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NNodely: An Open Framework for Model-Structured Neural Networks in Robotics

September 29^{th}, 2025

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Dr. Mattia Piccinini

University of Trento & Technical University of Munich

Overview

1. Motivation

1.1 Beyond Black-Box Neural Networks

1.2 Physics-Guided Learning

2. NNodely

2.1 Model-Structured Neural Networks (MS-NNs)

2.2 Framework

3. Use Cases

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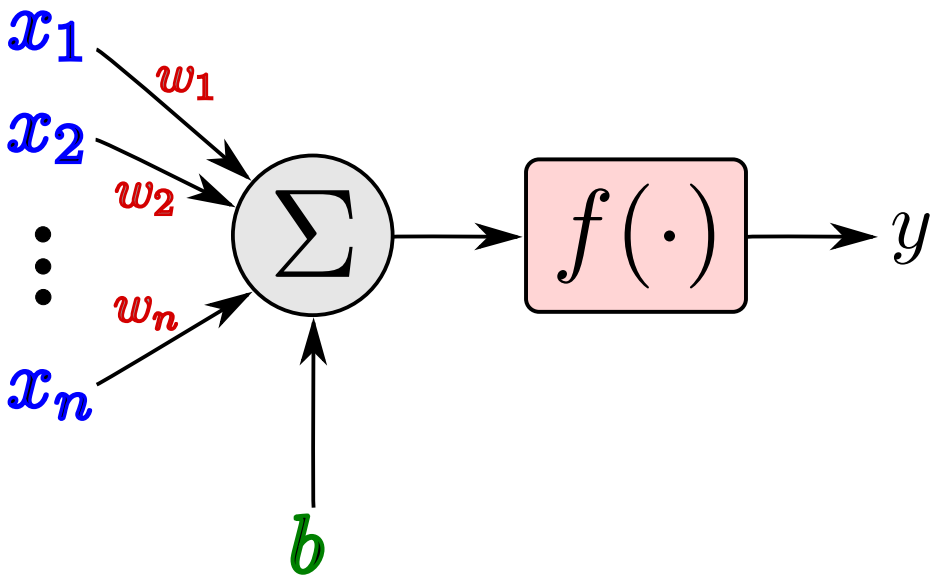
Motivation

Motivation

Beyond Black-Box Neural Networks

The Perceptron

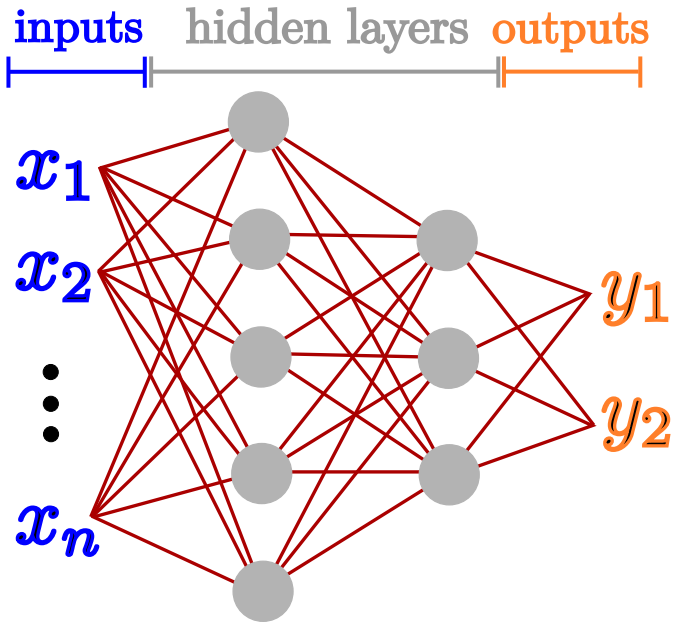
The basic component of a **neural network** (NN) is the **Perceptron**[1]



$$y = f\left(\sum_{k=1}^{n} x_k \cdot w_k + b\right)$$

[1]Frank Rosenblatt. "The perceptron: a probabilistic model for information storage and organization in the brain.". In: *Psychological review* (1958).

Multi-layer Perceptron (MLP)



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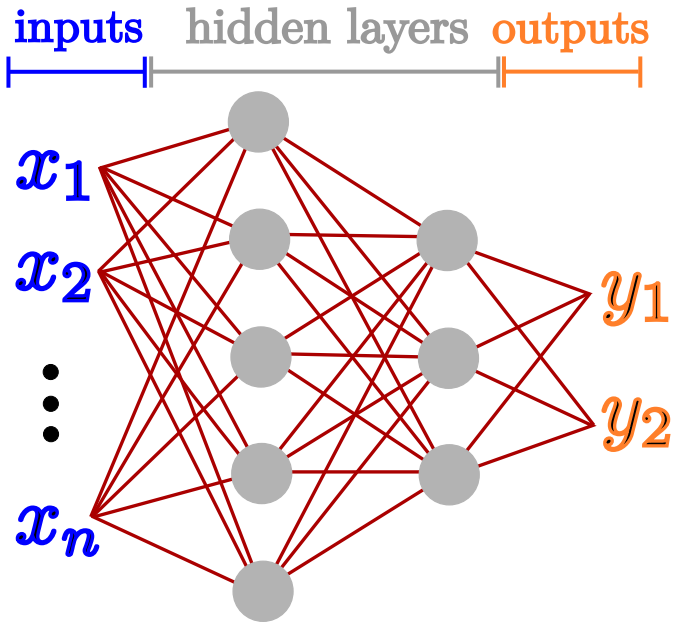

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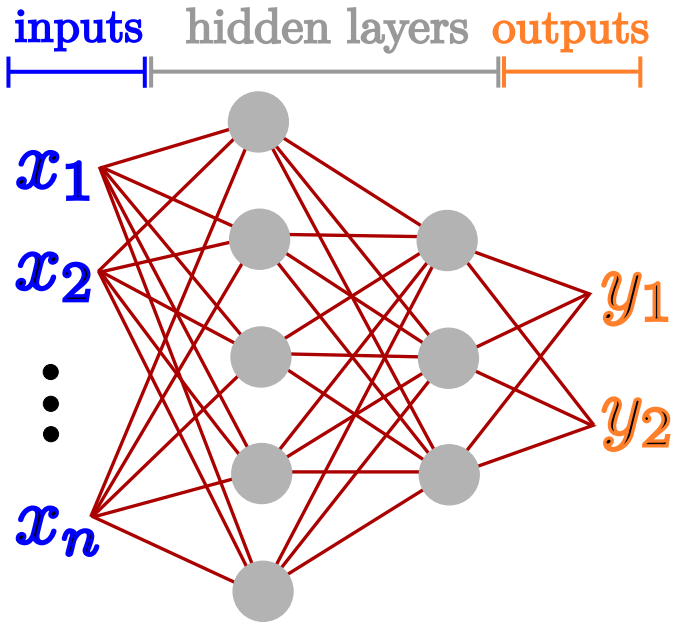

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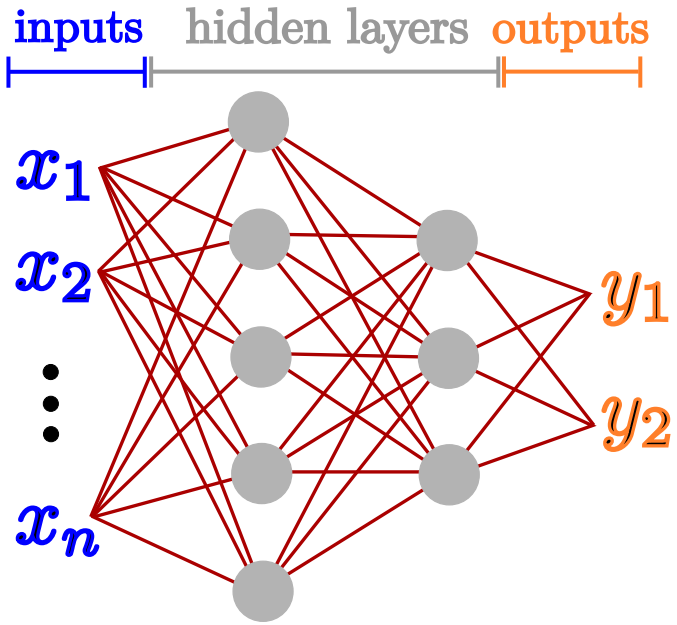

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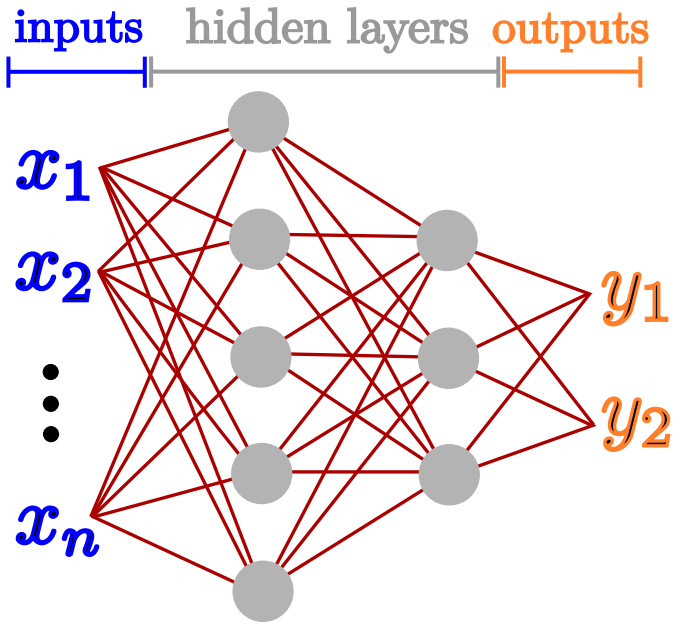

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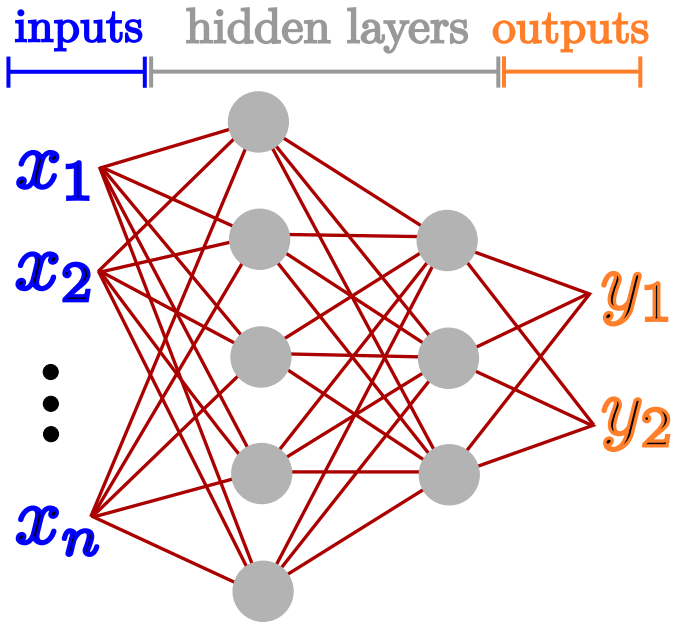

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  - The **internal architecture** of a NN matters
    ⟶ Try this: Tensorflow Playground

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Literature Examples

- *Computer vision*: **convolutional neural networks**, embedding the concept of spatial invariance[3]

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Can we devise **new NN architectures**
to model/control **physical systems**? (e.g. robots)

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Motivation

Physics-Guided Learning

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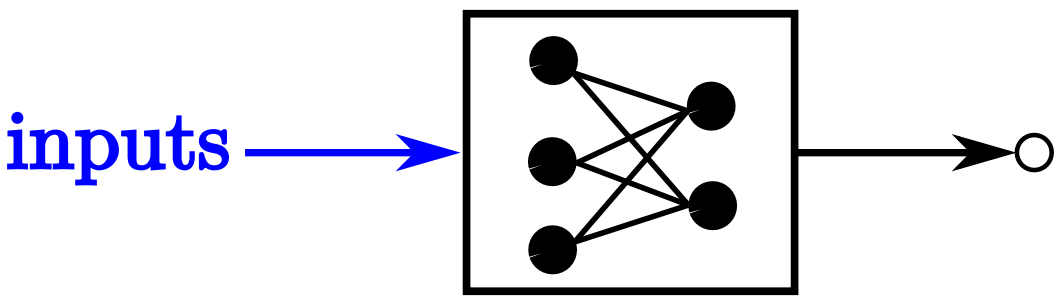
How to **embed physics**- or model-based knowledge in NNs?

- Curate the training data or **NN inputs**



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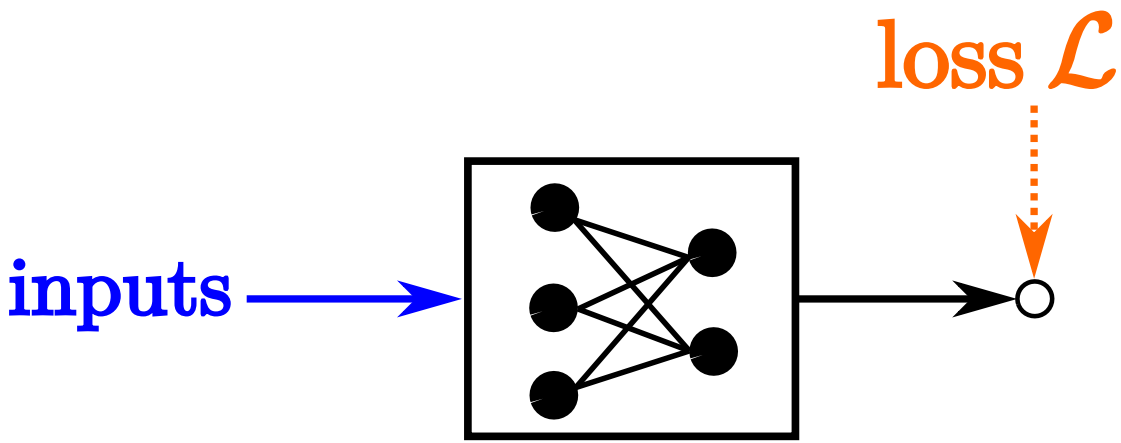

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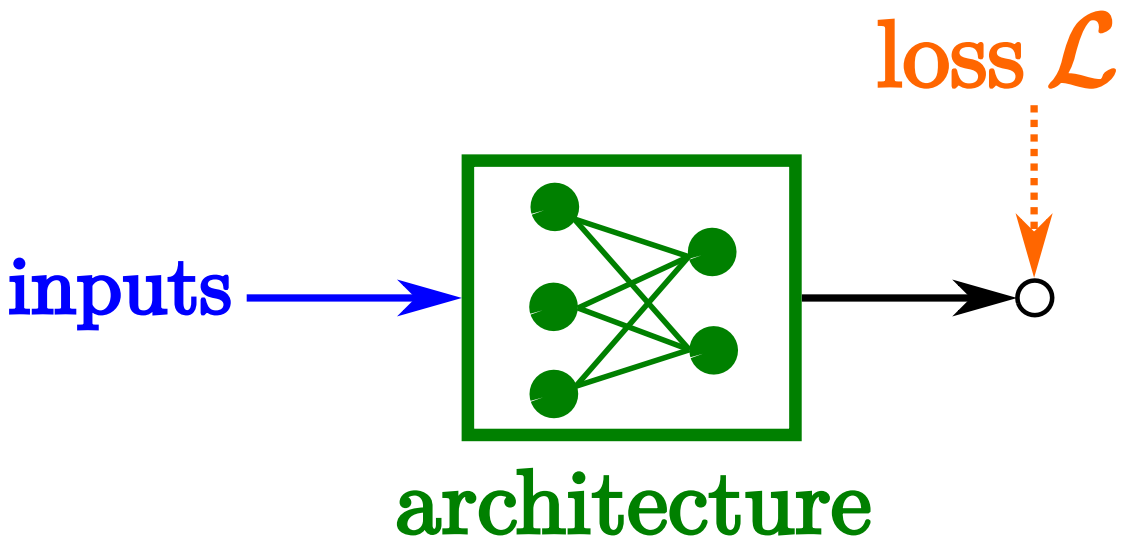

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How to **embed physics**- or model-based knowledge in NNs?

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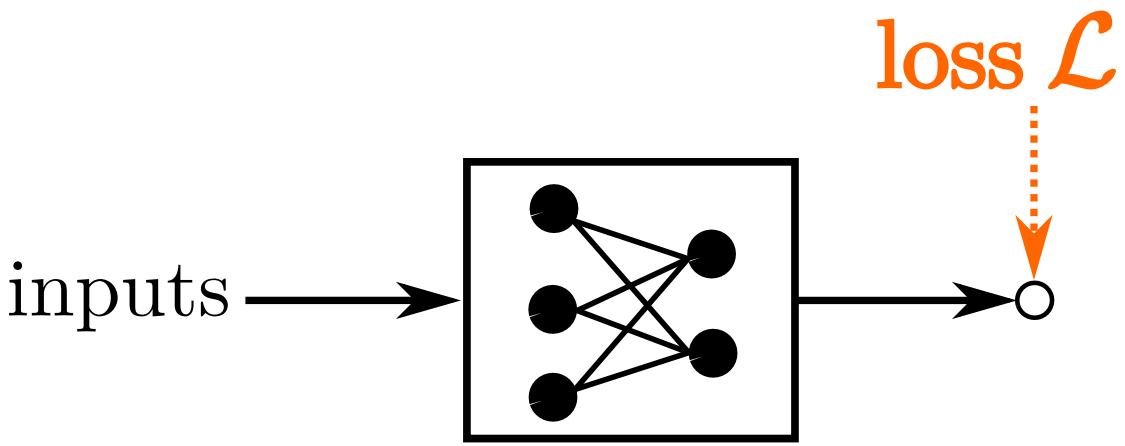
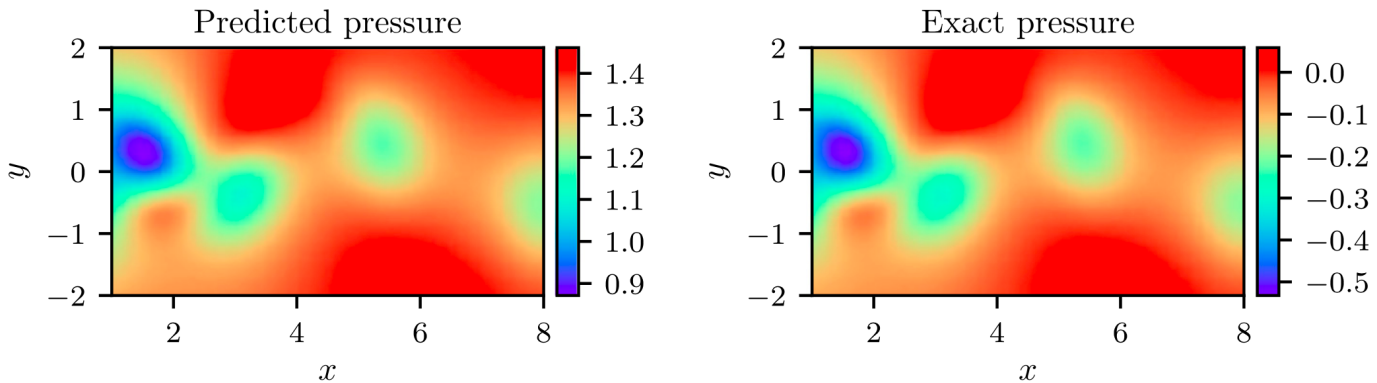
- Design the internal architecture



Physics-informed NNs (PINNs), Raissi et at. (2019)

- **Idea**: Data-driven solution or discovery of complex PDEs



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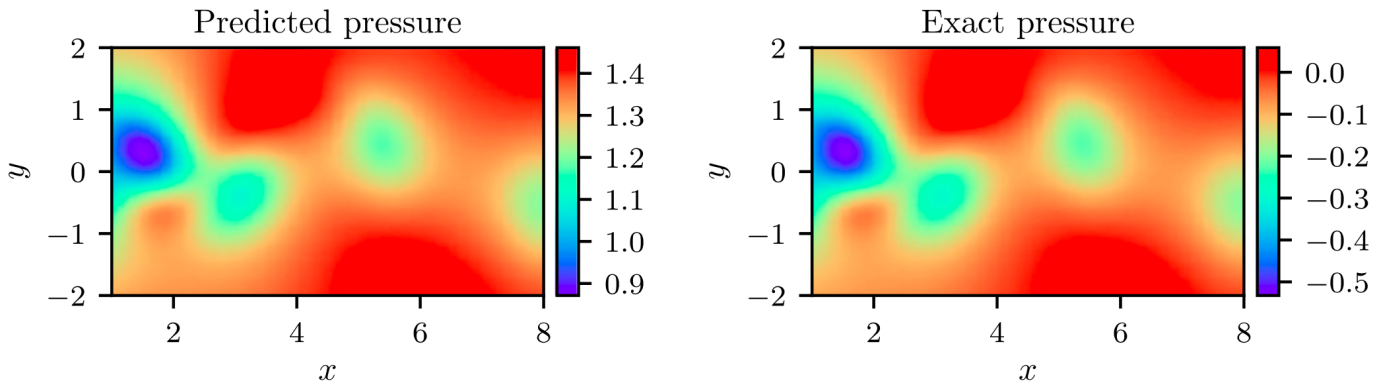

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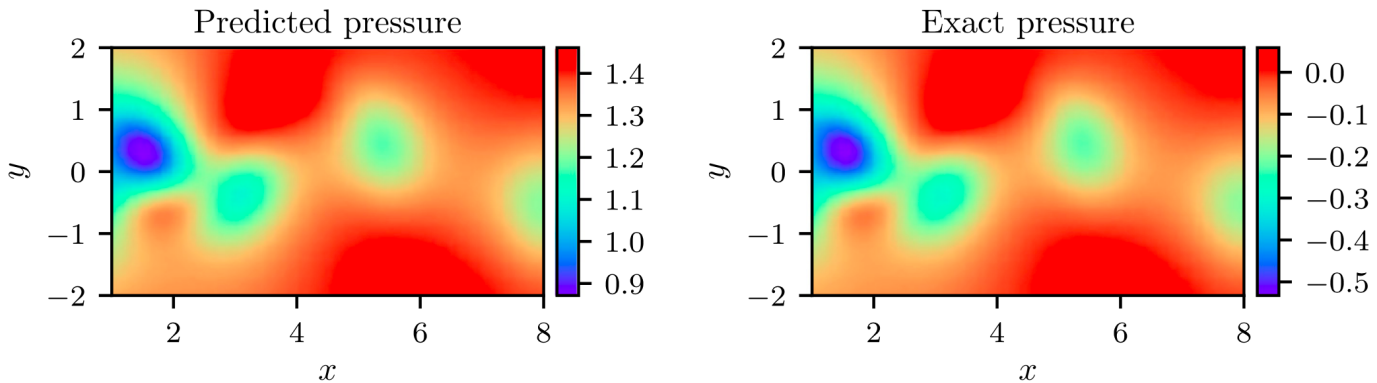

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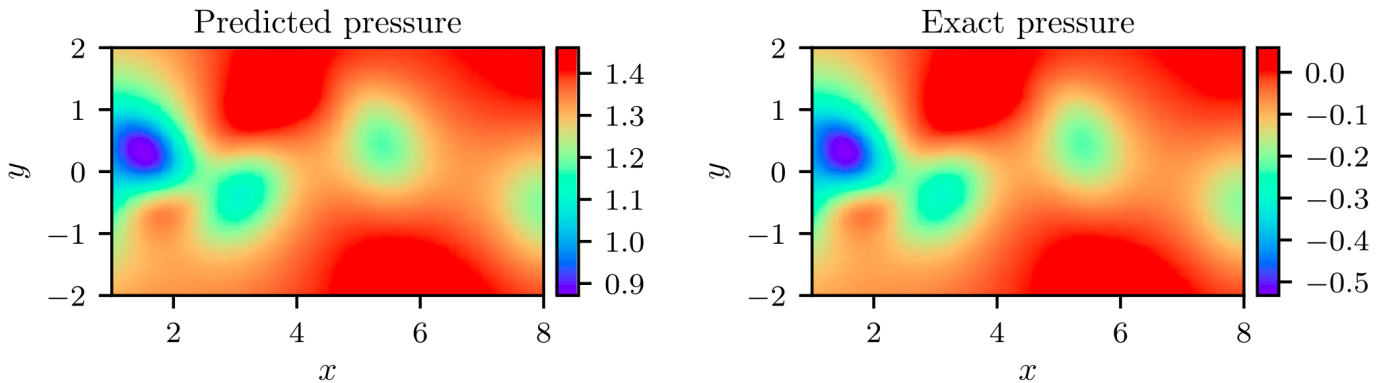
- **Examples**: Fluid dynamics (Navier Stokes), quantum mechanics, solid mechanics, reaction-diffusion[6]. **Note**: no modeling of real physical systems, only PDEs



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Other approaches related to PINNs

- **Hamiltonian**[7] and **Lagrangian NNs**[8] that learn to conserve energy in mechanical systems and robotic tasks
- **Pontryagin AI**[9] to learn the policies of optimal control tracking problems (OCPs):
  - NN to approximate the controls of an OCP
  - NN trained with a tracking loss function
  - No need to solve the adjoint equations of the OCP
- NNs to approximate the value function of Hamilton-Jacobi-Bellman equations for **dynamic programming**[10]

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[7] Sam Greydanus, Misko Dzamba, and Jason Yosinski. *Hamiltonian Neural Networks*. 2019.

[8] Michael Lutter, Kim Listmann, and Jan Peters. "Deep Lagrangian Networks for end-to-end learning of energy-based control for under-actuated systems". In: 2019.

[9] Lucas Böttcher, Nino Antulov-Fantulin, and Thomas Asikis. "AI Pontryagin or how artificial neural networks learn to control dynamical systems". In: *Nature Communications* (2022).

[10] Murad Abu-Khalaf and Frank L. Lewis. "Nearly optimal control laws for nonlinear systems with saturating actuators using a neural network HJB approach". In: *Automatica* (2005).

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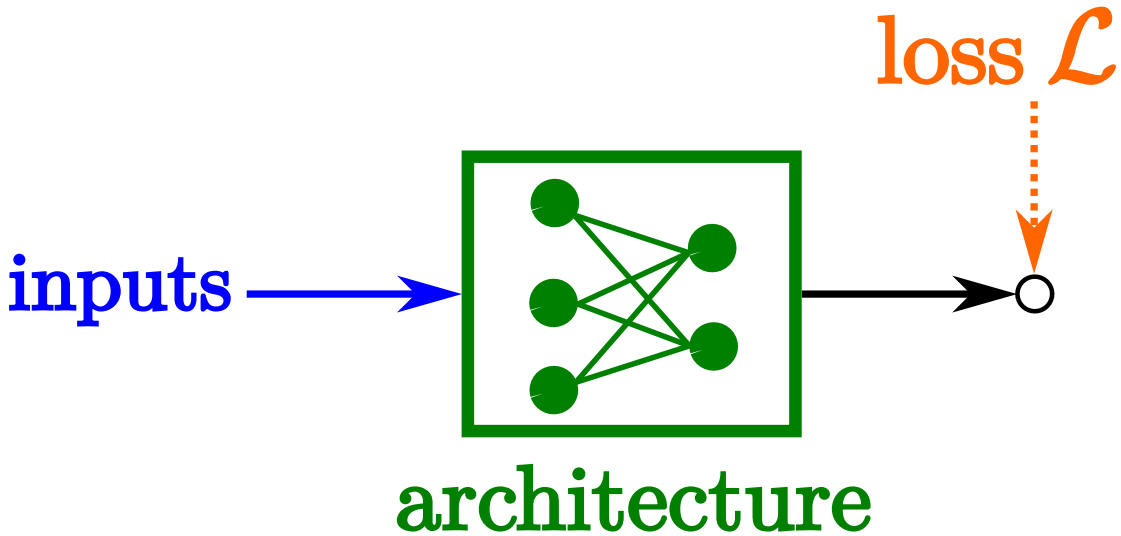

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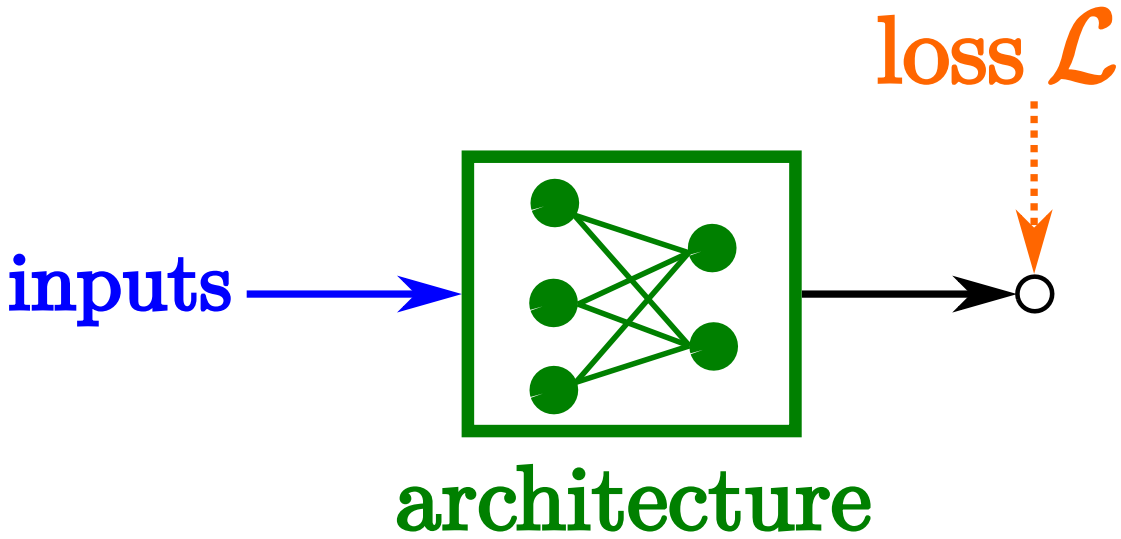
  → **Model-Structured NNs** (MS-NNs)



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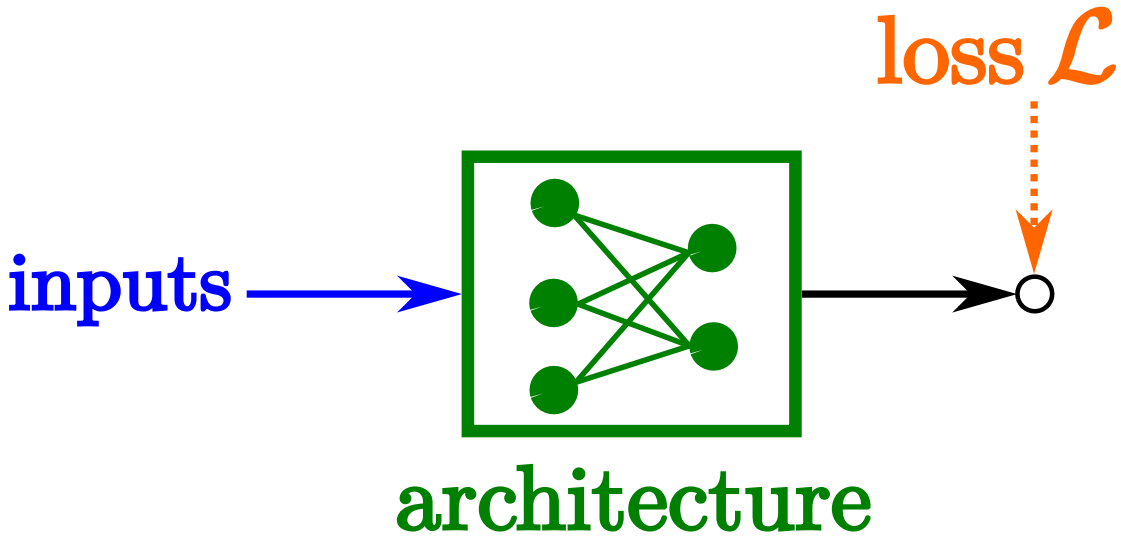

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Start from a physics-based model and ***neuralize*** its structure

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Use

Modeling, *control* and *estimation* of physical systems

Example: Longitudinal Vehicle Dynamics

Inputs: pedal $p \in [-1, 1]$, speed v_x,
Output: longitudinal accel. a_x

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We actually know the vehicle dynamics!

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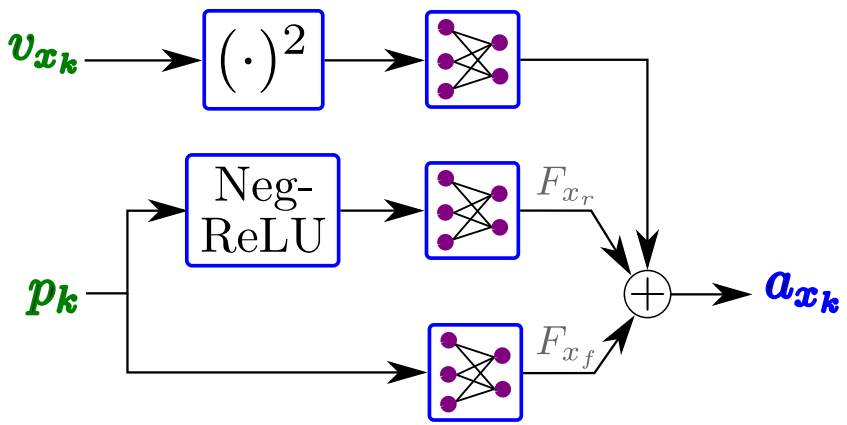

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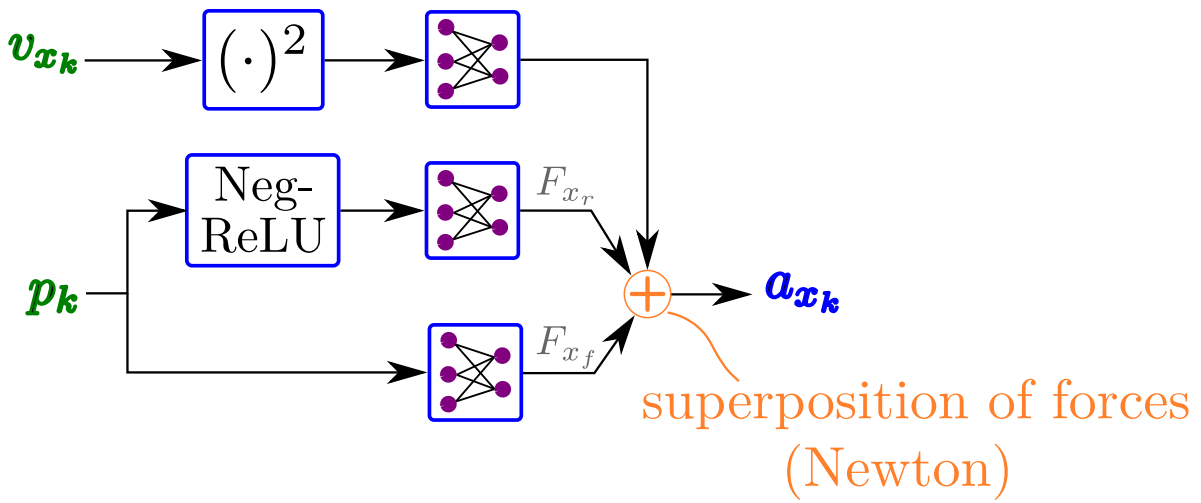

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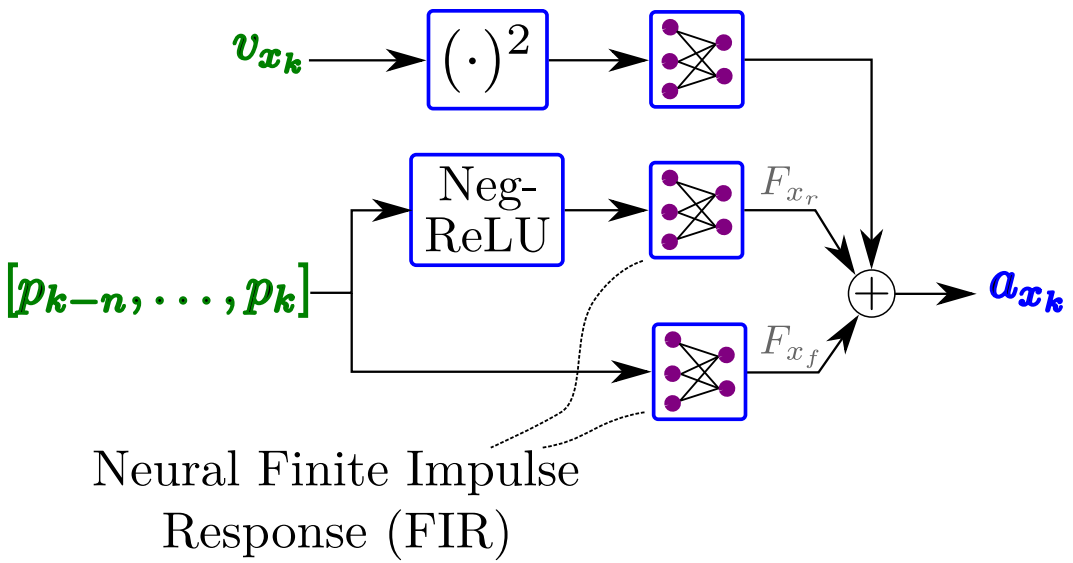

Example: Longitudinal Vehicle Dynamics

Inputs: pedal $p \in [-1, 1]$, speed v_x, gear g,
Output: longitudinal accel. a_x

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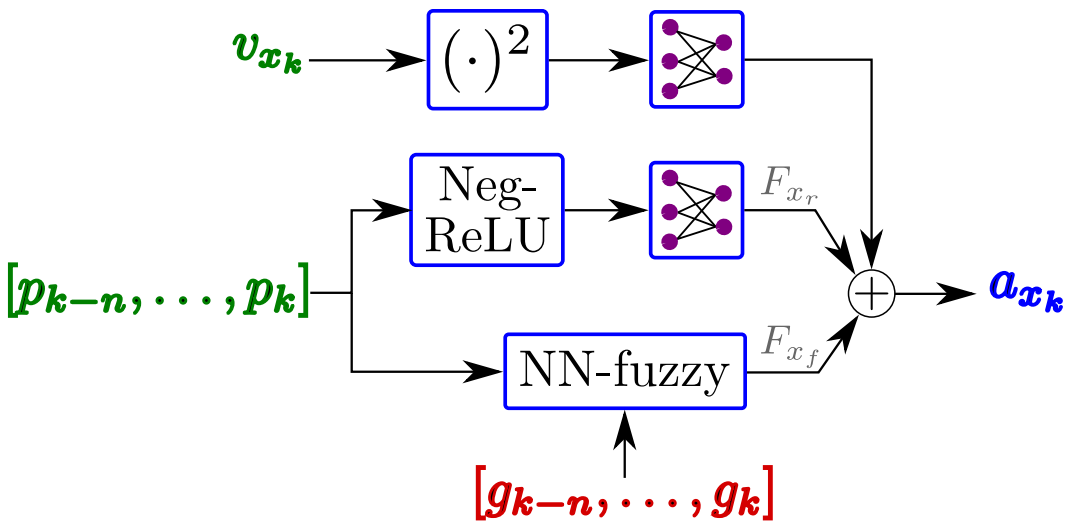

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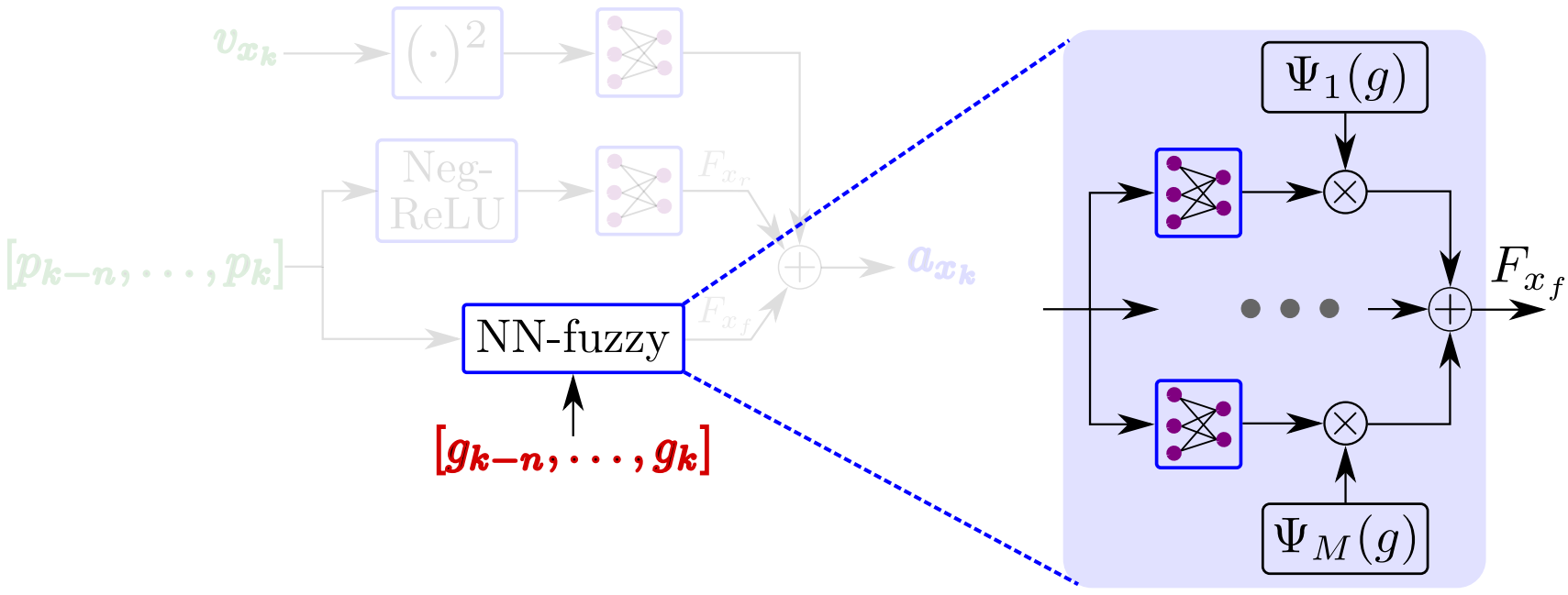

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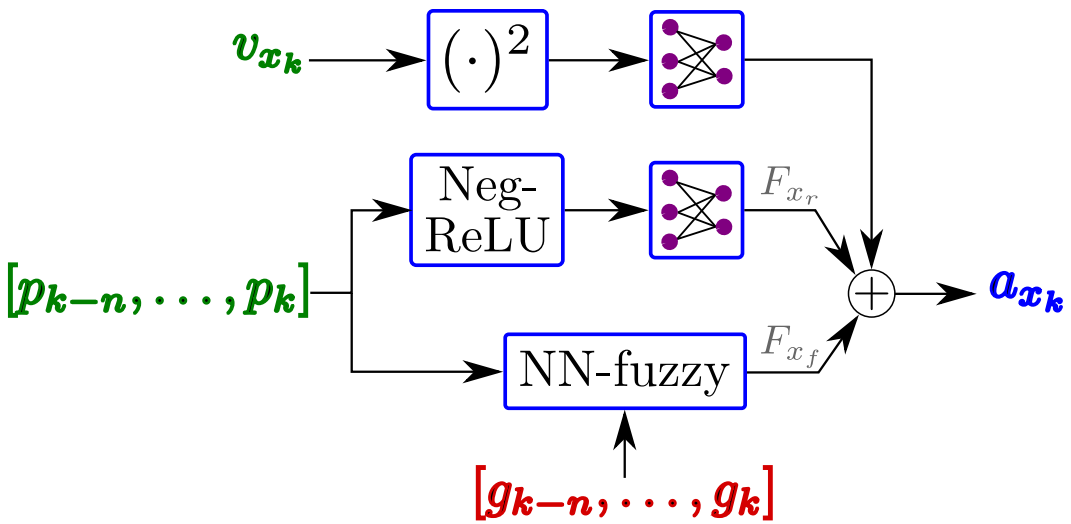

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Inputs: pedal $p \in [-1, 1]$, speed v_x, gear g, steer δ, lateral accel. a_y
Output: longitudinal accel. a_x

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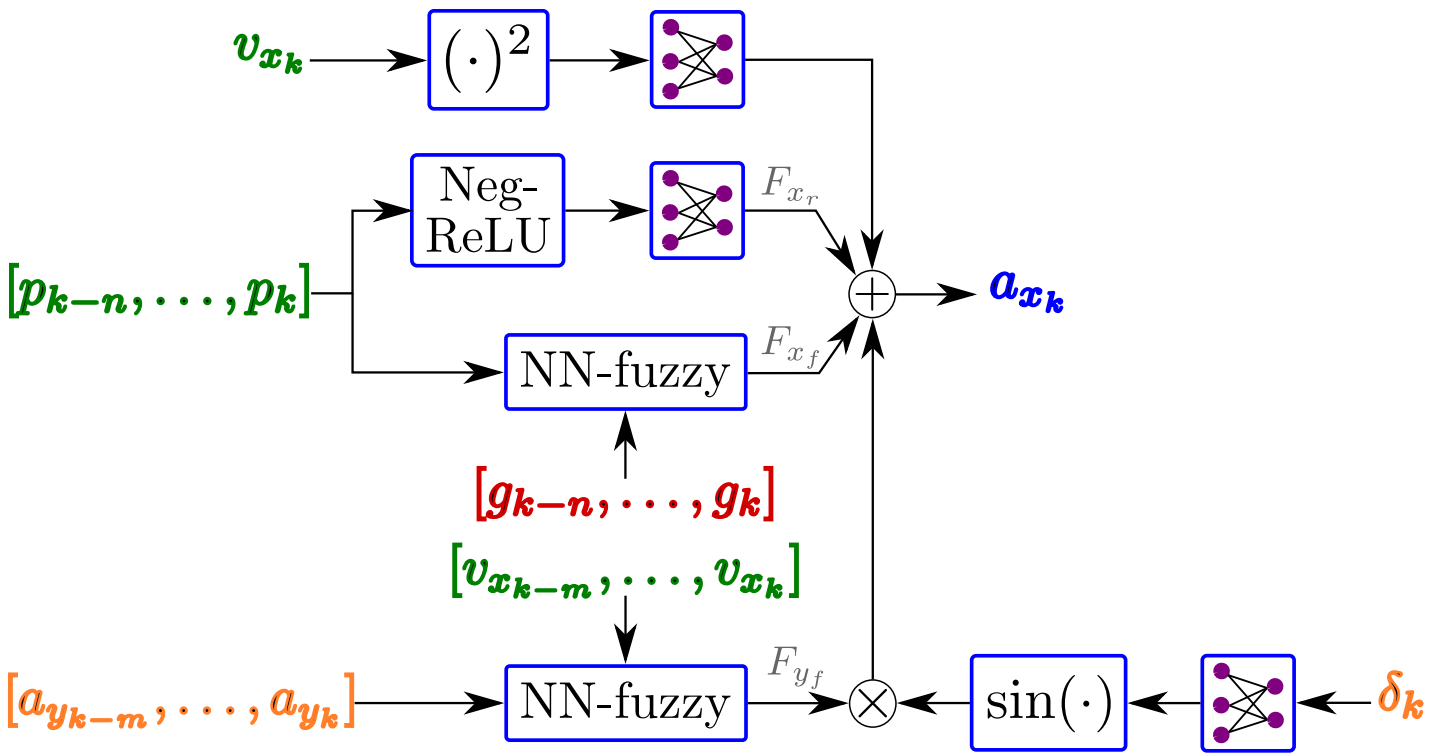
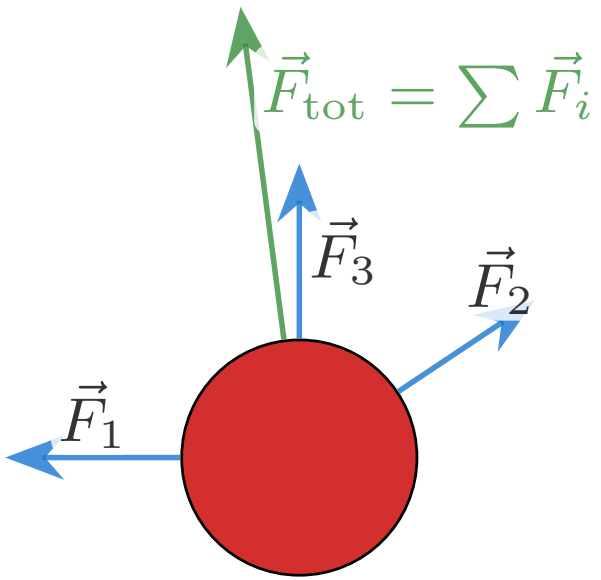


Embedding Physical Principles in MS-NNs

- Linear **superposition of forces**

$$\dot{x} = f(x,u) = f_x(x) + f_1(x,u_1) + f_2(x,u_2) + \ldots + f_n(x,u_n)$$



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- Linear **superposition of forces**
- Discrete-time system dynamics modeled with finite/infinite impulse response layers (**FIR** or **IIR**)

FIR
$$y[n] = b_0 x[n] + b_1 x[n-1] + \cdots + b_N x[n-N] = \sum_{i=0}^{N} b_i \cdot x[n-i],$$

IIR
$$y[n] = \sum_{i=0}^{P} b_i x[n-i] + \sum_{i=1}^{Q} a_i y[n-i]$$

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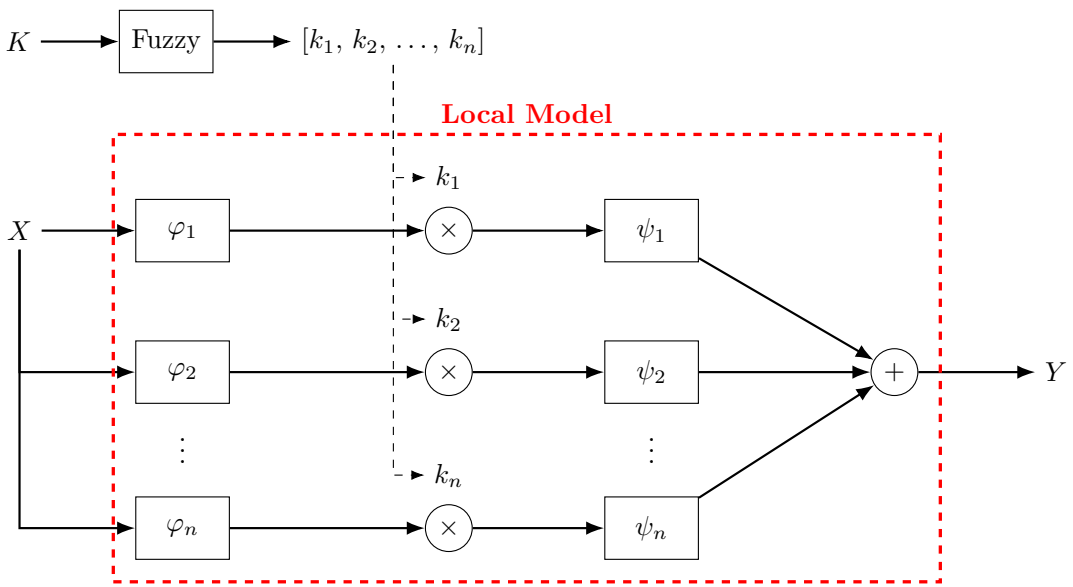

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- Unknown nonlinearities addressed with neuro-fuzzy **local models**
- Capturing the residuals of analytical models (such as friction, delays, and backlash) through **ad-hoc neuralization** with **custom funct.**

Embedding Physical Principles in MS-NNs

- Linear **superposition of forces**
- Discrete-time system dynamics modeled with finite/infinite impulse response layers (**FIR** or **IIR**)
- Unknown nonlinearities addressed with neuro-fuzzy **local models**
- Capturing the residuals of analytical models (such as friction, delays, and backlash) through **ad-hoc neuralization** with **custom funct.**
- Embedding the concept of **time** inside the NN

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- Flexible managing of custom **recursive networks**

NNodely

Framework

Aims

- **Speed-up** the development of MS-NNs w.r.t. standard deep-learning frameworks (e.g., pure PyTorch or TensorFlow)

The code is reduced by **75%**

Aims

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- **Support professionals** with classical modeling backgrounds, such as physicists and engineers, in developing **physics-guided ML** solutions

Ease of use for **non-experts** in ML

Aims

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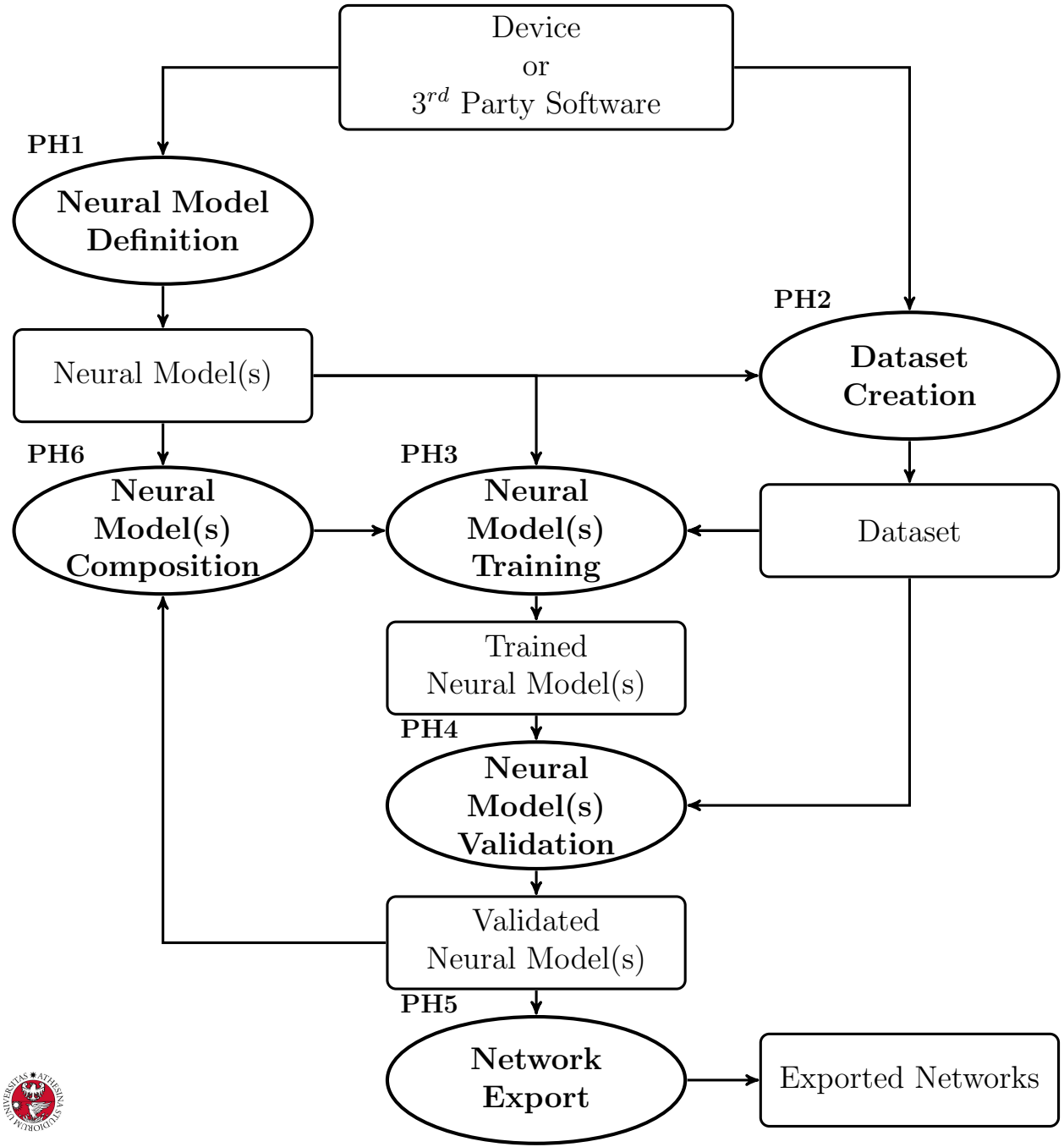
- A **repository** of incremental **know-how** to collect examples of MS-NNs for various applications

Workflow



modely
neuralize your model

Model-Structured Neural Networks with nnodely

MS-NNs Definition (PH1)

- Defining **Inputs**
- Defining **Outputs**
- Defining **Relations**:
  - Aritmetic operations
  - Trigonometric operations
  - Custom functions
  - Local models
  - Fuzzification
  - ...

MS-NN Manipulation

- Data loading and dataset creation (PH2)
- Fitting objectives (PH3)
- Network composition and connection (PH6)
- Training (PH3)
- Validation using model based criteria (PH4)
- MS-NN export (PH5) in **PyTorch** and **ONNX** format

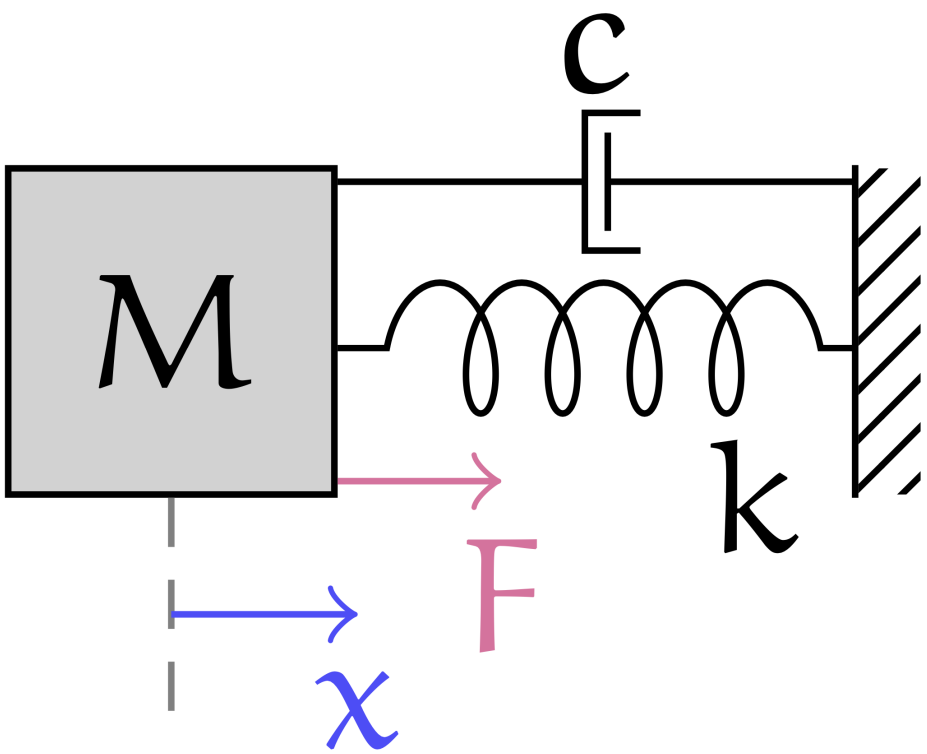
Use Cases

Use Cases

Modeling and Control of a Mass-Spring-Damper System

Mass-Spring-Damper: Modeling

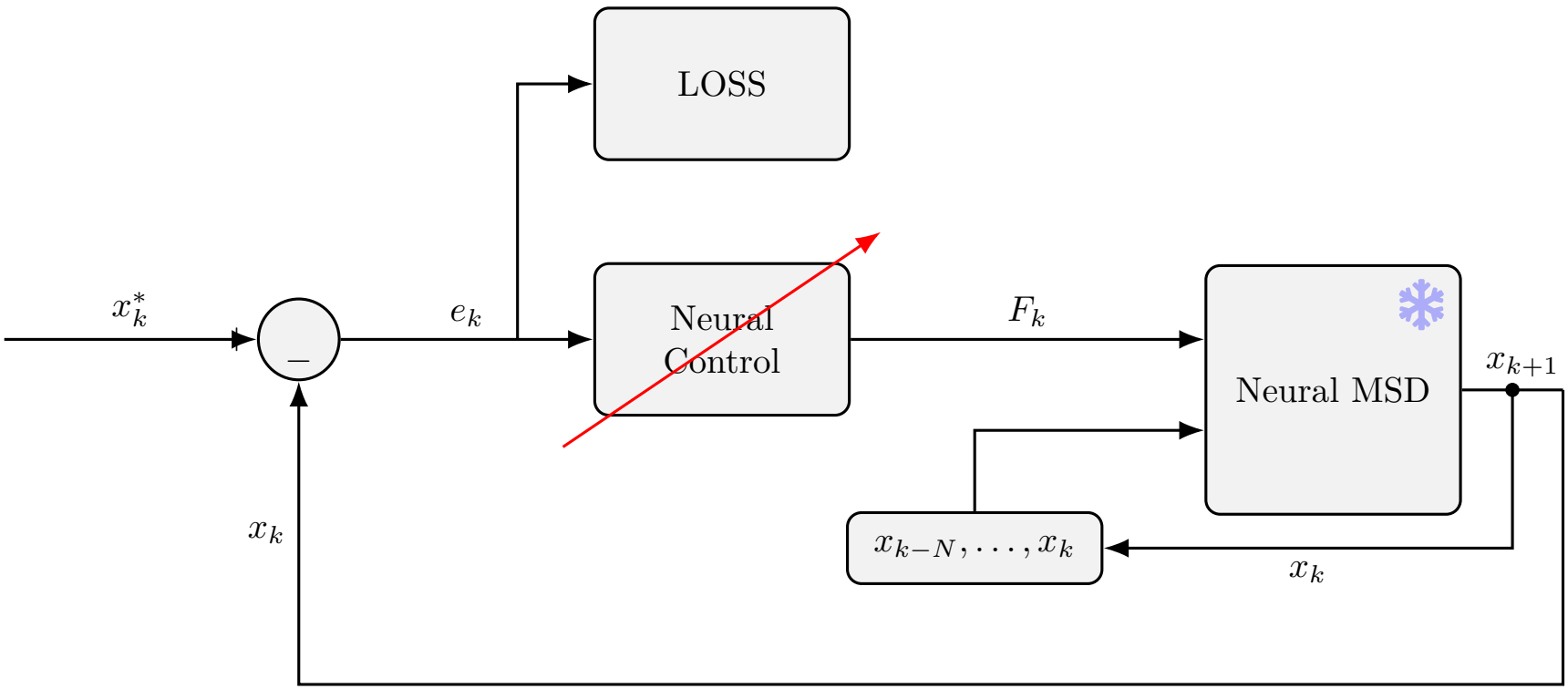
Learn the **dynamics** of a Mass-Spring-Damper system (neural MSD)



$$x_{k+1} = \overbrace{\sum_{k=0}^{N_x-1} x[-k]\cdot h_x[(N_x-1)-k]}^{\mathrm{FIR}(\bar{x})} + \overbrace{F[0]\cdot h_F}^{\mathrm{FIR}(F)}$$

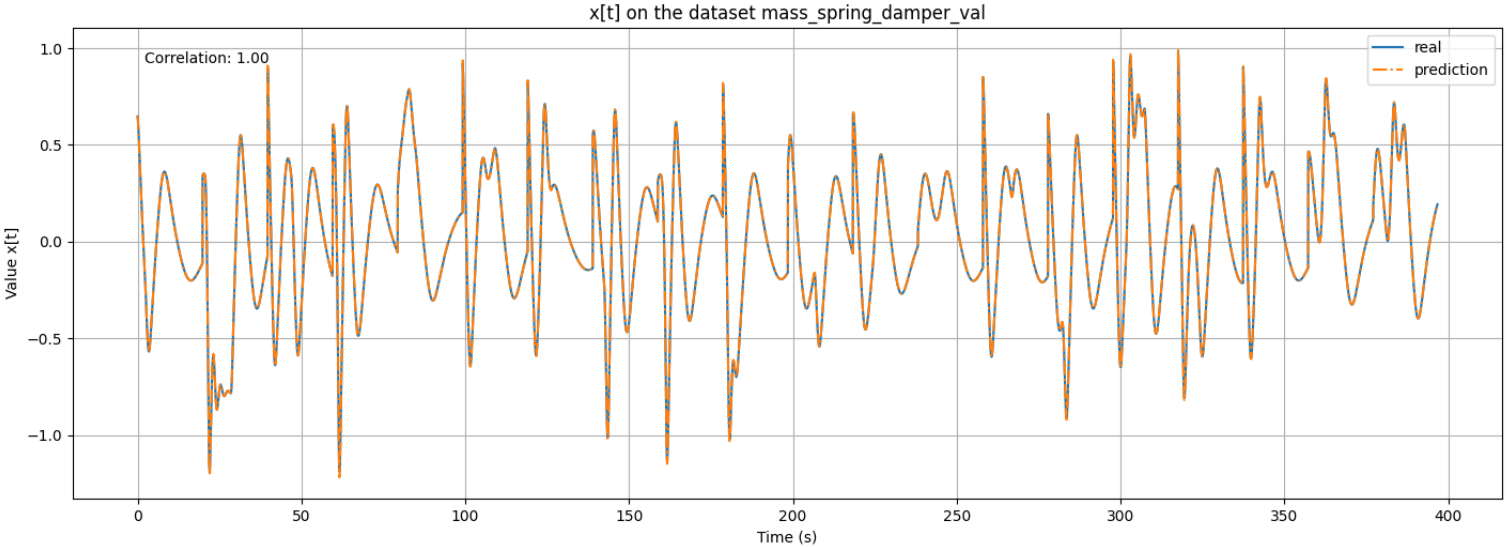
Mass-Spring-Damper: Control

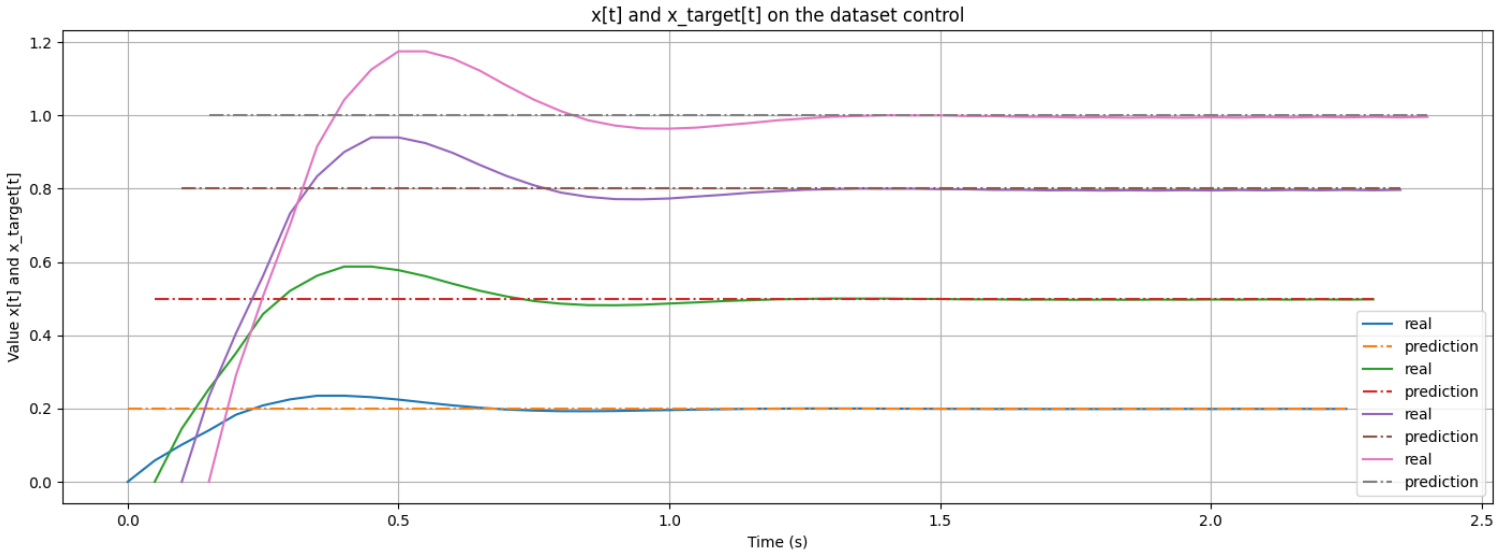
- Learn a **Neural PID** to control a mass-spring-damper system
- Controller gradients are propagated through the learned dynamic model (neural MSD) $\longrightarrow$ **differentiable end-to-end** controller training



$$\text{LOSS} = \sum_{\text{examples}} e_k^2 = \sum (x_k - x_k^*)^2$$

Mass-Spring-Damper: Results for Modelling and Control



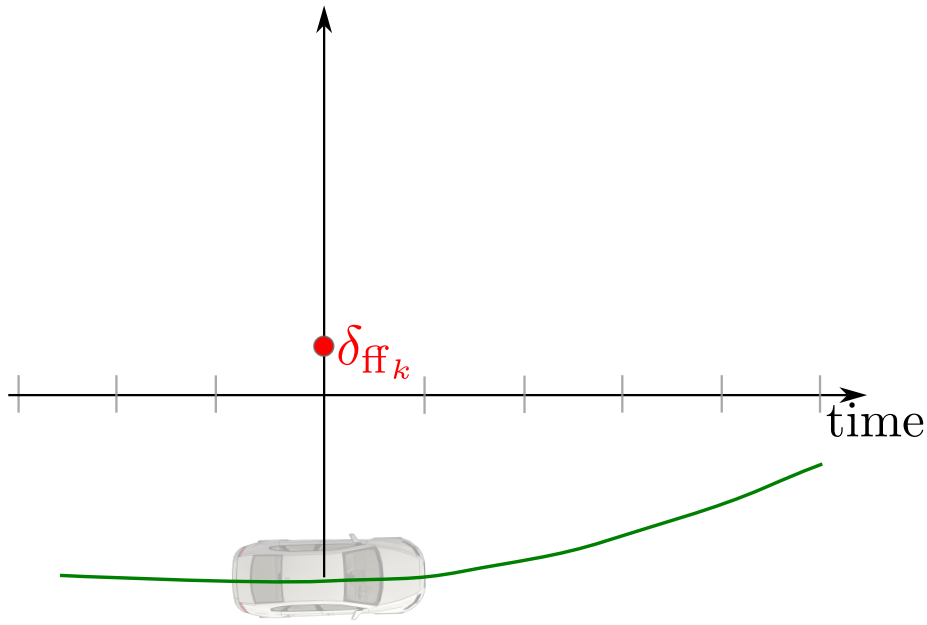


Use Cases

Modeling and Control of the Vehicle Dynamics

Inverse dynamic problem

NN output: steering wheel angle δ_{ff_k}



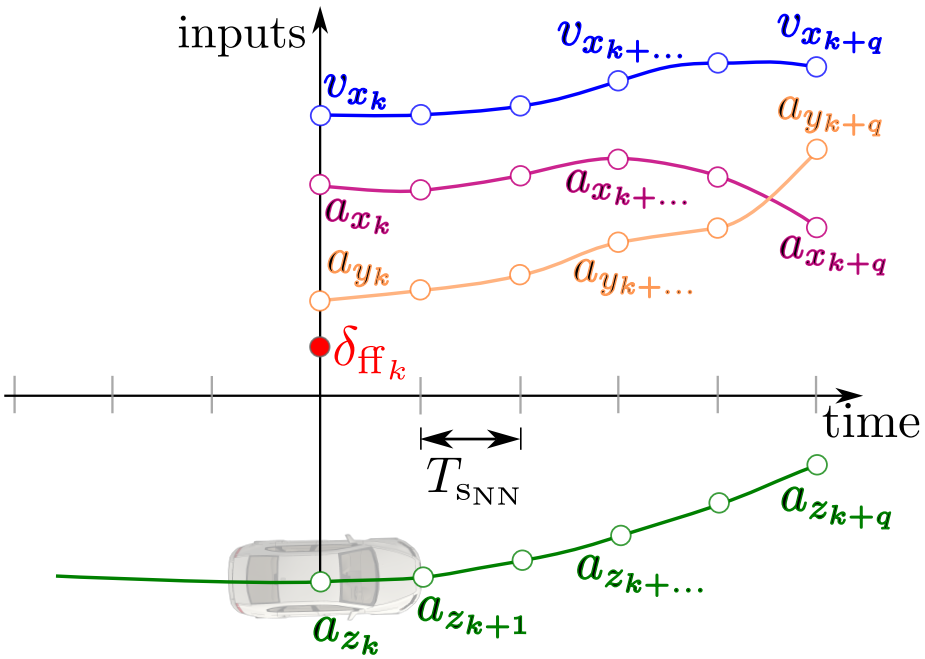
Inverse dynamic problem

NN output: steering wheel angle δ_{ff_k}

NN inputs:

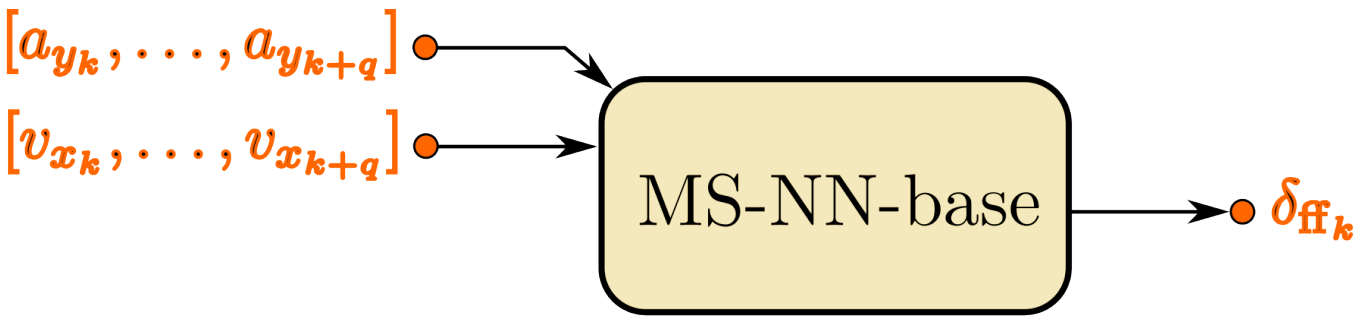
Future reference trajectories: lateral, longit., vertical accelerations and velocity

- $a_{y\,k} = \left[a_{y_k}, \ldots, a_{y_{k+q}}\right]$
- $a_{x\,k} = \left[a_{x_k}, \ldots, a_{x_{k+q}}\right]$
- $a_{z\,k} = \left[a_{z_k}, \ldots, a_{z_{k+q}}\right]$
- $v_{x\,k} = \left[v_{x_k}, \ldots, v_{x_{k+q}}\right]$



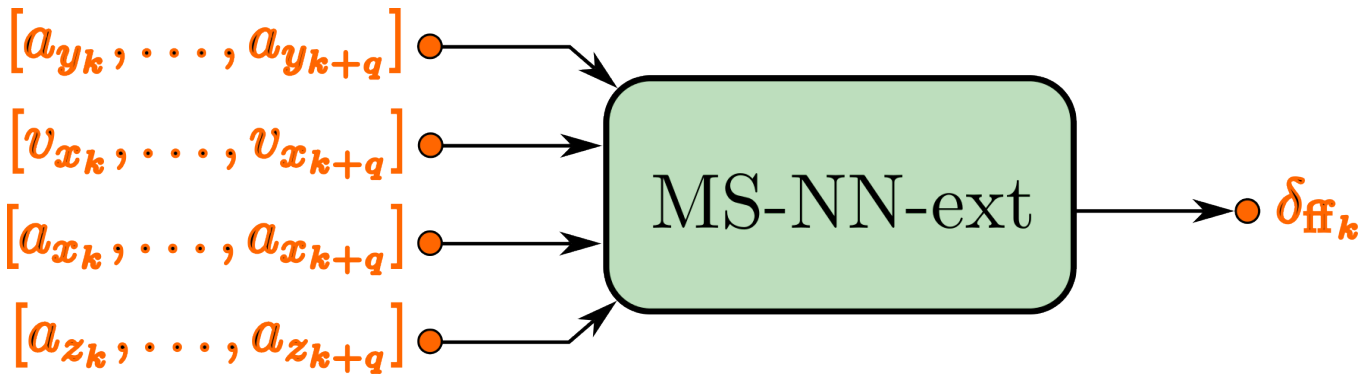
Two incremental variants

- **MS-NN-base** → pure lateral nonlinear dynamics (2D road)



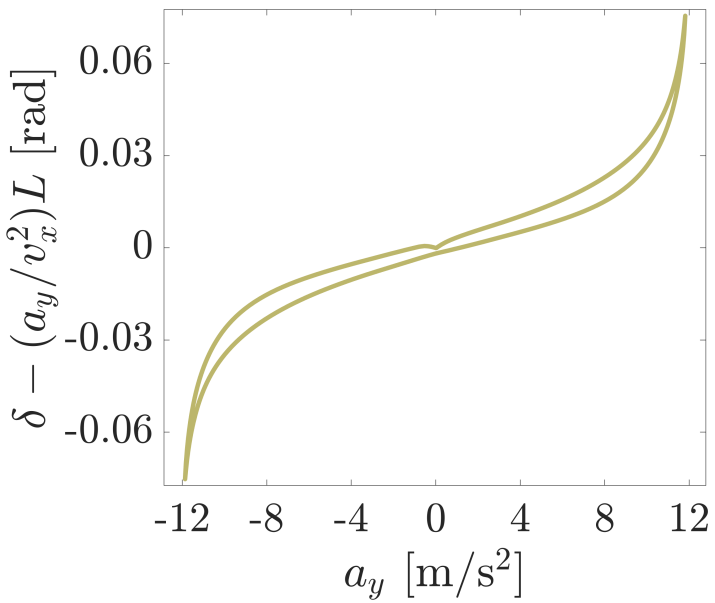
Two incremental variants

- **MS-NN-base** → pure lateral nonlinear dynamics (2D road)
- **MS-NN-ext** → effects of longitudinal and vertical accelerations (3D road)



Steady-state pure lateral dynamics

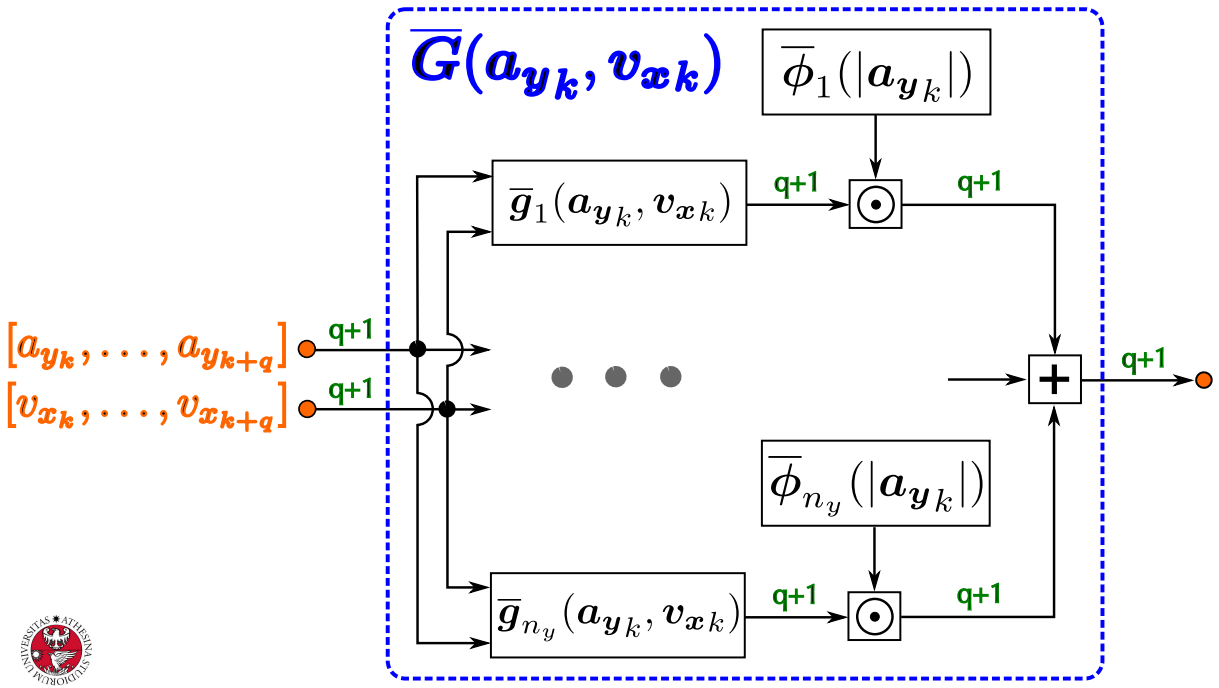
Handling diagram

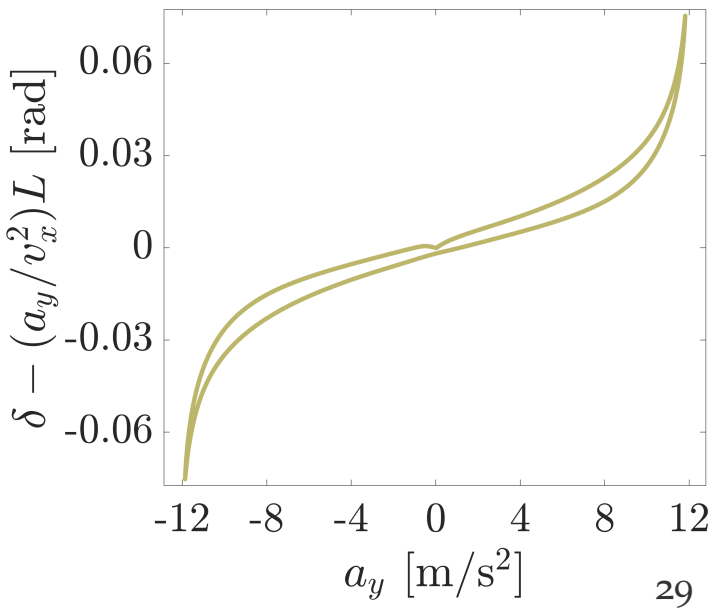


Steady-state pure lateral dynamics

Handling diagram

- **Local neuro-fuzzy** models



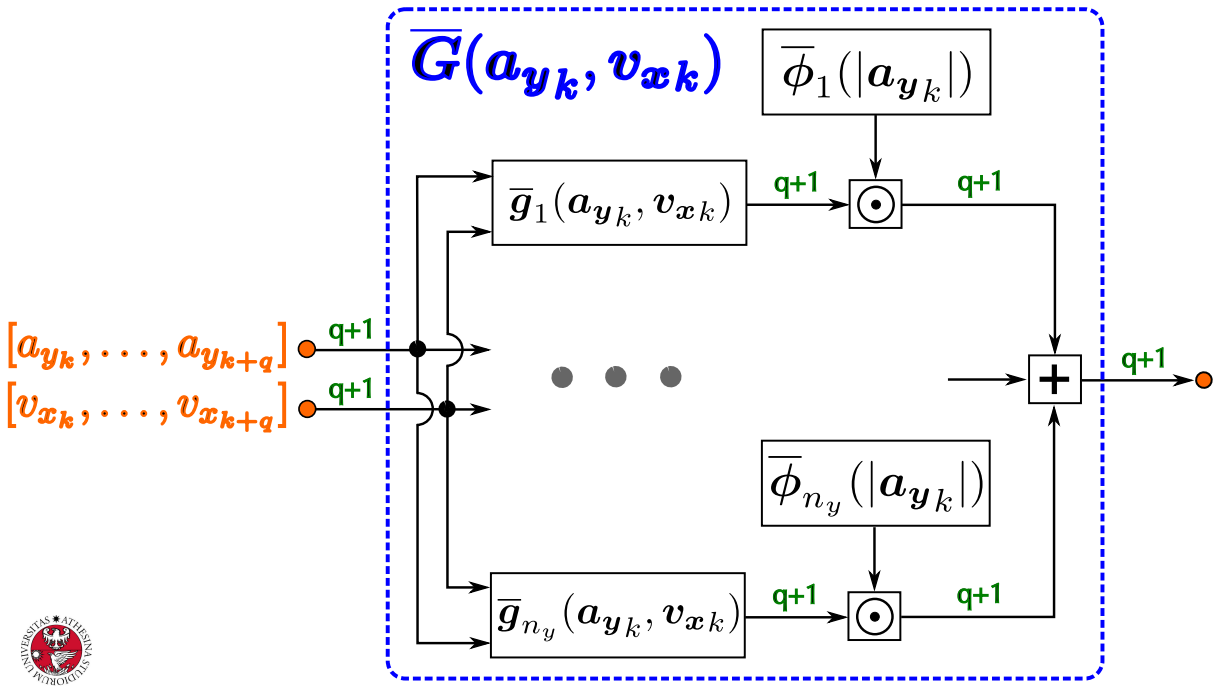


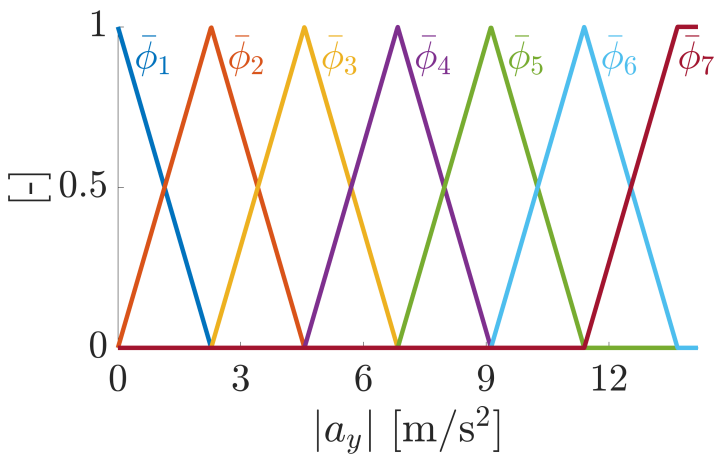
Steady-state pure lateral dynamics

Handling diagram

- **Local neuro-fuzzy** models

$$\bar{g}_i(a_y, v_x) = \frac{a_y}{v_x^2} L + \operatorname{sign}(a_y)\, \mathrm{k}1_i + \left(a_y - a_{y0_i} \operatorname{sign}(a_y)\right) \mathrm{k}2_i$$





Steady-state pure lateral dynamics

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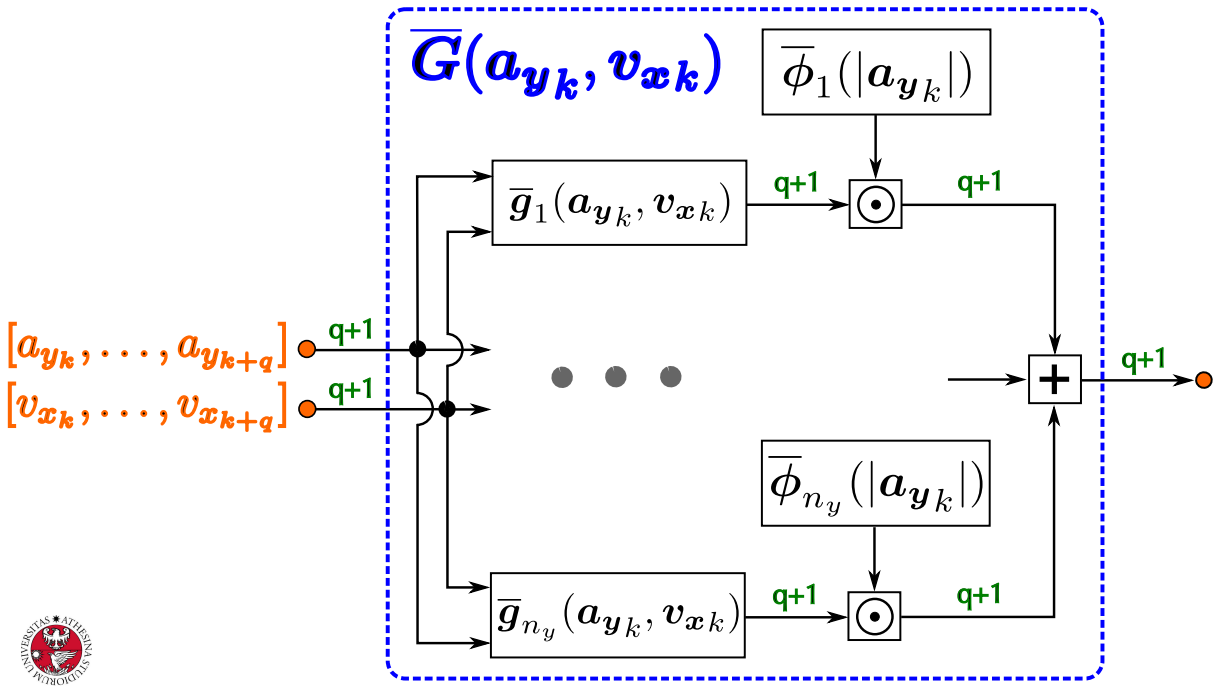
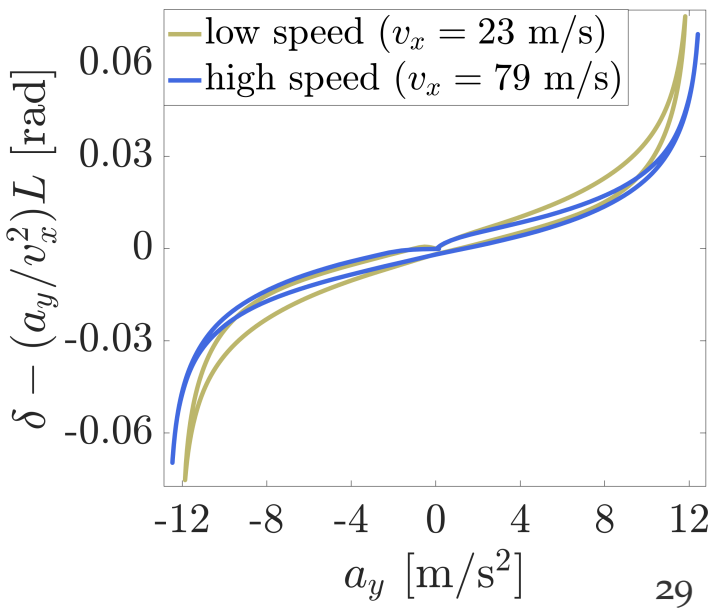
- **Local neuro-fuzzy** models

$$\bar{g}_i(a_y, v_x) = \frac{a_y}{v_x^2} L + \text{sign}(a_y)\, \text{k}1_i \qquad + \left(a_y - a_{y0_i}\, \text{sign}(a_y)\right) \text{k}2_i$$



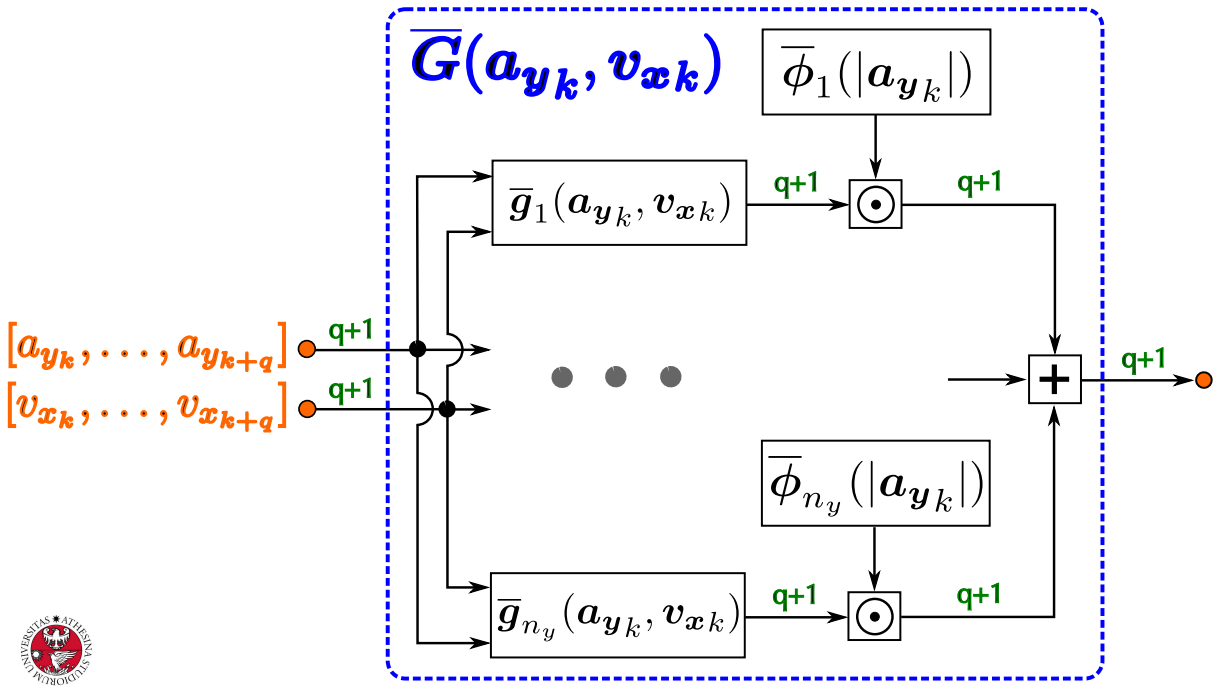


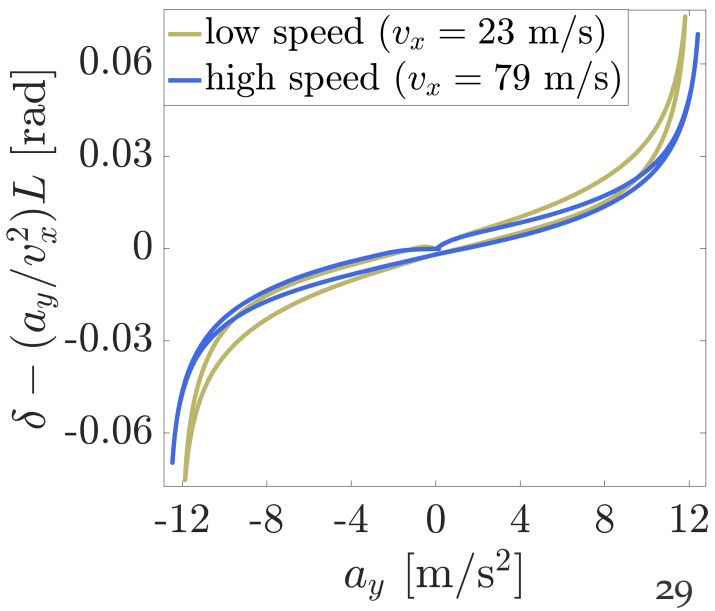
Steady-state pure lateral dynamics

Handling diagram

- **Local neuro-fuzzy** models with v_x-dependency

$$\bar{g}_i(a_y, v_x) = \frac{a_y}{v_x^2} L + \text{sign}(a_y)\, \text{k}1_i(v_x) + \left(a_y - a_{y0_i}\text{sign}(a_y)\right) \text{k}2_i(v_x)$$





Steady-state pure lateral dynamics

Handling diagram

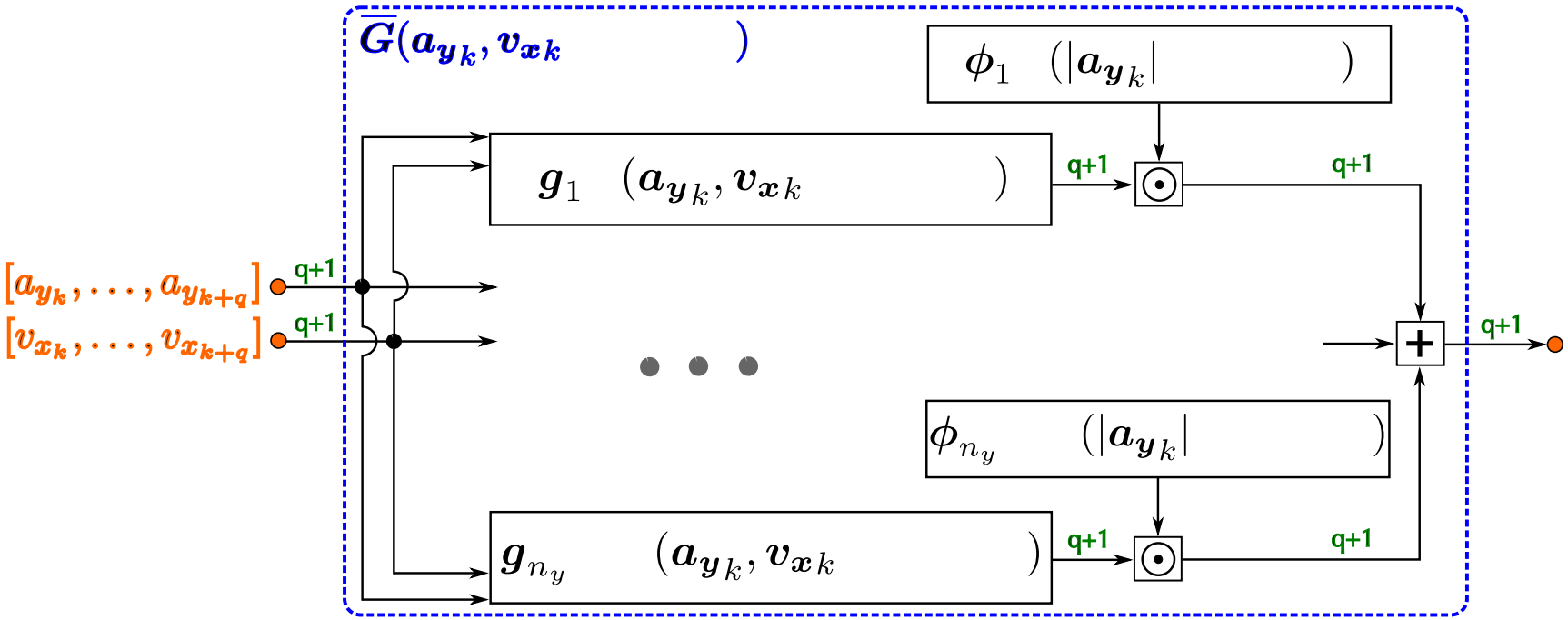
- **Local neuro-fuzzy** models with v_x-dependency

$$\bar{g}_i(a_y, v_x) = \frac{a_y}{v_x^2} L + \text{sign}(a_y)\, \text{k1}_i(v_x) + \left(a_y - a_{y0_i}\, \text{sign}(a_y)\right) \text{k2}_i(v_x)$$

```
def handling_diagr_local(ay,vx,  # inputs
                         ay_0,L,          # constants
                         k1_vx,k2_vx,     # learnable arrays of parameters
                         ):
  sign_ay = torch.sign(ay)  # sign of the lateral acceleration

  # compute k1, as a function of vx
  k1_vx_fun = k1_vx[0,0,0]
  for ii in range(1,k1_vx.size(2)):
    k1_vx_fun = k1_vx_fun + k1_vx[0,0,ii]*torch.pow(vx,ii)

  # compute k2, as a function of vx
  k2_vx_fun = k2_vx[0,0,0]
  for ii in range(1,k2_vx.size(2)):
    k2_vx_fun = k2_vx_fun + k2_vx[0,0,ii]*torch.pow(vx,ii)

  # output of the local model of the handling diagram
  output = (ay/vx**2)*L + k1_vx_fun*sign_ay + k2_vx_fun*(ay - ay_0*sign_ay)
  return output

handling_diagr = ParamFun(handling_diagr_local)

activ_fcns_ay = Fuzzify(centers=chan_centers_ay, functions='Triangular')(ay_abs)

out_local_models_handling_diagr = LocalModel(input_function=handling_diagr_gen, pass_indexes=True)((ay,vx),
                                                                                                     (activ_fcns_ay))
```

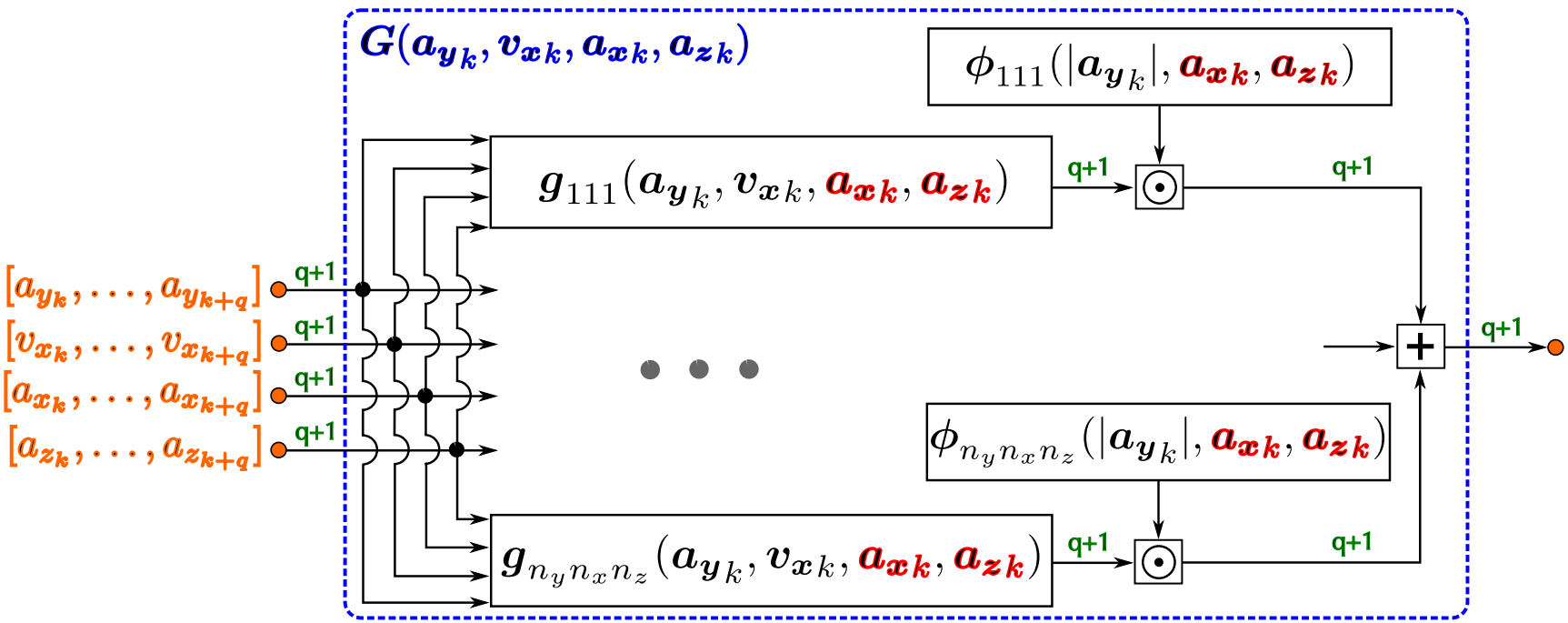
Quasi steady-state combined lateral dynamics

- **Local neuro-fuzzy** models in overlapping regions of a_y



Quasi steady-state combined lateral dynamics

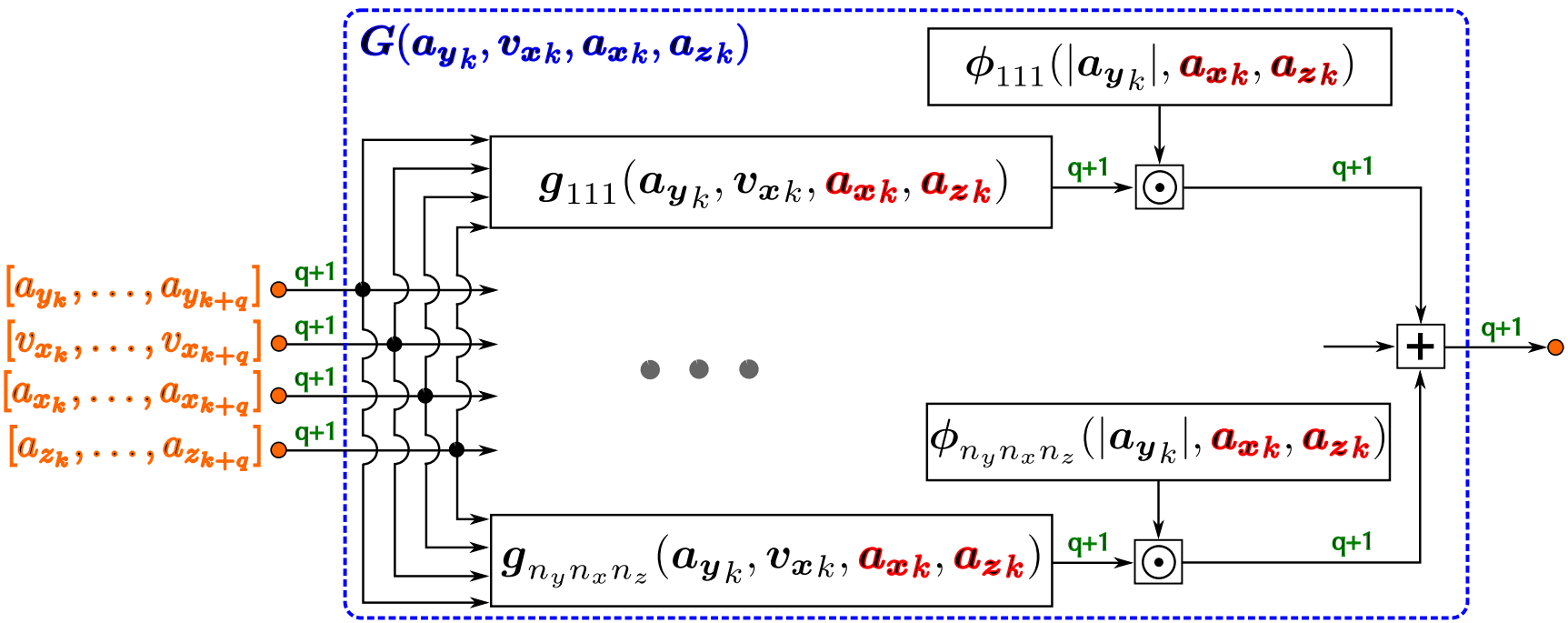
- **Local neuro-fuzzy** models in overlapping regions of a_y, a_x, a_z



Quasi steady-state combined lateral dynamics

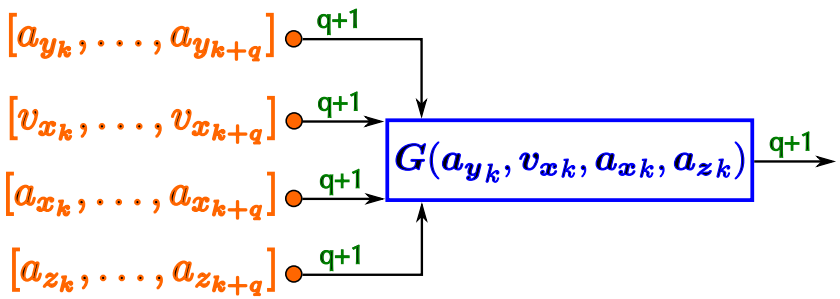
- **Local neuro-fuzzy** models in overlapping regions of a_y, a_x, a_z

  $g_{ijk}(\cdot) \rightarrow$ local approximation of a nonlinear double-track model around $\{a_{y0_i}, a_{x0_j}, a_{z0_k}\}$



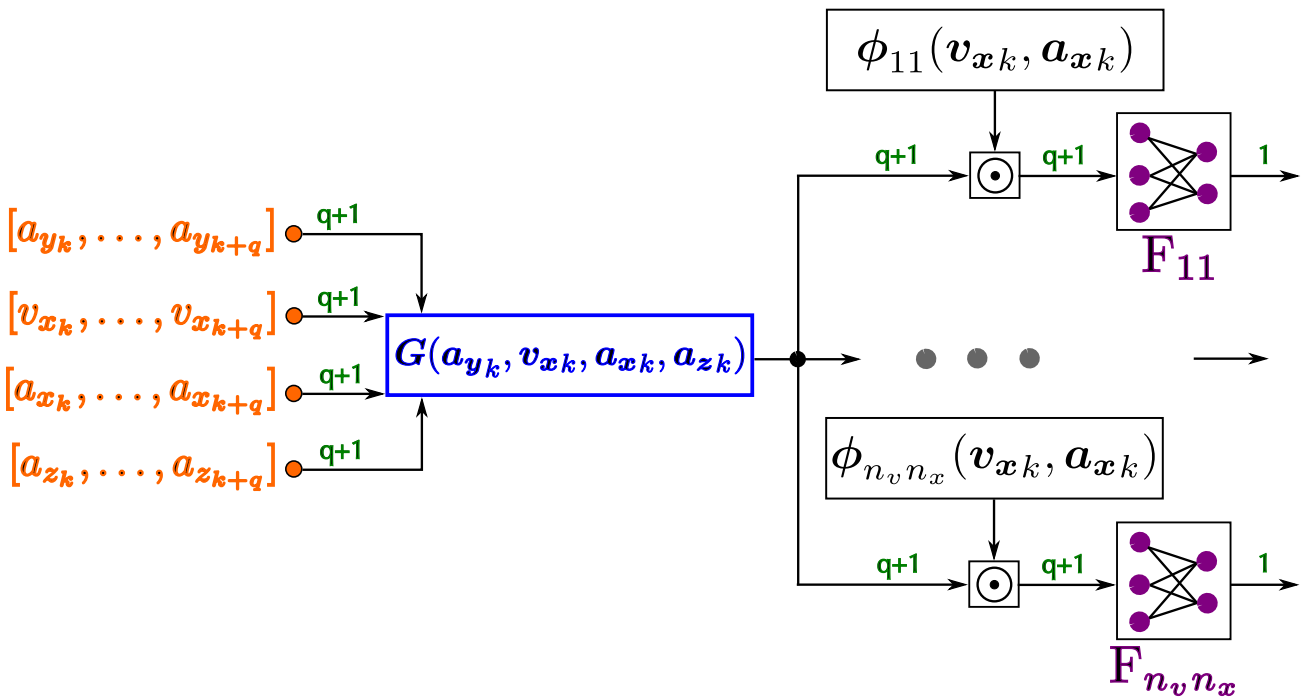
Transient combined lateral dynamics

- Leverage the **future** vehicle behavior to learn the dynamic response



Transient combined lateral dynamics

- Leverage the **future** vehicle behavior to learn the dynamic response
- **Local fully connected** layers in overlapping regions of v_x and a_x



Transient combined lateral dynamics

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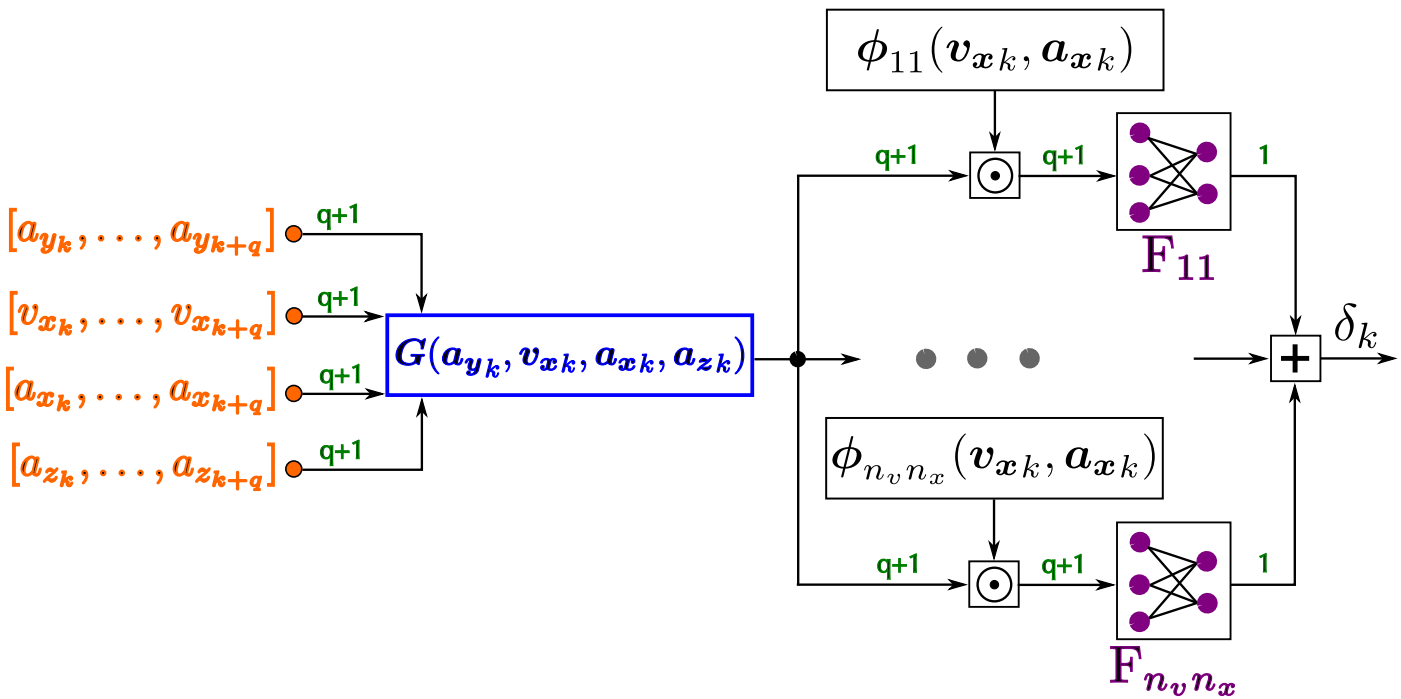

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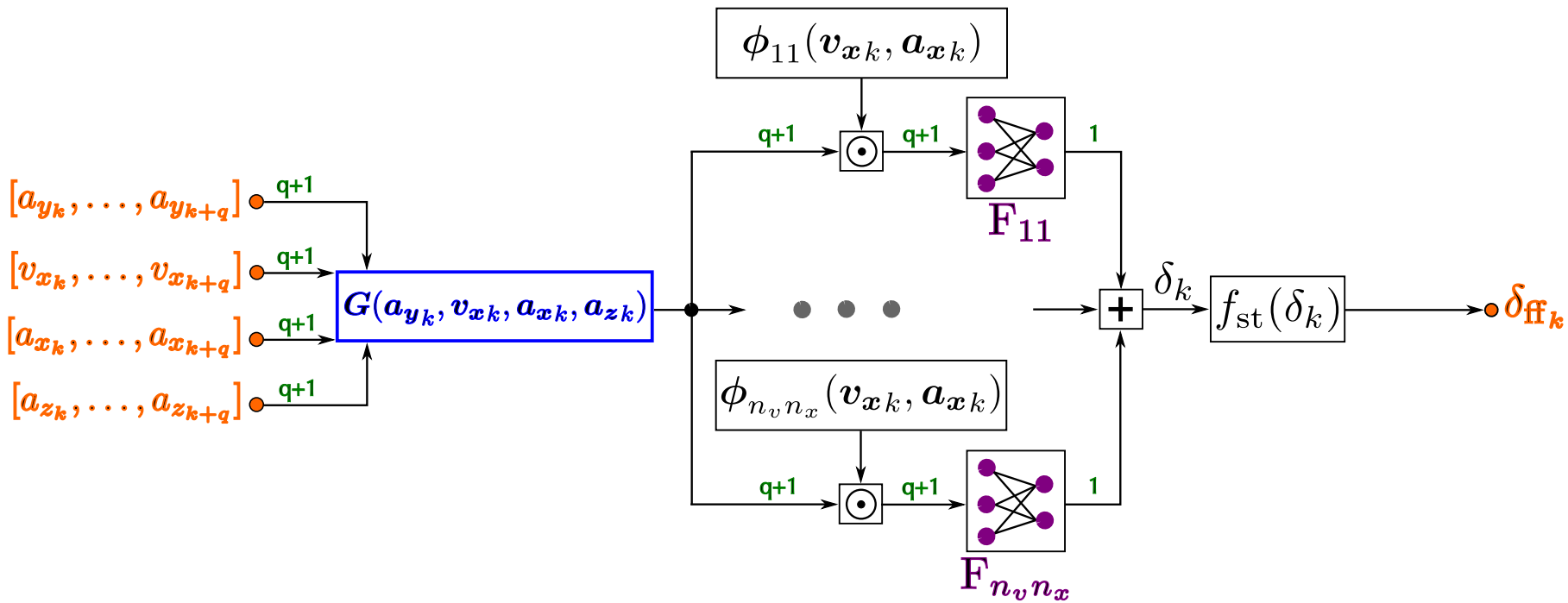
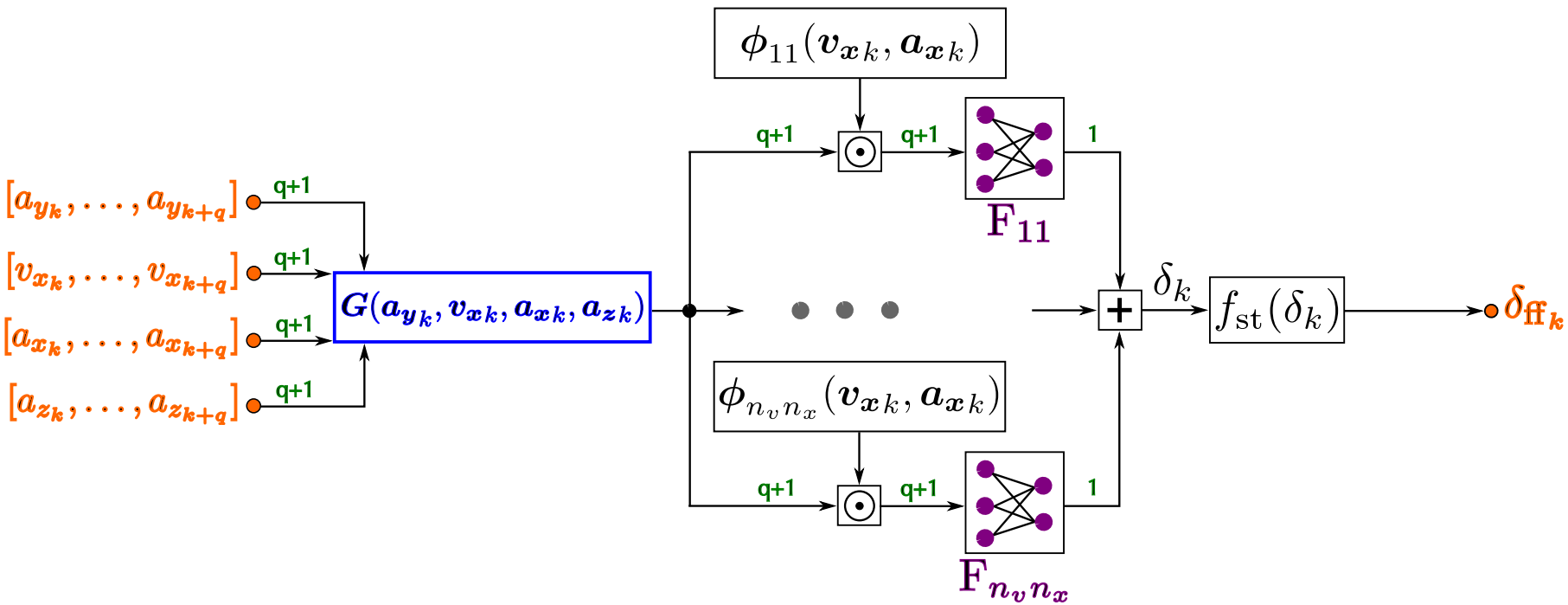


MS-NN-ext

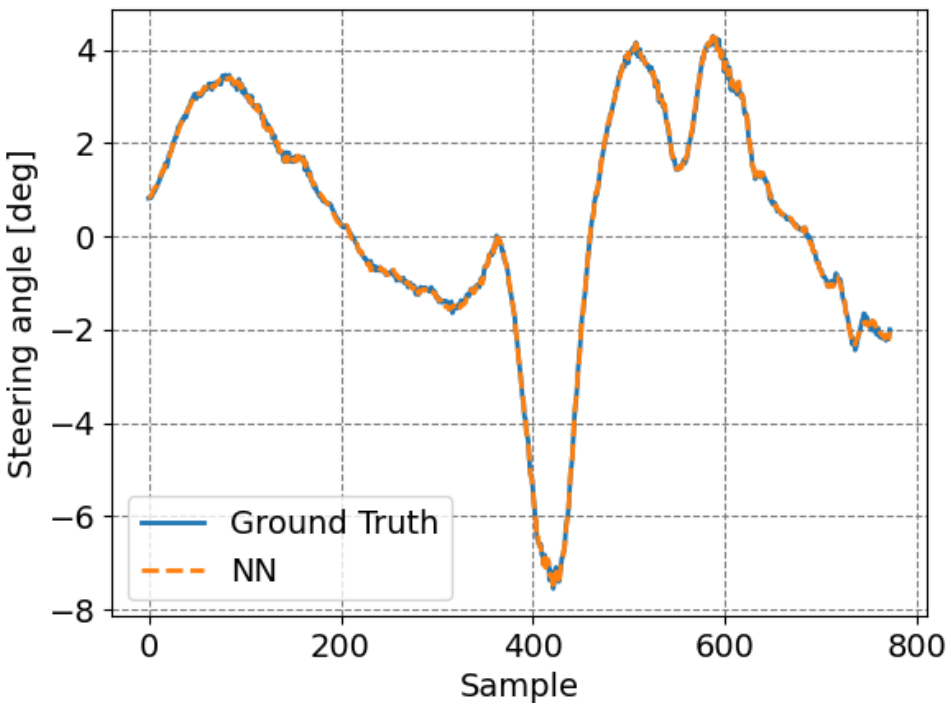
```
activ_fcns_vx = Fuzzify(centers=chan_centers_vx, functions='Triangular')(vx.sw([0,num_samples_future_feedfw]))

local_model_trans_dyna = LocalModel(output_function=lambda: Fir(W_init = init_exp,
                                                                W_init_params={'size_index':0, 'max_value':first_value,
                                                                               'lambda':5, 'monotonicity':'decreasing'}))
out_local_model_trans_dyna = local_model_trans_dyna(out_local_models_handling_diagr, (activ_fcns_vx,activ_fcns_ax))
```



Steering Control for Autonomous Racing: Summary

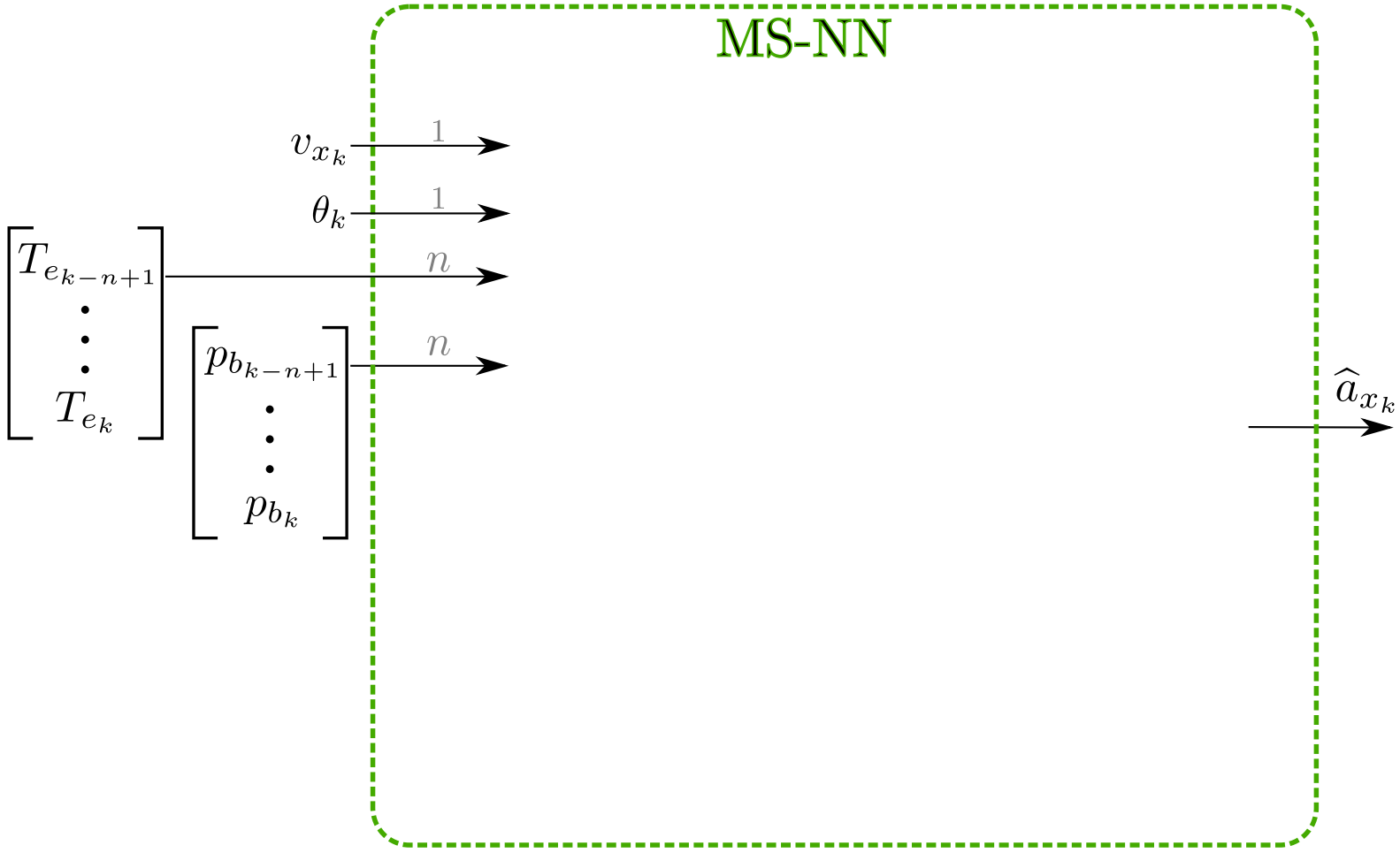
More details in:

- M. Piccinini, A. Mungiello, G. Jank, G. P. R. Papini, F. Biral, J. Betz, "Model-Structured Neural Networks to Control the Steering Dynamics of Autonomous Race Cars," in IEEE International Conference on Intelligent Transportation Systems (ITSC), 2025, accepted.
- M. Piccinini et al., "A Physics-Driven Artificial Agent for Online Time-Optimal Vehicle Motion Planning and Control," in IEEE Access, vol. 11, pp. 46344-46372, 2023, doi: 10.1109/ACCESS.2023.3274836.

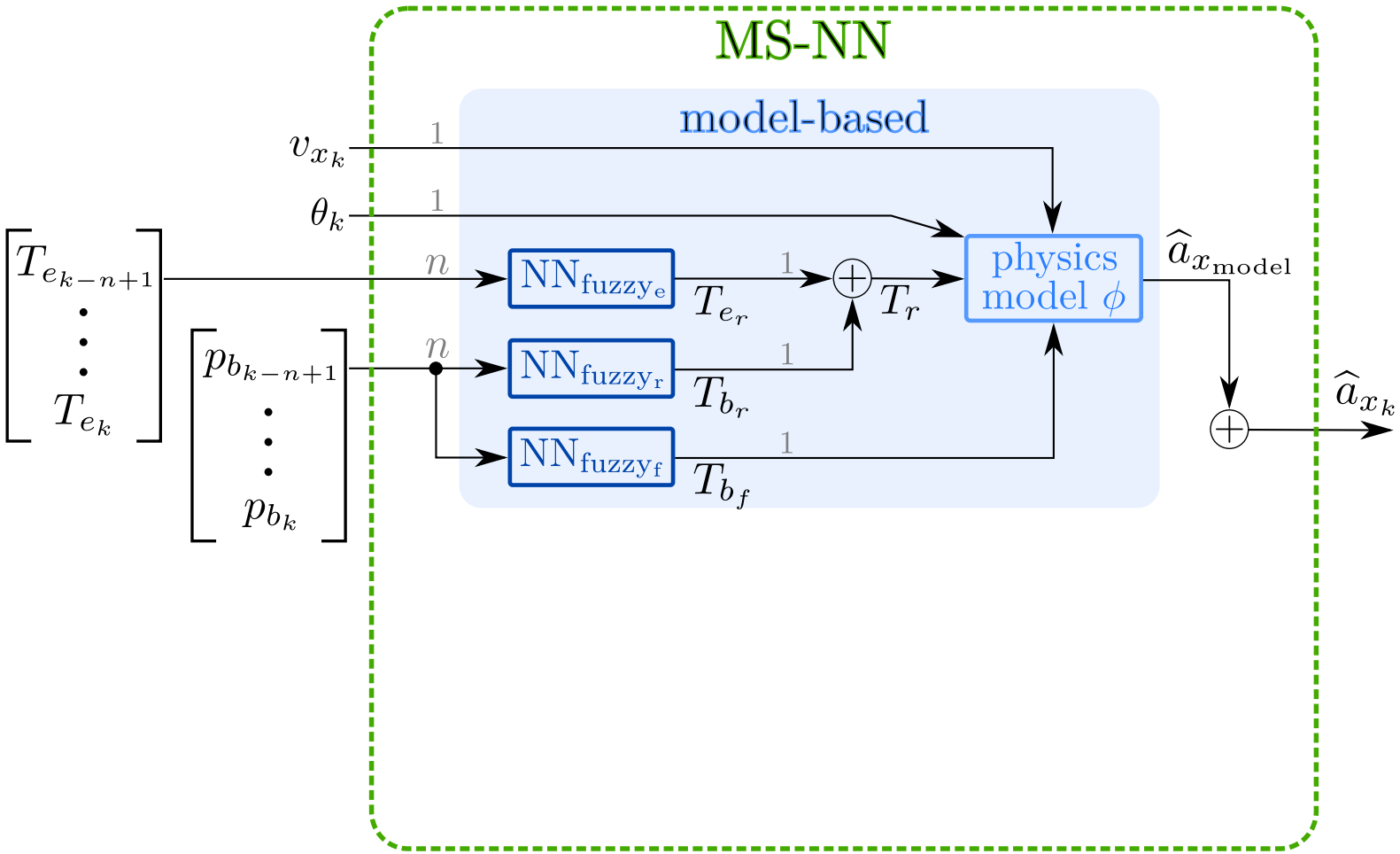


Show video

Longitudinal Vehicle Dynamics

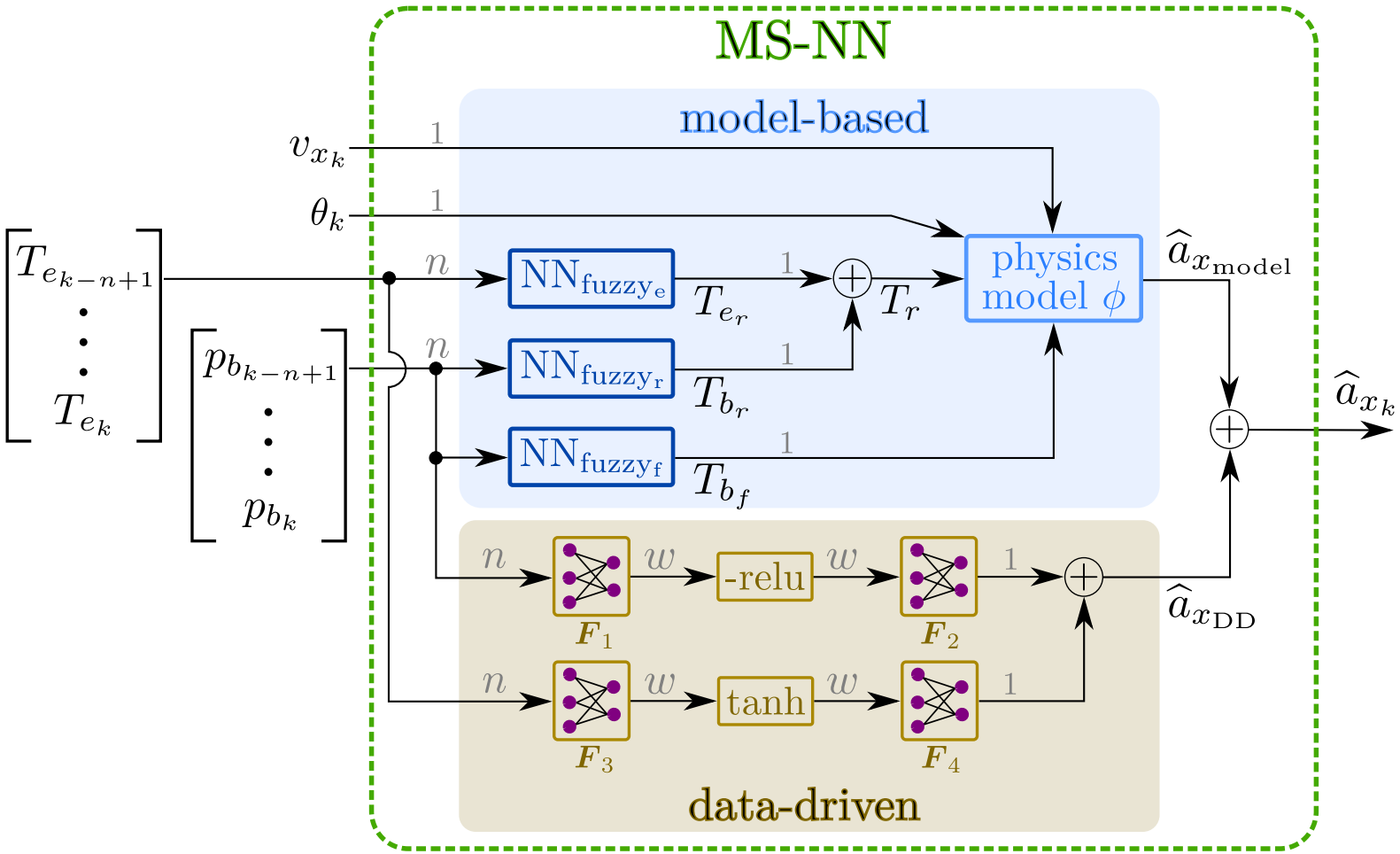


Longitudinal Vehicle Dynamics



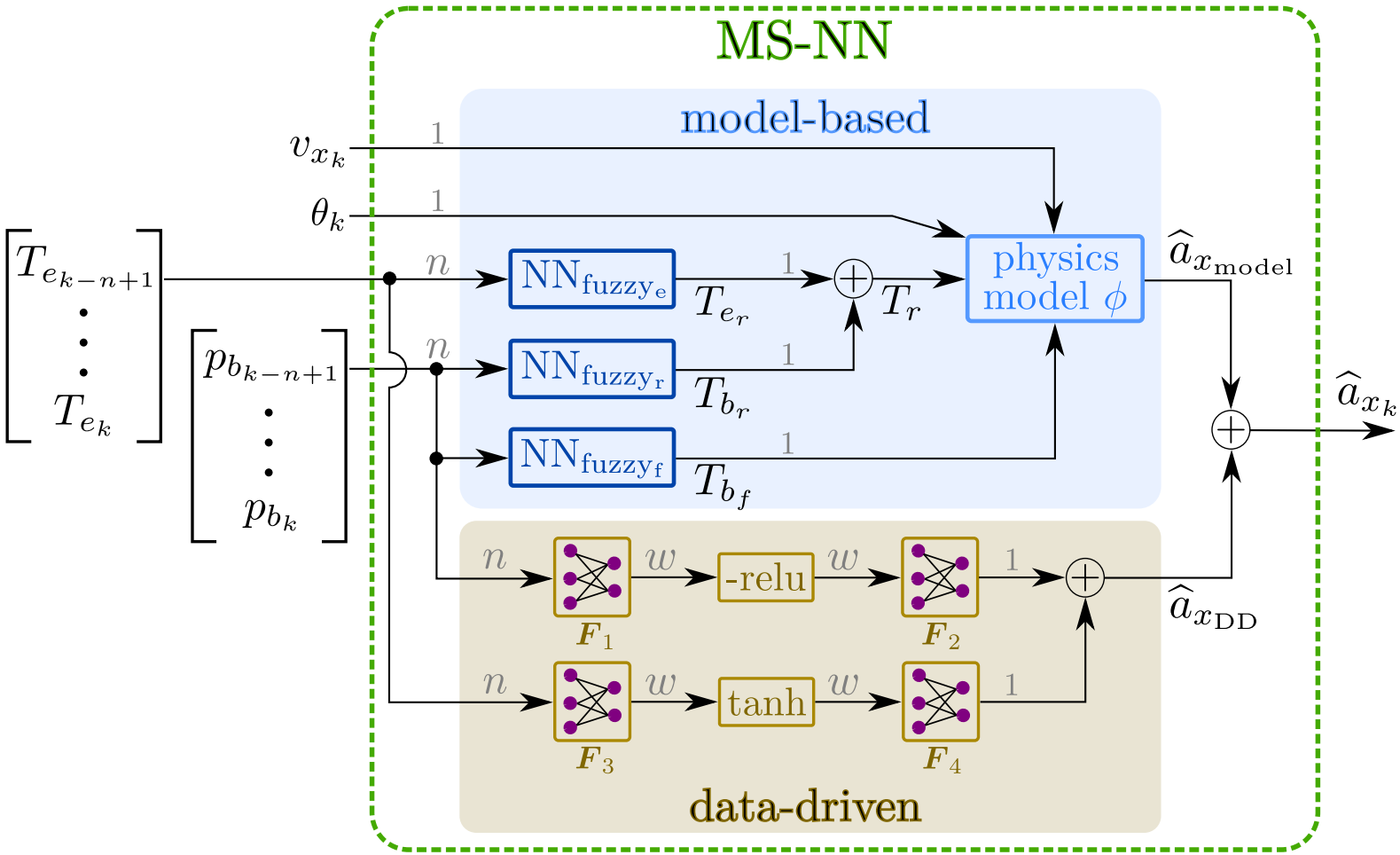
$$\widehat{a}_{x_{\mathrm{model}}} = \frac{\frac{1}{m}\left(\frac{T_f}{r_f} + \frac{T_r}{r_r} - k_d\, v_x^2 - c_v\, v_x\right) - g\, c_r \cos(\theta) - g \sin(\theta)}{1 + \frac{2}{m}\left(I_f / r_f^2 + I_r / r_r^2\right)}$$

Longitudinal Vehicle Dynamics



$$\widehat{a}_{x_k} = \widehat{a}_{x_{\mathrm{model}_k}} + \widehat{a}_{x_{\mathrm{DD}_k}}$$

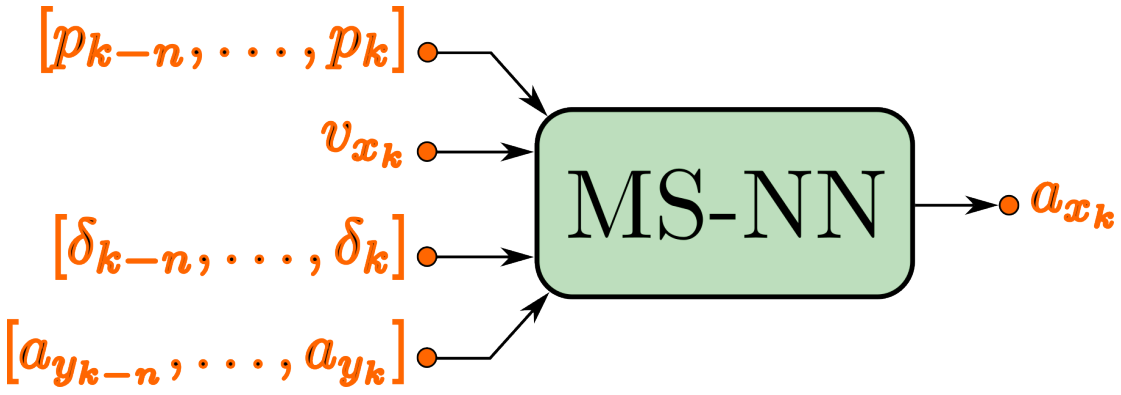
Longitudinal Vehicle Dynamics

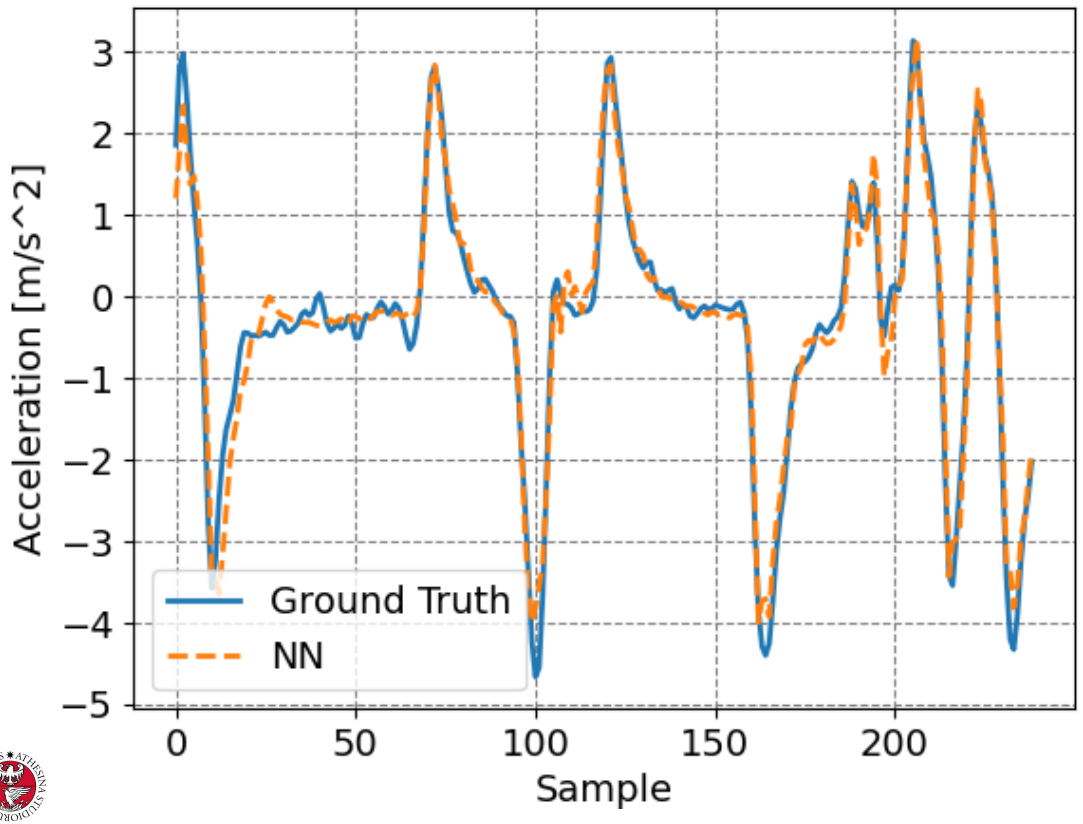


More details in:

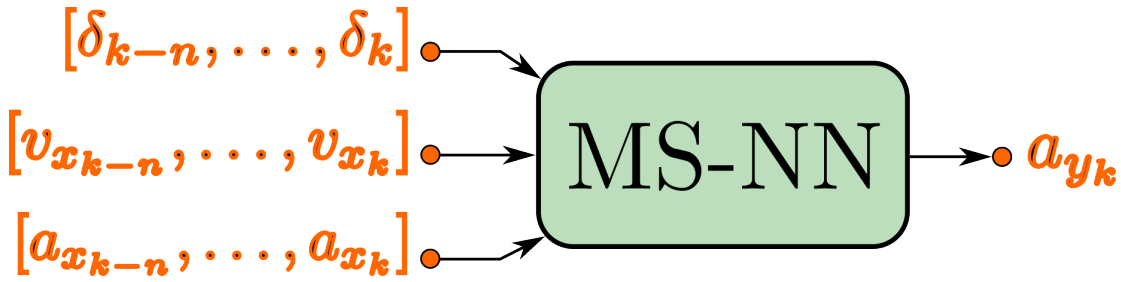
M. Piccinini, M. Zumerle, J. Betz and G. Pietro Rosati Papini, "A Road Friction-Aware Anti-Lock Braking System Based on Model-Structured Neural Networks," in IEEE Open Journal of Intelligent Transportation Systems, 2025.

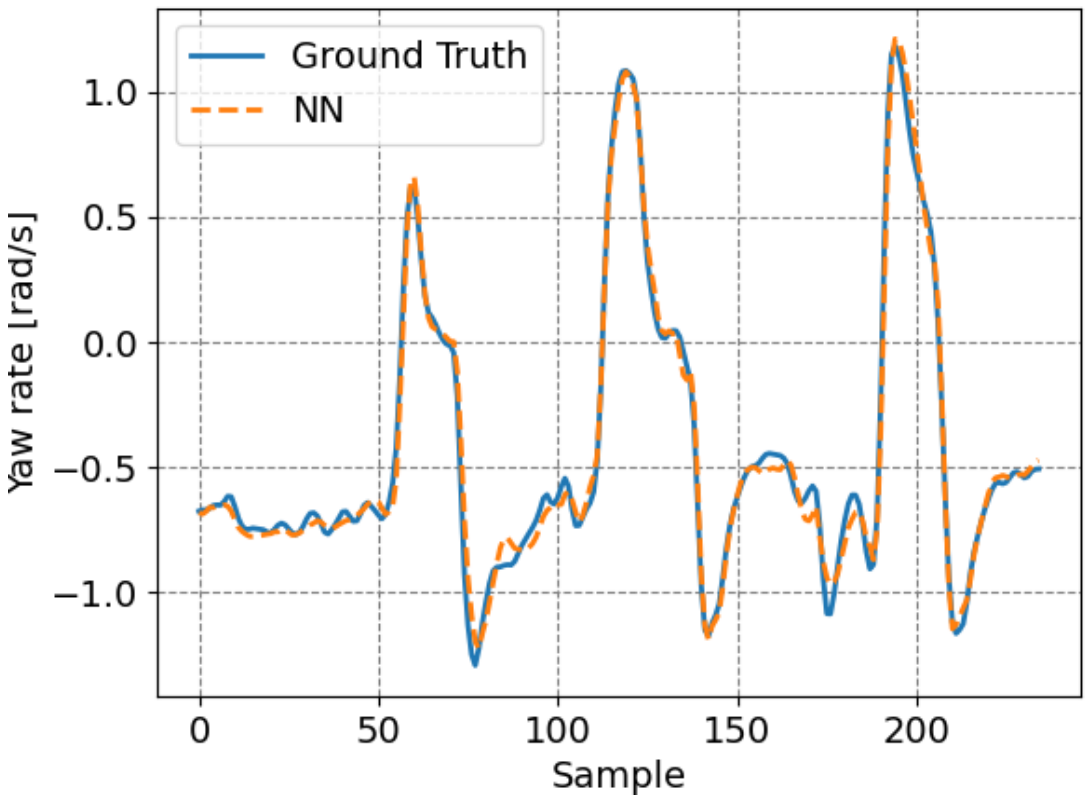
Combined Longitudinal Dynamics of an F1TENTH Car





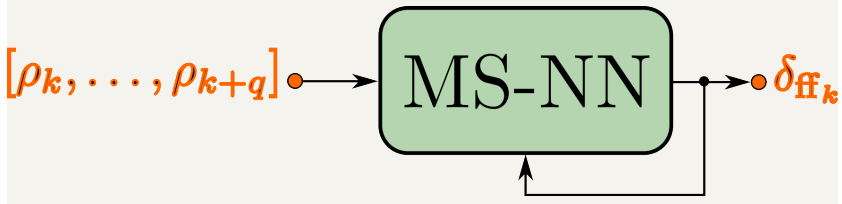
Combined Lateral Dynamics of an F1TENTH Car

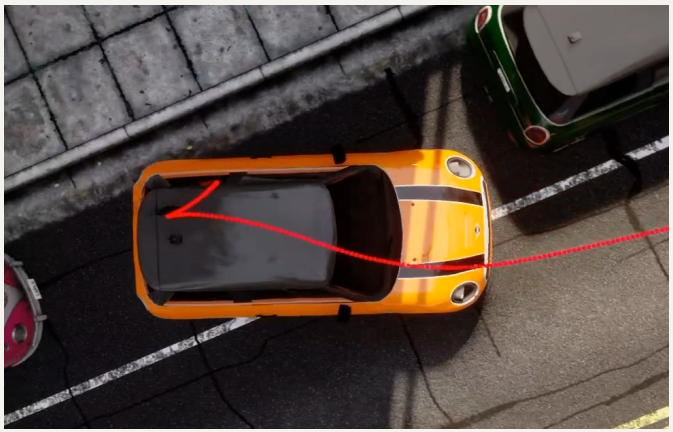




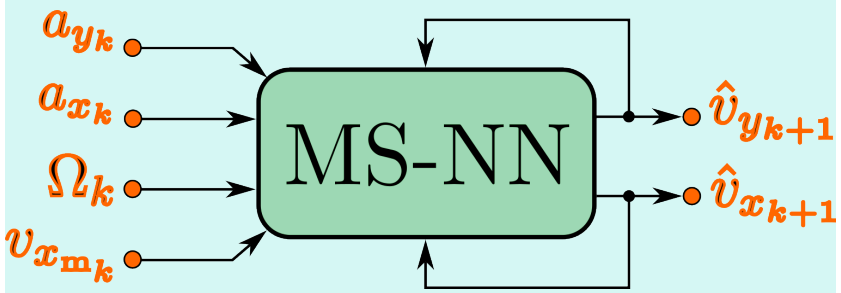
Other Application Examples for Vehicle Dynamics

Steer control for parking





Lateral speed estimation



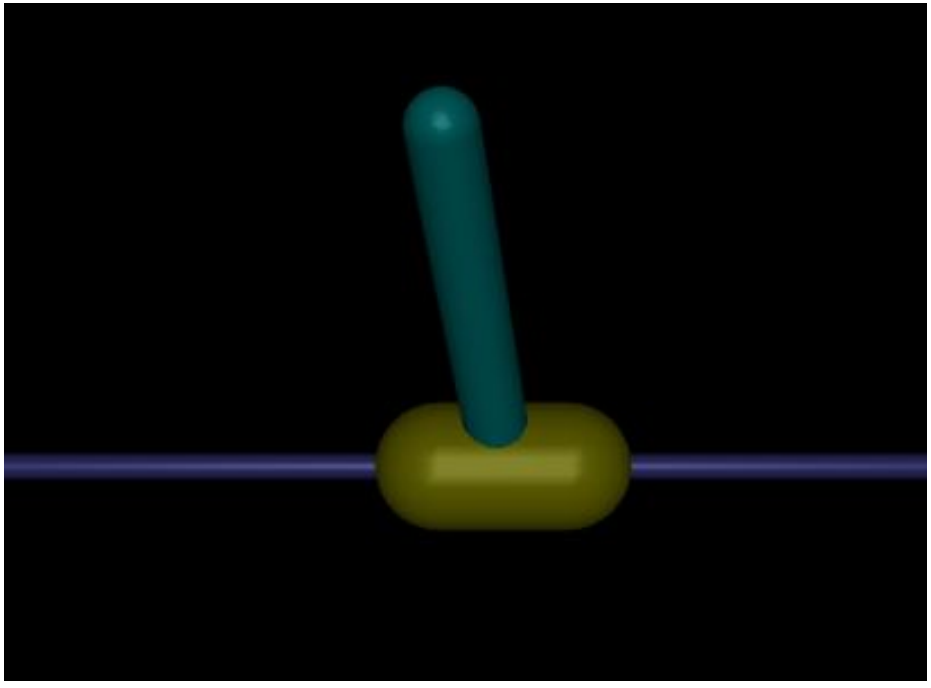
More details in:

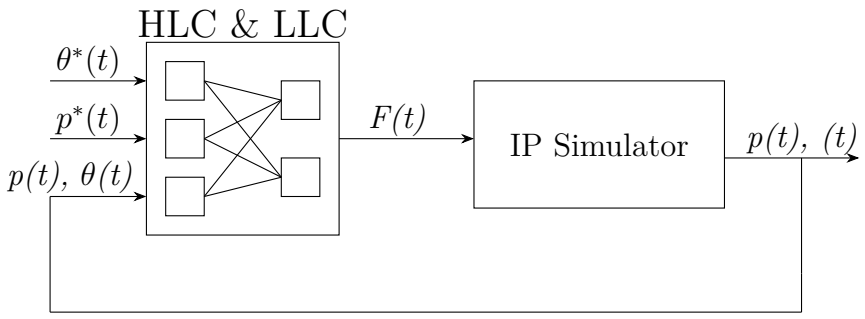
- M. Da Lio, M. Piccinini and F. Biral, "Robust and Sample-Efficient Estimation of Vehicle Lateral Velocity Using Neural Networks With Explainable Structure Informed by Kinematic Principles," in IEEE Transactions on Intelligent Transportation Systems, 2023.
- E. Pagot, M. Piccinini, E. Bertolazzi and F. Biral, "Fast Planning and Tracking of Complex Autonomous Parking Maneuvers With Optimal Control and Pseudo-Neural Networks," in IEEE Access, 2023.

Use Cases

Other Examples of MS-NNs in Different Domains

Control of an Inverted Pendulum

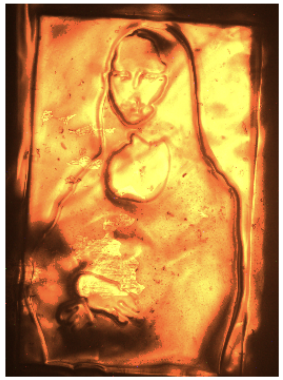


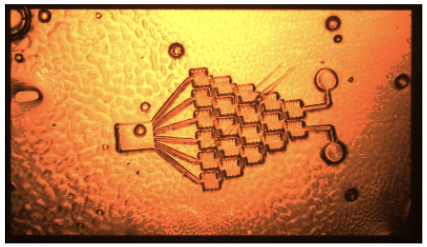


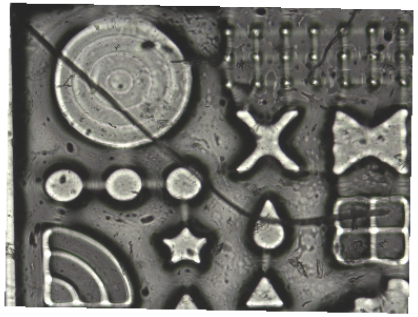
Show video

Controlling a 3D Printing Process

MS-NN to learn a 3D printing process parameters







$$\phi(t) = 1 - \exp^{-t^3 k}$$

Models nucleation and growth in crosslinking during polymerization.

$$d_c = D_p \log\left(\frac{E}{E_C}\right)$$

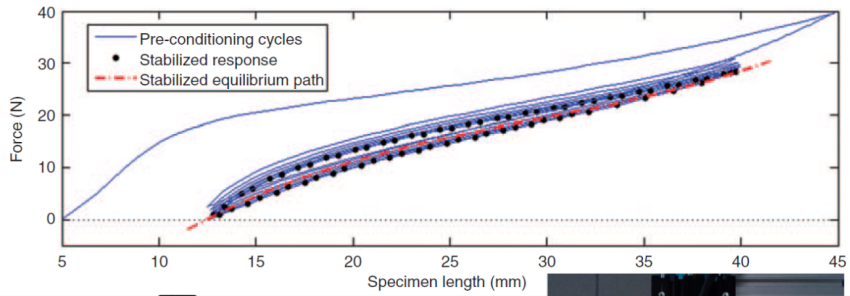
Describes how deep the resin will cure, depending on $\frac{E}{E_C}$.

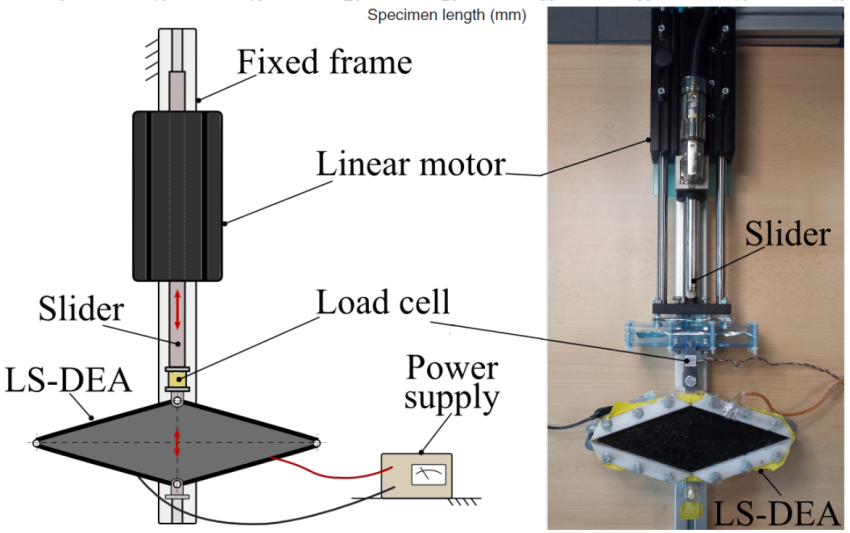
- Degree of polymerization $\phi(t)$ (unitless)
- Reaction rate constant k (s^{-n})
- Cure depth d_c (μm)
- Penetration depth D_p (μm)
- Delivered energy dose E (mJ/cm^2)
- Critical energy E_C (mJ/cm^2)

Model the Dynamics of Electroactive Polymers

MS-NN for physical modeling of a viscoelastic material

$$f_{\text{tot}} = f_{\text{e}}(\lambda) + f_{\text{d}}\left([\lambda_t, \ldots, \lambda], [\dot{\lambda}_t, \ldots, \dot{\lambda}]\right) + f_{\text{v}}(V, \lambda)$$



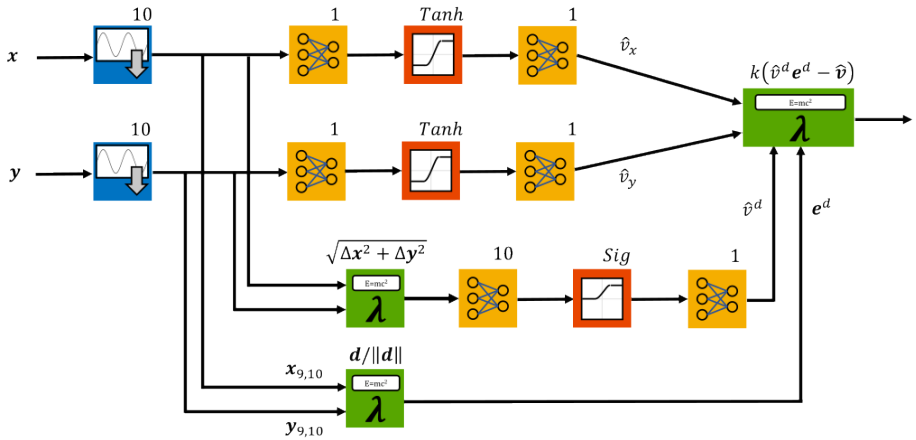


- total force realized: f_{tot}
- stretch: λ
- voltage: V
- elastic force: f_{e}
- viscoelastic and hysteretic force: f_{d}
- electric force: f_{v}

Learning a Pedestrian's Dynamics

MS-NN based on social force model[11]

$$\mathbf{f}(t) = m\frac{v^d(t)\mathbf{e}^d(t) - \mathbf{v}(t)}{\tau} + \sum_w \mathbf{f}_w^W(t)$$

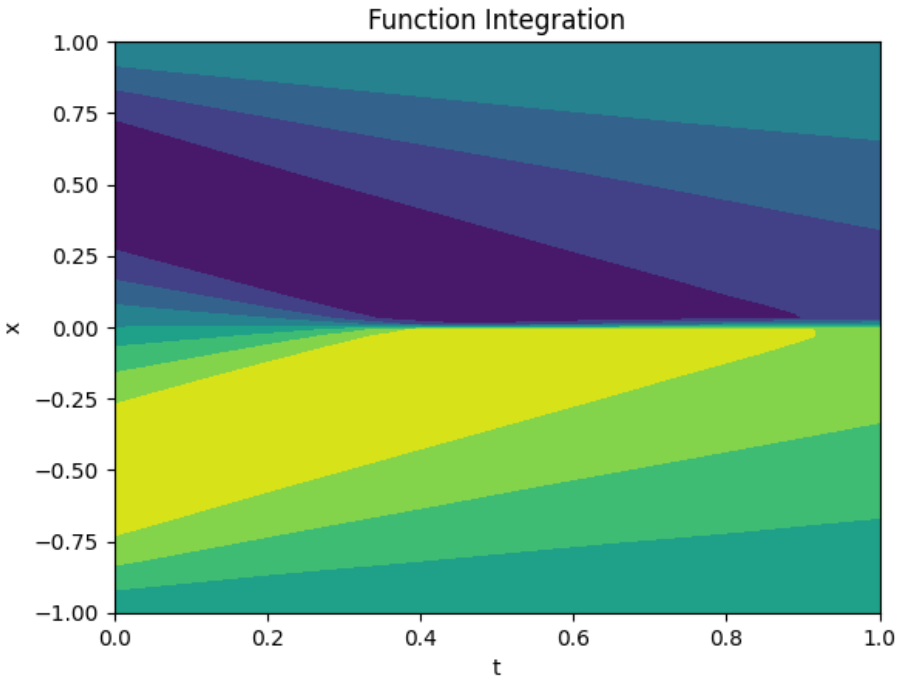


- forces on pedestrian: $\mathbf{f}$
- pedestrian mass: m
- pedestrian speed: $\mathbf{v}$
- desired velocity: v^d
- waypoint direction: $\mathbf{e}^d$
- velocity change rate: τ
- obstacle forces: $\mathbf{f}_w^W$

[11] Alessandro Antonucci et al. "Efficient Prediction of Human Motion for Real-Time Robotics Applications With Physics-Inspired Neural Networks". In: *IEEE Access* (2022).

Support to Physics-Informed Neural Networks (PINNs)

Integrate the Burger's equation[12] in the range $x \in [-1, 1]$, $t \in [0, 1]$.



$$u = NN(t, x),$$

$$\frac{u}{dt} + u\frac{u}{dx} - \left(\frac{0.01}{\pi}\right)\frac{u}{dx^2} = 0,$$

$$u(0, x) = -\sin(\pi x),$$

$$u(t, -1) = u(t, 1) = 0.$$

[12] M. Raissi, P. Perdikaris, and G.E. Karniadakis. "Physics-informed neural networks: A deep learning framework for solving forward and inverse problems involving nonlinear partial differential equations". In: *Journal of Computational Physics* (2019).

Advantages of MS-NNs

MS-NNs vs Analytical Models

- Improved **learning potential** through custom neural blocks

Advantages of MS-NNs

MS-NNs vs Analytical Models

- Improved **learning potential** through custom neural blocks

MS-NNs vs Multi-Layer Perceptrons

- Better **generalization** to unseen data with small training sets
- Enhanced **interpretability**
- Less sensitive to the weights' initialization

NNodely-applications on GitHub

Our applications are available at

https://github.com/tonegas/nnodely-applications

Some of our Papers about MS-NNs

1. M. Piccinini et al., "A Physics-Driven Artificial Agent for Online Time-Optimal Vehicle Motion Planning and Control," in IEEE Access, vol. 11, pp. 46344-46372, 2023, doi: 10.1109/ACCESS.2023.3274836.
2. M. Da Lio, M. Piccinini and F. Biral, "Robust and Sample-Efficient Estimation of Vehicle Lateral Velocity Using Neural Networks With Explainable Structure Informed by Kinematic Principles," in IEEE Transactions on Intelligent Transportation Systems, vol. 24, no. 12, pp. 13670-13684, 2023, doi: 10.1109/TITS.2023.3303776.
3. E. Pagot, M. Piccinini, E. Bertolazzi and F. Biral, "Fast Planning and Tracking of Complex Autonomous Parking Maneuvers With Optimal Control and Pseudo-Neural Networks," in IEEE Access, vol. 11, pp. 124163-124180, 2023, doi: 10.1109/ACCESS.2023.3330431.
4. M. Piccinini, M. Zumerle, J. Betz and G. Pietro Rosati Papini, "A Road Friction-Aware Anti-Lock Braking System Based on Model-Structured Neural Networks," in IEEE Open Journal of Intelligent Transportation Systems, vol. 6, pp. 522-536, 2025, doi: 10.1109/OJITS.2025.3563347.
5. M. Da Lio, R. Donà, G. P. R. Papini, F. Biral and H. Svensson, "A Mental Simulation Approach for Learning Neural-Network Predictive Control (in Self-Driving Cars)," in IEEE Access, vol. 8, pp. 192041-192064, 2020, doi: 10.1109/ACCESS.2020.3032780.
6. M. Da Lio, D. Bortoluzzi and G. P. R. Papini, "Modelling longitudinal vehicle dynamics with neural networks", in Vehicle System Dynamics, vol. 58, no. 11, pp. 1675-1693, 2020, doi:1080/00423114.2019.1638947.
7. M. Piccinini, A. Mungiello, G. Jank, G. P. R. Papini, F. Biral, J. Betz, "Model-Structured Neural Networks to Control the Steering Dynamics of Autonomous Race Cars," in IEEE International Conference on Intelligent Transportation Systems (ITSC), 2025, accepted.
8. A. Antonucci, G. P. R. Papini, P. Bevilacqua, L. Palopoli and D. Fontanelli, "Efficient Prediction of Human Motion for Real-Time Robotics Applications With Physics-Inspired Neural Networks," in IEEE Access, vol. 10, pp. 144-157, 2022, doi: 10.1109/ACCESS.2021.3138614.
9. A. Mungiello, F. Jahncke, G. P. R. Papini, S. Santini, J. Betz, M. Piccinini, "Model-Structured Neural Networks to Learn the Dynamics of Robotic Vehicles," in Vehicle System Dynamics, 2025, under review.

Conclusions

Summary

- **Model-Structured NNs**: a new class of NNs embedding prior physics- or domain knowledge in their architecture
- **NNodely**: an open framework for *physics-guided learning* with physical systems
  - support for MS-NNs, PINNs, differentiable end-to-end training, and more
  - designed to speed-up rapid prototyping
- **Applications** in different physical systems

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Aim Model, control and estimation of physical systems with MS-NNs

Outcome the modely framework, a **website** collecting MS-NN applications

Use Cases Robotic Vehicles, Drones, Quadrupeds, ...

More details at https://tonegas.it/

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