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Visualizing Scientific Inference

David C. Gooding

Department of Psychology, Science Studies Centre, University of Bath

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Abstract

The sciences use a wide range of visual devices, practices, and imaging technologies. This diversity points to an important repertoire of visual methods that scientists use to adapt representations to meet the varied demands that their work places on cognitive processes. This paper identifies key features of the use of visualization in a range of scientific domains and considers the implications of this repertoire for understanding scientists as cognitive agents.

Keywords: Cognition; Discovery; Imaging; Perception; Visualization; Visual inference; Visual models

1. Introduction

The ability to create and manipulate visual representations is cognitive skills acquired as a scientist becomes an accomplished participant in the methods that define a particular domain. In fields such as physical chemistry and developmental biology, visual modeling techniques are so important that textbook presentation is driven by the adoption of new imaging technologies (Atkins, 2006; Gilbert & Singer, 2006). In others, such as physics, visualization skills are integral to mathematical and modeling techniques and are usually learned implicitly along with these. Such skills are learned by example—by seeing how models are constructed, used, evaluated, and refined by a group. This requires active participation in the practices of the group (Alac & Hutchins, 2004). Nevertheless, such knowledge continues to have an important personal component. It is learned by individuals so that they can contribute to the knowledge-producing activity of the group. Innovations, in particular, requires the ability to introduce novel ways of seeing and thinking into an existing framework of concepts, categories, and models. Innovations may be provoked by anomalies in

The journal regrets to report that Professor Gooding passed away while this issue of *topiCS* was in production. We are honored to publish his last work.

observational data (Alberdi, Sleeman, & Korpi, 2000; Gooding, 1986; Trickett, Schunn, & Trafton, 2005; Tweney, Mears, & Spitzmuller, 2005, pp. 151–154) and by the need to integrate information that originates from disparate sources. In her study of the visualization of the sodium ion channel in molecular neurobiology, Trumpler documents the importance of scientists' personal mental images. She notes that while any two-dimensional representation on paper shows only one aspect of the sodium ion channel, ''the convergence of the various representations and the plasticity of imagination yields a complex mental image which can incorporate all perspectives simultaneously, reflect differing time scales at will, and [can be a] collage of various molecular models'' (Trumpler, 1997, pp. 68, 87–89). The important feature of a representation is not whether it is a ''private'' mental image or a ''public'' expression but rather its plasticity and integrative power. These enable its adaptation to the changing social and cognitive demands of a creative process. Ethnographic and in vivo studies of dyads and historical studies of written exchanges show that interpersonal exchanges enable creativity through a dialectical play of personal and public representations (Goodwin, 1995; Latour and Woolgar, 1986; Trickett, Fu, Schunn, & Trafton, 2000; Trickett et al., 2005). Variations arise both from operations by individuals and in trading zones where meanings, interpretations and validation criteria are negotiated between individuals and groups (Gorman, 2005; Henderson, 1999; Roth, 2004). The importance of plasticity and the integrative power of multiple images has also been shown by laboratory-based cognitive studies (Cheng, 2002; Nersessian, 2008) and by fine-grained historical methods that include physical reconstruction and reenactment of procedures described in laboratory notebooks (Gooding, 2006; Tweney, 1992; Tweney et al., 2005).

1.1. Imaging and perception across the sciences

This paper describes a widely used method of exploiting and managing this adaptability in the context of domain knowledge (facts, theories, problem-solving methods), social constraints (imaging conventions), and material resources (imaging technologies). Shepard argued that personal factors such as a measure of independence of convention and tradition are important for innovation and was concerned to show how internal and external representation are related (Shepard, 1978, pp. 156–165). The examples considered here show how visible and tangible objects and products form a material, cultural context for cognition that generates new possibilities and meanings.

In what follows a *visual representation* is an *interpreted image*. Von Laue's X-ray photograph (Fig. 1) is an image, whereas Bragg's labeled diagram of its features (Fig. 2) is a representation. Representations are *hybrid*, that is, they combine visual, verbal, numerical, or symbolic modes of conveying information. Examples include labeled *camera lucida* diagrams (Fig. 6) of fossil imprints (Fig. 5), visualizations of numerical data such as graphs, plots, and contour maps. Marking with labeling and captions makes an image into a scientific object (Lynch, 1990; Roth, 2004). The photographs in Figs. 1 and 5 represent nothing scientific, by contrast to the point-projection diagram (Fig. 3) and *camera lucida* diagram (Fig. 6). The diagrams select and label features relevant to interpreting and explaining the prepared sources. Diagrammatic abstractions move the eye and the mind from a barely

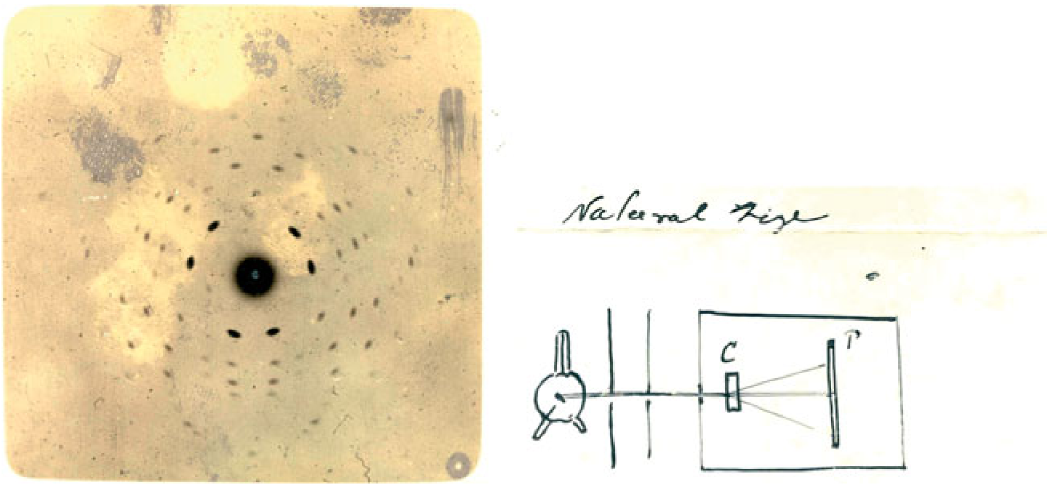

Fig. 1. W. L. Bragg's photograph of an X-ray diffraction pattern produced by a simple crystal. Bragg sketched the experimental setup below (Bragg, 1913a; fig. 3).

Fig. 2. One of several sets of labeled points made by pricking through the spots on the photograph onto paper and indicating the magnitude of each spot (Royal Institution Bragg MS WLB86, courtesy of the Royal Institution of Great Britain).

interpreted visual source to a meaningful word-image construct that combines pictorial, verbal, numerical, and symbolic forms. Such ''moves'' from image to representation are motivated by two key goals of science: the desire to understand and to communicate that understanding.

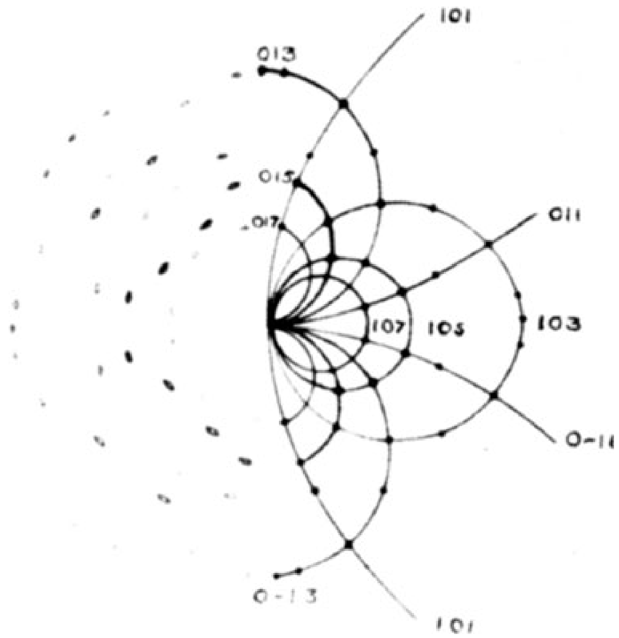

Fig. 3. The projection diagram generated from the labeled points in Fig. 2 (Bragg, 1913b; fig. 4). This 2D diagram represents a 3D structure that in turn represents a diffracted X-ray emerging approximately perpendicular to the page.

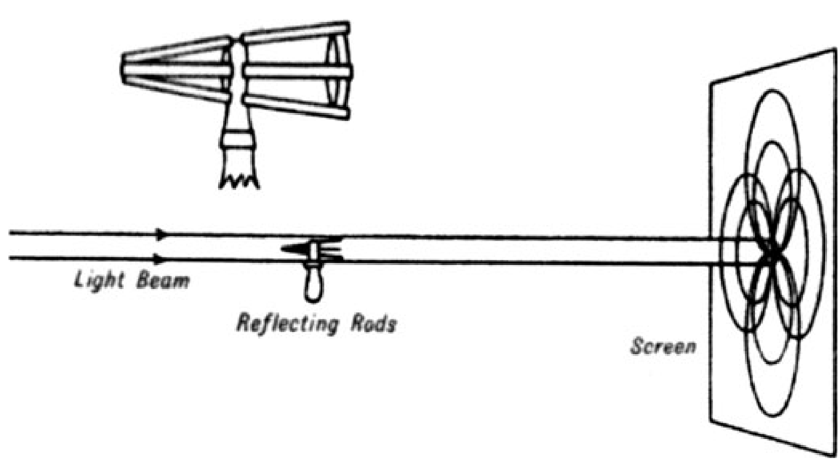

Fig. 4. The physical model consisting of converging glass rods arranged around an axis that demonstrates how diffraction can produce the elliptical patterns that correspond to positions of spots on the X-ray photographs such as Fig. 1 (from Bragg, 1933; fig. 19).

Representations are essential to visualization or visual inference, an active process of image manipulation that link sets of representations to source data needing interpretation and to images that integrate the information the interpreted sources convey. Imaging

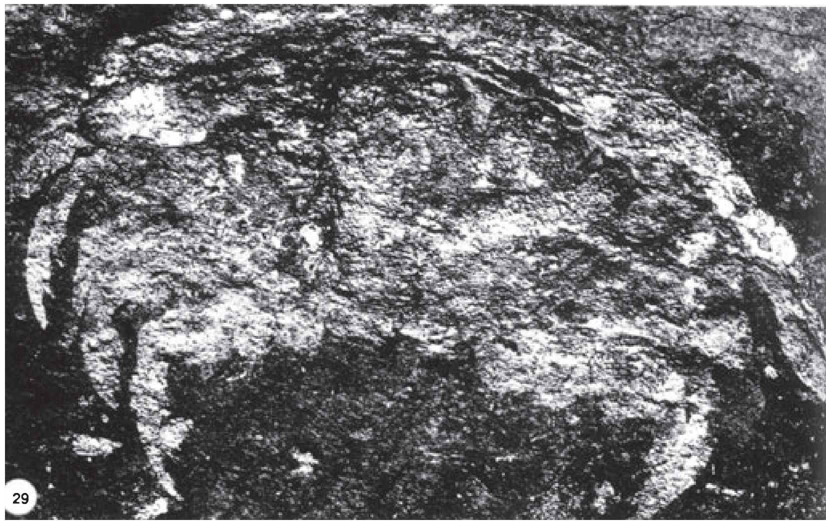

Fig. 5. Photo of an imprint for the arthropod *Sidneyia inexpectans*.

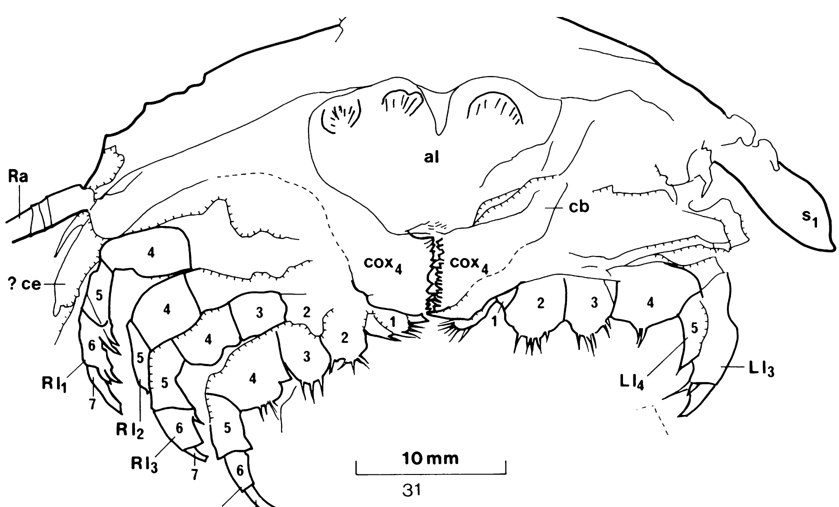

Fig. 6. The corresponding camera lucida diagram, from Bruton (1981); used by permission of the Royal Society.

technology—so called scientific visualization—supports these inferences by producing images such as data displays (Alac & Hutchins, 2004; Trickett et al., 2005), which can be interpreted as representations of new, puzzling features and by making it possible to transform images so as to produce hypotheses and theories that explain visualized data. Here I shall concentrate on the interaction of visual perception as a biological capacity rooted in evolution (e.g., automatic recognition of something as a face, or as a pattern) with visualizations as constructed, representational objects (such as diagrams or a data plots) and with the active, deliberative process of making inferences by manipulating images that represent features of the world. Perceptual inferences appear automatic in the sense that they are generated either by evolved mechanisms (examples are the Face of Cydonia or Kanisza's triangle) or by learned, socially engendered skills that invoke such biological mechanisms. Scientific examples of the latter include seeing the regular array of dark and light shades in Fig. 1 as an X-ray diffraction pattern, seeing the image in Fig. 5 as the fossilized imprint of an organism, and seeing a tree-diagram as having particular features (such as branching) that represent real events in a larger process (Darwin, 1882, pp. 120–121). In such cases an image is perceived, via automatic cognitive processes and learned interpretations, as a representation of some thing or process in the world.

Richard Gregory and Seymour Zeki have argued that perception is a form of inference linking sensory perception and comprehension (Gregory, 1981; Zeki, 1992). The holistic view that visual inference is analogous to perceptual inference does not show how more complex types of inference function in scientific problem solving. The answer proposed here is that they do so via active analysis and manipulation of multiple representations such as comparing the features of diagrams, rotating wire-frame models of a molecule or looking for receptor sites in 3D visualizations of molecules. This notion of inference goes beyond the analogy between inference and perceptual processes. On the basis of a range of case studies, I propose a schematic model that addresses important features of visualization. These are found in many scientific domains. They include the following: the sheer variety of modes of representation, frequent variation of images during problem solving, the close relationship between images and the techniques and technologies used to produce and transform them, and the relationship between personal, mental images and public representations. This model provides a framework to investigate further the relationship between sketches and diagrams and more complex objects such as structural and process models that can integrate domain knowledge and have predictive power. It also suggests a link between active variation of visual representations and the need to manage the changing cognitive demands of the processes of discovery, evaluation, and communication.

In his programmatic discussion on applying the psychology of doing science, Simonton asks, ''What are the mental processes that contribute to scientific discovery?'' and ''… is there a one-size fits-all creative procedure, or is creativity domain-specific?'' (Simonton, 2009, p.3). The work described here provides a partial answer to his first question: It identifies one set of mental processes, and it identifies a visualization strategy that is found in many different domains. It shows that some general features of visual inference can be discerned in the variety of visual representations. The argument of this paper is that these general features identify image-based strategies that scientists use to develop and interpret the phenomenology of a domain and to define and solve problems. This in turn suggests that these visual practices invoke distinct, biologically endowed human cognitive capacities such as pattern recognition and mental rotation, and learned skills for moving between 2D, 3D and 4D representations. An important cognitive constraint is the ease of reading a visual representation (accessing its meaning) and of manipulating it to generate new information. There is an inverse relationship between the accessibility of a representation and its information content. High information content is useful for higher-order operations such as synthesizing knowledge into a single model; lower information content aids generativity and ease of communication. What drives variation is the need to balance the complexity of representations against their ability to inform, generate and communicate. I describe a model of this process in section 3.

As to Simonton's second question this work shows that this visual method is widely used (Gooding, 2004) yet is far from being ''one-size fits-all.'' Scientists actively adapt visual processes and methods in response to each stage of the problem-solving process and to the conceptual and material ecology of their domain. I shall therefore focus on the active manipulation of representations rather than on images as objects or on imaging techniques. I provide an account of how visual models mediate between the interpretation of images (as sources of information) and visual representations (which express explanations of such data), showing that there is a close connection between making images, making perceptual inferences about them, and manipulating them in order to construct visual theories that explain them.

My investigation of the uses of visual objects and inferences relies on the findings of a range of ethnographic and historical case studies. Gorman and others have extended Dunbar's classification (Dunbar & Fugelsang, 2005) labeling these respectively as in vivo and sub specie historiae (Gorman, Tweney, Gooding, & Kincannon, 2005; pp. 5–13). Cognitive-historical and cognitive-ethnographic approaches argue the importance and feasibility of studying cognitive processes in context (in vivo) as well as in the psychologist's laboratory (in vitro). Ethnographic studies produce transcripts of laboratory work from which protocols can be abstracted (Nersessian, 2005, 2008). Historical studies can reconstruct experiments to reach beyond records of procedures and conversations in letters, diaries, and publications (Tweney, 2004). Reconstruction makes it possible to produce detailed procedural narratives. These are similar to verbal protocols and incorporate a wide variety of objects and processes (Gooding 1990; Gooding, 1992; Tweney & Hoffner, 1987). In order to address the needs of cognitive psychology a methodology that combines historical, ethnographic, and experimental methods needs to be developed (Nersessian, 2005, pp. 36–50; Nersessian, 2008, pp. 62–65). These are a step toward ''visual-spatial 'protocols''' (Shepard, 1978; p. 156) that can complement verbal protocols without imposing the assumption that protocols must be analyzed in terms of a particular cognitive model (Roth, 2004).

Historical studies tend to be specific to individuals and ethnographic studies are domain specific, but the cases considered in section 2 describe and compare visual practices across a range of scientific domains. It could be argued that case studies cannot establish general features of visual reasoning and therefore cannot demonstrate the existence of strategies and processes at work throughout the sciences. However, by comparing features identified in even a small number of cases we can make a prima facie case for further investigation of those features that turn up in all of the studies. Such features display the interconnectedness of cognitive processes in visual reasoning in a way that task-based laboratory studies can only do by presupposing a theory—such as a production rule system (Ericsson & Simon, 1984)—that specifies how these processes must relate.

2. How do scientists vary their images?

Case studies of different scientific fields show that scientists vary representations by making transformations between 2D forms (such as patterns and diagrams), 3D forms (structures), and 4D temporal- or process-representations (Gooding, 2004). For example, in order to interpret the 2D image in Fig. 1 W. L. Bragg devised geometrical methods to develop a 3-dimensional model from diagrams of the 2D images. He assumed that X-rays are diffracted in three dimensions in the same way that light rays are affected by a diffraction grating. Treating the crystal lattice as a 3D diffraction grating allowed him to apply a structural representation of optical interference to X-rays. He could then use stereographic projection methods (see Figs. 2 and 3) to locate the planes of the crystal lattice in which the atoms diffracting the rays lie.

These 3D model-based methods provided an explanation in terms of crystal structure, of the distribution and sizes of the spots and smudges found in early X-ray diffraction images. Bragg later developed a physical analog that allowed him to vary the axis of projection (see Fig. 4). Varying the alignment of the axis of this device with respect to the light source produced changes in the pattern cast onto the screen, demonstrating that structures of diffracted rays produce the features abstracted in Figs. 2 and 3.

Similarly in paleobiology, Conway Morris, Bruton, Whittington, and others abstracted 2D diagrams (Fig. 6) of photographs of fossil imprints (Fig. 5). Using shadow projection from mental and physical models, they constructed 3D structures as interpretations of the abstracted features (Bruton & Whittington, 1983; Conway Morris, 1979, 1999). These models draw on extensive domain knowledge relating to possible organisms, their habits and ecology, and the effects of geological processes on their remains.

At first 3D construction is done informally and mentally. This can be hard work, especially as the 2D section extracted by mentally rotation of a 3D structure may be difficult to verify mentally (Gould, 1989, pp. 92, 99–101). Many transformations are made. Projections that can be matched to diagrams of fossil imprints are developed into structural models. Procedures such as optical projection from paper- or wire-frame models (Fig. 7) save the cognitive effort of making 2D sectional shadows of 3D models, and do so more reliably. When a structural model (Figs. 7 and 8) generates 2D projections that match features of the diagrams (Fig. 6), these correspondences of form provide an evidence base for an explanation of the source imprints (Fig. 5). Computational methods were also devised to regularize and speed-up transformations between 2D and 3D representations. The computational models are dynamic, externalized representations of mental models and of their transformations.

Features to note in these examples include abstraction via sketches or diagrams and the use of physical models to aid frequent moves from two to three dimensions and back again. The models represent analogies of structure, allow projection of images that correspond to feature diagrams, and enable these images to be varied in the search for correspondences of form and feature. The method of producing correspondences of form is found across the sciences. (For more detailed accounts of these and other examples, see Gooding, 2004). The ''forms'' are generated in different ways, for example, by visualizing or plotting numerical

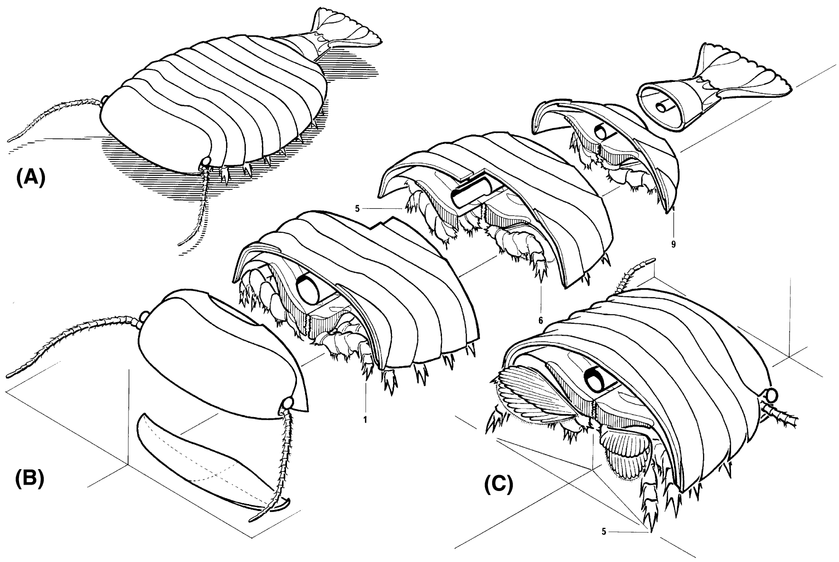

Fig. 7. A graphical reconstruction drawing of 3D sectional model of Sidneyia.

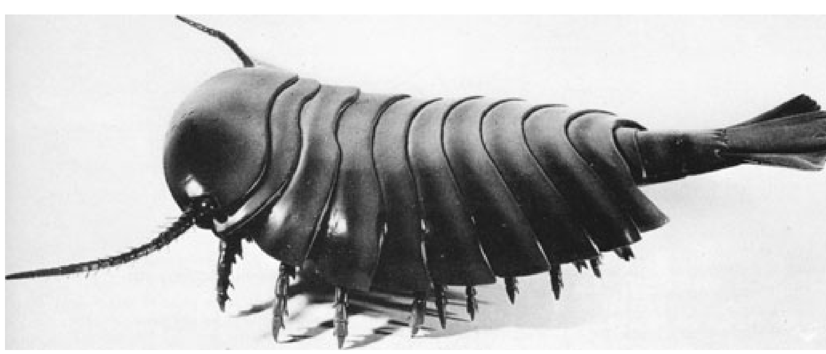

Fig. 8. Photograph of a physical reconstruction model of Sidneyia. From Bruton (1981), used by permission of The Royal Society.

data or abstracting features from photographs, X-rays, or data-plots. The process of abstraction is often complex, pushing at the limits of current imaging technologies. For example, Aaron Klug's attempts to solve the structure of the polio virus in the 1960s brought him up against the limitations of electron microscopy. Impressed by the spatial resolution of virus structures achieved by this method, Klug believed that the structure of viral particles might be read from patterns in their surface features. The patterns were crucial clues to understanding the process of generation and regeneration of viruses, which required an understanding of the structure of viral particles. But he found that his own micrographs collapsed near and distant features, apparently flattening what should be a 3D (spherical) form. Realizing that traditional staining techniques were to blame, Klug began experiments on pictorial representation so as to understand how visual information about a 3D structure appears on the flat plane of the electron micrograph (Anderson, 2007).

These visual experiments included making stereographic images of micrographs of objects placed at different distances inside the microscope and photographs of the changing shadow-projections of candidate-models of viral particles, so as to test for matches between the features produced by shadow-projection and those found in micrographs. The analogs are simpler to observe and manipulate than the more complex images of the target structures so this process could not produce correspondences with features of known objects until Klug had learned how to read patterns in electron micrograph (via analogies to visual perception of known objects and structures). To extract information about structure, he combined techniques of X-ray diffraction and electron microscopy producing a new imaging method he called crystallographic electron microscopy. As with paleobiology, physical models and experiments assisted the cognitive process of interpreting 2D images as representations of sections cut through 3D structure. These material procedures led to computer-based tools to analyze electron-density maps of diffraction patterns (Hogle, Chow, & Filman, 1987). Computational tools such as these have the same function as their physical analogs, namely to reduce the cognitive work involved in generating visual models of 2D images of very complex structures. They can effect transformations that are difficult if not impossible for humans to perform at this level of complexity. They also make it possible to generate virtual models that can solve very large numbers of structures: The development of computational structure-solving from the analog methods described here turned X-ray crystallography into the new discipline of structural genomics.

Klug's experiments on the visual syntax of micrographs use physical simulation to analyze perceptual experience. They performed the same cognitive function as simulations that Faraday developed to analyze how the interaction of physical and perceptual processes affects what is actually seen (Gooding, 2006; Tweney, 1992). Faraday analyzed the appearance under a microscope of an actual rotating structure of the cilia of aquatic rotifers. He wanted to determine whether a standing wave or pattern of interference could produce the same experience of a single rotating structure. Realizing that he could not analyze his visual experience directly into processes that produce it Faraday designed a strobe device that allowed him to vary the parameters of the appearance of rotation. This made a personal percept into a public object of experience. He used it to argue that the appearance emerges from the inability of the eye to resolve rapid sequences of occlusions of a light source by a toothed wheel. He could then argue by analogy (and from the biological implausibility of a wheel-axle arrangement) for an alternative hypothesis: The rotifers do not really have propellers because the appearance of rotation was due to oscillations in a fixed ring of cilia at a frequency higher than the eye can resolve. The use of simulation methods to relate structure to process requires an extension of our analysis.

3. Visualizing inference

The need to generate, model, and test perceptual inferences arises because the aim of most science is to capture complex process via simple, invariant features of change. Invariant features can be keys to the solution of complex processes. (An analogy to an invariant feature of a process is constant acceleration, as a quantitative descriptor of a constant change in velocity or direction). In our examples invariant features of crystal structure helped explain the dynamics of X-ray diffraction (Bragg); long-extinct life processes were explained by the morphology of an arthropod as derived from many fossil imprints (Conway Morris), and capturing stable patterns of optical interference in rapidly moving structures resolved a problem about the appearance of rotifers (Faraday).

As the Klug and Faraday examples show, these features are not always accessible to unmediated human perception. Faraday also discerned a structural relationship of electric, magnetic, and motive actions by transforming an intimate, kinesthetic knowledge of the relation of electricity and magnetism into a mathematical model of a propagating electromagnetic wave (see Gooding, 2006, figs. 8 and 11; Tweney, 2009 [this volume]). Psychologists have noted the importance of invariance both for specific mental tasks (pattern matching, mental rotation [Shepard, 1978]) and for visual problem solving (Gibson, 1974, p. 42). Gruber argued that altering the modality of a representation is a means of discovering invariant properties. By moving ''… from visual imagery, to sketches, to words and equations explaining (i.e., conveying the same meaning as) the thinker is pleased to discover that certain structures remain invariant under these transformations: These are his ideas'' (Gruber 1974; Gruber, 1994, pp. 410–11). The problem is most difficult where scientists work with uninterpreted complex phenomena or with information that is presented in a static form (as in a published diagram or data plot). As remarked in section 1 neither the ''snapshot'' nor the unresolved process is scientifically useful until it has been interpreted. To interpret new or anomalous phenomena, scientists must escape the limitations of static, printed representations such as plots and state-descriptions (Trickett et al., 2005, p. 101). They do this by producing representations that convey process as well as structure.

Bragg's analog model (Fig. 4) is a simple example of a process-representing device that not only reproduces features of the source phenomenon as a pattern but also allows for physical manipulation of input and output. A process model represents a process unfolding in time in a way that identifies both patterns of change and causes of and constraints upon that change. It combines a series of descriptions to suggest how one state is transformed into the next. In this respect, process models differ from 2D representations of change such as time-series data plots. The extra dimensionality of visual process representations helps explain the source phenomenology and can predict new phenomena. Moving from interpreted sources to structural models and on to process models generates visual theories that satisfy the explanatory aims of science. This transformation from simpler to more complex representations increases information content, enabling models to incorporate more domain knowledge. The extra representational power of 3D and 4D (process) models explains both the widespread use of sketches and diagrams in the development of modern science and, in the 20th century, the rapid take-up of computational methods of generating and animating them. Since the mid-20th century, animated, real-time presentation has become crucial to many fields. For example, in embryology and molecular biology, real-time display aids understanding the migration of leukocytes where it has been used to decide between rival hypotheses about wound-closure (Stramer et al., 2005; Wood & Jacinto, 2004).

Our examples show that the static 2D visualizations that still dominate publications (Roth, 2004, p. 596) convey information that scientists have extracted by a complex sequence of mental- and material manipulations. These transformations are summarized diagrammatically in Fig. 9. The diagram serves as an heuristic that suggests how to unpack the distinct processes that relate images, visual perception, technologies, and the articulation of evidence-based arguments for particular models and explanations. The arcs symbolize inferential processes that may be simple (making a shadow projection from a model) or complex (interpreting and refining a structural model in terms of wider domain knowledge). In the simplest case an interpretation develops via arc A $\rightarrow$ B, moving from a source image (node A) to a plot or diagram (node B), and via arc B $\rightarrow$ C to a structural representation (node C). The latter may be developed into a process-model (node D). This may be represented non-visually, for example, by a transformation rule operating on a set of state descriptions or by a set of mathematical equations, as in Maxwell's field equations (Tweney, 2009). Moves between nodes C and D are the most complex form of inference as they rely upon (and are validated by) a wide range of techniques and incorporate knowledge from several domains, as indicated in Fig. 10. The process also involves testing the complex models at C and D by deriving from them features of the existing phenomenology (node A) as abstracted in a diagram or other image (arc A $\rightarrow$ B) and by deriving new phenomena or features (arc D $\rightarrow$ E).

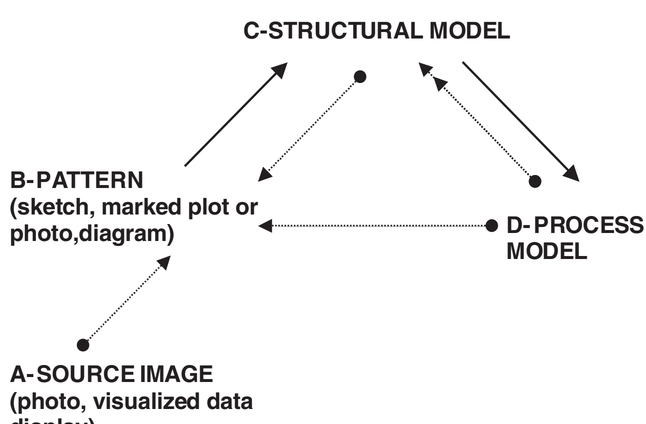

Fig. 9. Drawing inferences. Diagram of visual inference showing typical transformations that produce a pattern (B) or abstract other visible features from an image at A (arc A $\rightarrow$ B), generate a structural interpretation of this phenomenon (arc B $\rightarrow$ C), construct a process-model for the structure (arc C $\rightarrow$ D), and generate correspondences of form that validate the structure and process models (nodes C, D; arcs C $\rightarrow$ B; D $\rightarrow$ B). Arcs represent inferences or procedures on objects located at the nodes.

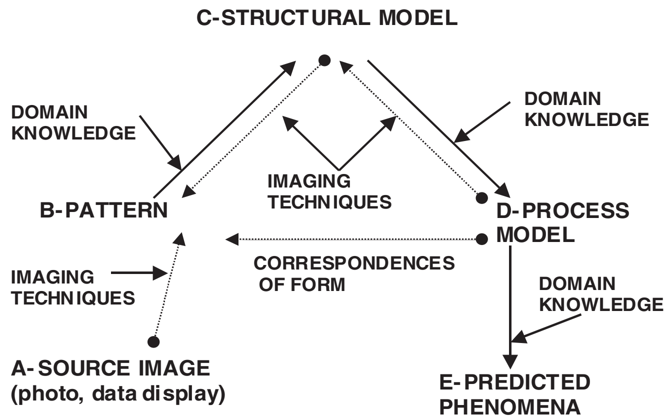

Fig. 10. Diagram of visual inference showing application of technologies and domain knowledge to produce a structural model (arc B $\rightarrow$ C) and its expansion into a process model (arc C $\rightarrow$ D). Models at C and D are validated by deriving known phenomenology (arcs C $\rightarrow$ B, D $\rightarrow$ B) and by predicting new phenomena or features (D $\rightarrow$ E).

4. Why do scientists vary their images?

Scientists moves from complex to simpler visual objects for two reasons. First, deriving a 2D pattern from a structure (arcs C $\rightarrow$ B, D $\rightarrow$ B, D $\rightarrow$ E) allows for empirical verification and testing of a model by checking for correspondences of form and feature. The second reason has to do with the increased cognitive demands of using complex structural and process models. As they accumulate more domain knowledge, these models become more difficult to understand and use. To manage this complexity scientists have developed well-known abstract representational systems such as the calculus, Feynman diagrams, and genetic regulatory graphs. These involve symbol manipulation according to strict transformation rules. Scientists also use visual inference to alter the complexity of representations so as to enable comprehension, analysis, and application. Historical and ethnographic studies show that transformations between objects at nodes B, C, and D run ''both ways'' depending on whether there is a need to reduce or to increase the complexity and information content of a representation. Moves from pattern to structure (arc B $\rightarrow$ C) and from structure to process (arc C $\rightarrow$ D) generate visual models having greater information content and explanatory power than their sources. Representations at nodes C and D are the most complex. They have greater predictive and explanatory potential than the diagrams but can be difficult to understand. As we have seen, scientists simplify these representations, abstracting and expressing essential features of a process model in terms of a labeled pattern or structural diagram. Moves from unresolved phenomena or data to a set of features or relationships such as a data-plot, pattern, or diagram (arcs A $\rightarrow$ B), or from structure or process to pattern (C $\rightarrow$ B, D $\rightarrow$ B) generate new visualizations that are simpler than their sources.

Representations have an integrative function that is well documented (Denis, 1991; Gooding, 2006, pp. 52–58; Gould, 1989, p. 100; Trickett et al., 2005; Trumpler, 1997, pp. 87–89; Tversky, 1998). A model at node C or D in Fig. 10 integrates many representations—each bearing different information that may be presented in different modalities. This requires greater information-density than is needed at node B. This is because it has a dual function: A diagram or data-plot at node B requires interpretation (via models at nodes C and D) but also provides *evidence* for those models which may eventually *explain* the existence of features that objects at node B abstract from the source image A or its data-set. The actions that the arrows in Fig. 9 represent may be accomplished mentally by individuals (e.g., Conway Morris' mental rotations), by dyads (Trickett et al., 2000, 2005), by human-machine dyads (Giere & Moffat, 2003), and by groups and interactions between groups (Alac & Hutchins, 2004; Goodwin, 1995; Trumpler, 1997).

Representations of differing type and complexity invoke—and make different demands upon—a range of cognitive capacities. Consider, for example, an arithmetic calculation done by mental arithmetic, with an abacus, with pencil and paper, and by a pocket calculator. Each technique combines a form of representation and a procedure. Each invokes different combinations of cognitive capacities. There are limitations to the size of computation that each technique can accomplish. The image-transformations indicated by the arcs in Figs. 9 and 10 produce changes in the complexity of visual objects at the nodes, called for at different points in a discovery process and determined in part by what can be processed by available methods. This complexity reflects the changing role that these visualizations can have. Transformations that run from A → B → C typically evoke hypotheses, running ''bottom-up'' from data to interpretation. Transformations that run ''top down'' from C → B or D → B enable empirical validation by checking for correspondences between features derived from models and observed features. These moves generate an explanation once an integrated model **D** has been constructed. This may involve many iterations of the whole processes diagrammed in Fig. 9. Finally, moves from C → D → E predict new phenomena allowing verification (Fig. 10).

5. Investigating visual inference

Analyzed in terms of the Pattern-Structure-Process schema in Fig. 10, the cases described in section 2 suggest that scientists' visual strategies are motivated and constrained by the capacities and limitations of biologically endowed cognitive capacities. Each of the inferential activities represented by the arrows occurs in the context of a larger process that makes varying demands on cognition. The diagram shows this without implying a particular logical, computational or cognitive model of the process.

These examples show that visual inference involves a series of moves that transform mental, material, and virtual objects (Gooding, 2004). It is compatible with the widely held view that scientific reasoning is abstract thinking that draws on the same biologically endowed cognitive processes as perception (Gregory, 1981). Shepard argued that complex deliberative inferences rely on an innate, evolved kinematic understanding constrained by invariant features of lived experience of a 3D world in which verticality is highlighted by the existence of gravity (Shepard, 1978, p. 157, 1984, p. 422). It is often argued that science extends and refines cognitive capacities, although the relative importance of intrinsic and external factors remains controversial (Carruthers, 2002; Nersessian, 2008). But the analogy between perception and inference is sometimes pushed too far, conflating visual perception with interpretation. Thus, Barry argues that ''the formation of unified images of the way things work … is essentially the same way perception works'' because abstract thinking ''reflects a holistic logic that has its foundation in the evolution of perception … '' (Barry, 1997, p. 8; 24–27). This visual holism does not indicate either how to investigate how scientific methods extend and utilize more basic perceptual processes nor how the relationships between them may be unpacked. Human vision is often used to explore and it involves perceptual hypothesis-testing (Gregory, 1982, p. 383, 392). But ordinary seeing is not explicitly motivated by the type and level of explanation that scientists seek. We can express this difference in terms of the pattern-structure-process diagram in Fig. 10 by pointing out that the 3D representations (node C) are motivated by the need to interpret and explain by recourse to complex, abstract process models (node D) and that validation involves determining whether simpler abstractions (node B) match existing data-visualizations and predictions (node E).

This approach retains features suggested by scientists' use of visualization, just as Tweney's study of the representational function of mathematics (Tweney, 2009) and Clements' studies of problem-solving protocols (Clement, 2008) identify features of other cognitive practices. Thus, the two dimensions of the diagram convey the fact that visual inferences are nonlinear and recursive. By contrast cognitive science theories have tended to order images according to their complexity and abstraction. Marr's multilevel theory of vision, for example, proceeds from a two-dimensional visual array (on the retina) of a scene to a three-dimensional description of the world as output. The output of this process is a continuous, three-dimensional rendering of the scene. In the terms of the pattern-structure-process schema abstracting a diagram or plot B from an image or other data-source, A corresponds to what Marr called a primal-sketch—''primal'' because it involves extracting fundamental components of a scene such as edges, alignments, and regions (Marr, 1982). The objects at nodes B and C correspond to what Marr called a 2-1/2 D sketch in which texture and shading convey depth. The scientific analog would be labeled diagrams and plots expressing an interpretation which combines visual and nonvisual elements according to representational conventions. Like Shepard's, this theory highlights the importance of dimensionality. However, it implies a unidirectional process leading from sensory inputs to a 3D model. Thus, it fails to capture the variability and recursivity of visual inference as scientists constantly shift between biologically endowed perceptual processes and learned, expert perceptual skills, between the personal, mental imaginative processes and public representations, and between personal views and those of colleagues and critics.

Newell's unified theory of cognition also implies a unidirectional processing of sensory information. Newell assigns cognitive processes to distinct bands—biological, cognitive, rational, and social. Each cognitive process operates within a particular band and each depends on those lower in the hierarchy (Newell, 1990). According to Newell's cognitive hierarchy, an image is used to generate new concepts (cognitive band), to evaluate them (rational band), and to enlist support for their existence and interpretations of them (rational and social bands). This requires that we investigate scientific discovery by reconstructing it as a running from automatic biological processes to complex social band processes. Each of these operates at very different timescales (Anderson, 2002) and is investigated by different methods. Thus, recognition of patterns and of similarities between pattern-like features (at node B in Fig. 9) involves biological-band processes. However, some of those 2D representations are abstractions generated from more complex representations of structure or process. If we take ''direct'' perception of similarities as biologically engendered pattern matching, then the cases we have described suggest that processing in the biological, cognitive, and rational bands works together as part of the same connected process and not sequentially. Similarly the integrative function of structure- and process-representations at nodes C and D suggests the interaction of processes in Newell's cognitive, rational, and social bands. An example is Bragg's derivation of the 2D array of diffraction nodes (Fig. 2) as a consequence of the 4D crystal diffraction process (node D) as modeled via the analogy between a crystal lattice and a diffraction grating and between light and X-rays (node C). These transformations are deliberative and goal-oriented, hence they are rational-band processes aimed at solving particular aspects of a larger problem. Yet they require manipulation and interpretation (cognitive-band processes) which are often motivated by social interaction (social band) and pattern matching that uses biological band processes but is also subject to interpretation and negotiation (cognitive and social bands).

The diagram of visual inferences in Fig. 10 resembles some computation-oriented models of visual inference that do not represent all processes as operating on a hierarchy of goals and subgoals. It can be restated in the terms of Josephson and Josephson's (1994, p. 242–44) layered abduction model. In their terms, evocation of hypotheses involves inferences along arcs $A \to B \to C$ and $C \to B$; instantiation or evaluation of explanatory potential of a model involves moves along arcs $D \to C \to B$, $D \to B$ and $C \to D \to E$. Instantiation is followed by composition, the interaction of hypotheses ($C \to D$, $D \to C$) to produce an coherent, integrated model that is considered to be the best explanation of existing and predicted phenomena (arcs $D \to B$, $D \to E$).

The process diagrammed in Figs. 9 and 10 is meant to convey a dynamical and non-hierarchical relationship between biological and social elements of cognitive processes. The diagrams express the fact that the images we see scientists using are part of a dialectical movement between the interpretative, creative stages of discovery in which representations are plastic (arcs $A \to B$, $B \to C$ in Fig. 9) and the deliberative, rational stages in which transformation rules and evaluative criteria are applied to correspondences of form (arcs $B \to C$, $C \to D$, $C \to B$, $D \to B$). What appears to be the same image or object can function in different ways: as presenting an anomaly requiring explanation, as a challenge to an existing interpretation, as an instance of an interpretation, and as evidence for an interpretation. As we saw in section 2, abstracting patterns to represent possible features of long-extinct organisms is accomplished between nodes A and B with continual reference to possible structures at C. The structures are developed into process-models that integrate factual information with knowledge from several domains. In the case of paleobiology these relate to morphology, physiological processes, ecological factors such as food sources and predators, and geological processes (nodes C, D), (Briggs & Williams, 1981). Pattern recognition again comes to the fore when the objects hypothesized and represented by models are tested. By comparing the 2D patterns it is possible (or impossible) to generate from them with diagrams of extant fossil images. Finally, linking these diagrams to photographs (B $\rightarrow$ A) and new phenomena (D $\rightarrow$ E) provides epistemic validation of the diagrams as depictions that refer to real features in the fossil traces of a real organism. New information can force a reevaluation of what external representations are supposed to represent, especially if it presents anomalies (Anderson, Barker, & Chen, 2006, pp. 59–65). Achieving consensus about the adequacy of a representation depends on getting correspondences of form and feature between images at node B and the structures and processes that generate them at nodes C and D (see Fig. 9).

Despite its emphasis on mental images, this account of visual perception and inference does not locate cognition either inside the head or inside machines. Cognition in science depends crucially on being embodied and networked and so involves physical and social processes that occur both ''in'' the embodied brain and beyond it. What any individual scientist imagines, thinks, or believes that she knows has importance and is interesting only insofar as it draws upon and contributes to a larger, collective enterprise. It is the common currency of that enterprise—discourse, images, arguments, articles, software, technologies, mathematical procedures—that is external and distributed. The case studies cited in section 2 illustrate the diverse cognitive functions of procedures, techniques, and machines in the larger interplay of images, perceptions, and material- and imaginary objects expressed in Figs. 9 and 10.

This model of visual inference can clarify what it means to claim that a knowledge-bearing representation is distributed. In a hybrid cognitive system there is no dualism of subjective (internal) and collective (externalized) knowledge. Visual representations are hybrid, mental-material objects that enable visual-tactile thinking (Baird, 2004; Magnani, 2001) or guide some procedure, such as performing a mathematical operation. Thus, knowledge emerges from the interaction of real and imagined objects. Where a knowledge-bearing representation involves devices or machines, it is distributed *between* minds and machines, for example, computer displays and the sharing of large numerical datasets to produce fMRI scan images (Beaulieu, 2001; Alac & Hutchins, 2004).

Representations convey knowledge that is produced and held in many different *ways* (e.g., by people, machine-based procedures, software-based procedures, organizations, and institutions) and at different levels of relationship (from human-machine dyads [Giere & Moffat, 2003] to systems for directing and organizing research [Nersessian, 2005, 2008]). Such knowledge production also relies on control systems that ensure that existing resources are available where needed and that new knowledge is communicated to those skilled enough to evaluate it (Goodwin, 1995; Hutchins, 1995). It follows that the cognitive content of distributed representations does not reside in any single contributing source or element of the system. Technology-based, externalized images such as those in Figs. 1, 4, and 5 (section 2) are no more- or less important than visual mental images, although images can—like experimental findings—develop a crucial role in arguments about theories (LeGrand, 1990).

Scientists draw attention to how science has been transformed since the advent of cheap, powerful computers, particularly as to the increased visuality of science (Barrow, 2008). Has the widespread use of computation thereby made mental processes less important? New digital technologies afford greater opportunities for visual representation, but it hardly follows that they eliminate the need for laborious mental and material processes as described in section 2. Imaging technologies have the same functionality in enabling perception, interpretation, modeling, and empirical validation as the older material, mechanistic techniques described in section 2. Computational processes typically implement human cognitive procedures (Gooding, 2003), they continue to rely on human intervention, and they address and use the same cognitive capacities of the biologically evolved brain (Feist, 2006; chapter 2). Computer technologies have made huge advances in the production and quality of scientific images but are still unable to perform the interpretative and evaluative judgments that make up the dynamic diagrammed in Figs. 9 and 10. These require types of expertise that we have so far failed to externalize in machines (Collins & Kusch, 1998).

The analysis offered here goes some way toward explaining why this should be. It demonstrates the historical continuity of human cognitive capacities alongside their partial displacement by machines, and it highlights the importance to science of the basic visual skills that enable scientists to make visual inferences. Like the analog imaging technologies that preceded them, computational tools ''re-present'' data in a form that individual humans can interpret and understand. Whether representation is accomplished by analog or by computational techniques is less important than how well each representation engages available cognitive capabilities so as to enable problem solving. Technologies extend analog modes of reasoning into new domains so that scientists can apply them to more complex problems. That images are generated and manipulated in computers rather than in human minds does not diminish the importance of mind-based representations.

6. Conclusion

The visualization examples display both variety in representation and the need to move readily between different kinds of representation, and they display the same types of image-transformation and patterns of transformation. These features are interdependent. I have argued that they indicate the existence of a common approach to the use of images across the sciences. This incorporates mental imaginings and externally represented objects without prioritizing either type of object. I have identified several types of problem solving—interpretation of source data, model construction, model expansion, and the validation and testing of models. Image-based thinking stimulates a demand for external representations and helps scientists to interpret and validate images and data by producing new visualization techniques. I have expressed this interdependence as a schematic model of visual inference in Figs. 9 and 10. These diagram an empirical hypothesis based on features of inference present in a wide range of scientific discoveries. They identify a dynamical structure for visual thinking by showing how visual representation allows scientists to combine processes as cognitively diverse as pattern matching, deductive inference, and tool use.

The scheme displays the connectedness of cognitive, social, and technological aspects of cognition by showing how representation-producing inferences connect each of the overlapping contexts of scientific work—the personal realm of the mind's eye, external representations of embodied interaction with the world, technologies that mediate images, perception and visual inference, and the social domain of communication and negotiation. As an hypothesis about patterns of representational behavior, this schema challenges psychologists to devise ways of investigating mechanisms that support the types of inference identified in the schema and the patterns of activity that produce scientific discoveries.

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