

Suggested further readings

Pytorch - papers:

automatic differentiation library; some tutorials <https://openreview.net/pdf?id=BJJsrnfCZ>

Recommended review papers:

Richards, B. A., Lillicrap, T. P., Beaudoin, P., Bengio, Y., Bogacz, R., Christensen, A., ... & Kording, K. (2019). A deep learning framework for neuroscience. *Nature neuroscience*, 22(11), 1761-1770.

Lindsay, G. (2020). Convolutional neural networks as a model of the visual system: past, present, and future. *Journal of Cognitive Neuroscience*, 1-15.

Intro:

Large list of papers comparing DNNs and the brain:

Heuer, K., Gulban, O. F., Bazin, P. L., Osoianu, A., Valabregue, R., Santin, M., ... & Toro, R. (2019). Evolution of neocortical folding: A phylogenetic comparative analysis of MRI from 34 primate species. *Cortex*, 118, 275-291.

Zhou, B., Khosla, A., Lapedriza, J., Oliva, A., & Torralba, A. (2015). Object Detectors Emerge in Deep Scene CNNs. In *ICLR*.

Zhou, B., Bau, D., Oliva, A., & Torralba, A. (2018). Interpreting deep visual representations via network dissection. *IEEE transactions on pattern analysis and machine intelligence*, 41(9), 2131-2145.

Hasson, U., Nastase, S.A. & Goldstein, A. (2020). Direct Fit to Nature: An Evolutionary Perspective on Biological and Artificial Neural Networks. *Neuron*, 105, 3, 416-434.

Cichy, R. M., Khosla, A., Pantazis, D., Torralba, A., & Oliva, A. (2016). Comparison of deep neural networks to spatio-temporal cortical dynamics of human visual object recognition reveals hierarchical correspondence. *Scientific reports*, 6, 27755.

Tutorials:

Dataset:

Stringer, C., Michaelos, M., Pachitariu, M. (2019). High precision coding in visual cortex. *bioRxiv*. ([figshare link](#))

Deep learning used for encoding models:

McIntosh, L., Maheswaranathan, N., Nayebi, A., Ganguli, S., & Baccus, S. (2016). Deep learning models of the retinal response to natural scenes. In *Advances in neural information processing systems* (pp. 1369-1377).

Batty, E., Merel, J., Brackbill, N., Heitman, A., Sher, A., Litke, A., ... & Paninski, L. (2016). Multilayer recurrent network models of primate retinal ganglion cell responses. *ICLR*.

Cadena, S. A., Denfield, G. H., Walker, E. Y., Gatys, L. A., Tolias, A. S., Bethge, M., & Ecker, A. S. (2019). Deep convolutional models improve predictions of macaque V1 responses to natural images. *PLoS computational biology*, 15(4), e1006897.

Walker, E. Y., Sinz, F. H., Cobos, E., Muhammad, T., Froudarakis, E., Fahey, P. G., ... & Tolias, A. S. (2019). Inception loops discover what excites neurons most using deep predictive models. *Nature neuroscience*, 22(12), 2060-2065.

Comparing deep networks and the brain:

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Kriegeskorte, N., Mur, M., & Bandettini, P. A. (2008). Representational similarity analysis-connecting the branches of systems neuroscience. *Frontiers in systems neuroscience*, 2, 4.

Mohsenzadeh, Y., Mullin, C., Lahner, B., & Oliva, A. (2020). Emergence of Visual center-periphery Spatial organization in Deep convolutional neural networks. *Scientific Reports*, 10(1), 1-8.

Yamins, D. L., Hong, H., Cadieu, C. F., Solomon, E. A., Seibert, D., & DiCarlo, J. J. (2014). Performance-optimized hierarchical models predict neural responses in higher visual cortex. *Proceedings of the National Academy of Sciences*, 111(23), 8619-8624.

Khaligh-Razavi, S. M., & Kriegeskorte, N. (2014). Deep supervised, but not unsupervised, models may explain IT cortical representation. *PLoS computational biology*, 10(11), e1003915.

Gü lü, U., & van Gerven, M. A. (2015). Deep neural networks reveal a gradient in the complexity of neural representations across the ventral stream. *Journal of Neuroscience*, 35(27), 10005-10014.

Deep learning:

Nielsen, M. (2019). A visual proof that neural nets can compute any function.

Olah, C. Conv Nets: A Modular Perspective.

Goh, G. (2017). Why momentum really works.

Li, H., Xu, Z., Taylor, G., Studer, C., & Goldstein, T. (2018). Visualizing the loss landscape of neural nets. In *Advances in Neural Information Processing Systems* (pp. 6389-6399).

He, K., Zhang, X., Ren, S., & Sun, J. (2016). Deep residual learning for image recognition. In *Proceedings of the IEEE conference on computer vision and pattern recognition* (pp. 770-778).

Ioffe, S., & Szegedy, C. (2015). Batch normalization: Accelerating deep network training by reducing internal covariate shift. *arXiv preprint arXiv:1502.03167*.

Outro 1

Schrimpf, M., Kubilius, J., Hong, H., Majaj, N. J., Rajalingham, R., Issa, E. B., ... & Yamins, D. L. (2018). Brain-score: Which artificial neural network for object recognition is most brain-like?. *BioRxiv*, 407007.

Jozwik, K. M., Kriegeskorte, N., Storrs, K. R., & Mur, M. (2017). Deep convolutional neural networks outperform feature-based but not categorical models in explaining object similarity judgments. *Frontiers in psychology*, 8, 1726.

Nili, H., Wingfield, C., Walther, A., Su, L., Marslen-Wilson, W., & Kriegeskorte, N. (2014). A toolbox for representational similarity analysis. *PLoS computational biology*, 10(4), e1003553.

Storrs, K. R., Kietzmann, T. C., Walther, A., Mehrer, J., & Kriegeskorte, N. (2020). Diverse deep neural networks all predict human IT well, after training and fitting. *bioRxiv*.

Kriegeskorte, N., & Douglas, P. K. (2018). Cognitive computational neuroscience. *Nature neuroscience*, 21(9), 1148-1160.

Kietzmann, T. C., Spoerer, C. J., S. rensen, L. K., Cichy, R. M., Hauk, O., & Kriegeskorte, N. (2019). Recurrence is required to capture the representational dynamics of the human visual system. *Proceedings of the National Academy of Sciences*, 116(43), 21854-21863.

Lillicrap, T. P., Santoro, A., Marris, L., Akerman, C. J., & Hinton, G. (2020). Backpropagation and the brain. *Nature Reviews Neuroscience*, 1-12.

Tang, H., Schrimpf, M., Lotter, W., Moerman, C., Paredes, A., Caro, J. O., ... & Kreiman, G. (2018). Recurrent computations for visual pattern completion. *Proceedings of the National Academy of Sciences*, 115(35), 8835-8840.

Kubilius, J., Schrimpf, M., Kar, K., Rajalingham, R., Hong, H., Majaj, N., ... & Nayebi, A. (2019). Brain-like object recognition with high-performing shallow recurrent ANNs. In *Advances in Neural Information Processing Systems* (pp. 12805-12816).

Spoerer, C. J., Kietzmann, T. C., Mehrer, J., Charest, I., & Kriegeskorte, N. (2020). Recurrent networks can recycle neural resources to flexibly trade speed for accuracy in visual recognition. *BioRxiv*, 677237.

Outro 2

Chambers, C., Seethapathi, N., Saluja, R., Loeb, H., Pierce, S., Bogen, D., Prosser, L., Johnson, M.J. and Kording, K.P. (2019). Computer vision to automatically assess infant neuromotor risk. *BioRxiv*, 756262.

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