

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 m² of flooring per day
- ▶ *Floor in Motion*: a floor-based sensor for elderly care

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Objective

Providing tools for elderly monitoring
in nursing homes



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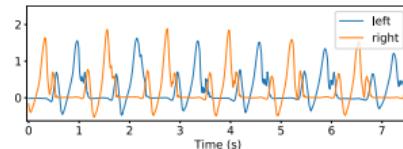


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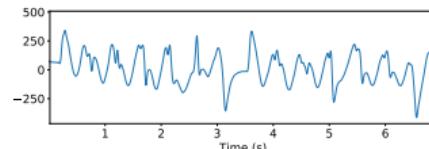
Providing tools for elderly monitoring
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Scientific context

- ▶ Processing and understanding time series
- ▶ Real world application



Foot-attached accelerometer



Tarkett's floor sensor

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3. Transfer learning
4. Elderly activity recognition
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Monitoring systems for fall detection

Sensors

What makes a good monitoring system ?

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

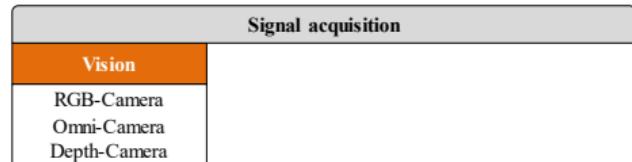
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Intrusiveness
Signal quality / info
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Criteria	RGB cam	Depth cam
Coverage/Occlusion	★☆☆	★☆☆
Intrusiveness	★☆☆	★☆☆
Signal quality / info	★★★	★★★
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Signal acquisition	
Vision	Wearable
RGB-Camera	
Omni-Camera	Accelerometer
Depth-Camera	Gyroscope
	Barometric pressure

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

What makes a good monitoring system ?

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

Criteria	RGB cam	Depth cam	Wearable	Acoustic	Radar / Wi-Fi	Vibration	Floor
Coverage/Occlusion	★☆☆	★☆☆	★★★	★☆☆	★☆☆	★★★	★★★
Intrusiveness	★☆☆	★☆☆	★☆☆	★☆☆	★☆☆	★★★	★★★
Signal quality / info	★★★	★★★	★☆☆	★☆☆	★☆☆	★☆☆	★☆☆
Robustness	★☆☆	★★★	★★★	★☆☆	★☆☆	★☆☆	★☆☆
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Information extraction

How to process the inputs ?

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

Signal acquisition		
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RGB-Camera	Accelerometer	Microphone
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Depth-Camera	Barometric pressure	Wi-Fi
		Vibrational
		Pressure



Feature extraction		
Vision	Wearable	Ambient
Position	Position	Statistical measures
Motion	Velocity	Fourier transform
Shape	Angle	Wavelet transform
		Cepstrum features

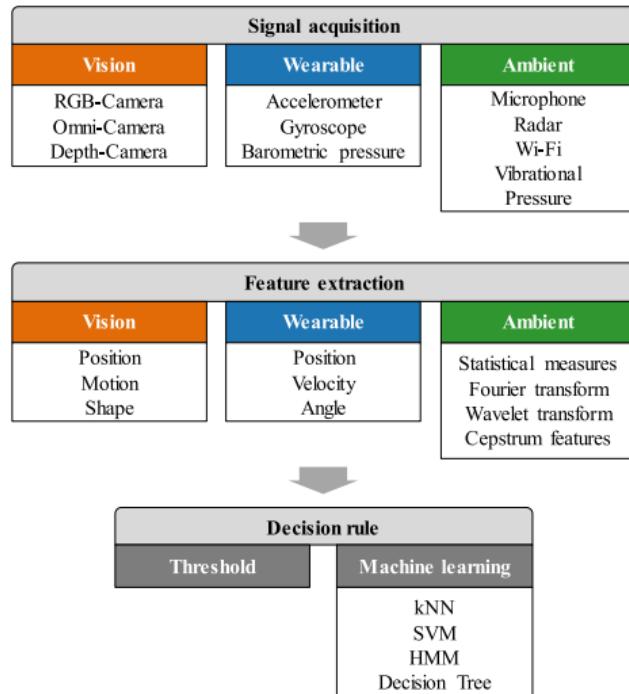
Information extraction

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 feature signals ?

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



A fall detection system

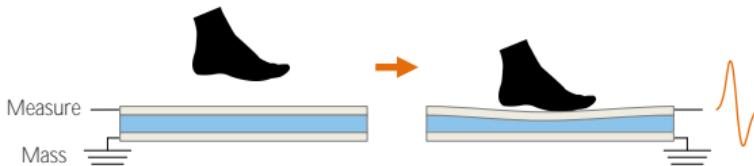
Tarkett sensor

- ▶ Piezoelectric principle:

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

(simple version) with d the *piezoelectric constant*.

When stressed or squeezed, the material emits charges.



Tarkett sensor

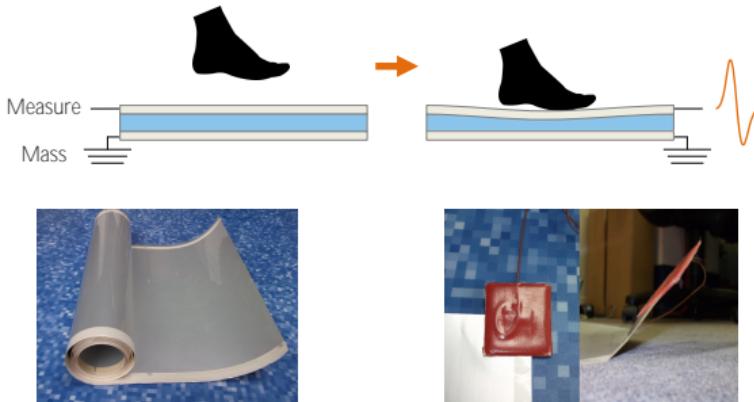
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- ▶ How does this look like ?
0.3 mm thick and 60 cm wide roll
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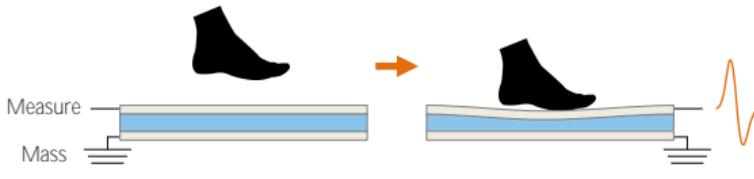
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When stressed or squeezed, the material emits charges.

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

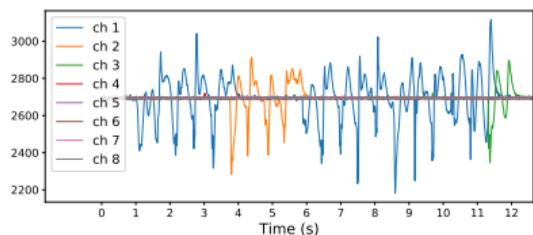
- ▶ Under the flooring
- ▶ Several connected bands for each area, hence one area corresponds to one input



Data

Preprocessing

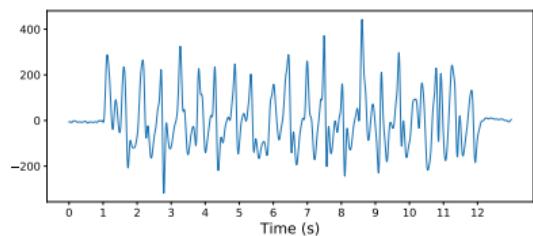
- ▶ linear detrending
- ▶ low-pass filtering
- ▶ zeroing low energy channels
- ▶ sum over all channels



Data

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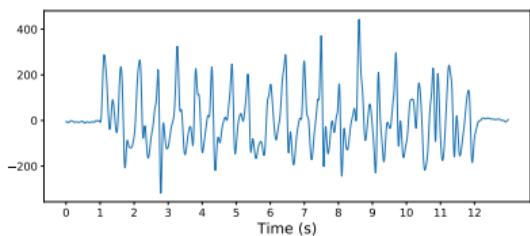
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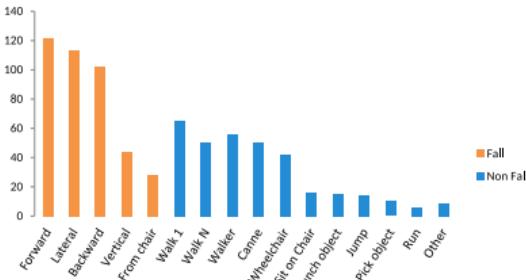
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Experimental dataset

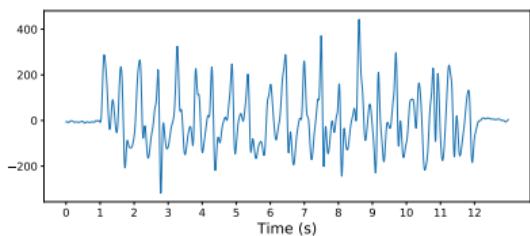
- ▶ 742 signals collected in **controlled environment**
- ▶ 55% *fall*, 45% *non-fall*
- ▶ varied fall events (forward, backward...) and activities of daily living (walking, sitting...)



Data

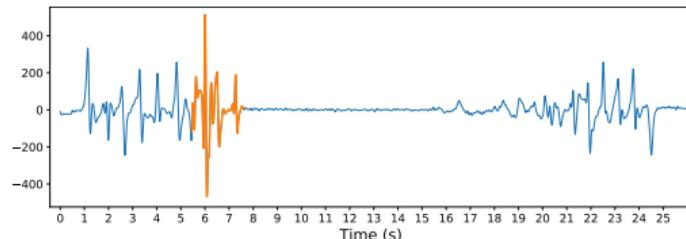
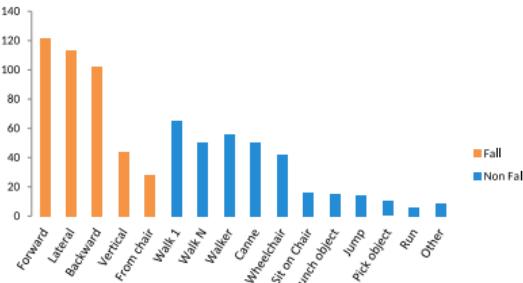
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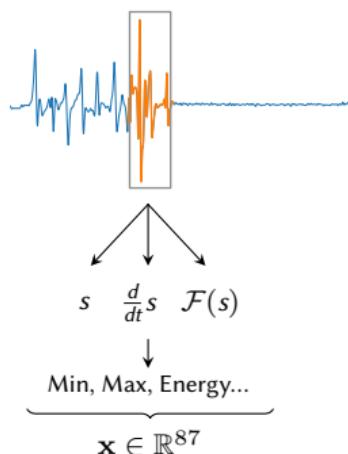


Method

Model

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

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

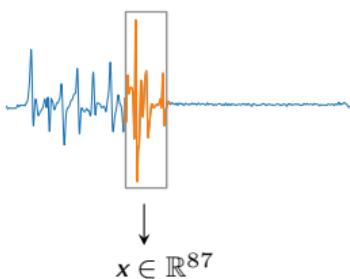


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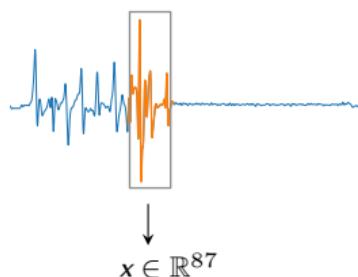


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3. Classification model: Random Forest [1], based on **decision trees**

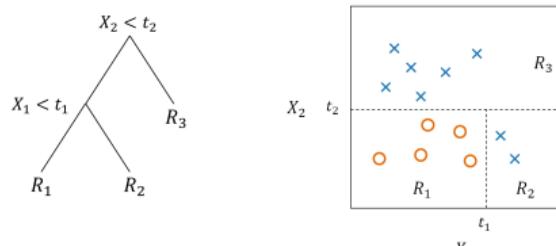
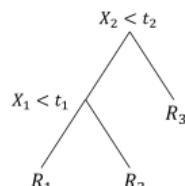
Decision tree

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

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

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

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



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

Method

Model

Random forest

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

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

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

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

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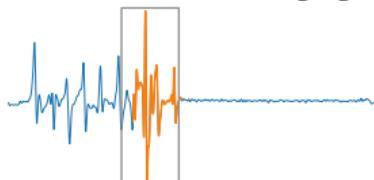
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Data augmentation

Select r windows in training signals



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

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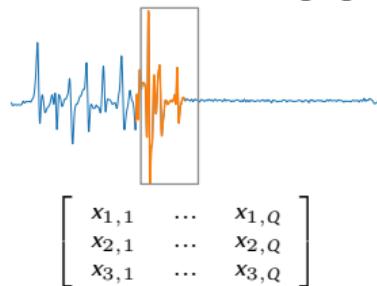
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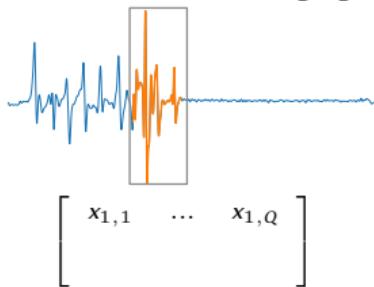
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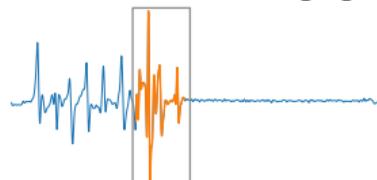
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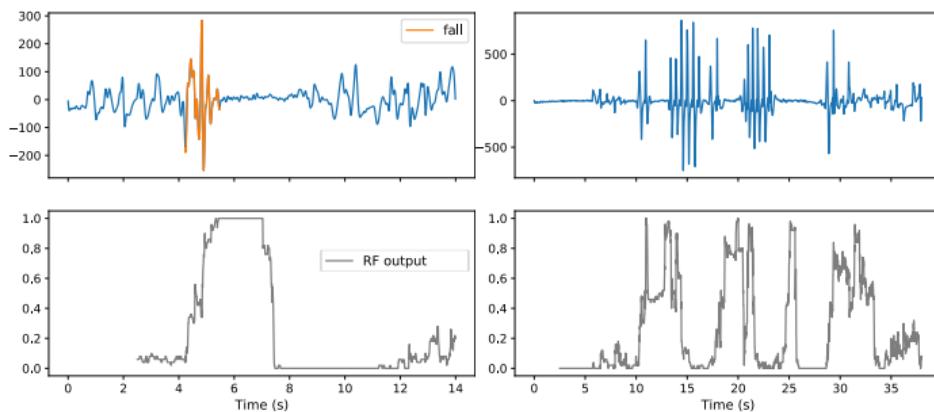
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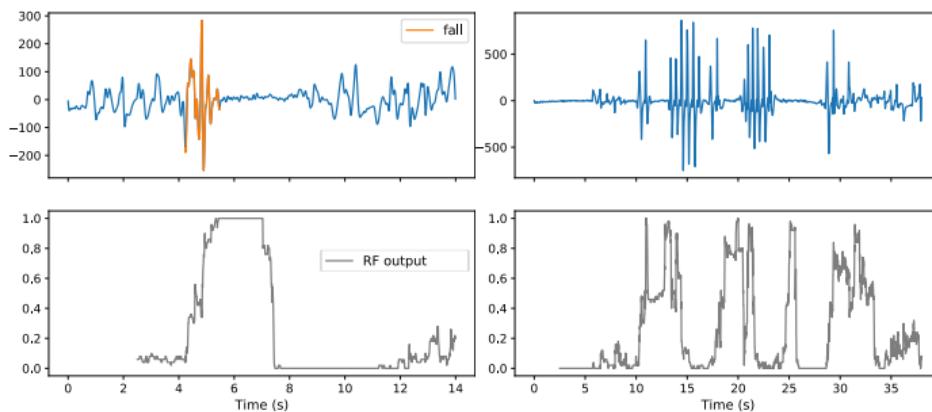
Method

Time aggregation



Method

Time aggregation



Time aggregation

$N_f(t)$: number of trees voting for *fall*

Use a buffer $B_s \in \mathbb{N}$ and a threshold $T_h \in [0, 1]$

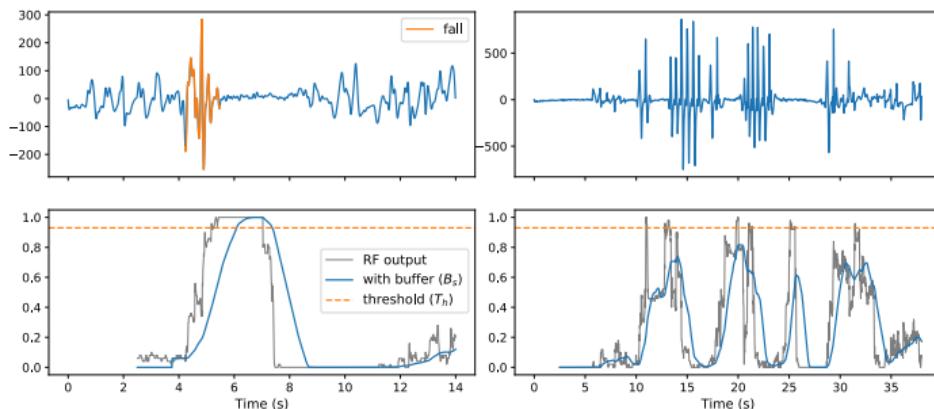
$$g(t) = \frac{\sum_{u=t-B_s+1}^t N_f(u)}{B_s \times N_T}$$

New binary classification function:

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

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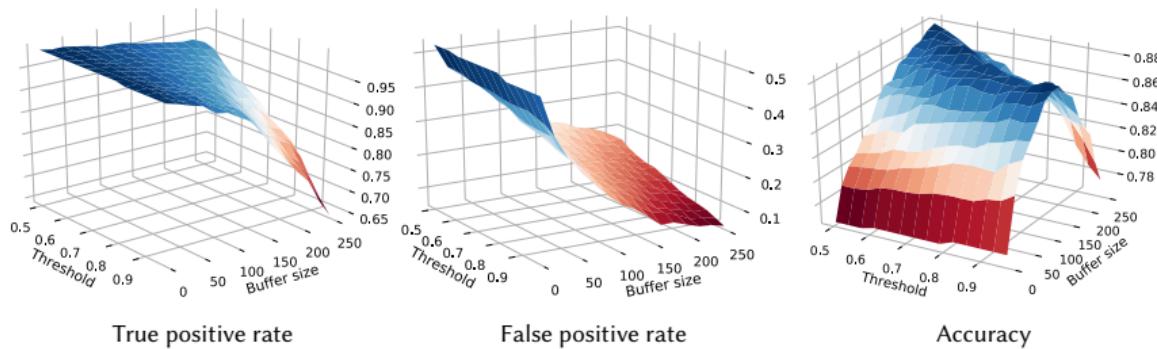
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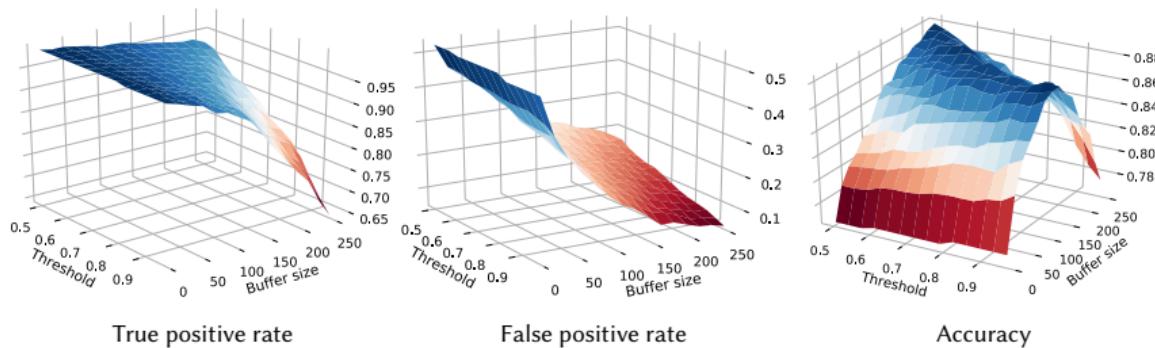
Methods

Time aggregation



Methods

Time aggregation



Decision rule is ready. Is it implementable ?

Feature selection

Feature importance

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

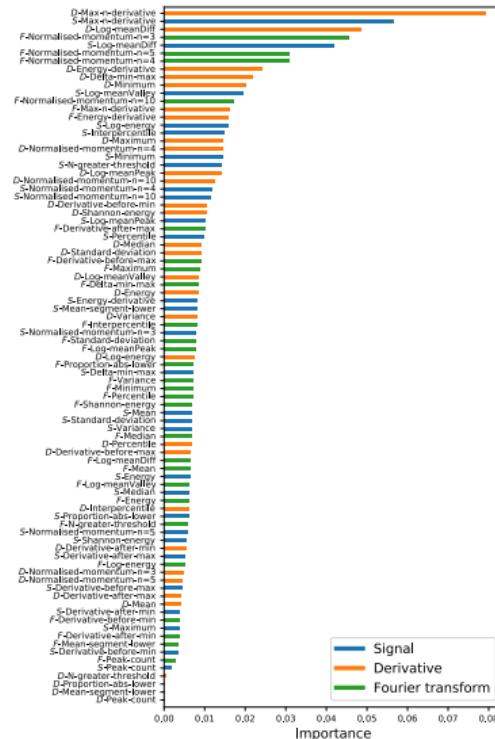
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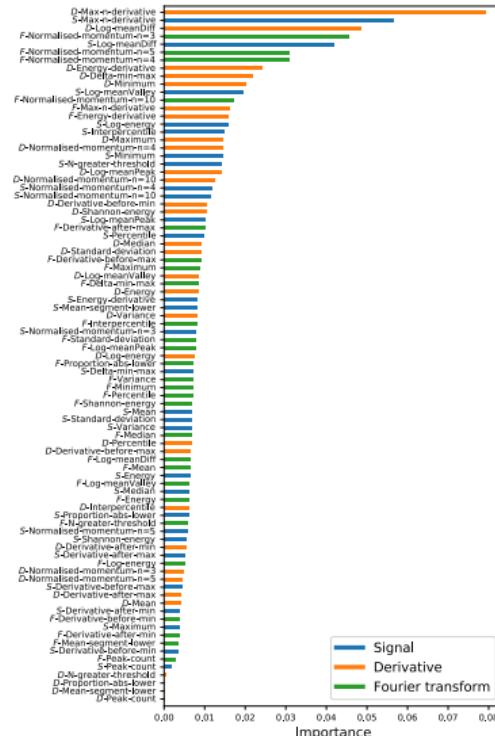
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Recursive feature elimination

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



Feature selection

Feature importance

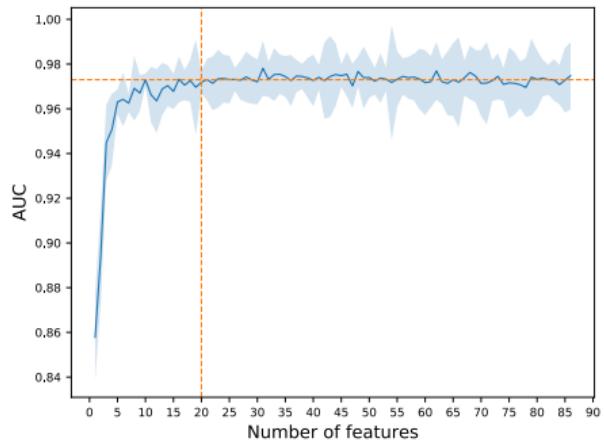
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Results

Set up:

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

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

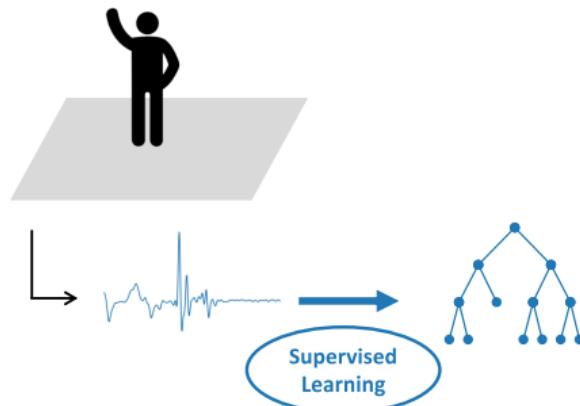
Comments:

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

Transfer learning on decision tree

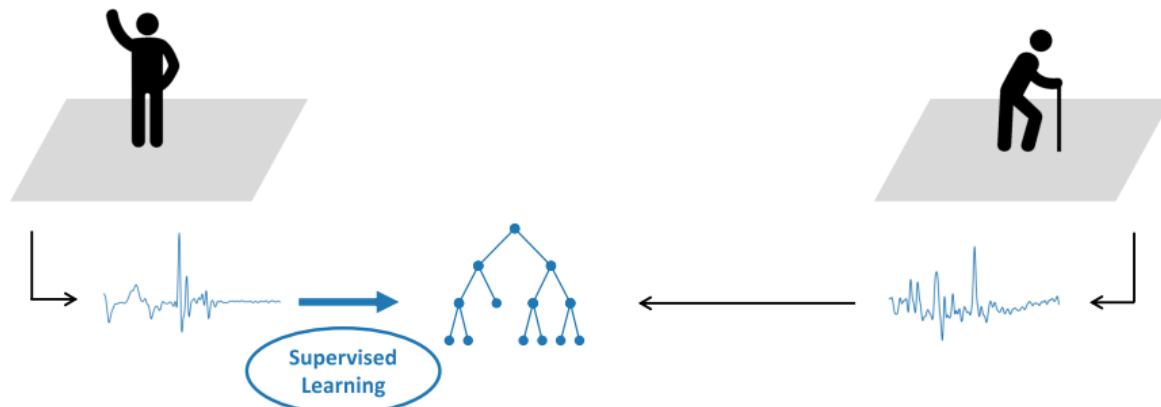
Context

Experimental vs. operational



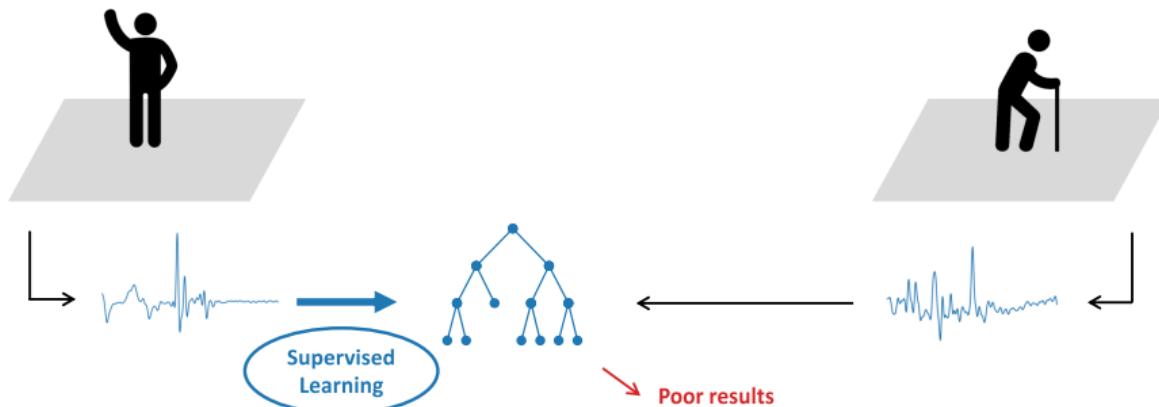
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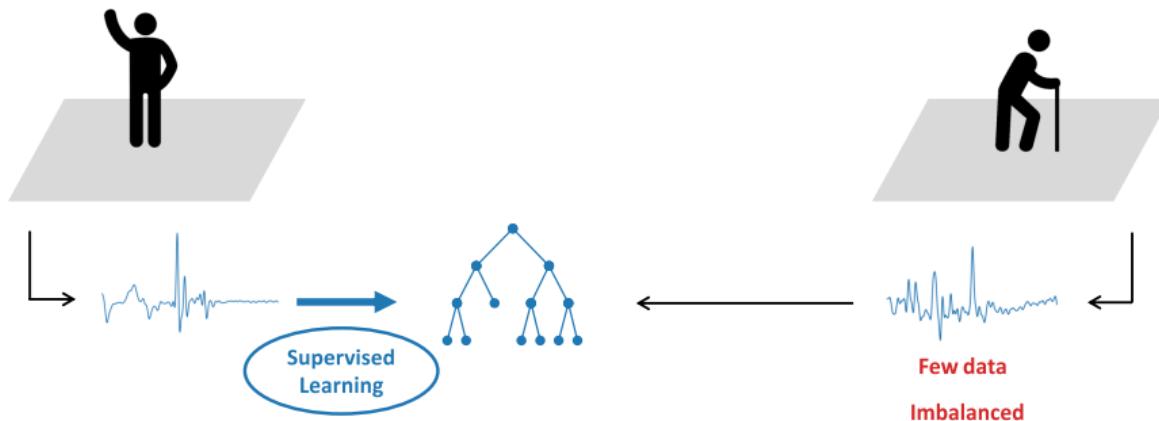
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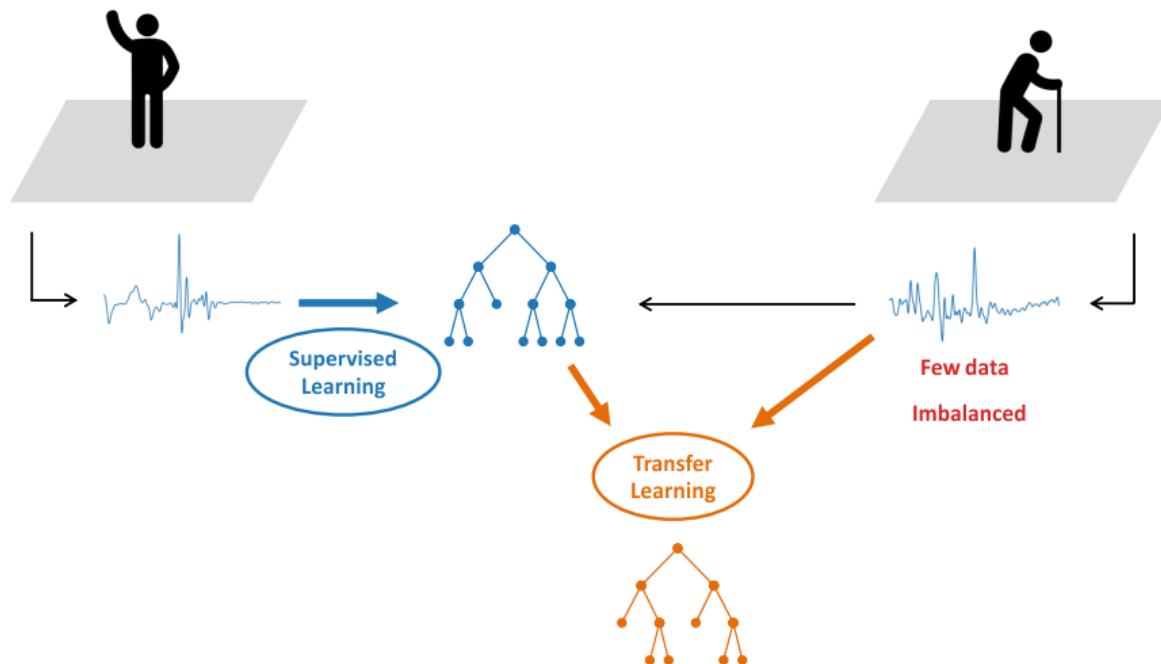
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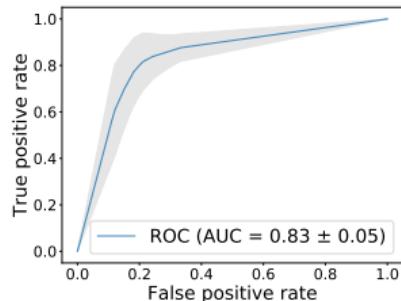
Transfer learning

Transfer learning

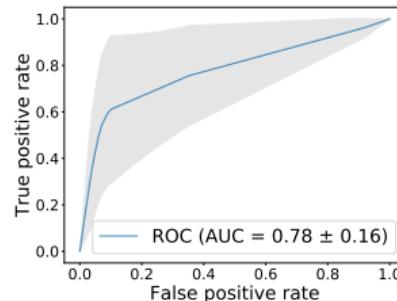
- ▶ Source domain: $\mathcal{D}_S = \{\mathcal{X}_S, P(X_S)\}$
- ▶ Target domain: $\mathcal{D}_T = \{\mathcal{X}_T, P(X_T)\}$
- ▶ Source task: $\mathcal{T}_S = \{\mathcal{Y}_S, f^S\}$
- ▶ Target task: $\mathcal{T}_T = \{\mathcal{Y}_T, f^T\}$

Our case

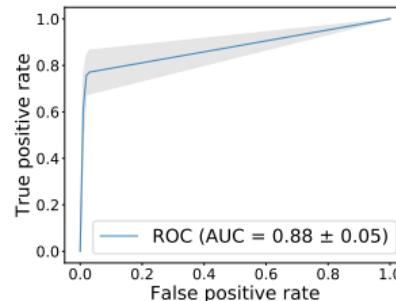
- ▶ $\mathcal{X}_S = \mathcal{X}_T$
- ▶ $P(X_S) \neq P(X_T)$
- ▶ $\mathcal{Y}_S = \mathcal{Y}_T$
- ▶ $f^S \neq f^T$



Source tested on source



Source tested on target

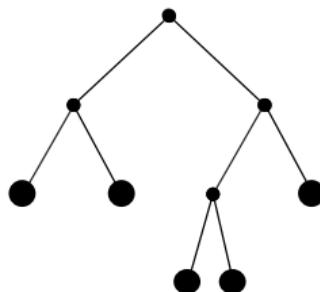


Target tested on target

Model-based transfer

Segev et al. [7]

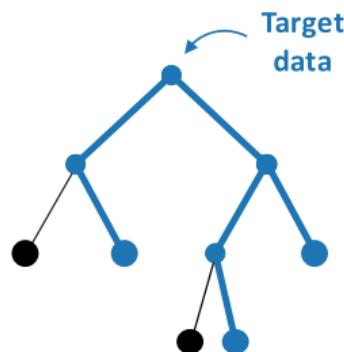
Structure Expansion / Reduction (SER)



Model-based transfer

Segev et al. [7]

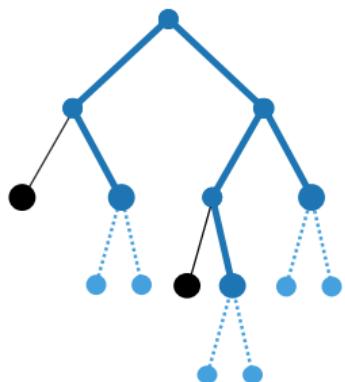
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Structure Expansion / Reduction (SER)

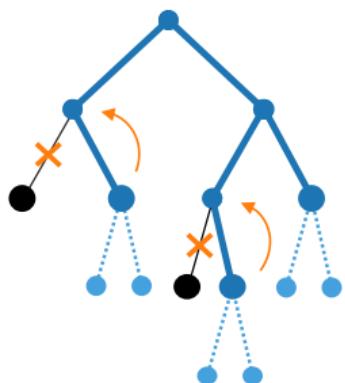


1. Expansion

Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)

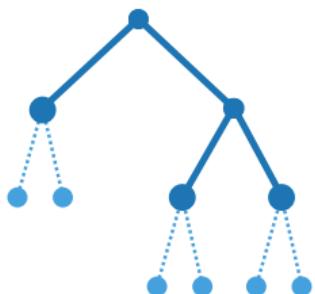


1. Expansion
2. Reduction

Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)

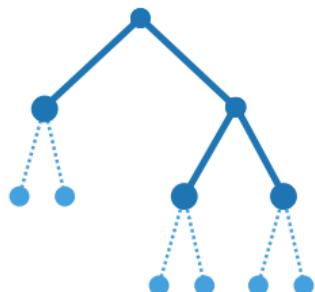


1. Expansion
2. Reduction

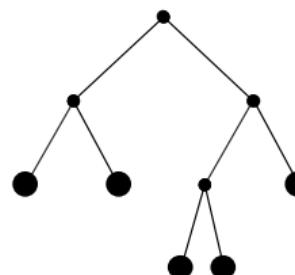
Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)



Structure Transfer (STRUT)

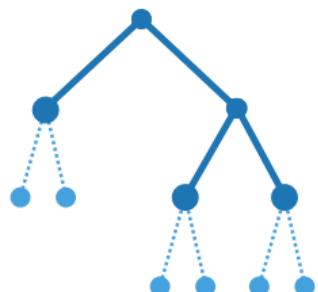


1. Expansion
2. Reduction

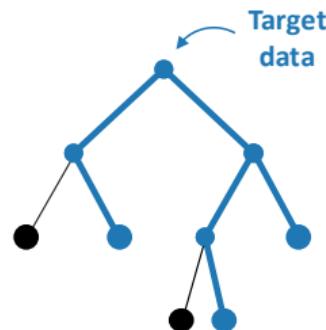
Model-based transfer

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Structure Expansion / Reduction (SER)



Structure Transfer (STRUT)

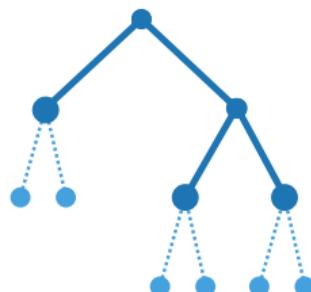


1. Expansion
2. Reduction

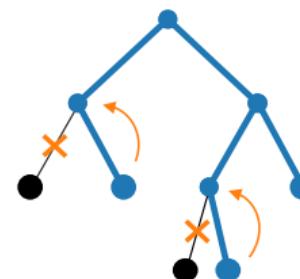
Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)



Structure Transfer (STRUT)



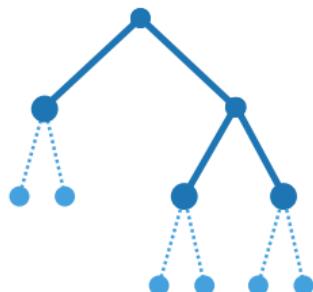
1. Pruning

1. Expansion
2. Reduction

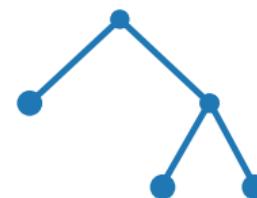
Model-based transfer

Segev et al. [7]

Structure Expansion / Reduction (SER)



Structure Transfer (STRUT)



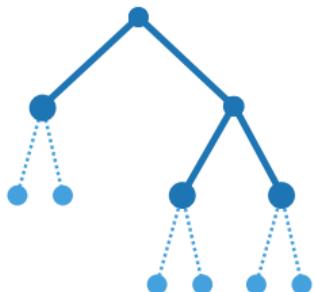
1. Pruning

1. Expansion
2. Reduction

Model-based transfer

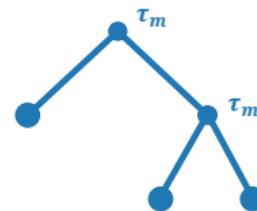
Segev et al. [7]

Structure Expansion / Reduction (SER)



1. Expansion
2. Reduction

Structure Transfer (STRUT)

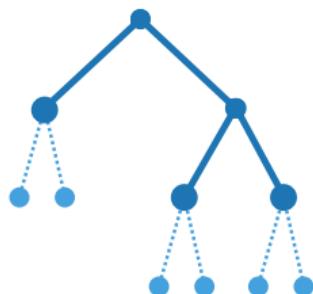


1. Pruning
2. Threshold update

Model-based transfer

Segev et al. [7]

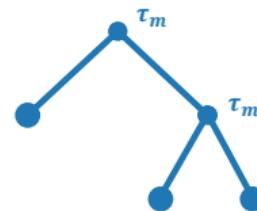
Structure Expansion / Reduction (SER)



1. Expansion
2. Reduction

Partition refinement or simplification

Structure Transfer (STRUT)



1. Pruning
2. Threshold update

Drifts

Leaf loss risk

Homogeneous class imbalance

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

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

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

Leaf loss risk

Homogeneous class imbalance

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

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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:

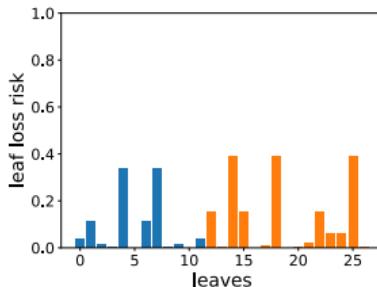
$$R_L(l) = P^T(x \notin l | y = k_{min})^{n_{k_{min}}}$$

Leaf loss risk under homogeneous class imbalance

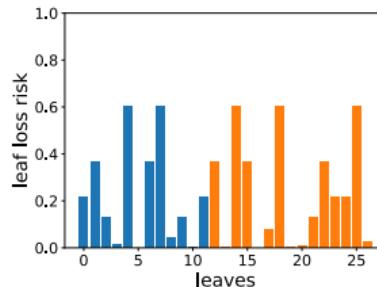
$$\forall k \neq k_{min}, \quad \lambda_{k_{min}} P^S(y = k_{min} | x \in l) > \lambda_k P^S(y = k | x \in l)$$

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

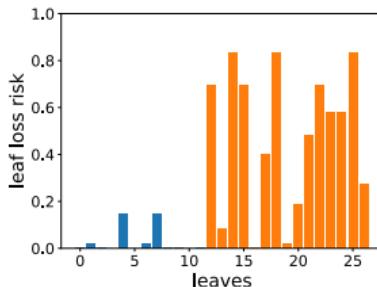
Leaf loss risk



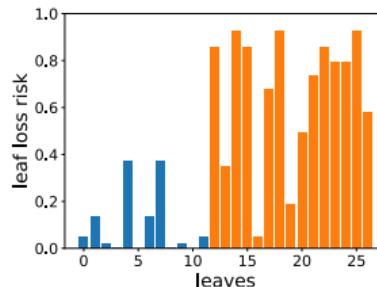
(a) Balanced data with 200 instances



(b) Balanced data with 100 instances



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

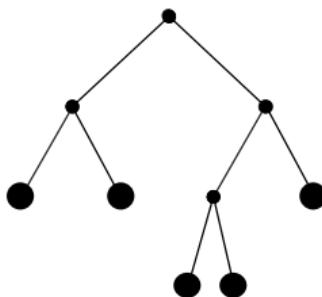


(d) Imbalanced data (10% ratio) with 100 instances

SER for class imbalance

SER_R, SER_{LL}

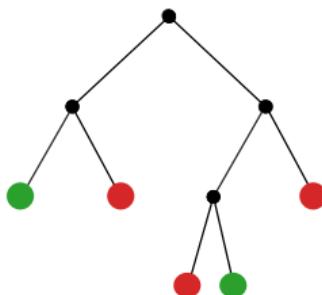
Structure Expansion and controlled Reduction



SER for class imbalance

SER_R, SER_{LL}

Structure Expansion and controlled Reduction

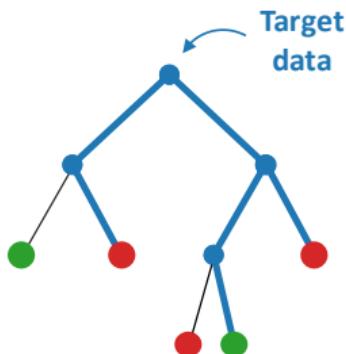


Minority class

SER for class imbalance

SER_R, SER_{LL}

Structure Expansion and controlled Reduction

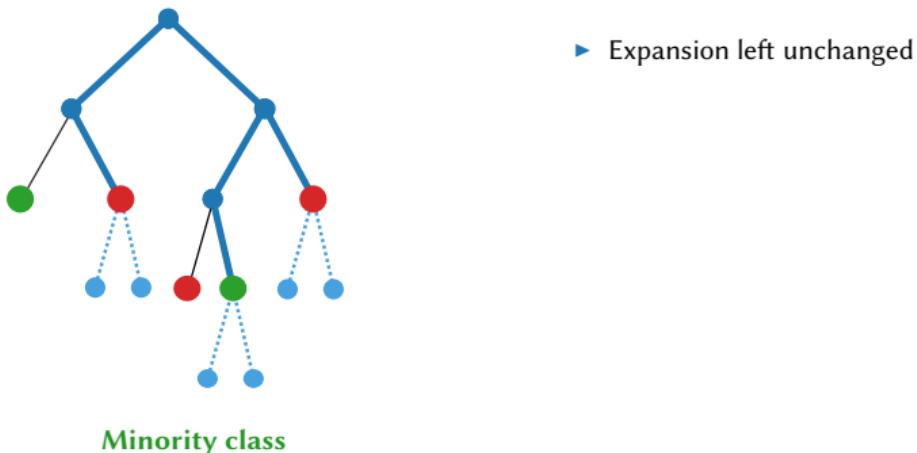


Minority class

SER for class imbalance

SER_R, SER_{LL}

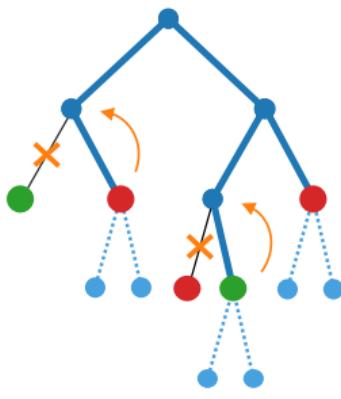
Structure Expansion and controlled Reduction



SER for class imbalance

SER_R, SER_{LL}

Structure Expansion and controlled Reduction



- ▶ Expansion left unchanged
- ▶ Reduction constrained

SER_R

If node is of minority class, then no pruning

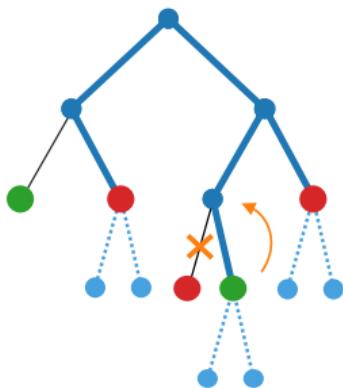
SER_{LL}

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



- ▶ Expansion left unchanged
- ▶ Reduction constrained

SER_R

If node is of minority class, then no pruning

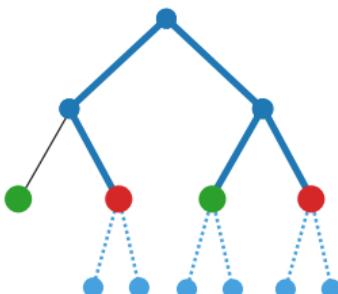
SER_{LL}

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

- ▶ Expansion left unchanged
- ▶ Reduction constrained

SER_R

If node is of minority class, then no pruning

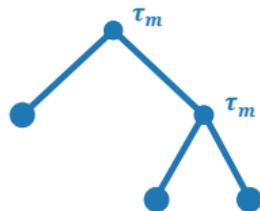
SER_{LL}

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

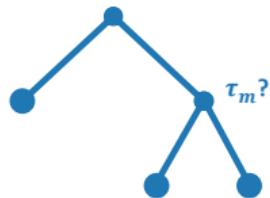
STRUT: How are updated the new thresholds ?



STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?

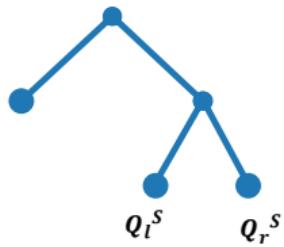


STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?

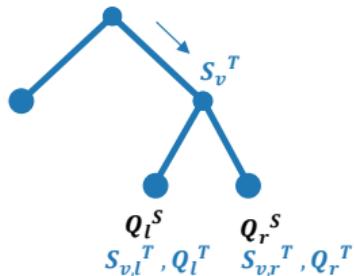
Q_l^S, Q_r^S : class proportions of source data in children w.r.t. the *original* split



STRUT for class imbalance

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

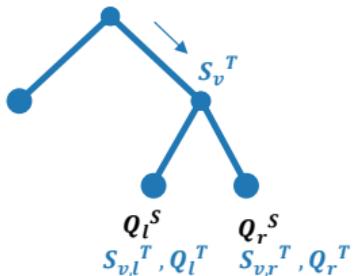
$S_{v,l}^T, S_{v,r}^T$: subsets of S_v^T that fall in the children nodes of v

$Q_l^T(\tau), Q_r^T(\tau)$: class proportions of target data in children w.r.t. the *new* split

STRUT for class imbalance

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

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:

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

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

Kullback-Leibler divergence:

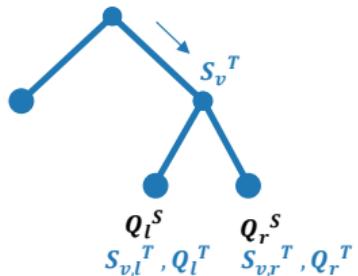
$$D_{KL}(P||Q) = \sum_k P(k) \ln \left(\frac{P(k)}{Q(k)} \right)$$

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)

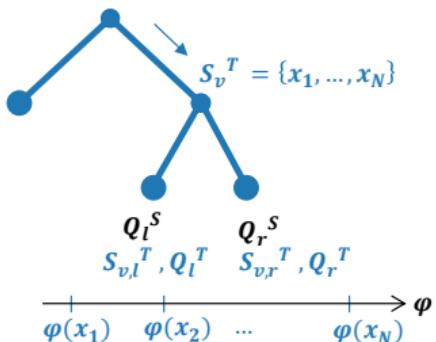


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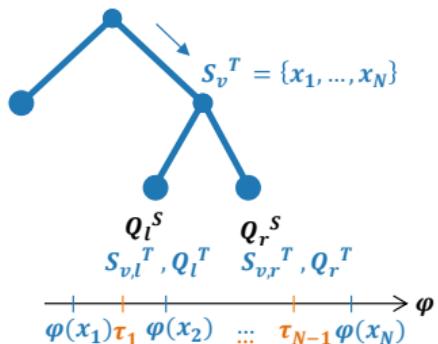


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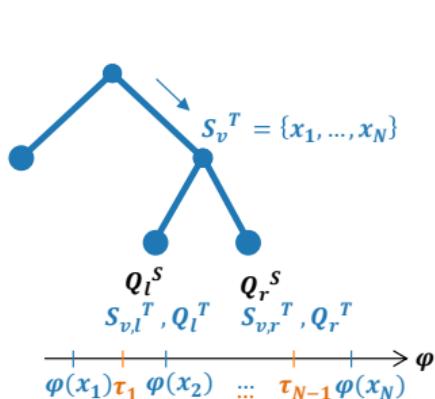


STRUT for class imbalance

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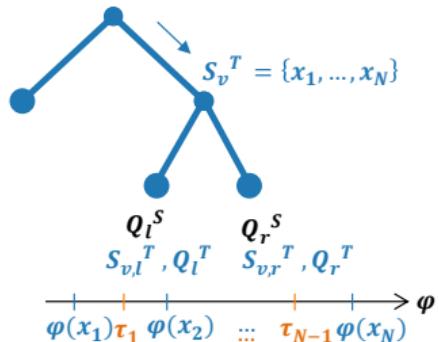
$$\tau_m = \arg \max_{\tau \in T_v} (DG(\tau, Q_l^T(\tau), Q_r^T(\tau)))$$

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

STRUT for class imbalance

STRUT optimization

STRUT: How are updated the new thresholds ?



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

$$\tau_m = \arg \max_{\tau \in T_v} (DG(\tau, Q_l^T(\tau), Q_r^T(\tau)))$$

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

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

STRUT for class imbalance

STRUT_{IG}, STRUT_{HI}

STRUT_{IG}

STRUT without DG: maximization of IG

STRUT for class imbalance

STRUT_{IG}, STRUT_{HI}

STRUT_{IG}

STRUT without DG: maximization of IG

STRUT_{HI}

Framework of homogeneous class imbalance, use

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

to change the source class proportions in DG:

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

STRUT for class imbalance

STRUT_{IG}, STRUT_{HI}

STRUT_{IG}

STRUT without DG: maximization of IG

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Framework of homogeneous class imbalance, use

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

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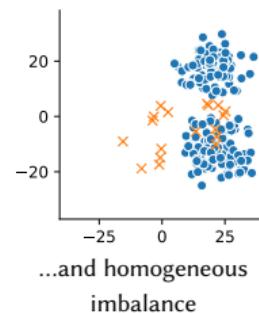
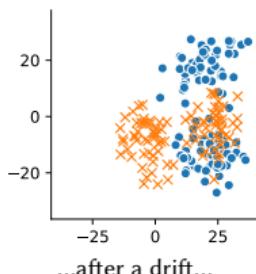
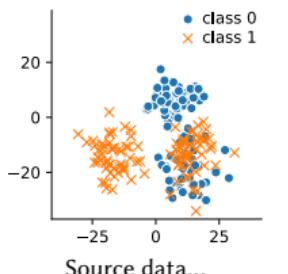
STRUT_{HI} can be seen as a generalization of STRUT

Results

Synthetic data

Gaussian generator

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



Transformations

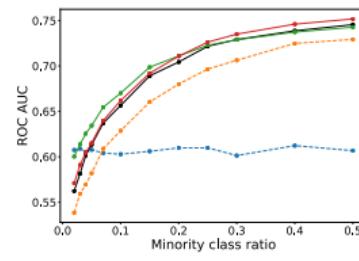
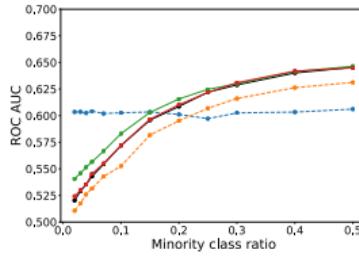
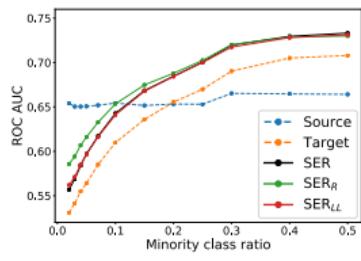
Basic transformations on Source clusters are applied to get a Target dataset:

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

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

Results

Synthetic data



(a) Drift

(b) Stretch / Squeeze

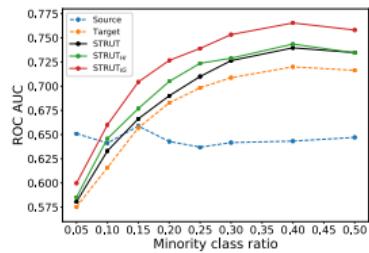
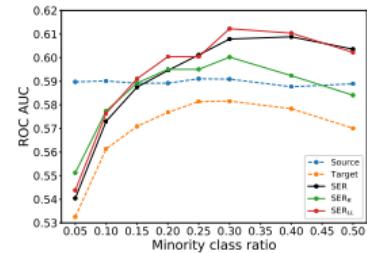
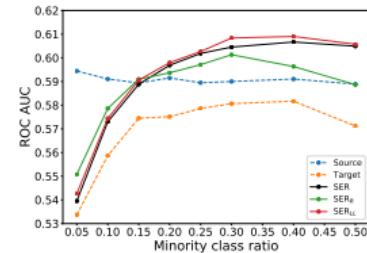
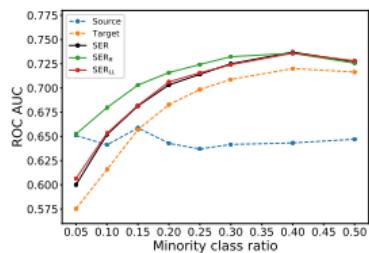
(c) Add / Remove

- ▶ Strong imbalance leads to negative transfer
- ▶ SER: SER_{LL} close to SER, SER_R better than SER (esp. with high imbalance)
- ▶ STRUT: both variants beat the original STRUT

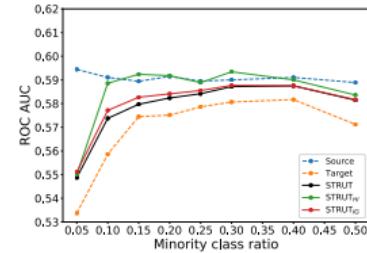
Results

Public data

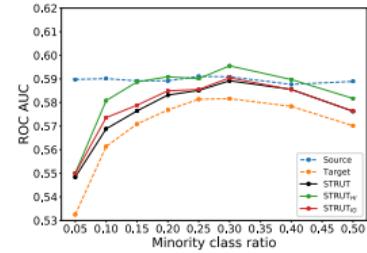
Two real data sets where the imbalance ratio is controlled with downsampling.



(a) Magic Gamma Telescope



(b) Office-Caltech: *amazon* \rightarrow *webcam*



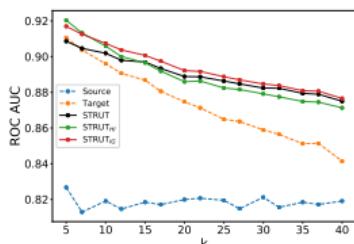
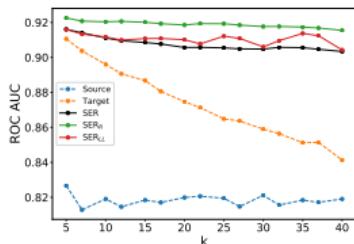
(c) Office-Caltech: *caltech* \rightarrow *webcam*

- ▶ SER: SER_{LL} close to SER, SER_R either better... or worse
- ▶ STRUT: both variants perform as well or better

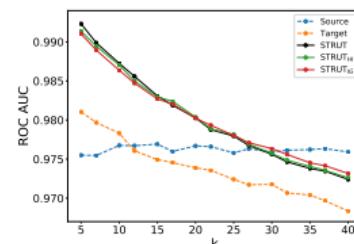
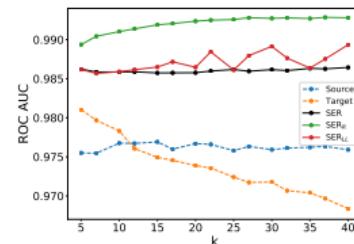
Results

Fall data

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



(a) Decision tree model



(b) Random forest model with 10 decision trees

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

- ▶ Same overall conclusions

Results

Overall

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

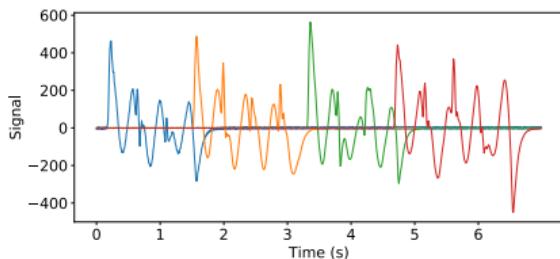
Elderly activity recognition with convolutional representations

Motivation

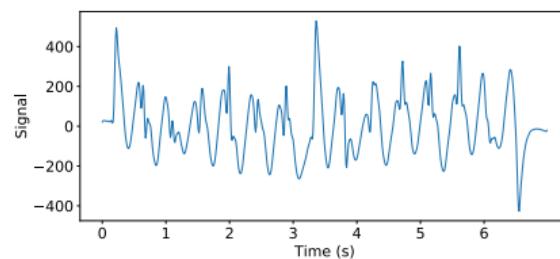
- ▶ **Issue:** one-dimensional signals for large areas
- ▶ Goal: Classify elderly from other individuals
 - ▶ Most signals are made of walks of staff individuals
- ▶ Subtask: Bring the model's attention over step-related signals

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



(a) Raw signal

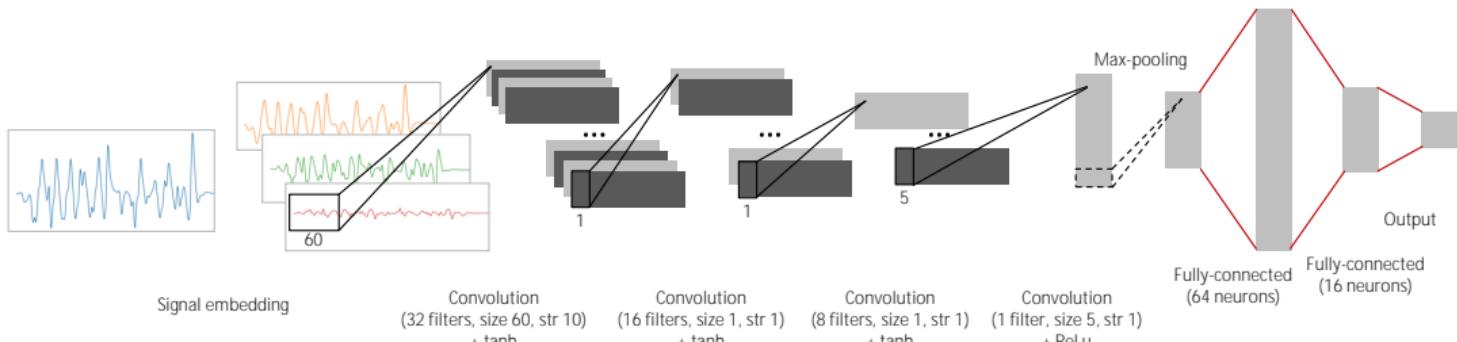


(b) Preprocessed signal

What we propose: A model to recognize elderly activity using a convolutional neural network and three training steps:

1. Signal embedding using convolutional dictionary learning
2. Step proposal network inspired from Region proposal network
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

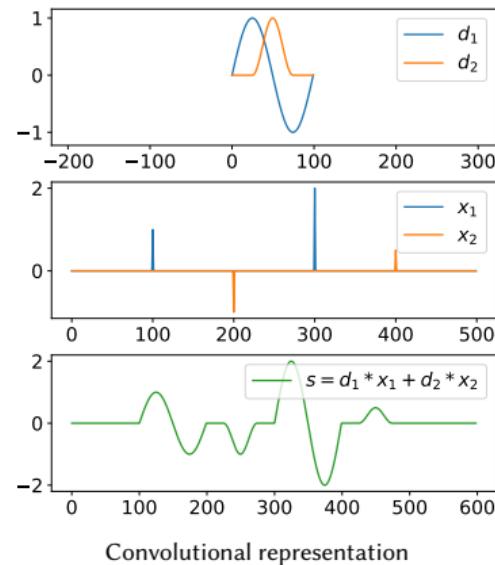
Signal embedding

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- ▶ $*$: convolution



Convolutional representation

Signal embedding

Convolutional dictionary learning

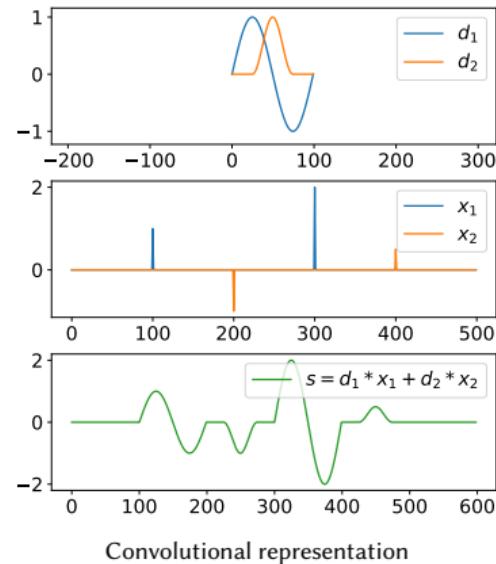
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CDL general problem:

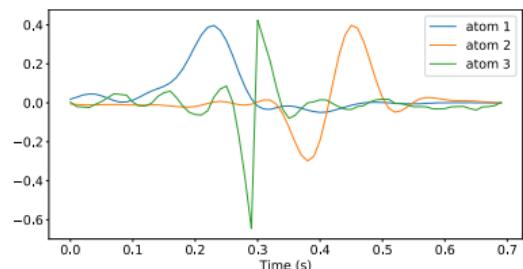
$$\begin{aligned} \arg \min_{\mathbf{x}_m, \mathbf{d}_m} & \frac{1}{2} \left\| \sum_{m=1}^M \mathbf{x}_m * \mathbf{d}_m - \mathbf{s} \right\|_2^2 + \lambda \sum_{m=1}^M \|\mathbf{x}_m\|_1 \\ \text{s.t. } & \|\mathbf{d}_m\|_2 \leq 1 \quad \forall m . \end{aligned}$$



Signal embedding

Learning step atoms

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

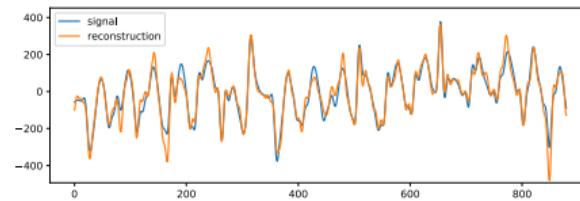
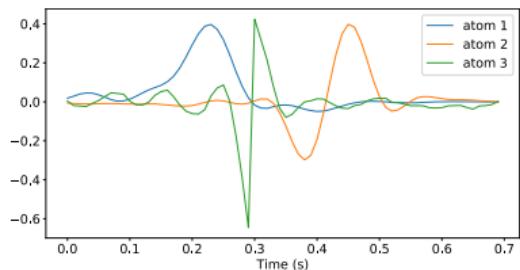


Dictionary

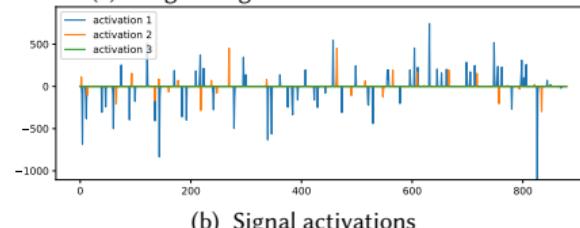
Signal embedding

Learning step atoms

- ▶ Learning with Alternating Direction Method of Multipliers (ADMM) [3]
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(a) Original signal and its reconstruction



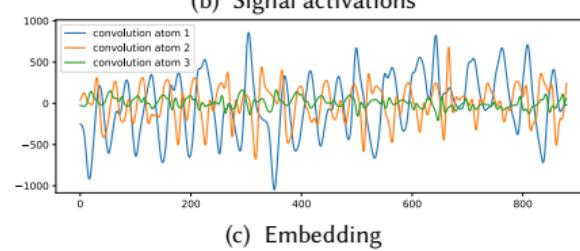
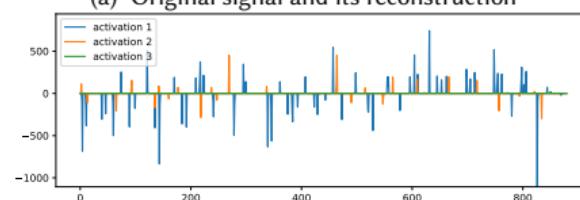
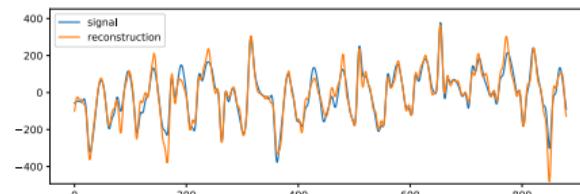
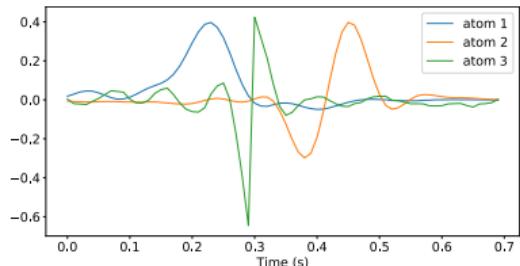
(b) Signal activations

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:

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



Region proposal network

Object detection

- ▶ Classification: What is the image class ?

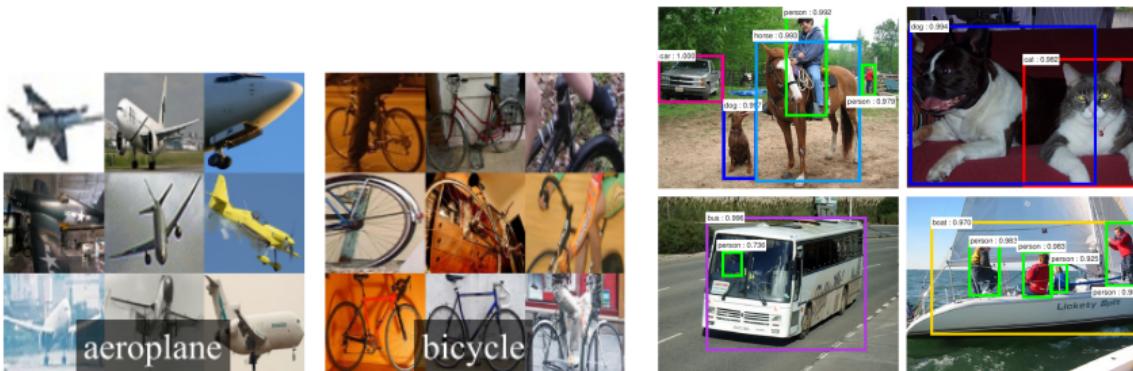


Classification vs Object detection. Source: Girshick et al. [4], Ren et al. [6]

Region proposal network

Object detection

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

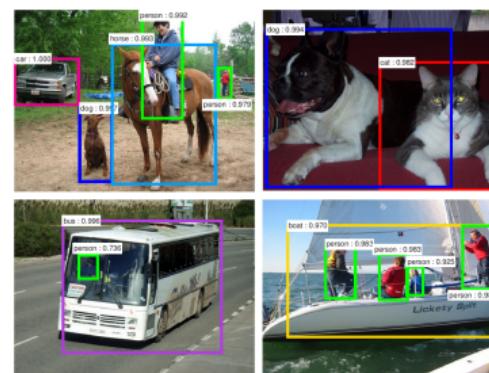


Classification vs Object detection. Source: Girshick et al. [4], Ren et al. [6]

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])

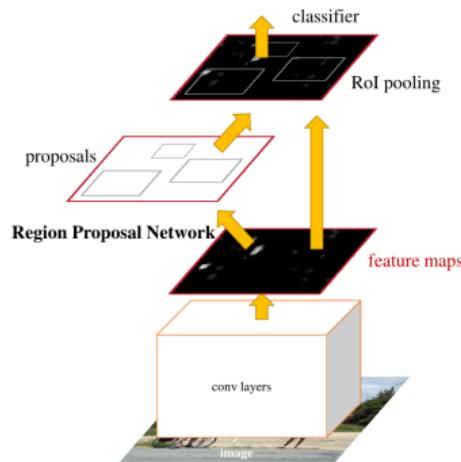


Classification vs Object detection. Source: Girshick et al. [4], Ren et al. [6]

Region proposal network

Faster R-CNN

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

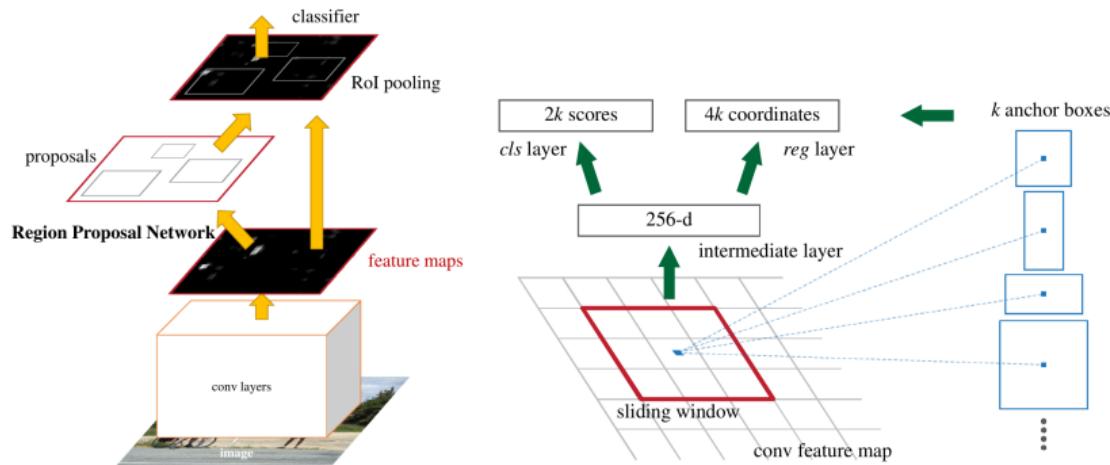


Region proposal network. Source: Ren et al. [6]

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)

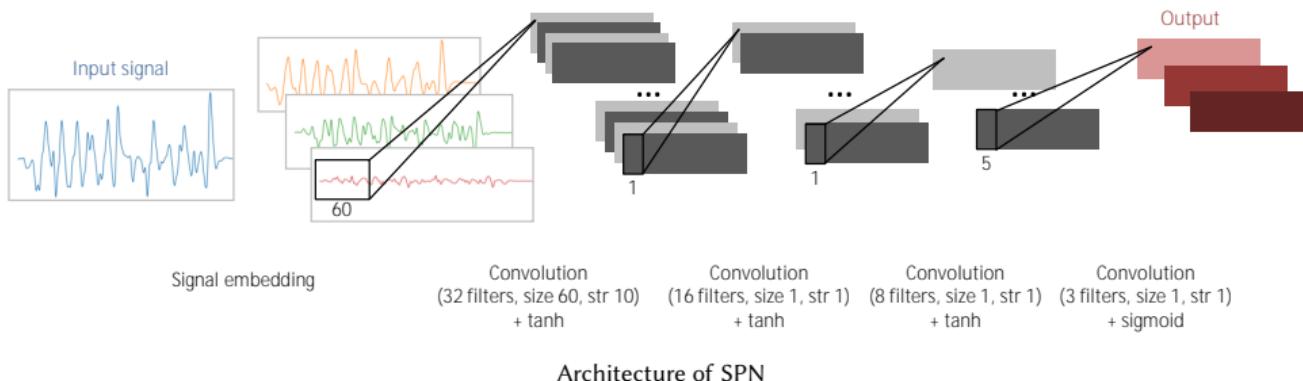


Region proposal network. Source: Ren et al. [6]

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

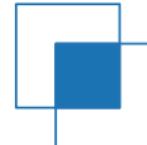


Step proposal network

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:

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

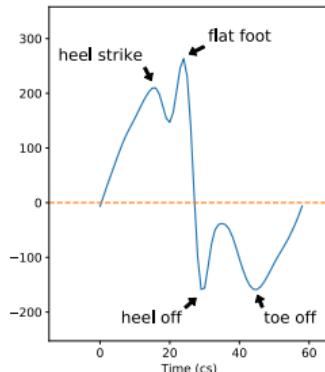
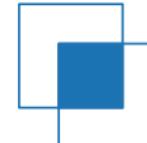


Step proposal network

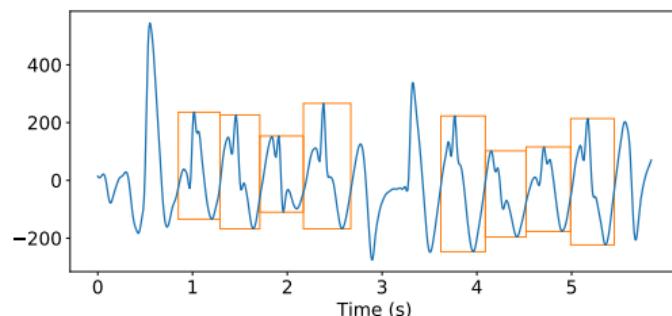
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(a) Step signal



(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: $\text{IoU}(b_t^k) > \sqrt{0.7}$
- ▶ Negative boxes: $\text{IoU}(b_t^k) < \sqrt{0.3}$
- ▶ Other are not used for training

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

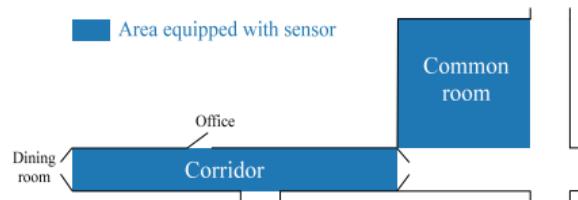
$$\mathcal{L}(\mathbf{s}, \mathbf{W}) = \sum_t \sum_{k \in [1, 2, 3]} \mathbb{1}_{\text{IoU}(b_t^k) > \sqrt{0.7}} \log(\mathbf{W}_{t,k}) + \mathbb{1}_{\text{IoU}(b_t^k) < \sqrt{0.3}} \log(1 - \mathbf{W}_{t,k}).$$

Step proposal network

Results

Data

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

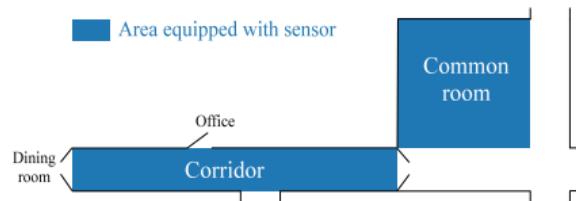


Step proposal network

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Training

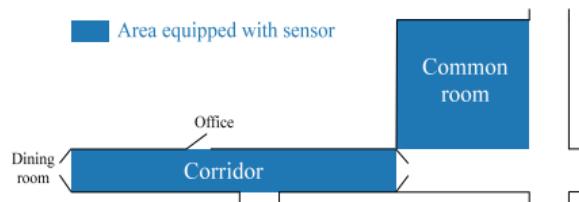
- ▶ SPN is trained using classical gradient descent
- ▶ Training time: < 5 minutes
- ▶ Inference (detection over a 10s signal): < 1 second
- ▶ Optimization details
 - ▶ learning rate of 10^{-3}
 - ▶ learning rate decay ($\times 0.9$ every 10 epochs)
 - ▶ Nesterov momentum

Step proposal network

Results

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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%

Training

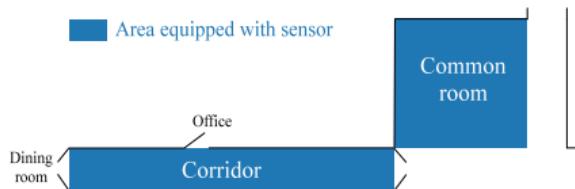
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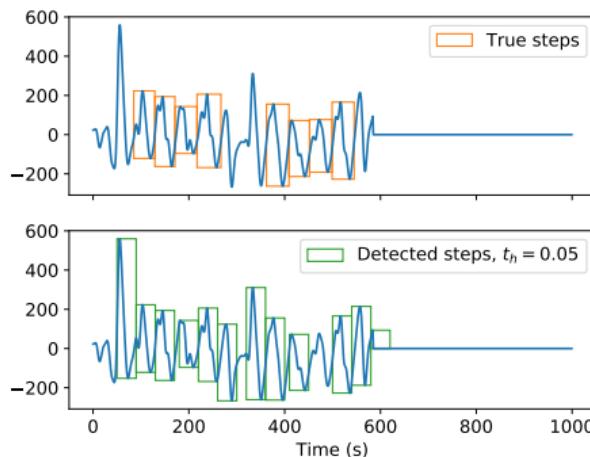


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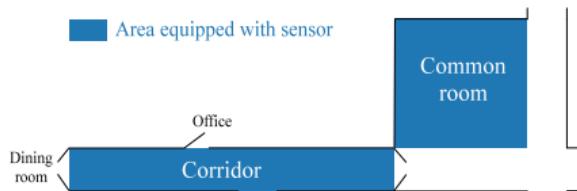


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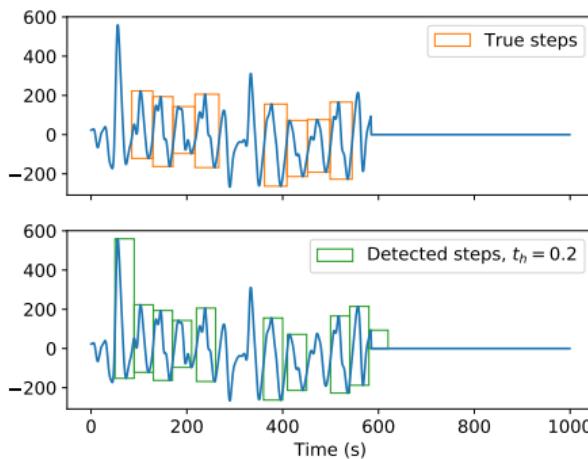


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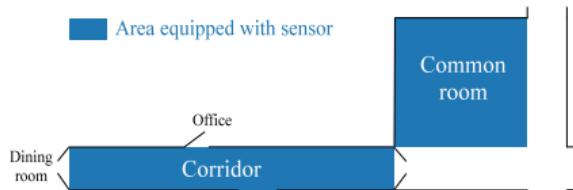


Step proposal network

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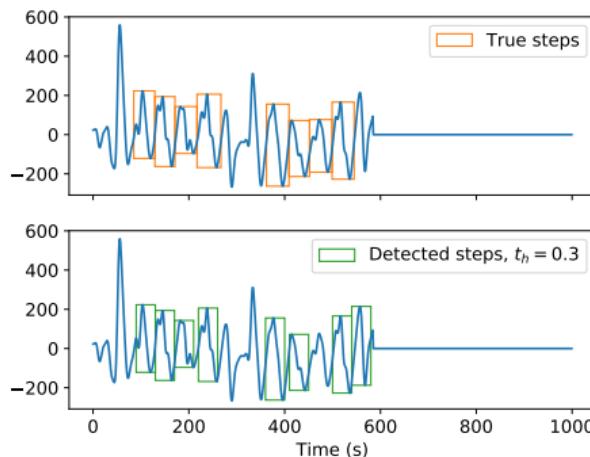


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Classification

Training

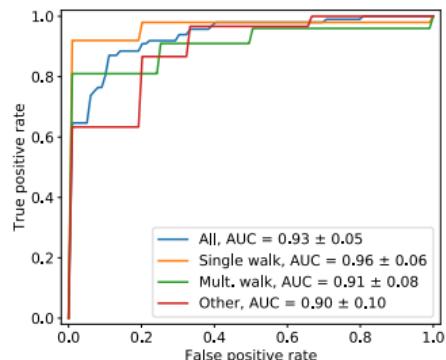
$$\mathcal{L}(\mathbf{s}_i, \hat{y}_i) = -(\mathbb{1}_{y_i=1} \log(\hat{y}_i) + \mathbb{1}_{y_i=0} \log(1 - \hat{y}_i))$$

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

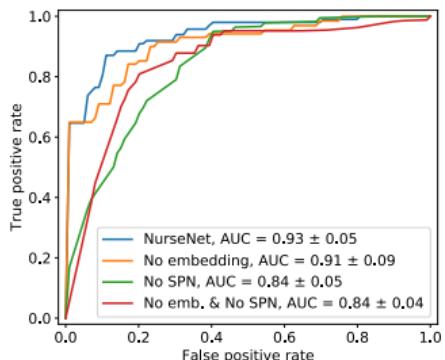
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Classification

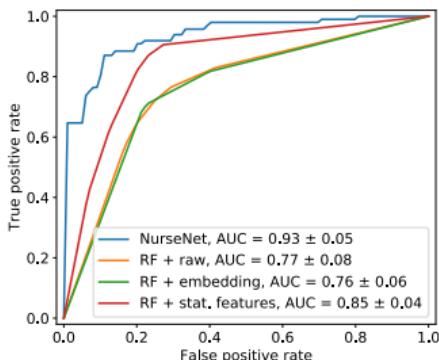
Results



(a) NURSENET results



(b) NURSENET ablation analysis



(c) NURSENET and several RF-based models

Conclusion

Conclusion

Contributions

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

Future work

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

Publications and communications

Publications

- ▶ L. Minvielle, M. Atiq, R. Serra, M. Mougeot, and N. Vayatis. [Fall detection using smart floor sensor and supervised learning](#). In *2017 39th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, pages 3445–3448, July 2017
- ▶ L. Minvielle, M. Atiq, S. Peignier, and M. Mougeot. [Transfer learning on decision tree with class imbalance](#). In *2019 IEEE 31st International Conference on Tools with Artificial Intelligence (ICTAI)*, pages 1003–1010, Nov 2019
- ▶ Ludovic Minvielle and Julien Audiffren. [Nursesnet: 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.
- [6] Shaoqing Ren, Kaiming He, Ross Girshick, and Jian Sun. Faster r-cnn: Towards real-time object detection with region proposal networks. In *Advances in neural information processing systems*, pages 91–99, 2015.
- [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.