

The (Un)Surprising Effectiveness of Pre-Trained Vision Models for Control Simone Parisi*, <u>Aravind Rajeswaran</u>*,

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Policy Learning from Visual Inputs



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Applications





Robotics (physical hardware) Embodied AI agents in virtual worlds

Others: content recommendation based on visual characteristics, egocentric personal assistants etc.

Policy Learning for Control/Robotics

Type 1 : Compact State Spaces

Directly from simulators



From motion capture systems





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Type 2 : Tabula-Rasa End-to-End Policies



(Mostly) learn entire visuo-motor policy from scratch, or (Sometimes) highly domain specific pretraining

Pre-Training & Self-Supervision in Vision/NLP

Task-Agnostic Pre-Training





Large & Flexible Neural Model



Pre-Training

Objective

(Contrastive, masking..)





GPT-X / BERT / ROBERTa 1+ trillion words



(ImageNet without labels)



OpenAI CLIP, 400 million **Image-Caption pairs**

Pre-Training & Self-Supervision in Vision/NLP



Can a single vision model, pre-trained entirely on

out-of-domain passive datasets, work for diverse control tasks?

Pre-Training & Self-Supervision in Vision/NLP



We will evaluate pre-trained visual representations with *few-shot imitation learning*



Evaluation Domains

Habitat ImageNav (Replica Dataset; 5 scenes)





Franka Kitchen (5 tasks)





DeepMind Control Suite (5 tasks)











Results with Frozen PVRs

Q: How well do pre-trained vision models work off-the-shelf?

- Frozen PVRs (off-the-shelf) > frozen random features / end-to-end learning
- Self-supervised representations > supervised representations



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Q: How well do pre-trained vision models work off-the-shelf?

- Frozen PVRs (off-the-shelf) > frozen random features / end-to-end learning
- Self-supervised representations > supervised representations
- > V Habitat: MoCo features competitive with states out-of-the-box!
- > X Remaining domains: Still sizable gap between states and PVRs



Recognition vs Control

Q: Does augmentations make a difference in SSL?



Increase similarity between embeddings of all these images



- Crop augmentations are most important
 (consistent with prior works, e.g. CURL, DrQ)
- Removing color aug helps in most cases

Semantic Recognition and Control require different visual invariances

Image Credit: Chen et al. 2020 (SimCLR)

Different Layers Encode Different Invariances



> V Later layer features are better for high-level semantic tasks (Habitat ImageNav)



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- > **Solution Early layer** features are better for fine-grained control tasks (manipulation in MuJoCo)



- > Later layer features are better for high-level semantic tasks (Habitat ImageNav)
- > *Early layer* features are better for fine-grained control tasks (manipulation in MuJoCo)
- Series are competitive with ground truth states in MuJoCo tasks
- > Trends consistently true across multiple models, environments, and datasets



- ➤ Combine features from multiple layers → single vision model that works across the board?
- ➢ MoCo with Layer 5 : X MuJoCo ☑ Habitat
- MoCo with Layer 3 : MuJoCo X Habitat
- ➢ MoCo layers 3-4-5 : ☑ MuJoCo ☑ Habitat



Summary

Can a single vision model, pre-trained entirely on

out-of-domain passive datasets, work for diverse control tasks?

YES !!!



Take Home Message



https://sites.google.com/view/pvr-control