We thank the reviewers for their detailed feedback, and especially appreciate the suggestions on future research directions for C-RBP. Our revision will reflect the reviewers' comments, which we believe greatly improve its clarity.

Future directions R1, R2, R4: Each of the reviewers offered suggestions for future directions for our C-RBP method. We included a section *Future directions and limitations* in the SI, but we will move this to the main text and expand it in the final version of the paper to include the reviewer's suggestions, including the following:

R1 Extending C-RBP to other tasks, like object classification. In this domain, we are especially excited to compare the decision strategies of a C-RBP-trained object classification model to human or non-human primate observers.

R1, 2, 4 Extending C-RBP to other types of RNNs and data. The reviewers mention that our approach might have an even greater impact on other types of RNNs (*e.g.* graph neural networks) and datasets. We are particularly excited about extensions to domains with dynamic inputs, such as RL and spatiotemporal classification.

Typos, formatting, and extended broader impact R1, R3: We will fix these issues, thanks for pointing them out.

Reviewing other online-approximations to BPTT R3: We discuss some heuristics for controlling RNN memory complexity in the main text, such as gradient checkpointing, but the reviewer is right to point out that there are many other methods that we did not have room to include. The reviewer's comment was cut off, so we would appreciate additional guidance. One thought is that we could discuss online-approximations to BPTT motivated by Neuroscience, such as (1), which introduces eligibility traces to approximate BPTT-derived gradients. Note that this approach hasn't been extended to large-scale computer vision challenges, which was the goal of our work.

Details for reproducibility R1: We included code and data for model training, dataset creation, and generating results/figures in the SI zip file. We apologize for any confusion on how to run the code. In our revision we will include a link to a GitHub repository containing these files. Please advise on other details you'd like us to include.

Streamlining manuscript organization R4: We will move Figure 1 and lengthy explanations of the *Pathfinder* challenge/results to the SI. However, we would like to keep Figure 2 because it is an important motivation for C-RBP: BPTT-optimized RNNs can clearly solve segmentation tasks, but might do so using a sub-optimal dynamic routine.

An intuitive explanation of Panoptic Quality R4: Panoptic Quality (PQ) is sensitive to object recognition and instance/semantic segmentation, making it a difficult challenge. The baseline FPN-ResNet-101 PQ (43.0) vs. the baseline FPN-ResNet-50 PQ (39.4) implies the former improves segmentation on 3.60% of an image. In contrast, our R-FPN-ResNet-50 (41.6 PQ) outperforms a FPN-ResNet-50 by 2.23% despite having $\sim$1M fewer parameters.

Skeptical about the utility of C-RBP for Panoptic Segmentation R4:

- Our goal was to understand the effect of C-RBP and recurrent processing on Panoptic Segmentation while controlling for the effects of hyperparameters and pre/post-processing routines used on the challenge. Few of the models on the Panoptic Segmentation leaderboard are published, and those that are rely on loss function engineering and heuristics like test-time augmentations, ensembling, etc. Thus, we stuck with the FPN-ResNet as a strong baseline for a difficult challenge and demonstrated that an R-FPN trained with C-RBP outperforms it.
- We agree with the reviewer's prediction that *"the same [C-RBP] approach would improve the state-of-the-art"*. Indeed we offer evidence that C-RBP is generally useful for Panoptic Segmentation. An R-FPN-ResNet-50 trained with C-RBP outperforms a standard FPN-ResNet-50 (Figure 4). We also find that an R-FPN-ResNet-101 outperforms a standard FPN-ResNet-101 (Fig S9). R-FPNs use $\sim$1M fewer parameters than their respective FPN baselines.
- In retrospect, we regret not placing more emphasis on the *visual strategy* learned by an R-FPN trained with C-RBP for solving Panoptic Segmentation, which serves as qualitative evidence of our approach's *"convincing value for 'real' tasks"*. The R-FPN learns to segment objects by "flood-filling" – without any supervision or constraints to do this. It first seeds objects at their center then recurrently fills them to their boundaries (Fig. 1). This strategy gives models flexibility when segmenting and resembles theory from cognitive science on the visual routines of human observers for object segmentation. In our revision we will link to a website with animations that clarify this point.

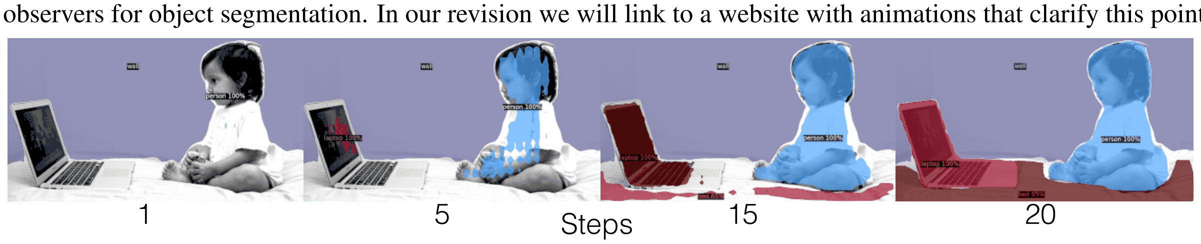

Figure 1: R-FPNs trained with C-RBP learn to segment objects by "flood-filling" without any instruction to do so.

References

[1] Roth, C., Kanitscheider, I., Fiete, I.: Kernel rnn learning (kernl). In: ICLR. (2018)