Unveiling the Feature Geometry of Robot Foundation Models via Nyström NCut

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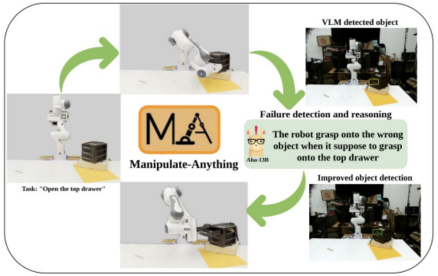
Content

1 What is a VLA?

- VLA: Vision-Language-Action model
- Uses the latent space of an LLM to comprehend generalised robot tasks
- Allows robots to be instructed with words, and to produce lingual outputs
- Can be combined with backend ML model for correction of failed actions [1][2]
- We focus on exploring OpenVLA and OpenPi 0.5 [3][4]



2 Nyström NCut – Our Use Case

Problem: VLAs are Black Boxes – hard to debug!

Proposition: Use NCut to visualise hidden layers [5]

Result: Humans may infer the reasoning & semantic understandings of VLA

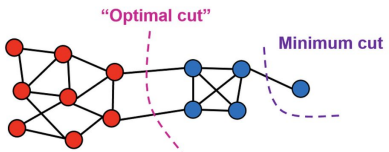
- What might we find?

Eigenvectors

- Visual clustering of image in latent space:
  - What objects are recognised? How are they segmented?
  - Where is the VLA paying attention?

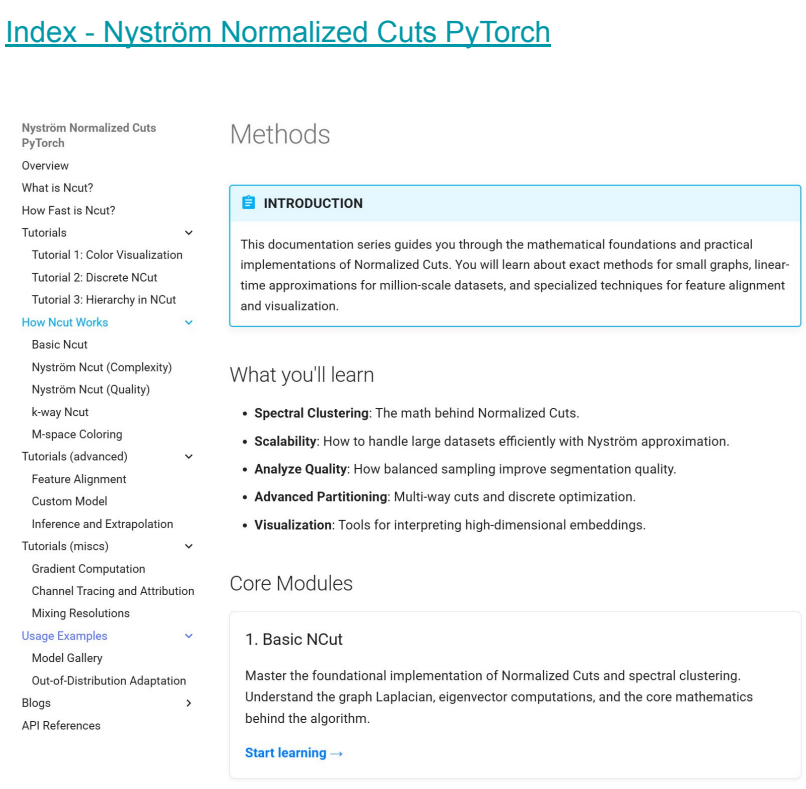
[6]

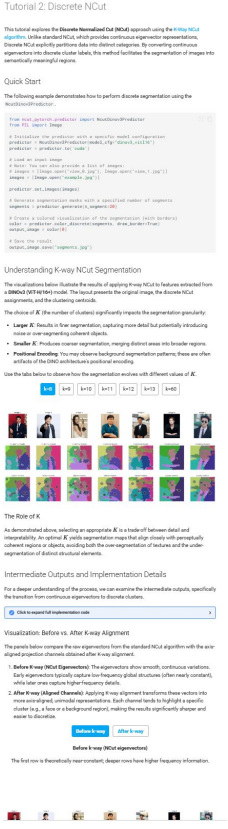
- Visual clustering of language in latent space:
  - How do words in the instructions related to the environment which the robot sees?



2 Nyström NCut – How to do visual debugging

[Index - Nyström Normalized Cuts PyTorch]





2 Nyström NCut – How to do visual debugging

0.Assumption

The easier Ncut can separate the clusters, it will be easier for the downstream models to learn

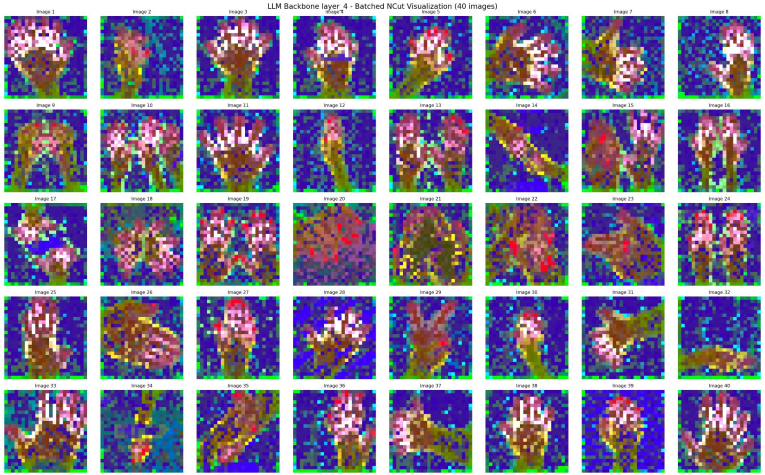
NCut_for_Visual_Debugging/README.md at main · NZ-Liam-Zhong/NCut_for_Visual_Debugging

2 Nyström NCut – How to do visual debugging

1.Curate a batch of similar photos that expose the suspected failure mode, then run batched Nyström NCut on that batch. For example, if LLaVA miscounts fingers, collect hands with different finger counts and segment them together; inspect how cluster colors change under these controlled variations.

2 Nyström NCut – How to do visual debugging

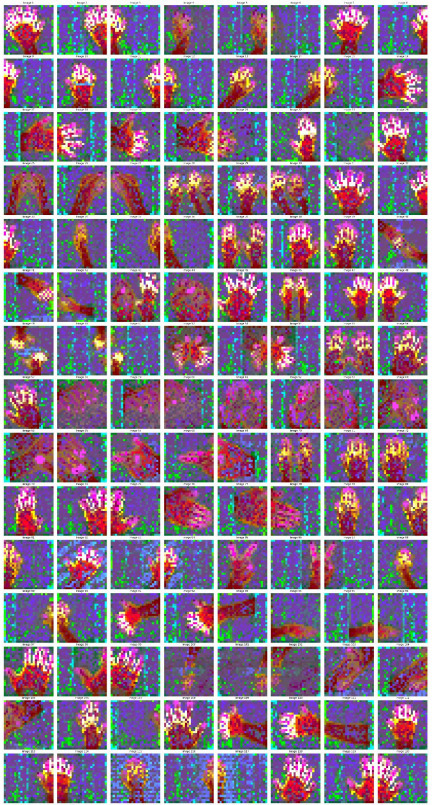
2.Analyze per layer with the entire batch side by side. If a small perturbation in one photo causes color shifts only in that case, the model is highly sensitive to that factor. If colors stay stable across the batch despite perturbations, the model is insensitive to that semantic cue. First, we can visualize the results of layer 4 of vision-language backbone of LLAVA (the text tokens can get information from the image tokens in every single layer of vision-language backbone, not necessarily only the last feature).



Row \ Col	1	2	3	4	5	6	7	8
01-08	5 Fingers	4 Extended	5 Fingers	5 Fingers	5 Fingers	5 Fingers	5 Fingers	5 Fingers
09-16	Unknown	16 Fingers	5 Fingers	4 Upwards	10 (2 Hands)	Unknown	5 Fingers	10 Total
17-24	10 Total	12 Visible	10 Fingers	10 Fingers	4 Visible	10 Visible	4 Extended	10 (2 Hands)
25-32	5 Fingers	5 Fingers	5 Fingers	5 Fingers	4 Fingers	5 Fingers	5 Fingers	4 Extended
33-40	5 Fingers	4 Fingers	10 (Clasped)	5 Fingers	5 Fingers	5 Fingers	5 Fingers	5 Fingers

2 Nyström NCut – How to do visual debugging

3.Trace across layers (and submodules when the model has multiple parts). For multi-branch systems like LLaVA, separately inspect the vision tower and the vision-language backbone to localize which component fails to preserve the relevant structure.



Finger numbers predicted by AI

Row \ Col	1	2	3	4	5	6	7	8
01-08	5 Fingers	4 Extended	5 Fingers	5 Fingers	5 Fingers	5 Fingers	5 Fingers	5 Fingers
09-16	Unknown	16 Fingers	5 Fingers	4 Upwards	10 (2 Hands)	Unknown	5 Fingers	10 Total
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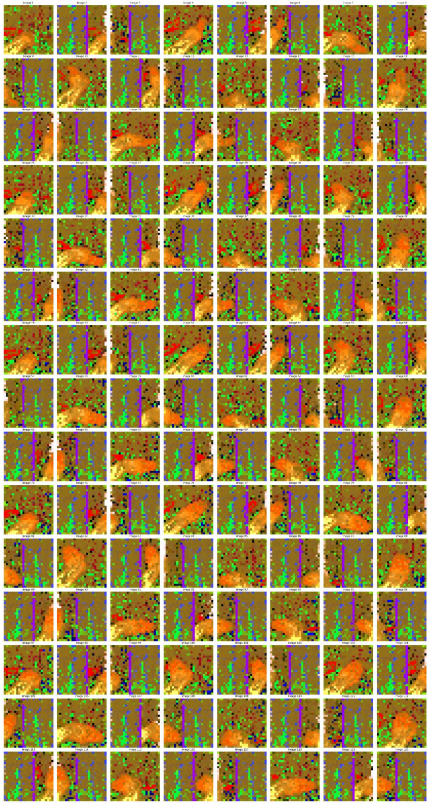
33-40	5 Fingers	4 Fingers	10 (Clasped)	5 Fingers	5 Fingers	5 Fingers	5 Fingers	5 Fingers

2 Nyström NCut – How to do visual debugging

Other Examples:

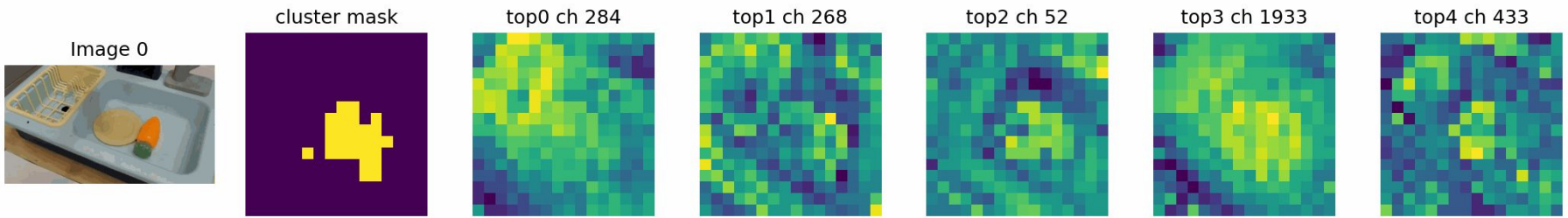
LLAVA prediction

1: 3	2: 4	3: 4	4: 4	5: 4	6: 4	7: 1	8: 4
9: 3	10: 3	11: 3	12: 3	13: 1	14: 3	15: 3	16: 4
17: 3	18: 4	19: 3	20: 3	21: 3	22: 4	23: 3	24: 3
25: 4	26: 4	27: 4	28: 4	29: 4	30: 4	31: 3	32: 3
33: 4	34: 4	35: 4	36: 4	37: 1	38: 4	39: 4	40: 3



2 Nyström NCut – How to do visual debugging

What's more: See what channels contribute to the cluster



3 VLA Encoder Extraction

- Vision backbone produces patch/grid tokens; language stack produces text tokens; cross-attention fuses modalities before decoding text
- Encoder Sourcing: HuggingFace AutoProcessor and Local Cache (spatial)
- Images + Prompt → Processor (pixel_values, input_ids, attention_mask) → Model Forward → capture vision backbone tokens + language layer of Encoder → concatenate across batch → NCut → t-SNE to RGB → render (NCut grids, colored tokens, videos/HTML)

- Ncut with language token alignment
  - Gather all language token embeddings from the final language layer across the batch into one matrix. Run NCut to partition that graph; each token gets an eigenvector-based coordinate. Map those NCut-derived coordinates back to each sample's token list
- Tsne to RGB
  - High-D NCut Eigen → t-SNE down to 3-D → Treat 3-D as RGB values
  - Each token's NCut position is now a color

4 Dataset Preparation (quick side-note)

Many real-world robot-action datasets exist, including compilation meta-datasets (e.g. Open X-Embodiment).

Nevertheless, there are major shortcomings of open-source datasets of robot actions and operations, even in Pick n' Place:

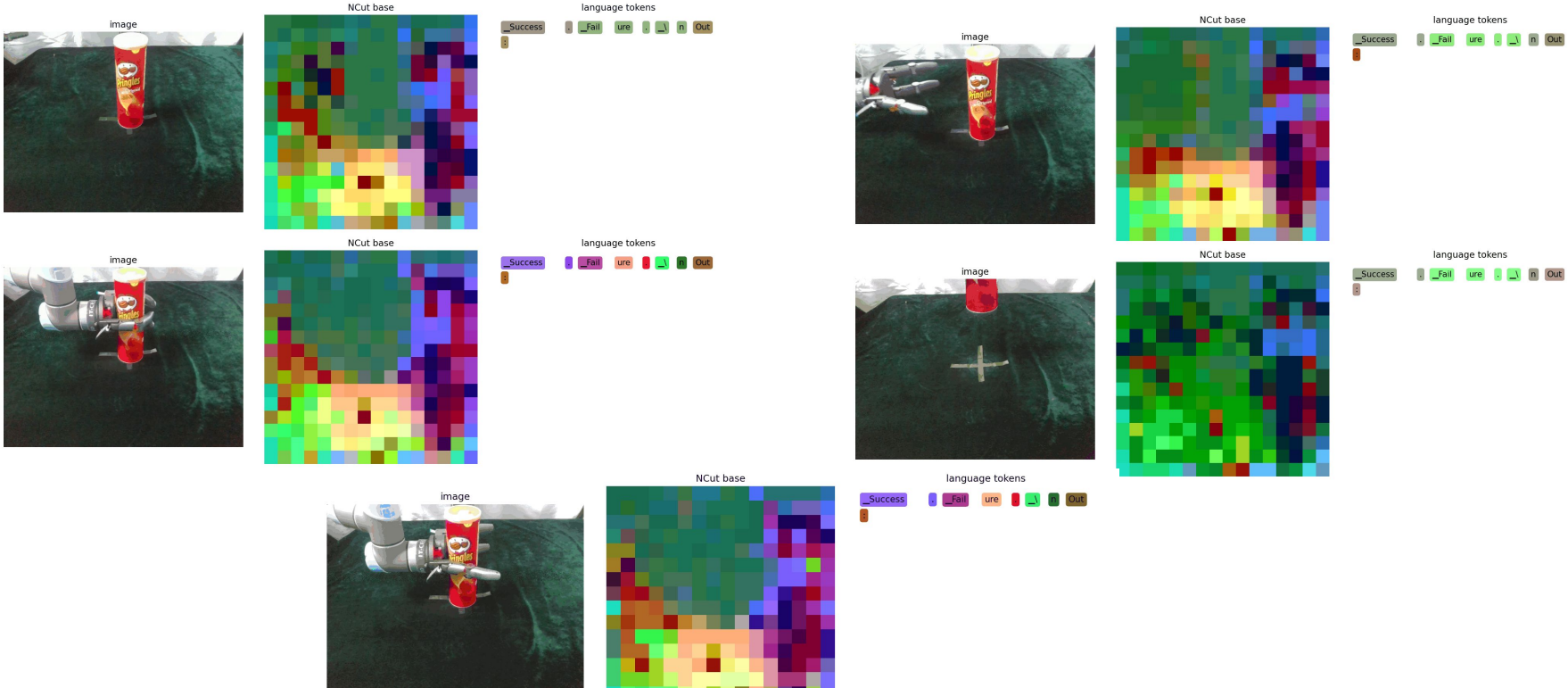
- Significant lack of structured datasets including fail cases - most often completely removed during curation
- Fail case explorations mostly explored in simulations, often offering niche use cases and implementation code only
- Datasets which do offer fail cases typically either:
  - Lacked size
  - Lacked action diversity
  - Lacked thorough labelling
  - Focused on fail cases specific to one application only
- Researchers often have to resort to self-curated datasets
  - Limited formality in curation – setup, data collection, inappropriate data, erroneous data – problematic for certain applications
  - Large 'gaps' in the datasets' generality, operation breadth, and edge cases
  - Limited information as to strategies for replicating dataset generation

We made use of a dataset, which while informal and sometimes containing erroneous data, offered the Pick n' Place tasks we wanted to focus on. For our application, irregularities and drastic permutations served as an advantage in exploring task generalisation [7]:

1. Manual labelling of task success
2. Removal of unnecessary/incomplete data
3. Frame extraction for N-cut processing

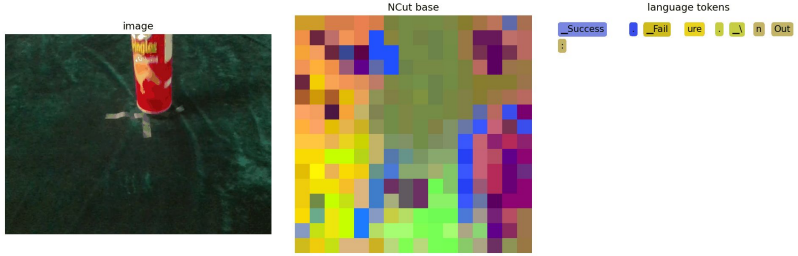
5 Findings – Text-image Semantics

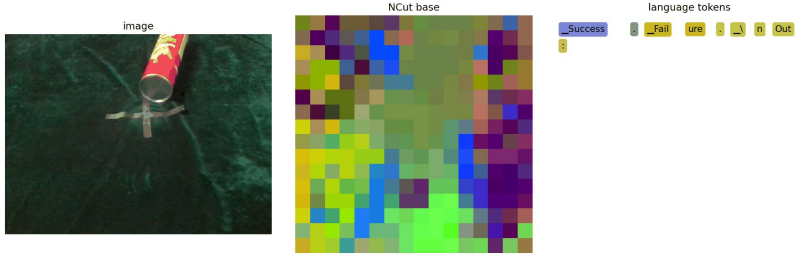
Recognition of key objects for robot interactions:



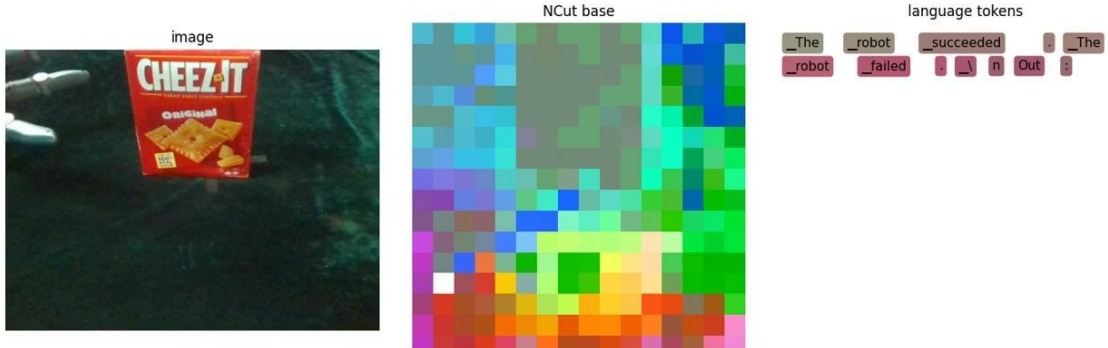
5 Findings – Text-image Semantics

Semantic sensitivity to indicators of typical robotics failures:

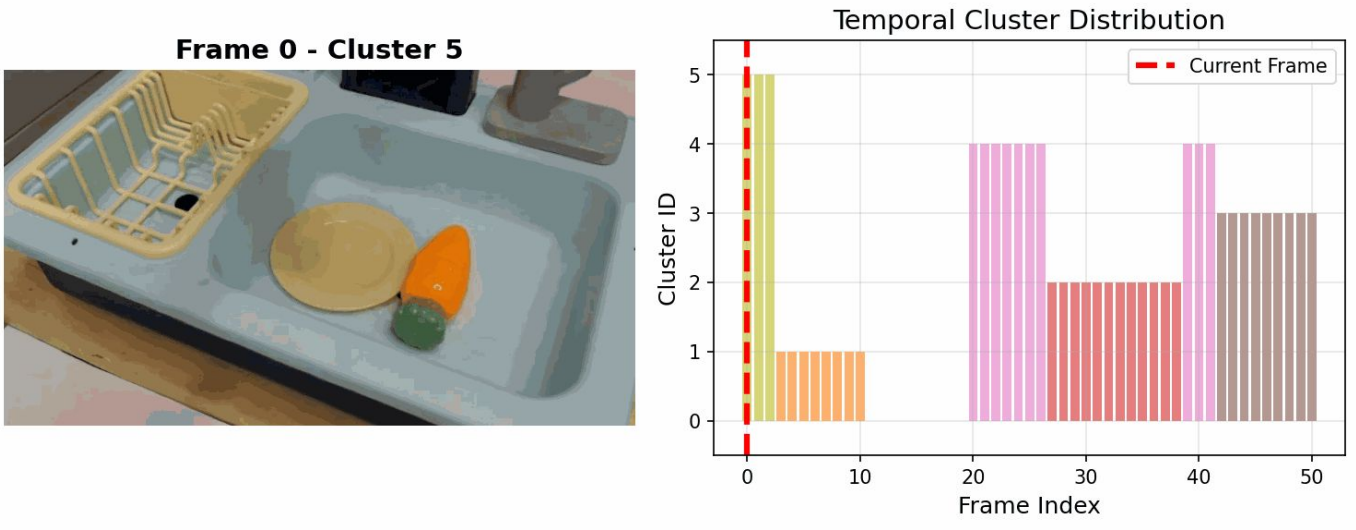




Significant semantic shifts at key points of robot interactions:



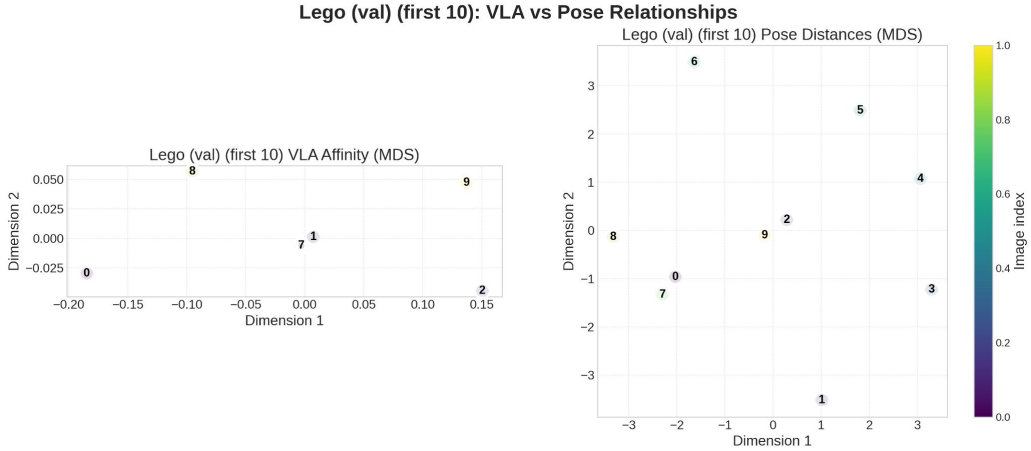
5 Findings – Temporal NCut



5 Findings – Input Sensitivity

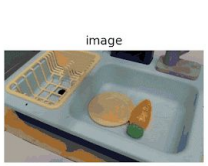
1. I have split the text in coco datasets and cluster them. For example, there are 30 images containing the word "push" in the image datasets. I took the features from those 30 images and averaged them as templates. And calculate the cosine similarities with other pics to calculate the MAP of the classification results.
   - Nouns Raking：
     - room（≈0.363）、street（≈0.291）、field（≈0.272）、grass（≈0.255）、plate（≈0.200）、building（≈0.186）、group（≈0.154）
     - ：picture（≈0.085）、shirt（≈0.071）、water（≈0.115）、area（≈0.123）
   - Verbs Ranking：
     - park（≈0.451）、sit（≈0.375）
     - walk（≈0.122）、ride（≈0.107）、play（≈0.097）
     - look（≈0.098）、wear（≈0.075）、fill（≈0.068）、show（≈0.051）
2. I have changed verbs ,nouns and images. And see the change of feature space. And I see the changes in images > 10 times change in verbs > change in nouns. The output of VLAs doesn't really care about the text but only cares about the images

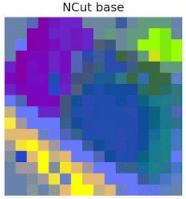
5 Findings – Spatial/orientation Comprehension

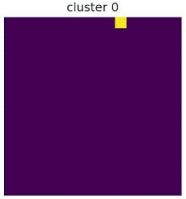


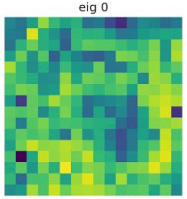
I use mlps to fit nerf datasets (features->poses). In the train set, the loss is 0.003 and the test is 0.998. It seems that the feature <->poses pair are one to one mapping but lacks generalizations in terms of spatial intelligence. It seems it had learned nothing about spatial information.

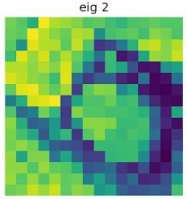
5 Findings – Back Propagation

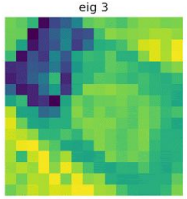


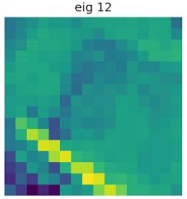


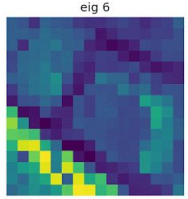




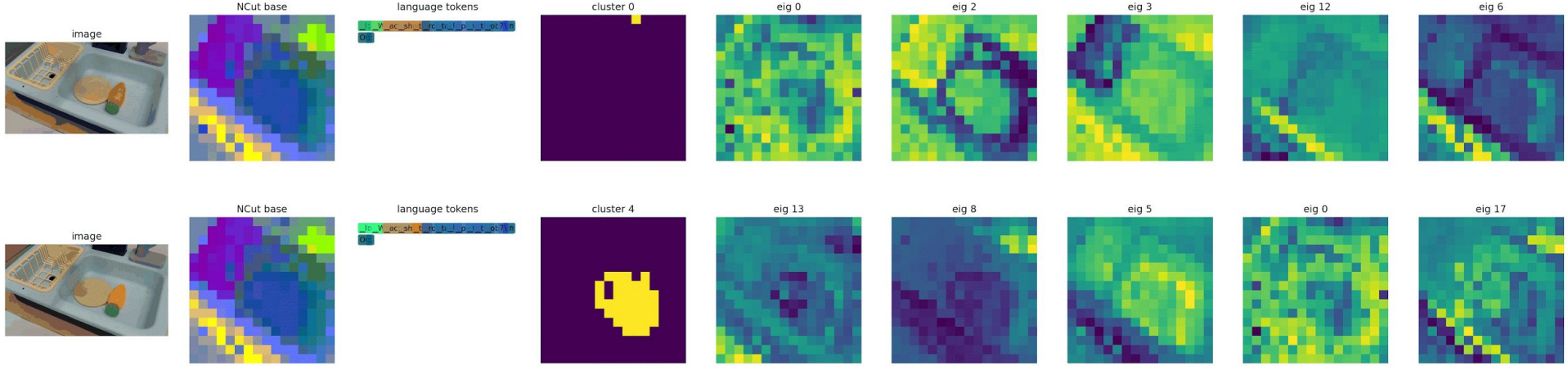




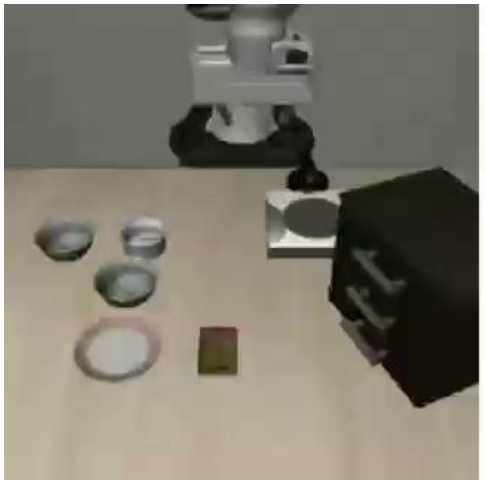




5 Findings – Back Propagation



5 Findings – Simulation



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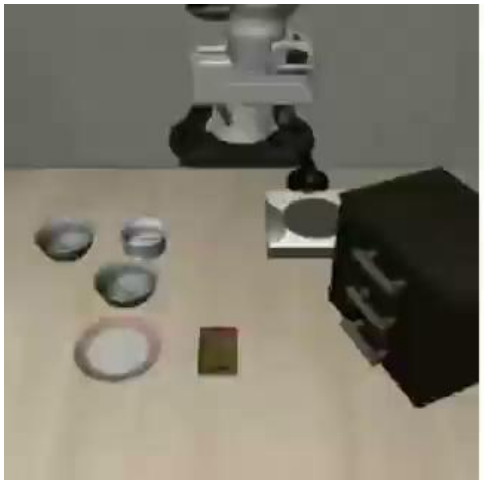

5 Findings – Simulation

- ~70.83%

~80%

6 Future Work

- Apply to OpenPi 0.5

- Deeper semantic information?
  - Does temporal Ncut coincide with prompt/instruction text?
  - Can the model predict future or missing tasks given limited context?

- Making OpenVLA Fail

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