KYUNG HEE UNIVERSITY
Department of Computer Science & Engineering
Ubiquitous Computing Laboratory

Semantic-aware Data Imputation for Unobtrusive Complex Human Activity Recognition

Ph.D. Dissertation Presentation

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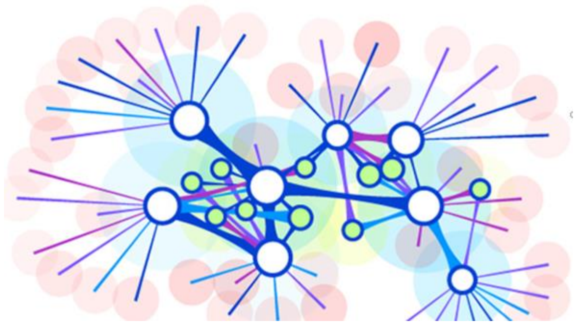

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(Prof. Sungyoung Lee)
(Prof. Seungkyu Lee)

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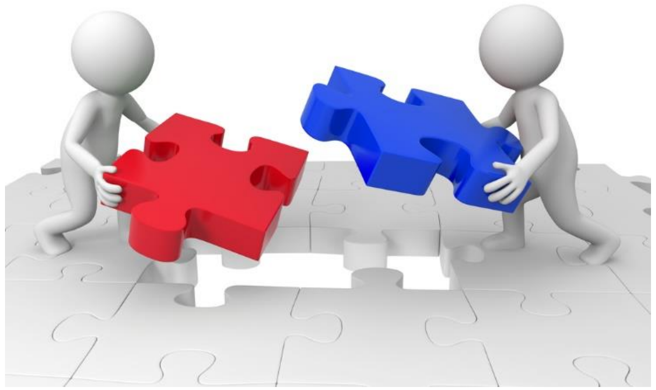
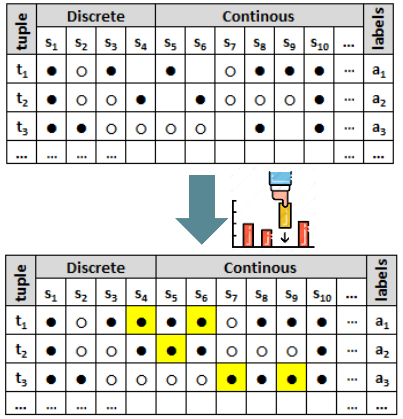
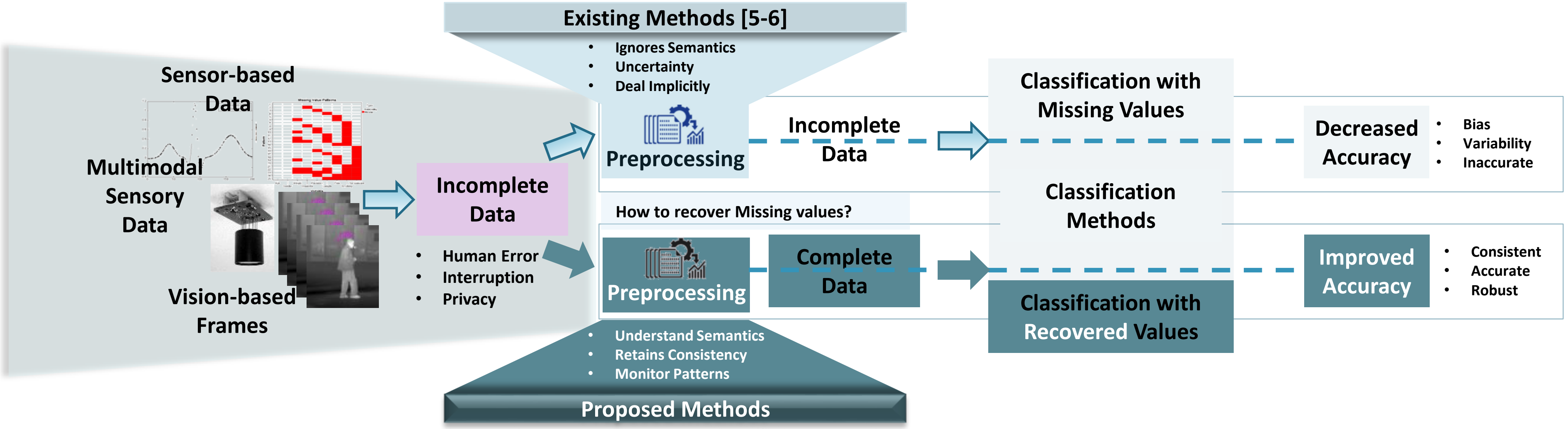


Background

1. In real-world Human Activity Recognition (HAR) applications,
   - **missing values** [5] results in loss of **data integrity** [6],
   - **misleading conclusions** [20],
   - and **unfair performance** [22].
2. To **recover** missing values, statistical **recovery** methods [2]
   - improve **prediction accuracy** [4] in classification tasks,
   - making the models **less efficient** by **ignoring** internal **semantics**.
3. **Preprocessing** [7] observed data
   - using **semantics** [19] information
   - with appropriate **inference** [24] adjustment
   - can improve **prediction accuracy** [16]
   - can address **classification** in **time series** prediction problems.





Motivation$_{(1/3)}$

Why to recover missing values?

For building a viable **predictive model** [6] **preprocessing** of missing values during data preparation is an important and critical step.

Following **benefits** propel us to perform this work:-

- **Accurate estimation** for statistical analysis [7].
- Preservation of inter-variable **semantics** [17-18].
- Minimize the **bias** between the missing and complete data [7].
- Sampling of **different** and **irregular** time-series data [15].
- Reduction of misleading **inferences** [16].
- Handling **variety** of Data [7].

Accurate

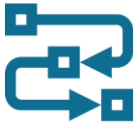
Preserved Semantics

Existing Approaches

- R — Numerous Statistical methods exists
- R — Missing values mostly deleted or correlations ignored

Proposed Research

Methodology



Research Outcomes

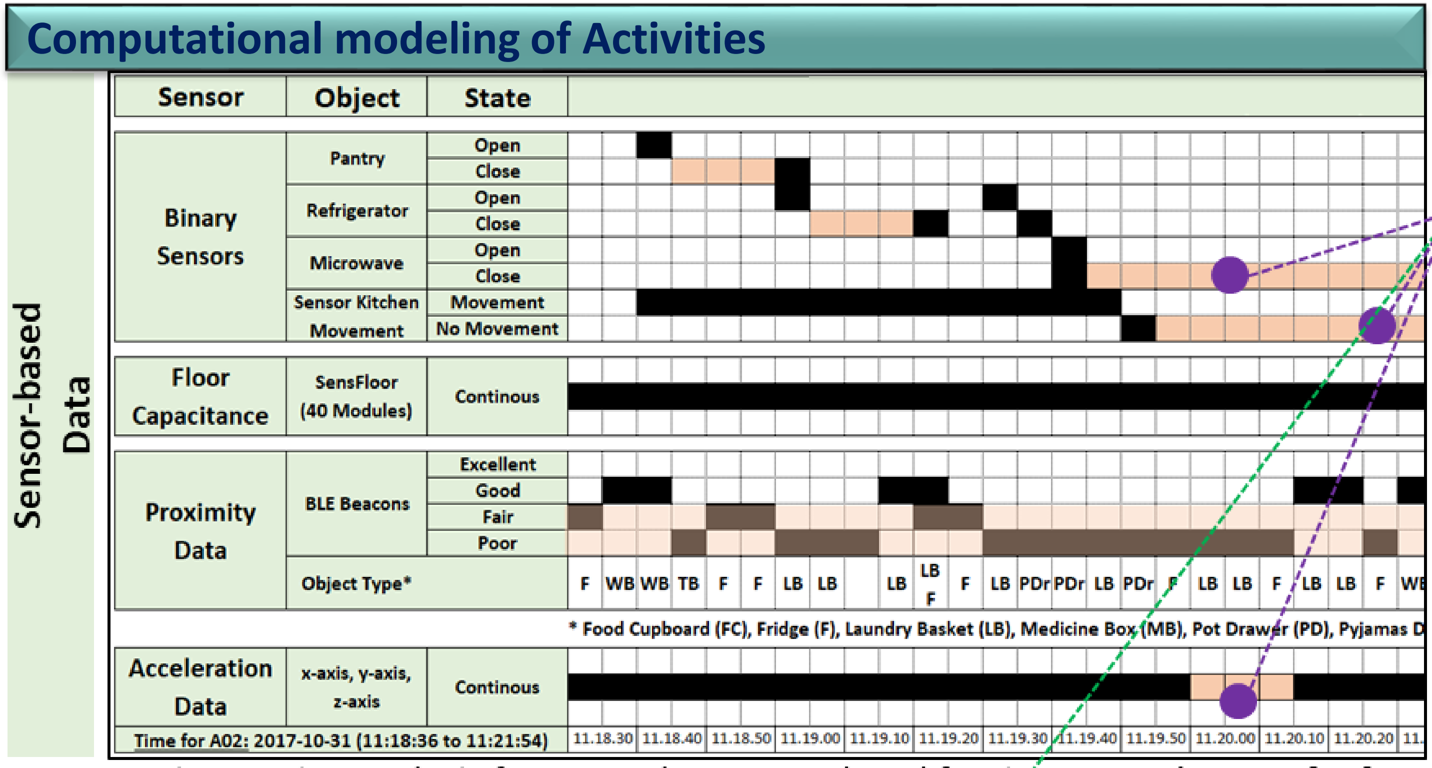
- C — Enrich semantic properties of data
- A — Improves Data Quality
- C — Bias Minimization
- A — Ensures Data Consistency

R Reasons C Characteristics A Advantages

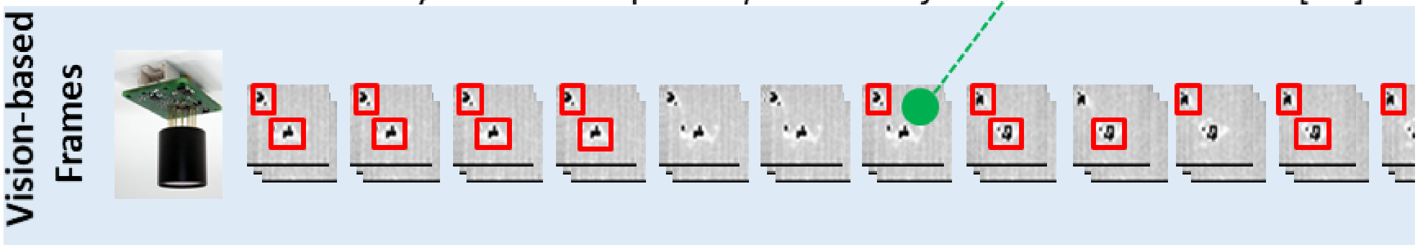
Motivation(2/3)

Variety of Data Formats in smart-homes environment

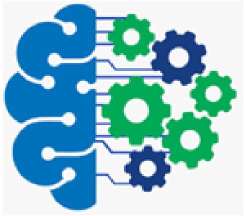
- **Structured**
  - **Discrete** (Numerical)
  - **Continuous** (Numerical)
  - **Nominal** (Categorical)
- **Unstructured**



Time series analysis for example *Prepare breakfast* in *UCamI* dataset [11]



Data Imputation: Recovery of Missing values in **Structured** & **Unstructured** datasets is **important** Step



Classification Model

Motivation(3/3)

Existing Approaches [28,42]

Data Imputation

Explicit Modeling

- \+ Preserves the Data and easy to use.
- \+ Give better estimates
- − Decreases variance in MCAR, unnecessary correlations
- ❖ Examples: Mean, Regression etc.

Knowledge-based Modeling

- \+ Uncertainty Inclusion, learning ability, able to represent complex relations
- − Human Expertise requirement
- ❖ Examples: ontology rules, decisions with variable relationships.

Estimation-based Modeling

- \+ Accurate estimations of past, present and future states
- − Development and validation require time & effort
- ❖ Examples: Kalman filter based methods etc.

Research Taxonomy [1,5, 6,11-15,17,28, 42]

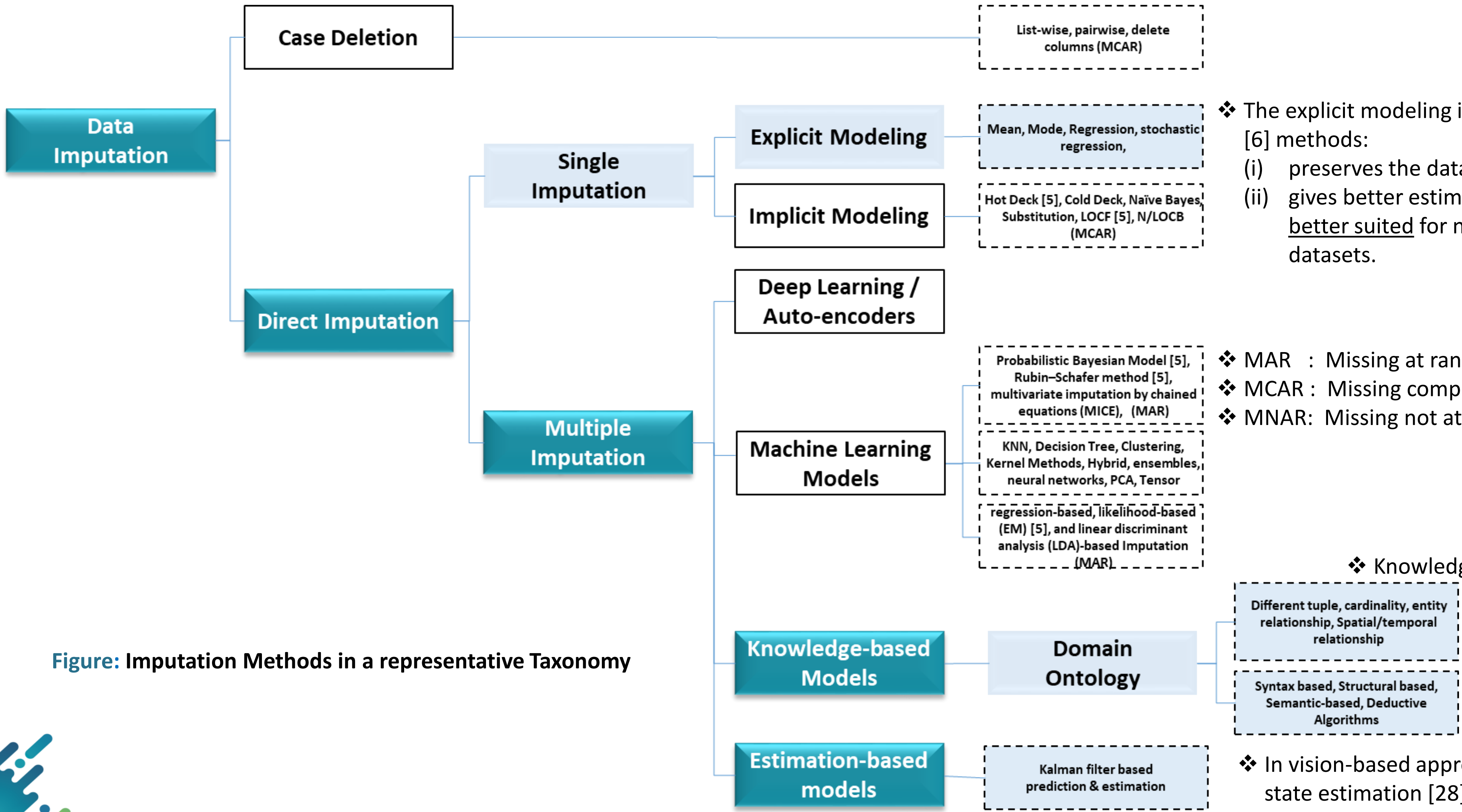


Figure: **Imputation Methods in a representative Taxonomy**

Choose

- ❖ The explicit modeling imputation [6] methods:
  - (i) preserves the data,
  - (ii) gives better estimates and are <u>better suited</u> for numeric datasets.

- ❖ MAR : Missing at random
- ❖ MCAR : Missing completely at random
- ❖ MNAR: Missing not at random

- ❖ Knowledge-based imputation models allows [42]:
  - (i) Solution for uncertainty,
  - (ii) easy to implement,
  - (iii) cater data semantics,
  - (iv) represents complex data semantics,
  - (v) robust to noisy data.

- ❖ In vision-based approach, provides accurate state estimation [28]

Problem Statement

Problem Statement

In the real world environment, building an ***accurate activity recognition model*** [1,2] remains a problem due to ***missing data*** [7], which causes ***loss of semantics*** thereafter resulting in ***reduced*** overall ***performance*** [3] and ***robustness*** [4,5] of the smart home environment.

Identified Challenges

- **C1** How to minimize the missing values and maximize the quality of datasets by keeping ***semantics intact***? [7,8]
- **C2** How to provide an empirical method to prove data ***consistency*** and improve ***accuracy*** for ***structured*** HAR data? [16]
- **C3** How to prove HAR ***robustness*** for ***unstructured*** HAR dataset[4]

Related Works

Categories	Methodologies	Multiple Data Sources	Semantic Data Enrichment	Data Biasness handling	Extract New Knowledge	Benefits	Limitations
Knowledge-based Modeling C1 C2	[SDI] Semantic based data Imputation [42]	○	○	○	●	Low Computation Cost	Cannot deal with Numerical Data, Time-based data
	[CEL] Ontologies based ADL [9]	●	●	○	●	Automatic feature generation	Cannot handle time-dependent missing values
	[RADL] Recognizing ADLs using ontology [8]	●	○	○	●	Discovers new patterns	Lacks handling of missing data and associated rule simplification
	[KCAR] Knowledge-based Concurrent Activities [43]	●	○	○	○	Models Sensor events in ontology	Lack capability to distinguish activity models
	[OSCAR] Ontology-driven Concurrent Activities [1]	●	○	○	●	Data-driven & knowledge-driven	Hard to achieve action sequences and missing data handling
	[TSSD] Semantic Sensor Data Modeling [38]	○	○	○	○	Provides semantic similarities	ML methods with ontology approach ignores most of information with biased results
Estimation-based Modeling C3	[RKN] Uncertainty Integration [33]	○	●	●	○	Accurate uncertainty estimates	Uses filter process which lacks to handle estimation & data association
	[RSM] Detection Tracking & Classification [32]	●	●	●		Foreground segmentation & ML Feature extraction	Single user method lacking support for multi-user data association
	[DMF] Morphological Filtering [27]	○	○	○	●	Effective for binary images	Lack method for explicit feature extraction
Semantic-aware Data Modeling	**Semantic-aware Data Imputation**	**Unstructured & Structured**	**Semantic enriched Data Preparations**	**Ontology Modeling & State Modeling**	**Inferencing Support**	**Accurate & Robust**	**Prior knowledge of Data Domain**

Limitations of Existing Work

- Lack method to keep the ***internal semantics***
- Lack of support to handle ***multivariate data***
- Lack methods for keeping the data ***consistent***
- Not fully compliance with ***missingness*** for data completeness

- No proven method for ***explicit features*** for objects per frames
- Lack techniques to handle per frame object ***data association***
- Less attention to trace ***missed detection*** per frame
- Few methods deal with detection, ***re-identification***, tracking and classification

Our Approach: Limitation, Objective, and Proposed Solution

Limitations and Challenges	Proposed Solution	Objectives
Challenge: 1 ○ ***Multivariate data modeling*** **by keeping the internal** ***semantics***	**Solution-1a** ○ **Implicit knowledge discovery through inference using** ***SemImputOnt*** **Ontology by modelling datasets**	○ ***Understand*** **accurately** ***semantics*** **for multivariate HAR data**
Challenge: 2 ○ **Data** ***Consistency*** **&** ***Completeness***	**Solution-1b** ○ **Apply semantic structural and instance properties with** ***Multi-strategy Imputation Methods***	○ **Retain** ***consistency*** **after Structural and missing values imputation resulting in** ***complete data***
Challenge: 3 ○ **Object** ***data association*** **per frame with preserved semantics and** ***identification*** **of** ***missing objects***	**Solution-2** ○ ***Multioccupant State Imputation*** **using Low resolution thermal frames**	○ ***Impute missing states*** **in unstructured data representing multioccupant per frame**

Goal

Recognition of **Highly Accurate** Human Activities over Semantically Imputed HAR dataset

Thesis Map

Input

Multimodal Dataset

Challenges

- Uncertainty
- Lack of multivariate semantics
- Incompleteness
- Inconsistent
- Accurate estimation

Structured Data

Solution 1a

Algorithm 1
SemImputOnt Modelling
C1 [1]

Problem: Multivariate Semantics?
Output: Transform Structured data into instance-based Knowledge model

Solution 1b

Algorithm 2
Multi-strategy Imputation Method
C2 [2]

Problem: Inconsistency & Missingness
Output: Completeness Consistency & Multivariate Semantic preservation

Unstructured Data

Solution 2

Algorithm 3
Multioccupant Feature Vector
C3 [3]

Problem: Per Frame Object Semantics
Output: Array of morphological features for multioccupant per frame

Algorithm 4
Multioccupant State Imputation
C3 [3]

Problem: State Imputation & Data Association
Output: Detects, Tracks, Re-identify, impute object per frame with data association

Output

HAR

Outcomes

- High Accuracy
- Increased Robustness

Existing Methods

Uses relational data based statistical models but **lack inference** mechanism

Existing Methods

Single / Multiple Imputation methods most often involve **implicit correlations** leading to **biasness**

Existing Methods

Extract implicit **shape-based** and **motion-based** features on high resolution **RGB** Frames

Existing Methods

CV-based classification methods ignore **object semantics** for missed detections

Outcomes

- Loss of efficiency
- Poor Accuracy
- Data Analysis Complications

[1] Razzaq, Muhammad Asif, et al. "mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification." MDPI, Sensors 17.10 (2017): 2433.
[2] Razzaq, Muhammad Asif, et al. "SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition." MDPI, Sensors 20.10 (2020): 2771.
[3] Razzaq, Muhammad Asif, et al. "uMoDT: an unobtrusive multi-occupant detection and tracking using robust Kalman filter for real-time activity recognition." Springer, Multimedia Systems Journal 26.5 (2020).

Proposed Solutions

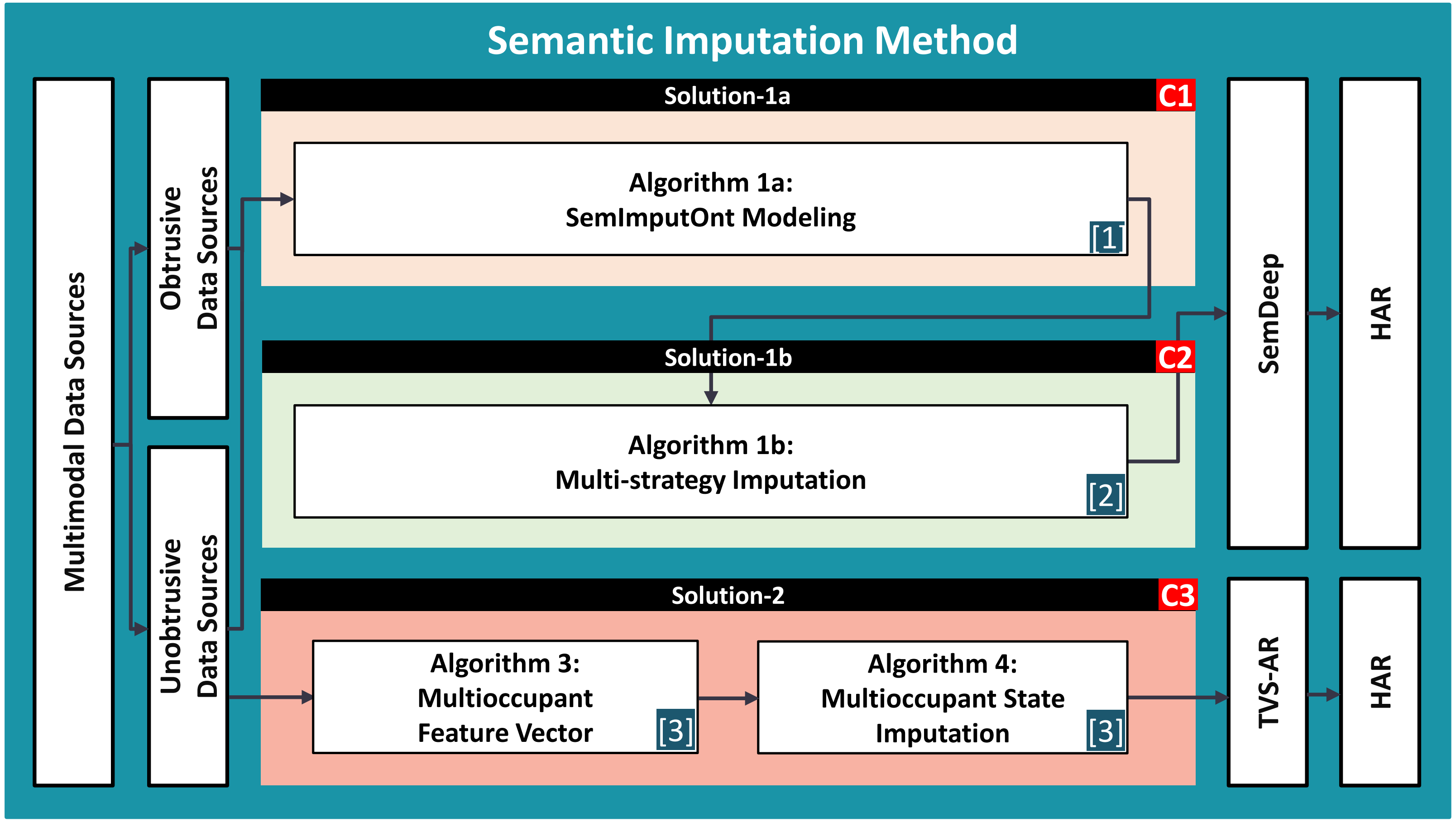
Limitations

1

[1,8,9,38,43] Existing methodologies mainly uses statistical data imputation methods by *ignoring multivariate semantics* leading to unnecessary *correlations*, *biasness* and *inconsistency* in the data after imputation, which leads to *inaccurate* results.

2

[27,32,33] Existing approaches mainly deal with RGB images for HAR without describing *data association* per frame by *ignoring semantics* during detection and tracking.



Solutions

1

1a Proposed a practical scheme for keeping multivariate ***semantics intact*** amongst time series HAR data.

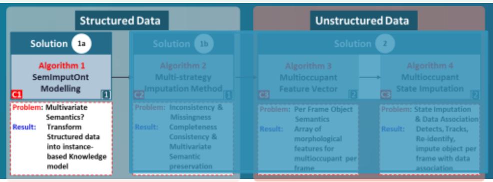
1b Proposed an ***efficient*** imputation approach for Data ***consistency*** after replacing missing values.

2

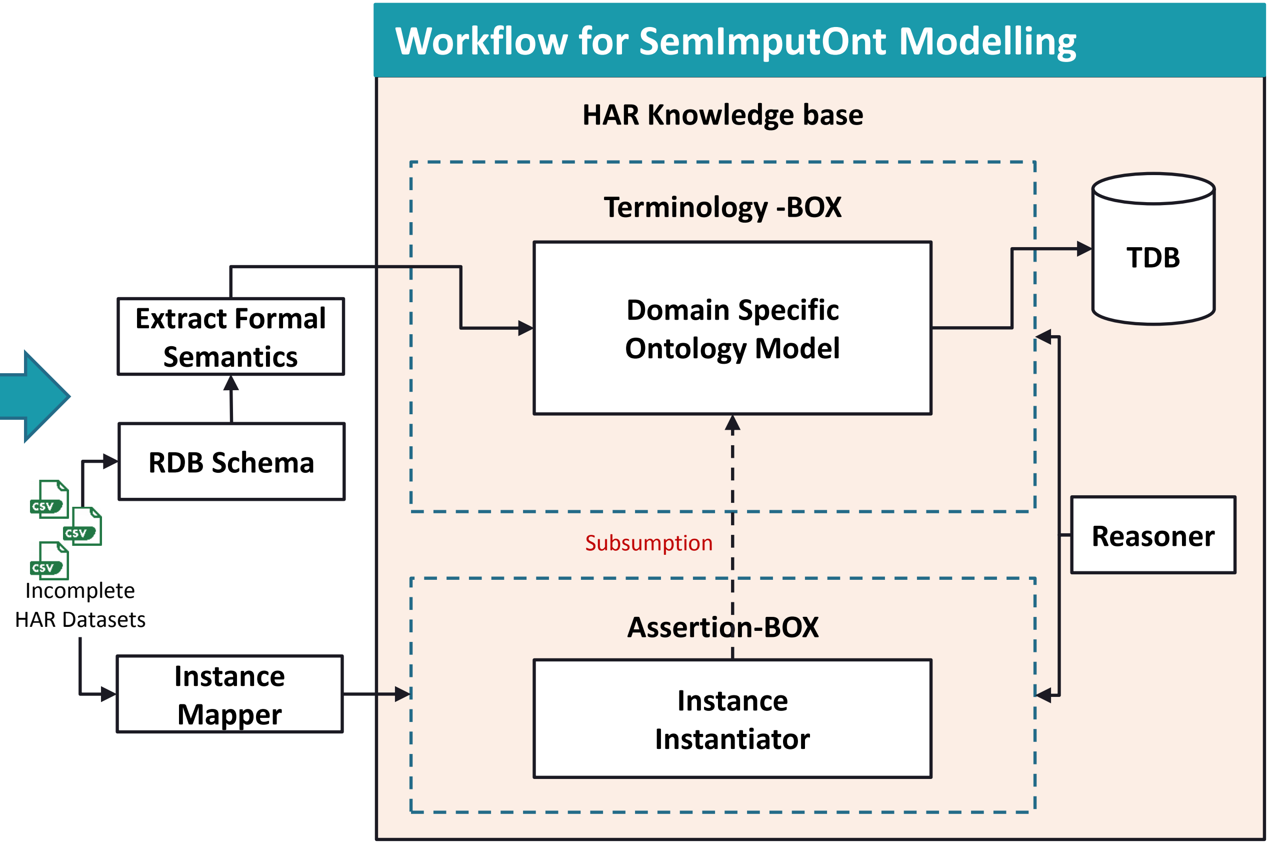
Introduced a ***robust*** HAR approach with multi-occupant state ***estimation*** using real-time privacy preserved technique with ***per frame*** occupant ***data association.***

[1] Razzaq, Muhammad Asif, et al. mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification." **MDPI, Sensors** 17.10 (2017): 2433.
[2] Razzaq, Muhammad Asif, et al. "SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition." **MDPI, Sensors** 20.10 (2020): 2771.
[3] Razzaq, Muhammad Asif, et al. "uMoDT: an unobtrusive multi-occupant detection and tracking using robust Kalman filter for real-time activity recognition." **Springer, Multimedia Systems Journal** 26.5 (2020).

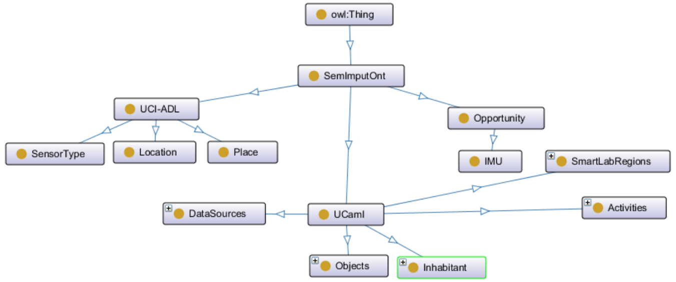
Solution-1a: *SemImputOnt* Modelling

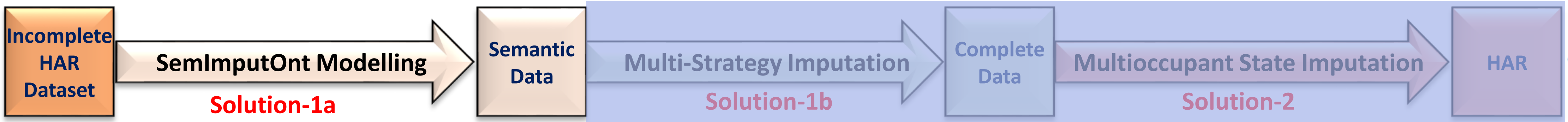


Input
*Struct*ured Data

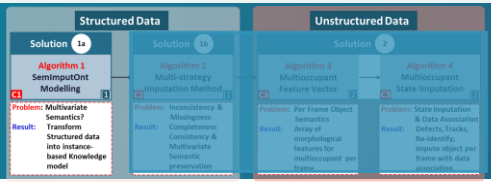


Output
Semantic Data

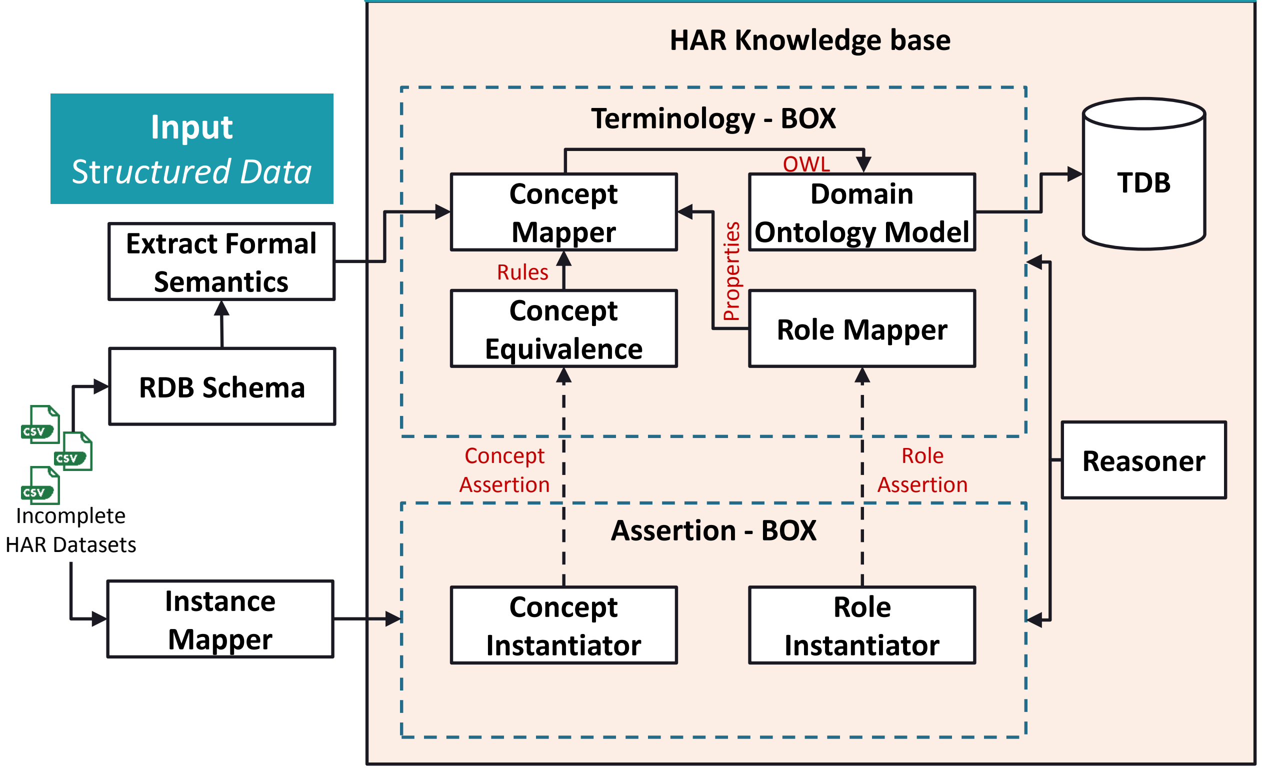




Solution-1a: *SemImputOnt* Modelling (1/4)



Workflow for SemImputOnt Modelling



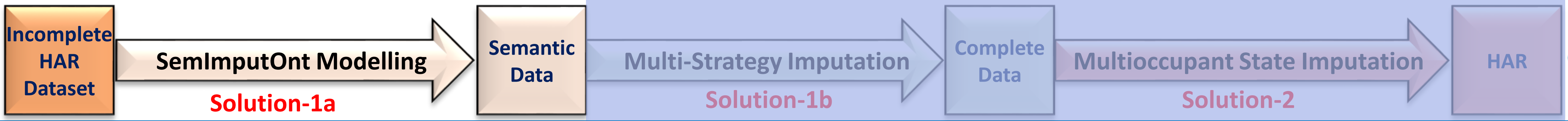
Output
Semantic Data

Highlights of the idea

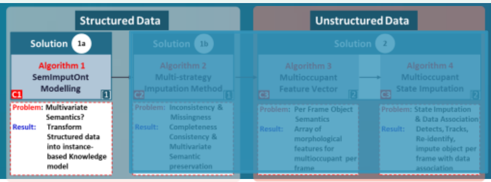
- Identifies the **Class** Concepts, **Relationships** (Object Properties & Data properties).
- Constructs the **semantic rules** defining individual **complex human activities**.
- SemImput Ontology model **maps time-series** HAR datasets by understanding semantics.

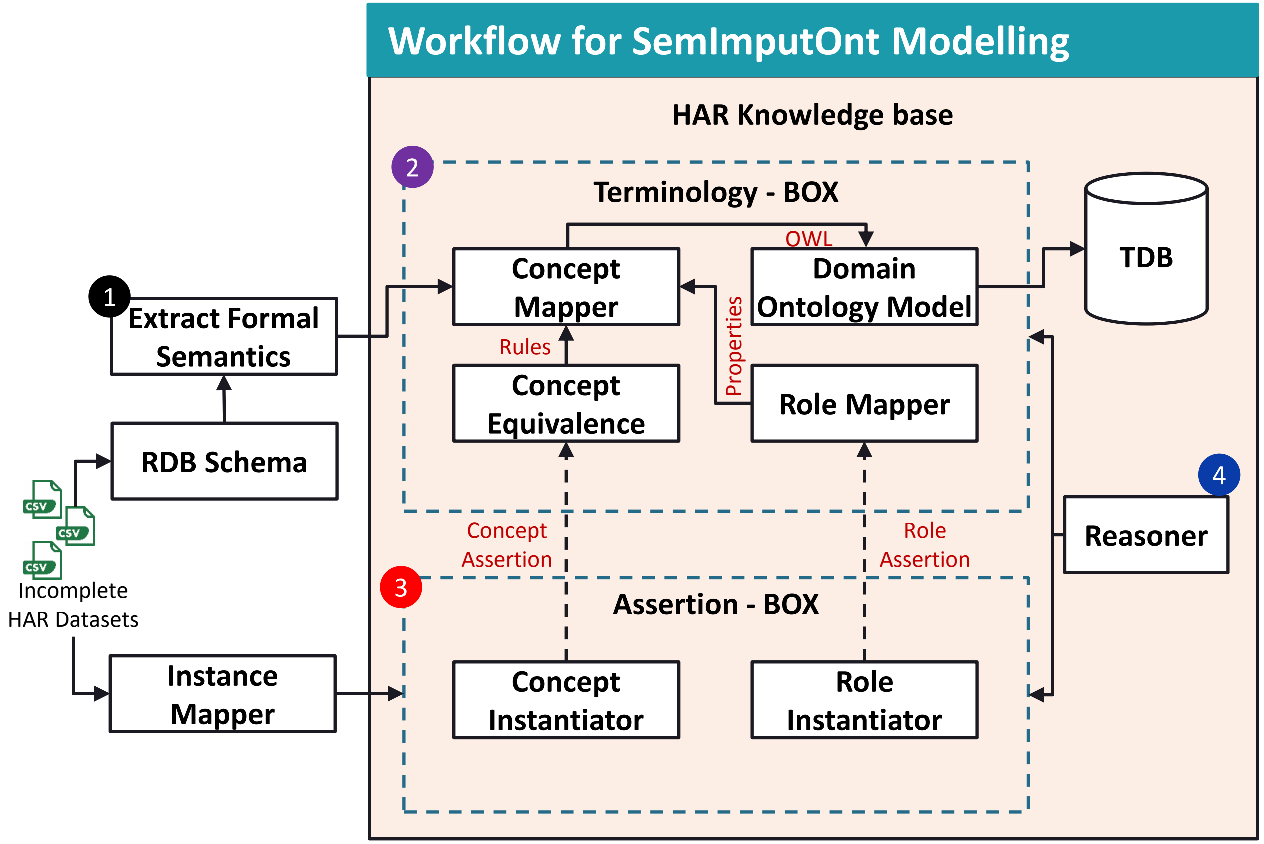
Different to existing approaches

- Data usually stored in **flat files** or relational **databases** using relational dependencies.
- Statistical models introduce **biasness** in the data by selecting **equality neighbors** for data repair.
- Statistical Imputation increases unnecessary **correlations**, which lead to **performance degradation**.



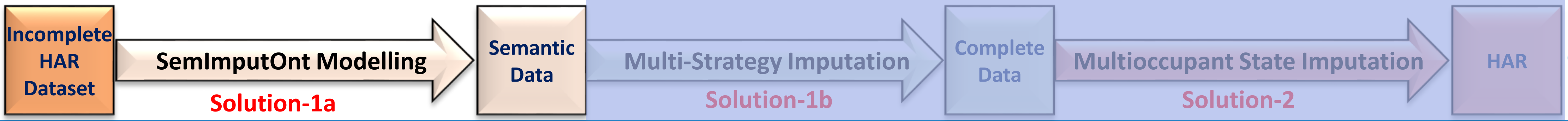
Solution-1a: *SemImputOnt* Modelling (2/4)





Proposed Algorithm 1 : *SemImputOnt Modelling*

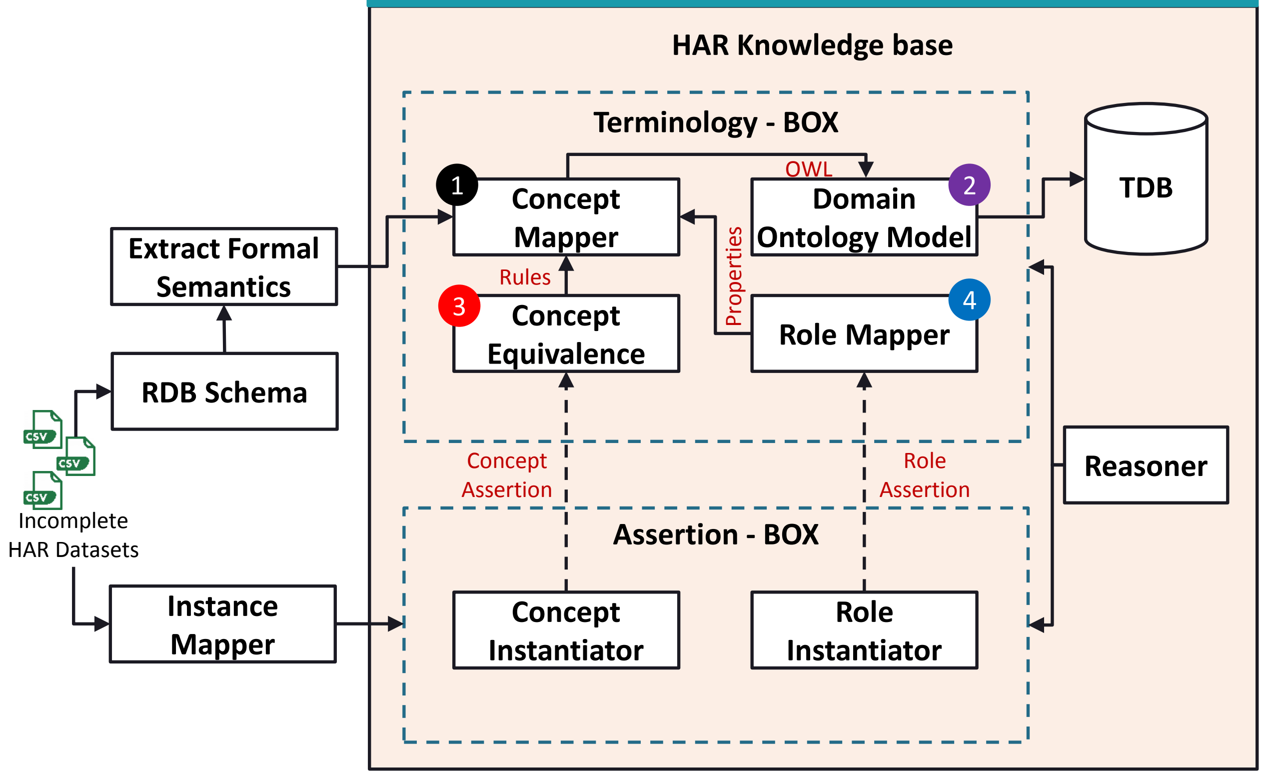
1. **Analyse** and **sample** the raw sensor time-based to 1-sec and store in temporary DB.
   - Identify **core vocabulary** to represent the complex concurrent sensor **temporal patterns.**
2. Design and construct **SemImputOnt** ontology using extracted knowledge as **T-Box** terminologies.
   - Identifies formal **structural semantics** mappings for **correlated variables** through SemImputOnt HAR Knowledge base for each activity.
3. Each of **multivariate variable** comprising an activity is **defined** by a **separate conjunction** for every involved sensors
   - Ensures each of activity structure and instance is linked with **ranges of time**.
4. Performs the **consistency** checking for each of the object and instance using **Reasoner**.



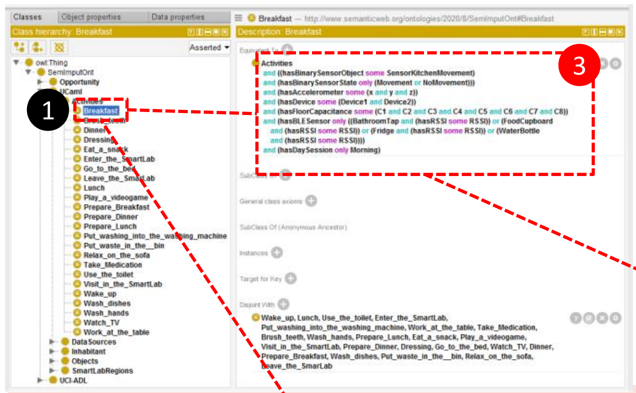
Razzaq, Muhammad Asif, et al. **mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification.**" **MDPI, Sensors** 17.10 (2017): 2433.

Solution-1a: *SemImputOnt* Modelling (3/4) (Proof of Concept)

Workflow for SemImputOnt Modelling

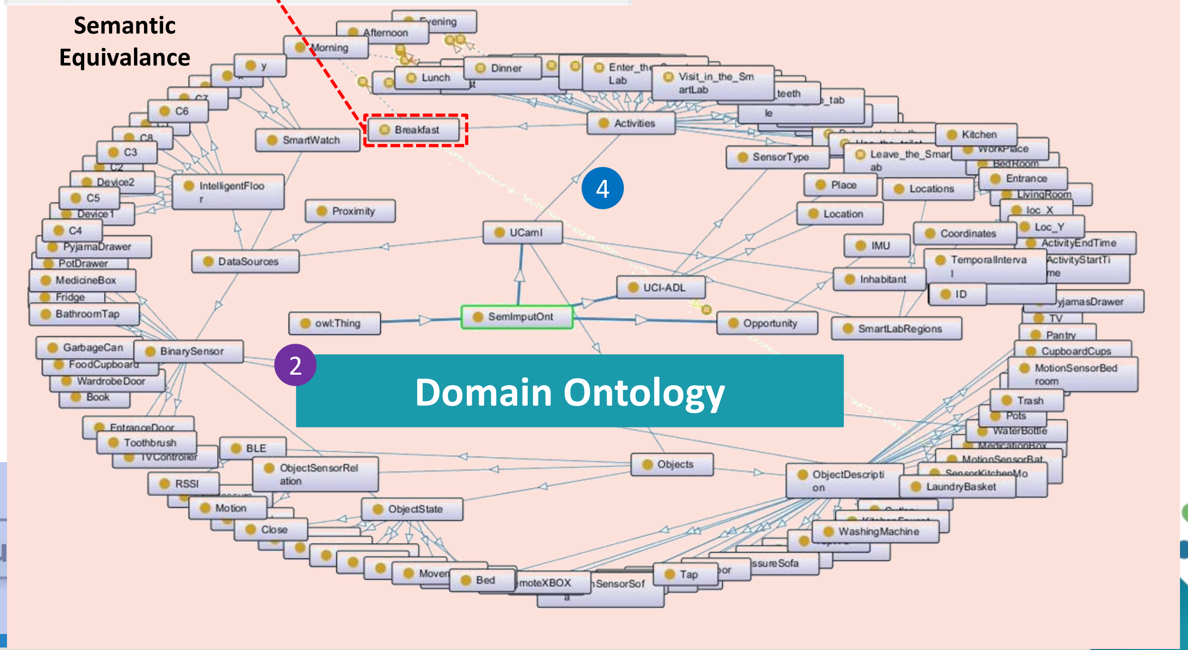


Class Definition Axioms



Class Equivalent Axioms

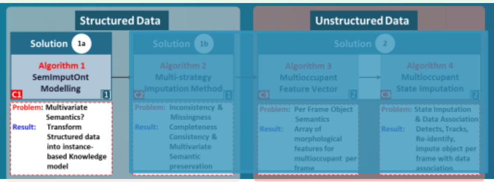
Breakfast ≡ Activities ∩ ∃ hasBinarySensorObject.SensorKitchenMovement ∩ ∀ hasBinarySensorState.(Movement U NoMovement) ∩ ∃ hasAccelerometer.(x ∩ y ∩ z) ∩ ∃ hasDevice.(Device1 ∩ Device2) ∩ ∃ hasFloorCapacitance.(C1 ∩ C2 ∩ C3 ∩ C4 ∩ C5 ∩ C6 ∩ C7 ∩ C8) ∩ ∀ hasBLESensor.(Tap ∩ ∃ hasRSSI.RSSI U FoodCupboard ∩ ∃ hasRSSI.RSSI U Fridge ∩ ∃ hasRSSI.RSSI U WaterBottle ∩ ∃ hasRSSI.RSSI) ∩ ∀ hasDaySession.Morning



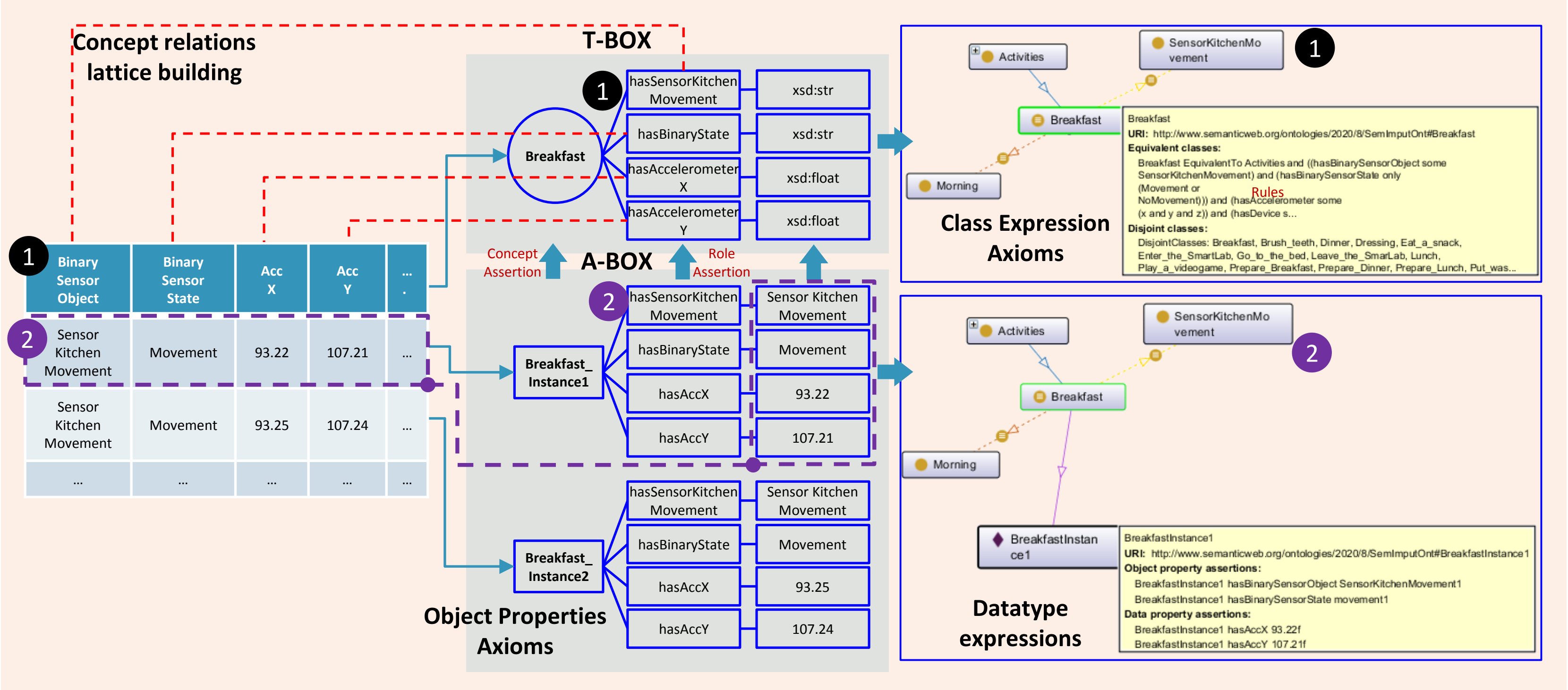
Incomplete HAR Dataset → SemImputOnt Modelling → Semantic Data → Multi-Strategy Impu…

Solution-1a   Solution-1b

Solution-1a: *SemImputOnt* Modelling (4/4) (Proof of Concept)



Relationship Modelling, Segmentation & Instance Initialization



Breakfast Instance in OWL/RDF

<owl:NamedIndividual
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<rdf:type rdf:resource="http://www.semanticweb.org/ontologies/2020/8/SemImputOnt#Breakfast"/>
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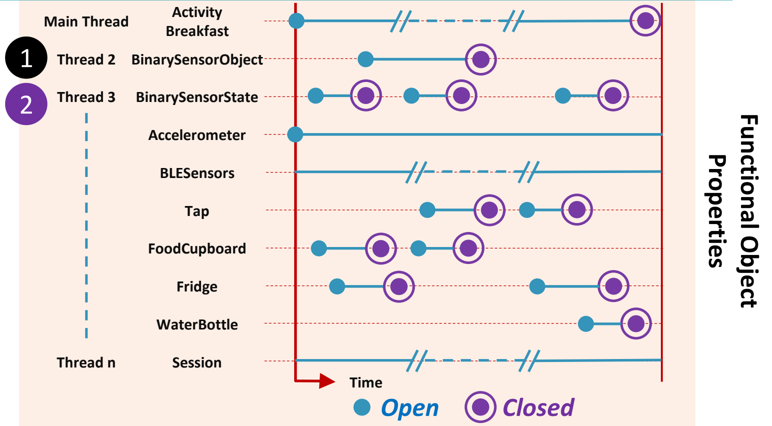
rdf:resource="http://www.semanticweb.org/ontologies/2020/8/SemImputOnt#SensorKitchenMovement1"/> 2
<SemImputOnt:hasBinarySensorState
rdf:resource="http://www.semanticweb.org/ontologies/2020/8/SemImputOnt#movement1"/>
<SemImputOnt:hasAccX
rdf:datatype="http://www.w3.org/2001/XMLSchema#float">93.22</SemImputOnt:hasAccX>
<SemImputOnt:hasAccY

Concurrent States Management



Inconsistencies Analysis

- *cq1*: Valid *Open* sensor state
- *cq2*: Valid *Closed* sensor state
- *cq3*: *Start-time* of *Next*, sensor state
- *cq4*: Sensor having *Open* state within the sliding window
- *cq5*: Sensor having *Closed* state within the sliding window
- cq6: start-time and still *Open* sensor states
- cq7: start-time but *Closed* sensor states
- cq8: end-time but still *Open* sensor states
- cq9: end-time but *Closed* sensor states

Allen's temporal-based logic primitives

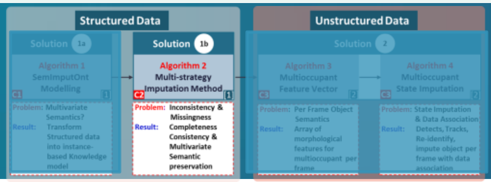
Highlights of the idea

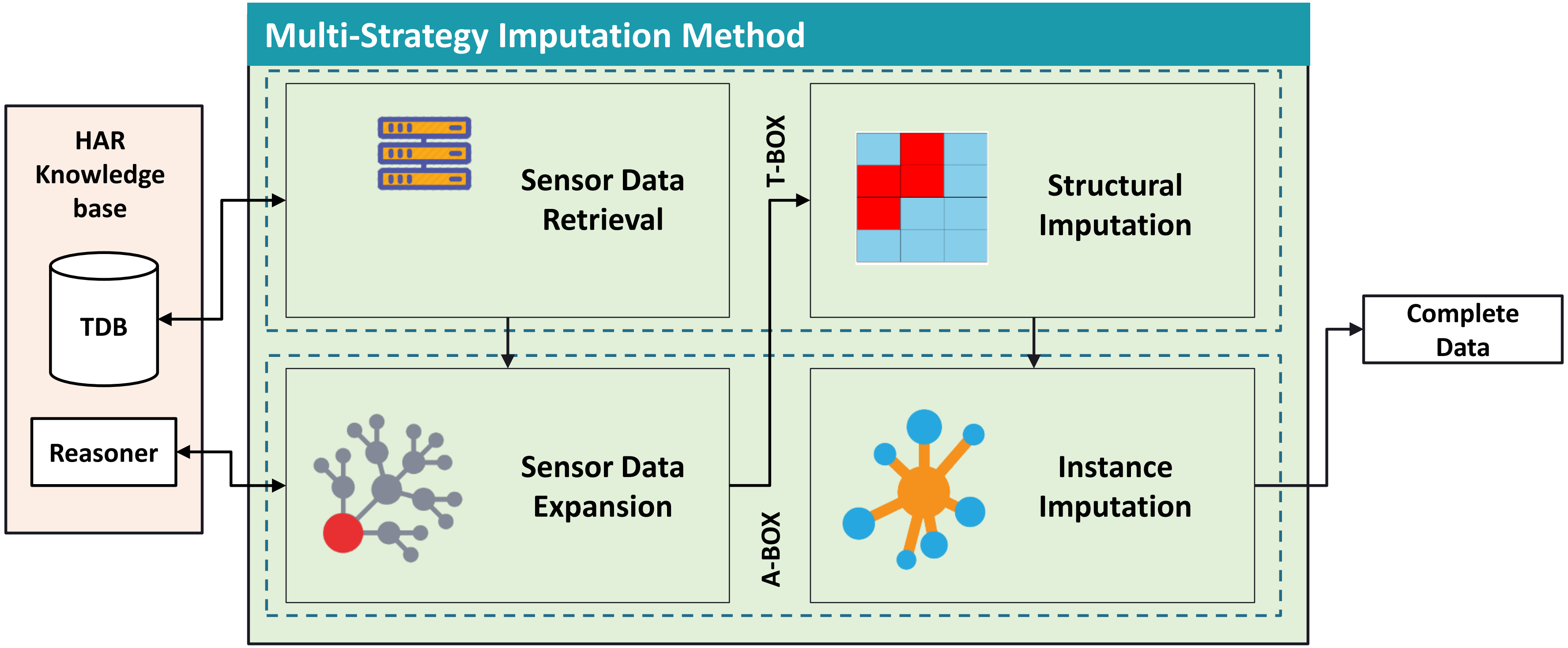
- Identify **mappings** of structural data with ontology knowledge base for each of instance representing Activities.
- Perform the **consistency** checking for each of the instance in a sliding window (3-Sec)
- Each of **conjunction** represents and initializes thread for each involved sensor

Different to existing approaches

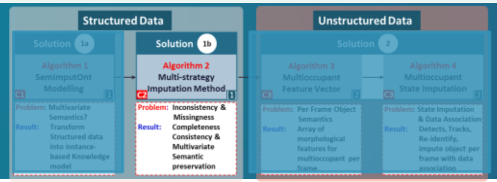
- Most of the statistical methods **initialize inter-variable** mappings implicitly which introduces unnecessary **relations**.
- **No mechanism** of checking data **consistency** exists until the process of classification is achieved.

Solution-1b: *Multi-Strategy Imputation*

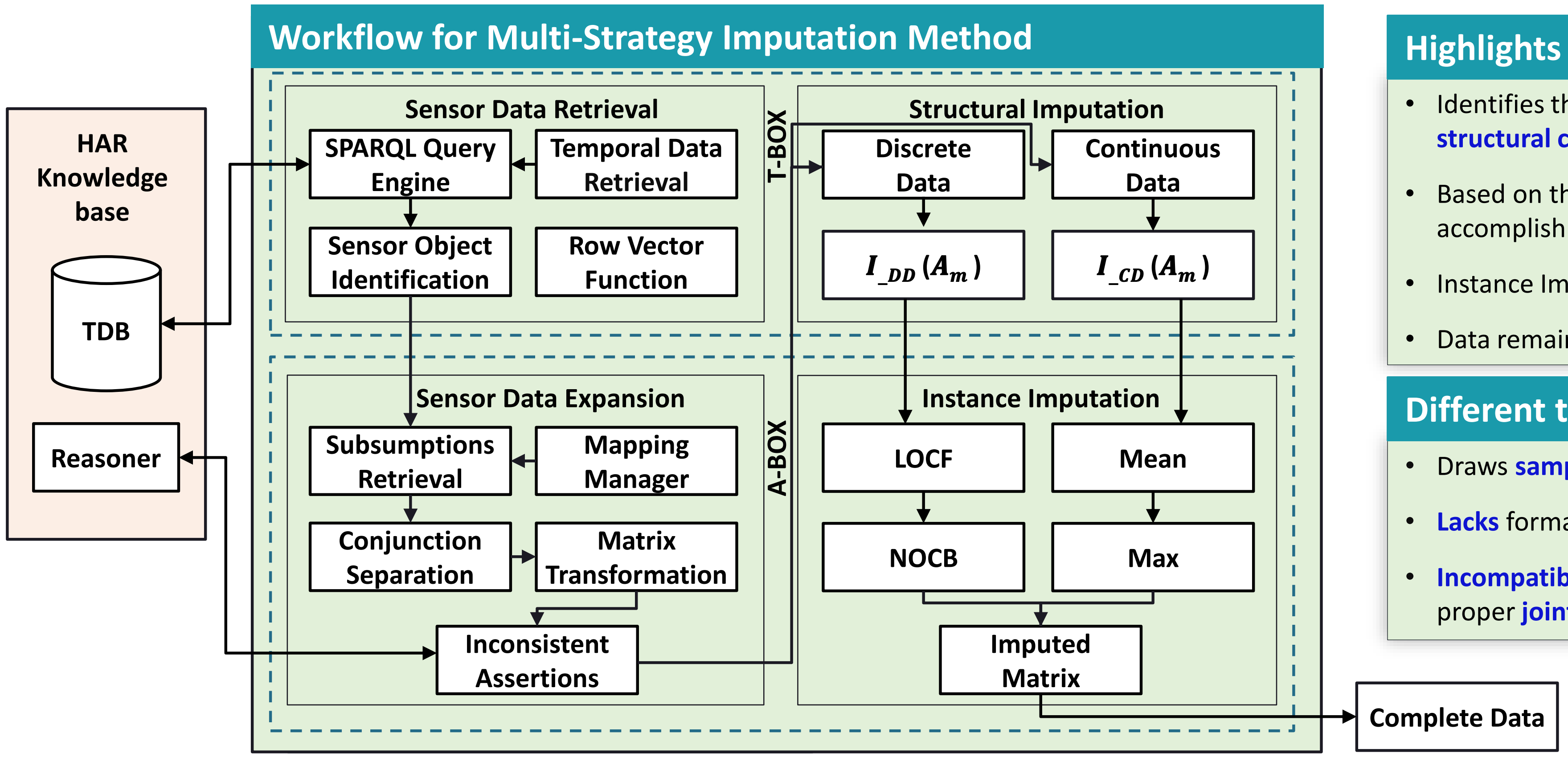




Razzaq, Muhammad Asif, et al. "SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition." MDPI, Sensors 20.10 (2020): 2771.



Solution-1b: *Multi-Strategy Imputation* (1/4)



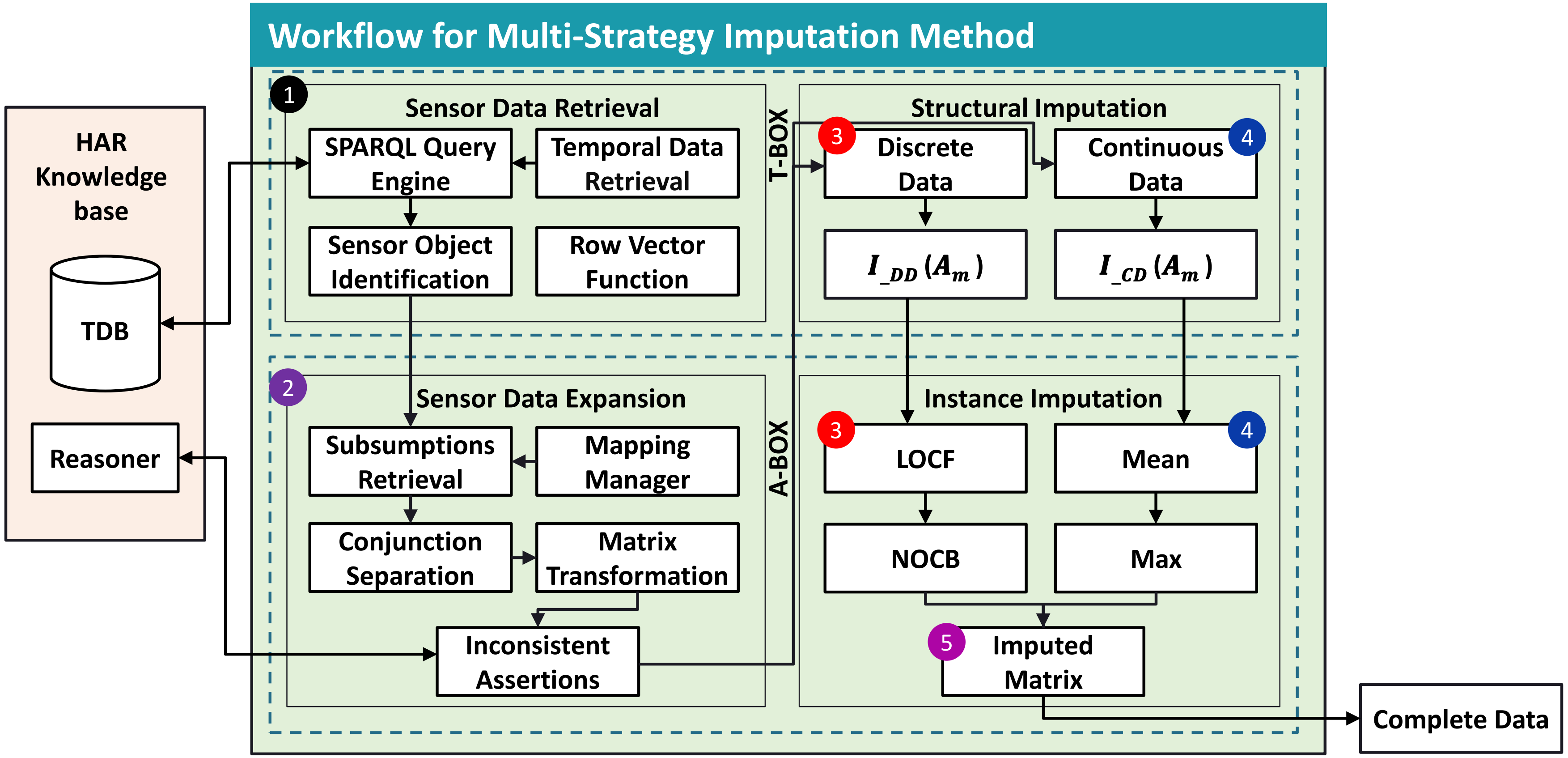
Highlights of the idea

- Identifies the structures of the labelled data and ensures **structural completeness** in target instances.
- Based on the nature of incomplete data, **appropriate strategy** to accomplish **instance repair** is selected.
- Instance Imputation uses time-based **SPARQL** constructs.
- Data remains **consistent** after multi-strategy imputation.

Different to existing approaches

- Draws **samples** and initiate **unnecessary** attribute relations.
- **Lacks** formal theoretical justification.
- **Incompatibility** of fully conditional specifications for which no proper **joint multivariate** distribution exists.

Solution-1b: *Multi-Strategy Imputation* (2/4)



Structural Imputation

Variable Similarity

$$I_{SS}(A_m) = \mathrm{Sim}_{SS}(A_n, A_m) = \frac{\sum_{j=1}^{k} A_n \times A_m}{\left(\sum_{j=1}^{k} A_n^2 + \sum_{j=1}^{k} A_m^2 - \sum_{j=1}^{k} A_n \times A_m\right)}$$

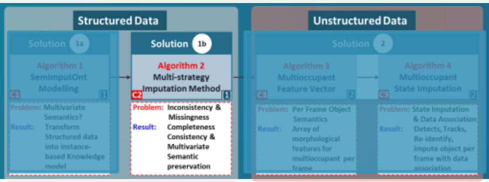
Instance Imputation

Neighborhood Similarity

$$I_{SI}(A_m) = \mathrm{Sim}_{SI}(A_n, A_m) = \max_{m} \frac{\mathrm{overlap}(A_n, A_m, m)}{A_n \uplus A_m}$$

Proposed Algorithm 2

```
procedure SEMANTICIMPUTATION
  for all timestamp t = 1 to T do
    function ImputeBinSens(A_m, CQ, A, T)          ▷ BinSens_attrib with their state imputation
      for (cq_i ∈ CQ) do
        BinSens_Attrib ← execute(cq_i).filter(BinSens, A_m)      ▷ using SPARQL Queries
        BinSens_Target ← execute(cq_i).filter(BinSens_Attrib, T)
        A_BSatt ← BinSens_Attrib
        A_BStar ← BinSens_Target
        max(I_SS) ← Compute I_SS(A_BStar, A_BSatt)                ▷ Equation (10)
        A_BSatt ← A_BSatt ∪ (A_BStar \ A_BSatt)    ▷ Update missing BinSens Attribute
        BinSens_mappings ← retrieve.mappingsLists(BinSens_LOCF, BinSens_NOCB)
        while A_BSatt(state) = φ do        ▷ Load Updated BinSens attributes
          if (A_BSatt in BinSensList_LOCF) then        ▷ based on BinSens characteristics
            A_BSstate ← execute(cq_i).retrieveLastState.(A_BSatt)
            A_BS ← I_L(A_BSatt, A_BSstate)
          else if (A_BSatt in BinSensList_NOCB) then
            A_BSstate ← execute(cq_i).retrieveNext, State.(A_BSatt)
            A_BS ← I_L(A_BSatt, A_BSstate)
          end if
        end while
      end for
      Return Imputed A_BS
    end function
    function ImputeProximity(A_m, CQ) ▷ Imputation for Proximity Sensors and their values
      for (cq_i ∈ CQ) do
        A_Prox ← execute(cq_i).filter(Proximity, A_m)
        Prox_max ← maxValue(A_Prox)
        A_Prox ← Update A_Prox(Prox_max)
      end for
      Return Imputed A_Prox
    end function
    function ImputeFloor(A_m, CQ, A) ▷ Imputation for Floor sensors and their values
      for (cq_i ∈ CQ) do
        A_mfloor ← execute(cq_i).filter(Floor, A_m)
        A_tfloor ← execute(cq_i).filter(A_mfloor, A)
        mean(floortuples) ← Compute I_SI(A_tfloor, A_mfloor)        ▷ Equation (13)
        A_floor ←Update A_mfloor ∪ mean(floortuple)        ▷ update using mean for tuples
      end for
      Return Imputed A_floor
    end function
    function ImputeAccelerometer(A_m, CQ, A)        ▷ Imputation for accelerometer values
      for (cq_i ∈ CQ) do
        A_mAcc ← execute(cq_i).filter(Acc, A_m)
        A_tAcc ← execute(cq_i).filter(A_mAcc, A)
        mean(acctuples) ← Compute I_SI(A_tAcc, A_mAcc)
        A_Acc ←Update A_mAcc ∪ mean(acctuples)    ▷ update using mean for last 10 tuples
      end for
      Return Imputed A_Acc
    end function
  end for
  A_m^Imp ← A_BS || A_Prox || A_floor || A_Acc
  increment t by 3 sec
end procedure
```



Solution-1b: *Multi-Strategy Imputation* (3/4) (Proof of Concept)

```
http://www.semanticweb.org/ontologies/2020/8/SemImputOnt#
BreakfastInstance1
:BreakfastInstance1 rdf:type owl:NamedIndividual,
                    :Breakfast ;
                    :hasBinarySensorObject : NULL ;
                    :hasBinarySensorState  : NULL ;
                    :hasBLESensor          : NULL ;
                    :hasRSSI " " ;
                    :hasAccX "0.37"^^xsd:float ;
                    :hasAccY "-9.7"^^xsd:float ;
                        :
http://www.semanticweb.org/ontologies/2020/8/SemImputOnt#
BreakfastInstance2
:BreakfastInstance1 rdf:type owl:NamedIndividual ,
                    :Breakfast ;
                    :hasBinarySensorObject
                    :SensorKitchenMovement ;
                    :hasBinarySensorState :No Movement ;
                    :hasBLESensor :WaterBottle ;
                    :hasRSSI " " ;
                    :hasAccX "-0.10"^^xsd:float ;
                    :hasAccY "-9.73"^^xsd:float ;
```

	TS	Discrete		Continuous										ID	
		objdetail	state	id	object	rssi	device1	c1	---//---	c8	x	y	z		
3-sec	11:22:13	NULL	NULL	NULL	NULL	NULL	4	2	---//---	-1.17	0.37	-9.7	-1.17	Act05	InConsistent
	11:22:14	Sen K Mov	No movement	fc0a6	WATERBOTTLE	NULL	NULL	2	---//---	-1	-0.1	-9.73	-0.97	Act05	Consistent
	11:22:14	Sen K Mov	Movement	NULL	WATERBOTTLE	NULL	5	1	---//---	0	-0.1	-9.73	-0.97	Act05	Consistent
	11:22:15	Sen K Mov	Movement	06099	FOOD CUPBOARD	-85	4	-4	---//---	-1	0.21	-9.72	-1.11	Act05	Consistent
	11:22:15	Sen K Mov	Movement	b924c	FRIDGE	-89	NULL	NULL	---//---	NULL	NULL	NULL	NULL	Act05	InConsistent
3-sec	11:22:16	Sen K Mov	No movement	06099	FOOD CUPBOARD	-85	NULL	NULL	---//---	NULL	0.21	-9.72	-1.11	Act05	InConsistent
	11:22:19	Sen K Mov	Movement	b924c	TOOTHBRUSH	-89	4	-0.5	---//---	-1	0.26	-9.71	-1.17	Act05	Consistent
3-sec	11:22:20	Sen K Mov	Movement	fc0a6	WATERBOTTLE	-102	4	-0.75	---//---	-1	NULL	NULL	NULL	Act05	Consistent
	11:22:21	Sen K Mov	Movement	NULL	FOOD CUPBOARD	NULL	4	3	---//---	2	NULL	NULL	NULL	Act05	Consistent
	11:22:22	Sen K Mov	Movement	NULL	FOOD CUPBOARD	NULL	4	0.25	---//---	0	NULL	NULL	NULL	Act05	Consistent

Structural Similarity

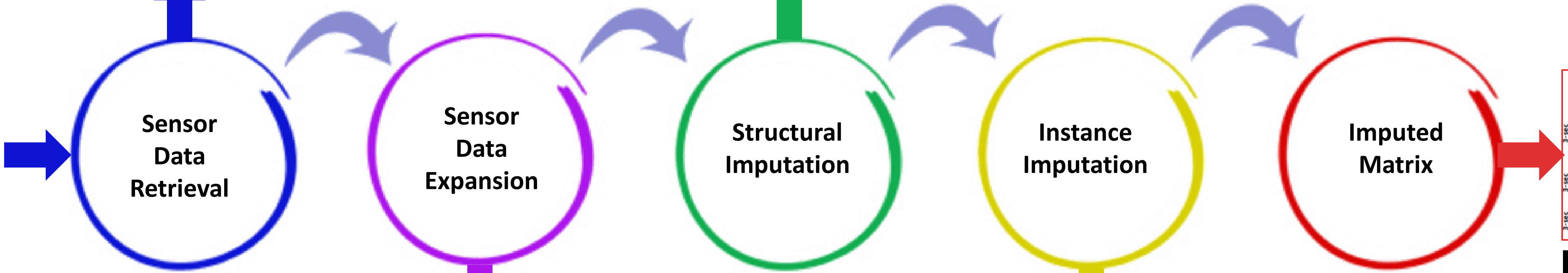
Structural Imputation

$$I_{SS}(A_m) = \mathrm{Sim}_{ss}(A_n, A_m)$$
$$= \frac{\sum_{j=1}^{k} A_n \times A_m}{\left(\sum_{j=1}^{k} A_n^2 + \sum_{j=1}^{k} A_m^2 - \sum_{j=1}^{k} A_n \times A_m\right)}$$

$$\mathcal{K} = (\mathcal{T}, \mathcal{A})$$
$$\mathcal{K} = (\mathcal{T}, \mathcal{A}^{I})$$

Consistent

$$\mathcal{A}^{\mathrm{I}} = \mathcal{A} \cup \mathrm{I}(\mathrm{A_m})$$
$$\mathrm{I}(A_m) = \mathrm{I}_{SS}(A_m) + \mathrm{I}_{SI}(A_m) + \mathrm{I}_{L}(A_m)$$



Missing Values

	TS	Discrete		Continuous										ID	
		objdetail	state	id	object	rssi	device1	c1	---//---	c8	x	y	z		
3-sec	11:22:13	NULL	NULL	NULL	NULL	NULL	4	2	---//---	-1.17	0.37	-9.7	-1.17	Act05	InConsistent
	11:22:14	Sen K Mov	No movement	fc0a6	WATERBOTTLE	-85	4	2	---//---	-1	-0.1	-9.73	-0.97	Act05	Consistent
	11:22:14	Sen K Mov	Movement	fc0a6	WATERBOTTLE	-85	5	1	---//---	0	-0.1	-9.73	-0.97	Act05	Consistent
	11:22:15	Sen K Mov	Movement	06099	FOOD CUPBOARD	-85	4	-4	---//---	-1	0.21	-9.72	-1.11	Act05	Consistent
	11:22:15	Sen K Mov	Movement	b924c	FRIDGE	-89	4	1	---//---	-0.79	0.1	-9.72	-1.06	Act05	Consistent
3-sec	11:22:16	Sen K Mov	No movement	06099	FOOD CUPBOARD	-85	4	-4	---//---	-1	0.21	-9.72	-1.11	Act05	Consistent
	11:22:19	Sen K Mov	Movement	b924c	TOOTHBRUSH	-89	4	-0.5	---//---	-1	0.26	-9.71	-1.17	Act05	Consistent
3-sec	11:22:20	Sen K Mov	Movement	fc0a6	WATERBOTTLE	-102	4	-0.75	---//---	-1	-0.1	-9.73	-0.97	Act05	Consistent
	11:22:21	Sen K Mov	Movement	06099	FOOD CUPBOARD	-85	4	3	---//---	2	0.21	-9.72	-1.11	Act05	Consistent
	11:22:22	Sen K Mov	Movement	06099	FOOD CUPBOARD	-85	4	0.25	---//---	0	0.21	-9.72	-1.11	Act05	Consistent

Output: Complete Data

Input: Semantic Data

Missing Values

Incomplete Data

	TS	Discrete		Continuous										ID	
		objdetail	state	id	object	rssi	device1	c1	---//---	c8	x	y	z		
3-sec	11:22:13	NULL	NULL	NULL	NULL	NULL	4	2	---//---	-1.17	0.37	-9.7	-1.17	Act05	InConsistent
	11:22:14	Sen K Mov	No movement	fc0a6	WATERBOTTLE	NULL	NULL	2	---//---	-1	-0.1	-9.73	-0.97	Act05	Consistent
	11:22:14	Sen K Mov	Movement	NULL	NULL	NULL	5	1	---//---	0	-0.1	-9.73	-0.97	Act05	InConsistent
	11:22:15	NULL	NULL	06099	FOOD CUPBOARD	-85	4	-4	---//---	-1	0.21	-9.72	-1.11	Act05	InConsistent
	11:22:15	Sen K Mov	Movement	b924c	FRIDGE	-89	NULL	NULL	---//---	NULL	NULL	NULL	NULL	Act05	InConsistent
3-sec	11:22:16	Sen K Mov	No movement	06099	FOOD CUPBOARD	-85	NULL	NULL	---//---	NULL	0.21	-9.72	-1.11	Act05	InConsistent
	11:22:19	Sen K Mov	Movement	b924c	TOOTHBRUSH	-89	4	-0.5	---//---	-1	0.26	-9.71	-1.17	Act05	Consistent
3-sec	11:22:20	NULL	NULL	fc0a6	WATERBOTTLE	-102	4	-0.75	---//---	-1	NULL	NULL	NULL	Act05	InConsistent
	11:22:21	NULL	NULL	NULL	FOOD CUPBOARD	NULL	4	3	---//---	2	NULL	NULL	NULL	Act05	InConsistent
	11:22:22	NULL	NULL	NULL	NULL	NULL	4	0.25	---//---	0	NULL	NULL	NULL	Act05	InConsistent

	TS	Discrete		Continuous										ID	
		objdetail	state	id	object	rssi	device1	c1	---//---	c8	x	y	z		
3-sec	11:22:13	NULL	NULL	NULL	NULL	NULL	4	2	---//---	-1.17	0.37	-9.7	-1.17	Act05	InConsistent
	11:22:14	Sen K Mov	No movement	fc0a6	WATERBOTTLE	-85	4	2	---//---	-1	-0.1	-9.73	-0.97	Act05	Consistent
	11:22:14	Sen K Mov	Movement	fc0a6	WATERBOTTLE	-85	5	1	---//---	0	-0.1	-9.73	-0.97	Act05	Consistent
	11:22:15	Sen K Mov	Movement	06099	FOOD CUPBOARD	-85	4	-4	---//---	-1	0.21	-9.72	-1.11	Act05	Consistent
	11:22:15	Sen K Mov	Movement	b924c	FRIDGE	-89	4	1	---//---	-0.79	0.1	-9.72	-1.06	Act05	Consistent
3-sec	11:22:16	Sen K Mov	No movement	06099	FOOD CUPBOARD	-85	4	-4	---//---	-1	0.21	-9.72	-1.11	Act05	Consistent
	11:22:19	Sen K Mov	Movement	b924c	TOOTHBRUSH	-89	4	-0.5	---//---	-1	0.26	-9.71	-1.17	Act05	Consistent
3-sec	11:22:20	Sen K Mov	Movement	fc0a6	WATERBOTTLE	-102	4	-0.75	---//---	-1	-0.1	-9.73	-0.97	Act05	Consistent
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	11:22:22	Sen K Mov	Movement	06099	FOOD CUPBOARD	-85	4	0.25	---//---	0	0.21	-9.72	-1.11	Act05	Consistent

Neighborhood Similarity

Instance Imputation

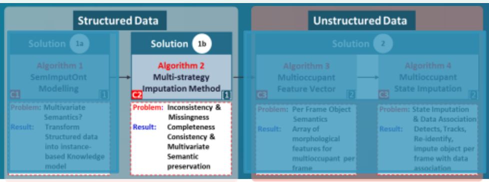
$$I_{SI}(A_m) = \mathrm{Sim}_{SI}(A_n, A_m)$$
$$= \max_{m} \frac{\mathrm{overlap}(A_n, A_m, m)}{A_n \uplus A_m}$$

Highlights of the idea

- Identifies the structures of the labelled data and ensures **semantics completeness** in test instances.

- Based on the nature of Incomplete data, **appropriate strategy** for Instance Imputation is selected.
- Instance Imputation is performed for **MAR**, **MCAR** and **MNAR**.

Solution-1b: *Multi-Strategy Imputation* (4/4)



Existing Method

Algorithm: Multivariate Imputation by Chained Equations

Define Y as a $n \times p$ data matrix where rows represent samples and columns represent variables.
Data: Incomplete dataset $Y = \left(Y^{obs}, Y^{mis}\right)$
Result: Incomplete dataset $Y^T = \left(Y^{obs}, Y^{mis,T}\right)$ at iteration T
Define Y_j as the j^{th} feature column of Y where $Y_j = \left(Y_j^{obs}, Y_j^{mis}\right)$
for $j \leftarrow 1$ to p do
| imputation model for incomplete variable $Y_j \leftarrow P\left(Y_j | Y_{-j}, \theta_j\right)$
∟ starting imputations $Y_j^{mis,0} \leftarrow$ draws from Y_j^{obs}
Define $Y_{-j}^t = \left(Y_1^t, Y_2^t, \cdots, Y_{j-1}^t, Y_{j+1}^{t-1}, \cdots, Y_{p-1}^{t-1}, Y_p^{t-1}\right)$ where Y_j^t is the j^{th} feature at iteration t
for $t \leftarrow 1$ to T do
| for $j \leftarrow 1$ to p do
| | $\theta_j^t \leftarrow$ draw from posterior $P\left(\theta_j | Y_j^{obs}, Y_{-j}^t\right)$
∟ ∟ $Y_j^{mis,t} \leftarrow$ draws from posterior predictive $P\left(Y_j^{mis} | Y_{-j}^t, \theta_j^t\right)$
return Y^T

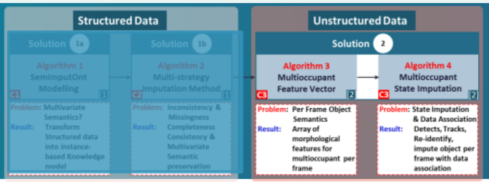
Existing Approaches Limitations: [1,5-6,9,11]

- Works with **Missing at Random** data only.
- Produces **biased estimates** with non linarites, not MAR data or data with high dimensionality.
- Deals **multidimensional data** with same **criteria.**
- Requires two models i.e. **imputation model** and **analysis model** to perform analysis on imputed data.

Algorithm 2: Multi-strategy Imputation Methods

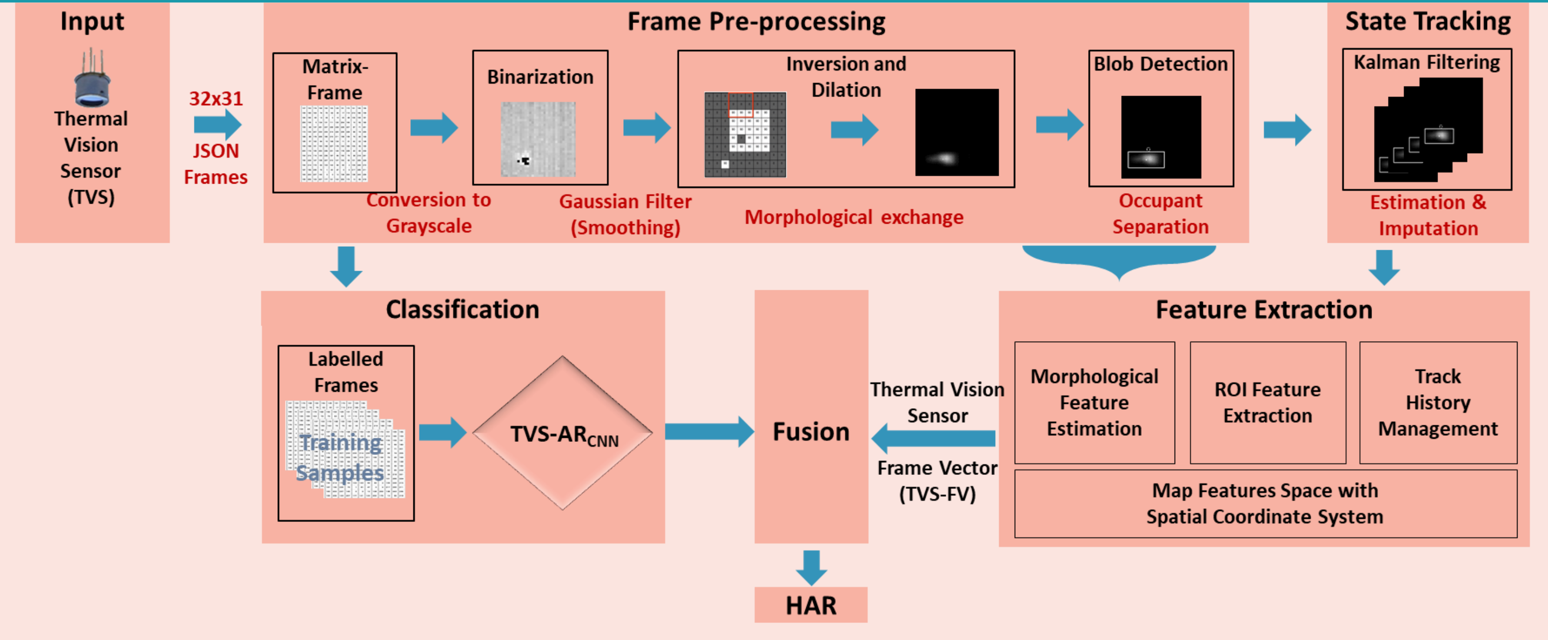
Input: Incomplete Segmented Data A_m, A, D_{seg}
Output: Complete Data with Imputation A_m^{Imp} ▷ Segmented Imputed Dataset.
procedure SEMANTICIMPUTATION
  for all timestamp t = 1 to T **do**
    function $ImputeBinSens(A_m, CQ, A, T)$ ▷ $BinSens_{attrib}$ with their state imputation
      for $(cq_i \epsilon CQ)$ **do**
        $BinSens_{Attrib} \leftarrow execute(cq_i).filter(BinSens, A_m)$ ▷ using SPARQL Queries
        $BinSens_{Target} \leftarrow execute(cq_i).filter(BinSens_{Attrib}, T)$
        $A_{BS_{att}} \leftarrow BinSens_{Attrib}$
        $A_{BS_{tar}} \leftarrow BinSens_{Target}$
        $max(\mathcal{I}_{SS}) \leftarrow Compute\ \mathcal{I}_{SS}(A_{BS_{tar}}, A_{BS_{att}})$ ▷ Equation (10)
        $A_{BS_{att}} \leftarrow A_{BS_{att}} \cup (A_{BS_{tar}} \setminus A_{BS_{att}})$ ▷ Update missing BinSens Attribute
        $BinSens_{mappings} \leftarrow retrieve.mappingsLists(BinSens_{LOCF}, BinSens_{NOCB})$
        while $A_{BS_{att}}(state) = \phi$ **do** ▷ Load Updated *BinSens* attributes
          if $(A_{BS_{att}}$ in $BinSensList_{LOCF})$ **then** ▷ based on *BinSens* characteristics
            $A_{BS_{state}} \leftarrow execute(cq_i).retrieveLastState.(A_{BS_{att}})$
            $A_{BS} \leftarrow \mathcal{I}_L(A_{BS_{att}}, A_{BS_{state}})$
          else if $(A_{BS_{att}}$ in $BinSensList_{NOCB})$ **then**
            $A_{BS_{state}} \leftarrow execute(cq_i).retrieveNext, State.(A_{BS_{att}})$
            $A_{BS} \leftarrow \mathcal{I}_L(A_{BS_{att}}, A_{BS_{state}})$
          end if
        end while
      end for
      Return Imputed A_{BS}
    end function
    function $ImputeProximity(A_m, CQ)$ ▷ Imputation for Proximity Sensors and their values
      for $(cq_i \epsilon CQ)$ **do**
        $A_{Prox} \leftarrow execute(cq_i).filter(Proximity, A_m)$
        $Prox_{max} \leftarrow maxValue(A_{Prox})$
        $A_{Prox} \leftarrow Update\ A_{Prox}(Prox_{max})$
      end for
      Return Imputed A_{Prox}
    end function
    function $ImputeFloor(A_m, CQ, A)$ ▷ Imputation for Floor sensors and their values
      for $(cq_i \epsilon CQ)$ **do**
        $A_{mfloor} \leftarrow execute(cq_i).filter(Floor, A_m)$
        $A_{tfloor} \leftarrow execute(cq_i).filter(A_{mfloor}, A)$
        $mean(floortuples) \leftarrow Compute\ \mathcal{I}_{SI}(A_{tfloor}, A_{mfloor})$ ▷ Equation (13)
        $A_{floor} \leftarrow$Update $A_{mfloor} \cup mean(floortuple)$ ▷ update using mean for tuples
      end for
      Return Imputed A_{floor}
    end function
    function $ImputeAccelerometer(A_m, CQ, A)$ ▷ Imputation for accelerometer values
      for $(cq_i \epsilon CQ)$ **do**
        $A_{mAcc} \leftarrow execute(cq_i).filter(Acc, A_m)$
        $A_{tAcc} \leftarrow execute(cq_i).filter(A_{mAcc}, A)$
        $mean(acctuples) \leftarrow Compute\ \mathcal{I}_{SI}(A_{tAcc}, A_{mAcc})$
        $A_{Acc} \leftarrow$Update $A_{mAcc} \cup mean(acctuples)$ ▷ update using mean for last 10 tuples
      end for
      Return Imputed A_{Acc}
    end function
  end for
  $A_m^{Imp} \leftarrow A_{BS} \| A_{Prox} \| A_{floor} \| A_{Acc}$
  increment t by 3 sec
end procedure

Proposed Idea



Solution-2: *Multioccupant State Imputation* (1/3)

Workflow for Multioccupant State Imputation

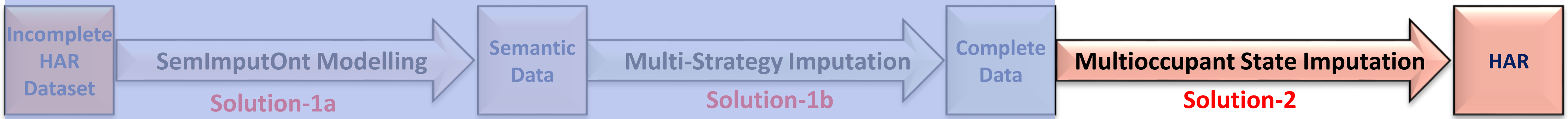


Highlights of the idea

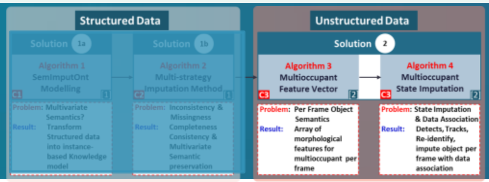
- **Multi-occupant state estimation** using real-time privacy preserved technique through low-resolution thermal vision grayscale frames.
- Efficient method to **locate** occupant, **predict** motion and manage inter-frame **data association**.
- A Robust method for complete, coherent and correct detection, tracking and **classification** of an occupant's activities.

Different to existing approaches

- **Shape-based** and **motion-based** classification without any evidence of **object semantics** explicitly.
- Avoid **complexities** related to detection, tracking and classification of **complex activities,** which further increases with **low resolution frames**.

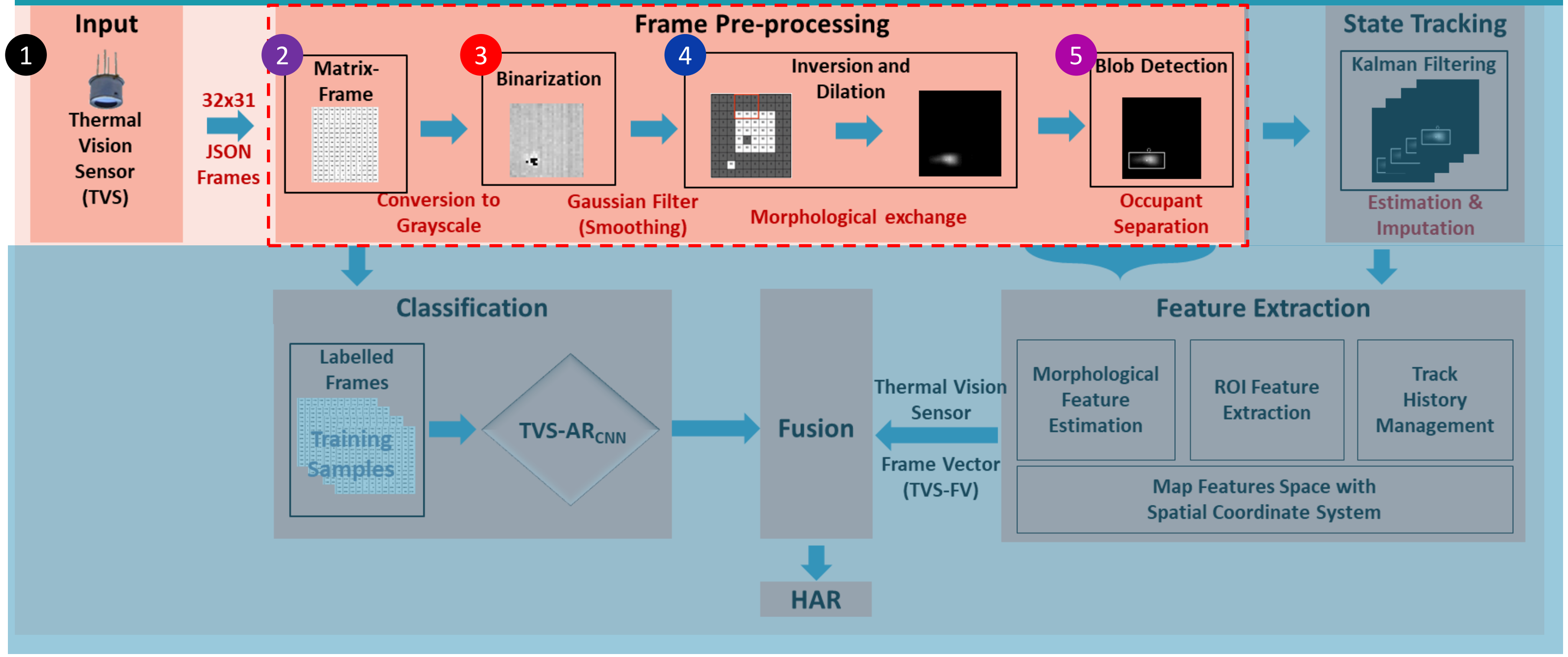


Razzaq, Muhammad Asif, et al. "uMoDT: an unobtrusive multi-occupant detection and tracking using robust Kalman filter for real-time activity recognition." Springer, Multimedia Systems Journal 26.5 (2020).



Solution-2: *Multioccupant State Imputation* (2/3)

Workflow for Multioccupant State Imputation



Algorithm 3

1 **Input TVS_F:** Thermal Vision Sensor grayscale sequence frames;
Output: Multi-occupant Frame Vector TVS_{MoFV}.

procedure TVS_MATPREPROCESSING

2 Load $TVS\_F_{seq} \leftarrow \{TVS\_F_1, TVS\_F_2 \dots TVS\_F_n\}$ where i = $\{1, 2, \dots n\}$
Read Matrix TVS_F_{seq} ▷ Reads sequence of frames TVS_F_{seq}
for all TVS_F_i to TVS_F_n **do**

function $Low\_thresholding(TVS\_F_i)$
$TVS\_F_i - TVS\_F_{i-1} > TVS_{Th}$ ▷ Frame differencing sensitive to threshold
$\mathbf{B}_n \leftarrow TVS\_F_i$ ▷ Identify 'n' Occupants as Blobs
$TVS\_F_i \leftarrow \mathbf{Gauss}_{k,l}(TVS\_F_i)$ ▷ Smoothing by Gaussian blur k=l=3
end function

3 **function** $morphologicalTVSPreProcessing(TVS\_F_i)$ ▷ Morphological filtering
$TVS\_F_i \leftarrow \mathbf{E}_{k_w,k_h}(TVS\_F_i)$ ▷ Erode: width 'w' & height 'h' =8
$TVS\_F_i \leftarrow \mathbf{D}_{k_w,k_h}(TVS\_F_i)$ ▷ Dilate: width 'w' & height 'h' =8
end function

4 **function** $Detect\_Contour(TVS\_F_i)$
$Cnt_n \leftarrow TVS\_F_i$
Find $Cnt_n Contours$
for all i = 1 to n **do**
$min(\mathbf{B}) < Cnt_i < max(\mathbf{B})$ ▷ $min\_Blob\_Area < ContourArea < max\_Blob\_Area$

5 $\mathbf{P}_{x_i,y_i} \leftarrow Cnt_i(p_{x_i}, p_{y_i})$
$\mathbf{BR}_n \leftarrow boundingrectangle(\mathbf{P}_{x_i,y_i})$ ▷ Assign $Bounding\_Rectangle$
array $[\mathbf{BR}] \leftarrow \mathbf{BR}_n$ ▷ Populate $Rectangle\_Array$
$\mathcal{P}_\square \leftarrow$ array $[\mathbf{BR}]$ ▷ GetContourFeatures $Perimeter$
$\mathcal{A}_n \leftarrow area(\mathbf{P}_{x_i,y_i})$ ▷ GetContourFeatures $Area$
$\mathcal{A}_\blacksquare \leftarrow$ array $[\mathbf{BR}]$
$\mathcal{P}_{\mathbf{avg}} \leftarrow Average_{pixels}(\mathbf{BR}_n)$ ▷ Compute pixel p, average avg for $Bounding\_Rectangle$
end for

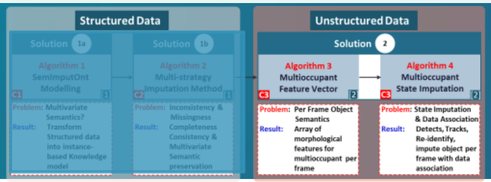
end function
end for
return $TVS_{MoFV} \leftarrow [\mathbf{P}_{x_i,y_i}, \mathcal{P}_\square, \mathcal{A}_n, \mathcal{A}_\blacksquare, \mathbf{Cnt_n}]$
end procedure

Highlight of the proposed idea

- Using TVS frame sequence, segments to **detect foreground** and apply the **Low thresholding**.
- Estimate the **occupant features** using morphological filtering, binarization and computing **occupant semantics** such as centroid, perimeter, area within bounding box.

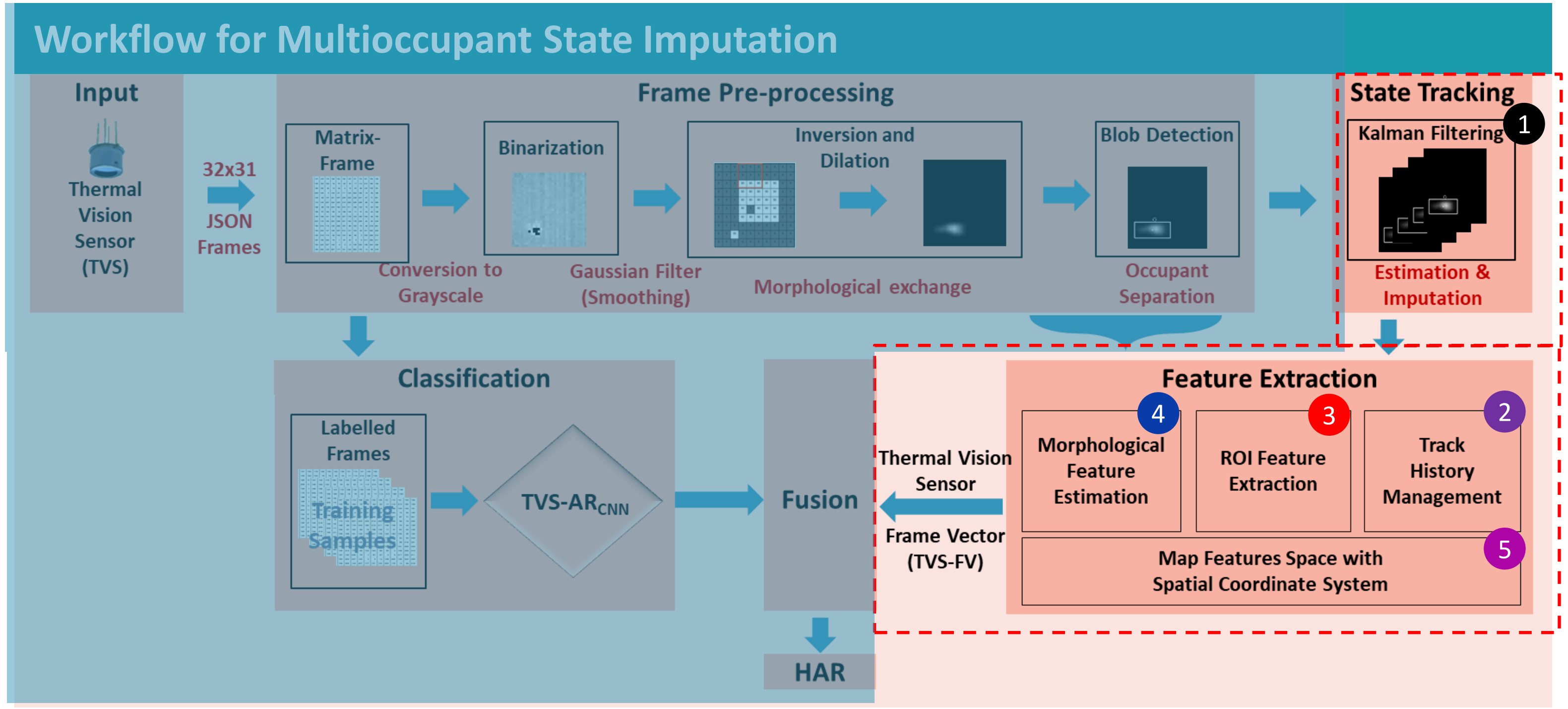
Different to existing approaches

- Most of the methods either **directly detect** using **classification** methods without any evidence of object **semantics explicitly**.
- Very few methodologies deal with such a **low resolution of frames** obtained through thermal vision sensor for recognizing **complex activities**.



Solution-2: *Multioccupant State Imputation* (3/3)

Workflow for Multioccupant State Imputation



Algorithm 4

procedure TVS_MATPREPROCESSING
Load $TVS\_F_{seq} \leftarrow \{TVS\_F_1, TVS\_F_2 \ldots TVS\_F_n\}$ where i = $\{1, 2, \ldots n\}$
Read Matrix TVS_F_{seq} ▷ Reads Sequence of Frames TVS_F_{seq}
for all TVS_F_i to TVS_F_n **do**
function VECTORPOINT $\mathcal{V}_p(TVS\_F_i, \mathcal{C}nt_n)$ ▷ Detect_VectorPoint
for all i = 1 to n **do**
$\mathcal{P}_c^+ \leftarrow \mathbf{BR}_n \{\mathcal{C}nt_n\}$ ▷ Iterate *Contours*
array $[\mathbf{D}] \leftarrow \mathcal{P}_c^+$ ▷ Array of detections
$TVS\_F_i \leftarrow$ Draw $(\mathbf{BR}_n, TVS\_F_i)$ ▷ $drawRectangle \leftarrow Contours$
$TVS\_F_i \leftarrow$ Draw $(\mathcal{P}_c^+, TVS\_F_i)$ ▷ $drawCenterPoint \leftarrow Contours$
end for
end function
1
function TRACK $\mathcal{T}_i(\mathcal{C}nt_n, \mathbf{D}, TVS\_F_i)$ ▷ initialize $(NoOfTracks, TrackSize)$
for all i = 1 to Size $([\mathbf{D}])$ **do**
$\mathcal{T}_i \leftarrow$ new$(\mathcal{T}, \mathbf{D})$
$Cost\,[i]\,[i] \leftarrow Euclid(\mathcal{T}_i^{pred}, \mathbf{D})$ ▷ Euclidean distance between prediction & detection
$\mathcal{C} \leftarrow Cost\,[i]\,[j]$
$\vec{\mathcal{A}} \leftarrow Vector(Assignment)$
$\mathcal{T}_i^{assign} \leftarrow HungarianAssignment\,(\mathcal{C}, \vec{\mathcal{A}})$
if $(\mathcal{C} > \mathcal{D}_{threshold})$ **then** ▷ Identify $unAssigned\_tracks$
$[\mathcal{T}_i^{unassinged}] \leftarrow$ add$(\mathcal{T}_i^{unassinged})$ ▷ Search $Un\_Assigned\_Tracks$
end if
if $([\mathcal{TVS}\_\mathcal{F}_i^{skipped}] > max_f)$ **then**
$\mathcal{TVS}\_\mathcal{F}_i \leftarrow$ remove $(\mathcal{TVS}\_\mathcal{F}_i)$ ▷ Remove not detected tracks
$\vec{\mathcal{A}} \leftarrow$ remove $(\vec{\mathcal{A}_i})$ ▷ Remove assignments
end if
if $(size(\mathbf{D}_i^{unassigned}) > 0)$ **then**
$\mathcal{T}_i \leftarrow$ add$(\mathcal{T}_i, \mathbf{D}_i^{unassigned})$ ▷ Initialize New_Tracks for un_Assigned_Detects
end if
$\mathcal{T}_i \leftarrow \mathcal{T}_i^{skipped} > \mathcal{TVS}_{SkippedAllowed}$
/* Update Kalman for All Detected Contours */
$\mathcal{TVS} \leftarrow UpdateKalman(TVS\_F_i, \mathbf{D})$ ▷ Predict, Update Kalman Occupant State
/* Iterate the No of contours, detections in the $\mathcal{TVS}\_\mathcal{F}_i$ */
2
for all t = 1 to Size $(\vec{\mathcal{A}})$ **do**
$\mathcal{T}_{id} \leftarrow \mathcal{T}_i(t)$
$\mathcal{TVS}\_\mathcal{F}_i \leftarrow \mathcal{TVS}\_\mathcal{F}_{append}(\mathcal{TVS}\_\mathcal{F}_i, \mathcal{T}_{id}, \mathcal{P}_c^+)$ ▷ Draw tracks
$[\mathcal{TVS}\_\mathcal{F}_i]_{history} \leftarrow \mathcal{TVS}\_\mathcal{F}_{append}(\mathcal{TVS}\_\mathcal{F}_i, \mathcal{P}_c^+)$ ▷ Contours & Tracks History
end for
3
/* Update $\mathcal{TVS}\_\mathcal{F}_i$ with Kalman Prediction and Correction */
$\mathcal{I}t \leftarrow n\,(\mathcal{C}nt_n)$ ▷ Number of Contours
4 5
while $\mathcal{I}t.hasnext$ **do**
$TVS\_F_i \leftarrow$ update $(TVS\_F_i, \mathcal{P}_c^+, [\mathcal{TVS}\_\mathcal{F}_i]_{history})$ ▷ Kalman Effect
$TVS\_F_i \leftarrow$ draw $(\mathcal{P}_c^+, [\mathcal{TVS}\_\mathcal{F}_i]_{history})$ ▷ Kalman prediction updation
$TVS\_F_i \leftarrow$ draw_line $(\mathcal{P}_c^+, \mathcal{T}_{i-1}, \mathcal{T}_i, [\mathcal{TVS}\_\mathcal{F}_i]_{history})$
end while
end for
end function
end for return T_{MoDT}
end procedure

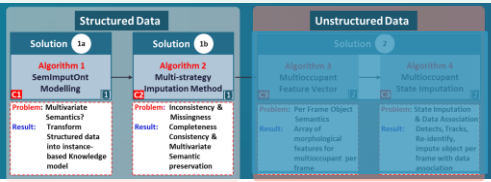
Highlight of the proposed idea

- The detected contours are iterated per frame for tracking occupant's **motion model** and their state **history maintenance**.
- Hungarian method for data association, and **Kalman Filter** for **estimation and position prediction**.

Different to existing approaches

- Most of the method don't consider **semantics** of **detected object per frame** with respect to the background information.
- Least importance is given to **errors** in object **detection** and **localization.**

Solution-1a & 1b: Experimental Setup & Results (1/4)



HAR Dataset	No. of Activities	No. of Sensors	Sensor States	Description
UCamI [12]	24	54	Discrete, Continuous	30 Binary, Floor Sensors, 15 BLE, Accelerometer
Opportunity [13]	18	72	Continuous	7 IMU sensors (3D ACC, Gyro & Mag.) & 12 Acc
UCI-ADL A & B [14]	10	14	Motion, Opening & closing binary states	PIR, Magnetic, Pressure, Electric, Passive IR, Reed Switches, and Float sensors.

Experimental Settings

Steps performed in **Java development environment** for **prototype modeling** of Semantic Imputation Method:

- **Step-I:** Synchronize the dataset based on the timestamps.
- **Step-II:** Retrieve the samples based on sliding window of 3 sec.
- **Step-III:** Ensure extraction for the no of features.
- **Step-IV:** Group feature samples per variable, apply concatenation function and validate the input.
- **Step-V:** Train the NN model based on the parameter detailed mentioned below.
- **Step-VI: Apply** the NN model on test data (Leave one day out method).
- **Step-VII:** Measure the statistical performance of classification task for trained model and test data.
- **Step-VIII:** Apply model on test-sets for each of the dataset.

Classifier	Split Ratio	Sampling	Activation	Hidden Layer Size	Epochs
Deep Learning Multi-Layer Network (NN)	0.7	Shuffled	Rectified Linear Unit	50	10

Evaluation Metrics

- **Classification Performance:** : Precision, Recall, F-Measure, and Accuracy
  - **Precision** = TP / (TP + FP)
  - **Recall** = TP / (TP + FN)
  - **F-measure** = 2 ∗ (Recall ∗ Precision) / (Recall + Precision)
  - **Accuracy** = (TP + TN) / (TP + FP + FN + TN)
- **Processing Speed:** Model Training (Average 0.894 seconds)
- **Validation**: Tested on test data using leave one day out.

Development Environment

- **Prototype development** in **Java IDE environment** for Semantic Imputation Method with Deep Learning for Complex Human Activities Recognition.
- **Trained** the MLN (NN) Model using **non-imputed** and **semantically enriched imputed** HAR datasets.

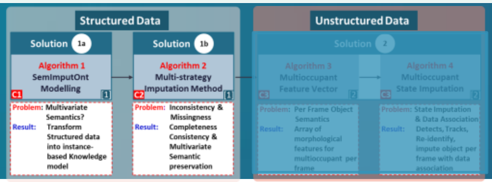
Development APIs

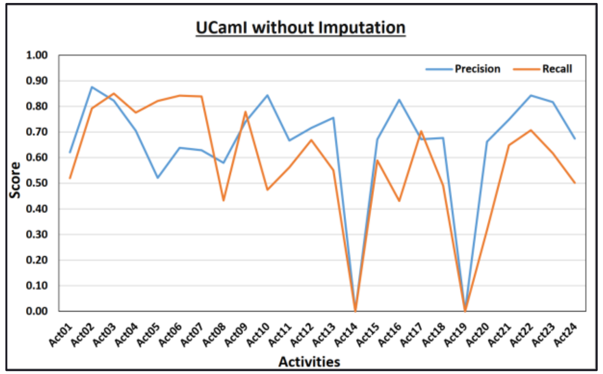
- Open-source, distributed, deep learning library for the JVM **Deep Learning for Java**
- OWL API, Jena API, SPARQL queries

DL4J Jena W3C SPARQL

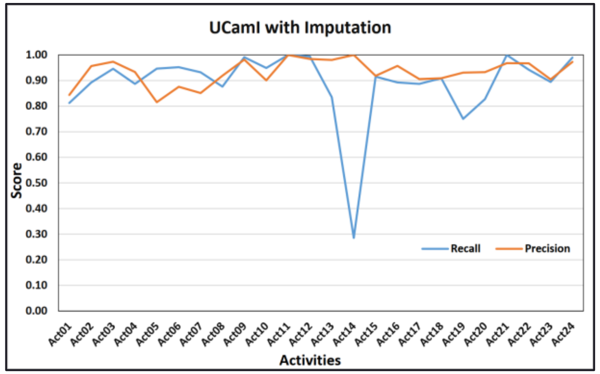
[1] Razzaq, Muhammad Asif, et al. **mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification**." **MDPI, Sensors** 17.10 (2017): 2433.
[2] Razzaq, Muhammad Asif, et al. "**SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition**." **MDPI, Sensors** 20.10 (2020): 2771.

Solution-1a & 1b: Results & Discussion (2/4)

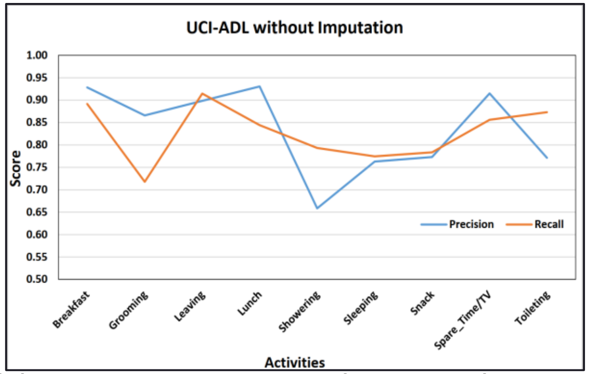




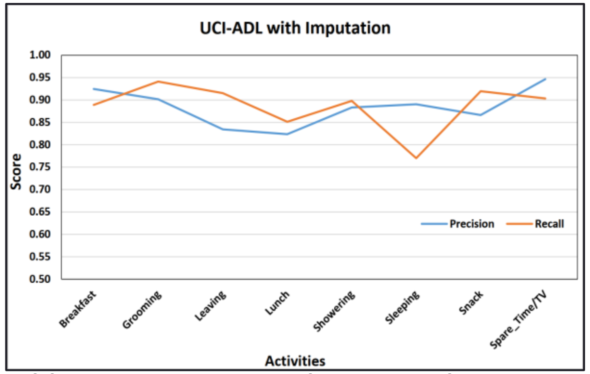
(a) Non-imputed *UCamI* dataset



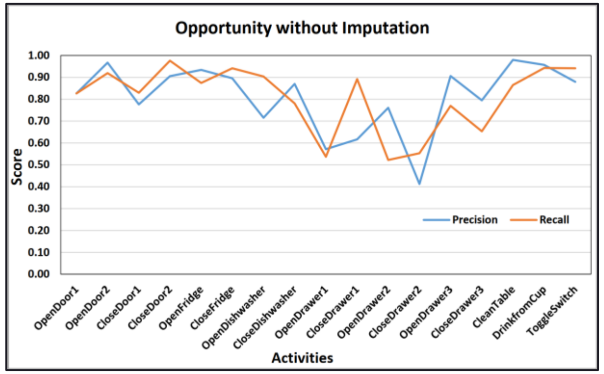
(b) Imputed *UCamI* dataset



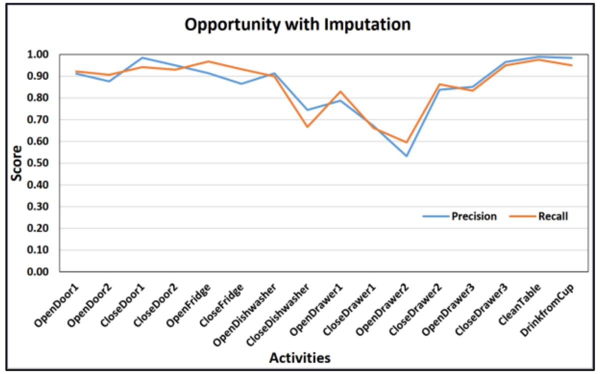
(e) Non-imputed *UCI-ADL* (OrdóñezA) dataset



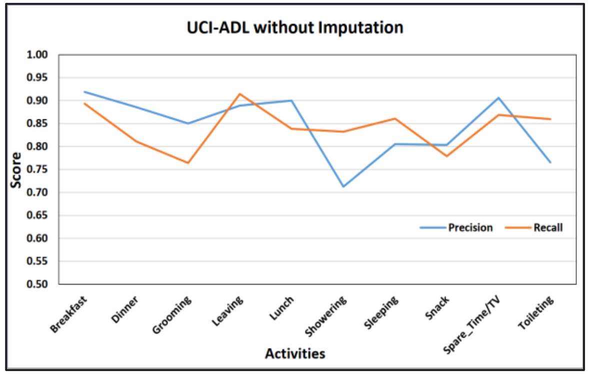
(f) Imputed *UCI-ADL* (OrdóñezA) dataset



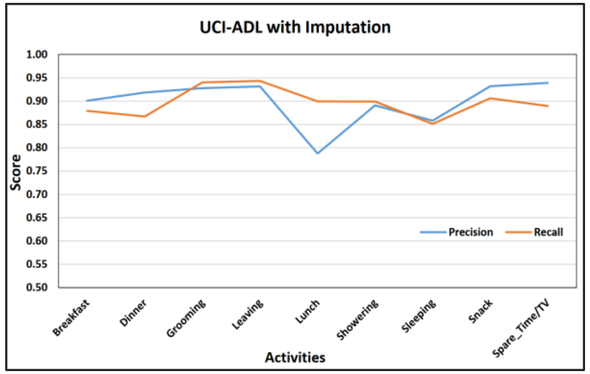
(c) Non-imputed *Opportunity* dataset



(d) Imputed *Opportunity* dataset



(g) Non-imputed *UCI-ADL* (OrdóñezB) dataset



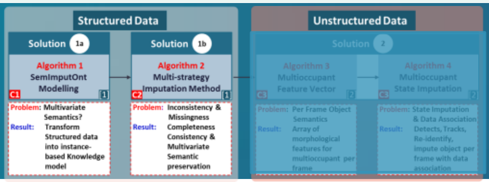
(h) Imputed *UCI-ADL* (OrdóñezB) dataset

Experimental Findings

- The Proposed SemImput method increases an **overall accuracy** of **71.03%** for a set of activities from non-imputed **UCamI** dataset to **92.62%** by augmenting semantically enriched values.
- **Opportunity** dataset also showed significant rise in accuracy of **86.57%,** to **91.71%.**
- An overall classification results were also improved for **UCI-ADL Ordóñez-A** raw dataset with **82.27%** to **89.20%** with missing value imputation.
- A global accuracy for **UCI-ADL Ordóñez-B** dataset was improved from **84.0%** to **90.34%.**

[1] Razzaq, Muhammad Asif, et al. **mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification**." **MDPI, Sensors** 17.10 (2017): 2433.
[2] Razzaq, Muhammad Asif, et al. "**SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition**." **MDPI, Sensors** 20.10 (2020): 2771.

Solution-1a & 1b: Results & Discussion (3/4)



Experimental Findings

- Achieved **improved Accuracy** as compared to Non Imputed Datasets.
- Activity Breakfast (Act05) having the lowest recognition precision of **81.54%** was most often classified as the activity Prepare breakfast (Act02) in **UCamI**.
- Activities Play a videogame (Act11) and Visit in the SmartLab (Act14) were recognized with **100% accuracy**, which were having lower accuracies with the non-imputed data.
- **Opportunity** dataset without the 'Null' class obtained an overall accuracy of **86.57%**, and an increased accuracy with the imputed dataset by **91.71%**.

(Non-imputed)

Ground Truth Activities (columns) / Predicted Activities (rows)

	Act_{1}	Act_{2}	Act_{3}	Act_{4}	Act_{5}	Act_{6}	Act_{7}	Act_{8}	Act_{9}	Act_{10}	Act_{11}	Act_{12}	Act_{13}	Act_{14}	Act_{15}	Act_{16}	Act_{17}	Act_{18}	Act_{19}	Act_{20}	Act_{21}	Act_{22}	Act_{23}	Act_{24}
Act_{1}	62.07	0	0.69	4.48	0	0	5.52	0	0	0.69	0	0	0	0	13.79	0	2.07	0	1.38	2.41	0	6.90	0	0
Act_{2}	0	87.55	0	0	4.06	0	0	0	0	0	0	0	0.14	0	0	0.14	0.70	0.14	0	2.10	0.42	4.48	0	0.28
Act_{3}	0.67	0	82.23	0	0	3.04	0	3.88	1.07	1.69	0	0.67	0	0	2.81	0	0.73	0.90	0.39	1.80	0	0.11	0	0
Act_{4}	5.70	0	0	70.50	0	0	7.43	0	0	3.76	0.61	0	0	0	6.71	0	2.75	0.51	0.61	0	0	1.42	0	0
Act_{5}	0	10.25	0	0	52.14	0	0	0	0	0	0	0	0	0	0	2.29	8.66	3.08	0	1.00	9.05	2.29	0	11.24
Act_{6}	0	0	9.43	0	0	63.85	0	1.38	9.92	1.28	0	5.89	0	0	2.95	0	2.46	0.49	0.59	1.38	0	0.39	0	0
Act_{7}	5.89	0	0	13.72	0	0	62.89	0	0	2.12	4.24	0	0	0	4.51	0	2.12	0	0.18	0	0	2.95	1.38	0
Act_{8}	1.54	0	11.28	0	0	4.62	0	57.95	4.62	0	0	0	0	0	3.59	0	1.03	3.08	0	7.69	0	4.62	0	0
Act_{9}	0.31	0	7.28	0	0	2.29	0	1.87	74.01	1.77	0	2.81	0.94	0.31	2.91	0	3.01	1.35	0.10	0.42	0	0.62	0	0
Act_{10}	0	0	2.23	0	0	0	0	0	0	84.36	0	0	0	2.23	11.17	0	0	0	0	0	0	0	0	0
Act_{11}	0	0	0	2.33	0	0	10.08	0	0	0.78	66.67	0	0	0	6.20	0	6.20	0.78	1.55	0	0	4.65	0.78	0
Act_{12}	0.34	0	10.14	0	0	0.34	0	0	10.14	1.69	0	71.62	0	0	3.72	0	1.01	1.01	0	0	0	0	0	0
Act_{13}	0	9.30	0	0	0	1.16	0	0	1.16	0	0	0	75.58	1.16	8.14	0	1.16	0	0	0	1.16	1.16	0	0
Act_{14}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Act_{15}	2.33	0	2.20	3.76	0	2.33	2.20	2.20	1.55	3.63	0.26	0.52	5.18	0.78	67.10	0	1.94	0.39	0.39	0.39	0	2.72	0.13	0
Act_{16}	0	0.76	0	0	0	0	0	0	0	0	0	0	0	0	0	82.58	9.85	1.52	0	0	0	2.27	0	3.03
Act_{17}	0.51	0.68	0.51	0.51	1.70	1.10	0.59	1.44	2.55	0.34	1.02	0.17	0	0	2.97	8.50	67.20	3.74	0.08	0.17	0.34	4.93	0.34	0.59
Act_{18}	0	0	2.49	0	0.50	1.49	0	1.99	0	2.99	0	0	0	0	0.50	1.49	11.94	67.66	1.00	5.47	0	1.99	0	0.50
Act_{19}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Act_{20}	1.25	1.25	6.25	0	2.50	1.25	0	11.25	0	0	0	0	0	0	2.50	0	3.75	0	2.50	66.25	0	1.25	0	0
Act_{21}	0	8.49	0	0	9.27	0	0	0	0	0	0	0	0	0	0	1.93	1.54	0.39	0	0	74.90	1.16	0	2.32
Act_{22}	0.27	2.01	0	0	1.34	0	0.40	0	0	0.13	0.13	0	0.40	0	0.81	0.40	4.83	0.81	0	0.13	0.27	84.30	2.01	1.74
Act_{23}	0	0	0	0	0	0	2.82	0	0	0	0	0	0	0	1.41	0	2.82	1.41	0	0	0	9.86	81.69	0
Act_{24}	0	2.75	0	0	12.84	0	0	0	0	0	0	0	0	0	0	4.13	3.21	1.38	0	0	1.83	6.42	0	67.43

Proposed

(Imputed)

Ground Truth Activities (columns) / Predicted Activities (rows)

	Act_{1}	Act_{2}	Act_{3}	Act_{4}	Act_{5}	Act_{6}	Act_{7}	Act_{8}	Act_{9}	Act_{10}	Act_{11}	Act_{12}	Act_{13}	Act_{14}	Act_{15}	Act_{16}	Act_{17}	Act_{18}	Act_{19}	Act_{20}	Act_{21}	Act_{22}	Act_{23}	Act_{24}
Act_{1}	84.38	0	1.20	0.90	0	0.30	6.01	0	0	0	0	0	0	0	3.60	0	1.50	0	1.20	0	0	0.90	0	0
Act_{2}	0	95.66	0	0	3.39	0	0	0	0	0	0	0	0	0	0	0.14	0.54	0.14	0	0	0	0.14	0	0
Act_{3}	0.12	0	97.36	0	0	1.50	0	0	0	0	0	0	0	0	0.18	0	0.78	0	0.06	0	0	0	0	0
Act_{4}	1.76	0	0	93.31	0	0	3.99	0	0	0.12	0	0	0	0	0.59	0	0.23	0	0	0	0	0	0	0
Act_{5}	0	10.65	0	0	81.54	0	0	0	0	0	0	0	0.13	0	0	0	6.87	0	0	0	0	0.81	0	0
Act_{6}	0.24	0	9.49	0	0	87.54	0	0	0	0	0	0	0.12	0	0.24	0	2.25	0	0.12	0	0	0	0	0
Act_{7}	4.27	0	0	9.45	0	0	85.15	0	0	0	0	0	0	0	1.01	0	0.11	0	0	0	0	0	0	0
Act_{8}	0	0	0	0	0	0	0	91.90	0	0	0	0	0	0	3.24	0	0	0	0	4.45	0	0.40	0	0
Act_{9}	0	0	0	0	0	0	0	0	98.16	0	0	0	0	1.08	0	0	0	0.76	0	0	0	0	0	0
Act_{10}	0	0	0.90	2.10	0	0	0	0	0	90.09	0	0	0	0	5.41	0	1.50	0	0	0	0	0	0	0
Act_{11}	0	0	0	0	0	0	0	0	0	0	100.0	0	0	0	0	0	0	0	0	0	0	0	0	0
Act_{12}	0	0	0	0	0	0	0	0	0	0	0	98.44	0.94	0	0	0	0.31	0	0	0	0	0.31	0	0
Act_{13}	0	0	0	0	0	0	0	0	0	0	0	0	98.06	0	0	0	0	0.97	0	0	0	0.97	0	0
Act_{14}	0	0	0	0	0	0	0	0	0	0	0	0	0	100.0	0	0	0	0	0	0	0	0	0	0
Act_{15}	0.34	0	0.23	0.45	0	0.11	0	2.16	0.23	1.48	0	0.23	0.11	0	91.82	0	0.91	0.45	0.34	0.91	0	0.23	0	0
Act_{16}	0	0.43	0	0	0	0	0	0	0	0	0	0	0	0	0	95.73	2.14	1.28	0	0	0	0	0	0.43
Act_{17}	0.36	0.18	0.36	0.27	0.54	0.91	0.09	0.18	0.36	0.18	0	0	0.91	0	1.27	1.00	90.55	0.73	0	0.18	0	1.91	0	0
Act_{18}	0	0.36	0	0	0	0	0	0.36	0.73	0	0	0	0	0	0	4.74	0.73	90.88	0	1.09	0	0.36	0	0.73
Act_{19}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	6.90	0	0	0	93.10	0	0	0	0	0
Act_{20}	0	0	0	0	0	0	0	6.71	0	0	0	0	0	0	0	0	0	0	0	93.29	0	0	0	0
Act_{21}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0.32	1.28	0	0	0	96.79	1.60	0	0
Act_{22}	0.12	0	0	0	0.35	0	0	0	0	0	0	0	0.12	0	0.12	0	0.81	0	0	0.58	0	96.74	1.16	0
Act_{23}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1.06	0	0	0	0	0	0	8.51	90.43	0
Act_{24}	0	0.67	0	0	0	0	0	0	0	0	0	0	1.00	0	0	0.33	0	0.33	0	0	0	0.33	0	97.32

Confusion matrix for per-class HAR using non-imputed & imputed UCamI dataset

(Non-imputed)

Ground Truth Activities (columns) / Predicted Activities (rows)

	OpenDoor1	OpenDoor2	CloseDoor1	CloseDoor2	OpenFridge	CloseFridge	OpenDishwasher	CloseDishwasher	OpenDrawer1	CloseDrawer1	OpenDrawer2	CloseDrawer2	OpenDrawer3	CloseDrawer3	CleanTable	DrinkfromCup	ToggleSwitch
OpenDoor1	82.65	0	16.33	0	0	0	0	0	0	0	0	0	0	0	0	0	1.02
OpenDoor2	0	91.98	0.62	7.41	0	0	0	0	0	0	0	0	0	0	0	0	0
CloseDoor1	17.05	0	82.95	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CloseDoor2	0	1.57	0.79	97.64	0	0	0	0	0	0	0	0	0	0	0	0	0
OpenFridge	0.26	0.26	0	0	87.47	7.42	2.81	0.51	0	0.26	0	0	0	0	0.26	0.26	0.51
CloseFridge	0	0	0	0	3.65	94.16	0	0.36	0.36	0.73	0	0	0	0	0	0.36	0.36
OpenDishwasher	0	0	0	0	2.40	0	90.42	2.99	0.60	0	0	0	0	1.20	0	1.20	1.20
CloseDishwasher	0	0	0	0	2.92	0	10.95	78.10	0	0	0	1.46	0	4.38	0	0.73	1.46
OpenDrawer1	0	0	0	0	0	0	1.49	2.99	53.73	25.37	0	1.49	0	2.99	0	0	11.94
CloseDrawer1	0	1.35	0	0	1.35	0	0	0	6.76	89.19	1.35	0	0	0	0	0	0
OpenDrawer2	0	0	0	0	1.49	0	1.49	0	19.40	11.94	52.24	4.48	1.49	0	0	0	7.46
CloseDrawer2	0	0	0	0	2.13	0	0	8.51	4.26	21.28	6.38	55.32	2.13	0	0	0	0
OpenDrawer3	0	0	0	0	0	0	4.42	0	1.77	0	6.19	3.54	76.99	6.19	0	0	0.88
CloseDrawer3	0	0	0	0	0	0	0	0.99	0	0	0	26.73	6.93	65.35	0	0	0
CleanTable	0	0	0	0	1.18	0.59	1.76	0	0	0	0	0	0	0	86.47	10.00	0
DrinkfromCup	0.18	0.18	0.37	0.18	0	0	4.40	0.18	0	0	0	0	0	0	0.18	94.32	0
ToggleSwitch	0	0	0.58	0	0.58	0	0	0	1.75	1.75	0	0	0	0	0.58	0.58	94.15

Proposed

(Imputed)

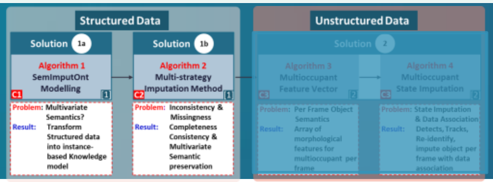
Ground Truth Activities (columns) / Predicted Activities (rows)

	OpenDoor1	OpenDoor2	CloseDoor1	CloseDoor2	OpenFridge	CloseFridge	OpenDishwasher	CloseDishwasher	OpenDrawer1	CloseDrawer1	OpenDrawer2	CloseDrawer2	OpenDrawer3	CloseDrawer3	CleanTable	DrinkfromCup	ToggleSwitch
OpenDoor1	90.00	0	10.00	0	0	0	0	0	0	0	0	0	0	0	0	0	0
OpenDoor2	0	92.26	0	1.19	0	0	0	0	0.60	1.79	0	1.19	2.98	0	0	0	0
CloseDoor1	1.16	0	90.70	0	1.16	1.16	5.81	0	0	0	0	0	0	0	0	0	0
CloseDoor2	0	3.62	0	94.20	0	0	0	0.72	0.72	0.72	0	0	0	0	0	0	0
OpenFridge	0.52	0	0	0	93.04	5.67	0.52	0	0	0	0	0	0	0	0	0	0.26
CloseFridge	0	0.79	0	0	1.98	96.84	0	0.40	0	0	0	0	0	0	0	0	0
OpenDishwasher	0.56	0	0	0	3.35	0	93.30	2.23	0.56	0	0	0	0	0	0	0	0
CloseDishwasher	0	0	0	0	1.55	0	7.75	89.92	0	0	0	0.78	0	0	0	0	0
OpenDrawer1	0	1.75	0	0	0	0	5.26	1.75	66.67	10.53	3.51	1.75	5.26	1.75	0	0	1.75
CloseDrawer1	1.06	1.06	1.06	0	1.06	0	5.32	0	1.06	82.98	0	0	0	1.06	3.19	2.13	0
OpenDrawer2	0	1.41	0	0	5.63	0	0	1.41	8.45	2.82	66.20	8.45	1.41	0	0	2.82	1.41
CloseDrawer2	0	4.76	0	0	0	0	0	4.76	2.38	11.90	9.52	59.52	0	7.14	0	0	0
OpenDrawer3	0	2.94	0	0	0	0	0	0	0	0	7.84	0	86.27	2.94	0	0	0
CloseDrawer3	0	0	0	0	0	0	0	0	0	0	2.08	9.38	5.21	83.33	0	0	0
CleanTable	0	0	0	0	0	0	0	0	0	0	2.22	1.67	0	0	95.00	1.11	0
DrinkfromCup	0.17	0	0	0	0	0	0.17	0.17	0	0.34	0.51	0	0	0.51	0.51	97.62	0
ToggleSwitch	0	0	0	0	0	0	0	0	1.00	1.00	0	0	1.49	1.49	0	0	95.02

Confusion matrix for per-class HAR using non-imputed & imputed Opportunity dataset

[1] Razzaq, Muhammad Asif, et al. **mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification**." MDPI, Sensors 17.10 (2017): 2433.
[2] Razzaq, Muhammad Asif, et al. "**SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition**." MDPI, Sensors 20.10 (2020): 2771.

Solution-1a & 1b: Results & Discussion (4/4)



(Non-imputed) Ground Truth Activities (rows: Predicted Activities)

	Breakfast	Grooming	Leaving	Lunch	Showering	Sleeping	Snack	Spare_Time/TV	Toileting
Breakfast	89.12	0.20	2.20	0.74	3.21	3.92	0	0.51	0.10
Grooming	2.46	71.00	9.21	2.30	5.26	6.67	2.01	0.62	0.47
Leaving	0.23	0.02	91.12	0.23	0.32	2.23	2.73	3.02	0.10
Lunch	3.20	0.09	0.10	84.41	3.62	4.61	3.26	0.12	0.59
Showering	0.01	5.30	0	0	79.12	4.33	8.64	0.32	2.28
Sleeping	0	4.49	0.01	0	5.21	77.15	6.23	0.20	6.71
Snack	0.12	0.02	0.04	3.32	12.54	0.02	77.50	3.20	3.24
Spare_Time/TV	0.05	0.10	0	0.02	4.32	0.88	0	85.10	9.54
Toileting	1.20	1.05	0.18	0.12	8.12	1.20	0	0	88.13

Proposed

(Imputed) Ground Truth Activities (rows: Predicted Activities)

	Breakfast	Grooming	Leaving	Lunch	Showering	Sleeping	Snack	Spare_Time/TV	Toileting
Breakfast	96.51	0.21	0.35	1.21	0.32	0.01	0.04	0.02	1.33
Grooming	0.12	88.01	7.20	3.39	0.83	0.04	0.18	0	0.23
Leaving	0.14	0.21	94.02	0	0.50	1.79	3.10	0.13	0.11
Lunch	1.21	4.45	1.65	91.12	0.75	0.41	0.03	0.38	0
Showering	0	0.62	0.75	2.10	85.23	2.20	6.11	2.98	0.01
Sleeping	0.87	0.55	0.02	5.45	4.39	88.69	0.01	0.02	0
Snack	0.01	0.74	0	5.64	2.21	6.88	77.02	7.01	0.49
Spare_Time/TV	0	0.43	0	1.20	1.35	0.35	0.40	92.45	3.82
Toileting	1.01	0	0	0	8.60	0	0	1.32	89.07

Confusion matrix for per-class HAR using non-imputed & imputed UCI-ADL (OrdóñezA) dataset

(Non-imputed) Ground Truth Activities (rows: Predicted Activities)

	Breakfast	Dinner	Grooming	Leaving	Lunch	Showering	Sleeping	Snack	Spare$_T$ime/TV	Toileting
Breakfast	88.95	1.65	0	0.01	3.45	0.06	0.08	4.21	1.36	0.23
Dinner	0.64	81.06	1.23	0.98	4.55	0.16	1.88	7.26	2.24	0
Grooming	0.35	0.12	76.43	0.21	0	1.18	16.23	0.45	4.61	0.42
Leaving	0	0.02	0.29	91.49	0.36	0.12	0	0.30	3.10	4.32
Lunch	2.01	1.71	2.36	0.92	83.90	0.26	0.08	4.68	3.45	0.63
Showering	0.83	1.65	1.65	3.70	0	83.17	0.61	0.84	0.12	7.43
Sleeping	2.34	4.65	3.87	4.62	0.15	2.64	81.73	0	0	0
Snack	1.60	0.65	0.23	0	0.45	0	0	77.92	5.75	13.40
Spare$_T$ime/TV	0	0	2.89	0.54	0.03	6.25	0	0	90.29	0
Toileting	0.03	0	1.01	0.50	0.32	8.16	0.90	0	3.08	86.00

Proposed

(Imputed) Ground Truth Activities (rows: Predicted Activities)

	Breakfast	Dinner	Grooming	Leaving	Lunch	Showering	Sleeping	Snack	Spare$_T$ime/TV	Toileting
Breakfast	97.10	0.01	0.20	0.12	0	0.65	0.32	1.41	0	0.19
Dinner	0.80	87.90	1.65	0.65	1.32	0.53	2.64	3.21	1.21	0.09
Grooming	0.32	2.40	86.69	0.07	2.45	2.89	0.05	4.08	0.10	0.95
Leaving	0.01	1.12	0.98	94.01	0.51	0.03	1.32	0.85	0.05	1.12
Lunch	0.45	0.06	0	1.32	94.30	0.12	1.24	1.19	1.32	0
Showering	0.78	1.36	1.40	0.45	0.09	94.47	0.08	0.01	0.24	1.12
Sleeping	0.63	1.89	0	1.61	0.65	3.99	89.87	0.31	0.08	0.97
Snack	1.10	2.45	1.77	1.74	1.11	0.99	2.10	85.10	2.49	1.15
Spare$_T$ime/TV	0	0.32	0.65	0.89	0.47	1.54	3.19	2.15	90.58	0.21
Toileting	0.01	0.09	1.05	0.45	0.25	7.14	0.06	0.89	1.11	88.95

Confusion matrix for per-class HAR using non-imputed & imputed UCI-ADL (OrdóñezB) dataset

Experimental Findings

- Recognition **accuracy** for UCI-ADL Ordóñez-A significantly up to **89.20%**.
- The global accuracy for UCI-ADL Ordóñez-B dataset was improved from **84.0%** to **90.34%**.

Recognition accuracy gain using the Multi-strategy Imputation. (Unit:%)

Method	Datasets	Number of Activities	(Mean Recognition Accuracy) Non-Imputed	Imputed	Standard Deviation
Proposed SemImput	Opportunity	17	86.57	91.71	±2.57
	UCI-ADL OrdóñezA	9	82.27	89.2	±3.47
	UCI-ADL OrdóñezB	10	84	90.34	±3.17
	UCamI	24	71.03	92.62	±10.80

Comparison results: Proposed Multi-strategy Imputation vs state-of-the-art HAR methods.

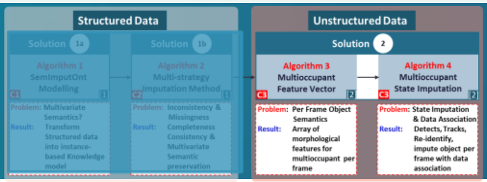
State-of-the-Art methods	Datasets	Number of Activities	Mean Recognition Accuracy(%)	SemImput Gain
Razzaq et al. [15]	UCamI [12]	24	47.01	45.61
Salomón et al. [18]	UCamI [12]	24	90.65	1.97
Li et al. [34]	Opportunity [13]	17	92.21	-0.5
Salguero et al. [9]	UCI-ADL OrdóñezA [34]	9	95.78	-6.58
	UCI-ADL OrdóñezB [34]	10	86.51	3.83

Comparison Evaluation

- Proposed method improved the **individual activity accuracy** in each dataset
- Improved the **global accuracy** over each dataset.
- Performance of proposed method with state-of-the-art show potential **accuracy gain**.

[1] Razzaq, Muhammad Asif, et al. mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification." MDPI, Sensors 17.10 (2017): 2433.
[2] Razzaq, Muhammad Asif, et al. "SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition." MDPI, Sensors 20.10 (2020): 2771.

Solution-2: Experimental Setup & Results (1/4)



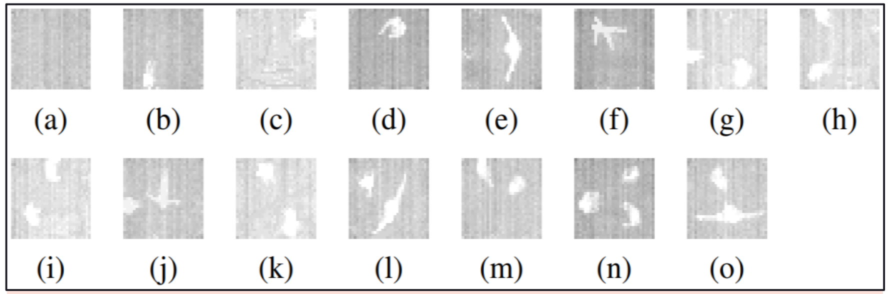
Steps performed to pre-process the benchmarks & TVFs

sensor frames for occupant detection, state estimation and prediction:

- **Step-1:** Java-based standard libraries **OpenCV** [29] are used for processing **JSON** frames and sequences.
- **Step-2:** **Optimal binary threshold** [36] value is sorted suited for each sequence for maximum number of occupants.
- **Step-3:** Identify the detection using **rectangular box** identified by ID.
- **Step-4:** Perform the **feature extraction** for each bounding box in every frame of the sequences in the dataset.
- **Step-5:** Process the occupant **state estimation** per frame and manage history.
- **Step-7:** Use MATLAB interfaces API to perform **per frame classification**.

Table: List of benchmark dataset sequences and their details

ID	Dataset	Sensor	Resolution	Frames	Threshold
1	**ETHZ-CLA [35]**	FLIR TAU320	324×256	659	115
2	**Soccer [40]**	3×AXIS Q-1922	1920×480	3,000	120
3	**Crouching [40]**	FLIR A655SC	640×480	625	125
4	**Depthwise Crossing [40]**	FLIR A655SC	640×480	858	135
5	**Crowd [40]**	FLIR Photon 320	640×512	78	110
6	**TVS_F$_{seq}$**	Heimann	32×31	57,290	155



(a) Empty smart living room. Single occupant activities shown as (b) Sitting (c) Standing (d) Walking (e) Stretching (f) Fall Down. Multi-occupant activities shown as (g) Two persons Sitting (h) One person Sitting while other Standing (i) One person Sitting while other Walking (j) One person Standing while other Fall Down (k) Both persons Standing (l) One person Standing while other Stretching (m) Both persons Walking (n) All are Walking (o) one person Walking while other one Stretching

Development Environment

- **Real-time** prototype development in Java IDE using Open Source OpenCV.

VOT visual object tracking challenge

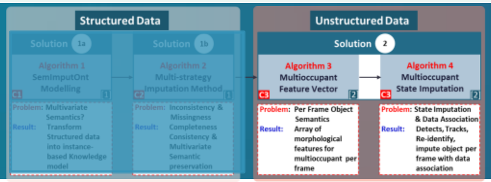
OpenCV

Evaluation Criteria

- **Pascal, Intersection over Union (IoU)** Bounding Rectangle, Ground-truth **(threshold ~ 0.5)**
- **MOTA**
- **MSE**
- **Accuracy, Robustness**

❖ $IoU(BR_n, G_i) = BR_n \cap G_i \,/\, BR_n \cup G_i$
❖ $MOTA = 1 - \sum_t (FN_t + FP_t + IDS_t) \,/\, \sum_t (G_t)$
❖ $MSE = 1/n \sum_n^{i=1} (BR_n - Gi)^2$

Solution-2: Results & Discussion (2/4)



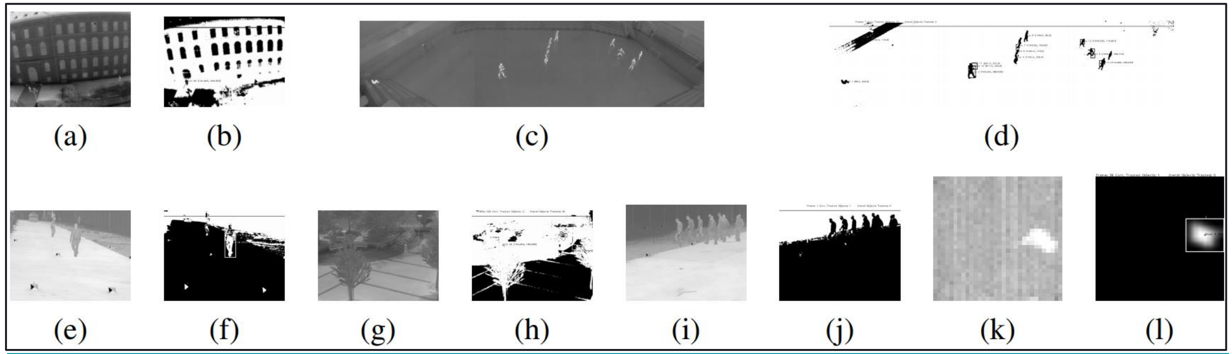


Figure: Examples of raw Input (I) frames and processed Output (O) frames using proposed framework. (a) & (b) ETHZ-CLA (I&O) (c) & (d) Soccer (I&O) (e) & (f) Crouching (I&O) (g) & (h) Depth wise Crossing (I&O) (i) & (j) Crowd (I&O) (k) & (l) TVS-F (I&O)

Experimental Findings

- VOT-TIR2016 challenge provides labelled data whereas **Ground truth** in the TVS_F_{seq} was labelled using **LabelImg** an open API.
- Use proposed methodology to detect and predict the occupants in the benchmark and TVS data.
- **Quantitative** evaluations using an automatic integration of **counting algorithm** with **Kalman Filter** occupant state **prediction** proves comparative better results.
- The best counting success rate for **Soccer sequence** with around **94.76%** and whereas, **TVS_Fseq** achieved an accuracy of **88.46%**.

Figure: Quantitative evaluations

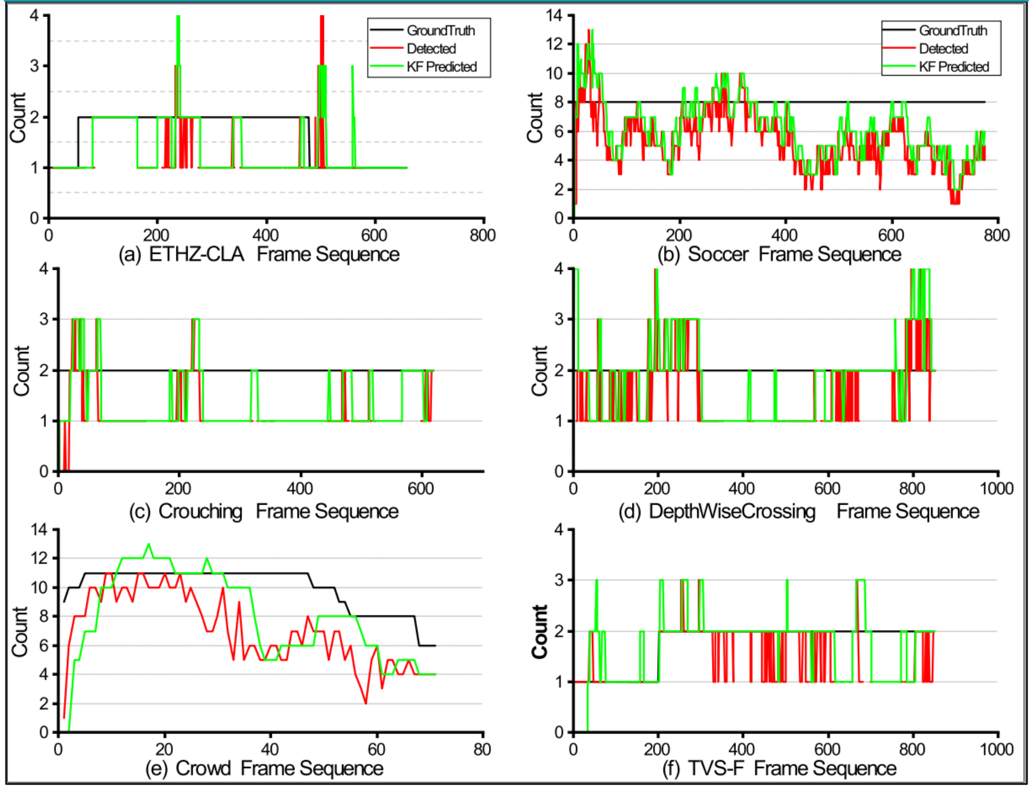
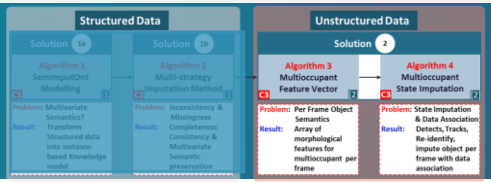


Figure: Quantitative evaluations shown in (a) ETHZ-CLA, (b) Soccer, (c) Crouching, (d) Depthwise Crossing, (e) Crowd, (f) TVS-F

Solution-2: Results & Discussion (3/4)



Experimental Findings

- ROC curves for accumulated TPR and FPR using G_i and predicted BR_n with **IoU>0.5. TVS_Fseq** has shown a larger area under the curve and proves the robustness.
- A highest area under the curves with an average **97.16%** precision rate for TVS_F_{seq} and the lowest one with around **72.04%** for ETHZ-CLA sequence.
- Effectiveness of the proposed method to be most **robust** (computed through **reliability** function defined by $e^{-S(F_0/N)}$) on $TVS\text{-}F_{seq}$ (**positioned most right**) but it was surpassed by Crouching sequence which appeared to be more accurate (**positioned higher**).
- Proposed method demonstrated better performance in terms of **MOTA** for benchmark like **Soccer** sequence score of **74.42%** and for **TVS_F_{seq}** score of **64.26%**.

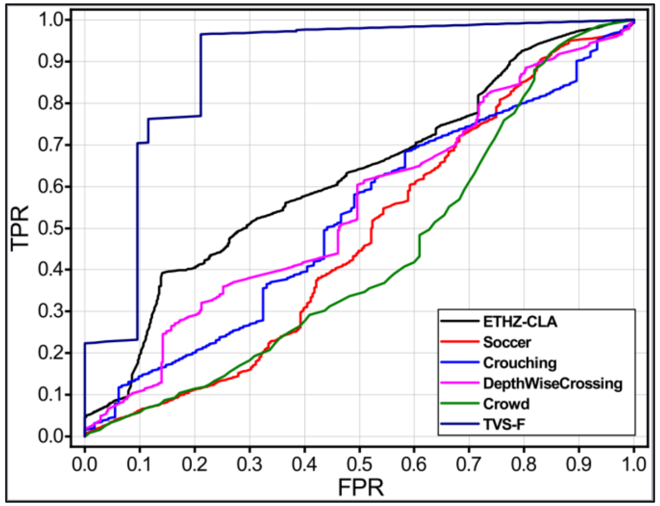


Figure: ROC curves for benchmark sequences & TVS_F_{seq}

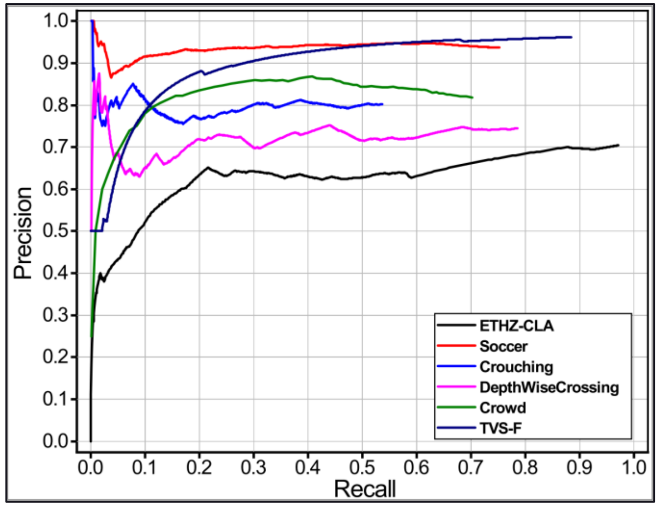


Figure: Precision-recall curves for benchmark sequences and TVS_F_{seq}

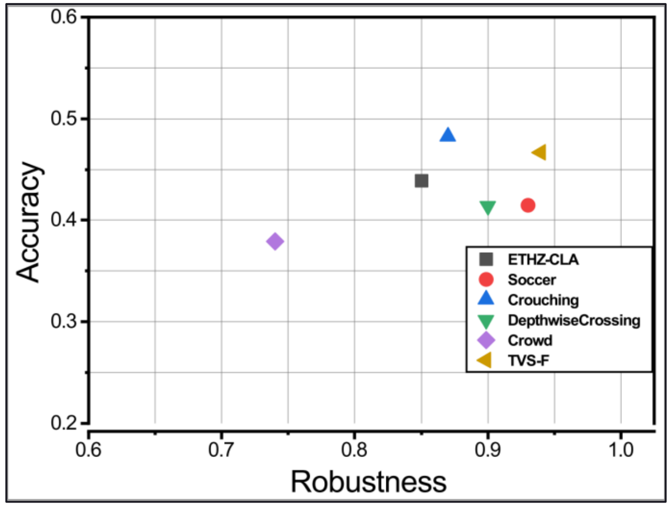


Figure: Accuracy-robustness plot for the uMoDT with benchmarks and TVS_F_{seq}

Dataset	FP↓	FN↓	MOTA↑	IDS↓	Precision↑	Recall↑	MSE↓
ETHZ-CLA	441	414	5.58	210	0.61	**0.44**	1.04
Soccer	311	1540	**74.42**	246	**0.94**	0.39	5.19
Crouching	163	428	57.17	243	0.8	0.29	1.08
Depthwise	456	408	53.03	180	0.72	0.38	0.96
Crowd	110	211	57.4	110	0.81	0.41	12.27
TVS_Fseq	52	469	**64.26**	72	**0.87**	0.42	**0.84**

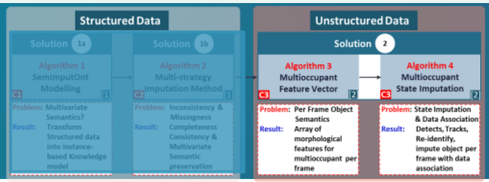
Table: Evaluation comparison of the uMoDT framework for benchmark sequences and TVS_F_{seq}

Method	FP↓	FN↓	MOTA↑	IDS↓
Bochinski et al.[30]	5702	70278	57.1	2167
Wan et al. [31]	10604	56182	62.6	1389
Bewley et al. [36]	7318	32615	33.4	1001
Murray et al. [37]	3130	76202	27.4	786
Chen et al. [10]	9253	85431	47.6	792
Gade et al. [29]	9.80%	18.80%	70.36	219
uMoDT (TVS_F_{seq})	52	469	**64.26**	72

Table: Evaluation comparison for the uMoDT framework against other techniques

- Razzaq, Muhammad Asif, et al. "uMoDT: an unobtrusive multi-occupant detection and tracking using robust Kalman filter for real-time activity recognition." **Springer, Multimedia Systems Journal** 26.5 (2020).
- **OpenSource:** uMoDT framework source code. https://github.com/masifrazzaq/TVS-DTC

Solution-2: Results & Discussion (4/4)



Experimental Findings

- An average accuracy of **97.34%** was achieved with a learning rate of 0.01 for 28,485 TVS_F$_{seq}$.
- The test split contained 1,920 TVS-F for validating **16 activities** as mentioned in the confusion matrix.
- Precision, Recall and F-Measure. By visualizing these, it can be concluded that multi-occupant activity, i.e., (Act_8) with both occupants Standing and (Act_{10}) with one occupant Standing and other one Walking has shown the lowest performance for the test split of TVS_F$_{seq}$.

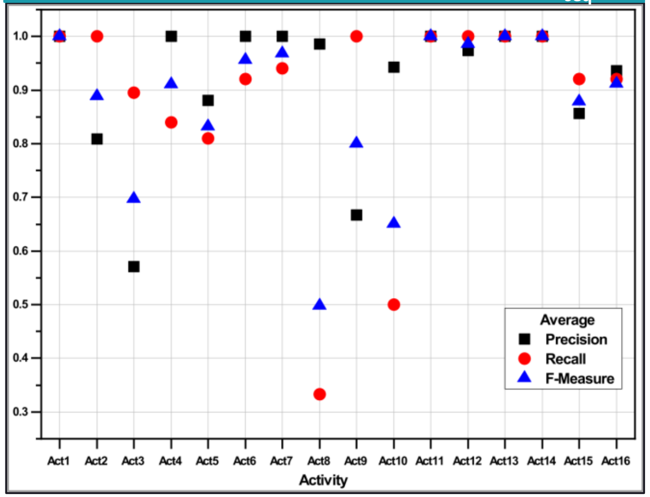
Activity ID	Activity type	Activity name	No. of occupants
Act 1	Single	FallDown	1
Act 2, Act3	Single, Multi	Sitting	1, 2
Act 4	Multi	SittingStanding	2
Act 5	Multi	SittingWalking	2
Act 6, Act8	Single, Multi	Standing	1, 2
Act 7	Multi	StandingFallDown	2
Act 9	Multi	StandingStretching	2
Act 10	Multi	StandingWalking	2
Act 11	Single	Stretching	1
Act 12, Act15, Act16	Single, Mutli	Walking	1, 2, 3
Act 13	Multi	WalkingFallDown	2
Act 14	Multi	WalkingStretching	2

Table: List of 16 activities recorded for data collection

Algorithm	Dataset	Duration(s)
TVS-MoDT	ETHZ-CLA [35]	3.91×10^{-6}
	Soccer [40]	2.99×10^{-6}
	Crouching[40]	6.35×10^{-6}
	Depthwise [40]	2.93×10^{-6}
	Crowd [40]	2.93×10^{-6}
	TVS_F$_{seq}$	4.88×10^{-6}
TVS-AR	TVS_F$_{seq}$($O = 1$)	7.1×10^{-2}
	TVS_F$_{seq}$($O = 2$)	8.3×10^{-2}
	TVS_F$_{seq}$($O = 3$)	9.0×10^{-2}

Table: Processing time for benchmarks & TVS_Fseq with TVS-MoDT & TVS-AR algorithms

Figure: Classification accuracy CNN -TVS-F$_{seq}$



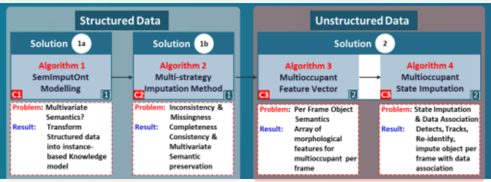
Ground Truth Activities (columns); Predicted Activities (rows)

	Act_1	Act_2	Act_3	Act_4	Act_5	Act_6	Act_7	Act_8	Act_9	Act_{10}	Act_{11}	Act_{12}	Act_{13}	Act_{14}	Act_{15}	Act_{16}
Act_1	120	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Act_2	0	120	0	0	6	0	0	0	0	0	0	0	0	0	0	0
Act_3	0	0	117	0	0	0	0	80	0	0	0	0	0	0	0	0
Act_4	0	0	0	96	0	0	0	0	0	0	0	0	0	0	0	0
Act_5	0	0	0	24	114	0	0	0	0	0	0	0	0	0	0	0
Act_6	0	0	0	0	0	120	0	0	0	0	0	0	0	0	0	0
Act_7	0	0	0	0	0	0	120	0	0	0	0	0	0	0	0	0
Act_8	0	0	3	0	0	0	0	40	0	0	0	0	0	0	0	0
Act_9	0	0	0	0	0	0	0	0	120	60	0	0	0	0	0	0
Act_{10}	0	0	0	0	0	0	0	0	0	60	0	0	0	0	0	0
Act_{11}	0	0	0	0	0	0	0	0	0	0	120	0	0	0	0	0
Act_{12}	0	0	0	0	0	0	0	0	0	0	0	120	0	0	0	0
Act_{13}	0	0	0	0	0	0	0	0	0	0	0	0	120	0	0	0
Act_{14}	0	0	0	0	0	0	0	0	0	0	0	0	0	120	0	0
Act_{15}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	120	0
Act_{16}	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	120

Table: Average accuracy confusion matrix for multi-occupant HAR

- Razzaq, Muhammad Asif, et al. "uMoDT: an unobtrusive multi-occupant detection and tracking using robust Kalman filter for real-time activity recognition." **Springer, Multimedia Systems Journal** 26.5 (2020).
- **OpenSource:** uMoDT framework source code. https://github.com/masifrazzaq/TVS-DTC

Conclusion



Thesis Contributions

1. An accurate and comprehensive ***multi-strategy Imputation*** method to keep data ***semantics*** intact.
   - Design and Implementation of an ontology based proposed method for modeling HAR datasets.
   - Achieved an average ***~6.13% increase*** in ***accuracy*** as compared to state-of-the-art approaches.
2. A robust and unobtrusive method for ***multioccupant state imputation*** using per frame ***object semantics***.
   - Designed and developed real-time multi-occupant detection, tracking, missing state estimation per frame activities classification.
   - Achieved highest accuracy ***74.42%*** on publicly available VOT-TIR2016 benchmark with ***~9.43%*** global accuracy gain.

Uniqueness

- An ***accurate*** and ***robust*** methodology to improve the quality of HAR multimodal publicly available datasets.
- An ***end-to-end*** real-time implementation and evaluation method, which can deal with ***any form*** of incomplete HAR datasets.

[1] Razzaq, Muhammad Asif, et al. **mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification**." **MDPI, Sensors** 17.10 (2017): 2433.
[2] Razzaq, Muhammad Asif, et al. "**SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition**." **MDPI, Sensors** 20.10 (2020): 2771.
[3] Razzaq, Muhammad Asif, et al. "uMoDT: an unobtrusive multi-occupant detection and tracking using robust Kalman filter for real-time activity recognition." **Springer, Multimedia Systems Journal** 26.5 (2020).

Future Work

Applications

Proposed methodology contributes in pre-processing and ***enhancing*** the ***quality of data***, which is the key step in most of Pervasive computing applications in addition to:

- Smart home systems[1,2]
- Elderly care[3]
- Health and Wellness applications1[1,2]
- Security and Surveillance[3]
- Industrial applications[3]

Limitation

- ***Prior*** knowledge of Sensors, data outputs to represent activities in ***Domain-Specific Ontologies***.

Future work

- Extend the methodology for ***automatic*** generation of ***ontology*** through sensor data.
- Extend the multi-occupant ***position estimation*** using ***multiple*** thermal cameras.

[1] Razzaq, Muhammad Asif, et al. **mlCAF: Multi-level cross-domain semantic context fusioning for behavior identification**." **MDPI, Sensors** 17.10 (2017): 2433.
[2] Razzaq, Muhammad Asif, et al. "**SemImput: Bridging Semantic Imputation with Deep Learning for Complex Human Activity Recognition**." **MDPI, Sensors** 20.10 (2020): 2771.
[3] Razzaq, Muhammad Asif, et al. "uMoDT: an unobtrusive multi-occupant detection and tracking using robust Kalman filter for real-time activity recognition." **Springer, Multimedia Systems Journal** 26.5 (2020).

Publications

Published papers

- Patents (01)
  - 01 Korean Registered, 01 Applied
- SCI / SCIE Journals (12)
  - First Author: (03)
    - SCI (01): Springer: Multimedia Systems, (IF 1.956; 2020)
    - SCIE (02): MDPI: Sensors, (IF 3.275; 2017, 2020)
  - Co-author (09)
- Non-SCI Journal (01)
  - Co-author (01)
- Conferences (17)
  - International (06)
  - Domestic (04)
  - Co-author (06)
  - Co-author Domestic (01)

Publication

Total Publications (31)

First Author Publications (15)

Papers in progress

- SCIE Journal (01)
  - Asif et. al.. "Multimodal Feature Fusion for Emotion Recognition". PLOS ONE. To be submitted, Nov 2020.
- Patent to be applied (01)

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Thank you
for your attention

Q & A ?