L1: Introduction

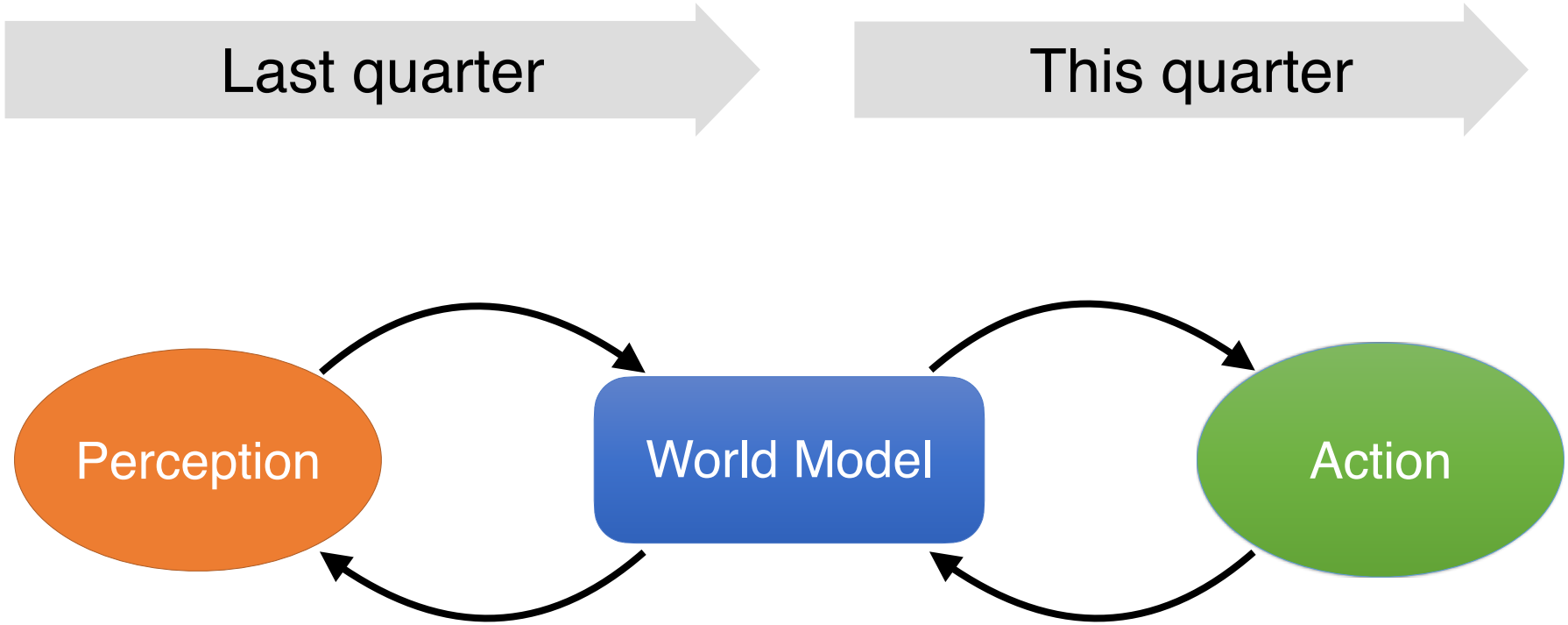
Hao Su

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

Agenda

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

Syllabus


Last quarter
This quarter
Perception
World Model
Action

Vision → Robotics

Passive AI

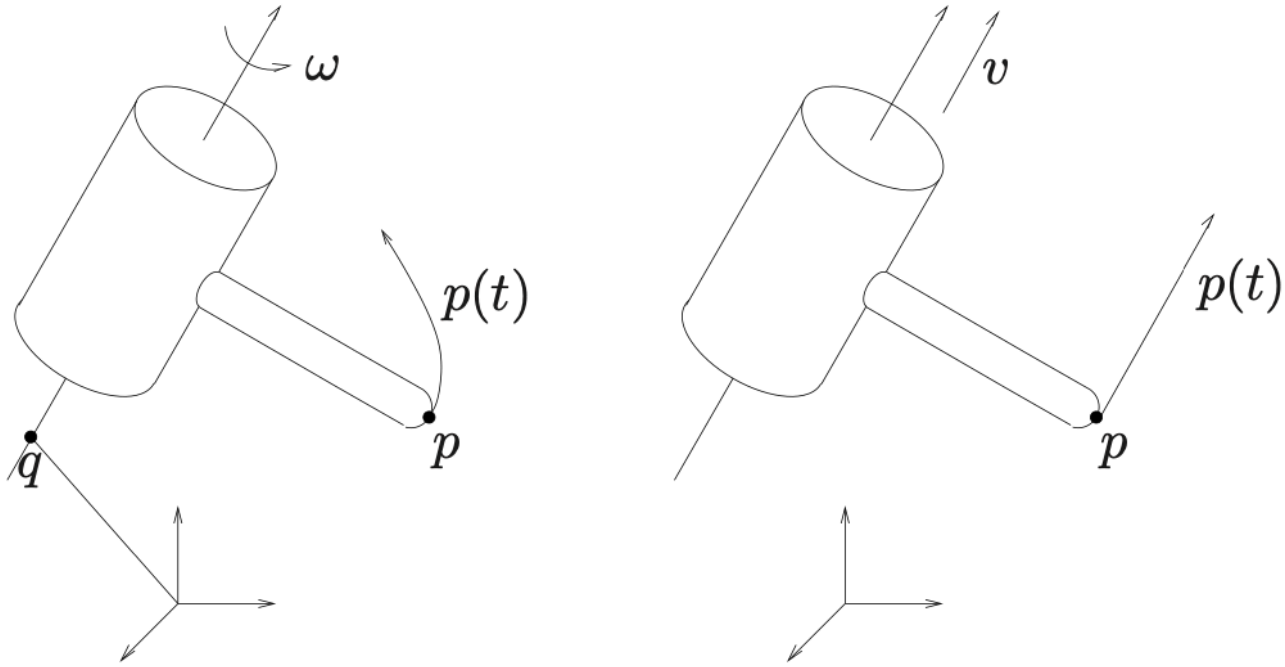
- We know how to fit data well (by “deep learning”)
  - e.g., computer vision, natural language processing

Vision → Robotics

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

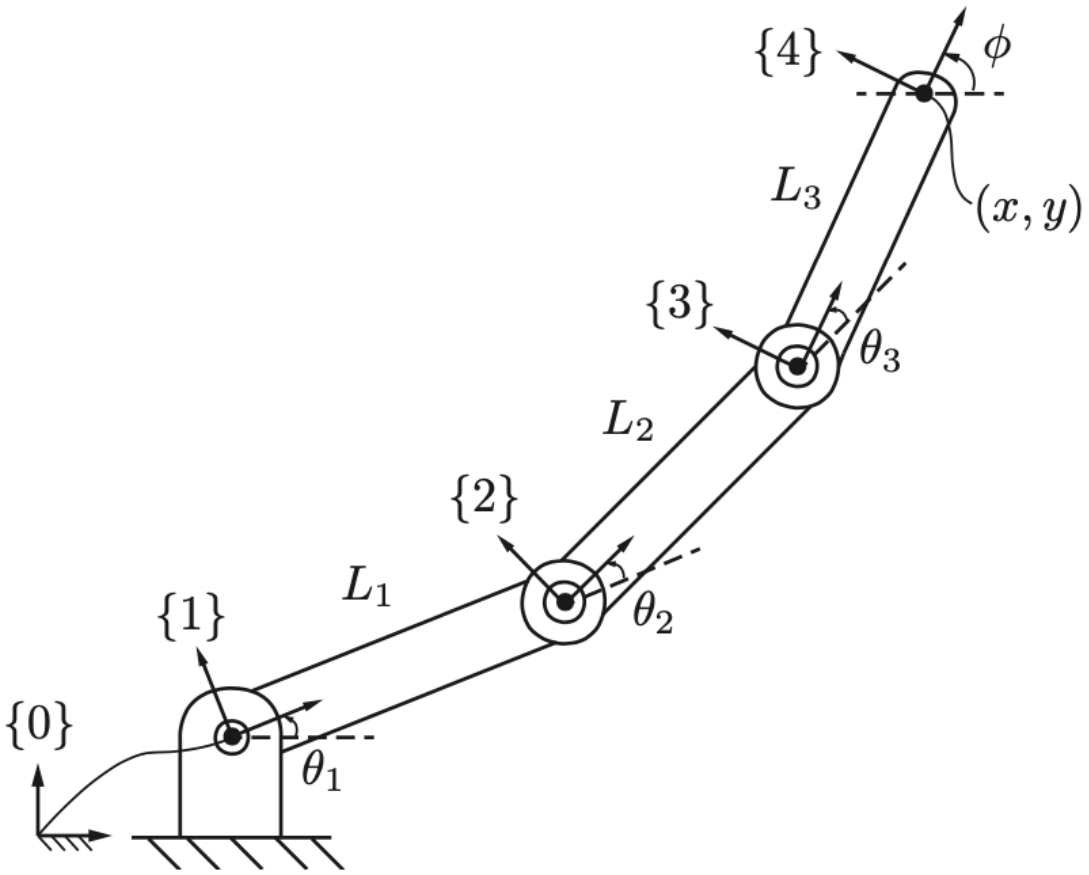
Topics Covered in This Course

- Modeling Robots by Rigid-Body Geometry



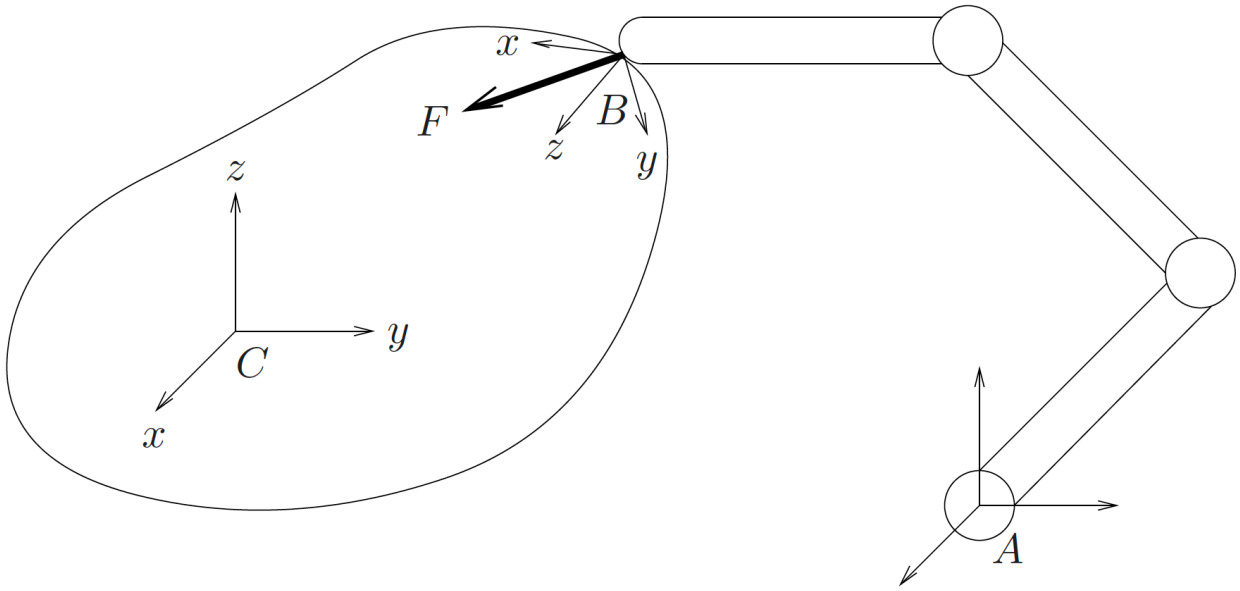
Topics Covered in This Course

- 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

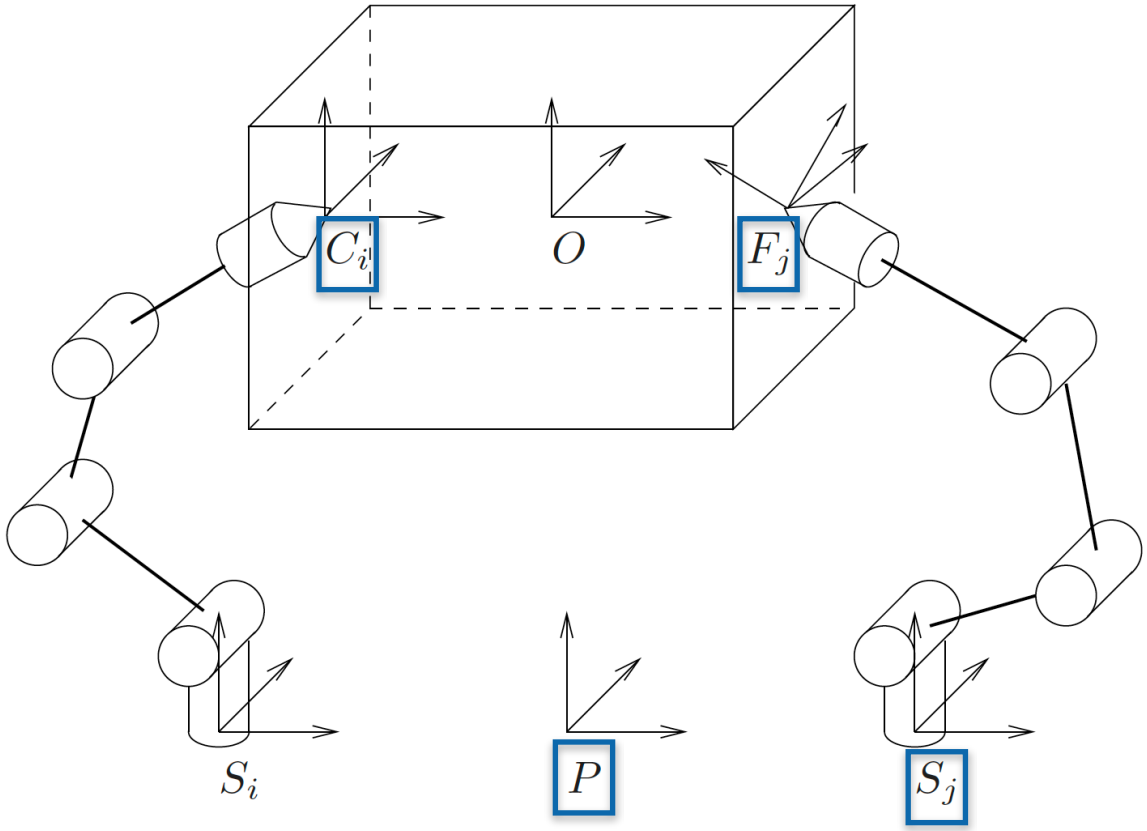
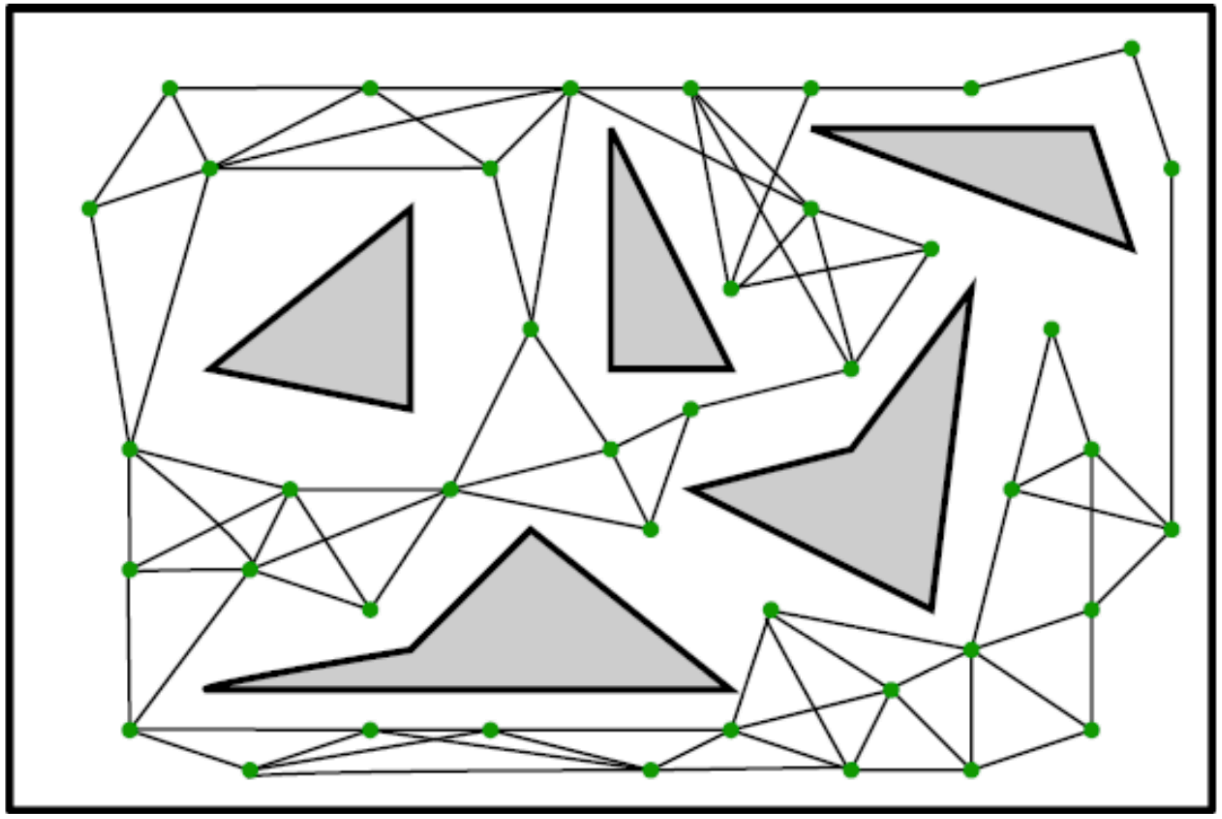


Figure 5.14: Grasp coordinate frames.

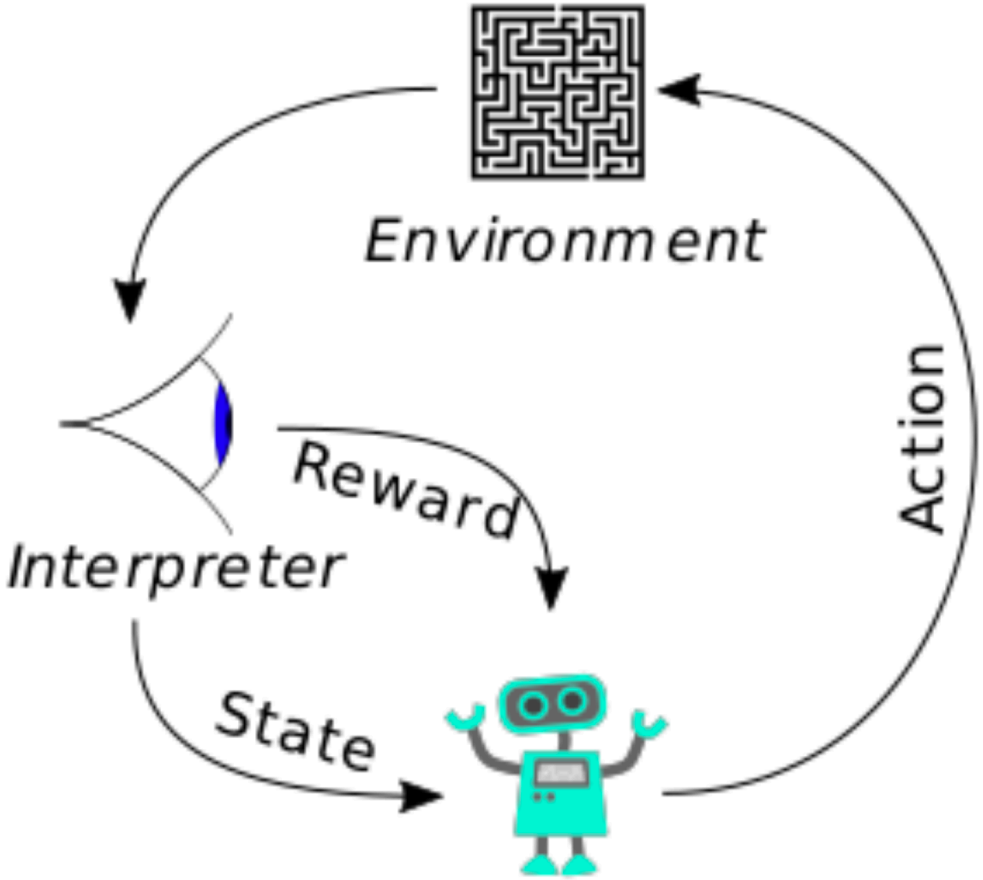
Topics Covered in This Course

- Classical Planning and Control



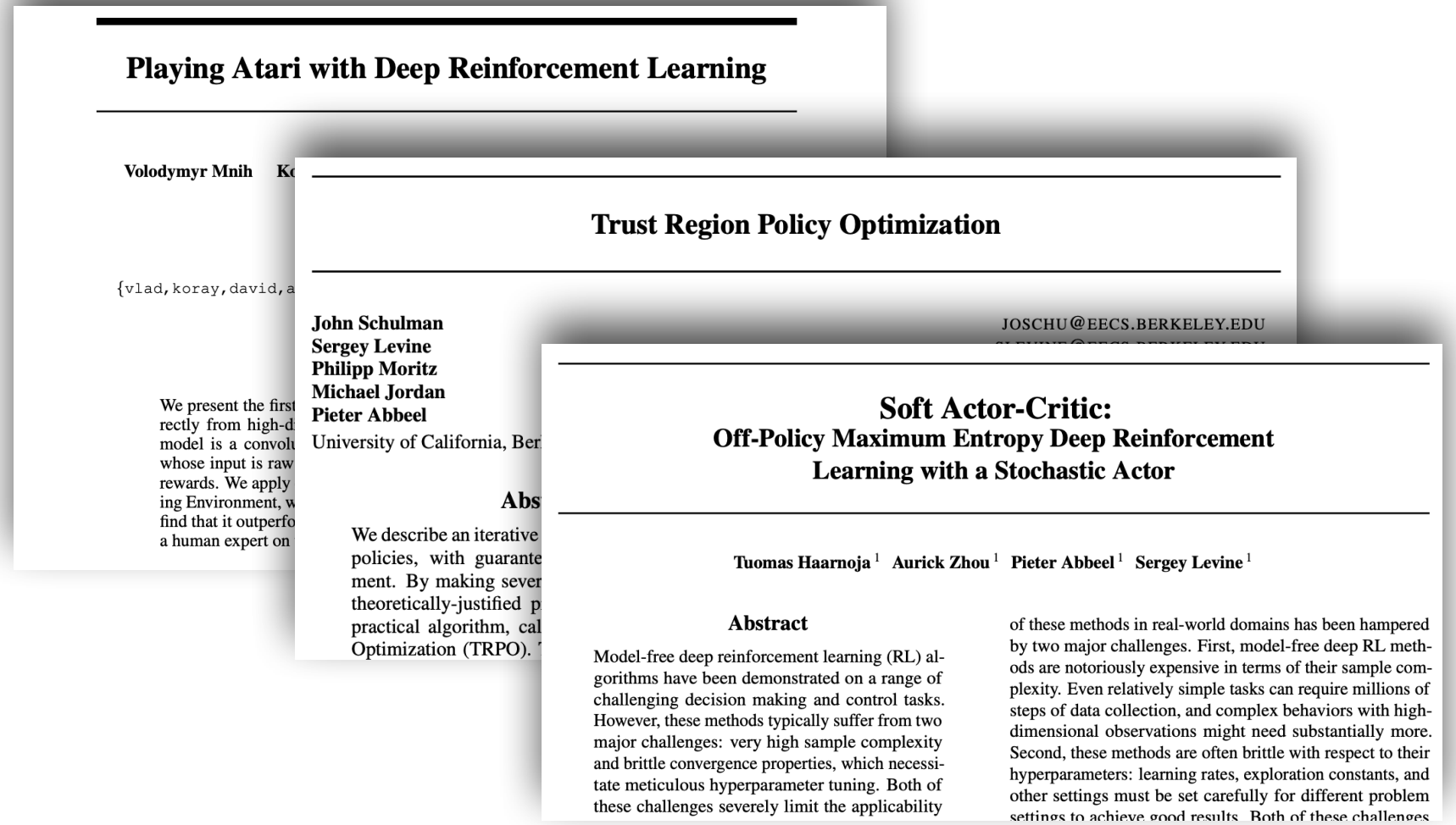
Topics Covered in This Course

- Concepts of Reinforcement Learning



Topics Covered in This Course

- Deep RL Frameworks



Playing Atari with Deep Reinforcement Learning

Volodymyr Mnih

{vlad,koray,david,a

We present the first
rectly from high-d
model is a convolu
whose input is raw
rewards. We apply
ing Environment, w
find that it outperfo
a human expert on

Trust Region Policy Optimization

John Schulman
Sergey Levine
Philipp Moritz
Michael Jordan
Pieter Abbeel
University of California, Ber

JOSCHU@EECS.BERKELEY.EDU

Abs

We describe an iterative
policies, with guarante
ment. By making sever
theoretically-justified p
practical algorithm, cal
Optimization (TRPO).

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

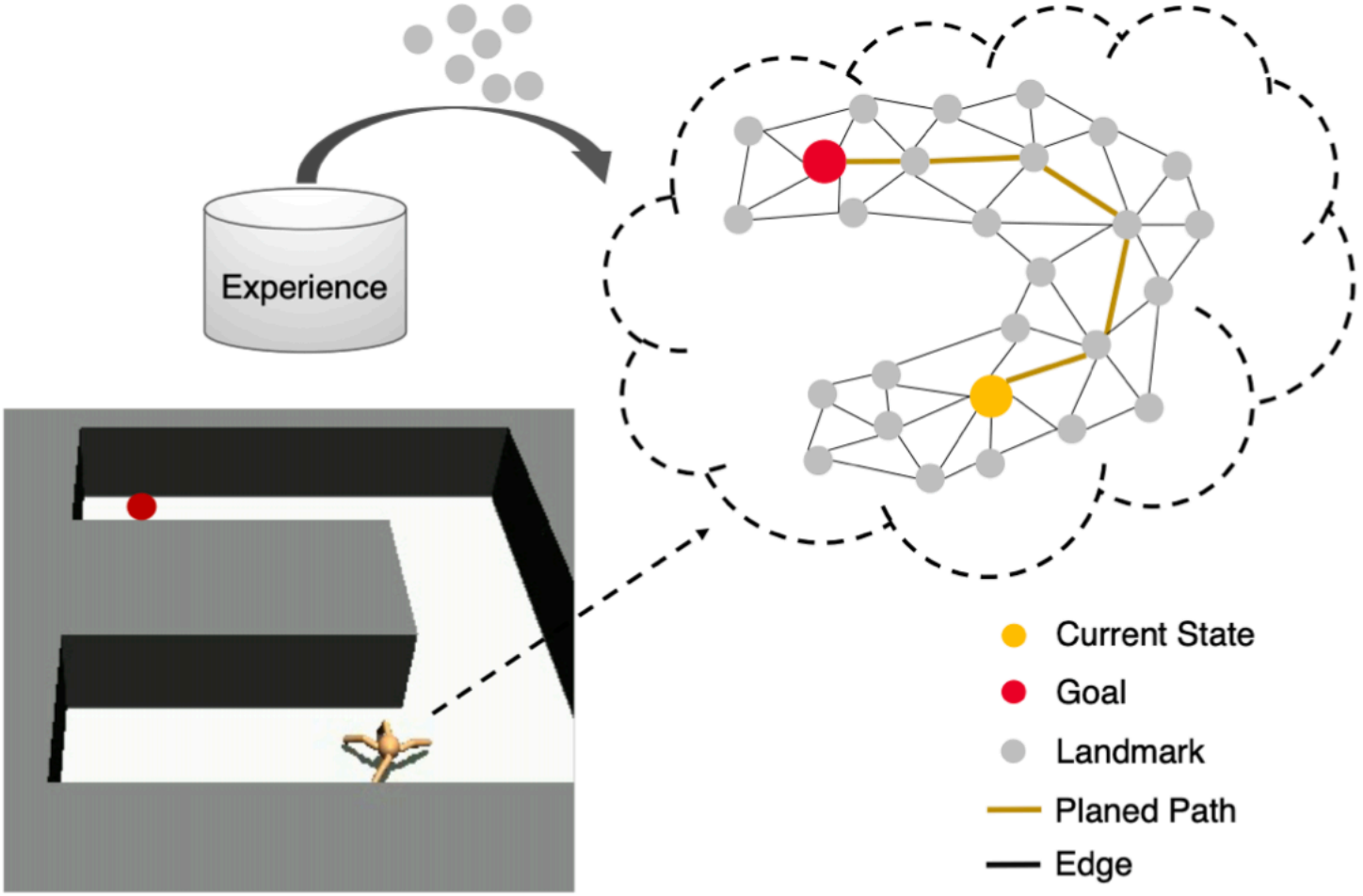
Tuomas Haarnoja [1] Aurick Zhou [1] Pieter Abbeel [1] Sergey Levine [1]

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

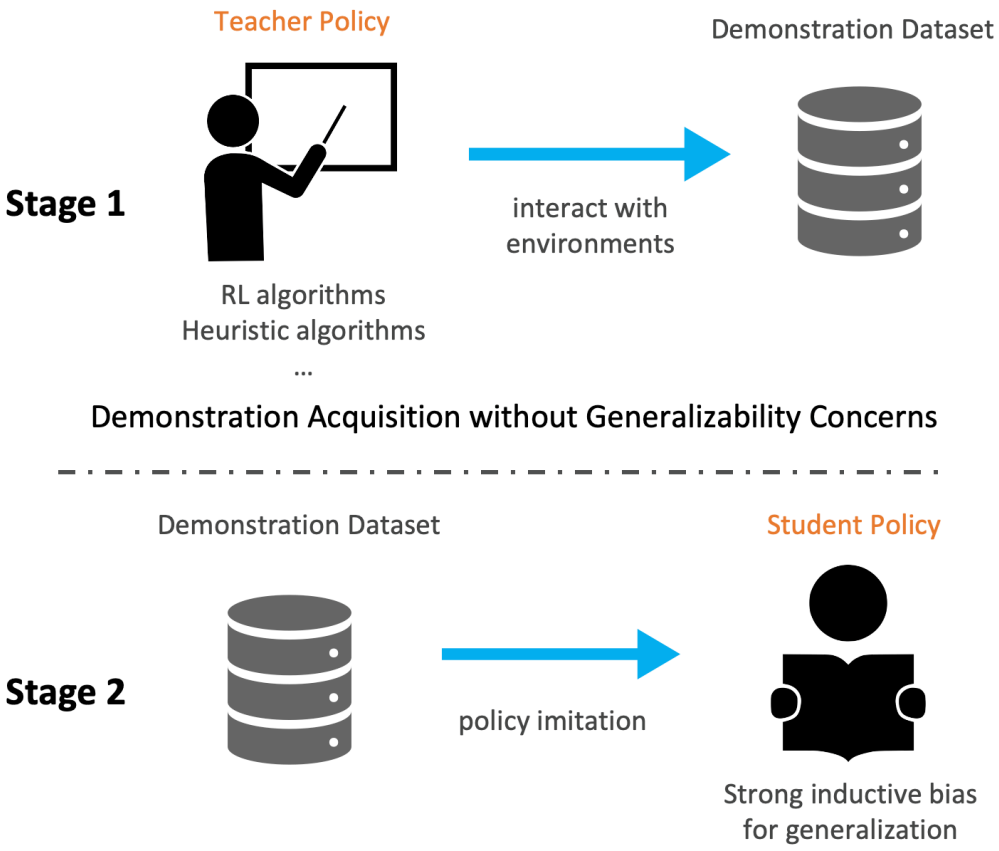
Topics Covered in This Course

- Hierarchical RL



Topics Covered in This Course

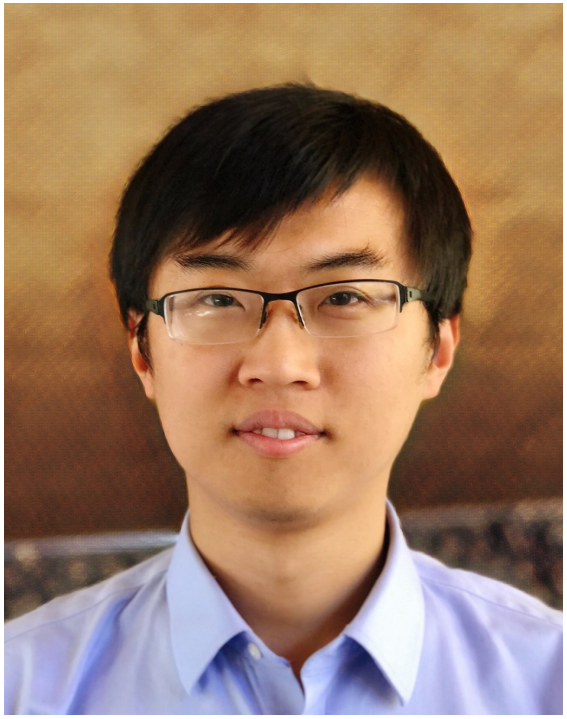
- Generalizability of RL



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:
  >= 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.

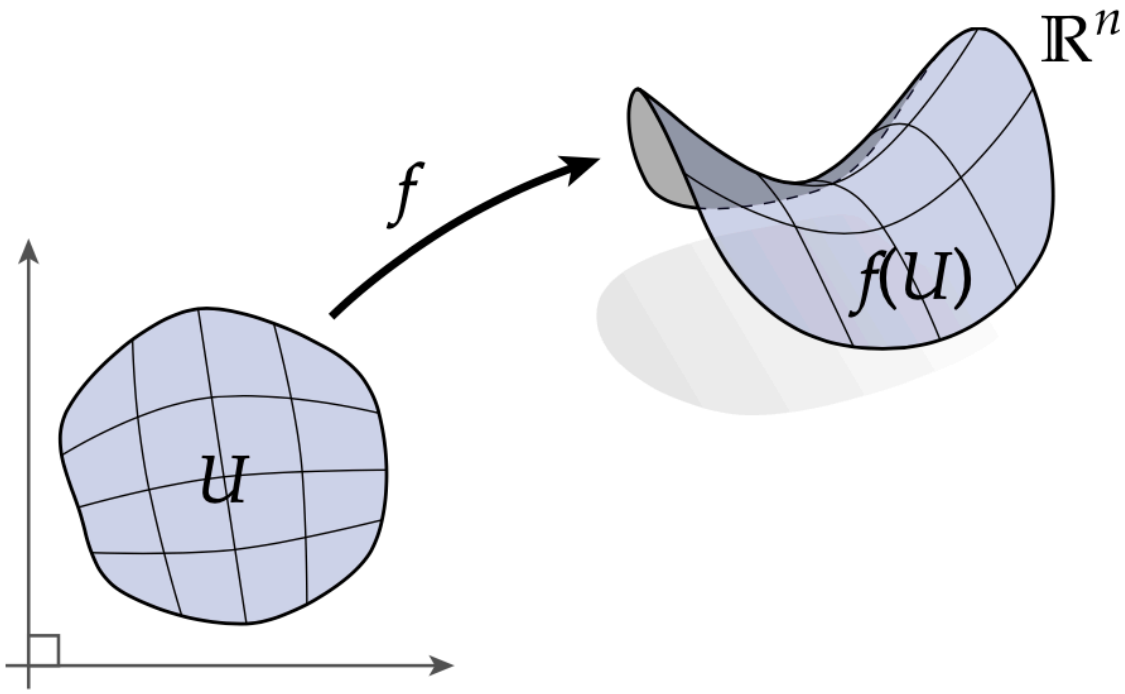
Questions?

Concepts of Differential Geometry

Parameterized Surfaces

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

$f : U \to \mathbb{R}^n$



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

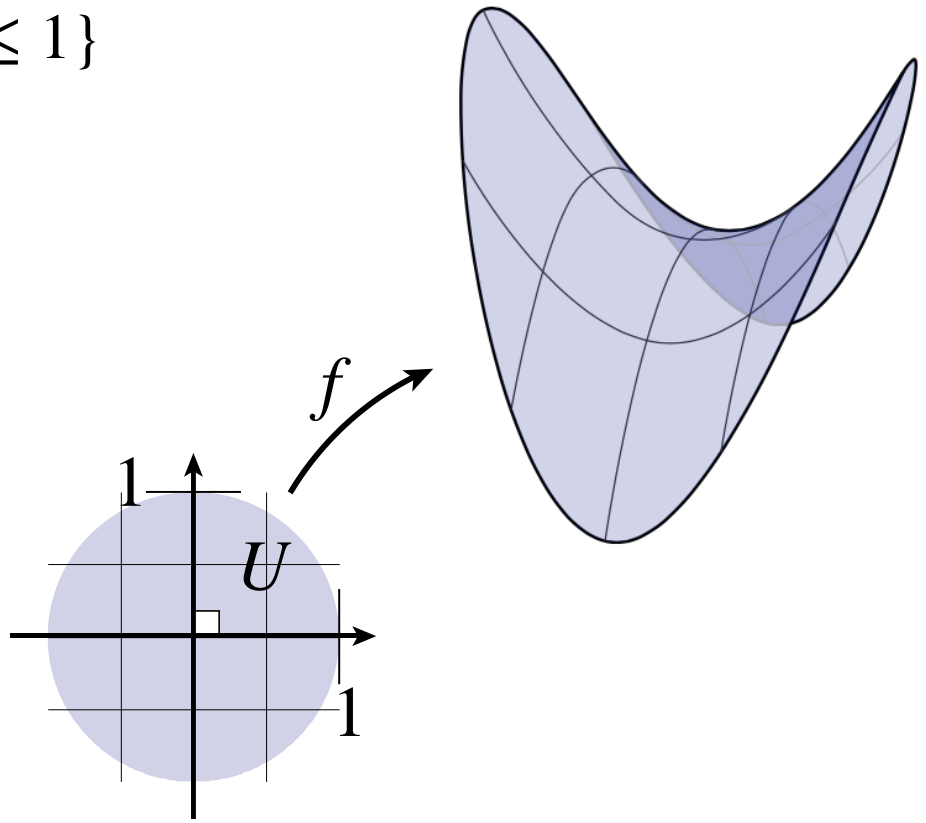
Image from Wikipedia

Example

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

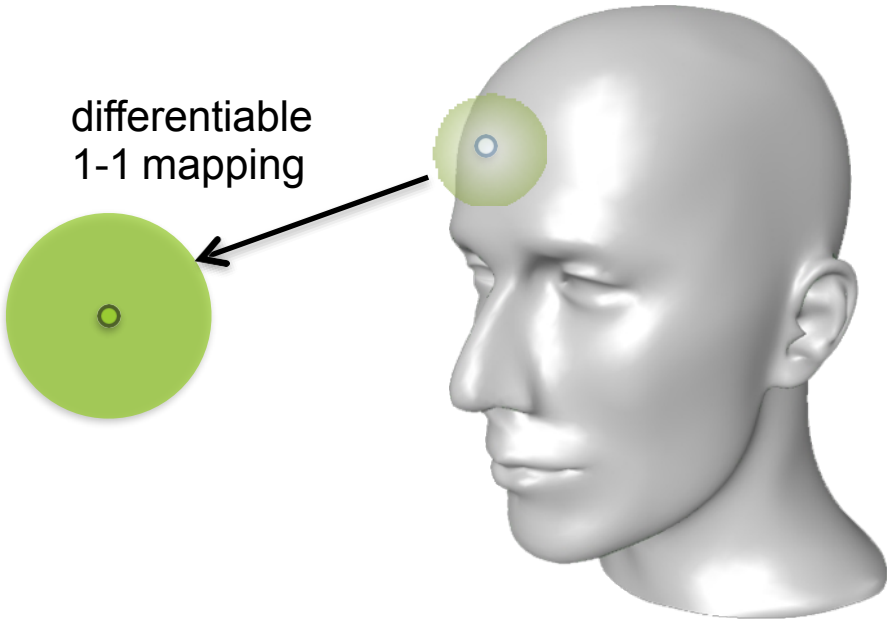
$$U := \{(u, v) \in \mathbb{R}^2 : u^2 + v^2 \leq 1\}$$

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



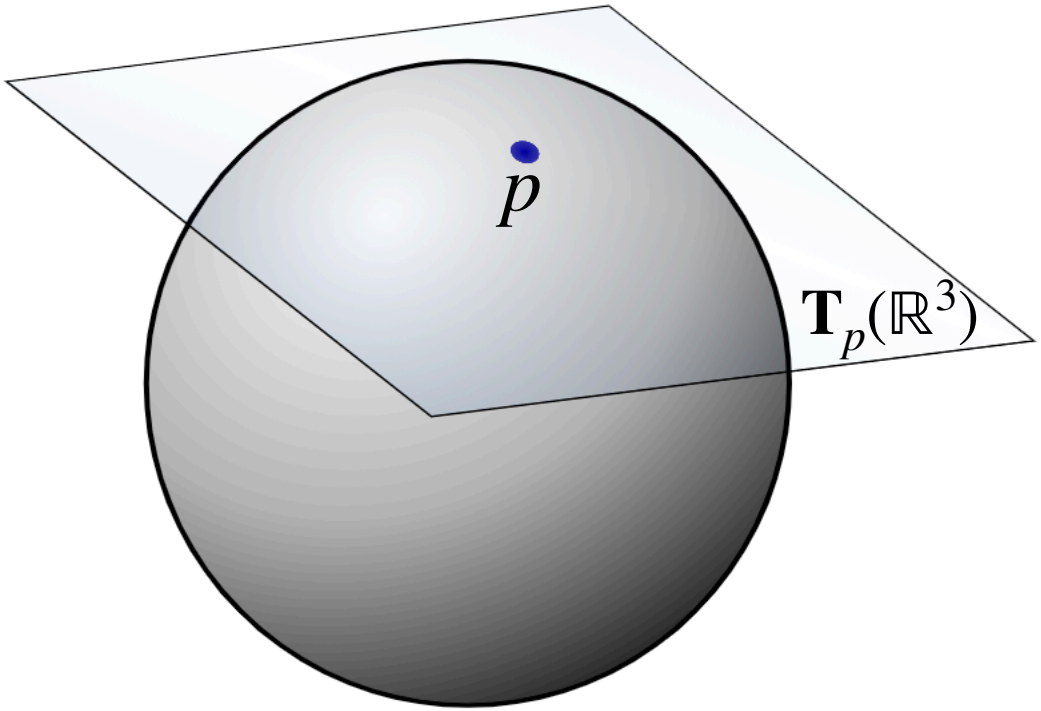
Manifold

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



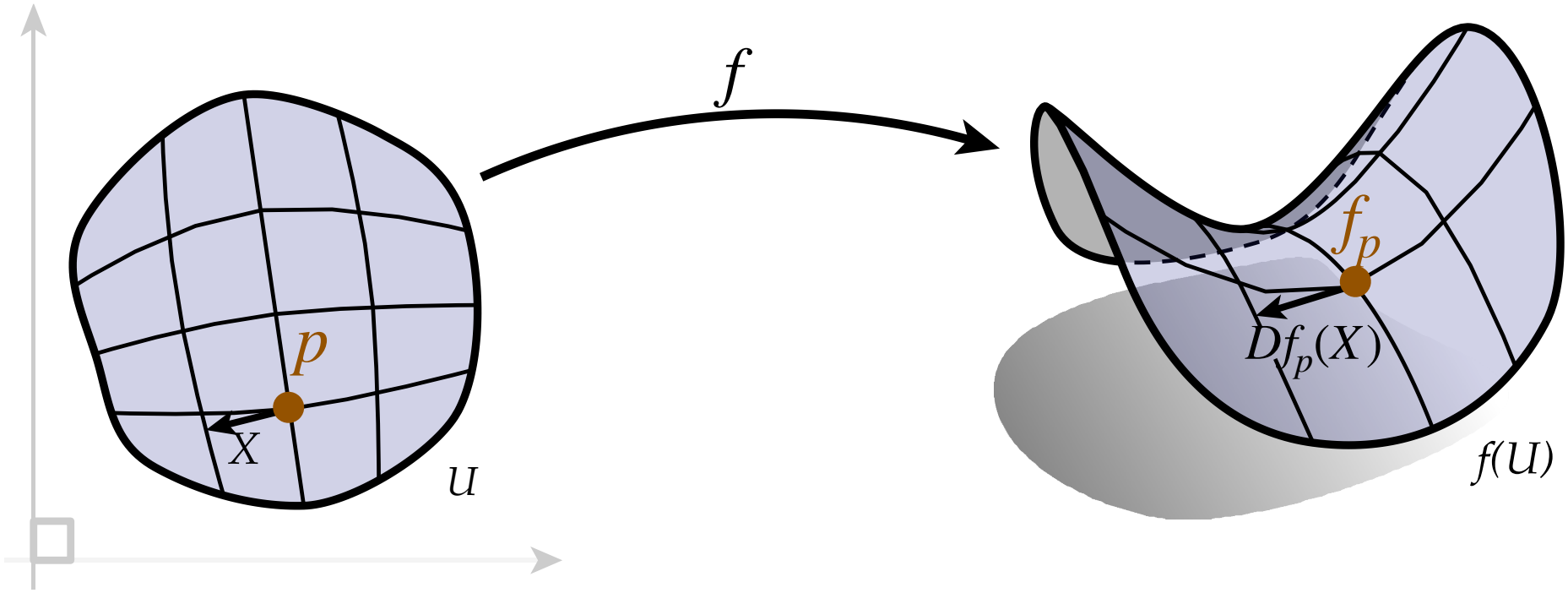
Tangent Plane

- 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.

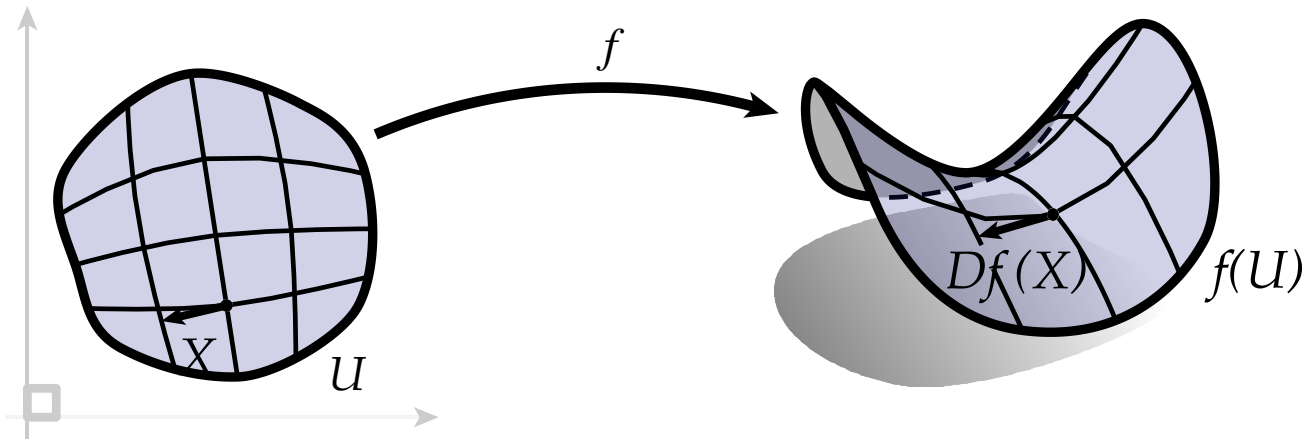


Differential of a Surface

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



Differential of a Surface

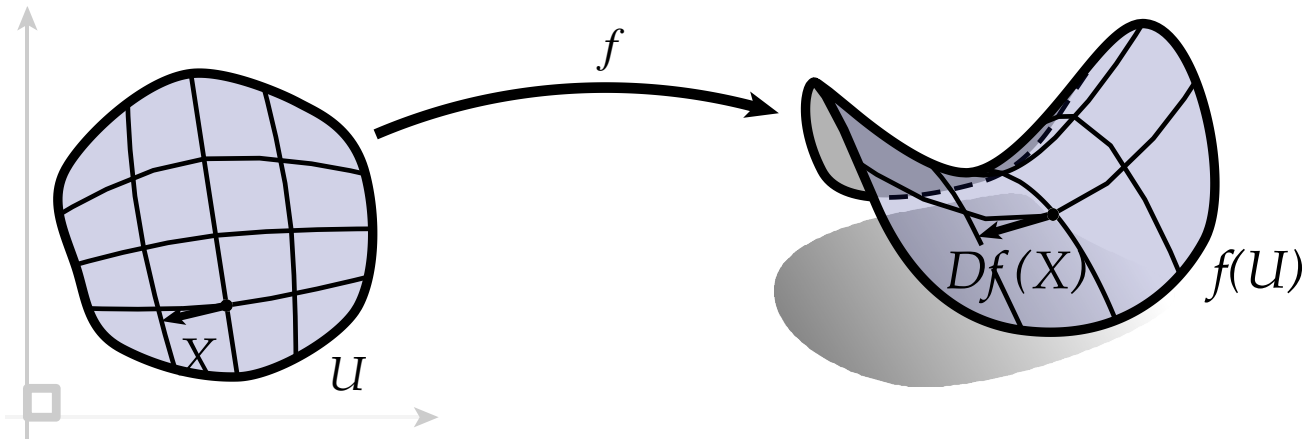


Total differential: $df = \frac{\partial f}{\partial u}du + \frac{\partial f}{\partial v}dv \Rightarrow \Delta f \approx \frac{\partial f}{\partial u}\Delta u + \frac{\partial f}{\partial v}\Delta v$

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

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

Differential of a Surface



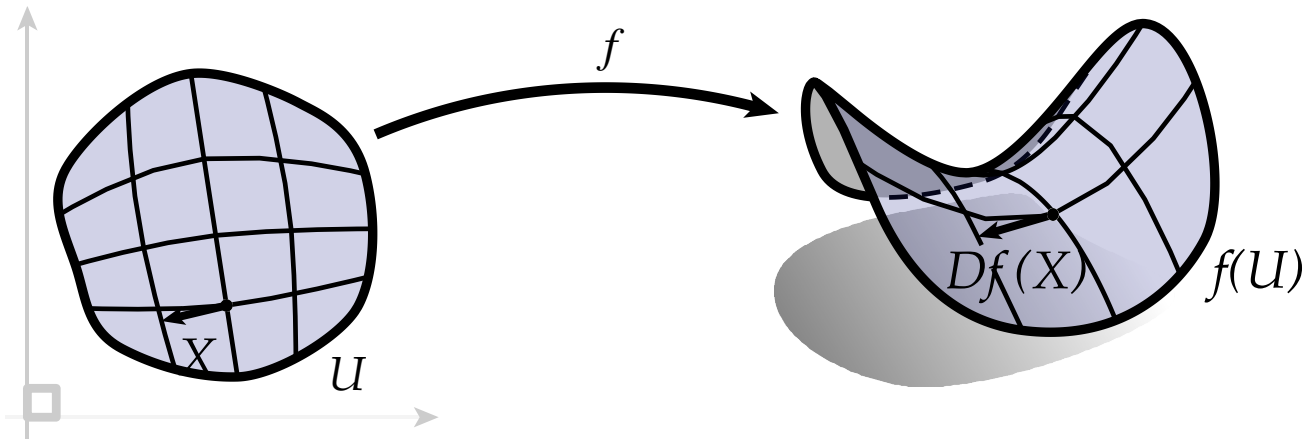
Total differential: $df = \frac{\partial f}{\partial u} du + \frac{\partial f}{\partial v} dv$

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

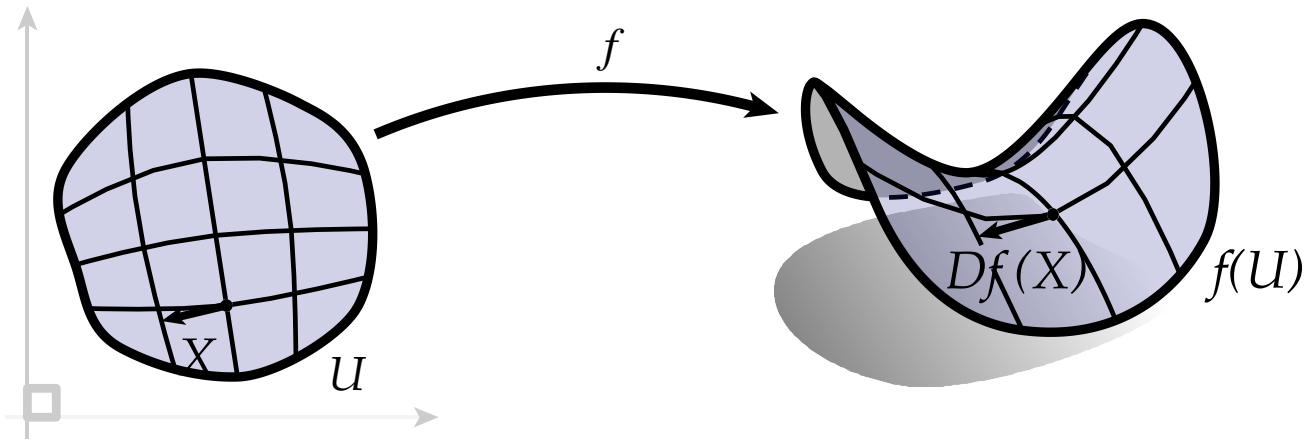
If point $p \in \mathbb{R}^2$ moves with velocity $X = [u, v]^T$ by ϵ, the movement of f_p is:

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

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

Df_p: differential (Jacobian), a linear map.

Differential of a Surface



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

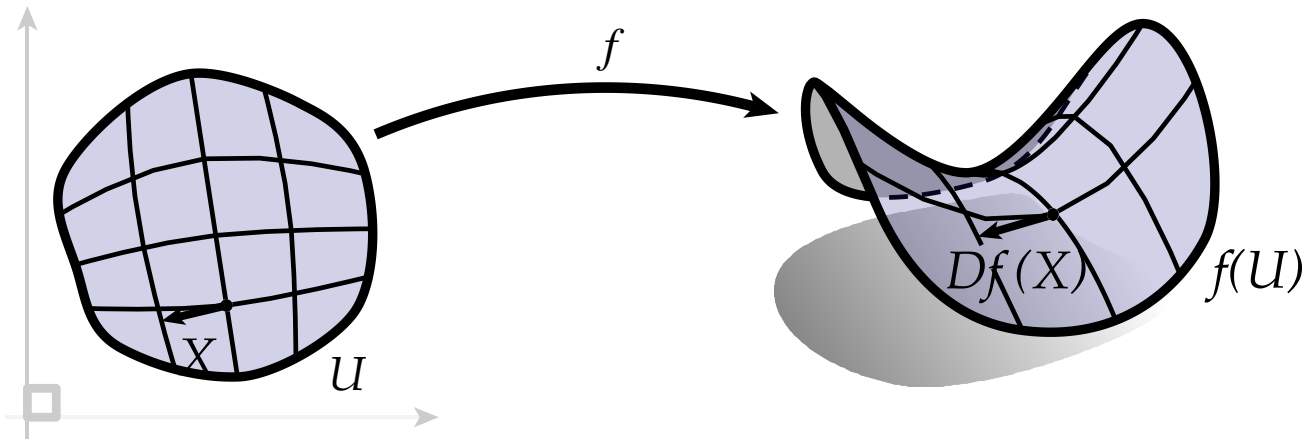
If point $p \in \mathbb{R}^2$ moves with velocity $X = [u, v]^T$ by ϵ, the movement of f_p is:

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

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

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

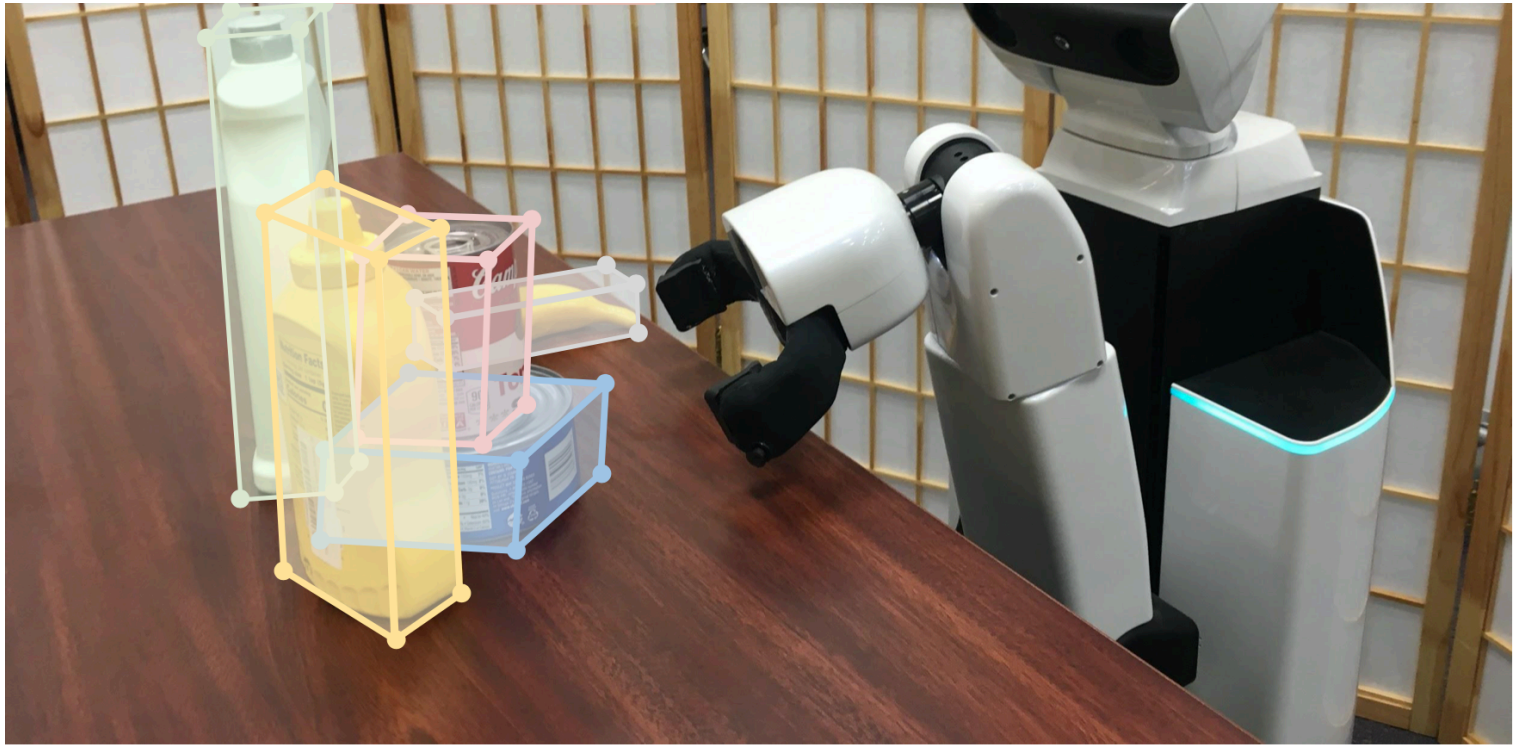
$$\Delta f_p \approx \frac{\partial f}{\partial u}(\epsilon u) + \frac{\partial f}{\partial v}(\epsilon v) = \epsilon \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v}\right] \begin{bmatrix} u \\ v \end{bmatrix} = \epsilon [Df_p] X$$

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

velocity in 2D domain

Rigid Transformation

Describe the Pose of Agent and Objects

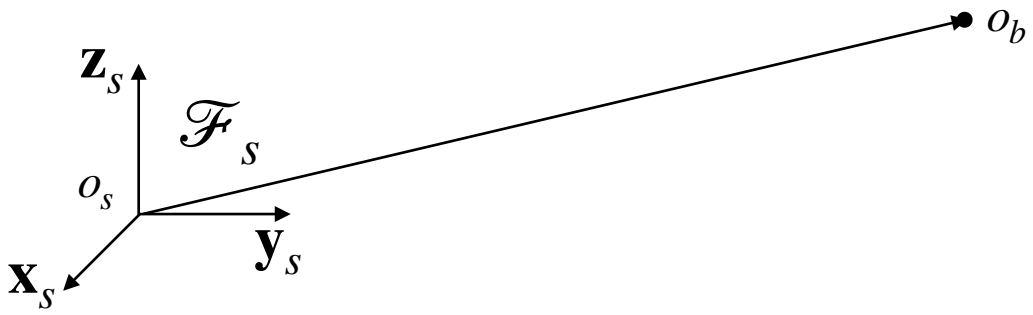


Wang et al., "**DenseFusion: 6D Object Pose Estimation by Iterative Dense Fusion**", *CVPR 2019*

Describe the Pose of Agent and Objects

Wang et al., "**DenseFusion: 6D Object Pose Estimation by Iterative Dense Fusion**", *CVPR 2019*

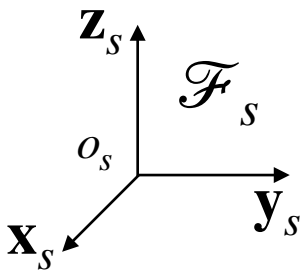
Notation Convention

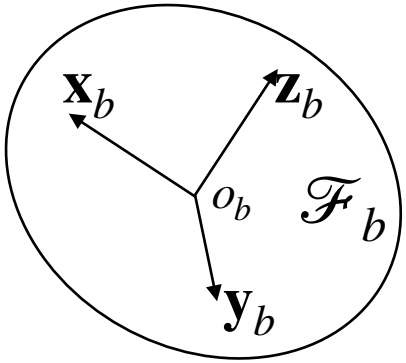


- An observer **records** the position of any point in the space **using a frame** $\mathcal{F}_s$
- We use ordinary letters to denote points (e.g., p), and bold letters to dente **vectors (e.g., $\mathbf{v}$)**
- When **writing equations**, we add a superscript to symbols to denote the recording frame, e.g.,

$$o_b^s = o_s^s + \mathbf{t}_{s \to b}^s$$

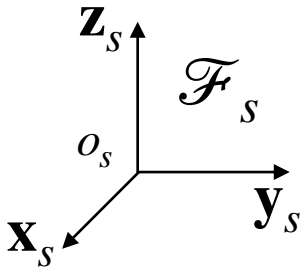
Rigid Transformation

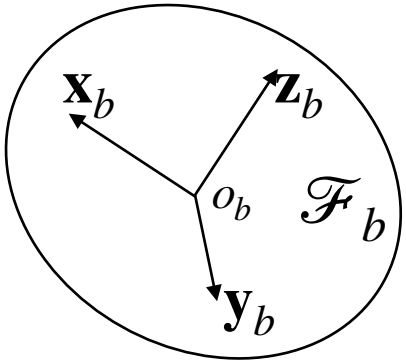




- There is a rigid object, to which we bind a frame $\mathscr{F}_b$ (body frame) tightly, so that $\mathscr{F}_b$ moves along with the object

Rigid Transformation

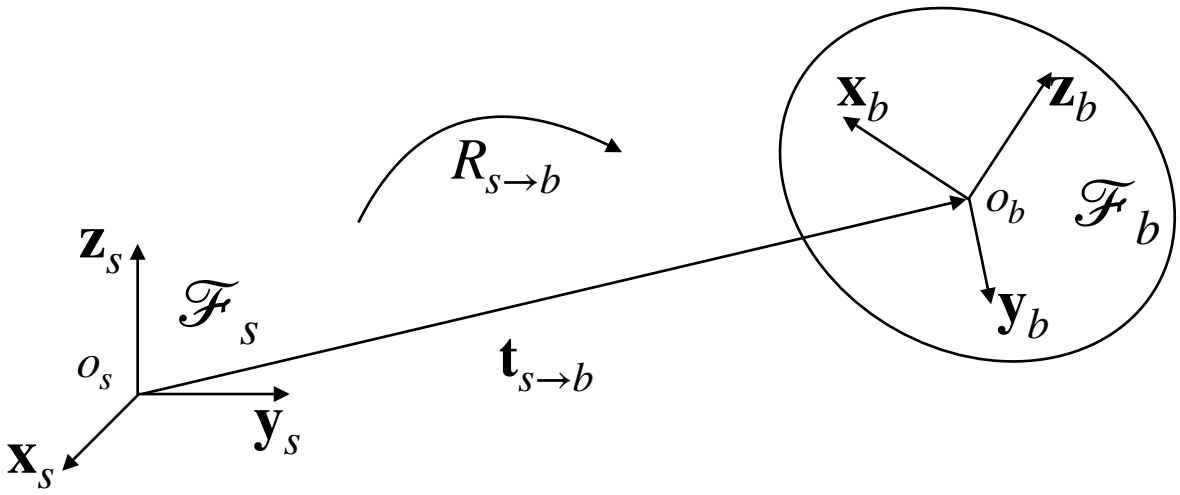




- When talking about the pose of the *rigid* object, we ask:

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

Rigid Transformation

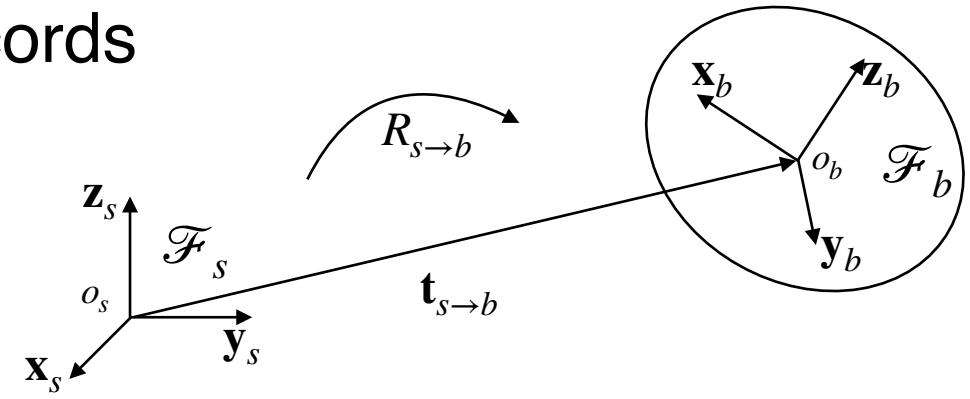


- We first translate $\mathscr{F}_s$ by $\mathbf{t}_{s\to b}$ to align o_s and o_b
- And then rotate by $R_{s\to b}$ to align $\{\mathbf{x}_i, \mathbf{y}_i, \mathbf{z}_i\}$ $(i = s \text{ or } b)$

Rigid Transformation

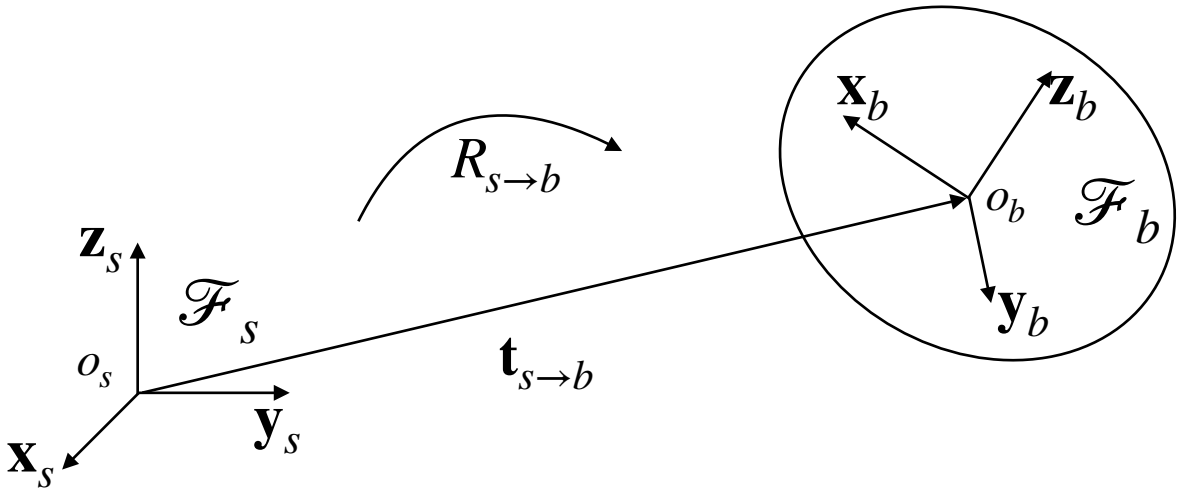
- Formally,
  - $o_b^s = o_s^s + \mathbf{t}_{s\to b}^s$
  - $[\mathbf{x}_b^s, \mathbf{y}_b^s, \mathbf{z}_b^s] = R_{s\to b}^s [\mathbf{x}_s^s, \mathbf{y}_s^s, \mathbf{z}_s^s]$

- Since the observer records everything using $\mathcal{F}_s$,
  - $o_s^s = 0$
  - $[\mathbf{x}_s^s, \mathbf{y}_s^s, \mathbf{z}_s^s] = I_{3\times 3}$



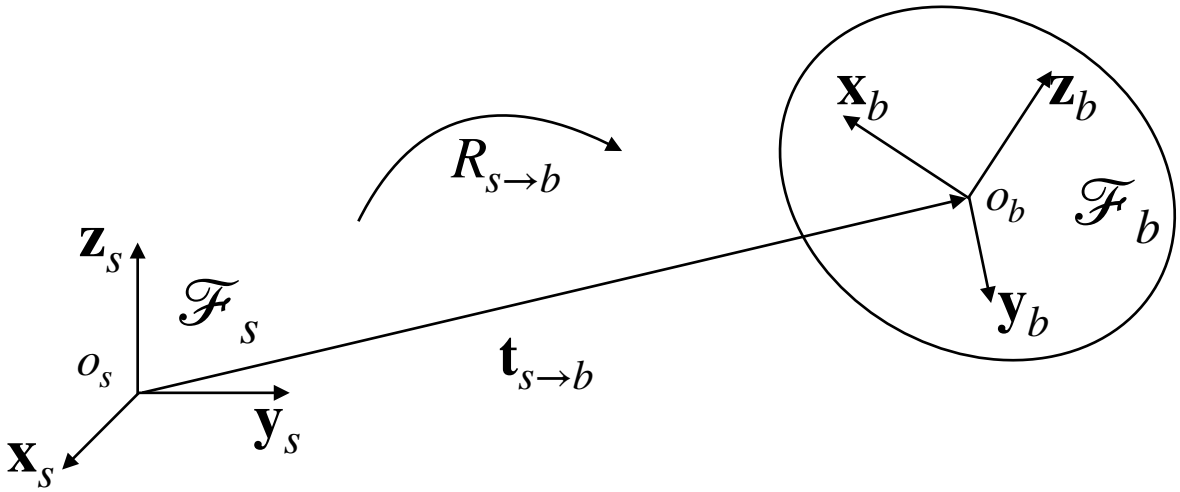
- Therefore,
  - $\mathbf{t}_{s\to b}^s = o_b^s$
  - $R_{s\to b}^s = [\mathbf{x}_b^s, \mathbf{y}_b^s, \mathbf{z}_b^s] \in \mathbb{R}^{3\times 3}$

$(R_{s\to b}, \mathbf{t}_{s\to b})$ to Transform Points in $\mathscr{F}_b$



- Assume a second observer that records coordinates by $\mathscr{F}_b$
- Assume a point p on the body. Since $\mathscr{F}_b$ moves along the body, its coordinate recorded in $\mathscr{F}_b$, denoted as p^b, should not change.

$(R_{s\to b}, \mathbf{t}_{s\to b})$ to Transform Points in $\mathscr{F}_b$



- Imagine a process: $\mathscr{F}_b$ moves from $\mathscr{F}_s$ to the current location. This is how we define $(R^s_{s\to b}, \mathbf{t}^s_{s\to b})$.
- Since p moves along $\mathscr{F}_b$, it is moved from the initial position, $p^s = p^b$, to the current location:

$$p^s = R^s_{s\to b} p^b + \mathbf{t}^s_{s\to b}$$

$\mathbb{SO}(3)$ **and** $\mathbb{SE}(3)$

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:

$$T^s_{s\to b} = \begin{bmatrix} R^s_{s\to b} & \mathbf{t}^s_{s\to b} \\ 0 & 1 \end{bmatrix}$$

- Rigid transformation under linear form:

$$\tilde{x}^s = T^s_{s\to b}\tilde{x}^b$$

- Composition: $T^s_{a\to c} = T^s_{b\to c}T^s_{a\to b}$

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

- $\mathbb{SE}(3) := \left\{ T = \begin{bmatrix} R & \mathbf{t} \\ 0 & 1 \end{bmatrix}, R \in \mathbb{SO}(3), \mathbf{t} \in \mathbb{R}^3 \right\}$
- $\mathbb{SE}(3)$: "Special Euclidean Group"

- "Group": roughly, closed under matrix multiplication
- "Euclidean": R and $\mathbf{t}$
- "Special": $\det(R) = 1$

- 6 DoF