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

Soutenance de thèse

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Thèse industrielle entre l'ENS Paris-Saclay et Tarkett

Mercredi 15 Juillet 2020

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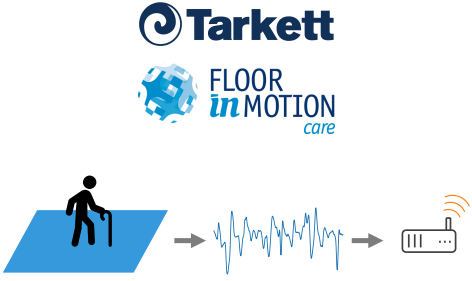
Introduction

Context

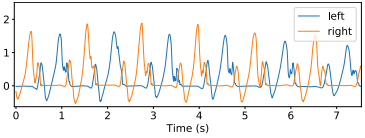
- Elderly population is growing
- Higher levels of frailty globally
- Increasing demand for reliable monitoring devices
- Tarkett, French company with 12,500 employees, 13 industrial sites, sells 1.3 millions m^2 of flooring every day
- *Floor in Motion*: a floor-based sensor for elderly care
- **Objective**: providing tools for elderly monitoring in nursing homes
  - First aimed application: fall detection



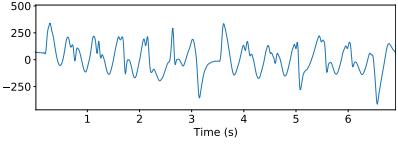
Introduction

Motivation

- Processing and understanding time series
  - Proliferation of sensor-based systems
  - Redundancy, interpretability, external pertubations
- Real world application
  - Real-time processing in a limited system
  - Convenient hypotheses not granted



Foot-attached accelerometer



Tarkett's floor sensor

A tour of monitoring systems

Systems

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
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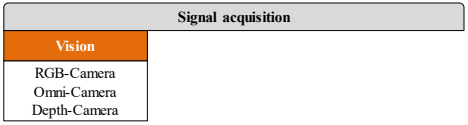

Criteria	RGB cam	Depth cam
Coverage/Occlusion	★☆☆	★☆☆
Intrusiveness	★☆☆	★☆☆
Signal quality / info	★★★	★★★
Robustness	★★☆	★★★
Ease of instal. / use	★☆☆	★☆☆
Scalability	★☆☆	★☆☆

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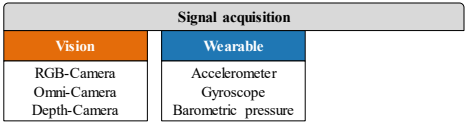

Criteria	RGB cam	Depth cam	Wearable
Coverage/Occlusion	★☆☆	★☆☆	★★★
Intrusiveness	★☆☆	★☆☆	★★☆
Signal quality / info	★★★	★★★	★★☆
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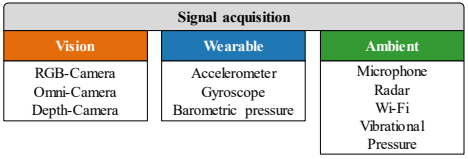


Criteria	RGB cam	Depth cam	Wearable	Acoustic	Radar / Wi-Fi	Vibration	Floor
Coverage/Occlusion	★☆☆	★☆☆	★★★	★★☆	★☆☆	★★★	★★★
Intrusiveness	★☆☆	★☆☆	★★☆	★☆☆	★★☆	★★★	★★★
Signal quality / info	★★★	★★★	★★☆	★★☆	★☆☆	★★☆	★★☆
Robustness	★★☆	★★★	★★★	★☆☆	★☆☆	★☆☆	★★☆
Ease of instal. / use	★☆☆	★☆☆	★★☆	★★☆	★★☆	★★★	★☆☆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

A tour of monitoring systems

Information extraction

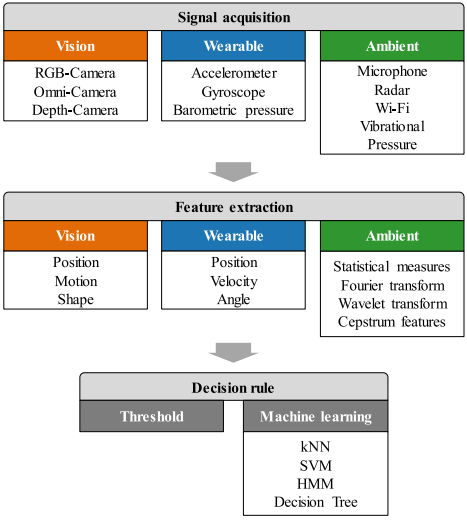
How to process the inputs ?

- 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...)



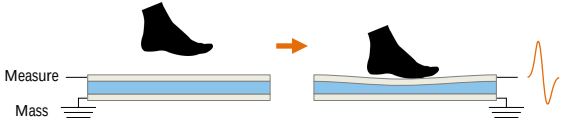
A tour of monitoring systems

Tarkett sensor

- Piezoelectric principle:

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

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



A tour of monitoring systems

Tarkett sensor

- Piezoelectric principle:

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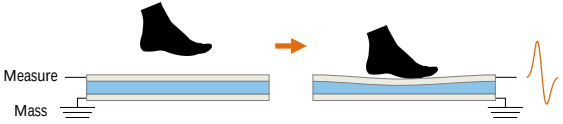
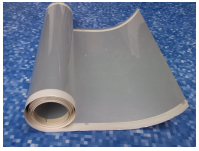
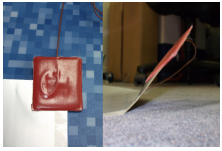
- How does this look like ?
0.3 mm thick and 60 cm wide roll with customizable length







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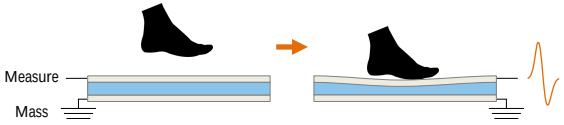
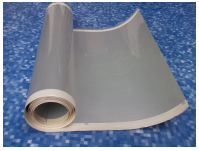
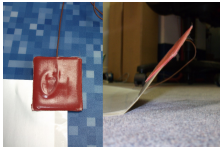
$$d = \frac{Q}{F},$$

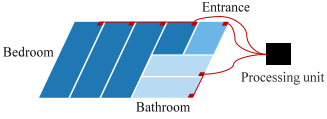
(simple version) with d the *piezoelectric constant*.
When stressed or squeezed, the material emits charges.

- How does this look like ?
0.3 mm thick and 60 cm wide roll with customizable length
- How is it installed ?
  - Under the flooring
  - Several connected bands for each area, hence one area corresponds to one input







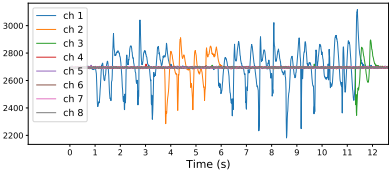


Fall detection

Data

Preprocessing

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



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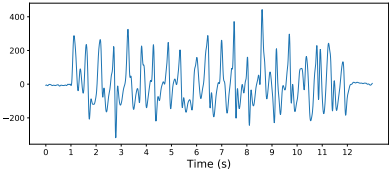

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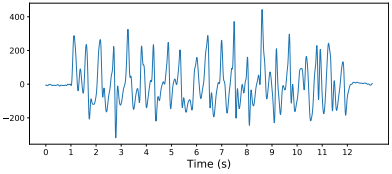
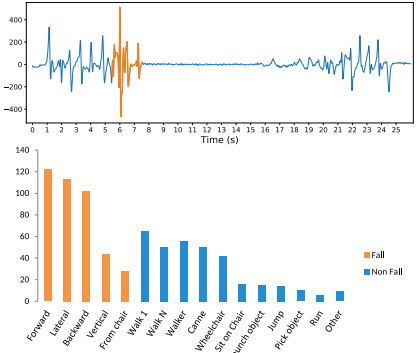


Experimental dataset

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

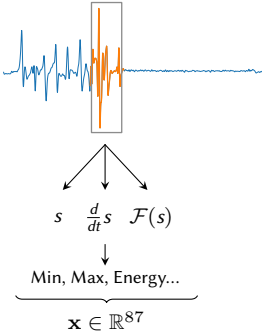


Fall detection

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



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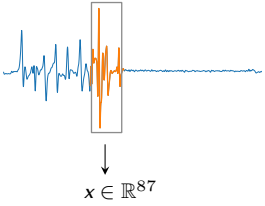

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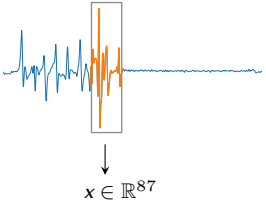


3. Classification model: Random Forest [Breiman, 2001], based on **decision trees**

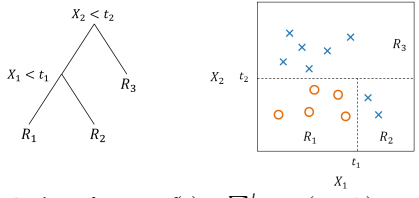
Decision tree

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 [Breiman et al., 1984] 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: $f(x) = \sum_{j=1}^{J} c_j \mathbb{1}(x \in R_j)$

Fall detection

Method

Random forest

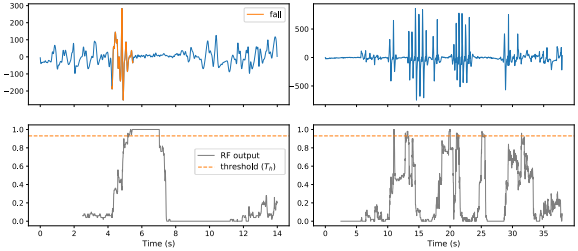
Decision trees $d_1, ..., d_{N_T}$ grown with two rules:

- 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

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

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



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

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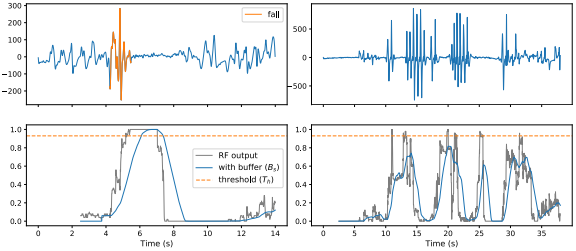

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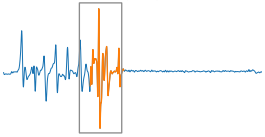
Fall detection

Method

Data augmentation

Select r windows in training signals



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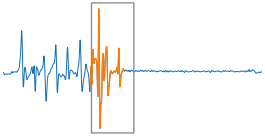


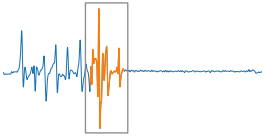
$$\begin{bmatrix} x_{1,1} & \dots & x_{1,Q} \\ x_{2,1} & \dots & x_{2,Q} \\ & & \end{bmatrix}$$

Fall detection

Method

Data augmentation

Select r windows in training signals



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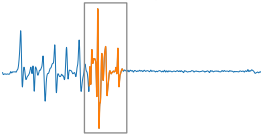

$$\begin{bmatrix} x_{1,1} & \cdots & x_{1,Q} \\ \vdots & & \vdots \\ x_{r,1} & \cdots & x_{r,Q} \end{bmatrix}$$

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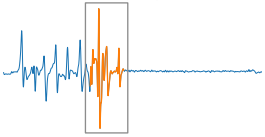

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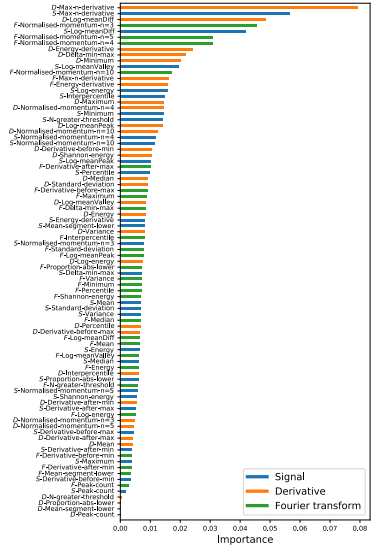
Feature reduction

Feature importance

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

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



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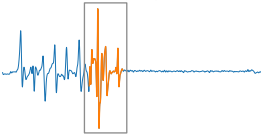

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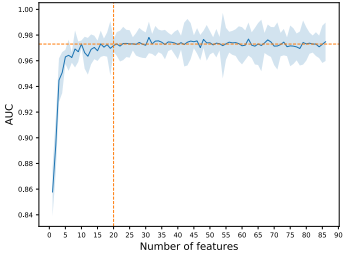
$$\text{Random forest: } I(X_q) = \frac{1}{N_T}\sum_{n=1}^{N_T} I(T_n, X_q)$$

Recursive feature elimination

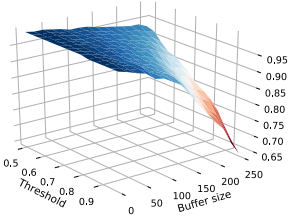
Initial pool of Q features $X_1, \dots, X_Q$.

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

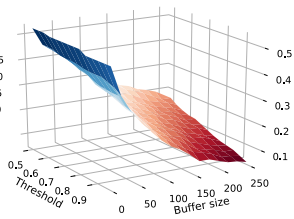


Fall detection

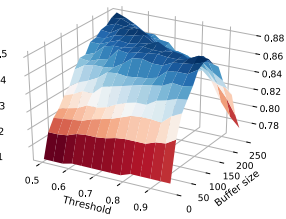
Results



True positive rate



False positive rate



Accuracy

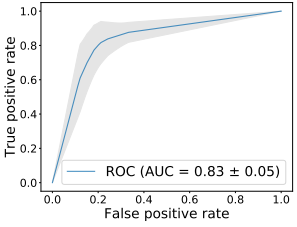
Model	Accuracy	TPR	FPR	$\text{TPR}_{\text{min}}^{\text{FPR}<10}$	$\text{TPR}_{\text{max}}^{\text{FPR}<10}$
			$r = 5,\ Q = 20$		
LR	86.8 ± 1.5	90.5 ± 2.4	17.7 ± 4.9	67.0 ± 10.8	80.4 ± 6.4
LDA	85.5 ± 1.2	91.0 ± 2.1	21.7 ± 3.7	56.9 ± 7.0	78.7 ± 3.8
k-NN	87.0 ± 1.9	89.2 ± 1.4	**16.0 ± 4.7**	63.1 ± 4.2	83.1 ± 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

Transfer learning on decision tree

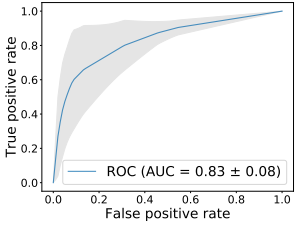
Experimental vs. operational

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

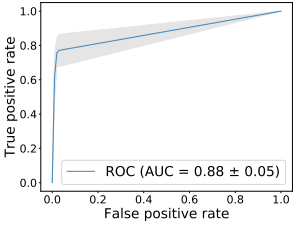
- $\mathcal{X}_S = \mathcal{X}_T$
- $P(X_S) \neq P(X_T)$
- $\mathcal{Y}_S = \mathcal{Y}_T$
- $P(Y_S|X_S) \neq P(Y_T|X_T)$



Source tested on source



Source tested on target

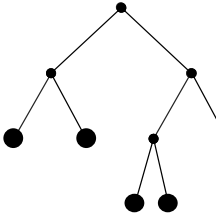


Target tested on target

Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



1. Expansion
2. Reduction

Partition refinement or simplification

Structure Transfer

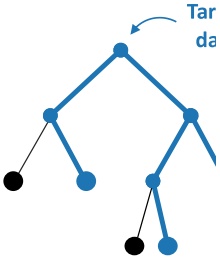
1. Pruning
2. Threshold update

Drifts

Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



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Partition refinement or simplification

Structure Transfer

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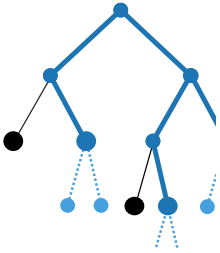
Drifts

Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



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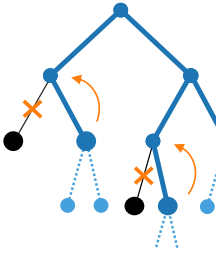
Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



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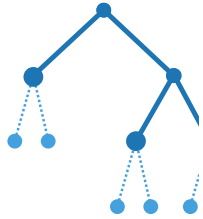
Structure Expansion / Reduction (SER)



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Partition refinement or simplification

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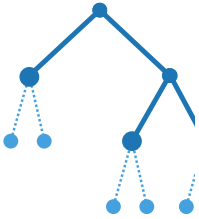
Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



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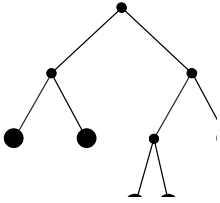
2. Reduction

Partition refinement or simplification

Structure Transfer



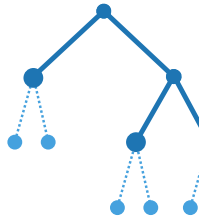
1. Pruning
2. Threshold update

Drifts

Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



1. Expansion
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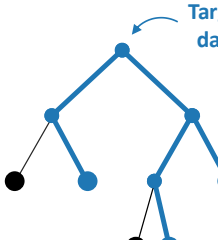
Partition refinement or simplification

Structure Transfer



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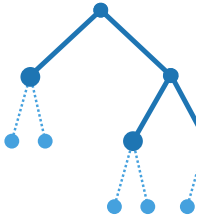
Drifts

Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



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Partition refinement or simplification

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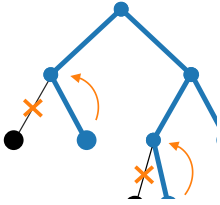

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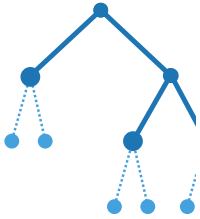
Drifts

Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



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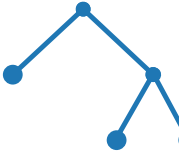

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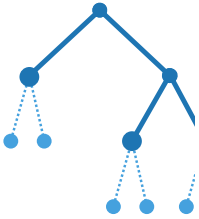
Drifts

Transfer learning on decision tree

Model-based transfer

Structure Expansion / Reduction (SER)



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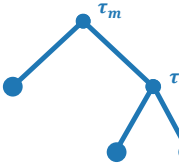
Structure Transfer



1. Pruning
2. Threshold update

Drifts

Transfer learning on decision tree

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 $\lambda_y = \frac{p_y^T}{p_y^S}$

Transfer learning on decision tree

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with $\lambda_y = \frac{p_y^T}{p_y^S}$

Leaf loss risk

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

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

Risk of losing the leaf:

$$R_{n_{k_{min}}}(l) = p^T(x \notin l/y = k_{min})^{n_{k_{min}}}$$

Transfer learning on decision tree

Leaf loss risk

Homogeneous class imbalance

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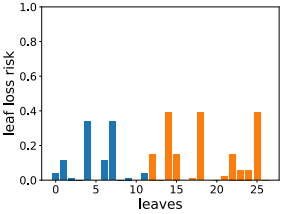
In homogeneous class imbalance:

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

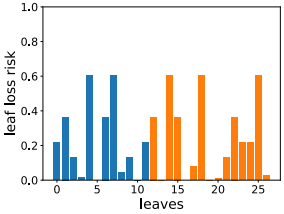
$$R_{n_{k_{min}}}(l) = p^S(x \notin l/y = k_{min})^{n_{k_{min}}}$$

Transfer learning on decision tree

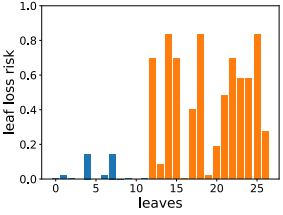
Leaf loss risk



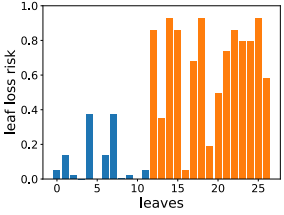
(a) Balanced data with 200 instances



(b) Balanced data with 100 instances



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

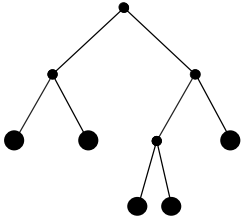


(d) Imbalanced data (10% ratio) with 100 instances

Transfer learning on decision tree

SER for class imbalance

Structure Expansion/Reduction



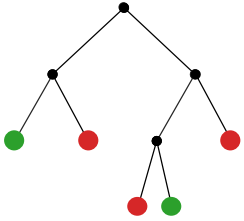
- Extension left unchanged
- Reduction constrained

Minority class

Transfer learning on decision tree

SER for class imbalance

Structure Expansion/Reduction



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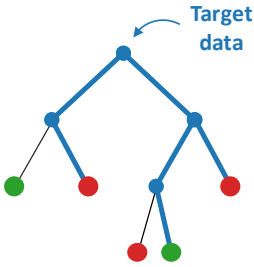
Minority class

Transfer learning on decision tree

SER for class imbalance

Structure Expansion/Reduction



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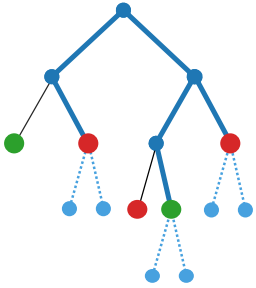
Minority class

Transfer learning on decision tree

SER for class imbalance

Structure Expansion/Reduction



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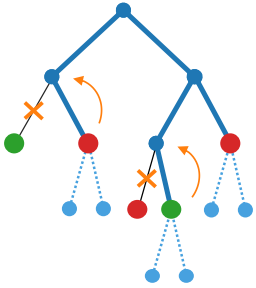
Transfer learning on decision tree

SER for class imbalance

Structure Expansion/Reduction



Minority class

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Transfer learning on decision tree

SER for class imbalance

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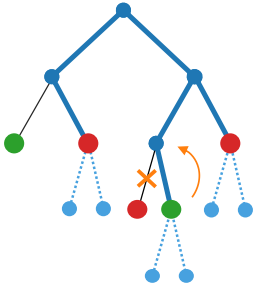

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SER for class imbalance

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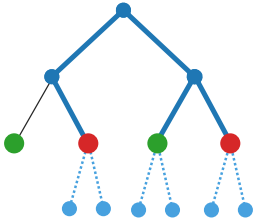

Minority class

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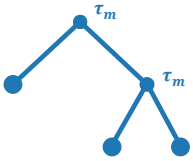
Transfer learning on decision tree

STRUT optimization

STRUT



Transfer learning on decision tree

STRUT optimization

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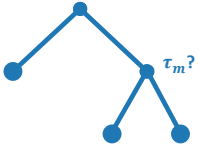

Transfer learning on decision tree

STRUT optimization

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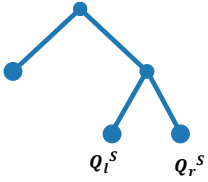


Q_l^S, Q_r^S: class proportions of source data in children w.r.t. the *original* split

Transfer learning on decision tree

STRUT optimization

STRUT

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

Transfer learning on decision tree

STRUT optimization

STRUT

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:

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

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

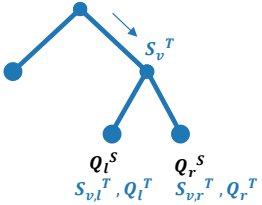
Kullback-Leibler divergence:

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

Transfer learning on decision tree

STRUT optimization

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



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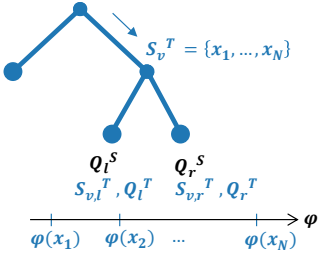

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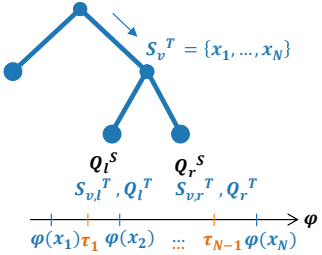

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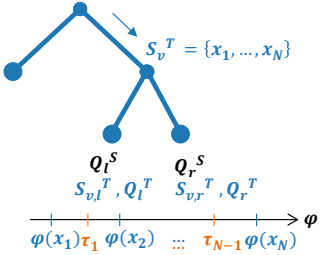

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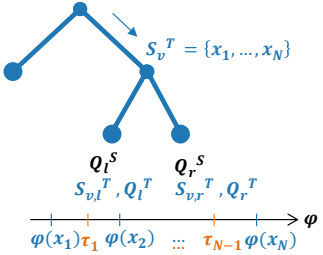
$$\tau_m = \underset{\tau \in \mathrm{T}_v}{\arg\max} \left(DG\left(\tau, Q_l^T(\tau), Q_r^T(\tau)\right)\right)$$

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

Transfer learning on decision tree

STRUT optimization



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

Introduction

- **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
- A model to recognize steps ?

Introduction

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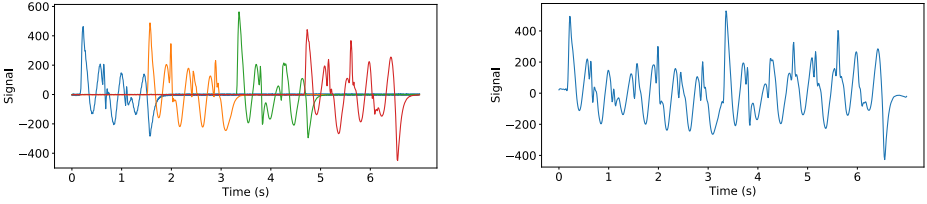

(a) Raw signal (b) Preprocessed signal

Figure: Healthy individual walking on the sensor.

- Signals are complex
- How to **localize** steps ?
- **This presentation:** A step detector using convolutional neural network: Step Proposal Network

Region proposal network

Object detection

- Classification: What is the image class ?

Figure: Classification vs Object detection. Source: [Girshick et al., 2014], [Ren et al., 2015]

Region proposal network

Object detection

- Classification: What is the image class ?
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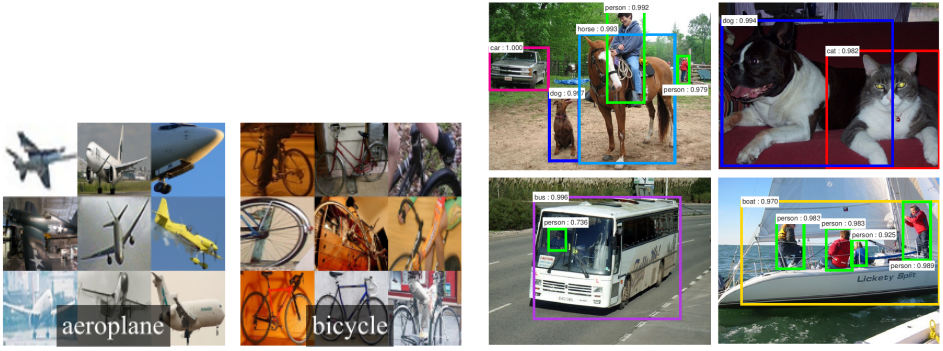

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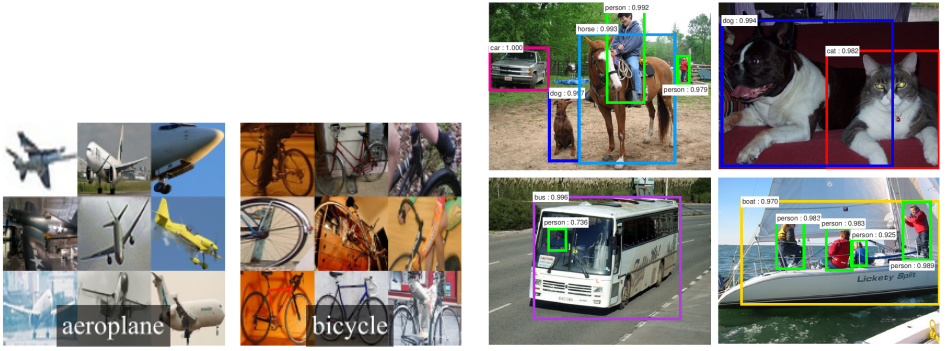
Region proposal network

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., 2016]
- Faster R-CNN [Ren et al., 2015]



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Region proposal network

Faster R-CNN

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

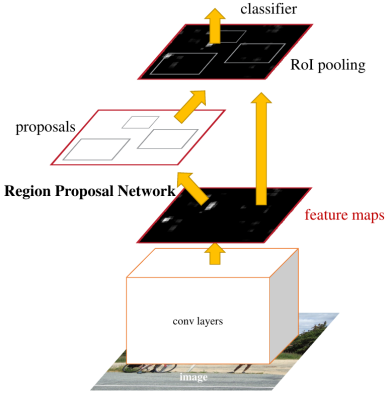

Figure: Region proposal network. Source: [Ren et al., 2015]

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)

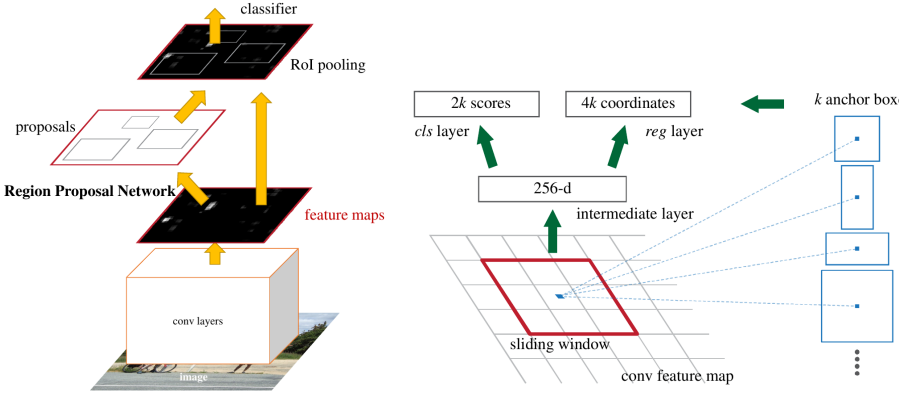

Figure: Region proposal network. Source: [Ren et al., 2015]

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

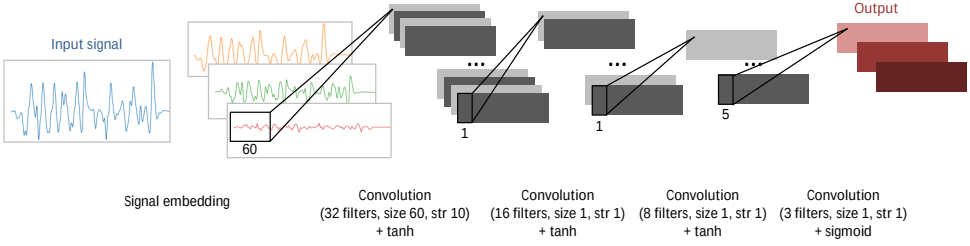

Figure: Architecture of SPN .

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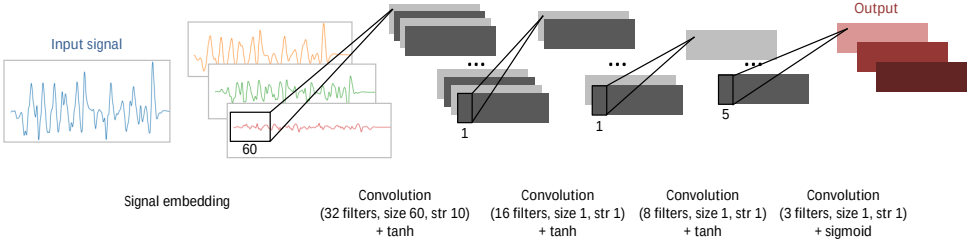

Figure: Architecture of SPN .

- Use the convolutional representation to “boost” training
- First layer (Signal embedding) of SPN 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

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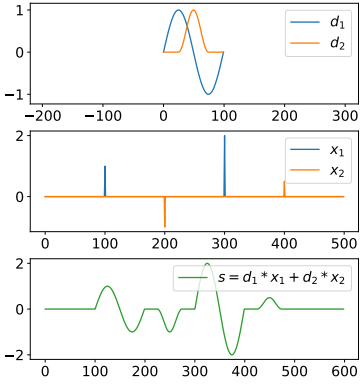

Figure: Convolutional dictionary learning.

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CDL general problem:

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

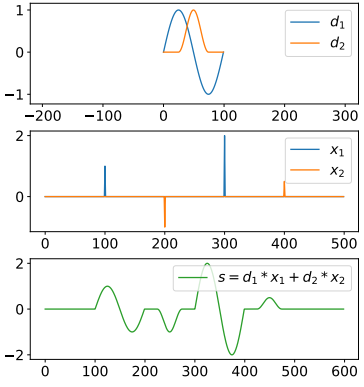

Figure: Convolutional dictionary learning.

Signal embedding

Learning step atoms

- Learning with Alternating Direction Method of Multipliers (ADMM) [Bristow et al., 2013]
- 3 atoms of length 0.7 second

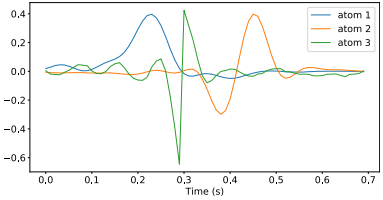

Figure: Dictionary.

Signal embedding

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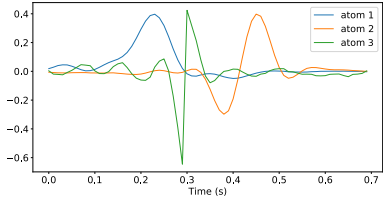

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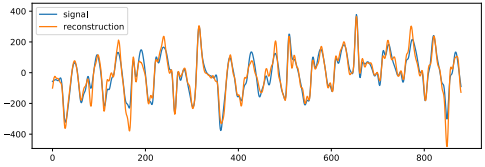
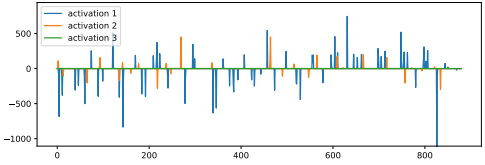


(a) Original signal and its reconstruction



(b) Signal activations

Signal embedding

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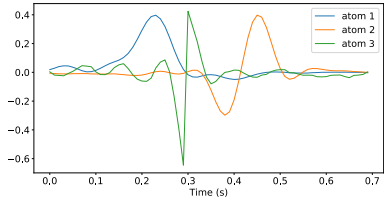
$$\mathbf{S} \doteq \left(\mathbf{s} * \mathbf{d}_m\right)_{1 \leq m \leq 3}$$



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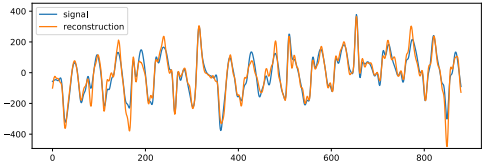

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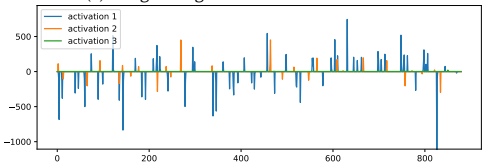

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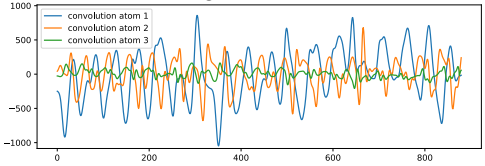

(c) Embedding

Signal embedding

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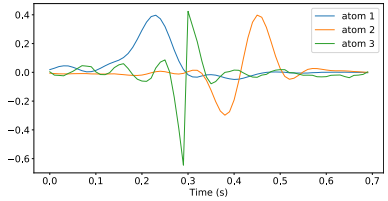

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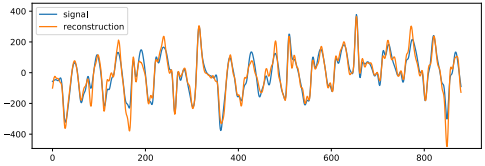

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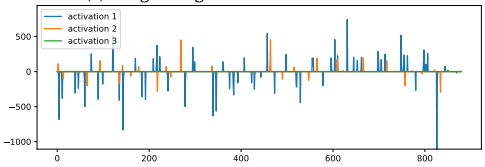

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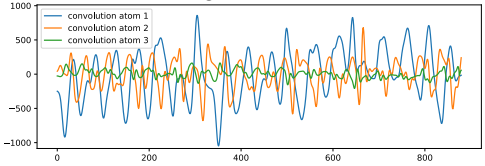


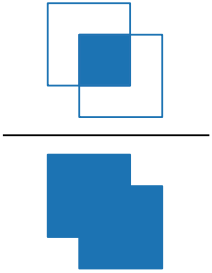
(c) Embedding

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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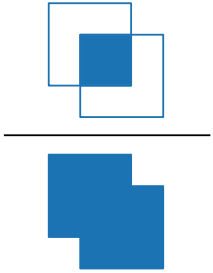

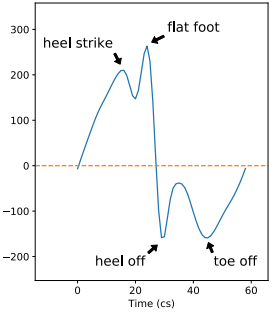

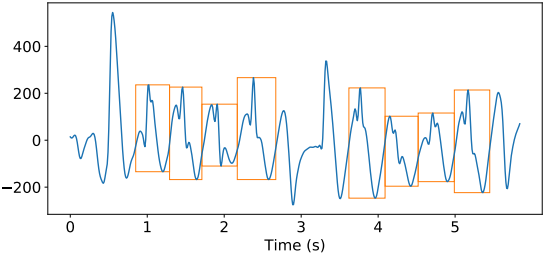

Step proposal network

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:

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

Results

Data

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

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

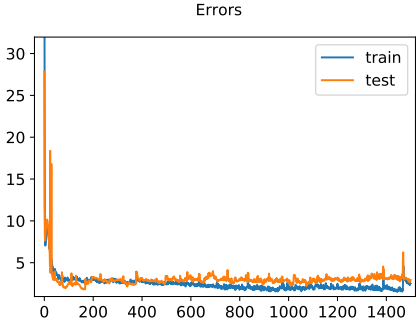

Figure: SPN training and testing errors.

Results

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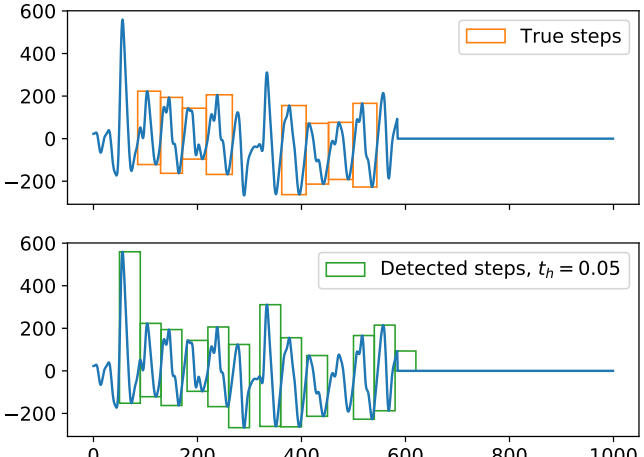

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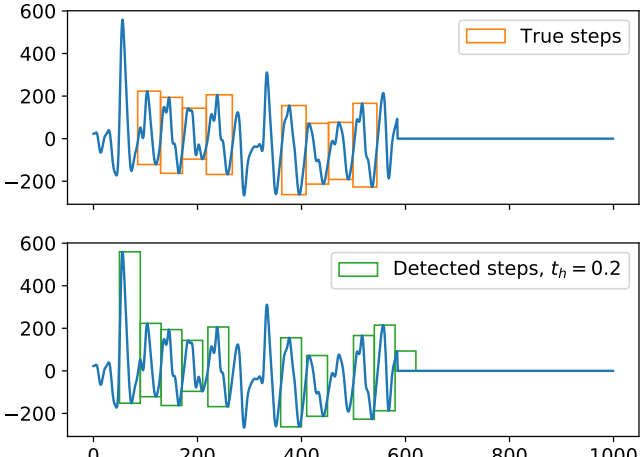

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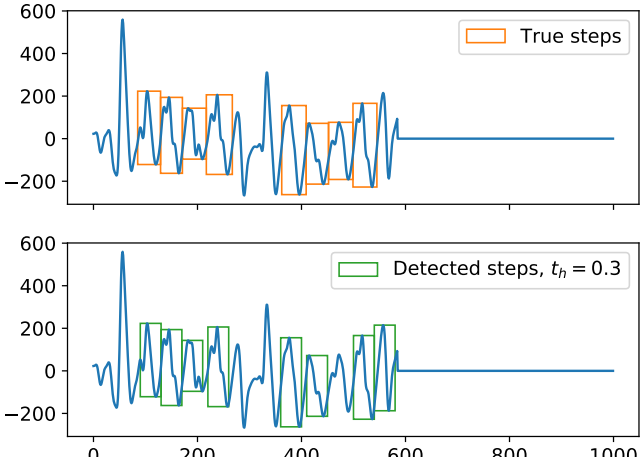

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- Training and inference are fast

Future work

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- Tests on step detection benchmarks data sets

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Thanks

Contact: minvielle@cmla.ens-cachan.fr

Reference: L. Minvielle and J. Audiffren. Nursenet : Monitoring elderly levels of activity with a piezoelectric floor. Sensors, 19(18), 2019 link

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