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FROM FALL DETECTION TO TIME SERIES CLUSTERING

A Computational Intelligence approach.

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- Previous research
- A reason for the change
- Fall detection
    - An introduction
    - Using wearables
    - Machine Learning developments
    - Current challenges
- TS balancing
    - Focusing on the type of TS problems
    - TS augmentation
- TS clustering
    - A review of the field
    - Current developments

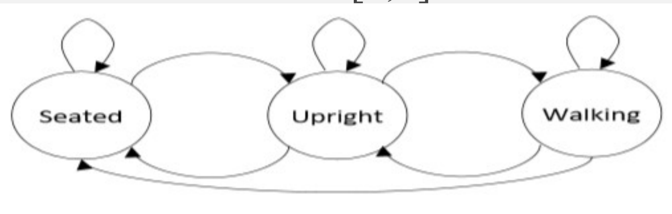
FROM FALL DETECTION TO TIME SERIES CLUSTERING

A Machine Learning approach

PREVIOUS RESEARCH

Wearable sensors and illness and abnormalities detection

- **Stroke movement detection** [1,2]

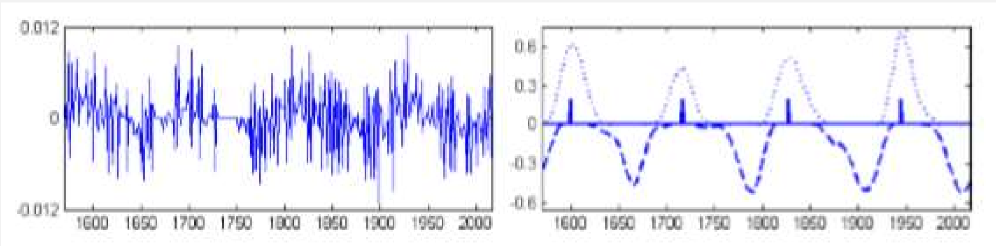


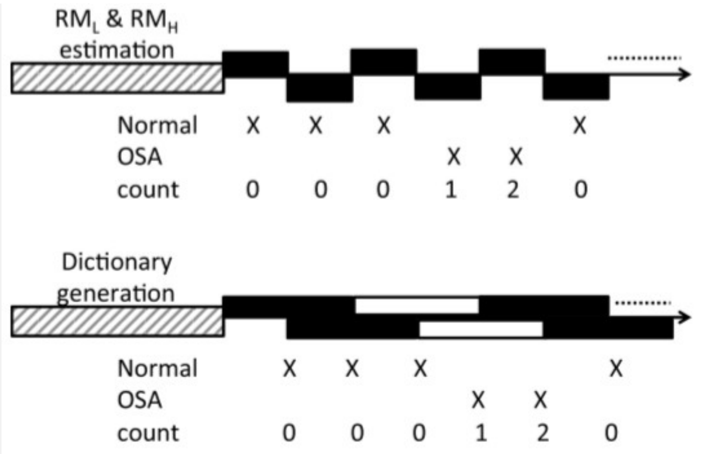
Procedure: Boosting Fuzzy Rules
Input:
  a data set of size m; the number of rules to learn N
Output:
  a rule base of size N
R=[]
for each rule r=1,…,N
  run a GA
    call *AddOneRule* for each individual
  add the rule of minimum fitness value to R
for j=1,…,N
  make all $s_k^j=0$ but the maximum one $s_{q(j)}^j$
return R

Fig. 6 The Boosting Fuzzy Rules learning algorithm with the single winner inference.

- **Sleep apnea detection, SAX dictionaries** [3]

1. Data pre-processing
2. Posture identification
3. Breath-cycle identification
4. Apnea identification



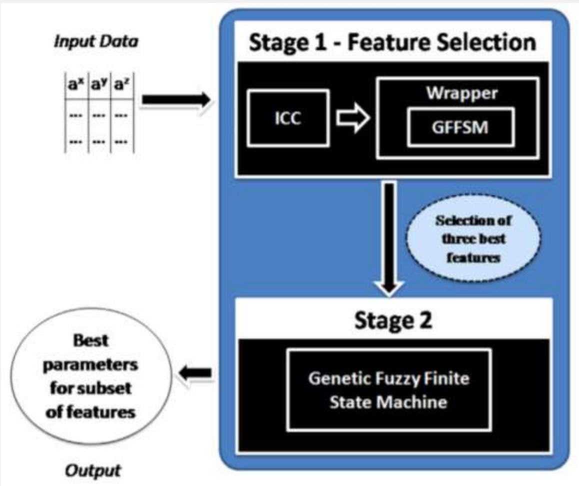


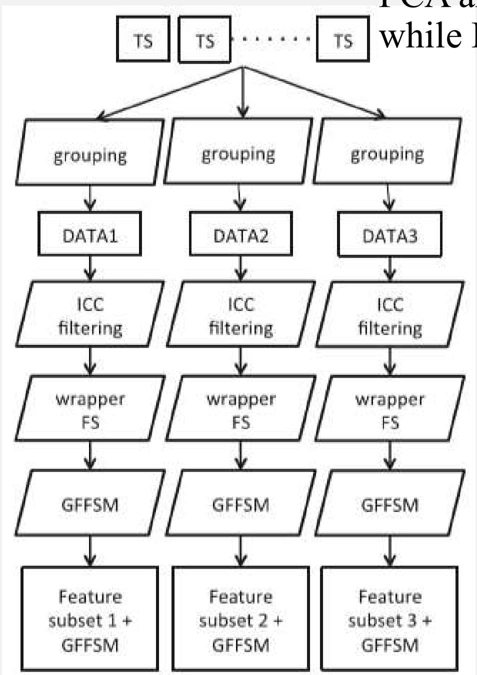
PREVIOUS RESEARCH

Wearable sensors and illness and abnormalities detection

- **Tonic-Clonic Epilepsy seizure detection** [4]
  - Finding the most interesting features that could be computed from a sliding window. A TS is represented with the most relevant features.
  - The main problem here was the availability of data.

- **Generalized models for abnormal movement detection** [5]
  - Is it possible to extract features and learn generalized models to identify abnormal movements?
  - PCA and Local PCA have been found suitable, while LLE did not.



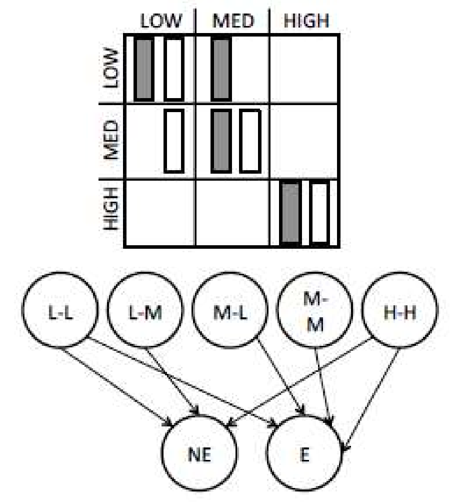


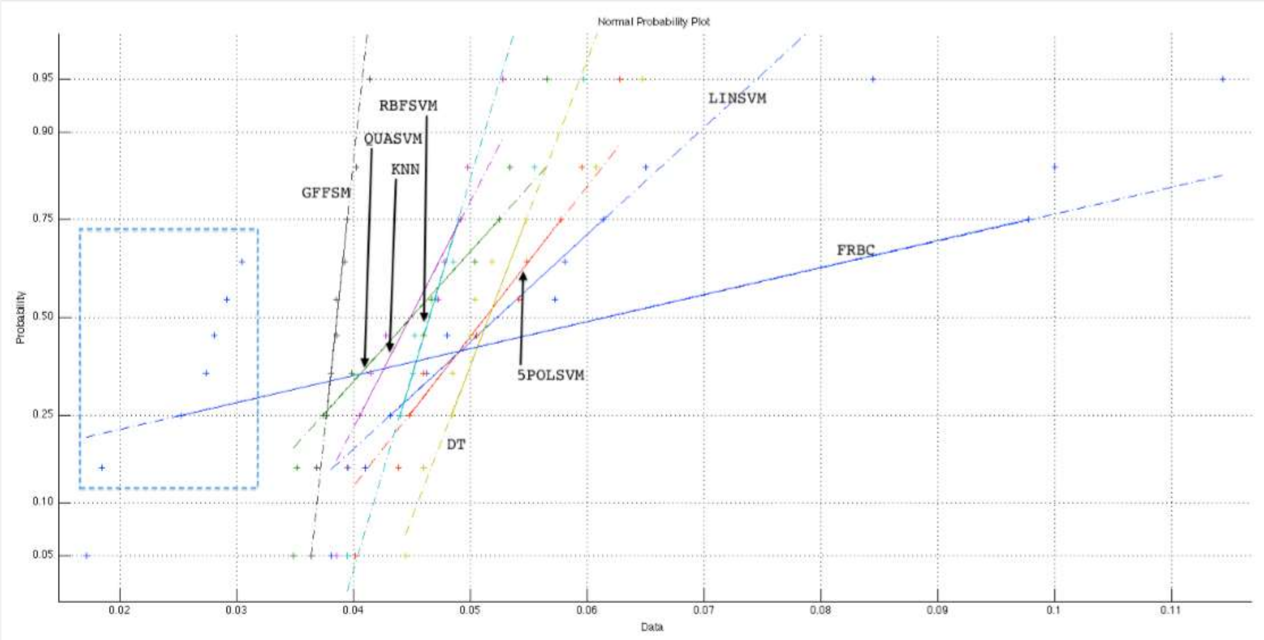
Fold	PCA			LPCA		
	3KNN	5KNN	DT	3KNN	5KNN	DT
1	0.9912	0.9916	0.9209	0.9591	0.9590	0.9373
2	0.9848	0.9872	0.9468	0.9686	0.9669	0.9716
3	0.9770	0.9783	0.9493	0.9269	0.9321	0.8840
4	0.9932	0.9937	0.9712	0.9508	0.9522	0.9446
5	0.9911	0.9894	0.9498	0.9644	0.9688	0.9516
6	0.9757	0.9762	0.9708	0.9430	0.9487	0.9036
7	0.9957	0.9950	0.9889	0.9752	0.9728	0.9642
8	0.9572	0.9515	0.8823	0.8308	0.8240	0.8154
9	0.9865	0.9862	0.9162	0.8894	0.8858	0.8262
10	0.9900	0.9900	0.9625	0.9878	0.9880	0.9834
Mean	0.9842	0.9839	0.9459	0.9396	0.9398	0.9182
Mdn.	0.9882	0.9883	0.9495	0.9550	0.9556	0.9409
Std.	0.0116	0.0129	0.0316	0.0472	0.0494	0.0594

PREVIOUS RESEARCH

Wearable sensors and illness and abnormalities detection

- **Tonic-Clonic Epilepsy seizure detection**
  - Not so many calculations to avoid draining the battery → sliding window and a restricted set of features.
  - Ant-Colony Optimization and Fuzzy Rule Based Systems [6]
  - Comparison of SVM, KNN, DT and Fuzzy Rule System [7]





PREVIOUS RESEARCH

Wearable sensors and illness and abnormalities detection

- **Tonic-Clonic Epilepsy seizure detection**
  - A wearable seizure epilepsy detection platform [8].

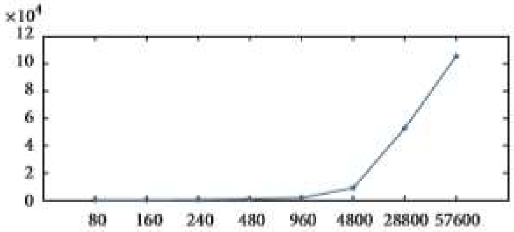


FIGURE 5: The exponential relationship between the data bunch size, x-axis, in KB, and the mean latency time, y-axis, in milliseconds, for the CC processing mode.

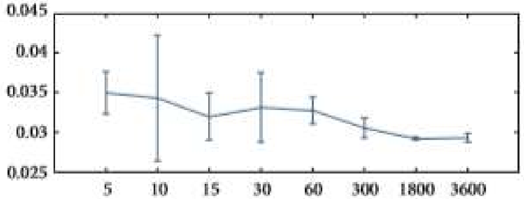
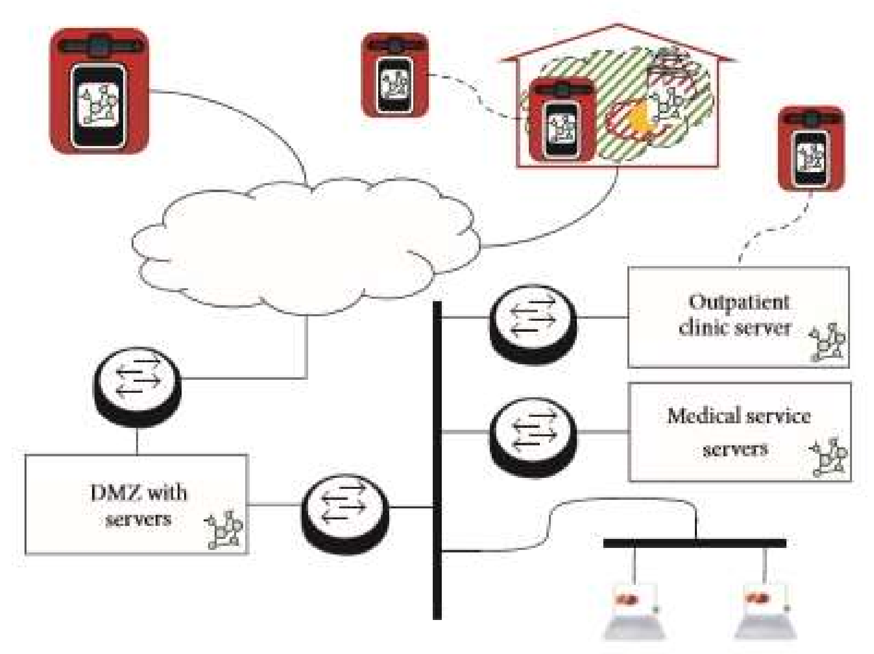


FIGURE 6: The relationship between the data bunch size and the ratio latency time versus the time between data bunch generation for the CC preprocessing mode. Some smaller sizes exhibit a wide spread; the higher the ratio, the narrower the variation in the performance.



Get to know the problem with the elder

- Falls occur everyday: one of three elderly people suffer a fall [9].
- The sooner the detection the better.
- Confidence is all.
- The ergonomic factor.

Hey, is fall detection still a CHALLENGE???

A REASON FOR A CHANGE

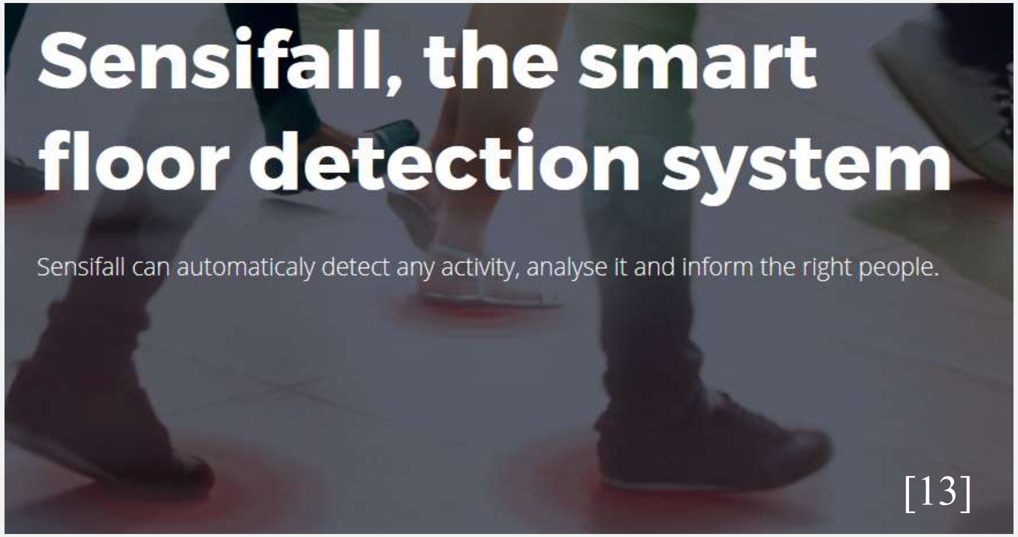
sometimes life turns in unexpected whirls

COMMERCIAL DEVICES

Video, sound, radar…

[11]

[12]



[13]

COMMERCIAL DEVICES

Personal emergency response systems (PERS) - Necklaces

Types of PERS

[14]

[15]

Characteristics

- False alarms: the price to pay.
- Access to health services 24/7 [16,17].
- Well, let's accept it: they are not nice to use… "That is a really neat feature at our age, instead of a necklace, says John Helmus, 76 [19].
- Confidence reinforcement.
- The person needs to be conscious and able to reach the button [9].
- 80% of older adults wearing a PERS did not use their alarm system to call for help after experiencing a fall [9].

COMMERCIAL DEVICES

Wearables and smartwatches

- Well-known trademarks are pursuing wearable fall detection systems.
- Apple Watch Series 4 [18]
  - Alarms when hard falls only.
  - If you are immobile → a Heatlh service call in 1 minute time.
  - If you keep moving, the call is delayed until a positive feedback.

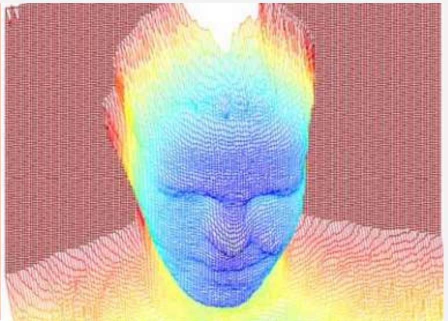
”Apple says it studied the falls of 2,500 people of varying ages. Yet the company hasn’t said how often it catches real falls or sets off false alarms.

Apple’s disclaimer says: “Apple Watch cannot detect all falls. The more physically active you are, the more likely you are to trigger Fall Detection due to high impact activity that can appear to be a fall.”[19,20]

SCIENTIFIC LITERATURE

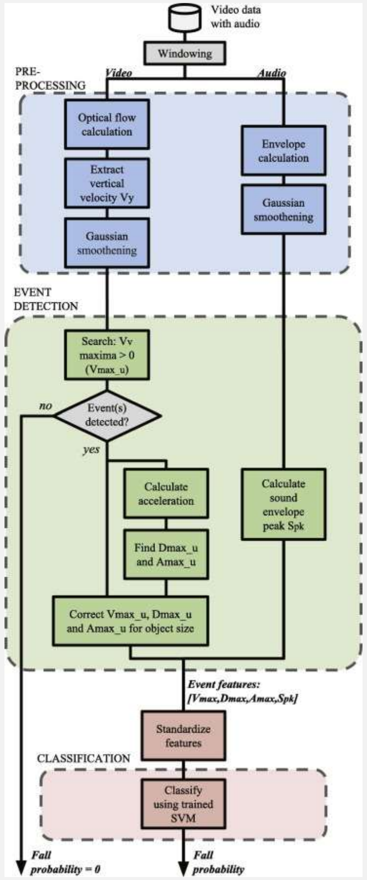
Video and motion sensor based solutions

3D Range cameras



- Video surveillance systems with/without sound.
- Simulated falls using stuntmen or volunteers.
- Participants are relatively young.
- Some studies analyse different types of fall events.
- All studies performed heuristic rules [23] or matching of specific patterns [24].
- Indoor only Privacy, Occlusions …

Video and sound [25]

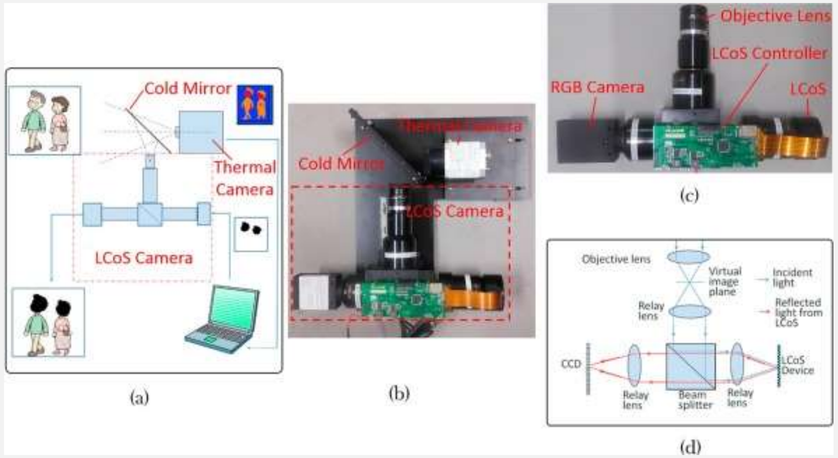


- Video and sound pre-processed independently.
- Event detection by determining the acceleration and speed of a subject PLUS a peak in the sound.
- Features are classified using a SVM.

SCIENTIFIC LITERATURE

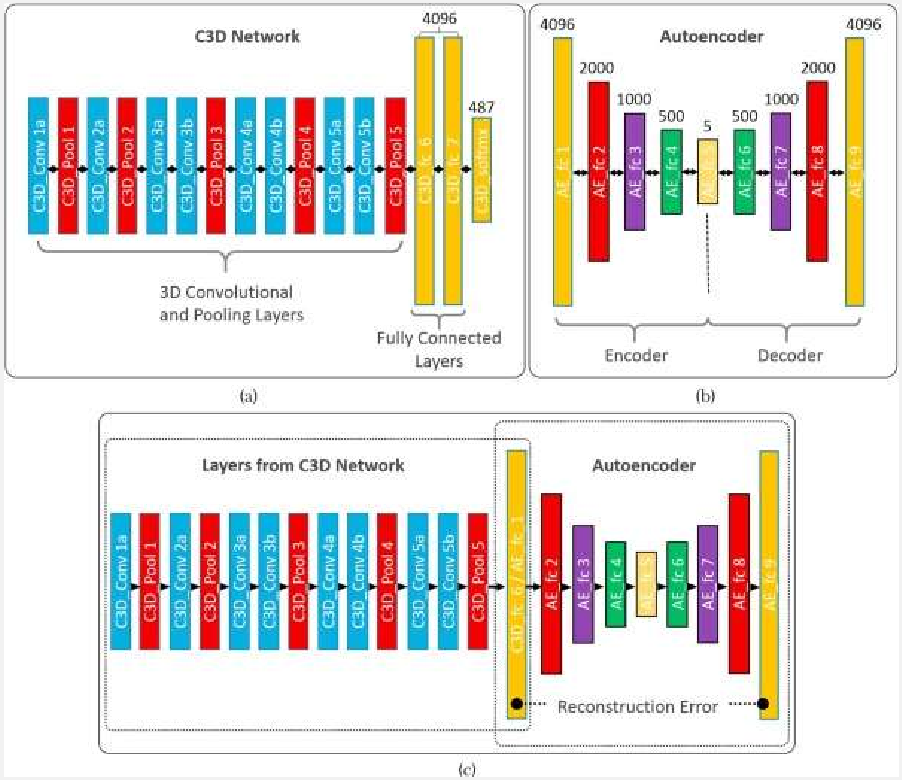
Video and motion sensor based solutions

Video and Deep Learning [26]



Motion sensors

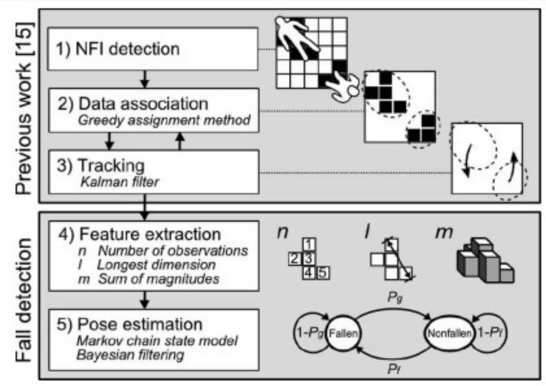
- Kinect and LiDAR have been reported [27,28].
- Spatio-temporal fall event detection using DeepLearning might solve part of the problem [29].



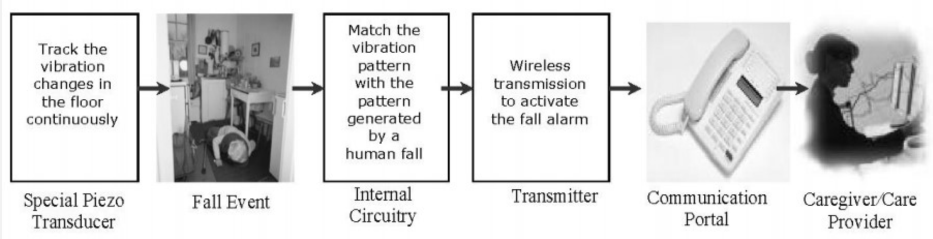
Perhaps video approaches need to focus on normal behavior: any other activity might be anomalous [30].

SCIENTIFIC LITERATURE

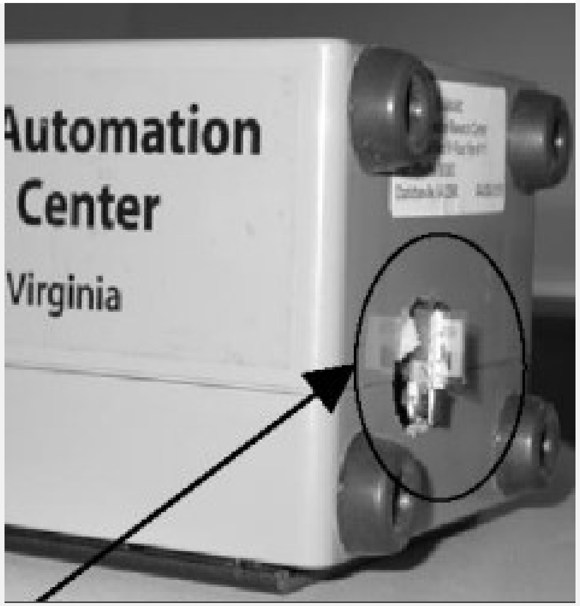
Sound and floor solutions



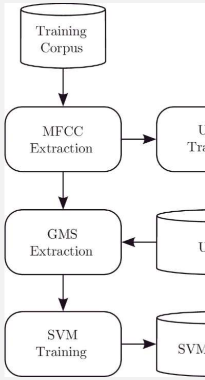
[32]



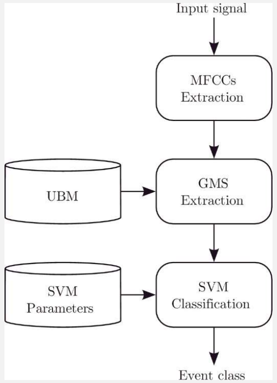
[31]



[34]



[33]



SCIENTIFIC LITERATURE

Wearables

- Wearables makes the use easier
- The focused population infers the sensor or sensors selection.
- The focused population infers the sensory location.

Why and where

Sensor type

- **3DACC**: [35,36,37,38,39, 41,42,43,44,45,46,47,48,49, 50,51,52,53,54,55,56,59]
- **Barometer**:[45,52]
- **Gyroscope**:[38,43,45,52,53]
- **Electromyography**:[60]
- **Sensor fusing**:[36], angle [58]

1. Record data using the sensory system.
2. Pre-process and feature extraction.
3. Learning a model.
4. Deployment.

General procedure

Modelling technique

- **SVM**: [42,44,45,49,50,51, 56]
- **KNN**: [42,49,50,51,54,57, 59]
- **NN**: [35,40,44,49]
- **Trees**: [38,42,51]
- **Rule Set**: [39,41,46,47,48,52, 53,55]
- **Heuristics**:[36,43]
- **HMM**

The **computation is run** on the device, on the edge or on the cloud.
The **data come from** an ad-hoc dataset, a published dataset or a combination of both.
Generalized Vs user-centered modelling.

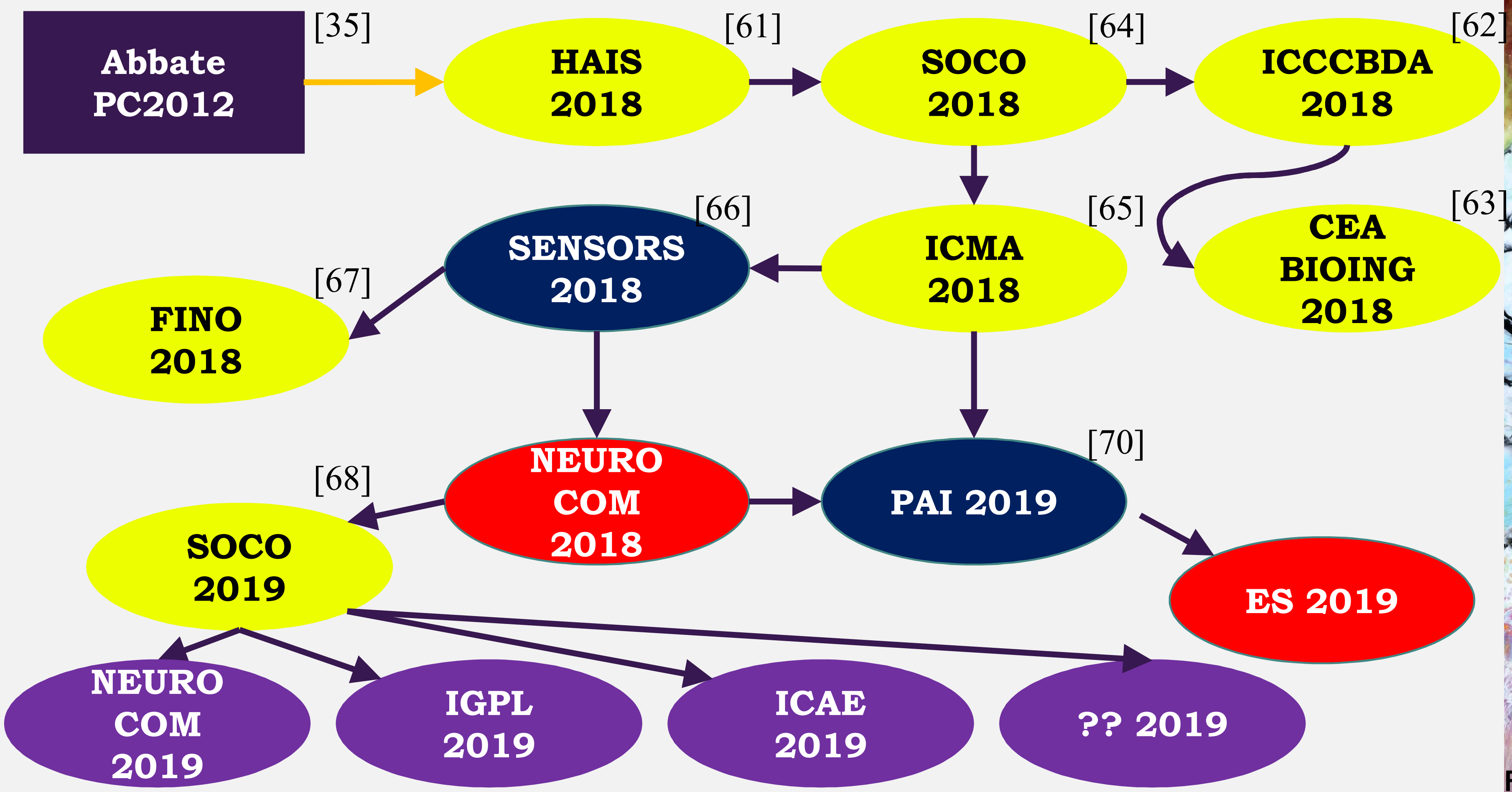
Design and learning

Sensor location

- **Wrist**: [36,37,39,40,41,42, 43,44,48,50,52,54,55,59]
- **Waist**: [35,38,45,46,47,53, 54,56,58]
- **Thigh**: [37,39,49,51,58]
- **Other**: chest [51], ankle [53]

FALL DETECTION: OUR ML DEVELOPMENTS

The publication path



FALL DETECTION: OUR ML DEVELOPMENTS

The publication path

Abbate PC2012

Sensor on the waist
Finite State Machine for Event Detection
Feature extraction
Neural Network

Highly imbalanced data
Too many thresholds and timers
Seems logical

HAIS 2018

Sensor on the **wrist** → more challenging
Finite State Machine for Event Detection
Feature extraction but changing a bit
Neural Network

Data Normalization
SMOTE 60/40 to balance the classes
UMA Fall
5x2 and 10-f cv

SOCO 2018

Reducing the computational cost of model evaluation: C5.0 decision trees.

ICCCBDA 2018 → **CEA BIO 2018**

Model tuning: fog/cloud computing.
Basic requirements for the design of a fall detection platform.

Developed platform to deploy at a Senior Residence Hall in Burgos (Spain), belonging to the Health Care System.

ICMA 2018

Analysis of the 5x2 cv results → **poor generalization capabilities**.
The models can not cope with the whole solution → new solutions are needed: i) user centred design, ii) ensemble of classifiers, iii) divide and conquer: a model per fall type.
Can a smartwatch analyse so many models?

FALL DETECTION: OUR ML DEVELOPMENTS

The publication path

ICMA 2018

SENSORS 2018

Participant based cross validation.
More models: NN, DT, RBS & NN.
Threshold analysis and optimization.
Are simulated falls similar to real?

UMA Fall
DaLIAC
UNIOVI EPILEPSY
FARSEEING

FINO 2018

Participant-based 5x2 cv.
DT (C5.0), NN, RBS, SVM.
Ensemble basic voting.

NEURO COM 2018

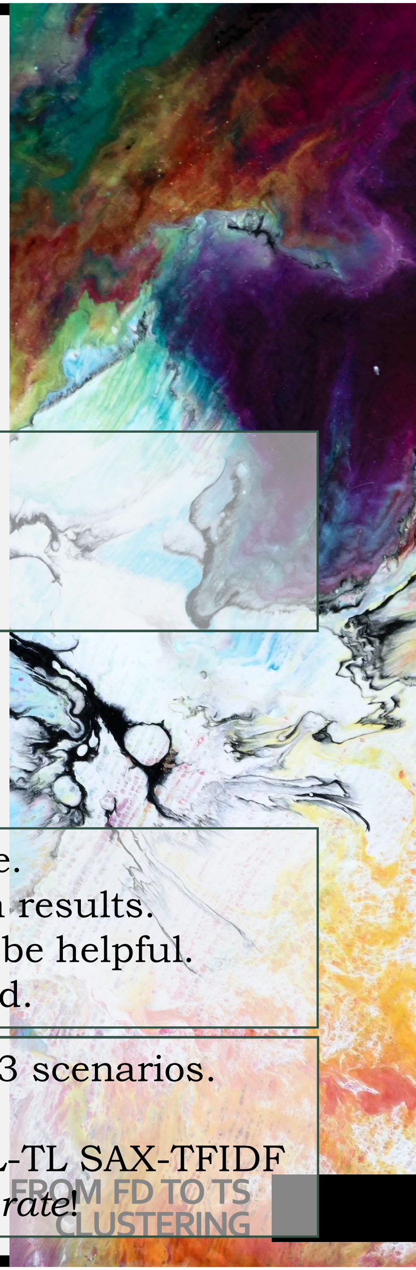
UMA FALL – TST – UNIOVI EPILEPSY – DaLIAC
Esemble (voting &weighted): RBS, SVM, NN. Also, Random Forest.

Solutions are far to be reliable.
Ad-hoc datasets allow smooth results.
User centred solutions might be helpful.
Data from real falls are needed.

PAI 2018

User centred.
* Supervised: KNN and SAX-TFIDF
* **On-line learning** & **Transfer learning**: SAX-TFIDF

More analysis on thresholds: 3 scenarios.
UMA FALL – TST
Too many false alarms but OL-TL SAX-TFIDF showed *the best fall detection rate*!



FALL DETECTION: OUR ML DEVELOPMENTS

The publication path

PAI 2019 → **NEURO COM 2018**

User centred. UMA FALL – TST
SAX-MAX to reduce false alarm rate
On-line Learning & Transfer Learning but
K-means to reduce the data base size

NEURO COM 2018 → **SOCO 2019**

FALLOVI draft 1 released.
4 Clustering scenarios

- F & NF + SVM on mixed clusters
- NF clusters + SVM for each cluster containing both F & NF
- NF clusters + F assignment and centroid recalculation + SVM for each cluster containing both F & NF
- F clusters + NF clusters + centroids KNN

SOCO 2019 → **NEURO COM 2019**, **ICAE 2019**

NEURO COM 2019

Three stage solution: Event Detection + SVM one class + SVM on suspicious
Automatic threshold setting

NEURO COM 2019 → **IGPL 2019**

IGPL 2019

More clustering strategies
UMA FALL + TST + Oznedir
A model per fall type
Perhaps, new features

ICAE 2019

Hierarchical HMM
Activity Level + ADL + Peak
Classify sequences of states
UMA FALL + TST + Oznedir

ICAE 2019 → **?? 2019**

?? 2019

Hierarchical HMM
Activity Level + ADL + Peak
Grammar of a fall
UMA FALL + TST + Oznedir

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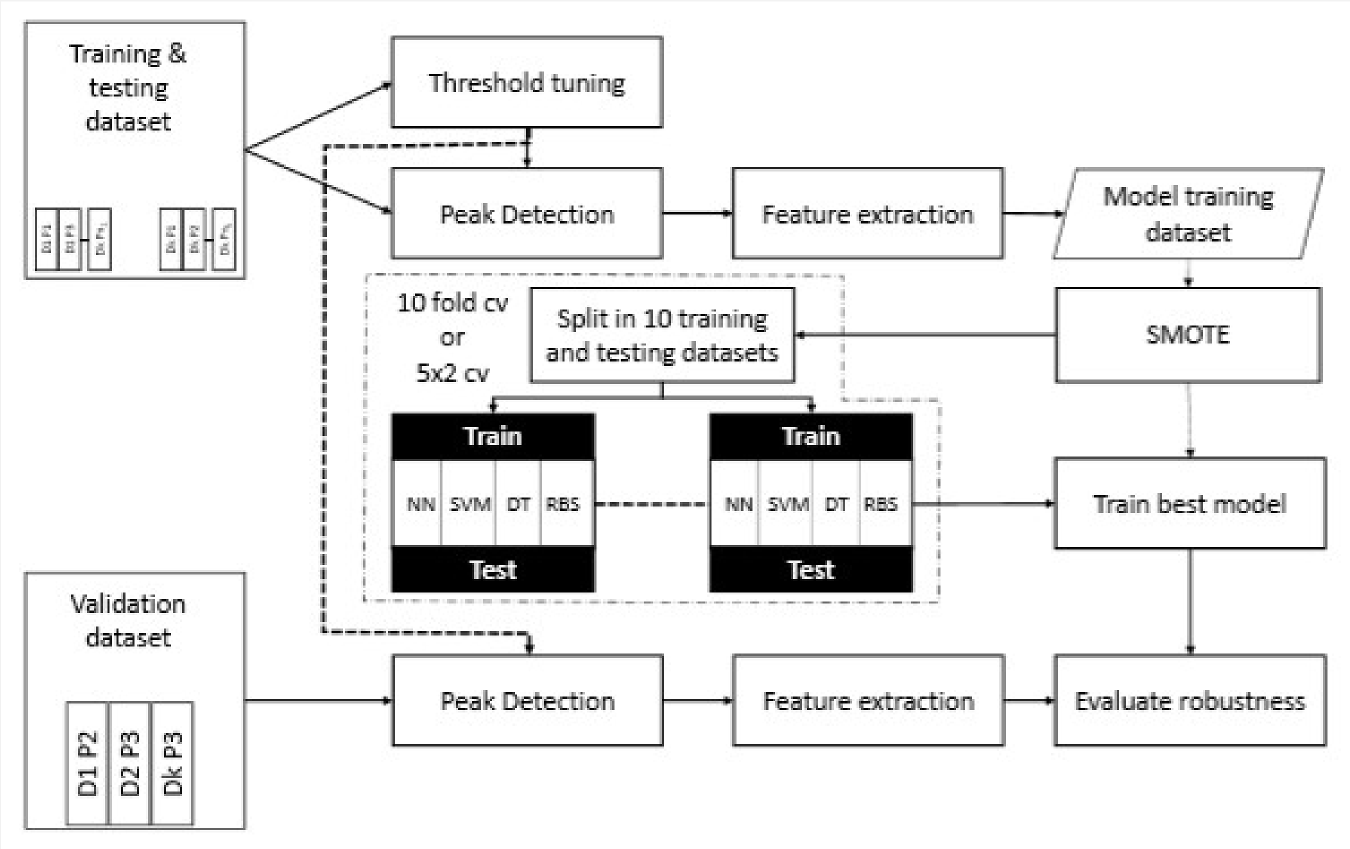
The publication path

SENSORS 2018



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SENSORS 2018

Fold	NN Acc	NN Kp	NN Se	NN Sp	NN Pr	NN G	DT Acc	DT Kp	DT Se	DT Sp	DT Pr	DT G
1	0.9226	0.8440	0.9239	0.9211	0.9341	0.9290	0.8988	0.7936	0.9565	0.8290	0.8713	0.9129
2	0.8810	0.7586	0.9130	0.8421	0.8750	0.8938	0.9286	0.8548	0.9674	0.8816	0.9082	0.9373
3	0.8810	0.7608	0.8696	0.8947	0.9091	0.8891	0.8333	0.6549	0.9674	0.6711	0.7807	0.8691
4	0.8750	0.7468	0.9022	0.8421	0.8737	0.8878	0.9048	0.8065	0.9457	0.8553	0.8878	0.9163
5	0.8988	0.7969	0.8804	0.9211	0.9310	0.9054	0.7798	0.5540	0.8152	0.7368	0.7895	0.8022
6	0.8869	0.7725	0.8804	0.8947	0.9101	0.8952	0.8810	0.7603	0.8804	0.8816	0.9000	0.8902
7	0.8988	0.7965	0.8913	0.9079	0.9214	0.9062	0.8691	0.7405	0.7935	0.9605	0.9605	0.8730
8	0.8810	0.7624	0.8370	0.9342	0.9390	0.8865	0.9226	0.8426	0.9674	0.8684	0.8990	0.9326
9	0.8691	0.7351	0.8913	0.8421	0.8723	0.8818	0.8929	0.7838	0.9022	0.8816	0.9022	0.9022
10	0.8750	0.7509	0.8261	0.9342	0.9383	0.8804	0.9167	0.8323	0.9130	0.9211	0.9333	0.9231
mean	0.8869	0.7725	0.8815	0.8934	0.9104	0.8955	0.8827	0.7623	0.9109	0.8487	0.8832	0.8959
median	0.8810	0.7616	0.8859	0.9013	0.9157	0.8915	0.8958	0.7887	0.9294	0.8750	0.8995	0.9075
std	0.0159	0.0320	0.0309	0.0380	0.0274	0.0147	0.0459	0.0935	0.0640	0.0856	0.0572	0.0403

Fold	RBS Acc	RBS Kp	RBS Se	RBS Sp	RBS Pr	RBS G	SVM Acc	SVM Kp	SVM Se	SVM Sp	SVM Pr	SVM G
1	0.9107	0.8200	0.9130	0.9079	0.9231	0.9181	0.9345	0.8671	0.9674	0.8947	0.9175	0.9421
2	0.8929	0.7847	0.8804	0.9079	0.9205	0.9002	0.8988	0.7955	0.9130	0.8816	0.9032	0.9081
3	0.8869	0.7694	0.9457	0.8158	0.8614	0.9025	0.9107	0.8200	0.9130	0.9079	0.9231	0.9181
4	0.8988	0.7936	0.9565	0.8290	0.8713	0.9129	0.9048	0.8069	0.9348	0.8684	0.8958	0.9151
5	0.8691	0.7387	0.8261	0.9211	0.9268	0.8750	0.9107	0.8192	0.9348	0.8816	0.9053	0.9199
6	0.9107	0.8196	0.9239	0.8947	0.9141	0.9189	0.8869	0.7730	0.8696	0.9079	0.9195	0.8942
7	0.8631	0.7290	0.7826	0.9605	0.9600	0.8668	0.9405	0.8790	0.9787	0.8947	0.9184	0.9478
8	0.9286	0.8545	0.9783	0.8684	0.9000	0.9383	0.8988	0.7951	0.9239	0.8684	0.8947	0.9092
9	0.9107	0.8196	0.9239	0.8947	0.9140	0.9189	0.9107	0.8183	0.9565	0.8553	0.8889	0.9221
10	0.9286	0.8562	0.9239	0.9342	0.9444	0.9341	0.9167	0.8326	0.9022	0.9342	0.9432	0.9225
mean	0.9000	0.7985	0.9054	0.8934	0.9135	0.9086	0.9113	0.8207	0.9294	0.8895	0.9110	0.9199
median	0.9048	0.8066	0.9239	0.9013	0.9172	0.9155	0.9107	0.8188	0.9294	0.8882	0.9114	0.9190
std	0.0224	0.0438	0.0602	0.0449	0.0300	0.0232	0.0162	0.0324	0.0325	0.0234	0.0164	0.0157

FALL DETECTION: OUR ML DEVELOPMENTS

The publication path

SENSORS 2018

Threshold 2.5											
	Reference			**Reference**			**Reference**			**Reference**	
NN	**Fall**	**Not Fall**	**DT**	**Fall**	**Not Fall**	**RBS**	**Fall**	**Not Fall**	**SVM**	**Fall**	**Not Fall**
Fall	10	47	**Fall**	10	20	**Fall**	10	42	**Fall**	8	18
Not Fall	2	250	**Not Fall**	2	277	**Not Fall**	2	245	**Not Fall**	4	279
Threshold 3.0											
	Reference			**Reference**			**Reference**			**Reference**	
NN	**Fall**	**Not Fall**	**DT**	**Fall**	**Not Fall**	**RBS**	**Fall**	**Not Fall**	**SVM**	**Fall**	**Not Fall**
Fall	12	52	**Fall**	11	18	**Fall**	11	29	**Fall**	10	12
Not Fall	0	245	**Not Fall**	1	279	**Not Fall**	1	268	**Not Fall**	2	285
Threshold 3.09290											
	Reference			**Reference**			**Reference**			**Reference**	
NN	**Fall**	**Not Fall**	**DT**	**Fall**	**Not Fall**	**RBS**	**Fall**	**Not Fall**	**SVM**	**Fall**	**Not Fall**
Fall	12	59	**Fall**	11	26	**Fall**	12	35	**Fall**	10	13
Not Fall	0	238	**Not Fall**	1	271	**Not Fall**	0	262	**Not Fall**	2	284

FALL DETECTION: OUR ML DEVELOPMENTS

The publication path

PAI 2019

		normTSnormTH: normalized TS and normalized thresholds							
		KNN				TF-IDF			
source	parID	TN	TP	FP	FN	TN	TP	FP	FN
TST	1	0	47	3	6	0	53	3	0
TST	2	0	57	0	3	0	60	0	0
TST	3	9	50	10	10	6	57	13	3
TST	4	0	60	4	0	0	43	4	17
TST	5	7	41	20	9	16	43	11	7
TST	6	0	55	0	0	0	55	0	0
TST	7	0	60	0	0	0	60	0	0
TST	8	0	63	3	4	0	66	3	1
TST	9	0	52	0	0	0	52	0	0
TST	10	0	57	7	3	0	52	7	8
TST	11	0	60	0	0	0	60	0	0
UMA Fall	1	14	85	16	10	16	93	14	2
UMA Fall	2	0	58	0	2	0	60	0	0
UMA Fall	3	20	76	23	14	33	73	10	17
UMA Fall	4	3	71	4	3	0	70	7	4
UMA Fall	9	0	82	3	11	0	93	3	0
UMA Fall	12	5	23	10	8	5	29	10	2
UMA Fall	15	2	41	12	4	2	45	12	0
UMA Fall	16	26	270	13	2	7	263	32	9
UMA Fall	17	0	57	16	6	3	54	13	9

FALL DETECTION: OUR ML DEVELOPMENTS

The publication path

PAI 2019

		normTSnormTH: normalized TS and normalized thresholds							
		KNN				TF-IDF			
source	parID	TN	TP	FP	FN	TN	TP	FP	FN
TST	1	57	47	3	13	57	53	3	7
TST	2	60	57	0	3	60	60	0	0
TST	3	50	50	10	10	47	57	13	3
TST	4	56	60	4	0	56	43	4	17
TST	5	40	41	20	19	49	43	11	17
TST	6	60	55	0	5	60	55	0	5
TST	7	60	60	0	0	60	60	0	0
TST	8	57	56	3	4	57	59	3	1
TST	9	60	52	0	8	60	52	0	8
TST	10	53	57	7	3	53	52	7	8
TST	11	60	60	0	0	60	60	0	0
UMA Fall	1	74	85	16	15	76	93	14	7
UMA Fall	2	90	58	0	2	90	60	0	0
UMA Fall	3	67	76	23	14	80	73	10	17
UMA Fall	4	96	71	4	9	93	70	7	10
UMA Fall	9	87	81	3	9	87	90	3	0
UMA Fall	12	100	23	10	17	100	29	10	11
UMA Fall	15	38	41	12	9	38	45	12	5
UMA Fall	16	307	270	13	10	293	263	27	17
UMA Fall	17	74	57	16	33	77	54	13	36

FALL DETECTION: OUR ML DEVELOPMENTS

The publication path

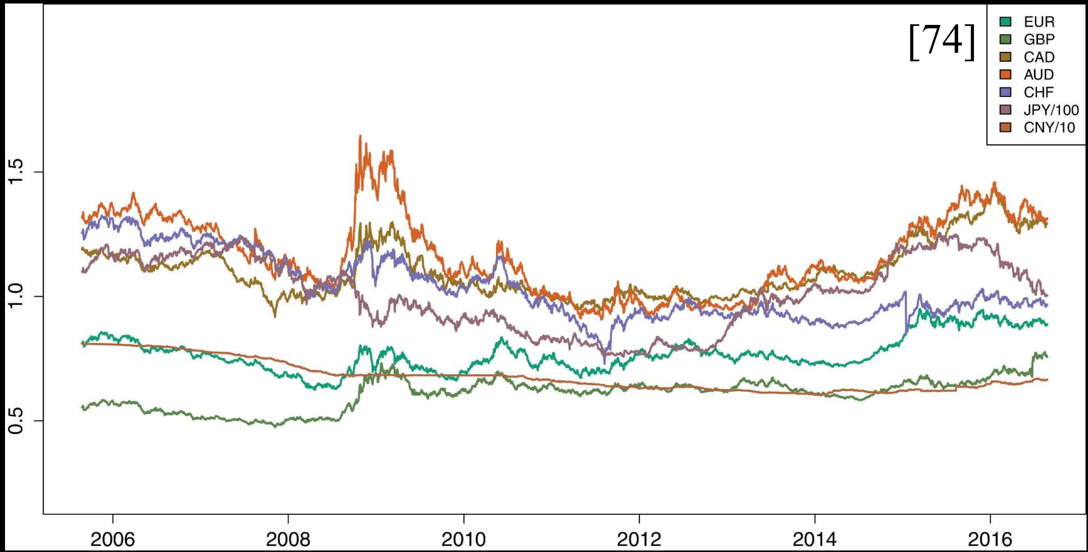
PAI 2019

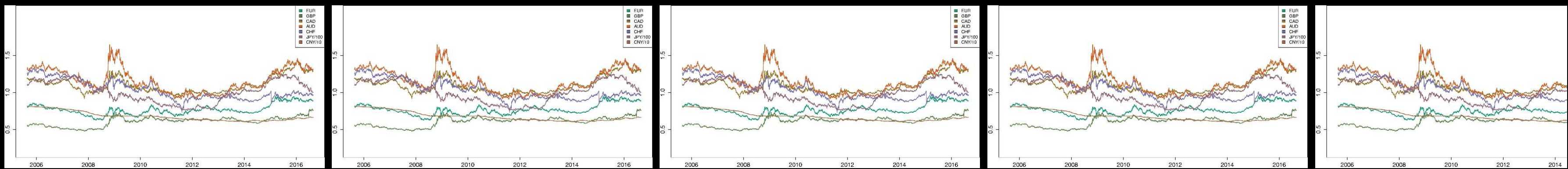
		normTSnormTH: normalized TS and normalized thresholds							
		TF-IDF				TF-IDF + TL			
source	parID	TN	TP	FP	FN	TN	TP	FP	FN
TST	1	0	53	3	0	0	53	3	0
TST	2	0	60	0	0	0	56	0	4
TST	3	9	55	10	5	0	60	19	0
TST	4	0	35	4	25	0	60	4	0
TST	5	17	35	10	15	0	50	27	0
TST	6	0	55	0	0	0	55	0	0
TST	7	0	60	0	0	0	60	0	0
TST	8	0	61	3	6	0	67	3	0
TST	9	0	52	0	0	0	52	0	0
TST	10	0	41	7	19	0	60	7	0
TST	11	0	60	0	0	0	60	0	0
UMA Fall	1	24	52	6	43	0	95	30	0
UMA Fall	2	0	60	0	0	0	60	0	0
UMA Fall	3	41	35	2	55	0	90	43	0
UMA Fall	4	2	64	5	10	0	74	7	0
UMA Fall	9	0	81	3	12	0	93	3	0
UMA Fall	12	7	13	8	18	0	31	15	0
UMA Fall	15	8	28	6	17	2	45	12	0
UMA Fall	16	35	217	4	55	0	272	39	0
UMA Fall	17	12	37	4	26	0	63	16	0

FALL DETECTION: OUR ML DEVELOPMENTS

CHALLENGES IN DEVELOPMENT

- **Gathering data from real falls**
  - Presumably, the fall events will be unusual.
  - From the ML point of view, is like no real data is given
- **Need to generate almost real TS**
  - Considering the few TS from real falls
  - What is "an almost real TS"?
- **Grouping or clustering TS**
  - Applications in many fields apart from fall detection





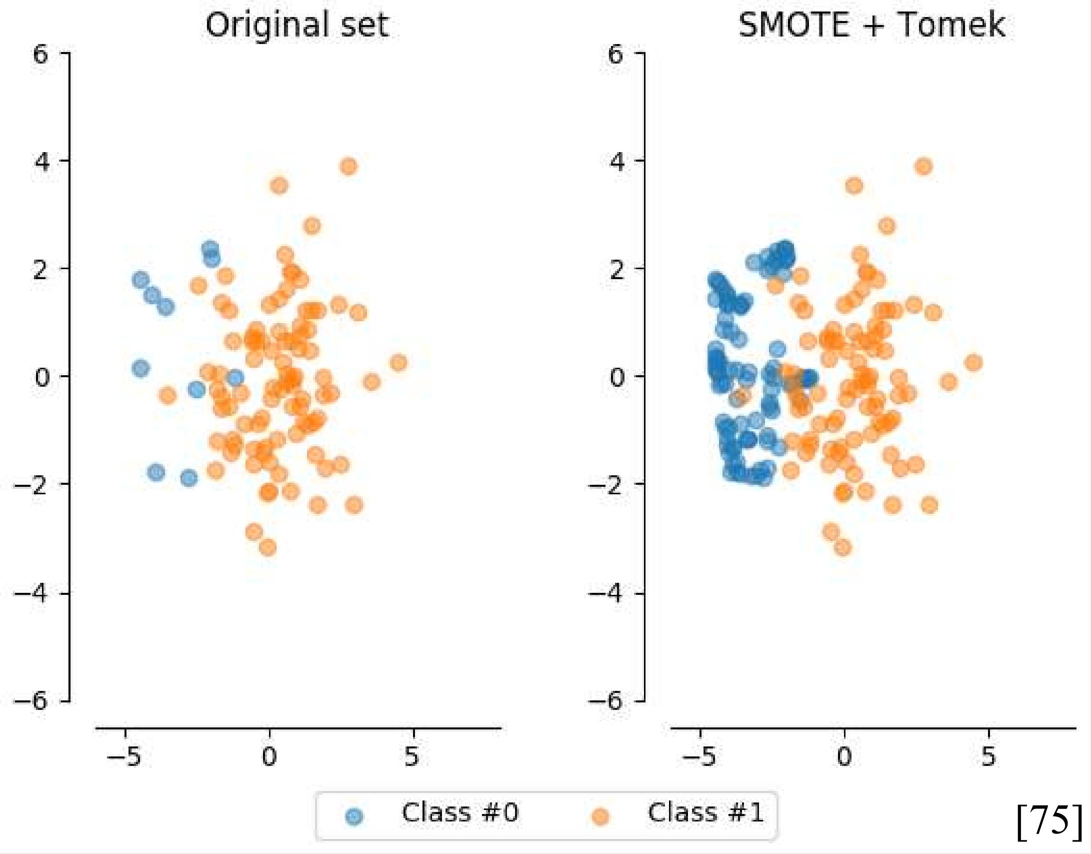
MULTIVARIATE TS BALANCING

What is it?

What is it for? [72,73]

MULTIVATIATE TS BALANCING

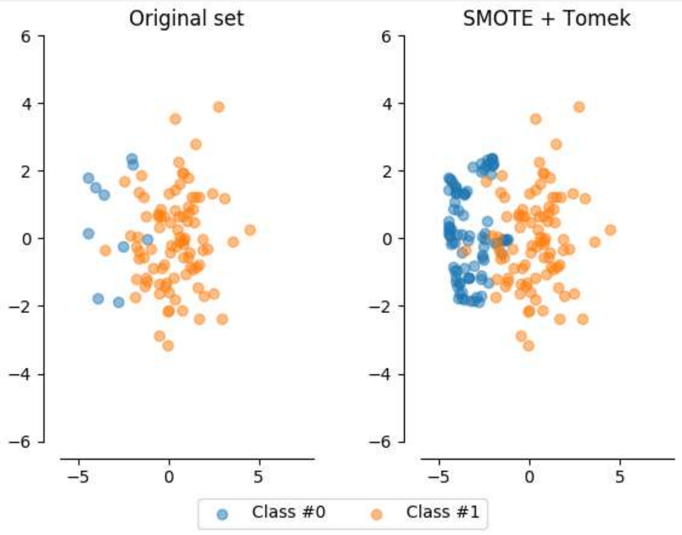
From SMOTE to TS SMOTE

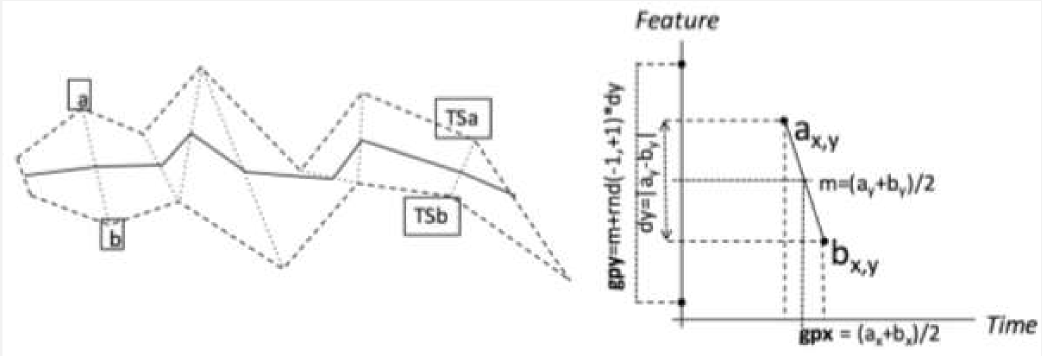


[75]

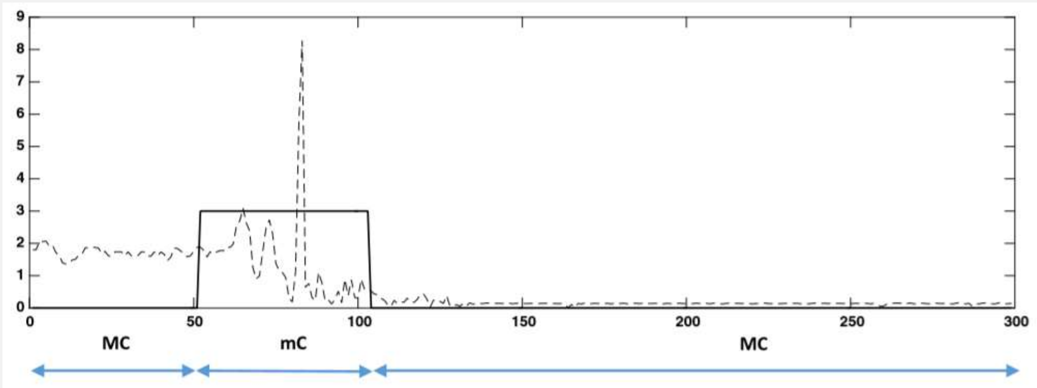
MULTIVATIATE TS BALANCING

From SMOTE to TS SMOTE



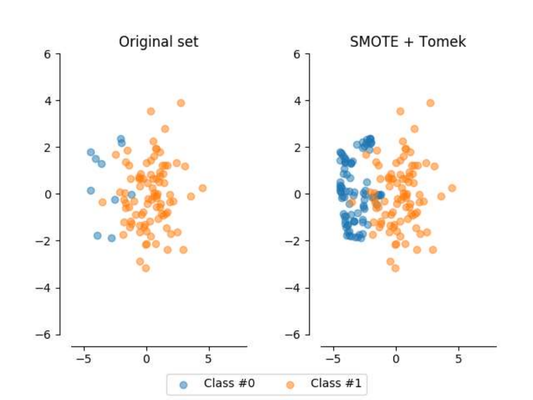


[76]



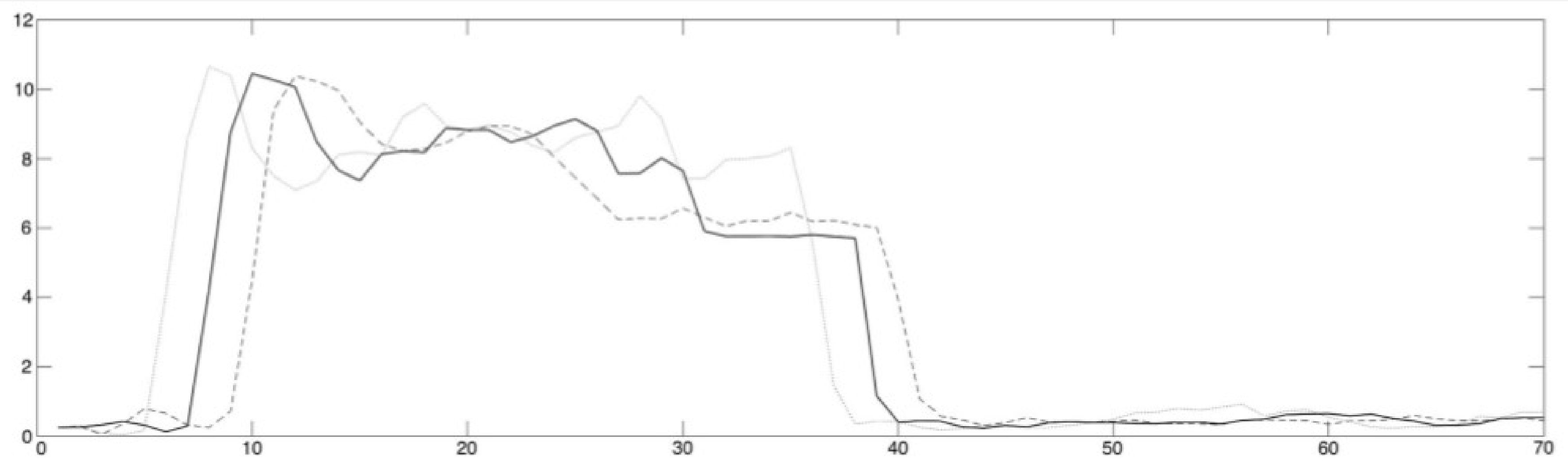
MULTIVATIATE TS BALANCING

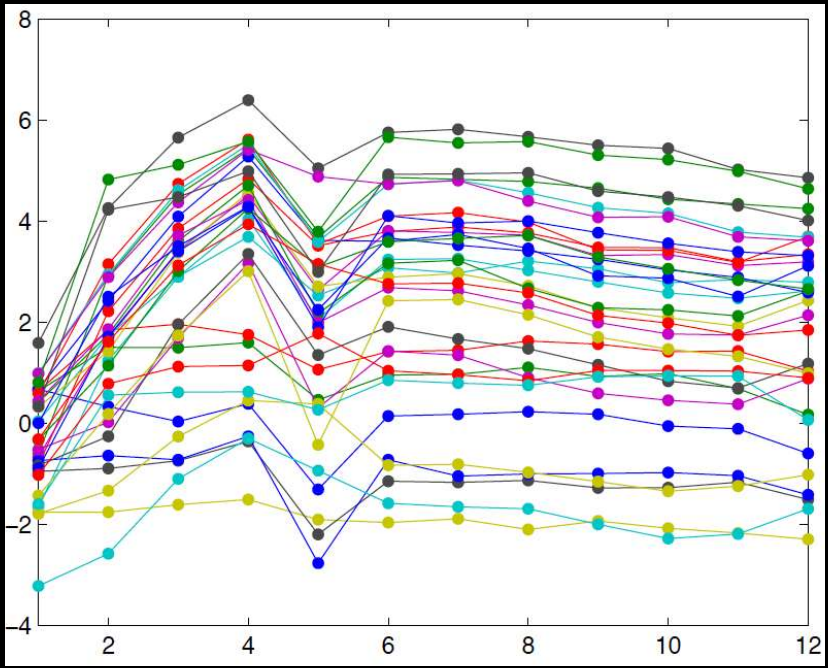
From SMOTE to TS SMOTE

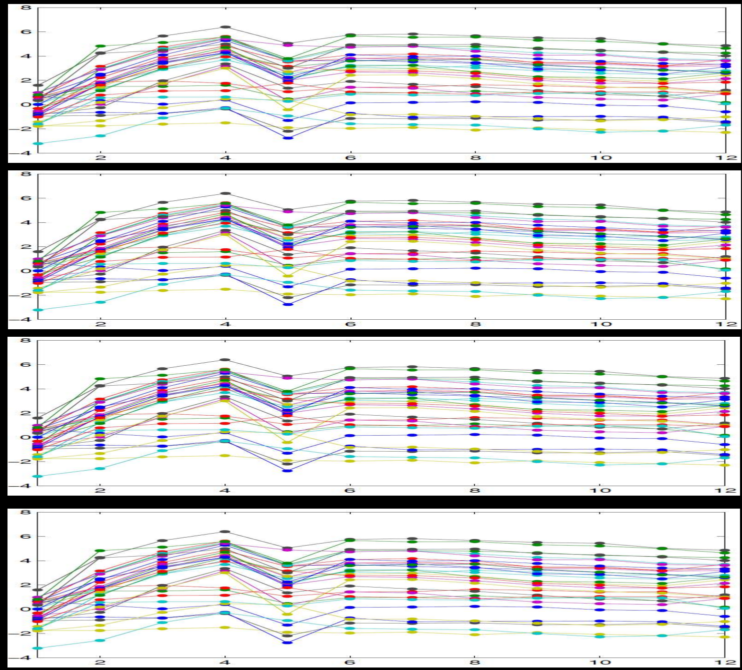


STILL PENDING	WHERE TO USE

• **Outlier avoidance**
  • but needs a clear definition.
• **Alternatives to the need of a guiding signal**
	• **Fall detection**
	  • TS augmentation in user centred
	• **Evaluation of the robustness of TS clustering**

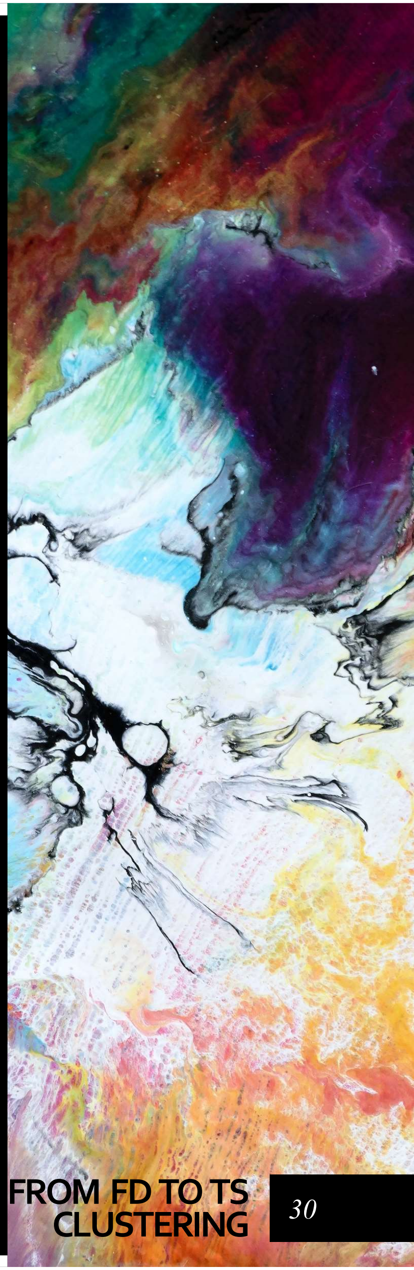






MULTIVARIATE TS CLUSTERING

To group mutually dependent variables



MULTIVARIATE TS CLUSTERING

TYPES OF mTS CLUSTER

- **Whole TS clustering**
- **Subsequence m-TS clustering**
- **Time point clustering**

WHOLE TS CLUSTERING

- **Model based: Gaussian Mixture Models [83], FE + SOM [84]**
- **Features based: PCA [79], discords [80], hash functions [81], stats & patterns [78]**
- **Shape based: HMM [82], Dynamic Time Warping [77]**
- **Hybridized and multi-step**

A PRELIMINARY STUDY **[85]**

- The prediction error of a **Recurrent Neural Networks (RNN)** serves as a distance measurement to compare variables within an instance.
- **Transfer learning** from one instance to others helps in relaxing the computational costs.

CLUSTERING ISSUES

- **TS representation:** raw data
- **RNN error prediction** as distance measurement
- **No prototyping needed**

MULTIVARIATE TS CLUSTERING

A preliminary study [85]

Algorithm 1 Computing similarities between features in an example

procedure IN-EXAMPLE-SIMILARITY(TS^i, LoRNN) ▷ LoRNN list of pre-learnt RNNs, if available
  $sim \leftarrow$ zeroes matrix of size $n \times n$
  for each variable j in TS^i **do**
    $X^i_j \leftarrow$ normalize(X^i_j)
    $RNN^i_j \leftarrow$ **Train-RNN**(X^i_j, LoRNN[j])
    $LoRNN[j] \leftarrow RNN^i_j$
    $e^i_j \leftarrow$ RMSE(RNN^i_j, test(X^i_j))
    for each variable k in TS^i, $k \neq j$ **do**
      $X^i_k \leftarrow$ normalize(X^i_k)
      $e^i_{jk} \leftarrow$ RMSE(RNN^i_j, test(X^i_k))
      $sim[j,k] \leftarrow abs(\frac{e^i_{jk} - e^i_j}{e^i_j})$
    end for
  end for
  return sim
end procedure

procedure TRAIN-RNN(X^i_j, RNN) ▷ RNN is a RNN, if available
  if is.NULL(RNN) **then**
    $RNN \leftarrow$ *full train* RNN for the train part of X^i_j
  else
    $RNN \leftarrow$ *tune* RNN for the train part of X^i_j
  end if
  return RNN
end procedure

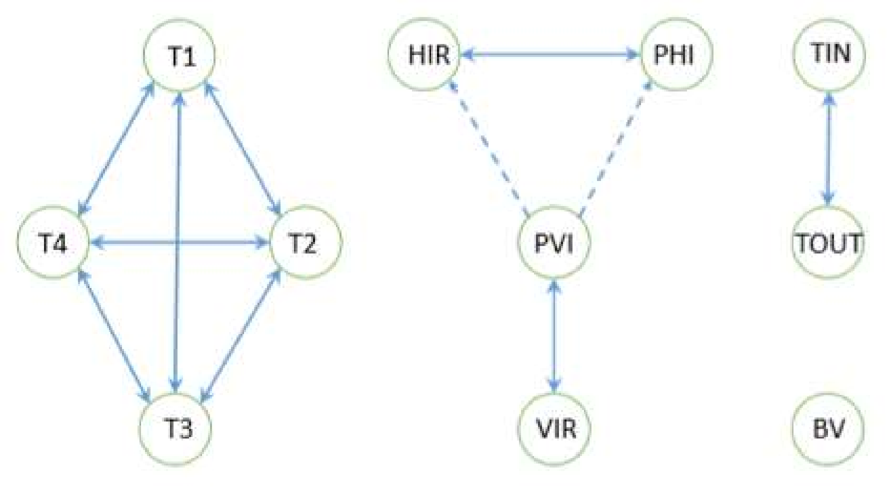
- Within-instance's similarities are converted to adjacency matrices
  - if $sim(j,k) \leq th_1$
    - For example i, $x_j predicts\ x_k$, denoted as $k \ll_i j$.
    - And $SIM_i[j,k] = 1$.
  - Otherwise $SIM_i[j,k] = 0$.
- Adjacency matrices from each instance are aggregated: SIM_{agg}.
- Thresholding the SIM_{agg} matrix.
  - If $SIM_{agg}[j,k] \geq th_2$
    - $SIM_{final}[j,k] = 1$
    - $k \ll j$
  - Otherwise
    - $SIM_{final}[j,k] = 0$
- This final adjacency matrix allows to represent the dependency graph!

MULTIVARIATE TS CLUSTERING

A preliminary study [85]

A toy problem

- Indoor and outdoor temperatures in the weather station (TIN, TOUT).
- Horizontal and Vertical Irradiance reference measurement (HIR and VIR).
- The voltage at the weather station's battery (BV).
- The temperature of 4 photovoltaic panels linked to an inverter (T1 to T4).
- An In-panel Horizontal and Vertical Irradiance measurement (PHI, VHI).



STILL PENDING

- Formal definition of all the stages
- Developing a more optimized and robust method.
- Extending the solution to cluster similar instances.
- Developing of suitable distances and efficiency measurements.
- Testing with a complete battery of m-TS datasets.





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Víctor M. González
Samad B, Khojasteh
Enrique de la Cal
Javier Sedano
José R. Villar

THIS IS OUR TEAM!

Of course, I am not alone!

Universidad de Oviedo
Universidá d'Uviéu
University of Oviedo

Athabasca University

FROM FALL DETECTION TO TIME SERIES CLUSTERING

A Computational Intelligence approach.

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