Aggregation Procedure of Gaussian Mixture Models for Additive Features

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Gaussian Mixture Models aggregation procedure

This new approach is able to *generate* Gaussian Mixture Models (GMMs) for the **classification** of a***ggregated time series***

We focus on time series that are aggregated together by adding their features

It consists of three steps:

- modelling the independent classes
- generation of the models for the class combinations
- simplification of the generated models

Algorithm 1. Aggregating schema

Input: data x_i, label c_i, aggregation level L
$\lambda^{new}(\boldsymbol{\mu}, \boldsymbol{\Sigma}, \pi) \leftarrow \mathrm{GMMs}(x_i, c_i)$
$\lambda^{old} \leftarrow \lambda^{new}$
for $l = 1$ **to** $L-1$ **do**
  $\lambda^{new} \leftarrow$ merge_models(λ^{new}, λ^{old})
  $\lambda^{new} \leftarrow$ simplify_models(λ^{new})
end for

Gaussian Mixture Models:

$$p(\mathbf{x} \mid \theta) = \sum_{k=1}^{K} \frac{w_k}{\sqrt{(2\pi)^D |\boldsymbol{\Sigma}_k|}} e^{[-\frac{1}{2}(\mathbf{x}-\boldsymbol{\mu}_k)^T \boldsymbol{\Sigma}_k^{-1} (\mathbf{x}-\boldsymbol{\mu}_k)]}$$

Merging:

Input: GMMs$'(\lambda')$, GMMs$''(\lambda'')$
$M \leftarrow$ total number of classes
for $m \leftarrow 1$ **to** M **do**
  $nGauss_1 \leftarrow$ total number of Gaussians for GMMs$'$
  $nGauss_2 \leftarrow$ total number of Gaussians for GMMs$''$
  $k \leftarrow 0$
  for $k_1 \leftarrow 1$ **to** $nGauss_1$ **do**
    for $k_2 \leftarrow 1$ **to** $nGauss_2$ **do**
      $\boldsymbol{\mu}_{m,k} \leftarrow \boldsymbol{\mu}'_{m,k_1} + \boldsymbol{\mu}''_{m,k_2}$
      $\boldsymbol{\Sigma}_{m,k} \leftarrow \boldsymbol{\Sigma}'_{m,k_1} + \boldsymbol{\Sigma}''_{m,k_2}$
      $w_{m,k} \leftarrow \pi'_{m,k_1} \cdot w''_{m,k_2}$
      $k \leftarrow k+1$
    end for
  end for
end for
Output: new models $\lambda(\boldsymbol{\mu}, \boldsymbol{\Sigma}, w)$

Simplification:

- *Optimal solution*. It consists in computing all the combinations of all the Gaussians and merging the two Gaussians with the minimum distance if below the threshold
- *Suboptimal solution*. This approach consists in analyzing all the combinations but greedily selecting the first occurrence that is below the threshold

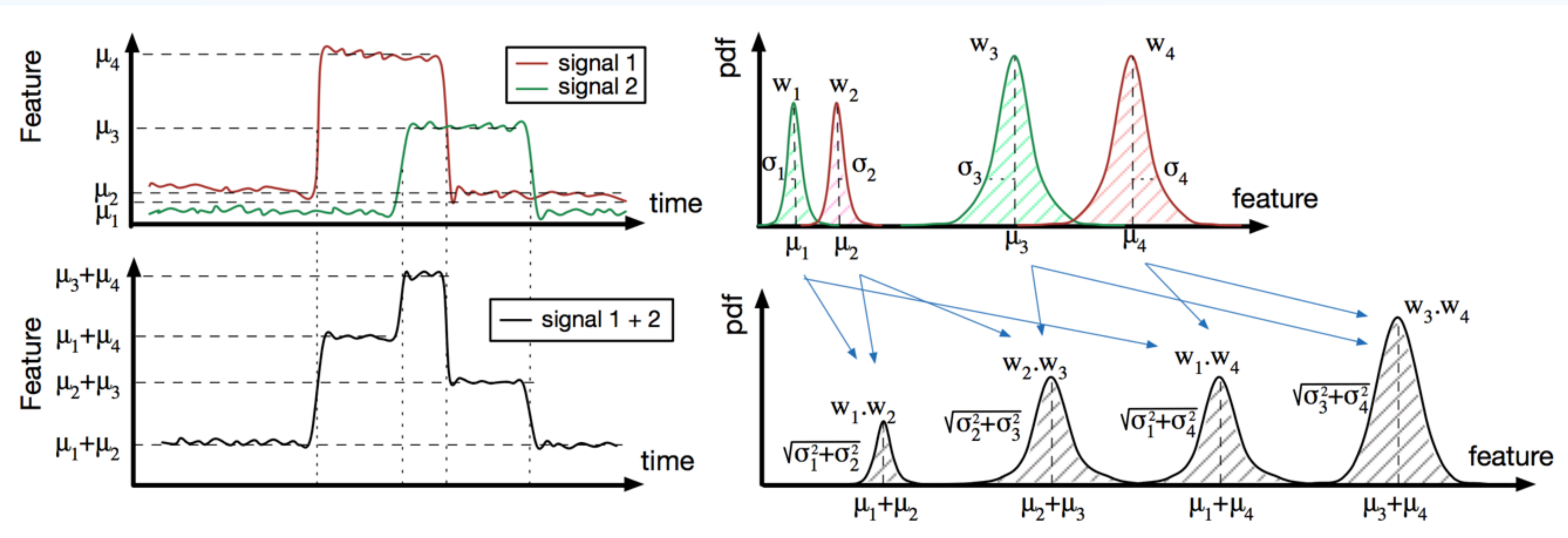
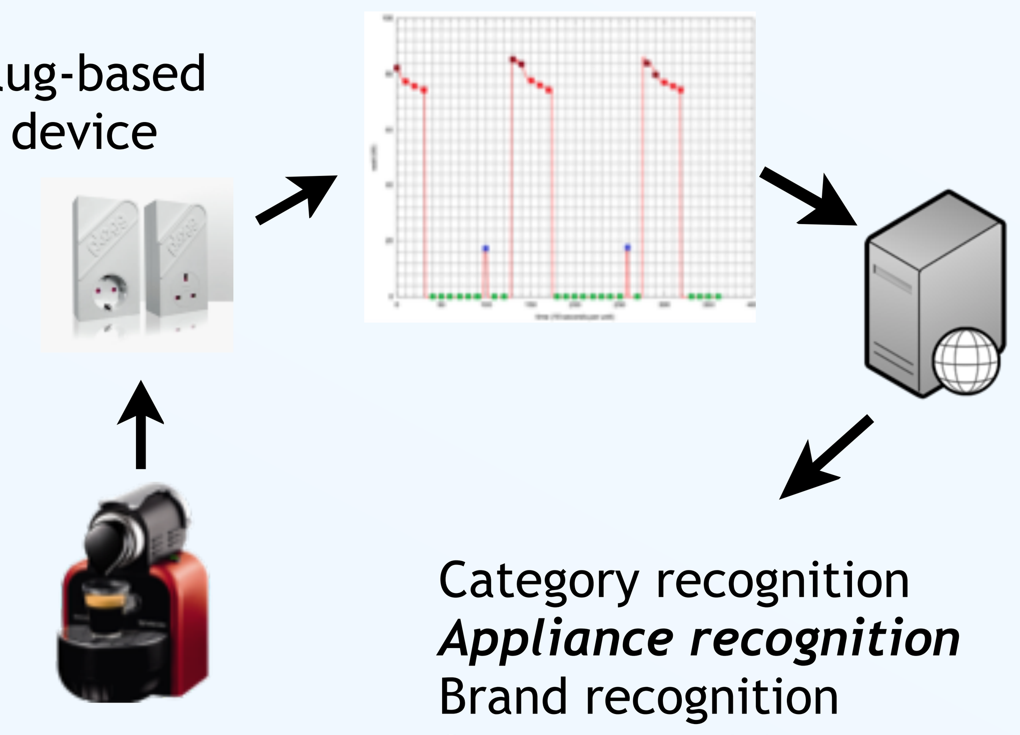


Figure 1. Synthetic example of the model merging for the classification of additive time series

Case of study: electrical appliance recognition

Electrical appliance recognition

Plug-based device



Appliance

Category recognition
Appliance recognition
Brand recognition
State recognition

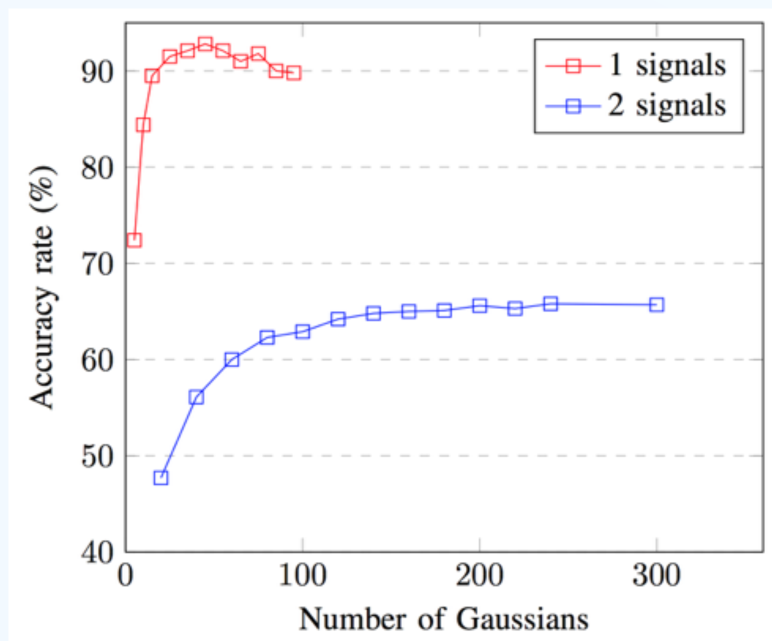
We used the **ACS-F2 Database:**

The electric consumption is recorded at low sampling frequency (10^{-1} Hz)

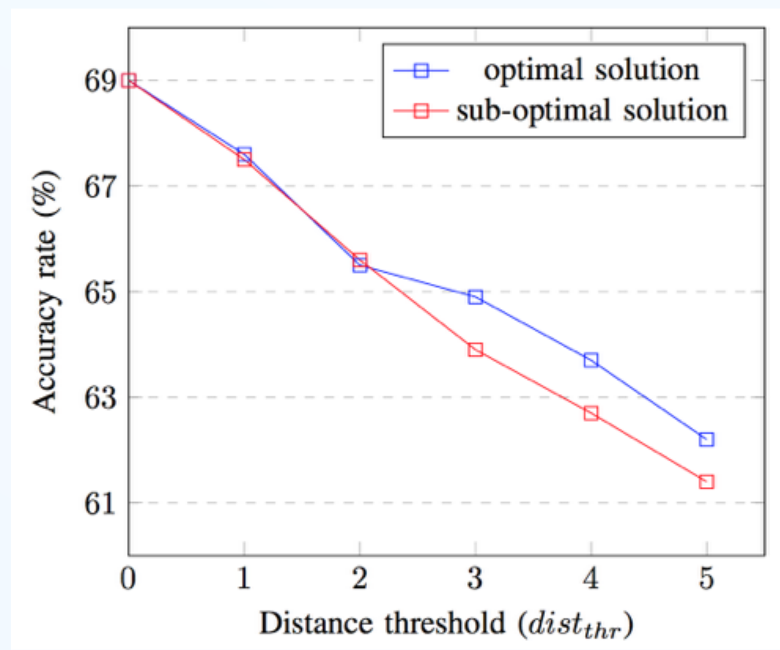
The database contains the electrical appliance consumption of 225 appliances uniformly spread between 15

Features:
Real power (W)
Reactive power (var)
RMS current (A)

Results:



Standard GMM



Aggregation procedure

We show a benefit in terms of accuracy rate and computational time

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