

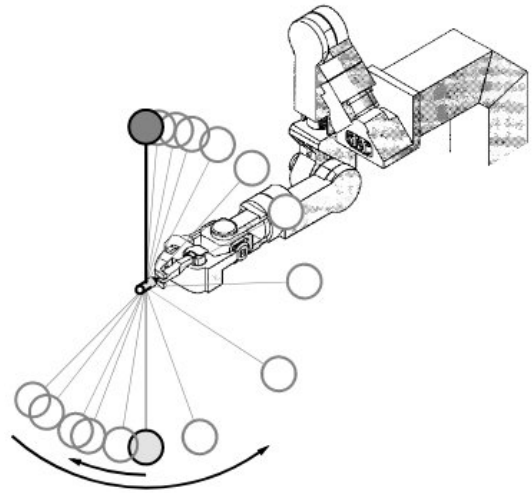
# Robotics MVA 2025–26 Final exam topics

## Learning pendulum swing ups from demonstrations

**Context:** In their 1997 work *Robot Learning from Demonstration* [1], Atkeson and Schaal learned both reward and model from human demonstrations. They showed pendulum swing ups performed by a real robotic arm. Jump forward 25 years, and some of our best manipulation systems [2] are based on behavior cloning [3].

(Figure adapted from [1].)

**Goals:** In this topic, we will reproduce [1] with concepts seen in class and modern robotics software. We would like to compare it to behavior cloning [3].



### Project plan:

1. Read reference [1].
2. Adapt section 5, *Learning to balance*, using the [Cart Pole environment of Gymnasium](#). What are the main steps to take?
  - a. Note that the cart-pole environment will implement its own dynamics, replacing equation (3).
  - b. You can find a ready-to-use Python implementation of *dlqr* in [control.dlqr](#) of the Python Control Systems library.
  - c. Alternatively, you can teach yourself on the Linear-Quadratic regulator and implement your own ``lqr`` function using for instance SciPy's [solve\\_continuous\\_are](#).
3. Pick a [robot arm description](#) and load it in PyBullet.
4. Apply `pybullet.TORQUE_CONTROL` with PD gains to make the robot go to a desired configuration.
  - a. Note that in PyBullet one needs to disable velocity control ``setJointMotorControl2(..., controlMode=p.VELOCITY_CONTROL, force=0)`` before sending torque-control commands
  - b. That is, we have a configuration vector  $q$  (of size `model.nq`) and a tangent velocity vector  $v$  (of size `model.nv`, for your tests you can start with  $v=0$ ), and we want each joint  $i$  to reach an angle  $q[i]$  and angular velocity  $v[i]$ . To achieve this, PD control sends a joint torque computed as:
    - i.  $\tau = K_p * (q[i] - q_{\text{measured}}[i]) + K_d * (v[i] - v_{\text{measured}}[i])$ .
  - c. You will have to find values of the two parameters  $K_p$  and  $K_d$  that work well for the robot arm model you have selected.

5. Use closed-loop inverse kinematics to command the robot's end effector position along a horizontal line of your choosing. You can implement your own, as in the inverse kinematics assignment, or use [Pink](#).
6. Modify the URDF file of the robot description to add a pendulum at the end effector of the arm. The pendulum will consist in:
  - a. A revolute joint that will be passive (i.e. always command it with zero torque).
  - b. A mass at the end of the child link of the revolute joint.
7. Can you adapt your solution from step 2 to this more realistic simulation?
8. Propose a way to adapt section 6, *Learning the swing up task*, using this simulation and any input device connected to your computer.
  - a. You can pick either a parametric or nonparametric model; no need to implement both.
  - b. Your solution should be feasible on a real robot as well, using some of the systems you have seen in class or in the lab.
  - c. Explain how you would perform the experiment on a real robot.
9. Implement and test it, report how many samples you need to realize a successful swing up. You can use [CasADi](#) for nonlinear trajectory optimization of pendulum trajectories.
10. Explain similarities and differences between this approach and behavior cloning [3].
11. *Bonus (optional) step*: Implement behavior cloning in your simulation. How many samples do you need to realize a successful swing up?

## References:

- [1] Atkeson, C. G., & Schaal, S. (1997, July). Robot learning from demonstration. In ICML (Vol. 97, pp. 12-20).
- [2] Vanhoucke, V., (2023). [Shifting Winds in Robot Learning Research](#).
- [3] Torabi, F., Warnell, G., & Stone, P. (2018). Behavioral cloning from observation. arXiv preprint arXiv:1805.01954.