UNIVERSITÀ DEGLI STUDI DI BERGAMO
Dipartimento di Ingegneria Gestionale, dell'Informazione e della Produzione
Control Automation Lab

ADAPTIVE LEARNING, ESTIMATION AND SUPERVISION OF DYNAMICAL SYSTEMS (ALES)

Case study 2: Nuclear particles classification

Master Degree in COMPUTER ENGINEERING

Data Science and Data Engineering Curriculum

SPEAKER
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PLACE
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Syllabus

1. **Recursive and adaptive identification**
   1.1 Recursive ARX estimation (RLS)
   1.2 Least Mean Squares (LMS)
   1.3 Instrumental Variables (IV)

2. **Closed-loop identification**

3. **Subspace and MIMO identification**
   3.1 Singular Value Decomposition
   3.2 Impulse data: Ho-Kalman, Kung algorithms
   3.3 Generic I/O data: the MOESP algorithm

4. **Supervision of dynamical systems**
   4.1 Introduction to fault diagnosis
   4.2 Model-based fault diagnosis
   4.3 Parity space approaches
   4.4 Observer-based approaches
   4.5 Signal-based fault diagnosis
   4.6 Knowledge-based fault diagnosis

CASE STUDIES

- Virtual Reference Feedback Tuning
- Nuclear particles classification
- Leak detection in an industrial valve
- Bearing fault identification

Outline

1. Problem statement and Experimental setup

2. Classification of LCP via learning-based system identification

    a) Reduce data noise

    b) Subspace System Identification

    c) LCP classification

3. Results and conclusion

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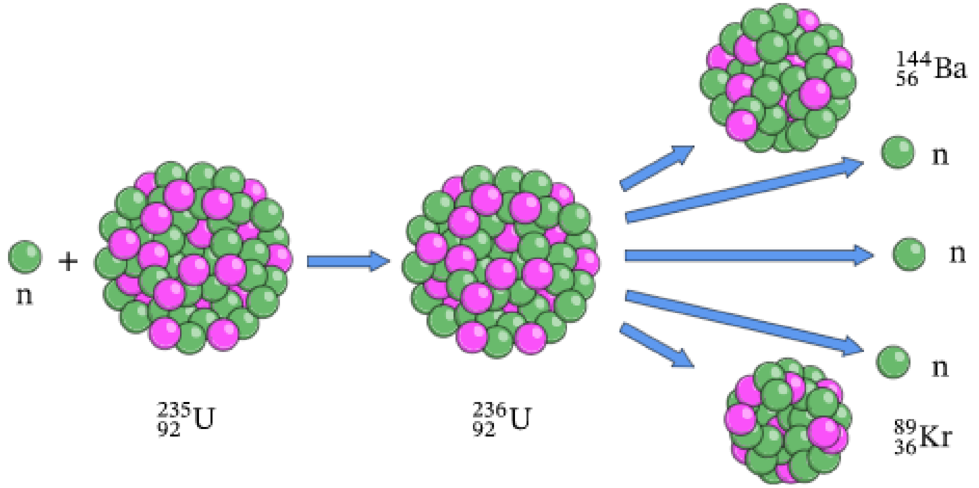
Problem statement and experimental setup

One of the most interesting goals of the **intermediate energy heavy ion** research is to investigate the characteristics of the nuclei under **extreme conditions** of density and temperature

In these physics' experiments, the standard approach is the measurement and analysis of the **collision effects** of a heavy ion beams over a target

The nuclear reactions induced by the nucleus-nucleus collision produce a large number of fragments with **different energy, charge** and **mass values**



Problem statement and experimental setup

To **identify** almost all the produced fragments, a suitable experimental device able to capture the particles that move away from the collision point in all directions is needed

This kind of devices present specific **detector cells** that generate an **electrical signal when hit by a particle**

However, the availability of these detectors **does not automate the classification** of the detected particles' fragments that are often **manually classified by visual inspection** of the measured electrical quantities

An efficient **automatic algorithm** is strongly advised

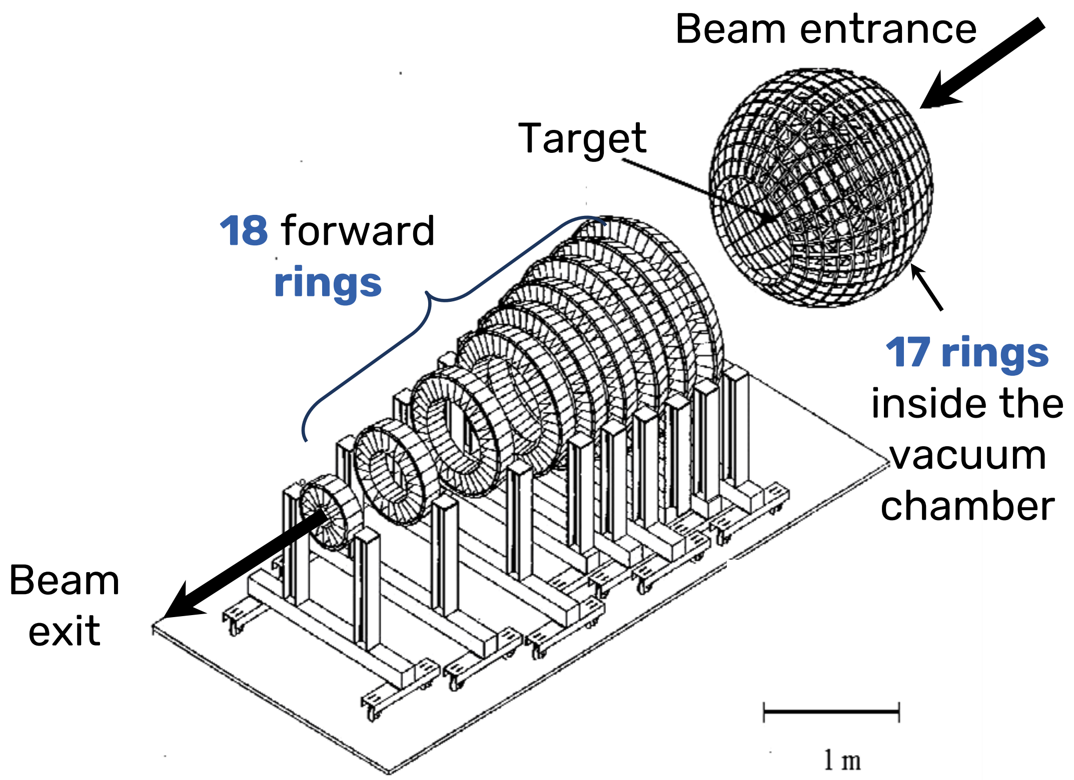
Problem statement and Experimental setup

The detector considered is the large detector array **CHIMERA** (Charge Heavy Ions Mass and Energy Resolving Array)

Problem statement and Experimental setup

The CHIMERA detector is designed to investigate heavy ion nuclear physics at intermediate energies

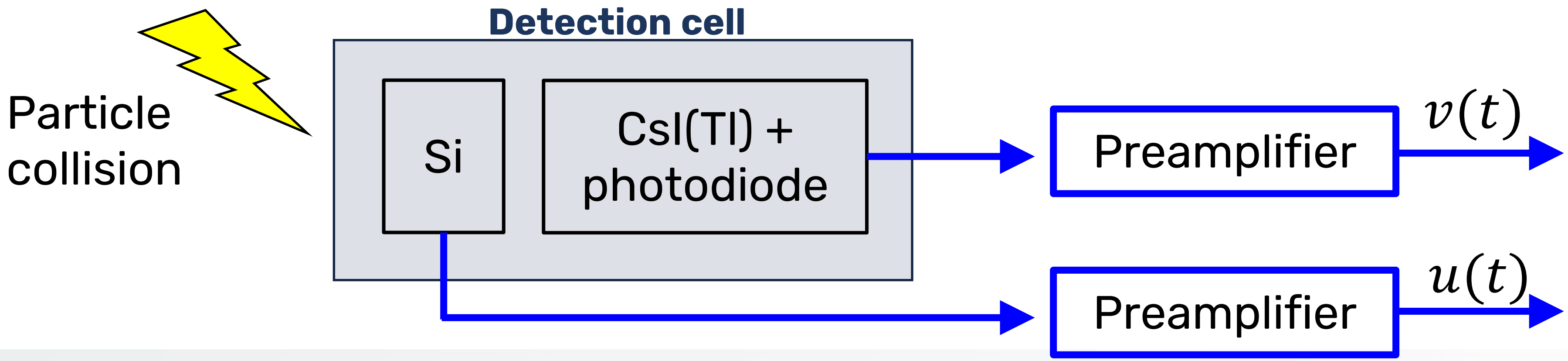
- A ^{20}Ne **beam** at 21MeV hits a ^{12}C **target**, generating the different particle fragments
- **1192 detection cells** arranged in **35 rings**



Problem statement and Experimental setup

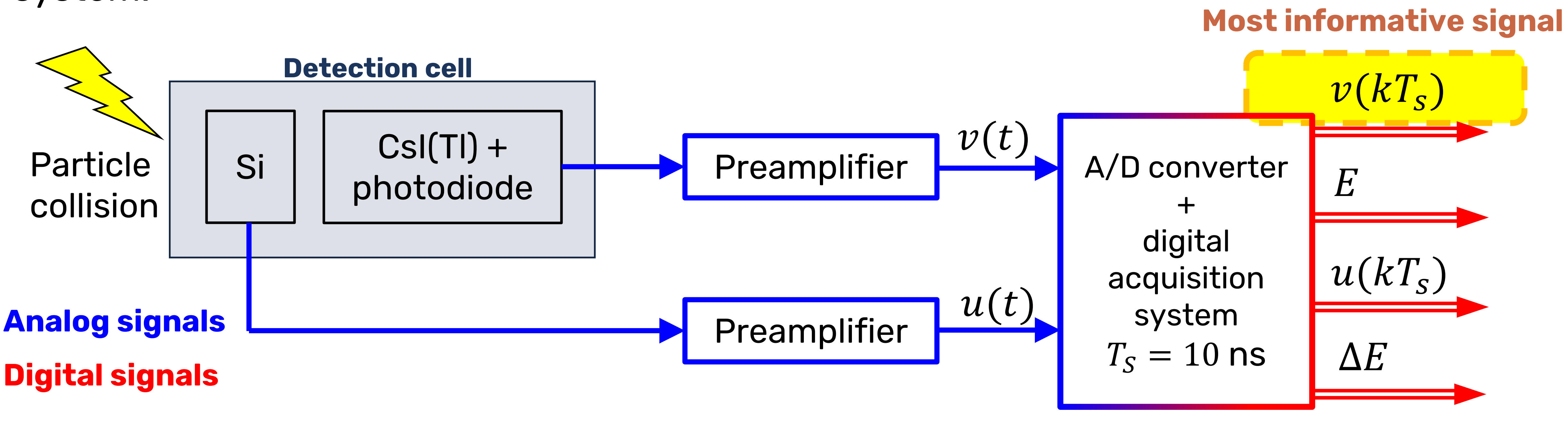
Each detection cell is a telescope composed by **2 elements**

- **Si** detector: through the photovoltaic effect provides a means of transforming light energy to an electrical current
- **CsI(Tl)** scintillator crystal: produces a **light impulse** when hit by a particle that a **photodiode** collects producing a current output which is converted into a **measurable voltage signal** $v(t)$



Problem statement and Experimental setup

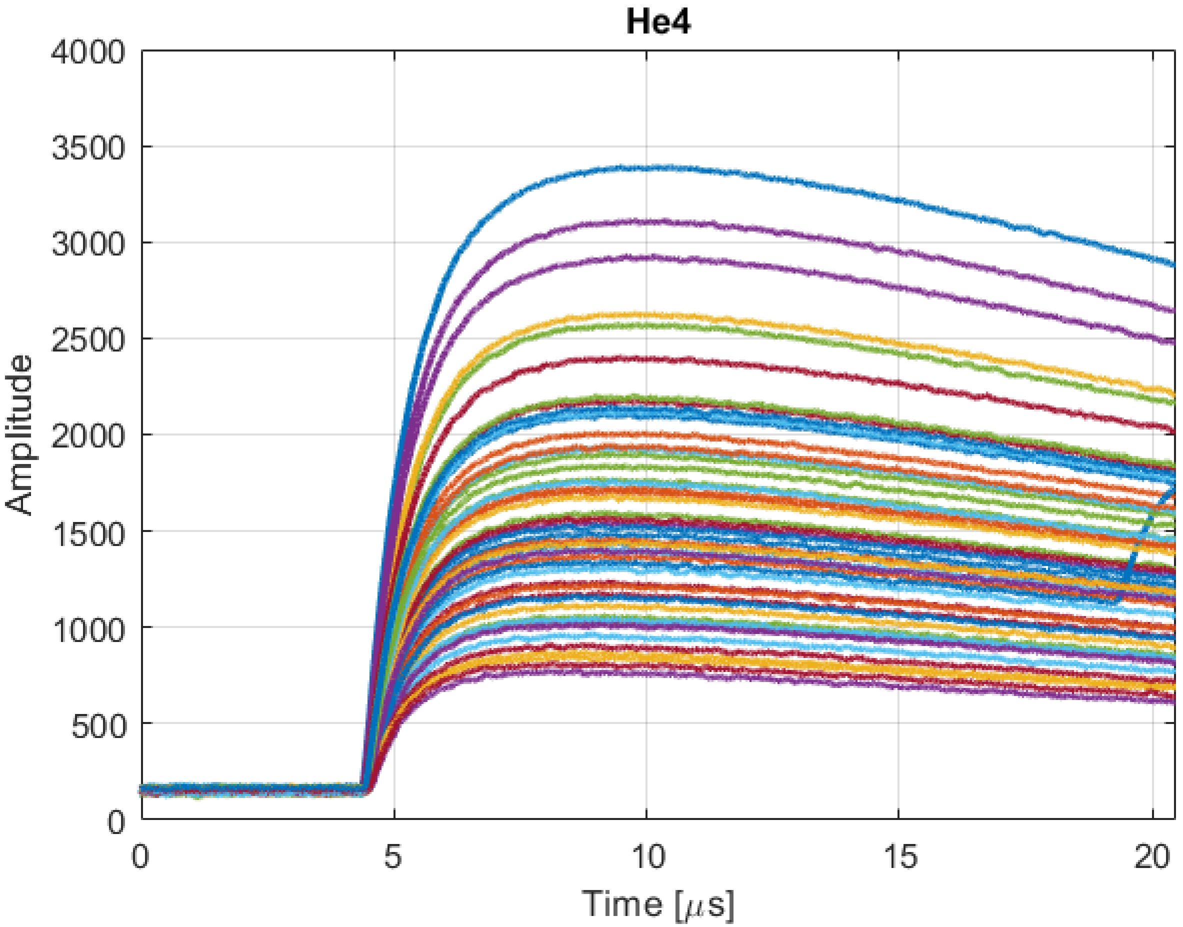
The complete **measurement chain** has an A/D converter and a digital acquisition system:

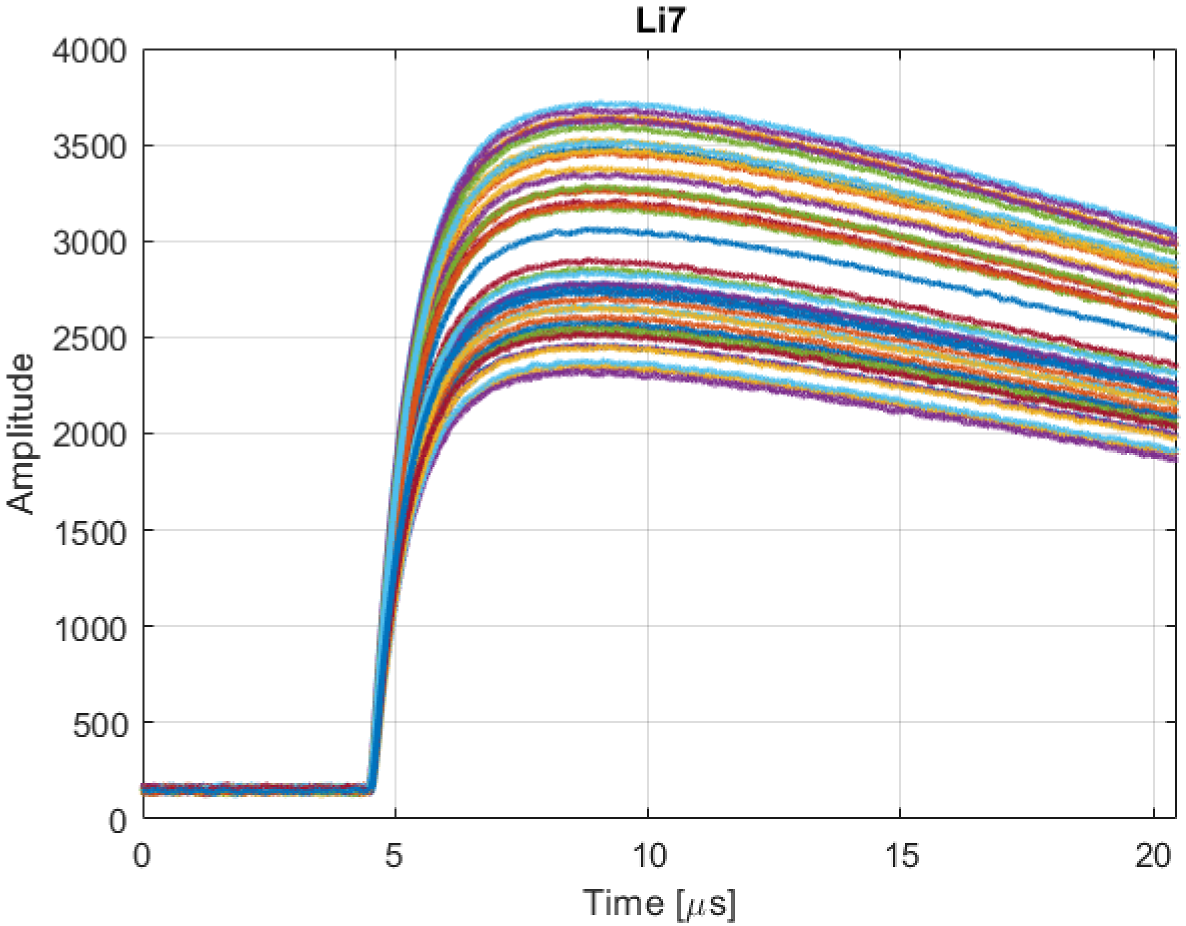


The signal $v(t)$ contains **all the information** necessary for ions classification (**charge** and **mass**)

Problem statement and Experimental setup

Typical experiment result (after multiplication by -1 to get a positive curve)





Problem statement and Experimental setup

To eliminate the **preamplifier dynamics**, approximated as a derivation, a **two-gate method** is used

The produced impulse measurements from CsI(Tl) sensor can be modeled (approximately, by ignoring sensor dynamics) by

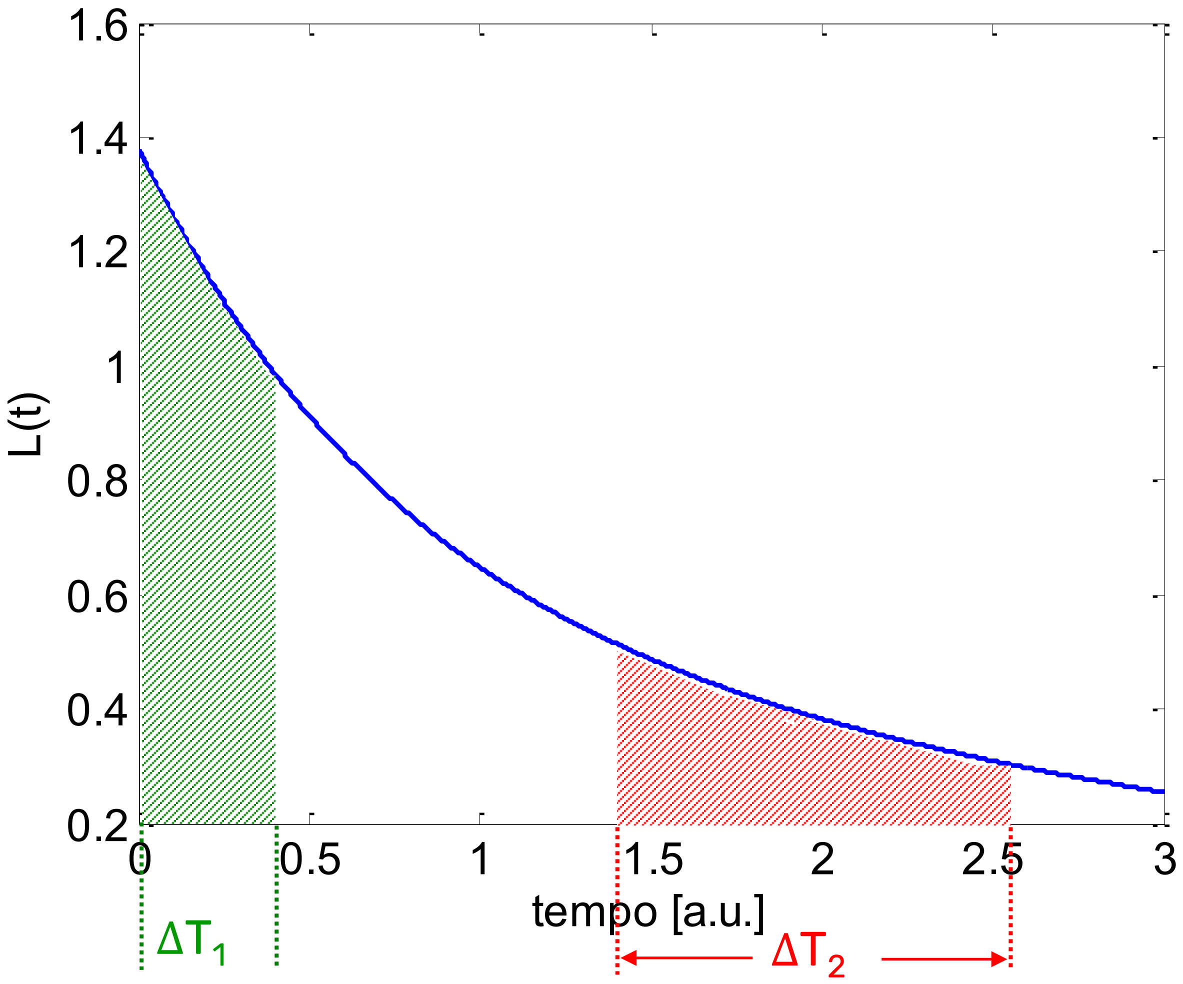
$$l(t) = L_s e^{-\frac{t}{\tau_s}} + L_f e^{-\frac{t}{\tau_f}}$$

whose decay rate depends on **two time constants**, a «**fast**» one τ_f and a "**slow**" one τ_s, that are correlated **only** with ions charge and mass (L_s, L_f depend also on energy),

Problem statement and Experimental setup

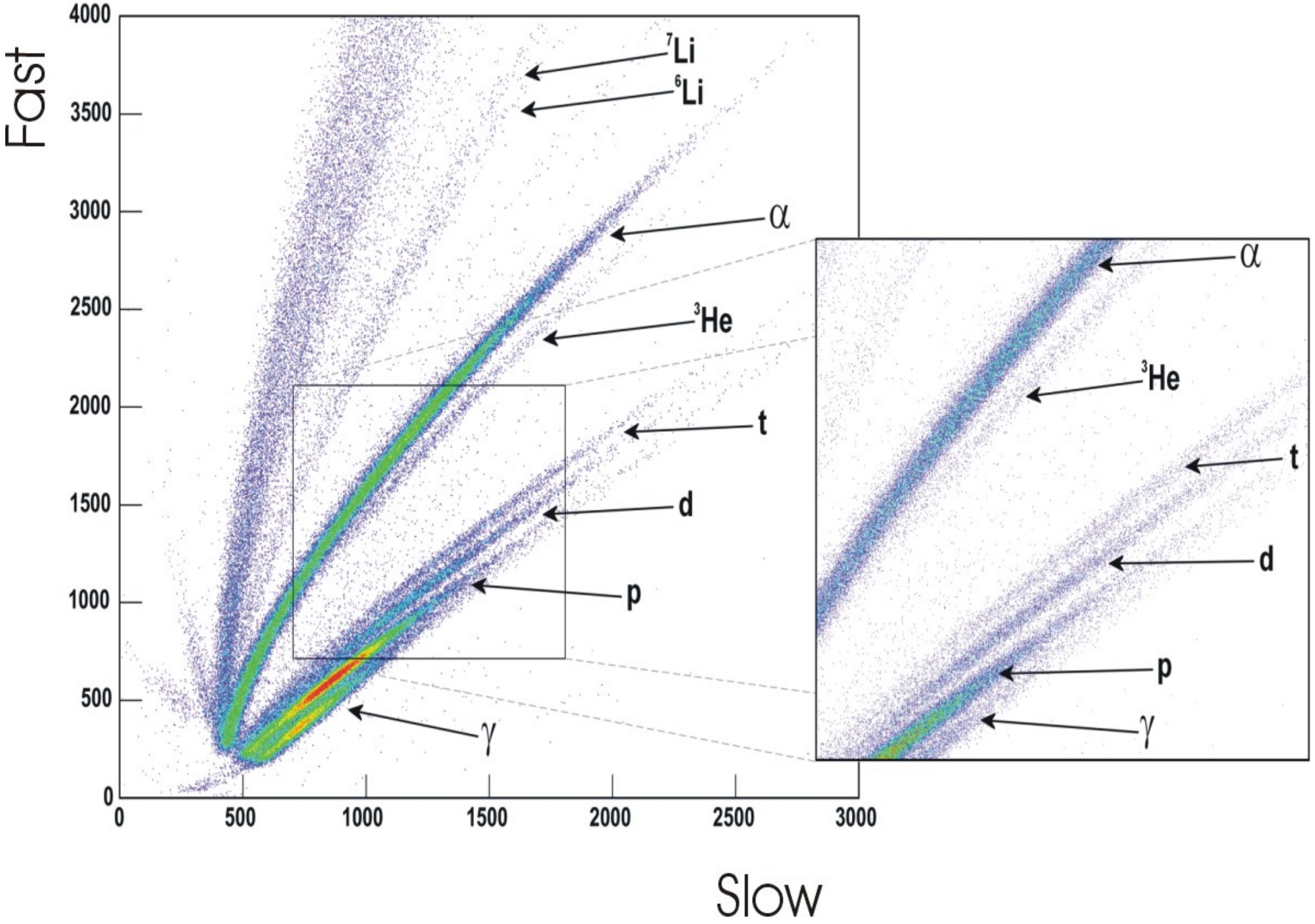
It is possible to integrate over two time intervals ΔT_1 and ΔT_2, one for the fast component and another one for the slow component

Classification is obtained by a visual inspection of the fast-slow plot



Problem statement and Experimental setup

Classification is obtained by a visual inspection of the fast-slow plot.



An automatic method is strongly advisable!

Outline

1. Problem statement and Experimental setup

2. **Classification of LCP via learning-based system identification**

    a) Reduce data noise

    b) Subspace System Identification

    c) LCP classification

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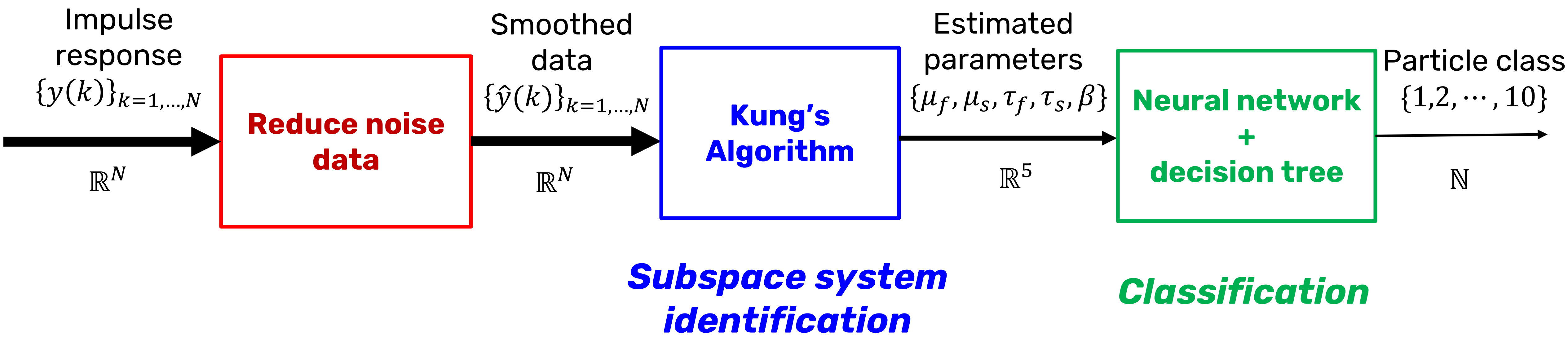
Classification of LCP via learning-based system identification

Aim of the work: automatically identify the **number** and **type** of the generated light charged particles (LCP).

The proposed method:

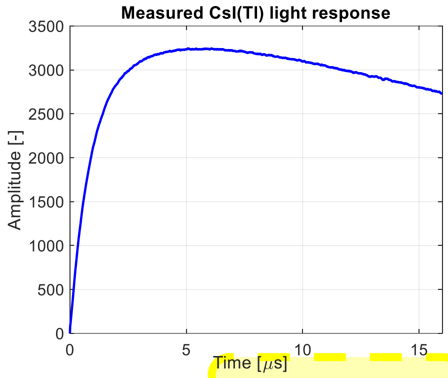
- smooths data, **reducing data noise**;
- performs a **subspace state space system identification** (Kung's algorithm)
- uses a **black-box classification scheme** based on Neural Networks and Decision Trees

Classification of LCP via learning-based system identification



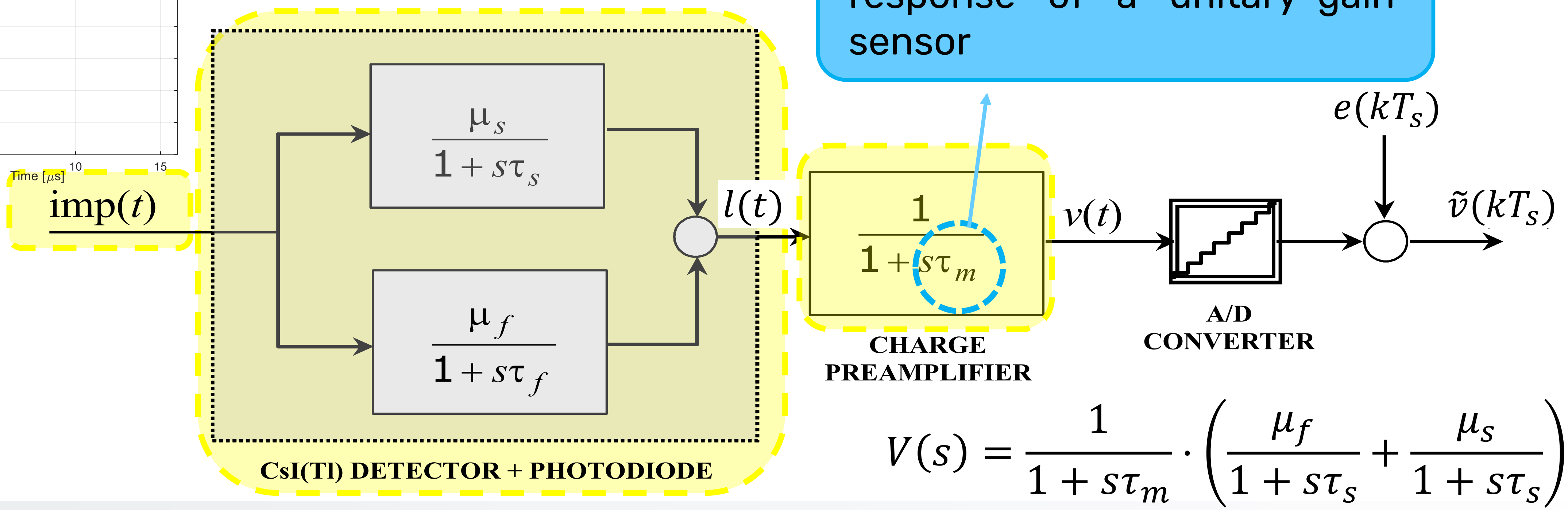
Modeling hypothesis

- The **CsI(Tl) voltage signal** is modeled as the output of a **3° order LTI** system
- The dynamics of the **preamplifier** is modeled as a **1° order LTI** system



$$l(t) = L_s e^{-\frac{t}{\tau_s}} + L_f e^{-\frac{t}{\tau_f}}$$

τ_m models the dynamic response of a unitary-gain sensor

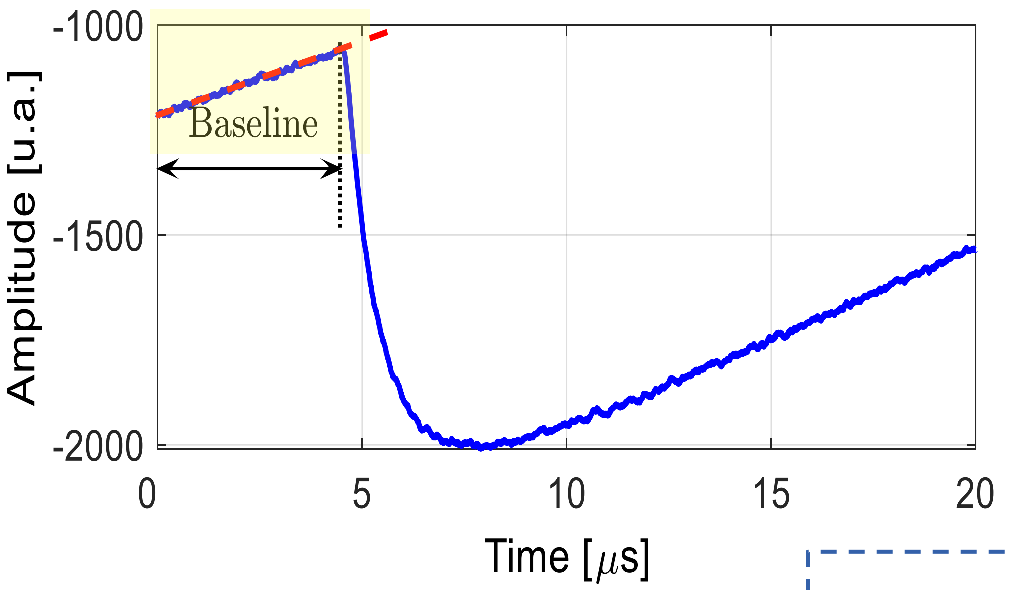


$$V(s) = \frac{1}{1+s\tau_m} \cdot \left(\frac{\mu_f}{1+s\tau_s} + \frac{\mu_s}{1+s\tau_s} \right)$$

Preprocessing phase

Before model identification, a **preprocessing phase on raw data** is done:

- Due to the post-triggering acquisition setup and acquisition chain's offsets the measured $v(t)$ has a "deadzone"



Two actions are mandatory:

1. **Remove the baseline**
   - by fitting a line ($g(k) = mk + l$) on the first μs of the measurement, obtaining

$$z(k) = \tilde{v}(k) - g(k)$$

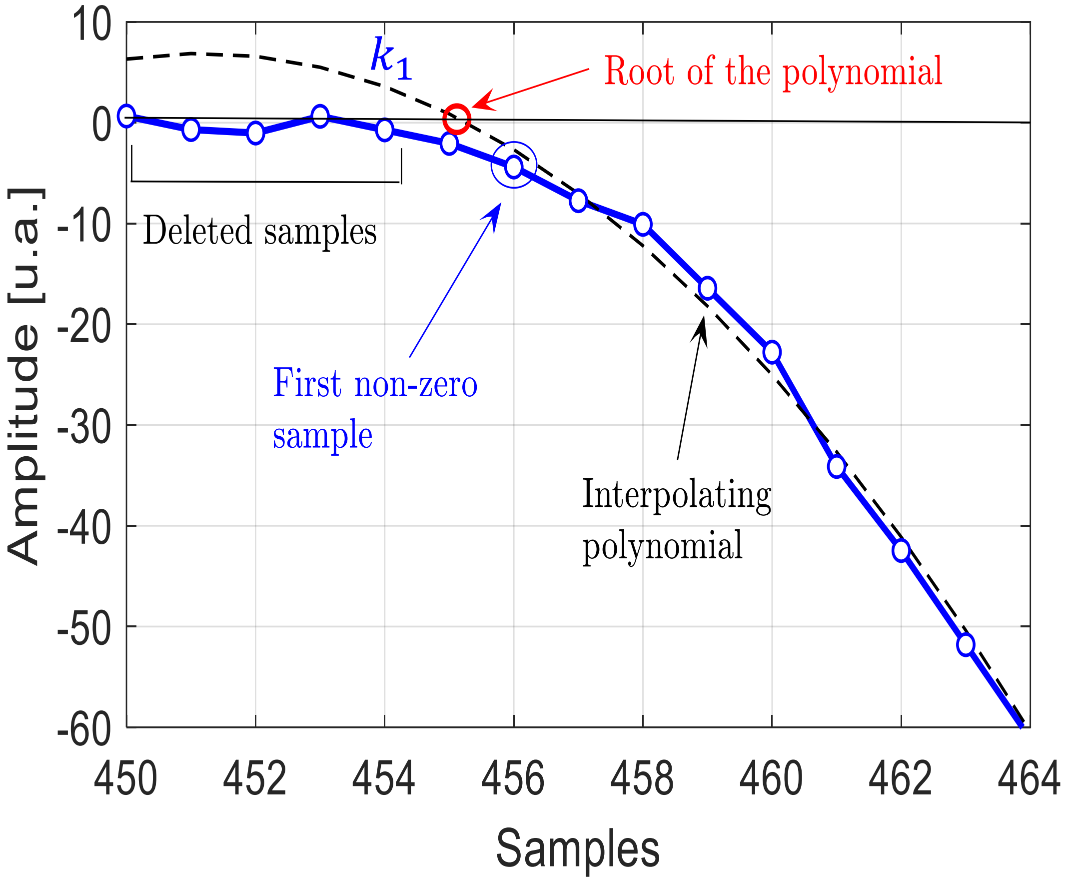
2. **Detect the impulse starting time**

Suppose that the data are affected by stationary zero-mean additive noise $\tilde{v}(k) = v(k) + e(k)$

Preprocessing phase

2. Detect the impulse starting time

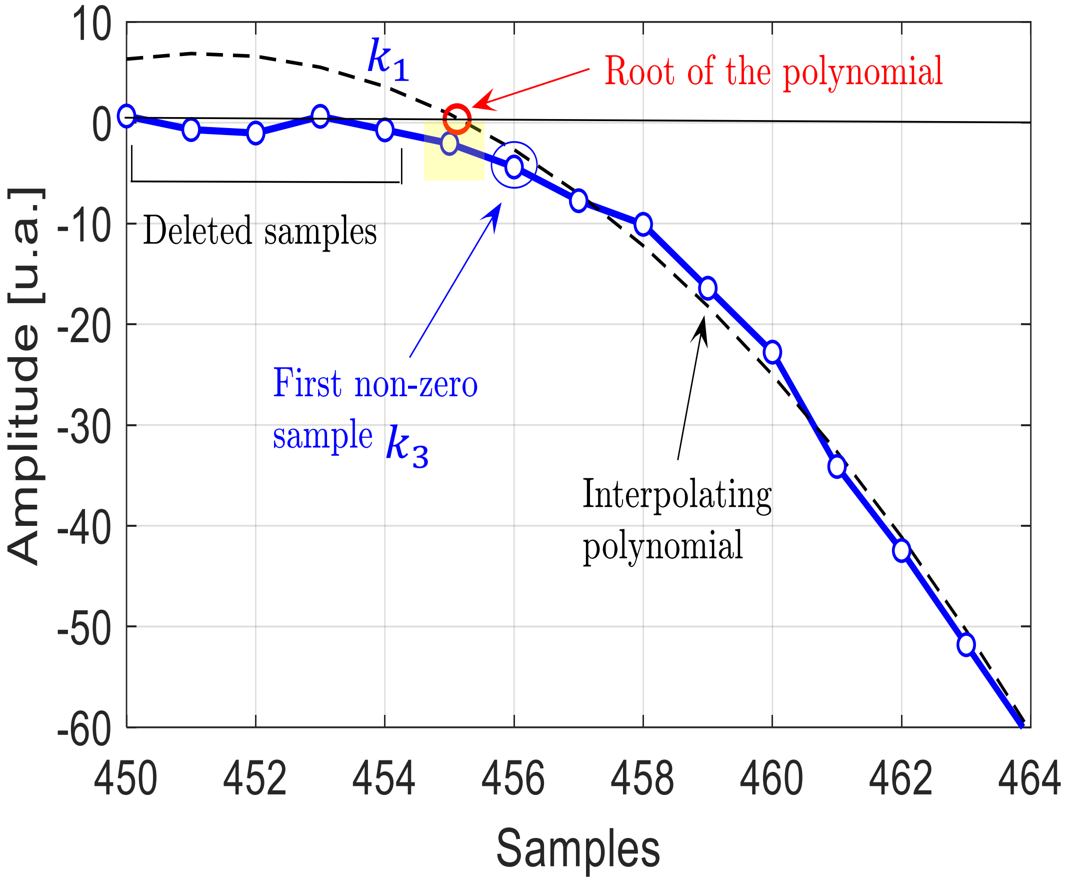
- Compute the discrete time derivative of $z(k)$ as $dz(k) = (z(k) - z(k-1))/T_s$.
    - A first estimate k_1 of the initial condition is made when $dz(k)$ exceeds a predefined threshold
- Fit a third order polynomial $p(t)$ on the first 10 points after k_1.



Preprocessing phase

2. Detect the impulse starting time

- Compute the root r of $p(t)$ that is nearest to k_1
  - Consider the nearest sampled point k_3 successive to r as the first non-null impulse sample.
- The starting point k^* is taken as the time instant before k_3, posing $z(k^*) = 0$.
  - Samples before k^* are deleted.
- Multiply data for minus 1 to obtain an impulse response of a system with positive gain.



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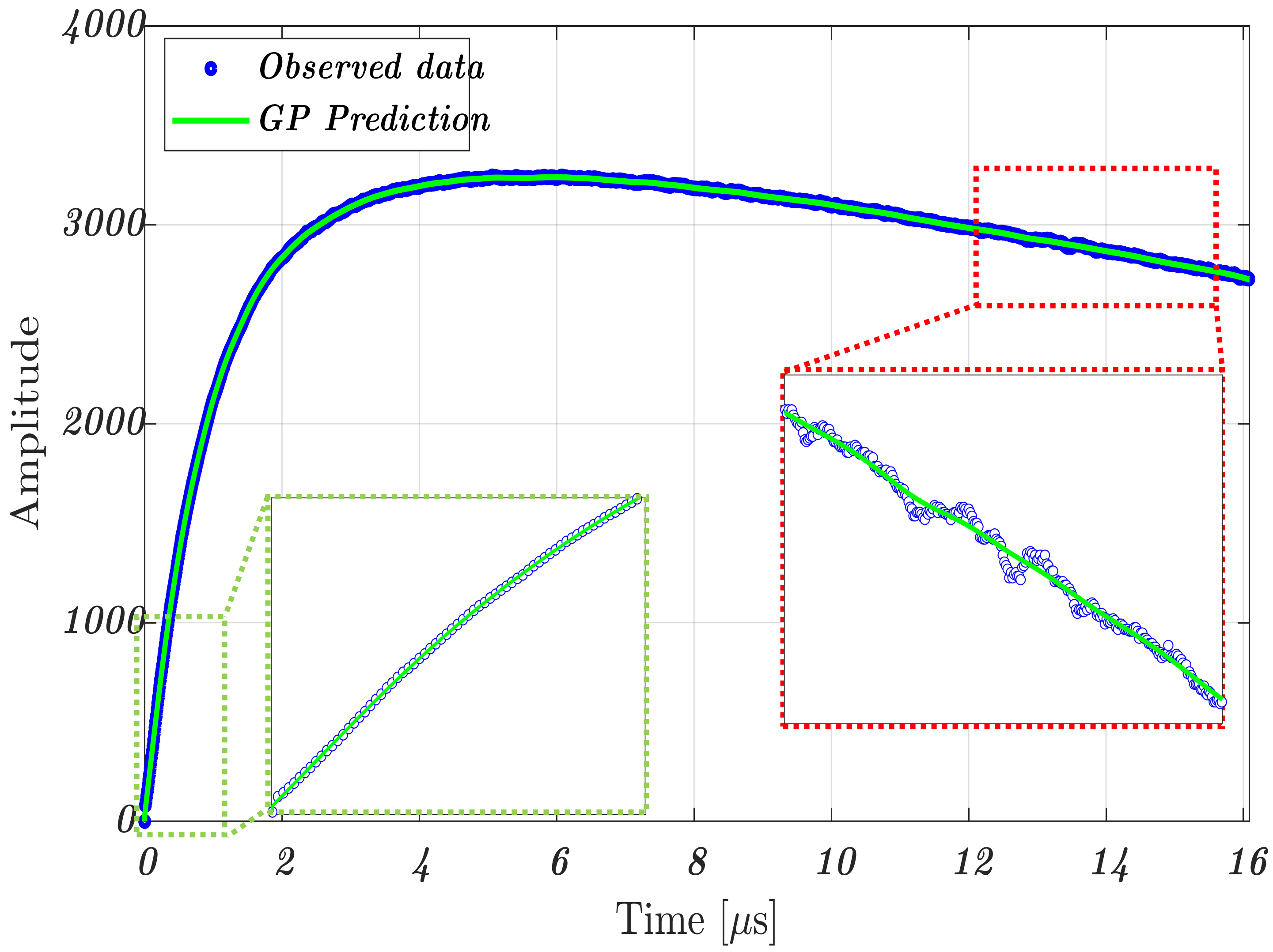
Reduce data noise



the method has efficiently reduced the noise present in the data

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Subspace System identification

Reduce data noise → **Kung's algorithm** → Neural network + decision tree

Aim: **get a parametric LTI state-space model**

From modeling hypothesis the method employs the dynamic system model:

$$V(s) = \frac{1}{1+s\tau_m} \cdot \left(\frac{\mu_f}{1+s\tau_s} + \frac{\mu_s}{1+s\tau_s} \right)$$

Consider the state-space representation of a discrete-time SISO LTI system:

$$\begin{cases} \boldsymbol{x}(t+1) = A\boldsymbol{x}(t) + Bu(t) \\ y(t) = C\boldsymbol{x}(t) + Du(t) \end{cases}$$

where $\boldsymbol{x}(t) \in \mathbb{R}^{n\times 1}, u(t) \in \mathbb{R}, y(t) \in \mathbb{R}$ are the system state, input and output, respectively.

$D = 0$ since the impulse data are preprocessed to start from zero.

Subspace System identification

Reduce data noise → **Kung's algorithm** → Neural network + decision tree

$$\begin{cases} \boldsymbol{x}(t+1) = A\boldsymbol{x}(t) + Bu(t) \\ y(t) = C\boldsymbol{x}(t) \end{cases}$$

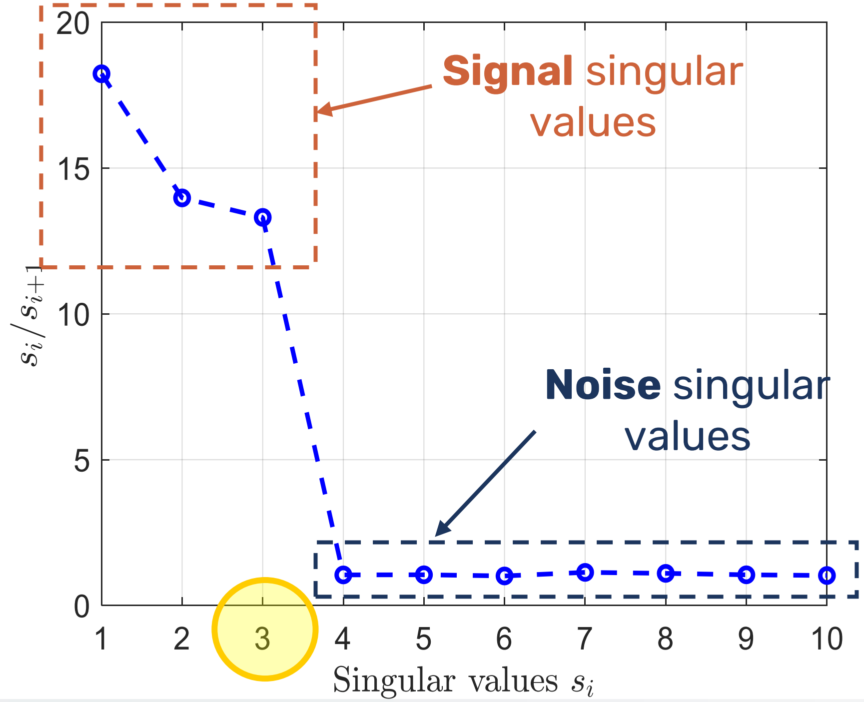
With the smoothened data, a **minimum-order realization** of $\boldsymbol{x}(t+1) = A\boldsymbol{x}(t) + Bu(t)$ can be found by employing the **Kung's algorithm**:

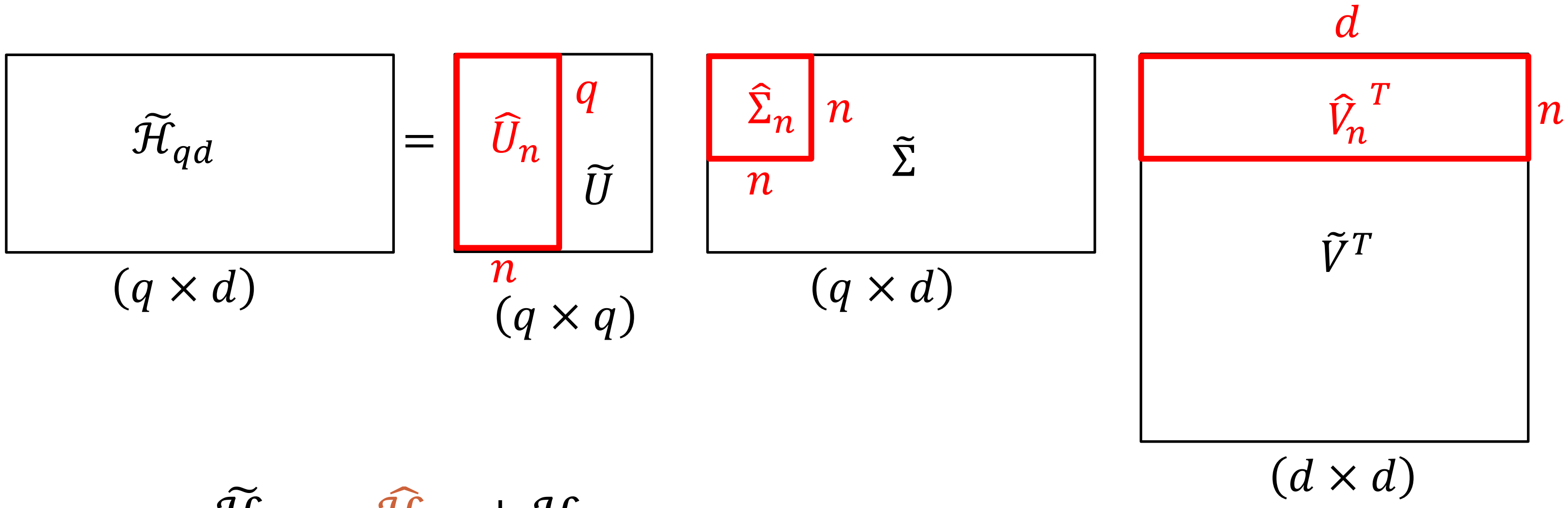
1. Create an Hankel matrix $\widetilde{\mathcal{H}}_{qd}$ composed by the noisy measurements

- Instead of creating $\widetilde{\mathcal{H}}_{qd}$ with the noisy data $\tilde{v}(t)$, the idea is to use **the smoothened ones** $\hat{y}(t)$

Subspace System identification

2. Reduce rank of $\widetilde{\mathcal{H}}_{qd}$ performing a Singolar Value Decomposition (SVD) and estimate the Observability and Reachability matrices





$$\widetilde{\mathcal{H}}_{qd} = \widehat{\mathcal{H}}_{qd} + \mathcal{H}_{res}$$

The **signal** part

The **noise** part

$$q \approx \frac{1}{2} d$$

Subspace System identification

2. Reduce rank of $\widehat{\mathcal{H}}_{qd}$ performing a Singolar Value Decomposition (SVD) and estimate the Observability and Reachability matrices

- **Estimated extended observability** matrix of order q

$$\hat{\mathcal{O}}_q = U_n \Sigma_n^{1/2}$$

- **Estimated extended reachability** matrix of order d

$$\hat{\mathcal{R}}_d = \Sigma_n^{1/2} V_n^T$$

Subspace System identification

Reduce data noise → **Kung's algorithm** → Neural network + decision tree

3. Compute an estimate of $\{\hat{A}, \hat{B}, \hat{C}\}$ from the estimate of the Observability and Reachability matrices of the system

$$\hat{A} = \hat{\mathcal{O}}_q(1{:}\,q-1,:)^{\dagger} \cdot \hat{\mathcal{O}}_q(2{:}\,q,:)$$

$$\hat{B} = \hat{\mathcal{R}}_d(:,1)$$

$$\hat{C} = \hat{\mathcal{O}}_q(1,:)$$

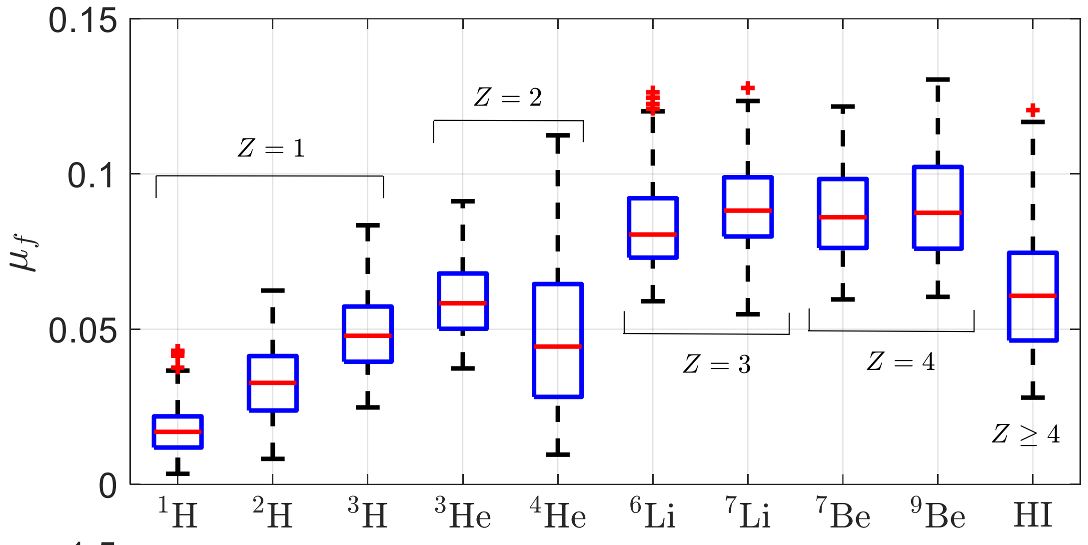
- An estimate of the unknown parameters $\{\mu_f, \mu_s, \tau_f, \tau_s, \tau_m\}$ of

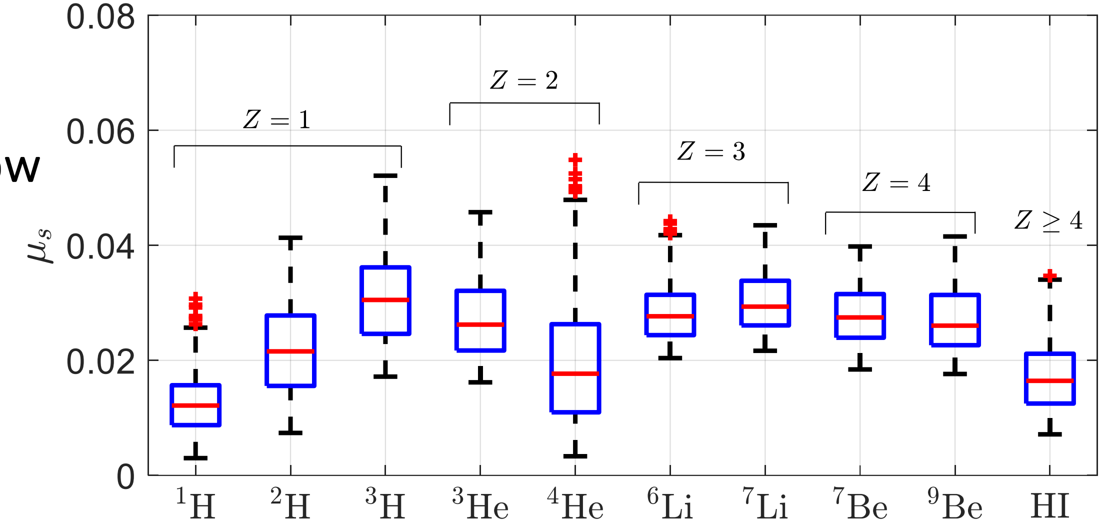
$$V(s) = \frac{1}{1+s\tau_m} \cdot \left(\frac{\mu_f}{1+s\tau_s} + \frac{\mu_s}{1+s\tau_s} \right)$$

can be computed by **converting the discrete system into a continuous one**

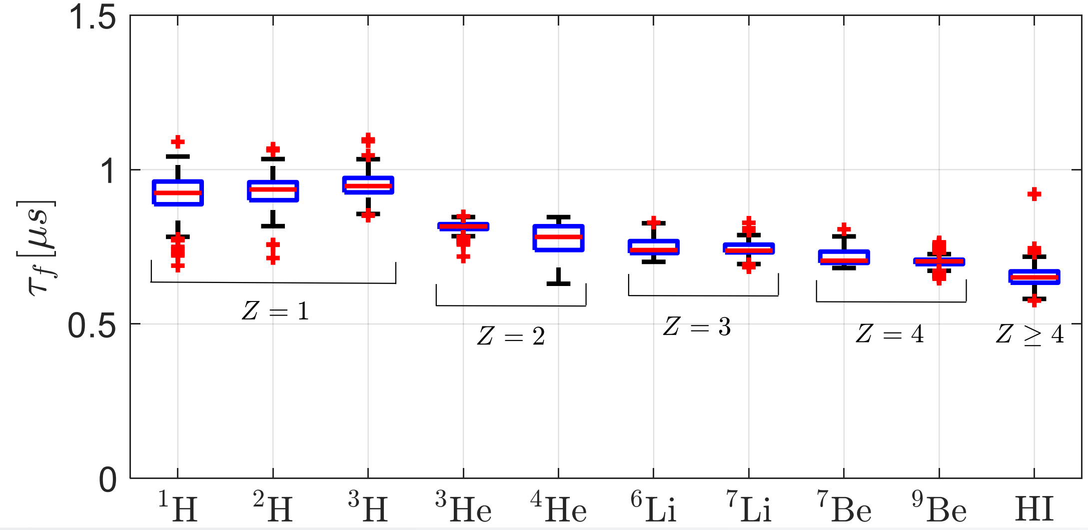
Subspace System identification

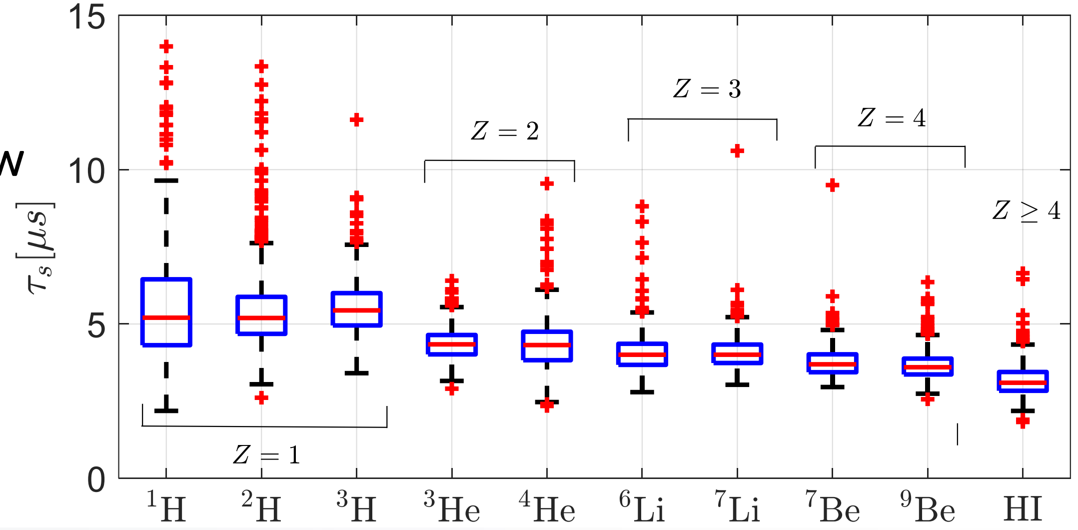
Reduce data noise → **Kung's algorithm** → Neural network + decision tree





Fast and slow **gains**





Fast and slow **time constants**

$$\tau_f \approx 0.6 - 0.9\ \mu s$$

Results agree with literature

$$\tau_s \approx 3 - 6\ \mu s$$

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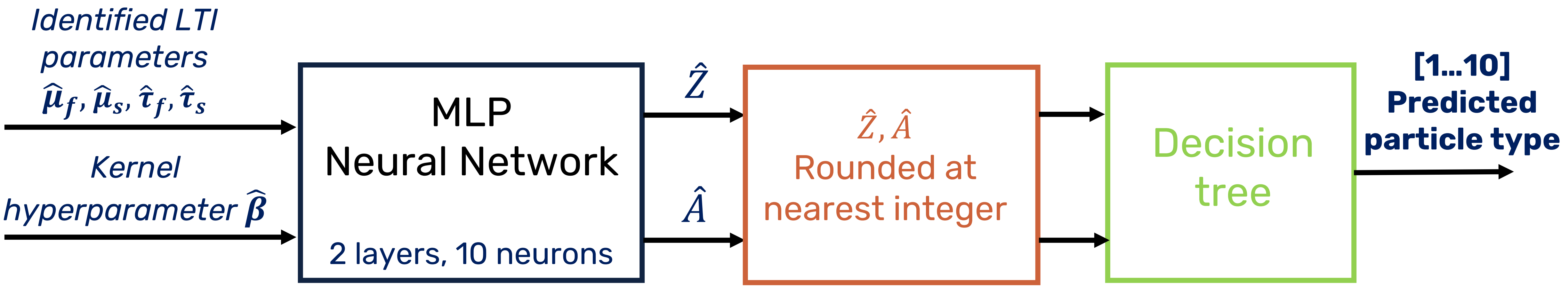
LCP Classification

A particle type is **completely defined** by its **charge**, given by its atomic number Z, and its **mass**, given by its atomic mass number A

Aim:

- **Regress** the known particle atomic number Z and atomic mass number A with a **MLP neural network**
- **Classify** particles with a **decision tree** based on the predicted $\hat{Z}$ and $\hat{A}$



LCP Classification

In the previous steps, the proposed method **reduce data noise** and then **performs a subspace system identification**

- Result of these two steps is the possibility to represent each impulse response as a **feature vector** $\phi = [\mu_f, \mu_s, \tau_f, \tau_s, \beta]^T \in \mathbb{R}^{5\times 1}$.

From reduced data noise step

The **LCP classification** is done as follows:

1. Train a **feedforward neural network** (NN) to predict, for each observation, its atomic number Z and atomic mass number A
2. Classify the particle with a **decision tree** based on the predicted $\hat{Z}$ and $\hat{A}$

LCP Classification

1. Train a **feedforward neural network** (NN) to predict, for each observation, its atomic number Z and atomic mass number A.

- The choice of using a NN model relies on the fact that **it can efficiently handle multi-dimensional outputs**, as in this case.
- The NN is composed by:
  - 2 hidden layers with 10 neurons each;
    - ***Hyperbolic tangent*** *activation function.*
  - A final layer (output layer) with 2 outputs.
    - ***Linear*** *activation function.*
- The NN structure has been chosen by cross-validation.

LCP Classification

1. Train a **feedforward neural network** (NN) to predict, for each observation, its atomic number Z and atomic mass number A

- The **labeled outputs** consist in the couple

$$Q = [A, Z]^{\mathsf{T}} \in \mathbb{R}^{2\times 1}$$

- **The training data** were standardized to zero mean on unitary variance

- **The test data** were standardized with mean and variance computed on the training set

- **The training of the NN** has been performed using the **Levenberg-Marquardt minimization algorithm**

LCP Classification

1. Train a **feedforward neural network** (NN) to predict, for each observation, its atomic number Z and atomic mass number A.

- The NN predicts a vector

$$q = [q_1, q_2]^\top \in \mathbb{R}^{2\times 1}$$

which is the **real-valued prediction** of A and Z

LCP Classification

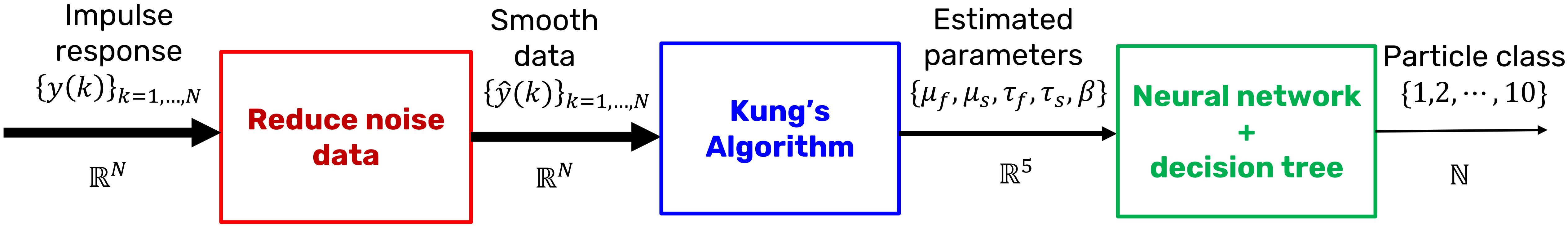
2. Classify the particle with a **decision tree** based on the predicted $\hat{Z}$ and $\hat{A}$

- Decision tree **inputs**: the **estimates values** of Z and A, $\hat{Z}$ and $\hat{A}$ respectively

- Decision tree **output**: an **integer number** that represent the class of each observation

LCP Classification

Complete schematic of the classification procedure



Subspace system identification

Parametric LTI state-space model

Classification

Regress atomic number and atomic mass number.
LCP classification.

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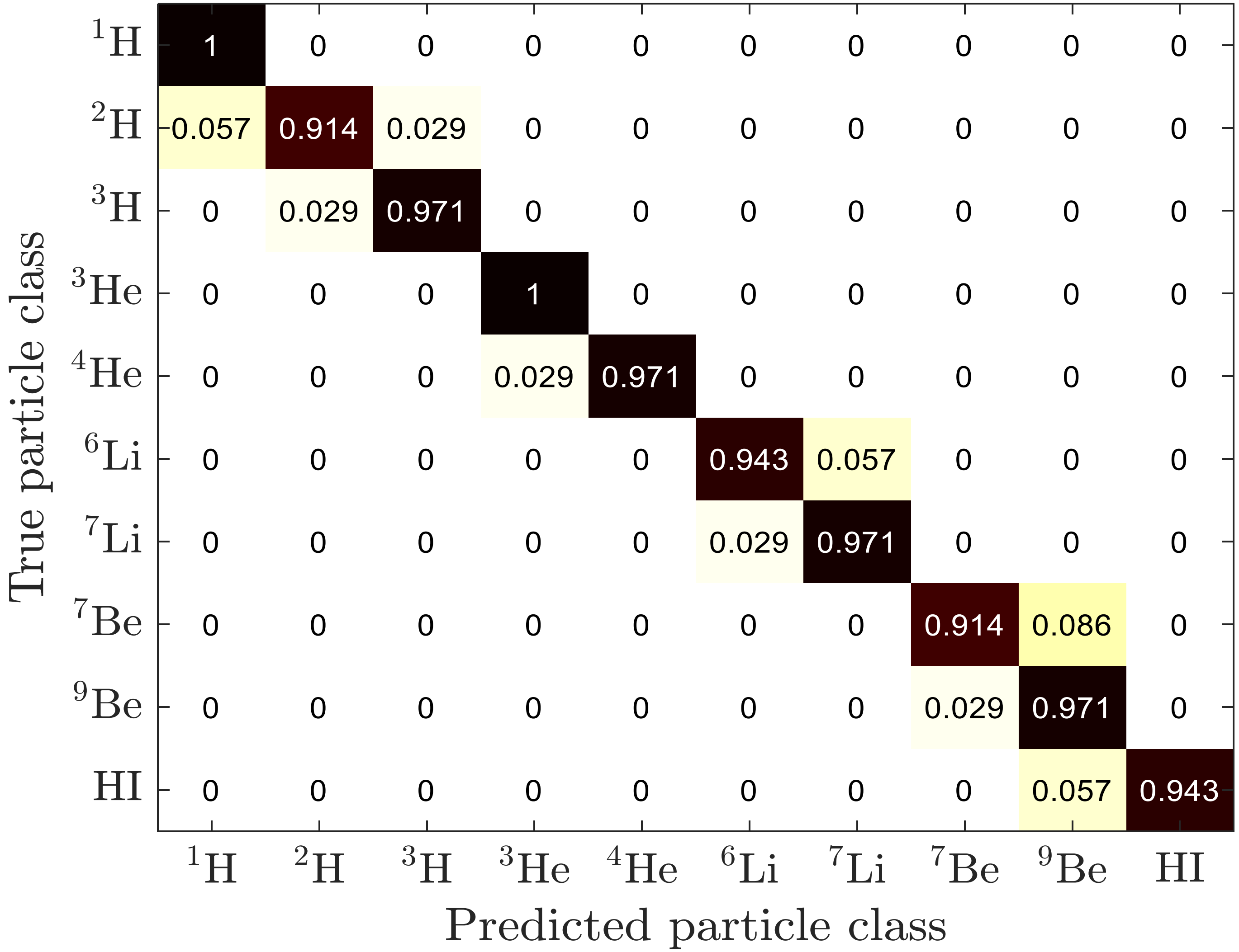
Results and conclusion

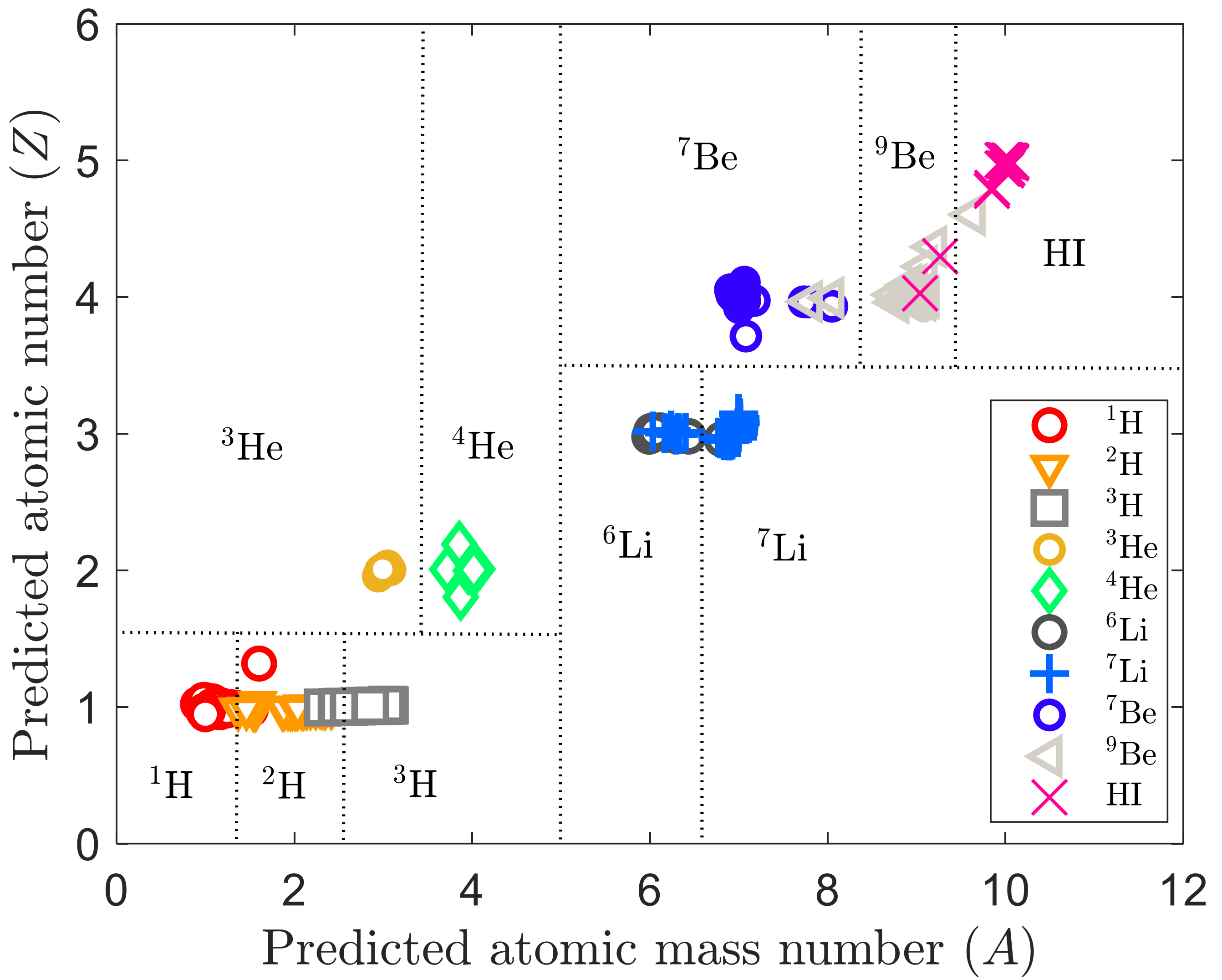
Classification results

96% accuracy



Results and conclusion

- The decision tree finds **very interpretable** bounds
- It basically classifies looking at **mid-points** of each predicted atomic and mass number
- The learnt bounds are intuitive and **could be set by human visual inspection**



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