Tensor-based ECG Signal Processing Applied to Atrial Fibrillation Detection

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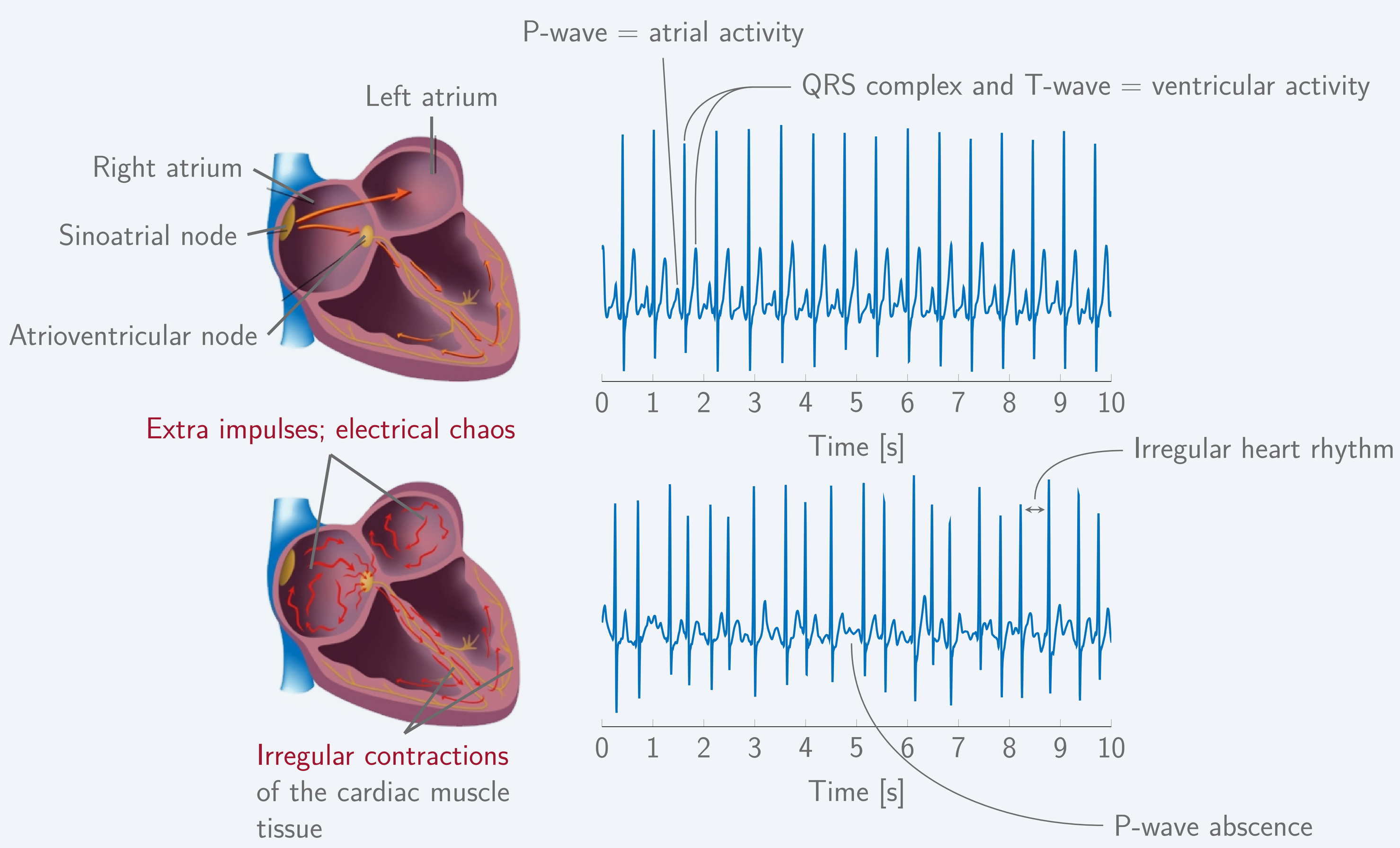
Atrial fibrillation (AF) is the most common arrhythmia



Some facts:

- 1 out of 4 will develop AF
- 1% of general population
- Latent risks: cloths of blood → pulmonary embolism, stroke, ...

Some trends:

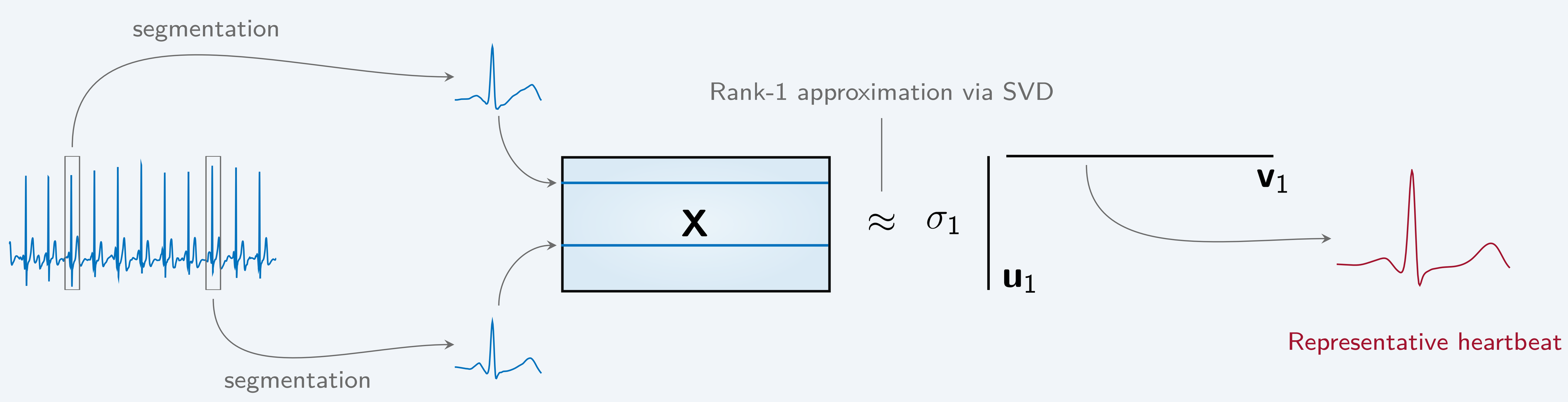
1. Need for accurate and early detection
2. More and more data become available (*mHealth*)

Motivate this research:

Goal

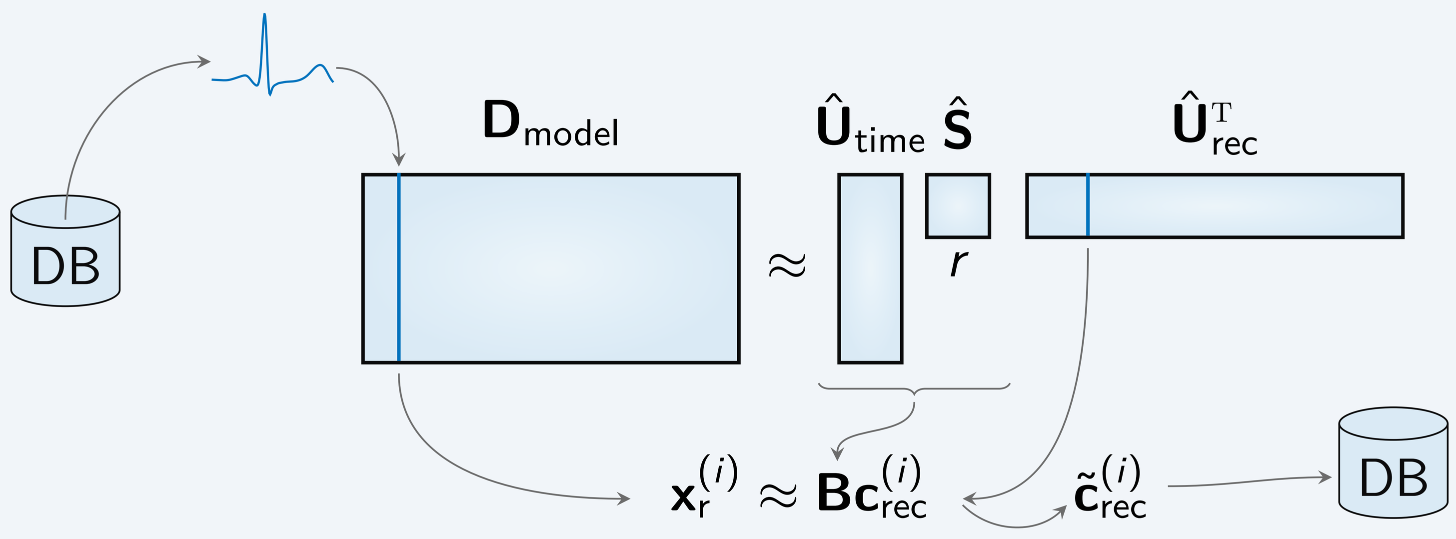
The *automatic* detection of AF in ECG signals

Represent ECG recording by compressing it in single representative beat: results in fixed-length representation and extra denoising



SVD-based detection for single-channel ECG

Modeling phase: truncated SVD



Classification phase: classifying a new ECG recording $\mathbf{x}_r^{(new)}$

- Morphological features:

  Solve:

  $$\mathbf{x}_r^{(\text{new})} = \mathbf{B}\mathbf{c}_{\text{rec}}^{(\text{new})} \rightarrow \tilde{\mathbf{c}}_{\text{rec}}^{(\text{new})}$$

  Compute for each class c, $f_c^{(\text{new})}$, based on:

  $$f_c^{(\text{new})} = \sum_{i \in c} w_i s_i, \text{ with } s_i = \tilde{\mathbf{c}}_{\text{rec}}^{(\text{new})\mathrm{T}} \tilde{\mathbf{c}}_{\text{rec}}^{(i)}, \forall i : 1 \leq i \leq M$$

A clear separation between the AF class and normal class (NSR) shown by the morphological features on the PhysioNet/Cinc challenge 2017 dataset.

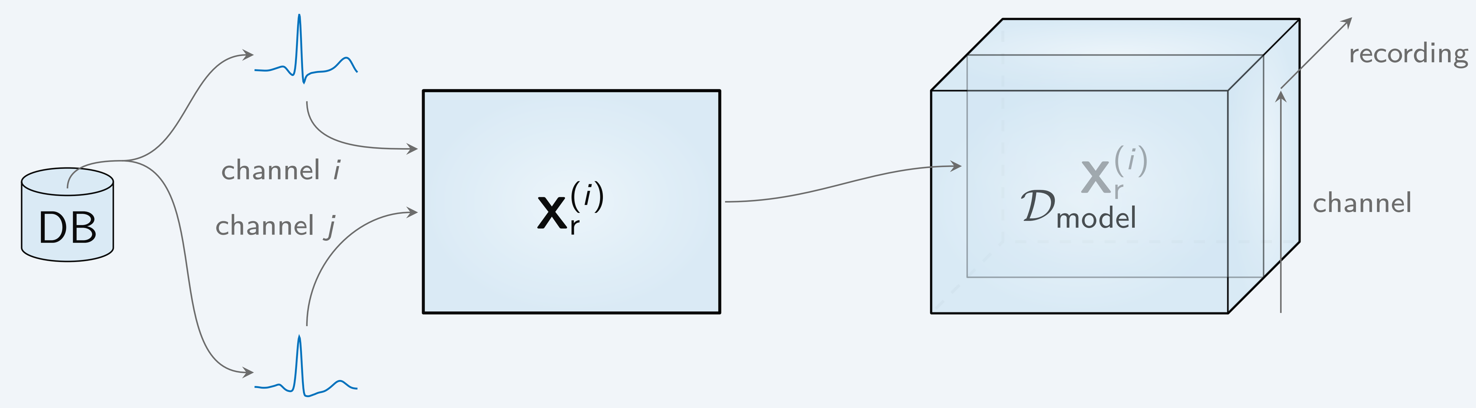
- Morphological + classical heart rate variability (HRV) features

Feature set	$P(\%)$	F_{1n}	F_{1a}	F_{1o}	F_1
HRV	77.6	0.85	0.76	0.59	0.73
SVD	70.0	0.81	0.57	0.40	0.59
SVD + HRV	**80.2**	**0.87**	**0.80**	**0.65**	**0.77**

Combining the new morphological features with classical HRV features with an SVM classifier leads to higher performances. This is shown on the PhysioNet/Cinc challenge 2017 dataset.

MLSVD-based detection for multi-channel ECG

Tensorization



Modeling phase: truncated MLSVD

$$\mathcal{D}_{\text{model}} \approx \hat{\mathcal{S}} \cdot_1 \hat{\mathbf{U}}_{\text{channel}} \cdot_2 \hat{\mathbf{U}}_{\text{time}} \cdot_3 \hat{\mathbf{U}}_{\text{rec}}.$$

For one slice $\mathbf{X}_r^{(i)}$:

$$\mathbf{X}_r^{(i)} \approx \underbrace{\hat{\mathcal{S}} \cdot_1 \hat{\mathbf{U}}_{\text{channel}} \cdot_2 \hat{\mathbf{U}}_{\text{time}}}_{\mathcal{B}} \cdot_3 \mathbf{c}_{\text{rec}}^{(i)\mathrm{T}} \Leftrightarrow \text{vec}\left(\mathbf{X}_r^{(i)}\right) \approx \mathbf{B}_{(3)}^{\mathrm{T}} \mathbf{c}_{\text{rec}}^{(i)}.$$

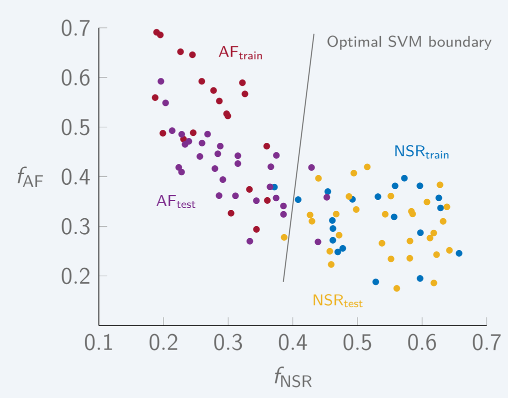
Classification phase: classifying a new multi-channel ECG recording $\mathbf{X}_r^{(new)}$

- Morphological features:

  Solve:

  $$\text{vec}\left(\mathbf{X}_r^{(\text{new})}\right) = \mathbf{B}_{(3)}^{\mathrm{T}} \mathbf{c}_{\text{rec}}^{(\text{new})} \rightarrow \tilde{\mathbf{c}}_{\text{rec}}^{(\text{new})},$$

  compute $\mathbf{f}^{(\text{new})}$ in a similar way



An almost perfect separation is possible based on the morphological features (MIT-BIH Arrhythmia + AFTDB dataset).

- Morphological + classical heart rate variability (HRV) features

Feature set	AUC	F_1
HRV	1.000	0.983
MLSVD	0.990	0.933
MLSVD + HRV	**1.000**	**1.000**

The new morphological features result in a very high performance, using an SVM classifier (MIT-BIH Arrhythmia + AFTDB dataset).

Conclusion

The designed morphological features contain a lot of information by themselves and complement the classical HRV features when other rhythms, besides NSR and AF, are present (clinically relevant)

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