上海科技大学

ShanghaiTech University

CS289: **Mobile Manipulation Fall 2025**

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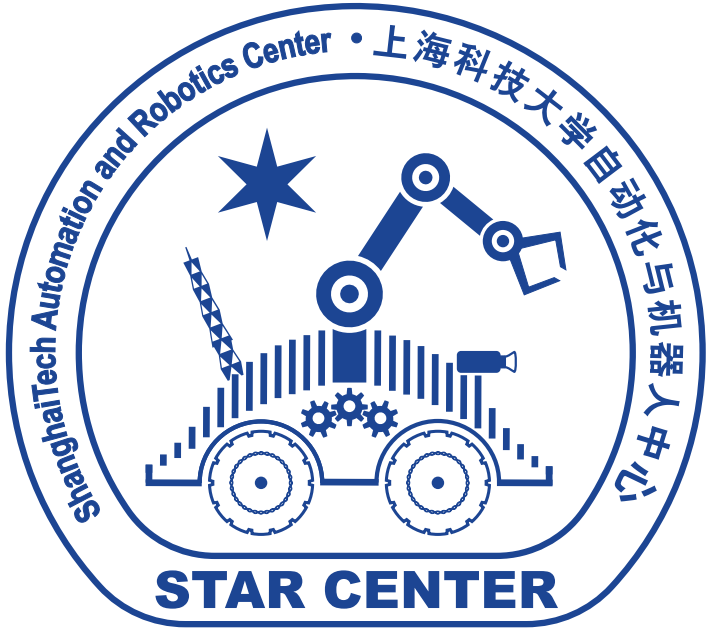
ShanghaiTech University



Outline

- Mission Planning
  - POMDP
  - LLMs
- Calibraiton
- Sensor Fusion

MISSION **PLANNING**

Overview

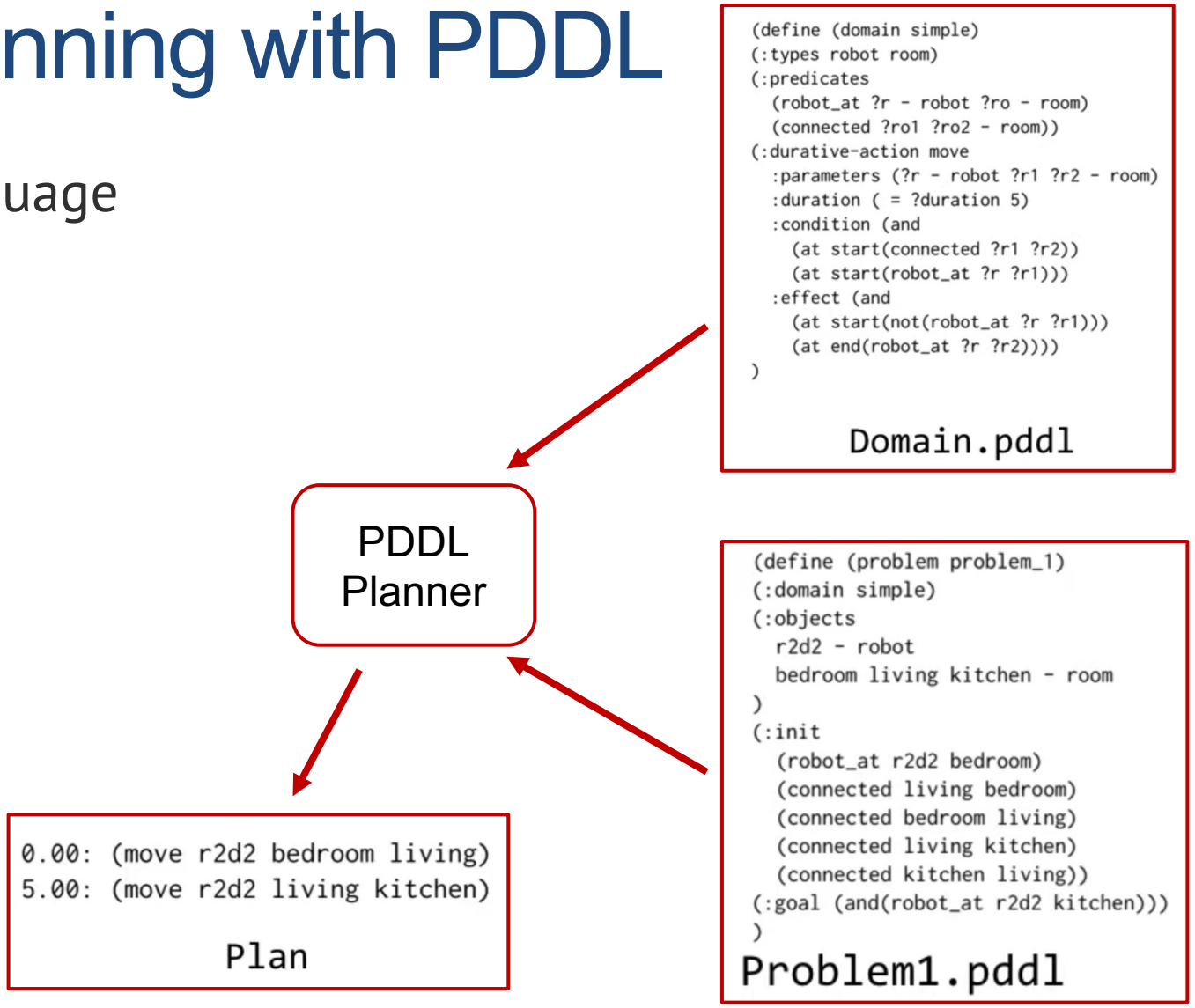
- Planning
  - PDDL: Language to define the state, problem, …
  - Planner: e.g. STRIPS
    - Precondition and effects on the state space

- Feedback via online replanning

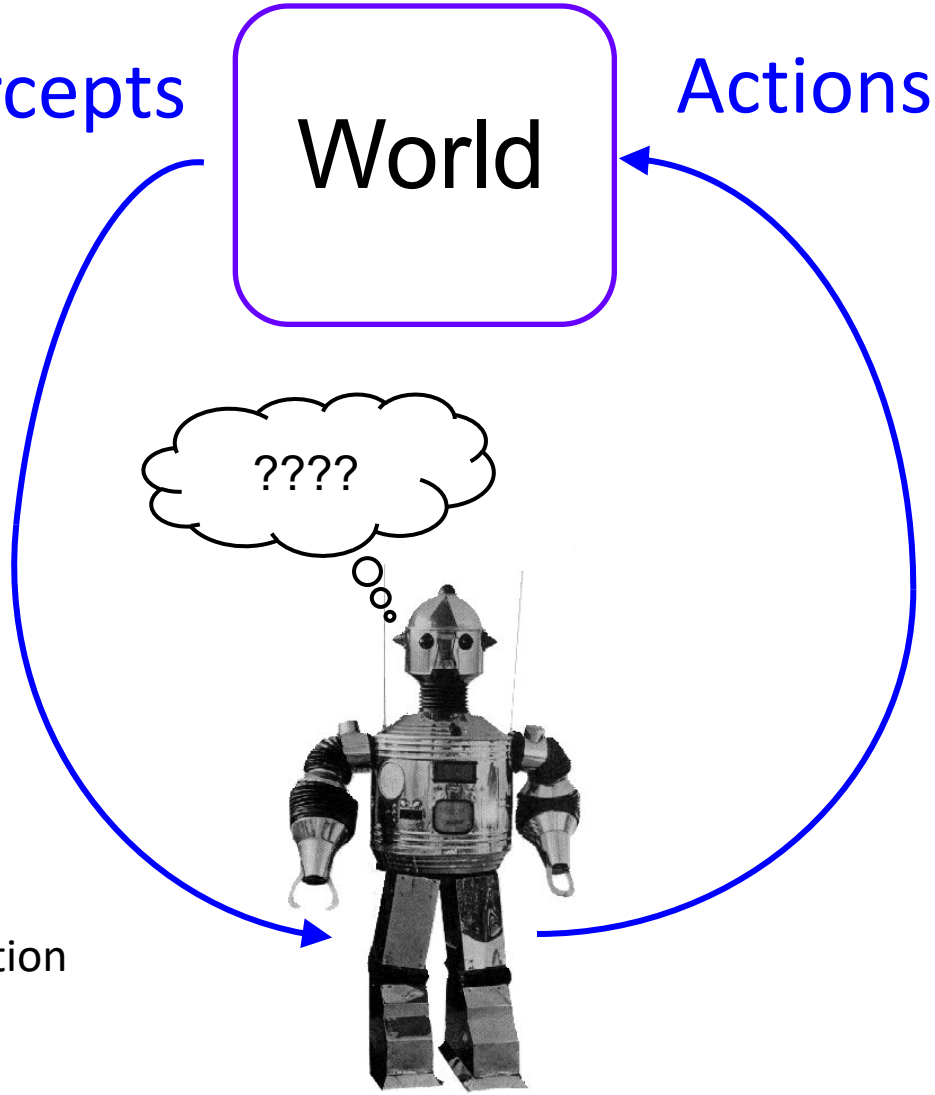
- Sometimes need Task and Motion Planning together:
  - Motion planner would fail if not did a specific action (e.g. remove obstacle) first

Mission and Task Planning with PDDL

- Planning Domain Definition Language
- Establish the rules (Domain)
- Present a situation and goal (Problem)
- Use a plan solver
- Get a plan



Classical Planning Assumptions



perfect

fully observable

sole source of change

deterministic

instantaneous

Goal

achieve goal condition

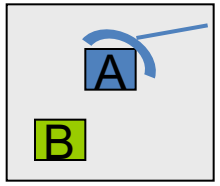
Material: Alan Fern; Daniel Weld
Oregon State University
https://web.engr.oregonstate.edu/~afern/classes/cs533/notes/strips-intro.pptx

STRIPS Planning Problem

A **STRIPS planning problem** specifies:
1) an initial state *S*
2) a goal *G*
3) a set of STRIPS actions

Objective: find a "short" action sequence reaching a goal state, or report that the goal is unachievable

Example Problem:



holding(A)
clear(B)
onTable(B)

Initial State

Solution: (PutDown(A,B))

on(A,B)

Goal

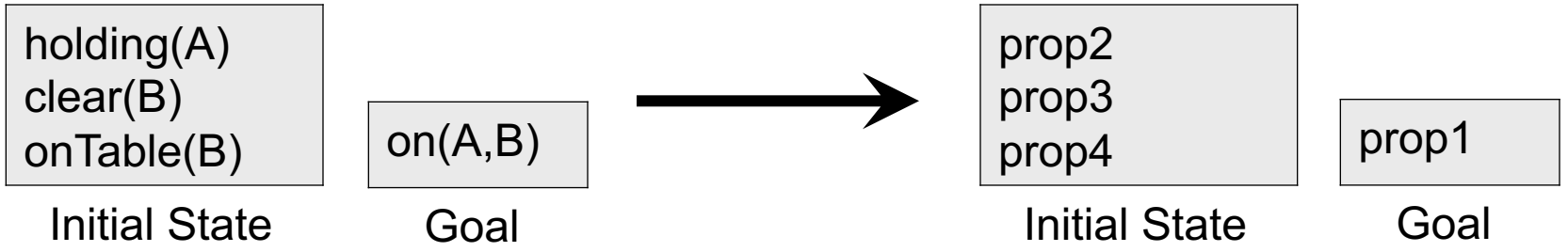
PutDown(A,B):
PRE: { holding(A), clear(B) }
ADD: { on(A,B), handEmpty, clear(A)}
DEL: { holding(A), clear(B) }

PutDown(B,A):
PRE: { holding(B), clear(A) }
ADD: { on(B,A), handEmpty, clear(B) }
DEL: { holding(B), clear(A) }

STRIPS Actions

Propositional Planners

- So far: written propositions (e.g. on(A,B)) in terms of objects (e.g. A and B) and predicates (e.g. on).
- But: planners ignore the internal structure of propositions such as on(A,B).
- Such planners are called **propositional planners** as opposed to first-order or relational planners
- => no difference to the planner if we replace “on(A,B)” in a problem with “prop1” (and so on)
- It feels wrong to ignore the existence of objects. But currently propositional planners are the state-of-the-art.

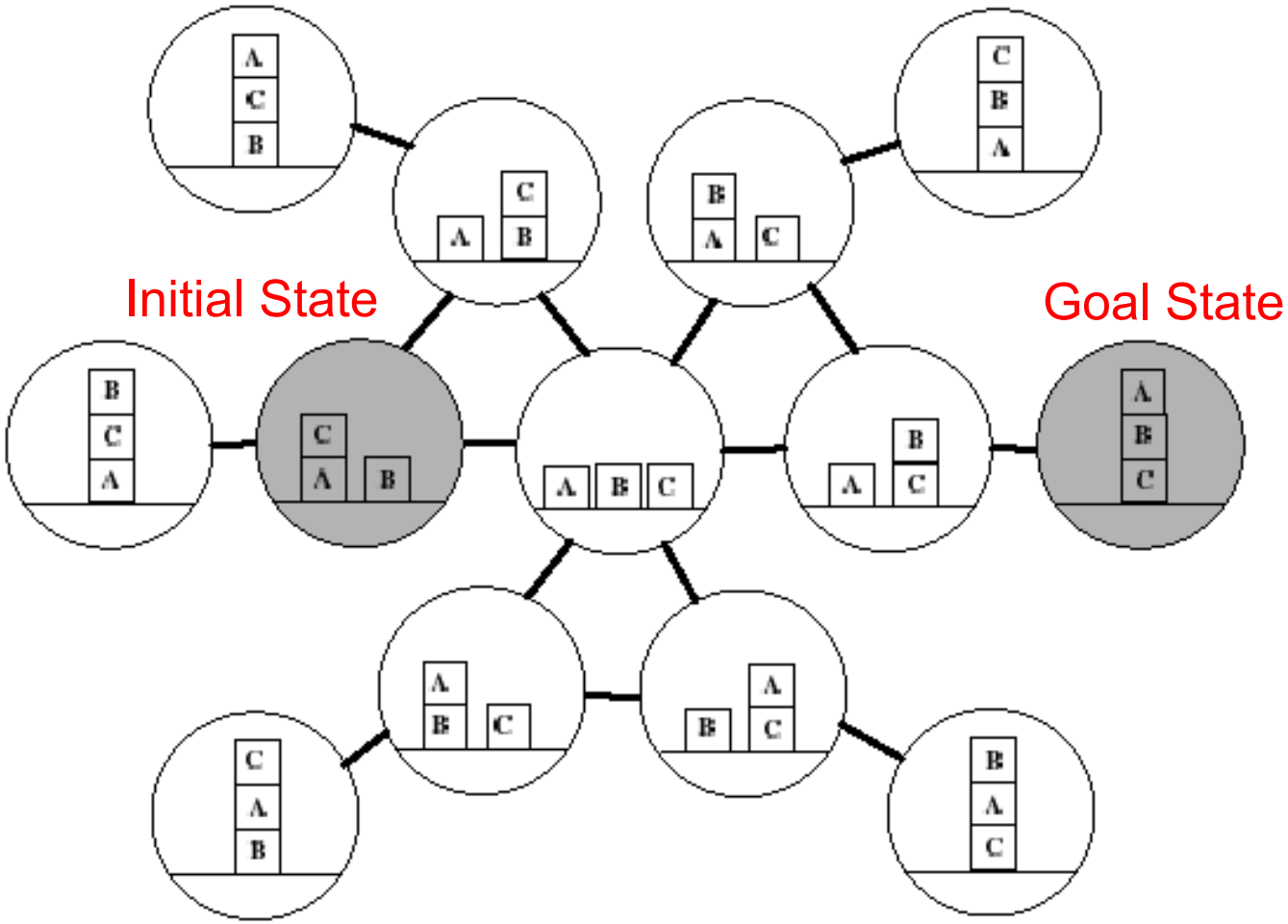


Planning as Graph Search

- It is easy to view planning as a graph search problem
- Nodes/vertices = possible states
- Directed Arcs = STRIPS actions
- Solution: path from the initial state (i.e. vertex) to one state/vertices that satisfies the goal

Search Space: Blocks World

Graph is finite



Planning as Graph Search

- Planning is just finding a path in a graph
  - Why not just use standard graph algorithms for finding paths?
- **Answer:** graphs are exponentially large in the problem encoding size (i.e. size of STRIPS problems).
  - But, standard algorithms are poly-time in graph size
  - So standard algorithms would require exponential time

- Do better:
  - We can use A*, but we need an admissible heuristic
    1. Divide-and-conquer: sub-goal independence assumption
    - Problem relaxation by removing
    2. … all preconditions
    3. … all preconditions and negative effects
    4. … negative effects only: Empty-Delete-List

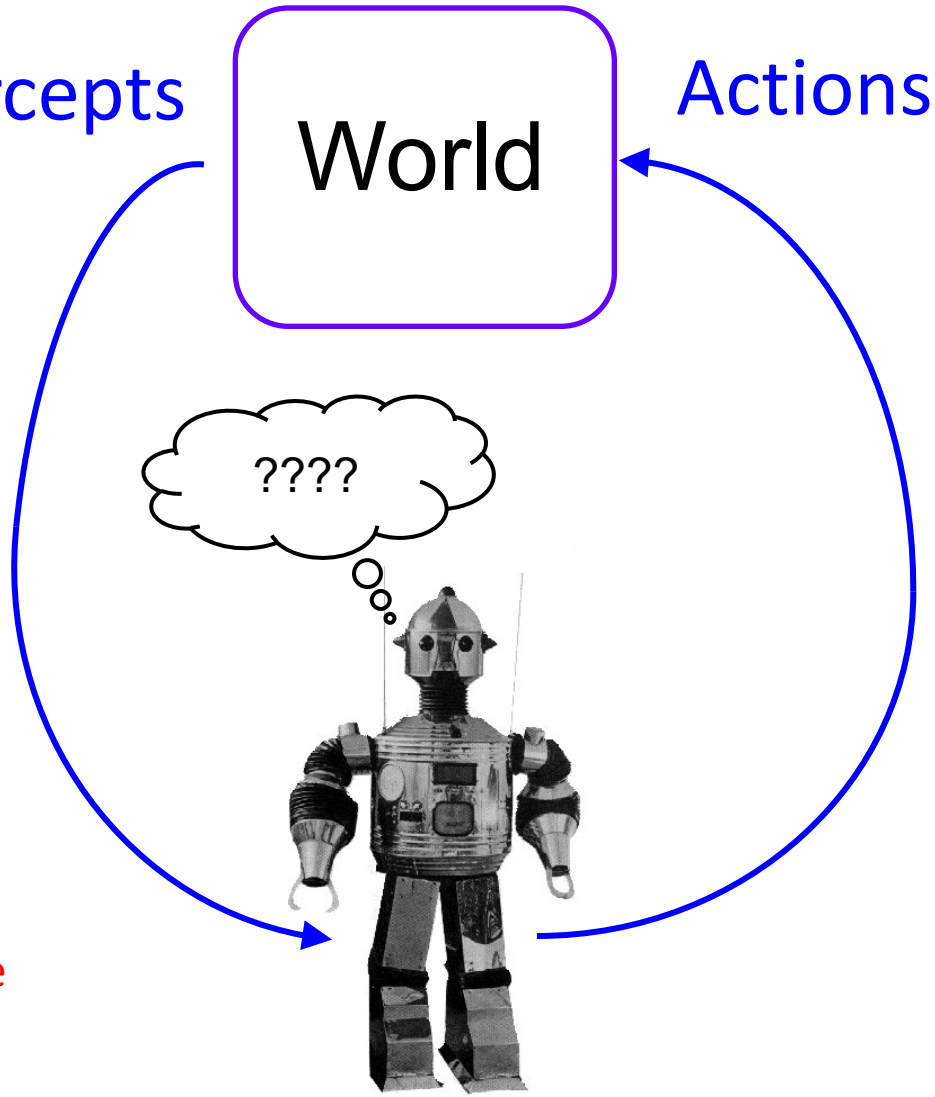
Partial Order Planning (POP)

- State-space search
  - Yields totally ordered plans (linear plans)
- POP
  - Works on subproblems independently, then combines subplans
  - Example
    - Goal(RightShoeOn $\wedge$ LeftShoeOn)
    - Init()
    - *Action*(RightShoe, PRECOND: RightSockOn, EFFECT: RightShoeOn)
    - *Action*(RightSock, EFFECT: RightSockOn)
    - *Action*(LeftShoe, PRECOND: LeftSockOn, EFFECT: LeftShoeOn)
    - *Action*(LeftSock, EFFECT: LeftSockOn)

Berthe Y. Choueiry (Shu-we-ri)
University of Nebraska Lincoln

POMDP

Stochastic/Probabilistic Planning: Markov Decision Process (MDP) Model



perfect

fully observable

sole source of change

stochastic

instantaneous

Goal

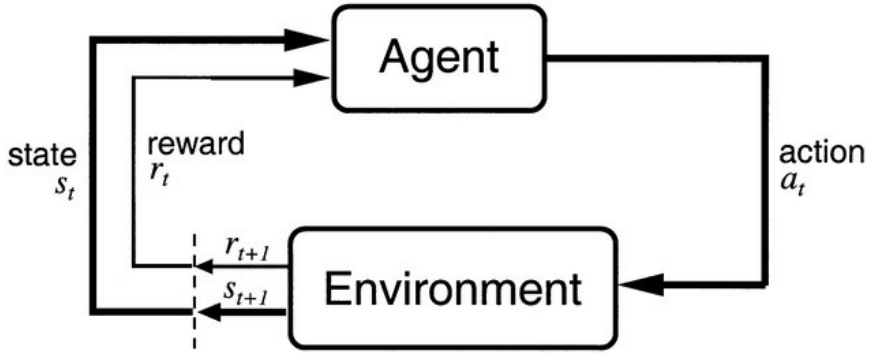
maximize expected reward over lifetime

POMDPs

- A special case of the Markov Decision Process (MDP)
- MDP:
  - Sequential decision making
  - Outcome uncertain
  - the environment is fully observable
  - Markov assumption for the transition model
    - Distribution of next state only depends on current state and action =>
  - the optimal policy depends only on the current state.

- For POMDPs, the environment is only partially observable

Markov Decision Process (S, A, H, T, R)



Given

- S: set of states
- A: set of actions
- H: horizon over which the agent will act
- T Transition dynamics: S x A x S x {0,1,…,H} ➜ [0,1] , $T_t(s,a,s') = P(s_{t+1} = s' \mid s_t = s, a_t = a)$
- R Reward: S x A x S x {0, 1, …, H} ➜ $\mathbb{R}$, $R_t(s,a,s')$ = reward for $(s_{t+1} = s', s_t = s, a_t = a)$

Goal: Policy π

- Find : S x {0, 1, …, H} ➜ A that maximizes expected sum of rewards, i.e.,

$$\pi^* = \arg\max_{\pi} \mathrm{E}[\sum_{t=0}^{H} R_t(S_t, A_t, S_{t+1})|\pi]$$

https://ai.stanford.edu/~gwthomas/notes/mdps.pdf

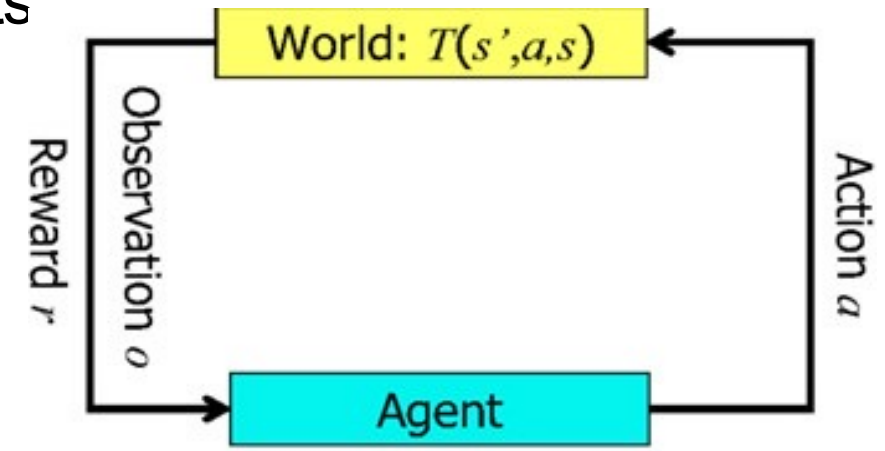
Material: Sachin Patil
Pieter Abbeel, Alex Lee
UC Berkeley

POMDP – Partially Observable MDP

= MDP

BUT

don’t get to observe the state itself, instead get sensory measurements



Now: what action to take given current probability distribution rather than given current state.

POMDPs: Tiger Example

S0
"tiger-left"
Pr(o=TL | S0, listen)=0.85
Pr(o=TR | S1, listen)=0.15

S1
"tiger-right"
Pr(o=TL | S0, listen)=0.15
Pr(o=TR | S1, listen)=0.85

Actions={ 0: listen,
1: open-left,
2: open-right}

Reward Function

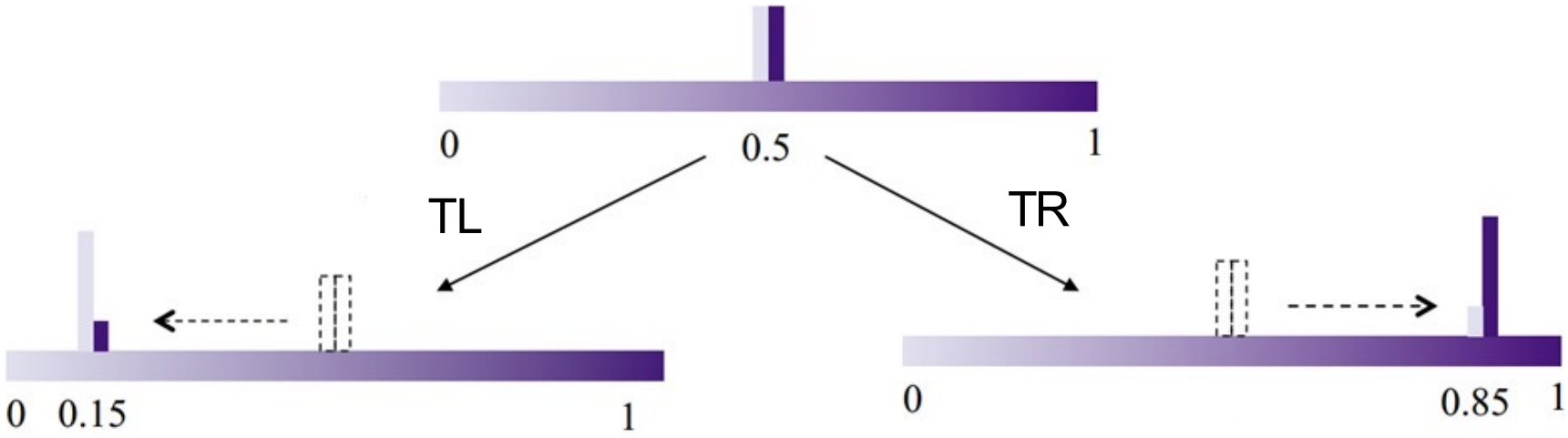
- *Penalty for wrong opening: -100*
- *Reward for correct opening: +10*
- *Cost for listening action: -1*

Observations

- *to hear the tiger on the left (TL)*
- *to hear the tiger on the right(TR)*

Belief State

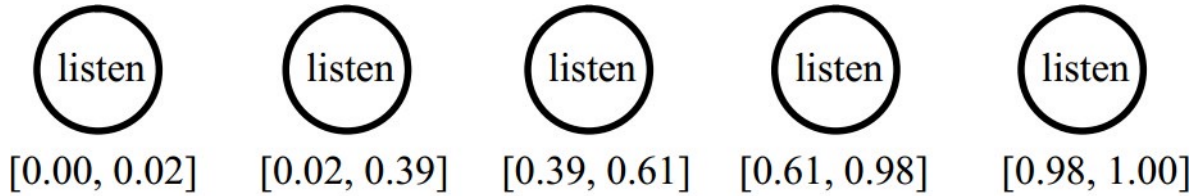
- Probability of S0 vs S1 being true underlying state
- Initial belief state: p(S0)=p(S1)=0.5
- Upon listening, the belief state should change according to the Bayesian update (filtering)



Policy – Tiger Example

- Policy π is a map from [0,1] → {listen, open-left, open-right}
- What should the policy be?
  - Roughly: listen until sure, then open
- But where are the cutoffs?

Tiger example optimal policy for $t = 1$



Tiger example optimal policy for $t = 2$

Some Solution Techniques

- Most exact solution algorithms (value iteration, policy iteration) use dynamic programming techniques
  - transform from one value function (the transition model in physical space, which is piecewise linear and convex - PWLC) to another that can be used in an MDP solution technique
  - Dynamic programming algorithms: one-pass (1971), exhaustive (1982), linear support (1988), witness (1996)
  - Better method – incremental pruning (1996)

COMBINED TASK & MOTION PLANNING

Differentiable Task Assignment and Motion Planning

Jimmy Envall, Roi Poranne, Stelian Coros

ETH zürich

CRL Computational Robotics Lab

אוניברסיטת חיפה
University of Haifa
جامعة حيفا

Envall, J., Poranne, R., & Coros, S. (2023, October). Differentiable task assignment and motion planning. In *2023 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)* (pp. 2049-2056). IEEE. https://arxiv.org/pdf/2304.09734

https://www.youtube.com/watch?v=zq3WyQFE5mA

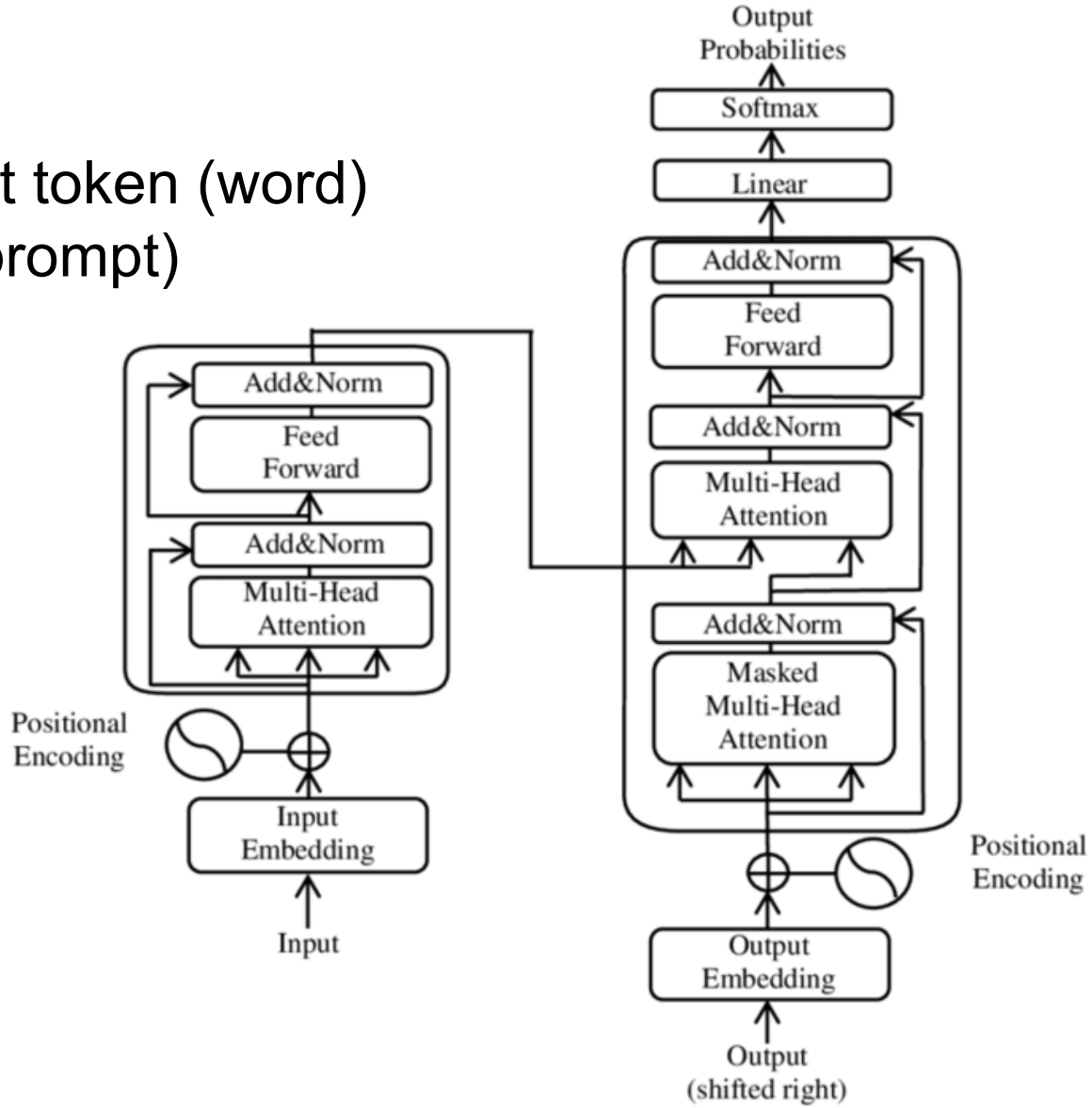
LLM

Large Language Model

- Transformer-based model outputting next token (word) with highest probability based on input (prompt)

- Powerful AI tool because:
  - “Understands” natural language (and other structured text) input
  - Through training has good world knowledge
  - Some form of (limited) reasoning

  - => useful in robotics, especially
    - Human Robot Interaction
    - All kinds of planning tasks
    - Various other purposes



LLM for Robotics

- Do As I Can, Not As I Say: Grounding Language in Robotic Affordances
  —4 Apr 2022: Robotics at Google, Everyday Robots
- ChatGPT for Robotics: Design Principles and Model Abilities
  —20 Feb 2023: Microsoft Autonomous Systems and Robotics Research
- Palm-E: An embodied multimodal language model
  —6 Mar 2023: Robotics at Google, TU Berlin, Google Research
- RT-2: New model translates vision and language into action
  —28 Jul. 2023: Google DeepMind
- RobotGPT: Robot Manipulation Learning from ChatGPT
  —3 Dec 2023: Samsung Research China, Tsinghua University
- Large Language Models for Robotics:Opportunities, Challenges, and Perspectives
  —9 Jan 2024: Northwestern Polytechnical University, Univ. Georgia, etc.
- Large Language Models for Robotics: A Survey
  —13 Nov 2023: Jinan University, University of Illinois Chicago
- Toward General-Purpose Robots via Foundation Models: A Survey and Meta-Analysis
  —14 Dec 2023: CMU, FAIR at Meta, Google DeepMind
- A Survey of Language-Based Communication in Robotics
  —6 Jun 2024: University of Southampton

LLM for Robotics

https://github.com/GT-RIPL/Awesome-LLM-Robotics

Awesome-LLM-Robotics

awesome

This repo contains a curative list of **papers using Large Language/Multi-Modal Models for Robotics/RL**. Template from awesome-Implicit-NeRF-Robotics

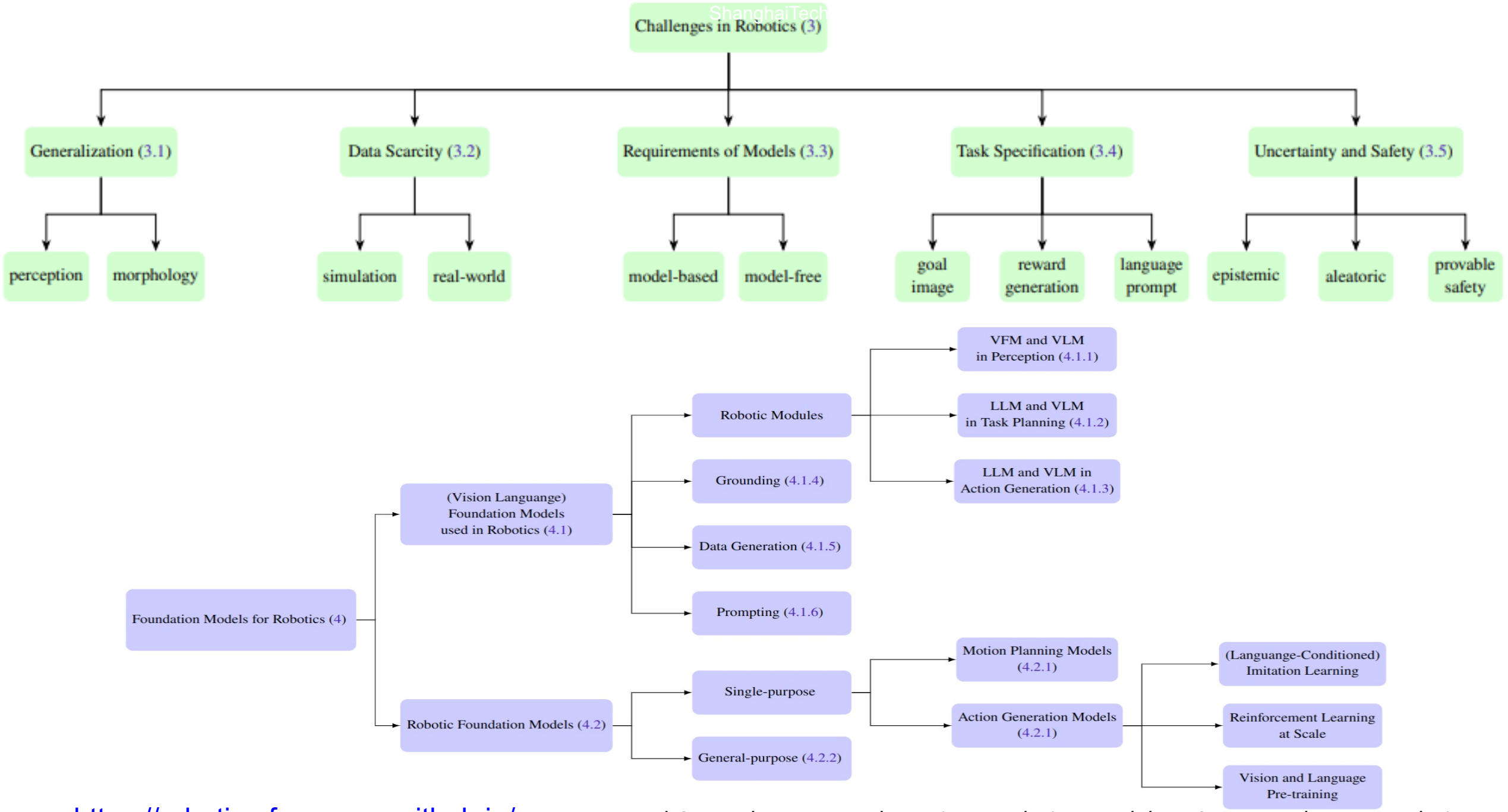
Please feel free to send me pull requests or email to add papers!

If you find this repository useful, please consider citing and STARing this list. Feel free to share this list with others!

Overview

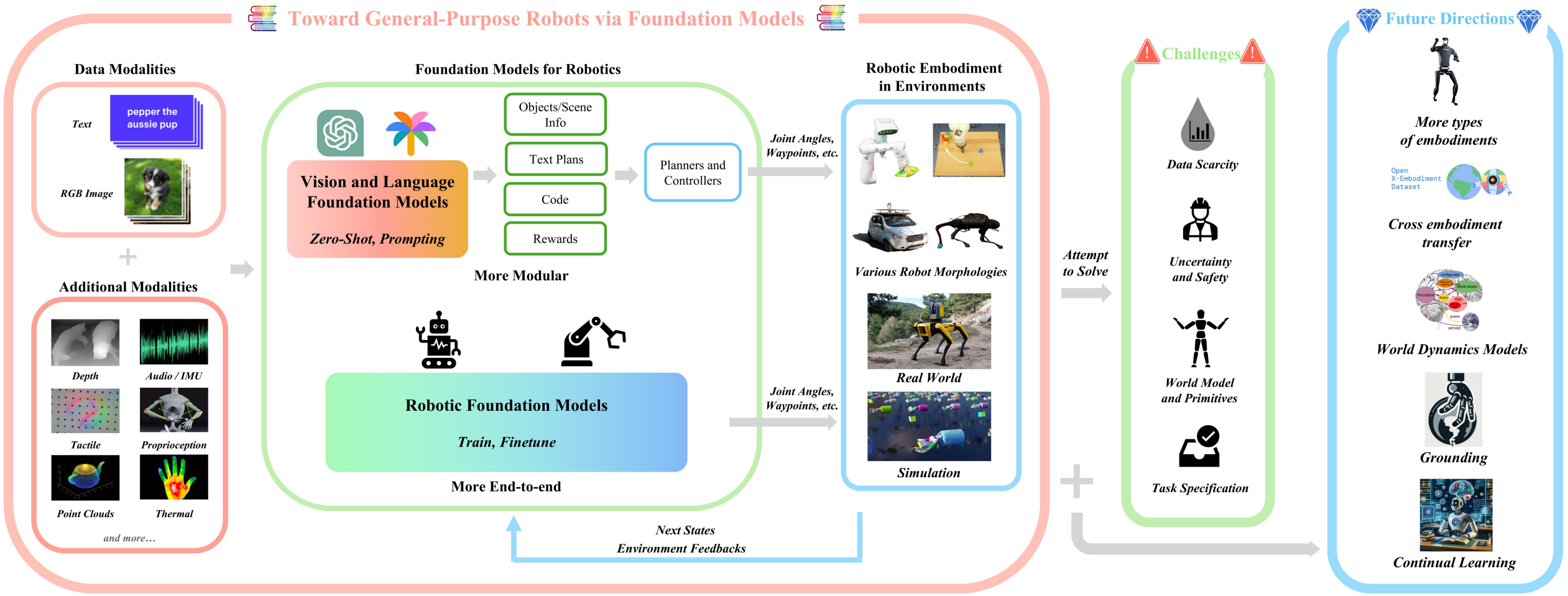
Surveys

- "Neural Scaling Laws for Embodied AI", *arXiv, May 2024*. [Paper]
- "Toward General-Purpose Robots via Foundation Models: A Survey and Meta-Analysis", *arXiv, Dec 2023*. [Paper] [Paper List] [Website]
- "Language-conditioned Learning for Robotic Manipulation: A Survey", *arXiv, Dec 2023*, [Paper]
- "Foundation Models in Robotics: Applications, Challenges, and the Future", *arXiv, Dec 2023*, [Paper] [Paper List]
- "Robot Learning in the Era of Foundation Models: A Survey", *arXiv, Nov 2023*, [Paper]
- "The Development of LLMs for Embodied Navigation", *arXiv, Nov 2023*, [Paper]



https://robotics-fm-survey.github.io/ - *Toward General-Purpose Robots via Foundation Models: A Survey and Meta-Analysis*

Toward General-Purpose Robots via Foundation Models: A Survey and Meta-Analysis



ChatGPT for Robotics: Design Principles and Model Abilities

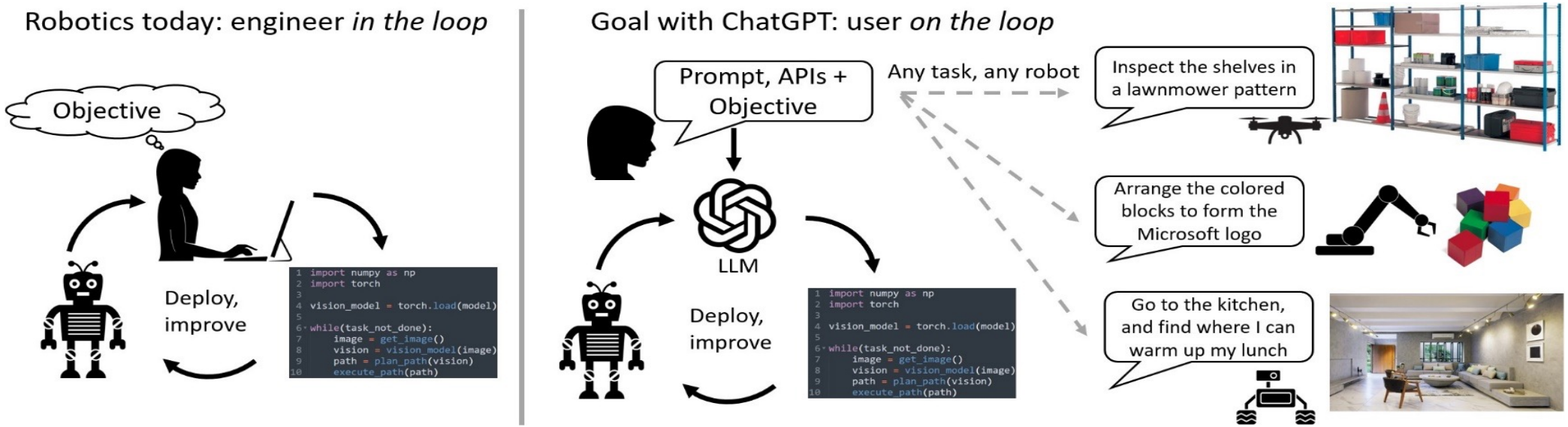


Figure 1: Current robotics pipelines require a specialized engineer in the loop to write code to improve the process. Our goal with ChatGPT is to have a (potentially non-technical) user on the loop, interacting with the language model through high-level language commands, and able to seamlessly deploy various platforms and tasks.

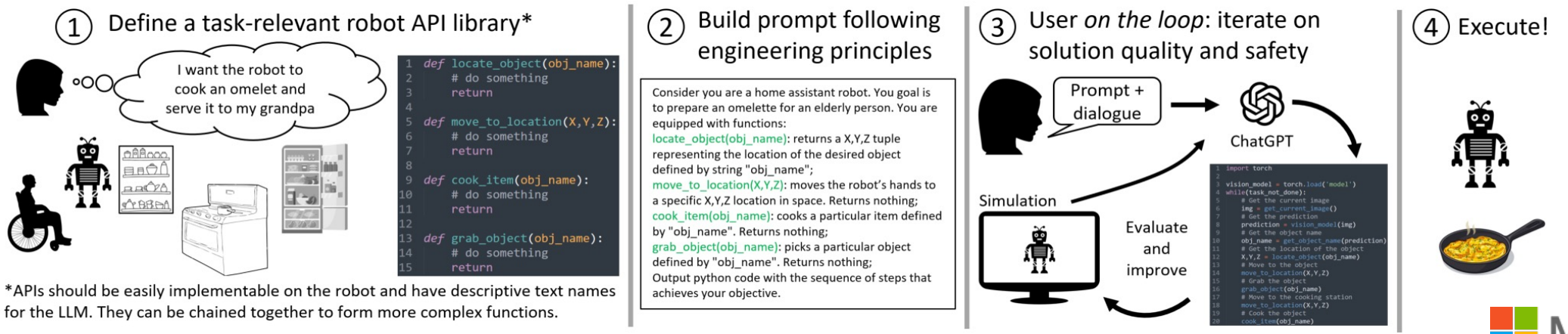
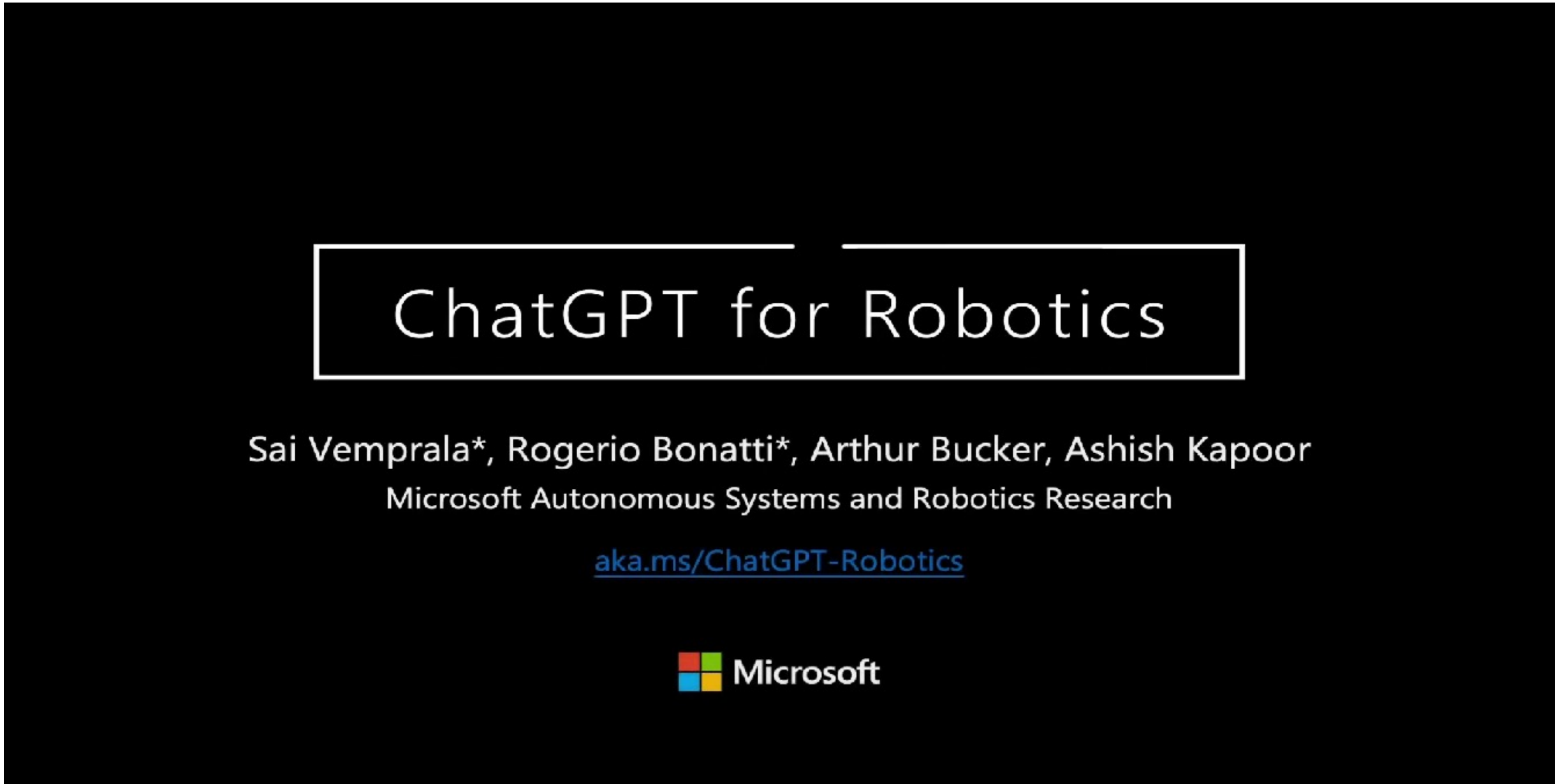


Figure 2: Robotics pipeline employing ChatGPT with the user on the loop to evaluate the output's quality and safety.

Microsoft

ChatGPT for Robotics: Design Principles and Model Abilities



PaLM-E: An Embodied Multimodal Language Model

Robotics at Google

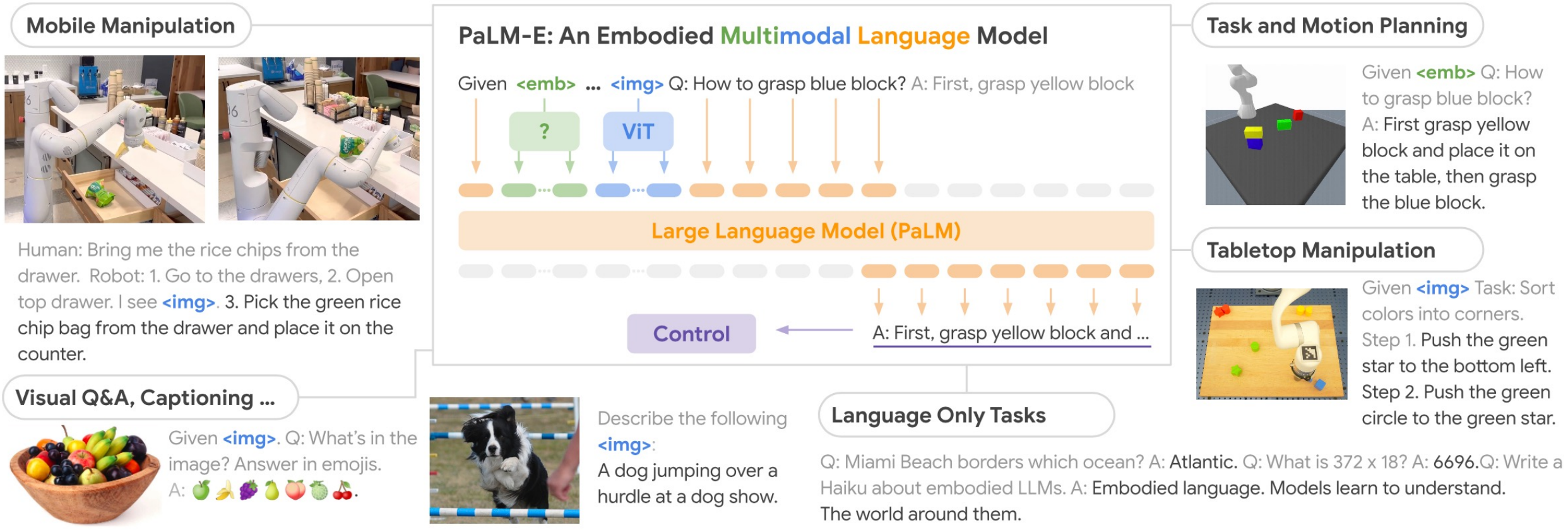
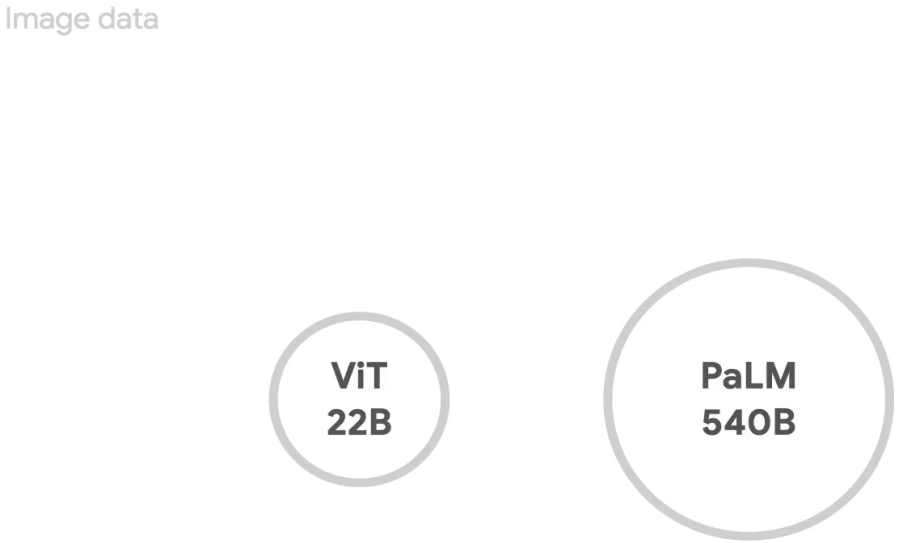


Figure 1: PaLM-E is a single general-purpose multimodal language model for embodied reasoning tasks, visual-language tasks, and language tasks. PaLM-E transfers knowledge from visual-language domains into embodied reasoning – from robot planning in environments with complex dynamics and physical constraints, to answering questions about the observable world. PaLM-E operates on multimodal sentences, i.e. sequences of tokens where inputs from arbitrary modalities (e.g. images, neural 3D representations, or states, in green and blue) are inserted alongside text tokens (in orange) as input to an LLM, trained end-to-end.

PaLM-E: An Embodied Multimodal Language Model



Abstract

Large language models have been demonstrated to perform complex tasks. However, enabling general inference in the real world, e.g. for robotics problems, raises the challenge of grounding. We propose embodied language models to directly incorporate real-world continuous sensor modalities into language models and thereby establish the link between words and percepts. Input to our embodied language model are multi-modal sentences that interleave visual, continuous state estimation, and textual input encodings.

Robotics at Google

This video has audio

Language Models as Zero-Shot Planners:

Extracting Actionable Knowledge for Embodied Agents

Wenlong Huang
UC Berkeley

Pieter Abbeel
UC Berkeley

Deepak Pathak*
CMU

Igor Mordatch*
Google

- Language Models as Zero-Shot Planners: Extracting Actionable Knowledge for Embodied Agents, ICML 2022

RT-2: Vision-Language-Action Models, Transfer Web Knowledge to Robotic Control

Google DeepMind

RT-2: Vision-Language-Action Models Transfer Web Knowledge to Robotic Control

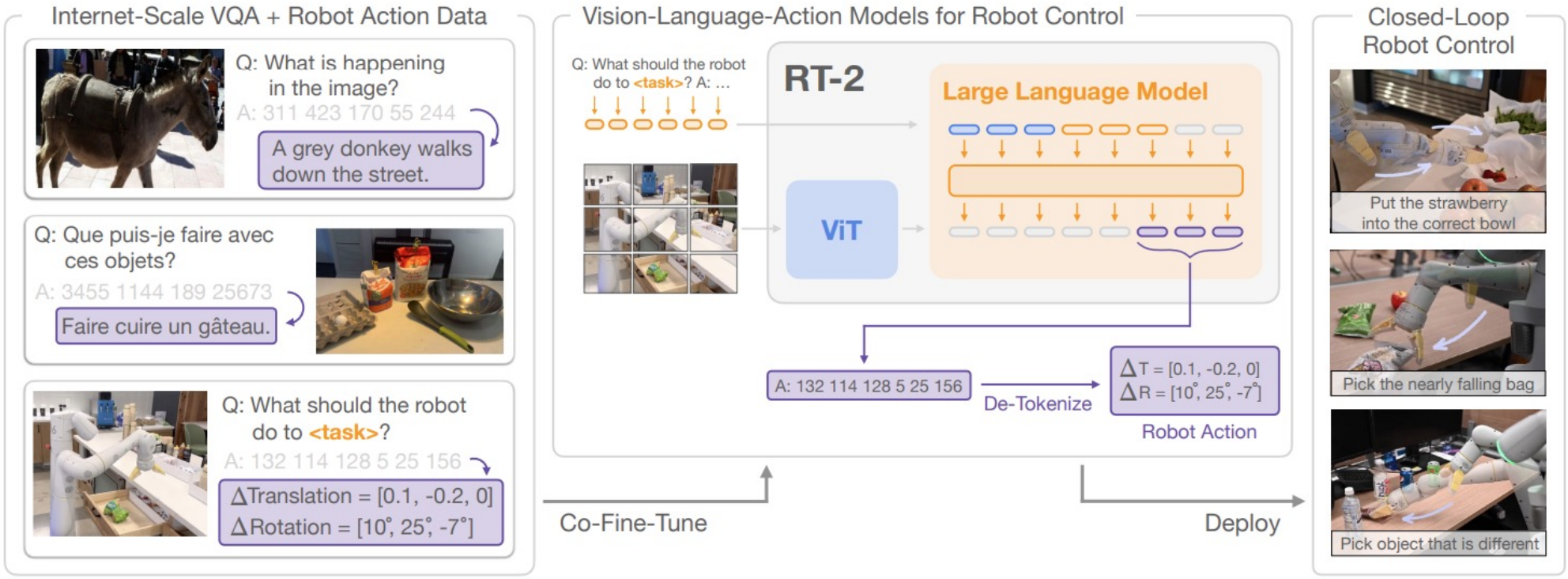
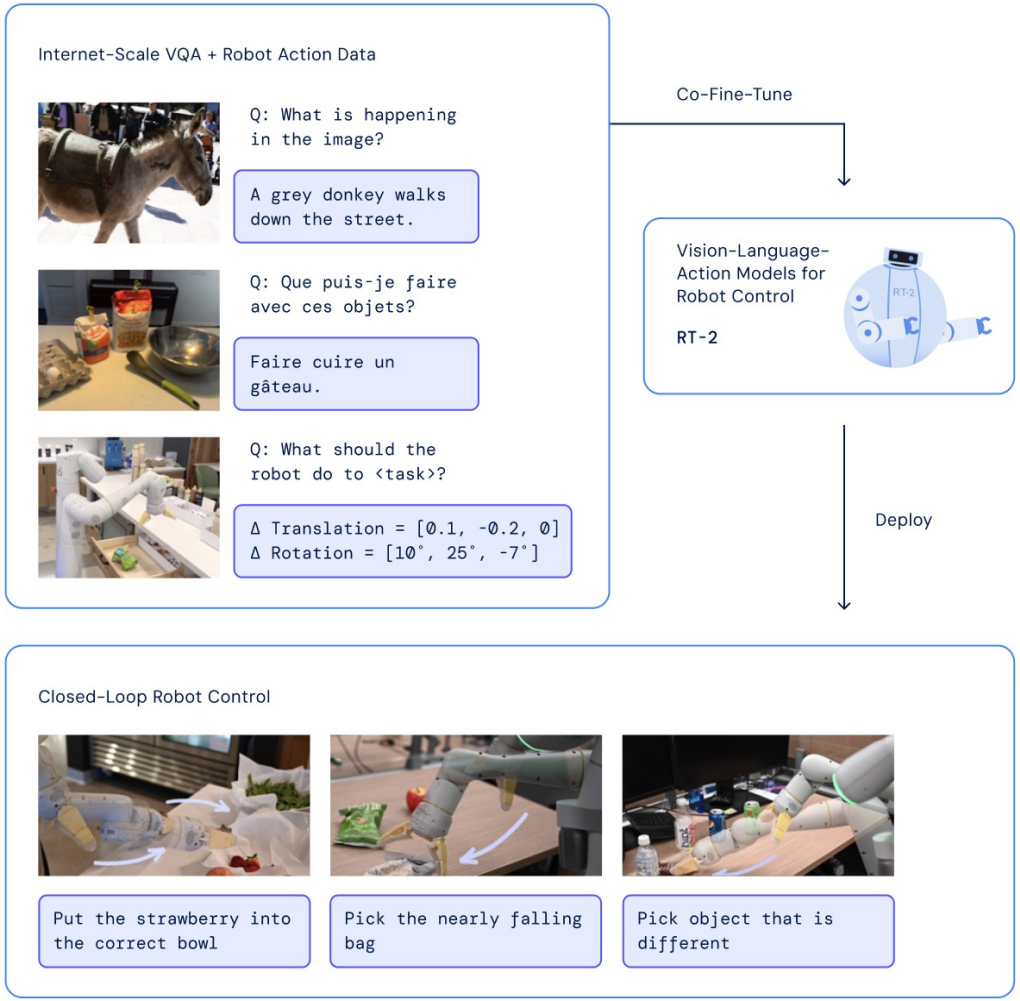


Figure 1 | RT-2 overview: we represent robot actions as another language, which can be cast into text tokens and trained together with Internet-scale vision-language datasets. During inference, the text tokens are de-tokenized into robot actions, enabling closed loop control. This allows us to leverage the backbone and pretraining of vision-language models in learning robotic policies, transferring some of their generalization, semantic understanding, and reasoning to robotic control. We demonstrate examples of RT-2 execution on the project website: robotics-transformer2.github.io.

RT-2: Vision-Language-Action Models, Transfer Web Knowledge to Robotic Control

Google DeepMind

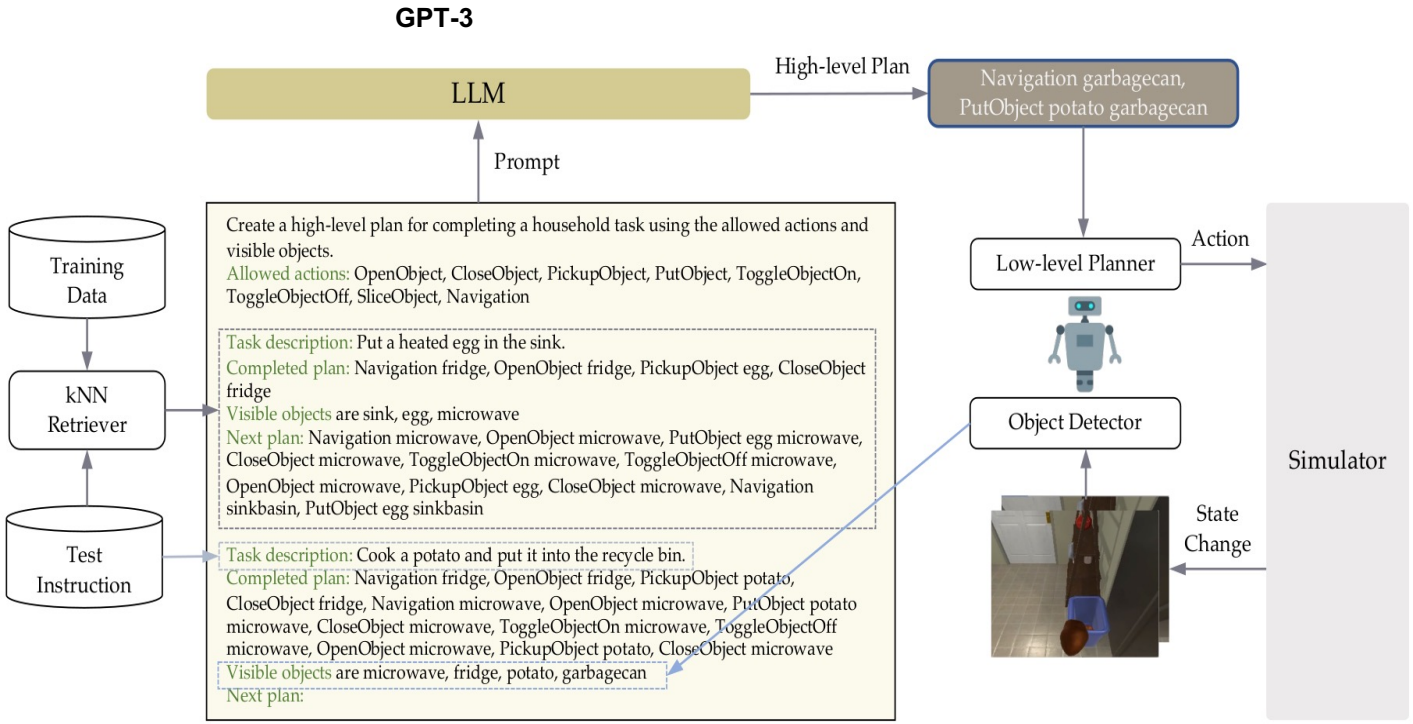


RT-2 architecture and training

- Song C H, Wu J, Washington C, et al.

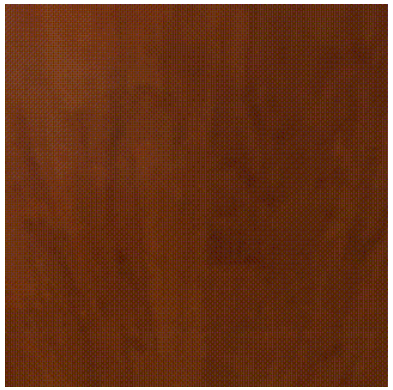
LLM-planner: Few-shot grounded planning for embodied agents with large language models

Proceedings of the IEEE/CVF International Conference on Computer Vision. 2023: 2998-3009.



- Dataset/ Simulator:

Alfred: vision-and-language navigation dataset: https://askforalfred.com/



- Another Embodied AI Simulator: Habitat: https://research.facebook.com/publications/habitat-a-platform-for-embodied-ai-research/

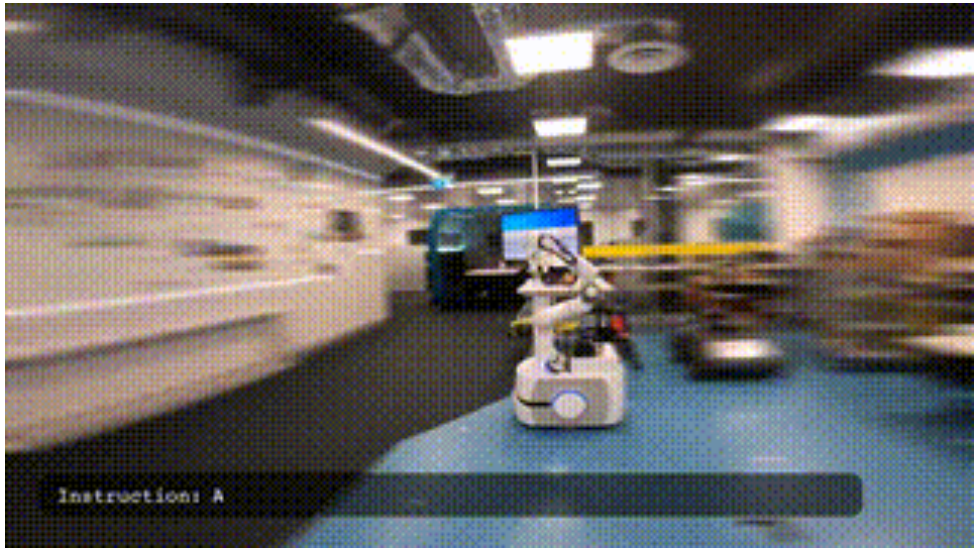
Table V: Robot datasets collected by recent VLAs. VIMA skills refer to "meta-tasks" in their original paper. We use the newer BridgeData V2. PC: point cloud.

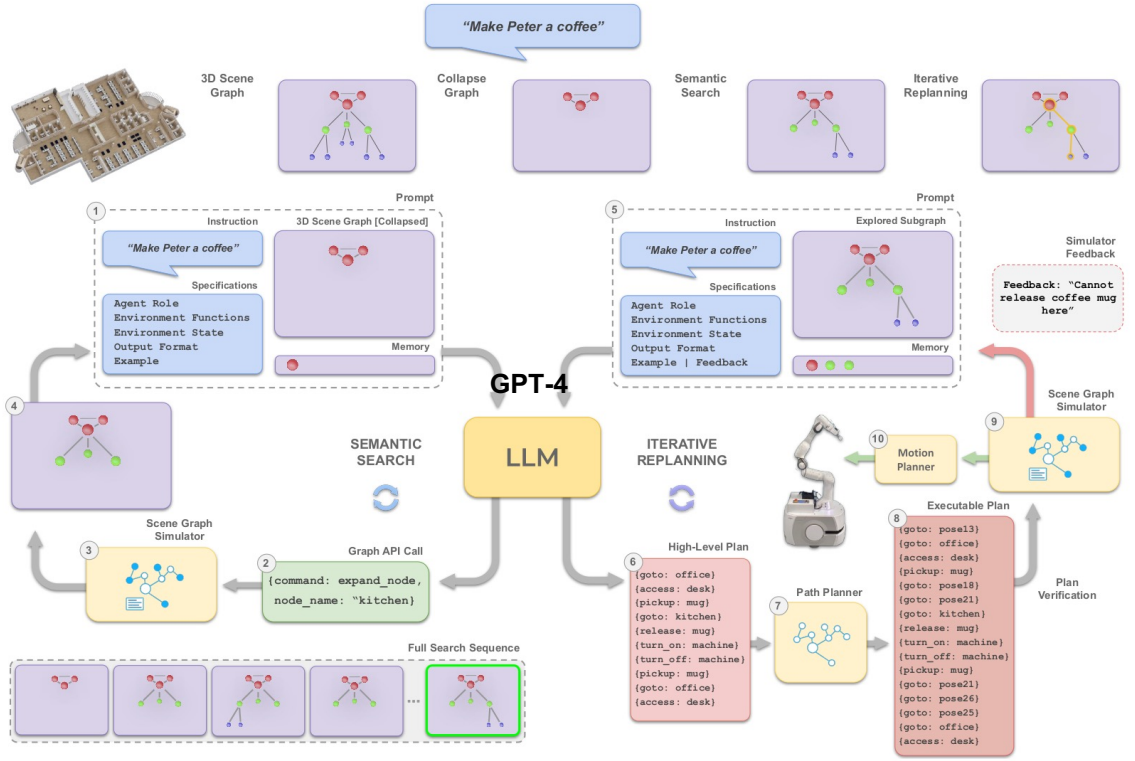
Name	Type	Instruction	Observation	Robot	Skills	Tasks	Objects	Episodes
RoboNet [165]	Real-world	Goal image	RGB	7 embodiments	-	-	-	162K
MT-Opt [71]	Real-world	Lang	RGB	7 embodiments	2	12	-	800K
BC-Z [24]	Real-world	Lang, Demo	RGB	Everyday	9	100	-	25.9K
RT-1 [33]	Real-world	Lang	RGB	Everyday	12	700+	16	130K
MOO [42]	Real-world	Multi-modal	RGB	Everyday	5	-	106	59.1K
VIMA [41]	Simulator	Multi-modal	RGB	UR5	17	-	29	650K
RoboSet [166]	Real-world	Lang	RGB, D	Franka	12	38	-	98.5K
BridgeData [167]	Real-world	Lang	RGB, D	WidowX 250	13	-	100+	60.1K
OXE [37]	Real-world	Lang	RGB, D, PC	22 embodiments	527	160,266	-	1M+

Ma Y, Song Z, Zhuang Y, et al. A Survey on Vision-Language-Action Models for Embodied AI[J]. arXiv preprint arXiv:2405.14093, 2024.

Planning: Grounding large language models using 3d scene graphs for scalable task planning

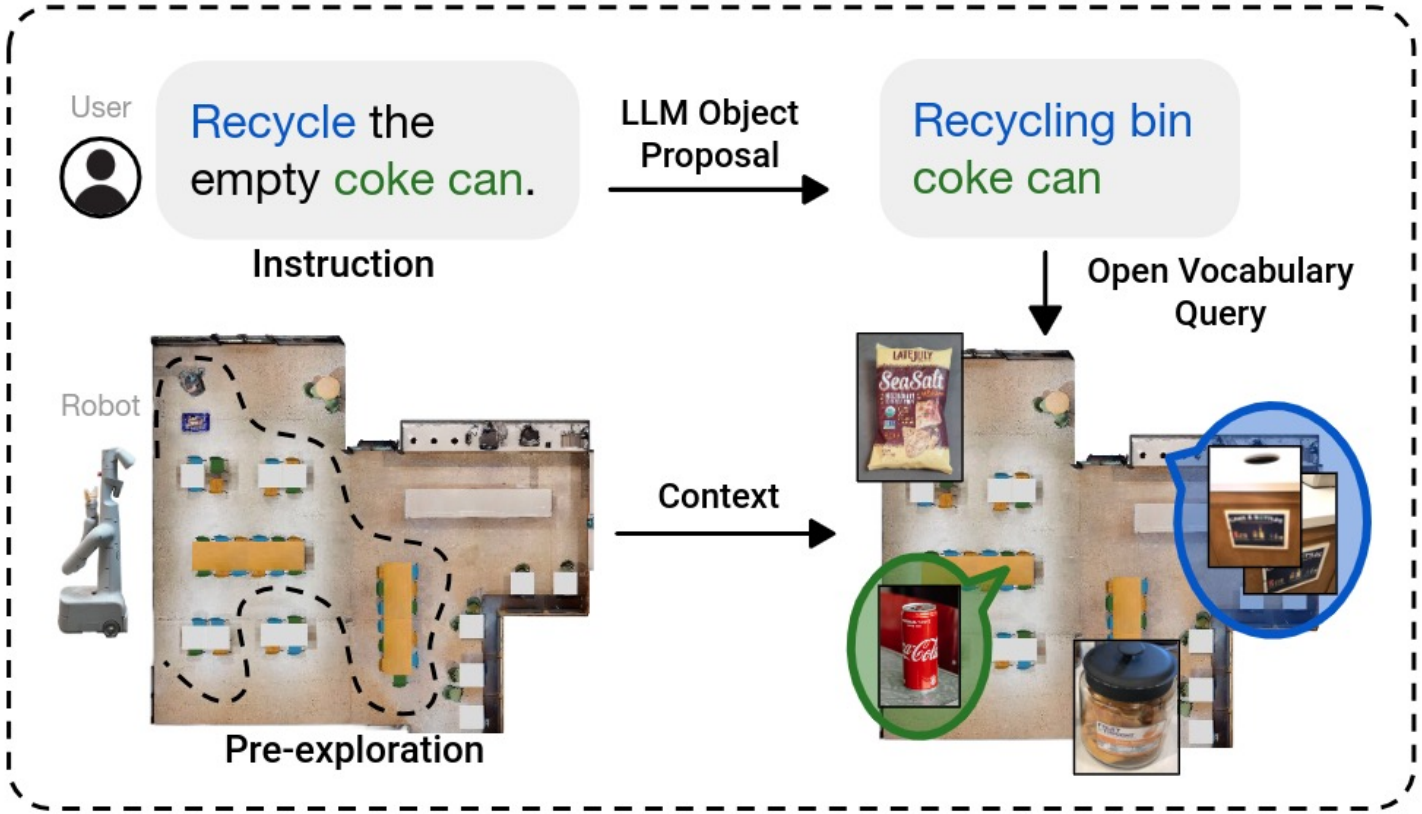
- Rana K, Haviland J, Garg S, et al. Sayplan: Grounding large language models using 3d scene graphs for scalable task planning[J]. arXiv preprint arXiv:2307.06135, 2023.





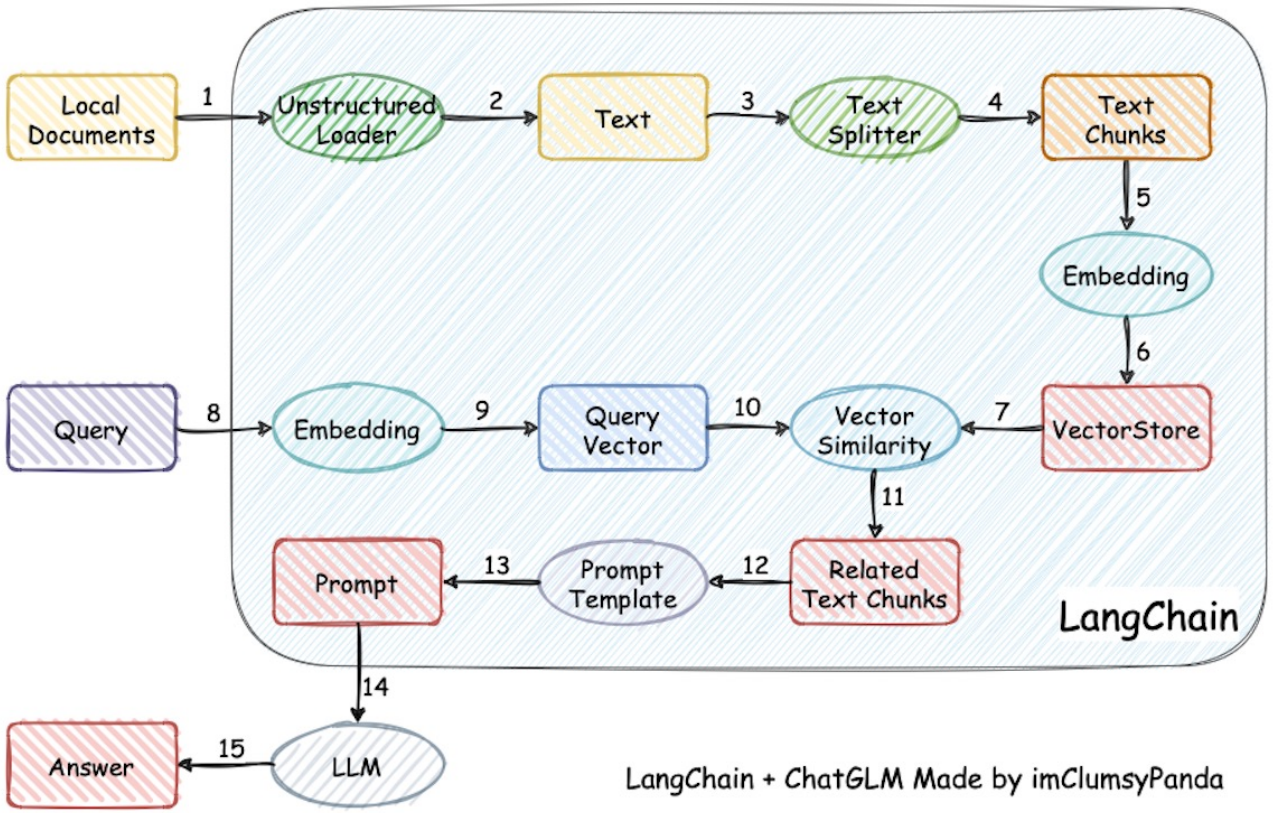
Mission Planning :

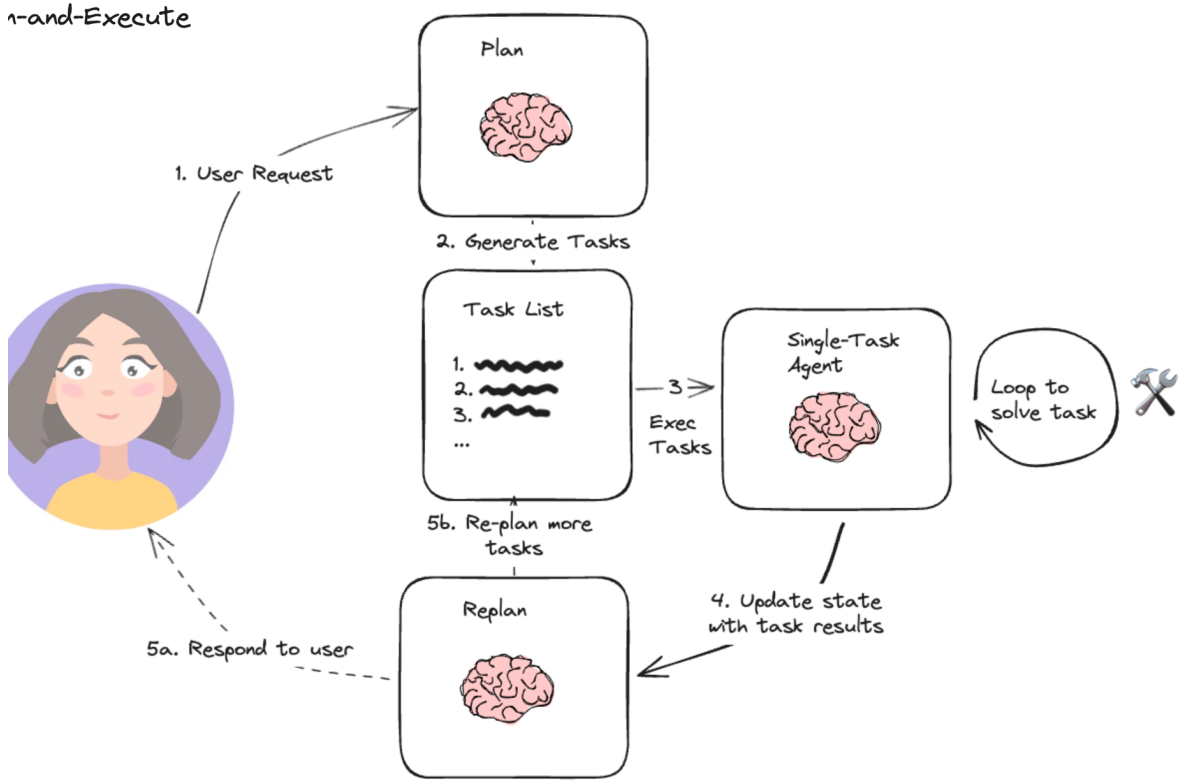
Open-vocabulary queryable scene representations for real world planning



Chen, B., Xia, F., Ichter, B., Rao, K., Gopalakrishnan, K., Ryoo, M. S., ... & Kappler, D. (2023, May). Open-vocabulary queryable scene representations for real world planning. In *2023 IEEE International Conference on Robotics and Automation (ICRA)* (pp. 11509-11522). IEEE.

Retrieval Augmented Generation: LangGraph





https://langchain-ai.github.io/langgraph/

SPINE:
Online Semantic Planning for Missions with Incomplete Natural Language Specifications in Unstructured Environments

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https://zacravichandran.github.io/SPINE/

Prompt engineering

- Ask the LLM to provide uncertainty of the prompts:
  - Ren A Z, Dixit A, Bodrova A, et al. Robots that ask for help: Uncertainty alignment for large language model planners[J]. arXiv preprint arXiv:2307.01928, 2023.
  - SaySelf: Teaching LLMs to Express Confidence with Self-Reflective Rationales

CALIBRATION

Calibration

- Intrinsic calibration:
  - Correct raw sensor data such that:
    - It adheres to certain standards
    - Reduces the error/ noise
  - Robotics/ autonomous driving:
    - Camera calibration!
    - LiDARS can also be calibrated (factory calibration typically sufficient)
    - All sensors …
- Extrinsic calibration:
  - Determine the pose (position and orientation) of sensors w.r.t. a frame of reference

Camera Calibration Parameters

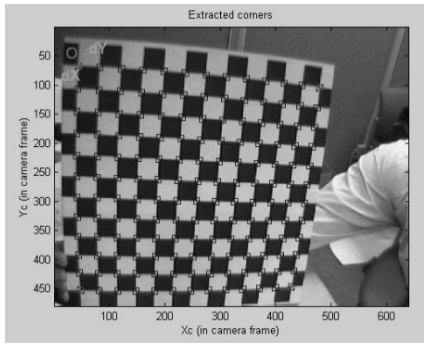
- Different models possible – typical one:
- α_u, α_v: focal length and size of pixel
- u_0, v_0: position of the sensor w.r.t optical center
- k_1: radial distortion

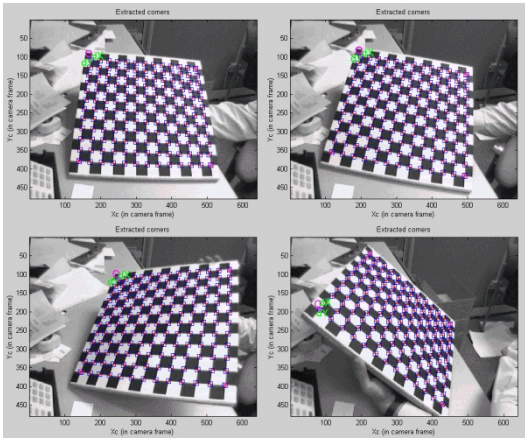
$$\lambda \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha_u & 0 & u_0 \\ 0 & \alpha_v & v_0 \\ 0 & 0 & 1 \end{bmatrix} \cdot R \begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} + T \qquad \begin{bmatrix} u_d \\ v_d \end{bmatrix} = (1 + k_1 \rho^2) \cdot \begin{bmatrix} u \\ v \end{bmatrix}$$

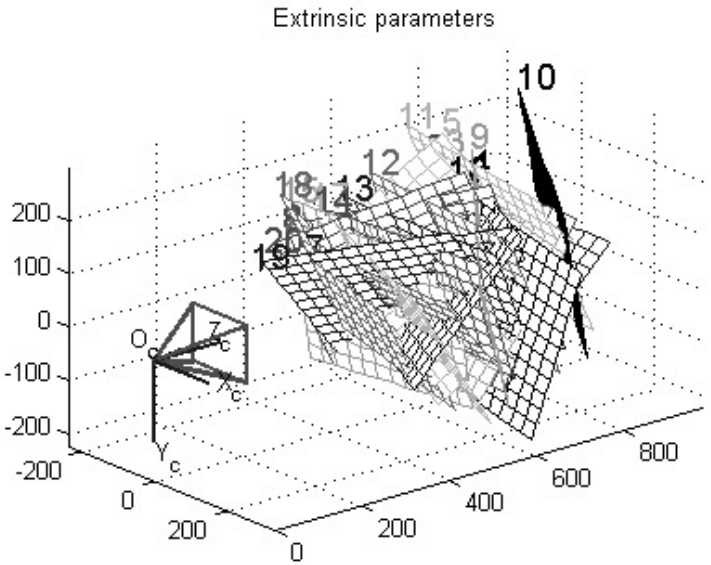
Camera Calibration

- Parameters: govern mapping from scene points to image points
- Idea: known:
  - pixel coordinates of image points p
  - 3D coordinates of the corresponding scene points P
  - => compute the unknown parameters A, R, T by solving the perspective projection equation

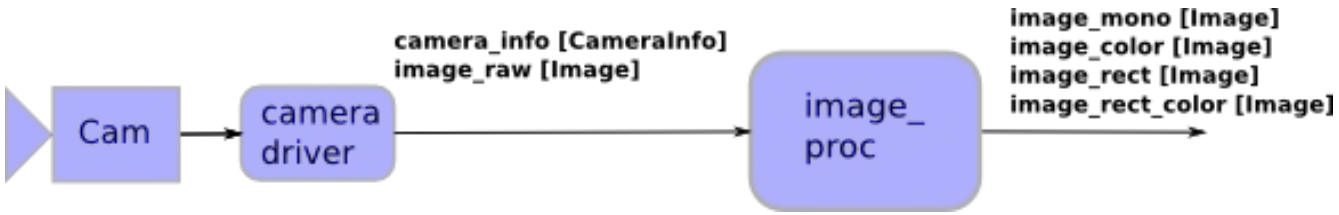
$$\lambda \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha_u & 0 & u_0 \\ 0 & \alpha_v & v_0 \\ 0 & 0 & 1 \end{bmatrix} \cdot R \begin{bmatrix} x_w \\ y_w \\ z_w \end{bmatrix} + T$$







ROS Image Processing



sensor_msgs/CameraInfo

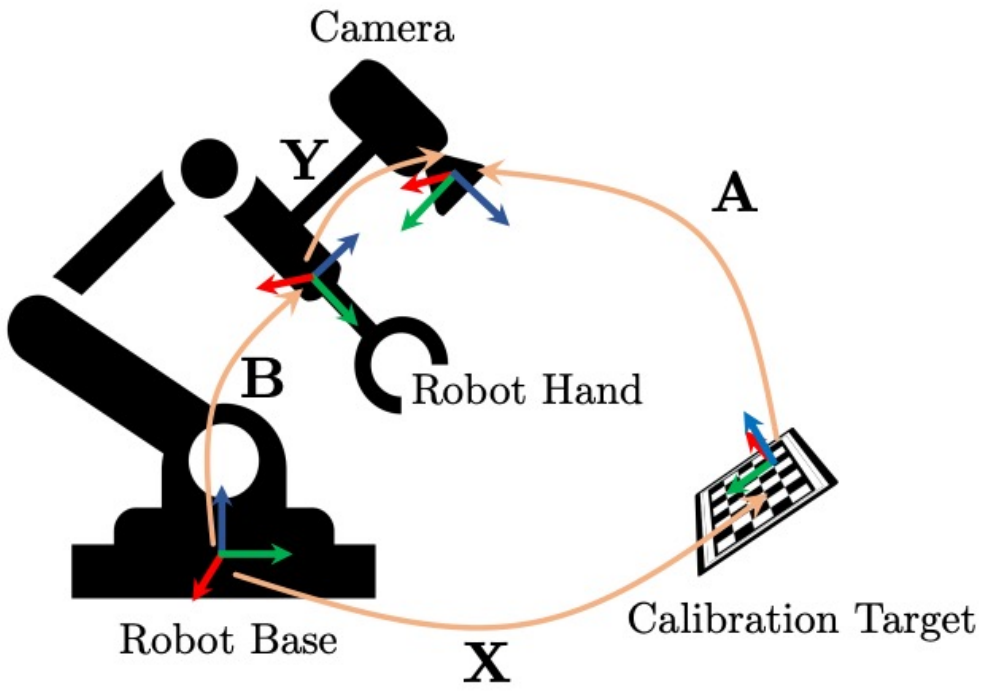
std_msgs/Header header
uint32 height
uint32 width
string distortion_model
float64[] D
float64[9] K
float64[9] R
float64[12] P
uint32 binning_x
uint32 binning_y
sensor_msgs/RegionOfInterest roi

- image_proc : Image processing node
  - Take calibration data from sensor_msgs/CameraInfo to calibrate/ rectify images
  - http://wiki.ros.org/image_proc
- Calibrate cameras:
  - http://wiki.ros.org/camera_calibration/Tutorials/MonocularCalibration
  - http://wiki.ros.org/camera_calibration/Tutorials/StereoCalibration

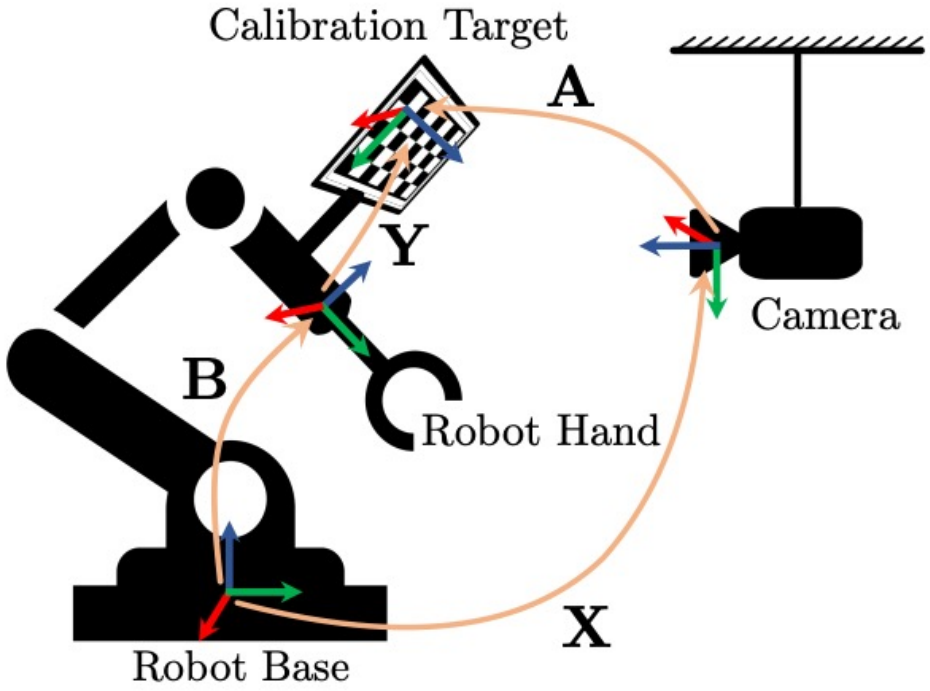
Extrinsic Calibration

- Find pose of sensor w.r.t:
  - another sensor of same type
    - registration/ scan matching
  - another sensor of a different type
    - Heterogeneous calibration (e.g. LiDAR, camera, IMU)
  - a robot/ the arm frame – arm coordinate system
    - Hand-eye calibration
  - many other sensors:
    - Multi-sensor calibration

Manipulation: Hand-Eye-Calibration



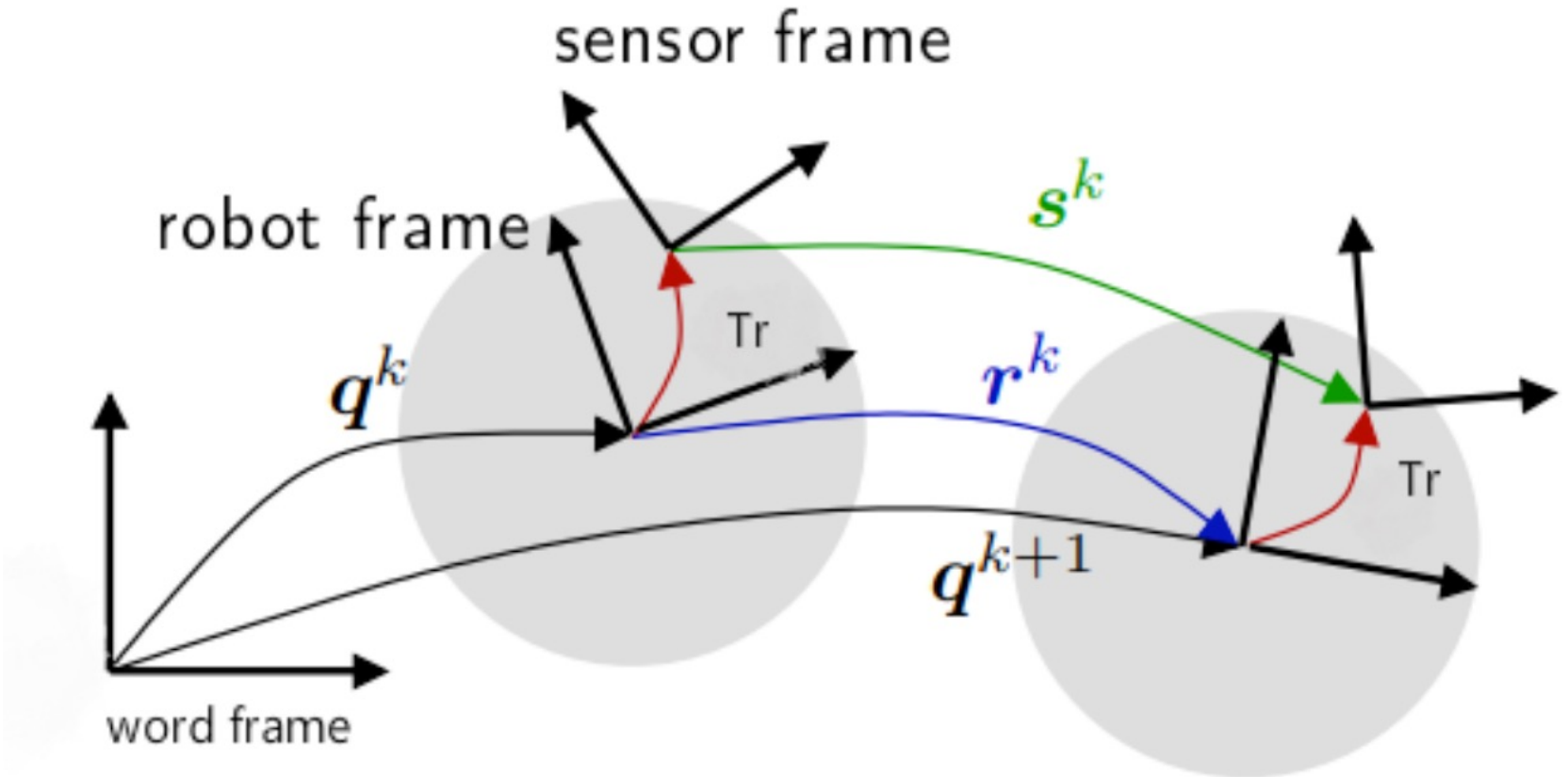
(a) eye-on-hand; aka: eye-in-hand



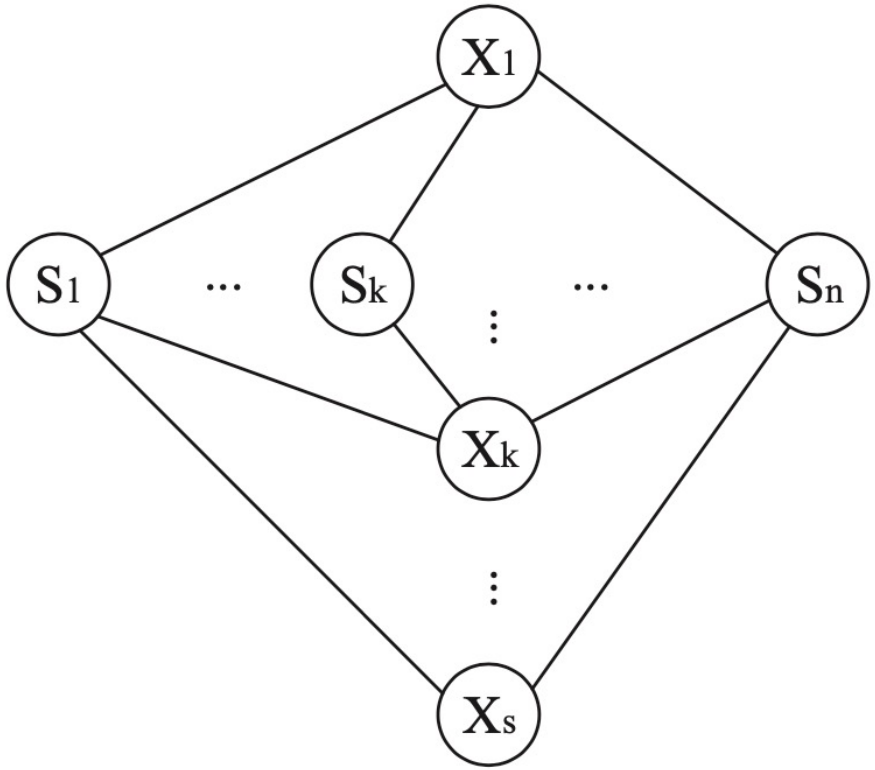
(a) eye-to-base; aka: eye-to-hand

Fig. 2. Visualization of the hand-eye/robot-world calibration problem. Both (a) *eye-on-hand* and (b) *eye-to-base* cases are constrained by $\mathbf{AX} = \mathbf{YB}$.

Hand-Eye calibration: robot to sensor transform



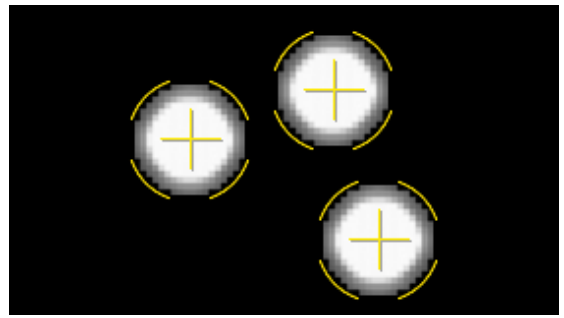
Heterogeneous Multi-sensor Calibration based on Graph Optimization



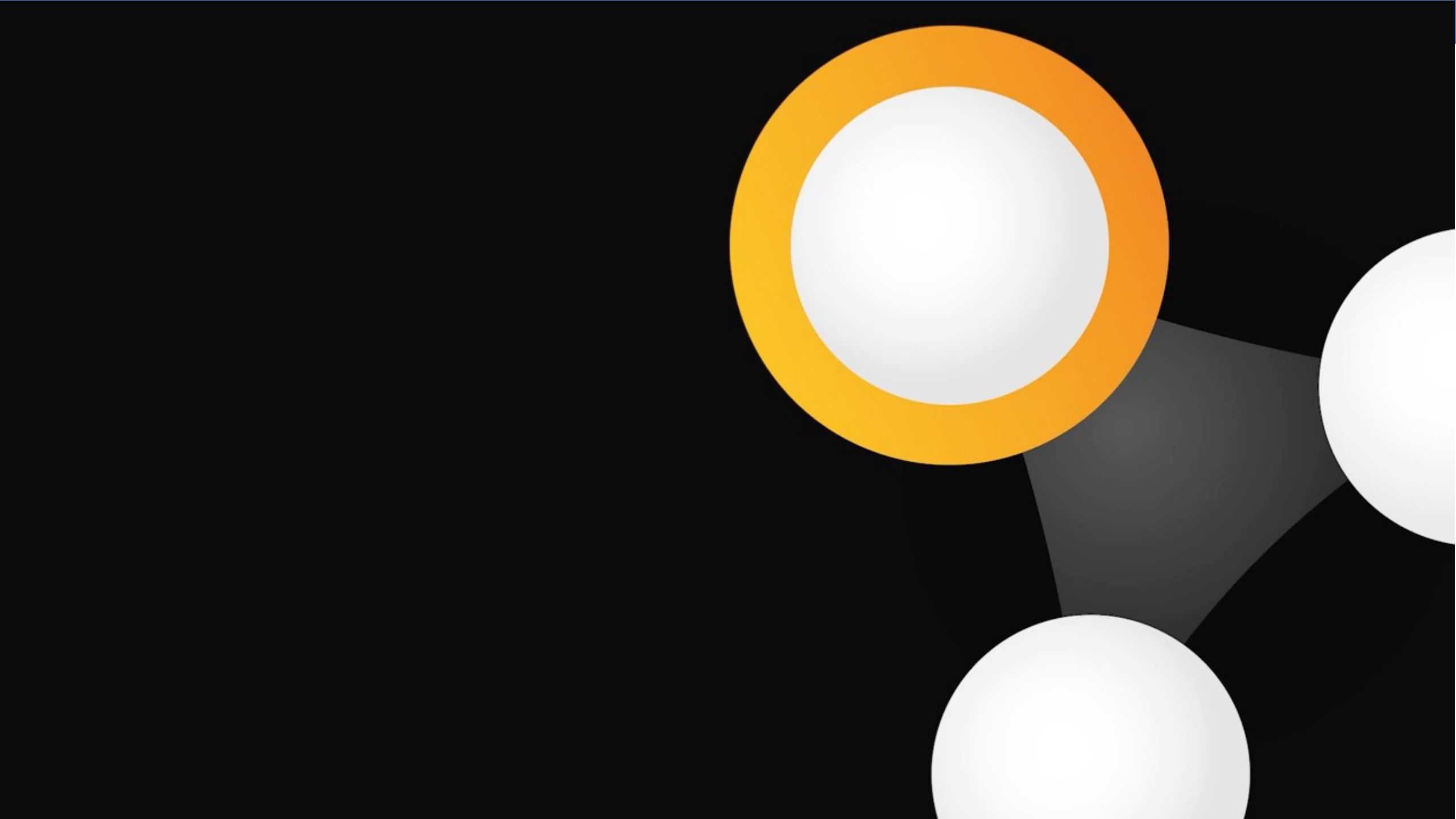
5.6 The graph representing the relationships between different sensors. $X_1 ... X_s$ and $S_1 ... S_n$ are different types of sensors such as camera and Velodyne. An edge between two nodes represents a direct sensor-to-sensor calibration between these two devices.

Segway: Tracking Systems

- Use cameras to detect infrared markers
- Triangulate 3D marker position from multiple cameras
- Create groups of markers to estimate 3D poses of groups
- Cameras need to be intrinsically & extrinsically calibrated
- Cameras report only marker (image) positions to system => one system can handle many cameras
- Famous vendors: Vicon, Optitrack
- E.g. Optitrack system at STAR Center:
  - 240Hz
  - Error: +-0.20 mm
  - 21 cameras



Video next slide: https://www.youtube.com/watch?v=o2xufLT8hUs
Video next next slide: https://www.youtube.com/watch?v=m0szHx3St-M



Calibration

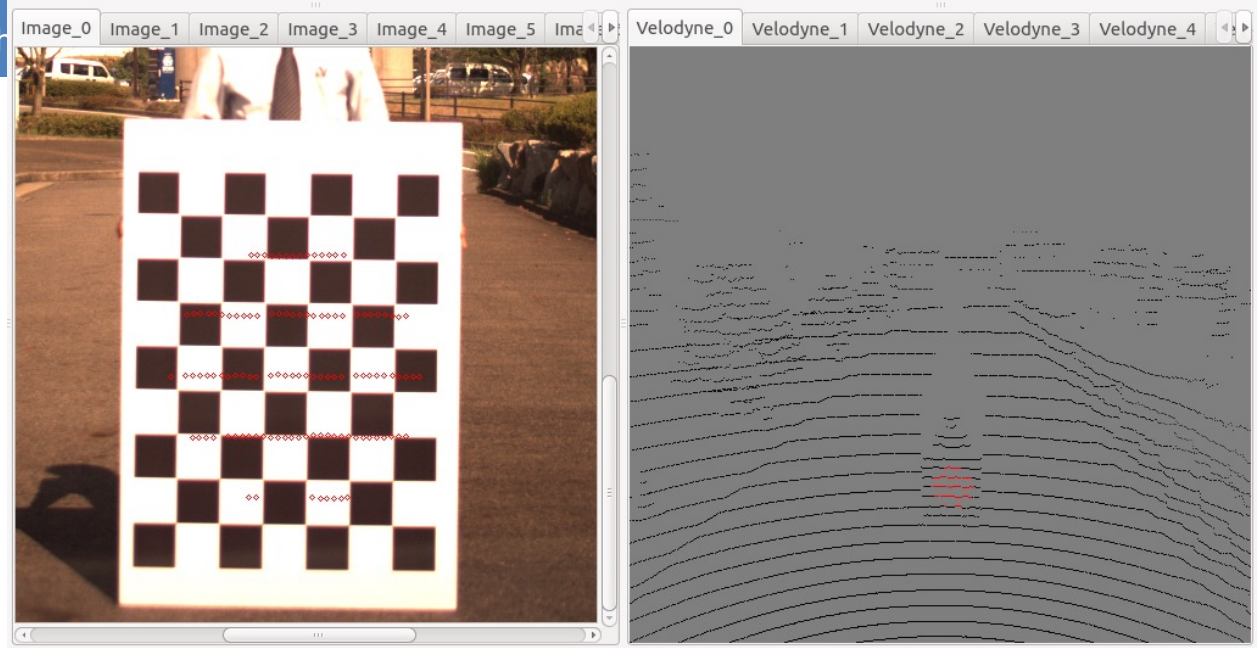
Manipulator Calibration

- Move manipulator ->
  track “tool center point (tcp)” motion
  (or link to which camera is attached)
  - Use arm forward kinematics OR
  - Use tracking system. Difficulty:
    Calibration from tracking markers to tool needed
- Eye-on-hand:
  - Observe static target -> use Perspective-n-Point (PnP) to estimate camera transforms
- Eye-to-base
  - Static camera: observe moving target to estimate target transforms

Multi-Sensor Calibration

- Robot with multiple sensors
- Option 1: Hand-eye approach:
  - Move robot (with sensors)
  - Estimate motions in all sensor frames
  - Use optimization to find transforms that explain all motions
- Option 2: Moving target approach:
  - Move a target around robot
  - Target needs to be observable by the sensors
  - Ideally: track target pose in tracking system
  - Use optimization to find transforms
  - Cannot estimate IMU pose

Tools & Tutorials I



- Camera to Camera:
  - Stereo calibration (see previous)
- Camera to LiDAR:
  - https://github.com/CPFL/Autoware/wiki/Calibration
  - https://www.youtube.com/watch?v=pfBmfgHf6zg
  - Needs Autoware: https://github.com/cpfl/Autoware
- Point Cloud to Point Cloud (3D LiDAR):
  - Any point cloud registration, e.g. ICP
  - Example: Normal Distributions Transform https://pointclouds.org/documentation/tutorials/normal_distributions_transform.html

Tools & Tutorials II

- Camera to IMU:
  - https://github.com/ethz-asl/kalibr
  - Offers multi-camera calibration; camera IMU calibration
  - Tutorial: https://github.com/ethz-asl/kalibr/wiki/Camera-IMU-calibration
  - Install: https://github.com/ethz-asl/kalibr/wiki/installation
- Hand-Eye Calibration:
  - E.g. Simultaneous Hand-Eye Calibration and Reconstruction
    - Doesn't use calibration targets
    - https://github.com/STAR-Center/shecar
  - Or: https://github.com/IFL-CAMP/easy_handeye
- Multi-sensor Calibration:
  - Optimize the results of a graph of individual calibrations…
  - "Heterogeneous Multi-sensor Calibration based on Graph Optimization" https://arxiv.org/pdf/1905.11167.pdf
  - **Multical: Spatiotemporal Calibration for Multiple IMUs, Cameras and LiDARs** https://github.com/zhixy/multical