Optimal window size generalizes

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ABSTRACT

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CCS CONCEPTS

• **Human Activity Recognition**; • **Machine learning**; • **Time Series**; • **Classification**;

KEYWORDS

ACM proceedings, LaTeX, text tagging

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1 INTRODUCTION

Thanks to the potential application prospects of Human Activity Recognition(HAR)in security, virtual reality, sports training and health care[2], it has become a very hot and interesting research field for the machine-learning community in the past decades. It takes advantage of data coming from internal sensors like accelerator and gyroscope to automatically classify user activities. Since the structure of data coming from sensors is stochastic over time, in order to classify them, we have to apply one of the time series classification techniques such as sliding window.

2 EXPERIMENT SETTING

2.1 Dataset

It is very important to use an adequate representative dataset to evaluate the impact of window size on the performance of the classifier in the recognition process. In this paper, one of the most complete human activity recognition dataset [2] in terms of the number of considered activities and subjects is used. This dataset is composed of data collected from 17 subjects of diverse profiles while wearing 9 Xsens inertial measurement units on different parts of their body and perform 33 fitness activities [Table 1] ranging from Warm up to fitness exercises in an out-of-lab environment. Each sensor node provides tri-directional acceleration, gyroscope, and magnetic field measurements as well as orientation estimates in quaternion format (4D). Although using several sensors help to capture the body dynamics, here only the acceleration data is used to study. This dataset provides data for three sensor displacement scenarios to compare the sensor anomalies(out of the scope of this work); thus, only the data from default scenario is used.

Activities	
Walking (1 min)	Upper trunk and lower body opposite twist (20x)
Jogging (1 min)	Arms lateral elevation (20x)
Running (1 min)	Arms frontal elevation (20x)
Jump up (20x)	Frontal hand claps (20x)
Jump front & back (20x)	Arms frontal crossing (20x)
Jump sideways (20x)	Shoulders high amplitude rotation (20x)
Jump leg/arms open/closed (20x)	Shoulders low amplitude rotation (20x)
Jump rope (20x)	Arms inner rotation (20x)
Trunk twist (arms outstretched) (20x)	Knees (alternatively) to the breast (20x)
Trunk twist (elbows bended) (20x)	Heels (alternatively) to the backside (20x)
Waist bends forward (20x)	Knees bending (crouching) (20x)
Waist rotation (20x)	Knees (alternatively) bend forward (20x)
Waist bends (reach foot with opposite hand) (20x)	Rotation on the knees (20x)
Reach heels backwards (20x)	Rowing (1 min)
Lateral bend (10x to the left + 10x to the right)	Elliptic bike (1 min)
Lateral bend arm up (10x to the left + 10x to the right)	Cycling (1 min)
Repetitive forward stretching (20x)	

Table 1: Activity set

2.2 Setup

In this section, the applied setups for activity recognition process which was explained in section "if we add a section to explain the classification, it should be referred here" are described. Regarding the prepossessing step, in order to avoid the removal of relevant information, here no prepossessing of the data is applied. As for segmentation,the overlapping (sliding at 200ms i.e., each 5s window shares 4.8s of data with the previous window) [5] and non-overlapping [3] sliding window approach with diverse window sizes ranging from .25 s to 7 s in the steps of .25 s are applied which this range covers most of the window sizes were used in previous studies[]. Although we believe that the non-overlapping sliding window approach overlooks some valuable patterns of movements between close windows, here it uses for the sake of comparison. In feature extraction part, three different feature sets(FS) are used namely FS1 = mean, FS2 =mean and standard deviation and FS3 = mean, standard deviation, maximum, minimum and mean crossing rate.Most of these features have been used in previous works[] due to their speed in the calculation and being informative over each window. Finally in recognition part, several powerful and common machine learning models are selected for discrimination of activities: Decision Tree (DT),k-nearest neighbors(KNN), Naive Bayes (NB), Nearest centroid classifier (NCC), Random forest(RF)and Logistic regression classifier(LR).
Here, a ten-fold cross-validation (10-fold CV) process which according to [1] is the most accurate approach for model selection is used in order to compare the performance of diverse models under different window size. However, due to the fact that data coming from sensors are temporal, we introduce two more realistic and

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promising cross-validation process which will be explained deeply in the next section.
As can be seen in Figure 1, the dataset is extremely imbalance meaning that there are more data-points for some classes(activities)in the dataset. Under such circumstances, the f1-score which conveys the balance between the precision and the recall based on the is an appropriate metric for evaluating the performance of the models. It reaches its best value at 1 (perfect precision and recall) and worst at 0.

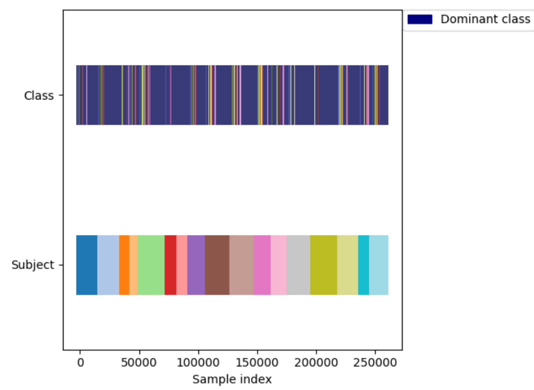

Figure 1: Example of distribution of activities and subjects in overlapping windowed dataset with window size=.5 s.The class 0 which means doing nothing accounts for more than 72 percent of the classes

2.3 Time Series vs. Classic Cross-Validation

In this section, different type of Cross-Validation(CV) strategies are explained and the reason that why classic CV is not suitable for activity recognition process.

- **Classic Cross-validation**: The main hypothesis of this type of CV is that samples are Independent and Identically Distributed (i.i.d.).It means that all the data points sampled from the same distribution and also the distribution has no memory of past generated samples **??**. Under such an assumption, as shown in Figure 2 the test set can be any part of the dataset. However, we know that samples coming from sensors are characterized to have correlation and the i.i.d. assumption of the CV is violated. Thus, evaluation models through classic CV would result in an illogical choosing of test and training set since the test set can be before the training set which is unreasonable. Although one may claim that after partitioning the dataset into some windows based on the Markov chain [4] they are i.i.d..However, through splitting the dataset by a window size, there is no guarantee to find the best number of samples to make a window completely independent of others.
- **Time-series Cross-validation** Due to the correlation between observations in Time-series based datasets, it is very crucial to train the model on the past samples and tests it on the future samples to estimate the generalization error of the trained model in the practice under a real-world scenario. As clearly illustrated in Figure 3, the Time-series CV focuses on splitting the dataset in such a way that the indices of the test set be higher than those of training set. It chooses the first K folds as training set and (K+1)-th as the test set. It should be noted that the training sets are included the training sets that come before them. As an example in Figure 3 the training set of fold #3 includes training set #2 and it includes #1 and so on.

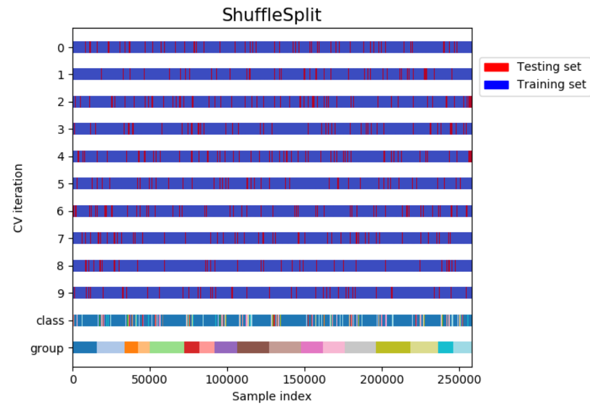

Figure 2: 10-CV process in overlapping windowed dataset by window size=.5 s

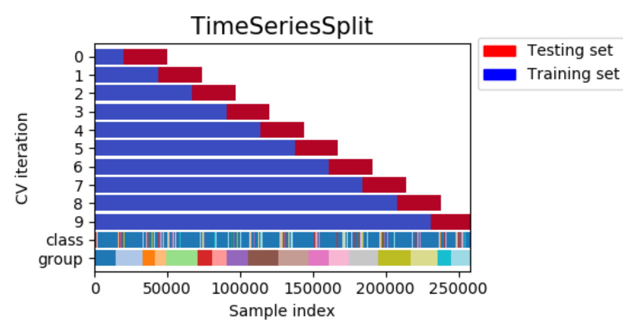

Figure 3: 10-TCV process in overlapping windowed dataset by window size=.5 s

- **Subjective Cross-validation**
  Will write down

3 RESULT

Not Ready yet

4 DISCUSSION

5 CONCLUSIONS

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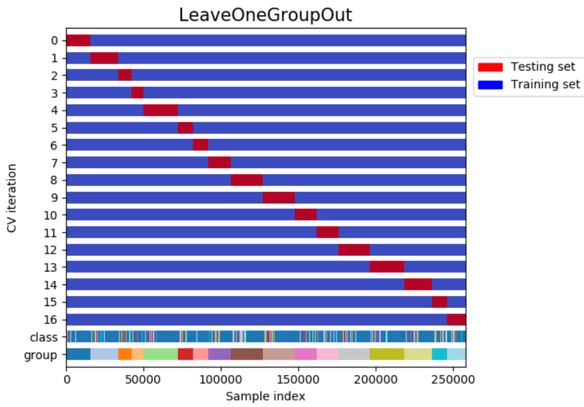

Figure 4: 10-SCV process in overlapping windowed dataset by window size=.5 s

ACKNOWLEDGMENTS

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