BC-Z: Zero-Shot Task Generalization with Robotic Imitation Learning

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Project Website: https://sites.google.com/corp/view/bc-z/home
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Can robots learn *tasks* in the *real world*?
Can robots learn **tasks** in the **real world**?

Yes!

- Many other predecessors

Kalashnikov et al. ‘18

Cabi et al. ‘19

This Work
Can robots learn several tasks in the real world?
Can robots learn **several tasks** in the **real world**?

Yes!

Kalashnikov et al ‘21

Zeng et al ‘20

... and many other recent works
Can robots learn tasks they haven’t been trained on in the real world?
Model Architecture

FiLM-Conditioned ResNet with different policy heads for each action component.

Task embedding from \textit{pre-trained, frozen} sentence encoder or video encoder.
Training Tasks

Object set 1 (m21)

“Place sponge in ceramic bowl”

Object set 2 (m79)

“Wipe tray with sponge”

Table 3: Training vs. generalization performance, averaged across 21 of the training tasks and all 28 held-out tasks.

<table>
<thead>
<tr>
<th>Setting</th>
<th>Task Conditioning</th>
<th>Success</th>
</tr>
</thead>
<tbody>
<tr>
<td>Train</td>
<td>One-hot</td>
<td>42%</td>
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<tr>
<td></td>
<td>Language</td>
<td>40%</td>
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<td>Held-Out</td>
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<td>Video</td>
<td>4%</td>
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Generalization To New Tasks

Object set 1 (m21)  
“Place grapes in ceramic bowl”

Object set 2 (m79)

32% success rate at 28 unseen manipulation tasks

Table 3: Training vs. generalization performance, averaged across 21 of the training tasks and all 28 held-out tasks.

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Held-out Tasks

Videos of some held-out tasks with 0 robot demos

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What Can Large Language Models (LLMs) do for Robotics?

- BC-Z generalizes to unseen points in some well-organized task embedding space.
- LLMs are much more than a way to provide a policy with a task
  - Language compose semantics together (e.g. unseen subject+object+verb combinations).
  - Chomskian recursion (embed clauses inside other clauses, logical reasoning within language, even fuzzy logic is OK)
  - Language as a *substrate* for improving generalization.
- ML perspective on generalization: invariance = many continuous variations *meaning* the same thing = continuous signal → discrete token
How Far Can We Push LLM-based Generalization?

• Linguist view: words are discrete unit of “meaning”. Language is about composing discrete tokens into more complex meaning.
• LLMs might provide an interface for compositional, recursive, reasoning-based generalization
  o Step 1: Describe your data (e.g. robot episodes) with rich human language
  o Step 2: Train data model with language model
  o Step 3: Use language to compose data in any way that language permits
  o “Just Ask for Generalization” https://evjang.com/2021/10/23/generalization.html
Not Covered (See Website!)

- Link to paper and supplemental video
- Single-Task Performance on Sorting and Door Opening in Real
- Use of HG-DAgger to help scale training and evaluation
- Tricks to make this all work
- Email: ejang@google.com