SENSEMAKING OF SENSOR DATA AND CASE STUDIES

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Agenda

- Sensemaking for sensor data
- *<Morning Break>*
- Sensemaking for sensor data (Cont’d)
- *<Lunch Break>*
- Case studies of sensemaking for sensor data
- *<Afternoon Break>*
- Written assessment

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Module objective

Module: Making sense of sensor data

Knowledge and understanding

- Understand the fundamentals of sense making pipeline of both single type of sensor data and multiple types of sensor data

Key skills

- Design, build, implement intelligent sensing system for real-world applications

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Major reference

- [Introduction] O. Tickoo and R. Iyer, ***Making Sense of Sensors: End-to-End Algorithms and Infrastructure Design from Wearable-Devices to Data Centers***, Apress, 2016.
- [Intermediate] L. A. Klein, ***Sensor and Data Fusion: A Tool for Information Assessment and Decision Making***, SPIE Press, 2012.
- [Advanced] T. Giannakopoulos, ***Multimodal Information Processing & Analysis***, https://github.com/tyiannak/multimodalAnalysis
- [Advanced] ***Advanced Multimodal Machine Learning***, CMU, https://piazza.com/cmu/spring2017/11777/home

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Topics

- Introduction to making sense of sensor data
- Case studies of sensor data sensemaking

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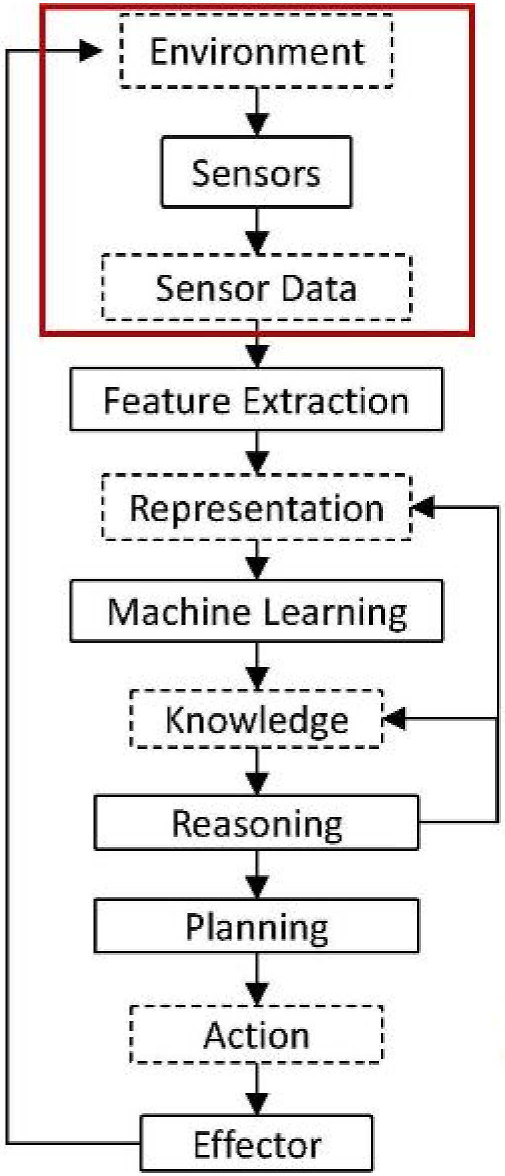
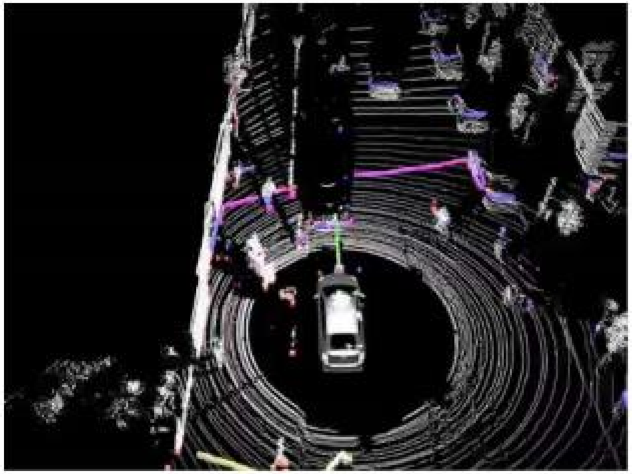
Overview of intelligent sensing system (1)





Source: MIT 6.S099: Artificial General Intelligence, https://agi.mit.edu/

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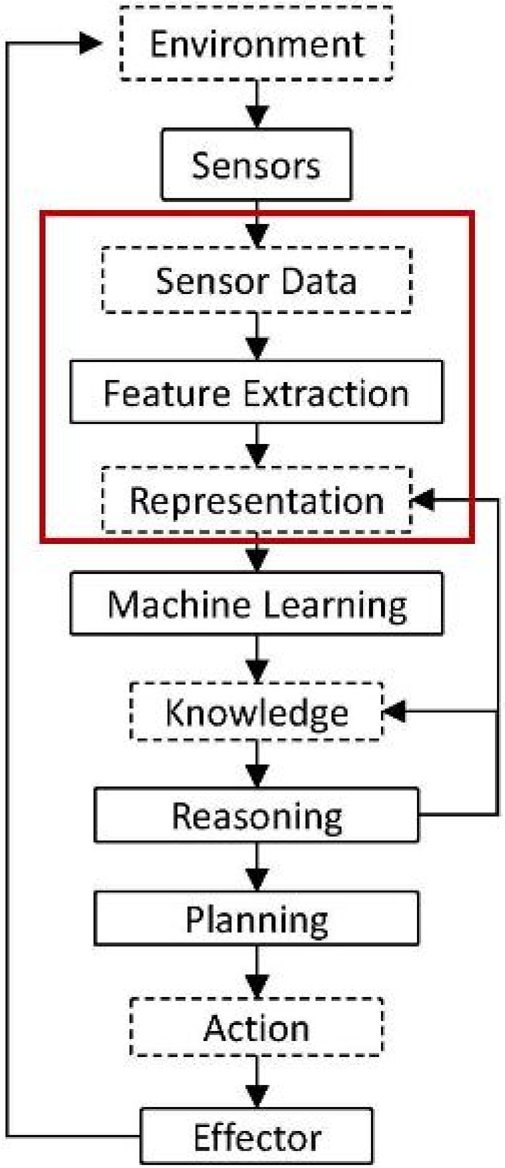
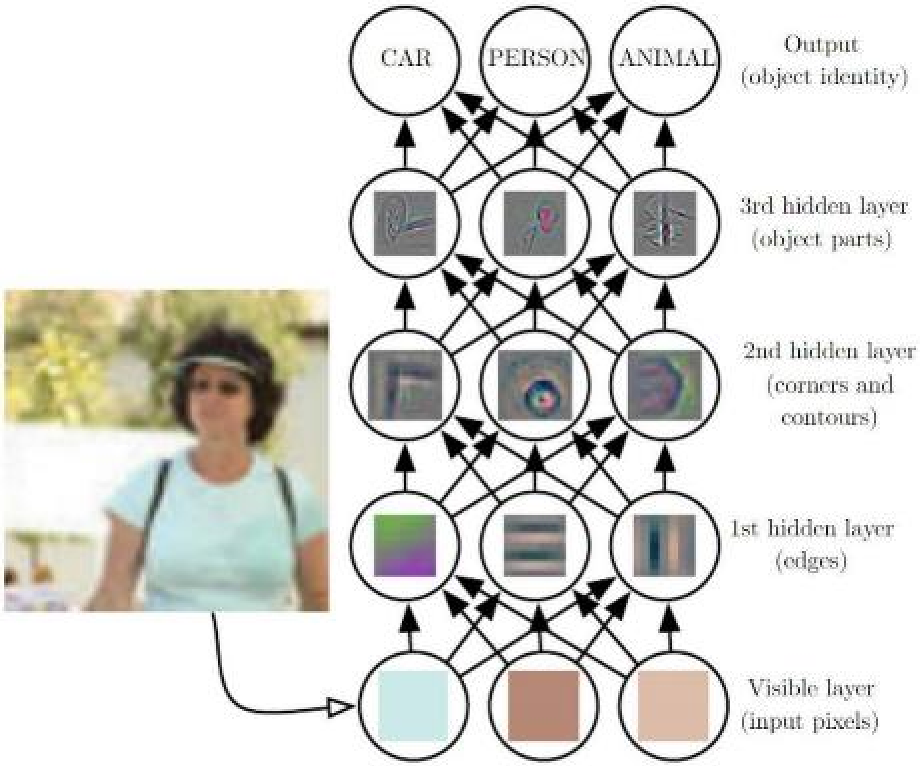
Overview of intelligent sensing system (2)





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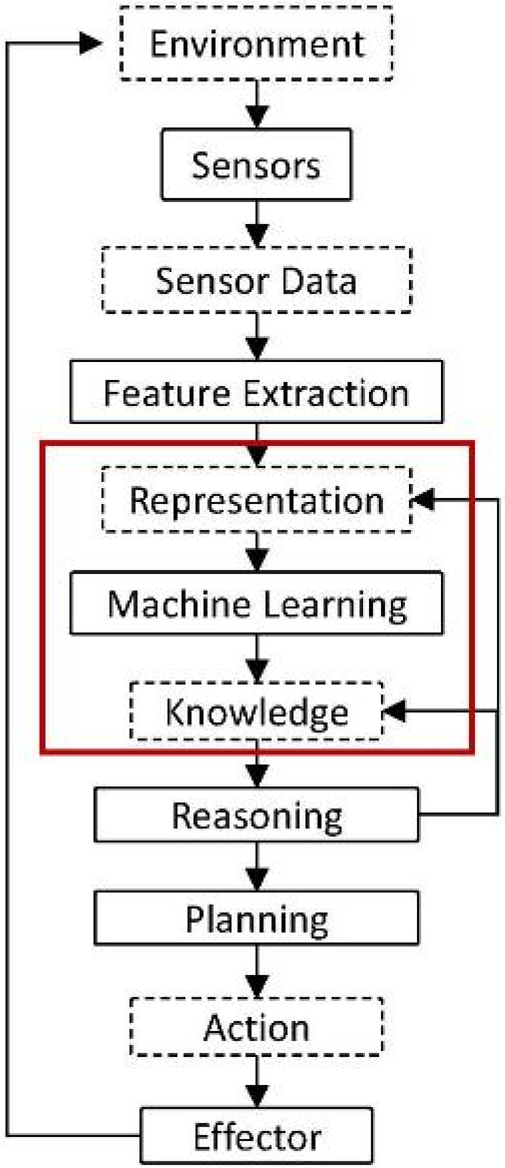
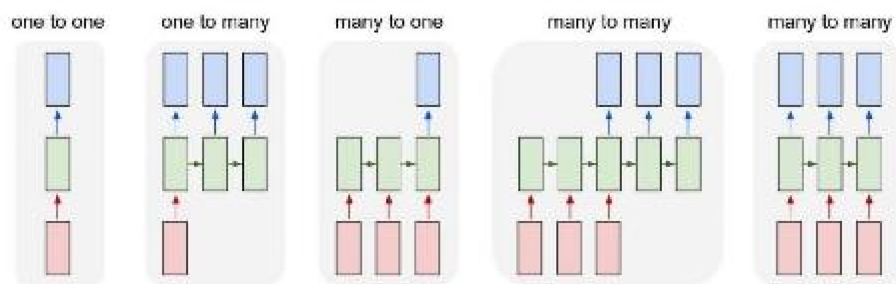
Overview of intelligent sensing system (3)





Source: MIT 6.S099: Artificial General Intelligence, https://agi.mit.edu/

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Overview of intelligent sensing system (4)

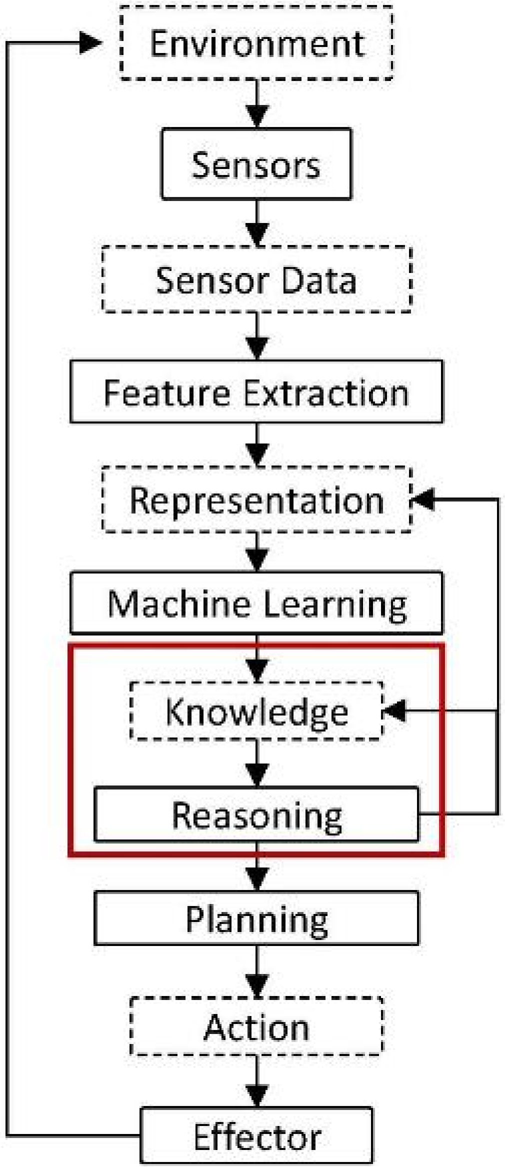

Image Recognition:
If it looks like a duck

Audio Recognition:
Quacks like a duck

Activity Recognition:
Swims like a duck

Source: MIT 6.S099: Artificial General Intelligence, https://agi.mit.edu/

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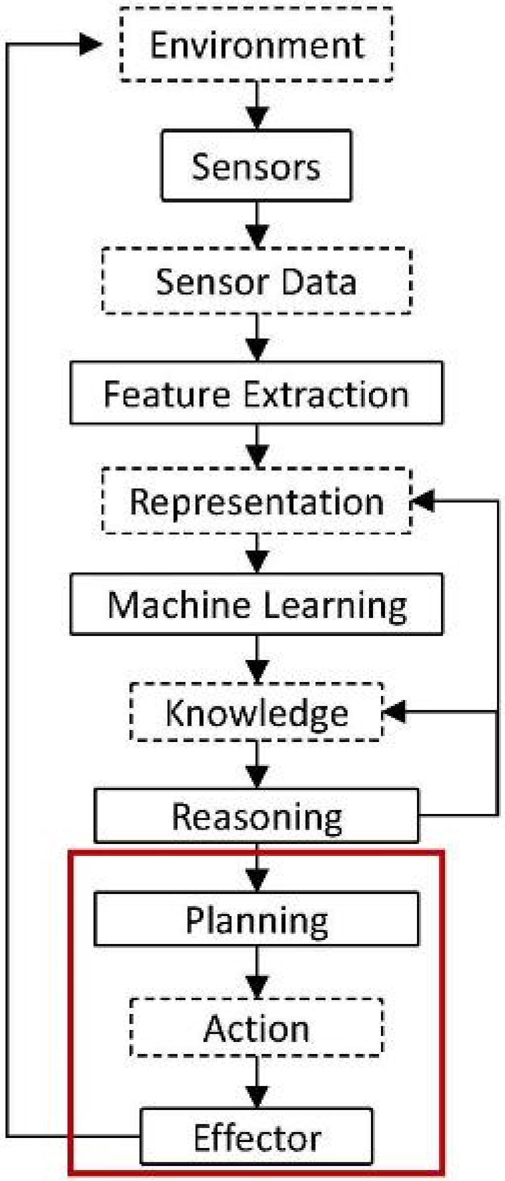
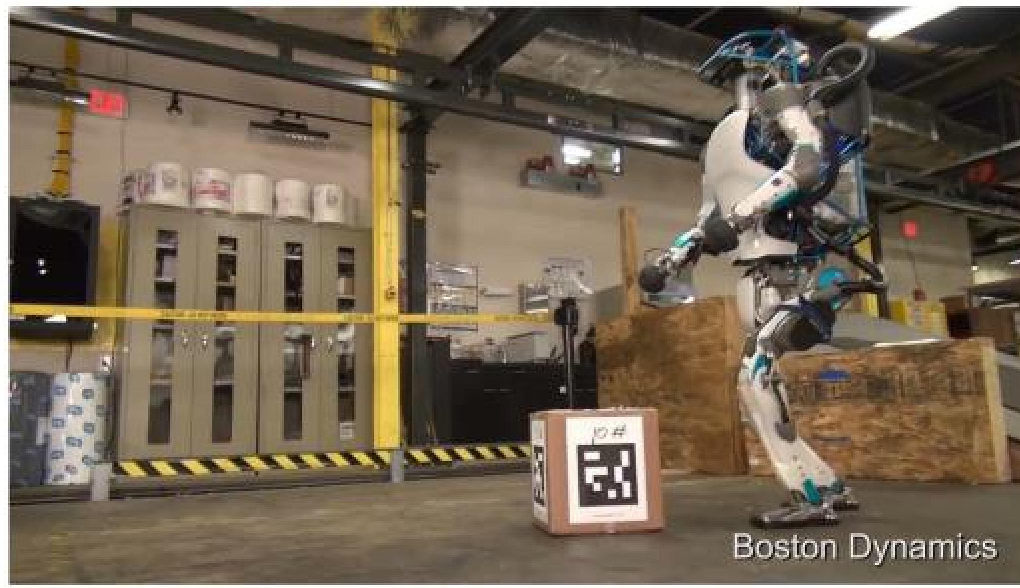
Overview of intelligent sensing system (5)





Source: MIT 6.S099: Artificial General Intelligence, https://agi.mit.edu/

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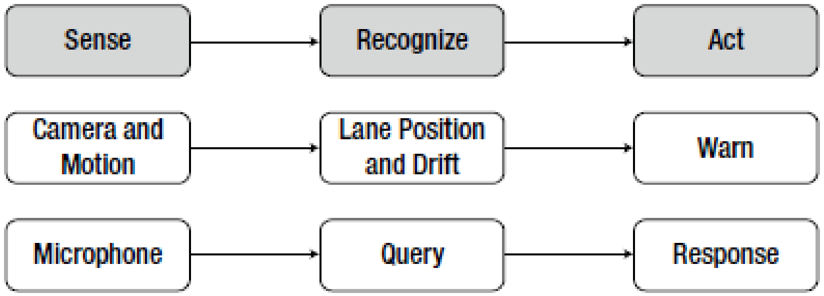
An example

Example: Automatic Driver Assistance System (ADAS)

- It uses a set of sensors like cameras, motion sensors, etc. to provide a driver with assistance for safety and comfort, such as tracking the position of a car in the traffic lanes and provide audible warnings in case the car drifts from its lane (Lane Departure Warning).
- It works on the fundamental processing principles of *Internet of Things* (IoT) comprising of sensors collecting data (cameras, motion sensors), algorithms recognizing the data (relative position of the car in the lane, car drift), and applications acting on the recognized data (audible warning on/off).



Source: O. Tickoo and R. Iyer, Making Sense of Sensors: End-to-End Algorithms and Infrastructure Design from Wearable-Devices to Data Centers, Apress, 2016.

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Making sense of sensor data pipeline (1)

Raw Sensor Data → Features → Recognized Entities → Semantic Relationship → Contextual Relationship → Knowledge

Raw Sensor Data

- Raw (or unprocessed) sensor data is captured by sensors at the front end of the pipeline
- **Vision**: Camera sensors take still or video shots of a scene
- ***Audio/Speech****:* The microphone-like sensors typically capture the audio and analog-to-digital conversion is applied
- **Motion:** Inertial sensors typically measure the acceleration and motion
- **BMI sensors**: The Brain Machine Interface sensors, like EEG and EKG, report the brain activity measurements as activity graphs
- **Other IoT sensors**: temperature, humidity, etc.

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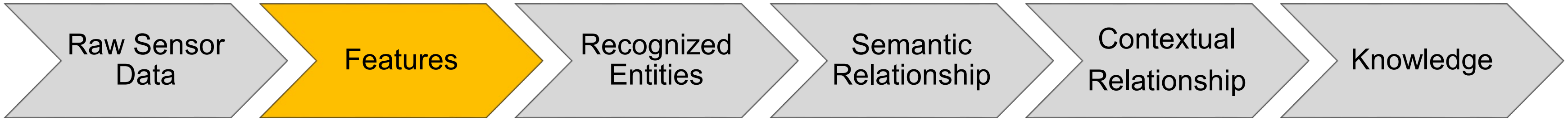
Making sense of sensor data pipeline (2)



Category	Representative features
Geometrical	Edges, lines, line widths, line relationships (e.g., parallel, perpendicular), circles, shapes, size of enclosed area
Structural	Surface area; relative orientation; orientation in vertical and horizontal ground plane;
Statistical	Number of surfaces, area and perimeter, moments, Fourier descriptors, mean, variance, kurtosis, skewness, entropy
Spectral	Color coefficients, spectral peaks and lines
Time domain	Pulse characteristics (rise and fall times, amplitude), pulse width, pulse repetition interval, moments
Frequency domain	Fourier coefficients, time-frequency domain feature such as Wavelet

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Making sense of sensor data pipeline (3)

Raw Sensor Data → Features → **Recognized Entities** → Semantic Relationship → Contextual Relationship → Knowledge

Recognized Entities

- Complex task involving spatial and temporal analysis of the extracted features to map the aggregate to pre-known entities.
- For vision, the recognition task may involve classifying the extracted features to recognize shapes like objects and faces
- For audio, statistical analysis and classification of features allows for aggregated features to be recognized as words

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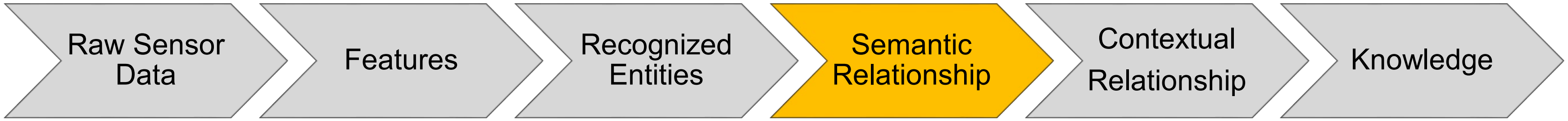
Making sense of sensor data pipeline (4)



Semantic Relationship

- The connection between various recognized entities, for example the semantic relationship between a key and a lock refers to the operation of opening or closing the lock with the key
- For audio, the sentence “*I like coffee*” connects "I" (the subject) with "coffee“ (object) using the predicate "like.“
- For vision: semantic context of the video can be analyzed based on identified entities (multiple objects, locations, people, and activities) and scoring these entities with respect to their co-occurrence as well as relation to the type of classification scenario of importance.

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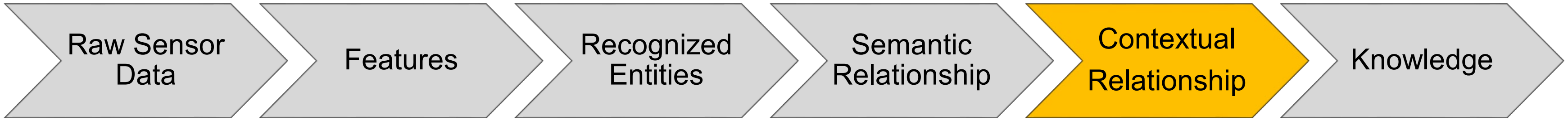
Making sense of sensor data pipeline (5)



Contextual Relationship

- Understand the recognized data in context. The context can be obtained in multiple ways. These include using other sensors as well as using the history of recognized data for context recognition.
- For vision: A face recognition surveillance system can identify a potential invasion or normal operation depending on when the recognition takes place (day vs. night) or depending on the person that is recognized.

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Making sense of sensor data pipeline (6)

Raw Sensor Data → Features → Recognized Entities → Semantic Relationship → Contextual Relationship → Knowledge

Knowledge

- Knowledge representation: Knowledge needs to be stored and represented in a manner such that the semantic information and relationships between various concepts is retained and is modifiable.
- Knowledge operations: These include tools, APIs, and programming languages to insert and extract data from the knowledge database. This involves understanding the incoming semantic data and providing a mechanism to find and manipulate the correct relationships. The extraction process involves responding to different queries targeting relationships between different entities and concepts.

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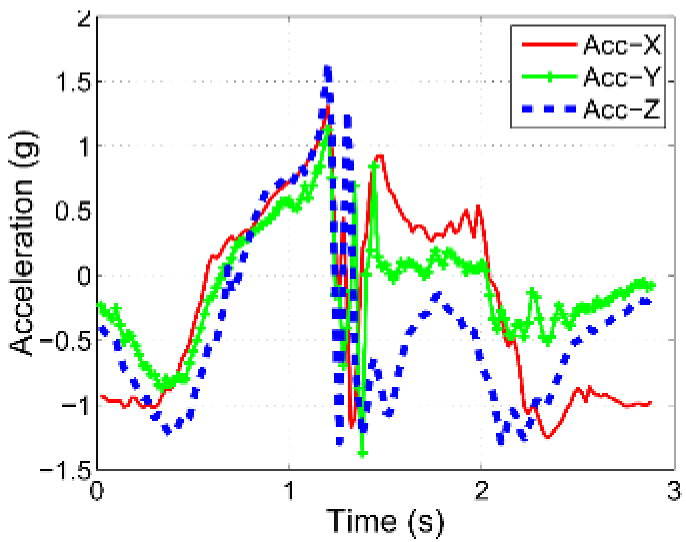
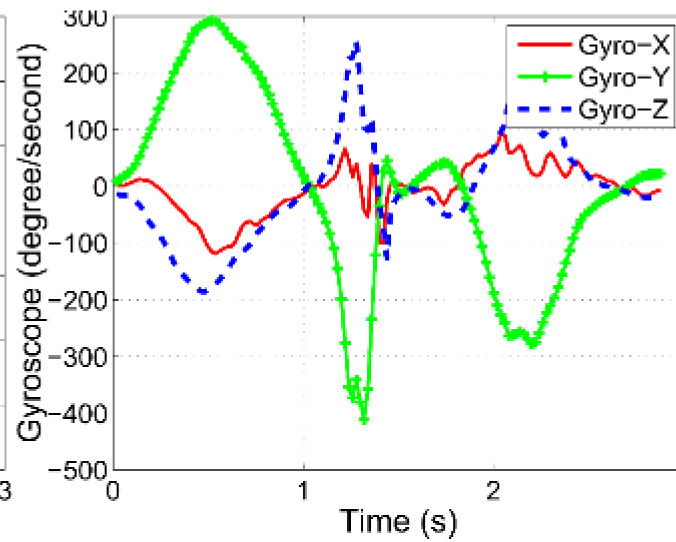
Single type of sensor data: Inertial

- An accelerometer essentially measures the force (proper acceleration) along x, y and z-axes.

Use cases

- Understanding of position/orientation helps mobile phones re-orient the screen in portrait or landscape mode and reverse direction as required.
- Gesture recognition based on buffering continuous data and looking at the change in force and orientation.





Source: http://www.utdallas.edu/~kehtar/UTD-MHAD.html

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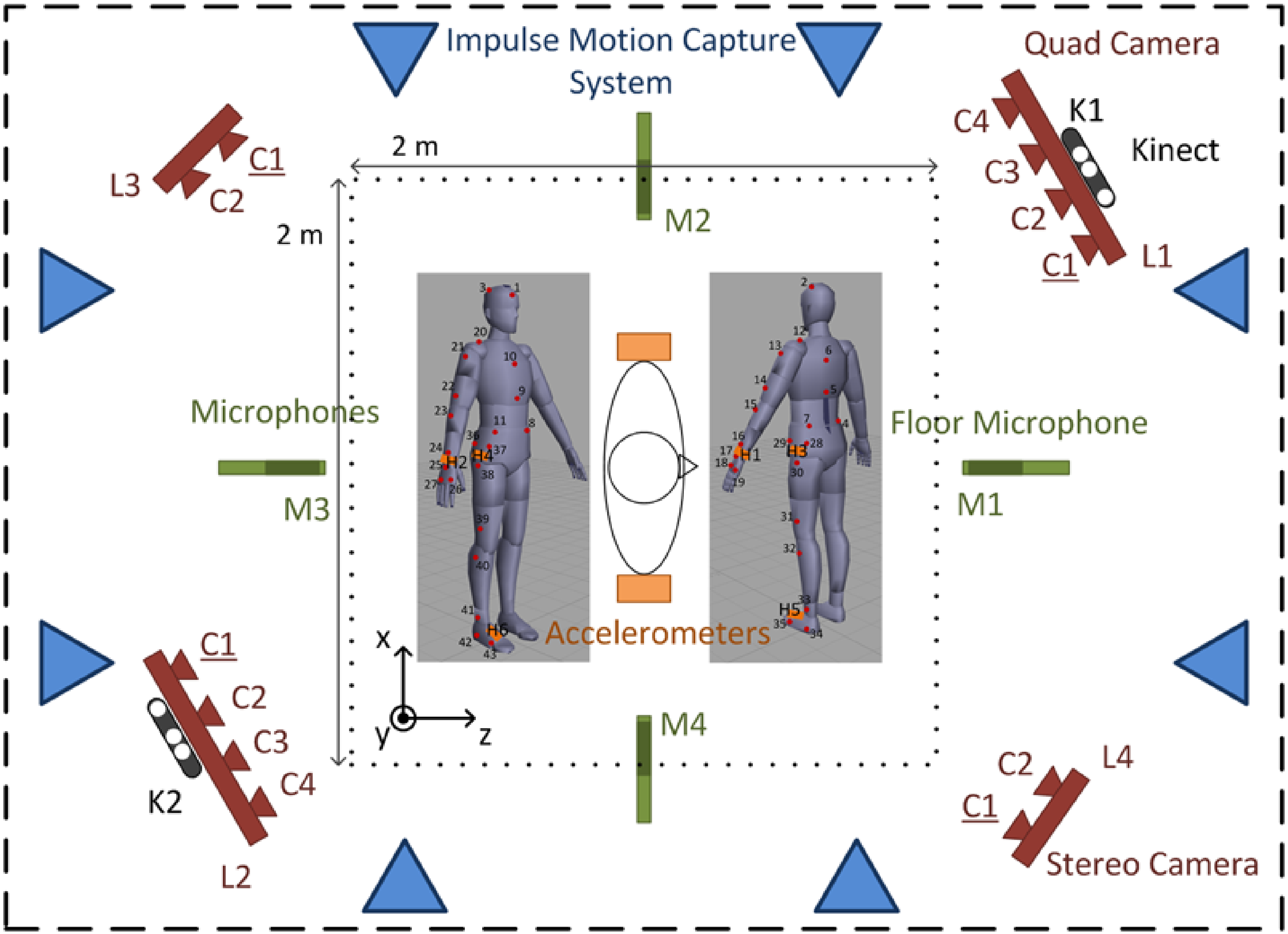
Example: Berkeley Multimodal Human Action Database (MHAD)



Source: http://tele-immersion.citris-uc.org/berkeley_mhad

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Single type of sensor data: Audio

- Audio classification: A common IoT use case for microphones is to classify the environment that the sound was captured in.
- Voice activity detection: Another common use case is voice activity detection. Here the focus is on attempting to determine whether there is voice in the captured audio.
- Speaker recognition: Speaker recognition, sometimes also referred to as voice recognition, attempts to determine who is speaking.
- Keyword recognition: Recognize whether a particular word was uttered. Keyword recognition can also be generalized to keyphrase recognition and both are typically used as triggers for additional activity such as starting a session of commands or bringing up an application.
- Command and control: Command and control refers to using a small set of phrases in speech recognition. For illustration, this could include a set of commands to control a toy car such as “move forward,” “move backward,” “go faster,” “go slower,” “turn right/left,” etc.

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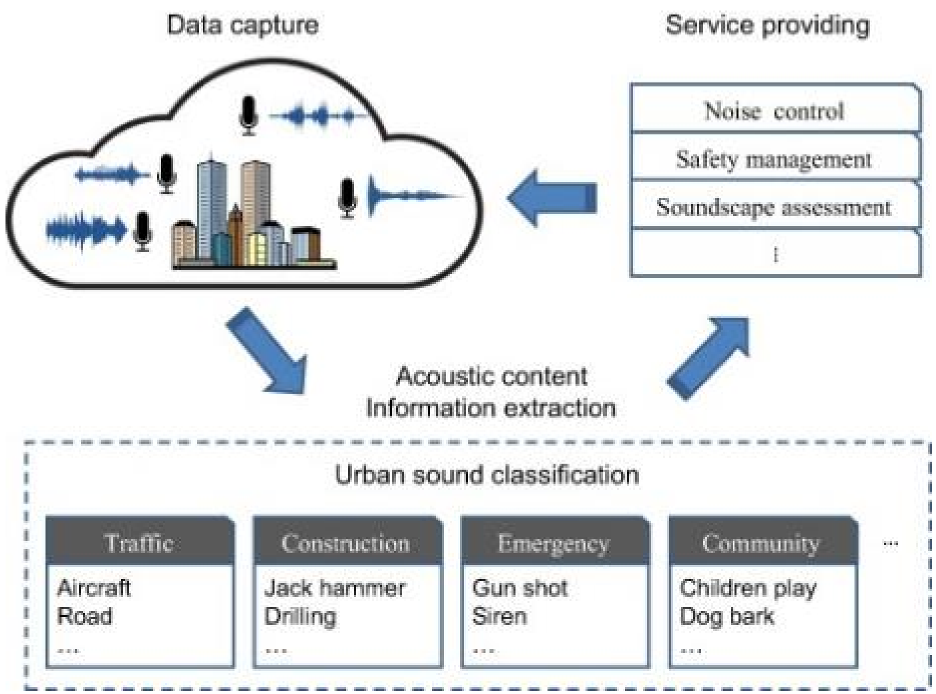
Example: Urban sound classification

- Dataset: Urban sound dataset, https://urbansounddataset.weebly.com/urbansound.html
- It contains 1302 labeled sound recordings. Each recording is labeled with the start and end times of sound events from 10 classes: air_conditioner, car_horn, children_playing, dog_bark, drilling, enginge_idling, gun_shot, jackhammer, siren, and street_music.



Source: https://www.sciencedirect.com/science/article/abs/pii/S0003682X16302274

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Single type of sensor data: Vision

- Object recognition: Identify objects in an image and potentially matching them to a pre-existing database of objects that have been captured before.
- Face recognition: Detect a face in an image as well as matching that face against a database to label the face accordingly.
- Gesture recognition: Recognize static poses or moving gestures either specific to the hand/arm or the human body.
- Scene recognition: Identify multiple objects, faces, and people in an image and using that information to determine the likely activity or context.
- Anomaly detection: Identify if any anomaly occurred which should trigger additional analysis.
- Video summarization: Summarize the salient aspects of a long video stream. This includes scene changes, key scenarios and objects/characters that are the focus of the video.

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Example: YouTube-8M video understanding

- Dataset: YouTube-8M, a video understanding challenge, https://ai.googleblog.com/2017/02/an-updated-youtube-8m-video.html

Source: https://ai.googleblog.com/2017/02/an-updated-youtube-8m-video.html

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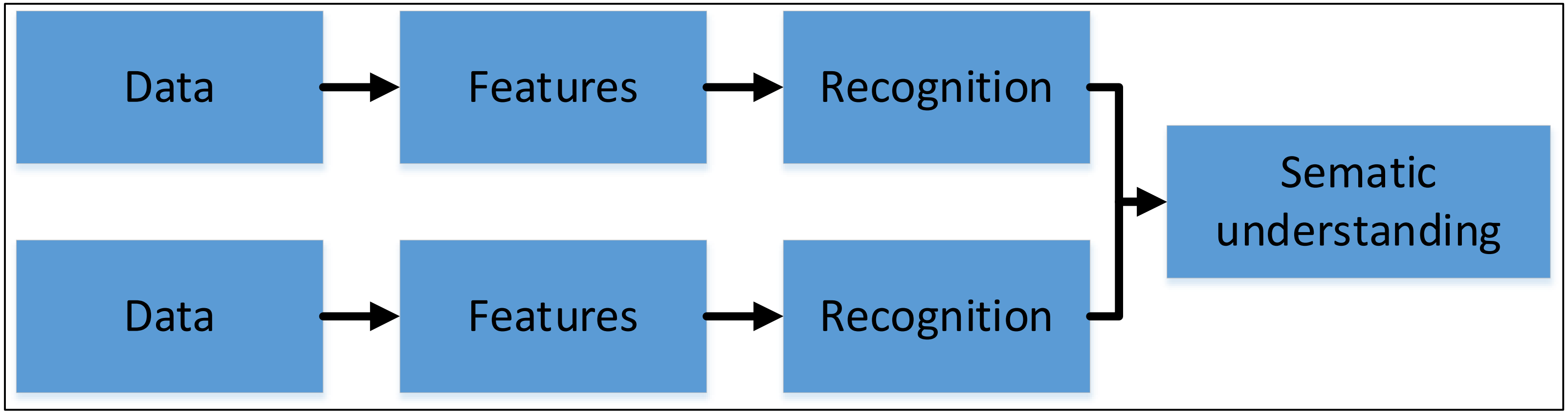
Multimodal sensor data recognition (1)

- Uncoupled sensor data fusion/Semantic fusion: The data fusion occurs at the last possible stage in the respective pipelines. The advantage of this method is that the sensor fusion is simple and can be accomplished using existing technology pipelines for recognition. Domain experts like this approach because cross-domain technical knowledge requirements are minimal.



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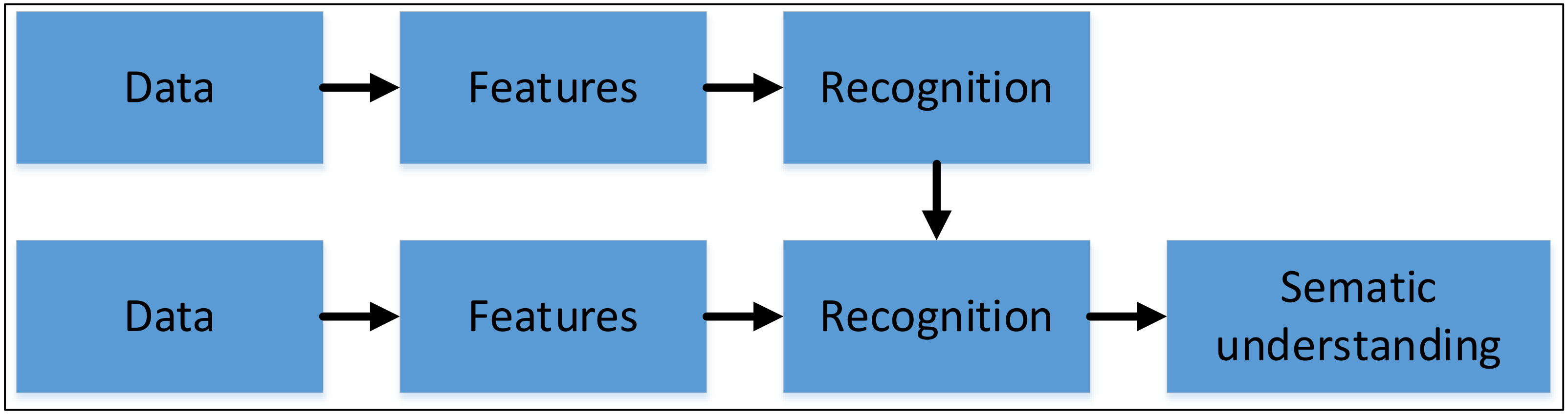
Multimodal sensor data recognition (2)

- **Loosely coupled sensor data fusion/Restricted recognition**: Restricts the recognition search space of mode modality based on the results from the other. In this approach, one recognition pipe helps to set the context for the other. Once that is accomplished, the second recognition pipe need only perform recognition within the established context boundaries, leading to potential savings in compute and higher performance.



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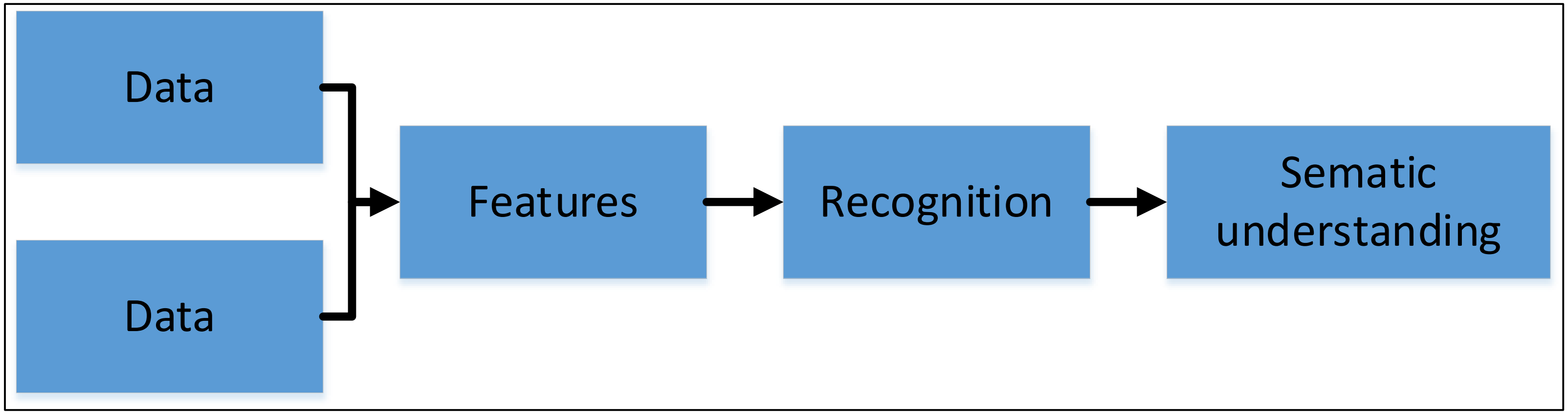
Multimodal sensor data recognition (3)

- Tightly coupled sensor data fusion/data-feature level fusion: It allows for virtual combination of multiple sensors that the combined sensors appear as a single complex sensor for most of the application stack. Data representation at the lower levels of stack is very sensor-specific, so experts are needed to make sensible decisions for merging data from multiple sources. Each sensor model has a different data representation format at the lowest level, making it very hard to come up with a homogenous representation that preserves the information content.



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Sensor data fusion (1)

- **Representation.** The information of the fusion process has an abstract level higher than each input data set.
- **Certainty.** If V is the sensor data before fusion and $p(V)$ is the *a priori* probability of the data before fusion, then the gain in certainty is the growth in $p(V)$ after fusion.
- **Accuracy.** The standard deviation on the data after the fusion process is smaller than the standard deviation provided directly by the sources.
- **Completeness.** Bringing new information to the current knowledge on an environment allows a more complete the view on this environment.

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Sensor data fusion (2)

- **Fusion across sensors.** A number of sensors nominally measure the same property as a number of temperature sensors measuring the temperature of an object.
- **Fusion across attributes.** A number of sensors measure different quantities associated with the same experimental situation as in the measurement of air temperature, pressure and humidity to determine air refractive index.
- **Fusion across domains.** A number of sensors measure the same attribute over a number of different ranges or domains. This arises, for example, in the definition of a temperature scale.
- **Fusion across time.** Current measurements are fused with historical information, for example, from an earlier calibration.

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Sensor data registration

- Spatial alignment. Transformation of the local spatial positions to a common coordinate system. The process involves geo-referencing the location and field-of-view of each sensor.
- Temporal alignment. Transformation of the local times to a common time axis. In many applications, is performed using a dynamic time warping algorithm.
- Semantic alignment. Conversion of the multiple inputs so they refer to the same objects or phenomena. In many applications the process is performed using an assignment algorithm.

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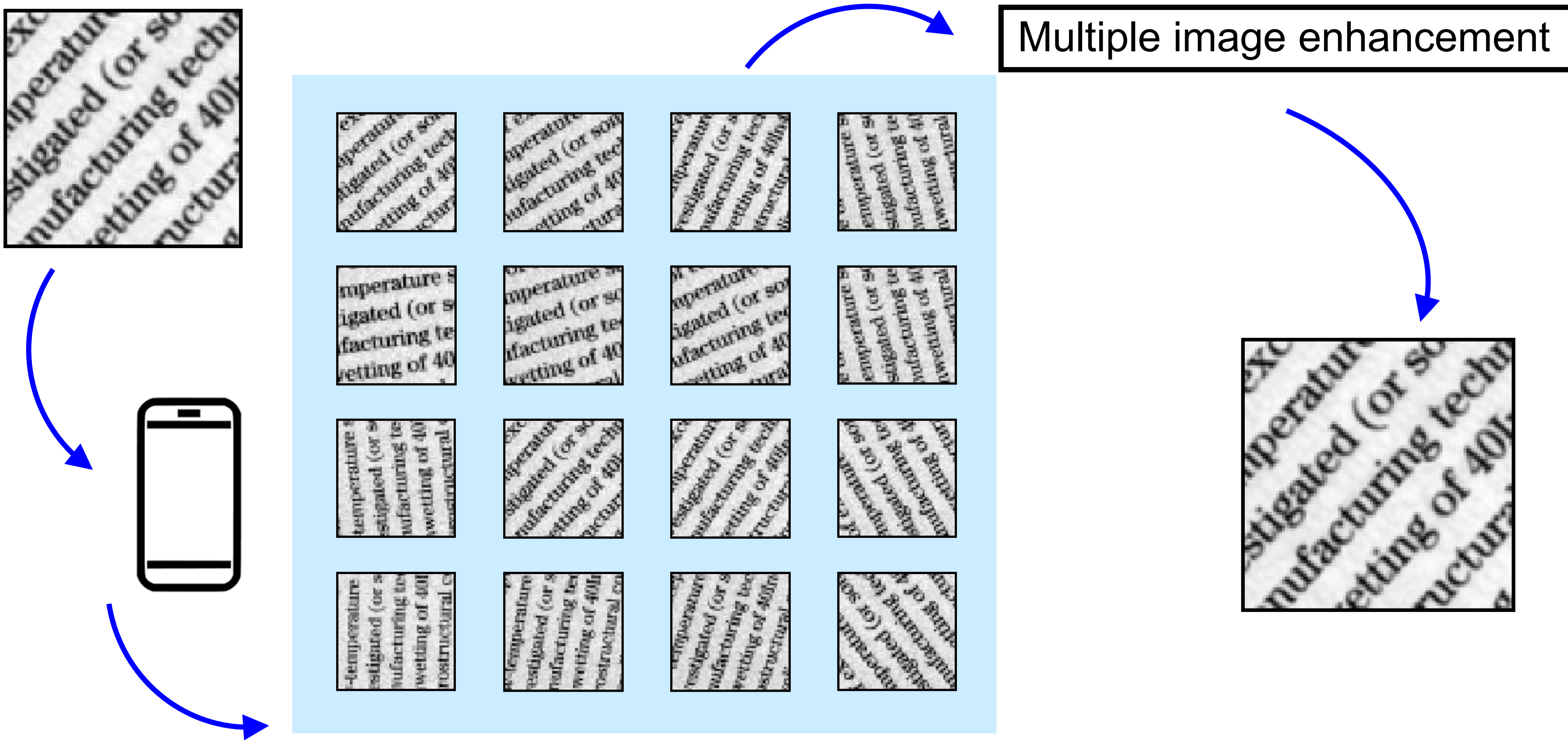
Spatial registration (1)

- At different times (multi-temporal fusion)



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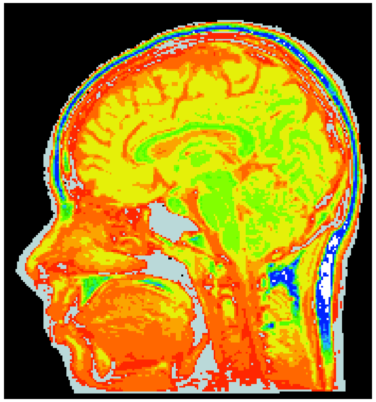
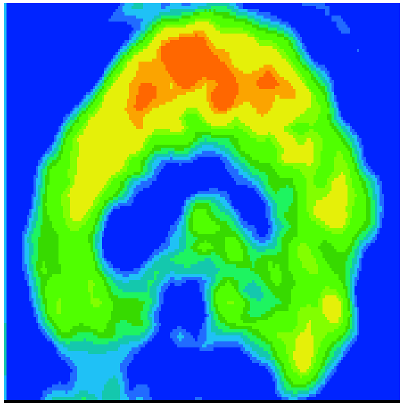
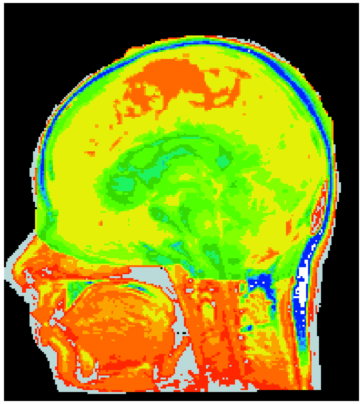
Spatial registration (2)

- With different sensors (multi-modal fusion)







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Spatial registration (3)

- From different viewpoints (multi-view fusion)

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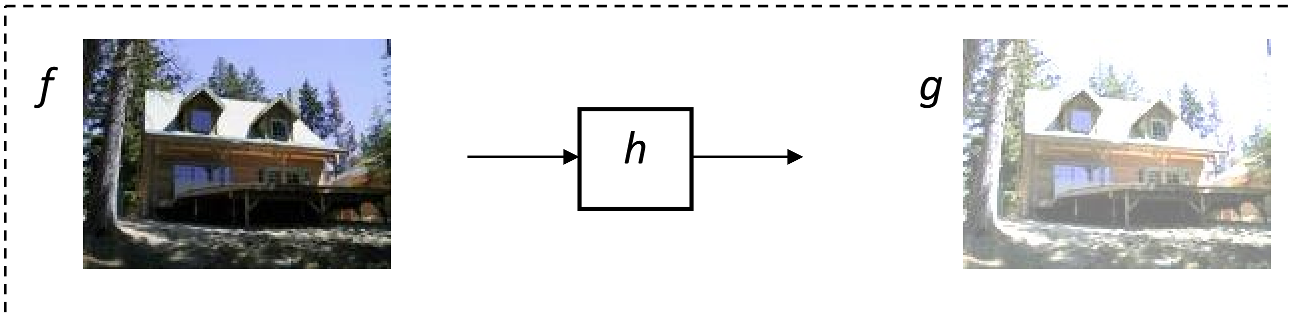
Data warping

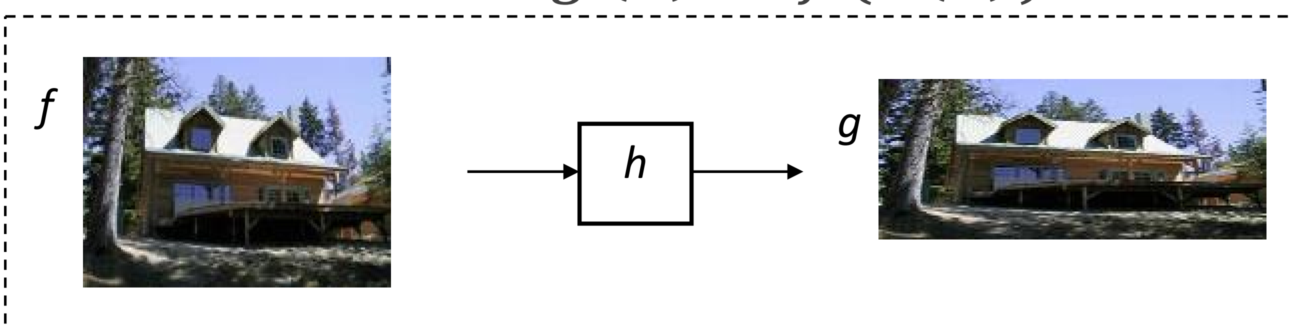
- Image filtering: change *range* of image

$$g(x) = h(f(x))$$



- Image warping: change *domain* of image

$$g(x) = f(h(x))$$



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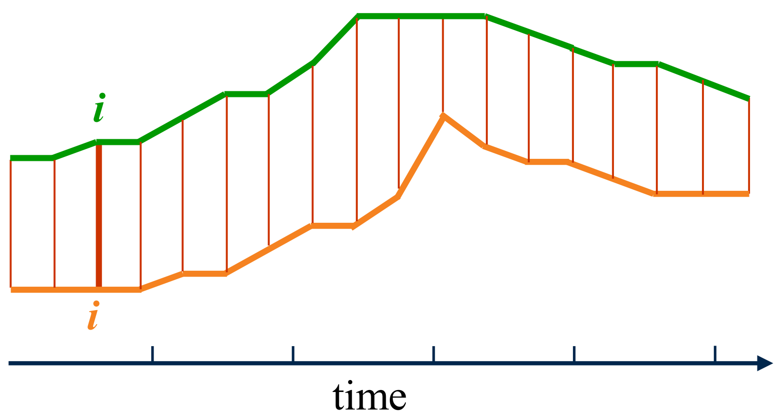
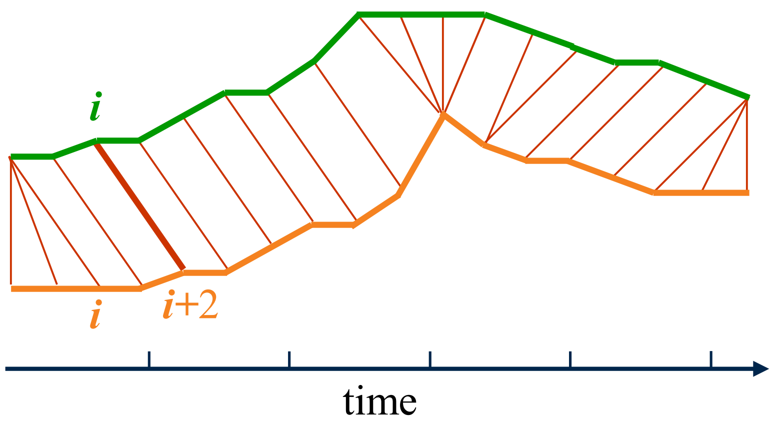
Temporal registration: Audio





Any distance (Euclidean, Manhattan, …) can be used to align the *i*-th point on one time series with the *i*-th point.

A non-linear alignment allows similar shapes to match even if they are out of phase in the time axis.

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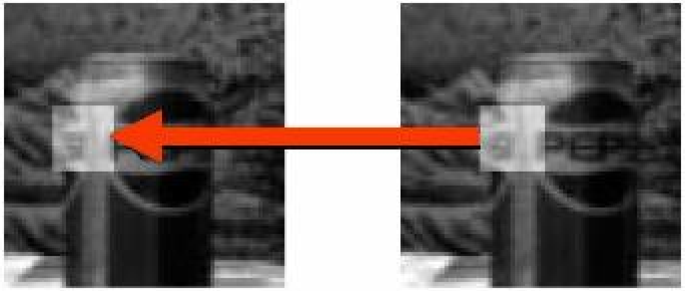
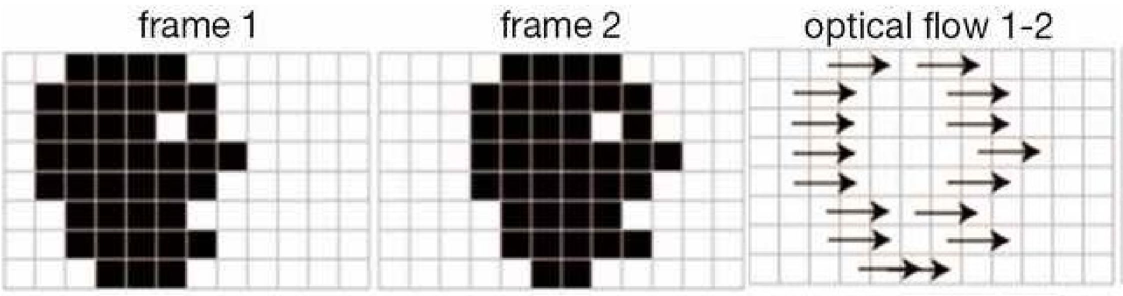
Temporal registration: Video

- Find point to point correspondence between two images.
  - The pixel intensities of an object do not change between consecutive frames.
  - Neighbouring pixels have similar motion.





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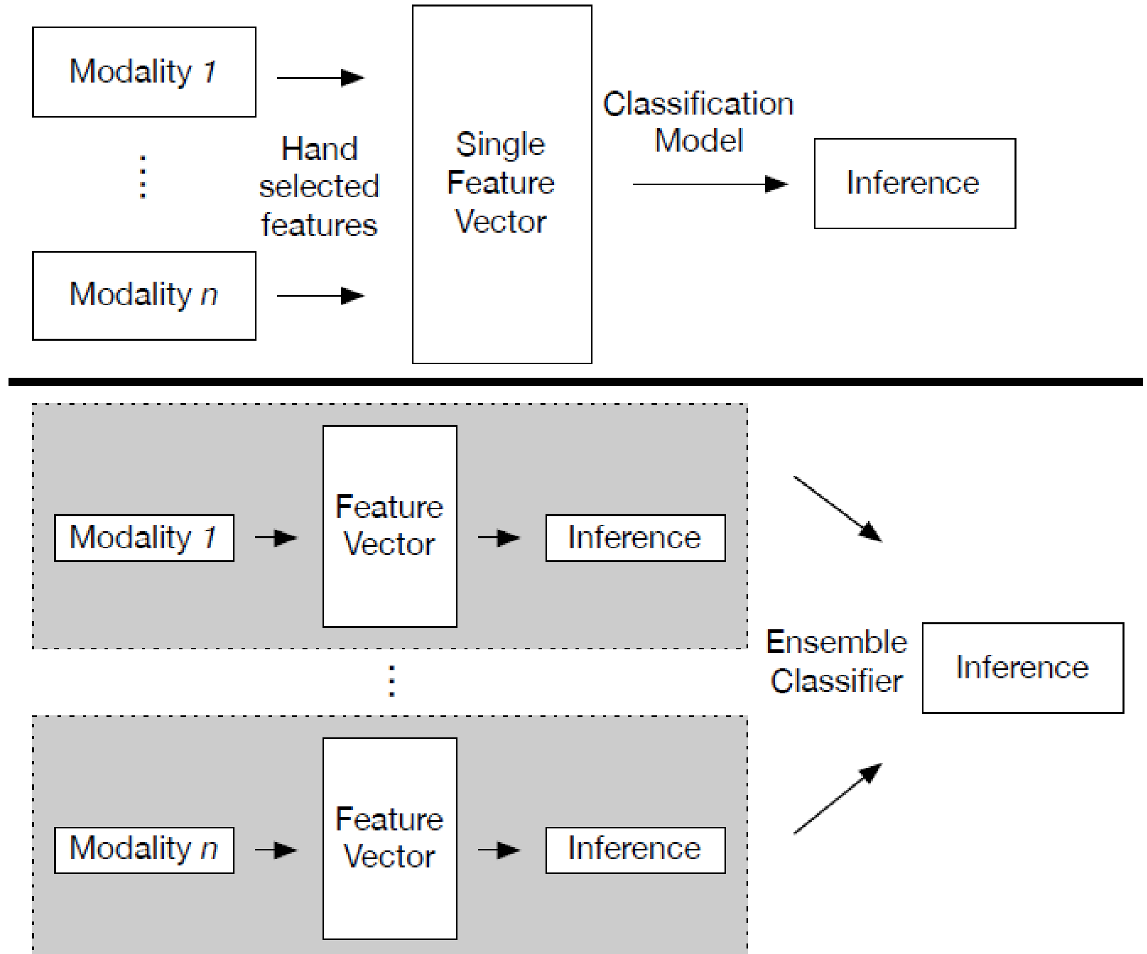
Sensor data fusion (1)

- **Feature concatenation with shallow classifiers**: Hand-selected features from each modality are combined into a single feature vector presented to a classifier for detection across all features.
- **Ensemble of shallow classifiers**: Separate classifiers operating on each sensor (modality) provide their estimation. These estimations provided by each sensing modality classifier are fused to yield an overall class estimation.



Reference: V. Radu, et al., Multimodal Deep Learning for Activity and Context Recognition, 2018, http://www.fahim-kawsar.net/papers/Radu.UbiComp2018-Camera.pdf

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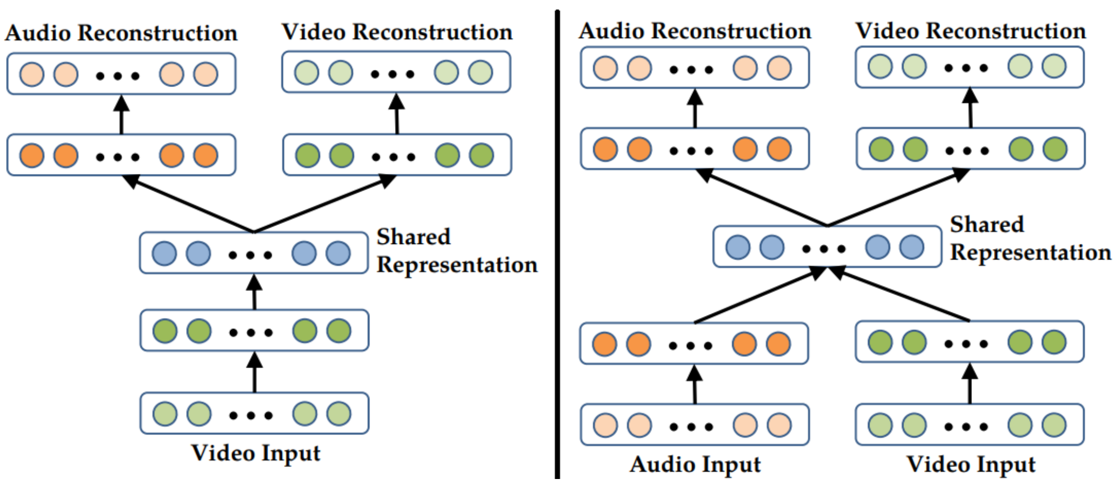
Sensor data fusion (2)

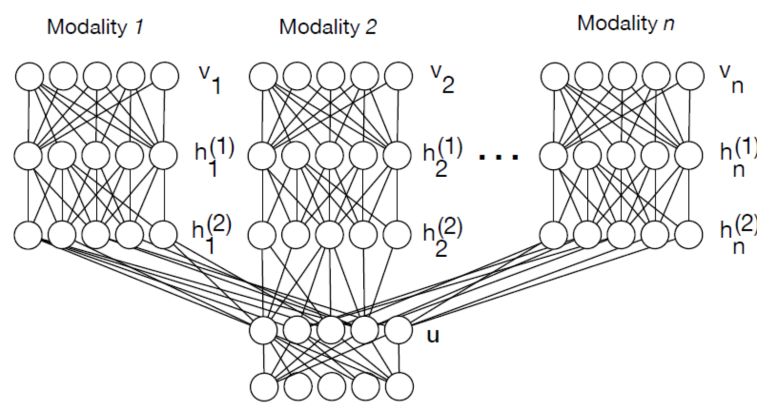
- Feature Concatenation Deep Learning

Sensor fusion is performed right at the input layer by concatenating raw sensor streams (or lightly processed data) of multiple modalities, to achieve a single large input space. Data propagation pipeline inside the network proceeds performing a set of transformations on the concatenated input.

- Modality-Specific Architecture in Deep Learning

Separate architectures are built for each modality to first learn sensor-specific information before their generated concepts are unified through representations that bridge across all the sensors (i.e., shared modality representations) later in the network.





Reference: J. Ngiam, et al., Multimodal Deep Learning, ICML 2011, https://people.csail.mit.edu/khosla/papers/icml2011_ngiam.pdf

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Data augmentation

- Data augmentation can be viewed as an injection of prior knowledge about the invariant properties of the data against certain transformations. Augmented data can cover unexplored input space, prevent overfitting, and improve the generalization ability of a machine learning model.
- Scaling changes the magnitude of the data in a window by multiplying by a random scalar.
- Magnitude warping changes the magnitude of each sample by convolving the data window with a smooth curve varying around one.
- Jittering is simulating additive sensor noise. These data augmentation methods may increase robustness against multiplicative and additive noise and improve performance.
- Time-warping perturbs the temporal location. By smoothly distorting the time intervals between samples, the temporal locations of the samples can be changed using time-warping.

Reference: T. T. Um et al., “Data augmentation of wearable sensor data for parkinson’s disease monitoring using convolutional neural networks,” ACM Int. Conf. on Multimodal Interaction, New York, NY, USA, 2017, pp. 216–220.

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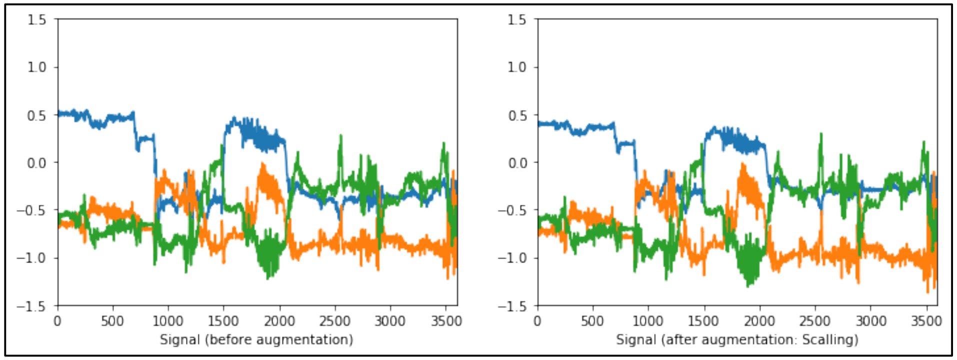
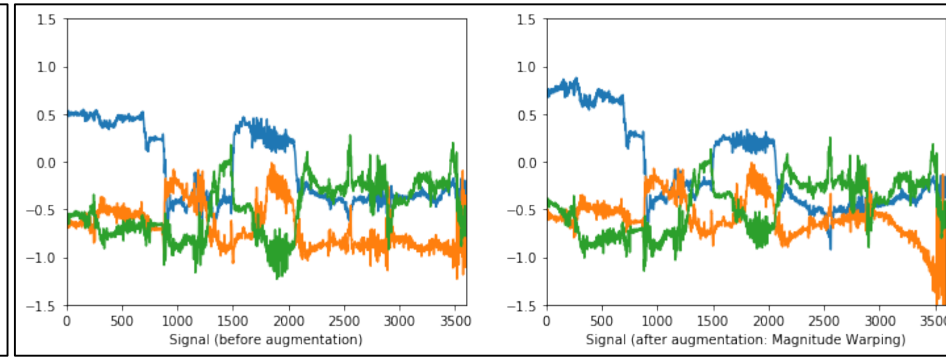
Data augmentation

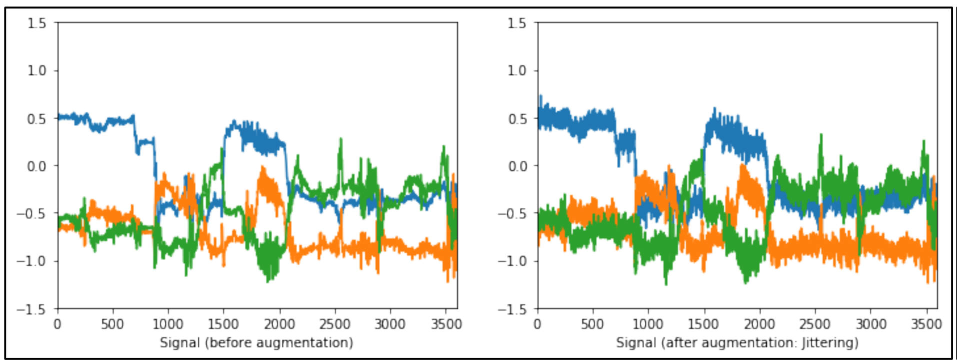
Scaling



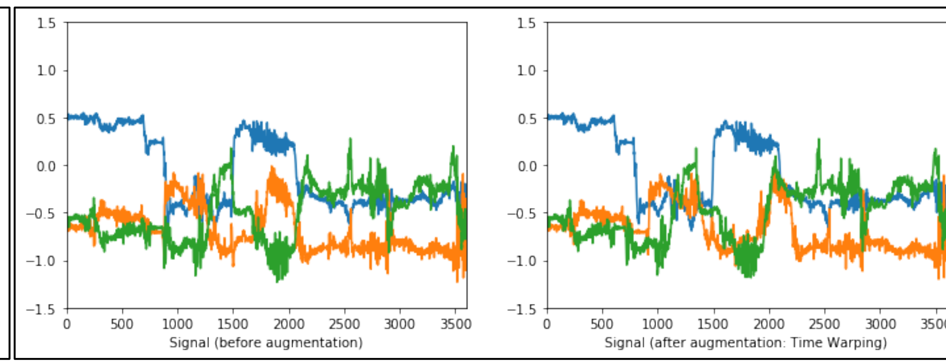
Magnitude warping



Jittering



Time-warping



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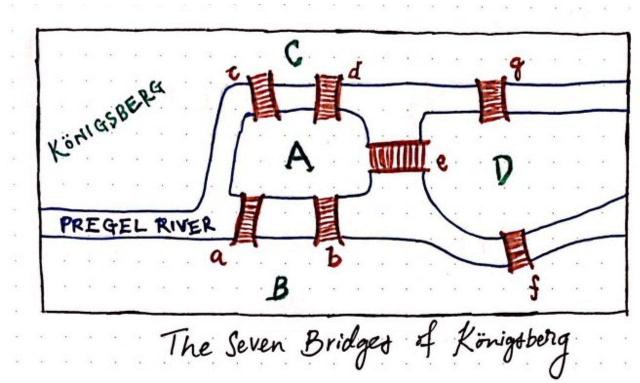
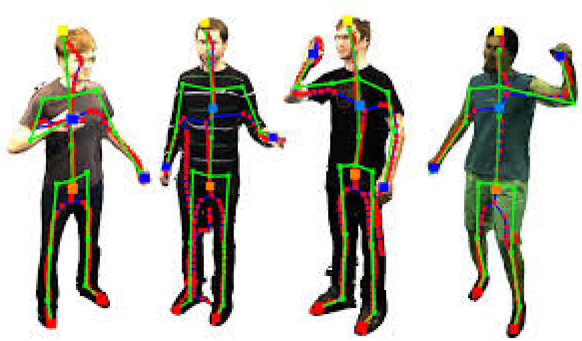
How about non-Euclidean signal?

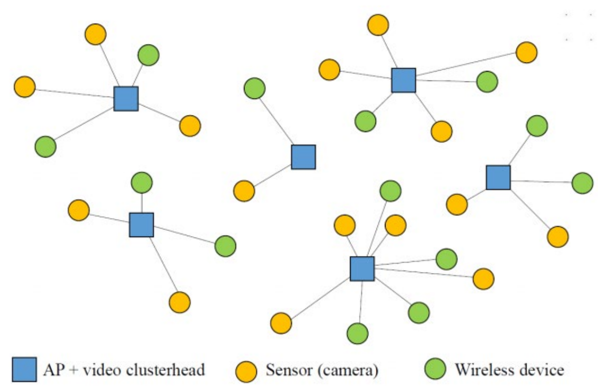
In-built graphs
- Sensor networks: Brain connectivity and functionality, Networking Devices
- Transportation networks: Trains, Cars, Airplanes, Pedestrians
- Power networks: Electricity, Water
- Social networks: Facebook, LinkedIn, Twitter

Constructed graphs (from data)
- 3D meshes
- Human skeleton

Idea: A graph signal representation. The famous problem of “Seven Bridges of Königsberg” in 1736, can we find a path through the city that cross each bridge once and only once?







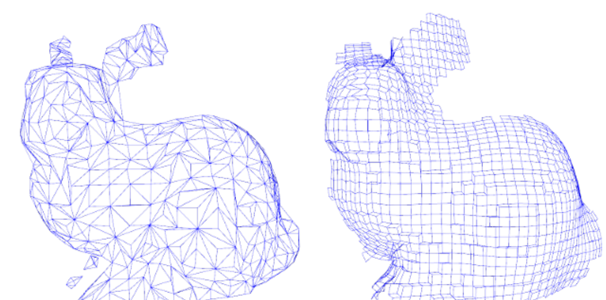


Photo: https://mappingignorance.org/2016/11/30/negotiating-wi-fi-channels-improve-bandwidth-surveillance-networks/figure-2-graph-model-of-a-wireless-surveillance-sensor-network/; https://medium.com/basecs/k%C3%B6nigsberg-seven-small-bridges-one-giant-graph-problem-2275d1670a12

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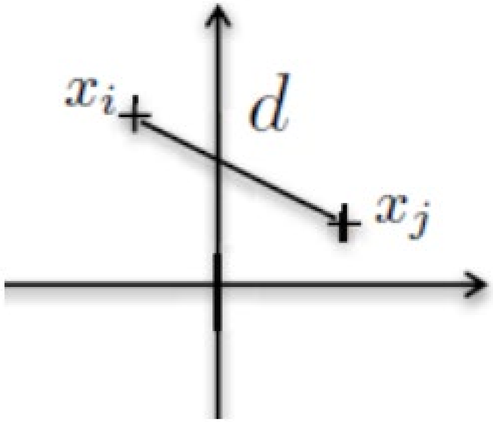
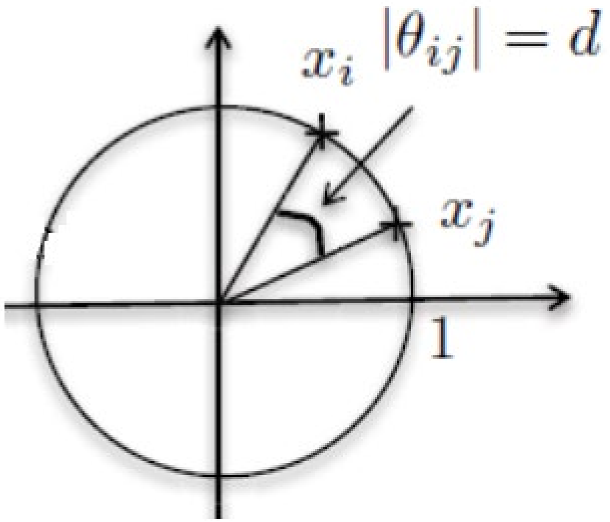
Graph signal representation

- What distances between data?
- What data features?
  - Raw features (e.g. raw sensor signal readings, etc)
  - Hand-crafted features (e.g. image color or gradient features in computer vision)
  - Learned features (PCA, sparse coding, or deep learning)
- Optimal graph construction is an open problem, depends on data and analysis tasks.



Euclidean distance

$$d(x_i, x_j) = \|x_i - x_j\|_2 = \sqrt{\sum_{m=1}^{d} |x_{i,m} - x_{j,m}|^2}$$



Cosine distance

$$d(x_i, x_j) = \left| \cos^{-1} \left(\frac{\langle x_i, x_j \rangle}{\|x_i\|_2 \|x_j\|_2} \right) \right|$$

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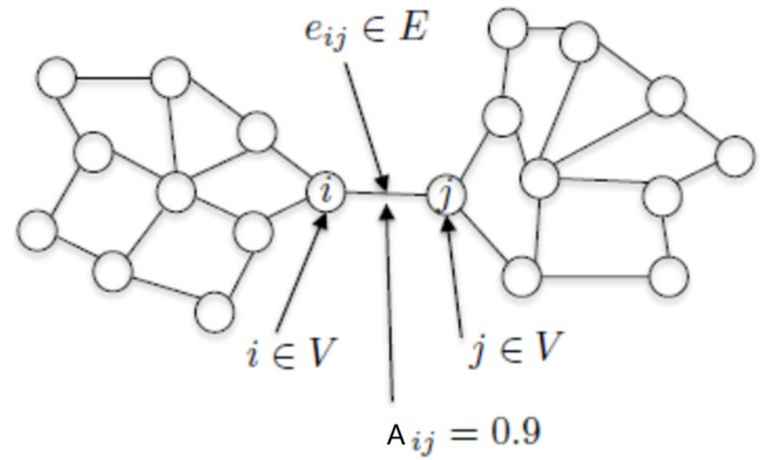
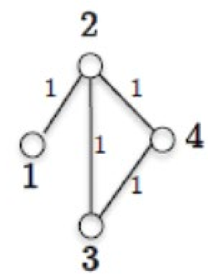
Graph signal representation

A graph of N nodes is defined by $G = (V, E, A)$

- V set of vertices/nodes
- E set of edges, and $|V| = N$
- A similarity/adjacency matrix

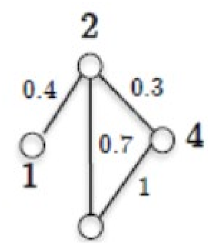


Binary: $A_{ij} = \begin{cases} 1 & \text{if } (i,j) \in E \\ 0 & \text{otherwise} \end{cases}$

$G=$ 

$$\Rightarrow A = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 1 \\ 0 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

Weighted: $A_{ij} = \begin{cases} a_{ij} \in [0,1] & \text{if } (i,j) \in E \\ 0 & \text{otherwise} \end{cases}$

$G=$ 

$$\Rightarrow A = \begin{array}{c} \\ 1 \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{c} \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{bmatrix} 0 & 0.4 & 0 & 0 \\ 0.4 & 0 & 0.7 & 0.3 \\ 0 & 0.7 & 0 & 1 \\ 0 & 0.3 & 1 & 0 \end{bmatrix} \end{array}$$

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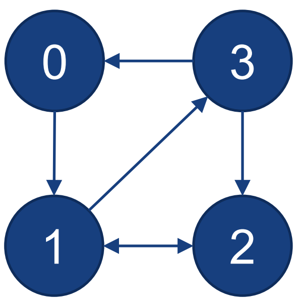
Graph signal representation: GCN

A *graph convolutional network* (GCN) is a neural network that operates on graphs.

- Given a graph $G = (V, E)$, a GCN takes an input feature matrix $\mathbf{X}$ (a dimension of $N \times F$), where N is the number of nodes and F is the number of input features for each node, and an adjacency matrix $\mathbf{A}$ (a dimension of $N \times N$).
- A hidden layer in the GCN is $\mathbf{H}^{(n)} = f\left(\mathbf{H}^{(n-1)}, \mathbf{A}\right)$, where $\mathbf{H}^{(0)} = \mathbf{X}$ and $f()$ is a propagation function. Each layer $\mathbf{H}^{(n)}$ corresponds to a feature matrix where each row is a feature representation of a node. At each layer, these features are aggregated to form the next layer's features using the propagation rule $f()$.
- Example: $\mathbf{H}^{(n)} = f\left(\mathbf{H}^{(n-1)}, \mathbf{A}\right) = \sigma\left(\mathbf{A}\mathbf{H}^{(n-1)}\mathbf{W}\right)$, where $\mathbf{W}$ is the weight matrix and σ is a non-linear activation function such as the Sigmoid function.



A toy example (directed graph)

$$\mathbf{A} = \begin{bmatrix} 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 \end{bmatrix} \quad \mathbf{X} = \begin{bmatrix} 0 & 0 \\ 1 & -1 \\ 2 & -2 \\ 3 & -3 \end{bmatrix} \quad \mathbf{W} = \mathbf{I}$$

$$\mathbf{H}^{(0)} = \mathbf{X}$$

$$\mathbf{H}^{(1)} = \mathbf{A}\mathbf{X} = \begin{bmatrix} 1 & -1 \\ 5 & -5 \\ 1 & -1 \\ 2 & -2 \end{bmatrix}$$

- The representation of each node (each row) is a weighted sum of its neighbors' features!
- The weight matrix is convolved recurrently.

Reference: Learning Convolutional Neural Networks for Graphs, ICML 2016, https://arxiv.org/abs/1605.05273

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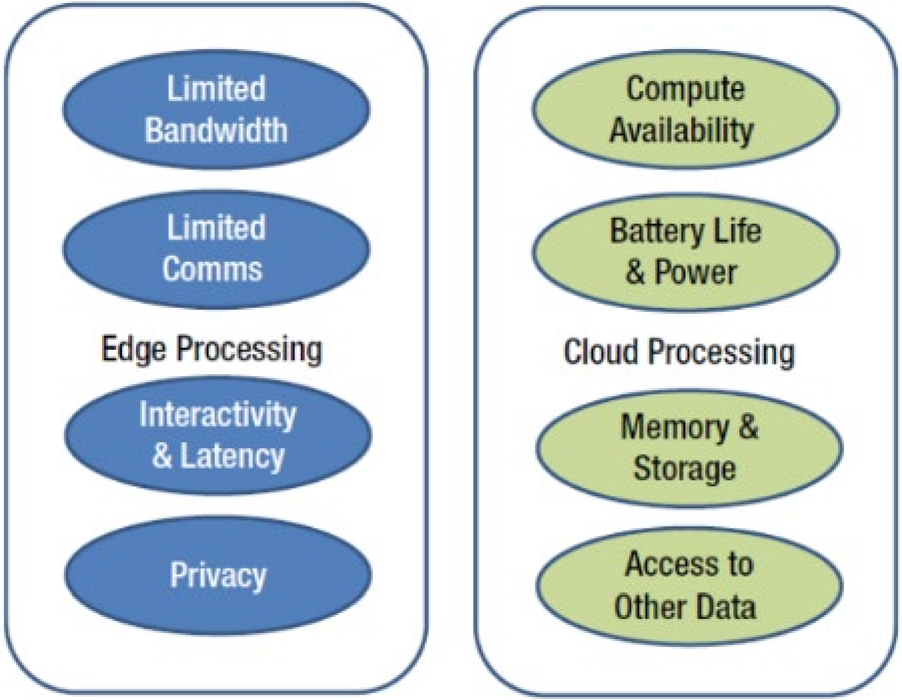
System considerations

- Compute Capability
  - A sensor node may only be able to accomplish a little amount of processing, while sending the data to the gateway or cloud can enable much richer analytics and services.
- Battery Life & Power Constraints
  - Sleep or send to cloud for major processing
- Storage & Memory Constraints
  - Limited on a local edge device, better on cloud
- Access to other data (crowd-sourced or expert data)
  - Tap on cloud platform where all crowdsourced data can be aggregated, processed, and stored
- Interactivity and Latency
  - Run as much of the processing closer to the device as possible to minimize the latency of sending data to the cloud
- Security and Privacy



Source: O. Tickoo and R. Iyer, Making Sense of Sensors: End-to-End Algorithms and Infrastructure Design from Wearable-Devices to Data Centers, Apress, 2016.

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Topics

- Introduction to making sense of sensor data
- Case studies of sensor data sensemaking

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Example: Smart living in HDB

Smart HDB Home pricing	Bundled with	Description	Functionality
Utilities Management	S$6.99/month	1 x Smart Hub 1 x Energy Clamp 1 x Water MIU (Meter Interface Unit)	Help residents make more informed decisions on how to save energy and water at home. Service packages available to monitor individual household appliance energy consumption as well as overall household water and energy consumption
Elderly Care	S$13/month	1 x smarthub 4 x Wireless Motion sensors 1 x door sensor 1 x panic button Free installation 12-month warranty	Helps families to monitor elderly relatives living alone at home by collecting information from sensors placed in flats, and by providing alerts via text message to authorised caregivers.

Source:
https://www.m1.com.sg/AboutM1/NewsReleases/2016/M1%20supports%20Smart%20HDB%20Home%20programme%20with%20affordable%20Elderly%20Care%20and%20Utilities%20Mgt.aspx

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Example: Classification of manufacturing defects

Images: (a) without defect, (b)-(c) with small defects, and (d)-(f) with big defects.

(a)

(b)

(c)

(d)

(e)

(f)

Source: O. Essid, H. Laga, C. Samir, Automatic detection and classification of manufacturing defects in metal boxes using deep neural networks, ***PLOS ONE***, Nov. 2018, https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0203192

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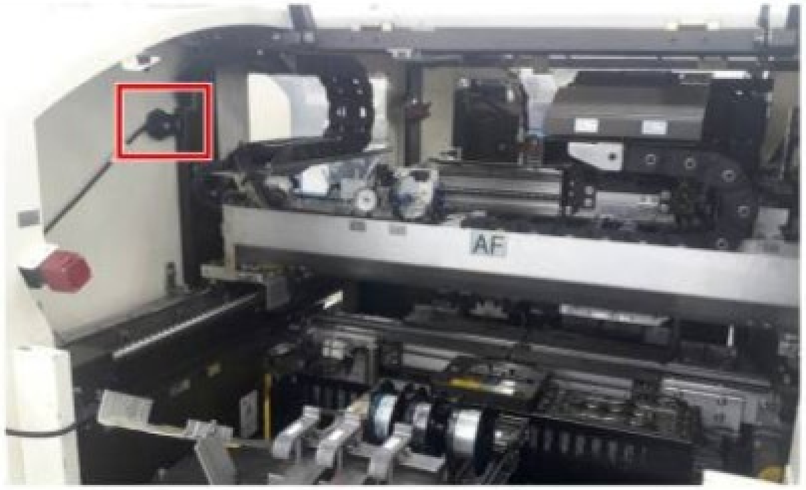
Example: Anomaly detection of time series sound data

Sound data is acquired from SMD assembly machine with 192 kHz of sampling rate. The data collection process is shown in (a). Sequential machine operational sound data are collected from an operating SMD assembly machine placing a microphone as indicated by the red bounding box in (b).

(a) the Surface Mounted Device (SMD) assembly machine



(b) the microphone for collecting data

Source: Y. Park and I. Yun, Fast Adaptive RNN Encoder–Decoder for Anomaly Detection in SMD Assembly Machine, ***Sensors***, Oct. 2018, https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6211082/

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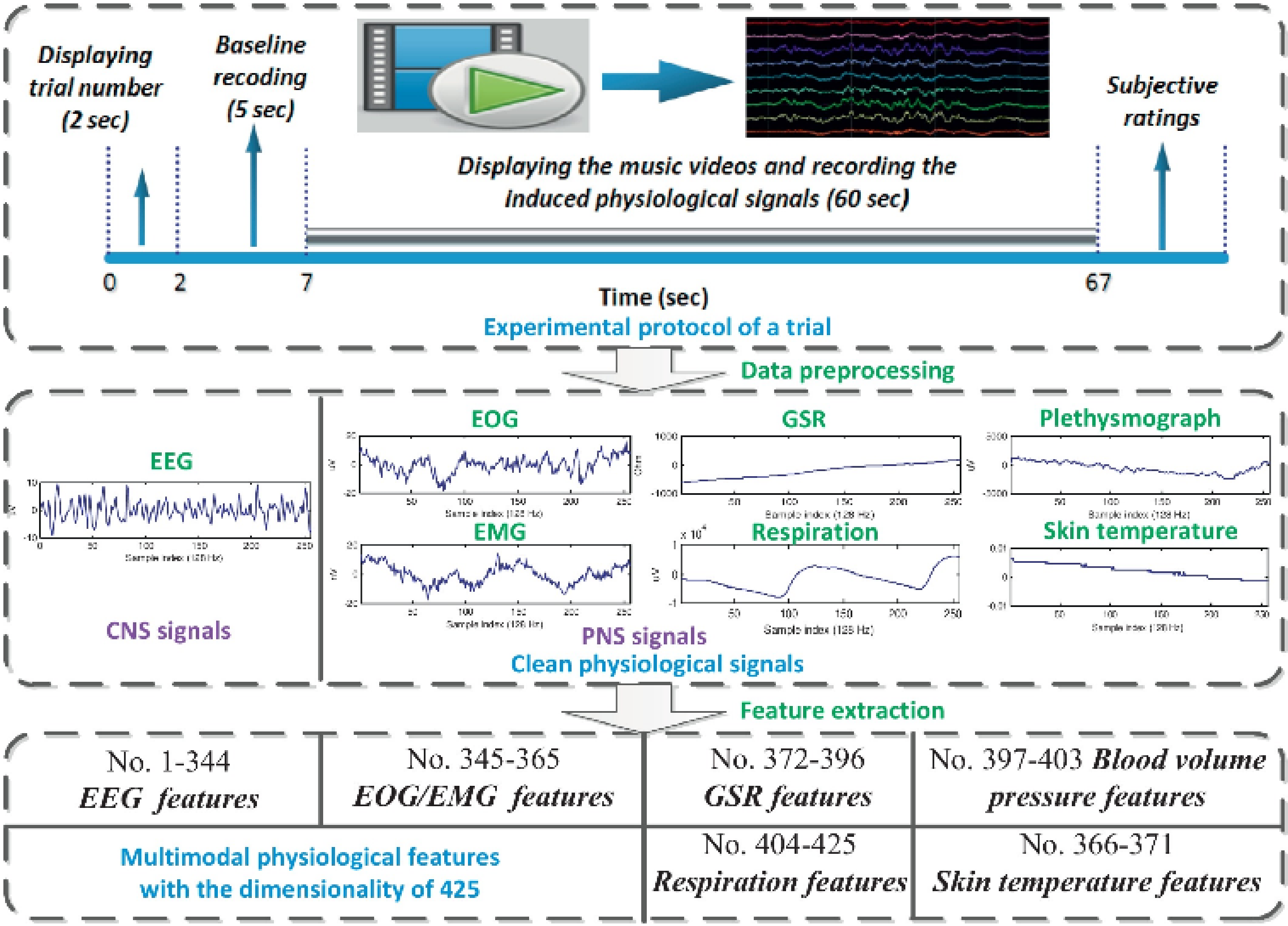
Example: Human emotion recognition



Source: Z. Yin, M. Zhao, Y. Wang, J. Yang, J. Zhang, "Recognition of emotions using multimodal physiological signals and an ensemble deep learning model," ***Computer Methods and Programs in Biomedicine***, Vol. 140, Mar. 2017, pp. 93-110.

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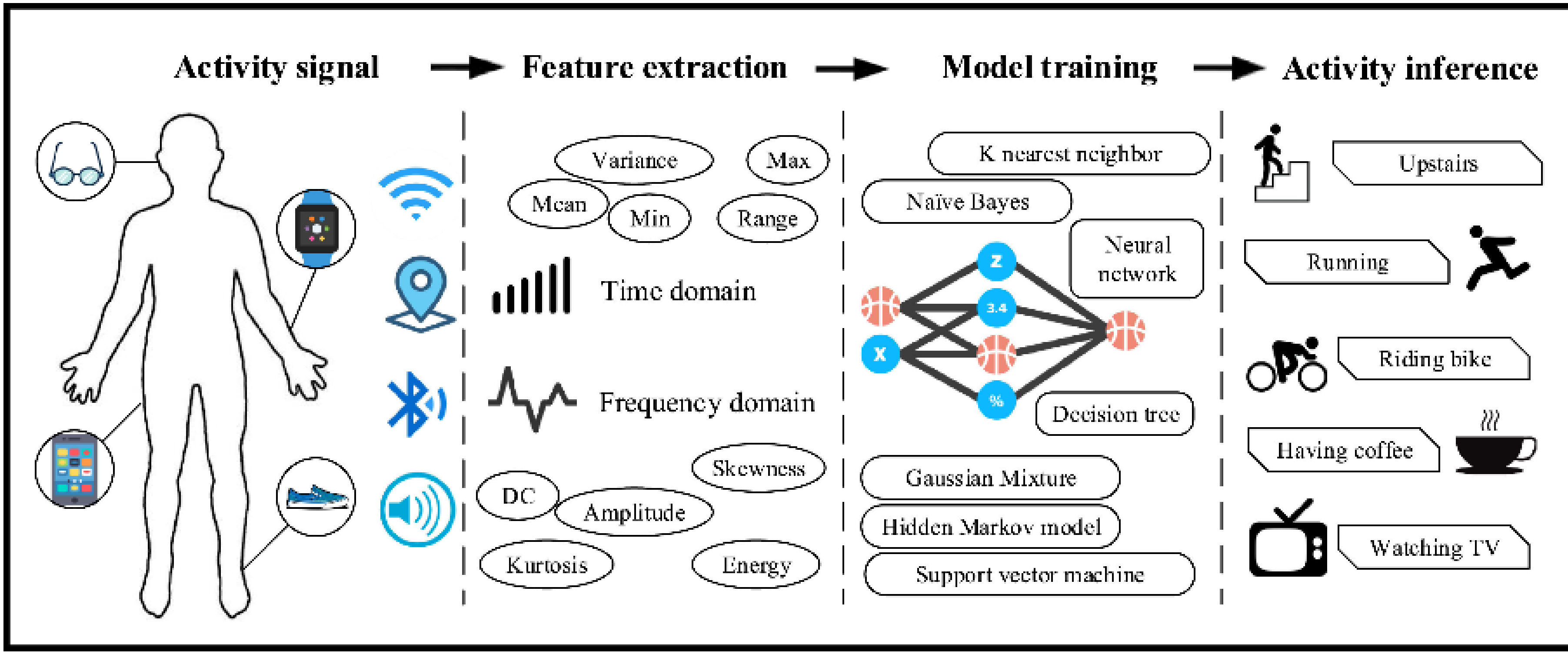
Example: Sensor-based human activity recognition



Source: J. Wang, Y. Chen, S. Hao, X. Peng, and L. Hu, “Deep learning for sensor-based activity recognition: A survey,” ***Pattern Recognition Letters***, Vol. 119, Mar. 2019, pp. 3-11.

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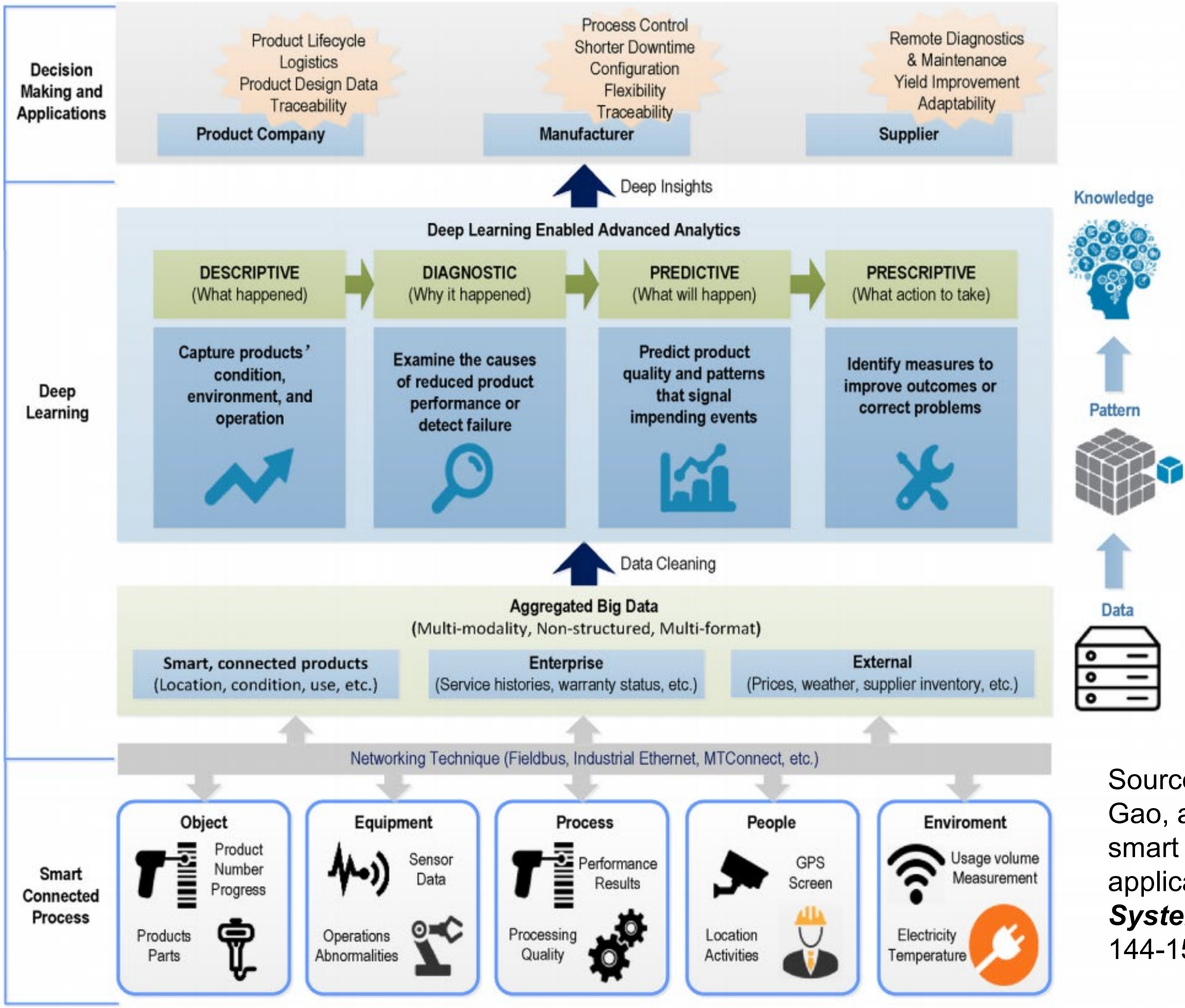
Example: Smart manufacture



Source: J. Wang, Y. Ma, L. Zhang, R. Gao, and D. Wu, "Deep learning for smart manufacturing: Methods and applications," ***Journal of Manufacturing Systems***, Vol. 48, Part C, Jul. 2018, pp. 144-156

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Example: Design an intelligent sensing system for smart living

- Activity Recognition in Home Using Ubiquitous Sensors, http://courses.media.mit.edu/2004fall/mas622j/04.projects/home
- Sensor: Switch sensor
- Description: Around 80 sensor data collection boards equipped with reed switch sensors were installed in two single-person apartments for two weeks. The sensors were installed in everyday objects such as drawers, refrigerators, containers, etc. to record opening-closing events (activation deactivation events) as the subject carried out everyday activities.

Source: http://courses.media.mit.edu/2004fall/mas622j/04.projects/home

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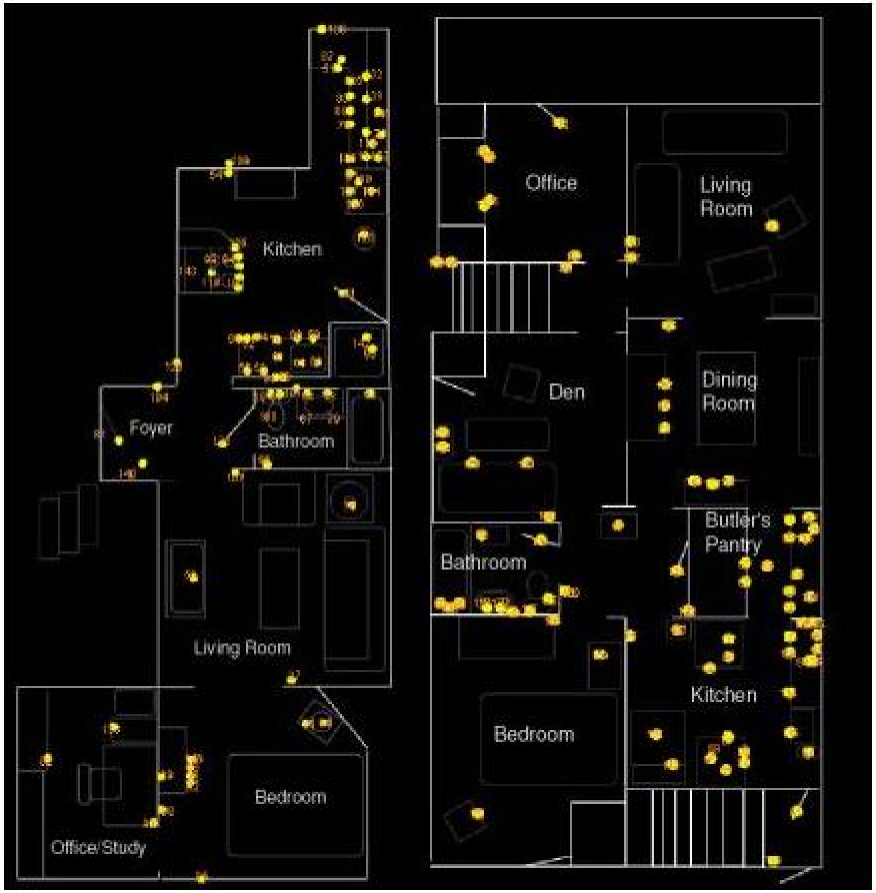
Example: Design an intelligent sensing system for smart living

Example data

Number of Examples per Class		
Activity	**Subject 1**	**Subject 2**
Preparing dinner	8	14
Preparing lunch	17	20
Listening to music	-	18
Taking medication	-	14
Toileting	85	40
Preparing breakfast	14	18
Washing dishes	7	21
Preparing a snack	14	16
Watching TV	-	15
Bathing	18	-
Going out to work	12	-
Dressing	24	-
Grooming	37	-
Preparing a beverage	15	-
Doing laundry	19	-
cleaning	8	-



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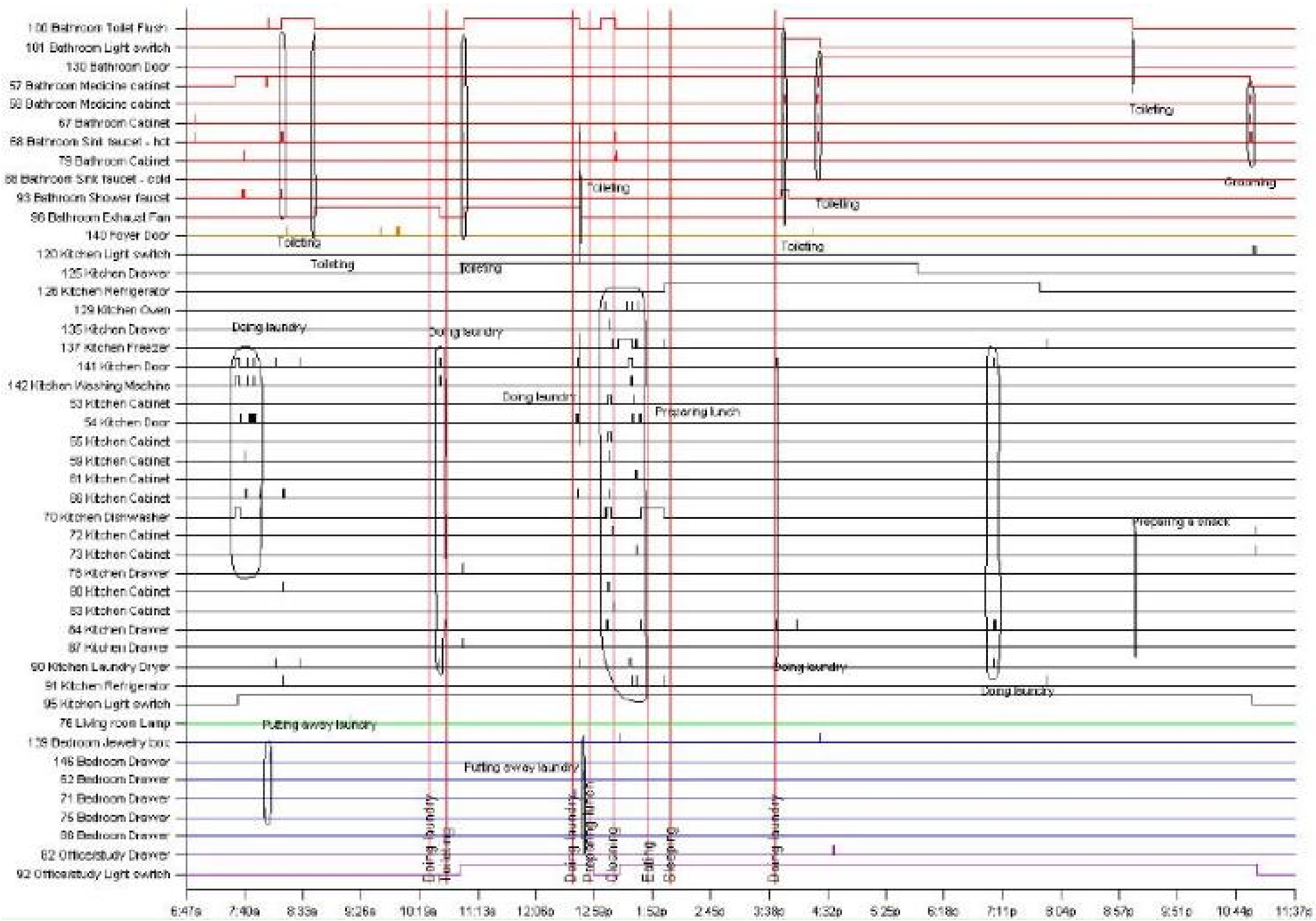
Example: Design an intelligent sensing system for smart living

Example data



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Discussion: Transportation

Public transport analytics: Various sensor data, such as fare cards, Wi-Fi, CCTV systems and cellular networks are used to better model commuter flows, improve planning.

- Bus Arrival XML
- Bus Routes XML
- Bus Services XML
- Bus Stops XML
- Carpark Availability XML
- ERP Rates XML
- Estimated Travel Times XML
- Faulty Traffic Lights XML
- Road Openings XML
- Road Works XML
- Taxi Availability XML
- Traffic Images XML
- Traffic Incidents XML
- Traffic Speed Bands XML
- VMS / EMAS XML

Reference: https://www.mytransport.sg/content/mytransport/home/dataMall.html; https://sgtrafficwatch.org/

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Discussion: Transportation

- Study the LTA datamall, answer following questions in Google spreadsheet individually.

I propose to	
develop	application, e.g., bus route optimization
for	target organization, e.g., SMRT
because	impact of your proposed application
I propose to	
use	types of sensor/data
and use	methods of feature extraction / representation / machine learning / sense making

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Summary

- Making sense of sensor data pipeline
- Single type of sensor data analytics
- Multiple types of sensor data analytics
- Case studies on designing an intelligent sensing system

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Thank you!

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