- We would like to thank the reviewers for their comments, especially those concerning clarity and context of our work.
- 2 Our first change will be to the paragraph titled "Convergence Consistency". The observed inconstancy was due to poor
- 3 learning rate choices for internal RGrVAE representations. We will instead focus the paragraph on general convergence
- 4 properties (including learning rate) and robustness. This alongside a reduction of Figure captions (which restated text in
- 5 places) will allow us the space to address reviewer comments. We now address the comments of each reviewer in turn.
- To Reviewer #1 First, we thank you for your summary of related work in reinforcement learning, we hadn't considered the context of our work in this setting. We will be adding a paragraph to our prior work section to address this.
- Concerning task simplicity, we agree that work should strive to present results on datasets as close to the real world as possible. However, we feel moving straight to noisy real world data is a large jump, especially for linear disentanglement work where current state of the art [2] can extract up to 5 (synthetic) symmetries and required special metrics (e.g. generative factor labels), failing when applied directly to pixels. The most extracted from pixels is 2. We intended Section 5 to show RGrVAE performs comparably to it's supervised counterpart [1], not to show superiority. However, we would be happy, if deemed appropriate, to present RGrVAE applied to dSprites as evidence on datasets with more
- Regarding experimental comparisons to RL methods, whilst we see interesting parallels between your references and (VAE) disentanglement, it is difficult for us to determine how to appropriately compare them. This is mostly due to little existing work bridging disentanglement in VAEs and RL, they use different datasets, different metrics and often different (perhaps perceived) aims (ie independently controllable factors). Certainly there is space to explore comparisons under shared methodology, but we believe this would constitute an interesting but separate work to ours.
- Finally, we do agree that presenting weaknesses is important. As stated at the top of our response, we intend to replace the consistency paragraph with one on policy convergence. It will (amongst other things) discuss robustness under visual noise (salt+pepper, backgrounds, etc.) which, as a minor variation of the work already presented, we feel would not require overly detailed analysis or additional figures. We will add full results to the supplementary material.
- 4 To Reviewer #3 We first apologise that the supplementary material was incomplete, this oversight will be rectified.
- To begin we completely disagree that we have not shown evidence of linear disentanglement. Models that are not linearly disentangled completely fail to reconstruct the post action latent and observation, please compare Tables 1 and 3a. In fact, the ability to reconstruct the latent (i.e. find an independent f) is literally the definition of linear disentangled.
- Concerning the choice of number of actions, this is a hyper-parameter that (if symmetry structure is unknown) we have 28 to guess in the same way we guess the number of latents for VAE models (if the generative factors are unknown). The 29 usual approach is to allow more latents than you expect are required and the same can be done with the number of 30 actions. In Figure 3b we show that allowing more actions than present in the symmetry structure does not significantly 31 effect the policy network and thus the representation. On this note, we notice a typo in this figure where the number 32 of actions reported is per latent pair, not the total number available. We shall amend the figure and rephrase the 33 "Over representation" paragraph to be explicitly concerned with this choice. Furthermore, your suggestion of Dirichlet 34 processes for deciding the number of actions is intriguing, and we hope to explore this in the future. 35
- Concerning additional tasks, we intended Section 5 to demonstrate that RGrVAE performs comparably to its supervised counterpart [1], not to show superiority or extend it. We do however have positive preliminary results on dSprites, as you suggested. If the reviewers think it is appropriate for the section, we would be happy to include RGrVAE action traversals and independence measures as evidence on more complex datasets. Regarding instability of REINFORCE, after using appropriate learning rates we found that it was extremely consistent. Furthermore, we intend to discuss convergence under visual noise. We hope this and the possible addition of dSprites helps lessen your concerns.
- We thank you for your notes on clarity, which we will address in turn. 1) This 5 is the step size (pixels) of the agent per action. This absolutely should have been stated in the text and will be added. 2) This is the vector dot product, we will bold vectors for additional clarity. 3) Irreducible representations of dimension 2 or higher act on 2 latent dimensions or more, resulting in a low MIG, despite being linear disentangled. Perhaps expressive is not the correct word, we shall rephrase to reflect that linear disentangled representations have low MIG. 4) Eq. 4 has higher reward the closer the predicted post action latent is to the true value encouraging policies that select representations which best approximate the action. The prediction loss \mathcal{L}_{pred} (Eq. 5) encourages approximating the post action code accurately.
- 49 **To Reviewer #4** We thank you for your review and expressing your belief in the novelty and soundness of our work.
- 50 [1] Caselles-Dupré et al. "Symmetry-Based Disentangled Representation Learning requires Interaction with Environ-51 ments." NeurIPS. 2019.
- [2] Pfau et al. "Disentangling by Subspace Diffusion", ArXiv. 2020

symmetries and as suggested by Reviewer #3.

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