Data-Efficient Approaches to Imitation Learning for Autonomous systems

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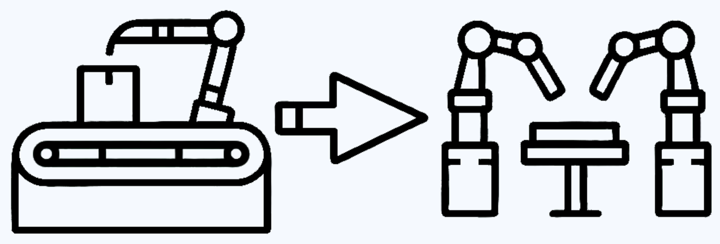
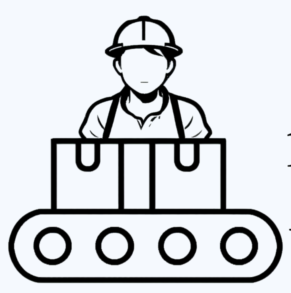
Motivation & Background

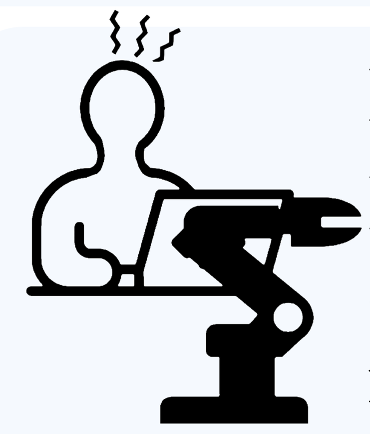


Automation and robotic have improved efficiency, accuracy, and productivity across industries ranging from manufacturing to healthcare.



Some domains remain largely **unautomated.**

Unmet need for **experts** to program automated systems *[1]*

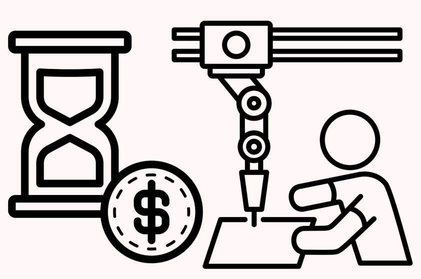


Difficult to **manually program** the dexterous and adaptable behaviors required by certain tasks.

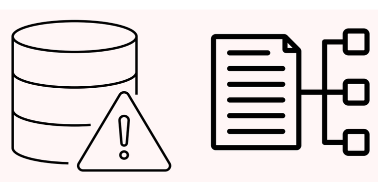
Imitation Learning (IL) has gained significant attention due to these properties: 1) Transfer *human-like skills*. 2) Enables *non-experts* to instruct and train systems effortlessly.

Problem

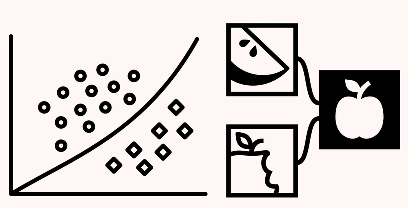
Common Challenges in IL



Time consuming and expensive Data collection: collecting high-quality expert demonstrations takes time. Specialized data is scarce and costly to collect *[2][3]*



Existing datasets: Often application specific structured robot data, which is hard to use on a different case



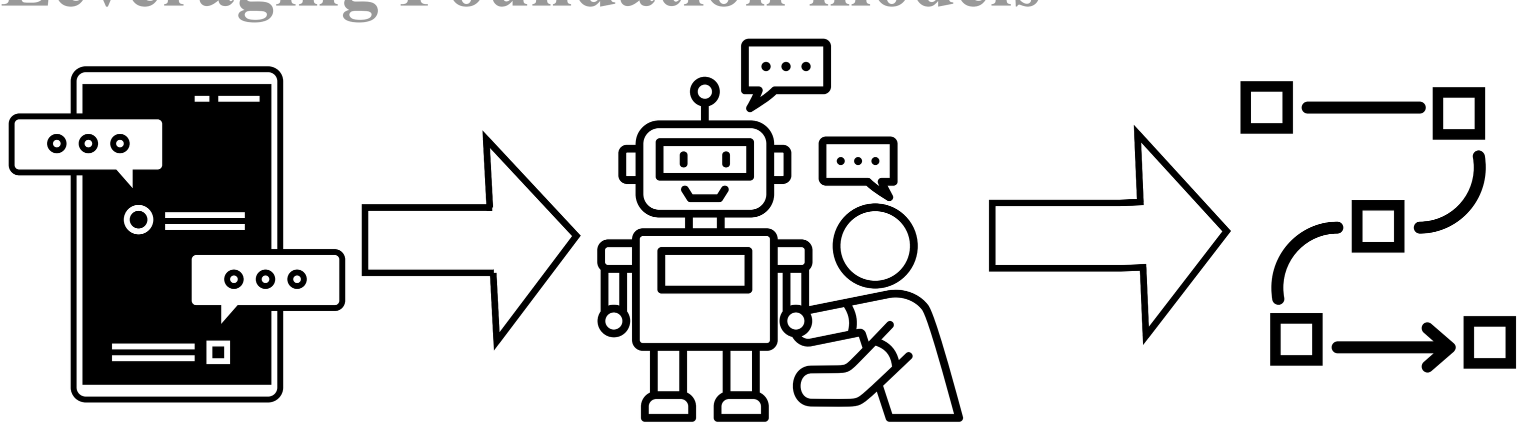
Data Efficiency: Training models require large amounts of data, which lead to long training time *[4]*

Properties for solution

- Learn from less data
- Learn general skills across domains
- Improved Generalization

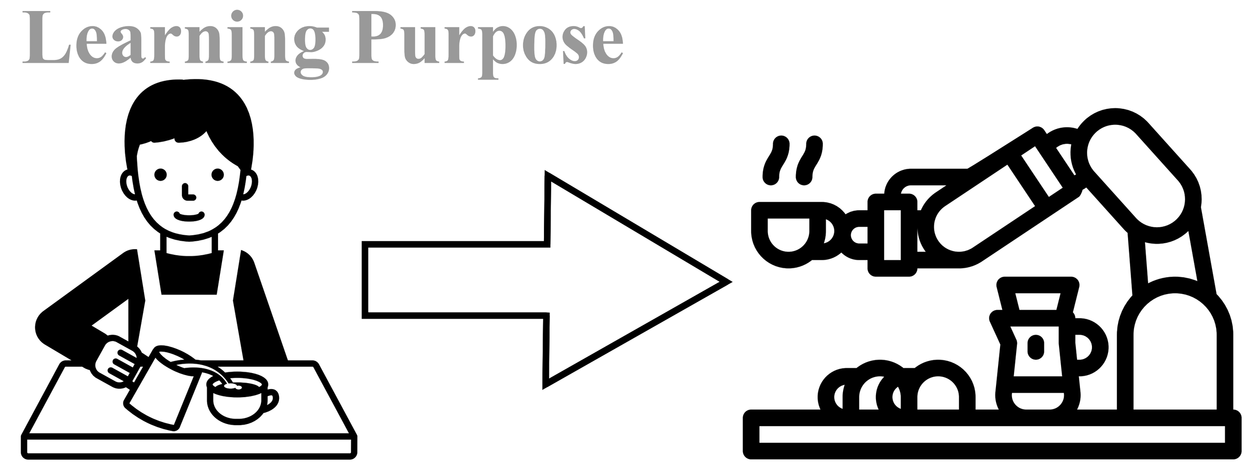
Approach

Leveraging Foundation models



Using **Foundation model** for high-level knowledge, decision-making, planning, and context comprehension

Learning Purpose



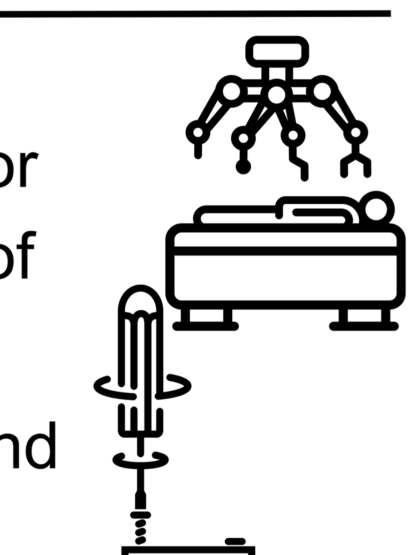
Learning the **purpose of a task**, rather than low-level behavioral cloning. Train data driven world model. $f_\theta(I_t) = I_{t+1}$. Use optimal control with learned cost function and world model

Abstracting from low level learning

Split into long- and short-horizon planning: 1) *Behavioral cloning* for long horizon. Can learn in high-dimensions and multimodal action distributions. 2) *Movement primitives* for short horizon for online adaptation. Control-theoretic methods for safety and convergence guarantees.

Cases

The developed methods will be valuable for the **medical domain** with limited amount of expert demo's and data and for **industrial disassembly** task, where high variance and unseen cases is common



References

[1] Arne Muxfeldt, Jan-Henrik Kluth, and Daniel Kubus. "Kinesthetic Teaching in Assembly Operations – A User Study". In: Simulation, Modeling, and Programming for Autonomous Robots. Ed. by Davide Brugali et al. Cham: Springer International Publishing, 2014, pp. 533–544. isbn: 978-3-319-11900-7.
[2] Guofei Xiang and Jianbo Su. "Task-oriented deep reinforcement learning for robotic skill acquisition and control". In: IEEE transactions on cybernetics 51.2 (2019), pp. 1056–1069.
[3] Mengjiao Yang, Sergey Levine, and Ofir Nachum. TRAIL: Near-Optimal Imitation Learning with Suboptimal Data. 2021. arXiv: 2110 . 14770 [cs.LG]
[4] Harish Ravichandar et al. "Recent advances in robot learning from demonstration". In: Annual review of control, robotics, and autonomous systems 3 (2020), pp. 297–330.

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