# PR-454: RT-2: Vision-Language-Action Models Transfer Web Knowledge to Robotic Control

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Google DeepMind. Authors listed in alphabetical order, with contributions listed in Appendix A.

PR by Yunsung Lee

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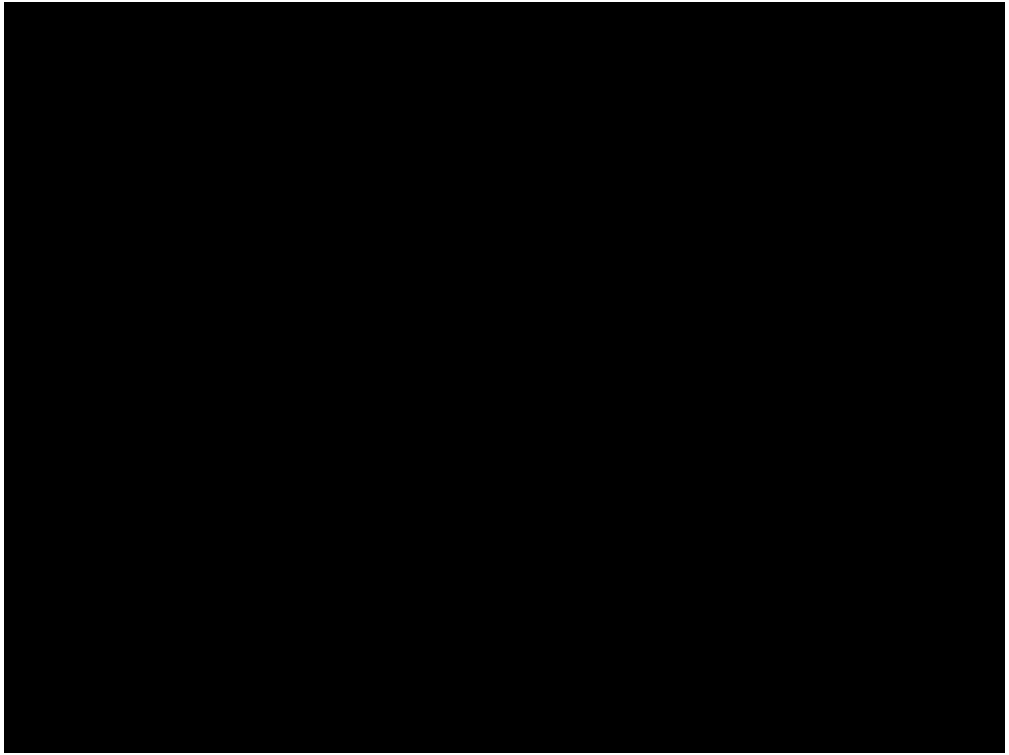
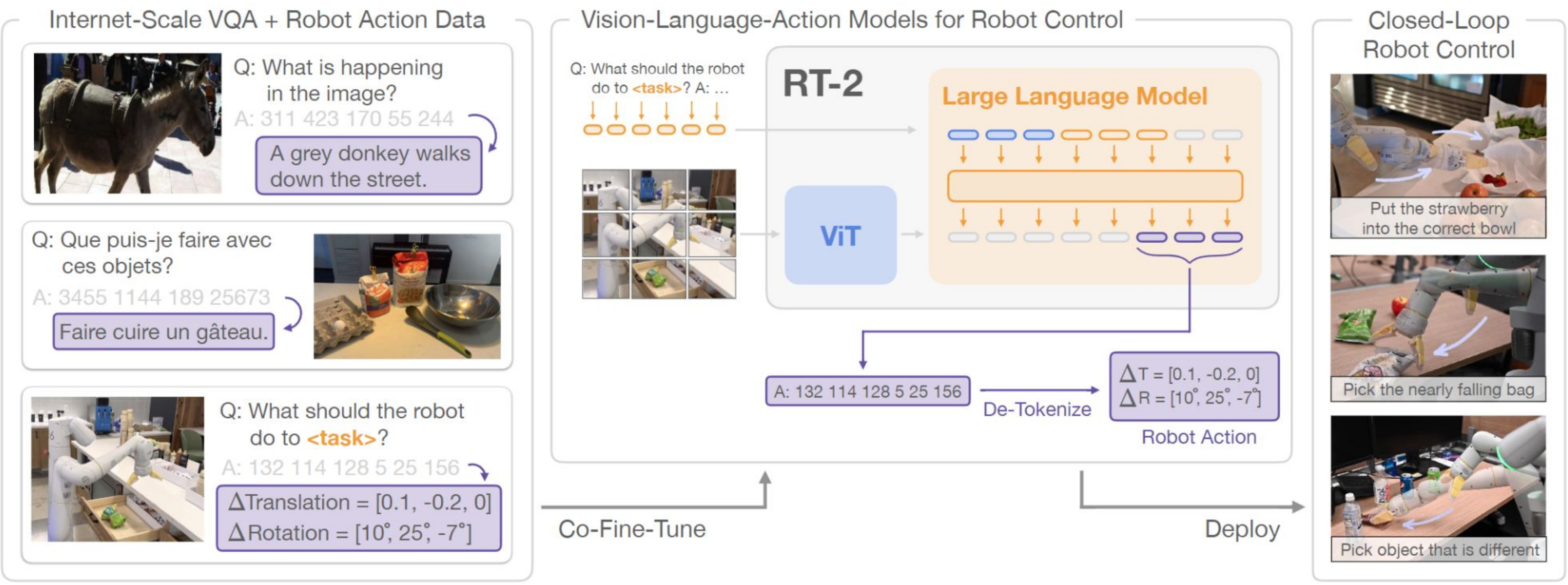
# Overview



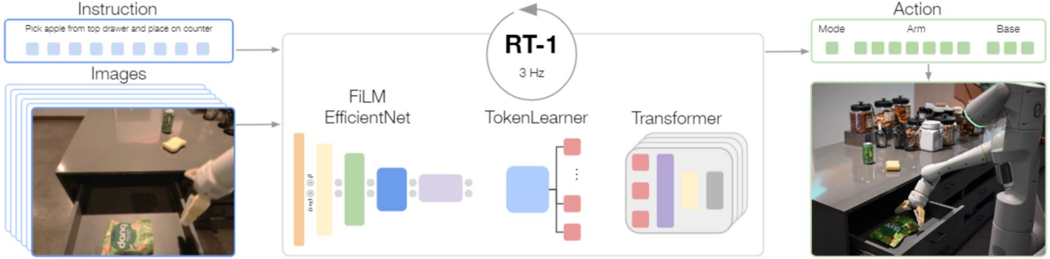
Videos: https://robotics-transformer2.github.io/#videos

# Overview

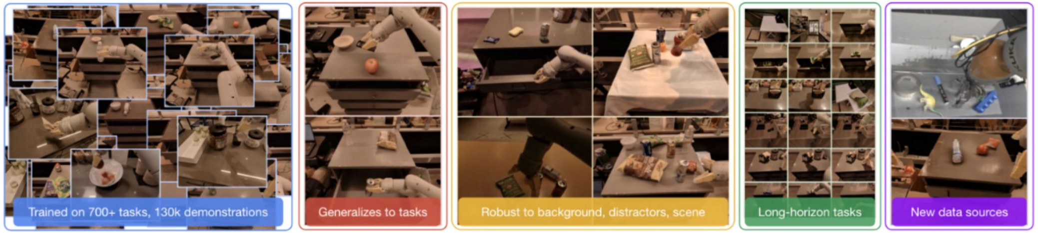



represent robot actions as another language,
which can be cast into text tokens and trained together with Internet-scale vision-language datasets.

# Related Work - RT-1



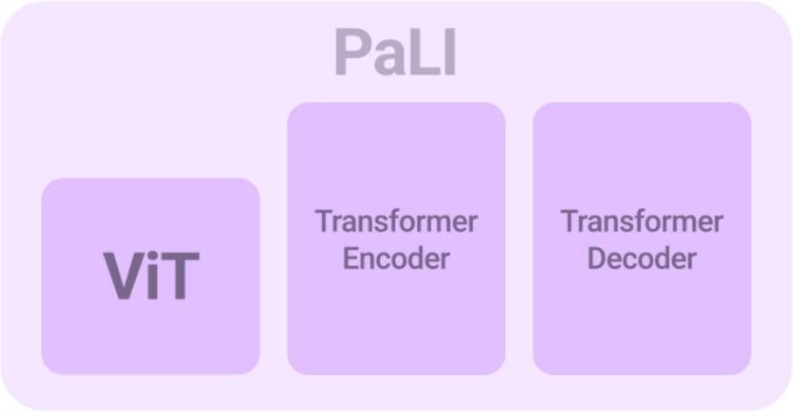

(a) RT-1 takes images and natural language instructions and outputs discretized base and arm actions. Despite its size (35M parameters), it does this at 3 Hz, due to its efficient yet high-capacity architecture: a FiLM (Perez et al., 2018) conditioned EfficientNet (Tan & Le, 2019), a TokenLearner (Ryoo et al., 2021), and a Transformer (Vaswani et al., 2017).

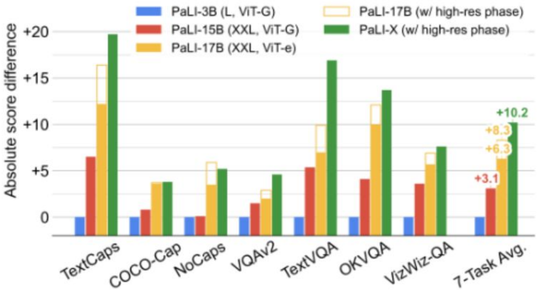



(b) RT-1's large-scale, real-world training (130k demonstrations) and evaluation (3000 real-world trials) show impressive generalization, robustness, and ability to learn from diverse data.

Figure 1: A high-level overview of RT-1's architecture, dataset, and evaluation.

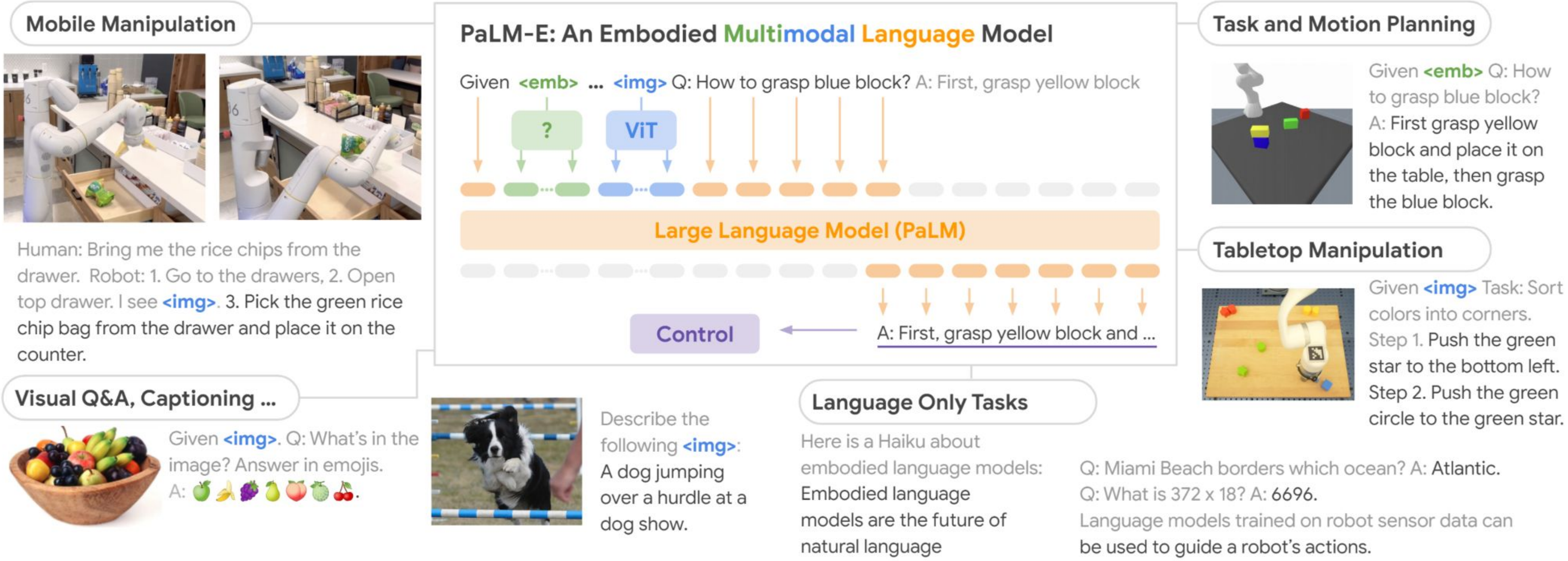
# Related Work - PaLI-X

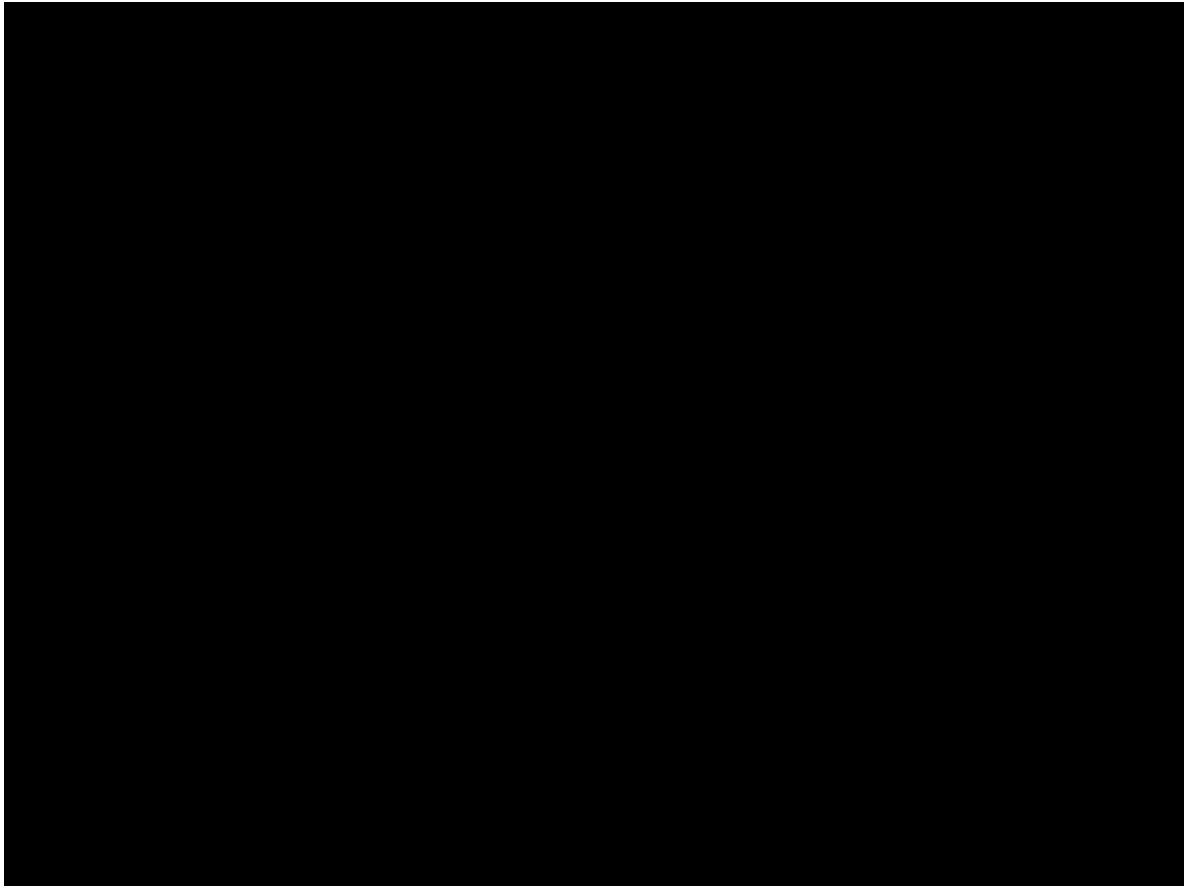


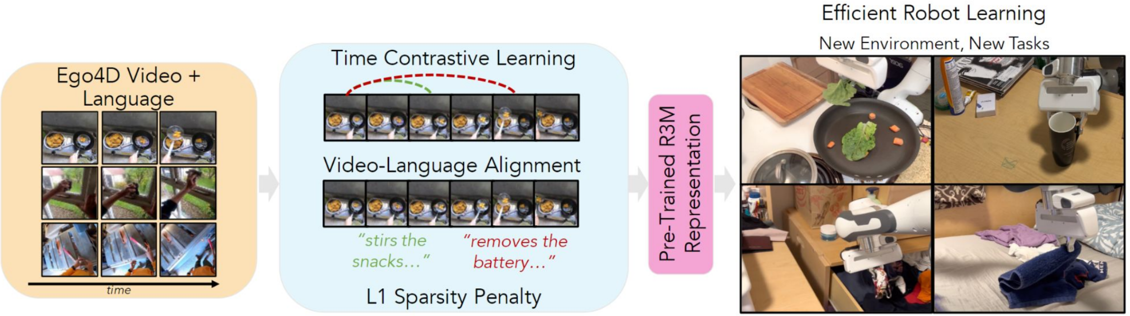

PaLI-X: 55B

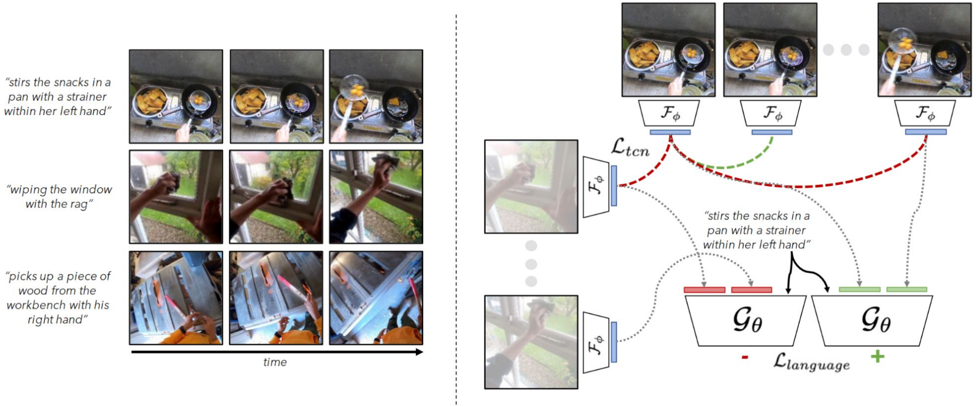
# Related Work - PaLM-E





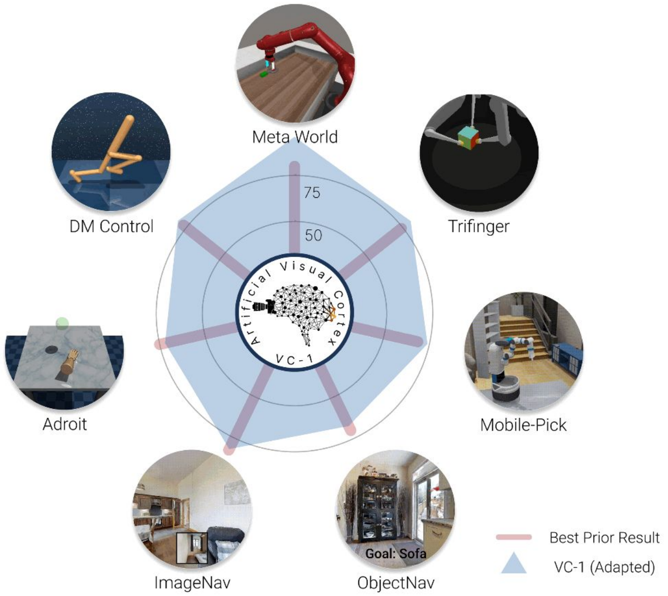
# Related Work - R3M



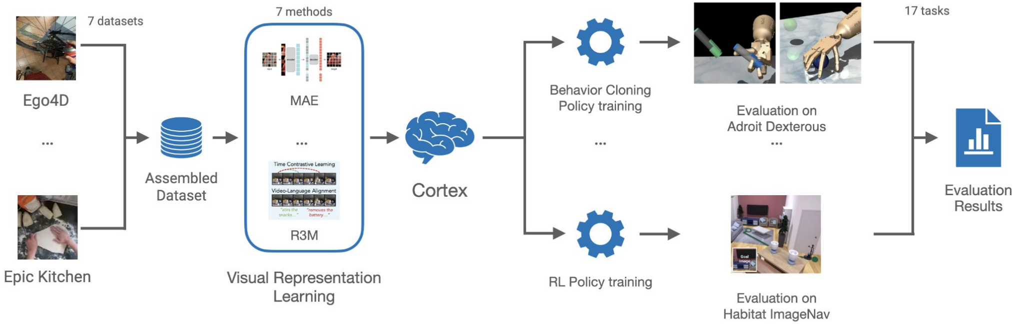




Opensource!

# Related Work - VC-1




CortexBench

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arXiv | Blog | Code | Models | Benchmark | Dataset

# Related Work - RoboSet

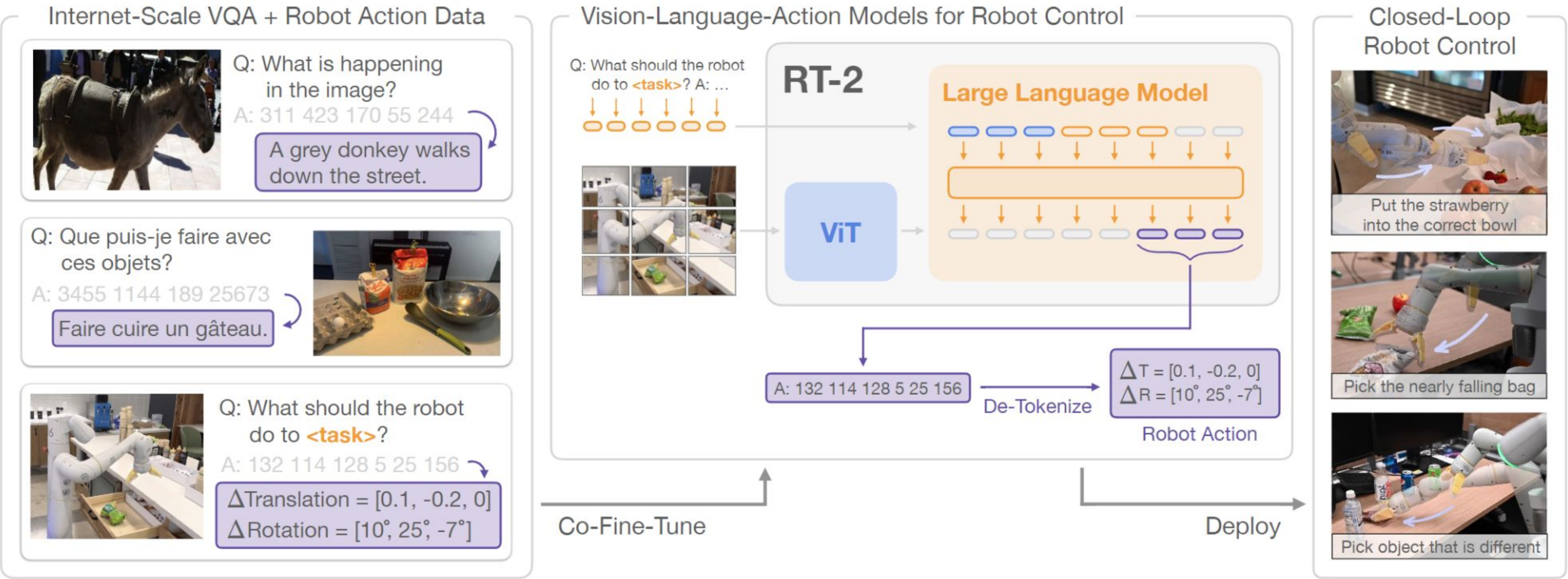
Data

Search by task name

| Activity | Task | Scene | Number of demonstrations | Example | Download |
|---|---|---|---|---|---|
| **Baking Prep** | Slide-Open Drawer | Scene 1 | 250 Demonstrations |  | Download now |
| **Baking Prep** | Slide-Open Drawer | Scene 4 | 250 Demonstrations |  | Download now |
| **Baking Prep** | Pick Butter | Scene 1 | 250 Demonstrations |  | Download now |
| **Baking Prep** | Pick Butter | Scene 4 | 250 Demonstrations |  | Download now |
| **Baking Prep** | Place Butter | Scene 1 | 250 Demonstrations |  | Download now |

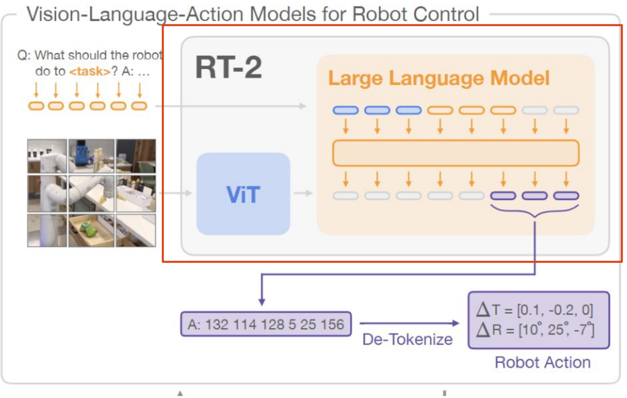
a large-scale real-world multi-task dataset collected across a range of everyday household activities in kitchen scenes

# RT-2: Vision-Language-Action Models



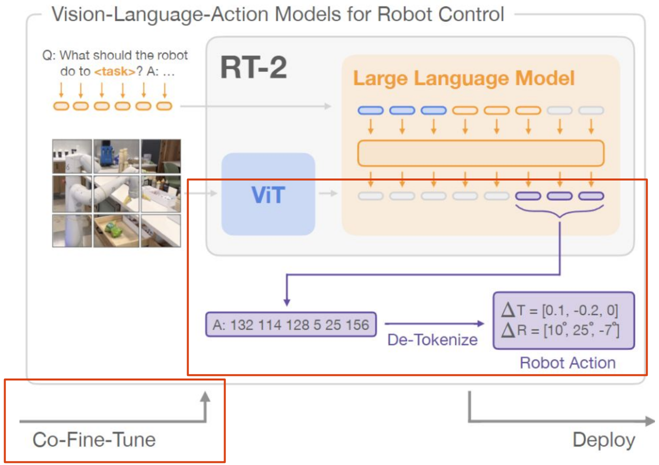
# RT-2: Vision-Language Models

- Adapt two previously proposed VLMs
  - PaLI-X and PaLM-E
- Range in size from billions to tens of billions
  - PaLI-X 5B & 55B
  - PaLM-E 12B



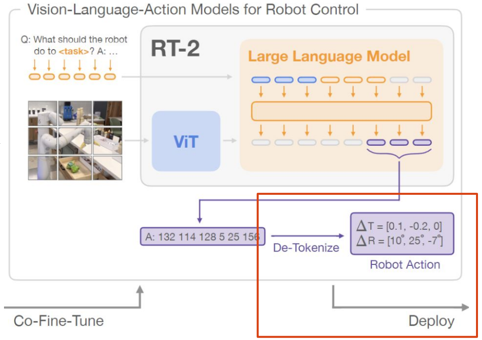
# RT-2: Robot-Action Fine-tuning

- To enable VLMs to control a robot
  - must be trained to output actions
- Action encoding on the discretization by RT-1
  - 256 tokens to serve as action tokens
  - "terminate $\Delta pos_x$ $\Delta pos_y$ $\Delta pos_z$ $\Delta rot_x$ $\Delta rot_y$ $\Delta rot_z$ gripper_extension".
  - 256 least frequently used tokens
    - form of symbol tuning (Wei et al., 2023)
- Co-Fine-Tuning
  - A key technical detail of training recipe
  - Co-fine-tuning robotics data with the original web data instead of naive finetuning on robot data only



# RT-2: Inference

- Output Constraint
  - When model is prompted with a robot-action
  - constrain its output vocabulary via only sampling valid action tokens
- Real-Time Inference
  - Infeasible to directly run 55B models on on-robot GPUs
  - Multi-TPU cloud service and querying this service over the network
  - 55B model can run at a frequency of 1-3Hz
  - 5B model can run at a frequency of 5Hz



# Experiments

## 4 Key Questions

1. How does RT-2 perform on seen tasks and more importantly, generalize over new objects, backgrounds, and environments?

2. Can we observe and measure any emergent capabilities of RT-2?

3. How does the generalization vary with parameter count and other design decisions?

4. Can RT-2 exhibit signs of chain-of-thought reasoning similarly to vision-language models?

# Experiments - Generalizable?

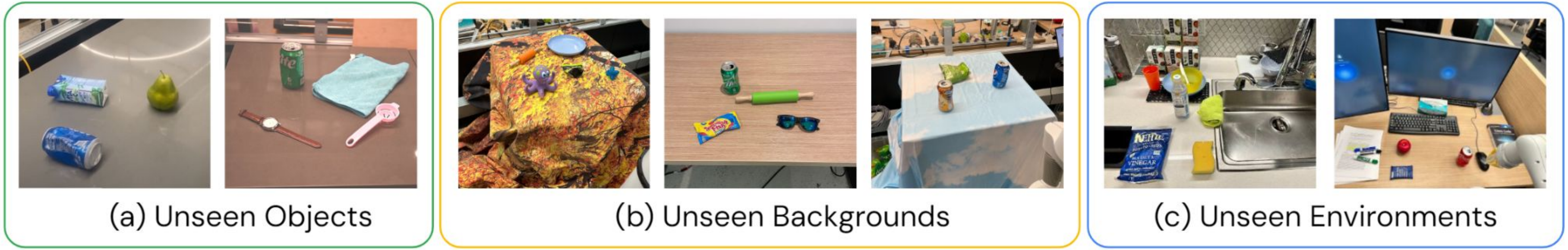



Figure 3 | Example generalization scenarios used for evaluation in Figures 4 and 6b and Tables 4 and 6.

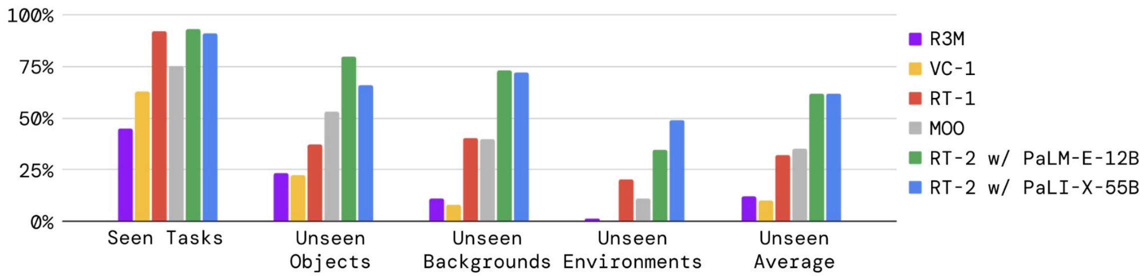



Figure 4 | Overall performance of two instantiations of RT-2 and baselines across seen training tasks as well as unseen evaluations measuring generalization to novel objects, novel backgrounds, and novel environments. Appendix Table 4 details the full results.

# Experiments - Generalizable?

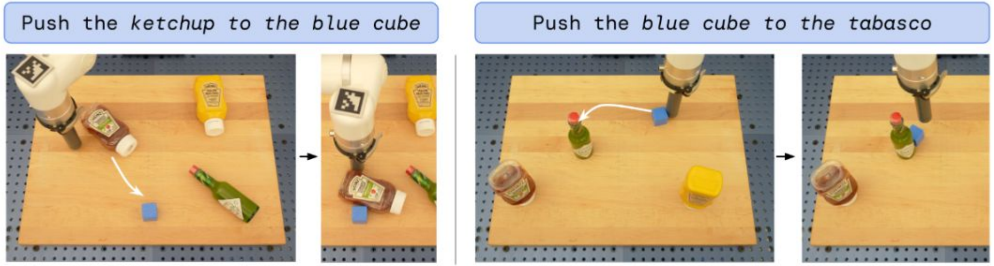



Figure 5 | Real-world out-of-distribution behaviors in the Language Table environment. Identical RT-2-PaLI-3B model checkpoint is used as in Tab. 1.

| Model | Language-Table |
|---|---|
| BC-Zero (Jang et al., 2021) | 72 ± 3 |
| RT-1 (Brohan et al., 2022) | 74 ± 13 |
| LAVA (Lynch et al., 2022) | 77 ± 4 |
| **RT-2-PaLI-3B (ours)** | **90 ± 10** |

Table 1 | Performance on the simulated Language-Table tasks (Lynch and Sermanet, 2020).

# Experiments - Emergent capabilities?

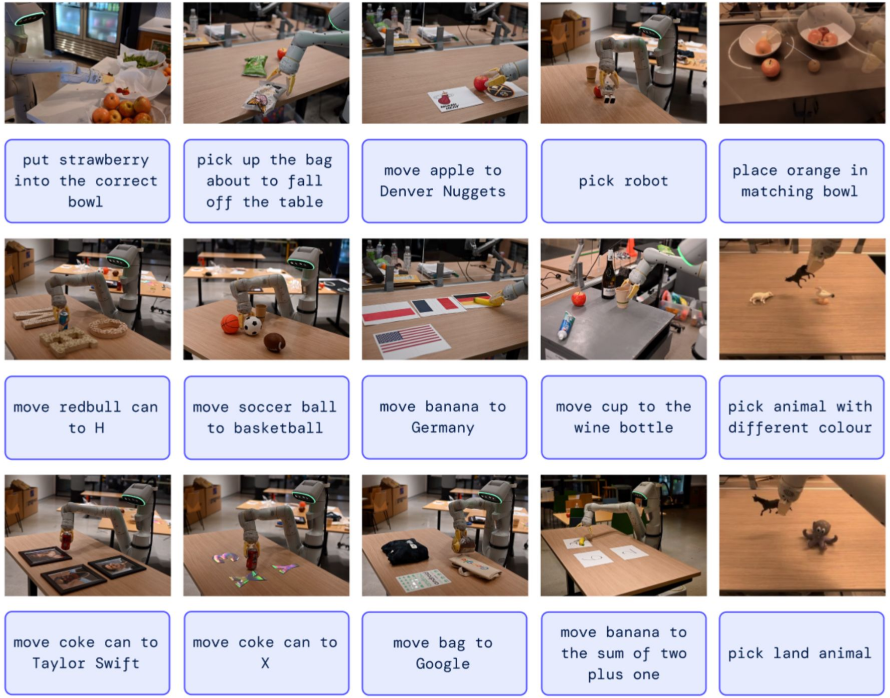
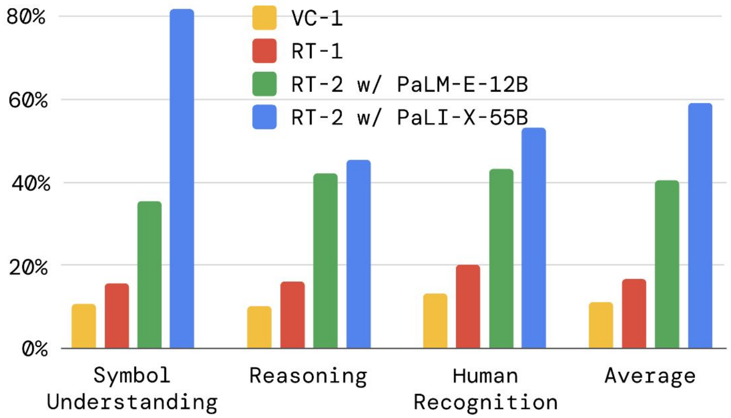
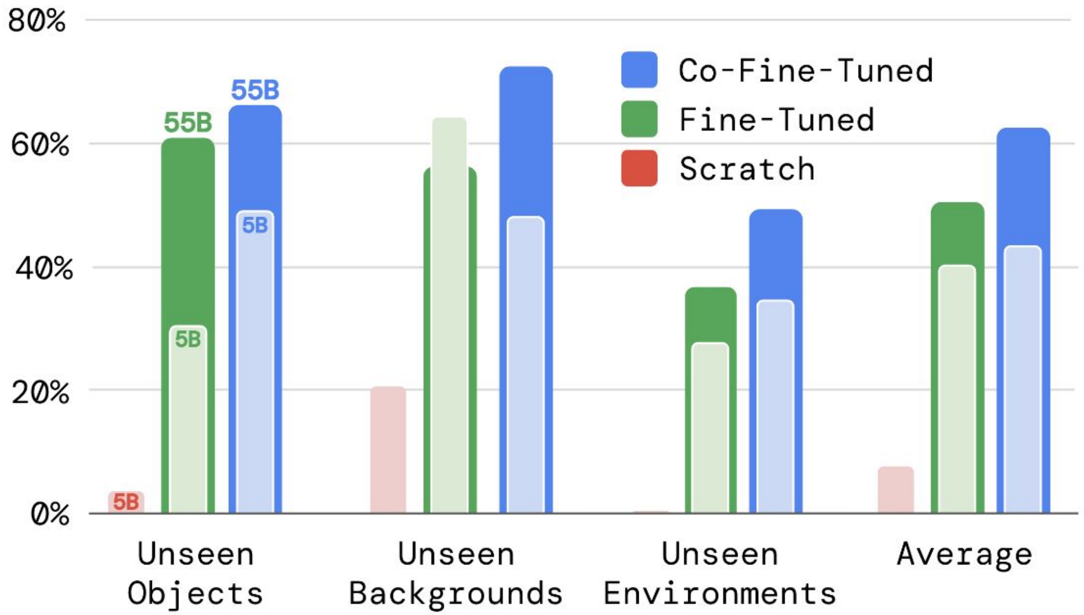



Figure 2 | RT-2 is able to generalize to a variety of real-world situations that require reasoning, symbol understanding, and human recognition. We study these challenging scenarios in detail in Section 4.




(a) Performance comparison on various emergent skill evaluations (Figure 8) between RT-2 and two baselines.

# Experiments - Vary parameter count and design?




(b) Ablations of RT-2-PaLI-X showcasing the impact of parameter count and training strategy on generalization.

# Experiments - Chain-of-thought reasoning?

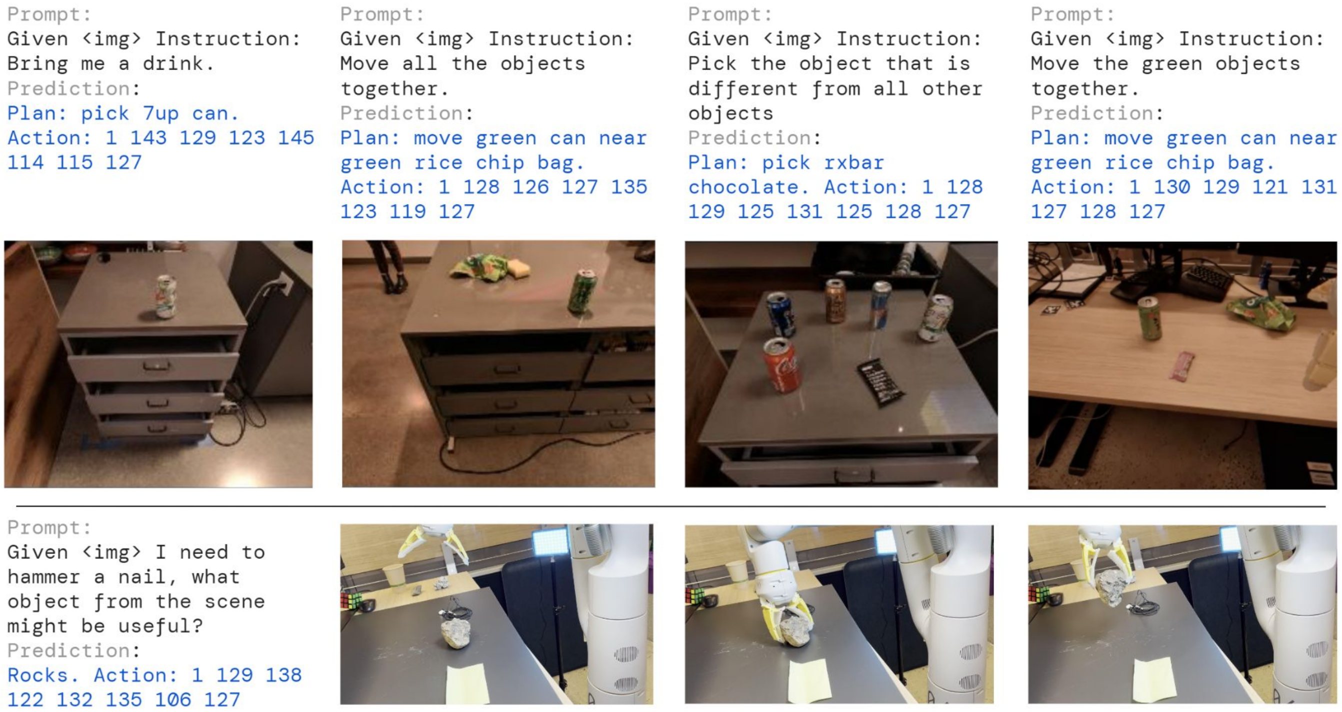



Figure 7 | Rollouts of RT-2 with chain-of-thought reasoning, where RT-2 generates both a plan and an action.