A generative model for primate brain shapes

Katja Heuer, Marian Kleineberg, Russell Dinnage, Chet C. Sherwood, William Donald, Hopkins, Ernst Schwartz, Georg Langs, Romain Valabregue, Mathieu D. Santin, Marc Herbin, & Roberto Toro

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The shape of primate brains varies widely from small lissencephalic lemurs to large and richly folded brains of great apes. Studying this morphological diversity across phylogeny allows us to better understand the way in which primate brains adapt, and in particular, the evolutionary context of the human brain.

Here **we explore the utilisation of deep neural networks to generate shapes of primate brains, based on a sample of close to 100 individual brains from 34 different primate species** from Heuer et al. (2019). During the last few years, these networks have demonstrated a striking ability to generate realistic new data (Park et al. 2019).

Method. We started from a series of brain meshes which were then voxelised. Before that, the meshes were eroded to make sulci wider. For all meshes the resulting volume had dimensions 128^3. Meshes were normalised in size to fit this volume. We trained an autoencoder 3D CNN on the voxel volumes (Wu et al., 2016). **The resulting 32-D latent space is represented in 2D using a t-SNE embedding t-SNE** (Van Der Maaten and Hinton, 2008).

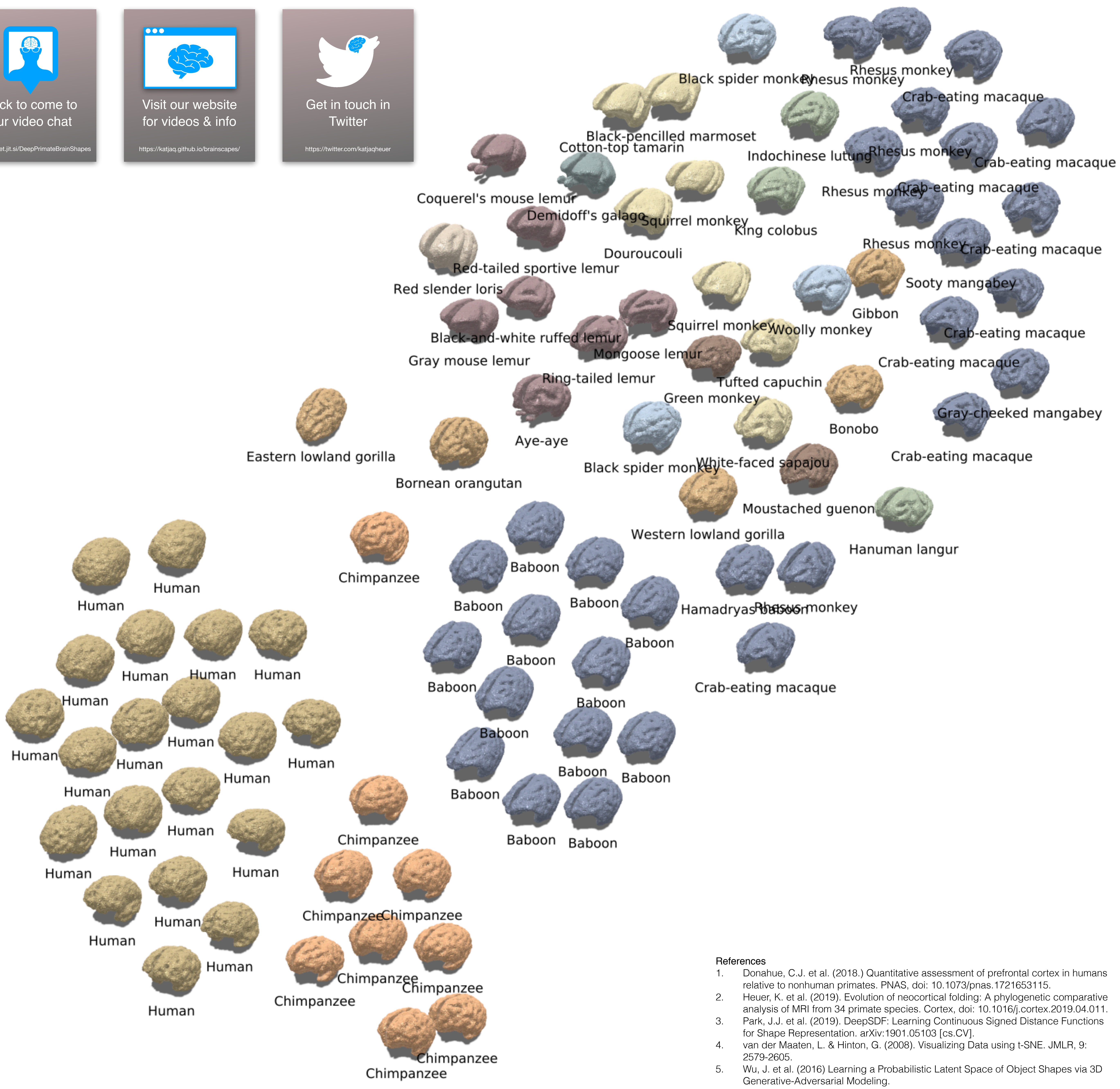
Results. The autoencoder was also able to reconstruct the shapes of new latent codes, such as codes obtained by interpolating between known shapes. The training duration was ~5000 epochs. Our network successfully learnt a landscape of global changes in shape. Finer details of the folding patterns were, however, not captured. Brains of comparable volume appeared close in the learnt space, despite having been size-normalised. This suggests that **changes in volume are consistently concomitant with changes in shape.** Indeed, brains with large volumes tend to be rounder. This rounding seems to come from a more pronounced dorsal development in large brains, the orbital region occupying progressively a more ventral position.

Conclusion. We developed a deep learning algorithm **able to learn the space of morphological variation across primates, and to generate new data. We generated possible brain shapes for all ancestral states of the primate phylogenetic tree, and evolutionary trajectories for each of our species back to the brain of the common ancestor.**

Our network was only able to capture long and deep sulci. In particular, the network was rather successful at learning the folding pattern of lemurs and to a lesser extent of atelids. However, the folding patterns of great apes were only learnt as a noisy texture. This relationship between success of learning and brain volume may hint to a problem with resolution. Indeed, our 3D CNN has a size of 128^3 voxels which may not be sufficient for capturing the small tertiary folding of great apes. However, increasing the number of voxels in the 3D CNN imposes exponential increases in the number of parameters to learn and the amount of memory required.

Further improvements should be achieved by increasing the number of species and individual MRIs included. Another potential approach for improving the quality of the brain generation algorithm would be the inclusion of neuroanatomical priors, for example, imposing a left/right symmetry, or aiming at sampling sulci more densely.

We successfully trained a deep neural network to learn the space of morphological variation across primates, and to generate new data along the phylogenetic tree. We obtained evolutionary trajectories of extant primate brains all the way back to the common ancestor.



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