

5.1.3 Computing the Householder Vector

There are a number of important practical details associated with the determination of a Householder matrix, i.e., the determination of a Householder vector. One concerns the choice of sign in the definition of v in (5.1.2). Setting

$$v_1 = x_1 - \|x\|_2$$

has the nice property that Px is a positive multiple of e_1 . But this recipe is dangerous if x is close to a positive multiple of e_1 because severe cancellation would occur. However, the formula

$$v_1 = x_1 - \|x\|_2 = \frac{x_1^2 - \|x\|_2^2}{x_1 + \|x\|_2} = \frac{-(x_2^2 + \cdots + x_n^2)}{x_1 + \|x\|_2}$$

suggested by Parlett (1971) does not suffer from this defect in the $x_1 > 0$ case.

In practice, it is handy to normalize the Householder vector so that $v(1) = 1$. This permits the storage of $v(2:n)$ where the zeros have been introduced in x , i.e., $x(2:n)$. We refer to $v(2:n)$ as the *essential part* of the Householder vector. Recalling that $\beta = 2/v^T v$ and letting $\text{length}(x)$ specify vector dimension, we obtain the following encapsulation:

Algorithm 5.1.1 (Householder Vector) Given $x \in \mathbb{R}^n$, this function computes $v \in \mathbb{R}^n$ with $v(1) = 1$ and $\beta \in \mathbb{R}$ such that $P = I_n - \beta vv^T$ is orthogonal and $Px = \|x\|_2 e_1$.

```
function: [v, beta] = house(x)
    n = length(x)
    sigma = x(2:n)^T x(2:n)
    v = [ 1
          x(2:n) ]
    if sigma == 0
        beta = 0
    else
        mu = sqrt(x(1)^2 + sigma)
        if x(1) <= 0
            v(1) = x(1) - mu
        else
            v(1) = -sigma/(x(1) + mu)
        end
        beta = 2*v(1)^2/(sigma + v(1)^2)
        v = v/v(1)
    end
end
```

A production version of Algorithm 5.1.1 may involve a preliminary scaling of the x vector ($x \leftarrow x/\|x\|$) to avoid overflow.

5.1.4 Applying Householder Matrices

It is critical to exploit structure when applying a Householder reflection to a matrix. If $A \in \mathbb{R}^{m \times n}$ and $P = I - \beta vv^T \in \mathbb{R}^{m \times m}$, then

$$PA = (I - \beta vv^T) A = A - vw^T$$

where $w = \beta A^T v$. Likewise, if $P = I - \beta vv^T \in \mathbb{R}^{n \times n}$, then

$$AP = A(I - \beta vv^T) = A - wv^T$$

where $w = \beta Av$. Thus, an m -by- n Householder update involves a matrix-vector multiplication and an outer product update. It requires $4mn$ flops. Failure to recognize this and to treat P as a general matrix increases work by an order of magnitude. *Householder updates never entail the explicit formation of the Householder matrix.*

Both of the above Householder updates can be implemented in a way that exploits the fact that $v(1) = 1$. This feature can be important in the computation of PA when m is small and in the computation of AP when n is small.

As an example of a Householder matrix update, suppose we want to overwrite $A \in \mathbb{R}^{m \times n}$ ($m \geq n$) with $B = Q^T A$ where Q is an orthogonal matrix chosen so that $B(j+1:m, j) = 0$ for some j that satisfies $1 \leq j \leq n$. In addition, suppose $A(j:m, 1:j-1) = 0$ and that we want to store the essential part of the Householder vector in $A(j+1:m, j)$. The following instructions accomplish this task:

$$\begin{aligned} [v, \beta] &= \text{house}(A(j:m, j)) \\ A(j:m, j:n) &= (I_{m-j+1} - \beta vv^T) A(j:m, j:n) \\ A(j+1:m, j) &= v(2:m-j+1) \end{aligned}$$

From the computational point of view, we have applied an order $m-j+1$ Householder matrix to the bottom $m-j+1$ rows of A . However, mathematically we have also applied the m -by- m Householder matrix

$$\bar{P} = \begin{bmatrix} I_{j-1} & 0 \\ 0 & P \end{bmatrix} = I_m - \beta \bar{v} \bar{v}^T \quad \bar{v} = \begin{bmatrix} 0 \\ v \end{bmatrix}$$

to A in its entirety. Regardless, the “essential” part of the Householder vector can be recorded in the zeroed portion of A .

5.1.5 Roundoff Properties

The roundoff properties associated with Householder matrices are very favorable. Wilkinson (1965, pp. 152-62) shows that `house` produces a Householder vector \hat{v} very near the exact v . If $\hat{P} = I - 2\hat{v}\hat{v}^T/\hat{v}^T\hat{v}$ then

$$\|\hat{P} - P\|_2 = O(u)$$

meaning that \hat{P} is *orthogonal to machine precision*. Moreover, the computed updates with \hat{P} are close to the exact updates with P :

$$fl(\hat{P}A) = P(A + E) \quad \|E\|_2 = O(u\|A\|_2)$$

$$fl(A\hat{P}) = (A + E)P \quad \|E\|_2 = O(u\|A\|_2)$$

5.1.6 Factored Form Representation

Many Householder based factorization algorithms that are presented in the following sections compute products of Householder matrices

$$Q = Q_1 Q_2 \cdots Q_r \quad Q_j = I - \beta_j v^{(j)} v^{(j)T} \quad (5.1.3)$$

where $r \leq n$ and each $v^{(j)}$ has the form

$$v^{(j)} = (\underbrace{0, 0, \dots, 0}_{j-1}, 1, v_{j+1}^{(j)}, \dots, v_n^{(j)})^T.$$

It is usually not necessary to compute Q explicitly even if it is involved in subsequent calculations. For example, if $C \in \mathbb{R}^{n \times q}$ and we wish to compute $Q^T C$, then we merely execute the loop

```
for j = 1:r
    C = Q_j C
end
```

The storage of the Householder vectors $v^{(1)} \dots v^{(r)}$ and the corresponding β_j (if convenient) amounts to a *factored form* representation of Q . To illustrate the economies of the factored form representation, suppose that we have an array A and that $A(j+1:n, j)$ houses $v^{(j)}(j+1:n)$, the essential part of the j th Householder vector. The overwriting of $C \in \mathbb{R}^{n \times q}$ with $Q^T C$ can then be implemented as follows:

```
for j = 1:r
    v(j:n) = [ 1
               A(j+1:n, j) ]
    C(j:n, :) = (I - beta_j v(j:n) v(j:n)^T) C(j:n, :)
end
```

(5.1.4)

This involves about $2qr(2n - r)$ flops. If Q is explicitly represented as an n -by- n matrix, $Q^T C$ would involve $2n^2q$ flops.

Of course, in some applications, it is necessary to explicitly form Q (or parts of it). Two possible algorithms for computing the Householder product matrix Q in (5.1.3) are *forward accumulation*,

```

Q = I_n
for j = 1:r
    Q = Q Q_j
end

```

and *backward accumulation*,

```

Q = I_n
for j = r: -1:1
    Q = Q_j Q
end

```

Recall that the leading $(j-1)$ -by- $(j-1)$ portion of Q_j is the identity. Thus, at the beginning of backward accumulation, Q is “mostly the identity” and it gradually becomes full as the iteration progresses. This pattern can be exploited to reduce the number of required flops. In contrast, Q is full in forward accumulation after the first step. For this reason, backward accumulation is cheaper and the strategy of choice:

```

Q = I_n
for j = r: -1:1
    v(j:n) = [ 1
               A(j+1:n, j) ]
    Q(j:n, j:n) = (I - β_j v(j:n)v(j:n)^T) Q(j:n, j:n)
end

```

(5.1.5)

This involves about $4(n^2r - nr^2 + r^3/3)$ flops.

5.1.7 A Block Representation

Suppose $Q = Q_1 \cdots Q_r$ is a product of n -by- n Householder matrices as in (5.1.3). Since each Q_j is a rank-one modification of the identity, it follows from the structure of the Householder vectors that Q is a rank- r modification of the identity and can be written in the form

$$Q = I + WY^T \quad (5.1.6)$$

where W and Y are n -by- r matrices. The key to computing the *block representation* (5.1.6) is the following lemma.

