# Robotics

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## 1 Robotic Generalization to New Tasks

One of the grand challenges in robotics is enabling robots to handle novel tasks and environments in out-of-distribution contexts. In previous years, robots have typically struggled outside of narrow, pre-defined scenarios. From 2023 to 2025, significant research has gone into making robots more general-purpose and adaptable.

A notable trend is training generalist robots that can learn many skills at once and leverage that knowledge for new tasks.

- In 2023 Google DeepMind introduced RoboCat, a single AI agent that learned to operate different types of robot arms and solve a variety of manipulation tasks [2].
- Google's RT-2 (Robotics Transformer 2) in 2023 combined vision, language, and action; it was trained on both robot data and vast web images/text so that it could interpret instructions and attempt actions it hadn't explicitly been trained on [3].
- A novel development is leveraging internet videos to perform out-of-distribution tasks. Gen2Act takes a description of the task, fetches a relevant human video from the web (like a person watering a plant), and then imagines a video of how it, the robot, might do the task [1]. The researchers showed that the robot could handle some completely new tasks in a kitchen environment without additional real-world training.

Vision-Language-Action models (VLAs) have also become more popular:

- PaLM-E, a large AI model that connects vision and language, enabling a robot to respond to spoken or written commands with appropriate movements by "understanding" the task context. These language-conditioned policies have shown impressive flexibility, i.e. a robot can be instructed in plain English to fetch an object from another room, and it can interpret the request and attempt it even if that exact request was never in training [5].

Researchers are also leveraging imitation learning from video:

- In 2022, BC-Z (Beta Cascade) showed that feeding a robot a large number of human demonstration videos (for 100 different tasks) plus a description of the goal allows it to perform tasks it never saw during training [8].
- A closely related method is transfer learning, where a pre-trained robot applies knowledge gained from one task to a related but different task on another robot. The Open X-Embodiment dataset is an example of an effort to enable this goal in future research [4].

Another method is introducing synthetic obstacles or new and diverse environments (domain randomization) to improve generalization.

- "The Colosseum" was introduced to systematically evaluate a robot policy's generalization across 20 different manipulation tasks and 14 axes of variation [10].

## 2 Data Scarcity in Robotics

Data is scarce and costly to obtain for robot learning, unlike language models (where it is possible to scrape terabytes or petabytes of internet data). However, the robotics community has studied the possibility of running experiments in simulation as one method to relieve this problem:

- NVIDIA's Isaac Gym is a high performance learning platform to train policies for wide variety of robotics tasks and types in simulation [9]. The environment offers realistic physics simulations and the neural network policy training on device.
- In 2024, RialTo was developed by MIT researchers, which lets users create a "digital twin" of a real home using just a smartphone scan. Then, a robot can train in that simulation (i.e. for navigation or cleaning tasks) as if it were in your home [11].
- Simulation also enables domain randomization as mentioned earlier. By varying conditions in the sim, the robot learns to handle variety. To mitigate the imperfections of modeling the real world using simulation (sim-to-real gap), physics engines have been developed to handle contact, fluid, and deformable objects much more accurately.

Aside from difficulties in collecting data, labeling it is another challenge. One important method is using self-supervised methods, in which the robot gets feedback from the environment naturally (it tries an action, and it can determine success or failure consequently). Early projects at Google (around 2016-2018) used dozens of robot arms to collectively grasp objects, resulting in a large dataset of attempts that the robots then used to train a grasping neural network.

- In recent years, robots have been able to use touch sensors, cameras, and even proprioceptive sensors (detecting their joint positions / effort) to label results (i.e. 'object slipped from gripper' vs. 'object secure in hand').
- Another method is to use human video as surrogate training data for robots. Learning from human action may allow for activity recognition, but there are challenges around developing robotic hardware that closely resembles 3D human attributes [6].

Finally, synthetic data has contributed much to language modeling and it is an emerging technique in the robotics field as well, although not as developed.

- Diffusion models, which are widely used for image generation, are being applied to robotics. For example, one technique is to generate plausible future motion trajectories that a robot might need to perform, and then using those as additional training samples [7].

## 3 Policy and Ethics around Robotics

### 3.1 US

In contrast to the EU and China, there has not been a centralized national robotics policy in the US. However, there are a patchwork of initiatives and proposed laws. Here are a few highlights:

- The No Robot Bosses Act (2024), forbids employers from making decisions solely by AI and require human oversight of workplace AI tools.
- The National Defense Authorization Act highlights the importance of autonomous systems and uncrewed robots for national security.
- The 2024 edition of "A Roadmap for U.S. Robotics: Robotics for a Better Tomorrow" called for stronger coordination between government, academia, and industry to maintain U.S. leadership.

- The White House's Blueprint for an AI Bill of Rights (2022) and an AI Safety Executive Order (Oct 2023) encourage agencies to ensure AI systems (including robots) are transparent, free from bias, and have human oversight for high-stakes use cases.

## 3.2 EU

The EU has also been proactive in regulating AI and robotics:

- The EU approved a sweeping Artificial Intelligence Act, which began entering into force on August 1, 2024. It mandates that autonomous robots are safe, transparent, and non-discriminatory, requiring strict risk management, transparency, and human oversight.
- The EU updated its Machinery regulation (adopted July 2023) to include advanced machines and robots. The new rules provide the guidelines on which collaborative robots, autonomous machines, and AI-integrated equipment are able to be sold commercially in Europe.

## 3.3 China

China has been investing heavily in robotics and simultaneously tightening oversight:

- The government is subsidizing robotics development and pushing for automation across industries. Furthermore, they became the world's largest consumer of robots and aims to control key robot components by 2025.
- China's Ministry of Industry and IT issued guidelines for humanoid robotics development, calling for an "innovation system" for humanoid robots by 2025.
- The government explicitly called for the mass production of humanoid robots by 2025 as a national goal. At the same time, Shanghai released China's first local guidelines on humanoid robot governance.

## 3.4 International Regulations

Internationally, robot safety standards (like ISO 10218 for industrial robot safety and ISO 13482 for personal care robots) have been updated as their use cases become more proliferate. In the industrial control system security space, standards like ISA/IEC 62443 and frameworks from NIST are being applied to robotics. However, new risks due to robotic development also exist. For example, internet connectivity in robots (from factory machines to home vacuum robots) brings security risks. In 2023, manufacturing was the most targeted industry for cyberattacks, and many attacks aimed at connected industrial machines.

## References


[1] H. Bharadhwaj, D. Dwibedi, A. Gupta, S. Tulsiani, C. Doersch, T. Xiao, D. Shah, F. Xia, D. Sadigh, and S. Kirmani. Gen2act: Human video generation in novel scenarios enables generalizable robot manipulation, 2024.

[2] K. Bousmalis, G. Vezzani, D. Rao, C. Devin, A. X. Lee, M. Bauza, T. Davchev, Y. Zhou, A. Gupta, A. Raju, A. Laurens, C. Fantacci, V. Dalibard, M. Zambelli, M. Martins, R. Pevceviciute, M. Blokzijl, M. Denil, N. Batchelor, T. Lampe, E. Parisotto, K. Żołna, S. Reed, S. G. Colmenarejo, J. Scholz, A. Abdolmaleki, O. Groth, J.-B. Regli, O. Sushkov, T. Rothörl, J. E. Chen, Y. Aytar, D. Barker, J. Ortiz, M. Riedmiller, J. T. Springenberg, R. Hadsell, F. Nori, and N. Heess. Robocat: A self-improving generalist agent for robotic manipulation, 2023.

[3] A. Brohan, N. Brown, J. Carbajal, Y. Chebotar, X. Chen, K. Choromanski, T. Ding, D. Driess, A. Dubey, C. Finn, P. Florence, C. Fu, M. G. Arenas, K. Gopalakrishnan, K. Han, K. Hausman, A. Herzog, J. Hsu, B. Ichter, A. Irpan, N. Joshi, R. Julian, D. Kalashnikov, Y. Kuang, I. Leal, L. Lee, T.-W. E. Lee, S. Levine, Y. Lu, H. Michalewski, I. Mordatch, K. Pertsch, K. Rao, K. Reymann, M. Ryoo, G. Salazar, P. Sanketi, P. Sermanet, J. Singh, A. Singh, R. Soricut, H. Tran, V. Vanhoucke, Q. Vuong, A. Wahid, S. Welker, P. Wohlhart, J. Wu, F. Xia, T. Xiao, P. Xu, S. Xu, T. Yu, and B. Zitkovich. Rt-2: Vision-language-action models transfer web knowledge to robotic control, 2023.

[4] E. Collaboration, A. O'Neill, A. Rehman, A. Gupta, A. Maddukuri, A. Gupta, A. Padalkar, A. Lee, A. Pooley, A. Gupta, A. Mandlekar, A. Jain, A. Tung, A. Bewley, A. Herzog, A. Irpan, A. Khazatsky, A. Rai, A. Gupta, A. Wang, A. Kolobov, A. Singh, A. Garg, A. Kembhavi, A. Xie, A. Brohan, A. Raffin, A. Sharma, A. Yavary, A. Jain, A. Balakrishna, A. Wahid, B. Burgess-Limerick, B. Kim, B. Schölkopf, B. Wulfe, B. Ichter, C. Lu, C. Xu, C. Le, C. Finn, C. Wang, C. Xu, C. Chi, C. Huang, C. Chan, C. Agia, C. Pan, C. Fu, C. Devin, D. Xu, D. Morton, D. Driess, D. Chen, D. Pathak, D. Shah, D. Büchler, D. Jayaraman, D. Kalashnikov, D. Sadigh, E. Johns, E. Foster, F. Liu, F. Ceola, F. Xia, F. Zhao, F. V. Frujeri, F. Stulp, G. Zhou, G. S. Sukhatme, G. Salhotra, G. Yan, G. Feng, G. Schiavi, G. Berseth, G. Kahn, G. Yang, G. Wang, H. Su, H.-S. Fang, H. Shi, H. Bao, H. B. Amor, H. I. Christensen, H. Furuta, H. Bharadhwaj, H. Walke, H. Fang, H. Ha, I. Mordatch, I. Radosavovic, I. Leal, J. Liang, J. Abou-Chakra, J. Kim, J. Drake, J. Peters, J. Schneider, J. Hsu, J. Vakil, J. Bohg, J. Bingham, J. Wu, J. Gao, J. Hu, J. Wu, J. Wu, J. Sun, J. Luo, J. Gu, J. Tan, J. Oh, J. Wu, J. Lu, J. Yang, J. Malik, J. Silvério, J. Hejna, J. Booher, J. Tompson, J. Yang, J. Salvador, J. J. Lim, J. Han, K. Wang, K. Rao, K. Pertsch, K. Hausman, K. Go, K. Gopalakrishnan, K. Goldberg, K. Byrne, K. Oslund, K. Kawaharazuka, K. Black, K. Lin, K. Zhang, K. Ehsani, K. Lekkala, K. Ellis, K. Rana, K. Srinivasan, K. Fang, K. P. Singh, K.-H. Zeng, K. Hatch, K. Hsu, L. Itti, L. Y. Chen, L. Pinto, L. Fei-Fei, L. Tan, L. J. Fan, L. Ott, L. Lee, L. Weihs, M. Chen, M. Lepert, M. Memmel, M. Tomizuka, M. Itkina, M. G. Castro, M. Spero, M. Du, M. Ahn, M. C. Yip, M. Zhang, M. Ding, M. Heo, M. K. Srirama, M. Sharma, M. J. Kim, N. Kanazawa, N. Hansen, N. Heess, N. J. Joshi, N. Suenderhauf, N. Liu, N. D. Palo, N. M. M. Shafiullah, O. Mees, O. Kroemer, O. Bastani, P. R. Sanketi, P. T. Miller, P. Yin, P. Wohlhart, P. Xu, P. D. Fagan, P. Mitrano, P. Sermanet, P. Abbeel, P. Sundaresan, Q. Chen, Q. Vuong, R. Rafailov, R. Tian, R. Doshi, R. Mart'in-Mart'in, R. Baijal, R. Scalise, R. Hendrix, R. Lin, R. Qian, R. Zhang, R. Mendonca, R. Shah, R. Hoque, R. Julian, S. Bustamante, S. Kirmani, S. Levine, S. Lin, S. Moore, S. Bahl, S. Dass, S. Sonawani, S. Tulsiani, S. Song, S. Xu, S. Haldar, S. Karamcheti, S. Adebola, S. Guist, S. Nasiriany, S. Schaal, S. Welker, S. Tian, S. Ramamoorthy, S. Dasari, S. Belkhale, S. Park, S. Nair, S. Mirchandani, T. Osa, T. Gupta, T. Harada, T. Matsushima, T. Xiao, T. Kollar, T. Yu, T. Ding, T. Davchev, T. Z. Zhao, T. Armstrong, T. Darrell, T. Chung, V. Jain, V. Kumar, V. Vanhoucke, W. Zhan, W. Zhou,

W. Burgard, X. Chen, X. Chen, X. Wang, X. Zhu, X. Geng, X. Liu, X. Liangwei, X. Li, Y. Pang, Y. Lu, Y. J. Ma, Y. Kim, Y. Chebotar, Y. Zhou, Y. Zhu, Y. Wu, Y. Xu, Y. Wang, Y. Bisk, Y. Dou, Y. Cho, Y. Lee, Y. Cui, Y. Cao, Y.-H. Wu, Y. Tang, Y. Zhu, Y. Zhang, Y. Jiang, Y. Li, Y. Li, Y. Iwasawa, Y. Matsuo, Z. Ma, Z. Xu, Z. J. Cui, Z. Zhang, Z. Fu, and Z. Lin. Open x-embodiment: Robotic learning datasets and rt-x models, 2024.

[5] D. Driess, F. Xia, M. S. M. Sajjadi, C. Lynch, A. Chowdhery, B. Ichter, A. Wahid, J. Tompson, Q. Vuong, T. Yu, W. Huang, Y. Chebotar, P. Sermanet, D. Duckworth, S. Levine, V. Vanhoucke, K. Hausman, M. Toussaint, K. Greff, A. Zeng, I. Mordatch, and P. Florence. Palm-e: An embodied multimodal language model, 2023.

[6] C. Eze and C. Crick. Learning by watching: A review of video-based learning approaches for robot manipulation, 2024.

[7] H. He, C. Bai, L. Pan, W. Zhang, B. Zhao, and X. Li. Learning an actionable discrete diffusion policy via large-scale actionless video pre-training, 2024.

[8] E. Jang, A. Irpan, M. Khansari, D. Kappler, F. Ebert, C. Lynch, S. Levine, and C. Finn. Bc-z: Zero-shot task generalization with robotic imitation learning, 2022.

[9] V. Makoviychuk, L. Wawrzyniak, Y. Guo, M. Lu, K. Storey, M. Macklin, D. Hoeller, N. Rudin, A. Allshire, A. Handa, and G. State. Isaac gym: High performance gpu-based physics simulation for robot learning, 2021.

[10] W. Pumacay, I. Singh, J. Duan, R. Krishna, J. Thomason, and D. Fox. The colosseum: A benchmark for evaluating generalization for robotic manipulation, 2024.

[11] M. Torne, A. Simeonov, Z. Li, A. Chan, T. Chen, A. Gupta, and P. Agrawal. Reconciling reality through simulation: A real-to-sim-to-real approach for robust manipulation, 2024.