On-line time series classification:

Robust data representation for real-time data stream analysis

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On-line time series classification

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Dr. V. Alarcon-Aquino, UDLAP, Mexico.

1. Content

1. Internet of Things and Big Data

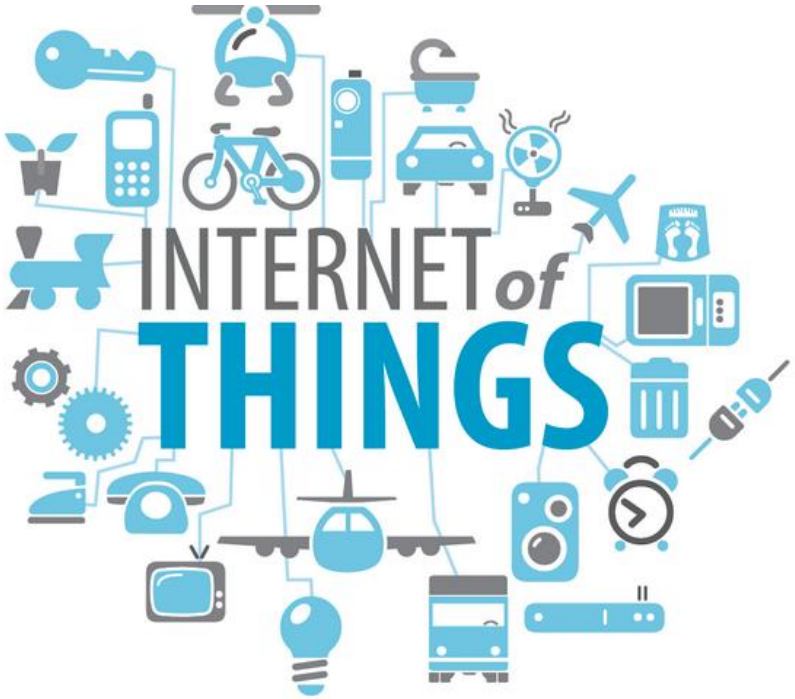
2. On-line Time Series Classification Framework
   - Pattern Recognition Approaches
   - Robust Data Representation
   - Novel Anomaly Detection Approach

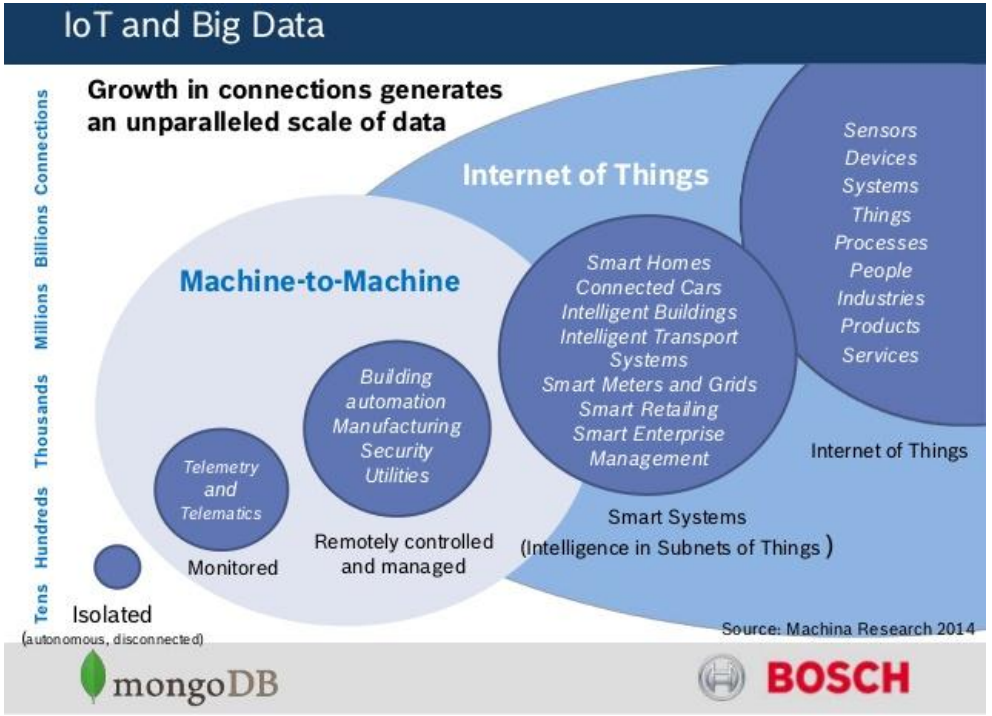
3. Real Time Monitoring Applications

4. Imperial College London

5. Final Remarks

1. The Internet of Things (IoT) and Big Data



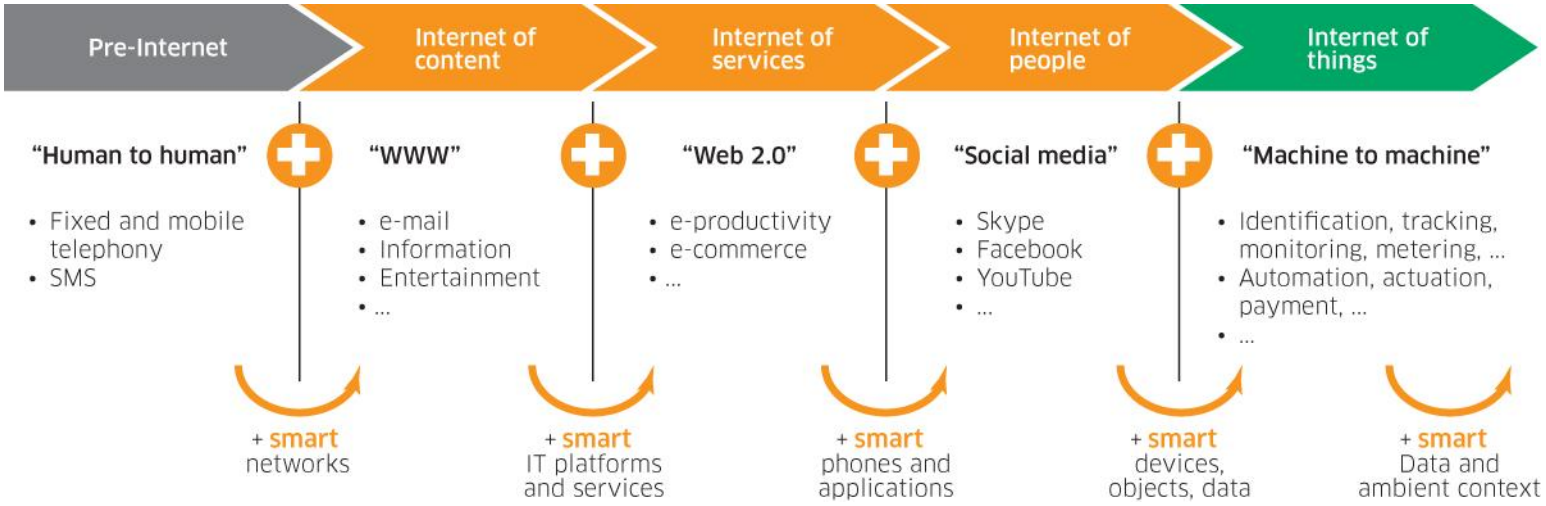


http://www.smartdatacollective.com

https://www.mongodb.com/presentations/

https://machinaresearch.com/

IoT and Big Data (2/10)



- Any application
- Any network
- Any service

https://techzine.alcatel-lucent.com/

Source: Alcatel-Lucent

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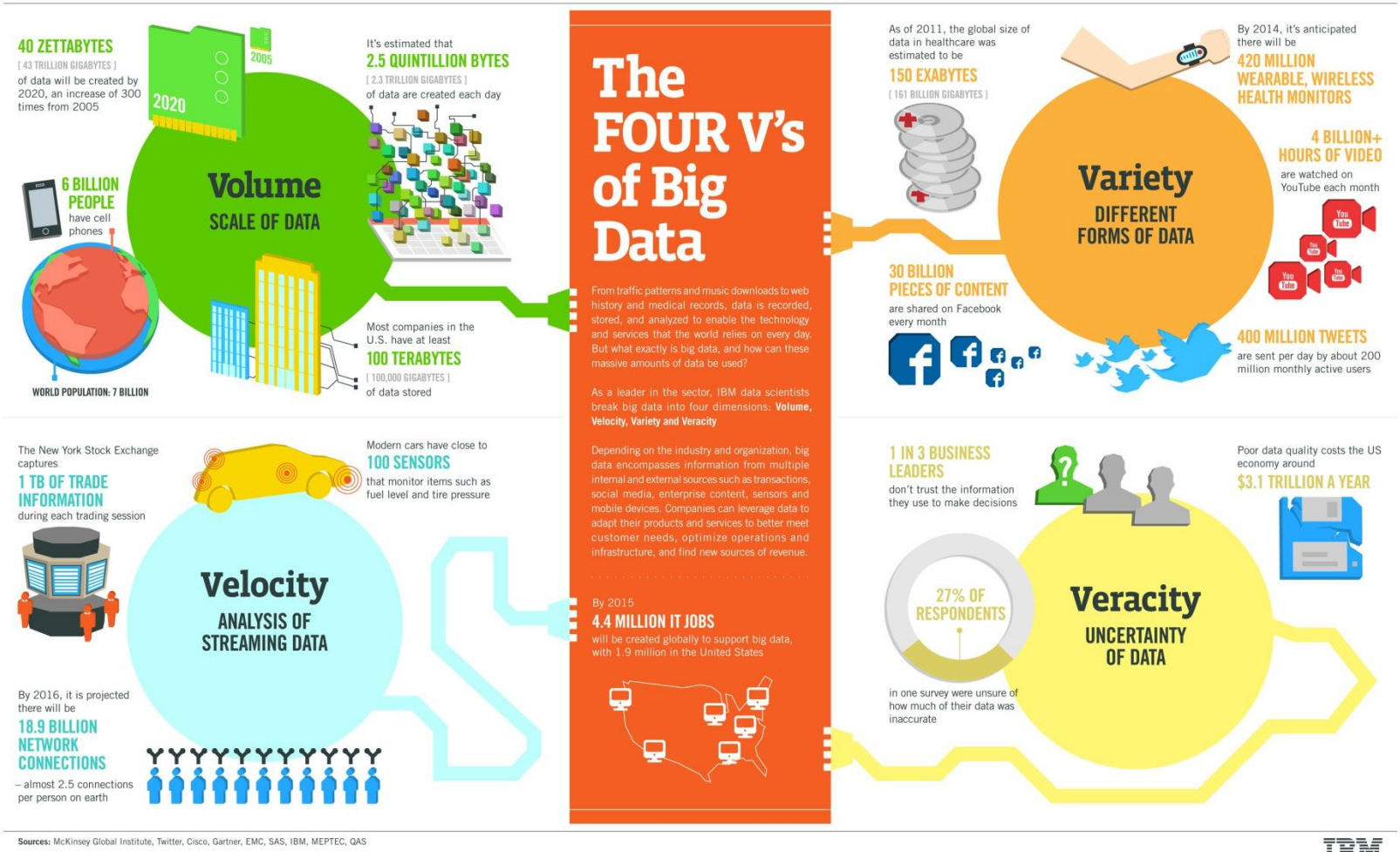
Big Data: the Four V's (3/10)



Source: http://www.ibmbigdatahub.com/infographic/four-vs-big-data

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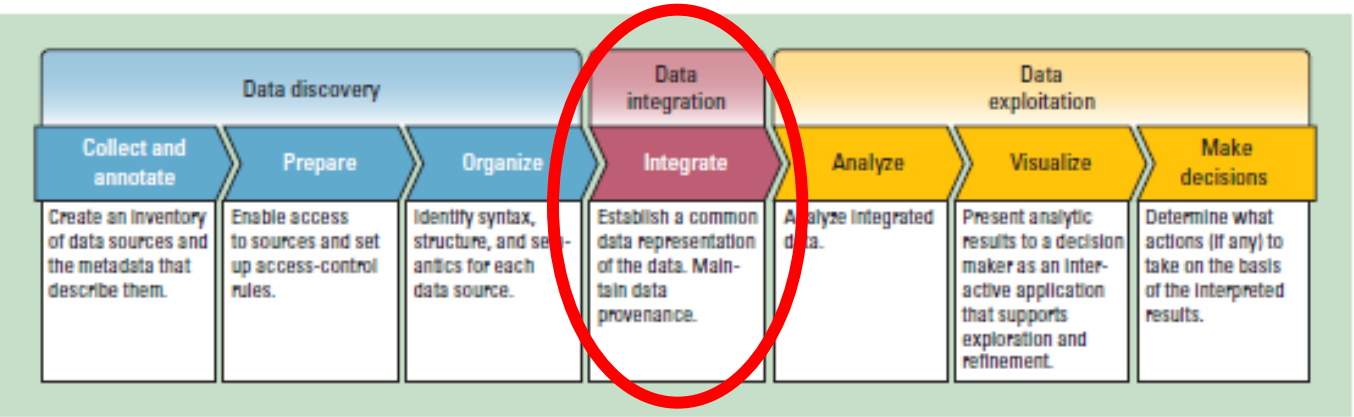
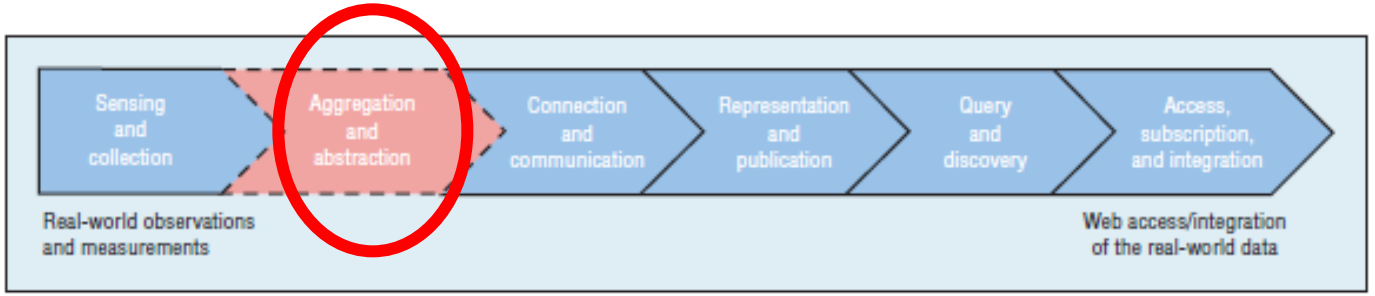
Data Representation (4/10)

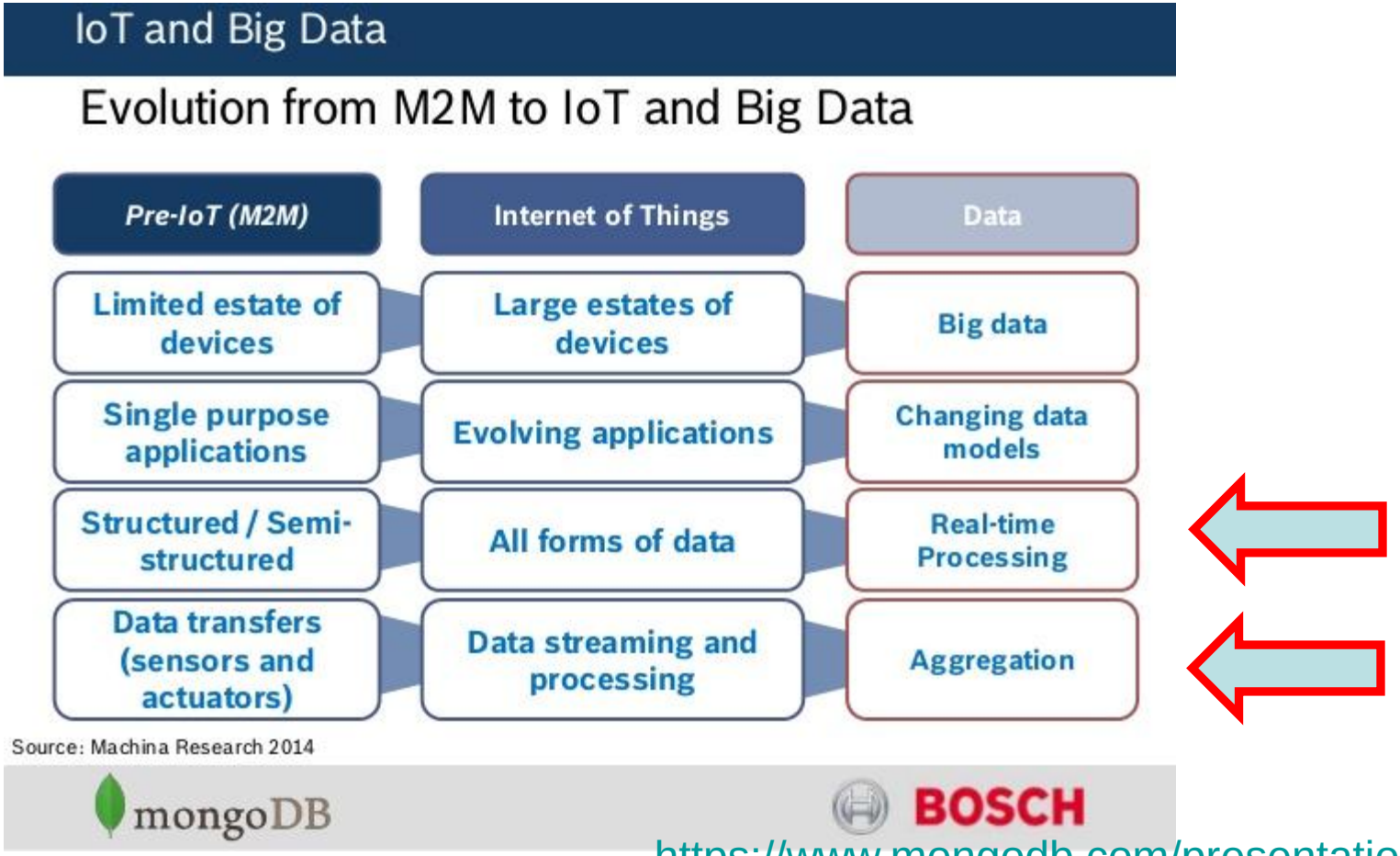


Re.: H. G. Miller and P. Mork, “From Data to Decisions: A Value Chain for Big Data,” It Pro., v. 15, no. 1, pp. 57–59, 2013.



Re.: P. Barnaghi, A. Sheth, and C. Henson, "From Data to Actionable Knowledge: Big Data Challenges in the Web of Things [Guest Editors' Introduction]," Intelligent Systems, IEEE, v.28, no.6, pp.6,11, Nov.-Dec. 2013

From M2M to IoT and Big Data (5/10)



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Big Data Management (6/10)

- From important competency to a critical differentiation: From Volume & Variety to Velocity.
- Big Data Technology: Operational vs. Analytical.
  - Operational features: Real-time & interactive intelligence – low latency, on-line capture.
  - Analytical features: Complex analysis – high throughput. http://www.mongodb.com
- Combine Operational and Analytical technologies.

➢ Generic/global fast solutions rather that application specific solutions.

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Data Streaming: Volume, Variety and Velocity(*) (7/10)

- Support a wide variety of data(*)
- Focus on agility and flexibility rather than conformity(*)

➢ Domain Independent framework: builds the foundation to unsupervised classification algorithms.

Source: **(*) http:** //www-935.ibm.com/services/us/gbs/thoughtleadership/2014analytics/

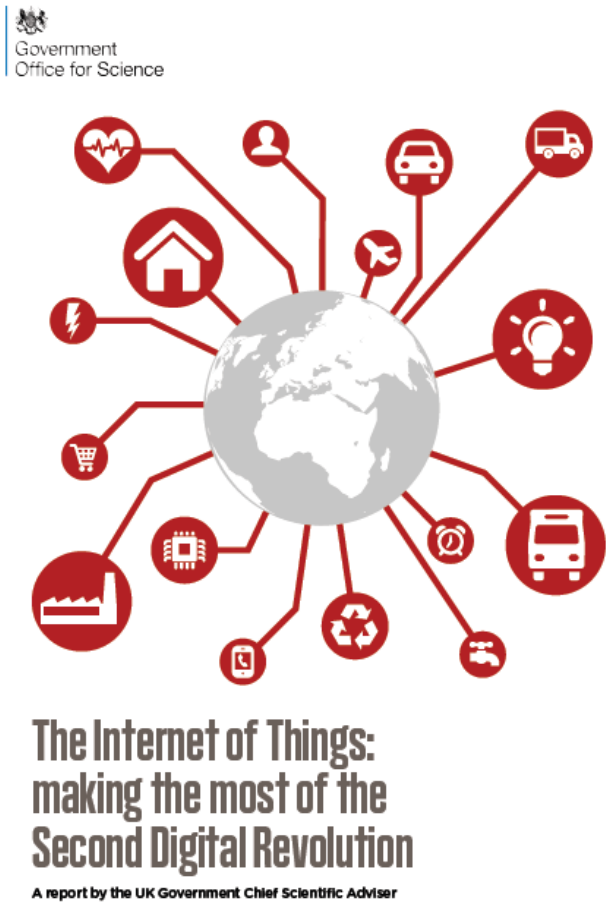
Data Streaming: Volume, Variety and Velocity(*) (8/10)

- Foster rapid data consumption(*)
- Provide prompt access to relevant information(*)
- Make pervasive use of predictive analytics a priority (*).

➢ Real-time/on-line time series classification problems.

Source: **(*) http:** //www-935.ibm.com/services/us/gbs/thoughtleadership/2014analytics/

Applying the Internet of Things (9/11)



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- Transport
- Energy
- Healthcare
- Agriculture
- Buildings

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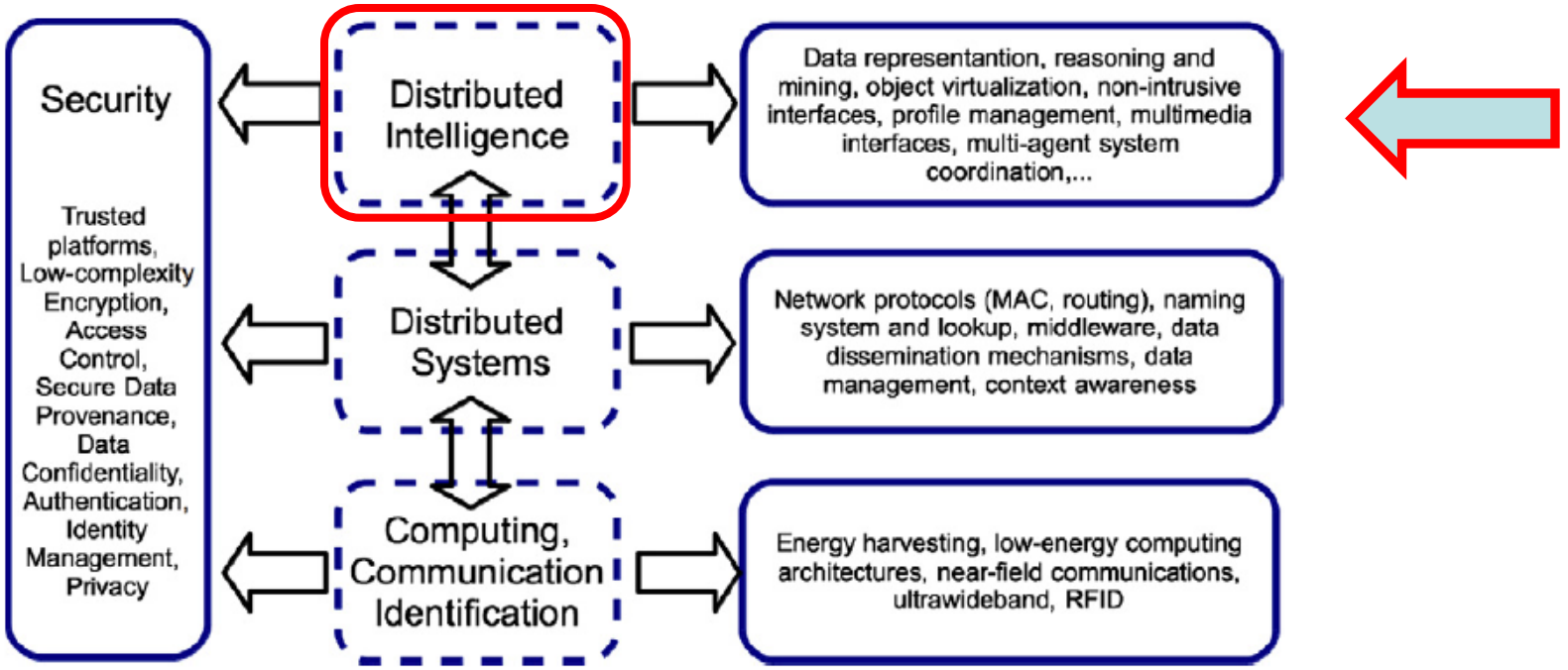
IoT Relevant Research areas (10/10)



(D. Miorandi, S. Sicari, F. De Pellegrini, and I. Chlamtac, “Internet of things: Vision, applications and research challenges,” Ad Hoc Netw., vol. 10, no. 7, pp. 1497–1516, 2012.)

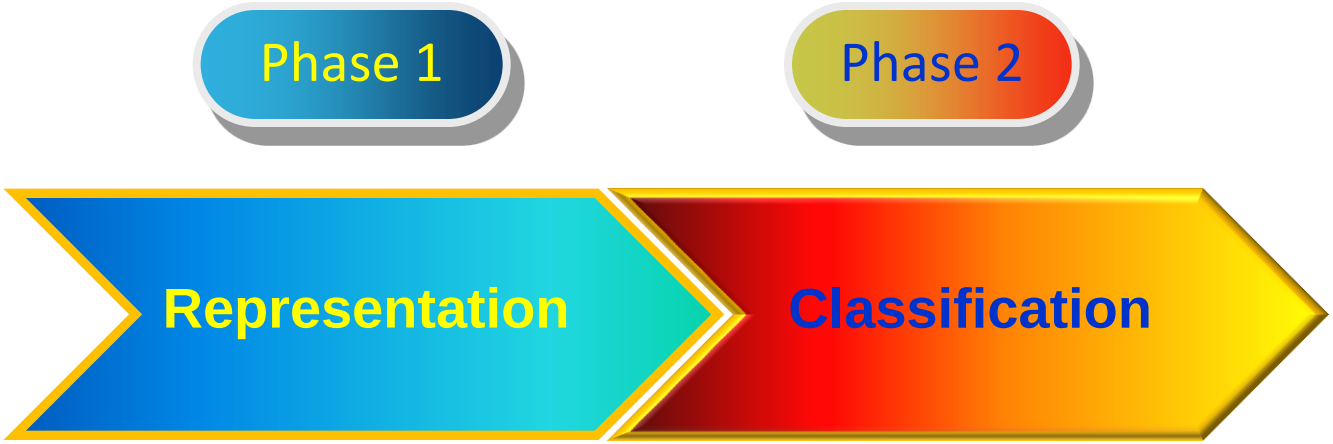
2. On-line Time Series Classification Framework

One important on-line Big Data application is: Real-time monitoring & anomaly detection.

- *Health condition monitoring* as well as *anomaly detection* are classification problems.
- They are time series classification problems because they involve the *time element* (e.g. short-term and long-term condition changes).
- *Pattern recognition* frameworks belongs to the field of classification methods.

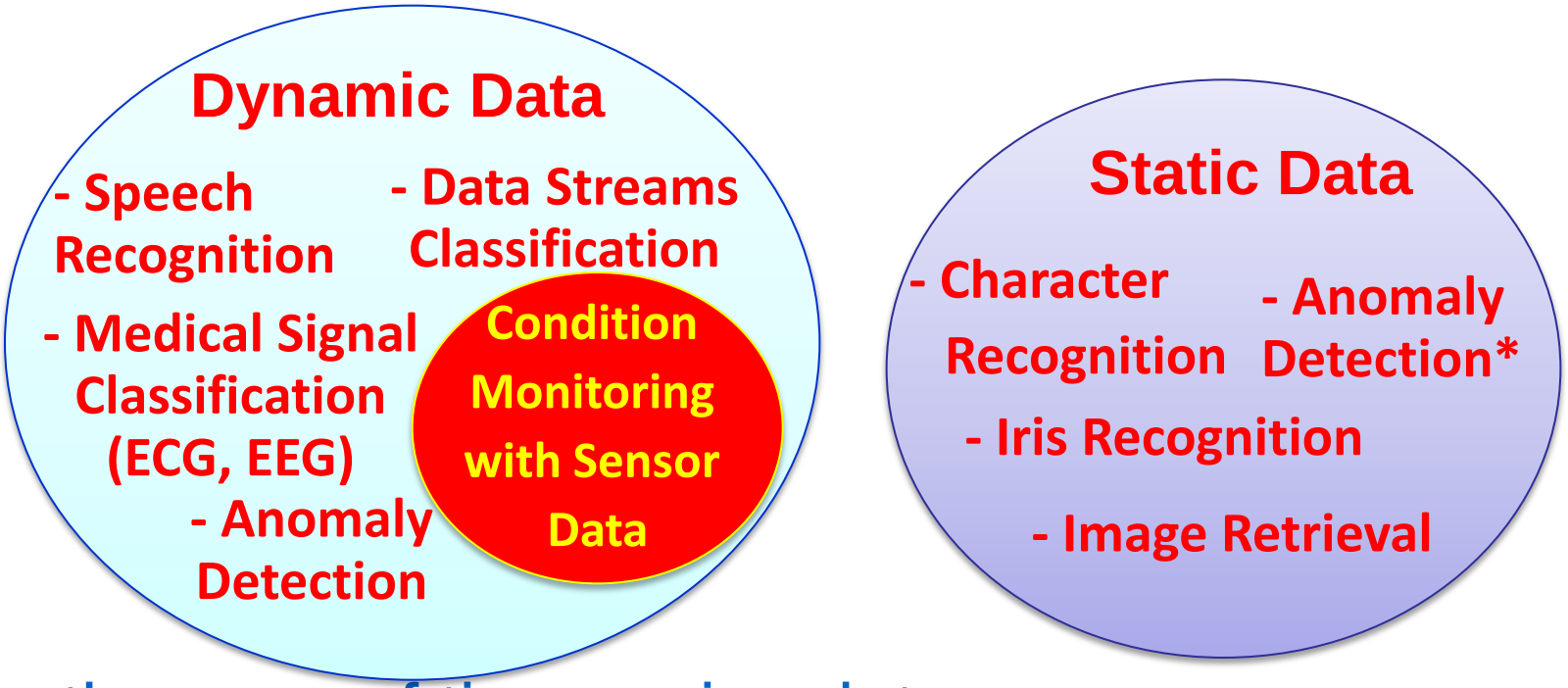
2.1. The Pattern Recognition (PR) Approaches (1/5)

- Composed of two phases:



- Extracting appropriate properties or features.
- Mapping the features to a particular class.

Different Data type: Different Applications (2/5)



For the case of time series data:

- A major concern is finding *appropriate pattern representations*.
- Most of the approaches treat time series as static data (hence they do not offer suitable representations).

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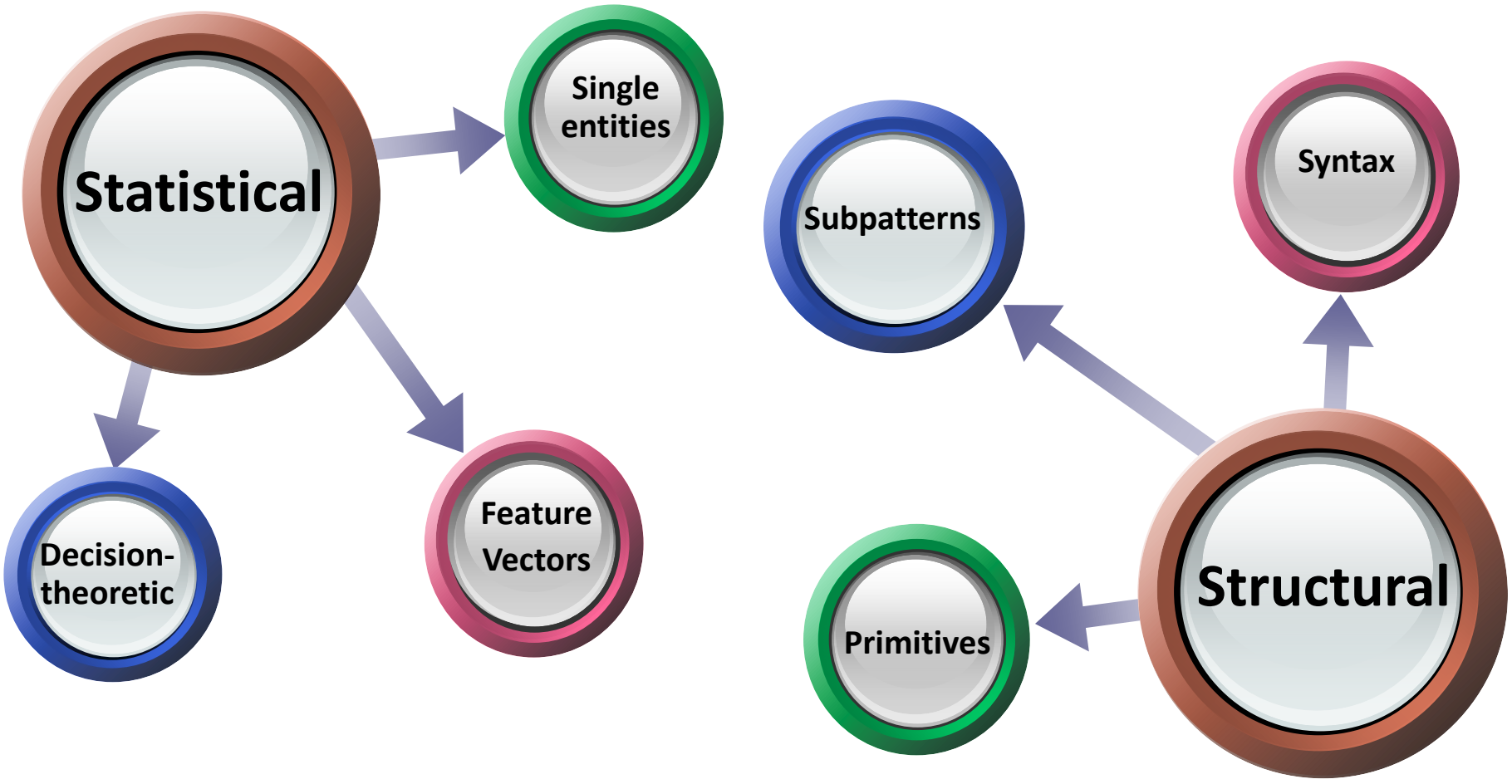
Pattern Recognition Paradigms (3/5)



Pattern Recognition Paradigms (4/5)

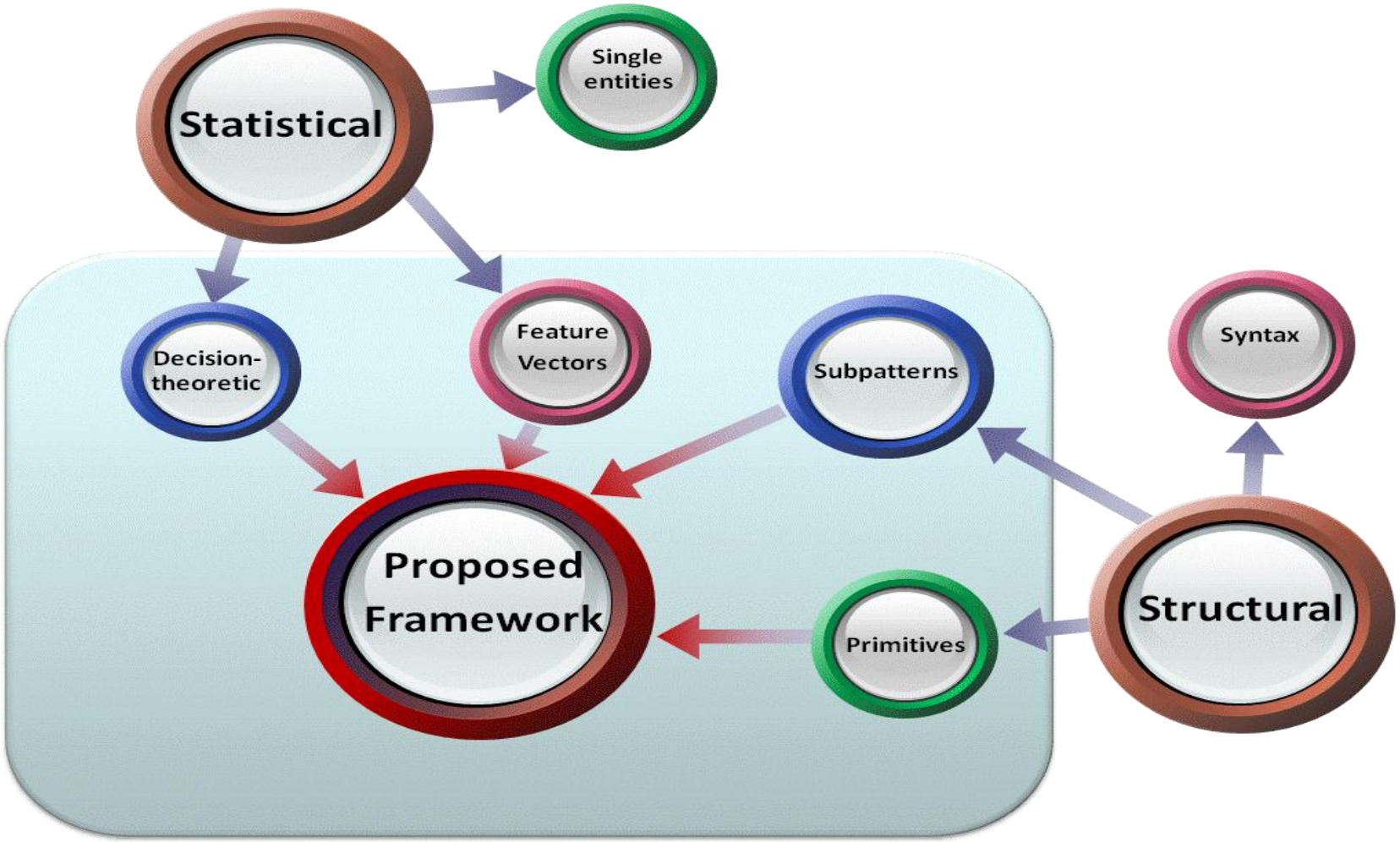
Statistical:

- Patterns treated as single entities and described by numerical feature vectors.
- The classification involves the partition of the feature space into regions.

Structural:

- Patterns treated as combination of multiple entities and described by its topological relations.
- The classification involves matching the structural representation according to a syntax.

Proposed Approach: New PR Representation Framework (5/5)



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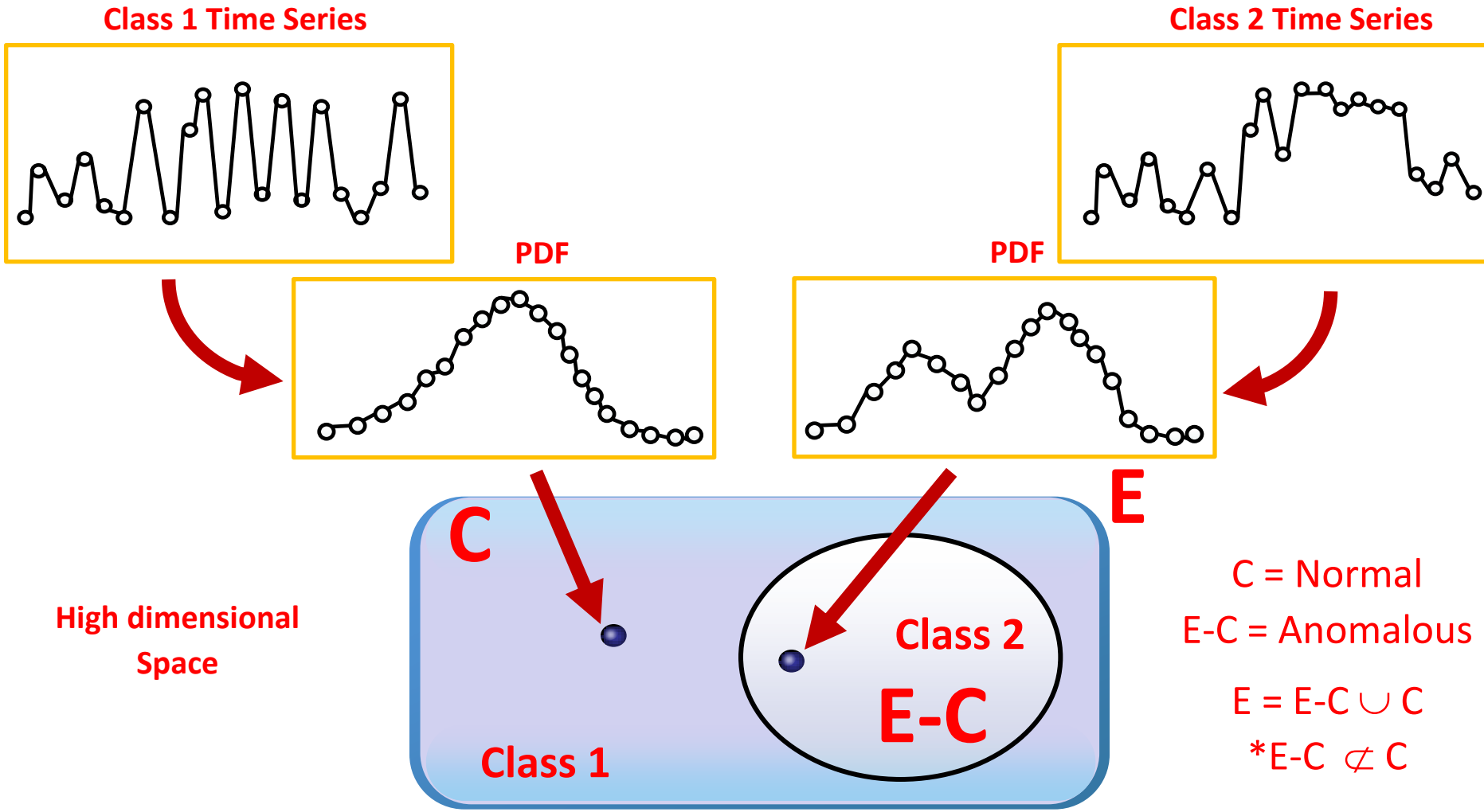
2.2. Robust Data Representation (1/2)



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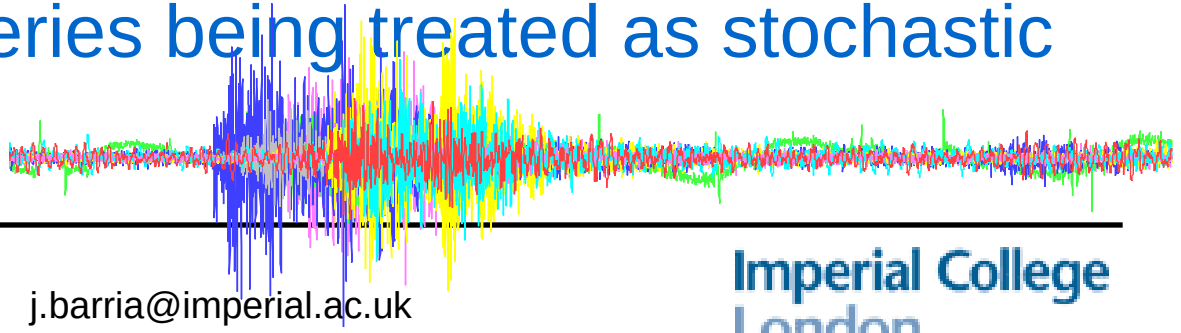
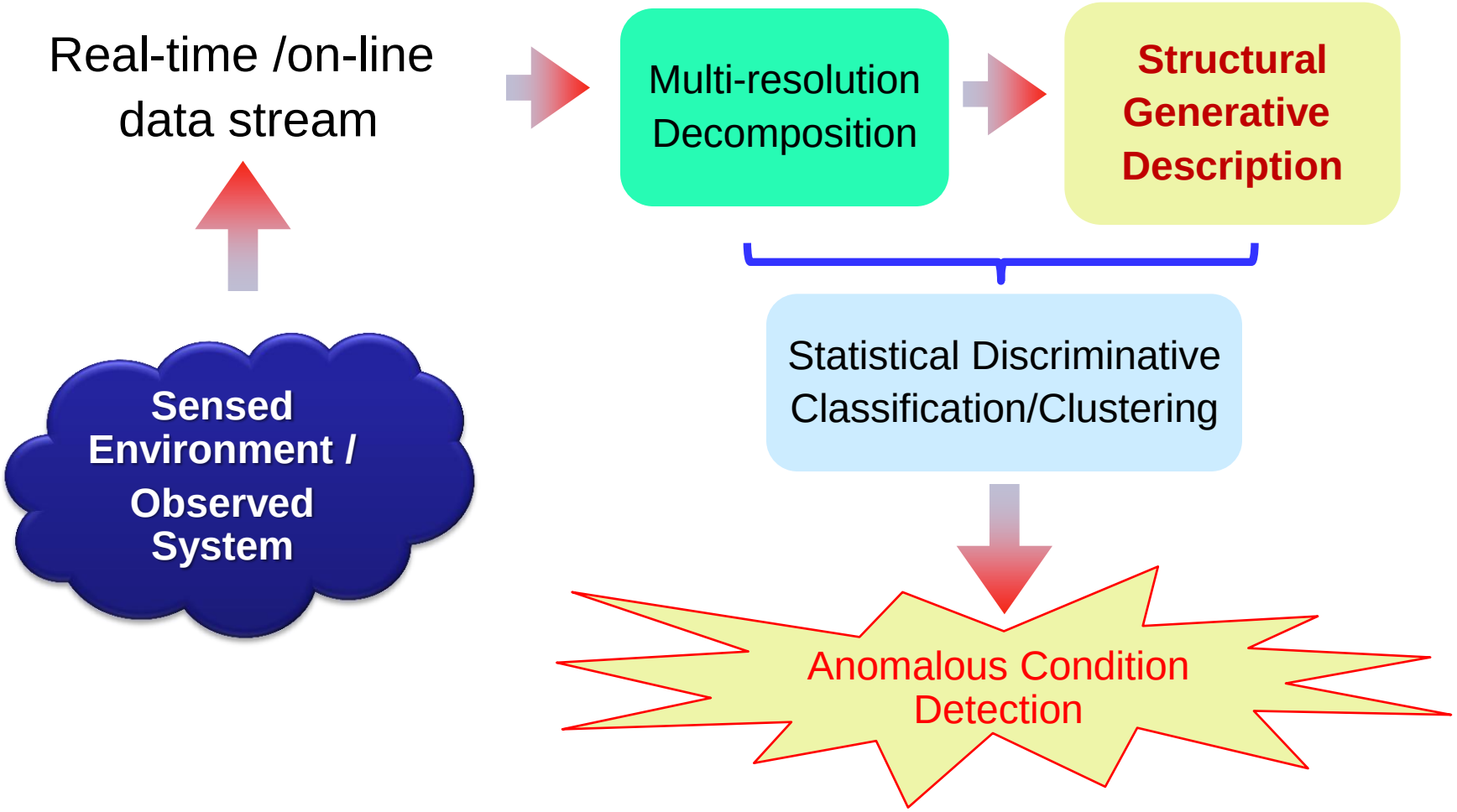
Structural Generative Description (SGD): The Proposed Approach (2/2)

- **Domain independent** : which makes the framework suitable for a wide variety of applications.
- It is an on-line / real-time approach.
- Constructs robust time series represenations.
- Based on time series being treated as stochastic processes.



2.3. Novel Anomaly Detection Approach (1/2)



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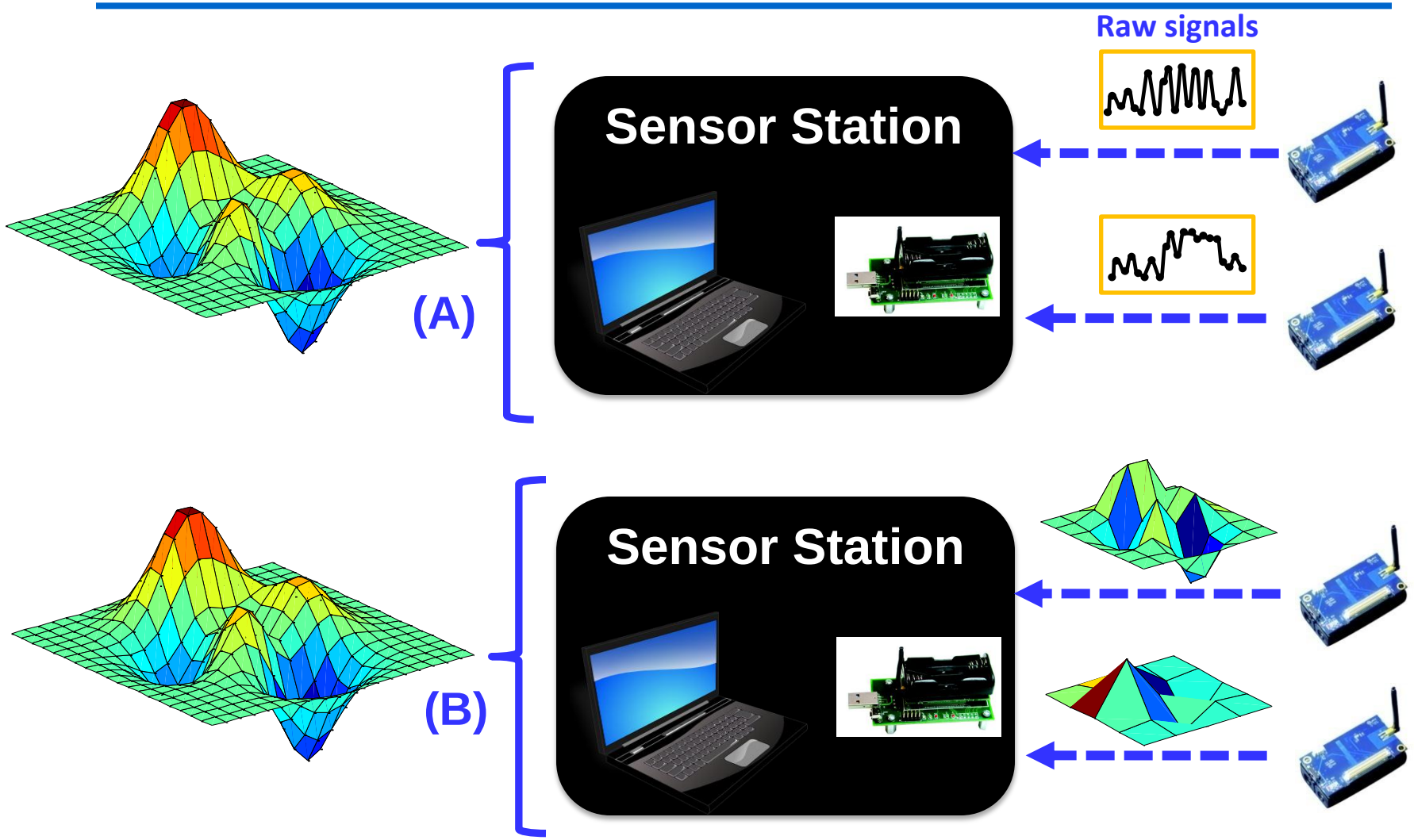
Implementation: Centralised (A) vs Distributed (B) (2/2)



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3. Real-time Monitoring: Applications

On-line time series classification framework and its applications:

3.1. Biometric Recognition and Forensics,

3.2.i. Smart Infrastructures Monitoring,
3.2.ii. Machine/motor Health Conditioning Monitoring,

3.3. Distributed Charging of EVs,

3.4.i. Transportation Networks Monitoring,
3.4.ii. Environmental (pollution) Monitoring.

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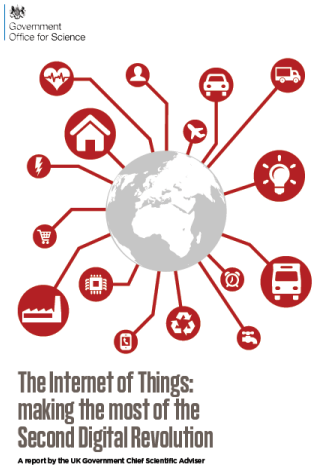
3.1. Applying the Internet of Things: Healthcare

- Healthcare

➢Prevention and early identification,

- Research,
- Data security and ownership,
- Hardware security and interoperability,
- Change management.



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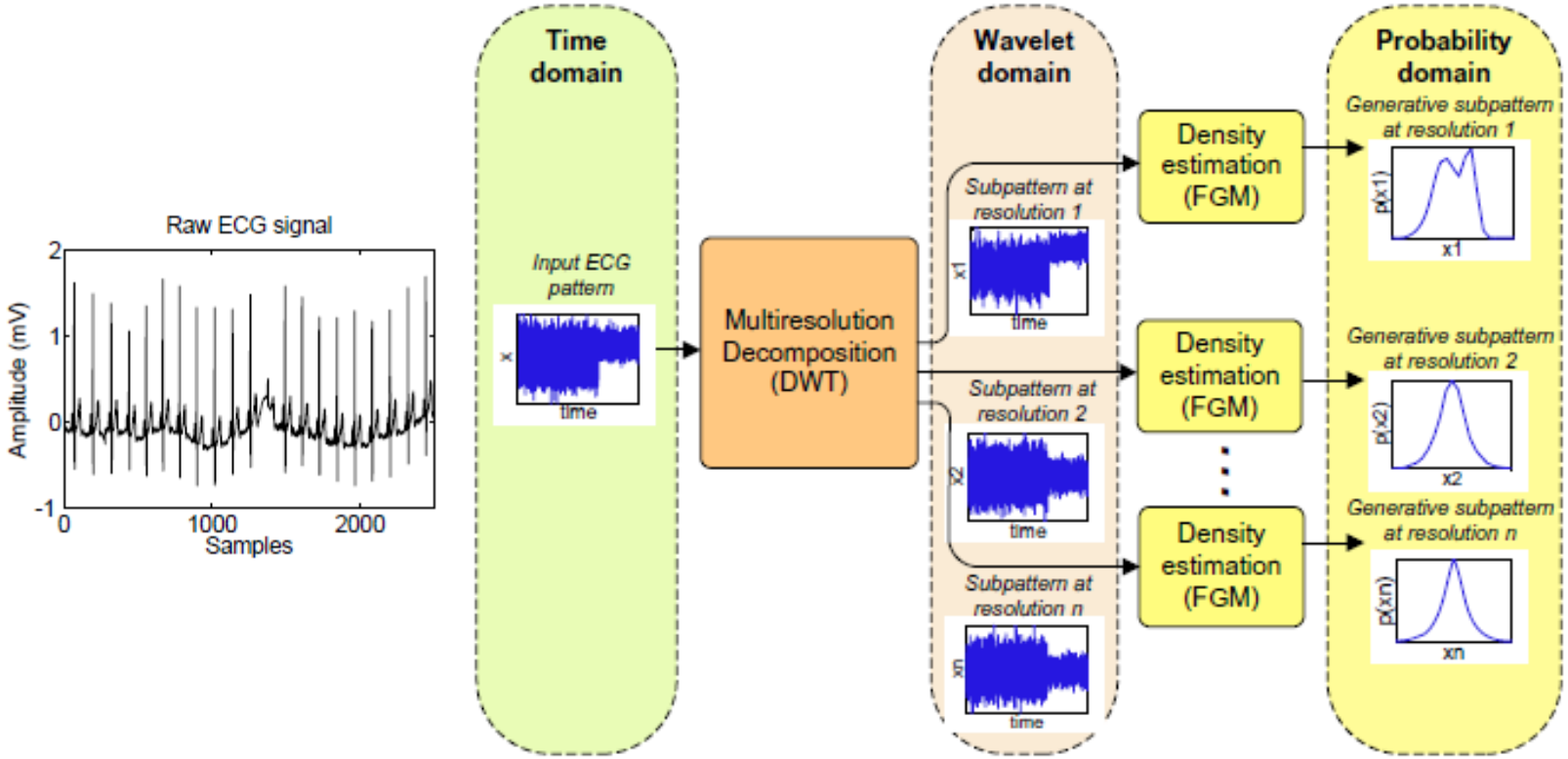
Biometric Recognition and Forensics (1/2)



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Biometric Recognition and Forensics (2/2)

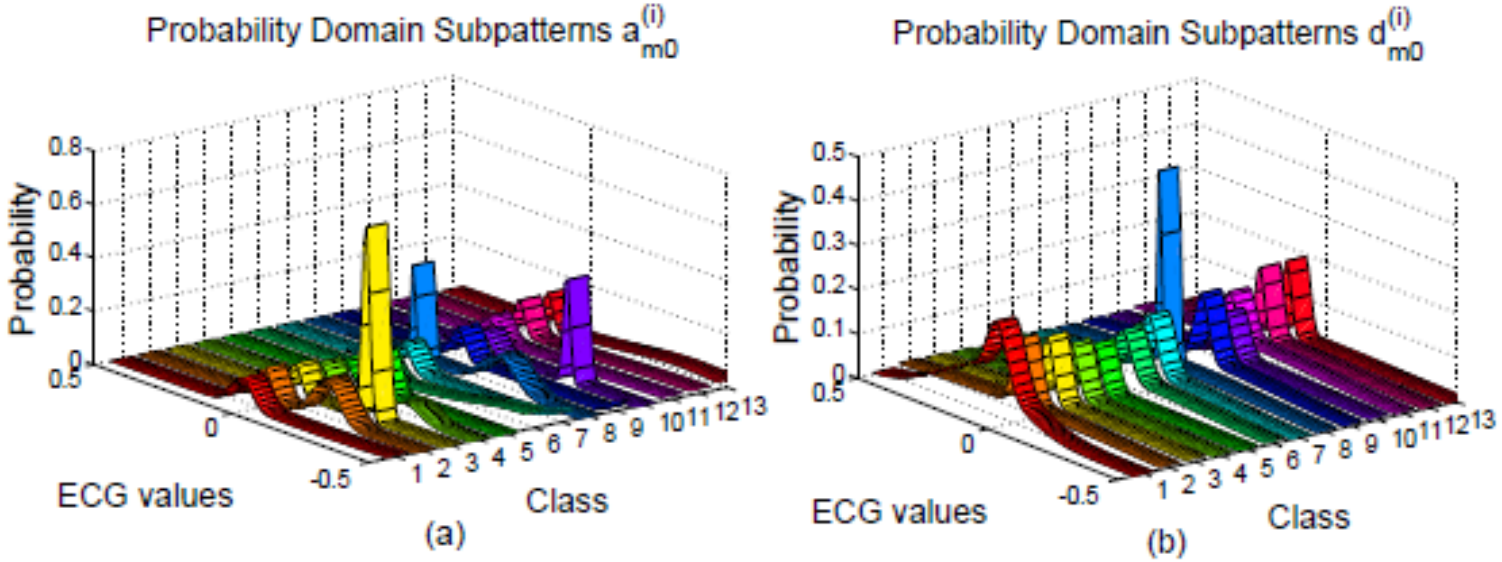

Fig. 5: Probability domain subpatterns for ECG data windows from the thirteen classes with *db*3, $W = 12$, $M = 1$, $G = 6$, $I = 2^9$, $T = 2^{-4}$, $C = 2^6$, $\lambda = 2^{-3}$. (a) Scaling coefficients; (b) Detail coefficients.

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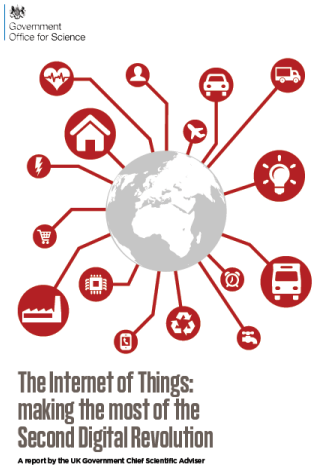
3.2. Applying the Internet of Things: Buildings

- Buildings

  ➢Optimising design and minimising costs,

  - Increasing comfort,

  ➢Security and safety.



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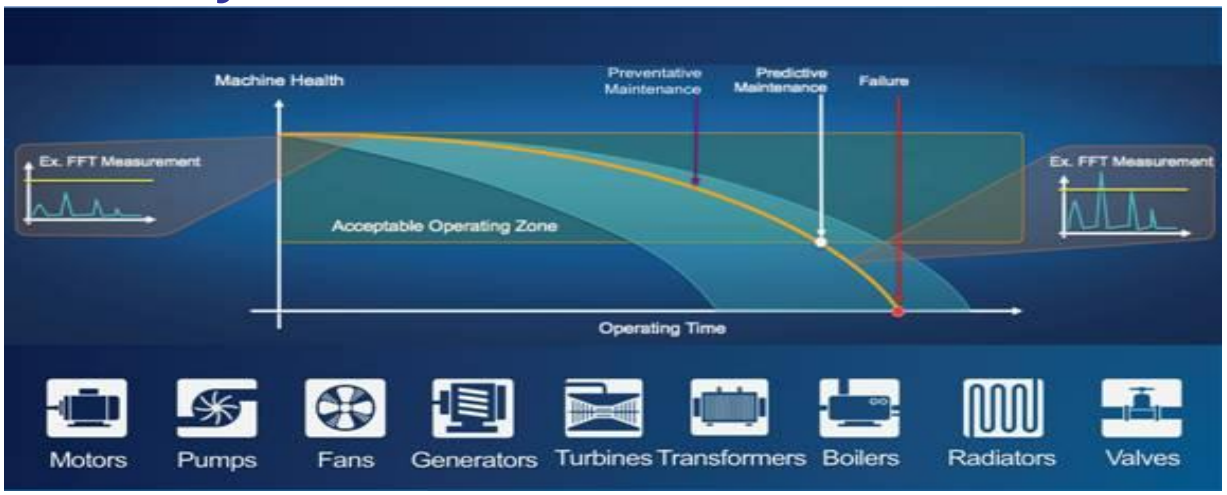
I. Smart Infrastructures: SI (1/3)

- Real time assessment of the deterioration of civil infrastructure (i.e. bridges, tunnels, water pipelines).
- Framework based on WSN, condition monitoring, and anomaly detection.



(http://www.ni.com/newsletter/52418/en/)

- Proactive classification into e.g. adequate condition, maintenance required, and in need of replacement.

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SI: Machine Health Conditioning Monitoring (2/3)

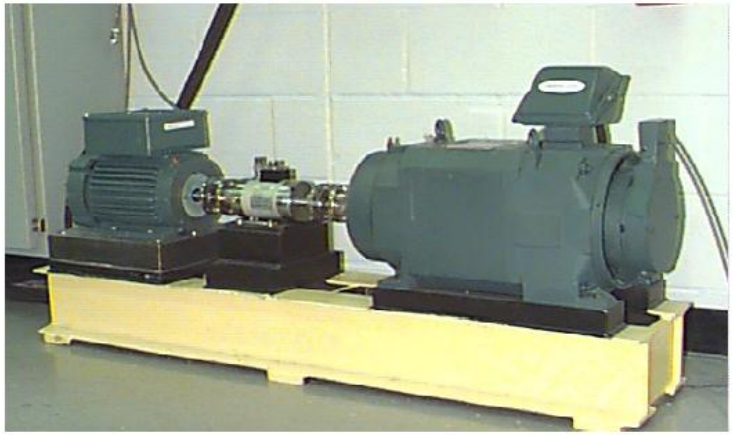


Fig. 3: Test stand for Experiment 1 [68]

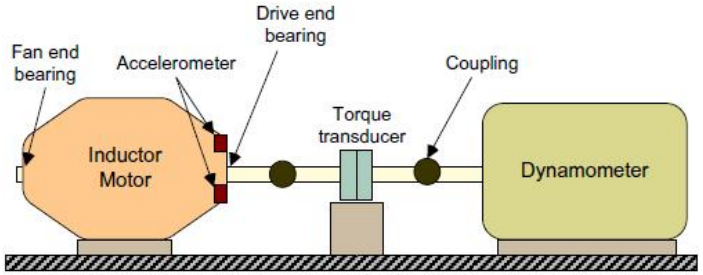
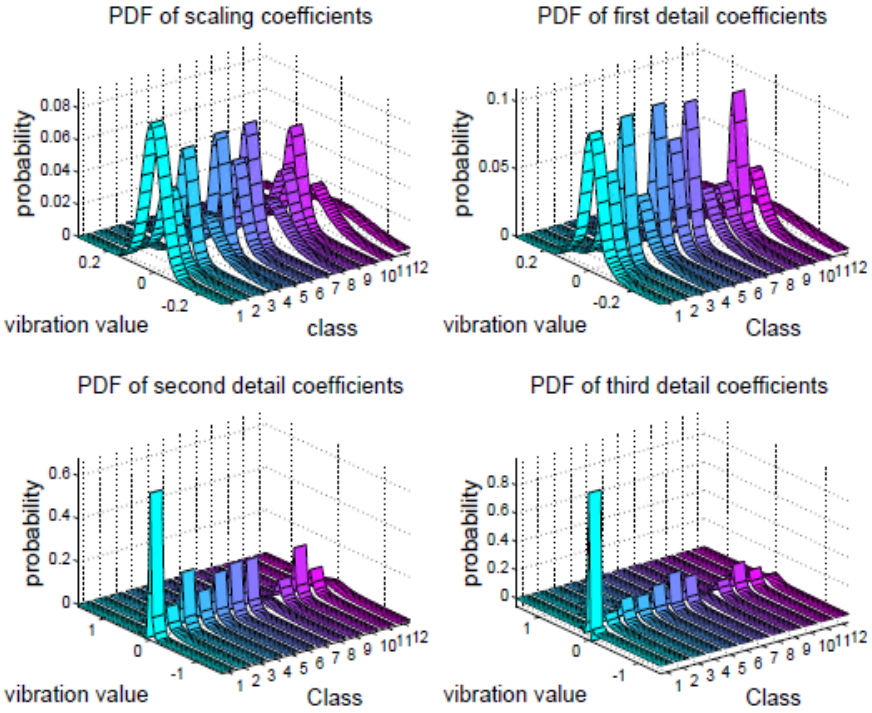
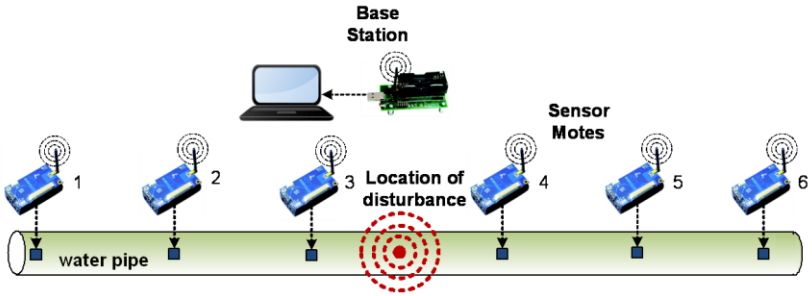


Fig. 4: Scheme diagram of test stand for Experiment 1 [66]

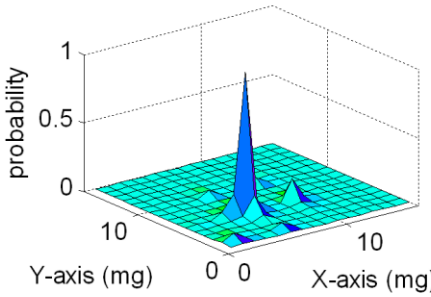


(http://www.eecs.case.edu/laboratory/bearing/)

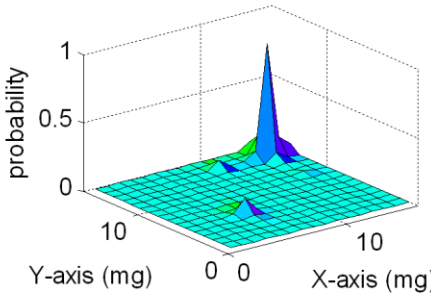
SI: Sensor Network Resilience: Design (3/3)



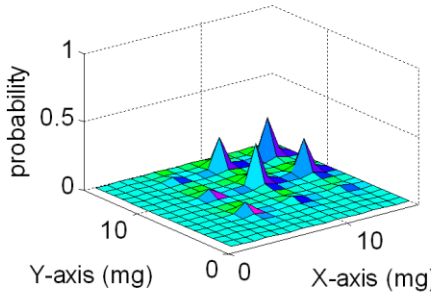
PDF Sensor ID:01 Vibration: Normal



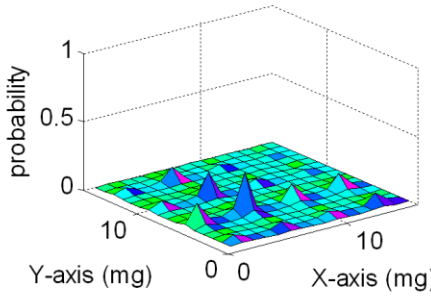
PDF Sensor ID:01 Vibration: Pattern 1

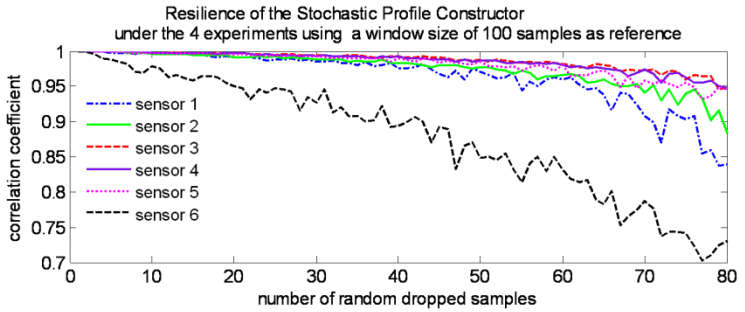


PDF Sensor ID:01 Vibration: Pattern 2



PDF Sensor ID:01 Vibration: Pattern 3





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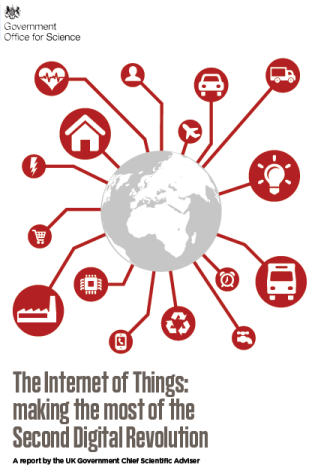
3.3. Applying the Internet of Things: Energy

- Energy
  - Reducing energy demand,
  - ➢Managing energy patterns,
  - Driving innovation,
  - Increased energy demand,
  - Security and standards,
  - Variable access.



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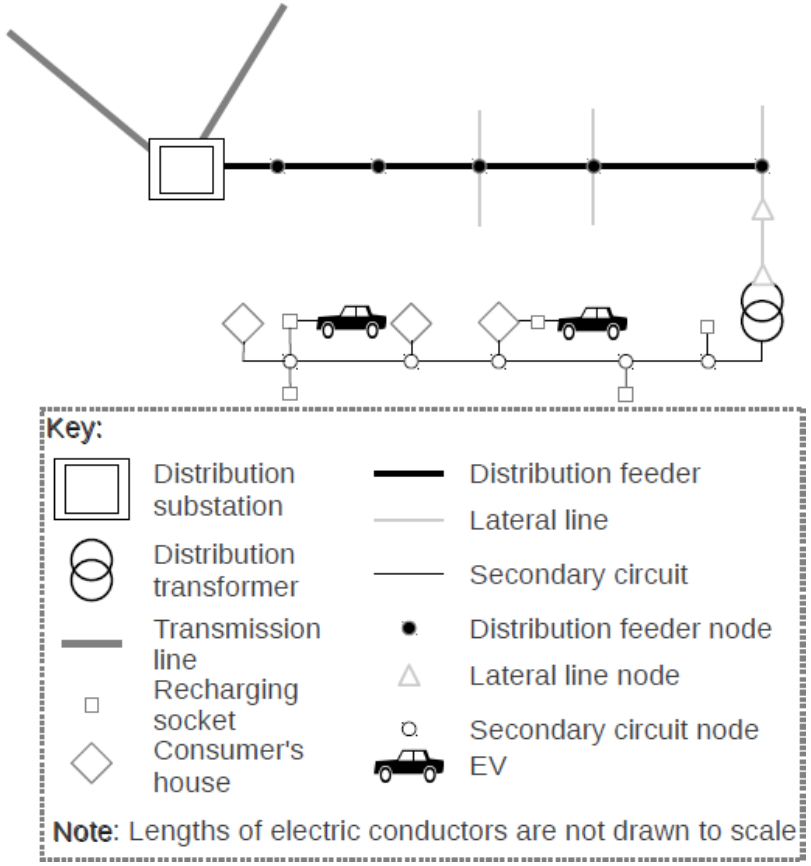
EVs participation for Frequency Regulation Service (1/3)

Power Distribution Network Scenario



- Two mechanism to facilitate EVs participation in operational aspects of a smart grid.
  - Frequency regulation,
  - Congestion avoidance.
- The solution needs to be distributed and dynamic.

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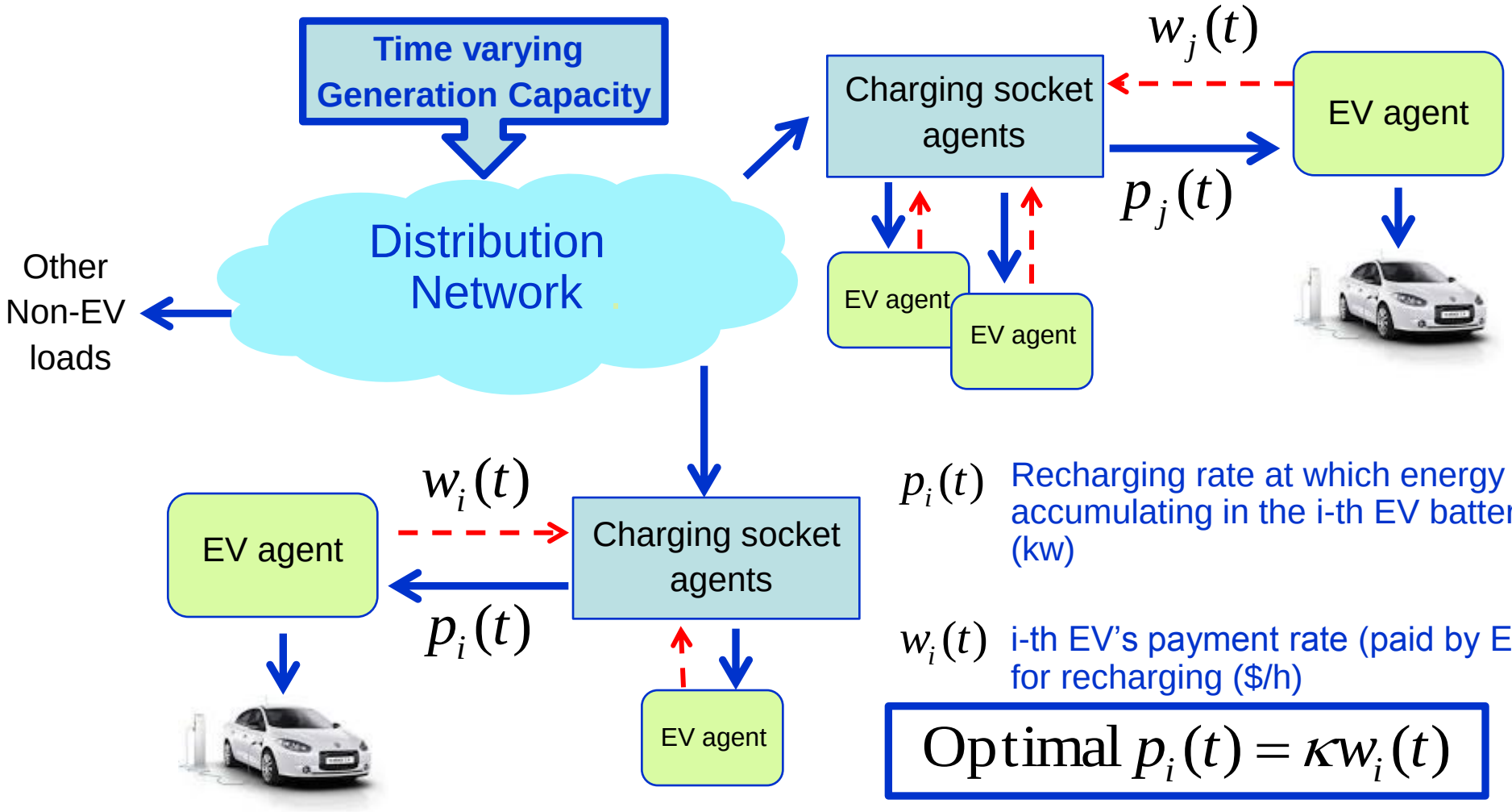
Frequency Regulation Service (2/3)



$p_i(t)$ Recharging rate at which energy is accumulating in the i-th EV battery (kw)

$w_i(t)$ i-th EV's payment rate (paid by EV) for recharging ($/h)

$$\text{Optimal } p_i(t) = \kappa w_i(t)$$

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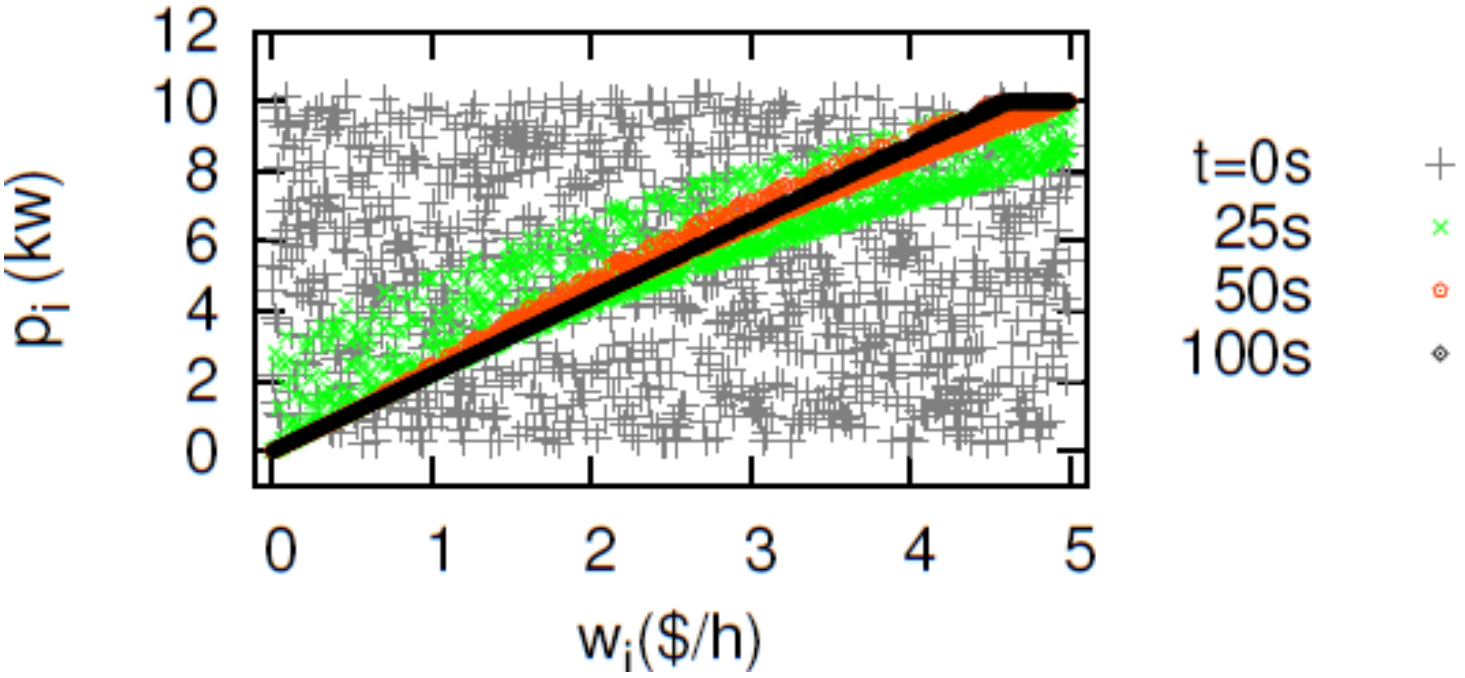
Convergence of Recharging rates of 1000 EVs (3/3)

$$p_i(t) = \kappa w_i(t)$$



Note: The initial recharging rates $p_i(t)$ are randomly assigned.

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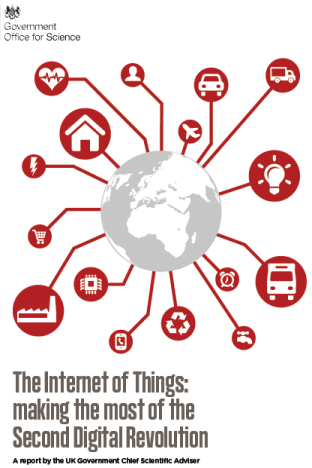
3.4. Applying the Internet of Things: Transport

- Transport
  - Passenger journeys,
  - ➢Increased safety,
  - Transporting goods,
  - Security, reliability and regulation.



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I. Transportation Networks: ITS (1/2)

- Management Tools for Safe Mobility
- Classification of Vehicular Traffic Anomalies
- Spatial Inference of Traffic Conditions

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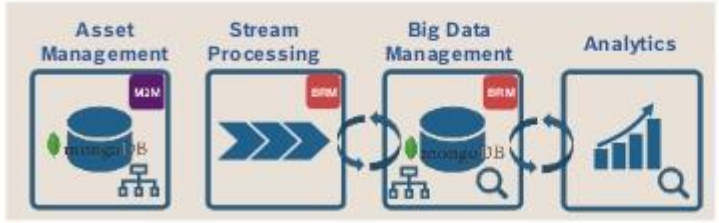
Transport vehicles: ITS (2/2)

IoT and Big Data

Use Case 3: Field Data Capturing



Project SCFD

- Structured Capturing of Field Data
- Components: Car brakes, power steering, etc.
- Usage patterns: temperature, voltage, etc.
- Predictive maintenance, product optimization

Why MongoDB:

- Constantly evolving system, from a data capturing and a data analytics point of view
- Large amount of streaming data

mongoDB BOSCH

https://www.mongodb.com/presentations/

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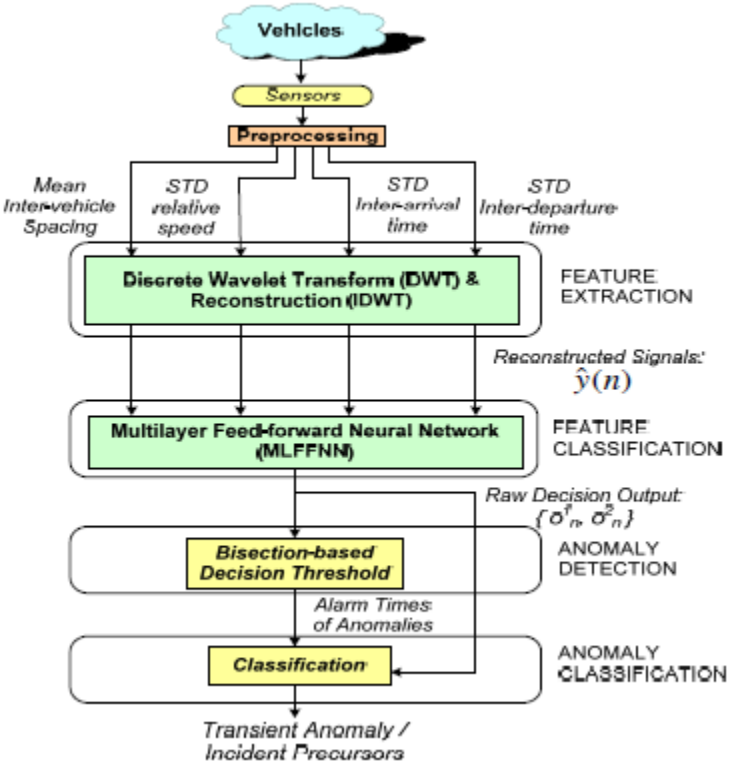
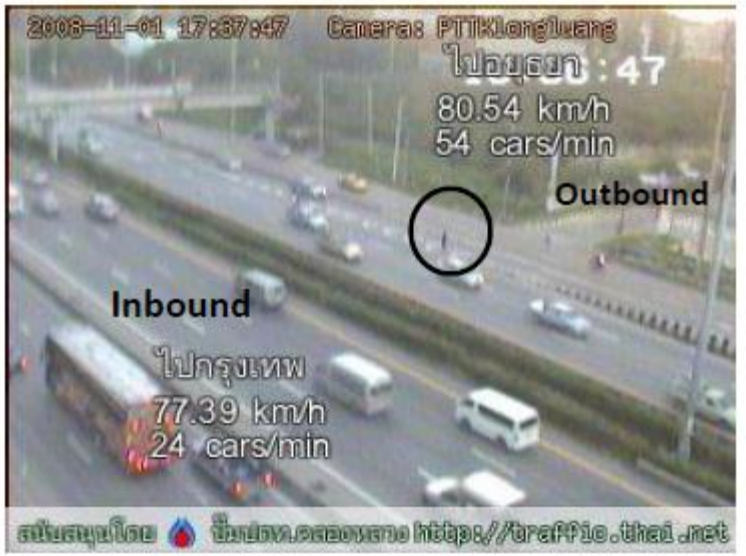
ITS: Distributed Classification of Vehicular Traffic Anomalies (1/2)





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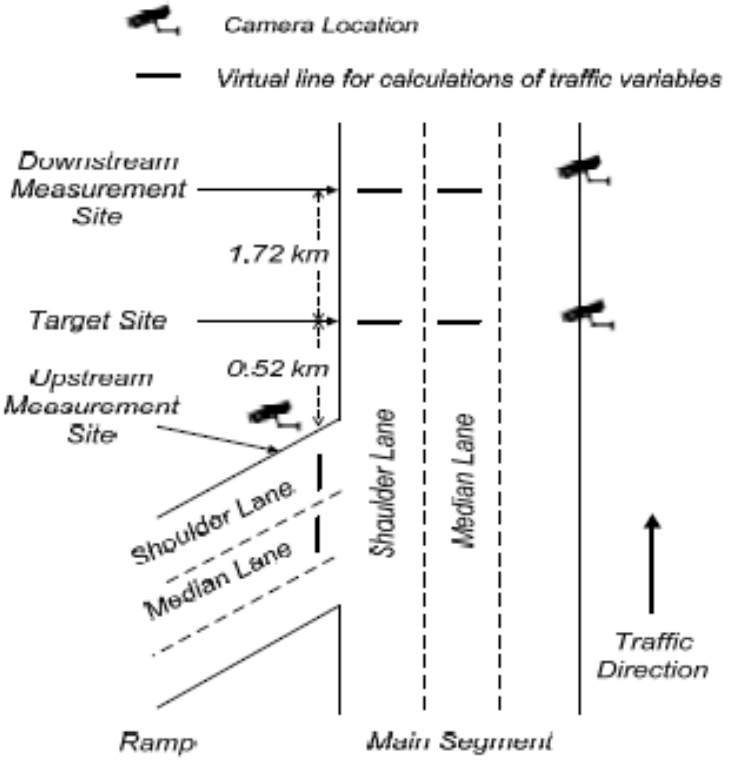
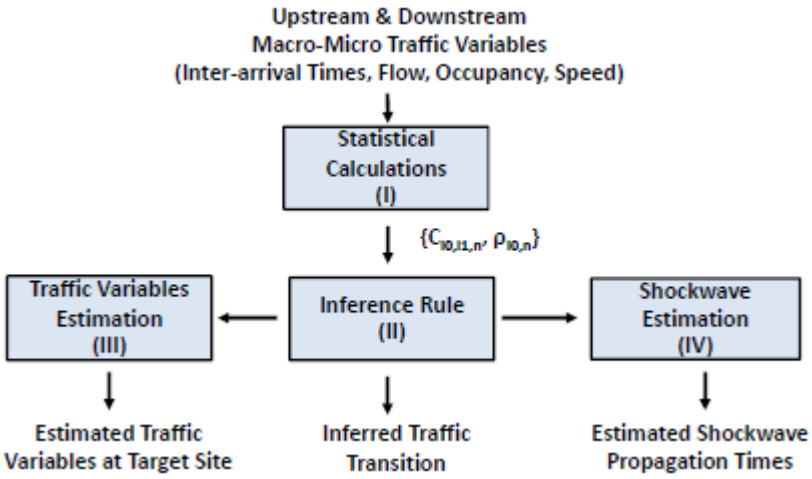
ITS: Spatial Inference of Traffic Transitions (2/2)





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II. Real time Environmental Monitoring (1/3)

- Monitoring of vehicle(s) behaviour and real-time construction of environmental pollution patterns map.
- Intelligent monitoring systems for real-time characterisation and construction of pollution level maps.

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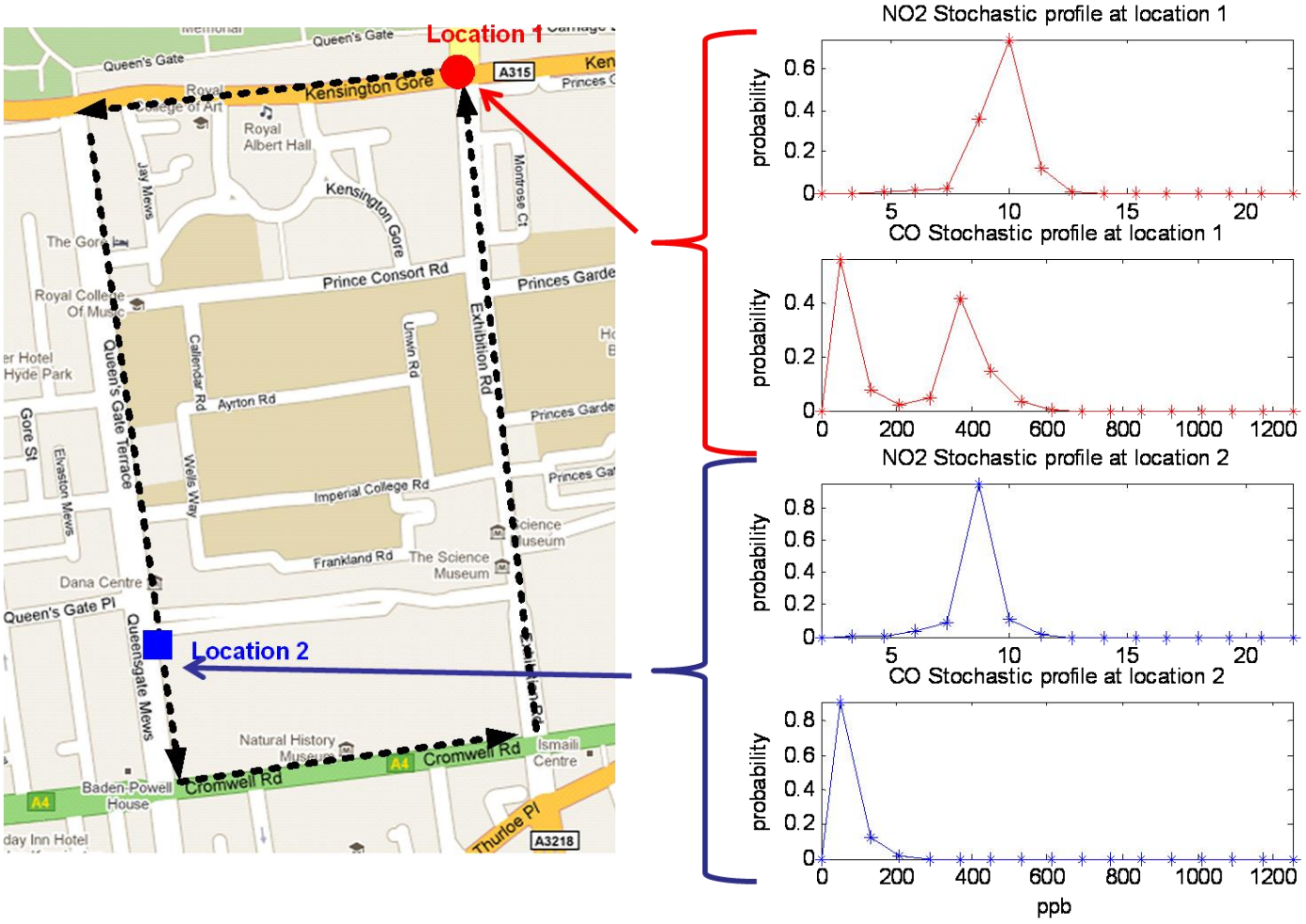
Real time Construction of Pollutant levels (pdf) (2/3)



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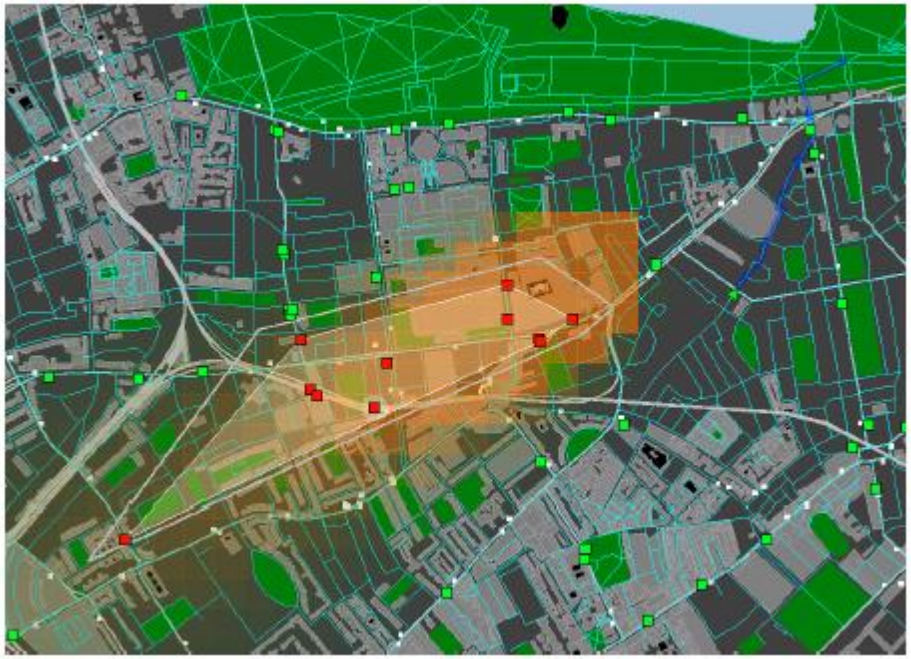
Participatory Sensing Mobility Models (3/3)



- Urban Environment.
- Mission-oriented, participatory sensor network deployment.
- Combining fixed and mobile sensor nodes.

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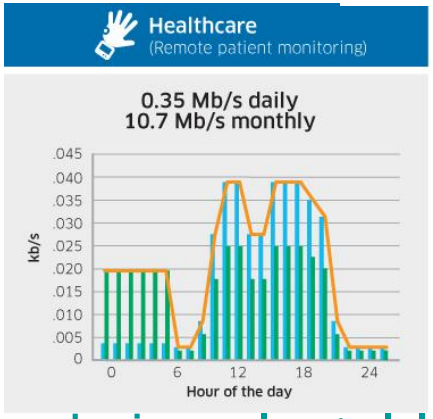
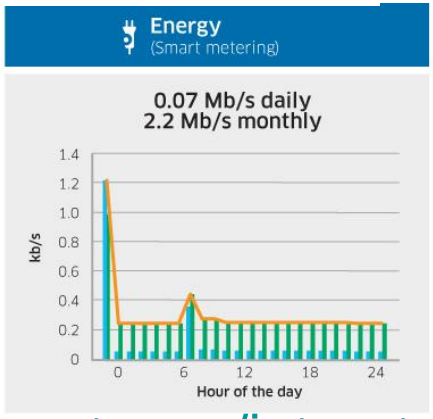
Interoperability across networks: new traffic patterns

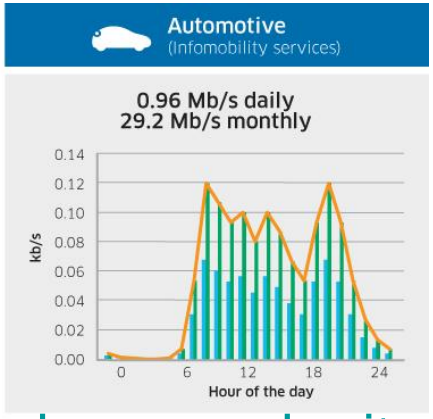
- Any service
- Any application
- Any network

- Applications
- Connectivity
- Devices
- Sensors

Source: Alcatel-Lucent







https://techzine.alcatel-lucent.com/iot-network-can-make-it-or-break-it

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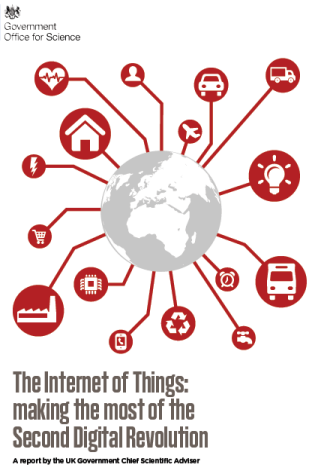
3.5. Applying the Internet of Things: Agriculture

- Agriculture
  - Maximising yield,
  - Improving food traceability,
  - Tackling environmental challenges,
  - Incompatibility,
  - Lack of infrastructure,
  - Technical expertise.



https://www.gov.uk

4. Imperial College London, July 2014

https://www.imperial.ac.uk

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5. Final Remarks

From competency to a critical differentiation:
From Volume & Variety to Velocity.

- Big Data Technology: Operational vs. Analytical.
- Combine Operational and Analytical technologies.
- Generic/global fast solutions rather that application specific solutions.

- Domain Independent framework.
- Real-time time series classification problems.
- Foundation to unsupervised classification algorithms.

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7. More Information

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