



Figure 5: For Macaque-Synthetic dataset, trajectories of similarity score with model layer depth are plotted. The models are divided into two groups: ViT and CNN&SNN. The normalized layer depth ranges from 0 (the first layer) to 1 (the last layer). The calculation and plotting of the trajectories are the same as Figure 3.

analyses, as described in the above paragraph, the properties that enable networks to achieve higher neural similarity are not yet clear. Taken together, the computational mechanism of the better models may reveal core processing divergence to different types of stimuli in the visual cortex.

### Discussion

In this work, we take large-scale neural representation similarity experiments as a basis, aided by analyses of the similarities across models and the visual cortical regions. Compared to other work, we introduce SNNs in the similarity analyses with biological neural responses for the first time, showing that SNNs achieve higher similarity scores than CNNs that have the same depth and almost the same architectures. As analyzed in Section 3.1, two properties of SNNs might serve as the explanations for their high similarity scores.

The subsequent analyses of the models' simulation performance and structures indicate significant differences in functional hierarchies between macaque and mouse visual cortex. As for macaques, we observed a clear sequential hierarchy. However, as for mouse visual cortex, some work (?) exhibits that the trend of the model feature complexity roughly matches the processing hierarchy, but other work suggests that the cortex (??) is organized into a parallel structure. Our results are more supportive of the latter. Furthermore, we provide computational evidence not only that the increased ratio of the receptive field size in cortical regions across the mouse visual pathway is smaller than those across the macaque visual pathway, but also that there may be multiple pathways with parallel processing streams between mouse cortical regions. Our results also clearly reveal that the processing mechanisms of macaque visual cortex differ to various stimuli. These findings provide us with new insights into the visual processing mechanisms of macaque and mouse, which are the two species that dominate the research of biological vision systems and differ considerably from each other.

Compared to CNNs, the study of task-driven deep SNNs is just in its initial state. Although we demonstrate that SNNs outperform their counterparts of CNNs, SNNs exhibit similar properties as CNNs in the further analyses. In this work, we only build several new SNNs by taking the hints from the biological visual hierarchy, while many well-established structures and learning algorithms in CNNs have not been applied to SNNs yet. In addition, the neural datasets used in our experiments are all collected under static image stimuli, lacking rich dynamic information to some certain, which may not fully exploit the properties of SNNs. Given that SNNs perform well in the current experiments, we hope to explore more potential of SNNs in future work. In conclusion, as more biologically plausible neural networks, SNNs may serve as a shortcut to explore the biological visual cortex. With studies on various aspects of SNNs, such as model architectures, learning algorithms, processing mechanisms, and neural coding methods, it's highly promising to better explain the sophisticated, complex, and diverse vision systems in the future.

### Ethics Statement

The biological neural datasets used in our experiments are obtained from public datasets or from published papers with the authors consent.

### Acknowledgements

We thank L. Chang for providing Macaque-Face dataset. This work is supported by the National Natural Science Foundation of China (No.61825101, No.62027804, and No.62088102). Veniam inventore quidem tempore nemo consequatur qui eos necessitatibus officiis, explicabo ex sed odio dolores sit expedita temporibus corrupti voluptate? Molestiae quas cumque odit nostrum porro, quam odit tempore, voluptatibus fugiat ab laudantium magnam, illo eligendi corrupti deleniti inventore. Sint accusantium similique, animi error tenetur culpa corrupti sit dolorum, nobis necessitatibus dolorum deserunt doloremque eum possimus vitae

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