

Lecture Date: 16<sup>th</sup> & 17<sup>th</sup> Apr '04

## Solving Least Squares

### The problem

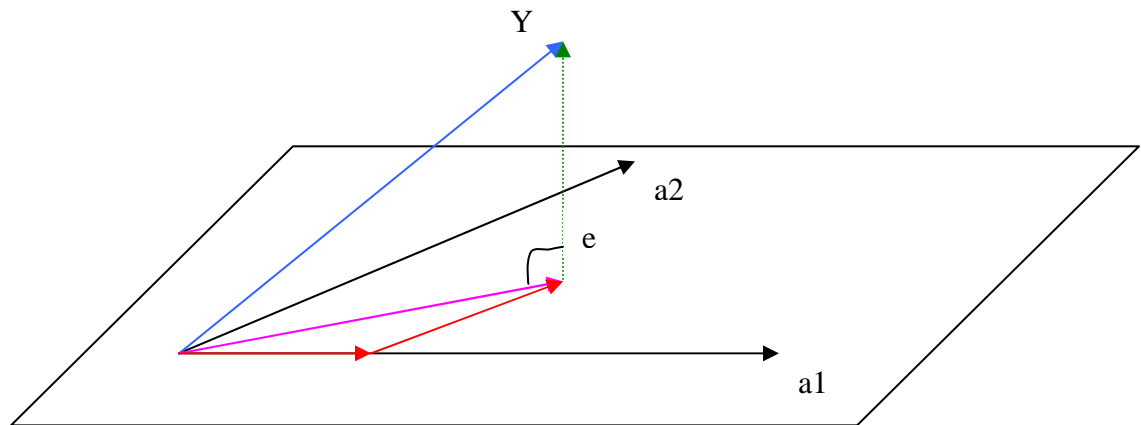
Given a vector  $Y$  and a set of basis vectors  $A = \{a_1, a_2, \dots, a_n\}$ , we want to find the measure of  $Y$  in terms of  $A$  i.e. find  $M$  such that

$$MA = Y$$

The vector space spanned by  $Y$  and  $A$  differs, giving us a set of over-determined equations. So, we find an  $M$  such that

$\|Y - MA\|$  is minimum.

So, we are basically trying to - find the shadow of  $Y$  in the subspace spanned by  $A$ , and also find the linear combinants, which add up to that shadow. This is illustrated by the figure below. The vectors in red are the linear combinants in the direction of  $a_1$  &  $a_2$ .



The vector in pink is the shadow of  $Y$  in the subspace of  $A$ . 'e' is the error, which is **orthogonal to the subspace spanned by  $A$** .

We notice that if the  $A$  is an orthogonal basis, the solution to the problem is simplified. If the basis is orthogonal, then the linear combinants are just the coordinate values of  $Y$  (the analysis and synthesis matrix is same).

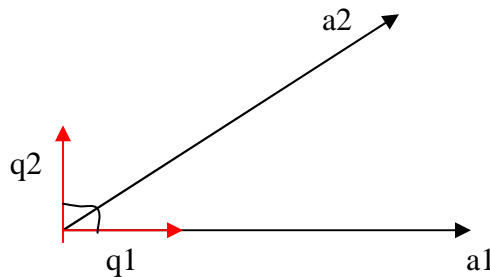
Mathematically, the same can be justified by the fact that the inverse of an orthogonal matrix is its conjugate transpose.

To find the linear combinants we need the inverse of the basis matrix as shown below.

$AC = Y$ ,  $C$  is  $[\lambda_1, \lambda_2, \dots, \lambda_n]$ , the scales by which each direction in  $A$  needs to be scaled so that they all add up to  $Y$ .  
 $C = A^{-1} Y$ .

Thus the least square problem is reduced to finding a set of orthogonal set of basis  $Q$  such that  
 $\text{Span} \{ Q \} = \text{Span} \{ A \}$   
 i.e. a set of Orthogonal vector space spanning the same subspace as that of the given basis.

For example in a 2-D subspace, it can be shown as below.  $q_1$  and  $q_2$  are the normalized orthogonal vectors for the subspace of  $a_1$  &  $a_2$

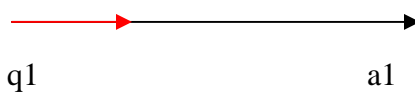


Therefore we have different methods of orthogonalizing the basis vector  $A$ .

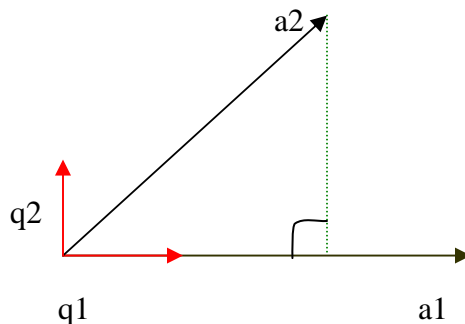
### I. Graham Schmidt Method

This is the successive orthogonalization (the QR method).  
 Let  $A$  contain  $n$  linearly independent vectors. We want to find the orthonormal basis for  $A$

$q_1$  is  $a_1/|a_1|$

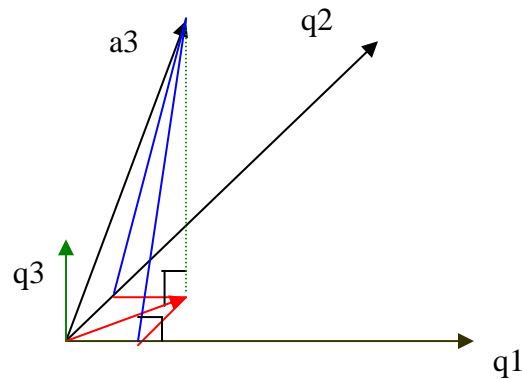


For  $a_2$ , we take the projection of  $a_2$  on  $a_1$ , to find the orthogonal vector  $q_2$



$\therefore q_2 = a_2 - \text{proj of } a_2 \text{ on } a_1 / |a_2 - \text{proj of } a_2 \text{ on } a_1|$   
 $q_3$  is a vector orthogonal to subspace of  $a_1$  &  $a_2$ . Its simple to see this a least squares problem. (given vector  $a_3$ , and need to find its shadow in  $a_1$  &  $a_2$ , so that we can find the direction of the error which is orthogonal to  $a_1$  &  $a_2$ )

Hence we use the orthogonal vectors  $q_1$  and  $a_2$  to find  $q_3$ . First we drop perpendicular to  $q_1$  and  $q_2$  (refer to the figure below) shown in blue. Assume  $a_3$  is coming out of the monitor.



Now, if we look at  $a_3$  to be made up of 2 parts, 1 which lies in the subspace of  $q_1, q_2$  and the other remaining is the component orthogonal to  $q_1$  &  $q_2$ .

By, dropping perpendiculars on  $q_1$  and  $q_2$  we find the projection of  $a_3$  in  $q_1$  &  $q_2$ . Since  $q_1, q_2$  are ortho to each other, these projections when added up will give the shadow of  $a_3$  in  $q_1$  &  $q_2$ . Subtracting this from  $a_3$  gives us the component that not in  $q_1$  &  $q_2$  i.e orthogonal.

In the figure, the shadow of  $a_3$  is in red.

$$\therefore q_1 = a_1$$

$$\therefore q_2 = a_2 - \text{proj}_{q_1} a_2$$

$$\therefore q_3 = a_3 - \text{proj}_{q_1} a_3 - \text{proj}_{q_2} a_3$$

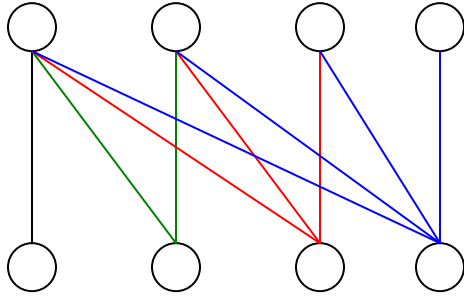
The same can be shown by the following transfer network

A can be considered to be made of 2 vectors Q and R, such that

$A = QR$ , Q is the orthogonal basis and R is an upper triangular matrix, which is the transfer n/w shown in the figure.

The reason it is easy to invert A is that triangular matrices are simple to invert.

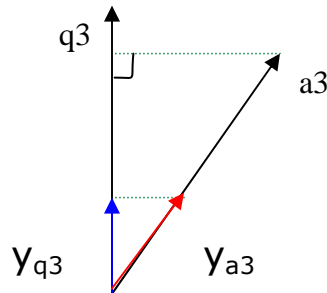
A →



← Transfer Network

Q →

We have the linear combinants of Y in terms of Q, namely Y's coordinate values. But, what we actually want are the linear combinants in terms of A. This can be done in a simple way shown by the figure below.



We find the projection vector of  $a_3$  on  $q_3$ . (Note, for a 3-D space, only  $a_3$  can have any energy along  $q_3$ ). We use the same proj vector to find a vector along  $a_3$  such that  $Y_{q_3}$  is its projection. By similarity we see that this all the energy Y can have along  $a_3$ . We subtract this from Y, so the only components left in Y would be of  $a_1$  and  $a_2$ . They can too be found in the same way.

Why this method is not that good

It is easy to see in this method that the error seeps through. If we have to find the Q for n vector space, the final error is n times as large as the initial error.

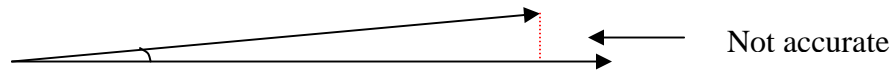
Solution: Modified Graham Schimdt's Method

Similar to GSM, but after finding an ortho vector  $q_n$ , we find the energy of each remaining vector in A along  $q_n$  and subtract this energy. It is easy to see that the two methods are equivalent, but the

energy is reduced stepwise from each vector. This gives better numerical results.

### Why both methods are bad

For ill-conditioned vectors, we get numerically bad results. Consider two vectors very close to each other, the result after subtraction has low resolution, giving bad results.



## II Givens Rotation

Instead of finding the orthogonal basis, we start with an orthonormal basis and then rotate it into to match the given subspace. The error here will be because of the fact that the subspaces spanned by the 2 basis may not be identical, but the error doesn't get amplified proportionally to the no. of vectors in the basis.

The important thing to note here is that we are doing planar rotations, so at a time only 2 co-ordinates change, the ones which are in the plane of rotations

We need to match  $q_1$  with  $a_1$ ,  $q_2$  with  $a_2$  and so on. We do this in steps.

1. Take  $a_1$  and rotate it into  $q_1$  (the inverse rotations are the ones required to rotate  $q_1$  into  $a_1$ ).
2. Then we rotate  $a_2$  into the plane of  $q_1$  &  $q_2$  such that the component along  $q_1$  does not change.

We successively do this till  $A$  is rotated into  $Q$ .

Consider a 3-D space. If we want to rotate  $a_1$  into  $X$  axis, we could first rotate in the  $X-Z$  plane and then in the  $X-Y$  plane or first in the  $X-Y$  plane and then in the  $X-Z$  plane. We choose the following method

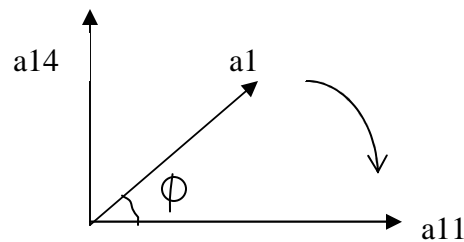
Choose the plane with one axis as the one you want to zero out, and the other the axis which we want to move into.

For a 4-D space

$$a_1 = \begin{pmatrix} a_{11} \\ a_{12} \\ a_{13} \\ a_{14} \end{pmatrix} \quad a_2 = \begin{pmatrix} a_{21} \\ a_{22} \\ a_{23} \\ a_{24} \end{pmatrix} \quad \text{and so on.}$$

For moving  $a_1$  in  $q_1$ , we want to zero out  $a_{14}$  component, so choose the  $a_{11}$ - $a_{14}$  plane of rotation.

$$\therefore \text{Rotation matrix} = \begin{pmatrix} \cos \Phi & 0 & 0 & \sin \Phi \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ -\sin \Phi & 0 & 0 & \cos \Phi \end{pmatrix}$$



Then we use  $a_{11}$ - $a_{13}$  plane of rotation followed by  $a_{11}$  -  $a_{12}$ .

For rotating  $a_2$  into X-Y plane, we have to ensure that X component is not in the plane of rotation.

So, we choose  $a_{22}$  -  $a_{24}$  as plane of rotation and then  $a_{22}$  -  $a_{23}$  as plane of rotation.

We want to solve for 'x' using least squares

$$\therefore Ax = B$$

$$\therefore A = QR$$

$$\begin{aligned} QRx &= B \\ Rx &= Q'B \quad (Q' = Q^{-1}) \\ x &= R^{-1} Q'B \end{aligned}$$

Since, we need the inverse of Q anyway, we do not solve for the inverse rotations. The above rotation matrices are  $Q^{-1}$ , and the upper triangular matrix formed by applying these transformations to A, is R.

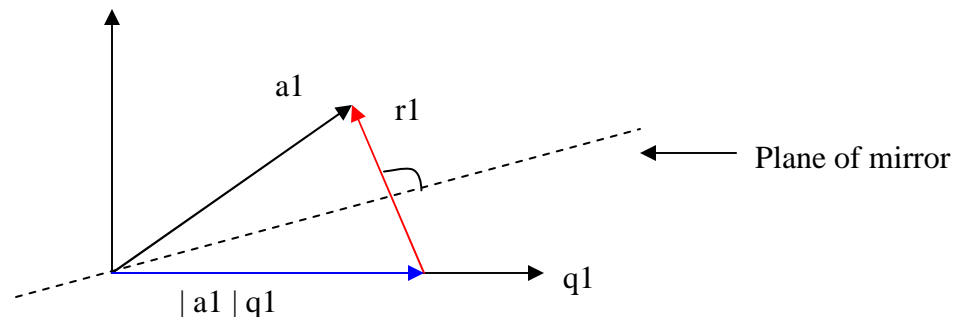
## Householder Reflections

"No our reflections are upside down, left-right flipped, back-fwd flipped. The man in the mirror is actually an alien, with no symmetry or is it up down symmetric. It's all about how we turn!"

"Dabum dubum thubum...!"

## Householder Reflections

The reason we use reflections to match the orthogonal basis to  $A$ , is that reflections are less expensive than rotations.



Therefore,  $r_1 = a_1 - |a_1| q_1$

We want to reflect  $A$  in the direction of  $r_1$ .

This is given by  $r_1^T A$ . If we think of  $A$  to consists of two parts, one component along in the mirror, and the other ortho to it. So, the component in the mirror does not change, and the other gets flipped.

Therefore, after flipping we get  $- r_1^T A$ .  
 Then we reconstruct the vector i.e  $- r_1 r_1^T A$ .  
 The component that doesn't change is  $A - r_1 r_1^T A$ .

$\therefore$  the final vector is the addition of these two vectors

$$\begin{aligned} A - r_1 r_1^T A - r_1 r_1^T A \\ = (I - 2 r_1 r_1^T) A \end{aligned}$$

For, reflecting  $a_2$  into  $q_2$ , we must ensure that component along  $q_1$  doesn't change. So, we flatten this dimension, so that it is just point and lies in the mirror.

$$a_2 = \begin{pmatrix} a_{21} \\ a_{22} \\ a_{23} \\ a_{24} \end{pmatrix} \left. \begin{array}{l} \leftarrow \text{Don't consider this component} \\ \\ \end{array} \right\}$$

Thus Q is the matrix formed by  $(I - r r^T)$  and R is the triangular matrix formed transforming A.