

# Self-taught learning for activity spotting in on-body motion sensor data

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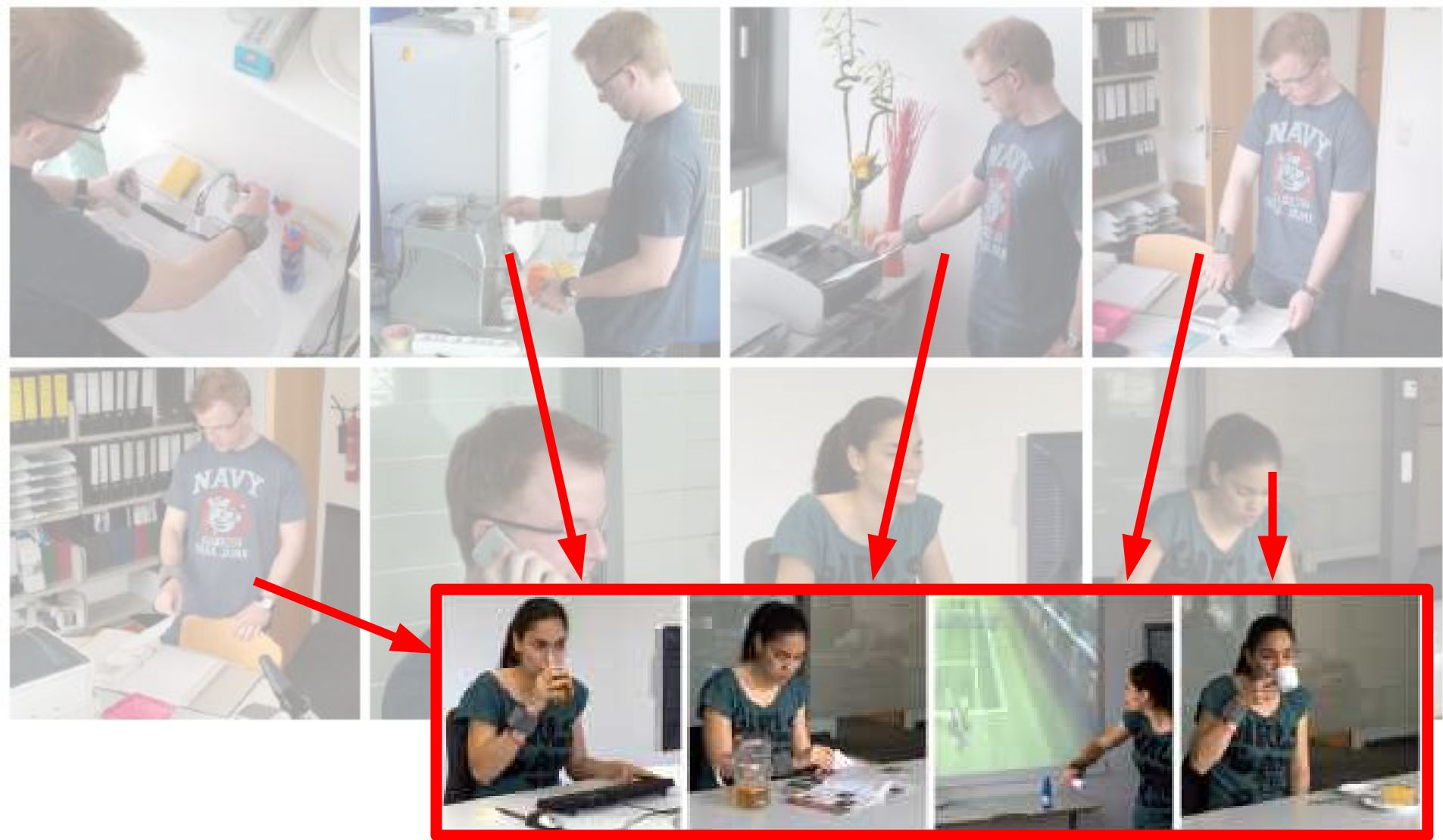
TU Eindhoven



# Interpreting daily routines

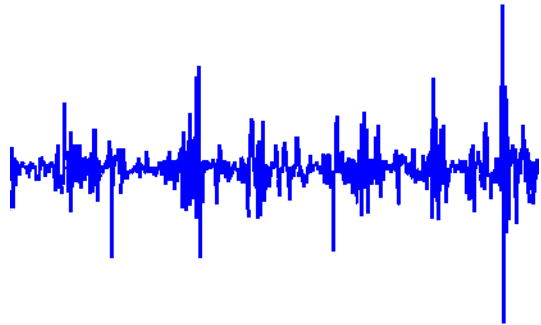


# Picking relevant events:



# What is activity spotting?

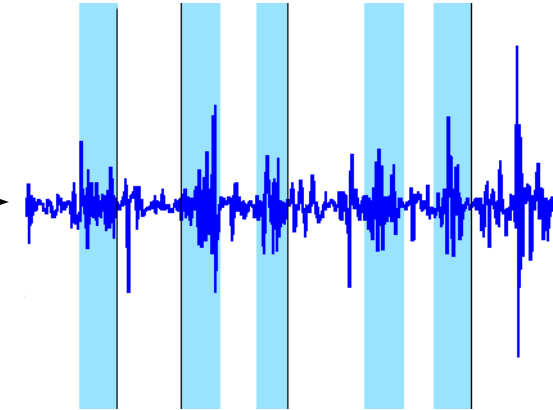
Sensor data  $S$



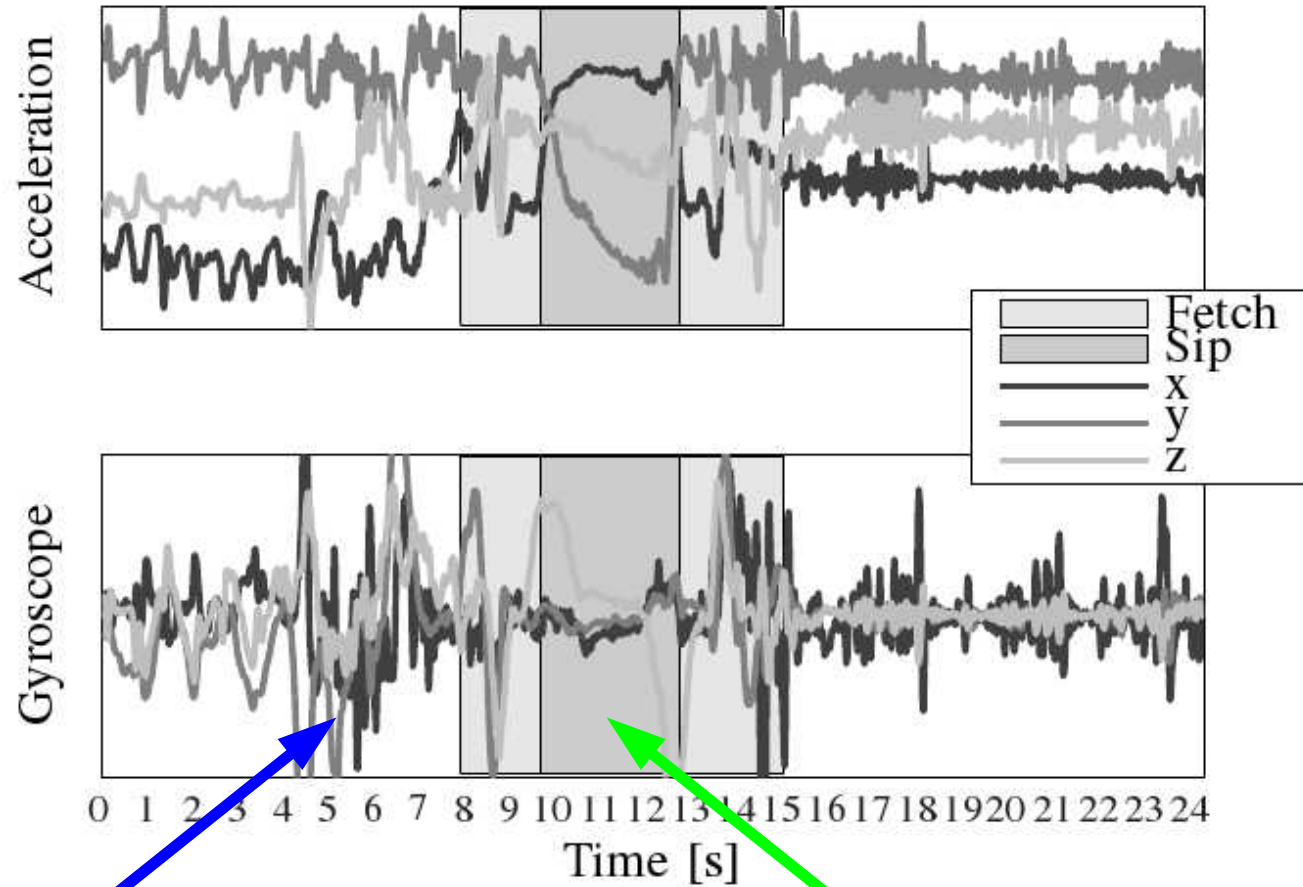
Activity event  
spotting

$$h_{Event} : S \rightarrow e_{C,T}^*$$

Retrieved activity events



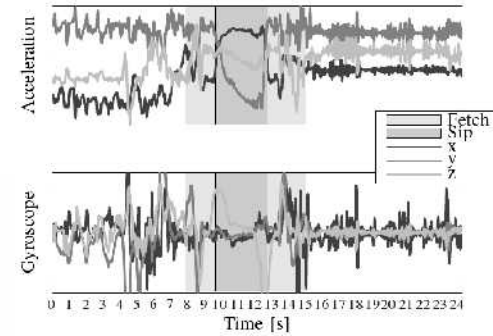
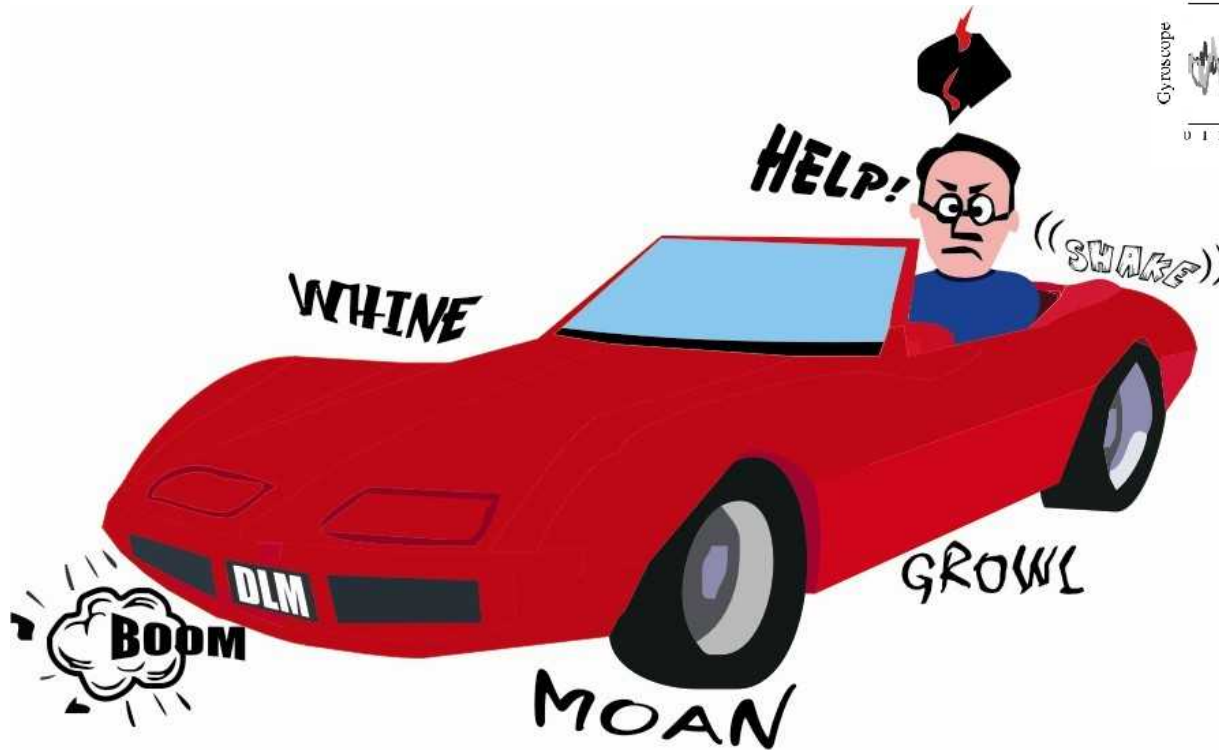
# Example: drinking motion spotting



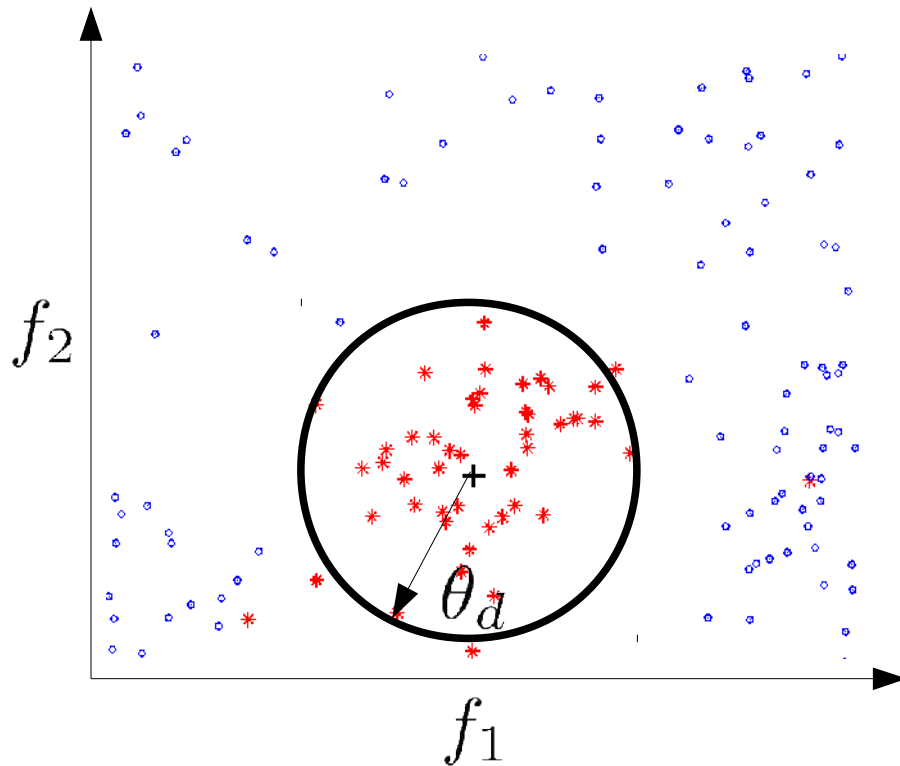
**Unsupervised**

**Supervised**

# How does self-taught learning help?



# How does activity spotting work? (Example)



$$\mathcal{X}_{Train} = \{ \underline{\mathbf{f}}_{Train}^+, \underline{\mathbf{f}}_{Train}^- \}$$

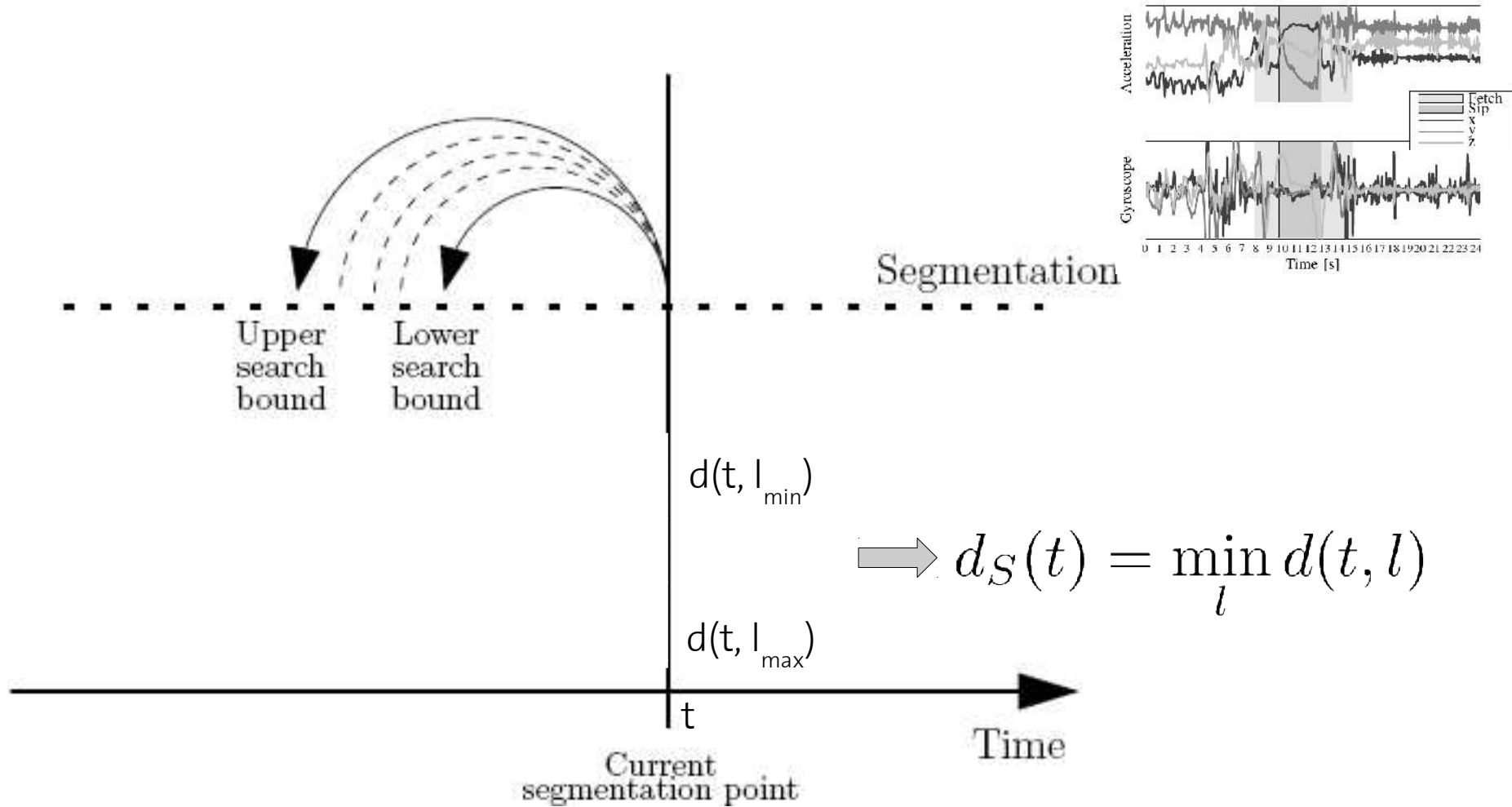
Centroid Model:

$$d(\mathbf{f}) = \sqrt{\sum_{i=1}^{|\mathbf{f}^+|} \left( \frac{f_i^+ - \bar{f}_i^+}{s_i} \right)^2}$$

$$h_{FSS} = \begin{cases} true, & d_S \leq \theta_d \\ false, & otherwise \end{cases}, [p]$$

$$\theta_{d,Train} = \underset{\theta_d}{\operatorname{argmin}} \varepsilon_{emp}(h_{FSS}, \theta_d, \mathcal{X}_{Train})$$

# The Feature Similarity Search (FSS) method

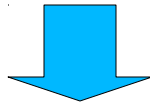
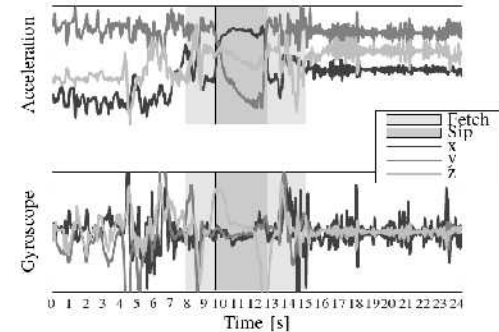




# Self-taught learning

Approach: learn from background

1. Learn representation  $\{b_j, a_j^{(i)}\}$  from unlabelled data  $x_u^{(i)}$
2. Apply  $\{b_j, a_j^{(i)}\}$  using labels  $x_l^{(i)}$  to derive features  $\hat{a}$
3. Use supervised spotting learner to obtain model  $h : \hat{a}(x_l^{(i)}) \rightarrow e_{C,T}$



1. Optimisation problem:

$$\min_{\{b_j\}, \{a^{(i)}\}} \underbrace{\sum_{i=1}^k \|x_u^{(i)} - \sum_{j=1}^s b_j a_j^{(i)}\|_2^2}_{\text{red underline}} + \beta \underbrace{\sum_{i=1}^m \sum_{j=1}^s \phi(a_j^{(i)})}_{\text{blue underline}}$$

s.t.  $\|b_j\|^2 \leq c, \forall j = 1, \dots, s$

2. Higher-level features:

$$\hat{a}(x_l^{(i)}) = \underset{a^{(i)}}{\operatorname{argmin}} \|x_l^{(i)} - \sum_{j=1}^s b_j a_j^{(i)}\|_2^2 + \gamma \sum_{j=1}^s \|a^{(i)}\|_1$$

# Evaluation dataset used



Office



Gaming



Eating

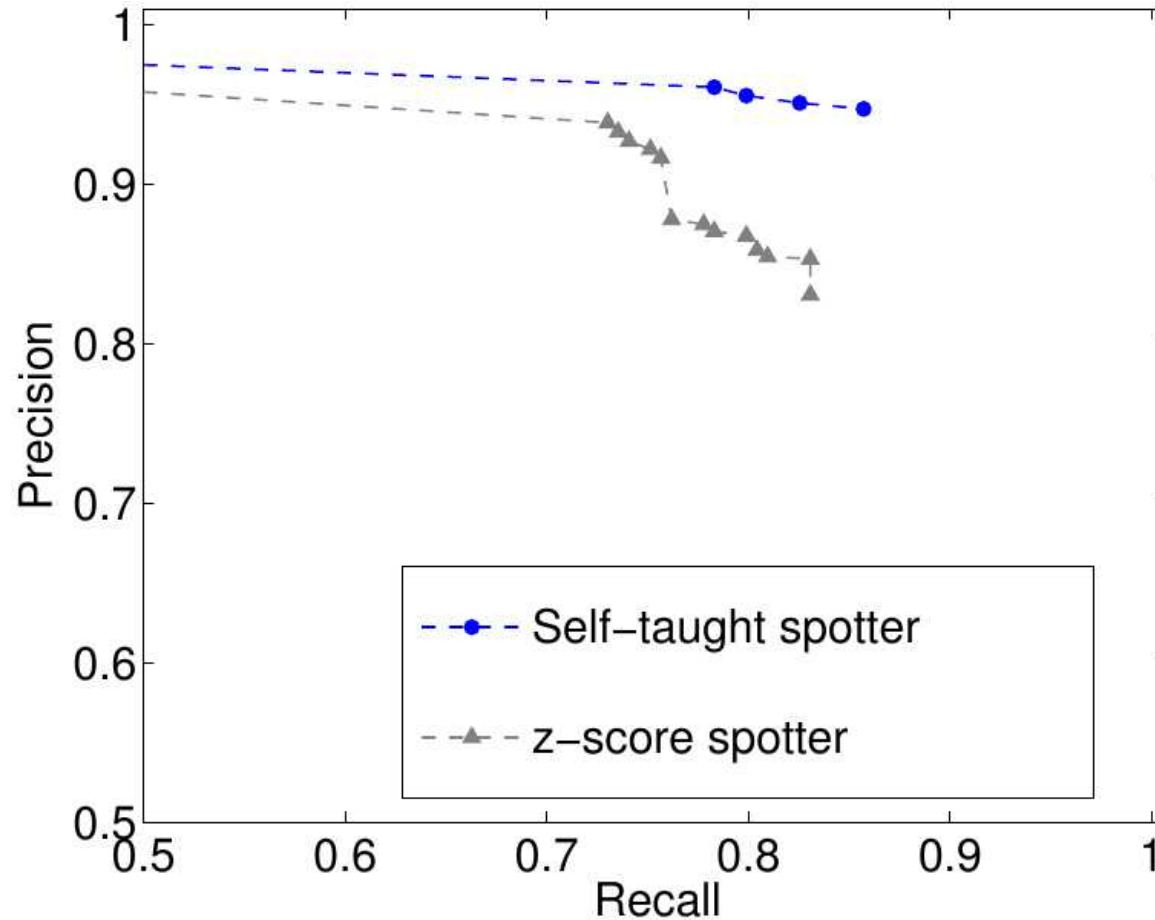


Leisure

Dataset properties:

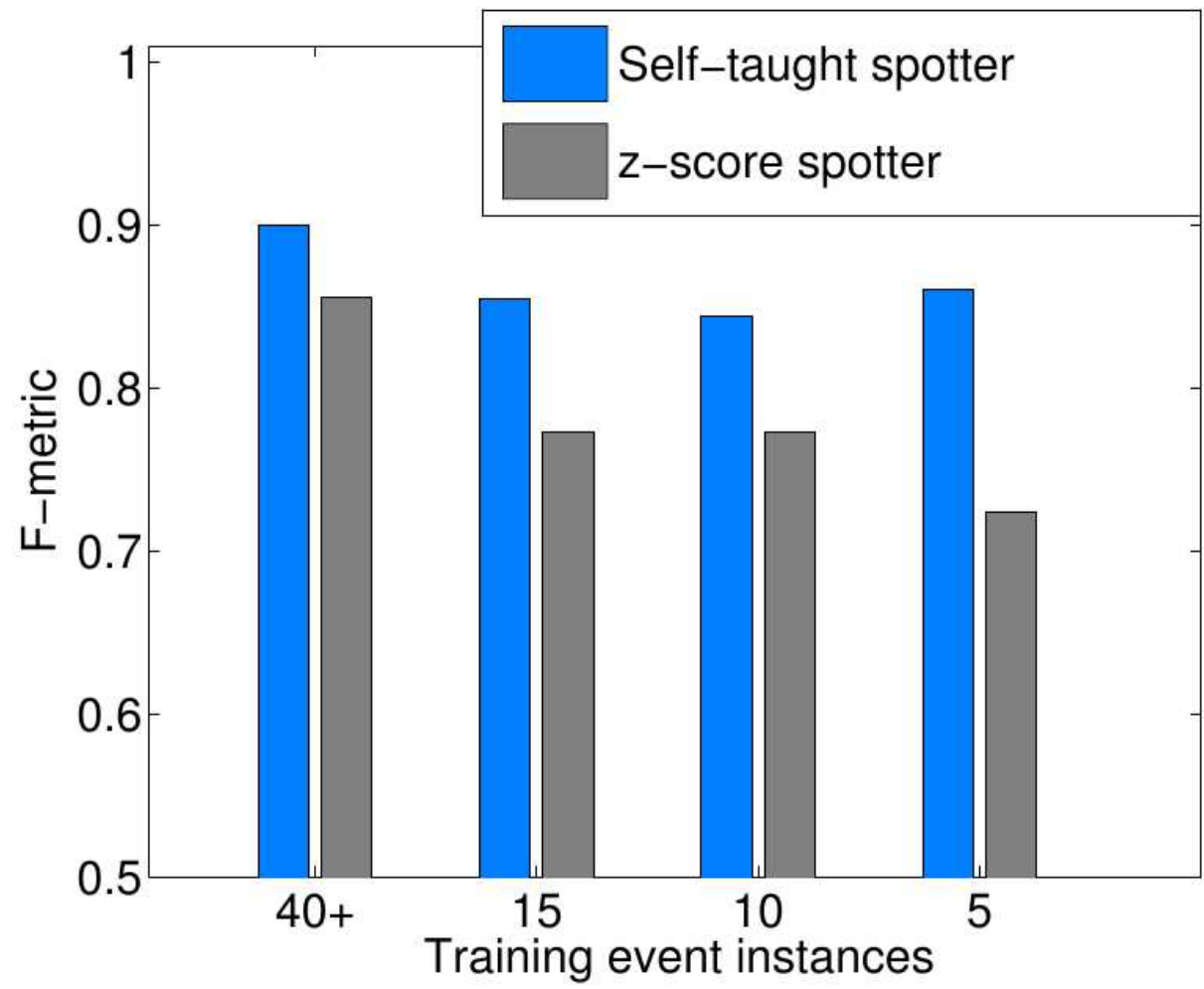
- wrist inertial sensor
- six students
- 5.84 h data
- 655 annotated sips
- $(1-g) > 90\%$

# Performance comparison\*



\* FSS decision threshold sweep.

# Constraint training performances



## **Main messages:**

- Properties of self-taught approach fit well with activity spotting problem.
- Self-taught spotting yields better performance in motion/gesture spotting.
- Self-taught spotter showed improved robustness when limited training examples are available.

# Acknowledgements

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