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OBJECT PERCEPTION AS BAYESIAN INFERENCE

Daniel Kersten
Department of Psychology, University of Minnesota, Minneapolis, Minnesota 55455; email: kersten@umn.edu

Pascal Mamassian
Department of Psychology, University of Glasgow, Glasgow G12 8QB, Scotland

Alan Yuille
Departments of Statistics and Psychology, University of California, Los Angeles, Los Angeles, California 90095-1554

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■ **Abstract** We perceive the shapes and material properties of objects quickly and reliably despite the complexity and objective ambiguities of natural images. Typical images are highly complex because they consist of many objects embedded in background clutter. Moreover, the image features of an object are extremely variable and ambiguous owing to the effects of projection, occlusion, background clutter, and illumination. The very success of everyday vision implies neural mechanisms, yet to be understood, that discount irrelevant information and organize ambiguous or noisy local image features into objects and surfaces. Recent work in Bayesian theories of visual perception has shown how complexity may be managed and ambiguity resolved through the task-dependent, probabilistic integration of prior object knowledge with image features.

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OBJECT PERCEPTION: GEOMETRY AND MATERIAL

Object perception is important for the everyday activities of recognition, planning, and motor action. These tasks require the visual system to obtain geometrical information about the shapes of objects, their spatial layout, and their material properties.

The human visual system is extraordinarily competent at extracting necessary geometrical information. Navigation, judgments of collision, and reaching rely on knowledge of spatial relationships between objects and between the viewer and object surfaces. Shape-based recognition and actions such as grasping require information about the internal shapes and boundaries of objects.

Extracting information about the material that objects are made of is also important for daily visual function. Image features such as color, texture, and shading depend on the material reflectivity and roughness of a surface. Distinguishing different materials is useful for object detection (e.g., texture differences are cues for separating figure from ground) as well as for judging affordances such as edibility (e.g., ripe fruit or not) and graspability (e.g., slippery or not).

Understanding how the brain translates retinal image intensities to useful information about objects is a tough problem on theoretical grounds alone. The difficulty of object perception arises because natural images are both complex and objectively ambiguous. The images received by the eye are complex high-dimensional functions of scene information (Figure 1, see color insert). The complexity of the problem is evident in the primate visual system in which approximately ten million retinal measurements are sent to the brain each second, where they are processed by some billion cortical neurons. The ambiguity of image intensities also poses a major computational challenge to extracting object information. Similar three-dimensional (3-D) geometrical shapes can result in different images, and different shapes can result in very similar images (Figure 1*A*,*B*). Similarly, the same material (e.g., polished silver) can give rise to drastically different images depending on the environment, and the same image can be due to quite different materials (Figure 1*C*,*D*).

This review treats object perception as a visual inference problem (Helmholtz 1867) and, more specifically, as statistical inference (Knill & Richards 1996, Kersten 1999, Rao et al. 2002a). This approach is particularly attractive because it has been used in computer vision to develop theories and algorithms to extract information from natural images useful for recognition and robot actions.

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Computer vision has shown how the problems of complexity and ambiguity can be handled using Bayesian inference, which provides a common framework for modeling artificial and biological vision. In addition, studies of natural images have shown statistical regularities that can be used for designing theories of Bayesian inference. The goal of understanding biological vision also requires using the tools of psychophysics and neurophysiology to investigate how the visual pathways of the brain transform image information into percepts and actions.

In the next section, we provide an overview of object perception as Bayesian inference. In subsequent sections, we review psychophysical (Psychophysical, below), computational, (Theoretical and Computational Advances, below) and neurophysiological (Neural Implications, below) results on the nature of the computations and mechanisms that support visual inference. Psychophysically, a major challenge for vision research is to obtain quantitative models of human perceptual performance given natural image input for the various functional tasks of vision. These models should be extensible in the sense that one should be able to build on simple models, rather than having a different model for each set of psychophysical results. Meeting this challenge will require further theoretical advances and Theoretical and Computational Advances (below) highlights recent progress in learning classifiers, probability distributions, and in visual inference. Psychophysics constrains neural models but can only go so far, and neural experiments are required to further determine theories of object perception. Neural Implications (below) describes some of the neural implications of Bayesian theories.

INTRODUCTION TO BAYES

How to Resolve Ambiguity in Object Perception?

The Bayesian framework has its origins in Helmholtz's idea of perception as unconscious inference. Helmholtz realized that retinal images are ambiguous and that prior knowledge was required to account for perception. For example, differently curved cylinders can produce exactly the same retinal image if viewed from the appropriate angles, and the same cylinder can produce very different images if viewed at different angles. Thus, the ambiguous stimulus in Figure 2*A* could be interpreted as a highly curved cylinder from a high angle of view, a flatter cylinder from a low angle of view, or as a concave cylinder from yet another viewpoint. Helmholtz proposed that the visual system resolves ambiguity through built-in knowledge of the scene and how retinal images are formed and uses this knowledge to automatically and unconsciously infer the properties of objects.

Bayesian statistical decision theory formalizes Helmholtz's idea of perception as inference[1]. Theoretical observers that use Bayesian inference to make optimal

[1]Recent reviews include Knill et al. (1996), Yuille & Bülthoff (1996), Kersten & Schrater 2002, Kersten & Yuille 2003, Maloney (2001), Pizlo (2001), and Mamassian et al. (2002).

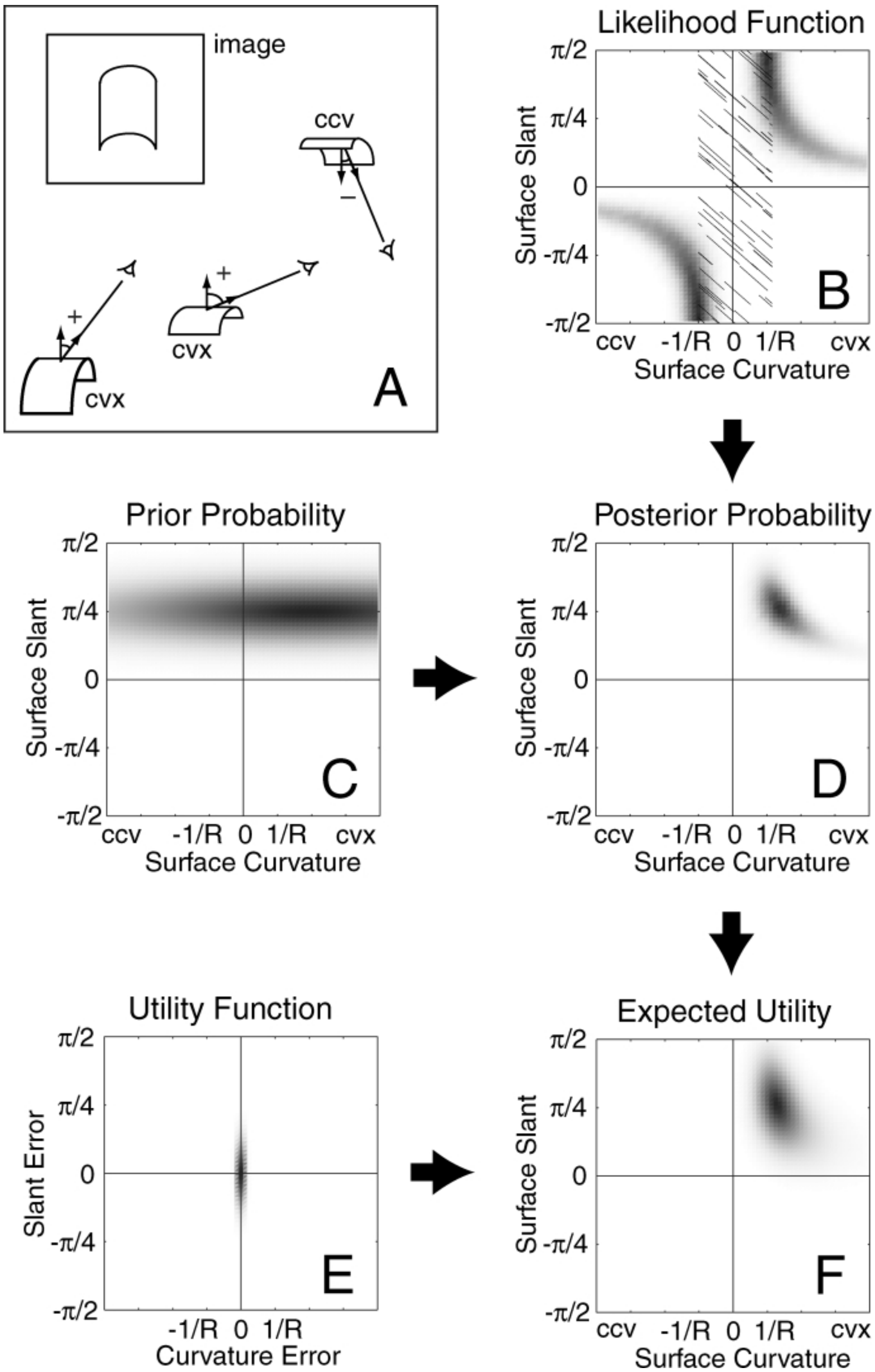
image
ccv
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cvx
A
Likelihood Function
π/2
π/4
0
-π/4
-π/2
Surface Slant
ccv -1/R 0 1/R cvx
Surface Curvature
B
Prior Probability
C
Posterior Probability
D
Utility Function
Slant Error
-1/R 0 1/R
Curvature Error
E
Expected Utility
F

interpretations are called ideal observers. We first consider one type of ideal observer that computes the most probable interpretation given the retinal image stimulus. Technically, this observer is called a maximum a posteriori (MAP) observer. The ideal observer bases its decision on the posterior probability distribution—the probability of each possible true state of the scene given the retinal stimulus. According to Bayes' theorem, the posterior probability is proportional to the product of the prior probability—the probability of each possible state of the scene prior to receiving the stimulus—and the likelihood–the probability of the stimulus given each possible state of the scene. In many applications, prior probability distributions represent knowledge of the regularities of possible object shapes, materials, and illumination, and likelihood distributions represent knowledge of how images are formed through projection onto the retina. Figure 2 illustrates how a symmetric likelihood [a function of the stimulus representing the curvature of the two-dimensional (2-D) line] can lead to an asymmetric posterior owing to a prior toward convex objects. The ideal (MAP) observer then picks the most probable interpretation for that stimulus—i.e., the state of the scene (3-D surface curvature and viewpoint slant) for which the posterior distribution peaks in panel *D* of Figure 2. An ideal observer does not necessarily get the right answer for each input stimulus, but it does make the best guesses so it gets the best performance averaged over all the stimuli. In this sense, an ideal observer may "see" illusions.

We now take a closer look at three key aspects to Bayesian modeling: the generative model, the task specification, and the inference solution.

THE GENERATIVE MODEL The generative model, $S \to I$, specifies how an image description I (e.g., the image intensity values or features extracted from them) is determined by the scene description S (e.g., vector with variables representing surface shape, material reflectivity, illumination direction, and viewpoint). The

Figure 2 The ideal observer. (*A*) The image of a cylinder is consistent with multiple objects and viewpoints, including convex cylinders viewed from above and concave cylinders viewed from below. Therefore, different scene interpretations for this image vary in the estimated surface curvature and slant (the viewing angle). (*B*) The likelihood represents the compatibility of different scene interpretations with the image ($1/R$ is the curvature in the image). The hatched region represents those surface curvatures that are never compatible with the image, indicating that, for instance, a plane will never project as a curved patch in the image. (*C*) The prior probability describes an observer preference for convex objects viewed from above. (*D*) A Bayesian observer then combines likelihood and prior to estimate a posterior probability for each interpretation given the original image. The maximum a posteriori (MAP) is the set of scene parameters for which the posterior is the largest. (*E*) The utility function represents the costs associated to errors in the estimation of the surface slant and curvature and is dependent on the task. (*F*) Finally, the posterior probability is convolved with the utility function to give the expected utility associated with each interpretation.

likelihood of the image features, $p(I|S)$, and the prior probability of the scene description, $p(S)$, determine an external generative model. As illustrated later in Figure 5, a strong generative model allows one to draw image samples—the high-dimensional equivalent to throwing a loaded die. The product of the likelihood and prior specifies an ensemble distribution $p(S, I) = p(I|S)p(S)$, which gives a distribution over problem instances (Theoretical and Computational Advances, below). In Bayesian networks, a generative model specifies the causal relationships between random variables (e.g., objects, lighting, and viewpoint) that determine the observable data (e.g., image intensities)[2]. Below, we describe how Bayesian networks can be used to cope with the complexity of problems of visual inference.

THE TASK SPECIFICATION There is a limitation with the MAP ideal observer described above. Finding the most probable interpretation of the scene does not allow for the fact that some tasks may require more accurate estimates of some aspects of the scene than others. For example, it may be critical to get the exact object shape, but not the exact viewpoint (represented in the utility function in Figure 2*E*). The task specifies the costs and benefits associated with the different possible errors in the perceptual decision. Generally, an optimal perceptual decision is a function of the task as well as the posterior.

Often, we can simplify the task requirements by splitting S into components (S_1, S_2) that specify which scene properties are important to estimate (S_1, e.g., surface shape) and which confound the measurements and are not worth estimating (S_2, e.g., viewpoint, illumination).

THE INFERENCE SOLUTION Bayesian perception is an inverse solution, $I \rightarrow S_1$, to the generative model, which estimates the variables S_1 given the image I and discounts the confounding variables. Decisions are based on the posterior distribution $p(S|I)$, which is specified by Bayes as $p(I|S)p(S)/p(I)$. The decision may be designed, for example, to choose the scene description for which the posterior is biggest (MAP). But we've noted that other tasks are possible, such as only estimating components of S. In general, an ideal observer convolves the posterior distribution with a utility function (or negative loss function)[3]. The result is the expected utility (or the negative of the expected loss) associated with each possible interpretation of the stimulus. The Bayes ideal observer picks the interpretation that has the maximum expected utility (Figure 2*F*).

[2]When not qualified, we use the term generative model to mean an external model that describes the causal relationship in terms of variables in the scene. Models of inference may also use an internal generative model to test perceptual hypotheses against the incoming data (e.g., image features). We use the term strong generative model to mean one that produces consistent image samples in terms of intensities.

[3]Optimists maximize the utility or gain, whereas pessimists minimize their loss.

How Does Vision Deal with the Complexity of Images?

Recent work (Freeman et al. 2000, Schrater & Kersten 2000, Kersten & Yuille 2003) has shown how specifying generative models in terms of influence graphs (or Bayesian networks) (Pearl 1988), together with a description of visual tasks, allow us to break problems down into categories (see the example in Figure 3*A*). The idea is to decompose the description of a scene S into n components $S_1, \ldots, S_n$; the image into m features $I_1, \ldots, I_m$; and express the ensemble distribution as $p(S_1, \ldots, S_n; I_1, \ldots, I_m)$. We represent this distribution by a graph where the nodes correspond to the variables $S_1, \ldots, S_n$ and $I_1, \ldots, I_m$, and links are drawn between nodes that directly influence each other. There is a direct correspondence between graphical structure and the factorization (and thus simplification) of the joint probability. In the most complex case, every random variable influences every

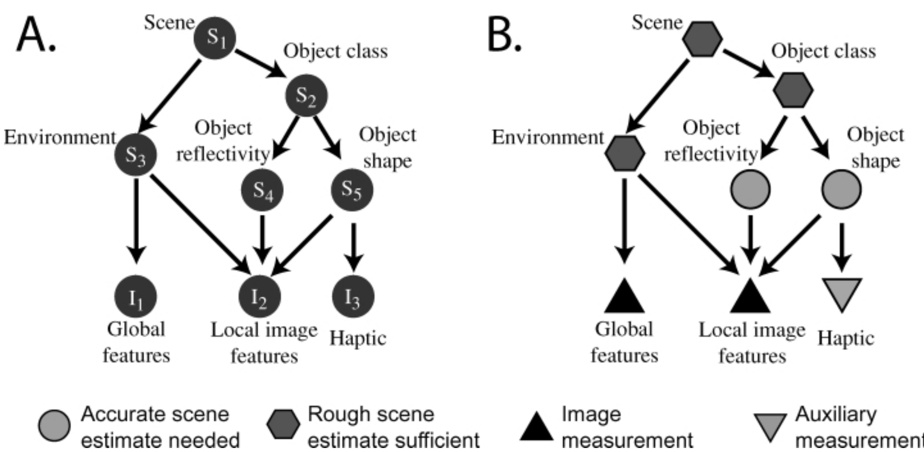

Figure 3 Infuence graphs and the visual task. (*A*) An example of an influence graph. Arrows indicate causal links between nodes that represent random variables. The scene class (indoor or outdoor) influences the kind of illumination and background that determine the environment. The scene also determines the kinds of objects one may find (artifactual or not). Object reflectivity (paint or pigment) and shape are influenced by the object class. The model of lighting specified by the environment interacts with reflectivity and shape to determine the image measurements or features. The environment can determine large-scale global features (e.g., overall contrast and color, spatial frequency spectrum) that may be relatively unaffected by smaller-scale objects of interest. Global features can serve to set a context. (*B*) The inference problem depends on the task. The task specifies which variables are important to estimate accurately (*disks*) and which are not (*hexagons*). Triangles represent image measurements or features. For the purpose of later illustration of explaining away, we also distinguish auxiliary features (*upside-down triangles*) that are available or actively sought and which can modulate the probability of object variables that do not directly influence the auxiliary variable. Note that perceptual inference goes against the arrows.

other one, and the joint probability cannot be factored into simpler parts. In order to build models for inference, it is useful to first build quantitative models of image formation—external generative models based on real-world statistics. As we have noted above, the requirements of the task split S into variables that are important to estimate accurately for the task (disks) and those which are not (hexagons) (Figure 3*B*). The consequences of task specification are described in more detail in Discounting and Task Dependence (below).

In the next section, Psychophysics, we review psychophysical results supporting the Bayesian approach to object perception. The discussion is organized around the four simple influence graphs of Figure 4 (see color insert).

PSYCHOPHYSICS

Psychophysical experiments test Bayesian theories of human object perception at several levels. Ideal observers (below) provide the strongest tests because they optimally discount and integrate information to achieve a well-defined goal. But even without an ideal observer model, one can assess the quality of vision's built-in knowledge of regularities in the world.

In Basic Bayes: The Trade-Off Between Feature Reliability and Priors (below), we review the perceptual consequences of knowledge specified by the prior $p(S)$, the likelihood $p(I|S)$, and the trade-off between them. Psychophysical experiments can test theories regarding knowledge specified by $p(S)$. For example, the perception of whether a shape is convex or concave is biased by the assumption that the light source (part of the scene description S) is above the object. Psychophysics can test theories regarding knowledge specified by the likelihood, $p(I|S)$. The likelihood characterizes regularities in the image given object properties S, which include effects of projecting a 3-D object onto a 2-D image. For example, straight lines in three dimensions project to straight lines in the image. Additional image regularities can be obtained by summing over S to get $p(I) = \sum_S p(I|S)p(S)$. These regularities are expected to hold independently of the specific objects in the scene. Image regularities can be divided into geometric (e.g., bounding contours in the image of an object) and photometric descriptions (e.g., image texture in a region).

As illustrated in the examples of Figure 4, vision problems have more structure than basic Bayes. In subsequent sections (Discounting and Task Dependence, Integration of Image Measurements and Cues, and Perceptual Explaining Away), we review psychophysical results pertaining to three additional graph categories, each of which is important for resolving ambiguity: discounting variations to achieve object constancy, integration of image measurements for increased reliability, and perceptual explaining away given competing perceptual hypotheses.

Ideal Observers

Ideal observers provide the strongest psychophysical tests because they are complete models of visual performance based on both the posterior and the task.

A Bayesian ideal observer is designed to maximize a performance measure for a visual task (e.g., proportion of correct decisions) and, as a result, serves as a benchmark with which to compare human performance for the same task (Barlow 1962, Green & Swets 1974, Parish & Sperling 1991, Tjan et al. 1995, Pelli et al. 2003). Characterizing the visual information for a task can be critical for proper interpretation of psychophysical results (Eckstein et al. 2000) as well as for the analysis of neural information transmission (Geisler & Albrecht 1995, Oram et al. 1998).

For example, when deciding whether human object recognition uses 3-D shape cues, it is necessary to characterize whether these cues add objectively useful information for the recognition task (independent of whether the task is being peformed by a person or by a computer). Liu & Kersten (2003) show that human thresholds for discriminating 3-D asymmetric objects is less than for symmetric objects (the image projections were not symmetric); however, when one compares human performance to the ideal observer for the task, which takes into account the redundancy in symmetric objects, human discrimination is more efficient for symmetric objects.

Because human vision is limited by both the nature of the computations and its physiological hardware, we might expect significant departures from optimality. Nevertheless, Bayesian ideal observer models provide a first approximation to human performance that has been surprisingly effective (cf. Knill 1998, Schrater & Kersten 2002, Legge et al. 2002, Ernst & Banks 2002, Schrater et al. 2000).

A major theoretical challenge for ideal observer analysis of human vision is the requirement for strong generative models so that human observers can be tested with image samples I drawn from $p(I|S)$. We discuss (below) results from statistical models of natural image features that constrain, but are not sufficient to specify the likelihood distribution. In Theoretical and Computational Advances (below), we discuss relevant work on machine learning of probability distributions. But we first present a preview of one aspect of the problem.

The need for strong generative models is an extensibility requirement that rules out classes of models for which the samples are image features. The distinction is sometimes subtle. The key point is that images features may either be insufficient to uniquely determine an image or they may sometimes overconstrain it. For example, suppose that a system has learned probability models for airplane parts. Then sampling from these models is highly unlikely to produce an airplane—the samples will be images, but additional constraints are needed to make sure they correspond to airplanes (see Figure 5*A*). M.C. Escher's pictures and other impossible figures, such as the impossible trident, give examples of images that are not globally consistent. In addition, local feature responses can sometimes overconstrain the image locally. For example, consider the binary image in Figure 5*B* and suppose our features ΔL are defined to be the difference in image intensity L at neighboring pixels. The nature of binary images puts restrictions on the values that ΔL can take at neighboring pixels. It is impossible, for example, that neighboring $\Delta L s$ can both take the value $+1$. So, sampling from these features will not give a consistent image unless we impose additional constraints. Additional consistency conditions are also needed in 2-D images (see Figure 5*C*) where the local image differences

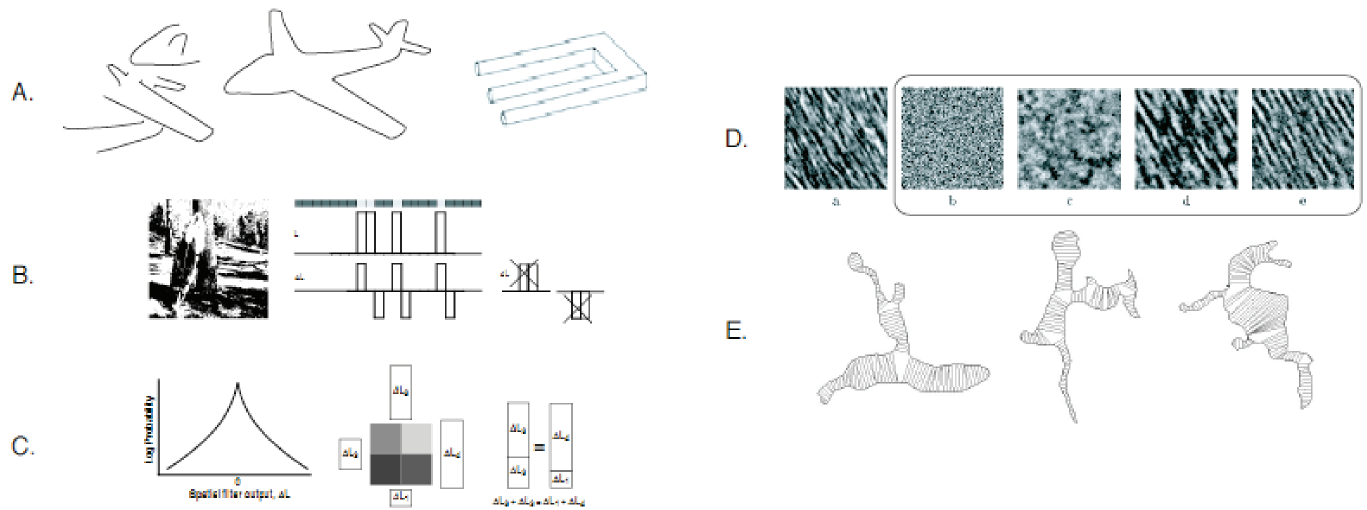

Figure 5 The challenge of building strong generative models. The samples of strong generative models are images that can be used as stimuli for ideal observer analysis of human vision. But models specified by image features may be unable to generate images because the image features may either underconstrain or overconstrain the image. (*A*) A model whose features are airplane parts must impose additional constraints to ensure that the samples form a plane (*left and center panels*). Constraints must prevent an image from being globally inconsistent (*right panel*). (*B*) The nature of binary images (*left panel*) imposes constraints on the feature values (*center panel*) and means that some feature configurations are inconsistent with any image (*right panel*). (*C*). Measurements of natural image statistics (Simoncelli & Olshausen 2001) have shown that the probability distribution of intensity differences between pixels has a characteristic distribution (*left panel*), but to produce natural image samples requires an additional consistency constraint on neighboring filter values (*center and right panels*). (*D*) Samples from a strong generative model learned from image features (Zhu et al. 1997). Panel (*a*) shows the original picture of fur. Panels (*b*)–(*e*) show image samples drawn from several $p(I \;\; fur)s$ with increasing numbers of spatial features and hence increased realism. (*E*) Samples drawn from a generative model for closed curves (Zhu 1999) learned from spatial features.

in the horizontal, ΔL_1, ΔL_3, and vertical, ΔL_2, ΔL_4, directions must satisfy the constraint $\Delta L_2 + \Delta L_3 = \Delta L_1 + \Delta L_4$ (this is related to the surface integrability condition that must be imposed on the surface normals of an object to ensure that the surface is consistent).

It is important to realize that strong generative models can be learned from measurements of the statistics of feature responses (discussed more in Theoretical and Computational Advances, below). Work by Zhu, Wu, and Mumford (Zhu et al. 1997, Zhu 1999) shows how statistics on image, or shape, features can be used to obtain strong generative models. Samples from these models are shown in Figure 5*D*,*E*.

Basic Bayes: The Trade-Off Between Feature Reliability and Priors

The objective ambiguity of images arises if several different objects could have produced the same image description or image features. In this case, the visual system is forced to guess, but it can make intelligent guesses by biasing its guesses toward typical objects or interpretations (Sinha & Adelson 1993, Mamassian & Goutcher 2001, Weiss et al. 2002) (see Figure 4*A*). Bayes formula implies that these guesses, and hence perception, are a trade-off between image feature reliability, as embodied by the likelihood $p(I|S)$ and the prior probability $p(S)$. Some perceptions may be more prior driven, and others more data driven. The less reliable the image features (e.g., the more ambiguous), the more the perception is influenced by the prior. This trade-off has been illustrated for a variety of visual phenomena (Bülthoff & Yuille 1991, Mamassian & Landy 2001).

In particular, Weiss et al. (2002) addressed the aperture problem of motion perception: How to combine locally ambiguous motion measurements into a single global velocity for an object. The authors constructed a Bayesian model whose prior is that motions tend to be slow and which integrates local measurements according to their reliabilities (see Yuille & Grzywacz 1988 for the same prior applied to other motion stimuli). With this model (using a single free parameter), the authors showed that a wide range of motion results in human perception could be accounted for in terms of the trade-off between the prior and the likelihood. The Bayesian models give a simple unified explanation for phenomena that had previously been used to argue for a bag of tricks theory requiring many different mechanisms (Ramachandran 1985).

PRIOR REGULARITIES $p(S)$: OBJECT SHAPE, MATERIAL, AND LIGHTING Psychophysics can test hypotheses regarding built-in visual knowledge of the prior $p(S)$ independent of projection and rendering. This can be done at a qualitative or quantitative level.

Geometry and shape Some prior regularities refer to the geometry of objects that humans interact with. For instance, the perception of a solid shape is consistently biased toward convexity rather than concavity (Kanizsa & Gerbino 1976, Hill & Bruce 1993, Mamassian & Landy 1998, Bertamini 2001, Langer & Bülthoff 2001). This convexity prior is robust over a range of object shapes, sizes, and tasks.

More specific tests and ideal observer models will necessitate developing probability models for the high-dimensional spaces of realistic objects. Some of the most highly developed work is on human facial surfaces (cf. Vetter & Troje 1997). Relating image intensity to such measured surface depth statistics has yielded computer vision solutions for face recognition (Atick et al. 1996) and has provided objective prior models for face recognition experiments, suggesting that human vision may represent facial characteristics along principal component dimensions in an opponent fashion (Leopold et al. 2001).

Material The classical problems of color and lightness constancy are directly tied to the nature of the materials of objects and environmental lighting. However, most past work has implicitly or explicitly assumed a special case: that surfaces are Lambertian (matte). Here, the computer graphics communities have been instrumental in going beyond the Lambertian model by measuring and characterizing the reflectivities of natural smooth homogeneous surfaces in terms of the bidirectional reflectance distribution function (BRDF) (cf. Marschner et al. 2000), with important extensions to more complicated textured surfaces (Dana et al. 1999), including human skin (Jensen et al. 2001). Real images are, of course, intimately tied to the structure of illumination, and below we review psychophysical results on realistic material perception.

Lighting Studies of human object perception (as well as computer vision) have traditionally assumed simple lighting models, such as a single-point light source with a directionally nonspecific ambient term. One of the best-known examples of a prior is the assumption that light is coming from above. This assumption is particularly useful to disambiguate convex from concave shapes from shading information. The light from above prior is natural when one considers that the sun and most artificial light sources are located above our heads. However, two different studies have now shown that humans prefer the light source to be located above-left rather than straight above (Sun & Perona 1998, Mamassian & Goutcher 2001). A convincing explanation for this leftward bias remains to be advanced.

Apparent motion in depth of an object is strongly influenced by the movement of its cast shadow (Kersten et al. 1997, Mamassian et al. 1998). This result can be interpreted in terms of a stationary light source prior—the visual system is more likely to interpret change in the image as being due to a movement of the object or a change in viewpoint, rather than a movement of the light source.

Do we need more complex lighting models? The answer is surely yes, especially in the context of recent results on the perception of specular surfaces (Fleming et al. 2003) and color given indirect lighting (Bloj et al. 1999), both discussed in Discounting and Task Dependence (below). Dror et al. (2001) have shown that

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spatial maps of natural illumination (Debevec 1998) show statistical regularities similar to those found in natural images (cf. Simoncelli et al. 2001).

IMAGE REGULARITIES $p(I) = \sum_S p(I|S)p(S)$ Image regularities arise from the similarity between natural scenes. They cover geometric properties, such as the statistics of edges, and photometric properties, such as the distribution of contrast as a function of spatial frequency in the image.

Geometric regularities Geisler et al. (2001) used spatial filtering to extract local edge fragments from natural images. They measured statistics on the distance between the element centers, the orientation difference between the elements, and the direction of the second element relative to the orientation of first (reference) element. A model derived from the measured statistics and from a simple rule that integrated local contours together could quantitatively predict human contour detection performance. More detailed rules to perceptually organize a chain of dot elements into a subjective curve with a corner or not, or to be split into one versus two groups, have also been given a Bayesian interpretation (Feldman 2001).

Elder & Goldberg (2002) measured statistics of contours from images hand segmented into sets of local tangents. These statistics were used to put probability distributions on three Gestalt principles of perceptual organization: proximity, continuation, and luminance similarity. The authors found that these three grouping cues were independent and that the proximity cue was by far the most powerful. Moreover, the contour likelihood distribution (the probability of a gap length between two tangents of a contour) follows a power law with an exponent very close to that determined psychophysically on dot lattice experiments.

The work of Geisler et al. deals with distributions on image features, namely edge pairs. To devise a distribution $p(I)$ from which one can draw true contour samples, one needs to also take into account the consistency condition that edge pairs have to lie in an image (see Figure 5*A* for an airplane analogy). Zhu (1999) describes a procedure that learns a distribution on the image itself, and thus samples drawn from it produce contours (see Figure 5*E*; Elder & Goldberg 2002).

Photometric regularities It is now well established that natural scenes have a particular signature in their contrast spatial frequency spectrum in which low spatial frequencies are over-represented relative to high spatial frequencies. This regularity is characterized by a $1/f^{\beta}$ spectrum, where f is spatial frequency and β is a parameter that can be fit from image measurements (Field 1987, Simoncelli & Olshausen 2001). Human observers are better at discriminating changes in β for Gaussian and natural images when the values of β are near (Knill et al. 1990) or at the value measured from natural images (Parraga et al. 2000), suggesting that the visual system is in some sense tuned to the second-order statistics (i.e., spatial frequency spectrum) of natural images.

The histograms of spatial filter responses (e.g., the simplest filter being differences between neighboring pixel intensities) of natural images also show consistent regularities (Olshausen & Field 2000, Simoncelli & Olshausen 2001). The histograms are non-Gaussian, having a high kurtosis (see first panel in Figure 5*C*). Zhu & Mumford (1997) have derived a strong generative model they call a generic image prior based on filter histogram statistics.

IMAGE LIKELIHOOD $p(I|S)$ The likelihood characterizes how image regularities result from projection and rendering of objects as a function of view and lighting, and it is related to what is sometimes called the forward optics or computer graphics problem.

Geometrical descriptions Object perception shows biases consistent with preferred views. Mamassian & Landy (1998) show how the interpretation of a simple line drawing figure changed with rotations of the figure about the line of sight. They modeled their result with a simple Bayesian model that had a prior probability for surface normals pointing upward (Figure 2). This prior can be interpreted as a preference for a viewpoint situated above the scene, which is reasonable when we consider that most of the objects we interact with are below the line of sight.

Why does a vertical line appear longer than the same line when horizontal? Although there have been a number of recent studies of the statistics of image intensities and contours, Howe & Purves (2002) directly compare statistics on the separation between two points in the image with measurements of the causes in the originating 3-D scene. The authors found that the average ratio of the 3-D physical interval to the projected image interval from real-world measurements shows the same pattern as perceived length.

Photometric descriptions The global spatial frequency amplitude spectrum is an inadequate statistic to capture the structure of specific texture classes. Recent work has shown that wavelet representations provide richer models for category-specific modeling of spatially homogeneous texture regions, such as text, fur, grass, etc. (Portilla & Simoncelli 2000, Zhu et al. 1997). As with the contour case, a future challenge is to develop strong generative models from which one can draw samples of images from $p(I|S)$ (Theoretical and Computational Advances, below). Promising work along these lines is illustrated in Figure 5*D* (Zhu et al. 1997).

WHERE DO THE PRIORS COME FROM? Without direct input, how does image-independent knowledge of the world get built into the visual system? One pat answer is that the priors are in the genes. Observations of stereotyped periods in the development of human depth perception do in fact suggest a genetic component (Yonas 2003). In another domain, the strikingly rapid development of object concepts in children is still a major mystery that suggests predispositions to certain kinds of grouping rules. Adults, too, are quick to accurately generalize from a relatively small set of positive examples (in many domains, including objects) to a whole category. Tenenbaum (2000; Tenenbaum & Xu 2000, Tenenbaum &

Griffiths 2001) provides a Bayesian synthesis of two theories of generalization (similarity-like and rule-like) and provides a computational framework that helps to explain rapid category generalization.

The accurate segmentation of objects such as the kayaks in Figure 1 likely requires high-level prior knowledge regarding the nature of the forms of possible object classes. Certain kinds of priors, such as learning the shapes of specific objects, may develop through what Brady & Kersten (2003) have called opportunistic learning and bootstrapped learning. In opportunistic learning, the visual system seizes the opportunity to learn object structure during those relatively rare occasions when an object is seen under conditions of low ambiguity, such as when motion breaks camouflage of an object in plain view. Bootstrapped learning operates under intermediate or high conditions of ambiguity (e.g., in which none of the training images provide a clear view of an object's boundaries). Then later, the visual system can apply the prior knowledge gained to high (objective) ambiguity situations more typical of everyday vision. The mechanisms of bootstrapped learning are not well understood, although there has been some computer vision work (Weber et al. 2000) (see Theoretical and Computational Advances, below).

General purpose cortical learning mechanisms have been proposed (Dayan et al. 1995, Hinton & Ghahramani 1997); however, it is not clear whether these are workable with complex natural image input. We discuss computer vision methods for learning priors in Theoretical and Computational Advances (below).

Discounting and Task Dependence

How does the visual system enable us to infer the same object despite considerable image variation owing to confounding variables such as viewpoint, illumination, occlusion, and background changes? This is the well-known problem of invariance or object constancy. Objective ambiguity results when variations in a scene property change the image description of an object. As we have seen, both viewpoint and 3-D shape influence the 2-D image.

Suppose the visual task is to determine object shape, but the presence of unknown variables (e.g., viewpoint) confounds the inference. Confounding variables are analogous to noise in classical signal detection theory, but they are more complicated to model and they affect image formation in a highly nonlinear manner. For example, a standard noise model has $I = S + n$, where n is Gaussian noise. Realistic vision noise is better captured by $p(I|S)$, as illustrated in Figure 6*B*. Here, the problem is making a good guess independent of (or invariant to) the true value of the confounding variable. The task itself can serve to reduce ambiguity by discounting the confounding variable (Freeman 1994, Kersten 1999, Schrater & Kersten 2000, Geisler & Kersten 2002). Discounting irrelevant scene variations (or accounting for object invariance) has received recent attention in the functional madnetic resonance imaging (fMRI) literature, where certain cortical areas show more or less degrees of invariance to size, translation, rotation in depth, or illumination (cf. Grill-Spector et al. 2003).

From the Bayesian perspective, we can model problems with confounding variables by the graph in Figure 4*B*. We define an ensemble distribution $p(S_1, S_2, I)$, where S_1 is the target (e.g., keys), S_2 is the confounding variable (e.g., pose), and I is the image. Then we discount the confounding variables by integrating them out (or summing over them),

$$p(S_1, I) = \sum_{S_2} p(S_1, S_2, I)$$

This is equivalent to spreading out the loss function completely in one of the directions (e.g., extending the utility function vertically in Figure 2*E*). As noted above, the choice of which variables to discount will depend on the task. Viewpoint is a confounding variable that can be discounted if the task is to discriminate objects independent of viewpoint. Illumination is a confounding variable if the task is to recognize or determine the depth of an object, but it is not if the task is to determine the light-source direction. This can be related to notions of utility[4]; discounting a variable is equivalent to treating it as having such low utility that it is not worth estimating (Yuille & Bülthoff 1996) (see Theoretical and Computational Advances, below).

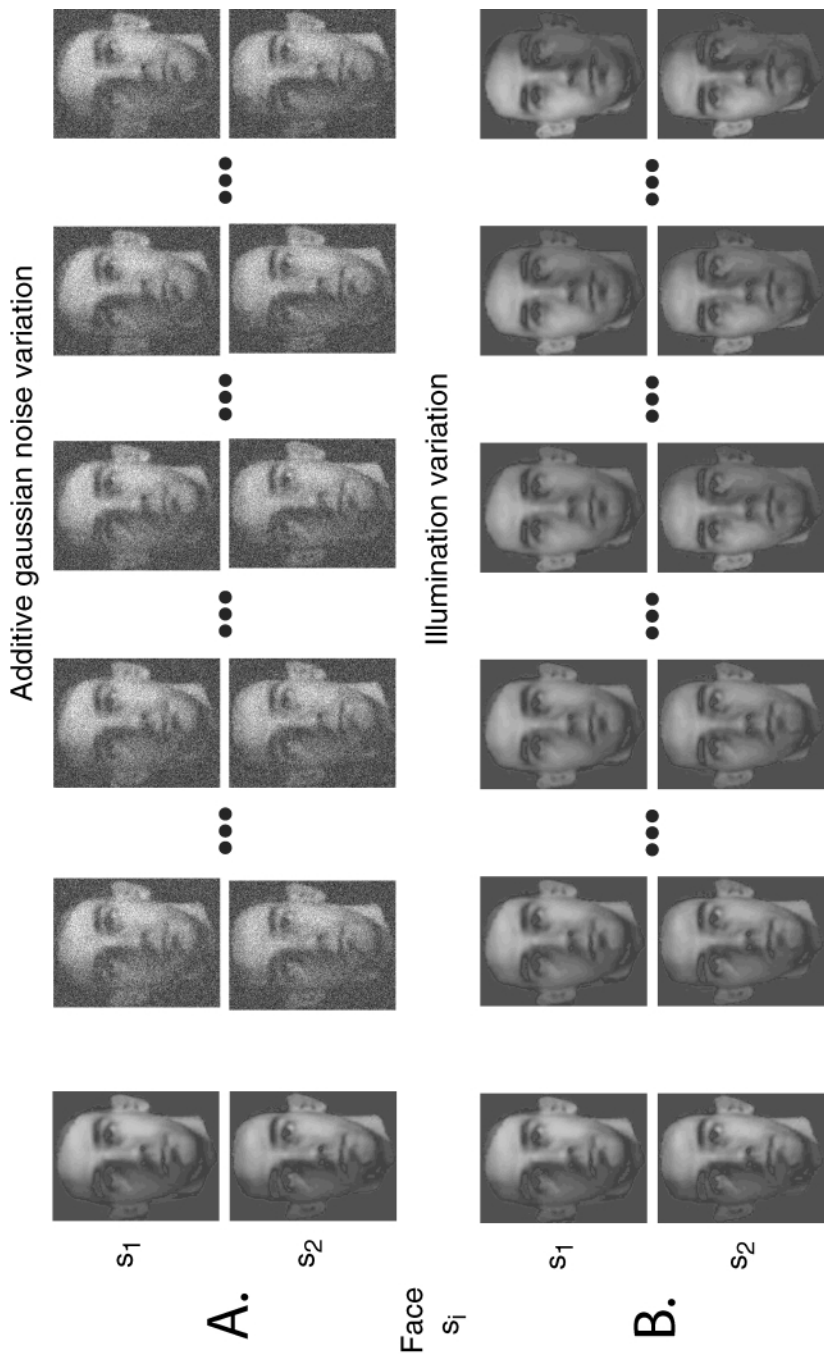
Viewpoint variation When interpreting 2-D projections of 3-D shapes, the human visual system favors interpretations that assume that the object is being viewed from a general (or generic), rather than accidental, viewpoint (Nakayama & Shimojo 1992, Albert 2000). Freeman (1994) showed that a Bayesian observer that integrates out viewpoint can account for the generic view assumption.

How does human vision recognize 3-D objects as the same despite changes in viewpoint? Shape-based object recognition models range between two extremes—those that predict a strong dependence of recognition performance on viewpoint (e.g., as a function of familiarity with particular views) and those that, as a result

[4]Bayesian decision theory (see Theoretical and Computational Advances, below) provides a precise language to model the costs of errors determined by the choice of visual task (Yuille & Bülthoff 1996). The cost or risk $R(\alpha; I)$ of guessing α when the image measurement is I is defined as the expected loss (or negative utility):

$$R(\alpha; I) = \sum_{S} L(\alpha, S) p(S|I),$$

with respect to the posterior probability, $p(S|I)$. The best interpretation of the image can then be made by finding the α that minimizes the risk function. The loss function $L(\alpha, S)$ specifies the cost of guessing α when the scene variable is S. One possible loss function is $-\delta(\alpha - S)$. In this case, the risk becomes $R(\alpha; I) = -p(\alpha|I)$, and then the best strategy is to pick the most likely interpretation. This is MAP estimation and is the optimal strategy for the task requiring an observer to maximize the proportion of correct decisions. A second kind of loss function assumes that costs are constant over all guesses of a variable. This is equivalent to integrating out, summing over, or marginalization of the posterior with respect to that variable.


A.
B.
Face
s_i
s_1
s_2
s_1
s_2
Additive gaussian noise variation
Illumination variation

of using view-invariant features together with structural descriptions of objects, do not (Poggio & Edelman 1990, Ullman & Basri 1991, Tarr & Bülthoff 1995, Ullman 1996, Biederman 2000, Riesenhuber & Poggio 2002). By comparing human performance to several types of ideal observers that integrate out viewpoint variations, Liu et al. (1995) showed that models that allow rigid rotations in the image plane of independent 2-D templates could not account for human performance in discriminating novel object views. More recent work by Liu & Kersten (1998) showed that the performance of human observers relative to Bayesian affine models (which allow stretching, translations, rotations, and shears in the image) is better for the novel views than for the template views, suggesting that humans have a better means to generalize to novel views than could be accomplished with affine warps. Other related work describes the role of structural knowledge (Liu et al. 1999), the importance of view-frequency (Troje & Kersten 1999), and shape constancy under perspective (Pizlo 1994).

Bayesian task dependence may account for studies where different operationalizations for measuring perceived depth lead to inconsistent, though related, estimates. For instance, the information provided by a single image of an object is insufficient for an observer to infer a unique shape (see Figure 1*B*). Not surprisingly, these ambiguities will lead different observers to report different depth percepts for the same picture, and the same observer to report different percepts when using different depth probes. Koenderink et al. (2001) show that most of this variability could be accounted for by affine transformations of the perceived depth, in particular, scalings and shears. These affine transformations correspond to looking at the picture from a different viewpoint. The authors call the perceived depth of a surface once the viewpoint has been discounted pictorial relief.

Figure 6 Traditional visual noise versus illumination variation. Example of face recognition given confounding variables. The first row and second rows of the top and bottom panels show images of faces s_1 and s_2, respectively. (*A*) Face recognition is confounded by additive Gaussian contrast noise. Bayesian ideal discriminators for this task are well understood. However, the Gaussian assumption leads to a least squares metric for measuring the similarities between faces. But the similarity between two images of the same face under different lighting can be bigger than the least squares distance between two faces. (*B*) Face recognition is confounded by illumination variation. This type of uncertainty is more typical of the type of variation encountered during natural visual tasks. The human visual system seems competent at discounting illumination, but Bayesian theories for general illumination variation are more difficult to formulate (cf. Yuille et al. 2001). The columns show different illumination conditions of the two faces. Light direction gradually varies from right (*left-most column*) to left (*right-most column*). In this example, illumination changes are relatively large compared to the illumination-invariant features corresponding to facial identity. The illumination direction changes are ordered for clarity. In actual samples, the illumination direction may not be predictable.

Illumination variation Discounting illumination by integrating it out can reduce ambiguity regarding the shape or depth of an object (Freeman 1994, Yuille et al. 2003, Kersten 1999). Integrating out illumination level or direction has also been used to account for apparent surface color (Brainard & Freeman 1997, Bloj et al. 1999).

Work so far has been for extremely simple lighting, such as a single-point light source. One of the future challenges will be to understand how the visual system discounts the large spatial variations in natural illumination that are particularly apparent in many surfaces typically encountered, such as metal, plastic, and paper (see Figure 1*C*). Fleming et al. (2003) showed that human observers could match surface reflectance properties more reliably and accurately for more realistic patterns of illumination. They manipulated pixel and wavelet properties of illumination patterns to show that the visual system's built-in assumptions about illumination are of intermediate complexity (e.g., presence of edges and bright light sources) rather than depending on high-level knowledge, such as recognizable objects.

Integration of Image Measurements and Cues

The visual system likely achieves much of its inferential power through sophisticated integration of ambiguous local features. This can be modeled from a Bayesian perspective (Clark & Yuille 1990). For example, a depth discontinuity typically causes more than one type of cue (stereo disparity and motion parallax), and visual inference can exploit this to improve the reliability and accuracy of the depth estimate. Given two conflicting cues to depth, the visual system might get by with a simple averaging of each estimate, even though inaccurate. Or in cases of substantial conflict, it may determine that one measurement is an outlier and should not be integrated with the other measurement (Landy et al. 1995, Bülthoff & Mallot 1988). Ruling out outliers is possible within a single modality (e.g., when integrating disparity and texture gradients in vision) but may not be possible between modalities (e.g., between vision and touch) because in the latter case, single cue information appears to be preserved (Hillis et al. 2002). The visual system is often more sophisticated and combines image measurements weighted according to their reliability (Jacobs 2002, Weiss et al. 2002), which we discuss next.

Figure 4*C* illustrates the influence graph for cue integration with an example of illumination direction estimation. From a Bayes net perspective, the two cues are conditionally independent given the shared explanation. An important case is when the nodes represent Gaussian variables that are independent when conditioned on the common cause and we have estimates for each cue alone (i.e., $\hat{S}_i$ is the best estimate of S_i from $p(S|I_i)$). Then optimal integration (i.e., the most probable value) of the two estimates takes into account the uncertainty owing to measurement noise (the variance) and is given by the weighted average,

$$\hat{S} = \hat{S}_1 \frac{r_1}{r_1 + r_2} + \hat{S}_2 \frac{r_2}{r_1 + r_2},$$

where r_i, the reliability, is the reciprocal of the variance. This model has been used to study whether the human visual system combines cues optimally (cf. Jacobs 2002 for a review and a discussion of integration in the context of Kalman filtering, which is a special case of Bayesian estimation).

For instance, visual and haptic information about object size are combined and weighted according to the reliability of the source (Ernst & Banks 2002, Gepshtein & Banks 2003). Object size can be perceived both visually and by touch. When the information from vision and touch disagree, vision usually dominates. The authors showed that when one takes into account the reliability of the sensory measurements, information from vision and touch are integrated optimally. Visual dominance occurs when the reliability of the visual estimation is greater than that of the haptic one.

Integration is also important for grouping local image elements likely to belong to the same surface. The human visual system combines spatial frequency and orientation information optimally when detecting the boundary between two regions (Landy & Kojima 2001). Human observers also behave like an optimal observer when integrating information from skew-symmetry and disparity in perceiving the orientation of a planar object (Saunders & Knill 2001). The projection of a symmetric flat object has a distorted or skewed symmetry that provides partial information about the object's orientation in depth. Saunders & Knill show that human observers integrate symmetry information with stereo information weighted according to the reliability of the source.

Prior probabilities can also combine like-weighted cues. We discussed above that human observers interpret the shape of an object assuming that both the viewpoint and the light source are above the object (Mamassian et al. 1998, Mamassian & Goutcher 2001). Mamassian & Landy (2001) manipulated the reliability of each of the two constraints by changing the contrast of different parts of the stimuli. For instance, increasing the shading contrast increased the reliability of the light-source prior and biased the observers' percept toward the shape most consistent with the light-source prior alone. Their interpretation of the results was that observers modulated the strength of their priors based on the stimulus contrast. As a consequence, prior constraints behaved just like depth cue integration: Cues with more reliable information have higher weight attributed to their corresponding prior constraint.

Not all kinds of cue integrating are consistent with the simple graph of Figure 4*C*. Yuille & Bülthoff (1996) have argued that strong coupling of visual cues (Clark & Yuille 1990) is required to model a range of visual phenomena (Bülthoff & Mallot 1988). The graph for explaining away (Figure 4*D*) provides one useful simple extension to the graphs discussed so far, and we discuss this next.

Perceptual Explaining Away

The key idea behind explaining away is that two alternative perceptual hypotheses can compete to explain the image. From a Bayesian perspective, the competition

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results from the two (otherwise independent) hypotheses becoming conditionally dependent given the image.

Pearl (1988) was one of the first to emphasize that, in contrast to traditional artificial intelligence expert systems, human reasoning is particularly good at explaining away the effects of alternative hypotheses. In a now classic example, imagine that you emerge from your house in the morning and notice that the grass is wet. Prior probabilities might tell you that it was unlikely due to rain (e.g., you live in Los Angeles), and thus you have probably left the sprinkler on overnight. But then you check the neighbor's lawn and notice that it too is wet. This auxiliary piece of evidence now undercuts the earlier explanation and lowers the probability that you left the sprinkler on. The more probable explanation is that it rained last night, explaining why both lawns are wet. Both the sprinkler and the rain hypothesis directly influence the observation "your lawn is wet," but only the rain hypothesis affects both lawns' being wet.

Human perception is also good at explaining away, but automatically and without conscious thought[5]. In perception, the essential idea is that if two (or more) hypotheses about an object property can explain the same image measurements, then lowering the probability of one of the explanations increases the probability of the other. One can observe explaining away in both material (e.g., lightness and color) and shape perception.

Material In the Land & McCann (1971) version of the classic Craik-O'Brien Cornsweet illusion, two abutting regions that have the same gradual change of luminance appear to have different reflectances. Knill & Kersten (1991) found that the illusion is weakened when a curved occluding contour (auxiliary evidence) bounding the regions above and below suggests that the variation of luminance is due to a change in surface orientation (Figure 4*D*). The lightness gradients are explained away by the gradual surface curvature. Buckley et al. (1994) extended this result when binocular disparities were used to suggest a 3-D surface. These results indicate that some scene attributes (in this case surface curvature) influence the inference of the major scene attributes (material reflectance) that are set by the task.

Another study asked whether human vision could discount the effects of the color of indirect lighting (Bloj et al. 1999). Imagine a concave folded card consisting of a red half facing a white half. With white direct illumination, pinkish light radiates from the white card because of the indirect additional illumination from the red card. Does vision use shape knowledge to discount the red illuminant in order to perceive the true material color, which is white? A change in retinal disparities (an auxiliary measurement) can cause the concave card to appear as convex, without any change in the chromatic content of the stimulus. When the card appears convex, the white card appears more pinkish, as if perception has lost

[5]Some related perceptual phenomena Rock described as "perceptual interactions" (Rock 1983).

its original explanation for the pinkish tinge in the image and now attributes it to reddish pigment rather than reddish light.

Geometry and shape Explaining away occurs in discounting the effects of occlusion, and when simple high-level object descriptions overide more complex interpretations of line arrangements or moving dots (Lorenceau & Shiffrar 1992, McDermott et al. 2001, Murray et al. 2002). We describe this in more detail in Neural Implications (below).

Explaining away is closely related to previous work on competitive models, where two alternative models compete to explain the same data. It has been argued that this accounts for a range of visual phenomena (Yuille & Bülthoff 1996), including the estimation of material properties (Blake & Bülthoff 1990). This approach has been used successfully in computer vision systems by Tu & Zhu (2002), including recent work (Tu et al. 2003) in which a whole class of generative models, including faces, text, generic shading, and texture models compete and cooperate to explain the entire image (Theoretical and Computational Advances, below). In particular, the generic shading models help detect faces by explaining away shadows and glasses.

Failures to explain away Visual perception can also unexpectedly fail to explain away. In one simple demonstration, an ambiguous Mach folded card can be interpreted as a concave horizontal edge or a convex vertical edge. A shadow cast over the edge by an object (e.g., pencil) placed in front provides enough information to disambiguate the percept, and yet humans fail to use this information (Mamassian et al. 1998). There has yet to be a good explanation for this failure.

THEORETICAL AND COMPUTATIONAL ADVANCES

Psychophysical and neurophysiological studies of vision necessarily rely on simplifications of both stimuli and tasks. This simplification, however, must be extensible to the visual input experienced during natural perceptual functioning. In the previous sections, several psychophysical studies used models of natural image statistics, as well as models of prior object structure, such as shape. Future advances in understanding perception will increasingly depend on the efficient characterization (and simulation) of realistic images to identify informative image statistics, models of scene properties, and a theoretical understanding of inference for natural perceptual functions. In this section, we discuss relating Bayesian decision theory to current theories of machine learning, learning the probability distributions relevant for vision, and determining algorithms for Bayesian inference.

Bayes Decision Theory and Machine Learning

The Bayesian approach seems completely different from the type of feedforward models required to recognize objects in 150 ms (VanRullen & Thorpe 2001). How does the Bayesian approach relate to alternative models based on neural networks, radial basis functions, or other techniques?

This subsection shows the relationships using concepts from Bayes decision theory (Berger 1985, Yuille & Bülthoff 1996) and machine learning (Vapnik 1998, Evgeniou et al. 2000, Schölkopf & Smola 2002). This relationship also gives a justification for Bayes rule and the intuitions behind it.

We first introduce additional concepts from decision theory: (*a*) a decision rule $S^* = \alpha(I)$ and (*b*) a loss function (or negative utility) $L(\alpha(I), S)$, which is the penalty for making the decision $\alpha(I)$ when the true state is S (e.g., a fixed penalty for a misclassification). Suppose we have a set of examples $\{I_i, S_i : i = 1, \ldots, N\}$, then the empirical risk (Vapnik 1998, Schölkopf & Smola 2002) (e.g., the proportions of misclassifications) of the rule $\alpha(I)$ is defined to be

$$R_{emp}(\alpha) = (1/N) \sum_{i=1}^{N} L(\alpha(I_i), S_i). \tag{1}$$

The best decision rule $\alpha^*(.)$ is selected to minimize $R_{emp}(\alpha)$. For example, the decision rule is chosen to minimize the number of misclassifications. Neural networks and machine learning models select rules to minimize $R_{emp}(\alpha)$ (Vapnik 1998, Evgeniou et al. 2000, Schölkopf & Smola 2002).

Now suppose that the samples $\{S_i, I_i\}$ come from a distribution $p(S, I)$ over the set of problem instances. Then, if we have a sufficient number of samples[6], we can replace the empirical risk by the true risk:

$$R(\alpha) = \sum_I \sum_S L(\alpha(I), S) p(S, I). \tag{2}$$

Minimizing $R(\alpha)$ leads to a decision rule that depends on the posterior distribution $p(S|I)$ obtained by Bayes rule $p(S|I) = p(I|S)p(S)/p(I)$. To see this, we rewrite Equation 2 as $R(\alpha) = \sum_I p(I)\{\sum_S p(S|I)L(\alpha(I), S)\}$, where we have expressed $p(S, I) = p(S|I)p(I)$. So the best decision $\alpha(I)$ for a specify image I is given by

$$\alpha^*(I) = \arg\min_{\alpha} \sum_S p(S|I) L(\alpha(I), S), \tag{3}$$

and depends on the posterior distribution $p(S|I)$. Hence, Bayes arises naturally when you start from the risk function specified by Equation 2.

There are two points to be made here. First, the use of the Bayes posterior $p(S|I)$ follows logically from trying to minimize the number of misclassifications in the empirical risk (provided there are a sufficient number of samples). Second, it is possible to have an algorithm, or a network, that computes $\alpha(.)$ and minimizes the Bayes risk but that does not explicitly represent the probability distributions $p(I|S)$ and $p(S)$. For example, Liu et al. (1995) compared the performance of

[6]The number of samples required is a complicated issue (Vapnik 1998, Schölkopf & Smola 2002).

ideal observers for object recognition with networks using radial basis functions (Poggio & Girosi 1990). It is possible that the radial basis networks, given sufficient examples and having sufficient degrees of freedom, are effectively doing Bayesian inference.

Learning Probability Distributions

Recent studies show considerable statistical regularities in natural images and scene properties that help tame the problems of complexity and ambiguity in ways that can be exploited by biological and artificial visual systems. The theoretical difficulties of the Bayesian approach reduce to two issues. First, can we learn the probability distributions $p(I|S)$ and $p(S)$ from real data? Second, can we find algorithms that can compute the best estimators $\alpha^*(.)$? We briefly review the advances in learning distributions $p(I|S)$, $p(S)$, $p(I)$, $p(S|I)$, and decision rules $\alpha(I)$.

The Minimax Entropy theory (Zhu et al. 1997) gives a method for learning probability models for textures $p(I|S)$, where S labels the texture (e.g., cheetah fur). These models are realistic in the sense that stochastic samples from the models appear visually similar to the texture examples that the models were trained on (see Figure 5*D*). Learning these models is, in principle, similar to determining the mean and variance of a Gaussian distribution from empirical samples (e.g., setting the mean of the Gaussian to be the average of the samples from the Gaussian). The inputs to Minimax Entropy learning are the same histograms of filter responses that other authors have shown as useful for describing textures (Portilla & Simoncelli 2000). The distributions learned by Minimax Entropy are typically non-Gaussian, but lie in a more general class of distributions called exponential models. More advanced models of this type can learn distributions with parameters representing hidden states (Weber et al. 2000).

For certain problems it is also possible to learn the posterior distribution $p(S|I)$ directly, which relates to directly learning a classifier $\alpha(I)$. For example, the AdaBoost learning algorithm (Freund & Schapire 1999) has been applied very successfully to build a decision rule $\alpha(I)$ for classfiying between faces (seen from front-on) and nonfaces (Viola & Jones 2001). But the AdaBoost theory shows that the algorithm can also learn the posterior distributions $p(\mathit{face}|I)$ and $p(\mathit{non\,face}|I)$ (Hastie et al. 2001, Tu et al. 2003). Other workers have learned posterior probabilities $p(\mathit{edge}|\phi(I))$ and $p(\mathit{not\text{-}edge}|\phi(I))$, where $\phi(I)$ are local image features (Konishi et al. 2003). Similarly, Oliva and colleagues have learned a decision rule $\alpha(I)$ to determine the type of scene (urban, mountain, etc.) from feature measurements (Oliva & Schyns 2000, Oliva & Torralba 2001). Fine & Macleod (2003) used the statistics of the spatio-chromatic structure of natural scenes to segment natural images into regions likely to be part of the same surface. They computed the probability of whether or not two points within an image fall on the same surface given measurements of luminance and color differences.

Visual Inference

It is necessary to have algorithms to perform Bayesian inference after the probability distributions have been learned. The complexity of vision makes it very unlikely that we can directly learn a classifier $\alpha(I)$ to solve all visual tasks. (The brain may be able to do this but we don't know how to). Recently, however, there has been some promising new algorithms for Bayesian inference. Particle filters have been shown to be very useful for tracking objects over time (Isard & Blake 1998). Message passing algorithms, such as belief propagation, have had some success (Freeman et al. 2000). Tu & Zhu (2002) have developed a general purpose algorithm for Bayesian inference known as the Data Driven Markov Chain Monte Carlo (DDMCMC). This algorithm has been very successful at segmenting images when evaluated on datasets with specified ground truth. It works, loosely speaking, by using low level cues to propose high-level models (scene descriptions), which are validated or rejected by generative models. It therefore combines bottom-up and top-down processing in a way suggestive of the feedforward and feedback pathways in the brain, described in the next section. The algorithm has been extended to combine segmentation with the detection and recognition of faces and text (Tu et al. 2003).

NEURAL IMPLICATIONS

What are the neural implications of Bayesian models? The graphical structure of these models often makes it straightforward to map them onto networks and suggests neural implementations. The notion of incorporating prior probabilities in visual inference is frequently associated with top-down biases on decisions. However, some prior probabilities are likely built into the feedforward processes through lateral connections. More dramatically, some types of inverse inference (e.g., to deal with ambiguities of occlusion, rotation in depth, or background clutter) may require an internal generative process that in some sense mirrors aspects of the external generative model used for inference (Grenander 1996, Mumford 1992, Rao & Ballard 1999, Tu & Zhu 2002a, Tu et al. 2003) or for learning (Dayan et al. 1995, Hinton & Ghahramani 1997). There is evidence that descending pathways in cortex may be involved in computations that implement model-based inference using bottom-up and top-down interactions of the sort suggested by the phenomena of perceptual explaining away. In the next two sections, we discuss Bayesian computations in networks with lateral connections and in larger-scale cortical models that combine bottom-up with top-down information.

Network Models with Lateral Connections

One class of Bayesian models can be implemented by parallel networks with local interactions. These include a temporal motion model (Burgi et al. 2000), which was designed to be consistent with neural mechanisms. In this model, the priors and likelihood functions are implemented by synaptic weights. Another promising approach is to model the lateral connections within area MT/V5 to account for the integration and segmentation of image motion (Koechlin et al. 1999).

Anatomical constraints will sometimes bias the processing of information in a way that can be interpreted in terms of prior constraints. For instance, the specific connections of binocular sensitive cells in primary visual cortex will dictate the way the visual system solves the correspondence problem for stereopsis. Some recent psychophysical work suggests that the connections between simple and complex binocular cells implement a preference for small disparities (Read 2002).

There are also proposed neural mechanisms for representing uncertainty in neural populations and thereby give a mechanism for weighted cue combination. The most plausible candidate is population encoding (Pouget et al. 2000, Oram et al. 1998, Sanger 1996).

Combining Bottom-Up and Top-Down Processing

There is a long history to theories of perception and cognition involving top-down feedback or analysis by synthesis (MacKay 1956). The generative aspect of Bayesian models is suggestive of the ascending and descending pathways that connect the visual areas in primates (Bullier 2001, Lamme & Roelfsema 2000, Lee & Mumford 2003, Zipser et al. 1996, Albright & Stoner 2002). The key Bayesian aspect is model-based fitting in which models need to compare their predictions to the image information represented earlier, such as in V1.

A possible role for higher-level visual areas may be to represent hypotheses regarding object properties, represented, for example, in the lateral occipital complex (Lerner et al. 2001, Grill-Spector et al. 2001), which could be used to resolve ambiguities in the incoming retinal image measurements represented in V1. These hypotheses could predict incoming data through feedback and be tested by computing a difference signal or residual at the earlier level (Mumford 1992, Rao & Ballard 1999). Thus, low activity at an early level would mean a good fit or explanation of the image measurements. Experimental support for this possibility comes from fMRI data (Murray et al. 2002, Humphrey et al. 1997). Earlier fMRI work by a number of groups has shown that the human lateral occipital complex (LOC) has increased activity during object perception. Murray et al. use fMRI to show that when local visual information is perceptually organized into whole objects, activity in human primary visual cortex (V1) decreases over the same period that activity in higher, lateral occipital areas (LOC) increases. The authors interpret the activity changes in terms of high-level hypotheses that compete to explain away the incoming sensory data.

There are two alternative theoretical possibilities for why early visual activity is reduced. High-level areas may explain away the image and cause the early areas to be completely suppressed—high-level areas tell lower levels to "shut up." Such a mechanism would be consistent with the high metabolic cost of neuronal spikes (Lennie 2003). Alternatively, high-level areas might sharpen the responses of the early areas by reducing activity that is inconsistent with the high level interpretation—high-level areas tell lower levels to "stop gossiping." The second possibility seems more consistent with some single-unit recording experiments (Lee et al. 2002). Lee et al. have shown that cells in V1 and V2 of macaque monkeys respond to the apparently high-level task of detecting stimuli that pop-out owing to shape-from-shading. These responses changed with the animal's behavioral adaptation to contingencies, suggesting dependence on experience and utility.

Lee & Mumford (2003) review a number of neurophysiological studies consistent with a model of the interactions between cortical areas based on particle filter methods, which are non-Gaussian extensions of Kalman filters that use Monte Carlo methods. Their model is consistent with the "stop gossiping" idea. In other work, Yu & Dayan (2002) raise the intriguing possibility that acetylcholine levels may be associated with the certainty of top-down information in visual inference.

Implementation of the Decision Rule

One critical component of the Bayesian model is the consideration of the utility (gain or negative loss in decision theory terminology) associated with each decision. Where and how is this utility encoded? Platt & Glimcher (1999) systematically varied the expectation and utility (juice reward) linked to an eye movement performed by a monkey. The activity of cells in one area of the parietal cortex was modulated by the expected reward and the probability that the eye movement will result in a reward. It will be interesting to see whether similar activity modulations occur within the ventral stream for object recognition decisions.

Gold & Shadlen (Gold & Shadlen 2001) propose neural computations that can account for categorical decisions about sensory stimuli (e.g., whether a field of random dots is moving one way or the other) by accumulating information over time represented by a single quantity representing the logarithm of the likelihood ratio favoring one alternative over another.

CONCLUSIONS

The Bayesian perspective yields a uniform framework for studying object perception. We have reviewed work that highlights several advantages of this perspective. First, Bayesian theories explicitly model uncertainty. This is important in accounting for how the visual system combines large amounts of objectively ambiguous information to yield percepts that are rarely ambiguous. Second, in the context of specific experiments, Bayesian theories are optimal, and thus define ideal observers. Ideal observers characterize visual information for a task and can thus be critical for interpreting psychophysical and neural results. Third, Bayesian methods allow the development of quantitative theories at the information processing level, avoiding premature commitment to specific neural mechanisms. This is closely

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related to the importance of extensibility in theories. Bayesian models provide for extensions to more complicated problems involving natural images and functional tasks as illustrated in recent advances in computer vision. Fourth, Bayesian theories emphasize the role of the generative model and thus tie naturally to the growing body of work on graphical models and Bayesian networks in other areas, such as language, speech, concepts, and reasoning. The generative models also suggest top-down feedback models of information processing in the cortex.

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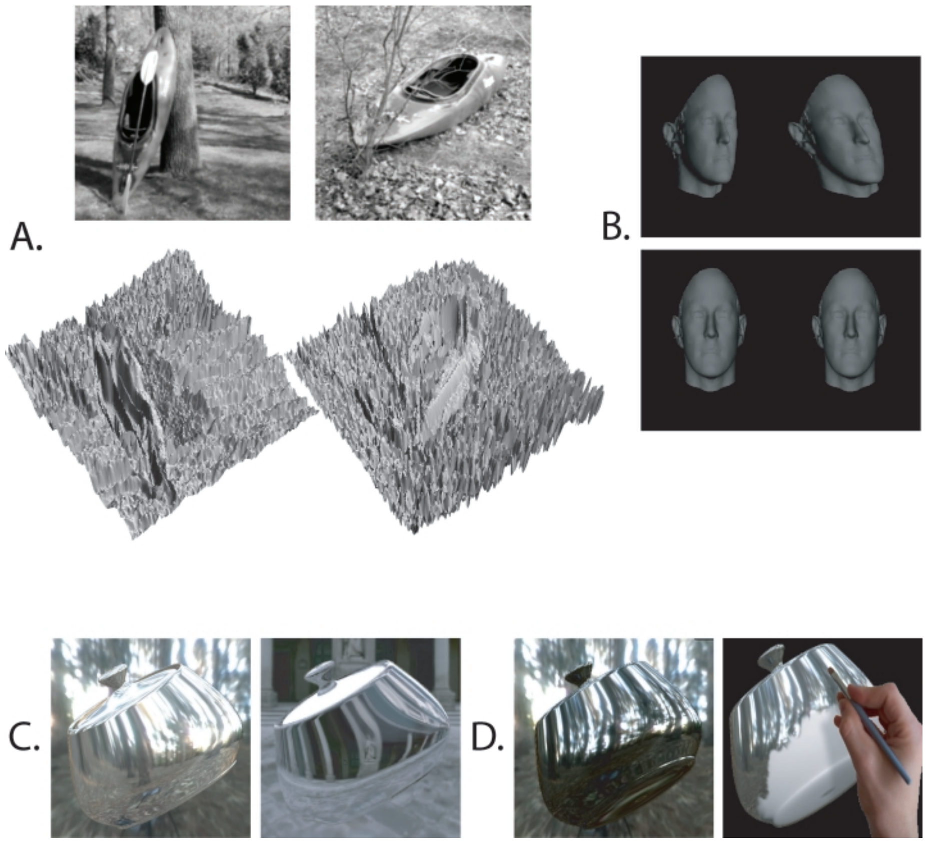

Figure 1 Visual complexity and ambiguity. (*A*). The same object, a kayak, can produce different images. The plots below the images show surface plots of the intensity as a function of position, illustrating the complex variations typical of natural image data that result from a change in view and environment. (*B*). Different shapes (three-quarter views of two different facial surfaces in the *top panel*) can produce the same image (frontal view of the two faces in the *bottom panel*) with an appropriate change of illumination direction. (*C*). The same material can produce different images. A shiny silver pot reflects completely different patterns depending on its illumination environment. (*D*). Different materials can produce the same images. The image of a silver pot could be the result of paint (*rightmost panel*). The silver pot renderings were produced by Bruce Hartung using illumination maps made available at: http://www.debevec.org/Probes/ (Debevec 1998).

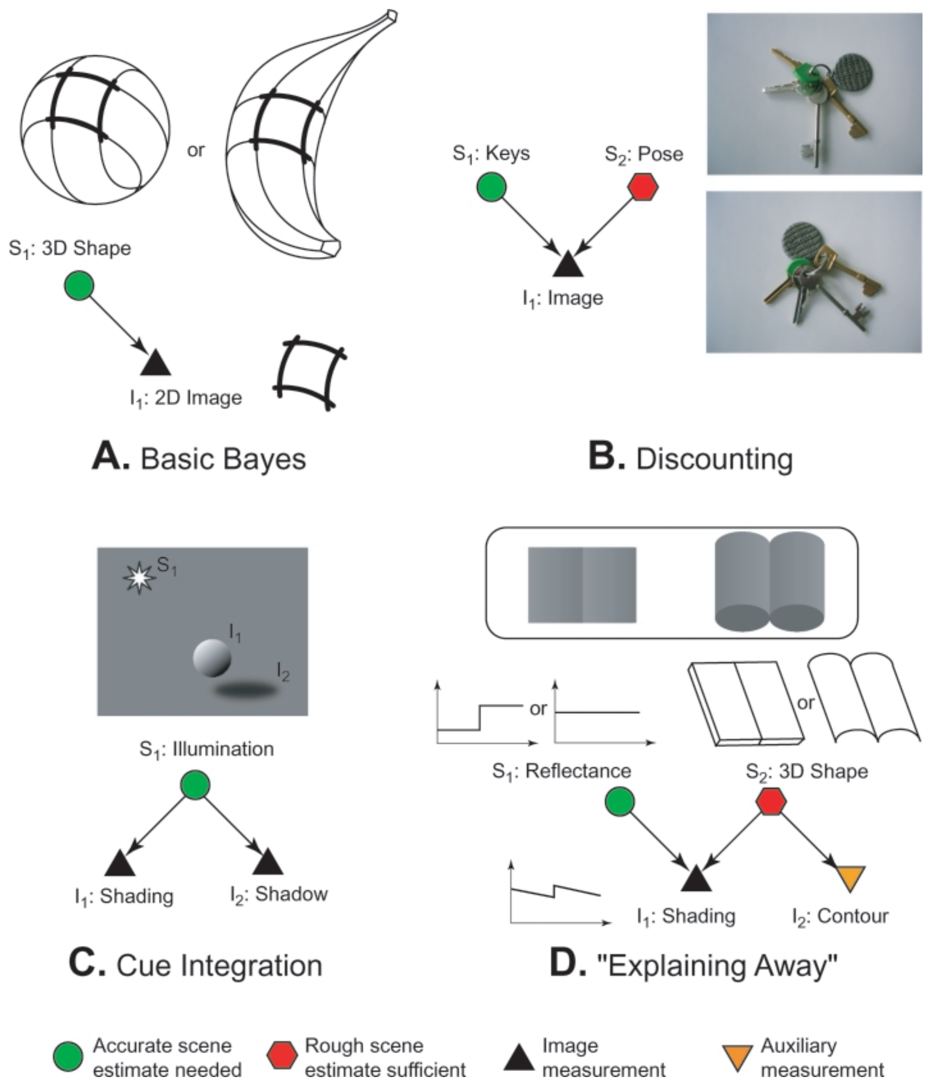

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Figure 4 Four simple categories of influence graphs. (*A*) Basic Bayes. The four curved line segments are consistent with a spherical and saddle-shaped surface patch (and an infinite family of other 3-D interpretations). Human observers prefer the convex spherical interpretation (Mamassian & Landy 1998). (*B*) Discounting. A given object or object class can give rise to an infinite variety of images because of variations introduced by confounding variables, such as pose, viewpoint, illumination, and background clutter. Robust object recognition requires some degree of object invariance or constancy requiring vision to discount confounding variables, such as pose, illustrated here. There is a one-to-one relationship between graph structure and factorizing the joint probability. If I_i and S_j indicate the i^{th} image and j^{th} object variables, respectively, then $p(\ldots, S_j, \ldots, I_i, \ldots)$ is the joint probability. For this graph, $p(S_1, S_2, I) = p(I|S_1, S_2)p(S_1)p(S_2)$. (*C*) Cue integration. A single cause in a scene can give rise to more than one effect in the image. Illumination position affects both the shading on the ball and the relationship between the ball and shadow positions in the image. Both kinds of image measurement can, in principle, be combined to yield a more reliable estimate of illumination direction than either alone, and it is an empirical question to find out if human vision combines such cues, and if so, how optimally. For this graph, $p(S_1, I_1, I_2) = p(I_1|S_1)p(I_2|S_1)p(S_1)$. (*D*) Explaining away. An image measurement (ambiguous horizontal shading gradients) can be caused by a change in reflectance or a change in 3-D shape. A change in the probability of one of them being the true cause of the shading (from an auxiliary contour measurement) can change the probability of the putative cause (from different to same apparent reflectance). For this graph, $p(S_1, S_2, I_1, I_2) = p(I_2|S_2)p(I_1|S_1, S_2)p(S_1)p(S_2)$.