Condition monitoring with unsupervised learning

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Outline

- Background
- Data acquisition
- Source separation
- MF ICA
- Example
- Non-stationary

Background

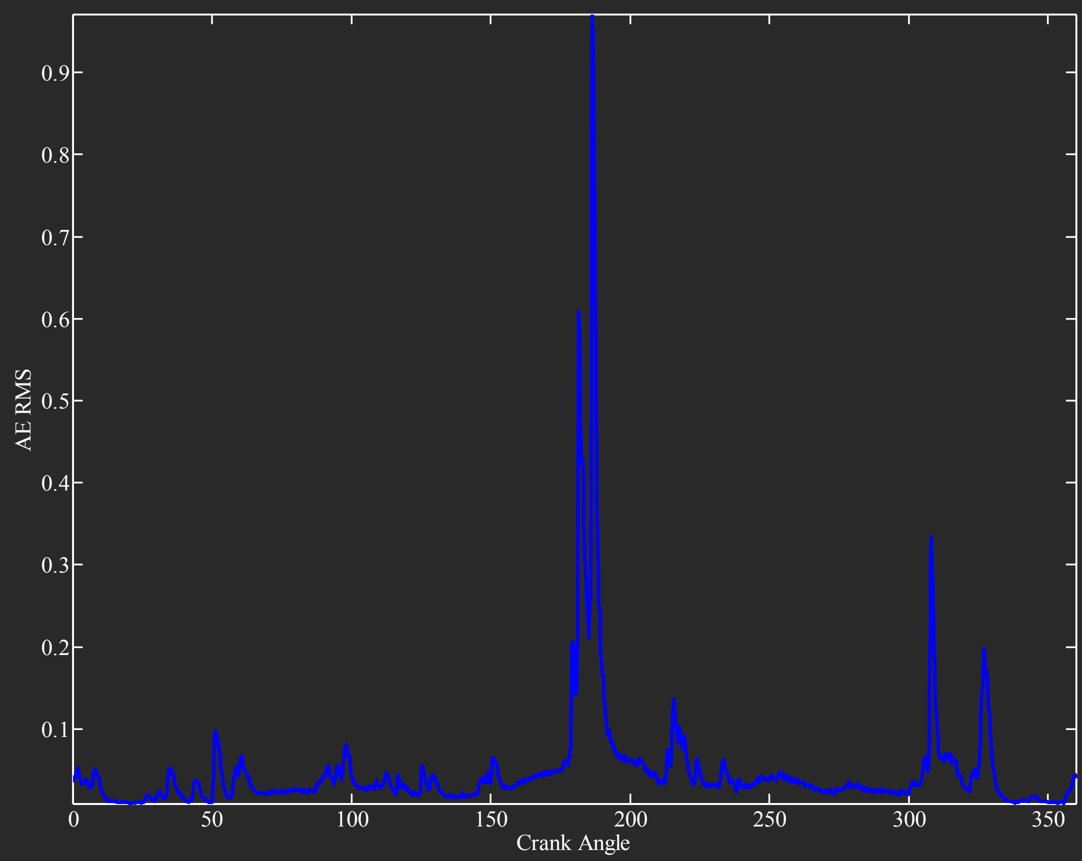
- Test engine 10.000 Hp (similar to 100 cars)
- Height as 3 storage house
- Makes a lot of noise!

- Acoustic emission: 100 kHz to 1 MHz
- Ultrasonic stress waves generated by inner cracking in material
- Decays faster than vibration, thus more localized

Data acquisition

- Conditioning
  - RMS “downsampling” to 20 kHz
  - Partitioning into cycles from Top Dead Center Marker
  - Crank angle sampling from Angle encoder
- Output
  - Non-negative signals
  - Fixed sample length independent of running speed
  - Clearly visible events

Acoustic Emission signal



Comparing

- Generative models that describe what we hear
  - Hidden sources
  - Activation of sources
  - Noise
- Unsupervised learning with the model
  - We learn the normal condition from normal data

Blind Source Separation Model

- Instead of simultaneous recordings we have successive recordings
- We stack cycles to build a training matrix **X**
- From the training matrix **X**=**AS** we will learn the hidden sources **S** and the mixer matrix **A**.
- Since **S** is independent/principal/else **A** is the part that is dependent – thus describing the mode

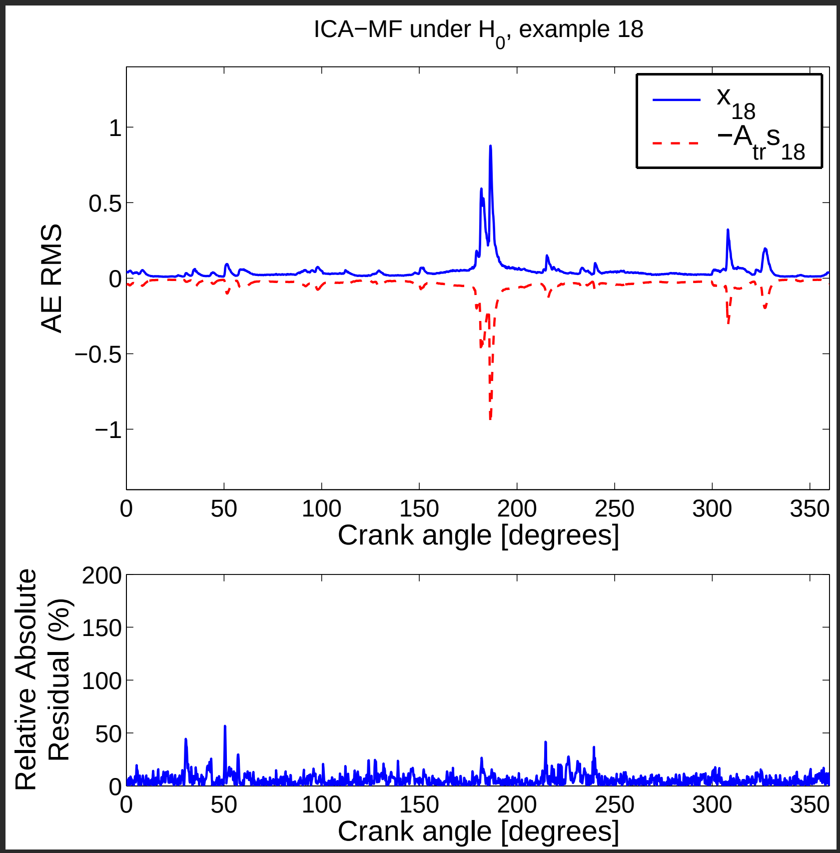
Idea

- The normal mode has a
  - well defined signatures (mixer matrix)
  - well defined noise level
  - well defined behaviour for sources (activation of signatures)
- A fault might manifest itself as
  - Higher noise level as the model cannot describe the observed
  - Higher value of certain components, e.g. a louder impact

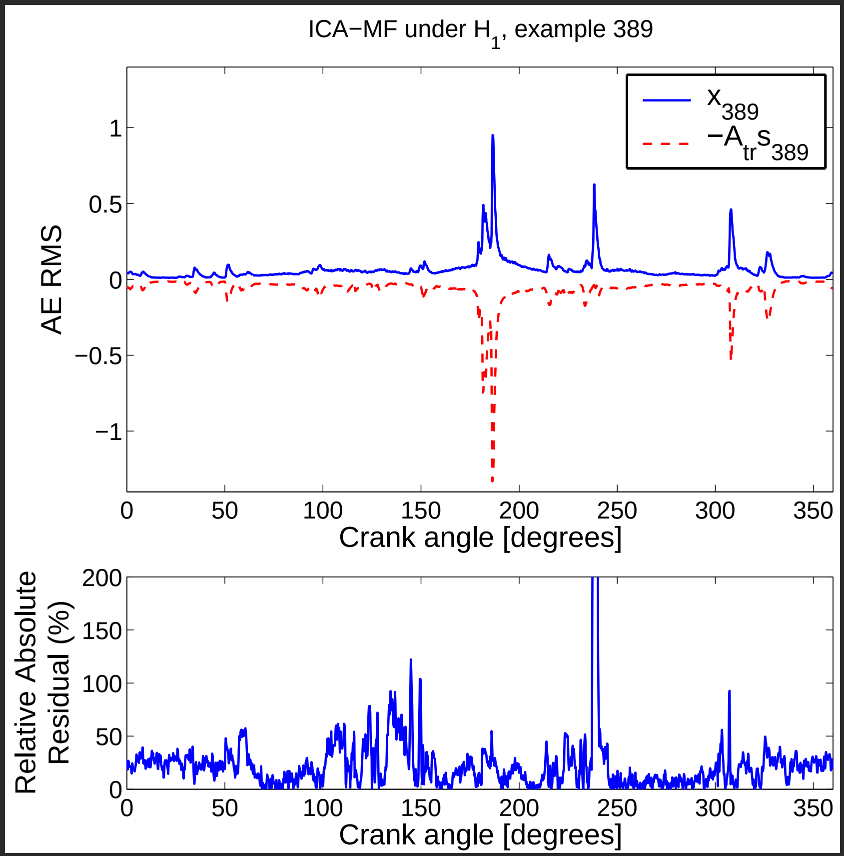
Mean Field ICA

- RMS data is non-negative
- MF ICA priors allows for positive mixer matrix and positive exponential source matrix

MF examples

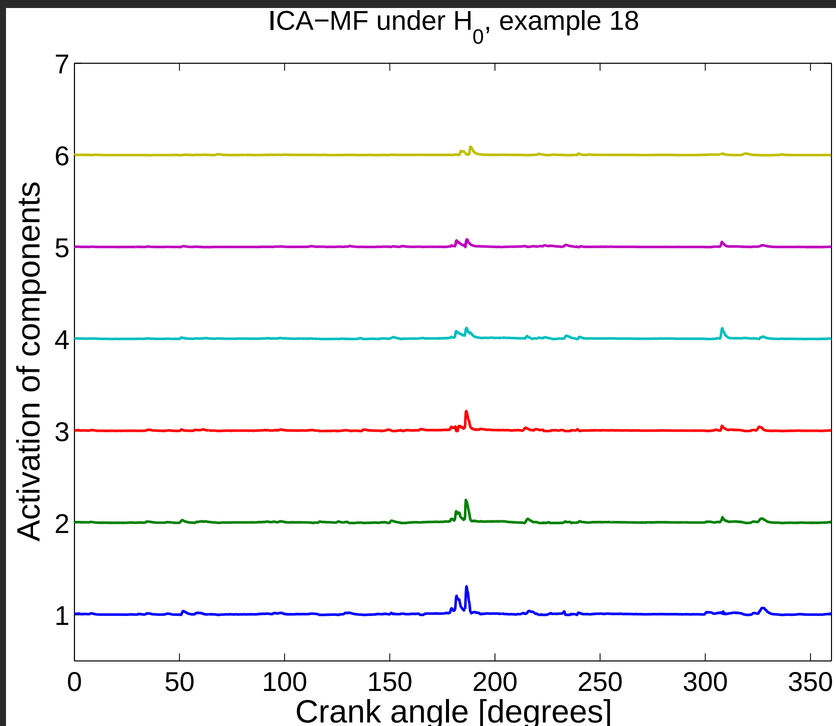


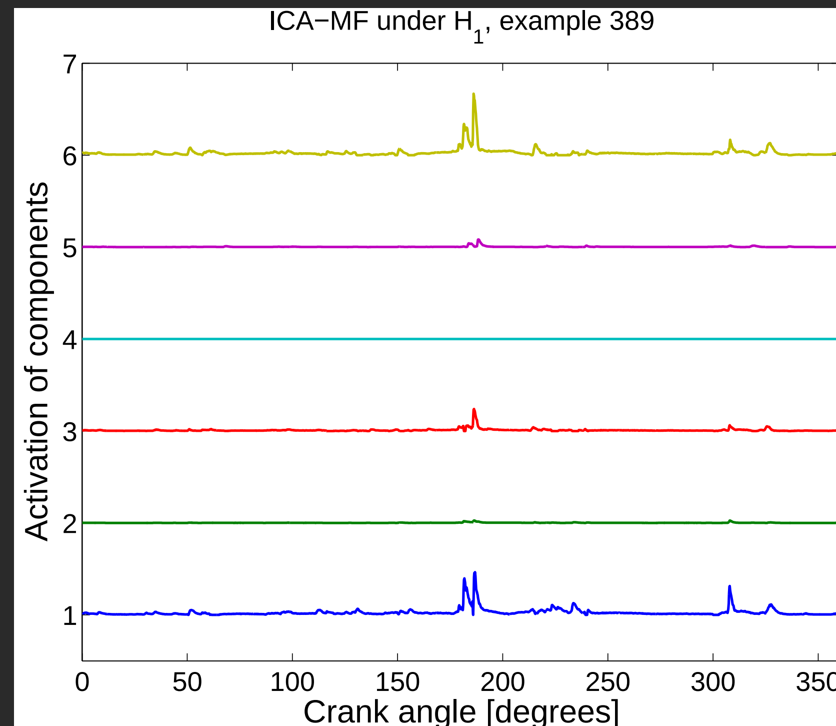
ICA−MF under H0, example 18
x18
−Atr s18
AE RMS
Crank angle [degrees]
Relative Absolute Residual (%)



ICA−MF under H1, example 389
x389
−Atr s389
AE RMS
Crank angle [degrees]
Relative Absolute Residual (%)

MF examples


ICA−MF under H0, example 18
Activation of components
Crank angle [degrees]
0
50
100
150
200
250
300
350
1
2
3
4
5
6
7


ICA−MF under H1, example 389
Activation of components
Crank angle [degrees]
0
50
100
150
200
250
300
350
1
2
3
4
5
6
7

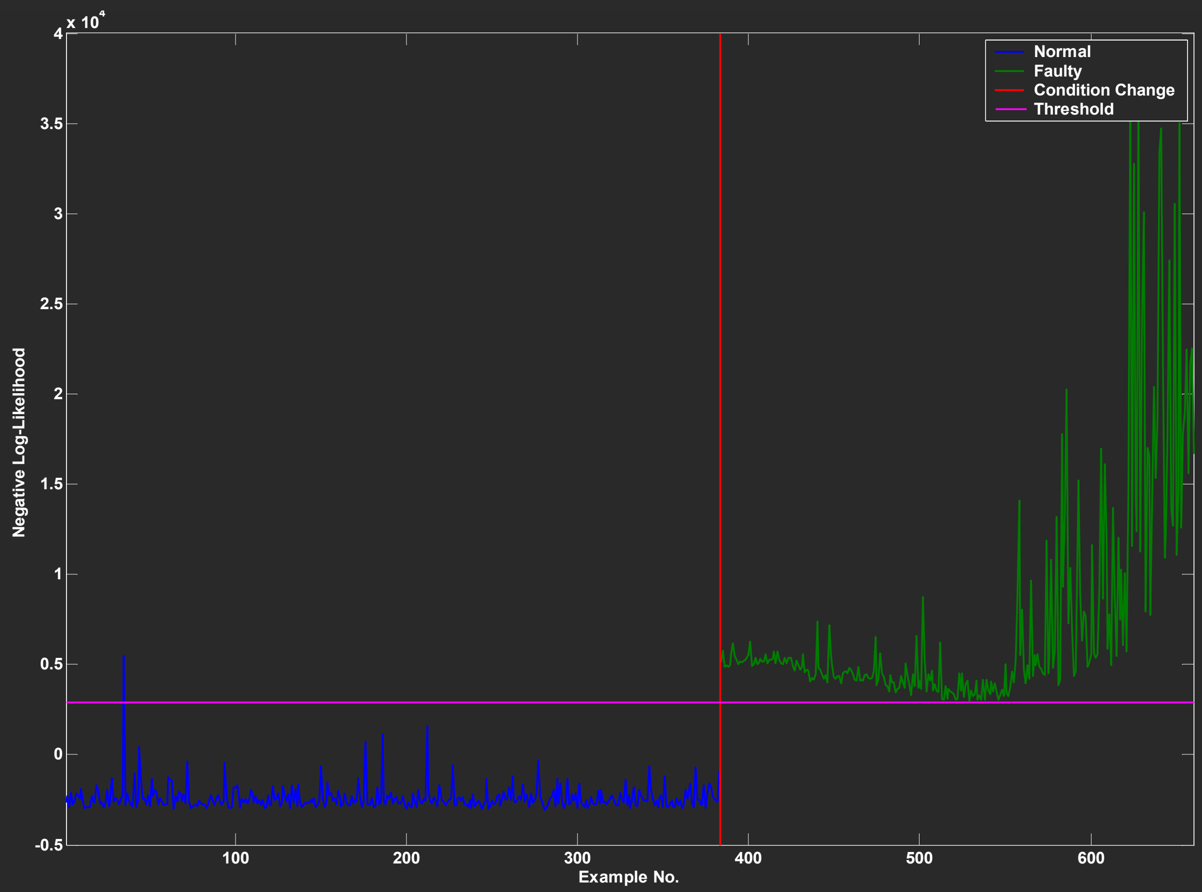
Other models

- Gaussian Processes
  - Mean over: mean and hyper parameters
- Principal component analysis:
  - Projection matrix **U**, noise level and “size” of pc’s
- BS ICA
  - Mixer matrix, source prior.

Normal or faulty

- For each cycle calculate the negative log-likelihood.
- Normal cycles should have low values, faulty: high.
- The log-likelihood incorporates sources and noise.
- From cumulated density functions over the we obtain the empirical probability that a cycle isn't normal.

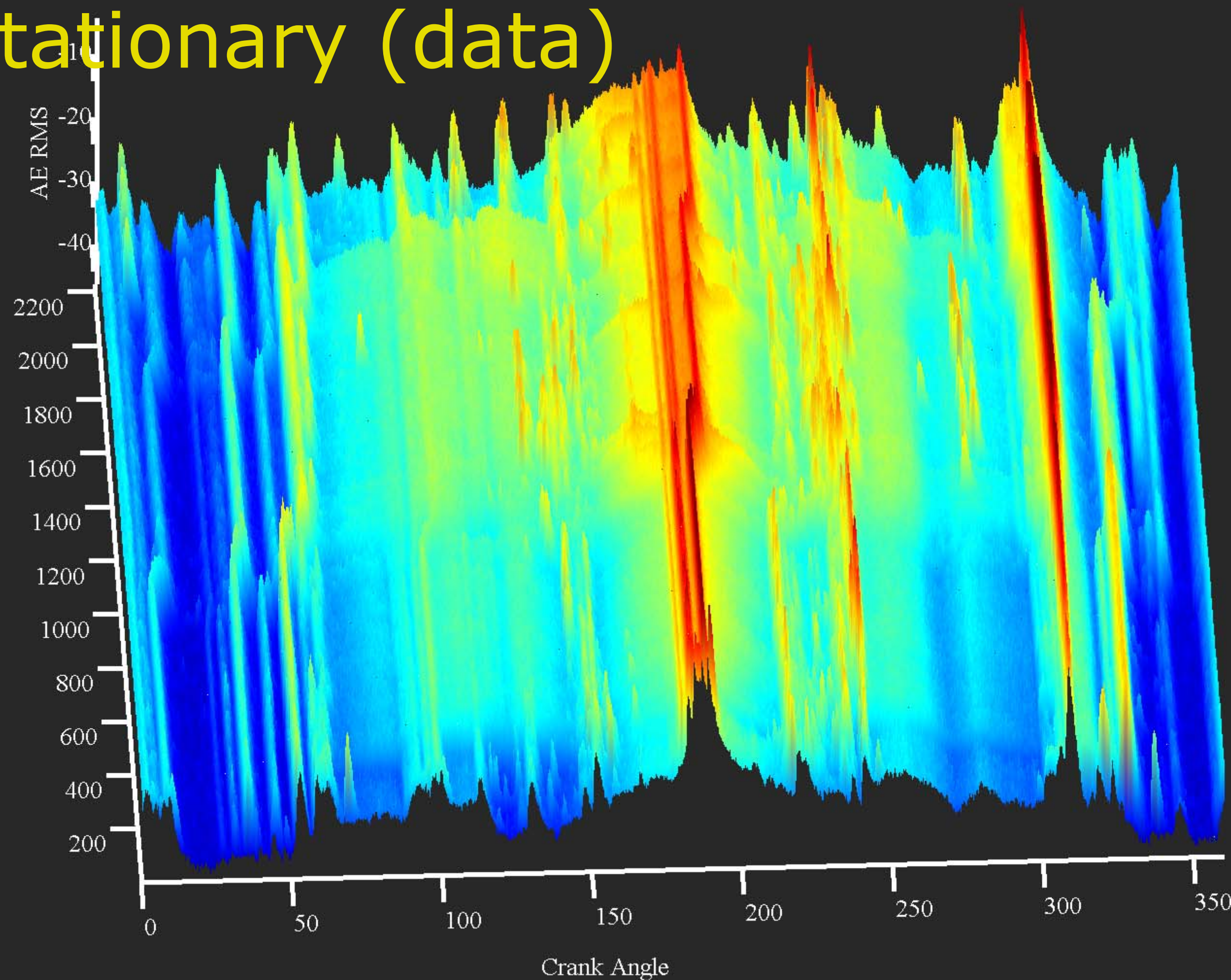
Negative log likelihood



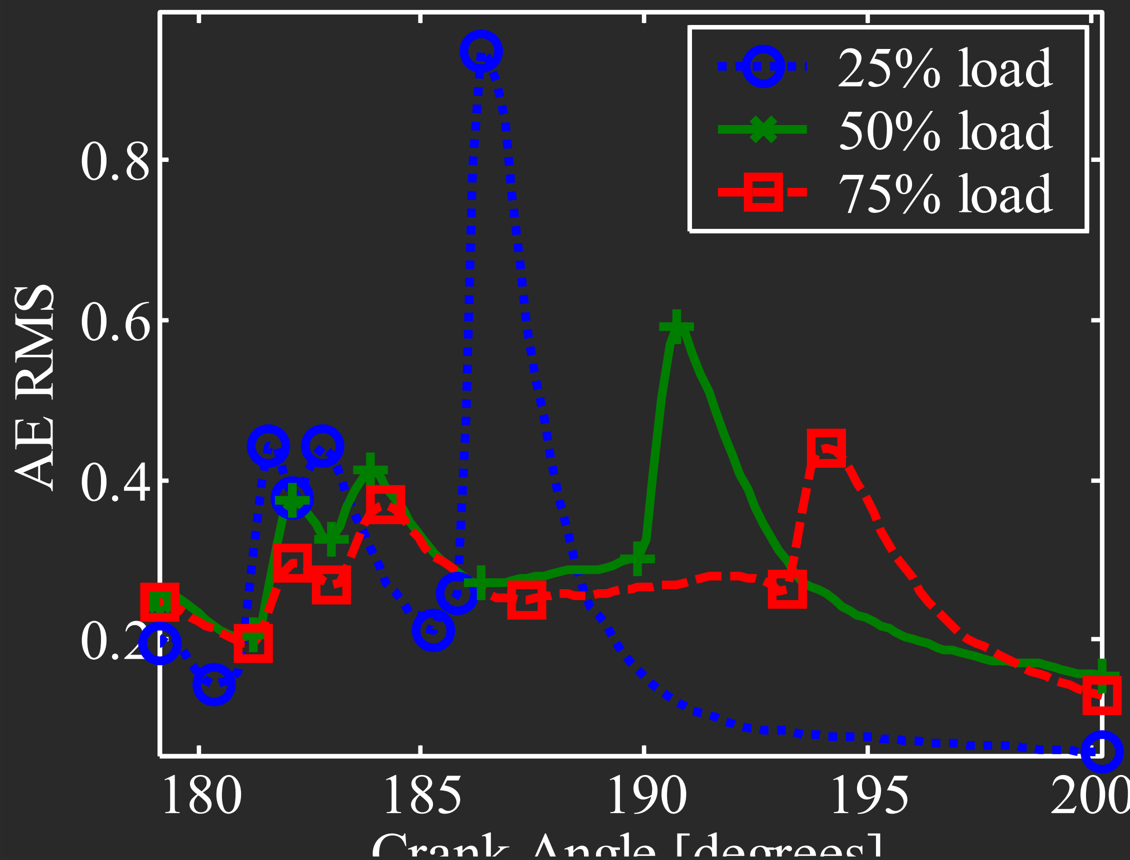
Non-stationary

- Timing and duration of events change as a function of the operating parameters, e.g. load and rpm
- Conflicting with the hidden sources
  - Or should we go convolutive?

Non-stationary (data)



Non-stationary (Injection)



Current approach

- Maintain unsupervised mode
  - Learn warp from normal modes to reference mode
  - Model for the timing changes
    - Alignment of landmarks, e.g. begin, peak and end for important events
    - Model for amplitude warp
    - Cubic spline interpolation between landmarks to obtain warp path
    - x[n]=y[f[n]], f[n] is the warp path
- Overfitting possible, alignment = more “normal”

End

Thanks to collaborators, especially Jan Larsen, Sigurdur Sigurdsson, Torben Fog and Ryan Douglas