Optimal time window for temporal segmentation of sensor streams in multi-activity recognition

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Outline

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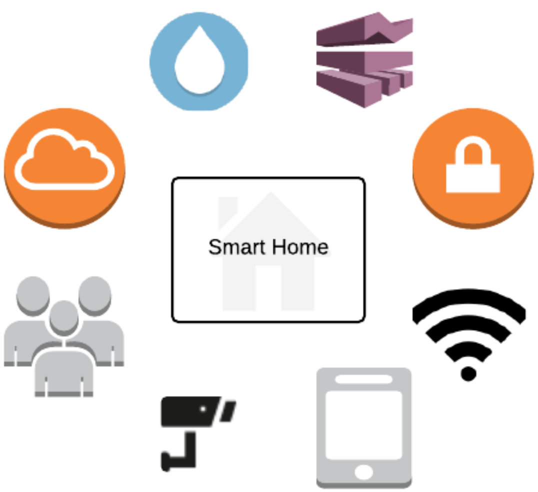
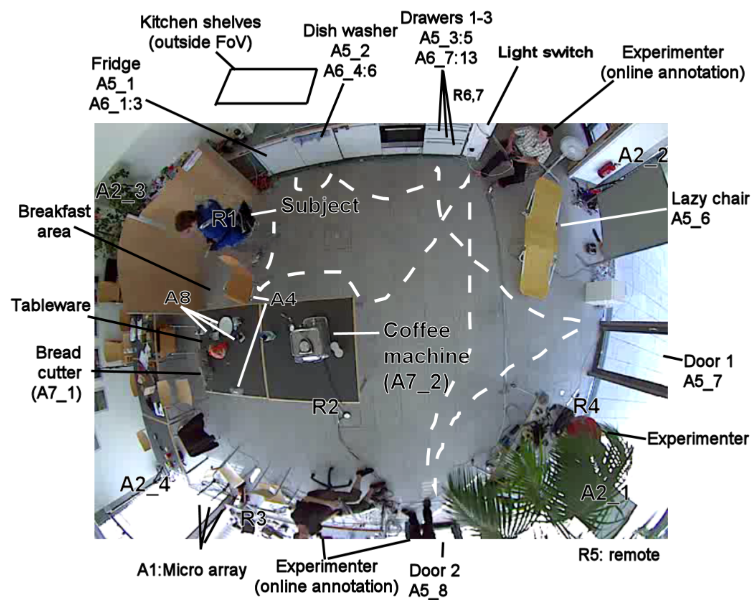
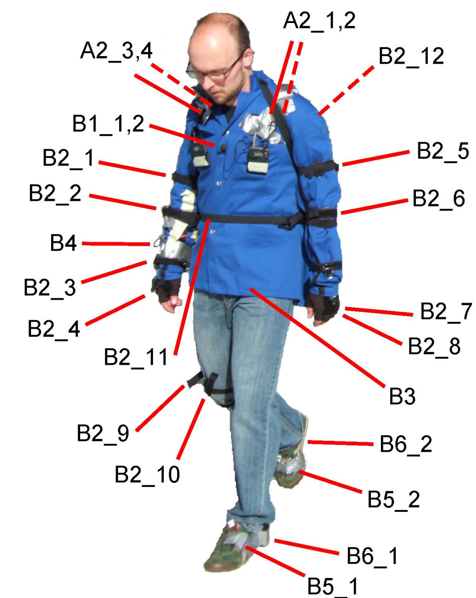
Introduction

- Ubiquitous computing offers limitless applications to support everyday life.
- These applications are enabled through the availability of mobile sensors that can be used to recognise and track activities.
- Emerging challenges are derived from continuous streaming of data from heterogeneous sensors.



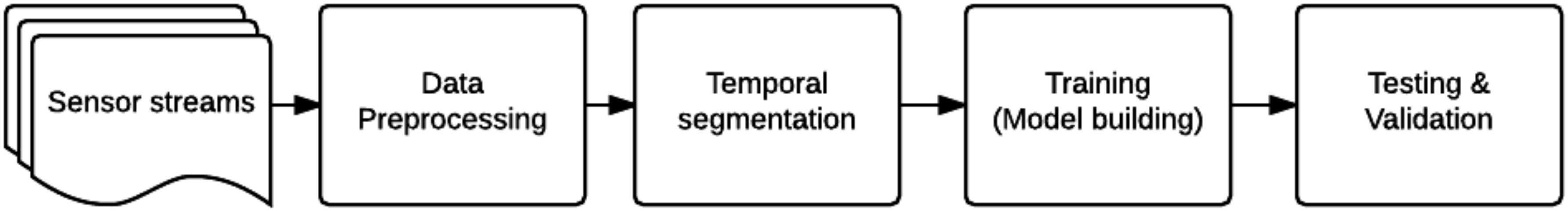




Smart home scenario from OPPORTUNITY dataset [1]

Background

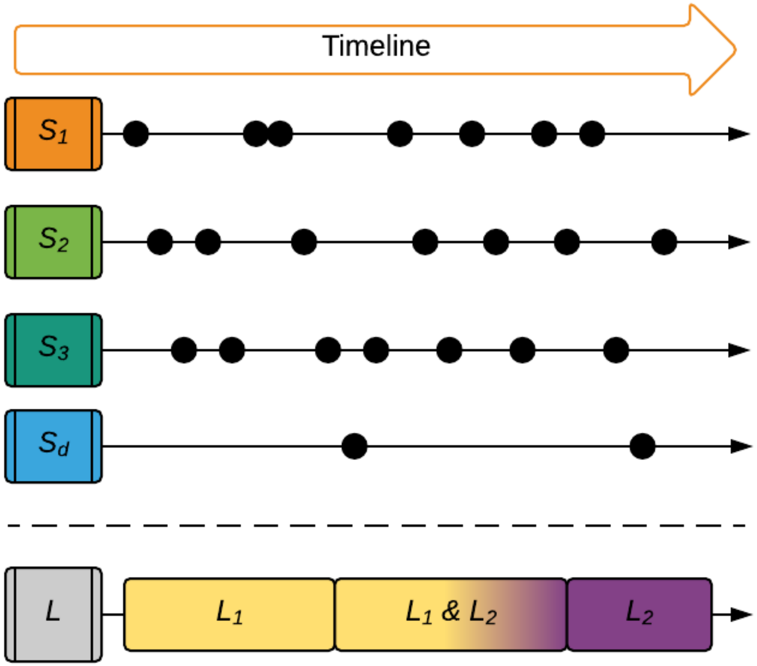
- Human annotation data may not be aligned consistently in terms of boundary between activities.
- General process in activity recognition:



- Real-time activity recognition requires feature extractions from temporal segmentation.
- Since sensor data is represented in time series, time interval based temporal segmentation is typically performed on the sensor streams.
- Therefore, impurity during temporal segmentation process can inflict a significant impact on classifier's results.

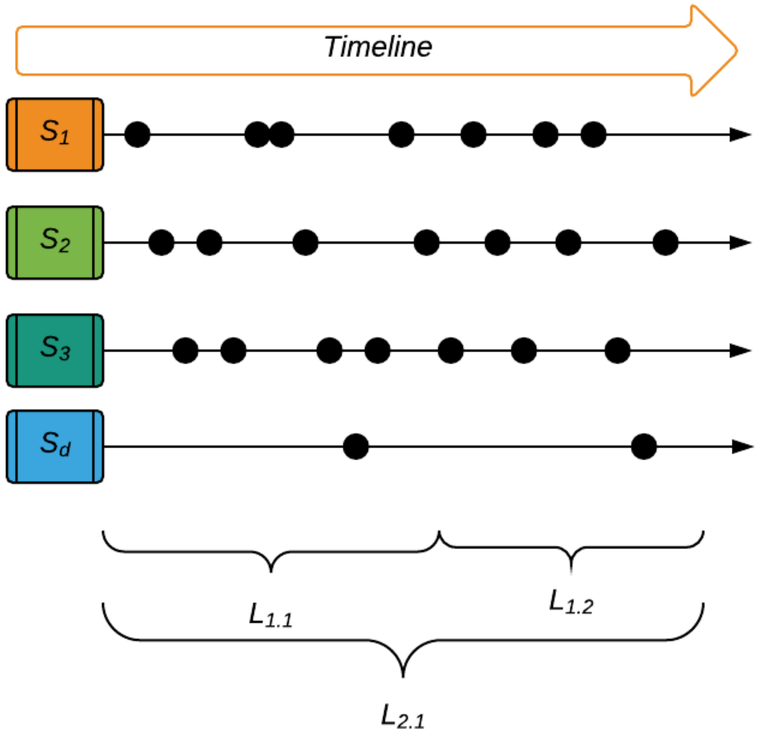
Problem illustration

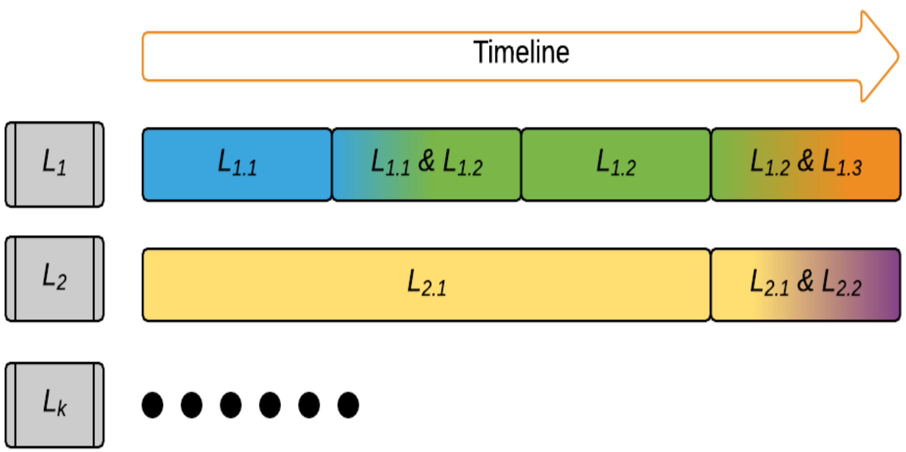
– Impurity in temporal segmentation
  An impure segment is composed of more than one label.



Problem illustration

- Multi-label problem in temporal segments





Problem definition

- Typical process in data processing involves temporal segmentation.
- Common approach in finding a suitable time window is to perform sensitivity analysis.

- Alternatively, this can be achieved through the assumption of 1 second window size as the heuristic [2,3,4,5].
- In addition, many of current studies are restricted for single activity recognition scenarios (i.e. single-label problem) [6,7,8,9,10].

- In order to find optimal time window size for temporal segmentation, multi-objective approach is proposed by gaining the balance between:
  - Minimising impurity of segments in data streams
  - Maximising factor for class separability based on k number of label sets.

- To achieve the objective, two metrics are used:
  - Impurity proportion of segments
  - Class separability score

Metric 1: impurity proportion

- An impure segment contains a mixture of multiple annotations (which can indicate important information of transition between activities).
- The impurity proportion can be computed via:

$$pimpure = \frac{m_{impure}}{m}$$

where m_{impure} is the count of impure segments over total m segments in data streams.

Metric 2: class separability – KL divergence

- Class separability refers to distinct separation between features with respect to each class label.
- The objective of computing class separability score in data streams:
  - Identifying which features are dominant towards a class label.
- Kullback-Leibler divergence [11] is used to calculate class separability score. It is a measure of difference between two probability distributions *P* and *Q*.
- Assumption: streaming sensor data is constrained by numeric features.
- For each feature f, we calculate maximum score of the class separability (i.e. maximum divergence of f) as:

$$mdivergence_f = \max_{\substack{1 \leq i \leq n \\ 1 \leq j \leq n}} KL_f(i, j),$$

where n is number of class labels in a label set L_k and $KL_f(i, j)$ is the KL distance between two distributions.

- The KL distance between two distributions (histograms) class labels i and j corresponds to the following:

$$KL_f(i, j) = \sum_{m=1}^{b} Pr_f(m \mid i) \, log\left(\frac{Pr_f(m \mid i)}{Pr_f(m \mid j)}\right)$$

where b is the number of bins in the histograms.

OPTWIN: Finding optimal time window size

- The OPTWIN algorithm (refers to our paper) requires three main input parameters: ws_{start}, ws_{end}, and ws_{step}.
- In order to find the optimal time window size for each label set, the previously computed metrics are used: impurity proportion and normalised squared deviation of divergence score.
- As both values are normalised between 0 and 1, the first intersection point at a time window size is derived as the optimal one.

- Normalised squared deviation of divergence score ndd_i can be computed as the following:

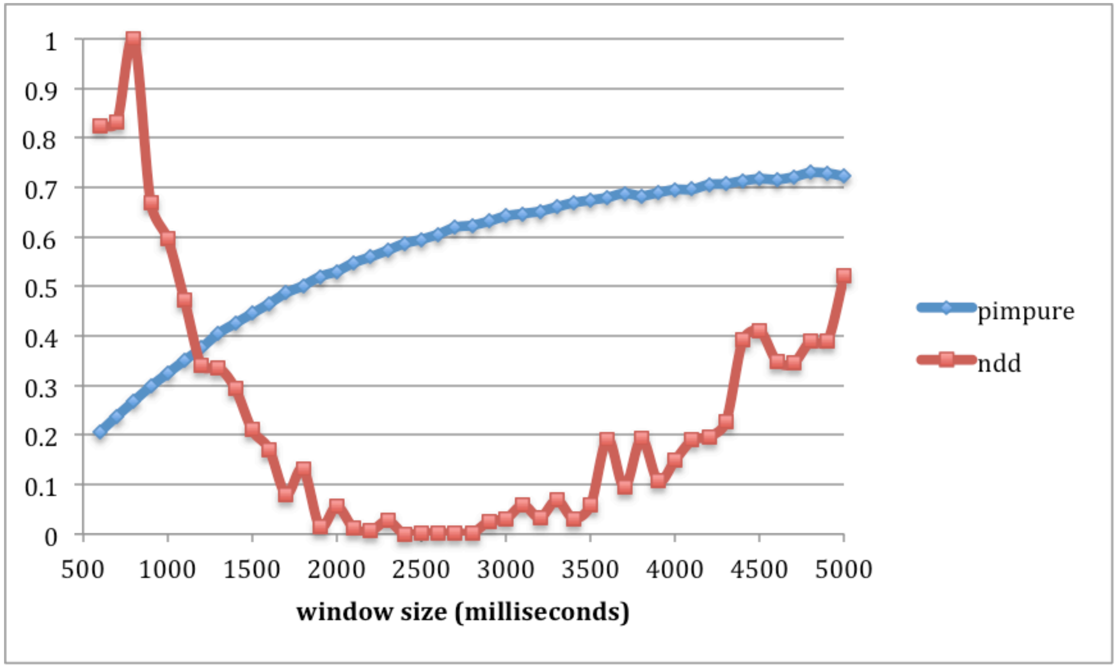
$$ndd_i = \frac{dd_i - \min(dd)}{\max(dd) - \min(dd)}$$

- where squared deviation dd_i of divergence score ds_i is defined as:

$$dd_i = (ds_i - \overline{ds})^2$$

OPTWIN: Finding optimal time window size

- As previously mentioned, the optimal time window size is found based on the intersection of impurity proportion and normalised squared deviation of divergence score.
- For example, 1.2 seconds is derived as optimal window size for multi-activity label set:



Data and Features

OPPORTUNITY
Activity and Context Recognition with Opportunistic Sensor Configurations

- Dataset: OPPORTUNITY [1] from UCI repository (4 human subjects)
- 101 features (from on-body sensors) are used out of total 242 features
- Each instance is associated with labels from the following:
  - High Level Activity (HLA) denoted as L_1
  - Locomotion Activity (LA) denoted as L_2
  - Gesture Activity (GA) denoted as L_3

$$L_1 = \left\{ \begin{array}{l} \text{Relaxing,} \\ \text{Coffee time,} \\ \text{Early morning,} \\ \text{Cleanup,} \\ \text{Sandwich time,} \\ \text{None} \end{array} \right\}$$

$$L_2 = \{\text{Stand, Walk, Sit, Lie, None}\}$$

$$L_3 = \left\{ \begin{array}{l} \text{Open Door 1, Close Door 1,} \\ \text{Open Door 2, Close Door 2,} \\ \text{Open Fridge, Close Fridge,} \\ \text{Open Dishwasher, Close Dishwasher,} \\ \text{Open Drawer 1, Close Drawer 1,} \\ \text{Open Drawer 2, Close Drawer 2,} \\ \text{Open Drawer 3, Close Drawer 3,} \\ \text{Clean Table, Drink from Cup, Toggle Switch,} \\ \text{None} \end{array} \right\}$$

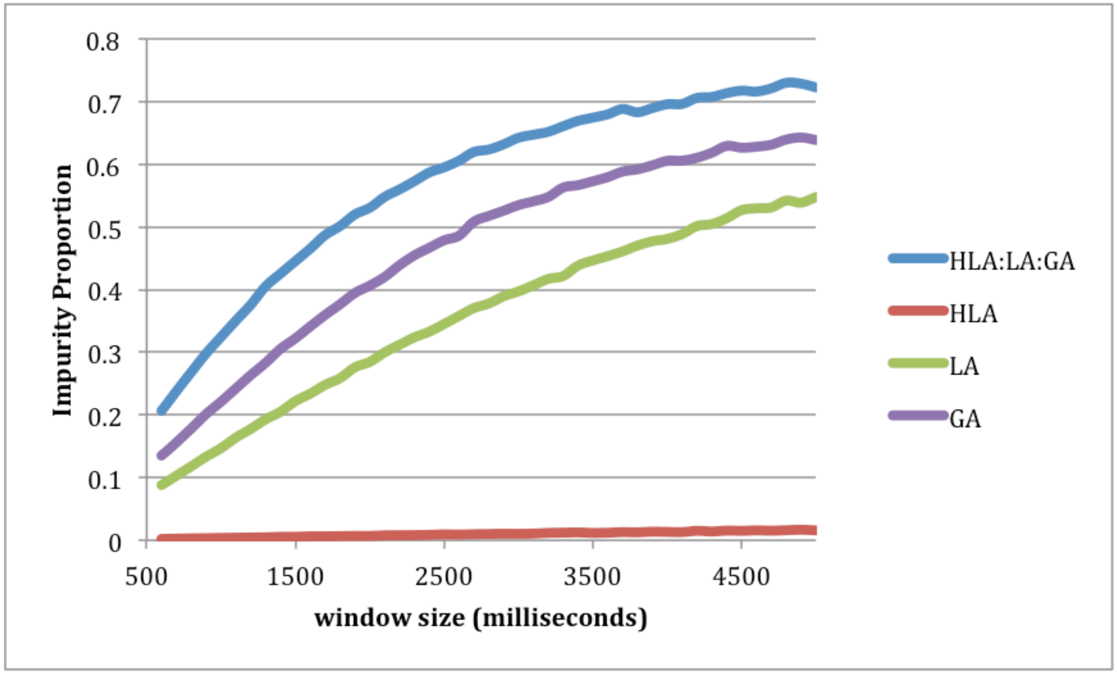
Feature Extraction

- For each window (temporal segment), the following statistical features are extracted:
  1. Mean
  2. Minimum
  3. Maximum
  4. Standard deviation
  5. IQR (interquartile range)
  6. Median
  7. RMS (root-mean-square)

- In total, 707 features are used in model building to recognise activity sets.

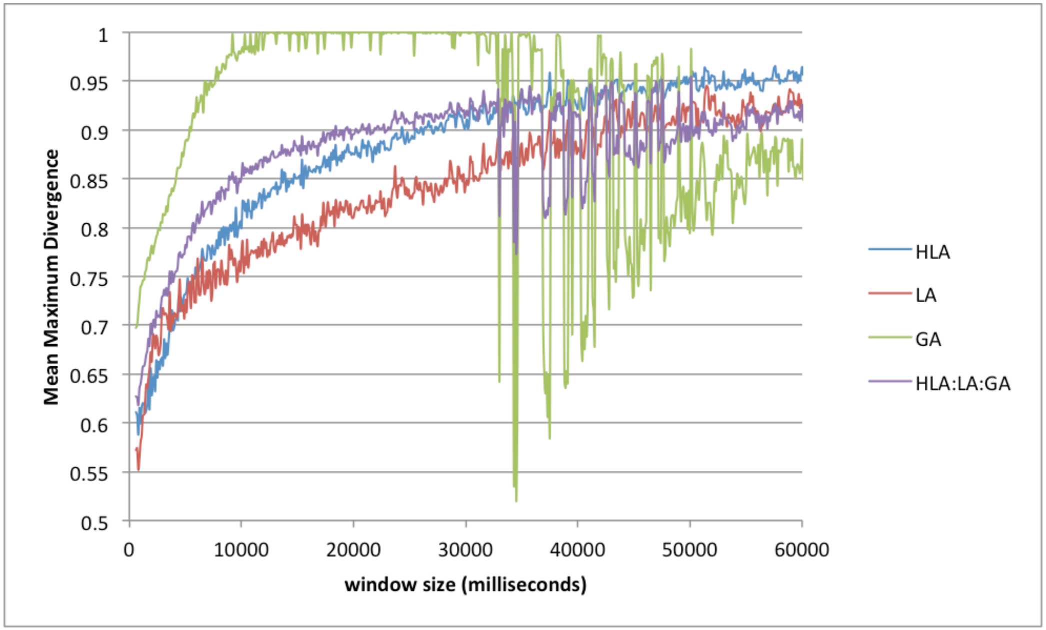
Data characteristics: impurity proportion

- Impurity proportion for multi-activity labels is generally higher than single activity labels.



Data characteristics: mean maximum divergence

- Mean maximum divergence increases as time window is expanded.
- It is expected to degrade after reaching the peak at a certain time window size.
- However, it should be noted that there is a potential degradation of label set dimension as the window size grows.



Experiments: classifiers

- To recognise the activities, the following classifiers are leveraged:
  - Naïve Bayes (**NB**) classifier
  - Decision Tree (**DT**) classifier
  - Random Forests (**RF**) classifier

- Experiments are performed using WEKA 3.8, with default parameters for each classifier.

- For multi-activity recognition, a new label set (denoted as **HLA:LA:GA**) is generated from composition of high level activity, locomotion activity, and gesture activity.

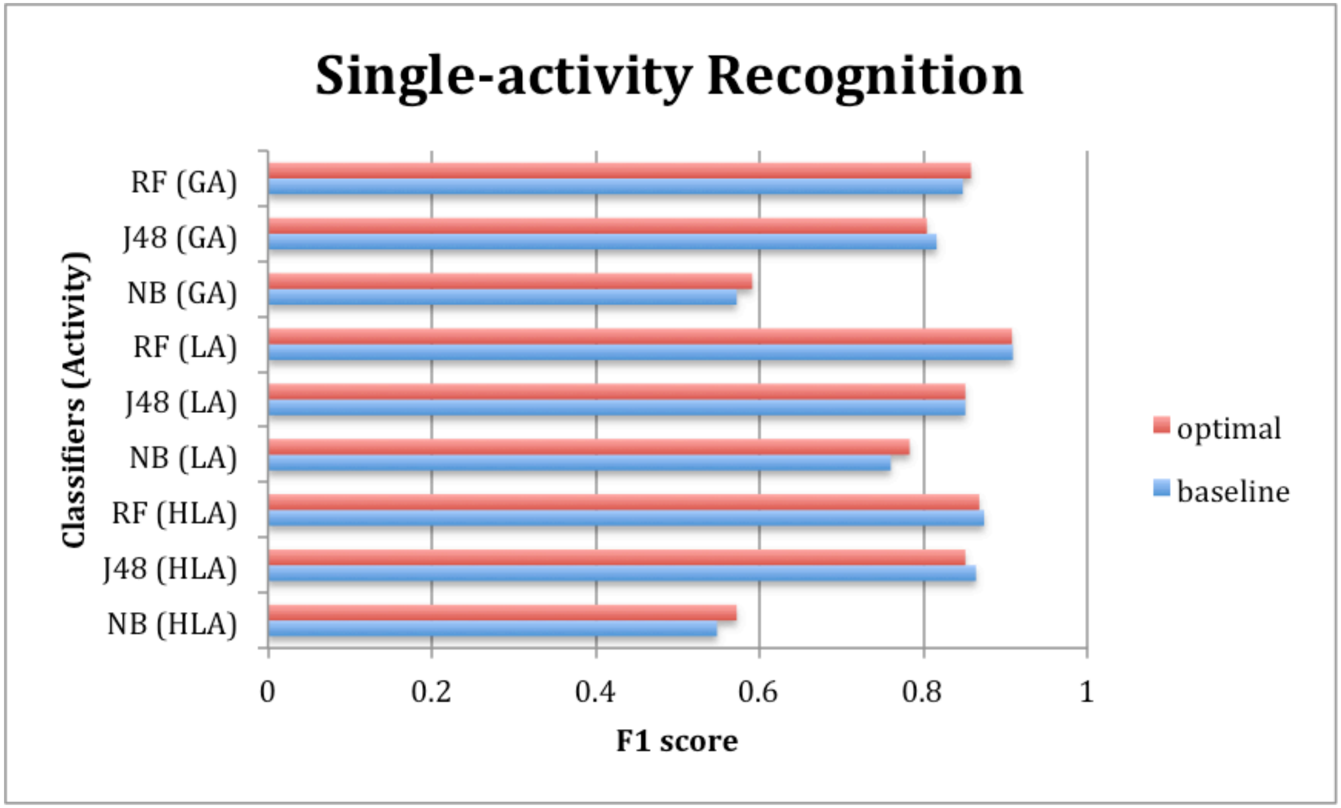
Training and Testing

- Baseline: 1 second heuristic.
- Performance of classifier is evaluated based on F1 score (harmonic mean between precision and recall).
- Validation process: 10-folds CV (Cross Validation).

- The following time window sizes are produced from OPTWIN:
  - **HLA**: 2.4 seconds - single-activity recognition
  - **LA**: 1.5 seconds - single-activity recognition
  - **GA**: 1.4 seconds - single-activity recognition
  - **HLA:LA:GA**: 1.2 seconds - multi-activity recognition

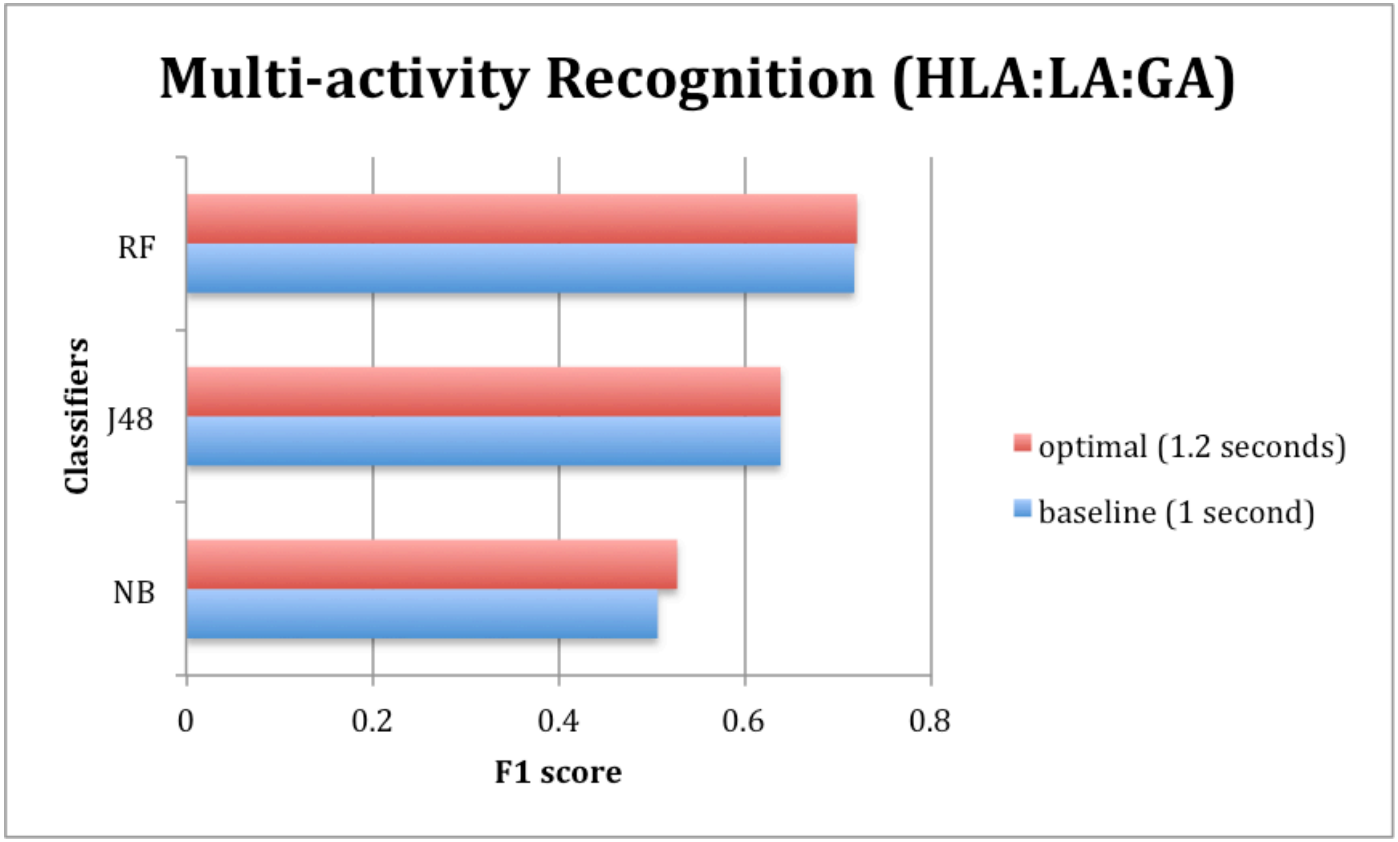
Evaluation

- Single Activity Recognition



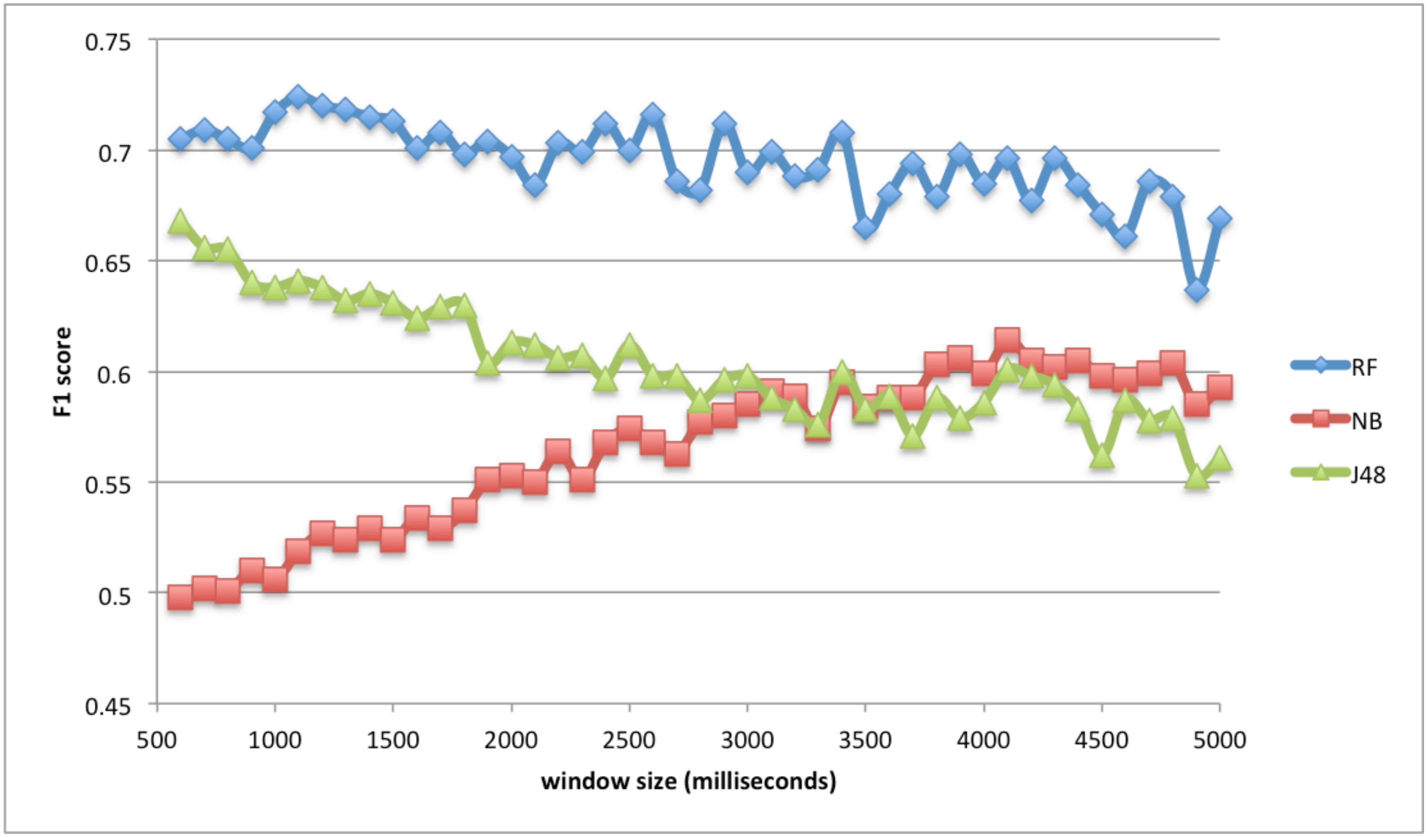
Evaluation (Cont'd)

- Multi-activity recognition



Sensitivity Analysis

- The sensitivity analysis (for multi-activity recognition) is performed within the same boundary defined for OPTWIN parameters.



Conclusion

- OPTWIN technique is proposed to find optimal window size for time-interval based temporal segmentation.
- Hence, the contribution of the technique is achieved through:
  - Minimising label impurity while maximising class separability for time-interval based temporal segmentation.
  - Adaptation for multi-activity recognition scenario (multi-label problem)
- The optimal time windows are found to improve the quality of classifier performances from simple heuristic (such as 1 second window size).
- It is found to be simple and effective. As a result, it is less time consuming compared to typical sensitivity analysis tasks in finding reasonable time window size.

Future Works

- Adaptation of window size to expand and shrink in data stream according to activity context.
- More robust and accurate classification solution for inherent multi-label problem in multi-activity recognition, where the study of dependency between activity label sets should be considered.

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Thank you: Q&A

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