

Special Topics in Wireless Networking IoT Environments Fog & Edge Paradigms

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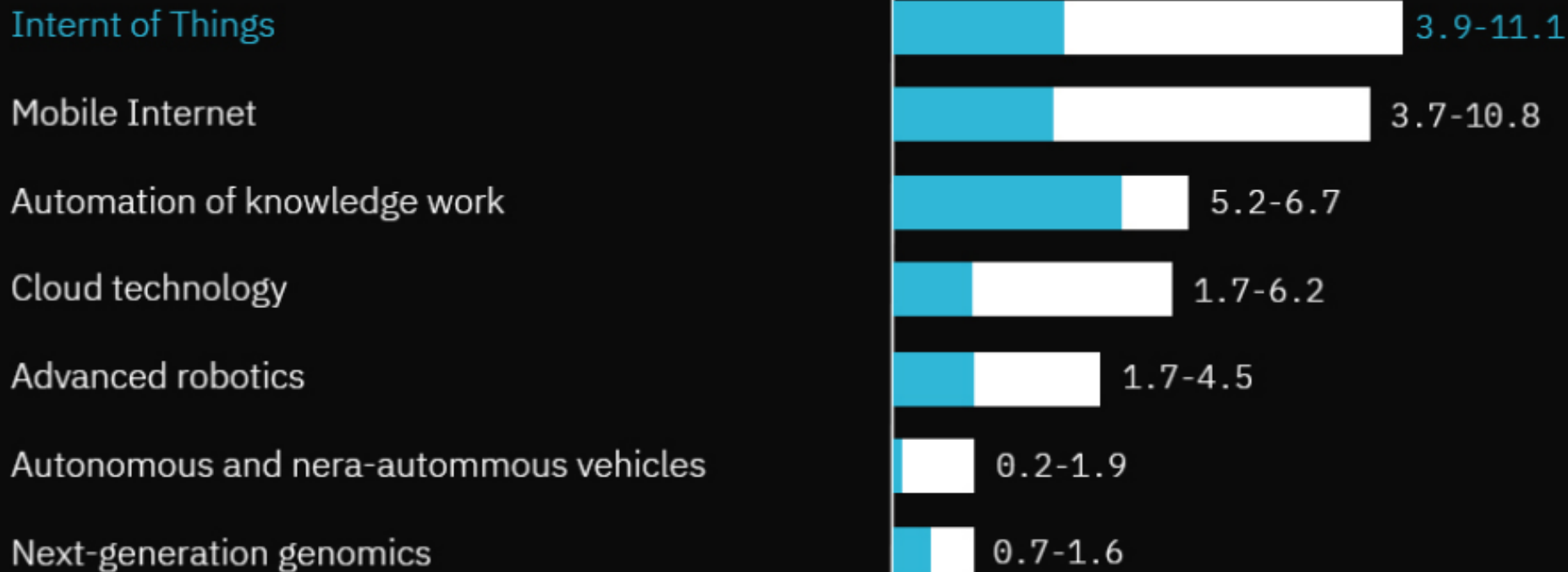
ACKNOWLEDGE & THANKS:

Slides & material obtained by Professor Gorlatova's lectures (Duke University)

<https://maria.gorlatova.com/teaching/spring-2020-ece590-compsci590-edge-computing/>

McKinsey&Company predicts that, by 2025, the overall economic impact of the IoT could reach \$11.1 trillion, surpassing sectors such as "Mobile Internet", "Automation of knowledge work" and "Cloud technology".

Range of sized potencial econmic impact  X-Y
Low High



Challenges in Networking

- **Growing amount of data** which require processing & bandwidth (e.g. big data, UHD)
- **Growing number of users and devices** (e.g. IoT environments)
- **Ultra-low latency applications** (e.g. industry automation, health-care, entertainment)
- **Security & privacy risks** associated with large-scale data storage & analysis in the cloud

Bringing the Physical & Digital World Together

- Various organizations are increasingly exploring them for city planning, smart infrastructure, manufacturing, emergency operations, and more
- While technologies that simulate the physical world have been around for years, the combination of cheap sensors and IoT, machine learning, and cloud enables more sophisticated analyses, real-time simulations, and fast emulations
 - **understand what-if scenarios clearly**
 - **simulate various conditions**
 - **predict results**

Models + data = insights and real value

Internet of Things (IoT)

Technologies & systems enabling the **virtualization of the physical world**

- Realized through the **use of standalone or embedded networked sensors & microprocessors** deployed in physical objects or environments that are then **connected to back-end systems & applications** via network protocols & **architectures**
- Creates value by combining sensor capabilities with back-end & front-end systems that **turn raw data into information services of value:**
- Captures & stores data and data analytics to turn that data into **actionable insight** and enable **value-added services**
- Can control physical systems remotely or autonomously

Architecture Paradigms

Multi-tier Architectures

Sensors (one tier), gateways (second tier), edge or cloud (third tier)

Gateway:

Participate in different architectural paradigms

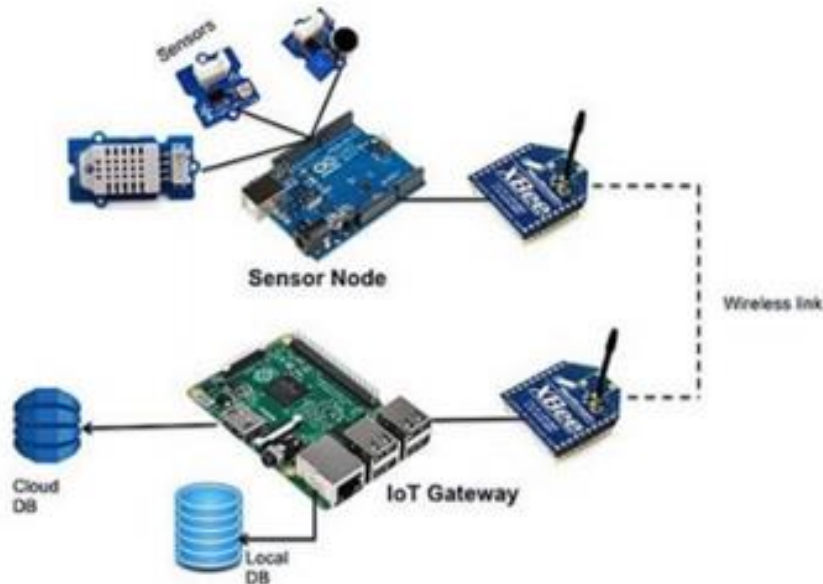
- IoT node centralization & aggregator
- Unified cloud access
- Wearable: everyone has a cell phone
- In-home or in-office installations: every device can access a single control unit (e.g., set-top box paradigm)
- Drone or robot: mobile gateway

IoT environments

- Tightly constrained design space
- Reduced energy consumption
- (Extremely) low computing capability

Standard IoT Architectures

- **IoT nodes --> Gateway --> Cloud**



Note-to-gateway communication

6LoWPAN	DASH7	Wireless M-Bus
ANT	ISA100	Z-Wave
Bluetooth	Wireless HART	Zigbee and Zigbee IP

Other IoT Architectures: Direct WiFi Connectivity

- Usually for plugged-in devices
 - Have the power budget for it
- Low-end mobile devices: uncommon
- Amazon Dash Button
 - Setup via ultrasound
 - On-demand communication via WiFi



Other Architectures: Low-power Wide Area Communications

Long-range connectivity, specifically for the IoT

- Narrow band IoT – cellular standards
- Low-power wide-area networking solutions: SigFox, LoRa

OR

Gateways: Mobile Phones

- Wearables



Gateways: Dedicated Hubs

A stationary plugged-in device

Smart homes, smart factories, ...

Many different ones:
“Best smart home hubs of 2018”



Samsung Smart Things Hub Exam



- Lights, speakers, locks, thermostats, sensors
- Z-Wave, Zigbee
- “The brain of the smart home”

Gateways: Dedicated Hubs

- A stationary plugged-in device
- Smart homes, smart factories, ...
- Many different ones: *“Best smart home hubs for 2019”*

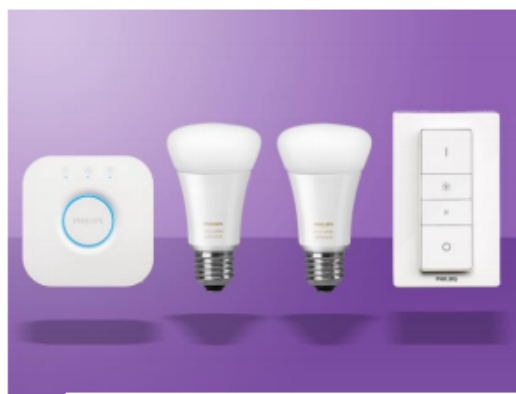


Gateways can easily collect a lot of local and remote information on system behavior and properties

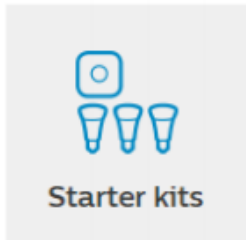
End-User Clients or Near-User Edge Devices: A Range of Options

- Gateways, stationary or mobile
- Set-top boxes
- Servers, cloudlets
- Mini-datacenters
- Different properties

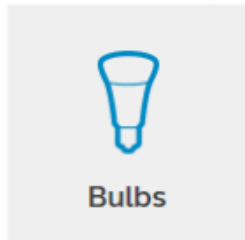




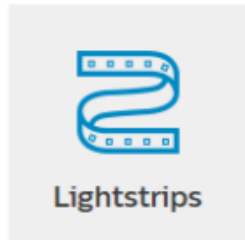
- Control your lights
 - White, color
- Switches and lights



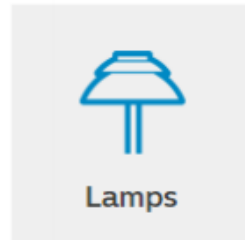
Starter kits



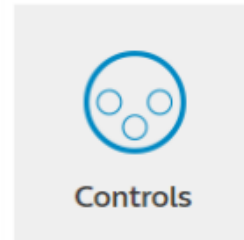
Bulbs



Lightstrips



Lamps



Controls



- Zigbee Light Link communications
 - Low-power
 - Low data rate
 - Short distance
- Hue Bridge: “the heart of the system”

QoE in IoT

- Service latency
- Energy consumption
- Task completion success rate

Higher-End Mobile Devices



- Mobile phones: prevalent use case
- AR/VR, drones, smart cars – emerging use cases

- Complex, often high-volume, data: various sensors (accelerometers, video, audio)
 - More complex operations
- Thinking in full application pipelines, rather than individual tasks
- Battery-limited ➤How long they last ➤How much heat they produce • Usability limited by the batteries

Cloud computing

- Provides computing resources like CPU resources, operating system environment & application development, which are broadly distributed over the Internet
- QoS: technical parameters that determine the quality of processing, storage and network used for transferring data from cloud to client but does not take the customer into consideration
- QoE defines the performance of cloud processing, storage & network from the customer perspective
- Manage & provide services according to customer's demand

Cloudlets

- Local mini-clouds
- Envisioned properties:
- Powerful, well-connected, and safe
- Close at hand
- Build on standard cloud technology

Aims of Edge & Fog Computing

- Move decision making operations as close to data sources as possible by leveraging resources on the edge, such as mobile base stations, gateways, network switches, routers, to reduce **response time & network latency**
- Fulfill increasingly **complex requirements** that demand the composition of multiple services
- Achieve **reliability & improve sustainability**, services spanning across multiple geographically distributed CDCs have also become more widespread

Catalysts for Edge & Fog Computing

- Rapid advances in processing & storage capability of devices
e.g., home set top boxes, smartphones, wearable devices
- Much of the data does not need to go to cloud
 - Stay-at-home, in office, in built environment infrastructure
 - Aggregation is your friend in many ways

Combines several research areas/technologies: systems, networking, hardware, **algorithms/machine-learning**

Improve the user Quality of Experience & engagement

Edge Computing Architecture

Employs end-user clients or near-user edge devices to carry out a substantial amount of **computation, storage, communication, & control**



Making Things Easier: AWS Greengrass, Azure IoT Edge

- Can create your own gateway
 - Connect devices with the cloud and with one another
- Physical protocol translation is separate
 - E.g., for low-power BLE devices, needs a BLE/WiFi gateway

Data Collection Applications: Via Additional Edge Nodes



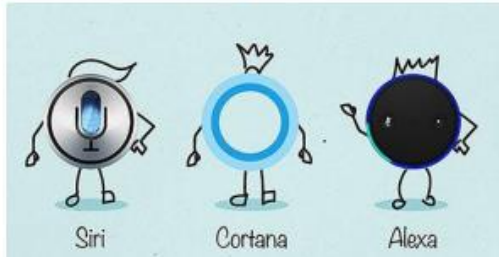
Sensors

Edge nodes

Cloud

How Edge Helps: Mobile Offloading

- Executing code **not** on the mobile device
- E.g., image, video, audio, other sensor data processing
 - Face detection, person identification
 - Language translation, speaker identification
 - Activity tracking, gesture recognition



- All offload processing to the cloud

Reducing Mobile Device Energy Consumption

- Energy to {transmit data + receive results} < Energy to {execute the operation on the mobile device}

Design principles:

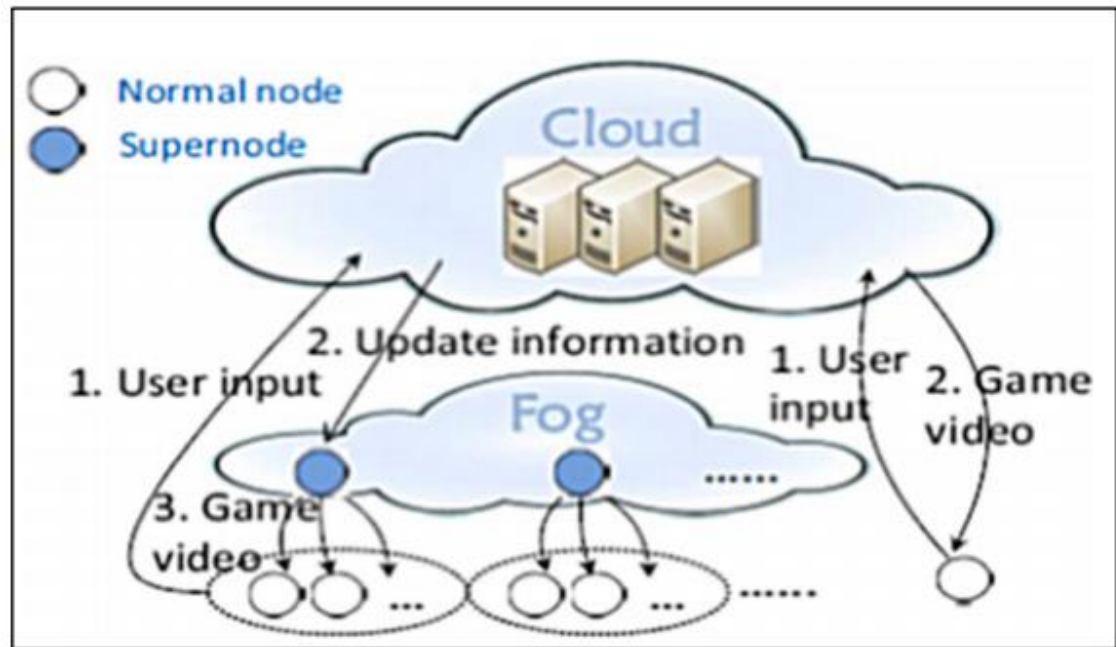
- Pick the **most compute-intensive parts of the operation**
- Reduce the size of what is transmitted: data and results
- Order-of-magnitude mobile energy savings possible

Often: transmit partially processed rather than raw, data

- Energy to {**extract features** + transmit extracted features + receive results} < Energy to {transmit data + receive results}
- Energy to {extract features + transmit extracted features + receive results} < Energy to {execute the operation on the mobile device}

Fog & Edge Computing

- Supernodes: closed to end users & connected to clouds
- EdgeCloud uses servers in the nearby location to clients to improve delay but the long distance of users to cloud is still a major problem



Fog vs. Edge Computing

S. no.	Fog computing	Edge computing
1	Device <u>independent</u> , intelligent, and <u>knowledge of whole fog network</u>	Device and services aware, no knowledge of entire network
2	<u>Controls all devices in the network</u>	<u>Limited control in the edge network</u>
3	Fog computing extends cloud to fog level in a continuum	Edge computing is cloud unaware
4	Complete network scope	<u>Limited network scope</u>
5	<u>Enables multiple IoT verticals and provides support for them</u>	No IoT vertical awareness
6	Supports integration of multiple verticals	No IoT vertical integration
7	Versatile fog nodes that perform variety of tasks like website hosting and management	Edge device is controlled and communicated with edge controllers
8	End-to-end security	Security scope is limited to devices

Gartner.

This research note is restricted to the personal use of Kathleen Reilly (kathleen.reilly@gartner.com).

Maverick* Research: The Edge Will Eat the Cloud

Published: 22 September 2017 ID: G00338633

Analyst(s): *Thomas J. Bittman*

Summary

The growth of the Internet of Things and the upcoming trend toward more immersive and interactive user interfaces will flip the center of gravity of data production and computing away from central data centers and out to the edge. (Maverick research exposes unconventional thinking and advice.)

Overview

Specific Maverick Caution

This research contradicts prevailing views on the future of cloud computing, the topology of computing architectures and the nature of applications as we move toward digital business. Instead of continued growth of mega data centers, compute and storage will move toward the edge, due to the Internet of Things and new user/machine interfaces.

More on This Topic

This is part of an in-depth collection of research. See the collection:

SERIES OVERVIEW

Maverick* Insights Drive Creative Destruction of Business as Usual: A Gartner Trend Insight Report (<https://www.gartner.com/document/code/342945?ref=grbody&refval=3806165>)

"forty percent of large enterprises will be integrating edge computing principles into their 2021 projects, up from less than 1% in 2017"

Edge Computing

- Brings **cloud computing** functionalities closer to the **end users**
- **Provides computing & caching resources**
- Enables **computation & data offloading** to the network edge to achieve **low latency** and **high bandwidth** requirements
- Allows **reduction of backbone network traffic** through edge processing
- Provides “**cognition**”: advanced intelligence close to users

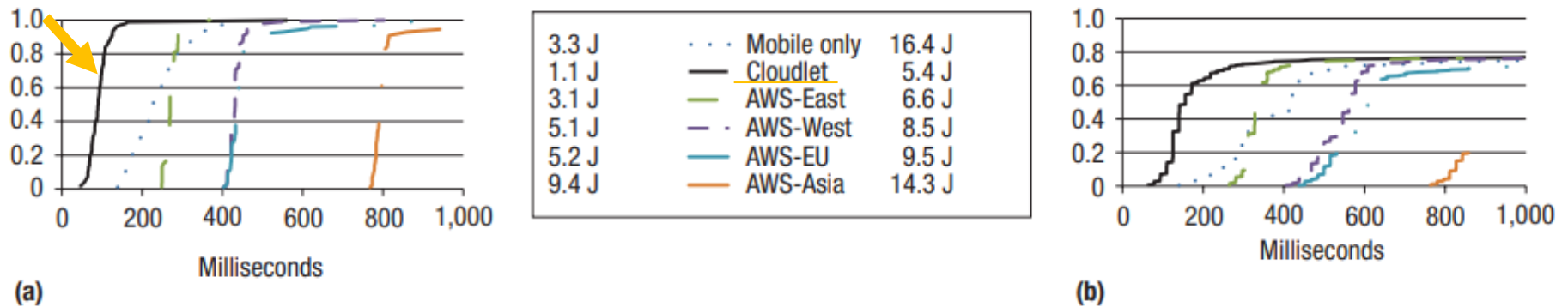
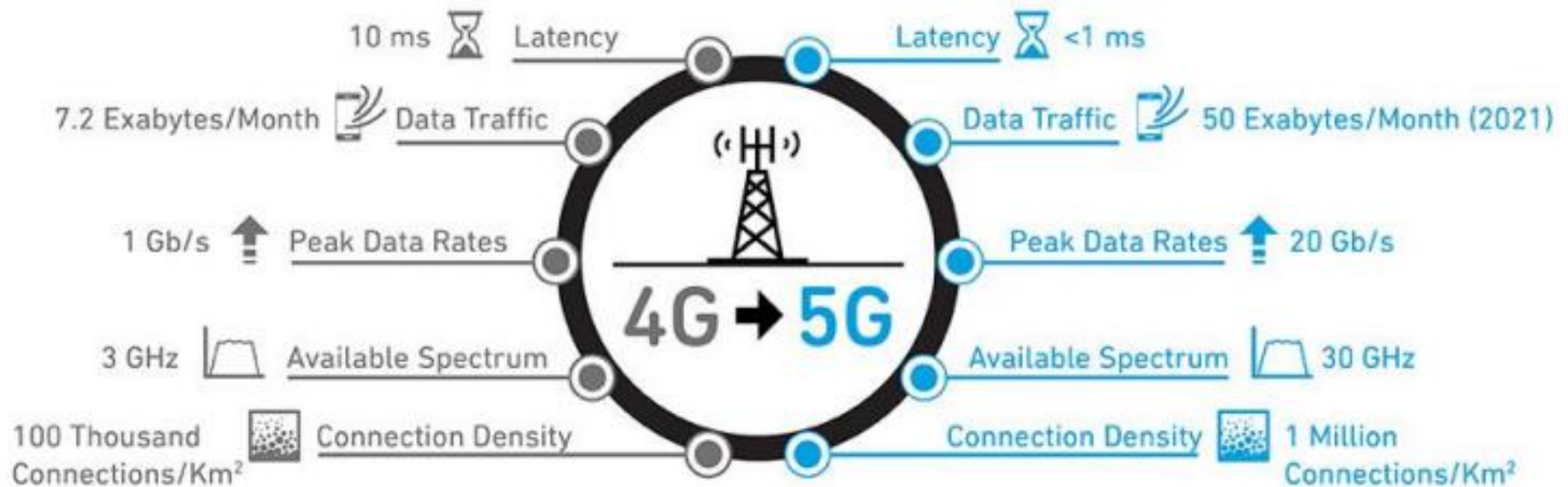


FIGURE 1. Response time distribution and per-operation energy cost of an (a) augmented reality and (b) face recognition application on a mobile device, in which an image from the device is transmitted over a Wi-Fi first hop to a cloudlet or an Amazon Web Services (AWS) datacenter. The ideal is best approximated by a cloudlet, demonstrating the importance of low-latency offload services. Figure adapted from K. Ha et al., "The Impact of Mobile Multimedia Applications on Data Center Consolidation," *Proc. 2013 IEEE Int'l Conf. Cloud Eng. (IC2E 13)*, 2013, pp. 166–176.

Towards 5G

- Pilot deployments, trials ongoing

Comparing 4G and 5G



Edge Computing is a Part of 5G

- One of the building blocks, offering:
- Lower latency
- **Reduced load on core network**
- Idea: **co-locate edge computing servers with cellular base stations**

ETSI MEC Standardization effort:

European Telecommunications Standards (ETSI)

Multi-access Edge Computing (MEC)

Since 2014

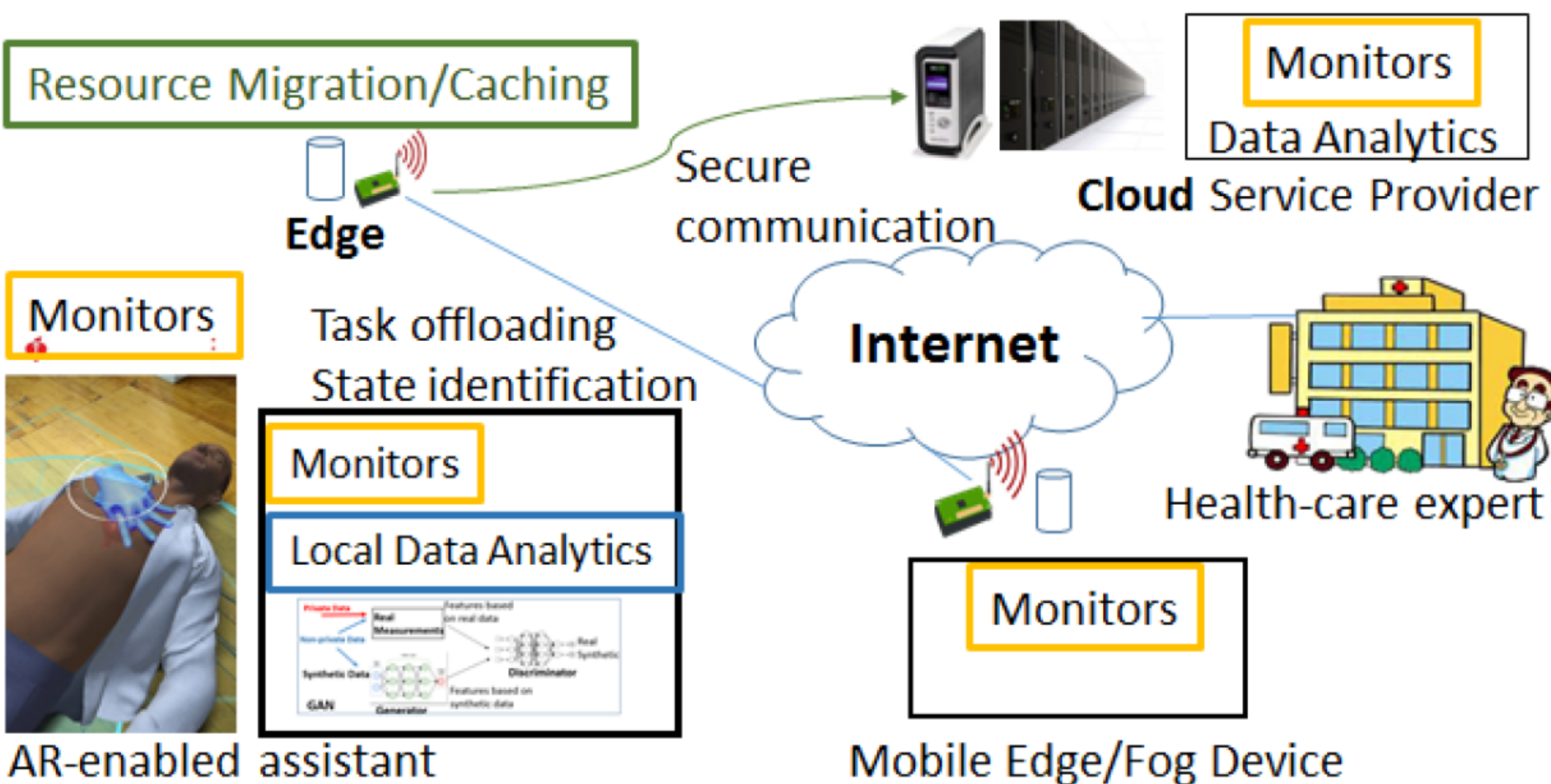
- UE identity API
- System, host, and platform management
- Bandwidth management API
- UE application interface
- Application lifecycle, rules and requirements management
- Radio Network information API

Telecom Edge vs. Cloudlet Edge

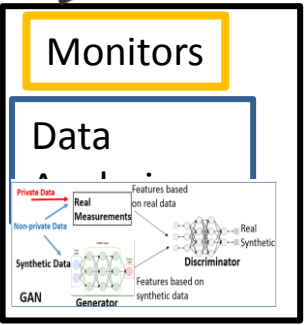
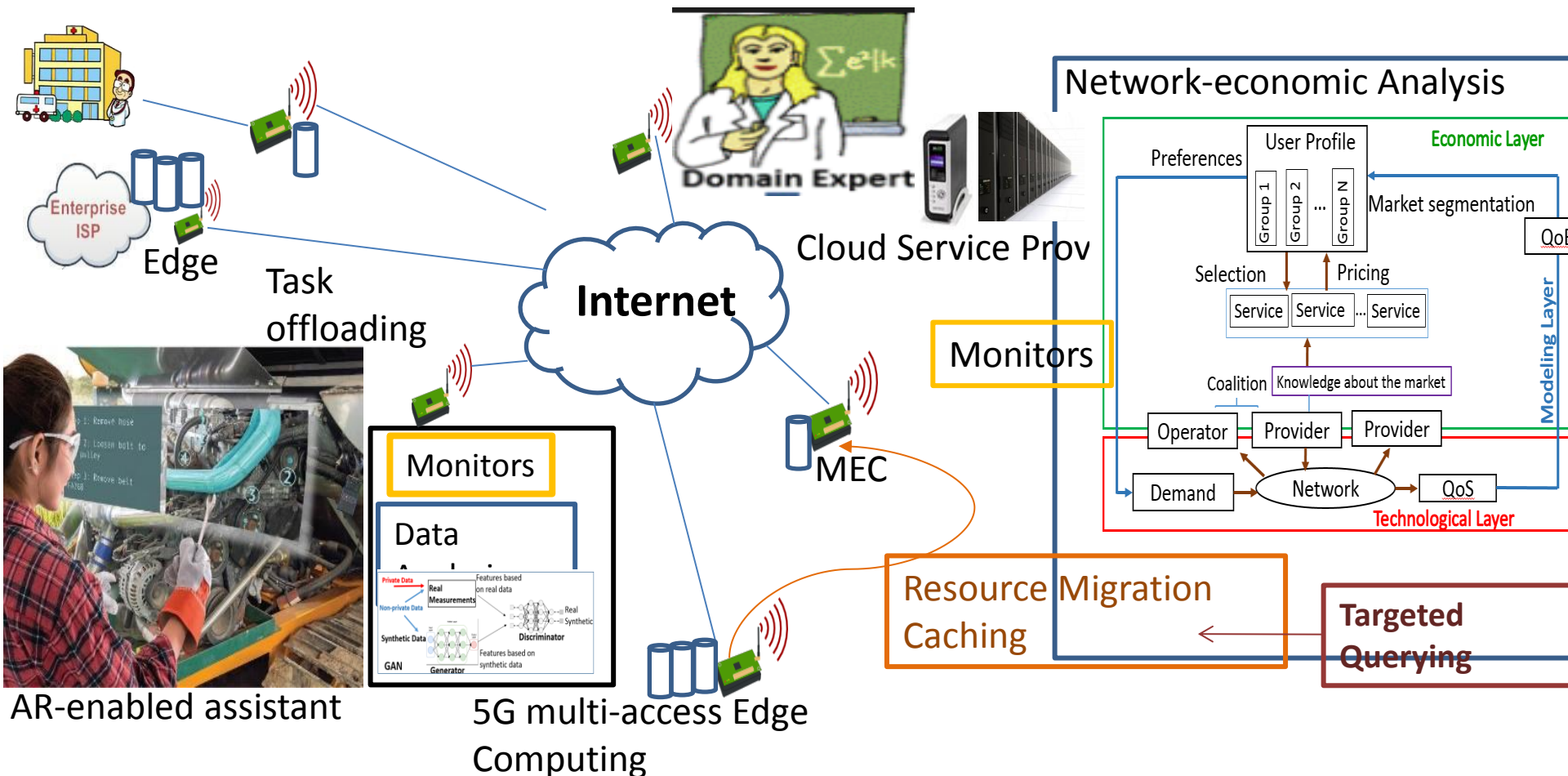
- Existing pervasive infrastructure
- Minimal possible latency for cellular devices
- Know all about mobility
- Have a concept of location – can geo-locate without a GPS
- Know how to handle handoff

However, computing handoff \neq wireless hand-off

- Different mentality than Amazon, Microsoft, Google:
 - Reliability-oriented
 - Slow to change
 - Standards rather than iterative deployments
 - Far less experience in creating developer ecosystems



A patient that faces a medical emergency in a remote area could be supported by a health professional or a “good samaritan” bystander that have access to an AR-support



AR-enabled assistant

5G multi-access Edge Computing

Stress features

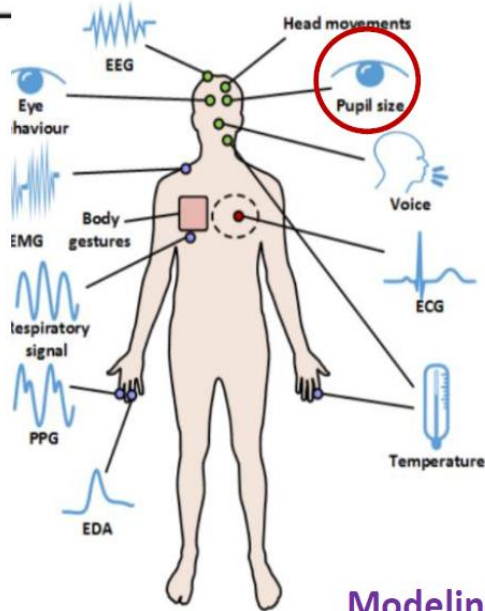
Feature

δ activity
 θ activity
 α activity
 β activity
 γ activity
 β/α ratio

Asymmetry index

Coherence
 β Coherence
 α Coherence

Brain Load Index
ApEn
Linear CMIF
Non-linear CMIF



QoE features

Depends on the application of interest req.

User engagement

- Fixation in target areas of the display
- Duration of the session
- Revisit pattern

Alertness:

- pupil size

Modeling approaches

- Mathematical models (e.g., Weber-Fechner Law, IQX)
- Signal processing techniques
- Machine-learning algorithms

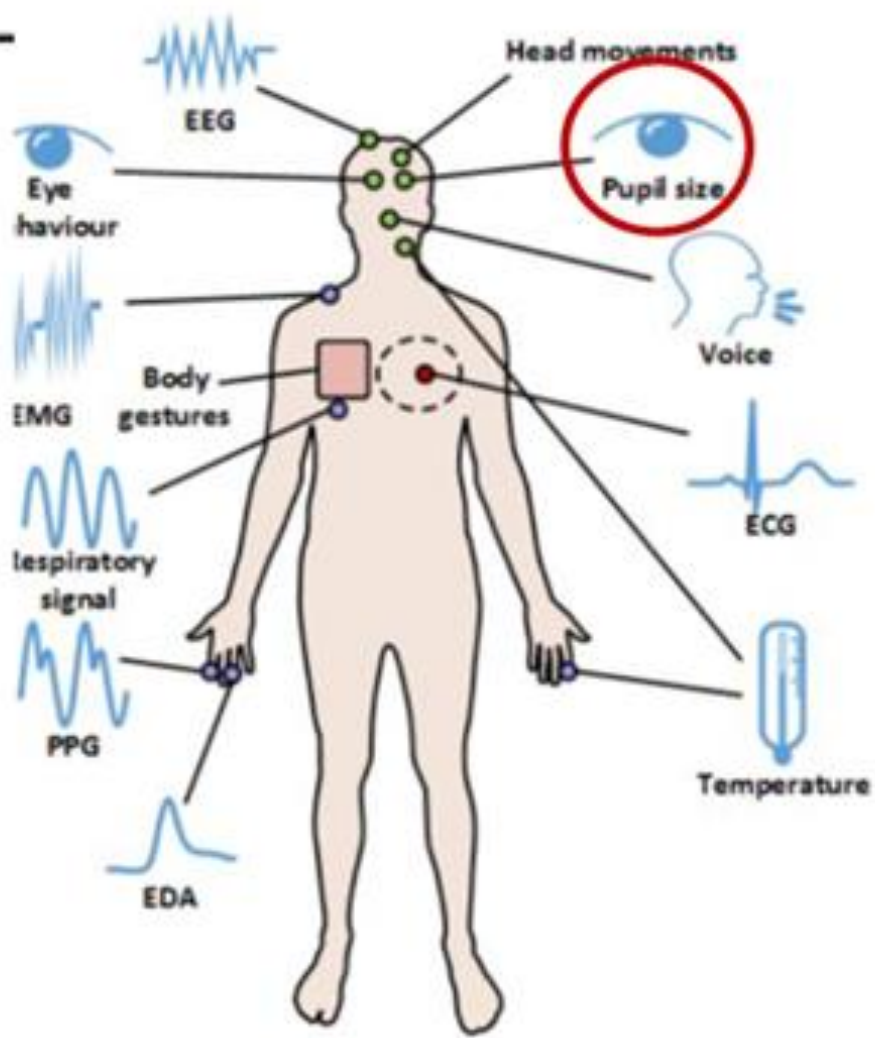
[Giannakakis et al. Review on psychological stress detection using biosignals. IEEE Trans. Affective Computing 2020

Perdiz et al. Emotional State Detection Based on EMG and EOG Biosignals: a Short Survey.

Kim et al. Stress and Heart Rate Variability: A Meta-Analysis and Review of the Literature. Korean Neuropsychiatric Association 2018

Lefter et al. Recognizing Stress Using Semantics and Modulation of Speech and Gestures. IEEE Trans. On Affective Computing 2016

Haritha et al. Automating Anxiety Detection using Respiratory Signal Analysis. IEEE Symposium TENSYP 2017]



Sensors and monitoring tools to collect measurements
Analyze them to infer various conditions

Improving the QoE in Edge/Fog Environment – Data Analysis Perspective

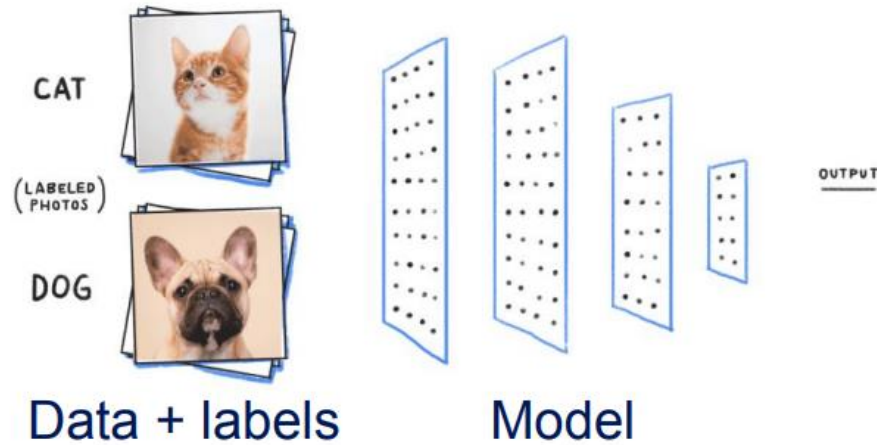
Prediction

- Content popularity
- Contextual conditions & mobility of the user
- Demand & resource availability at the edge
- Channel quality & network performance

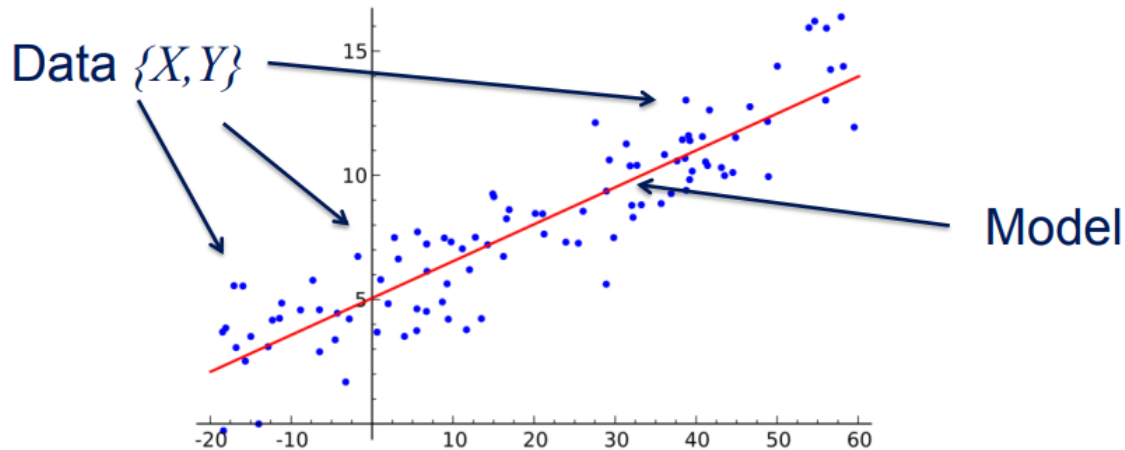
Identification of State Changes

Examples of Types of States:
position or activity of a user
condition of a channel
demand at the edge

ML Application: Classification



ML Application: Regression



Classification Algorithms

1. **Support Vector Machines** (linear, Gaussian, polynomial)
2. **Naïve Bayes** (continuous values, Gaussian distribution)
3. **K-means** (variation to fit classification, aiming to catch possible sub-classes)

Leave One Out Cross Validation (LOOCV) for calculating the mean accuracy

Traditional Distributed Learning

- Collect data from multiple devices
- **Train the model**
 - *Distributing processing between multiple cores and multiple servers*
- Send the model to multiple devices



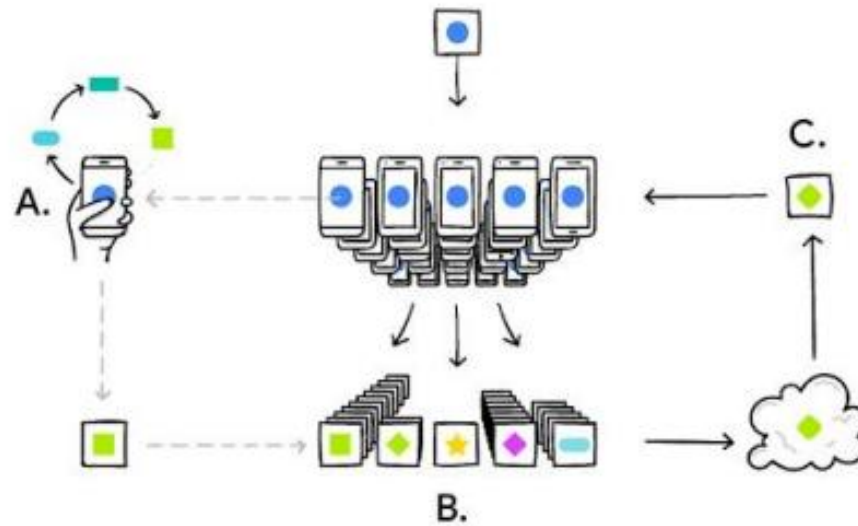
Changes Possible With Edge

- Instead of collecting data from multiple devices
 - Keep some or all data local
- Instead of training **the** model
 - Train different local models: incremental models, private models, ...

Emerging lines of work

Keeping (more) Data Local with Edge

- Some of the training happens on the edge device



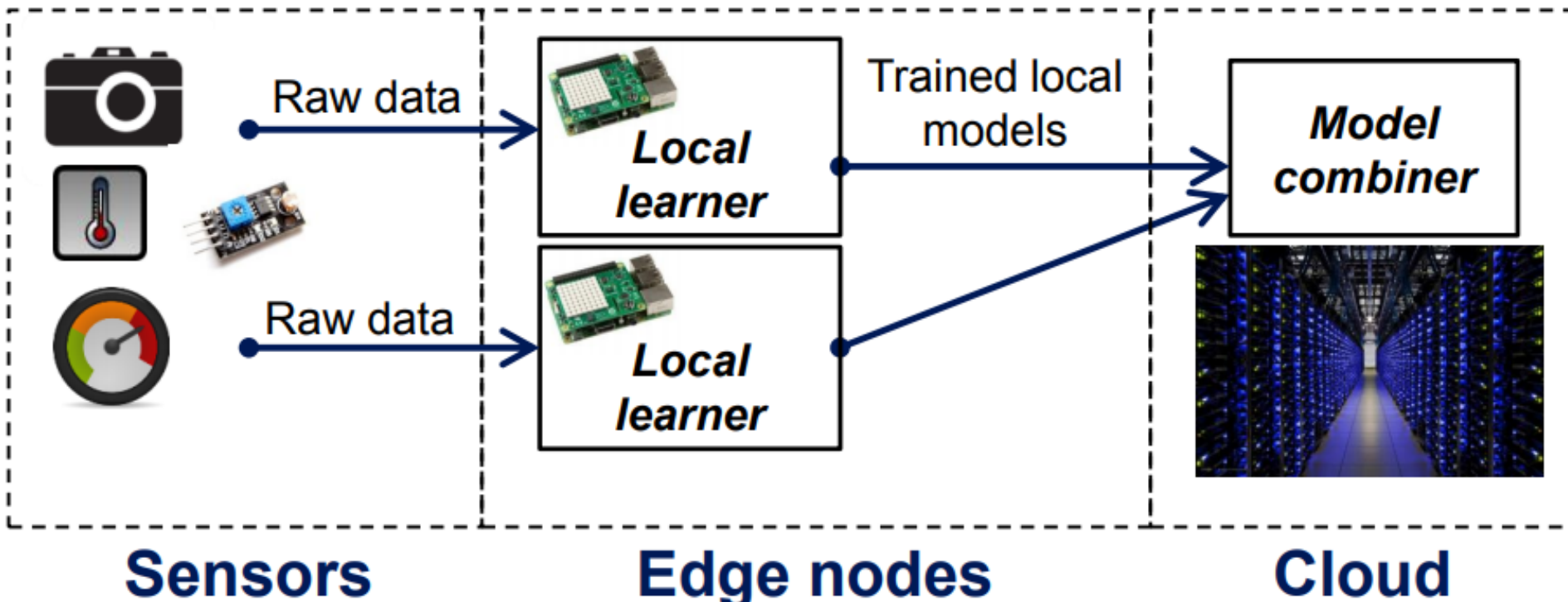
Federated Learning

- Take batches of clients at a time
 - Have each client in the batch compute the gradient on its local data, and iterate on it
 - Average the results on the cloud
- Keep going

“Federated learning can be made practical”

Communication-Efficient Learning of Deep Networks from Decentralized Data,
McMahan et al, arXiv, Feb. 2017.

Ensemble Learning at Edge



TWO EXAMPLES FOR DISCUSSION FROM OUR OWN RESEARCH

1. **GestureKeeper**: Hand-gesture identification & recognition
2. **DysLexML**: screening tool for dyslexia

General Approaches for Gesture Identification & Recognition

1) Camera-based

- High recognition accuracy
- High computational cost & sensitivity in environmental conditions

2) Sensor-based

- Practical considerations (e.g., smaller sensor size, efficient, low cost)
- Energy constrains

3) Wireless Access-Point based

- Practical considerations. No intervention
- Sensitivity in dynamic environmental conditions

[+] "GestureKeeper: Gesture Recognition for Controlling Devices in IoT ..."
[-] Vasileios Sideridis et al. (2019)

> Home



Vasileios Sideridis, Andrew Zacharakis, George Tzagkarakis, Maria Papadopouli:
GestureKeeper: Gesture Recognition for Controlling Devices in IoT Environments. EUSIPCO 2019: 1-5

GestureKeeper

Long-term objective: Allow user to control devices through hand gestures

Hand-gesture identification & recognition based on wearable **inertial measurements unit (IMU)**

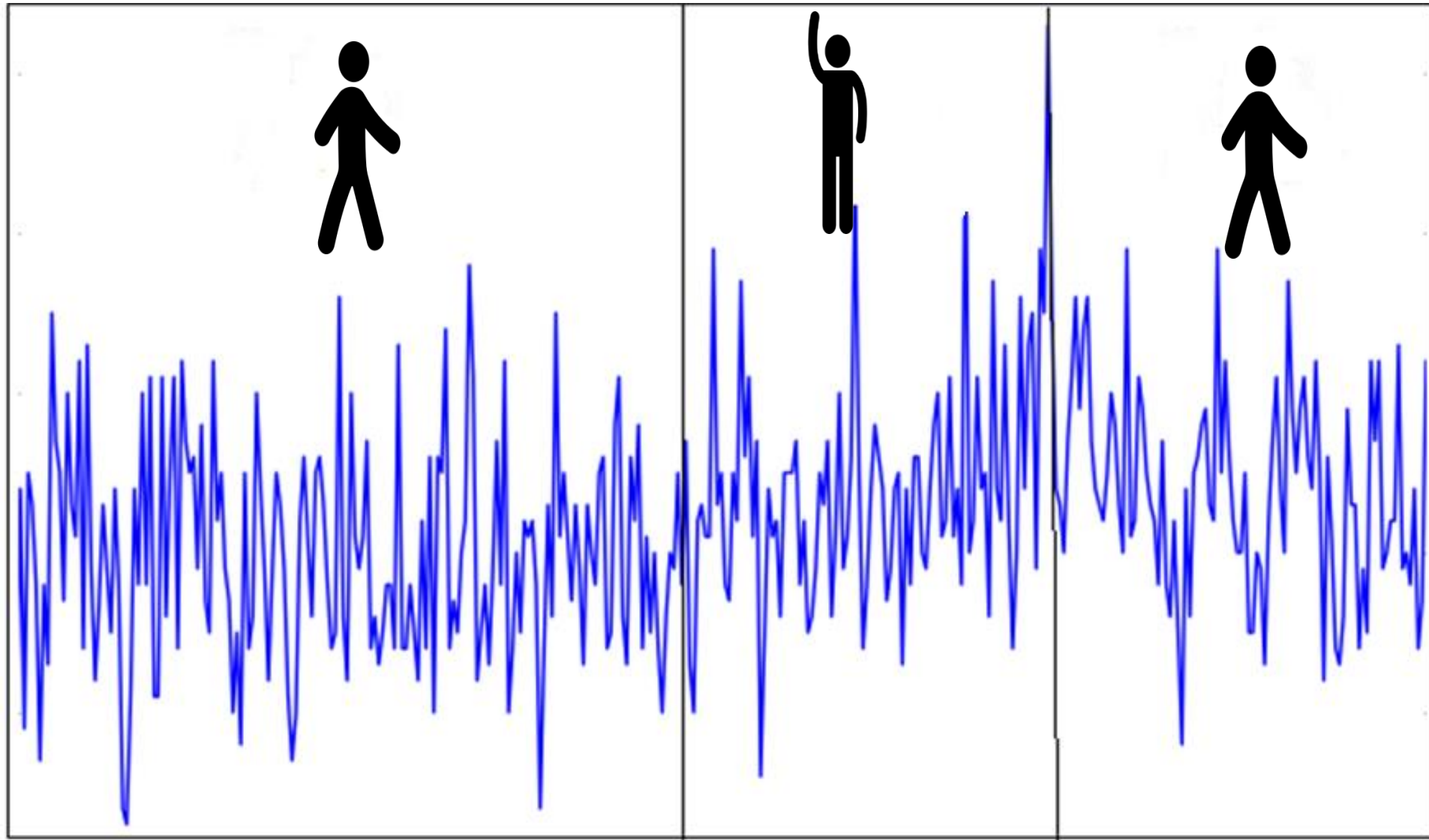
Identify **the start of gesture** by exploiting underlying dynamics of collected time-series

- First automatic hand-gesture **identification** system based only on **accelerometers**

Recognize accurately a **dictionary** of 12 hand-gestures

- Wearable sensor sends periodically collected measurements to server
- Server performs gesture **identification & recognition**

Identification: Aims to **Identify** Time Windows at a Certain State

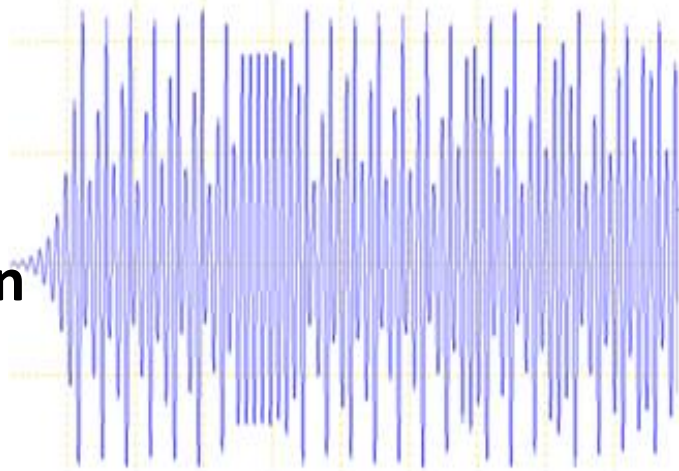


Recurrence Quantification Analysis (RQA)

- Powerful tool that uses theory of **non-linear dynamics** based on the topological analysis of the phase space of the underlying dynamics
- Enables the understanding of the **behavior of a complex dynamic system**
- Does **not make any assumption about the model** that governs the system or the data
- Can handle short time-series, non-stationary data
- Is robust to outliers

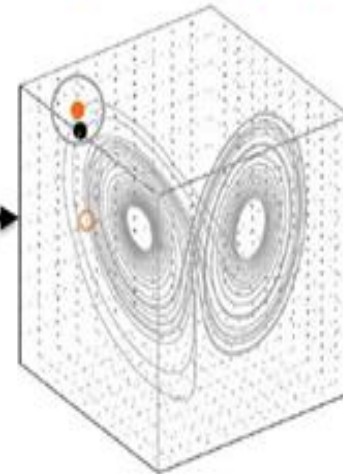
Phase Space Representation

Original time series



Time-Delay Embedding

States (Phase Space)

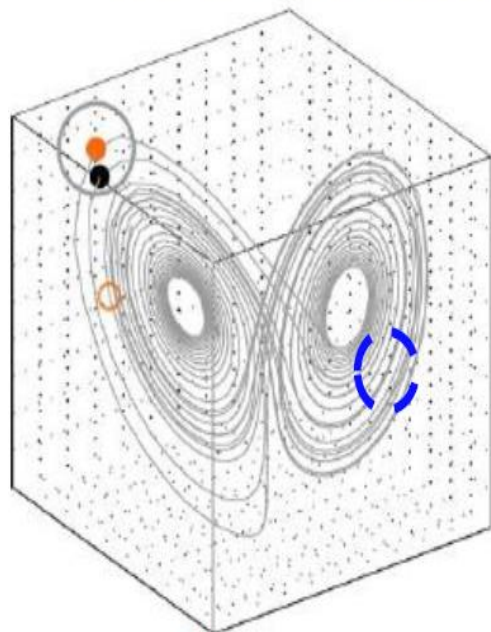


$$\mathbf{r} = \{r_i\}_{i=1}^n \quad x_i = [r_i, r_{i+\tau}, \dots, r_{i+(m-1)\tau}] \quad i = 1, \dots, N$$



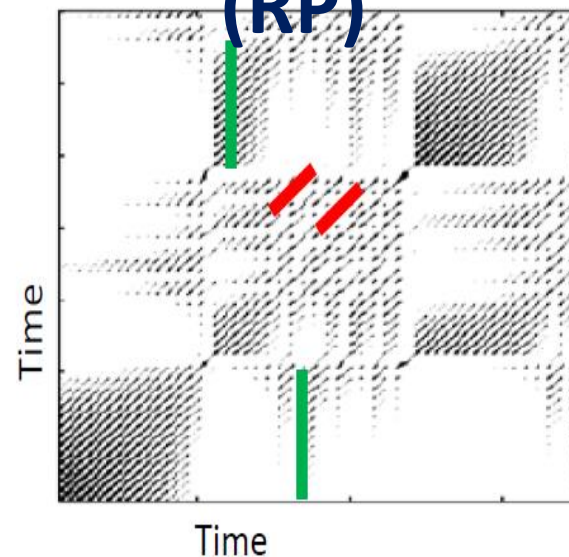
Critical Parameters	
m	Embedding dimension
tau	Delay

States (Phase Space)



Binary
Recurrence
Matrix

Recurrence Plot (RP)



$$\mathbf{x}_i = [r_i, r_{i+\tau}, \dots, r_{i+(m-1)\tau}]$$

$$\mathbf{R}_{i,j} = \Theta(\varepsilon - d(\mathbf{x}_i, \mathbf{x}_j)) \quad i, j = 1, \dots, N$$

$$\Theta(n) = \begin{cases} 1, & \text{if } n \geq 0 \\ 0, & \text{if } n < 0 \end{cases} \longrightarrow \mathbf{R}_{i,j}(\varepsilon) = \begin{cases} 1, & d(\mathbf{x}_i, \mathbf{x}_j) \leq \varepsilon \quad \bullet \\ 0, & \text{otherwise} \quad \circ \end{cases}$$

Performance of the Identification Task

GestureKeeper employs two RQA metrics to form the feature matrix

- **Recurrence Rate (RR)**: percentage of recurrence points in the RP
- **Transitivity (TRA)**: measures regular dynamics, as present in each periodic window

High **imbalance** between **gesture** & **ADL** samples (0.5% vs. 99.5%)

- Random selection of ADL samples with **equal size** to gesture class

All subjects are used for training except one, which is used for testing

- SVM (polynomial kernel of 3rd degree, cost 3, gamma 0.95)
- **Mean accuracy of 87.21%** for each testing subject

Gesture Recognition

- **GestureKeeper** classifies the performed gesture, out of 12-gesture dictionary, using **SVM**
- 63 **statistical** & 30 **sample-based** features
 - **Statistical features**: e.g., acceleration mean, median, skewness in 3 dimensions
 - **Sample-based features**: fixed-length acceleration data samples per window

Iterative Feature Selection

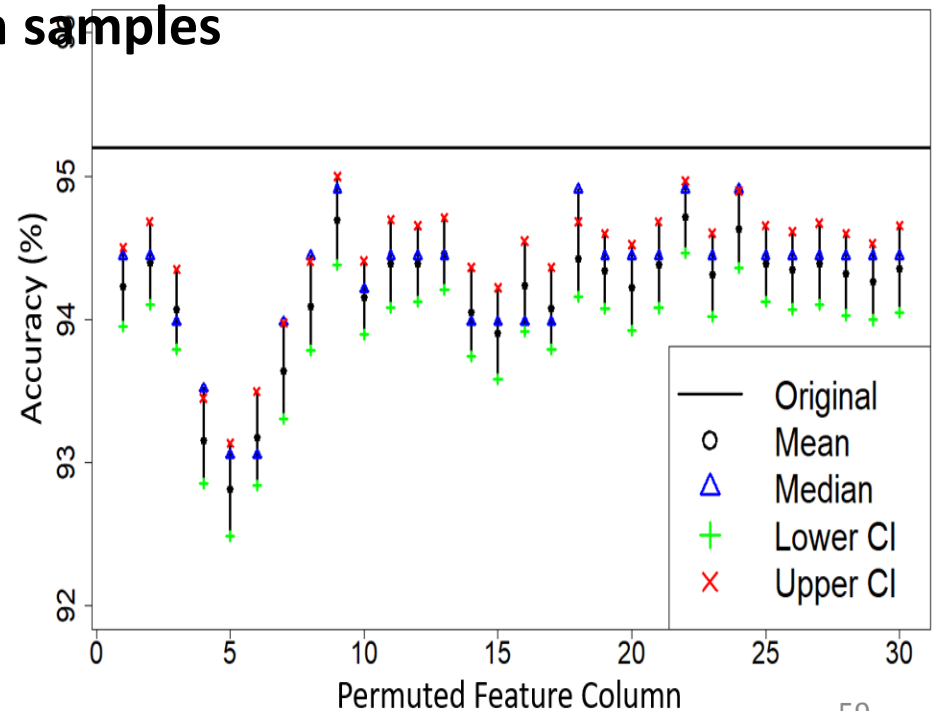
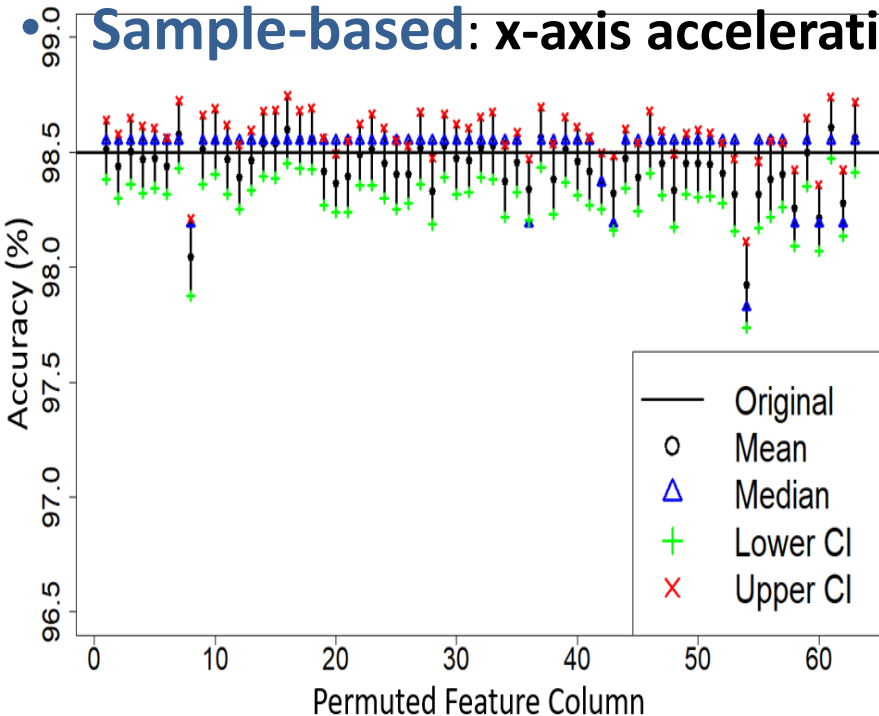
For each feature:

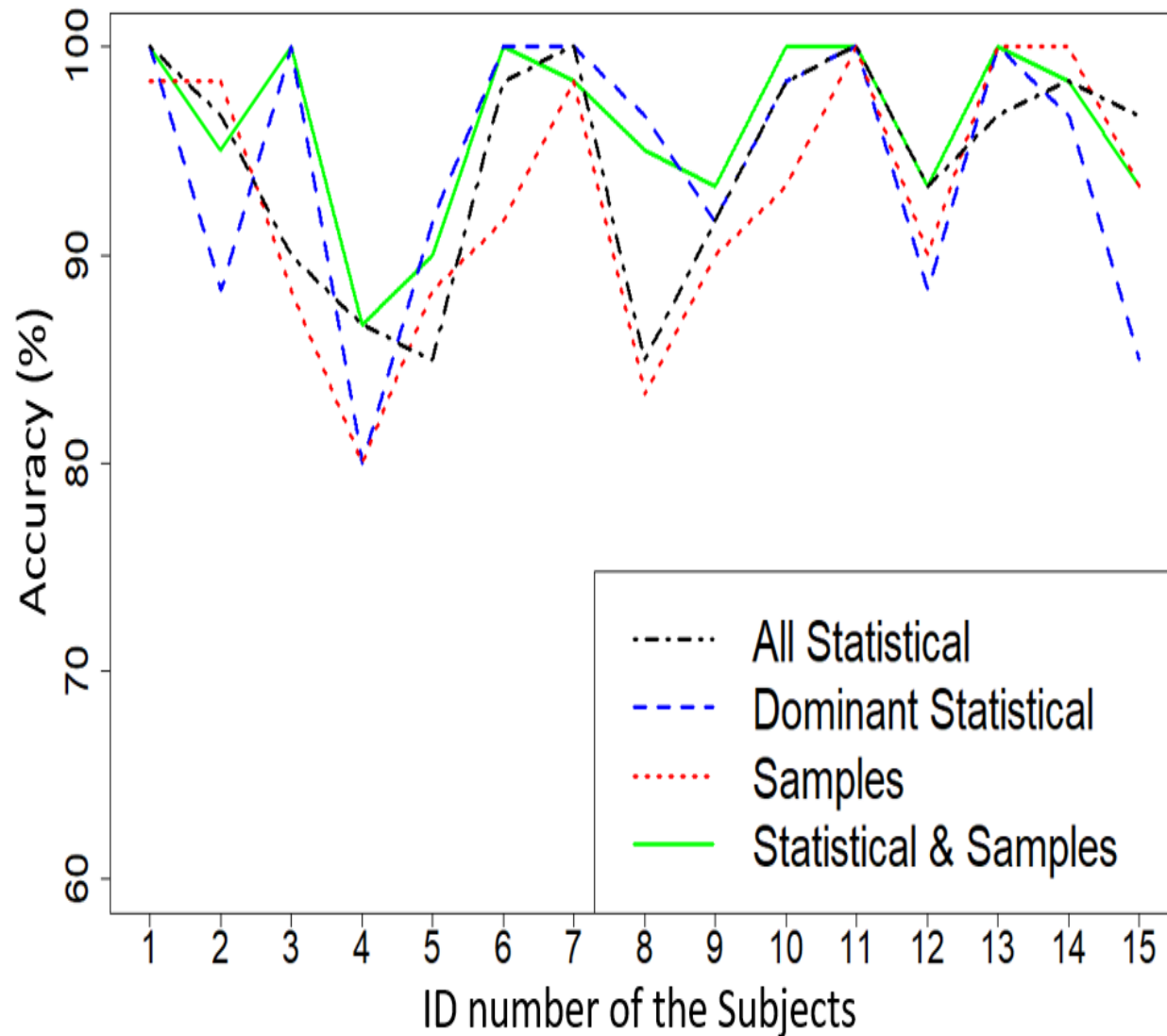
- 1) Permute its values, keeping the values of other features fixed
- 2) Train and test with “one-against-one” approach

Select features based on largest decrease in accuracy, with **43** statistical & **10** sample-based significant

- **Statistical:** mean & skewness of z-axis angular velocity

- **Sample-based:** x-axis acceleration samples





All subjects are used for training except one, which is used for testing

- **SVM** (radial kernel, cost 1, gamma 0.005)

Additional Performance Analysis

- Classifiers based on **Random Forests** were developed
 - Accuracy of 88%
- Impact of noise on accuracy of recognition sub-system was assessed
 - Mean accuracy of 97.89%

Rich Information can be collected from eye-trackers

Example:

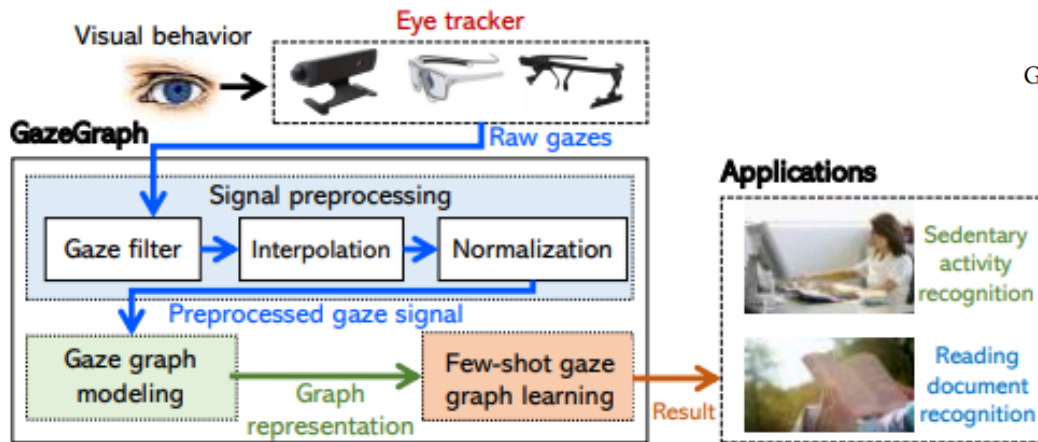


Figure 3: System architecture of GazeGraph.

GazeGraph: Graph-based Few-Shot Cognitive Context Sensing from Human Visual Behavior

Guohao Lan, Bailey Heit, Tim Scargill, Maria Gorlatova
 Duke University, Durham, North Carolina
 {guohao.lan, bailey.heit, ts352, maria.gorlatova}@duke.edu

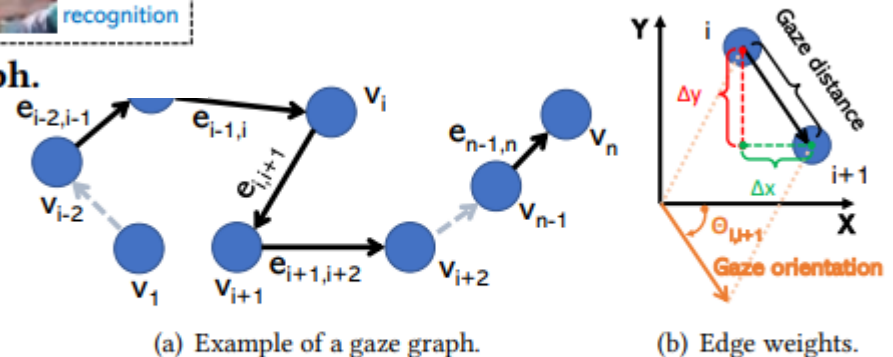


Figure 6: (a) Example of a temporal gaze graph \mathcal{G}_{TGG} constructed from a time series of n gaze samples. (b) The gaze distance and gaze orientation between nodes v_i and v_{i+1} .

Towards a robust and accurate screening tool for dyslexia with data augmentation using GANs

Thomais Asvestopoulou ^{1,2}, Victoria Manousaki ^{1,2},
Antonis Psistakis ^{1,2}, Erjona Nikolli ^{1,2}, Vassilios
Andreadakis ³, Ioannis M. Aslanides⁴, Yannis Panatazis ⁵,
Ioannis Smyrnakis ^{2,3} and Maria Papadopouli ^{1,2}

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⁴Emmetropia Eye Institute, Heraklion, Greece,

⁵Institute of Applied and Computational Mathematics, Heraklion, Greece

Typical Reader

Πηγαίνοντας με το λεωφορείο να επισκεψτώ την
αδερφή μου που είχε κάνει μια εγχείρηση πέρασα
μπροστά από το τετράγωνο που βρισκόταν το
εργαστάσιο στο οποίο δούλευε η μητέρα μου. Το
εργαστάσιο κατασκεύαζε πλυντήρια είναι πολύ
χρήσιμο να υπάρχει ένα πλυντήριο στο σπίτι.

Dyslexic Reader

Πηγαίνοντας με το λεωφορείο να επισκεψτώ την
αδερφή μου που είχε κάνει μια εγχείρηση πέρασα
μπροστά από το τετράγωνο που βρισκόταν το
εργαστάσιο στο οποίο δούλευε η μητέρα μου. Το
εργαστάσιο κατασκεύαζε πλυντήρια είναι πολύ
χρήσιμο να υπάρχει ένα πλυντήριο στο σπίτι.

Dyslexic readers manifest:

- longer and more frequent fixations
- shorter saccade lengths
- more backward refixations

1. Use a light source to to illuminate the eye causing highly visible reflections, and a camera to capture an image of the eye showing these reflections.

2. The image captured by the camera is used to identify the reflection of the light source on the cornea (glint) and in the pupil.

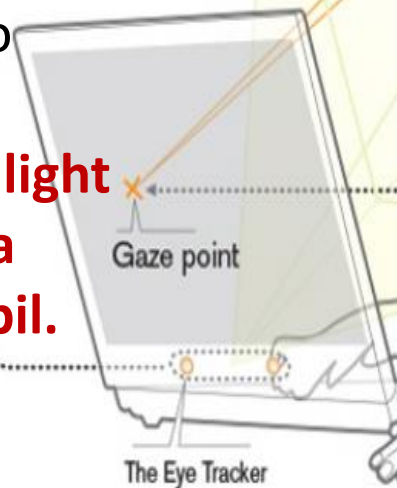
1 An eye tracker consists of cameras, illuminators and algorithms.

2 The illuminators create a pattern of near-infrared light on the eyes.

3 The cameras take high-resolution images of the user's eyes and the patterns.

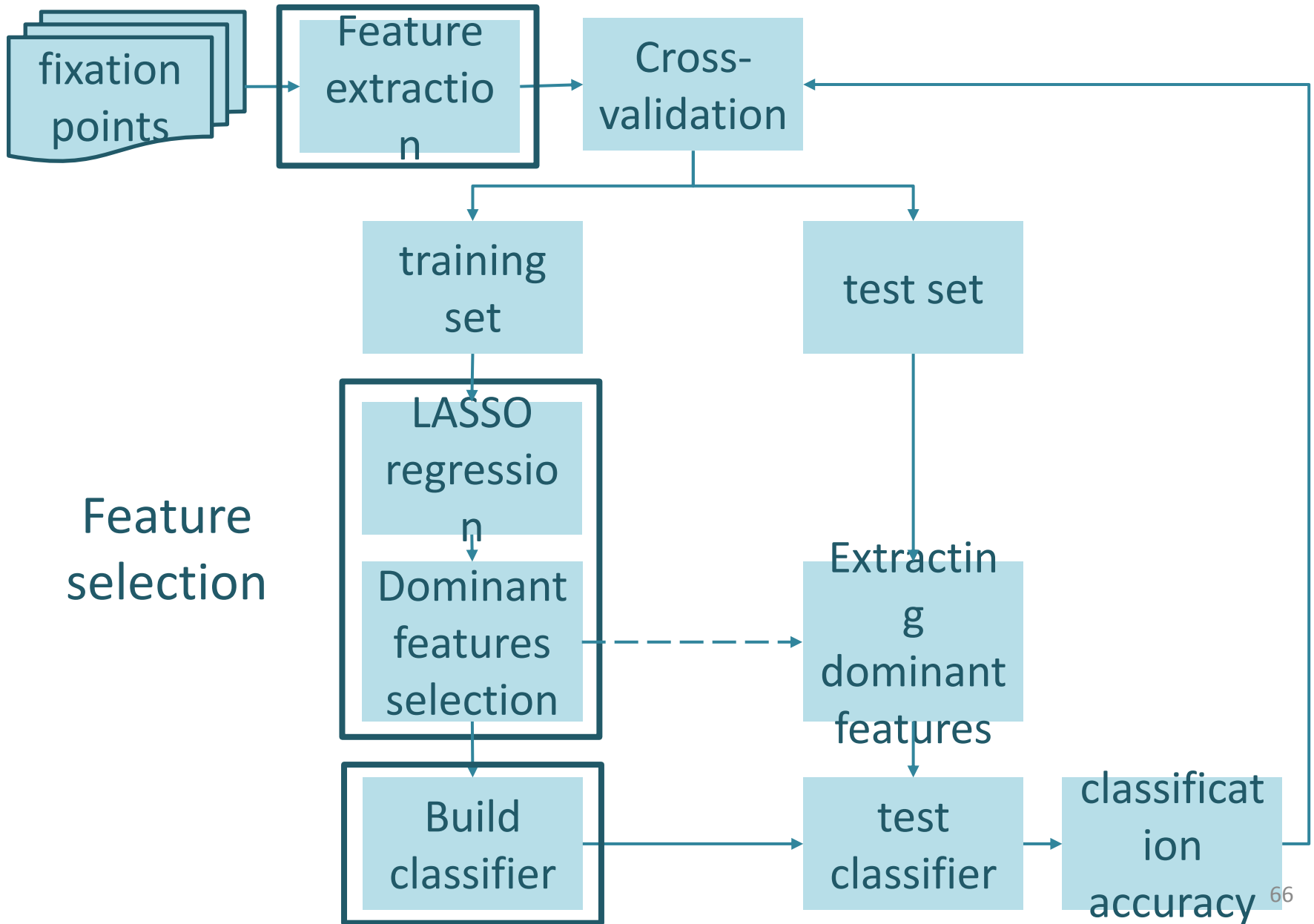
4 The image processing algorithms find specific details in the user's eyes and reflections patterns.

5 Based on these details the eyes' position and gaze point are calculated, for instance on a computer monitor, using a sophisticated 3D eye model algorithm.



3. Calculate a vector formed by the angle between the cornea and pupil reflections the direction of this vector, combined with other geometrical features of the reflections, is then used to calculate the gaze direction.

DysLexML



Feature selection

Classification Algorithms

1. **Support Vector Machines** (linear, Gaussian, polynomial)
2. **Naïve Bayes** (continuous values, Gaussian distribution)
3. **K-means** (variation to fit classification, aiming to catch possible sub-classes)

Leave One Out Cross Validation (LOOCV) for calculating the mean accuracy

Dominant Features

- Number of fixations
- **Number of short forward movements**
- Fixation median duration
- Median length of medium forward movements
- **Number of multiply fixated words**
- Age

	Accuracy (%)	
	without age	with age
K-means, k=2, LASSO ($\lambda_{\min}\text{MSE}$)	71.71	69.07
K-means, k=4, LASSO ($\lambda_{\min}\text{MSE}$)	65.13	70.39
K-means, k=2, LASSO ($\lambda_{1\text{SE}}$)	72.36	68.42
K-means, k=4, LASSO ($\lambda_{1\text{SE}}$)	71.71	72.36
SVM, linear, LASSO ($\lambda_{\min}\text{MSE}$)	69.07	82.89
SVM, linear, LASSO ($\lambda_{1\text{SE}}$)	67.76	84.21
Naive Bayes, LASSO ($\lambda_{\min}\text{MSE}$)	69.73	71.05
Naive Bayes, LASSO ($\lambda_{1\text{SE}}$)	72.36	71.05
trivial	53.63	53.63

1st field study

custom
made eye-
tracker

use of chin
rest

age span
8.5-12.5
years old

69 participants
(39 typical, 32
dyslexic)

Recording images up to 60Hz, resolution of 1600 x 1200 pixels

2nd field study

Tobii 4C
eye-tracker

Non-
invasive
procedure

age span 7-
17 years
old

152 participants
(80 typical, 72
dyslexic)

Recording images up to 90Hz (no chin rest was used)

Easy text: 143 words, mostly of 1 or 2 syllables

Difficult text: 181 words, many multi-syllable

All participants were native Greek speakers

Research Topics of Interest

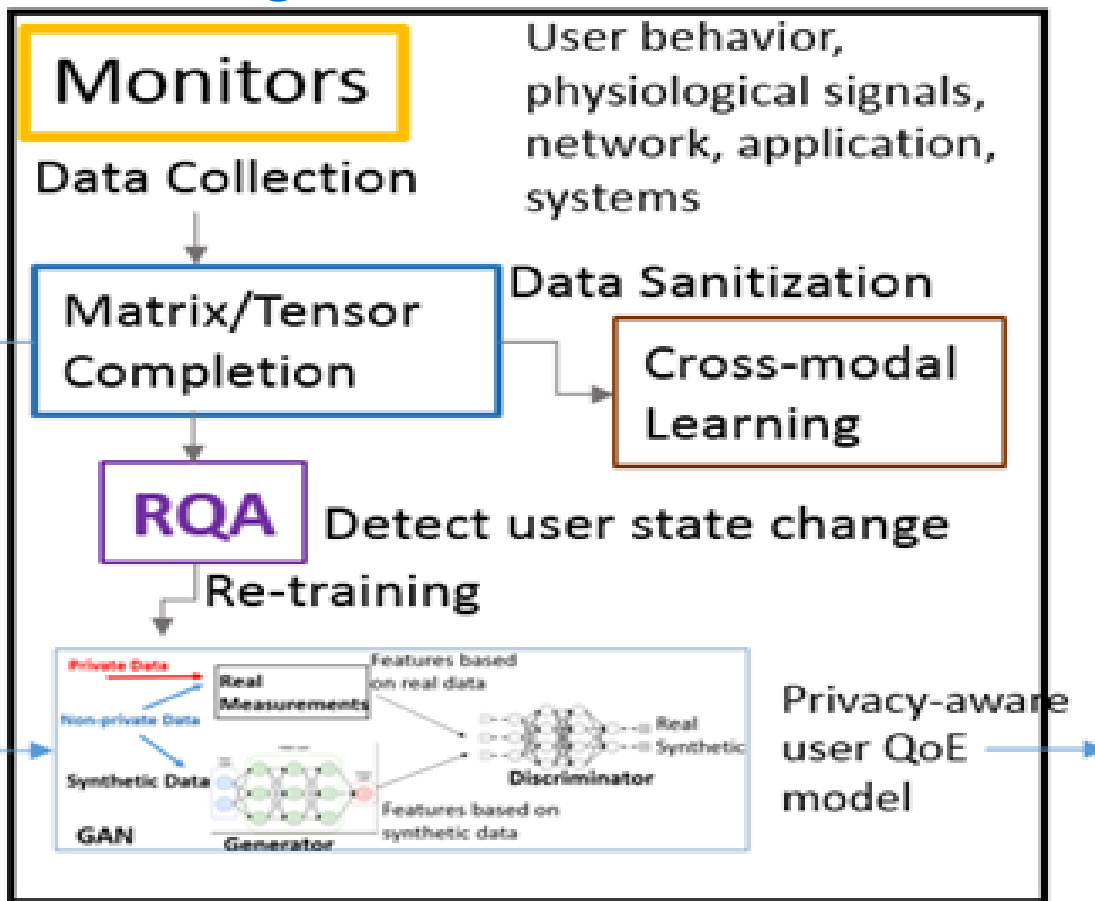
Optimizing QoE: MEC + SDN

- MEC servers provide computing resources & caching while reducing the time to respond to users requests
- SDN can optimize the resource allocation of MEC servers
- Due to the time-varying demand, some nodes may have redundant resources, so **resource consolidation optimization** of edges can effectively avoid resource waste
- Efficient configuration of resources allows the edge to handle more tasks and it can also reduce response time to demand
- Via network programming, SDN simplifies network management, perform efficient network configuration, thereby improving network performance, monitoring

Potential Research Directions: Sophisticated user QoE models

1. QoE metrics & benchmarks for distributed **multi-partied applications**
e.g., teleconference, games, AR

At the edge/user-device



2. **Privacy-aware user QoE models**

Trained with relatively small datasets locally

3. **Cross-modal learning algorithms** to analyze data collected from multiple-sources simultaneously

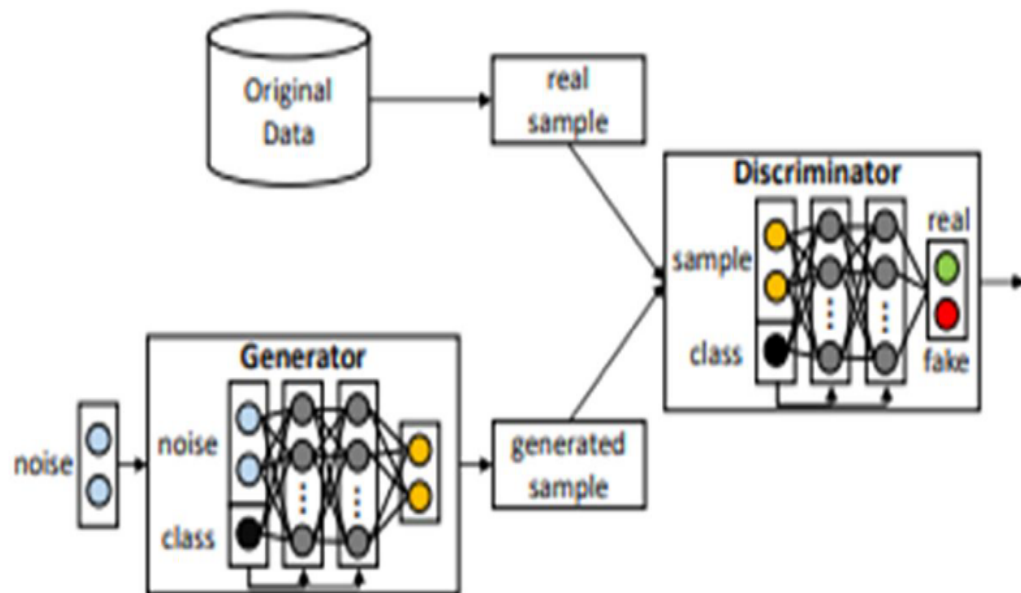
Research Issues – Data Analysis

- Tradeoff between **accuracy** (of the modality) to predict/classify the QoE or condition **vs. time lag vs. intrusiveness vs. privacy**

e.g., EEG can be too intrusive, while heart rate variability and/or pupil size can be more appropriate (accurate and less intrusive)

GAN-generated data are almost indistinguishable from the real data

- **Multi-modal fusion algorithms** to improve the accuracy & delay



- Consider the variability across users
- Detect the state changes during a session/episode

Potential Research Directions: Improving the Edge

4. Apply **state change identification & prediction** to
 - optimize resource allocation & consolidation at the edge
 - due to time-varying demand, some nodes may have redundant resources

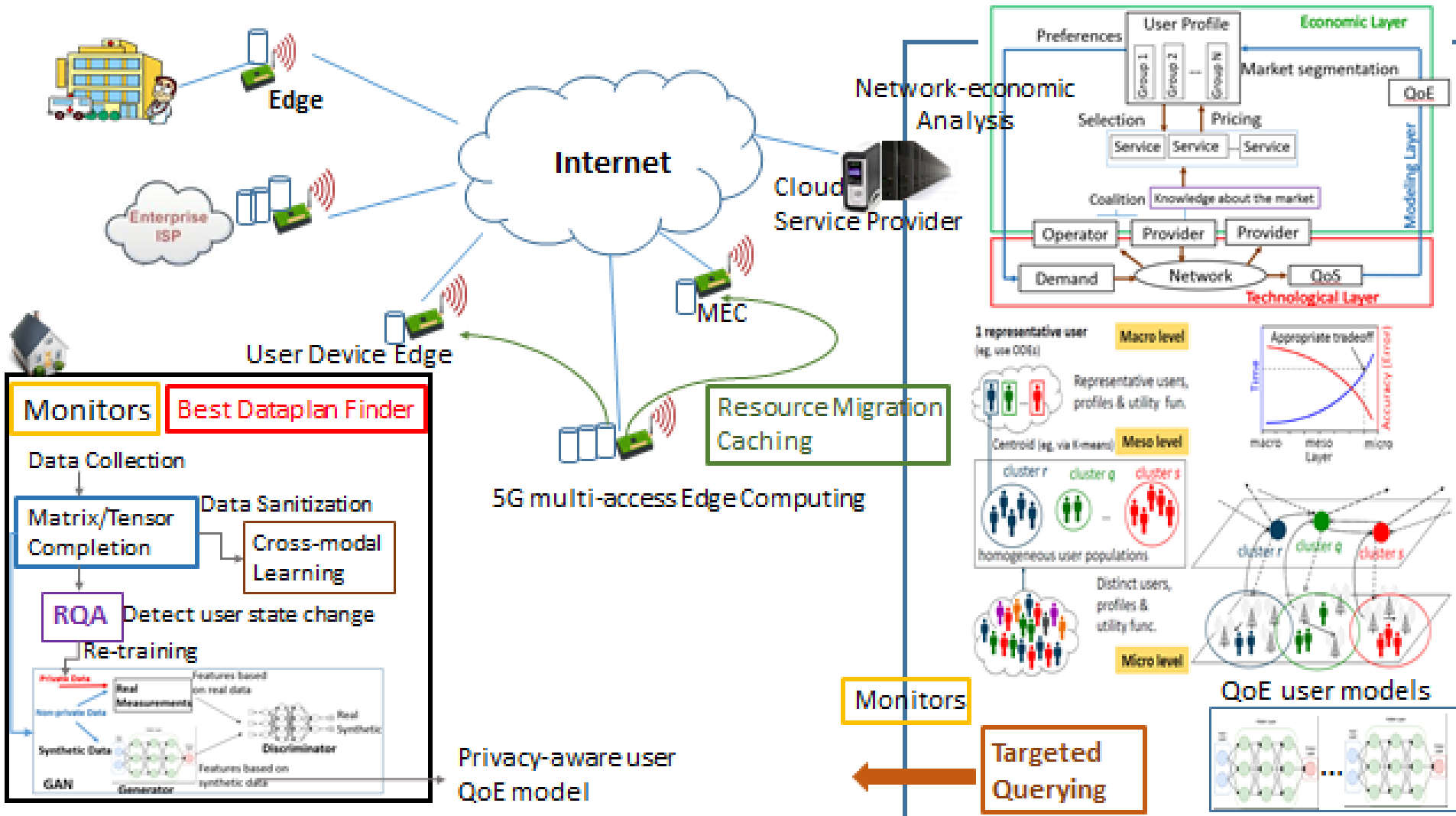
Considering SDN which simplifies network management, perform efficient network configuration, thereby improving network performance, monitoring

Integrating user QoE models

Different (multi-tier) architectural paradigms

Potential Research Directions: Network Economic Analysis of Edge-Cloud Markets

5. Multi-scale game-theoretical framework



An End-to-End Approach for IoT Applications

Key aspects:

- **Secure & user-friendly** communication channel between IoT devices (smart objects) & application server
- **Data collection paradigms under different scenarios:**
 - a data collection & offloading based on the **opportunistic** and **participatory crowd-sensing** paradigm
 - a **disaster scenarios**, in which **drones build an ad-hoc** communication infrastructure to support rescue operations
 - a **light-weight data reduction**, without penalizing the accuracy

Research Topics of Interest

1. **Secure bootstrapping** without user-intervention and energy-efficient for IoT devices
2. **Offloading** IoT sensory data in highly-dense dynamic environments
3. **Incentive** mechanisms in mobile crowdsourcing for collecting data by changing the user mobility pattern
4. Ad-hoc communication **for efficient data provisioning during disaster** scenarios using drones
5. **Scalable** pre-processing of sensory data of reduced size

ACKNOWLEDGEMENT

- https://www.researchgate.net/profile/Arslan_Ahmad3/publication/331013590_QoE--aware_Multimedia_Service_Management_and_Monitoring_through_OTT_and_ISP_Collaboration/links/5c61455292851c48a9c98a46/QoE--aware-Multimedia-Service-Management-and-Monitoring-through-OTT-and-ISP-Collaboration.pdf
- <https://link.springer.com/content/pdf/10.1007%2Fs11213-018-9471-x.pdf>
- <https://link.springer.com/article/10.1007/s41233-017-0009-2>