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

Soutenance de thèse

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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
- **Objective**: providing tools for elderly monitoring in nursing homes

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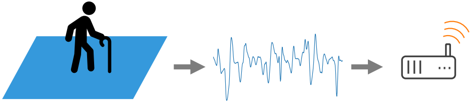

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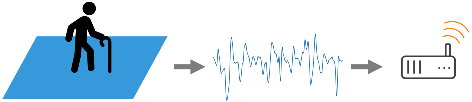
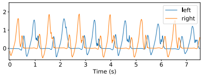
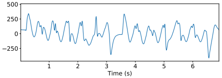


Scientific context

- Processing and understanding time series
- Real world application



Foot-attached accelerometer



Tarkett's floor sensor

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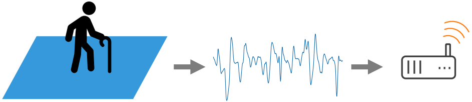

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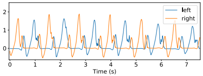

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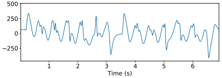

Tarkett's floor sensor

Questions

- Is a floor-based system a good idea ?
- How to build a fall detector out of it ?
- How to use real data to improve our model ?
- The signal is unidimensional: can we still distinguish people ?

Table of contents

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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Sensors

What makes a good monitoring system ?

- coverage and occlusion
- intrusiveness
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- robustness
- ease of installation / use
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Signal acquisition

Vision	**Wearable**
RGB-Camera Omni-Camera Depth-Camera	Accelerometer Gyroscope Barometric pressure

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

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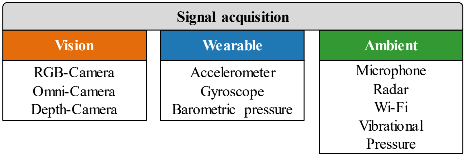


Criteria	RGB cam	Depth cam	Wearable	Acoustic	Radar / Wi-Fi	Vibration	Floor
Coverage/Occlusion	★☆☆	★☆☆	★★★	★★☆	★☆☆	★★★	★★★
Intrusiveness	★☆☆	★☆☆	★★☆	★☆☆	★★☆	★★★	★★★
Signal quality / info	★★★	★★★	★★☆	★★☆	★☆☆	★★☆	★★☆
Robustness	★★☆	★★★	★★★	★☆☆	★☆☆	★☆☆	★★☆
Ease of instal. / use	★☆☆	★☆☆	★★☆	★★☆	★★☆	★★★	★☆☆
Scalability	★☆☆	★☆☆	★★★	★★☆	★☆☆	★★☆	★★★

Information extraction

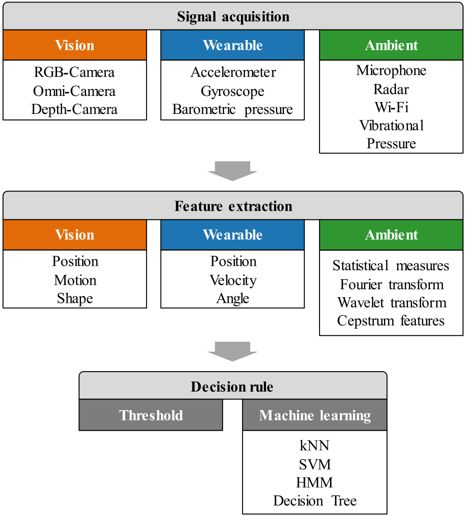
How to process the inputs ?

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

How to deal with processed signals ?

Time series classification

1. Series as *sequences*
   - Distance-based methods
2. Series as *feature vectors*
   - Computing several measures over a fixed size
   - Classification models (Anomaly detection, classical supervised models...)



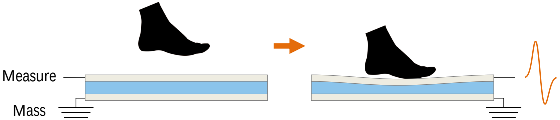
A fall detection system

Tarkett sensor

- Piezoelectric principle:

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

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



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- Piezoelectric principle:

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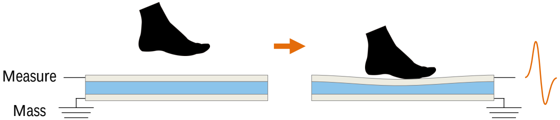
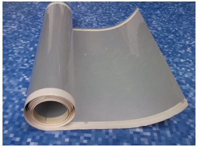
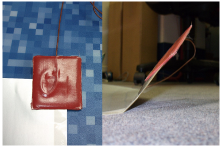
  When stressed or squeezed, the material emits charges.
- How does this look like ?
  0.3 mm thick and 60 cm wide roll with customizable length







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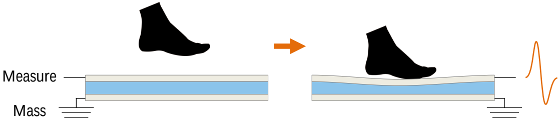
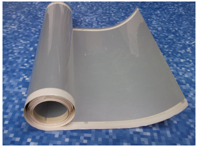
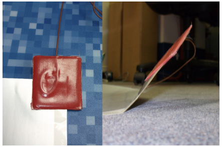
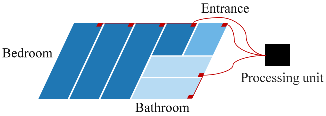
  (simple version) with d the *piezoelectric constant*.
  When stressed or squeezed, the material emits charges.
- How does this look like ?
  0.3 mm thick and 60 cm wide roll with customizable length
- How is it installed ?
  - Under the flooring
  - Several connected bands for each area, hence one area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





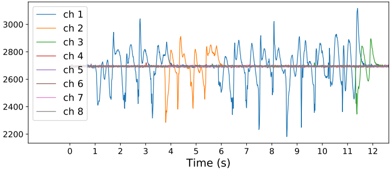




Data

Preprocessing

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



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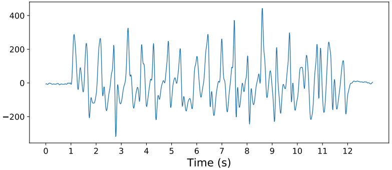

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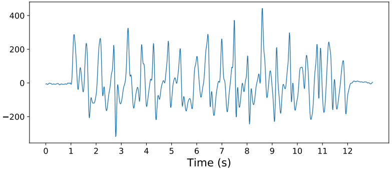
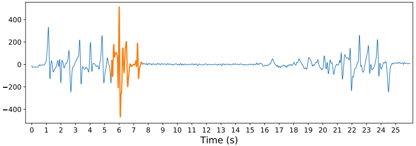
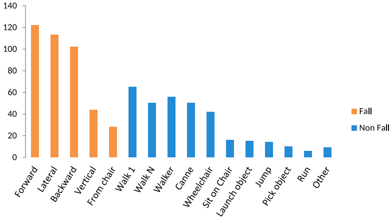


Experimental dataset

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

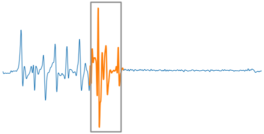




Method

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



$s \quad \frac{d}{dt}s \quad \mathcal{F}(s)$

$\downarrow$

$$\underbrace{\text{Min, Max, Energy...}}_{\mathbf{x} \in \mathbb{R}^{87}}$$

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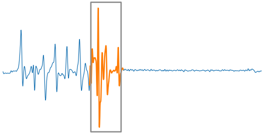

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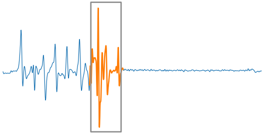


$$\downarrow$$

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

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

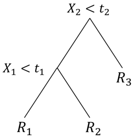
Decision tree

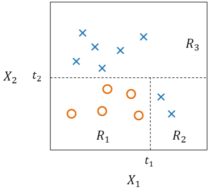
Feature space $\mathcal{X} = \mathbb{R}^Q$. Division of $\mathcal{X}$ into non-overlapping regions $R_1, \ldots, R_J$. Algorithm CART: recursive binary splits [2] that solve:

$$\arg\min_{X_q, \tau} \mathrm{IG} \ ,$$

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

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





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

Method

Random forest

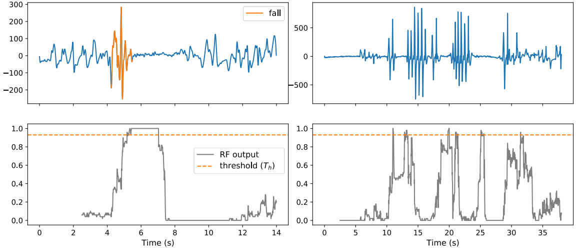
Decision trees $d_1, \ldots, d_{N_T}$ grown with two rules:

- 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 prediction function is then

$$f(x) = \arg\max_k f_k(x) \ ,$$

$$\text{with} \quad f_k(x) = \frac{1}{N_T} \sum_{i=1}^{N_T} \mathbb{1}\left(d_i(x) = k\right)$$



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

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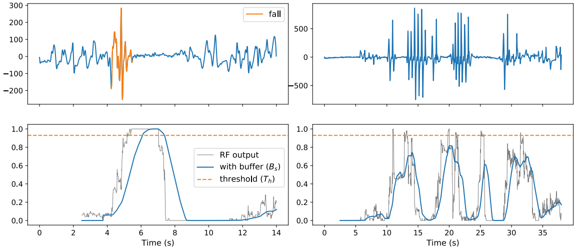

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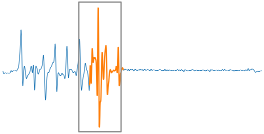
Data augmentation

Select r windows in training signals



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

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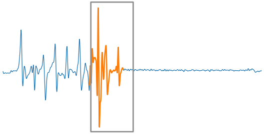

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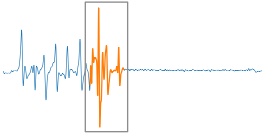

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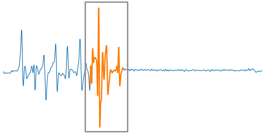

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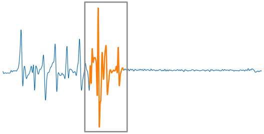

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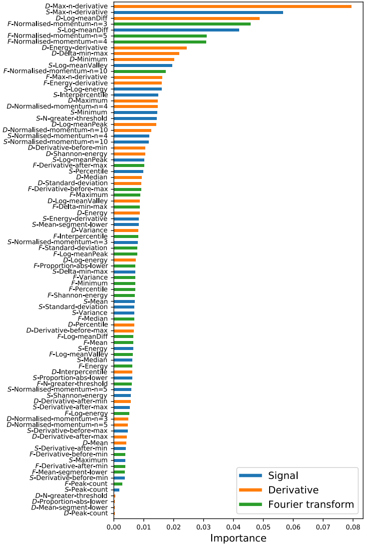
Feature reduction

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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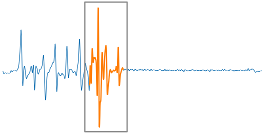

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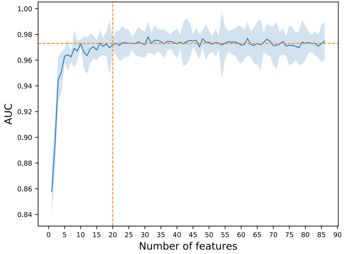
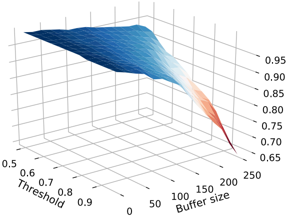
Recursive feature elimination

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

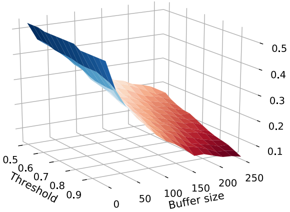
1. Train several times and record variable importances
2. Average of importances over trainings. $X_q* = \arg\min_{X_i} I(X_i)$
3. Remove X_q* from the pool of features and back to step 1



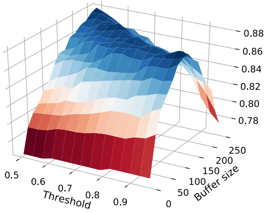
Results



True positive rate



False positive rate



Accuracy

Model	Accuracy	TPR	FPR	$\text{TPR}_{\text{min}}^{\text{FPR}<10}$	$\text{TPR}_{\text{max}}^{\text{FPR}<10}$
			$r = 5, \ Q = 20$		
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	$\mathbf{16.0 \pm 4.7}$	63.1 ± 4.2	83.1 ± 2.5
SVM	87.6 ± 3.2	90.0 ± 4.5	$\mathbf{15.5 \pm 6.8}$	69.2 ± 2.1	82.9 ± 3.2
MLP	$\mathbf{88.2 \pm 1.5}$	$\mathbf{92.4 \pm 1.2}$	17.3 ± 4.1	71.4 ± 4.5	85.1 ± 2.1
RF	$\mathbf{88.2 \pm 1.5}$	$\mathbf{91.7 \pm 3.5}$	16.2 ± 6.2	63.8 ± 6.8	84.3 ± 7.9

Transfer learning on decision tree

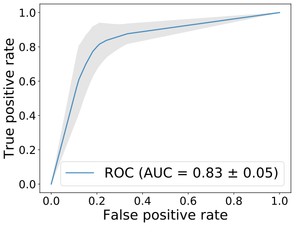
Experimental vs. operational

Transfer learning

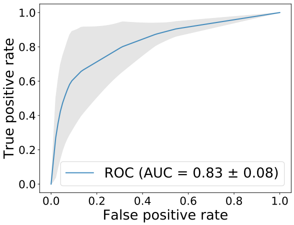
- Source domain: $\mathcal{D}_S = \{\mathcal{X}_S, P(X_S)\}$
- Target domain: $\mathcal{D}_T = \{\mathcal{X}_T, P(X_T)\}$
- Source task: $\mathcal{T}_S = \{\mathcal{Y}_S, f^S\}$
- Target task: $\mathcal{T}_T = \{\mathcal{Y}_T, f^T\}$

Our case

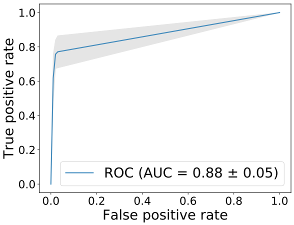
- $\mathcal{X}_S = \mathcal{X}_T$
- $P(X_S) \neq P(X_T)$
- $\mathcal{Y}_S = \mathcal{Y}_T$
- $f^S \neq f^T$



Source tested on source



Source tested on target

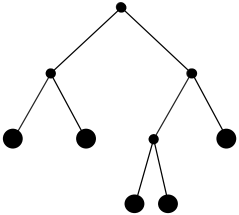


Target tested on target

Model-based transfer

Segev et al. [7]

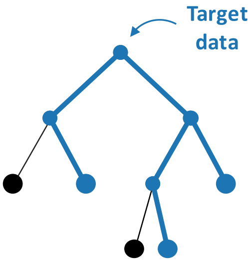
Structure Expansion / Reduction (SER)



Model-based transfer

Segev et al. [7]

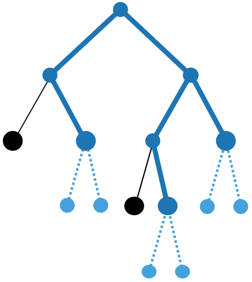
Structure Expansion / Reduction (SER)



Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)

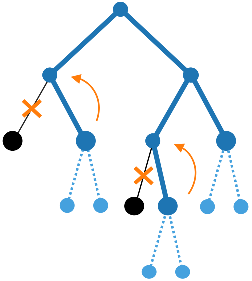


1. Expansion

Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)

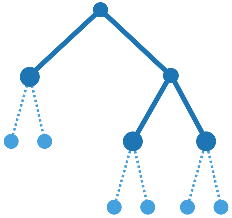


1. Expansion
2. Reduction

Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)



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Model-based transfer

Segev et al. [7]

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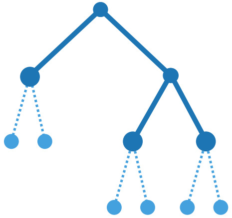
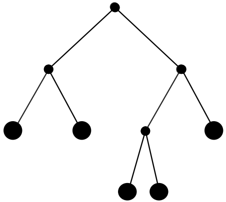


1. Expansion
2. Reduction

Structure Transfer (STRUT)



Model-based transfer

Segev et al. [7]

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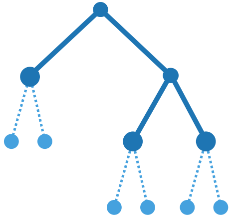

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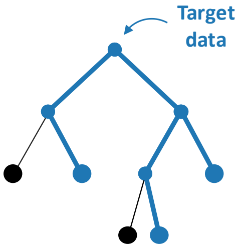
2. Reduction

Structure Transfer (STRUT)



Model-based transfer

Segev et al. [7]

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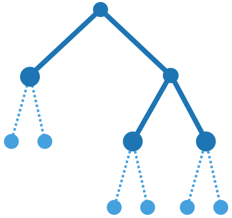
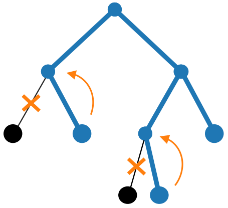


1. Expansion
2. Reduction

Structure Transfer (STRUT)

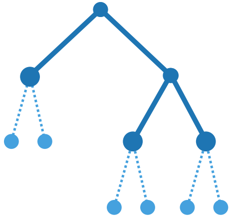


1. Pruning

Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)



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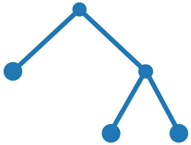

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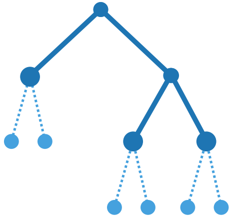
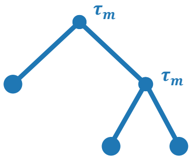


1. Expansion
2. Reduction

Structure Transfer (STRUT)

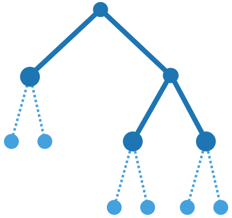


1. Pruning
2. Threshold update

Model-based transfer

Segev et al. [7]

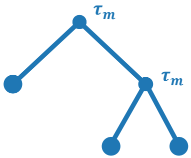
Structure Expansion / Reduction (SER)



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

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Leaf loss risk:

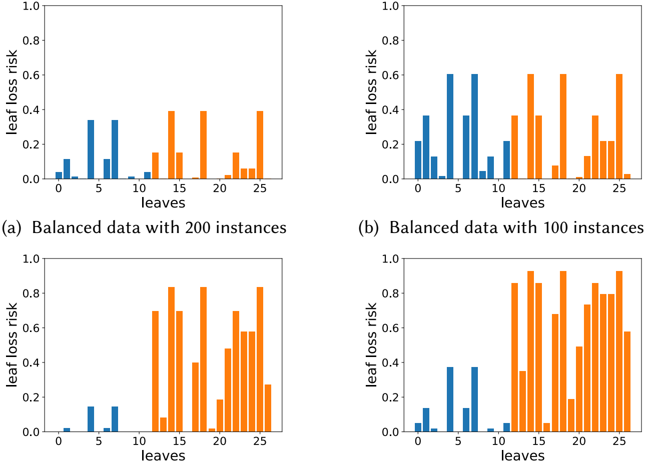
$$R_L(l) = P^T(x \notin l \,|\, y = k_{min})^{n_{k_{min}}}$$

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

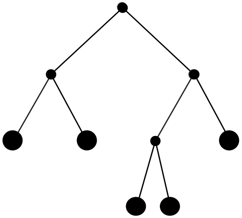
(c) Imbalanced data (10% ratio) with 200 instances

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

SER for class imbalance

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

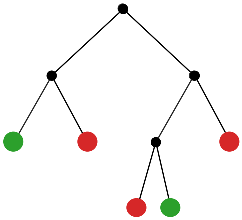
Structure Expansion and controlled Reduction



SER for class imbalance

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

Structure Expansion and controlled Reduction

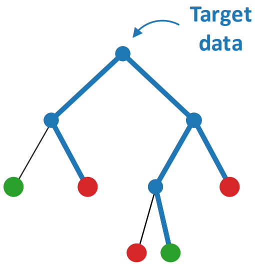


Minority class

SER for class imbalance

SER_R, SER_{LL}

Structure Expansion and controlled Reduction

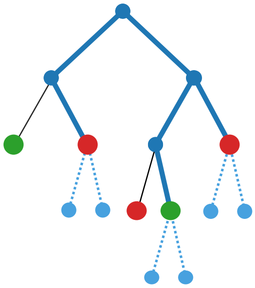


Minority class

SER for class imbalance

SER_R, SER_LL

Structure Expansion and controlled Reduction



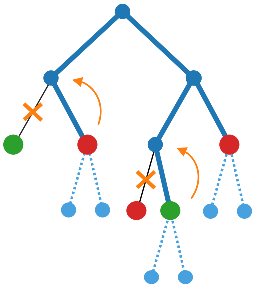
Minority class

- Extension left unchanged

SER for class imbalance

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

Structure Expansion and controlled Reduction



Minority class

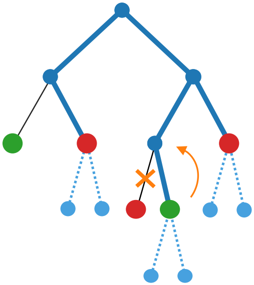
- Extension left unchanged
- Reduction constrained

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



Minority class

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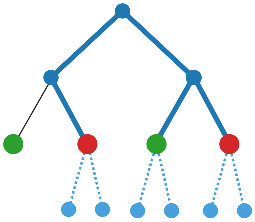
SER for class imbalance

SER_R, SER_LL

Structure Expansion and controlled Reduction



Minority class

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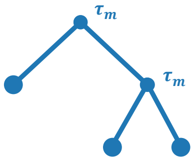
SER_R	SER_LL
If node is of minority class, then no pruning	If node is of minority class **and** still significant considering Target **and** $R_L > 0.5$, then no pruning

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?



STRUT for class imbalance

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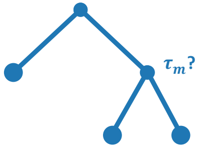

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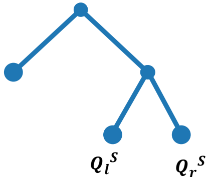
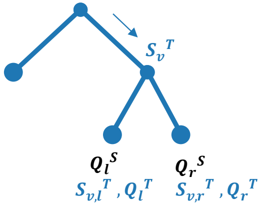


Q_l^S, Q_r^S: class proportions of source data in children w.r.t. the *original* split

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

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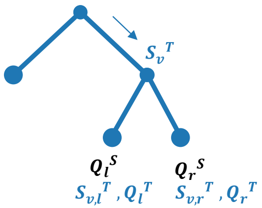

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$S_{v,l}^T$, $S_{v,r}^T$: subsets of S_v^T that fall in the children nodes of v
$Q_l^T(\tau)$, $Q_r^T(\tau)$: class proportions of target data in children w.r.t. the *new* split
Divergence Gain: similarity between the original label distributions and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

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

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

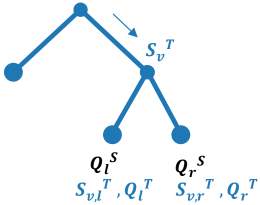
Kullback-Leibler divergence:

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

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?

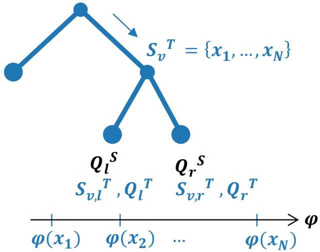


Goal: Maximize DG while being in a local maximum of Information Gain (IG) (here IG = Gini gain)

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?



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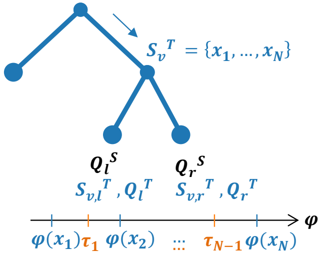

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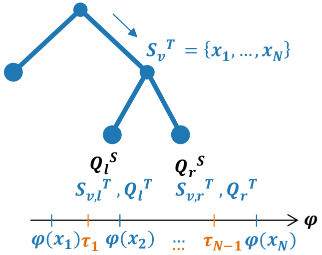


Goal: Maximize DG while being in a local maximum of Information Gain (IG) (here IG = Gini gain)

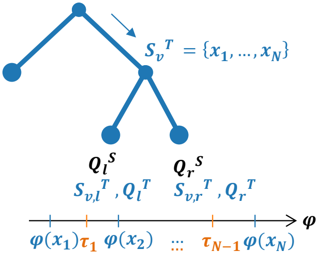
$$\tau_m = \underset{\tau \in \mathrm{T}_v}{\arg\max} \left(DG\left(\tau, Q_l^T(\tau), Q_r^T(\tau)\right)\right)$$

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

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?



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

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

- 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

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

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

STRUT without DG: maximization of IG

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

Framework of homogeneous class imbalance, use

$$p^T(y/x) = \lambda_y \frac{p^S(y/x)}{\int \lambda_y p^S(y/x)dy} \tag{2}$$

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

STRUT_{IG}, STRUT_{HI}

STRUT_{IG}

STRUT without DG: maximization of IG

STRUT_{HI}

Framework of homogeneous class imbalance, use

$$p^T(y/x) = \lambda_y \frac{p^S(y/x)}{\int \lambda_y p^S(y/x)dy} \tag{2}$$

to change the source class proportions in DG:

$$Q_l^{S\prime} = \lambda_k \frac{Q_l^S}{\sum\limits_k \lambda_k Q_l^S} \qquad Q_r^{S\prime} = \lambda_k \frac{Q_r^S}{\sum\limits_k \lambda_k Q_r^S}$$

STRUT_{HI} can be seen as a generalization of STRUT

Data

Gaussian Generator

Each dataset consists of a combination of several Gaussian cluster. For each class k with N_k clusters of this class :

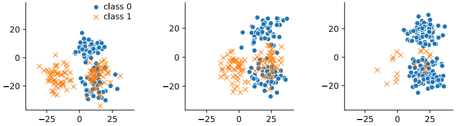
$$C^k = \{\mathcal{N}(\mu_1, \sigma_1), ..., \mathcal{N}(\mu_{N_k}, \sigma_{N_k})\}$$

$$\forall k, (X, Y = k) \sim \sum_{j=1}^{N_k} w_j^k \mathcal{N}(\mu_j, \sigma_j)$$

Dataset synthetic transformations

Some basics synthetic transformations on Source clusters are applied to get a Target dataset

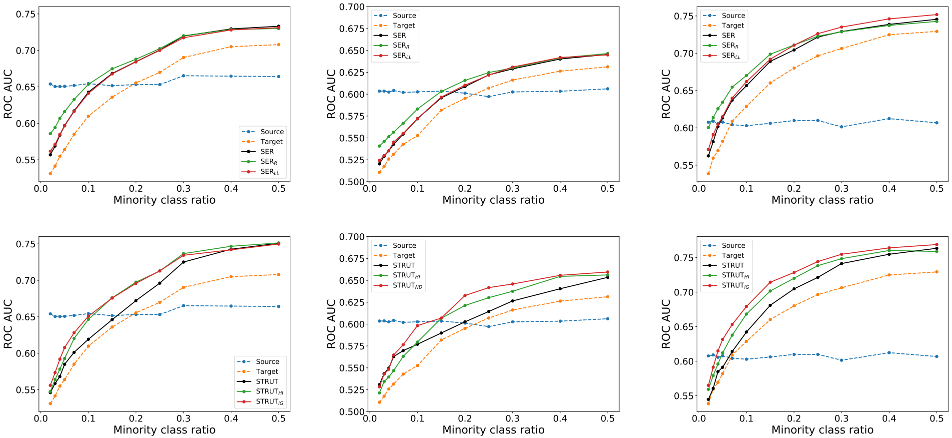
- Imbalance : Clusters weights changes (w_j^k)
- Drifts (μ_j)
- Squeezes and Stretches (σ_j)
- Adding or removing clusters



Source data... ...after a drift... ...and homogeneous imbalance

Results

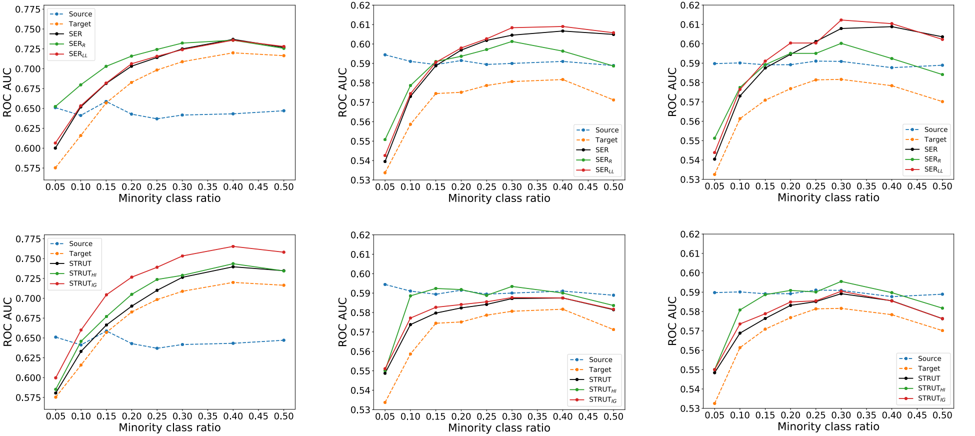
Synthetic data



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

Results

Real data

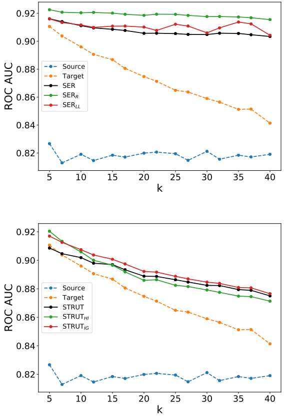


(a) Magic Gamma Telescope (b) Office-Caltech: *amazon* $\rightarrow$ *webcam* (c) Office-Caltech: *caltech* $\rightarrow$ *webcam*

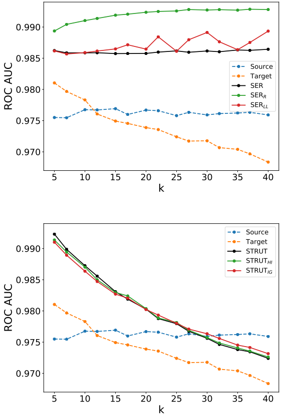
Results

Fall data

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



(a) Decision tree model



(b) Random forest model with 10 decision trees

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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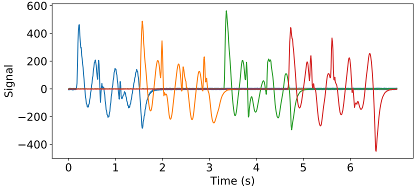
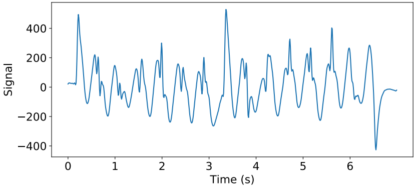


(a) Raw signal



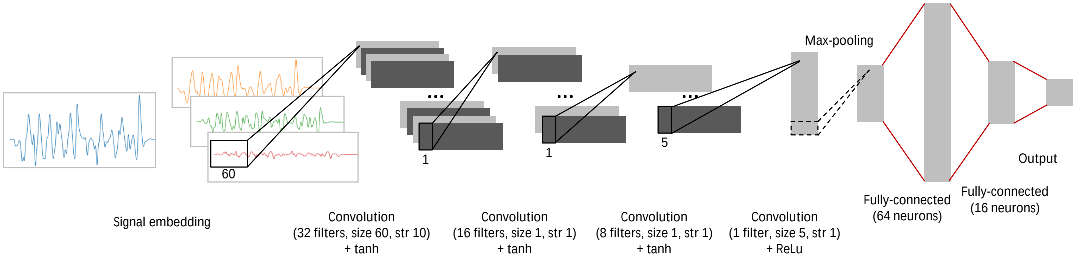
(b) Preprocessed signal

- 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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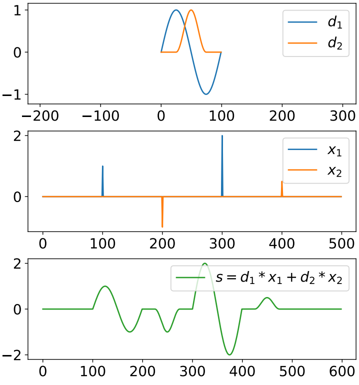

Convolutional representation

Signal embedding

Convolutional dictionary learning

- $\mathbf{s}$: data to be represented
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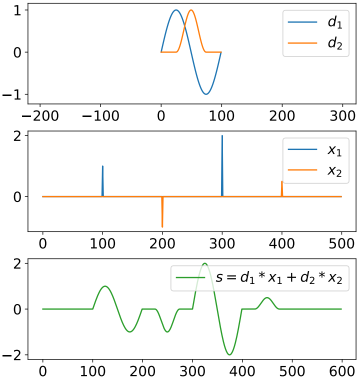
$$\mathbf{s} \approx \sum_{m=1}^{M} \mathbf{x}_m * \mathbf{d}_m$$

- $*$: convolution

CDL general problem:

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

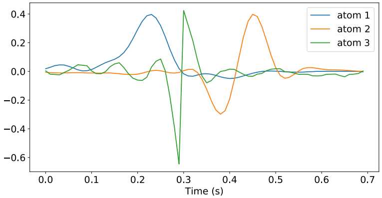


Convolutional representation

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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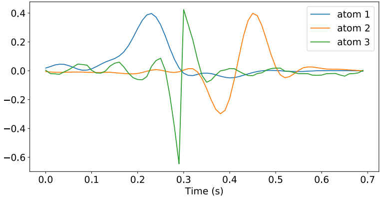

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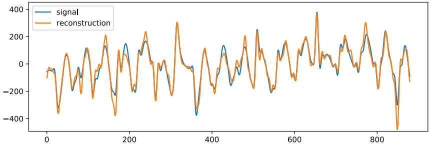
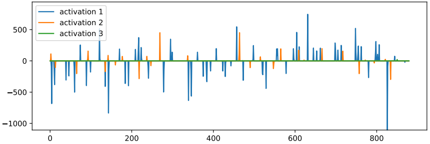


(a) Original signal and its reconstruction



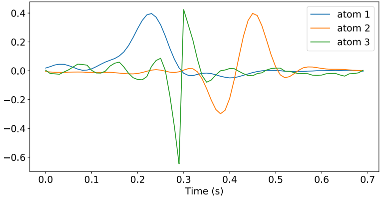
(b) Signal activations

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:

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



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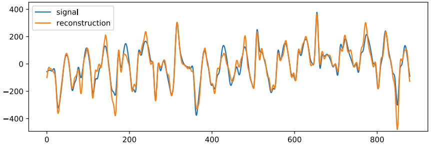

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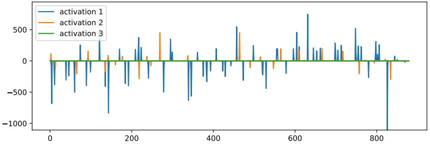
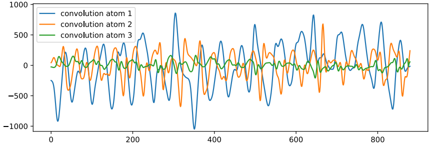


(b) Signal activations



(c) Embedding

Region proposal network

Object detection

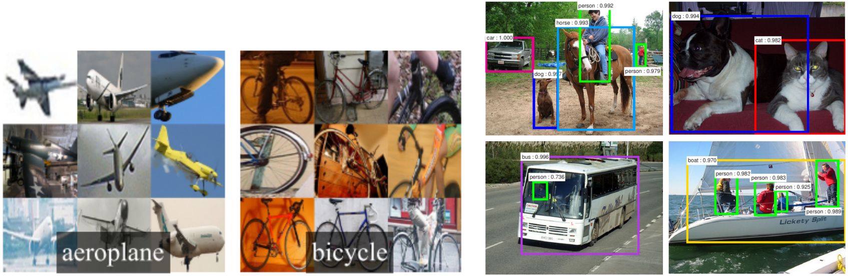
- Classification: What is the image class ?

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 ?

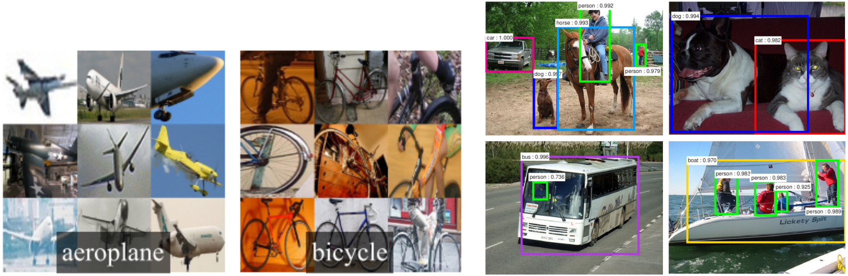


Classification vs Object detection. Source: Girshick et al. [4], Ren et al. [6]

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])

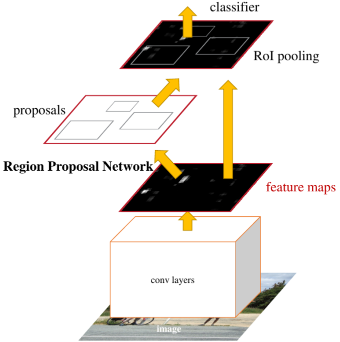


Classification vs Object detection. Source: Girshick et al. [4], Ren et al. [6]

Region proposal network

Faster R-CNN

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

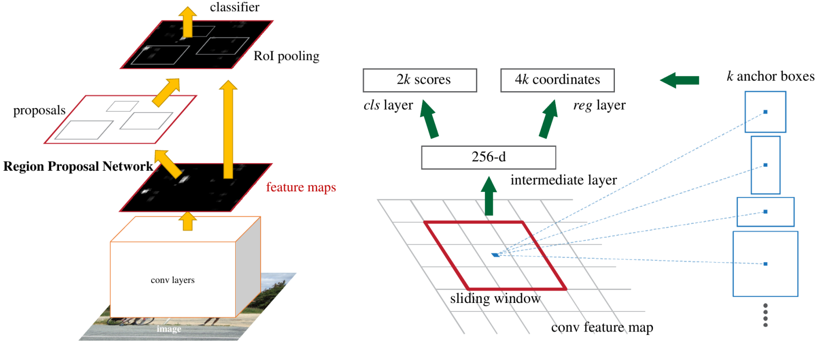


Region proposal network. Source: Ren et al. [6]

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)

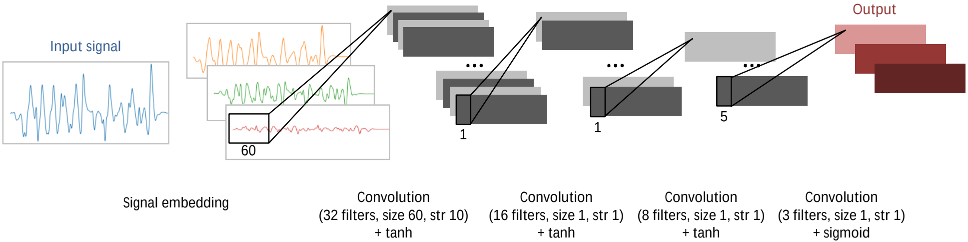


Region proposal network. Source: Ren et al. [6]

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



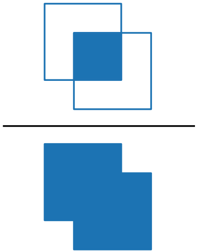
Architecture of SPN

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:

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



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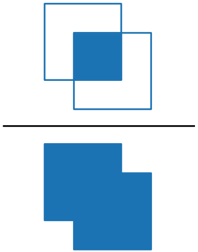
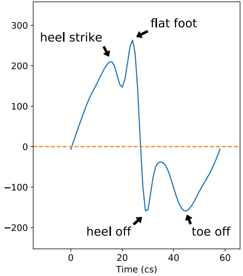
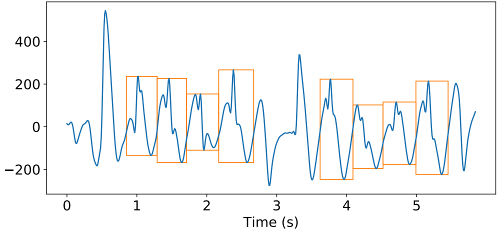




(a) Step signal



(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:

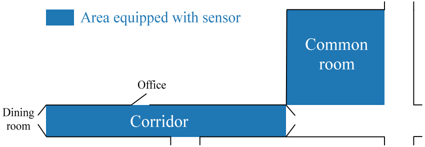
$$\mathcal{L}(\mathbf{s}, \mathbf{W}) = \sum_t \sum_{k \in [1,2,3]} \mathbb{1}_{\mathrm{IoU}(b_t^k) > \sqrt{0.7}} \log(\mathbf{W}_{t,k}) + \mathbb{1}_{\mathrm{IoU}(b_t^k) < \sqrt{0.3}} \log(1 - \mathbf{W}_{t,k}).$$

Step proposal network

Results

Data

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



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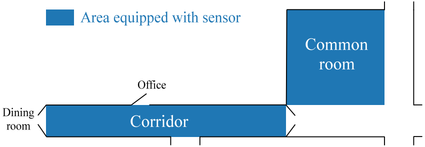

Training

- 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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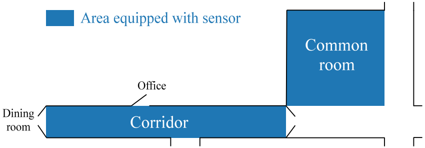

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Results

- 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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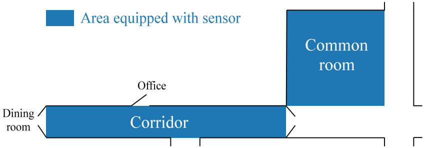

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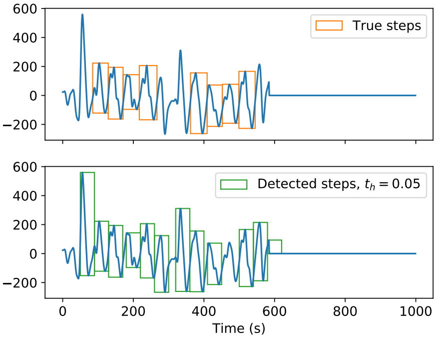

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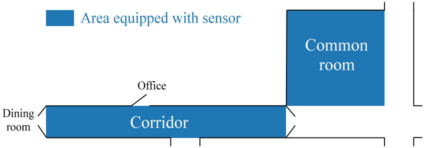

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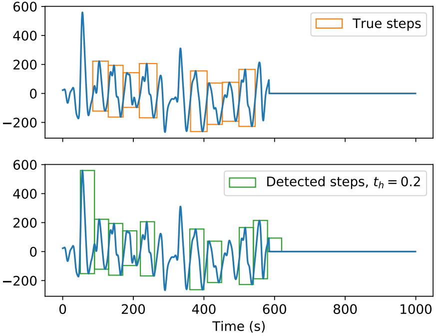

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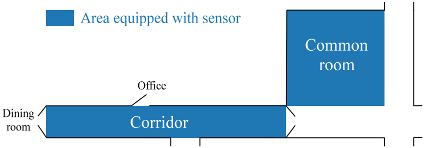

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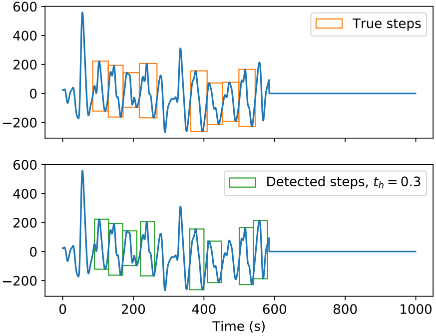

Classification

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
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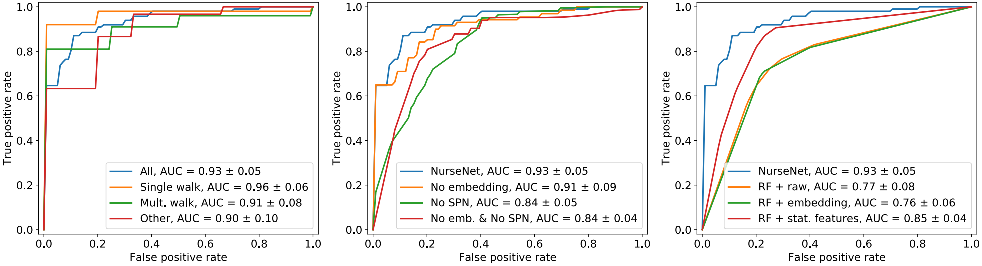

(a) NurseNet results

(b) NurseNet ablation analysis

(c) NurseNet and several RF-based models

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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[1] Leo Breiman. Random forests. *Machine Learning*, 45(1):5–32, 2001.

[2] Leo Breiman, Jerome H. Friedman, Richard A. Olshen, and Charles J. Stone. *Classification and regression trees.* Monterey, CA: Wadsworth & Brooks/Cole Advanced Books & Software, 1984.

[3] Hilton Bristow, Anders Eriksson, and Simon Lucey. Fast convolutional sparse coding. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, June 2013.

[4] R. Girshick, J. Donahue, T. Darrell, and J. Malik. Rich feature hierarchies for accurate object detection and semantic segmentation. In *2014 IEEE Conference on Computer Vision and Pattern Recognition*, pages 580–587, 2014.

[5] J. Hosang, R. Benenson, P. Dollár, and B. Schiele. What makes for effective detection proposals? *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 38(4):814–830, 2016.

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[7] N. Segev, M. Harel, S. Mannor, K. Crammer, and R. El-Yaniv. Learn on source, refine on target: A model transfer learning framework with random forests. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 39(9):1811–1824, Sep. 2017.