

SIO 230 Geophysical Inverse Theory 2009

Supplementary Notes

1. Introduction

In geophysics we are often faced with the following situation. We have measurements made at the surface of the Earth of some quantity, like the magnetic field, or some seismic waveforms, and we want to know some property of the ground under the place where the data were measured. Furthermore, the physics is well understood, and if the property we are seeking were accurately known, we would be able to reconstruct quite accurately the observations that we have taken. Now we wish to infer the unknown property from the measurements. This is the typical *geophysical inverse problem*. It is called an inverse problem, because it reverses the process of predicting the values of the measurements, which is called the *forward problem*. The inverse problem is always more difficult than the forward problem; in fact we have to assume that the forward problem is completely under control before we can even begin to think about the inverse problem, and of course there are plenty of geophysical systems where the forward problem is still incompletely understood, such as in the geodynamo problem, or the problem of earthquake fault dynamics.

Why is the inverse problem more difficult? There are mathematical reasons why recovering unknown functions that appear as factors in differential equations is a complicated business, but the practical issue is less esoteric: the measurements are finite in number and of limited precision, but the unknown property is a function of position, and requires in principle infinitely many parameters to describe it. We are always faced with the problem of *nonuniqueness*: more than one solution can reproduce the data in hand. What can we do?

The most obvious response is to artificially complete the data, by interpolating, filling in the gaps somehow. Then in some circumstances it may be possible to prove a uniqueness theorem, which states that only one model corresponds to each complete data set. When this can be done (which may be hard) you might think the difficulties have been conquered, but that turns out not to be true. Most geophysical inverse problems are *ill-posed* in the sense that they are unstable: then an infinitesimal perturbation of a special kind in the data can result in a finite change in the model. As a consequence the details of the interpolation process used to complete the data are not irrelevant details as one would wish, but they can control gross features of the answer, in contrast to the forward problem, where it is invariably the case that the solution is not only unique, it is stable too.

Another strategy, more commonly used in the past before the advent of larger computers, is to drastically oversimplify the model, for example,

by claiming the unknown structure consists of a small number of layers or zones within which the unknown property is uniform. If there are good geological reasons for doing this, it is still a viable option, but when there is no evidence for this arrangement, even if the simplified model can be made to match the data (and usually it cannot), the inherent nonuniqueness means we are uncertain of the significance of our solution. None-the-less geometrical simplification is powerful tool, and often it is the only way to extract useful information. For example, reduction of two- or three-dimensional variations to one dimension may often be a reasonable approximation. The major features of a system can be captured by the assumption that the property varies only with depth, or radius in a spherical Earth, or horizontally.

Clearly if we assume, for example, that electrical conductivity varies only with depth, we are looking for a simple model. The next strategy takes the idea of seeking simplicity explicit while allowing as much complexity as necessary: this is called *regularization*. Here, instead of simplifying the model by reducing its degrees of freedom, we ask for the simplest model consistent with observation. Obviously simplicity can be defined in various ways, but as we will see, the idea is usually to reduce the wigginess, or roughness in the solution as far as possible. Unstable problems manifest themselves by the introduction of short wavelength oscillations, often of large amplitude, that are not required by the data, but appear because of minor imperfections in the measurements or even because of numerical round-off in the finite-precision computer calculations. By choosing from among the family of models the one with the least roughness, we avoid as far as possible being deceived that there are “interesting” features in the ground, that are in fact accidental. Regularization is today a completely commonplace strategy in inverse theory.

But even after we have obtained the “simplest possible” model by regularization, what do we know with certainty about the Earth? Geophysicists are lamentably quick to assume that the properties of the regularized solution are properties of the true Earth, but that is not guaranteed. If we want to be mathematically rigorous, not a lot is known about the question except for the so-called *linear inverse problems*. For measurements of a single number, we expect to be able to assign an uncertainty, usually an estimate of the standard error derived from statistics: for example, $a = 6371.01 \pm 0.02$ km. Why can’t we just assign a similar uncertainty to the solution at every point in the model? That seems very reasonable, at first. But, unless we are willing to make other assumptions about the model, assumptions not contained in the measurements, such uncertainties cannot be derived from the data. The reason for this is that it is always possible for a very thin layer to be present, with huge contrasts in value, without making an observable perturbation to the observations. Such a model is therefore consistent with the data, and is in the set of all solutions to the inverse problem. At any point, the allowed deviations can be arbitrarily large and so we cannot (from the measurements

alone) ascribe a point-wise uncertainty.

One solution to this dilemma is to say we are never interested in the model value at a point, only its *average value* over some region. This is a practical matter: in well logs we see large oscillations in properties that we could never expect to match with models based on surface measurements like seismics or magnetics, and so we are always content if the seismic model matches a smoothed version of the well-log record. The uncertainty in a solution may be limited *if we specify an averaging scale*. That is the basis for the *resolution* available in a solution, something we will spend some time on. Averaging over a scale can be useful in its own right and even applies to nonlinear problems; see Medin, Parker, and Constable, 2007. Another idea, hinted at already, is to assume some reasonable model property as an additional *constraint*. For example, if we can plausibly assert that conductivity must increase with depth because of increasing temperature, then that eliminates the very possibility of a thin layer; with this assumption point-wise uncertainties can be computed. See Stark and Parker, 1987. Another popular assumption (but not my favorite) is to assign a probabilistic framework to the problem: in my opinion too much must be assumed (such as Gaussian statistics and a known autocovariance function) without any real justification.

A word on notation. Equations of these Supplementary Notes begin anew at (1) in each numbered section. When I refer to equation outside the current section I will use the form 5(2), which means section 5, equation number (2). When I refer to an equation *Geophysical Inverse Theory* (GIT), I will use the form 2.05(13), which means section 2.05 in Chapter 2, equation (13).

References

- Medin, A. E., Parker, R. L., and Constable, S., Making sounding inferences from geomagnetic sounding, *PEPI*, 160, 51-9, 2007.
- Parker, R. L., *Geophysical Inverse Theory*, Princeton Univ. Press, 1994.
- Stark, P. B. and Parker, R. L., Velocity bounds from statistical estimates of $\tau(p)$ and $X(p)$, *J. Geophys. Res.*, 92, 2713-9, 1987.

2. An Illustration

To give you an idea of the sort of thing we will encounter, here is a seemingly simple, and to some familiar, geophysical problem that has attracted the attention of marine geologists and geophysicists for 40 years. A seamount is a marine volcano, which can be formed at a ridge or in the middle of a plate. Most seamounts are strongly magnetic, and they produce a magnetic anomaly at the sea surface that is easy to observe. A seamount is depicted below in Figure 2.1, and its magnetic anomaly is shown schematically in Figure 2.2. We would like to deduce the internal magnetization vector for the seamount, and in particular the direction of magnetization, because this vector gives paleomagnetic information about the motion of the plate since the time of formation of the volcano – most seamounts form quickly, so the magnetization vector can be used as a kind of snapshot of the paleomagnetic latitude.

Let us first solve the forward problem. The magnetic anomaly is the magnetic field remaining after the main geomagnetic field has been removed, which can be done fairly accurately using satellite models of the longest wavelength fields. The magnetic field due to the seamount is

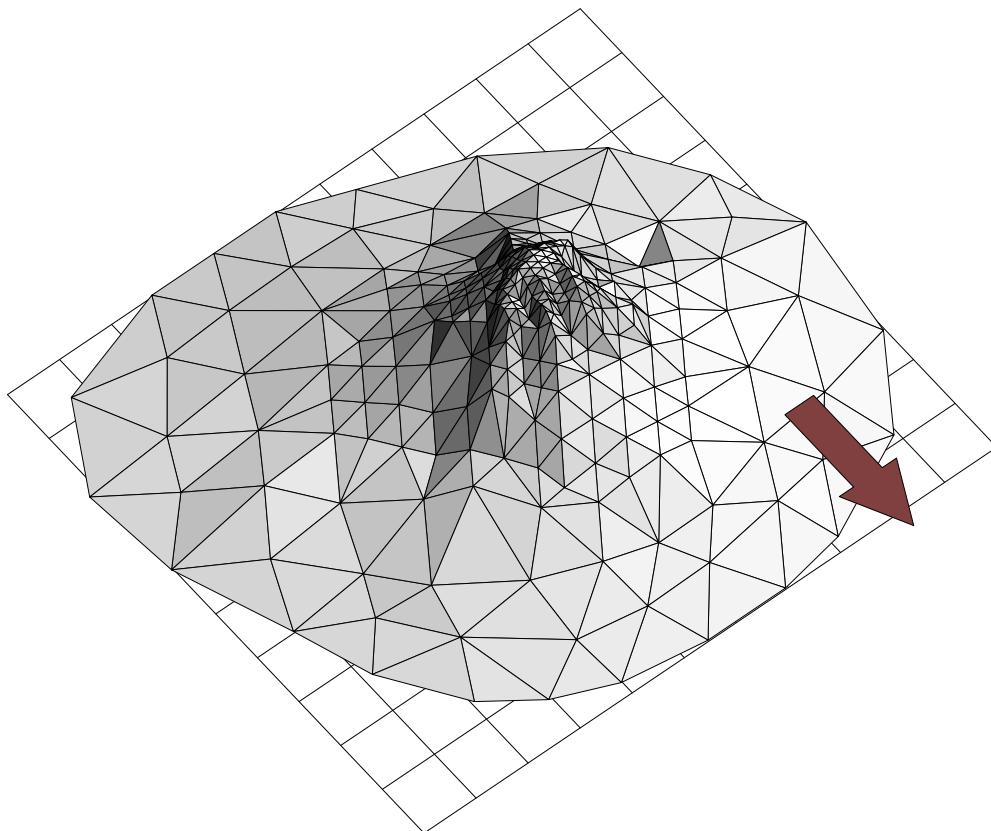


Figure 2.1: Model bathymetry of seamount LR148.8W (48.2°S , 148.8°W). Each square in the base is 5 km on a side and the arrow points north.

given by

$$\Delta\mathbf{B}(\mathbf{r}) = \int_V \mathbf{G}(\mathbf{s}, \mathbf{r}) \cdot \mathbf{M}(\mathbf{s}) d^3\mathbf{s} \quad (1)$$

where \mathbf{M} is the magnetization vector at the point \mathbf{s} within the seamount V and the vector valued function \mathbf{G} is given by

$$\mathbf{G}(\mathbf{s}, \mathbf{r}) = \frac{\mu_0}{4\pi} \hat{\mathbf{B}}_0 \cdot \nabla \nabla \frac{1}{|\mathbf{r} - \mathbf{s}|} \quad (2)$$

where ∇ acts on \mathbf{s} , and $\hat{\mathbf{B}}_0$ is a known constant unit vector and $\mu_0 = 4\pi \times 10^{-7} \text{ Hm}^{-1} = 100 \text{ nT m A}^{-1}$ the permittivity of free space in SI units. All the grad operators here act on the coordinate \mathbf{s} . Equations (1)-(2) just state that the observed field at \mathbf{r} is the sum of the fields from all the elementary dipoles within V . If we knew \mathbf{M} , which is just the density of dipole moments, we could compute $\Delta\mathbf{B}$ from (1) and (2), which means the forward problem has been solved.

The inverse problem is to discover \mathbf{M} from measurements of $\Delta\mathbf{B}$. Figure 2.2 shows that the actual measurements, which were taken by a Scripps *Thomas Washington* in 1984. Notice that data are collected on an irregular profile. While in reality there are only a few hundred values on $\Delta\mathbf{B}$ on the profile, let us pretend we know $\Delta\mathbf{B}$ everywhere on the ocean surface, and that we know it without error. Surely then we would be in position to determine \mathbf{M} . But that turns out to be untrue, because there is

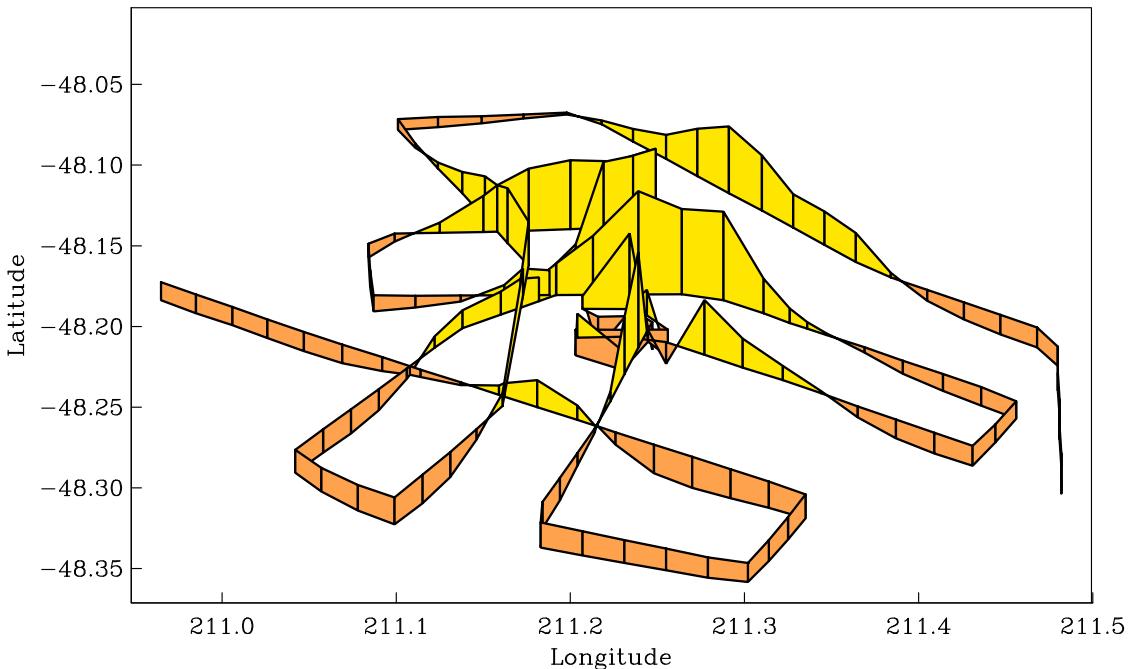


Figure 2.2: Ship track and magnetic anomaly over the seamount LR148.8W.

no uniqueness theorem for this inverse problem, even when perfect data like these are available. We demonstrate the nonuniqueness with some simple vector calculus. First rewrite (1) as

$$\Delta\mathbf{B}(\mathbf{r}) = \int_V \nabla g \cdot \mathbf{M}(\mathbf{s}) d^3\mathbf{s} \quad (3)$$

where

$$g(\mathbf{s}, \mathbf{r}) = \frac{\mu_0}{4\pi} \hat{\mathbf{B}}_0 \cdot \nabla \frac{1}{|\mathbf{r} - \mathbf{s}|} \quad (4)$$

which is OK because $\hat{\mathbf{B}}_0$ is constant. Next consider a magnetization vector inside V given by $\mathbf{m} = \nabla f$ where f is some smooth function. Then (3) becomes

$$\Delta\mathbf{B}(\mathbf{r}) = \int_V \nabla g \cdot \nabla f d^3\mathbf{s} \quad (5)$$

$$= \int_V [\nabla \cdot (f \nabla g) - f \nabla^2 g] d^3\mathbf{s} \quad (6)$$

where I have used the very useful vector identity: $\nabla \cdot (f \mathbf{V}) = \nabla f \cdot \mathbf{V} + f \nabla \cdot \mathbf{V}$. But it is easily seen that $\nabla^2 g = 0$: it is the Laplacian of $1/R$, the potential of a point charge, which vanishes except at the point \mathbf{r} ; since the observation site is never inside V , it follows that the second term in the integral in (6) vanishes. Next we apply Gauss's Divergence Theorem to the other term:

$$\Delta\mathbf{B}(\mathbf{r}) = \int_V \nabla \cdot (f \nabla g) d^3\mathbf{s} = \int_{\partial V} f \hat{\mathbf{n}} \cdot \nabla g d^2\mathbf{s} \quad (7)$$

where $\hat{\mathbf{n}}$ is the outward facing normal to the volume V , and ∂V denotes the surface of V . Suppose now I choose any smooth function $f(\mathbf{s})$ that vanishes on ∂V . We see from (7) that the magnetic anomaly $\Delta\mathbf{B}$ due to a magnetization $\mathbf{m} = \nabla f$ vanishes identically outside V .

The consequences of this result are that whatever the true magnetization \mathbf{M}_{true} may be, I can add a magnetization function like \mathbf{m} to it to form

$$\mathbf{M} = \mathbf{M}_{\text{true}} + \mathbf{m} \quad (8)$$

and the new magnetization distribution will match the data just as well as \mathbf{M}_{true} . From (1):

$$\Delta\mathbf{B} = \int_V [\mathbf{G} \cdot [\mathbf{M}_{\text{true}} + \mathbf{m}] d^3\mathbf{s} \quad (9)$$

$$= \int_V \mathbf{G} \cdot \mathbf{M}_{\text{true}} d^3\mathbf{s} + \int_V \mathbf{G} \cdot \mathbf{m} d^3\mathbf{s} = \int_V \mathbf{G} \cdot \mathbf{M}_{\text{true}} d^3\mathbf{s} + \int_V \mathbf{G} \cdot \nabla f d^3\mathbf{s} \quad (10)$$

$$= \int_V \mathbf{G} \cdot \mathbf{M}_{\text{true}} d^3\mathbf{s} + 0. \quad (11)$$

Thus, from the field observations, there is no way to distinguish between the true magnetization and any member of an infinitely large family of alternatives. The magnetization inverse problem does not have a unique solution even with perfect data. The magnetization \mathbf{m} is called, rather dramatically, a *magnetic annihilator* for this problem.

The first answer to the dilemma of nonuniqueness was the *Drastic Simplification* strategy, introduced for the seamount problem in 1962 (Vacquier, 1962), and still in widespread use today! It is simply asserted that within V the magnetization is uniform, in other words, $\mathbf{M}(\mathbf{s})$ is not a function of position at all, but a constant vector. Then there are exactly three unknowns, the x , y and z components, instead of infinitely many, quite a reduction. In the 1960s there was no compelling evidence to contradict this simple model, but now we know it is wide of the mark. As various seamounts were surveyed magnetically it quickly became clear that the uniform magnetization model was incapable of matching the data, but as I said, people continue to use it to infer paleopoles to this day.

Regularization in this problem (Parker, et al., 1987) takes the following form. We write the magnetization distribution as the sum of two terms:

$$\mathbf{M}(\mathbf{s}) = \mathbf{U} + \mathbf{R}(\mathbf{s}) \quad (12)$$

where \mathbf{U} is a constant vector, and \mathbf{R} varies with \mathbf{s} ; obviously any \mathbf{M} can be written this way. To regularize the inverse problem, we ask for the model that makes \mathbf{R} as small as possible, in other words, we look for the most nearly uniform model that fits the observations. Now we can always match the measurements, and obtain a vector \mathbf{U} for the uniform part. We have constructed a regularized solution, the kind of thing done all the time in seismic tomography, and surface wave inversion, and magnetotelluric sounding, and on and on. But how reliable is vector \mathbf{U} , which is the geologically significant product of the calculation? As we will see, in a linear problem like this, \mathbf{U} is really still completely undetermined, unless we are willing to make some further assumptions, or place additional restrictions on \mathbf{M} . The information cannot come from observations of $\Delta\mathbf{B}$, which as we have seen by themselves leave a huge amount of ambiguity.

There are several ways we can limit the ambiguity. One approach is to say that we know based on samples of rocks from the seafloor and shallow drill holes in marine basalts that the magnitude of the magnetization $\|\mathbf{M}\|$ is limited in a way we would be willing to specify. In the Hilbert space machinery that we will soon be studying, the simplest way to do this is to introduce a norm of magnetization:

$$\|\mathbf{M}\| = \left[\int_V |\mathbf{M}(\mathbf{s})|^2 d^3\mathbf{s} \right]^{1/2}. \quad (13)$$

Samples would allow us to say that $\|\mathbf{M}\| \leq m_0 V$ with some confidence. We will discuss how to do such calculations later in the class. While this approach is a good idea in principle, it does not work very well for this particular problem in practice. We find the allowed range of directions of \mathbf{U} is very large. And that might be the final answer; after all, it could be that the data we have and the reasonable assumptions we might make, do not in fact allow us to determine \mathbf{U} accurately enough to be geologically interesting.

But we shouldn't give up too soon. A fact of paleomagnetism long exploited in other problems is that rocks are magnetized with a constant direction in large units. It would make no sense for a paleomagnetist to take samples on the surface of an exposed unit if it was not plausible to assume the directions are fairly uniform within. Approximate uniformity of direction is indeed found to be the case, but not for the intensity of magnetization: magnetic intensity is found to vary over two or three orders of magnitude, which is why the oversimplified model of Vacquier doesn't work. So we will restrict the model to be unidirectional in \mathbf{M} ; we call that direction the unit vector $\hat{\mathbf{M}}_0$. If the geomagnetic field reversed during the formation of the seamount we would need both $+\hat{\mathbf{M}}_0$ and $-\hat{\mathbf{M}}_0$. Most seamounts form rapidly enough that this is a low probability. With that single assumption, unidirectionality, the inverse problem becomes a lot harder to solve, but it turns out, it adds a lot of power to the data and rather good results are obtained; see Parker (1991).

References

- Parker, R. L., Shure, L., and Hildebrand, J., The application of inverse theory to seamount magnetism, *Rev. Geophys.*, 25, 17-40. 1987.
- Parker, R. L., A theory of ideal bodies for seamount magnetism, *J. Geophys. Res.*, B10, 16101-12, 1991.
- Vacquier, V., A machine method for computing the magnetization of a uniformly magnetized body from its shape and a magnetic survey, 123-37, Benedum Earth Magnetism Symposium, Univ. Pittsburgh Press, 1962.

3. Abstract Linear Vector Spaces

This section begins a review of linear algebra and simple optimization problems on finite-dimensional spaces. We will cover some of these problems again but in the more abstract setting of Hilbert space in Chapters 1 and 2 of GIT. The current segment (Section 3) is a slightly modified version of Section 1.01 in GIT.

The definition of a linear vector space involves two types of object: the **elements** of the space and the **scalars**. Usually the scalars will be the real numbers but occasionally complex scalars will prove useful; we will assume real scalars are intended unless it is specifically stated otherwise. The elements of the space are much more diverse as we shall see in a moment when we give a few examples. First we lay out the rules that define a **real linear vector space** (“real” because the scalars are the real numbers): it is a set \mathcal{V} containing elements which can be related by two operations, addition and scalar multiplication; the operations are written

$$f + g \quad \text{and} \quad \alpha f$$

where $f, g \in \mathcal{V}$ and $\alpha \in \mathbb{R}$. For any $f, g, h \in \mathcal{V}$ and any scalars α and β , the following set of nine relations must be valid:

$$f + g \in \mathcal{V} \tag{1}$$

$$\alpha f \in \mathcal{V} \tag{2}$$

$$f + g = g + f \tag{3}$$

$$f + (g + h) = (f + g) + h \tag{4}$$

$$f + g = f + h, \text{ if and only if } g = h \tag{5}$$

$$\alpha(f + g) = \alpha f + \alpha g \tag{6}$$

$$(\alpha + \beta)f = \alpha f + \beta f \tag{7}$$

$$\alpha(\beta f) = (\alpha\beta)f \tag{8}$$

$$1f = f. \tag{9}$$

In (9) we mean that scalar multiplication by the number *one* results in the same element. The notation $-f$ means *minus one* times f and the relation $f - g$ denotes $f + (-g)$. These nine “axioms” are only one characterization; other equivalent definitions are possible. Notice in (7) the meaning of the plus sign is different on the two sides, and in (8) there are two kinds of multiplication going on. An important consequence of these laws (so important, some authors elevate it to axiom status and eliminate one of the others), is that every vector space contains a unique zero element $\mathbf{0}$ with the properties that

$$f + \mathbf{0} = f, \quad f \in \mathcal{V}$$

and whenever

$$\alpha f = \mathbf{0}$$

either $\alpha = 0$ or $f = \mathbf{0}$. If you have not seen it you may like to supply the proof of this assertion.

Here are a few examples of linear vector spaces, most of which we will come across later on. First there is the obvious space \mathbb{R}^n . There are two ways to think about this space. One is simply as an ordered n -tuples of real numbers. So an element $\mathbf{x} \in \mathbb{R}^n$ is just

$$\mathbf{x} = (x_1, x_2, \dots, x_n) \tag{10}$$

where $x_j \in \mathbb{R}$. The definition of addition of two vectors and multiplication by a scalar is self-evident, and if we check off the list of axioms, they are all very obviously true for this collection of elements. The alternative way of looking at \mathbb{R}^n is as the set of column vectors:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{bmatrix}. \tag{11}$$

This form highlights the fact that \mathbb{R}^n is really a special case of one of the spaces of real matrices, $\mathbb{R}^{m \times n}$; in fact, to use the form (11) we should write the space as $\mathbb{R}^{n \times 1}$.

This brings to the space of real matrices $\mathbb{R}^{m \times n}$. As you could easily guess, it is the collection of all real rectangular arrays of real numbers in the form:

$$\mathbf{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \cdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix}. \tag{12}$$

Once again it is clear what it means to add two matrices of the same size, and multiplication by a scalar simply means every entry is multiplied by that number. We will be discussing matrix algebra in the next section. Notice that I did not use the proper mathematical notation for this space in GIT, an unfortunate oversight on my part.

Perhaps less familiar to you are spaces whose elements are not finite sets of numbers, but *functions*. For example, consider the real-valued function f that takes a real argument x restricted the closed interval $[a, b]$; a mathematician would write this specification as $f : [a, b] \rightarrow \mathbb{R}$, and you should consider it too. The collection of all such functions that are continuous form a space called $C^0[a, b]$. Again, there is no difficulty in seeing what it means to add two such functions, and that the sum of two continuous functions is itself continuous. Scalar multiplication presents

no difficulty either, nor any of the other rules. There is a short table of named function spaces on p 6 of GIT.

In a linear vectors space, you can always add together a collection of elements to form a **linear combination** thus:

$$g = \alpha_1 f_1 + \alpha_2 f_2 + \cdots + \alpha_k f_k \quad (13)$$

where $f_j \in \mathcal{V}$ and the $\alpha_j \in \mathbb{R}$ are scalars; obviously $g \in \mathcal{V}$ too. This kind of operation is at the heart of almost everything we do in linear vector spaces.

To a large extent all that is going on here is *classification*, just a way of organizing things with names we can all agree on. But this is very useful, and you must learn this language and use it.

4. Essential Linear Algebra

The next few lectures will be on linear algebra and its computational aspects. An elementary book for much of the material is by Strang, *Introduction to Applied Mathematics* (Wellesley-Cambridge, 1986); more advanced and a classic in the field is *Matrix Computations*, 3rd Edition, by Golub and Van Loan (Johns Hopkins Univ. Press, 1996) The program MATLAB which you must learn for this class, manipulates matrices very naturally.

A **matrix** is a rectangular array of real (or possibly complex) numbers arranged in sets of m rows with n entries each see 3(12); or equivalently, there are n columns each m long. The set of such m by n matrices is called $\mathbb{R}^{m \times n}$ for real matrices and $\mathbb{C}^{m \times n}$ for complex ones. If $m=1$ the matrix is called a **row vector** and if $n=1$ it is a **column vector**; notice that the space of column vectors will usually be written \mathbb{R}^m rather than $\mathbb{R}^{m \times 1}$. The entries of the array $A \in \mathbb{R}^{m \times n}$ are referred to by indices, a_{ij} which means the entry on the i -th row and the j -th column. A **square** matrix has $m=n$ of course. It is customary to denote a row or column vector by a lower case letter, say x , and then the i -th element is written x_j . Here is a list of names of special matrices defined by the systematic distribution of zeros in them:

<i>Diagonal</i>	$a_{ij}=0$ whenever $i \neq j$
<i>Tridiagonal</i>	$a_{ij}=0$ whenever $ i-j > 1$
<i>Upper triangular</i>	$a_{ij}=0$ whenever $i > j$
<i>Sparse</i>	Most entries zero

Upper triangular matrices are also called *Right triangular*. Lower triangular matrices are defined in the analogous manner, with the inequality reversed. Notice these definitions apply to nonsquare matrices as well as square ones. A diagonal matrix is often conveniently written by specifying its diagonal entries in order, thus:

$$D = \text{diag}(d_1, d_2, \dots, d_n). \quad (1)$$

In MATLAB this is `D = diag(d)` where `d` is a column or a row vector; MATLAB distinguishes between column and row vectors in most circumstances, so be careful. The square, diagonal matrix with only unity on the diagonal is usually denoted I (a very few authors use E) and is called the **unit matrix**. In MATLAB you form the unit matrix $I \in \mathbb{R}^{m \times n}$ by the weird statement `I = eye(n)`. Sparse matrices are very important because they arise very frequently, and a great of work has been put into numerical algorithms for dealing with them efficiently.

As I mentioned in the previous section, the set of matrices $\mathbb{R}^{m \times n}$ forms a **linear vector space** under the obvious rules of addition:

$$A = B + C \text{ means } a_{ij} = b_{ij} + c_{ij} \quad (2)$$

and scalar multiplication:

$$B = c A \text{ means } b_{ij} = c a_{ij} \quad (3)$$

where $A, B, C \in \mathbb{R}^{m \times n}$ and $c \in \mathbb{R}$.

Another basic manipulation, which you all know, is **transposition**:

$$B = A^T \text{ means } b_{ij} = a_{ji} . \quad (4)$$

Some authors and MATLAB denote transpose by A' ; this is to be discouraged in technical writing. Transposition is just the reversal of the roles of the columns and rows. A **symmetric** matrix is its own transpose: $A^T = A$; it is obviously square.

Most important is **matrix multiplication** ($\mathbb{R}^{m \times n} \times \mathbb{R}^{n \times p} \rightarrow \mathbb{R}^{m \times p}$):

$$C = A B \text{ means } c_{ij} = \sum_{k=1}^n a_{ik} b_{kj} . \quad (5)$$

Notice that you can only multiply two matrices when the numbers of columns in the first one equals the number of rows in the second; but the other dimensions are not important, so nonsquare matrices can be multiplied. The combination of the operations of addition and matrix multiplication allows one to define matrix arithmetic analogous to real number arithmetic. The standard arithmetic law of distribution is valid: $A(B+C)=AB+AC$. Less obviously, association of multiplication holds: $A(BC)=(AB)C$, when the orders of the matrices are the correct size to permit the product. So we get used to doing algebra on matrices as if they were numbers, **but multiplication is not commutative**. This means in general the order of multiplication matters, that is:

$$A B \neq B A \quad (6)$$

unless some special property exists.

When one multiplies a matrix into a column vector, there are a number of useful ways of interpreting this operation:

$$y = A x . \quad (7)$$

If the vectors x and y are in the same space, R^m one can view A as providing a linear mapping or linear transformation of one vector into another. This is especially valuable for 3-vectors and then A represents the components of a tensor (referred to a particular frame). For example, x might be angular velocity about some point, A the inertia tensor, and y would be the angular momentum about the point; or x could be magnetizing magnetic field, A the susceptibility tensor, and y the resultant magnetization vector in a specimen. Another linear transformation performed by matrices in ordinary space is rigid body rotation, used in plate-tectonic reconstruction, and space-ship animation and CAD applications; this involves a special square nonsymmetric matrix to be defined later.

Another useful perspective on matrix multiplication is supplied by thinking about A as the ordered collection of its columns as column vectors:

$$y = A x = [a_1, a_2, \dots, a_n] x = x_1 a_1 + x_2 a_2 + \dots + x_n a_n \quad (8)$$

so that the new vector is just a *linear combination of the column vectors* of A with coefficients given by the elements of x . This is the way we typically think about matrix multiplication when it applies to fitting a model: here y contains data values, the columns of A are the predictions of a theory that includes unknown weight factor given by the entries in x .

We can interpret matrix multiplication this way too. Now let the columns of B be the focus; then

$$A B = A [b_1, b_2, \dots, b_p] = [A b_1, A b_2, \dots, A b_p]. \quad (9)$$

In other words, A simply transforms the column vectors of B one at a time. As a matter of fact, it is useful sometimes to partition a large matrix into a set of rectangular submatrices or blocks. Then if you have two matrices, both partitioned into blocks in a consistent manner, you can multiply them together, treating the blocks just as if they were numbers.

There are two ways of multiplying two vectors. The **outer product** if $x \in \mathbb{R}^p$ and $y \in \mathbb{R}^q$:

$$x y^T = \begin{bmatrix} x_1 y_1 & \cdots & x_1 y_q \\ \vdots & \ddots & \vdots \\ x_p y_1 & \cdots & x_p y_q \end{bmatrix} \in \mathbb{R}^{p \times q}. \quad (10)$$

And the **inner product** of two column vectors of the same length:

$$x^T y = x_1 y_1 + x_2 y_2 + \dots + x_n y_n = y^T x. \quad (11)$$

Of course the inner product is just the vector **dot product** of vector analysis. Notice that if we write A and B as column vectors:

$$A = [a_1, a_2, \dots, a_m] \text{ and } B = [b_1, b_2, \dots, b_n] \quad (12)$$

then the matrix product $C = A^T B$ is by definition (5) a collection of inner products:

$$c_{jk} = a_j^T b_k, \quad j=1, 2, \dots, m, k=1, 2, \dots, n \quad (13)$$

The unit matrix I is special for matrix multiplication. Whenever the product $I A$ is permitted, the matrix A is unchanged; the unit matrix plays the role of the number one in arithmetic. Also if A is square and if there is a matrix B so that $A B = I$, the matrix B is called the **inverse** of A and is written A^{-1} . When it exists, the inverse matrix is unique. Square matrices A that possess no inverse are called **singular**; when the inverse exists, A is called **nonsingular**. The inverse of the transpose of A is the transpose of the inverse:

$$(A^T)^{-1} = (A^{-1})^T \quad (14)$$

and sometimes authors write $(A^{-1})^T = A^{-T}$. I don't like this notation, however, and so I will never use it.

The idea of the inverse is supposed to be useful for solving linear systems of algebraic equations. When we write (7) and we suppose that the vector y is known and A is square and known too, we can recover the unknown vector x by multiplying both sides of (7) with A^{-1} :

$$A^{-1}y = A^{-1}A x = I x = x . \quad (15)$$

As we will see shortly, calculating the inverse and then multiplying it into y is considered a poor way to do this numerically. How is the inverse actually calculated? We will not go into this in detail, but the ideas behind the numerical calculation of y in (15) are important enough for us to look at later. Once you know how to solve $A x = y$, it is a simple step to find A^{-1} from (9) setting $B = I$.

Two cute results. When you transpose the product of two matrices, you can get the same result by transposing first, but you must invert the order:

$$(A B)^T = B^T A^T . \quad (16)$$

And the same goes for the operation of inverting:

$$(A B)^{-1} = B^{-1} A^{-1} \quad (17)$$

Exercises

4.1 Exhibit an explicit numerical example of a pair of 4 by 4 matrices A and B that commute with each other subject to these rules: neither of them is allowed to be diagonal and A must not be a scalar multiple of B or its inverse. Explain the logical process that led to your answer.

4.2 Our definition, that $A B = I$, strictly defines the *right inverse* of A . Prove that if the left inverse exists, it is also B ; that is $B A = I$; in other words, prove a nonsingular matrix commutes with its inverse. Do not assume the truth of (17). Can you prove a left inverse exists whenever a right one does?

4.3 Show that the inverse of a nonsingular matrix is unique.

4.4 Under what conditions is the product of two symmetric matrices also symmetric?

4.5 Prove (16) and (17).

4.6 In analysis a real self adjoint operator is a linear mapping that satisfies $(x, Ay) = (Ax, y)$ for every vector x, y , where (\cdot, \cdot) is an inner product. Show that for matrices and column vectors, and the inner product (11), that from this definition A must be a symmetric matrix.

Now let us concentrate on square matrices, the kind that arise classically in the solution of linear systems. First, there is the **determinant**.

This is a real number that measures the "volume" of the image of a unit cube after the matrix A has been applied to the space \mathbb{R}^n . The value of the determinant isn't much use, except to tell whether it is zero, or not; Here is one way to find it: define $\det(A) = a_{11}$ for $A \in \mathbb{R}^{n \times n}$ with $n=1$, in other words, a 1×1 matrix. For larger values of n we work up by recurrence:

$$\det(A) = \sum_{j=1}^n (-1)^{j+1} a_{1j} \det(A^{1j}) \quad (18)$$

where A^{1j} is the matrix in $\mathbb{R}^{n-1 \times n-1}$ found by deleting row 1 and column j of A . A useful simple case is that of a triangular matrix: the determinant is the product of the diagonal elements. Some other important properties of the determinant which we will not prove:

- (a) $\det(AB) = \det(A)\det(B)$
- (b) $\det(A^T) = \det(A)$
- (c) $\det(A) = 0$, if and only if A is singular

The determinant is used for proving theorems but in numerical work it is seldom used.

Here are the definitions of some important kinds of square matrix.

<i>Symmetric</i>	$A^T = A$
<i>Skew-symmetric</i>	$A^T = -A$
<i>Positive definite</i>	$x^T A x > 0, x \neq 0 \in \mathbb{R}^n$
<i>Positive</i>	$a_{ij} > 0$, all i, j
<i>Orthogonal</i>	$A^T A = I$
<i>Normal</i>	$A^T A = A A^T$
<i>Projection</i>	$A^T = A$ and $A^2 = A$
<i>Diagonally dominant</i>	$ a_{ii} > \sum_{j \neq i} a_{ij} $

The orthogonal matrix obviously has the properties that

$$Q^{-1} = Q^T \text{ and thus } Q Q^T = I . \quad (19)$$

Consider an orthogonal matrix Q to be composed of column vectors:

$$Q = [q_1, q_2, \dots, q_n] . \quad (20)$$

Then the definition and (13) show that the vectors q_j and q_k are always orthogonal when $j \neq k$, and they are of unit Euclidean length. In other words the columns are a collection of mutually orthogonal unit vectors. But (19) shows that this also means the rows have exactly the same property!

As you probably know the orthogonal matrix is the generalization of the operation of rotation and reflection in a mirror in n -dimensional

space. We can show this in several ways. First we can easily show the orthogonal matrix leaves the volume of an element unchanged, because the determinant of Q is ± 1 . Here is the proof: From (18) or the idea that I leaves a space unchanged, $\det(I)=1$. But

$$Q^T Q = I . \quad (21)$$

So

$$1 = \det(Q^T Q) = \det(Q) \det(Q^T) = \det(Q)^2 . \quad (22)$$

Hence the result. A negative sign indicates the mapping Q involves reflection, as well as rotation. But equal volume transformations aren't necessarily rotations. The key is that the inner product of two any vectors is preserved.

$$(Qx)^T (Qy) = x^T Q^T Q y = x^T (Q^T Q) y = x^T y . \quad (23)$$

When $x=y$ this proves the length of every vector is preserved and in addition the angle between any two vectors is unchanged; so any rigid body will be preserved in shape, which is rotation, and possible reflection.

Suppose we are in \mathbb{R}^3 and we want to know the orthogonal matrix for a rotation about the origin, on an axis $\hat{\mathbf{n}}$ (a unit vector) and by an angle θ . Then

$$R \mathbf{x} = \mathbf{x} \cos \theta + \hat{\mathbf{n}} \hat{\mathbf{n}} \cdot \mathbf{x} (1 - \cos \theta) + \hat{\mathbf{n}} \times \mathbf{x} \sin \theta \quad (24)$$

where \times is the ordinary vector cross product in \mathbb{R}^3 . So the elements of R are

$$r_{ij} = \delta_{ij} \cos \theta + (1 - \cos \theta) n_i n_j + \sin \theta \sum_k \varepsilon_{ijk} n_j \quad (25)$$

where ε_{ijk} is the **alternator** with the properties: $\varepsilon_{ijk}=0$, whenever two indices are equal; $\varepsilon_{ijk}=+1$ whenever ijk is a cyclic permutation of 123; $\varepsilon_{ijk}=-1$ otherwise. You may find this formula useful one day.

Here is another interesting orthogonal matrix – the elementary **Householder matrix**. Suppose $u \in \mathbb{R}^n$ is of unit Euclidean length, meaning $u^T u=1$. Then the matrix

$$Q = I - 2u u^T \quad (26)$$

is orthogonal. Proof: First note that Q is symmetric; therefore

$$Q^T Q = Q^2 = (I - 2u u^T)(I - 2u u^T) \quad (27)$$

$$= I - 4u u^T + 4u u^T u u^T = I \text{ [QED]} . \quad (28)$$

So Q is both symmetric and orthogonal. (Can you think of a general specification of the class of symmetric orthogonal matrices?) The transformation of Q is quite simple to visualize as follows: Consider the vector $y=Qx=x-2u(u^T x)$. The vector $u(u^T x)$ is the component of x lying in the u direction. So y has that component reversed. That means x has been

reflected in the subspace normal to the direction n . (This means $\det(Q) = -1$; can you prove this independently?) The reason these particular matrices are important is that they play a central role in a special matrix factorization called **QR**, invented by Alston Householder in the 1950s, and the QR method solves least-squares problems; more of this later.

Next we go over some further ideas about linear vector spaces. First, a set of vectors $\{a_1, a_2, \dots, a_n\}$ in a linear vector space (for example, \mathbb{R}^m) is said to be **linearly independent** if

$$\sum_{j=1}^n \beta_j a_j = 0 \text{ implies } \beta_1 = \beta_2 = \dots = \beta_n = 0 \quad (29)$$

where $\beta_j \in \mathbb{R}$. If a nontrivial linear combination of vectors can equal the zero vector of the space, the set is called **linearly dependent**. A **subspace** of linear vector space is a set of vectors that is also a linear vector space. For example, any plane in ordinary space through the origin of coordinates; but not a plane that misses the origin. The **spanning set** or more simply the **span** of a collection of vectors, is the linear vector space that can be built from that collection by taking linear combinations of them. Formally,

$$\text{span}\{a_1, a_2, \dots, a_n\} = \left\{ \sum_j \beta_j a_j \mid \beta_1, \beta_2, \dots, \beta_n \in \mathbb{R} \right\}. \quad (30)$$

A linearly independent spanning set forms a **basis** for a vector space. The number of elements in a basis is called the **dimension** of the space, and it can be proved every basis for a particular space has exactly the same dimension, which is a number that characterizes the "size" of the vector space. In intuitive terms, the dimension is the number of free parameters needed to specify uniquely an element in the space. Every collection of more than n vectors in an n -dimensional space must be linear dependent. These ideas apply quite generally to linear vector spaces (that might contain functions or operators), but we are interested here on elements that are collections of real numbers.

For a matrix in $\mathbb{R}^{m \times n}$ there are two important spaces. First the **range space**, also called the **column space** of A , which we write $\mathcal{R}(A)$. It is simply the linear vector space formed by taking linear combinations of the column vectors of A . Recall (8); this means that for all $x \in \mathbb{R}^n$

$$Ax \in \mathcal{R}(A). \quad (31)$$

Obviously

$$\text{If } A = [a_1, a_2, \dots, a_n] \text{ then } \mathcal{R}(A) = \text{span}\{a_1, a_2, \dots, a_n\} \dots \quad (32)$$

The dimension of the column space of a matrix in $\mathbb{R}^{m \times n}$ can never be more than n the number of columns but it can be less. That dimension is so important it has its own name: the **rank** of A :

$$\text{rank}(A) = \dim[\mathcal{R}(A)]. \quad (33)$$

It can be shown that $\text{rank}(A) = \text{rank}(A^T)$, so the rank of a matrix is the maximal number of linearly independent rows or columns. A matrix in $\mathbb{R}^{m \times n}$ is said to be of **full rank** if $\text{rank}(A) = \min(m, n)$ and to be **rank deficient** otherwise.

The other side of the coin of the columns space is the **null space** of A . This is given by the set of x s that cause $Ax = 0$: for $A \in \mathbb{R}^{m \times n}$

$$\mathcal{N}(A) = \{x \in \mathbb{R}^n \mid Ax = 0\} \quad (34)$$

We agree to define as zero, the dimension of the space comprising a single element, the zero vector, then

$$\dim [\mathcal{N}(A)] = n - \text{rank}(A). \quad (35)$$

For the important case $m = n$ the following are equivalent:

- (a) A is nonsingular
- (b) $\dim \mathcal{N}(A) = 0$
- (c) $\text{rank}(A) = n$
- (d) $\det(A) \neq 0$

References

Golub, G. H., and C. F. Van Loan, *Matrix Computations*, Johns Hopkins University Press, Baltimore, 1983.

Strang, G., *Introduction to Applied Mathematics* Wellesley-Cambridge Press, 1986

5. Simple Least Squares Problems

Least squares problems are examples of optimization problems that involve the simplest of **norms**. We are going to solve these problems in several ways, to illustrate the use of Lagrange multipliers and a few other things. The bible for the numerical aspects of LS is the ancient Lawson and Hanson, 1974. First what is a norm? Informally, a norm is a real number that measures the size of an element in a linear vector space. Assigning a norm to a linear vector space is said to **equip** the space with a norm. Most linear vector spaces can be so equipped (spaces of functions, operator, matrices, etc), but here we will consider only the simplest norm for \mathbb{R}^m , the Euclidean length: when $x \in \mathbb{R}^m$

$$\|x\| = \sqrt{\sum_{k=1}^n x_k^2}. \quad (1)$$

We can obviously express this in other ways, for example $\|x\| = (x^T x)^{1/2}$. The space \mathbb{R}^m is then properly called E^m , but we won't be pedantic. Here is an approximation problem often encountered in geophysics, the classical least squares problem. We will state it as a problem in linear algebra.

Suppose we are given a collection of n vectors $a_k \in \mathbb{R}^m$ and we wish to approximate a target vector y by forming a linear combination of the a_k ; when $n < m$, as we shall assume, we will not expect to be able to do this exactly, and so there will be an error, called in statistics the **residual**:

$$r = y - \sum_{k=1}^n x_k a_k. \quad (2)$$

In data analysis, straight-line regression is in this form, or fitting any simple linear model to a data set. In numerical analysis you might want to approximate a complicated function by a polynomial. To get the *best approximation* in some sense, we want the size of the vector $r \in \mathbb{R}^m$ to be as *small* as possible. Once we've picked a way to measure the size, we have a minimization problem. The simplest norm for computational purposes is the Euclidean length, and this leads to the **overdetermined least squares problem**. If we can rewrite (2) in matrix notation:

$$r = y - Ax \quad (3)$$

where $x \in \mathbb{R}^n$ and the matrix $A \in \mathbb{R}^{m \times n}$ is built from columns that are the a_k :

$$A = [a_1, a_2, \dots, a_n]. \quad (4)$$

So the minimization problem is to solve

$$\min_{x \in \mathbb{R}^n} f(x) \quad (5)$$

where

$$f(x) = \|r\|^2 = r^T r = (y - Ax)^T (y - Ax). \quad (6)$$

Obviously we can square the norm if it simplifies the algebra.

I will offer you several solutions to this problem, some of which may be unfamiliar. First the classical approach, which is to multiply descend into subscripts, and differentiate:

$$f = \sum_{j=1}^m r_j^2. \quad (7)$$

Then

$$\frac{\partial f}{\partial x_k} = 2 \sum_{j=1}^m r_j \frac{\partial r_j}{\partial x_k} \quad (8)$$

$$= 2 \sum_{j=1}^m (y_j - \sum_{i=1}^n a_{ji} x_i) \times (-a_{jk}) \quad (9)$$

$$= -2 \sum_{j=1}^n a_{jk} y_j + 2 \sum_{i=1}^n (\sum_{j=1}^m a_{jk} a_{ji}) x_i \quad (10)$$

and this is true for each value of k . At the minimum we set all the derivatives to zero, which leads to:

$$\sum_{i=1}^n (\sum_{j=1}^m a_{jk} a_{ji}) x_i = \sum_{j=1}^n a_{jk} y_j, \quad k = 1, 2, \dots, n. \quad (11)$$

Translated into matrix language these are the so-called **normal equations**:

$$A^T A x = A^T y. \quad (12)$$

Note that $A^T A$ is a square n by n matrix, and the left side is a column n -vector. So the unknown expansion coefficients are found by solving this system of linear equations, formally by writing

$$x = (A^T A)^{-1} A^T y \quad (13)$$

a result that should be familiar to you.

This answer looks ugly and seems to have no intuitive content. But a geometrical interpretation can help a lot. Suppose we assume that the vectors a_k are linearly independent (which they must be if we can write (13)). Then the collection of all vectors that can be formed from linear combinations of them is a **subspace** of \mathbb{R}^m which we will call \mathcal{A} ; it is the column, or range, space of the matrix A , and so $\mathcal{A} = \mathcal{R}(A)$ from 4(33). The approximation problem we are solving can be stated as finding the vector in \mathcal{A} that comes as close to y as possible. We rewrite (12) as

$$0 = A^T (A x - y) = A^T r \quad (14)$$

$$= \begin{bmatrix} a_1^T r \\ a_2^T r \\ \vdots \\ a_n^T r \end{bmatrix}. \quad (15)$$

Remember the zero on the left is the vector $0 \in \mathbb{R}^n$. So what this equation is saying is that the residual vector, the error in the approximation to y , is orthogonal to every one of the basis vectors of the space \mathcal{A} (because $a_i^T r$ is the dot product between a_i and r). And that is what you might expect from a geometrical interpretation as shown in Figure 5.1.

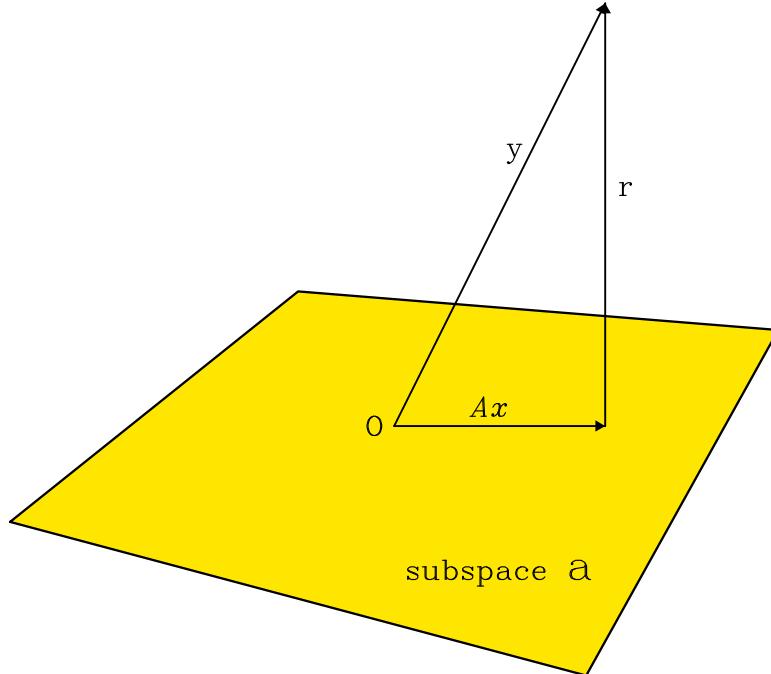
Let us give a name to the approximation we have created, let $Ax = \tilde{y}$. Then \tilde{y} is called the **orthogonal projection** of y into the subspace \mathcal{A} . The idea of a projection relies on the **Projection Theorem** for Hilbert spaces. The theorem says, that given a subspace like \mathcal{A} , every vector can be written uniquely as the sum of two parts, one part that lies in \mathcal{A} and a second part orthogonal to the first. The part lying in \mathcal{A} is orthogonal projection of the vector onto \mathcal{A} . Here we have

$$y = \tilde{y} + r. \quad (16)$$

There is a linear operator, $P_{\mathcal{A}}$ the projection matrix, that acts on y to generate \tilde{y} , and we can see that

$$P_{\mathcal{A}} = A(A^T A)^{-1} A^T. \quad (17)$$

Figure 5.1: Orthogonal projection of y onto the column space of A .



Recall from Section 4 that a projection matrix must be symmetric and satisfy $P^2 = P$. The second property is natural for a projection, because acting once creates a vector falling into the given subspace, acting again leaves it there. Verify these properties for $P_{\mathcal{A}}$.

We describe next a completely different way of looking at the least-squares (LS) problem, which often offers considerable improvement in numerical accuracy. Let us return to Householder's **QR factorization** of a matrix, mentioned briefly in the previous section: every matrix $A \in \mathbb{R}^{m \times n}$ where A is tall (meaning $m \geq n$) can be written as the product:

$$A = Q R \quad (18)$$

where $Q \in \mathbb{R}^{m \times m}$, $R \in \mathbb{R}^{m \times n}$, and Q is *orthogonal*, and R is *upper triangular*; recall that upper triangular means all zeros below the diagonal so that $R_{ij} = 0$ when $i > j$. We can write

$$R = \begin{bmatrix} R_1 \\ O \end{bmatrix} \quad (19)$$

where $R_1 \in \mathbb{R}^{n \times n}$ and is also upper triangular. For how the QR factorization is found in practice and why QR is numerically stable, see GIT 1.13 and the references there. To solve the LS problem we look to the Euclidean norm of r :

$$\|r\| = \|y - Ax\| = \|y - QRx\|. \quad (20)$$

Recall that $Q Q^T = I$, so

$$\|r\| = \|QQ^T y - QRx\| = \|Q(Q^T y - Rx)\|. \quad (21)$$

Now recall that the length of a vector is unchanged under mapping with an orthogonal matrix: $\|z\| = \|Qz\|$. So

$$\|r\| = \|Q^T y - Rx\| = \|\hat{y} - Rx\|. \quad (22)$$

Next square the norm and partition the arrays inside the norm into two parts, the top one with n rows:

$$\|r\|^2 = \left\| \begin{bmatrix} \hat{y}_1 \\ \hat{y}_2 \end{bmatrix} - \begin{bmatrix} R_1 \\ O \end{bmatrix} x \right\|^2 = \left\| \begin{bmatrix} \hat{y}_1 - R_1 x \\ \hat{y}_2 \end{bmatrix} \right\|^2 \quad (23)$$

$$= \|\hat{y}_1 - R_1 x\|^2 + \|\hat{y}_2\|^2. \quad (24)$$

The second term $\|\hat{y}_2\|^2$ in the sum is indifferent to the choice of x ; but we can reduce the first term to zero by solving

$$R_1 x = \hat{y}_1. \quad (25)$$

So this must be the solution to finding the smallest norm of r . Because R_1 is upper triangular, (25) is solved by **back substitution**, starting at the bottom and working upwards, which is very simple. This doesn't look like a very efficient way to find the LS answer, but it can be made very

efficient: for example, there is no need to store the matrix Q , because one can calculate the vector $\hat{y} = Q^T y$ without it. The QR factorization is competitive with the normal equations for execution times (it is slightly slower but, as mentioned earlier, it is numerically more stable against the accumulation of numerical error. The key to understanding the accuracy in the solution of $Ax = b$ is $\kappa(A) = \|A\| \|A^{-1}\|$ called the **condition number** of A , which estimates the factor by which small errors in b or A are magnified in the solution x . This can sometimes be very large ($> 10^{10}$). It is shown in GIT that the condition number in solving the normal equations (13) is *the square* of the condition number for (25), which can sometimes lead to catastrophic error build up. Therefore, for not too large systems, QR is the proper way to go. In MATLAB, while you can get the QR factors with the call

`[Q R] = qr(A);`

the LS problem is *solved automatically* for you by the QR method if you simply write

`x = A\y;`

Finally, suppose you substitute the QR factors into the expression for the projection matrix. We find after some algebra that

$$P_A = Q^T \begin{bmatrix} I_n & 0 \\ 0 & O \end{bmatrix} Q \quad (26)$$

where $I_n \in \mathbb{R}^{n \times n}$ is the unit matrix and the rest of the entries are zero. Numerically this way of finding the projection is very stable because one never needs to solve a linear system. But (26) also shows that if one imagines rotating the data space onto new coordinates with Q , the projection operator then becomes the matrix in the middle of (26), which is the projection that simply zeros out all the components of a vector after the n th one.

Exercises

5.1 Show that the last $m - n$ columns in the factor Q of the QR factorization are never used in the LS calculation.

5.2 The *Gram-Schmidt* process is a method of creating a set of orthonormal vectors from a given ordered set of linearly independent vectors by forming linear combinations of one, then two, then three, etc, of the given vectors. Show how the QR process does the same thing.

Hint: First show that the inverse of an right triangular matrix is also right triangular.

Reference

Lawson, C. L., and Hanson, R. J., *Solving Least Squares Problems*, Prentice-Hall, Englewood Cliffs, NJ, 1974.

6. Lagrange Multipliers and More Least Squares

There is more. We now consider solving minimization problems with **Lagrange Multipliers**. For proofs see GIT 1.14 and the references mentioned there. The minimization we solved in Section 5 (5) was an example of an **unconstrained minimization** in which we found the smallest possible value of a function. But suppose there is a side condition, called a **constraint**, that must hold for all solutions. The Figure 6.1, taken from GIT, show the general idea for single condition. If the constraint condition is expressed the in form:

$$g(x) = 0 \quad (1)$$

then the minimum of the constrained problem

$$\min_{x \in \mathbb{R}^n} f(x) \text{ with } g(x) = 0 \quad (2)$$

occurs at a stationary point of the *unconstrained function* function

$$u(x, \mu) = f(x) - \mu g(x) \quad (3)$$

where we must consider variations of x and μ ; of course μ is called a Lagrange multiplier. If there are n constraint conditions in the from $g_k(x) = 0$, $k = 1, 2, \dots, n$, each would be associated with its own Lagrange multiplier:

$$u(x, \mu_1, \mu_2, \dots, \mu_n) = f(x) - \sum_{k=1}^n \mu_k g_k(x). \quad (4)$$

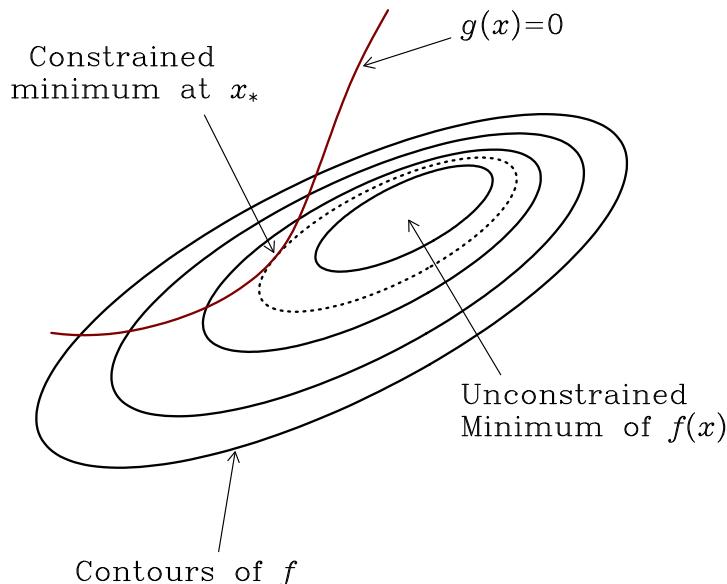


Figure 6.1: An optimization problem in 2 unknowns with 1 constraint.

As an example consider again the overdetermined LS problem solved by 5(13). We wish to find the minimum of the function $f(r) = \|r\|^2$, with $r \in \mathbb{R}^m$. As an unconstrained problem the answer is obviously zero. But we have the following m conditions on r :

$$0 = y - Ax + r \quad (5)$$

where $y \in \mathbb{R}^m$ and $A \in \mathbb{R}^{m \times n}$ are known, while the vector $x \in \mathbb{R}^n$ is also unknown and free to vary. So, writing (5) out in components and giving each row its own Lagrange multiplier, (4) becomes for this problem

$$u(r, x, \mu_l) = \sum_{j=1}^m r_j^2 - \sum_{j=1}^m \mu_j (y_j - \sum_{k=1}^n a_{jk} x_k + r_j). \quad (6)$$

Differentiating over r_i , x_i and μ_i , the stationary points of u occur when

$$\frac{\partial u}{\partial r_i} = 0 = 2r_i - \mu_i \quad (7)$$

$$\frac{\partial u}{\partial x_i} = 0 = - \sum_{j=1}^m a_{ji} \mu_j \quad (8)$$

$$\frac{\partial u}{\partial \mu_i} = 0 = y_i - \sum_{k=1}^n a_{ik} x_k + r_i . \quad (9)$$

Equation (7) says the vector of Lagrange multipliers $\mu = 2r$; then using this fact and translating (8), (9) into matrix notation:

$$A^T \mu = 2A^T r = 0 \quad (10)$$

$$Ax - r = y. \quad (11)$$

If we multiply (11) from the left with A^T and use (10) we get the normal equations 5(12) again. But let us do something else: we combine (10) and (11) into a single linear system in which the unknown consists of both x and r :

$$A = \begin{bmatrix} & \text{[Gray rectangle]} \\ \text{[Black diagonal line]} & \end{bmatrix} \quad A^T A = \begin{bmatrix} & \text{[Gray square]} \\ \text{[Black square]} & \end{bmatrix}$$

Figure 6.2: An example of loss of sparseness in forming the normal equations.

$$\begin{bmatrix} -I_m & A \\ A^T & O_n \end{bmatrix} \begin{pmatrix} r \\ x \end{pmatrix} = \begin{pmatrix} y \\ 0 \end{pmatrix} \quad (12)$$

where $I_m \in \mathbb{R}^{m \times m}$ is the unit matrix, where $O_n \in \mathbb{R}^{n \times n}$ is square matrix of all zeros. This system has the same content as the normal equations, but solves for the residual and the coefficients at the same time. If A is sparse, (12) can be a better way to solve the LS problem than by the normal equations or by QR, particularly as QR does not have a good adaptation to sparse systems. The situation is illustrated for a common form of overdetermined problem in Figure 6.2.

We turn next to the so-called **underdetermined least-squares** problem. While the overdetermined LS problem occurs with monotonous regularity in statistical parameter estimation problems, the underdetermined LS problem looks quite a lot like an *inverse problem*. Instead of trying to approximate the known y by a vector in the column space of A , we can match it exactly: we have

$$y = Ax. \quad (13)$$

where $A \in \mathbb{R}^{m \times n}$, but now $m < n$ and A is of full rank. This is a finite-dimensional version of the linear forward problem, in which the number of measurements, y , is less than the number of parameters in the model x . So instead of looking for the smallest error in (13), which is now zero, we ask instead for the *smallest model*, x . We are performing a simplified regularization, in which size, here represented by the Euclidean length, stands for simplicity. This problem is solved just as the last one, with a collection of m Lagrange multipliers to supply the constraints given by (13), but with $\|x\|^2$ being minimized instead of $\|r\|^2$. I'll run through the process quickly. The unconstrained function is

$$u(x, \mu_k) = \sum_{j=1}^n x_j^2 - \sum_{i=1}^m \mu_i (\sum_{k=1}^n a_{ik} x_k - y_i) \quad (14)$$

$$\frac{\partial u}{\partial x_j} = 2x_j - \sum_{i=1}^m a_{ij} \mu_i \quad (15)$$

$$\frac{\partial u}{\partial \mu_i} = - \sum_{k=1}^n a_{ik} + y_i. \quad (16)$$

Setting these derivatives to zero leads to a pair of linear systems which can be written in matrix notation

$$x = \frac{1}{2} A^T \mu \quad (17)$$

$$Ax = y \quad (18)$$

Equation (17) contains a key piece of information: the norm minimizer lies in the range space of A or, in other words, x is a linear combination of the column vectors of A . If we substitute the first of these into the second

we have

$$\frac{1}{2}AA^T\mu = y . \quad (19)$$

which we imagine solving somehow, then substituting for μ in the first member of (17)

$$x = A^T(AA^T)^{-1}y . \quad (20)$$

These are the normal equations for the underdetermined (smallest norm) problem. Explicitly following equation (20) is rarely a good way to compute the solution, however. First, if matrix A is sparse we loose that property forming AA^T : then it is better to combine (17) and (18) into a large sparse system combining μ and x in a longer unknown vector as we did in (12). Second, we can use QR to find a numerically stable result.

Like the normal equations, (19) too suffers from poor conditioning numerically. And as before QR comes to the rescue, but in a cute way. Recall that the classic QR factorization works only if $m \geq n$, here that is violated. So we write instead that

$$A^T = QR \quad \text{or} \quad A = R^T Q^T . \quad (21)$$

Then (13) can be written

$$y = R^T Q^T x = R^T \hat{x} \quad (22)$$

where $\hat{x} \in \mathbb{R}^m$ is just $Q^T x$. Then, since Q is an orthogonal matrix

$$x = Q\hat{x} \quad (23)$$

and it follows that x and \hat{x} have the same norm, ie. Euclidean length. Recall that R is upper triangular; so (22) is

$$y = [R_1^T \ O] \begin{pmatrix} \hat{x}_1 \\ \hat{x}_2 \end{pmatrix} \quad (24)$$

where $R_1 \in \mathbb{R}^{n \times n}$, and $\hat{x}_1 \in \mathbb{R}^n$. If we multiply out the partitioned matrix we see that

$$y = R_1^T \hat{x}_1 + O \hat{x}_2 = R_1^T \hat{x}_1 . \quad (25)$$

Because the second term vanishes, (25) shows that we can choose \hat{x}_2 (the bottom part of \hat{x}) in any way we like and it will not affect the match to the data: only \hat{x}_1 influences that. So we match the data exactly by solving the system

$$R_1^T \hat{x}_1 = y . \quad (26)$$

Now observe that

$$\|x\|^2 = \|\hat{x}\|^2 = \|\hat{x}_1\|^2 + \|\hat{x}_2\|^2 . \quad (27)$$

So to match the data we solve (26), then to get the smallest norm we simply put $\hat{x}_2 = 0$. Thus \hat{x} has been found that minimizes the norm, and the corresponding x is recovered from (23).

The underdetermined LS problem is artificial in the sense that (13) the condition that the model fit the data *exactly* is unrealistic: if there is noise in the data y , we must not demand an exact fit. It is more realistic to say that we would be satisfied with a reasonably close fit, as measured by the Euclidean norm; so replace (13) with

$$\|Ax - y\| \leq \gamma \quad (28)$$

where we get choose γ from a statistical criterion that depends on the noise in y . Problems with a single inequality constraint turn out to be very similar to those with equality constraints. One of two scenarios can apply: (a) the unconstrained problem satisfies (28); (b) equality holds in (28), in which case a Lagrange multiplier can be used for the minimization. For the moment, let us concentrate on (b), which is the usual state of affairs. We need a single Lagrange multiplier to apply (28). To complicate things slightly more, instead of minimizing the norm of x , we will minimize

$$f(x) = \|Px\|^2 \quad (29)$$

where $P \in \mathbb{R}^{p \times n}$ is a matrix that suppresses undesirable properties, for example, it might difference x to minimize slopes instead of magnitudes. Now we have the unconstrained function

$$u(x, \mu) = \|Px\|^2 - \mu(\gamma^2 - \|Ax - y\|^2) \quad (30)$$

where I have squared the condition factor because it will simplify things later. A trivial rearrangement gives:

$$u(x, \mu) = \|Px\|^2 + \mu\|Ax - y\|^2 - \mu\gamma^2. \quad (31)$$

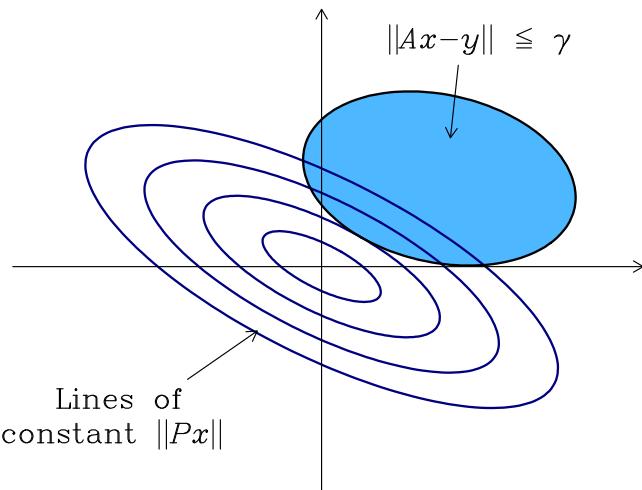


Figure 6.3: Minimization of $\|Px\|$ subject to $\|Ax - y\| \leq \gamma$ for $x \in \mathbb{R}^2$.

It can be shown (see GIT, Chapter 3) that $\mu > 0$. Then for a fixed value of μ , the function u can be interpreted as finding a compromise between two undesirable properties, large Px , and large data misfit. If we minimize over x with a small μ we give less emphasis to misfit and find models that keep Px very small; and conversely, large μ causes minimization of u to yield x with small misfit. This is an example of a **trade-off** between two incompatible quantities: it is shown in GIT that decreasing the misfit always increases the penalty norm, and vice versa.

We could solve this problem by differentiating in the usual tedious way. Instead we will be a bit more clever. As usual, differentiating by μ just gives the constraint (28). The derivatives on x don't see the γ term in (31) so we can drop that term when we consider the stationary points of u with respect to variations in x :

$$\hat{u}(x) = \|Px\|^2 + \mu \|Ax - y\|^2 \quad (32)$$

$$= \|Px - 0\|^2 + \|\mu^{1/2}Ax - \mu^{1/2}y\|^2. \quad (33)$$

Both of the terms are norms acting on a vector; we can make the sum into a single squared norm of a longer vector, the reverse of what we did on equation 5(24):

$$\hat{u}(x) = \left\| \begin{bmatrix} P \\ \mu^{1/2}A \end{bmatrix} x - \begin{pmatrix} 0 \\ \mu^{1/2}y \end{pmatrix} \right\|^2 \quad (34)$$

$$= \|Cx - d\|^2. \quad (35)$$

The matrix $C \in \mathbb{R}^{(p+m) \times n}$ must be tall, that is $p+m > n$, or the original problem has a trivial solution (Why?), (35) is just an ordinary *overdetermined least squares problem*; indeed the matrix C is the one illustrated in Figure 6.2. So for any given value of μ , we can find the corresponding x through our standard LS solution. But this doesn't take care of (28). The only way to satisfy this misfit criterion is by solving a series of versions of (35) for different guesses of μ in an iterative way, because unlike all the other systems we have met so far, this equation is nonlinear. We will discuss the details later (see GIT, Chap 3).

What about scenario (a)? We need to verify that the unconstrained problem, the minimizer of $\|Px\|^2$ satisfies (28). When P is nonsingular, that is easy, because then the unique solution is $x = 0$, and that can be checked trivially in (28). If P is singular the solution to the unconstrained problem is not unique, and we could set up the minimization of $\|Ax - y\|$ over the null space of P . But in fact we will discover in solving (31) that (28) is satisfied for all $\mu > 0$ as part of the search in μ , so solving (28) with an equality is all we need ever to do.

7. Other Matrix Factorizations

The QR factorization is one of a number of matrix factorizations that appear in the numerical analysis of linear algebra. The rule that numerical analysts repeat with great regularity is that to solve the linear system

$$Ax = y \quad (1)$$

never, never, never calculate the inverse A^{-1} and multiply this into the vector y . The reasons are that it is numerically inaccurate, and inefficient. The recommended way is via one of several factorizations. To solve (1) in MATLAB you should always type:

`x = A \ y;`

Recall that when $A \in \mathbb{R}^{m \times n}$ and the problem is overdetermined ($m > n$), this gets you the least-squares solution via QR. When $m = n$, the system is solved, with QR, but by **Gaussian elimination** which can also be written as a matrix factorization called **LU** decomposition:

$$A = LU. \quad (2)$$

Here $A, L, U \in \mathbb{R}^{n \times n}$ and L is lower triangular, while U is upper triangular, called U because for some unknown reason the word ‘upper’ is always used here instead of ‘right’ (which is always the name used in QR). Formally the solution to (1), once you have the LU factors is to solve by back substitute the two systems

$$Lz = y, \text{ and } Ux = z. \quad (3)$$

You don’t need to know this of course just to use back-slash. Unlike QR factorization, LU decomposition of a sparse matrix A results in two sparse factors L and U , which is a very important property for large systems of equations.

A special case arises when A is symmetric, and positive definite. Then A can be factored with the **Cholesky factorization**

$$A = LL^T \quad (4)$$

where L is lower triangular. Notice that this factorization is almost like a square root of A , and is handy in a number of situation when a matrix square root could be useful. Cholesky factorization is one of the fastest and most numerically stable schemes in numerical linear algebra.

Next let me briefly remind you about the elementary theory of eigenvalue systems for square matrices. You will recall that a square symmetric matrix always has **eigenvalues**, which are the real numbers λ satisfying

$$Au = \lambda u, \text{ and } u \neq 0. \quad (5)$$

When $A \in \mathbb{R}^{n \times n}$ is not symmetric λ need not be real, and in some cases there are no solutions to (5); the symmetric case covers almost all those of practical interest. When A is symmetric, there are at most n distinct values of λ , call them λ_k , and n corresponding **eigenvectors** u_k .

Conventionally, these are normalized so that $\|u_k\| = 1$, in the 2-norm. A most important property of the eigenvectors is that they are mutually orthogonal:

$$u_j^T u_k = 0, \quad \text{when } j \neq k. \quad (6)$$

When there are fewer than n eigenvalues, the system is said to be **degenerate** and can be treated as if there are repeated values of λ ; and then the eigenvectors of the degenerate eigenvalues are not uniquely defined. But they can always be chosen to be orthogonal so that (6) can be forced to be true, and always is in computer programs. The simplest illustration of all this is the unit matrix: every vector is an eigenvector of I with eigenvalue 1; so the eigensystem is n -fold degenerate, that is, there are n eigenvalues, all the same, all equal to one.

The eigenvalue problem can be written as a matrix factorization, as we shall now see. Form the square matrix U from columns of the orthogonal eigenvectors:

$$U = [u_1, u_2, \dots, u_n] \quad (7)$$

The matrix U is an orthogonal matrix, because its columns are mutually orthogonal unit vectors. Then

$$AU = [Au_1, Au_2, \dots, Au_n] = [\lambda_1 u_1, \lambda_2 u_2, \dots, \lambda_n u_n] = U\Lambda \quad (8)$$

where $\Lambda = \text{diag}(\lambda_1, \lambda_2, \dots, \lambda_n)$. Now multiply on the right with U^T and we have the **spectral factorization** of A :

$$A = U\Lambda U^T \quad (9)$$

This can be written another way that is most instructive:

$$A = \lambda_1 u_1 u_1^T + \lambda_2 u_2 u_2^T + \dots + \lambda_n u_n u_n^T \quad (10)$$

$$= \lambda_1 P_1 + \lambda_2 P_2 + \dots + \lambda_n P_n \quad (11)$$

Here the outer product matrices $u_k u_k^T$ are projection matrices each of which maps a vector into the subspace comprised of the corresponding eigenvector. Equation (11) is decomposing the action of A into components in an orthogonal coordinate system, where each component receives a particular magnification by the corresponding λ_k . Think about what this means when there is degeneracy. It should be observed that numerical techniques for discovering the eigenvalues and eigenvectors of symmetric matrices are based on performing the factorization (9), not on evaluating some huge determinant, which would take an eternity.

There is a spectral factorization for nonsquare matrices as well, called **singular value decomposition** usually called **SVD**. Suppose $A \in \mathbb{R}^{m \times n}$ with $m > n$, then A can be factorized into the product of three matrices, two orthogonal and one diagonal:

$$A = U \Sigma V^T \quad (12)$$

where $U \in \mathbb{R}^{m \times m}$ and $V \in \mathbb{R}^{n \times n}$ are orthogonal and $\Sigma \in \mathbb{R}^{m \times n}$ with

$$\Sigma = \text{diag}(s_1, s_2, \dots, s_n) \quad (13)$$

The real numbers $s_k \geq 0$ are called the **singular values** of A . One can solve LS problems with SVD. There are number of people who claim SVD is the answer to almost all LS problems because of its great numerical stability and because of its use in censoring the poorly resolved features in simple minimization problems. I believe these advantages are usually overstated; also the procedure is numerically very expensive, and not readily adapted to sparse systems, and therefore not suitable for large systems.

SIO 230 Geophysical Inverse Theory 2009

Supplementary Notes

8. A New Magnetic Problem

In GIT the first few chapters revolve around a marine magnetic problem based on a small set of artificial “data”, supposedly collected at the North Pole. This example is too simple these days for two reasons: first, the number of observations (thirty) is trivially small; second, the idealization of the problem covers up so many of the real difficulties, particularly the questions surrounding the proper form of the forward problem. I want to work with a more realistic illustration, based on actual data, to give you a better idea of how to handle real-life situations that you may come across. However, I still want to stick to a one-dimensional geometry, to keep the graphics simple. It is another marine magnetic problem, like the one in GIT, except that the observations were taken near the sea floor in 1995 on a deep-tow vehicle (the “fish”) built by the Marine Physical Lab at SIO. The profile runs across the Juan de Fuca rise (35°N , 130°W) off the coast of Washington, with a strike direction of 107° east of true north; these details will become important shortly. The profile in Figure 8.1 shows a short section of 100 points taken out a much longer profile; the age of the

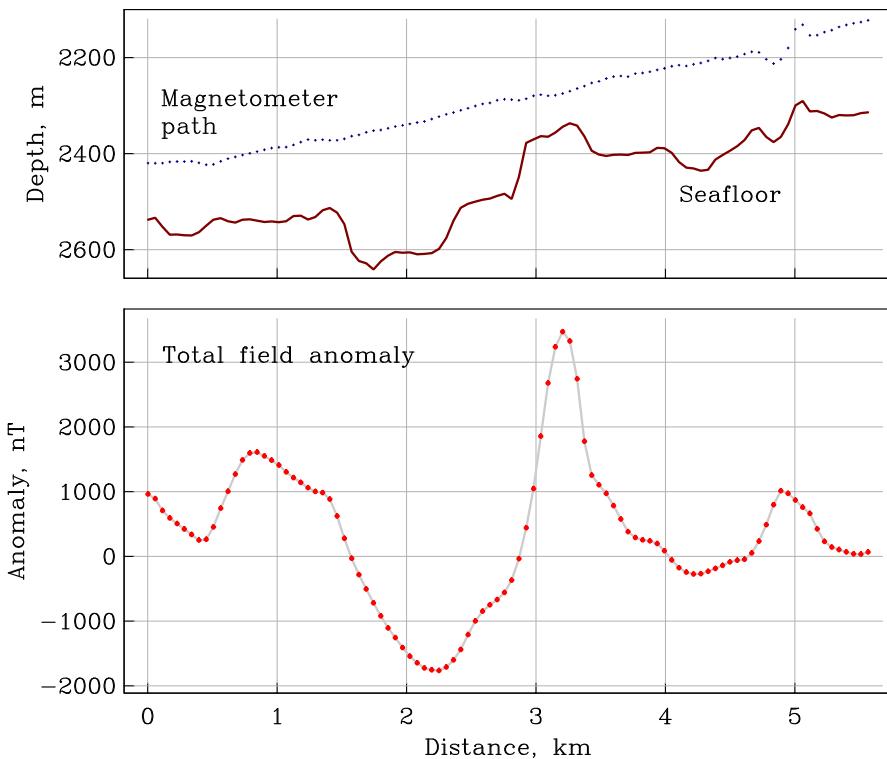


Figure 8.1: Magnetic anomaly and fish track.

oceanic crust is about 0.2 Ma, so we are in the Bruhnes normal chron, which ended 0.78 Ma ago.

In a moment we are going to make a number of simplifications to get at the crustal magnetization here. Recall from 2(1-2) that the original magnetization forward problem has a solution that looks like this:

$$\Delta\mathbf{B}(r) = \int_V \mathbf{G}(\mathbf{s}, \mathbf{r}) \cdot \mathbf{M}(\mathbf{s}) d^3\mathbf{s} \quad (1)$$

with \mathbf{G} fully expanded now to

$$\mathbf{G}(\mathbf{s}, \mathbf{r}) = \frac{\mu_0}{4\pi} \hat{\mathbf{B}}_0 \cdot \nabla \nabla \frac{1}{R} = \frac{\mu_0}{4\pi} \left[\frac{3\hat{\mathbf{B}}_0 \cdot (\mathbf{r}-\mathbf{s})(\mathbf{r}-\mathbf{s})}{R^5} - \frac{\hat{\mathbf{B}}_0}{R^3} \right] \quad (2)$$

and $R = |\mathbf{r}-\mathbf{s}|$. Remember the magnetization \mathbf{M} is a vector-valued function of position \mathbf{s} within the volume V ; the grad acts on the \mathbf{s} coordinate here, although since $G(\mathbf{r}, \mathbf{s}) = G(\mathbf{s}, \mathbf{r})$ that is unimportant in (2). In (1) \mathbf{G} is known and \mathbf{M} is the function we seek. In fact we do not have continuous values of $\Delta\mathbf{B}$, but samples at specific points on the sea surface $\mathbf{r}_1, \mathbf{r}_2, \dots, \mathbf{r}_m$. So we can specialize (1) to this situation

$$d_j = \Delta\mathbf{B}(\mathbf{r}_j) = \int_V \mathbf{G}_j(\mathbf{s}) \cdot \mathbf{M}(\mathbf{s}) d^3\mathbf{s}, \quad j = 1, 2, \dots, m \quad (3)$$

where we assign particular function $G_j(\mathbf{s})$ to each observation:

$$\mathbf{G}_j(\mathbf{s}) = \mathbf{G}(\mathbf{s}, \mathbf{r}_j) = \frac{\mu_0}{4\pi} \hat{\mathbf{B}}_0 \cdot \nabla \nabla \frac{1}{|\mathbf{r}_j - \mathbf{s}|} \quad (4)$$

Notice that each measured number d_j is obtained in (3) via a **linear functional** of the unknown \mathbf{M} . The set of vector-valued magnetizations within the volume V can be considered to be linear vector space \mathcal{V} ; there are obvious rules for adding two magnetizations and for multiplying a given magnetization by a scalar. Suppose we equip \mathcal{V} with the following **inner product**:

$$(\mathbf{f}, \mathbf{g}) = \int_V \mathbf{f}(\mathbf{s}) \cdot \mathbf{g}(\mathbf{s}) d^3\mathbf{s} \quad (5)$$

The we automatically get a **norm** for the space; the new normed space will be called \mathcal{H} for Hilbert. The implied size of a given magnetization function is this:

$$\|\mathbf{M}\| = \sqrt{\int_V \mathbf{M} \cdot \mathbf{M} d^3s} \quad (6)$$

This is almost the RMS magnetization; to get $\|\mathbf{M}\|$ to be RMS magnetization we have to normalize by the volume: $M_{\text{RMS}} = \|\mathbf{M}\|/V^{1/3}$.

The key question is whether or not we can write (3) as an inner product or not. It is a linear functional as we already stated, but is it a **bounded** linear functional? Suppose I write (3) as an inner product:

$$d_j = (\mathbf{G}_j, \mathbf{M}) \quad (7)$$

Then (7) is a valid inner product if and only if $\|G_j\| < \infty$, that is \mathbf{G}_j is a proper element of \mathcal{H} , the normed space. In this case that is easy to verify. Equation (2) looks complicated, but \mathbf{r} and \mathbf{s} never become identical, because the magnetometer is at the ocean surface \mathbf{r}_j and the sources at \mathbf{s} are under water. This means the function $\mathbf{G}_j(\mathbf{s})$ never becomes infinite anywhere in V ; and the volume V is finite too. Hence $\mathbf{G}_j \in \mathcal{H}$. In this way have put the seamount magnetization problem in a Hilbert space setting, writing the solution to the forward problem in a natural manner as an inner product, and using essentially RMS magnetization as a norm. I must add that it would be possible to choose other forms for norm and inner product here, (based on gradients, to smooth things out, for example) but they add complications, best avoided for now.

The shape of seamounts is complex and the computational problem rather large so we return to the profile I plotted earlier from the Juan de Fuca Rise for another version of the magnetization inverse problem. To simplify things we are going to assume next: (i) No variation of magnetization into the plane of the profile, the y direction; (ii) Direction of magnetization constant, $\hat{\mathbf{M}}_0$; (iii) The magnetized layer has a constant thickness Δz ; (iv) Strength of magnetization varies only with x the horizontal coordinate, and not with z within the layer. Then (1) becomes an integral of x alone involving the magnetic intensity $m(x)$; we evaluate the j -th measurement made at the point \mathbf{r}_j :

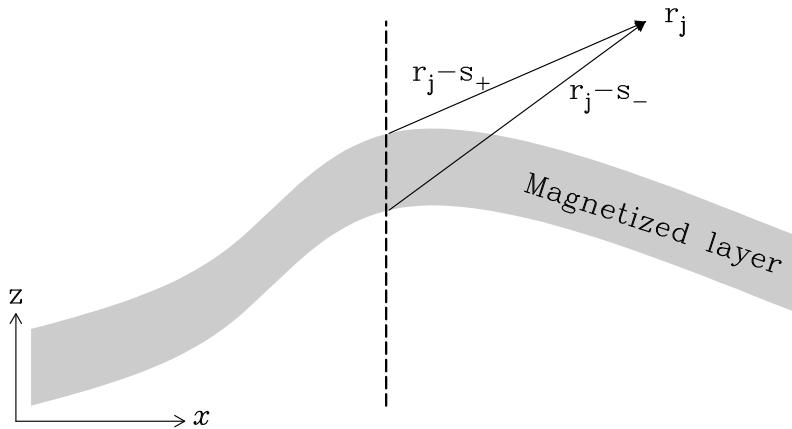


Figure 8.2: Model of magnetic layer.

$$d_j = \Delta \mathbf{B}(\mathbf{r}_j) = \int g(\mathbf{r}_j, x) m(x) dx \quad (8)$$

$$g(\mathbf{r}_j, x) = \frac{\mu_0}{2\pi} \hat{\mathbf{I}}(\hat{\mathbf{B}}_0, \hat{\mathbf{M}}_0) \cdot \left[\frac{\mathbf{r}_j - \mathbf{s}_+(x)}{|\mathbf{r}_j - \mathbf{s}_+(x)|^2} - \frac{\mathbf{r}_j - \mathbf{s}_-(x)}{|\mathbf{r}_j - \mathbf{s}_-(x)|^2} \right] \quad (9)$$

where $\hat{\mathbf{I}}$ is the unit vector given by

$$\hat{\mathbf{I}} = \begin{bmatrix} \sin(I_B + I_M) \\ -\cos(I_B + I_M) \end{bmatrix} \quad (9a)$$

and the angles I_B and I_M are the inclinations of the field and magnetization vectors in the x - z plane. Also \mathbf{s}_+ and \mathbf{s}_- are vectors in the plane pointing to the top and bottom of a vertical column of magnetic material (see Figure 8.2). To get this equation we have integrated (2) both vertically through the layer and from $-\infty$ to ∞ in the y direction. For the data shown in Figure 8.1, because the crust is young we can assume $\hat{\mathbf{M}}_0 = \hat{\mathbf{B}}_0$, the ambient field direction at the site; both these vectors must be projected onto the observation plane. Then, after finding the inclination and dip at the Rise in 1995, (57.42° , 15.42°), we calculate that $\hat{\mathbf{B}}_0 = (0.018, -0.99986)$ in the plane of the profile, essentially vertically downward. We will use the approximation that $\hat{\mathbf{M}}_0 = \hat{\mathbf{B}}_0 = \hat{\mathbf{z}}$ from now on. This problem is interesting and we may return to it later in this form. But to get a magnetization inverse problem so simple we can solve all the integrals analytically we need even more drastic simplification.

We make two further approximations that will be relaxed later: first, we will take the track and the surface of the basement to be horizontal, flat lines. This looks like a serious error from Figure 8.1, but there is a factor of 15:1 in the plot of the track and bathymetry. And finally, we will take the layer thickness, Δz to be small, so that the magnetization can be treated as a thin sheet of dipoles. This assumption is highly suspect: magnetic layer thicknesses at oceanic rises are thought to be at least 500 m. With these further approximations (8) and (9) become:

$$d_j = \int g_j(x) m(x) dx \quad (10)$$

with

$$g_j(x) = \frac{\mu_0 \Delta z}{2\pi} \frac{h^2 - (x - x_j)^2}{(h^2 + (x - x_j)^2)^2} \quad (11)$$

Here the height above the basement is the constant $h = 174$ meters on average; measurements of the anomaly are taken at the horizontal coordinates x_j . This is the result used in GIT 2.06(2), with the addition of the factor Δz , omitted there by oversight, because $\Delta z = 1$ km in all the calculations!

We have to decide on an interval for the integration. In the idealized problem we will pretend the magnetic layer extends over the whole real

line. This gross idealization does not get us into trouble until a bit later, and is very handy for solving the integrals. If we like the norm

$$\|m\| = \left(\int_{-\infty}^{\infty} m(x)^2 dx \right)^{1/2} \quad (12)$$

then the space of magnetization models becomes the classic Hilbert space $L_2(-\infty, \infty)$, with inner product

$$(f, g) = \int_{-\infty}^{\infty} f(x) g(x) dx \quad (13)$$

Is (11) an inner product in this space? The answer is yes if we can show that

$$\|g_j\|^2 = \frac{\mu_0^2 \Delta z^2}{4\pi^2} \int_{-\infty}^{\infty} \frac{(h^2 - (x - x_j)^2)^2}{(h^2 + (x - x_j)^2)^4} dz \quad (14)$$

is finite. Later we will evaluate this messy integral exactly. For now we can show it is bounded, by a couple of simple observations: the function $g_j(x)^2$ is bounded and continuous (in fact it is analytic on the real line); as $|x| \rightarrow \infty$ we can easily verify that $g(x) \rightarrow \mu_0 \Delta z / 2\pi x^2$ so that $g(x)^2 \rightarrow \text{constant}/x^4$. This dies away fast enough to have a finite integral and there we can write (10) as

$$d_j = (g_j, m), \quad j = 1, 2, \dots, m \quad (15)$$

Again, this may not be the only norm we will want to use, but to get things started $L_2(-\infty, \infty)$ is a good place to start.

You may be asking, when would the linear functions fail to be bounded, and what would be the consequences of that failure? In this problem, we can cause the integrals like (14) to be undefined simply by setting h the height of the observation line, go to zero, effectively setting the magnetometer directly on the sources, instead of above them; this is not an impossible experimental geometry. One way to look at the failure is to examine the limit as h tends to zero: we find the norm minimizing magnetization becomes more and more closely concentrated around the observation sites, and has a smaller and smaller norm, in the limit, $\|m\| = 0$. The model space L_2 is inappropriate because it does not lead to a geophysically plausible, let alone a simple solution. The original justification for norm minimizers was that they should select models with the fewest extraneous features, to be as bland and unobjectionable as possible. When h is set to zero, L_2 fails to do this, and we should look for a different approach; the best way is to leave Hilbert space entirely.

9. The Continuous Problem

Before getting into the application of our general Hilbert-space based approach, let us look at a naive treatment of the 1-D, flat layer problem that relies on its special characteristics. While the method in its bare form fails miserably, it provides some useful insights of a general nature and, as we shall see later, it can be modified to yield quite satisfactory answers. First pretend that we have dense observations on the whole real line. Then 8(10) becomes

$$d(y) = \int_{-\infty}^{\infty} k(y-x) m(x) dx \quad (1)$$

where

$$k(x) = \frac{\mu_0 \Delta z}{2\pi} \frac{h^2 - x^2}{(h^2 + x^2)^2} \quad (2)$$

Written this way, it is clear that the solution to the forward problem when the data d are known on $(-\infty, \infty)$ is a *convolution*.

Convolutions are very common in geophysics, and just as in this case, we frequently want to undo them: this is called the **deconvolution** problem. Geophysical examples include undoing the effects of an instrument, like a seismometer, or a magnetometer (Constable and Parker, 1991), or removing path effects from a seismogram using the empirical Green's function (Prieto, et al, 2006).

Whenever you see a convolution (which you know can be written $d = k * m$) you should think of the **Convolution Theorem**, which says

$$\mathcal{F}[k * m] = \mathcal{F}[k] \mathcal{F}[m] = \hat{k} \hat{m} \quad (3)$$

where of course \mathcal{F} is the Fourier transform (FT) given by

$$\mathcal{F}[f] = \hat{f}(\lambda) = \int_{-\infty}^{\infty} f(x) e^{-2\pi i \lambda x} dx \quad (4)$$

Thus, if we take the FT of (1) we see

$$\hat{d} = \hat{k} \hat{m} \quad (5)$$

and the solution to the inverse problem is obtained merely by division, since the complicated integral in (1) has been converted into a simple multiplication. (Mathematicians would say the convolution has been *diagonalized*.) The result for m is just

$$m(x) = \mathcal{F}^{-1} \left[\frac{\hat{d}}{\hat{k}} \right] \quad (6)$$

The inverse problem is apparently finished, since the solution has been reduced to three FTs and a division.

In fact we can go one step further: the FT of $k(x)$ can be found in terms of elementary functions. Those of you who took SIO-239 from me

should think about how to go about this calculation, starting from the well-known FT of $1/(h^2 + x^2)$. I will just give you the answer, the amazingly simple:

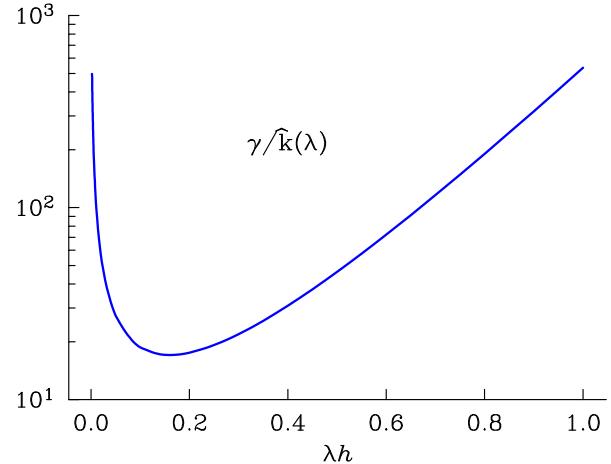
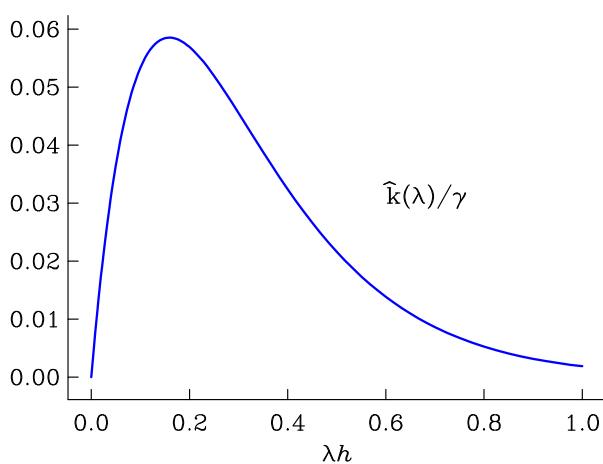
$$\hat{k}(\lambda) = \pi \mu_0 \Delta z |\lambda| e^{-2\pi h |\lambda|} \quad (7)$$

This function is shown in Figure 9.1; it is obviously even in λ .

At first glance, equation (6) seems to imply there is a unique solution to the inverse problem: for every function d , there is a unique \hat{d} and so there is just one \hat{m} and one m that results: in other words, complete and exact data provide a single, one-dimensional magnetization model $m(x)$. That is in complete contrast to the 3-D problem considered at the beginning of the class, where exact data can be matched with a enormous array of different internal magnetizations. However, things aren't quite so straightforward. Look at (7): notice that $\hat{k}(0) = 0$. This means that the integral of $k(x)$ over all x vanishes, and therefore any constant magnetization generates zero magnetic anomaly. A constant magnetization may be present in any amount and it will always be undetectable: it is the **magnetic annihilator** for the problem. Hence the solution to this inverse problem is not unique — there is a single uncontrolled degree of freedom. We conclude that the many additional assumptions and simplifications we introduced have almost, but not quite, suppressed the vast ambiguity of the original problem posed in Section 2 of these notes.

The analytic solution also highlights the instability associated with short-wavelength anomalies. Equation (6) states that to obtain the magnetization function we must apply a spatial filter with transfer function $\hat{k}(\lambda)^{-1}$, a function shown in Figure 9.1. Because $\hat{k}(\lambda)$ decays essentially exponentially, small-scale components of d are magnified with an exponentially growing factor as the scale decreases. With realistic signals, noise does not decay exponentially with wavenumber, and so above some value of λ , noise will be preferentially amplified by this deconvolution.

Figure 9.1: The function $\hat{k}(\lambda)$ and its reciprocal. The constant $\gamma = \pi \mu_0 \Delta z / h$.



And the same thing happens, though less explosively at small wavenumbers. So both the longest and the short wavelengths are amplified in a singular way, making them the least reliable parts of the solution.

Applying (6), an “exact” solution, to real data presents serious difficulties. We don’t have a continuous function $d(x)$ for all real x , but finite set of numbers. If we interpolate the samples to create values at short scales, we are introducing values just where the filter $1/\hat{k}$ generates the greatest exaggeration. If we extend the finite profile by some other kind of extrapolation, the longest wavelengths are invented, and yet these are given the unbounded emphasis by the filter! So, while we could attempt to approximate the analytic inversion with a Fast Fourier Transform of the actual data, we will turn instead to a process that takes into account the finiteness of the data set, and its uncertainties.

References

- Constable, C. G. and Parker, R. L., Deconvolution of long-core paleomagnetic measurements: Spline therapy for the linear problem, *Geophys. J. Int.* 104, 453-468, 1991.
- Prieto, G. A., Parker, R. L., Vernon, F. L., Shearer, P. M., and Thomson, D. J., Uncertainties in earthquake source spectrum estimation using empirical Green functions, in *Earthquakes: Radiated Energy and the Physics of Faulting*, Geophysical monograph 170, eds Abercrombie, McGarr, Kanamori, and Di Toro, American Geophysical Union, Washington, 2006.

10. The Minimum Norm Solution

Staying with the very idealized 1-D problem in a flat, thin layer, we address directly the question of a finite data set using the Hilbert space theory. In the previous Section we found that trying to complete the set of observations to make them suitable for the exact solution automatically introduced artificial values exactly where the wavenumber filter put the most emphasis, the longest and shortest wavelengths. To get around this problem we acknowledge from the start the finite of the data set by writing

$$d_j = \int_{-\infty}^{\infty} g_j(x) m(x) dx, \quad j = 1, 2, \dots, N \quad (1)$$

Notice that the model is still defined as a real function on $(-\infty, \infty)$. However, the price to be paid is the fact that there cannot now be a unique solution, since only finitely many conditions result from (1), but a function is needed. So we invoke the principle of minimum complexity, and look only for models that are small in some sense to avoid the exponential magnifications implied by the deconvolution study. The sense will be the norm, and for simplicity of calculation we shall say that $m \in L_2(-\infty, \infty)$. Therefore we write (1) as a set of inner products in L_2 :

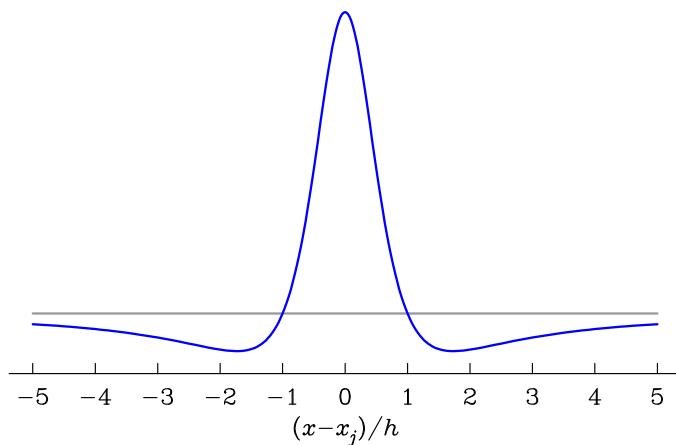
$$d_j = (g_j, m), \quad j = 1, 2, \dots, N \quad (2)$$

where from 8(11)

$$g_j(x) = \frac{\mu_0 \Delta z}{2\pi} \frac{h^2 - (x - x_j)^2}{(h^2 + (x - x_j)^2)^2} \quad (3)$$

These N elements of L_2 are the **representers** for the problem, although it has not yet been proved that the linear functionals in (2) are in fact bounded (they are), or equivalently that $\|g_j\|$ exists. Figure 10.1 depicts a typical representer; they are all the same shape, just shifted in x because (1) is a convolution.

Figure 10.1: A typical representer for the simplified magnetic problem.



Recall the result from GIT that the element that achieves the smallest norm while satisfying (2) is the linear combination of representers:

$$m_0 = \sum_{j=1}^N \alpha_j g_j \quad (4)$$

The coefficients α_j are found by substituting this expansion back into (2) and solving the linear system

$$\sum_{k=1}^N \Gamma_{jk} \alpha_k = d_j, \quad j = 1, 2, \dots, N \quad (5)$$

where Γ_{jk} are the entries of the **Gram matrix** of representers:

$$\Gamma_{jk} = (g_j, g_k), \quad j = 1, 2, \dots, N; \quad k = 1, 2, \dots, N \quad (6)$$

It is shown in GIT that if the representers are linearly independent, Γ is nonsingular and so (6) has a unique solution. We will prove that at the end of this Section.

To make progress we must evaluate the Gram matrix; the integrals seem at first sight to be quite daunting. But if we recall the result that an inner product is invariant under Fourier transformation:

$$(g_j, g_k) = (\hat{g}_j, \hat{g}_k) \quad (7)$$

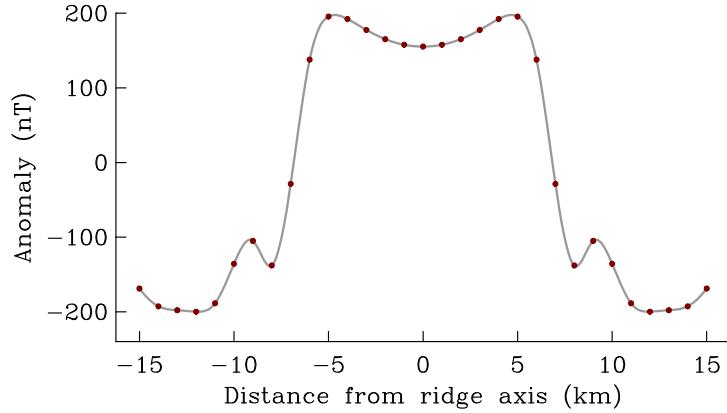
the task becomes more tractable, especially in view of the simplicity of the FT in 9(7). We find after a modest amount of work (see GIT, p 80) that

$$\Gamma_{jk} = \frac{\mu_0^2 \Delta z^2 h}{\pi} \frac{4h^2 - 3(x_j - x_k)^2}{[4h^2 + (x_j - x_k)^2]^3} \quad (8)$$

Since $\Gamma_{jj} = \|g_j\|^2$, this result proves the norms of the representers are finite, and the integrals in (1) are bounded linear functionals as we have assumed.

Before applying an inversion to real data it is wise to test it on an artificial set generated from a known model. So that is what we do next, the data set is drawn from Chapter 2 of GIT and is shown below. Here the scale is very different from the near-bottom data shown in Section 8.

Figure 10.2: Fake marine magnetic anomaly data.



the water depth $h = 2 \text{ km}$ and the layer thickness $\Delta z = 1 \text{ km}$. The minimum L_2 norm solution is obtained by a few lines of MATLAB:

```

h=2; dz=1; muo=4*pi*100;
c = muo^2*dz^2*h/pi;

x = [-15 : 15]';
d =[-168.72,-192.57,-197.78,-199.79,-188.49,-135.62, ...
-104.91,-137.87,-28.557,138.00,195.60,192.36,177.66, ...
165.33,157.87,155.41,157.87,165.33,177.66,192.36,195.60, ...
138.00,-28.557,-137.87,-104.91,-135.62,-188.49,-199.79, ...
-197.78,-192.57,-168.72]';

% Build Gram matrix
[X Y]=meshgrid(x,x);
G=c*(4*h^2-3*(X-Y).^2)./(4*h^2+(X-Y).^2).^3;

% Solve linear system
a=G\ d;

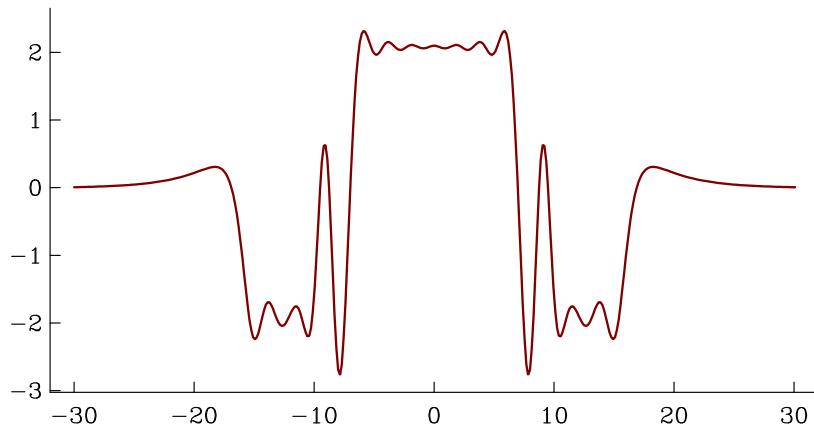
% Represents are columns of g
y=linspace(-30,30,200);
[X Y]=meshgrid(x,y);
g=(muo*dz/(2*pi))*(h^2-(X-Y).^2)./(h^2+(X-Y).^2).^2;

% Solution is a linear combo of representers
mo = g*a;

```

The norm minimizer, m_0 , is plotted below. You can guess what the original model was that generated the data from this solution. The result is fairly wiggly, though it has small amplitude as it should. We should now think about suppressing these wiggles, say by finding the solution that minimizes $\|dm/dx\|$. This is discussed in GIT, using a pure Hilbert

Figure 10.3: L_2 norm minimizing magnetization from artificial data shown in Figure 10.2.



space method. We will look at this from a numerical view point in a later Section. The results are not very impressive — the wiggles are still there.

In GIT the linear independence of the representers for the 1-D magnetic anomaly inverse problem was proved using the Fourier transform. I will present here an alternative proof, which is more useful because it gives a method that I have found works for a number of linear inverse problems, especially those arising out of potential theory like this one. The approach is successful for problems in two and three dimensional problems too.

Here we have a set of N functions on the real line given by:

$$g_j(x) = \frac{h^2 - (x - x_j)^2}{(h^2 + (x - x_j)^2)^2}, \quad j = 1, 2, \dots, N \quad (9)$$

where all the x_j are different (why?). I have dropped all the constant factors for obvious reasons. Although the setting of the original problem is the space $L_2(-\infty, \infty)$, we can use properties of g_j that functions in L_2 don't all possess for our proof. The normal way to prove this kind of proposition is by contradiction: we shall assume the set is **linearly dependent** and then show that leads to a contradiction. The statement for LI is that there are scalars β_j not all zero, such that

$$\sum_{j=1}^N \beta_j g_j(x) = 0, \text{ for all } x. \quad (10)$$

If this is true, we can choose one of the functions g_k multiplied by a nonzero coefficient, and move it onto the other side thus:

$$g_k(x) = \sum_{j \neq k} (-\beta_j / \beta_k) g_j(x) \quad (11)$$

which says that the representer g_k can be built from a linear combination of the others.

To get a contradiction we need to focus on a value of x where $g_k(x)$ goes to infinity. There is no such place on the real line, but never mind — we can choose x to be **complex** if we wish! Looking at (9) we see that the denominator vanishes whenever $(x - x_j)^2 = -h^2$ or

$$x_* = x_j \pm ih. \quad (12)$$

These are the singularities of g_j in the complex x plane. Suppose now I consider the function $g_k(x)$ in (11) when $x - x_k = ih + \varepsilon$ where ε is a small real quantity of our choosing; in other words, x is very near a singular point of the function $g_k(x)$. From the definition of g_k we see that

$$g_k(x) = \frac{h^2 - (ih + \varepsilon)^2}{(h^2 + (ih + \varepsilon)^2)^2} = -\frac{2h^2 + 2ih\varepsilon + \varepsilon^2}{\varepsilon^2(2ih + \varepsilon)^2} \quad (13)$$

$$= \frac{1}{2\varepsilon^2} \left[1 + O(\varepsilon) \right]. \quad (14)$$

It is clear that by making ε small enough we can get the magnitude of $g_k(x)$ as large as we wish. For the same x on the other side of (11) we look at the denominators and we see a value that does not go to zero as ε gets small:

$$(h^2 + (x - x_j)^2)^2 = ((x_k - x_j + \varepsilon)^2 + 2ih(x_k - x_j + \varepsilon))^2 \quad (15)$$

$$= (x_k - x_j + \varepsilon)^2(x_k - x_j + \varepsilon + 2ih)^2. \quad (16)$$

This number is not zero for small ε because $x_j \neq x_k$ and both of the x s are real. The same thing is true for every j on the right of (11). This means that as ε tends to zero, the left side of (11) grows and grows, while the right side tends to some constant value. That is a contradiction, which means that constants like β_j do not exist.

Almost exactly this argument works for the representers in the more complicated magnetic problems considered in Section 8 of the Supplementary Notes, while the Fourier treatment probably could not be made to apply. Setting up an equation like (11) in which one side is constant, while the other grows to infinity (or shrinks to zero) is a classic way to show linear dependence of a set of functions. Doing this in the complex plane is a very natural thing, because every analytic function has a singularity in the complex plane, except the constant.

11. The Numerical Alternative

The functional analysis approach to the norm minimization problem in Hilbert space shows how an exact theory can be worked out retaining the essential asymmetry between data and model: data are finite in number, but the model is a function that lives on an infinite-dimensional space. But real-world situations in which the Gram matrix can be calculated exactly, while not nonexistent, are in the minority. I mention for your edification two of my papers where exact Gram matrices are in fact found: Shure, L., Parker, R. L., and G. E. Backus: Harmonic splines for geomagnetic modeling, in *Phys. Earth Planet. Inter.*, 28, 215-29, 1982 and Parker, R. L.: Calibration of the pass-through magnetometer-I. Theory, in *Geophys. J. Internat.*, 142, 371-83, 2000. Numerical methods will in any case appear at some point in every calculation and so we will now develop a treatment based on linear algebra that is founded on a finite-dimensional approximation for the forward problem.

The key is that the linear functional that captures the solution to the forward problem, written in Chapter 2 of GIT as

$$(g_j, m) = d_j, \quad j = 1, 2, \dots, M \quad (1)$$

can be written in an approximation as a finite sum

$$g_j^T m = d_j, \quad j = 1, 2, \dots, M \quad (2)$$

where $g_j, m \in \mathbb{R}^N$; so now the model and representers are vectors of dimension N . Of course (2) is more compactly written

$$Gm = d \quad (3)$$

where $G \in \mathbb{R}^{M \times N}$ and $d \in \mathbb{R}^M$ and the rows of the matrix G are the (row) vectors g_j^T . At this point in the class when the models are simple, we tend to think of M , the number of data, being a lot smaller than the N the dimension of the model space, but when big data sets are involved that isn't always the case.

In the vast majority of practical cases the inner product in (1) is representing an integral, as in the inner product of L_2 . To make the transition to (2) one must **discretize** the underlying continuous problem. The most primitive way of doing this which, quite honestly I prefer, is to break the model space up into boxes and replace the integral by a simple sum. On the real line, for example, in the simple one-dimensional magnetization problem, we could use uniform sampling, Δx , and then

$$\int_a^b f(x) dx = \sum_{k=1}^N w_k f(a + (k-1)\Delta x) + \varepsilon \quad (4)$$

where $\Delta x = (b-a)/(N-1)$, w_k are a set of weights, and ε is the error approximation. The easiest, and in most circumstances least accurate formula of this kind is the **trapezoidal rule** where one takes:

$$w_1 = w_N = \frac{1}{2}\Delta x, \quad w_2 = w_3 = \cdots = w_{N-1} = \Delta x \quad (5)$$

which has the effect of replacing the original function $f(x)$ by the straight-line approximation, shown in Figure 11.1. The error term then tends to zero as Δx^2 , provided f is smooth enough to be twice differentiable. Another favorite is **Simpson's rule**; here

$$w_1 = w_N = \frac{1}{3}\Delta x, \quad w_2 = w_4 = \cdots = w_{N-1} = \frac{4}{3}\Delta x \quad (6)$$

$$w_3 = w_5 = \cdots = w_{N-2} = \frac{2}{3}\Delta x$$

and the number of samples N must be odd. Now instead of straight lines between sample points, the effective approximation is that of parabolic arcs (quadratic interpolation). The error decreases as Δx^4 but the function must be four-times differentiable. If one relaxes the constraint the sample in x be even, one can increase the accuracy of the approximation considerably, with **Gaussian quadrature**. Here one looks for the highest degree polynomial approximation to the integral; this idea is dealt with in every text on numerical analysis. Less well known are the rules for integrating over surfaces and volume elements, often by building upon the Gaussian method. For these see Stroud, A. H., *Approximate Calculation of Multiple Integrals* Prentice-Hall Book Co. 1971.

Another idea is to say the model itself consists of a piece-wise constant or a piece-wise linear function, and to perform the integral analytically over the chosen region. This can be done for many 3-dimensional polyhedral shapes for potential fields (gravity and magnetism), and has the advantage of avoiding large errors that can arise when the observer is very near, or actually in contact with, the source material. See Blakely, R. J., *Potential Theory in Gravity and Magnetic Applications*, Cambridge University Press, New York, 1995, for lots of messy formulas, and

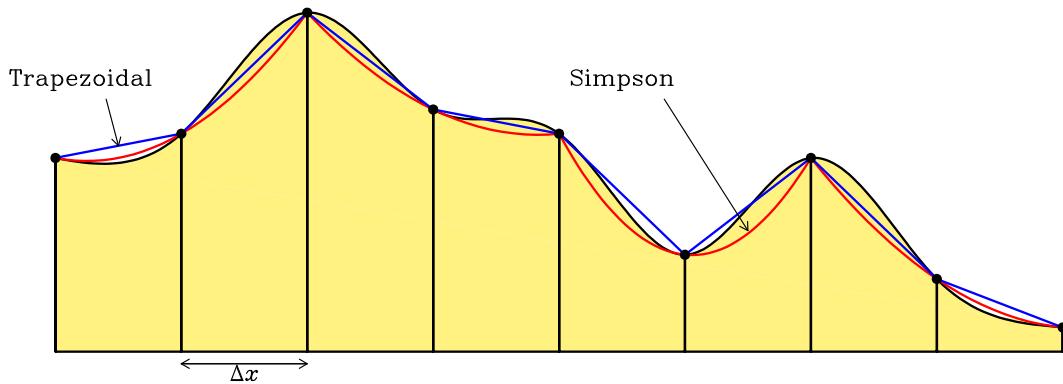


Figure 11.1: Trapezoidal and Simpson quadrature.

FORTRAN code too! This approach may be necessary when the representer is unbounded (as it is with gravity or magnetic measurements made on the surface of the source region) because then trapezoidal or Simpson quadrature can give infinite answers.

Let us try some of these ideas out on the 1-dimensional crustal magnetization problem. First consider the norm minimizing model. We are going to numerical approximations of the norm:

$$\|f\| = \left(\int_{-\infty}^{\infty} f(x)^2 dx \right)^{1/2} \quad (7)$$

and the corresponding inner product. The first thing that must go is the infinite interval of integration, which was a mathematical fiction anyhow. To represent the integral by a finite sum we will have at least two ways: (a) we can just truncate the interval to a finite one; (b) we could use a change of variable, that maps the real line onto some interval (a, b) and then we use (4)—a possible candidate might be $x = h \tan \theta$ which sends the real line into $(-\frac{1}{2}\pi, \frac{1}{2}\pi)$. Here I will pursue (a). We will simply assume that the magnetization is confined between ± 25 km, adding 2.5 times the water depth h to each end of the interval containing the measurements. So now the model norm is found from

$$\|m\|^2 = m^T W m \quad (8)$$

where $m \in \mathbb{R}^N$ a vector of evenly spaced samples of the model, and $W \in \mathbb{R}^{N \times N}$ is the diagonal matrix:

$$W = \text{diag}(w_1, w_2, \dots, w_N) \quad (9)$$

and we choose the weights w_k according some integration rule, say Simpson. Then the statement that the model fits the data looks like this

$$G W m = d. \quad (10)$$

Here each row of $G \in \mathbb{R}^{M \times N}$ is a vector of samples of the representer g_j and the N points ξ_k :

$$G_{jk} = g_j(\xi_k) = \frac{\mu_0 \Delta z}{2\pi} \frac{h^2 - (\xi_k - x_j)^2}{(h^2 + (\xi_k - x_j)^2)^2}, \quad j=1, 2, \dots, M, k=1, 2, \dots, N. \quad (11)$$

The matrix W is doing the integration here. It is natural to choose $N > M$, more model points than data, and so we have an underdetermined LS problem to solve. It is not quite in the form we considered earlier in sections 5 and 6, but that can easily be fixed by a simple substitution. Suppose I introduce $n \in \mathbb{R}^N$ as

$$m = W^{-1/2} n \quad (12)$$

where by $W^{-1/2}$ I mean the diagonal matrix $\text{diag}(w_1^{-1/2}, w_2^{-1/2}, \dots, w_N^{-1/2})$. Then in terms of n (8) becomes

$$\|m\|^2 = (W^{-1/2}n)^T W (W^{-1/2}n) = n^T (W^{-1/2})^T W W^{-1/2} n \quad (13)$$

$$= n^T n. \quad (14)$$

So the norm of m is L_2 becomes the Euclidean length of the vector n . And putting n into (10) gives

$$(GW^{1/2})n = d \quad (15)$$

This is an ordinary underdetermined LS problem for n with the matrix $A = GW^{1/2} \in \mathbb{R}^{M \times N}$. We can use QR on this for example if we need extra stability. If we use the normal equations, recall the solution 6(20):

$$n = A^T(AA^T)^{-1}d = (GW^{1/2})^T[GW^{1/2}(GW^{1/2})^T]^{-1}d \quad (16)$$

$$= W^{1/2}G^T[GWG^T]^{-1}d. \quad (17)$$

The matrix $GWG^T \in \mathbb{R}^{N \times N}$ is the *numerical approximation of the Gram matrix*. So $a = [GWG^T]^{-1}d$ is the approximation for the vector of coefficients α in 10(4), for example, and you will easily verify that after we multiply through by $W^{-1/2}$ as indicated in (12), we get

$$m = G^T[GWG^T]^{-1}d = G^T a \quad (18)$$

the equation which is the numerical equivalent to

$$m = \sum_{j=1}^M \alpha_j g_j \quad (19)$$

the standard solution from the recipe from Hilbert space.

The numerical results for the idealized magnetic profile are shown in Figure 11.2; here I have chosen the number of sample points N to be 101. Three solutions are plotted superimposed: the two numerical models using Simpson's rule and trapezoidal rule and the analytic result found by solving the system in $L_2(-\infty, \infty)$. A surprising result is that the analytic model and trapezoidal rule track almost exactly, and the Simpson rule solution is slightly different, visible as the slightly less wiggly curve in the magnified picture. The 2-norm of all of these solutions is 15.4; the distance between the Simpson solution and the exact one is 0.51 in the norm, while it is only 0.0079 between the trapezoidal solution and the exact result.

When we come to a seminorm minimization, one that could penalize the gradient for example, we can replace (8) by

$$\|Pm\|^2 = (Dm)^T W_1 Dm = m^T (D^T W_1 D) m \quad (20)$$

where $D \in \mathbb{R}^{N-1 \times N}$ is the upper triangular matrix approximating the first difference:

$$D = \frac{1}{\Delta x} \begin{bmatrix} -1 & 1 & & & \\ & -1 & 1 & & \\ & & -1 & 1 & \\ & & & \dots & \\ & & & & -1 & 1 \end{bmatrix} \quad (21)$$

where entries that are not ± 1 are zeros. And, since D is not square, W_1 is a weight matrix in $\mathbb{R}^{N-1 \times N-1}$. We cannot perform the same trick as in the norm minimization, because the matrix $(D^T W_1 D)$ is not of full rank, (a constant vector is mapped to zero) and cannot therefore be inverted. Inversion is implied when one forms $W^{-1/2}$ from W . So we have a form of LS problem that we did not meet earlier:

$$x_0 = \arg \min_{Ax = y} x^T Bx \quad (22)$$

where $A \in \mathbb{R}^{M \times N}$, with $N > M$, $B \in \mathbb{R}^{N \times N}$ and B is not necessarily of full rank. We can solve this with the introduction of M Lagrange multipliers, or equivalently a vector $\mu \in \mathbb{R}^M$. Then the unconstrained function is

$$u(x, \mu) = x^T Bx - \mu^T (Ax - y). \quad (23)$$

The usual differentiation leads to a linear system to be solved:

$$\begin{bmatrix} 2B & -A^T \\ A & O_M \end{bmatrix} \begin{pmatrix} x \\ \mu \end{pmatrix} = \begin{pmatrix} 0 \\ y \end{pmatrix}. \quad (24)$$

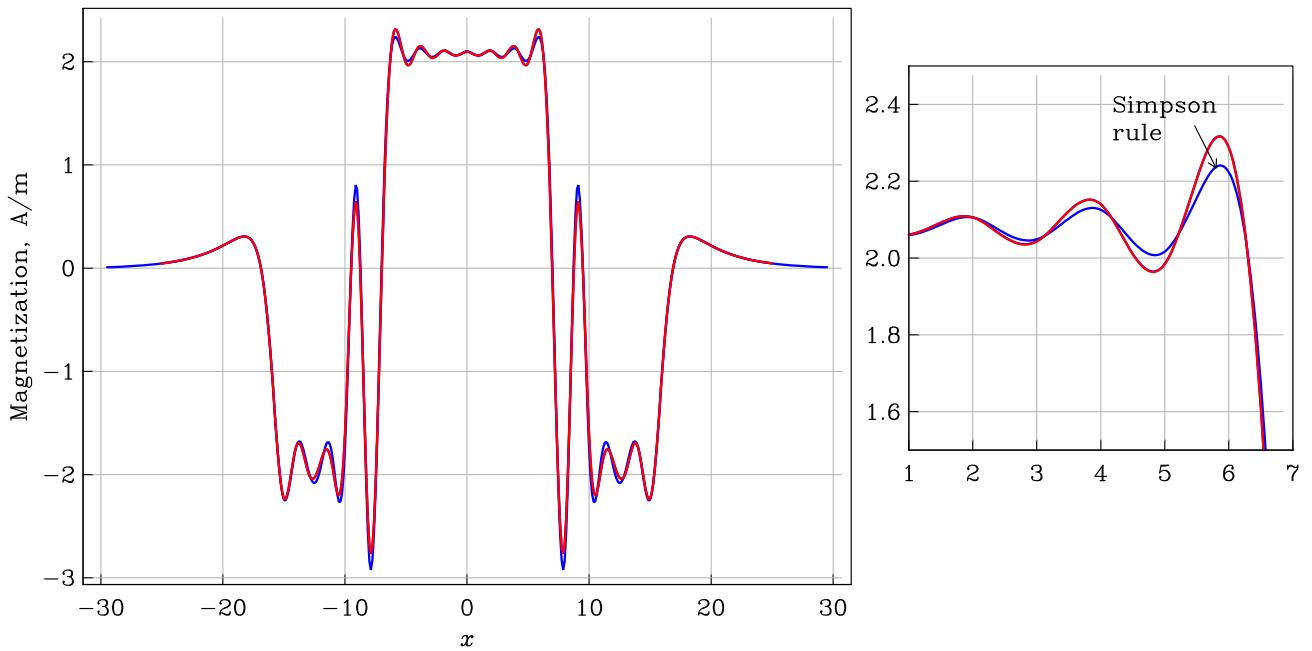


Figure 11.2: Numerical and analytic solutions.

This is a rather large matrix, but in our example $B = D^T W_1 D$ is tridiagonal, and therefore mostly zeros, and the lower right matrix is all zeros, so sparse techniques are applicable to speed up the solution if the M and N get large. The relationship between this solution and the one found in Hilbert space in GIT pp 74-78 is not at all obvious. I will not get into the correspondence, because we will hardly ever use (24) in future.

Now that we have machinery for solving more realistic problems, let us return to the real magnetic anomaly profile taken near the seafloor at the Juan de Fuca Rise, plotted in Figure 8.1 of the notes. The forward problem is solved with 8(8-9), which I will repeat here for convenience, but you will need to look at Figure 8.2 also.

$$d_j = \int g(\mathbf{r}_j, x) m(x) dx = \sum_k w_k g(\mathbf{r}_j, x_k) m(x_k) \quad (25)$$

where w_k are the quadrature weights, and the representer is

$$g(\mathbf{r}_j, x) = \frac{\mu_0}{2\pi} \left[\frac{\hat{\mathbf{z}} \cdot (\mathbf{r}_j - \mathbf{s}_+(x))}{|\mathbf{r}_j - \mathbf{s}_+(x)|^2} - \frac{\hat{\mathbf{z}} \cdot (\mathbf{r}_j - \mathbf{s}_-(x))}{|\mathbf{r}_j - \mathbf{s}_-(x)|^2} \right]. \quad (26)$$

Notice I have inserted the approximation that $\hat{\mathbf{M}}_0 = \hat{\mathbf{B}}_0 = \hat{\mathbf{z}}$, so that $\hat{\mathbf{I}} = \hat{\mathbf{z}}$. We form the matrix $G \in \mathbb{R}^{M \times N}$, whose rows are the representers:

$$G_{jk} = g(\mathbf{r}_j, x_k), \quad j = 1, 2, \dots, M, \quad k = 1, 2, \dots, N. \quad (27)$$

As before I am going to sample evenly, and it is important to have more model points than data. Also we cannot go to infinity, in x , and as before I take a modest extension of 0.5 km, a small multiple of the observation height, at each end. Below I give you a code fragment of MATLAB that generates the matrix G . On entry to this part of the code, the are vectors $\mathbf{x}_o, \mathbf{z}_o \in \mathbb{R}^M$ containing the observer coordinates, and $\mathbf{x}_b, \mathbf{z}_b \in \mathbb{R}^N$ holding coordinates of the basement topography. What I want to illustrate is how the MATLAB function `meshgrid` makes it possible to prepare a matrix like G in a way that almost exactly mirrors the algebra: compare the code with (26). The only somewhat odd feature is that the arrays like \mathbf{z}_o etc have a *row* dimension inherited from the *second* vector in the argument, where I would expect the row dimension to be defined by the first vector.

```
[Zo Zb] = meshgrid(zo, zb);
[Xo Xb] = meshgrid(xo, xb);

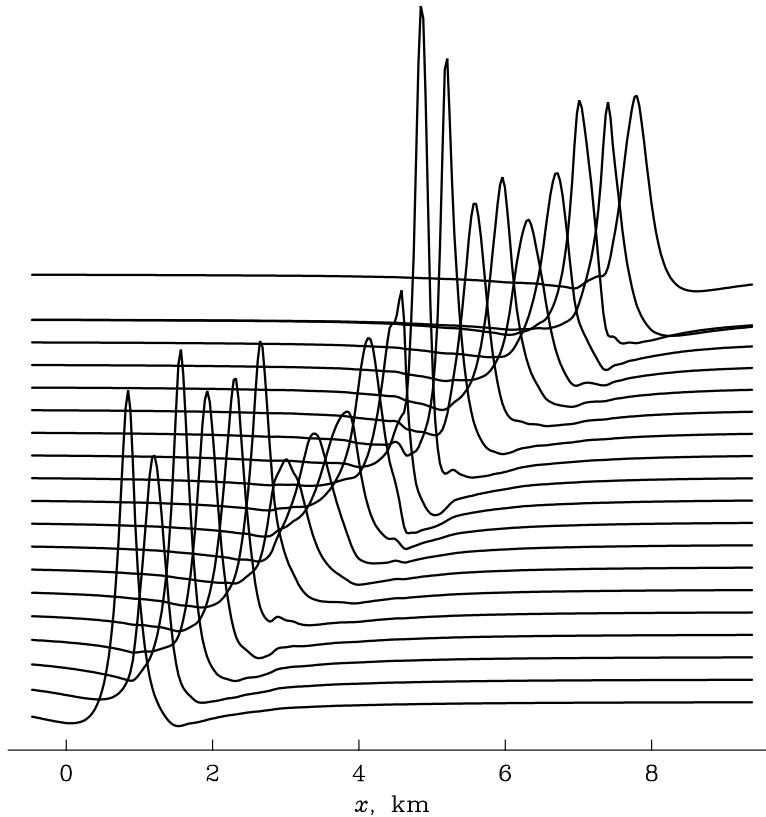
G1 = (Zo - Zb) ./ ((Zo-Zb).^2 + (Xo-Xb).^2);
Zb = Zb - dz;
G2 = (Zo - Zb) ./ ((Zo-Zb).^2 + (Xo-Xb).^2);
G = (mu0/(2*pi)) * (G1 - G2);
```

So now G has columns of representers, which is convenient if one wishes to plot them. What do the representers for the realistic problem look like?

In Figure 11.3 I plot every fifth one. Notice they resemble the simple g_j representers of the original L_2 problem, but with variable amplitudes and irregular shapes. To speed execution it would be reasonable to set the small-amplitude portions to zero thus making G sparse.

Next we calculate the smallest m in L_2 . I use the trapezoidal rule for simplicity, and for stability apply QR to equation (15). The horrible result appears in Figure 11.4. This is the smallest norm model, yet the magnetic intensities are *two orders of magnitude larger* than those typically found in marine basalts! What has gone wrong? This inverse problem was based on real field data, not artificially generated exact numbers. We see here the effect of instability in the presence of noise in the measurements—quite small errors have been amplified grotesquely, even though we are attempting to find small solutions. It is time to lift the artificial demand that the data must be fitted exactly.

Figure 11.3: Representers from equation (26) plotted with vertical offsets.



References

Blakely, R. J., *Potential Theory in Gravity and Magnetic Applications*, Cambridge Univ. Press, New York, 1995.

Useful reference for classical geophysical treatment of potential fields, although the inverse theory presented is somewhat weak.

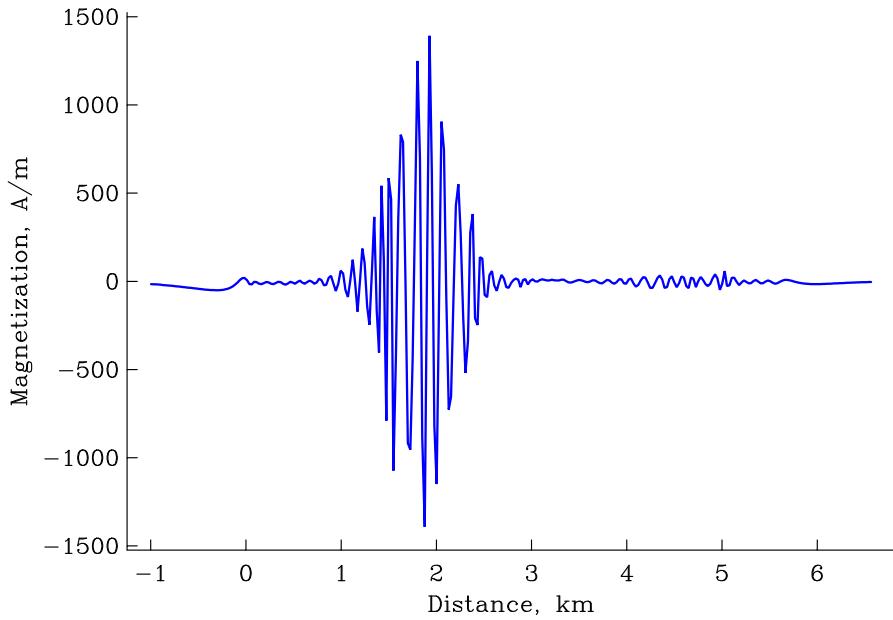
Parker, R. L., Calibration of the pass-through magnetometer-I. Theory, *Geophys. J. Internat.*, 142, 371-83, 2000.

Shure, L., Parker, R. L., and G. E. Backus: Harmonic splines for geomagnetic modeling, in *Phys. Earth Planet. Inter.*, 28, 215-29, 1982.

Stroud, A. H., *Approximate Calculation of Multiple Integrals* Prentice-Hall Book Co. 1971.

Still the classic book on integration over plane and solid regions.

Figure 11.4: Minimum 2-norm model fitting near-bottom magnetic profile exactly.



12. Estimating the Noise Parameters

In Chapter 3 of GIT we saw that the concept of an adequate fit of model predictions to the measured values depends on having a quantitative estimate of the measurement uncertainty, most conveniently, an estimate of the noise **variance**. This is often very difficult to do objectively, and in seismology in particular, people often say it's too difficult to do. In ordinary parameter estimation in statistics, fitting a straight line for example, we have many more data than parameters, and the misfit to the model gives a measure of uncertainty all on its own. A standard result for linear parameter estimation, used to estimate the noise, is

$$\mathbb{E} \left[\sum_{j=1}^N (d_j - \Theta_j)^2 \right] = (N - P) \sigma^2 \quad (1)$$

where Θ_j are the predictions of the linear model, P is the number of parameters in the model, and σ is the standard error of the noise in the measurements d_j . The number $N - P$ is often called the number of degrees of freedom in the data. In the linear inverse problem, this result presents us with a difficulty: in principle P is infinite! With linearly independent representers (the normal situation) we can always reduce the misfit to zero if necessary.

How can we get a value for σ ? In some inverse problems there data themselves are often composites estimated by averaging over large numbers of actual measurements. The best example of this electromagnetic sounding, in which the response of the Earth is obtained by time-series

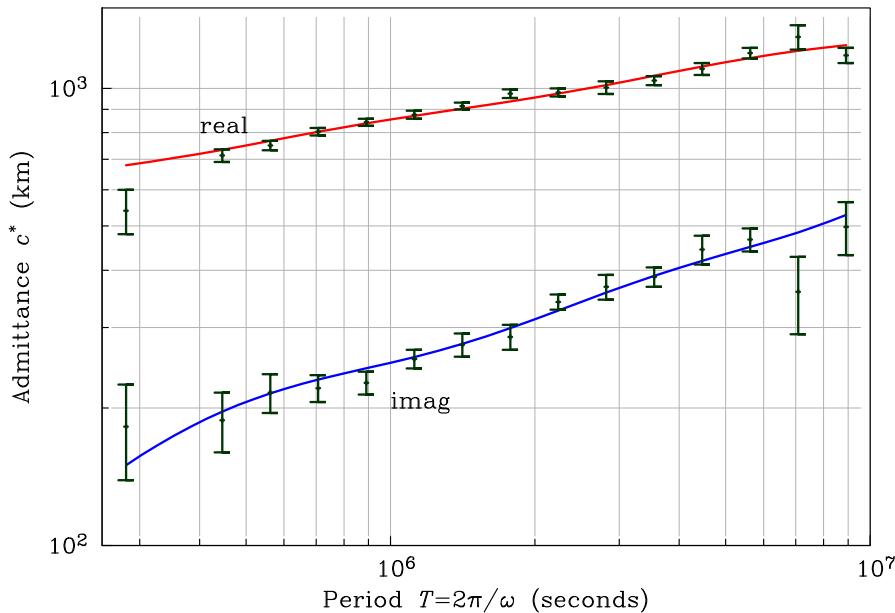


Figure 12.1: Global electromagnetic response with one-standard-deviation error bars.

analysis of long data series of electric and magnetic fields. Those field measurements themselves are never used directly. In this subject a complex function of frequency (called an *admittance* or a *transfer function*) is found statistically, and comes with error bars already; consult Egbert, G. D., and Booker, J. R., Robust estimation of geomagnetic transfer functions, *Geophys. J. R. Astron. Soc.*, 87, 173-94, 1986. Alternatively, when Steve Constable wanted to calculate a global transfer function, he averaged together responses from several independent studies made in scattered locations, and came up with response whose uncertainties were estimated by their deviation from the mean; see Figure 12.1 and Constable, S., Constraints on mantle electrical conductivity from field and laboratory measurements, *J. Geomag. Geoelectr.*, 45, 707-9, 1993.

If we are to identify and quantify noise in data, we need a characteristic that separates it from signal. When the noise is uncorrelated from point to point, it will have a flat power spectral density; even if it is not completely uncorrelated, the noise spectrum is usually much flatter than

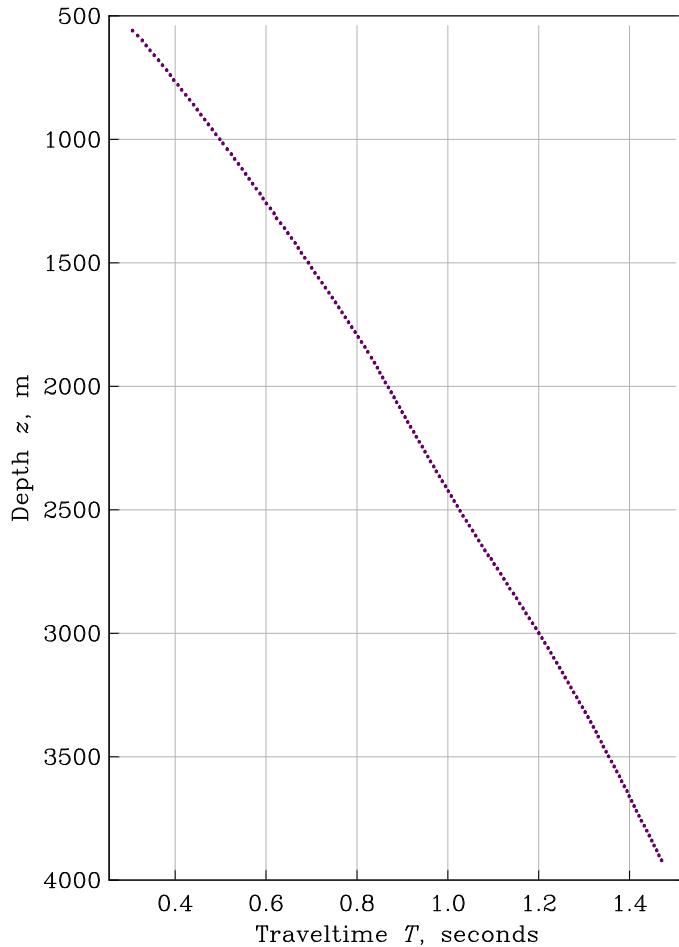


Figure 12.2: Travel-time picks from geophones in a well: the check-shot data.

that of the signal. When the measurements are made serially in time, or in space (along a profile, for example) it is usually possible to estimate the power spectrum, or power spectral density (PSD), from the data set. There is no space to go into how PSD are calculated here; that will be covered in the course on geophysical data analysis in the Spring Quarter. For a good reference see: Priestley, M. B., Spectral Analysis and Time Series, Academic Press, New York, 1981.

On the previous page we see an example of seismic “check-shot” data. These are first-arrival travel time picks from geophones in an oil well, from a charge fired at the surface. If we want to invert this record we will need an estimate of uncertainties. One way would be to look at the original traces, and to take a guess at how accurately the first pulse emerges from the ambient noise, but I don’t have the original records, just the time picks. So we take the power spectrum, from the 169 data. The result, show in Figure 12.3 is remarkably revealing. The two curves belong to different estimation methods for the PSD. What we see is a steeply falling part (a **red spectrum**), out to a wavenumber of around 0.006 m^{-1} , and then a plateau. The flat portion is characteristic of **white noise**, or an uncorrelated random signal. A very compelling interpretation of this spectrum is that the red part comes from the geophysical signal, and the white spectrum is the result of noise in the data. We will assume the noise spectrum continues to the smallest wavenumbers, but is

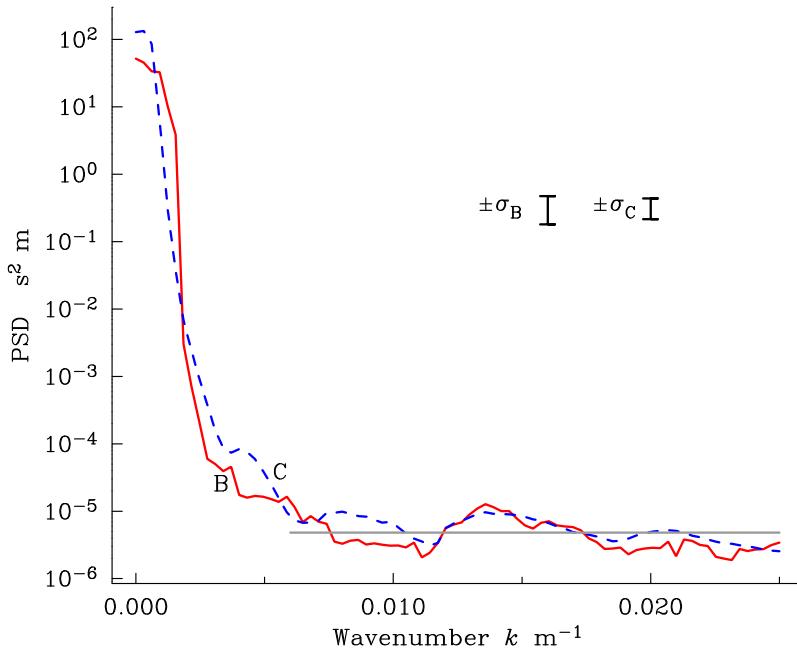


Figure 12.3: Power spectral density of checkshot data.

completely overwhelmed by signal below 0.006 m^{-1} . Then we use the famous result that

$$\text{var}[X] = \int_0^{k_{\max}} P_X(k) dk \quad (2)$$

The variance is just the area under the PSD curve. This gives us approximately $\sigma^2 = 0.03 \times 4 \times 10^{-6} = 1.2 \times 10^{-7} \text{ s}^2$; hence $\sigma = 0.00035 \text{ s}$, or 0.35 milliseconds. The uncertainty in these data would plot as an error bar too small to see on Figure 12.2. A completely different approach leads to almost exactly the same error estimate: see Malinverno, A., and Parker, R. L., Two ways to quantify uncertainty in geophysical inverse problems, *Geophysics*, 71, 15-27, 2005.

We will use the same technique on the near seafloor magnetic data, since it is part of a long serial record. The PSD of our magnetic anomaly is shown as the solid curve in Figure 12.4. At first the picture is not as convincing as it is for the checkshot seismic data, where there is a completely clear division between a red and a flat spectrum, but in this case there is a bit of theory to guide us in what to expect; see Parker, R. L., and O'Brien, M. S., Spectral analysis of vector magnetic field profiles, *J. Geophys. Res.*, 102, 24815-24824, 1997. If the track were level and the basement were flat and contained a random magnetization, we would expect

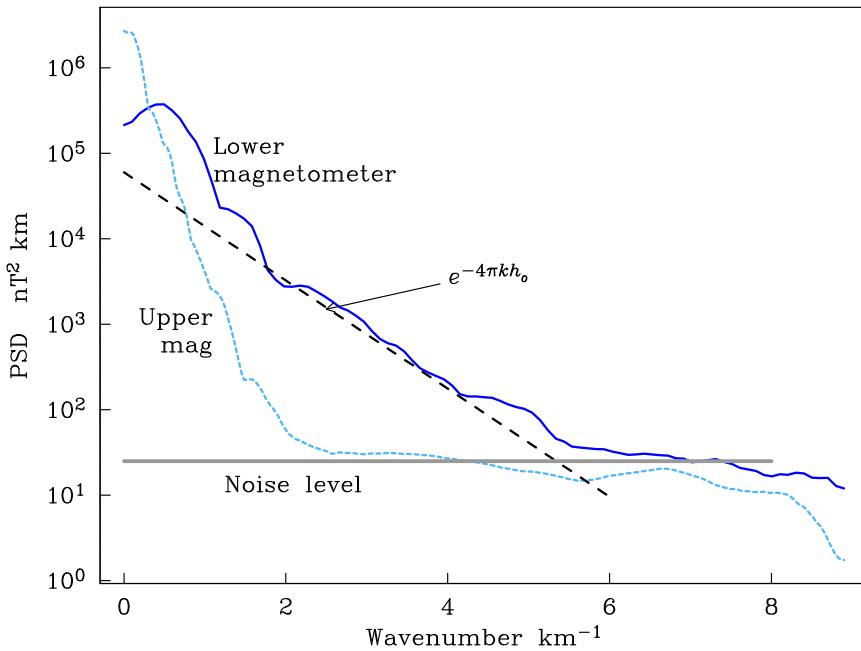


Figure 12.4: PSD of a segment of the near-bottom magnetic anomaly profile.

the magnetic anomaly PSD to fall approximately exponentially, like $\exp(-4\pi kh)$. The elevation of the magnetometer above the basement lies roughly between 116 m and 200 m, and the lower level will dominate at the higher wavenumbers; the long dashed line shows the exponential fall-off for the lower value of h , and it fits the spectrum rather well. There is a break at about 6 km^{-1} , which I will interpret as the point where noise begins to exceed signal. In marine magnetic surveys the noise is caused by other environmental magnetic fields, such as time-varying fields due to currents in the ionosphere, and also those from electric currents in the water caused by induction. I will assume the PSD of the noise is approximately white, and follows the horizontal grey line. The corresponding variance from (2) is $8.5 \times 25 = 210 \text{ nT}^2$ which yields a value for $\sigma = 14.5 \text{ nT}$. Remarkable confirmation for this model comes from the second PSD, shown with short dashes. Unusually in a survey of this kind, a second magnetometer was tethered to the cable 300 m higher up than the one we have been using. By the theory I mentioned, its spectrum falls much faster, so the PSD hits the noise level at a lower wavenumber, and as we see in the figure, it levels out at the same value, because it is in essentially the same noise environment as the lower instrument. Thanks to the second magnetometer we can be confident in our estimate for the uncertainty.

The spectral approach requires a number of additional assumptions about the noise, primarily, that it is *statistically stationary*. This means that the random process responsible for the noise is the same everywhere in the data series. That is often a plausible assumption, and would be accepted for the marine data. The message I want to leave you with is that the power spectrum usually gives an important clue about the noise, because the noise persists out to the highest frequencies, while most natural processes have a red spectrum, and the components of the signal at the high frequencies (or wavenumbers) are usually attenuated, thus permitted the noise spectrum to show itself. If this doesn't happen the data are not being sampled at a high enough rate, and there is danger of aliasing, which means the signal is being sampled too slowly to capture its true behavior.

References

- Constable, S., Constraints on mantle electrical conductivity from field and laboratory measurements, *J. Geomag. Geoelectr.*, 45, 707-9, 1993.
- Egbert, G. D., and Booker, J. R., Robust estimation of geomagnetic transfer functions, *Geophys. J. R. Astron. Soc.*, 87, 173-94, 1986.
- Malinverno, A., and Parker, R. L., Two ways to quantify uncertainty in geophysical inverse problems, *Geophysics*, 71, 15-27, 2005.
- Parker, R. L., Coherence of signals from magnetometers on parallel paths, *J. Geophys. Res.*, 102, 5111-7, 1997.
- Parker, R. L., and O'Brien, M. S., Spectral analysis of vector magnetic field profiles, *J. Geophys. Res.*, 102, 24815-24824, 1997.
- Priestley, M. B., *Spectral Analysis and Time Series*, Academic Press, New York, 1981.

13. Fitting within a Tolerance

The statistical theory of the early sections of Chapter 3 in GIT tell us that a good fit to the observations can be expressed in the form

$$\|\Sigma^{-1}(d - \Theta(m))\| \leq T \quad (1)$$

where $d, \Theta \in \mathbb{R}^M$ are vectors containing the measurements and the predictions of the model $m \in \mathbb{R}^N$; $\Sigma \in \mathbb{R}^{M \times M}$ is usually a diagonal matrix of standard errors (for the rare case of correlated errors something else replaces the diagonal matrix); and T is tolerance that we arrive at by a subjective decision about what we regard as acceptable odds of being wrong. For mere model building, a loose 50% level is just fine. We will almost always use the 2-norm on the data space, and thus the chi-squared statistic will be our guide.

From here on in our discussion we will take the purely practical road, and so the vector of theory, Θ will not be a collection of inner products in a Hilbert space, but instead

$$\Theta(m) = G W m \quad (2)$$

where $m \in \mathbb{R}^N$ is a vector representing the model itself, and $G \in \mathbb{R}^{M \times N}$ is a matrix with rows sampling the representers, and $W \in \mathbb{R}^{N \times N}$ is the quadrature matrix, another diagonal matrix.

We seek the smallest model, or the simplest solution, and for now that idea will be encapsulated in the minimization of **penalty function**, a norm or seminorm:

$$\|Rm\| \quad (3)$$

where $R \in \mathbb{R}^{L \times N}$ is a regularizing matrix, which might not be of full rank, and might penalize only part of the solution, so that $L < N$ as in 11(20); recall the brief discussion on pp 51-52 in the Notes, where we differenced m . A welcome feature of the numerical approach (as opposed to the analytic one) is that the treatment is indifferent to which of the two choices, norm or seminorm, is made. At first glance the normal strategy of calling in a Lagrange multiplier to handle the constraint (1) is inapplicable because of the inequality. But as GIT demonstrates at great length, we can still use this useful tool after all, with the caveat that we must first check that a model satisfying

$$Rm = 0 \quad (4)$$

cannot satisfy (1). If such a model does exist, then clearly zero is the minimum of the penalty function. In practice, this will almost never happen, and so then the problem to be solved is to find the stationary value of the unconstrained function

$$u(m, v) = \|Rm\|^2 + v[\|\Sigma^{-1}(d - GWm)\|^2 - T^2] \quad (5)$$

where v is the Lagrange multiplier accompanying the constraint:

$$\|\Sigma^{-1}(d - GW m)\| = T. \quad (6)$$

To reduce the clutter I introduce a couple of abbreviations: let

$$\hat{d} = \Sigma^{-1}d, \quad \text{and} \quad B = \Sigma^{-1}GW. \quad (7)$$

This gives us the new unconstrained function

$$u(m, \nu) = \|R m\|^2 + \nu[\|\hat{d} - B m\|^2] - T^2]. \quad (8)$$

Notice that, for a fixed value of T , minimization of this expression can be regarded as seeking a compromise between two undesirable properties of the solution: the first term represents model complexity, which we wish to keep small; the second measures model misfit, also a quantity to be suppressed as far as possible. By making $\nu > 0$ but small we pay attention to the penalty function at the expense of data misfit, while making ν large works in the other direction, and allows large penalty values to secure a good match to observation. Let us continue.

We can differentiate (8) with respect to m by writing out the expression in terms of components; I will spare you the intermediate steps which we have seen several times in slightly different contexts. At a stationary point of (8) the gradient of u vanishes and we find the vector m_0 obeys

$$R^T R m_0 + \nu B^T B m_0 - \nu B^T \hat{d} = 0. \quad (9)$$

Or, equivalently, m_0 satisfies the linear system

$$(B^T B + \frac{1}{\nu} R^T R) m_0 = B^T \hat{d}. \quad (10)$$

Differentiating with ν returns the constraint, now written as

$$\|\hat{d} - B m_0\| = T. \quad (11)$$

If we knew the value of ν , we could find the model by solving (10). So the tactic for solving (10) and (11) together, as we must, requires solving (10) for a sequence of ν s seeking the vector m_0 that gives (11). We need to show that as ν increases, the misfit norm in (11) decreases. This result is intuitive from our discussion after (8), but it also is useful to have the derivative itself. Consider the squared misfit in (11) to be purely a function of ν :

$$F(\nu) = \|\hat{d} - B m_0(\nu)\|^2. \quad (12)$$

Then differentiating on ν

$$\frac{dF}{d\nu} = -2(\hat{d} - B m_0(\nu))^T B \frac{dm_0}{d\nu} = -2(B^T(\hat{d} - B m_0))^T \frac{dm_0}{d\nu}. \quad (13)$$

By rearranging (9) we see that

$$B^T(\hat{d} - B m_0) = \frac{1}{\nu} R^T R m_0 \quad (14)$$

and hence

$$\frac{dF}{dv} = -\frac{2}{v} (R^T R m_0)^T \frac{dm_0}{dv}. \quad (15)$$

Now to get dm_0/dv , differentiate both sides of (10):

$$(B^T B + \frac{1}{v} R^T R) \frac{dm_0}{dv} - \frac{1}{v^2} R^T R m_0 = 0. \quad (16)$$

Solving for dm_0/dv and plugging the answer into (15) gives the glorious result

$$\frac{dF}{dv} = -\frac{2}{v^3} (R^T R m_0)^T (B^T B + \frac{1}{v} R^T R)^{-1} (R^T R m_0). \quad (17)$$

The inverse matrix in the middle is positive definite, because it is composed of the sum of positive definite pieces; then, since $v > 0$ the whole thing must be negative.

This simplifies the strategy for solving the pair (10)-(11), because now we know that when a guess for v yields a value of F that is too high, we must increase v , and conversely. Better yet we can even use **Newton's method**, which you will recall can be used for solving equations in a single variable: in this case the equation is

$$F(v_0) = T^2. \quad (18)$$

We begin with an initial value $v_1 > 0$, and we perform a one-term Taylor expansion on (18) as follows:

$$T^2 = F(v_1 + v_0 - v_1) = F(v_1) + (v_0 - v_1)F'(v_1) + \varepsilon \quad (19)$$

where F' denotes the derivative, and ε is error due to the neglect of higher order terms in the series. Rearranging this expression gives

$$v_0 = v_1 - \frac{F(v_1) - T^2}{F'(v_1)} + \frac{\varepsilon}{F'(v_1)}. \quad (20)$$

If the ε , the second order term in the Taylor expansion is neglected, (20) gives a recipe for the next step in an iterative process which we write

$$v_{n+1} = v_n - \frac{F(v_n) - T^2}{F'(v_n)}, \quad n = 1, 2, \dots \quad (21)$$

It is shown in GIT that this procedure always converges, provided the initial guess obeys $v_1 < v_0$. But surprisingly perhaps, a faster rate of convergence is usually obtained by writing (18) as

$$\ln(F(v_0)) = 2 \ln T \quad (22)$$

and solving this equation with Newton's method.

Let us summarize the process. Recall the abbreviations introduced in (7). We wish to discover the solution vector m_0 and the Lagrange multiplier v_0 which solve simultaneously the linear system (10) and the misfit constraint (11). We make an initial guess for v which we call v_1 , and with

it we solve (10). We take the resultant model vector and put it into (12) which gives us F . We also solve the system (17), which provides us with dF/dv . If F is close enough to T^2 we stop. Otherwise we use (21) to obtain a revised version of v , with which we can begin the cycle again.

There are a number of points, before we examine this process in an illustration. Equation (10) can be written as the solution to an *overdetermined* least-squares approximation problem:

$$\begin{bmatrix} B \\ v^{-1/2}R \end{bmatrix} m_0 \sim \begin{pmatrix} \hat{d} \\ 0 \end{pmatrix} \quad (23)$$

you will easily verify that the normal equations for this overdetermined least squares problem is exactly (10). We can write a similar equation for dm_0/dv

$$\begin{bmatrix} B \\ v^{-1/2}R \end{bmatrix} \frac{dm_0}{dv} \sim \begin{pmatrix} 0 \\ v^{-3/2}Rm_0 \end{pmatrix} \quad (24)$$

There are two possible reasons for treating (10) as the solution of (23). First, when the size of the system is modest, we can solve (23) by QR factorization and avoid poor numerical stability. Second, R is almost always sparse, so when the system is large we can take advantage of the sparse LS form of the solution, 6(13) in our notes on linear algebra. And if the system is very large, that form can be conveniently solved by the method of conjugate gradients, as we will see later.

Let us now apply this approach to our near-bottom magnetic anomaly problem. You may recall that we looked for the smallest magnetization model in L_2 that fit the measured values exactly and obtained a mess, plotted in Figure 11.4. The model is one hundred times larger than a reasonable solution should be, yet it is the smallest model. The fault is the demand of an exact fit. In Section 11 of these Notes I obtained a noise estimate of $\sigma = 14.5$ nT, a quantity too small to be distinguished in a plot showing the full range of the data; can such a small misfit reduce the size of the solution to a reasonable level? We decide in advance what will be acceptable as a plausible size of misfit. I suggest that we take the expected value of error norm as a trial value. Thus, as shown in GIT on p 124

$$\mathbb{E}[\|d - \Theta\|/\sigma] = \sqrt{N}[1 - \frac{1}{4N} + \dots] \quad (25)$$

where we have used the fact that noise will be treated as iid. Then since $N = 100$, we calculate that the misfit tolerance in 11(6) is $T = 9.975$. The target misfit for Newton's method is T^2 . We will minimize the L_2 norm as before, using trapezoidal rule for all the integrations.

In the figure on the next page we see the progress of the iterative solution, which starts with $v = 0.001$ and then goes down in F and up in v . The starting guess lies below the solution v_0 , and so Newton is

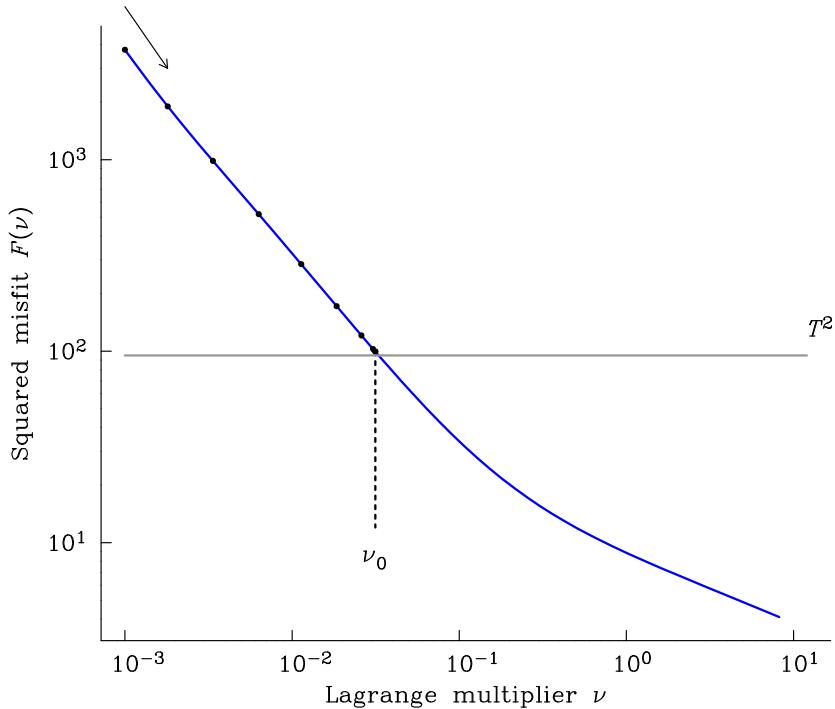


Figure 13.1: Squared misfit vs Lagrange multiplier.

guaranteed to converge. If the guess had been too high, we could not reliably use the Newton iterate, because it can ask for negative values, which are forbidden; so in those circumstances we just divide the guess by ten and try again. In this example the procedure took 10 steps to converge to about 4 significant figures. It is obvious we could get much more rapid convergence if logarithmic values (both $\ln F$ and $\ln \nu$) were used, because the curve is nearly straight in these variables, and Newton's method is based on a linear approximation. I leave the details for a homework exercise.

The norm of the new model m_0 is considerably smaller than the one obtained by an exact fit: now $\|m_0\| = 6.26$, while a precise match yields a norm of 697. The new model is considerably more reasonable in size, as we had hoped. And this is confirmed in Figure 13.2, where the solid line is the L_2 norm minimizer. This solution is spiky but keeps its magnetization in a range of perfectly acceptable numbers. Notice the sign is predominantly positive, which we might perhaps expect as the profile is the Bruhnes normal magnetic period. The strongly reversed section between 1.6 and 2.5 km is interesting, because it is not a well recognized brief reversal. Are any of the model's reversed magnetization sections real, or can they be dispensed with while still matching the measurements? This is a question we must wait to answer.

In the same figure shown dashed is the minimizer of the 2-norm of dm/dx ; it is noticeably smoother, and a little larger. The nasty spike in

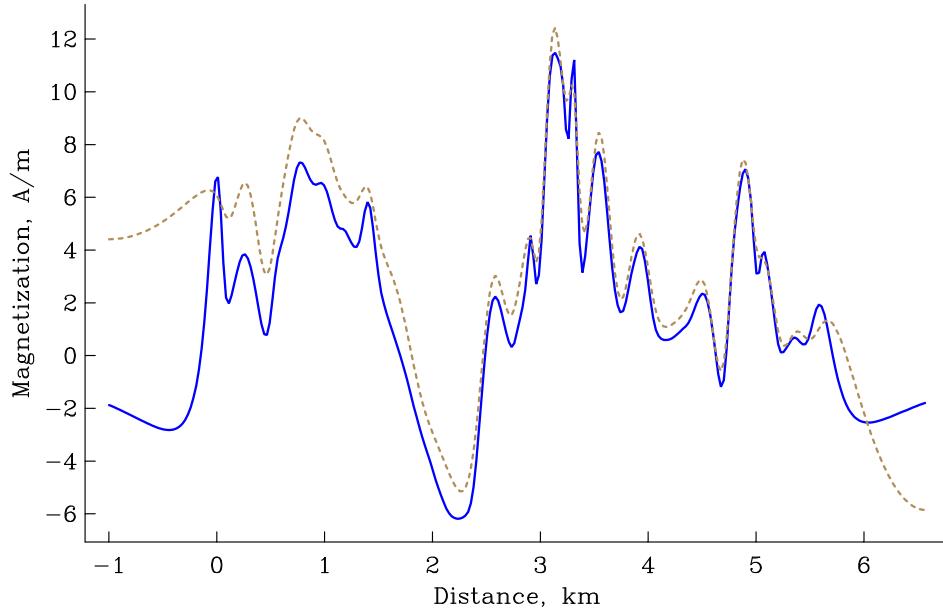


Figure 13.2: Minimum norm and seminorm magnetizations with plausible misfits.

m_0 near 3.2 km has been greatly reduced, but that is hard to see in this graph. We probably can conclude that the crustal magnetization is far from constant along this profile, and that big swings in the original field are not due to effects of topography (changes in range of the magnetometer from the sources), but are a genuine reflection of variable magnetic intensity in the basement. But whether or not reversed magnetization is required has not been established; it certainly looks like it on the present evidence.

A few other loose ends. The data misfit I selected, $T^2 = 99.3$ corresponds to $P = 0.5$ for χ_N^2 . The minimum L_2 norm turns out to be $10.970 \text{ Am}^{1/2}$. Suppose now I select a more generous misfit, $P = 0.95$, so that the true misfit will be smaller 95% of the time in hypothetical repeat surveys. Then $T^2 = 124.3$ and the new model has norm $10.923 \text{ Am}^{1/2}$. This very small reduction arises from the very small difference between the two models: $\|m_{0.5} - m_{0.95}\| = 0.14 \text{ Am}^{1/2}$. Indeed, the models are so similar one cannot distinguish between them on a graph of the normal size! As I mentioned earlier, the precise choice of P or T^2 turns out to have little effect provided it is large enough.

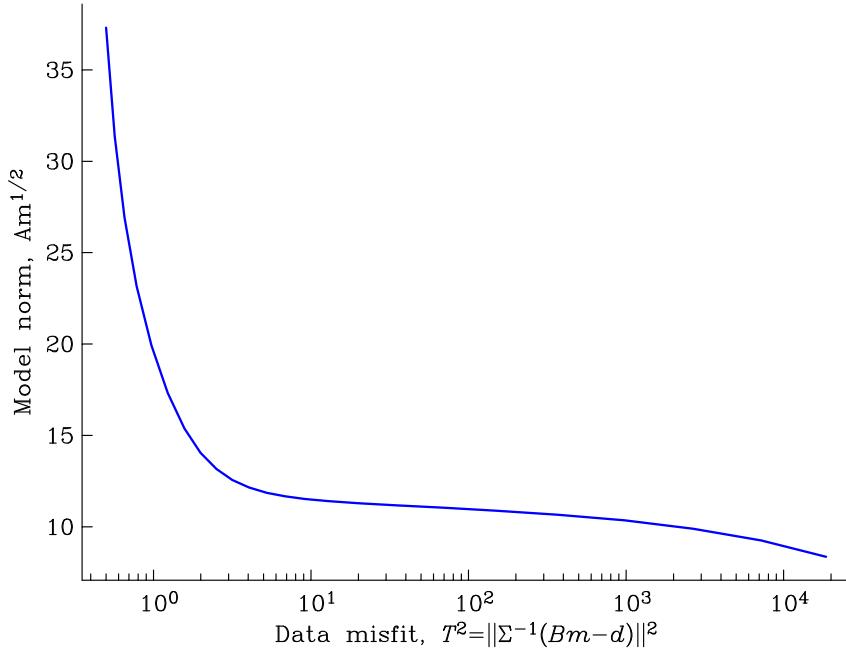


Figure 13.3: The L curve — minimum model norm against data misfit for the marine anomaly system.

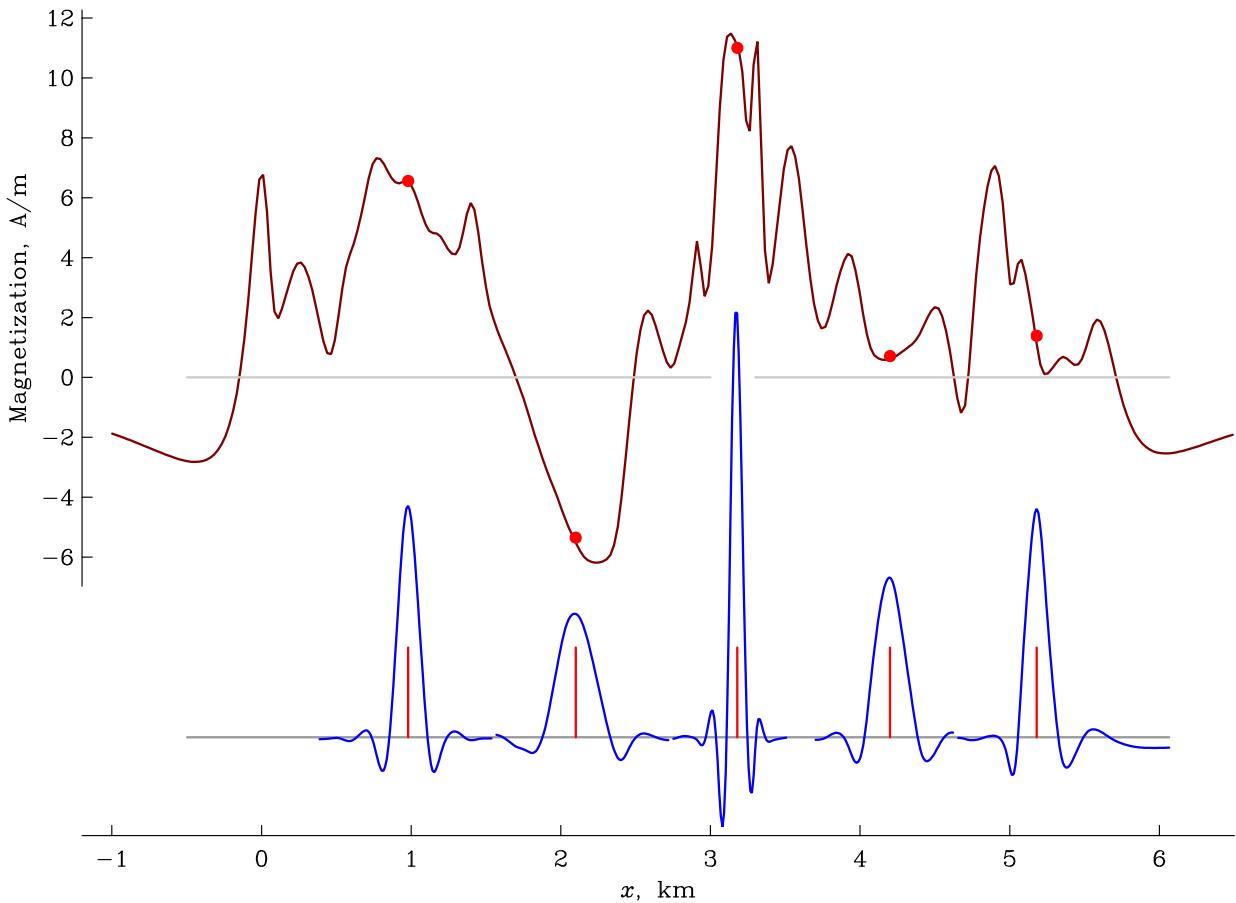
This observation leads to the graph of the infamous L curve shown in Figure 13.3. The minimum model norm $\|m\|$, here the L_2 norm, varies with choice of data misfit, T^2 and as we must expect the norm decreases as misfit rises. But there is an enormous plateau in the norm as the misfit varies over a very wide range. Notice that our interest concentrates on the region near $T^2 = 100$. There is a school of thought that asserts the proper choice of misfit is at the “knee” in the L curve, somewhere about $T^2 = 3$. We know from the spectral study that is too small, and the solution would be too rough for that misfit.

14. Resolution in the Marine Magnetics Example

We carry out the resolution analysis for the model on the Juan de Fuca Ridge that has been our standard vehicle in the linear theory. As explained in class, one of the fairly traditional ways of doing this is to calibrate the regularization process by testing it with artificial data, generated from special models, often delta functions, at various points. This must be done using exactly the same parameter settings as were used in making the regularized model. Then we see at each point how badly smeared out a very sharp feature would be after being processed through the inversion machinery. This gives us a qualitative assessment of the length scales resolved in the solution.

Figure 14.1 shows the results for five locations of the test function. We see the resolution varies by quite a large factor from place to place, but is reasonably satisfactory everywhere. At $x = 2$ km we may be resolving structure only down to about 0.5 km, while near 3 km the resolution improves to almost 0.1 km. The cause of the variation is easy to discover in this case: resolving scale is apparently proportional to the distance to the nearest source material, as you can easily see by comparing this figure with Figure 8.1.

Figure 14.1: Top: L_2 -norm minimizing magnetization. Bottom: Resolution functions for various sites.



15. Practical Calculation of a Bound

In Section 4.03 of GIT I treat the question of finding the range of a linear functional subject to constraints from data (linear functions) and a nonlinear conditions, that the norm be restricted as well. There in the noise-free case an elegant theory is developed for the noise-free case (data matched exactly by the model), and a number of predictions, also in the form of linear functionals. The problem with noise seems to be much more clumsy. Here I want to give a simpler for numerically formulated problems.

To motivate the discussion look again at Figure 14.1 and the negative magnetization near $x = 2$ km. According to the resolution calculations, the regularized model should be trustworthy on the scale of a kilometer, and so we are inclined to accept the reality of reversed magnetization in this region. But is that truly required by the data? As GIT 4.03 shows us, we cannot be sure without introducing some further information. Suppose we say we know the L_2 norm of m . If we confine all magnetic material to $-0.5 \leq x \leq 6$ then $\|m\|/\sqrt{6.5} = M_{\text{RMS}}$, and we might be willing to specify an upper limit on plausible RMS magnetizations, from samples of fresh marine basalts. Then one way we might answer the question of a possible record of magnetic reversal is to consider the *average* value of magnetization over the x interval (x_1, x_2) where the regularized model dips negative; numerically this is (1.8, 2.4) km. We will call this $\langle m \rangle$:

$$\langle m \rangle = \frac{1}{x_2 - x_1} \int_{x_1}^{x_2} m(x) dx. \quad (1)$$

We challenge the hypothesis that the negative $\langle m \rangle$ is required: if the every model that adequately matches the anomalies and has a *positive* average possesses an implausibly large RMS magnetization then a reversal is demanded in the interval. The converse, a positive average consistent with a reasonable RMS, does not mean the absence of a reversal however, because negative segments might still be needed, even with a positive average—it is just an average; we'll return to this later.

The idea then is to seek the smallest norm of the discretized model $m \in \mathbb{R}^N$:

$$\min_{m \in \mathbb{R}^N} \|Rm\| \quad (2)$$

subject to an adequate fit to the measurements:

$$\|\hat{d} - Bm\| \leq T \quad (3)$$

and the constraint on a linear functional of the model, in the example the average given in (1):

$$l^T m = b \quad (4)$$

where the scaled data \hat{d} and matrix $B \in \mathbb{R}^{M \times N}$ are given in 13(8); $l \in \mathbb{R}^N$

is vector which approximates averaging the model over a region. If the smallest norm found in (2) is too large when (2) and (3) hold, we know that (3) cannot be supported. How does one apply the *equality* constraint (4)? Obviously one approach is introduce a second Lagrange multiplier, in addition to the one needed to account for (3). Let me describe a simpler approach. We treat (4) as another fictitious "observation" to be fitted (almost) exactly by including it in (3). Write a data vector $\hat{d}_1 \in \mathbb{R}^{N+1}$ and a new $B_1 \in \mathbb{R}^{(M+1) \times N}$ and a scalar γ :

$$B_1 = \begin{bmatrix} \gamma l^T \\ B \end{bmatrix}; \quad \hat{d}_1 = \begin{bmatrix} \gamma b \\ \hat{d} \end{bmatrix} \quad (5)$$

where $\gamma > 0$ is a very large constant. This clearly has the effect in the fitting problem of giving (4) a heavy weight, so that it will be fit more accurately than the rest of the data. Now we solve the standard norm minimization problem (2) subject to misfit (3) achieving a specified tolerance exactly as in (3), where B and \hat{d} are replaced by B_1 and \hat{d}_1 . But wait a minute—shouldn't we have to designate a new T as well? We have messed up the fitting process by including a very accurate fake datum. The answer is no: it can be shown (in Chapter 22, of *Solving Least Squares Problems*, by Lawson and Hanson, 1974) that if γ is large enough, the misfit component introduced by the new row in B_1 is negligible! How large is that? Lawson and Hanson give a very conservative figure; I find that if $\gamma \|l\| = 100 \|B\|$ we can get very good results. Too large a value for γ leads to numerical instability, unfortunately. The advantage of this approach is that we use exactly the same code when we bound the linear function l as when we find a regularized model.

We apply these ideas to the near-bottom magnetic anomalies. The linear functional we are interested in is the average value $\langle m \rangle$ in the interval where the regularized model goes negative, so if the length of that interval is $D = x_2 - x_1$ and the spacing in the discretized model is Δx , the vector l in (4) looks like this if we use the trapezoidal rule to approximate (1):

$$l = \frac{\Delta x}{D} [0, 0, \dots, 0, \frac{1}{2}, 1, 1, 1, 1, \dots, 1, \frac{1}{2}, 0, 0, \dots, 0]^T. \quad (6)$$

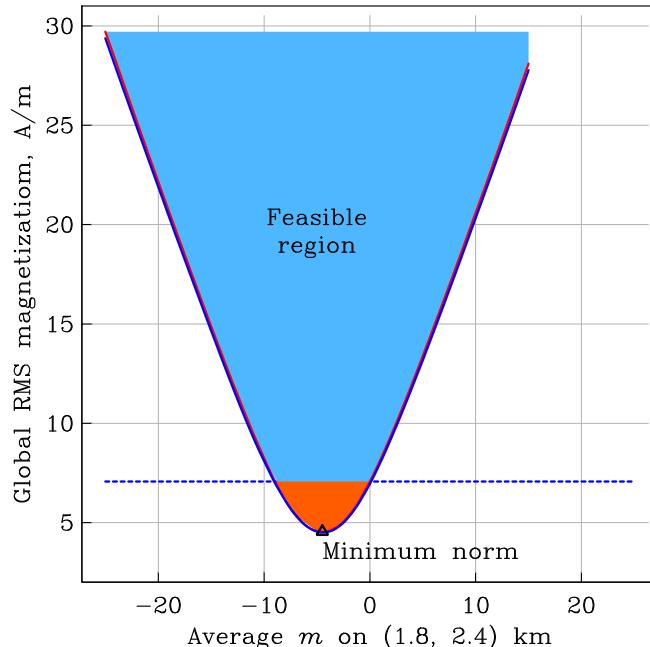
The first choice for b the bound in (4) might be zero, but in fact considerable insight is gained if we sweep b through a range of values. The results are plotted in Figure 15.1. For each value of $\langle m \rangle$ we plot the minimum possible norm, normalized to be RMS magnetization. That means

models exist with values above the point, but not below. Thus the curve of all such points is the boundary between models possessing the possible pairs of average-magnetization/RMS-magnetization and impossible pairs. So if we draw a horizontal line at some value of the RMS, the corresponding segment in the feasible zone gives us the largest and smallest $\langle m \rangle$ for that RMS, the bounds on the linear functional (4). So we have solved the problem for finding the upper and lower bounds on the linear functional. When we refer to the Figure we see that the value of $\langle m \rangle$ must certainly be negative if the RMS magnetization is less than 7.07 A/m, the orange region. Unfortunately, RMS magnetizations might easily be larger than this—it is not a very high value. The calculation is inconclusive. Note that this result *does not* back up the resolution analysis, which seems to say that we can trust the average value of the model in a 1-km interval. Apparently models with reasonable norms exist that have positive averages $\langle m \rangle$.

What value of tolerance T should be used here? In fact we should use a larger T because we want to be really sure the misfit is not accidental. But as in earlier examples the choice makes hardly any difference: in the graph I have plotted the curves for expected value of T , and for a value that would not be exceeded in 95 percent of random realizations. The curves can only just be distinguished near the top of the graph; one is red, the other blue.

Let us look next at a model with a non-negative (i.e., slightly positive) mean value and reasonable norm, computed in the course of this

Figure 15.1: Minimum norm for specified value of the average magnetization $\langle m \rangle$.



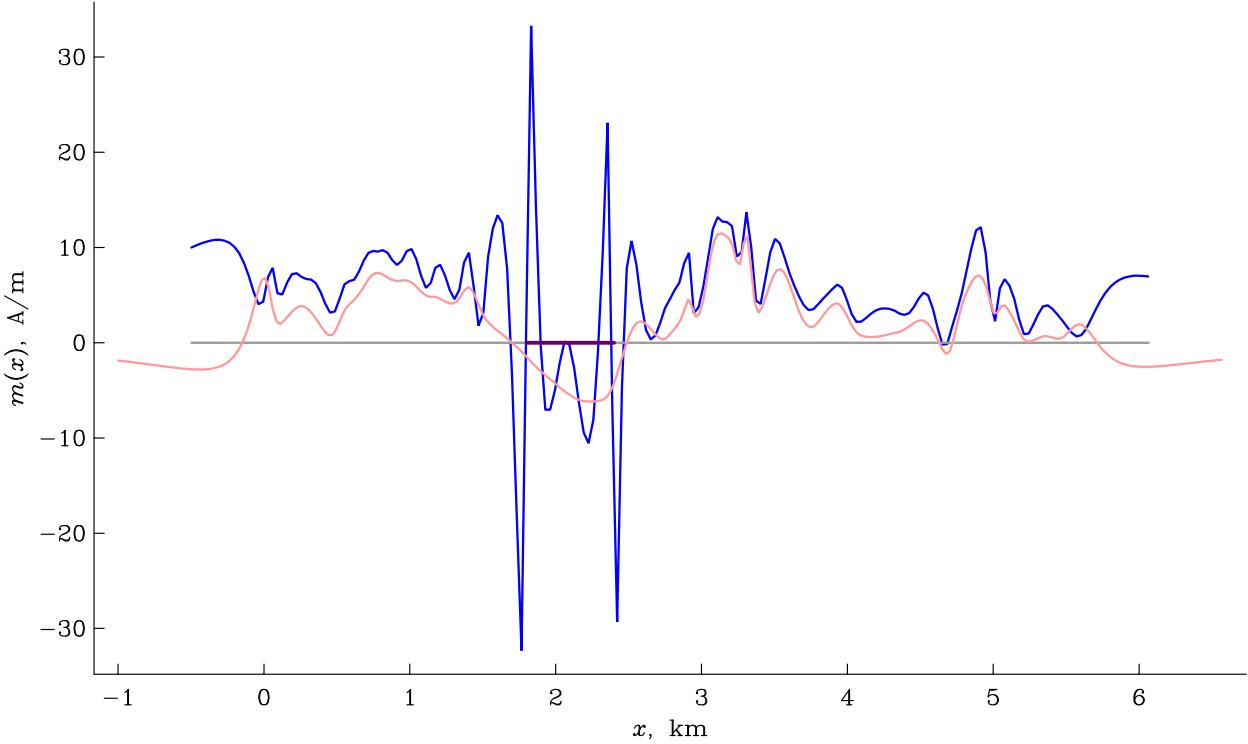


Figure 15.2: Model with reasonable RMS, fitting the data, and possessing a positive mean $\langle m \rangle = 1 \text{ A/m}$. The L_2 norm minimizer is shown light.

solution. The model with $\langle m \rangle = 1 \text{ A/m}$ and RMS value 8.2 A/m is shown in Figure 15.2. Despite having an overall positive average over the interval of interest, the function *is still negative* in places, and a reversed magnetization is required. Furthermore, the model has large peak values, both negative and positive that make it seem unreasonable. Particularly troubling are the large negative swings, *just outside* the averaging interval. All of this strongly suggests that in this problem the use of the average value to test a hypothesis is not very effective. If we could test the hypothesis that any magnetization that is positive *everywhere* on the interval will not fit the data, then we might have a really strong test. That is the direction we are heading.

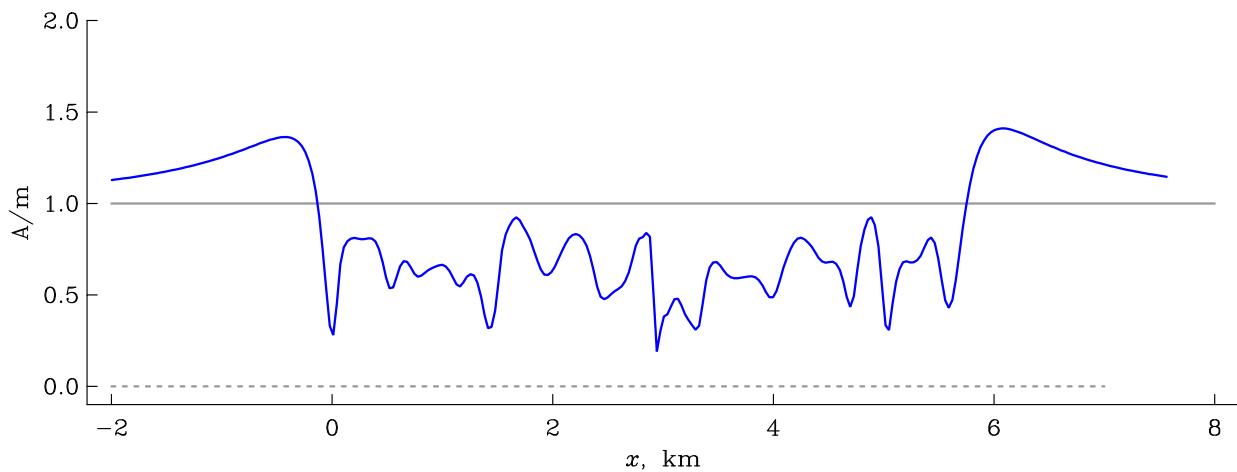
We have been pursuing the possibility that our magnetic data may demand a reversely magnetized section of crust, which would be quite interesting if it turned out to be true; in fact, because such a reversed segment has not been documented elsewhere, we want to be particularly certain it is required. So far, the evidence is not convincing. A reason peculiar to marine magnetic studies, is the very small response of the system to long wavelength magnetizations. Recall from Section 9, in the idealized case of a flat layer and horizontal observation track, a constant magnetization is completely invisible in the data: then $(g_j, c) = 0$ for

$c = \text{constant}$. In the more realistic model, this will not be true, but a long wavelength **annihilator** (a magnetization without a magnetic anomaly) is surely present. How can we find it? If one exists, it means the whole model m can be shifted up or down by arbitrary amounts without affecting the fit. This is a problem we already know how to solve: if u the uniform (that is constant) magnetization, we seek $n \in \mathcal{H}$ as close as possible to u while satisfying $(g_j, n) = 0$. When closeness is measured in the usual way by the norm, we have the problem of finding a model near to a preferred structure, subject to constraints from data, here all zero in value. In symbols

$$n = \underset{m \in \mathcal{H}}{\operatorname{argmin}} \|m - u\|, \quad \text{with } (g_j, m) = 0, \quad j = 1, 2, \dots, N \quad (7)$$

The solution of this problem is one we have looked at briefly early on in class and in GIT (p 73). The result is rather too irregular, and so we weaken the demand requiring exactly zero magnetic signal, to that of an RMS signal of 0.73 nT. The result is shown below,. The solution is rather irregular, and so we weaken the demand from requiring exactly zero magnetic signal, to having an RMS signal of 10 nT. The result is shown below. While the function is far from constant, it is certainly positive, and can be added to any solution with a weight of up to 20 before reaching a significant misfit.

Figure 15.3: Annihilator approximating a constant 1 A/m with RMS misfit 0.73 nT.



16. NNLS and BVLs

Linear programming is able to solve linear inverse problems, with inequality constraints imposed, provided we can tolerate a different norm for measuring the misfit between model predictions and observations. While the sup norm $\|\cdot\|_\infty$ and $\|\cdot\|_1$ can both be treated in the LP setting, only the latter is really useful, because relying on the sup norm gives too much leverage to the noisiest data, clearly an inadvisable state of affairs. To exploit a quadratic measure of misfit, like the familiar

$$X[m]^2 = \sum_{j=1}^M \frac{(d_j - L_j[m])^2}{\sigma_j^2} \quad (1)$$

requires us to consider **Quadratic Programming**. Those QP problems which are convex are much easier to solve reliably than the non-convex ones, and I shall concentrate on two special convex cases that I have found invaluable in my scientific career. First, is the special QP problem called **Non-Negative Least Squares** (NNLS). This is simply the regular least-squares problem with the positivity constraint attached:

$$x_* = \arg \min_{x \geq 0} \|Ax - y\|_2 \quad (2)$$

where this notation, used extensively in the optimization literature, means that x_* is the vector x that achieves the minimum value (assuming it is unique); here $x, x_* \in \mathbb{R}^N$, $y \in \mathbb{R}^M$, and $A \in \mathbb{R}^{M \times N}$. In (2) there is no restriction on the relative sizes of M and N ; the problem is interesting and nontrivial whether $N > M$, which is the natural geophysical situation, or not. There is a general property of optimization problems, somewhat similar to the Fundamental Theorem of LP called the Kuhn-Tucker conditions, which in NNLS leads to an interesting and valuable result: a solution to (2) exists in which no more than $M - 1$ components of x_* are positive (and so by implication, at least $N - M + 1$ of them must be zero, when $M < N$). When the dimension of the model space is large, as it will be in a discretized version of a continuous problem, this means the same thing as it did in the LP examples, that the solution vector x is mostly zeroes, with a few positive spikes, delta functions in the limit of a continuum. In many practical problems we find that the number of positive elements in the solution vector, while it can be as large as $M - 1$, often much smaller than M .

Let me give a little graphical demonstration of the ideas as illustrated in Figure 16.1, which I will explain. First, consider the domain of the solution set in \mathbb{R}^N , the set $x \geq 0$, called the **positive orthant**. It is a convex region in the space, whose edges comprise the positive extensions of all the positive unit vectors. In three dimensions, the edges of the positive orthant (called the positive octant in \mathbb{R}^3) are the positive x , y , and z axes. Now consider mapping the positive orthant into \mathbb{R}^M with the linear map A , where we will assume that $M < N$. The image of the orthant will be a fan-shaped region as shown in the Figure, where $M = 2$ and $N = 4$.

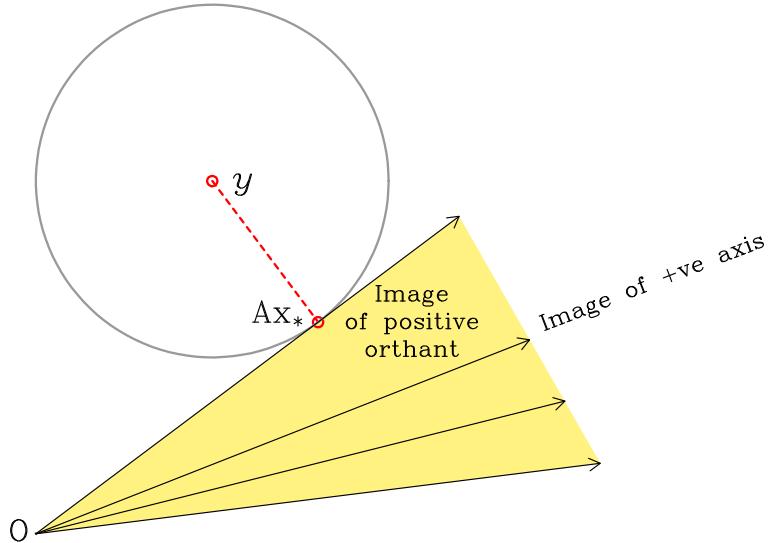


Figure 16.1: Image of the positive orthant and its edges under a linear map A taking \mathbb{R}^M into \mathbb{R}^N . The point Ax_* is the closest point in the image set to y .

The boundary of the image of the orthant comprises surfaces in \mathbb{R}^M , and a surface in \mathbb{R}^M locally is of dimension one less: $M - 1$; most of the positive axes are mapped into the interior of the image, the shaded region. Now consider the minimization problem (2). If an exact fit cannot be found, the point y lies outside the image. Then the smallest distance is achieved at a point in the boundary of the image, as shown, which is Ax_* . In the Figure, where $M = 2$ it is clear the point x_* falls on the image of one of the positive axes in \mathbb{R}^N ; in higher dimensions x_* lies in the subspace spanned by no more than $M - 1$ images of the positive axes, because the others are not in the boundary in \mathbb{R}_M . If several of the positive axes are mapped into a single line in the range space, we can always choose just one of them. This illustrates the assertion that the norm minimizer in (2) need have no more than $M - 1$ positive components.

The solution to the NNLS problem can be extended like the LP problem to include nonpositive unknowns. One can add linear equality constraints on the unknowns by including them in the A matrix with large positive weights, so that the minimization process essentially satisfies those rows exactly and, as before, if the weight is large enough, the contribution from those rows to the misfit budget is negligible.

In MATLAB an algorithm for NNLS is provided called `lsqnonneg`. It is very slow since it is written as a MATLAB M-file and not optimized as the linear system solution is or the QR and eigenvalue codes are. There is a bug in the MATLAB code concerning the "warm start" feature—it doesn't work and generates wrong answers! For homework problems the MATLAB

code is fine, but any realistic problem you will need a Fortran program called `nnls.f` by Lawson and Hanson which you can get from me.

Suppose instead of merely demanding positivity of the unknown in (2) we wanted some (or all) of the components to lie between specified bounds:

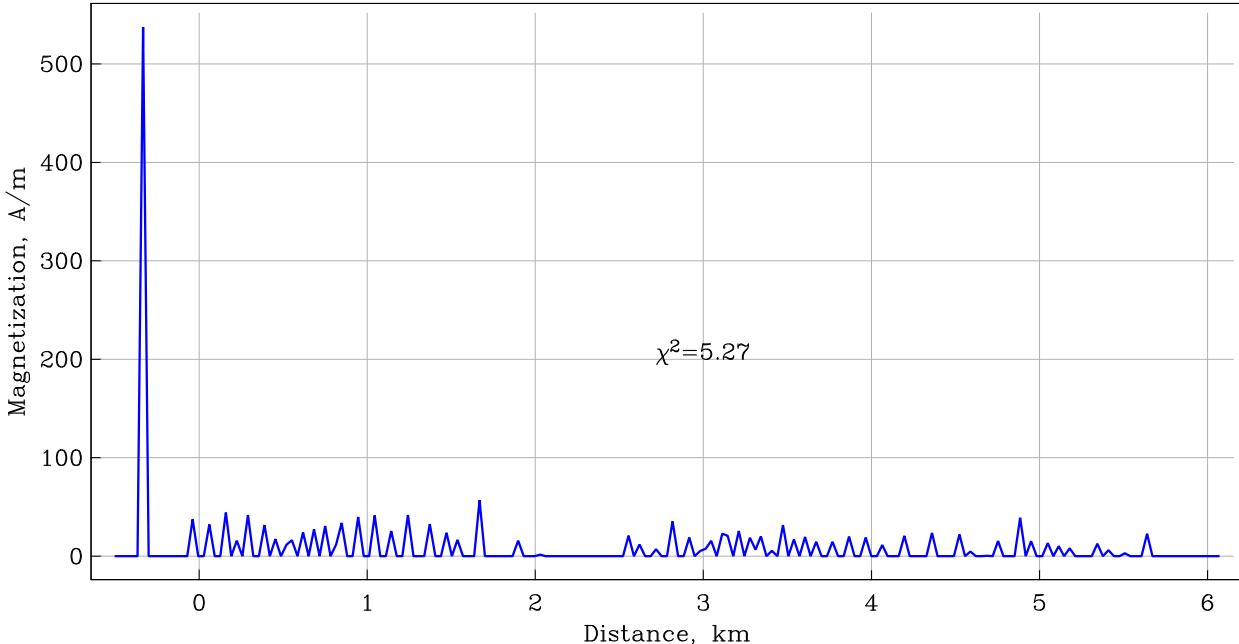
$$l_j \leq x_j \leq u_j \quad (3)$$

This can be accomplished with NNLS; I leave this as an exercise for the student. However, the size of the problem to be solved is greatly increased and causes unnecessary waste of computer time, because there exists a specific Fortran program for this task called `bvls.f` which stands for **Bounded Variable Least-Squares**. Again I can provide you with the source should you ever need it.

As I mentioned in my discussion of ideal bodies, once we introduce inequality constraints even with a linear forward problem we face the possibility that solutions to the constrained optimization system may not exist at all; the data and the conditions may be inconsistent. In LP language this is a statement that there is no feasible solution. The NNLS and BVLS problems always have solutions, but are set up in a way to test whether the imposed conditions are consistent with observation. Returning to the near-bottom magnetic anomaly problem, we can now ask the question, "Are there any magnetization models that fit the data without going negative somewhere?" This we do by simply minimizing the data misfit with NNLS over the set of non-negative m :

$$\min_{m \geq 0} \| \hat{d} - Bm \|_2 \quad (4)$$

Figure 16.2: Minimum misfit, all positive magnetization solution.



If this value is larger than a reasonable tolerance T according to the χ^2 distribution, then we have demonstrated the need for a magnetic reversal in the section. Notice that we now don't specify a particular interval—we'll allow the model complete freedom. The Figure shows the results of this calculation. An amazingly small misfit can be achieved, but at the expense of some rather large amplitudes. We should not be too worried about the peak on the left, since it is in a zone not controlled by data since the magnetic field measurements begin at $x = 0$. We could use BVLS to check how large the positive amplitudes need to be. Instead, however, I will demonstrate an alternative, perhaps more familiar looking approach: regularization. We simply add to (4) a term penalizing the size of the model in the 2-norm:

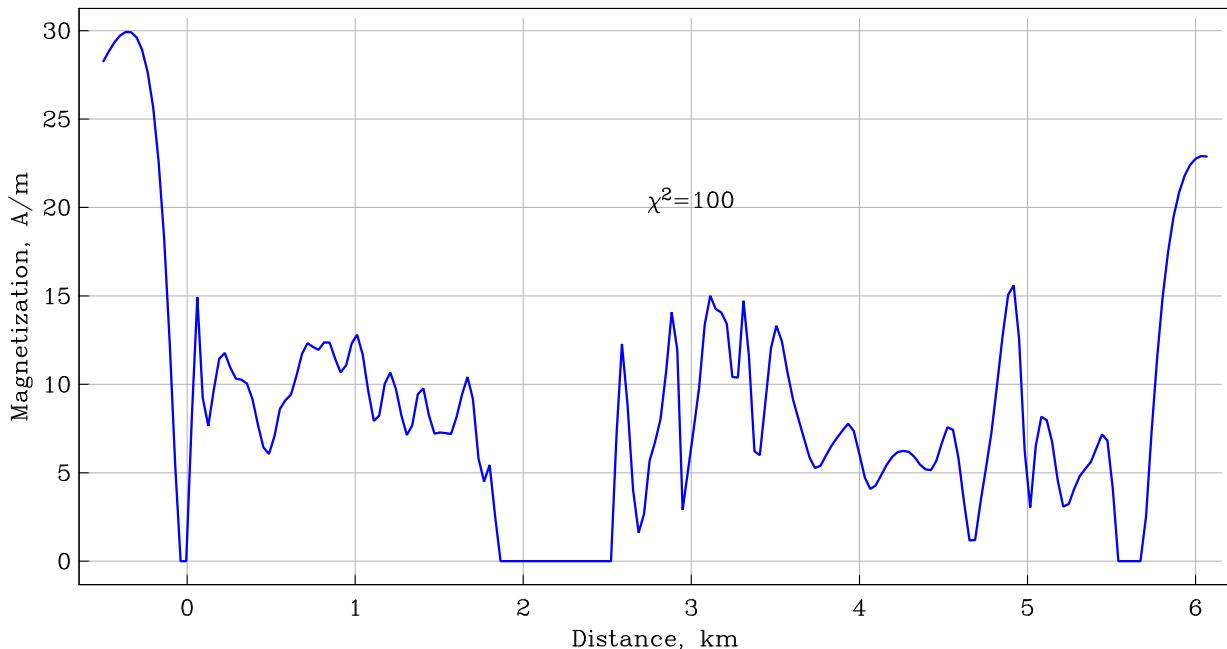
$$\min_{m \geq 0} \| \hat{d} - Bm \| ^2 + w \| m \| ^2 \quad (5)$$

where the 2-norm is implied, and $w > 0$ is a weight, which we can treat as a Lagrange multiplier. We rewrite (5) as

$$\min_{m \geq 0} \left\| \begin{bmatrix} B \\ w^{1/2}I \end{bmatrix} m - \begin{bmatrix} \hat{d} \\ 0 \end{bmatrix} \right\|^2 \quad (6)$$

which is exactly in the form of the NNLS problem. Now sweep though positive values of w : for small values we get misfits close to the one shown in Figure 16.2, but as w increases the misfit term increases as (5) pays more attention to the size of m . When the misfit reaches the expected tolerance, we inspect the solution, which is of course still everywhere non-negative. The result is plotted in Figure 16.3, where the misfit has been allowed to rise to $\chi^2 = 100$ the expected value for 100 data. The model

Figure 16.3: Regularized, all positive magnetization solution.



magnetizations are not extraordinary, and we must conclude that there are reasonable-looking solutions without negative segments: *the reversed magnetization is not demanded by these data.*

17. Steepest Descent Optimization

In geophysical inverse theory, and in many other geophysical contexts, we need to find the minimum of a real function F of many variables. (Let us say $F: \mathbb{R}^N \rightarrow \mathbb{R}$.) This is an example of an **optimization** problem, because the function F is regarded as a penalty of some kind, and minimizing it represents doing the best possible job in some sense. We have already come across a simple example of this kind in section 3, the least-squares problem, where $F = \|Ax - y\|^2$, and we are minimizing the distance between a data vector y and model predictions Ax . Sometimes the minimization must be carried out subject to side conditions, or **constraints**, and then the problem is a **constrained optimization**. Again the underdetermined least squares systems is an example of this kind. Now we consider briefly general methods for solving these problems, though in fact we will look only at the unconstrained system for simplicity. The standard reference for numerical techniques is by Gill, P. E., Murray, W. and M. H. Wright, *Practical Optimization*, Academic Press, New York, 1981; Philip Gill is on the UCSD math department faculty. Our books on reserve, by Strang and by Golub and Van Loan also provide a lot of information about the topic too.

We shall assume the function F is smooth, at least twice differentiable, for otherwise things get messy. We will also assume that we can obtain an analytic expression for the derivatives of F , the gradient of F :

$$\mathbf{g} = \nabla F = \left[\frac{\partial F}{\partial x_1}, \frac{\partial F}{\partial x_2}, \dots, \frac{\partial F}{\partial x_n} \right]^T. \quad (1)$$

Then the condition that we are at a local minimum is of course that the gradient vanishes, that is all the components:

$$\nabla F(\mathbf{x}) = \mathbf{0}. \quad (2)$$

This is a system of n equations in n unknowns, and unless F is quadratic (which it is for least-squares problems) (2) may be impossible to solve in terms of elementary functions; when F is quadratic (2) is a set of linear equations. We will return to the quadratic case later, because it is surprisingly important. Notice (2) locates any local minimum, maximum or saddle; if there are multiple minima, they will all satisfy the system, and we must pick the best one, a fundamental difficulty in general optimization problems.

We examine first a very simple-minded idea called **steepest descent**. Suppose we are the vicinity of a local minimum, at the point $\mathbf{x}^0 \in \mathbb{R}^N$ (Because subscripts denote components of a vector, we have to use superscripts, which do not mean powers of x ; there should be no confusion since we normally do not exponentiate vectors). Then as usual we write the local behavior of F using a Taylor expansion:

$$F(x) = F(x^0 + s) = F(x^0) + s^T \nabla F(x^0) + O\|s\|^2. \quad (3)$$

If we take $s = -\gamma \nabla F(x^0)$ with small γ , then

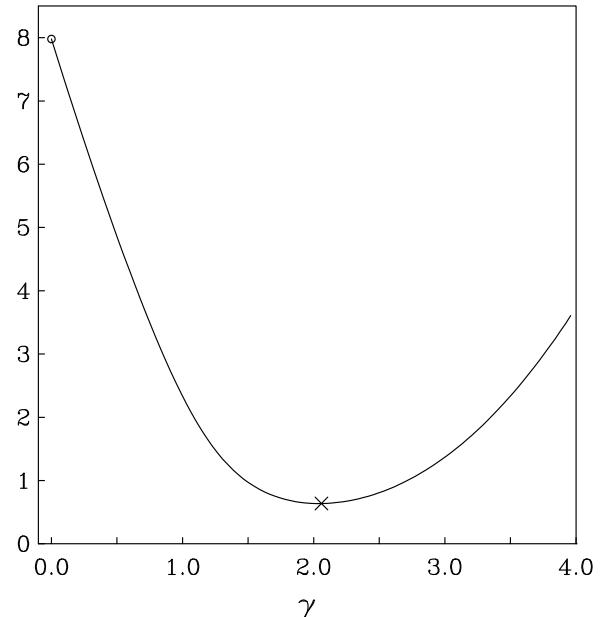
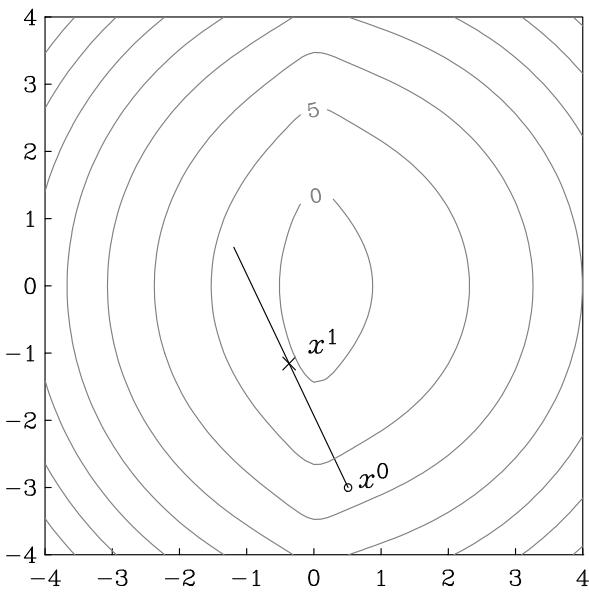
$$F(x) = F(x^0) - \gamma \|\nabla F(x^0)\|^2 + O(\gamma^2) \quad (4)$$

and from this we see that for some choice of $\gamma > 0$ we must be able to find a value of $F(x)$ smaller than $F(x^0)$, and therefore better, because from small enough γ the linear term will dominate the quadratic one. (This is provided $\nabla F(x^0)$ does not vanish, but then we would be at a stationary point.) Looking at the 2-dimensional example in the figure below we see that taking the new $x = x^0 - \gamma \nabla F(x^0)$ is to select a value on the line perpendicular to the local contour, that is to head downhill as rapidly as possible, hence the name steepest descent). But what value of γ should be selected?

The answer to this question is fairly obvious: we keep going until F starts to increase again. In other words we go to the minimum along the direction of initial steepest gradient, as illustrated below. In general this point must be determined by numerical experiment: in a systematic way we try various values of γ in a **line search** until the least value has been found in the direction of $\nabla F(x^0)$. Clearly it is most unlikely that the result will be the true minimum, and so the process will have to be repeated. But the analysis guarantees an improvement will be obtained for every iteration, and so if there is a local minimum, the procedure will converge to it.

So the algorithm is as follows: at the k -th step we compute the next approximation from

Figure 17.1: Contours of F from (6), and values of F on the line of steepest descent starting at x_0 .



$$x^{k+1} = x^k - \gamma \nabla F(x^k), \quad k = 0, 1, 2, \dots \quad (5)$$

where $\gamma > 0$ is chosen to minimize $F(x^{k+1})$, by a line search; x^0 is an arbitrary initial guess vector.

Below we illustrate the continuation of the iterations, using the solution from the previous line search as a starting point for another, and repeating for several steps. Incidentally, the function used for illustration is:

$$F(x_1, x_2) = (x_1 - 0.5)^2 + x_2^2 + \ln(x_1^2 + 0.1) \quad (6)$$

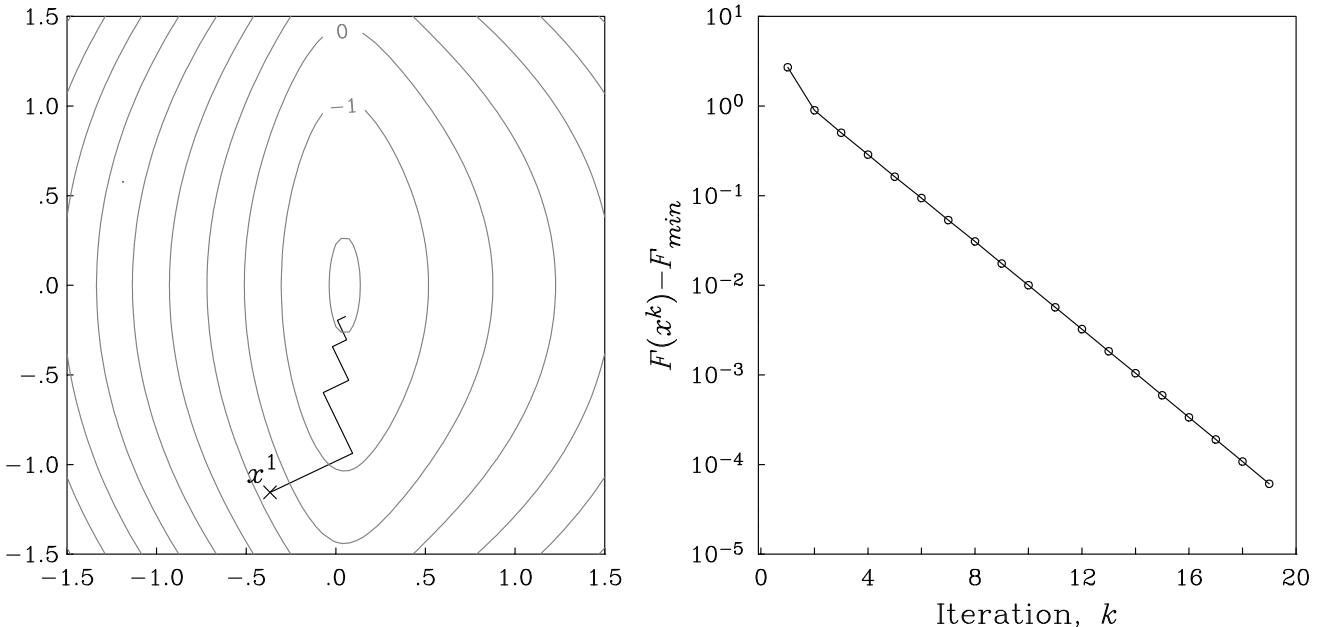
$$\nabla F = [2x_1 - 1 + 2x_1/(x_1^2 + 0.1), \quad 2x_2]^T. \quad (7)$$

After a little thought it should be clear that the steepest descent path must be orthogonal to the previous one, and therefore the trajectory consists of a zig-zag path downhill. The error in the minimum decreases geometrically as you can see from the right panel, and while this looks fairly impressive, it is not very good for a simple two-dimensional minimum; recall every point on the graph requires a separate line search.

It is easy to write a crude line-search program, as you can imagine. But a fair amount of care is needed to be efficient and avoid blunders. See *Numerical Recipes* for a classic algorithm.

To understand, and then perhaps correct, this poor behavior we study the simplest system, the quadratic form. If the second derivative $\nabla \nabla F = H$ does not vanish at x^* , the local minimum, then the behavior of any smooth function of many variables is quadratic and is modeled by

Figure 17.2: Steepest descent path and convergence of objective function for (6).



$$F(x) = F(x^*) + \frac{1}{2}(x - x^*)^T H(x - x^*) \quad (8)$$

where we have dropped the terms from the third and higher derivative in a Taylor series expansion. If x^* truly is the site of a local minimum then H is positive definite. Then it can be proved that the error in the estimate of the minimum value at the k -th step behaves like $c[1 - 1/\kappa_2(H)]^k$ where c is a constant, and κ_2 is the condition number in the 2-norm (Recall $\kappa_2 = \lambda_{\max}/\lambda_{\min}$). For example, condition numbers greater than 1,000 are commonplace, and then the convergence would be as 0.999^k . This is very poor behavior.

Before discussing the most popular remedy for this ailment, we should notice that (8) is essentially identical to the function minimization arising from the underdetermined least-squares problem: we must minimize

$$G(x) = \|Ax - b\|^2 = (Ax - b)^T(Ax - b) \quad (9)$$

$$= b^T b - 2b^T Ax + x^T A^T Ax \quad (10)$$

$$= b^T b - y^T y + (x - y)^T A^T A(x - y) \quad (11)$$

where $y = (A^T A)^{-1} A^T b$ (we arrived at y by completing the square). Comparing (9) with (11) we see they are the same (up to an additive constant), after identifying $A^T A$ with $\frac{1}{2}H$ and y with x^* . For sparse systems, in which lots of elements in A might be zero, QR is unable to take much advantage of sparsity. So when the system is large (> 1000 unknowns) it might be very useful to minimize G in (9) directly by an iterative method, since one evidently only needs to be able to perform the operation Ax a lot of times, and it is often possible to simply skip large chunks of the array, both in storage and in arithmetic, associated with zero entries. Furthermore, QR attempts to get an "exact" solution (up to limitations of round-off), but an iterative approach might find a less accurate, but for many purposes completely satisfactory, answer in a much shorter time. For these reasons, large linear systems, even the solution of $Ax = y$ for square matrices A , are converted to quadratic minimizations. But they cannot be efficiently solved by steepest descent; we need a better tool: conjugate gradients.

18. Conjugate Gradients

The steepest descent path is clearly the best one can do if one is permitted only a single operation. But each stage of the scheme behaves as though we have been given a completely new problem — it doesn't use any information from the earlier steps, and as the Figure 17.2 shows, the procedure seems condemned to repeat itself, zig-zagging back and forth instead of heading down the axis of the valley in F . The conjugate gradient method takes advantage of earlier steps. It modifies the steepest descent direction in the light of previous history, and achieves remarkable gains, as we shall soon see. First let me simply describe the algorithm without attempting to justify it.

The **conjugate gradient** algorithm chooses a search direction s for a line search based on the local gradient, and on previous search directions like this:

$$x^{k+1} = x^k + \gamma p^k, \quad k = 0, 1, 2, \dots \quad (1)$$

where

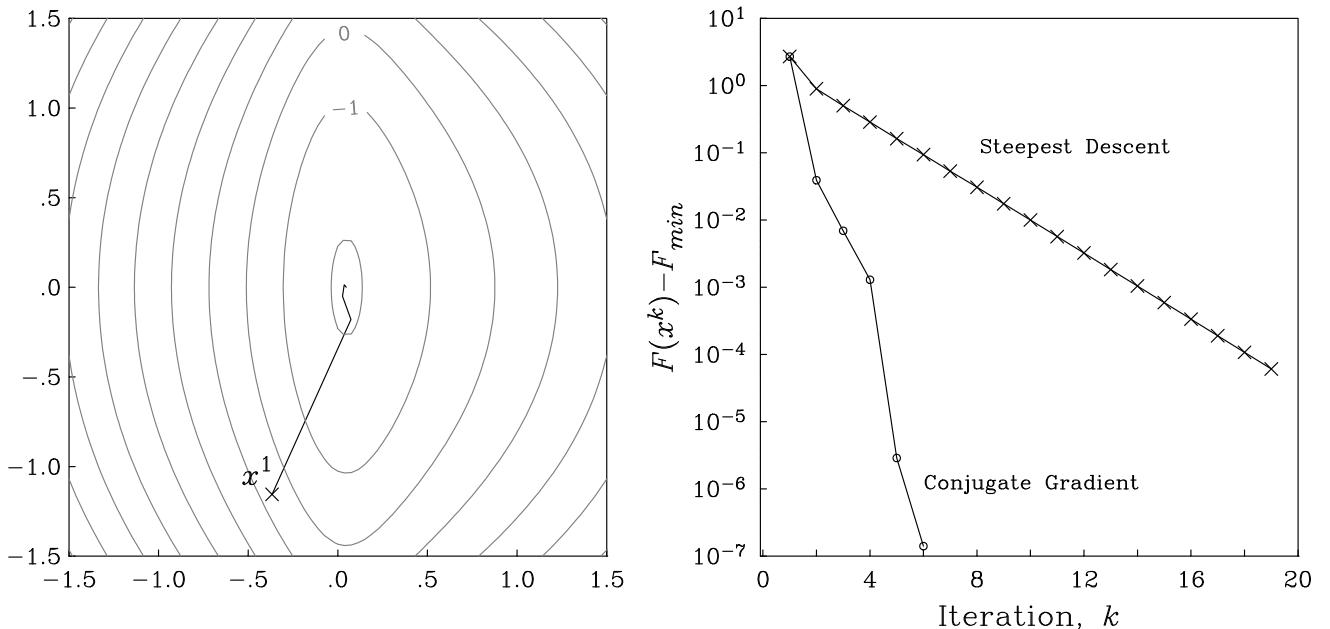
$$p^k = -\nabla F(x^k) + \beta p^{k-1}, \quad k > 0 \quad (2)$$

and

$$\beta = \frac{\nabla F(x^k)^T (\nabla F(x^k) - \nabla F(x^{k-1}))}{\|\nabla F(x^{k-1})\|^2}. \quad (3)$$

For the initial iteration, $k = 0$, when there is no previous search direction, $p^0 = -\nabla F(x^0)$, the steepest descent direction. At each step γ in (1) is determined as before by minimizing $F(x^{k+1})$ along the line.

Figure 18.1: Conjugate gradient and objective convergence for (6).



On the previous page we show the results of the application to the minimization of (5). The improvement on steepest descent is extraordinary, as the right panel shows. Notice also that the convergence is not a steady exponential decline in error; the rate varies. This is a feature of conjugate gradient optimization: it may chug along reducing the penalty only modestly, then make a huge gain, then settle back to slower progress. Such behavior makes a termination strategy difficult to devise, because one cannot tell when the penalty has been reduced to its minimum value. Remember, the convergence plots in these notes are cheats, because I know the real answer, something obviously not normally available.

The design of the conjugate gradient method is centered on the goal of solving a problem with a quadratic penalty function, like (8), exactly after precisely n iterative steps, where n is the dimension of the space of unknowns. When solving a very large system (with $n > 1000$, say), one would not want to have to take so many steps, but it is often the case that an exact answer is not required, and a perfectly satisfactory reduction in the penalty function will have been achieved long before $k = n$. It also turns out that for very large systems, exact answers cannot be obtained in practice even after n iterations, because of the accumulation of round-off error in the computer arithmetic.

Here is an explanation of how conjugate gradients work, taken from Gill et al., Chap 4. Strang, and Golub and Van Loan, offer different derivations which are longer. As just remarked the procedure is set up to solve a quadratic problem, which we will take to be the minimization of

$$F(x) = c \cdot x + \frac{1}{2}x \cdot Gx \quad (4)$$

where $G \in \mathbb{R}^{n \times n}$ and is positive definite and symmetric. For this last proof we will use the familiar notation $x \cdot y$ to be the inner product of two vectors because it is much cleaner: so recall $x \cdot y = x^T y = y^T x$. Also, since G is symmetric, note that $x \cdot Gy = y \cdot Gx$.

The exact minimum of F is easily seen to be the point $x^* = -G^{-1}c$, so solution of (4) by conjugate gradients is equivalent to solving that linear system of equations. You will easily verify that

$$\nabla F(x) = c + Gx. \quad (5)$$

We look at the process at iterative step k ; we assume we have an approximation for the minimizer x^k and we are going build the next approximation by a linear combination of vectors, p^0, p^1, \dots, p^k collected over previous iterations, together with the current approximation to the solution; we will explain later how the vectors p^k are chosen. For now we assert:

$$x^{k+1} = x^k + \sum_{j=0}^k w_j p^j \quad (6)$$

$$= x^k + P_k w \quad (7)$$

where the matrix $P = [p^0, p^1, \dots, p^k]$ and the vector w contains the weights. Our first job is to find w so that x^{k+1} in (7) minimizes F . This is a straightforward least-squares problem, details omitted. We find

$$w = -(P_k^T G P_k)^{-1} P_k^T g^k \quad (8)$$

where the vector g^k is defined as the gradient:

$$g^k = \nabla F(x^k) = c + Gx^k. \quad (9)$$

Plugging (8) into (7) gives

$$x^{k+1} = x^k - P_k(P_k^T G P_k)^{-1} P_k^T g^k. \quad (10)$$

At this point we note a useful property of the process: the gradient at the $k+1$ -st approximation is orthogonal to all the current vectors p^i . Proof — calculate:

$$P_k^T g^{k+1} = P_k^T \nabla F(x^{k+1}) = P_k^T (c + Gx^{k+1}) \quad (11)$$

$$= P_k^T (g^k - Gx^k + G(x^k - P_k(P_k^T G P_k)^{-1} P_k^T g^k)) \quad (12)$$

$$= P_k^T g^k - P_k^T G P_k (P_k^T G P_k)^{-1} P_k^T g^k \quad (13)$$

$$= 0. \quad (14)$$

By expanding P_k into column vectors we see this means:

$$P_k^T g^{k+1} = [p^0 \cdot g^{k+1}, p^1 \cdot g^{k+1}, \dots, p^k \cdot g^{k+1}]^T = [0, 0, \dots, 0]^T \quad (15)$$

and therefore

$$p^i \cdot g^{k+1} = g^{k+1} \cdot p^i = 0, \quad i = 0, 1, 2, \dots, k. \quad (16)$$

Now if we assert that all the x^k to this point have been found in the same way, it must be true that for $j = 1, 2, \dots, k$

$$p^i \cdot g^j = g^j \cdot p^i = 0, \quad i < j. \quad (17)$$

Thus the gradient vector g^j is orthogonal to every earlier p^i vector, as advertised.

With this information let us calculate the product $P_k^T g^k$ at the end of (10):

$$P_k^T g^k = [p^0 \cdot g^k, p^1 \cdot g^k, \dots, p^k \cdot g^k]^T = [0, 0, \dots, 0, \alpha]^T \quad (18)$$

where $\alpha = p^k \cdot g^k$.

So far the only property assumed of the p^i has been linear independence, needed for the inverse in (8). Let us now assert that we would like another property (which we will have to build into process somehow): let us propose that the vectors p^i are mutually **conjugate** under the action of G . This means that they orthogonal in the G inner product, or explicitly that

$$(p^i, p^j)_G = p^i \cdot G p^j = 0, \quad i \neq j. \quad (19)$$

Then the matrix $P_k^T G P_k$ in (10) becomes a diagonal matrix. Combining that fact with (18), which is always true, the expression x^{k+1} in (10) simplifies to

$$x^{k+1} = x^k + \gamma_k p^k \quad (20)$$

which is (1). In other words, when we started, the search for the minimum at step k was over the complete set of previous vectors p^j , but with conjugacy we find only the most recent vector need be searched over to achieve the optimal result. The parameter γ_k which we happen to know is

$$\gamma_k = -\frac{\alpha}{p^k \cdot G p^k} = -\frac{p^k \cdot g^k}{p^k \cdot G p^k} \quad (21)$$

could be found by a line search, and would have to be if this were a linearization of a nonquadratic system.

To summarize: if we can somehow arrange the vectors p^i to be mutually conjugate, they are the search directions at each iterative step, and at the end of that step, F has achieved its minimum over the space spanned by the vectors p^0, p^1, \dots, p^k . Since these vectors are linearly independent and at step $n-1$ there are n of them, they must span \mathbb{R}^n , and therefore at this last step we must have the global minimum of F over all vectors in \mathbb{R}^n . Our task is to set up a scheme for producing search direction vectors p^i with the property of conjugacy under G .

We set about building the p^i from the available gradients as follows. First we take $p^0 = -g^0$ (the steepest descent direction; why?). Subsequently we say

$$p^k = -g^k + \sum_{j=0}^{k-1} \beta_{kj} p^j \quad (22)$$

that is, the new direction is found from the current gradient and a linear combination of previous search directions. In what follows we work towards determining the values of the unknown coefficients β_{kj} in this expansion. By a simple rearrangement, it follows from the recipe (22) that g^k is a linear combination of the p^j up to $j = k$: Consider $i < k$ and dot a gradient vector with any earlier gradient vector:

$$g^k \cdot g^i = g^k \cdot \sum_{j=0}^i \sigma_j p^j = \sum_{j=0}^i \sigma_j g^k \cdot p^j \quad (23)$$

$$= 0 \quad (24)$$

because of (17). So the gradient vectors are mutually orthogonal too!

To discover the coefficients β_{kj} we make use of the mutual conjugacy of the p^i vectors — we pre-multiply (22) by G , then dot on the left with p^i :

$$p^i \cdot Gp^k = - p^i \cdot Gg^k + \sum_{j=0}^{k-1} \beta_{kj} p^i \cdot Gp^j. \quad (25)$$

Then for $i < k$, because of the conjugacy, (19), the left side vanishes and so do most of the terms in the sum:

$$0 = - p^i \cdot Gg^k + \beta_{ki} p^i \cdot Gp^i, \quad i < k \quad (26)$$

$$= - g^k \cdot Gp^i + \beta_{ki} p^i \cdot Gp^i. \quad (27)$$

From (9), the definition of g^i , and using (20) we see

$$g^{i+1} - g^i = G(x^{i+1} - x^i) = \gamma_i Gp^i. \quad (28)$$

This allows us to substitute for Gp^i in (27):

$$0 = - \frac{1}{\gamma_i} g^k \cdot (g^{i+1} - g^i) + \beta_{ki} p^i \cdot Gp^i. \quad (29)$$

But now the orthogonality of the gradients, (24), means that when $i < k-1$ the first term on the right automatically vanishes too; since $p^i \cdot Gp^i$ must not be zero,

$$\beta_{ki} = 0, \quad i < k-1. \quad (30)$$

Hence we have just shown that to get conjugacy of search directions, the new search direction at each step involves the current gradient and the previous direction only; (22) has become:

$$p^k = - g^k + \beta_{k,k-1} p^{k-1} \quad (31)$$

which is of course (2). Finally we need to find the coefficient $\beta_{k,k-1}$ explicitly. Premultiply (31) by G then dot with p^{k-1} ; conjugacy makes $p^{k-1} \cdot Gp^k$ on the left side vanish, and so, rearranging we find

$$\beta_{k,k-1} = \frac{p^{k-1} \cdot Gg^k}{p^{k-1} \cdot Gp^{k-1}} \quad (32)$$

$$= \frac{(g^k - g^{k-1}) \cdot g^k}{g^{k-1} \cdot g^{k-1}} \quad (33)$$

$$= \frac{g^k \cdot g^k}{g^{k-1} \cdot g^{k-1}} = \frac{\|g^k\|^2}{\|g^{k-1}\|^2} \quad (34)$$

where (33), (34) follow from applications of (16), (24) and (28). The form (33) is used in the nonquadratic application (3) rather than (34) because when the problem is not quadratic, orthogonality of the successive gradients is only approximate.

Powerful as CG certainly is, it still may require a lot of numerical work when the dimension of the system becomes very large. Then there are further tricks that can improve the convergence rate, but they are dependent on special structure a particular problem may exhibit, and are not

generally available. The concept is called **preconditioning**, and is covered in Golub and Van Loan, Chapter 10.

Bibliography

Gill, P. E., Murray, W. and Wright, M. H., *Practical Optimization*, Academic Press, New York, 1981.

A treasure trove of numerical methods for every kind of optimization problem: linear, nonlinear, constrained, unconstrained, sparse, full, linear programming.

Golub, G., and Van Loan , C., *Matrix Computations*, 3rd Edition, Johns Hopkins Univ. Press, 1996.

The one reference for matrix linear algebra.

Lawson, C. L., and Hanson, R. J. , *Solving Least Squares Problems*, 1974.

Classic text for full analysis of QR and SVD in least squares.

Strang, G., *Introduction to Applied Mathematics*, Wellesley-Cambridge, 1986.

Readable treatment of many topics, though sometimes a little off base.

19. Application to the Gravity Anomaly Problem

The nonlinear gravity inversion problem in GIT was solved there by means of Occam and by B-G creeping. As a finale we will apply steepest descents and conjugate gradients to it. We have already computed (in GIT) the Fréchet Derivative for the problem, but as I want to stress here, those derivatives do not all need to be stored, or a Gram matrix inverted for SD or CG. This makes them more suitable for very large problems, which the gravity problem is not, of course.

First we need a scalar function to minimize. This immediately points up one of the disadvantages of these optimization methods: *they are designed for unconstrained optimization*. If we are seeking a regularized solution we will need to minimize something like

$$U(h, \lambda) = \sum_{j=1}^N (\hat{d}_j - F_j[h])^2 + \lambda \|h\|^2 \quad (1)$$

where λ is the unknown Lagrange multiplier whose value we discover by achieving the appropriate misfit. In nonlinear problems, however, the first order of business is to get *any* solution at all, and so initially we might choose λ to be very small, or zero. In case of the gravity problem we first want to fit the data almost exactly, and since the topography is order of magnitude unity, setting $\lambda = 0.01$ will insure most emphasis is placed on the first term. The derivative of U is just a vector in the discretized form: $\nabla U \in \mathbb{R}^L$, where $L =$ the number sample points in $h(x)$; while the Fréchet derivative is approximated by the matrix $D \in \mathbb{R}^{N \times L}$. We easily calculate that

$$\nabla U = 2D^T(\hat{d} - F) + 2\lambda h \quad (2)$$

where $\hat{d} - F \in \mathbb{R}^N$ is the vector of misfits. We should not forget to note that:

$$d_j = F_j[h] = g\Delta\rho \int_0^a \ln \left[\frac{(x - x_j)^2 + h(x)^2}{(x - x_j)^2} \right] dx \quad (3)$$

$$D_j(x) = \frac{2g\Delta\rho h(x)}{(x - x_j)^2 + h(x)^2} \quad (4)$$

The discretized form of (3) and (4) follows easily by replacing the function $h(x)$ with the vector of samples $[h_1, h_2, \dots, h_L]$. In the calculations that follow we take $L = 50$.

First we perform the minimization using steepest descent steps, starting at the model that is a constant $h(x) = 1$ km; $\lambda = 0.01$. The squared norm of misfits is shown in Figure 19.1, plotted against step number: each step involves the line search along the steepest descent direction. At the end of 50 line searches the penalty function U in (1) was reduced to 0.327 mGal² and the norm of misfits was 0.391 mGal. Next we perform the conjugate gradient minimization, starting at the same initial

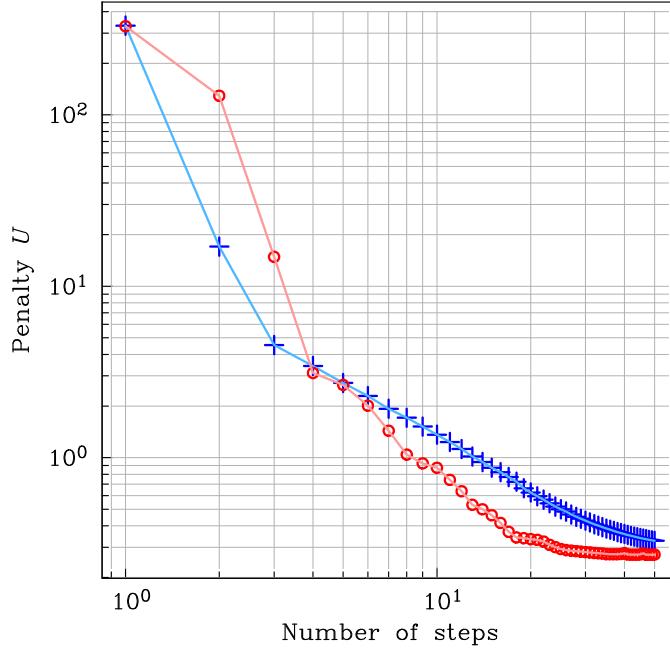


Figure 19.1: Penalty function U after n line searches with (+) steepest descents; (o) conjugate gradients.

guess. This is shown in the Figure too. Notice how the initial performance is worse than steepest descents, but then the method beats steepest descents: after 50 steps we have a penalty of 0.272 mGal² and a misfit 2-norm of 0.300 mGal. The models are shown on the next page in Figure 19.2.

At first glance these methods appear to be at a severe disadvantage to Occam, which needed only four line searches to reach a similar misfit level. But that is not necessarily the case, as we now discuss. Each line search in Occam requires the solution of the linear system of equations

$$\left(\frac{1}{\mu} I + D D^T \right) \alpha = \hat{d} \quad (5)$$

(This is (25) on p 315 of GIT.) This uses on the order of N^3 computer operations, since $D D^T \in \mathbb{R}^N$. Whereas the single line search in SD or CG involves nothing more than operations of addition and subtraction of vectors, for which the computer costs are only order N . In fact, the largest cost in each step is the evaluation of ∇U , which here takes order N^2 operations. For large data sets CG (or SD) have a much lower cost per step. In this light, the cost for 50 steps of CG is about the same as 4 steps of Occam, since $N = 12$. So when N is very large, say hundreds or even thousands, CG may be the only practical approach.

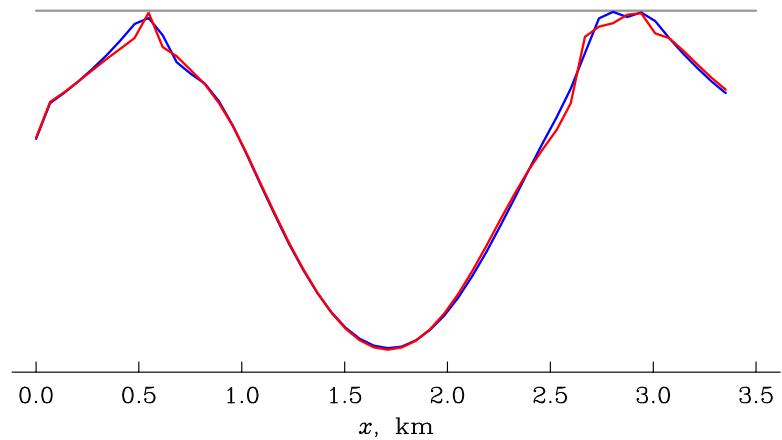


Figure 19.2: Valley profiles obtained by steepest descents (blue); conjugate gradients (red).