The Evolution of Scientific Visualisations: A Case Study Approach to Big Data for Varied Audiences

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Abstract

Visual representations of complex data are a cornerstone of how scientific information is shared. By taking large quantities of data and creating accessible visualisations that show relationships, patterns, outliers, and conclusions, important research can be communicated effectively to any audience. The nature of animal cognition is heavily debated with no consensus on what constitutes animal intelligence. Over the last half-century, the methods used to define intelligence have evolved to incorporate larger datasets and more complex theories - moving from relatively simple comparisons of brain mass and body mass to explorations of brain composition and how neuron count changes between specific groups of animals. The primary aim of this chapter is therefore to explore how visualisation choice influences the accessibility of complex scientific information, using animal cognition as a case study. As the datasets concerned with animal intelligence have increased in both size and complexity, have the visualisations that accompany them evolved as well? We first investigate how the basic presentation of visualisations (figure legends, inclusion of statistics, use of colour, etc.) has changed, before discussing alternative approaches that might improve communication with both scientific and general audiences. By building upon the types of visualisation techniques that everyone is taught at school (bar charts, XY scatter plots, pie charts, etc.), we show how small changes can improve our communication with both scientific and general audiences. We suggest that there is no single right way to visualise data, but careful consideration of the audience and the specific message can help, even where communications are constrained by time, technology or medium.

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1 Introduction

Humans have communicated using pictures since our ancestors first made cave art over 45,000 years ago (Brumm et al., 2021). Today, outside of the arts, visualisation is gaining importance across domains including journalism, education, science, public information, and workplaces (Kennedy and Engebretsen, 2020). Visual tools are particularly important for conveying scientific information. The information being shared often takes the form of abstract ideas and numerical findings that are much easier to understand when represented pictorially. At their best, as Kennedy and Engebretsen (2020, pg.19) note, "visual representations of statistics and other, often quantitative data can convey complex facts and patterns quickly and effectively". Just as everyone is aware that a picture can paint 1000 words, a complicated statistical finding, if visualised effectively, can be made accessible to a much wider audience than when it is presented only as prose.

To foster scientific literacy, everyone taking high school mathematics or science is taught to make and interpret simple visualisations like bar charts, pie charts, histograms, and boxplots (**Fig.1**). These visualisations follow some straightforward rules, at least as we first encounter them – pie charts are for showing proportions of a whole, and XY scatterplots for showing the relationship between two variables, for example (Hawkins, 2019). Mastering these rules gives the student the tools to read and understand a broad spectrum of classic scientific literature, as well as the necessary background for advanced statistics courses that build on these foundations. In the modern life sciences, where testing a hypothesis increasingly requires 'big data' (Pal et al., 2020), we rely on developments in computing, statistics, and – ultimately – visualisations, to make sense of our findings.

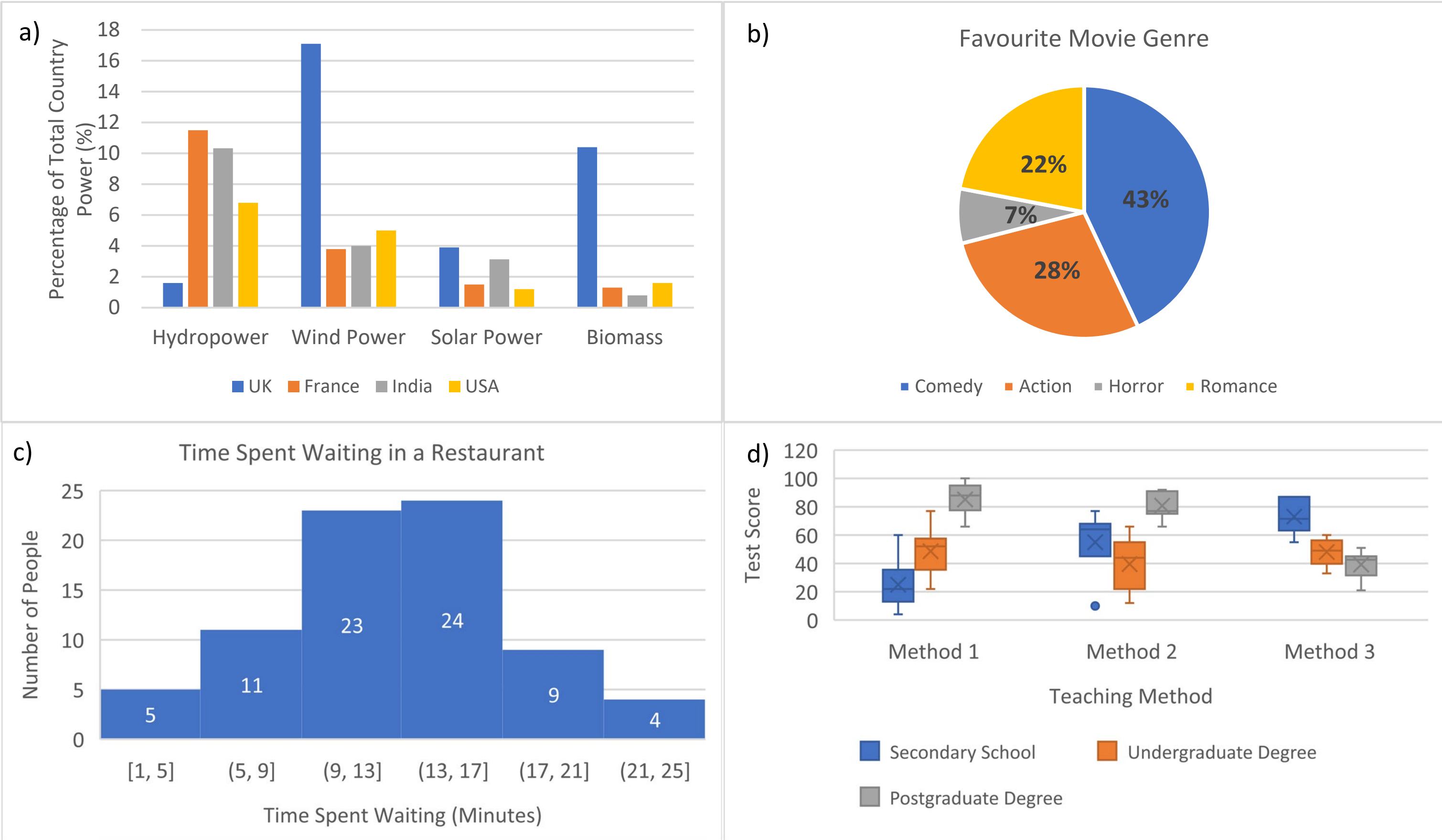


Fig 1: (a) bar chart, used to show quantities in specific categories; (b) pie chart, used to show numerical proportions in specific categories; (c) histogram, an approximate representation of numerical distribution of a data set; (d) box plot, used to show the range and average in different samples, as well as outliers. Example data sets created by author.

It is interesting, therefore, that even as life science datasets are increasing in size and complexity, scientists' options when it comes to visualising their outputs seem to have remained more circumscribed. This may be because scientists are not explicitly trained in the creation of innovative imagery (McInerny et al., 2014), with existing courses – like Edward Tufte's famous workshops on Analysing and Presenting Data and Information – primarily taking place outside of academia. Ongoing scientific discussions of the challenges of 'big data' in biology, furthermore, often mention challenges with storing, allowing access to, processing, and analysing vast datasets (Alyass et al., 2015; Marx, 2013; Pal et al., 2020), but rarely consider the challenges of visualisation. The example at the centre of this chapter comes from the study of brain size and cognition. Humans seem to have absolutely and relatively large brains (Preuss, 2017), at least when compared to other animal species. The question of exactly *how* large our brains are, and why they became that way, is one that neuroscientists and zoologists have been exploring for fifty years or more. One might think that we would see almost half a century's worth of development and change in the visualisations used in the scientific literature. In fact (see Section 2), while the types of data and measurements used have changed, sometimes quite dramatically, the same basic approach to visualisation can be seen in papers from 1980 and 2020. Our primary aim in writing this chapter is therefore to explore this pattern in more detail and show how scientists' *choices* about visualisation – at various stages and scales – influence the accessibility of scientific information for a variety of audiences.

To find out, we first delve deeper into our chosen example (Section 2). Although scientists studying the brain size-body size relationship and biological indicators of intelligence are using the same broad approach to visualisation, we wondered whether the availability of technology and their choices about symbols, legends, colour, titles, placement, and other factors have an impact on accessibility. How are scientists creating images, and what level of interpretive skill and statistical knowledge do they assume in their audience? Then, in Sections 3 and 4, we consider alternative approaches that might improve communication with scientific and general audiences respectively. The development of new statistics packages, and new functions in existing ones, allows writers to handle larger and larger datasets. These have changed the playing field for scientific visualisation. Can new techniques and visualisation approaches improve the way scientists communicate with one another? Do these new techniques also have the potential to help with wider scientific communication (e.g. across disciplinary boundaries or with non-specialists and public audiences)? A discussion of complex relationships relying on statistical values may quite quickly become near meaningless to non-specialist readers, even if they have a keen interest in the subject. The way that data is visualised is thus key to engaging quickly and effectively with a variety of readers. Through this chapter we will demonstrate that there is no universal 'right answer' to visualisation, but that more effective visual communication can often be achieved through careful consideration of the intended audience and the message to be communicated.

2. Visualisation Case Study: Animal Cognition

The visual representation of complex information is, without a doubt, one of the most important parts of scientific research. By translating numbers and observations into pictures, the data can be understood much more readily and relationships, outliers, and patterns can be shown in a way that is immediately accessible to the reader. Good visualisation is especially important where datasets are large, and relationships can only be described in terms of secondary numbers (statistics). This is because the human brain is not well-equipped to memorise large datasets, let alone to manipulate them, which means mathematics done on paper or on a computer needs translation to become meaningful.

Animal cognition research is a field that has used large datasets for decades, and tackles some of the most heavily debated questions in the life sciences. How can we measure intelligence or cognitive capacities, especially in animals we cannot communicate with? Identifying specific traits that might indicate a higher level of cognition from knowledge of an animal's natural behavioural repertoire is tricky, to say the least. To bypass the problems associated with intelligence experiments using behavioural traits, there has been a big push within the life sciences to find a quantitative *biological* proxy for intelligence. This search, however, has been challenging and - like many things in science - ideas about how we can best measure cognition have changed over the last few decades with the emergence of new technology, techniques, and information.

As animal cognition science has evolved, so have the visualisations that have accompanied it. Cognition studies usually look for relationships between two variables, one typically being some measure of cognition or intelligence, e.g. ability to use different kinds of tools, and the other the proposed biological indicator, e.g. brain volume. Alternatively, studies may look at brain volume and body size, to look for purely biological relationships. Due to the nature of this sort of data (which typically comprises two continuous measures), the broad nature of the visualisations and statistics used have remained very similar for the past ~40+ years. The standard analysis used is a linear regression. Linear regression is a statistical method which tries to predict the value of one thing (e.g. tool use) from a measure of the other (e.g. brain volume). It is usually represented via a graph with two axes and a scattering of points, one per animal. A line is usually added to show the best fitting statistical relationship. Points may fall above and below this line and (very occasionally) on it. In this section, by starting with the literature on this specific relationship and looking at how scientists' visual choices have affected the appearance and the accessibility of their data, we aim to consider how small decisions about colour, style, symbology and figure presentation affect the accessibility of our target area of research. We start with a little contextual information.

2.1 How Linear Regressions are Visualised

2.1.1 Context: Measuring Brains

Brain mass has long seemed a likely contender for a biological measure of cognitive potential, on the assumption that a larger brain allows more neural connections and hence more learning. Body size, however, poses a problem for any absolute measure of brain mass. For example, an elephant or whale brain comfortably exceeds the mass of human and ape brains, without these animals necessarily being more intelligent: they have bigger brains but these brains may be a smaller proportion of their total weight and use a smaller fraction of their energy intake. By taking a relative brain mass (i.e. measuring brain mass and dividing by body mass), species of different body sizes can be compared more easily. Scientists generally anticipate that animals with larger brains relative to their body size will be more intelligent. The proportion of body mass made up by the brain decreases as bodies grow larger (Herculano-Houzel, 2016; Jerison, 1973; Roth & Dicke, 2005). Relatively bigger brains do seem to indicate higher levels of intelligence in primates, birds, carnivores, bats, and even some fish like guppies (Benson-Amram, et al., 2016; Garamszegi & Eens, 2004; Kotrschal, et al., 2013; Madden, 2001; Ratcliffe, et al., 2006; Reader & Laland, 2002; Sol, et al., 2005). Some authors today prefer to look at absolute brain size (which has not been adjusted for body mass), or at other indicators, but a large quantity of the papers from the past forty years of cognition research have explored or used relative brain size data.

2.*1.2 Position of Visualisations Within the Article*

Given that most scientists working on animal cognition are using the same types of data and the same statistical tools, the fact that they usually choose the same graphs is not surprising. There are, however, some variations in the ways that these graphs are presented in papers from different decades and with different priorities. The first of these relates to where graphs are put into an article, and how they relate to one another.

The following two figures are classic examples of figures from the relative brain mass/animal cognition literature. They each explore relative brain mass in a multitude of species, in the form of a XY scatter plot. **Fig.2** shows two figures (originally labelled figure 1 and 2) from a 1981 paper by Robert D. Martin, which examined the relationship between body weight and brain weight across 548 species of mammals, birds, and reptiles. Martin was interested in how proportional brain mass affects how much energy animals need, and whether knowing more about this could tell scientists something about constraints on the evolution of brains. **Fig.3** on the other hand shows a figure from Lefebvre, et al. (2004). Lefebvre and colleagues showed that innovation rate, which they used as an indicator of higher intelligence, increases in proportion to the size of certain parts of the brain in birds and primates.

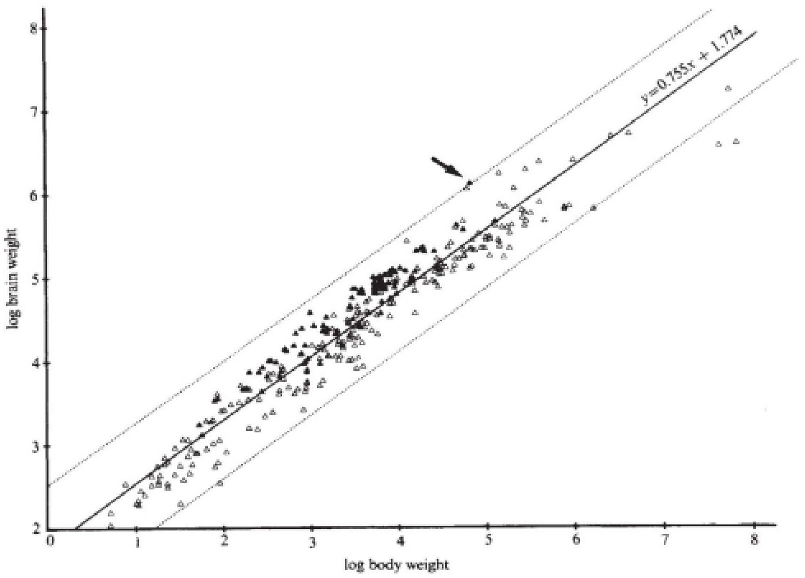


Fig. 1 Allometric relationships between brain and body weights for 309 extant placental mammal species. The solid line is the major axis; dotted lines represent fivefold variation above and below. Primates (▲) are typical of precocial mammals in exhibiting relatively large brains. The closest species to man (arrowed) is not another primate but a cetacean (dolphin).

Fig. 2 Allometric relationships between brain and body weights for 180 extant bird species (▲) and 59 extant reptile species (△). Solid lines are major axes; dotted lines represent 2.5-fold variation above and below. There is no overlap between the birds and reptiles and the separation between the major axes correspond to a typical 10-fold difference in brain size between birds and reptiles (see ref. 7 for an example of grade differentiation).

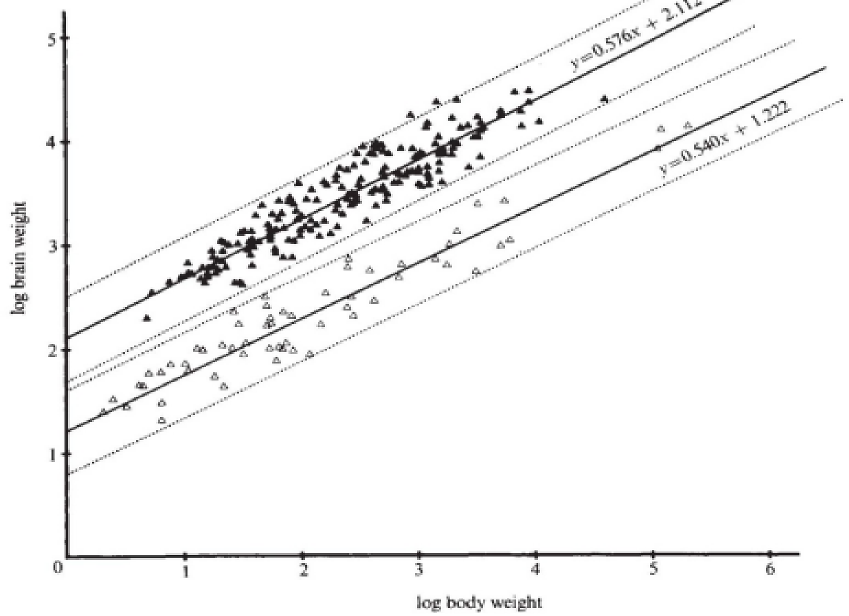


Fig 2: Figures 1 and 2 (and legends) from Martin, R. D., 1981. Two XY scatter plots of body weight against brain weight in primates and other mammals (figure 1) and birds and reptiles (figure 2), showing the relationships between the body weight and brain weight. Primates and the remainder of mammals are grouped together, while birds and reptiles form two separate distinct groups with no overlap. Reprinted by permission from "Springer Nature": Springer Nature, Nature, *Martin, R. D., 1981. Relative brain size and basal metabolic rate in terrestrial vertebrates. Nature, 293(5827), pp. 57-60*. Copyright ©1981

Fig. 2. Avian (**A**) and primate (**B**) innovation rate and (i) relative brain size (Neo-HV in birds, isocortex and striatum in primates), (ii) the frequency of reported tool use, and (iii) individual learning. Numbers indicate the taxa (**A**) or species (**B**), to allow identification of points these data are presented rather than independent contrasts. Some points are not numbered due to space limitations. **A** 1: Corvida, 2: Psittaciformes, 3: Trochiliformes, 4: Ciconiida, 5: Passerida, 6: Charadriida, 7: Apodiformes, 8: Craciformes, 9: Sulida, 10: Caprimulgi, 11: Scolopacida, 12: Columbiformes, 13: Anseriformes, 14: Odontophorida, 15: Struthioniformes, 16: Phasianida, 17: Grui. **B** 1: *Pan troglodytes*, 2: *Pongo pygmaeus*, 3: *Cebus apella*, 4: *Papio anubis*, 5: *Gorilla gorilla*, 6: *Macaca fuscata*, 7: *Papio papio*, 8: *Pan paniscus*, 9: *Cercopithecus mitis*, 10: *Alouatta seniculus*, 11: *Lemur catta*, 12: *Macaca mulatta*, 13: *Saimiri sciureus*, 14: *Cebus albifrons*, 15: *Ateles geoffroyi*, 16: *Callithrix jacchus*. Innovation data are taken from the current avian data set (see text) or from Reader and Laland [2002]. Avian brain data sources are given in the text, primate data are from Stephan et al. [1981] and Zilles and Rehkämper [1988]. Where Stephan et al. [1981] identify only the genus, the species identity was assumed to be as in Stephan et al. [1988; c.f., Reader and Laland, 2002]. **B** (ii) presents a reanalysis of the data from Reader and Laland [2002], excluding all species where neither innovation or tool use were reported (r = 0.78, p < 0.0001). Avian individual learning data are errors in reversal learning, taken from Gossette [1968; see Timmermans et al., 2000]. Primate individual learning data are laboratory learning set data from the compilation of Riddell and Corl [1977]; Spearman rank correlation, corrected for ties: $r_s = 0.77$, N = 6, $p_{one\text{-}tailed} = 0.042$. The regression line on **B** (iii) is shown for illustration.

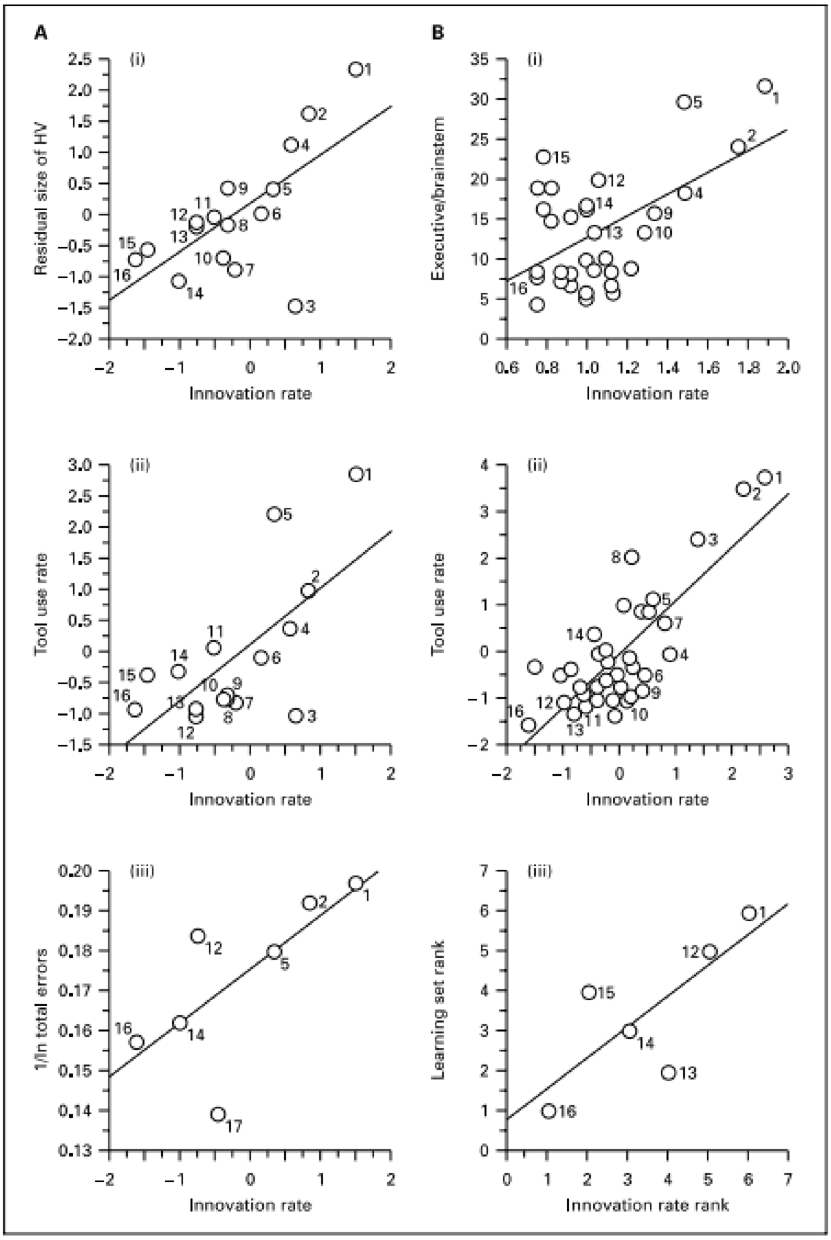


Fig 3: Figure 2 (and legend) from Lefebvre, L., 2004. A panel of six graphs showing how innovation rate (an indicator of higher intelligence) varies among primates and birds. Here Lefebvre shows that innovation rate is positively correlated with relative brain size. Reprinted by permission from "S. Krager AG": Krager, Brain, Behaviour, and Evolution. *Lefebvre L, Reader S, M, Sol D: Brains, Innovations and Evolution in Birds and Primates. Brain Behav Evol 2004;63:233-246. doi: 10.1159/000076784*. Copyright ©2004

The first difference one might see when comparing these two examples is the location of the figures relative to one another within their respective articles. Martin's figures (**Fig.2**) are located one after the other, with the text explaining the results on the next page. For a reader, this allows easy comparison between figures, but requires that they refer back to them when reading the supporting text. Lefebvre and colleagues (**Fig.3**) on the other hand display their figure followed immediately by a small section of text discussing the associated results, before presenting their next finding. This allows the reader to see the figure and the supporting text together, without having to refer back several figures and increases the overall readability of the text. However, it assumes that the reader can absorb the content of a figure and remember it for comparison with other visualisations. Each of these approaches has advantages and disadvantages, and different readers may have their own preference. A visually-oriented and statistically-savvy reader, for instance, may not need all the text detail to get the message of Martin's paper, while someone who prefers the unfolding of a detailed storyline, with visuals as backup, might engage more with Lefebrve et al.'s more incremental approach. Certainly they suggest that the authors of these papers were either operating within different constraints (e.g. numbers of full pages that could be devoted to figures) or else making choices, consciously or otherwise, about which comparisons they wanted to encourage readers to make. Without consulting the authors and journals, it is impossible to say for sure whether each figure was more shaped by choice or constraint. Their differences, however, arguably interact with other small variations in, for example, symbology to shape the reader's experience in quite distinctive ways.

2.1.3 Data Point Identification

In **Fig.2**, Martin uses a solid triangle (▲) for points that represent primates, and a hollow one (△) for other mammals. The same symbols, on another chart, are used for birds (▲) and reptiles (△). This makes it simple for a reader looking at a single chart to tell apart the two groups it compares, but does not facilitate easy comparison between charts – unlike the placement of figures, which seemed at first look to encourage it. This use of symbols prioritises the reader spotting the difference between birds and reptiles (which plot out separately) and primates and mammals (whose symbols overlap). It's much harder to see how birds and mammals would compare. Differences in the two figures' axes and shapes, for instance, make it difficult to imagine them superimposed even if the reader is confident enough in their statistical understanding to be sure direct comparison was possible.

Lefebvre, et al. (2004) also use labels to identify specific points, giving information about taxonomic family (**Fig.3** (**A**)) and species (**Fig.3** (**B**)), but instead of shapes they use numbers with corresponding information in the figure legend. Numbers like this allow the interested reader to locate specific animals in the chart, but the bird and primate charts use the same numbering system (1-16), so a given number doesn't always mean the same thing. Number 1, for instance, is either a corvid or a chimpanzee depending on which panel you look at. The primate analysis (**Fig.3** (**B**)), furthermore, only expressly labels 16 species, saying "some points are not numbered due to space limitations". Labelling all the data points might well have led to visual overload and obscured the pattern the chart is meant to show.

2.1.4 Figure Legends

Another important part of the figure which has a huge impact on its accessibility to the reader is the figure legend. The figure legend is a piece of accompanying text that describes the figure and helps the reader understand it without reference to the rest of the manuscript. In 2009, Yu and his colleagues looked at how well people understood information when they were just given a short and highly condensed summary of the paper (the abstract), a particular figure, and the legend that goes with it. They found that people only understood roughly a third of what they were reading by comparison with their understanding if they were given the full text to read. This suggests that improving figure legends would do a lot to help readers to skim articles for cruical information, and might reduce reliance on textual summaries like abstracts. It is particularly useful for legends to stand alone, so that in papers like Martin's (above), a reader who is visually inclined and statistically knowledgeable can extract the detail of key findings from a single page, without having to refer backwards or forwards in the text. This does, however, imply that different papers will require different lengths and levels of detail in their legends depending on the complexity of their figures. Comparing Martin (**Fig.2**) to Lefevbre et al. (**Fig.3**) above, for instance, shows that the numbered symbols in the latter necessitate a much longer legend. Decisions about symbology, legends and other visual elements have knock-on effects for one another.

Despite Yu et al.'s findings that figures and legends alone, with a text abstract, did not convey the full contents of a paper, visual abstracts are increasingly popular in new academic journals. They sometimes use a key figure from the text, but can also be stand-alone designs a bit like cartoons or tiny conference posters. Visual abstracts are particularly useful for those needing to 'preview' an article and decide how much more time to invest in it, and for sharing at meetings or on social media (Ramos & Concepcion, 2020). Adopting some of the techniques used in creating visual abstracts might help scientists with ordinary figure legends too – though proponents of the new approach note that maintaining quality is already a challenge, so this requires further exploration.

2.2 Known Issues with Brain Size-Body Size Approaches to Intelligence

The simple use of relative brain mass to predict intelligence has its critics. Some smaller animals, such as the elephant shrew (Family: Macroscelididae), appear to have much larger brain sizes relative to their body sizes than we might expect, with their brains making up around 10% of their total body weight (Roth & Dicke, 2005). Human brains, by comparison, are around ~2% of their total mass (Bélanger, et al., 2011; Snodgrass, et al., 2009). If intelligence was only about proportional brain size, then you would expect elephant shrews to be smarter than humans, and there is no evidence to support this assumption. There have been various efforts to correct for these presumed outliers, or adjust measurements to recognise scaling variation and find broader patterns instead of simply calculating proportional brain size.

One such adjusted measure is the encephalisation quotient. In 1973, Harry J Jerison proposed the encephalisation quotient (EQ) which measures the 'actual' brain mass compared with the 'expected' brain mass, to create a numerical value that attempts to indicate the level of intelligence (Jerison, 1973). For our example above, if we used a sample of animals that included both elephant shrews and humans to characterise how brains change as you increase in body size, we can see whether the human value of 2% is *unusually* large or small for a mammal of human size, rather than just larger or smaller overall than that of the elephant shrew. There are thus no universal EQ values as the expected brain size is calculated each time for a study, based on the animals sampled. This means that the results of an analysis of EQs depend on which animals are included in any particular calculation. If, for example, you had a study that looked at the relative EQ of humans and elephants, that would give a different EQ score for humans than a study that compared humans and sheep. The value itself indicates how much larger or smaller the brain of the animal in question is compared to its expected mass, which has been calculated using the larger dataset of all included animals. In a wide sample of mammals, a typical value of 1 (the expected brain mass is the same as the actual brain mass) is usually assigned to cats, with humans obtaining the highest values at around 7~8. The suggestion therefore is that the human brain is 7~8 times larger than would be expected, while a cat is a ‘typical’ mammal with a brain exactly as large as we might predict (Roth & Dicke, 2005). However, EQ does not consider other factors such as age, gender, or body fat percentage (Cairó, 2011). A study by Minervini, et al. (2016), who calculated EQ values for the domestic pig (*Sus scrofa*), demonstrates this by showing how the EQ values varied between piglets (2.42), young adults (0.58), and adult pigs (0.38) without a noticeable change within their behaviorual repertoire that would indicate changes in intelligence. Ultimatly, in visual terms, the use of EQ means that after fitting the line that describes the overall pattern of a XY scatterplot, instead of comparing which animal falls *absolutely* highest on the y-axis you can look at which falls proportionally highest above the line.

Another alternative to using relative brain measures is using absolute brain size, or the raw data on the mass of a species’ brain. The absolute mass of the brain in mammals ranges from <0.1g in the Etruscan shrew (Naumann, 2015) to ~9000g in some species of whale (Roth & Dicke, 2005), and so, on its own, cannot be used as an indicator of intelligence. It might, however, have advantages when comparing animals that are broadly similar in size. In particular, absolute brain mass has been suggested to provide a more accurate indication of higher-order brain function when working within a certain animal group or taxonomic orders (Benson-Amram, et al., 2016; Deaner, et al., 2007; MacLean, et al., 2014; Street, et al., 2017). This is because within such a group of animals, all species share the same brain scaling rules and are likely to be similar in size and ecology, making comparisons of actual size differences in the brain more meaningful than when comparing animals of very different groups.

2.3 How Linear Regressions are Visualised Continued

2.3.1 Figure Axes Titles

The questions scientists ask when working within groups of animals are different to those they might look at on a broader scale, and often focus more on the relationship between brain size and some systematically applied measure of practical intelligence. This is because behavioural or ecological indicators of cognitive capacities that apply to animals with different diets, body plans and social systems can be hard, but it is much easier to do for groups that are more uniform. As an example, **Fig.4** shows a figure from Deaner, et al. (2007) (pg. 115), who suggests that "absolute brain size measures were the best predictors of primate cognitive ability" when compared with the encephalisation quotient and relative brain mass measures.

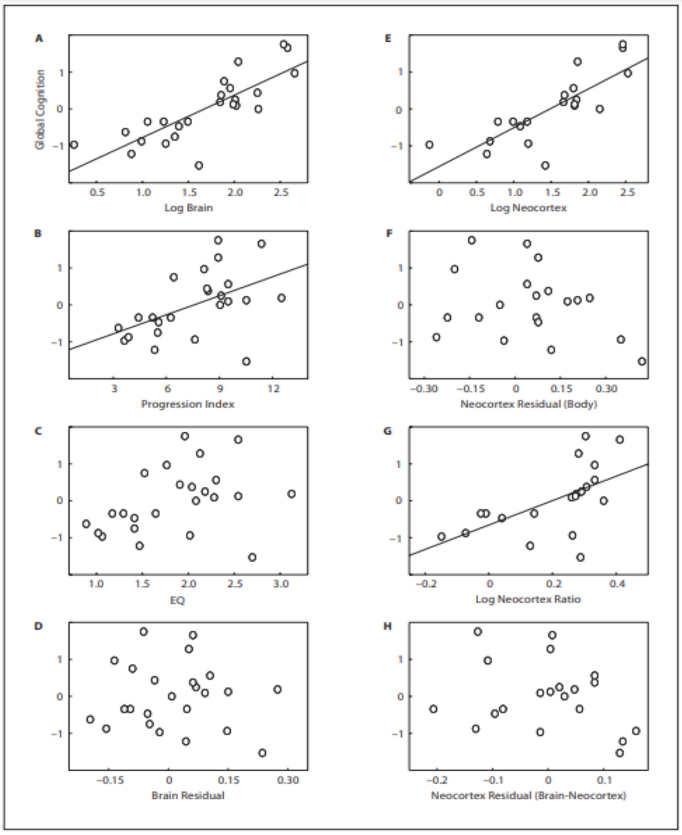


Fig. 1. Relationships between global cognitive ability of primate genera, as assessed by Deaner et al. [2006], and various neuroanatomical measures, using unweighted regression. Regression curves indicate significant correlations.

Fig.4 Figure 1 (and legend) from Deaner, R.O. et al., 2007 who suggest that absolute brain size measures were the best predictors of primate cognitive abilities. The bigger the primate brain, the more intelligent they seem to be. The important graph for this finding is (A) and (B) as it shows the total size of the brain or neocortex (where intelligence is thought to originate from) having a positive correlation with their cognition score. Reprinted by permission from "Krager Publishers": Krager. Brain, Behavior and Evolution. *Deaner, R.O., Isler,K., Burkart, J., and Van Schaik, C., 2007. Overall brain size, and not encephalization quotient, best predicts cognitive ability across non-human primates. Brain, Behaviour and Evolution, 70(2), pp.115-124*. Copyright © 2007, Krager Publishers, Basel, Switzerland

Fig.4 contains a lot of complicated information that, unless you are a specialist in the area and have been able to read the accompanying method text in detail, is perhaps harder to understand. For example, a lay reader may not start the paper knowing what unweighted regression, progression index, or global cognition mean. Even if they have read the method, a quick note reminding them of the definition of the progression index or global cognition within the figure legend could aid quick comprehension of the figure. Having only one y-axis label ("Global Cognition") is an effective way of reducing the figure's word count and increasing the clarity. Labelling each of the 6 graphs within the figure with the y-axis wouldn't add anything specifically helpful to the graph but would increase the visual 'clutter' of an already complex figure. The x-axes, on the other hand, could have their readability slightly improved. For example, saying "log brain **mass**" instead of just "log brain" does not really impact on the overall impression of the figure, but could reduce the cognitive load on the reader who no longer has to refer back to the methods to interpret an abbreviation as well as their definitions. There is an obvious trade-off here between readability and clarity, and perhaps another between house style (e.g. a stated preference for short, succinct legends) and the broader accessibility of the figure. This might be particularly important if a paper is intended to have a wide audience, or to be used for science communication, e.g. as a visual abstract, but it is worth considering at other times too.

2.3.2 Statistics

The inclusion of statistical information within a figure is quite often used to aid quick understanding of the data, though it arguably only works if the reader already has an understanding of statistics or specific field knowledge. The presentation of statistical visualisations to a general, non-specialist audience is discussed in Section 4, but even within the scientific literature intended for a more specialist audience, attention to how statistics can be incorporated into visuals is important.

As discussed previously, figures and their legends should ideally be self-contained so all the information the reader requires is present without reference to the remainder of the article. If we look back at **Fig.2** (Section 2.1.2), even though this graph is from 1981, statistics are still included in the form of regression line equations. As figures are, by definition, visualisations, using additional visual features upon the graph is a good way of adding more information. **Fig.4** does this by adding regression lines to the charts which demonstrate significant differences only, therefore, immediately showing the reader which charts are significant. Within statistics, this could also be the inclusion of the asterisk symbol (*) to indicate the level of significance. Using a note in the legend that states, "*p>0.05 (NS), p<0.05 (*), p<0.01 (**), p<0.005 (***), p<0.001 (****)*", and then labelling the figure with the corresponding symbol would show the reader the level of significance within the figure. This is a good way of conveying a lot of information through a simpler, visual means, and is useful for the reader that already understands what a p-value is. It is helpfully also unlikely to be too distracting for those who don't understand the p-value, as the asterisk symbology doesn't dominate the figures.

2.3.3 The Use of Colour

The use of colour in scientific visualisations is a fairly new development, which has become widespread as online publication has become more normal. Traditionally, all science communication has been through physical journals, usually held in University libraries, and the technology used in both the printing and dissemination of journal articles has undergone a quantum change over the last few decades. Even comparing 1981 (**Fig.2**) and 2007 (**Fig.4**) there is a noticeable lack of colour in both our chosen figures, and some journals still require black-and-white versions for print, which might discourage its addition. Colour is, however, not only visually appealing to the reader, but, if used correctly, it can add an additional layer of information to the figure. Similarly to using shapes (as discussed earlier), additional layers of information through the addition of colour allow for more patterns, relationships, and outliers to be visualised on the figure, and can potentially enhance the reader's intuitive ability to grasp patterns.

In 2014, MacLean and his colleagues undertook behaviour experiments (two tests, called the "A not B task" and "Cylinder test") to assess cognitive ability in eight groups of animals. The measurements that they took for both tasks were combined to create a composite graph (**Fig.5**). The findings suggested that across species, the absolute brain volume (marked as ECV on the figure) was "a robust predictor of performance" across all tests. This method of taking two similar graphs and combining them to create a composite graph can be used if you want to run a series of different tests, but end up with an overall result. It is also a nice example of an animal cognition chart that uses colour effectively to bolster communication of its findings.

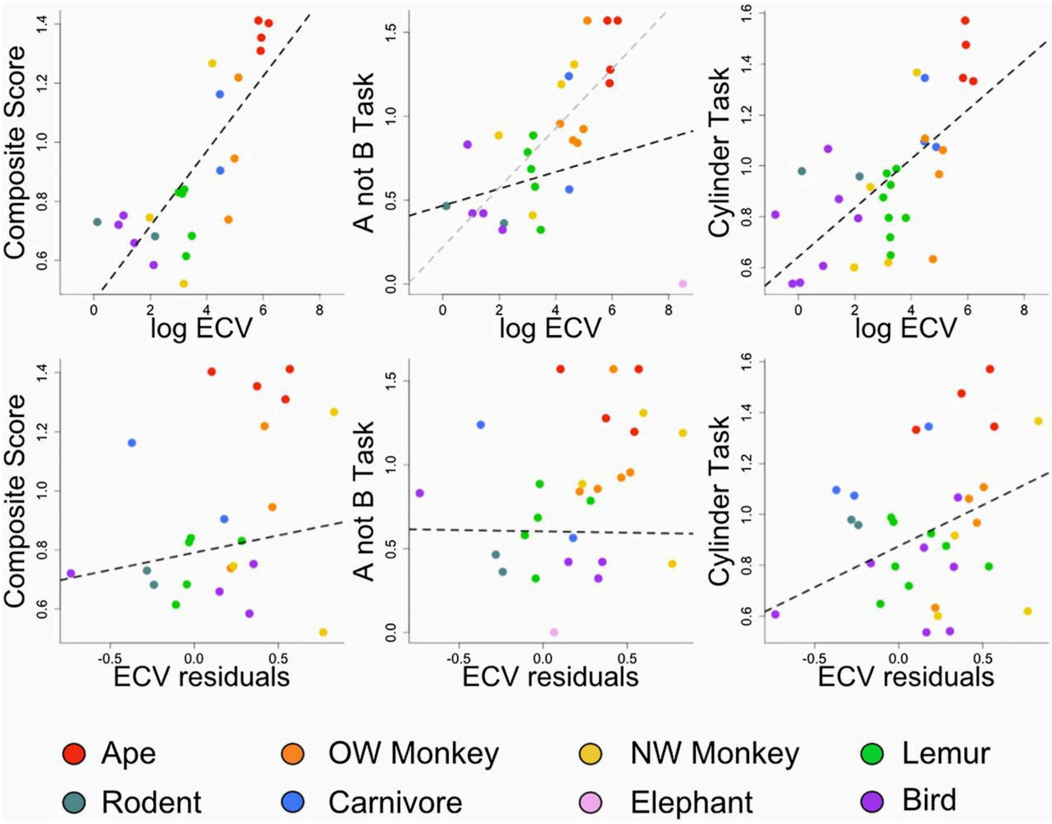


Fig. 2. Cognitive scores as a function of log endocranial volume (ECV) and residual brain volume (ECV residuals). In both tasks and in the composite measure, ECV was a significant predictor of self-control. Relative brain volume universally explained less variance. Plots show statistically transformed data (see *Methods* for details). The gray dashed line shows an alternate model excluding the elephant from analysis. NW, New World; OW, Old World.

Fig.5 Figure 2 (and legend) from MacLean, E.L. et al., 2014. Eight groups of animals were tested in two different cognition experiments, the "A not B test" and "Cylinder test". The panel displays results from those two tests and a composite score of both for Endocranial Volume (ECV or Absolute Brain Mass) and Endocranial Volume Residuals. Reprinted by permission from "Proceedings of the National Academy of Sciences": PNAS. MacLean, E.L., Hare, B., Nunn, C.L., Addessi, E., Amici, F., Anderson, R.C., Aureli, F., Baker, J.M., Bania, A.E., Barnard, A.M. and Boogert, N.J., 2014. The evolution of self-control. *Proceedings of the National Academy of Sciences,* 111(20), pp.E2140-E2148.

Fig.5 clearly demonstrates the benefits of using colour to distinguish between species, especially if compared with the black-and-white symbol approach shown in **Fig. 2**. It is visually appealing, and a reader can immediately see that apes (red) consistently performed highest in both tests while birds (dark purple), lemurs (green), and some New World monkeys (yellow) scored on the lower end. It also clearly identifies elephants (pink) as an outlier point on the top middle graph (log ECV against "A not B task").

So, even just looking at two example figures (**Fig.4** and **Fig.5**) that use absolute brain mass as a proxy for intelligence, it has become clear how the presentation of the data has evolved, even over a short time, to become more accessible to readers of both specialist and non-specialist backgrounds. However, there are still problems with using absolute brain mass as an indicator of higher cognition. For those who want to understand cognition more broadly, the hunt is still on: there is still a need to find a single, clear-cut and easily interpretable biological proxy for intelligence. Recent efforts have tended to focus on cortical neuron counts and scaling relationships that describe patterns in brain *composition*, rather than just in size.

2.4 Cortical Neuron Count as a Biological Proxy for Intelligence

While absolute brain mass has been shown to correlate with cognitive abilities, it can only be used within those animal groups (taxonomic orders) which share the same brain scaling rules. Scaling, when used in the context of brains, describes how the neuron composition of the brain changes as each brain type changes in volume/mass. There are no universal brain scaling rules. Instead, specific groups like primates or carnivores each have their own scaling patterns. Understanding the differences help us show, for example, that in a rat (or any rodent) as the brain increases in size, the neurons get larger and are added at a slower rate, whereas in humans the neurons remain the same size, so as the brain gets larger, proportionally more neurons are added. Ultimately, this results in more neurons within a primate brain compared to a rodent brain of the same mass, which allows primates to pack in more neurons without the additional costs of a larger (and heavier) brain (Gabi, et al., 2010; Herculano-Houzel, et al., 2007; Herculano-Housel, 2009).

Looking at scaling rules gives us a more nuanced way to assess potential intelligence. The human brain is divided into three different broad sections: the brain stem, which controls basic functions such as heartrate and breathing, the midbrain or cortex that includes feelings and emotions such as fright and flight, and the new or neocortex which is the part on the outside with the distinctive folds in it. This section, the human neocortex, is where abilities and attributes indicative of higher intelligence are thought to originate from. In humans it contains around 16 billion neurons which makes up a massive proportion of the overall brain neuron count (around 19% of a total of 86 billion neurons) (Azevedo, et al., 2009). Humans have the largest number of cortical neurons of any species on the planet (Herculano-Houzel, 2012), and it is this, the sheer amount of cortical neurons, that has been suggested to account for our enhanced cognitive abilities. Even when compared with brains that are 3~4 times larger than ours, such as the African elephant's (*Loxodonta africana*) (whose whole brain contains 257 billion total neurons), different mammalian scaling patterns mean that humans still have far greater numbers of cortical neurons (16 billion as opposed to 5.6 billion) (Herculano-Houzel, et al., 2014).

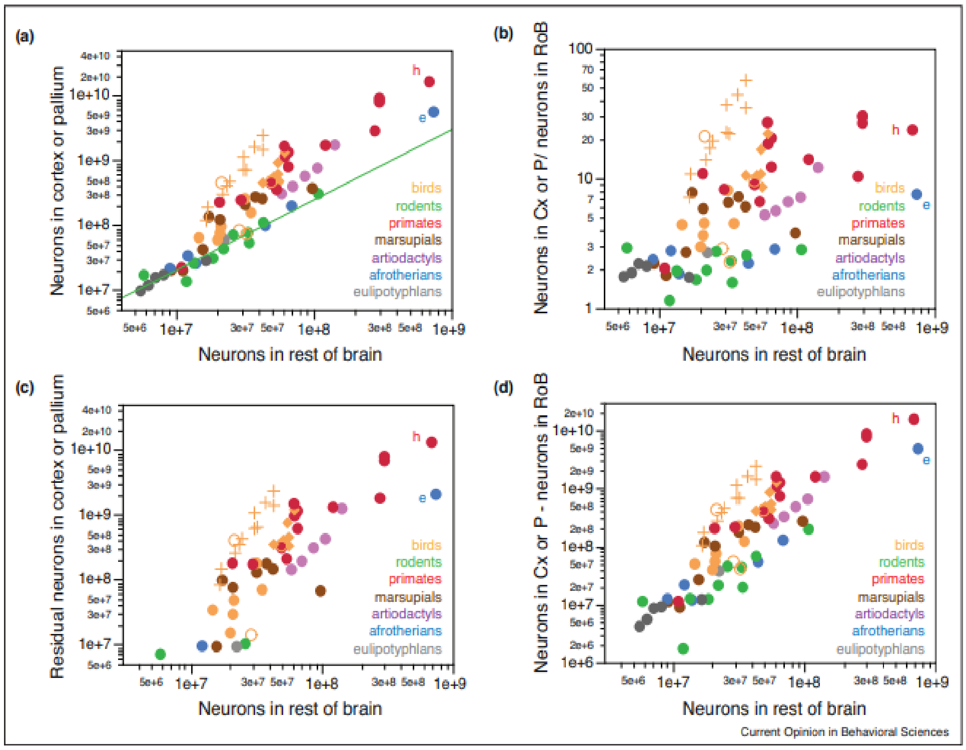
If cortical neuron count is an accurate indicator of what currently constitutes 'intelligence', it could potentially be used to compare animals across the vertebrates. Non-mammalian vertebrates have an equivalent structure to the neocortex, called the dorsal pallium (Herculano-Houzel, 2017). The amount of neurons in either of these two structures thus gives us a new contender for a simple biological proxy for intelligence that has neither of the disadvantages we have already considered. It does not use body mass (such as relative brain mass or the encephalisation quotient do), and so does not have the associated problems discussed earlier in the chapter, and as it bypasses the issues of brain scaling, can be applied much more widely than any absolute measure of brain size. This leads to a new generation of papers looking at cortical neuron counts. This methodology tends to use quite complex datasets, and correspondingly relies on combinations of strategies to make figures more accessible (see below).

2.5 Points of Interest and Print/Disability Friendly Figures

2.5.1 Flagging Points of Interest

Suzana Herculano-Houzel's 2017 paper (**Fig.6**) highlights how the number of neurons in the cortex (or pallium) correlates with cognition measures, and how the pallium within birds can pack more neurons than some primate cortices do of similar masses. This specific visualisation is a good way of pulling lots of the previous points made in this chapter together to form a more accessible visualisation despite it including some very complex data.

Figure 2



Scaling of numbers of neurons in the cerebral cortex or pallium against numbers of neurons in the rest of brain.
Each point represents one species belonging to the different clades according to the colors in the legend. Among birds, Passeriformes are represented by orange filled circles and lozenges; psittaciformes by orange crosses; and barn owl, emu, pigeon and jungle fowl by unfilled orange circles. **(a)** Scaling of absolute number of neurons in the cerebral cortex with absolute number of neurons in the rest of brain. Exponents, *p*-values and r^2 values for the different clades: afrotherians, 1.264 ± 0.073, $p < 0.0001$, 0.987; artiodactyls, 1.904 ± 0.172, $p = 0.0016$, 0.976; eulipotyphlans, 0.932 ± 0.142, $p = 0.0072$, 0.935; marsupials, 1.374 ± 0.245, $p = 0.0008$, 0.818; primates, 1.457 ± 0.120, $p < 0.0001$, 0.919; rodents, 1.103 ± 0.130, $p < 0.0001$, 0.900; Passeriformes, 2.089 ± 0.188, $p < 0.0001$, 0.918; Psittaciformes, 2.768 ± 0.212, $p < 0.0001$, 0.950; ensemble of afrotherians (minus the African elephant), eulipotyphlans and rodents, 1.089 ± 0.064, $p < 0.0001$, 0.938 (plotted); all data points together, 1.526 ± 0.093, $p < 0.0001$, 0.776. **(b)** Scaling of the ratio between numbers of neurons in the cerebral cortex of mammals (or pallium of birds) with the number of neurons in the rest of brain. **(c)** Scaling of the residual number of neurons in the cerebral cortex of pallium after regressing onto the number of neurons in the rest of brain, as in (a), with the absolute number of neurons in the rest of brain. **(d)** Scaling of the difference between number of neurons in the cerebral cortex or pallium and rest of brain with the absolute number of neurons in the rest of brain. h, human data point; e, African elephant data point.

Fig.6 Figure 2 (and legend) from Herculano-Houzel, S., 2017. This figure shows how the number of neurons in the cortex (or pallium) correlate with cognition measures, and how the pallium within birds can pack more neurons than some primate cortices do of similar masses Reprinted by permission from "Elsievier": Current Opinion in Behavioral Sciences. *Herculano-Houzel, S., 2017. Numbers of neurons as biological correlates of cognitive capability. Current Opinion in Behavioral Sciences, 16, pp.1-7.*Copyright © 2017, Elsievier

Fig.6 has a very detailed legend that explains what each part of the plot shows, as well as the significance values for the graph which are in a consistent format – making it easier to read, at least for those readers with the statistical knowledge required to understand this content (see Section 2.3). It also uses clear, concise axis titles and colour schemes with legends on the figures to allow quick interpretation.

A new visual strategy this figure deploys is the combination of letters and colours as labels to pick out points of interest. The human ("h") and African elephant ("e") are labeled on all graphs while remaining the same colour as their close relatives. Furthermore, the letter labels are discreet enough not to cause visual clutter or distraction, but prominent enough to be easily spotted and looked up in the legend by a curious reader. Identifying points of interest is not necessarily a new feature of figure creation, as (for instance) Martin used an arrow to identify a dolphin in his 1981 figure (**Fig.2**). But using these identifiers helps place the data in context for the audience, and is a good way of identifying points at either extreme as well as possible outliers. **Fig.7,** by Lunn et al., (2021), shows another example where points of interest are identified through imagery rather than letters. For example, **Fig. 7** highlights that pigs lie away from the remaining points in their group (Artiodactyls), donkeys are the only member of their group included (Perissodactyla), and wolves and dogs can be rapidly compared by those interested in intelligent carnivores. Both **Fig. 6** and **Fig. 7** thus manage to highlight *both* the overall patterns their authors found, *and* the placement of specific animals that might be of particular interest to some or all of their readers.

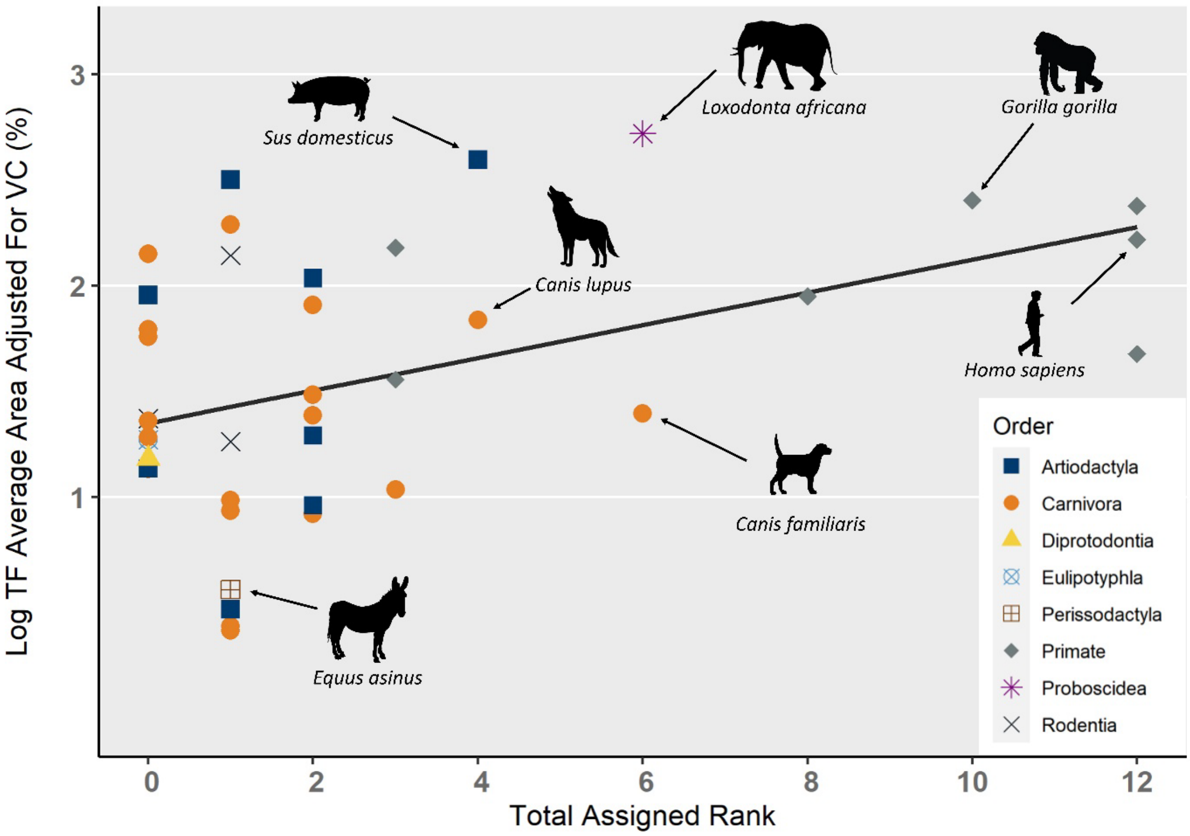


Figure 4.1) A linear regression of the logged transverse foramina area adjusted for the area of the vertebral canal and the total assigned rank across 40 Mammalian species from 8 taxonomic orders. A positive significant relationship was found ($R^2(38) = 0.1879, p<0.01$**), and some key species are illustrated.

Fig.7 Figure 4.1 (and legend) created from Lunn et al., (2021) showing a linear regression analysis of measurements on a feature on cervical vertebra (transverse foramina) which indicates the level of blood flow to the brain, and a ranking system that is indicative of intelligence, where the higher the rank, the higher the proposed intelligence. Transverse foramina measurements are averages between both foramina present, and then displayed as a percentage of the vertebral canal (also present on the cervical vertebrae) to adjust for total organism size across the data set. This figure indicates that the higher the blood supply to the brain (so larger average transverse foramina measure), the more behavioural traits indicative of higher intelligence the species has.

2.5.2 Print and Disability Friendly Figures

The use of colours and shapes has become increasingly more common to add additional layers of information to figures, but if you've ever opened an exam paper or journal article and been greeted by a photocopied graph in varying shades of grey, you will have some indication of the difficulties with using a wide variety of colour without explicit attention to what happens in reproduction or subsequent iterations. One final improvement that could be made to the graphs just discussed is to design the colour in such a way that the figure can be reproduced and read in a greyscale format or by someone with a disability (such as red-green "colour blindness", hereafter referred to as "colour vision deficiency"). Red-green colour vision deficiency is the most common type of colour vision deficiency, with 1 in 200 women and 1 in 12 men affected (or 0.5% and 8% respectively) (National Health Service, 2019; Levine, 2008). Photocopiers that only work in black and white, or black and white reproductions of colour figures available only in online versions of journal articles affect many more of us. Usefuly, some resources, such as Microsoft Office PowerPoint, now have built in accesibility features, and other online sources (such as Coblis (Wickline & HCIRN, 2022) which allows a user to see what their visualisations look like to someone with colour vision deficiency) are allowing authors to see their visualisations in different ways, and, hopefully, resulting in more inclusive and accesible visualisations.

Fig.8 visualises these differences by using an example, fictitious, data set created by the author to show how colour choice can affect the figure and therefore the reader.

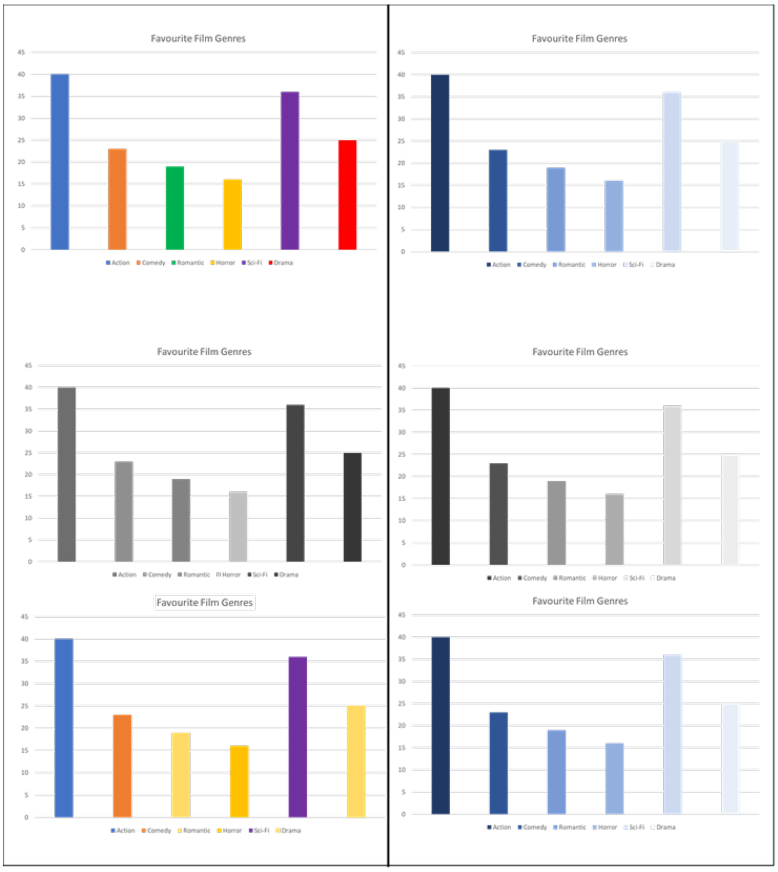


Fig.8 Bar charts with a fictitious data set created by the author to demonstrate how colour choice can affect the figure (and therefore, the reader). The left hand demonstrates a 'bad example' with multiple colours, while the right-hand side demonstrates a 'better example' with a blue monochrome scale. The first horizontal row represents how the graph would look in its natural colour form. The second horizontal row represents a greyscale version of the same graph. The third horizontal row shows a proposed view for someone with colour vision deficiency – specifically red-green.

Fig.8 shows how a bar chart (right) in a monochrome scale (blue in this example) can be read in its natural form, a greyscale print, and for someone who lacks the full range of colour vision (red-green colour vision deficiency), compared with a graph with a range of colours (left). It is important to note here that the colour vision deficiency graph is simply used as an indication of how someone who is affected by it, *may* see the figure. Colour vision deficiency can affect each person differently, with some people seeing duller versions of the colour while others may be unable to differentiate between the two extremes of the red-green axis, or are affected more strongly by only one end of the axis (National Health Service, 2019). From **Fig.8**, it quickly becomes obvious that although the graph with multiple colours (left-hand side) is visually appealing, in it's original form, it becomes much harder to read either in greyscale, or with a disability. The monochrome scale on the other hand (right-hand side), is still visually appealing and is greyscale/disability friendly. By taking the colour scheme and readability of figures into account, graphics and articles can become more inclusive, comprehensible, and accessible to everyone.

2.6 The Evolution of Cognitive Abilities and Brain-Body Mass Visualisations

As the science investigating the relationship between cognitive ability and biological indicators/methods of measuring cognition has evolved, so have the datasets used and their visualisations. In particular, there has been a major move away from using relative brain size measures as proxies for intelligence, and towards either restricted but simple measures like absolute brain size or – more recently – measures like cortical neuron count. While the basic display of this data has remained the same, in the form of XY scatterplots representing linear regression analyses, the complexity of charts has changed in line with changes in the datasets used, and as technology has progressed. As science has moved on to online publishing and efficient printing, detailed computer-generated graphs with finite details and additional features (such as colour, etc.) have been added into figures. There also seemed to be a trend in earlier research that assumed much more about the statistical competence of the reader, though some elements even of recent figures (like **Fig. 6**'s exponential axis labels) suggest this assumption still holds for academic papers. While many readers will understand the statistics within these articles, making figures and legends more detailed and easier to comprehend improves the accessibility of science to anyone and everyone, and fits well with the current trend towards greater inclusivity in general, e.g. via use of colour and greyscale (print) friendly formats. Overall, our explorations of even this small part of the scientific literature has turned up multiple ways in which authors' choices and constraints both affect the accessibility of their visuals.

3 Approaching Visualisation Differently

Figures can be invaluable tools for scientists. Scientific writing is typically concise, with articles using a standard introduction, method, results, discussion, conclusion (sometimes called IMRaD) structure and journals imposing a word count to constrain the authors. As an author, this means that if the word count can be reduced while the readability and accessibility increase, that is a win-win scenario. Figures and visualisations are key to displaying findings and, especially when considering complex datasets, are the parts of the research that really "pull" people in. Figures can take a long time to make, however, so there is little point in having a graph or figure if a "single simple sentence can convey all the information more efficiently" (Schriger & Cooper, 2001). It is, as we've already discussed, important to take each dataset case-by-case and consider which visualisation methods are most appropriate. This section aims to describe *some* of the alternative visualisations scientists might use, and the advantages and disadvantages of each.

(*Note: The following visualisations were created using RStudio (v.1.4.1106) with the additional packages: beanplot; dplyr; ggplot2; ggpubr; ggsci; ggsignif; ggthemes; gridExtra; lattice; rstatix and, scales.)*

3.1 Alternatives to XY Scatterplots

As Section Two showed, in the field of animal cognition the use of brain-body mass ratios and specific biological proxies for intelligence usually results in articles that analyse data with linear regressions. In papers from 1980 to 2000, the natural visualisation method has been an XY scatter plot. XY scatter plots, as noted, are good at displaying the relationship between two continuous numerical variables and can be useful for identifying patterns or outliers within the data set. A simple addition to a basic XY scatter plot is the separation of data by a third categorical or numerical value (i.e. through different colours or symbols). In the examples shown in Section Two, these categorical variables may be groups of animals or species. With the exception of resolving overplotting (an issue where data points overlap one another resulting in some data points becoming difficult to read), there are few ways in which an XY scatter plot can be improved to aid readability once general figure considerations (axis titles, point shape, and legends, for example), have been addressed. However, it is possible to envision ways to add detail to a XY scatterplot, to reinforce or clarify the relationships it shows

For instance, a scientists can add visualisations of each of the variables outside the main chart. These are called marginal density plots. **Fig. 9** adapts data from Lunn et al. (2021) to show the relationship between a ranking system indicative of animal intelligence, and the average transverse foramina area, or diameter of the holes in the neck bones (cervical vertebrae) that the vertebral blood vessels flow through to get to the brain. This measurement can be used as a proxy for blood flow to the brain through these arteries. Here, marginal density plots have been added in the form of boxplots (**Fig. 9a**) and density curves (**Fig. 9b**) on both axes. These show the reader that primates (in grey on the chart and in the box plot) are both more intelligent and have more blood flowing to the brain through the vertebral arteries than the other two groups. The additional information the marginal plots convey (ranges, median values, and densities for example) can also be useful in showing the reader contextual information about the data that could not easily be incorporated into the symbology of the main plot.

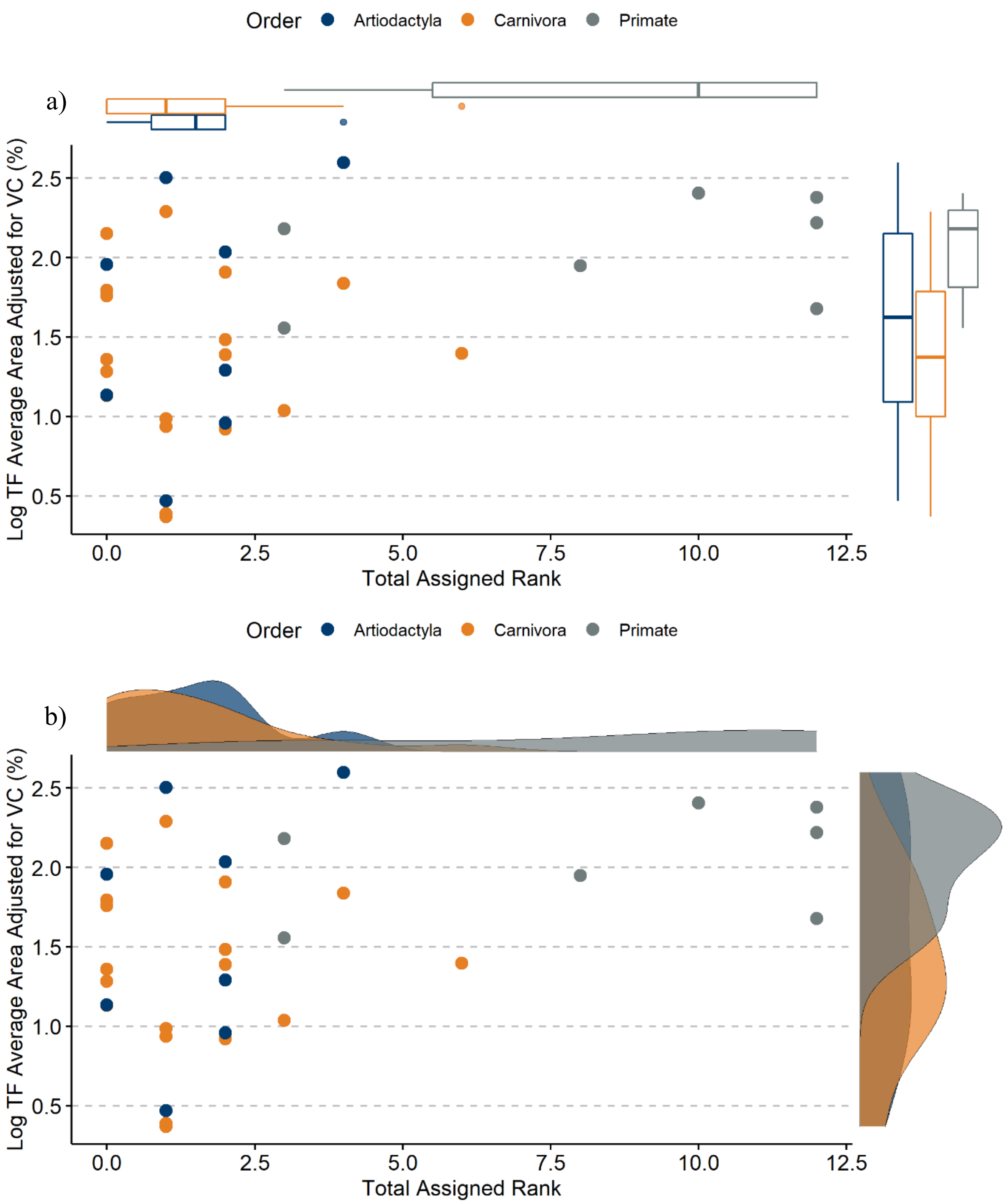


Fig.9 Two XY scatter plots with marginal density plots adapting data from Lunn et al. (2021) to show the relationship between a ranking system indicative of animal intelligence (“Total Assigned Rank”) and the logged average transverse foramina area (an accurate indicator of vertebral artery blood flow to the brain), adjusted for overall size through measurements of the vertebral canal on cervical vertebrae. Three taxonomic orders (*Artiodactyla: Blue, Carnivora: Orange,* and *Primate: Grey*) are plotted with two types of marginal density plot (boxplots (a) and density curves (b)) included to demonstrate the additional information that can be added to standard XY scatter plots.

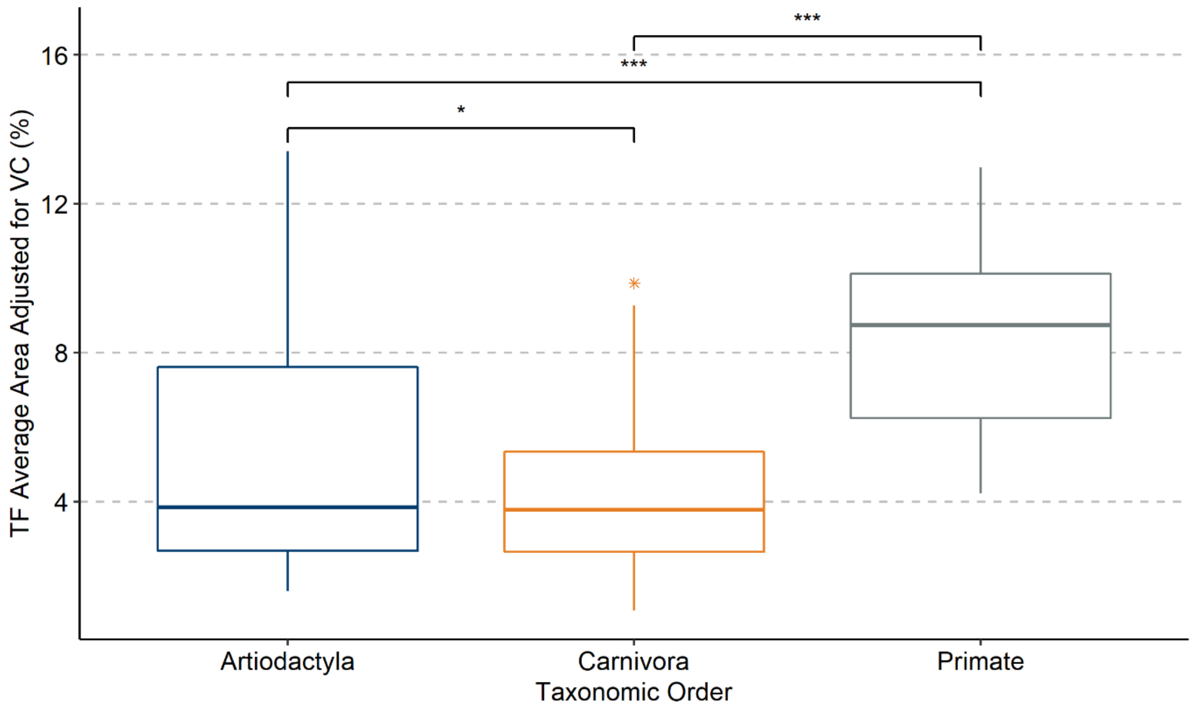
3.2 Boxplots and Beanplots

While those working on measuring intelligence and brain size usually use XY scatterplots, it can be informative to consider alternatives. Another typical visualisation approach is through boxplots. Boxplots are designed to show the distribution(s) of values of a continuous variable within one or more groups. As an example, a boxplot could show the range and amount of overlap in ranges of heights of males and females in a single population side by side. Boxplots are good for comparing distributions of large datasets, but do not usually work on smaller datasets and generally do not show the individual data points (Franzblau & Chung, 2012; Schriger & Cooper, 2001).

Fig.10 again adapts data from Lunn, et al. (2021) to show how blood flow to the brain varies between three animal groups. **Fig.10a** shows the data visualised as a boxplot, while **Fig.10b** shows the same information visualised in a beanplot. Beanplots expand upon boxplots to include individual data points as well as the density curve (bean shape). The inclusion of a density curve has already been visualised as a marginal density plot (**Fig.9b**), but in a beanplot, it is integral to the visualisation. The 'shape' of the data can be easily identified through this method as well as the density of data, i.e. where most of the data points fall on the graph. Specifically, a beanplot doesn't create an artificial box shape around a set of averages and extreme values the way a boxplot does. Instead, each beanplot shape is different, with a wide part of the plot indicating lots of variation, and a narrow part indicating limited variation.

For example, when comparing the two parts of **Fig.10**, you can instantly see on the beanplot the small cluster of artiodactyl points (even-toed ungulates including pigs, sheep, cattle, giraffes, deer, hippopotami, etc). These would not be picked out on the boxplot. Furthermore, it is easier to see on the beanplot that more of the primate points fall above the median line than below it (where there is a larger spread). This tells the reader that there are more primates that are above their group average, and that more carnivores and artiodactyls are below their group's average. Ultimately, as for most visualisation choices for figures, the quality and attractiveness of the final output of a boxplot or beanplot is dependent on the specific dataset and author/editor preference – but it is still important to consider all options in light of how much information the author wants or needs to communicate, and how effectively each approach can do this.

a)



b)

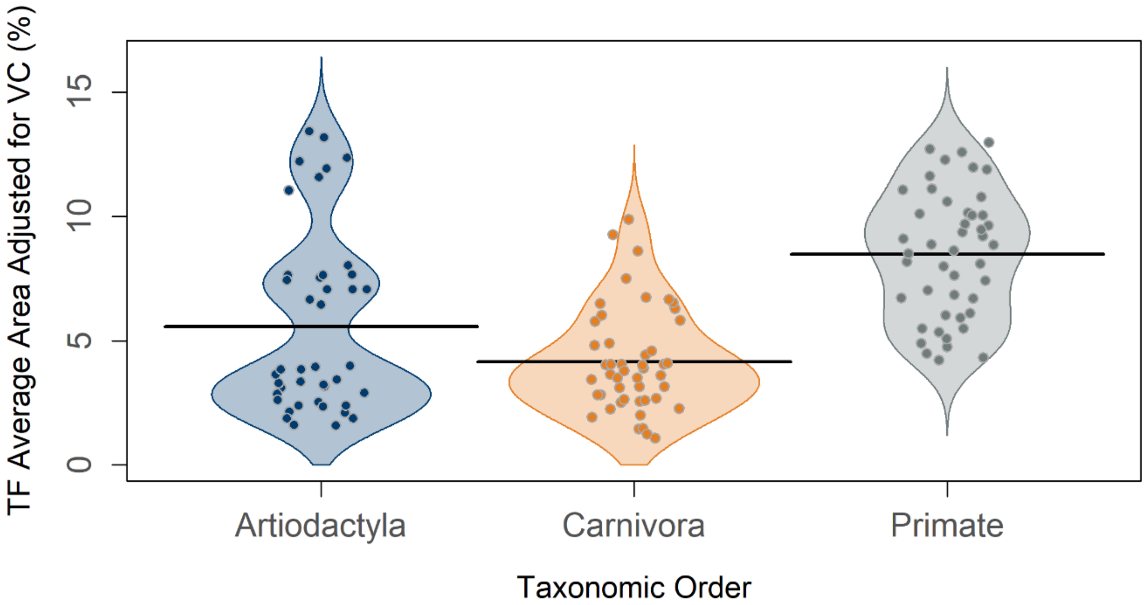
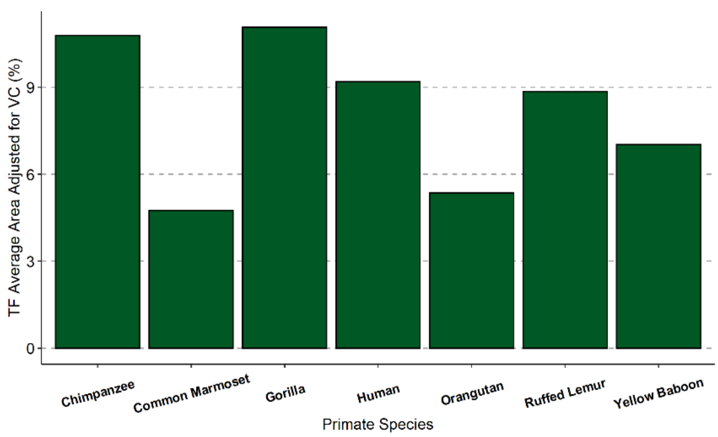


Fig.10a Boxplot of taxonomic order (*Artiodactyla: Blue, Carnivora: Orange,* and *Primate: Grey*) with average transverse foramina area (an indicator of blood flow to the brain through the vertebral arteries), adjusted for total organism size through measurements of the vertebral canal. Data adapted from Lunn et al. (2021). A one-way ANOVA test was undertaken and found a statistically significant difference between taxonomic orders and average foramina area (*F(2,132)=28.588, p<0.005****). Further Tukey post-hoc analysis showed specifically strong significant differences between Artiodactyl and Primates (*p<0.005****) and Carnivores and Primates (*p<0.005****), with primates obtaining larger average transverse foramina areas. Between Artiodactyl and Carnivora there was also a statistically significant difference (*p<0.05**), however this was less strong. Outliers are shown through 8-point star symbols. Tukey-HSD post-hoc significance values are shown above each 'box' (*p>0.5 = ns, p<0.5 = *, p<0.01 = **, p<0.005=****). **Fig.10b** Uses the same data (and, therefore, same statistical values) as the boxplot but offers an alternative visualisation method for the data. Individual data points (dots), the median value (horizontal black line) and density of points (density-curve/"bean" shape) are all shown upon the plot.

3.3 Bar Charts and Pie Charts

As well as box- and bean-plots, another common way to visualise measurement data is through the production of bar charts (or graphs) and pie charts. Bar charts are widely used for making comparisons and reading them relies on the ability of the reader to judge the relative height of columns. Being relatively simple to read, however, does not mean they require less careful attention to their construction than other types of visualisations. All the usual figure elements such as labelling, text size, and axes configuration need to be thoughtfully considered, and some features that may visually pull in the reader, such as the use of 3D plots or colour simply for decoration, are best avoided as they may detract from the clarity of information presentation (Franzblau & Chung, 2012). Even with simple plots that only compare a few groups, other alterations can be made to increase the clarity of the figure. **Fig.11** demonstrates just a few of these possible alterations using data from Lunn, et al. (2021). For example, in **Fig.11b** the bars have been reordered from alphabetical order to descending order. This allows values that are close to one another (such as the gorilla and chimpanzee) to be directly compared. Furthermore, the use of colour, here within the same colour palette, increases the visual appeal and separates each bar visually from the next. It is important to note that the green colour palette here does not impede the accessibility as there is no comparison with other primary colours (red for example), and the shading will still be present even if the reader is affected by the green colour (perhaps seeing shades of grey or a dull green instead).

a)



b)

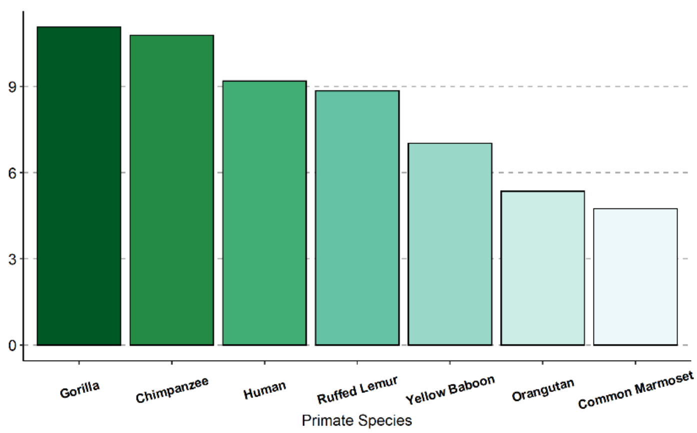


Fig.11 A standard bar chart (ordered alphabetically, as is typical in some statistics package default settings (**11a**), and right ordered in descending order (**11b**)) of seven primate species and the average transverse foramina area (an accurate indicator of blood flow to the brain through the vertebral arteries), adjusted for overall organism size through measurements of the vertebral canal on cervical vertebrae - data from Lunn et al. (2021). The use of colour within the right-hand graph indicates different species.

However, while this graph is easy to interpret, some data sets contain many more categories than this one. **Fig.12** shows bar charts of 40 mammal species and their average transverse foramina area sizes visualised in both an alphabetical order (**Fig.12a**), and descending order (**Fig.12b**). While both bar charts clearly label each animal, the sheer number of categories present detract from the overall readability and accessibility of either chart. Unless the intention is to show something about the distribution of scores (e.g. using descending order patterns to highlight an outlier or that some animals have high values and others have low values in a stepped pattern), these charts may not be helping the reader very much. Those interested in specific blood flow values for each species could extract those from a table or appendix, perhaps more easily than from a chart.

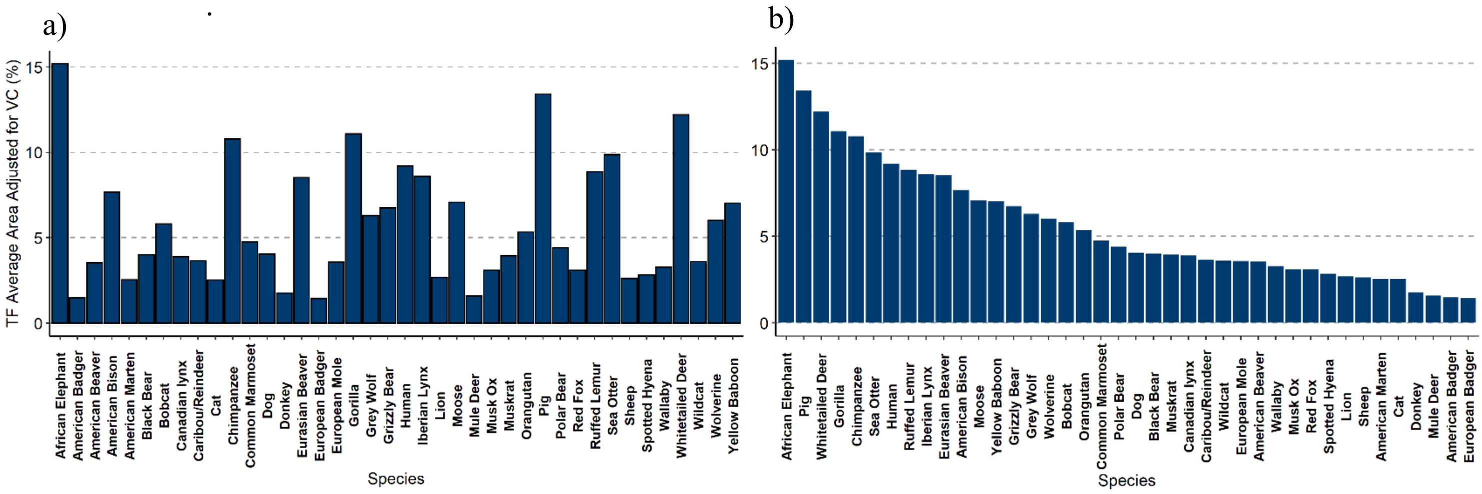


Fig.12 A standard bar chart (left ordered alphabetically (**12a**), and right ordered in descending order (**12b**)) of 40 mammal species and the average transverse foramina area (an accurate indicator of blood flow to the brain through the vertebral arteries), adjusted for overall organism size through measurements of the vertebral canal on cervical vertebrae - adapted from Lunn et al. (2021).

Is there nothing to be done to visualise this data more clearly? **Fig. 13** suggests otherwise. Using a combination of colour and re-ordering of bars, **Fig.13a** works better, though it has required much more conscious work to create. **Fig. 13a** gives the reader a clear idea of how values change within specific animal groups (visualised through different colours) and also emphasises trends within and between groups.

a)

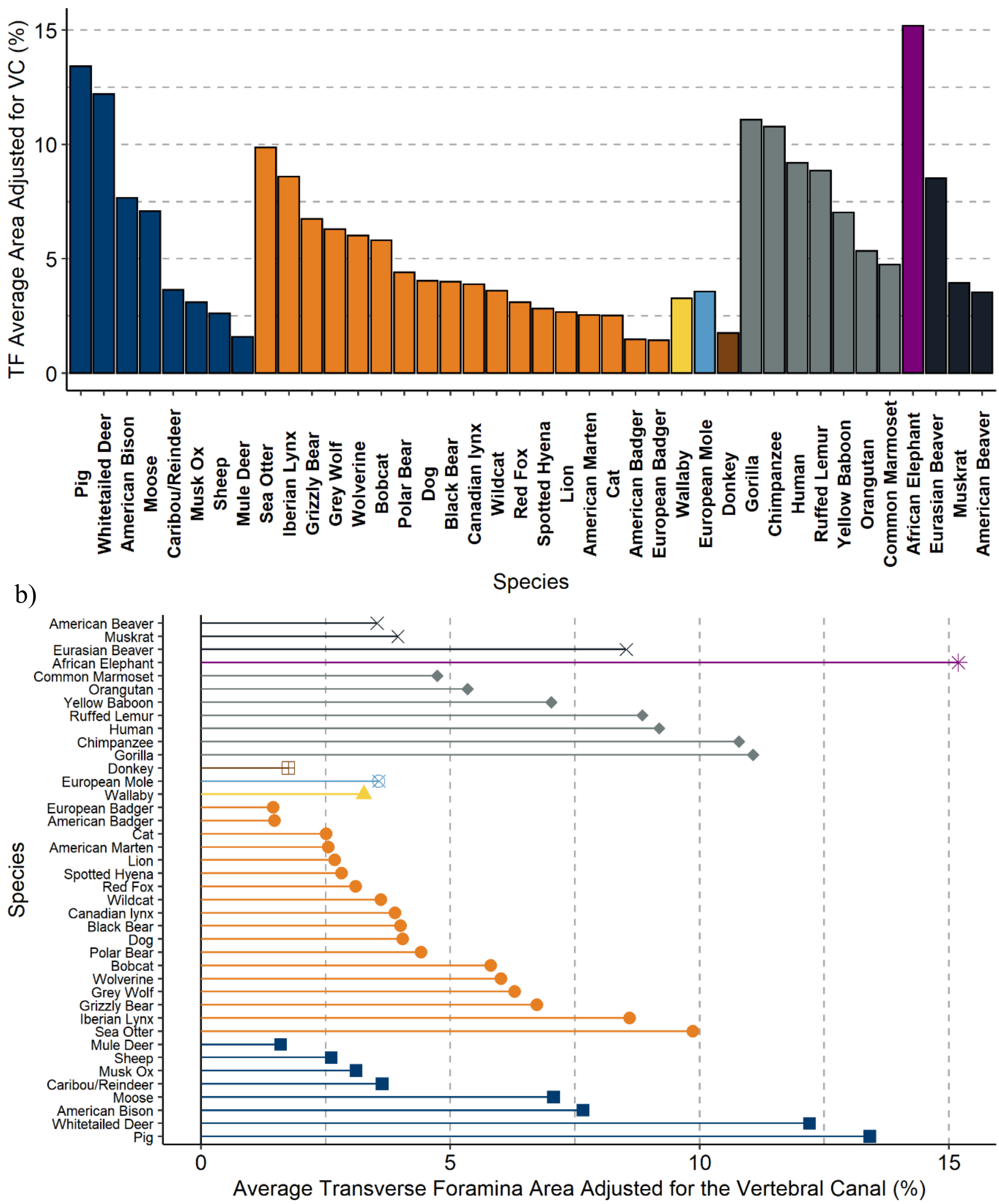


Fig.13a A bar chart of 40 mammal species and the average transverse foramina area (an indicator of blood flow to the brain through the vertebral arteries), adjusted for overall organism size through measurements of the vertebral canal on cervical vertebrae - data from Lunn et al. (2021). Data is ordered in decreasing values, as well as by taxonomic order. **Fig.13b** shows the same data but flipped (so the x-axis now runs vertically) and visualised in a stem plot form instead. *Artiodactyl: Dark Blue Square, Carnivora: Orange Circle, Diprotodontia: Yellow Triangle, Eulipotyphla: Light Blue Hollow Circle w/ Cross, Perissodactyl: Brown Hollow Square w/ Cross, Primate: Grey Diamonds, Proboscidea: Purple 8-Point Star, and Rodentia: Black Crosses*.

Fig.13b, in contrast, shows the same data but visualised as a stem plot as opposed to a bar chart. Stem plots maximises the "data-ink" ratio, where the intention is to have the most amount of data present while having the lowest amount of "ink" on the graph. This is helpful if you plan to print the figure (Kosourova, 2021) or want to avoid overlapping or densely packed elements. They therefore increase the clarity, accessibility, and readability of the data even further. The 'flip' of the plot, so the x-axis now runs vertically, adds the additional benefit of allowing the reader to easily read the species present on the figure without having to physically turn their head (as they would for **Fig.12** and **Fig.13a**). These changes for the stem plot further reduce the cognitive load placed upon the reader.

Unlike bar charts, solitary pie charts are rare in scientific publications. Schriger & Cooper, (2001) state that "solitary pies have no role in scientific publications since readers should be able to generate the picture from tabular data, making the picture redundant with text and tables." However, an exception to this is when multiple pie charts are used within the same figure (eg. **Fig.14**). This allows for easy comparisons of patterns within the dataset that would be less easy to spot in a table.

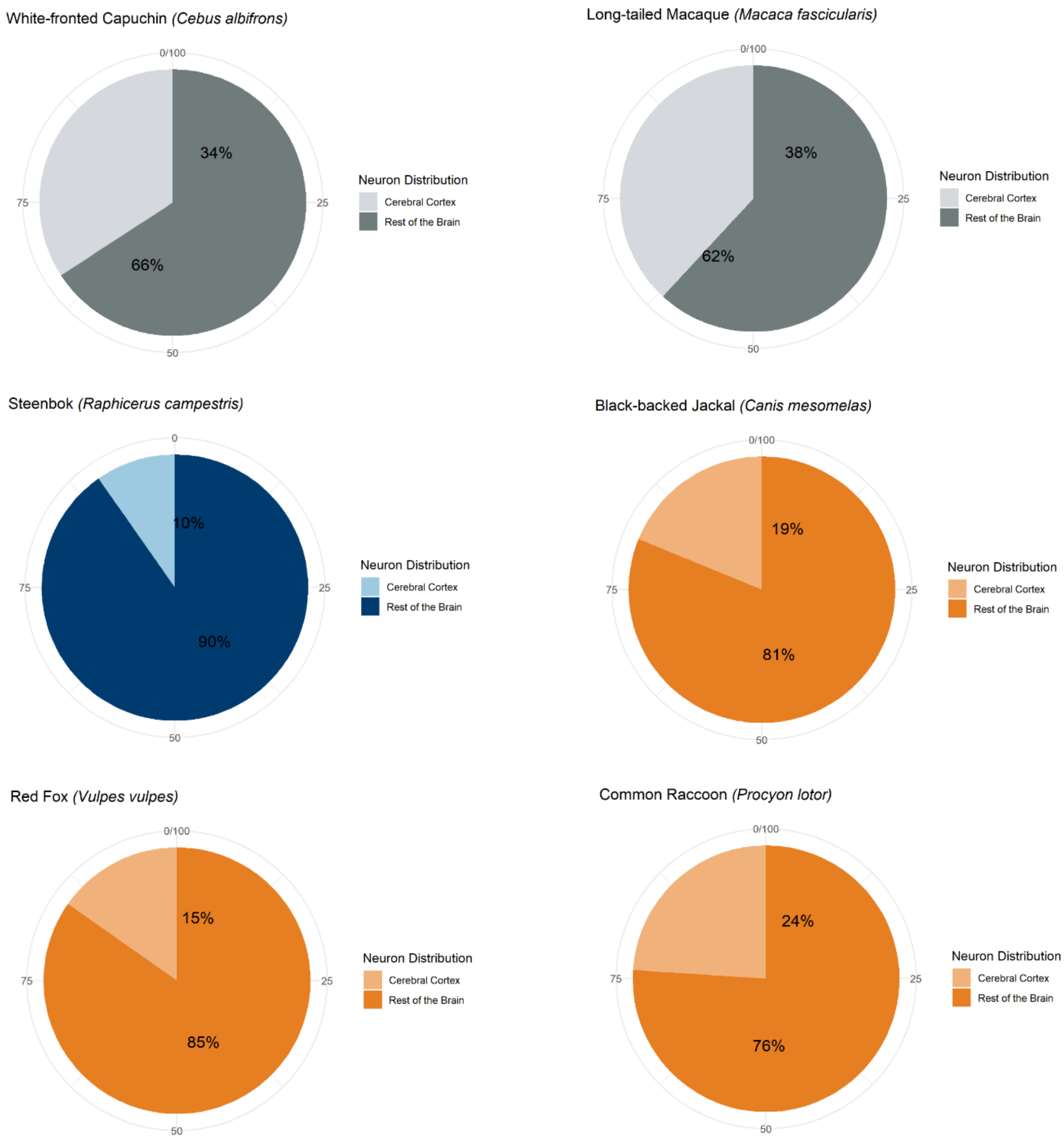


Fig.14 Comparison pie charts showing the percentage neuron distribution in the Cerebral Cortex and Rest of the Brain in six species within three taxonomic orders (*Primate: Grey, Artiodactyl: Blue, Carnivora: Orange*). Data from Herculano-Houzel, (2017), Herculano-Houzel, (2016) and Herculano-Houzel, et al., (2015).

Specifically, **Fig.14** shows a simplified example of a comparison pie chart, by showing the neuron distribution (%) in the cerebral cortex and rest of the brain within two primates (capuchin and macaque), one artiodactyl (steenbok), and three carnivores (jackal, red fox, and racoon) all with similar brain masses (between 44g~70g). While this figure indicates that the proportion of neurons in the cerebral cortex is larger in primates (a likely result of economic brain scaling rules as discussed in Section 2.4 (Herculano-Houzel, et al., 2006; Herculano-Houzel, 2011)), without supporting statistical information on the chart, it is impossible to say whether the difference in proportions is statistically significant

3.4 Infographics

Infographics are visualisations that convay complex information efficiently through the use of photos, maps, charts, graphics, and other visual elements (Naparin & Saad, 2017). They are becoming increasingly more common in science communication due to their ability to convey lots of information in a small space through both written and visual elements. Infographics convey information in a more visually appealing manner than some other visualisations already discussed.

As a way of comparing the level of information that can be conveyed by a pie chart or an infographic, compare **Fig.15** below to **Fig.14** which uses the same data and colour scheme. Instead of using pie charts, **Fig.15** uses coloured symbols (to indicate taxonomic order), written elements (species and Latin names), simple statistical values (percentages), and size differences between symbols (which reinforce the percentages) to show the data.

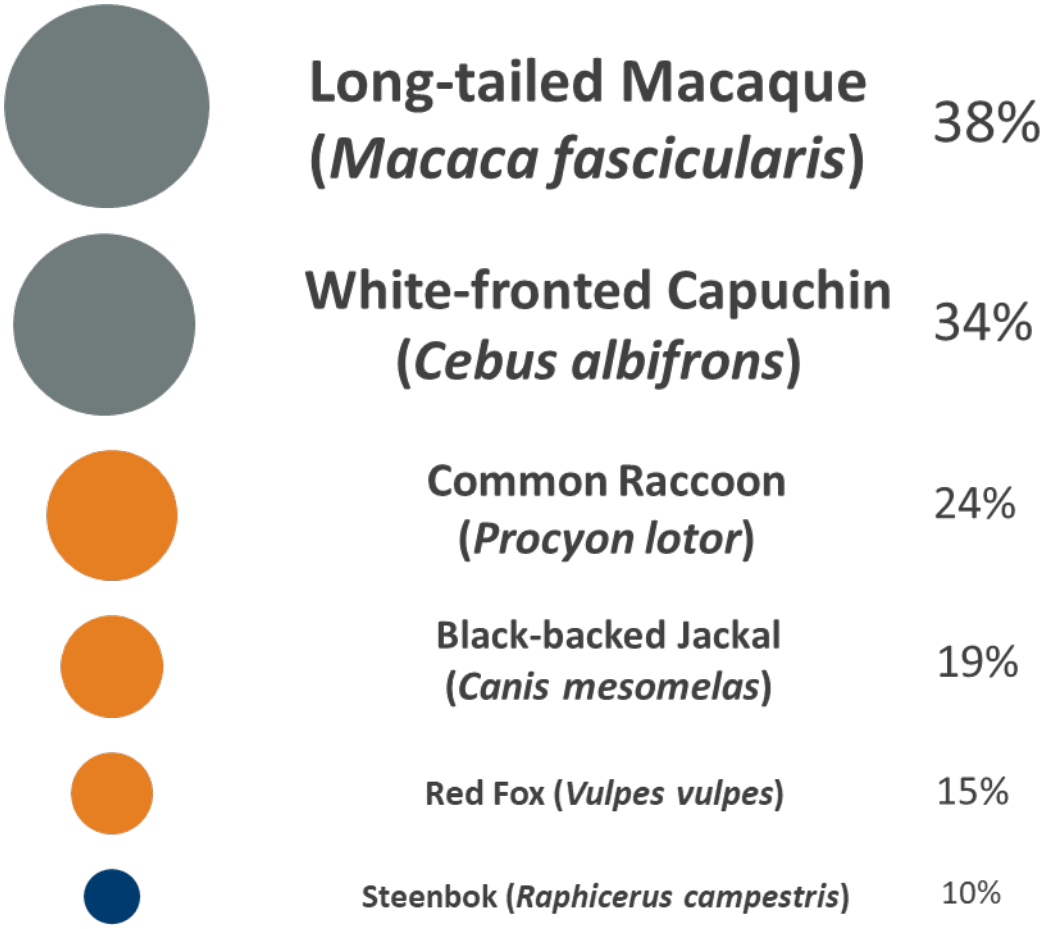


Fig.15 Infographic showing the percentage of neuron distribution within the cerebral cortex and rest of the brain in two primates, one artiodactyl and three carnivores. Coloured symbols indicate taxonomic order, written elements show species and Latin names, simple statistical values (percentages) and size differences (indicates the percentage value as well) are all included on the figure.

The type of infographic used in any given context will depend on the communication goal of its creator. **Fig.15** would be perfect for a presentation or communication to a general audience, but would perhaps not be included in a scientific publication. In an article, taking up this much space to convey the same information as could be covered in a table a fraction of the size would be considered overkill.

3.5 The Importance of Clear Goals When Creating Visuals

Ultimately, visualisations are created to aid in the comprehension of information and ensure a target audience gets the 'message' of a paper or data analysis as the author sees it. Those choosing visualisation strategies need to take into account both their target audience, and their goals - the most important points that they want to communicate to their reader. These two factors together are important because they determine how much detail and complexity a visualisation can reasonably contain without either over- or underestimating the audience's expectations and needs. The example given above of the pie charts and the infographics is a demonstration of choosing both how much information, and which format to present it in to fit different audiences and goals. Both expectations and needs will be substantially different at an academic conference made up of specialists in the same field as the author, and a talk for the general public with a broader interest in science. This section has shown a few ways in which conscious consideration of audience and goal can improve the accessibility of specific types of scientific visualisation, whether intended for scientists or a wider audience. This is by no means an extensive list or a 'recipe' for good visualisations; instead we have focused on the advantages and disadvantages of each choice in context. Some of the options suggested would involve only small changes to the figures shown in Section 2, while others are more ambitious. We would note, however, that such small changes, like adjustments to a colour palette, might give scientific visualisations much more flexibility and reach, within and beyond the audience of their peers. Communicating effectively with the interested public is, however, a rather different aim than communicating with other scientists – and our final section considers how visualisation choices might affect science communication specifically.

4 How Scientists Share Information

Public engagement is crucial for building strong connections between science and the public. It can limit the spread of misinformation, encouraging active involvement within science, and help the public see the relevance of scientific research. A stronger relationship between science and non-scientists also has the potential to foster real change in our lives and livelihoods. This can be clearly seen in the environmental sciences, where topics like climate change generate substantial public interest and engagement (Pham, 2016). It is important that scientists can learn to effectively convey information beyond a purely academic context. This effort is complicated, however, by the fact that most science degrees do not include any explicit training in science communication (Heard, 2021).

4.1 Presenting Science

4.1.1 Presentations to A General Audience

Only 20 years ago, talks about science were limited to in-person events, and most were aimed primarily, or exclusively, at other scientists. The proliferation of YouTube and specialist organisations like TEDTalks and National Geographic Live have dramatically changed this today. General audiences, we believe, find it easier to engage with talks with a story-like structure and find visualisations designed to tell a story easier to understand than traditional publication-style visualisations which focus on efficiency and accuracy (Dahlstorm, 2014; Grainger, et al., 2016). This is not to say that efficiency and accuracy are not important in scientific communication (quite the opposite in fact), but rather that if they wish to make information accessible to a wide audience, scientists' default approach to visualisation must change.

Expert talks often use narrative features to great effect in attracting and informing a general audience (Reynolds, 2011).Usually, the narrative is communicated orally, with visualisations as back-up. Here, we focus on two examples of good practice in our case study field, namely the TEDTalks "What is so special about the human brain?" by Suzana Herculano-Houzel (2013), and "What are animals thinking and feeling?" by Carl Safina (2015).

The visualisations in both talks are kept to a minimum to reduce the possibility of distraction to the audience. Both presenters typically show a single image on any given slide, with images selected to be visually interesting without detracting from the speaker. There is little-to-no text on any slides. For example, Herculano-Houzel uses an illustration to exemplify her point on brain scaling rules, while Safina uses amusing or dramatic wildlife photography as a backdrop for his presentation. The exception to using only one image is when some slides are used to demonstrate specific ideas (as discussed next).

Presentations like these may also combine visual and audio cues to convey specific scientific ideas. In these cases, the images are typically much more than simple decoration. For example, Herculano-Houzel uses a series of visualisations that each build upon one another to explain how primate brains contain a much larger number of neurons than rodent brains of a similar mass. The developing composite visualisation clearly shows how rodent neurons increase in size as the brain grows, while primate neurons always stay the same size, so can be more numerous (**Fig. 16**).

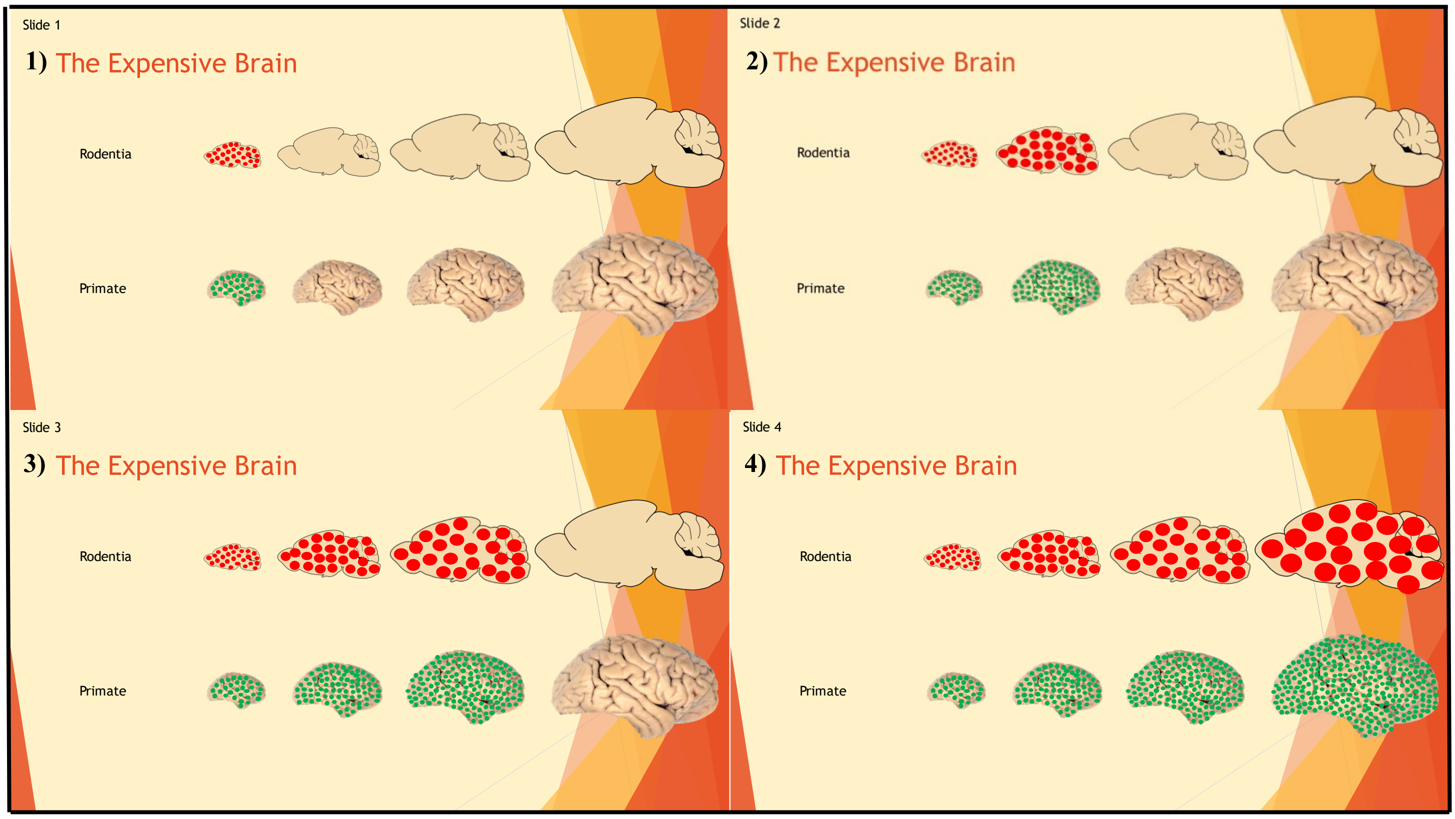


Fig.16 Mock-up visualisations from Suzanna Herculano-Houzel's 2013 TEDTalk "What is so special about the human brain?". The slides show a series of visualisations that build and expand upon one another to explain how primate brains contain a much larger number of neurons when compared to a rodent brain of a similar mass. Coloured circles (*Red=Rodent, Green=Primate*) are used to indicate neurons with the size of the circles indicating neuron size. This visualisation therefore shows that, in rodent brains, as the brain increases in size (between a mouse and capybara for example), the neuron size also increases, while in primates they do not. Therefore, allowing more neurons within a primate brain compared to a rodent brain of a similar mass.

Presentations also tend to use far fewer graphs and statistics than papers. In a scientific article, visualisations are often complex and multi-layered, and many require specialist knowledge to interpret. If the primary aim of science communication is to make science accessible to anyone, then it is obvious why they rarely include similar visuals. Graphs are typically only included within a public presentation if they are clear, simple, and are directly relevant to the narrative of the presentation. For example, the only graph Herculano-Houzel shows in her talk is used at the end to demonstrate the effect of cooking on human evolution. Cooking food allowed human ancestors to eat more calories in a set period of time, which in turn gives us more energy to power our brains' higher neuron counts. This graph is a simple line graph that is clearly labelled and looks to have been designed specifically to convey this point – it contains very little extraneous information (**Fig.17**). It is therefore much less 'complete' than a figure from a scientific paper might be but adds significantly to the talk's ability to communicate a finding. Similarly, in Safina's talk, maps are used to show the geographical distribution of animals. These maps are essential to the conclusions, are very visually appealing, and it would be difficult to convey the talk's core message without them.

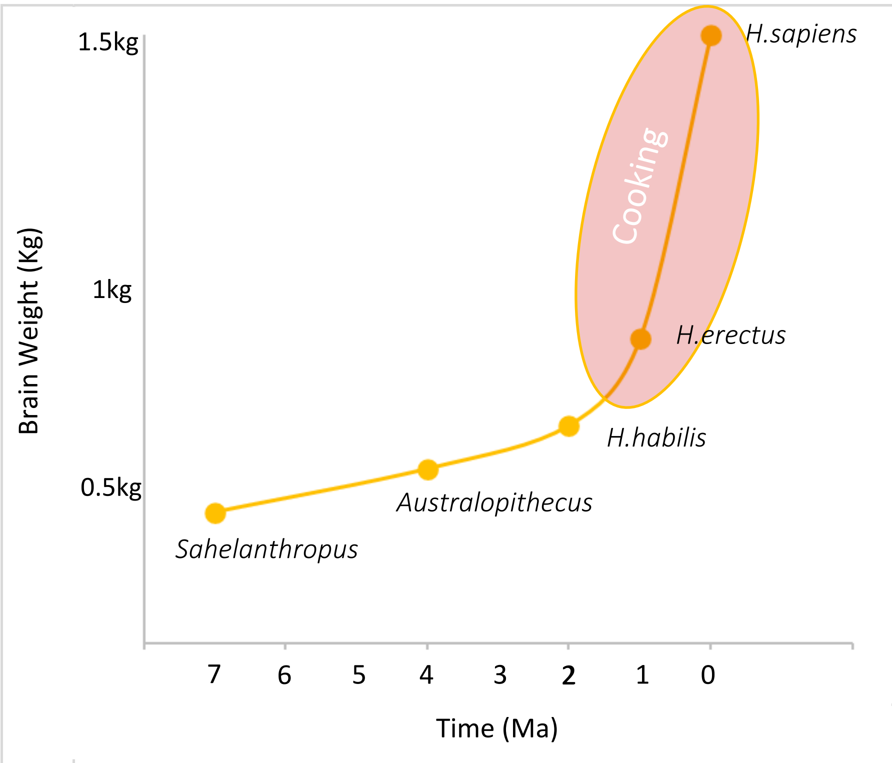


Fig.17 Mock-up visualisation from Suzanna Herculano-Houzel's 2013 TEDTalk "What is so special about the human brain?". A simple line graph to show the effect of cooking on brain size (here in weight, kg) in human evolution. This figure looks to have been designed specifically to convey that the development and evolution of cooking to create calorific dense foods that could be consumed and digested quicker, resulted in rapid brain expansion to a general audience. The axes are easy to understand (described in the talk as "Time in millions of years ago" (x-axis) and "Brain weight (kg)" (y-axis)) and overall aids the speaker in their delivery of the information.

Visualisations can also help scientists describe their methods for a wider audience. For example, in a National Geographic Live talk titled "Dolphins: Even Smarter Than You Thought", presenter Brian Skerry describes a series of behavioural experiments that show increasing evidence of dolphin intelligence. Both publications that he discusses ((Kuczaj, et al., 2015) and (Clark & Kuczaj, 2016)) contain very detailed, step by step methodologies. However, in his public engagement talk, instead of describing his experiments in detail, Skerry explains the broad principles orally and shows pictures of dolphins taking each test. This allows the audience to see how the animals reacted to the experiments without any detail of analysis or setup that would detract from the core questions being investigated. In this way, science communication presentations are more likely to focus on the main findings and implications of the research described, as these are the parts that contain the narrative and are the most interesting to the audience. If we compare a complex conclusion from Kuczaj, et al., (2015):

"However, tugging rate for both dolphins was significantly higher in the presence of the other animal than when interacting with the object alone (Alfonz, $t(22) = 2.86$, $P<.05$; Kimbit, $t(22) = 2.61$, $P<.05$)"

And a simpler explanation from the same manuscript:

"Our results suggest that dolphins can cooperate in order to achieve a common goal when given an unfamiliar task."

It quickly becomes obvious how more streamlined conclusions and, by extension, the simpler visualisations that accompany them are more suitable for a science communication presentation to a general audience.

4.1.2 Presentations for Younger Audiences.

The future of science relies on future generations. It is through education and accessible science in their everyday life, that we hope that young people will be inspired to engage with science and ultimately further human knowledge. Scientific training from a young age also helps develop other skills such as teamwork, communication, and problem-solving. Presentations for younger audiences place an even greater emphasis on narratives and visualisations than those for adult general audiences. They also tend to be shorter. For example, if we look at a TED-Ed talk (TED's education and youth initiative) by Lori Marino (2015) titled "How smart are dolphins?", in theory almost directly comparable to Skerry's dolphin TEDTalk described above, the increased importance of the visualisations in TED-Ed is immediately obvious. The ~5-minute video presents the information and research through a voice-over and continuous animation. The animation keeps the audience engaged and turns complex data into comprehensible information. There are no publication-like visualisations (XY scatterplots, bar chart, etc.) at any point in the presentation, just the animation. Furthermore, within the animated video, technical terms like encephalisation quotient are explained using images and simple spoken sentences rather than equations. The narrative focus and continued visual stimulation help summarise the findings from multiple dolphin intelligence studies in an accessible and memorable way, but one that is clearly different to the approach taken by talks aimed specifically at adult non-specialists.

4.2 Science Communication Articles

In addition to presenting specifically for non-specialists, science communicators can also write for them. The rapid expansion of the internet has led many consumers to become part of a culture that can access information immediately. If you need to find out the name of a film, buy a book, or update your friends and family on your holiday plans, you can do so at the click of a few buttons. And accessing science is no exception. How hot is the sun? Which dinosaurs lived in the Jurassic? Do chimpanzees have a theory of mind? It should come as no surprise to scientists that writing for the internet or wider-circulation magazines can be another way to encourage active involvement within science and limit the spread of misinformation.

Science communication articles can therefore take many forms depending on the author, editor, and type of article. If the information is presented in a news article (The New York Times, The Conversation, and Nature Briefing for example), then the narrative is usually rather short and to the point. As in scientific talks, statistics and graphical visualisations are rare as articles typically focus on the conclusions and any visualisations that are included usually take the form of an easily digestible infographic or picture. News articles often also include quotes from original pieces of work, an eye-catching image to draw in the reader, and bold statements or questions as titles. A good example of this is the 2012 BBC News Article entitled "Dolphins deserve same rights as humans, say scientists", which only contains 425 words and a single large photograph of dolphins. Outlets that have specific sections for science news may permit longer text but tend to follow the same less visual style. Rapp's (2021) Discover article "Just How Intelligent Are Dolphins?" for instance is over 1,200 words long but still only contains one image, a photograph. Askham's 2021 article "Evolving a Bigger Brain Isn't Always About Intelligence", by contrast, is roughly the same length but uses four different images to engage the reader. Three of these are photographs, but with captions that give detail of how the subjects fit with the science discussed, while the fourth is an artist's impression of mammal brain evolution, specifically created to communicate an idea about relationships among animals with different brains. These are very different visual choices to the more complex visualisations of data that Smaers et al. (2021) used in the scientific publication Askham is summarising.

4.3 Popular Science Books

The final, and perhaps most involved, format that scientists use to communicate with non-scientists is the popular science book. Popular science books are distinct from talks and articles in that they require sustained engagement from the reader and take a much longer and more detailed look at a subject. Although it might seem intuitively that science book authors will rely primarily on narrative text, many also use visualisations – and in a different way to scientists communicating via shorter media. In a 2016 book "The Human Advantage: How Our Brains Became Remarkable", for instance, Herculano-Houzel guides the reader through her research on brain anatomy to explain how we measure intelligence in animals, and how humans evolved their extraordinary cognitive abilities. As the science behind this is rather complex, both accessible language and visualisations are used throughout to engage the reader. The text focuses more on personal accounts and stories than summaries of projects and develops a strong narrative that helps place the science in context for the reader. In contrast to the scientific presentations and articles discussed earlier, however, this book also contains lots of graphical visualisations and statistical data (in fact, it is on the more complex end of the popular science spectrum). The visualisations are, however, adapted to make them more accessible and visually appealing.

When we compare images from Herculano-Houzel's book (2016) and the original papers that it is based on, for example, we see several strategies used to make the book visuals more engaging, including the use of wildlife imagery to label points on a graph (the effect is similar to **Fig.7**'s cartoon animals labelling points of interest, see Section 2.5.1). Other graphical features, such as regression lines (lines that best fit the data points to minimise variance) are also used in the book to make the key patterns and relationships within a graph jump out. These are likewise not always used in the corresponding articles, where the reader would instead be anticipated to be able to read the supporting statistical information. Finally, when you compare the figure legend, axis titles, and axis tick labels on Herculano-Houzel's book and article visualisations, they are much simpler in the book. By plainly saying "*Neurons in the cerebral cortex (millions)*" as an axis title (Chapter 4 of Herculoano-Houzel 2016), the reader has a much clearer idea of what the variable is, compared with "*Cx neurons (n)*" (the equivalent title in Herculano-Houzel, 2011).

4.4 Creating Accessible Science Communication

The importance of accessible science communication cannot be underestimated. Advances in communication technology have allowed important research to reach a much wider audience than it might of previously but necessitates changes in written and visual style to make it engaging and interesting. This section has considered some of the typical forms that science communication work can take, and how each one modifies or develops new visual styles to suit its audience and their needs. Overall, we would suggest that visualisations remain important in all forms of science communication, though their complexity and prominence may vary significantly. The same simple adjustments that can help scientists communicate more easily with their peers can suffice, in some cases, to communicate with a particularly interested general audience, like those willing to read a popular science book. For other more bitesize format, we see more adventurous and considered visualisations like infographics and animations coming into their own. The same principle of considering both audience and aim seems to hold true for visualisations intended for non-specialists as for specialists and produces some rather different outcomes in each case.

5 Conclusion

This chapter has shown that even small changes in how visualisations are presented can have a big effect on the accessibility of the information. Using our example of the science investigating biological indicators of intelligence in animals, it's easy to see how, as the science developed, the visualisations have also changed. Although authors writing for scientific audiences still use the same types of data, analysis and visualisation, they have also adjusted graphical features like colour, data point identification, titles, legends, etc. to make their visualisations more readable and to foreground different ideas and findings. Even small tweaks, like the addition of extra component graphs or changes to the sequence in which data are presented, can change the core message the reader takes away.

Whenever science is communicated, a meaningful and effective visualisation can only be created by actively considering both the identity and needs of the target audience and the most important points that you wish them to take away (which we have called the authors' goal). Different audiences – members of the same disciplinary community, of other disciplinary communities, from the wider academic world, and from other worlds entirely – have different expectations when they are presented with scientific information. It is not as simple as being able to assume more or less specialist knowledge depending on the reader's background. Different audiences also have different visual repertoires and experiences, and may find specific styles or approaches to visualising data more or less engaging, and more or less informative. Even where background knowledge is present and interest can be assumed to be high (for instance, where an audience has actively chosen to engage with a piece of science communication), visualisations created to communicate one purpose cannot be substituted for those created or adapted to communicate something else. Instead, we have shown that visualisation is an important subject in its own right, and merits scientists' attention even where disciplinary norms would initially suggest choices are limited. When we visualise our datasets well, we can increase their reach and impact substantially.

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