Détection d'événements à partir de capteurs sols – application au suivi de personnes fragiles

Soutenance de thèse

Ludovic Minvielle

Thèse industrielle entre le Centre Borelli (ENS Paris-Saclay) et Tarkett

Mercredi 15 Juillet 2020

Introduction

General context

- Elderly population is growing
- Higher levels of frailty globally
- Increasing demand for reliable monitoring devices
- Tarkett, French company: 12,500 employees, 13 industrial sites, 1.3 millions m^2 of flooring per day
- *Floor in Motion*: a floor-based sensor for elderly care

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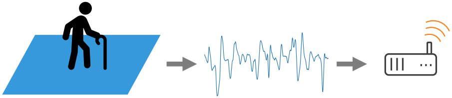
FLOOR in MOTION care



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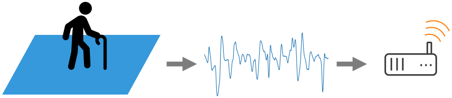

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Providing tools for elderly monitoring in nursing homes

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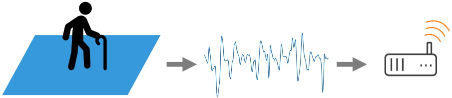
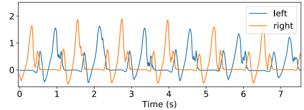


Objective

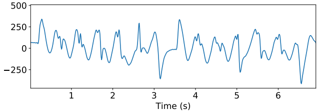
Providing tools for elderly monitoring in nursing homes

Scientific context

- Processing and understanding time series
- Real world application



Foot-attached accelerometer



Tarkett's floor sensor

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Monitoring systems for fall detection

Sensors

What makes a good monitoring system ?

- coverage and occlusion
- intrusiveness
- signal quality / information
- robustness
- ease of installation / use
- scalability

Criteria
Coverage/Occlusion
Intrusiveness
Signal quality / info
Robustness
Ease of instal. / use
Scalability

Sensors

What makes a good monitoring system ?

- coverage and occlusion
- intrusiveness
- signal quality / information
- robustness
- ease of installation / use
- scalability

Signal acquisition

Vision

RGB-Camera
Omni-Camera
Depth-Camera

Criteria	RGB cam	Depth cam
Coverage/Occlusion	★☆☆	★☆☆
Intrusiveness	★☆☆	★☆☆
Signal quality / info	★★★	★★★
Robustness	★★☆	★★★
Ease of instal. / use	★☆☆	★☆☆
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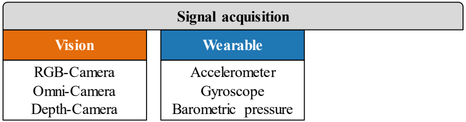

Criteria	RGB cam	Depth cam	Wearable
Coverage/Occlusion	★☆☆	★☆☆	★★★
Intrusiveness	★☆☆	★☆☆	★★☆
Signal quality / info	★★★	★★★	★★☆
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Sensors

What makes a good monitoring system ?

- coverage and occlusion
- intrusiveness
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- robustness
- ease of installation / use
- scalability

Signal acquisition

Vision	Wearable	Ambient
RGB-Camera	Accelerometer	Microphone
Omni-Camera	Gyroscope	Radar
Depth-Camera	Barometric pressure	Wi-Fi
		Vibrational
		Pressure

Criteria	RGB cam	Depth cam	Wearable	Acoustic	Radar / Wi-Fi	Vibration	Floor
Coverage/Occlusion	★☆☆	★☆☆	★★★	★★☆	★☆☆	★★★	★★★
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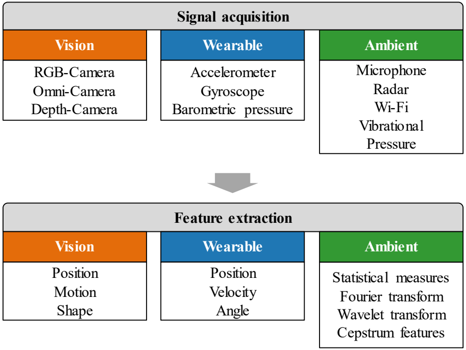
Information extraction

How to process the inputs ?

- All systems use feature extraction
- The “level” of feature engineering depends on the complexity / dimensionality of the input signal



Information extraction

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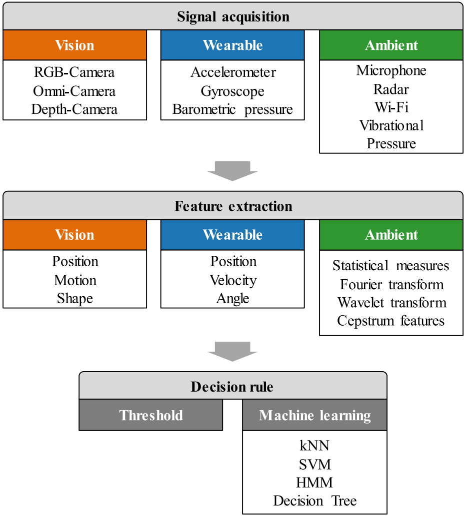
How to deal with feature signals ?

- Use simple thresholds
- Use them as feature vectors for classification models (anomaly detection, classical supervised models)



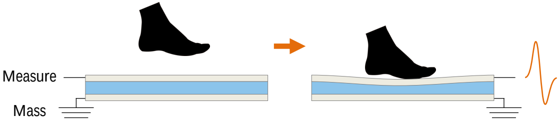
A fall detection system

Tarkett sensor

- Piezoelectric principle:

$$d = \frac{Q}{F},$$

(simple version) with d the *piezoelectric constant.*
When stressed or squeezed, the material emits charges.

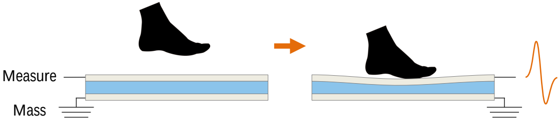


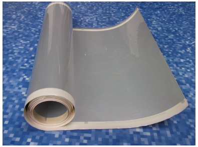
Tarkett sensor

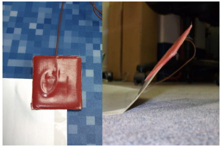
- Piezoelectric principle:

$$d = \frac{Q}{F},$$

  (simple version) with d the *piezoelectric constant*.
  When stressed or squeezed, the material emits charges.
- How does this look like ?
  0.3 mm thick and 60 cm wide roll with customizable length







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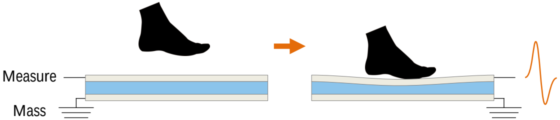
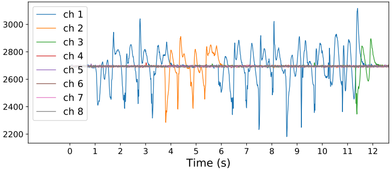
  (simple version) with d the *piezoelectric constant*.
  When stressed or squeezed, the material emits charges.
- How does this look like ?
  0.3 mm thick and 60 cm wide roll with customizable length
- How is it installed ?
  - Under the flooring
  - Several connected bands for each area, hence one area corresponds to one input



Data

Preprocessing

- linear detrending
- low-pass filtering
- zeroing low energy channels
- sum over all channels



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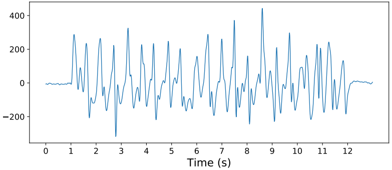

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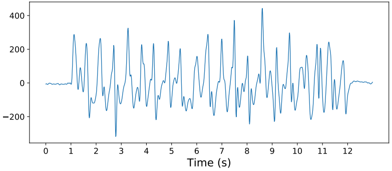
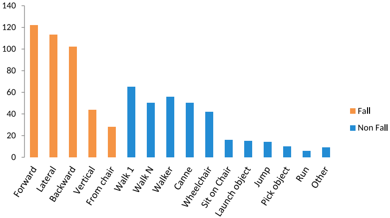


Experimental dataset

- 742 signals collected in **controlled environment**
- 55% *fall*, 45% *non-fall*
- varied fall events (forward, backward...) and activities of daily living (walking, sitting...)



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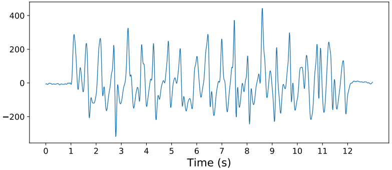

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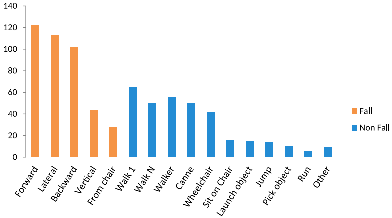
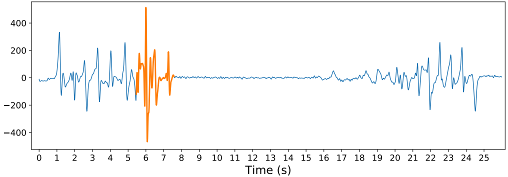


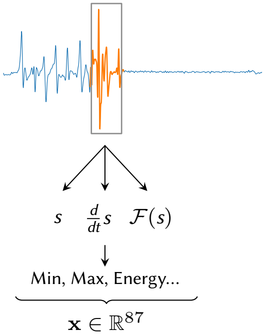


Method

Model

Time series as *feature vector*. At every timestamp:

1. Window over the signal: 2.5 s
2. Compute feature vector: 29 statistical measures (Min, Max, Shannon energy, Percentile,...) over three representations of the signal



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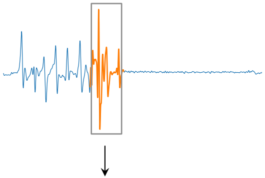

$\boldsymbol{x} \in \mathbb{R}^{87}$

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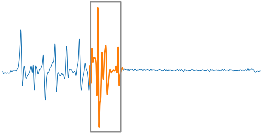


$$\downarrow$$

$$x \in \mathbb{R}^{87}$$

3. Classification model: Random Forest [1], based on **decision trees**

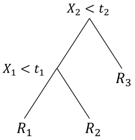
Decision tree

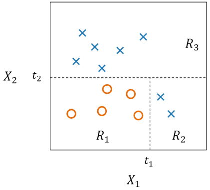
Feature space $\mathcal{X} = \mathbb{R}^Q$. Division of $\mathcal{X}$ into non-overlapping regions $R_1, \ldots, R_J$. Algorithm CART: recursive binary splits [2] that solve:

$$\arg\max_{X_q, \tau} \mathrm{IG} \;, \quad \text{(information gain)}$$

$$\text{with} \quad \mathrm{IG}(X_q, \tau) = I(n) - \frac{N_l}{N_n} I(l) - \frac{N_r}{N_n} I(r) \;,$$

$$\text{and} \quad I(n) = \mathrm{Gini}(n) = \sum_k p_{nk}(1 - p_{nk}) \;.$$





Predicion function: $f(x) = \sum_{j=1}^{J} c_j \mathbb{1}(x \in R_j)$

Method

Model

Random forest

Decision trees $d_1, \dots, d_{N_T}$ grown with two rules:

- Each tree is trained with a *bootstrap* of the training set
- At each split, access to a random subset of pool of features

Each tree is a "vote" for a class. The estimated probability of belonging to class k is then:

$$f_k(x) = \frac{1}{N_T} \sum_{i=1}^{N_T} \mathbb{1}(d_i(x) = k)$$

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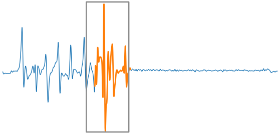
Data augmentation

Select r windows in training signals



$$\begin{bmatrix} x_{1,1} & \cdots & x_{1,Q} \\ x_{2,1} & \cdots & x_{2,Q} \\ & & \end{bmatrix}$$

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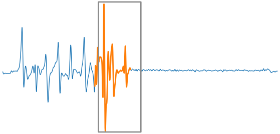

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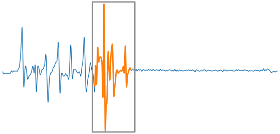

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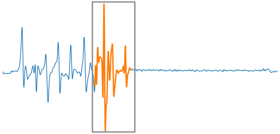

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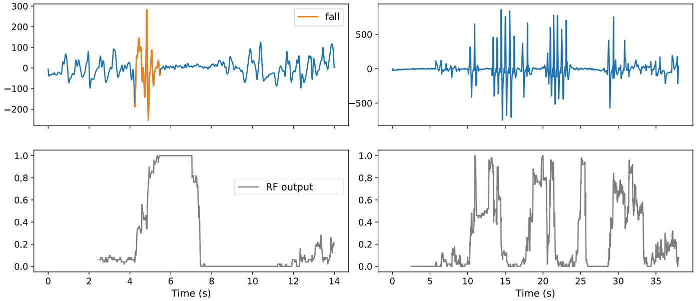

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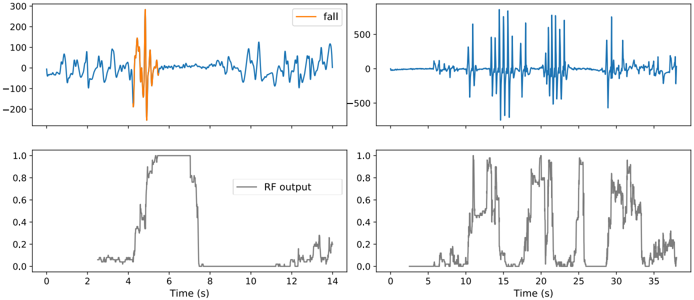


Time aggregation

$N_f(t)$: number of trees voting for *fall*
Use a buffer $B_s \in \mathbb{N}$ and a threshold $T_h \in [0, 1]$

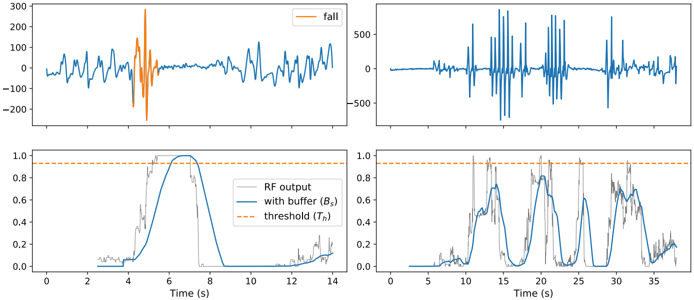
$$g(t) = \frac{\sum_{u=t-B_s+1}^{t} N_f(u)}{B_s \times N_T}$$

New binary classification function:

$$d(t) = \begin{cases} 1, & \textit{if } g(t) > T_h \\ 0, & \textit{otherwise} \end{cases}$$

Method

Time aggregation



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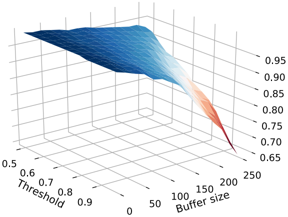
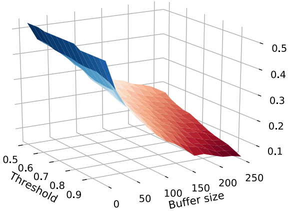
Time aggregation



True positive rate



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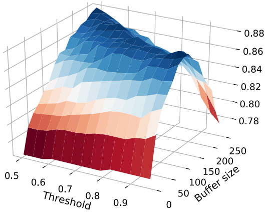
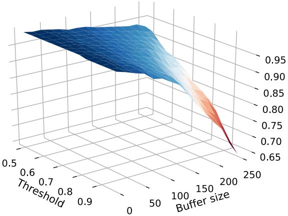


Accuracy

Methods

Time aggregation



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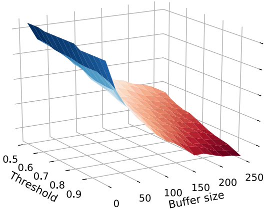

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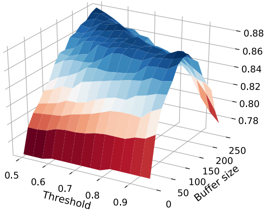

Accuracy

Decision rule is ready. Is it implementable ?

Feature selection

Feature importance

$$\text{Tree: } I(X_q) = \sum_{\text{nodes } t} p(t)\Delta i(t)\mathbb{1}(v(t) = X_q)$$

$$\text{Random forest: } I(X_q) = \frac{1}{N_T}\sum_{n=1}^{N_T} I(T_n, X_q)$$

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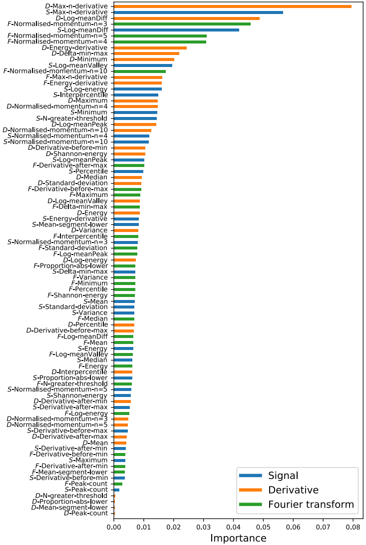

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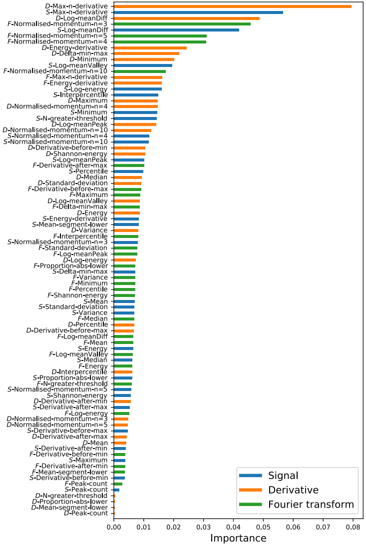
Recursive feature elimination

Initial pool of Q features $X_1, \ldots, X_Q$.

1. Train several times and record variable importances
2. Average of importances over trainings. $X_q* = \arg\min_{X_i} I(X_i)$
3. Remove X_q* from the pool of features and back to step 1



Feature selection

Feature importance

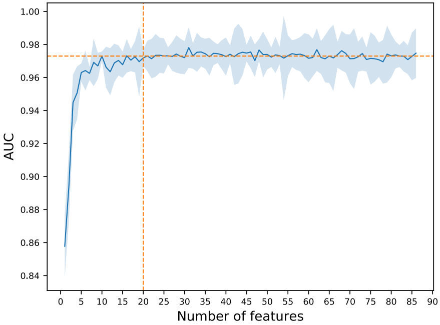
$$\text{Tree: } I(X_q) = \sum_{\text{nodes } t} p(t)\Delta i(t)\mathbb{1}(v(t) = X_q)$$

$$\text{Random forest: } I(X_q) = \frac{1}{N_T}\sum_{n=1}^{N_T} I(T_n, X_q)$$

Recursive feature elimination

Initial pool of Q features $X_1, \dots, X_Q$.

1. Train several times and record variable importances
2. Average of importances over trainings. $X_q* = \arg\min_{X_i} I(X_i)$
3. Remove X_q* from the pool of features and back to step 1



Results

Set up:

- Fixed params: r set to 5 and Q set to 20
- Varying T_h (0.5 to 1) and B_s (5 to 250)
- Record best Accuracy and show corresponding TPR, FPR
- If FPR is constrained to be max 10%, what is the range of TPRs ?

Model	Accuracy	TPR	FPR	$\mathrm{TPR}_{\mathrm{min}}^{\mathrm{FPR}<10}$	$\mathrm{TPR}_{\mathrm{max}}^{\mathrm{FPR}<10}$
			$r = 5, \ Q = 20$		
LR	86.8 ± 1.5	90.5 ± 2.4	17.7 ± 4.9	67.0 ± 10.8	80.4 ± 6.4
LDA	85.5 ± 1.2	91.0 ± 2.1	21.7 ± 3.7	56.9 ± 7.0	78.7 ± 3.8
k-NN	87.0 ± 1.9	89.2 ± 1.4	**16.0 ± 4.7**	63.1 ± 4.2	83.1 ± 2.5
SVM	87.6 ± 3.2	90.0 ± 4.5	**15.5 ± 6.8**	69.2 ± 2.1	82.9 ± 3.2
MLP	**88.2 ± 1.5**	**92.4 ± 1.2**	17.3 ± 4.1	71.4 ± 4.5	85.1 ± 2.1
RF	**88.2 ± 1.5**	**91.7 ± 3.5**	16.2 ± 6.2	63.8 ± 6.8	84.3 ± 7.9

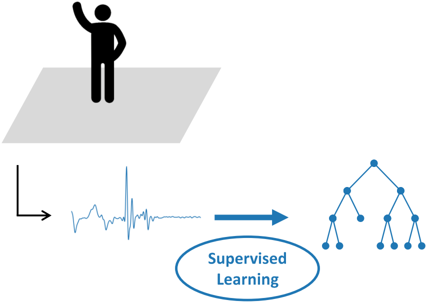
Comments:

- Parametric methods perform slightly worse than non-parametric
- RF is slightly better than others
- Buffer/threshold trade-off useful for maintaining low FPR while improving TPR

Transfer learning on decision tree

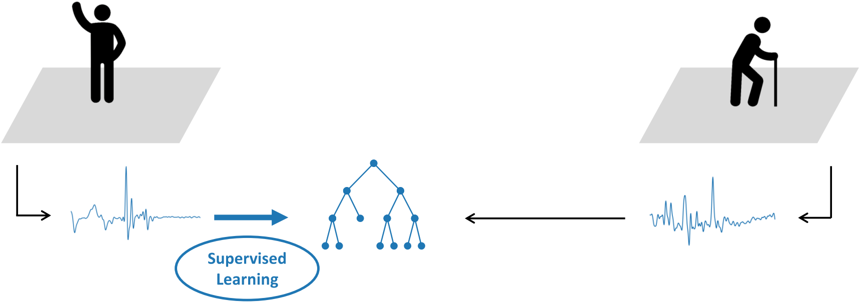
Context

Experimental vs. operational



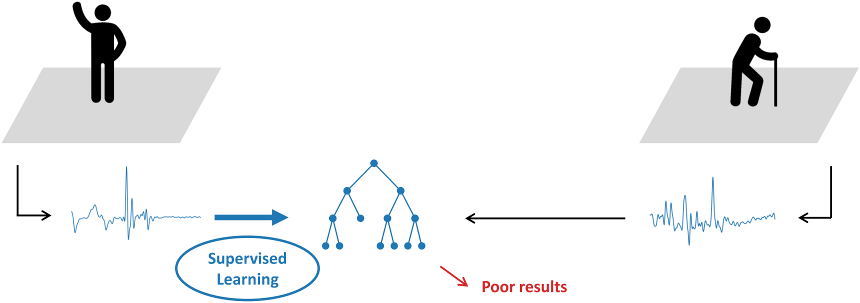
Context

Experimental vs. operational



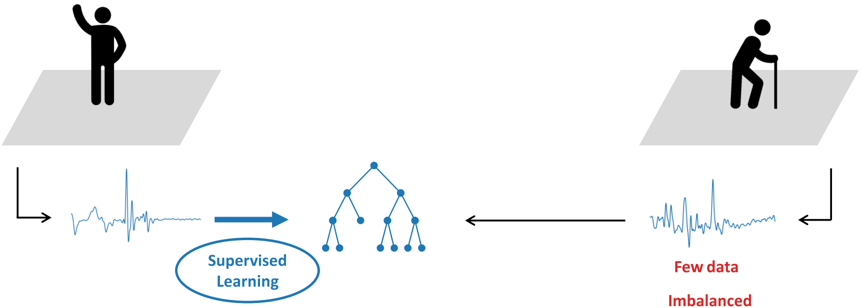
Context

Experimental vs. operational



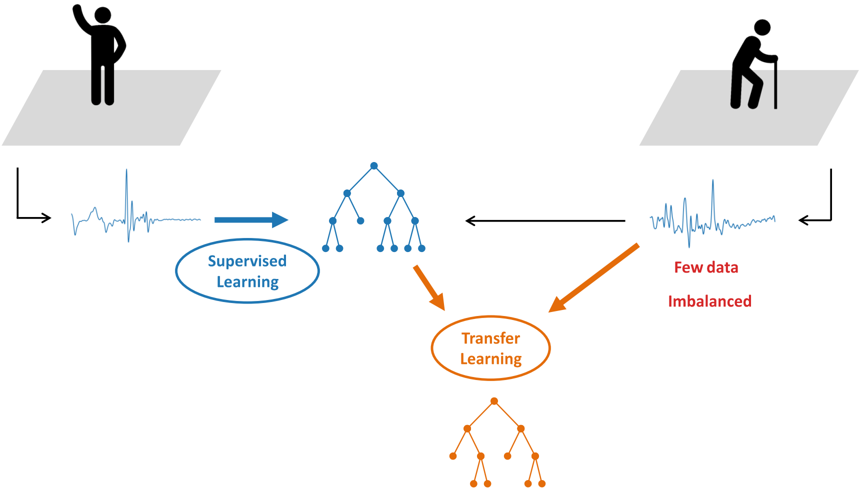
Context

Experimental vs. operational



Context

Experimental vs. operational



Context

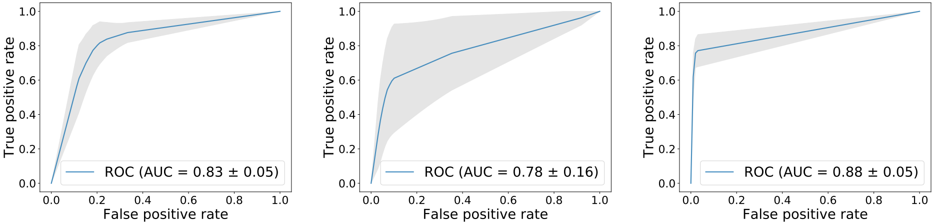
Transfer learning

Transfer learning

- Source domain: $\mathcal{D}_S = \{\mathcal{X}_S, P(X_S)\}$
- Target domain: $\mathcal{D}_T = \{\mathcal{X}_T, P(X_T)\}$
- Source task: $\mathcal{T}_S = \{\mathcal{Y}_S, f^S\}$
- Target task: $\mathcal{T}_T = \{\mathcal{Y}_T, f^T\}$

Our case

- $\mathcal{X}_S = \mathcal{X}_T$
- $P(X_S) \neq P(X_T)$
- $\mathcal{Y}_S = \mathcal{Y}_T$
- $f^S \neq f^T$

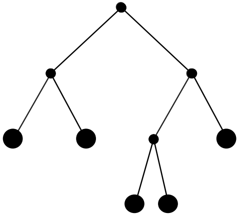


Source tested on source — *Source* tested on target — *Target* tested on target

Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)



Model-based transfer

Segev et al. [7]

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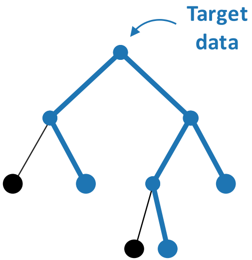
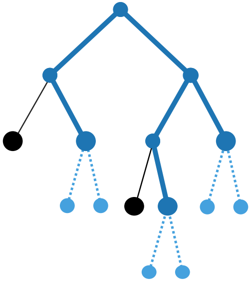


Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)

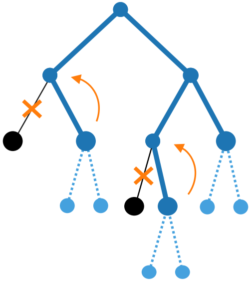


1. Expansion

Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)

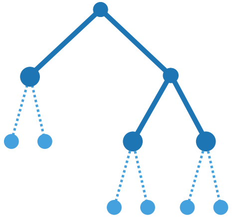


1. Expansion
2. Reduction

Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)

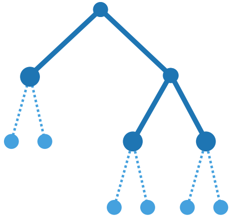


1. Expansion
2. Reduction

Model-based transfer

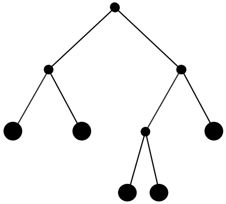
Segev et al. [7]

Structure Expansion / Reduction (SER)



1. Expansion
2. Reduction

Structure Transfer (STRUT)



Model-based transfer

Segev et al. [7]

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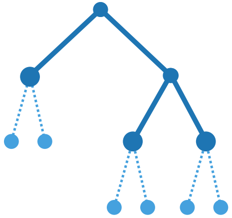

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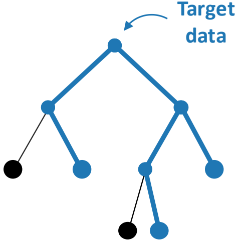
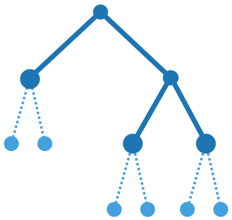


Model-based transfer

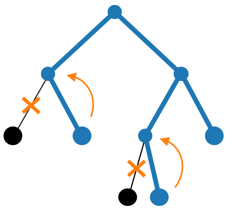
Segev et al. [7]

Structure Expansion / Reduction (SER)



1. Expansion
2. Reduction

Structure Transfer (STRUT)

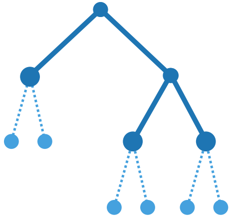


1. Pruning

Model-based transfer

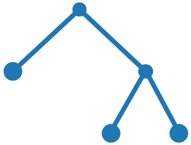
Segev et al. [7]

Structure Expansion / Reduction (SER)



1. Expansion
2. Reduction

Structure Transfer (STRUT)

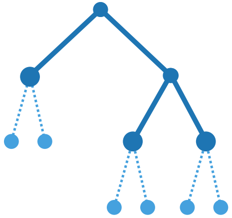


1. Pruning

Model-based transfer

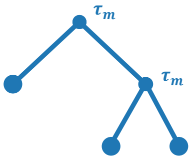
Segev et al. [7]

Structure Expansion / Reduction (SER)



1. Expansion
2. Reduction

Structure Transfer (STRUT)

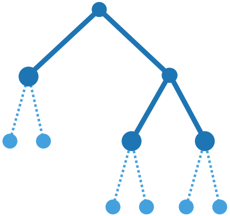


1. Pruning
2. Threshold update

Model-based transfer

Segev et al. [7]

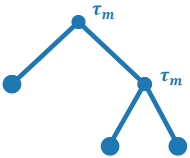
Structure Expansion / Reduction (SER)



1. Expansion
2. Reduction

Partition refinement or simplification

Structure Transfer (STRUT)



1. Pruning
2. Threshold update

Drifts

Leaf loss risk

Homogeneous class imbalance

$$P^T(x|y) = P^S(x|y)$$

$$P^T(y|x) = \lambda_y \frac{P^S(y|x)}{\int \lambda_y P^S(y|x)dy}$$

with $\lambda_y = \frac{P^T(y)}{P^S(y)}$

Leaf loss risk

Homogeneous class imbalance

$$P^T(x|y) = P^S(x|y)$$

$$P^T(y|x) = \lambda_y \frac{P^S(y|x)}{\int \lambda_y P^S(y|x)dy}$$

with $\lambda_y = \frac{P^T(y)}{P^S(y)}$

Leaf loss risk

Significant leaf: Leaf l that conserves the minority class k_{min} after Target update:

$$\forall k \neq k_{min}, \quad P^T(y = k_{min} \,|\, x \in l) > P^T(y = k \,|\, x \in l)$$

Leaf loss risk:

$$R_L(l) = P^T(x \notin l \,|\, y = k_{min})^{n_{k_{min}}}$$

Leaf loss risk

Homogeneous class imbalance

$$P^T(x|y) = P^S(x|y)$$

$$P^T(y|x) = \lambda_y \frac{P^S(y|x)}{\int \lambda_y P^S(y|x)dy}$$

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Leaf loss risk:

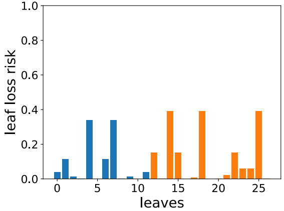
$$R_L(l) = P^T(x \notin l \,|\, y = k_{min})^{n_{k_{min}}}$$

Leaf loss risk under homogeneous class imbalance

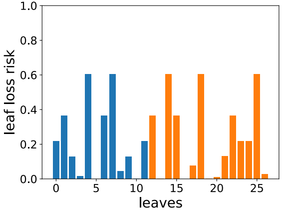
$$\forall k \neq k_{min}, \quad \lambda_{k_{min}} P^S(y = k_{min} \,|\, x \in l) > \lambda_k P^S(y = k \,|\, x \in l)$$

$$R_L(l) = P^S(x \notin l \,|\, y = k_{min})^{n_{k_{min}}}$$

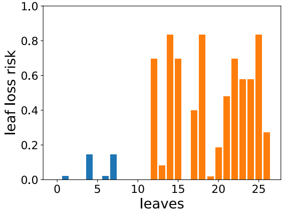
Leaf loss risk



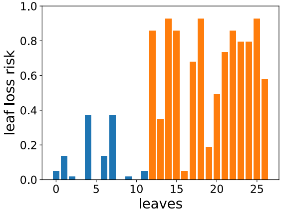
(a) Balanced data with 200 instances



(b) Balanced data with 100 instances



(c) Imbalanced data (10% ratio) with 200 instances

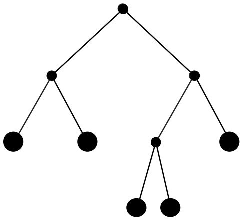


(d) Imbalanced data (10% ratio) with 100 instances

SER for class imbalance

$\mathrm{SER}_{\mathrm{R}}$, $\mathrm{SER}_{\mathrm{LL}}$

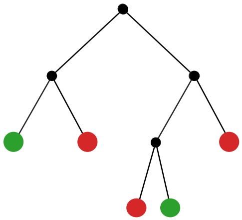
Structure Expansion and controlled Reduction



SER for class imbalance

$\mathrm{SER_R}$, $\mathrm{SER_{LL}}$

Structure Expansion and controlled Reduction

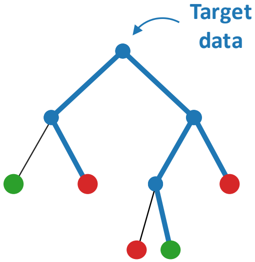


Minority class

SER for class imbalance

SER_{R}, SER_{LL}

Structure Expansion and controlled Reduction

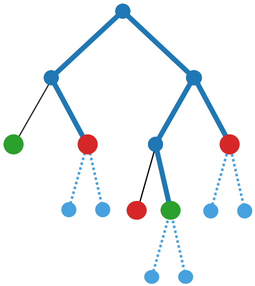


Minority class

SER for class imbalance

SER$_R$, SER$_{LL}$

Structure Expansion and controlled Reduction



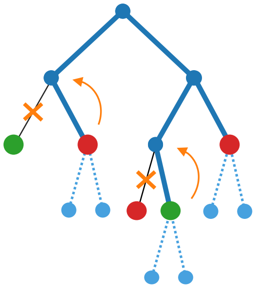
Minority class

- Expansion left unchanged

SER for class imbalance

SER_R, SER_LL

Structure Expansion and controlled Reduction



Minority class

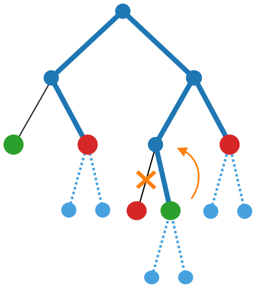
- Expansion left unchanged
- Reduction constrained

SER_R	SER_LL
If node is of minority class, then no pruning	If node is of minority class **and** still significant considering Target **and** $R_L > 0.5$, then no pruning

SER for class imbalance

SER_{R}, SER_{LL}

Structure Expansion and controlled Reduction



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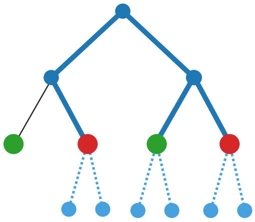
SER_{R}	SER_{LL}
If node is of minority class, then no pruning	If node is of minority class **and** still significant considering Target **and** $R_L > 0.5$, then no pruning

SER for class imbalance

$\mathrm{SER_R}$, $\mathrm{SER_{LL}}$

Structure Expansion and controlled Reduction



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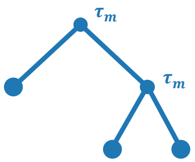
STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?



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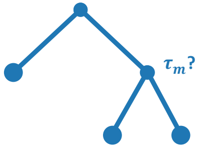

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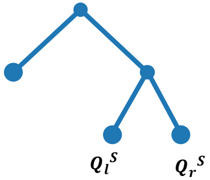
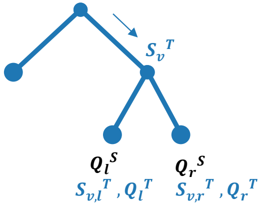


Q_l^S, Q_r^S: class proportions of source data in children w.r.t. the *original* split

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?



Q_l^S, Q_r^S: class proportions of source data in children w.r.t. the *original* split
$S_{v,l}^T$, $S_{v,r}^T$: subsets of S_v^T that fall in the children nodes of v
$Q_l^T(\tau)$, $Q_r^T(\tau)$: class proportions of target data in children w.r.t. the *new* split

STRUT for class imbalance

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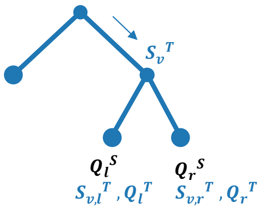


Q_l^S, Q_r^S: class proportions of source data in children w.r.t. the *original* split
$S_{v,l}^T$, $S_{v,r}^T$: subsets of S_v^T that fall in the children nodes of v
$Q_l^T(\tau)$, $Q_r^T(\tau)$: class proportions of target data in children w.r.t. the *new* split
Divergence Gain: similarity between the original label distributions and the new ones

$$DG(\tau) = 1 - \frac{|S_{v,l}^T|}{|S_v^T|} JSD(Q_l^S, Q_l^T) - \frac{|S_{v,r}^T|}{|S_v^T|} JSD(Q_r^S, Q_r^T)$$

Jensen-Shannon divergence:

$$JSD(P, Q) = \frac{1}{2}\left(D_{KL}(P||M) + D_{KL}(Q||M)\right)$$

$$M = \tfrac{1}{2}(P + Q)$$

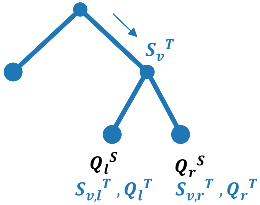
Kullback-Leibler divergence:

$$D_{KL}(P||Q) = \sum_k P(k) \ln\left(\frac{P(k)}{Q(k)}\right)$$

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?

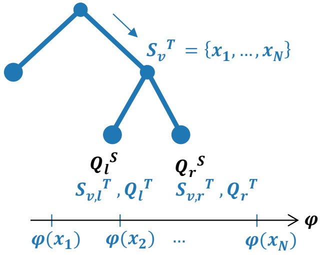


Goal: Maximize DG while being in a local maximum of Information Gain (IG) (here IG = Gini gain)

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?



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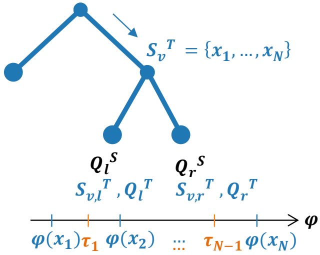

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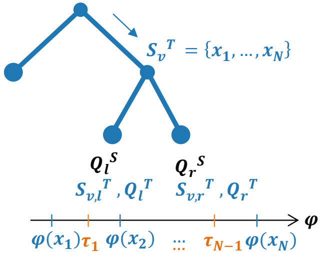


Goal: Maximize DG while being in a local maximum of Information Gain (IG) (here IG = Gini gain)

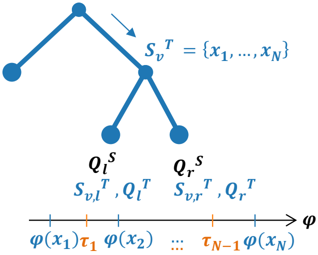
$$\tau_m = \underset{\tau \in \mathrm{T}_v}{\arg\max} \left(DG \left(\tau, Q_l^T(\tau), Q_r^T(\tau) \right) \right)$$

$$\text{s.t. } IG(\tau_{m-1}) < IG(\tau_m) \text{ and } IG(\tau_m) > IG(\tau_{m+1})$$

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?



Goal: Maximize DG while being in a local maximum of Information Gain (IG) (here IG = Gini gain)

$$\tau_m = \arg\max_{\tau \in \mathrm{T}_v} \left(DG \left(\tau, Q_l^T(\tau), Q_r^T(\tau) \right) \right)$$

$$\text{s.t. } IG(\tau_{m-1}) < IG(\tau_m) \text{ and } IG(\tau_m) > IG(\tau_{m+1})$$

- Q^S have less meaning when going deeper
- Do we really want to keep Q^S and Q^T close ?

STRUT for class imbalance

STRUT_{IG}, STRUT_{HI}

STRUT_{IG}

STRUT without DG: maximization of IG

STRUT for class imbalance

STRUT_{IG}, STRUT_{HI}

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STRUT without DG: maximization of IG

STRUT_{HI}

Framework of homogeneous class imbalance, use

$$p^T(y/x) = \lambda_y \frac{p^S(y/x)}{\int \lambda_y p^S(y/x)dy}$$

to change the source class proportions in DG:

$$Q_l^{S'} = \lambda_k \frac{Q_l^S}{\sum_k \lambda_k Q_l^S} \qquad Q_r^{S'} = \lambda_k \frac{Q_r^S}{\sum_k \lambda_k Q_r^S}$$

STRUT for class imbalance

$\mathrm{STRUT}_{\mathrm{IG}}$, $\mathrm{STRUT}_{\mathrm{HI}}$

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$\mathrm{STRUT}_{\mathrm{HI}}$ can be seen as a generalization of STRUT

Results

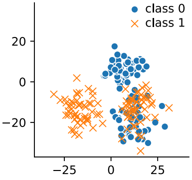
Synthetic data

Gaussian generator
Source dataset: combination of several multivariate Gaussian clusters. We use $N_{\text{source}} = 200$ and $N_{clust} = 10$. Initial parameters are randomly drawn from Uniform distribution: $\mu_i \in [-70, 70]$ and $\sigma_i \in [5, 15]$

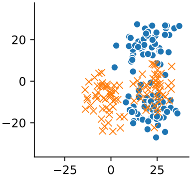
Transformations
Basic transformations on Source clusters are applied to get a Target dataset:

- Drifts (μ_i)
- Stretch / Squeeze (σ_i)
- Adding / Remove clusters

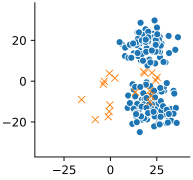
Transformations are combined with imbalance ratio (from 2% to 50%), and $N_{\text{target}} = 1000$



Source data...



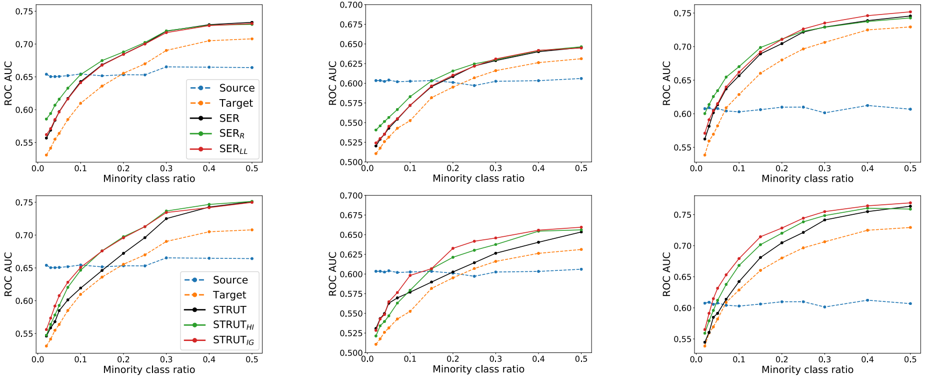
...after a drift...



...and homogeneous imbalance

Results

Synthetic data



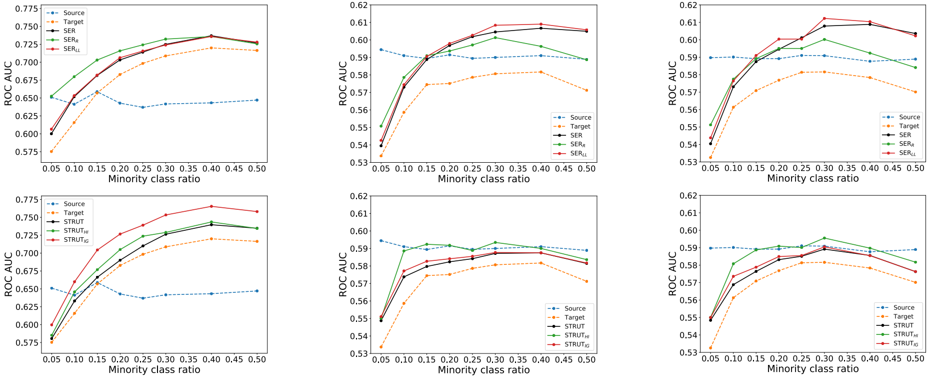
(a) Drift (b) Stretch / Squeeze (c) Add / Remove

- Strong imbalance leads to negative transfer
- SER: SER$_{\mathrm{LL}}$ close to SER, SER$_{\mathrm{R}}$ better than SER (esp. with high imbalance)
- STRUT: both variants beat the original STRUT

Results

Public data

Two real data sets where the imbalance ratio is controlled with downsampling.



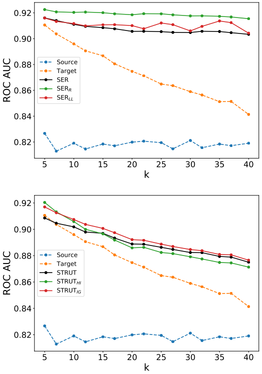
(a) Magic Gamma Telescope (b) Office-Caltech: *amazon* $\to$ *webcam* (c) Office-Caltech: *caltech* $\to$ *webcam*

- SER: SER$_{\mathrm{LL}}$ close to SER, SER$_{\mathrm{R}}$ either better... or worse
- STRUT: both variants perform as well or better

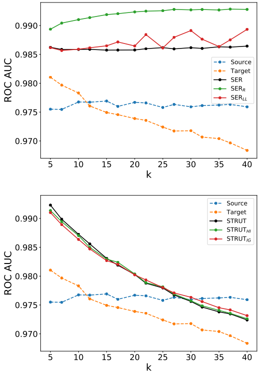
Results

Fall data

Operational data set: 174 fall events and 2619 non-fall events (6%)
k-fold testing with varying k to observe lack of data



(a) Decision tree model



(b) Random forest model with 10 decision trees

- SER: variants give similar or better results
- STRUT: STRUT_{IG} better, STRUT_{HI} better *only when enough data*

- Same overall conclusions

Results

Overall

- SER_{LL} quite close to original SER
- SER_{R} generally better except with one real dataset
- Both STRUT variants give better results with one exception on fall data (when data is scarce)
- This suggests a data-dependency of the algorithms

Elderly activity recognition with convolutional representations

Motivation

- **Issue**: one-dimensional signals for large areas
- Goal: Classify elderly from other individuals
  - Most signals are made of walks of staff individuals
- **Subtask**: Bring the model's attention over step-related signals

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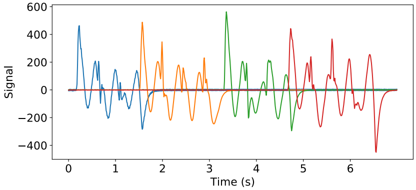
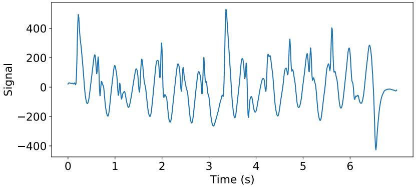


(a) Raw signal



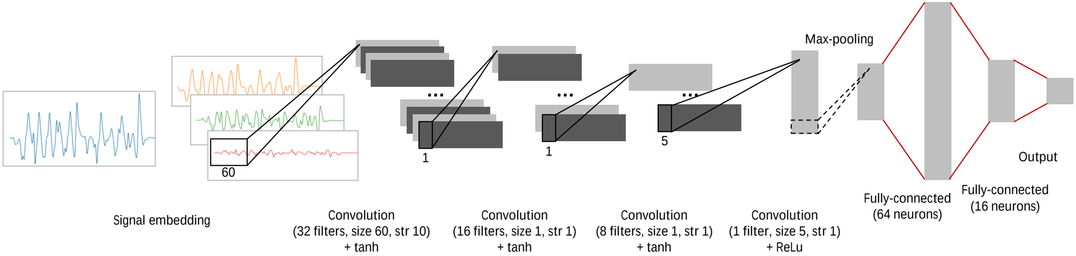
(b) Preprocessed signal

- Signals are rather complex

This work: A model to recognize elderly activity using convolutional representations and three training steps:

1. Step proposal network inspired from Region proposal network
2. Signal embedding using convolutional dictionary learning
3. The final classification task

Main architecture



- Use the convolutional representation to “boost” training
- First layer (Signal embedding) of NurseNet is trained **separately** using convolutional dictionary learning

Signal embedding

Convolutional dictionary learning

- $\mathbf{s}$: data to be represented
- Objective : find M atoms $\mathbf{d}_m$ and activation signals $\mathbf{x}_m$ such that

$$\mathbf{s} \approx \sum_{m=1}^{M} \mathbf{x}_m * \mathbf{d}_m$$

- $*$: convolution

Signal embedding

Convolutional dictionary learning

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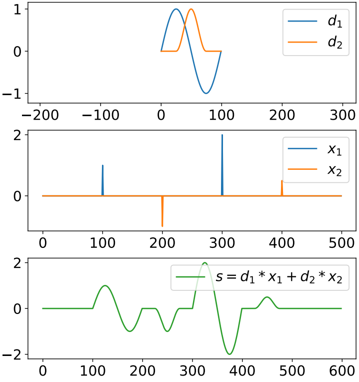

Convolutional representation

Signal embedding

Convolutional dictionary learning

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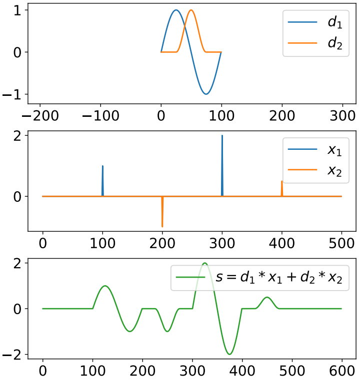
$$\mathbf{s} \approx \sum_{m=1}^{M} \mathbf{x}_m * \mathbf{d}_m$$

- $*$: convolution

CDL general problem:

$$\underset{\mathbf{x}_m, \mathbf{d}_m}{\arg\min} \ \frac{1}{2} \left\| \sum_{m=1}^{M} \mathbf{x}_m * \mathbf{d}_m - \mathbf{s} \right\|_2^2 + \lambda \sum_{m=1}^{M} \|\mathbf{x}_m\|_1$$
$$\text{s.t.} \quad \|\mathbf{d}_m\|_2 \leq 1 \quad \forall m \, .$$

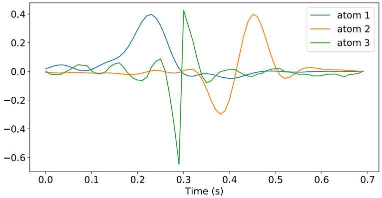


Convolutional representation

Signal embedding

Learning step atoms

- Learning with Alternating Direction Method of Multipliers (ADMM) [3]
- 3 atoms of length 0.7 second



Dictionary

Signal embedding

Learning step atoms

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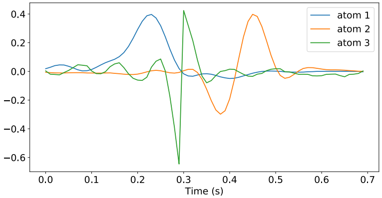

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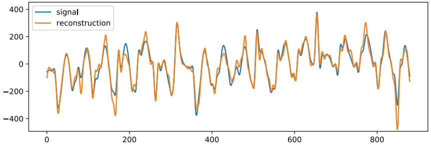
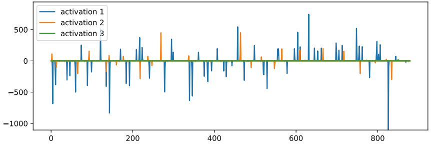


(a) Original signal and its reconstruction



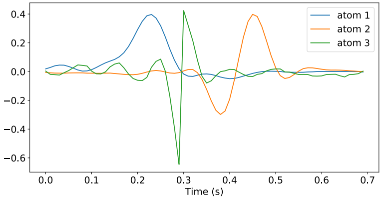
(b) Signal activations

Signal embedding

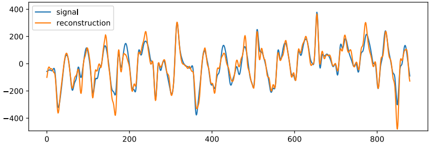
Learning step atoms

- Learning with Alternating Direction Method of Multipliers (ADMM) [3]
- 3 atoms of length 0.7 second
- Use the following embedding:

$$\mathbf{S} \doteq \left(\mathbf{s} * \mathbf{d}_m\right)_{1 \leq m \leq 3}$$



Dictionary



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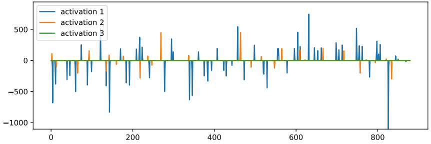
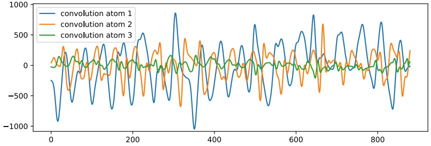


(b) Signal activations



(c) Embedding

Region proposal network

Object detection

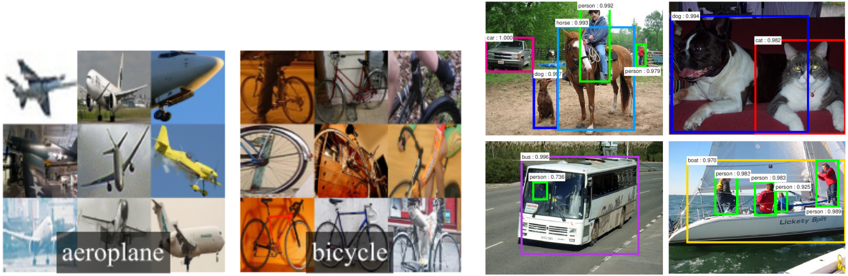
- Classification: What is the image class ?

Classification vs Object detection. Source: Girshick et al. [4], Ren et al. [6]

Region proposal network

Object detection

- Classification: What is the image class ?
- Object detection: Where are the objects and what are they classes ?

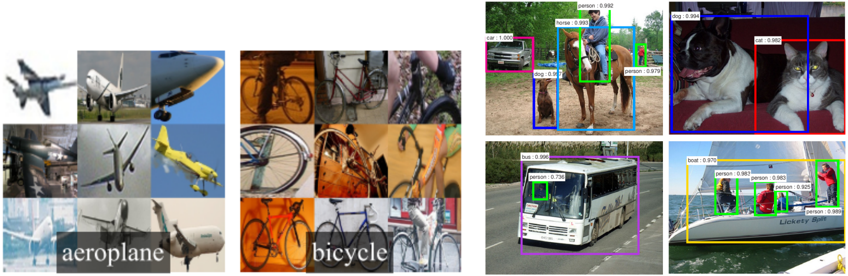


Classification vs Object detection. Source: Girshick et al. [4], Ren et al. [6]

Region proposal network

Object detection

- Classification: What is the image class ?
- Object detection: Where are the objects and what are they classes ?
- How to efficiently localize objects ?
- Proposal models (Hosang et al. [5])
- Faster R-CNN (Ren et al. [6])



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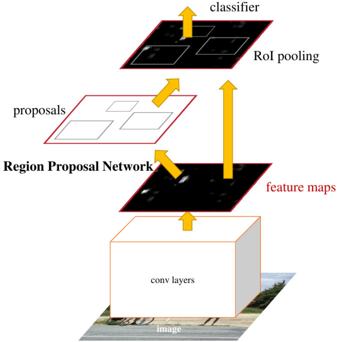
Region proposal network

Faster R-CNN

- Main idea: proposals are generated by a CNN called Region Proposal Network

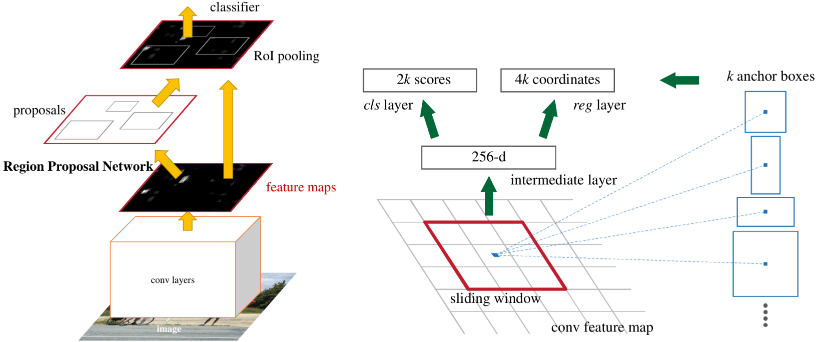


Region proposal network. Source: Ren et al. [6]

Region proposal network

Faster R-CNN

- Main idea: proposals are generated by a CNN called Region Proposal Network
- A sliding window is passed: multiple *anchors* over each location (various sizes and scales)
- Two layers: Classification (Object / Not Object) and Regression (anchor coordinates)

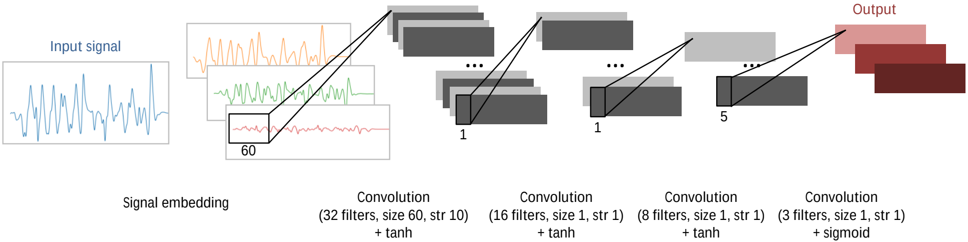


Region proposal network. Source: Ren et al. [6]

Step proposal network

Main architecture

- Directly inspired from RPN
- Simple architecture with three hidden layers, all **convolutional**
- Output: probability of having a step at a specific window location and size
  - Here 3 sizes and all discrete locations are considered



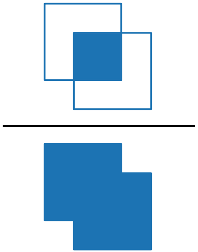
Architecture of SPN

Step proposal network

Principle

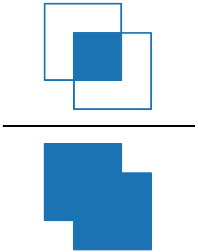
- Objective of SPN : output boxes with largest Intersection over Union (IoU)
- IoU: $\mathbf{b_j}$ are labelled boxes, $\hat{b}$ is an estimated box:

$$\mathrm{IoU}(\hat{b}) \doteq \max_j \frac{|\mathbf{b_j} \cap \hat{b}|}{|\mathbf{b_j} \cup \hat{b}|}$$



Step proposal network

Principle



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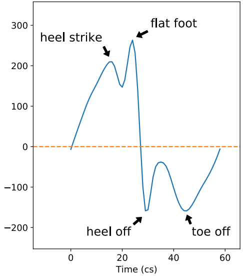
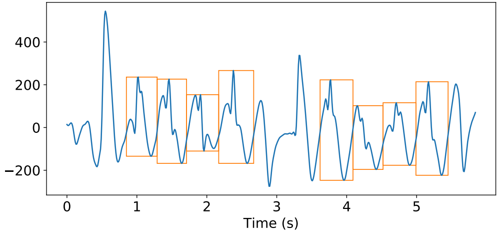


(a) Step signal



(b) Step labels over a walk signal

Step proposal network

Training

- Output: a matrix $\mathbf{W} \in \mathbb{R}^{T \times K}$
  - T: signal length
  - K: number of different box sizes
- $\mathbf{W}_{t,k}$: probability that the box b_t^k starting at time t and of size 0.4s, 0.5s, or 0.6s (for respectively $k = 1, 2$, or 3) has a large IoU score
- Positive boxes: $\mathrm{IoU}(b_t^k) > \sqrt{0.7}$
- Negative boxes: $\mathrm{IoU}(b_t^k) < \sqrt{0.3}$
- Other are not used for training

The loss function $\mathcal{L}$ over a signal $\mathbf{s}$ is defined as:

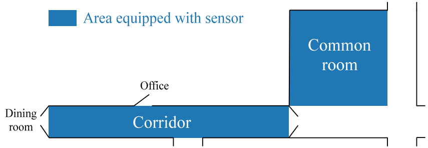
$$\mathcal{L}(\mathbf{s}, \mathbf{W}) = \sum_{t} \sum_{k \in [1,2,3]} \mathbb{1}_{\mathrm{IoU}(b_t^k) > \sqrt{0.7}} \log(\mathbf{W}_{t,k}) + \mathbb{1}_{\mathrm{IoU}(b_t^k) < \sqrt{0.3}} \log(1 - \mathbf{W}_{t,k}).$$

Step proposal network

Results

Data

- 43 signals recorded in a nursing home
- Manually labeled steps



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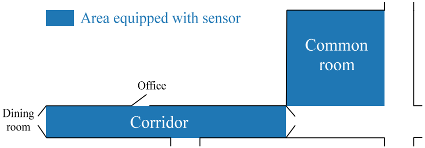

Training

- SPN is trained using classical gradient descent
- Training time: < 5 minutes
- Inference (detection over a 10s signal): < 1 second
- Optimization details
  - learning rate of 10^{-3}
  - learning rate decay ($\times 0.9$ every 10 epochs)
  - Nesterov momentum

Step proposal network

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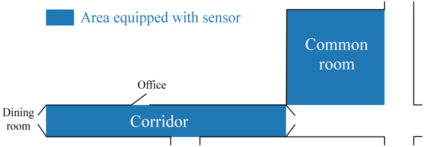

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Results

- Object detection use the mean Average Precision (mAP): area under the Precision-Recall curve
- **Without** embedding, mAP = 72,5%
- **With** embedding, mAP = 78,6%

Step proposal network

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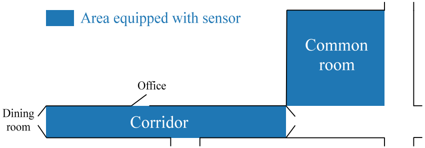

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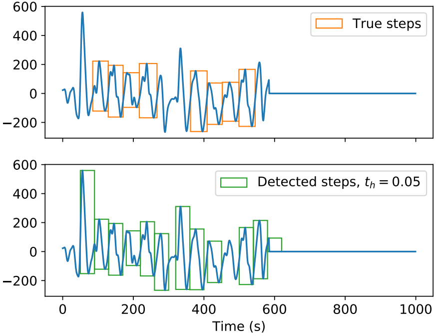

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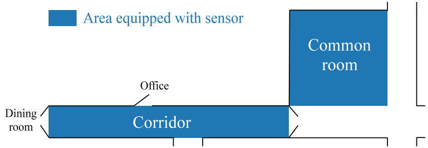

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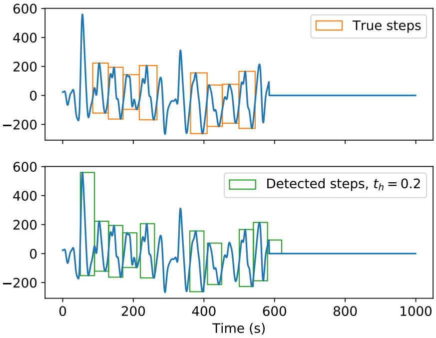

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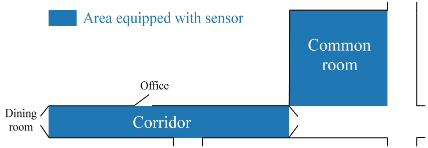

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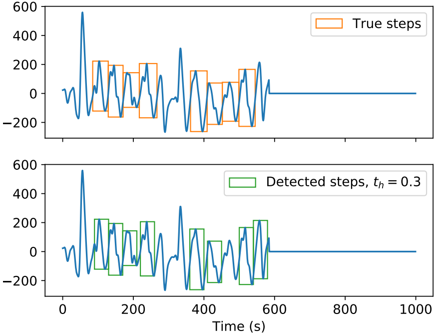

Classification

Training

$$\mathcal{L}(\mathbf{s}_i, \hat{y}_i) = -\left(\mathbb{1}_{y_i=1} \log(\hat{y}_i) + \mathbb{1}_{y_i=0} \log(1-\hat{y}_i)\right)$$

Sublabel	**Staff**	**Elderly**
Single walk	43	31
Multiple walks	19	11
Other	19	23

- SPN is trained using classical gradient descent
- Training time: < 5 minutes
- Inference (detection over a 10s signal): < 1 second
- Optimization details
  - learning rate of 10^{-3}
  - learning rate decay ($\times 0.9$ every 10 epochs)
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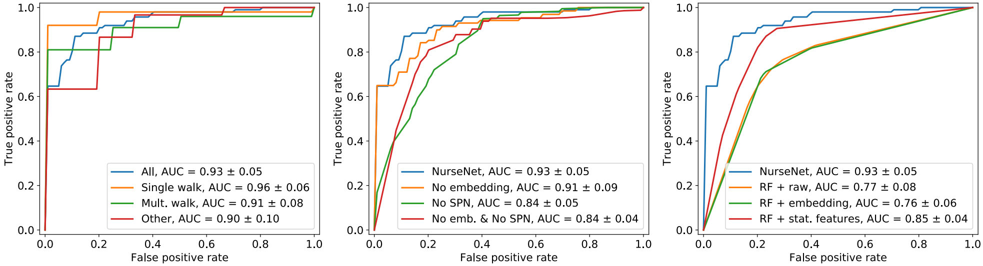
Classification

Results



(a) NurseNet results (b) NurseNet ablation analysis (c) NurseNet and several RF-based models

Conclusion

Conclusion

Contributions

- A simple and practical model for fall detection
- Transfer procedure for decision tree adapted to class imbalance
- A model to distinguish elderly vs. other with high accuracy

Future work

- Explore meta models for transfer procedures
- What if features change ? Consider heterogeneous transfer
- Improve step detection precision (with regression layer ?)
- Test on benchmarks step data sets
- Is it possible to distinguish activities or individuals ?

Publications and communications

Publications

- L. Minvielle, M. Atiq, R. Serra, M. Mougeot, and N. Vayatis. Fall detection using smart floor sensor and supervised learning. *In 2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 3445–3448, July 2017
- L. Minvielle, M. Atiq, S. Peignier, and M. Mougeot. Transfer learning on decision tree with class imbalance. *In 2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 1003–1010, Nov 2019
- Ludovic Minvielle and Julien Audiffren. Nursenet: Monitoring elderly levels of activity with a piezoelectric floor. *Sensors*, 19(18), 2019
- P. Humbert, B. Le Bars, L. Minvielle, and N. Vayatis. Robust Kernel Density Estimation with Median-of-Means principle. *Submitted to Neural Information Processing Systems 2020 (NeurIPS)*, 2020

Communications

- Transfer learning on decision tree with imbalanced data, 3rd Summer school on transfer learning, 2019, Passau, Germany
- Step detection with proposal network. 4th French-German Summer School on Artificial Intelligence, 2020, Online.

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