Meeting 2

LM-RTA · LIGHTWEIGHT MODELS FOR REAL-TIME APPLICATIONS

REAL-TIME SMARTWATCH SENSOR INTELLIGENCE: HOW DATA QUALITY AFFECTS HUMAN ACTIVITY RECOGNITION

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1 · Inspect data | 2 · Assess | 3 · Detect | 4 · Recover | 5 · Conclude

DATA COLLECTION

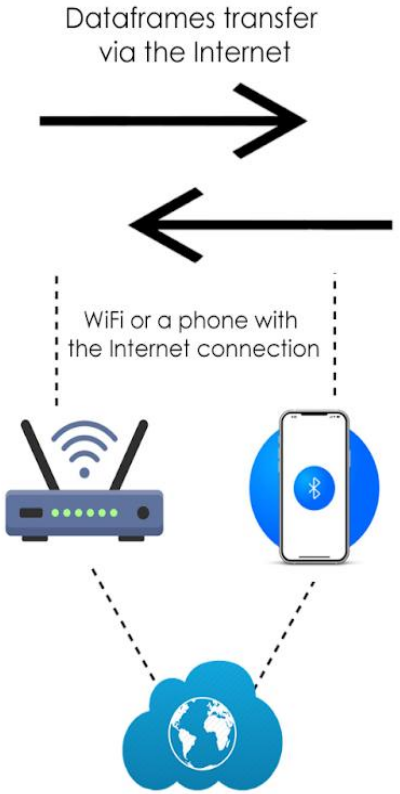
Galaxy Watch app (Kotlin, Wear OS)

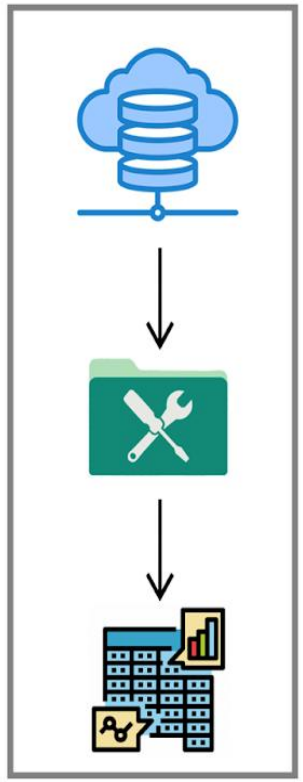
↓

Cloud database (Microsoft Azure)









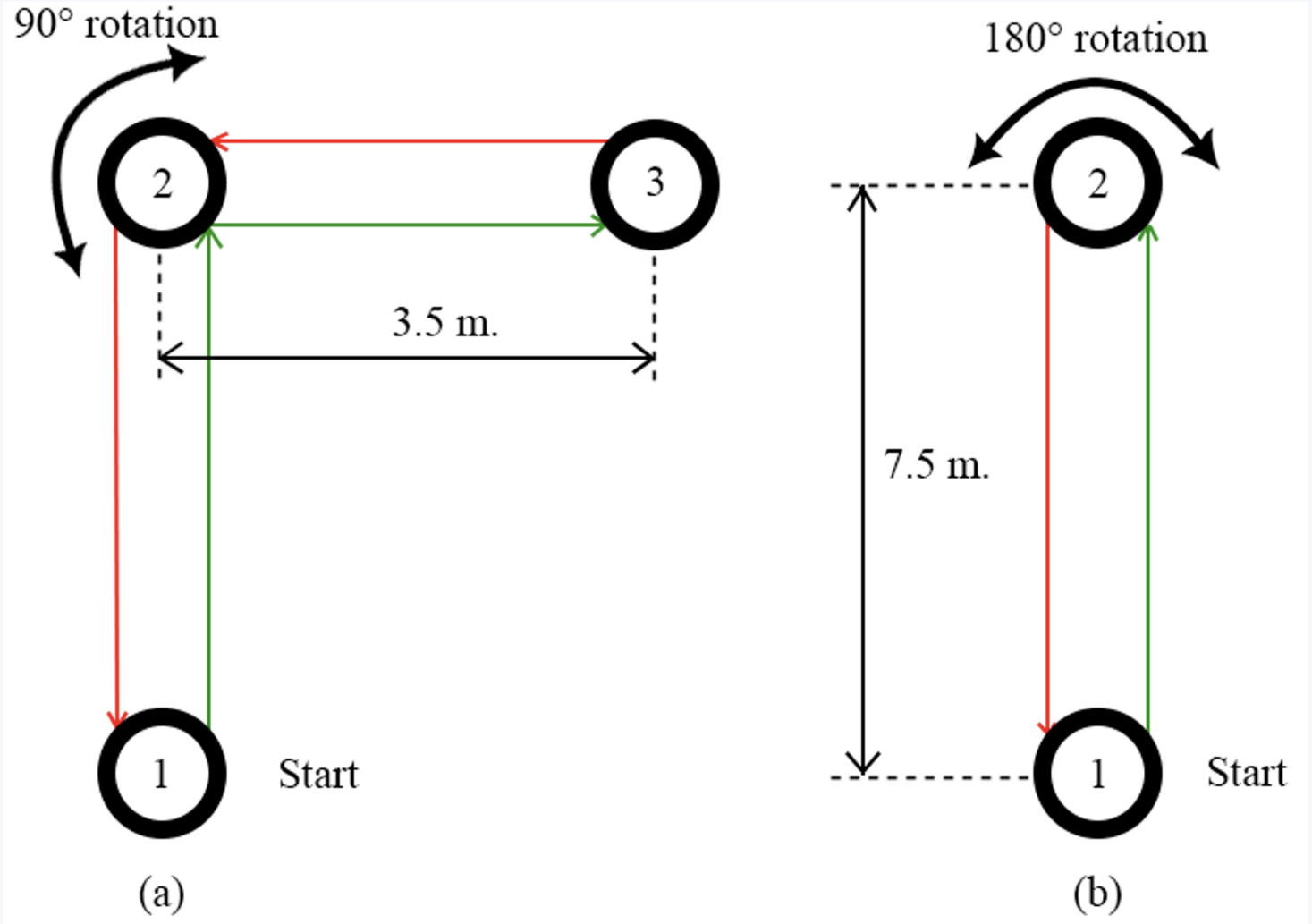
100 Hz
6 channels

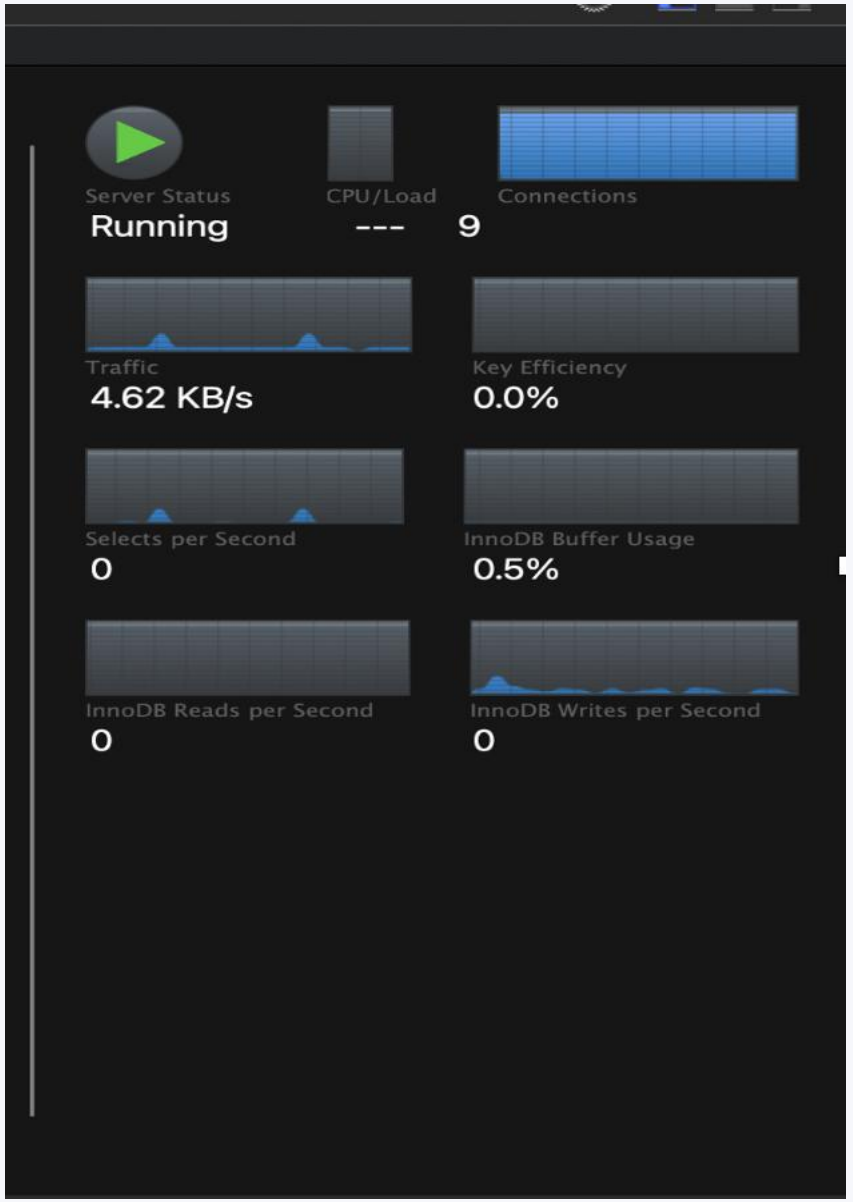
3 s
300 samples

over 50 h
over 600 sessions

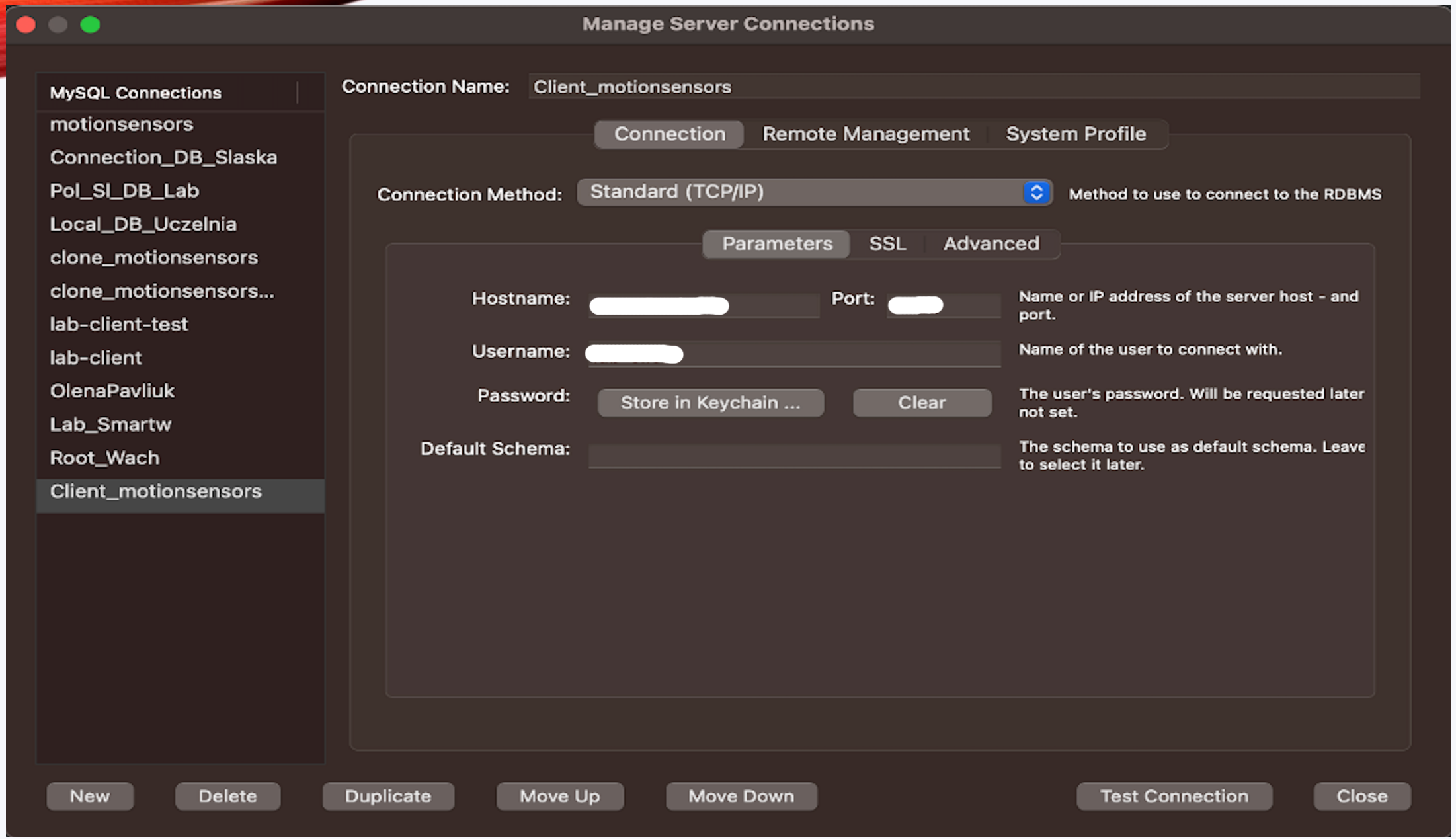
600
over subjects

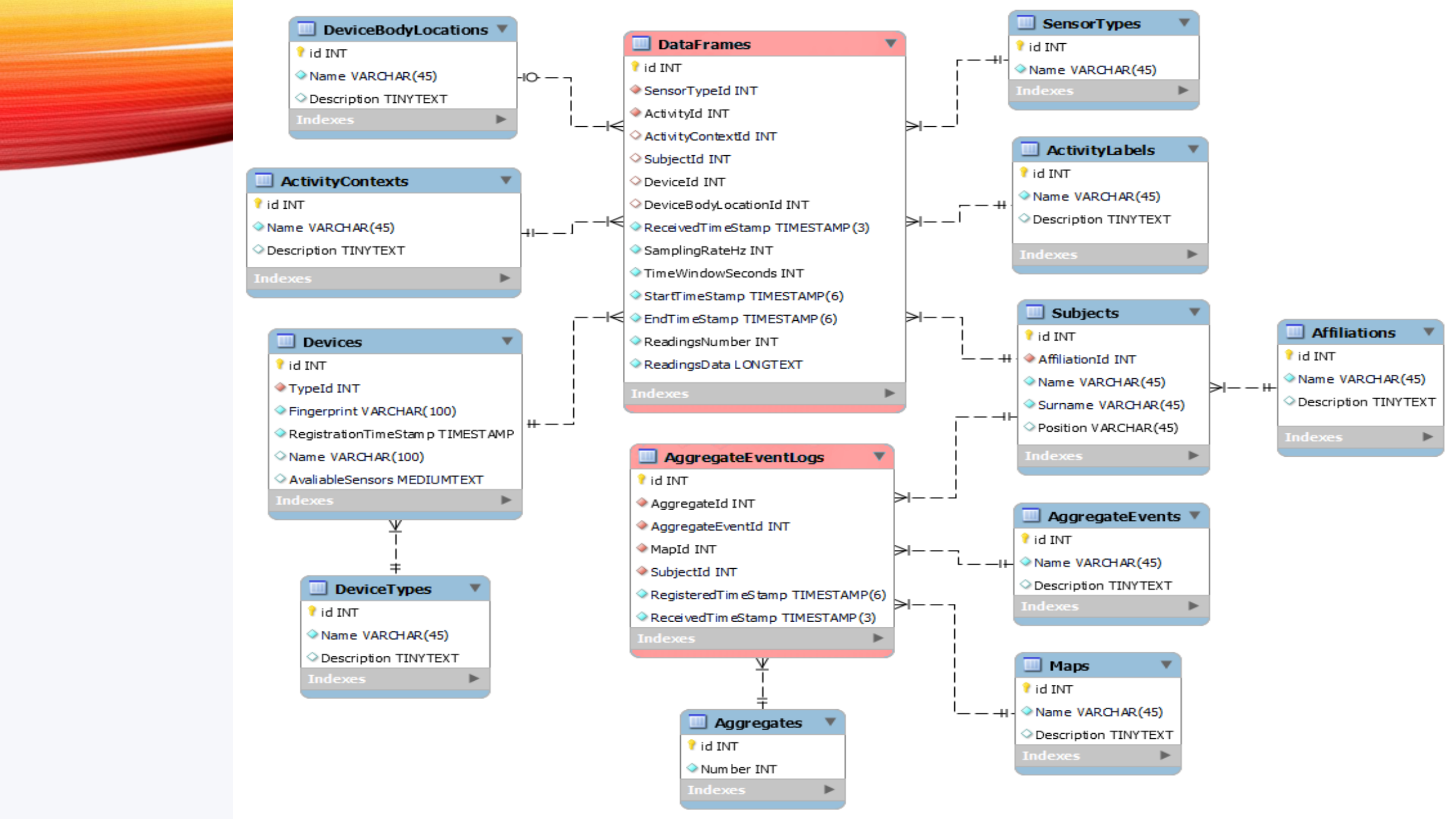
DATA COLLECTION IN REAL TIME



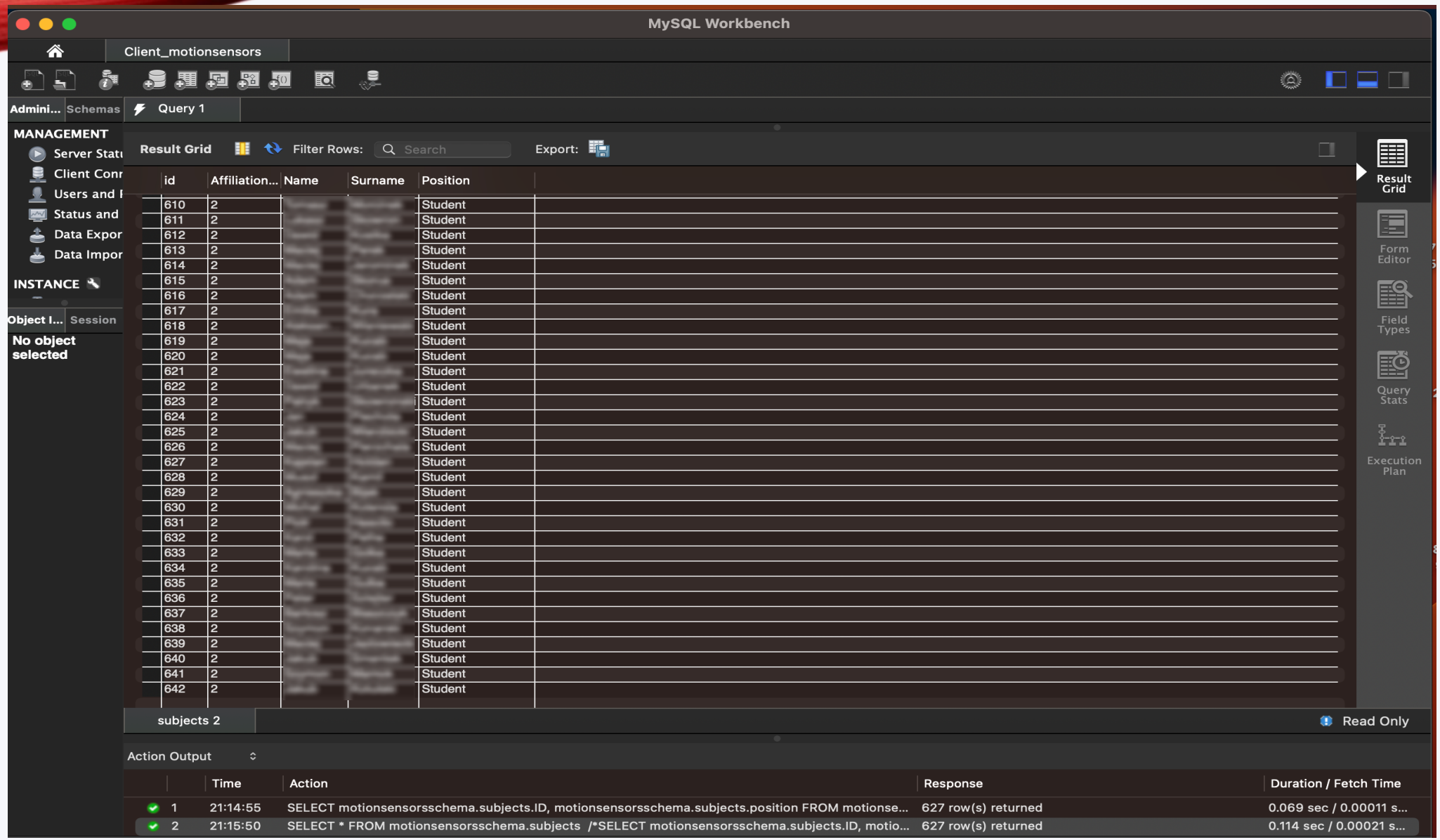


1 · INSPECT DATA




DeviceBodyLocations
id INT
Name VARCHAR(45)
Description TINYTEXT
Indexes
DataFrames
id INT
SensorTypeId INT
ActivityId INT
ActivityContextId INT
SubjectId INT
DeviceId INT
DeviceBodyLocationId INT
ReceivedTimeStamp TIMESTAMP(3)
SamplingRateHz INT
TimeWindowSeconds INT
StartTimeStamp TIMESTAMP(6)
EndTimeStamp TIMESTAMP(6)
ReadingsNumber INT
ReadingsData LONGTEXT
Indexes
SensorTypes
id INT
Name VARCHAR(45)
Indexes
ActivityContexts
id INT
Name VARCHAR(45)
Description TINYTEXT
Indexes
ActivityLabels
id INT
Name VARCHAR(45)
Description TINYTEXT
Indexes
Devices
id INT
TypeId INT
Fingerprint VARCHAR(100)
RegistrationTimeStamp TIMESTAMP
Name VARCHAR(100)
AvaliableSensors MEDIUMTEXT
Indexes
Subjects
id INT
AffiliationId INT
Name VARCHAR(45)
Surname VARCHAR(45)
Position VARCHAR(45)
Indexes
Affiliations
id INT
Name VARCHAR(45)
Description TINYTEXT
Indexes
AggregateEventLogs
id INT
AggregateId INT
AggregateEventId INT
MapId INT
SubjectId INT
RegisteredTimeStamp TIMESTAMP(6)
ReceivedTimeStamp TIMESTAMP(3)
Indexes
AggregateEvents
id INT
Name VARCHAR(45)
Description TINYTEXT
Indexes
DeviceTypes
id INT
Name VARCHAR(45)
Description TINYTEXT
Indexes
Maps
id INT
Name VARCHAR(45)
Description TINYTEXT
Indexes
Aggregates
id INT
Number INT
Indexes

ORIGINAL UNCLEANED DATA



DATA AT SCALE

DAY 2 · DATA

600+	5–15 min	≈600 h	≈120k
respondents	recorded per respondent	of sensor data in total	three-second windows

ACTIVITY IDS

1 standing · 2 sitting · 5 transitions · 12 walking. Walking dominates, so classes are imbalanced.

FREE DATASETS HAR

https://www.kaggle.com/datasets/niloy333/kuhar

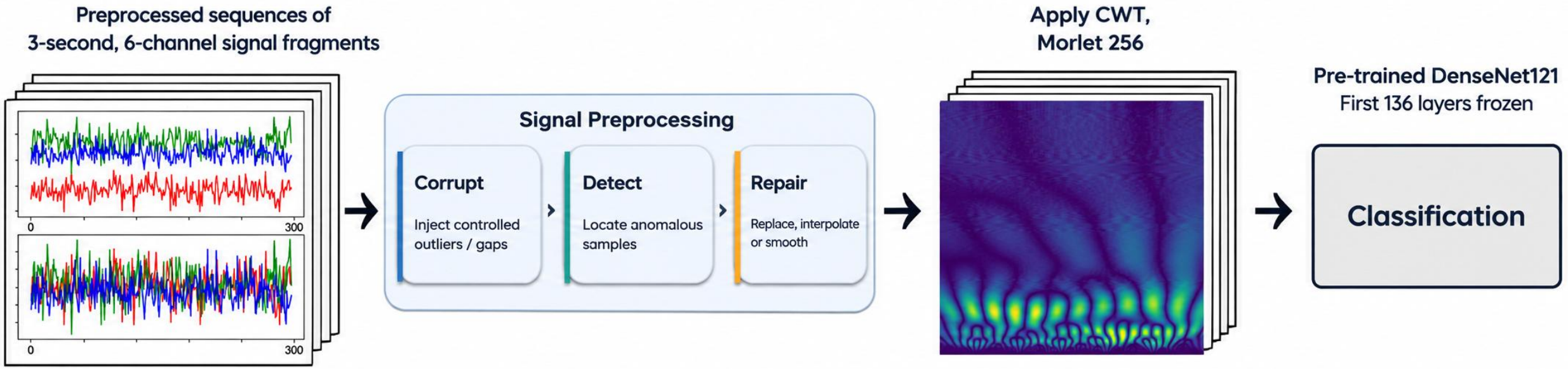
https://archive.ics.uci.edu/dataset/240/human%2Bactivity%2Brecognition%2Busing%2Bsmartphones?utm_source=chatgpt.com

https://www.nature.com/articles/s41597-026-08470-y?utm_source=chatgpt.com

https://zenodo.org/records/15830858

https://zenodo.org/records/8398688

HUMAN ACTIVITY RECOGNITION PIPELINE



PROBLEMS IDENTIFIED IN THE DATASET

DOCUMENTED DATA-QUALITY RISKS · TO BE QUANTIFIED IN THE AUDIT

SIGNAL LOSS

Lost frames
Frames undelivered after ~30 s of retries are lost; pausing drops partial frames.

Incomplete windows
Each axis is a separate record, so one window needs six aligned records.

Irregular records
Length ≠ 300 samples, empty or non-numeric values must be flagged, not repaired.

TIMING

Clock mismatch
Frames carry watch-local time, the server stores UTC; offset and drift must be separated.

Gaps and duplicates
Interrupted sessions and retransmissions create gaps, overlaps or repeated frames.

Channel alignment
Six channels need a fixed synchronisation tolerance to form one window.

LABELS AND CONTEXT

Boundary label noise
A label is set when a frame completes, so frames at activity changes may mix classes.

Metadata gaps
DeviceId and ActivityContextId are empty; wrist IDs are reversed

Class imbalance
Walking dominates, so per-class metrics matter more than accuracy.

THE RESEARCH PROBLEM

7 RESEARCH QUESTIONS

CENTRAL QUESTION

Which data-quality problems hurt activity recognition most, and which preprocessing keeps it robust at an acceptable cost?

Scope: 4 activities · 6 inertial channels · 100 Hz · 3 s windows · primary metric Macro-F1

RQ1	How do sensor-data imperfections affect activity recognition?
RQ2	Which outlier-detection methods are most effective?
RQ3	Which smoothing, interpolation, and approximation methods restore signals most effectively?
RQ4	Does lower reconstruction error (MAE/RMSE) lead to better classification?
RQ5	Which preprocessing pipeline achieves the best recognition performance using CWT and a pretrained CNN?
RQ6	Do restoration methods affect different activity classes differently?
RQ7	What are the trade-offs between restoration quality, classification performance, and computational cost?

THE HYPOTHESES TO INVESTIGATE

H1 **Impact of corruption**

Outliers and signal distortions reduce recognition performance; the effect depends on corruption type and severity.

H2 **Detection effectiveness**

Outlier-detection methods differ in effectiveness depending on anomaly type and distribution.

H3 **Restoration effectiveness**

The effectiveness of smoothing, interpolation, and approximation depends on the corruption pattern.

H4 **Error vs. classification**

Lower reconstruction error (MAE/RMSE) does not necessarily lead to higher classification performance (Macro-F1).

H5 **Preprocessing pipeline**

Appropriate detection and restoration before CWT improve recognition compared with corrupted, unrestored signals.

H6 **Activity-dependent effects**

Restoration methods affect activity classes differently, producing varying class-specific improvements.

PRELIMINARY RESEARCH PLAN FOR HYPOTHESIS TESTING

01 **Data audit & split**

Inspect sensor channels, labels, and window structure. Establish a clean reference and subject-independent train/validation/test sets.

02 **Corruption design**

Inject controlled outliers and signal distortions at predefined severity levels. Keep the original signals as ground truth.

03 **Outlier detection**

Compare Z-score, robust Z-score, IQR, and Hampel methods. Select thresholds using training and validation data only.

04 **Signal restoration**

Compare no repair with smoothing, interpolation, and approximation methods; assess each under the same corruption scenarios.

05 **CWT + pretrained CNN**

Apply CWT to the processed raw signals. Keep CWT settings, CNN architecture, and input shape fixed across experiments.

06 **Evaluation & comparison**

Measure detection (Precision/Recall/F1), restoration (MAE/RMSE), recognition (Macro-F1), and computational cost.