

L1: Introduction

Hao Su



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

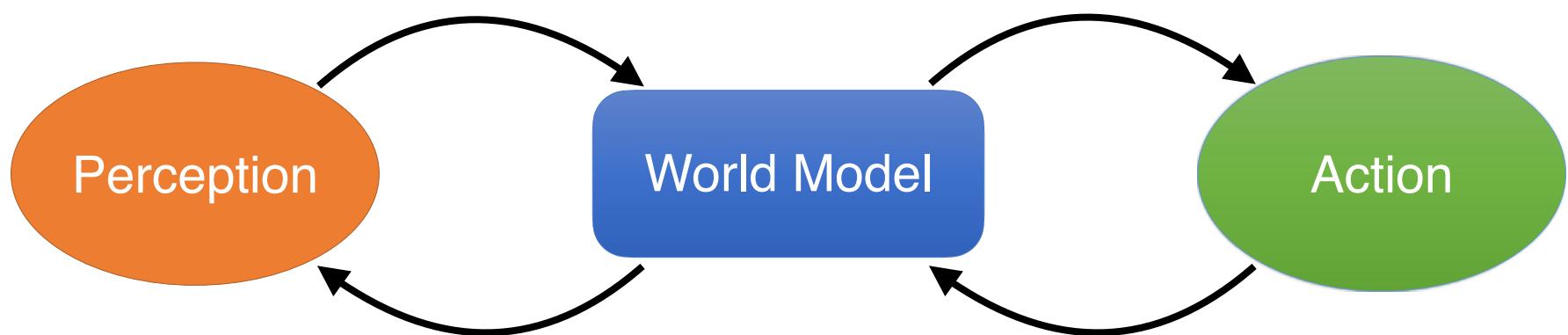
Agenda

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

Syllabus

Last quarter

This quarter

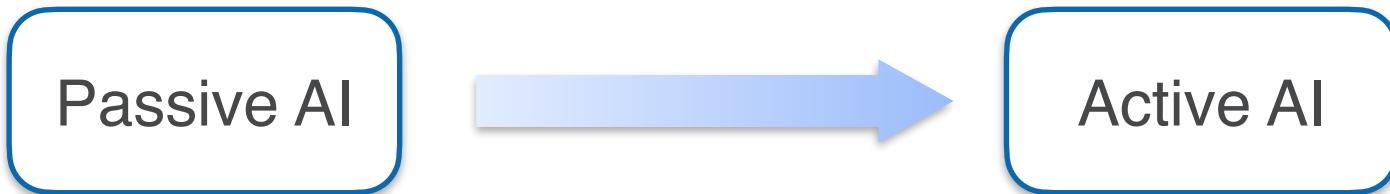


Vision → Robotics

Passive AI

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

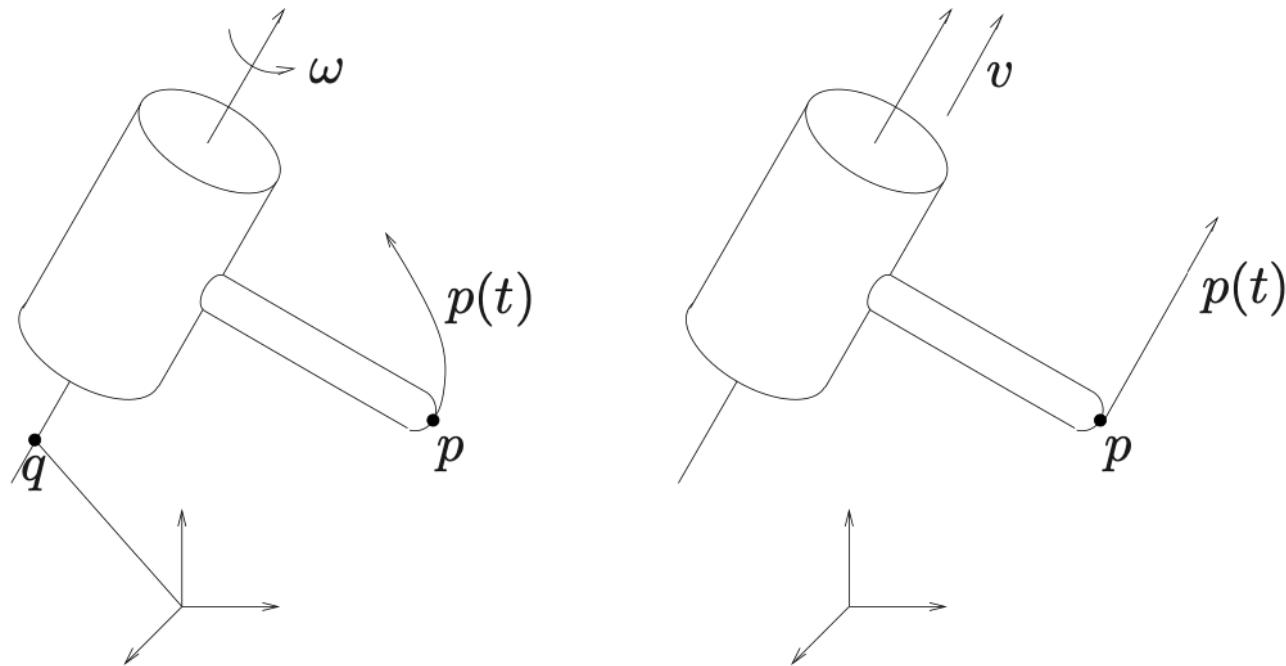
Vision → Robotics



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

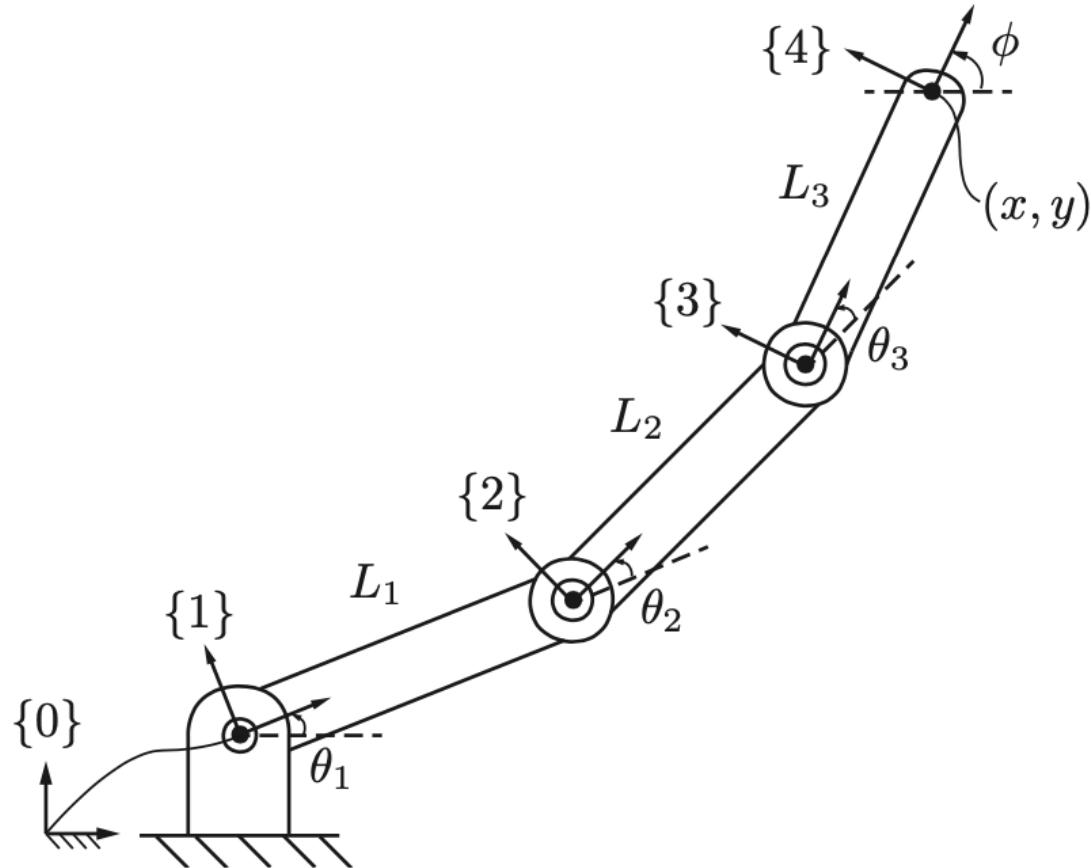
Topics Covered in This Course

- Modeling Robots by Rigid-Body Geometry



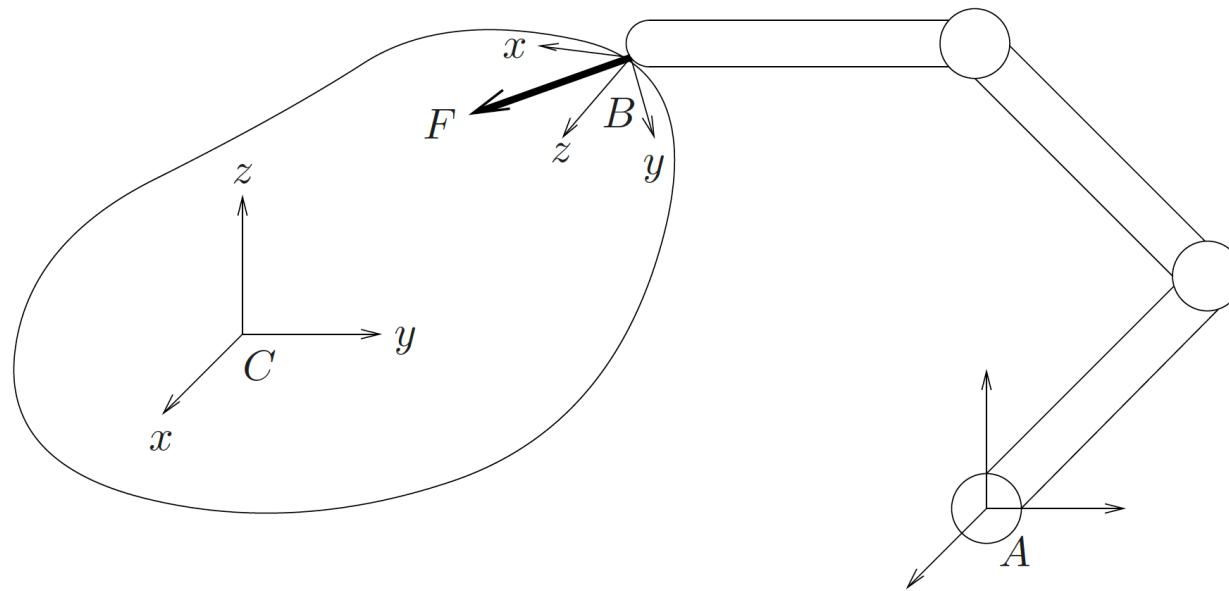
Topics Covered in This Course

- 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

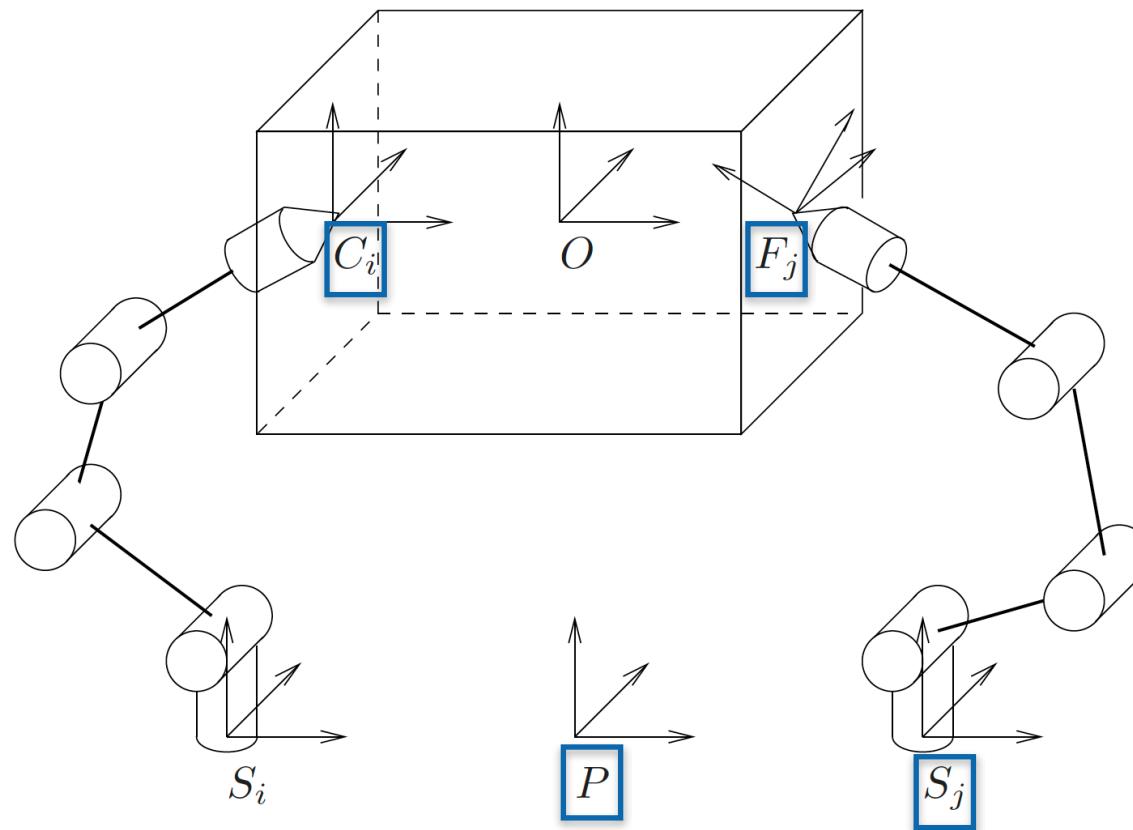
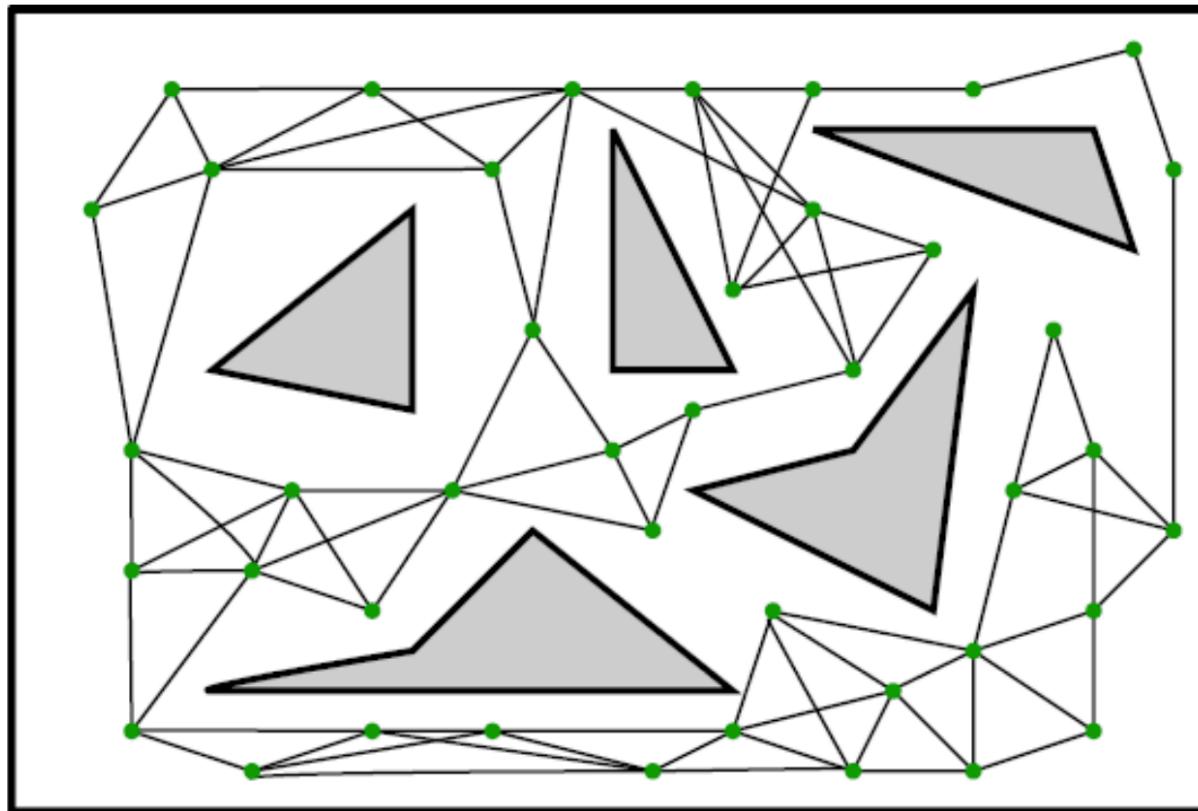


Figure 5.14: Grasp coordinate frames.

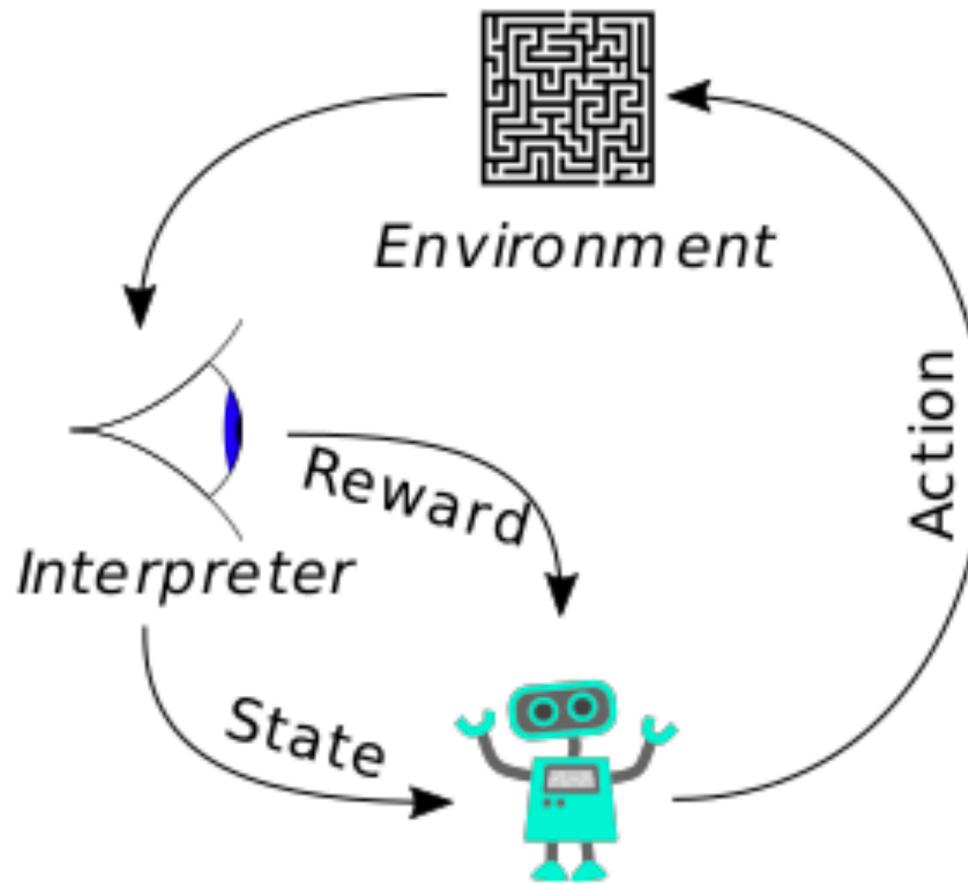
Topics Covered in This Course

- 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
Philipp 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

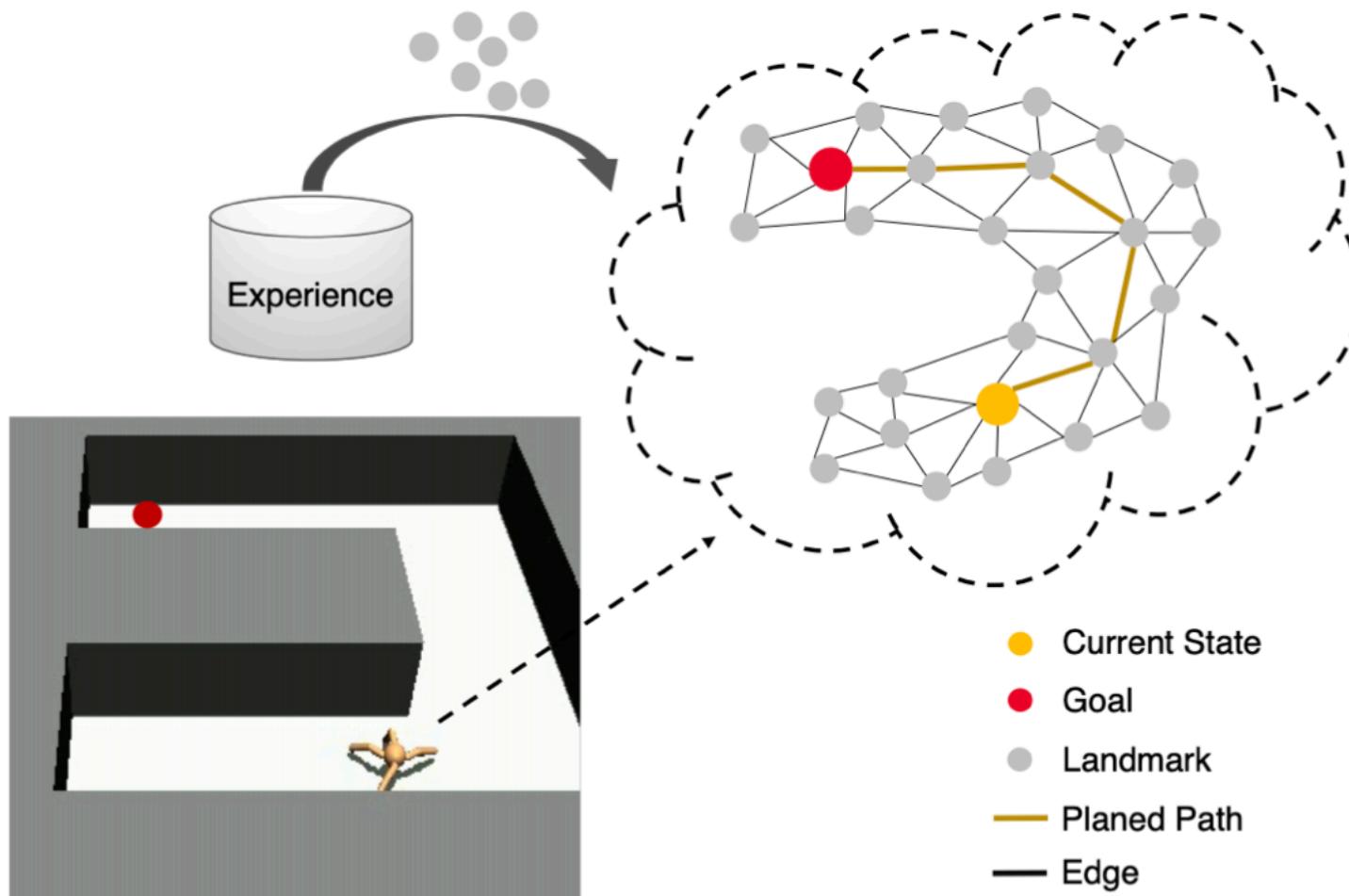
Abstract

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

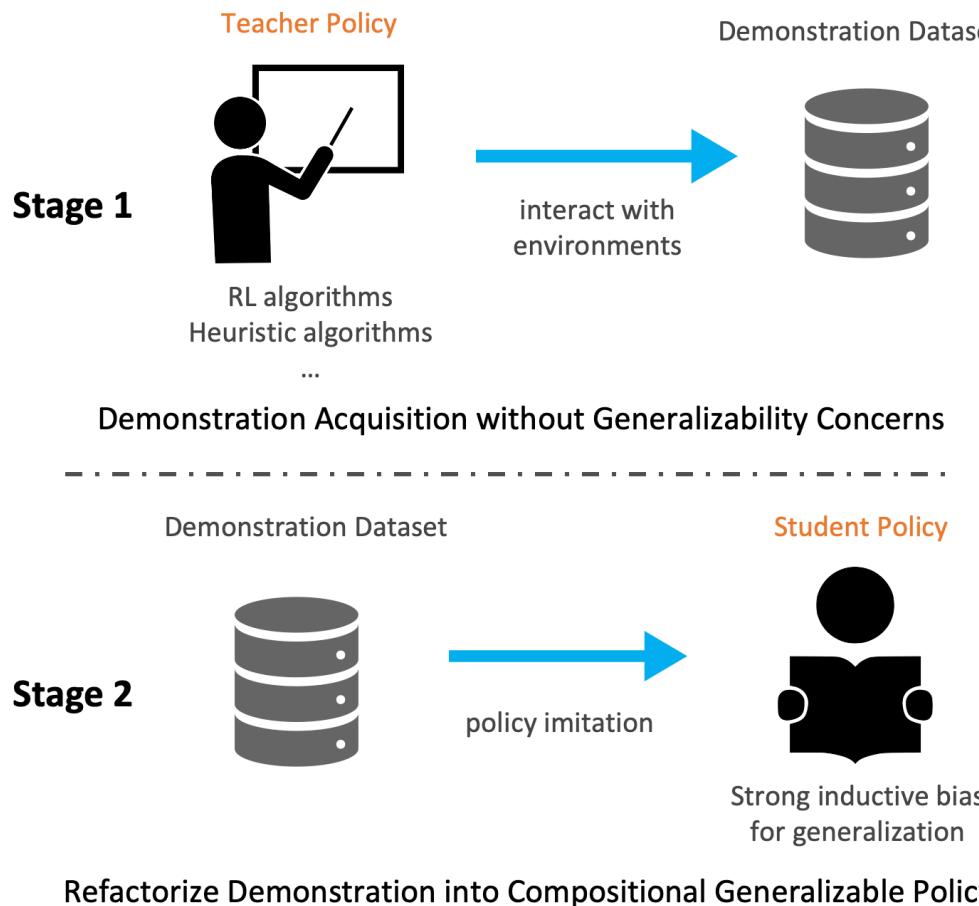
Topics Covered in This Course

- Hierarchical RL



Topics Covered in This Course

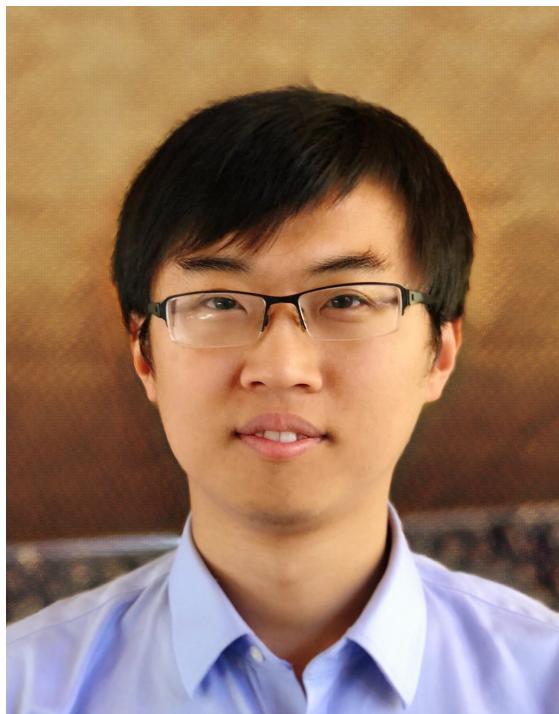
- Generalizability of RL



Course Logistic

Instructors

Instructor: Hao Su



TA: Zhiao Huang



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: 04/03/2022

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

- Weekly homeworks
 - Can drop one homework without penalty
- Final project: final week
- No mid-term/final exams
- Extra credit for participation 5% (ask/answer questions in class, attend office hours)

Assignments

- 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/SP22/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

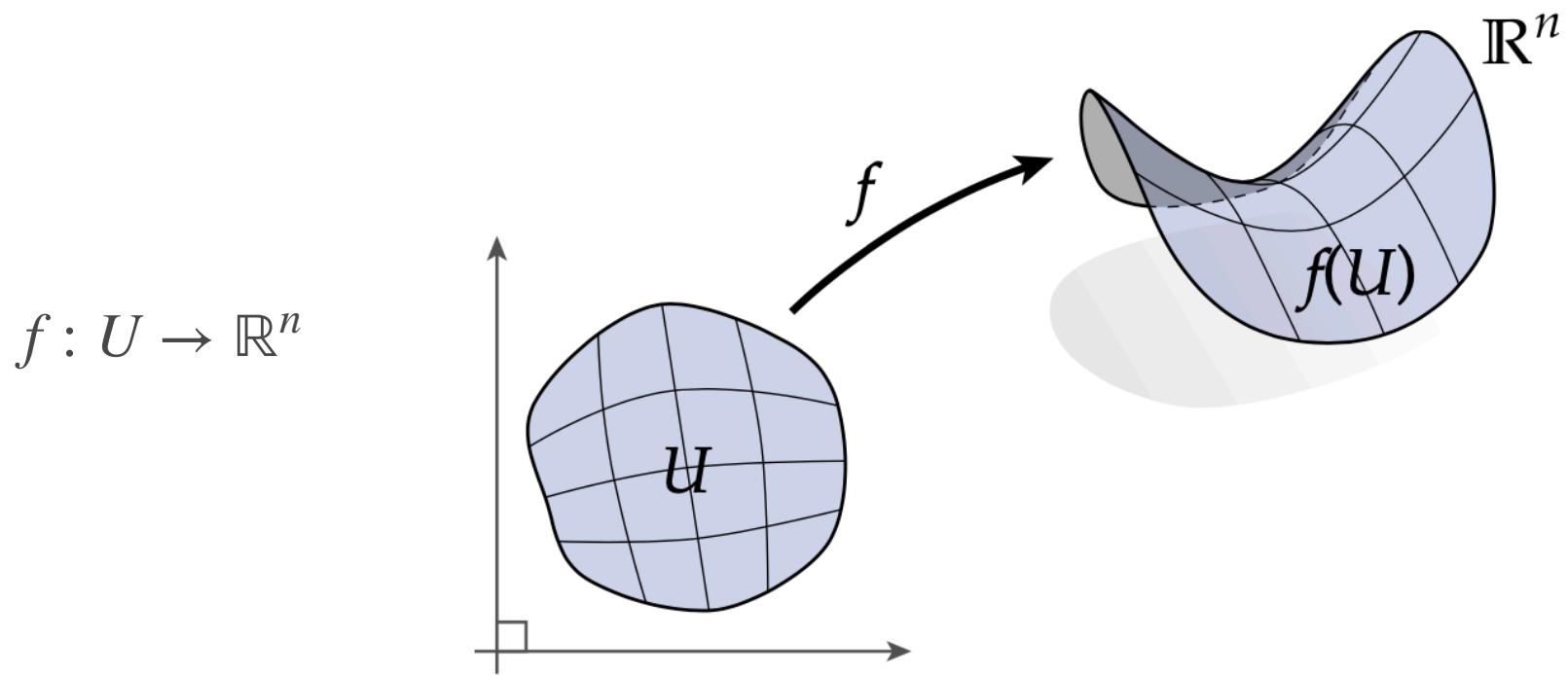
- Check course website

Questions?

Concepts of Differential Geometry

Parameterized Surfaces

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



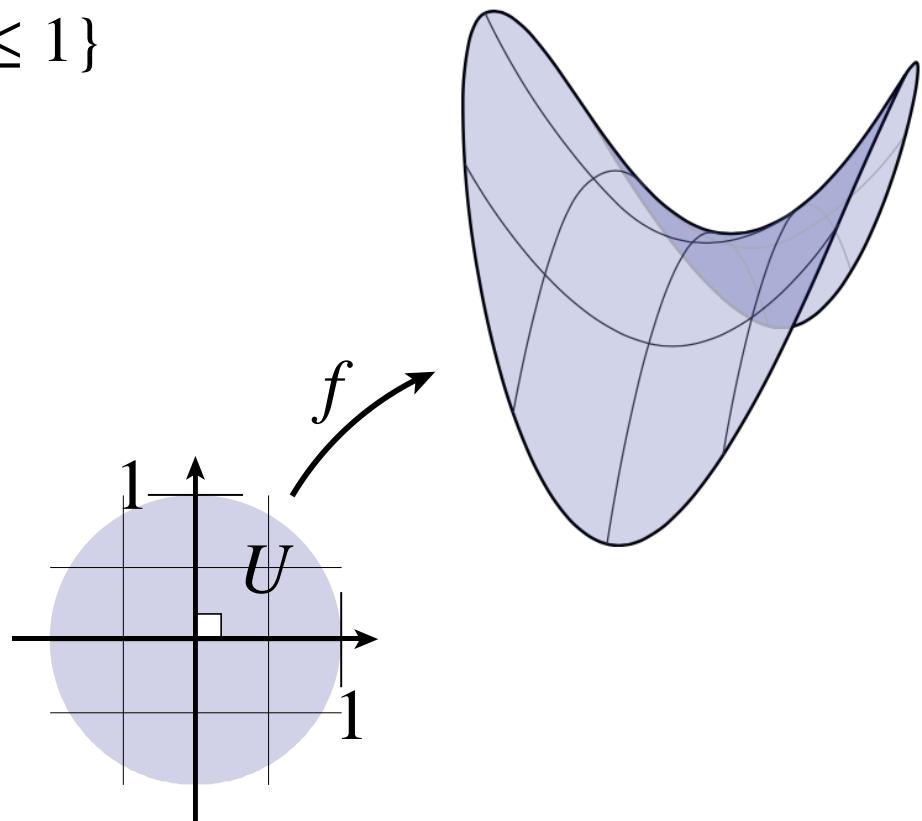
The set of points $f(U)$ is called the **image** of the parameterization.

Example

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

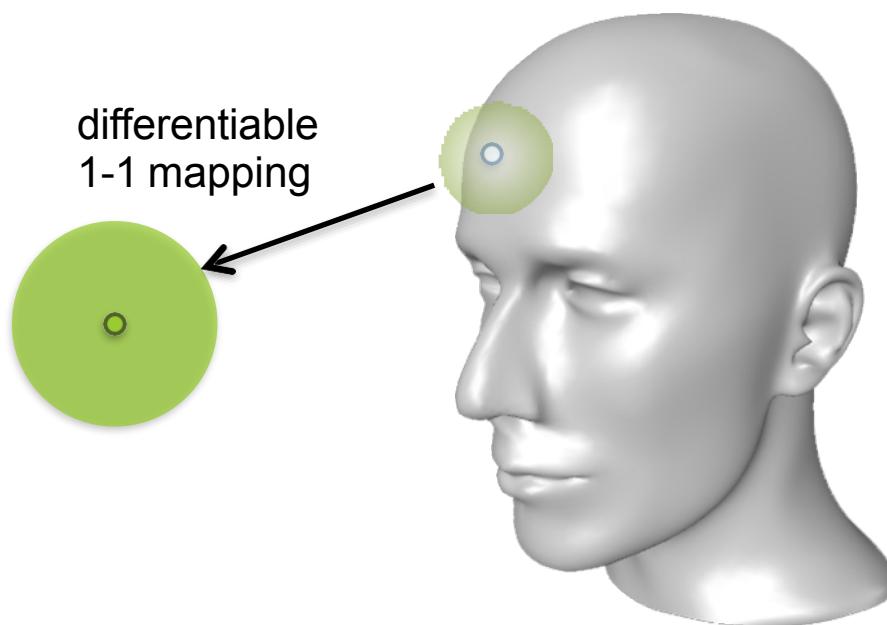
$$U := \{(u, v) \in \mathbb{R}^2 : u^2 + v^2 \leq 1\}$$

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



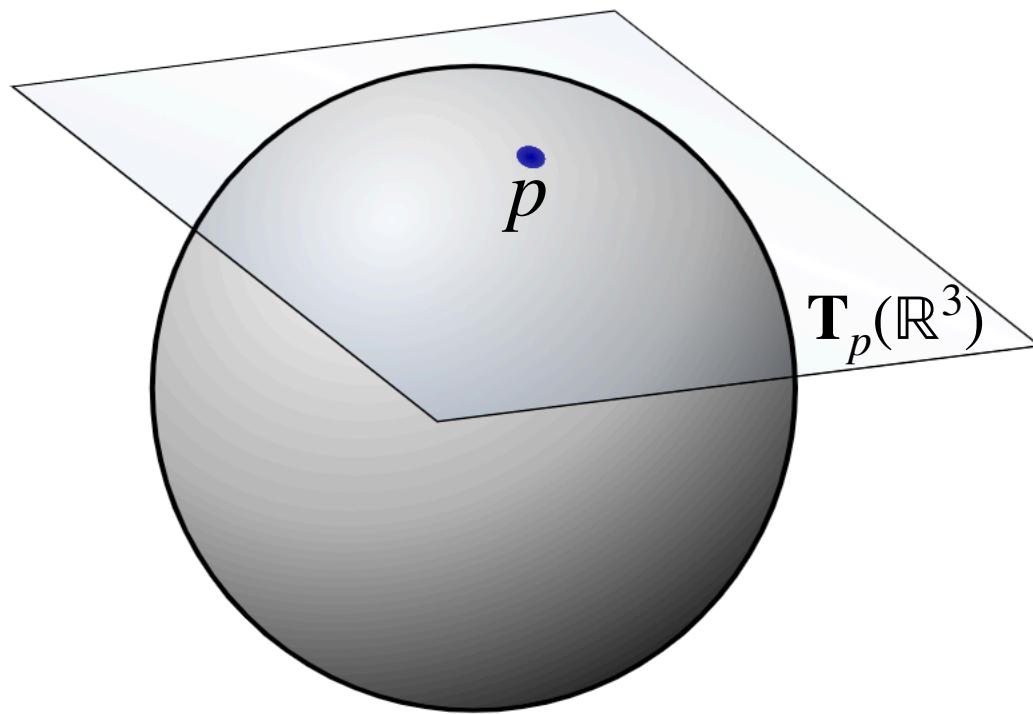
Manifold

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



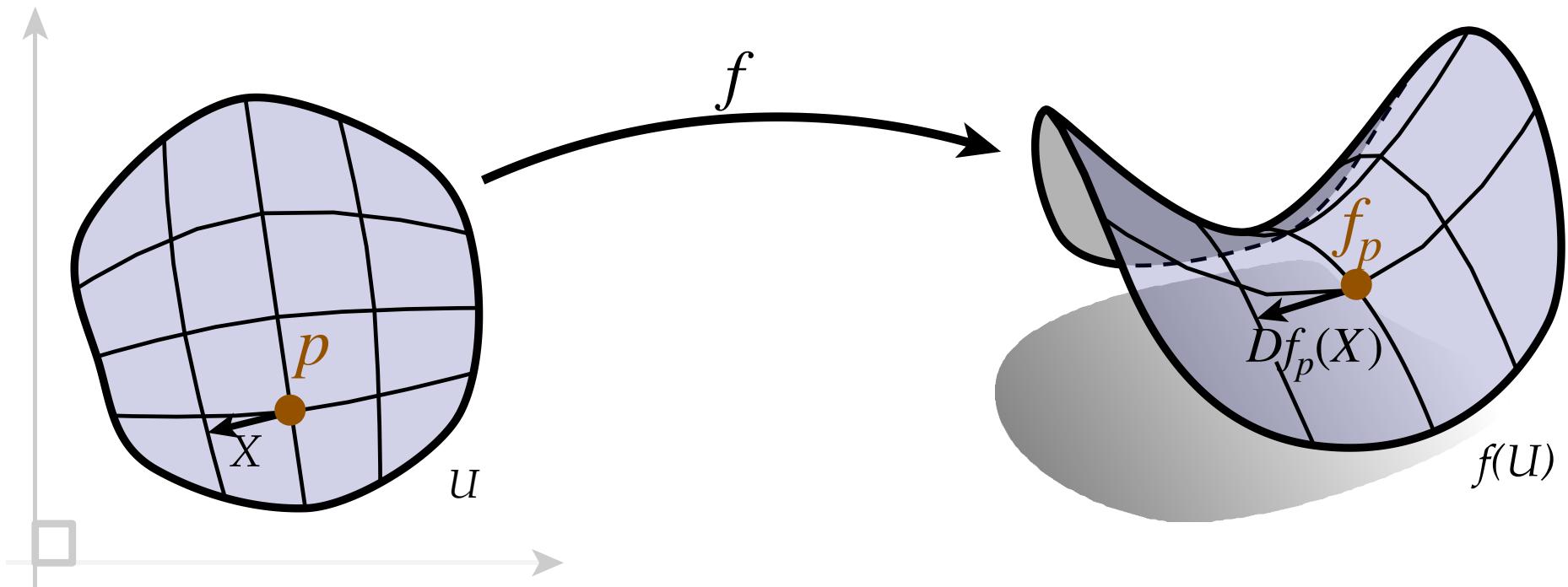
Tangent Plane

- 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 .

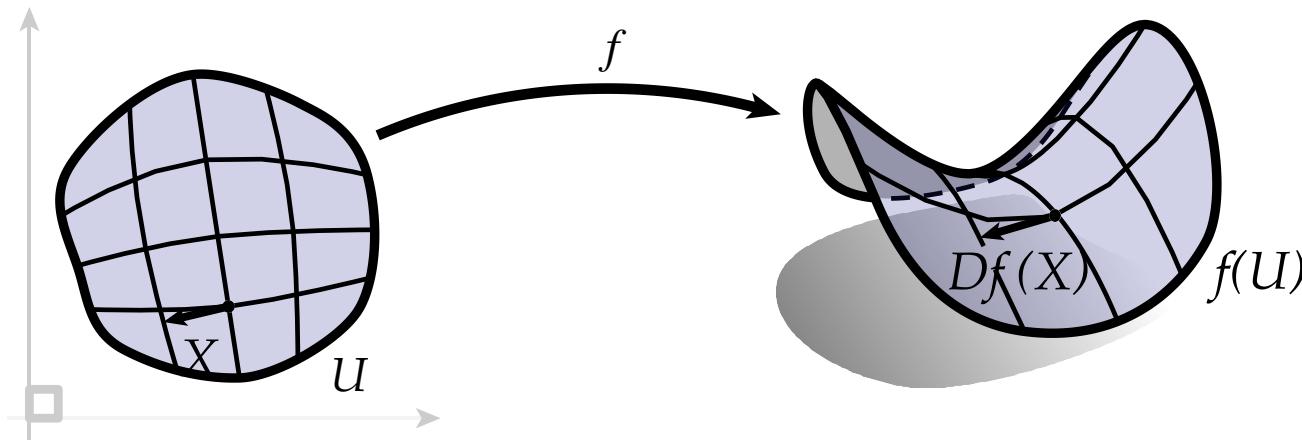


Differential of a Surface

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



Differential of a Surface

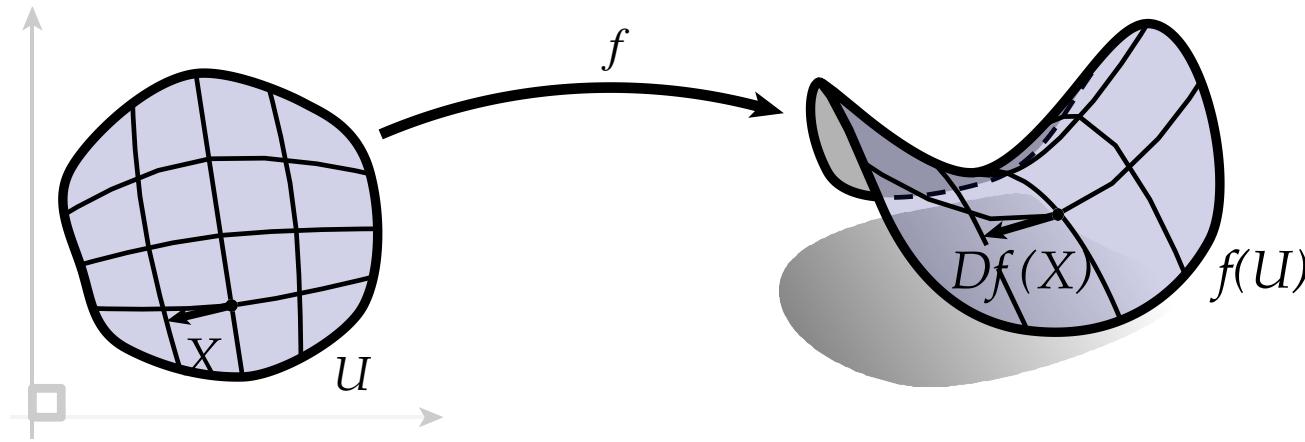


Total differential: $df = \frac{\partial f}{\partial u} du + \frac{\partial f}{\partial v} dv \implies \Delta f \approx \frac{\partial f}{\partial u} \Delta u + \frac{\partial f}{\partial v} \Delta v$

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



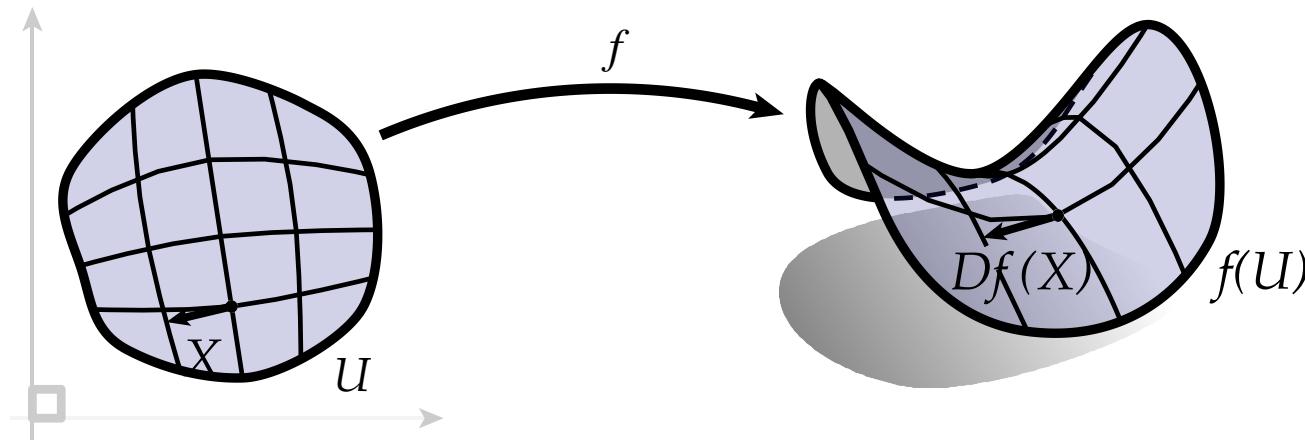
Total differential: $df = \frac{\partial f}{\partial u} du + \frac{\partial f}{\partial v} dv$

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

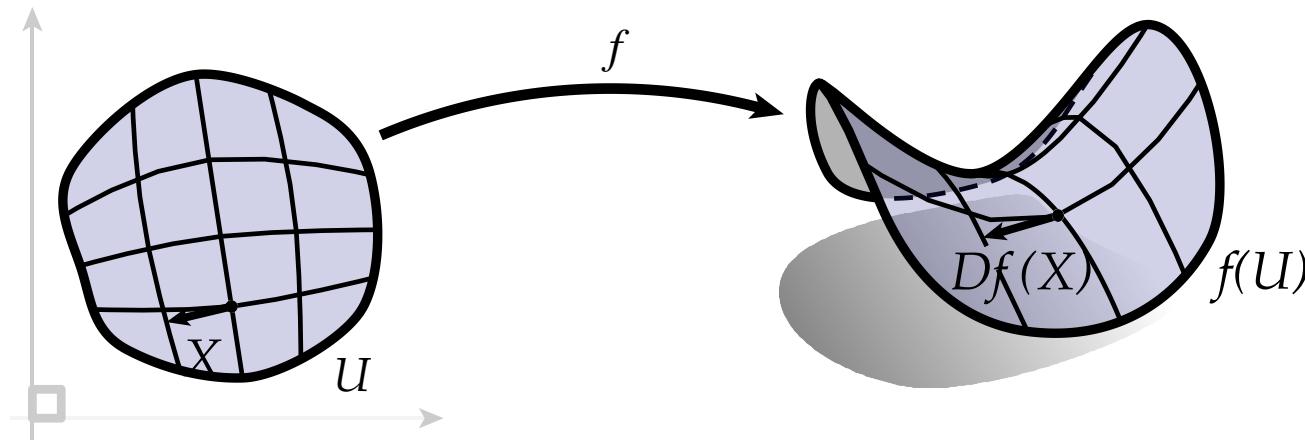
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Df_p : differential (Jacobian),
a linear map.

Differential of a Surface



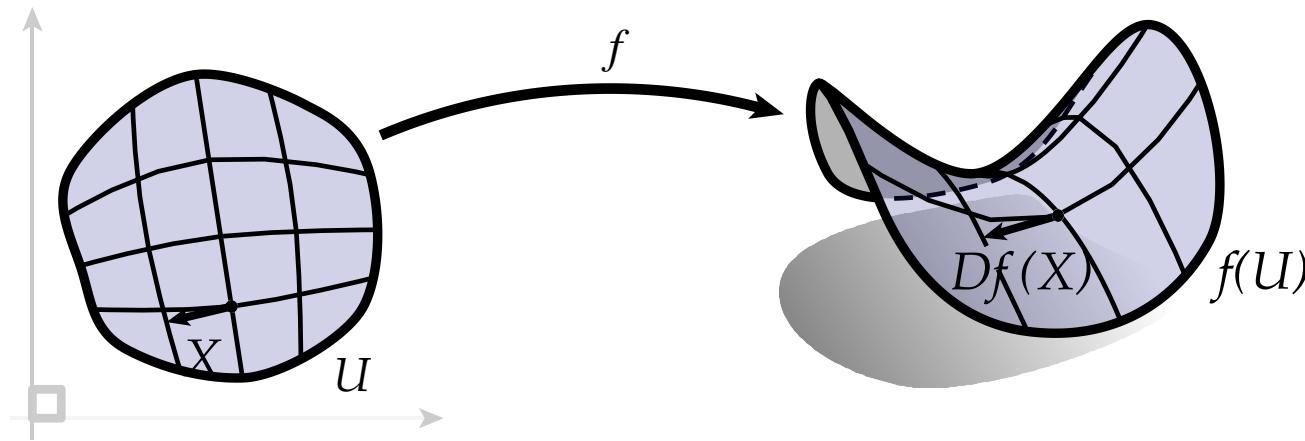
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$$Df_p := \left[\frac{\partial f}{\partial u}, \frac{\partial f}{\partial v} \right] \in \mathbb{R}^{3 \times 2} \quad \text{velocity in the 2D domain}$$

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