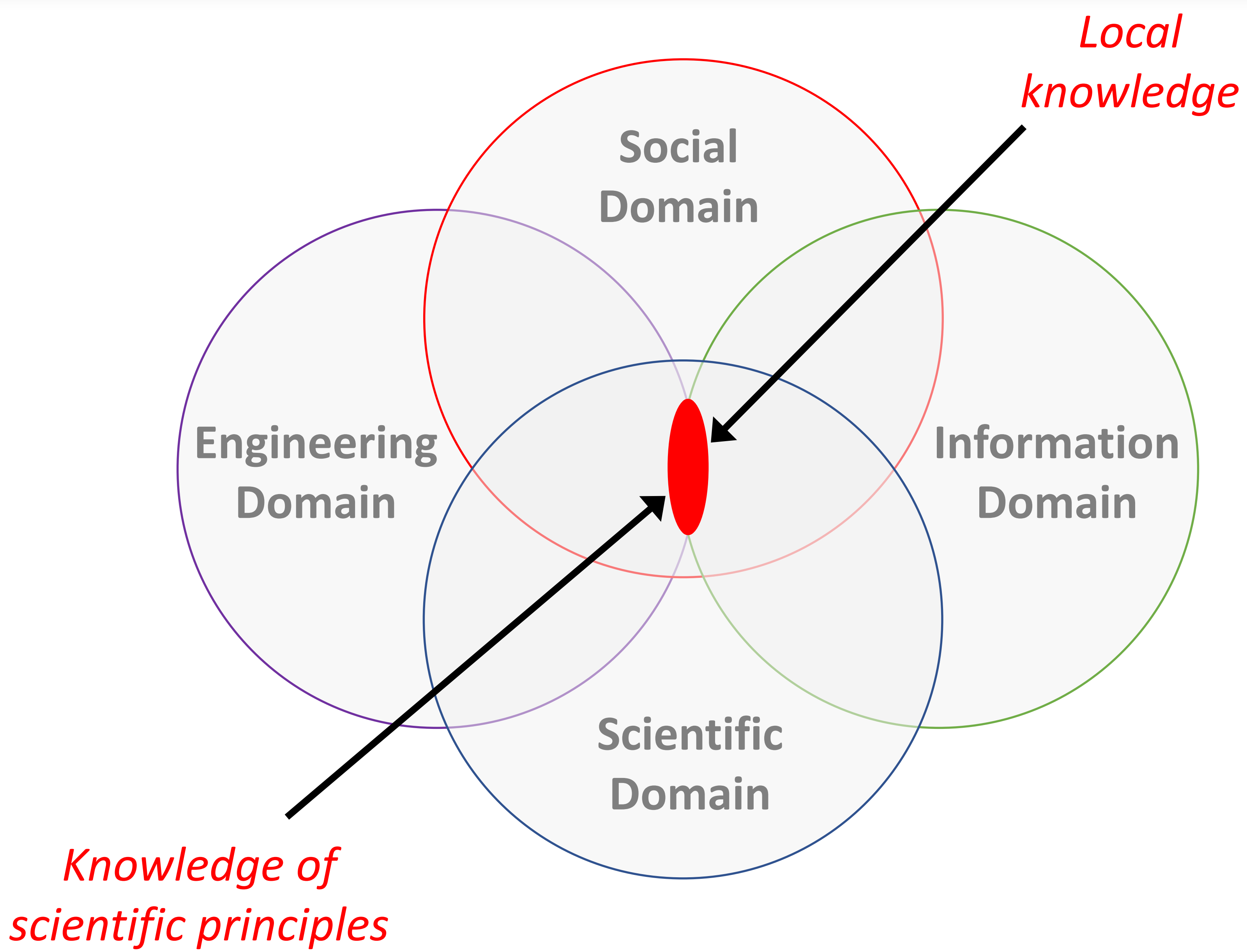
Engineering Domain

Sensor reading *Local knowledge*


Social Domain
Information domain
12
3
6
9
12
3
6
9
SCHOOL
Situation
Time constraint
POTENTIOMETRIC ELEMENT
ELECTRICAL CONNECTOR
WIPER ARM
BALL BEARING (BOURDON-TUBE SUPPORT)
HELICAL BOURDON TUBE
PRESSURE FITTING
Engineering Domain
E
FUEL
F
E
F
Sensor reading
Local knowledge

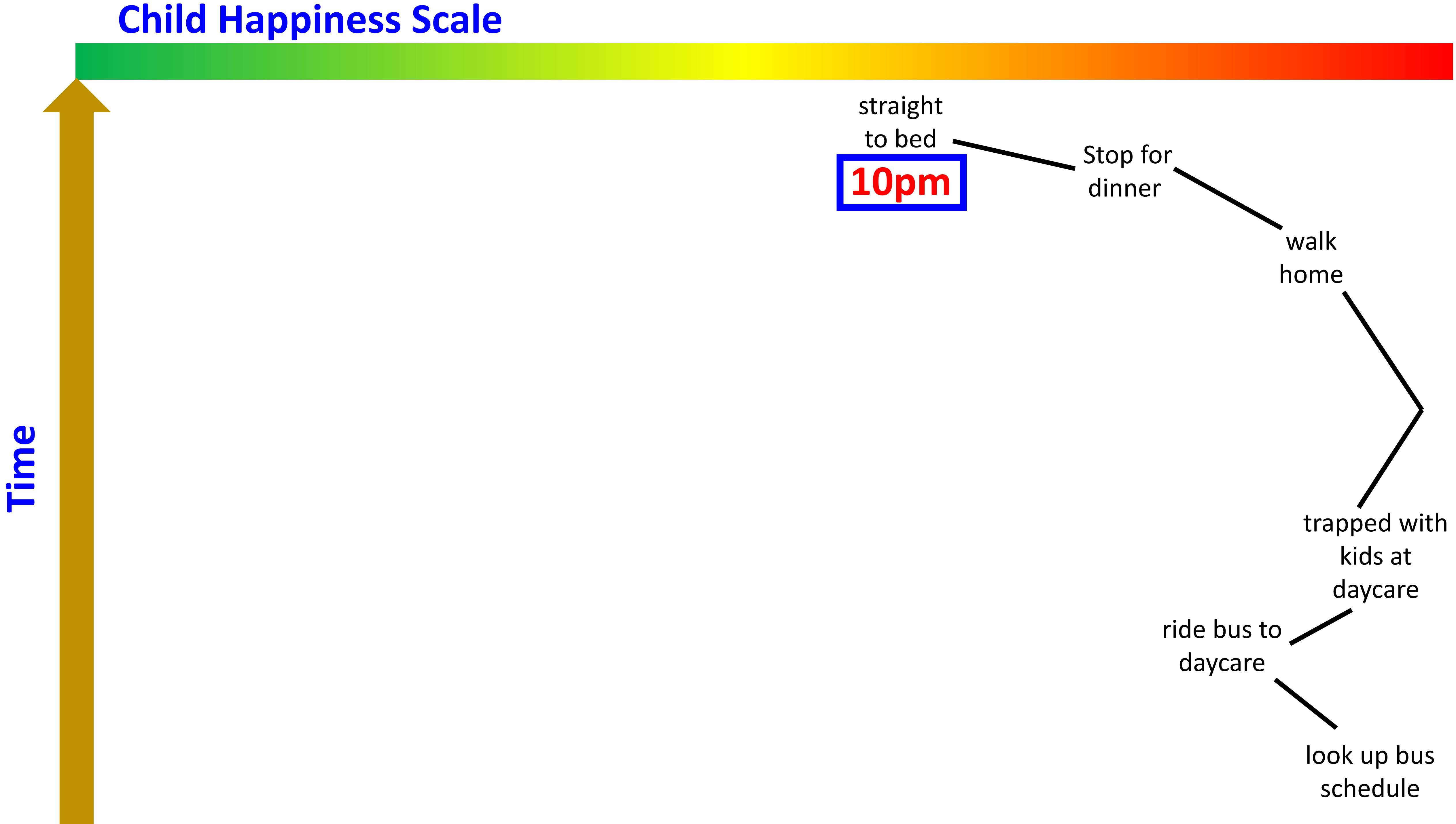

Social Domain
12
3
6
9
SCHOOL
Situation
Time constraint
Information domain
POTENTIOMETRIC ELEMENT
ELECTRICAL CONNECTOR
WIPER ARM
BALL BEARING (BOURDON-TUBE SUPPORT)
HELICAL BOURDON TUBE
PRESSURE FITTING
Engineering Domain
E
FUEL
F
Sensor reading
Local knowledge
Scientific domain
Functional working space
$\frac{\partial C}{\partial t} = \chi \frac{\partial^2 C}{dx^2}$
Knowledge of scientific principles
$Z = \frac{E(t)}{I(t)} = Z_o(\cos\psi + j\sin\psi)$
Sensor surface

Convergence

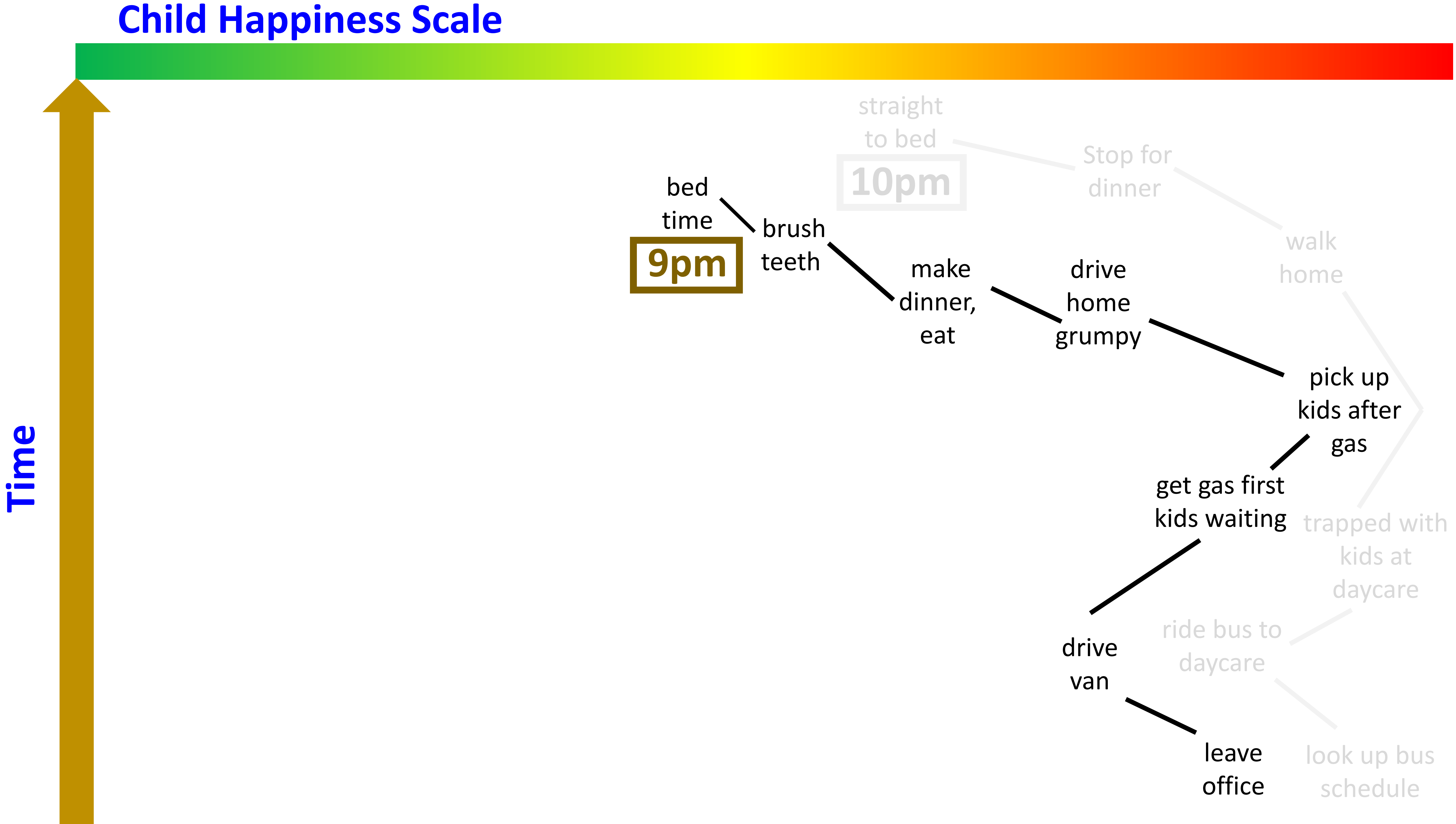


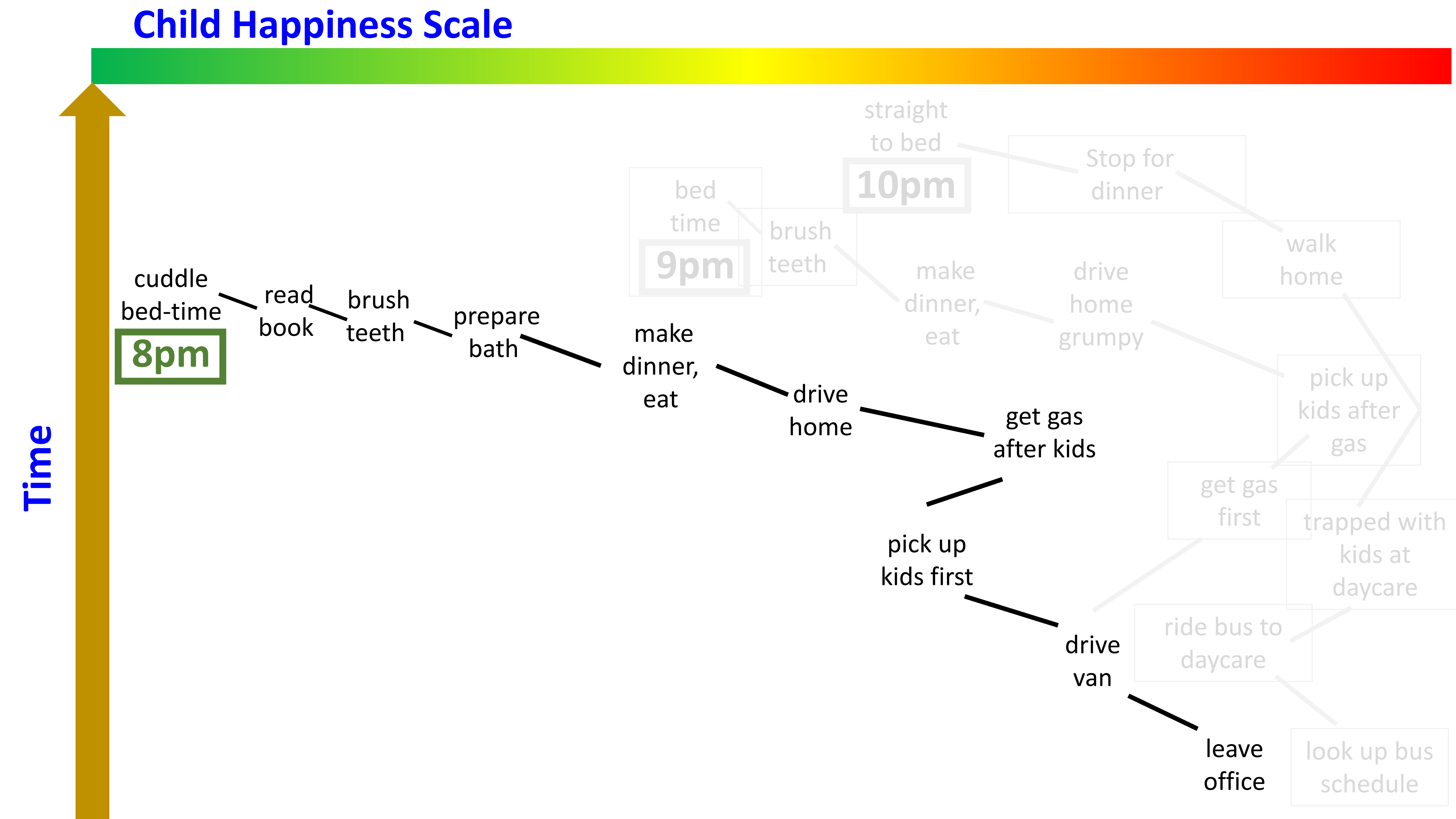
For humans, it is child's play

For systems, it's still a difficult task to select what is relevant, relative to the context, and connect (**R2C2**), distributed data, to extract information, to aid decisions or execute action for the situation, based on actionable knowledge.



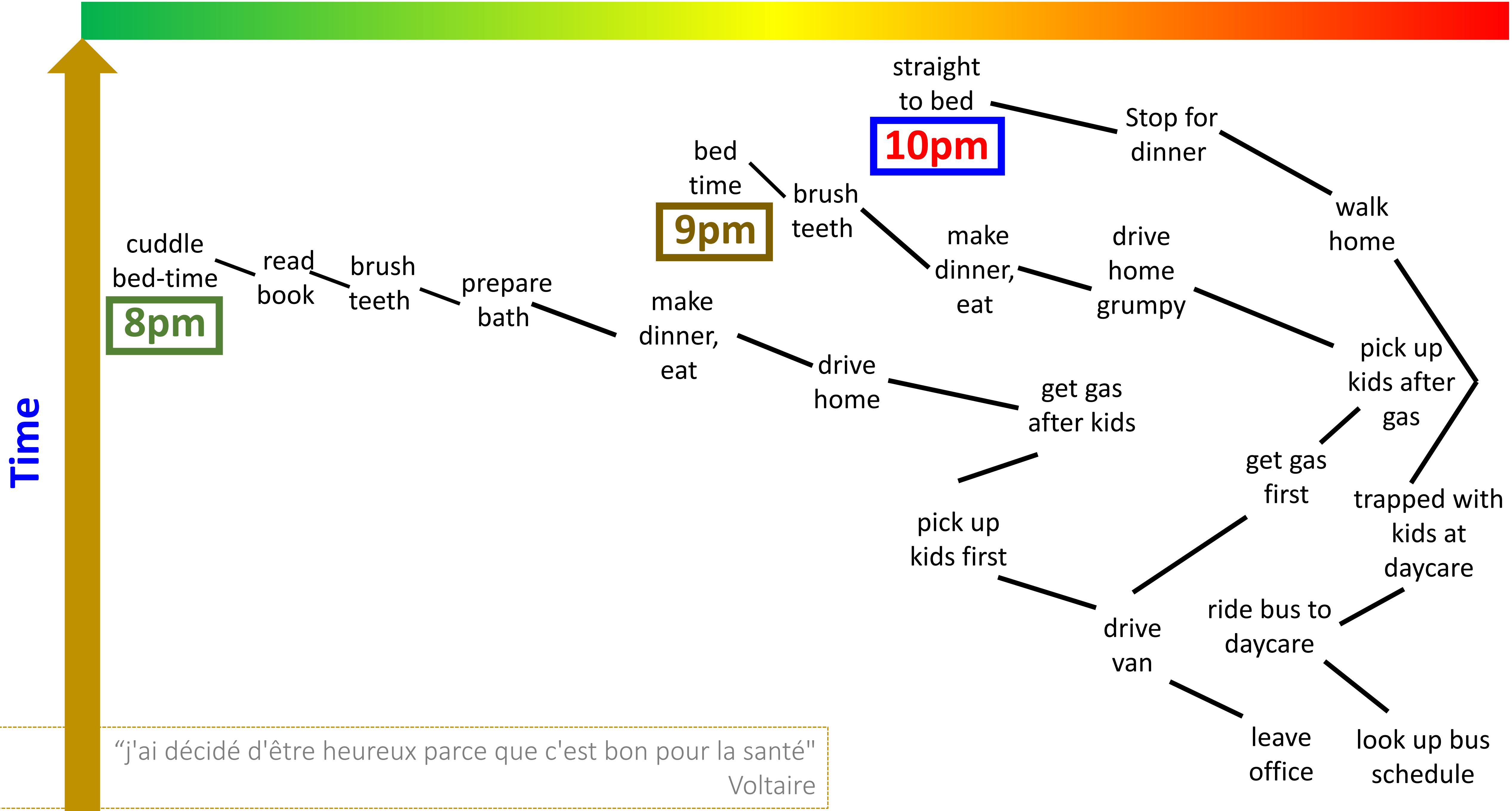
Child Happiness Scale
Time
straight to bed
10pm
Stop for dinner
walk home
trapped with kids at daycare
ride bus to daycare
look up bus schedule


Child Happiness Scale
Time
straight to bed
10pm
Stop for dinner
walk home
bed time
9pm
brush teeth
make dinner, eat
drive home grumpy
pick up kids after gas
get gas first kids waiting
trapped with kids at daycare
drive van
ride bus to daycare
leave office
look up bus schedule

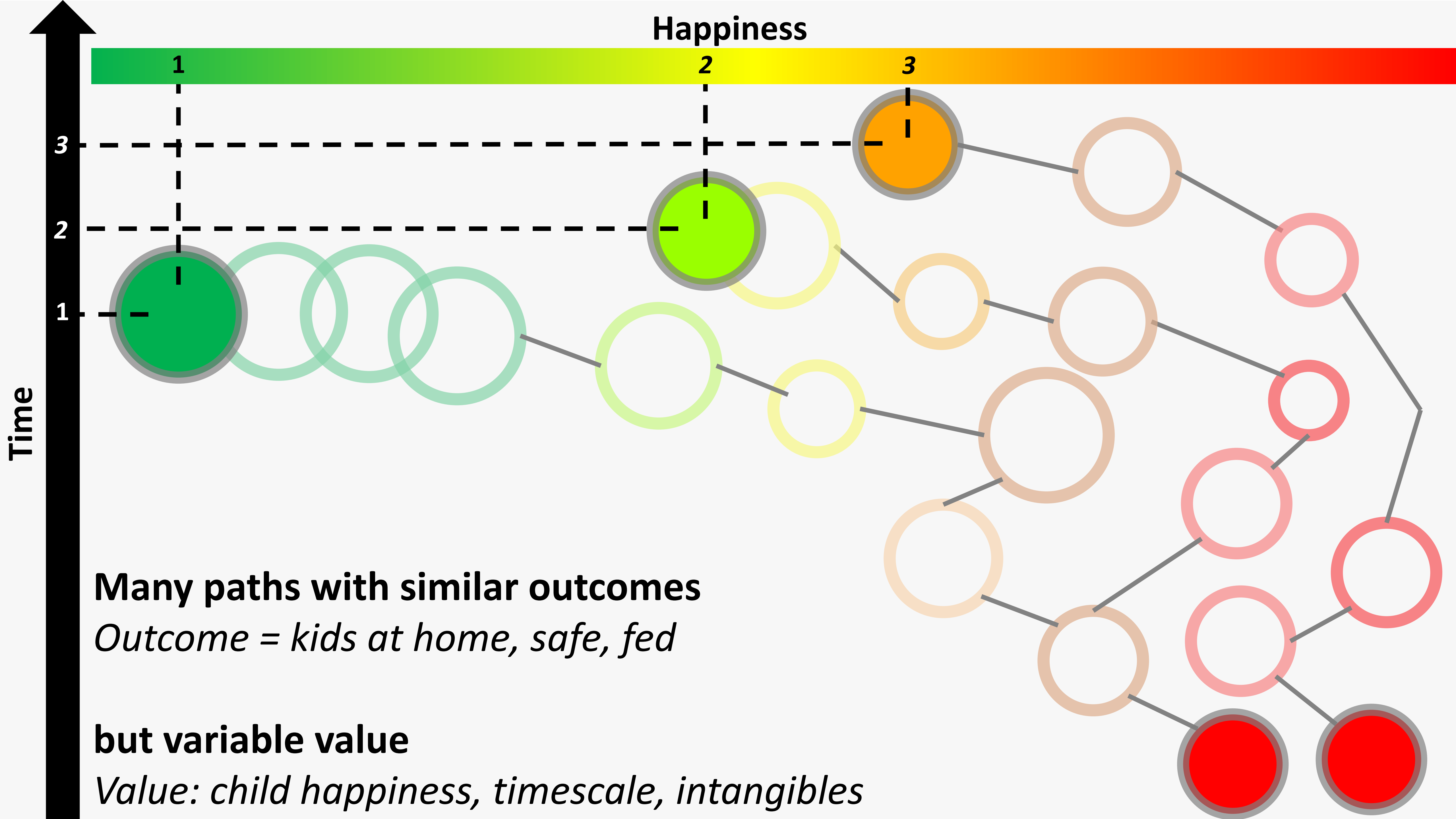


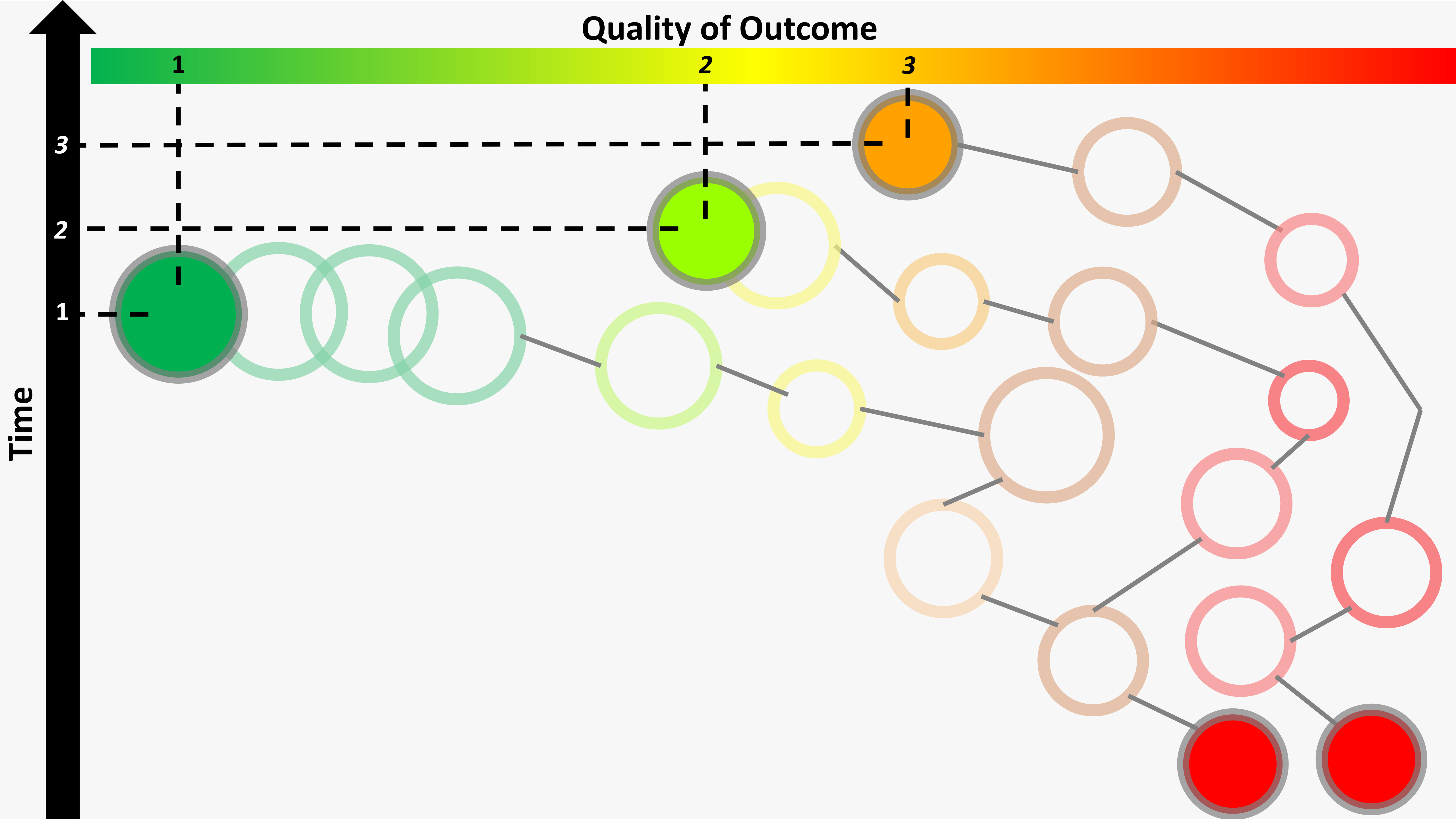
Child Happiness Scale
Time
cuddle bed-time
8pm
read book
brush teeth
prepare bath
make dinner, eat
drive home
get gas after kids
pick up kids first
drive van
leave office
bed time
9pm
brush teeth
straight to bed
10pm
Stop for dinner
walk home
make dinner, eat
drive home grumpy
pick up kids after gas
get gas first
trapped with kids at daycare
ride bus to daycare
look up bus schedule

Child Happiness Scale (clap along if you feel like happiness is the truth)

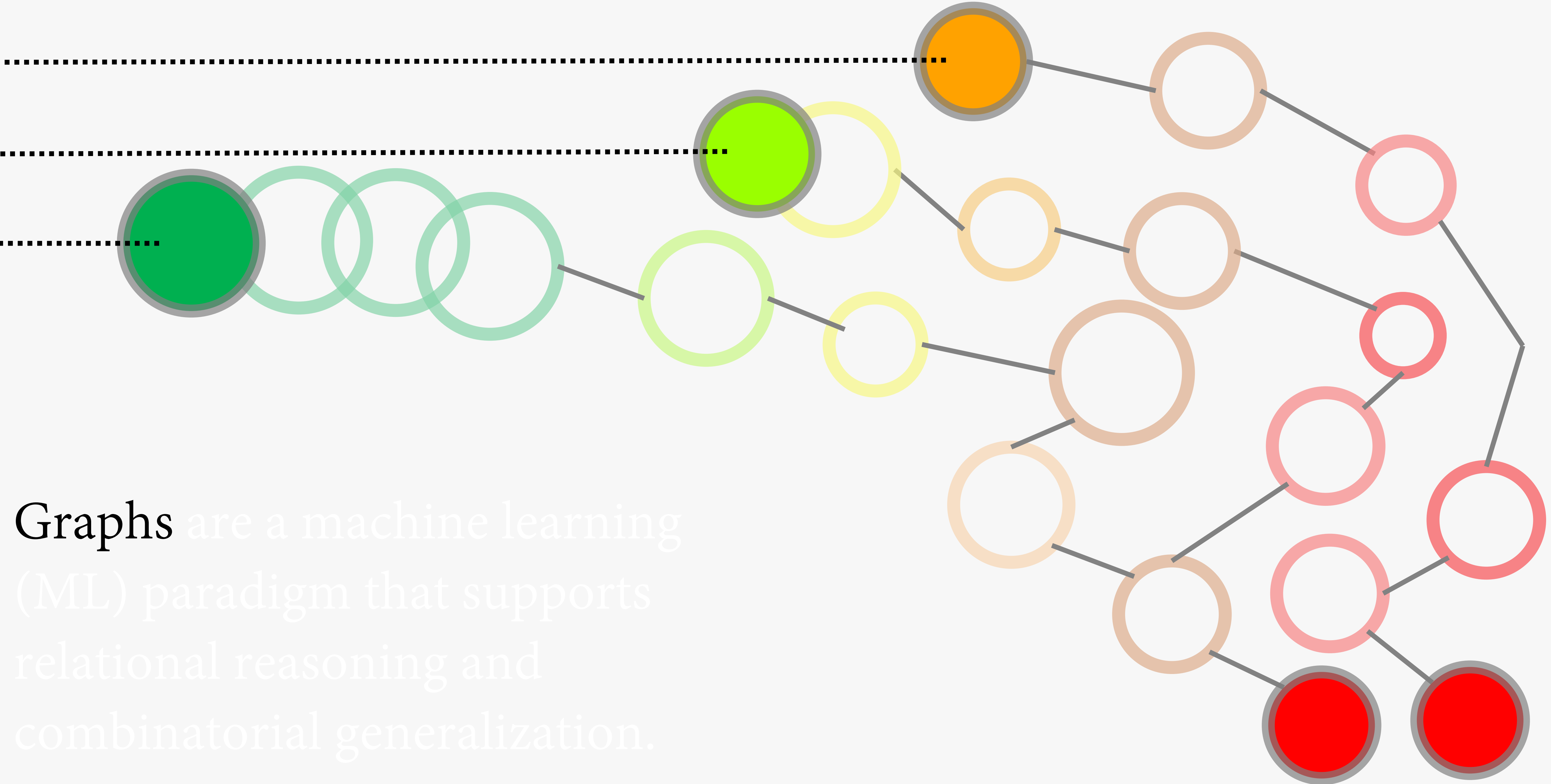


“j'ai décidé d'être heureux parce que c'est bon pour la santé"
Voltaire


Happiness
1
2
3
Time
3
2
1
Many paths with similar outcomes
Outcome = kids at home, safe, fed
but variable value
Value: child happiness, timescale, intangibles

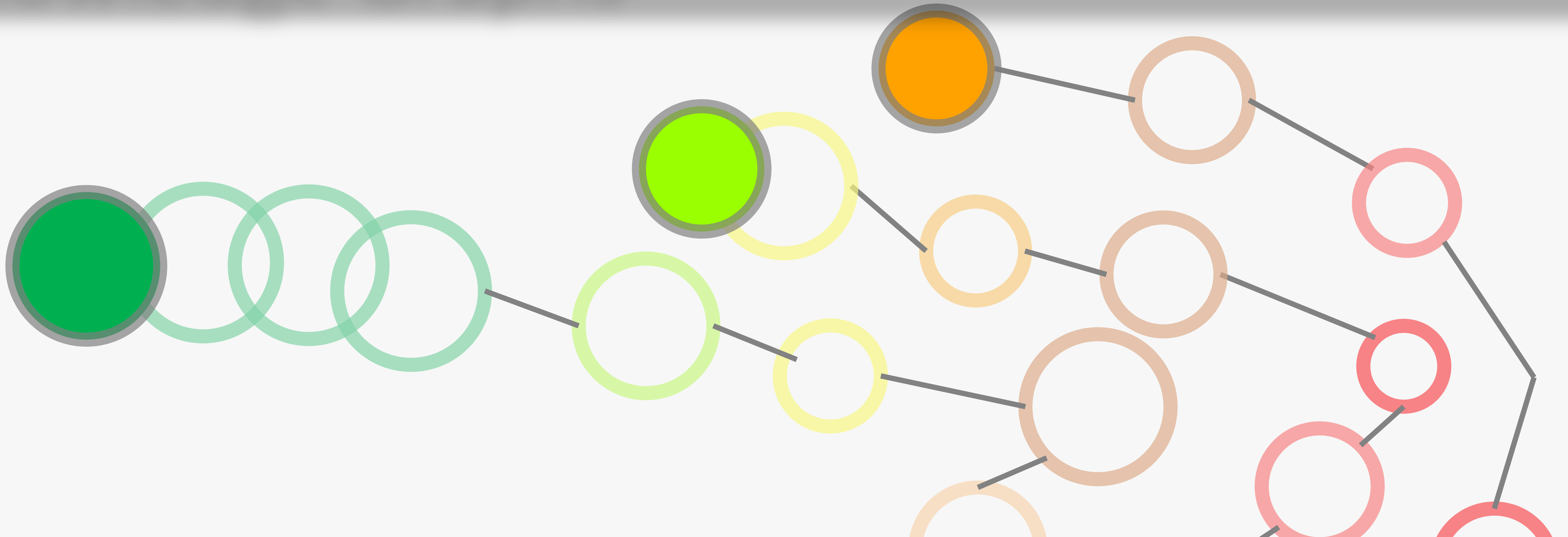


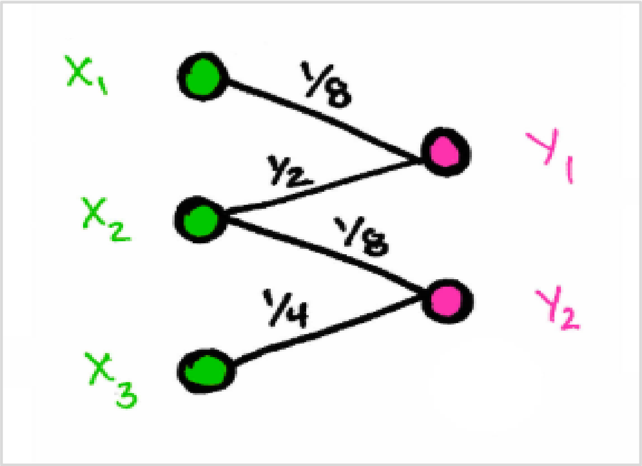
Quality of Outcome
1
2
3
Time
3
2
1



Graphs are a machine learning (ML) paradigm that supports relational reasoning and combinatorial generalization.

Knowledge Graphs

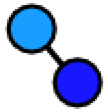




Graph networks are machine learning (ML) paradigms that support relational reasoning and combinatorial generalization.

http://www.mkbergman.com/2244/a-common-sense-view-of-knowledge-graphs/

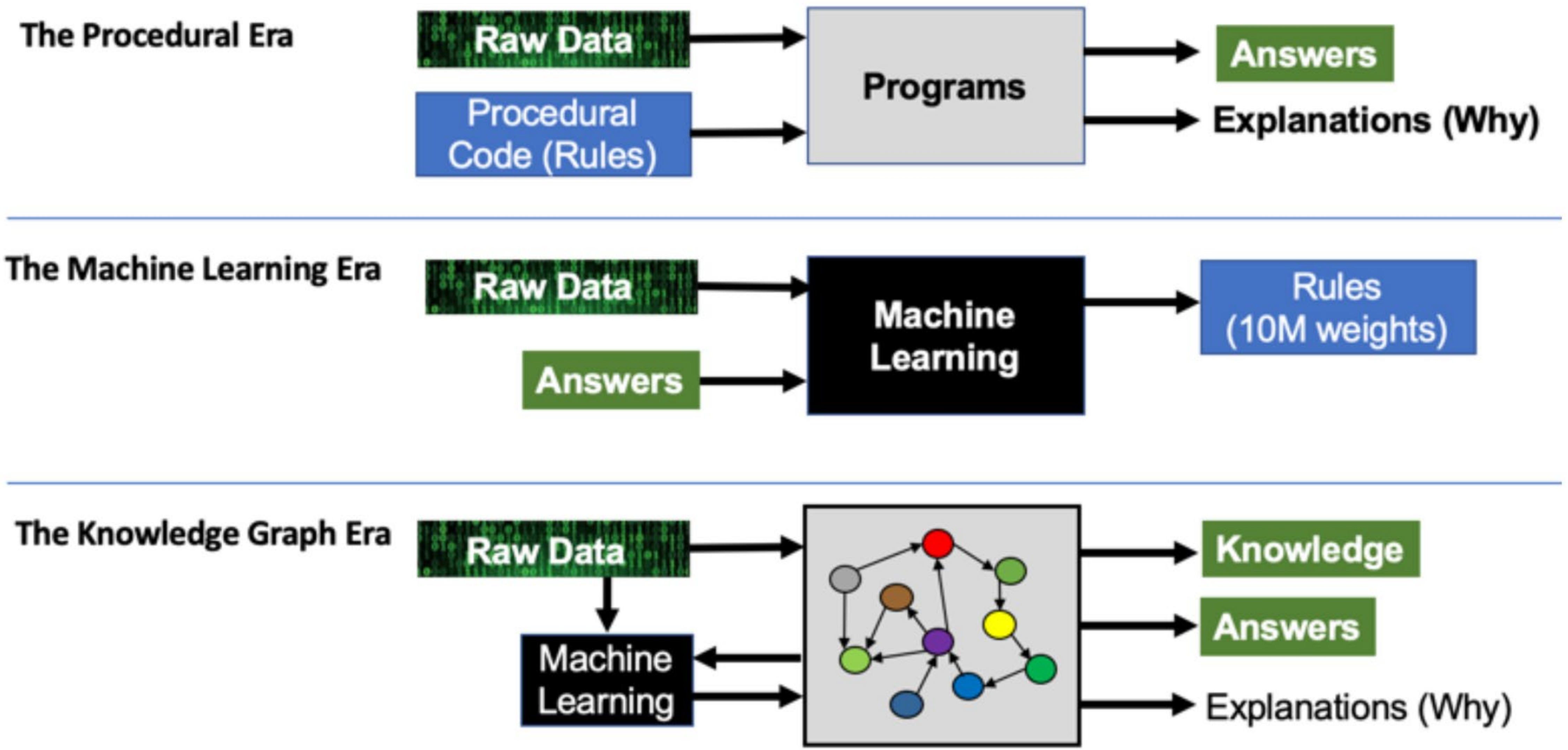
BOOK - http://bit.ly/Knowledge-Representation



https://www.springer.com/gp/book/9783319980911

http://www.mkbergman.com/wp-content/themes/ai3v2/images/2012Posts/ontology_build.gif

Knowledge Graphs: The core of the 3rd era of computing

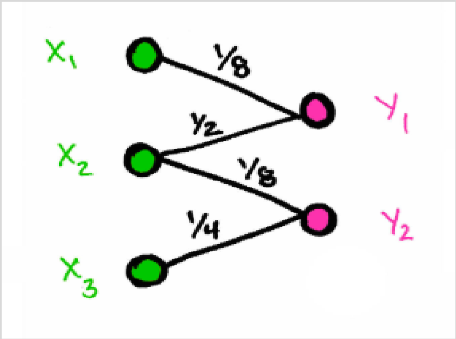


@dmccreary

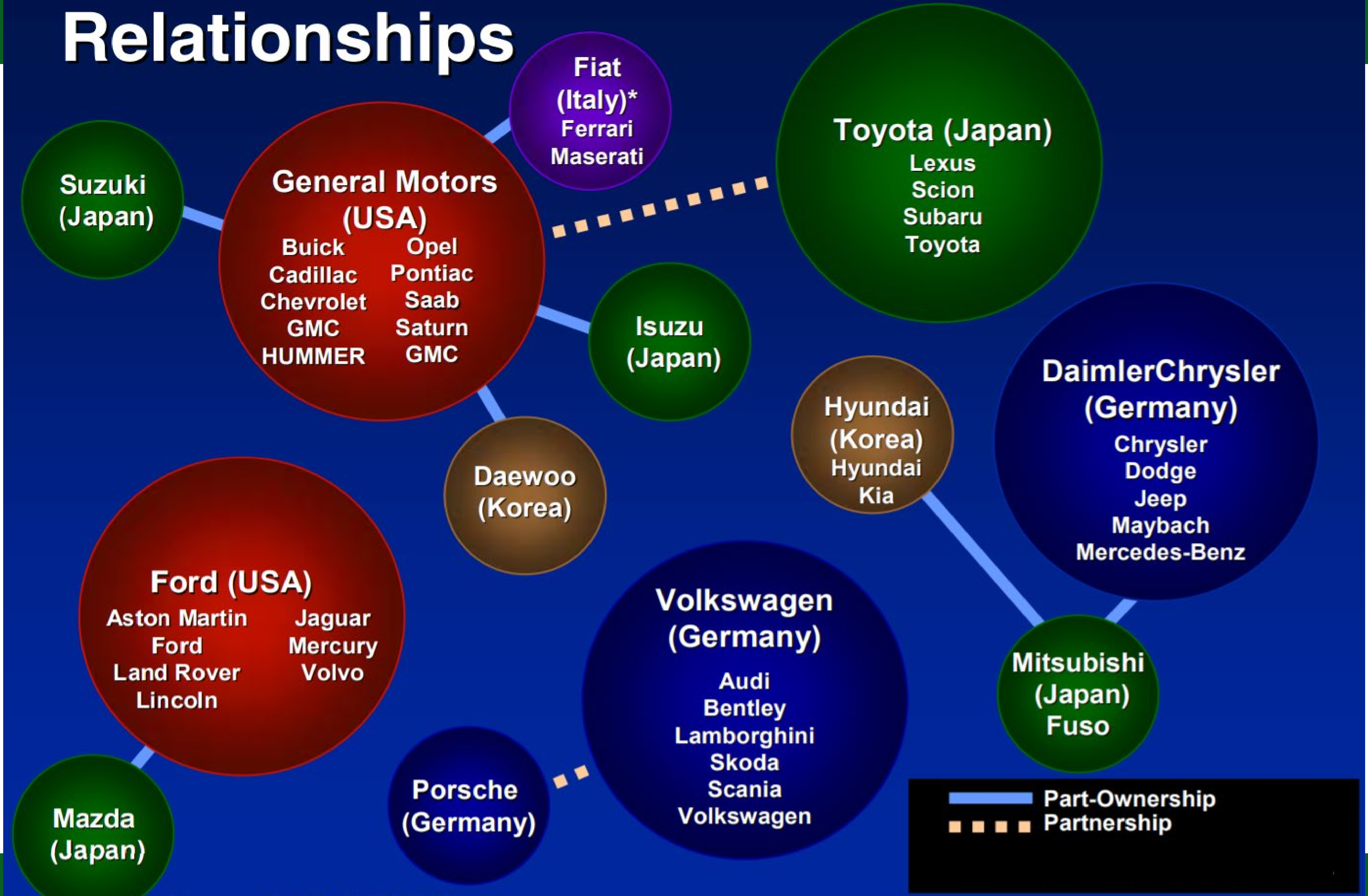
Use machine learning to continuously enrich knowledge

RELATIONSHIPS

between entities are critical in the context of making decisions. Data available to the human mind (or the system) in the context of entities or objects or processes, under consideration, are used directly (as data) or converted to information (by humans) to fuel decisions (outcomes). Knowledge graphs are a form of **bio-mimicry** tool, to enable non-human computer systems to understand relationships between entities, objects, processes, people, and things (think IoT, internet of things). Resource Description Framework **(RDF)** is a standard to describe resources and is based on principles of linguistics (noun, verb, subject, predicate).

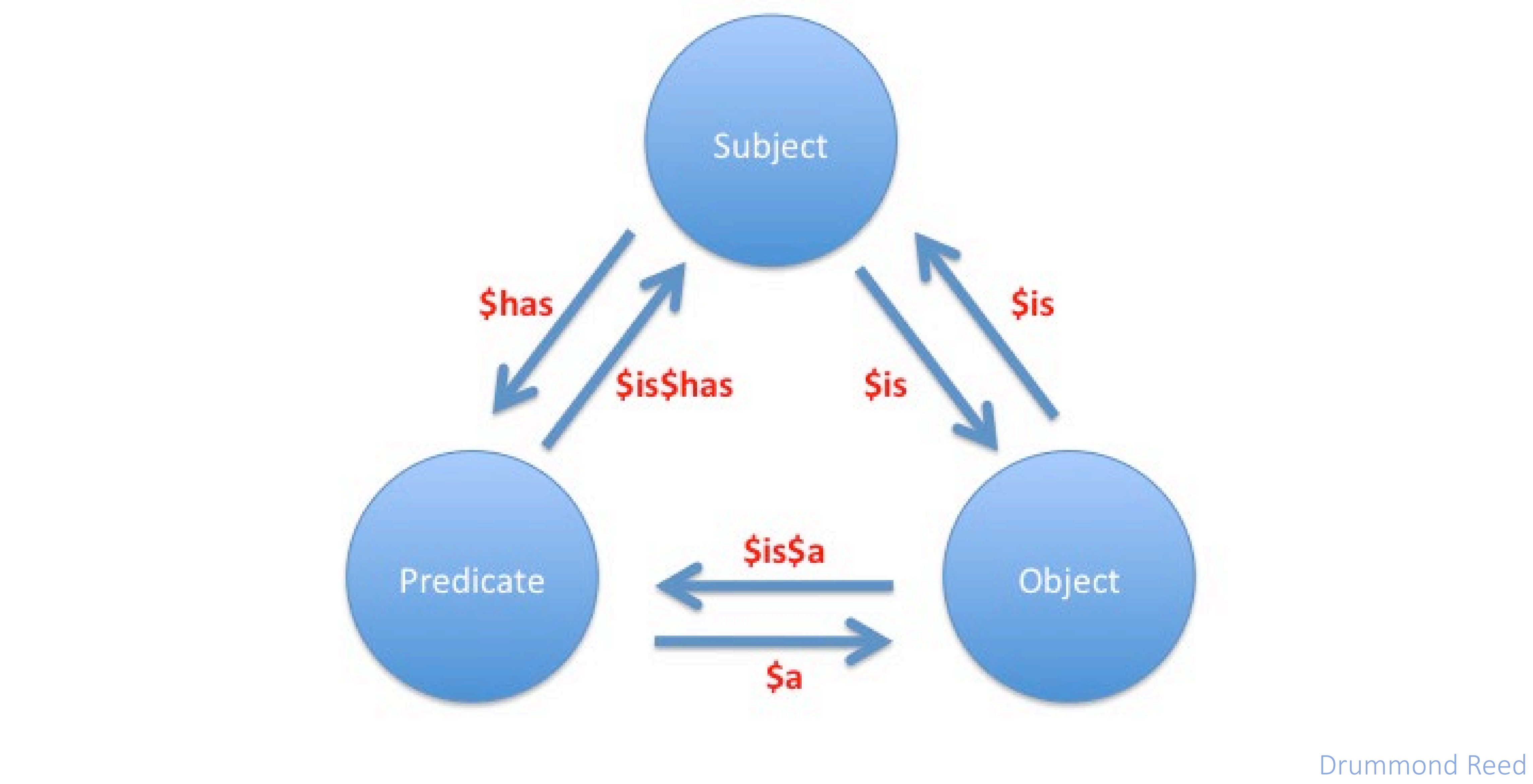


Relationships



Sources: *AAA World*, AV World ● https://www.researchgate.net/publication/228383625_Supply_chain_networks

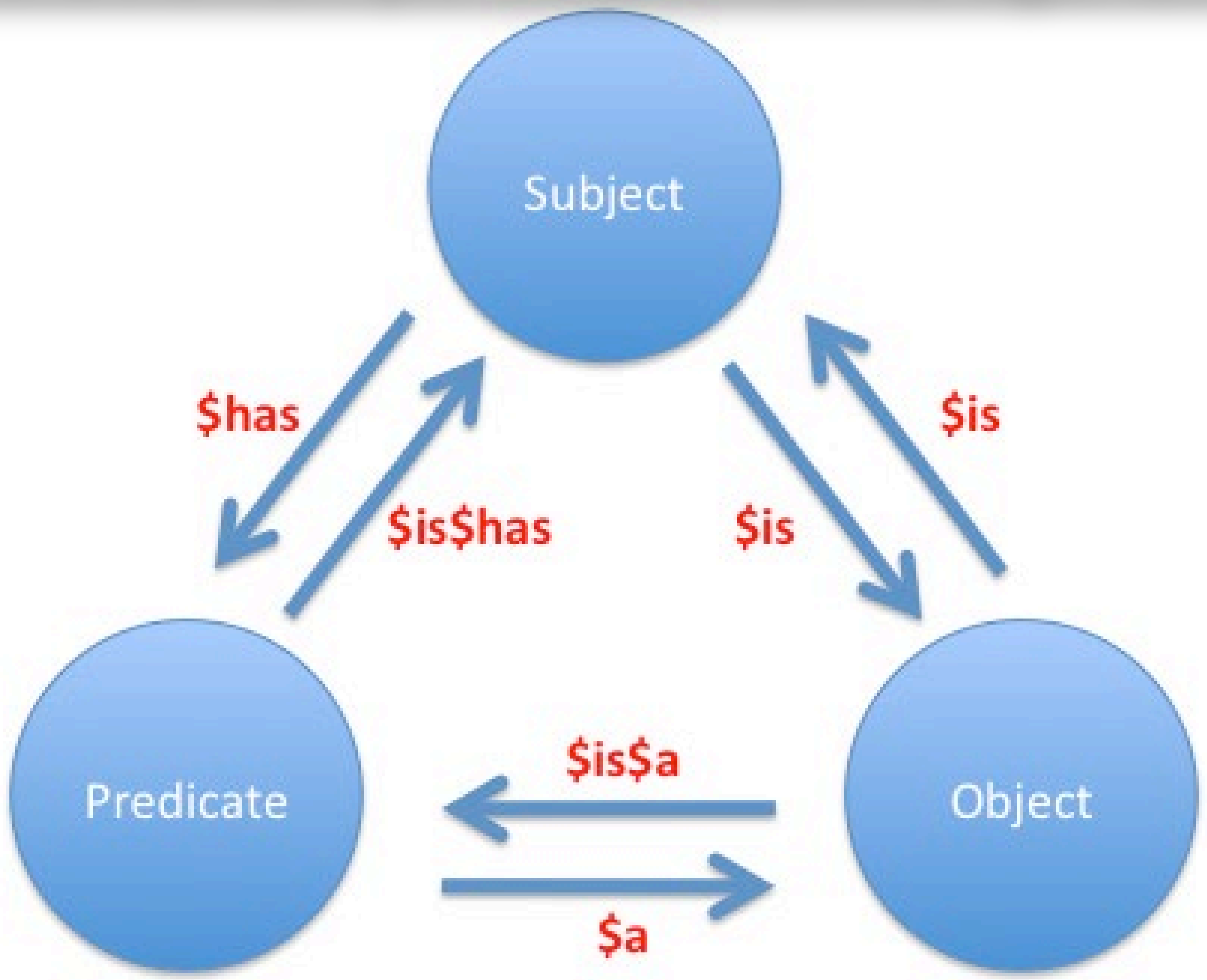
RDF expresses RELATIONSHIPS as “triples” which are based on principles of linguistics (noun, verb, subject, predicate).



Resource Description Framework (RDF) is a standard to describe resources. It is written in XML and machine-readable.

Linguistics, Relationships and Knowledge Graph Networks

In the “Golden Triangle" of metagraph relationships: hasa (which is literally $has/$has/$a) defines a subset of $has relationships in which the predicate is also an object. Asserting a predicate **as an object** is different than asserting it **as a predicate**. Neither implies that the other exists. They have a logical relationship, it is the same predicate involved in both cases, but asserting it as a predicate does not mean it is also an object, and asserting is as an object does not need it to be also a predicate.



$ is a subsegment delimiter (Global Context Symbols)
https://wiki.oasis-open.org/xri/XriThree/GcsDelimiter

Drummond Reed drummond.reed@xdi.org https://lists.oasis-open.org/archives/xdi/201004/msg00013.html

Are computational standards, syntax semantics and ontologies influenced by linguistic bias?

Subject	Predicate	
	linking verb	subject complement noun or adjective
The aliens	were	killers.
The rats	are	ugly.
The griff	is	grafunkulous.

- The predicate is <u>the</u> action
- Action verbs are easy to identify, but remember **verbs of being**: am, is, are, were, was
- A sentence *can* have more than one predicate

Subject and Predicate

MyEnglishTeacher.eu

What is a Subject?

- *A subject is the person or thing that is doing an action, or the person or thing that is the focus of the sentence*

What is a Predicate?

- *The predicate of the sentence is the part that contains the action.*

https://english.eagetutor.com/spoken-english-grammar/subject-predicate-and-object

What happens when the RDF ontology creator speaks a language where the rules of English grammar are not applicable?

At the heart of the predicate is a verb. In addition to the verb, a predicate can contain direct objects, indirect objects, and various kinds of phrases.

A sentence has two parts: the subject and the predicate. The subject is what the sentence is about, and the predicate is a comment about the subject.

www.grammar-monster.com/glossary/predicate.htm

Examples of Predicates of Sentences

Here are some examples of predicates. In each example, the predicate of the sentence is shaded and the verb in the predicate is in bold.

- Elvis **lives**.
- Adam **lives** in Bangor.
- The telegram **contained** exciting news.
- The girls in our office **are** experienced instructors.
- They **are** experienced instructors, who acquired their experience in France.

Predicates in Clauses

A clause contains a subject and predicate too. The examples below are all clauses not sentences. The predicate is shaded and the verb of the clause is in bold.

- who **lives** with her mother
  (The subject is the relative pronoun *who*.)
- which **was** somewhat unexpected
  (The subject is the relative pronoun *which*.)
- that **points** to the North Pole
  (The subject is the relative pronoun *that*.)

www.grammar-monster.com/glossary/predicate.htm

Why RDF may be just a part of the solution: Is linguistic bias embedded in the grammatical context of RDF triples?

Semantic Standards in other languages?

https://lists.w3.org/Archives/Public/www-archive/2005Feb/att-0050/eswc-i18n.pdf

https://www.ncbi.nlm.nih.gov/pmc/articles/PMC1892103/pdf/1471-2105-8-S3-S6.pdf

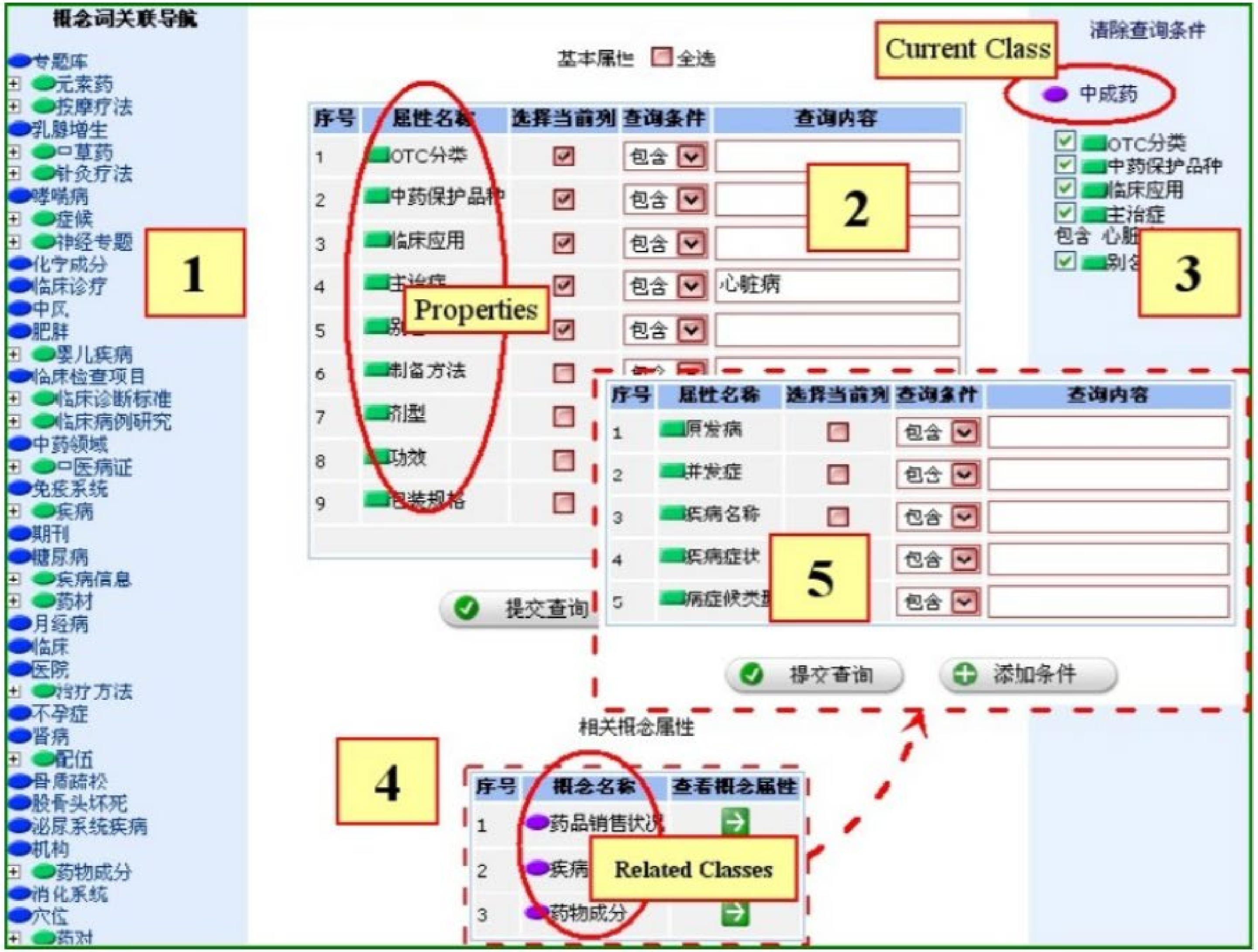
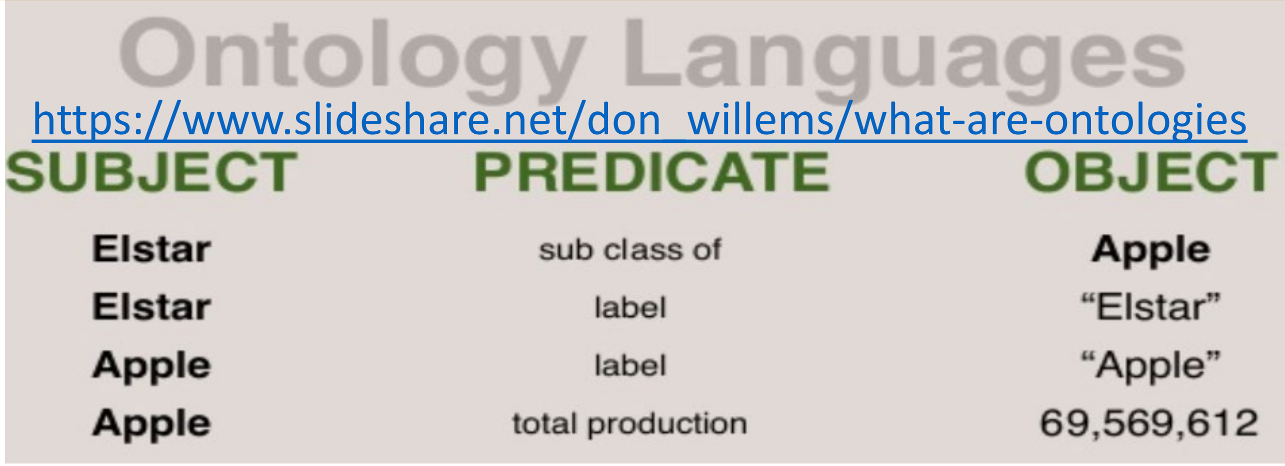


Figure 4
DartSearch. The default user interface for DartSearch.

Knowledge Graphs relevant to SENSEE, ART, & DIDA'S KIDS

When data is mapped against an OWL/RDF ontology, instances of the data are expressed based upon the idea of making statements about resources in the form of **subject–predicate–object** expressions. These expressions are known as *triples* in RDF terminology. The 'Subject' denotes the object, and the predicate denotes a single semantic trait or aspect of the object that can be a literal value or expressed as a relationship between the subject and another object that is the target of the relationship. For example, the notion "The soil has a pH of 8" in RDF triple is **subject** denoting "soil" and **predicate** denoting "pH" and an **object** denoting "8" which is the OWL/RDF take on using the object as the subject from the classical entity–attribute–value model within object-oriented design: object (soil), attribute (pH) and value (8). The object (soil) can also have another attribute (contains) that can point to another object (phosphate). The object (phosphate) might have an attribute (produces) another object (acidity). Yet again, the object (soil) might have an attribute (contains) another object (microbes). This is one reason why RDF triples, despite their shortcomings and potential for linguistic bias, enables the formation, to link a series of relationships, between two or more objects. The latter is the foundation on which directed graphs can be built. Hence, knowledge graphs.

https://slideplayer.com/slide/1045921/



https://www.slideshare.net/don_willems/what-are-ontologies

SUBJECT	PREDICATE	OBJECT
Elstar	sub class of	Apple
Elstar	label	"Elstar"
Apple	label	"Apple"
Apple	total production	69,569,612

Which / what nodes are the graphs connecting?

https://www.aac.or.at/smart-farming
https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/
http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

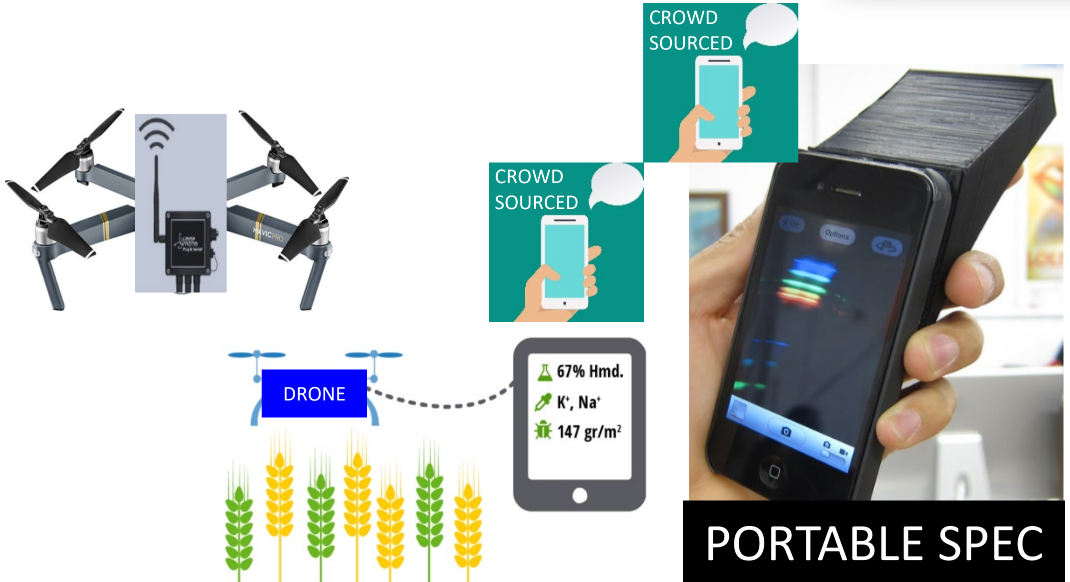
Which / what nodes are the graphs connecting?

SENSORS

CHAT, TALK

DATA, MAPS

IoT ECOSYSTEM

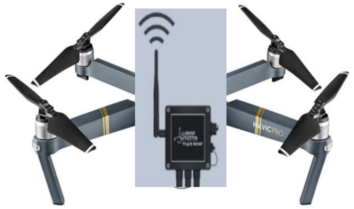


PORTABLE SPEC

https://www.aac.or.at/smart-farming
https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/
http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Web of Knowledge Graph Networks for SENSEE, ART, DIDA’S, KIDS

Nodes connected by graphs



https://www.aac.or.at/smart-farming
https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/
http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Must be connected to a mobile device?

https://www.aac.or.at/smart-farming
https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/
http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Web of Knowledge Graph Networks for SENSEE, ART, DIDA'S, KIDS

Connected KIDS

https://www.aac.or.at/smart-farming
https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/
http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Web of Knowledge Graph Networks are necessary for ART, DIDA'S, KIDS

Connect KIDS PEAS to other ecosystems

https://www.aac.or.at/smart-farming
https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/
http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Web of Knowledge Graph Networks are necessary for ART, DIDA'S, KIDS

Chromosomes of Knowledge

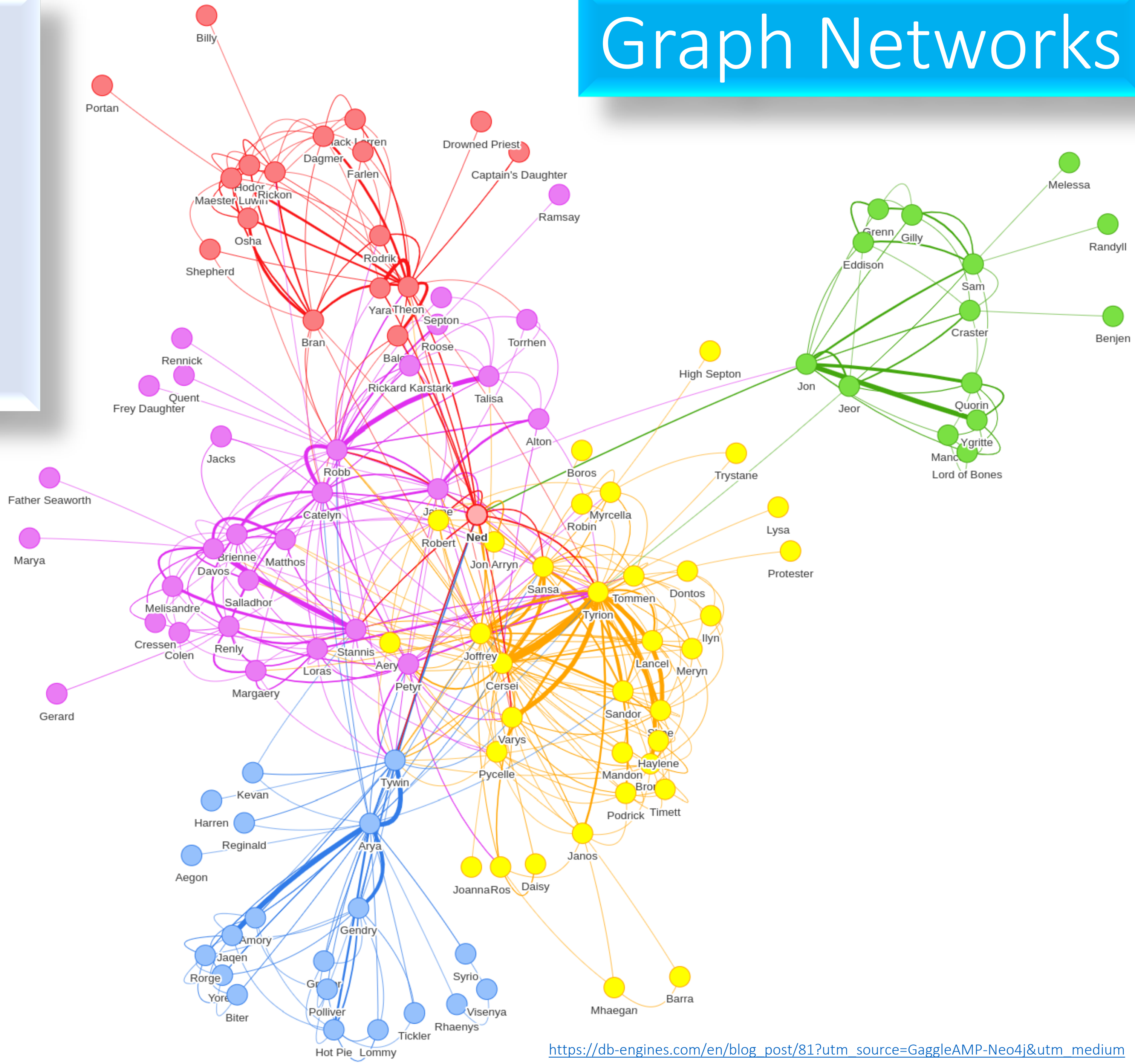
https://www.aac.or.at/smart-farming
https://www.findlight.net/blog/2018/09/01/spectroscopy-precision-agriculture/
http://trajectorymagazine.com/wp-content/uploads/2017/04/TRJ-009-Q1-2013_Final.pdf

Graph Networks

Increased adoption of tools based on graph theory. HTAP integrates graph transactions (OLTP) and analytic processing (OLAP) using graph databases and graph algorithms (relationships are key).

Graph algorithms provide one of the most potent approaches to analyzing connected data because their mathematical calculations are specifically built to operate on relationships. There are many types of graph algorithms and categories. The three classic categories consider the overall nature of the graph: pathfinding, centrality, and community detection. However, other graph algorithms such as similarity and link prediction algorithms consider and compare specific nodes.

- Pathfinding (and search) algorithms are fundamental to graph analytics and algorithms and explore routes between nodes. These algorithms are used to identify optimal routes for uses such as logistics planning, least cost routing, and gaming simulation.
- Centrality algorithms help us understand the roles and impact of individual nodes in a graph. They're useful because they identify the most important nodes and help us understand group dynamics such as credibility, accessibility, the speed at which things spread, and bridges between groups.
- Community algorithms evaluate related sets of notes, finding communities where members have more relationships within the group. Identifying these related sets reveals clusters of nodes, isolated groups, and network structure. This helps infer similar behavior or preferences of peer groups, estimate resiliency, find nested relationships, and prepare data for other analyses.
- Similarity algorithms look at how alike individual nodes are. By comparing the properties and attributes of nodes, we can identify the most similar entity and score differences. This helps build more personalized recommendations as well as develop ontologies and hierarchies.
- Link Prediction algorithms consider the proximity of nodes as well as structural elements, such as potential triangles between nodes, to estimate the likelihood of a new relationship forming or that undocumented connections exist. This class of algorithms has many applications from drug repurposing to criminal investigations.



https://db-engines.com/en/blog_post/81?utm_source=GaggleAMP-Neo4j&utm_medium

Web of Knowledge Graph – Select List of References

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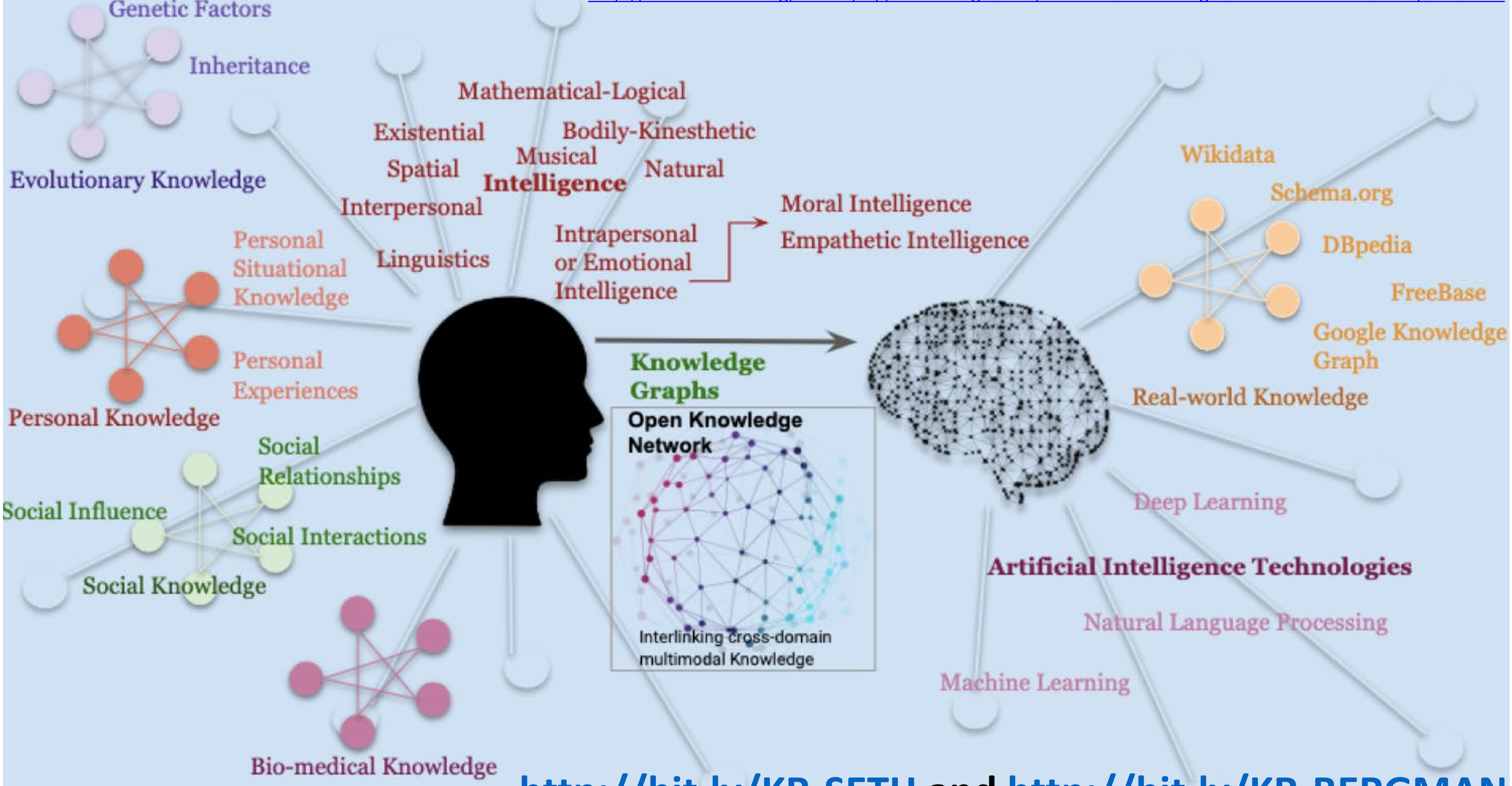
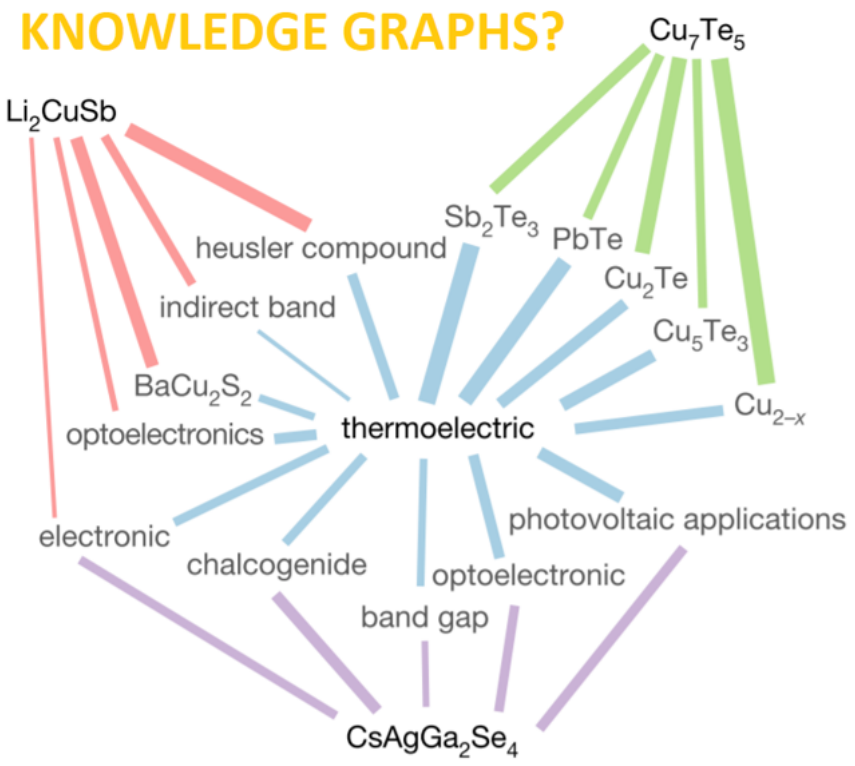
http://wiki.knoesis.org/index.php/Knowledge_Graphs_and_Knowledge_Networks:_The_Story_in_Brief



http://bit.ly/KR-SETH and http://bit.ly/KR-BERGMAN

Novel Paradigm for Machine-Assisted Graph Theoretic Approach to Mine Non-Obvious Relationships

The width of the edges between 'thermoelectric' and the context words (blue) is proportional to the cosine similarity between the word embeddings of the nodes, whereas the width of the edges between the materials and the context words (red, green and purple) is proportional to the cosine similarity between the word embeddings of context words and the output embedding of the material. The context words are top context words according to the sum of the edge weights between the material and the word 'thermoelectric'.



https://doi.org/10.1038/s41586-019-1335-8

Unsupervised word embeddings capture latent knowledge from materials science literature

Vahe Tshitoyan[1,3]*, John Dagdelen[1,2], Leigh Weston[1], Alexander Dunn[1,2], Ziqin Rong[1], Olga Kononova[2], Kristin A. Persson[1,2], Gerbrand Ceder[1,2]* & Anubhav Jain[1]*

https://www.nature.com/articles/s41586-019-1335-8

Novel Paradigm for Machine-Assisted Graph Theoretic Approach to Mine Non-Obvious Relationships

KNOWLEDGE GRAPHS?

https://www.nature.com/articles/s41586-019-1335-8

Scientific progress relies on the confluence of efficient assimilation of existing knowledge in order to minimize re-invention. The methodology in this paper may create a tool to plumb the depths of the unknown unknowns, where catalysts for scientific breakthroughs often reside. The authors are incisive to point out that this approach may be "generalized to other language models, such that the probability of an entity (a material or molecule) co-occurring with words, that represent a target application or property, can be treated as an indicator of performance." Entity-relationship mode remains the "bread and butter" of context-awareness while RDF is a more general model of entities (nodes) and relationships. Thus, the paper strengthens the notion that knowledge graphs may aid in unleashing new ideas. Context-aware embeddings such as NLP BERT or ELMo may improve predictions. This document (PEAS) and the accompanying ideas (SIGNALS) are in quest of these tools. The paper indicates the potential for new research at the nexus of natural language processing, linguistics, semantics, and science, to advance knowledge discovery.

Artificial Reasoning Outcomes → Reasonable Expectations

It is easy to illustrate, but quite difficult for systems to claim real ‘knowledge’ discovery.

Can graph networks catalyze data to reveal information?

But, beware of snake oil sales and stupidity

BEWARE OF STUPIDITY

www.foxbusiness.com/features/after-watson-ibm-looks-to-build-brain-in-a-box

https://emoshape.com/emoshape-enhances-its-cutting-edge-emotion-chip-with-the-addition-of-cloud-service/

EMOSHAPE
EMOTIONS NEXT FRONTIER

Emotion Synthesis | Products | Order | News

Emoshape Enhances Its Cutting Edge Emotion Chip with the Addition of Cloud Service

On: Jun 03 / Author: Patrick Levy-Rosenthal / Categories: Uncategorized /

The Lowest Common Denominator

We are immersed in **data** swamps.
Actions depend on **information**.
Informed by **knowledge**.
Learn from **experience**.

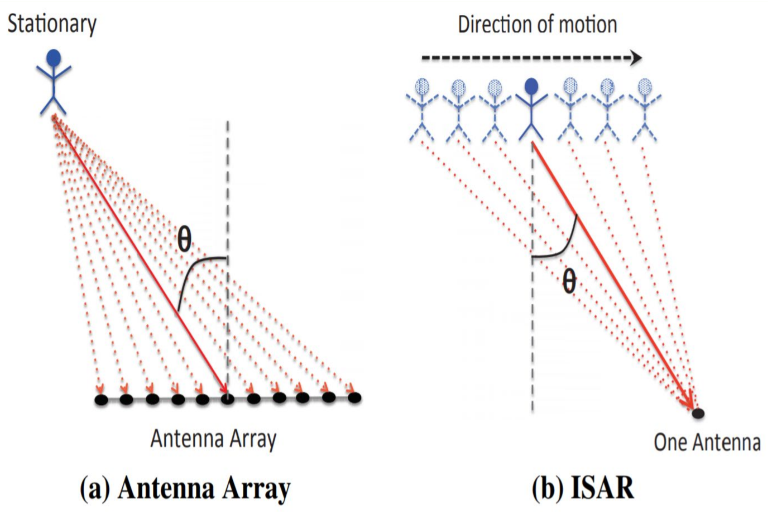
SENSEE → Choose sensors and then harvest DATA from specific SENSORS

S E N S E

SENSE

Don’t bind.
Reflect

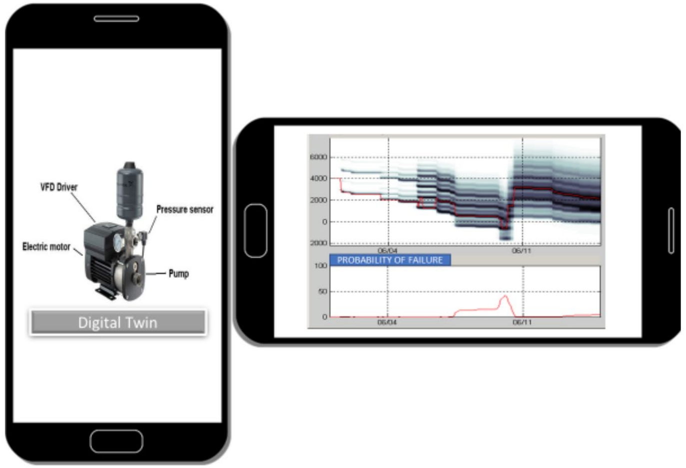
C O N V E R G E



SENSE RF REFLECTION

ANALYZE

TRANSMIT



DECISION SUPPORT

S Y N E R G I Z E

C
O
N
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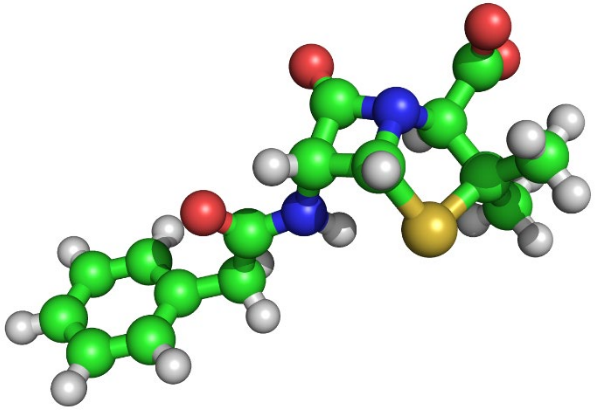
E
R
G
E

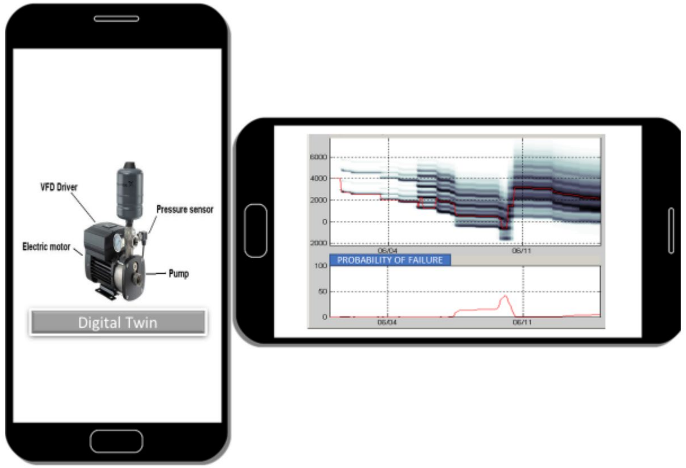


SENSE

BINDING OF ANALYTE

ANALYZE

TRANSMIT



DECISION SUPPORT

S
Y
N
E
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Z
E

How does a sensor work? Sensors that bind analytes.

https://onlinelibrary-wiley-com.libproxy.mit.edu/doi/pdf/10.1002/anie.199423751

The Key–Lock Theory and the Induced Fit Theory 1 / 4

There are sensors that may not bind analytes but are activated by reflected radio waves (WiFi, radar, sonar)

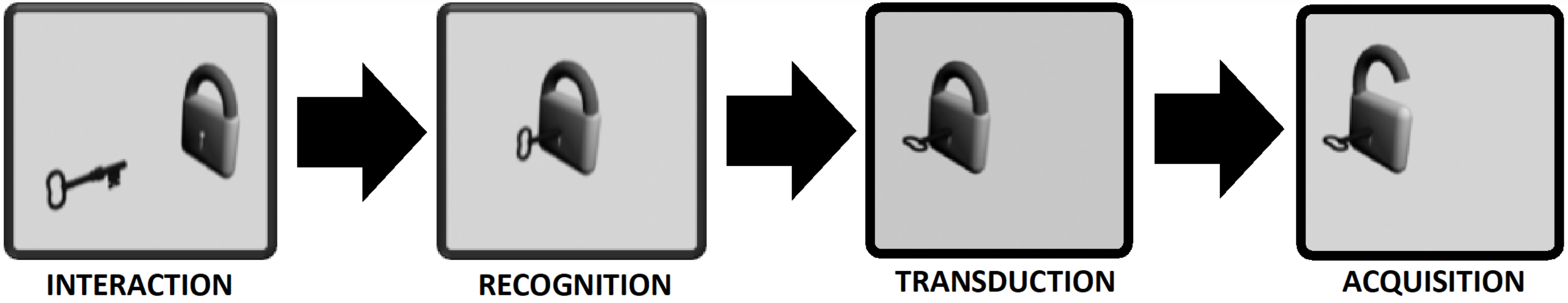
The Key–Lock Theory and the Induced Fit Theory

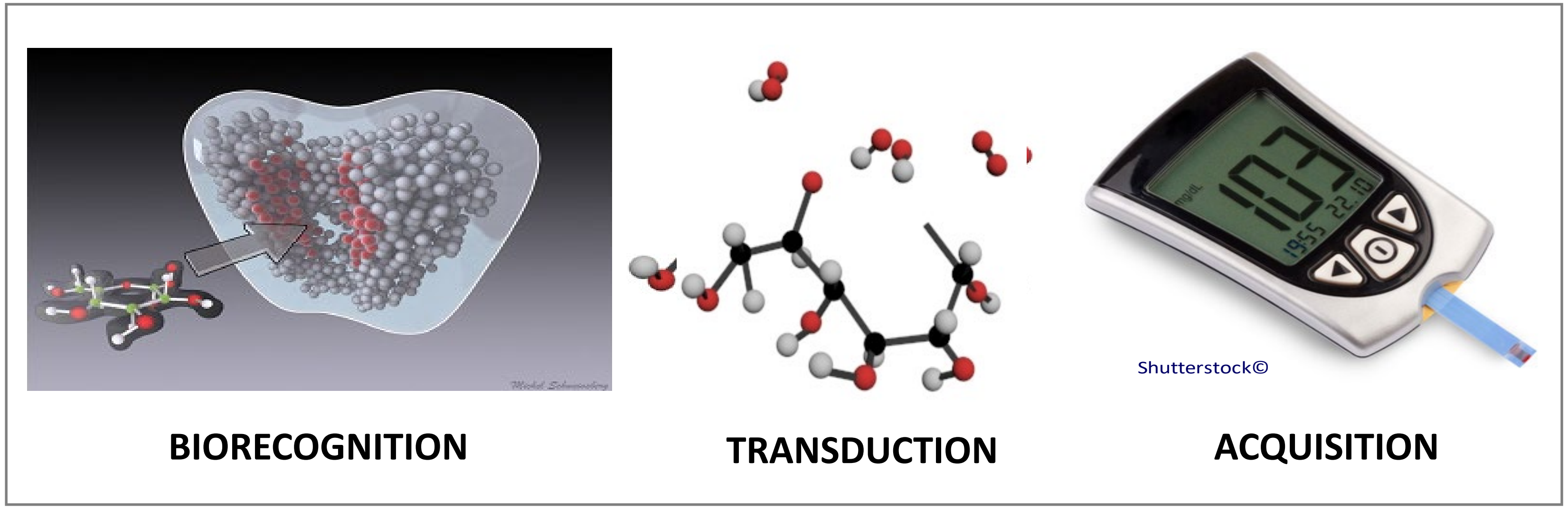
Daniel E. Koshland, Jr.

It is a great pleasure for me to contribute to this symposium honoring the great scientist Emil Fischer. My graduate thesis required me to synthesize [1-^{14}C]glucose, which introduced me to the famous Fischer–Kiliani synthesis of glucose and mannose from arabinose and HCN.[1] I was also particularly intrigued with his classic key–lock (or template) theory of enzyme specificity,[2, 3] which like all great theories seemed so obvious once one understood it.

https://onlinelibrary.wiley.com/doi/abs/10.1002/anie.199423751

How does a sensor work? The classical glucometer.





Step 1) Biorecognition
Step 2) Binding and transduction
Step 3) Acquisition and data analytics

https://onlinelibrary.wiley.com/doi/abs/10.1002/anie.199423751

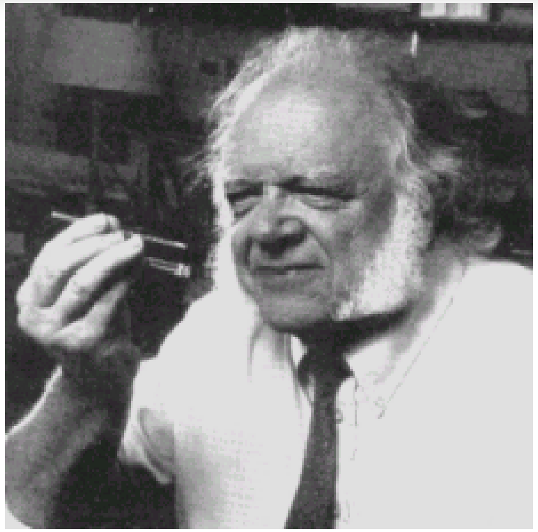
Unchanged: 1962 Classical Chemistry of Clark and Lyons

https://nyaspubs.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1749-6632.1962.tb13623.x

ELECTRODE SYSTEMS FOR CONTINUOUS MONITORING IN CARDIOVASCULAR SURGERY

Leland C. Clark, Jr., and Champ Lyons
Medical College of Alabama, Birmingham, Ala.

Instruments capable of continuously indicating the chemical composition of blood have proved to be useful in controlling heart-lung machines, in regulating operative and postoperative management of patients, and in teaching and research. At first, such instruments were used with sensors mounted directly in the extracorporeal blood circuit that is used for perfusion of open-heart surgery patients.[1] Later, continuous monitoring of both machine and patients was conducted by means of continuous withdrawal of blood pumped into external cuvettes equipped with appropriate sensors.



Leland C. Clark, Jr. (1959)

Unchanged: 1962 Classical Chemistry of Clark and Lyons

https://nyaspubs.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1749-6632.1962.tb13623.x

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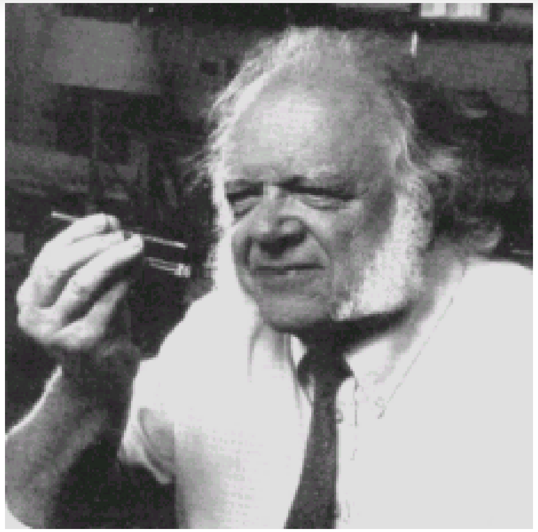
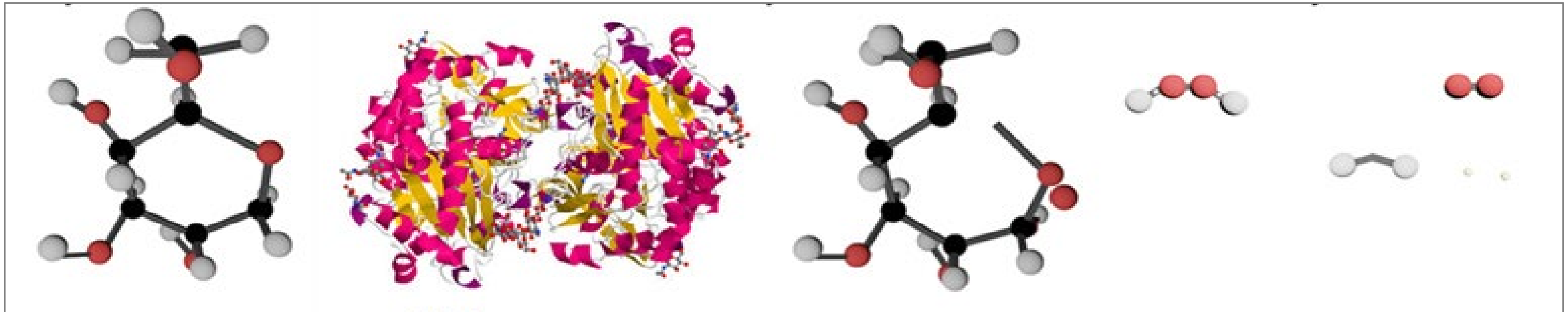
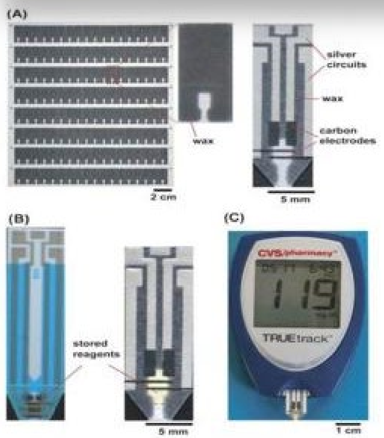


Leland C. Clark, Jr. (1959)



$$\text{Glucose} + O_2 \xrightarrow{GOX} \text{gluconic acid} + \mathrm{H_2O_2} \rightarrow 2H^+ + O_2 + 2e^-$$

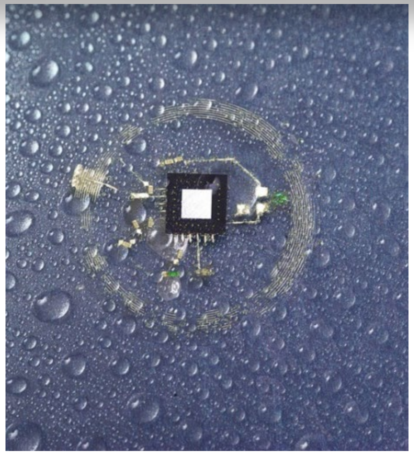
Glucometer – The Evolution of its Form and Function



Paper based (Whitesides)

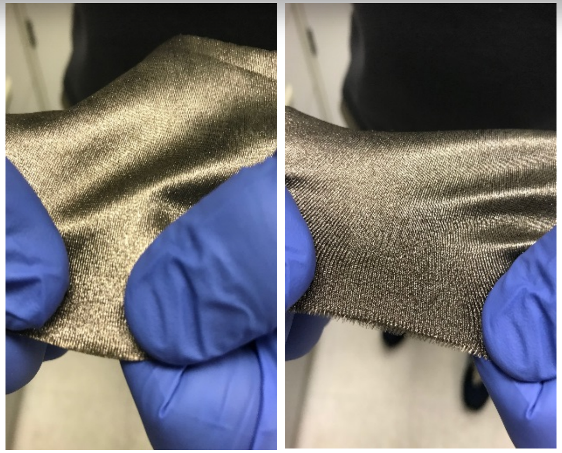
Noninvasive glycemic monitoring (Wang)

WISP: Wearable Interactive Stamp Platform (MC10)



Resorbable (Rogers)

Contact lens (Google, Inc.)



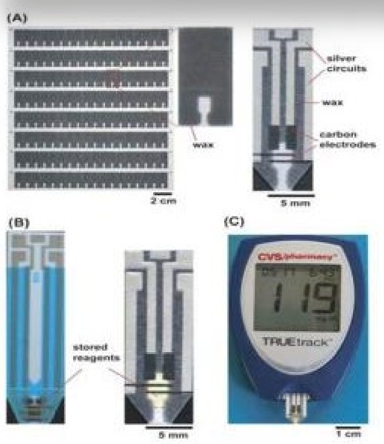
Stretchable fabric (Bhargava-UF)

Function	Form (elements and structure)
What a system does/could do	What a system is/could be
Creates behavior	Is aggregated and decomposed
Is a source of benefit/value	Is a source of costs
Requires form	Enables function

Source: E. Crawley, MIT Course Material

Glucometer – The Evolution of its Form and Function

https://onlinelibrary.wiley.com/doi/abs/10.1002/anie.200603817



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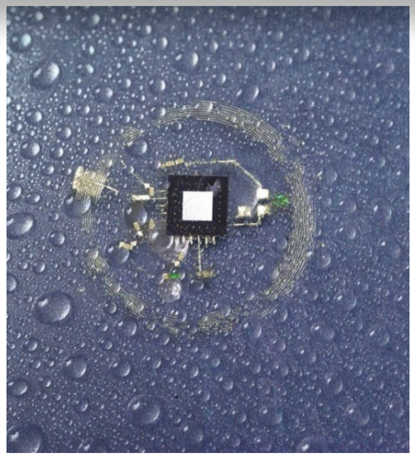

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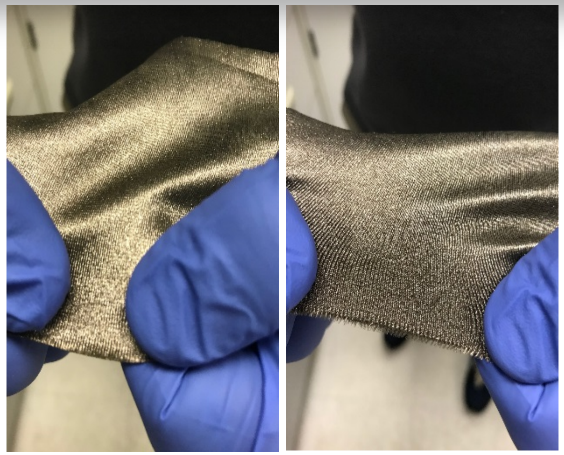
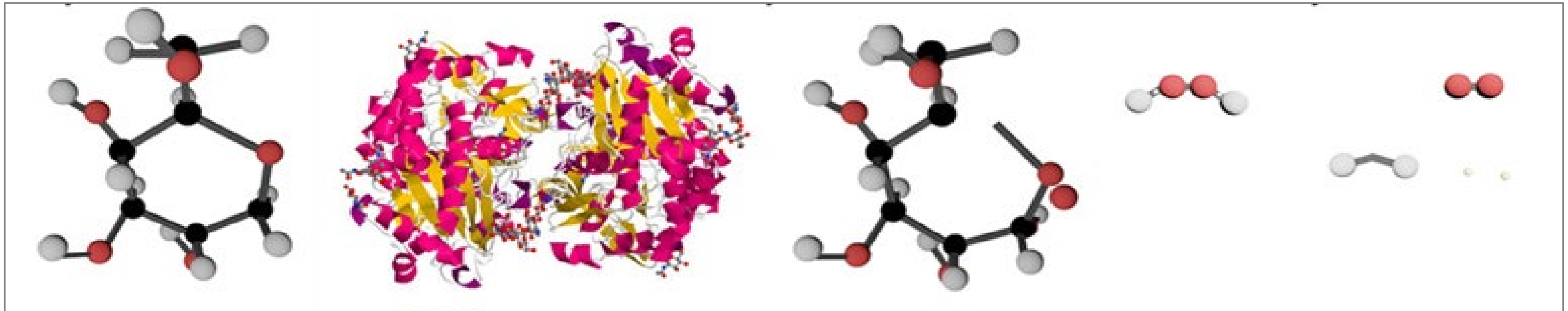


Stretchable fabric (Bhargava-UF)

https://www.cientperiodique.com/article/CPQME-2-1-40.pdf



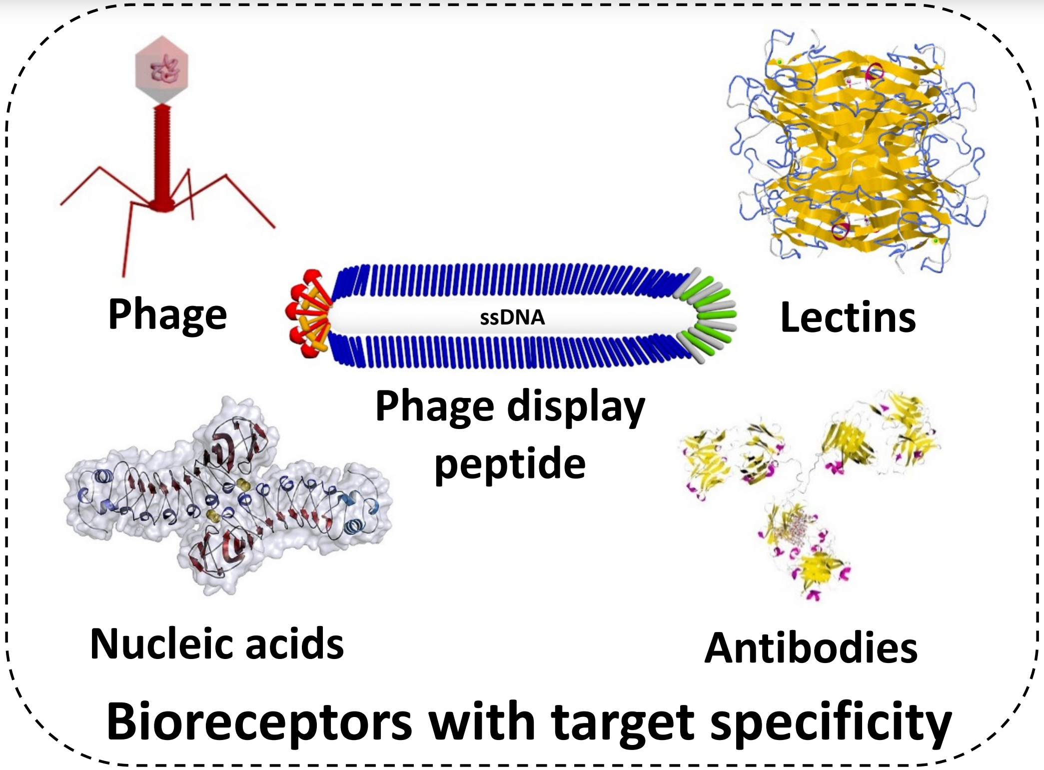
$$\text{Glucose} + O_2 \xrightarrow{GOX} \text{gluconic acid} + H_2O_2 \rightarrow 2H^+ + O_2 + 2e^-$$

The core chemistry developed by Clark and Lyons has not changed since 1962.

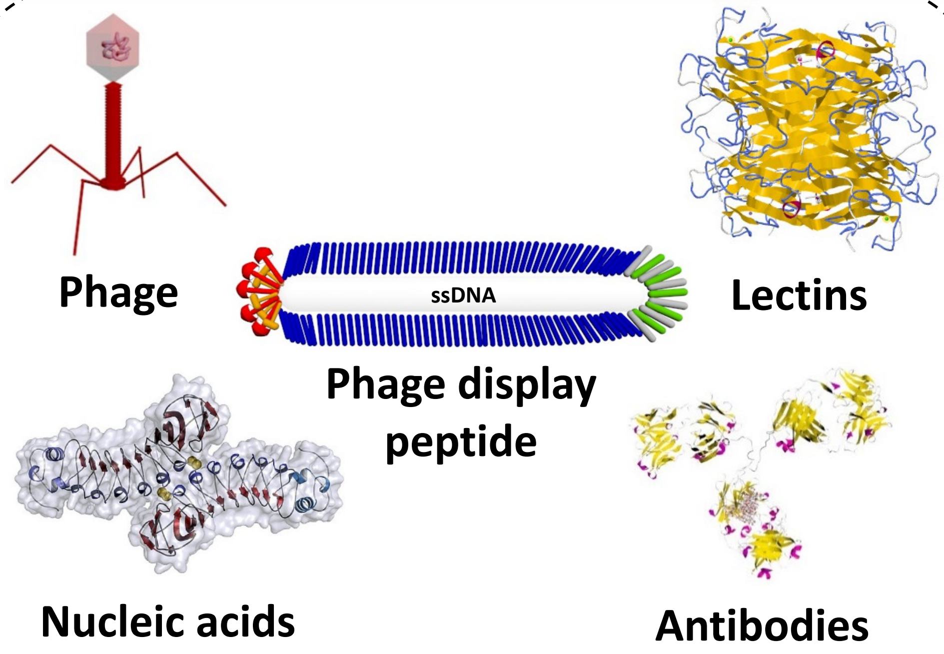
Evolution of Sensors ◆ Nano-bio Sensors

https://emclamor.wixsite.com/mclamorelab

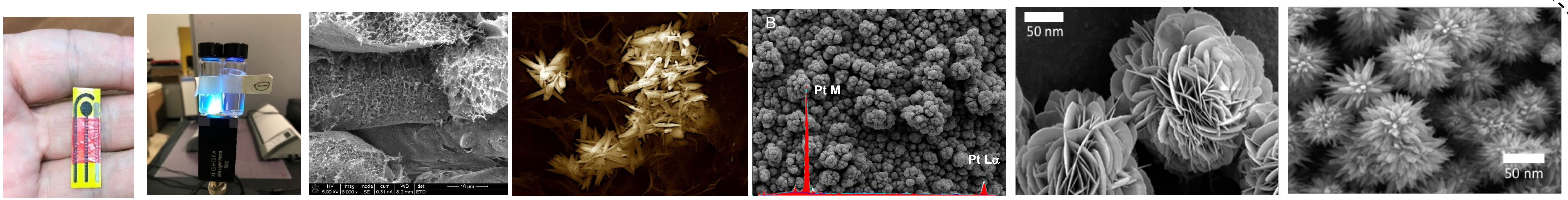
Evolution of Sensors ◆ Nano-bio Sensors



Evolution of Sensors ◆ Nano-bio Sensors

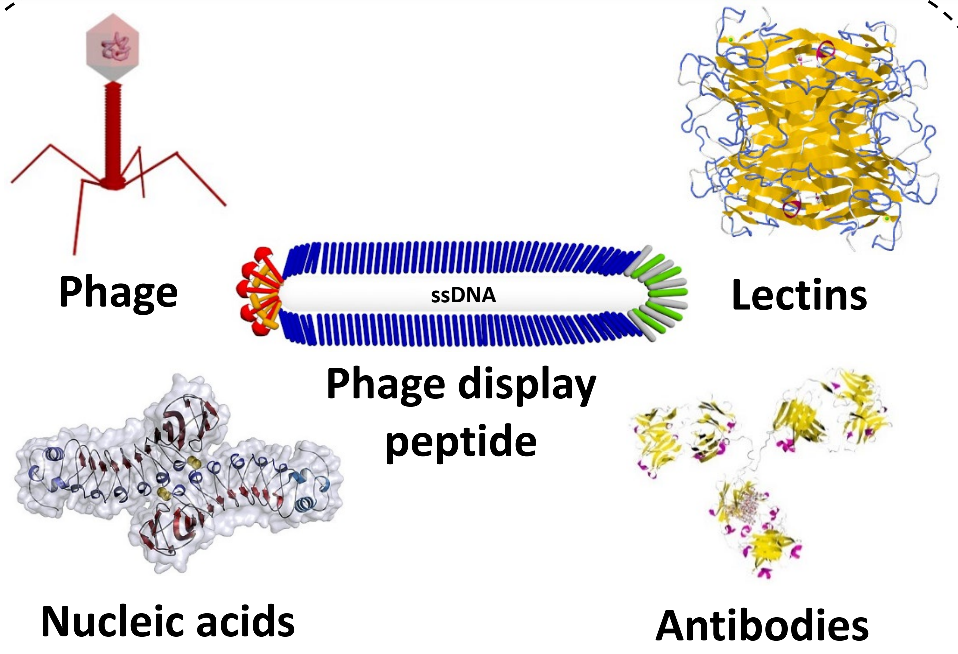


Bioreceptors with target specificity

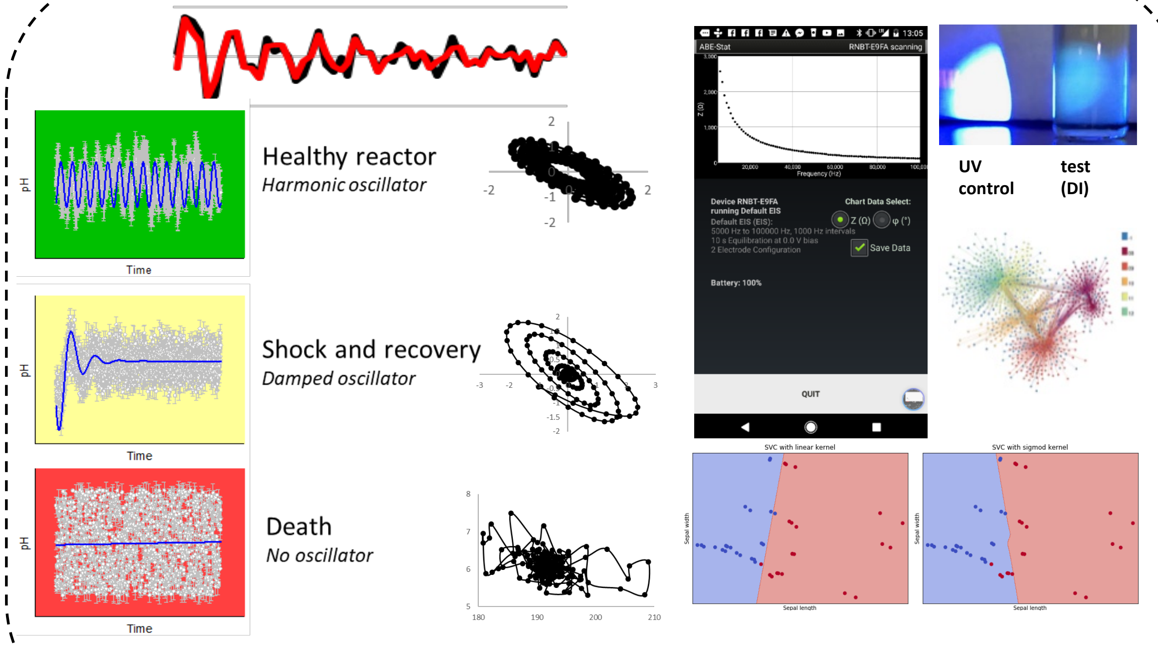


Nanomaterials improve signal transduction

Evolution of Sensors ◆ Nano-bio Sensors

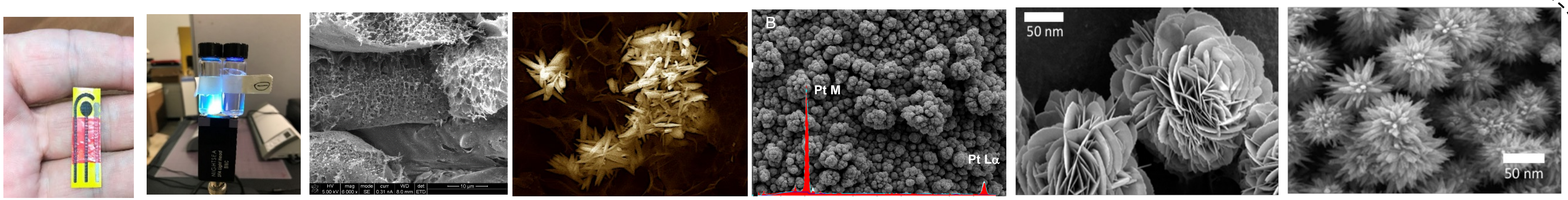


Bioreceptors with target specificity



Signal acquisition and data analytics

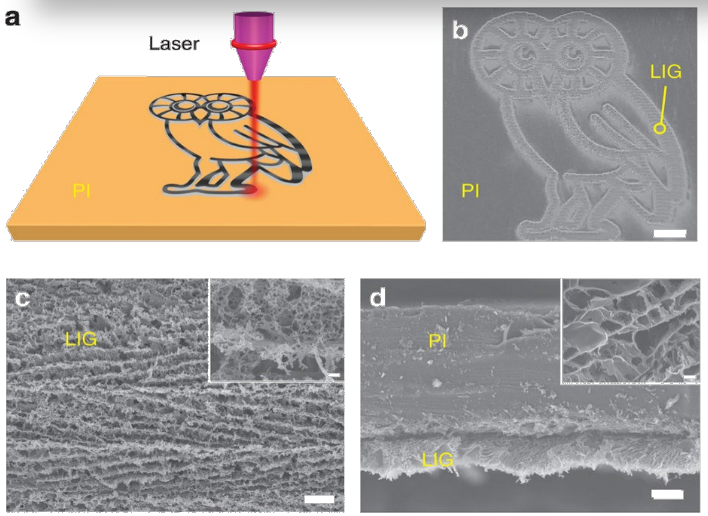
https://emclamor.wixsite.com/mclamorelab



Nanomaterials improve signal transduction

Evolution of Sensors ◆ 3D Printed Nano-bio Sensors

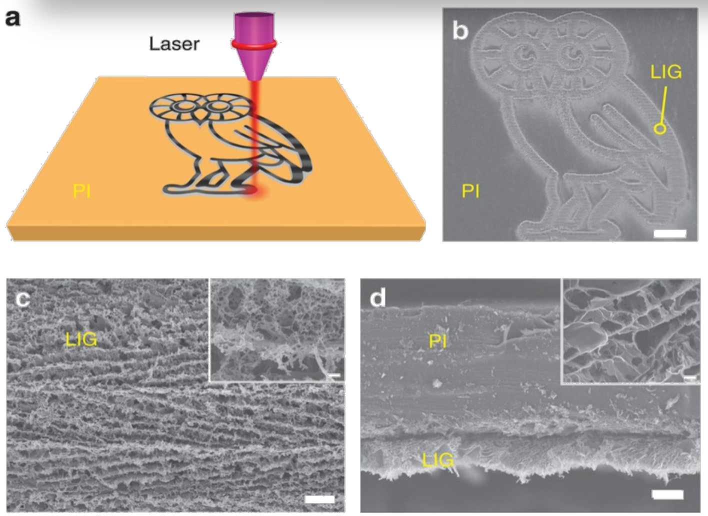
Laser Inscribed Graphene (LIG)



Lin et. al. (2014) develops LIG for supercapacitors

Evolution of Sensors ◆ 3D Printed Nano-bio Sensors

Laser Inscribed Graphene (LIG)



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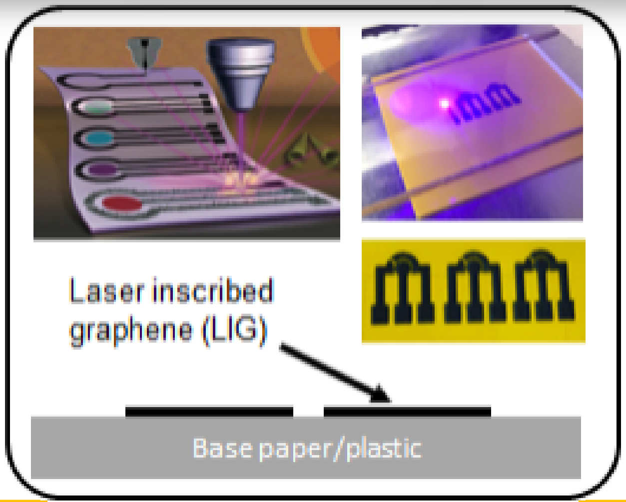
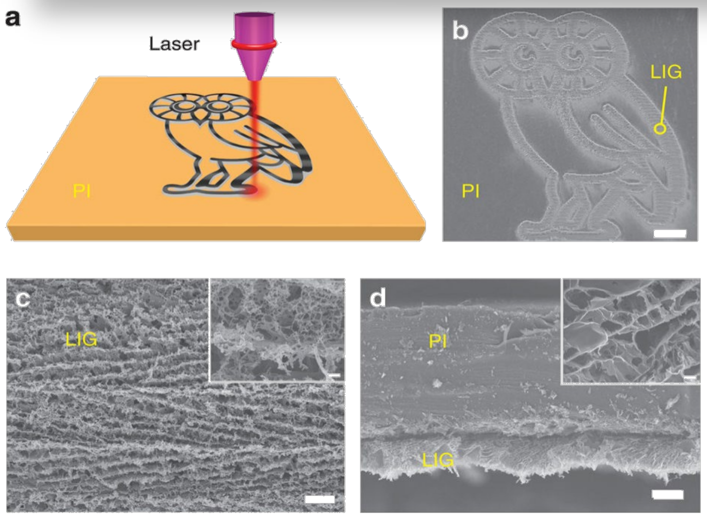


LIG for Sensing

- Sugars, organics
  - Tehrani et. al. (2016); Nayak et. al. (2016); Vanegas et al (2018)
- Ions
  - Garland et al (2019)

Evolution of Sensors ◆ 3D Printed Nano-bio Sensors

Laser Inscribed Graphene (LIG)



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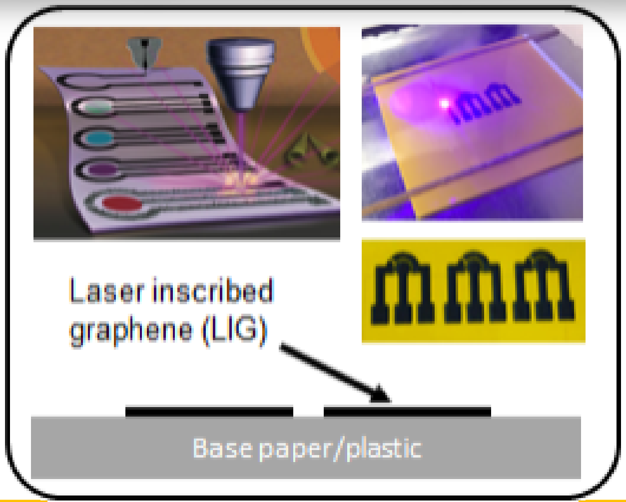

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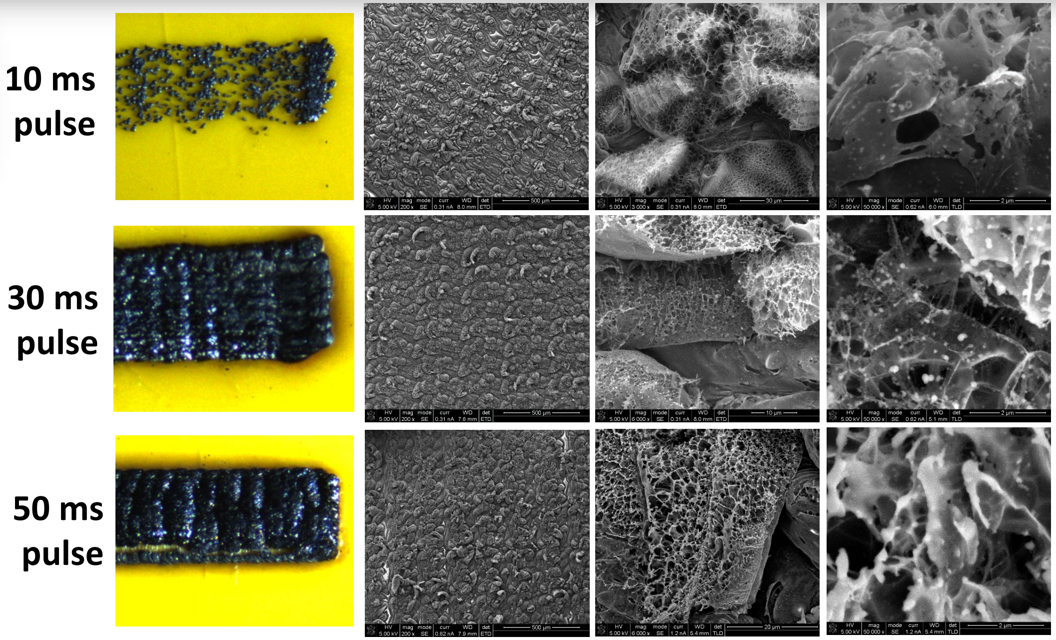
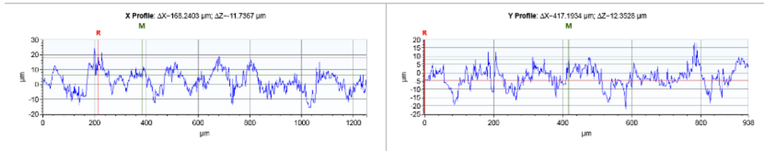
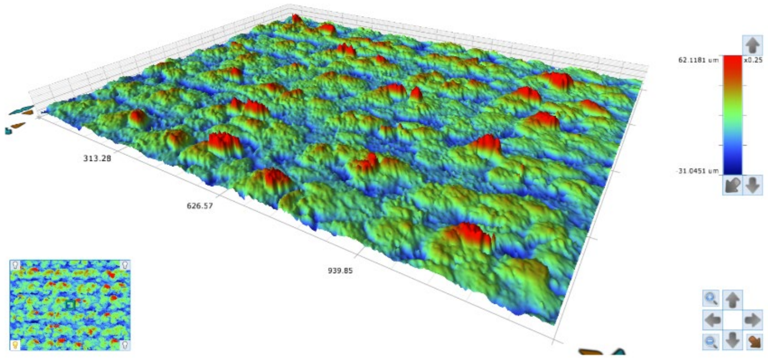
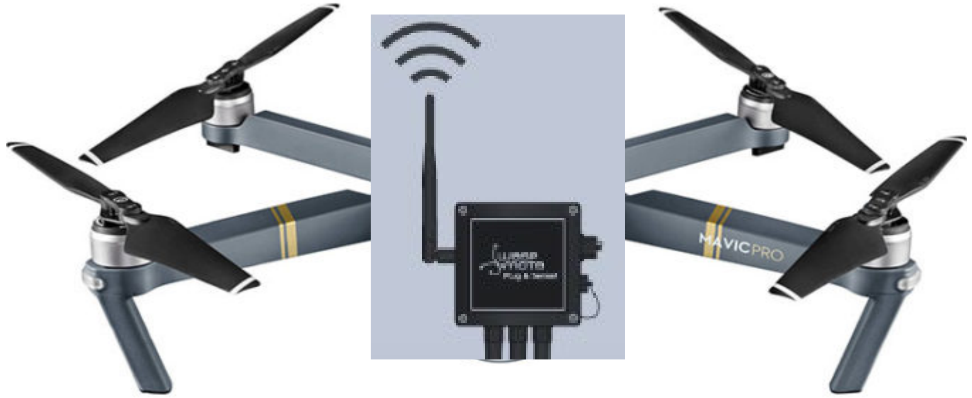


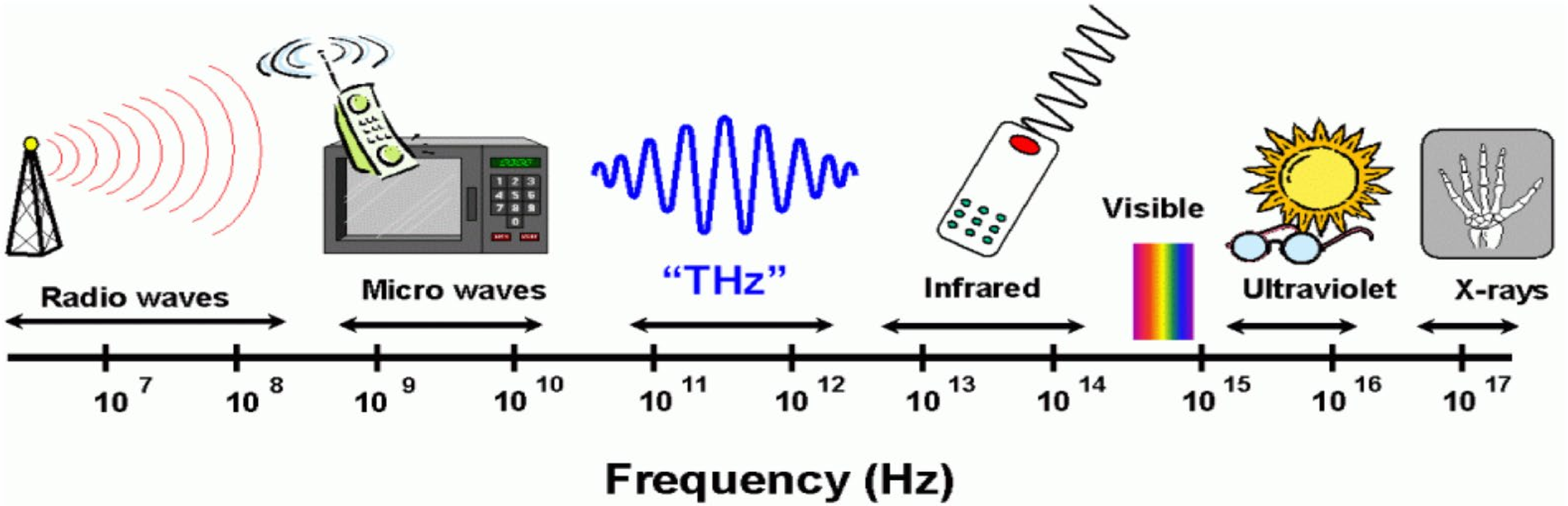




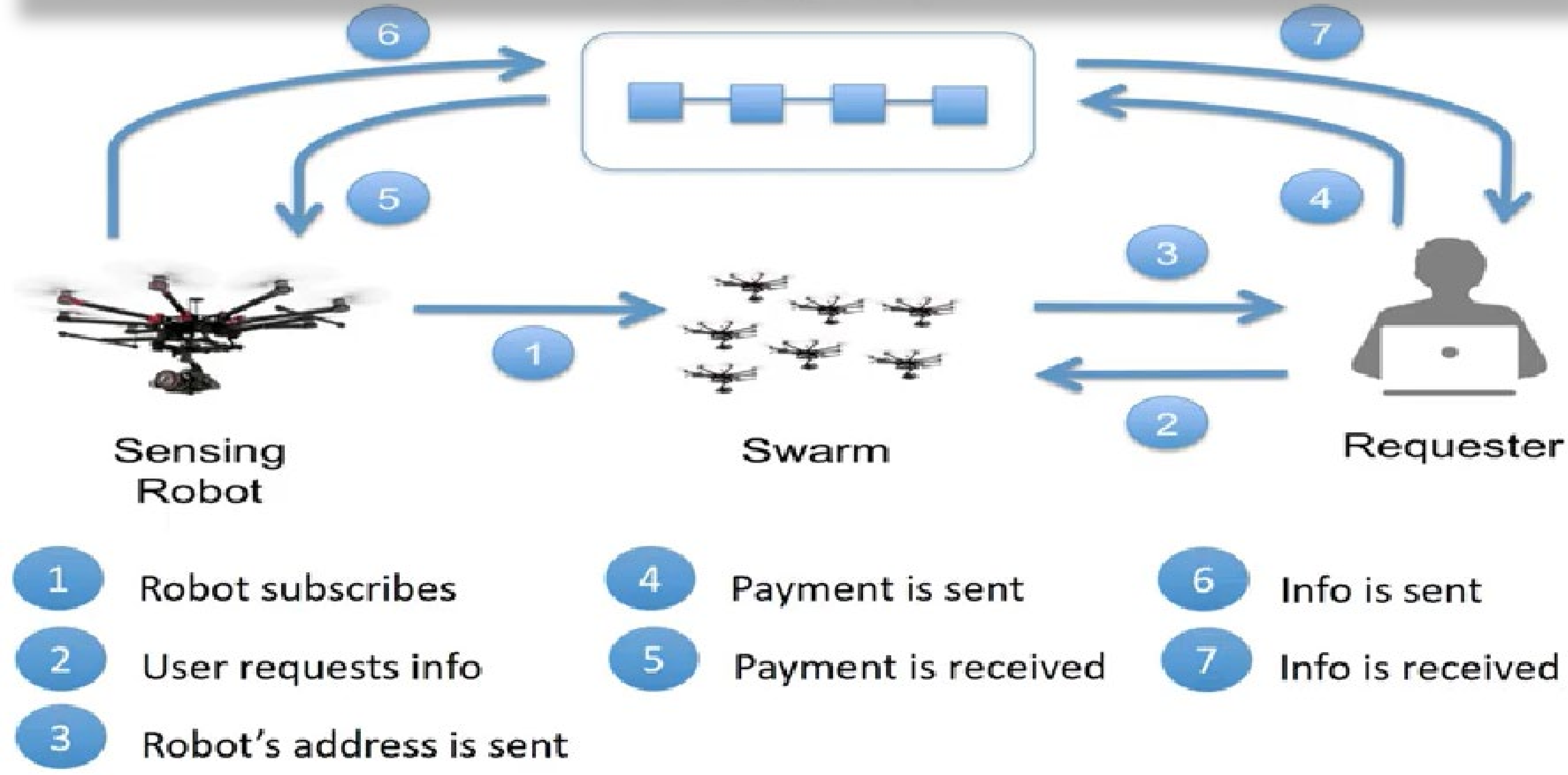
Drones carrying Mobile Sensors acquire Reflected RF Signals



Terahertz (THz) spectrum, occupying frequency range between 0.3 and 3 THz, has potential for transformative applications in communication, sensing, spectroscopy, and imaging due to its desirable properties such as non-ionizing photon energy, penetration capability through optically opaque materials, unique spectral signatures for macro-molecules and chemicals. https://www.nature.com/articles/s41467-019-09868-6



Rent-a-Robot drone-swarm “plug & play” remote sensors to collect desired data

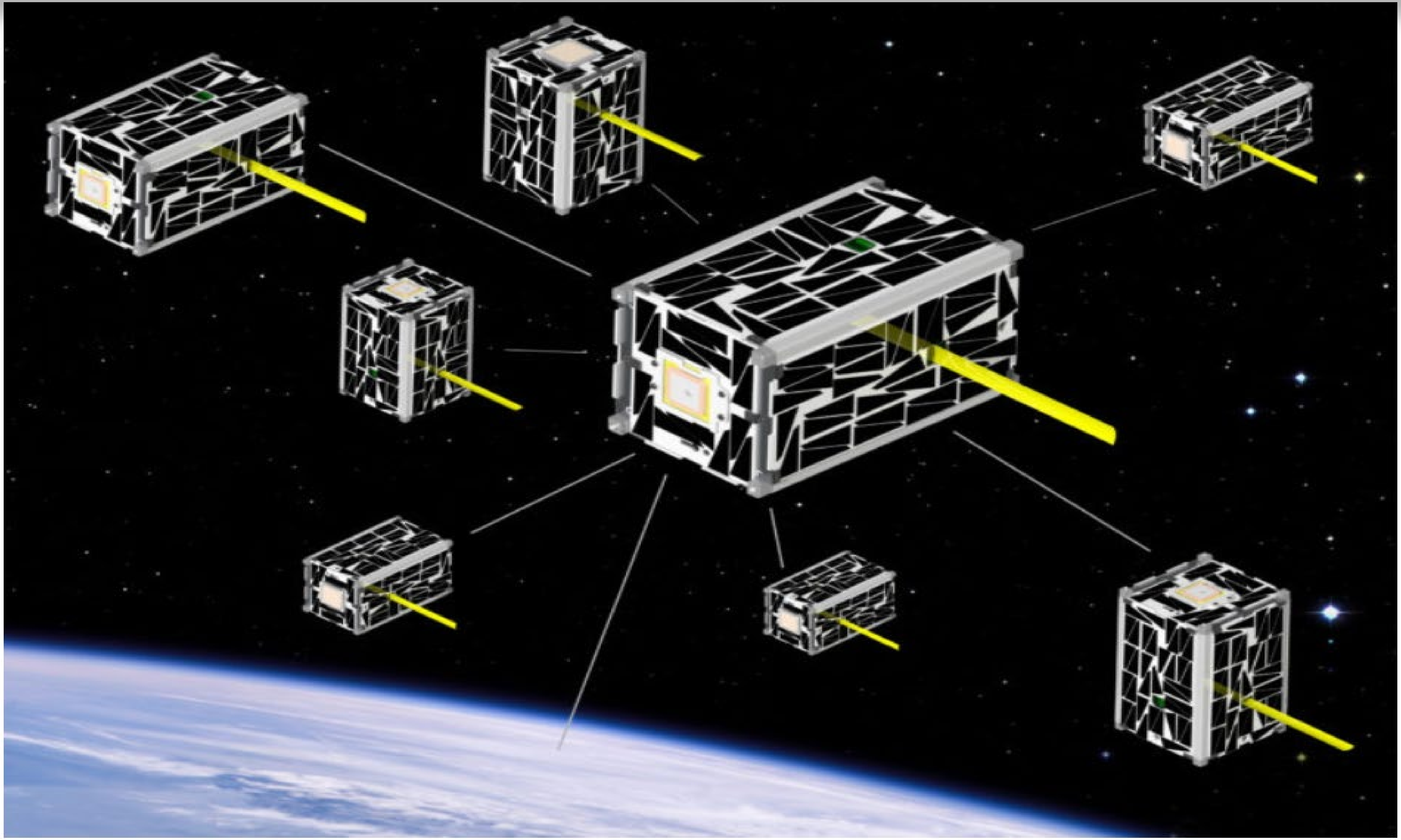


Mobile Sensor Swarms deployed on Drones-on-Demand

Swarm Intelligence, Swarm Robotics, Mobile Robotics

https://dl.acm.org/citation.cfm?id=37406; https://link.springer.com/chapter/10.1007%2F978-3-642-58069-7_38; https://vlsicad.ucsd.edu/Publications/Journals/j26.pdf

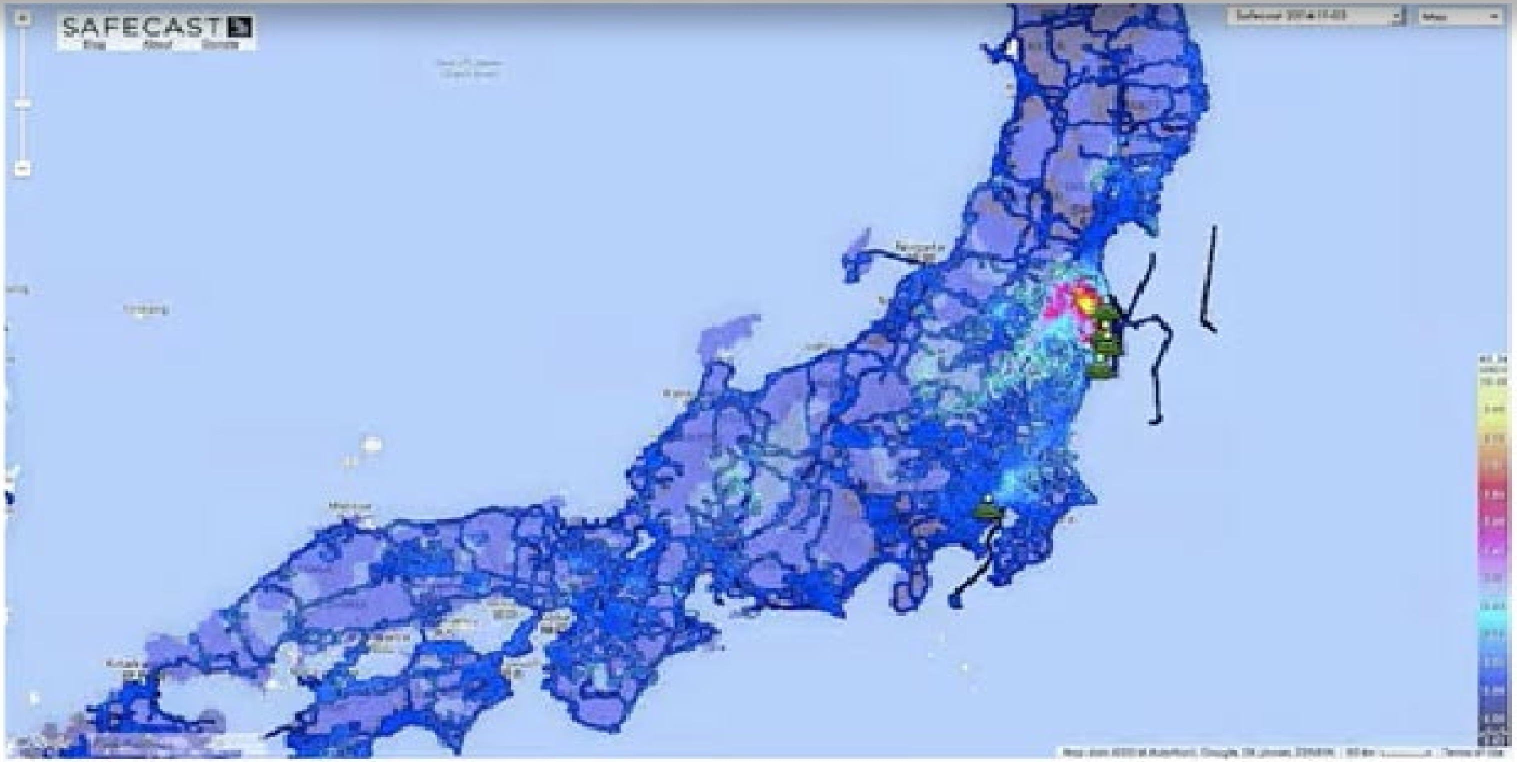
Sensor Swarm



NASA and Lockheed Martin have been studying how small satellites could be knit together into a distributed swarm. (NASA Illustration)

Crowd-sourced radiation sensor data after the explosion Fukushima Daiichi Nuclear Power Plant in Ōkuma (2013)

Safecast Nano - Mobile Radiation Monitoring
Wireless Geiger Counter, GPS with Bluetooth



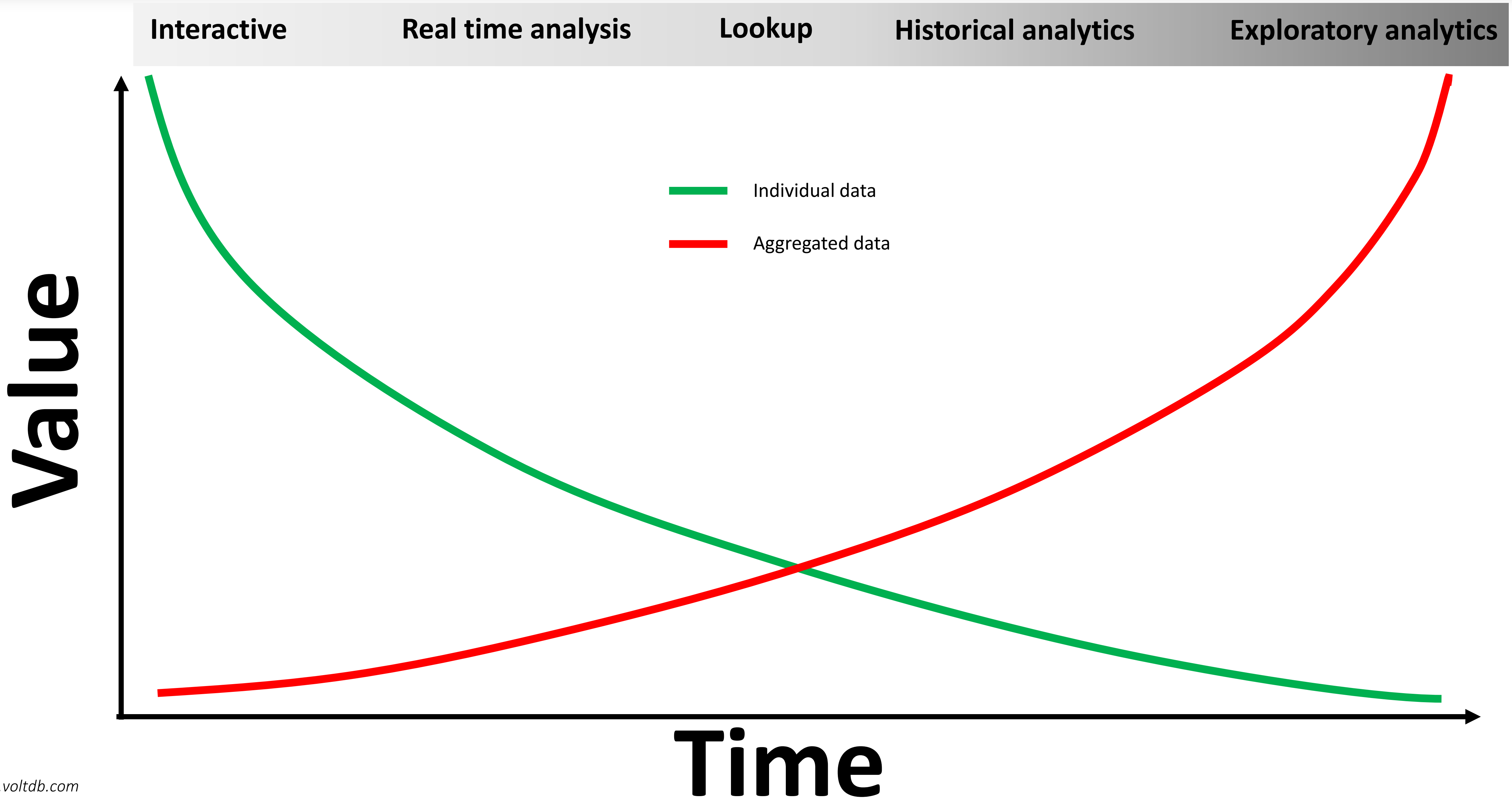
SAFECAST

http://bit.ly/EDUARDO-CASTELLO

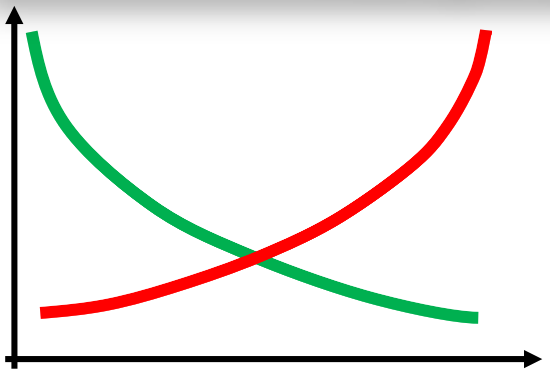
Source: Google Images Labeled for Reuse

DATA from SENSORS

Is data perishable?

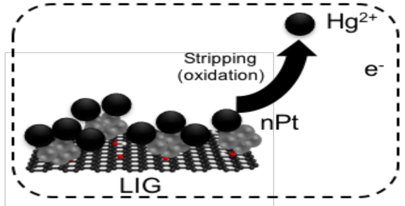


Varying Time-Sensitivity of Data from Sensors



Persistent

- Soil health
    - Erosion, degradation
- Agrochemical runoff
    - Nutrients, agrochemicals
- Land use change
    - Deforestation, mining



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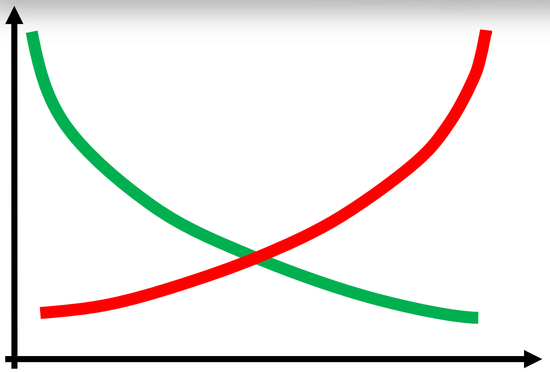
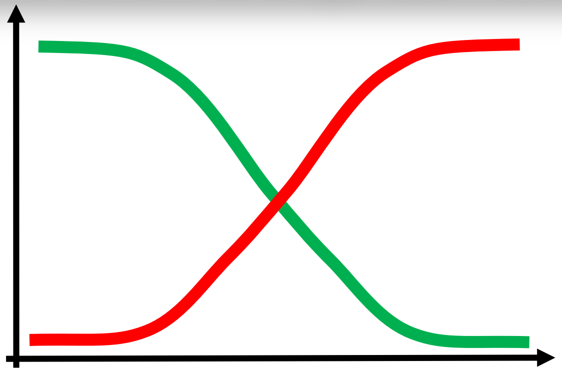
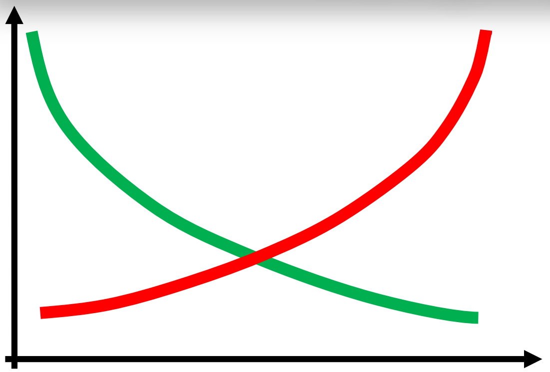


Persistent

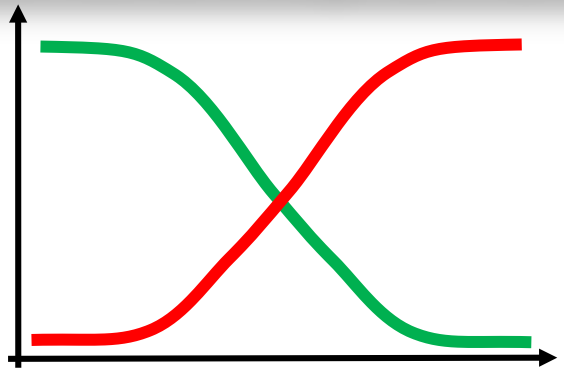


Urgent

Varying Time-Sensitivity of Data from Sensors

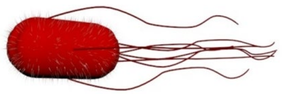


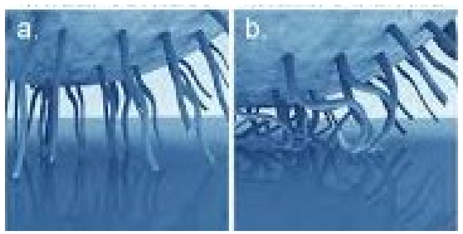
Persistent

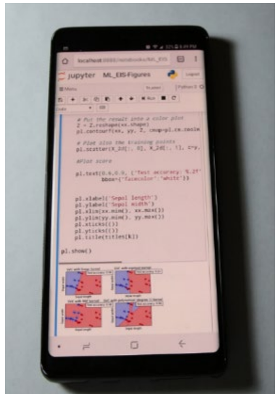


Urgent

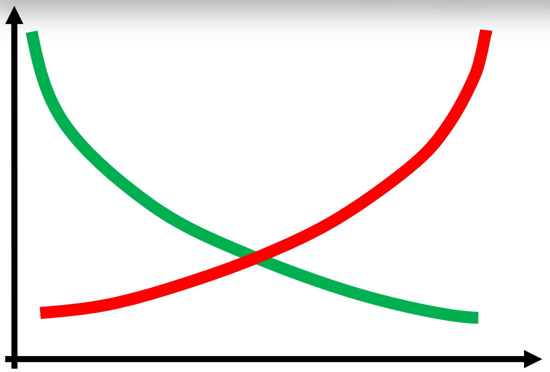
- Water scarcity
  - Quantity, quality
- Climate change
- Solid waste/wastewater
  - Pathogens, heavy metals







Varying Time-Sensitivity of Data from Sensors



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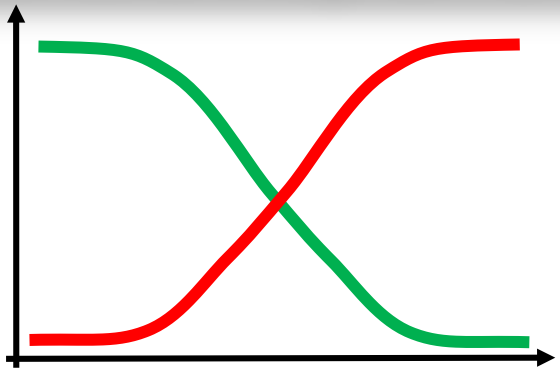
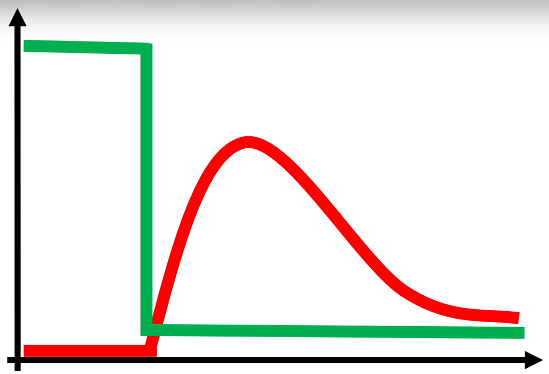
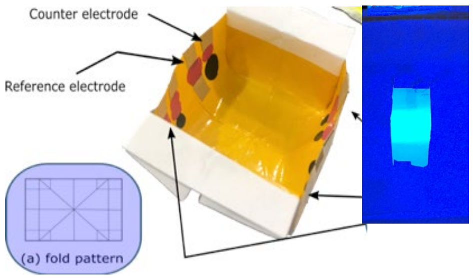


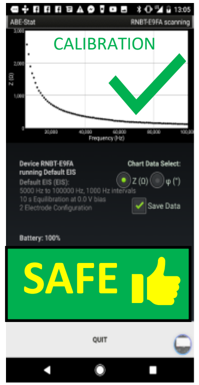
Urgent



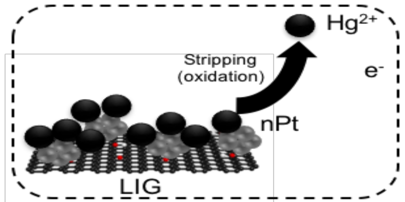
Triage

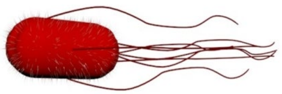
- Natural disaster
- Attack on infrastructure

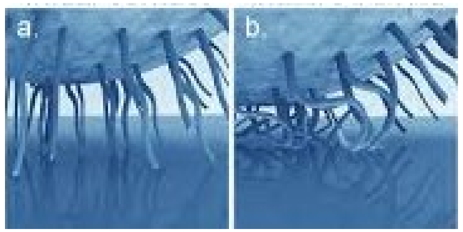


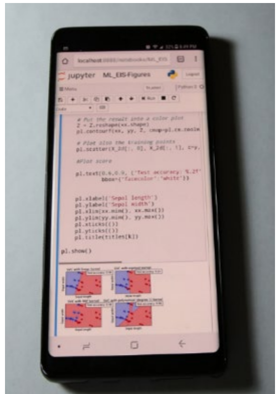


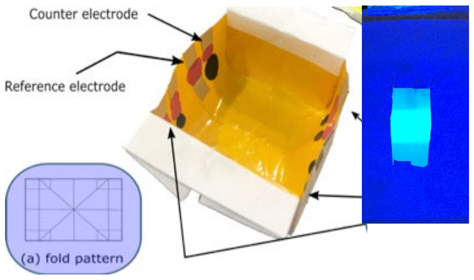
Data from the Perspective of Sensors

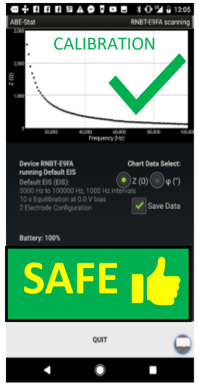












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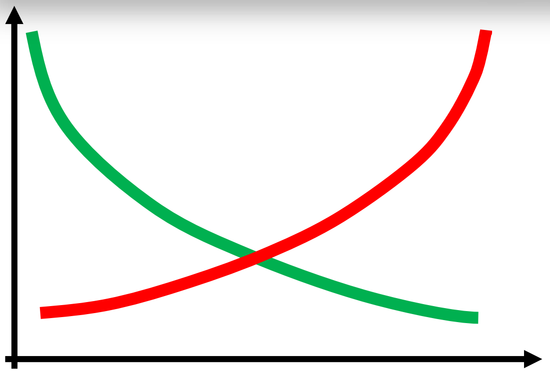
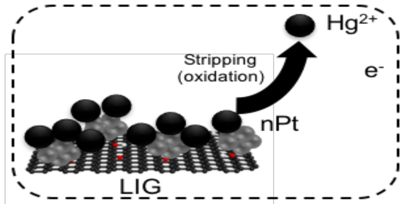
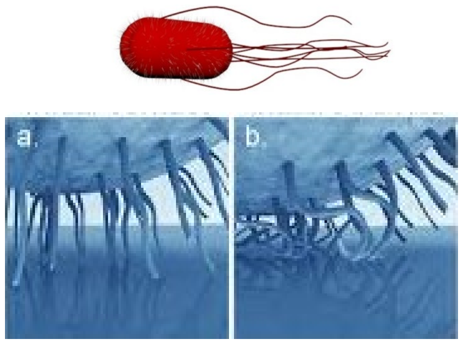
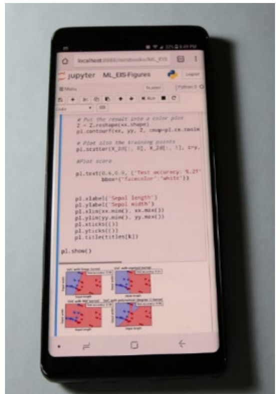
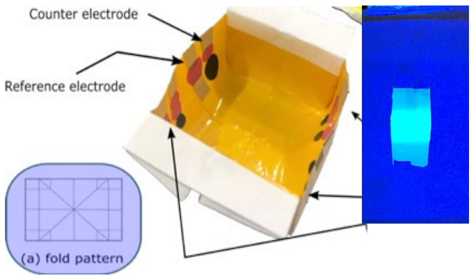


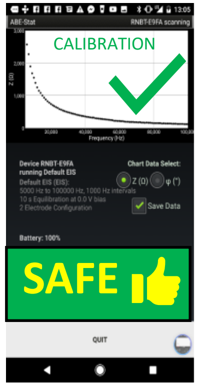
Persistent











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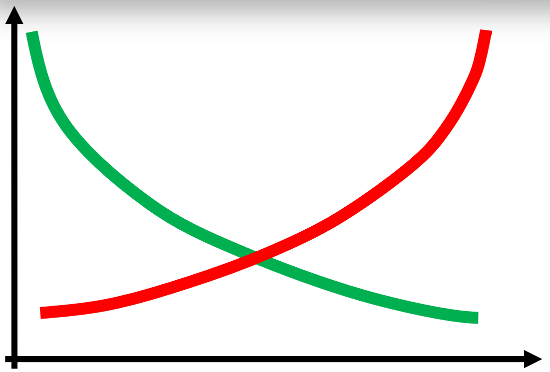

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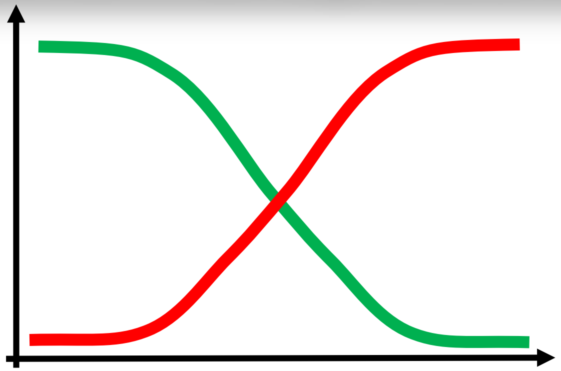

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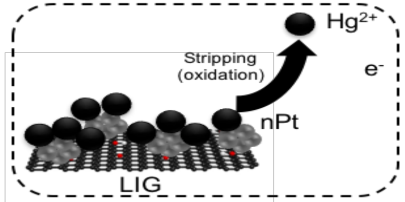

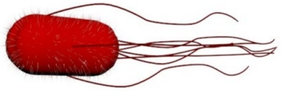

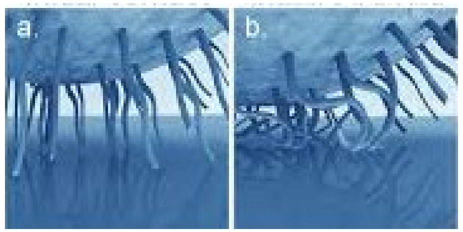

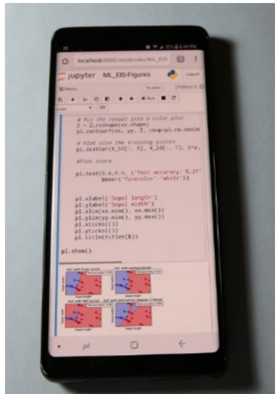

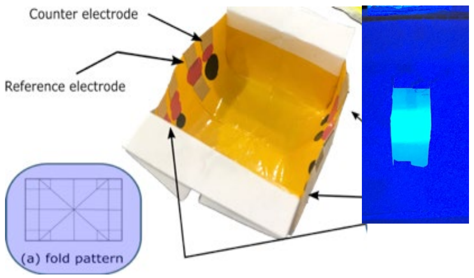

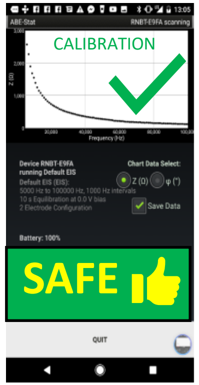

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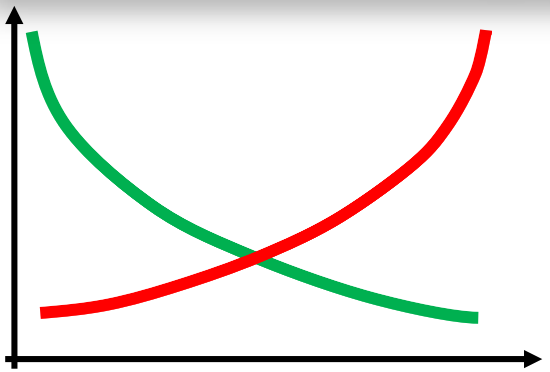

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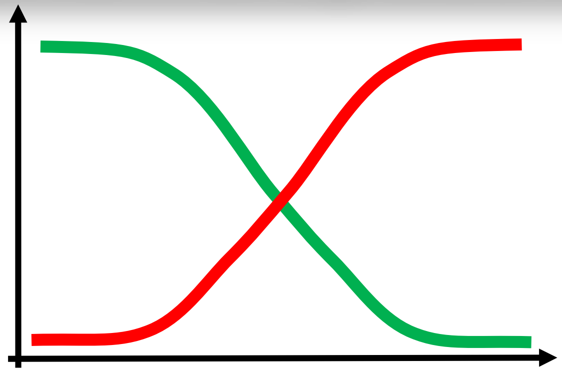

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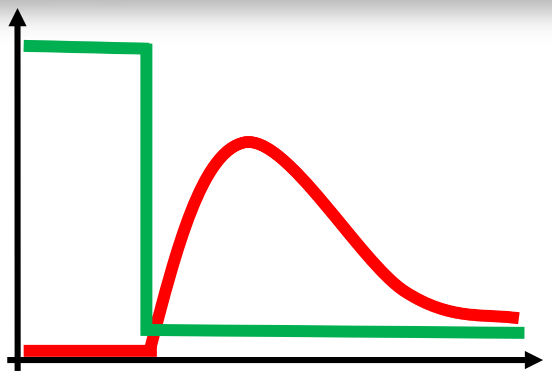
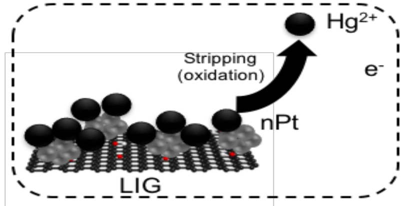
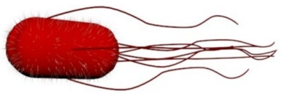
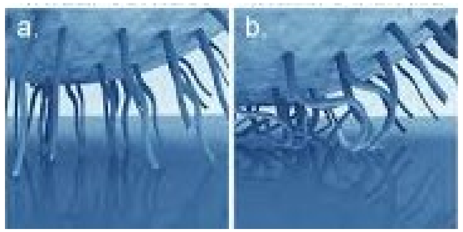
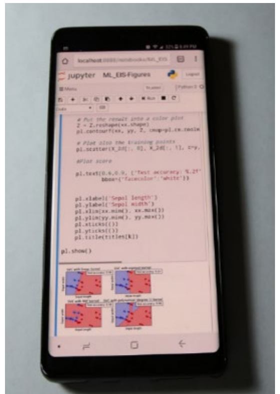


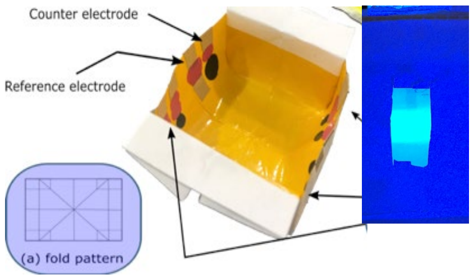
Triage

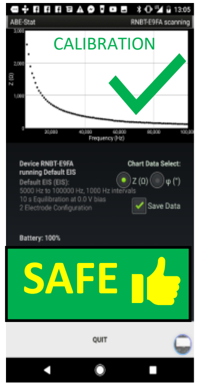




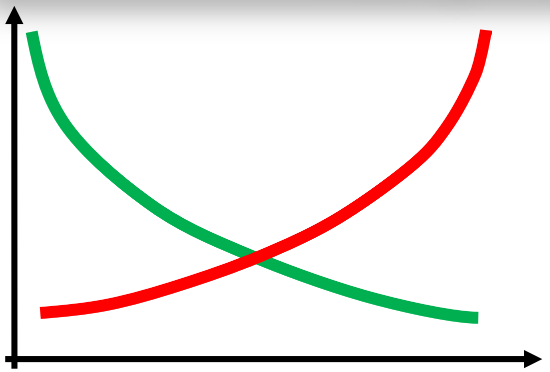






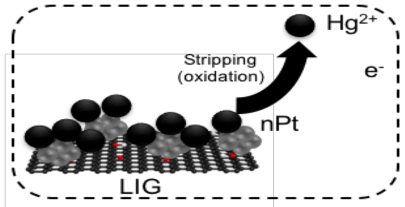


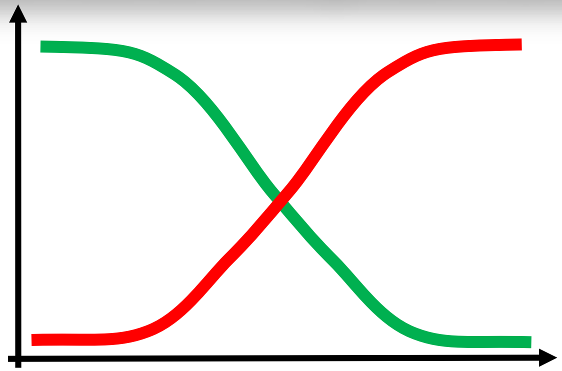
Varying Time-Sensitivity of Data from Sensors



Persistent

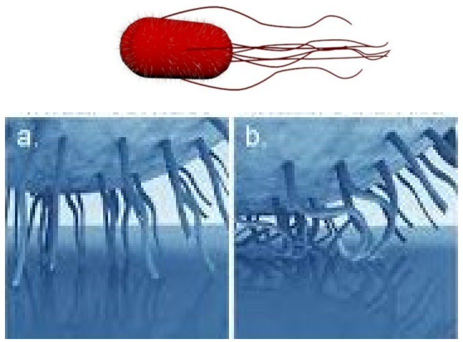
- Soil health
  - Erosion, degradation
- Agrochemical runoff
  - Nutrients, agrochemicals
- Land use change
  - Deforestation, mining

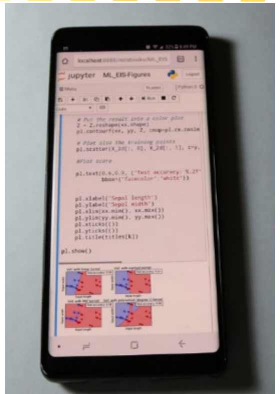


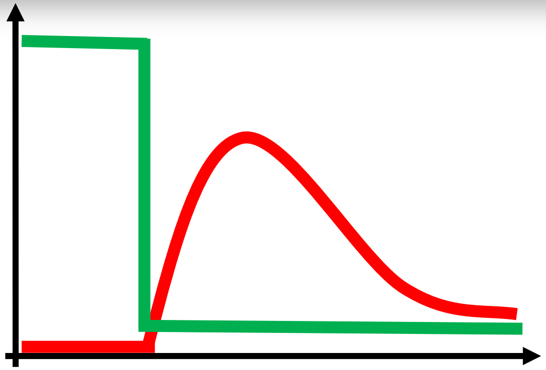


Urgent

- Water scarcity
  - Quantity, quality
- Climate change
- Solid waste/wastewater
  - Pathogens, heavy metals

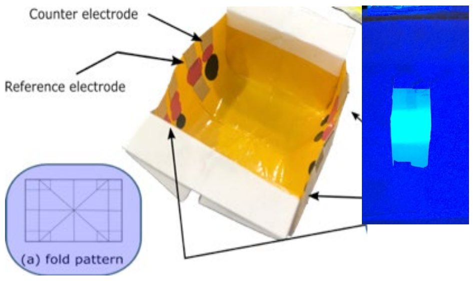


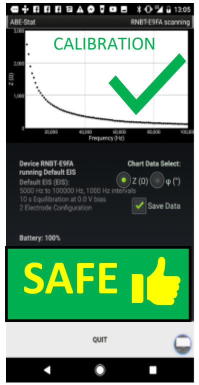




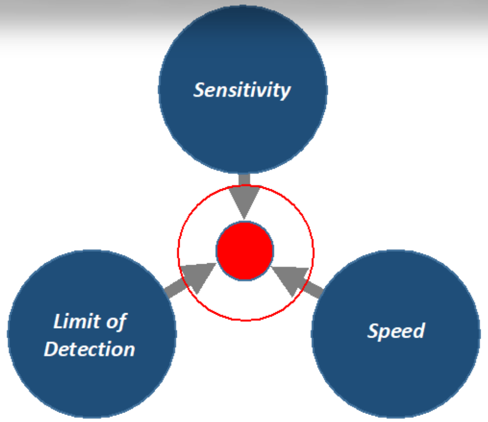
Triage

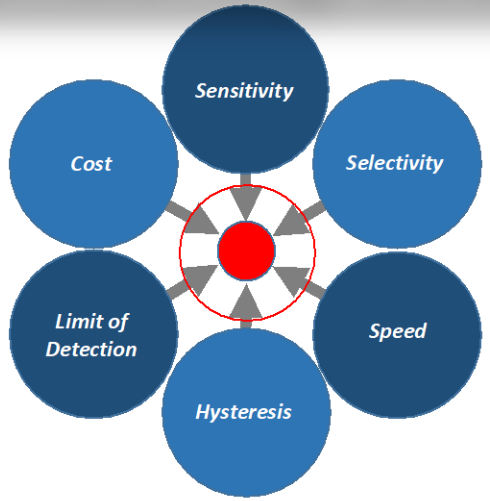
- Natural disaster
- Attack on infrastructure



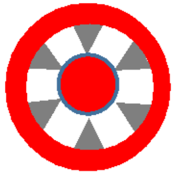


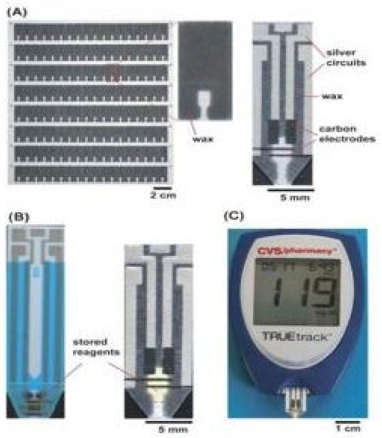
Has sensor engineering evolved with digital transformation

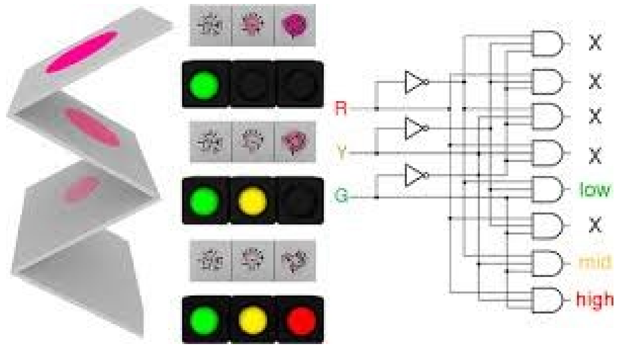




1990's 

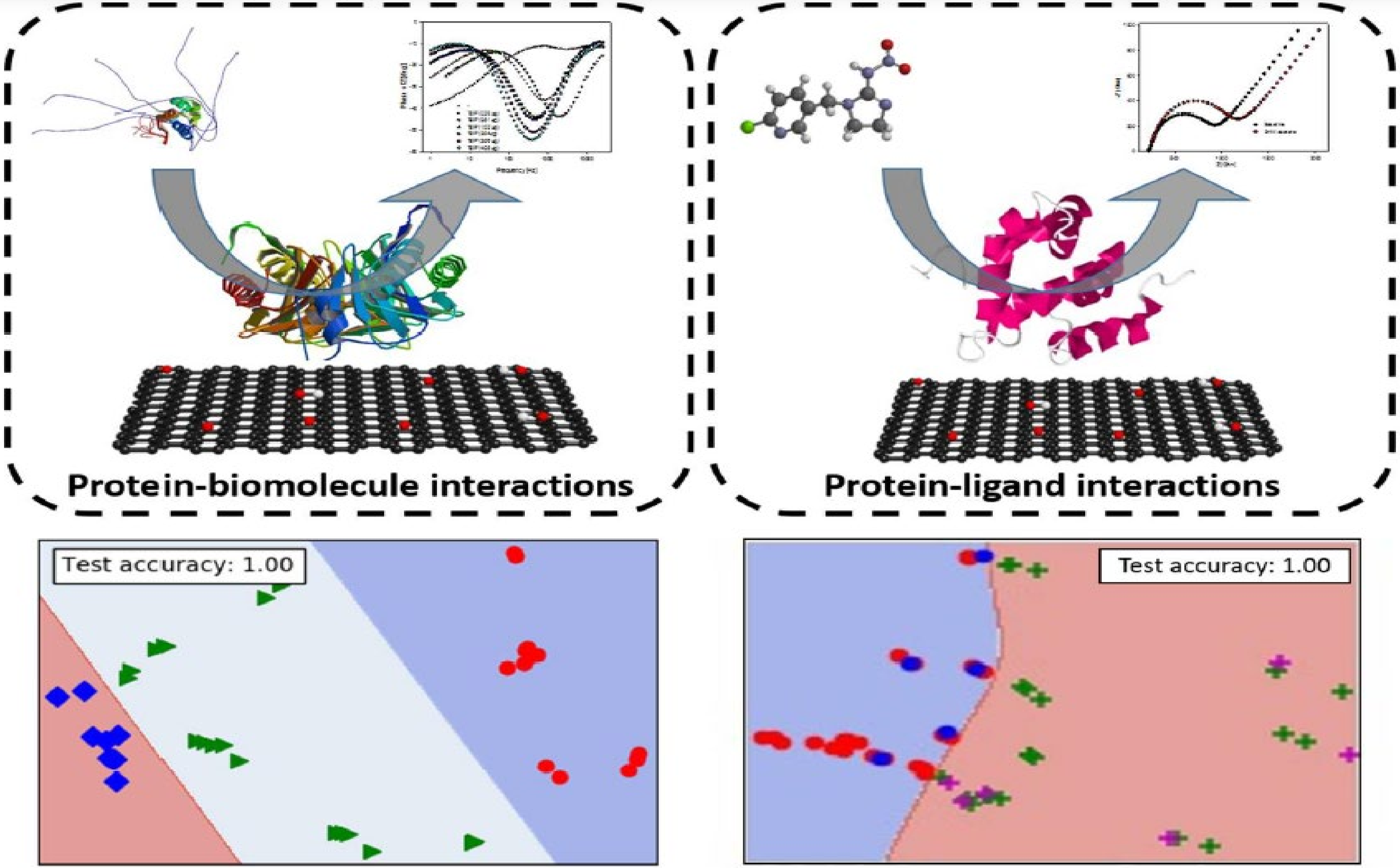
2000's 





Original innovation

Water Polluted by Mercury (Hg)



Professor Eric Scott McLamore, University of Florida ● www.ncbi.nlm.nih.gov/pubmed/29629449

Microbial Contamination of Water

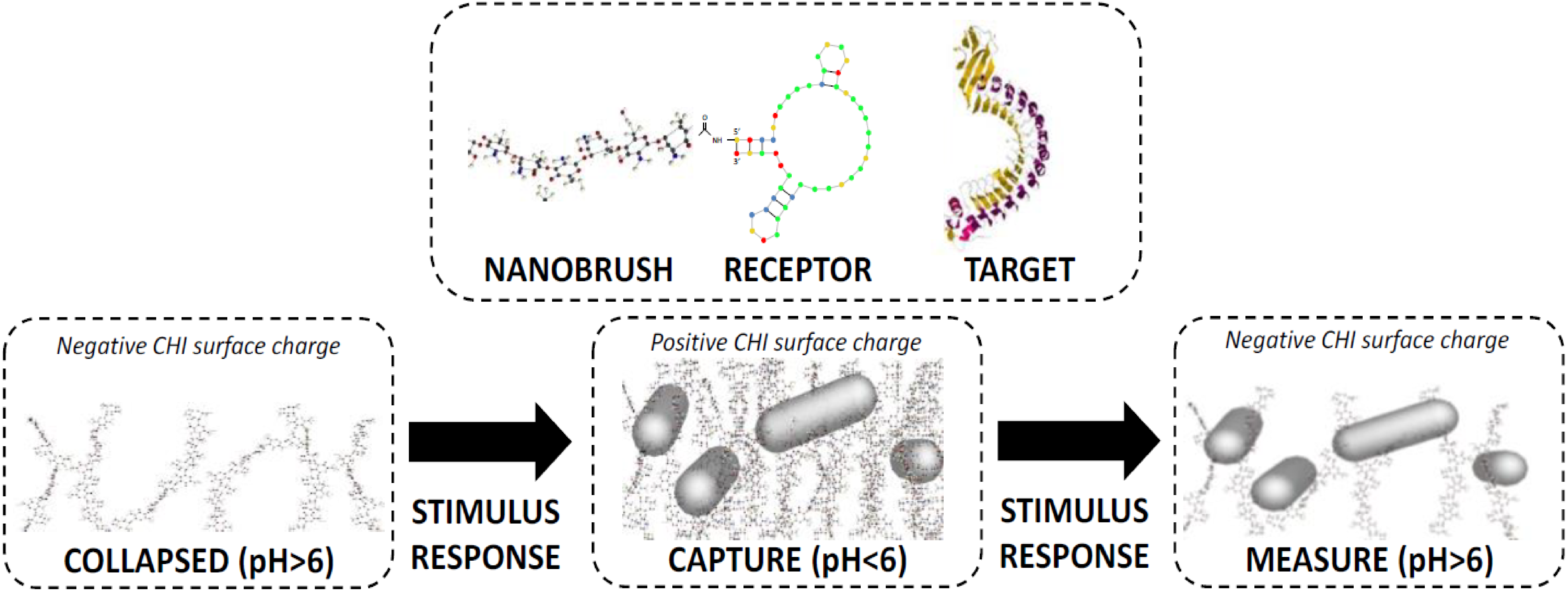


Image courtesy of Hills et al (2018), Analyst, 143(7): 1650-1661.

Professor Eric Scott McLamore, University of Florida ● www.ncbi.nlm.nih.gov/pubmed/29541704

Water Contamination Data Analysis

Prior to running the support vector machine (SVM) algorithm, PCA (principal component analysis) was applied through singular value decomposition (SVD) to reduce 152 features to 2 principal components. PCA was used to reduce the dimension of 152 features in the raw EIS data to a two-dimensional principal components matrix. Depending on number of components to extract, full or randomized truncated SVD was used. To ensure general applicability across other application-specific biosensors, code screens were prepared for four types of SVM: kernels (linear, sigmoidal, radial basis function, polynomial) to identify which approach best segregates the training data.

Tuning of Gaussian radial base function (RBF) hyper-parameters (C and gamma) for chemo-sensory proteins (CSP) acetone interactions. Recombinant insect chemosensory proteins (CSP) derived from *Glossina morsitans* (Gmm, tsetse fly) were heterologously expressed and purified from *E. coli* hosts. Representative support vector machine (SVM) classification results for one training and testing set show the effects of parameters C and g in the output of the RBF kernels. Red and blue circles represent the baseline samples in training and testing sets; green and purple plus symbols represent the positive signals in training and testing sets. The background blue and red region indicated the classifier decision surface, where all data fall into the red region are predicted as positive.

Professor Eric McLamore, University of Florida ● www.ncbi.nlm.nih.gov/pubmed/29629449

What is the value of this data analysis to the user ?

What is the value of this data analysis to the user ?

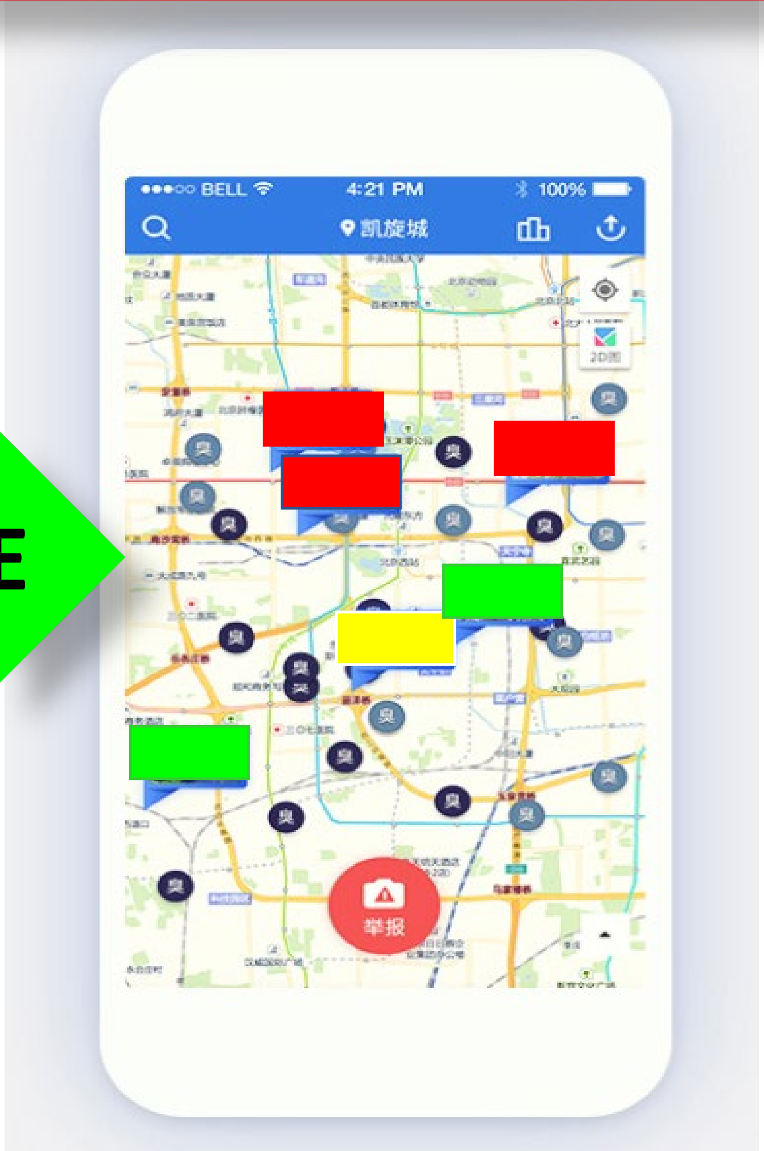
0

Z E R O

Professor Eric McLamore, University of Florida ● www.ncbi.nlm.nih.gov/pubmed/29629449

IoT-by-design: Data Analytics of Value to End-User

VALUE



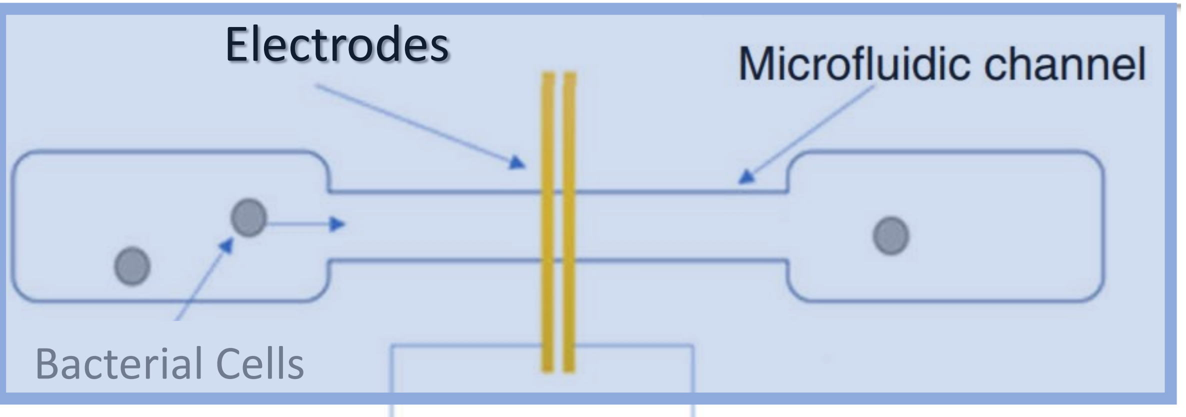
Professor Eric McLamore, University of Florida - www.ncbi.nlm.nih.gov/pubmed/29629449

Near Real-Time Analytics: Data-Informed Services at the Edge

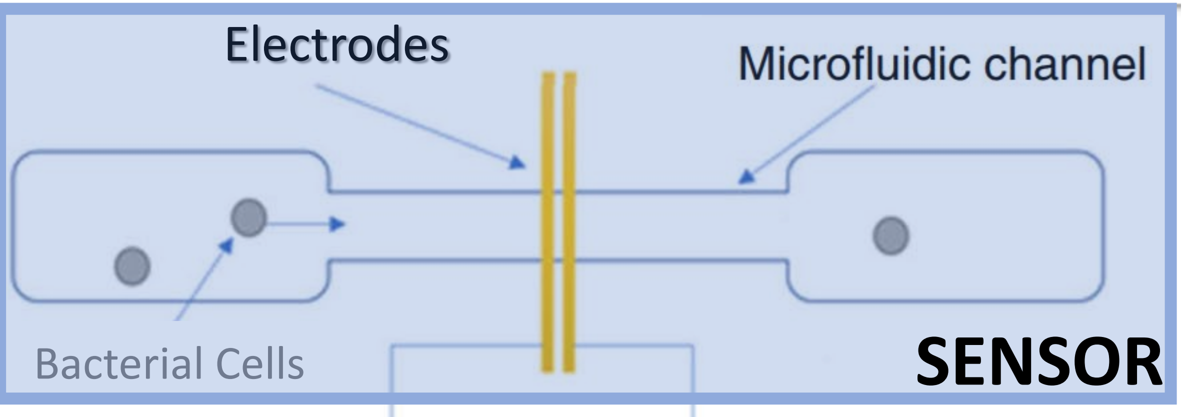
Bacterial Cells

IoT-by-design: Data Analytics of Value to End-User

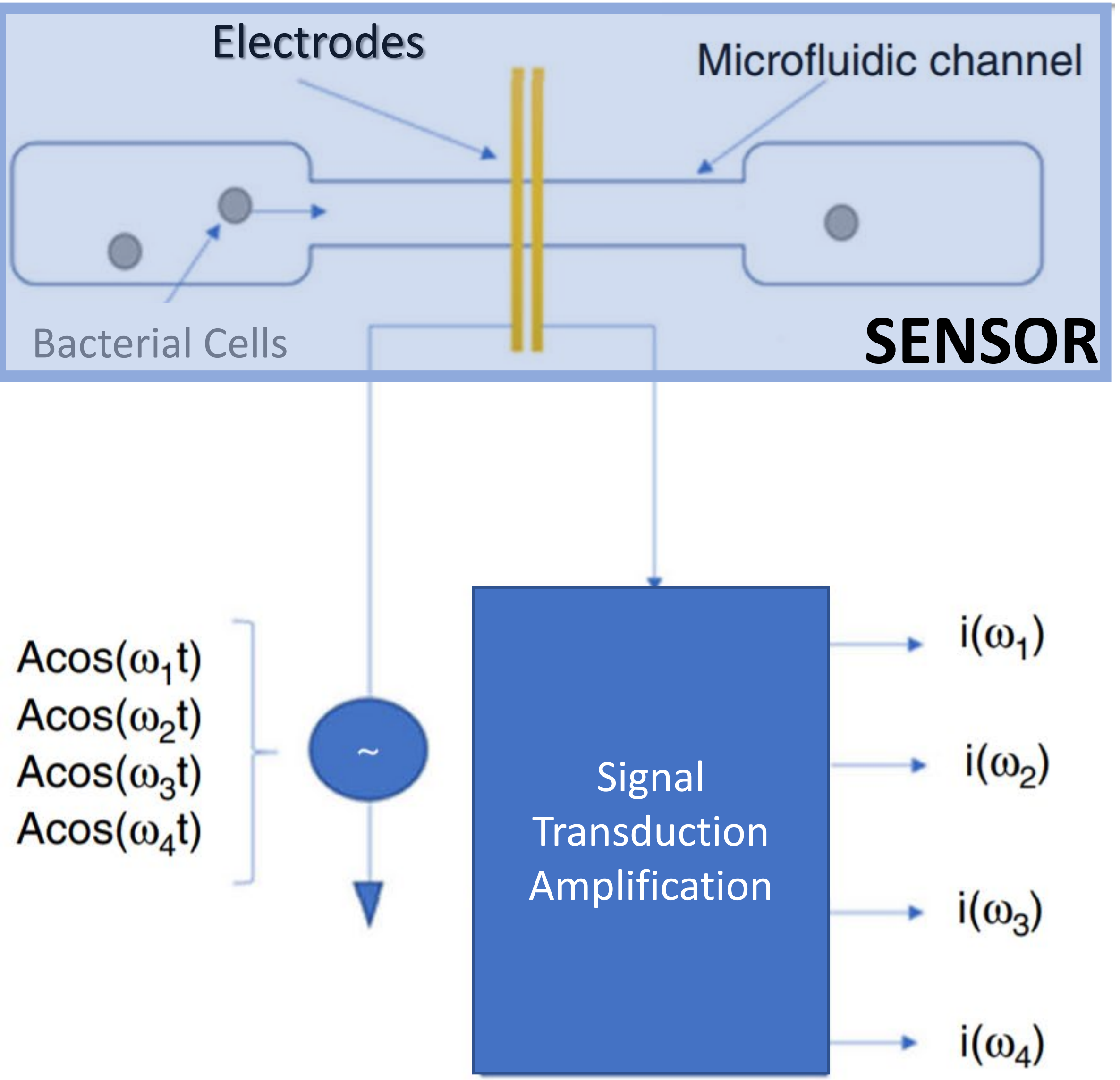
Near Real-Time Analytics: Data-Informed Services at the Edge



Near Real-Time Analytics: Data-Informed Services at the Edge



Near Real-Time Analytics: Data-Informed Services at the Edge



Ahuja *et al in* Microsystems & Nanoengineering (2019) 5:34
https://doi.org/10.1038/s41378-019-0073-2 and https://www.nature.com/articles/s41378-019-0073-2.pdf

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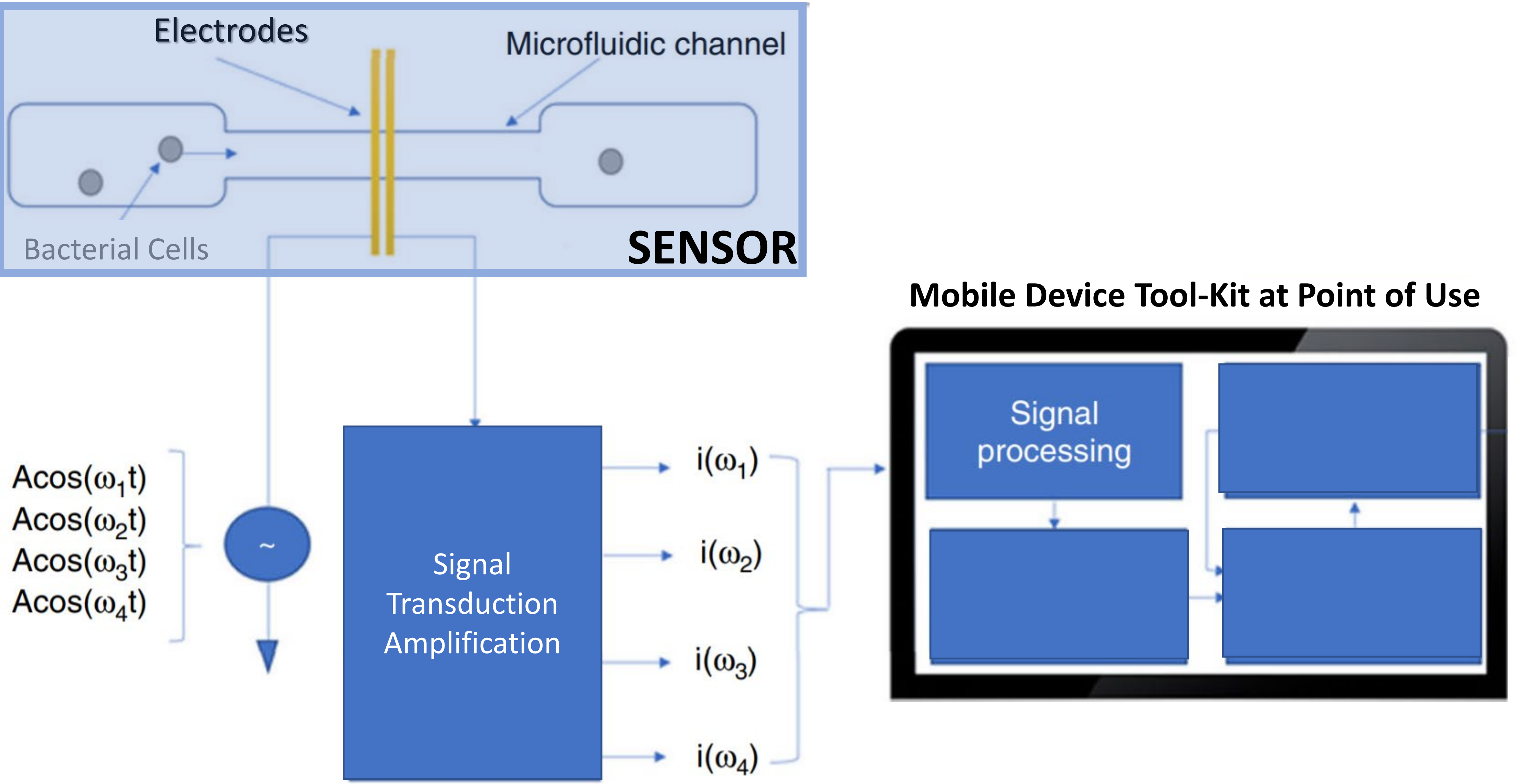

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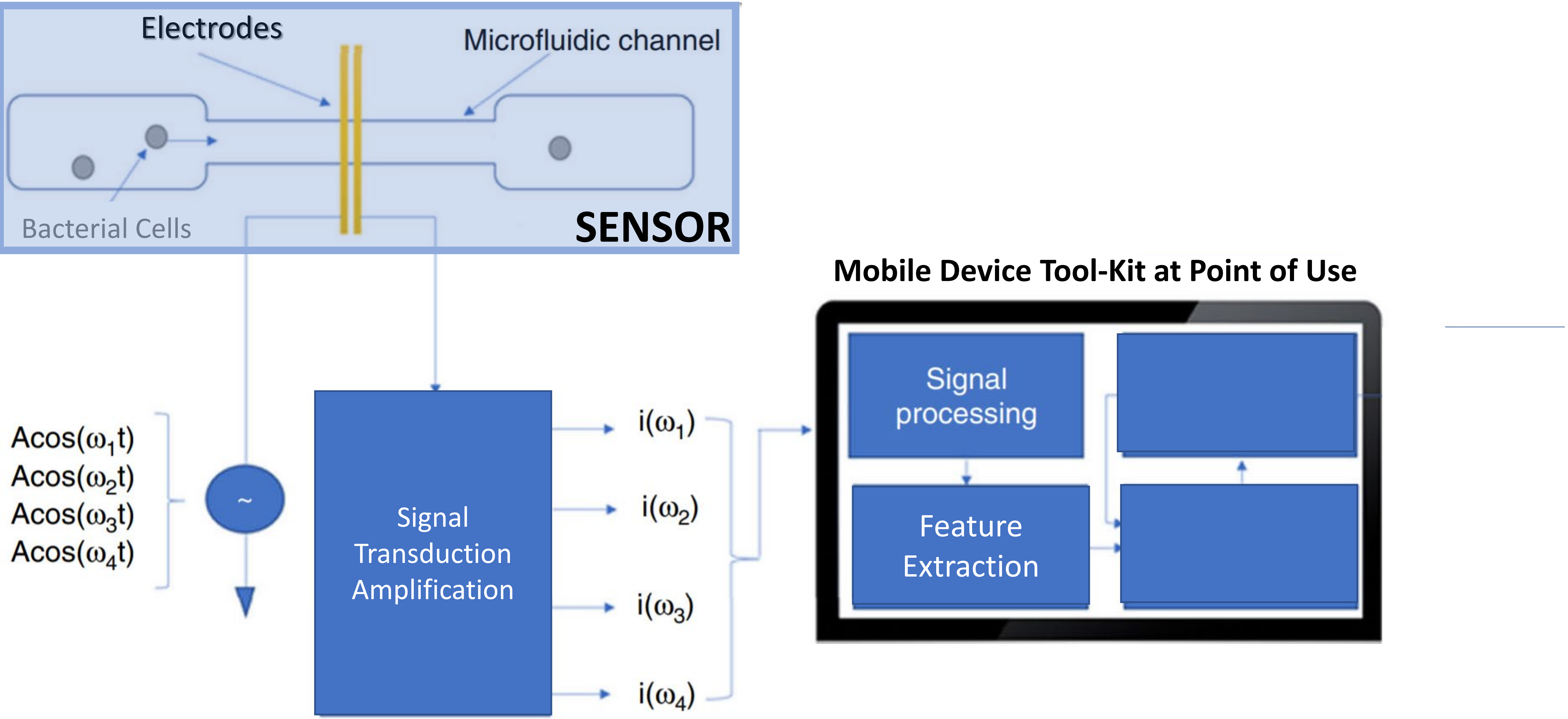

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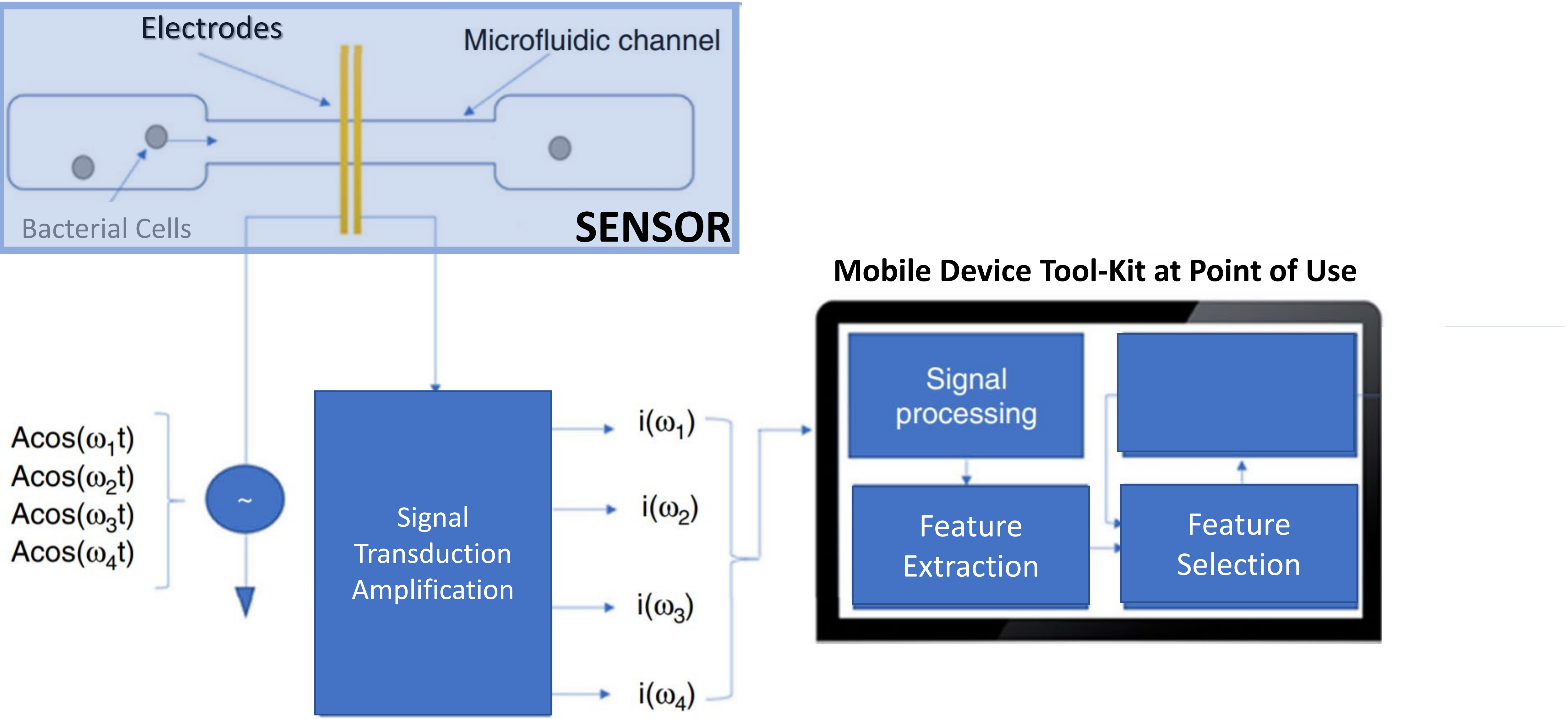

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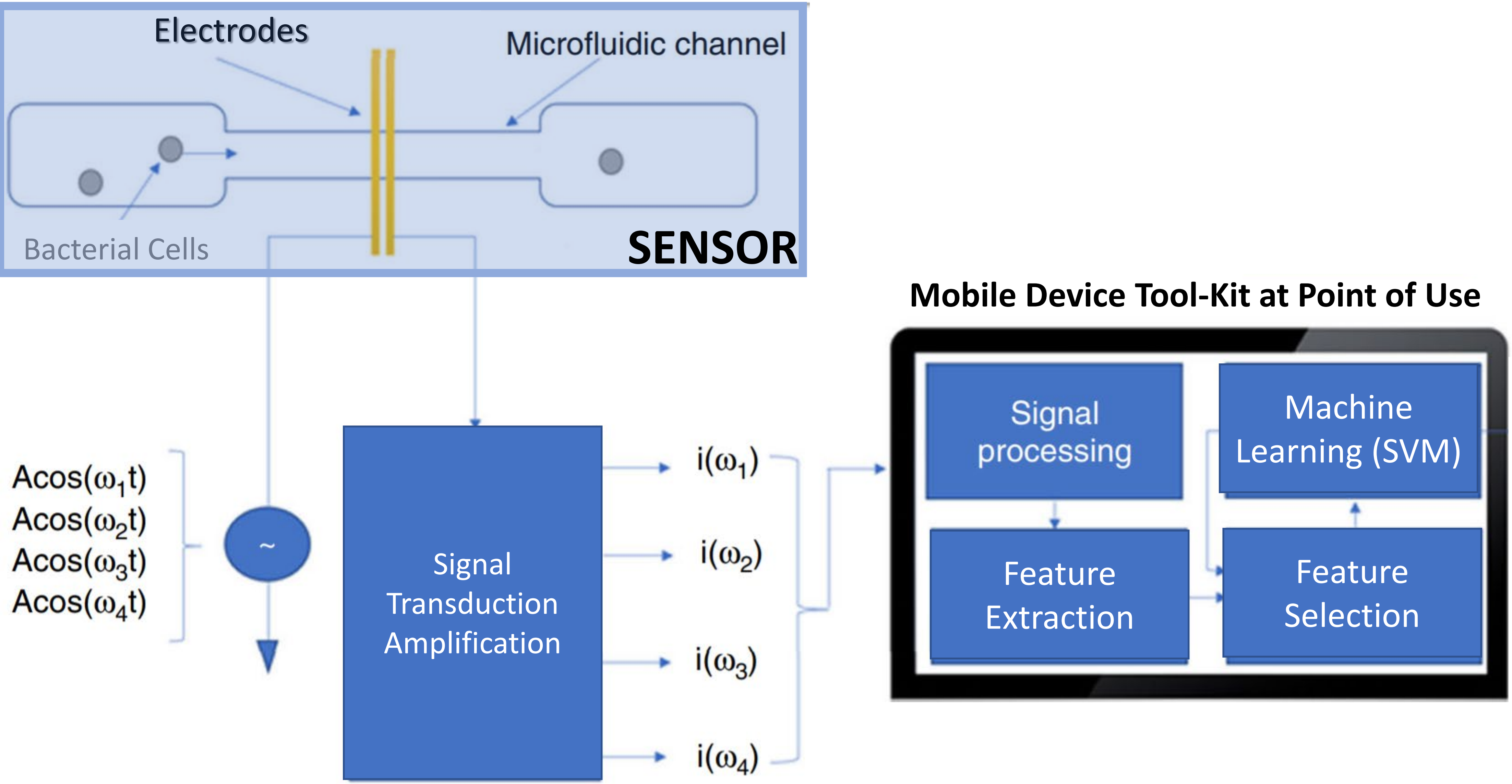

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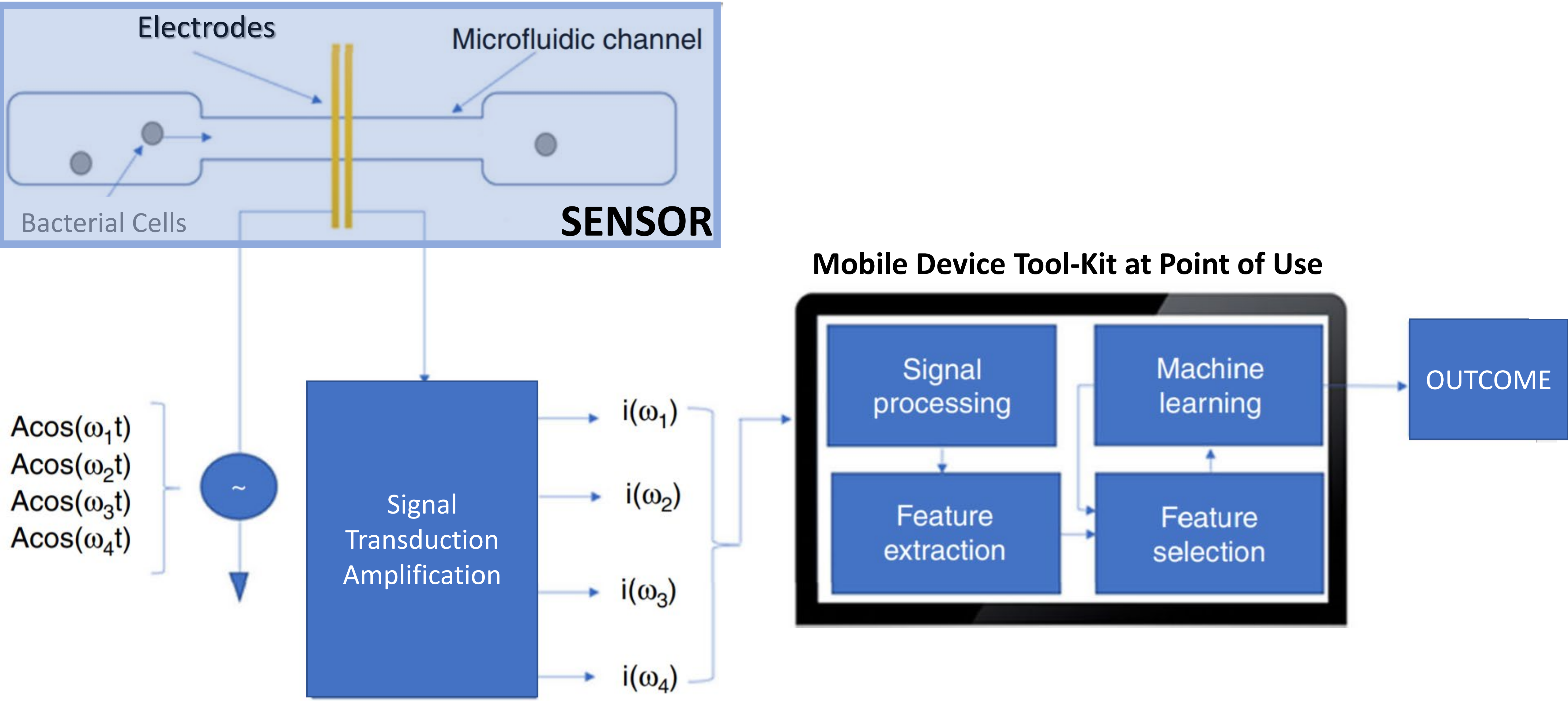

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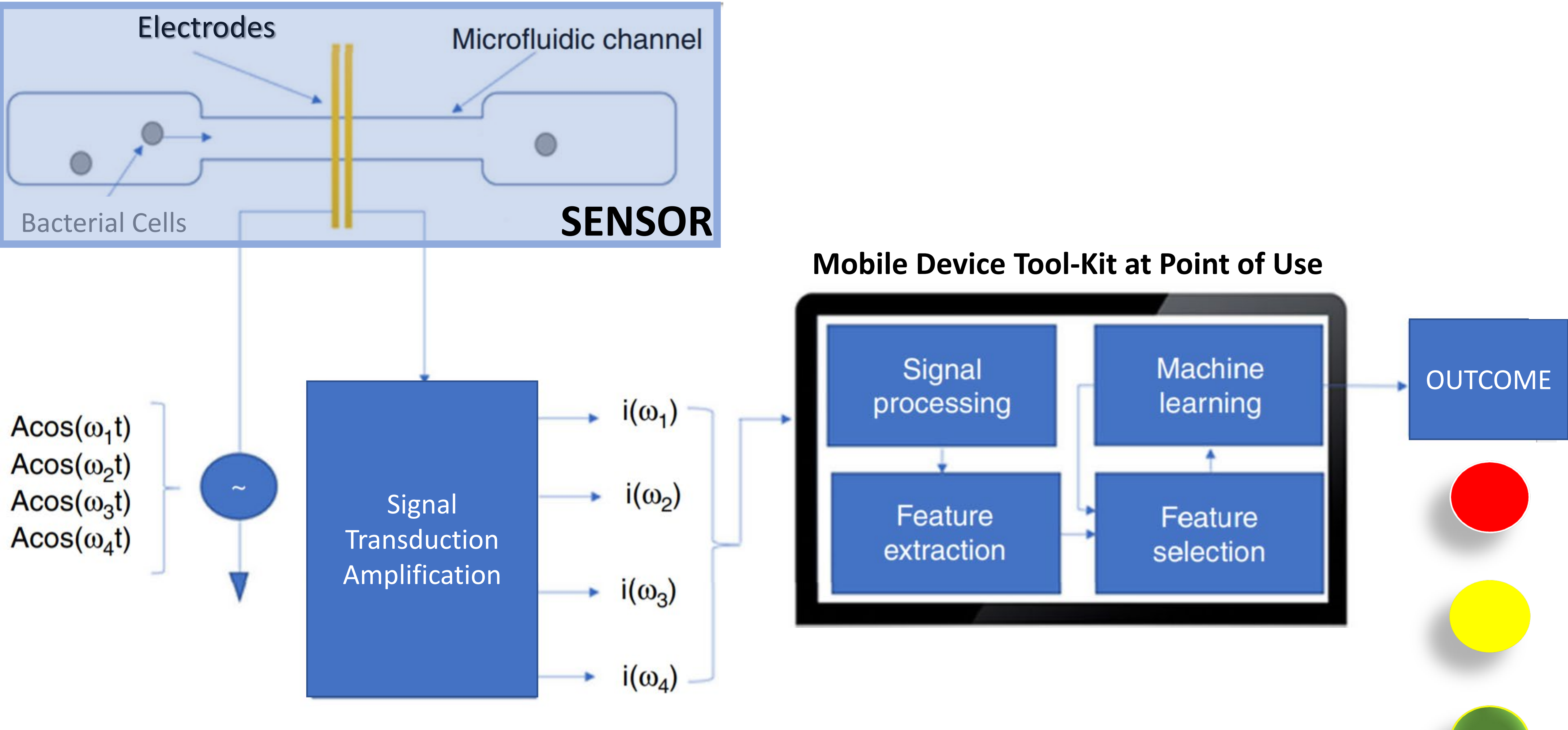

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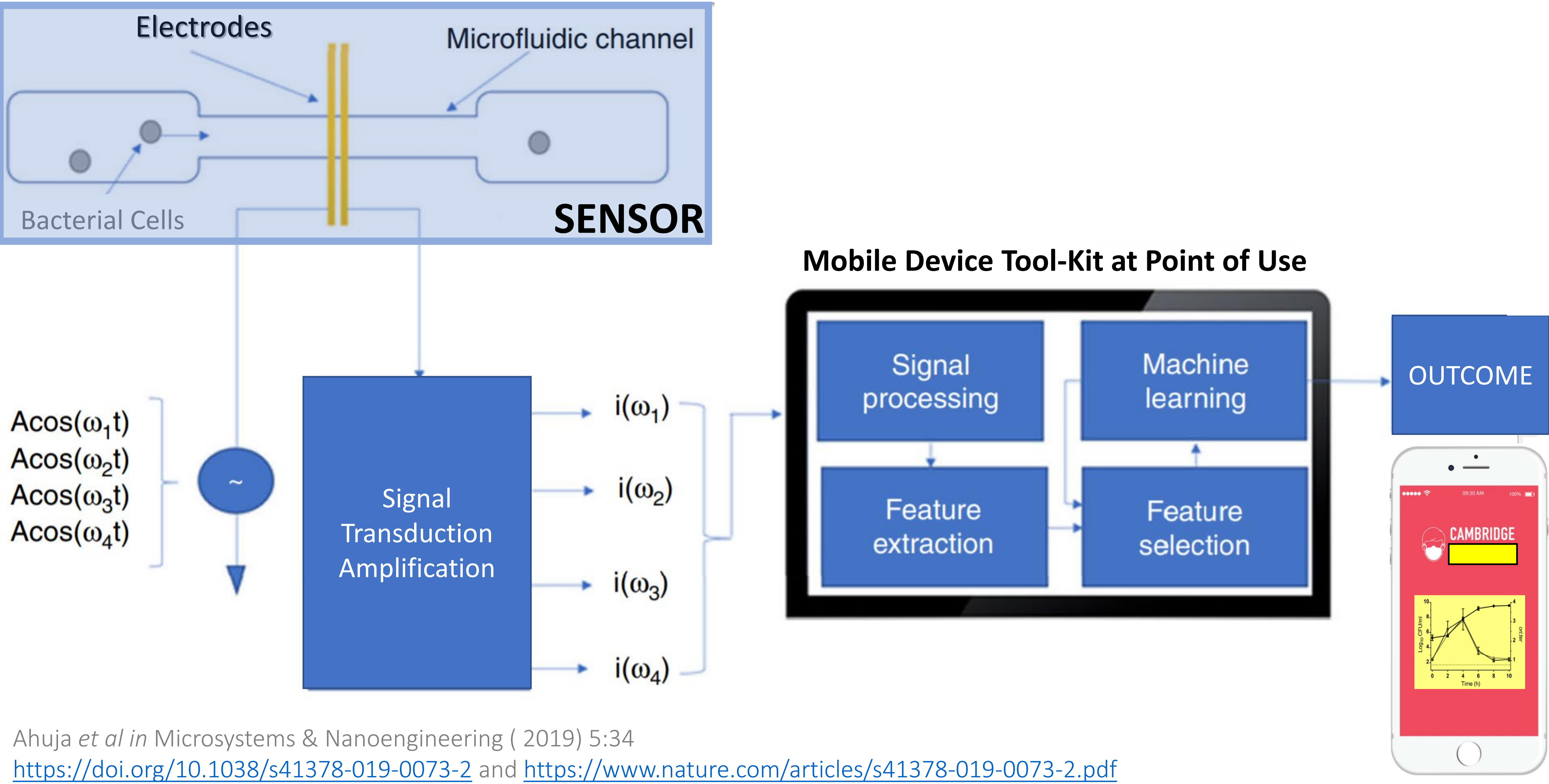

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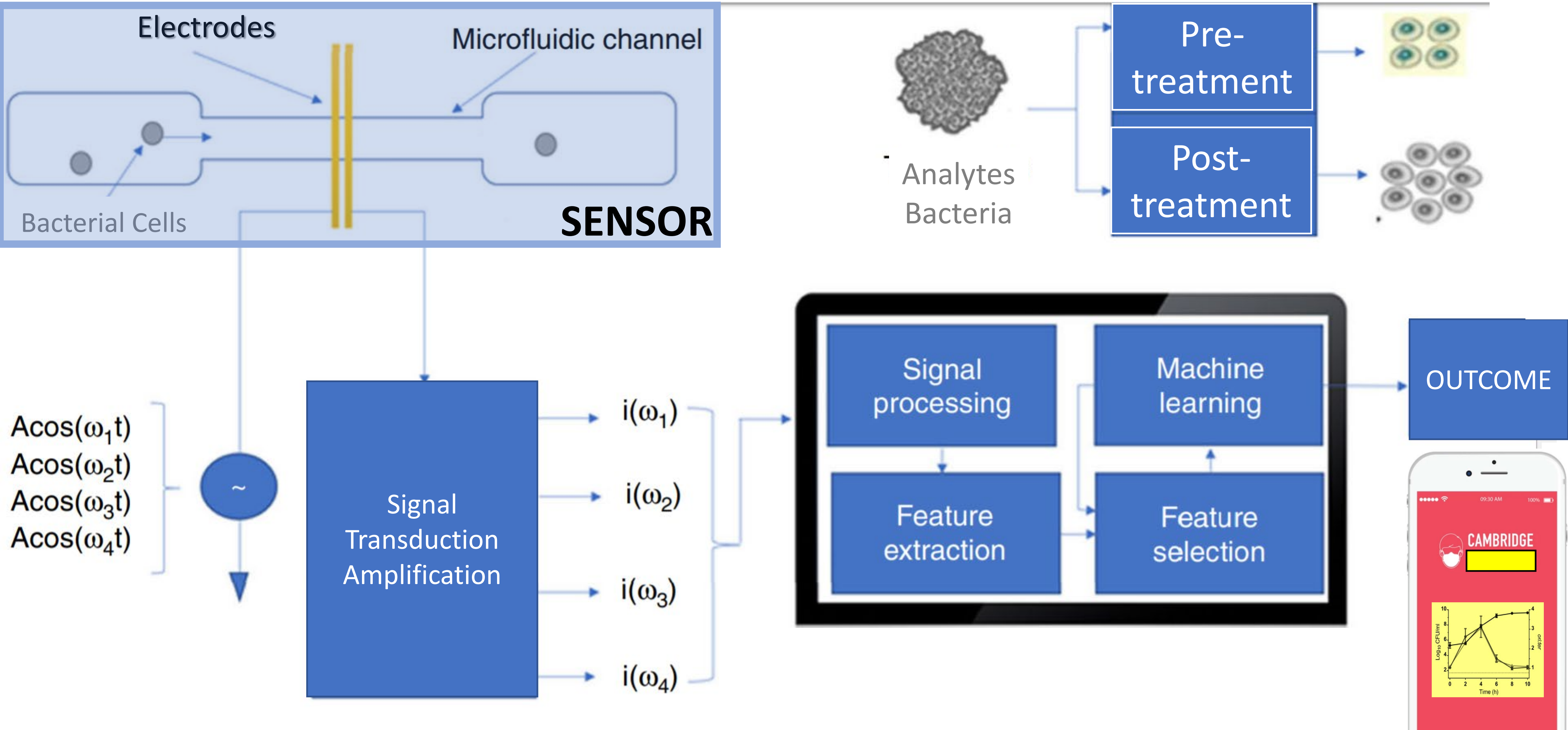

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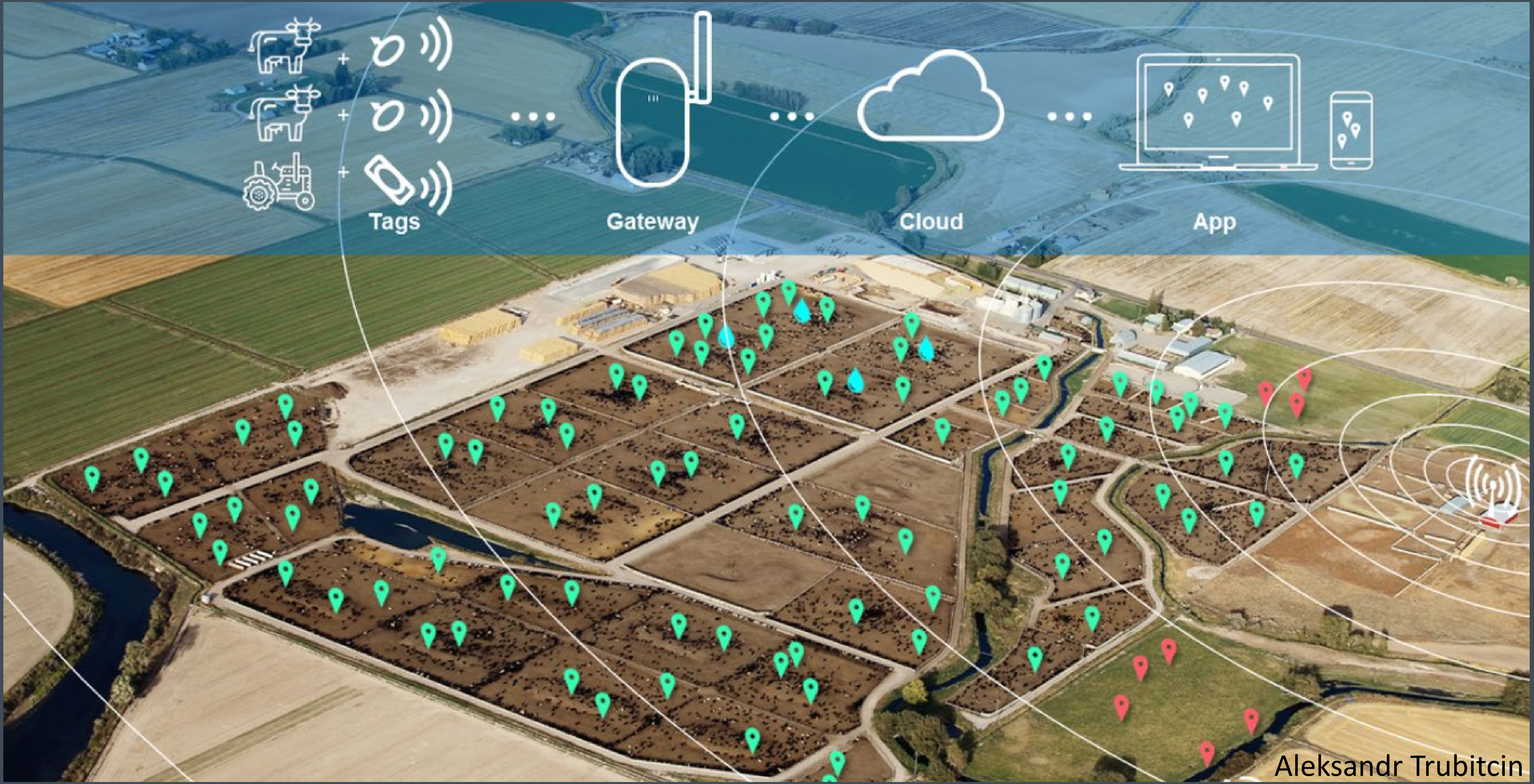
IoT-by-design: Data Analytics of Value to End-User

See SIGNALS - https://dspace.mit.edu/handle/1721.1/111021



LoRaWAN Cattle Ear Tags: 200 acre feed-lot for 10,000 cows

IoT-BY-DESIGN: PAY A PENNY PER UNIT (PAPPU) PARADIGM ?

See SIGNALS - https://dspace.mit.edu/handle/1721.1/111021

Fill in the details of your deployment.

Install Address
421 N 3200 E, Lewisville, ID 8343

Install Environment: Rural
Gateway Height: 50 ft

Select Gateway: Field 64c

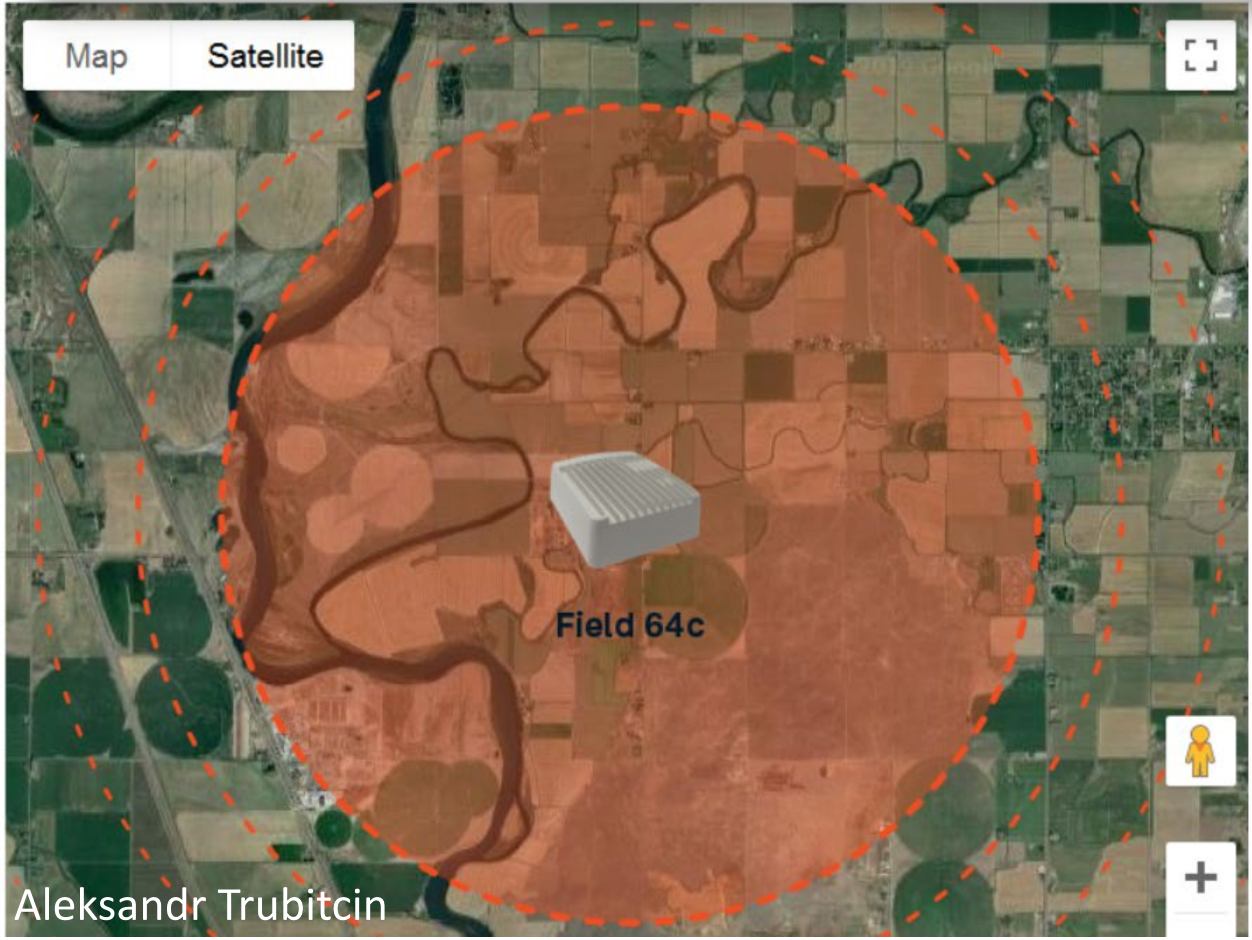
SF 7 | SF 8 | SF 9 | SF 10

Sensor Placement: Outdoor
Sensor Height: 1 ft

Sensor Tx Power: 14 dBm

Estimated Gateway Range
3.5 miles

CONNECTIVITY costs $0.00137 per cow per day



Field 64c gateway with 64 channels of LoRaWAN connectivity and Ethernet/cellular backhaul manufactured by Tektelic, Canada.

MachineQ prices:

Gateway Field 64c $2800 (CAPEX)

Software License $4979 pa (OPEX)

Cell $119 per gateway pa (OPEX)

Connectivity fee per animal (10,000) US $0.50 per year (50 cents pa)

0.001 cents

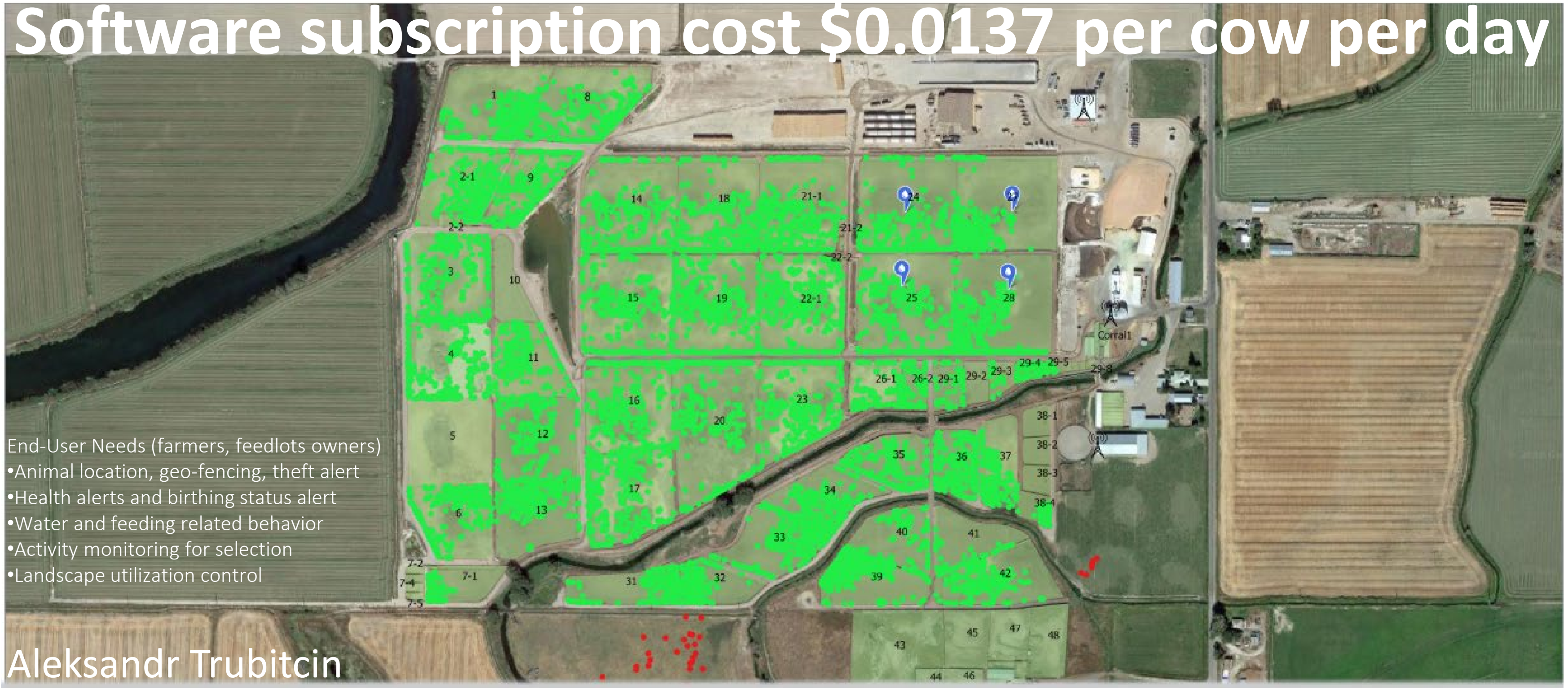
LoRaWAN Cattle Ear Tags: 200 acre feed-lot for 10,000 cows

IoT SYSTEMS: HOW NANO-FEES MAY GENERATE MEGA-MILLIONS

See SIGNALS - https://dspace.mit.edu/handle/1721.1/111021

The user will also need access to the cattle tracking and monitoring web application. For example, the cost of an annual subscription to the Cattle Tags Technologies app will be $5 per animal.

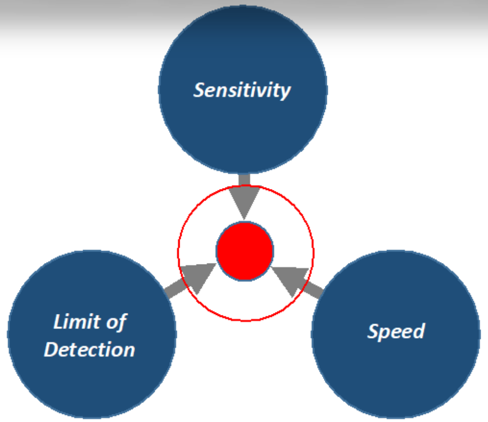
0.12 cents

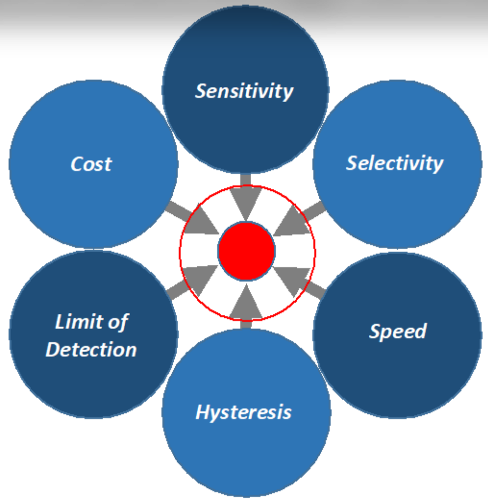


LoRaWAN ear tag from Cattle Tags Technologies starts from $39. Tags have embedded GPS receiver, accelerometer, temperature sensor and replaceable battery. Operator reads RFID-tag with Bluetooth reader (ID sent to ERP system). Installation of activated LoRaWAN ear tag follows. alex.trubitcin@gmail.com

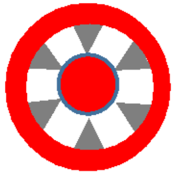
Digital Transformation (Connectivity+App+Tag) Cost $0.12 per cow per day

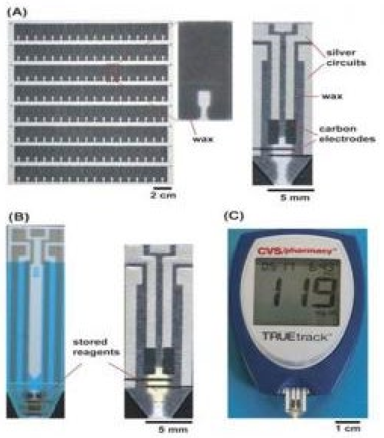
Has sensor engineering evolved with digital transformation

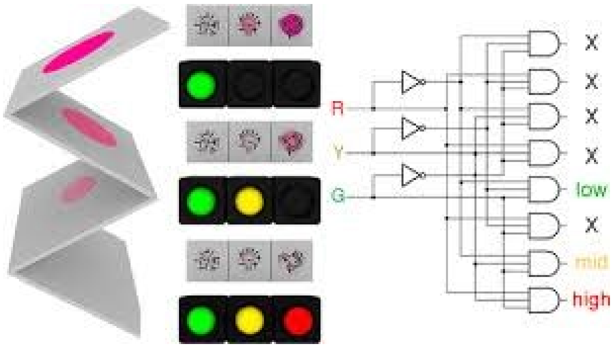




1990’s 

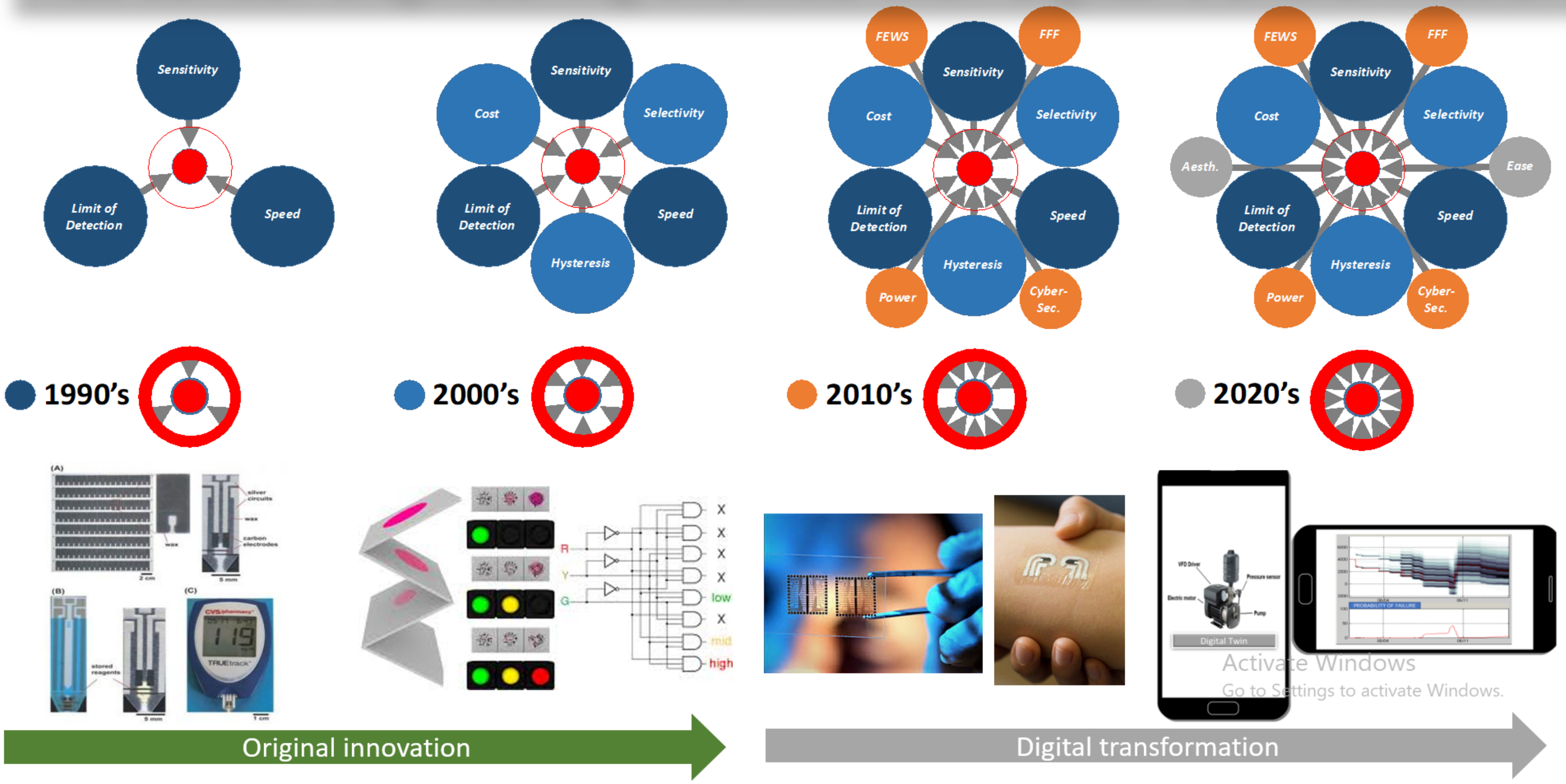
2000’s 





Original innovation

Has sensor engineering evolved with digital transformation



Sensor engineering has evolved with digital transformation

SENSE, ANALYZE, RESPONSE SYSTEMS – SARS

Convergence of

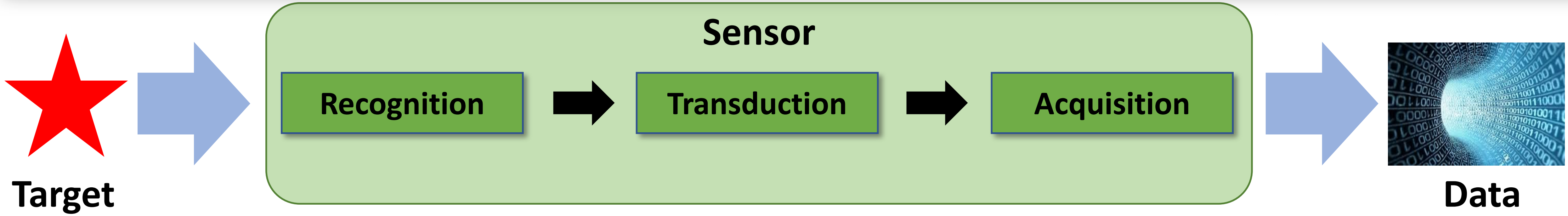
DATA from SENSORS

Role of Sensors and Sensor Data in Decision as a Service

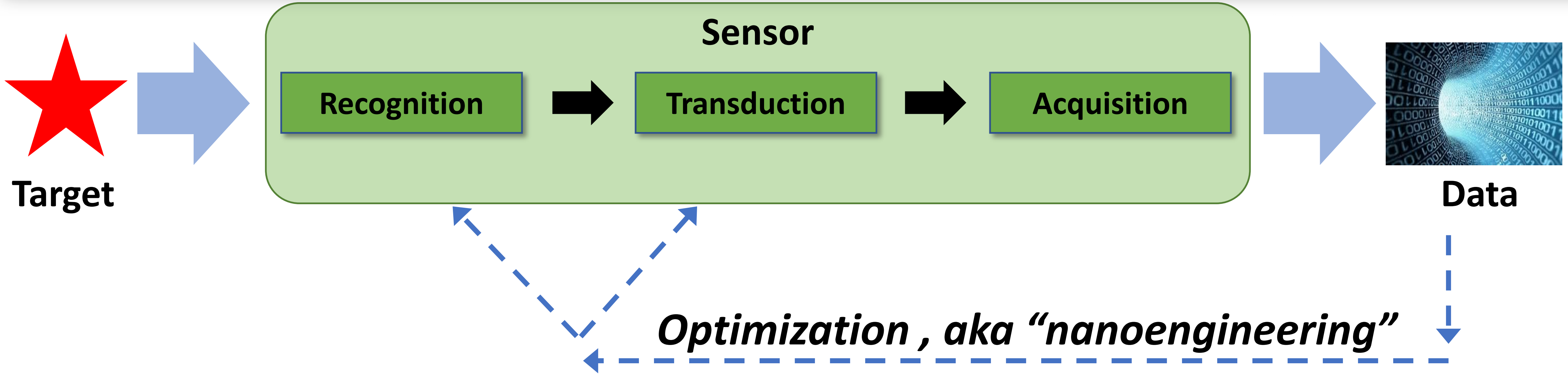
Target

Sensor

Role of Sensors and Sensor Data in Decision as a Service



Role of Sensors and Sensor Data in Decision as a Service



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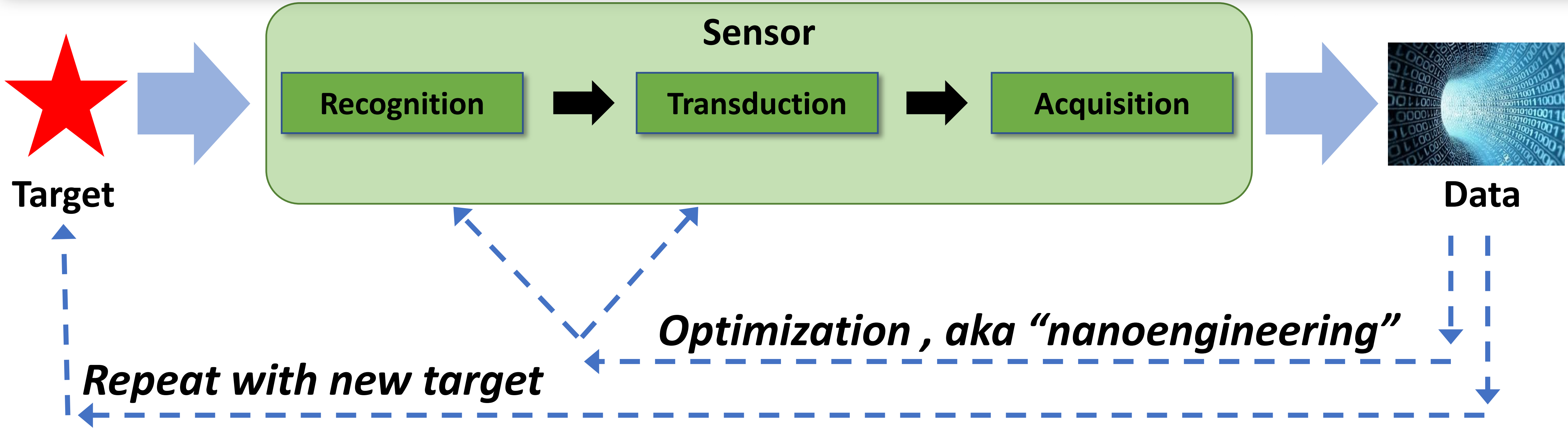
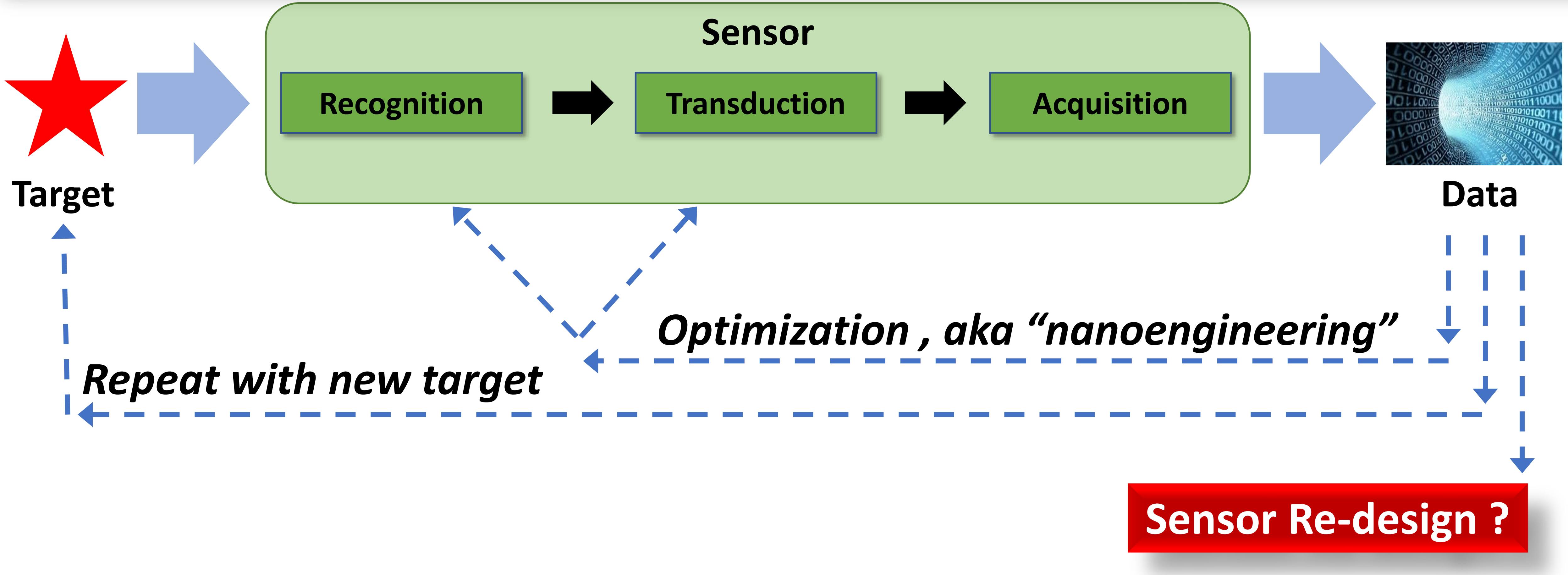


Role of Sensors and Sensor Data in Decision as a Service



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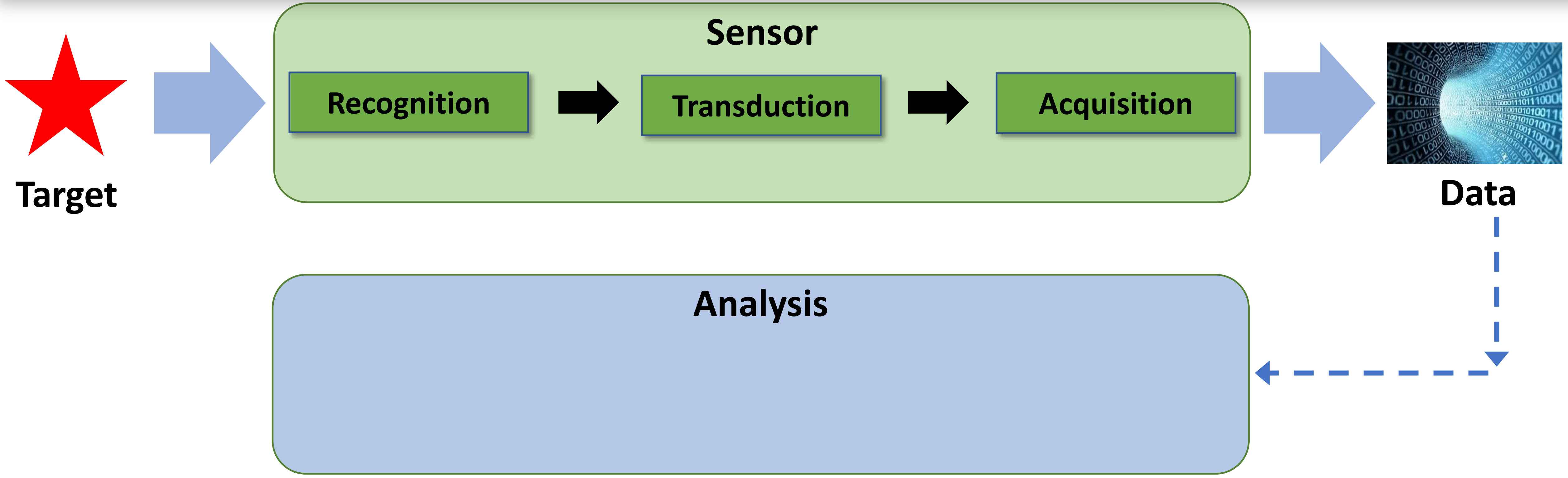

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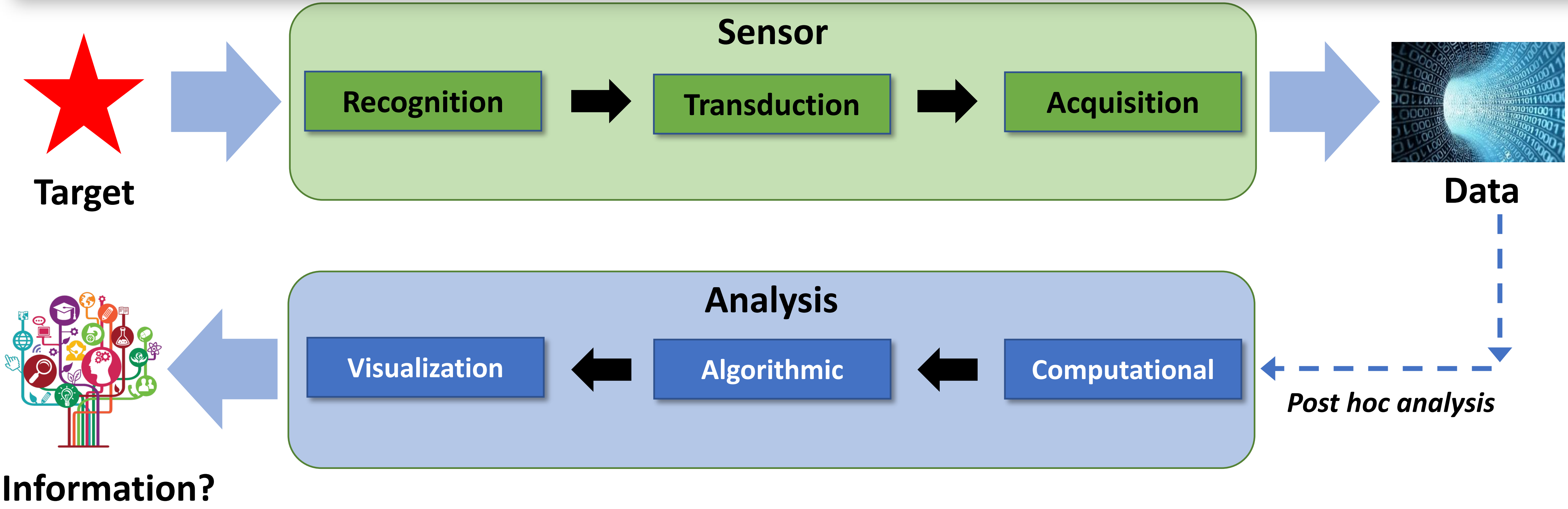
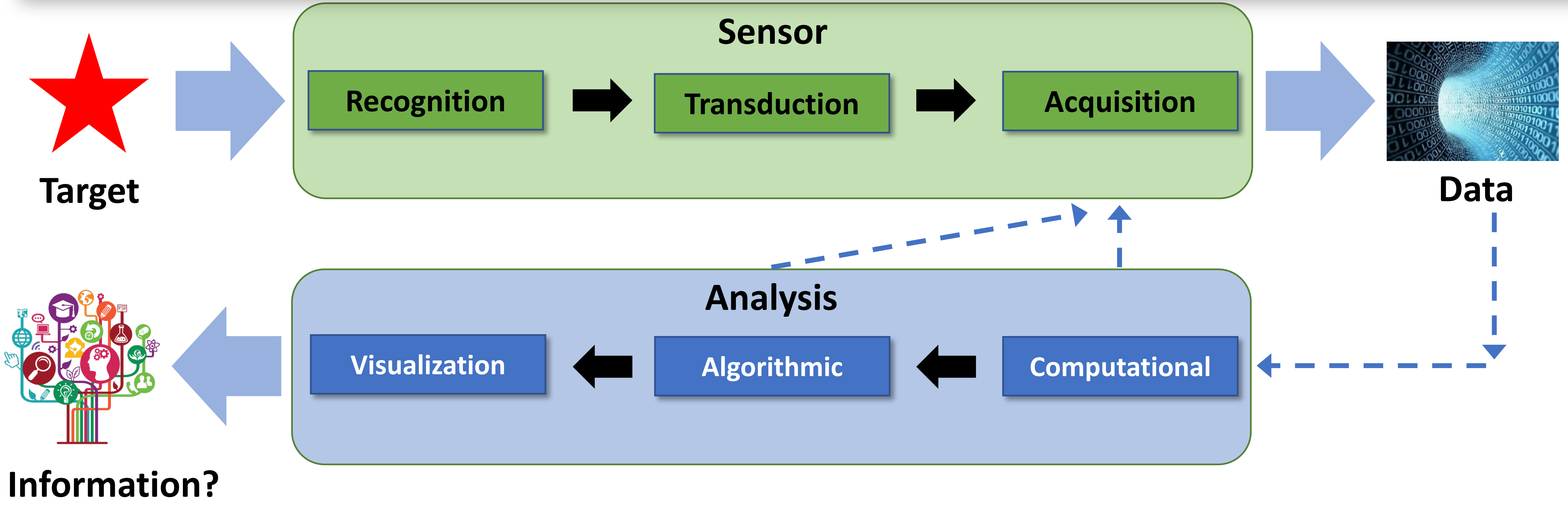
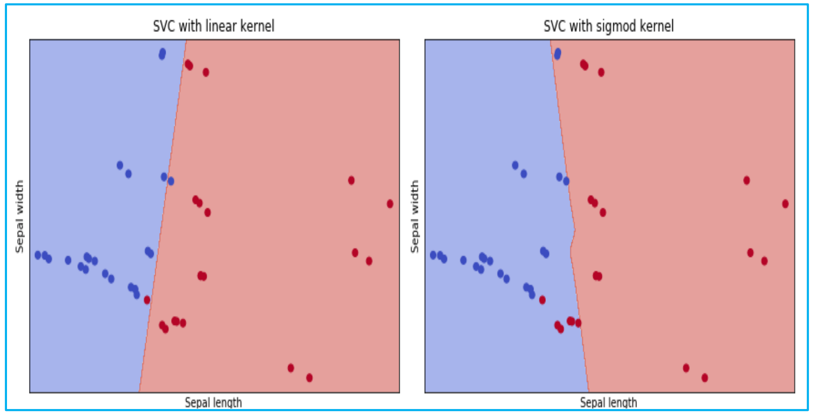
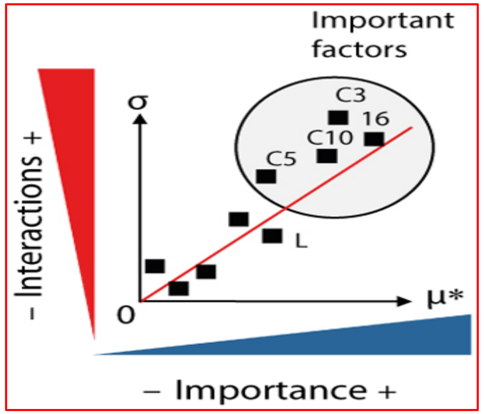
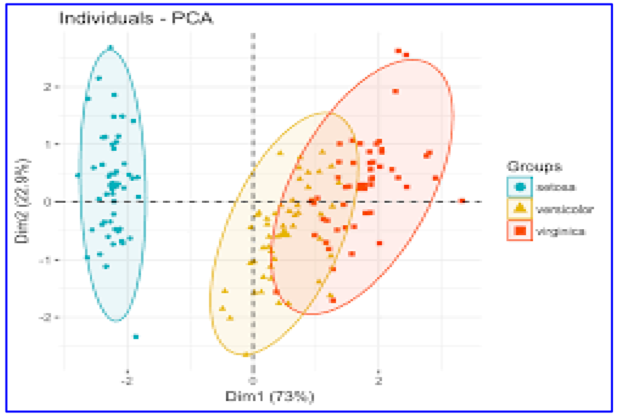


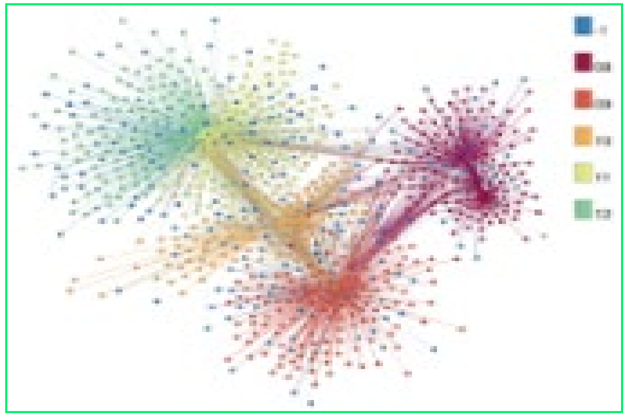
Role of Sensors and Sensor Data in Decision as a Service



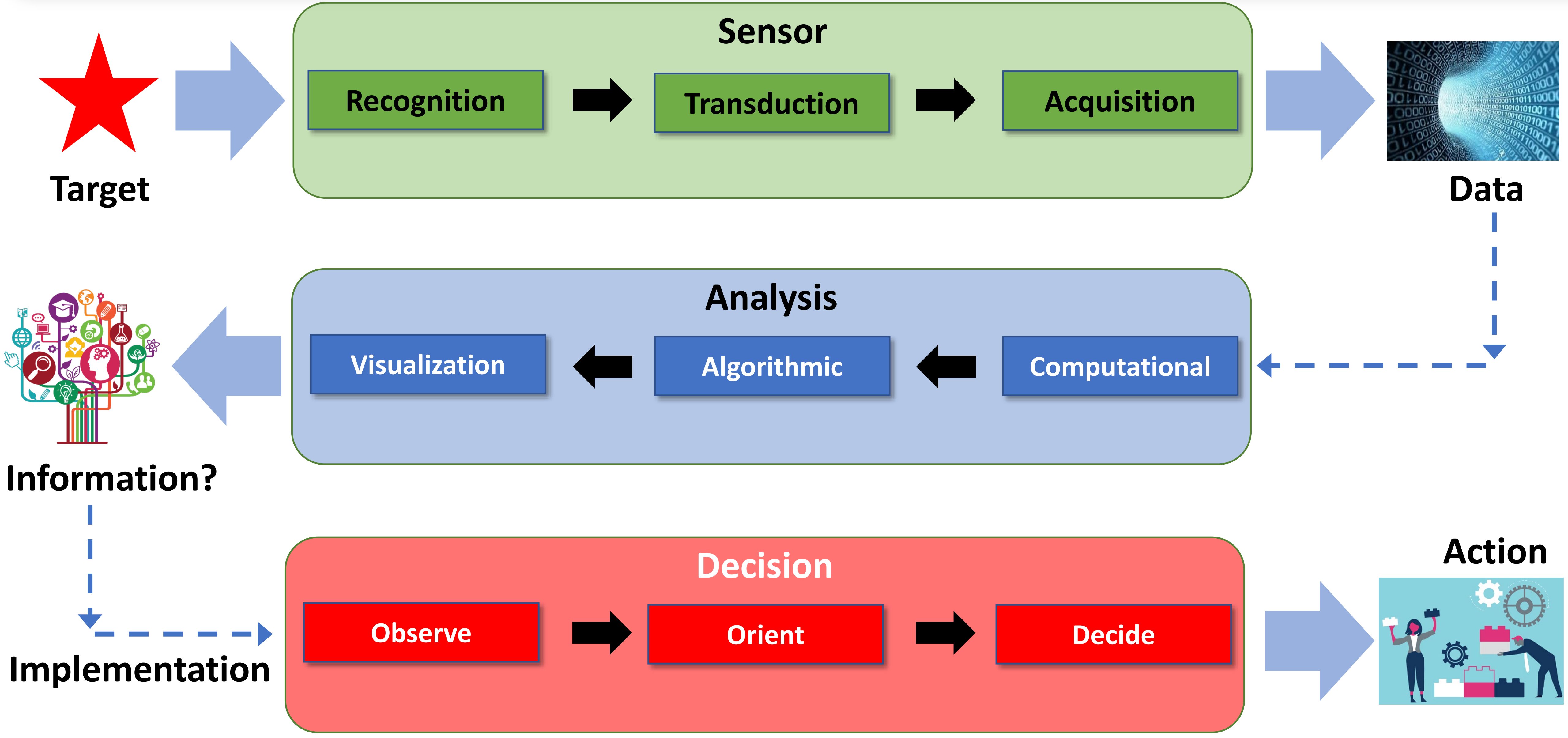




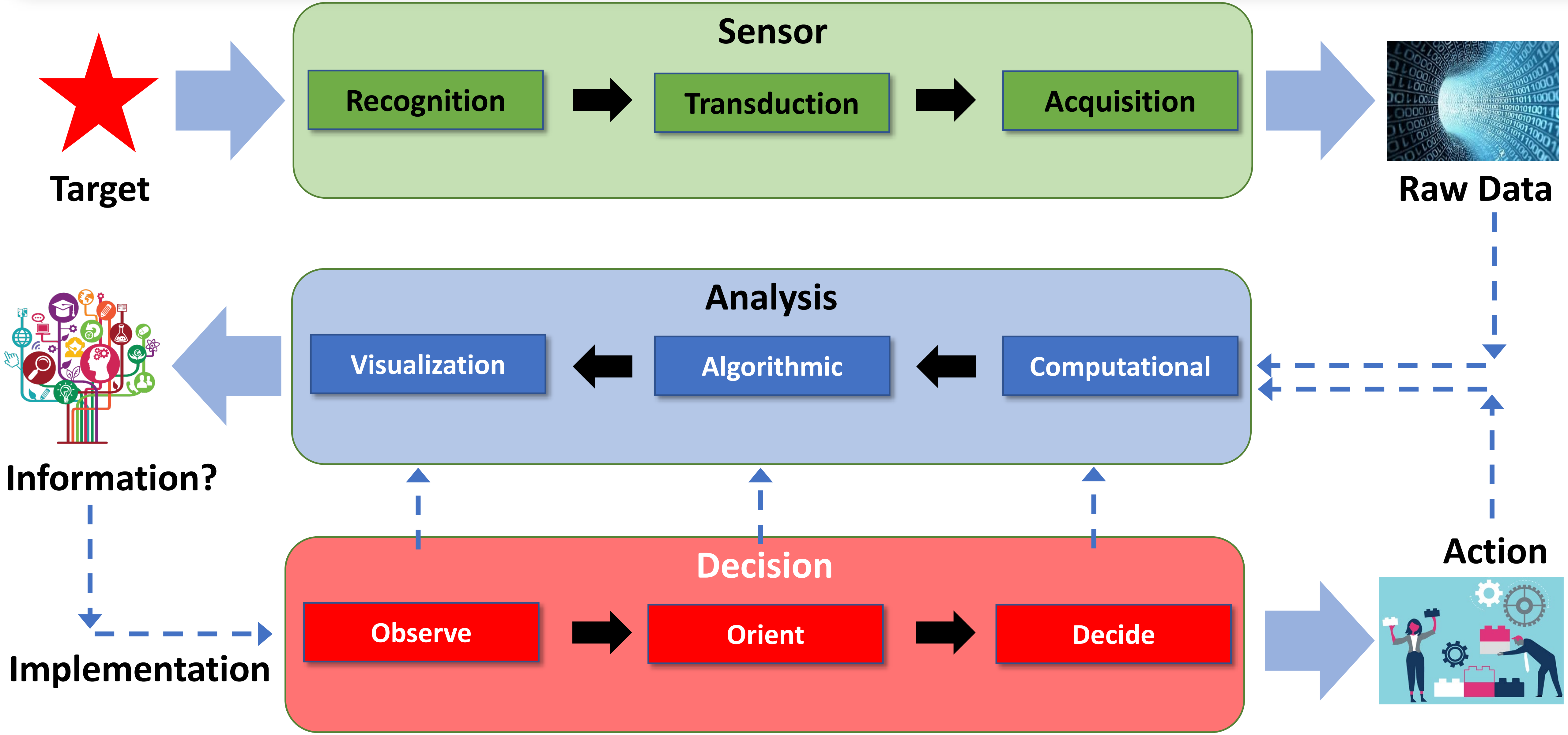




Role of Sensors and Sensor Data in Decision as a Service



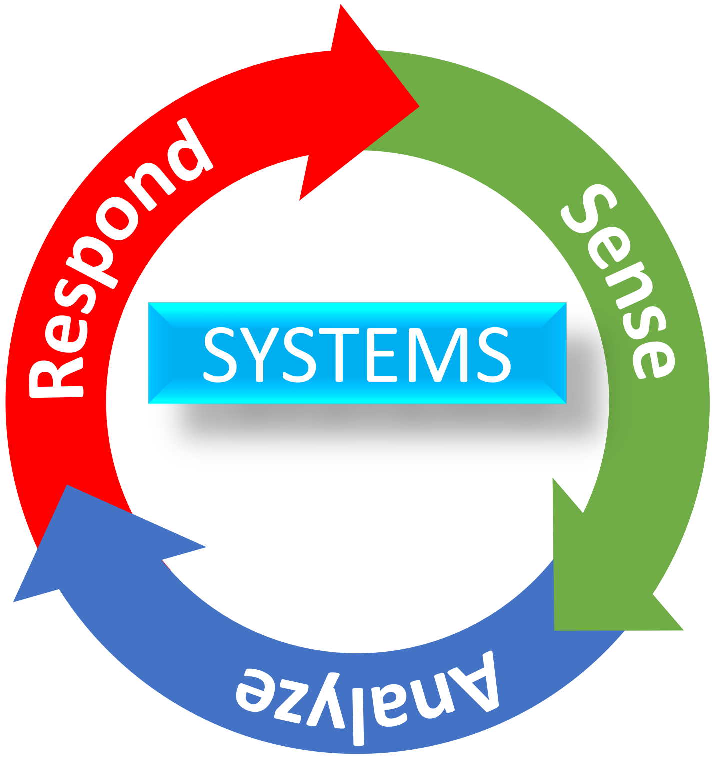
Data-Informed Decision as a Service



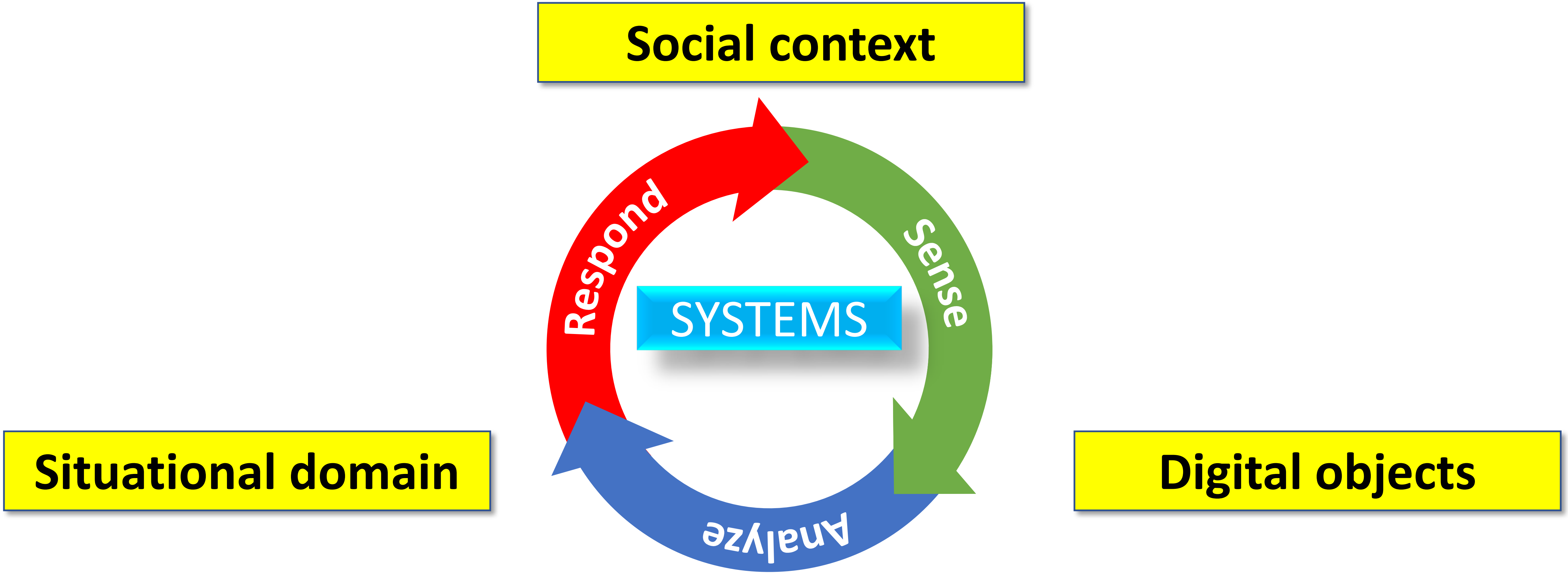
DIDA'S

Data-Informed Decision as a Service

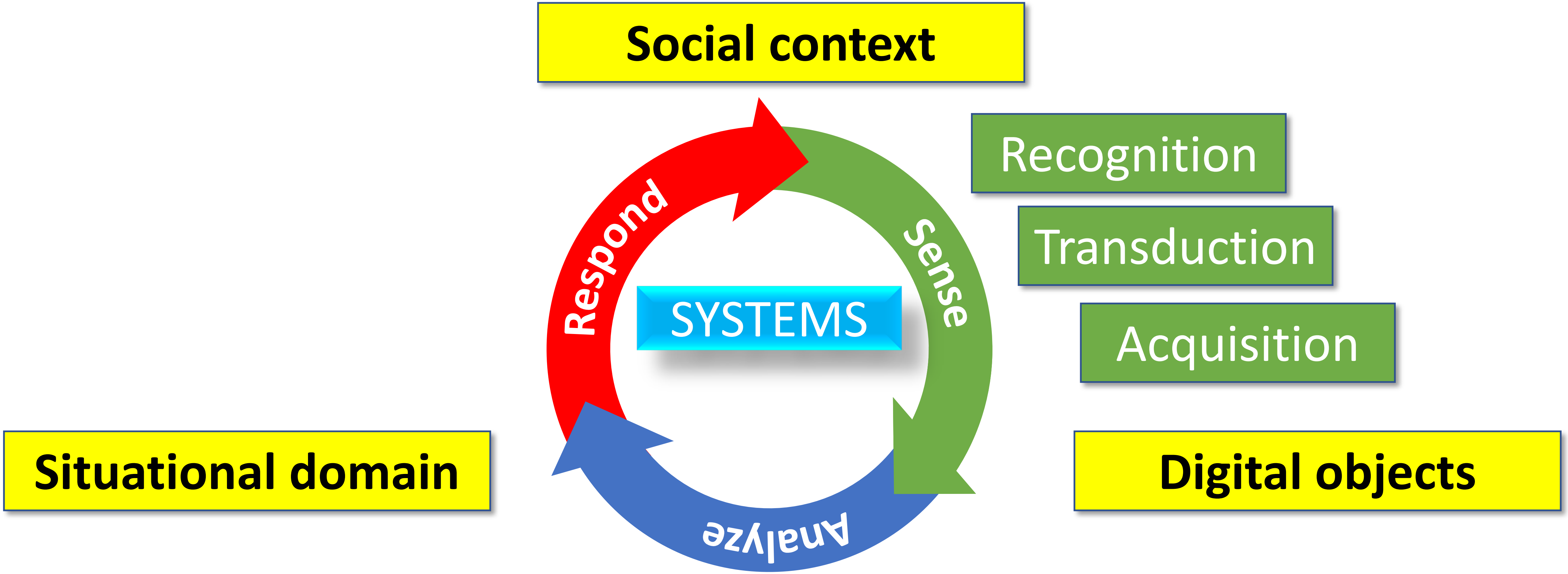
DIDA'S includes Sense, Analyze, Response, Systems (SARS)



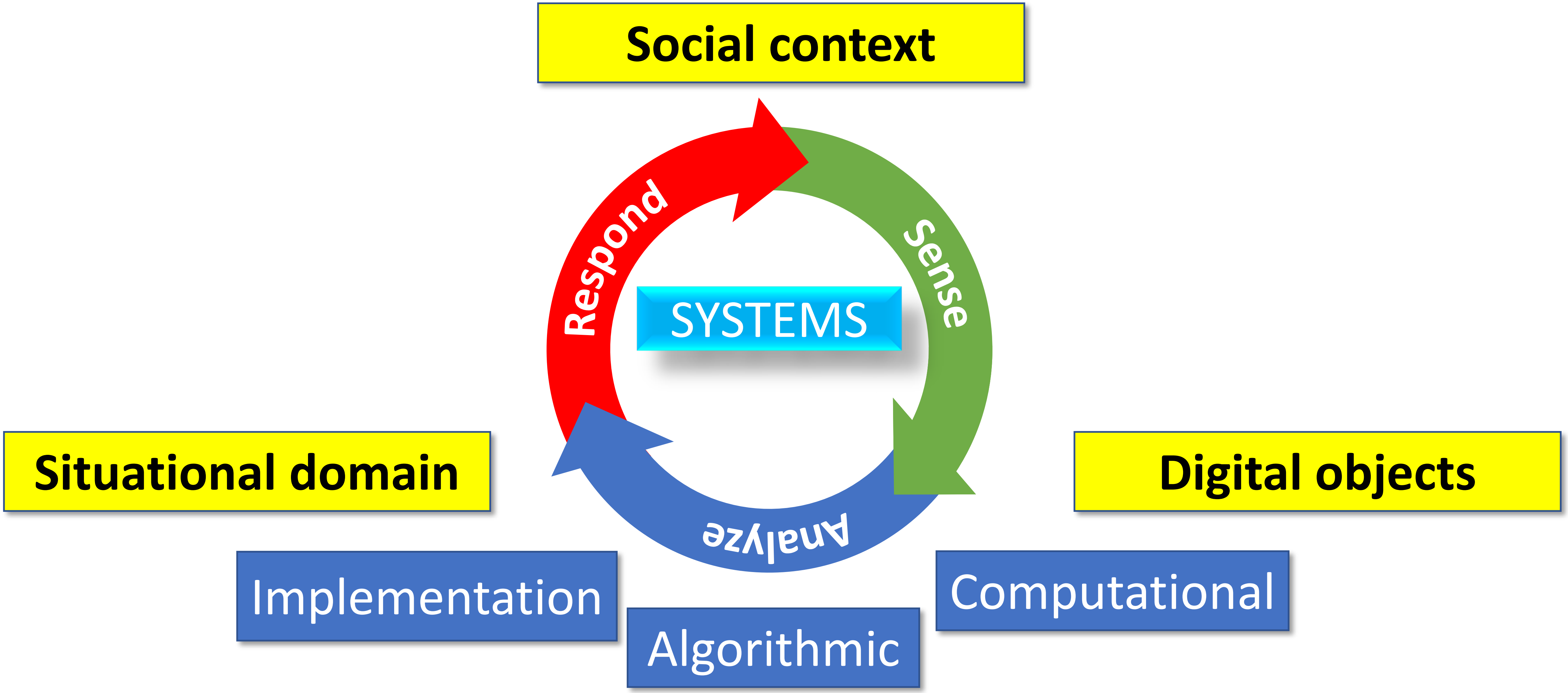
DIDA'S includes SARS context, objects and domains



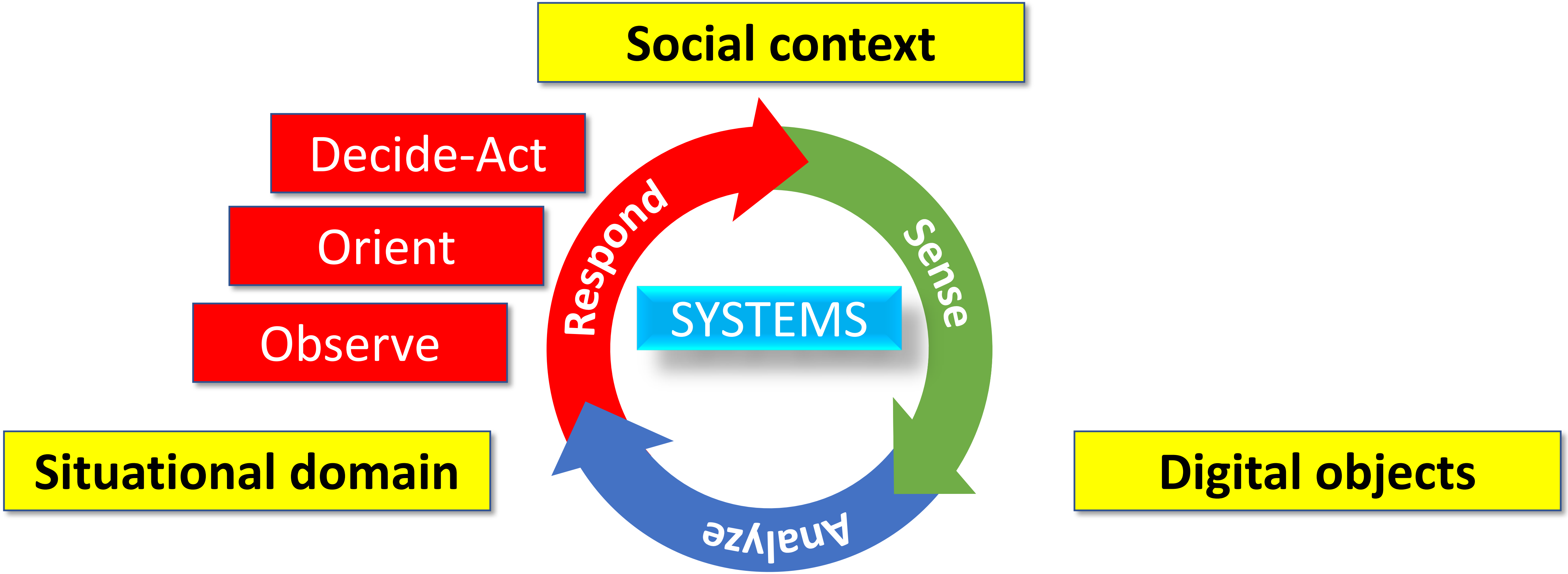
Granularity of the Data-Informed Decision as a Service



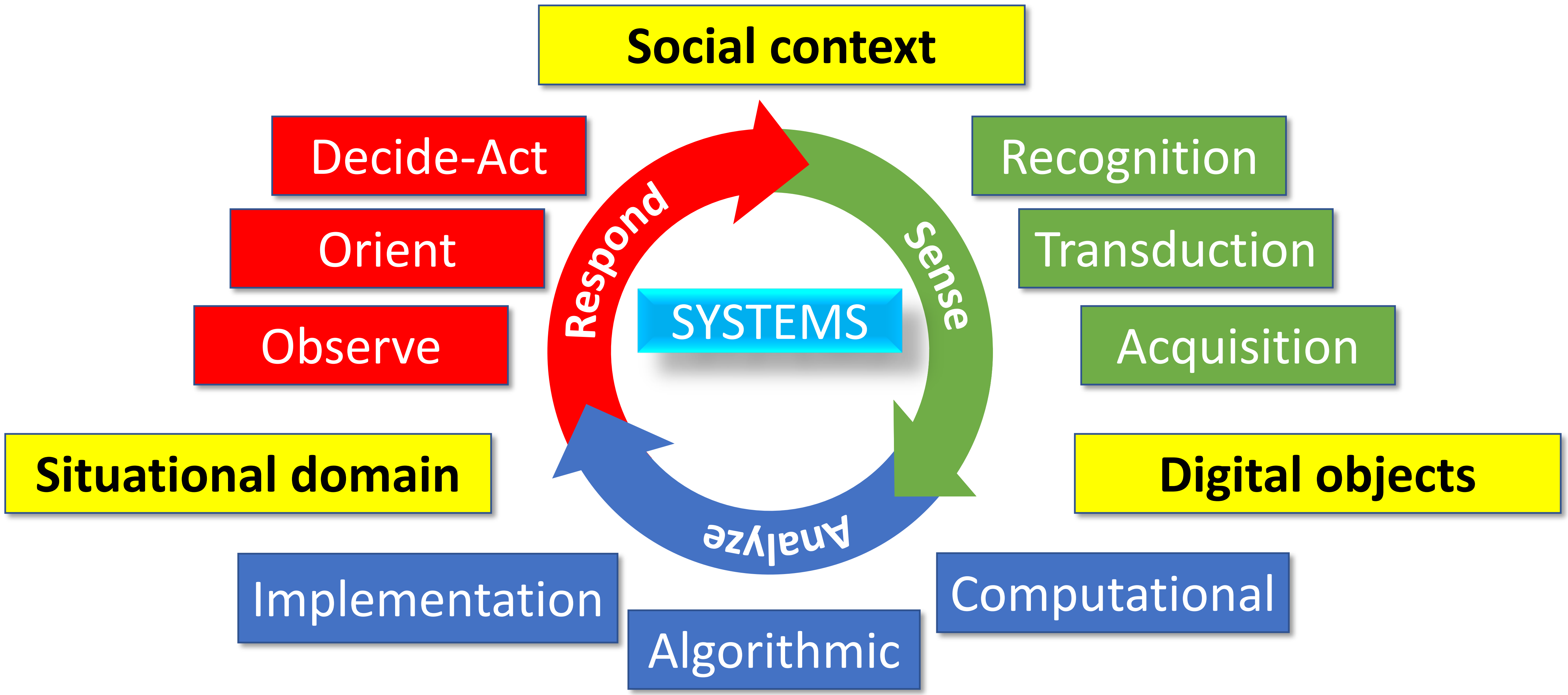
Granularity of the Data-Informed Decision as a Service



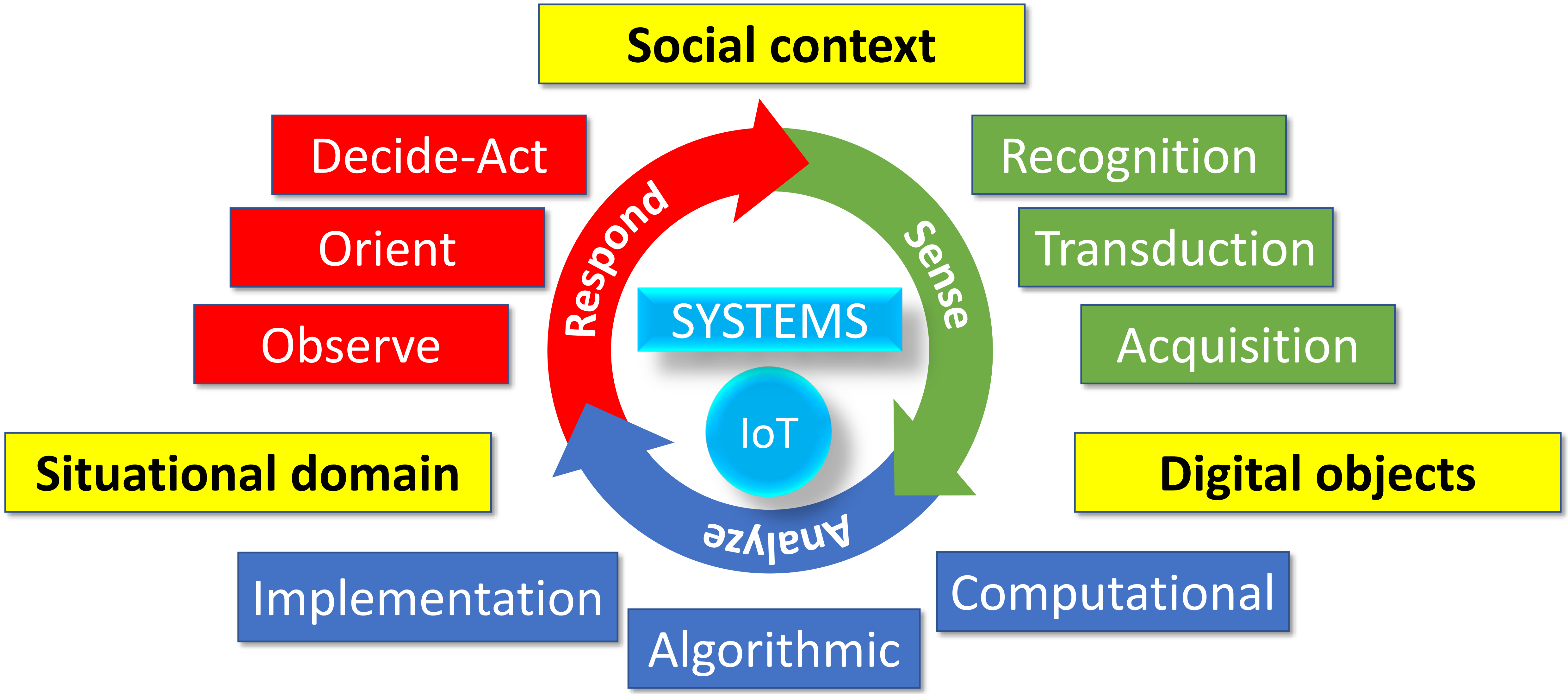
Granularity of the Data-Informed Decision as a Service



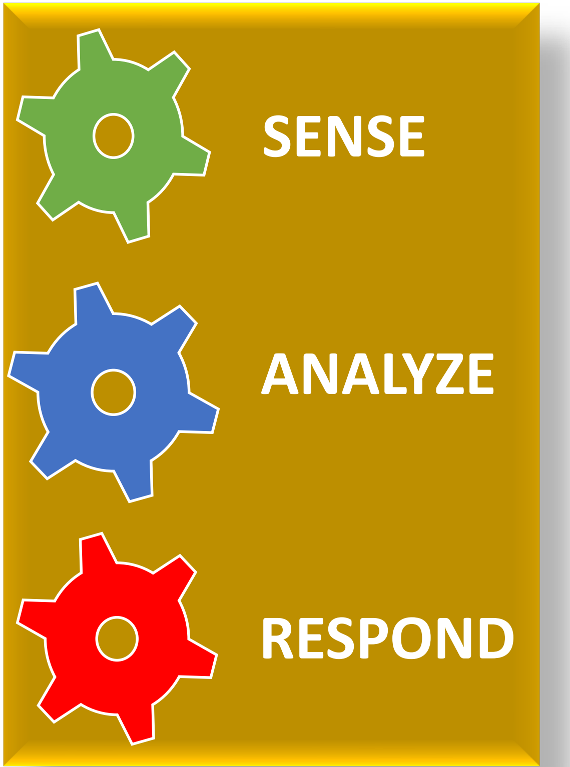
DIDA'S : Data-Informed Decision as a Service with SARS

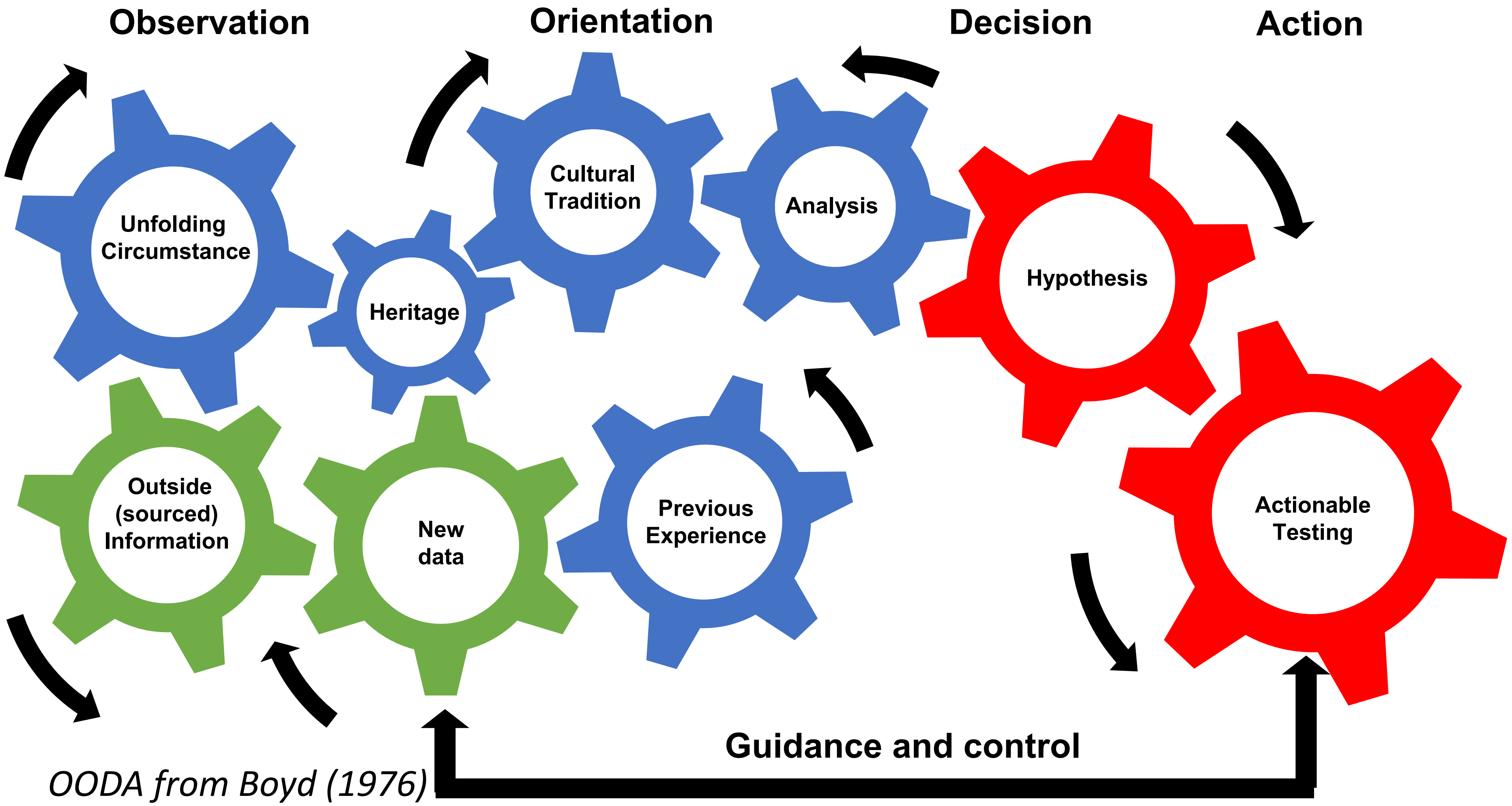


DIDA'S : Data-Informed Decision as a Service

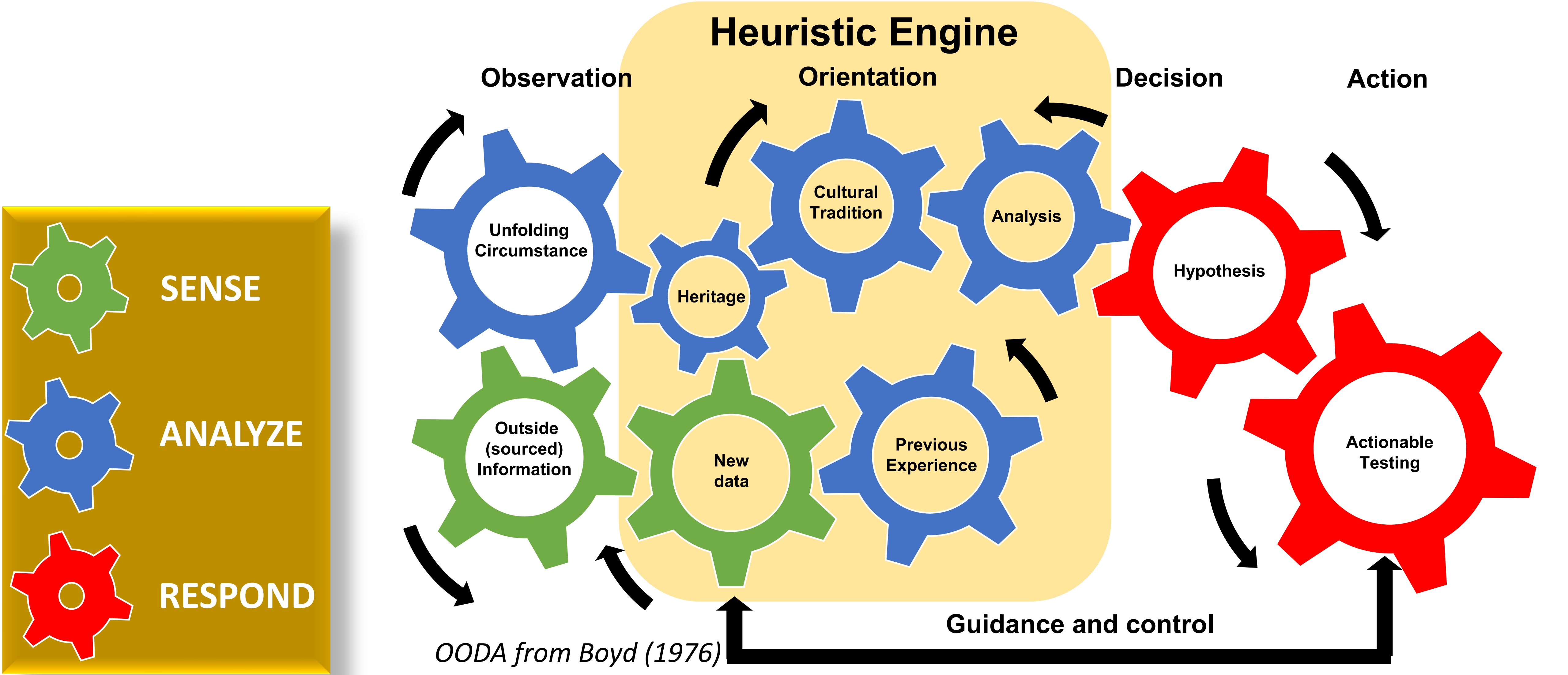


DIDA'S ENGINES : Data-Informed Decision Engines

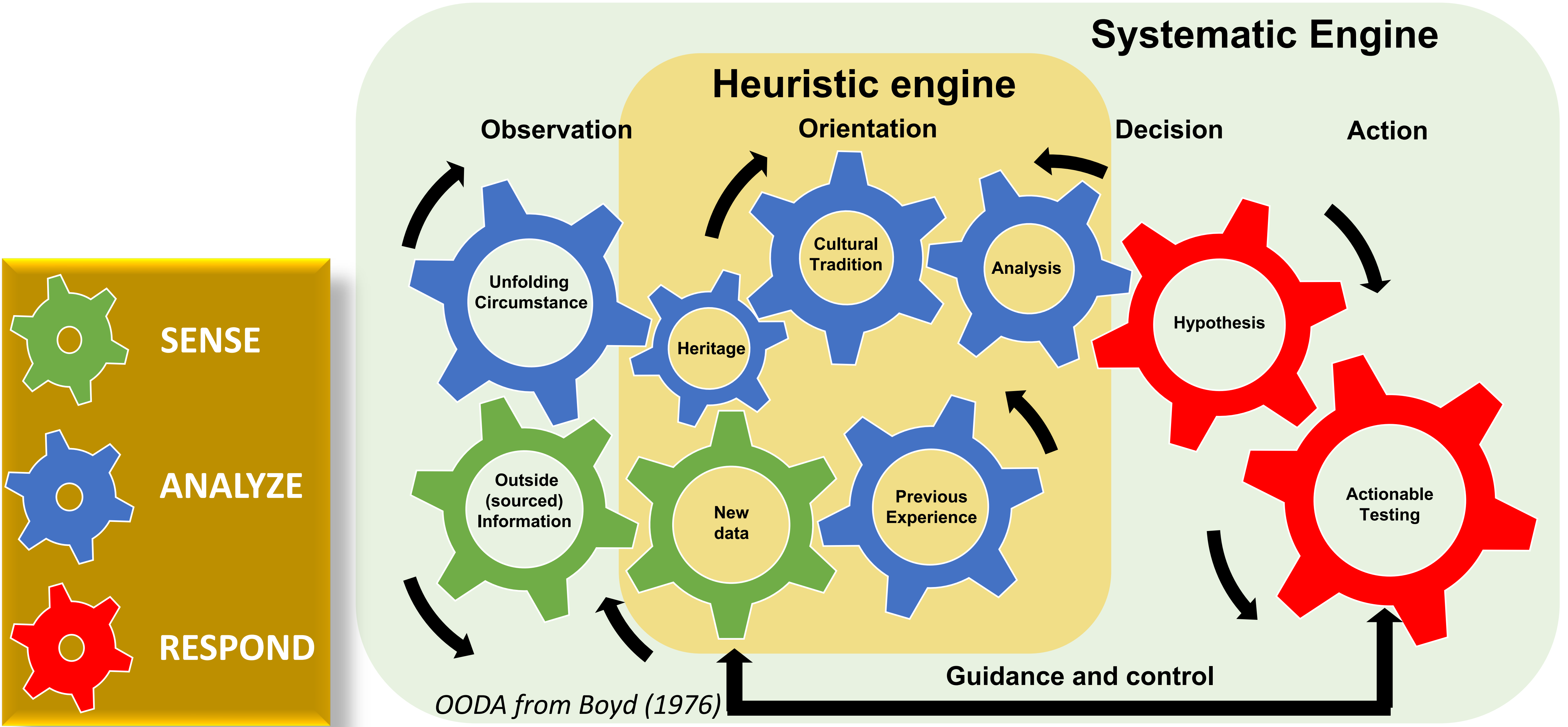




DIDA'S ENGINES : Data-Informed Decision Engines



DIDA'S ENGINES : Data-Informed Decision Engines



The Value of DIDA'S (Data-Informed Decision as a Service)

Is there consumer demand for this vegetable?

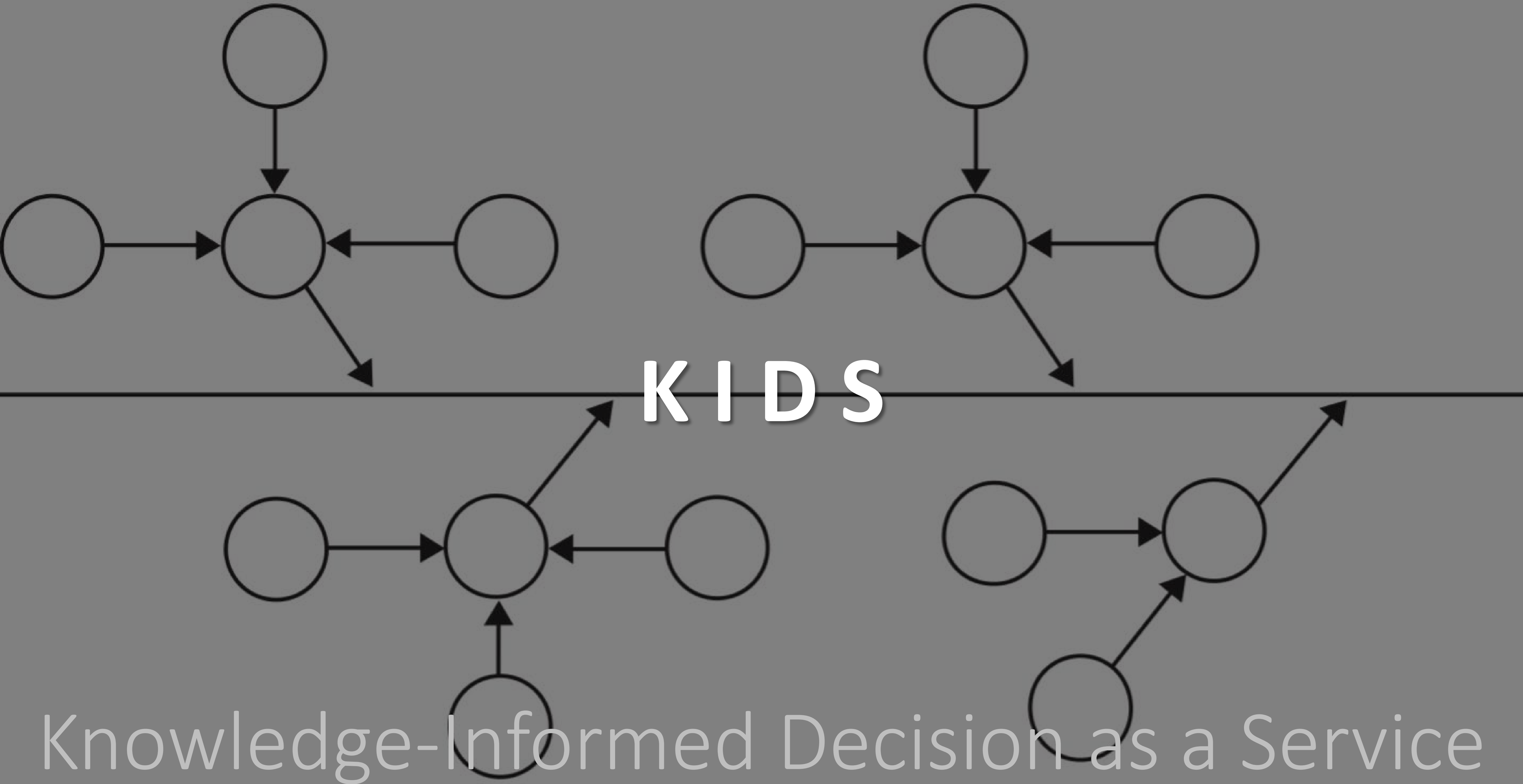
The Value of DIDA'S (Data-Informed Decision as a Service)

To realize the actual value of DIDA'S, the tool must be useful to end-users, if they can use the tool to ask questions and receive actionable information or if it can support the decision making process

The journey to DIDA'S must include and/or create and/or connect a multitude of domains to source data and synthesize relevant information. DIDA'S may lead to knowledge-informed decision as a service.

KIDS

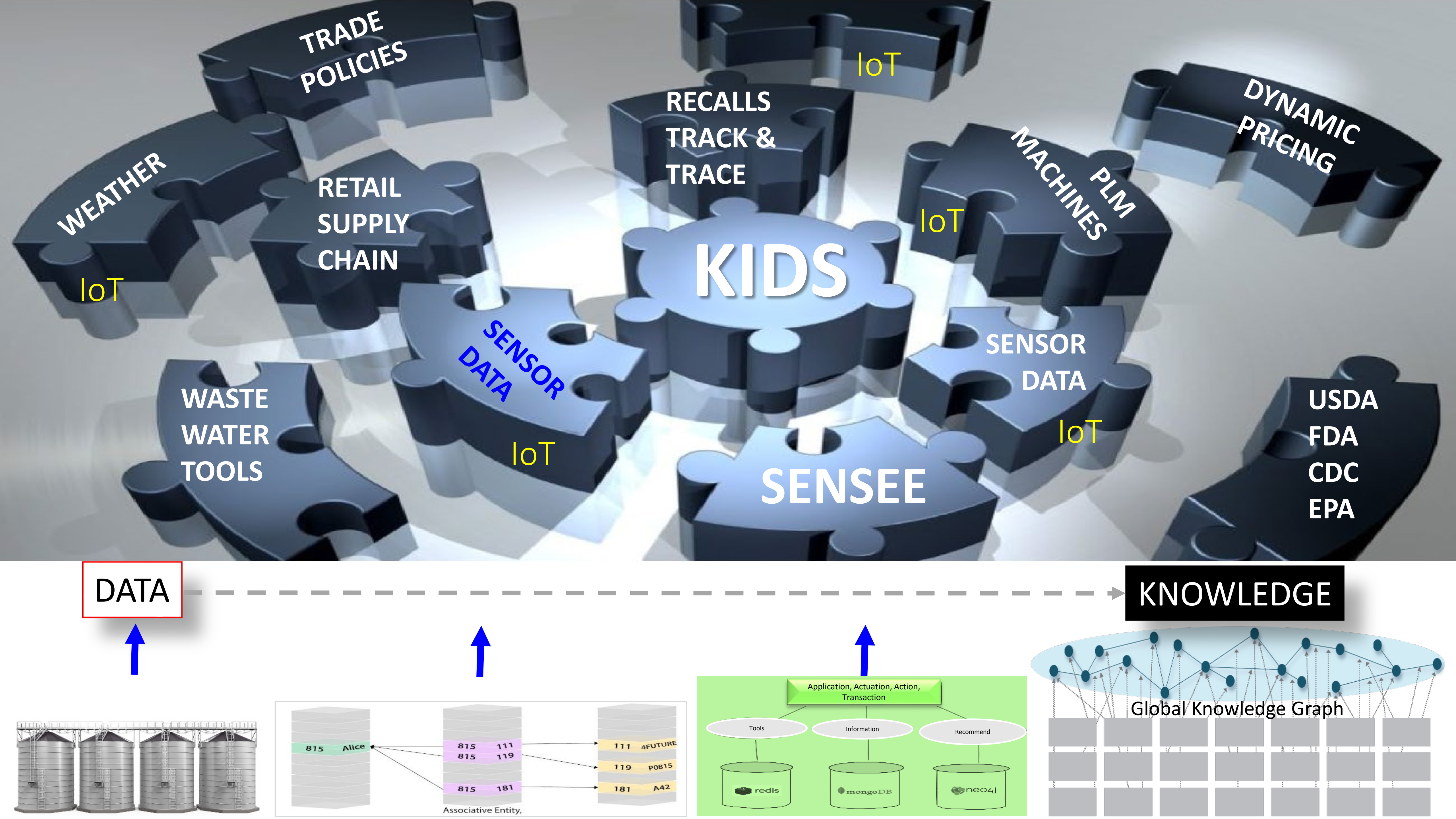
Knowledge-Informed Decision as a Service



K I D S

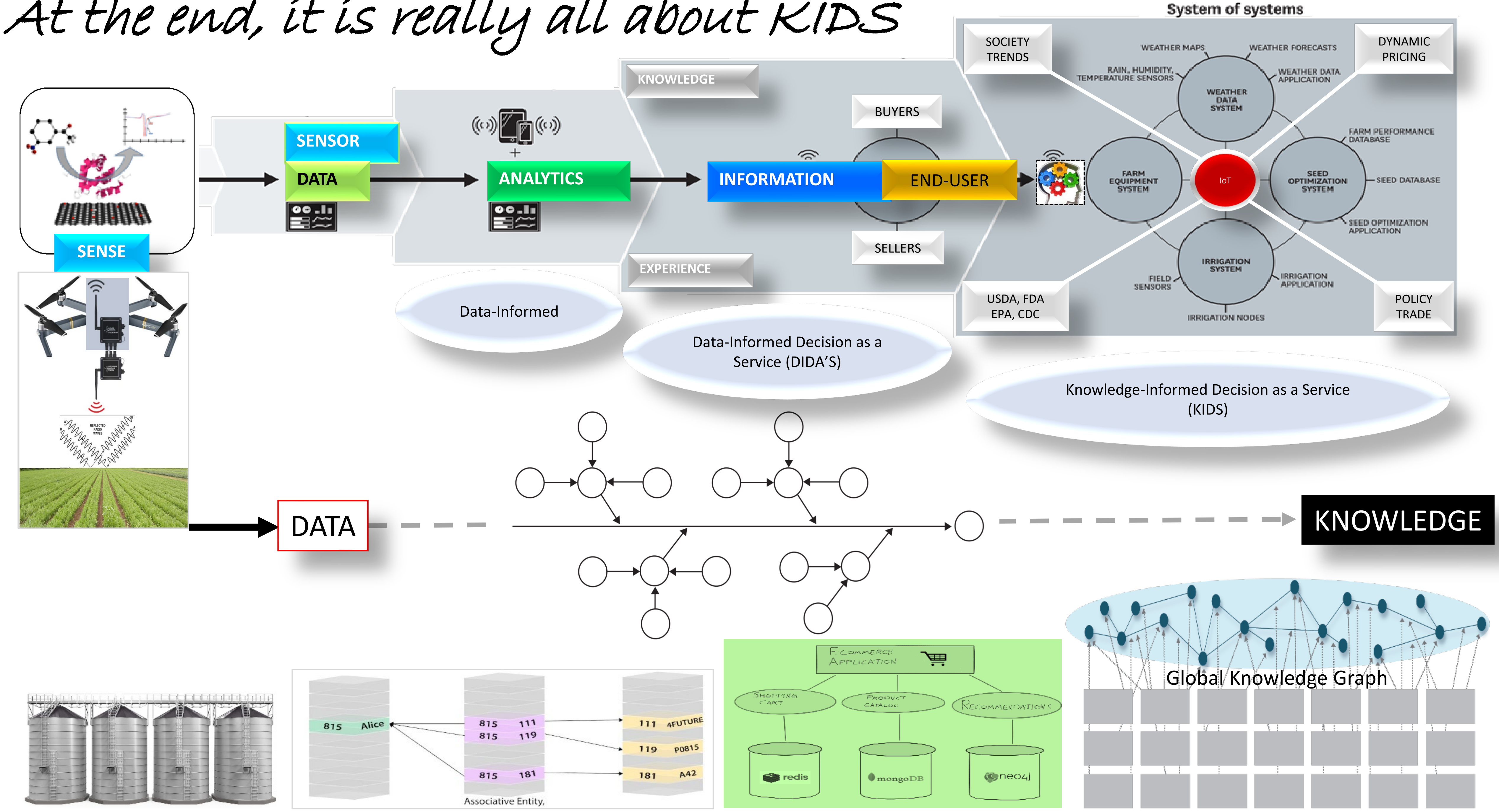
Knowledge-Informed Decision as a Service

KIDS is an open plan platform concept. Platforms are comprised of multiple applications and integrated solutions with embedded tools and databases that function as complete, seamless environments. Product innovation platforms are intended to support groups of users collaborating across various levels, domains, business units, and the ecosystem. These capabilities are increasingly needed throughout the entire extended enterprise in almost every vertical, agnostic of the type of application or function or users, including farmers, meat packers, produce growers, retail stores, customers, suppliers, and business partners. Developing open platform tools and technologies are not limited to any one domain because these modular tools can be applied, used and re-configured for re-use, almost anywhere, for example: error correction, search engine algorithms, NLU/NLP (natural language processing), automated feature engineering, drag and drop functions, analytics, workflows, and services, such as KIDS, where “open” means ‘plug & play’ user friendly human-computer interactions and interoperability between system of systems.

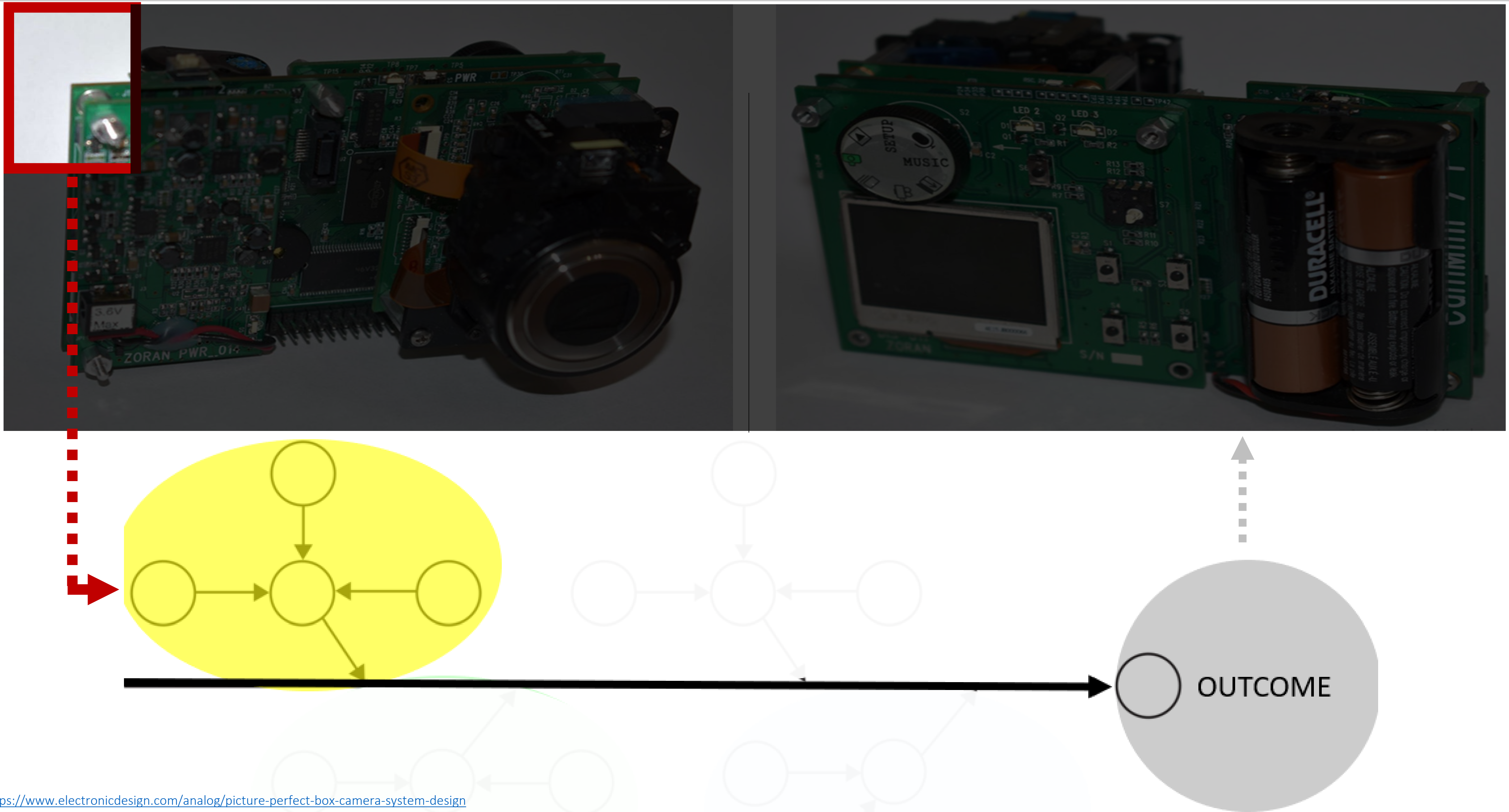


TRADE POLICIES
IoT
RECALLS TRACK & TRACE
DYNAMIC PRICING
WEATHER
RETAIL SUPPLY CHAIN
PLM MACHINES
IoT
KIDS
IoT
SENSOR DATA
SENSOR DATA
IoT
WASTE WATER TOOLS
IoT
SENSEE
USDA FDA CDC EPA
DATA
KNOWLEDGE
Global Knowledge Graph
815 Alice
815 111
815 119
815 181
111 4FUTURE
119 P0815
181 A42
Associative Entity,
Application, Actuation, Action, Transaction
Tools
Information
Recommend
redis
mongoDB
neo4j

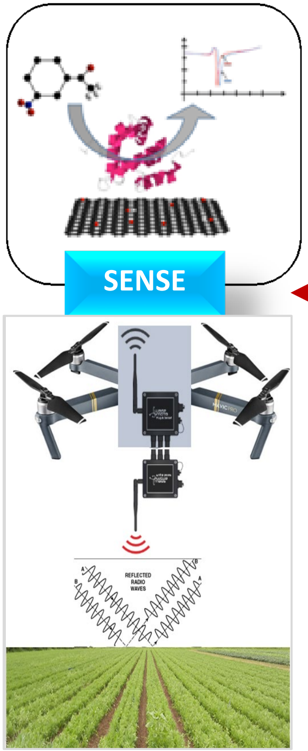
At the end, it is really all about KIDS



We are not even close

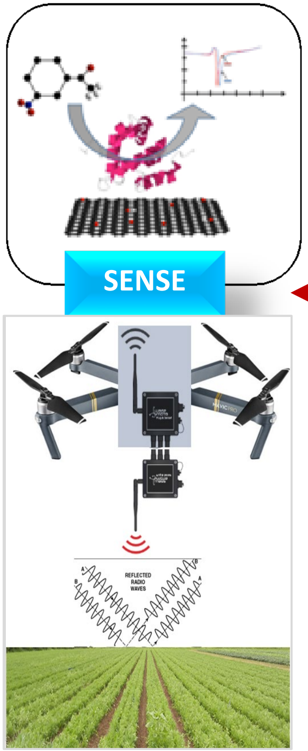


https://www.electronicdesign.com/analog/picture-perfect-box-camera-system-design



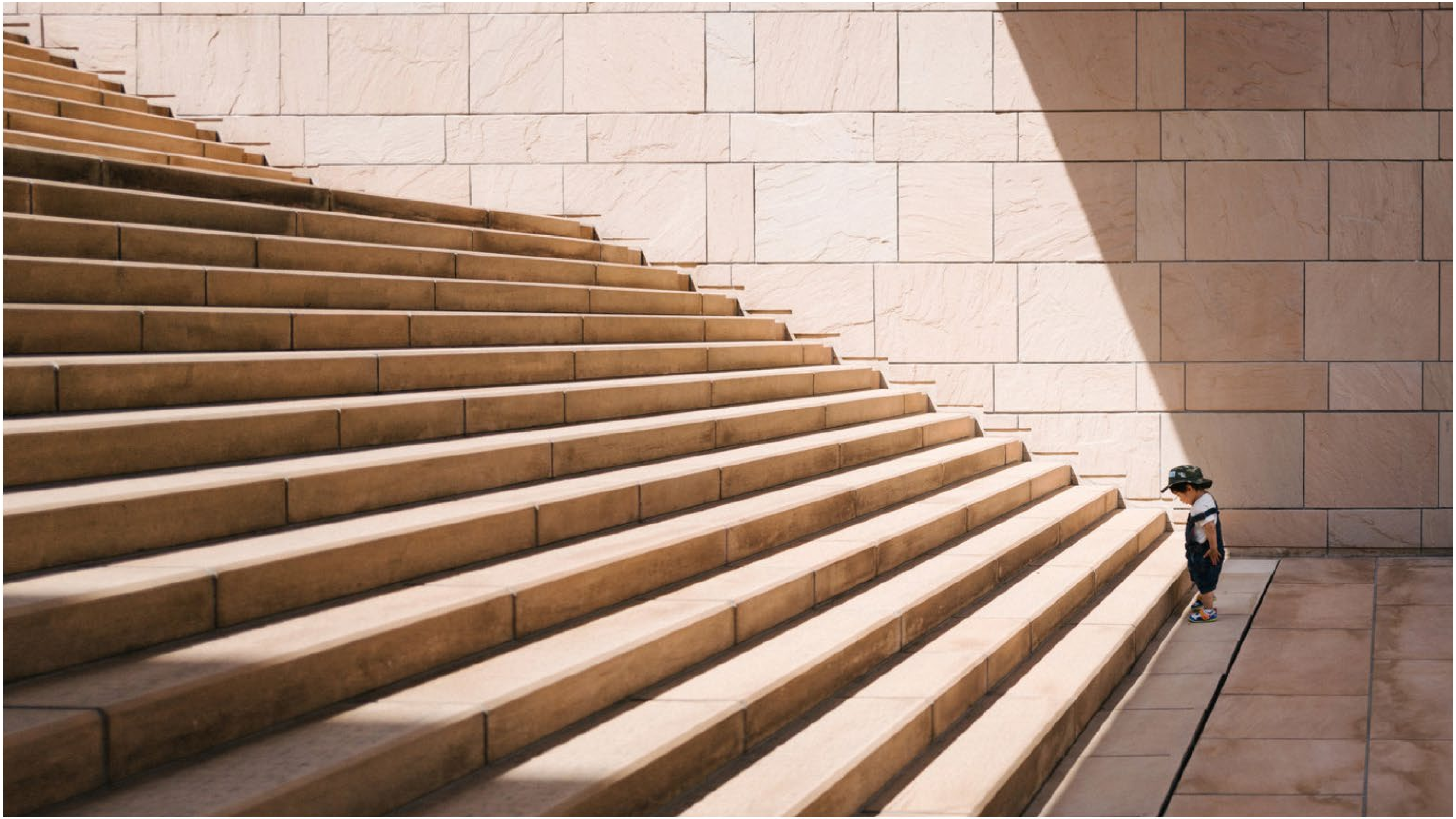
We are just starting here

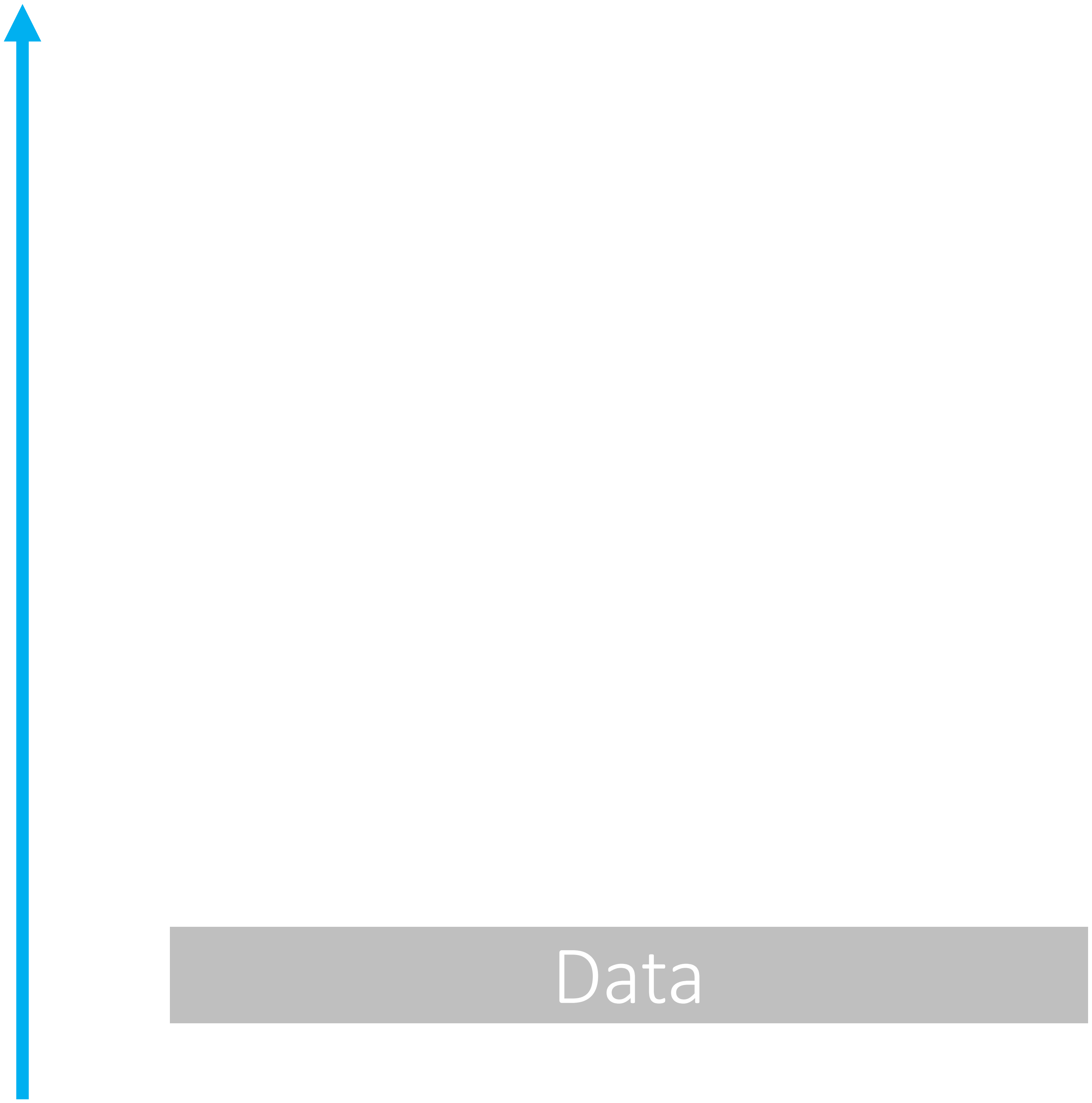
SENSEE



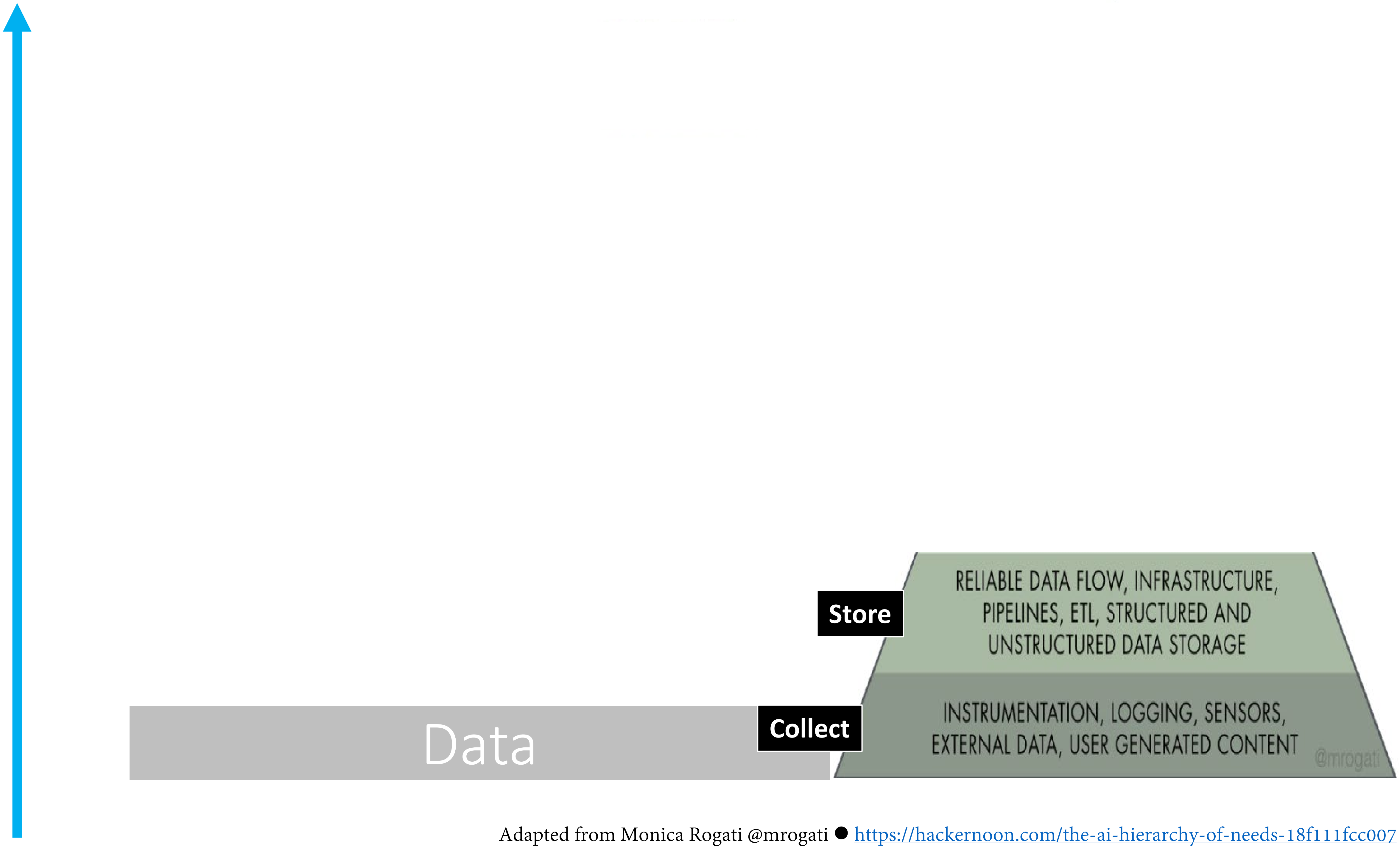
We are just starting here

SENsor **SE**arch **E**ngine




Data

Adapted from Monica Rogati @mrogati ● https://hackernoon.com/the-ai-hierarchy-of-needs-18f111fcc007



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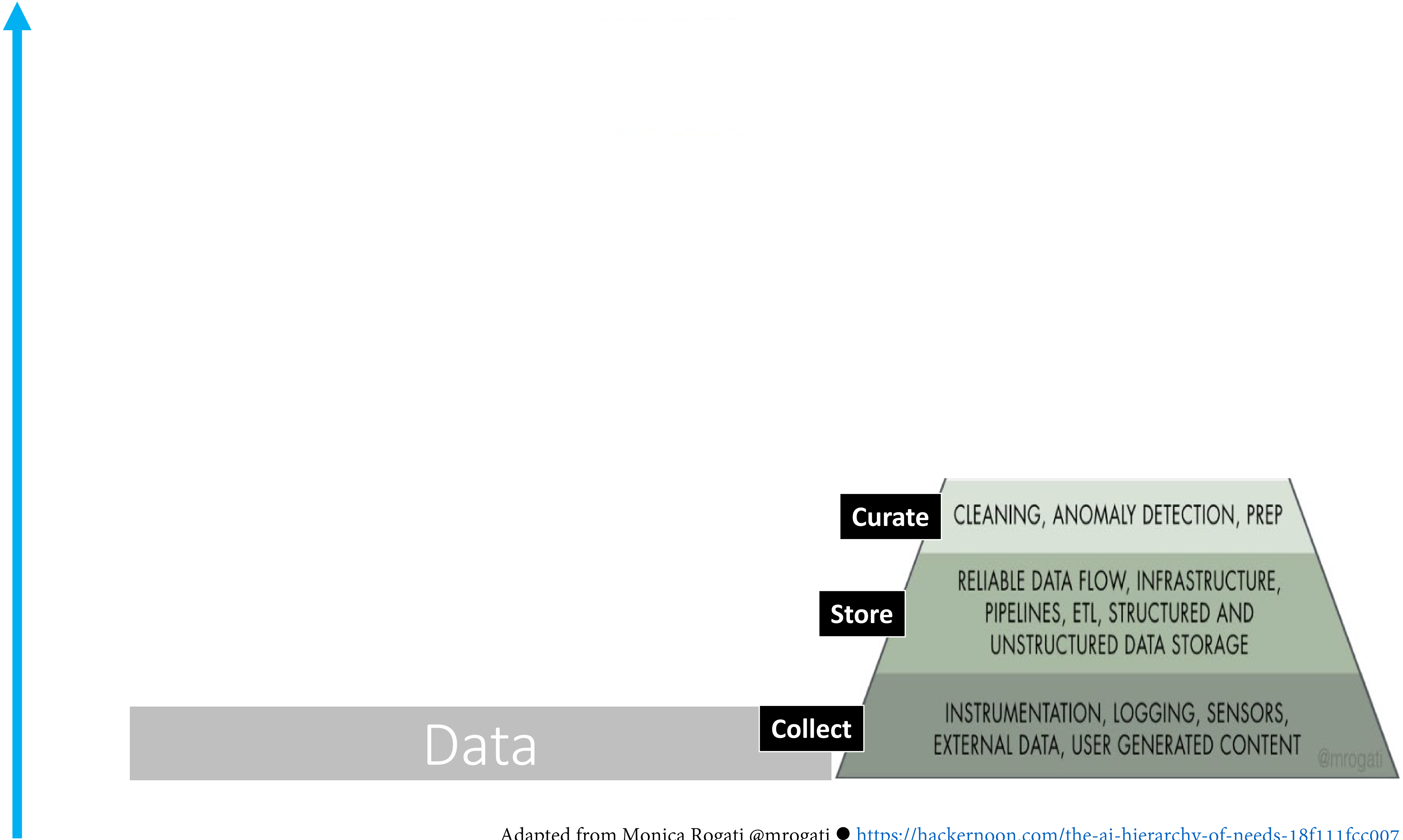

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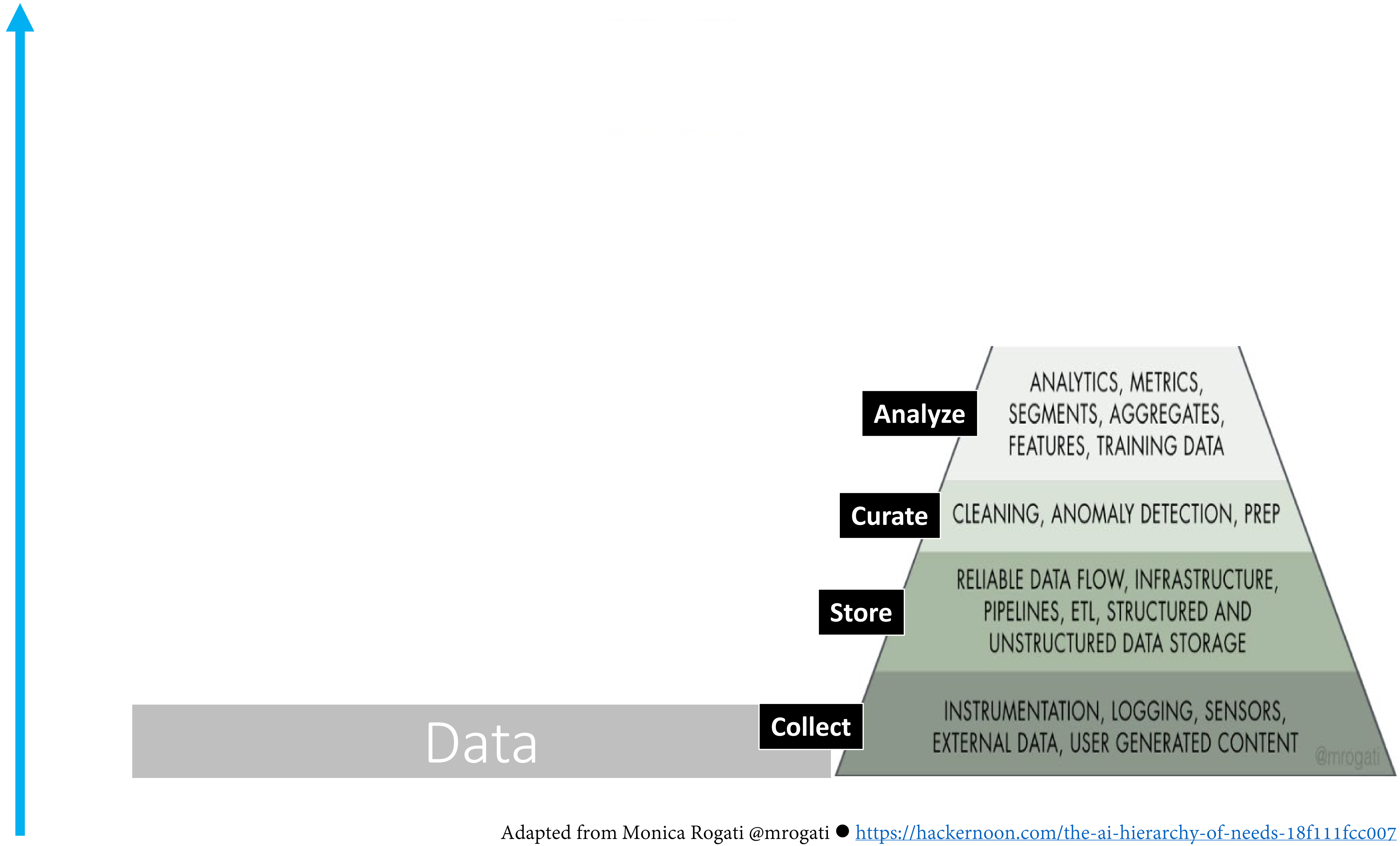

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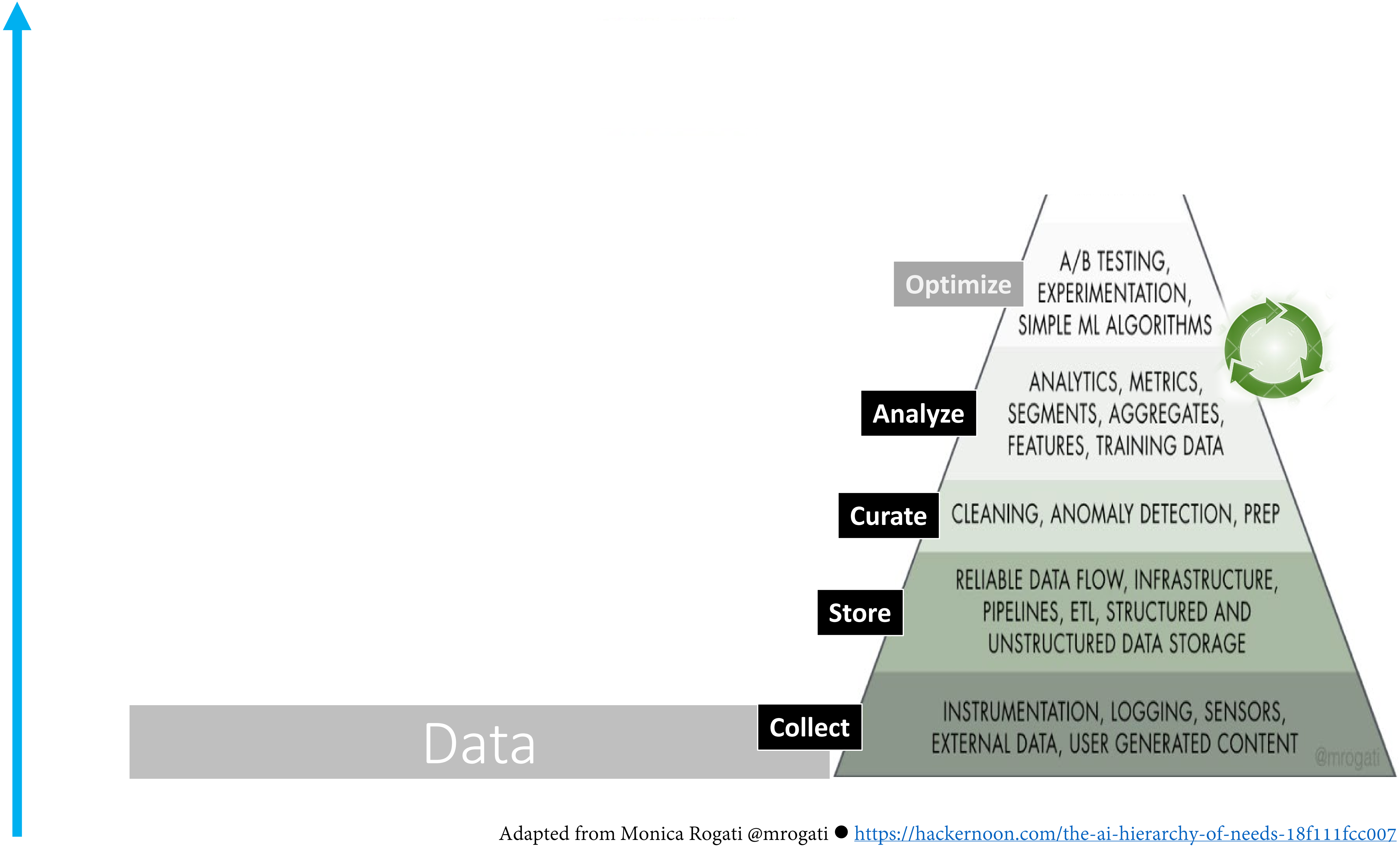

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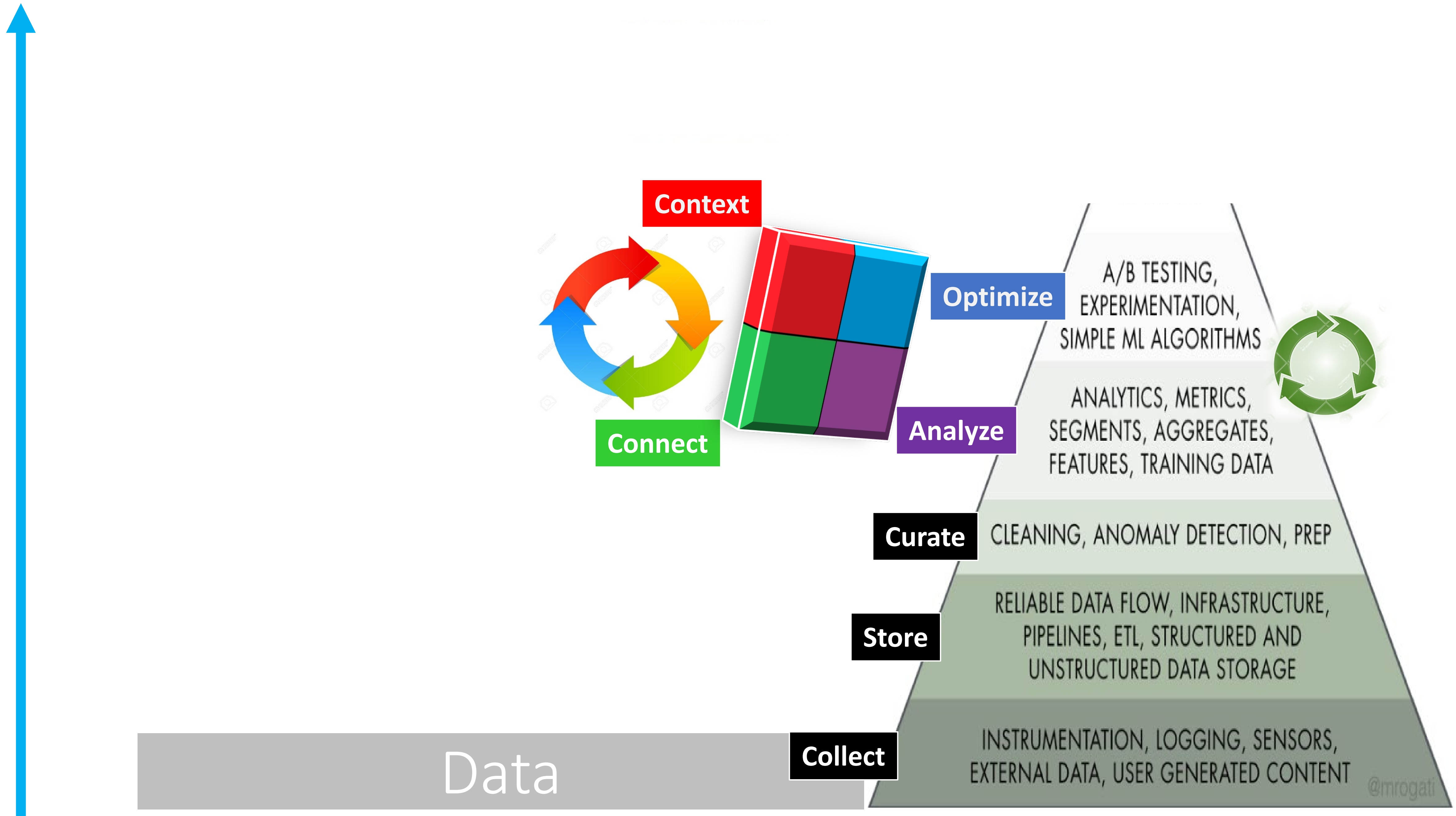

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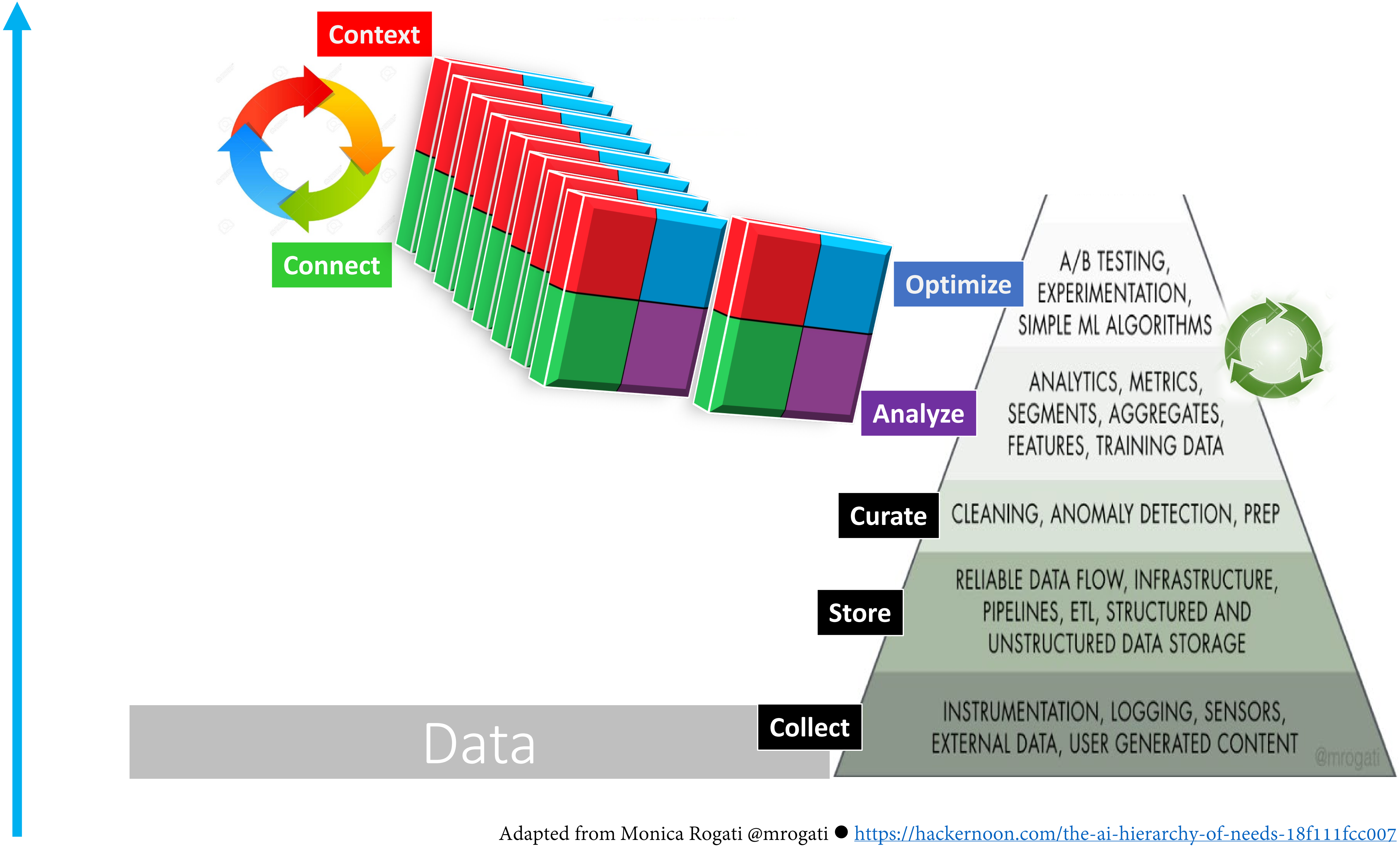

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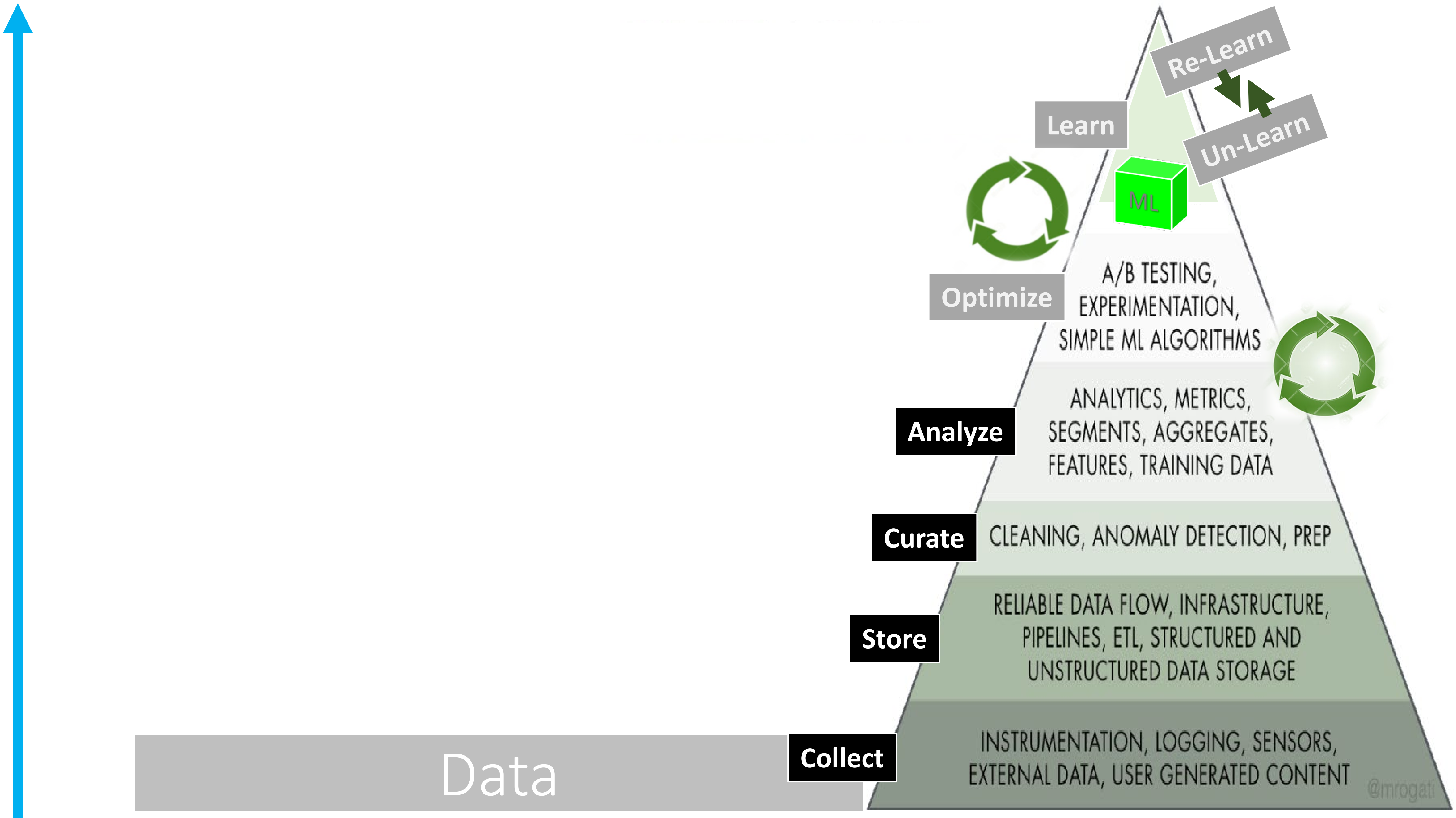

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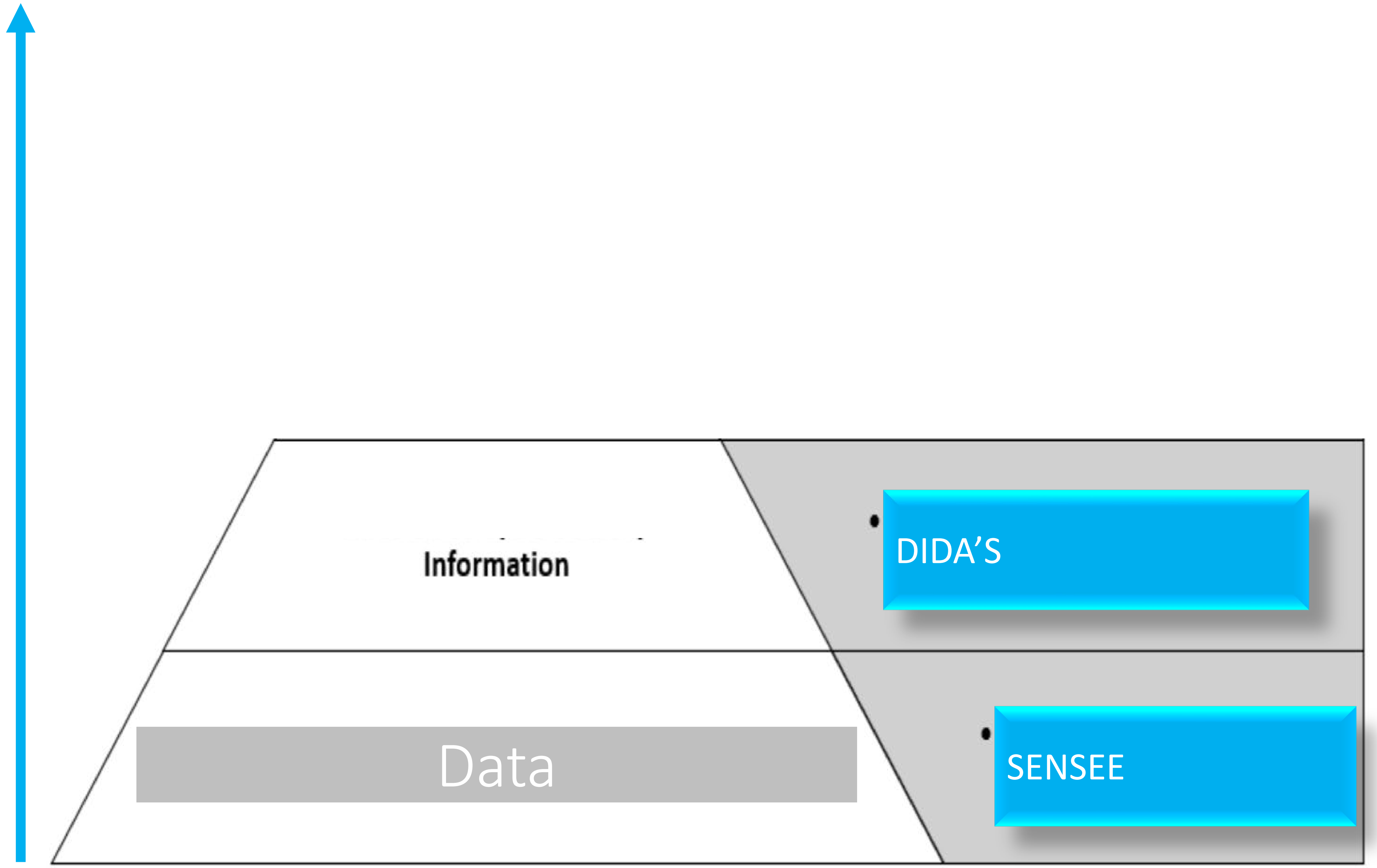
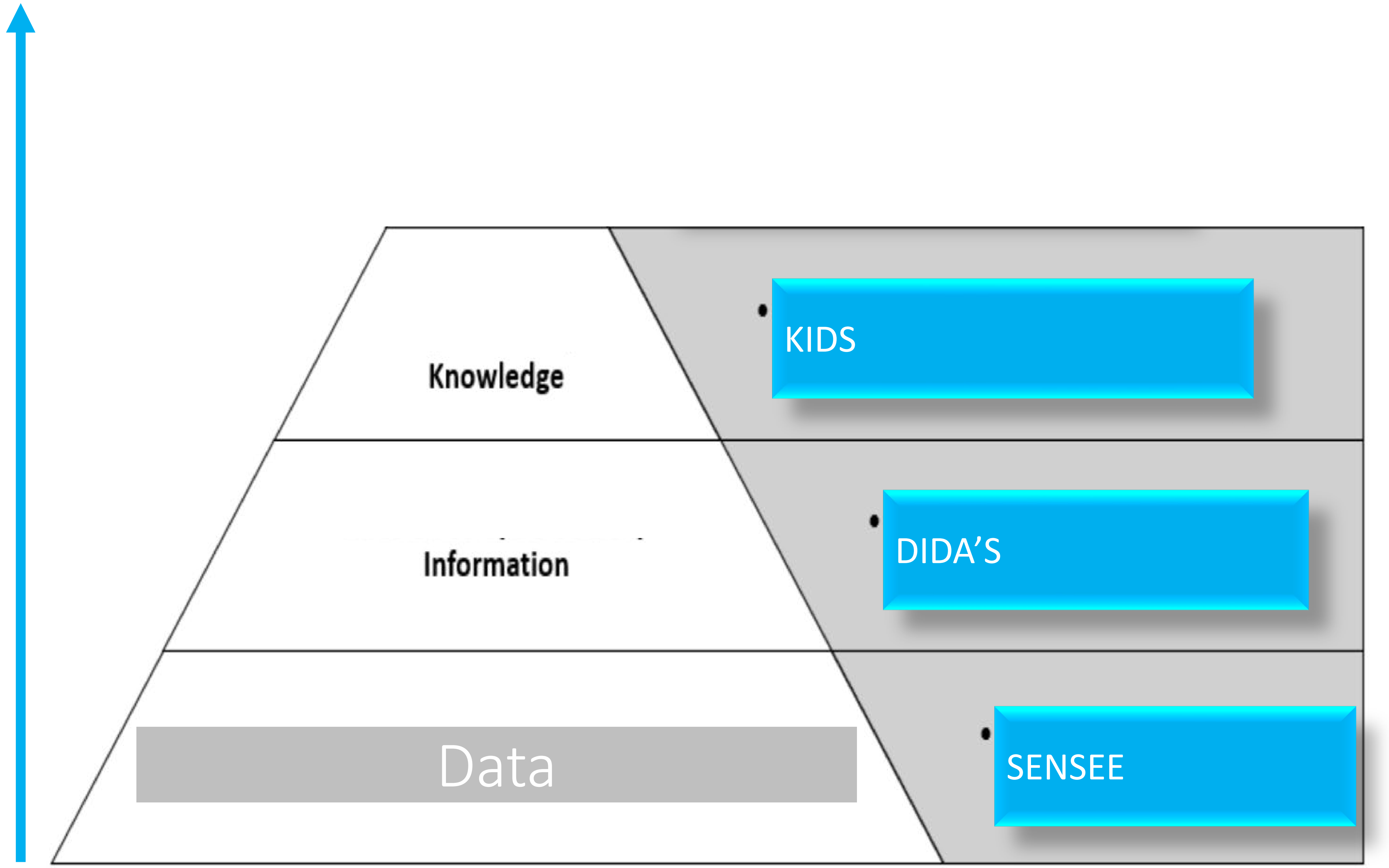
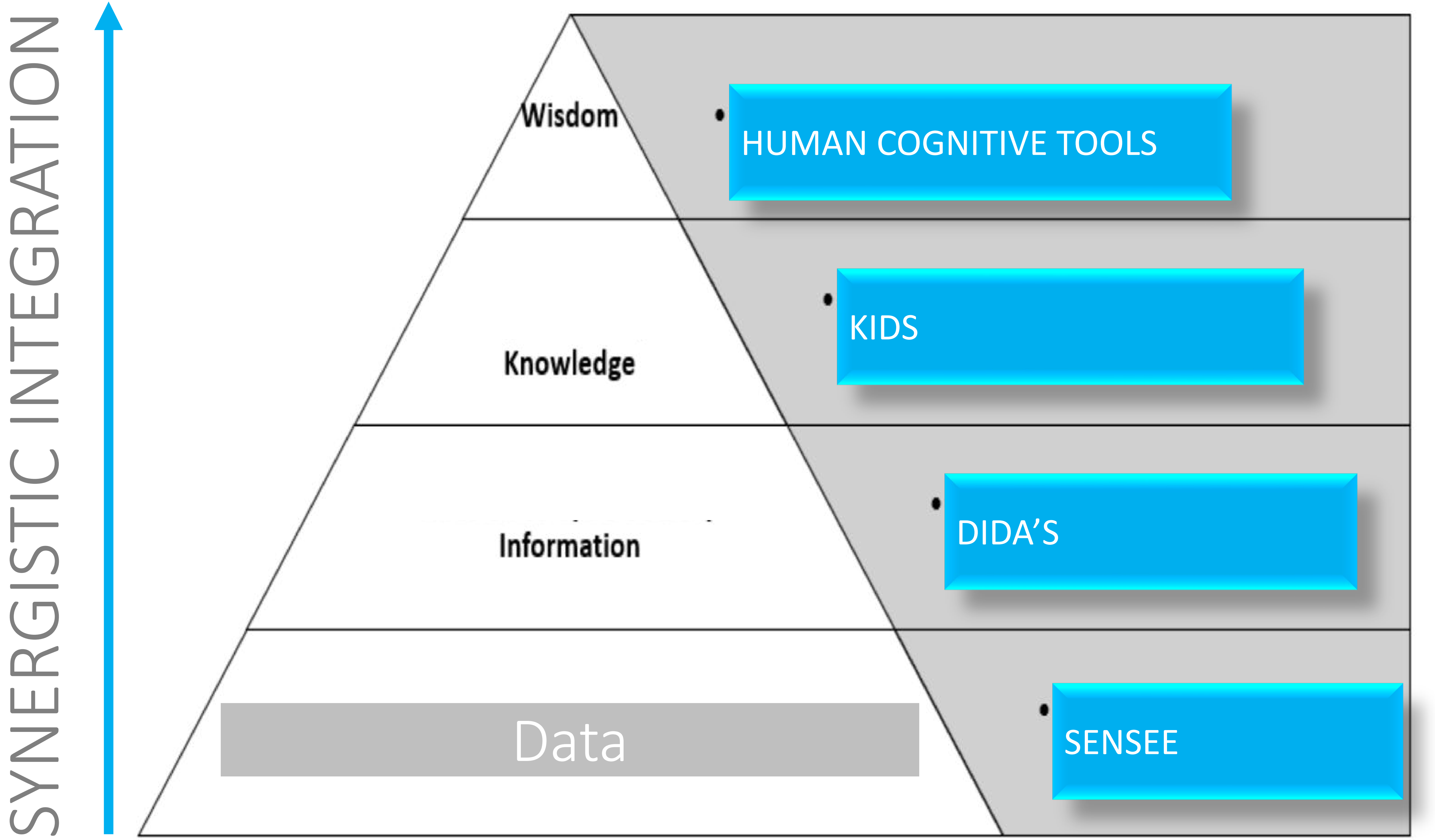
Data
SENSEE

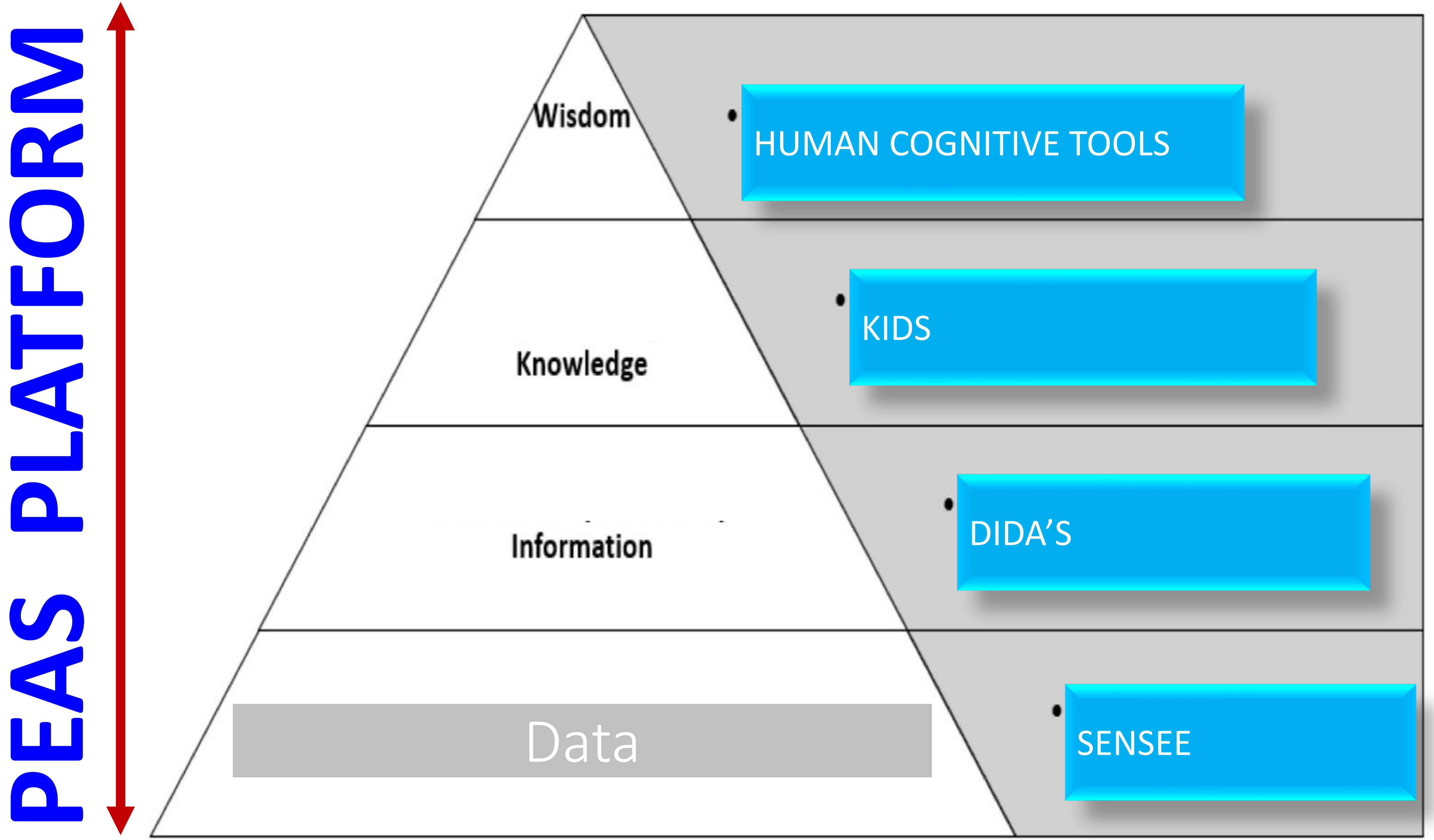


Information
DIDA’S
Data
SENSEE

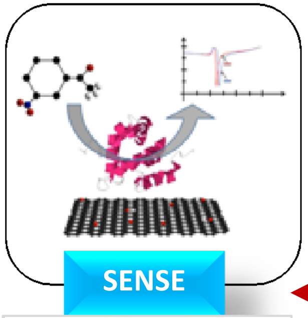

Knowledge
KIDS
Information
DIDA'S
Data
SENSEE

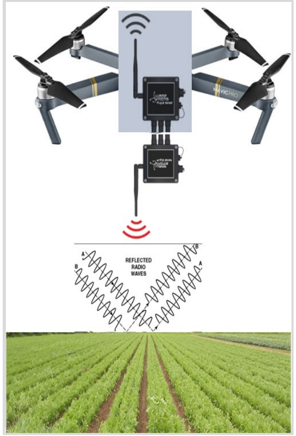


SYNERGISTIC INTEGRATION
Wisdom
Knowledge
Information
Data
HUMAN COGNITIVE TOOLS
KIDS
DIDA'S
SENSEE


PEAS PLATFORM
Wisdom
Knowledge
Information
Data
HUMAN COGNITIVE TOOLS
KIDS
DIDA’S
SENSEE

SENSEE





SENsor **SE**arch **E**ngine

Attempt to create an open source curated repository for different types of sensors created by academic and industrial labs, globally. Expect to connect with similar data from sensor manufacturers.

SENSEE

The curated repository containing descriptions of sensors may also serve as an unit or module for the hypothetical open source library to contain information about tools or technologies related to management of agricultural wastewater systems (AWS).

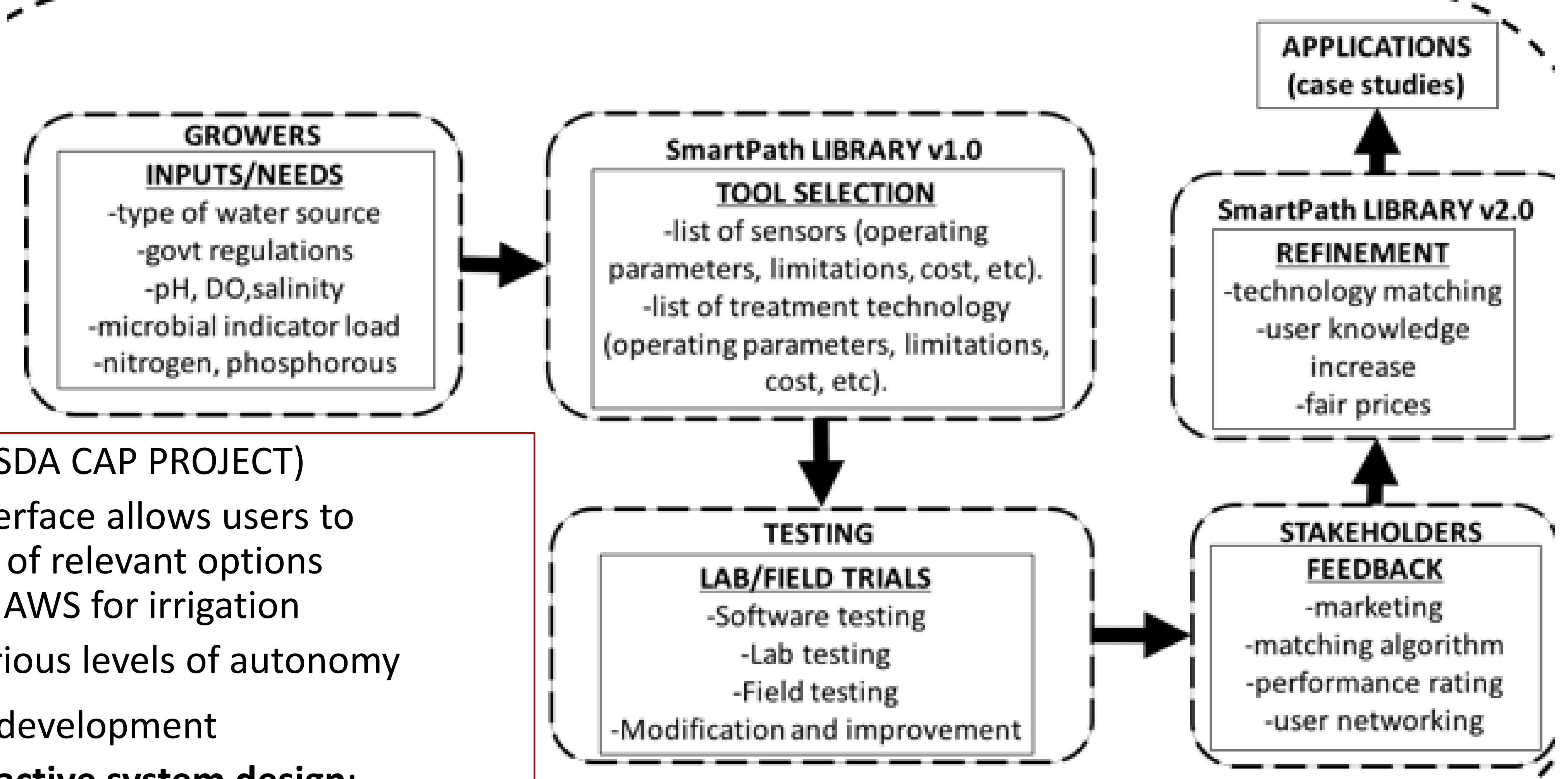
The purpose of the AWS library is to serve end-users (farmers, growers) who may ask questions pertaining to AWS for irrigation. Questions may be related to the detection of heavy metals and microbes (thus, sensors) or waste water treatment technologies (separate module to be developed by USDA SmartPath Project, not a part of SENSEE).

Development of an open source AWS technology repository (with mobile access)

Development of an open source AWS technology repository (with mobile access)

- SmartPath Library (USDA CAP PROJECT)
    - User-friendly interface allows users to explore a variety of relevant options related to use of AWS for irrigation
    - Open source, various levels of autonomy
- Tools/widgets under development
    - Software for **proactive system design**; selection of appropriate technologies (sensors from SENSEE and treatment module)
    - Software for assisting growers with **technology adoption** and assist with trade policies, pricing
    - Software for providing **decision support** for monitoring/treatment (SENSEE, DIDA'S, KIDS)

Development of an open source AWS technology repository (with mobile access)



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  - Software for assisting growers with **technology adoption** and assist with trade policies, pricing
  - Software for providing **decision support** for monitoring/treatment (SENSEE, DIDA'S, KIDS)

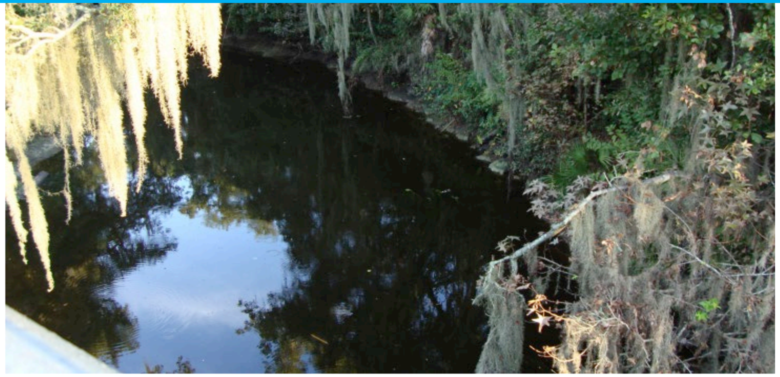
SENSEE

Expert users (academics, students, industrial labs) may be the short term beneficiary from the curated descriptions of sensors, if SENSEE contains a critical mass of sensor descriptions (expectation: sensor descriptions from 1,000 to 10,000 labs, globally). Google search may reveal millions of documents. SENSEE presents a curated list.

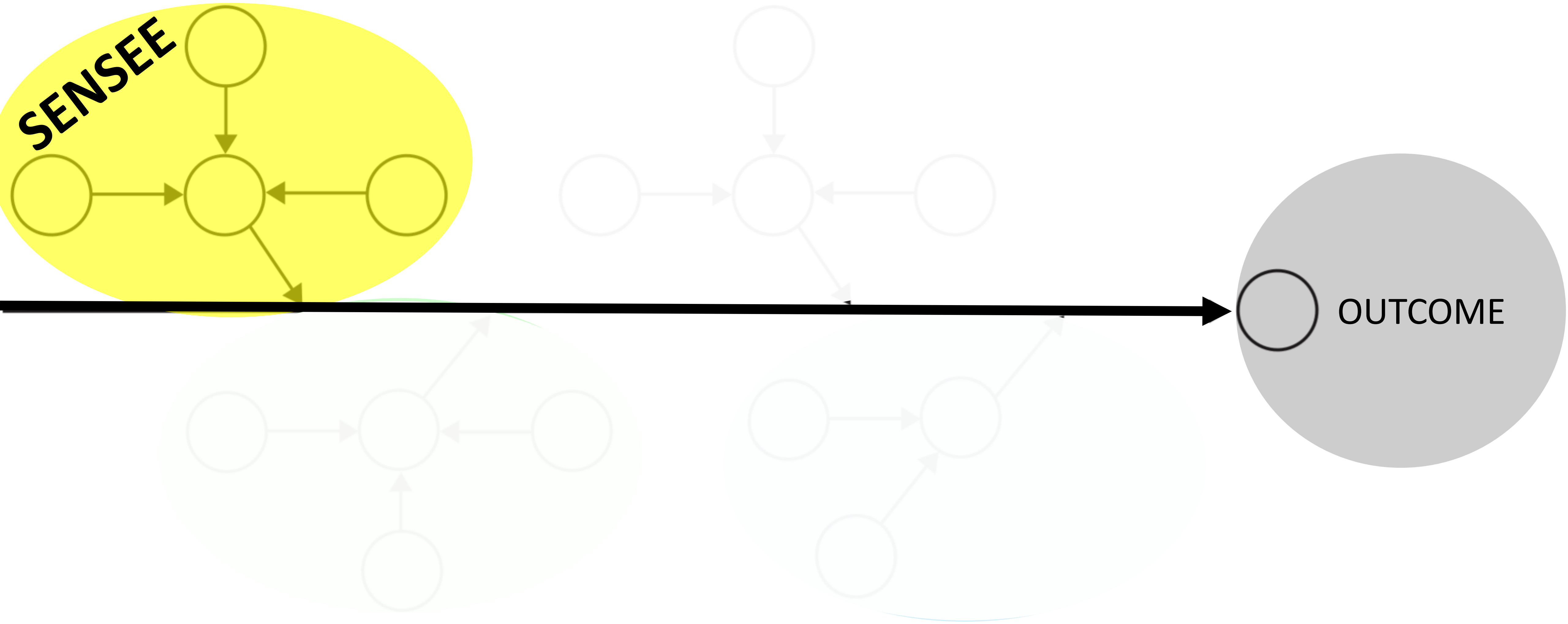
In the future, SENSEE will contain sensor descriptions (categories, attributes) **and** select data from specific sensors. Sensor data ingested in SENSEE will be determined by use cases for specific end-users (farms, grocery stores, food warehouse, food processing plant, packaging operations, retail distribution, food logistics, global transportation).

SENSEE is a start … but woefully inadequate as a solution

- End-user perspective and questions from the field (agro-ecosystem) are complex:
  - Is my ***water quality in compliance*** with FSMA produce safety rule (PSR)?
  - What are the ***costs*** associated with agricultural wastewater (AWS) reuse?
  - Does reuse of AWS add excessive ***management*** issues?
  - ***Who monitors*** return flows, aquifer recharge, and water quality?
  - What are the perceived and real ***health risks*** associated with AWS for irrigation?
  - Can ***technologies*** (sensors + treatment systems) add ***quantifiable*** value?
  - Are there ***legal implications*** of real time water quality data acquisition?
  - Are there ***economic penalties*** for buyers if data log shows poor water quality?

SENSEE is a start … but woefully inadequate as a solution

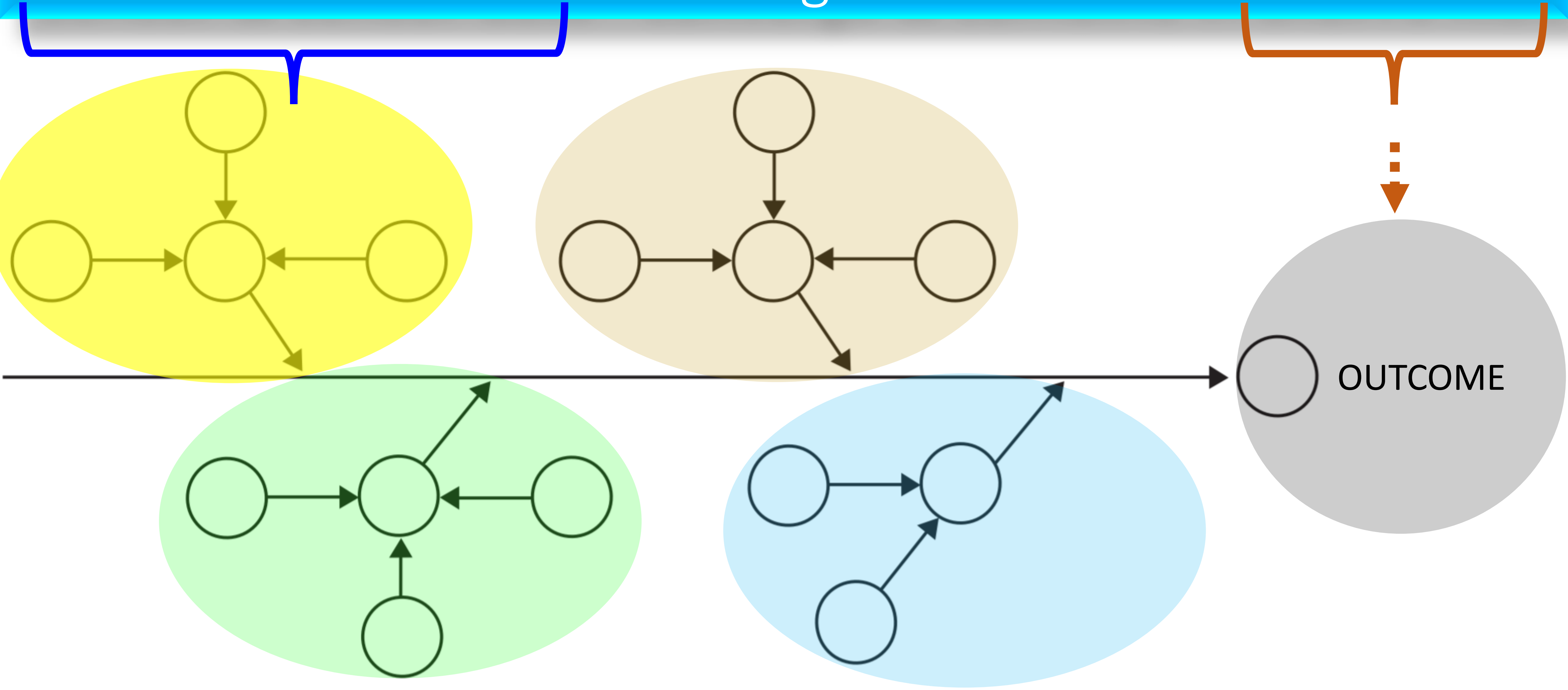


How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

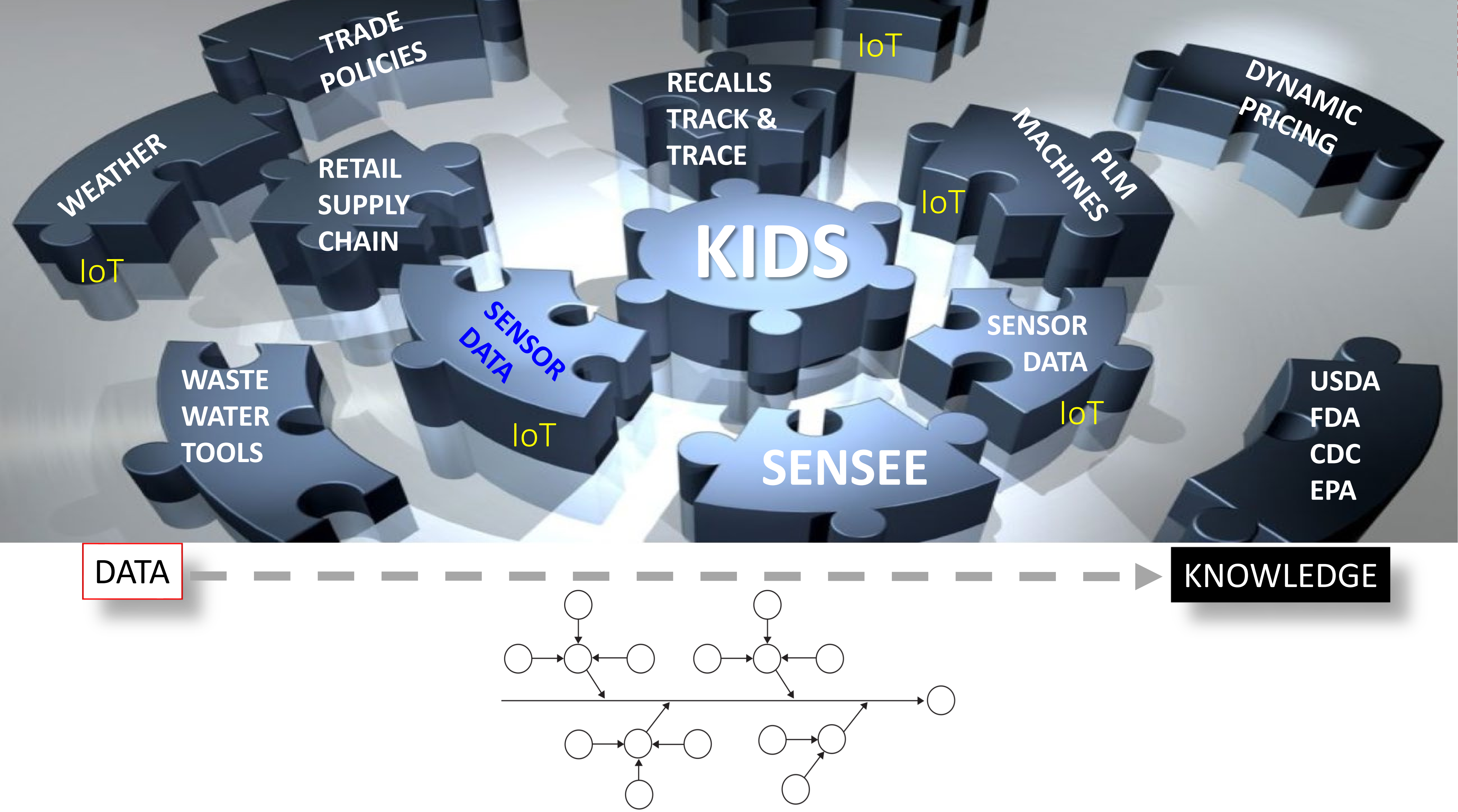
KIDS

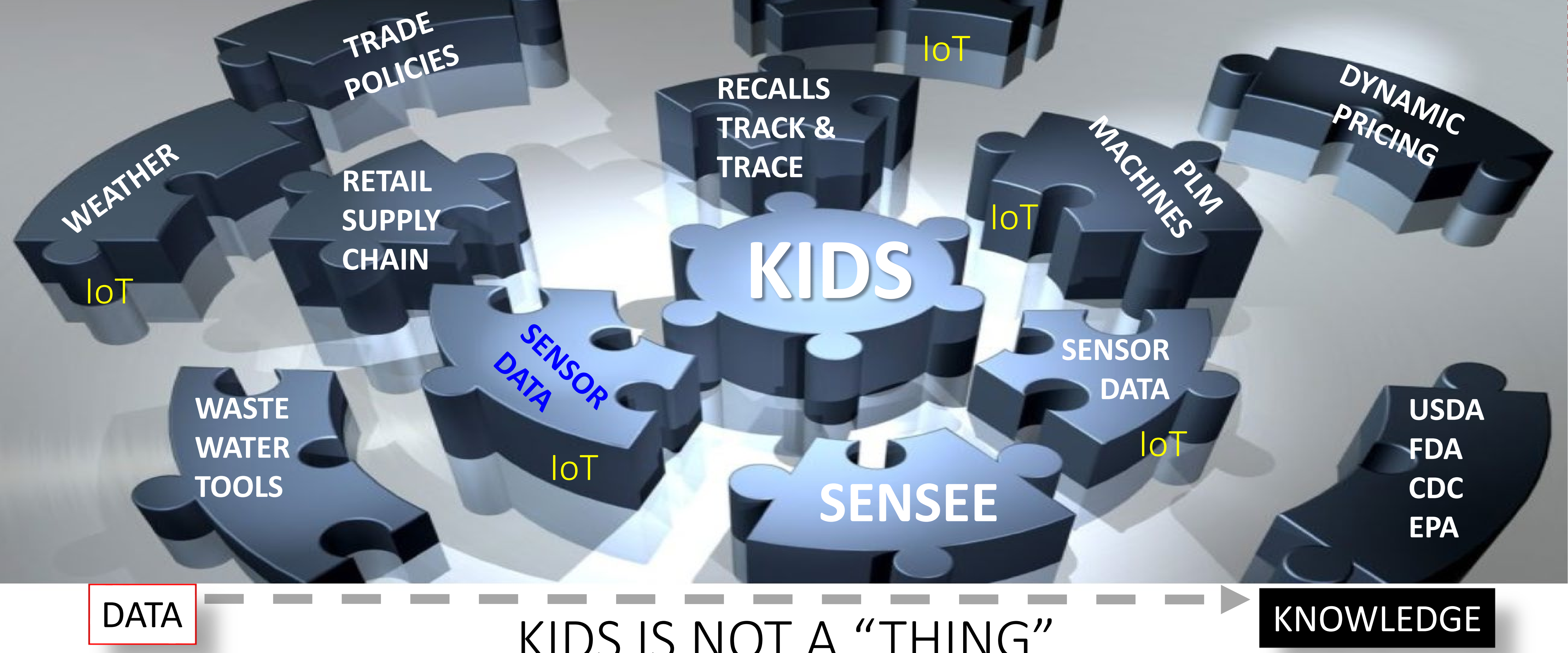
Do you sense the convergence?

Sensor & sensor data - converge & combine in DIDA'S KIDS



How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?


TRADE POLICIES
IoT
RECALLS TRACK & TRACE
DYNAMIC PRICING
WEATHER
RETAIL SUPPLY CHAIN
PLM MACHINES
IoT
KIDS
IoT
SENSOR DATA
SENSOR DATA
WASTE WATER TOOLS
IoT
IoT
SENSEE
USDA FDA CDC EPA
DATA
KNOWLEDGE

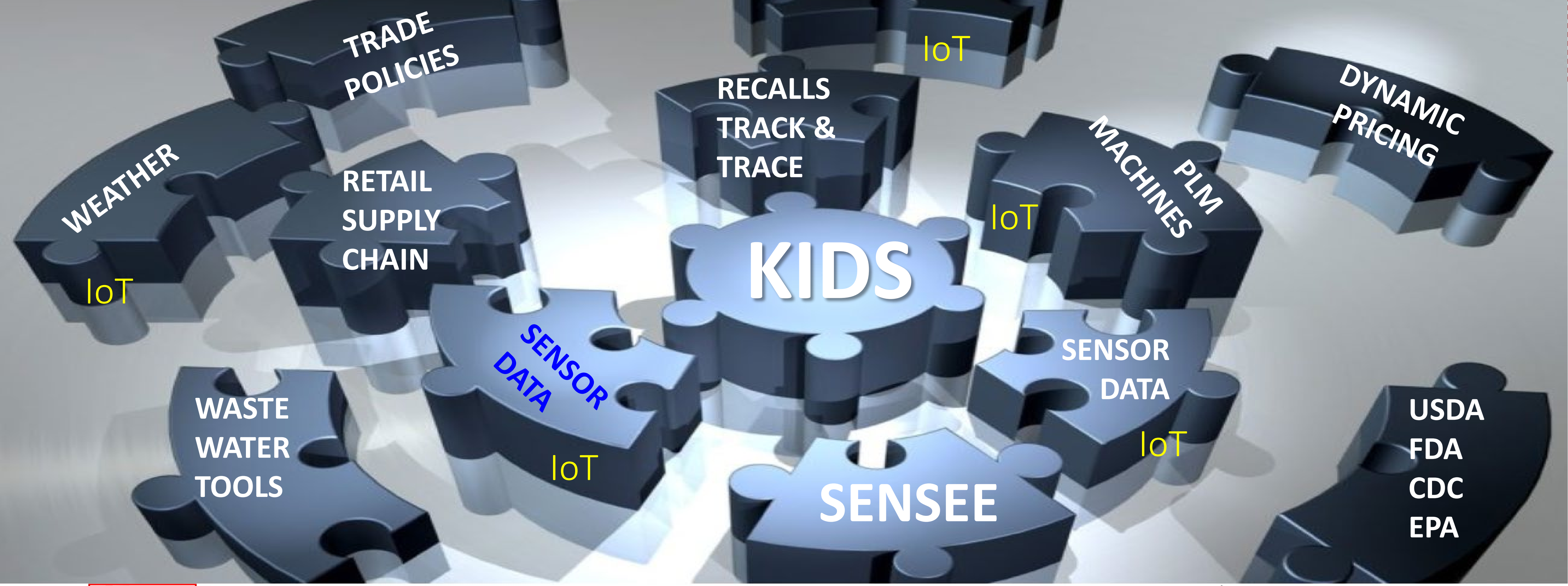


KIDS IS NOT A "THING"

ONE SIZE WILL NOT FIT ALL

KIDS IS A CONCEPTUAL DESIGN METAPHOR

KIDS IS A SYNERGISTIC KNOWLEDGE INTEGRATION PLATFORM



DATA → KNOWLEDGE

WHY SENSEE IS A TINY PART OF A SYSTEM

It may not be difficult to grasp that the questions from field users demand immense cross-pollination of data and information to converge with knowledge, logic and reasoning, to generate even a basic response.

End-user perspective and questions from the field (agro-ecosystem) are complex:

Is my ***water quality in compliance*** with FSMA produce safety rule (PSR)?
What are the ***costs*** associated with agricultural wastewater (AWS) reuse?
Does reuse of AWS add excessive ***management*** issues?
Who monitors return flows, aquifer recharge, and water quality?
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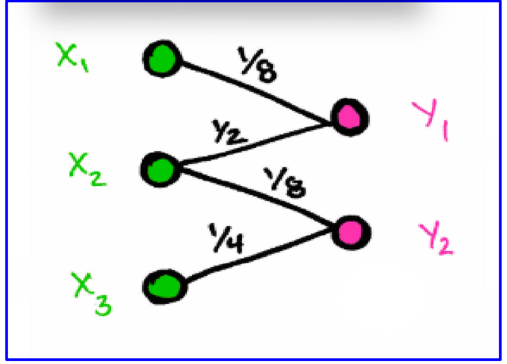
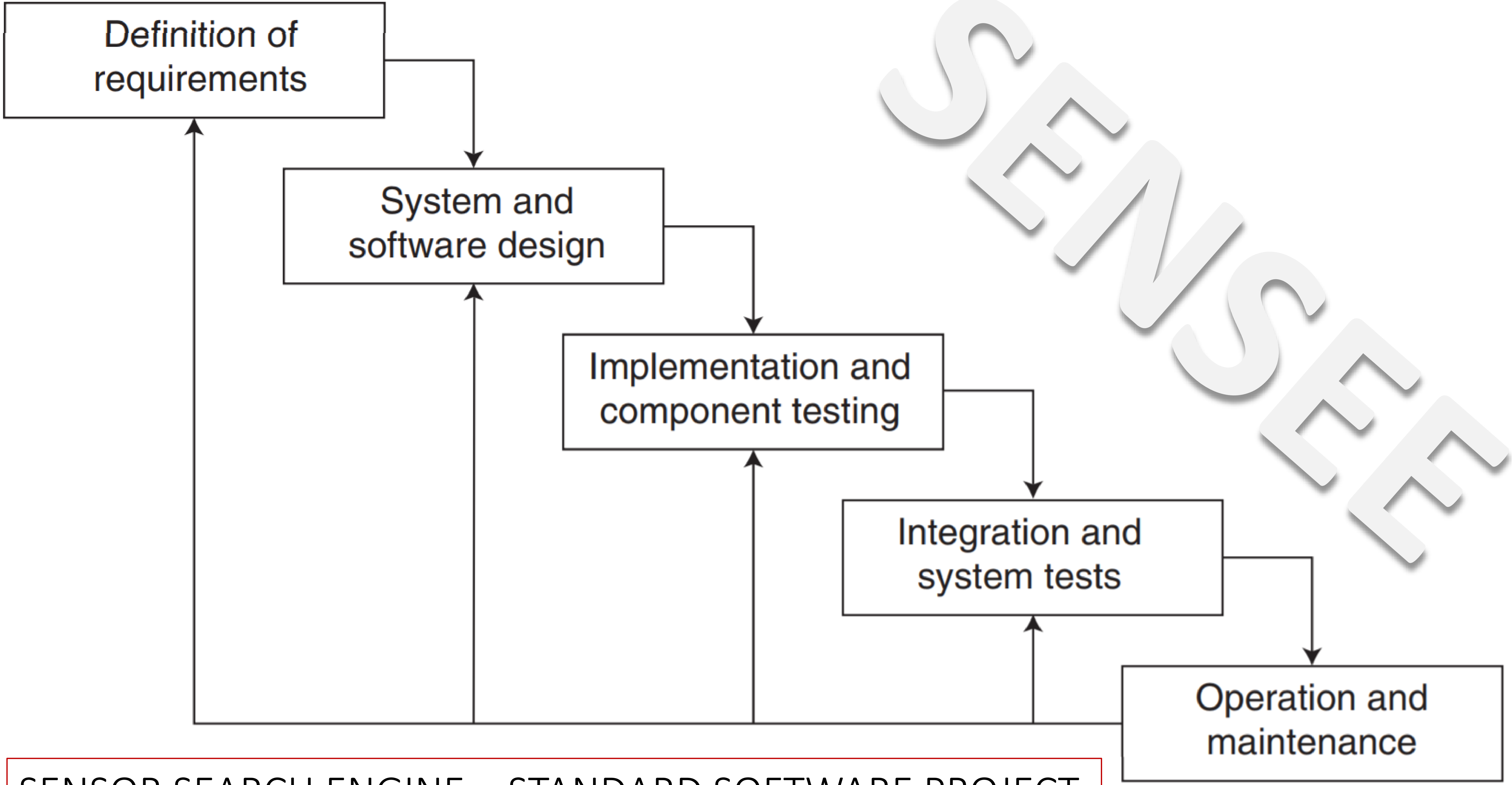


SENSEE

AT THIS TIME, SENSEE 1.0 CONTAINS ONLY SENSOR DESCRIPTIONS (CATEGORIES, ATTRIBUTES). SENSEE CAN ANSWER SELECT QUESTIONS.

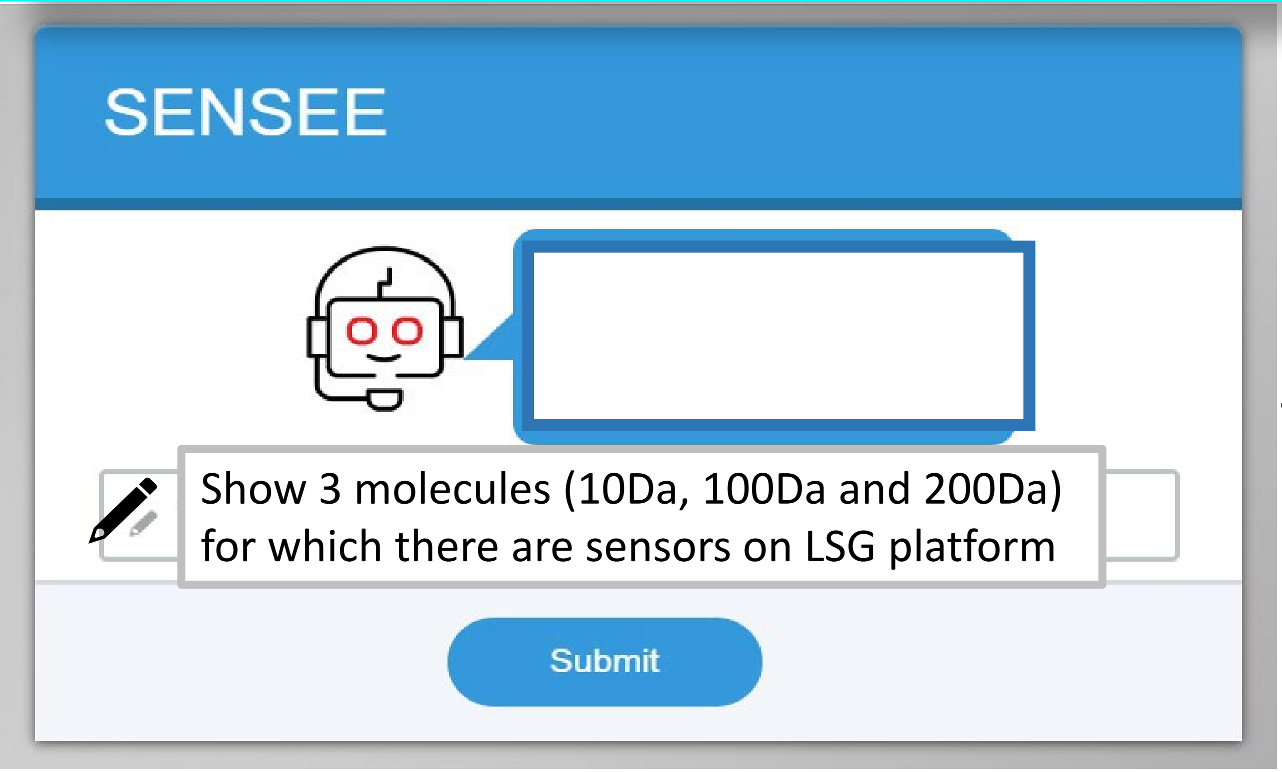
Expert users (academics, students, industrial labs) may benefit from the curated descriptions of sensors. In future, SENSEE may contain a critical mass of sensor descriptions. Google search reveal millions of docs but SENSEE is a curated list.

In the future, SENSEE will contain sensor descriptions (categories, attributes) **and** select **data** from specific sensors. Sensor data ingested in SENSEE will be determined by use cases for specific end-users (farms, grocery stores, food warehouse, food processing, packaging, retail distribution, logistics, agri-business, machine tools, supply chain).



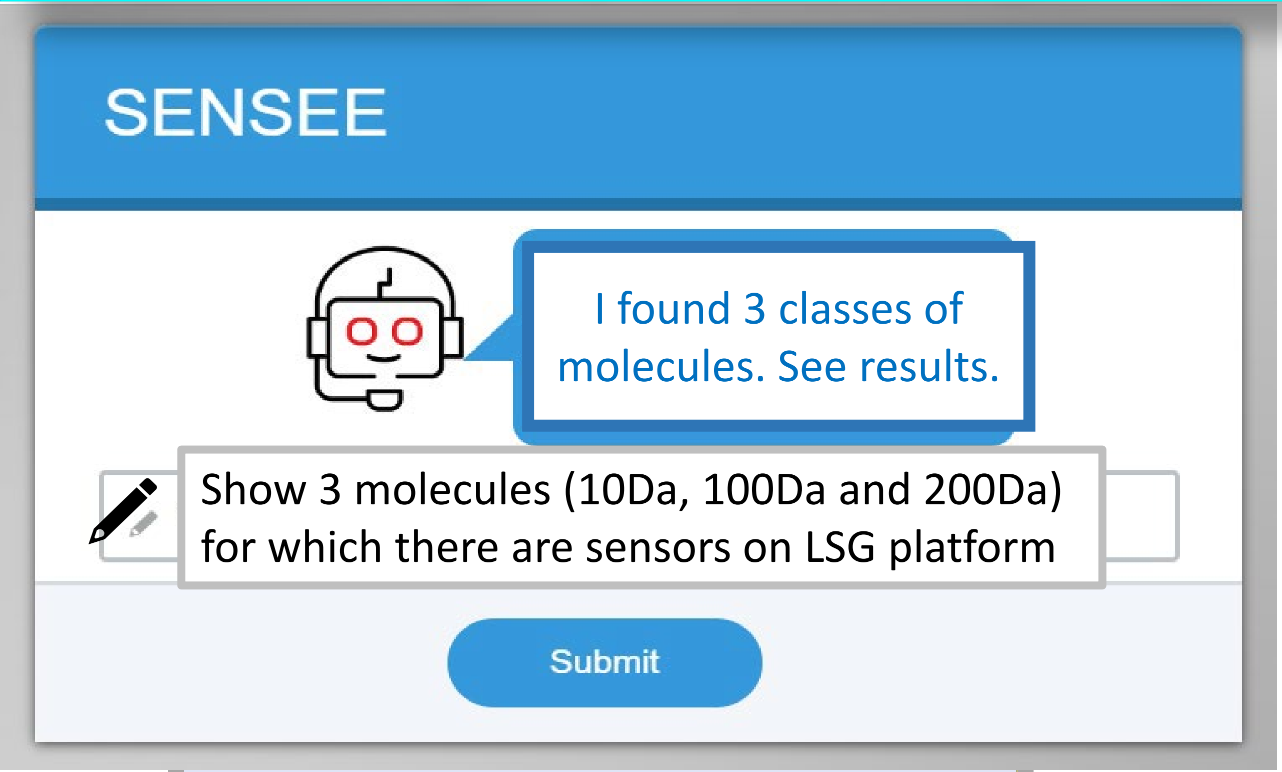
SENSOR SEARCH ENGINE – STANDARD SOFTWARE PROJECT

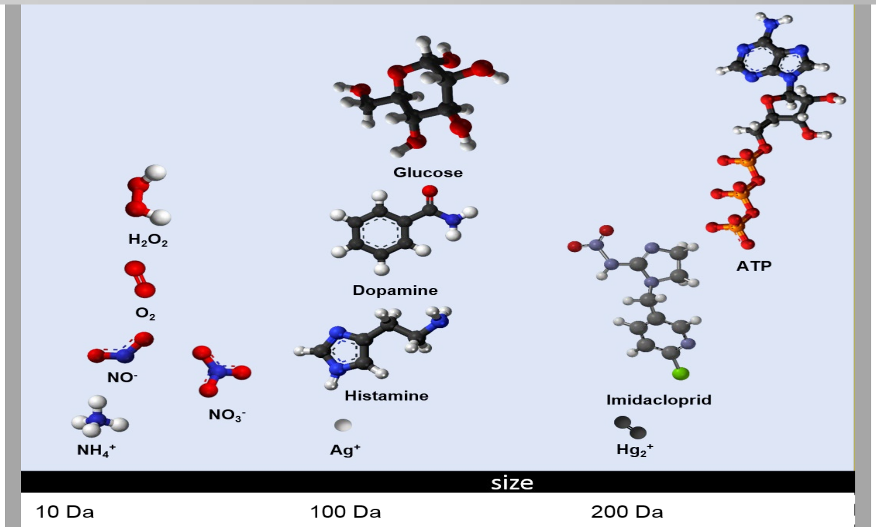
Experts can query SENSEE and perhaps receive a decent answer, in the near future



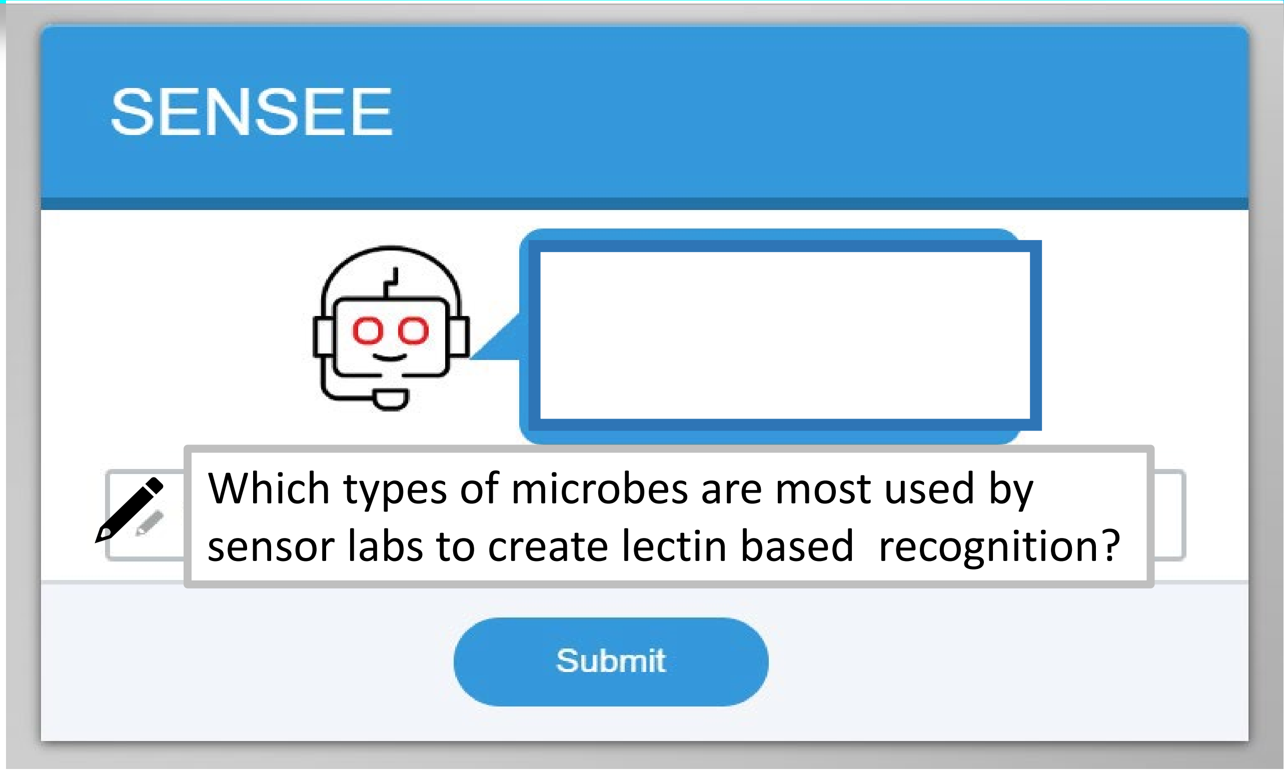
SENSEE WEB SERVICE (MOBILE APP EQUIVALENT)

Experts can query SENSEE and perhaps receive a decent answer, in the near future





Experts can query SENSEE and perhaps receive a decent answer, in the near future



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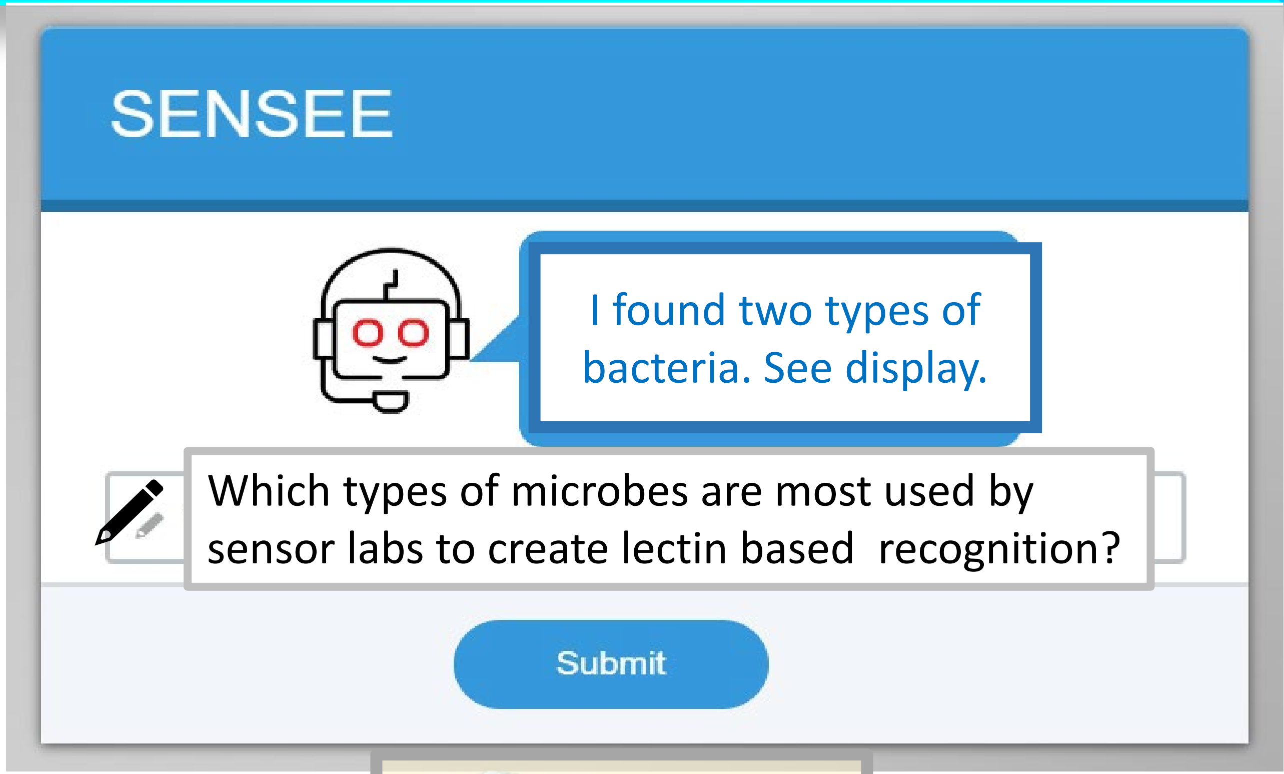
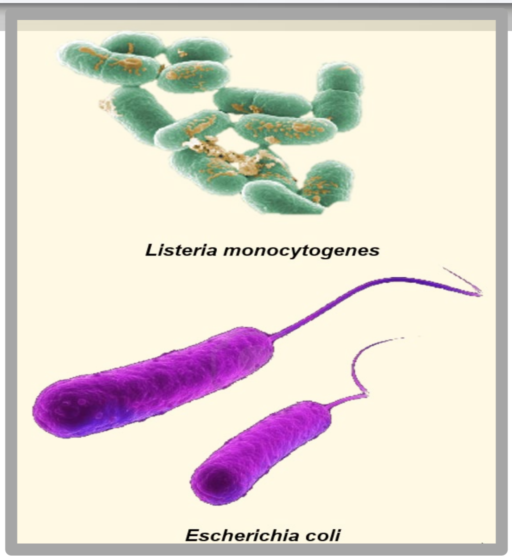
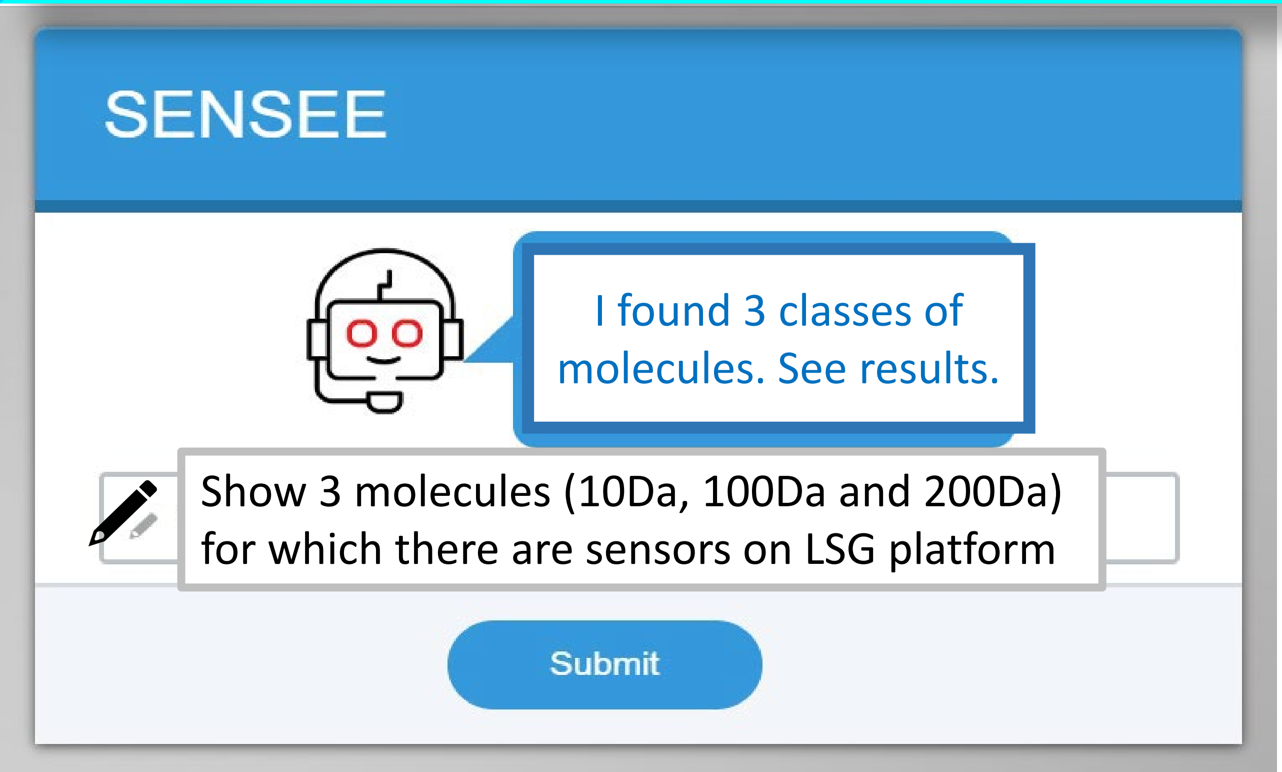
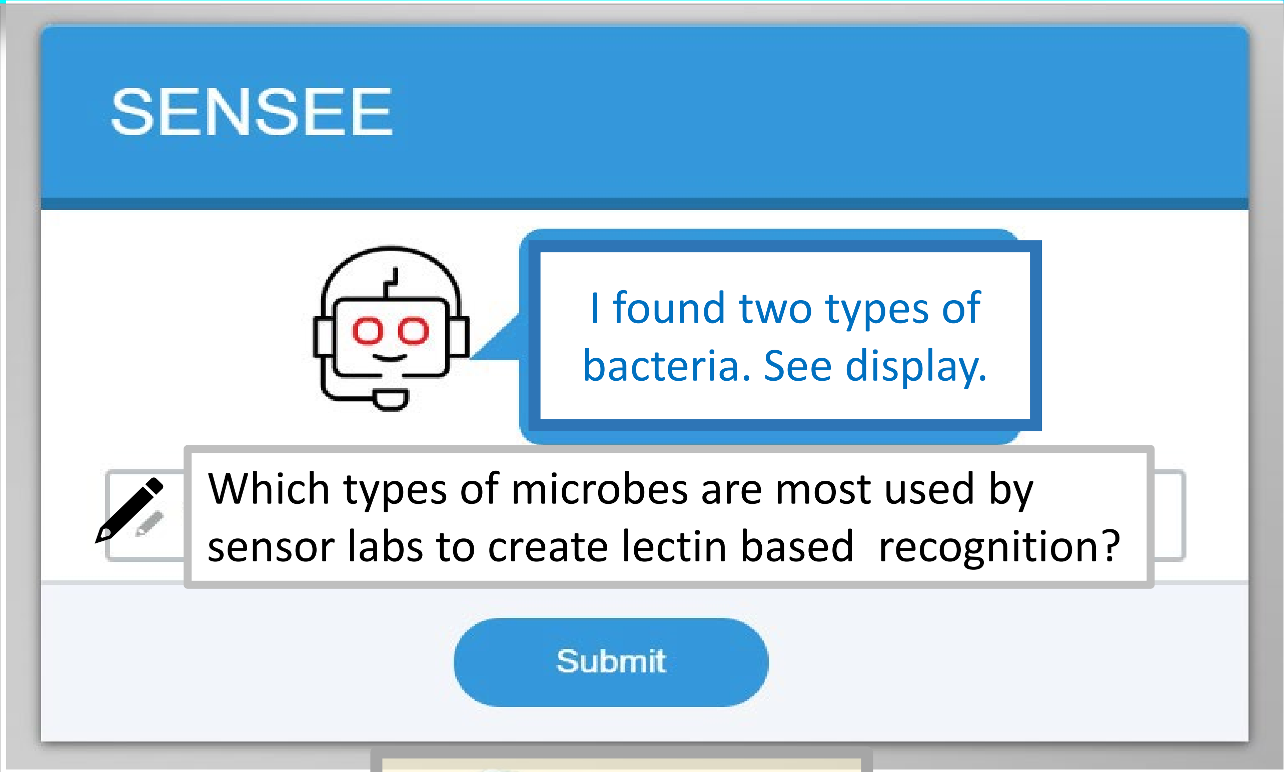
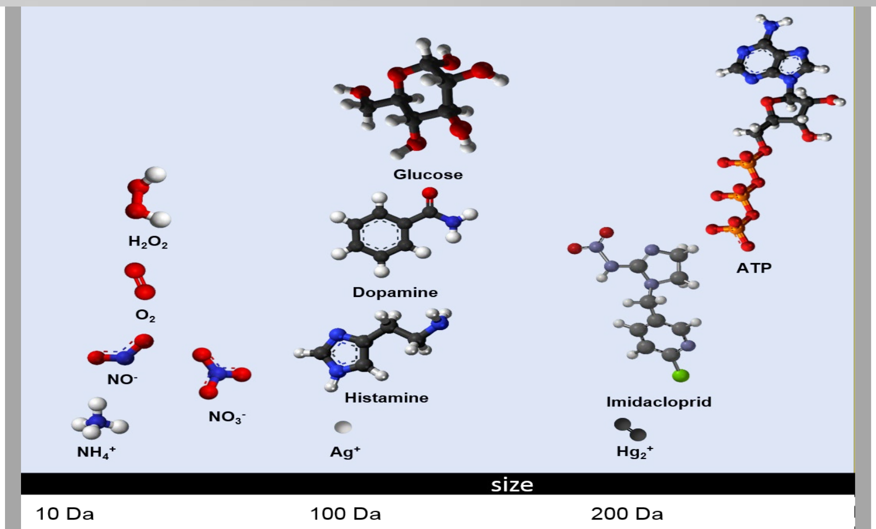


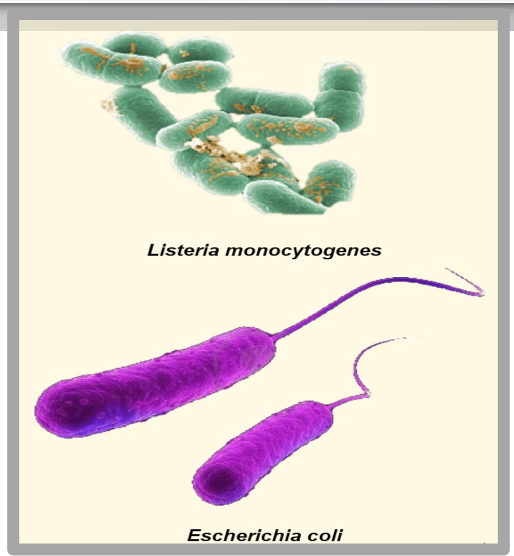


Experts may query SENSEE but is SENSEE capable of facing complex questions?



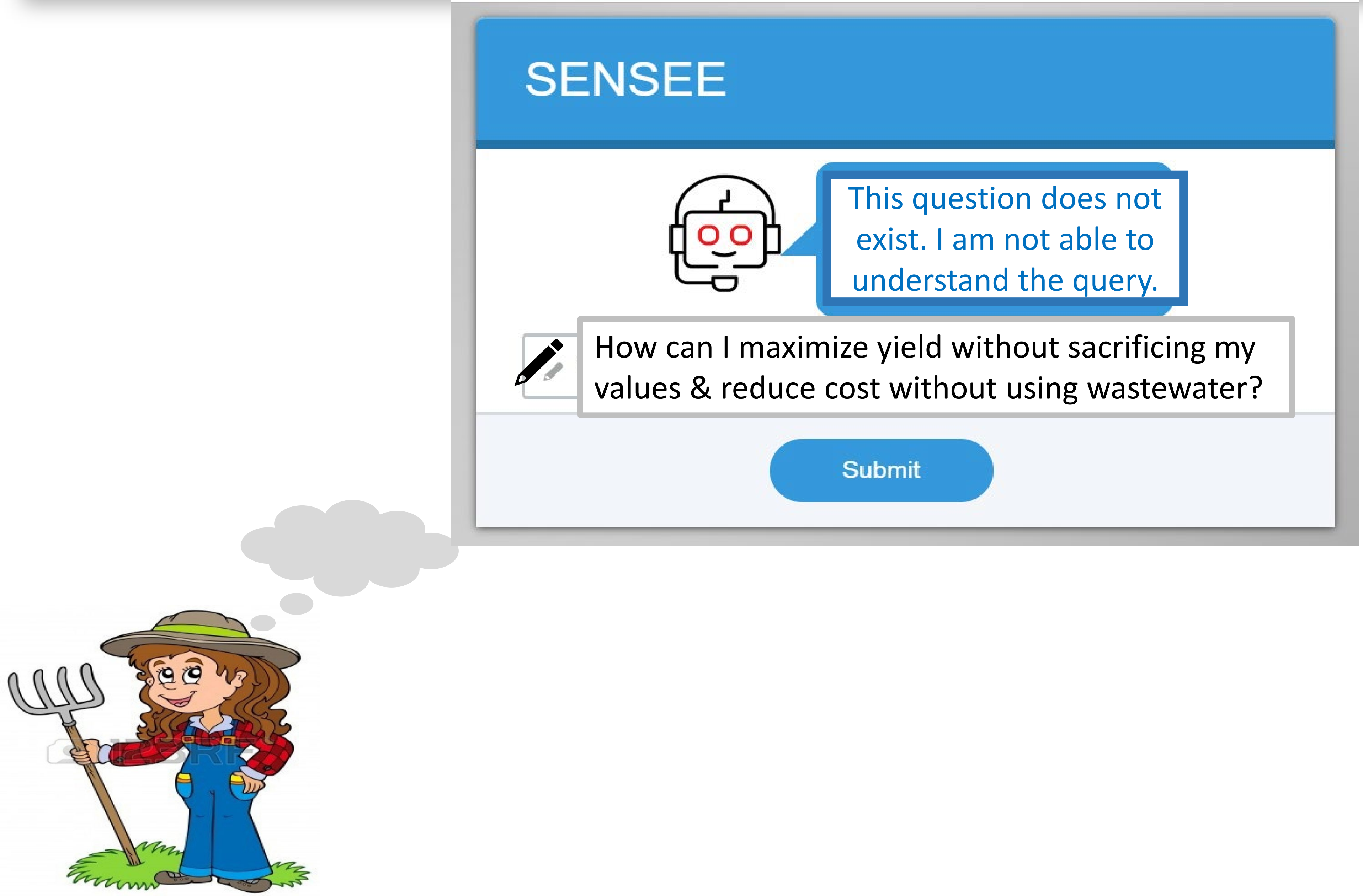






End-user perspective and questions from the field (agro-ecosystem) are complex

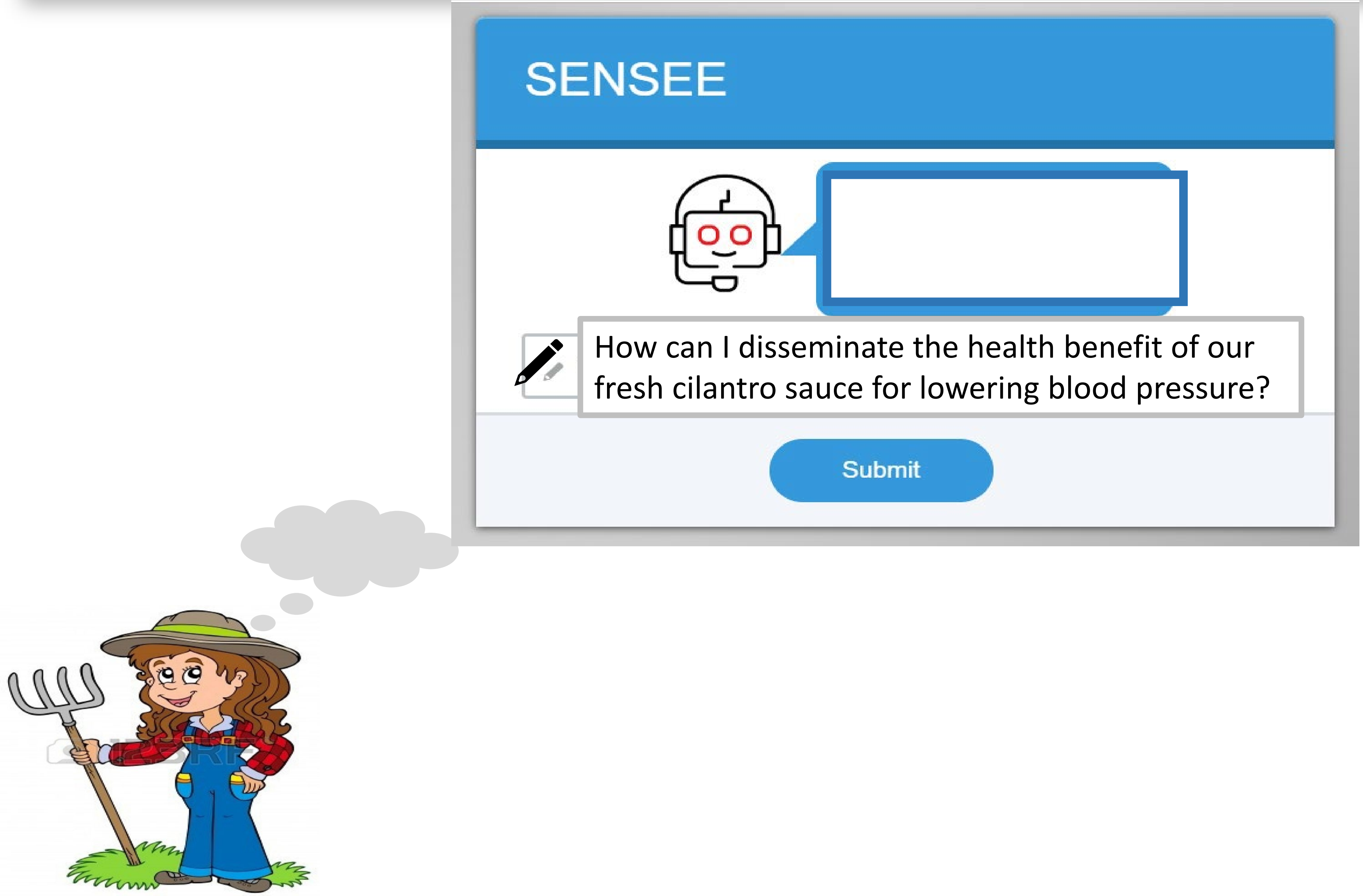
End-user perspective and questions from the field (agro-ecosystem) are complex



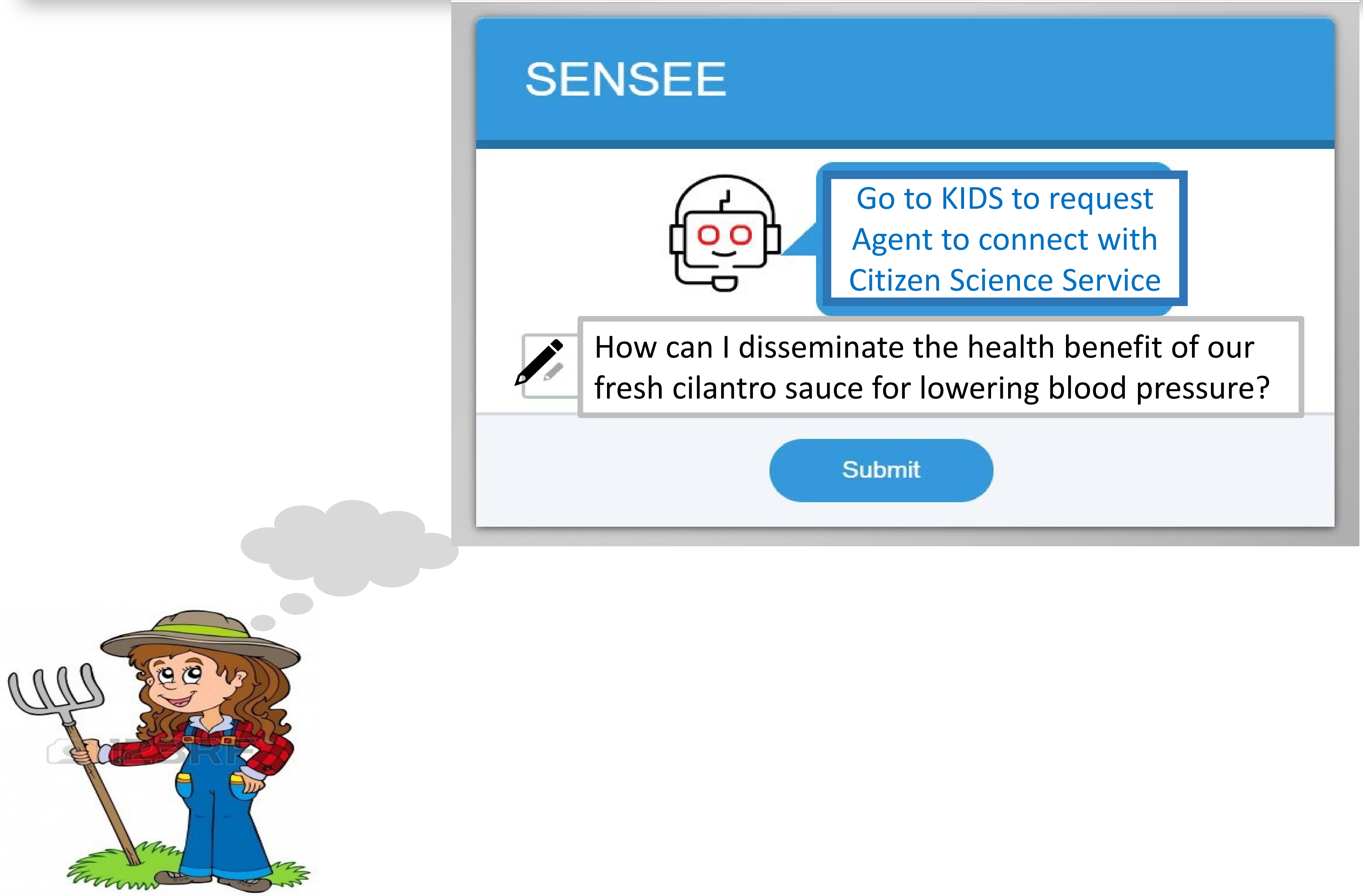
SENSEE 1.0 CANNOT HELP

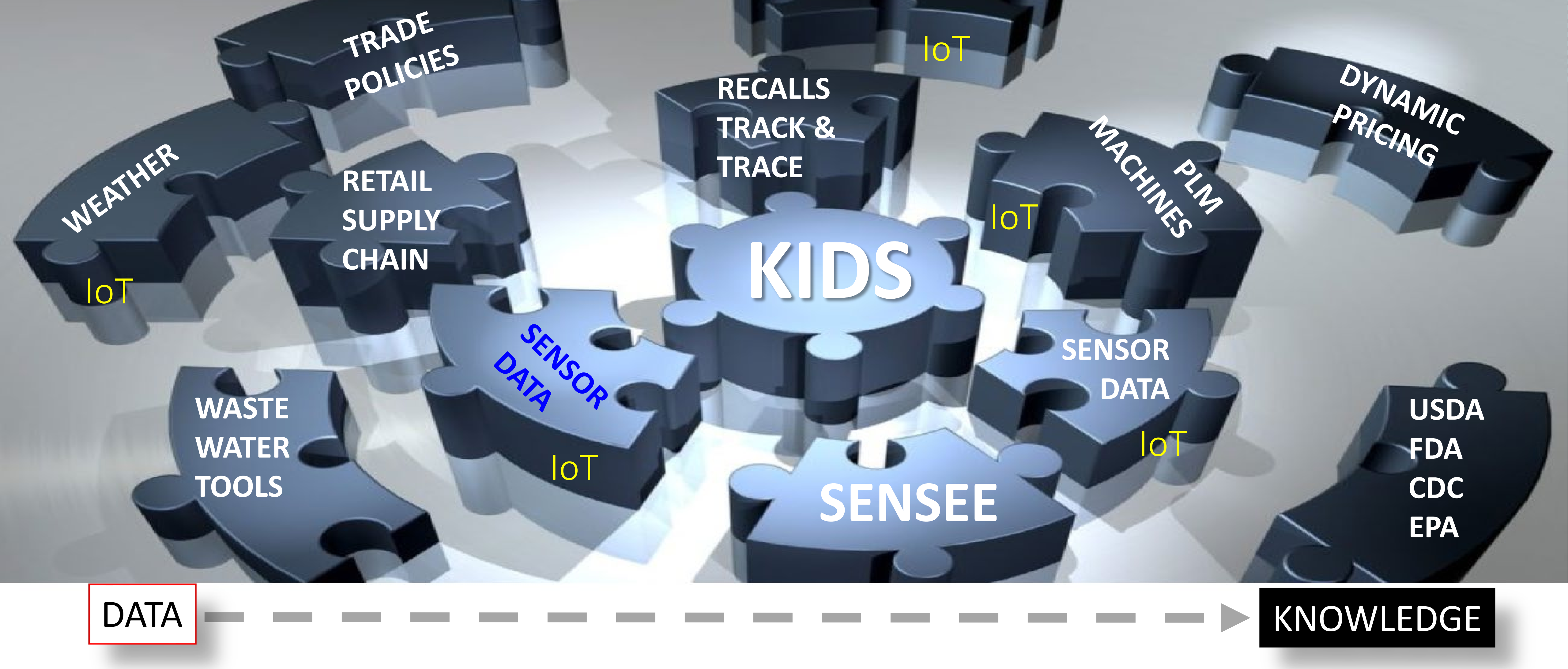
CAN ART HELP? CAN KIDS HELP?

End-user perspective and questions from the field (agro-ecosystem) are complex

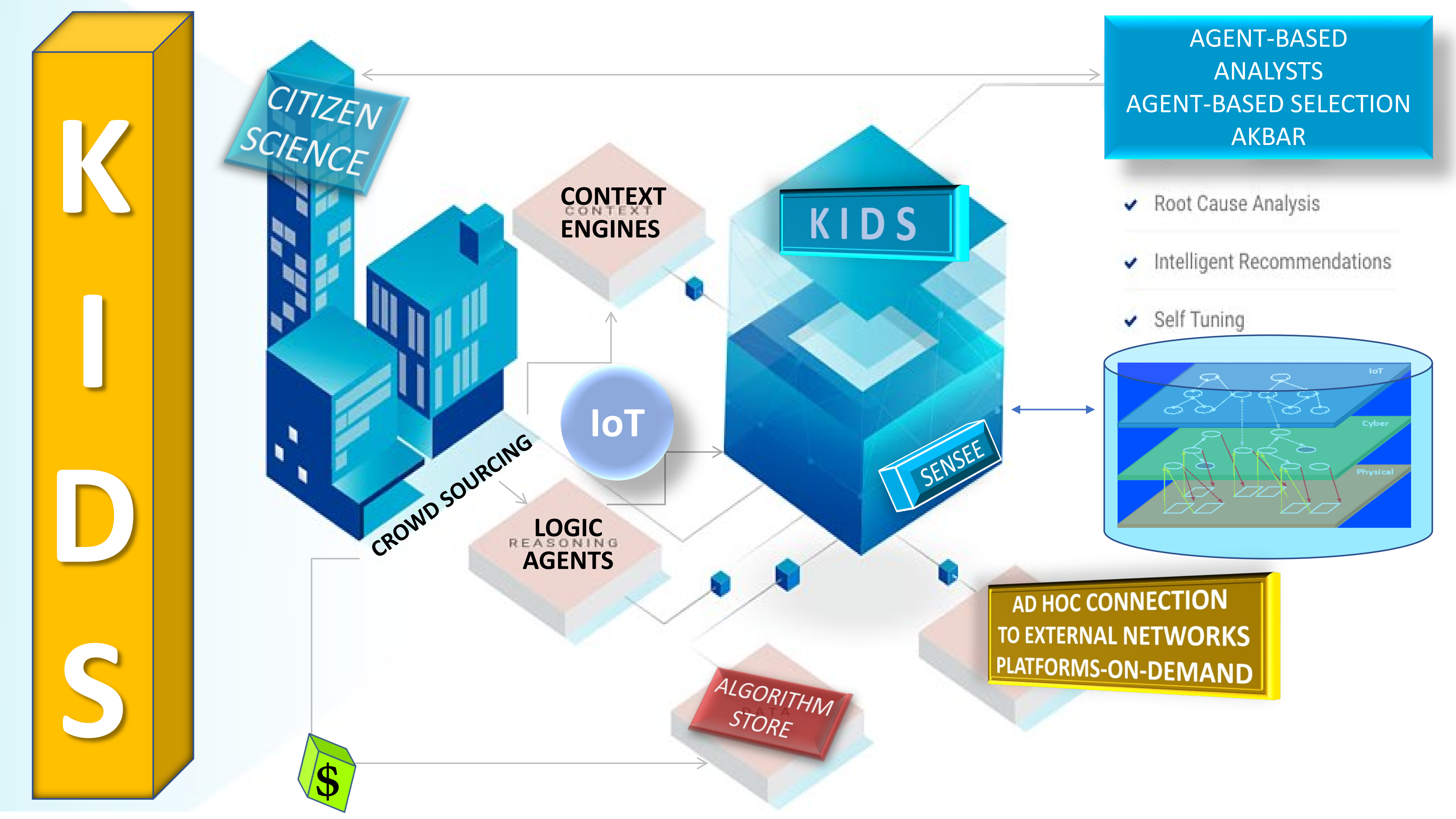


End-user perspective and questions from the field (agro-ecosystem) are complex



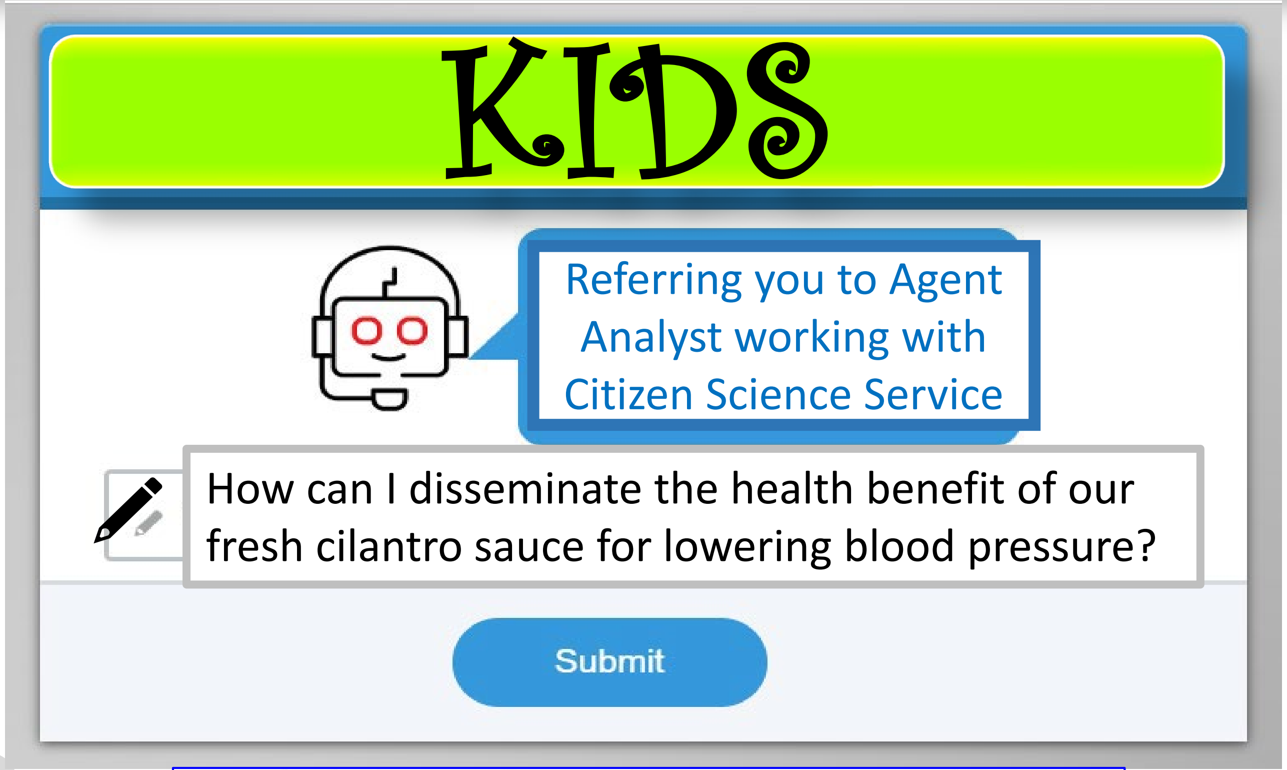


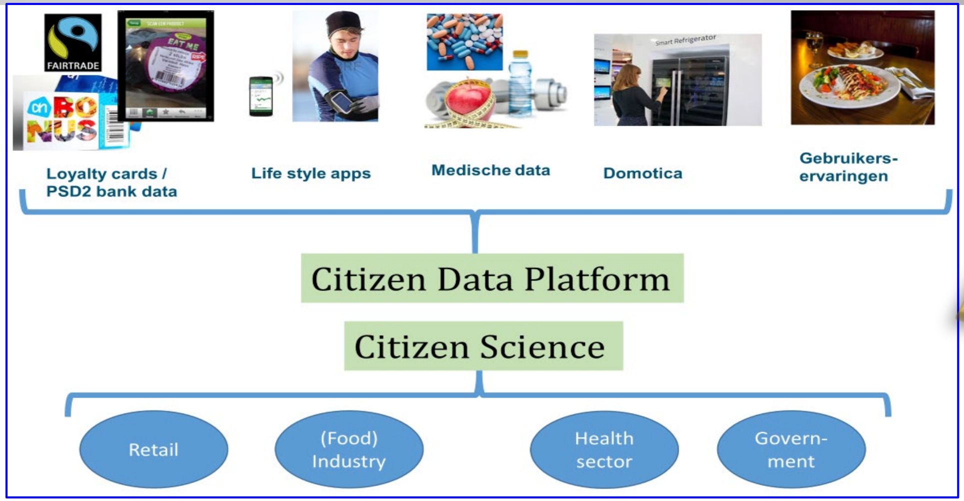
HOW KIDS IS DESIGNED TO ADDRESS COMPLEXITY. LET US TAKE ANOTHER LOOK.



KIDS
CITIZEN SCIENCE
CONTEXT ENGINES
KIDS
AGENT-BASED ANALYSTS
AGENT-BASED SELECTION
AKBAR
Root Cause Analysis
Intelligent Recommendations
Self Tuning
IoT
Cyber
Physical
IoT
SENSEE
CROWD SOURCING
LOGIC REASONING AGENTS
AD HOC CONNECTION
TO EXTERNAL NETWORKS
PLATFORMS-ON-DEMAND
ALGORITHM STORE
$

End-user perspective and questions from the field (agro-ecosystem) are complex

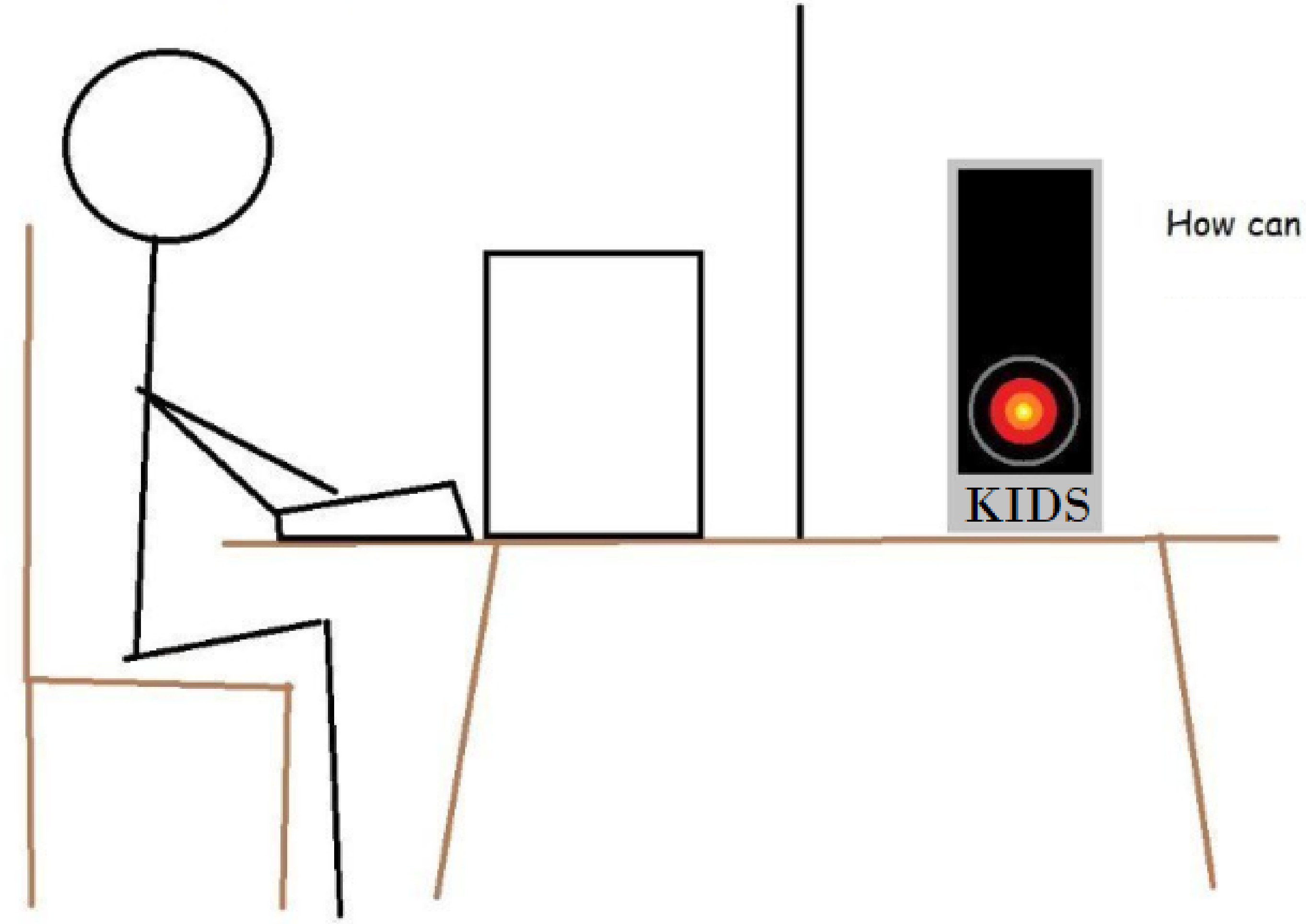




https://www.slideshare.net/knoesis/shreyansh-thesis-defense

K I D S

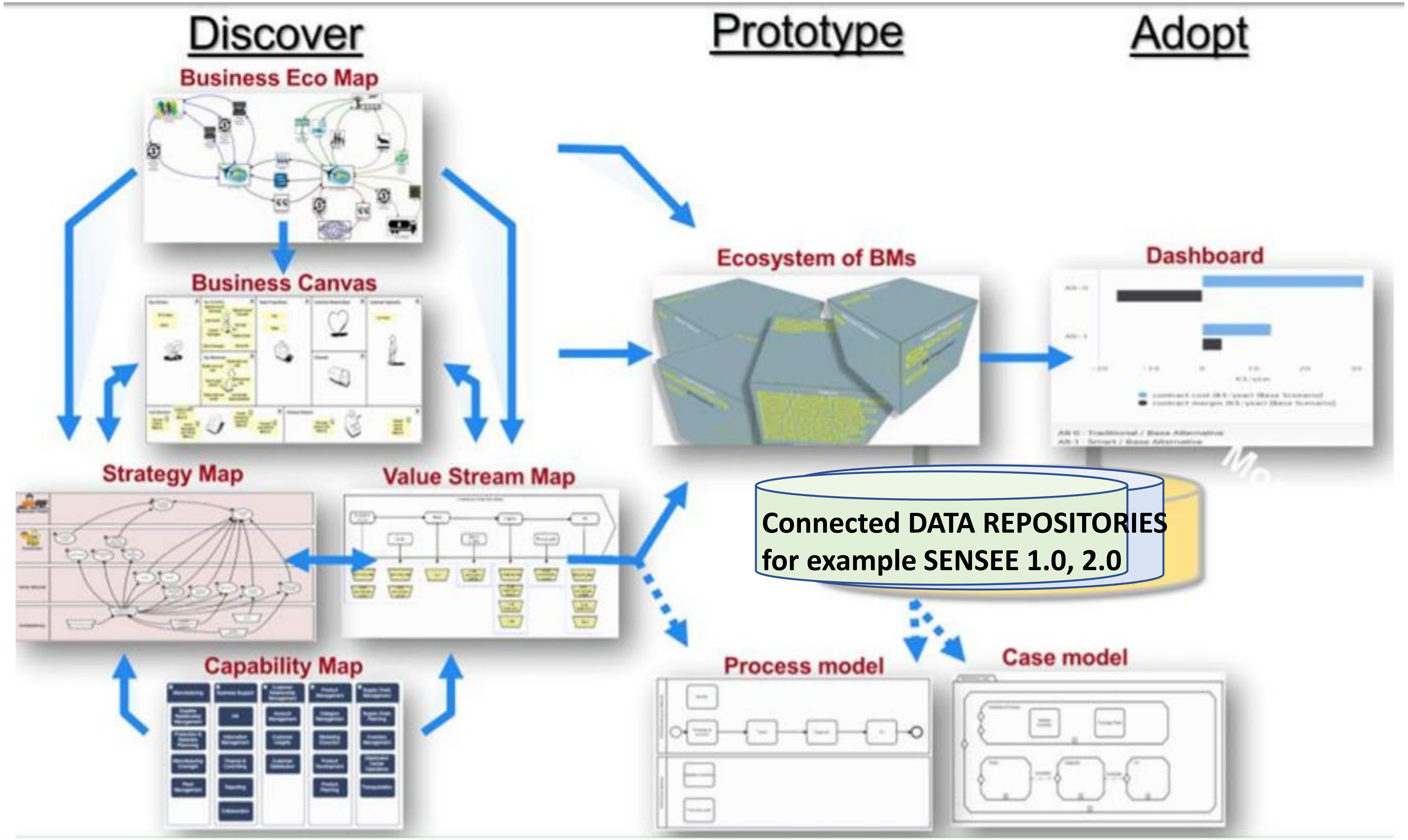
The use of Agents as virtual chat bots are common and may be modified for the agro-ecosystem.



Microsoft Virtual Agent and Dynamics 365 for Finance and Operations

KIDS

Dynamic discovery & composability of graph networks for continuous value modeling relative to demand.



www.vdmbee.com/wp-content/vmp-library/e-books/VDML_Based_CAV_Business_Modeling_V2.2.pdf

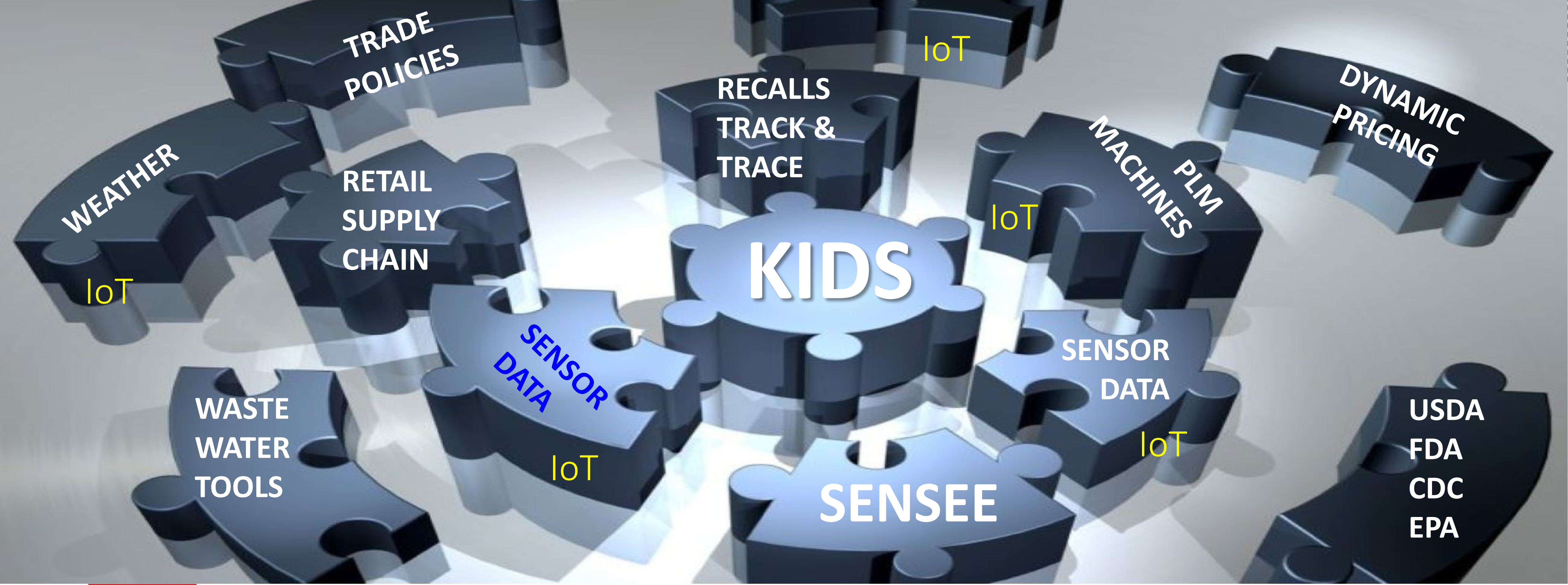
Continuous Business Model Planning - https://www.vdmbee.com/wp-content/vmp-library/e-books/VMBO_2019_paper_v1.pdf

End-user perspective and questions from the field (agro-ecosystem) are complex

PEAS, KIDS

makes sense?

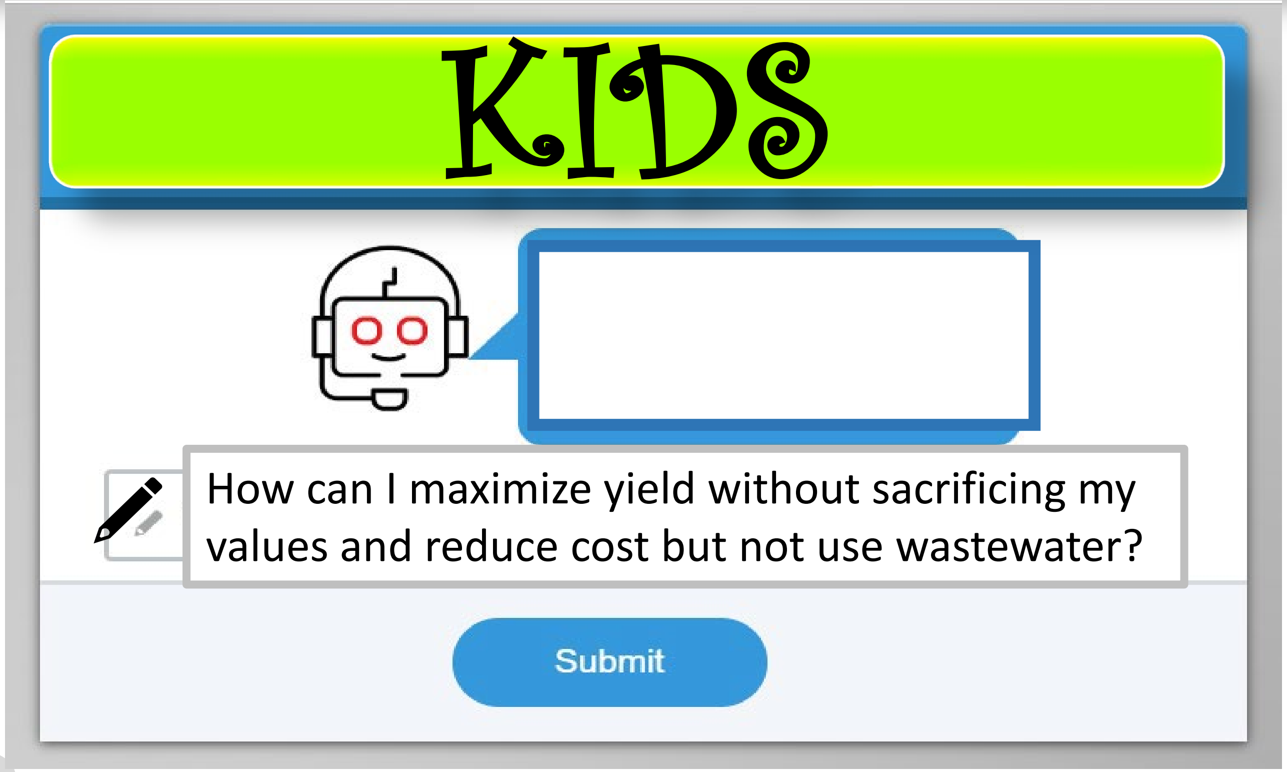
WHY SENSEE IS JUST A TINY STEP IN OUR JOURNEY TO KNOWLEDGE-INFORMED DECISIONS (KIDS)



DATA → KNOWLEDGE

How can I maximize yield without sacrificing my values and reduce cost but not use wastewater?

Can KIDS answer end-user questions? We don't know but that is the expectation.



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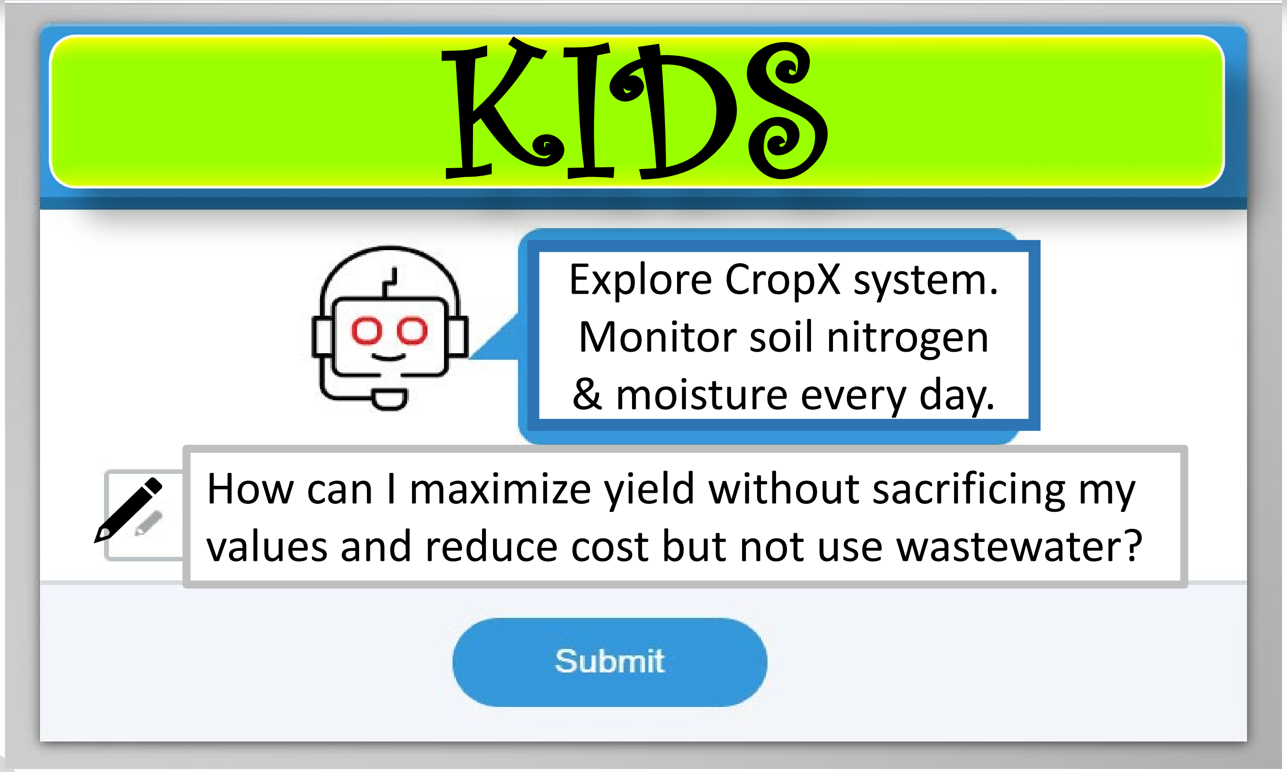


SENSEE

A journey of a thousand miles begins with a single step.

Developing SENSEE 1.0

Quote from Lao Tzu

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Spreadsheet

Sensor Properties

Library
PoC
DB

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Spreadsheet

Sensor Properties

	A	B	C	D	E	F	G	H	I	J	K	L
1	**MW [Da]**	**Category**	**Target**	**Recognition-transduction scheme**	**Platform**	**LOD [M]**	**Max range [M]**	**Selectivity (interferent species tested)**	**Response time [sec]**	**Durability**	**USECAT1**	**Link to paper(s)**
2	1	small molecule	H+	H+ ionophore (liquid)	glass capillary	1.00E-13	1.00E-04	excellent (K+, Na+, Ca2+, Mg2+)	2	High	hydroponics	https://www.ncbi.nlm.nih.gov/pubmed/26088926
3	1	small molecule	H+	anthocyanin/nanocellulose	paper filter	1.00E-15	1.00E-02	excellent	2	high	irrigation water	https://www.ncbi.nlm.nih.gov/pubmed/28884510
4	18	small molecule	Ammonium	NH4+ ionophore (liquid)	glass capillary	5.00E-09	1.00E-01	excellent	5	medium	wastewater	http://www.allelopathyjournal.org/archives/?Year=2016&Vol=37&Issue=2&Month=3
5	18	small molecule	Ammonium	NH4+ ionophore (solid)	LSG	2.80E-05	5.00E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
6	30	small molecule	N/O radicals	nanoplatinum/nanoceria	Pt electrode	1.00E-08	3.00E-06	medium	1	medium	ocean water	https://pubs.rsc.org/en/Content/ArticleLanding/2017/AY/C7AY01964E#!divAbstract
7	32	small molecule	DO	Pt porphyrin-nTiO2	fiber optic	1.00E-06	5.00E-06	excellent, temp sens	1	High	hydroponic media	https://www.sciencedirect.com/science/article/pii/S0925400514001117
8	32	small molecule	DO	Pt porphyrin	96 well	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	https://www.sciencedirect.com/science/article/pii/S016770121300331X
9	32	small molecule	DO	Pt porphyrin	glass vial	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	
10	34	small molecule	H2O2	fractal nPt	Pt electrode	5.00E-09	5.00E-05	excellent	1	high	ocean water	https://www.ncbi.nlm.nih.gov/pubmed/27121177
11	39	small molecule	K+	K+ ionophore (liquid)	glass capillary	1.00E-06	2.50E-01	excellent	2	low	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/24961073
12	41	small molecule	Ca2+	Ca2+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-01	excellent	1	low	Hoaglands media	https://onlinelibrary.wiley.com/doi/full/10.1002/jpln.201700319
13	58	small molecule	acetone	chemosensory proteins-nPt	Pt electrode	5.00E-06	1.00E-05	high	10	low	buffer	https://pubs.rsc.org/en/content/articlelanding/2018/an/c8an00065d#!divAbstract
14	62	small molecule	Nitrate	NO3- ionophore (liquid)	glass capillary	1.00E-06	2.00E-01	excellent	2	medium	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/18985610
15	62	small molecule	Nitrate	NO3- ionophore (solid)	LSG	2.00E-05	1.50E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
16	108	small molecule	Ag+	Ag+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-02	excellent	2	high	wound dressing	https://link.springer.com/article/10.1007/s11356-014-3058-6
17	111	small molecule	histamine	diamine oxidase-nCu	LSG	6.30E-05	1.00E-03	excellent	2	medium	fermented fish	https://www.mdpi.com/2079-6374/8/2/42
18	147	small molecule	Glutamate	CNT/nPt/GlOx	Pt electrode	1.00E-06	1.00E-03	excellent	2	low	INS1 tissue culture	https://www.sciencedirect.com/science/article/pii/S0165027010001196
19	147	small molecule	Glutamate	CNT/nPt/GlOx	Si biochip	1.00E-06	5.00E-01	excellent	2	low	INS1 tissue culture	https://pubs.rsc.org/en/content/articlelanding/2011/jm/c1jm11561h#!divAbstract
20	154	small molecule	catecholamines	nPt	LSG	5.00E-07	3.00E-03	excellent	2	high	ocean water	
21	154	small molecule	catecholamines	graphene anchored nCuO	LSG	3.00E-07	3.00E-03	high	2	medium	buffer	https://pubs.acs.org/doi/abs/10.1021/acssuschemeng.8b02510
22	176	small molecule	indole acetic acid	fractal nPt	Pt/Ir microwire	1.00E-06	1.00E-03	high	1	high	root growth media	https://link.springer.com/article/10.1007/s00344-017-9688-4
23	181	small molecule	Glucose	nPt/GOx	graphene paper	8.00E-08	1.00E-03	excellent	2	medium	buffer	https://www.ncbi.nlm.nih.gov/pubmed/27209574
24	181	small molecule	Glucose	nPt/GOx	Pt/Ir microwire	1.00E-07	5.00E-06	excellent	1	medium	blood	https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0166557
25	181	small molecule	Glucose	nPt/nCe/GOx	Pt electrode	1.00E-07	3.00E-06	excellent	1	medium	buffer	https://www.sciencedirect.com/science/article/pii/S0956566314000992

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Spreadsheet

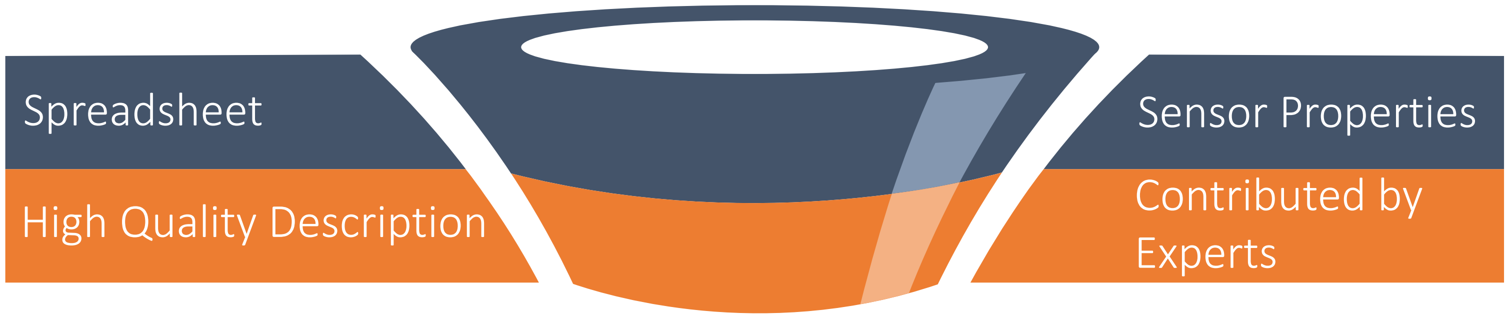
Sensor Properties

	A	B	C	D	E	F	G	H	I	J	K	L
1	**MW [Da]**	**Category**	**Target**	**Recognition-transduction scheme**	**Platform**	**LOD [M]**	**Max range [M]**	**Selectivity (interferent species tested)**	**Response time [sec]**	**Durability**	**USECAT1**	**Link to paper(s)**
2	1	small molecule	H^+	H^+ ionophore (liquid)	glass capillary	1.00E-13	1.00E-04	excellent (K^+, Na^+, Ca^{2+}, Mg^{2+})	2	High	hydroponics	https://www.ncbi.nlm.nih.gov/pubmed/26088926
3	1	small molecule	H^+	anthocyanin/nanocellulose	paper filter	1.00E-15	1.00E-02	excellent	2	high	irrigation water	https://www.ncbi.nlm.nih.gov/pubmed/28884510
4	18	small molecule	Ammonium	NH_4^+ ionophore (liquid)	glass capillary	5.00E-09	1.00E-01	excellent	5	medium	wastewater	http://www.allelopathyjournal.org/archives/?Year=2016&Vol=37&Issue=2&Month=3
5	18	small molecule	Ammonium	NH_4^+ ionophore (solid)	LSG	2.80E-05	5.00E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
6	30	small molecule	N/O radicals	nanoplatinum/nanoceria	Pt electrode	1.00E-08	3.00E-06	medium	1	medium	ocean water	https://pubs.rsc.org/en/Content/ArticleLanding/2017/AY/C7AY01964E#!divAbstract
7	32	small molecule	DO	Pt porphyrin-nTiO_2	fiber optic	1.00E-06	5.00E-06	excellent, temp sens	1	High	hydroponic media	https://www.sciencedirect.com/science/article/pii/S0925400514001117
8	32	small molecule	DO	Pt porphyrin	96 well	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	https://www.sciencedirect.com/science/article/pii/S016770121300331X
9	32	small molecule	DO	Pt porphyrin	glass vial	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	
10	34	small molecule	H_2O_2	fractal nPt	Pt electrode	5.00E-09	5.00E-05	excellent	1	high	ocean water	https://www.ncbi.nlm.nih.gov/pubmed/27121177
11	39	small molecule	K^+	K^+ ionophore (liquid)	glass capillary	1.00E-06	2.50E-01	excellent	2	low	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/24961073
12	41	small molecule	Ca^{2+}	Ca^{2+} ionophore (liquid)	glass capillary	1.00E-06	5.00E-01	excellent	1	low	Hoaglands media	https://onlinelibrary.wiley.com/doi/full/10.1002/jpln.201700319
13	58	small molecule	acetone	chemosensory proteins-nPt	Pt electrode	5.00E-06	1.00E-05	high	10	low	buffer	https://pubs.rsc.org/en/content/articlelanding/2018/an/c8an00065d#!divAbstract
14	62	small molecule	Nitrate	NO_3^- ionophore (liquid)	glass capillary	1.00E-06	2.00E-01	excellent	2	medium	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/18985610
15	62	small molecule	Nitrate	NO_3^- ionophore (solid)	LSG	2.00E-05	1.50E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
16	108	small molecule	Ag^+	Ag^+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-02	excellent	2	high	wound dressing	https://link.springer.com/article/10.1007/s11356-014-3058-6
17	111	small molecule	histamine	diamine oxidase-nCu	LSG	6.30E-05	1.00E-03	excellent	2	medium	fermented fish	https://www.mdpi.com/2079-6374/8/2/42
18	147	small molecule	Glutamate	CNT/nPt/GlOx	Pt electrode	1.00E-06	1.00E-03	excellent	2	low	INS1 tissue culture	https://www.sciencedirect.com/science/article/pii/S0165027010001196
19	147	small molecule	Glutamate	CNT/nPt/GlOx	Si biochip	1.00E-06	5.00E-01	excellent	2	low	INS1 tissue culture	https://pubs.rsc.org/en/content/articlelanding/2011/jm/c1jm11561h#!divAbstract
20	154	small molecule	catecholamines	nPt	LSG	5.00E-07	3.00E-03	excellent	2	high	ocean water	
21	154	small molecule	catecholamines	graphene anchored nCuO	LSG	3.00E-07	3.00E-03	high	2	medium	buffer	https://pubs.acs.org/doi/abs/10.1021/acssuschemeng.8b02510
22	176	small molecule	indole acetic acid	fractal nPt	Pt/Ir microwire	1.00E-06	1.00E-03	high	1	high	root growth media	https://link.springer.com/article/10.1007/s00344-017-9688-4
23	181	small molecule	Glucose	nPt/GOx	graphene paper	8.00E-08	1.00E-03	excellent	2	medium	buffer	https://www.ncbi.nlm.nih.gov/pubmed/27209574
24	181	small molecule	Glucose	nPt/GOx	Pt/Ir microwire	1.00E-07	5.00E-06	excellent	1	medium	blood	https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0166557
25	181	small molecule	Glucose	nPt/nCe/GOx	Pt electrode	1.00E-07	3.00E-06	excellent	1	medium	buffer	https://www.sciencedirect.com/science/article/pii/S0956566314000992

Library
PoC
DB

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

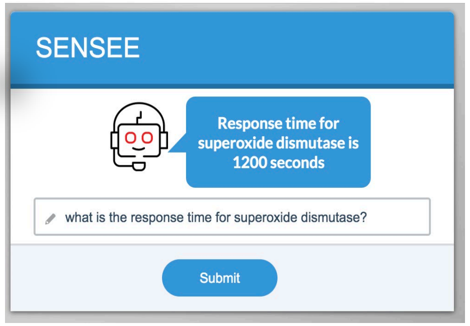
Sensor R&D Community



Library PoC DB

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Sensor R&D Community



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Library
PoC
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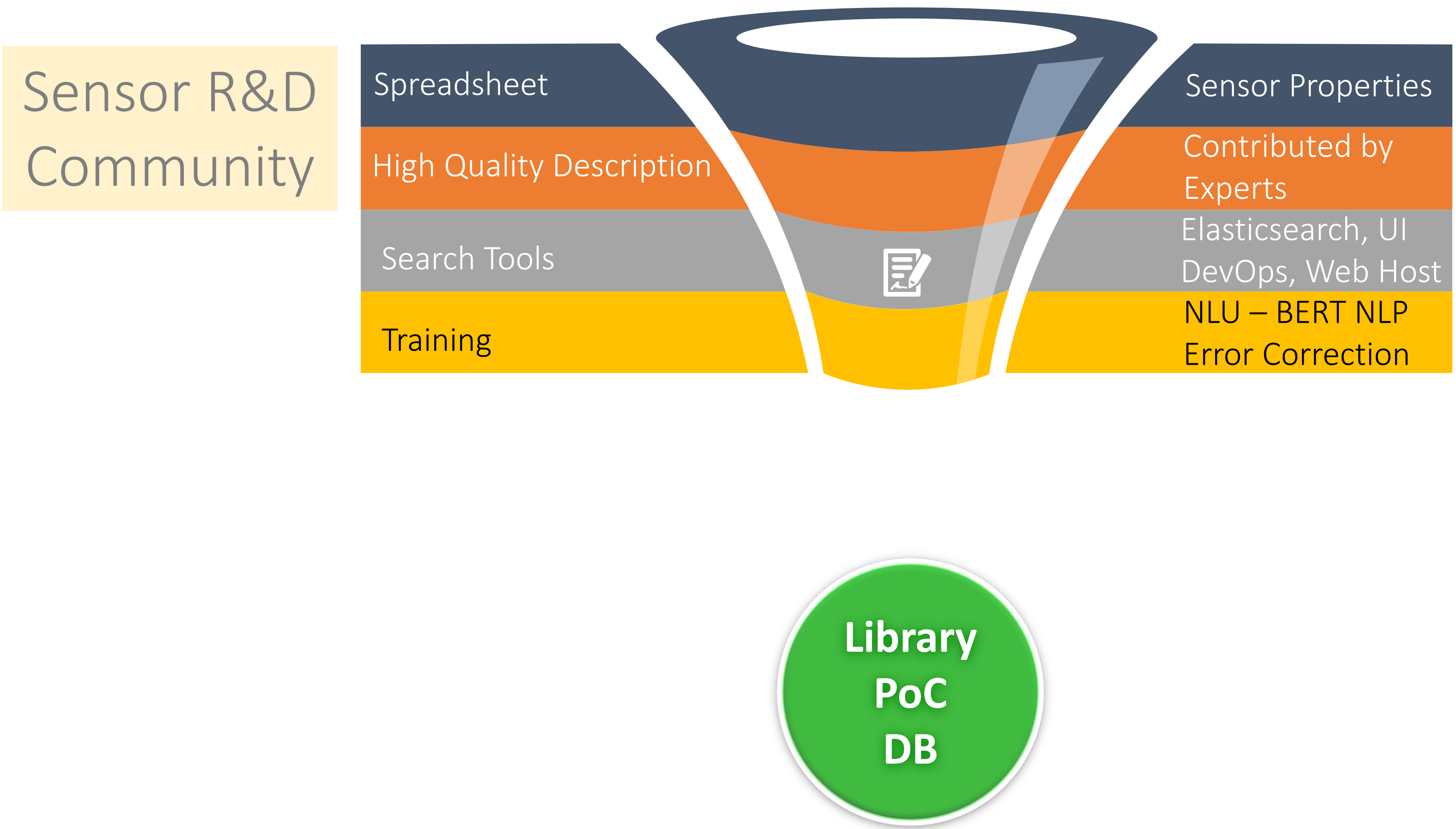
Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

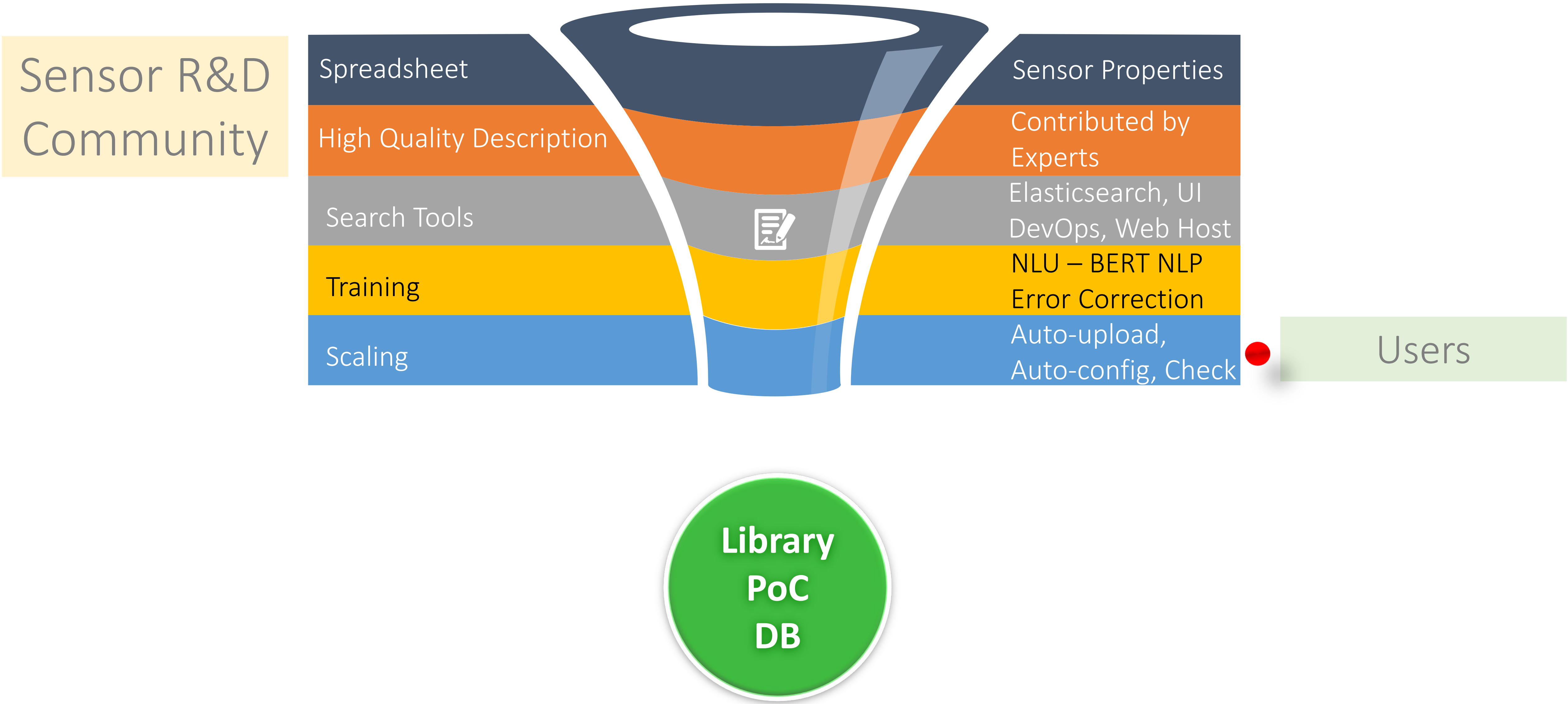


Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Sensor R&D Community

Library
PoC
DB

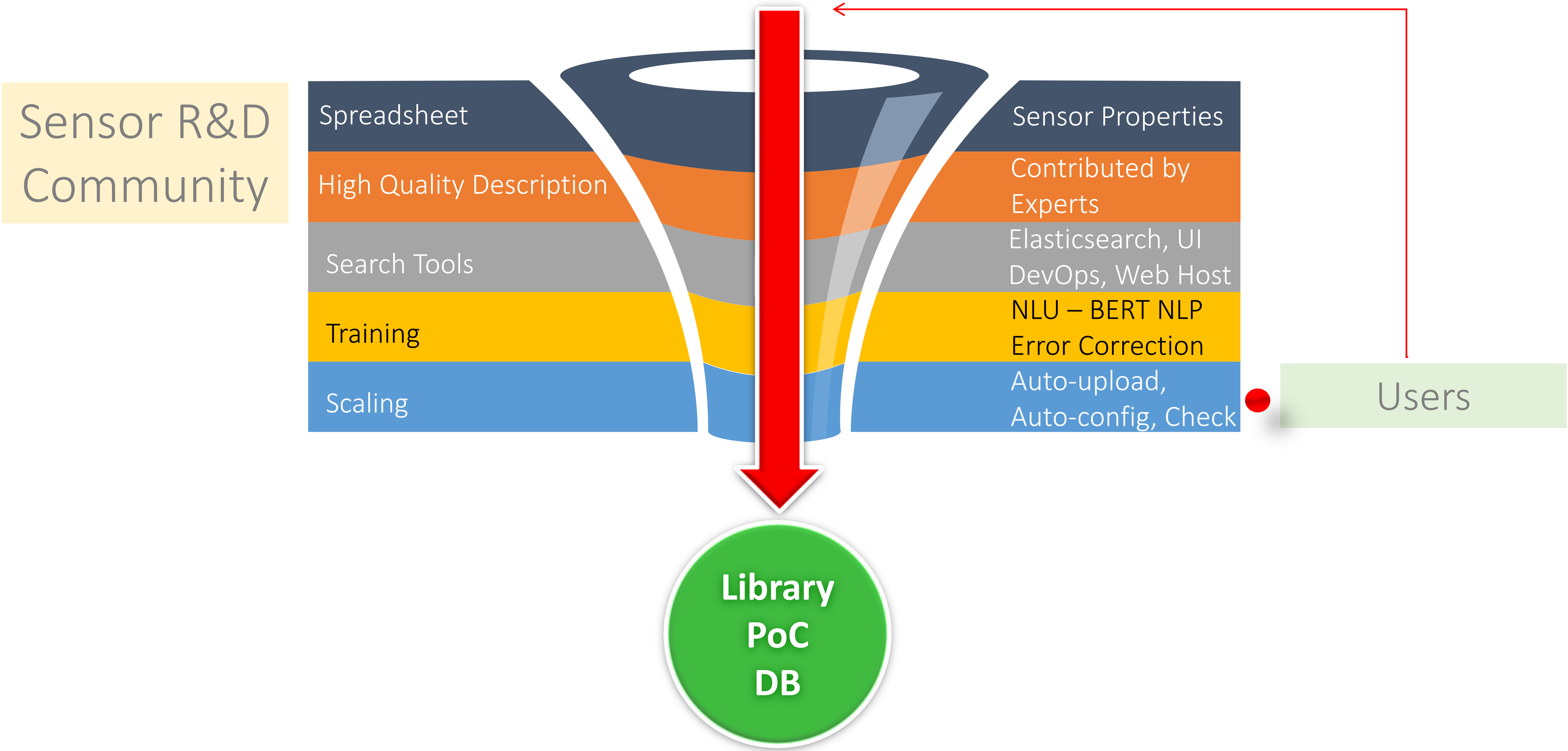
Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)



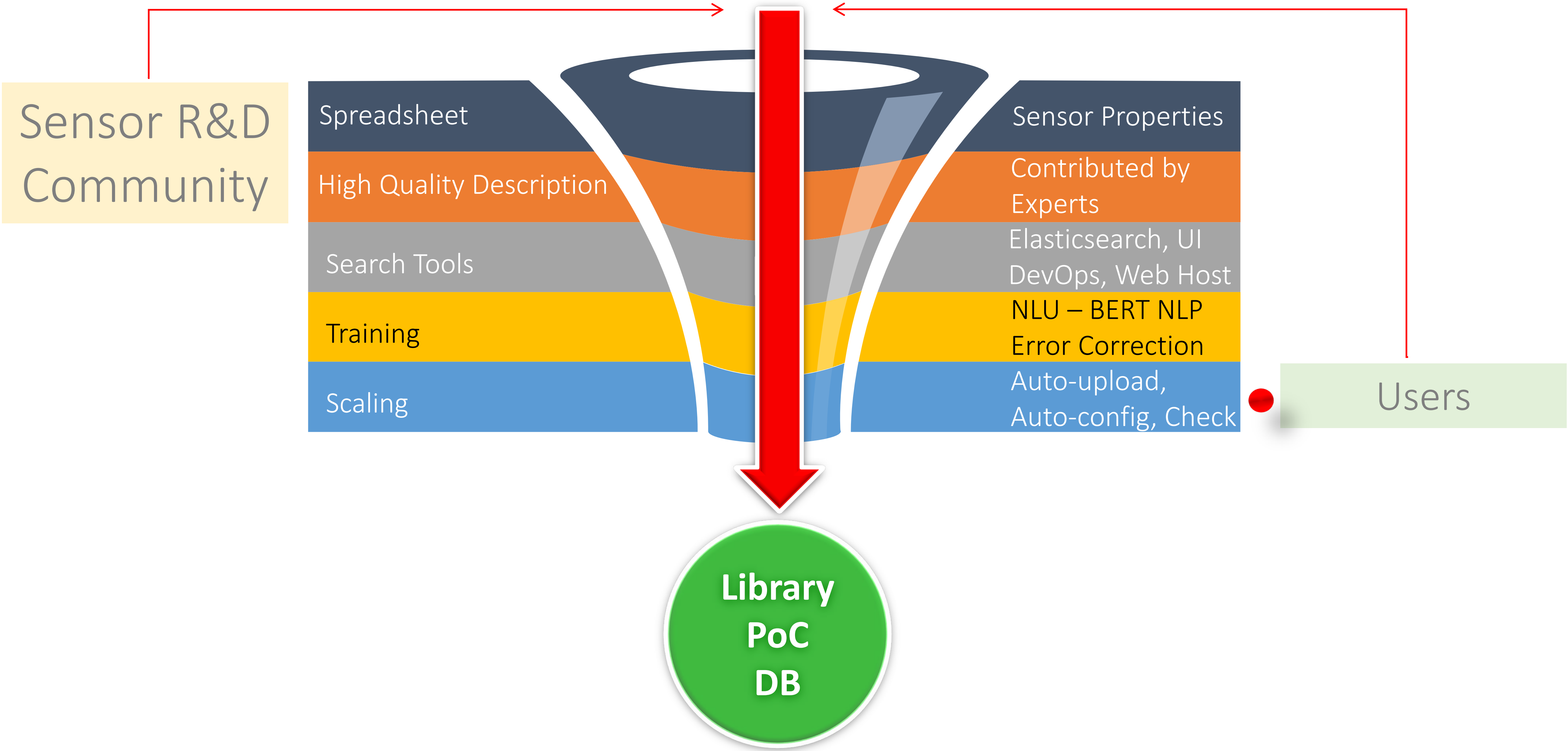
SENSEE 1.0 PROOF OF CONCEPT – TEST QUESTIONS

155) What molecules can be detected in breast milk using biosensors?
156) What is the difference in sensitivity between glucose biosensors based on graphene or platinum foil?
157) What is the most sensitive biosensor based on carbon nanotubes?
158) How many biosensors have been proposed for glucose determination?
159) Anthocyanin is used as a target for which biosensor?
160) Which biosensors can be used for hydroponic medium?
161) In which samples, glutamate and/or glutamine was determined using biosensors?
162) Which biosensors were proposed for catecholamine determination?
163) What is the lowest limit of detection for graphene-based biosensors?
164) What is the maximal range for nitrate biosensors?
165) What platforms can be used for ammonium detection and mercury detection?
166) Most durable recognition-transduction scheme for interferon gamma biosensors?
167) Best limit of detection achieved with phosphotriesterase-based biosensors?
168) How many biosensors were described for ATP determination?
169) What platforms were proposed for ATP-sensitive biosensors?
170) What is the average LOD of K+ sensors?
171) Which platform could be used for selective glutamate analysis?
172) What is largest analyte/molecule for which there is a sensor in the database?
173) Is there any cost associated with any type of sensor?
174) How many labs are making sensors to detect lead in water?
175) Are there sensors to detect air-borne viruses in the air?

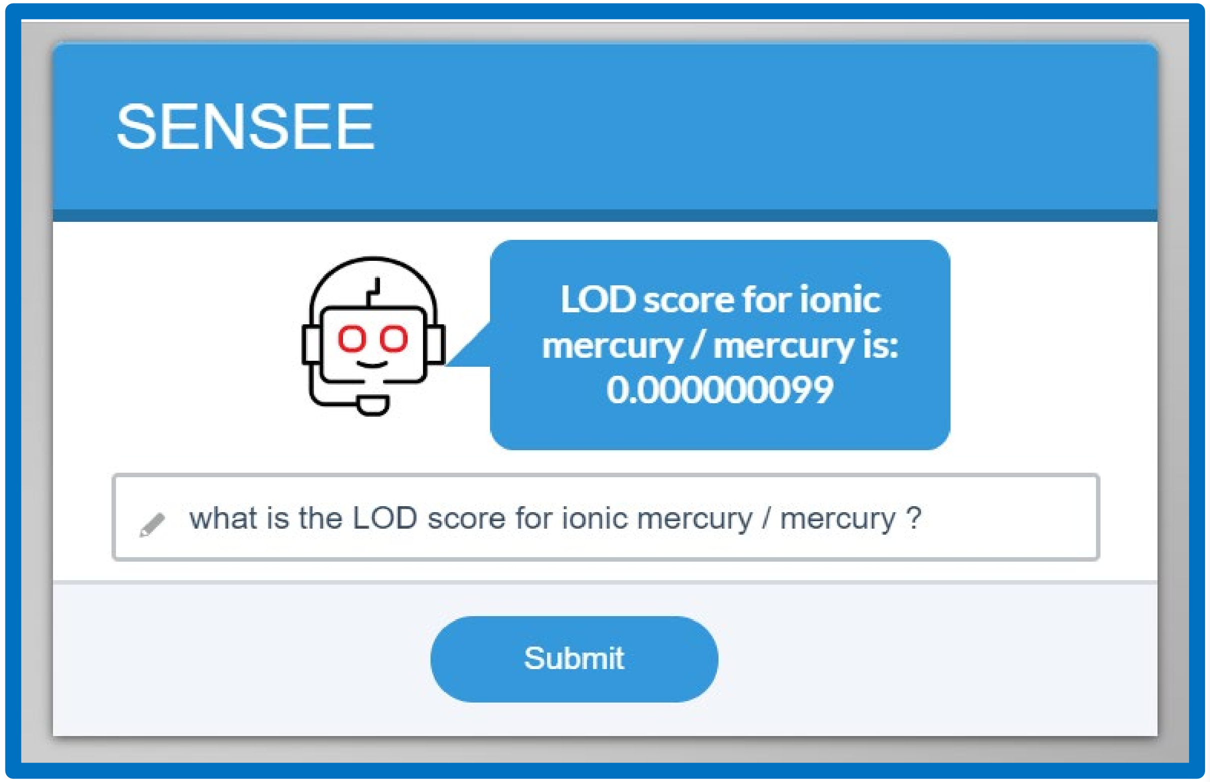
Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

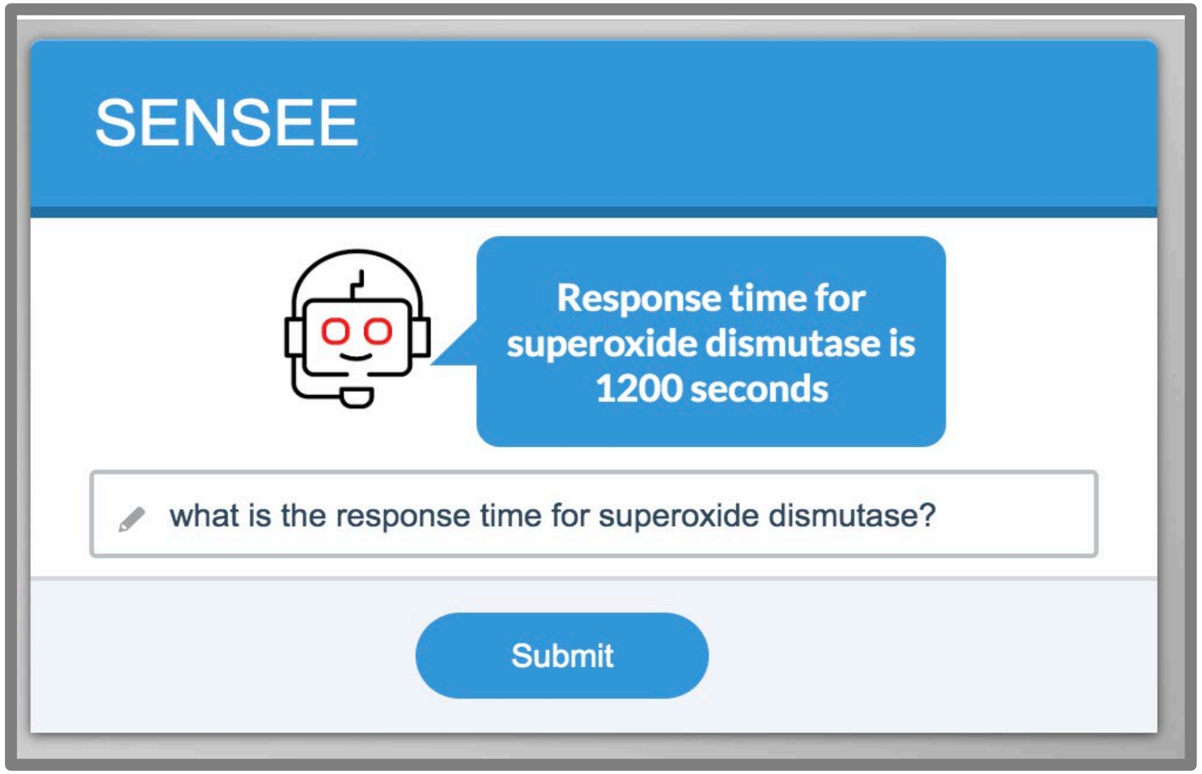


Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)



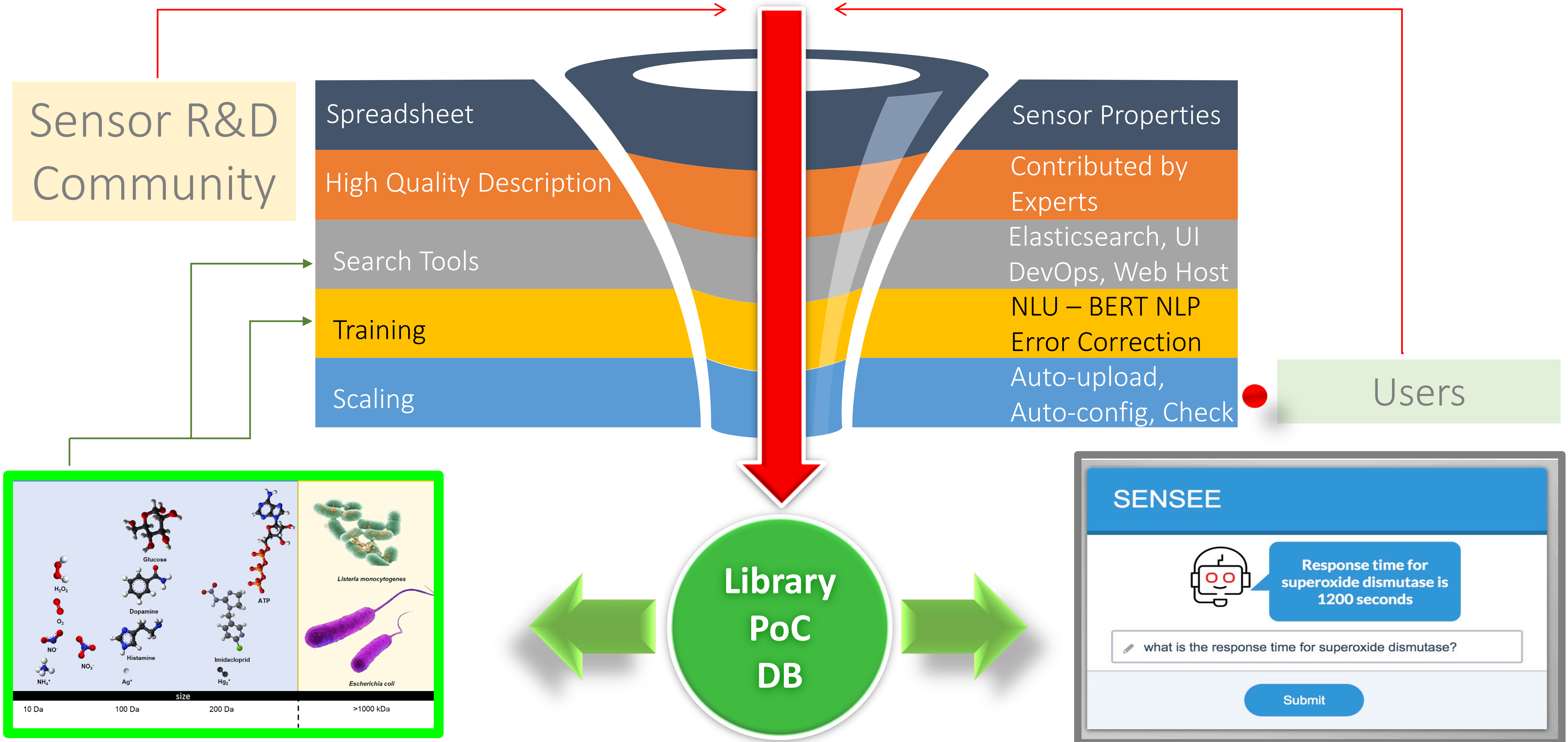
SENSEE 1.0 PROOF OF CONCEPT – DIALOG BOX APP





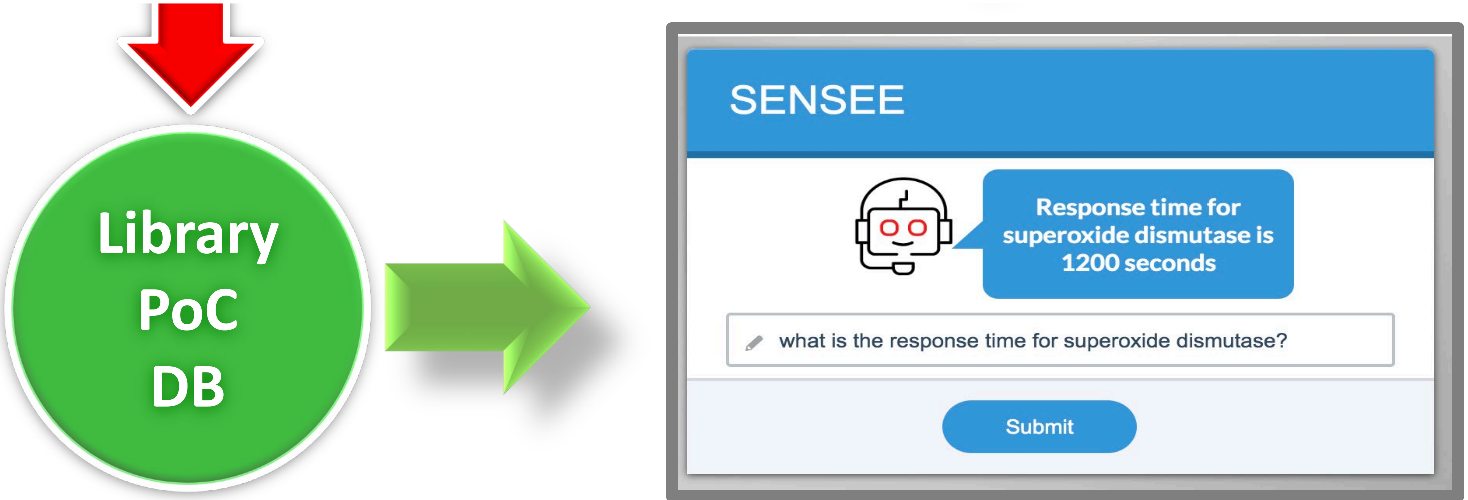
SENSEE PoC UI ● http://146.185.133.187/SENSEE1/ ● http://139.162.7.63/SENSEE/

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)



Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

This is where we are …



Development of SENSEE 1.0 – This is where we are

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

To move forward …

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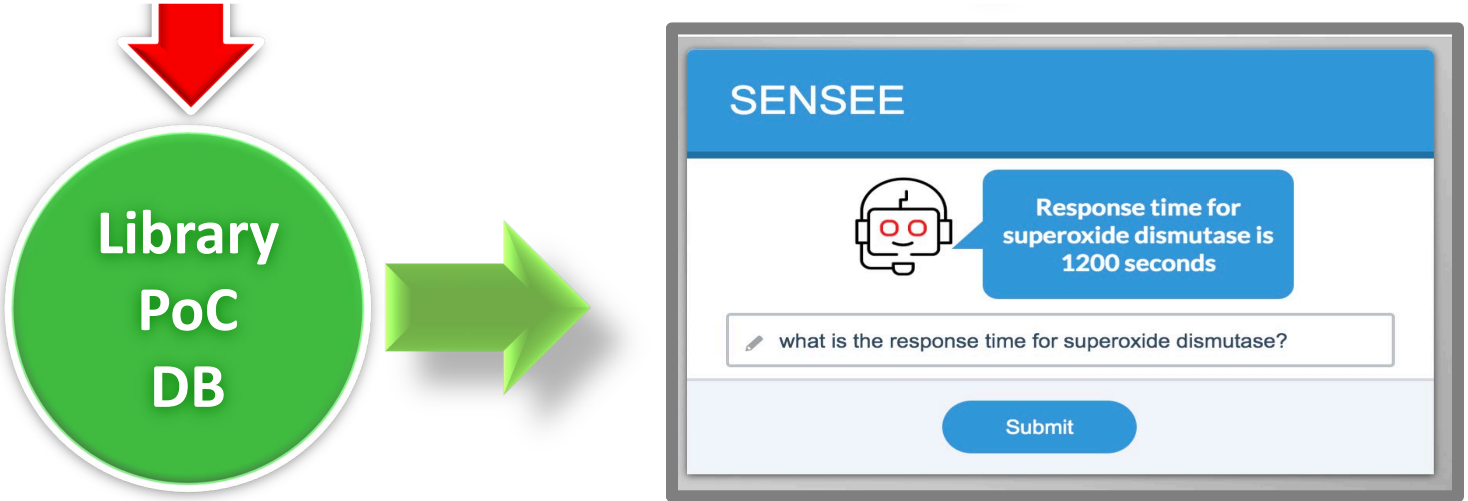


Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Research Community we need your help

Scaling

Auto-upload, Auto-config, Check

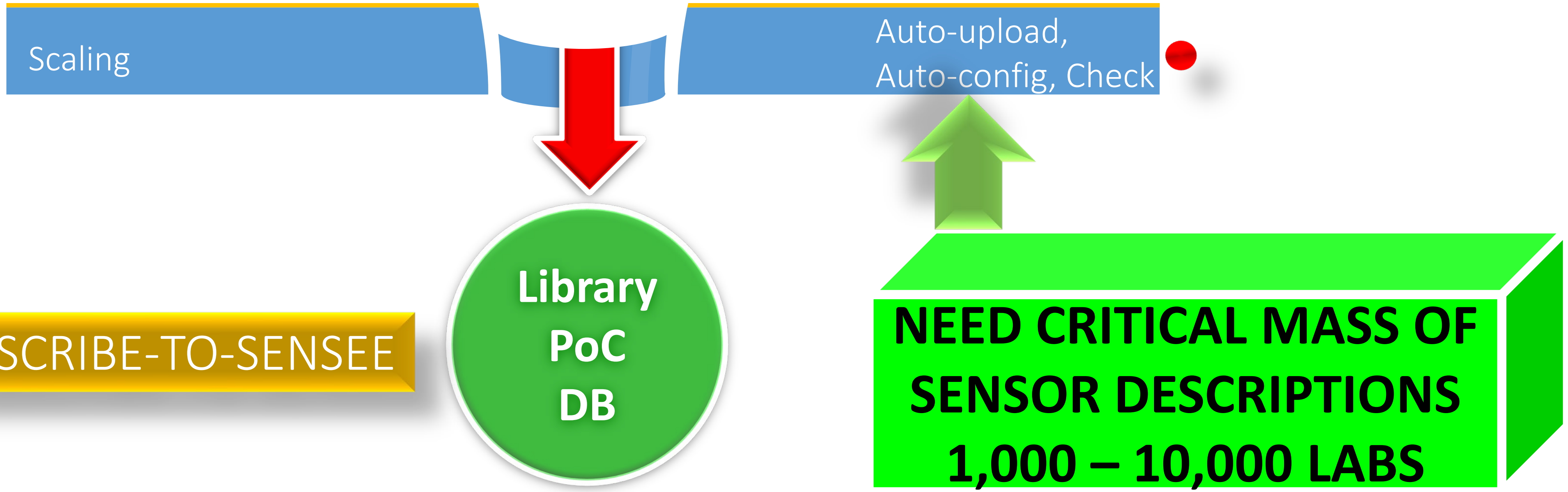
Library PoC DB

http://bit.ly/SUBSCRIBE-TO-SENSEE

NEED CRITICAL MASS OF SENSOR DESCRIPTIONS 1,000 – 10,000 LABS

Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

It is useless without sensor descriptions



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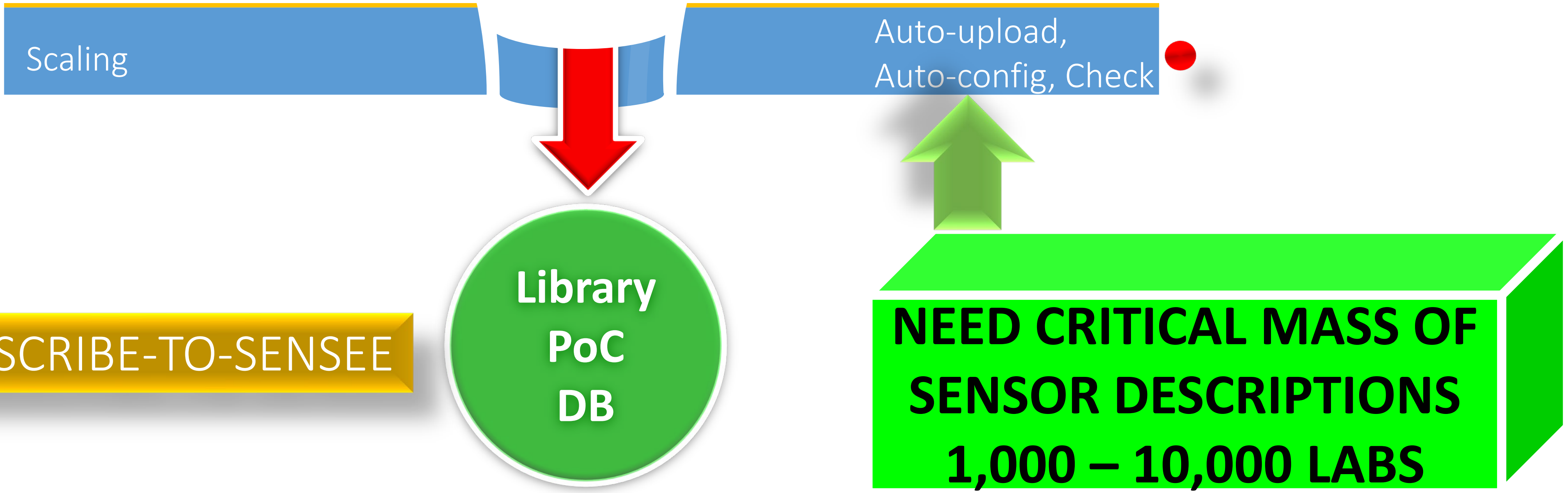
NO sensor data until 2.0

Your sensor descriptions



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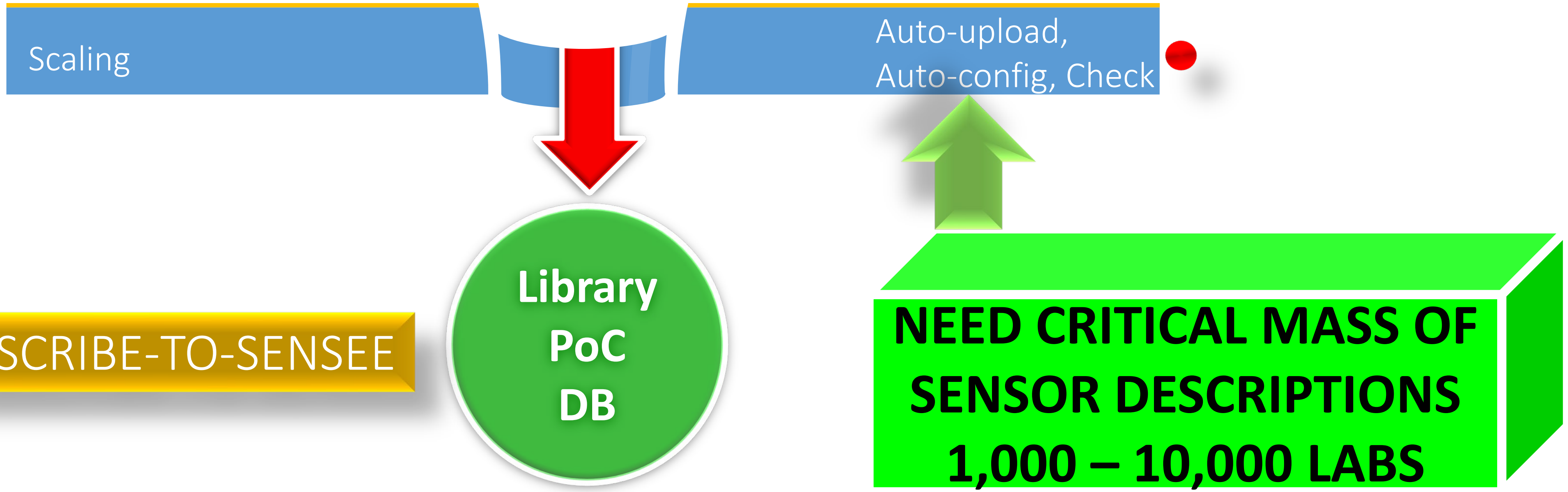
XL auto-UPLOAD tool for your sensor descriptions



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Your Spreadsheet

Sensor Properties

	A	B	C	D	E	F	G	H	I	J	K	L
1	**MW [Da]**	**Category**	**Target**	**Recognition-transduction scheme**	**Platform**	**LOD [M]**	**Max range [M]**	**Selectivity (interferent species tested)**	**Response time [sec]**	**Durability**	**USECAT1**	**Link to paper(s)**
2	1	small molecule	H+	H+ ionophore (liquid)	glass capillary	1.00E-13	1.00E-04	excellent (K+, Na+, Ca2+, Mg2+)	2	High	hydroponics	https://www.ncbi.nlm.nih.gov/pubmed/26088926
3	1	small molecule	H+	anthocyanin/nanocellulose	paper filter	1.00E-15	1.00E-02	excellent	2	high	irrigation water	https://www.ncbi.nlm.nih.gov/pubmed/28884510
4	18	small molecule	Ammonium	NH4+ ionophore (liquid)	glass capillary	5.00E-09	1.00E-01	excellent	5	medium	wastewater	http://www.allelopathyjournal.org/archives/?Year=2016&Vol=37&Issue=2&Month=3
5	18	small molecule	Ammonium	NH4+ ionophore (solid)	LSG	2.80E-05	5.00E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
6	30	small molecule	N/O radicals	nanoplatinum/nanoceria	Pt electrode	1.00E-08	3.00E-06	medium	1	medium	ocean water	https://pubs.rsc.org/en/Content/ArticleLanding/2017/AY/C7AY01964E#!divAbstract
7	32	small molecule	DO	Pt porphyrin-nTiO2	fiber optic	1.00E-06	5.00E-06	excellent, temp sens	1	High	hydroponic media	https://www.sciencedirect.com/science/article/pii/S0925400514001117
8	32	small molecule	DO	Pt porphyrin	96 well	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	https://www.sciencedirect.com/science/article/pii/S016770121300331X
9	32	small molecule	DO	Pt porphyrin	glass vial	1.00E-06	5.00E-06	excellent, temp sens	45	low	hydroponic media	
10	34	small molecule	H2O2	fractal nPt	Pt electrode	5.00E-09	5.00E-05	excellent	1	high	ocean water	https://www.ncbi.nlm.nih.gov/pubmed/27121177
11	39	small molecule	K+	K+ ionophore (liquid)	glass capillary	1.00E-06	2.50E-01	excellent	2	low	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/24961073
12	41	small molecule	Ca2+	Ca2+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-01	excellent	1	low	Hoaglands media	https://onlinelibrary.wiley.com/doi/full/10.1002/jpln.201700319
13	58	small molecule	acetone	chemosensory proteins-nPt	Pt electrode	5.00E-06	1.00E-05	high	10	low	buffer	https://pubs.rsc.org/en/content/articlelanding/2018/an/c8an00065d#!divAbstract
14	62	small molecule	Nitrate	NO3- ionophore (liquid)	glass capillary	1.00E-06	2.00E-01	excellent	2	medium	wastewater	https://www.ncbi.nlm.nih.gov/pubmed/18985610
15	62	small molecule	Nitrate	NO3- ionophore (solid)	LSG	2.00E-05	1.50E-01	excellent	2	medium	wastewater	https://pubs.acs.org/doi/10.1021/acsami.8b10991
16	108	small molecule	Ag+	Ag+ ionophore (liquid)	glass capillary	1.00E-06	5.00E-02	excellent	2	high	wound dressing	https://link.springer.com/article/10.1007/s11356-014-3058-6
17	111	small molecule	histamine	diamine oxidase-nCu	LSG	6.30E-05	1.00E-03	excellent	2	medium	fermented fish	https://www.mdpi.com/2079-6374/8/2/42
18	147	small molecule	Glutamate	CNT/nPt/GlOx	Pt electrode	1.00E-06	1.00E-03	excellent	2	low	INS1 tissue culture	https://www.sciencedirect.com/science/article/pii/S0165027010001196
19	147	small molecule	Glutamate	CNT/nPt/GlOx	Si biochip	1.00E-06	5.00E-01	excellent	2	low	INS1 tissue culture	https://pubs.rsc.org/en/content/articlelanding/2011/jm/c1jm11561h#!divAbstract
20	154	small molecule	catecholamines	nPt	LSG	5.00E-07	3.00E-03	excellent	2	high	ocean water	
21	154	small molecule	catecholamines	graphene anchored nCuO	LSG	3.00E-07	3.00E-03	high	2	medium	buffer	https://pubs.acs.org/doi/abs/10.1021/acssuschemeng.8b02510
22	176	small molecule	indole acetic acid	fractal nPt	Pt/Ir microwire	1.00E-06	1.00E-03	high	1	high	root growth media	https://link.springer.com/article/10.1007/s00344-017-9688-4
23	181	small molecule	Glucose	nPt/GOx	graphene paper	8.00E-08	1.00E-03	excellent	2	medium	buffer	https://www.ncbi.nlm.nih.gov/pubmed/27209574
24	181	small molecule	Glucose	nPt/GOx	Pt/Ir microwire	1.00E-07	5.00E-06	excellent	1	medium	blood	https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0166557
25	181	small molecule	Glucose	nPt/nCe/GOx	Pt electrode	1.00E-07	3.00E-06	excellent	1	medium	buffer	https://www.sciencedirect.com/science/article/pii/S0956566314000992

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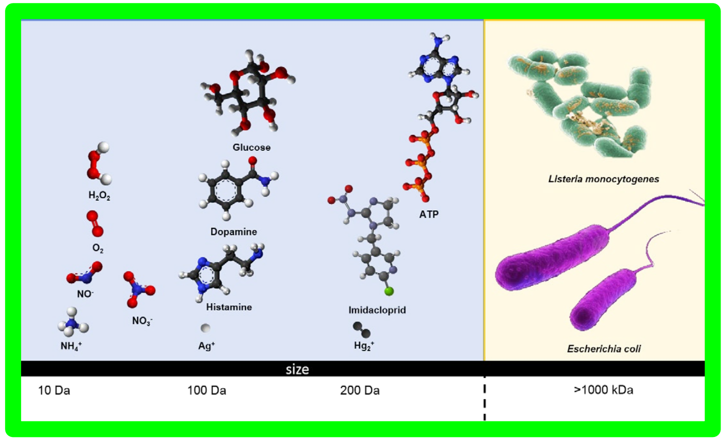
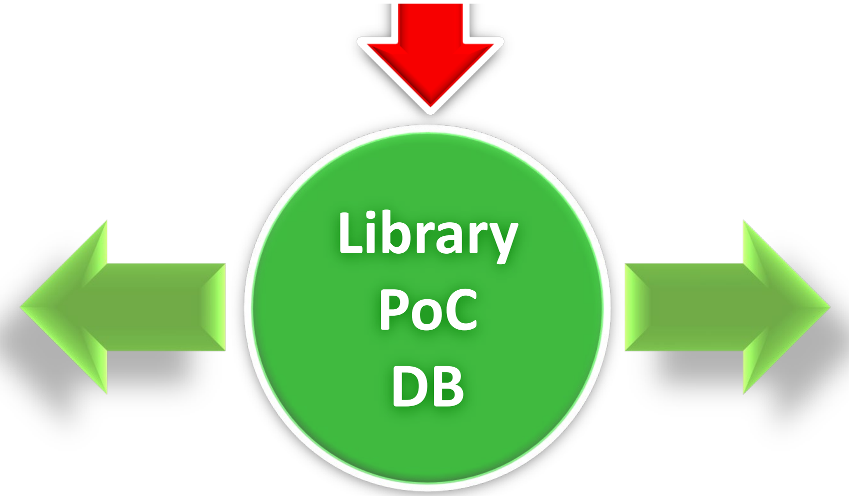
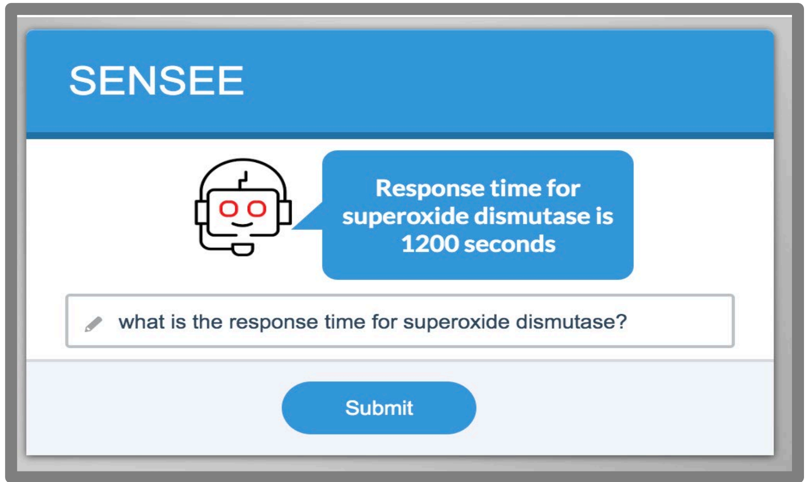
Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

We aim to improve visualization tool



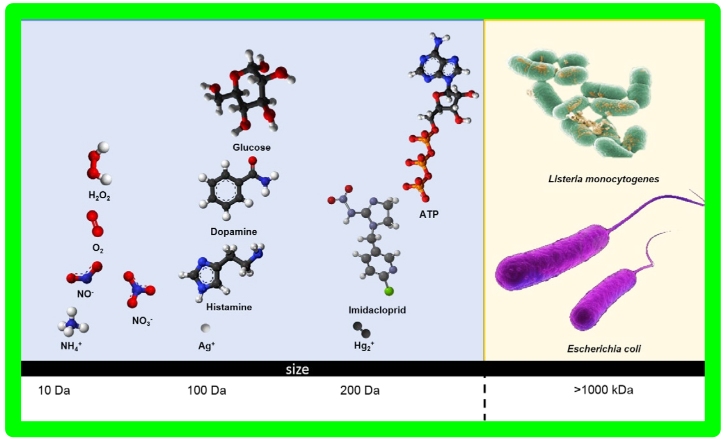


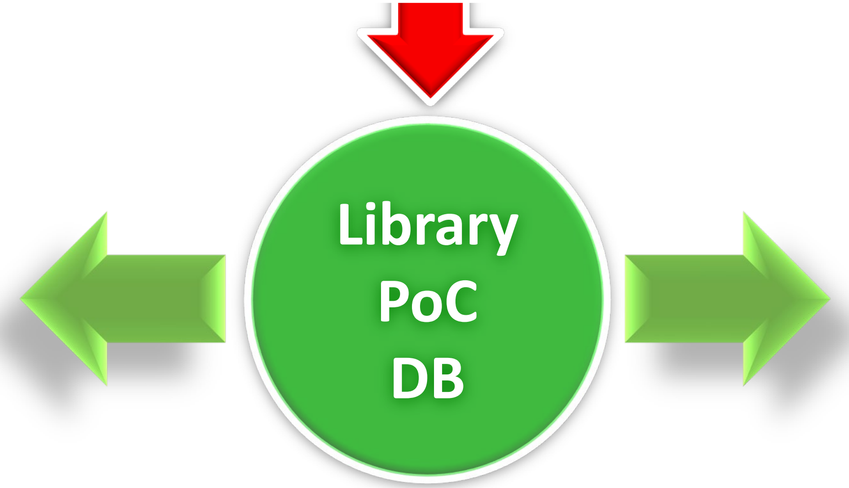


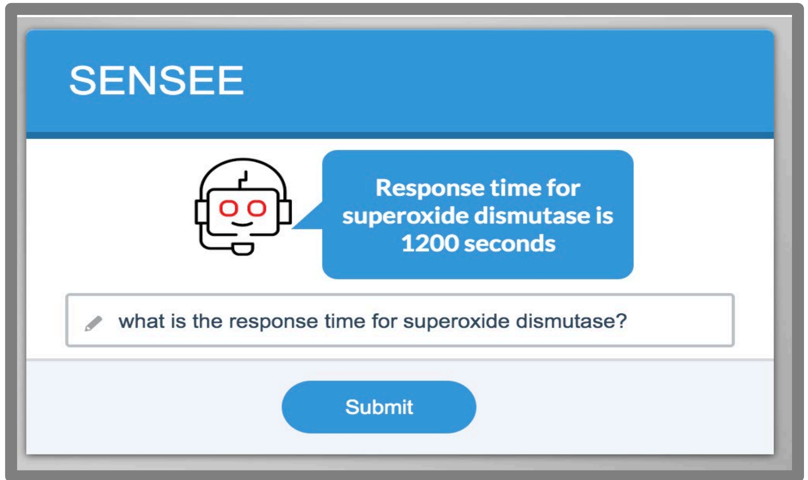
Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

What may follow

- ◆ Deploy SENSEE tool. Go live!
- Automate Feature Engineering
- Ingest Sensor-specific Data
- Use cases for DIDA'S PoC
- Knowledge Graph Algorithms
- Semantic Data Catalogs
- User directed search



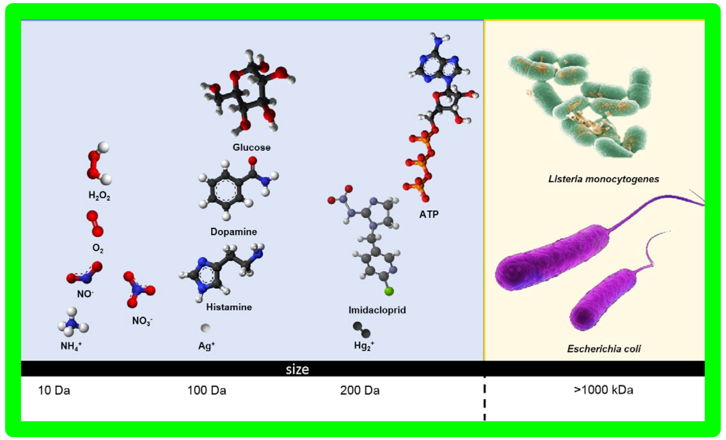


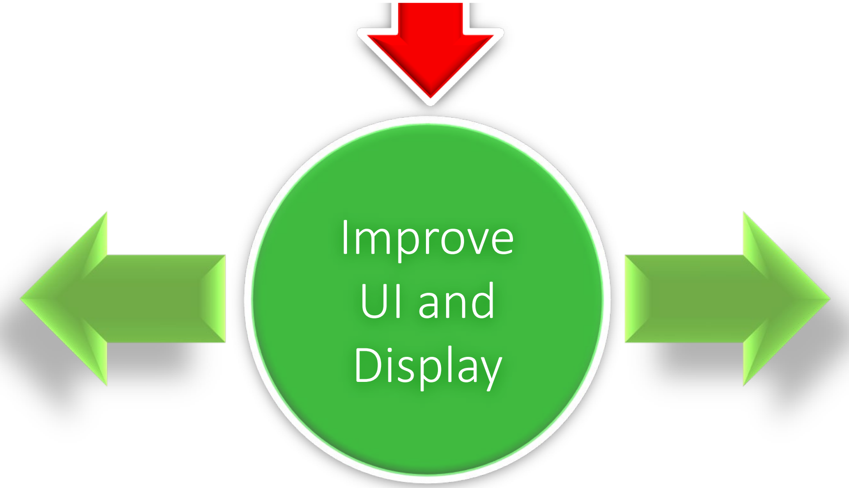


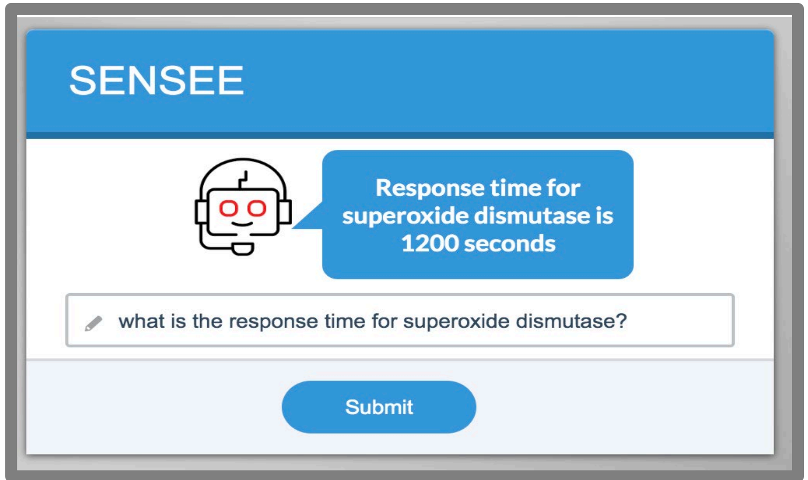
Development of SENSEE 1.0 (**SEN**sor **SE**arch **E**ngine)

Who will use SENSEE 1.0 tool? We anticipate that critical mass of sensor descriptions (categories, attributes) will improve the value of SENSEE 1.0 as a search tool for curated information. Users may be experts in academic and industrial labs. The task of sourcing, uploading, maintaining sensor descriptions may become cost-prohibitive unless a cooperative support structure is implemented to distribute and share the cost of professional services for SENSEE.

- Deploy SENSEE 1.0. Go live!







THE LONGEST JOURNEY

SENSEE

↓

DIDA’S

↓

KIDS

SENSEE 2.0

THE LONGEST JOURNEY

SENSEE

↓

DIDA'S

↓

KIDS

SENSEE 2.0

- Ingest Sensor-specific <u>Data</u>

THE LONGEST JOURNEY

SENSEE

↓

DIDA'S

↓

KIDS

SENSEE 2.0 INGESTS SENSOR-SPECIFIC DATA BASED ON USE CASES

The key performance indicator (KPI) for SENSEE will be a measure of its quality of service (QoS metric) with respect to the delivery of precision responses and value of recommendations. Description of sensor types (categories, attributes) in SENSEE 1.0 may enable end-users to choose sensors relative to use cases. But, without sensor-specific data, ***relative to the use case of the end-user***, the value of SENSEE diminishes. Acquisition of data from sensors in SENSEE 2.0 will be relative to use case. For example, if Comfrey Farms wishes to optimize quality of meat color in its pork product, the outcome (desired color of pork meat) may need to converge and combine data from ammonia sensors (amount of ammonia in the hog environment), homofermentative microbial species in feed (Lactobacillus sp) and colorimetric data from robotic arm involved in meat processing. SENSEE 2.0 aims to acquire end-user case-based sensor data to address problems and questions of pragmatic value. The feasibility of this approach may be challenged by sensor manufacturers (for example, ammonia gas sensor from C2Sense, microbial sensor from Thermo-Fisher and colorimetric sensor from Omron) who may want to aggregate their own data and encrypt data ports and data loggers to prevent data interoperability and distribution. Manufacturer's portals are focused on sensors specific to the manufacturer. SENSEE 2.0 is an open platform, catalyzing synergistic integration of data to synthesize information, with respect to the end-user's problem. The potential for profitability from data fusion followed by synthesis of actionable information, may be an economic incentive for end-users. It may encourage users to support the SENSEE-DIDA'S-KIDS platform approach by uploading sensor data to SENSEE 2.0 directly from their operations. DIDA'S, and in future DIDA'S KIDS, may evolve from data-informed DSS to synthesis of relevant information, followed by the knowledge-informed paradigm in decision science.

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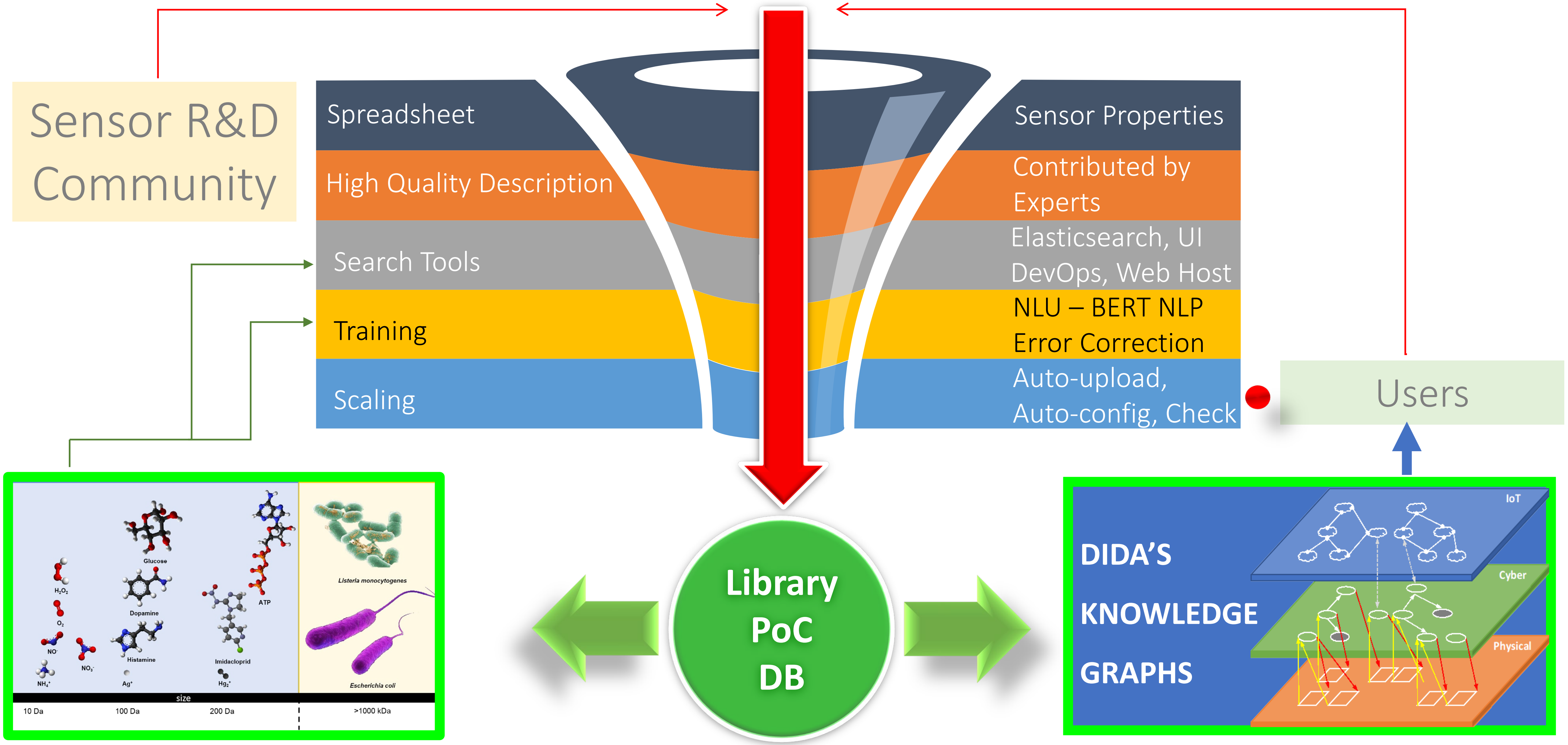
SENSEE 2.0 and DIDA'S

Data-Informed Decision as a Service

Progress of Development – SENSEE 2.0 and DIDA’S



THE
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DIDA'S

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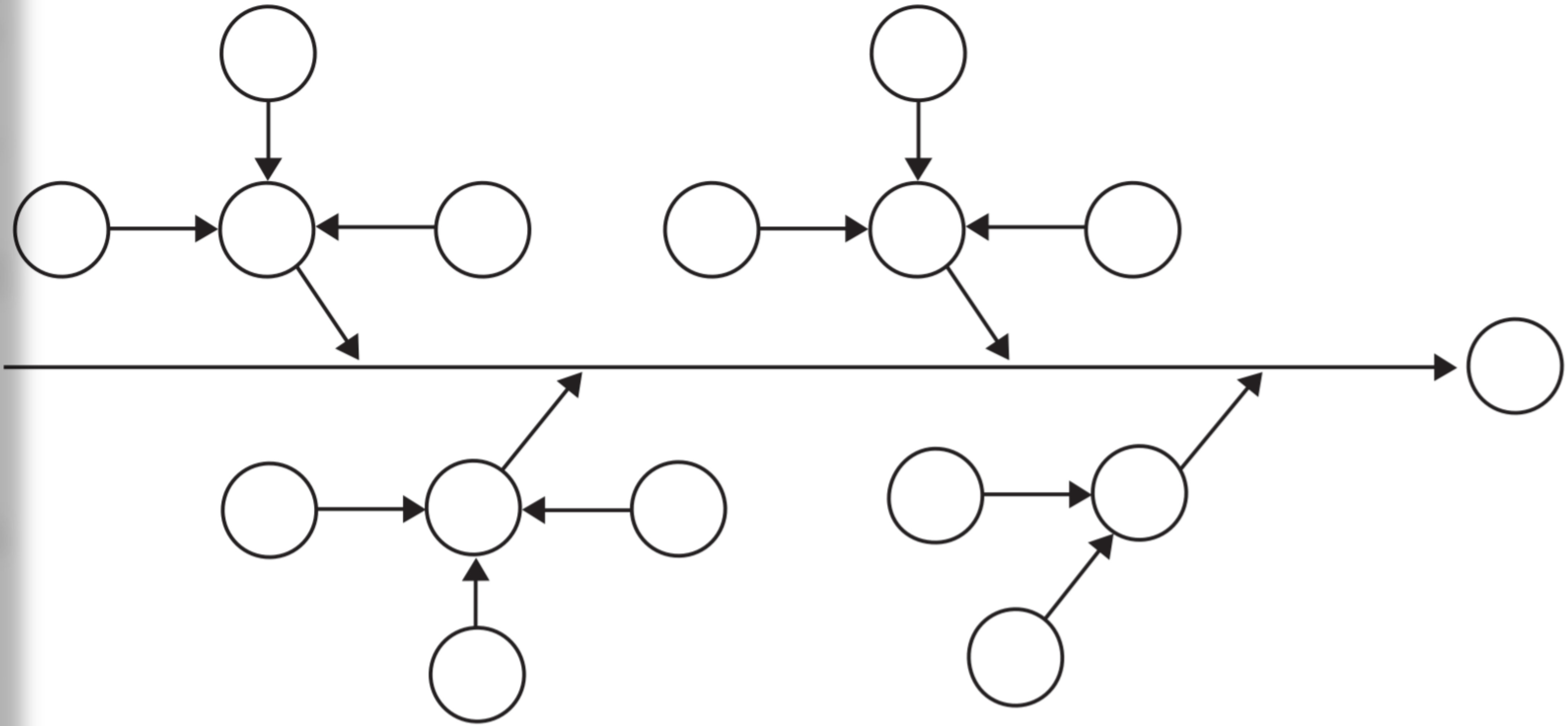
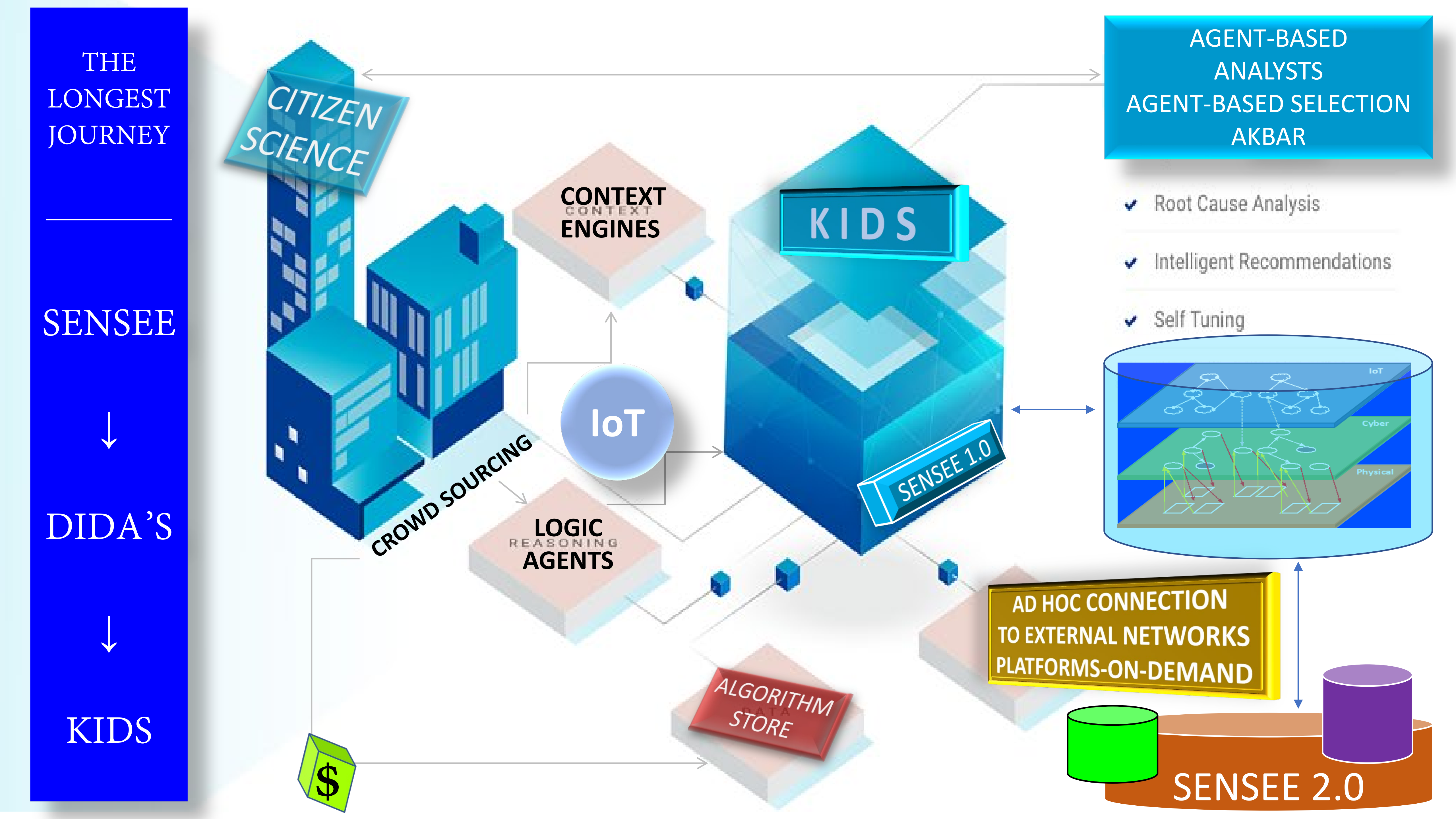
KIDS




THE LONGEST JOURNEY
SENSEE
↓
DIDA'S
↓
KIDS
CITIZEN SCIENCE
CONTEXT ENGINES
CONTEXT
KIDS
IoT
CROWD SOURCING
LOGIC AGENTS
REASONING
SENSEE 1.0
ALGORITHM STORE
$
AGENT-BASED
ANALYSTS
AGENT-BASED SELECTION
AKBAR
Root Cause Analysis
Intelligent Recommendations
Self Tuning
IoT
Cyber
Physical
AD HOC CONNECTION
TO EXTERNAL NETWORKS
PLATFORMS-ON-DEMAND
SENSEE 2.0

Anticipate challenges from manufacturers and users

SENSEE

2.0

Unless users allow access to raw data from sensors, the system may be unable to optimize outcomes or minimize risks, for questions which require specific case related data, from relevant sensors. With other general access data, for example, standard protocols for wastewater treatment, it may be possible to offer some degree of information or recommendation but then the value of convergence is limited in its scope.

Anticipated deliverables from SENSEE – Logic Tools?

SENSEE 1.0 (sensor descriptions) and SENSEE 2.0 (sensor-specific data) are tangible pursuits, which can deliver case based solutions, within the scope of [a] data-informed decision support for [b] limited interrelationships in a specific domain [c] restricted to information extraction and recommendation but [d] not approaching the extent of DIDA'S.

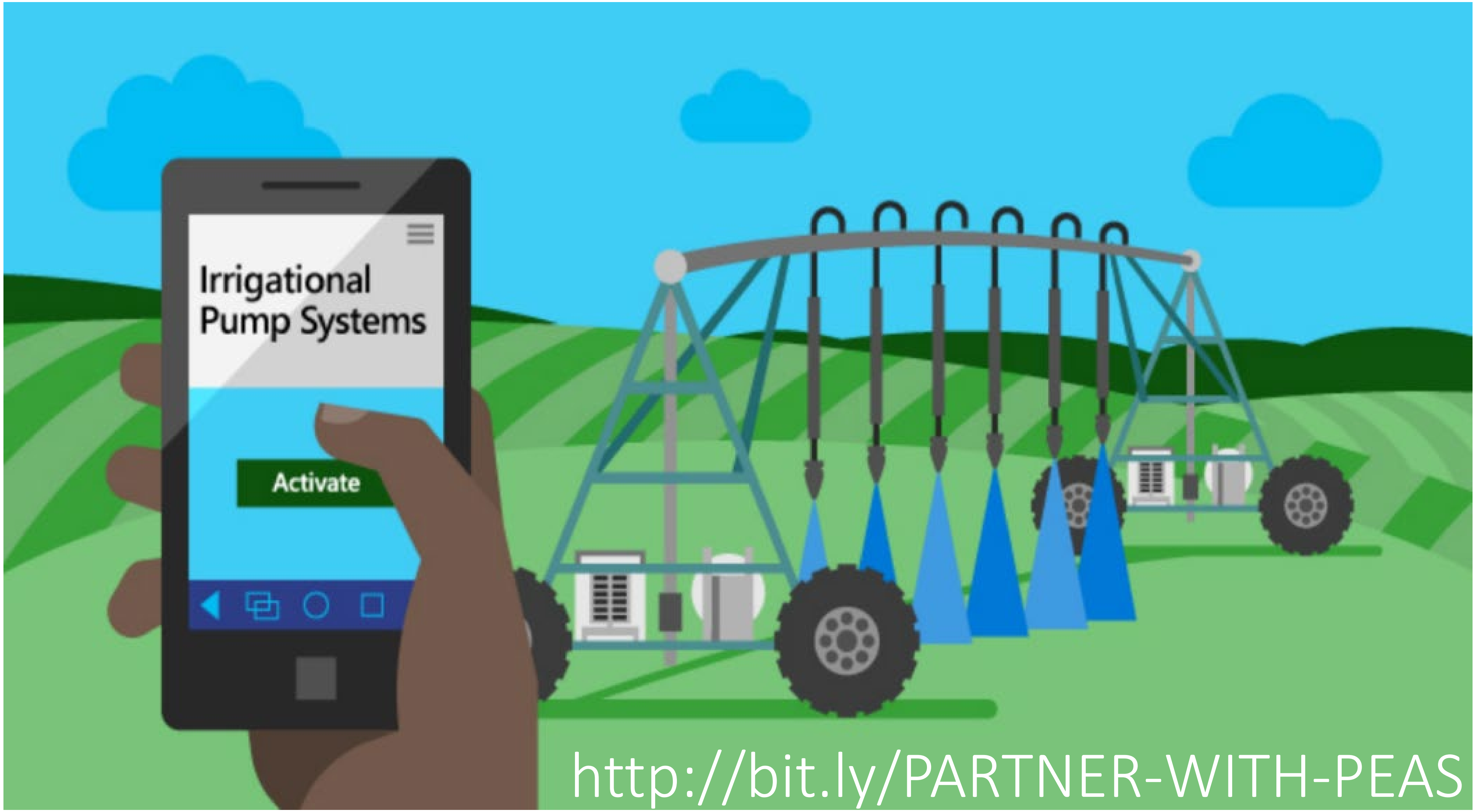
We can use data to create information (thrust of the current state of art with respect to so-called data science) and apply a set of rules and reasoning (logic, dependency, analytics, prior knowledge) to predict ***known*** unknowns, in the form of decision support for humans in the loop (recommendation without discovery or actuation) or venture to relinquish control for partial automation (risk-limited actuation) in an IFTTT (workflow) approach to basic service.

This is a form of data-driven, evidence-driven, ***reasoning*** solution with potential for partially automating workflow. The efficiency gains anticipated from "intelligent" decision support systems lies in our ability to integrate ***logic rules***. DIDA'S KIDS includes this format, as the foundation. Logic rules, if understood (semantics), integrated, optimized, and executed, may be the answer to 80% of the global problems, for a tiny fraction of the cost, which may accelerate market adoption and penetration of digital-agro services. Remaining 20% of issues may require DIDA'S KIDS to create dynamic knowledge composable tools embedded with statistical and mathematical modeling based machine learning solutions. These two approaches may be complimentary for 20% of the problems. But, knowledge tools may not be as critical for 80% of our everyday problems, eg, optimizing and actuating (partial automation) of irrigation water pump systems (control volume and distribution of water) based on soil moisture, salinity, ionic content and weather. Thus, we can focus on **logic tools.**

Anticipated deliverables from SENSEE (SENSEE.ES)

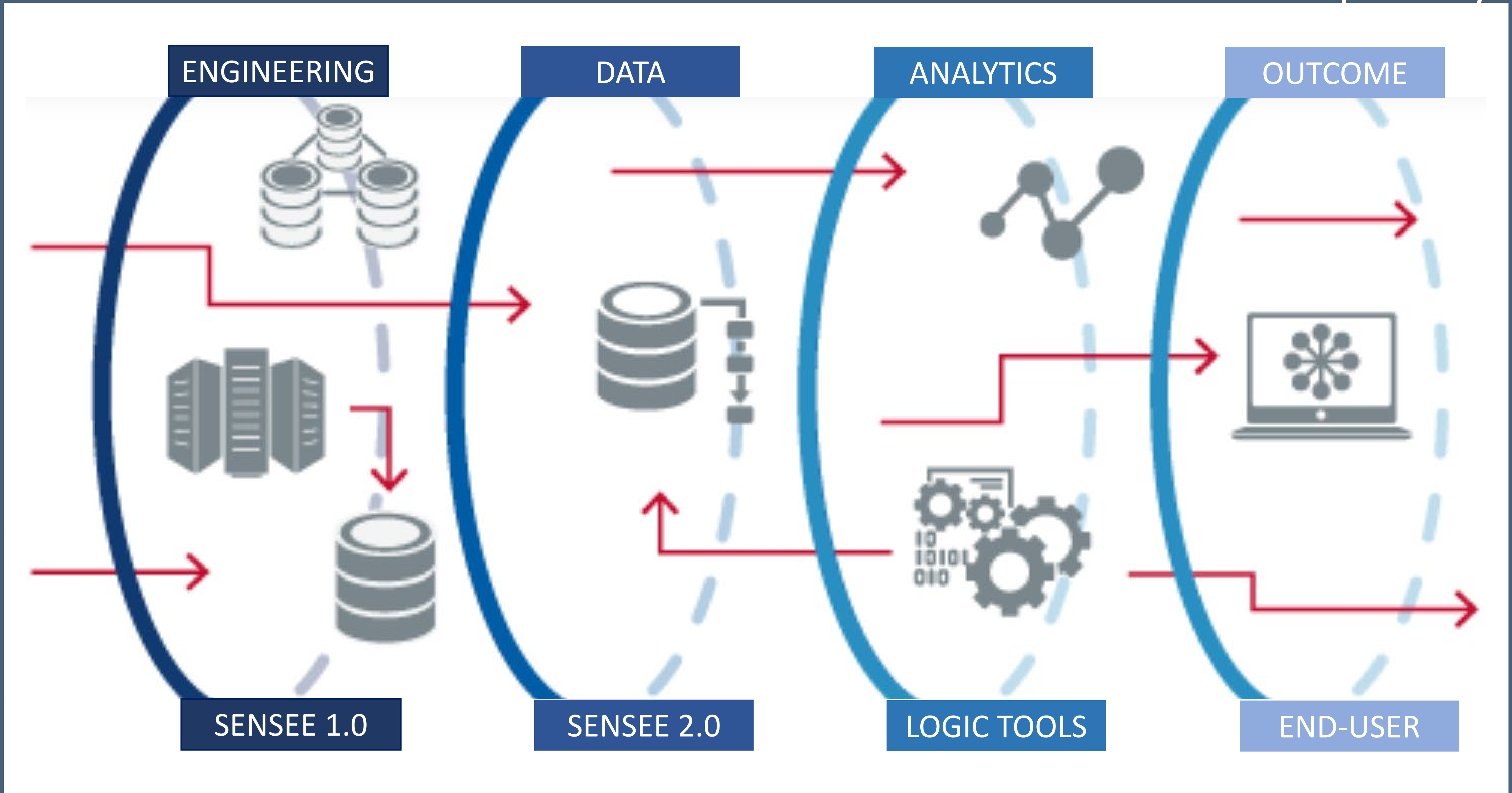
SENSEE 1.0 (sensor descriptions) and SENSEE 2.0 (sensor-specific data) repositories, combined with analytics and artificial reasoning, harks back to “expert systems” which preceded the snake oil sales of AI (artificial intelligence) to the stage where hyped-up “AI systems” exploded to near-extinction (1990’s “winter of AI”). The recent re-invention of AI (2010’s) has catalyzed its re-entry into the den of vipers. SENSEE may stay clear of the foggy panache of AI and focus on delivering expert services, in near real-time, which are profitable for users. An expert service requires we create a framework for an expert system to partially mimic the decision-making ability of human experts, who can solve problems by using data and reasoning aided by prior knowledge. The SENSEE concept of expert service (ES) is not the 1980’s version of expert systems. In SENSEE.ES we will use advanced tools: elasticsearch, NLP, semantic catalogs, graph networks, machine learning, and digital-by-design concepts from the internet of things (IoT), using mobile, agile, standards-based tools to optimize data interoperability, semantic intertoperability, technical interoperability (open platform approach) and, ambitious of all, policy interoperability, to be globally adaptable. In the hands of the human analyst, SENSEE 2.0 is the data source to extract evidence and make informed decisions to act on the evidence (SENSEE 2.0 data). The human analyst supplements this decision making logic using domain expertise and experience in the organization (enterprise, farm, factory) to prescribe analytics and orchestrate any necessary course of action based on the data, processes and reasoning. An Agent-based system (ABS) emulating this “human” step (a part of the **logic tools portfolio** of SENSEE.ES) plus IFTTT (if this then that) type workflow based low level decision-driven partial automation, if combined, may suffice to solve many problems, eg, irrigation water flow.

Deliverables from SENSEE – Logic Tools – call it ART ?



https://cloudblogs.microsoft.com/industry-blog/microsoft-in-business/2019/05/15/how-polaris-energy-services-is-transforming-the-agriculture-industry-in-the-cloud/

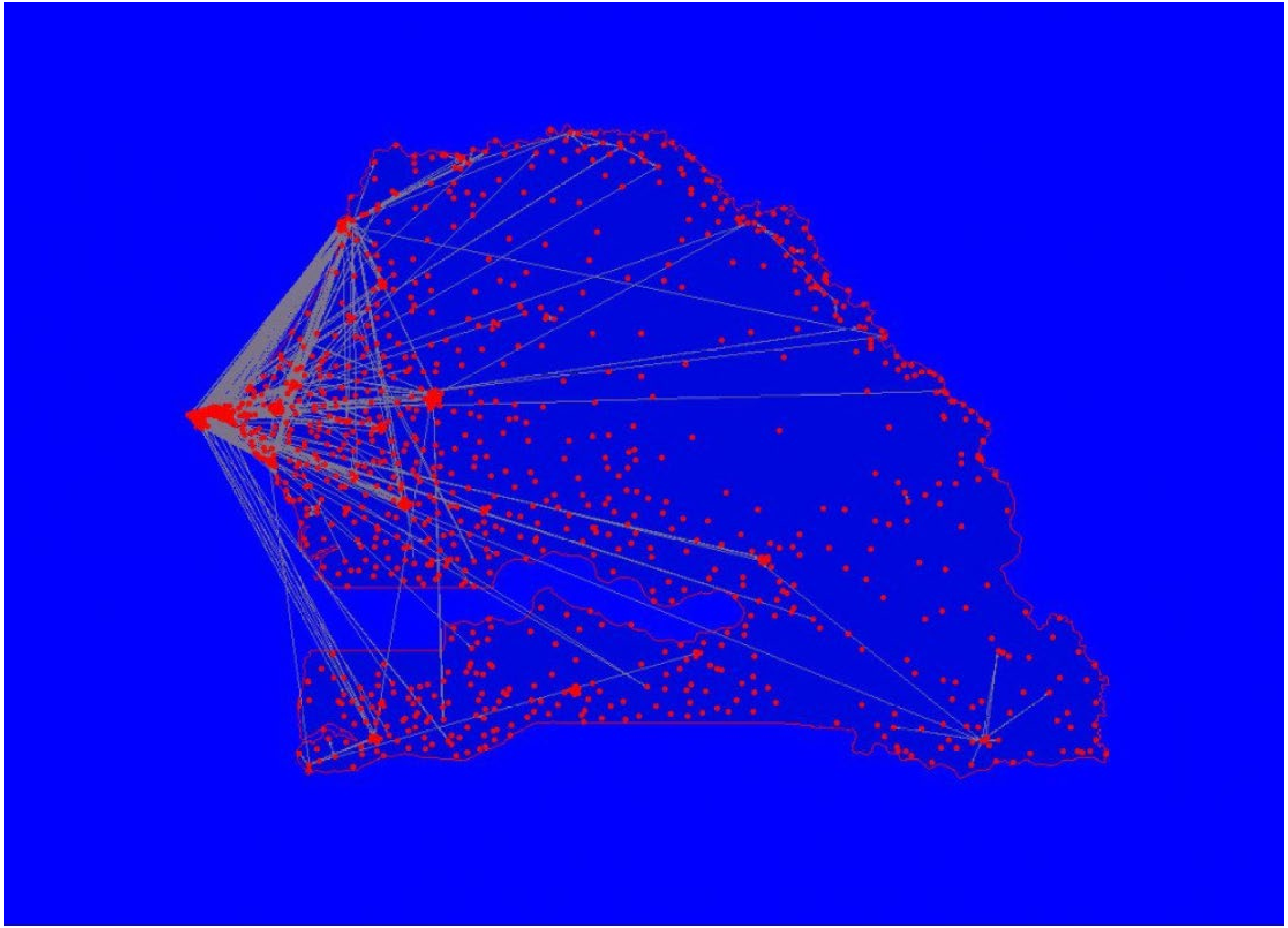
Short-term deliverable from SENSEE? ART of Simplicity



The nexus of hardware and software lead to the "Plug-n-Play" paradigm. Extending that synergistic simplicity to data and data-informed decision support (DIDA'S) may evolve into DADA ("Drag and Drop Analytics") and the subset SENSOR DADA.

http://bit.ly/PARTNER-WITH-PEAS

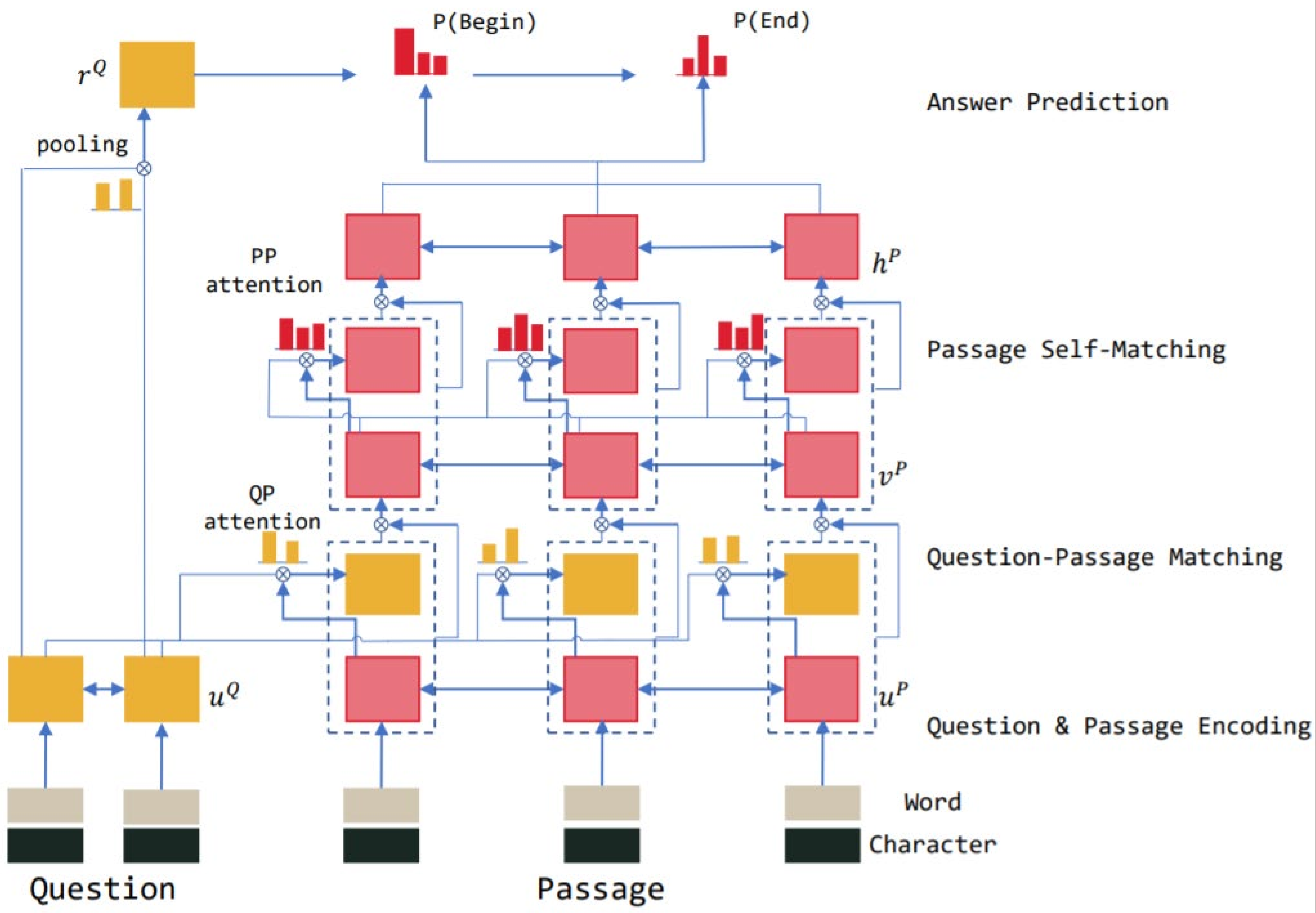
Short-term deliverable from SENSEE? ART of Aggregation



https://arxiv.org/ftp/arxiv/papers/1504/1504.03899.pdf and www.technologyreview.com/s/613987/how-much-electricity-does-a-country-use-just-ask-cell-phone-users

Short-term deliverable from SENSEE? Use natural language

Machine Reading Comprehension (MRC) uses neural network architecture, Reasoning Network (R-Net), to the mimic inferencing process (constrained by subject/predicate optimization/alignment).
https://arxiv.org/pdf/1609.05284.pdf
Another tool is BERT NLP which is also undergoing a series of tests.
https://arxiv.org/pdf/1810.04805.pdf
https://rajpurkar.github.io/SQuAD-explorer/
Convergence of MRC, R-Net, BERT, XLNet, HAN (hierarchical attention networks), etc, with KG (knowledge graphs) may help to mine contextual word embeddings. It may evolve as a tool not only for Q&A but for non-obvious relationship analysis (NORA) and extraction.
https://arxiv.org/pdf/1906.08237.pdf
https://arxiv.org/pdf/1810.06033.pdf
www.nature.com/articles/s41586-019-1335-8



https://blogs.microsoft.com/uploads/2018/02/The-Future-Computed_2.8.18.pdf

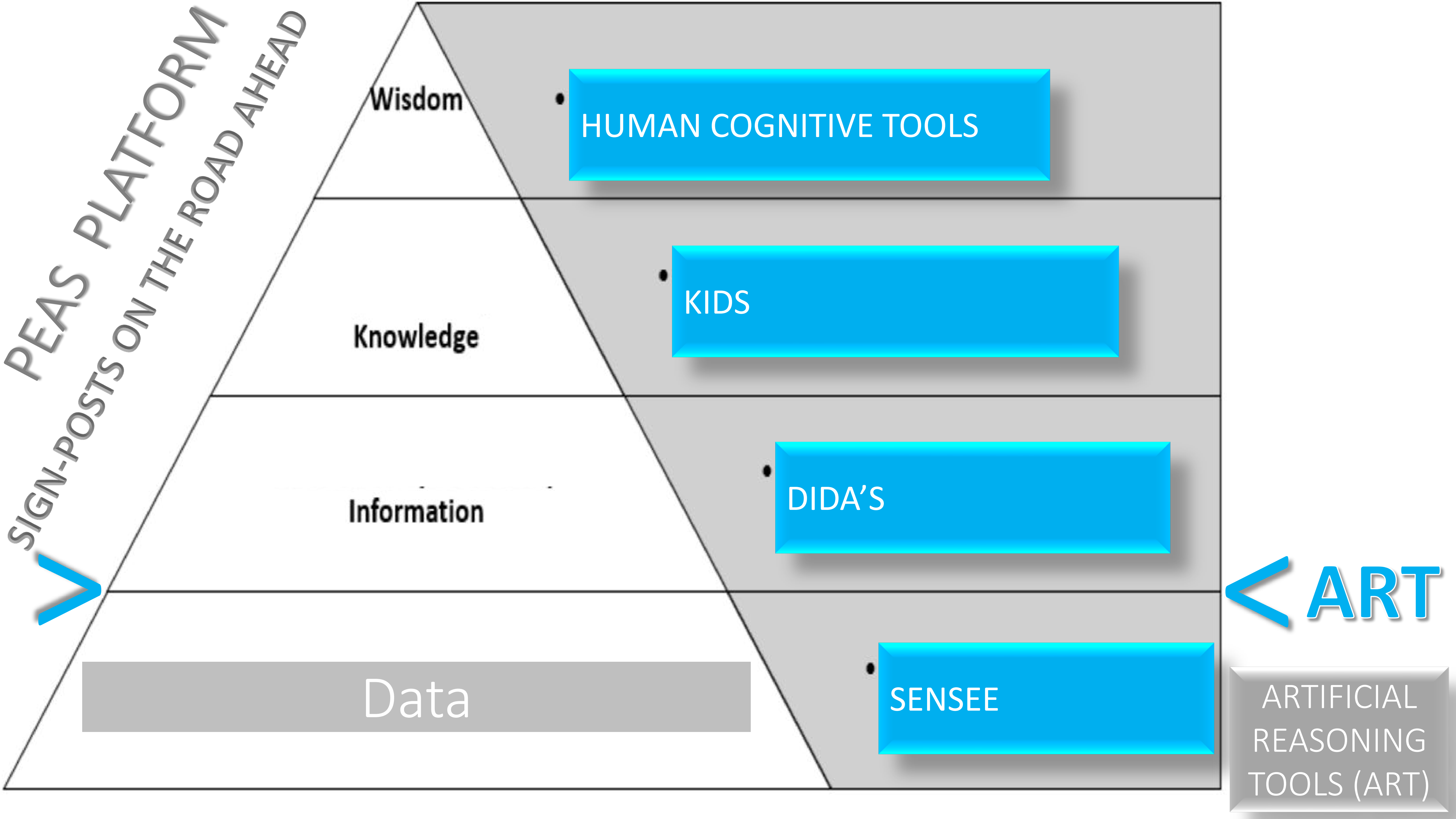
www.microsoft.com/en-us/research/wp-content/uploads/2017/05/r-net.pdf ■ www.microsoft.com/en-us/ai/ai-lab-experiments?activetab=pivot1:primaryr7

Deliverables from SENSEE – Logic Tools – call it ART ?

ART

Artificial Reasoning Tools

SENSEE leads us to ART, a logical middle ground that may deliver decision tools, as partial solutions for problems bounded by domains (not too expansive in scope) before DIDA'S KIDS.


PEAS PLATFORM
SIGN-POSTS ON THE ROAD AHEAD
Wisdom
HUMAN COGNITIVE TOOLS
Knowledge
KIDS
Information
DIDA'S
Data
SENSEE
ART
ARTIFICIAL REASONING TOOLS (ART)

But, is knowledge still the key performance indicator?

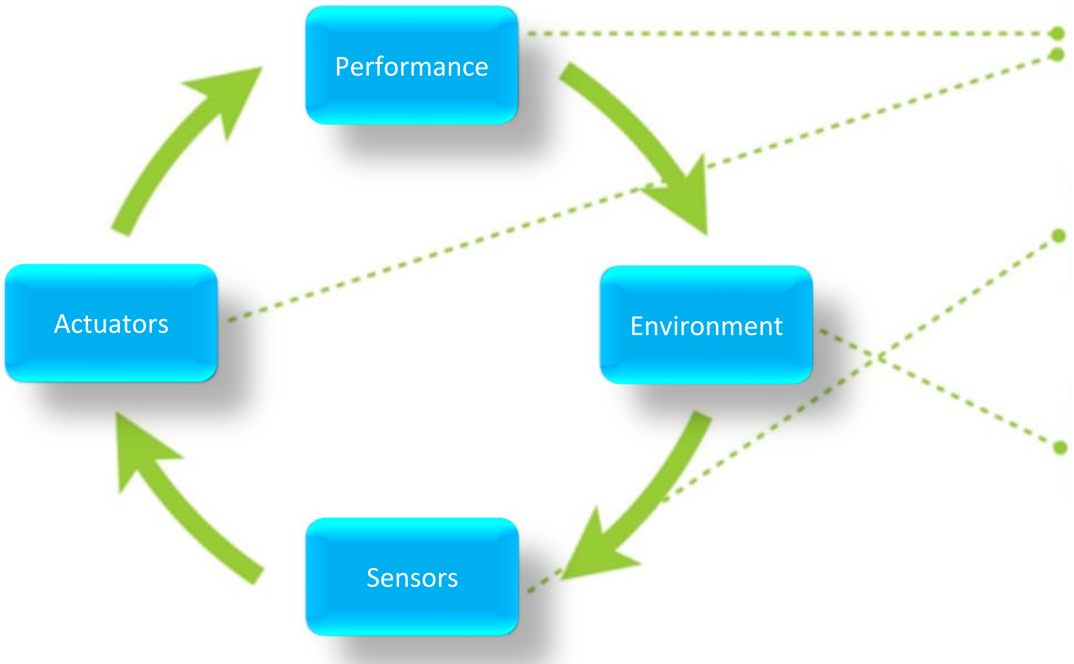
- P
- E
- A
- S

- Performance

- Sensors

Knowledge is the ultimate key performance indicator

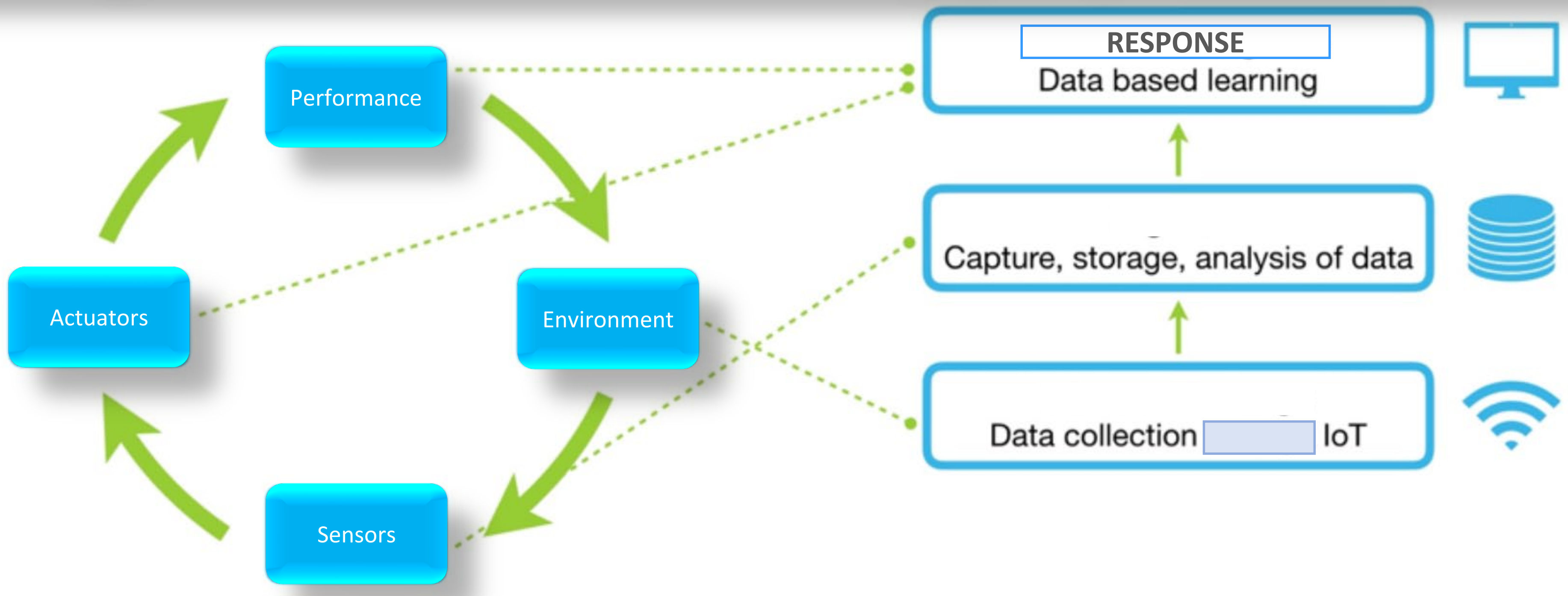
http://bit.ly/PARTNER-WITH-PEAS



https://courses.edx.org/asset-v1:ColumbiaX+CSMM.101x+1T2017+type@asset+block@AI_edx_intelligent_agents_new__1_.pdf

Knowledge is the ultimate key performance indicator

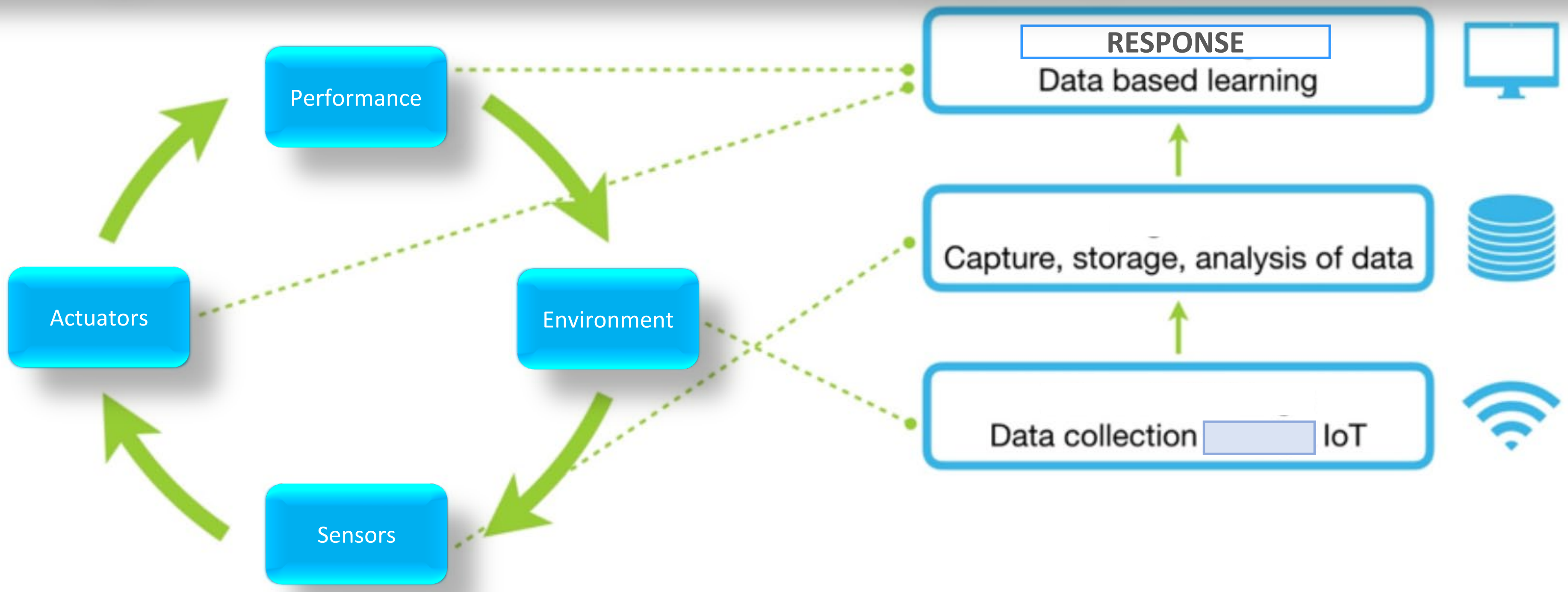
http://bit.ly/PARTNER-WITH-PEAS

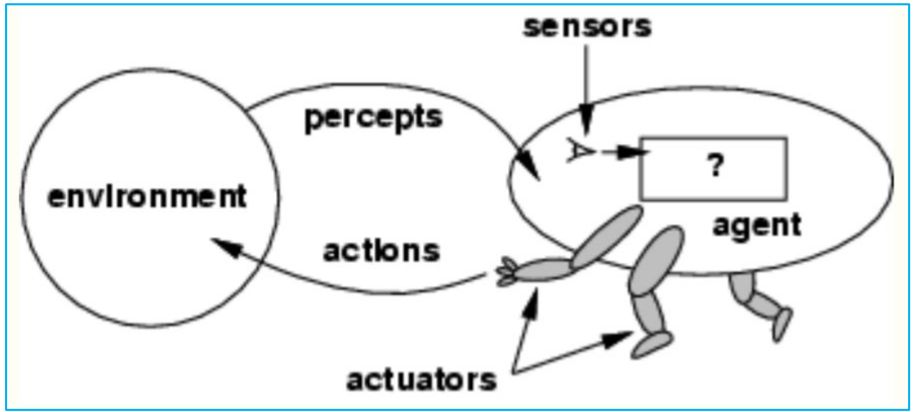


https://courses.edx.org/asset-v1:ColumbiaX+CSMM.101x+1T2017+type@asset+block@AI_edx_intelligent_agents_new__1_.pdf

Knowledge is the ultimate key performance indicator

http://bit.ly/PARTNER-WITH-PEAS





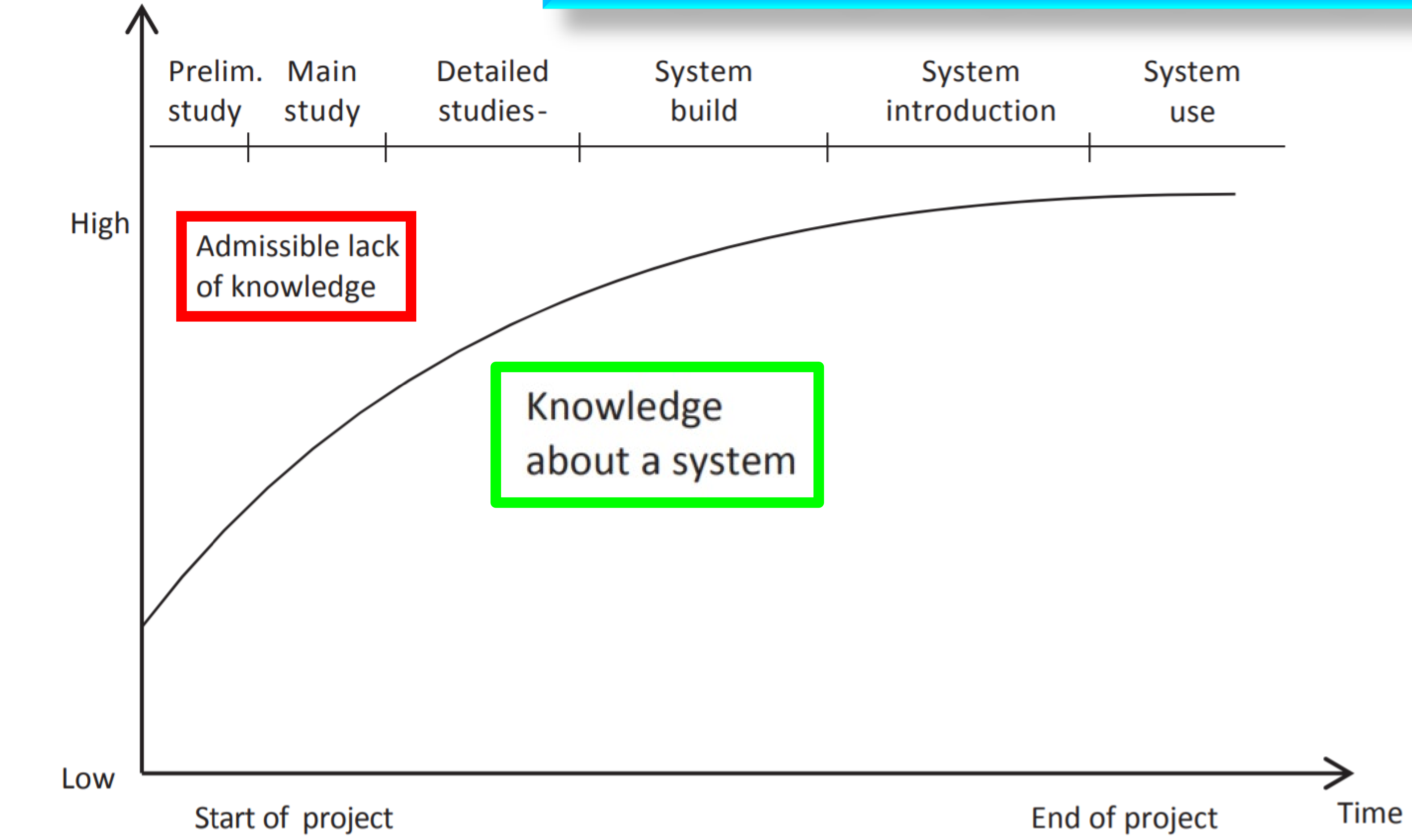
https://www.ics.uci.edu/~welling/teaching/ICS171fall10/Agents171Fall10.pdf

https://courses.edx.org/asset-v1:ColumbiaX+CSMM.101x+1T2017+type@asset+block@AI_edx_intelligent_agents_new__1_.pdf

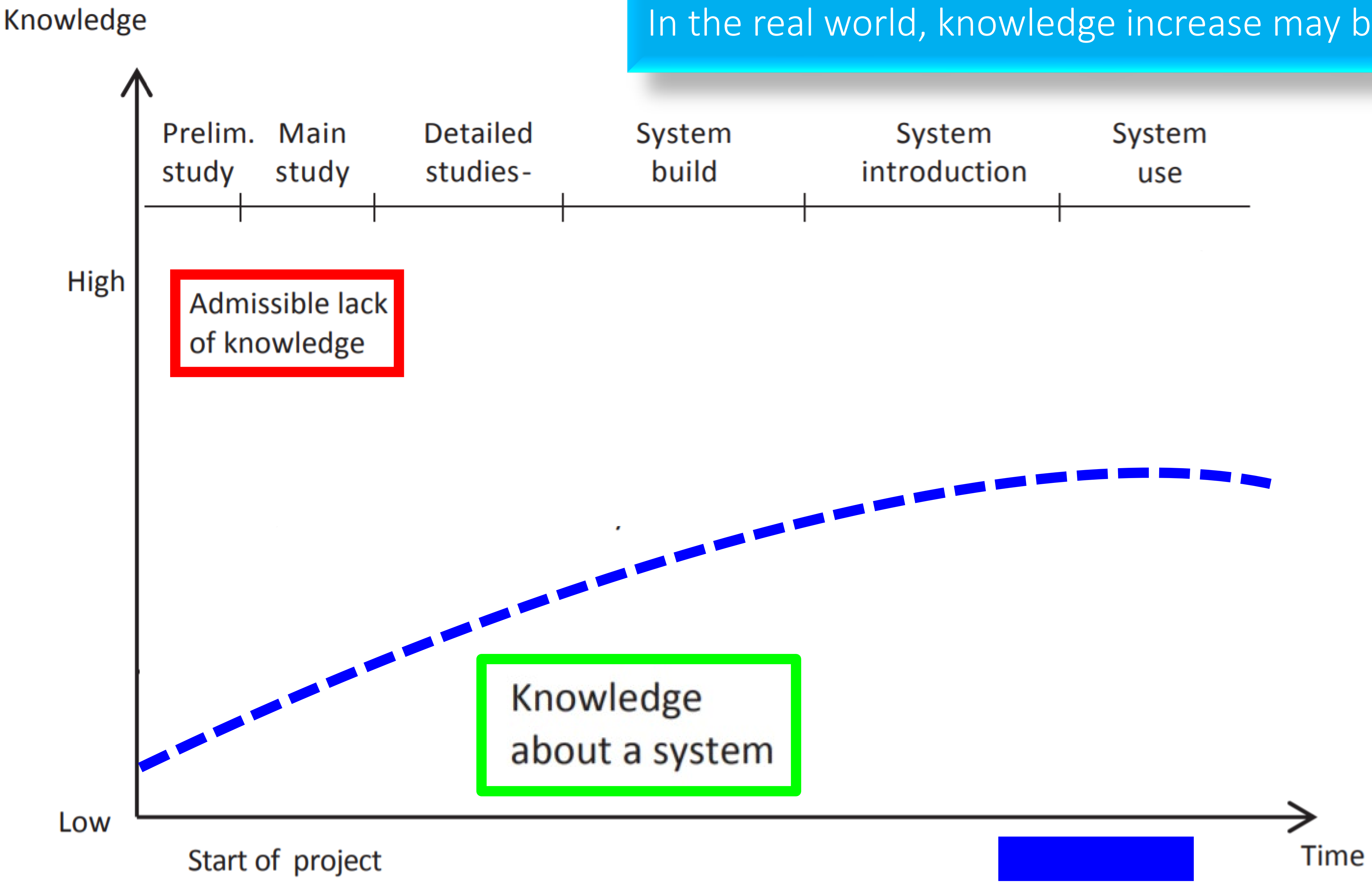
Have we gained ***knowledge*** from data and decisions?

An open question, for the long run …

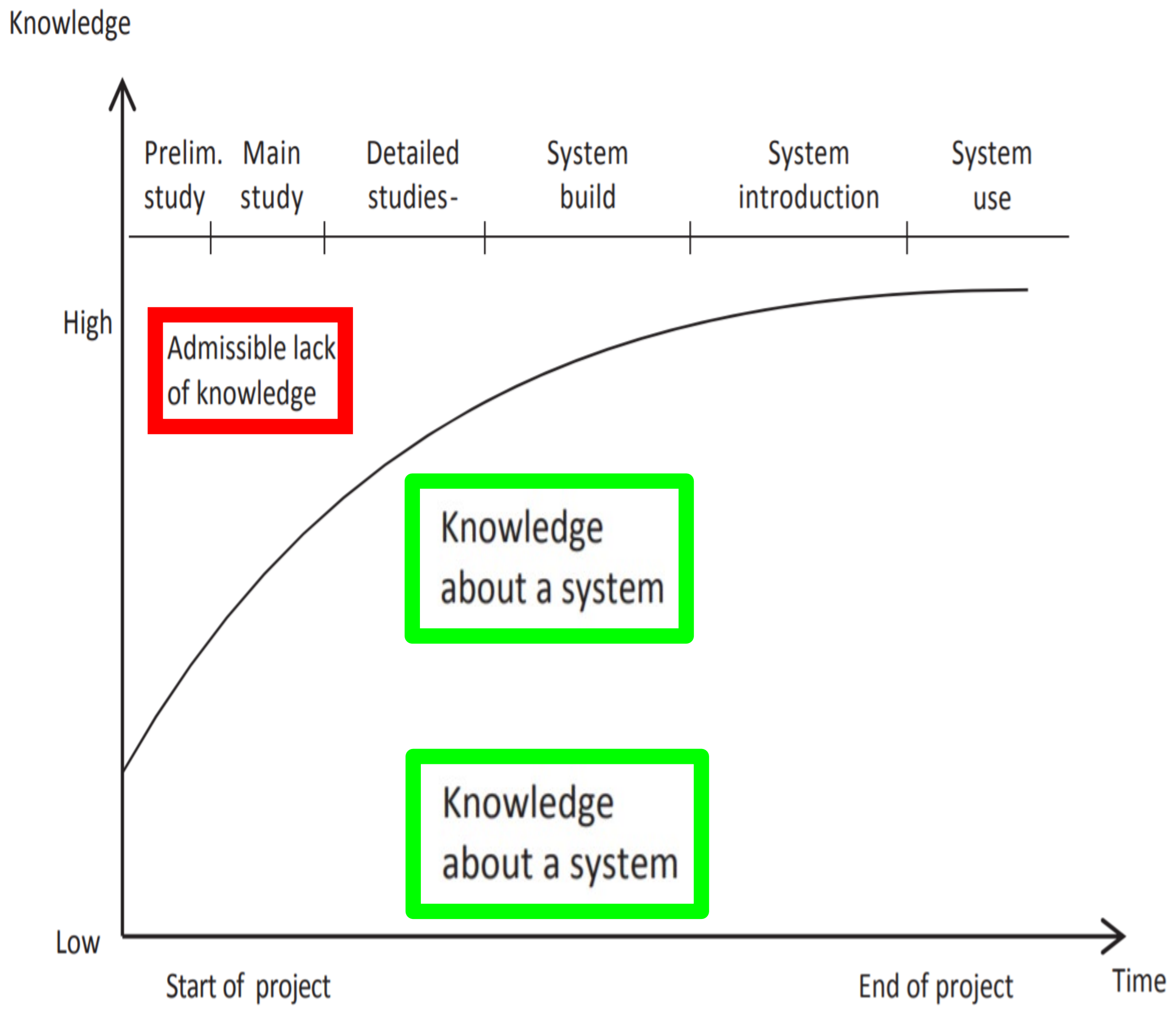
In a systems engineering approach, knowledge increases.

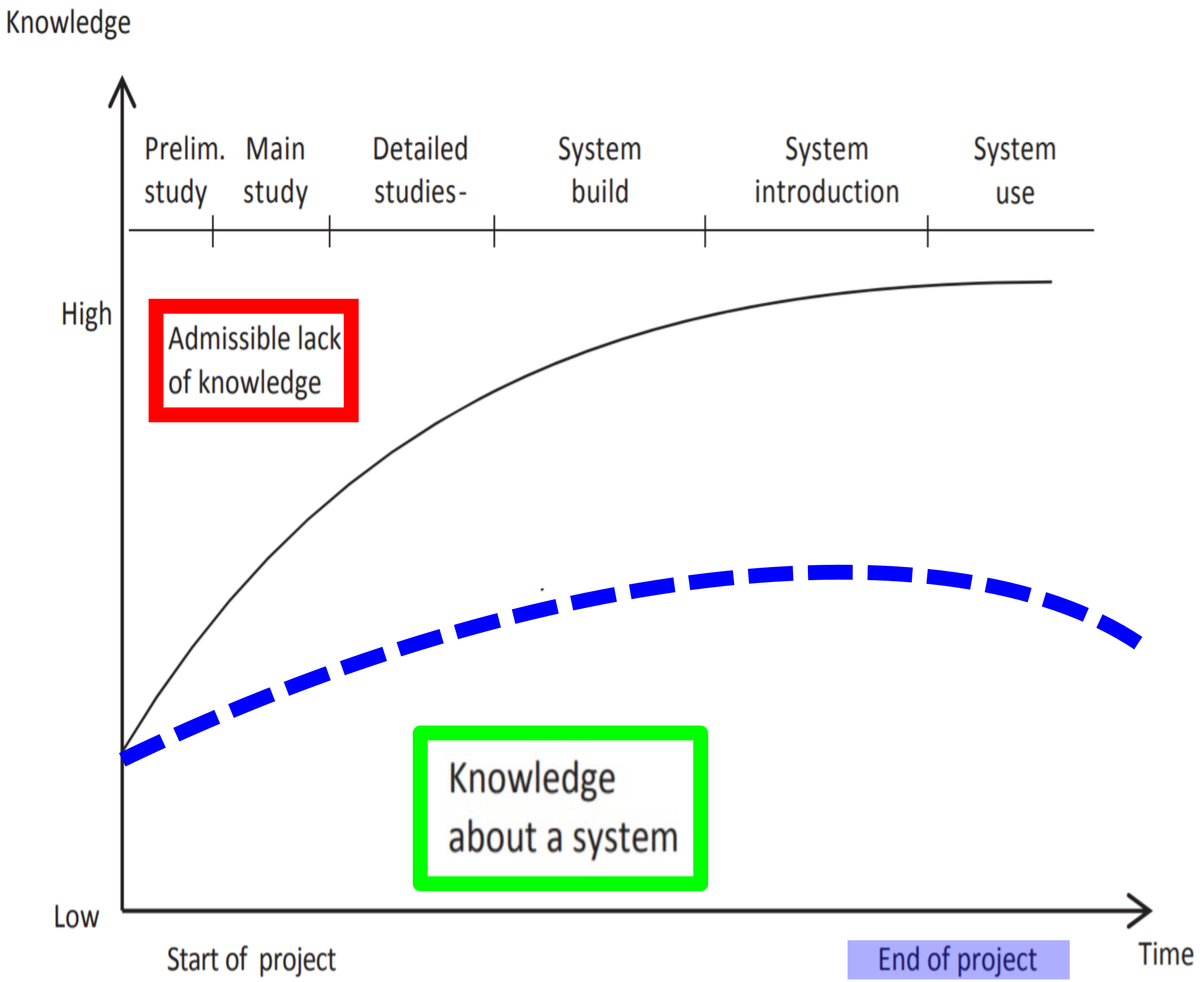


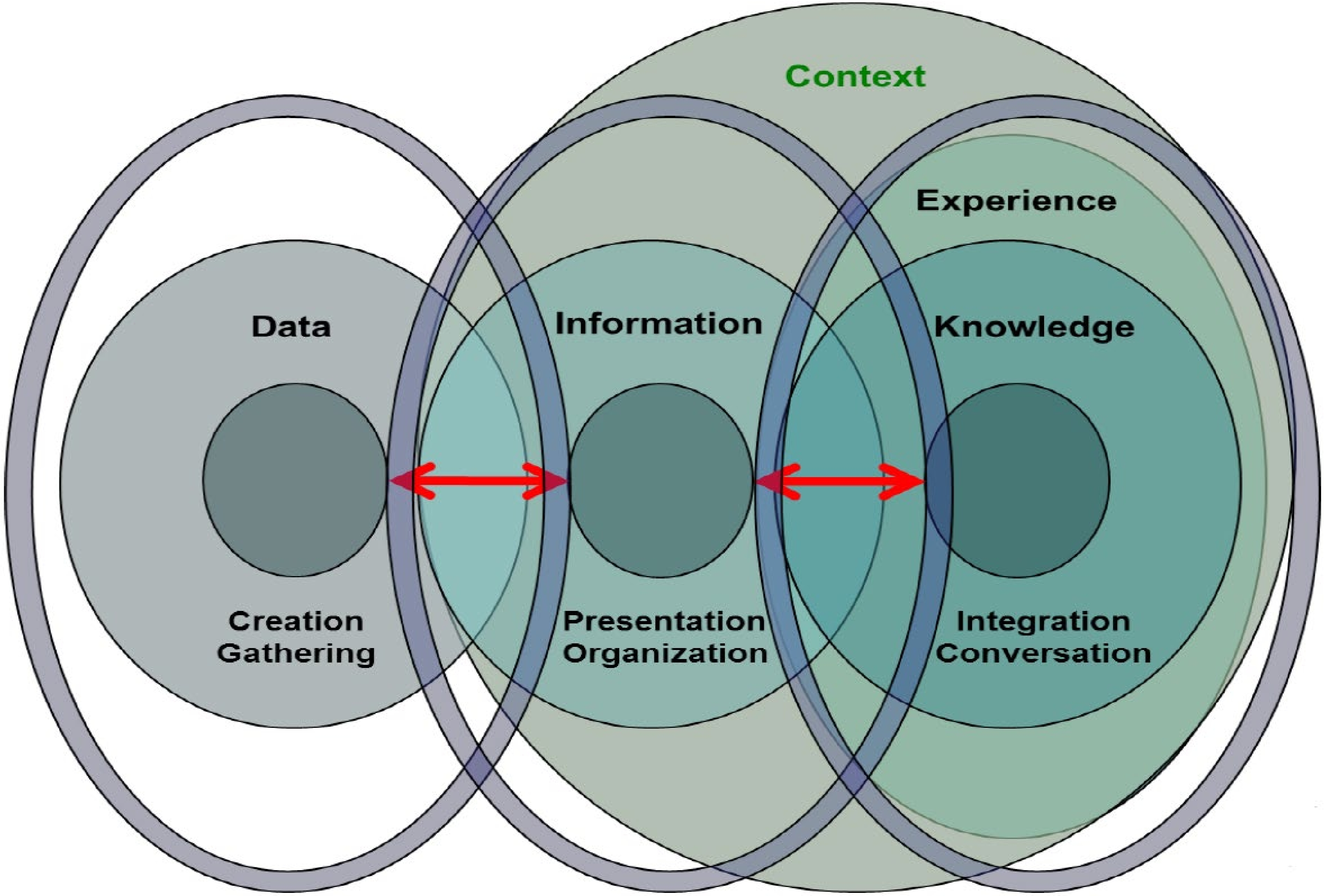
In the real world, knowledge increase may be bit sluggish.



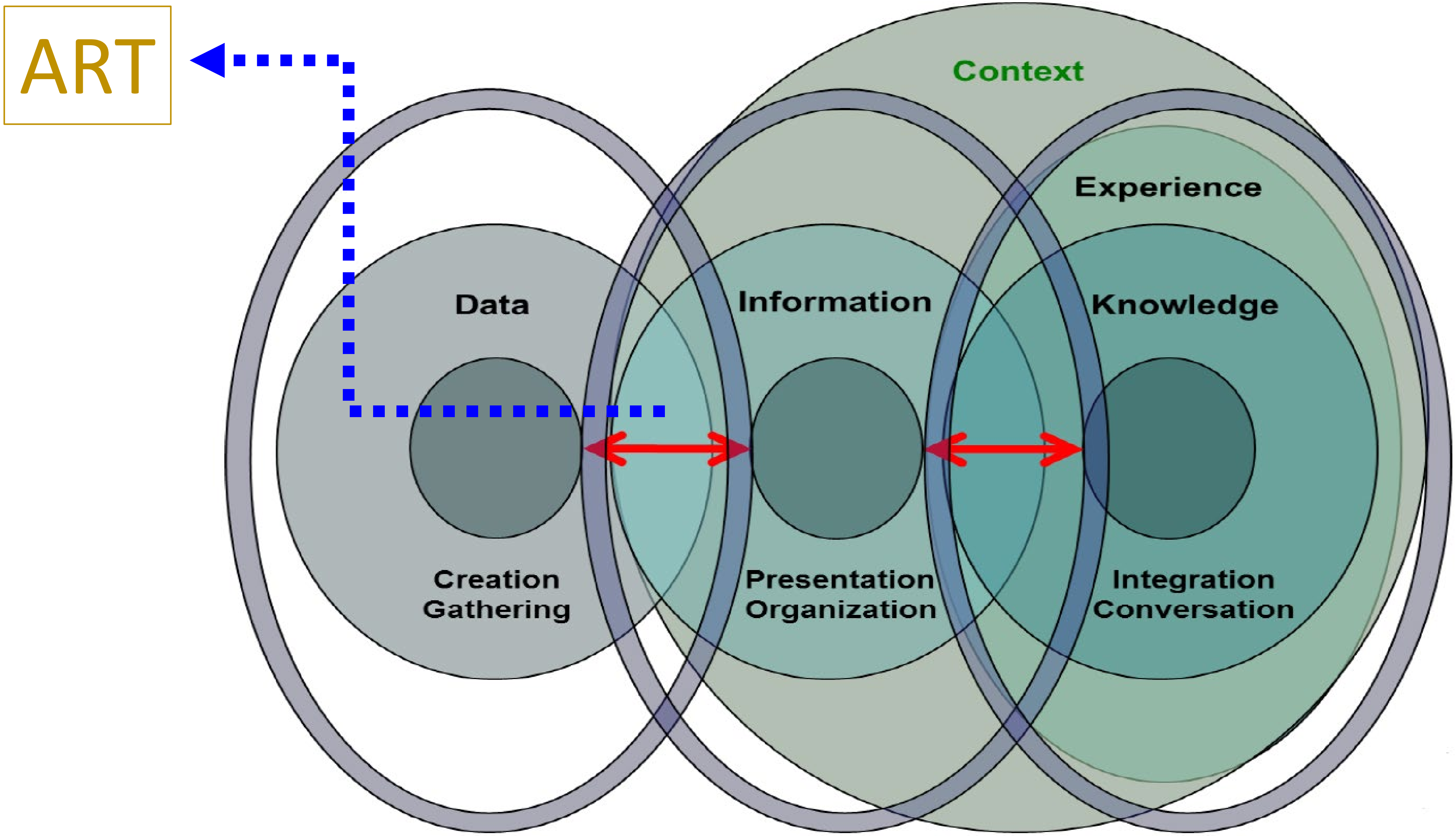
Have we gained knowledge from data and decisions?

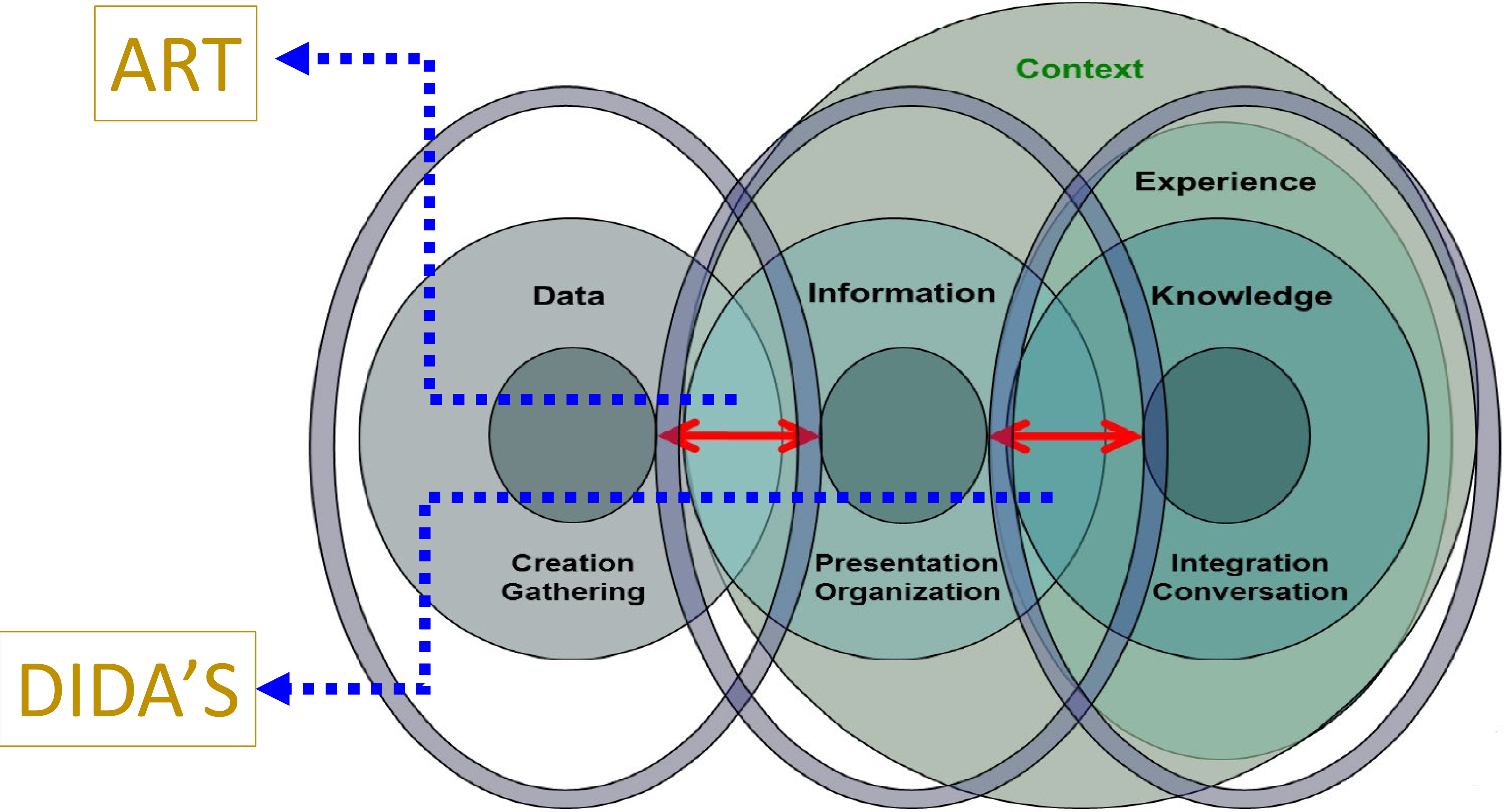




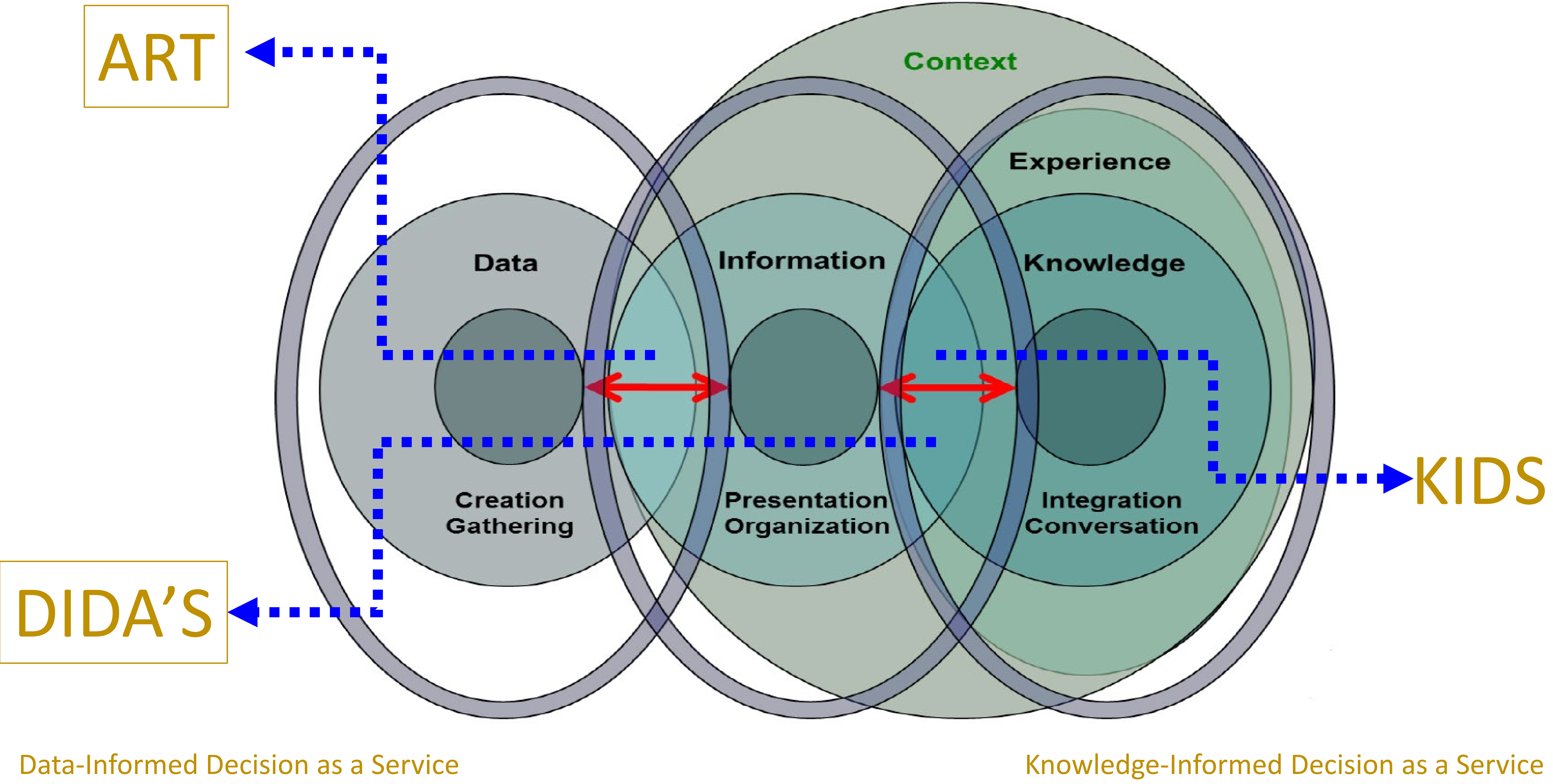

Context
Experience
Data
Information
Knowledge
Creation
Gathering
Presentation
Organization
Integration
Conversation

Artificial Reasoning Tools (ART)



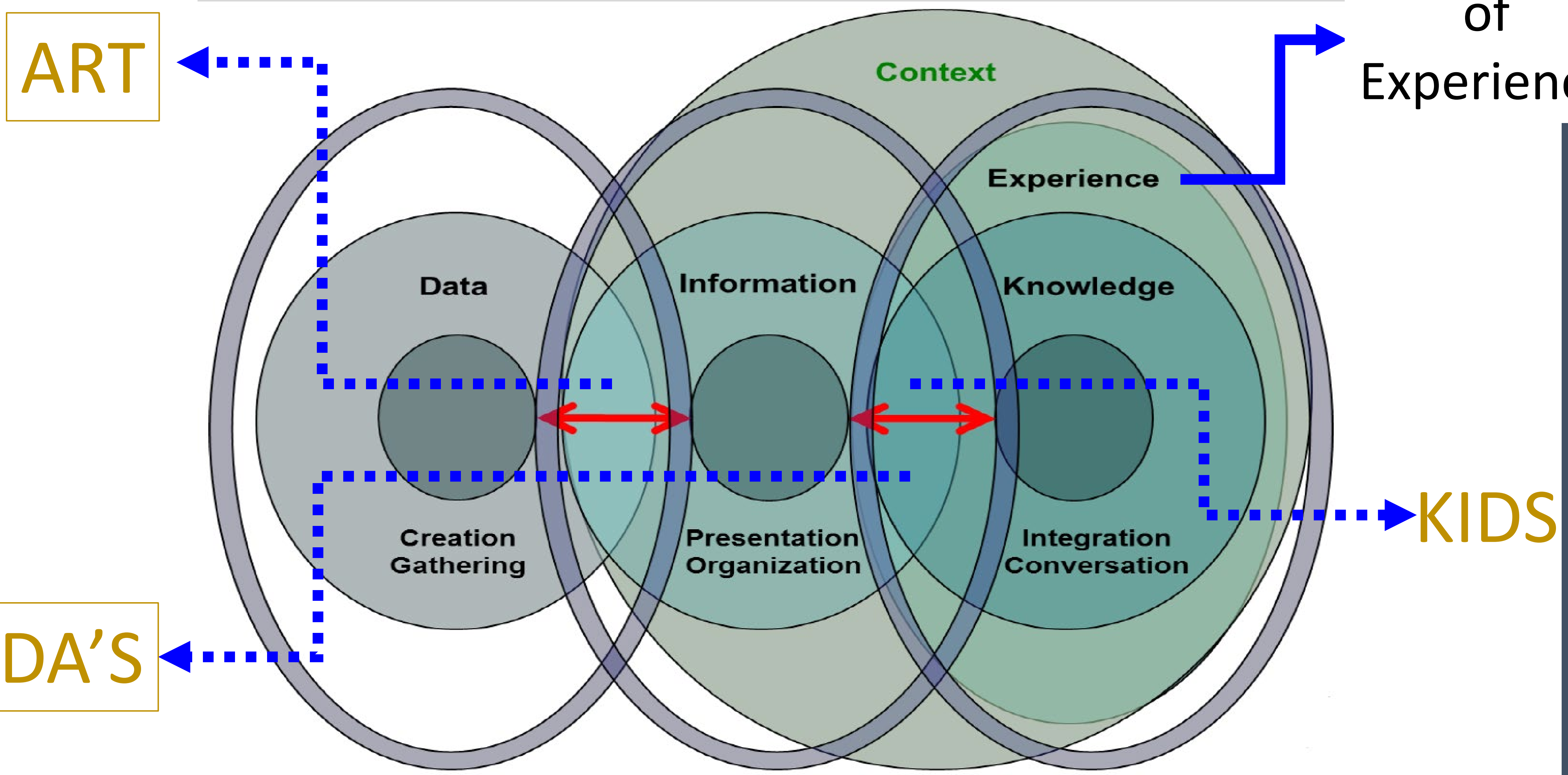


Data-Informed Decision as a Service

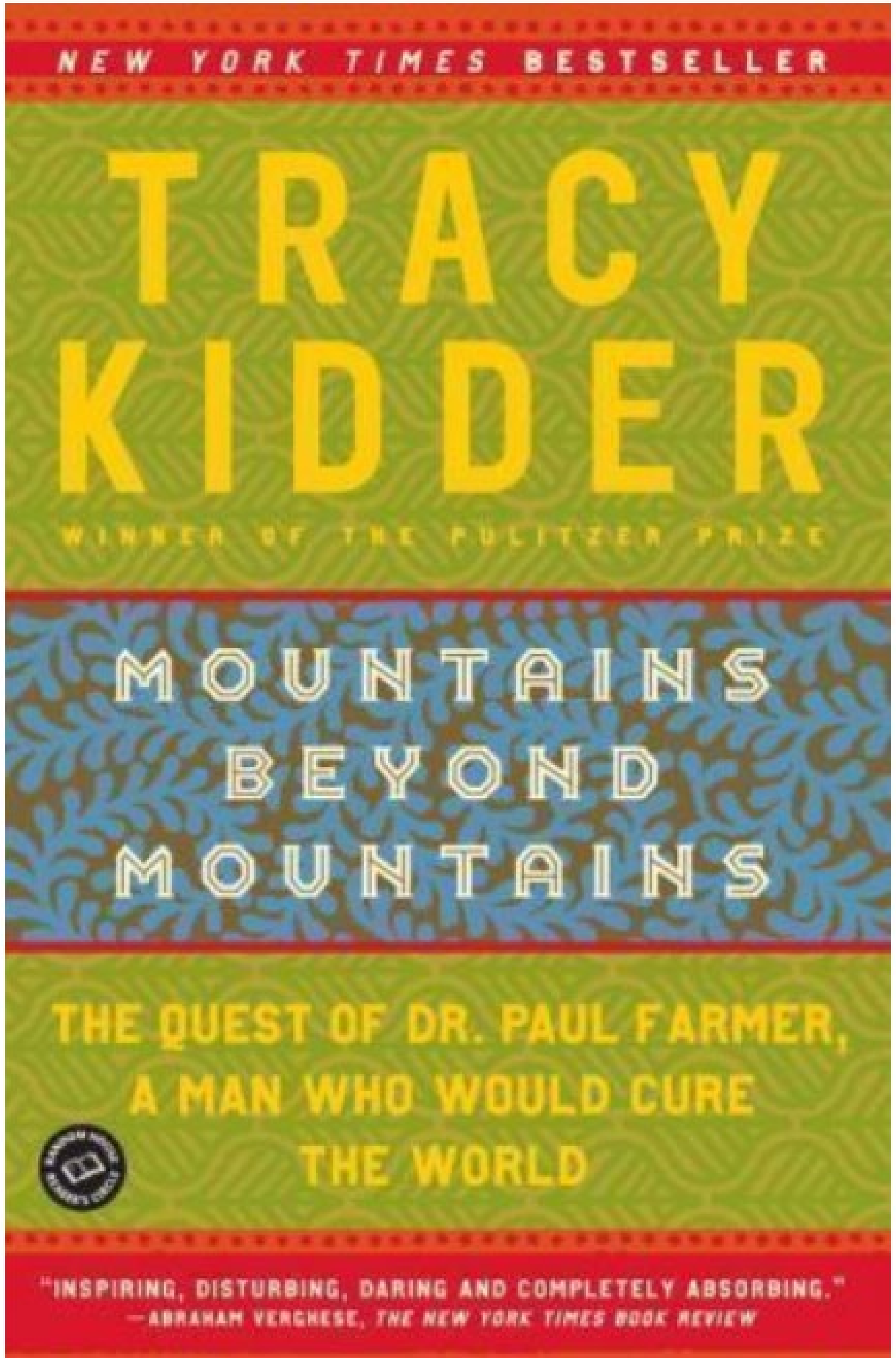

ART
Context
Experience
Data
Information
Knowledge
Creation
Gathering
Presentation
Organization
Integration
Conversation
KIDS
DIDA'S
Data-Informed Decision as a Service
Knowledge-Informed Decision as a Service

Beyond knowledge, experience

Realm of Experience

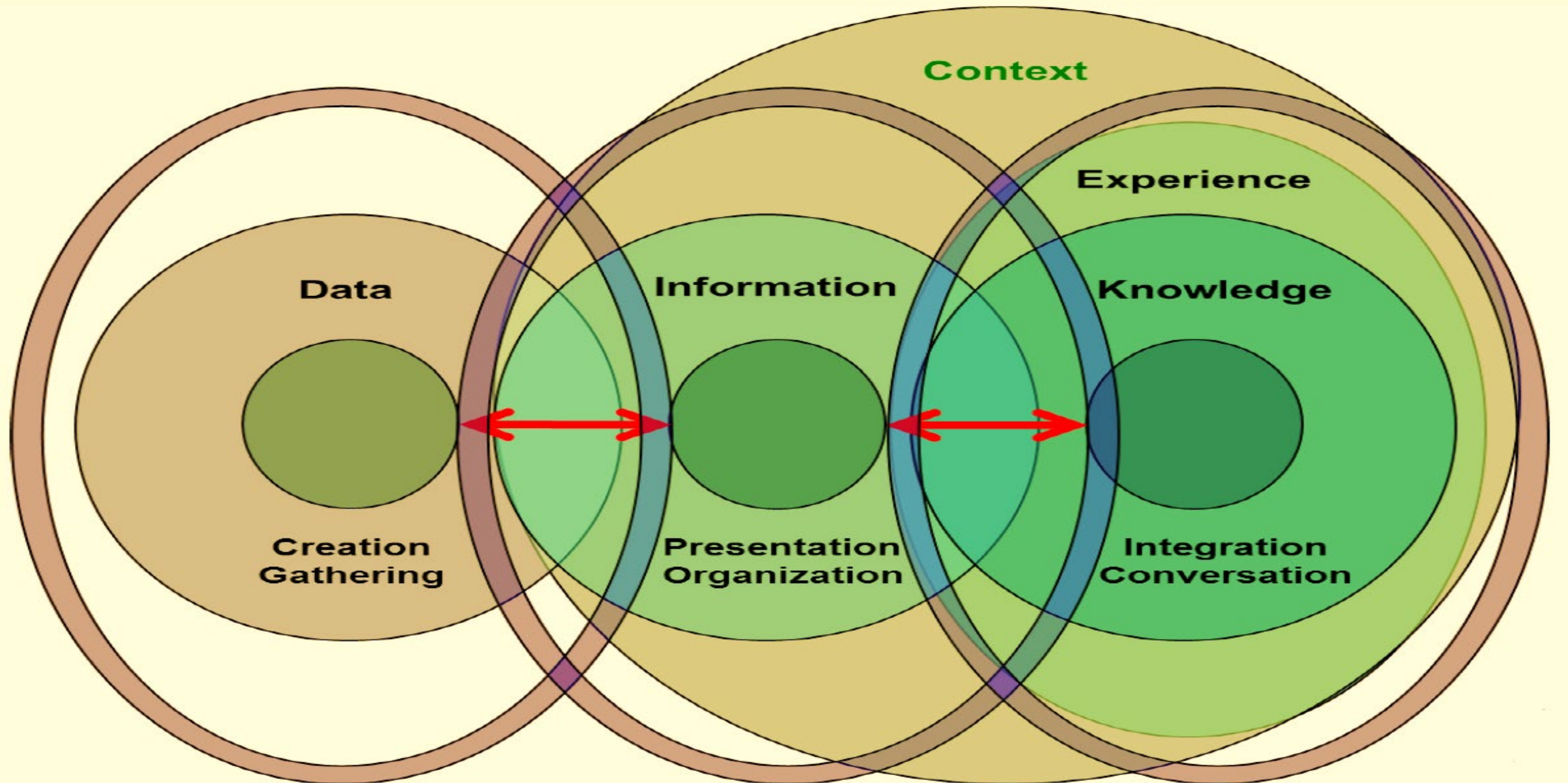


Cartoon by Jim Hendler

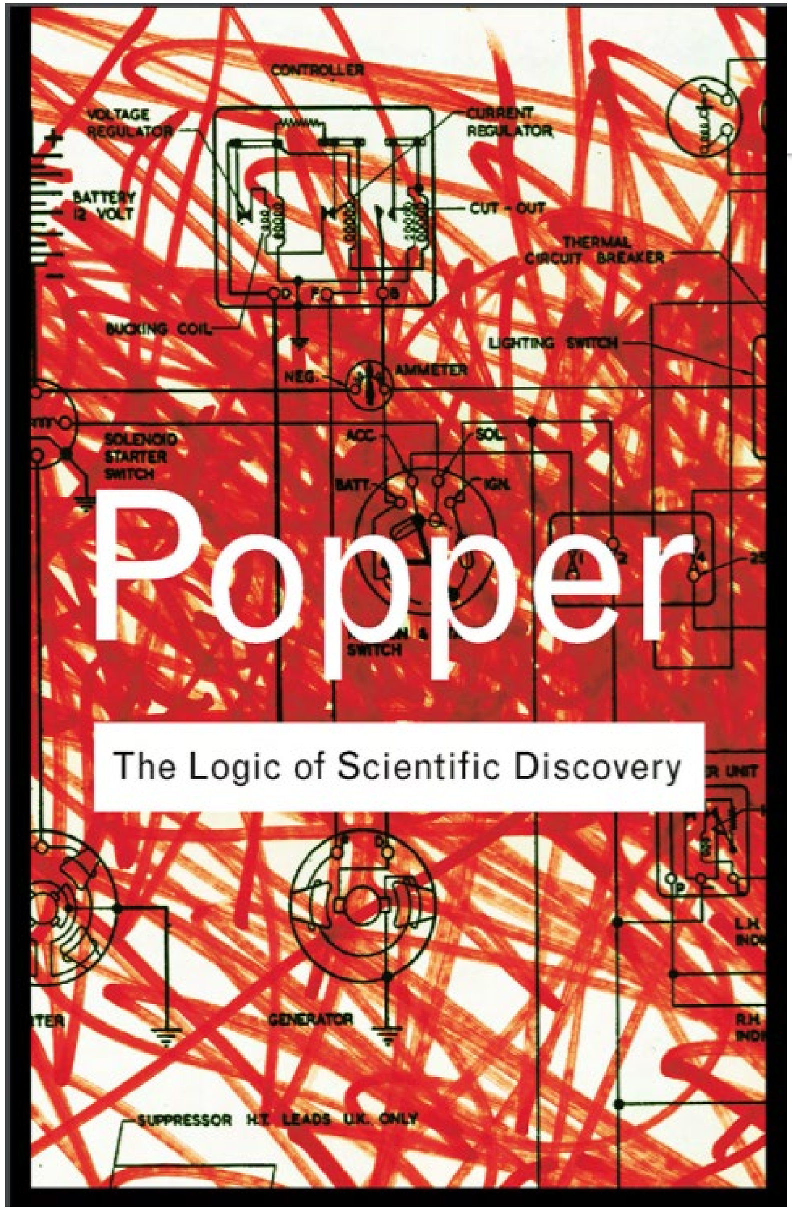


Beyond knowledge, experience

mountains beyond mountains



Beyond knowledge & beyond the grasp of artificial reasoning – Realm of Experience



But how is the system that represents our world of experience to be distinguished? The answer is: by the fact that it has been submitted to tests, and has stood up to tests. This means that it is to be distinguished by applying to it that deductive method which it is my aim to analyse, and to describe.

'Experience', on this view, appears as a distinctive *method* whereby one theoretical system may be distinguished from others; so that empirical science seems to be characterized not only by its logical form but, in addition, by its distinctive *method*. (This, of course, is also the view of the inductivists, who try to characterize empirical science by its use of the inductive method.)

The theory of knowledge, whose task is the analysis of the method or procedure peculiar to empirical science, may accordingly be described as a theory of the empirical method—*a theory of what is usually called 'experience'*.

http://strangebeautiful.com/other-texts/popper-logic-scientific-discovery.pdf

Elusive Quest for Knowledge
Advanced integration of information, data, decisions

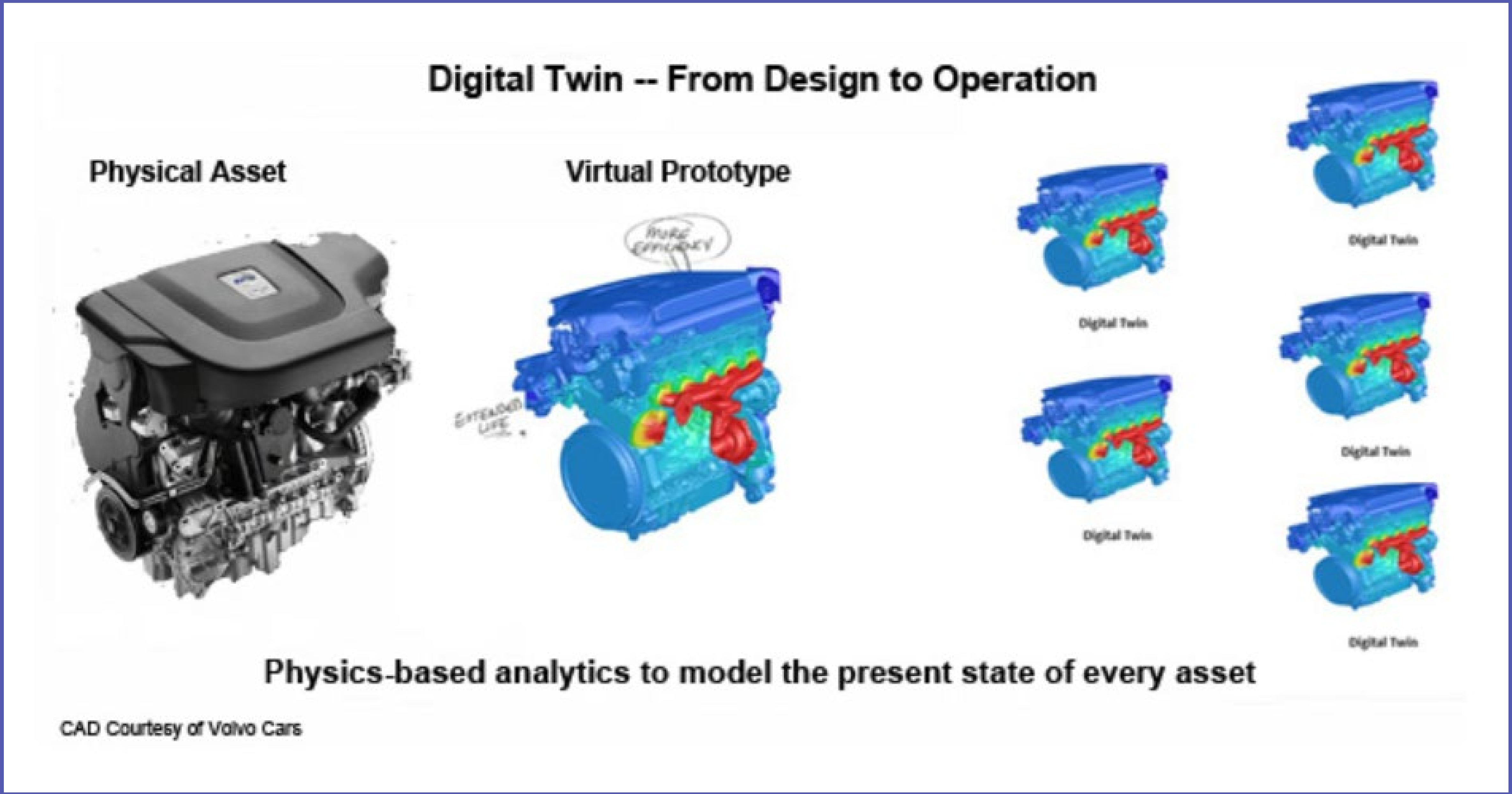
- KIDS may need TWINS

- KIDS may include SARA

KIDS need TWINS

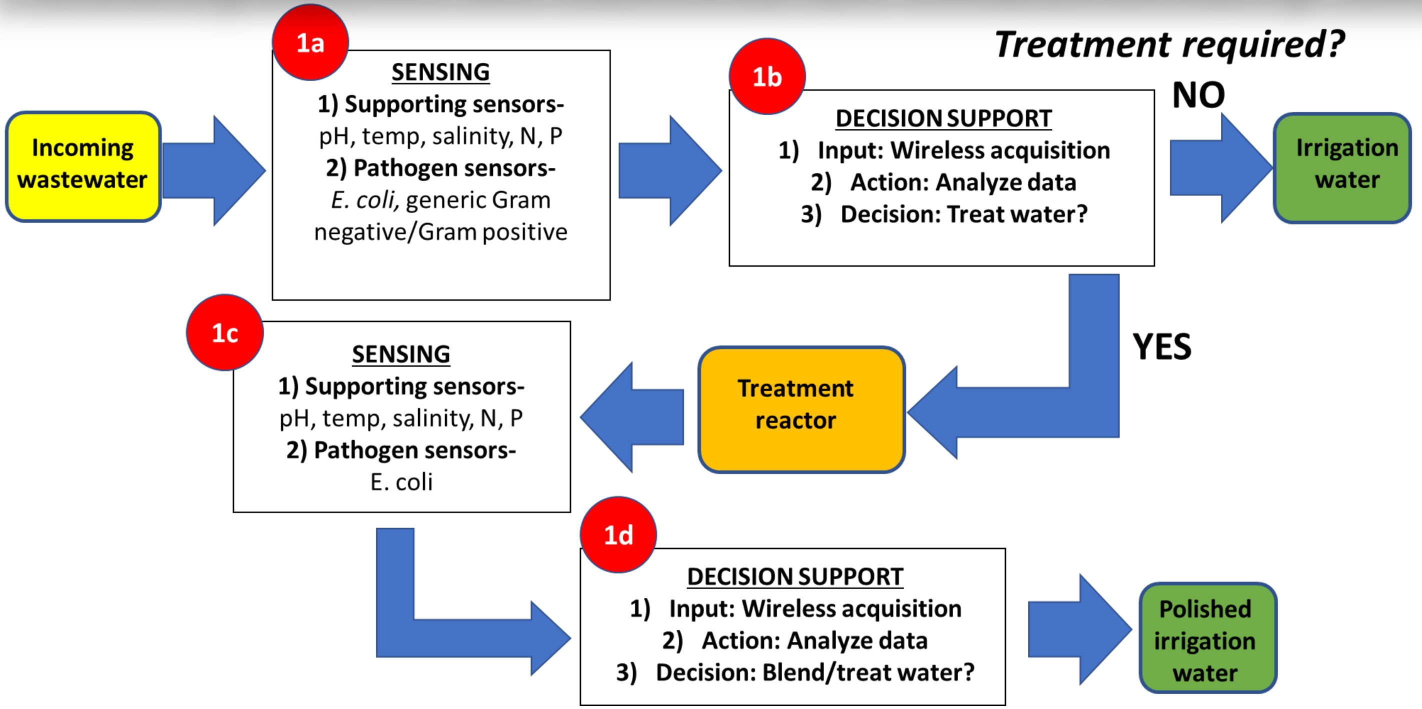
Adding PLM capacity in the form of Digital Twins to DIDA’S and KIDS

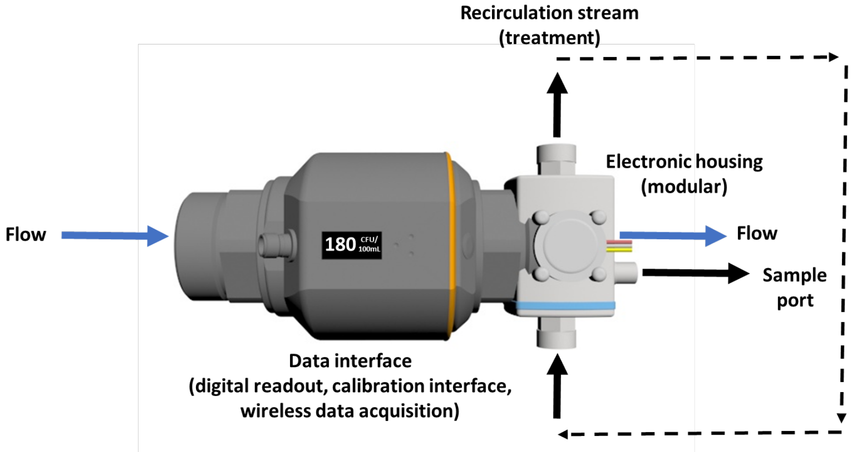
PLM sensor data – machine tools, pumps, pipelines, cold storage

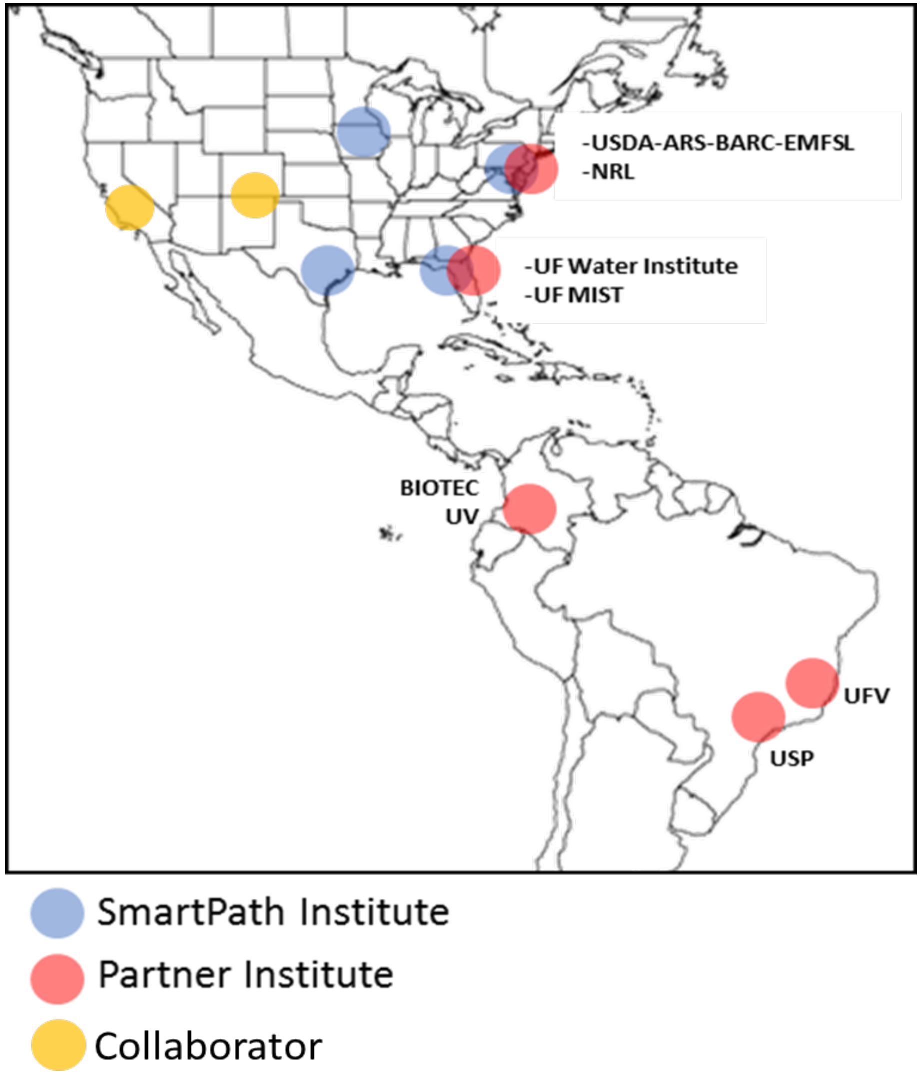


https://www.ansys.com/blog/digital-twin-pump

Use case: KIDS integrated with DIGITAL TWINS may improve the ecosystem in terms of machinery lifecycle in the agroecosystem





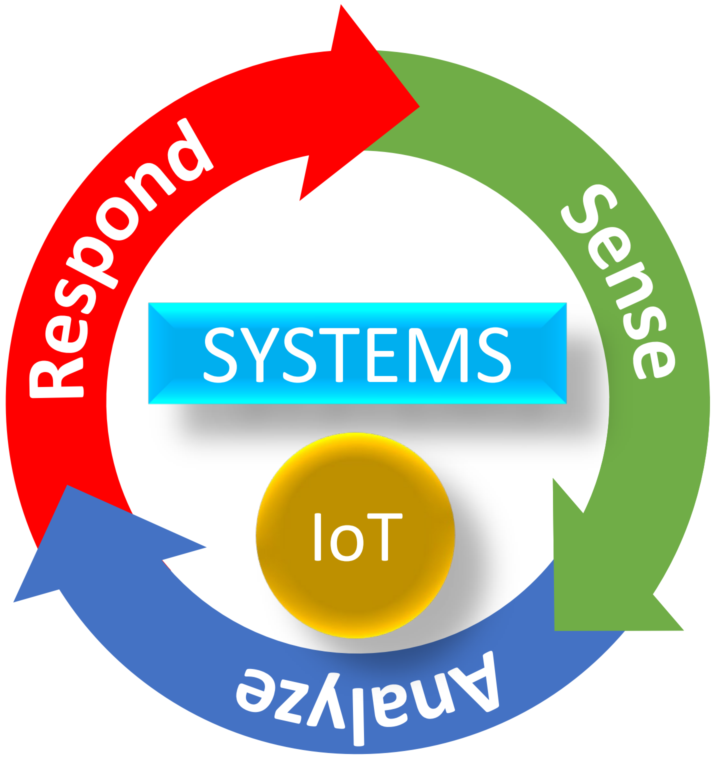


KIDS to include SARA

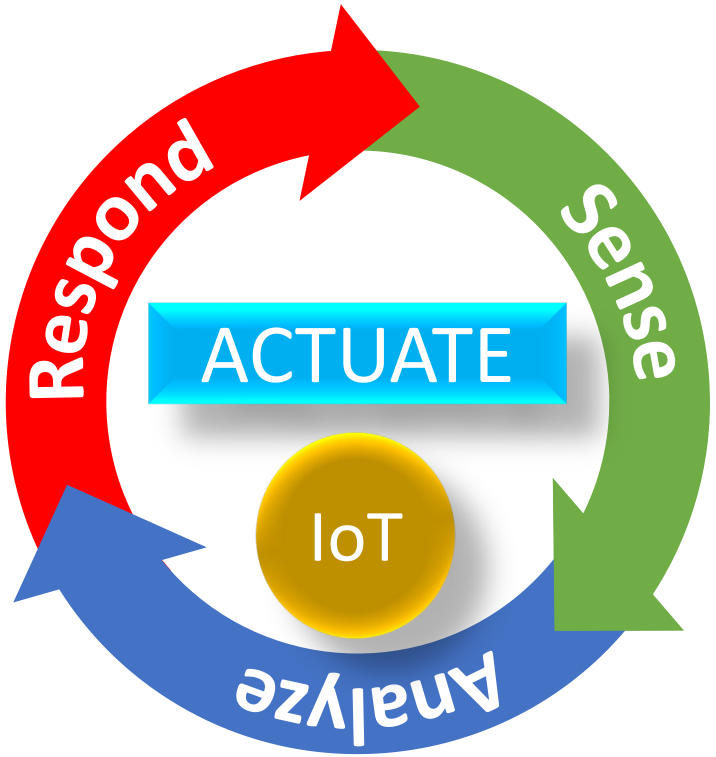
From sense, analyze, response, systems (SARS)

to sense, analyze, response, actuate (SARA)

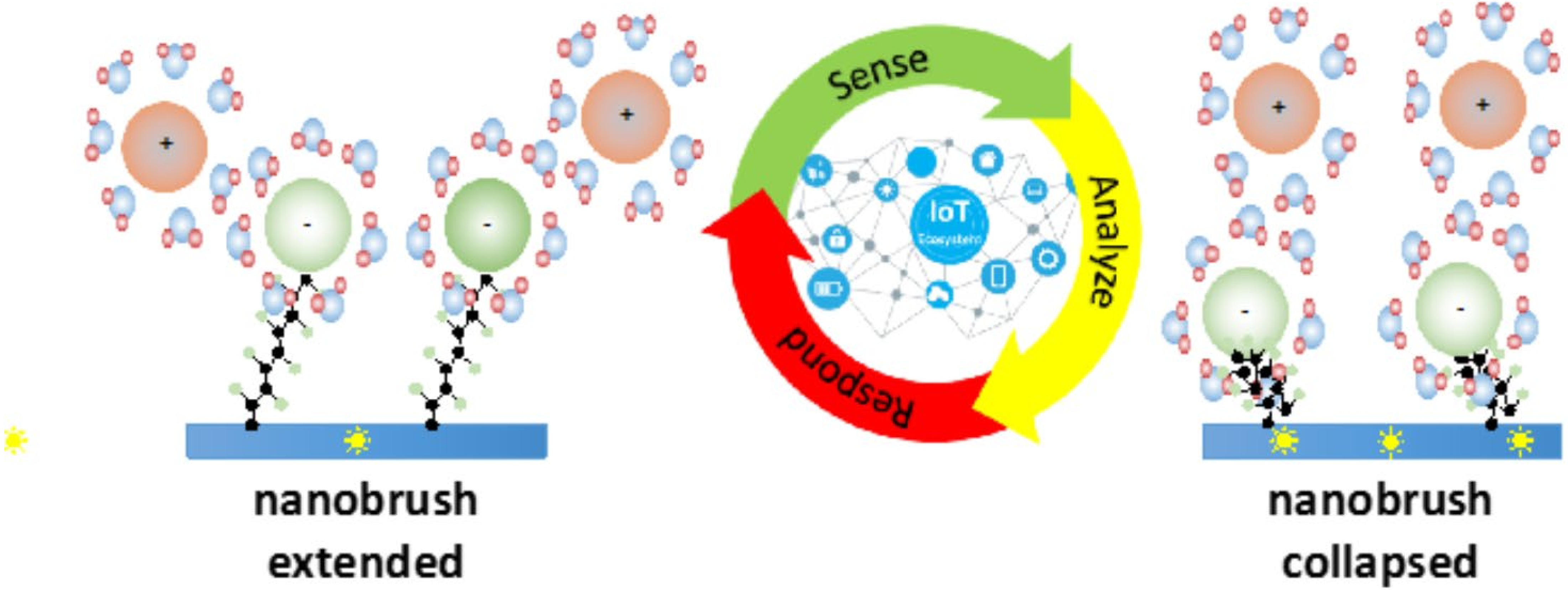
DIDA’S includes Sense, Analyze, Response, Systems (SARS)



KIDS to include Sense, Analyze, Response, Actuate (SARA)



Atoms to Bits - Sense, Analyze, Response, Actuate (SARA) Sensors using Smartphone



Nanomaterials can be monitored and controlled with smartphone

Future of digital transformation for the agro-ecosystem and emergence of digital products for traditional agri-businesses.

https://emclamor.wixsite.com/mclamorelab

Conventional Wisdom Questions Growth from Digital Transformation:

Conventional Wisdom Questions Growth from Digital Transformation:

BUSINESS INSIDER

TECH | FINANCE | POLITICS | STRATEGY | LIFE | ALL

BI PRIME | INTELLIGENCE

NASA is opening the space station to $35,000-a-night visits. A tourist who paid Russia $30 million to get there a decade ago says it's a 'seismic shift.'

Dave Mosher 2h

NASA plans to open up the International Space Station to tourists and, to an even larger degree, commercial activity. NASA; Alyssa Powell/Business Insider

Conventional Wisdom ?

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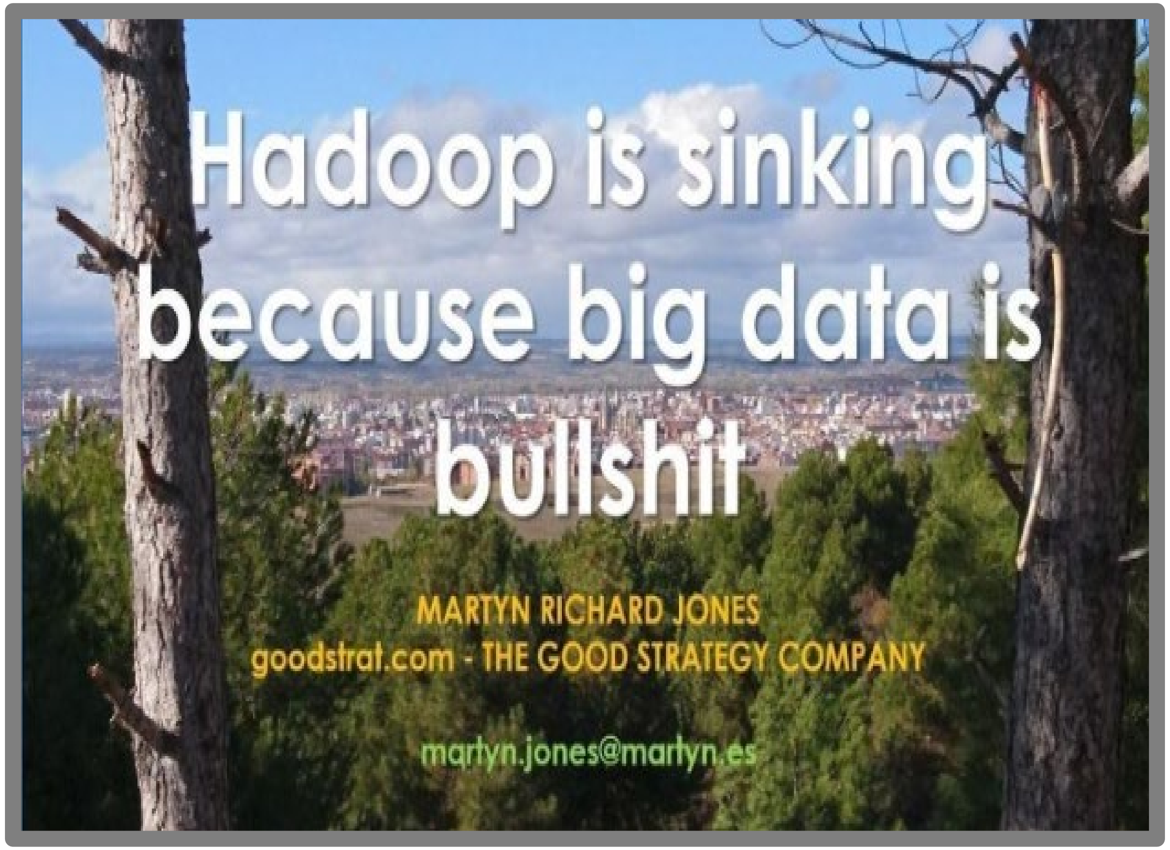
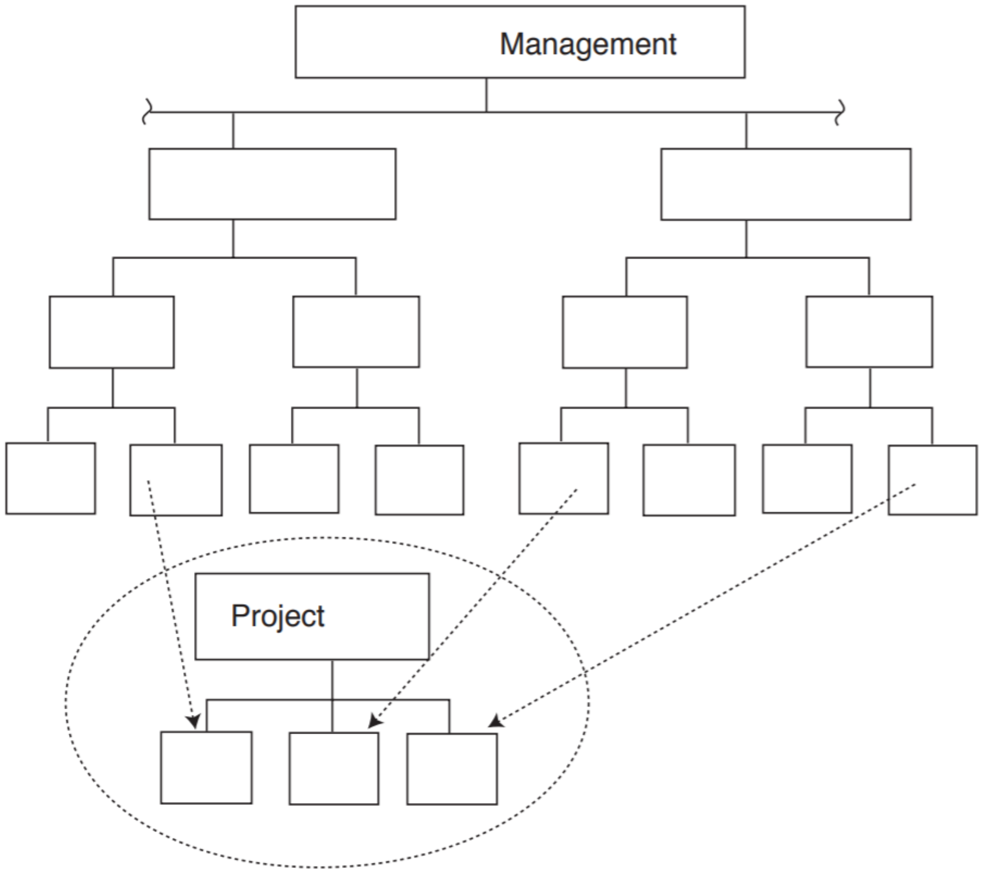
NASA plans to open up the International Space Station to tourists and, to an even larger degree, commercial activity. NASA; Alyssa Powell/Business Insider

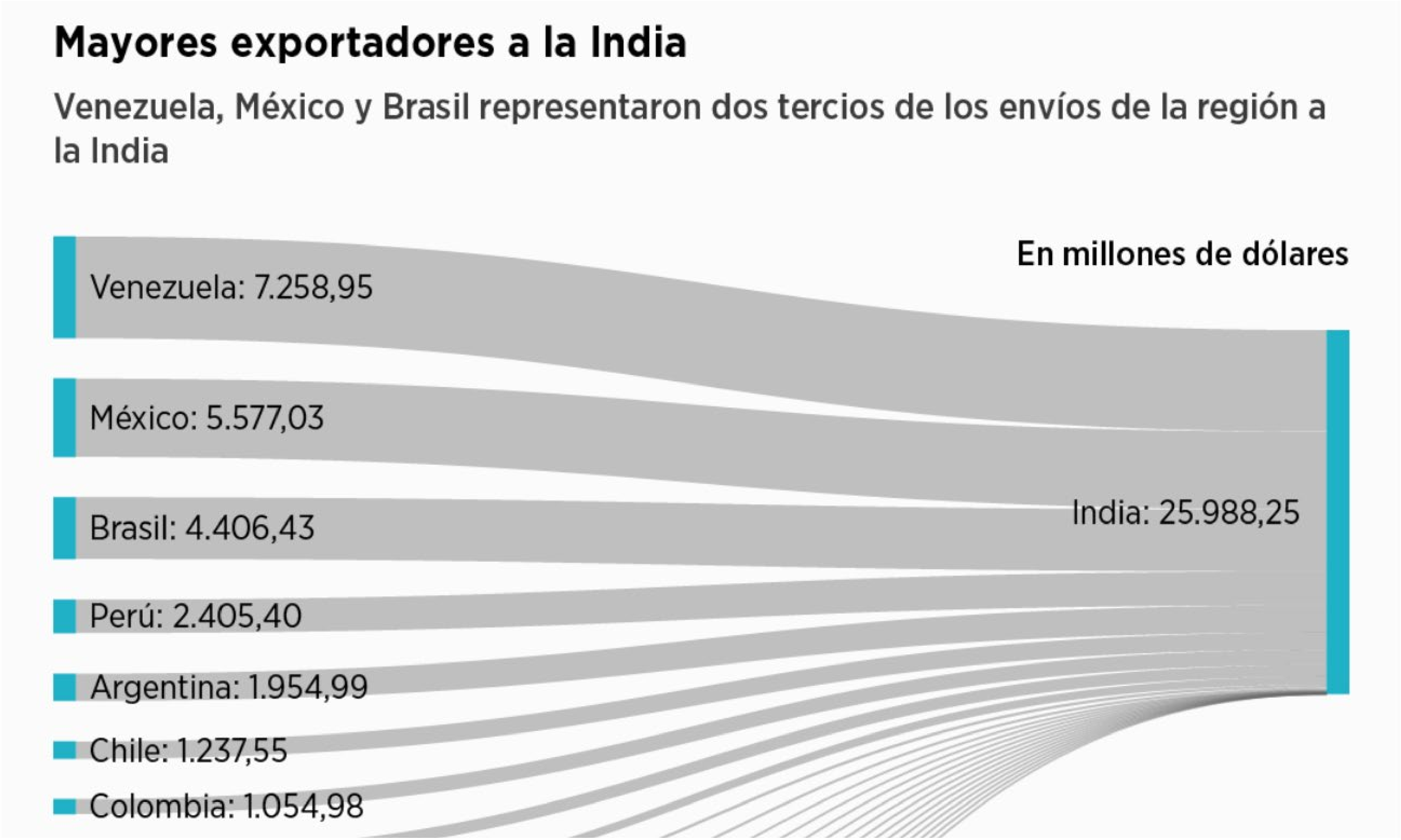


CONVENTIONAL WISDOM



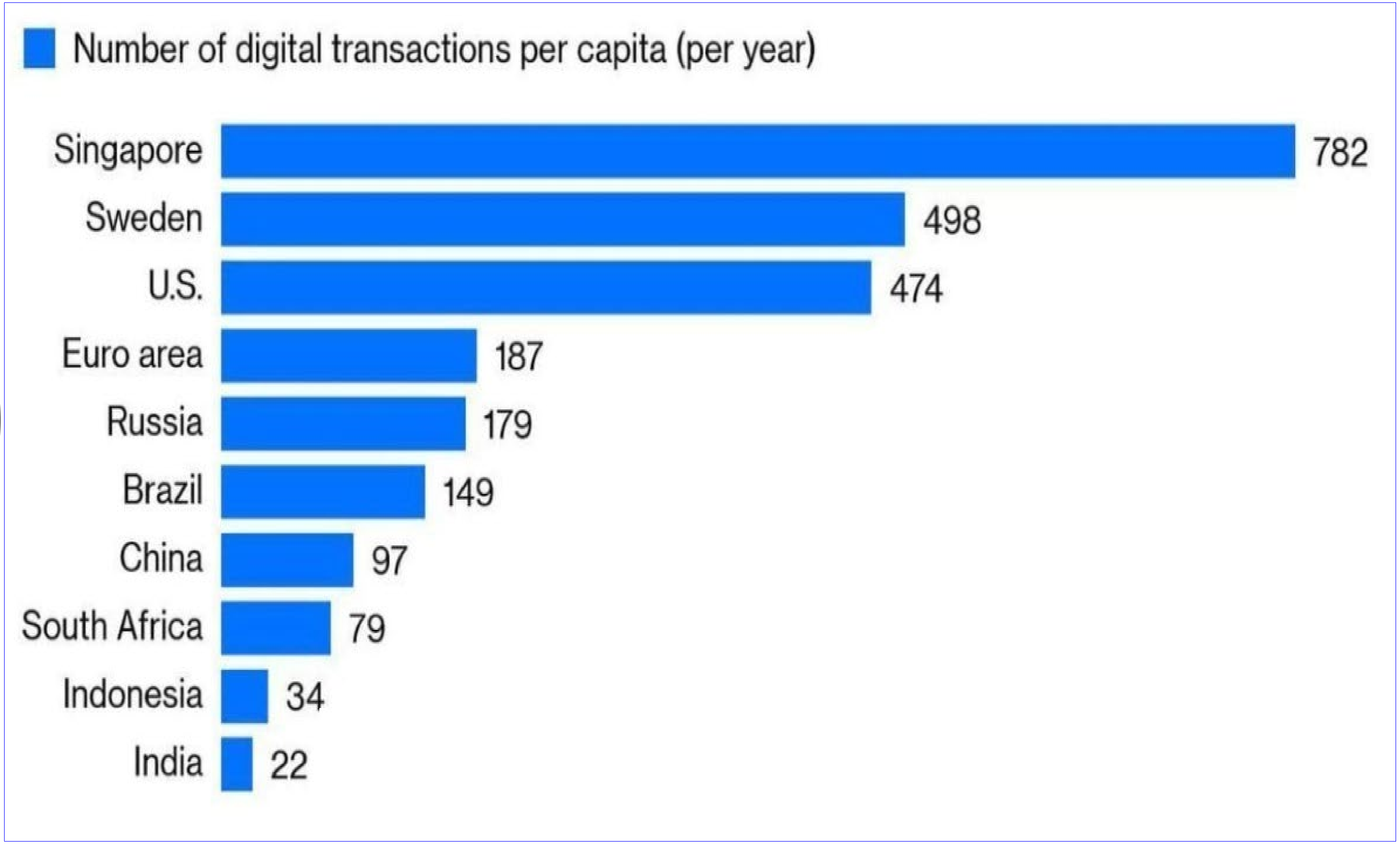
Think different. Think non-linear. Think outside the box. Think beyond boundaries.

Exports from Latin America to India was US$2 billion in 2000. In 2018, it exceeded US$25 billion.



https://www.iadb.org/en/improvinglives/can-india-become-latin-americas-next-trade-frontier

Is there a market for digital ART products in traditional agri-business?



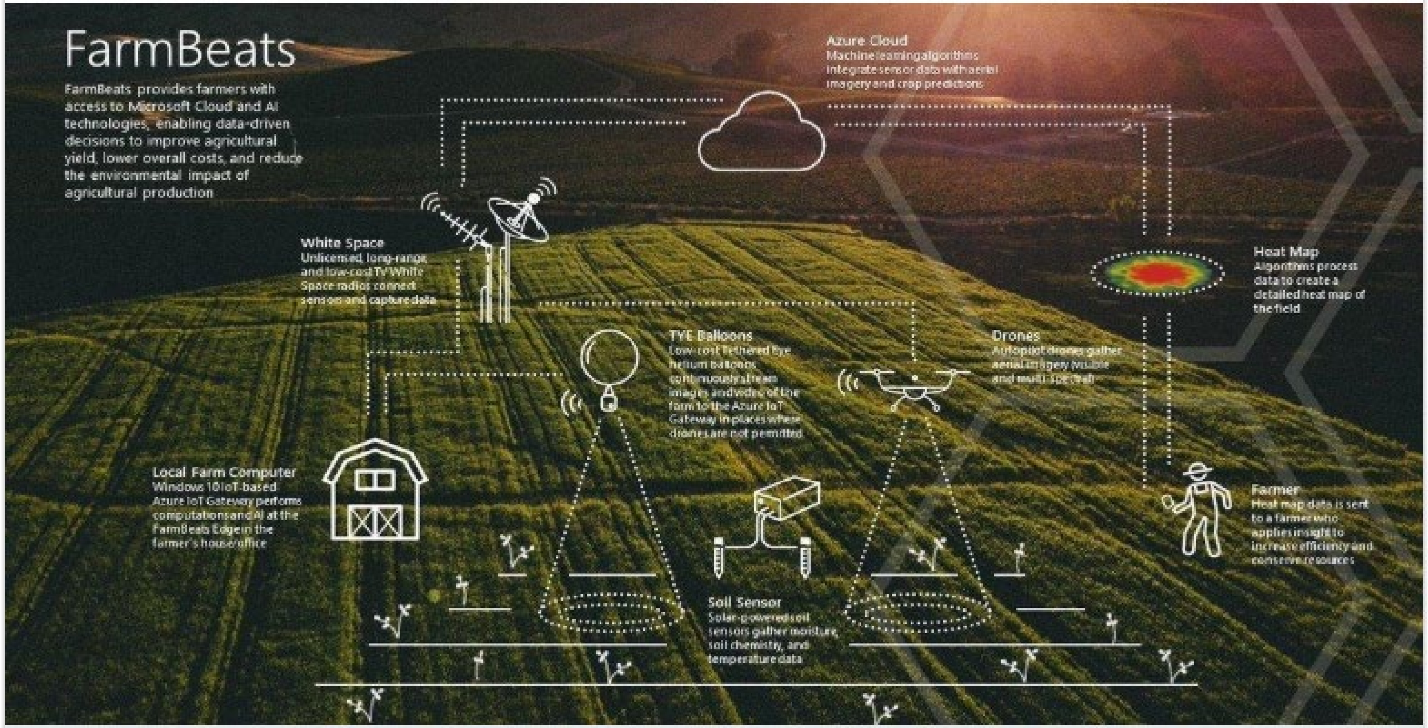
To obtain the volume of potential digital transactions, multiply the number shown with the population of the country.

https://www.washingtonpost.com/business/india-going-cashless-could-be-a-model-for-the-world/2019/06/05/d8fec830-87ee-11e9-9d73-e2ba6bbf1b9b_story.html

Ranveer Chandra
Chief Scientist, Azure Global at Microsoft

Tom Keane
Corporate Vice President of Azure Global - Microsoft Azure

Microsoft FarmBeats program uses Azure to connect agricultural devices and generate data intended to help farms transform business.



http://bit.ly/PARTNER-WITH-PEAS

http://bit.ly/SUBSCRIBE-TO-SENSEE

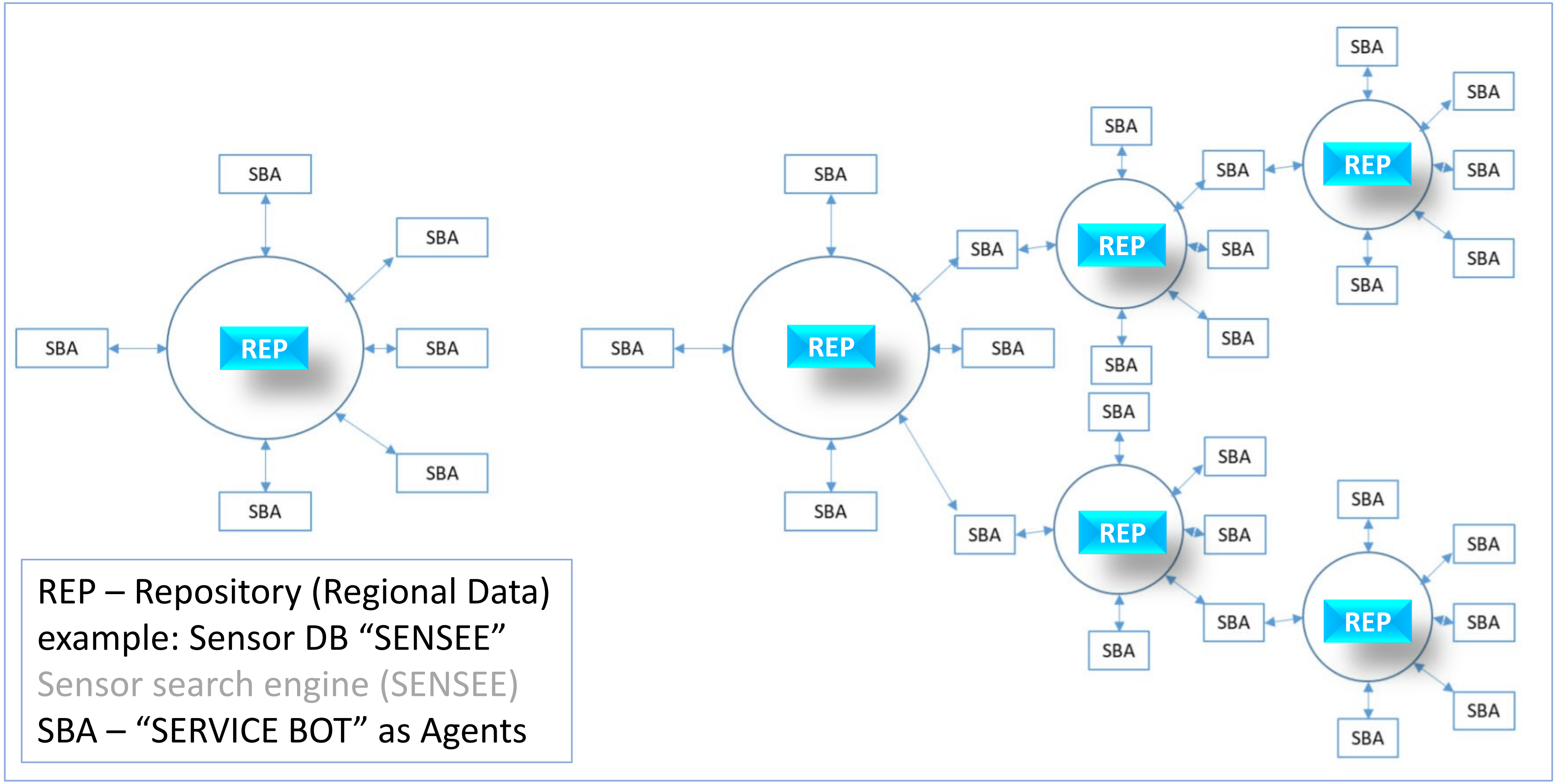
Practitioners who lack patience for pursuit of knowledge

Low hanging fruits in digital-agro

Prevention of food waste, global public health, water and food safety

Minimalistic approach combining SENSEE in a basic DIDA’S platform tasked with simple information arbitrage on mobile devices.

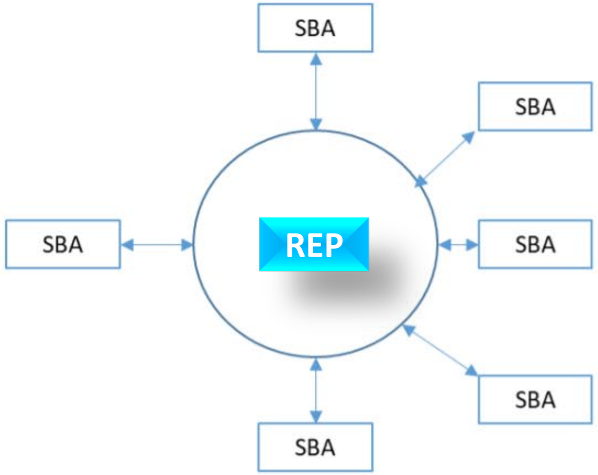
Intelligent Information Arbitrage

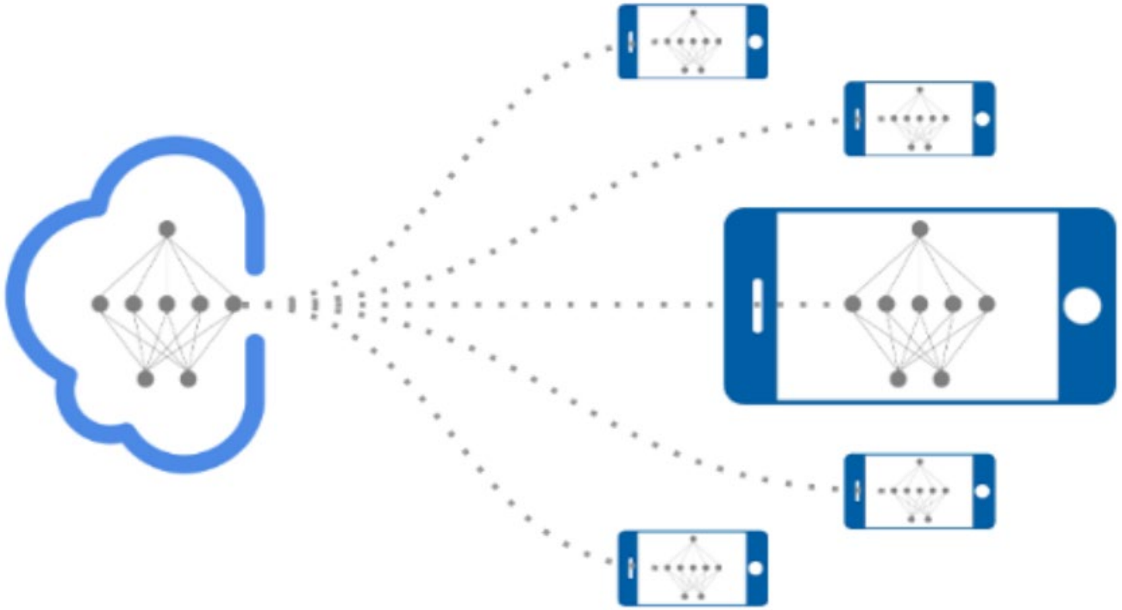


REP – Repository (Regional Data)
example: Sensor DB “SENSEE”
Sensor search engine (SENSEE)
SBA – “SERVICE BOT” as Agents

Locally distributed repositories [REP] containing data and questions (relevant to users and growers by crop or environment) can be globally connected using an Agent-based system

Intelligent Information Arbitrage

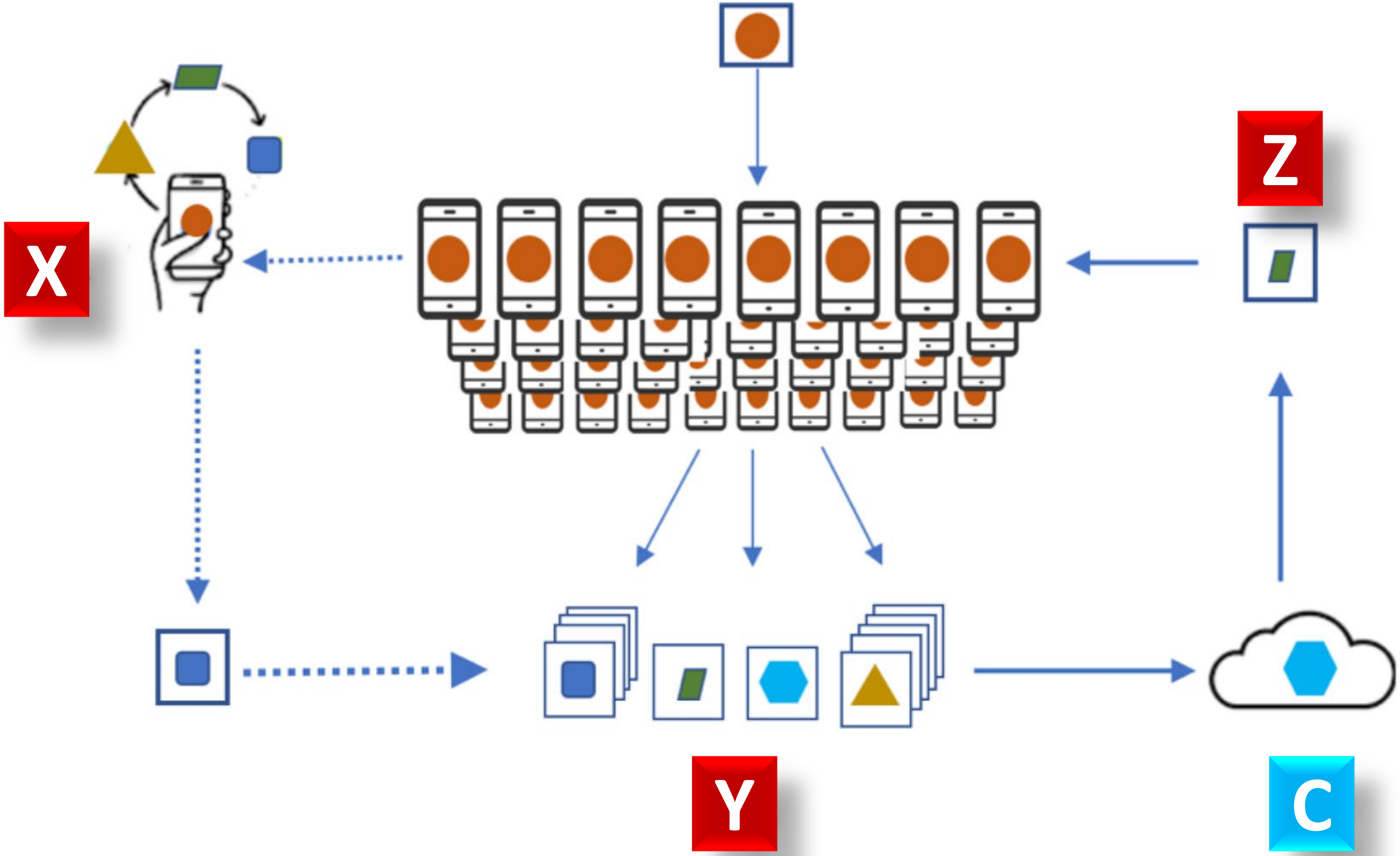




REP – Repository (Regional Data)
example: Sensor DB “SENSEE”
Sensor search engine (SENSEE)
SBA – “SERVICE BOT” as Agents

Locally distributed repositories [REP] containing data and questions (relevant to users and growers by crop or environment) can be globally connected and consumed by any system

Intelligent Information Arbitrage



https://medium.com/@SantanuB/a-beginners-guide-to-federated-learning-b29e29ba65cf

Intelligent Information Arbitrage

The value of the REP concept (SENSEE) may be enhanced by coupling publish-subscribe modes with crowd-sourced data adoption/dissemination. User “X” may update data, recommend tools or techniques or share outcomes/outputs (for example, growers can share photographs of infected produce or sinfully delicious tomatoes). Thus, local user personalization (point X, in the crowd) is sent/stored to the analytical platform (engine Y). An emerging consensus from contributed data (for example, improved technique or data with incorrect units or better use of a tool) is sent to cloud C for expert evaluation and critical analysis. Verified change Z is communicated to all subscribers, globally. This process repeats, to enhance open models and enrich common goals for public goods, using distributed data from crowdsourcing (users, farmers, growers, scientists, engineers, academics, politicians) but deploying a neutral/trusted analytical evaluator (cloud C) to deconstruct/reconstruct, aggregate/disaggregate data and models, to serve the best interest of the system. It may prevent data pollution, act to neutralize cyberthreats and stop, if possible, attacks perpetrated by GAN (general adversarial network) as infectious agents. This suggestion draws from “federated learning models” commonly used by financial institutions and banks to train fraud detection models without sharing their sensitive customer data. Popular frameworks now include TensorFlow Federated, an open source framework by Google for experimenting on decentralized data. PySyft is a open source library that is built on top of PyTorch for encrypted, privacy preserving deep learning. Federated AI Technology Enabler (FATE) is an open-source project initiated by Webank’s AI group to provide a secure computing framework to support the Federated AI ecosystem. Despite the hype whipped up by the glib snake oil salesmen of AI, there is value in this approach, if and when rationally analyzed, for specific purposes, using bonafide tools, which may be customized for specific applications and are based on rigorous mathematics and statistics. It may be useful for SITS and its ecosystem to explore these advanced tools of the future and enterprise solutions around federated learning and other secure computation techniques across different verticals. At present, the primary deployment challenge may be the computational constraint of edge devices (smartphone, tablet) to perform local training, cloud consultations and inferencing. However, smartphones and IoT devices are increasingly equipped with GPUs or sufficient computing hardware to run CNN/RNN and other AI models at the edge to augment near-real time “intelligent” decision support systems, at the point of use. REP/SENSEE may be the SmartPath/SITS approach to harvest these ideas and convert them into actionable transactions that can help the ag industry in the pursuit of food.

X

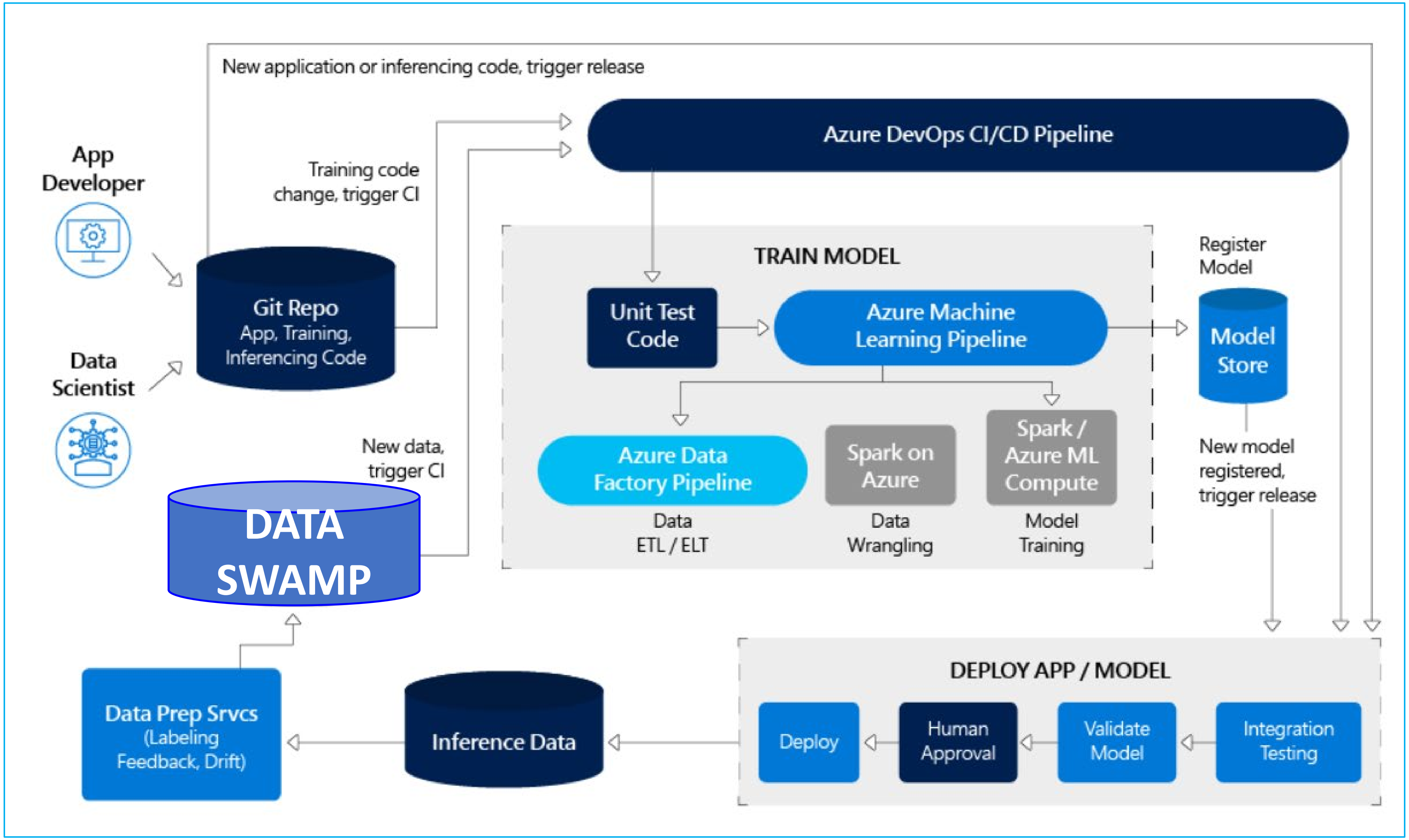
Z

Y

C

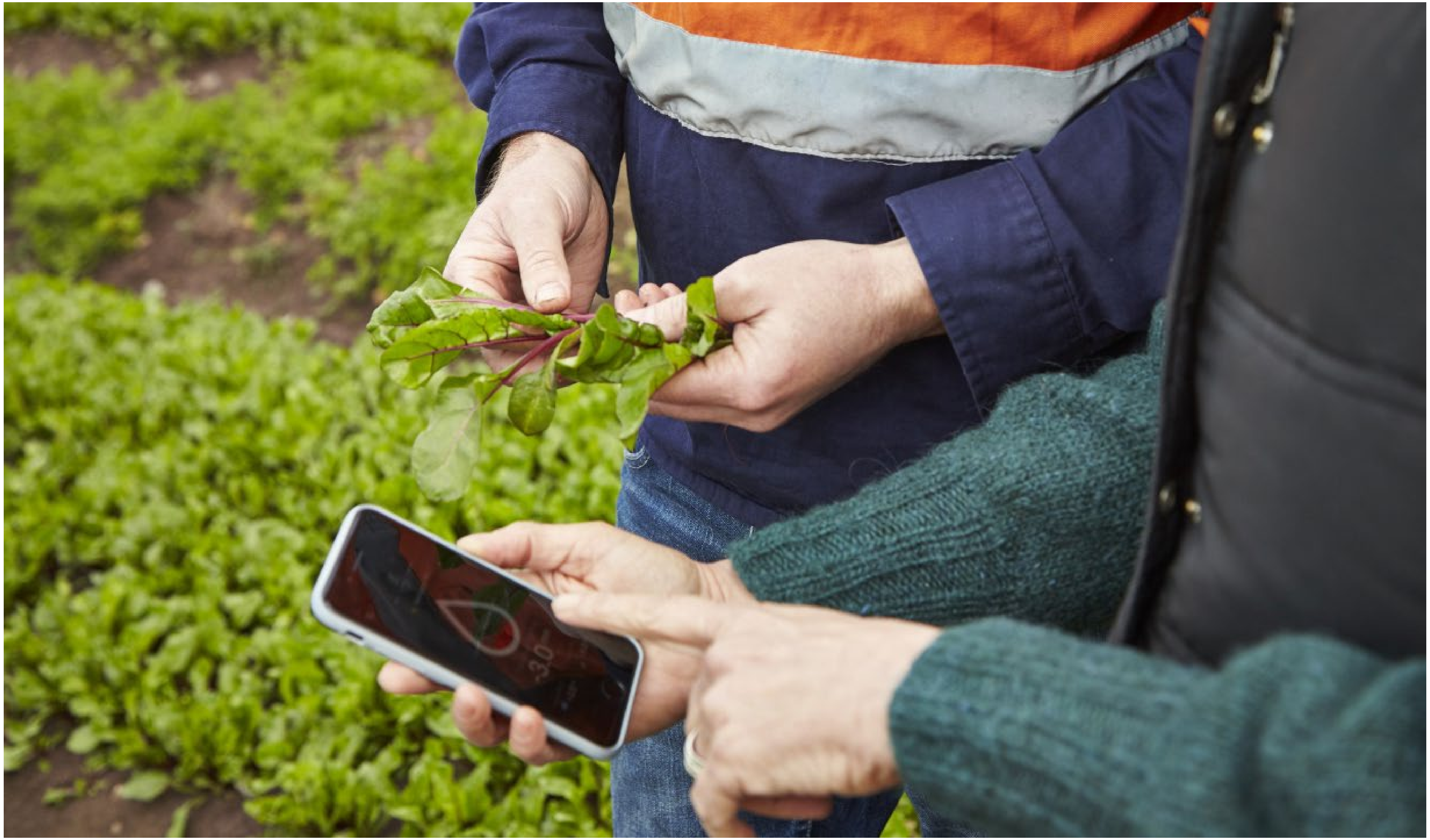
https://medium.com/@SantanuB/a-beginners-guide-to-federated-learning-b29e29ba65cf

Intelligent Information Arbitrage



https://azure.microsoft.com/en-us/blog/breaking-the-wall-between-data-scientists-and-app-developers-with-azure-devops/

Intelligent Information Arbitrage



HARVEST and INVEST in UNSTRUCTURED DATA and (MERGE DATA IN CONTEXT FOR INTELLIGENT) DATA ANALYTICS

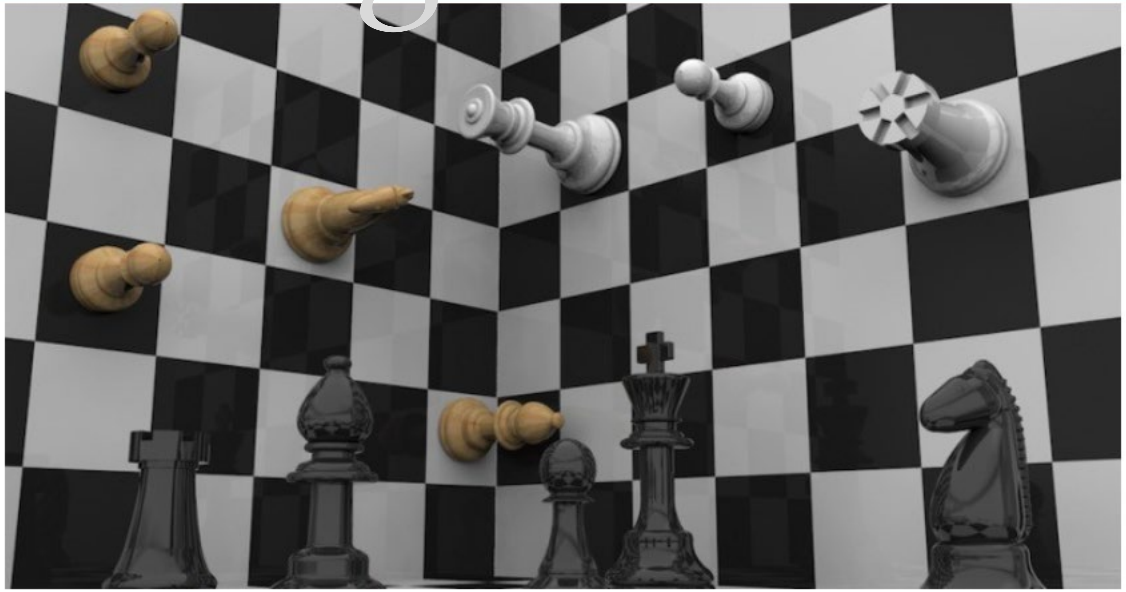
http://bit.ly/PARTNER-WITH-PEAS

http://bit.ly/SUBSCRIBE-TO-SENSEE

Intelligent Information Arbitrage

WATER v PEOPLE

Change the rules



SENSEE inside

https://www.who.int/news-room/detail/18-06-2019-1-in-3-people-globally-do-not-have-access-to-safe-drinking-water-–-unicef-who

World Health Organization | Health Topics | Countries | Newsroom | Emergencies | About Us

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1 in 3 people globally do not have access to safe drinking water – UNICEF, WHO

New report on inequalities in access to water, sanitation and hygiene also reveals more than half of the world does not have access to safe sanitation services.

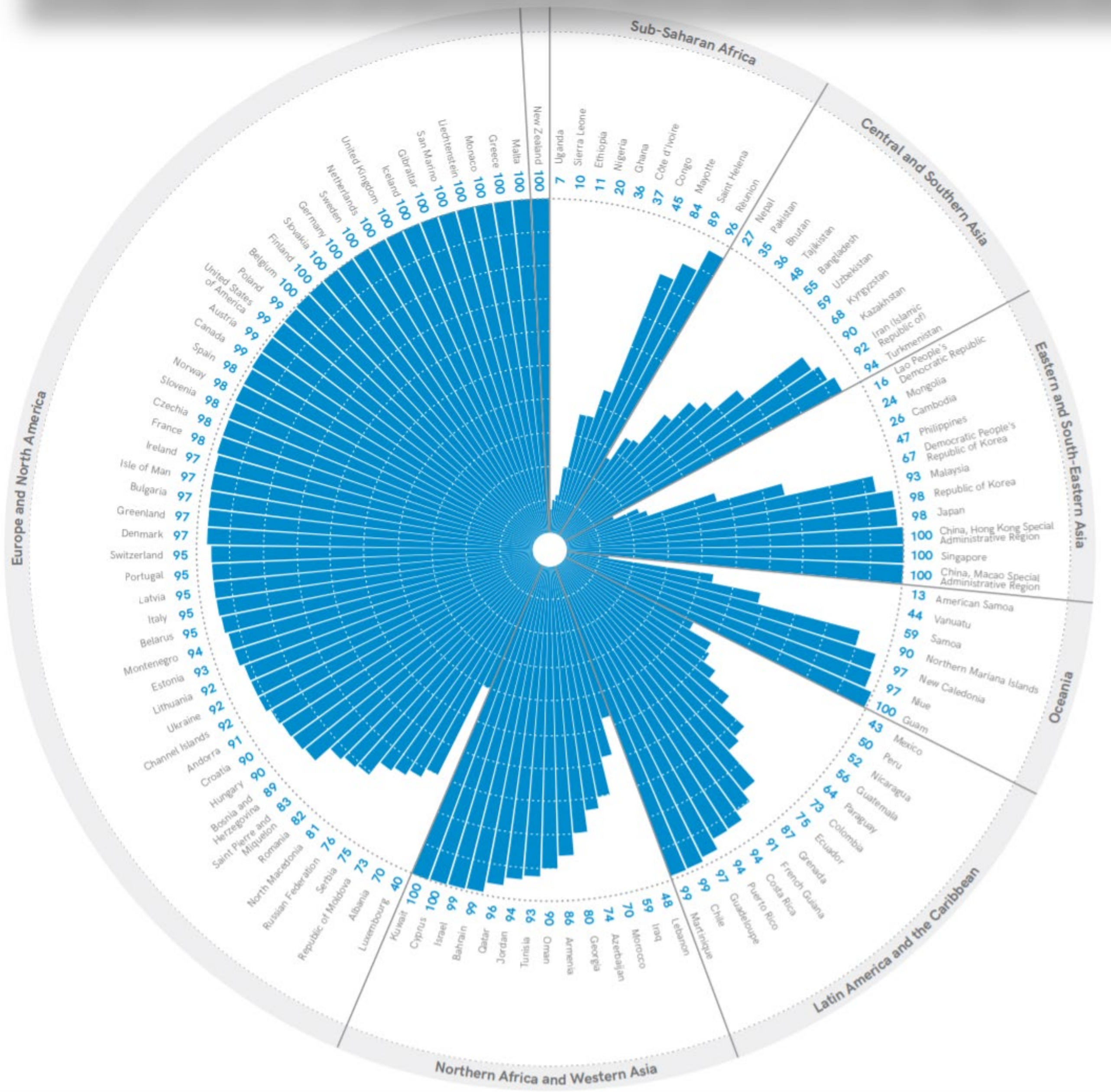
18 June 2019 | News release | New York, Geneva

Billions of people around the world are continuing to suffer from poor access to water, sanitation and hygiene, according to a new report by UNICEF and the World Health Organization. Some 2.2 billion people around the world do not have safely managed* drinking water services, 4.2 billion people do not have safely managed sanitation services, and 3 billion lack basic** handwashing facilities.

Nada Osseiran
Communications Officer
WHO
Mobile: +41 79 445 1624

www.who.int/water_sanitation_health/publications/jmp-2019-full-report.pdf?ua=1

Proportion of population with safely managed water (left) and sanitation (right) services, 2017 (%)



(L) Fig 51 (water) and (R) Fig 69 (sanitation) from www.who.int/water_sanitation_health/publications/jmp-2019-full-report.pdf?ua=1


gettyimages
Gina Pricope

Pb

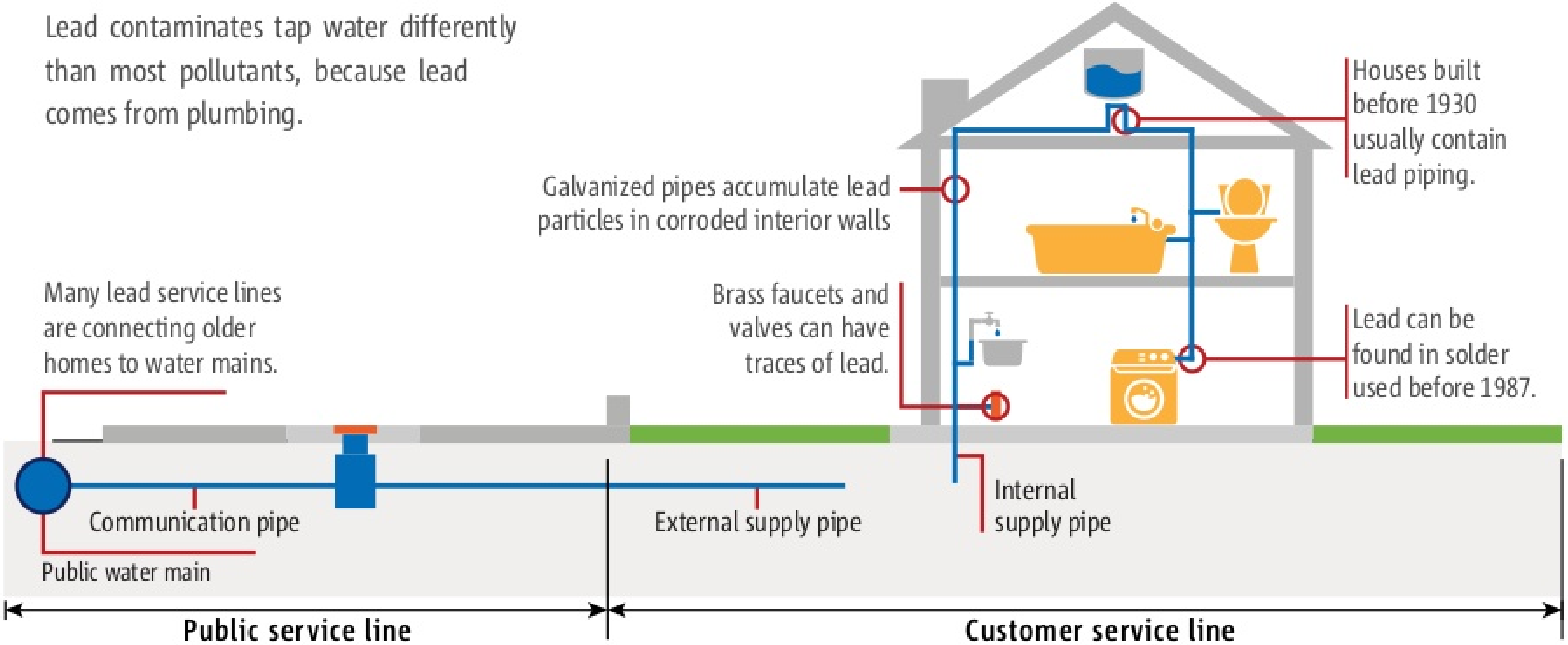
J Public Health Manag Pract. Author manuscript; available in PMC 2019 January 01.

Published in final edited form as:
J Public Health Manag Pract. 2019 ; 25(Suppl 1 LEAD POISONING PREVENTION): S84–S90. doi: 10.1097/PHH.0000000000000871.

The Flint Water Crisis: A Coordinated Public Health Emergency Response and Recovery Initiative

THE PIPES

Lead contaminates tap water differently than most pollutants, because lead comes from plumbing.

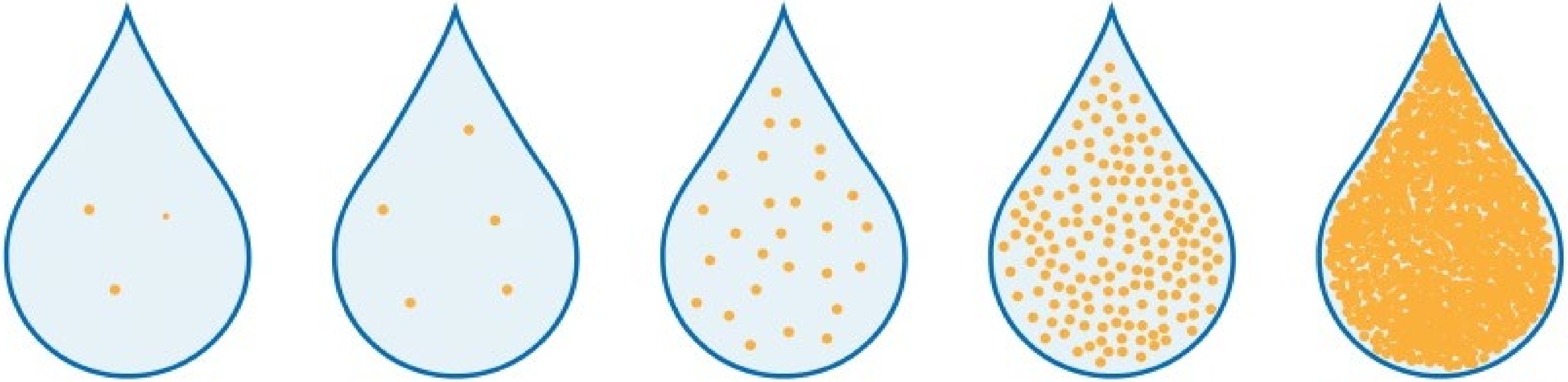


Summing up: water from Flint River moved through lead pipes, picking up the toxin as it went, and spread it throughout the population.

https://www.slideshare.net/lbuckfire/the-flint-michigan-water-crisis-causes-effects

THE KEY PROBLEM

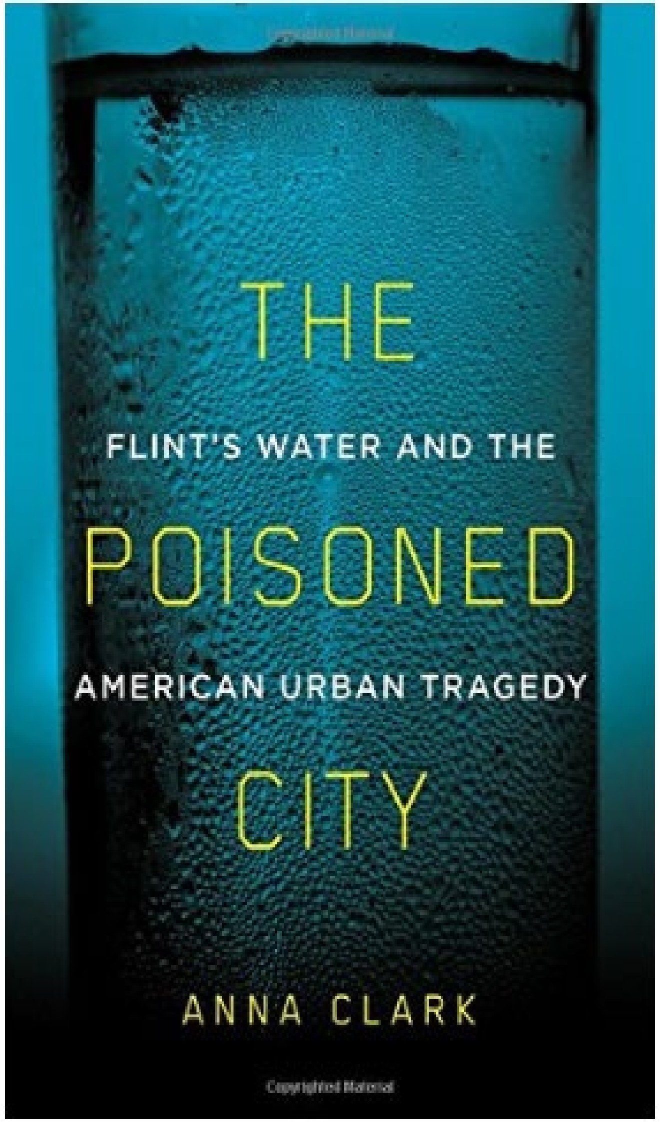
Water from the Flint River is highly corrosive (its water has about 8 times more chloride (Cl–) in it than Detroit water) to iron and lead. Unfortunately, these pipe materials are widely used throughout Flint.



2.3 parts per billion	5 parts per billion	27 parts per billion	158 parts per billion	13,000 parts per billion
Detroit water	Cause for concern	Flint water	Highest level found in Virginia Tech's Flint sample	Highest level found in Flint

And, if these pipes are exposed to corrosive water, or if water sits too long inside them, the lead could be released and may end up coming out of the tap.

https://www.slideshare.net/lbuckfire/the-flint-michigan-water-crisis-causes-effects



FLINT, MICHIGAN WATER CRISIS - **LEAD POISONING FACTS AND FIGURES**

THE KEY PROBLEM

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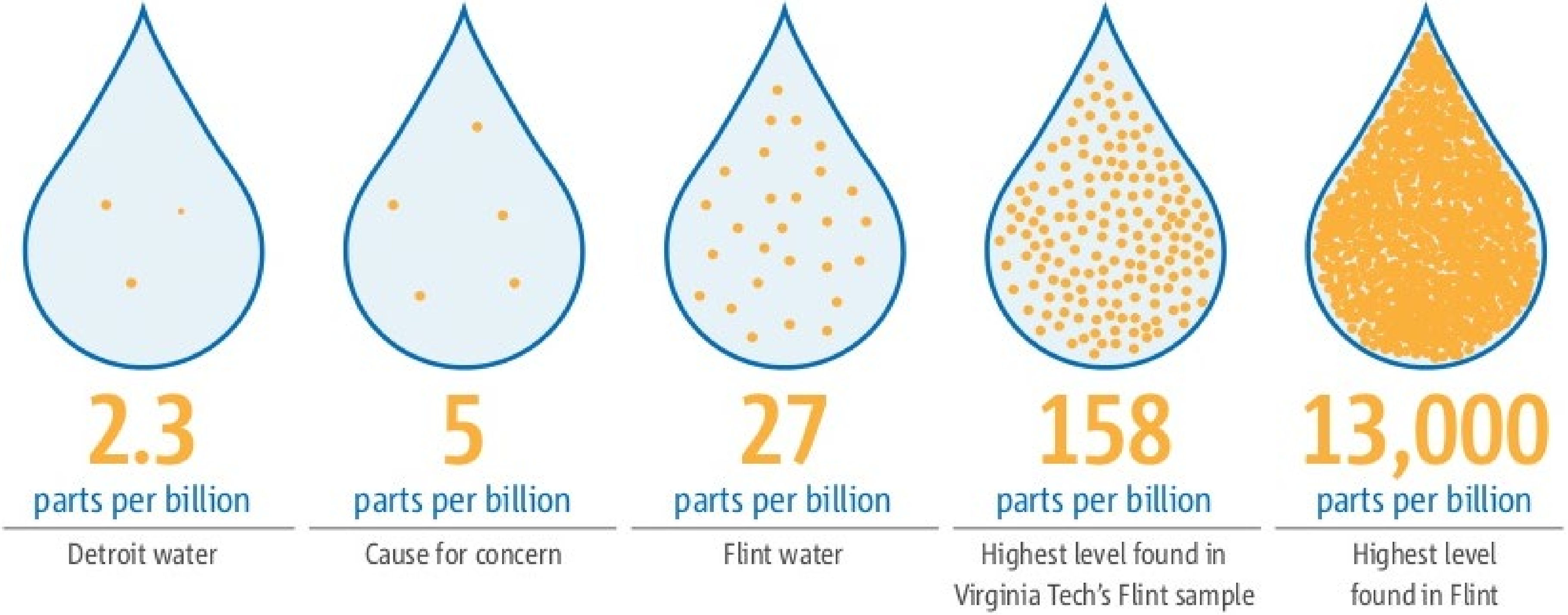

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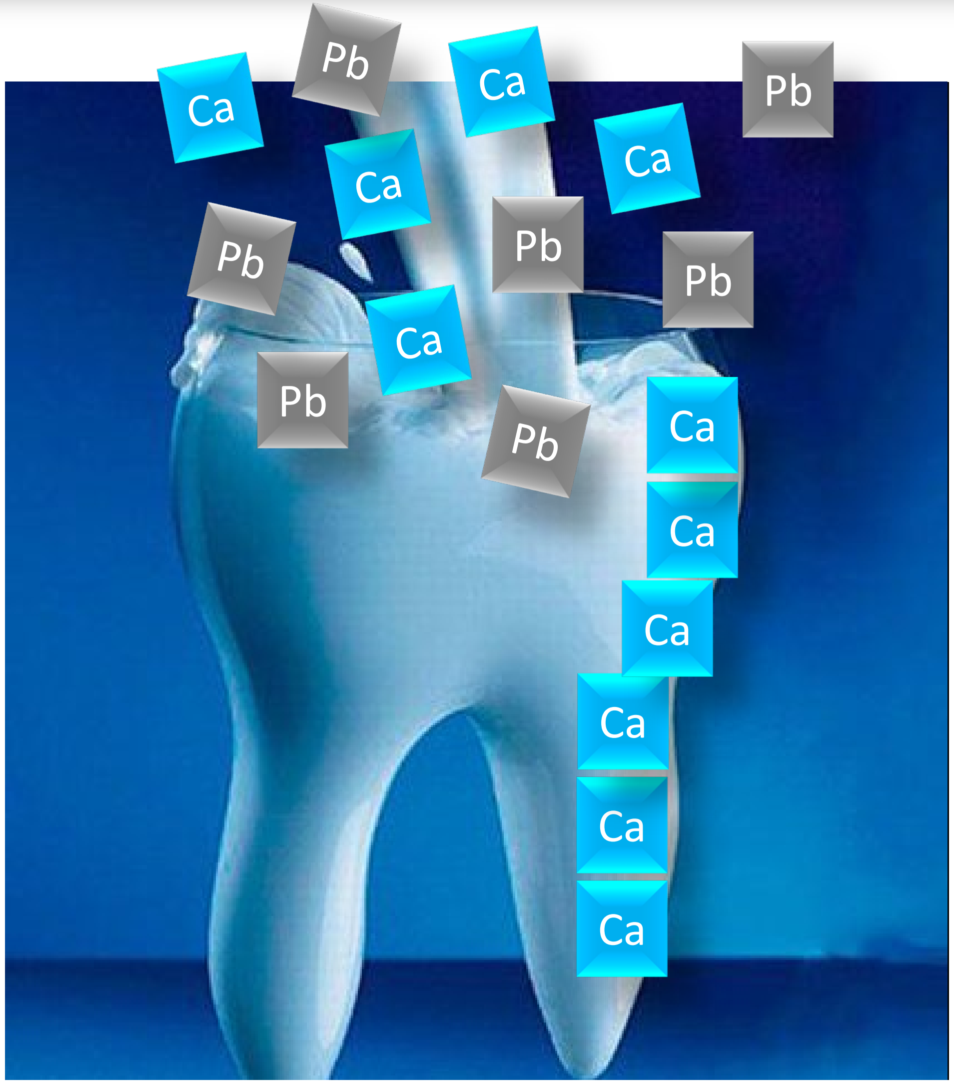
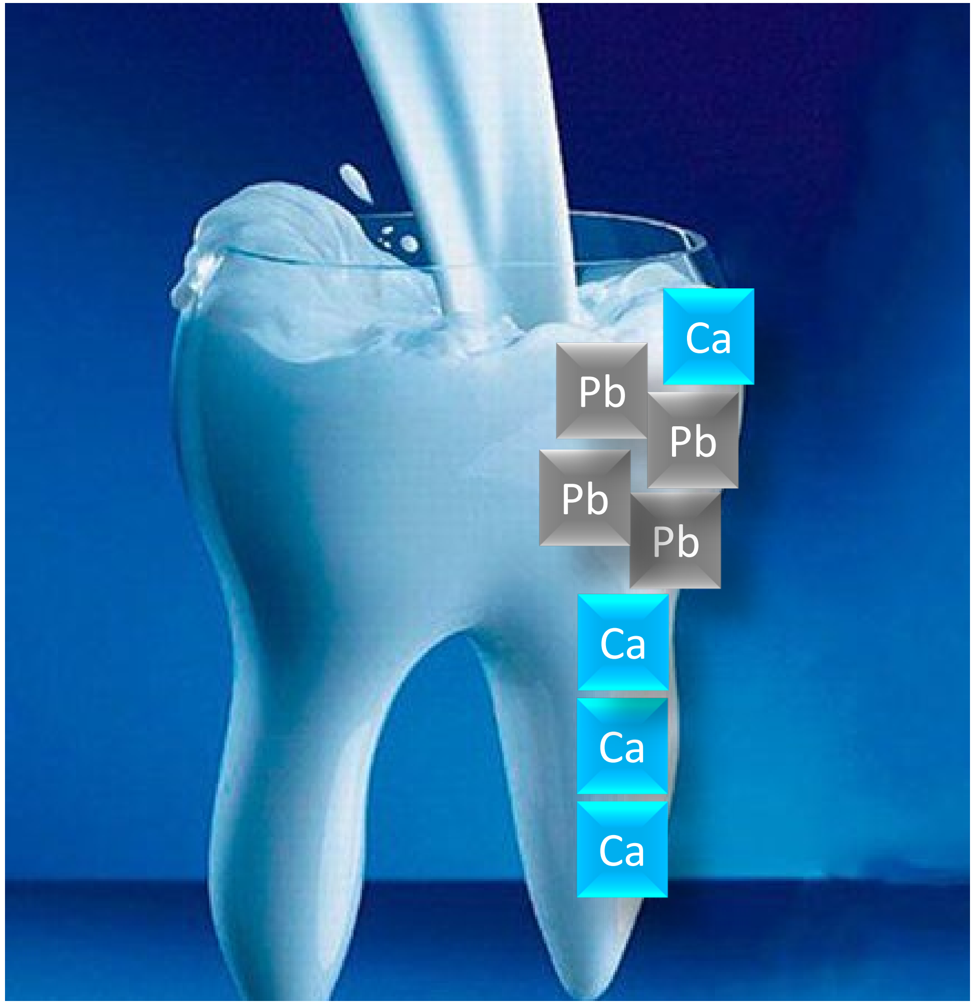
https://www.slideshare.net/lbuckfire/the-flint-michigan-water-crisis-causes-effects

Lead (Pb) accumulates in teeth and bones



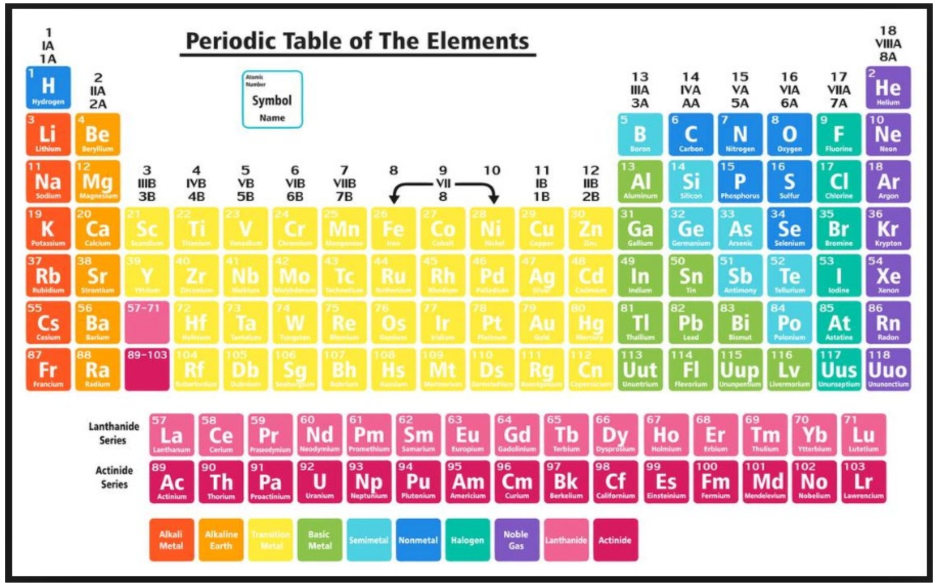
More lead exposure

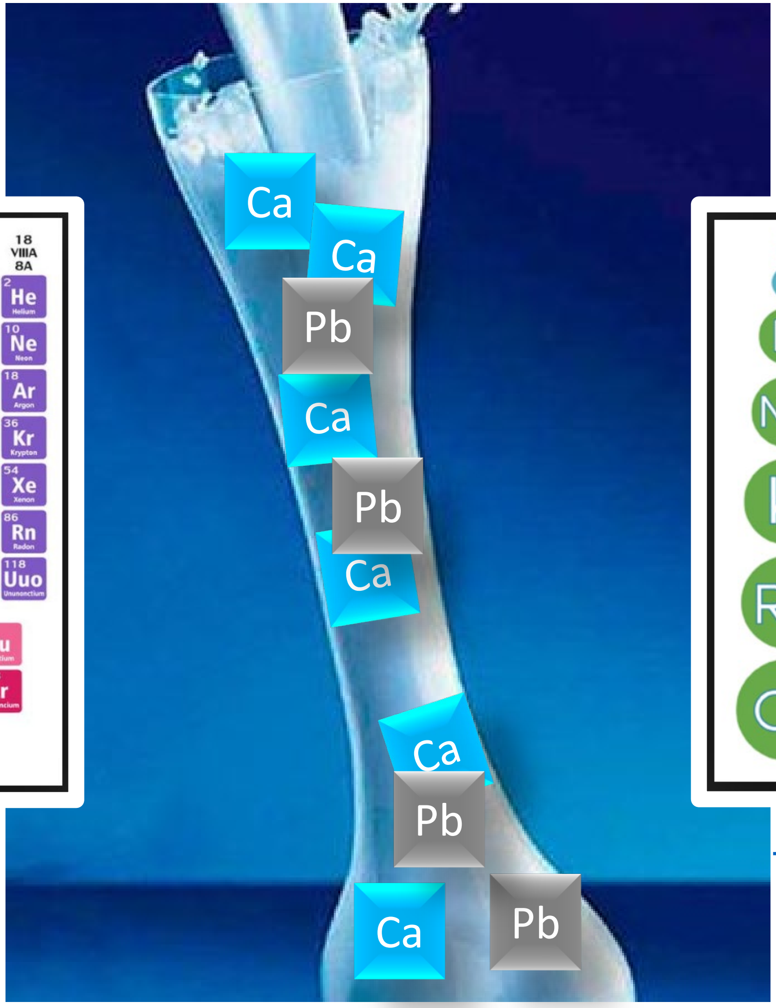
More lead is stored

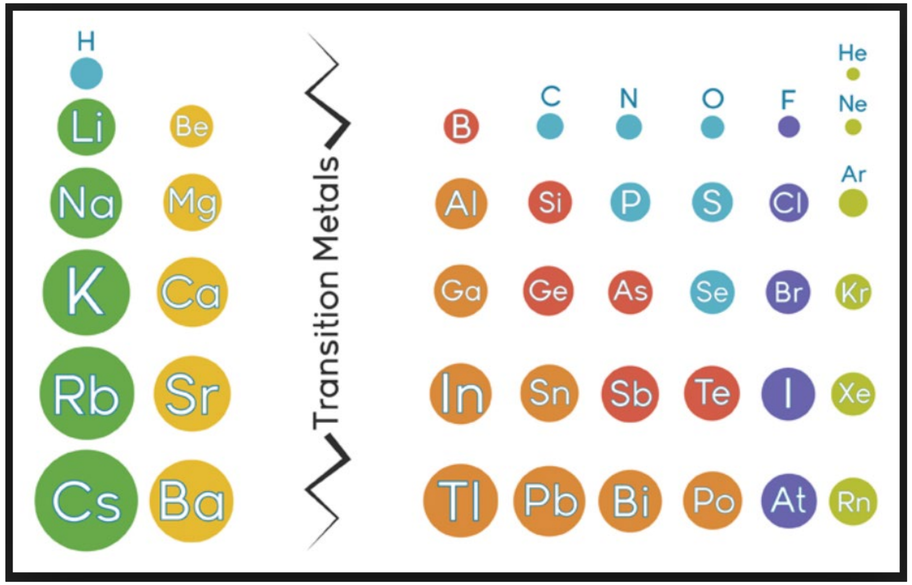


https://edu.glogster.com/glog/calcium/2ar2hn030do?=glogpedia-source

Lead (Pb) accumulates in teeth and bones



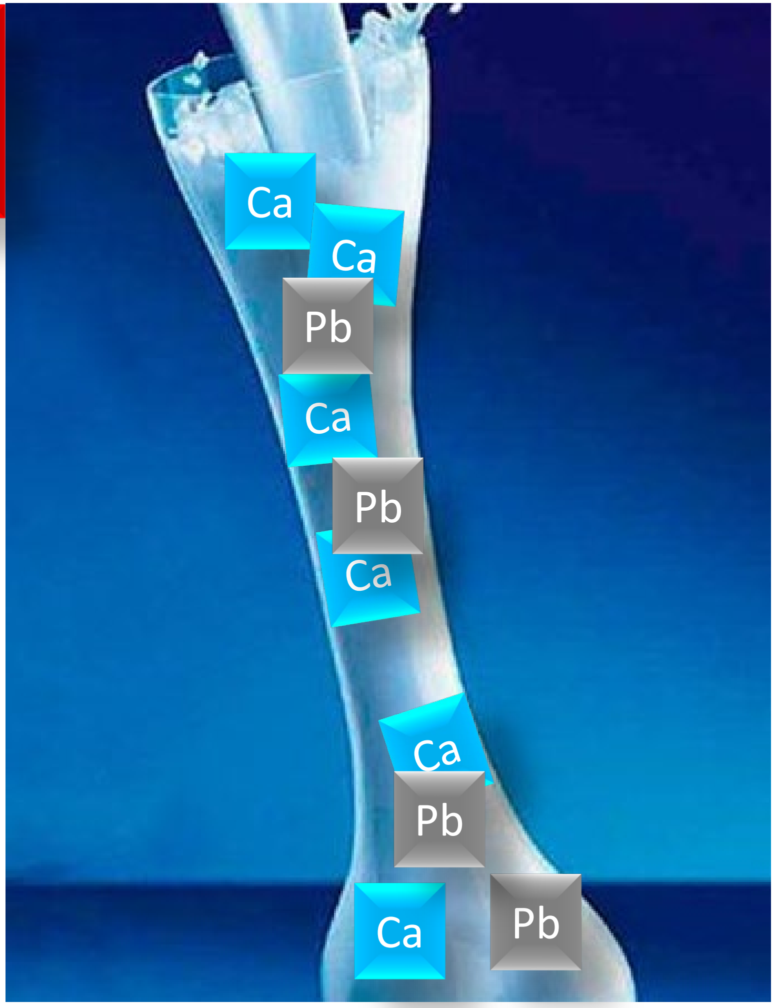




https://chemistryonline.guru/ionic-radius/

Lead (Pb) accumulates in teeth and bones

Osteoporosis

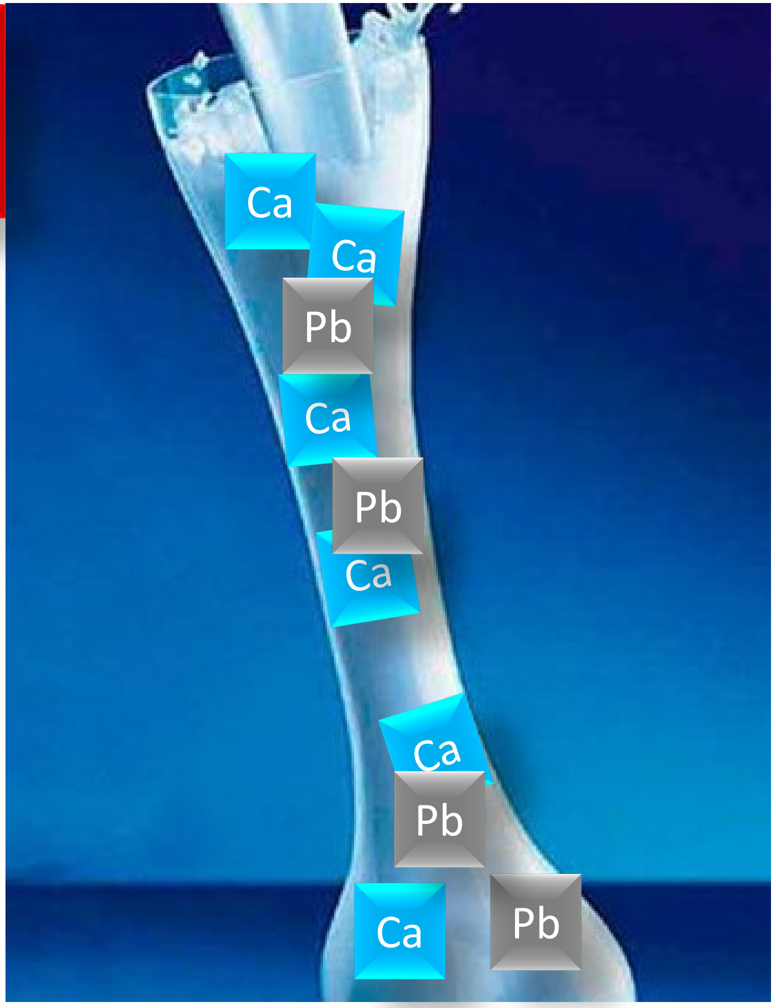


Pb Pb ? Pb Pb

What happens to the **Pb** in the bones?

Lead (Pb) concentration increases in the blood

Osteoporosis



Pb Pb ? Pb Pb

What happens to the **Pb** in the bones?

Childhood Lead Poisoning causes dementia in adults

Pb

ehp Environmental Health Perspectives
https://ehp.niehs.nih.gov/doi/10.1289/ehp.9716

The Association between Blood Lead Levels and Osteoporosis Adults—Results from the Third National Health and Nutrition Examination Survey (NHANES III)

James R. Campbell and Peggy Auinger

Published: 1 July 2007 | https://doi.org/10.1289/ehp.9716 | Cited by: 35

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Pb from water accumulates in teeth and bones. When Pb leaches out of bones, it may contribute to osteoporosis in adult life. Increased amount of Pb in blood may also contribute to dementia, Alzheimer's and neurotoxicity.

www.ncbi.nlm.nih.gov/pmc/articles/PMC3567843/pdf/nihms367232.pdf

NATIONAL INSTITUTES OF HEALTH
NIH Public Access
Author Manuscript
Curr Alzheimer Res. Author manuscript; available in PMC 2013 February 08.

Published in final edited form as:
Curr Alzheimer Res. 2012 June ; 9(5): 563–573.

Alzheimer's Disease and Environmental Exposure to Lead: The Epidemiologic Evidence and Potential Role of Epigenetics

Kelly M. Bakulski[1], **Laura S. Rozek**[1,2], **Dana C. Dolinoy**[1], **Henry L. Paulson**[3], and **Howard Hu**[1,4,5,*]

[1]University of Michigan, School of Public Health, Department of Environmental Health Sciences

[2]University of Michigan, Medical School, Department of Otolaryngology

[3]University of Michigan, Department of Neurology

[4]University of Michigan, Department of Epidemiology

[5]University of Michigan, Medical School, Department of Internal Medicine

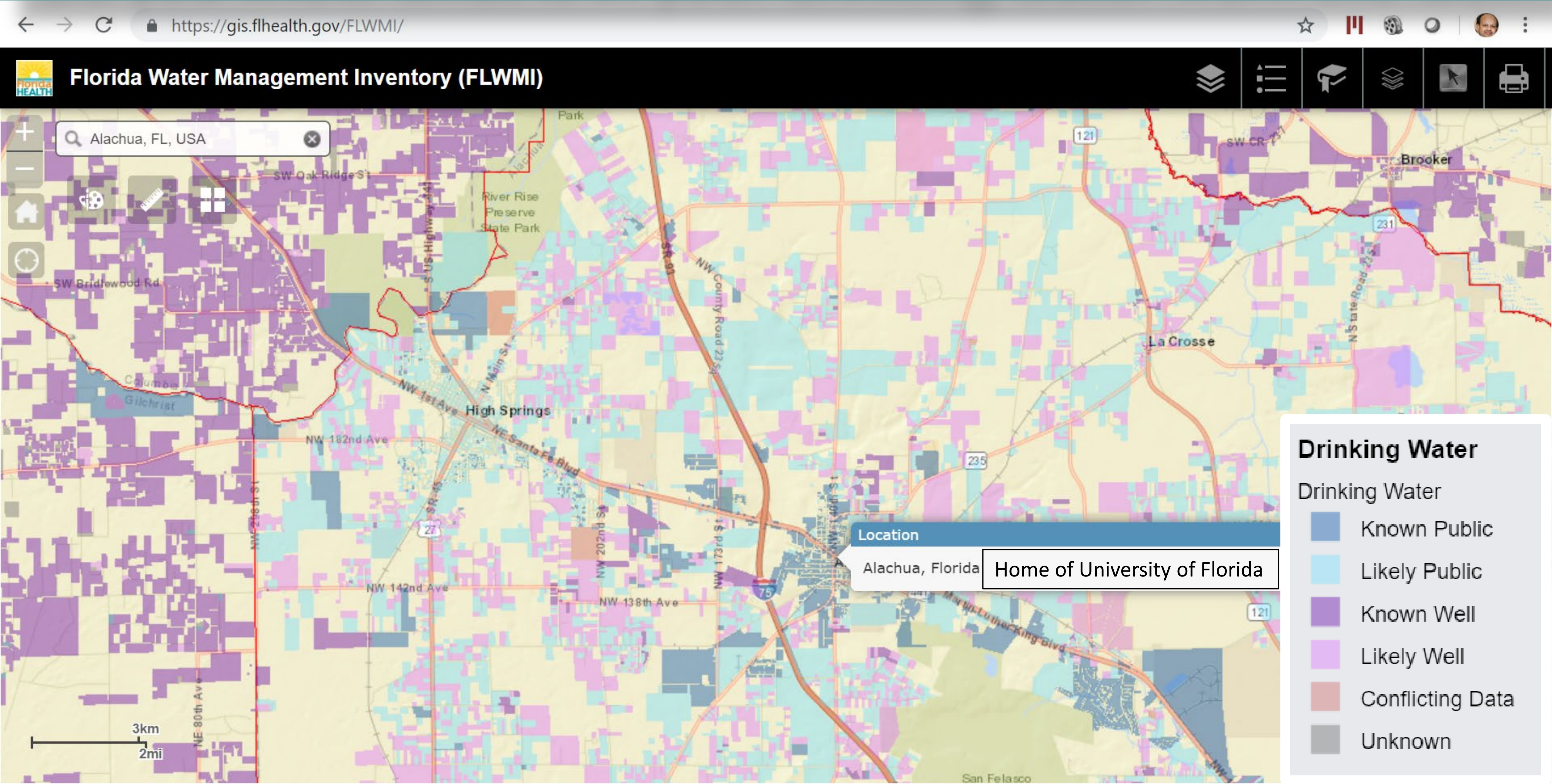
Abstract

Several lines of evidence indicate that the etiology of late-onset Alzheimer's disease (LOAD) is complex, with significant contributions from both genes and environmental factors. Recent research suggests the importance of epigenetic mechanisms in defining the relationship between environmental exposures and LOAD. In epidemiologic studies of adults, cumulative lifetime lead (Pb) exposure has been associated with accelerated declines in cognition. In addition, research in animal models suggests a causal association between Pb exposure during early life, epigenetics, and LOAD. There are multiple challenges to human epidemiologic research evaluating the relationship between epigenetics, LOAD, and Pb exposure. Epidemiologic studies are not well-suited to accommodate the long latency period between exposures during early life and onset of Alzheimer's disease. There is also a lack of validated circulating epigenetics biomarkers and retrospective biomarkers of Pb exposure. Members of our research group have shown bone Pb is an accurate measurement of historical Pb exposure in adults, offering an avenue for future epidemiologic studies. However, this would not address the risk of LOAD attributable to early-life Pb exposures. Future studies that use a cohort design to measure both Pb exposure and validated epigenetic biomarkers of LOAD will be useful to clarify this important relationship.

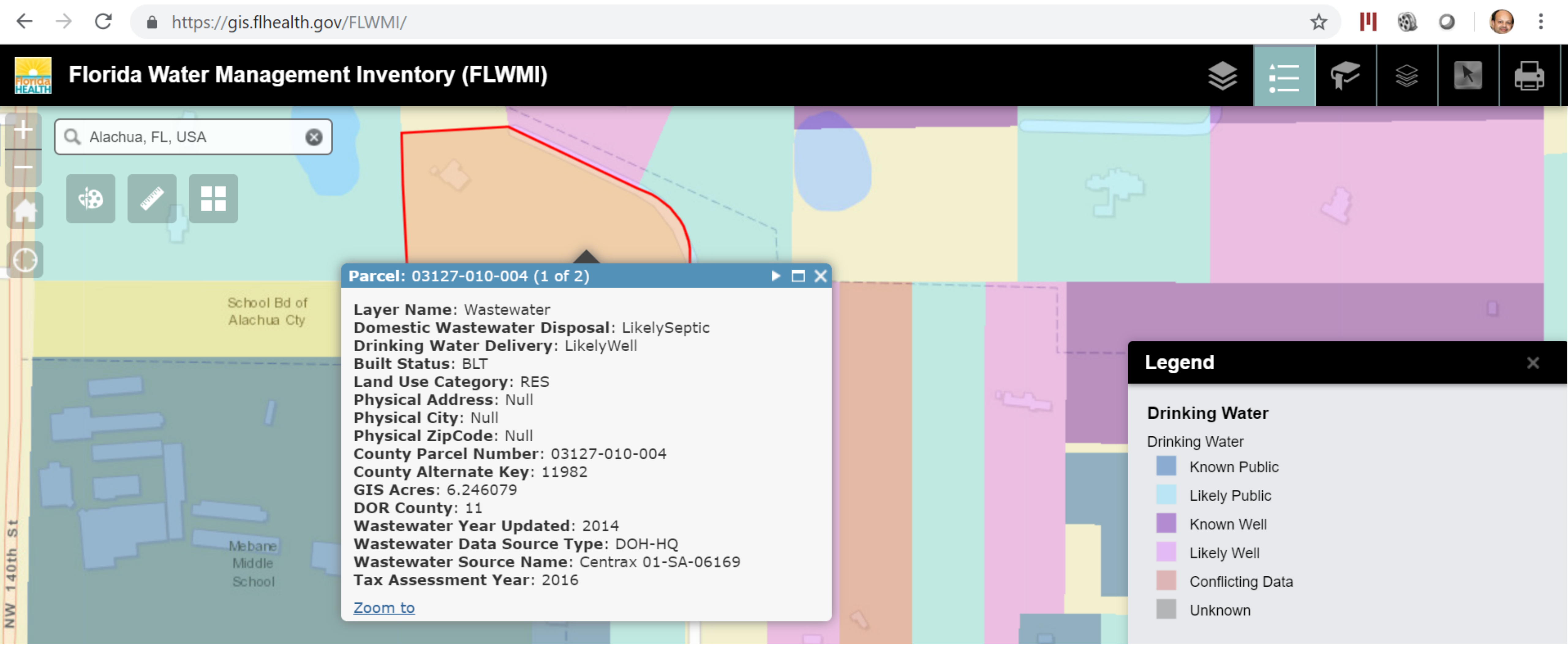
Do you know what is in your drinking water?

https://www.cdc.gov/nceh/lead/publications/nceh_prevent_childhood_lead_poisoning_508.pdf

Do you know what is in your drinking water from the well?



Drinking water from wells – schools near University of Florida



Drinking water from water treatment plant in Gainesville, FL

Gainesville Regional Utilities (GRU) - Murphree WTP

EWG's drinking water quality report shows results of tests conducted by the water utility and provided to the Environmental Working Group by the Florida Department of Environmental Protection, as well as information from the U.S. EPA Enforcement and Compliance History database (ECHO). For the latest quarter assessed by the EPA (July 2018 - September 2018), **tap water provided by this water utility was in compliance with federal health-based drinking water standards.**

WHAT ABOUT LEAD? WANT TO FILTER THESE CONTAMINANTS OUT?

3 contaminants detected above health guidelines

5 other detected contaminants

Includes chemicals detected in 2015 for which annual utility averages exceeded an EWG-selected health guideline established by a federal or state public health authority; chemicals detected under the EPA's Unregulated Contaminant Monitoring Rule (UCMR 3) program in 2013 to 2015, for which annual utility averages exceeded a health guideline established by a federal or state public health authority; radiological contaminants detected between 2010 and 2015.

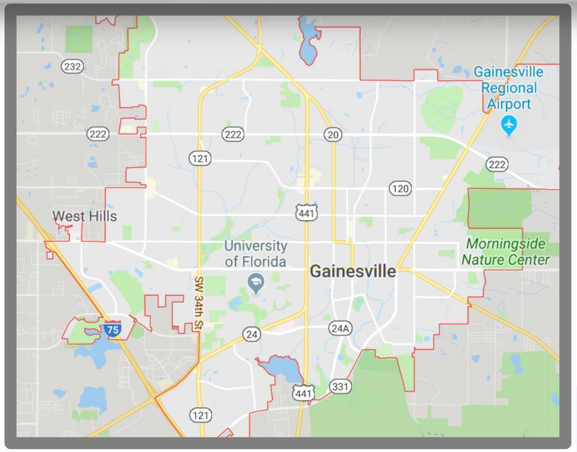
- Chromium (hexavalent) *cancer* +
- Radiological contaminants *cancer* +
- Total trihalomethanes (TTHMs) *cancer* +

WANT TO FILTER THESE CONTAMINANTS OUT?

Pollution sources

Click on each pollution source to see from which source contaminants come.

Agriculture | Industry | Treatment byproducts | Runoff & sprawl | Naturally occuring



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WHAT ABOUT LEAD? WANT TO FILTER THESE CONTAMINANTS OUT?

3 contaminants detected above health guidelines

5 other detected contaminants

Includes chemicals detected in 2015 for which annual utility averages were lower than an EWG-selected health guideline established by a federal or state public health authority; chemicals detected under the EPA's Unregulated Contaminant Monitoring Rule (UCMR 3) program in 2013 to 2015, for which annual utility averages were lower than an EWG-selected health guideline established by a federal or state public health authority.

- Chlorate +
- Chromium (total) +
- Haloacetic acids (HAA5) +
- Strontium +
- Vanadium +

WANT TO FILTER THESE CONTAMINANTS OUT?

www.ewg.org/tapwater/system.php?pws=FL2010946 https://www.nrdc.org/stories/flint-water-crisis-everything-you-need-know

February 12, 2019

In an agreement filed by the parties of the 2017 settlement, the city of Flint committed to using a data-driven approach to locate the remaining lead pipes delivering drinking water to residents' homes. The city will use a statistical model—already proven effective in earlier efforts—to guide its selection of homes for service line excavations in 2019. This approach will increase efficiency and help ensure all remaining lead pipes are identified and removed.

https://www.nrdc.org/stories/flint-water-crisis-everything-you-need-know

NRDC

OUR WORK OUR EXPERTS OUR STORIES GET INVOLVED ABOUT US

OUR STORIES › GUIDE

Flint Water Crisis: Everything You Need to Know

After officials repeatedly dismissed claims that Flint's water was making people sick, residents took action. Here's how the lead contamination crisis unfolded—and what we can learn from it.

November 08, 2018 | Melissa Denchak

https://www.nih.gov/news-events/news-releases/baby-teeth-link-autism-heavy-metals-nih-study-suggests

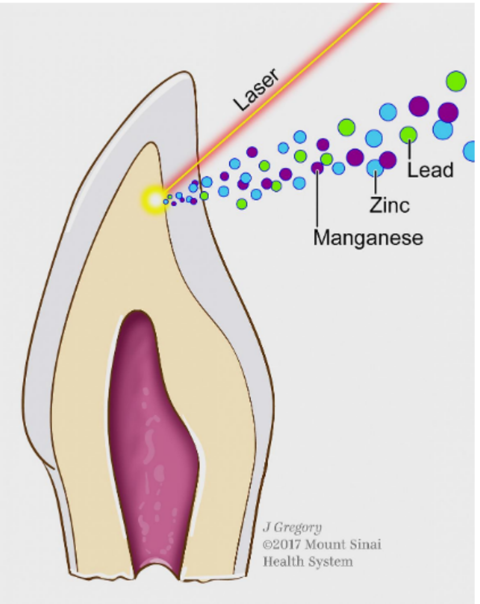
Thursday, June 1, 2017

Baby teeth link autism and heavy metals, NIH study suggests

Baby teeth from children with autism contain more toxic lead and less of the essential nutrients zinc and manganese, compared to teeth from children without autism, according to an innovative study funded by the National Institute of Environmental Health Sciences (NIEHS), part of the National Institutes of Health. The researchers studied twins to control genetic influences and focus on possible environmental contributors to the disease. The findings, published June 1 in the journal Nature Communications, suggest that differences in early-life exposure to metals, or more importantly how a child's body processes them, may affect the risk of autism.

The differences in metal uptake between children with and without autism were especially notable during the months just before and after the children were born. The scientists determined this by using lasers to map the growth rings in baby teeth generated during different developmental periods.

The researchers observed higher levels of lead in children with autism throughout development, with the greatest disparity observed during the period following birth. They also observed lower uptake of manganese in children with autism, both before and after birth. The pattern was more complex for zinc. Children with autism had lower zinc levels earlier in the womb, but these levels then increased after birth, compared to children without autism.



Cross-section of tooth showing laser removal of the dentine layer, in tan, for analysis of metal content. *Mount Sinai Health System*

https://guides.uflib.ufl.edu/precisionpublichealth/topic

Environmental Health Perspectives
https://ehp.niehs.nih.gov/doi/10.1289/ehp.9716

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The Association between Blood Lead Levels and Osteoporosis Adults—Results from the Third National Health and Nutrition Examination Survey (NHANES III)

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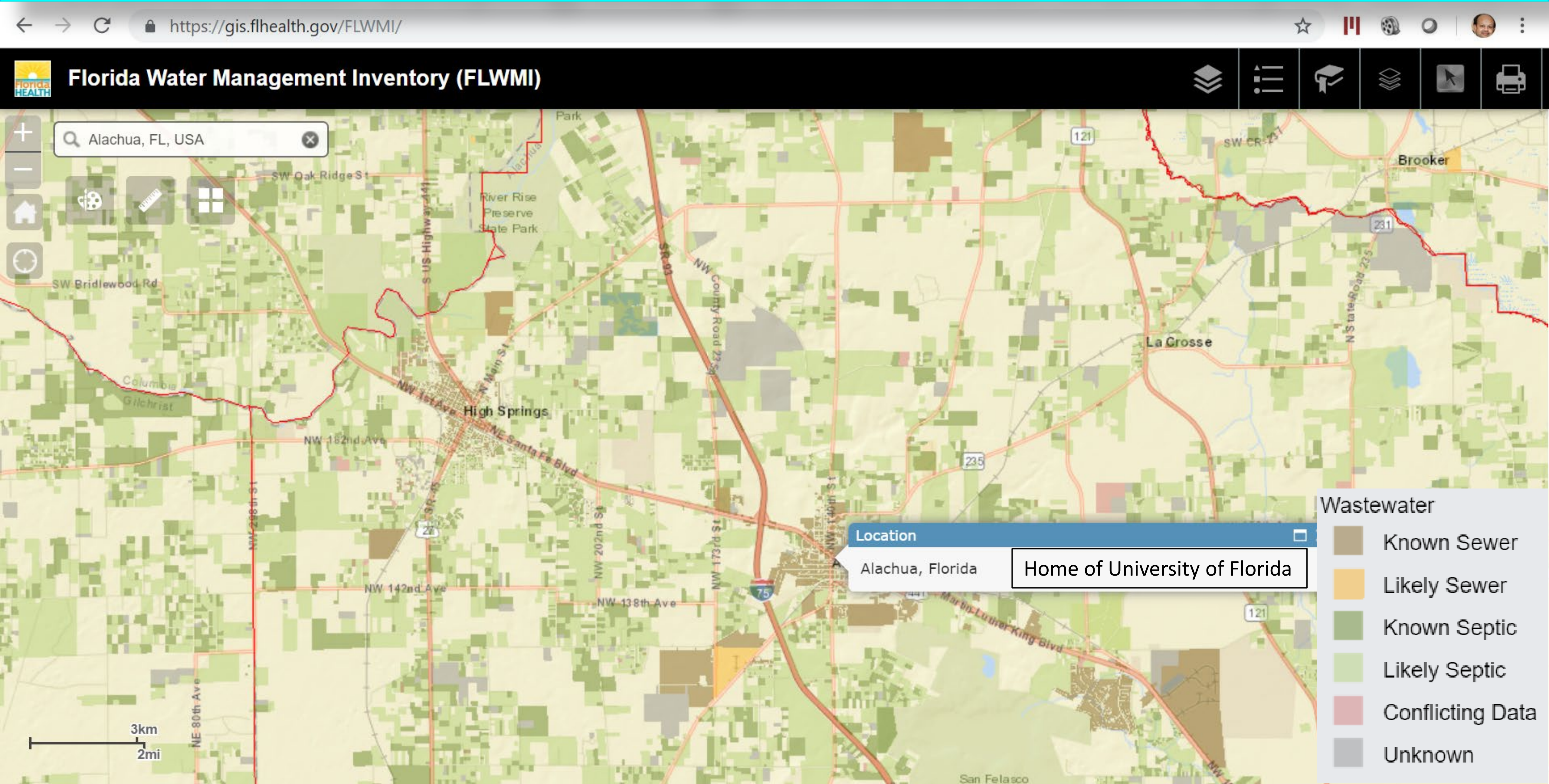
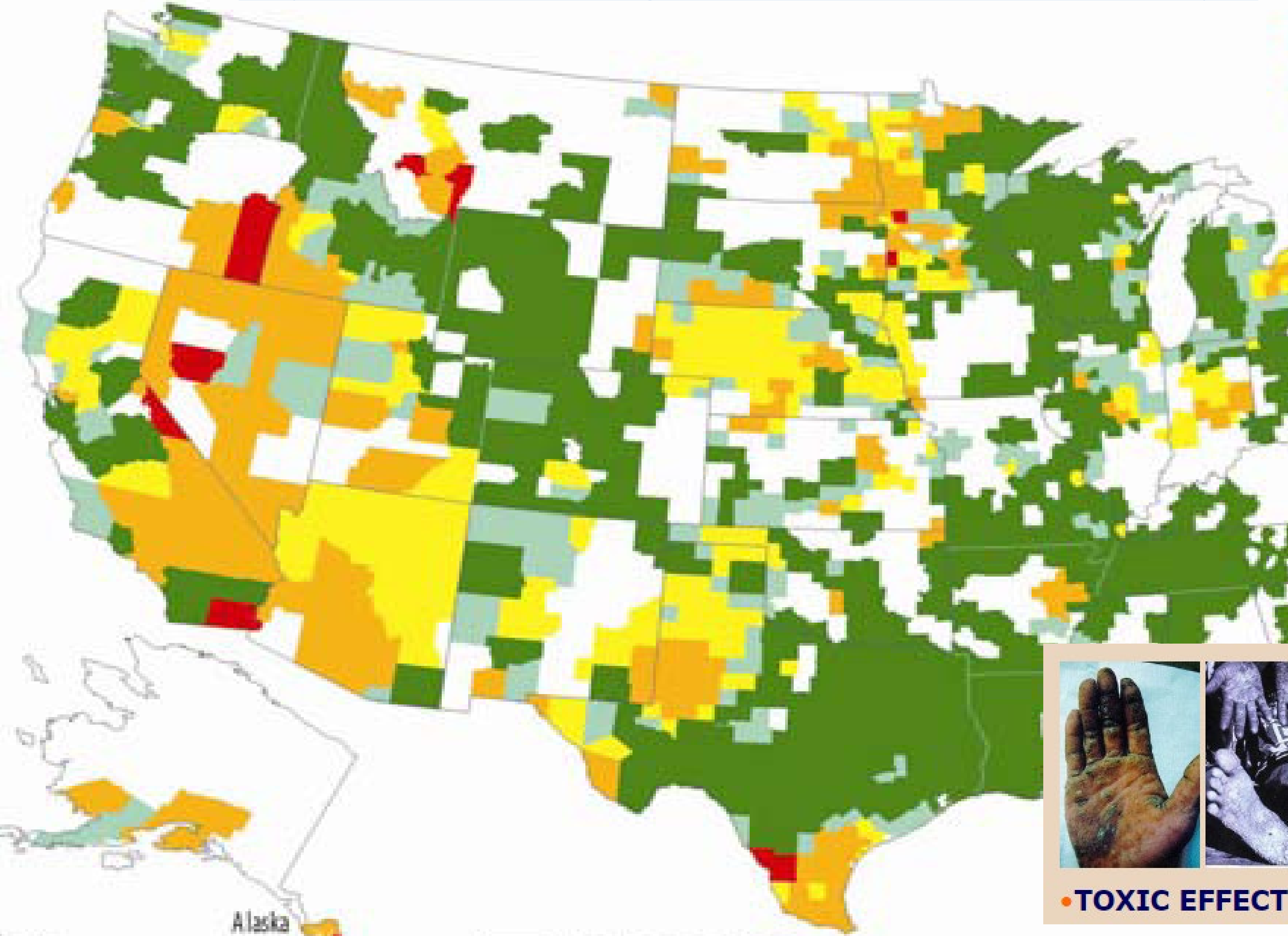
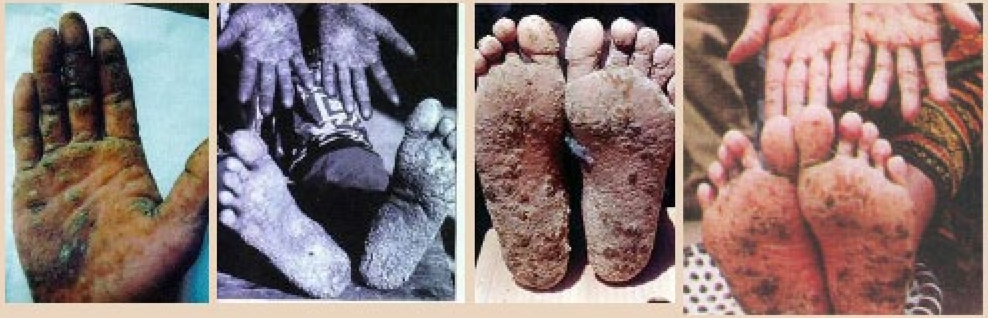
Wastewater seeping into groundwater from septic tanks?



https://www.atsdr.cdc.gov/csem/arsenic/docs/arsenic.pdf

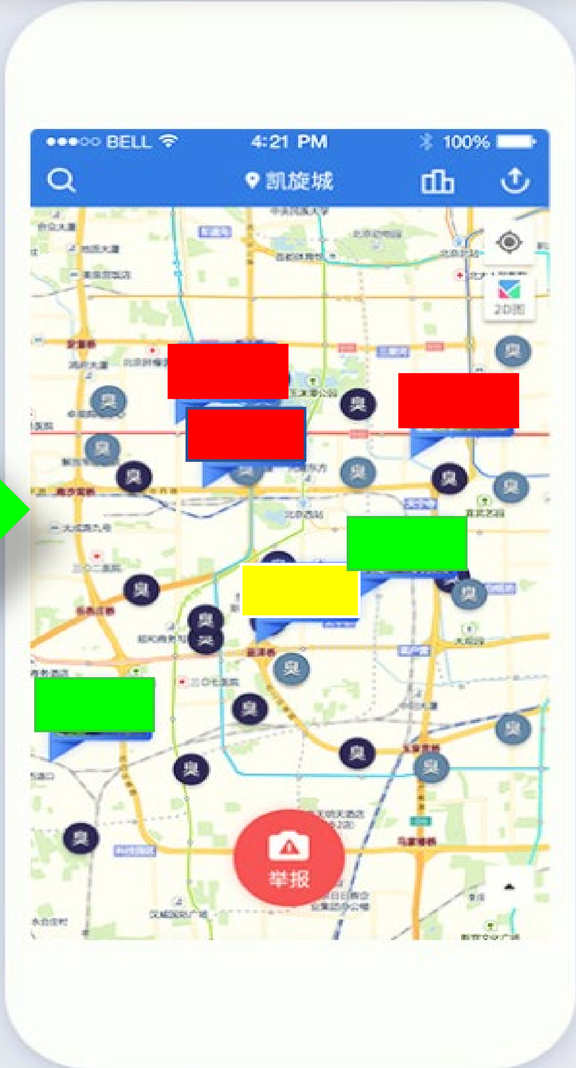




•TOXIC EFFECT OF ARSENIC www.sos-arsenic.net/

Water ART – IoT Data Analytics of Value to End-User

VALUE

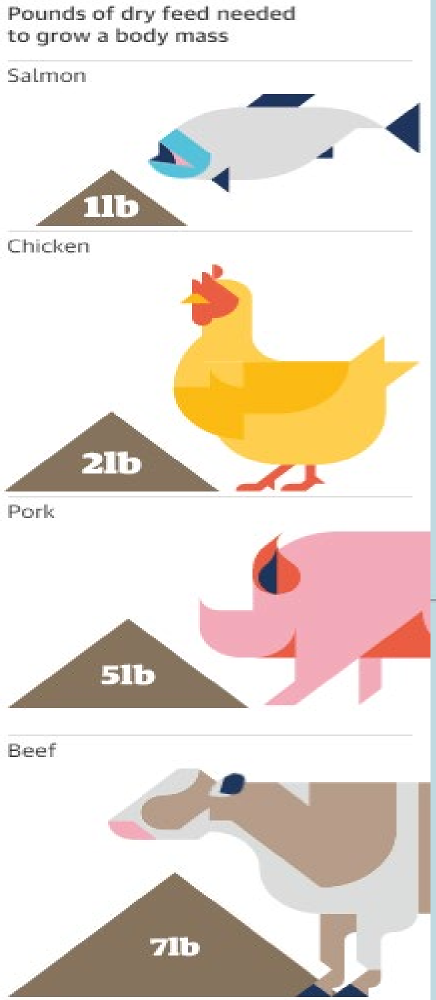


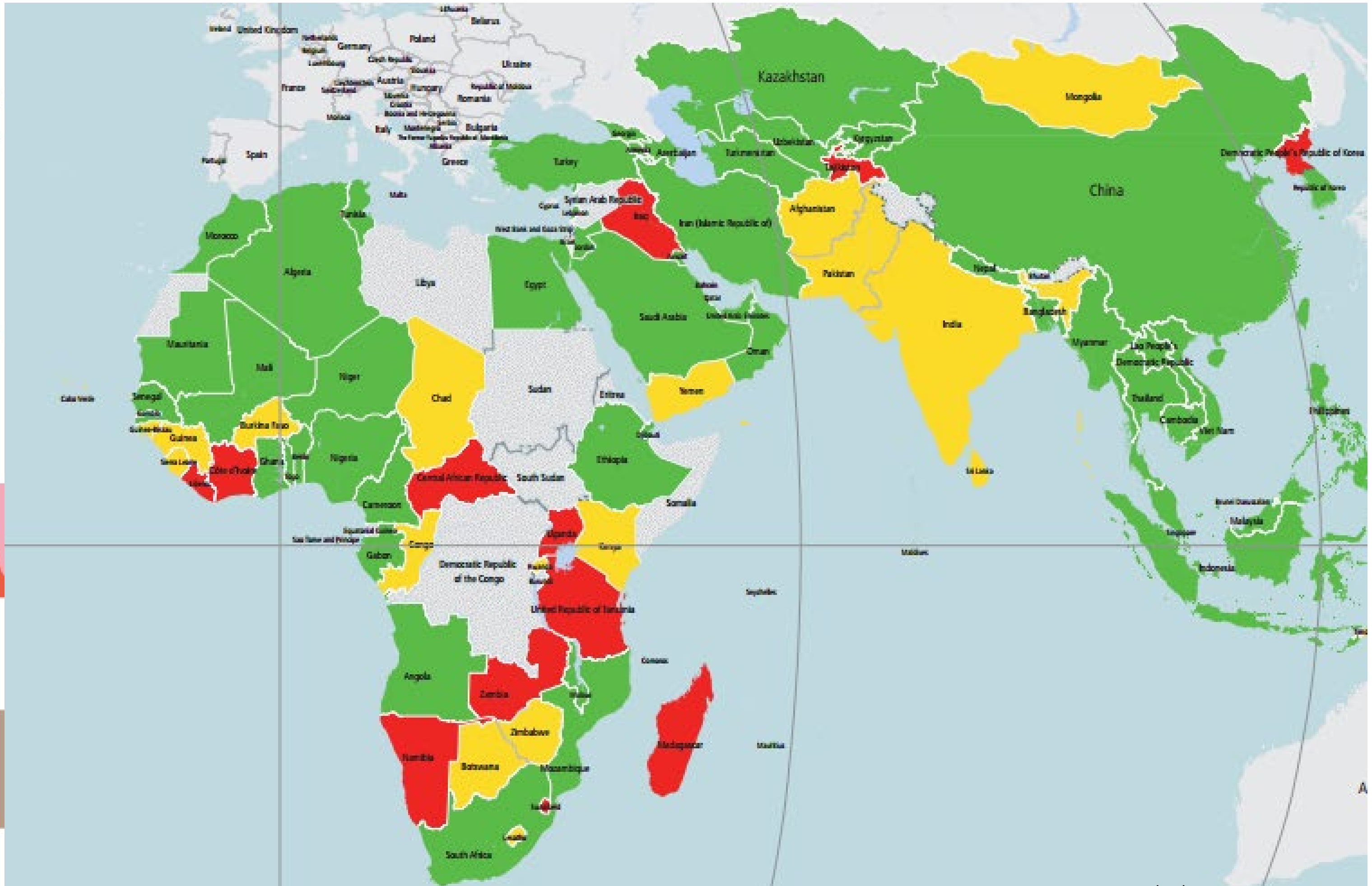
Professor Eric McLamore, University of Florida - www.ncbi.nlm.nih.gov/pubmed/29629449

FOOD v PEOPLE

Prevent Food Waste

Estimated 11 billion people to feed at the dawn of the 22nd Century





www.fao.org/3/a-i4674e.pdf

The End of Plenty
by Joel K Bourne

www.un.org/sustainabledevelopment/blog/2015/07/what-progress-has-been-made-in-ending-global-poverty/

http://www.fao.org/fileadmin/templates/wsfs/docs/expert_paper/How_to_Feed_the_World_in_2050.pdf

Do we really ***waste*** about 68% of the food in the US ?

More than two-thirds of total food wasted – which is ~ 63 million tons

Value wasted ~ $150 Billion (total food wasted value US$218 Billion)

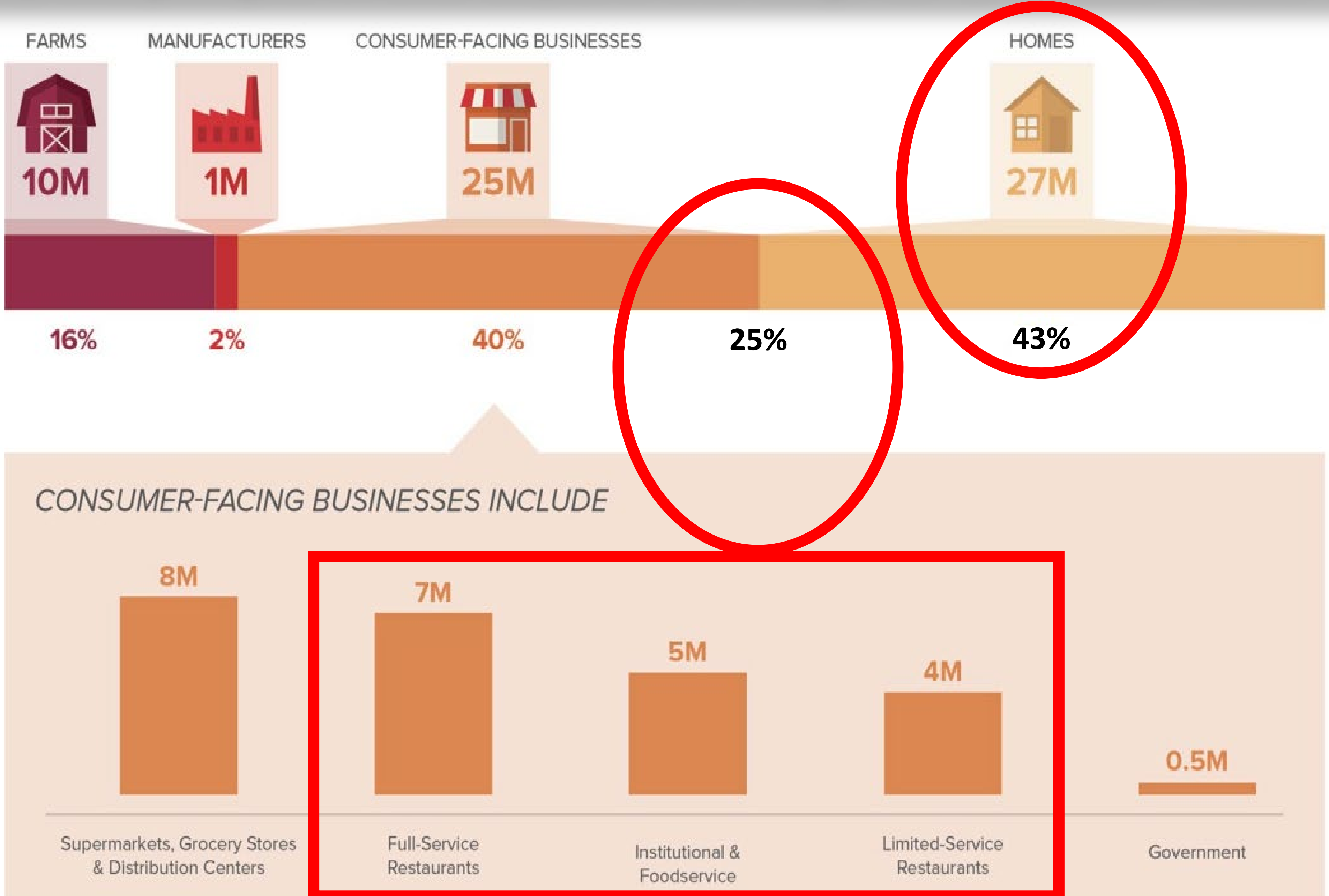
43

million tons

$150 Billion

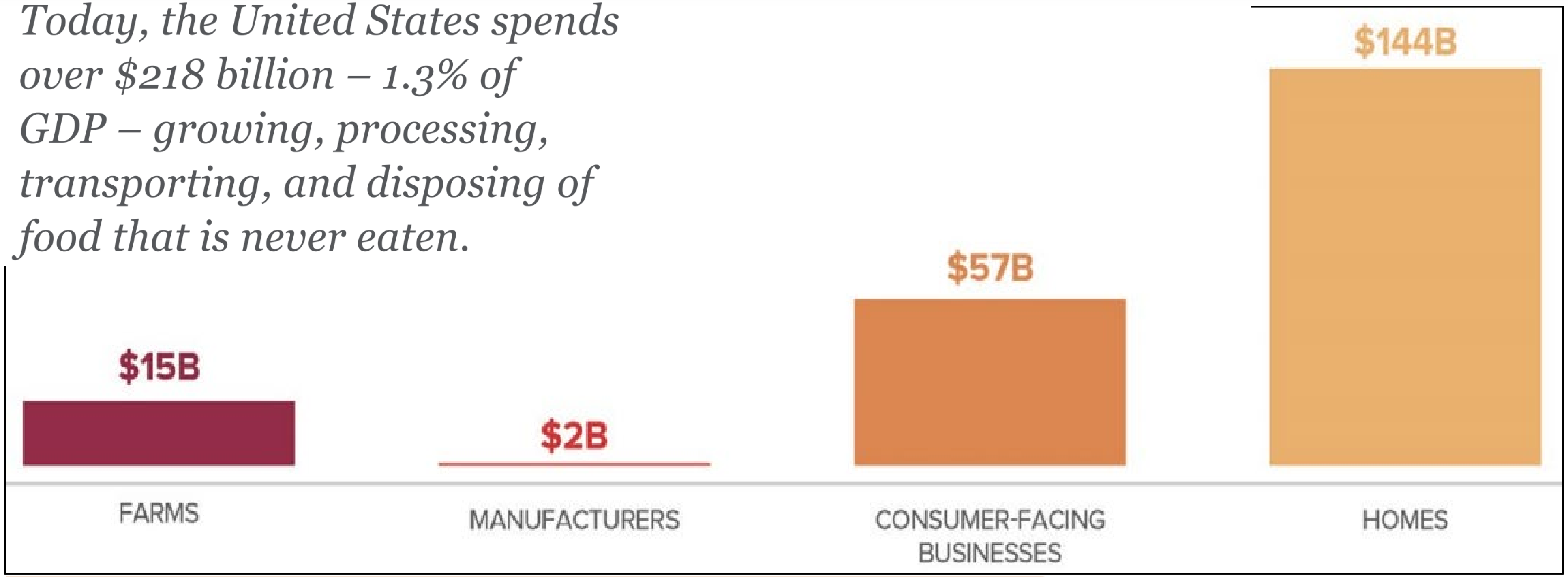
US Report ● http://www.refed.com/downloads/ReFED_Report_2016.pdf
EU Report ● http://data.consilium.europa.eu/doc/document/ST-10730-2016-INIT/en/pdf from www.eu-fusions.org/

Yes. We, the people in the US, are the culprits → ~68% FOOD WASTED



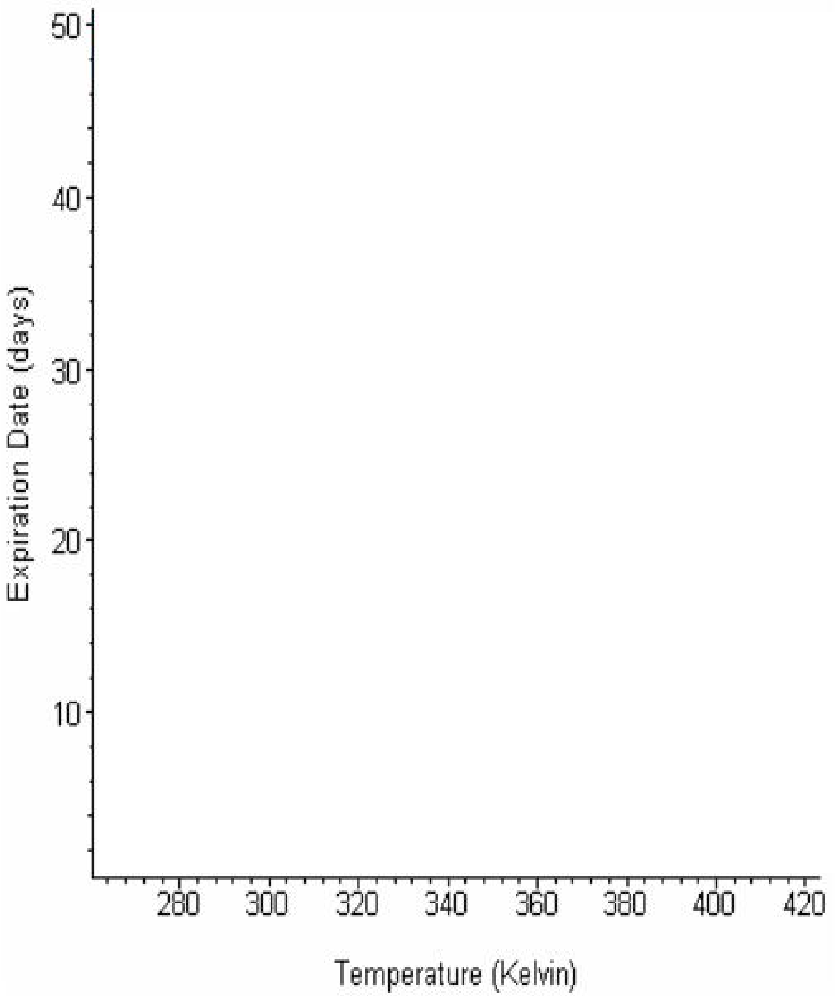
FOOD WASTE in the US: approx. 63 million tons, $218 billion, 1.3% GDP

Today, the United States spends over $218 billion – 1.3% of GDP – growing, processing, transporting, and disposing of food that is never eaten.



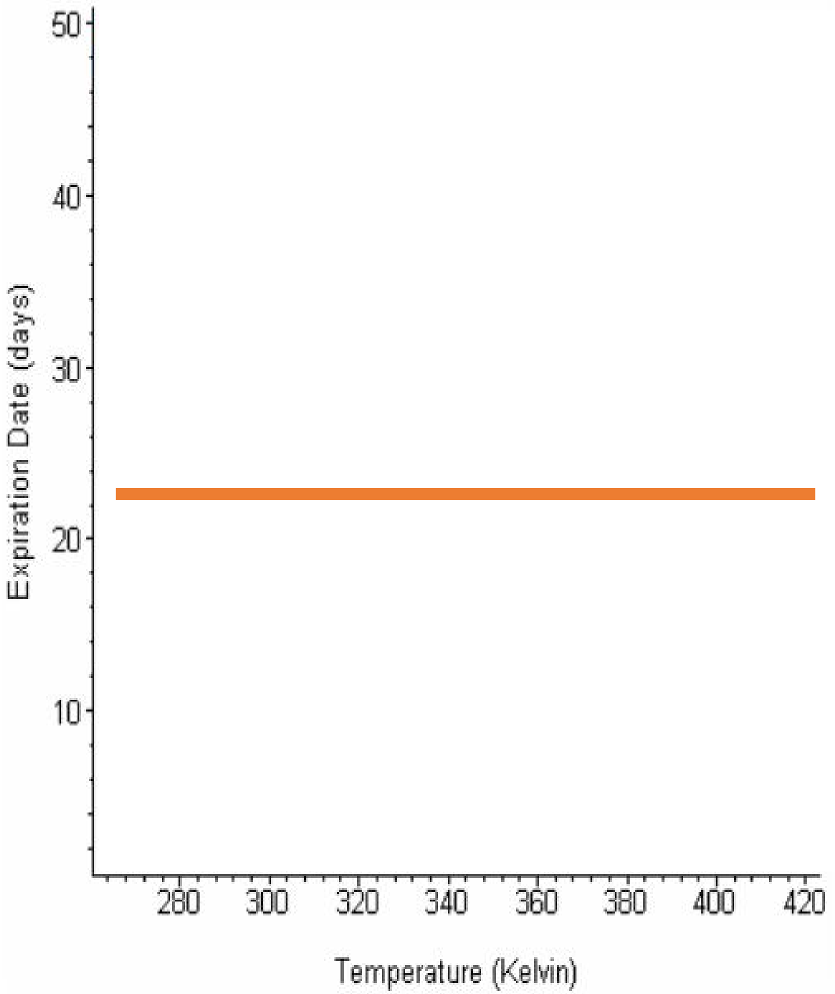
http://www.refed.com/downloads/ReFED_Report_2016.pdf

Storage



2003

Storage



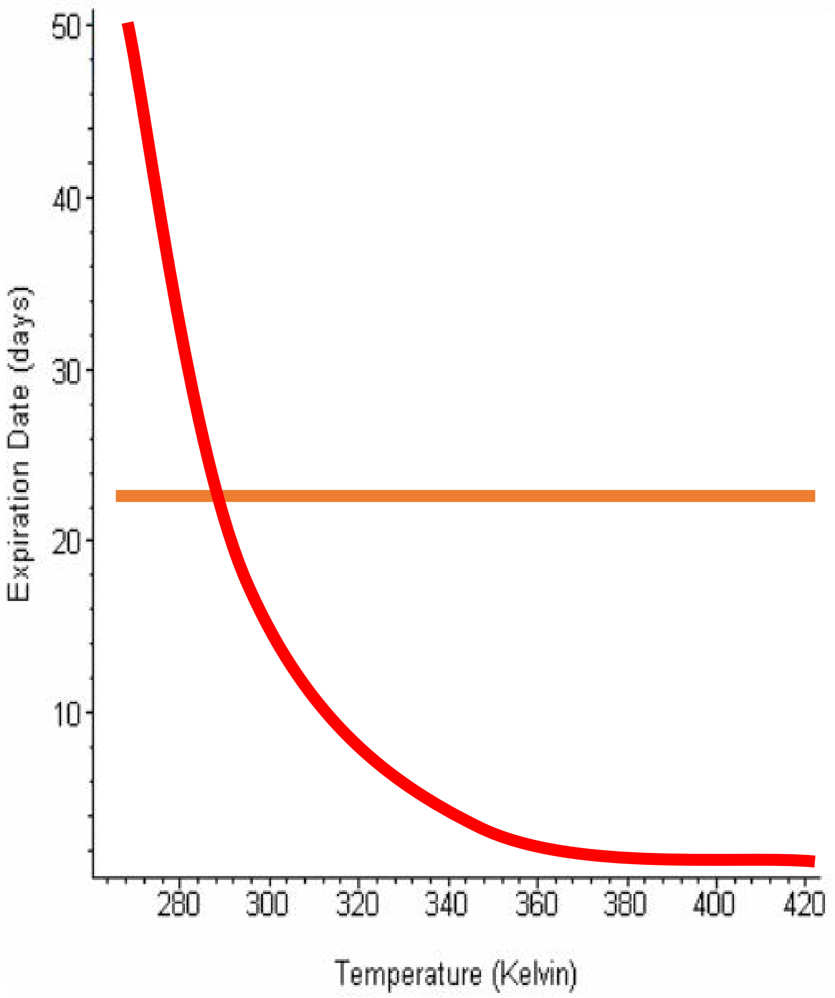
$$\frac{\partial Q}{\partial t} = -k_1 e^{\left[-\frac{E_a}{R_g T(t)}\right]} Q^n$$

Variables

- E_a Activation energy
- k_1 Arrhenius constant
- n Order of the reaction
- T Temperature
- Q Quality
- t Time

2003

Storage



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Variables

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- T Temperature
- Q Quality
- t Time

2003

Shelf Life

Name: ⊞ Activation Energy

Name: ⊞ Arrhenius Constant

Name: ⊞ Temperature

Name: ⊞ Quality

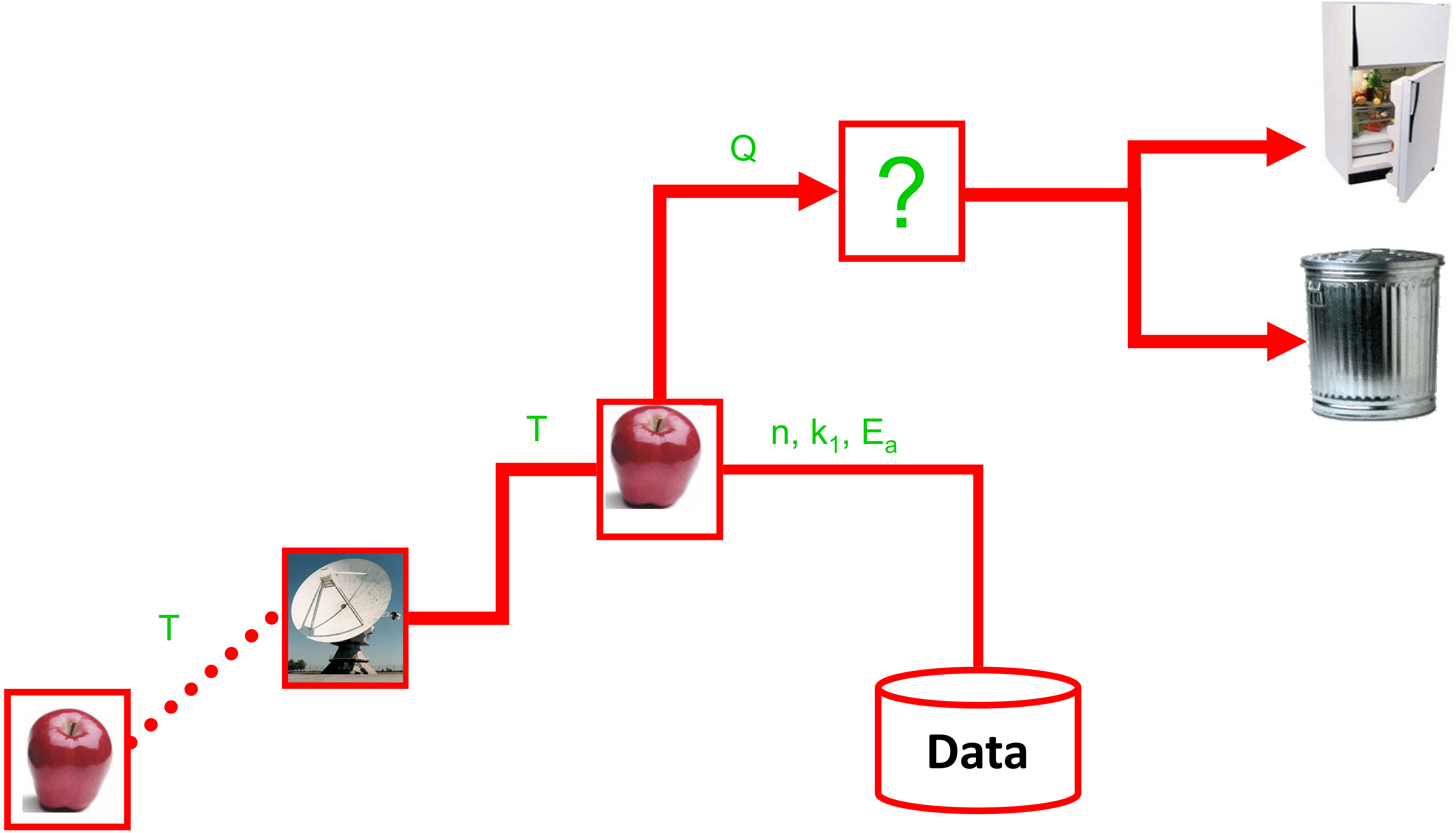
Name: ⊞ Order of Reaction
Description: ⊞ Order of Reaction
Symbol: n
Access: Read
ID: EPC: 010200841910000001289731
Class: Scalar
Type: Int
Unit:
Default: 1

Food Quality

Name: ⊞ Food Quality
Description: ⊞ Food Quality based Arrhenius
Developer: ⊞ Natick Army Laboratories
ID: EPC: 010300908808BF60000000AA
Comp: ⊞ $0.25 per month
Type: Analytic
Rate: ⊞ 1 to 10,000 sec
Algorithm: ⊞

2003

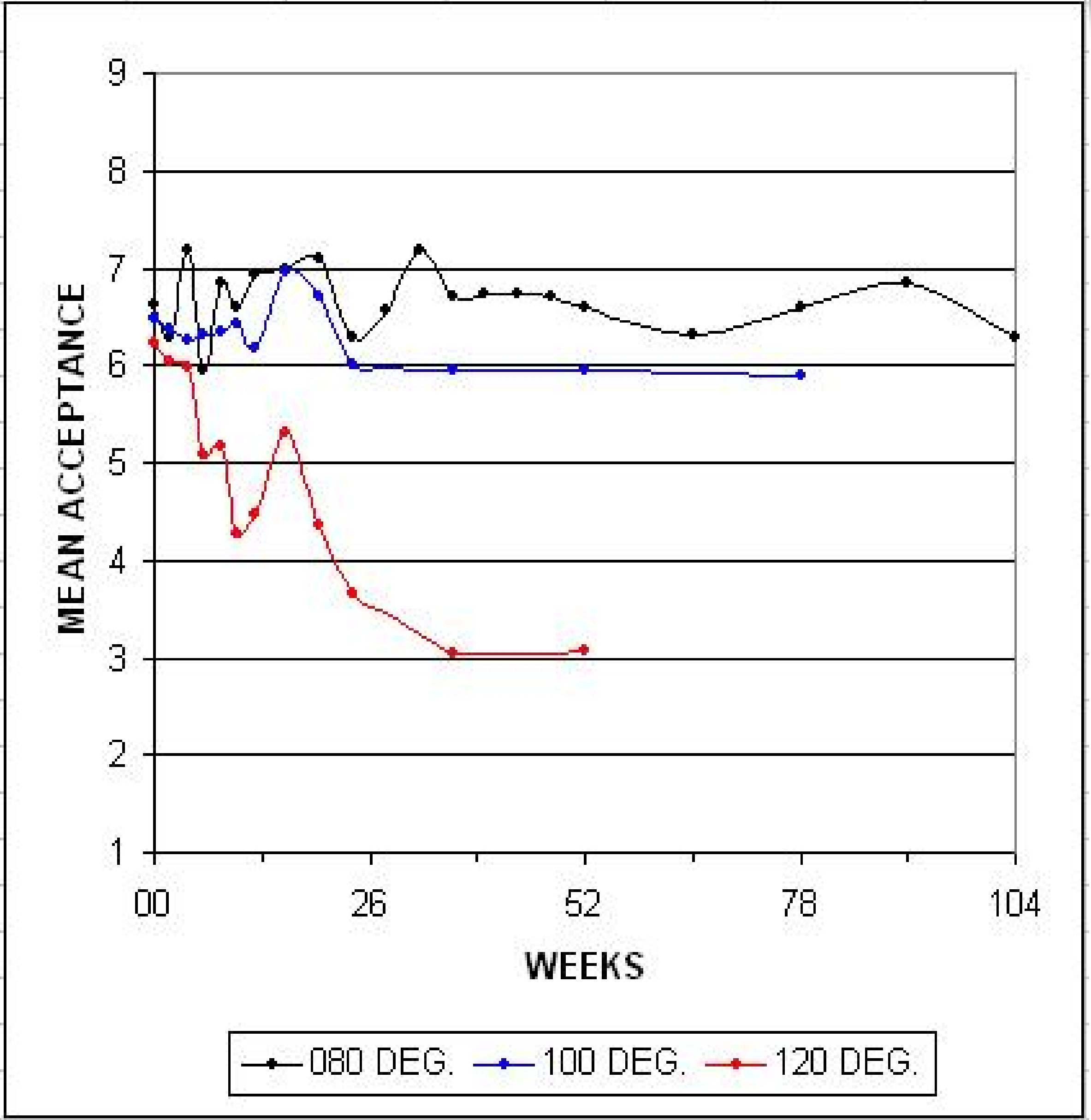
Shelf Life ➔ Answers (not numbers)



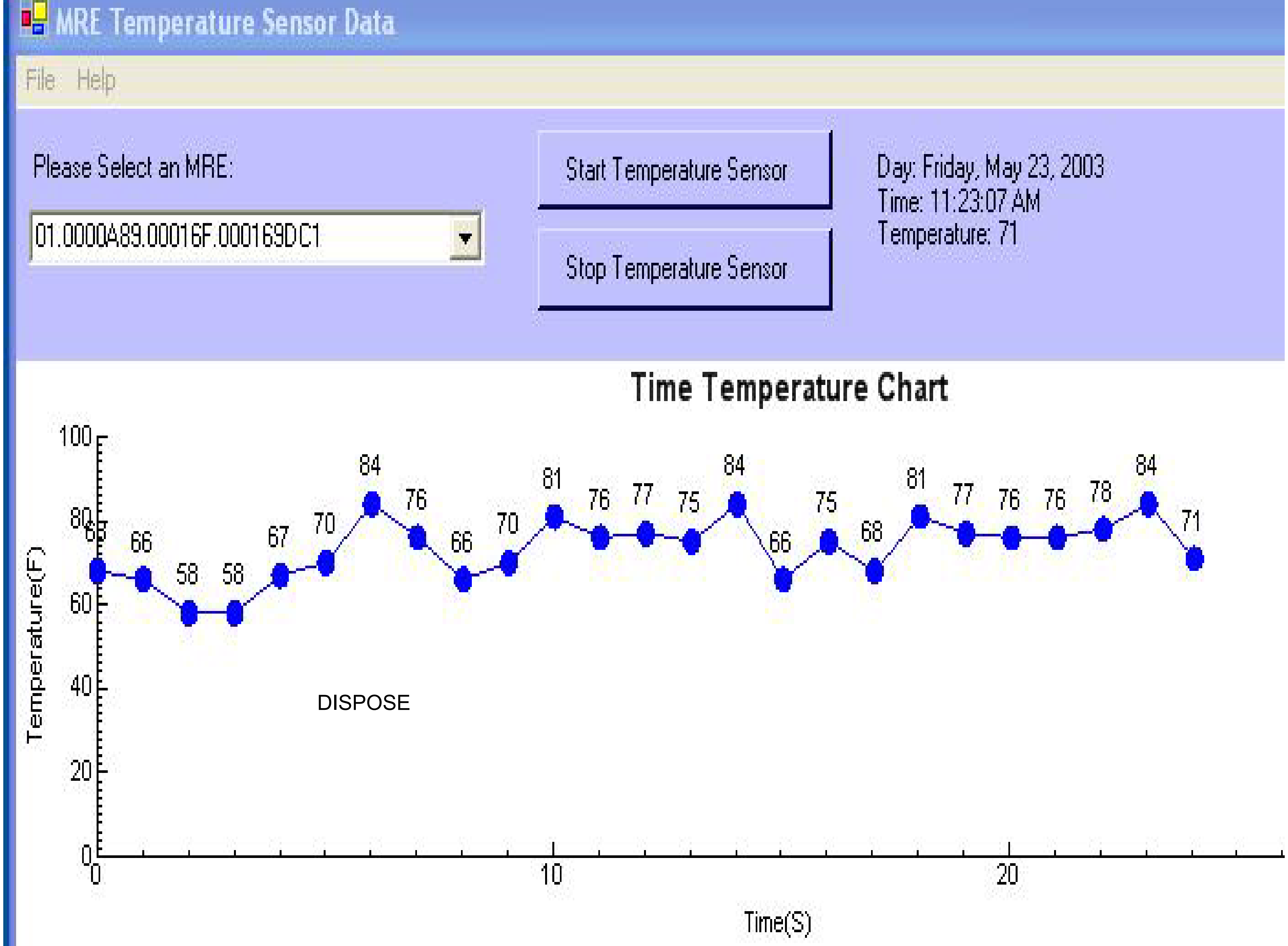
2003

Monitoring Perishables (MRE Simulation)

WKS	080 DEG.	100 DEG.	120 DEG
00	6.622	6.486	6.243
02	6.282	6.359	6.026
04	7.194	6.250	5.972
06	5.949	6.308	5.077
08	6.850	6.350	5.175
10	6.600	6.429	4.286
12	6.944	6.167	4.472
16	7.000	6.947	5.316
20	7.111	6.694	4.361
24	6.300	6.000	3.667
28	6.579		
32	7.189		
36	6.694	5.944	3.028
40	6.730		
44	6.730		
48	6.703		
52	6.583	5.944	3.056
65	6.316		
78	6.583	5.889	
91	6.842		
104	6.300		
130			
156			

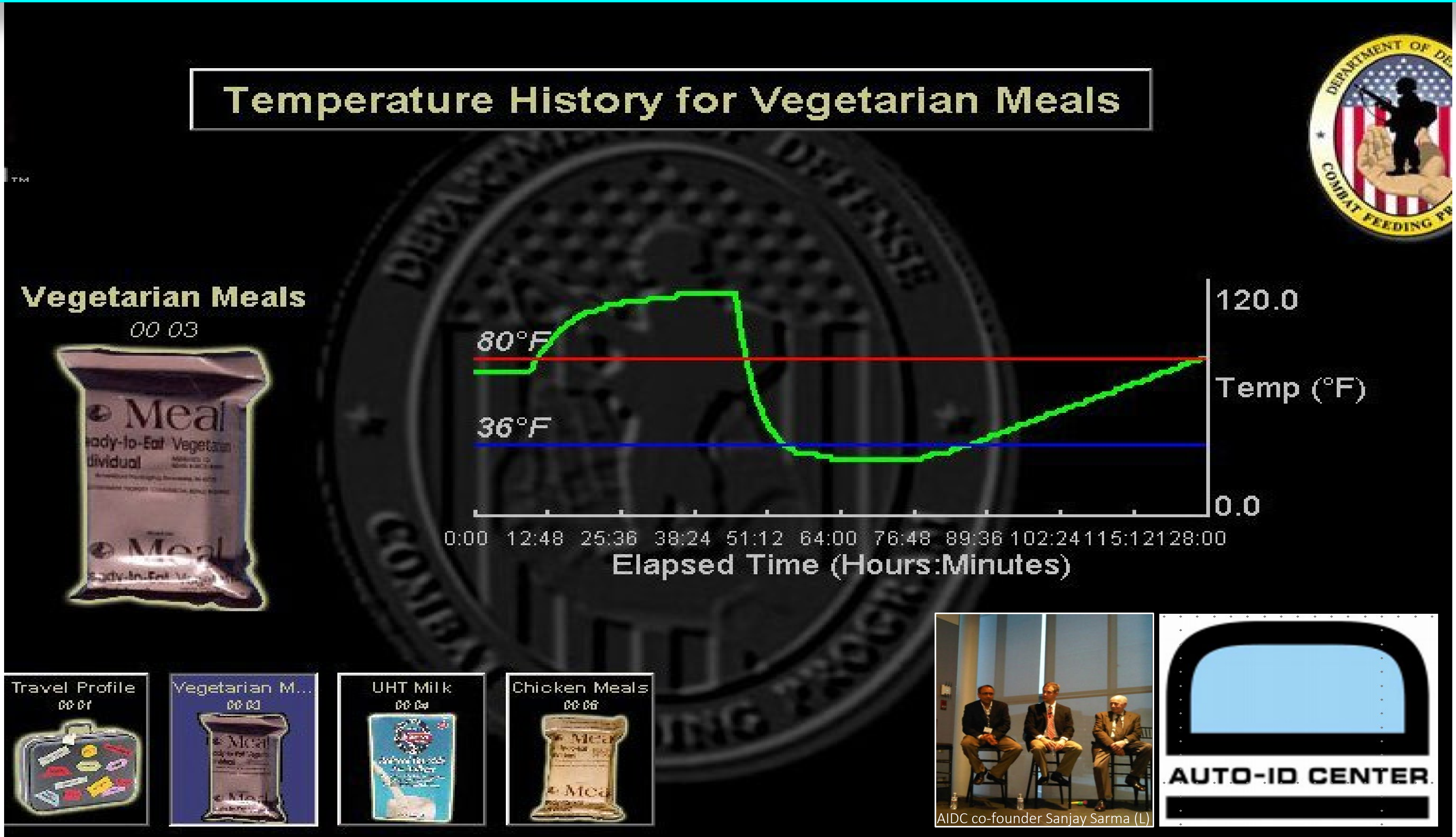


2003


MRE Temperature Sensor Data
File Help
Please Select an MRE:
01.0000A89.00016F.000169DC1
Start Temperature Sensor
Stop Temperature Sensor
Day: Friday, May 23, 2003
Time: 11:23:07 AM
Temperature: 71
Time Temperature Chart
Temperature(F)
Time(S)
DISPOSE
66 58 58 67 70 84 76 66 70 81 76 77 75 84 66 75 68 81 77 76 76 78 84 71

2003

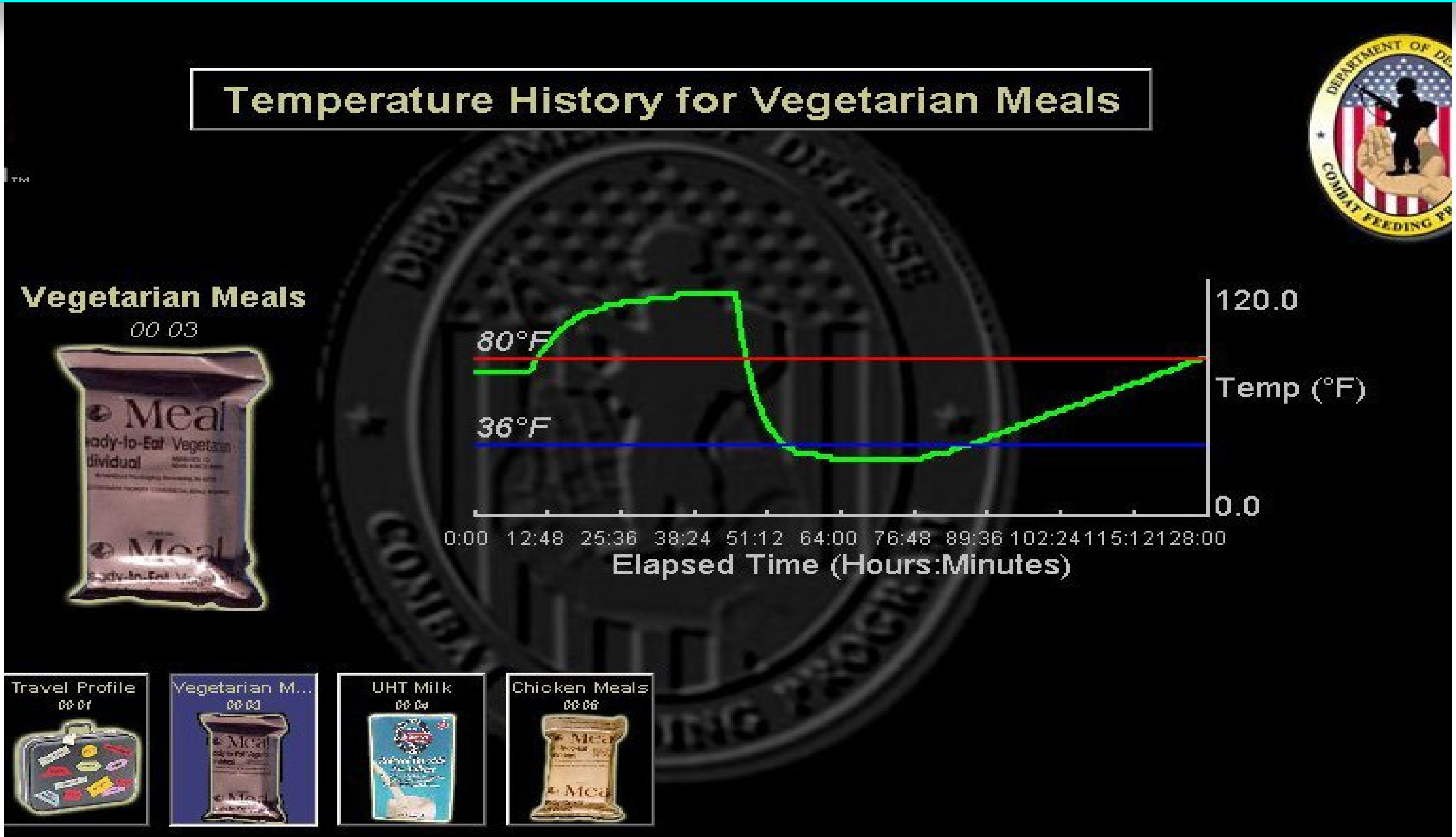
SENSEE can hold RFID + Temperature Sensor Data ● Convergence of Systems



AIDC co-founder Sanjay Sarma (L)

2003

Is this data analytics of value to the end-user on the front lines of a war zone?



2003

NOT GOOD

X

Knowledge Tools	Statistical Tools
•Agent-based model	•Stochastic
•Data-informed models	•Bayesian & Adaptive
•Data visualization	•Dynamic models
•Network models	•Hierarchical models
•Data & database modeling	•Factor analysis
•Document Modeling	•Monte Carlo models
•Metamodeling	•Population Modeling
•Ontological Modeling	•Dynamical system
•Business Process Modeling	•Stochastic system eqn
•Natural language processing	•Social network analysis
•Machine Learning, ANN, DL	•Topic modeling

2003

SIMPLICITY – THE TRAFFIC LIGHT OUTCOME – ANSWERS, not numbers

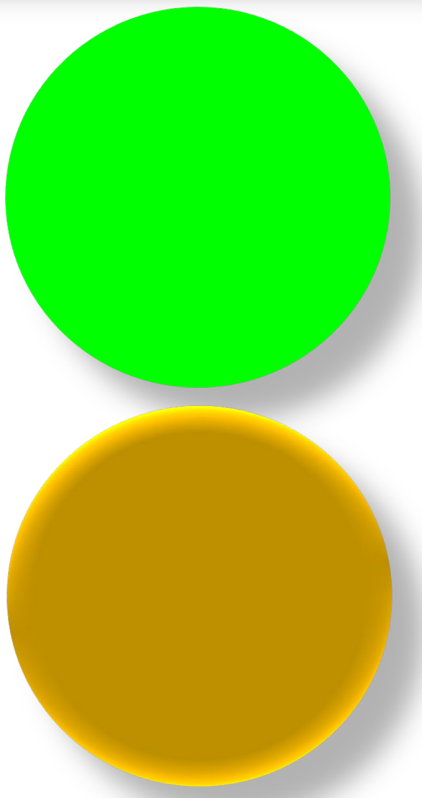
GOOD

2003

SIMPLICITY – THE TRAFFIC LIGHT OUTCOME – ANSWERS, not numbers

GOOD

INSPECT



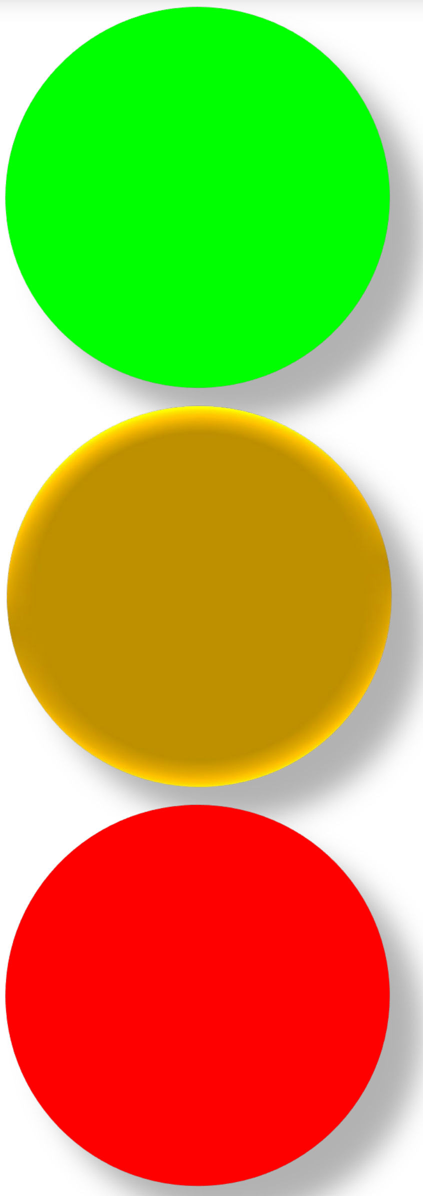
2003

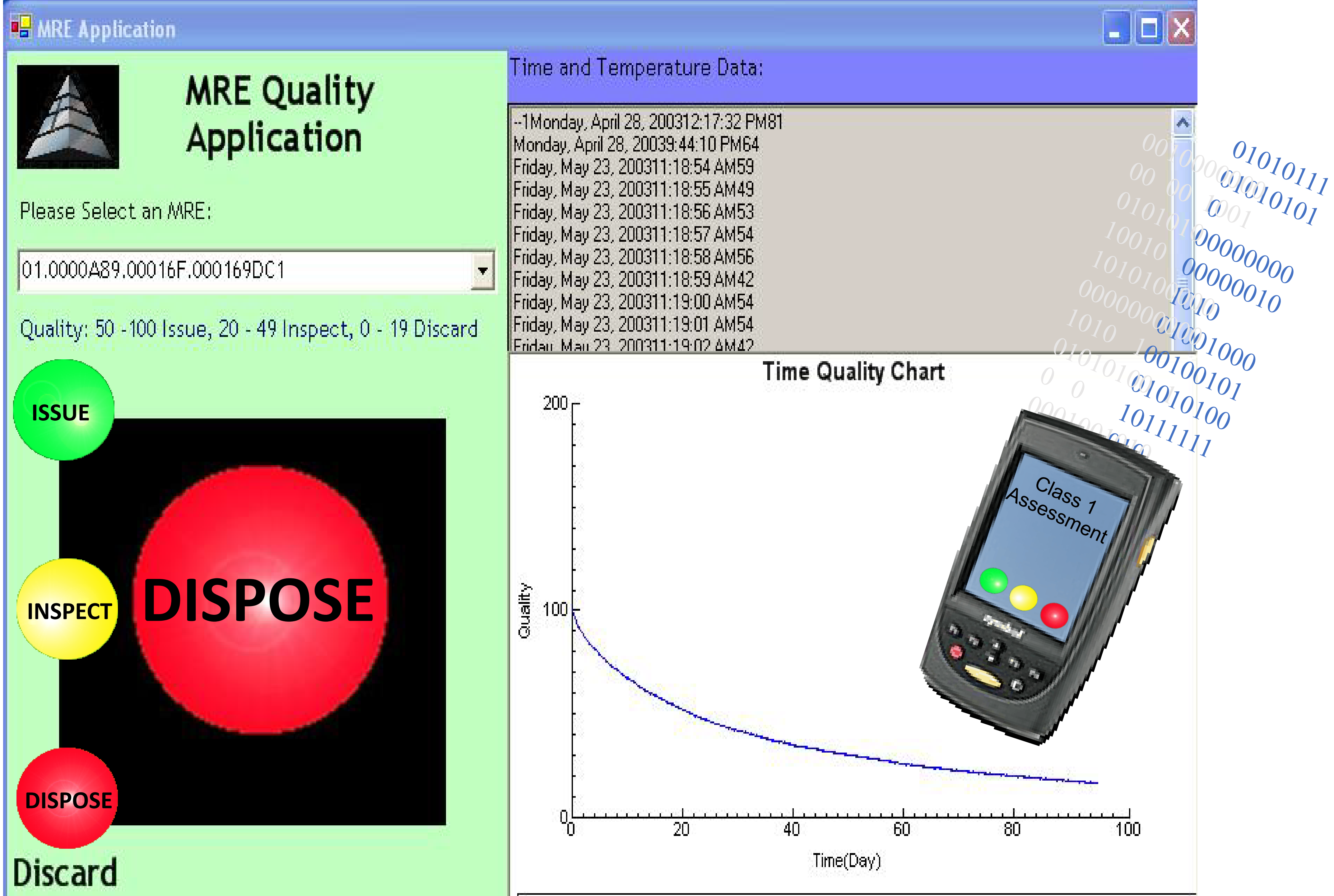
SIMPLICITY – THE TRAFFIC LIGHT OUTCOME – ANSWERS, not numbers

GOOD

INSPECT

REJECT




MRE Application
MRE Quality Application
Please Select an MRE:
01.0000A89.00016F.000169DC1
Quality: 50 - 100 Issue, 20 - 49 Inspect, 0 - 19 Discard
ISSUE
INSPECT
DISPOSE
DISPOSE
Discard
Time and Temperature Data:
--1Monday, April 28, 200312:17:32 PM81
Monday, April 28, 20039:44:10 PM64
Friday, May 23, 200311:18:54 AM59
Friday, May 23, 200311:18:55 AM49
Friday, May 23, 200311:18:56 AM53
Friday, May 23, 200311:18:57 AM54
Friday, May 23, 200311:18:58 AM56
Friday, May 23, 200311:18:59 AM42
Friday, May 23, 200311:19:00 AM54
Friday, May 23, 200311:19:01 AM54
Time Quality Chart
200
100
0
Quality
0
20
40
60
80
100
Time(Day)
Class 1 Assessment
01010111
01010101
00000000
00000010
01001000
00100101
01010100
10111111

2003

Grocery Store Perishability

Is the spinach fresh? Is the fish smelling fishy? Is the chicken safe to eat?

YOU WANT TO KNOW IF THE CHICKEN IS STILL GOOD TO EAT. YOU DON'T TRUST THE "SELL BY" DATE ON THE LABEL

WHAT IF THE PACK OF "CHICKEN" CAN TALK TO YOU AND OFFER YOU A REAL-TIME UPDATE ABOUT ITS QUALITY AND FOOD SAFETY?

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WHAT IF THE PACK OF "CHICKEN" CAN TALK TO YOU AND OFFER YOU A REAL-TIME UPDATE ABOUT ITS QUALITY AND FOOD SAFETY?


THIS IS A NON-TOXIC BIOGENIC AMINE SENSOR TO MONITOR THE SAFETY OF YOUR FRESH FOOD
HARVESTLAND
PERDUE
fresh: Chicken Thigh Filets
All Natural† • No Hormones or Steroids Added‡
No Antibiotics Ever
Fed All Vegetarian Diet
No Animal By-Products
Raised Cage Free
PROCESS USDA VERIFIED
USDA PROCESS VERIFIED
USDA A GRADE
Boneless and Skinless • Lean


Yes We Can!


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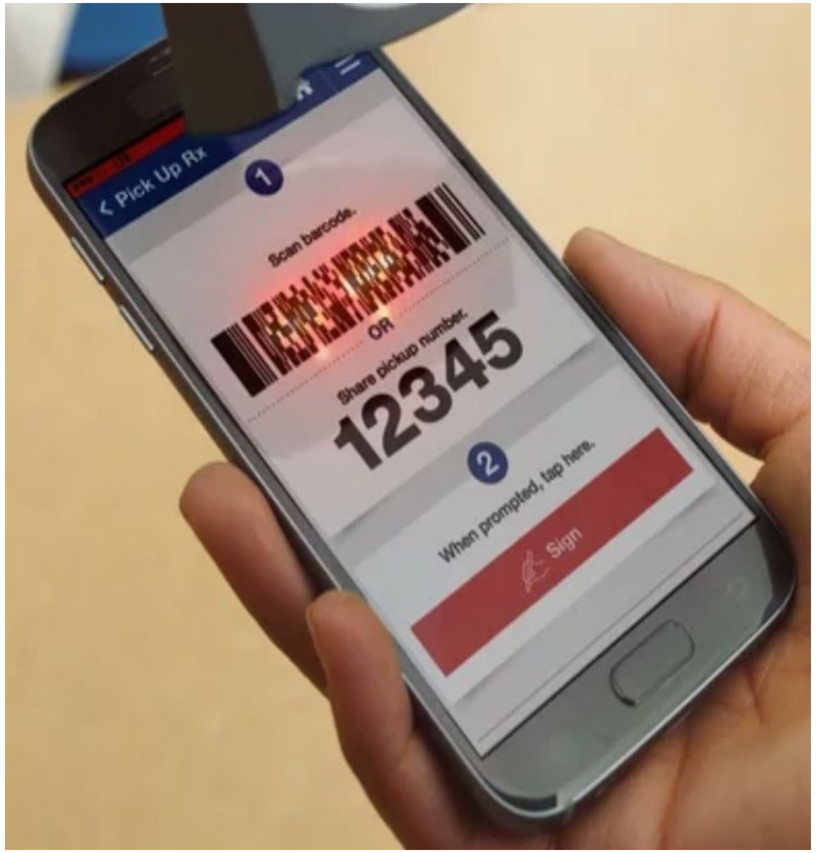
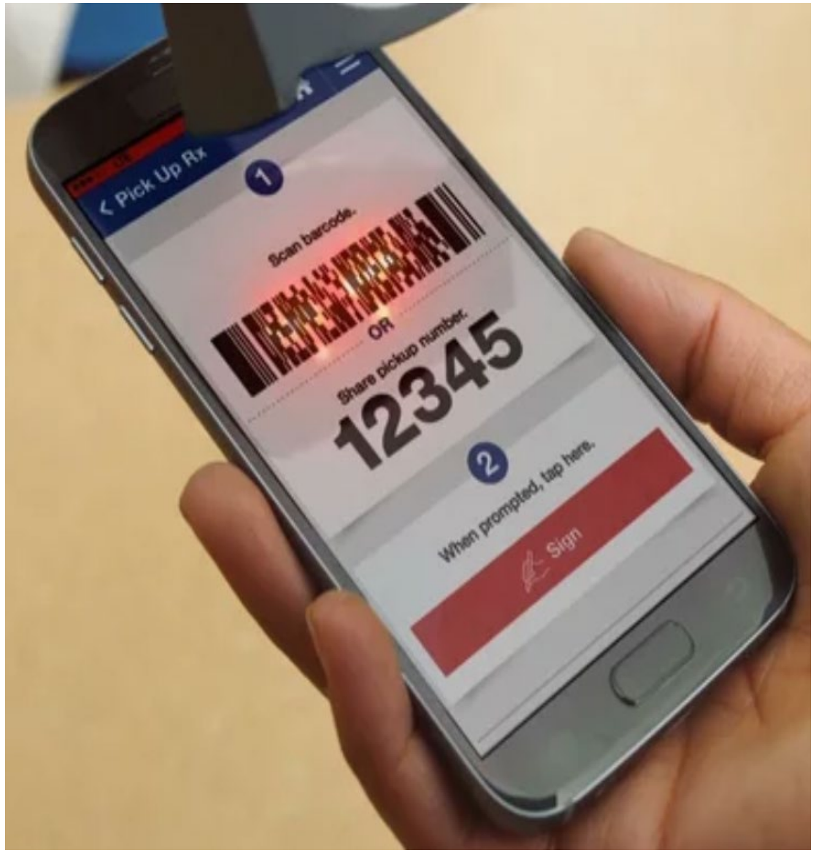
Raised Cage Free
PROCESS USDA VERIFIED
USDA PROCESS VERIFIED
USDA A GRADE
Boneless and Skinless • Lean


FOOD
SAFETY APP
SKU 12345
PROD CHK
QUALITY

THE SKU (PRODUCT NUMBER) SHOWS ON THE MOBILE APP

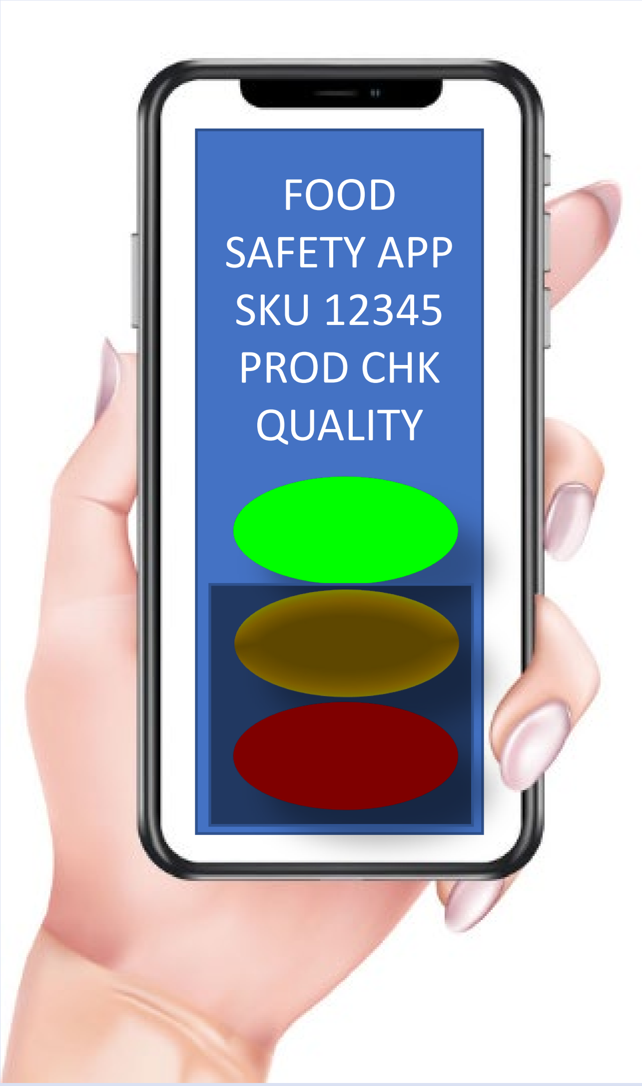


THE SKU (PRODUCT NUMBER) SHOWS ON THE MOBILE APP



WOULD YOU PAY 1 CENT TO USE THIS FOOD APP HEALTH SAFETY SERVICE ?

IT IS YOUR HEALTH



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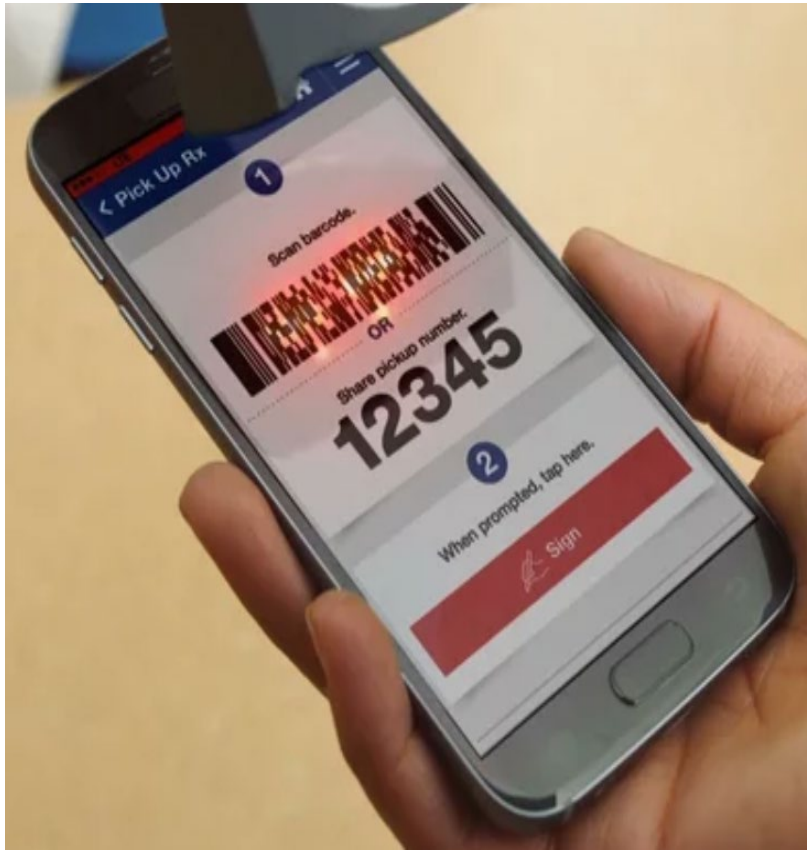

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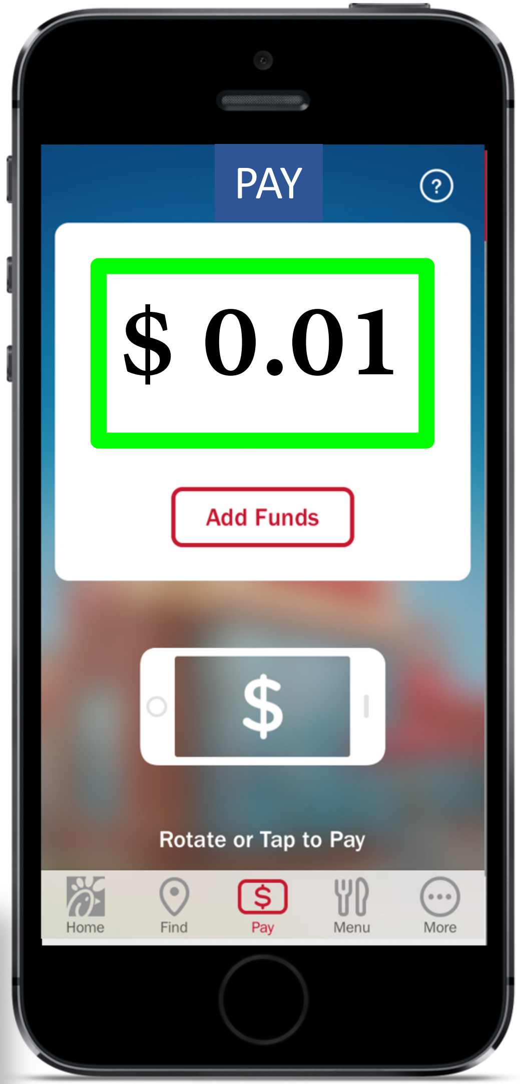
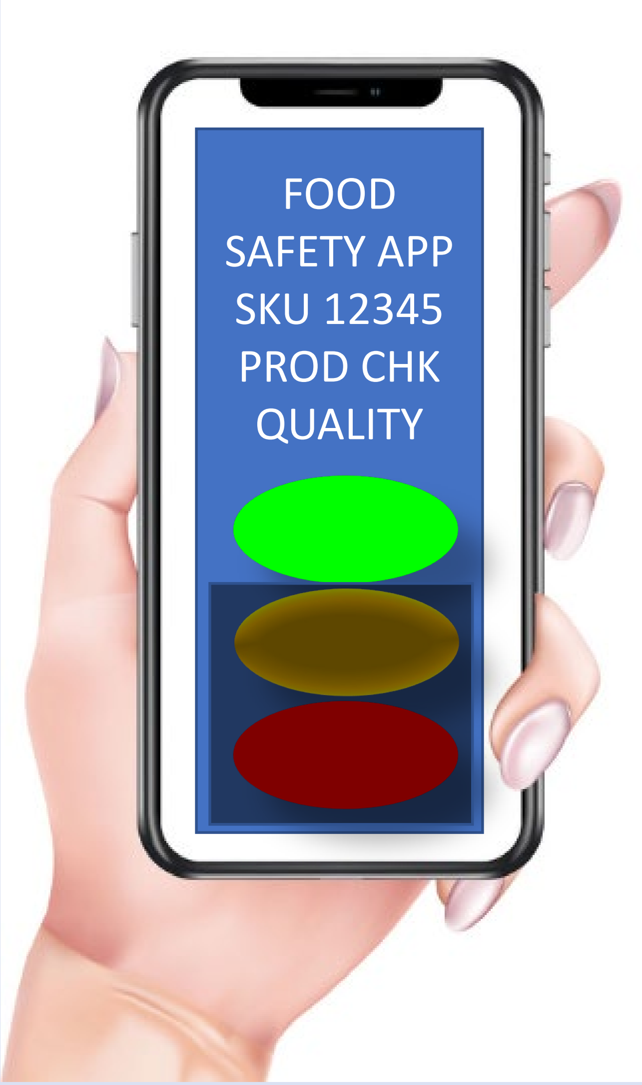
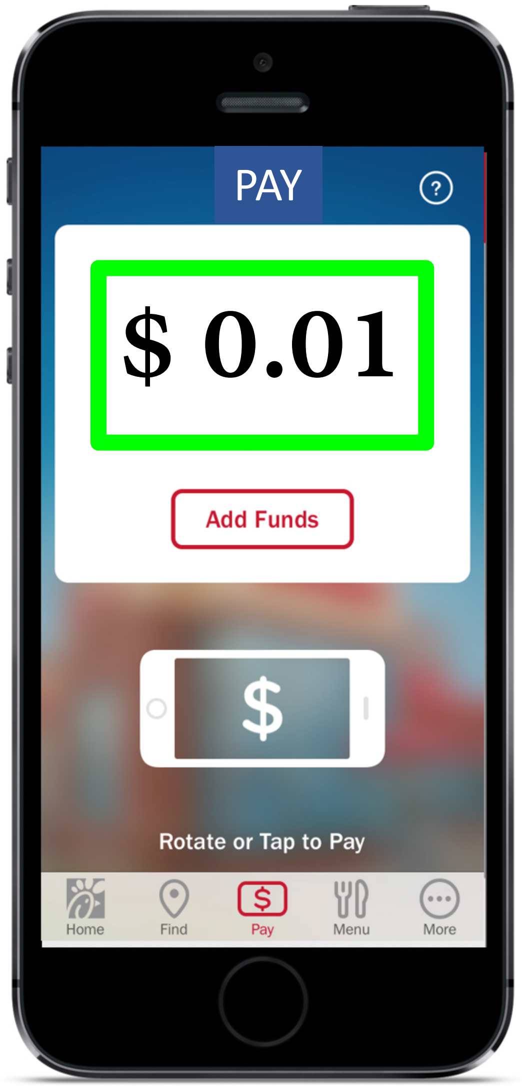


IT IS YOUR HEALTH

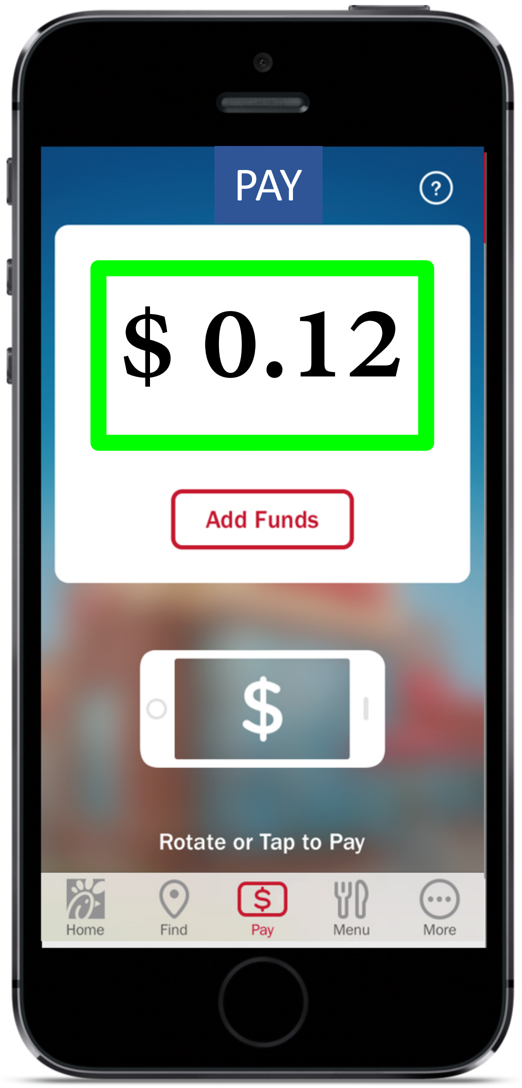


PEAS OF YOUR MIND


PAY
$ 0.01
Add Funds
$
Rotate or Tap to Pay
$
Home
Find
Pay
Menu
More

REMEMBER IoT ? HOW NANO-FEES MAY GENERATE MEGA-MILLIONS

0.12 cents

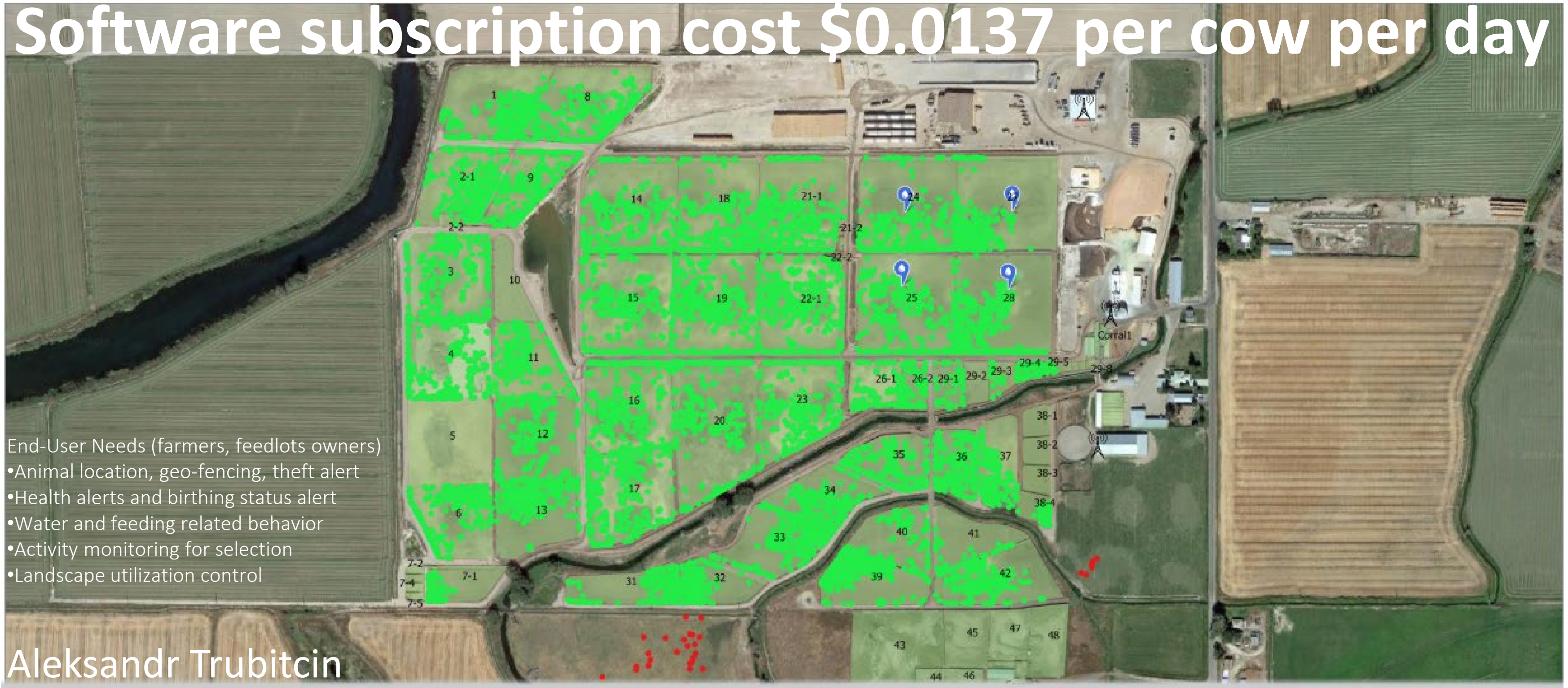


REMEMBER IoT ? HOW NANO-FEES MAY GENERATE MEGA-MILLIONS

See SIGNALS - https://dspace.mit.edu/handle/1721.1/111021

The user will also need access to the cattle tracking and monitoring web application. For example, the cost of an annual subscription to the Cattle Tags Technologies app will be $5 per animal.

0.12 cents



LoRaWAN ear tag from Cattle Tags Technologies starts from $39. Tags have embedded GPS receiver, accelerometer, temperature sensor and replaceable battery. Operator reads RFID-tag with Bluetooth reader (ID sent to ERP system). Installation of activated LoRaWAN ear tag follows.

alex.trubitcin@gmail.com

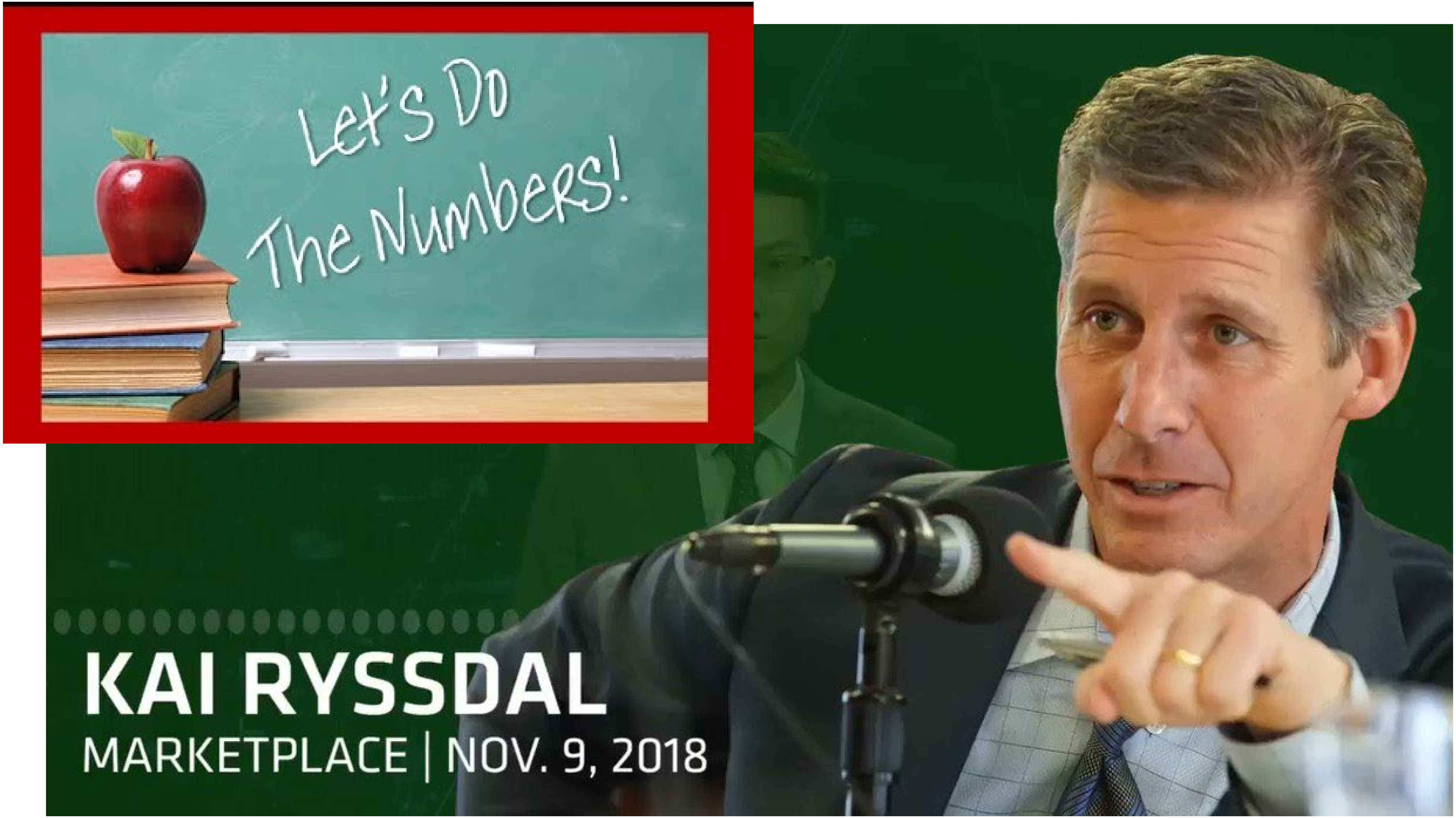
Digital Transformation (Connectivity+App+Tag) Cost $0.12 per cow per day

Proposal generates following remark from a VC (Mr Vinod Vaticinator, Venture Capitalist)

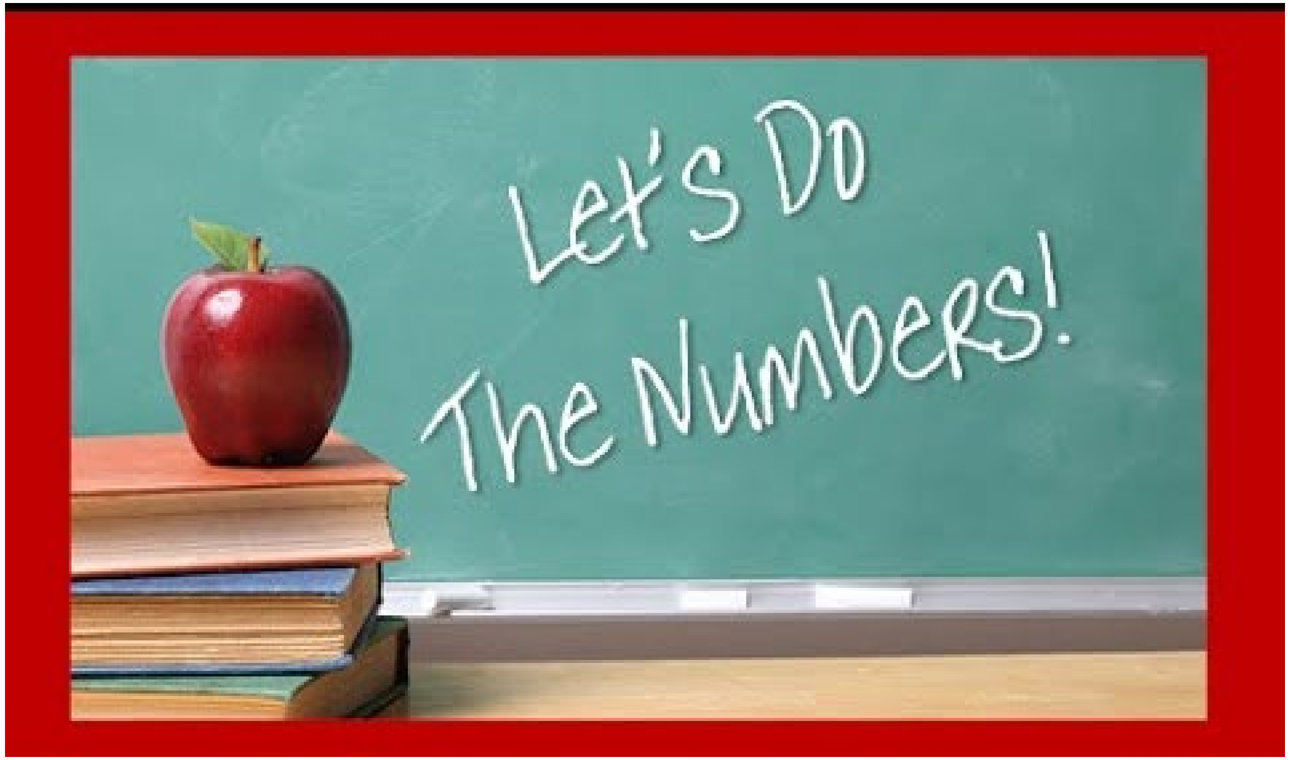
A joke? 1 cent ?

Bad business !!

You are fired !



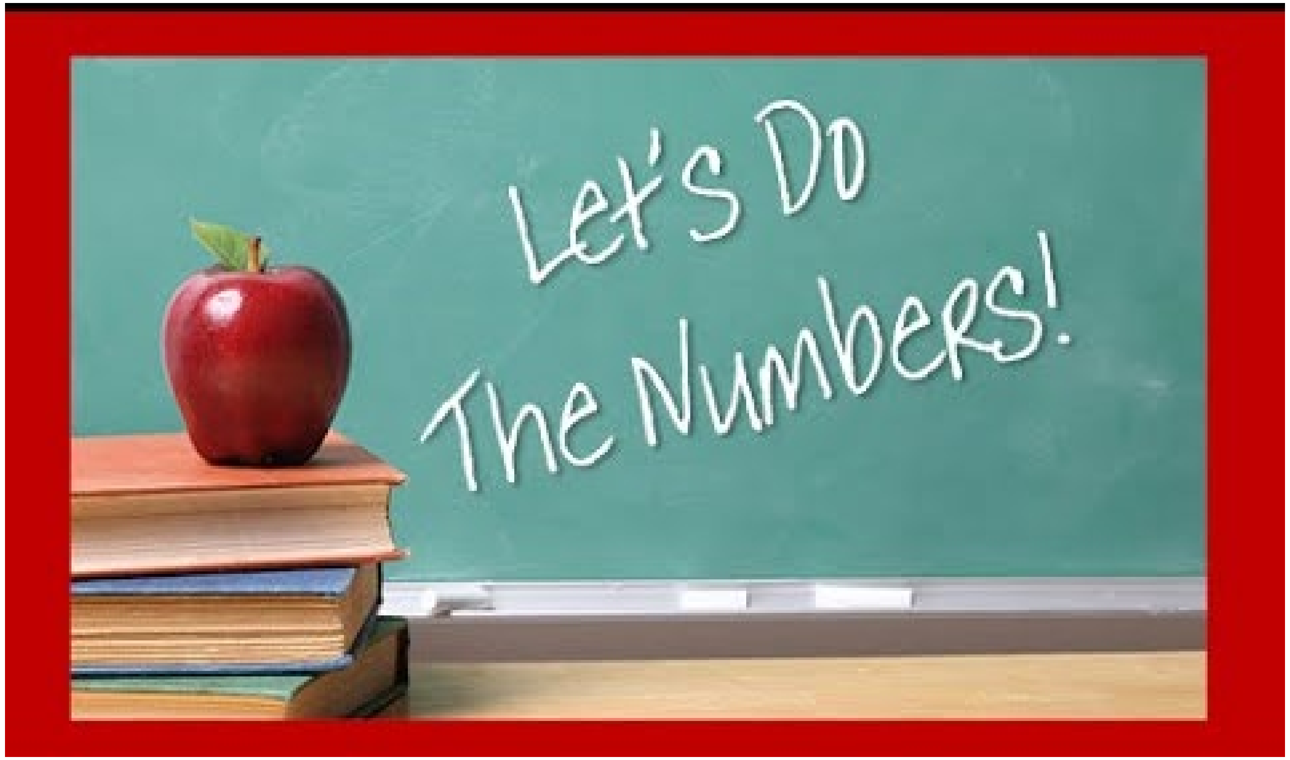
https://www.marketplace.org/shows/marketplace/07092018/



Number of Supermarkets - 2018	38,307
*2 million or more in annual sales Source: Progressive Grocer Magazine	

Transaction count is the metric you seek. Also known as customer count. It is the number of transactions per period. The most accessible of these is transactions per day. Even a smaller successful grocery store will approach 2000 transactions per a day. You can assume the actual foot traffic is higher as people shop together, but this number is not usually kept track of.

www.fmi.org/our-research/supermarket-facts
www.quora.com/What-is-the-average-foot-traffic-at-a-local-grocery-store



28 BILLION

ANNUAL GROCERY TRANSACTIONS IN US

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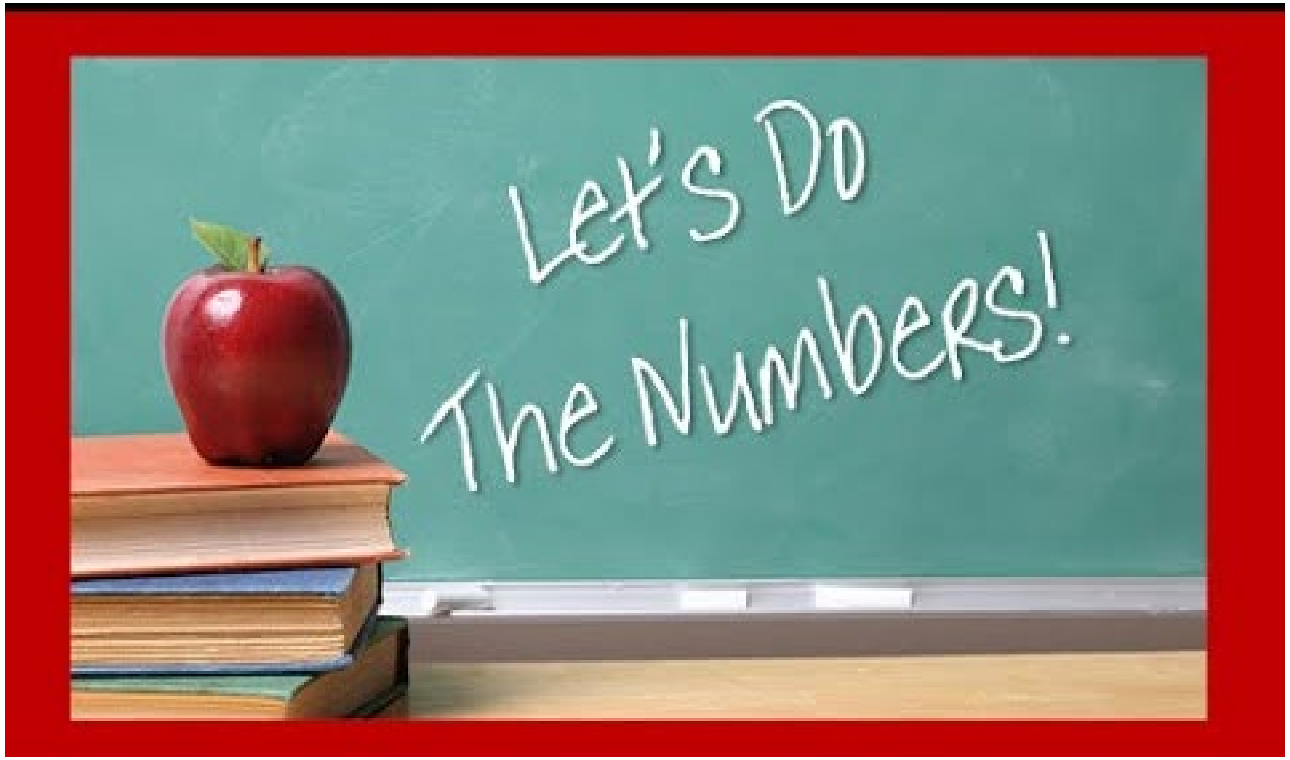

0.28 BILLION

ONLY 1% TRANSACTIONS BOUGHT CHKN AND CUSTOMER WILLING TO PAY 1 CENT

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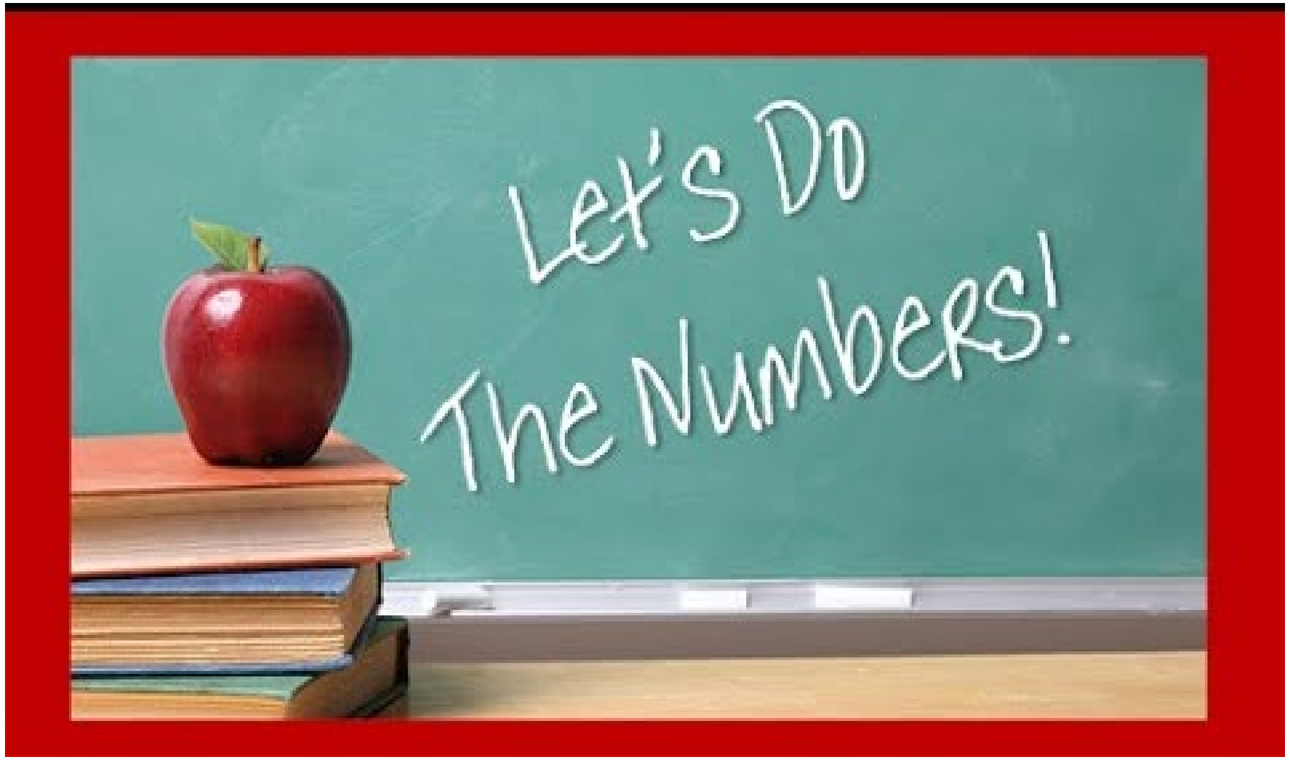


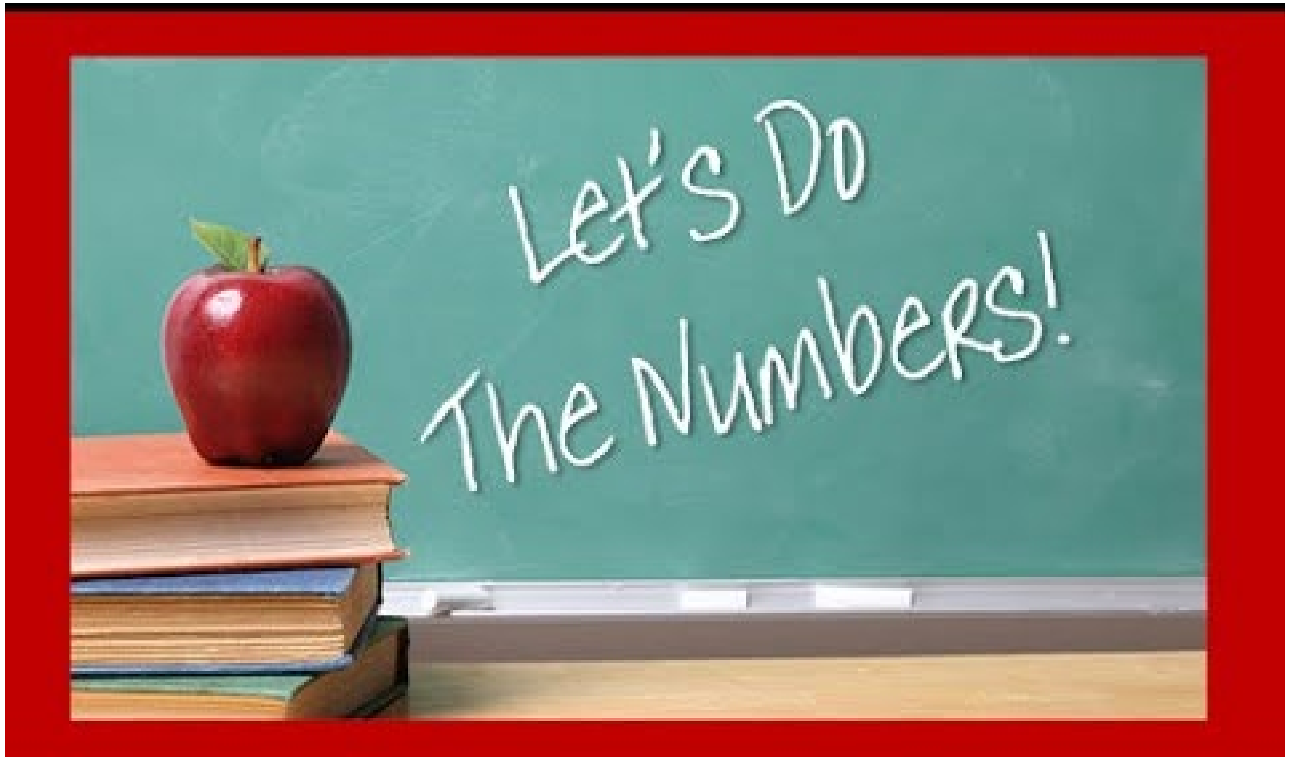
0.28 BILLION

ONLY 1% TRANSACTIONS BOUGHT CHKN
AND CUSTOMER WILLING TO PAY 1 CENT

FROM 1 USE - PAY A PENNY PER USE (PAPPU) - FOR ONLY 1 ITEM

$2.8 million

ANNUAL REVENUE ONLY IN USA



Average number items carried in a supermarket in 2017 **30,098**

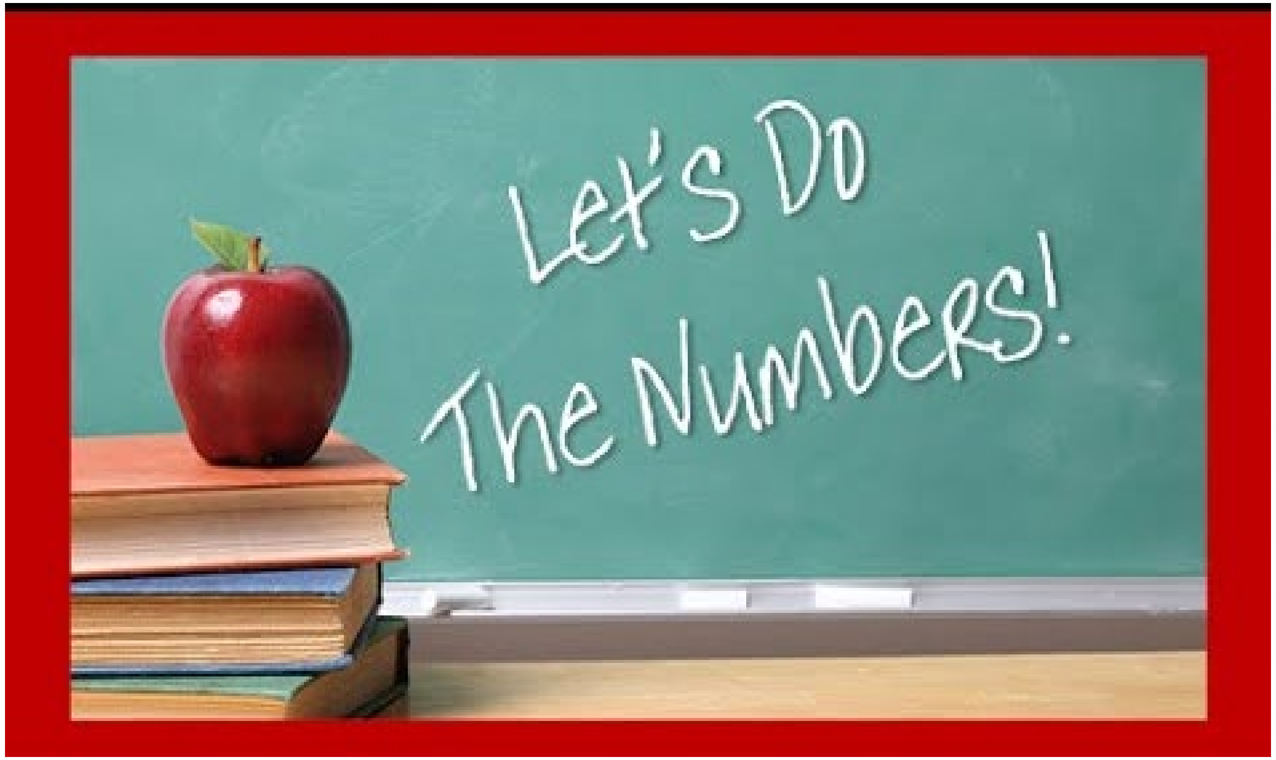
Source: Food Marketing Institute

1% OF ITEMS USE FOOD SAFETY SENSOR
CUSTOMERS PAY 10 CENT/TRANSACTION

FOOD SAFETY - PAY A PENNY PER USE (PAPPU) - 10% TRANSACTIONS

$280 million

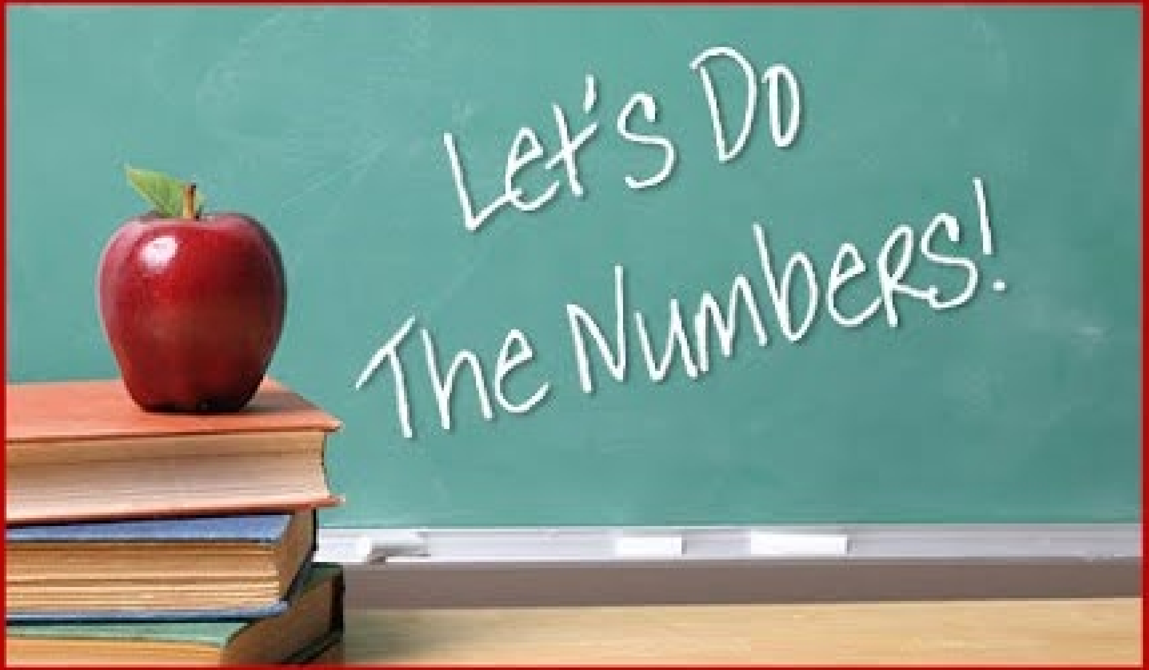
10% of 28 billion transactions pays $0.10 per transaction = $280 million revenue p.a.



FOOD SAFETY – PAY A PENNY PER USE (PAPPU) – GLOBAL POTENTIAL

Billion Dollar Industry?

ANNUAL GROSS REVENUE

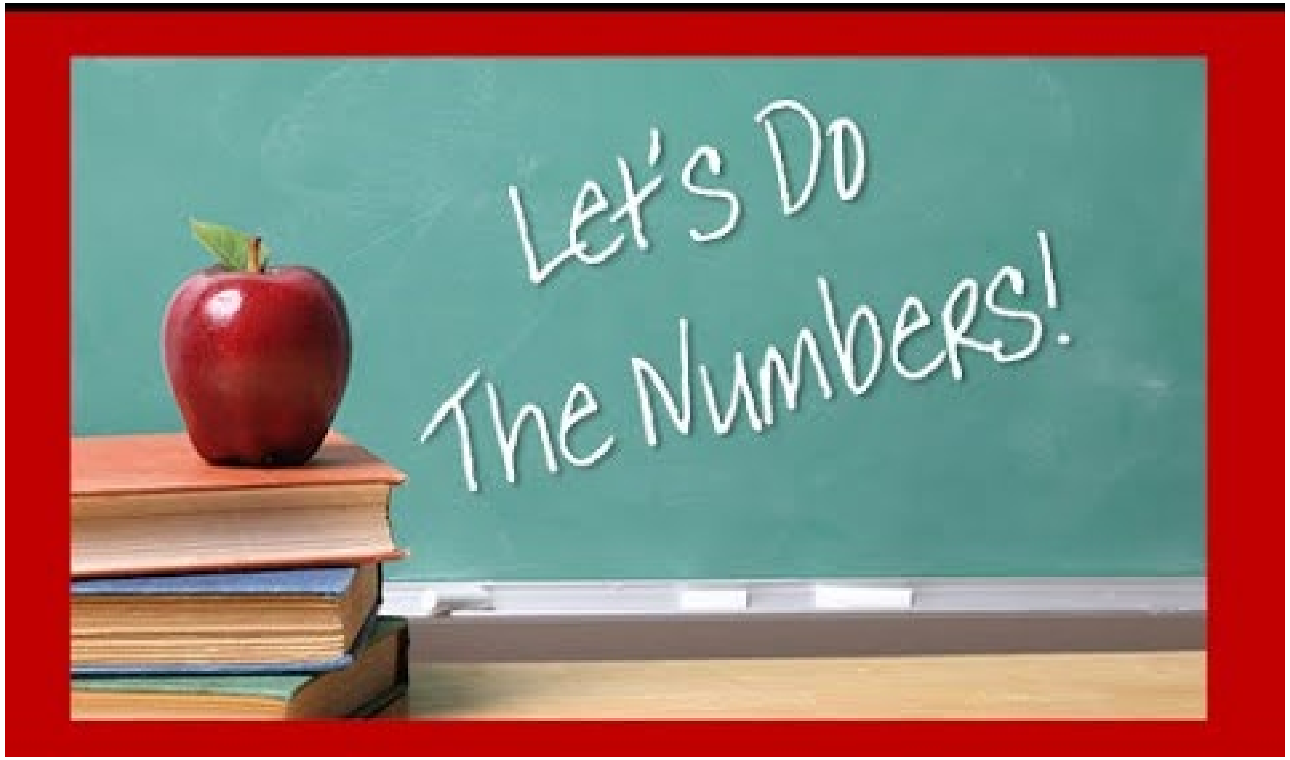


JUST
1 cent
PAPPU

FOOD SAFETY – PAY A PENNY PER USE (PAPPU) – GLOBAL POTENTIAL

Billion Dollar Industry

http://bit.ly/Economics-of-Technology
https://www.law.uchicago.edu/files/file/coase-nature.pdf
http://web.pdx.edu/~nwallace/EHP/TCEProgression.pdf
https://pdfs.semanticscholar.org/e4e8/a0486808360d056dbe212f7424273558538c.pdf
http://www.economics-ejournal.org/economics/discussionpapers/2007-3/at_download/file



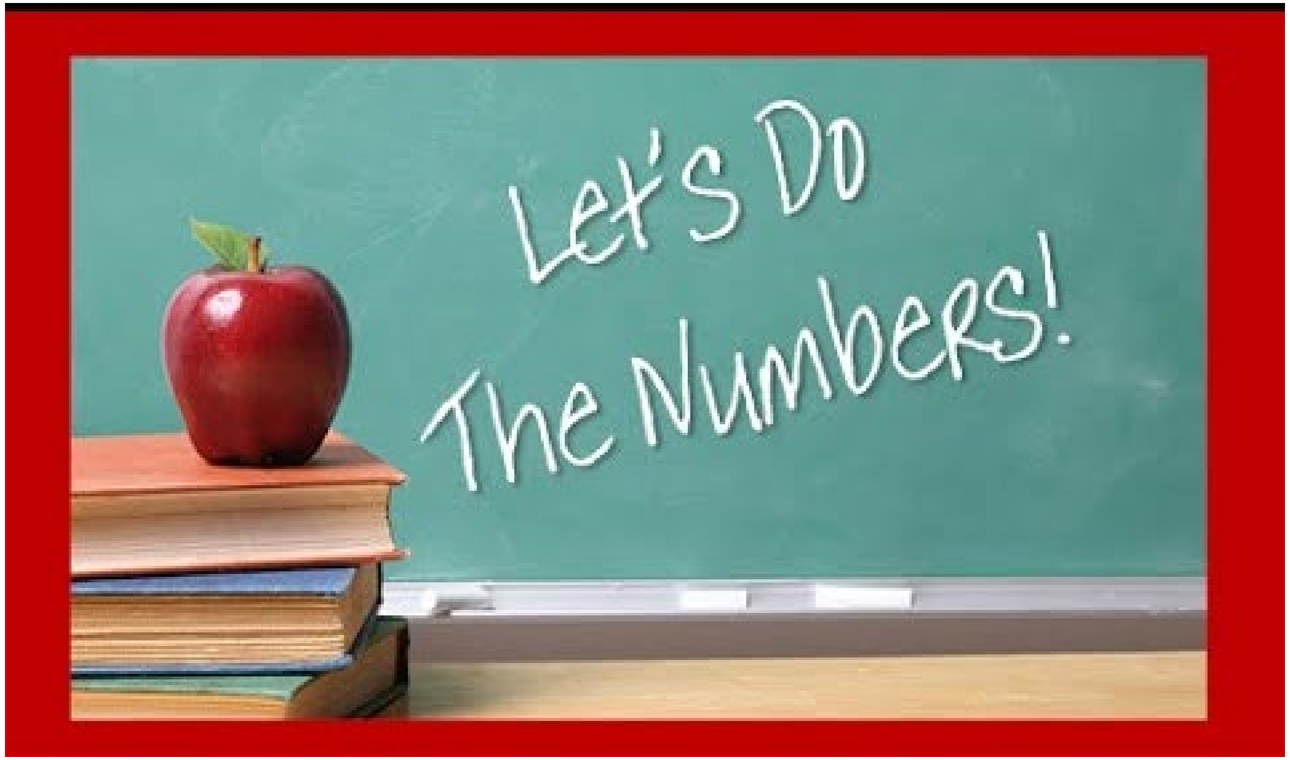
REALITY CHECK

Economies of scale may take several years to reach market penetration to generate mega revenues from nano payments, for example, the PAPPU model.

FOOD SAFETY – PAY A PENNY PER USE (PAPPU) – GLOBAL POTENTIAL

Billion Dollar Industry

THINK FOOD SAFETY AS PAY PER USE PERSONALIZED SERVICE



PAY A PENNY PER USE GLOBAL SERVICES

HPE CEO Pledges to Sell 'Everything as a Service' by 2022

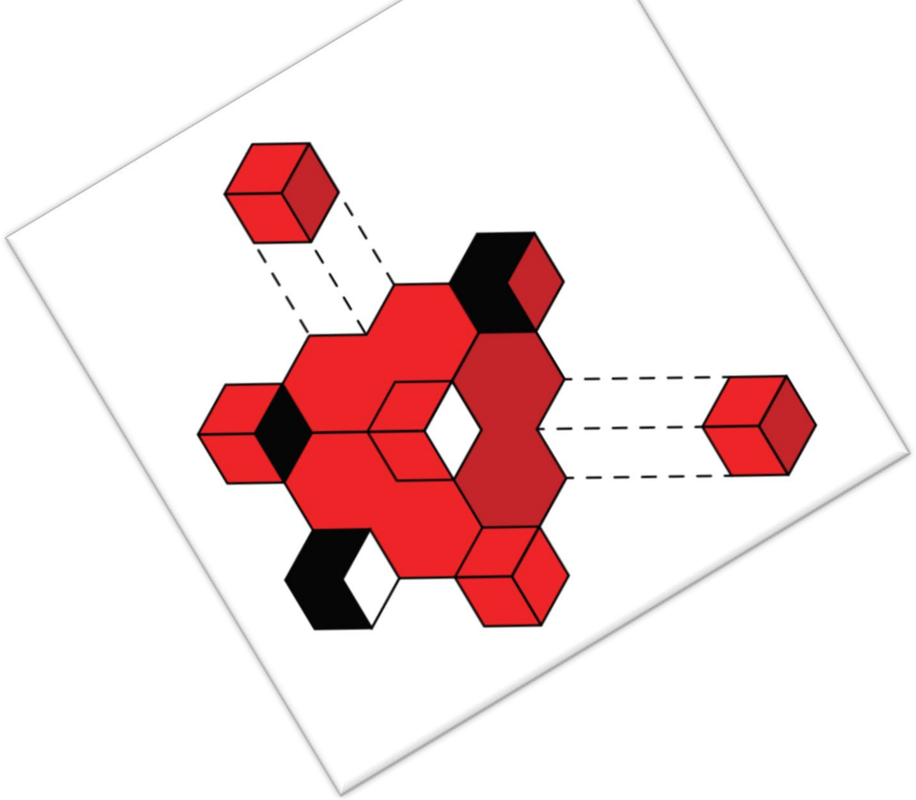
In its boldest move yet to make on-prem IT more like public cloud, the company says GreenLake is its future.

Yevgeniy Sverdlik | Jun 19, 2019

Three years from now, every product Hewlett Packard Enterprise sells will be available as a service. That's the pledge CEO Antonio Neri made from stage Tuesday afternoon during his keynote at the company's Discover conference in Las Vegas. The pledge covers both hardware and software in the enterprise tech giant's sprawling portfolio.

THINK FOOD SAFETY AS PAY PER USE PERSONALIZED SERVICE

https://www.datacenterknowledge.com/hewlett-packard-enterprise/hpe-ceo-pledges-sell-everything-service-2022



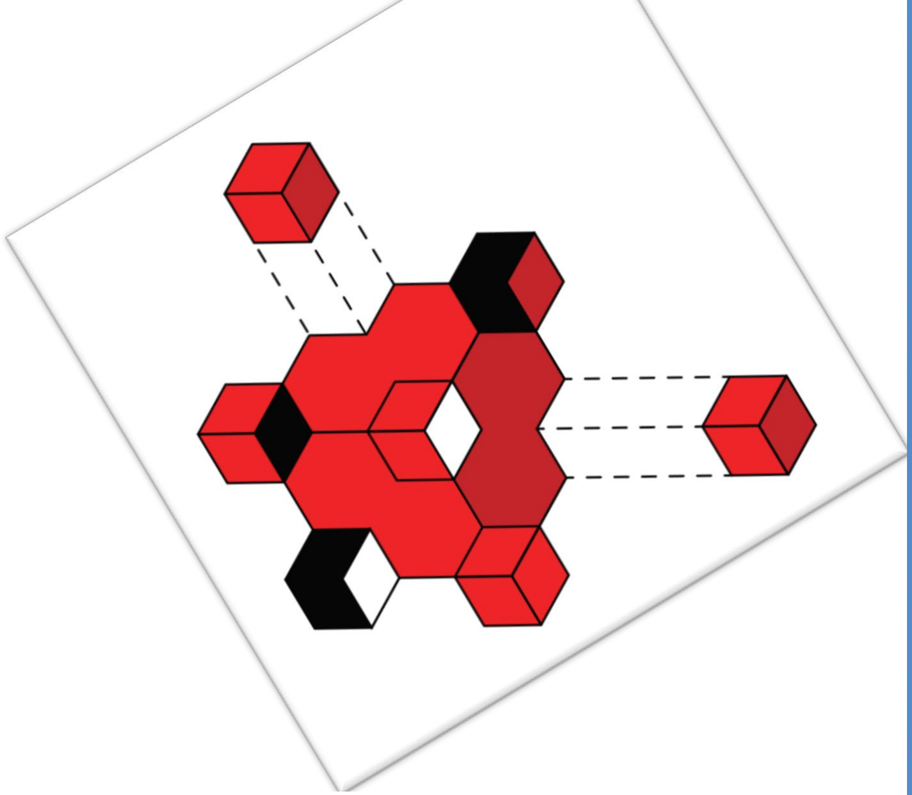
WORLD
ECONOMIC
FORUM

COMMITTED TO
IMPROVING THE STATE
OF THE WORLD

Insight Report

Top 10 Emerging Technologies 2019

http://www3.weforum.org/docs/WEF_Top_10_Emerging_Technologies_2019_Report.pdf



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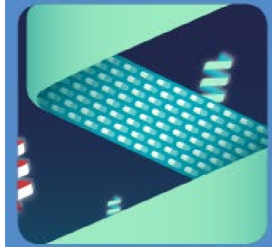
1. Bioplastics for a Circular Economy

2. Social Robots

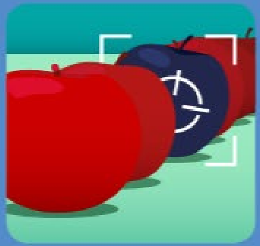
3. Tiny Lenses for Miniature Devices



4. Disordered Proteins as Drug Targets

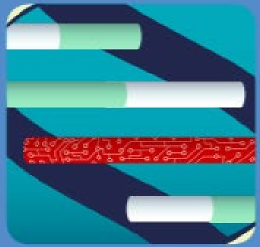
5. Smarter Fertilizers Can Reduce Environmental Contamination

6. Collaborative Telepresence



7. Advanced Food Tracking and Packaging

8. Safer Nuclear Reactors



9. DNA Data Storage

10. Utility-Scale Storage of Renewable Energy

http://www3.weforum.org/docs/WEF_Top_10_Emerging_Technologies_2019_Report.pdf

THINK FOOD SAFETY
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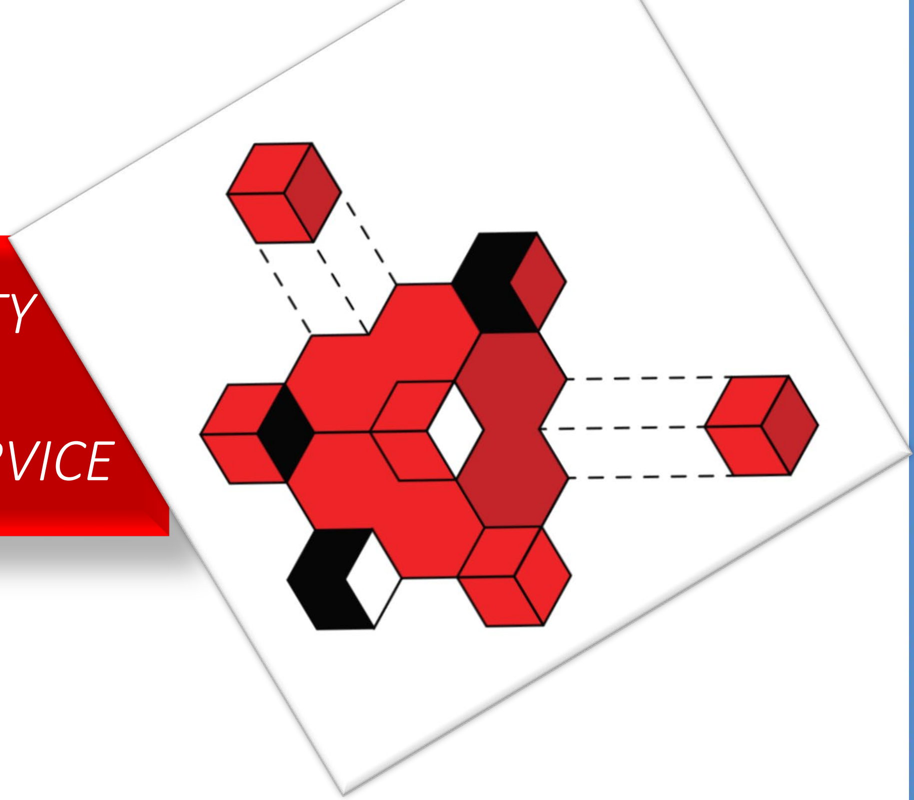

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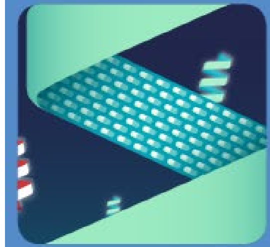

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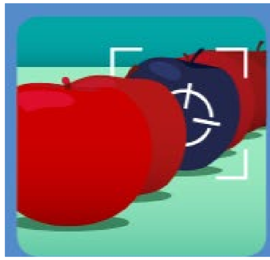

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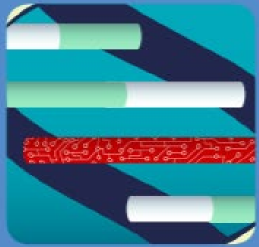

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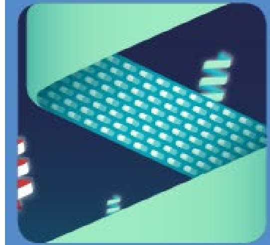

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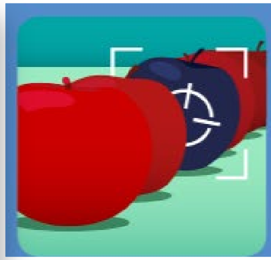

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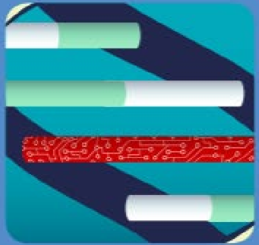

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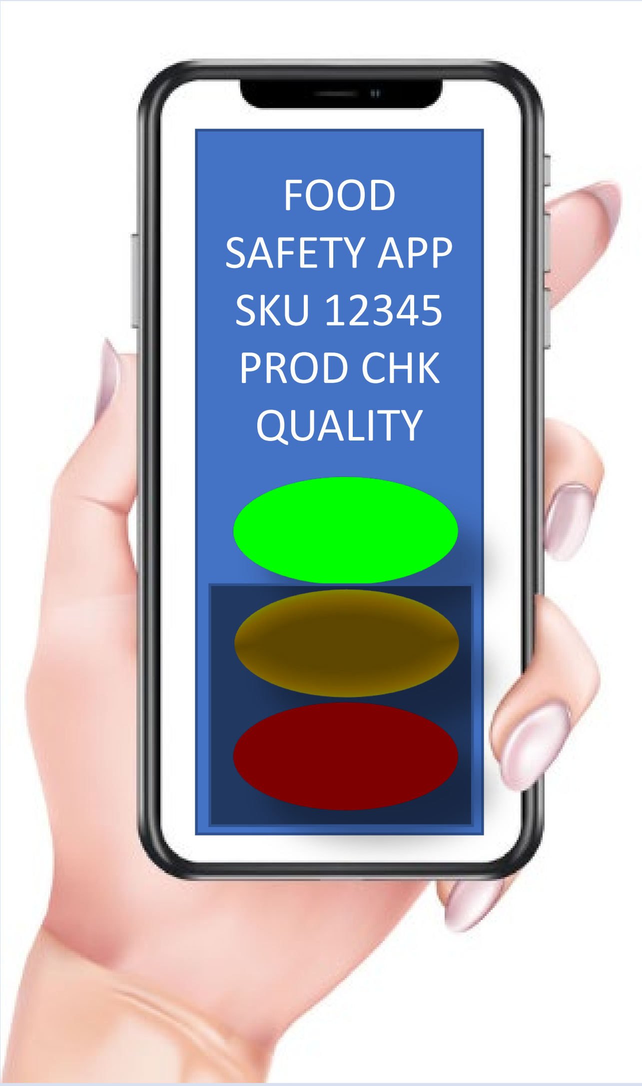
FOOD ART ?

In a Grocery Store Near You

IT IS YOUR HEALTH



PEAS OF YOUR MIND

FRESH SENSE™

CHECK WITH YOUR FOOD SAFETY APP

FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE

FRESH SENSE™

CHECK WITH YOUR FOOD SAFETY APP

SENSEE

SMALL PART BUT USEFUL

FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE

FRESH SENSE™

FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE

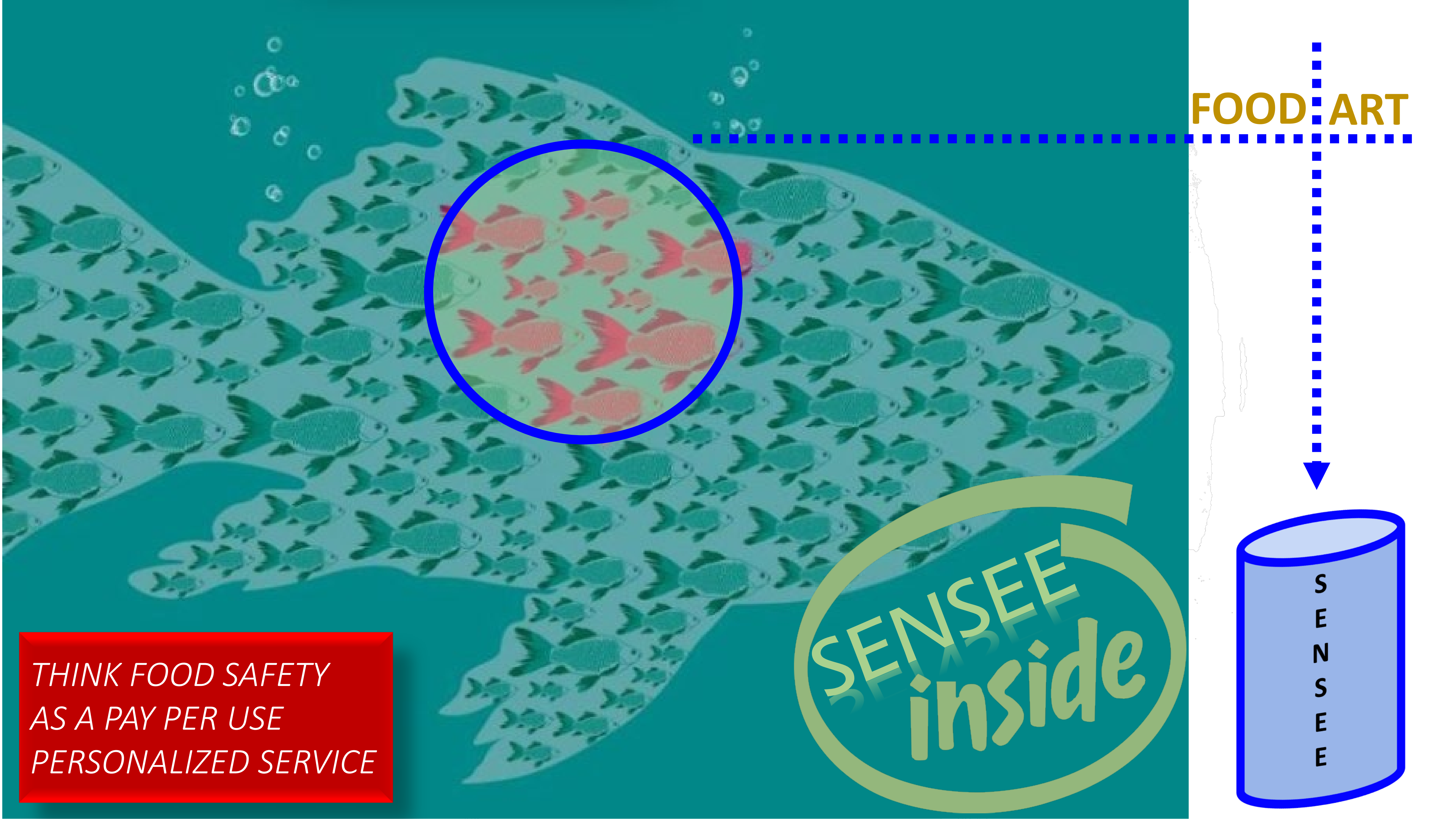
FRESH SENSE™

KIDS

FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE

FRESH SENSE – A TRADEMARKED SERVICE FROM SHOP-RITE TO GUARANTEE YOUR FRESHNESS IN REAL TIME ON YOUR PHONE

FRESH SENSE™
CHECK WITH YOUR FOOD SAFETY APP
FRUIT & VEG
Dole fresh
BABY SPINACH
ALDI
FOOD SAFETY APP
SKU 56789
PROD SPNH
QUALITY
SENSEE
FOOD SAFETY APP
SKU 98765
PROD FISH
QUALITY


FOOD ART
SENSEE inside
S E N S E E
THINK FOOD SAFETY
AS A PAY PER USE
PERSONALIZED SERVICE

Summary – A Sense of the Future

SENSEE, SNAPS, ART, DIDA'S, KIDS

Are these ingredients for a Google of Ag and/or fuel for future scientific research ?

PEAS

Platform for the Agro-Ecosystem

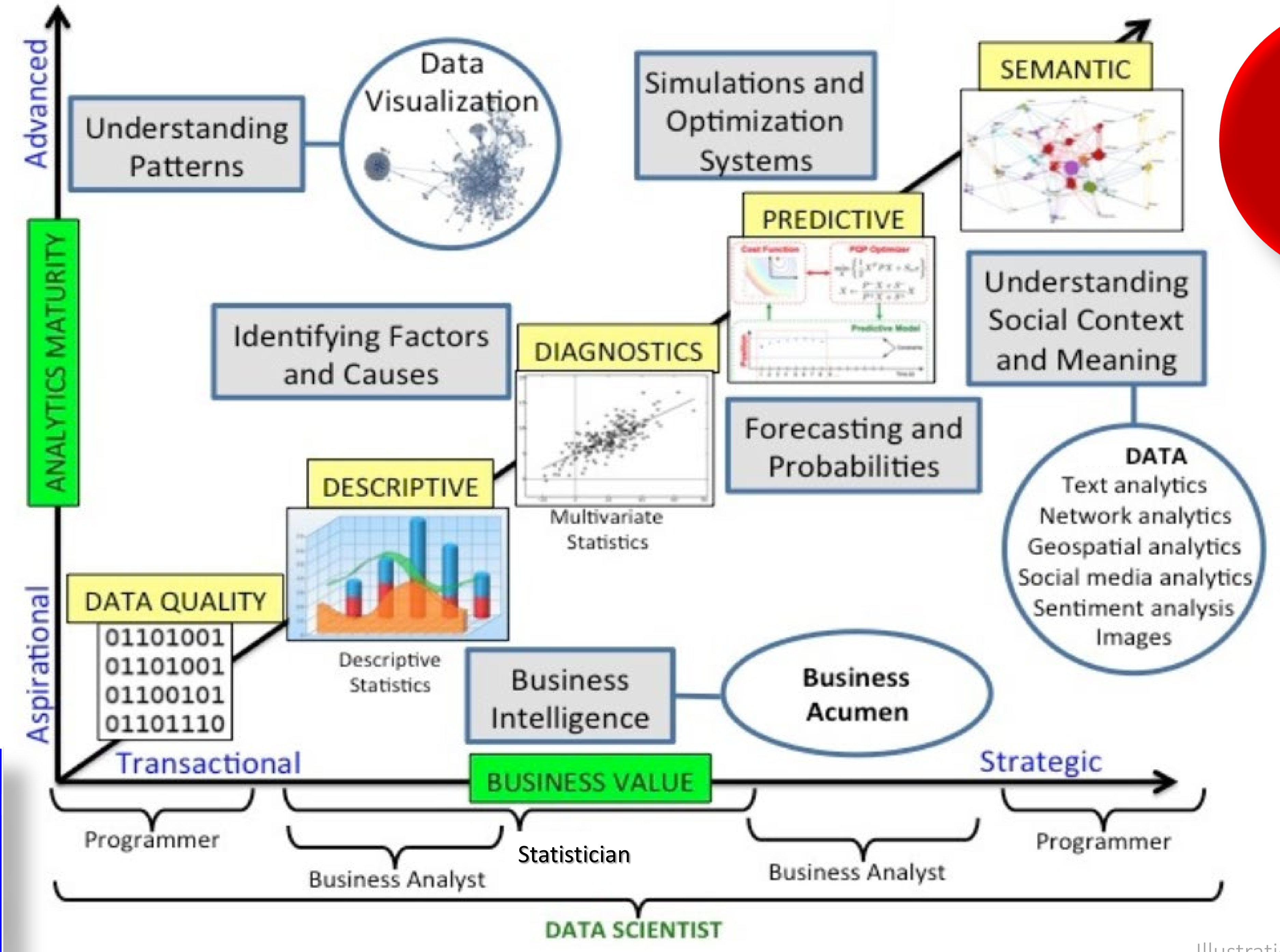
A few lofty goals, perhaps best attempted in stages, from data to data-informed, with knowledge-informed as a future performance index (KPI). Granularity of data from sensors feed decisions with information and knowledge. In the short term, offer logic tools (ART) for users, reduce food waste and contribute to food safety.

Being KIDS – Is “knowledge-informed” a challenging goal?

Knowledge combination/integration beyond (heterogenous) rules and ontologies are not only difficult, but calls for **new thinking**. The semantics of knowledge bases other than rules (for example, descriptions of temporal processes like workflows which could logically decide when the irrigation system must turn on/off the water pumps, or protocols in spatio-temporal logic) must be integrated. We may need some form of logic framework in which knowledge modules, having different native semantics, can be overlaid with meaningful semantics, preferably agnostic of linguistic bias, ideally as a “plug and play” operation, graph-friendly for non-expert end-users to decompose and/or re-compose the choice of logic and logic tools, based on experience from expert humans in the loop. Chaperoning convergence between distributed domain(s) knowledge, operational rules, data, information, and systems science, is a daunting and challenging goal.

Being KIDS – the path to "knowledge-informed"

Illustration by Rubens Zimbres



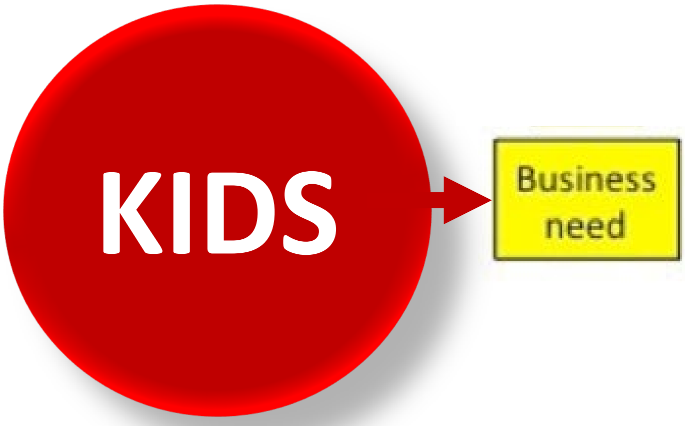
KIDS

SENSEE 1.0, 2.0

Illustration by Rubens Zimbres

KIDS → **USER**

In pursuing the knowledge-informed paradigm using the PEAS platform, users will be confronted with questions that they cannot answer. Unmet needs may fuel research. Hence, KIDS is a catalyst for new ideas, innovation, research in science and engineering.



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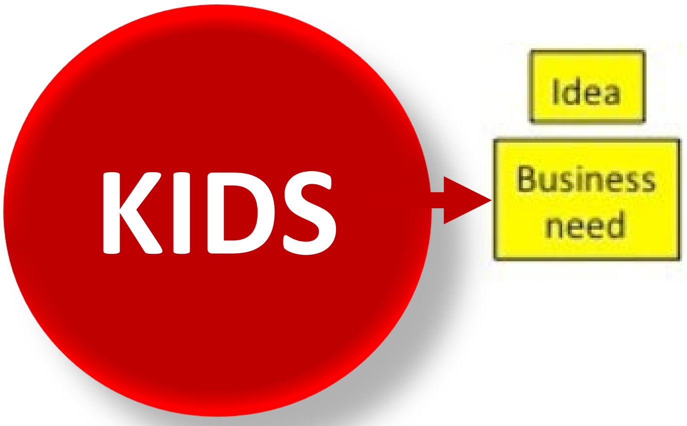

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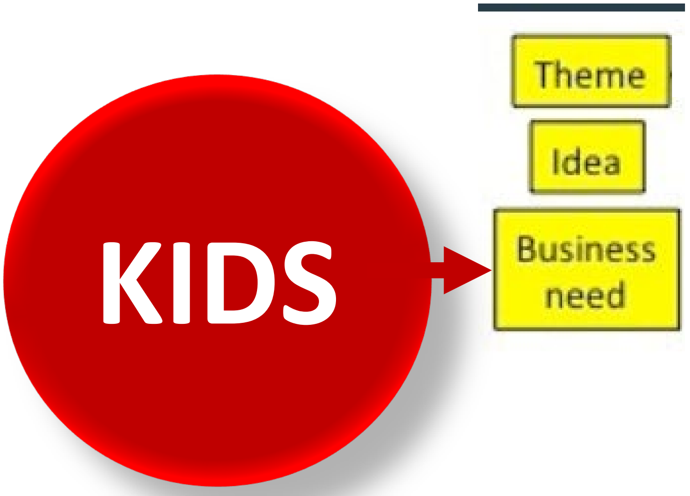

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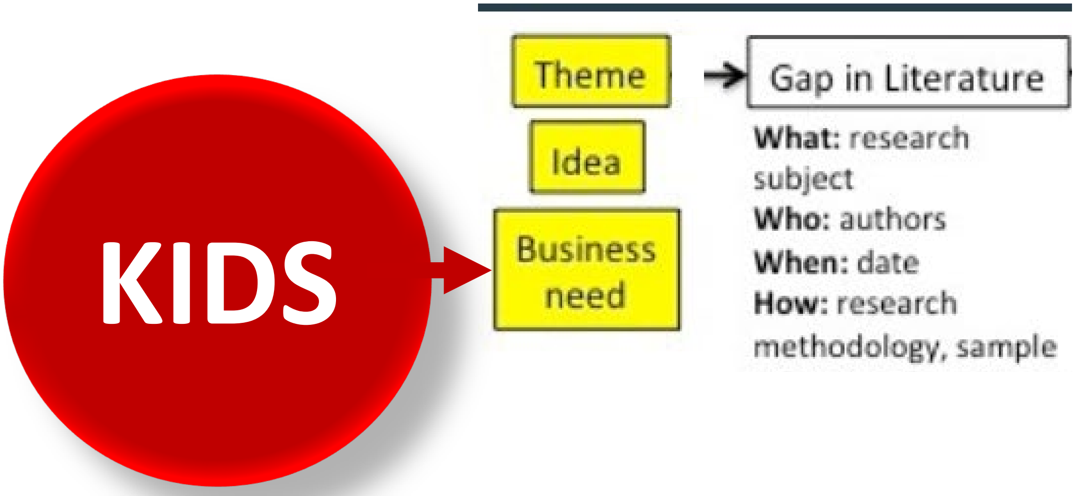

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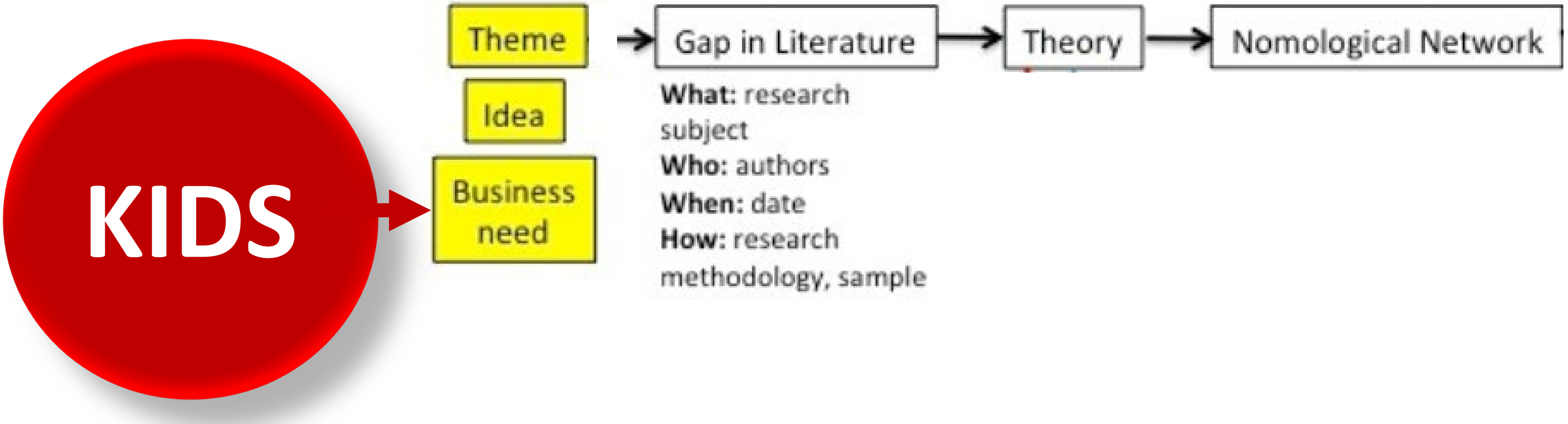

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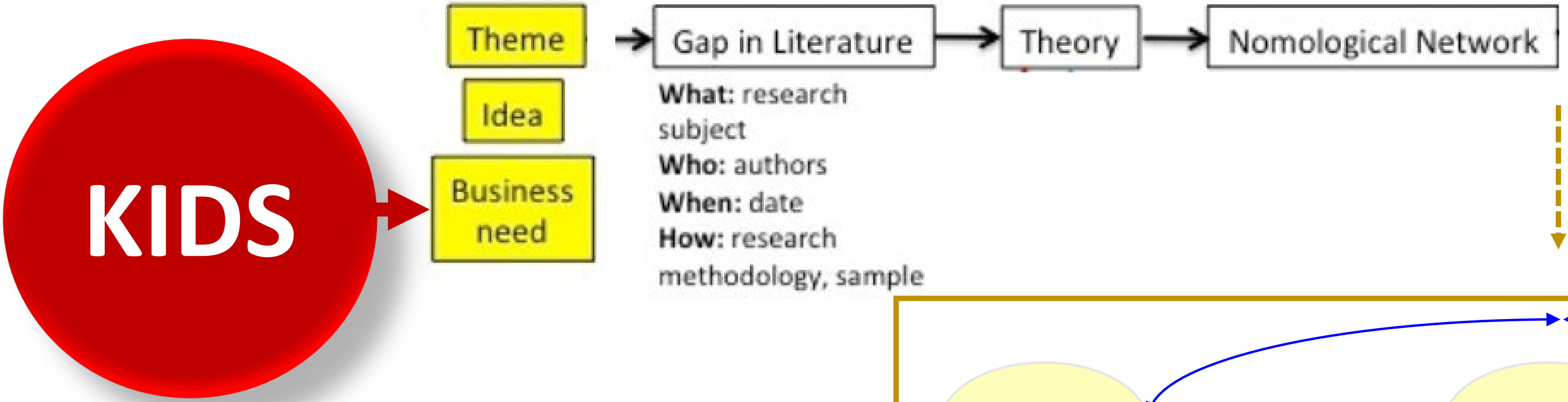

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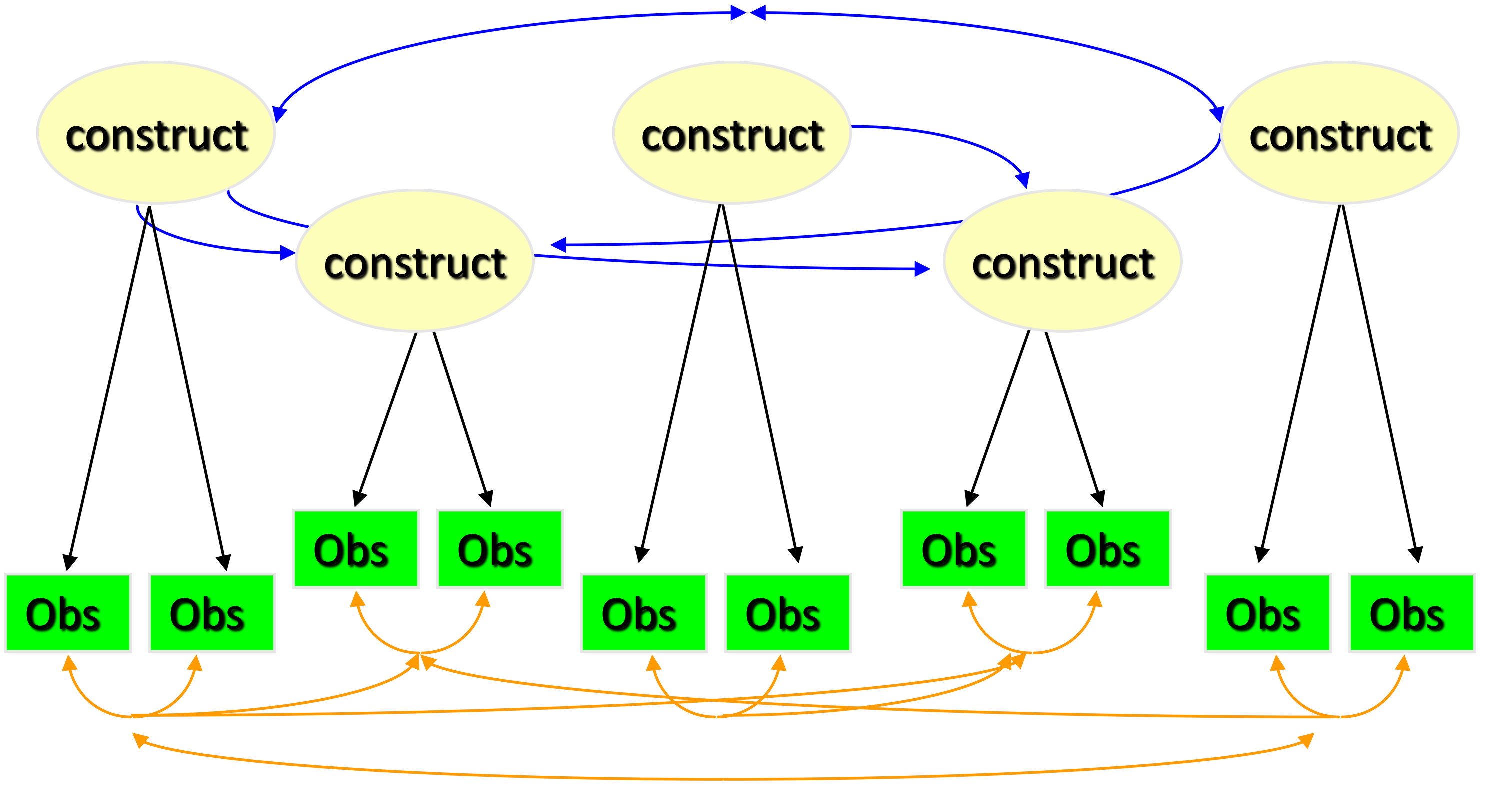
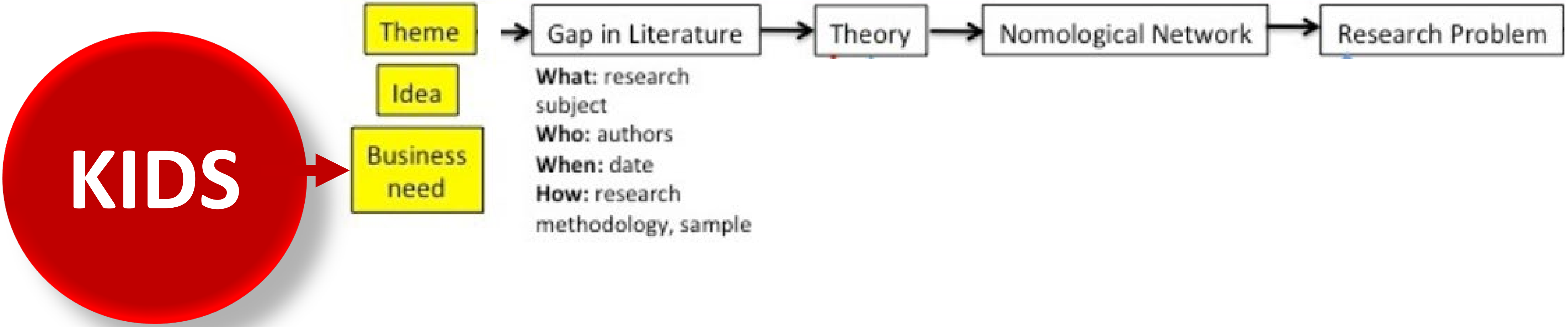


An idea circa 1955, the nomological net represents concepts (constructs) of interest, their observable manifestations and interrelationships. It appears to share common grounds with system dynamics and knowledge graphs.

https://psychclassics.yorku.ca/Cronbach/construct.htm ■ http://dx.doi.org/10.1037/h0040957 ■ https://conservancy.umn.edu/bitstream/handle/11299/184279/1_07_Cronbach.pdf?sequence=1



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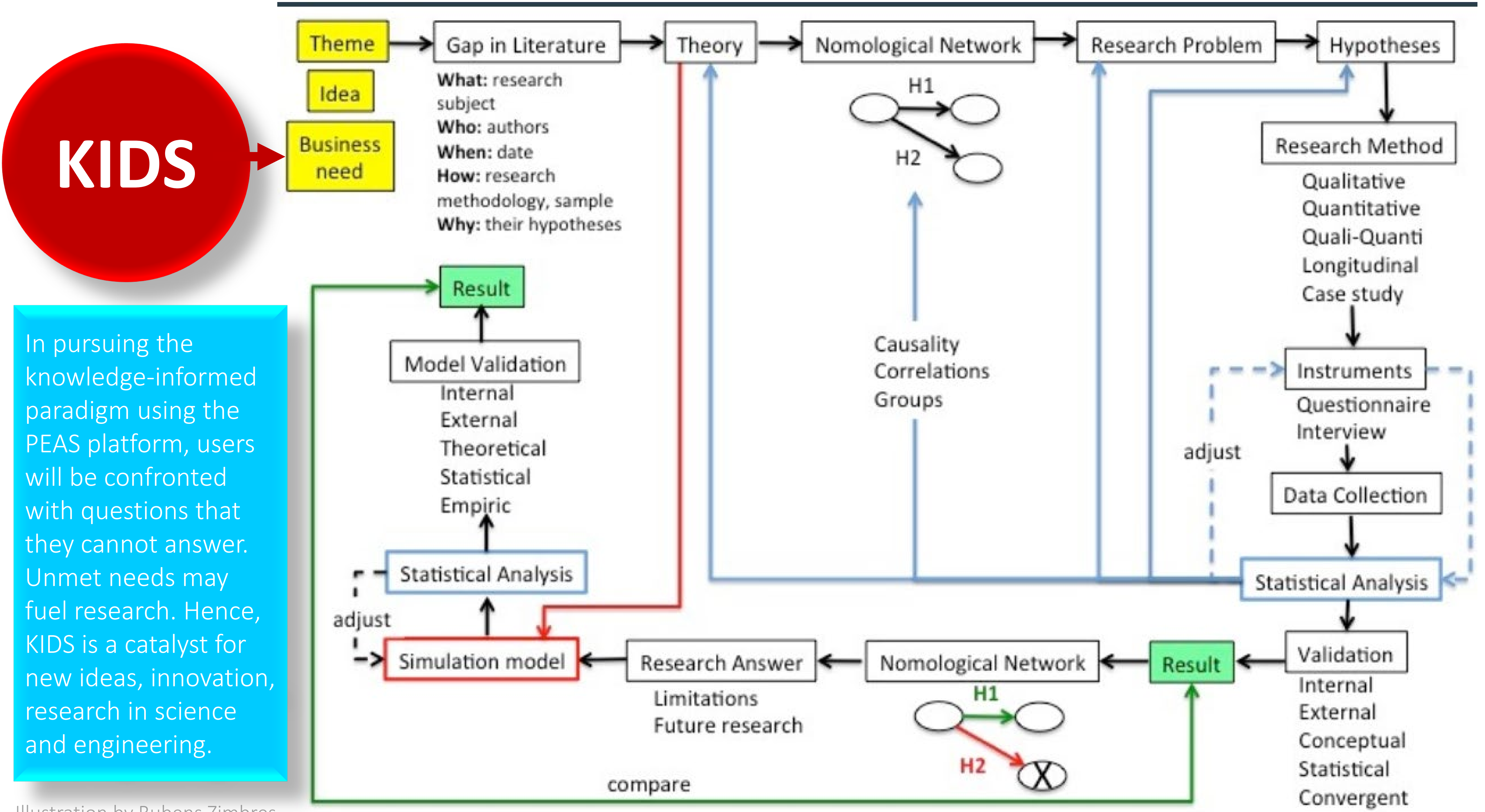

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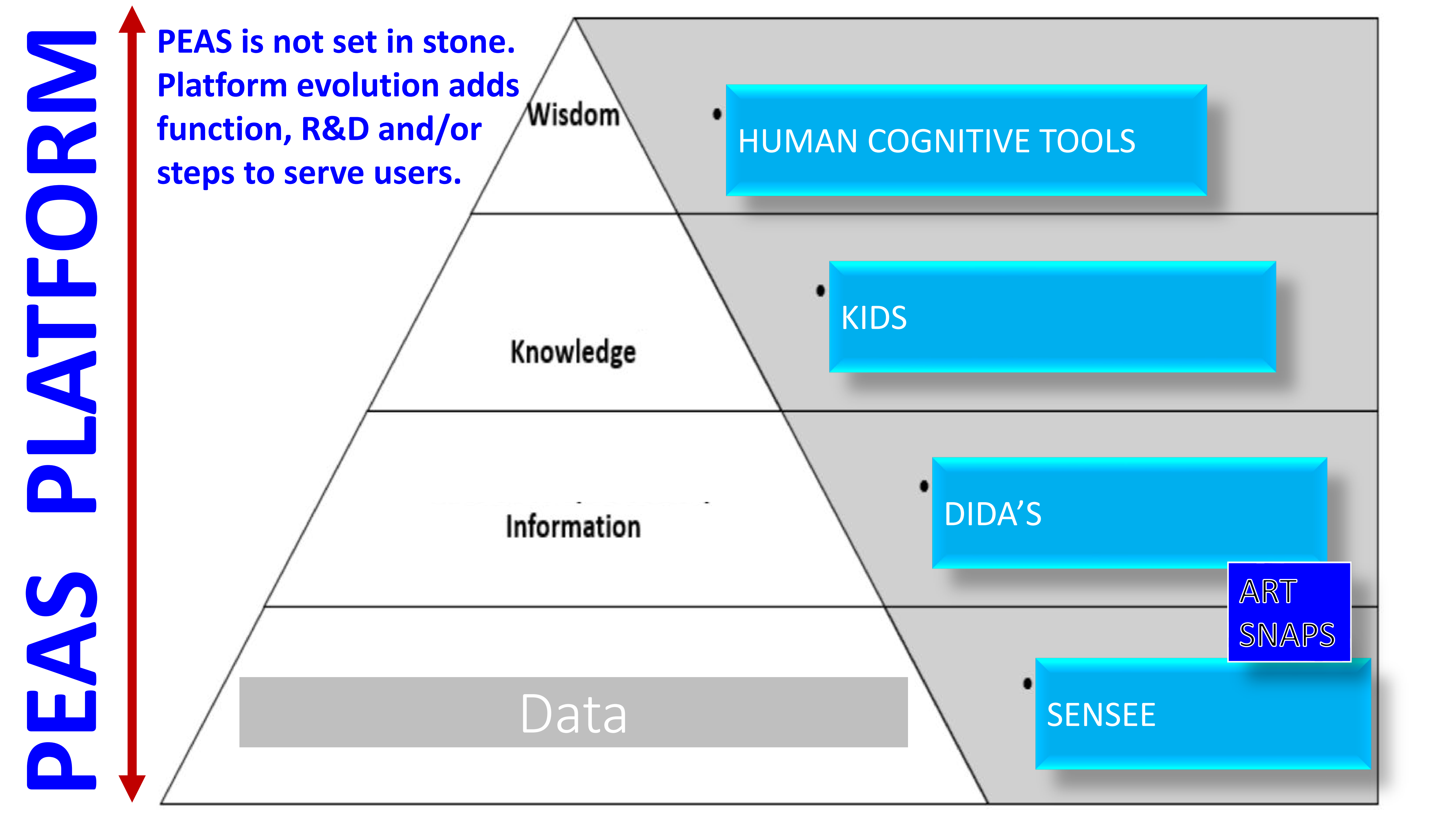
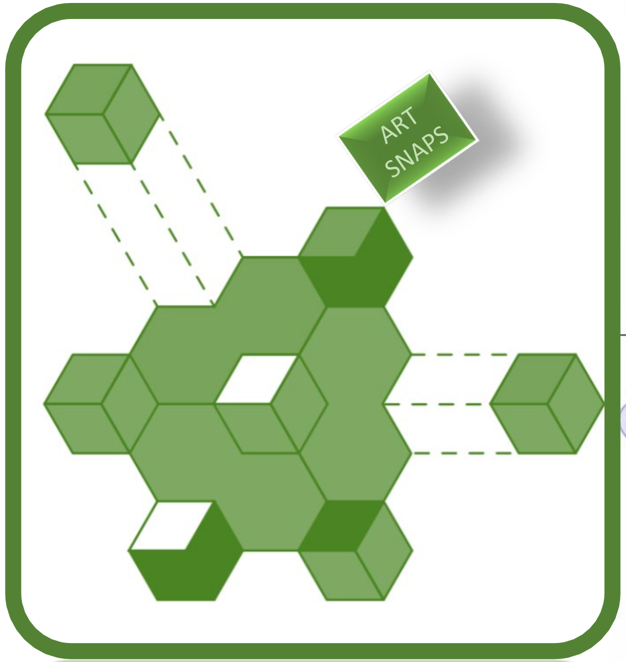
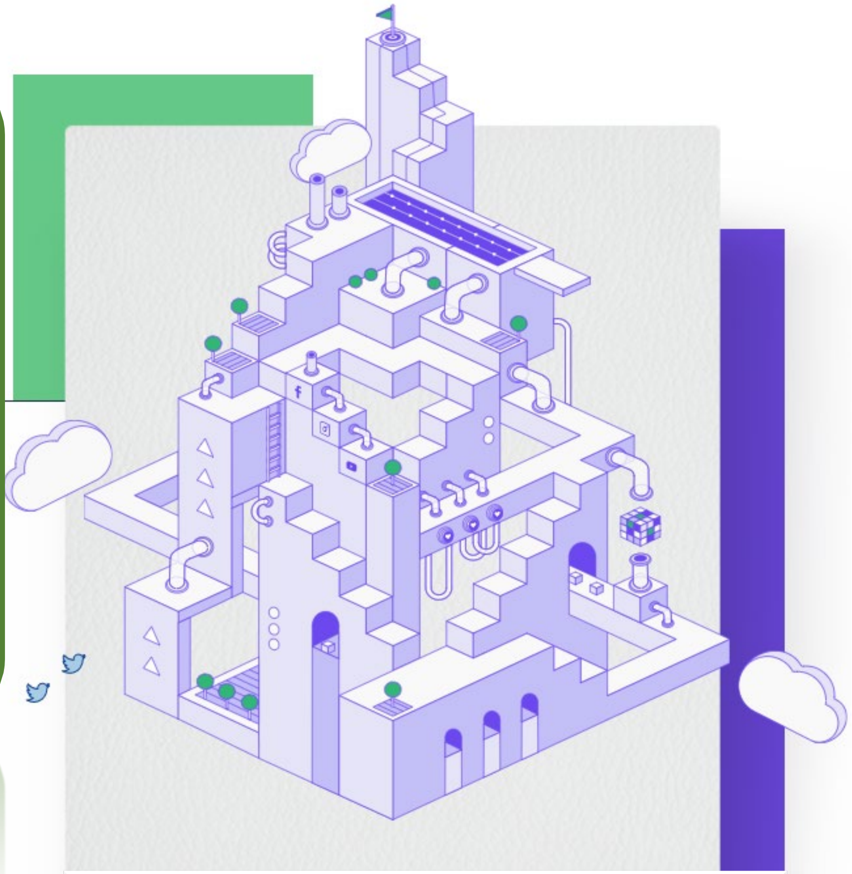
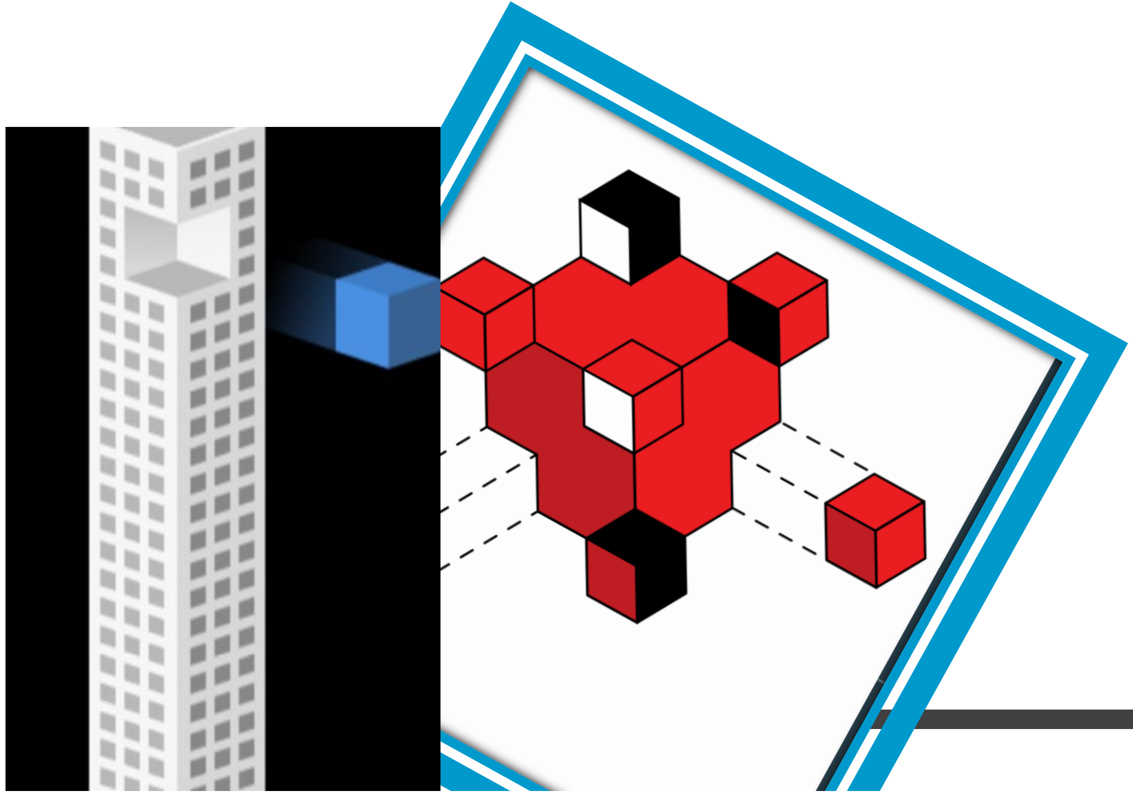

PEAS PLATFORM
PEAS is not set in stone.
Platform evolution adds
function, R&D and/or
steps to serve users.
Wisdom
Knowledge
Information
Data
HUMAN COGNITIVE TOOLS
KIDS
DIDA'S
ART
SNAPS
SENSEE





KNOWLEDGE SYSTEMS SOLUTIONS
ARE OFTEN MULTI-LAYERED IDEAS



WORLD ECONOMIC FORUM

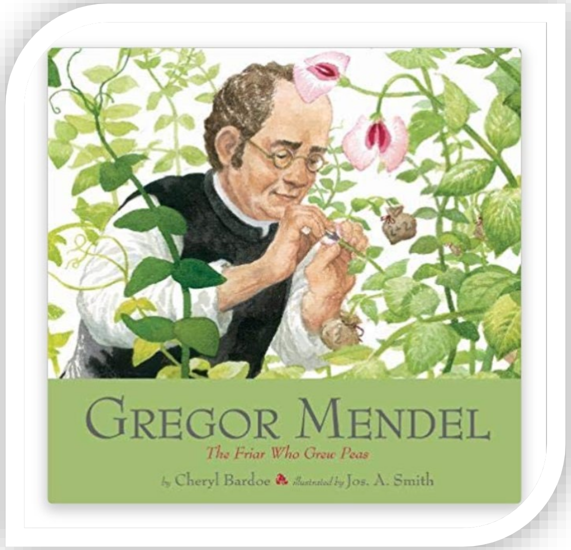
COMMITTED TO IMPROVING THE STATE OF THE WORLD

Insight Report

Top 10 Emerging Technologies 2019

http://www3.weforum.org/docs/WEF_Top_10_Emerging_Technologies_2019_Report.pdf

7. Advanced Food Tracking and Packaging



5. Smarter Fertilizers Can Reduce Environmental Contamination

SUMMARY

1) Data ≠ Information ≠ Knowledge
2) Develop portfolio of ART (pareto solutions - logic tools - for the next billion users)
3) Context determines the perishability phase of data > information > decision > knowledge
4) Relationships must be relative to context before connecting relevant contextual data (R2C2)

Suggested topics for in-depth exploration:

[0] https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-441-information-theory-spring-2010/

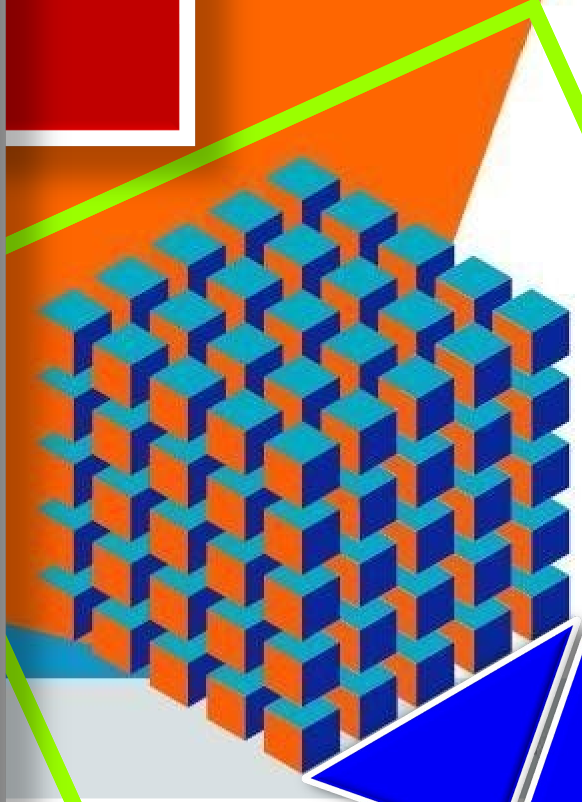
[1] https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-0002-introduction-to-computational-thinking-and-data-science-fall-2016/lecture-videos/index.htm

[2] https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-034-artificial-intelligence-spring-2005/

[3] https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-034-artificial-intelligence-fall-2010/lecture-videos/

[4] https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-825-techniques-in-artificial-intelligence-sma-5504-fall-2002/

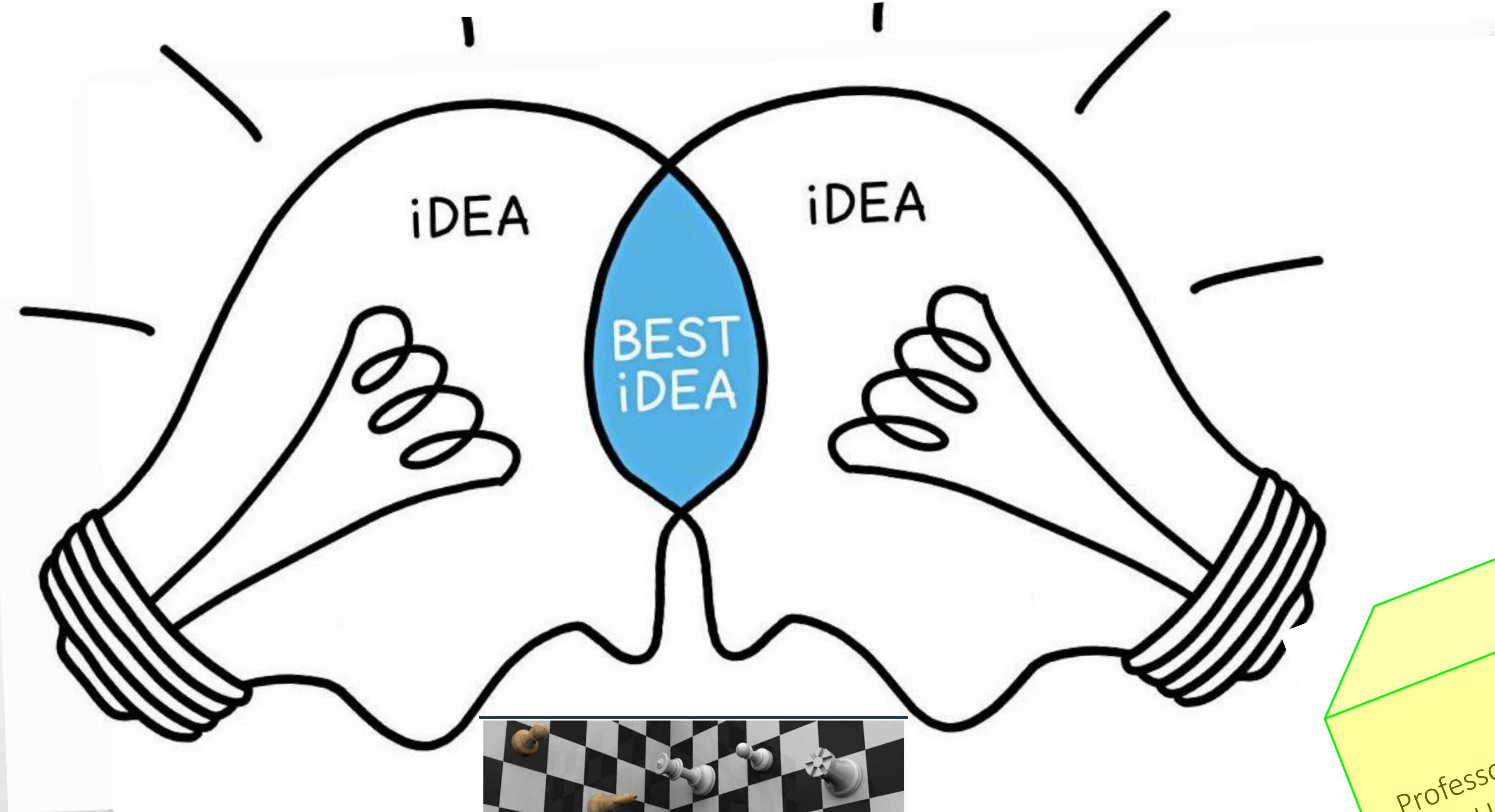
[5] https://ocw.mit.edu/courses/electrical-engineering-and-computer-science/6-868j-the-society-of-mind-fall-2011/video-lectures/

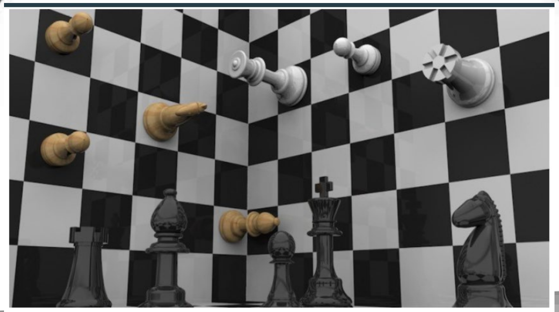


Professor Eric S McLamore
ABE, University of Florida
USDA Center of Excellence

Dr Shoumen Palit Austin Datta
http://bit.ly/SIGNALS-SIGNALS

"If your actions inspire others to dream more, learn more, do more and become more, then you are an enabler." JQA





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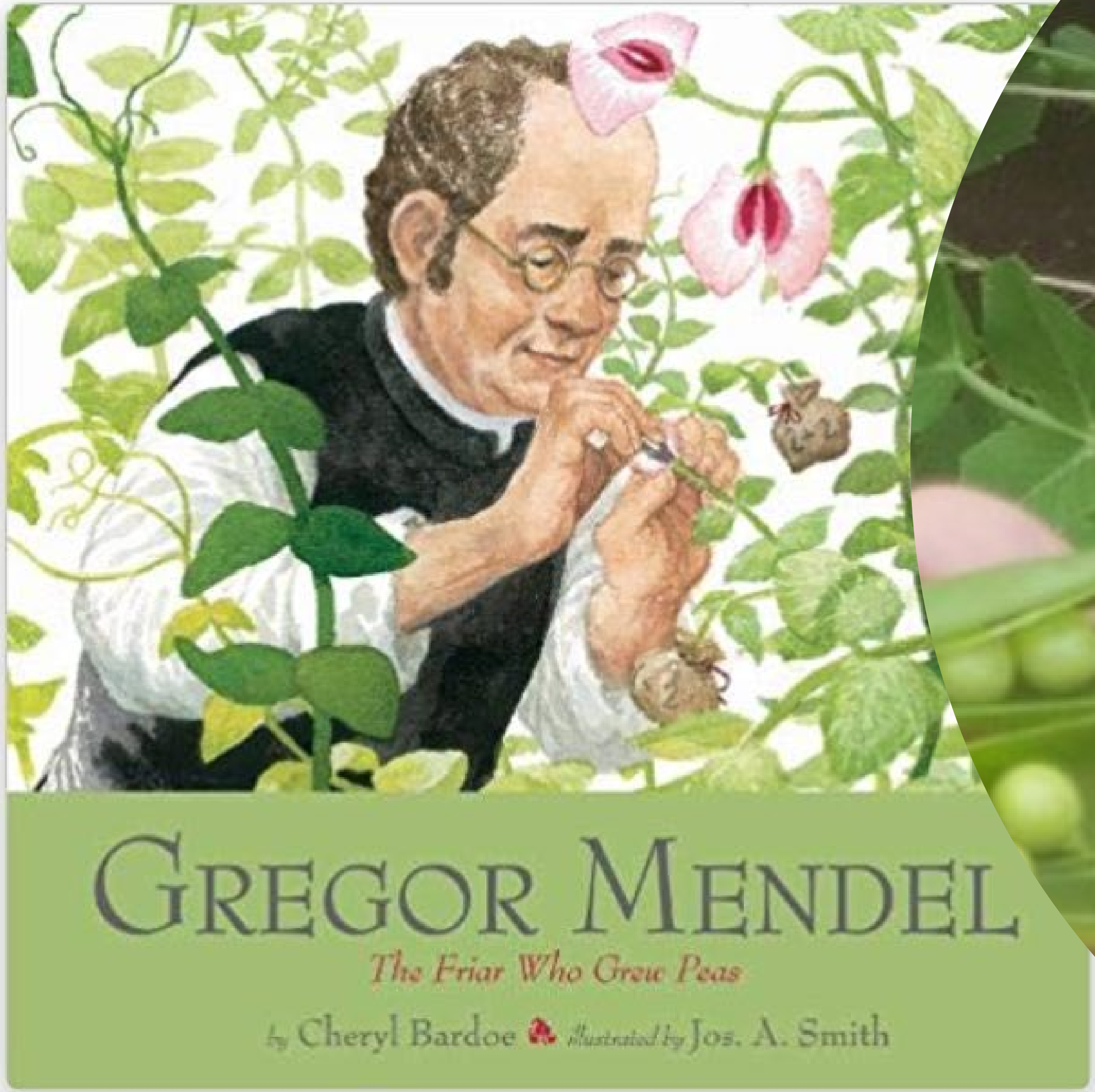
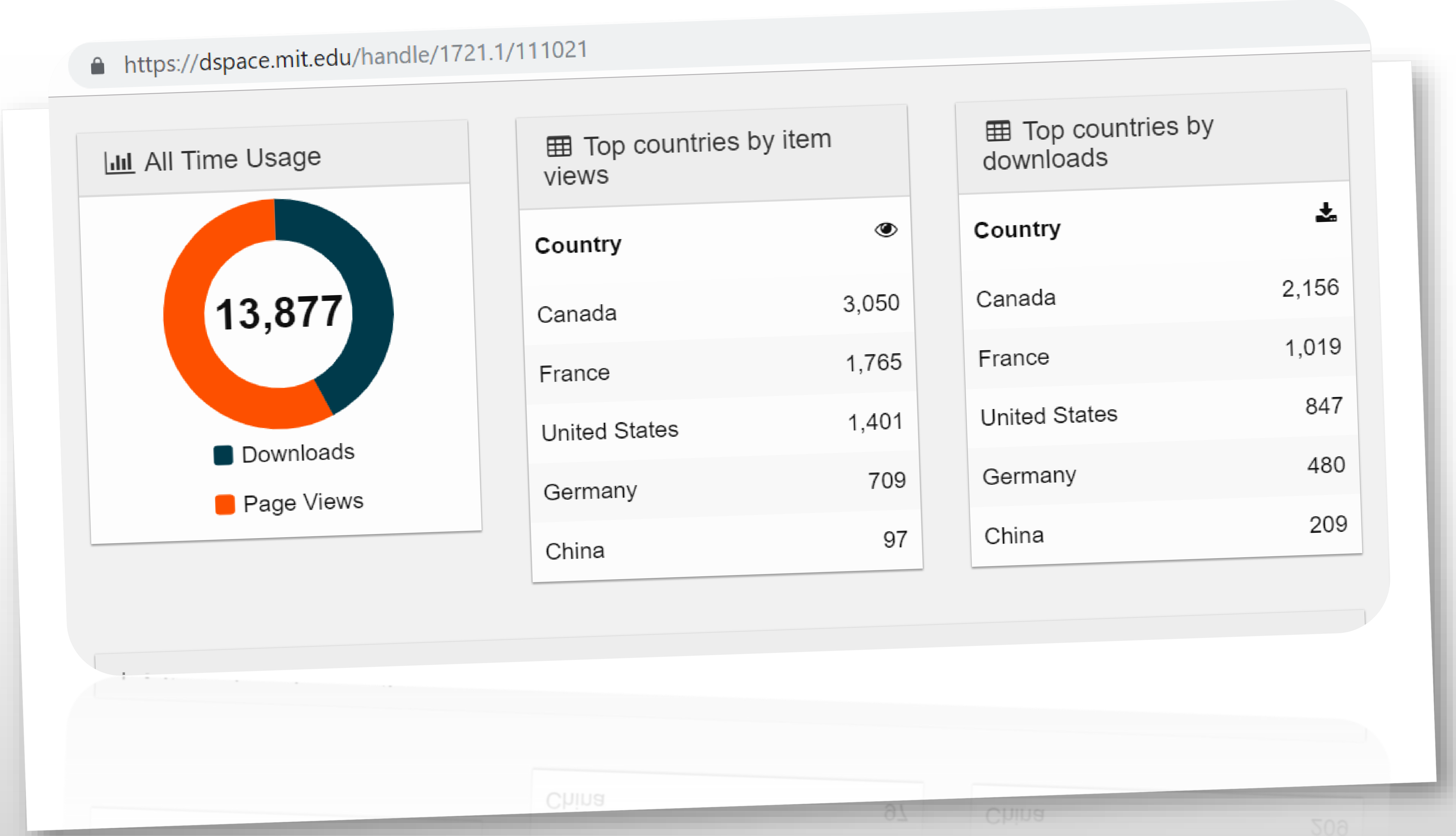

GREGOR MENDEL
The Friar Who Grew Peas
by Cheryl Bardoe illustrated by Jos. A. Smith

PEAS



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