The $Q R$ Decomposition

- Householder Reflections.
- Avoiding the $Q$.
- Uniqueness.


## Structred Least Squares problems

- Givens Rotations and Row updating.

Applications

- Circle fitting, Tikhonov Regularization, Image Deblurring.


## Reflections

Definition A Householder reflection is a matrix of the form,

$$
H(v)=I-2 \frac{v v^{T}}{v^{T} v}
$$

Lemma Let $x \in \mathbb{R}^{m}$ and $v=x+\operatorname{sign}\left(x_{1}\right)\|x\|_{2} e_{1}$ then,

$$
H x= \pm\|x\|_{2} e_{1}=\binom{ \pm\|x\|_{2}}{0}
$$

Remarks Computing $H x$ requires $\mathcal{O}(m)$ operations. Reflections are orthogonal and symmetric.

Lemma Let $A \in \mathbb{R}^{m \times n}, m>n$. Then $A$ can be factorized
as

$$
A=Q\binom{R}{0}
$$

where $Q \in \mathbb{R}^{m \times m}$ is orthogonal and $R \in \mathbb{R}^{n \times n}$ is triangular.

Remark Typically $m \gg n$ so $R$ is small but $Q$ is very large.

$$
\begin{aligned}
& \text { Example Let } x=(1,-1,2,-3)^{T} \text {. Then } \\
& \text { >> } \mathrm{v}=\mathrm{x} \text {; } \mathrm{v}(\mathrm{I})=\mathrm{v}(1)+\operatorname{norm}(\mathrm{x}) \text {; } \\
& \mathrm{V}^{\prime}= \\
& 4.8730-1.00002 .0000-3.0000 \\
& \gg y=x-2 *\left(v^{\prime} * x\right) /\left(v^{\prime} * v\right) * v \\
& \mathrm{y}^{\prime}= \\
& -3.8730-0.00000 .0000-0.0000
\end{aligned}
$$

Example Let $A$ be a $m \times 3$ matrix. Pick $x_{1}=A(1: m, 1)$, $v_{1}=x_{1}+\left\|x_{1}\right\|_{2} e_{1}$ and compute

$$
H\left(v_{1}\right) A=\left(\begin{array}{cc}
\left\|x_{1}\right\| & {\underset{\gamma}{1}}^{T} \\
0 & \widetilde{A}_{2}
\end{array}\right)=\left(\begin{array}{ccc}
+ & + & + \\
0 & + & + \\
0 & + & + \\
0 & + & +
\end{array}\right)=A_{2}
$$

Next let $x_{2}=A_{2}(2: m, 2)$ and $v_{2}=x_{2}+\left\|x_{2}\right\|_{2} e_{1}$. We obtain

$$
\left(\begin{array}{cc}
1 & 0 \\
0 & H\left(v_{2}\right)
\end{array}\right) A_{2}=\left(\begin{array}{ccc}
x & x & x \\
0 & + & + \\
0 & 0 & + \\
0 & 0 & +
\end{array}\right)=A_{3}
$$

## Avoiding the $\mathbf{Q}$

Solve min $\|A x-b\|_{2}$ with as little work as possible

Proposition Compute the decomposition of the augmented matrix
$[A, b]=Q\binom{R}{0}=Q\left(\begin{array}{cc}R_{1} & \gamma \\ 0 & \alpha \\ 0 & 0\end{array}\right), \quad R_{1} \in \mathbb{R}^{n \times n}, \gamma \in \mathbb{R}^{n}$
The least squares solution is $x=R_{1}^{-1} \gamma$. The residual is $|\alpha|$.

Conclusion We do not need $Q$ explicitly. Solving a least squares problem of size $m \times n$ requires $\mathcal{O}\left(m n^{2}\right)$ operations.

## Fitting a circle

Data points stored in two vectors x and y . In Matlab

```
>> A=[x.^2+y.^2 x y]; b=-ones(size(x));
>> R=triu( qr( [ A , b ],0) );
>> u=R(1:3,1:3)\R(1:3,4);
>> z=-u(2:3)/2/u(1)
>> r=sqrt( (u(2)^2+u(3)^2)/4/u(1)^2-1/u(1))
```

The result is $z \approx(1.4033,3.6658)^{T}$ and $r \approx 2.4215$.
The exact circle was $z=(1.2,3.4)^{T}$ and $r=2.7$. Need more data $\left(x_{k}, y_{k}\right)^{T}$ to improve accuracy.

## Structured least squares problems

Have computed $A_{1}=Q_{1} R_{1}, A_{1} \in \mathbb{R}^{13 \times 3}$, and minimzed $\left\|A_{1} u-b_{1}\right\|_{2}$.
Given an additional measurement $\left(x_{14}, y_{14}\right)^{T}$ we want to minimize

$$
\left\|\binom{A_{1}}{a_{14}^{T}} u-\binom{b_{1}}{b_{14}}\right\|_{2}=\left\|\binom{R_{1}}{a_{14}^{T}} u-\binom{Q_{1}^{T} b_{1}}{b_{14}}\right\|_{2}
$$

We need the $Q R$ decomposition of the structured matrix

$$
\left(\begin{array}{cc}
R_{1} & Q_{1}^{T} b_{1} \\
a_{14}^{T} & b_{14}
\end{array}\right)=\left(\begin{array}{cccc}
x & x & x & x \\
0 & x & x & x \\
0 & 0 & x & x \\
x & x & x & x
\end{array}\right)
$$

Already "almost" triangular! Want to take advantage of the structure!

## Givens Rotations

$$
\begin{aligned}
& \text { Lemma Suppose } x=\left(x_{1}, x_{2}\right)^{T} \text { and set } \\
& \qquad \cos (\theta)=\frac{x_{1}}{\sqrt{x_{1}^{2}+x_{2}^{2}}}, \quad \text { and, } \quad \sin (\theta)=\frac{x_{2}}{\sqrt{x_{1}^{2}+x_{2}^{2}}} .
\end{aligned}
$$

Then

$$
G x=\frac{1}{\|x\|_{2}}\left(\begin{array}{cc}
x_{1} & x_{2} \\
-x_{2} & x_{1}
\end{array}\right)\binom{x_{1}}{x_{2}}=\binom{\|x\|_{2}}{0}
$$

Definition A Givens rotation $G_{i j}$ rotates rows $i$ and $j$.

Observation A matrix $A \in \mathbb{R}^{m \times n}$ has $m n-\frac{1}{2} n^{2}$ subdiagonal
elements. One Givens rotation is needed to zero out each element.

Lemma Computing the $R$ using rotations requires $\mathcal{O}\left(m n^{2}\right)$ operations.

Remark Computing $R$, $Q$, or $Q_{1}$ using either reflections or rotations requires the same amount of work.

Example Let $A$ be a $4 \times 3$ matrix. Apply a sequence of Givens Rotations

$$
G_{14} G_{13} G_{12}\left(\begin{array}{ccc}
x & x & x \\
x & x & x \\
x & x & x \\
x & x & x
\end{array}\right)=\left(\begin{array}{ccc}
+ & + & + \\
0 & + & + \\
0 & + & + \\
0 & + & +
\end{array}\right)
$$

Next use $a_{22}$ to zero the elements $A(3: 4,2)$, and finally the element $a_{33}$ to zero $a_{43}$
$G_{34} G_{24} G_{23}\left(\begin{array}{ccc}x & x & x \\ 0 & x & x \\ 0 & x & x \\ 0 & x & x\end{array}\right)=G_{34}\left(\begin{array}{ccc}x & x & x \\ 0 & + & + \\ 0 & 0 & + \\ 0 & 0 & +\end{array}\right)=\left(\begin{array}{ccc}x & x & x \\ 0 & x & x \\ 0 & 0 & + \\ 0 & 0 & 0\end{array}\right)$

Thus $A=Q R$ where $Q=G_{12}^{T} G_{13}^{T} G_{14}^{T} G_{23}^{T} G_{24}^{T} G_{34}^{T}$.

## Row updating

Have $A_{1}=Q_{1} R_{1}$, where $A_{1} \in \mathbb{R}^{m \times n}$ and $R_{1} \in \mathbb{R}^{n \times n}$. Want the $Q R$ decomposition of

$$
\left(\begin{array}{cc}
R_{1} & Q_{1}^{T} b_{1} \\
a_{m+1}^{T} & b_{m+1}
\end{array}\right)=\left(\begin{array}{cccc}
x & x & x & x \\
0 & x & x & x \\
0 & 0 & x & x \\
x & x & x & x
\end{array}\right)
$$

First apply a Givens rotation $G_{14}$ and obtain

$$
G_{14}\left(\begin{array}{cccc}
x & x & x & x \\
0 & x & x & x \\
0 & 0 & x & x \\
x & x & x & x
\end{array}\right)=\left(\begin{array}{cccc}
+ & + & + & + \\
0 & x & x & x \\
0 & 0 & x & x \\
0 & + & + & +
\end{array}\right)
$$

## Fitting a circle

Continue and apply rotations $G_{24}$ and $G_{34}$ to obtain
$G_{34} G_{24}\left(\begin{array}{cccc}x & x & x & x \\ 0 & x & x & x \\ 0 & 0 & x & x \\ 0 & x & x & x\end{array}\right)=G_{34}\left(\begin{array}{cccc}x & x & x & x \\ 0 & + & + & + \\ 0 & 0 & x & x \\ 0 & 0 & + & +\end{array}\right)=\left(\begin{array}{cccc}x & x & x & x \\ 0 & x & x & x \\ 0 & 0 & + & + \\ 0 & 0 & 0 & +\end{array}\right)$.
Denote the matrix by $R_{2}$. The updated least squares solution is

$$
x=R_{2}(1: n, 1: n)^{-1} R_{2}(1: n, n+1)
$$

Remark Need $n$ Givens rotations to restore triangular shape! Only $\mathcal{O}\left(n^{2}\right)$ operations. Note that $Q$ is not needed!

Example We obtain another measurement $\left(x_{14}, y_{14}\right)$ and compute a new row $a_{14} u=b_{14}$. In Matlab:

```
>> a14=[x14.^2+y14.^2 x14 y14]; b14=-1;
>> R = [ R ; a14 , b14]
    R=
\begin{tabular}{rrrr}
-126.7605 & -9.9725 & -18.1245 & 3.5816 \\
0 & -4.8810 & 1.4620 & 0.3408 \\
0 & 0 & 0.3085 & -0.1882 \\
28.8479 & -0.6628 & 5.3300 & -1.0000 \\
for \(\mathrm{k}=1: 3\), & \(\mathrm{R}=\mathrm{Givens}(\mathrm{R}, \mathrm{k}, 4\) \\
\(\mathrm{R}=\) \\
130.0017 & 9.5768 & 18.8554 & -3.7142 \\
0 & 5.6568 & -1.8555 & -0.2029 \\
0 & 0 & -0.4133 & 0.3587 \\
0 & 0 & 0 & -0.1195
\end{tabular}
```


## Application: Tikhonov Regularization

If a linear system $A x=b$ is very ill-conditioned need to stabilize the numerical computations.

## Definition The Tikhonov functional is,

$$
f(\lambda)=\min _{x \in \mathbb{R}^{n}}\|A x-b\|_{2}^{2}+\lambda^{2}\|x\|_{2}^{2}
$$

Remark Tikhonov regularization is a very popular method for finding approximate solutions to very ill-conditioned systems. Need to solve the problem for many different values of the parameter $\lambda$.

The $m=14$ data points $\left(x_{k}, y_{k}\right)^{T}$ and estimated circle. Now we obtain $z \approx(1.2630,3.44)^{T}$ and $r \approx 2.6367$.

This is a structured least squares problem

## Application: Image Deblurring

$$
\binom{A}{\lambda I}=\left(\begin{array}{lll}
x & x & x \\
x & x & x \\
x & x & x \\
x & 0 & 0 \\
0 & x & 0 \\
0 & 0 & x
\end{array}\right)=\widetilde{Q}^{T}\left(\begin{array}{ccc}
x & x & x \\
0 & x & x \\
0 & 0 & x \\
x & 0 & 0 \\
0 & x & 0 \\
0 & 0 & x
\end{array}\right)
$$

Lemma Suppose we have the decomposition $A=Q R$. Then the Tikhonov functional can be evaluated using $\mathcal{O}(n)$ additional Givens rotations.

Proof See L. Eldén, Algorithms for the regularization of ill-conditioned least squares problems, BIT, 1977.

## The Point Spread function

Example The blurring effect of light passing through the atmosphere can be modelled as,

$$
P_{b}(i, j)=\exp \left(\frac{-i^{2}-j^{2}}{2 \sigma^{2}}\right)
$$

This means the recorded image is $I_{b}=A_{b} I$, where $A_{b}$ is a matrix.


The original $9 \times 9$ image $I$ the resulting blurred image $I_{b}=A_{b} I$.

Example The effect of object movement during camera exposure.
The recorded image is $I_{m}=A_{m} I$, where $A_{m}$ is a matrix.


The original $9 \times 9$ image $I$ and the resulting image $I_{m}$ due to object movement. The object appears at several pixels.

Example We look at a sattelite through a telescope. The sattelite moves horizontally through the image. The image we record is $I_{r}$ which is subject to a combination of object movement and blurring.


The original $128 \times 128$ image $I$ showing the "exact" sattelite. Also the degraded image $I_{r}$. Can we compensate for these effects?

Observation The Matrices $A_{b}$ and $A_{m}$ are both $16384 \times 16384$ and sparse. It is not feasible to compute the full $Q R$ decomposition of the combined matrix $A_{T}=A_{b} A_{m}$.

Alternative techniques are needed for realistic applications.

Results The restored images using Tikhonov regularization. We have $\lambda=10^{-5}$ (left) and $\lambda=10^{-2}$ (right). Too much regularization means the image is not clear. The movement is easily compensated for. The blurring is more difficult.

## Uniqueness

Question Is the $Q R$ decomposition unique?

Lemma Let $R_{1}, R_{2}$ be upper triangular. Then $R_{1} R_{2}$ and $R_{1}^{-1}$ are both upper triangular.

Lemma If $A$ is both triangular and orthogonal then $A$ is diagonal, and $a_{i i}= \pm 1$.

Proof See problem collection.

