

L1: Introduction

Hao Su



- <https://www.youtube.com/watch?v=fn3KWM1kuAw>

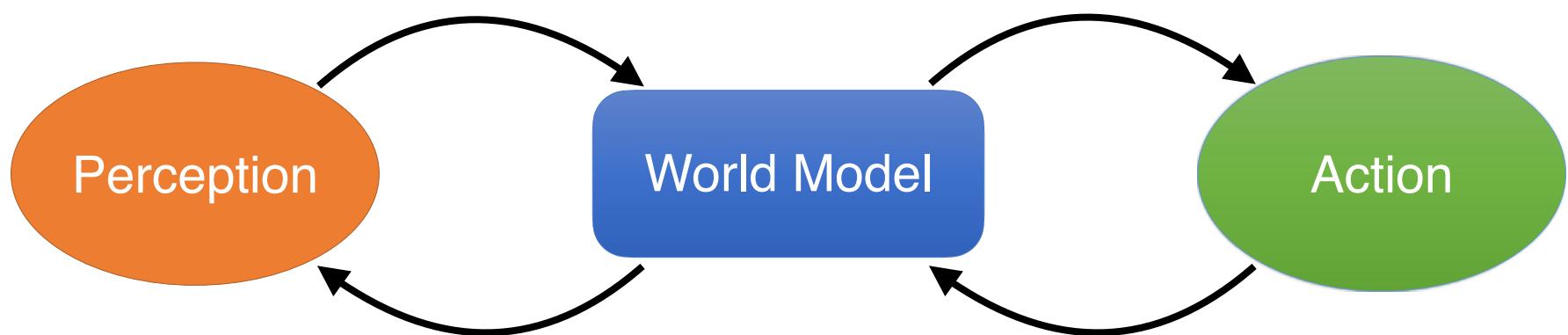
Agenda

- Syllabus
- Logistics
- $\text{SO}(3)$

Syllabus

Last quarter

This quarter



Vision → Robotics

Passive AI

- We know how to fit data well (by “deep learning”)
 - e.g., computer vision, natural language processing

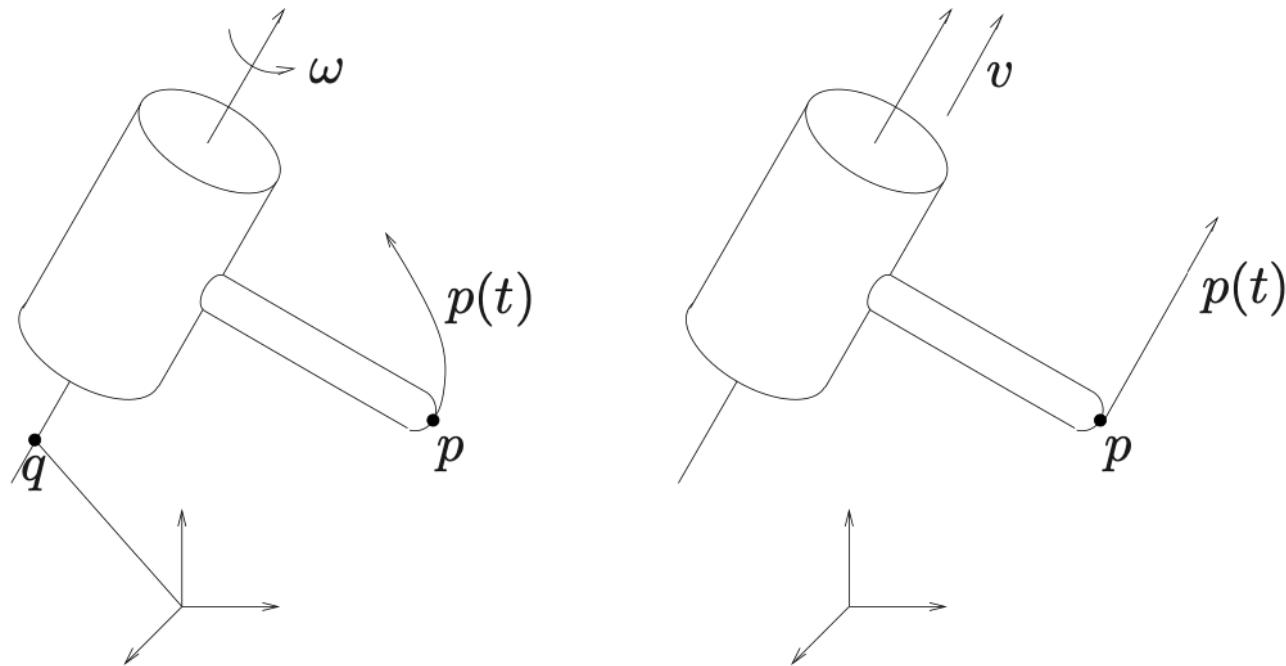
Vision → Robotics



- We aspire that autonomous agents can perform tasks and “grow” through interaction experiences
 - Need the ability to **interact**

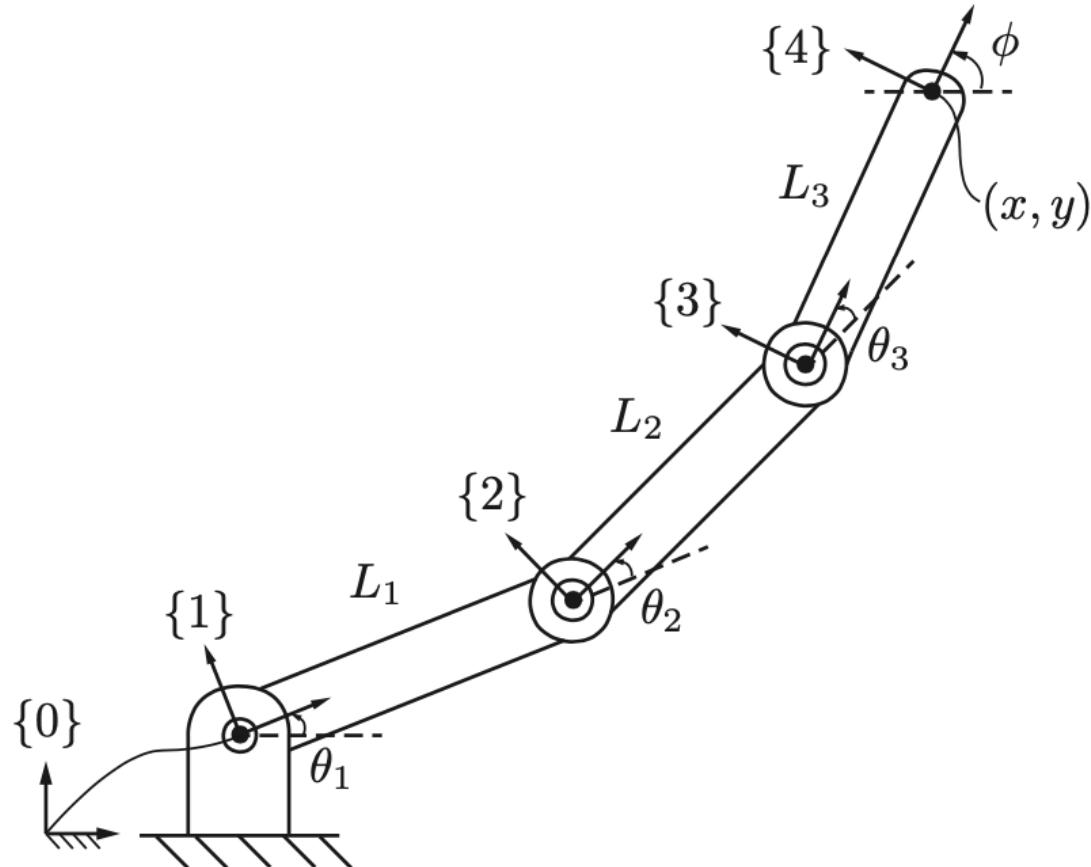
Topics Covered in This Course

- Modeling Robots by Rigid-Body Geometry



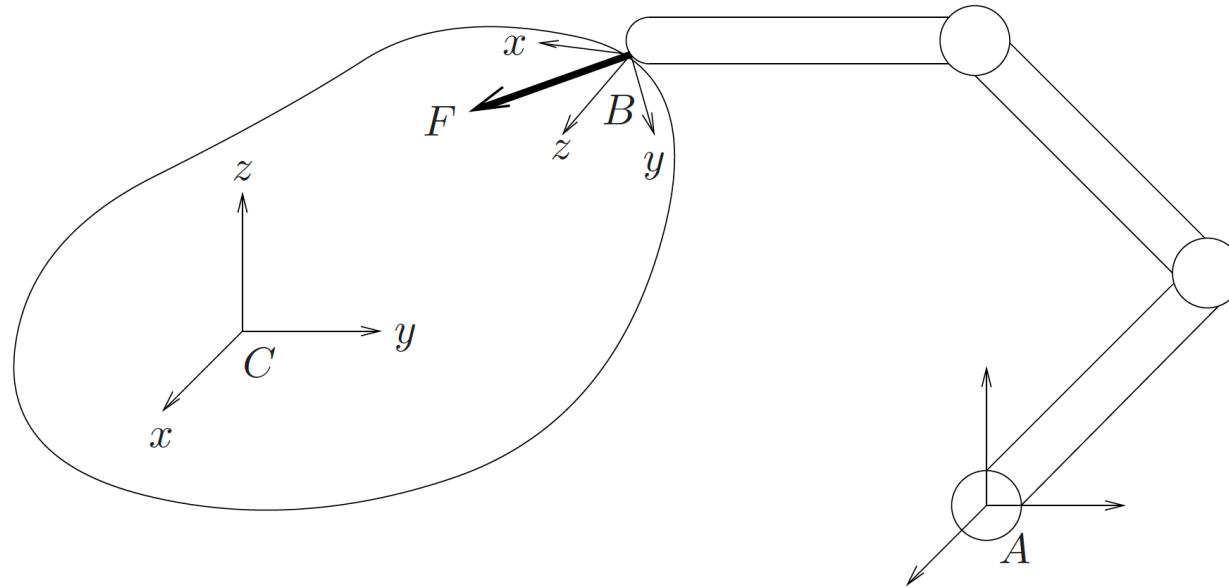
Topics Covered in This Course

- Forward and Inverse Kinematics of Robots



Topics Covered in This Course

- Generalized Force and Inertia



Topics Covered in This Course

- Friction, Contact Model, and Grasp

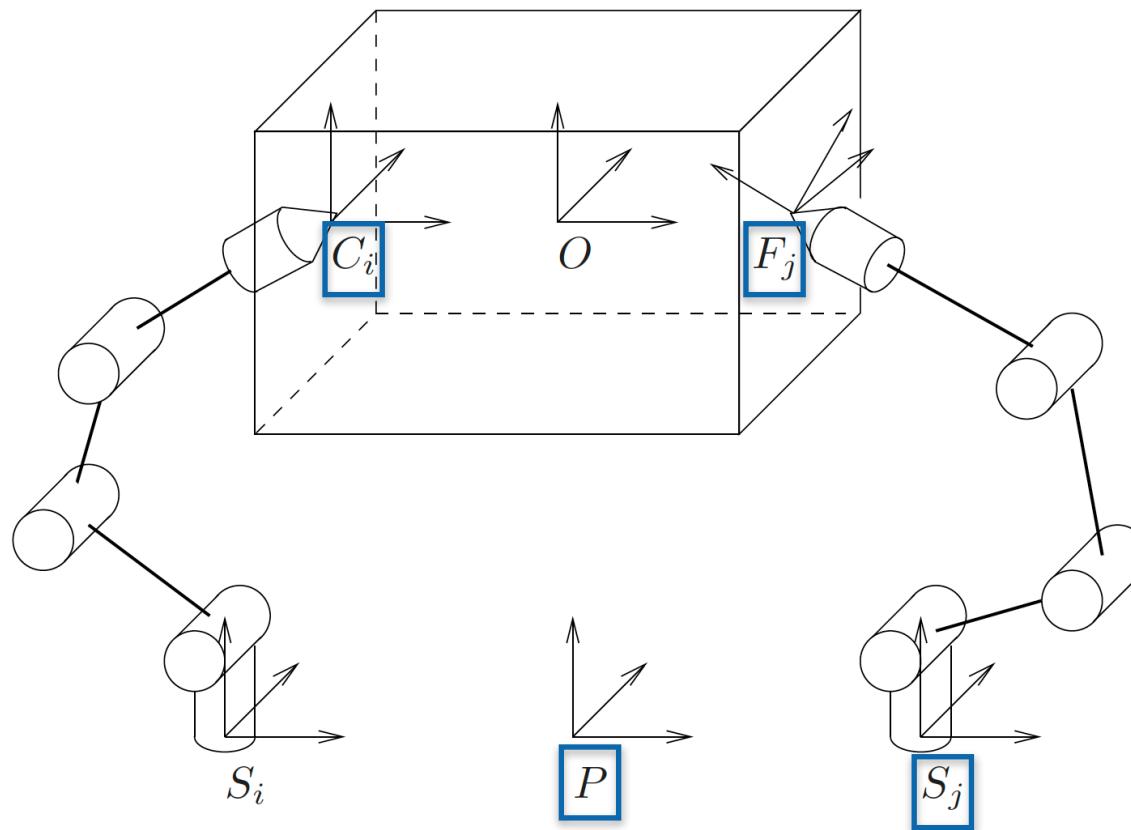
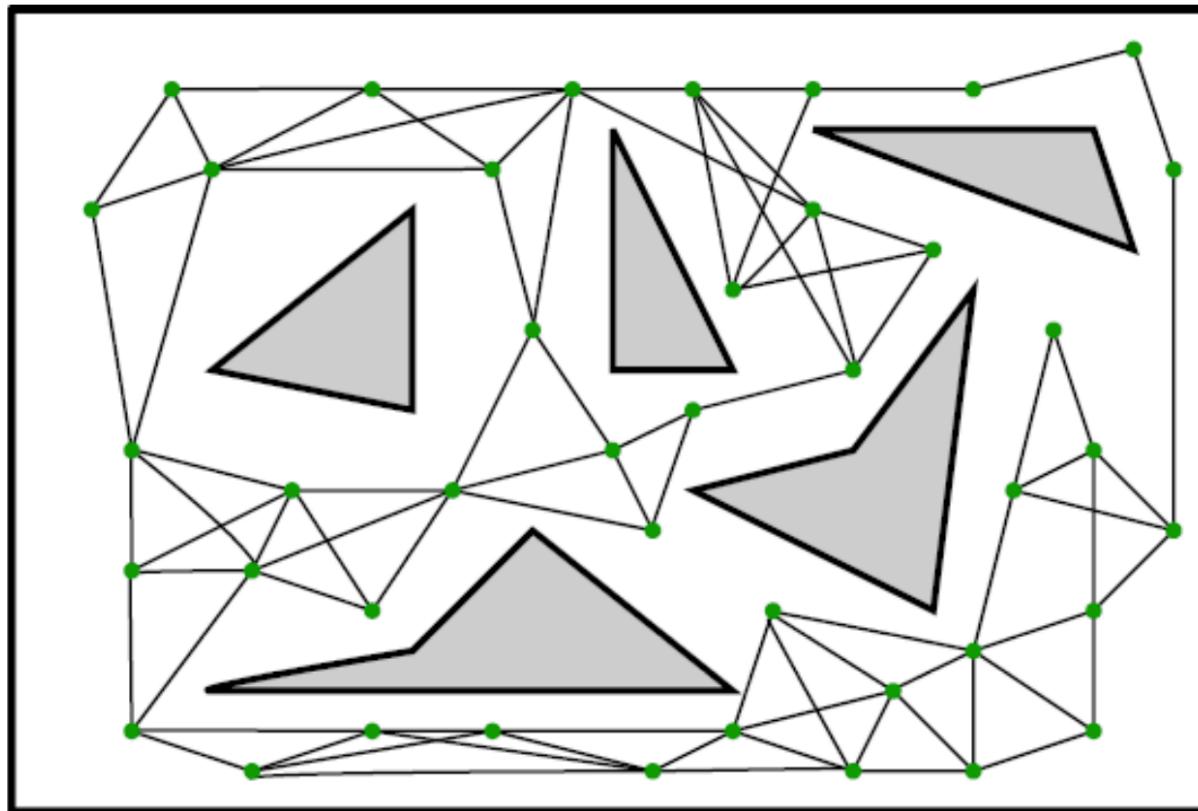


Figure 5.14: Grasp coordinate frames.

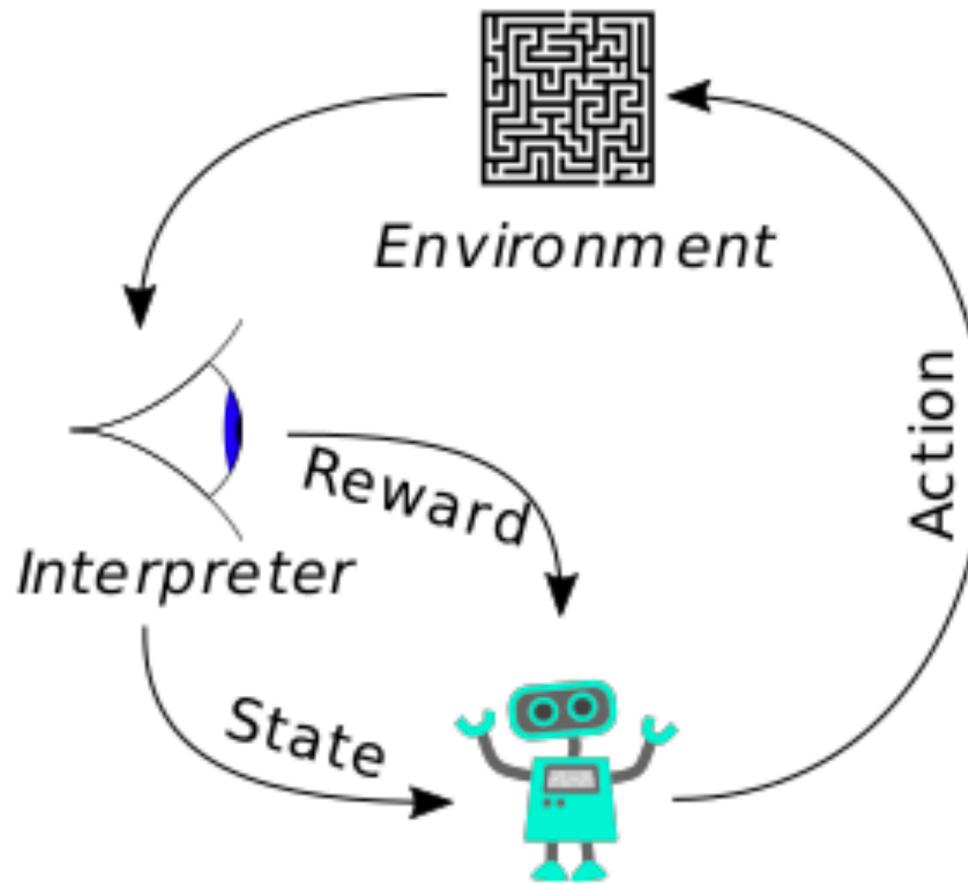
Topics Covered in This Course

- Classical Planning and Control



Topics Covered in This Course

- Concepts of Reinforcement Learning



Topics Covered in This Course

- Deep RL Frameworks

Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih Kd

Trust Region Policy Optimization

{vlad, koray, david, a

John Schulman

Sergey Levine

Philippe Moritz

Michael Jordan

Pieter Abbeel

We present the first directly from high-dimensional model is a convolutional neural network whose input is raw sensor data and rewards. We apply our model to the Mountain Car Environment, where we find that it outperforms a human expert on a task that requires planning.

Abs

We describe an iterative policies, with guarantee. By making several theoretically-justified practical algorithm, called Optimization (TRPO).

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Soft Actor-Critic: Off-Policy Maximum Entropy Deep Reinforcement Learning with a Stochastic Actor

Tuomas Haarnoja¹ Aurick Zhou¹ Pieter Abbeel¹ Sergey Levine¹

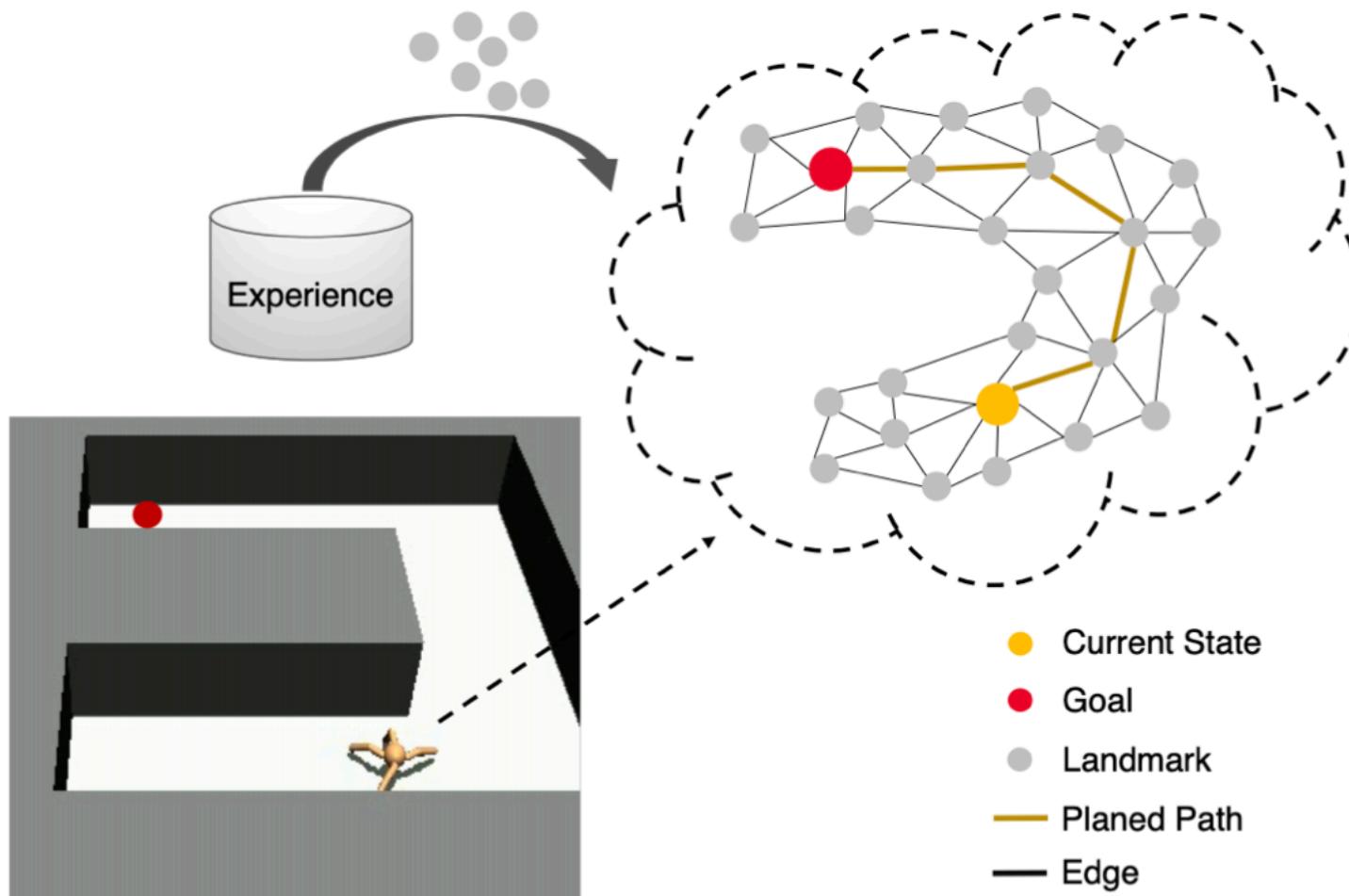
Abstract

Model-free deep reinforcement learning (RL) algorithms have been demonstrated on a range of challenging decision making and control tasks. However, these methods typically suffer from two major challenges: very high sample complexity and brittle convergence properties, which necessitate meticulous hyperparameter tuning. Both of these challenges severely limit the applicability

of these methods in real-world domains has been hampered by two major challenges. First, model-free deep RL methods are notoriously expensive in terms of their sample complexity. Even relatively simple tasks can require millions of steps of data collection, and complex behaviors with high-dimensional observations might need substantially more. Second, these methods are often brittle with respect to their hyperparameters: learning rates, exploration constants, and other settings must be set carefully for different problem settings to achieve good results. Both of these challenges

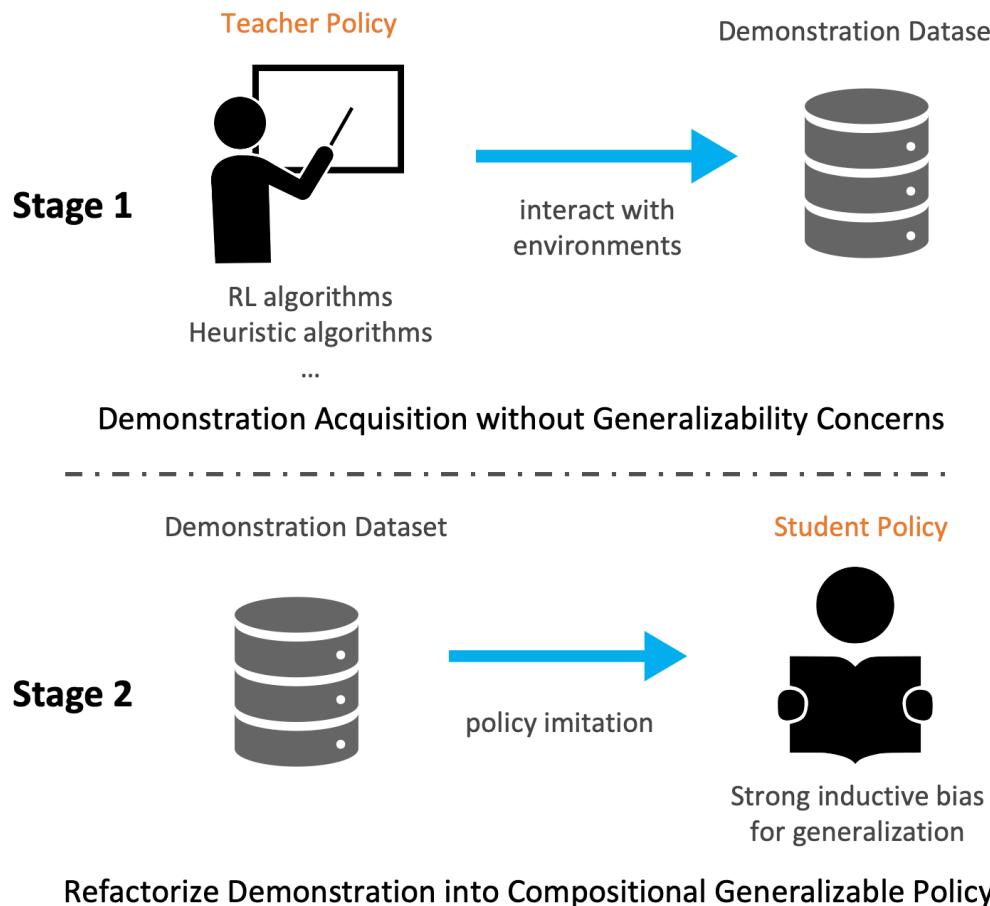
Topics Covered in This Course

- Hierarchical RL



Topics Covered in This Course

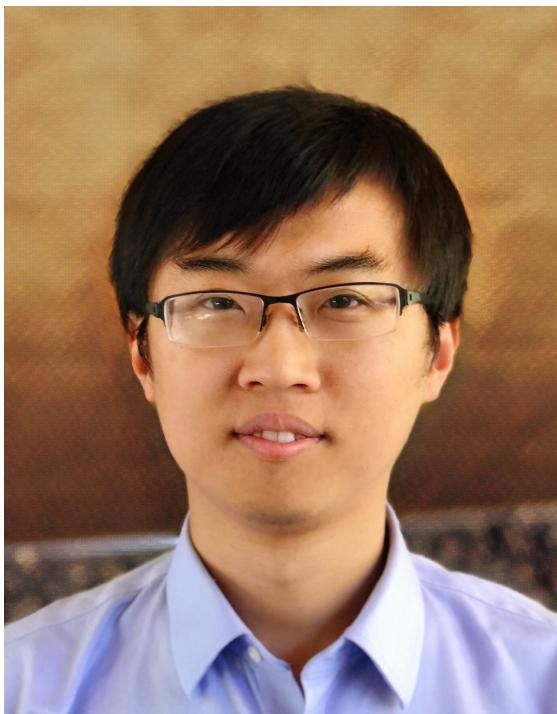
- Generalizability of RL



Course Logistic

Instructors

Instructor: Hao Su



TA: Minghua Liu



Teaching Goal

- Foundational
 - Programming problems ask you to **implement low-level modules from scratch**
- Hands-on
 - **Heavy** programming assignments to exercise what are taught in class

Pre-requisite: Technique

- **Skilled** in Linear Algebra, Multi-variable Calculus, and Deep Learning
- **Familiar** with Probability and Numerical Methods
- **Strong** programming skills
 - Familiar with Linux Toolchain
 - Familiar with python, numpy, and pytorch
- Course/project experiences in deep learning

Background Check

- On Piazza now (HW0)
 - Visible to enrolled and waitlist students
- 5 points in your final grade
- **Mandatory!** We will not grade your subsequent homeworks without seeing your HW0.
- If you are in the waitlist and intend to enroll, you need to submit HW0 by this deadline
- Due: 04/06/2021

Pre-requisite: Resources

- This course requires deep learning resources (to run reinforcement learning challenges)
- Unfortunately, we do not have computational resources to support ~50 students
- Please find the server with the following configuration:
 - $\geq 50G$ disk space
 - ≥ 1 GPU for deep learning

Assignments

- 4 assignments and 1 final project
 - HW0: due week 2 (5 points)
 - HW1: due week 4 (20 points)
 - HW2: due week 6 (20 points)
 - HW3: due week 8 (20 points)
 - Final project: final week (35 points)
 - No mid-term/final exams
- Extra credit for participation 5% (ask/answer questions in class, attend office hours)
- Late policy: 15% grade reduction for each 12 hours late. No acceptance 72 hours after the due time.

Assignments

- HW1-HW3: practice basic concepts and algorithms; build individual modules
- Final project: integrate modules and test new ideas. Score by performance ranking. Online evaluation system will be set up.
- We estimate **≥ 15 hrs per week** (out of class) solid time commitment
- We allow you to see homework (through Piazza) and attend the competition *even if you audit the course*

Course Resources

- Course website: <https://haosulab.github.io/ml-for-robotics/SP21/index.html> (Google “Hao Su” → Prof. Homepage → Teaching → this link)
 - Collaboration policy
 - Lecture slides
 - Office hour and location
- Piazza
 - Homework/Solution release
 - Discussions

Office Hour

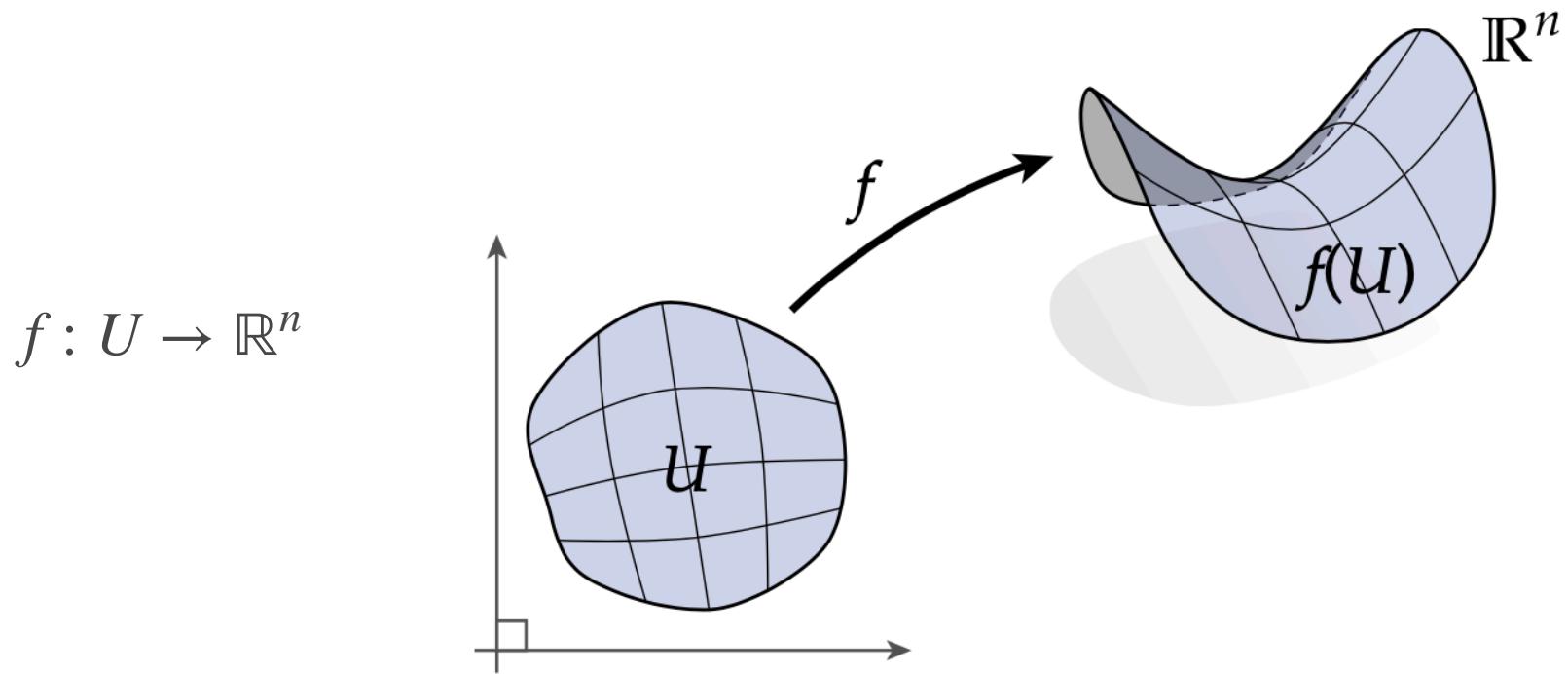
- Time to be determined.
- Please fill in our Piazza survey for information about time zone and etc.

Questions?

Concepts of Differential Geometry

Parameterized Surfaces

A **parameterization** is a map from the domain U into \mathbb{R}^n



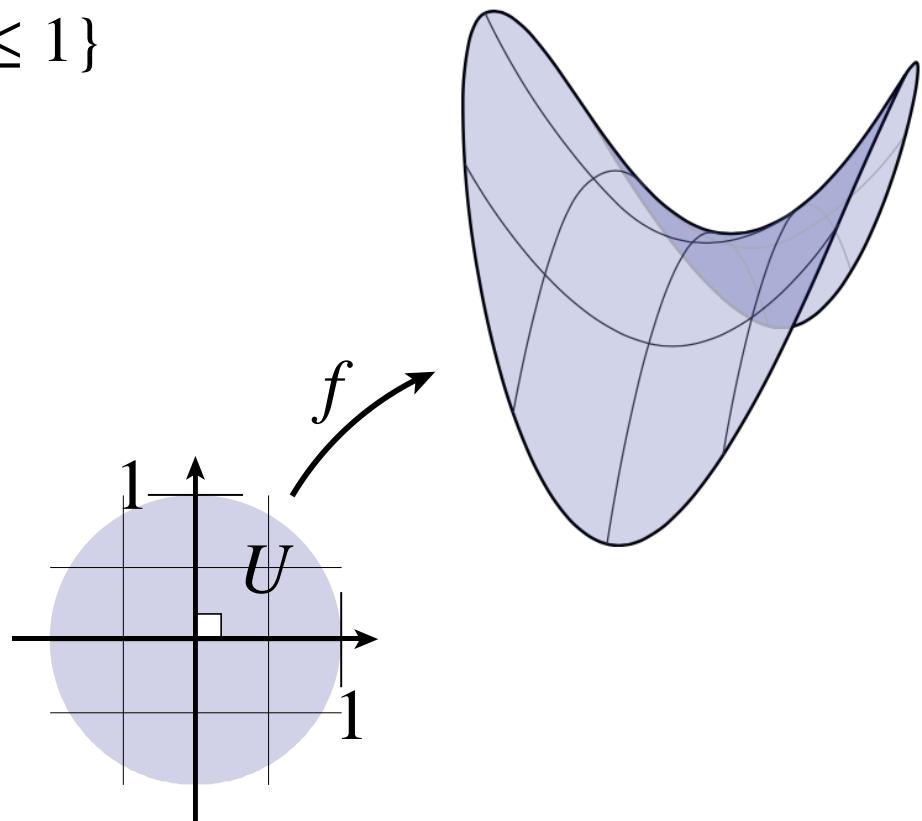
The set of points $f(U)$ is called the **image** of the parameterization.

Example

- Example: We can express a *saddle* as a *parameterized surface*:

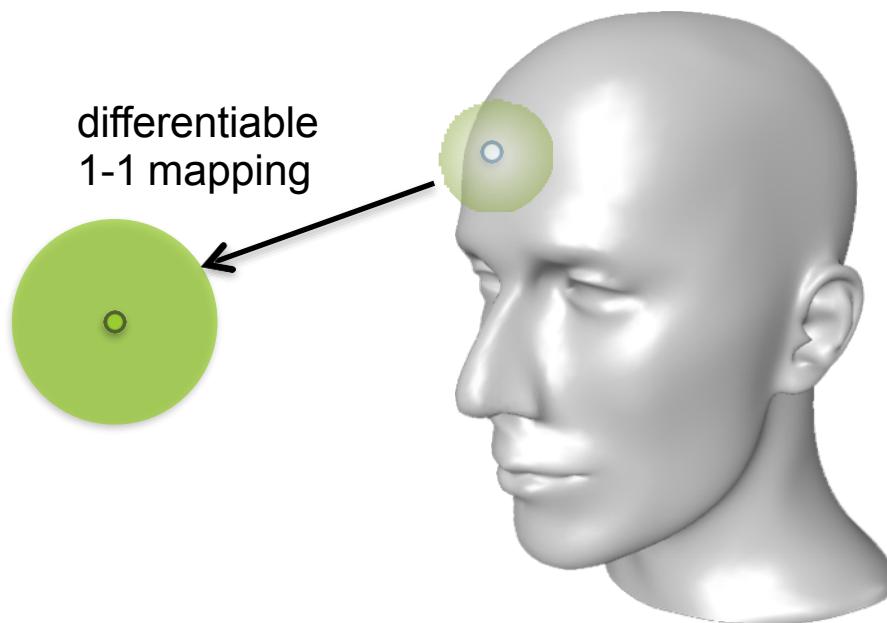
$$U := \{(u, v) \in \mathbb{R}^2 : u^2 + v^2 \leq 1\}$$

$$f(u, v) = [u, v, u^2 - v^2]^T$$



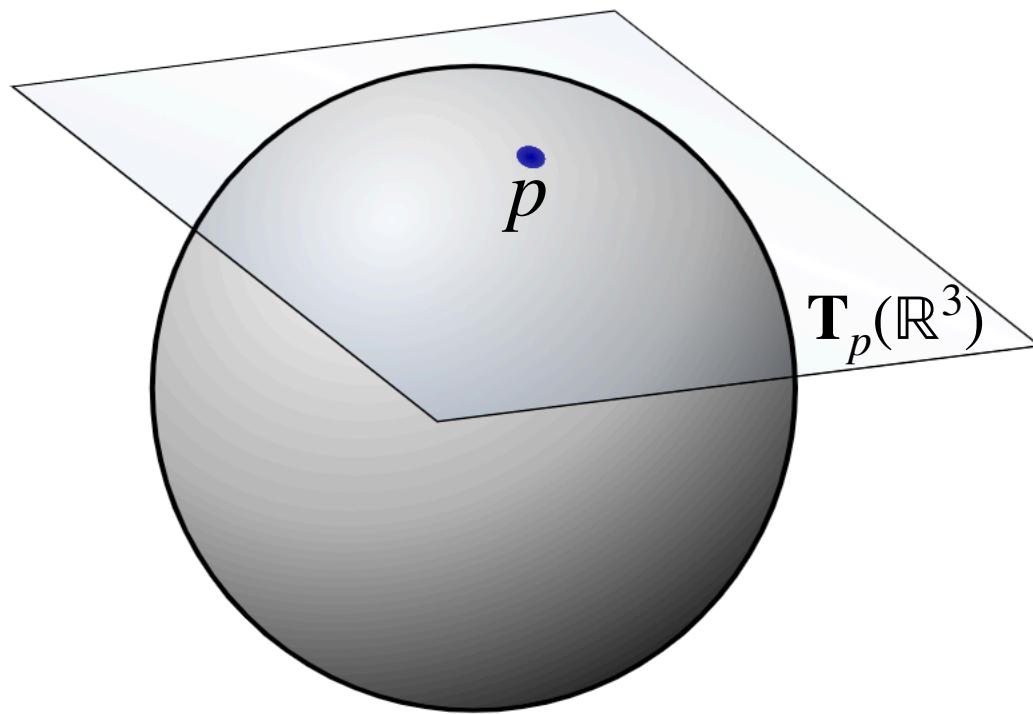
Manifold

- Things that can be discovered by local observation:
point + neighborhood



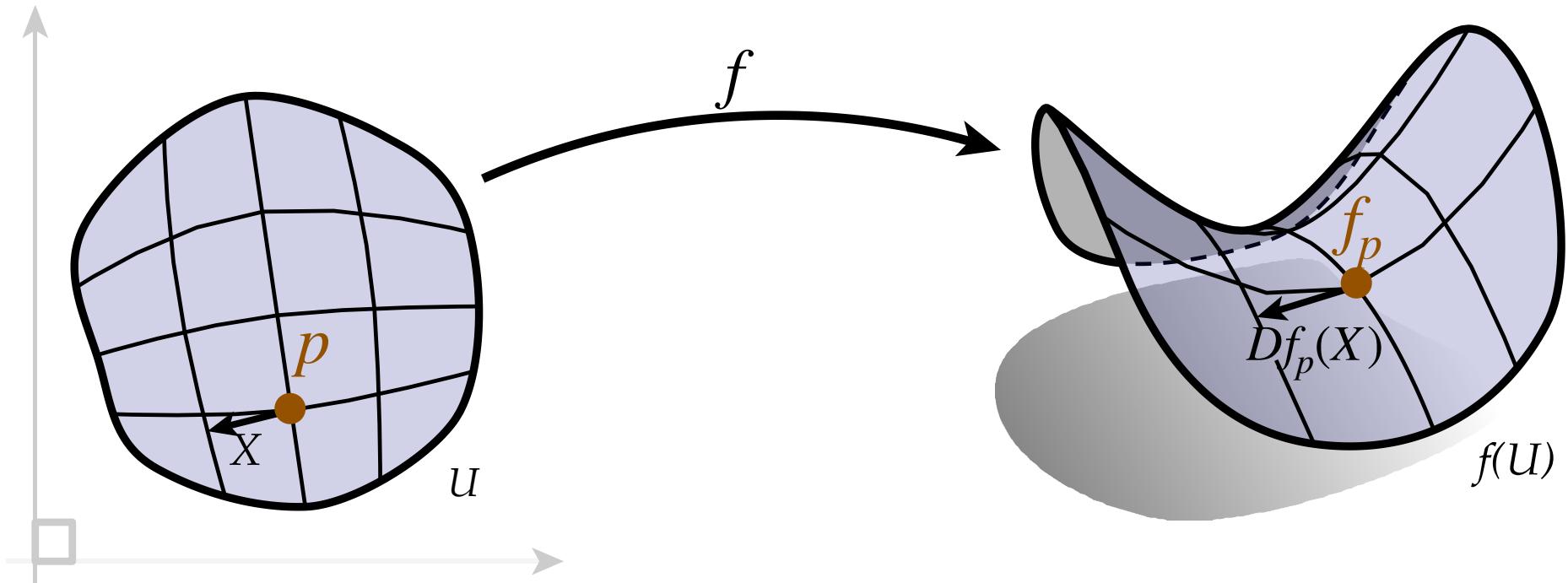
Tangent Plane

- One can attach to every point p a tangent plane \mathbf{T}_p
- Intuitively, it contains the possible directions in which one can tangentially pass through p .

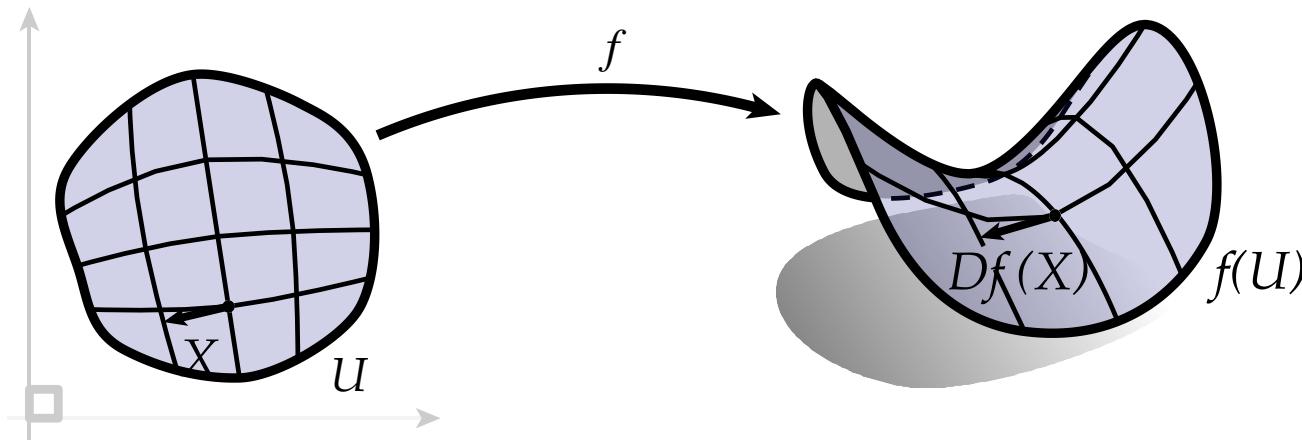


Differential of a Surface

- Relate the movement of point in the domain and on the image



Differential of a Surface

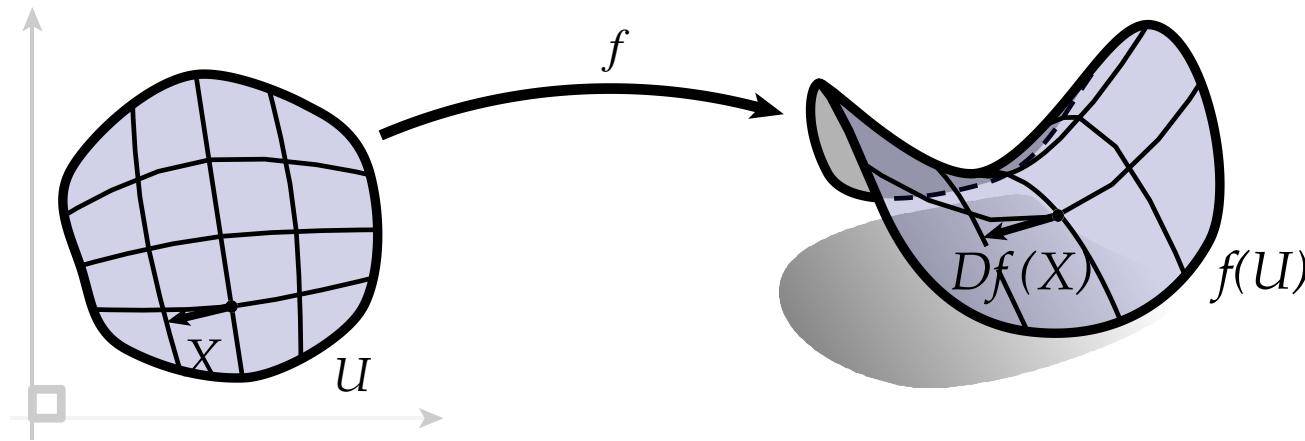


Total differential: $df = \frac{\partial f}{\partial u} du + \frac{\partial f}{\partial v} dv \rightarrow \Delta f \approx \frac{\partial f}{\partial u} \Delta u + \frac{\partial f}{\partial v} \Delta v$

If point $p \in \mathbb{R}^2$ moves along vector $X = [u, v]^T$ by ϵ , the movement of f_p is:

$$\Delta f_p \approx \frac{\partial f}{\partial u}(\epsilon u) + \frac{\partial f}{\partial v}(\epsilon v) = \epsilon \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v} \right] \begin{bmatrix} u \\ v \end{bmatrix}$$

Differential of a Surface



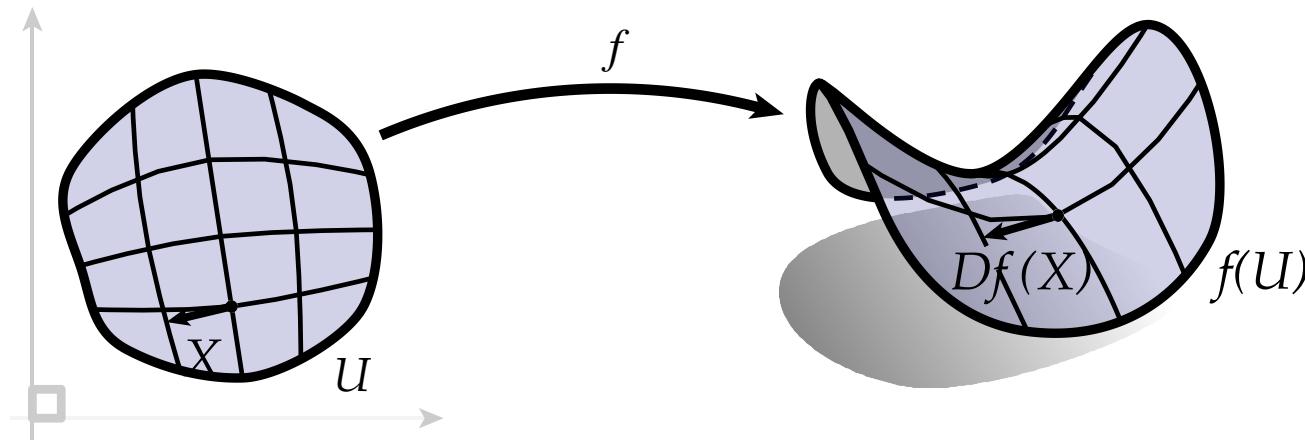
Total differential: $df = \frac{\partial f}{\partial u} du + \frac{\partial f}{\partial v} dv$

If point $p \in \mathbb{R}^2$ moves with velocity $X = [u, v]^T$ by ϵ , the movement of f_p is:

$$\Delta f_p \approx \frac{\partial f}{\partial u}(\epsilon u) + \frac{\partial f}{\partial v}(\epsilon v) = \epsilon \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v} \right] \begin{bmatrix} u \\ v \end{bmatrix}$$

$$Df_p := \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v} \right] \in \mathbb{R}^{3 \times 2}$$

Differential of a Surface



Total differential: $df = \frac{\partial f}{\partial u} du + \frac{\partial f}{\partial v} dv$

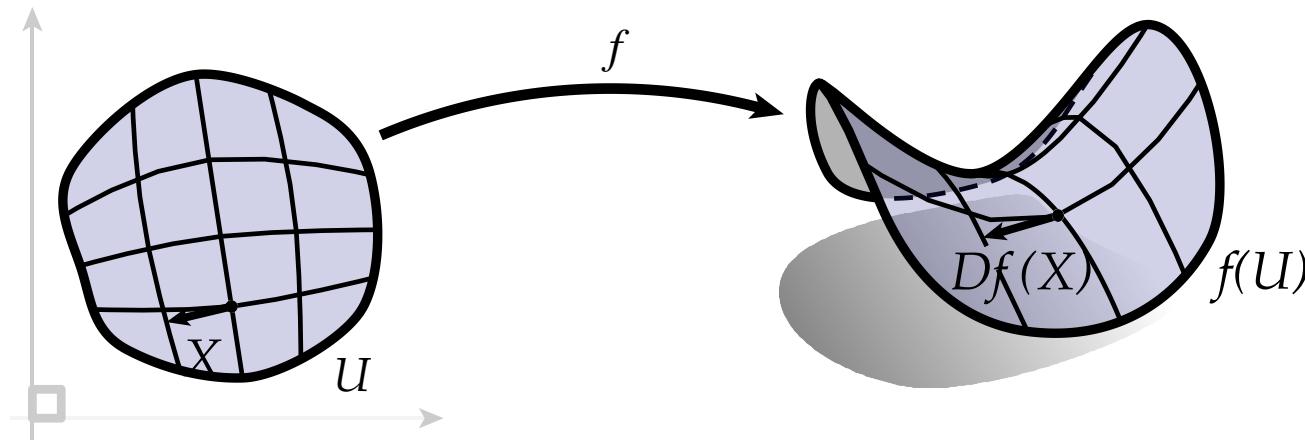
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$$Df_p := \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v} \right] \in \mathbb{R}^{3 \times 2}$$

Df_p: differential (Jacobian),
a linear map.

Differential of a Surface



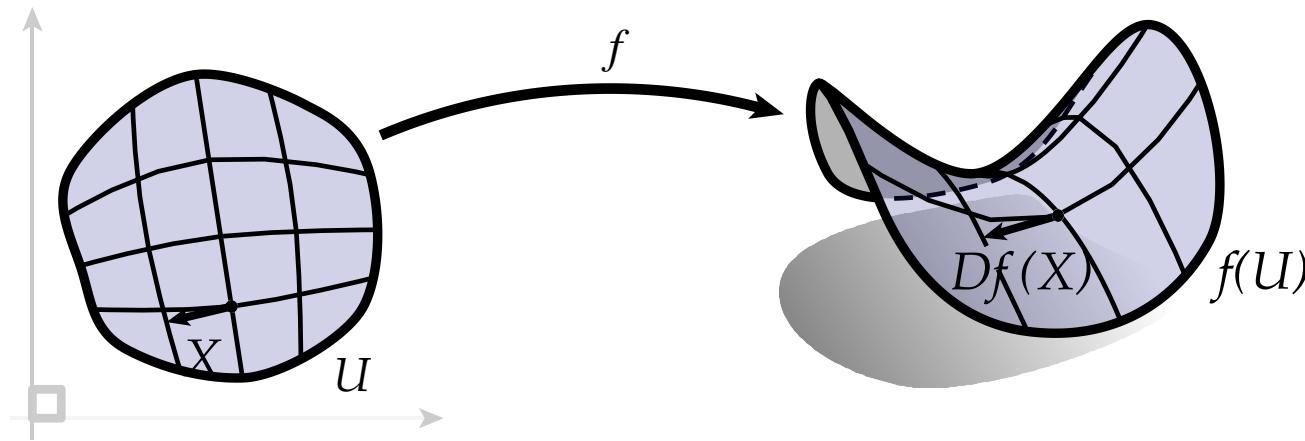
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$$Df_p := \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v} \right] \in \mathbb{R}^{3 \times 2} \quad \text{velocity in the 2D domain}$$

Differential of a Surface



Total differential: $df = \frac{\partial f}{\partial u} du + \frac{\partial f}{\partial v} dv$

If point $p \in \mathbb{R}^2$ moves with velocity $X = [u, v]^T$ by ϵ , the movement of f_p is:

velocity in 3D space

$$\Delta f_p \approx \frac{\partial f}{\partial u}(\epsilon u) + \frac{\partial f}{\partial v}(\epsilon v) = \epsilon \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v} \right] \begin{bmatrix} u \\ v \end{bmatrix} = \epsilon [Df_p] \boxed{X}$$

$$Df_p := \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v} \right] \in \mathbb{R}^{3 \times 2}$$

velocity in 2D domain

Rigid Transformation

Describe the Pose of Agent and Objects



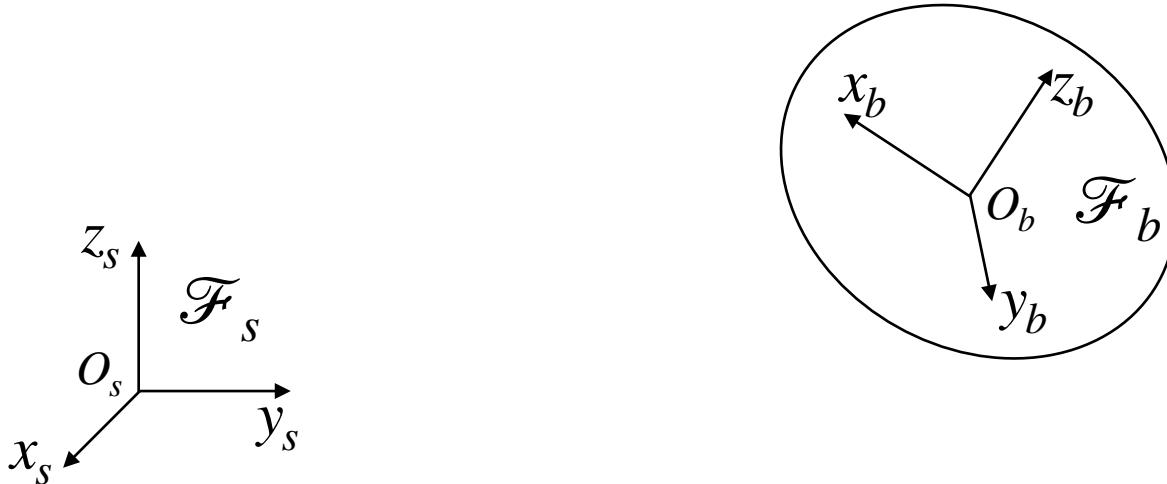
Describe the Pose of Agent and Objects



Position &
Orientation

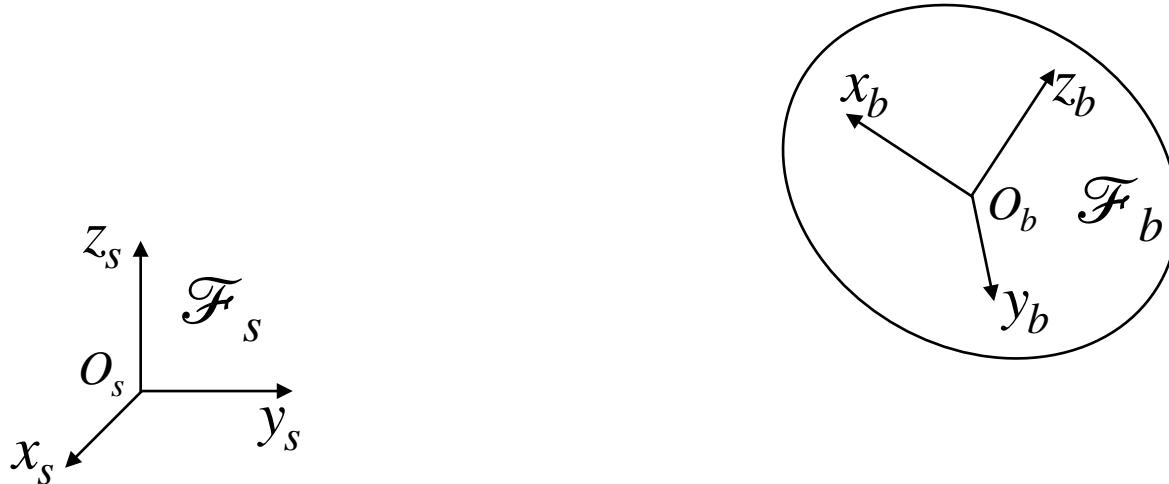


Rigid Transformation



- An observer **records** the position of any point in the space **using a frame** \mathcal{F}_s (space frame)
- There is a rigid object, to which we bind a frame \mathcal{F}_b (body frame) tightly, so that \mathcal{F}_b moves along with the object

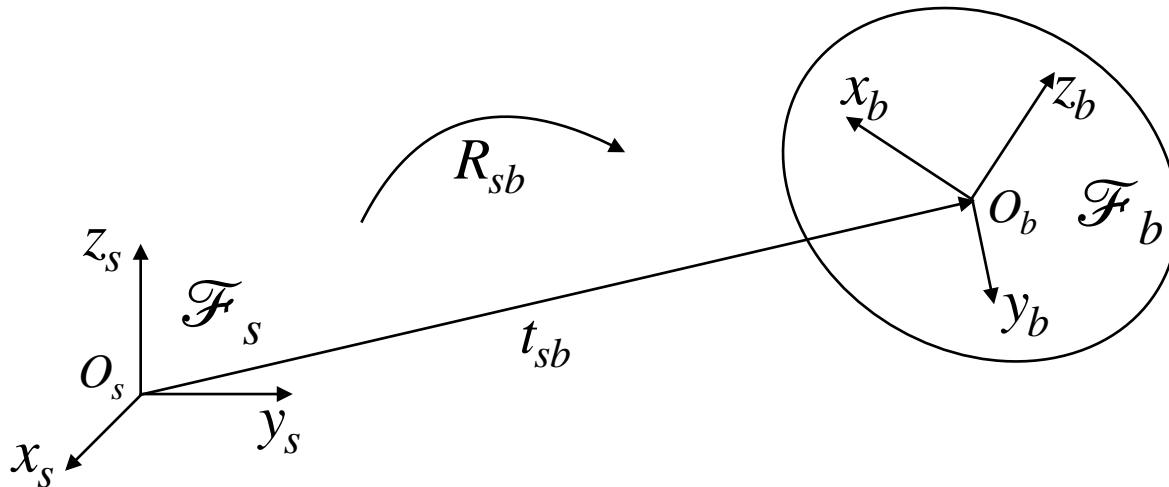
Rigid Transformation



- When talking about the pose of the *rigid* object, we ask:

How to **transform** \mathcal{F}_s so that it overlaps with \mathcal{F}_b ?

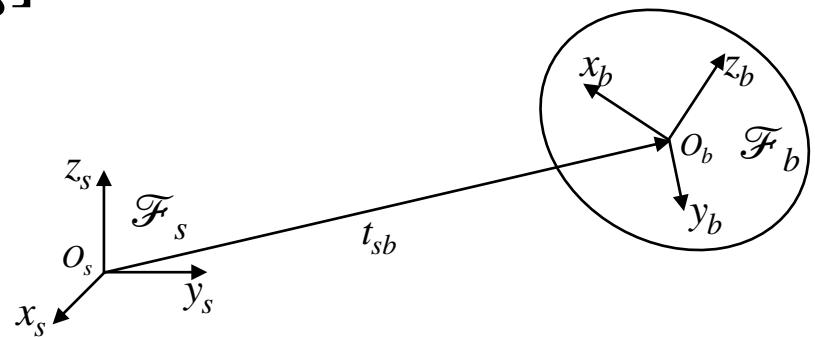
Rigid Transformation



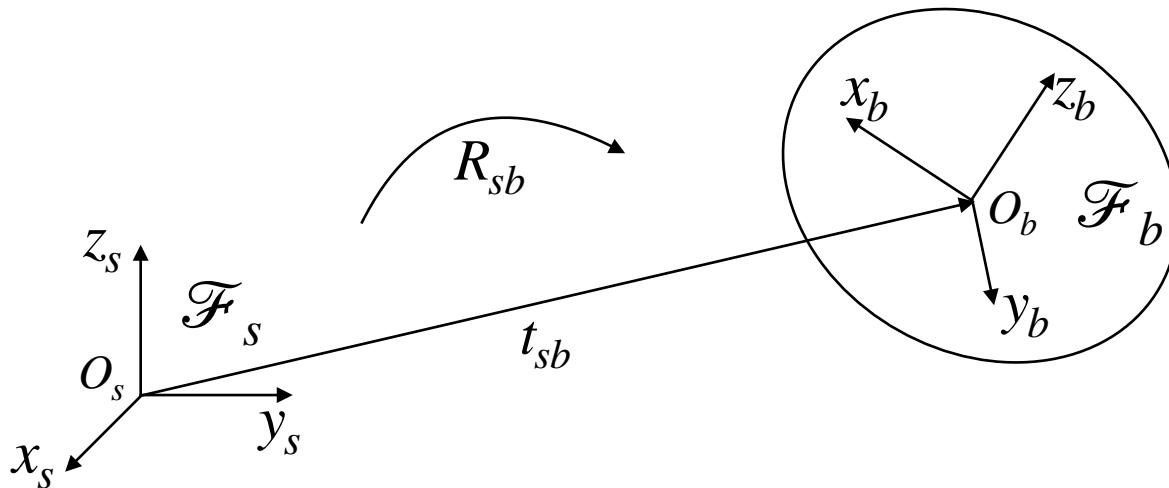
- We first translate \mathcal{F}_s by t_{sb} to align O_s and O_b
- And then rotate by R_{sb} to align $\{x_i, y_i, z_i\}$

Rigid Transformation

- Formally,
 - $O_b = O_s + t_{sb}$
 - $[x_b, y_b, z_b] = R_{sb}[x_s, y_s, z_s]$
- Since the observer records everything using \mathcal{F}_s ,
 - $O_s = 0$
 - $[x_s, y_s, z_s] = I_{3 \times 3}$
- Therefore,
 - $t_{sb} = O_b$
 - $R_{sb} = [x_b, y_b, z_b] \in \mathbb{R}^{3 \times 3}$



Effect of (R_{sb}, t_{sb}) on Frames



- First of all, (R_{sb}, t_{sb}) transforms any point in the *whole space*:

$$x' = R_{sb}x + t_{sb}$$

Effect of (R_{sb}, t_{sb}) on Frames

- Suppose $\mathcal{F}_p = \{O_p, (x_p, y_p, z_p)\}$ is a frame at an arbitrary point O_p
- **Then, the new origin is:** $O'_p = ?$

Effect of (R_{sb}, t_{sb}) on Frames

- Suppose $\mathcal{F}_p = \{O_p, (x_p, y_p, z_p)\}$ is a frame at an arbitrary point O_p
- **Then, the new origin is:** $O'_p = R_{sb}O_p + t_{sb}$

Effect of (R_{sb}, t_{sb}) on Frames

- Suppose $\mathcal{F}_p = \{O_p, (x_p, y_p, z_p)\}$ is a frame at an arbitrary point O_p
- **Then, the new origin is:** $O'_p = R_{sb}O_p + t_{sb}$
- How about the frame?
 - Assume three curves, $\gamma_x, \gamma_y, \gamma_z$, passing O_p at $t = 0$ with tangents x_p, y_p, z_p

Effect of (R_{sb}, t_{sb}) on Frames

- Suppose $\mathcal{F}_p = \{O_p, (x_p, y_p, z_p)\}$ is a frame at an arbitrary point O_p
- **Then, the new origin is:** $O'_p = R_{sb}O_p + t_{sb}$
- How about the frame?
 - Assume three curves, $\gamma_x, \gamma_y, \gamma_z$, passing O_p at $t = 0$ with tangents x_p, y_p, z_p
 - Then, the new tangents after transformation are:
$$\frac{d}{dt}R_{sb}\gamma_x(0), \frac{d}{dt}R_{sb}\gamma_y(0), \frac{d}{dt}R_{sb}\gamma_z(0)$$

Effect of (R_{sb}, t_{sb}) on Frames

- Suppose $\mathcal{F}_p = \{O_p, (x_p, y_p, z_p)\}$ is a frame at an arbitrary point O_p
- **Then, the new origin is:** $O'_p = R_{sb}O_p + t_{sb}$
- How about the frame?
 - Assume three curves, $\gamma_x, \gamma_y, \gamma_z$, passing O_p at $t = 0$ with tangents x_p, y_p, z_p
 - Then, the new tangents after transformation are:
$$\frac{d}{dt}R_{sb}\gamma_x(0) = R_{sb}x_p, \frac{d}{dt}R_{sb}\gamma_y(0) = R_{sb}y_p, \frac{d}{dt}R_{sb}\gamma_z(0) = R_{sb}z_p$$
- **So the new frame is:** $\mathcal{F}_{p'} = \{O'_p, R_{sb}[x_p, y_p, z_p]\}$

$\text{SO}(3)$ and $\text{SE}(3)$

Rotation in \mathbb{R}^3



3 Degree of Freedoms

$\mathbb{SO}(3)$: The Space of Rotations

- $\mathbb{SO}(n) = \{R \in \mathbb{R}^{n \times n} : \det(R) = 1, RR^T = I\}$
- $\mathbb{SO}(n)$: “Special Orthogonal Group”
- “Group”: roughly, closed under matrix multiplication
- “Orthogonal”: $RR^T = I$
- “Special”: $\det(R) = 1$
- $\mathbb{SO}(2)$: 2D rotations, 1 DoF
- $\mathbb{SO}(3)$: 3D rotations, 3 DoF

Homogenous Coordinates

- Homogeneous coordinate for 3D Space:

$$\tilde{x} := \begin{bmatrix} x \\ 1 \end{bmatrix} \in \mathbb{R}^4$$

- Homogeneous transformation matrix:

$$T_{sb} = \begin{bmatrix} R_{sb} & t_{sb} \\ 0 & 1 \end{bmatrix}$$

- Rigid transformation under linear form:

$$\tilde{x}' = T_{sb}\tilde{x}$$

- Composition: $T_{ac} = T_{ab}T_{bc}$

$\text{SE}(3)$: The Space of Rigid Transformations

- $\text{SE}(3) := \left\{ T = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix}, R \in \text{SO}(3), t \in \mathbb{R}^3 \right\}$
- $\text{SE}(3)$: “Special Euclidean Group”
- “Group”: roughly, closed under matrix multiplication
- “Euclidean”: R and t
- “Special”: $\det(R) = 1$
- 6 DoF

Multi-Link Rigid-Body Geometry

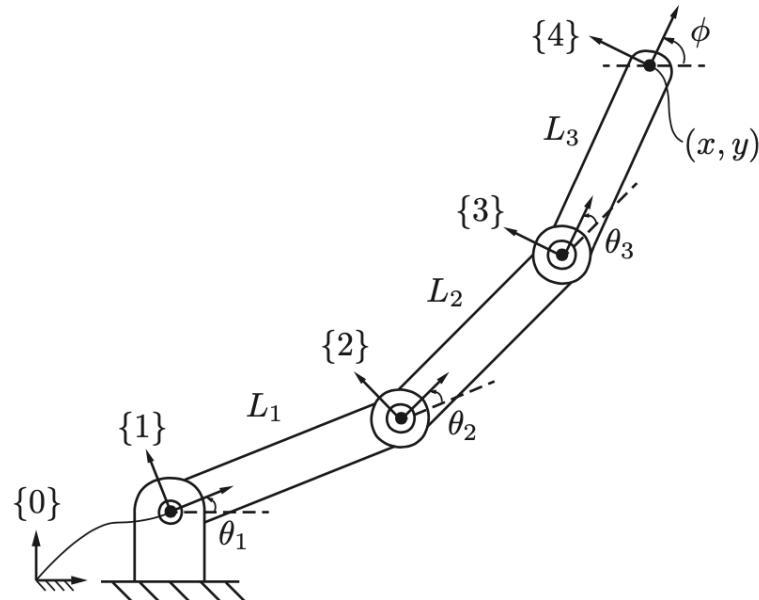
Link and Joint

Link:

- **Links** are the rigid-body connected in sequence

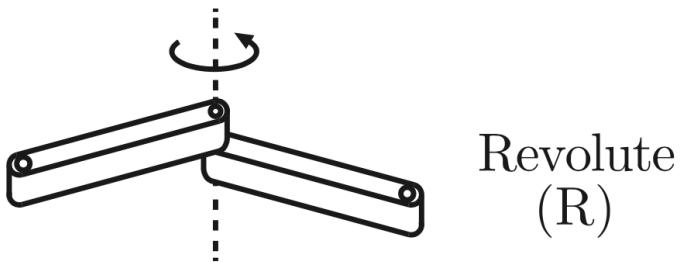
Joint:

- **Joints** are the connectors between links. They determine the DoF of motion between adjacent links



Two Common Joint Types

- Revolute/Hinge/Rotational joint



Revolute
(R)

- Prismatic/Translational joint



Prismatic
(P)

Kinematics: The Basic Geometry Calculation Task

- Kinematics: Describing the motion of bodies (position and velocity)
- Kinematics **does not consider** how to achieve motion via force



Kinematics Configuration

- Assuming frames are assigned to each link, we can parameterize **the pose of each joint**
 - Using the relative **angle** and **translation** between adjacent frames
- Two representations of the pose of the end-effector
 - **Joint space:** Each coordinate is a vector of joint poses (**angles around joint axis**)
 - **Cartesian space:** Each coordinate the rigid transformation of the end-effector (by (R, t))

Kinematics Equations

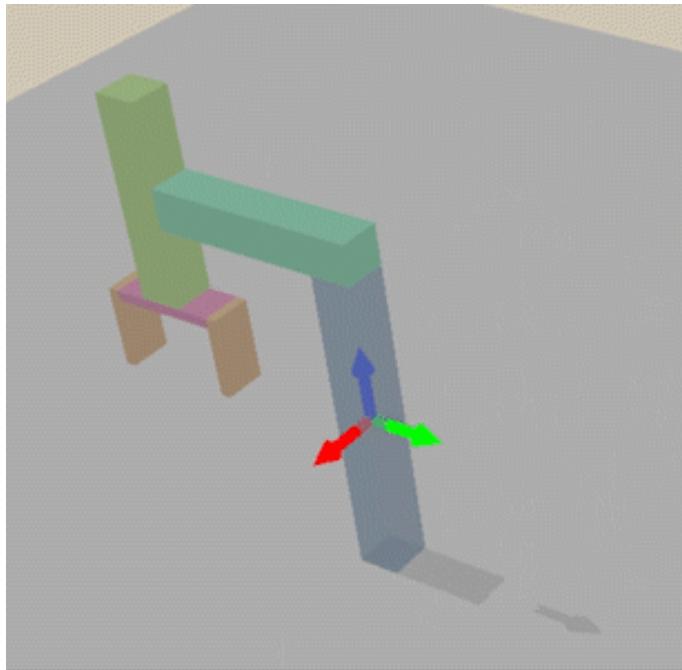
- Map the joint space coordinate $\theta \in \mathbb{R}^n$ to the Cartesian space coordinate $x \in \mathbb{R}^m$:

$$x = f(\theta)$$

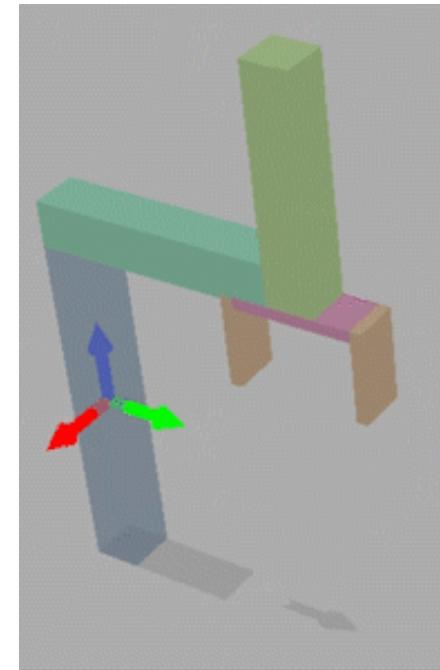
- Calculated by composing transformations along the kinematic chain

Example

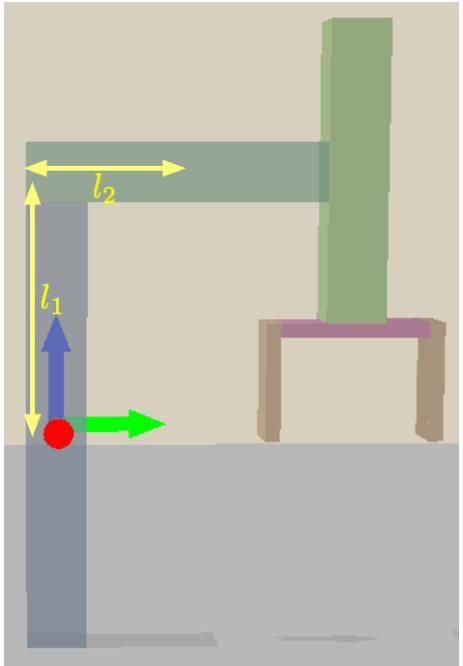
A simple 2 DoF robot arm



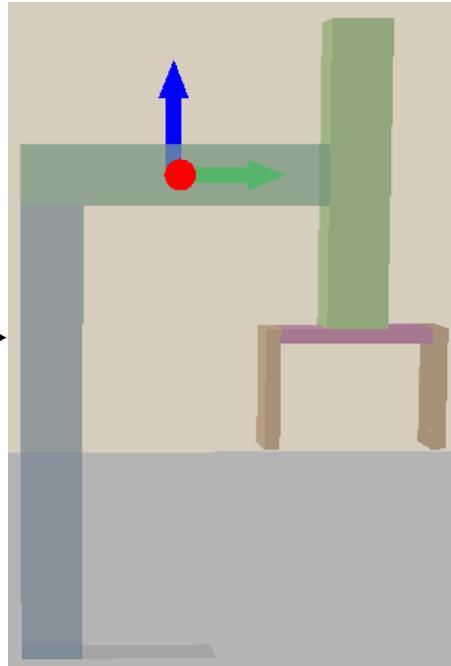
revolute(θ_1)



prismatic(θ_2)

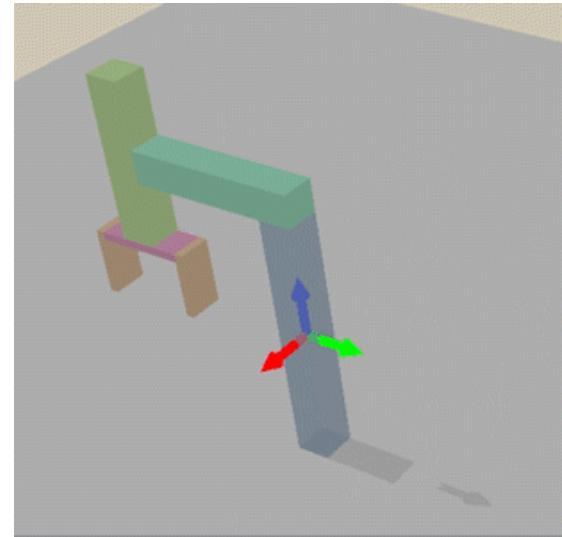


base

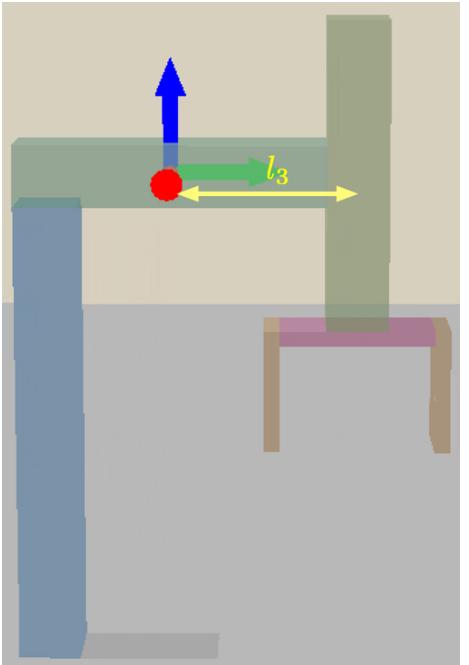


link1

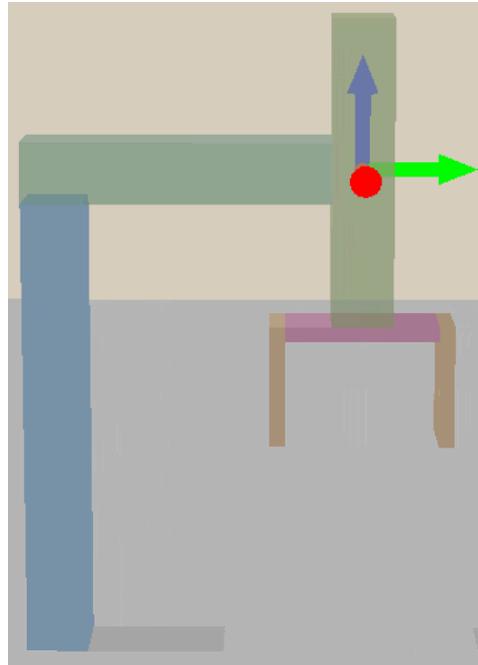
$$g_{01} = \begin{bmatrix} \cos \theta_1 & -\sin \theta_1 & 0 & -l_2 \sin \theta_1 \\ \sin \theta_1 & \cos \theta_1 & 0 & l_2 \cos \theta_1 \\ 0 & 0 & 1 & l_1 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$



revolute(θ_1)

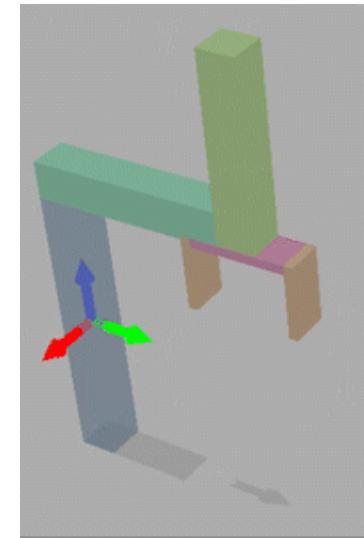


link1

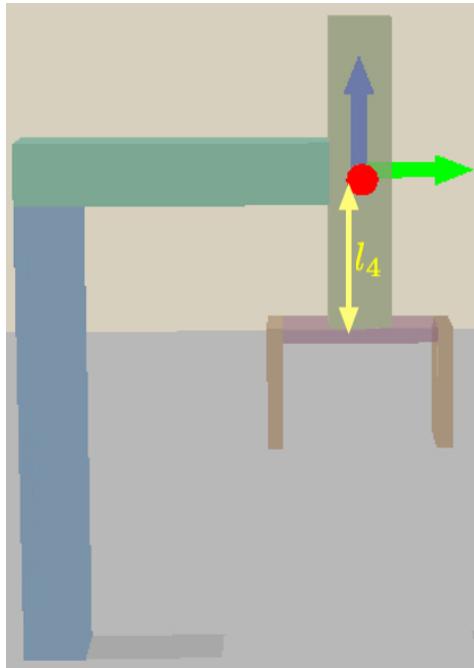


link2

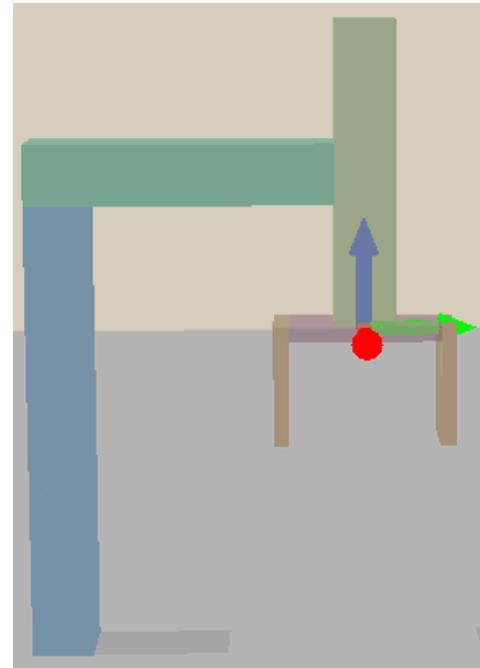
$$g_{12} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & l_3 \\ 0 & 0 & 1 & \theta_2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$



prismatic(θ_2)

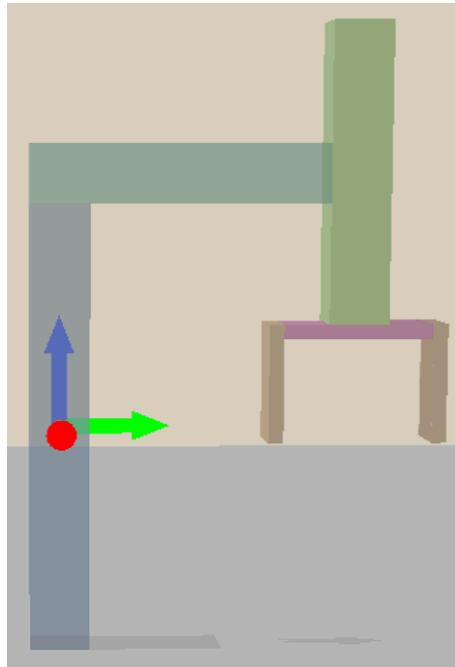


link2

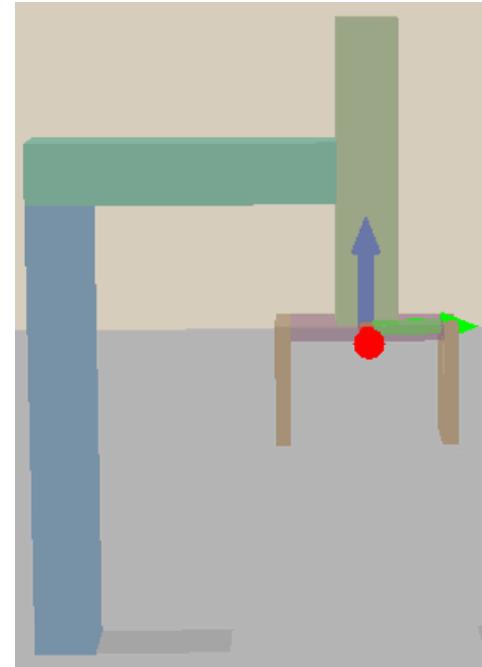


end_effector

$$g_{23} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & -l_4 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$



base



end_effector

$$g_{03} = g_{01}g_{12}g_{23} = \begin{bmatrix} \cos \theta_1 & -\sin \theta_1 & 0 & -\sin \theta_1(l_2 + l_3) \\ \sin \theta_1 & \cos \theta_1 & 0 & \cos \theta_1(l_2 + l_3) \\ 0 & 0 & 1 & l_1 - l_4 + \theta_2 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

How to Relate the Motion in Joint Space and Cartesian Space?

- Q1: If the robot moves by $\Delta\theta$ in the joint space, how much will it move in the Cartesian space? (Forward Kinematics)
- Q2: If the robot would move the end-effector by Δx in the Cartesian space, how shall it change its joint poses? (Inverse Kinematic)
- Suppose we parameterize (R, t) by the **angles** around **axis**, we need to derive the differential map

- We need some theoretical understanding of $\text{SO}(3)$ and $\text{SE}(3)$
 - The topological structure
 - The parameterization
 - The differentiable properties