Conf-9408207--1

LA-UR- 94-4385

Title: The Hard Truth (U)

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Submitted to: Workshop on Maximum Entropy and Bayesian Methods

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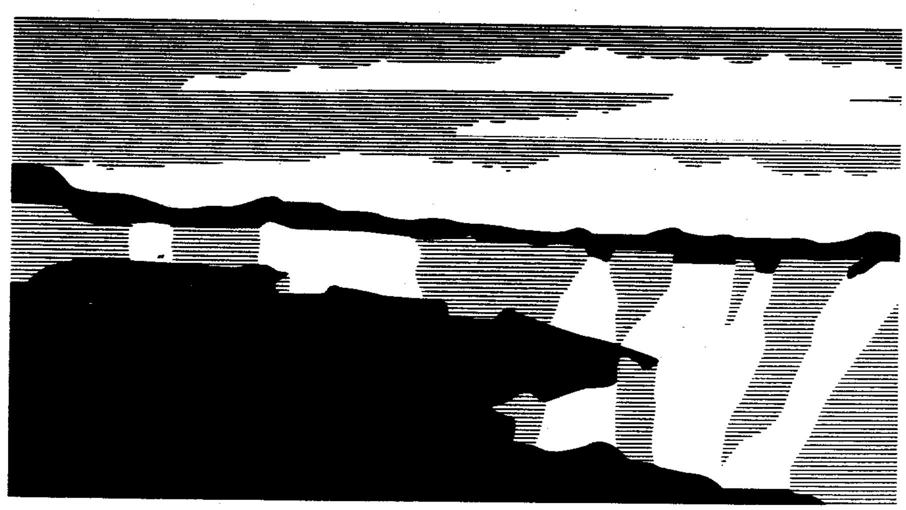

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THE HARD TRUTH

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ABSTRACT. In the Bayesian methodology, the posterior probability combines uncertainty about prior knowledge, and available data about alternative models of reality. The posterior quantifies the degree of certainty one has in inferring the truth in terms of those models. We propose a method to determine the reliability of a specific feature of a Bayesian solution. Our approach is based on an analogy between the negative logarithm of the posterior and a physical potential. This analogy leads to the interpretation of gradient of this potential as a force that acts on the model. As model parameters are perturbed from their maximum a posteriori (MAP) values, the strength of the restoring force that drives them back to the MAP solution is directly related to the reliability of those parameter estimates. The correlations between the uncertainties of parameter estimates can be elucidated.

1. Introduction

Bayesian analysis provides the foundation for a rich environment in which to explore inferences about models from both data and prior knowledge through the posterior probability. In an attempt to reduce an analysis problem to a manageable size, the usual approach is to present a single instantiation of the object model as "the answer", typically that which maximizes the posterior (the MAP solution). However, because of uncertainties in the measurements and/or because of a lack of sufficient data to define an unambiguous answer (in the absence of regularizing priors) [1], there is no unique answer to many real analysis problems. Rather, innumerable solutions are possible. Of course, some solutions are more probable than others. The beauty of the Bayesian approach is that it provides the probability of every possible solution, which, in a sense, ranks various solutions. The estimation of the uncertainty or reliability of the answer remains a pressing issue, particularly when the number of parameters in the model is large. Although there is a mathematically correct way to specify the covariance in the parameters, including the correlation between the uncertainties in any two parameters, it does not provide much insight.

One appealing way to get a feeling for the uncertainty in a Bayesian solution is to display a sequence of distinct solutions drawn from the posterior probability distribution. This approach was suggested by Skilling et al. [2], who produced a video display of a random walk through the posterior distribution. However, the calculational method used in that work was based on a Gaussian approximation of the posterior probability distribution in the neighborhood of the MAP solution. Later Skilling made some progress in dealing with non-Gaussian distributions [3]. While the probabilistic display of Skilling et al. provides

*Supported by the United States Department of Energy under contract number W-7405-ENG-36.

a general impression of the overall degree of possible variation in the solution, we desire a means to probe the uncertainty in the solution in a more directed manner.

We propose a technique to test hypotheses regarding perturbations of the MAP solution in a fashion that allows one to ask questions of particular interest. The approach we suggest makes use of an analogy between the negative logarithm of the posterior and a physical potential. The uncertainty of a particular change of the MAP solution is revealed in a tactile way as a force that tends to pull the solution back toward the MAP solution. Correlations between the perturbed set of parameters and the remaining parameters in the model are also brought to light. This innovative Bayesian tool is tangibly demonstrated within the context of geometrically-defined object models used for tomographic reconstruction from very limited projection data.

2. Traditional approach to uncertainty

Bayesian analysis revolves around the posterior probability of a model, where the model parameters are represented by the vector $\mathbf{a}$. The posterior $p(\mathbf{a}|\mathbf{d})$ incorporates data through the likelihood $p(\mathbf{d}|\mathbf{a})$ and prior information through a prior probability on the parameters $p(\mathbf{a})$. Bayes's law gives the posterior as $p(\mathbf{a}|\mathbf{d}) \propto p(\mathbf{d}|\mathbf{a})p(\mathbf{a})$. The most typical use of Bayesian analysis is to find the parameter values that maximize the posterior, called the MAP solution.

It is convenient to deal with the negative logarithm of the posterior, $\varphi = -\log\{p(\mathbf{a}|\mathbf{d})\}$. In the traditional approach to the estimation of uncertainty [4, 5], which we only summarize here, one calculates the curvature matrix of φ,

$$C_{ij} = \frac{\partial^2 \varphi}{\partial a_i \partial a_j} \ .$$

The error matrix $\mathbf{V}$, which gives the expected covariances between all the parameters, is the inverse of the curvature matrix,

$$\mathbf{V} = \mathbf{C}^{-1} \ .$$

Although this result is mathematically rigorous, it only provides the second moment of the parameter estimates and their correlations. It also suffers from not being very illuminating in terms of its consequences for the parametric model. Futhermore, for 10^6 parameters the full error matrix contains 10^{12} elements and can neither be practically calculated nor stored. We propose another approach to provide a more tangible indication of the degree of uncertainty in the inferred model as well as the ability to directly probe the uncertainty of specific features of the model.

3. Bayesian mechanics

If one draws an analogy between φ and a physical potential, then the gradient of φ is analogous to a force, just as in physics. The force $\mathrm{F}(a_i) = -\frac{\partial \varphi}{\partial a_i}$ is in the direction of the local minimum of φ, under suitable assumptions concerning the smoothness of the dependence of φ on the parameters. The condition for the MAP solution is $\nabla_{\mathbf{a}} \varphi = 0$, when there are no side constraints on the parameters. Therefore, the MAP solution can be interpreted as the situation in which the forces on all the variables in the problem balance so that the net force on each variable is zero. Further, when the variable a_i is perturbed slightly from the MAP solution, the force $F(a_i)$ pulls a_i back towards the MAP solution. The phrase "force of the data" takes on real meaning in this context.

A quadratic approximation to φ in the neighborhood of the MAP solution implies a linear force law, i.e. the restoring force is proportional to the displacement from equilibrium, as in a simple spring. In this quadratic approximation the curvature of φ is proportional to the covariance of the MAP estimate. A high curvature is analogous to a stiff spring and therefore represents a "rigid", reliable solution.

An interesting aspect of this approach is the possibility of decomposing the forces acting on the MAP solution into their various components. For example, the force derived from all data (through the likelihood), or even a selected set of data, may be compared to the force derived from the prior. In this way it is possible to examine the influence of the priors on the solution as well as determine which data have the largest effect on a particular feature of the solution.

We note that the notion of applying forces to model parameters in the preceding discussion must ultimately be stated in terms of pressures, that is, forces applied over finite-sized regions, acting on physically meaningful variables. The reason is that the physical world, which we usually model, exists as a continuum: the typical physical quantities of interest are a function of continuous spatial coordinates. Thus physically meaningful questions about reality should really be stated in terms of regions, not points. Furthermore, physically feasible measurements can only sample physical quantities over finite-sized regions. Point sampling is fundamentally impossible. As an example, a radiographic measurement in which the attenuation of an x-ray beam is measured always is lsubject to the effects of a blurring process that arises from a finite spot size for the source of x rays and the finite resolution of the x-ray detector. Thus the measured attenutation is necessarily an average over a cylinder in space. In truth, radiographic measurements can not provide line integrals of an attentuation coefficient through an object, as is often assumed as an approximation to the real process. As a result, uncertainies in an estimated physical quantity can only be addressed in terms of the average of that quantity over a finite region. As the concepts of Bayesian analysis mature, we will learn to only to deal with physical quantities that are functions of continuous independent variables and we will avoid referencing directly the underlying discrete parameters of the models.

One needs to be aware that any finite representation, which we are forced to use in computer models, has a limited resolution. Thus when one explores the model at a scale finer than the inherent resolution of the model, the model can only respond by using an interpolation of the underlying discrete model [6]. One can only meaningfully explore the model at resolutions coarser than this.

4. Perturbation from Equilibrium

We propose to exploit the above physical analogy to facilitate the exploration of the reliability of a MAP solution. The reliability of the solution is indicated by the rate at which the restoring forces increases as a user perturbs a single parameter, or group of parameters. Parameter correlations may be explored by altering some parameters, fixing them, and allowing the remaining parameters to readjust to minimize φ. The correlations between the fixed set and the others is demonstrated by how much and in what direction the variable parameters change. Ideally, these correlations could be seen through direct interaction with a rapidly-responding dynamical Bayesian system. Alternatively, they may be demonstrated by means of a video loop. As an aside, we use an adjoint method to efficiently calculate the required derivative with respect to the variables of interest [7].

For the present we will assume that φ is well approximated by a quadratic expansion in the neighborhood of the MAP point $\hat{\mathbf{a}}$:

$$\varphi = \tfrac{1}{2}(\Delta\mathbf{a})^{\mathrm{T}}\mathbf{C}\,\Delta\mathbf{a} + \varphi_0 \ ,$$

where $\Delta\mathbf{a} = \mathbf{a} - \hat{\mathbf{a}}$ is the displacement from the MAP point and $\varphi_0 = \varphi(\hat{\mathbf{a}})$. Suppose that we start from $\hat{\mathbf{a}}$ and displace the parameter values by a small amount $\Delta\mathbf{a}$. Then the gradient of φ, $-\nabla_{\mathbf{a}}\varphi$, represents a force that pulls the parameters back toward the MAP point. The units of the force are the reciprocal of the variance (or the square of the standard deviation) under the prevailing Gaussian assumption. The curvature in the direction of $\Delta\mathbf{a}$ is given by the ratio of $|\nabla_{\mathbf{a}}\varphi|$, evaluated at $\mathbf{a} + \Delta\mathbf{a}$, to $|\Delta\mathbf{a}|$, for vanishingly small displacements.

As an alternative to directly displacing parameters, their perturbation may be achieved by applying an external force to the parameters. Suppose that one pulls on the parameters with a force $\mathbf{s}$. Note that this force can act on just one parameter or on many. From the physical analogy, it is easy to write down the new potential;

$$\varphi = \tfrac{1}{2}(\Delta\mathbf{a})^{\mathrm{T}}\mathbf{C}\,\Delta\mathbf{a} - \Delta\mathbf{a}^{\mathrm{T}}\mathbf{s} + \varphi_0 \ .$$

The new minimum of φ occurs when

$$\nabla_{\mathbf{a}}\varphi = 0 = \mathbf{C}\Delta\mathbf{a} - \mathbf{s} \ .$$

Solving for the displacement in $\mathbf{a}$,

$$\Delta\mathbf{a} = \mathbf{C}^{-1}\mathbf{s} = \mathbf{V}\mathbf{s} \ .$$

Thus the ratio of $|\Delta\mathbf{a}|$ to the magnitude of the applied force s provides the covariance in the direction of the force.

We note that reoptimization amounts to following the minimum in the valley of φ in the space of $\mathbf{a}$. Doing so demonstrates the correlations between the uncertainties in all the parameters.

We can show that with reoptimization the dependence of φ on $\Delta\mathbf{a}$ is equivalent to marginalization over the parameter space perpendicular to $\Delta\mathbf{a}$, in the quadratic approximation. This marginalization is the proper thing to do in probability theory when one is interested only in the probability as a function of $\Delta\mathbf{a}$ and not in any other parameters, in which case the other parameters become nuisance variables.

Although we assumed that φ is quadratic, the above approach can be used when φ is nonquadratic. What is lost in that case is the statement that the $p(\Delta\mathbf{a})$ mapped out is the same as the properly marginalized probability for $\Delta\mathbf{a}$. Nonetheless we obtain a feeling for the uncertainty in $\Delta\mathbf{a}$ and the correlations between $\Delta\mathbf{a}$ and the other parameters. Any constraints on the parameters can be seen explicitly. For nonquadratic φ the plot of the value of φ versus the applied force provides the means to visualize the uncertainty in $\Delta\mathbf{a}$.

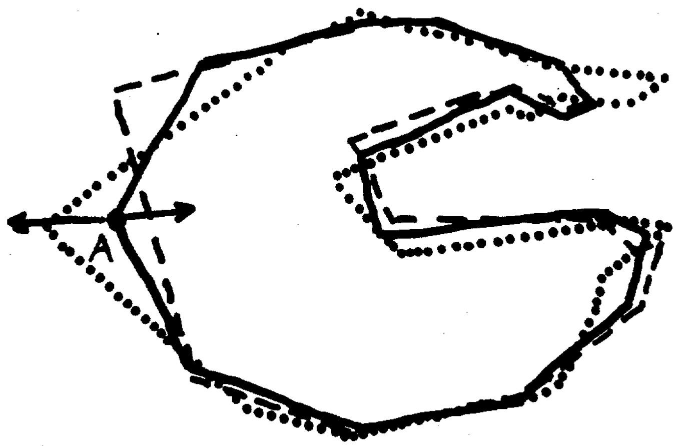

Figure 1: An example of how a polygon (solid line) can be distorted by either pushing node A inward (dashed line) or outward (dotted line), assuming that the measurements consist of two orthogonal projections. Note the effect on the overall shape of the object, which indicates the correlations between the nodes.

5. Use with Deformable Geometric Model

The above approach takes on a poignant interpretation when the reconstructed object is defined in terms of its geometric shape. The prior on the geometry is defined in terms of the default shape together with a prescription of how to assess the probability of other possible shapes. The latter is simply done by using a Gibb's form for the probability given as $\exp(-\beta W)$, where W is the deformation energy, i.e. the energy required to deform the geometry from the default shape into a new shape [8, 9, 10, 11, 12]. The parameter β regulates the strength of the prior on the geometry.

Figure 1 shows a polygon defined in terms of 20 control points or nodes. We assume that two sets of parallel projections, one vertical and one horizontal, are available and that they are subject to a very small amount of measurement noise. Starting from the known original polygon, a force is applied to the leftmost node (node A), pulling it outward. The plot of the applied force and the resulting horizontal displacement of the node is shown in Fig. 2. For positive forces node A moves outward steadily up to a breakpoint (at a displacement of 0.18), which we call point B. The dotted-line figure in Fig. 1 shows the configuration of the polygon at that point. We note that the act of displacing node A outward contradicts the vertical projections, which indicate that there is probably no material to the left of the original position of the node. Beyond point B the slope of the curve decreases substantially, principally because new configurations of the polygon are possible, which can reduce the

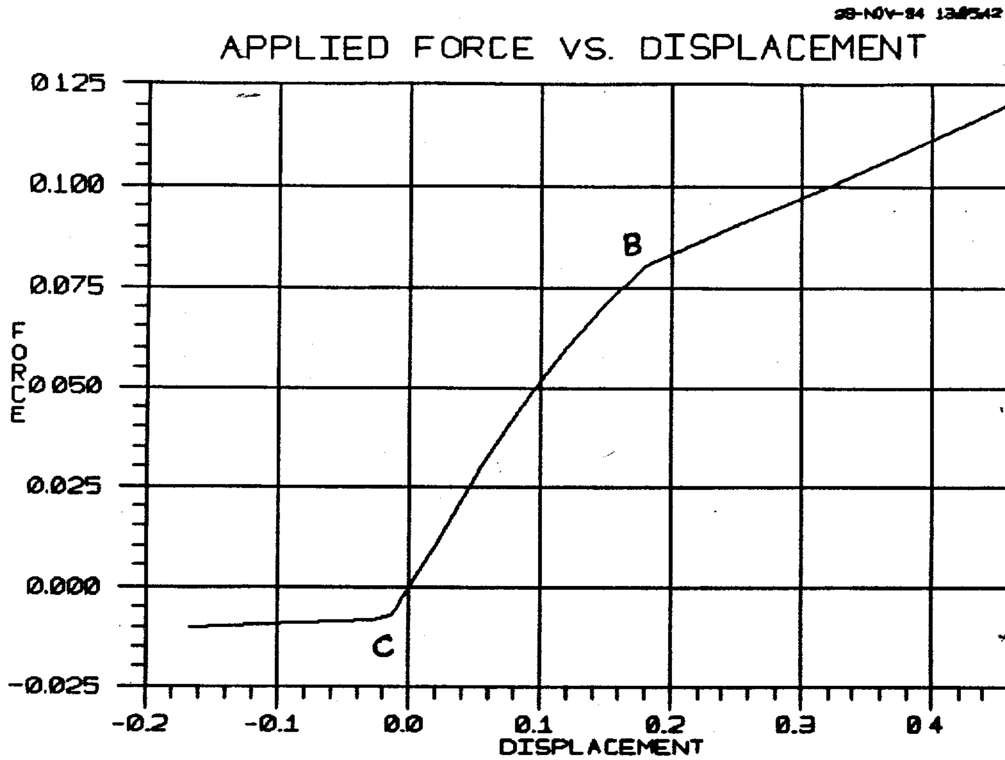

Figure 2: Plot of the force applied to node A of the polygon in Fig. 1 versus the resulting displacement of that node. The nonlinear nature of the force-displacement law for this problem is dramatically demonstrated. The configurations shown in Fig. 1 are at the two breakpoints in the curve: the dashed line corresponds to a force of -0.006 (inward) at point C and the dotted line to a force of 0.080 (outward) at B.

excessive projection values to the left of the original position of node A.

Applying the force inward (negative force values) results in quite a different behavior. For a small inward push, the displacement quickly reaches a breakpoint, point C in Fig. 2. The configuration of the polygon at this point is shown Fig. 1 as the dashed figure. Node A has just reached the line connecting its neighbors, one of which has moved outward to take its place in supplying the proper vertical projection. Pushing harder only makes node A slide down that line, which requires only a little force to achieve a large displacement. The position of node A is not well determined in this region. We notice that the shape of the object does not change during this process. The results for this situation are correct, but may not be what one has in mind when specifying the force. It seems desirable to avoid applying the force directly to the parameters. Rather the force should be applied to the object and its effect translated to the parameters. Also we observe that the only reason point C is not closer to the origin is that the coarseness of our polygon object model limits the flexibility of the object to respond. With many more degrees of freedom, we would expect neighboring sections of the object boundary to move out to take the place of node A in response to a slight inward force.

The correlation between node A and all other nodes in the polygon is demonstrated in Fig. 1. We observe that the nodes on the right side of the polygon move to maintain the measured horizontal projection. Of course, the constraints of the vertical projection also figure into the problem, making the overall movement of the sides of the polygon rather complex. This approach nicely handles the complex interaction between all the constraints arising from measurements and prior knowledge.

For an object modeled in terms of its geometry, poor reliability of the MAP estimate means that the object is soft or squishy, pliable. Good reliability of the estimate means that the object is firm. Therefore, "truth" is hard or rigid.

6. Discussion

In the future it may be possible to use the tools of virtual reality, coupled to turbocomputation, to explore the reliability of a Bayesian solution of complex problems through direct manipulation of the computer model. Force feedback will permit one to actually "feel" the stiffness of a model. Higher dimensional correlations might be "felt" through one's various senses.

The comments in Sect. 3 should be emphasized. We suggest that queries regarding physical quantities should be made in terms of averages over regions rather than in terms of point values. Furthermore, the uncertainties of individual parameters that, as a collection, are meant to describe a physical quantity as a function continuous coordinates, may have little meaning. Thus the question, "what is the rms error in a pixel value?" is almost irrelavent. Meaningful questions regarding images represented as a grid of pixels can only be made for areas larger than that of a single pixel. Furthermore, the correlations of an average value within a region with the rest of the image must be considered. Consequently our language must change. Instead of applying forces to individual parameters that are used to describe an object, we should speak of applying pressures over regions of the object. And it must be understood that when we ask about regions whose size is on the order of, or smaller, than the resolution of the model of the object, we will only learn about the interpolation properties of the model.

The approach to reliability testing described above is very general and can be used in virtually any other kind of Bayesian analysis. Examples of other contexts are as follows:

Bayesian spectrum analysis: In typical spectral analysis a scalar variable quantity is estimated for different discrete frequency values. Normally a single spectrum is estimated. Skilling et al. [3] probed the variability possible in the answer through their probabilistic display technique. That display gives one a true feeling for the range of answers possible for a given set of input data. With our technique, one can ask direct questions about the power at specific discrete frequencies or over a range of frequencies. The mode of interaction with the spectrum might be thought of as pushing down or pulling up on a point or over a region. In a virtual reality setting, the resistance to this attempted action indicates the degree of uncertainty in the solution. The uncertainties may be quantified, of course, in terms of cumulative probability or standard deviations.

Image reconstruction: The basic problem is to estimate the amplitudes in image pixels from data, each of which is a combination of many pixels, as in tomographic reconstruction from projections (line integrals) through the image, or deconvolution of blurred images. Interaction with the image can be provided by allowing one to push or pull on the amplitudes in an area of interest. The concepts behind this technique can be used to make binary decisions, for example, to decide whether an object is present or not, or to decide between two different signals [13].

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