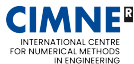


Data-driven systems theory, signal processing, and control

Ivan Markovsky



Free fall as a dynamical system

setup: mass m falling in gravitational field

- ▶ $w \in (\mathbb{R}^2)^{\mathbb{R}_+}$ — position in 2D plane
- ▶ $v := \dot{w} \in (\mathbb{R}^2)^{\mathbb{R}_+}$ — velocity
- ▶ $w(0), v(0) \in \mathbb{R}^2$ — initial condition

task: given initial condition, find the trajectory w

first work out the model-based approach

1. using physics, derive model (include friction force $-\gamma\dot{w}$)
2. write a function `w = fall(w0, v0, t, m, gamma)`

Modeling from first principles leads to affine time-invariant state-space model

second law of Newton + the law of gravity

$$m\ddot{w} = m \begin{bmatrix} 0 \\ -9.81 \end{bmatrix} + f, \quad \text{where } w(0) = w_{\text{ini}} \text{ and } \dot{w}(0) = v_{\text{ini}}$$

- ▶ 9.81 — gravitational constant
- ▶ $f = -\gamma v$ — force due to friction in the air

state $x := (w_1, \dot{w}_1, w_2, \dot{w}_2, x_5)$, where $x_5 = -9.81$

initial state $x_{\text{ini}} := (w_{\text{ini},1}, v_{\text{ini},1}, w_{\text{ini},2}, v_{\text{ini},2}, -9.81)$

Modeling from first principles leads to affine time-invariant state-space model

$$\dot{x} = \begin{bmatrix} 0 & 1 & & & \\ 0 & -\gamma/m & & & \\ & & 0 & 1 & \\ & & 0 & -\gamma/m & 1 \\ & & & & 0 \end{bmatrix} x, \quad x(0) = \begin{bmatrix} w_{ini,1} \\ v_{ini,1} \\ w_{ini,2} \\ v_{ini,2} \\ -9.81 \end{bmatrix}$$
$$w = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{bmatrix} x$$

data: N , T_d -samples long discretized trajectories

MATLAB function for free fall simulation

```
function [w, t, sys] = fall(w0, v0, t, m, gamma)
a1 = [0 1; 0 -gamma / m];
a = blkdiag(a1, a1, 0); a(4, 5) = 1;
c = zeros(2, 5); c(1, 1) = 1; c(2, 3) = 1;
sys = ss(a, [], c, []);
x0 = [w0(1); v0(1); w0(2); v0(2); -9.81];
[w, t] = initial(sys, x0, t);
```

the Control Toolbox `initial` simulates the LTI system

Data-driven approach to free fall simulation

simulate $T_d = 100$ -samples trajectories

- ▶ $N = 10$ “data” trajectories w_d^1, \dots, w_d^N and
- ▶ one “to-be-predicted” trajectory w

verify the data “informativity” condition

$$\text{rank} \begin{bmatrix} w_d^1 & \dots & w_d^N \end{bmatrix} = 5$$

implement and verify the data-driven method

1. solve
$$\begin{bmatrix} w_d^1(1) & \dots & w_d^N(1) \\ w_d^1(2) & \dots & w_d^N(2) \\ w_d^1(3) & \dots & w_d^N(3) \end{bmatrix} g = \begin{bmatrix} w(1) \\ w(2) \\ w(3) \end{bmatrix}$$

2. define
$$w := \begin{bmatrix} w_d^1 & \dots & w_d^N \end{bmatrix} g$$

Solution

```
%% simulation parameters
m = 1;           % mass
gamma = 0.5;    % friction coefficient
N = 20;         % number of experiments
T = 101;        % number of samples
MC = 100;       % Monte-Carlo repetitions

%% simulate data using the function fall.m
t = linspace(0, 1, T); % time vector
Wini = rand(2, N);     % initial positions
Vini = 5 * rand(2, N); % initial velocities
W0 = []; w0 = {};      % collect the trajectories
for i = 1:N
    w0i = fall(Wini(:, i), Vini(:, i), t, m, gamma);
    W0 = [W0 vec(w0i')]; w0{i} = w0i;
end
n = rank(W0) % -> 5
```

Solution

```
%% simulate the to-be-predicted trajectory
wini = rand(2, 1); vini = 5 * rand(2, 1);
w_new = fall(wini, vini, t, m, gamma);

%% validation criterion:
e = @(wh) 100 * norm(w_new - wh, 'fro') ...
      / norm(w_new, 'fro');

%% direct method with pseudo-inverse
g = pinv([Wini; Vini; ones(1, N)]) ...
      * [wini; vini; 1];
wh_dd = reshape(W0 * g, 2, T)';

%% results
e(wh_dd) % -> 0
```


Dynamical systems as set of signals

$\mathcal{B} \subset (\mathbb{R}^q)^{\mathbb{Z}}$ — q -variate discrete-time system

consider the identification problem $w_d \mapsto \mathcal{B}$

given data $w_d \in \mathcal{B}$, find $\hat{\mathcal{B}} \subset (\mathbb{R}^q)^{\mathbb{Z}}$, such that $w_d \in \hat{\mathcal{B}}$

questions

- ▶ is there a solution?
- ▶ if so, is it unique?
- ▶ if so, is $\hat{\mathcal{B}} = \mathcal{B}$?

Solution

always exist “trivial” solutions: $\hat{\mathcal{B}} = \{w_d\}$ and $\hat{\mathcal{B}} = (\mathbb{R}^q)^{\mathbb{Z}}$

the problem find $\hat{\mathcal{B}} \subset (\mathbb{R}^q)^{\mathbb{Z}}$, such that $w_d \in \hat{\mathcal{B}}$ is ill-posed

additional conditions are needed for well-posedness, e.g.,

1. $\hat{\mathcal{B}} \in \mathcal{M}$ — a given class of systems (e.g., linear systems)
2. find the “simplest” exact model in $\hat{\mathcal{B}} \in \mathcal{M}$
 $\rightsquigarrow \hat{\mathcal{B}} = \text{mpum}(w_d)$ — the most powerful unfalsified model

if $w_d \in \mathcal{B} \in \mathcal{M}$, $\text{mpum}(w_d) \subseteq \mathcal{B}$

additional conditions are needed for $\text{mpum}(w_d) = \mathcal{B}$

\rightsquigarrow identifiability conditions

Consider the case of linear static system \mathcal{B}

\mathcal{L}_0^q class of linear static systems

- ▶ static system with q variables: $\mathcal{B} \subset \mathbb{R}^q$
- ▶ linear static system — subspace \mathcal{B} of \mathbb{R}^q
- ▶ complexity of $\mathcal{B} \in \mathcal{L}_0^q$ — $:= \dim \mathcal{B}$

identification problem:

- ▶ given data: $\mathcal{W}_d = \{w_d^1, \dots, w_d^N\}$, $w_d^i \in \mathcal{B} \in \mathcal{L}_0^q$
- ▶ find $\hat{\mathcal{B}} = \text{mpum}(\mathcal{W}_d)$ in the model class \mathcal{L}_0^q
- ▶ when is $\hat{\mathcal{B}} = \mathcal{B}$?

Solution

$$\widehat{\mathcal{B}} = \text{mpum}(w_d) = \text{span } \mathcal{W}_d$$

$\widehat{\mathcal{B}} \subseteq \mathcal{B}$, equality holds iff $\dim \widehat{\mathcal{B}} = \dim \mathcal{B}$

computational procedure for checking $\widehat{\mathcal{B}} = \mathcal{B}$

$$\text{rank} \begin{bmatrix} w_d^1 & \cdots & w_d^N \end{bmatrix} = \dim \mathcal{B}$$

note that prior knowledge of $\dim \mathcal{B}$ is needed

Follow-up questions for self-work

how to representation $\mathcal{B} \in \mathcal{L}_0^q$?

how to find a representation from data $\mathcal{W}_d \subset \mathcal{B}$?

how to find a representation from “noisy data”

$$w_d = \bar{w} + \tilde{w}, \quad \text{where } \bar{w} \in \mathcal{B} \in \mathcal{L}^q \text{ and } \tilde{w} \text{ is noise}$$

Interpretation of $\dim \mathcal{B}|_L = \mathbf{m}(\mathcal{B})L + \mathbf{n}(\mathcal{B})$

question: does it make sense? explain

answer:

$\mathcal{B}|_L$ subspace of \mathbb{R}^{qL}

$\dim \mathcal{B}|_L$ # of degrees of freedom in choosing $w \in \mathcal{B}|_L$

$\mathbf{m}(\mathcal{B})$ # of degrees of freedom per time step

$\mathbf{m}(\mathcal{B})L$ # of degrees of freedom due to the inputs

$\mathbf{n}(\mathcal{B})$ # of degrees of freedom due to the initial conditions

Interpretation of $\mathcal{H}_L(\mathbf{w}_d)$

what is the system theory meaning of $\mathcal{H}_L(\mathbf{w}_d)$?

answer: by definition

$$\mathcal{H}_L(\mathbf{w}_d) := \left[(\sigma^0 \mathbf{w}_d)|_L \quad (\sigma^1 \mathbf{w}_d)|_L \quad \cdots \quad (\sigma^{T_d-L} \mathbf{w}_d)|_L \right]$$

\implies every column of $\mathcal{H}_L(\mathbf{w}_d)$ is L -samples trajectory of \mathcal{B}

Follow-up questions for self-work

what is the meaning of image $\mathcal{H}_L(w_d)$?

how to use it in practice, *e.g.*, for simulation?

try it out on a numerical example?

Comparison of the heuristic methods for dealing with noise on simulated data

implement (SOL) and try it on an example

1. using exact data (random trajectory of a random system)
2. using noisy data $w_d = \bar{w} + \tilde{w}$, where $\bar{w} \in \mathcal{B} \in \mathcal{L}^q$

modify the solution of (SOL)

1. using the pseudo-inverse
2. using SVD truncation, imposing rank $\mathbf{m}(\mathcal{B})L + \mathbf{n}(\mathcal{B})$
3. ℓ_1 -norm using regularization

comment on the results