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# THE SEVEN DONKEYS: SUPER A.I. PERFORMANCE IN ANIMAL CATEGORIZATION BY AN IMMATURE HUMAN BRAIN

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A PREPRINT

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## ABSTRACT

This paper reports image categorization performance exhibited by an immature Human brain, that beats current state-of-the art convolutional networks with regards to the training procedure (limited size of the training set and limited training budget). This observation highlights the limits of the current A.I. trend for backpropagation-trained neural networks dedicated to computer vision, as well as its differences with natural neural networks. Based on the identified limitations, I then introduces a new image categorization challenge (the *seven donkey challenge*).

**Keywords** Image categorization · Supervised learning · Human brain · Artificial Intelligence · Convolutional networks · Deep learning

## 1 Introduction

An increasing number of recent scientific studies in engineering report superhuman performance in varied automated tasks (Hershey et al., 2010; Van Den Berg et al., 2010; Staub et al., 2012; Gharghabi et al., 2017; Lee et al., 2017; Brown and Sandholm, 2019). This is especially observed in the field of computer vision, when performing recognition, classification or segmentation using deep learning approaches (Cireşan et al., 2012; Maninis et al., 2016; Tulbure and Bäuml, 2018).

There is also a strengthening trend, in the neuroscience community, to suggest that convolutional networks trained by deep-learning are good models of the Human brain (see for example Marblestone et al., 2016; Yamins and DiCarlo, 2016; Kietzmann et al., 2018). However, training deep-learning architectures usually requires the use of huge datasets, as well as extremely large number of training epochs that may not necessarily compare well with the training of real brains (De Schutter, 2018).

In order to illustrate this critical difference, that is usually referred to in colloquial terms rather than with specific data, I report in the present paper an observation of an immature Human brain which, after training with an uncontrolled set of natural images associated with various labels, managed to learn and generalise a completely new class with a very restricted training set and a short training period.

## 2 Methods

A 18 month old baby was repeatedly presented 7 images of donkey, over the course of two weeks, all extracted from the French language edition of "The book of Autumn" (Berner, 2005) (training set). These seven donkeys are almost identical (see Fig. 1). They are all presented in a profile point of view, walking to the right, with a yellow blanket on the back, and partially occluded in all the images.

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Figure 1: Training set: Top left: the cover of the book of Autumn, note the donkey on the right of the tree. Top right: the donkey extracted from the market place page. Bottom: the market place page, note the complexity of the image, the donkey is here located on the lower right. Note the similitude of the two examples.

The presentations were done once or twice a day, I can thus estimate that a maximum of 28 awake training epochs were performed (I can only speculate about the number of offline replays performed).

No other donkey (drawing, picture or real animal) had ever been presented to the child. Presentations were either accompanied with a pointing gesture directed toward the donkey, and the vocalization in Russian by the experimenter "ослик" (donkey, pronounced oslik), or by the question, without gesture "где ослик?" (where is the donkey?). In the latter case, when the subject did not answer by a pointing gesture (timeout of approx. 3 s), or when the pointing direction wasn't correct, the experimenter then pointed at the donkey. The word "ослик" had never been previously used in another context.



Figure 2: Test set: An orchestra of animals. The donkey is on the right, playing the cello. Note the numerous differences with the donkeys of the training set (color, pose, clothing, activity).

Test procedure: the baby was presented the first page (Fig. 2) from the book "Fête de la musique" (Cosneau, 2014) and asked "где ослик?".

No ethical committee was involved in the validation of the experiment, as this experiment was part of the so-called "education" natural Human cultural process, performed in ecological conditions. Indeed, the results reported were only a posteriori identified as deserving communication to the scientific community.

### 3 Results

The baby pointed the donkey playing cello without hesitation.

### 4 Discussion

I reported in this paper the observation of an immature Human brain learning to perform image categorization and segmentation with superAI performance. This brain used a limited (7 items) set of very similar images (samples on Fig. 1), and was able to generalise the newly learned category to a radically different image (Fig. 2), using a limited budget of training epochs.

Take that in your face, convolutional networks.

I am of course not the first to question superhuman capabilities of deep-learning systems, see for example (Toromanoff et al., 2019; Zador, 2019). This paper aims at participating to the questioning of such assertions, especially the metrics used for such comparisons. The training computational budget and the size of the training set are critical variables that need to be properly addressed before superhuman performance can be claimed. Refer for example to (Mouret, 2016; Shu, 2019) on the necessity to rely on smaller datasets. Stressing on superhuman performance of artificial systems, in the current context, may contribute to the misunderstanding of the general public about what neural network powered AI is really capable of, and how far we are from building Artificial General Intelligence.

#### 4.1 The Seven Donkeys

As a consequence to the observation reported here, I propose a new challenge for artificial systems dedicated to computer vision: the *Seven Donkeys* challenge. It consists in training a computer vision system to find the centroid of the seven labelled donkeys in the (Bernier, 2005) training set, and then to test it on its ability to locate the centroid of the donkey in the (Cosneau, 2014) test set.

The subject of our study clearly had many opportunities to experience natural and drawn images, and it had already been trained to learn various categories (other than "ослик") and to search for these categories in images. This pre-training is probably a key to its performance in the test donkey recognition. Therefore the artificial system is allowed (and even recommended) to be trained with any labelled or unlabelled image sets, previously to the training with the (Berner, 2005) set, as long as they don't contain any donkey (the no-donkey sets).

Two training budget will be considered to define two versions of the challenge: the *restricted seven donkey challenge* consists in solving the problem with only 28 training epochs (mimicking the 28 awake training epochs only), while the *extensive seven donkey challenge* allows for 1000 additional presentations of the training set images, without the label and centroid information, interleaved with images from its no-donkey training sets, if needed.

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## References

- Berner, R. S. (2005). *Le livre de l'automne*. La Joie de lire, Genève, Switzerland.
- Brown, N. and Sandholm, T. (2019). Superhuman ai for multiplayer poker. *Science*, 365(6456):885–890.
- Cireřan, D., Meier, U., Masci, J., and Schmidhuber, J. (2012). Multi-column deep neural network for traffic sign classification. *Neural networks*, 32:333–338.
- Cosneau, G. (2014). *Fête de la Musique*. Hachette Livre, Deux Coqs d’Or, Paris, France.
- De Schutter, E. (2018). Deep learning and computational neuroscience.
- Gharghabi, S., Ding, Y., Yeh, C.-C. M., Kamgar, K., Ulanova, L., and Keogh, E. (2017). Matrix profile viii: domain agnostic online semantic segmentation at superhuman performance levels. In *2017 IEEE International Conference on Data Mining (ICDM)*, pages 117–126. IEEE.
- Hershey, J. R., Rennie, S. J., Olsen, P. A., and Kristjansson, T. T. (2010). Super-human multi-talker speech recognition: A graphical modeling approach. *Computer Speech & Language*, 24(1):45–66.
- Kietzmann, T. C., McClure, P., and Kriegeskorte, N. (2018). Deep neural networks in computational neuroscience. *bioRxiv*, page 133504.
- Lee, K., Zung, J., Li, P., Jain, V., and Seung, H. S. (2017). Superhuman accuracy on the snemi3d connectomics challenge. *arXiv preprint arXiv:1706.00120*.
- Maninis, K.-K., Pont-Tuset, J., Arbeláez, P., and Van Gool, L. (2016). Deep retinal image understanding. In *International conference on medical image computing and computer-assisted intervention*, pages 140–148. Springer.
- Marblestone, A. H., Wayne, G., and Kording, K. P. (2016). Toward an integration of deep learning and neuroscience. *Frontiers in computational neuroscience*, 10:94.
- Mouret, J.-B. (2016). Micro-Data Learning: The Other End of the Spectrum. *ERCIM News*, (107):2.
- Shu, M. (2019). Deep learning for image classification on very small datasets using transfer learning.
- Staub, C., Lenz, C., Jensen, B., Can, S., Knoll, A., and Bauernschmitt, R. (2012). Micro camera augmented endoscopic instruments: Towards superhuman performance in remote surgical cutting. In *2012 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 2000–2006. IEEE.
- Toromanoff, M., Wirbel, E., and Moutarde, F. (2019). Is deep reinforcement learning really superhuman on atari? *arXiv preprint arXiv:1908.04683*.
- Tulbure, A. and Bäuml, B. (2018). Superhuman performance in tactile material classification and differentiation with a flexible pressure-sensitive skin. In *2018 IEEE-RAS 18th International Conference on Humanoid Robots (Humanoids)*, pages 1–9. IEEE.
- Van Den Berg, J., Miller, S., Duckworth, D., Hu, H., Wan, A., Fu, X.-Y., Goldberg, K., and Abbeel, P. (2010). Superhuman performance of surgical tasks by robots using iterative learning from human-guided demonstrations. In *2010 IEEE International Conference on Robotics and Automation*, pages 2074–2081. IEEE.
- Yamins, D. L. and DiCarlo, J. J. (2016). Using goal-driven deep learning models to understand sensory cortex. *Nature neuroscience*, 19(3):356.

Zador, A. M. (2019). A critique of pure learning and what artificial neural networks can learn from animal brains. *Nature communications*, 10(1):1–7.