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DEI DEPARTAMENTO DE ENGENHARIA INFORMÁTICA

LIACC

Novelty Detection in Physical Activity

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Agenda

- **Introduction**
- Motivation
- Goals
- Literature Review
- Approach
- Experimental Setup
- Results
- Conclusions and Future Work

Introduction

- Artificial Intelligence (AI) is continuously improving several aspects of our daily lives

- There has been a **great use of gadgets & monitoring devices for health and physical activity** monitoring

- By analyzing large amounts of data and applying Machine Learning (ML) techniques, we have been able to perform useful tasks, e.g. **Activity Recognition**
  - With Activity Recognition it is possible to **recognize and monitor our daily actions**

Motivation

- Typically, the main focus of the traditional systems is **only to detect pre-established activities** according to the previously configured parameters, and not to detect novel ones

- When applying activity recognizers in real-world applications, **it is necessary to detect new activities** that were not considered during the training of the model

Goals

- To apply a **method for Activity Recognition** in the context of Physical Activity
  - Aims to **classify each activity** from the standard classes in the training set

- To apply a **method for Novelty Detection** in the context of Physical Activity
  - Aims to **detect novel classes** that were **not seen** in the training set

Literature Review - Domains

- Novelty detection has its impact in many practical and real-life applications:
  - Information and Technology (IT) Security *[Helali, 2010]*
  - Industrial Monitoring *[Surace and Worden, 2010]*
  - Image Processing and Video Surveillance *[Yong et al., 2013]*
  - Text Mining *[Zhang et al., 2005]*
  - Sensor Networks *[Hasan et al., 2011]*
  - Healthcare Informatics and Medical Diagnosis *[Clifton et al., 2011]*
  - Activities of Daily Living (ADL) *[Rossi et al., 2018]*

Literature Review - Approaches

- Methods for Novelty Detection fall into distinct categories:
    - Probabilistic *[Clifton et al., 2012; Hazan et al., 2012]*
    - Distance-based *[Ghoting et al., 2008] [Viegas et al., 2018]*
    - Reconstruction-based *[Marchi et al., 2015; Xia et al., 2015]*
    - Domain-based *[Le et al., 2010; Peng and Xu, 2012]*
    - Information-theoretic techniques *[Wu and Wang, 2011]*
    - Deep Learning *[Mello et al. 2018; Sobokrou et al. 2018]*

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Our Approach - General Overview

01	**Data Collection**	● Choose a dataset that contains **data of distinct corporal/physical activities** ● Choose a dataset that contains **data of inertial measurement units** (IMU) for each activity
02	**Data Pre-Processing**	● **Clean, select** and **integrate** data
03	**Activity Recognition**	● Select data for <u>**three**</u> **of the available activities** ● **Build** and **train** models with distinct algorithms
04	**Novelty Detection**	● Select data for <u>**five**</u> **(the original three + two others)** of the available activities ● Establish a **threshold confidence value**, which determines whether an activity is novel or not

(1) Data Collection

- ***PAMAP2* dataset** *[Reiss and Stricker, 2012]*
  - From *UCI Machine Learning Repository*
- ***PAMAP2*** contains **18 different physical activities** (e.g, walking, cycling, etc…)
- We were able to retrieve **2,872,533 examples** (rows) equivalent to 10 hours of information
- **Each example** has the following **attributes**:
  - (1) timestamp; (2) activityID; (3) heart rate (bpm); (4-20) IMU hand; (21-37) IMU chest; (38-54) IMU ankle

(2) Data Pre-Processing

- **Cleaning**
  - Remove attribute Heart Rate since a substantial part (90%) of the values were missing
  - Remove attribute Timestamp (we did not consider it as relevant attribute)
  - The IMUs (IDs 2-4 and 5-7) attributes were dropped since they were invalid in this data collection
  - The examples that contained missing values were dismissed (only 0.5% of the whole dataset)

- **Selection** and **Integration**
  - Data for **Activity Recognition**:
    - Select examples corresponding to **lying**, **sitting** and **standing**
  - Data for **Novelty Detection**:
    - Select examples corresponding to **lying**, **sitting**, **standing**, **walking** and **running**

When later applying the novelty detection method we classify the five activities as novel or not: **walking** and **running** should be.

(2.1) Data Distribution

- Number of examples **(1,800)** for **Activity Recognition**:
  - lying (600)
  - sitting (600)
  - standing (600)
- Number of examples **(1,250)** for **Novelty Detection**:
  - lying (250)
  - sitting (250)
  - standing (250)
  - walking (250)
  - running (250)

(3) Activity Recognition

- We use the examples from the selected activities (**lying**, **sitting** and **standing**) to **train our classification models**

- We train the models using these algorithms:
  - **Decision Tree**
    - *maximal depth*: 100
  - **Random Forest**
    - *number of trees*: 100
    - *maximal depth*: 50
    - *splitting criterion*: information gain
  - **K-nearest Neighbors (k-NN)**
    - *k*: 5

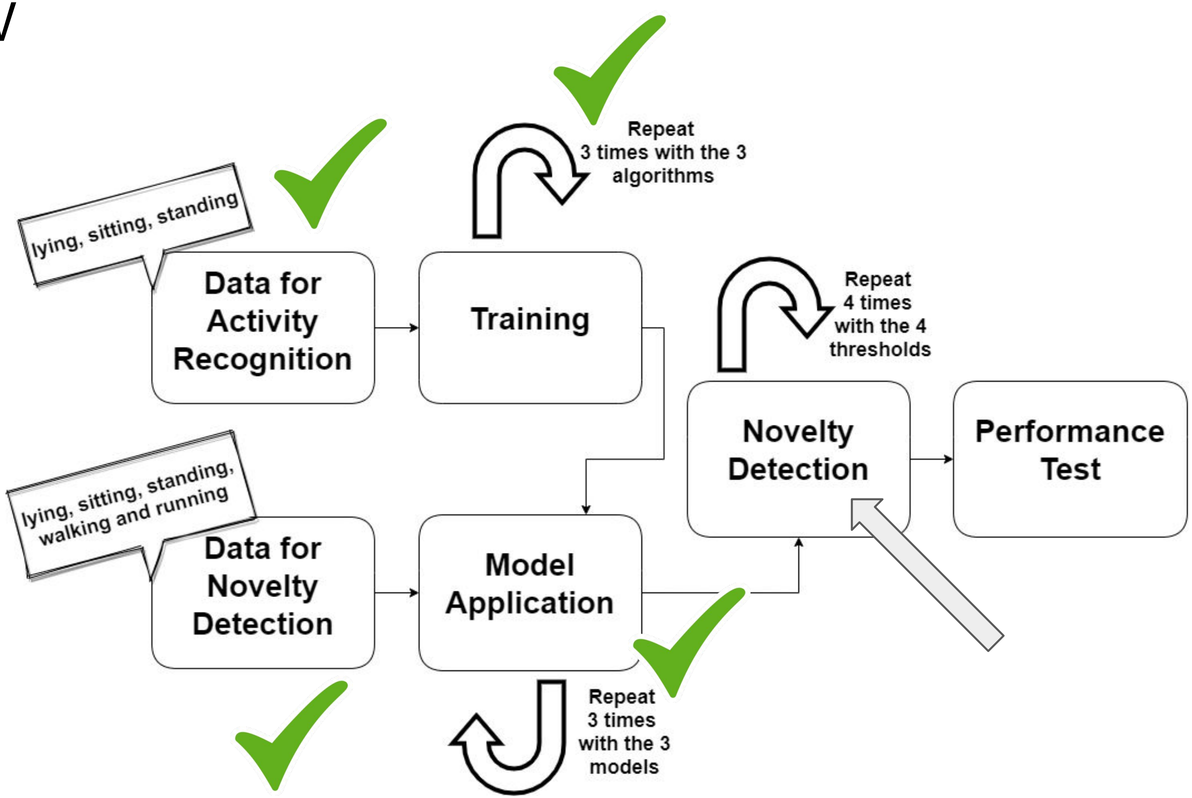
(3) Activity Recognition - Results

In order to **estimate the statistical performance of our learning models**, we perform **Cross-Validation** (10 folds). The performance results (Accuracy, Precision, Recall and F1-Score) can be analyzed in this table.

We recall that the presented models were trained considering **only lying, sitting and standing**.

Algorithm	Performance Measure (%)			
	Acc	**P**	**R**	**F1**
Decision Tree	94.4	94.5	94.4	94.4
Random Forest	96.7	96.7	96.7	96.7
k-NN	95.0	95.1	95.0	95.0

Review


lying, sitting, standing
Data for Activity Recognition
Training
Repeat 3 times with the 3 algorithms
lying, sitting, standing, walking and running
Data for Novelty Detection
Model Application
Repeat 3 times with the 3 models
Novelty Detection
Repeat 4 times with the 4 thresholds
Performance Test

(4) Novelty Detection

- For each ***prediction*** (**lying**, **sitting** and **standing**) each model presents the ***confidence*** value [0-1] for its respective decision

- In addition, each example has the ***activityID*** attribute that represents the correct/real activity

- Steps for Novelty Detection
  if ***activityID == (1 or 2 or 3)****, then* ***isNovel = false****, else* ***isNovel = true****)*
  for each **threshold** *value (* ***0.5****,* ***0.6****,* ***0.7*** *and* ***0.8***) do
  if ***confidence < threshold****; then* ***novelty_prediction = true****; else* ***novelty_prediction = false***

- Performance Test
  By comparing ***isNovel*** with ***novelty_prediction***

(4) Novelty Detection - Example

- Steps for Novelty Detection

  if ***activityID == (1 or 2 or 3)****, then* ***isNovel = false****, else* ***isNovel = true****)*

  for each ***threshold*** *value (* ***0.5****,* ***0.6****,* ***0.7*** *and* ***0.8****)* do

  if ***confidence < threshold****; then* ***novelty_prediction = true****; else* ***novelty_prediction = false***

activityID	isNovel	prediction of activity_ID	confidence	threshold	novelty_prediction	
1	false	1	0.90	0.8	false	**Not Novel**
4	true	3	0.70	0.8	true	**Novel**

(4) Novelty Detection - Results

Alg.	T.	Performance Measure (%)			
		Acc	P	R	F1
Decision Tree	0.5	60.0	50.0	0.60	1.2
	0.6	59.9	47.8	2.2	4.2
	0.7	59.8	47.7	4.2	7.7
	0.8	59.8	57.7	4.2	7.8
Random Forest	0.5	76.2	95.6	42.6	58.9
	0.6	85.7	92.1	70.2	79.7
	0.7	89.9	90.5	83.6	86.9
	0.8	90.9	85.1	93.8	89.3
k-NN	0.5	63.3	93.6	8.8	16.1
	0.6	70.2	88.0	29.4	44.1
	0.7	74.5	83.4	45.2	58.6
	0.8	80.2	84.9	61.6	71.4

- **Reasonable accuracy values** are achieved for the **Random Forest** and **k-NN**, which are increased as the threshold value increases
- **Decision Tree does not improve** its correctly predicted observations ratio
- In general, the **best results** go for Random Forest, when using a threshold value of 0.8
- **Precision** values for Random Forest and k-NN are indeed **very close** (85.1% and 84.9%)

(4) Novelty Detection - More about results

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	0.7	74.5	83.4	45.2	58.6
	0.8	80.2	84.9	61.6	71.4

- By **increasing the threshold** value:
  - more activities are classified as a novel
  - higher accuracy and recall
  - lower precision
- By **decreasing the threshold** value:
  - fewer activities are classified as a novel
  - lower recall and higher precision
- By **choosing a threshold** of **0.8**:
  - more novel activities are detected but the model is less precise

Conclusions

- We recall our motivation to **study novelty detection** in the context of **physical activity**
- Our **solution is based on the establishment of a threshold confidence value**, which determines whether an activity is novel or not
- We built and train our models with **3 different algorithms** and by experimenting **4 threshold values**
- The best results were obtained by using the **Random Forest** algorithm with a **threshold value of 0.8**
- A higher threshold: higher recall and lower precision
- A lower threshold: lower recall and higher precision

Future Work

- To study a mechanism that would allow us to divide novel activities into different categories
  - Although we are detecting if these examples are novel or not, it does not necessarily means that they belong to the same activity
- Perform the task of tuning process, e.g., by varying maximum depth of the decision tree and number of k for k-NN
- Make use of the latest deep learning techniques can help improve the performance of novelty detection
- We see a promising outlook for this research area in the future, as novelty detection can help us by recognizing and monitor our daily actions with the fruitful purpose of providing useful information

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Thank you!

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