Motor, Affective and Cognitive Scaffolding for iCub (MACSi)

Project supported by the RobotCub Open Call

Presented at the iCub Workshop

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Origins of the MACSi project

From the industrial to the service Robotics context . . .

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- Learning multiple tasks, multiple contexts $\rightarrow \infty$ **of representations**
- Designing all such representations by hand $\rightarrow$ impossible

Need for learning mechanisms able to build increasingly complex problem-specific representations as well as their solution from initially unstructured sensori-motor experiences.

Main goals of the MACSi Project

Central target of MACSi

Build mechanisms allowing a robot:

- to efficiently develop new basic sensorimotor skills
- in partially unknown environments

through both:

- autonomous exploration
- social interaction with humans.

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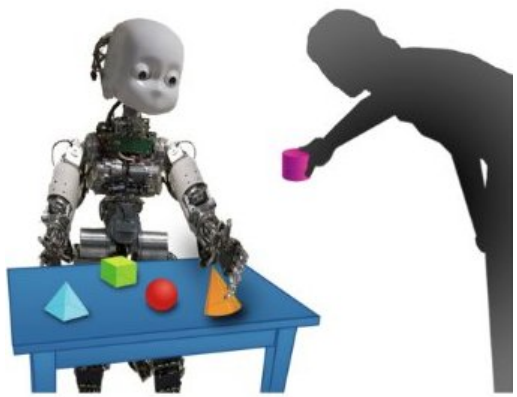
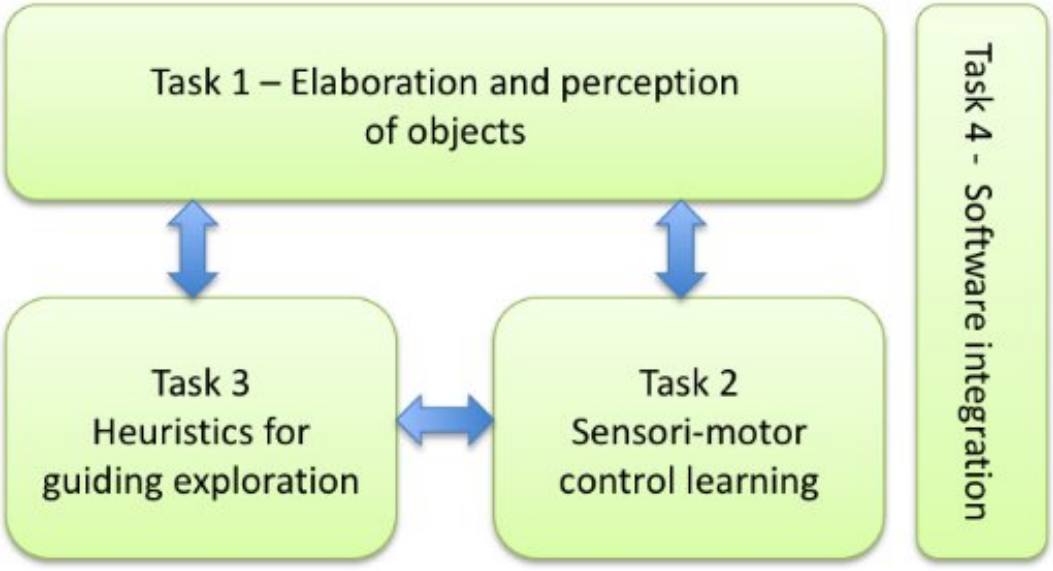
Goal experiment

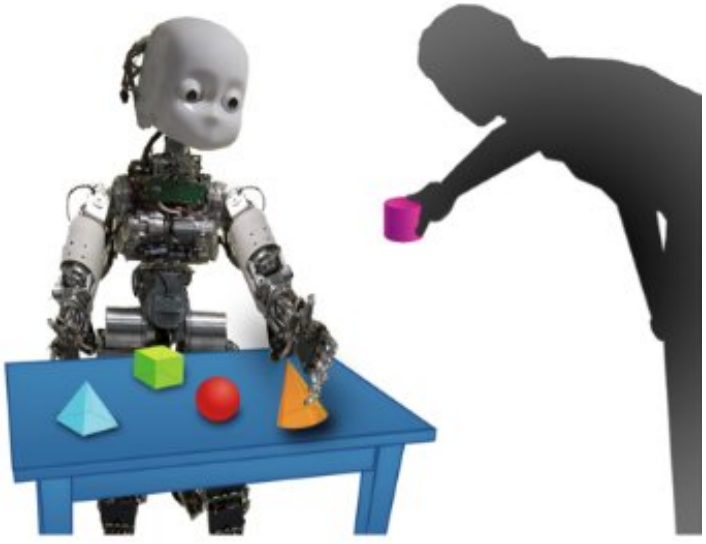
An experiment in which iCub will:

- progressively build perceptuo-motor abstractions and representations allowing iCub to differentiate its body from external objects;
- learn how to control its body to manipulate these surrounding objects;
- driven both by intrinsic motivation, i.e. artificial curiosity, and social guidance provided by a human partner.



Overview of the MACSi project





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INRIA Flowers

Cognitive Robotics ENSTA

GOSTAI Robotics for everyone

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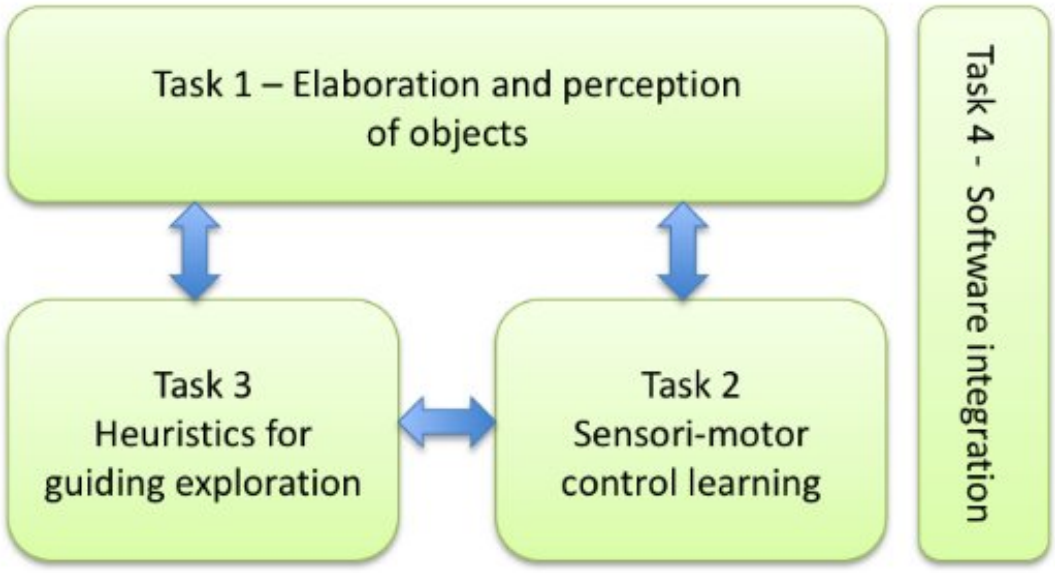

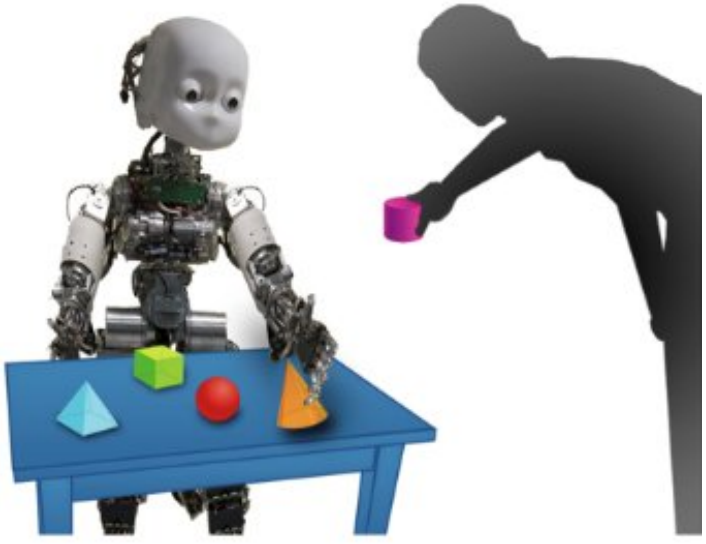

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→ In this presentation, focus is put on some of the work related to Task 2.

Models

Models

Which ones ?

- Of the robot itself;
- Of its environment.

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- Of its environment.

At which level ?

- Robot:
  - 3D geometry;
  - actuators dynamics;
  - joint space to task space direct and inverse mappings: kinematics, velocity kinematics, dynamics;
- Environment:
  - 3D geometry;
  - Interaction dynamics;
  - Behavioural.

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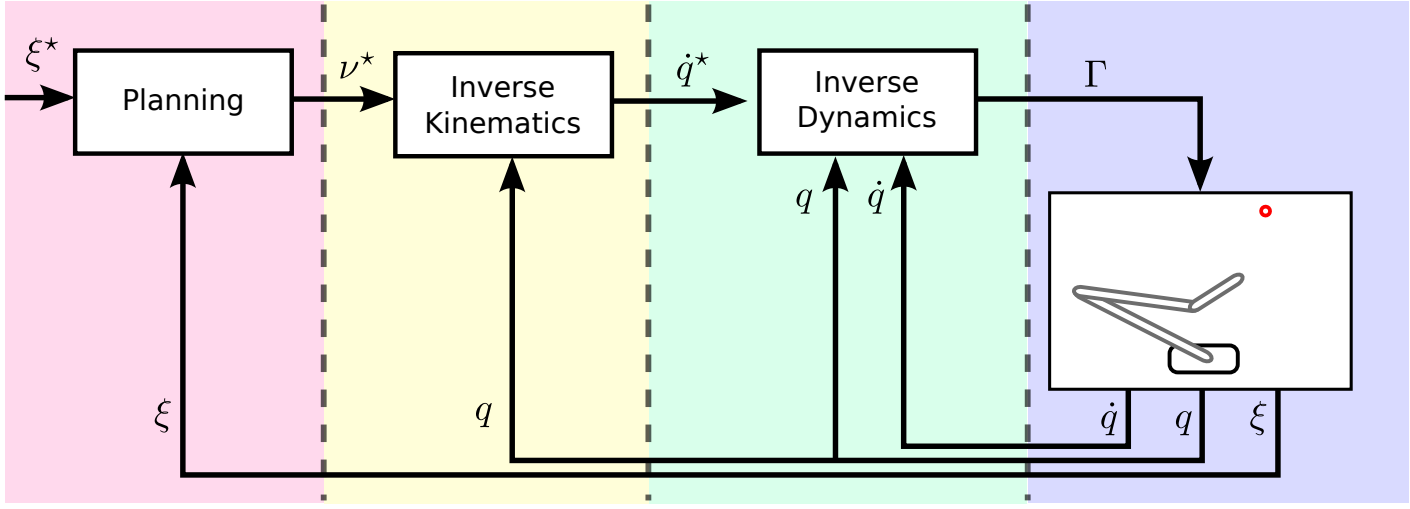
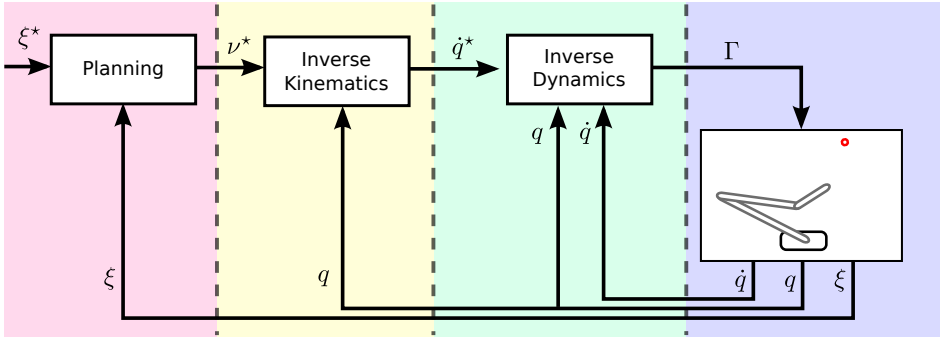
What for ?

- Tasks realization (control);
- Constraints satisfactions;
- Future states prediction.

Control: the velocity level task space loop closing example



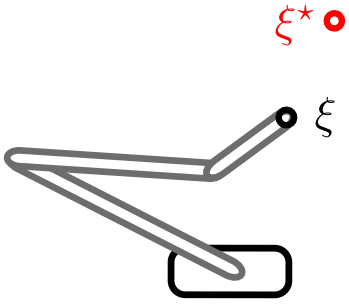
Planning: simplest implementation

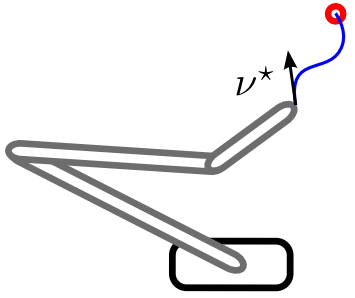


ξ: task space position

$\xi^\star$: desired task space position

$\nu^\star$: desired task space velocity





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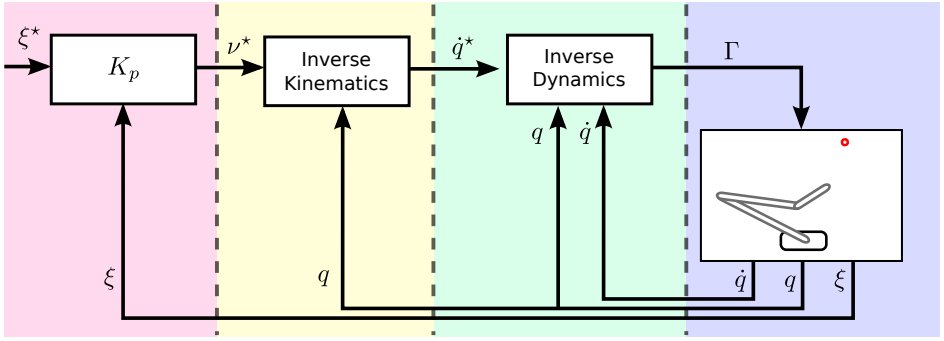

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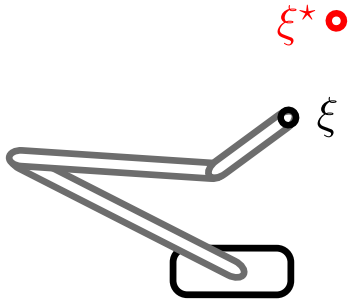
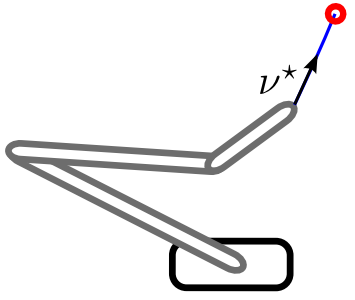
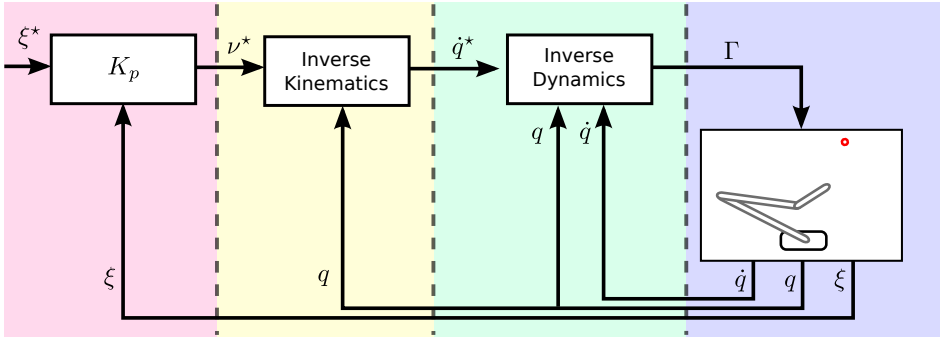




Goal attractor: $\nu^\star = K_p\,(\xi^\star - \xi)$

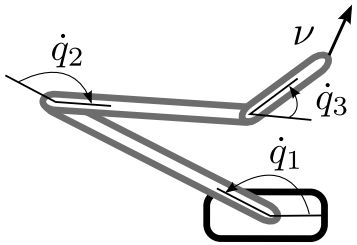
Inverse velocity kinematics



q: articular position

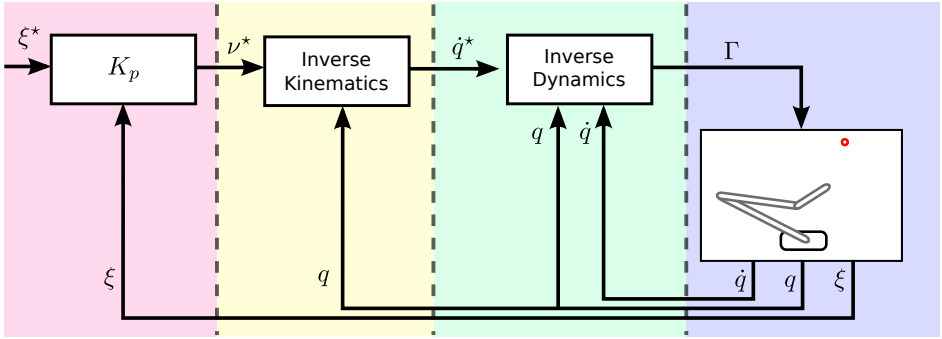
ν: task space velocity

$\dot{q}$: articular velocity



Velocity Kinematics: $\nu = J(q)\,\dot{q}$

Inverse velocity kinematics



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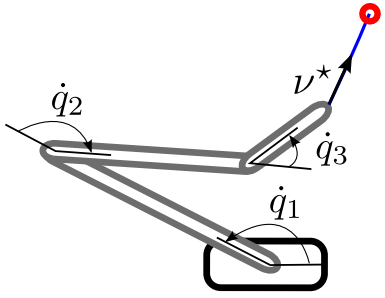
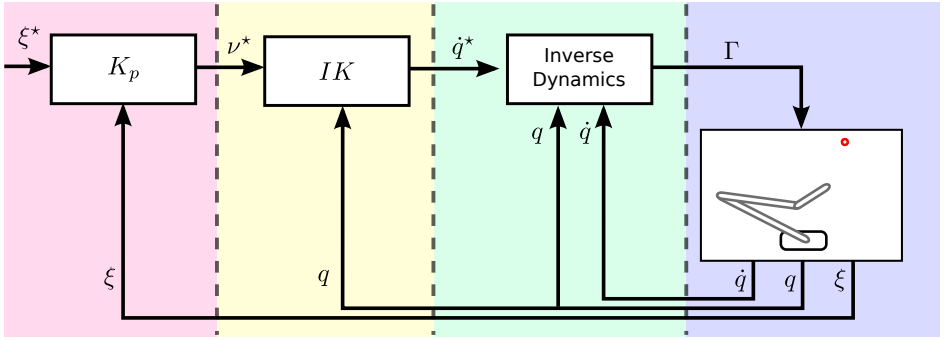


Inverse Velocity Kinematics: $\dot{q}^\star = J(q)^+ \nu^\star$

Inverse velocity kinematics



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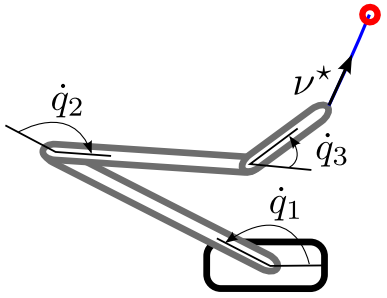
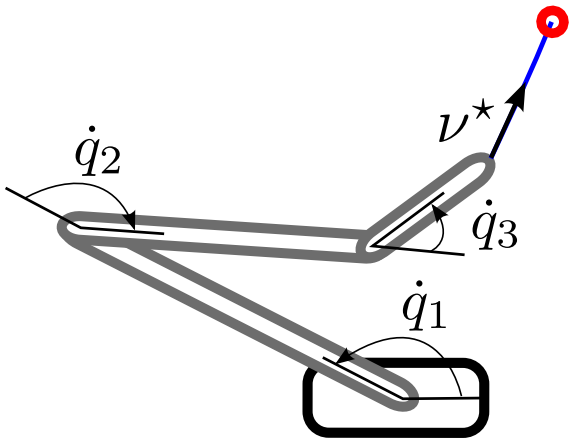
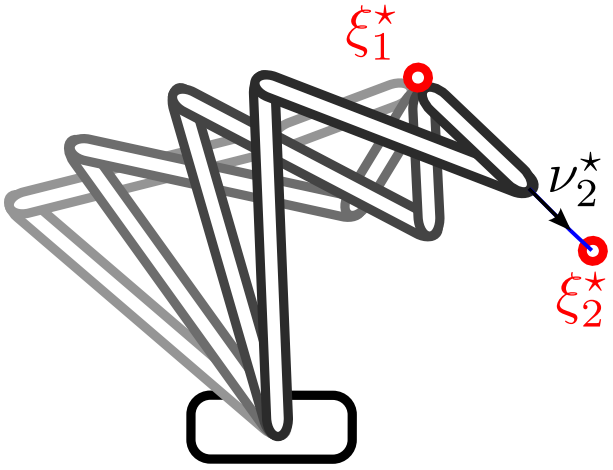


Inverse Velocity Kinematics: $\dot{q}^\star = IVK\,(q, \nu^\star)$

Control redundancy





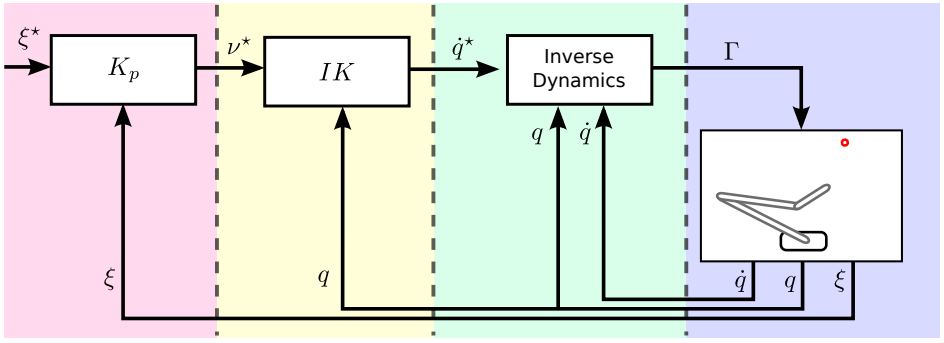
$$\dot{q}^\star = J(q)^+ \nu^\star$$

$$\dot{q}^\star = J_1(q)^+ \nu_1^\star + (J_2(q) P_{J_1})^+ \nu_2^\star$$

with $J^+ = J^t(JJ^t)^{-1}$ and $P_J = (I - J^+ J)$

- redundancy (short def.): "more actuated degrees of freedom than those necessary to realise a task"
- P_J is a projector onto the kernel of the Jacobian matrix J

Inverse Dynamics



Γ: torques

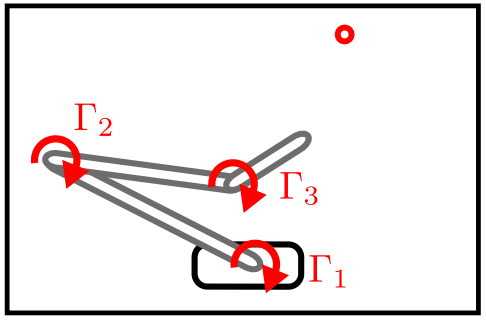
M: inertia matrix

b: Coriolis and centrifugal effects

g: gravity

ϵ: unmodeled effects

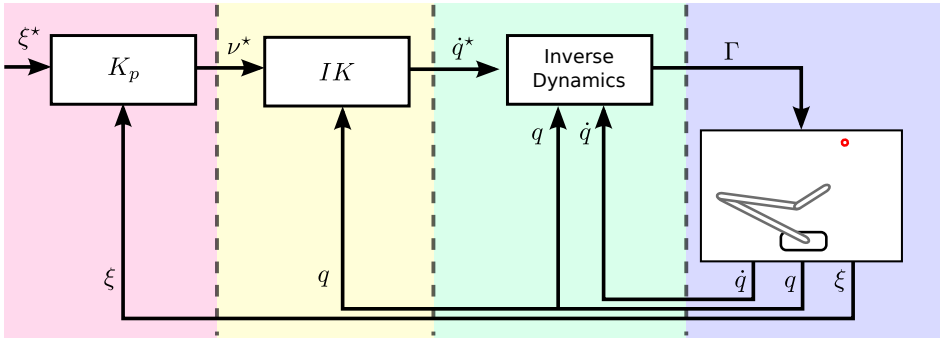
Γ^{ext}: external forces



Forward dynamics:

$$\ddot{q} = M^{-1}\left(\Gamma - b\left(q, \dot{q}\right) - g\left(q\right) - \epsilon\left(q, \dot{q}\right) + \Gamma^{ext}\right)$$

Inverse Dynamics



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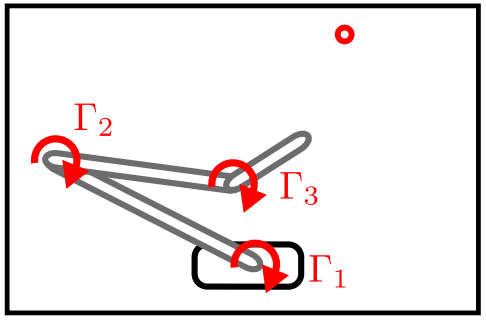
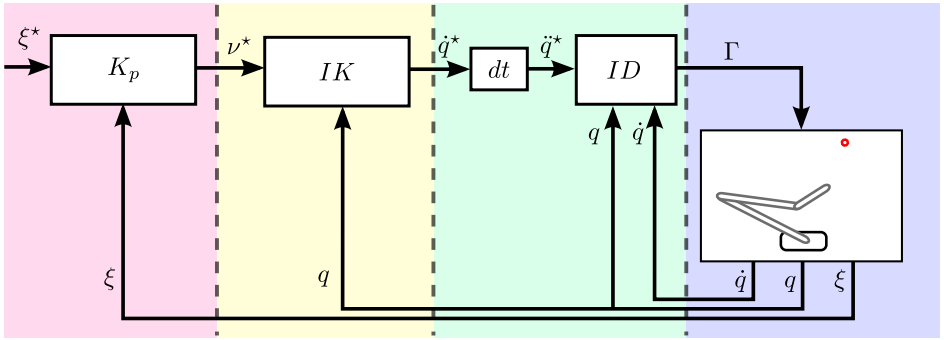


Inverse dynamics:

$$\Gamma = M(q)\,\ddot{q}^\star + b(q,\dot{q}) + g(q) + \epsilon(q,\dot{q}) - \Gamma^{ext}$$

Inverse Dynamics



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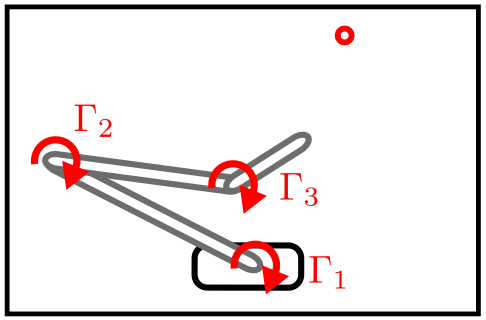
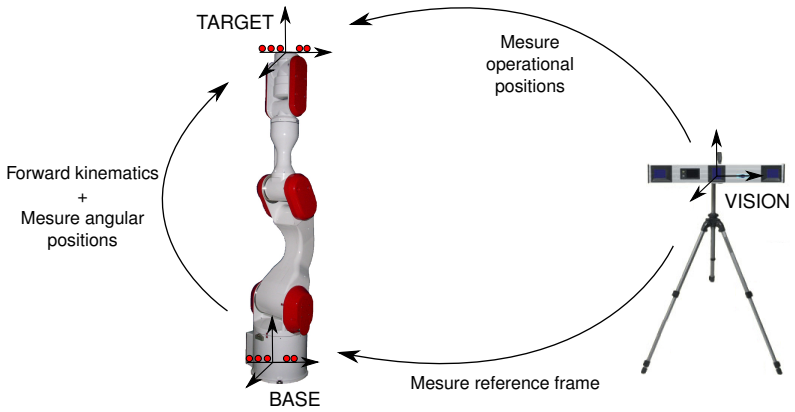


Inverse dynamics:

$$\Gamma = M(q)\,\ddot{q}^\star + b(q,\dot{q}) + g(q) + \epsilon(q,\dot{q}) - \Gamma^{ext}$$
$$\Gamma = ID(q,\dot{q},\ddot{q}^\star)$$

Identification

→ The control scheme presented here is an example of state-of-the-art result but requires a knowledge of the involved models.



Classical parametric identification:

+ least-squares minimization problem;
+ tuning of a parametered model;
+ suitable and robust for rigid-body systems;
- impossible to learn a non-modelized part;
- not suitable if the model structure evolves.

Why learning models for Robotics (from a roboticist point of view) ?

- Parametric identification approaches have limitations;
- Some phenomenon are hard to model and identify: friction, local mechanical compliance, etc.;
- Robots may, in the coming years, switch from rigid-body systems to structurally compliant systems;
- The models of the robot itself may be known but this is not true for its environment.

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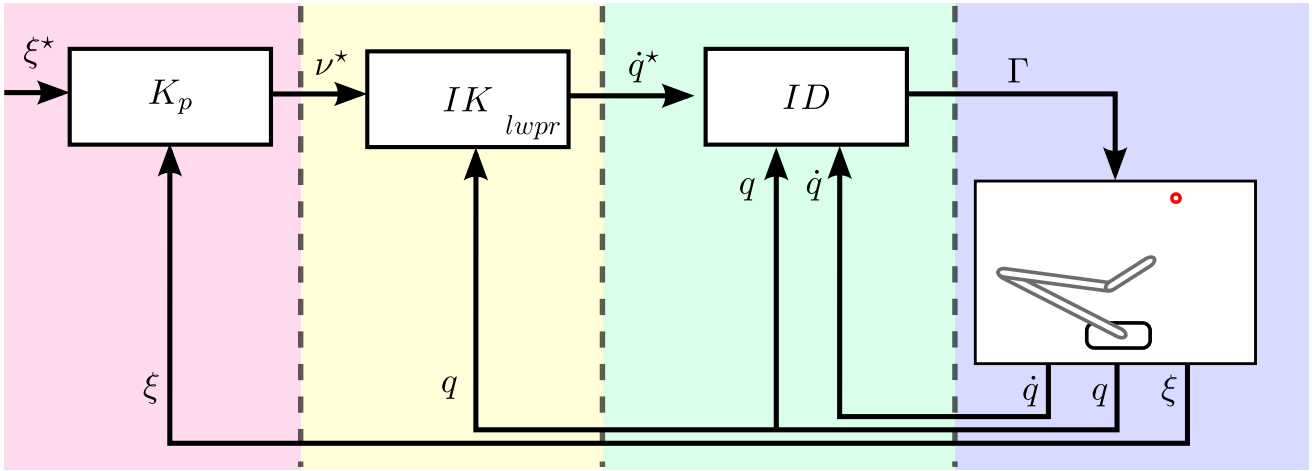
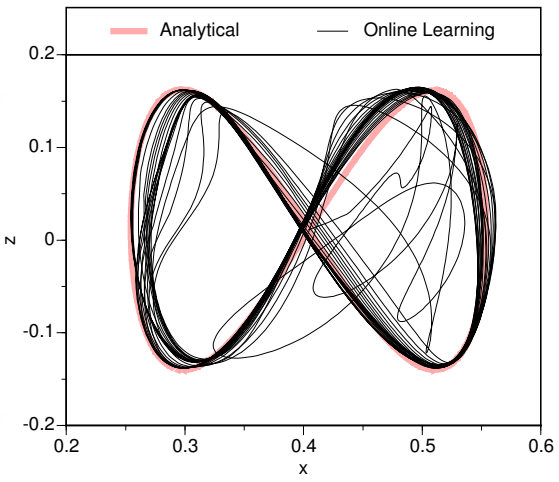
Does it work ?

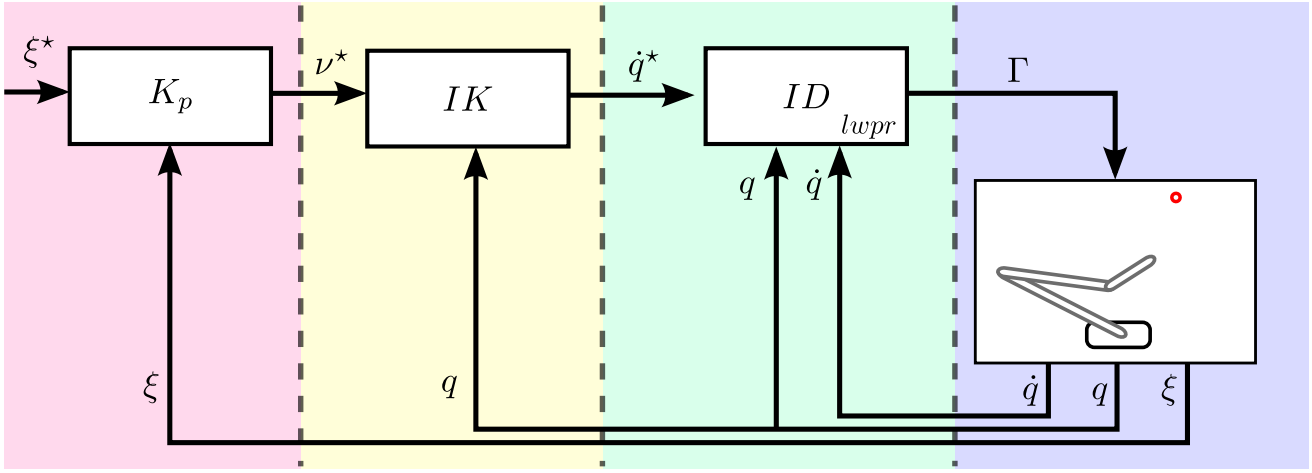
Learning inverse velocity kinematics



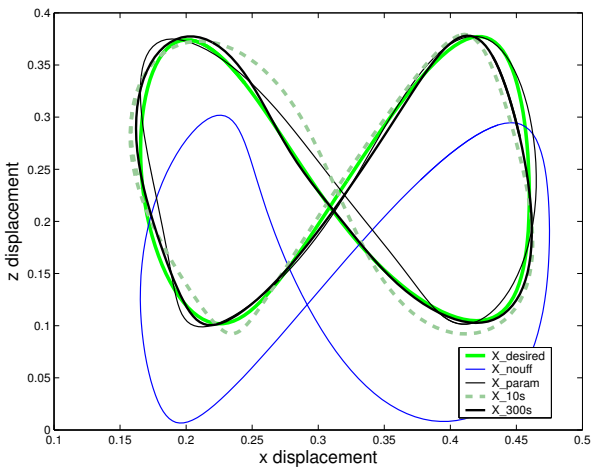
- D'Souza et al. (1) learn the inverse velocity kinematics model
- The model is learned along an task space trajectory
- Input dimension: $dim(xi + q) = 29$
- Output dimension: $dim(\dot{q}) = 26$



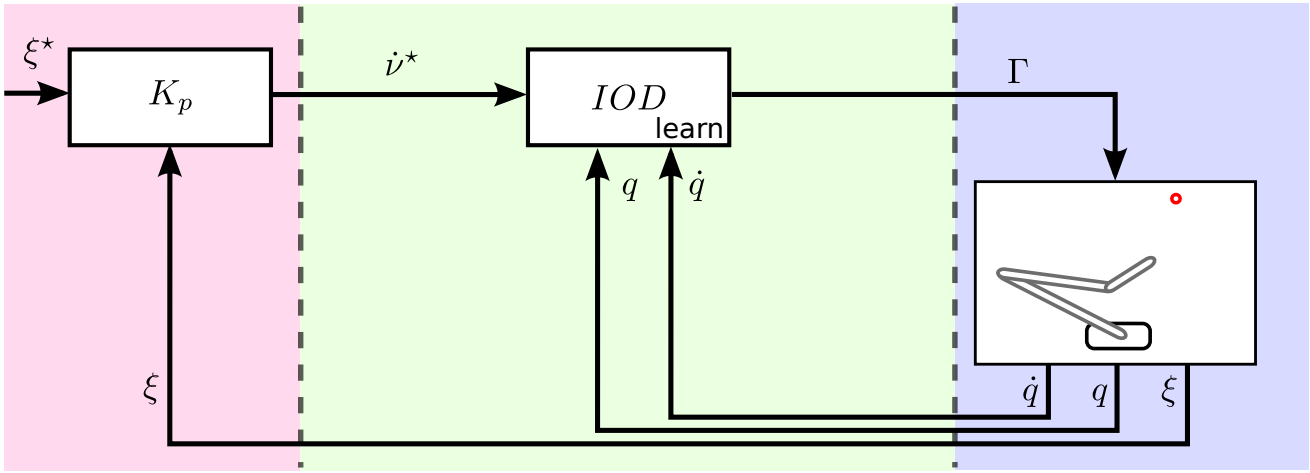
Learning inverse dynamics



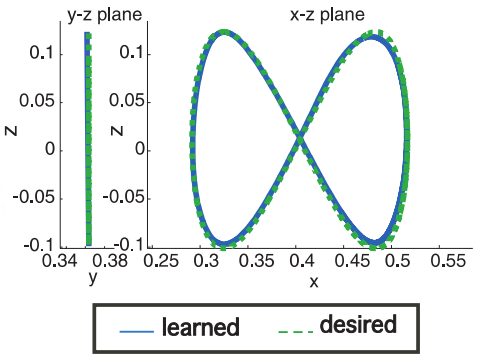
- Schaal et al. (2) learn the inverse dynamics model
- The model is learned along an task space trajectory
- Input dimension: $dim(q + \dot{q} + \ddot{q}) = 90$
- Output dimension: $dim(\Gamma) = 30$



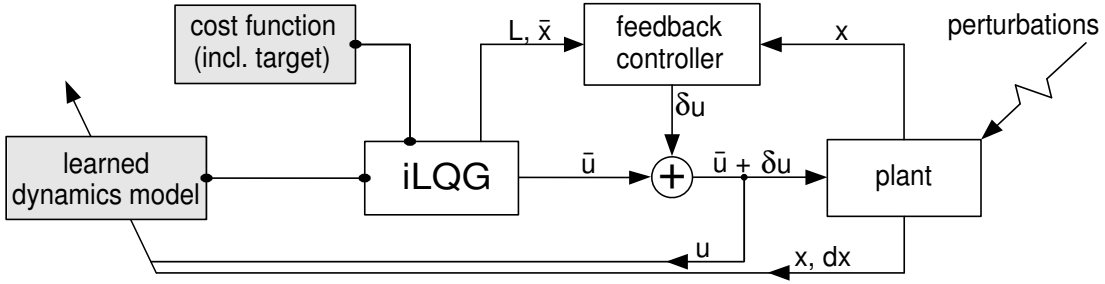
Learning inverse task space dynamics



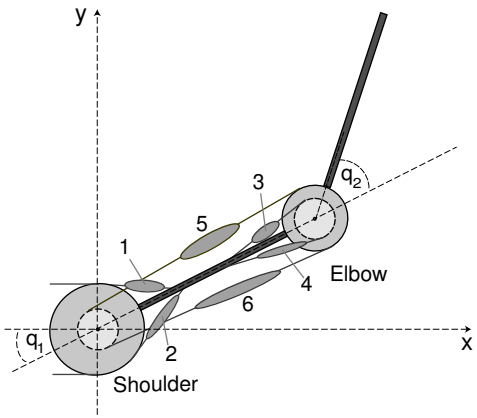
- Peters and Schaal (3) learn inverse dynamics in the task space space.
- The model is learned along an task space trajectory.
- Input dimension: 7+7+3=17. Output dimension: 7.



Optimal control with dynamics learned with LWPR



- Mitrovic et al. (4) learn inverse dynamics.
- The model is learned in the whole space.
- Input dimension:$dim(q + \dot{q} + u) = 10$.
  Output dimension: $dim(\ddot{q}) = 2$.
- $1,2.10^6$ training data points and 852 receptive fields



How does it work ?

Linear functions approximation:

Least Squares, Recursive Least Squares and Partial Least Squares

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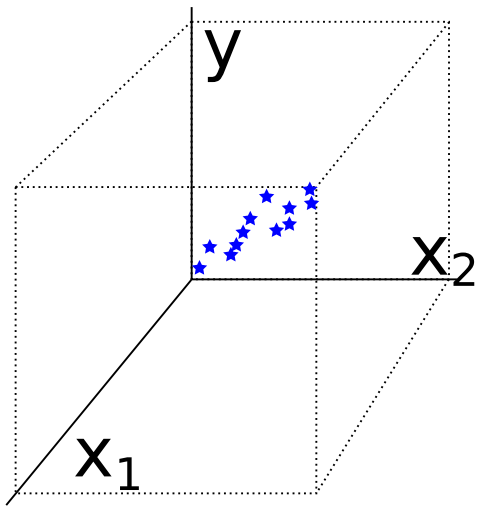
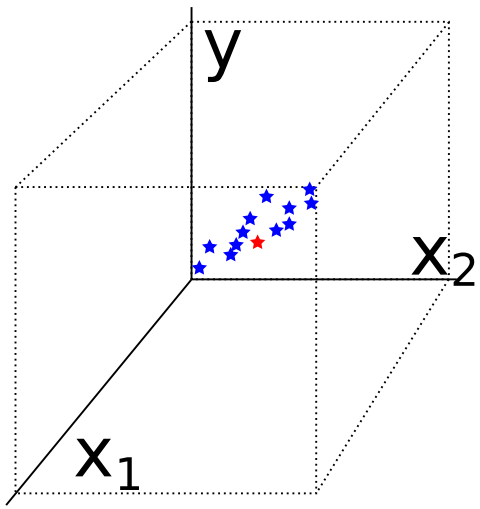


Least Squares

- Least Squares: Not incremental, need to save data and run a batch identification

Linear functions approximation:

Least Squares, Recursive Least Squares and Partial Least Squares



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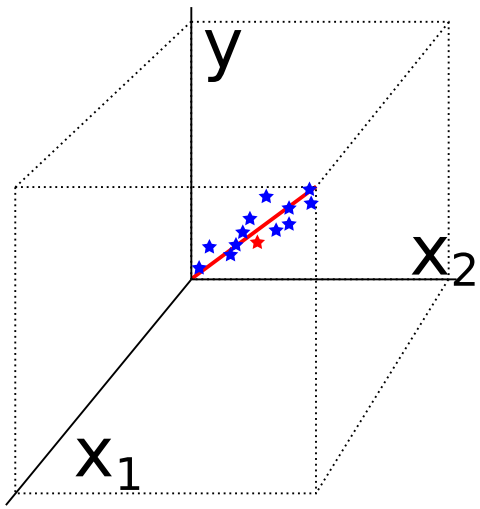

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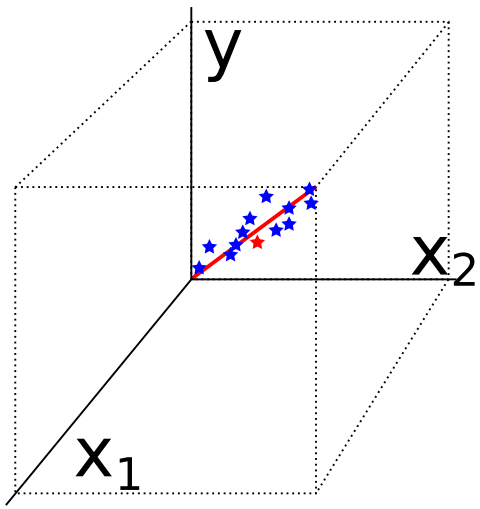

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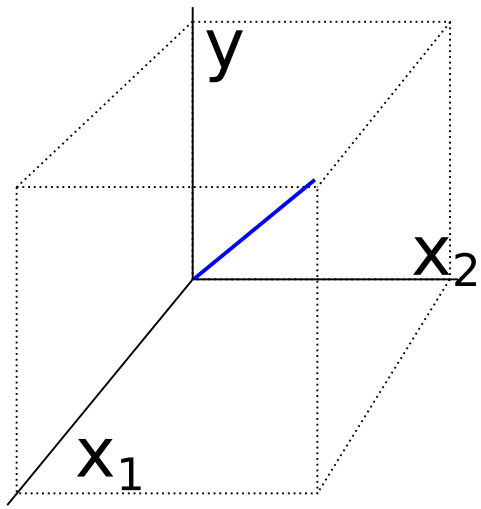

Recursive Least Squares

- Least Squares: Not incremental, need to save data and run a batch identification
- Recursive Least Squares: Incremental but diverges with linearly dependent inputs

How does it work ?

Linear functions approximation:

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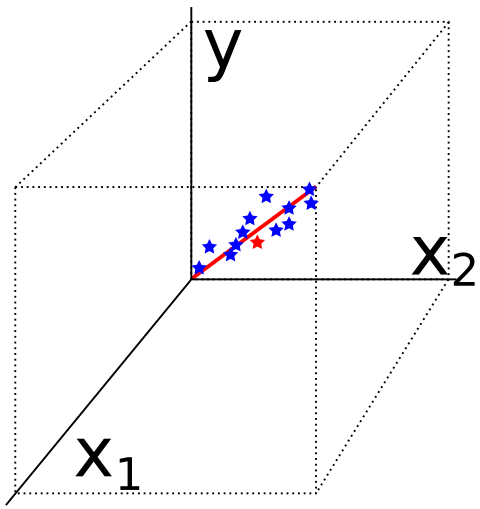
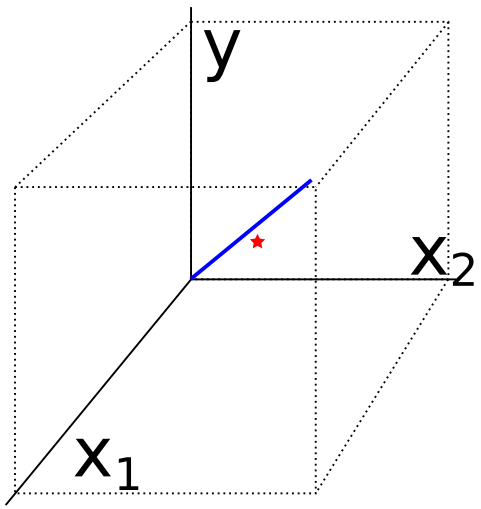


Least Squares



Recursive Least Squares

- Least Squares: Not incremental, need to save data and run a batch identification
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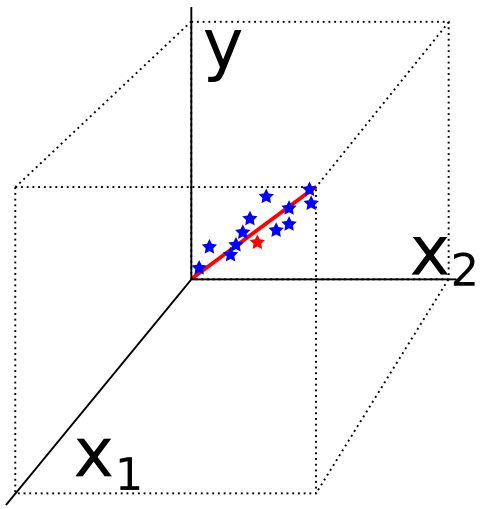
How does it work ?

Linear functions approximation:

Least Squares, Recursive Least Squares and Partial Least Squares



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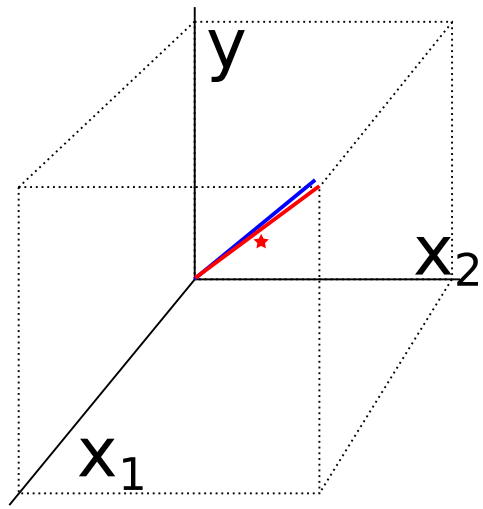

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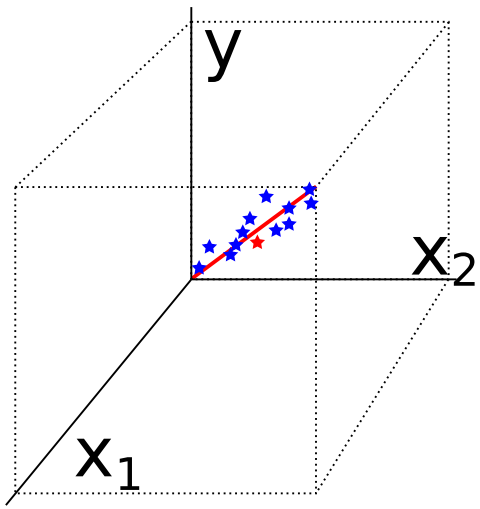

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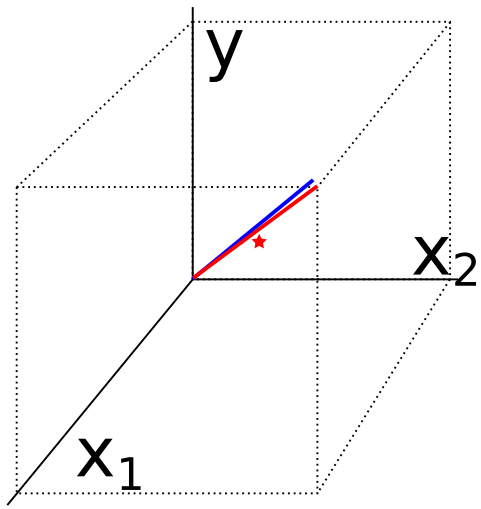

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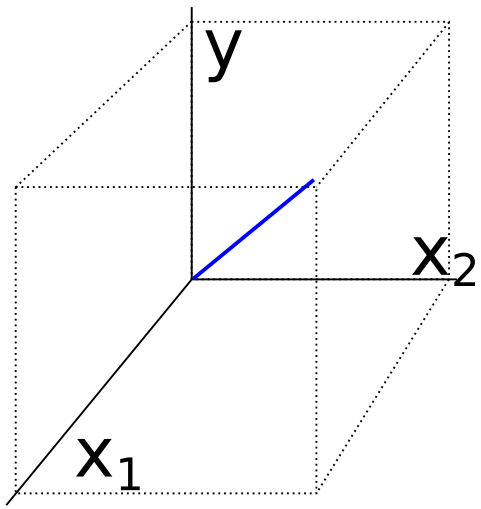

Partial Least Squares

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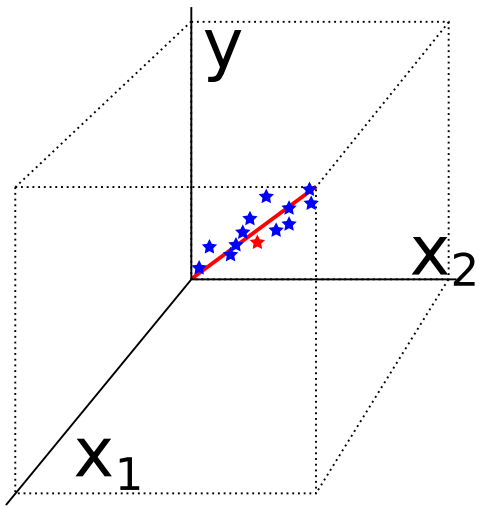
- Partial Least Squares: Projections to focus on relevant inputs

Linear functions approximation:

Least Squares, Recursive Least Squares and Partial Least Squares



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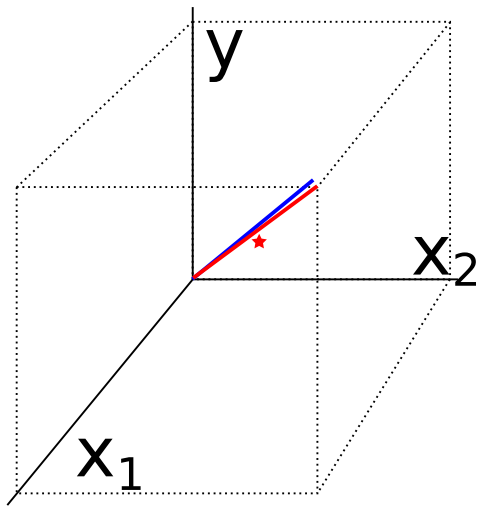

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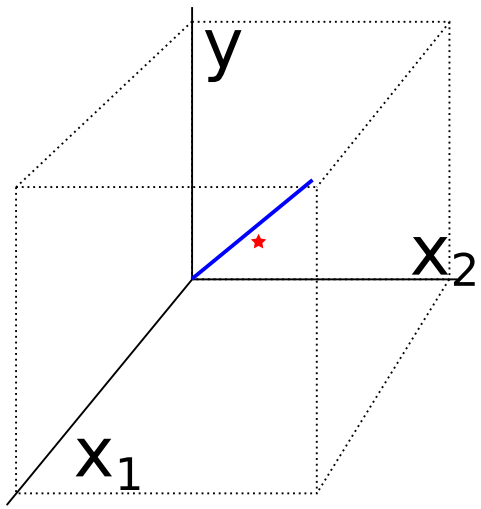

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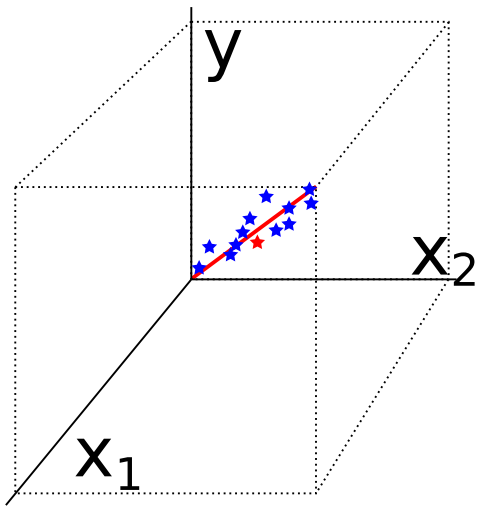

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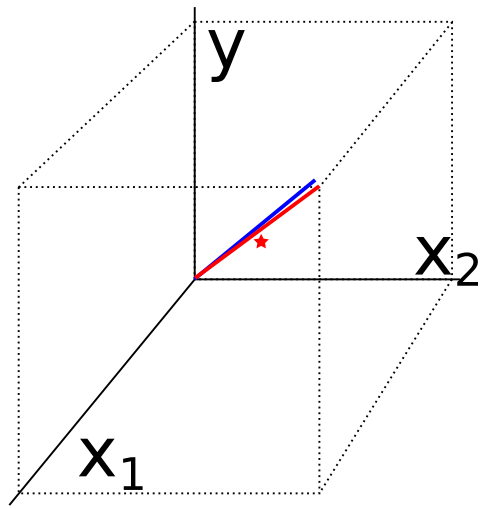

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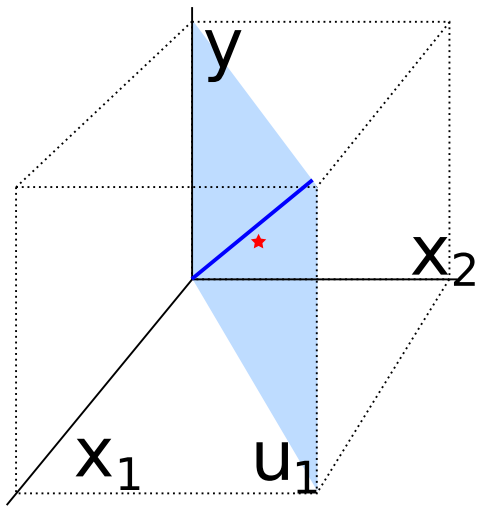

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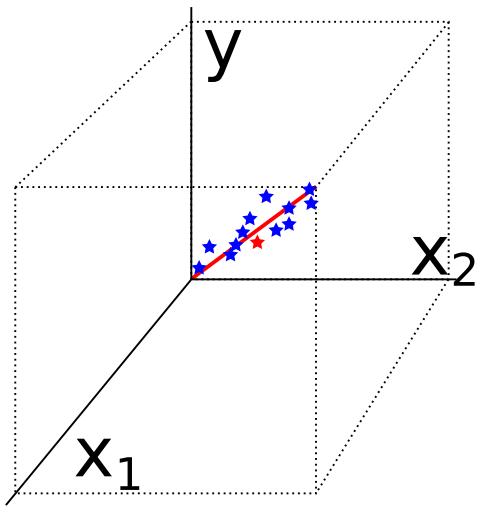

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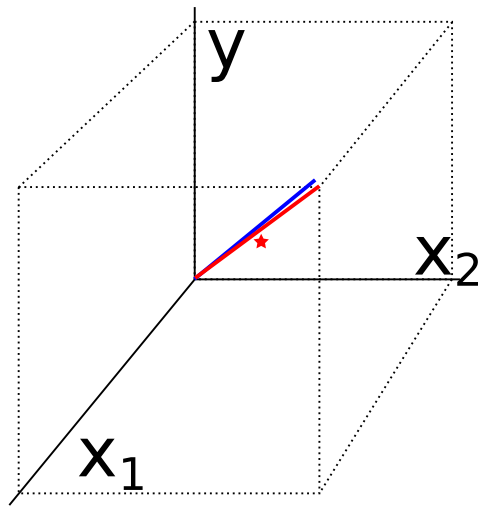

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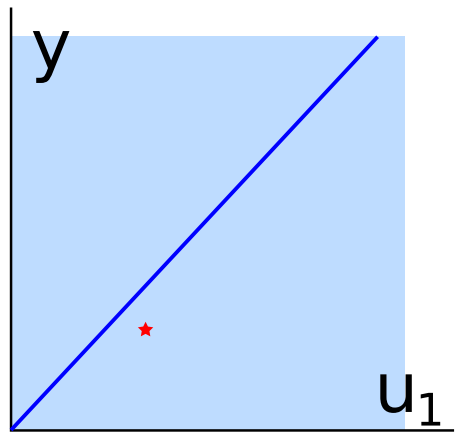

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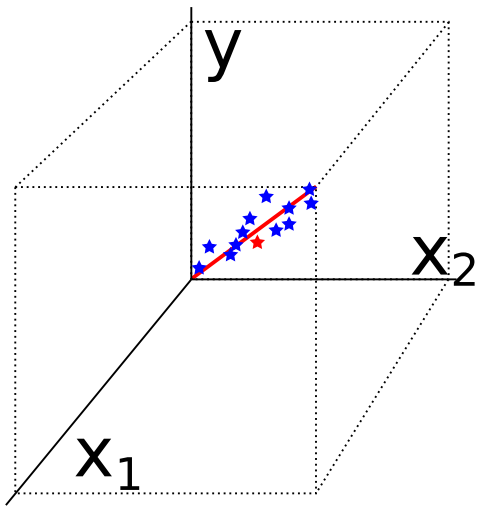

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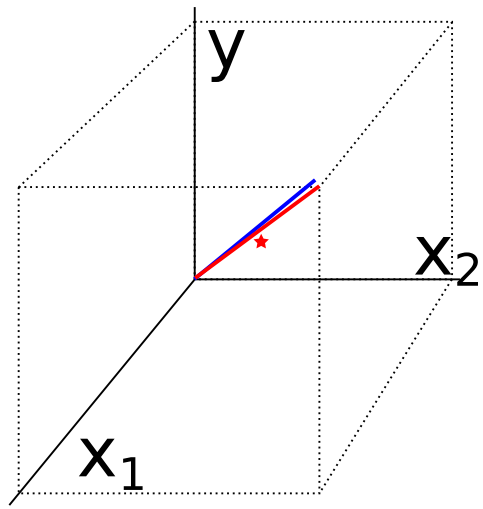

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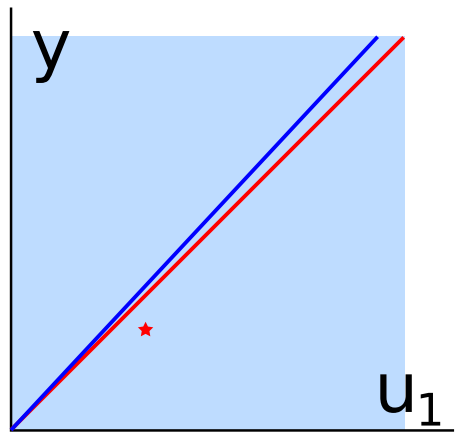

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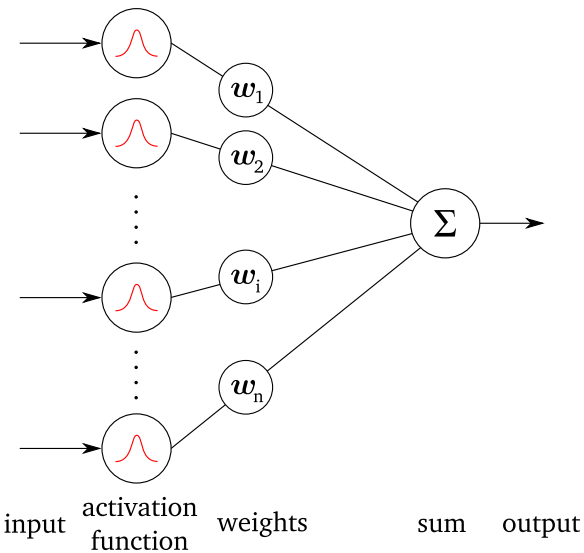
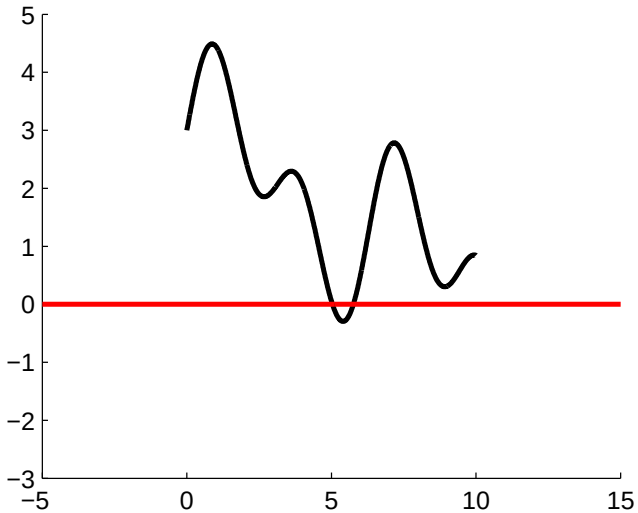
Nonlinear functions approximations using nonlinear elementary functions:

Radial Basis Function Networks





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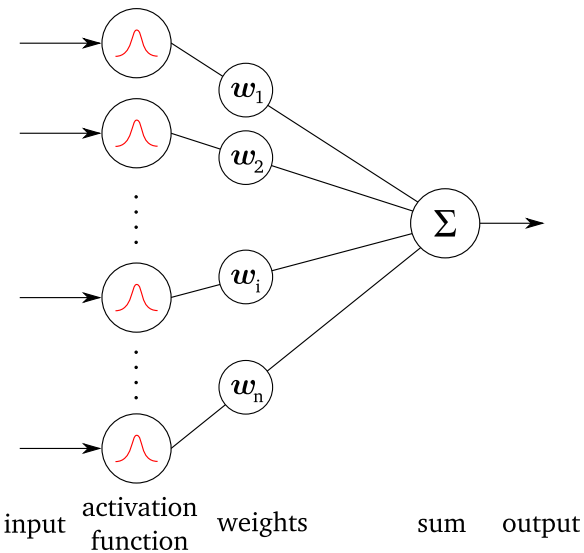
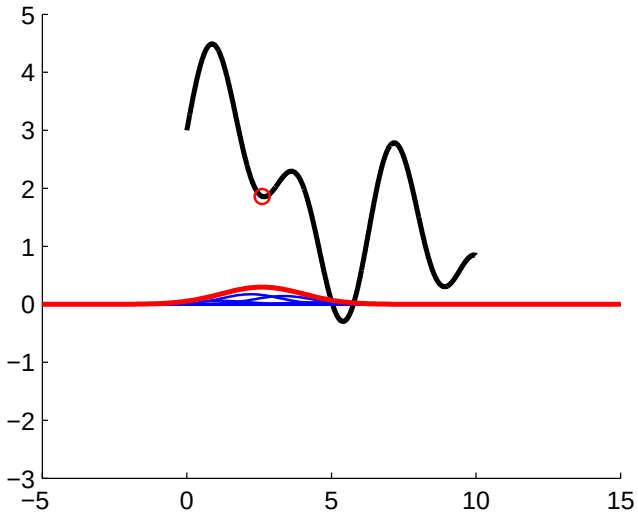
Nonlinear functions approximations using nonlinear elementary functions:

Radial Basis Function Networks





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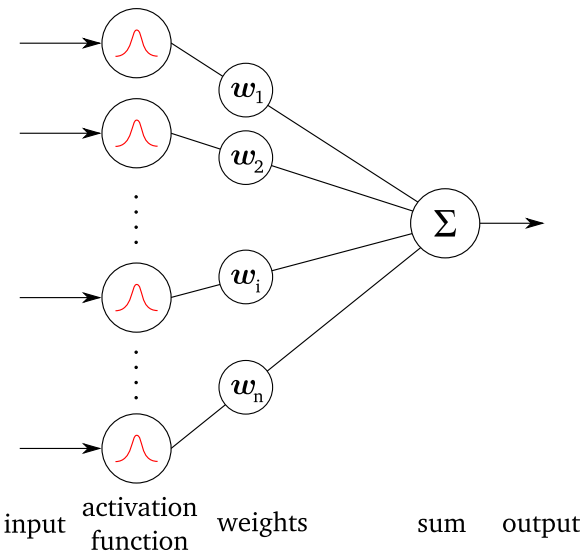

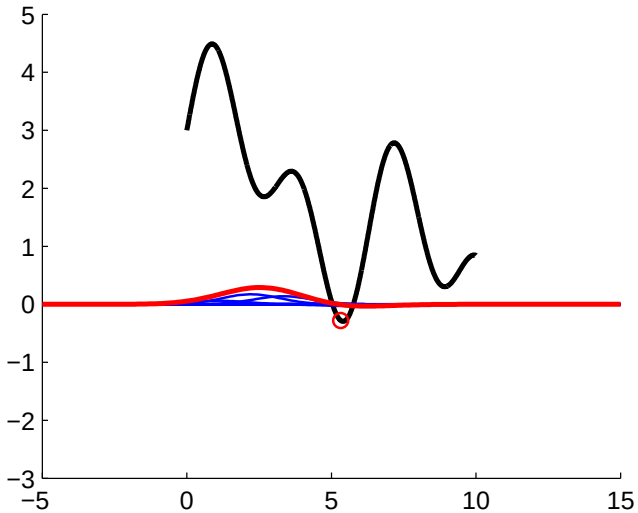

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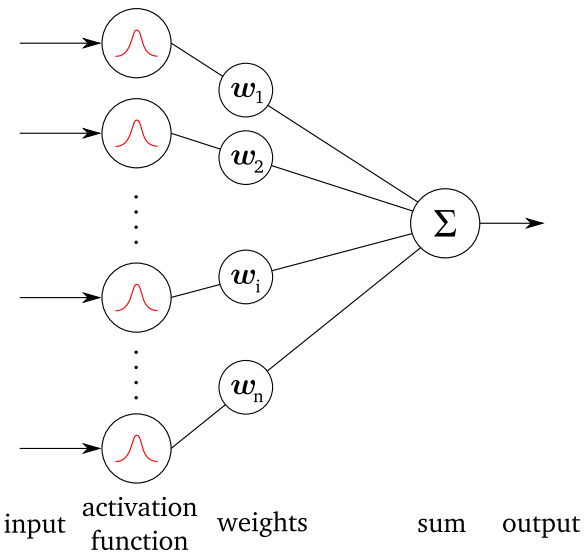

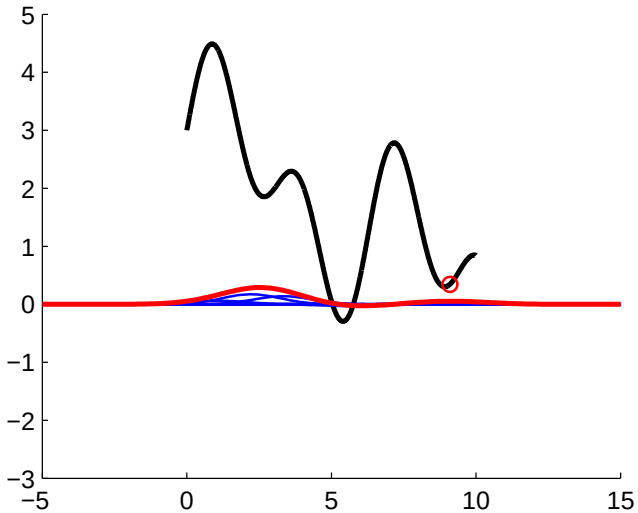

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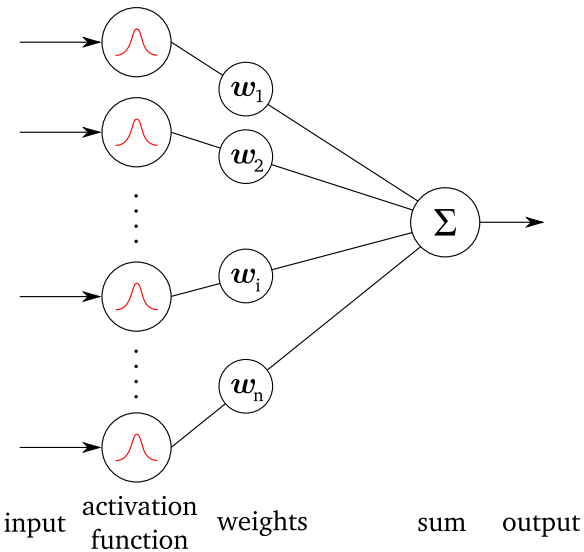

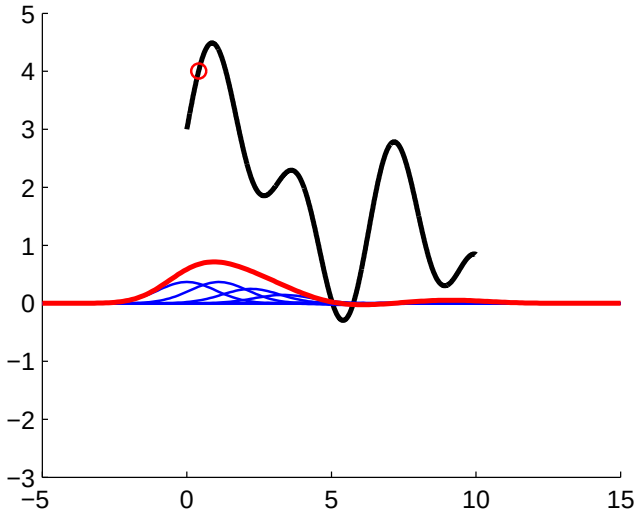

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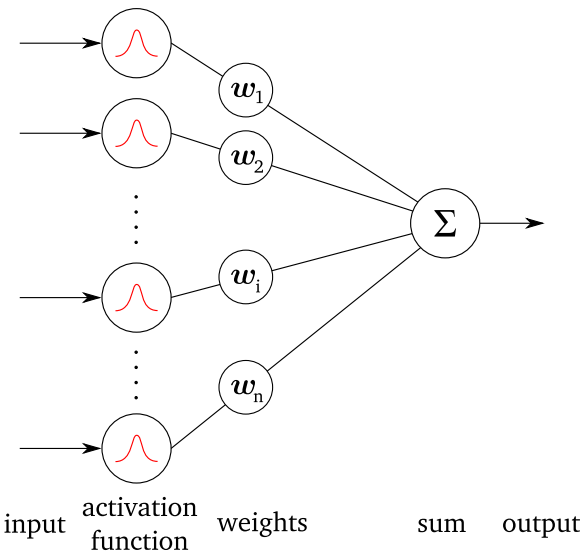

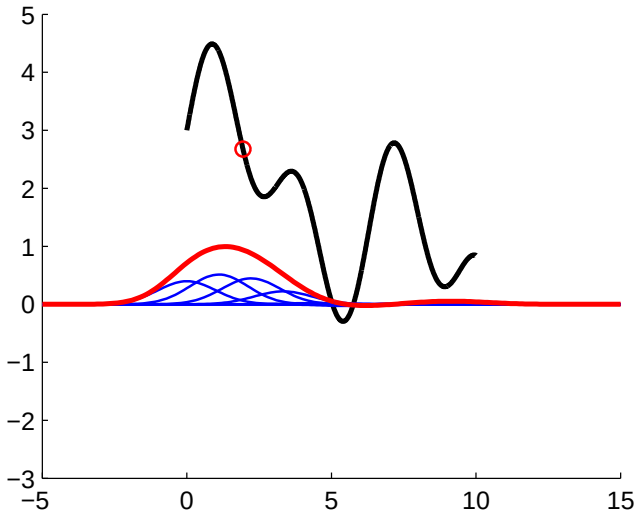

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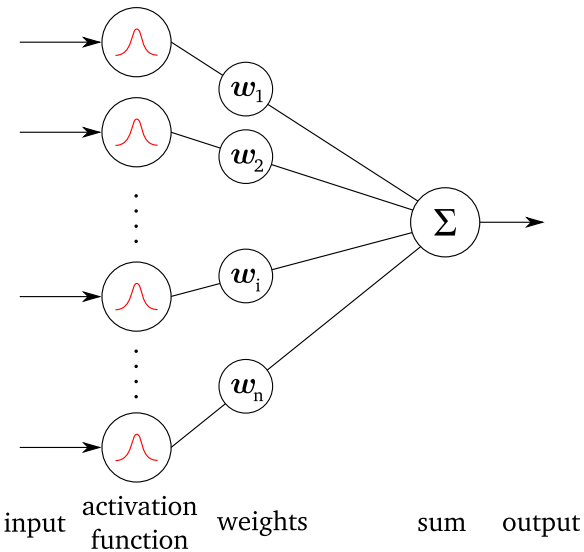

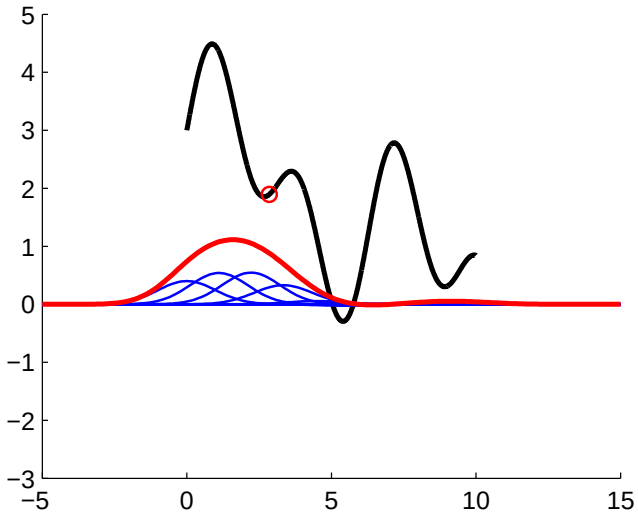

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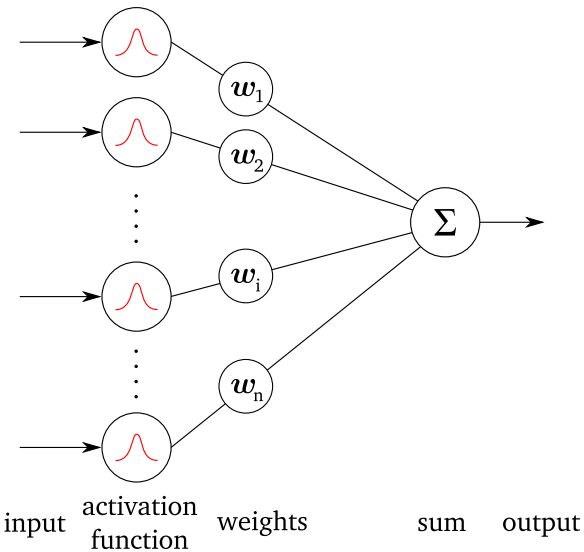

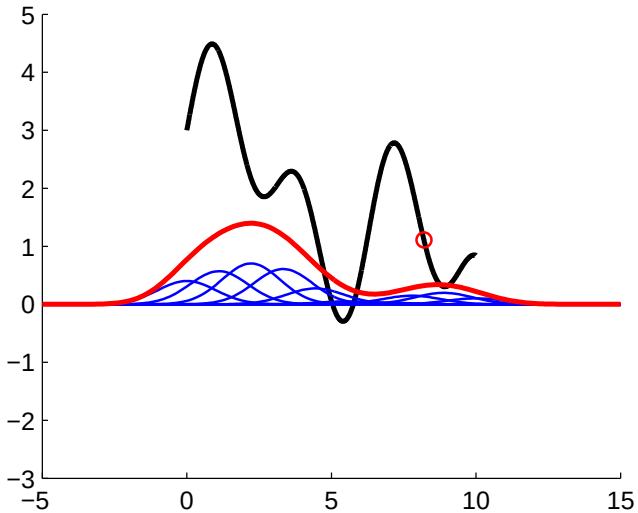

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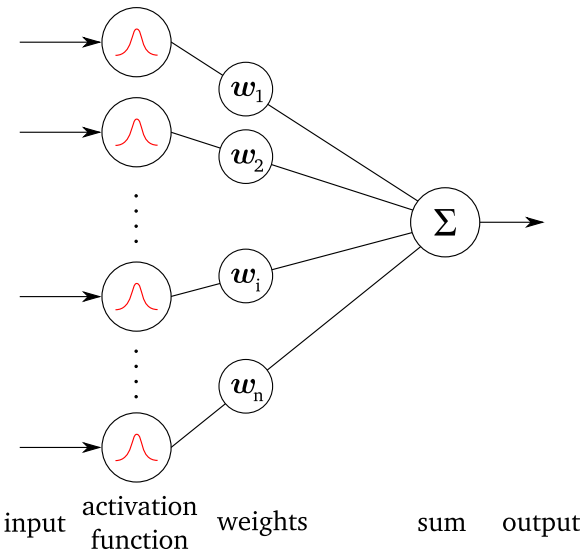

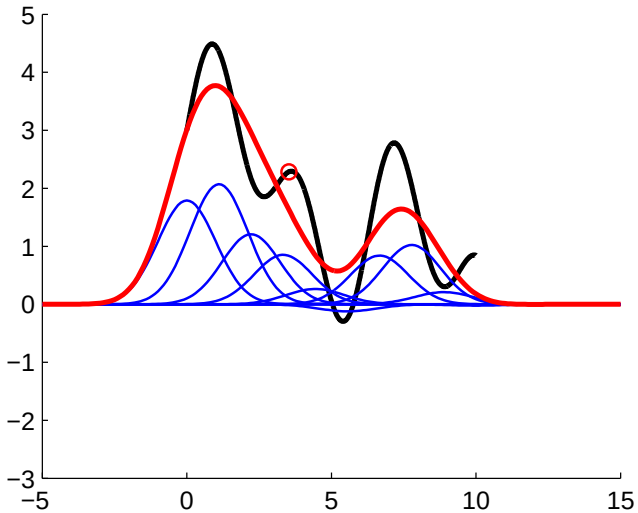

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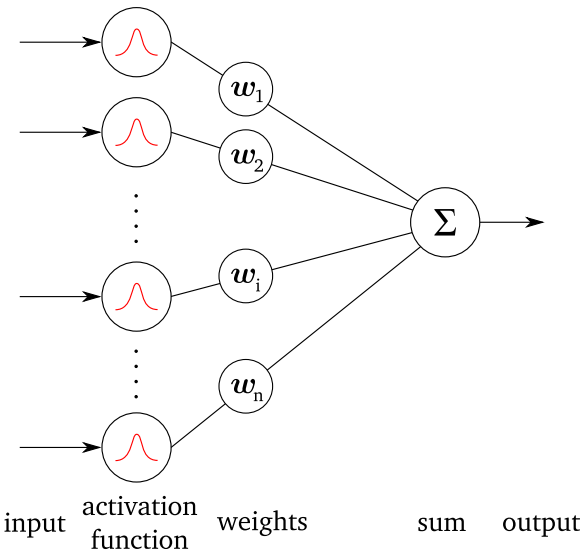

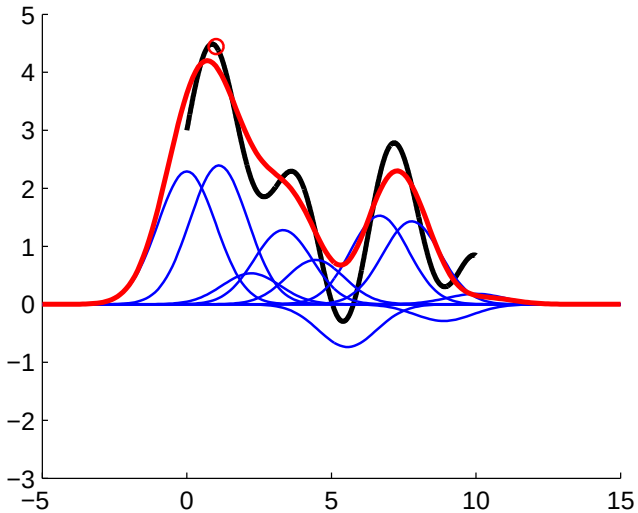

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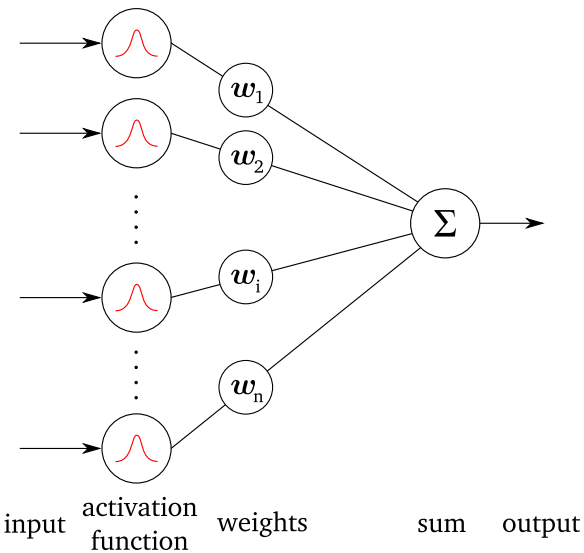

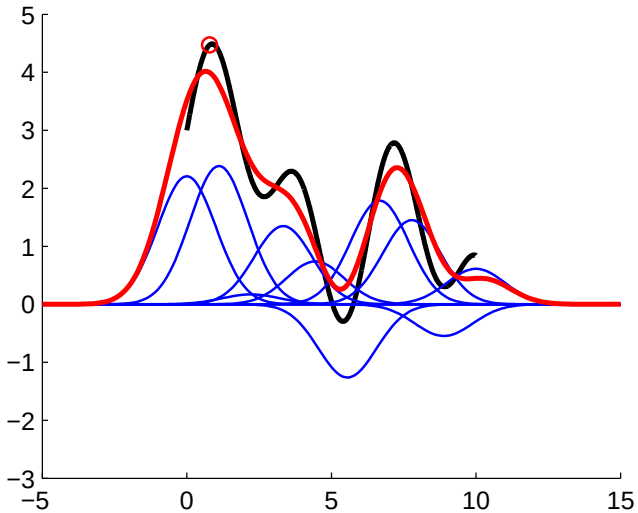

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Nonlinear functions approximations using nonlinear elementary functions:

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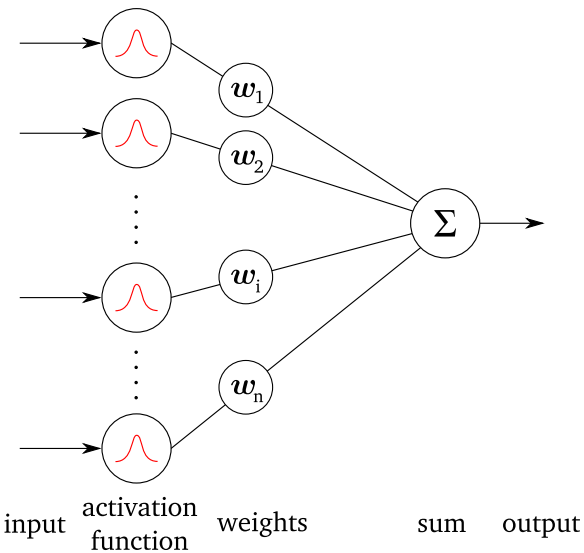

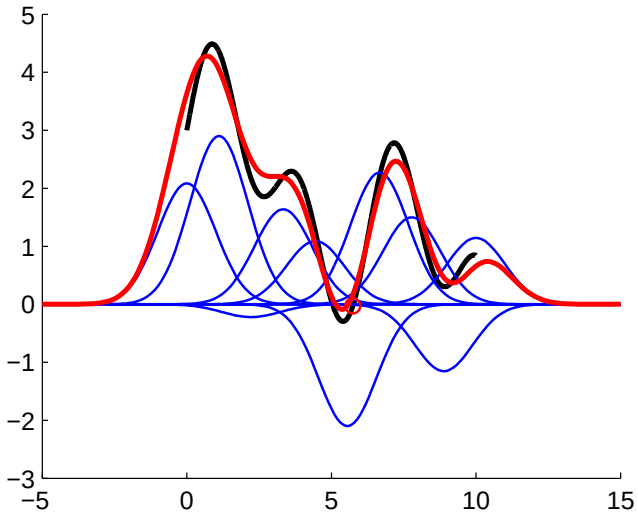

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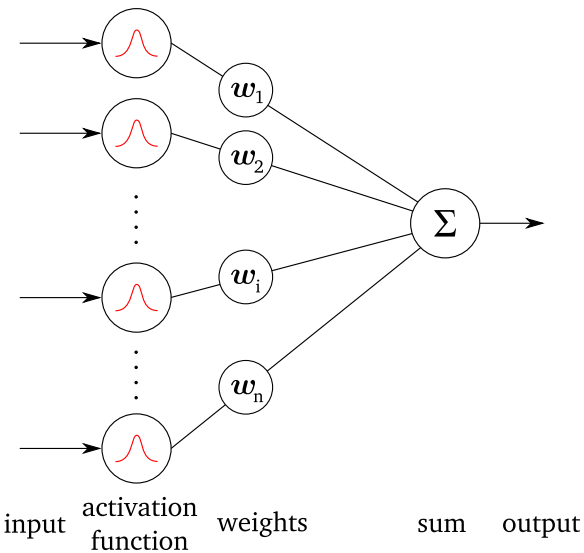

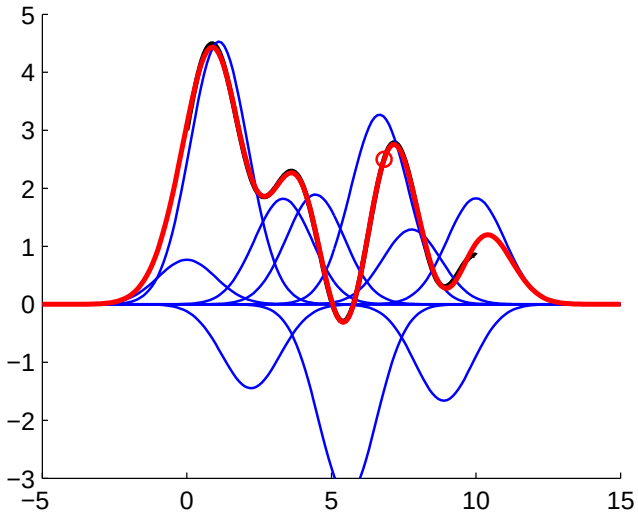

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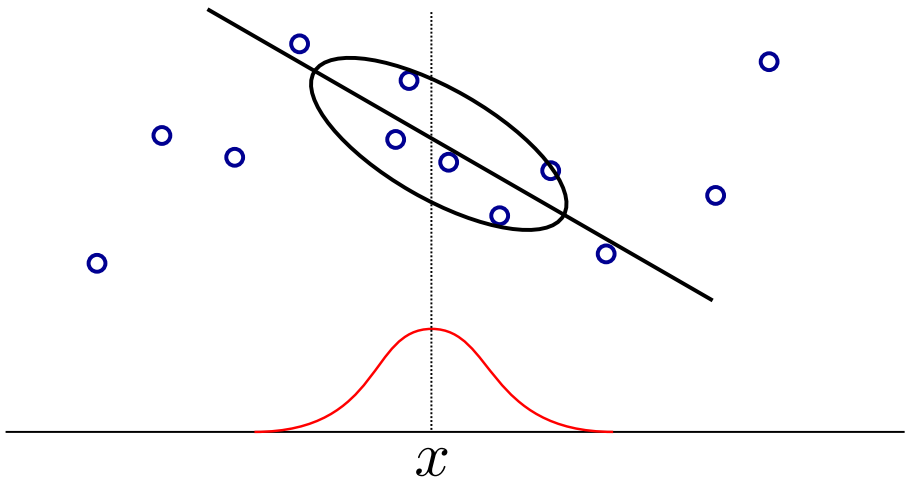
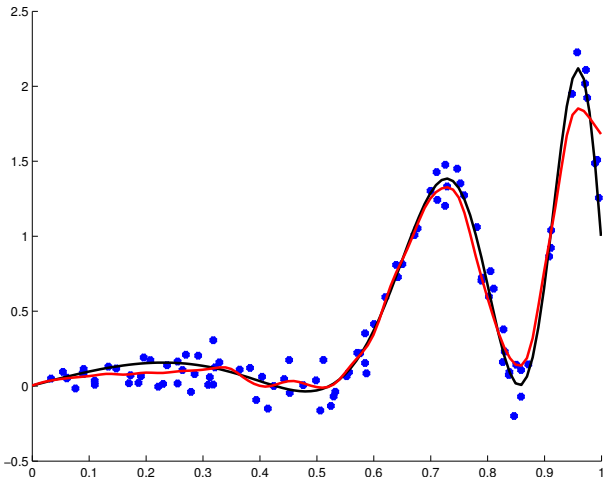
Nonlinear functions approximation using linear elementary functions:

Locally Weighted Regression

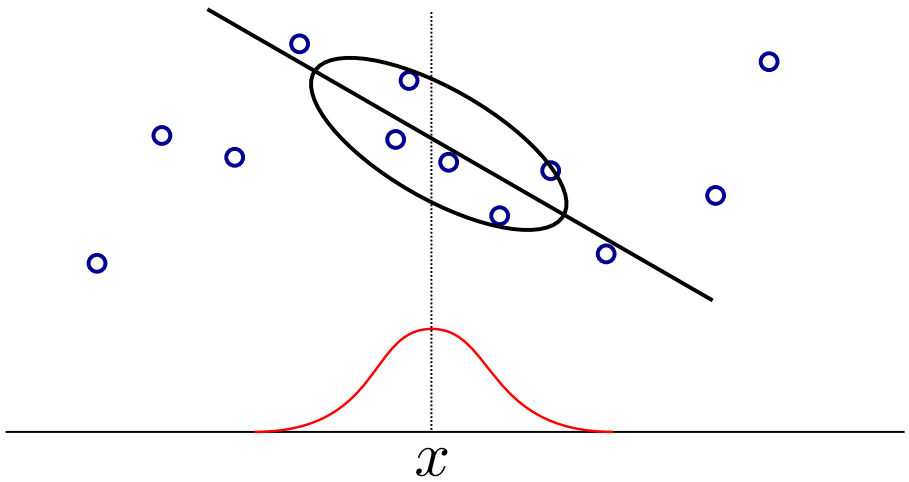


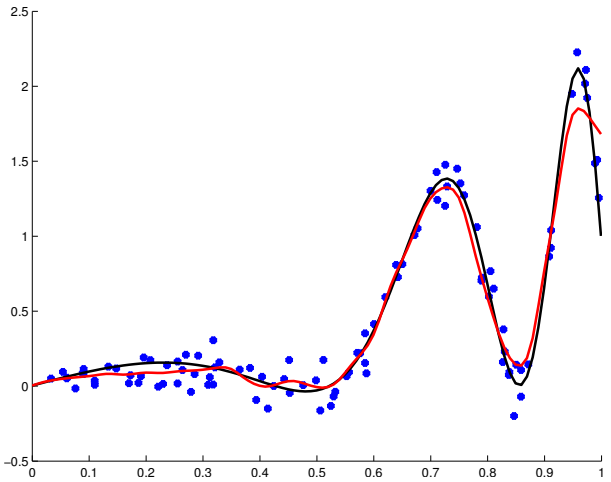


- $\phi_k = e^{-\frac{1}{2}(x_k - x)\sigma(x_k - x)}$ where $k \in [1\ q]$ span the number of saved points

Nonlinear functions approximation using linear elementary functions:

Locally Weighted Regression

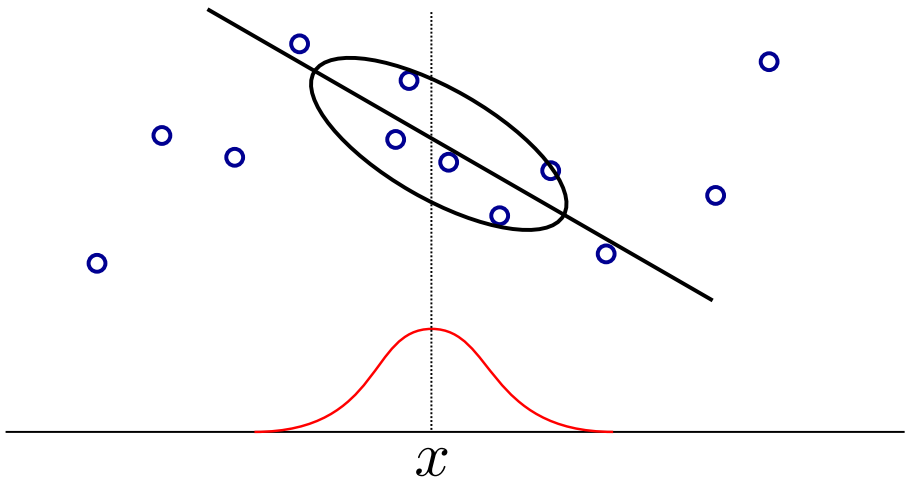


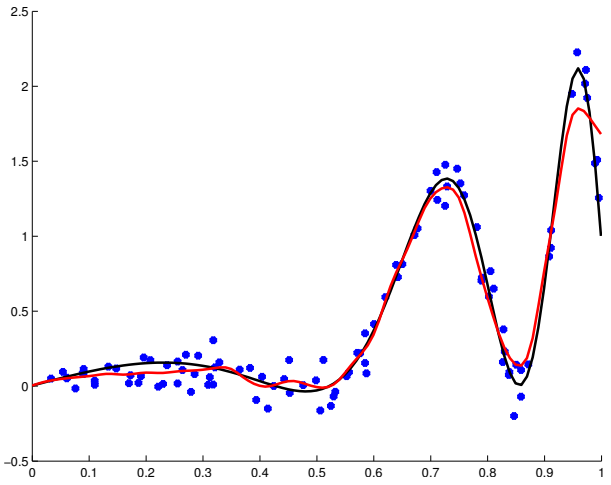


- $\phi_k = e^{-\frac{1}{2}(x_k - x)\sigma(x_k - x)}$ where $k \in [1\ q]$ span the number of saved points
- $\beta = X^{\Phi +} Y$ where $X = [x_1 \cdots x_q]$, $Y = [y_1 \cdots y_q]$ and $\Phi = [\phi_1 \cdots \phi_q]$.

Nonlinear functions approximation using linear elementary functions:

Locally Weighted Regression





- $\phi_k = e^{-\frac{1}{2}(x_k - x)\sigma(x_k - x)}$ where $k \in [1\ q]$ span the number of saved points
- $\beta = X^{\Phi+} Y$ where $X = [x_1 \cdots x_q]$, $Y = [y_1 \cdots y_q]$ and $\Phi = [\phi_1 \cdots \phi_q]$.
- $\hat{y} = \beta x$

Locally Weighted Projection Regression: Definition [(6), (1), (7)]

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- Incremental algorithm which approximates non-linear functions with huge input space taking into account only relevant information
- LWPR is based on Locally Weighted Regression and Partial Least Squares

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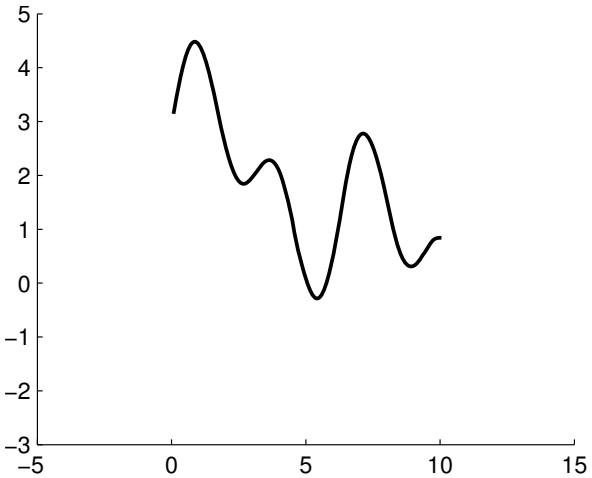

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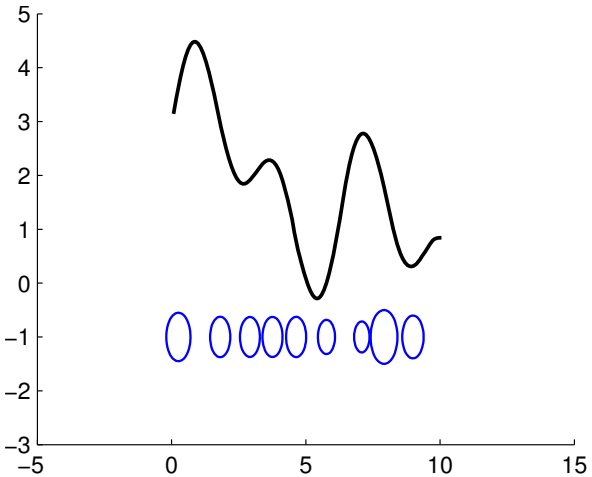

- $\phi_i = e^{-\frac{1}{2}(x-c_i)D_i(x-c_i)}$

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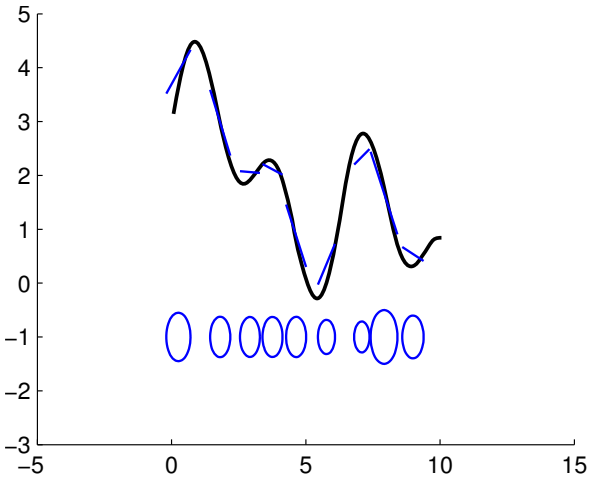

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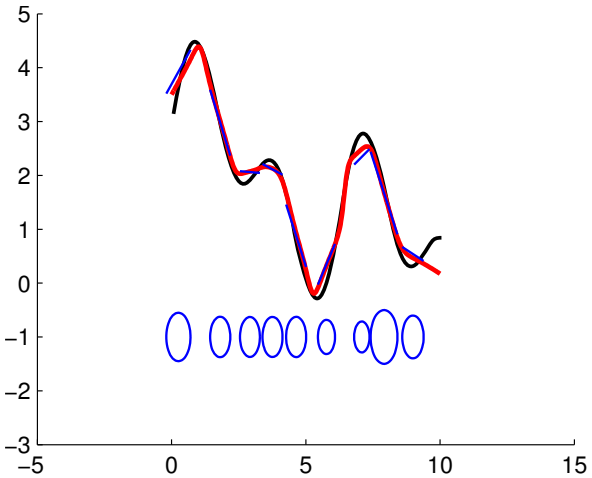

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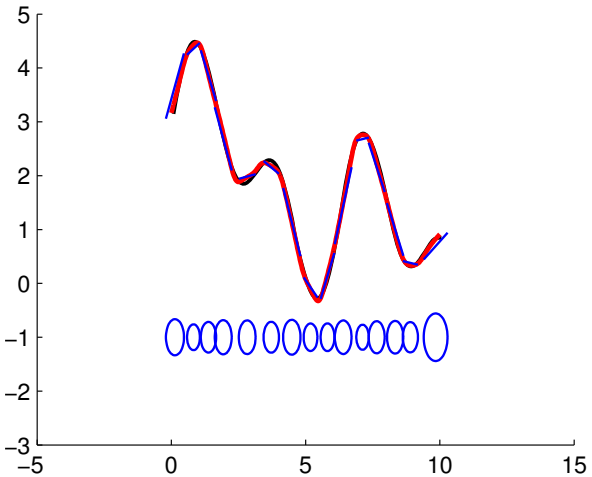

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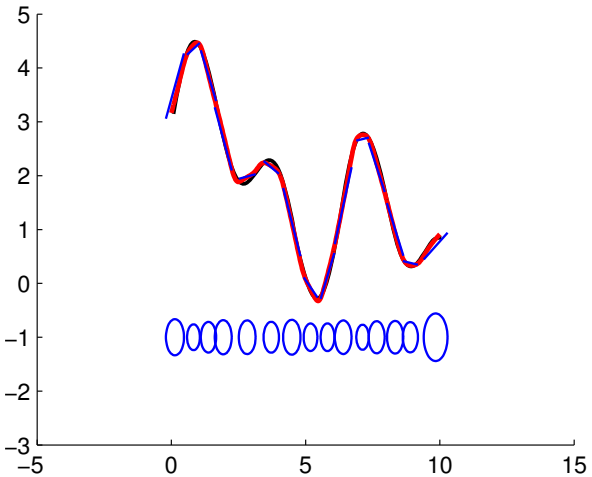

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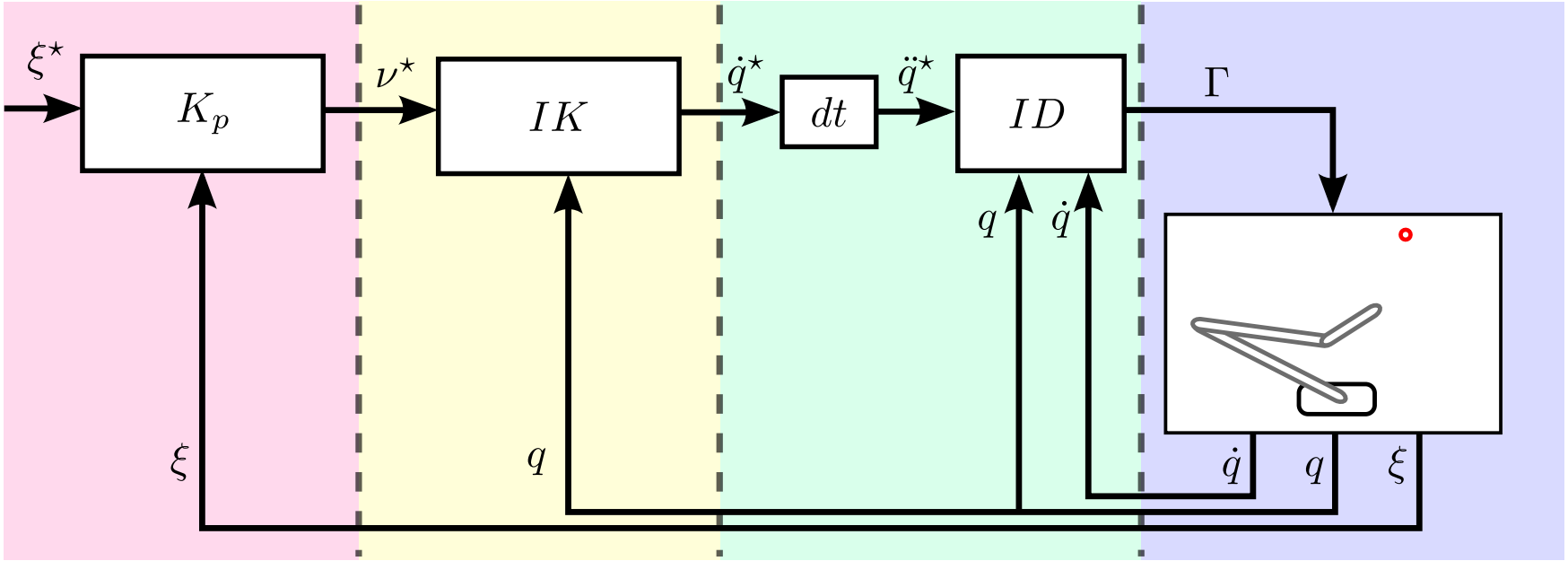
LWPR supply the derivative of the learnt model (5).

$$\frac{\partial \hat{y}}{\partial x} = \frac{1}{\Phi} \sum_{i=1}^{N} \left(\frac{\partial \phi_i}{\partial x} y_i + \phi_i \frac{\partial y_i}{\partial x} \right) - \frac{1}{\Phi^2} \sum_{i=1}^{N} \phi_i y_i \sum_{k=1}^{N} \frac{\partial \phi_k}{\partial x}$$

Our approach



Our claim: At the velocity level, one should rather learn forward mappings ((8)) for each task because ...

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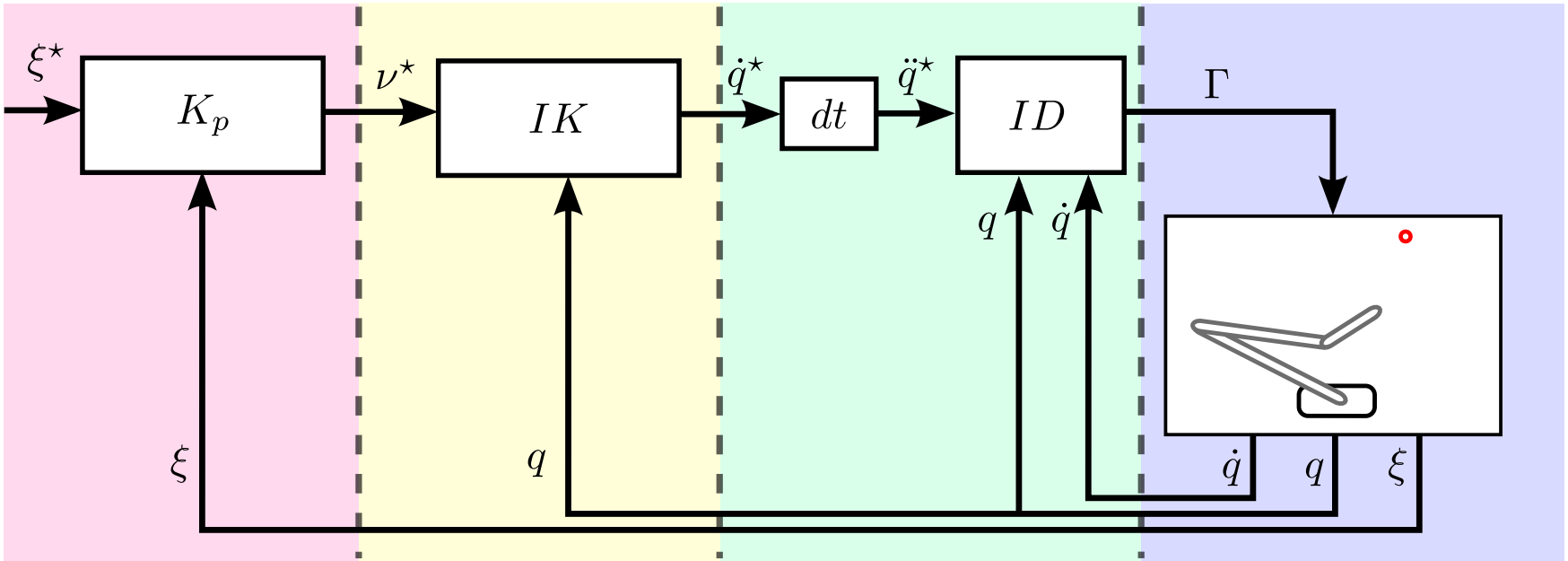

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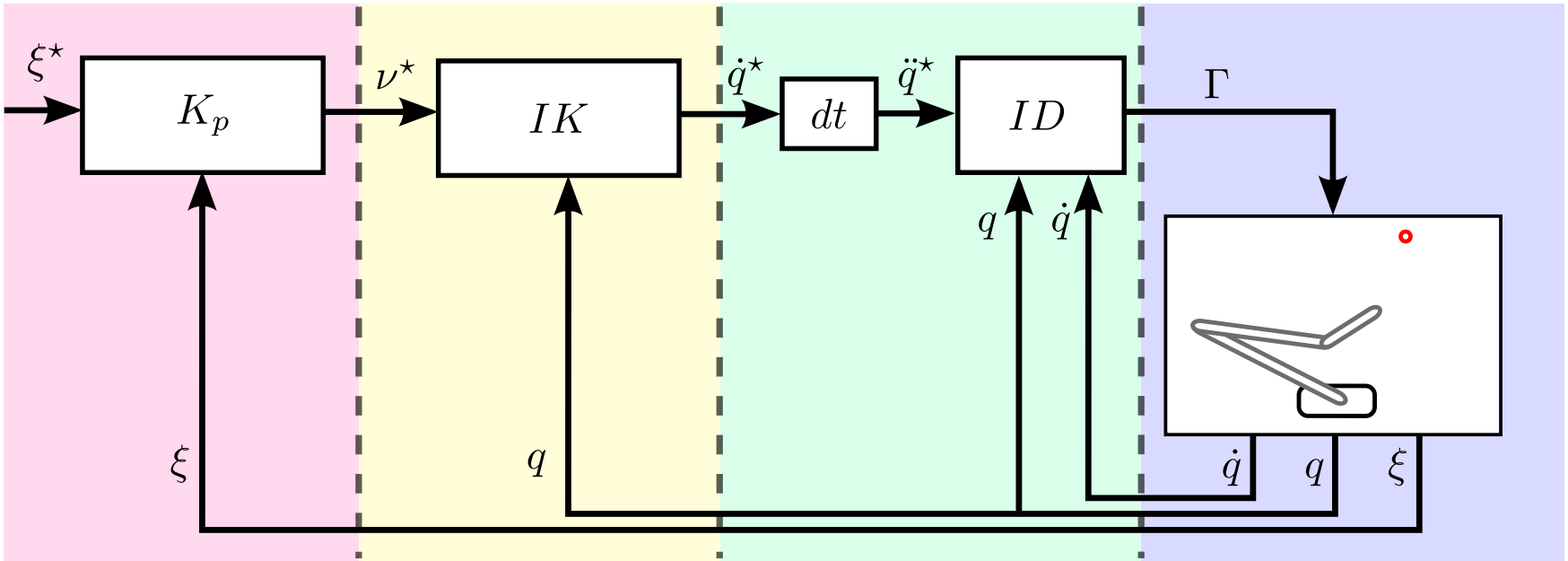

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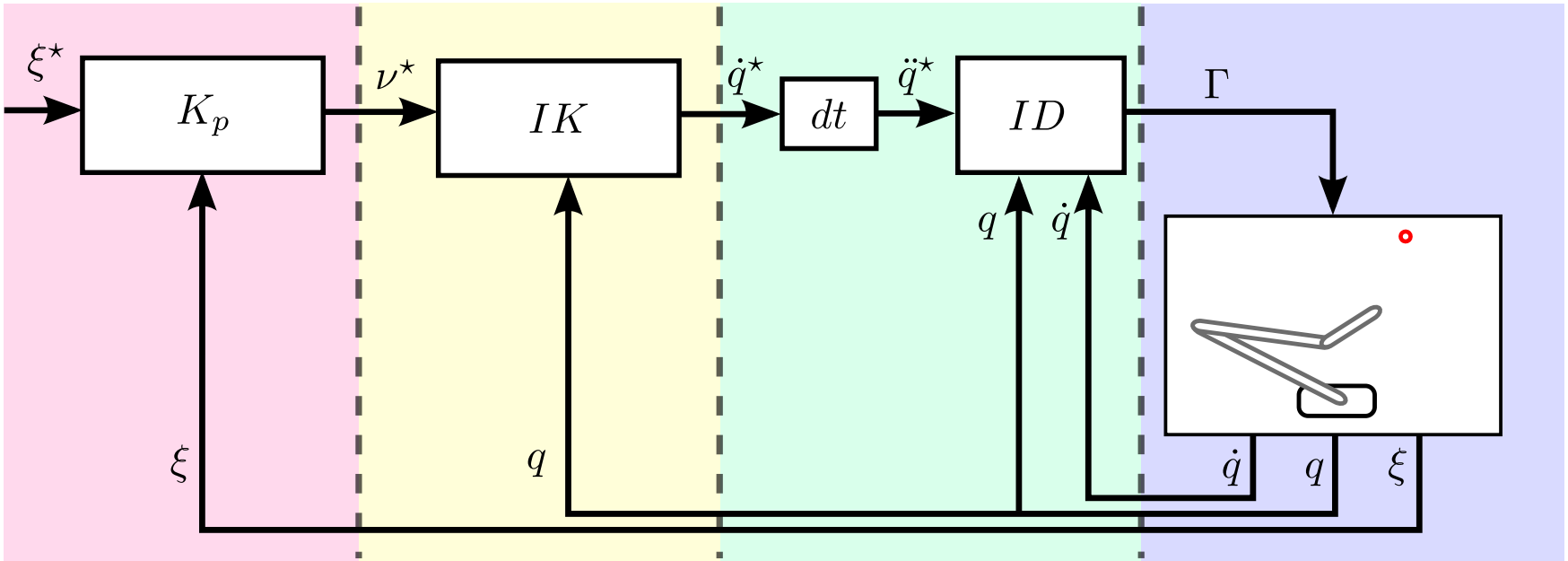

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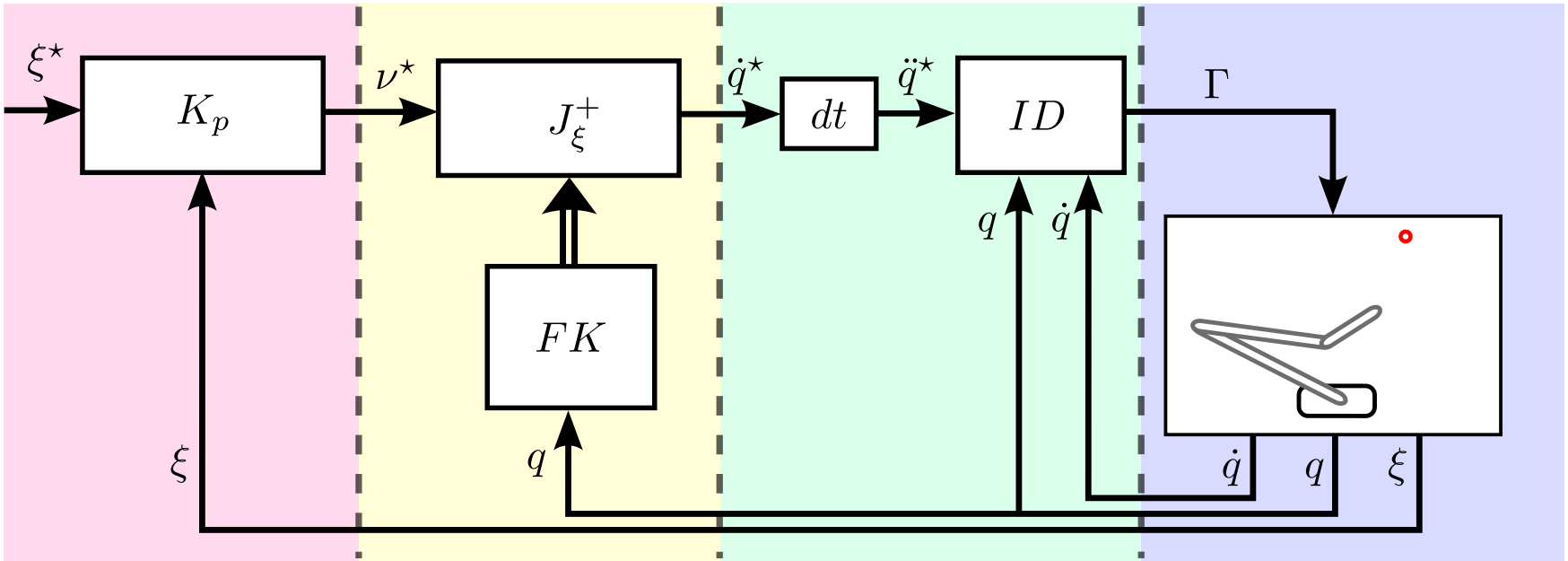

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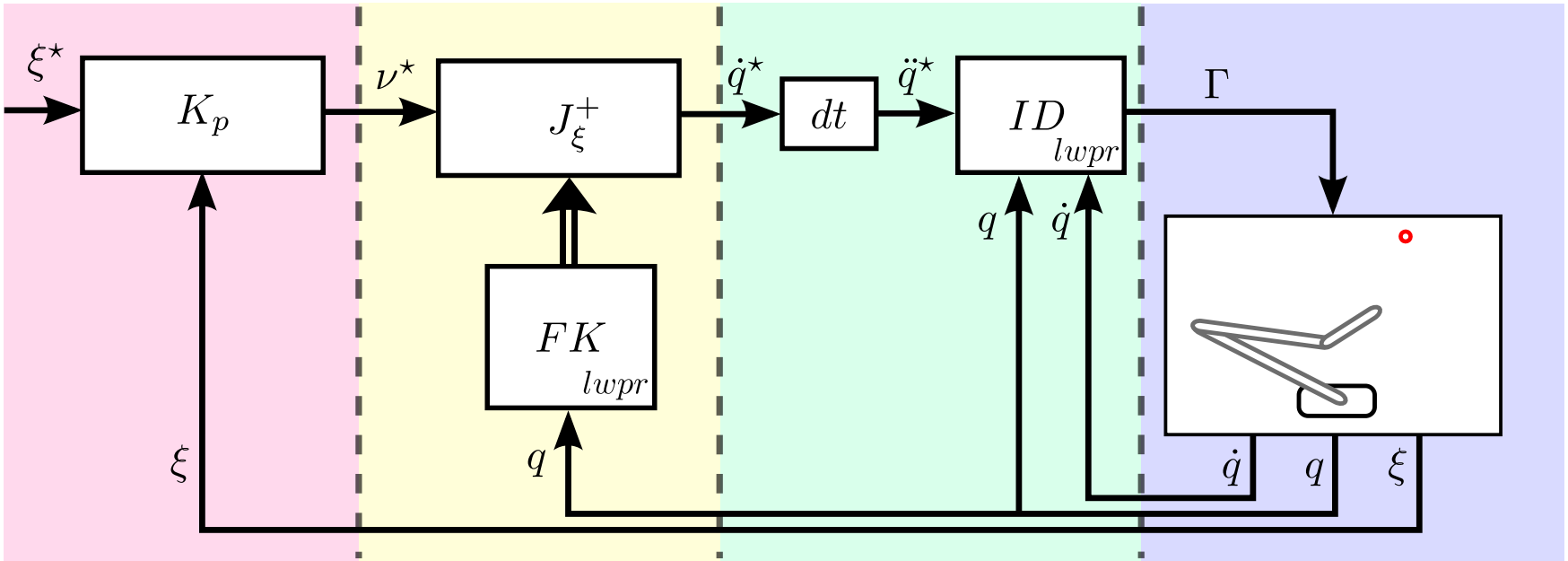

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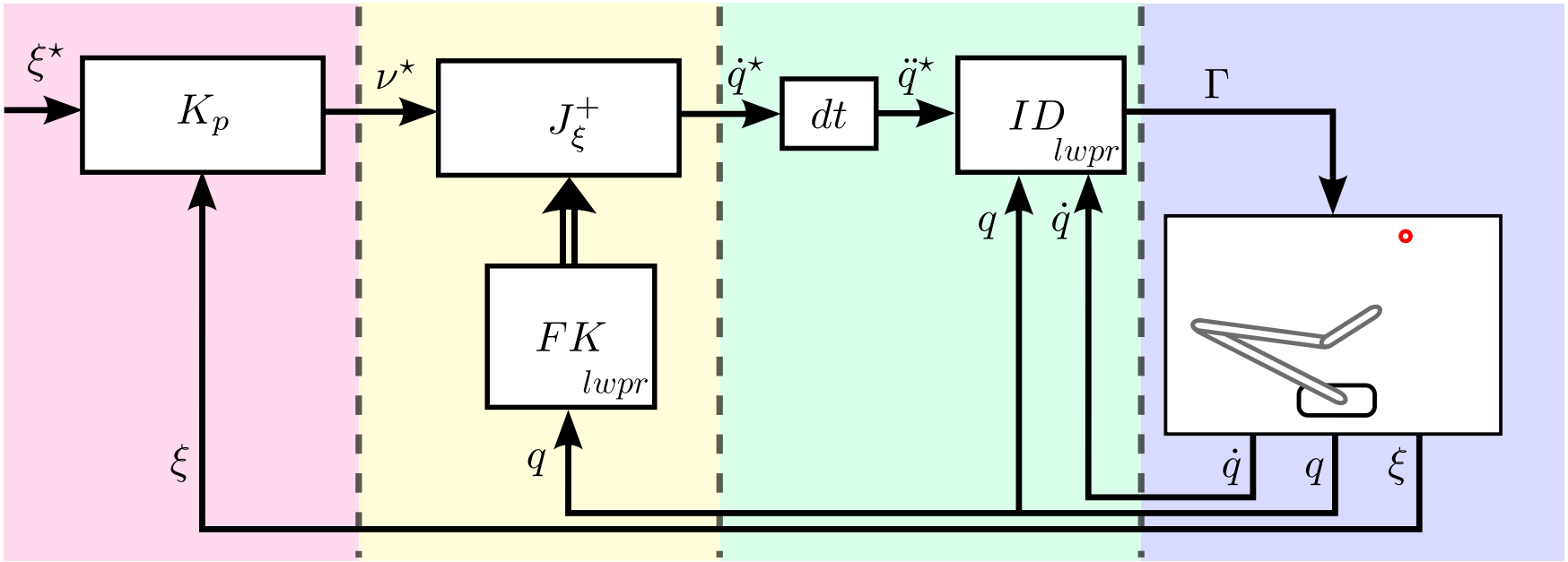

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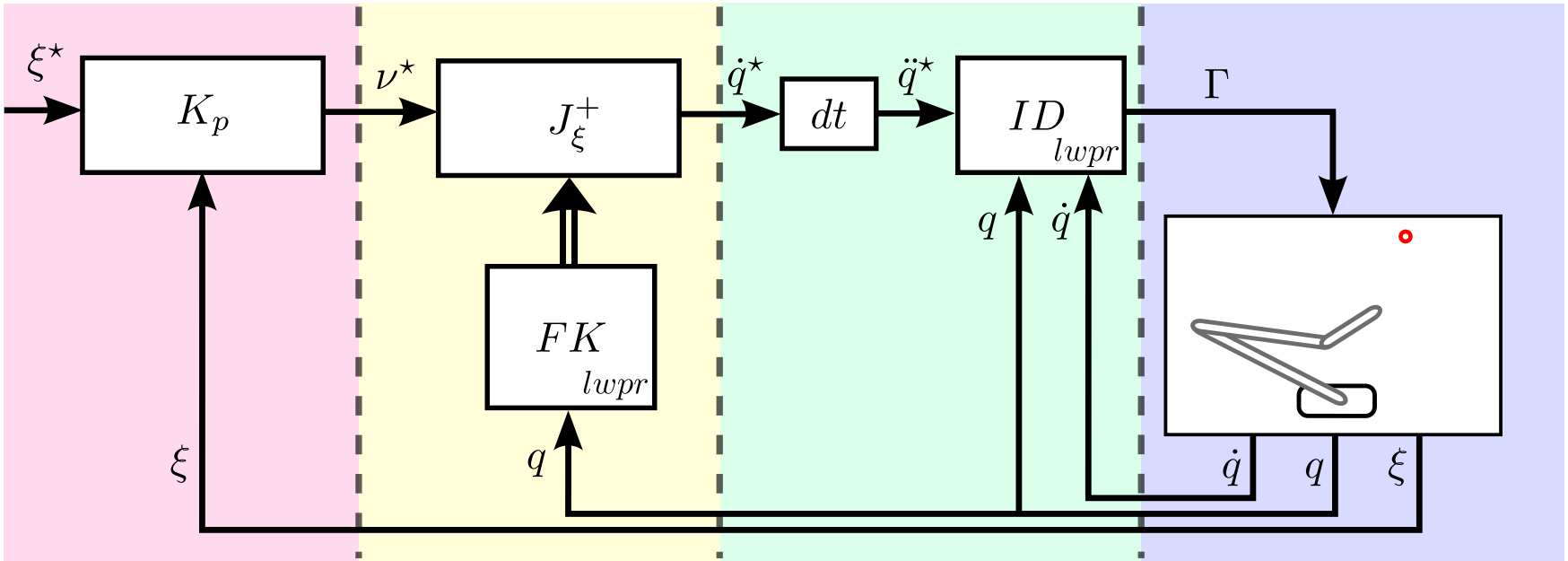

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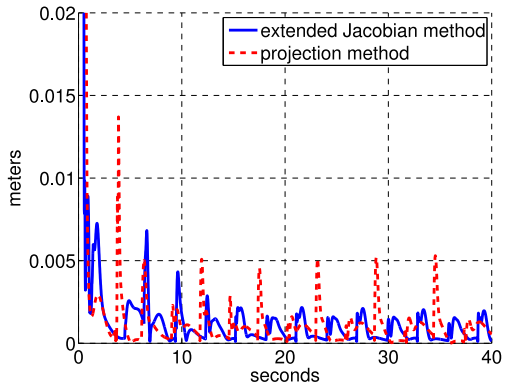
Figure: Point to point task with limited joint space babbling: 2000 samples.

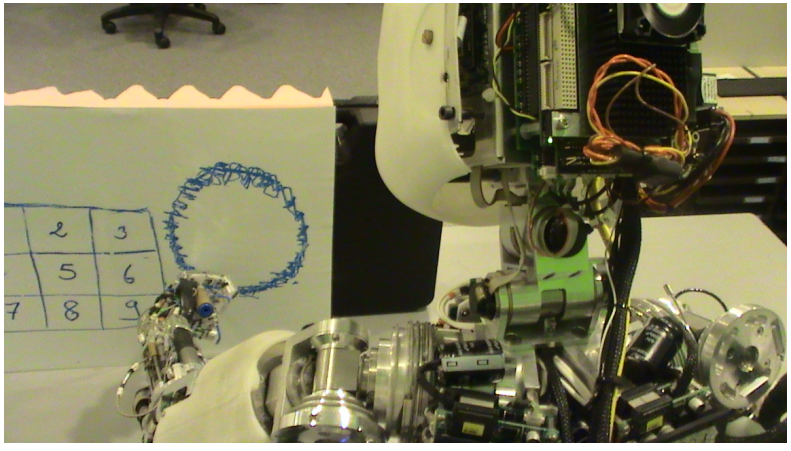
Controlling redundancy with LWPR

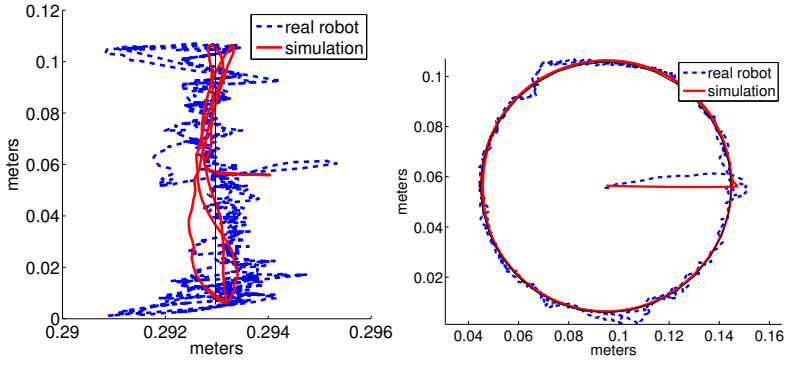


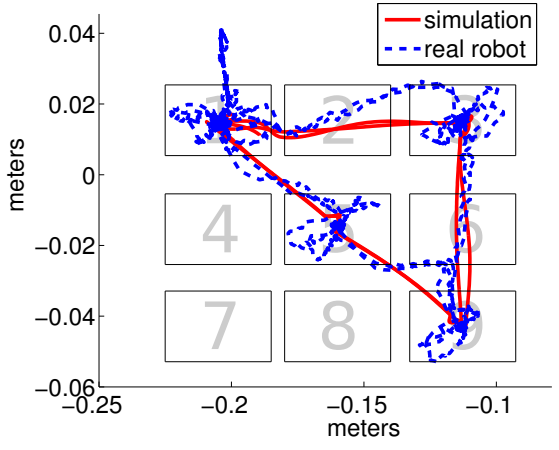
compatible task incompatible task normalized task space error

Figure: Point to point task with adaptation to an unknown external force (after 2 seconds)

Learning velocity kinematics on the real robot







Summary

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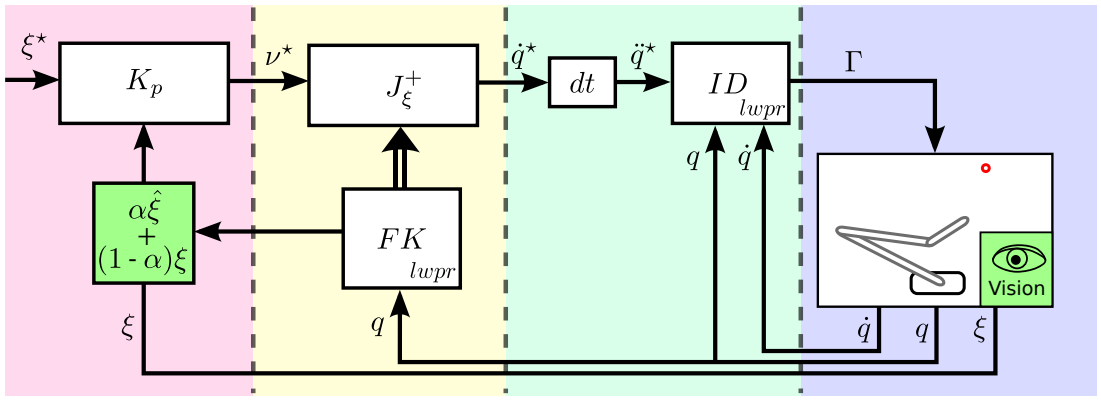
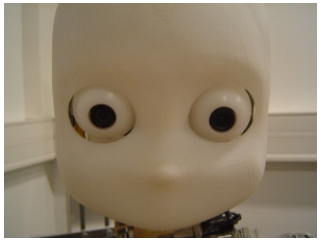
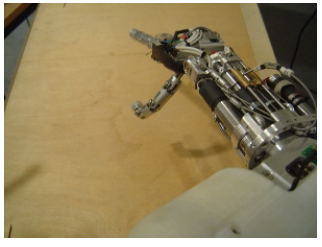
- ⋆ Salaun, C. and Padois, V. and Sigaud, O. (2010). Learning Forward Models for the Operational Space Control of Redundant Robots. From motor to interaction learning in robots Springer, publisher. Pages 169-192.
- ⋆ Salaun, C. and Padois, V. and Sigaud, O. (2009). A Two-Level Model of Anticipation-Based Motor Learning for Whole Body Motion. LNAI 5499: Anticipatory Behavior in Adaptive Learning Systems: From Psychological Theories to Artificial Cognitive Systems Springer, publisher. Pages 229–246.
- ⋆ Salaun, C. and Padois, V. and Sigaud, O. (2009). Control of Redundant Robots Using Learned Models: An Operational Space Control Approach. Proceedings of the IEEE/RSJ International Conference on Intelligent Robots and Systems. Pages 878–885. Saint-Louis, USA.

Close the loop at the vision level and combine proprioceptive and exteroceptive state estimation.







- Locate end-effectors;
- Differentiate objects, humans, the robot limbs;
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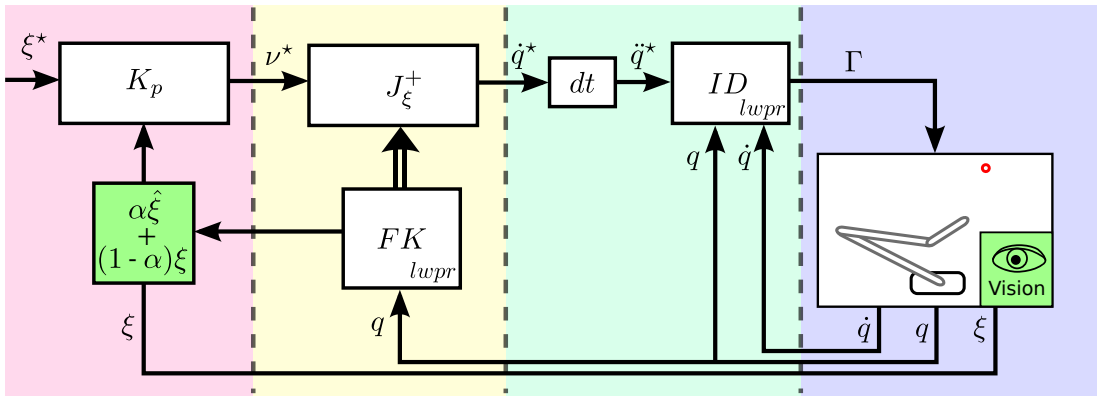

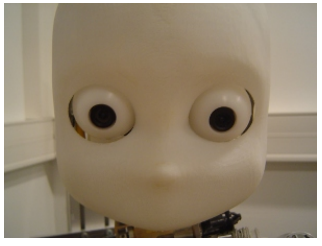

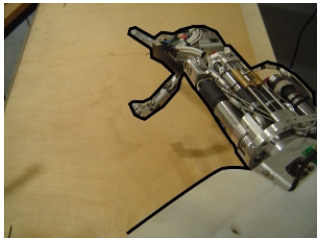

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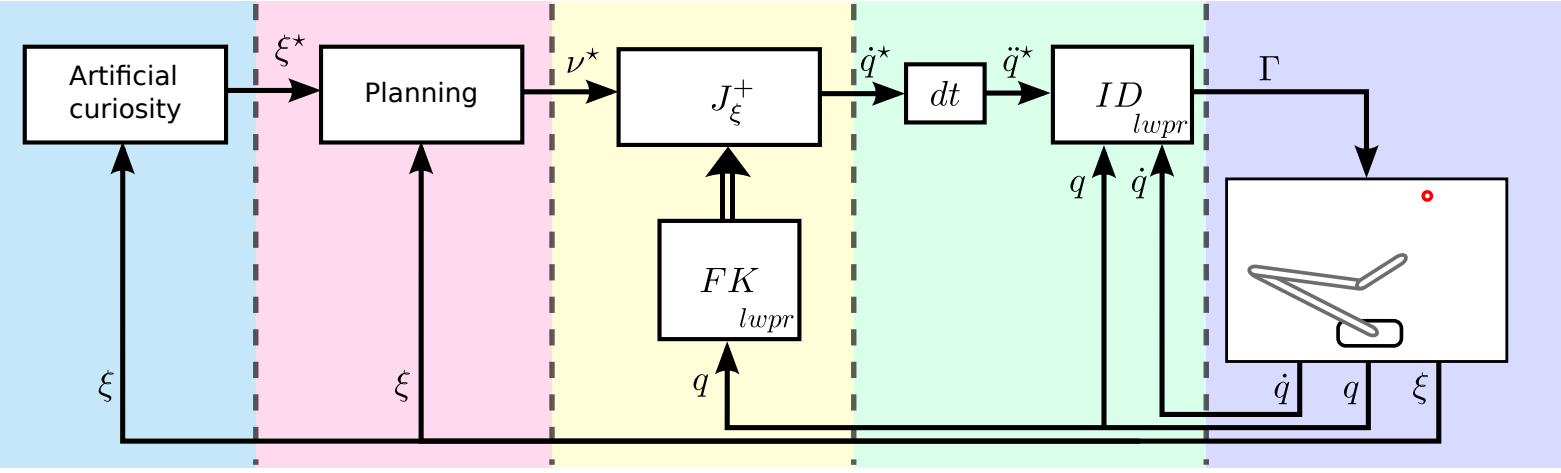
Solve the exloration problem.

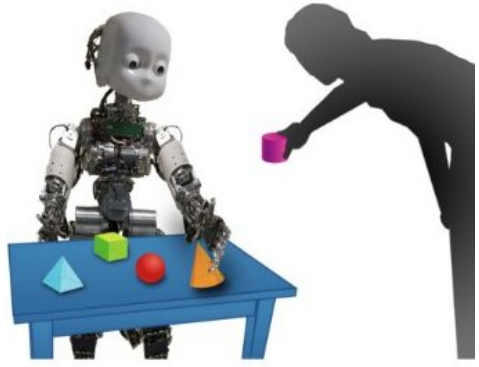


- Close the loop at a higher level;
- Combine artificial curiosity and human guidance.

Acknowledgments

- RobotCub for:
  - providing us with a great robot;
  - allowing both national and international scientific collaboration;
  - constant technical support.
- My colleagues and students working on this project:
  - Olivier Sigaud;
  - Pierre-Yves Oudeyer & Olivier Ly (INRIA Flowers);
  - David Filliat (ENSTA);
  - Jean-Christophe Bailli (Gostai);
  - Camille Salaün (PhD student);
  - Charles Clercq (former CS Master Student, now at IIT);
  - Guillaume Sicard (CS Master student);
  - Pierre Griffault, Kevin Hoang and Abhishek Agarwal (former interns).

Thank you for your attention.



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