Bootstrapping Human Activity Recognition Systems for Smart Homes from Scratch

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KDDI Research

Research in Smart Homes

- Smart Home Devices and Applications - to provide seamless interaction

- Technological advancements - reduced cost of sensors, advance in IoT technologies

- Ambient Assisted Living

https://www.samma3a.com/tech/en/best-buy/best-smart-home-devices-2021/

https://corp.smartbrief.com/original/2019/01/5-trends-smart-home-technology

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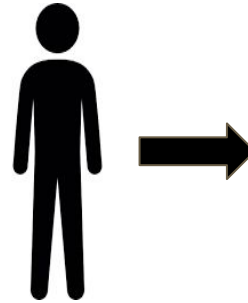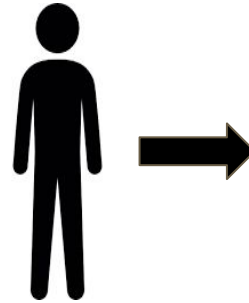
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Use-Case

- Cold-start scenario - smart home unaware of activity patterns of resident

- Bootstrap to learn activity patterns from sensor ever triggers

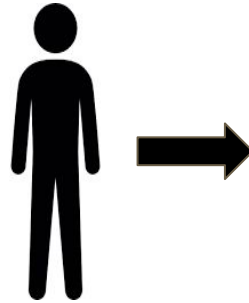- Active Learning - minimal supervision from resident

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Human Activity Recognition Systems for Smart Homes

Systematic Approach-

- Develop an activity recognition system, *from scratch* , with *minimal supervision*

- Evaluate on real smart home data

Guidelines for practitioners-

- Knowledge Discovery and Practical Guidelines for Smart Homes

# Human Activity Recognition Systems for Smart Homes

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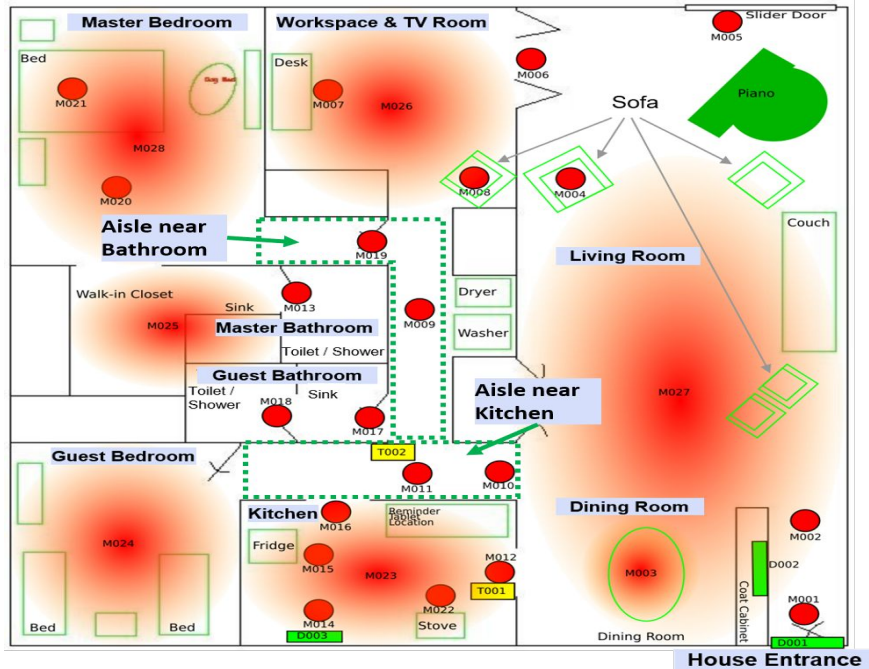- Evaluate on real smart home data

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CASAS-Aruba
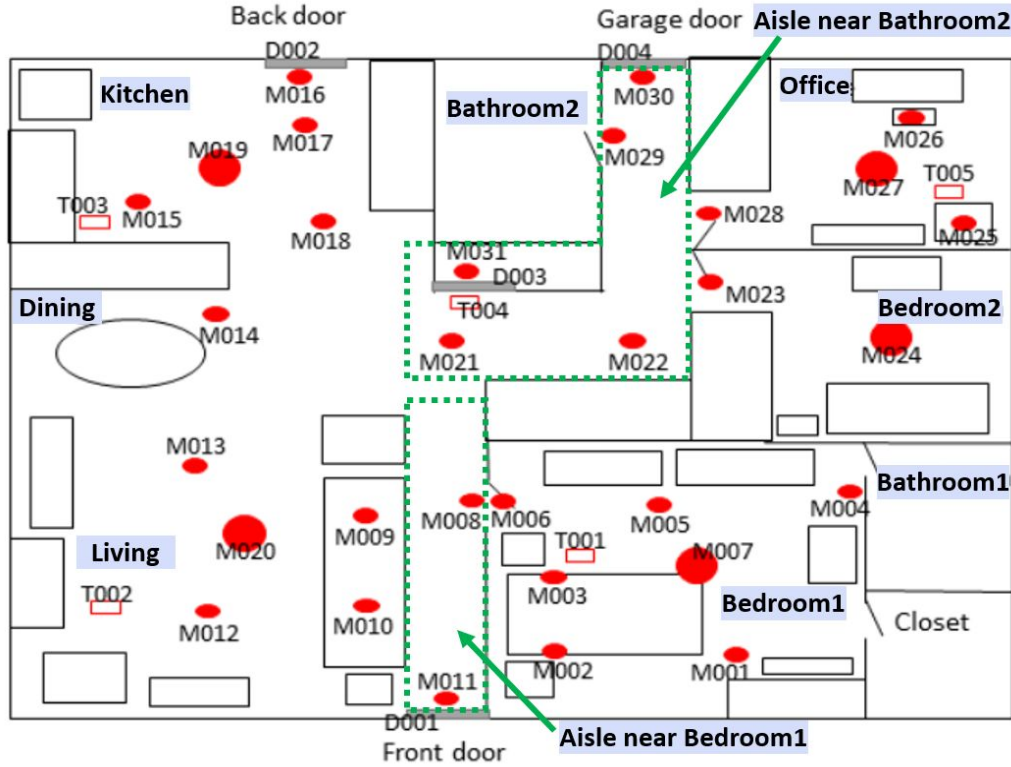
- Mxxx - Motion Sensor (ON/OFF)

- Dxxx - Door Sensor (OPEN/CLOSE)

- Txxx - Temperature sensor

CASAS-Milan

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Novel Bootstrapping Procedure

- **Phase 1 - Cold- Start → Cold-Phase**

- Phase 2 - Build Knowledge → Warm Phase

- Phase 3 - Deploy System → Hot Phase
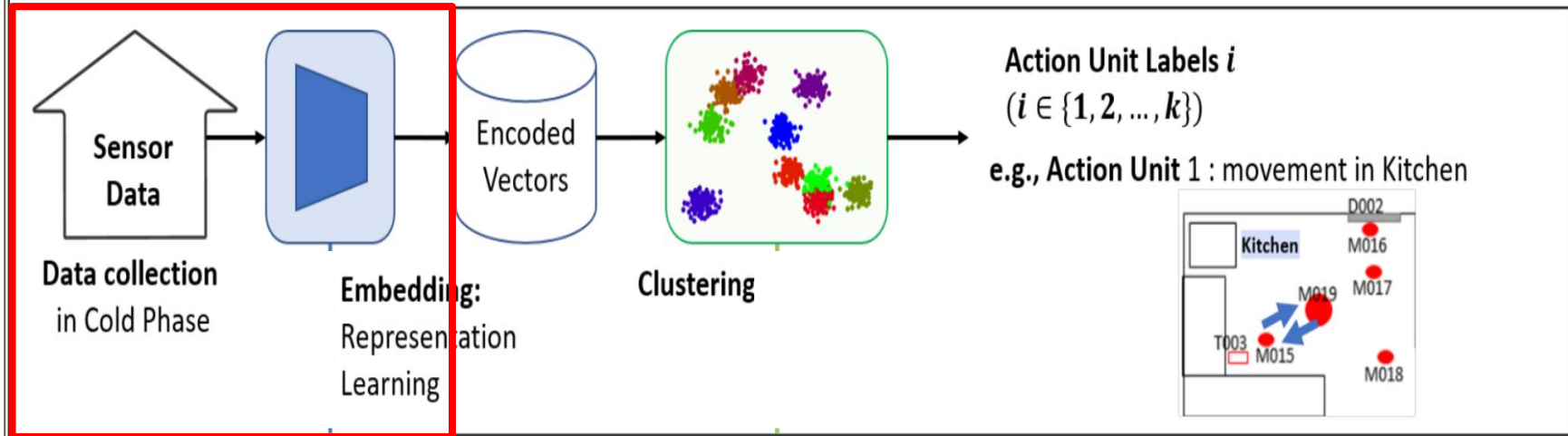
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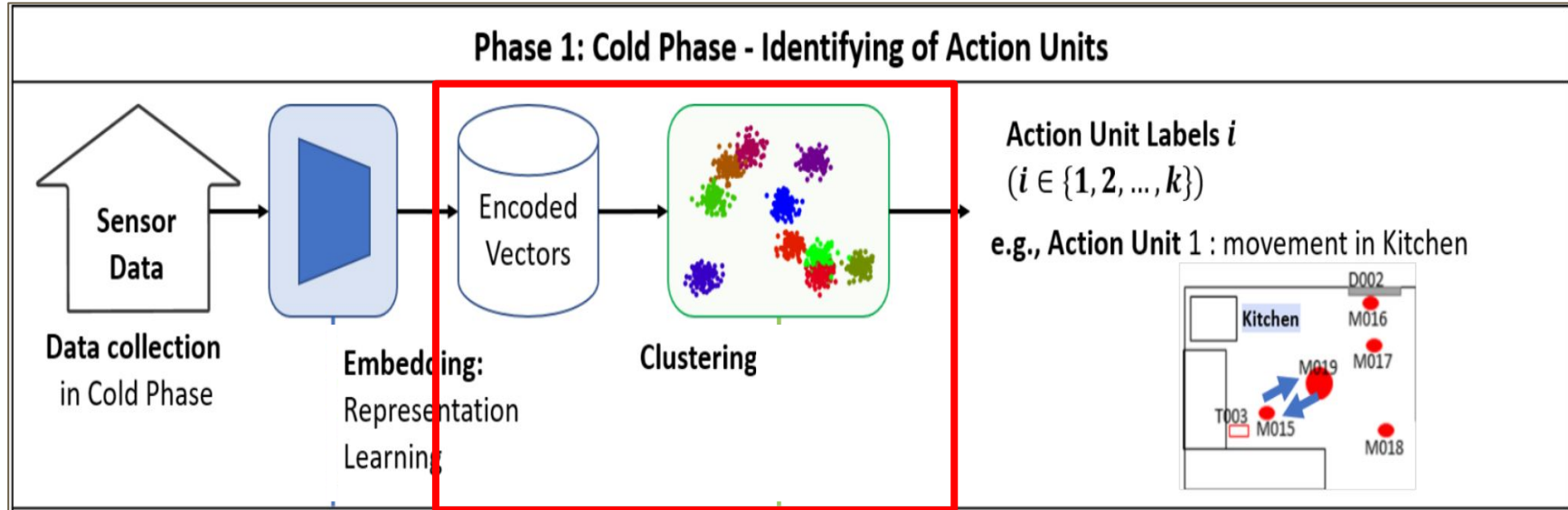
Novel Bootstrapping Procedure

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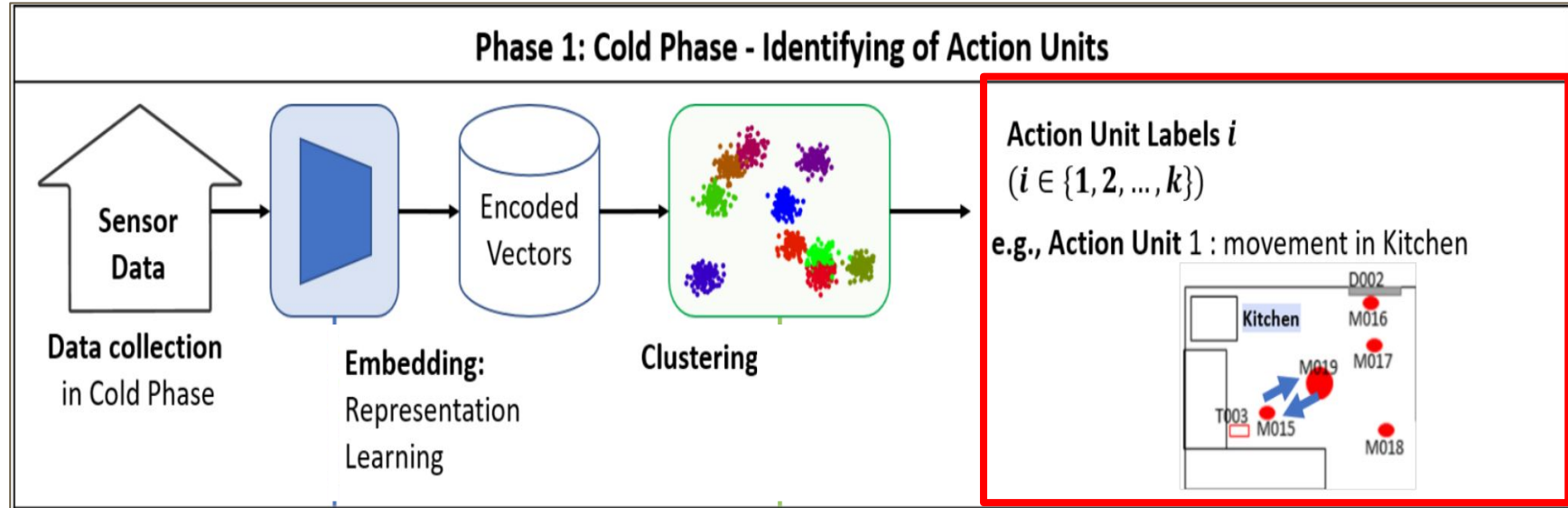# Phase 1: Cold Phase - Identifying Action Units

Phase 1: Cold Phase - Identifying of Action Units

Sensor Data → Embedding: Representation Learning → Encoded Vectors → Clustering → Action Unit Labels i ($i \in \{1, 2, ..., k\}$)

Data collection in Cold Phase

e.g., Action Unit 1 : movement in Kitchen

Phase 1: Cold Phase - Identifying Action Units

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Sensor Data

Data collection in Cold Phase

Embedding: Representation Learning

Encoded Vectors

Clustering

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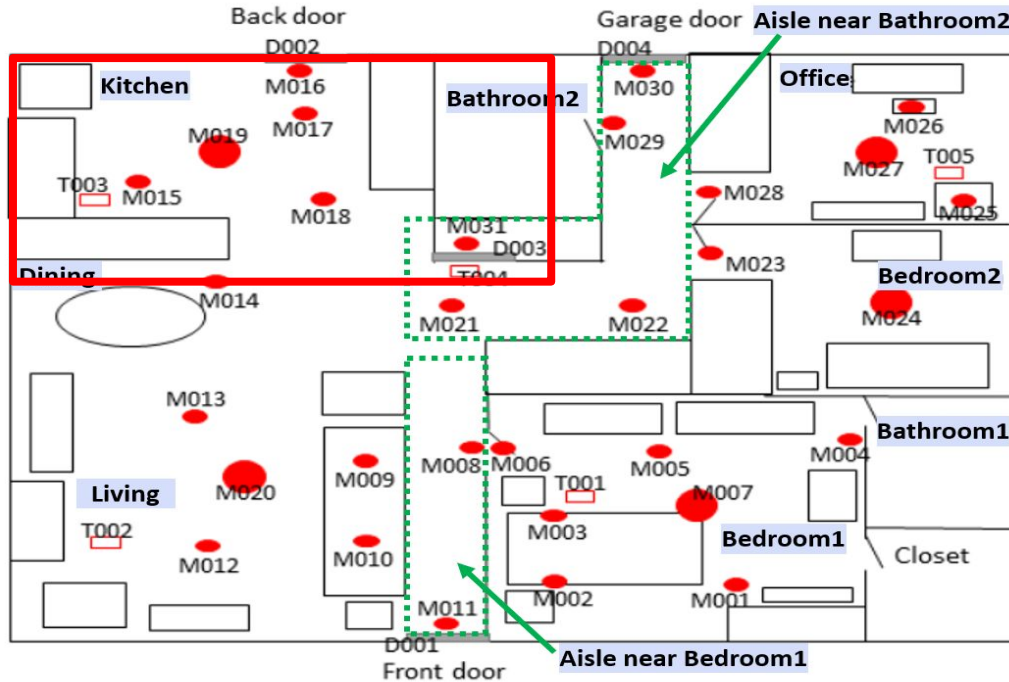
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Action Units identified in the *Cold Phase* for the CASAS-Aruba
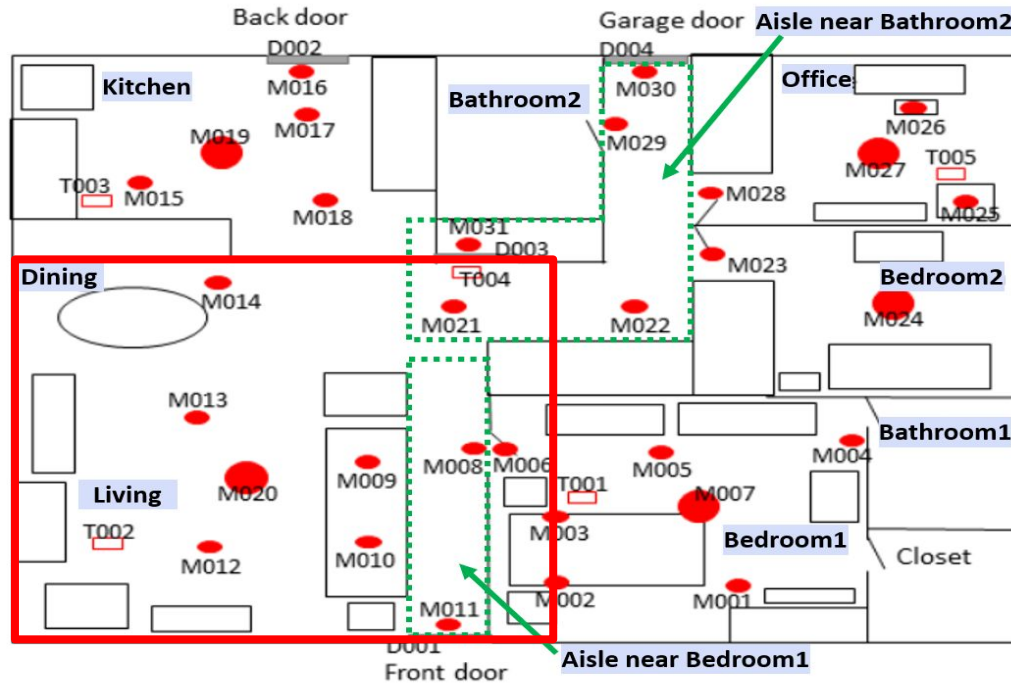
Action Unit: Movement in Living, Bedroom

Action Units identified in the _Cold Phase_ for the CASAS-Aruba

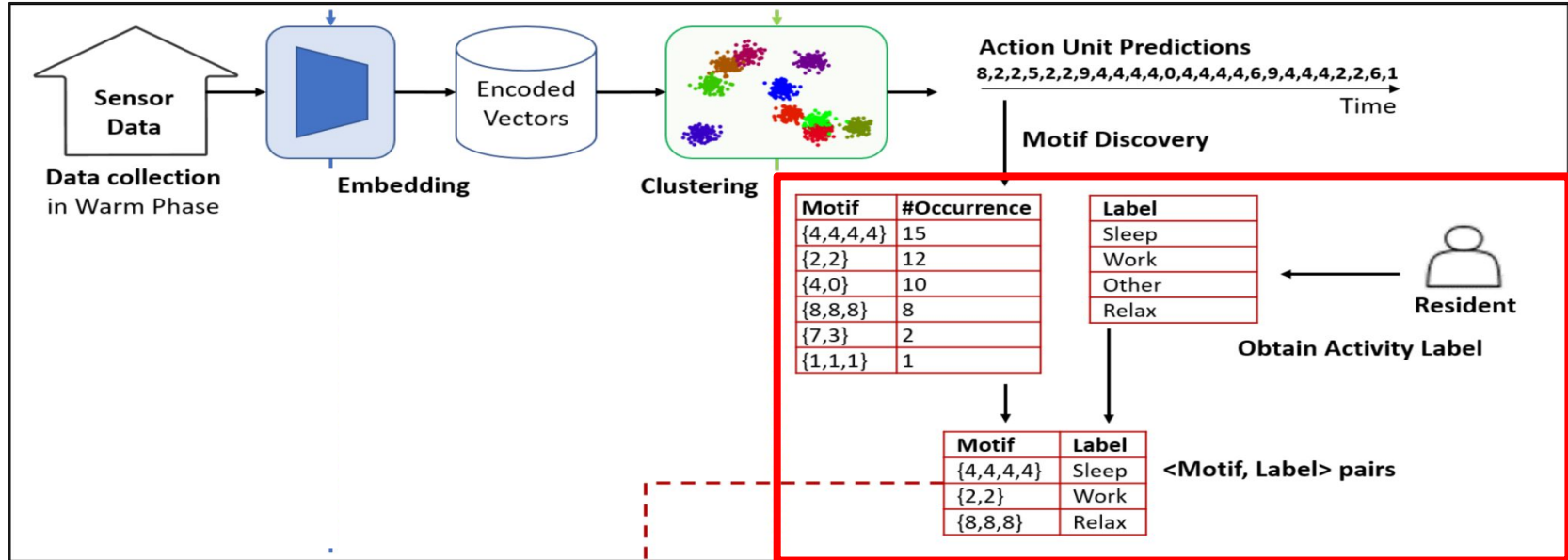Action Unit: Movement in Kitchen

Motifs
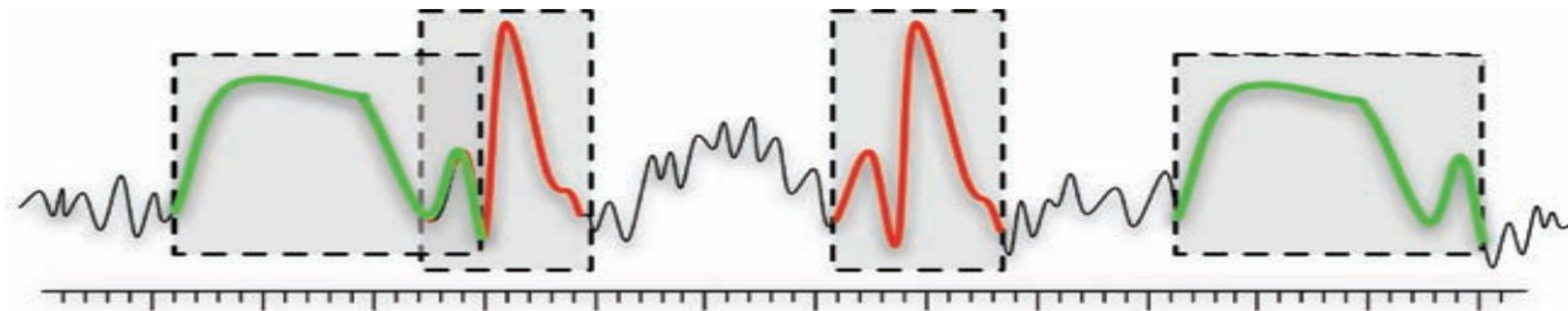
- Recurring sub-sequences in the time-series data

- Capture sequential nature of human activities

Esling, Philippe, and Carlos Agon. "Time-series data mining." *ACM Computing Surveys (CSUR)* 45, no. 1 (2012): 1-34.
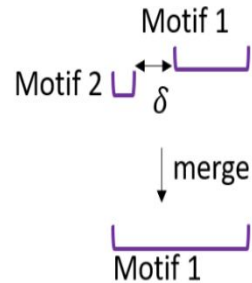
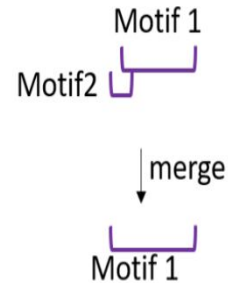# Phase 2a: Warm Phase - Motif Discovery

# Phase 2b: Warm Phase - Bottom-Up Merge of Motifs
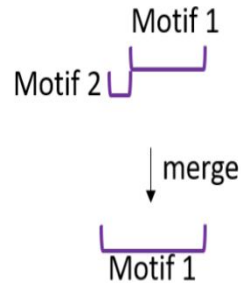
(a) Motif 2 precedes/follows Motif 1 in occurrence, both occur consecutively. Merge motifs through additive procedure
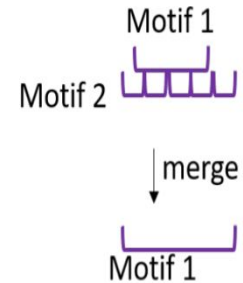
(b) Motif 2 precedes/follow Motif 1 in occurrence, both occur consecutively, within an allowable distance apart. Merge motifs through additive procedure

(c) Instances of Motif 2 overlaps with Motif 1. Merge motifs through additive procedure
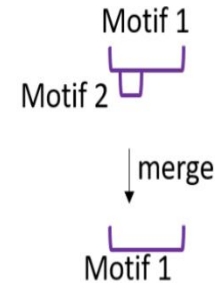
(d) Instances of Motif 2 overlap with Motif 1. Merge motifs through overlap procedure

(e) Instances of Motif 2 overlaps and precedes/follows with Motif 1. Merge motifs through additive and overlap procedure

Results of Warm Phase - Identified Motifs

Motifs discovered in the *Warm Phase* for the CASAS-Aruba dataset

Motifs	Activity
(2, 2), (2,2,2)	Work
(5,5), (5,5,5),..	Sleeping
(8,6), (8,8), (6,8,8),...	Relax
(4,3,4), (4,4,4), (4,4,3,4), (4,4,4,3),…	Meal_Prep

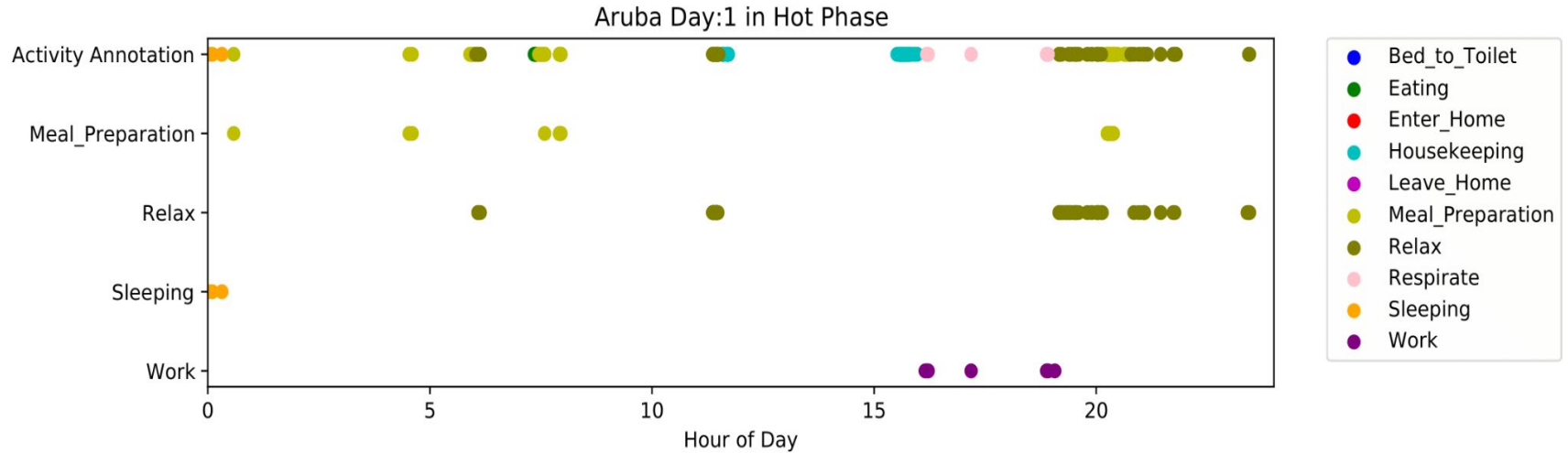# Phase 3: Hot Phase - Activity Recognition in Deployment
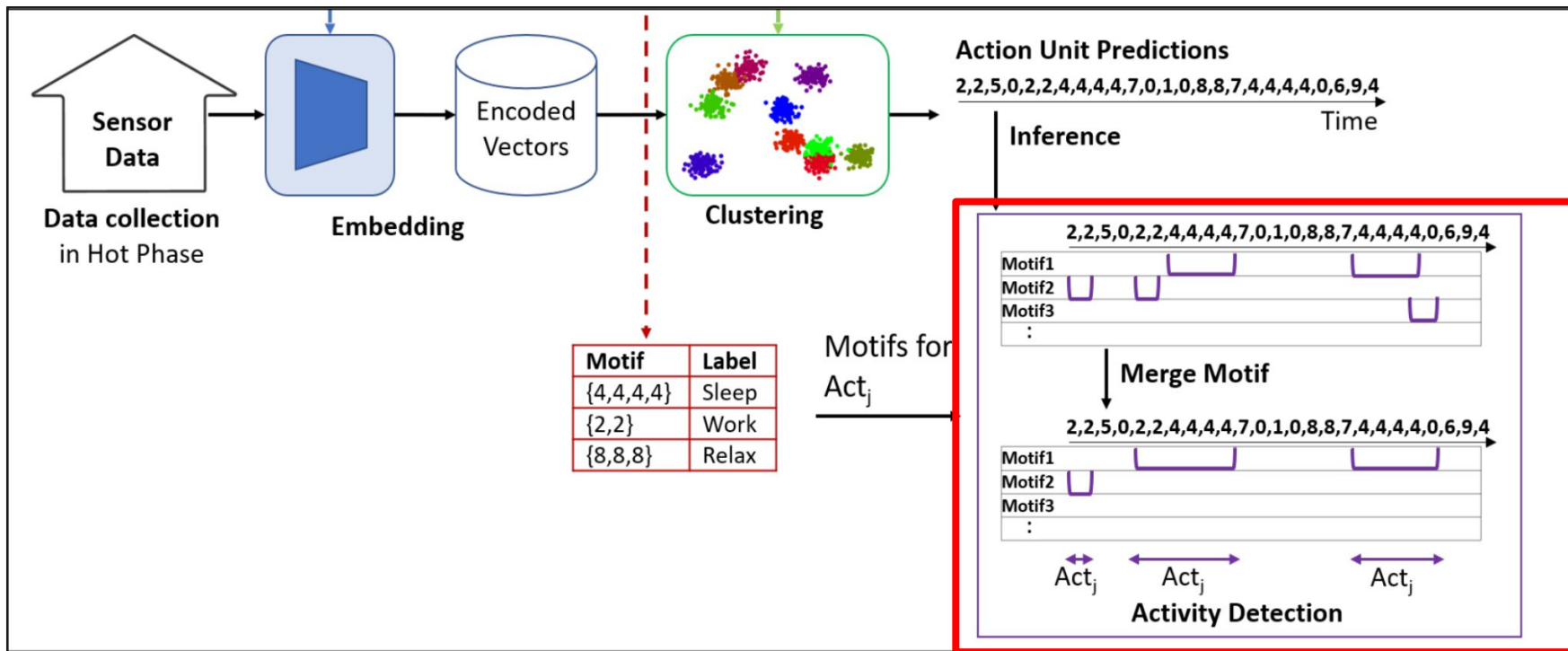
Results of Hot Phase: HAR system in Deployment

Activities Modeled through Bootstrapping Procedure

| Activity	Activity Detection Rate	#Activity Instances Detected	#Activity Instances Missed
Sleeping	0.944	253	15
Meal_Preparation	0.557	816	642
Relax	0.720	1803	698
Work	0.846	110	20

Activity Detection Rate: Instances Detected / (Instances Detected + Instances Missed)

Activity Recognition in Deployment - CASAS Aruba


Aruba Day:1 in Hot Phase

- Motif models correspond to most activities that occur during the day

- 'Exercise' predicted as 'Work' (similar movement patterns; lack of contextual data)

Activity Recognition in Deployment - CASAS Aruba

Aruba Day:100 in Hot Phase
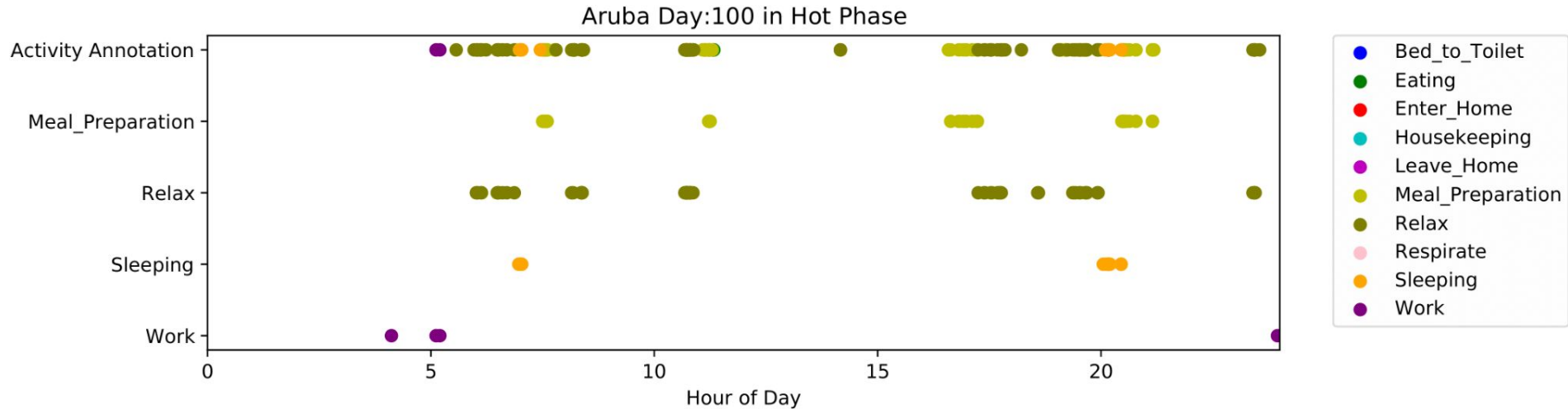
- 'Meal_Preparation' and 'Relax' are hard to differentiate

- Harder to discern activities occurring in similar spatial regions

Conclusion
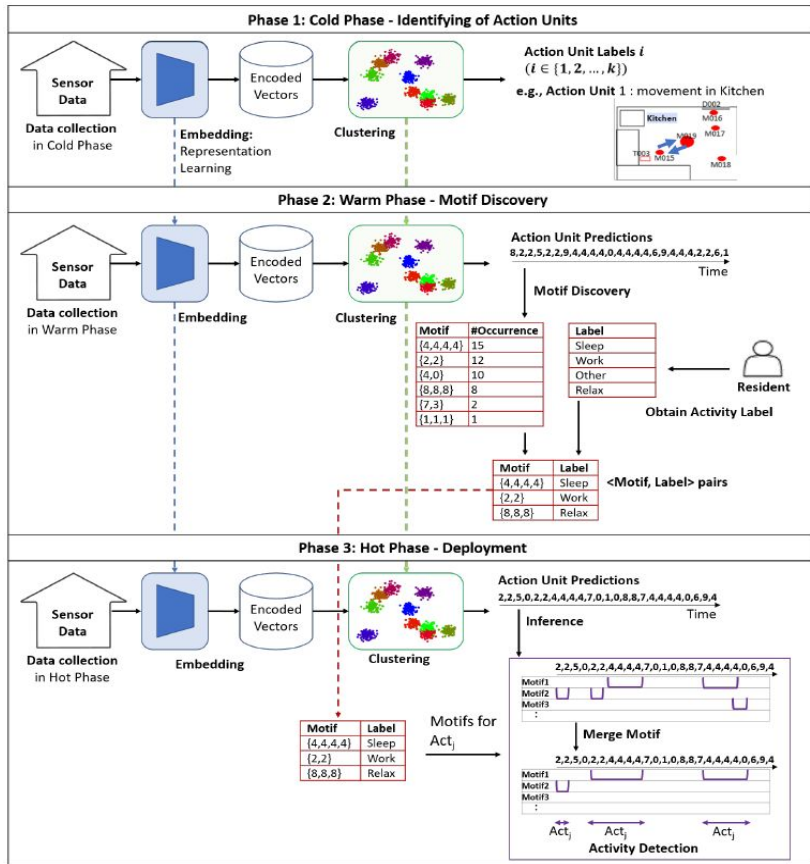
Identify action units - reusable movement patterns in smart homes

Build hierarchical knowledge through motif discovery

Deploy developed activity recognition system in the smart home

Limitations

- Bootstrapping procedure is ***always*** performed from scratch

- Method developed for ***single-resident households***

- Assuming sufficiency of ***2 weeks*** for the Cold and Warm Phase respectively

Future Work

Adaptive ML

https://ai.kuleuven.be/stories/post/2021-05-10-continual-learning/
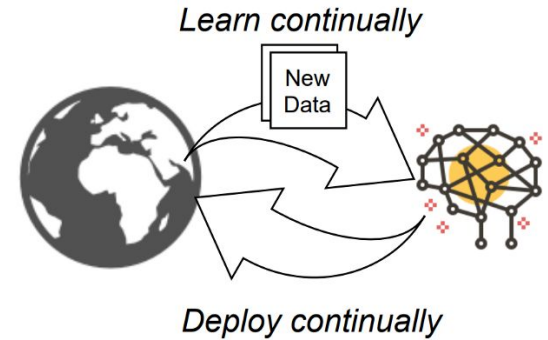
Continual Learning -

- Life is ever changing

- Adapt to changing data pattern in the smart home

Utilizing Human in the Loop-

- General proof of procedure

- Incorporate direct access to actual residents (Resident- in-the loop)
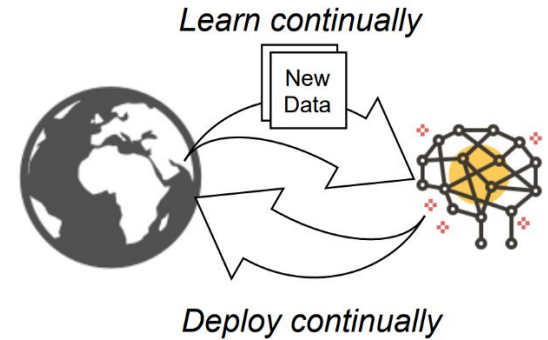
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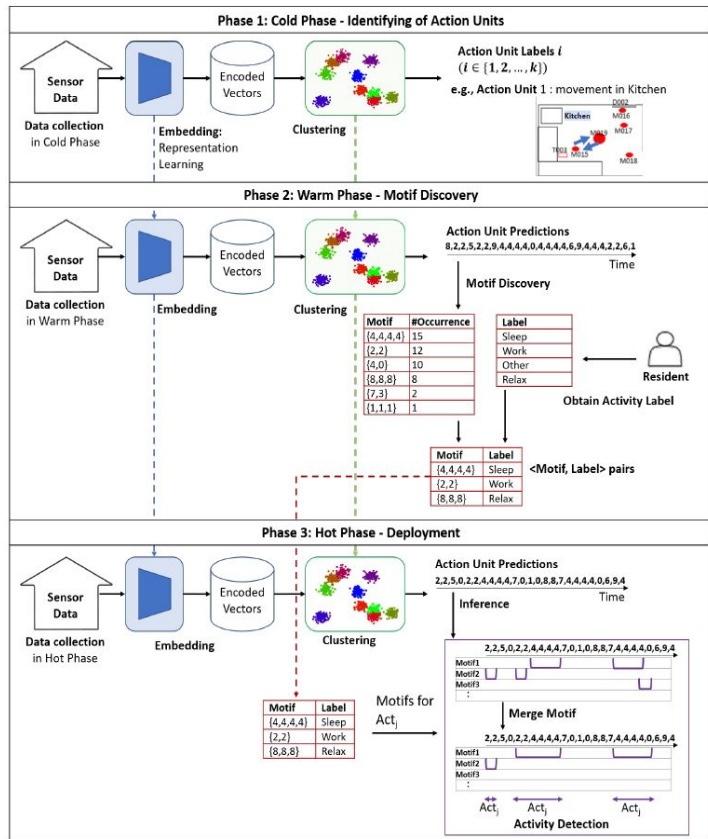- Incorporate direct access to actual residents (Resident- in-the loop)

Adaptive ML

Learn continually

New Data

Deploy continually

https://ai.kuleuven.be/stories/post/2021-05-10-continual-learning/

Resident

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Email:
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PDF:
https://dl.acm.org/doi/10.
1145/3550294