

1 We thank the reviewers for their constructive feedback and their appreciation of our experiments on this paper. The  
2 suggestions about adding more model variations are helpful; we will include more model variations (Alexnet, ResNet,  
3 and different initializations) in the revision. We have already performed comparisons of many architectures with the  
4 mouse data and achieve qualitatively similar results. We address some of the specific comments below.

#### 5 **Reviewer 1**

6 **novelty of findings** We appreciate the reviewer’s comments about the pseudo-depth metric and criteria for its robustness  
7 as novel findings. Our aim is to add another to the list: that we have used these tools to evaluate the *complexity* of  
8 visual processing in mouse cortex. Our analysis with VGG networks in the submission shows that even the primary  
9 area VISp (also called V1) computes substantially higher-order features than are commonly assumed in biological  
10 models of visual processing (such as HMAX); in our revision we will, as the reviewer rightly requests, evaluate this  
11 with shallower networks as well.

#### 12 **Reviewer 2**

13 **compare to mouse V1** VISp is an alternative nomenclature for V1, mentioned (we admit, briefly) in the text (L70). We  
14 will emphasize it more in the revision. This confusion coincidentally illustrates that “mouse visual cortical areas are  
15 relatively high order representations (including VISp) in a broad, more parallel organization” is, in fact, a surprising  
16 result. Our results show that even the earliest stage of the mouse visual cortex computes more higher-order features  
17 than is commonly assumed. This is consistent with a growing body of literature.

18 **shaded error bar** These are standard deviation. We will clarify this in the revision.

19 **scientific background** Functionally, very little is known about the visual areas in mice; we have nowhere near the level  
20 of detail we have about the primate cortex. There is some knowledge from anatomy (Harris, et al, 2019). There is  
21 some evidence for functional specialization in terms of spatial and temporal frequency processing (Andermann, et al,  
22 2002, Marshel, et al 2011). In the absence of such information, the VGG16 pseudo-length gives us a window into  
23 the functional organization of the higher visual areas, one that is roughly consistent with the relatively flat hierarchy  
24 observed in Harris, et al. We will add this discussion in the revision.

25 **SSM vs SVCCA** They are two different metrics that have different properties. SVCCA is invariant to affine transfor-  
26 mation on the features. SSM is invariant to monotonic transformation on the similarity matrices. We would therefore  
27 advocate using either depending upon the precise question. We will add this discussions in the revision.

28 **NeurIPS audience** This work provides a robust method that reveals the functional organization of a biological visual  
29 system (mouse) whose neural coding properties are currently – and relatively recently – the subject of very intense  
30 study across computational neuroscience. This is important, because data are available for the mouse on a totally  
31 unprecedented scale – which, as we show here, enables new questions to be asked. It is also important because this  
32 system appears to show, even in its early areas, distinctly higher-order coding properties when compared with the  
33 standard view of, say, the macaque ventral stream. Thus, our work provides new inroads at the interface between  
34 engineered and biological computing networks that have long been a mainstay of NeurIPS.

35 **Kornblith et. al. ICML 2019.** Thanks for pointing out this reference. Kornblith et. al. discussed the properties of the  
36 similarity metrics on comparing artificial neural networks. Our paper focuses on robustly studying systems in which  
37 one does not have access to all units, as at present must be the case for biological systems such as mouse visual cortex.  
38 We will add a citation in the revision.

#### 39 **Reviewer 3**

40 **2-photon data is usually deconvolved** The data is deconvolved by the algorithm in (Jewell et. al. 2018). Full information  
41 about how the data was processed is given in the Allen Institute paper de Vries, et al 2018. We will provide more  
42 information about the data in the revision.

43 **deconvolution is unable to identify scaling** SVCCA is invariant to affine transformation on the features, thus is also  
44 not affected by the scaling in the data.

45 **trial-to-trial variability and non-stationarity** This is a very important question. We will add results of bootstrapping  
46 trials to quantify the effects of trial-to-trial variability and non-stationarity among trials in the revision.

47 **why not use exactly those stimuli** The primary reason we use images other than those used for the Brain Observatory  
48 are so that we can study the sampling trends beyond 118 images (the number shown in the experiment). For the  
49 comparisons that don’t require this, we do use the exact stimuli (such as when comparing to the mouse data), including  
50 for the neural subsampling curves.